Arabic-English Google Translation Evaluation and Arabic Sentiment Analysis

by

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Abstract

Machine translation is one of the most important tasks in the automatic processing of the natural languages, but its systems are still very far from achieving any performance close to ideal human translation due to many obstacles and difficulties. For example, grammatical rules between different languages are different, also, some words in the source language may not have an equivalent translation in the target language and this will lead to accurate translation results. Also, sentiment analysis is another application of Natural Language Processing (NLP) which is the process of identifying the feelings or sentiments held in a piece of text and classifying them into positive, negative, or neutral.

This study sets out to examine the efficiency and accuracy of Google Translate's translation between the Arabic and English languages and to evaluate the qualification of sentiment analysis when we apply it to Arabic texts. My study will also examine how old texts and texts written in dialects of Arabic affect both sentiment analysis and Google Translate's performance. So, I used Arabic songs' lyrics which differ between each other in terms of precedence and formality where they can be old or new, and formal or informal.

To evaluate the results of Google Translate in this thesis, a lexical and grammatical analysis was used and the retrieval rate of words, sentences, and meanings of the text in the source language was calculated.

In this thesis, I proposed a new approach to sentiment analysis which I conducted over five Arabic songs' lyrics. Some of the lyrics are written in informal colloquial Arabic and some in Modern Standard Arabic (MSA). I performed sentiment analysis on those lyrics to evaluate the efficiency of the Google translation by comparing the results of the sentiment analysis of Arabic lyrics and the translated versions of those lyrics.

The results of the evaluation of Google Translate showed that Google Translate has failed to achieve adequate translation, especially in old complex informal and unstructured Arabic texts. In addition, the results of applying sentiment analysis to Arabic texts showed that old and informal texts lower the performance of sentiment analysis. Also, applying English sentiment analysis to the translated version gave different results than applying Arabic opinion mining to the Arabic original version. Furthermore, Google Translate lowered the accuracy of the English sentiment analysis compared to the results I got when I applied the English sentiment analysis to my suggested translation of the lyrics.

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Chapter 1: Introduction

The Arabic language has been considered as one of the most difficult languages to process orally or by writing due to the variety in its morphological, acoustical, and synthetical features which differ from other languages like English. Research on the automated processing of written Arabic began in the 1970s and the first studies focused on Arabic vocabularies and morphology. Due to the web globalization and the increased number of means of communication in Arabic, a large number of information applications in Arabic were developed and research activities expanded to include more general areas related to the Arabic language processing, such as studying Arabic structures, automated translation, document indexing, and information retrieval.

Over the past few years, computer science and linguistics scholars have been interested in Natural Language Processing (NLP) which is the study of human beings' languages using computer algorithms. NLP is used in processing the Arabic language and it is called Arabic Natural Language Processing (ANLP) (Farghaly & Shaalan, 2009). Furthermore, NLP has many applications like Machine translation (MT), speech synthesis and recognition, sentiment analysis, sound recognition, and intelligent learning systems (Bessou, 2016). The usage of those applications helps intelligence and security agencies (Farghaly & Shaalan, 2009).

The problem is that the NLP tools that are applied in Western languages like English are difficult to apply to the Arabic language due to its specific features like varied morphological and grammatical rules. The tools that I will analyze here are machine translation (Google Translate) and sentiment analysis, especially when applied to Arabic texts, specifically, Arabic songs' lyrics that can be written in dialectic Arabic or in formal Arabic. Google Translate does not give an acceptable translation when translating old dialectic Arabic songs' lyrics into English in terms of meaning and structures. However, it gives adequate results in translating new songs' lyrics that were written in formal Arabic. In addition, if we translated those lyrics into English, the sentiment intensity in those lyrics, which means how positive or negative the text is, will change and Google Translate might even change the polarity of the text from positive to negative or vice versa. The polarity of the text means that the text can have either a positive or a negative feeling and if it does not have any, the text would be neutral. In addition, the term "polarized words" means that words that contain a sentiment whether it is positive or negative. Furthermore, applying Arabic sentiment analysis approaches to Arabic songs' lyrics gives higher sentiment intensity than the intensity we get when we apply English sentiment analysis of their translation.

This thesis aims to answer the following questions:

- How efficient and accurate is Google Translate in translating between Arabic and English languages?
- How accurate is sentiment analysis of Arabic song's lyrics?
- What are the factors that affect the performance of Google Translate and sentiment analysis when we use them on Arabic texts?

This thesis is structured as follows. Chapter one is an introduction to the thesis with a summary of my research questions and outline. Chapter two provides a background in Arabic music and its differences from Western music. Literature reviews of other academic research in MT and sentiment analysis in chapter three. Chapter four establishes the methodology used to evaluate Google translation between Arabic and English. Chapter five presents the methodology used in evaluating sentiment analysis in Arabic texts. Finally, the sixth chapter concludes my findings and suggestions for future works in MT and sentiment analysis.

I chose Arabic songs' lyrics because lyrics are poetry that is sung. Singing and chanting poetry have existed in the Arabs' lives since the seventh century BC (Adonis, 2011; Farmer, 1929). This confirms that Arabic poetry is connected to music. In addition, Arabs have been famous for poetry, and its topics can vary in style and content, such as poetry about describing love, politics, mysticism, etc. Poetry also is a pure summary of human experiences, and a source for writing down their various knowledge, and this case applies to Arabic poetry. At present, there is a prominent influence of poetry in literary, intellectual, and political life.

Currently, folk songs are common in the Arab world among broad classes of people and communities. They are often simple, and many people sing them. Also, they may not be written, the author may not be known, and they change with the development of life and the environment in which they appear, but they maintain their own style. These songs carry people's feelings and knowledge. Therefore, sentiment analysis can help to understand the feelings of poetry and the singer.

Music of these songs plays an important role in making these words closer to people, but in this dissertation, we will not talk about music, but rather the lyrics of these songs. I chose three of the most well-known Arabic songs' lyrics that Arab people love and keep singing. But before starting to analyze these songs we need to have a background in the Arabic language, its morphology, phonology, and orthography in addition to NLP and ANLP.

- **Background in the Arabic Language**

The Arabic language is the language of Arab culture, heritage, and literature. It is considered as one of the Semitic languages that preserved its grammar and linguistic history until now. Semitic languages are a group of languages spoken in north Africa and the Arabian

Peninsula and they were derived form a larger family of Afro-Asiatic languages (Wood, 2020) like Arabic and Hebrew. Furthermore, the Arabic language is the Holy Quran's language and all Muslims in the world speak it, especially Arab Muslims.

Global interest in the Arabic language began in the middle of the last century, specifically in the year 1948, at a time when UNESCO decided to adopt the Arabic language after English and French languages to become the third official UNESCO language (History of the Arabic language at UNESCO, 2017). Besides, in 1960, it was recognized that the Arabic language had an influential and prominent role in making international publications influential among people all over the world. Furthermore, in the year 1974, the first conference was held by UNESCO for the Arabic language, and because of that, the Arabic language was recognized as one of the international languages that could be used in international conferences.

The Arab countries cover an area of about 14 million km^2, and all the people there speak Arabic. So, this language is spoken on about 10.2% of the land on Earth. As we can see from Figure 1, the Arabic language is spoken by 467 million people all over the world in 2015, so it became the fourth most popular language spoken between all languages after Chinese, Hindi/ Urdu, and English.

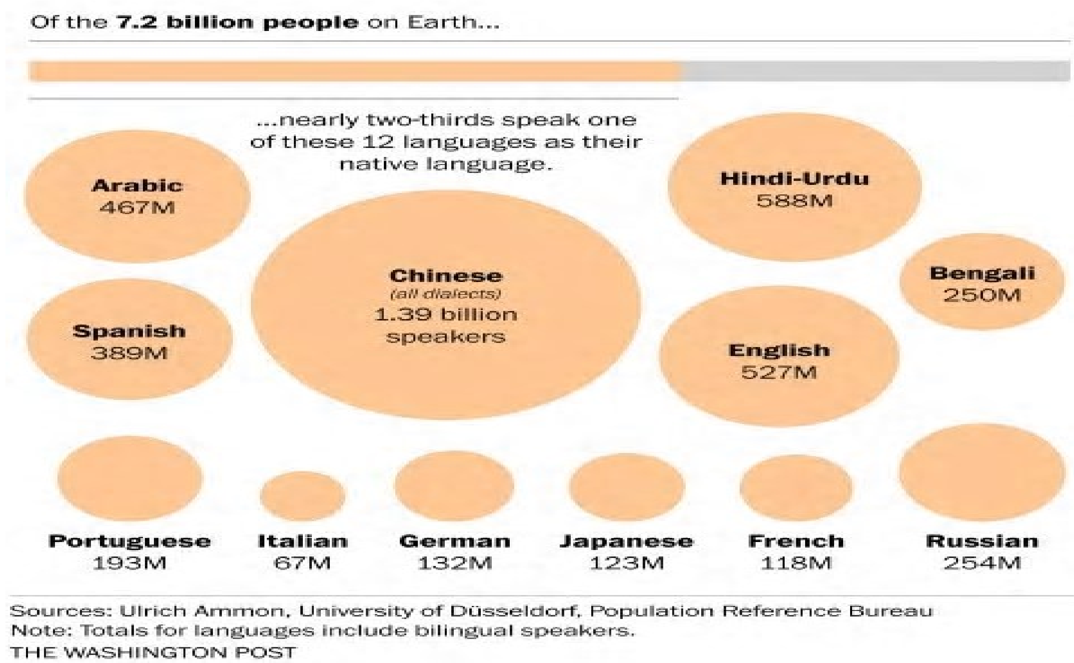

Figure 1: The world's most spoken Languages in 2015

According to Rick Noack & Lazaro Gamio (2015), there are 60 countries that speak Arabic all over the world as in the following figure.

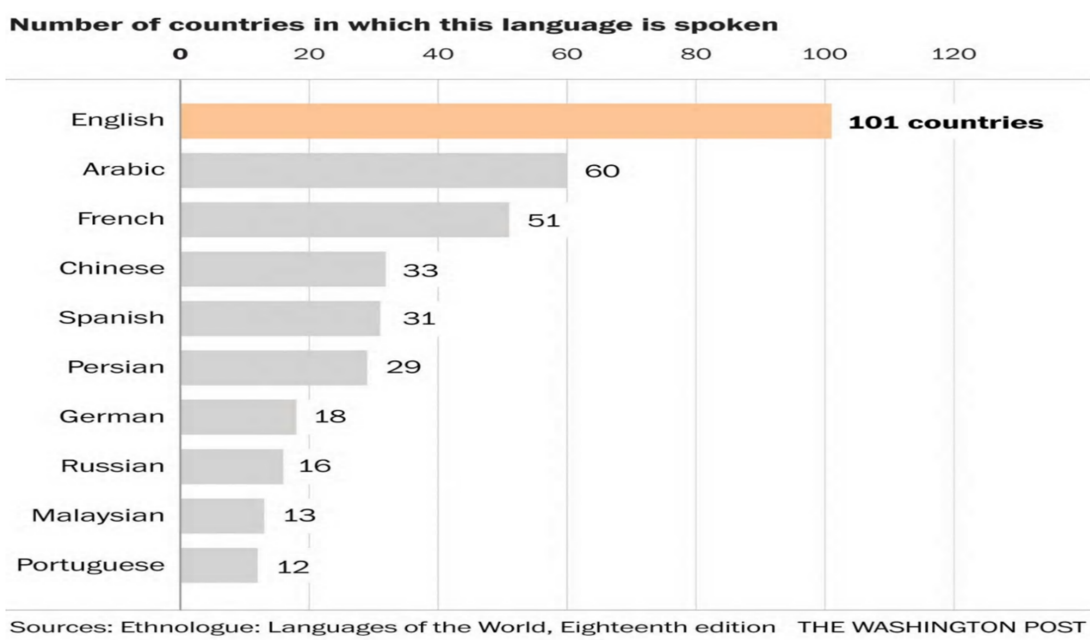

Figure 2: The number of countries in which Arabic language is spoken.

Before beginning the study of the Arabic language, a distinction must be made between standard Arabic or classical Arabic and its dialects. Modern Standard Arabic (MSA) is the official language in the Middle Eastern media, education, and government. It is a written language but not spoken, so it must be known that it is not the daily life language of any Arab native speaker. "The Arabic dialects, in contrast, are the true native language forms" (Habash, 2010). Common Arabic and dialects exist in folk songs, movies, and TV shows because it represents people's daily communication. It is spoken but not written, so it is not used in the official academic writings, but currently we can see people write it on social media such as on Facebook and Twitter. There are around 30 major Arabic dialects that differ from MSA and from each other phonologically, morphologically, and lexically (Habash, 2010). For example, people can post on social media using their dialect, and sometimes other Arab people who speak a different dialect can read the post but cannot understand it.

- **Arabic Phonology**

The term “phoneme” is any distinct unit of sound in a specific language that distinguishes one word from another. For example, in English, the element /p/ in the word “tap” represent a different phoneme from the element /g/ in the word “tag”. The study of the systems of sounds, or phonemes, in any spoken language is called “phonology”.

Recently, phonology has occupied a place in developing software for high-technology businesses, especially those in NLP fields like speech recognition which is the process of converting the speech signal into its corresponding text, and voice synthesis.

Although MSA is the official language in all Arab countries, each country has its own way of speaking it. I will show some differences in speaking MSA between Arab countries briefly with examples of that. This will clarify why it is difficult to apply speech recognition algorithms on the Arabic language.

We will divide the Arabic dialects into four types. The first is Levantine Arabic (LEV) which is the dialect spoken in Syria, Lebanon, Jordan, Palestine, and Cyprus. The second is Egyptian Arabic (EGY) which is spoken in Egypt. The third is the Gulf and Iraqi Arabic (GLF, IRQ) which is spoken in Iraq and in the Gulf countries like Saudi Arabia, Yemen, Qatar, etc. and the last one is Maghrebi Arabic which is called Darija and is spoken in Morocco, Libya, Algeria, and Tunisia.

The following are some examples of the differences in pronunciations of some letters and some words between different Arab countries:

- The letter /J/ج can be pronounced as /ˈg/ in Egypt, /y/ in the Gulf, and /J/in LEV. For example, جميل "handsome" is pronounced as/jamil/ in LEV, /'gamil/ in EGY, and /yamil/ in GLF.
- The letter /Q/ ق can be pronounced as / ˈg / in GLF and /'/ in LEV and EGY. For example, طريق "road" is pronounced as /tari'/ in LEV and /tari'g/ in Gulf.
- The letter / θ/ ث can be pronounced as / θ / in GLF and /T/ in LEV and EGY. For example, ثلاثة "three" can be pronounced as / θala θa/ in GLF and /talata/ in LEV.

Speech recognition has developed immensely since it started, but it is still not giving accurate results due to many reasons like the quality of the input voice, unwanted noises, accents, and variation of the pronunciation of the same word (Eugene P., 2020). All these examples above prove that we need more advanced speech recognition algorithms for detecting the right word in MSA which is pronounced differently between different Arabic dialects.

- **Arabic Orthography**

Orthography is the study of a language's spelling. It may contain emphasis, word breaks, capitalization, and punctuation. The Arabic language is written from right to left with 28 letters. The 28 letters contain 25 consonants and three vowels and they are /Ei/ي , /A/أ, and /Ou/و . In addition to those vowels, there are three diacritical marks and they are used as short vowels. They are /َ/ like /a/, /ِ/ like /i/, and /ُ/ like /u/. There is a great difference in the meaning of a word that has long vowels than the one which has short vowels. For example, قَتَلَ (Qatala) means to kill, and قاتَلَ (Qaatala) means to fight with someone.

Unlike English, the Arabic language does not have upper and lower cases, so it is hard for non-native speakers to distinguish names and names of places from it. Furthermore, in the Arabic language, letters can be connected to other letters from the left, right, or both sides. But there are six letters that can be connected from the right only and they are (أ، د، ذ، ر، ز،و) (Alif, Dal, Thal, Ra, Zai, and Waw). When connecting to other letters, some letters' shape does not change, but there are some letters that are hard to recognize when they are connected to other letters.

Short vowels are used above or below any Arabic letter for correct pronunciation and to give the right meaning. For example, the undiacritized word ذكر can have multiple meanings when diacritical marks are added: the word ذَكَرَ (Tha-Ka-Ra) means "Remembered", ذِكْرٌ (Thi-K-Ron) means "Mention", ذَكَرْ (Tha-Ka-R) means "Male". Nowadays, these marks are not added to any text on social media because native speakers can recognize the word within the phrase without these marks. This is considered as a limitation when processing Arabic texts computationally because the computer is not able to recognize the correct meaning without the diacritical marks.

- **Arabic Morphology**

Morphology is the study of words and how they are constructed. It studies parts of words like the root of each word and affixes such as prefixes or suffixes. It also studies how the context may change the word pronunciation or meaning in a sentence. The Arabic language has a very rich and complex morphology (Boudad et al., 2018). I will explain this idea in the next paragraph.

Derivational Morphology

In Arabic, we can generate verbs, nouns, adjectives, and other types of words from a word's root by adding some letters, and this process is called "derivation". The root should have three of four letters only, and the closest idea to a root in English is a stem in Arabic (Habash, 2010). This means the deletion of a few letters from a word to get the stem. Hence, words are created by adding some letters, which we will call a "morpheme", to the root as a prefix, a suffix or both. "Morphemes are the smallest units of meaning in a language" (Darin Flynn, 2012:6). For example, in English, the word "homelessness" can be divided into three parts: "home" + "less" + "ness". The part "home" is the root here and it is a noun. While the morpheme "less" is a suffix to convert the noun into an adjective, and "ness" is a morpheme to convert the adjective into a noun.

Arabic creates words differently in that we can add more than one morpheme as a suffix or prefix or both at the same time to the root. This morpheme can refer to pronouns, subjects, objects, adjectives, and other Part of Speech (POS). For example, the root لَزِمَ (La-Ze-Ma), which means “to commit to something”, can totally change with some suffixes and prefixes. I will analyze the word أنُلزِمكموها (A-Nol-Ze-Mo-ko-Mo-Ha) which is a word in the Holy Quran, and I will show how a phrase can be created in one word by adding some prefixes and some suffixes.

أ	ن	لزمُ	كم	وها
A	Nol	Zemo	Kom	Oha
Shall	We	Compel to	You	To accept it

Table 1: An example of one word in Arabic that creates a phrase in it

In this example, almost every letter has an indication of a verb, noun, or a pronoun. As we can see from this example, words in the Arabic language do not exist on their own or by the root only, but in shared context with other morphemes.

Words that share almost the same meaning or refer to the same topic share a portion of their letters and a portion of their sounds and this does not apply in English words. For example, in English, the words Book, Library, and Write almost refer to the same idea of writing and reading but there are no shared letters in them. While in Arabic, كَتَبَ (Kataba) means to write, مَكتَبة (Maktaba) means library, and كِتاب (Kitab) means book. In this example, all these Arabic words shared the same the letters “K”, “T”, “B” and other letters were added to indicate to another word.

In addition, the morpheme in Arabic can be one letter or more, and by adding it to the root, we have another part of speech. The words in Arabic indicate tense (Past, Present or Future), numbers (Single, Dual or Plural), persons (1^{st}, 2^{nd}, or 3^{rd}) and gender (Feminine or Masculine). For example, كَتَبَ (Kataba) means "He wrote", كَتَبَتْ (Katabat) means "She wrote", كَتَبا

(Kataba-a) means "Both of them wrote", كَتَبوا (Katabou) means "All of them wrote". As we can notice, these words share the same root letters which are “K” + “T” + “B”.

Processing Arabic dialects is considered a problem in ANLP because Arabic dialects have no standard orthographies and they do not follow any grammatical rules. Therefore, using tools and resources designed for MSA to process Arabic dialects generates considerably low performance in terms of accuracy, validity, and correctness. Boudad et al. (2018) demonstrated that earlier research concentrated only on texts written in MSA, but recent text analysis works dealt with social media posts which can be written in MSA or in any Arabic dialect. I will talk about this in the fifth chapter in this thesis and I will discuss how this limitation can be solved.

- **Background in NLP**

The term “Natural languages” is a term used to denote the prevalent human languages like Arabic, English, or French, etc. These languages are called “natural” because they were caused by natural development which means without any prior planning to establish their rules, terminology, sound synthesis, etc. For example, grammar was derived from the English language after its existence, not vice versa (Sakhar Alkhereyf, 2015). We use the term “natural languages” to distinguish those languages from constructed languages which were planned by human beings, whose rules and lingual properties were invented before the existence of the language among people. For example, programming languages like Java and Python are not considered to be natural languages.

NLP is a field of computer science, information engineering and artificial intelligence that is concerned with the interactions between computers and human (natural) languages. The main goal of it is to make the computer able to understand natural words, answer questions, translate words, summarize a specific topic, and so on. Thus, direct communication between the computer and the person is ensured in the natural human language.

NLP can be divided into three levels: lexical, syntactic, and semantic (Liddy, E. D., 2001). The lexical level, or part of speech tagging, means extracting speech sections from the text. For example, specifying whether a word type is a past or present tense verb, a name, or an adjective, etc. The classification of speech sections is one of the main things that is used in most applications of natural language processing, while syntactic parsing means looking at the sentence as a whole and then analyzing it. For example, the nonsensical phrase “The kid drew my housework” can be analyzed lexically as following: kid: noun, draw: verb, and housework: noun. Syntactically, the sentence is correct because it follows the order of Subject-Verb-Object (SVO); however, the meaning is not clear. So, in addition, we will need a context-level analysis which is called the semantic level. the semantic level, or meaning representation, means representing the desired meaning of the phrase in an easier way for the computer to understand, so the computer will be able to decide whether the meaning is correct or not. For example, the computer should decide that the previous phrase “the kid drew my housework” is wrong semantically and it should suggest some corrections such as “the kid did my housework” or “the kid drew my house”.

- **NLP importance**

There are many reasons why it is important to process natural languages. The increase in information is one of those — there are millions of documents generated every minute. In addition, that information is written in natural languages and governments, industry, academia, and individuals need this information. So, having NLP tools is very necessary.

NLP can also help in improving communication with the computer. Search methods in a regular language enable a person to communicate with a computer in French, Dutch, Arabic, or any other language. Communication with the computer in the spoken language will have a major impact on the work environment, so new and broad areas of information technology will emerge.

NLP can also help human beings communicate better, especially when using machine translation. Computer linguists built software to simplify the work of a human translator and improve productivity to a large extent. Even loose or literal machine translation provides a great help to information researchers who search for the meaning in large quantities of texts in foreign languages.

NLP helps in effective access to information too. For example, browsing, navigating, filtering, and processing information on the web require developed software to access information in documents and web pages. Thus, human language technology for content management is a necessary tool for converting the increased digital information into collective knowledge. Furthermore, multilingual content on the web is considered as an additional challenge to language processing because the World Wide Web can only be controlled with the help of multilingual tools to index and browse the web pages.

The most frequently reported application of NLP is machine translation (MT), which is considered as the oldest of all NLP applications, but still the most used one. Google Translate is the most well-known example of MT applications that can translate at both word-based scales and big document levels. In addition to MT, there are text analysis applications that include sentiment analysis or opinion mining of any text which I will analyze its performance on Arabic texts in this thesis.

However, many applications are still in the development stage and we will certainly see them in the future because of the great practical progress in the NLP field. For example, speech recognition, automatically generating texts or speech, question-answering, and automatic summarization that exceed the level of the sentences to the document level and convert the large text to a shorter richly abbreviated representation of the main document (Liddy, E. D., 2001).

- **Machine translation**

Machine Translation (MT) means using computer software to translate texts or speech from one human language to another. It is considered as one of the hardest applications in all NLP since the languages differ in the grammatical and morphological structure, and because some languages have terms or expressions that have no equivalent in the target language which is the language we translate to. For example, in the Arabic language there are three tenses of verbs (past, present, and future) while in English there are many more verb tenses like the past simple, perfect and continuous or the present simple, perfect and continuous and they do not have any equivalent in the Arabic language. All these differences make the translation process much more difficult.

In general, machine translation provides better results in governmental and legal texts that rely on formal sentences and phrases unlike more colloquial usage such as general texts and common conversations. Machine translation has succeeded in helping human translators to improve their work but in its entirety, it has not been able to overcome the human translator in this field, especially in translating dialogues and conversations. It becomes even more difficult if these conversations were in common or informal language. For example, Arabic dialects are hard to be translated because they do not follow any grammar, and English posts on social media may contain some numbers instead of letters and that will not be translated the way that formal English can be translated.

There are now nearly 1,000 automatic translation programs on the market. Although their quality is not generally good, the demand for them has increased. The Internet has increased the need for machine translation, which is also an easy way to deliver the translated material to those who need it. In contrast, Balahur et al. (2012) showed that in Natural Language Processing (NLP) tasks, there is a lack of using machine translation because of the poor quality of the translated text. That is why we need a complementarity between the work of human translators and machine translation, where human translators can help in developing MT work and take it to new horizons. In the fourth chapter, there will be more discussion about machine translation, especially Google Translate, its pros and cons, and challenges in MT.

➢ **Sentiment Analysis**

Currently, sentiment analysis is a new important discipline in the computational world. This discipline can be called opinion mining, subjectivity analysis, opinion extraction, sentiment mining or sentiment analysis. In this thesis, I will use the term sentiment analysis. This field of study is "a new research field in machine learning (ML), computational linguistics, and natural language processing (NLP)" (Shoukry et al., 2013). It has been one of the most active research areas in Natural Languages Processing (NLP) since early 2000 (Liu B, 2012). Sentiment analysis aims to explore and extract subjective information from texts written in any natural language such as people's opinions, attitudes, ideas, emotions, and sentiments in that text (Liu B, 2012).

Liu (2012) also demonstrated that this research has exceeded computer science and has spread to management and social sciences because of its importance in business and the whole society. For example, sentiment analysis can be applied in social media monitoring like analyzing tweets and Facebook posts and collecting people's opinions about specific products or social issues. In addition, sentiment analysis is important because our beliefs and choices we make depend to some degree on how others view and evaluate them. For this reason, when we need to make any decision, we often seek the opinions of others. This is true not only for individuals but also for organizations and institutions that produce a specific product and want to know how people react to it. So, sentiment analysis can be used in brand monitoring. For example, detecting people's opinions about a brand online through places like news and blogs, Twitter, and Facebook. Furthermore, opinion mining can be used in analyzing customer feedback, customer service and market research, advertising systems, public relations, financial modeling, and many others (Ding et al., 2009).

When we deal with sentiment analysis, we need to distinguish between subjective and objective sentences. Subjective sentences express emotions and feelings of the person who wrote them. For example, the sentence "the iPhone is awesome" is a positive subjective sentence (Pozzi et al., 2017). Objective sentences are fact sentences and they do not contain any emotions in them. For example, the sentence "the iPhone is a smartphone" is objective (Pozzi et al., 2017) and it does not indicate any polarity in it. So, when we apply sentiment analysis on it, the result will be neutral. Despite that, we cannot say that every objective fact sentence does not contain any opinion (Liu, 2010). For example, the sentence "more than 4 million kids died in Syria" is a negative fact sentence.

In subjective sentences, we need to determine whether the sentiment in it is explicit or implicit. It is easy to decide whether the sentiment in a sentence is explicit, while we need more work to be done to decide that the sentiment is implicit in a sentence (Pozzi et al., 2017). For example, “iPhone is awesome” is an explicit positive opinion because of the word “awesome”, while the sentence “I cannot wait to buy a new iPhone” has an implicit positive opinion.

In polarity classification, opinions can be classified into positive, negative, or neutral opinions. However, sometimes we want to be more accurate about the polarity level of opinion or to decide the intensity of the expressed feeling in the text. So, instead of just talking about positive, neutral, or negative opinions, we could consider the following categories: Very positive; Positive; Neutral; Negative and Very negative. This precise analysis is usually referred to as fine-grained sentiment analysis.

Sentiment analysis studies emotions or opinions on three levels: word or lexicon level, sentence level, and document level (Ding et al., 2008) (Al-Subaihin et al., 2011). So, with sentiment analysis, we can decide the polarity of words or sentences by themselves, or we can check if the whole document is positive, negative, or neutral, which is what I will do in this thesis.

- **Challenges in NLP**

Challenges in Natural Language Processing often include difficulties in understanding the natural language. For example, it is still difficult to match humans’ ability in speech recognition especially, with some noise in the background or when using distant microphones by using limited training data, in addition to achieving higher levels in distinguishing languages, dialects and methods of speech. Furthermore, there is another challenge in generating harmonious text or speech without errors by understanding the intended meaning.

Moreover, the meaning of any sentence may differ according to how it is divided into words. The proper lexical division depends on the semantic and syntactic properties of any phrase. This problem, to some extent, overlaps with text division of some languages that do not have breaks between words such as Chinese and Japanese and languages written in continuous letters such as Arabic, Persian, and Urdu.

In all languages, on the lexical level, some words can be interpreted in more than one way, or they have multiple meanings which can be determined by their location in the sentence or text For example, in Arabic, the word عين (Ain) can mean “eye”, “water spring” or “self”. Another example in English, the word “spring” can mean “water spring”, “to jump” or “helical metal coil that returns to its shape after pressing it”. Currently, there is an NLP application called Word Sense Disambiguation (WSD) which tries to understand the meaning of each word depending on the context and this tool is considered one solution to the words’ ambiguity problem in any language.

There is another challenge in the syntactic level where punctuation, stop, and stress on any word rather than other words can change the meaning. For example, the sentence “Students hate annoying professors” can have multiple different meanings like “Students hate (annoying professors)” and “Student hate annoying (professors)”. So, each meaning has a performative aspect that a computer cannot detect.

Another challenge can occur on the cultural level. We say that there is cultural ambiguity when a sentence has a meaning other than the true, common, and understandable meaning in the community of the native language. This will happen when these sentences are translated directly word by word, and this will make the target text seem strange. This ambiguity appears, especially when translating proverbs, wisdom, and idiomatic expressions (figures of speech). For example, the proverb “His name was on the tip of my tongue” does not mean that the name was located on the tongue, but rather, it means I have temporarily forgotten his name

As I declared above, Arabic is different from English in grammatical, lexical, synthetic, and semantic approaches. So, processing the Arabic language by a computer requires another procedure than the one used in English language processing which I will talk about later in this thesis.

Chapter 2: Introduction to Arabic Music

Middle Eastern music, or Arabic music, covers a wide range of areas, nations, and traditions. It is an independent and living music, and it has a long history of interacting with many musical styles in other regions and species. It is considered as a mixture of music by the people of the Arabian Peninsula and all people of today's Arab world. In this chapter I will talk about Arabic music, including Syrian music, and I will identify some characteristics of this distinguish music.

- **Arabic Musical Instruments**

Qanun, which means "law" in Arabic, is one of the most classical musical instruments in the Arabic music (Kemple, 2016). In addition, Oud (the Arabian short-necked lute), which dates back to several thousand years, is also considered as one of the classical Arabic instruments, despite the common claim that the Oud has its origins in ancient Egypt or Persia (Haines, 2001; Shannon, 2003; Lea, 2018; Shannon, 2006; Shannon, 2016). Rebab can be identified as an Arabic instrument too, and it was used in singing Nuba which is a North African Arabic music genre (Currey, 2002). We can add to the list above, the "Nay", the Arab violin "Kamanija", and a variety of rhythmical instruments which make sounds by using hands or sticks against the instrument such as the Darbakka that is made of metal or clay. Darbakka uses hands and fingers to hit the middle of it and produce the sound "Doom" or to hit the sides and produce the sound "Tak". Using these two sounds, the Darbakka adjusts and set up the musical piece (Alfadi Albaridi, 2015). From the 1990s, musicians started using some western instruments like the piano, accordion, and violin in their orchestral pieces ("Musical Trends in Middle Eastern Music," n.d.). In addition, the saxophone and guitar are used in the Armenian community (Saldaña, 2017).

Figure 3: Darbakka

Figure 4: Oud

- **Differences between Arabic and Western music**

Arabic music is different from the Western counterpart (Adileh, 2011; "Arabic Music Overview," n.d.; Currey, 2002; Haines, 2001; Kemple, 2016; "Musical Trends in Middle Eastern Music," n.d.; Racy, 1986; Taufiq, 2018) in terms of weights, tones, and rhythms. In addition, Arabic music is characterized by a quarter tone, which is absent from Western music. In this paragraph, I will talk about these differences in details.

Classical Arabic music is based on the Maqamat system which is like a musical scale ("Musical Trends in Middle Eastern Music," n.d.). It consists of 30 Maqamat (plural of Maqam). "The Arabic term 'Maqam' originally means 'pedestal', 'step', or simply 'location'" (Taufiq, 2018), but musically, it means a set of notes arranged in a specific way. Each "Maqam" is associated with a different psychological or emotional state, for example, the "Saba Maqam" arouses sadness and pain, and "Hijaz" recalls longing and nostalgia (Kemple, 2016). While in Western music, there is no Maqamat, but it has keys instead like A, B, C, D, etc. These keys are associated with emotions too; for example, C major is associated with innocent happiness, while C minor is associated with innocent sadness or lovesickness (Kaila, 2018).

In term of rhythms, Arabic music is richer in rhythms than Western music. Nevertheless, there are also Western rhythms that are not used in classical Arabic music but have been introduced into the Arabic music world such as tango and rumba. Sometimes rhythms are similar but appear different because of the way they are performed. For example, in Arabic music, the time units are divided into more beats than when performing Western rhythms.

In music, there are whole, half, quarter, and eighth tone which represent the duration of the tone which means knowing how long we need to hold the tone. In the whole tone, the note is held for four counts. For halftone, the note is held is two counts. In quarter tone, the tone is held for 1 count while in the eighth tone, the duration of holding is ½ count ("Arabic Music Overview," n.d.; "Musical Trends in Middle Eastern Music," n.d; Taufiq, 2018).

The term "Polyphony, such as we are accustomed to in Western orchestral music, does not exist in classical Arabic music" (Taufiq, 2018). This means that western music has more than one part or line to play and this indicated playing different notes at a different pitch, while monophony means playing music at a single vocal melody. In the next two figures, we can see that in monophony, one line of music is played while in polyphone, more than one line are played at the same time.

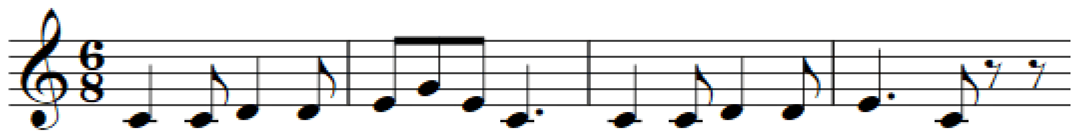

Figure 5: Monophony Music

Figure 6: Polyphony music

Because of the quarter tones, there are specific Arabic instruments that can produce these tones, so there are many differences between Western and Arabic instruments (Adileh, 2011). Western instruments cannot reproduce the quarter tones which are the core of Arabic music. However, there were some musicians who created a special piano that could play a quartertone (Taufiq, 2018).

Arabic musical instruments are well known for their specificity: for example, Qanun, lute, flute, bass, and rhythmic instruments like “Darbakka”. Those instruments are purely Arabic instruments that do not have similar Western counterparts, but that does not eliminate the existence of somewhat close Western instruments. Some of the Western instruments are a result of development of original Arabic instruments (“Arabic Music Overview,” n.d.; “Musical Trends in Middle Eastern Music,” n.d.). For example, the piano has evolved from the harpsichord which dates to the Arabic *Qanun*; the guitar evolved from the *Oud*, and there are many other examples (Haines, 2001). This development is not simple; it is a major and complex development.

In terms of classical singing, there is a great difference between Western operatic music, which is characterized by the use of fixed degrees and stable performance, and Arab singing which is full of aesthetic characteristics and “Tarab” songs which means songs that generate a state of musical and emotional enchantment experienced by their listeners. The reason for this difference can be due to the fact that classical Western singing was performed in large halls in front of kings and aristocrats, while Arabic singing was performed in small rooms or in front of a small crowd (Vitali, 2013).

In addition to all of the above, there are also many differences in music pedagogy between the Arabic and Western communities. Arabic music consists of two primary elements: “'Iqa” or rhythm, and “maqam” or mode. According to Currey (2002), “Sama’i or hearing” is the foundation of Arabic music pedagogy in Syria and other Arab countries: “Rather than teaching scales, as is the norm in the West, students of Arab music learn about modes, modulation, intonation, and techniques all through learning to play Sama'iyyat” (Currey, 2002,p. 13).

In all cases, it must be recognized that the differences I talked about here are general, but there are a lot of similar cross points between both types of music as I will show later in this chapter.

- **Influence of Arabic Music on Western Music**

During the Arab civilization in Andalusia and after the fall of this civilization, Arabic musical instruments like the Oud and guitar moved to Europe, and the melodies of these instruments also moved with them. In addition, a large population has moved to North Africa. Thus, Andalusian music had a significant impact on the music of Europe. Westerners also used some of the Arabic musical instruments that Arabs manufactured and exported to Europe commercially. For example, the lute was derived from the *Oud* and many other instruments (“Arabic Music Overview,” n.d.). This correlation can be seen in the names of some musical instruments that have entered the European language. For example, “Corno” in Italian, “cor” in

French and "horn" in English are originally named from the Arabic word "Qurn" which means horn. Because of the difficulty of the Arabic pronunciation among Europeans, there are many differences in the pronouncing the name of this instrument in the European languages (Asharman, 2005).

Also, there are some suggestions that the Western Solfège musical notation may have also had Arabic origins. "It has been argued that the Solfège syllables (do, re, mi, fa, sol, la, ti) may have been derived from the syllables of the Arabic solmization system Durr-i-Mufassal (Separated Pearls) (dal, ra, mim, fa, sad, lam)" ("Arabic Music Overview," n.d.).

The similarities between the French troubadour verses, and earlier Arabic poetry led to a theory that the troubadours were influenced by the Arabs (Haines, 2001). The troubadour tradition is an art where singers move from place to place singing their poems with their musical instruments like Arabic daff and Rababa. "According to historic sources, William VIII, the father of William IX, brought to Poitiers hundreds of Muslim Andalusian prisoners which the troubadour's form was derived from their poetry ("Arabic Music Overview," n.d). The researchers, who studied the troubadours, said that these tunes are very close to the heavy original Arab songs.

However, Arabic music stopped developing while Western music, which originated back to the East, continued to evolve steadily; hence the difference between Arabic and Western music began to be bigger, but both cultures (Arab-Islamic and Western) have remained mutually enriching.

- **Influence of Western Music on Arabic Music**

Although it is independent and lively, Arabic music has a long history of interaction with many other regional and musical styles. It is a mixture of many musical types in all countries of the Middle East ("Arabic Music Overview," n.d.). Some scholars question why Arabic music is now called this name because it is the result of influences of many nationalities on original Arabic music like ancient Greek, Persian, Kurdish, Assyrian, Turkish, Indian ("Arabic Music Overview," n.d.). The reason for calling it Arabic music is because of using the Arabic language in it and following the Maqamat system which exists only in Arabic music.

At the beginning of the 19th century, changing social conditions and an increase in the interaction with other civilizations, either by war or by trade, was another major role in the direction of society for change. Egypt is considered one of the first countries to have a direct contact with Western music, because it was under the British colonization for a long period of time which affected its music. In 1932, Egyptian composers included Western music and Western instruments, such as the violin, cello, and double bass, in their repertoire, and this was the beginning of the contemporary Arabic music that we have today (Taufiq, 2018). "The Arab world has incorporated instruments from the West, including the electric guitar, cello, double bass and oboe, and incorporated influences from jazz and other foreign musical styles" ("Arabic Music Overview," n.d.). Mohamad Abd-Alwahab, an Egyptian composer and singer, was one of the first people who added Western instruments in their music, for example, the electrical guitar in the song "Enta Omri" ("You Are My Life") in 1963.

Many music genres appeared in the Arabic music such as pop, jazz, and R&B. Early Arabic Rap also began to arise ("Musical Trends in Middle Eastern Music," n.d.). During the 1950s and the 1960s, some singers like the Egyptian *Dalida* started using Western tones in their music resulting the emergence of Arabic pop music by 1970s which consists of Western music with Arabic instruments and lyrics (“Arabic Music Overview,” n.d). Additionally, jazz music started when saxophone music was added to the Arabic music (“Arabic Music Overview,” n.d).

It is not only Egypt which has experienced Western culture and music, but also Beirut’s exposure to the West, which was long and extensive. After the First World War, Beirut was increasingly interested in Western instruments and musical genres derived from the West (Racy, 1986). Ziad Al-Rahbani, Fairouz’s son, who had been in Beirut, was one of the first composers who added saxophone to his Lebanese music which has enriched Arabic jazz music (“Arabic Music Overview,” n.d.).

- **Muwashahat and religious music (Whirling Dervish) Mawlawiyya**

The Muwashah is a modern lyrical art or rather it is "the art of poetry". According to Currey (2002), Muwashah is a traditional song genre in which poetry is set to music. It is generally from an Andalusian origin and it is a powerful sonic metaphor for the Arab past (Shannon, 2016). Most well-known Muwashahat (plural of Muwashah) are originally Andalusian, Aleppine (Shannon, 2006), or Egyptian. Many, if not almost all, of Syrian songs which were composed in Levant or Egypt, are called Andalusian Muwashahat, even though they were not composed in Al-Andalus or during the medieval period of Al-Andalus (Shannon, 2016).

The Muwashahat can be "sacred" or "mundane", or even we can say they are between sacred and folklore music (Shannon, 2003). Muwashahat do not belong to a specific religion, but, rather, Muwashahat can be sung by a Jewish, a Muslim, or a Christian singer (“Arabic Music Overview,” n.d.; Saldaña, 2017). Sometimes Islamic Muwashahat can be accompanied by the Whirling Dervishes like in Aleppo and those are used to express a sense of Tarab or spiritual ecstasy (Currey, 2002). Finally, Muwashah still exists today, but it lacks some traditional components, such as poetic structure and traditional instruments which is the core of the Muwashahat, so it is considered as a dying art (“Musical Trends in Middle Eastern Music,” n.d.).

- **Turko-Arab influence (Samaai)**

Turkey may have taken a lot from Arabic music in the past, more than it gave back. But since the middle of the last century, it evolved far more than the Arab music, and Arab composers have begun to take their music from Turkish composers such as Ismail Muzaffar, Salama Shahin and Khalil Cardoman. The overlap of geography and the Ottoman Empire played an important role in this musical exchange.

Arab used Turkish or Persian modes names, but this does not mean that the musical modes are Persian or Turkish: “For example, many of the names of the modes are merely ordinal numeral prefixes, such as the Persian yakah, dukah, sıkah, and jaharkah, which mean ‘first’, ‘second’, ‘third’ and ‘fourth’ respectively” (Shannon, 2006, p. 94).

Sama’i is a musical Turko-Arab instrumental genre (Currey, 2002). It is a composition of rhythms played at the beginning of the Arabic musical piece to help the singer to memorize the Maqam of the song, but currently it can be played as a separate musical piece. If the rhythms are 10/8, the type of Sama’i is called *Sama’i Thaqil,* while it is called *Sama’i Darij* if it has 6/8 rhythms pattern (sometimes it can be 5/8 or 7/8). Teaching this genre is the basis of all Arabic musical pedagogy which is different from Western music teaching. This genre dates to the Ottoman era and is practiced in the Mashriq region or currently known as the Middle East. This instrumental genre's composers are Armenians, Turks, and Arabs.

As a result of the long presence of Turkey in the Mashriq area, people in Syria and Egypt followed the Turkish musical style (Taufiq, 2018). For example, Sayyed Darwish, an Egyptian musician, inserted Turkish music in his music starting in the 1920s, but he did not use any Turkish words in his songs (Taufiq, 2018). “The Turks introduced European style Military bands to the region in the 1800s and many musicians began learning to play European style music and instruments to appeal to their colonial ruling classes” (“Musical Trends in Middle Eastern Music,” n.d.).

There are great tunes of Ottoman heritage, which are combinations of Arabic and Turkish music. During the reign of the Ottoman Empire (1293-1922), Arabic music was highly influenced by Turkish musical styles, especially, the Turkish pop genre (“Musical Trends in Middle Eastern Music,” n.d.).

Most of the greatest Turkish composers belonged to Mawlawiyya, or Sufism, such as Mercan Dede who incorporated Sufism in his music (Michele Rousseau, 2013). The Sufi melody is considered one of the most valuable melodies of Turkish music. Sufi singers used to sing religious songs to glorify the Prophet Muhammad using their simple instruments such as flute and daff, which is a rhythmic instrument that needs hands to hit it to produce the sound. Sometimes, Whirling Dervishes sing without a musical rhythm, but they all sing using one specific maqam. Sufi musicians are in the south of Turkey as well as Europe (Saldaña, 2017).

There are a lot of similarities between Turkish and Arabic Maqamat like the syntax and names. Dealing with Maqamat, however, is different between Turkish and Arabic music. For example, Turkish musicians play *Saba, Hijaaz* or any other Maqam with high notes or major keys, while in Arabic music, Maqamat are played with lower notes.

- **The Arabic Maqamat**

Classical Arabic Maqam (Plural is Maqamat) is built around a series of modes in which a cascade of musical notes according to certain dimensions and rules are set in order to classify the musical piece. We can say that Maqamat are “the arrangement in different combinatory sequences of the small and smallest melodic elements” (“Arabic Music Overview” n.d.). To simplify the Maqamat idea, we can say that the maqam is considered the pitch of an Arabic scale which is like the two modes of flat and sharp in European music (Taufiq, 2018). There are around 30 Maqamat in Arabic music and it can be played with some improvisations (Kemple, 2016).

What completely distinguishes the Maqam from its European counterparts is that the musician has complete freedom from the rhythm, and they can introduce variations to their music (Taufiq, 2018). The maqam depends on solo improvisation (Kemple, 2016). In addition, they can be performed with instrumental or vocal music, and they do not contain a rhythmic component (“Arabic Music Overview” n.d.).

Dealing with Arabic music, along with its components such as the arts of Maqamat, rhythms, and models that embody its identity is very sophisticated (Adileh, 2011). Teaching Maqamat can be done only by hearing it (“Arabic Music Overview” n.d.), which is like the Sama’i teaching. This is the only way to learn the Maqamat because there is no specific pattern of musical notes to memorize them. So, it requires practice for your ears to learn and memorize them. The same idea with colors: you know the color is red because your eyes know it and recognize it. So, in any song, after you learn those Maqamat, you can recognize the maqam of each song.

- **Tarab**

Tarab is a state of emotional and sensual interaction which is sought by the singer and the musician. For example, the singer or the musician seeks to use long crescendos to feel the Tarab himself before the recipient and thus the ecstasy will be felt by the listeners.

Tarab is a complex concept in Arabic music and there is no agreed-upon definition for it (Kemple, 2016; Saldaña, 2017). "There is no direct translation, but if you've ever felt swept away by the music you're listening to, then you've experienced Tarab" (Kemple, 2016, p.46). Some authors define it as enchantment or entertainment (Racy, 1986). To reach to the Tarab state, the singer should have a wide variety of qualities and competencies, in addition to using the Maqamat ("Musical Trends in Middle Eastern Music," n.d.). There is an expression to define the Tarab state in the Middle East, and it is called "Msaltin". The word "Msaltin", "enchanted", or feeling the ecstasy by listening to Arabic music, "describes a musician who develops a mental-musical state ideal for performing, particularly improvising, in a certain maqam (melodic mode)" (Racy, 1986, p. 423).

To feel Tarab, one might need to have two aspects: "realization (Idrak), which is mental, and emotions (Awatif) or spirit (Ruh), which is emotional" (Shannon, 2006, p, 98). Shannon also focused on an important idea, which is that familiar local music might not cause Tarab. For example, some people get bored with some familiar music after a little time of listening to it (Shannon, 2006).

We can say that the sense of Tarab can be defined as a spiritual ecstasy (Currey, 2002; Petzinger, 2016; Saldaña, 2017). "Sometimes *Tarab* can transport the entire audience" (Taufiq, 2018). It is a magical feeling that takes you beyond your conscious brain; sometimes people cannot stop applauding and shouting when they feel enchanted by music or cry for love (Taufiq, 2018).

However, Tarab is a dying art in modern music in the Middle East because of Western musical influences on Arabic music ("Musical Trends in Middle Eastern Music," n.d.). In addition, Arab youth prefer listening to fast Western music rather than listening to slow traditional Arabic songs or traditional Muwashahat.

- **Arabic Singers**

Some critics and historians in Arabic music consider that Umm Kulthum (1904-1975), Muhammad Abd Al-Wahab (1902-1991), and some other singers during that period of time are not Arab singers, because their music is not authentic. Because their music contains derivations from Western music, especially Turkish, they are sometimes called Turkish singers (Shannon, 2006). However, as I mentioned above, although Arabic music is a result of the influences of many nationalities on the original Arabic music, it is still considered "Arabic" music. Likewise, Arab singers cannot be considered Turkish just because they incorporate some derivatives from Turkish music. In this section, I will talk about some important Arab singers in Arabic musical history.

There are many important famous Arab singers in the Arab world and internationally such as Umm Kulthum who is still the most famous female Arab singer so far even though she died 45 years ago. Because of the strength of her voice, she could sing as low as the 2nd octave and as high as eighth octave at her vocal peak (Nur, 2015). Muhammad Abd Al-Wahab is also an Egyptian singer and composer and he was the first composer who added the Western guitar to his ensemble. He stopped singing when he was 60 years old because his voice has changed and was not as before anymore. So, the Egyptian president at that time, Jamal Abdol Naser, convinced him to compose some songs for Umm Kulthum, and the “Anta Omri” song was their first musical cooperation in 1964, and it is still one of the most well-known songs in the Arab world. Farid Al-Atrash, is a Syrian-Egyptian singer and he is the most famous composer who created a new genre of Arabic music which is based on improvisation called Taqsim (Currey, 2002). Fairouz is the most famous Lebanese singer, especially well known for her patriotic songs which were for countries not for their leaders.

Music is a good way to discuss complex aspects of history and identity. Arabic music has been, and it will remain, an influential music in other civilizations. Its distinction from other types of music does not prevent other cultures from influencing it and being derived from it. Arabic singers and musicians are international because currently, the media helps in distributing Arabic music all over the world. Over the years, Arabic music has changed so much, but it still has a lot of authenticity in it. Singing the Muwashahat and the Tarab songs is still required when judging the good Arab singers.

Chapter 3: Literature Review

The previous chapter demonstrated different concepts in Arabic music and the differences between Arabic and Western music. This section provides a more focused overview of the two applications of NLP that I use — Machine Translation and Sentiment Analysis — and their efficiency and accuracy when dealing with Arabic texts. Also, this chapter highlights the current Arab and international research and projects that have been completed in academia in the field of MT and sentiment analysis and it illustrates gaps in that research.

Natural Language Processing has made great progress in many countries in the world. However, processing the Arabic language is still limited due to its complexity and the lack of resources such as financial support, researchers, and previous projects. We see many mistakes in the machine translation of Arabic texts, as well as in the sentiment analysis of these texts. In this chapter, I will talk about these errors and discuss ways to solve them.

- **NLP Applications Accuracy in Arabic Language**

The Arabic language is one of the languages that took advantage of NLP applications and entered the computational linguistics field — for example, machine translation, sentiment analysis, diacritic generator, spelling and grammatical checker, and sound recognition.

The most accurate NLP applications on Arabic texts are the spelling and grammatical checker and the automated diacritic generator (Othman & Abu Bakr, n. d.). The first application aims to check spelling and grammar correctness according to some rules that were set by Arab linguists and not according to stored data in the databases (Othman & Abu Bakr, n. d.). However, it depends on the saved lexicon rather than a morphological or grammatical analyst.

Furthermore, there is a lack of computer linguistic experience in this application. Both of those problems are the reasons why some words or sentences can be linguistically wrong, and the spelling checker cannot indicate that.

The second application aims to generate diacritics on the last letter in words according to stored rules of diacritics positioning (Othman & Abu Bakr, n. d.). However, its results are still not accurate due to the lack of using a grammar analysis software.

Most of the NLP applications that I referred to above have not yet reached the required level in the Arabic language. However, the two mentioned applications helped in improving Arabic grammatical and syntactic self-learning and their databases are still improving (Othman & Abu Bakr, n. d.).

- **Introduction to MT and Google Translate**

There are now about 1,000 machine translation programs (Shoeeb, 2015) in the market. Although their quality is not generally good, the demand for them is very high. Furthermore, the Internet has increased the need for machine translation, which is also an easy way to deliver the translated material to those who need it.

Machine translation (MT) means using a computer to translate written texts or speeches from one language into another (Puchała-Ladzińska, 2016) and it is considered one of the most well-known and important applications of NLP (Puchała-Ladzińska, 2016). However, machine translation results are not as good as human translation. For example, MT cannot understand the idiomatic expressions that people use in communicating with each other (Puchała-Ladzińska, 2016).

Google was established in September 1998 with the aim to provide search services on website pages in the English language and then it started to provide other services such as email, e-books, news, maps, pictures, and statistical machine translation which is now called Google Translate. Google Translate can translate texts, entire websites, or even full documents (Puchała-Ladzińska, 2016). It is also one of the most widely used translation services because it is a free web-based service that translates around 100 languages. Google also released a free smartphone app called Google Translate (Groves & Mundt, 2015). According to Puchała-Ladzińska (2016), Google Translate was used by more than 200 million people daily in 2013.

Google translate is a human interactive MT application (Fatima. M, 2015; Groves & Mundt, 2015) and it allows its users to correct the output translation and this correction will be added to the system databases (Ferrell, n.d.; Groves & Mundt, 2015). With each edit, Google Translate updates its databases with users' suggestions of new lexicons, phrases, and expressions (Puchała-Ladzińska, 2016). However, because of the interactive nature of the Google translation process, it is impossible to set one correct translation for any giving phrase (Alyasin & Al-Khalil, 2018).

Google Translate started to use statistics-based translation in 2007 (Puchała-Ladzińska, 2016). Statistics-based translation system means that "the system calculates probabilities of various translations of a phrase being correct, rather than aiming for word-for-word translation" (Groves & Mundt, 2015; Ferrell, n.d.). This means in each translation process, Google Translate chooses the highest probability option of translation (Ferrell, n. d.). It learns by correlating more words together (Groves & Mundt, 2015; Puchała-Ladzińska, 2016) and then choosing the highest probability word (Ferrell, n. d.). Because of the immense amount of data that Google Translate has in its databases, it can produce adequate translations (Bellos, 2012). However, the translation between the source and the target language depends on the translation attempts before the current translation process (Bellos, 2012; Puchała-Ladzińska, 2016). This explains why the larger training set we have, the better the translation accuracy we get (Ferrell, n.d.). With less known languages and fewer translation attempts, the results will be less accurate (Puchała-Ladzińska, 2016) because there was no equivalence between the original text and the translated text (Ferrell, n.d.). In this case when there are no equivalent translation choices, Google Translate uses a word-for-word translation method (Ferrell, n.d.).

- **Machine translation:**

➢ **Current state-of-the-art in Machine translation**

To evaluate any automated translation tool's performance, we measure how close its translation is to human translation (Papineni et al. 2002). With all the improvements that machine translation is having, human translation is still more accurate (Groves & Mundt, 2015; Puchała-Ladzińska, 2016). But the best performance we can get is in combining automated translation with human help where after using MT, the result is given to a human translator to review and correct in addition to adding expressions and syntactical formations (Shoeeb, 2015).

Fatima (2015) showed that machine translation has three types: first: machine translation with post-editing which means a human translator edits the translation. Second: machine translation with pre-editing where the user simplifies complex phrases for the automated translation system to be able to understand it. And the third is the interactive translation where the translation is conducted on the test phrase by phrase and the user might ask the translation system about some words.

Nour Al-Deen and Yasin (2015) demonstrated that MT systems are divided into two systems according to their methodology and they are: first: Rule-Base Machine Translation (RBMT) which works to produce a translation and apply syntactical and morphological rules on the target texts. And the second is Corpus-Based Machine Translation (CBMT) which uses databases for texts with their translation to use them on new texts' translation. The statistical-based translation method is considered a part of it CBMT.

- **Big debates in Machine translation**

According to Kozłowski (2002), translating a text from one language into another is difficult to be fully automated. The quality of translation depends on the similarity morphologically and in grammar between languages (Puchała-Ladzińska, 2016) and the short geographical distance between countries. For example, it is easier to translate between Indo-European languages than translating between two far languages geographically like English and Arabic.

Another debate about online translation is whether it is confidential or not. When you use the online translation, the Non-Disclosure Agreement (NDA) is signed to keep your information from being shared or used (Thames, 2019). However, most translation websites have certain rights to analyze and publish your text and the result of the translation (Thames, 2019). According to Ferrell (n. d.), confidentiality is a major issue in online translation. For example, with each typed information, Google has a right to save it in its servers to improve the translation. So, this could be an ethical problem (Sheppard, 2011), especially when entering some confidential information like a company or patient information (Sian Jones, 2020).

Another important issue with machine translation is what is called “plagiarism translation detection”. The main idea of plagiarism detection software is to divide the text into smaller parts and make a comparison between these parts and the texts in the databases of the plagiarism detection software. Thus, if the same structure is present, it will be plagiarized (Ferrell, n. d.). It is considered plagiarism even if the sentence's structure got changed but the idea is the same without mentioning the author. Plagiarism translation means translating a text, whether it is academic or not, between two different languages without citations or credits for the original author (Ferrell, n. d.). Ferrell (n. d.) showed an example of this where it is considered plagiarism in translating a Russian text into English without mentioning the Russian author. One of the reasons for this problem is that languages may differ from each other in terms of grammatical structures (Bailey, 2011). So, the plagiarism software will not be able to detect it because it is not trained to identify plagiarism in translated academic texts. Currently, there are some trials to build plagiarism detection software that include more resources to find matches that have been plagiarized (Deep, 2014).

Idiom translation is hard for human translators even if they know the meaning of the words separately and it is even harder for automated translation systems. Machine translation is not able to detect human idiomatic expressions (Puchała-Ladzińska, 2016) and this could give a wrong translation (Ferrell, n. d.). This problem can be considered as cultural ambiguity which means when translating a common and well-known phrase or expression in the source language to any target language, the meaning will be different (Noor Al-Deen & Yasin, 2019) and it exists when translating proverbs and poetry from one language to another. To solve this problem, we need to identify the idiomatic expression first (Gaule & Josan, 2012), and then we need to enrich the databases of idiomatic expressions that the computer will use to translate between languages (Fatima, M., 2015). These databases are called "terminology banks" which work as a dictionary of terms in different areas of knowledge and help to find the most appropriate translation when needed (Fatima, M., 2015).

- **Google Translate efficiency in academic fields**

In academic fields, Google Translate is used to give an introductory draft (Ferrell, n.d.) but it does not help students to put their writings in an acceptable order academically (Groves & Mundt, 2015). Google Translate's results are far from achieving language proficiency (Groves & Mundt, 2015) because it works in "shallow literacy, not deep literacy" (Davies, 2007). So, proofreading is needed to be done after the translation to be accepted by the discourse community. However, in Ferrell's (n. d.) study, he showed that Google Translate was able to produce an accurate academically accepted translation, but the consistency of this quality in Google translation was a problem.

Word processing programs and applications make sure the spelling and the format are accurate because they have a spelling checker and auto-correcting features. Machine translation tools tend to have these features also because it is vital to produce a correctly-spelled text that we do not need to correct in a word processor later (Ferrell, n. d.). Google Translate is a great example of this as it allows people to check their writings and suggests corrections if there are any spelling errors. In machine translation, the results may contain poor syntax or vocabularies, and this will lead to giving another meaning and academically unacceptable text (Michaela Panter, n.d.). So, a writer can use MT to support his writings but not to achieve adequate professional academic writing (Scherf, 1992).

MT tools can produce some academically unacceptable mistakes that may affect the readability of the text. For example, we might get an incorrect order of phrases or words, word-for-word translation instead of context-dependent translation (Michaela Panter, n.d.), wrong word choices, or missing words (Groves & Mundt, 2015).

In translation, it is possible to get better and more accurate results when we are translating between two languages that have a long history of academic text translation like English and French rather than translation between languages that do not have much previous academic text translation attempts (Groves & Mundt, 2015).

According to Ferrell (n. d.), the community of English for Academic Purposes (EAP) is trying to find new techniques in translation that help to improve and assist academic writing, especially for international students and he stated that “However, it is easier said than done”.

- **Google Translate efficiency with texts from different eras**

The translation of old texts throughout the ages is a complicated issue, and in some cases a real dilemma, especially if the texts are very ancient (Al-Sonati, 2013). Google Translate is a helpful and suitable tool to translate simple sentences, but in terms of literary old texts, it does not always give an accurate translation (Chloe Gilholy, 2017). Chloe Gilholy (2017) tested Google Translate’s efficiency in translating Shakespeare texts and it did not leave a hint of the original text and the whole polished style of Shakespeare texts in the whole scenes got lost in Google translation.

Harmon (2016) proved that Google Translate cannot translate the holy Bible verses accurately. She also demonstrated that the Holy Bible has 611000 words in the original language, but to translate it using the statistical method, we might need millions of words. This is true because the words of the Holy Bible are old and difficult to translate from Hebrew into English. So, with more translation attempt, more words can be added to the Google Translate’s servers. In addition, there are translated versions of it in all languages and that was done by religious and linguistic people, so people usually go back to those translations before trying to translate it using MT programs. This will lead to lower the number of the Holy Bible translating attempts that, in turn, will result in not adding more translation results of its words to the Google Translate's databases.

Google Translate cannot differentiate between poetry and other types of documents (Harmon, 2016). So, it is complex and difficult for Google Translate to achieve a suitable translation for old texts that contain old expressions, words, and difficult meanings.

- **Google Translate efficiency between Arabic and English**

Machine translation from and to the Arabic language is growing slowly compared to what it achieves with other languages like English, Hebrew, and German (Shoeeb, 2015). To translate between two languages, we need to make sure that the results follow the syntactic rules of the target language (Shoeeb, 2015). Shoeeb (2015) also demonstrates that the Arabic language is a highly sensitive language to the syntactic rules. For example, verbs change according to the subjects they are correlated to in terms of being plural, singular, feminine, or masculine while verbs in English can change according to the tense whether it is past of present or if the subject is plural or singular.

Google Translate's results are still poor compared to professional human translators (Jabak, n. d.). Al-Dabbagh (2010) conducted a survey to evaluate Google translation between Arabic and English, where 100 participants assessed the accuracy of four different translated texts from English to Arabic by Google Translate. She found that Google Translate failed to give the idea of the original text where most of the participants found the Arabic results need extra translating and editing efforts to give the main idea of the English-source texts. She also carried out another study in 2013 to evaluate Google translation performance between English and

Arabic in the fields of journalism, economics, science, and technology. The findings were that Google Translate failed to translate between the two languages and produced lexical and grammatical errors regardless of the domain the original text was in. Two reasons for those mistakes are the different word order (Al-Qudsi et al., 2012) and different grammar (Kaltenbacher, 2000) between English and Arabic languages which can produce many errors. Another reason for those errors is that Google adds and deletes words in the results when there are no equivalent words in the original text (Izwaini, 2006).

Grove & Mundt (2015) conducted a study to compare Google Translate's performance between English and Malay and performance between English and Chinese and they showed that there were no spelling errors in addition to the correct use of prepositions and pronouns. However, we cannot rely on Google translation between Arabic and English because of the lexical and syntactic errors in addition to the lack of equivalence between idiomatic expressions in the Arabic and English languages due to the linguistical and cultural difference between them (Al-Yasin, 2018, Catford, 1978; Jabak, n. d.).

- **Google Translate accuracy in translating Arabic texts**

The lexical gap is another problem of translation between two languages and it happens when there are no equivalent words in the target language to the words in the original language. When lexical gaps happen between Arabic and English, Google Translate tends to rewrite the original word with the target language letters or delete it which will affect the accuracy of the translation (Fatima, 2015). Google Translate needs to acknowledge that it did not have an answer (Jabak, n. d.). In addition, linguistic ambiguity happens when there are words with multiple meanings in the source language. If this happened while Google is translating between Arabic and English, there will be a loss in the text's syntax and connotation (Fatima, 2015).

As I mentioned above, Google Translate uses the statistical method and produces the highest probability option, but it may not be the most accurate choice (Ferrell, n. d.). In addition, the larger size of the databases of equivalent words between two languages, the more accurate results we can get (Puchała-Ladzińska, 2016). So, performing more translations between Arabic and English will improve later Google translation attempts.

Furthermore, we can get more accurate translations when we translate between two languages that are close geographically and grammatically and morphologically (Puchała-Ladzińska, 2016). So, in Arabic and English, due to the long geographical distance between countries that speak both languages and differences in building words and grammar, the accuracy of translation is a big problem. So, Google Translate produces insufficient, inaccurate, and ineffective results when translating between Arabic and English (Jabak, n. d.).

- **Google translate efficiency in translating Arabic poetry**

Before I analyze Google Translate's performance, I will show some limitations of Google translation (Ferrell, n. d.). For example, it is hard for Google Translate to give accurate results when translating specialized topic texts (Ferrell, n. d.). Translating literary and poetic texts is even harder than scientific and legal texts because we need to translate the feeling and the meaning of the poems and not its apparent form (Al-Sonati, 2013) and because literature reflects the cultures and moral values shared by the linguistic group in which it originated (Fatima, 2015).

Fatima (2015) studied Google Translate's efficiency in translating Arabic scientific texts, holy Quran verses, and Arabic proverbs. She found that Google Translate's highest retrieval rate was in the scientific text in terms of vocabularies, structures, and meanings followed by proverbs and Quranic verses. These results are expected because the religious expressions accept one translation agreed by religion and translation specialists in addition to the cultural meanings of the words of the proverb which are correlated to the context. This suggests that it is harder to translate literary texts as compared to scientific texts.

Arabic poetry has a specific vertical form where, in the same line, we can find two verses and they complete one idea. Also, Arabic poetry has a lot of metaphors and idiomatic expressions which make it hard to understand the verses. Google Translate failed to translate Arabic poetry as it was unable to understand its vertical form and the organized order of words according to poetic rules (Fatima, 2015). In addition, the Google Translate system used literal translation which loses the connotation of the poems in the translation process and leads to wrong semantical interpretations (Fatima, 2015; Ferrell, n. d.).

Many researchers showed the importance of the context and the connotations of poems during the translation process and some demonstrated that poetry translation is an impossible mission (Fatima, 2015). This applies to all poetry translation all over the world not just the Arabic poems.

Poetry is a culture-specific concept like beliefs and types of food and that means that it may contain abstract words known only in the source language and unknown in the target language (Al-Yasin, 2018). This is considered a big problem, especially when we cannot find any equivalent lexicon for poetic words in the target language (Al-Yasin, 2018). So, MT systems cannot always produce an accurate English translation of Arabic proverbs considering the socio-cultural concepts in Arabic proverbs, and this is what Hadla et al (2014) found in their study.

- **Old Arabic texts and Google Translate accuracy**

Fatima (2015) conducted a study to evaluate Google Translate performance in translating pre-Islamic, Islamic, and modern poems and scientific texts to see how old text can affect the efficiency of Google translation. She translated those poems into English and then back into Arabic. She found that Google Translate could not retrieve the meanings of the pre-Islamic poem verses because Google Translate did not understand the meaning of those verses. For Islamic poems, Google Translate retrieved 25% of the verses' meanings, while in modern poems it retrieved 62% of the meanings. This shows that old texts with old complex and difficult to translate words negatively affect Google's translation accuracy. This also shows that the more accurate results and most of the current translation attempts are in translating Modern Standard Arabic (MSA) texts, not old formal Arabic texts. So, to improve old texts' translations we need to increase the number of attempts to translate them by Google Translate.

- **Texts in Dialects of Arabic and Google Translate**

Google Translate proved it can work better with formally structured texts than with unstructured texts (Puchała-Ladzińska, 2016). Texts in dialect are a type of informal unstructured texts and they are great to communicate with in the native language, but they are hard to be translated into other languages (*Translating Slang Terms and Colloquialisms*, 2013). In terms of slang texts or swear words, Google Translate tends to find similar meaning in the output language and this is called stylistic compensation (*Translating Slang Terms and Colloquialisms*, 2013).

Google Translate might be used to translate social media posts for non-native speakers. Those posts may contain abbreviations that are used by native people and informal communications. Often, Google Translate's system does not know them, so the translation accuracy is doubtful in these cases. For example, Google will not translate "BRB" to be "Be Right Back". However, previous translation attempts for some abbreviations will be added to the Google Translate databases and this will enable Google to translate them. For example, Google can translate "ASAP" to be "As Soon As Possible".

Translating Arabic colloquial texts or expressions is important, especially in subtitling Arabic movies. The translation of texts in Arabic dialects depends on a good understanding of the text and being aware of the context of the situation (Al-Kharabsheh & Yassin, 2017). For example, ربك حميد ما متنا, means "thank god we did not die" where the colloquial phrase ربك حميد means "thank god", but with the literal translation of Google means "The Lord is benign" which does not make sense (Al-Kharabsheh & Yassin, 2017).

Google Translate should translate everything and should not delete or change colloquial words to give the right meaning, especially in movie subtitling because any wrong translation of the words in the movie, the meaning or the context will be different. To solve this problem, we need to create a database for idiomatic-colloquialism in the source language and their equivalents in the target language (Al-Kharabsheh & Yassin, 2017).

➢ **Arabic-English Google Translate errors**

The expected errors in Google translation range from syntactic errors (Kaltenbacher, 2000) to stylistic errors (Jabak, n. d.; Sheppard, 2011). Groves & Mundt (2015) and Kirchhoff et al. (2011) found that most of Google Translate's errors were about word choices, morphological errors, and missing words. Also, Al-Dabbagh (2010) proved that those errors happen regardless the text type or domain.

Prepositions are a problem in translating from Arabic to English (Farghaly, 2010). For example, the phrase قرأت كتاب لشكسبير can be translated to "I read a book to Shakespeare" while it means "I read a book of Shakespeare's". In addition, there is a pronoun identification problem to decide which pronoun belongs to which entity, especially in long sentences (Shoeeb, 2015). So, to get a better translation, a Google Translate's user is responsible for simplifying complex, long sentences.

- **Sentiment analysis:**

➢ **Current state-of-the-art in sentiment analysis**

Sentiment Analysis (SA) is a new discipline that analyzes emotions and opinions in a text and many researchers study it (Al-Subaihin et al., 2011; Balahur & Turchi, 2012; Dashtipour et al., 2016; El-Beltagy et al., 2016). The initial reason to study it was to detect product features that people are talking about and whether their comments are positive or negative (Ding et al., 2008). We can consider the opinion mining to be correlated to information retrieval (IR) (Westerski, n.d.). According to Pang & Lee (2008), it has "subtasks such as subjectivity detection, polarity classification, review summarization, humor detection, emotion classification, sentiment transfer”. So, SA needs more steps than IR to analyze sentences and to detect whether they are positive, negative, or neutral (Westerski, n.d.).

Sentiment analysis can be done at word or aspect level, sentence level, or document level (Boudad et al., 2018). At document-level, we analyze the entire documents to see whether they are positive or negative — with one condition: that the document is talking about one object or entity and not comparing between multiple entities (Boudad et al., 2018). While at sentence-level, SA classifies the polarity of any sentence and it can work with comparative sentences of two or more objects (Boudad et al., 2018). At aspect-level, we are dealing with the words in a sentence to detect several things. We can detect, for example: (1) the object or the entity (for example “iphone6”); (2) the *aspect*, which is a feature in the entity like “battery life”; (3) sentiment orientation (whether the opinion about an entity or its features is positive, negative, or neutral; (4) the opinion holder or the person who is expressing his/her opinion (for example, “Sam said that the battery life is long in Iphone6 while Alex said that the camera quality is great in Iphone11”) ; and (5) the time in which the opinion was expressed (Boudad et al., 2018).

Most of the techniques that are used in sentiment analysis use opinion words (opinion lexicons) which consist of a list of positive words and a list of negative words (Ding et al., 2008). This method counts the number of positive and negative words in a text and if the number of positive words is higher than the negative words, then the text will be considered positive or else negative (Ding et al., 2008). It is a simple and good technique, but it has some limitations because it only works on collecting words without considering relations between those words (El-Halees, 2011).

Machine Learning (ML) is a new approach in sentiment analysis which helps in detecting emotions in a text according to training sets (Alwakid et al., 2017). This technique puts sentences into positive, negative, or neutral classes (Alhindi et al., 2012). Before applying ML algorithms, we need to populate the classes with examples of data in them and then apply ML approaches so we can classify new texts (Alwakid et al., 2017). There are some examples of ML systems and they are Naïve Bayes (NB) and Support Vector Machines (SVM) (Assiri et al., 2015). Both methods perform accurate polarity classification in many languages like English and Arabic (Arnaoty et al., 2012) where they can achieve over 80% accuracy (Pang et al., 2002), but they need an “annotated corpus to train a classifier” (El-Halees, 2011).

The current state of the art in sentiment analysis is in progress. For example, some companies are learning about the most requested features and brands in market to fulfill those requests and they do not only monitor their brands and people's opinions about them (Henschen, 2015).

- **Big debates in sentiment analysis**

Most of the opinion mining topics are about polarity classification. However, opinions are usually about an “entity” which can be an object, product, feature, or an organization. Entity discovery fits under a field called Named Entity Recognition (NER) which helps in identifying people, organizations, and locations names (Riloff & Wiebe, 2003) and it is considered one of the required sub-task in the sentiment analysis along with the opinion detection task. So, we need to decide the entity that we are talking about before deciding the polarity of the text because determining whether the text is positive or negative is difficult if we do not know what the text is about (Ding et al., 2009).

Subjectivity detection and sentiment analysis depend on context and the domain of the text (Pang & Lee, 2008). Despite of the presence of positive or negative words which stay positive and negative regardless of the domain like the word “good” and the word “bad”, some phrases may contain different sentiment according to the domain (Pang & Lee, 2008). Pang & Lee (2008) provided a good example of this: “go read the book,” a phrase that is positive for a book review but negative for a movie review. And there are some words whose polarity may differ according to the context of the text: the word “long” is positive in “the battery life is long”, but it is negative in “the road is long” (Ding et al., 2008). So, we need to be careful in choosing positive and negative lexicons.

Ding et al. (2008) talked about the “Intra- Sentence conjunction rule” situation which means that the polarity in a second sentence depends on the first sentence’s polarity and the conjoining word. If “and” is the conjoining word, the polarity direction does not change. For example, in “we took great pictures, and the battery life is long” sentence, the word “long” is positive because the first sentence is positive, and the second sentence is conjoined with “and” to it. While in the case of using the “but” conjoining word, the polarity direction will be the opposite of the first sentence. For example, the second clause in the sentence “we had a great time, but the road was long” is negative because the word “but” changed the positive polarity of the first sentence.

As I mentioned above, most sentiment analysis approaches use the opinion lexicon and this will be a problem when detecting positive or negative idioms (Ding et al., 2008). For example, the idiom “Caught between two stools[1]” is a negative idiom and it means it is hard to choose between two options, but we cannot decide it is a negative phrase by using opinion lexicons list as the words in it do not contain any sentiment in them. So, the best solution to this

[1] From “Caught between two stools” by the Daily Observer, 2015. https://www.observerbd.com/2015/04/05/81925.php

problem is to create two lists of positive and negative idioms and provide them to the community (Ding et al., 2008) to use.

To evaluate an object, we can examine direct opinion words like “good” or “bad or compare it to another object — for example “Car A is better than Car B” (Liu, 2010). From this example, we can see that there was no opinion expressed whether the cars are good or bad. So, it is important to detect the comparison here to know the preferred object.

- **Sentiment analysis accuracy in Arabic texts**

Speaking of lexicon-based sentiment analysis, there is a lack of Arabic opinion lexicon and training datasets (El-Beltagy et al., 2016) even though there were attempts to translate English opinion words into Arabic to fill this gap (Mourad & Darwish, 2013; Salameh et al., 2015).

Arabic social media posts may contain letters and numbers that are not used in Arabic and they are called the Roman Alphabet (Boudad et al., 2018; Rushdi-Saleh et al., 2011). Usually, Arab people use them to write when they do not have Arabic keyboards. For example, number “7” in the word “7ob” is the letter “H” and word would be “hob” which means “love”. So, to have accurate sentiment analysis results, we need to include all possible variants of each word in the Arabic language, and those can even include Roman numbers. This could be time-consuming and use more storage space.

The Arabic language is a rich language morphologically (Alwakid et al., 2017; Boudad et al., 2018). We need a morphological analysis of Arabic words and there are two methods to do that: rooting and light stemming. Rooting means removing all affixes and converting the word into its root which is the base part that does not have any affixes. Light stemming removes fewer affixes and keeps the meaning of the words (Alwakid et al., 2017). However, according to El-Beltagy et al. (2016), morphological analysis has a negative impact on sentiment analysis, and it does not help in improving its accuracy.

Before applying sentiment analysis on Arabic posts, cleaning of the text should be done. In that cleaning, there is a step called normalization where all repeated letters are deleted in order to have the base form of the words. For example, in English, the word “yessssssssss” will be normalized to be “yes”. However, some words already have two repeated letters in their base such as “will” in English. To handle this case, a Python code is written to delete repeated letters from a word until we get the saved base form of it even if it has repeated letters. For example, the phrase “I willlllllllll” will be normalized to “I will”.

Most Arabic names are derived from adjectives that might contain sentiment and this will affect the sentiment analysis accuracy (Tagwa Abd Elatif Mohammad, 2016). For example, a girl’s name جميلة means “beautiful” and it is a positive word in the positive lexicon list. So, we first need to decide whether the opinion lexicon word in a sentence is a name for a person, place, or organization or not. Usually, Part of Speech (POS) analysis would help in this situation, but in Arabic, it is difficult to apply it (Alwakid et al., 2017) because names in Arabic do not start with a capital letter.

It is necessary to include all possible variant forms of a word in the opinion lexicon lists which means adding all possible diacritics and affixes. Abdul-Mageed and Diab (2014) collected 224564 opinion words in MSA and multiple Arabic dialects which are considered large lists. Although those lists are large, using them by other scholars was limited because the words did not have diacritics on them.

It was noticed that the accuracy of Arabic sentiment analysis is low regardless of the domain due to the complexity of the Arabic language. To solve this problem, El-Halees (2011) suggested combining methods like lexicon-based and machine learning methods. It is a great idea because of the improvement in the results we can get.

- **Sentiment analysis efficiency in Arabic texts**

Due to lack of resources from previous projects in the Arabic sentiment analysis and the lack of availability of English resources (El-Halees, 2011), Rushdi-Saleh et al. (2011) created more English sentiment analysis resources. He created the Opinion Corpus for Arabic (OCA), translated it into English and called the English Version EVOCA. It helps researchers decide the polarity of Arabic texts. English translations cause a loss of precision, but the sentiment analysis results were "comparable with other sentiment analysis researches using English texts." (Rushdi-Saleh et al., 2011). So, he suggested using English sentiment analysis results on texts translated from Arabic into English for opinion mining.

Due to the absence of Part of Speech (POS) detection in Arabic sentiment analysis, entities' names can be confusing, especially when they are words in the opinion lexicon lists. "For example, جامعة طيبة (University of Taeba) will match with lexicon entry "طيبه" which means "kind" or "kindness" depending on the context" (El-Beltagy et al., 2016). This will affect the accuracy and efficiency of sentiment analysis.

➢ **Sentiment analysis errors in Arabic texts**

Sentiment analysis will be efficient in Arabic when we have high-quality opinion word lists (El-Beltagy et al., 2016), but as I mentioned above, it is time-consuming, and it needs large spaces to save the data.

Arabic social media contents are completely different from formally structured texts because the posts contain unstructured language, slang words, dialects, abbreviations, and spelling mistakes (Alwakid et al., 2017). Those challenges affect the opinion mining process and give inaccurate results because we cannot, a least for now, include every word in our opinion lexicon lists.

Writing in Arabic does not follow a strict rule-based punctuation system as in English texts. For example, it is hard to detect sentences' boundaries where a comma might be used to end a sentence in Arabic unlike English sentences which are ended with full stop (Alqinai, 2010). Furthermore, Arab people tend to write very long sentences with many commas between them and finish the whole paragraph with a stop at the end (Othman, 2004; p: 18). This causes a limitation in Arabic sentiment analysis on the sentence-level (Boudad et al., 2018). So, we need to define Arabic punctuation rules before we set the sentiment analysis approaches.

There are many morphological analyzers for the Arabic language that can tokenize, spell check, stem, and detect part of speech, like the Buckwalter Arabic Morphological Analyzer (BAMA) (Boudad et al., 2018). However, they cannot handle lexical ambiguity due to the absence of diacritics. So, applying sentiment analysis on texts after we analyze them morphologically gives better results, but it is still not completely accurate.

➢ Texts in Dialects of Arabic and sentiment analysis

Arabic speakers use their dialect to communicate with other people and the dialects are different from MSA morphologically, lexically, and phonologically (Boudad et al., 2018). There are around 30 Arabic dialects and they do not follow any standards in phrase building. So, using MSA tools to process them will produce low-performance results (Boudad et al., 2018) (Westerski, n.d.).

Despite the lack of Arabic sentiment analysis resources, most of the available resources are in Modern Standard Arabic (MSA) which can lower the efficiency in the Arabic world social media corpus (El-Beltagy et al., 2016): "MSA corpus to classify dialectical texts may lead to poor accuracy" (Oueslati et al., 2020).

In creating opinion lexicon lists, dictionaries are used to put the word with its synonym and antonyms on the same list. However, those dictionaries are only in MSA and not in dialectic Arabic. So, this may cause insufficient opinion word lists and that too will give inefficient sentiment analysis results.

• Conclusion

Google Translate uses a statistical machine-translation method which gives accurate results with texts like new and scientific articles or when comparing two close languages (Ferrell, n.d.), but it gives unacceptable results with idioms and literary texts (Harmon, 2016). So far, machine translation is far from being perfect translation (Ferrell, n. d.). However, the use of MT is growing, and Google databases will continue to grow and improve every day (Groves & Mundt, 2015).

The best translation we can get is when we combine human translators' efforts with machine translation and the results will be accurate, especially with formal and organized texts (Groves & Mundt, 2015; Puchała-Ladzińska, 2016). So, currently, MT is considered a translation aid to the human translators (Puchała-Ladzińska, 2016). In addition to Google Translate, many automated online machine translators are growing fast and getting more familiar — like the Facebook translator that helps users to communicate from more than 200 countries (Puchała-Ladzińska, 2016).

Sometimes MT causes loss of emotions and sentiments, and that happens when we get a neutral or a less-emotional meaning of a word or expression in the target language than the source one. This what happens when translating poetry and emotional literary texts (Alwakid et al., 2017).

To get better sentiment analysis results, we cannot use only one method, but we need to combine two approaches at least together like lexical-approach and machine learning (El-Beltagy et al., 2016).

Chapter 4: Machine Translation and Google Translate Evaluation

- **Introduction about MT and Google translate**

In this chapter, I will talk about machine translation and its applications in the Arabic language, especially Google Translate. This chapter aims to answer the following research question: how do modernity and the formality of Arabic texts affect Google Translate's performance? My research shows that Google Translate has better performance when translating new Arabic poems written in Modern Standard Arabic (MSA) as compared to older poems or poems written mostly in dialect. In addition, the modernity of the Arabic texts affects Google Translate's performance more than the effect of the type of Arabic — whether it is formal or dialect Arabic. Before I discuss these ideas, we need an introduction about MT history and theory in addition to a background in Google Translate.

There is no agreed-upon decision on the date of the emergence of the idea of creating a device to translate automatically. Some researchers said that this idea started early in the seventeenth century (Shoeeb, 2015). Others, like Jacqueline Léon, see that the myth of a translation apparatus precedes the emergence of a computer (Amenah Fatema Alzahraa, 2008). On the other hand, some researchers agree that once the computer was invented, research on using it in translation began. For example, in March 1949, Warren Weaver used the term "computer translation" to describe his work in this area (Noor Aldeen & Yasin, 2019; Shoeeb, 2015). In 1989, a new era began in the foundations of machine translation based on statistical information, when the IBM company carried out a project based on translation with optimization and many languages were used in this translation.

Computational linguistics is the scientific study of natural languages from a computer perspective. This study is not limited to one language, but it focuses on many natural languages and seeks to improve processing them using the computer. The goal of this science remains to develop a computer program that can understand and produce the human language. Machine translation is considered one of the most important fields that computational linguistics focuses on and this will be the core of this chapter.

One of the reasons for the importance of machine translation is that the commercial sector needs a translation that gives a good idea of industrial and commercial products, especially with the increased demand for such information, which is required to be translated and expanded to include new languages during our era of globalization. Furthermore, human translators often master one language beside their mother language while machine translation can translate between more languages, and this gives more importance to it. Machine translation has received special attention from researchers because of this increasing demand, whether it is online or offline. It has also become the most important way to dissolve the boundaries of linguistic and cultural differences and expand the knowledge horizon.

Before I start defining machine translation (MT), I will differentiate between the various types of translations already available to researchers. They can be divided into four types. First, Human Translation (HT), in which the human beings translate relying on their background knowledge without any machine help. Second, Machine-Aided Human Translation (MAHT), in which the human beings use machine help with the translation like Google Translate. Third, Human Aided Machine Translation (HAMT), in which the role of the human beings is limited to correcting the errors in the target text, by changing some words and making sure of the syntactic and morphological accuracy and deciphering any language confusion. And fourth, Machine Translation (MT), in which the computer translates the texts on its own without human interaction. Researchers were attempting to use MT to replace human beings entirely with a computer, which is what they expressed as "high-quality complete machine translation". Rebecca Ray (2010) and Hutchins W. John (1995) stated that the automatic translation or machine translation is a translation system that translates from one language to another automatically without the intervention of human translators.

Machine Translation (MT) is a branch of artificial intelligence that humans have long sought to develop and benefit from for its accuracy and ease of use. There is no specific definition of MT agreed by researchers. Some of them defined MT as transferring thoughts and speeches from one language to another while preserving the spirit of the text (Abd-Alaleem Alsaid Mansi & Abdollah Abdol Razek,1988). Others said that it is using the computer systems for producing text translations from one natural language to another (Al-humaidan Abollah bin hamad, 2001). The most detailed definition of machine translation was proposed in Shoeeb's (2015) study as the process of using an automated program to translate text from a natural language (such as English) to another natural language (such as Arabic), where the program transfers the syntactic structure from the source language (the text to be translated) to the target language (the translated text) after analyzing its structure and usage of special rules related to the arrangement of words, syntactic information, accurate analysis of sentence elements, etc. (Shoeeb, 2015).

Translation can be divided into three levels. First, the lexical level, in which the computer transfers each word from the source language to the target language using available bilingual dictionaries of the two languages. We should take into consideration that we need an enormous dictionary to complete this process, and that there are many words in a source language that do not have any compatible word, or that have more than one compatible word in the target language. Second, the syntactic level or the grammatical level, in which the computer uses grammar in the target language, such as putting the verb at the beginning of Arabic sentences and so on. And third, the morphological level, in which the grammar is applied in the target language such as grammar about the number of objects, genders of nouns, and verb tenses, etc.

Nabeel Ali (1998) pointed out that the translation of natural languages requires a lot of knowledge about:

- Grammar and structures.
- How to construct and arrange words to get acceptable phrases and sentences in that language.
- Meanings and connotations of words in that language.

As I mentioned above, Google Translate uses statistical-based methods in translation, but this is not the case in all MT tools and techniques. One technique in machine translation system first analyzes the input of the original language and creates an internal representation. This representation is processed and transferred to a target language model. Then, in the end, the output is created in the target language.

In all cases, the machine translation program must perform two main operations: the first step is called the "automatic transmission" which is the process of finding corresponding lexical and syntactic structures of the input text in the target language. For example, when translating the phrase "you asked me" into Arabic, each word will be translated on its own as following: أنت "Anta" which means "you", سألت "Sa'alta" which is in the past form of the verb "ask", and أنا "Ana" which means "me". The second step is the composition, or the synthesis process is formulating sentences according to the results of the previous step correctly in term of syntactic and semantic structure. For example, the composition step will produce the Arabic word سألتني "Sa'altani" which means "you asked me" depending on the results of the previous example. In addition, the composition step considers the position of each word in the target language. For example, in Arabic, the adjective is after the noun that we are describing. Aisha Hamza (2014) said, “The process of machine translation begins with the computer first identifying the vocabulary of the source language and analyzing it syntactically to know the root of each word and its source in defining the different forms of names and different verb tenses” (n.p.). This procedure is applied before translating an English phrase, for instance, into Arabic where any translator needs to know the root of each English word, and what part of speech it is whether it is a verb (past or present), or a noun, etc. For example, an English-Arabic translator will analyze the phrase “He ate an Apple” as following: “He” is a singular masculine subject and it translates to “هو” in Arabic; “Ate” is a past-tense verb and it translates to “أكلَ”; “Apple” is a singular noun and means “تفاحة” in Arabic, so the phrase will be “هو أكلَ تفاحة” in Arabic.

➢ **Bilingual and Multilingual systems**

Automated translation systems are designed either for translation between two languages only (bilingual systems) or for translation between several languages, in which case it is called a multilingual system. These systems either do the translation process in a single direction without translating in the other direction (one-way translation system) or do it in both directions (two-way translation systems). The term “one-way translation systems” means systems translate the text from its original language to the target language without being able to translate it back to its original language at the same time, while two-way translation systems (reversible systems) means to translate between two languages from the original language to the target language and vice versa at the same time. For example, in Google Translate which is a one-way translation system, if we want to translate the phrase “I love you” into Arabic, the system will translate it to

"احبك". If we want to make some changes to the results and then translate it back to English, we need to copy the new text and paste it back into the original text section and then choose Arabic as the original language and English as the target language to get the new results. If Google Translate was a reversible translation system, any change we made to the results would be translated immediately to English without copying and pasting the new text in the original text section and waiting to get the results. One expects that the process of translating between two given language is reversible without any change, but theoretically and practically, it is difficult to design these systems to fully achieve the reversible translation features. So, all bilingual systems can be considered as two one-way systems with some similarity between its components. The most interesting example of practical systems is the "Météo" weather application that translates weather forecasts between English and French and it was specifically designed for Canadians. For example, this application can translate weather forecasts from English to French for people in Quebec, and from French to English for people in Alberta. As we noticed, it works in a one-way direction.

- **Median Language**

There is a new tendency to use an intermediary language when translating between some contemporary natural languages. For example, when using the MT techniques to translate between English and French, that would be easy to do. But translating from Arabic to Korean is hard because of the lack of Arab people who can speak Korean and vice versa. But to have a language in between, like the English language for example, would be easier. It has been suggested that the English language should be the intermediary language between the modern European languages (Shoeeb, 2015) as it is the language of the World Wide Web (WWW), and it is the standard language for technology, academia and many other areas of life and work.

However, this idea of having a median global language has encountered difficulties in solving all problems of machine translation and it was not that successful process, which is why MT took another way of working which is the statistical translation.

- **Statistical Translation**

The goal of storing information inside a computer is to keep a record of that information and to ease access to it. The data retrieval process, its classification, and the different methods of searching for it in the computer is an automated process, which any programmer can do if he is provided with what the user wants. The statistical linguistics give the user a quantitative assessment of some of the language characteristics, such as use rates for letters, words, and syntactic formulas. This modern method aims to collect the largest possible linguistic databases and make the greatest statistical effort possible on it to be prepared for use in machine translation.

This translated corpus is mainly translated by human translators, and it is extracted from human experiences to benefit machine translation.

This statistical process is one of the important processes which many of the automated research studies of natural languages is based on, but machine translation requires texts available in two or more languages. The words in each language with their equivalents in the target language are stored in a two-dimensional array (matrix) where each row has the source word and the columns are the target words. Linguistic storage must be available in two languages and must be in an aligned matrix. For example, if the word “tree” exists in the second row and first column in English matrix, its equivalent word in Arabic شجرة “Shajara” must exist in the Arabic matrix in the second row and second column as in the following matrix:

English words and phrases	Arabic equivalent words and phrases
Tree	شجرة
Love	حب
Love	محبة

Table 2: An example of aligned matrix of English words ang their Arabic equivalent words

This method is based on using repeated phrases between the two languages which consist of two or more words. This method is what Google Translate uses in its translation. Translation of a specific phrase in more than one location of the stored databases with a preferred translation by different translators provides the machine translator with a preferred translation of that phrase, but if the translation differs between two locations of stored data, some statistical methods in choosing the most frequent translation are used. For example, the word "love" in (Table 2) exists in two places because it has two synonyms in Arabic, but by using some statistical equations, Google will use the more frequently used translation. This simple method gives an inaccurate translation but attaching grammatical and morphological information extracted from the stored data will increase the accuracy of the translation.

➢ **Google Translate**

Everyone can access Google Translate if they have their computer connected to the internet. In Google search engine just type Google Translate and translation page will be opened. Google Translate provides its users with the ability to correct errors during or after the translation process because it provides real-time, interactive translation to its users. This means when typing the text in the source language box, the translation appears instantly in the target language box. It also allows the user to save texts to use them at any time and gives direct possibilities within the original or the target text. The site is also provided with a bilingual electronic dictionary to explain vocabulary, whether related to the target language or source language. I want, through this chapter, to test the efficiency of Google Translate in the poetic field according to different eras, especially when translating between Arabic and English as well as to examine the factors that affect Google translation's performance.

- **Arabic Language in MT**

Arabic automated translation is still less accurate than automated translation of other languages such as English, German and Hebrew. The reason for that limitation is that the machine translation is expensive, and the money is with investors and businessmen who do not have enough language love to invest their money in research and technologies that do not return them to profit fast (Shoeeb, 2015). But there are some limited areas in which machine translation of the Arabic language has been successful such as scientific and governmental documents.

For a long time, people have been interested in translating their cultural heritage and values to ensure its continuation on one hand, and to spread it on the other hand. It was easy to translate prose, whereas poetry translators had difficulties in achieving good translations. The problem in poetry translation is that the literal translation of any literary text and poetry leads to a different meaning of the text and this is what we will discuss in this chapter.

- **Methodology**

There are some automated MT evaluation systems like the Bilingual Evaluation Understudy (BLEU) system which evaluates the quality of a text that has been translated by machine translation and sees how close that translation is to human translation. Another example of an automatic evaluation system is the "Meteor" system which aligns the text translated by MT systems to one or more references where “Alignments are based on exact, stem, synonym, and paraphrase matches between words and phrases” (Michael Denkowski & Alon Lavie, 2010). Those automatic evaluation systems are expensive to have and due to the weakness of financial abilities to get them, I decided to rely on personal analysis. Furthermore, the proposed translation after the analysis is subjective. In addition to not being able to determine the scientific standards to judge the validity of the translated texts, the judgment here is personal and independent without any external factors to affect it. I tried to be as scientific as possible and committed to objectivity, especially in practical implementation. However, being subjective at some stages in the analysis process is what stands behind any deficiency that may appear in this thesis. The methodology used here in this part is inferred from Fatima's (2015) methodology because it is rich, informative, and helpful to understand how Google Translate works. Fatima’s methodology includes translating some Arabic texts into English by using Google Translate and then counting the accuracy of the translation by checking the success rate of words, meanings, and structures translation. In addition to that, the success rate of retrieving the texts is calculated in this methodology.

I will evaluate Google Translate’s performance by analyzing three song lyrics. One of them is an old poem written in formal Arabic, the second one is a new song written in formal Arabic, and the third is a new song written in Lebanese dialectic Arabic. Google Translate’s performance when translating between Arabic and English depends on the complexity of Arabic words where old Arabic words are more complex than the new words. In addition, it is easier to translate Arabic words that are written in formal Arabic than the ones which are written in dialectic Arabic. So, by choosing those three songs we can decide Google translation’s quality when translating new vs old texts, and when translating formal vs dialect Arabic text.

- **The Arabic Lyric, Google translation, and Suggested Translation of each song**

The song "Ya Man Hawahu" which means "You, whose love humiliated me and elevated you" is an old song and its lyrics were written in formal Arabic. The lyrics were written by Saeed bin Al-Imam Ahmed bin Saeed Al-Busaidi in 1774 AC in Oman and was sung by Abol Rahman Mohammad in 2012. Google Translate gives good results in translating this song. I will use Google Translate's performance in this song as a baseline to compare to when I evaluate its performance in translating the other two songs.

Arabic lyrics	Google Translation	Suggested translation
يا من هواه أعزه وأذلني كيف السبيل الى وصالك دلني انت الذي حلّفتني وحلفت لي وحلفت أنك لا تخون فخنتني وحلفت أنك لا تميل مع الهوى أين اليمين وأين ما عاهدتني تركتني حيران صباً هائماً أرعى النجوم وأنت في عيشٍ هني لأقعدنّ على الطريق وأشتكي وأقول مظلوم وأنت ظلمتني ولأدعونّ عليك في غسق الدجى يبليك ربي مثلما أبليتني	O dearest and humiliated me How to reach me and show me It was you who swore on me and swore to me I swore that you did not betray me, you guessed me You swore that you are not inclined to fancy Where is the right and where do you pledge to me? Hiran left me wandering Take care of the stars while you live easy To sit on the road and complain I say wronged and you wronged me And to pray for you in the twilight of Dja God bless you just as you did me	You, whose love humiliated me and elevated you Show me how to reach you You are the one who made me swear to, and you swore to me You swore that you do not betray, and you betrayed me You swore that you will not incline to another love Where is that swearing, and where is what you promised me You left me confused, wanderer, and missing you I count the stars while you are living happily I swear, I will sit on the road and complain to God I will say I am oppressed, and you wronged me And I swear, I will pray in a very dark night For God to offend you as you did to me

Table 3: The first song "Ya Man Hawahu" Arabic lyrics, its Google translation, and the suggested translation of it

Google translate gives better results in translating the second song “Ohebbu Yadayka” which means “I love your hands” than the results of the first song’s translation. This better performance is because this song is a new song and its lyrics were written in formal Arabic. The lyrics were written by Mahdi Mansour and was sung by Faia Younan in 2015.

Arabic lyrics	Google Translation	Suggested translation
عيناك حلمي الذي سيكون كبيراً كما يحلم المتعبون كبيراً كخير بلادي	Your eyes are my dream which will be As big as tired dreams As big as my country	Your eyes are my dream which will be As big as tired people's dreams As big as the generosity of my country
يداك تلوّح للعائدين وتحمل خبزاً إلى الجائعين أحبُ يديكَ... وأكثر أكثر أحب بلادي	Your hands are waving to the returnees And carry bread to the hungry I love your hands ... And more the more I love my country	Your hands wave to the people returning home And carry bread to the hungry ones I love your hands But I love my country more and more
ستكون لي لو تعشق الأوطان مثلي سأكون لك لو عاد للأوطان أهلي عرسي هنالك حيث يحملني فؤادي وأموت فيك أموت فيك متى تموت على بلادي	It would be for me to love homelands like me I will be yours if you return home my family My wedding is where my heart holds me I die in you I die in you When will you die on my own	You will be mine if you adore homelands like I do I will be yours if my people get home back There my wedding will be, where my heart carries me And I die for you, die for you When you are ready to die for my country
وأنا أحبك كي ندوس على المدافع وتضيق بالأطفال ساحات الشوارع ومتى يعود الصبح من بين الرماد سأموت فيك أموت فيك وقد أخونك مع بلادي	And I love you to step on the guns Street children narrowed children And when the morning returns from the ashes I will die in you I will die in you Your brother has been with my country	And me... I love you so that we together could step on cannons And the streets get over-crowded with kids And when the morning arises from the ashes I will die for you, I will die for you

		And I might cheat on you with my country

Table 4: The second song "Ohebbu Yadayka" Arabic lyrics, its Google translation, and the suggested translation of it

Google Translate gives less accurate results than the previous performance in the song "Krehtak" which means "I hated you" as we will see later. The low performance here is because its lyrics were written in Lebanese dialectic Arabic even though it is a new song. The lyrics were written by A. R. Rahman and Prasoon Joshiand and was sung by Elissa in 2012.

Arabic lyrics	Google Translation	Suggested translation
علمتني كيف الكره بيكون حرمتني صدق بعمري عيون ضيعتني وياريت ما عرفتك شجعتني ع الدني قلت قويت سمعتني احلى حكي ومشيت ودعتني وياريت ما شفتك شو عملت فيي وانت اللي عارف اني مافيي منك انجرح شو عملت فيي قدام عينك انتى قلبي قلبي بيندبح ما بقى فيي ما بقى فيي اسهر لحالي ابكي ع حالي نسيتك انا ما بقى فيي قلك حبيبي كذب ع حالي كرهتك انا ما بقى فيي اسهر لحالي ابكي ع حالي نسيتك انا ما بقى فيي قلك حبيبي كذب ع حالي كرهتك انا ما بقى فيي غيرتني غيرت فيي كتير عودتني عيش الاسى بكير غيرتني وما عرفت غيرتك قسيتني ع الدني كلها قسيت بكيتني وقبلك انا ما بكيت موتتني مع اني عيشتك شو عملت فيي	She taught me how to hate Bacon My honesty has denied me my life You lost me and I wish you did not know you I was encouraged by my life, I said strong You heard me the best story and I walked She invited me and I wish I did not see you What did you do? And you who know that I cannot get hurt What did you do? In front of your eyes, you are my heart, my heart is barking What remains in me I am not staying up to my current crying I forgot you What is left in you, my beloved, is a lie I hate you I am not staying up to my current crying I forgot you What is left in you, my beloved, is a lie I hate you	You taught me to hate. You deprived me from believing in eyes for the whole of my life You lost me, and I wish I have never known you. You encouraged me, so I thought I got stronger. You made me listen to the most beautiful words and then you went away. You left me, and I would like I have never seen you. What have you done to me? And you are the one, who knows that I cannot get hurt from you. What have you done to me? And my heart hurts in front of your eyes. I cannot stand that anymore. I cannot spend the evening lonely crying about myself. I have forgotten you. I am not able to say my love to you anymore and lie to myself. I hated you. I cannot spend the evening lonely crying about myself. I have forgotten you.

	What remains in me It changed me, it changed me a lot It brought me back to live in distress You changed me and I did not know your jealousy You divided me all over the world I cried and before you I did not cry You died me while I lived What did you do?	I am not able to say my love to you anymore and lie to myself. I hated you I cannot do it anymore. You changed me a lot You made me used to the sorrow early. You changed me and I could not change you. You harden me, so I became cruel about the whole life You made me cry and I did not cry before you. You killed me, even though I lived for you. What have you done to me?

Table 5: The third song "Krehtak" Arabic lyrics, its Google translation, and the suggested translation of it

- **Lexical and grammatical analysis of the songs**

For each song, I applied two steps of analysis. The first step is the lexical and semantic analysis of each song to discover translation defects, starting with the correspondence of each word of the target text with its equivalent word from the source text. The validity of any target word is judged by the lexical and semantic meaning of the corresponding source word. I have relied on an Arabic-Arabic dictionary (Al-Jawhari. I, 1990) and I have attached each word with a model translation in English. I used a table here in our analysis because of its accuracy and organization. The results of this step are shown in Appendixes A, B, and C for the first, second, and the third song, respectively. The second step is the syntactic and grammatical analysis of each song. This analysis aims to show the syntactic and grammatical mistakes made by the Google Translate during the translation. In the tables, I divided the poem into verses, and the results are shown in the Appendixes.

- **Color-coding in the retrieved text**

After completing the last two steps, I analyzed the poems' retrieval and check for success by analyzing differences between the original and the retrieved text. Before I start the poem retrieval analysis, I will explain the types of the retrieval and the color coding I used in this analysis. There are three types of retrieval and they are vocabularies, sentences' structures, and meanings retrievals. In the vocabularies' retrieval analysis, I used the color-coding technique in each song vocabularies' retrieval. This method helps in translation's quality analysis. The colors refer to the following:

- Red-colored words: Words with opposite meaning and were not in the original text.
- Blue-colored words: Foreign words (translated literally with English letters).
- Green-colored words: words that are closed to the meaning.

Sentence structures and meanings will depend on how we divide the poem into verses. So, each verse will be considered as a sentence structure and it has its own meaning.

- **Equations to calculate success rate of retrieving vocabularies, structures, and meanings**

After the color-coding technique, I calculated the percentage of the presence of each colored word as follows:

- Vocabulary Retrieval Percentage %= $\frac{Number\ of\ retrieved\ words \times 100}{Total\ number\ of\ words\ in\ the\ original\ text}$

This percentage will indicate the success rate of vocabularies retrieval.

- Foreign Retrieved Vocabularies% = $\frac{Number\ of\ foreign\ words\ (Blue) \times 100}{Total\ number\ of\ words\ in\ the\ original\ text}$

- Vocabularies closed to the meaning%= $\frac{Number\ of\ close\ meaning\ words(Green)\times 100}{Total\ number\ of\ words\ in\ the\ original\ text}$

- Vocabularies opposite of the meaning% =

$$\frac{Number\ of\ words\ opposite\ of\ the\ meaning\ (Red)\times 100}{Total\ number\ of\ words\ in\ the\ original\ text}$$

The second step after vocabulary retrieval is the sentence structure retrieval and I calculated the success rate of this retrieval in each song by using the following equation:

- Structures Retrieval Percentage %= $\frac{Number\ of\ retrieved\ structures\times 100}{Total\ number\ of\ the\ original\ structures}$

The last retrieval success percentage is the meaning retrieval and I used the following equation:

- Meaning Retrieval Percentage % = $\frac{Number of retrieved meanings\times 100}{Total number of the original meanings}$

After calculating all success percentages of vocabularies, structures, and meanings, I calculated the total success rate by using the following equation:

- Total Retrieval Percentage % =

$$\frac{VocabularyRetrievalrate+StructuresRetrievalrate+MeaningRetrievalrate}{3}$$

You will see the implementation of those equations in each analysis of the three songs we have.

- **Poem Retrieval**

As with the songs, in poem retrieval, I will again check how close the original poem is to the retrieved poem in terms of vocabulary, sentence structures, and meaning.

Vocabulary Retrieval

I organized the original poem and the retrieved poem of each text in tables. In addition, I used the same color-coding to indicate how close the meaning of the retrieved words to the compatible original words.

Original text	Retrieved text
يا من هواه أعزه وأذلني	يا أعز وأذلني
كيف السبيل الى وصالك دلني	كيف تصل إلي وتبين لي
انت الذي حلّفتني وحلفت لي	كان أنت الذي أقسمت علي وأقسمت لي
وحلفت أنك لا تخون فخنتني	أقسمت أنك لم تخنني ، لقد خمنتني
وحلفت أنك لا تميل مع الهوى	أقسمت أنك لا تميل إلى الهوى
أين اليمين وأين ما عاهدتني	أين الحق وأين تتعهد لي؟
تركتني حيران صباً هائماً	تجول Hiran تركني
أرعى النجوم وأنت في عيشٍ هني	اعتني بالنجوم بينما تعيش بسهولة
لأقعدنّ على الطريق وأشتكي	الجلوس على الطريق والشكوى
وأقول مظلوم وأنت ظلمتني	أقول الظلم وأنت ظلمتني
ولأدعونّ عليك في غسق الدجى	Dja والصلاة من أجلك في شفق
يبليك ربي مثلما أبليتني	بارك الله فيك كما فعلت لي

Table 6: Original lyrics of the old song with formal lyrics and the retrieved lyrics

Original text	Retrieved text
عيناك حلمي الذي سيكون	عيناك حلمي الذي سيكون
كبيراً كما يحلم المتعبون	بحجم الأحلام المتعبة
كبيراً كخير بلادي	كبير مثل بلدي

يداك تلوّح للعائدين	يديك تلوح للعائدين
وتحمل خبزاً إلى الجائعين	واحمل الخبز للجياع
أحبُ يديكَ...	احب يديك ...
وأكثر أكثر أحب بلادي	وأكثر أحب بلدي
ستكون لي لو تعشق الأوطان مثلي	سيكون لي أن أحب الأوطان مثلي
سأكون لك لو عاد للأوطان أهلي	سأكون لك إذا عدت إلى المنزل عائلتي
عرسي هنالك حيث يحملني فؤادي	زفافي هو المكان الذي يحملني فيه قلبي
وأموت فيك أموت فيك	أموت فيك أموت فيك
متى تموت على بلادي	متى ستموت لوحدي
وأنا أحبك كي ندوس على المدافع	وأنا أحبك أن تدوس على المدافع
وتضيق بالأطفال ساحات الشوارع	أطفال الشوارع ضاقت بهم أطفال
ومتى يعود الصبح من بين الرماد	وعندما يعود الصباح من الرماد
سأموت فيك أموت فيك	سأموت فيك سأموت فيك
وقد أخونك مع بلادي	أخوك كان مع بلدي

Table 7:Original lyrics of the new song with its formal lyrics and the retrieved lyrics

Original text	Retrieved text
علمتني كيف الكره بيكون حرمتني صدق بعمري عيون ضيعتني وياريت ما عرفتك شجعتني ع الدني قلت قويت	علمتني كيف أكره لحم الخنزير المقدد لقد أنكر لي صدق حياتي لقد فقدتني وأتمنى ألا تعرفك قلت قوية ، لقد شجعتني حياتي سمعتني أفضل قصة مشيت دعتني واتمنى اني لم اراك ما الذي فعلته؟ وأنتم الذين يعرفون أنني لا يمكن أن تضار

سمعتني احلى حكي ومشيت ودعتني وياريت ما شفتك شو عملت فيي وانت اللي عارف اني مافيي منك انجرح شو عملت فيي قدام عينك انتى قلبي قلبي بيندبح ما بقى فيي ما بقى فيي اسهر لحالي ابكي ع حالي نسيتك انا ما بقى فيي قلك حبيبي كذب ع حالي كرهتك انا ما بقى فيي اسهر لحالي ابكي ع حالي نسيتك انا ما بقى فيي قلك حبيبي كذب ع حالي كرهتك انا ما بقى فيي غيرتني غيرت فيي كتير عودتني عيش الاسى بكير غيرتني وما عرفت غيرتك قسيتني ع الدني كلها قسيت بكيتني وقبلك انا ما بكيت موتتني مع اني عيشتك شو عملت فيي	ما الذي فعلته؟ أمام عينيك ، أنت قلبي ، قلبي ينبح ما تبقى في داخلي أنا لا أظل مستيقظًا لبكائي الحالي لقد نسيتك ما تبقى فيك ، يا حبيبي ، هو كذبة أنا أكرهكم أنا لا أظل مستيقظًا لبكائي الحالي لقد نسيتك ما تبقى فيك ، يا حبيبي ، هو كذبة أنا أكرهكم ما تبقى في داخلي لقد غيرتني ، لقد غيرتني كثيرًا أعادتني إلى العيش في محنة لقد غيرتني ولم أكن أعرف غيرتك لقد قسمتني في جميع أنحاء العالم بكيت وقبلك لم أبكي لقد ماتتني بينما كنت أعيش ما الذي فعلته؟

Table 8: Original lyrics of the new song with its Lebanese dialect lyrics and the retrieved lyrics

The following table contains the number of the retrieved vocabulary words, the retrieved foreign words (blue words), the retrieved words that are close to the meaning (green words), and the retrieved ones that ore opposite of the meaning (red words).

	Old song + Formal Arabic Lyrics	New song + Formal Arabic Lyrics	New song + Lebanese Dialectic Lyrics
Total Number of Words in the Original text	58	74	120
Total Retrieved Words	31	55	78
Retrieved Foreign words (Blue)	2	0	1
Retrieved Words close to the meaning (Green)	16	8	14
Retrieved Words Opposite of the meaning (Red)	16	7	31

Table 9: The number of the retrieved vocabularies, the retrieved foreign words, the retrieved words that are close to the meaning, and the retrieved ones that ore opposite of the meaning

According to the numbers in the table above and the equations I referred to before, we can calculate the percentages of the retrieved words, blue words, green words, and the red words in the retrieved text.

	Old + Formal Arabic Song	New + Formal Arabic Song	New + Dialectic Arabic Song
Vocabularies Retrieval Percentage	$\frac{31\times 100}{58} = 53.44\ \%$	$\frac{55\times 100}{74} =$ 74.32%	$\frac{78\times 100}{120} = 65\%$
Foreign Retrieved Vocabularies Percentage (Blue)	$\frac{2\times 100}{58} = 3.44\ \%$	$\frac{0\times 100}{74} = 0\%$	$\frac{1\times 100}{120} = 0.83\%$
Vocabularies Close to the Meaning Percentage (Green)	$\frac{16\times 100}{58} = 27.58\ \%$	$\frac{8\times 100}{74} = 10.81\%$	$\frac{14\times 100}{120} = 11.66\%$
Vocabularies Opposite of the Meaning Percentage (Red)	$\frac{16\times 100}{58} = 27.58\ \%$	$\frac{7\times 100}{74} = 9.45\%$	$\frac{31\times 100}{120} = 25.83\%$

Table 10:the percentages of: Retrieved vocabularies, retrieved foreign vocabularies, retrieved words that are close to the meaning, and retrieved vocabularies that are opposite of the meaning

For better understanding, I used the following chart to show those percentages.

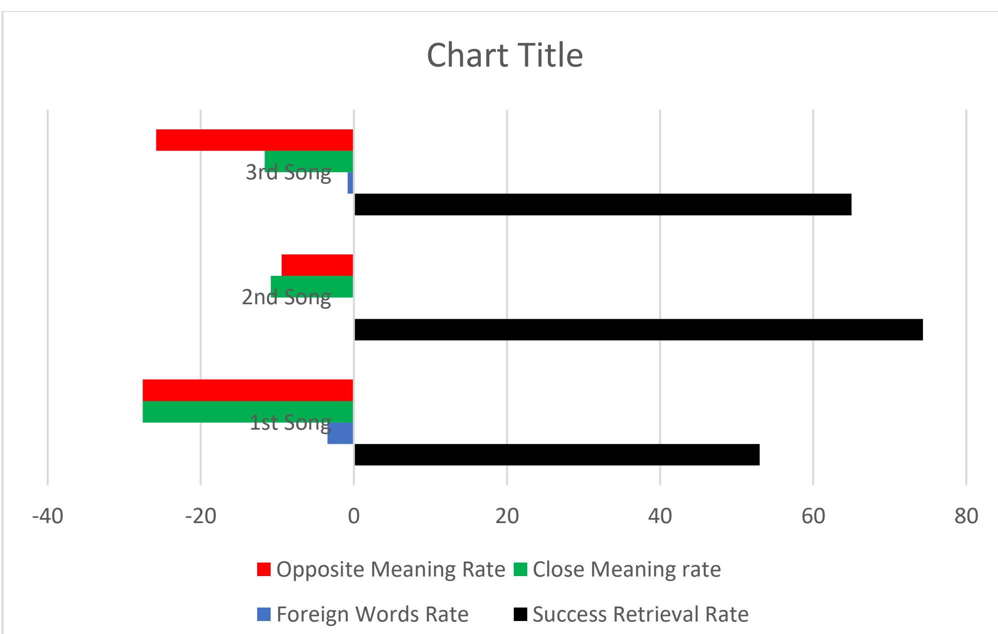

Figure 7: Vocabularies Retrieval Percentages

I plotted this chart where I put the success retrieval rate in positive values where the higher it is, the best results we can get. Also, I put the other retrieval rates (opposite meaning rate, close meaning rate, foreign words rate) in negative values where they should be as low as possible where the higher they are, the worst results we can get. It might be confusing to have the retrieval rates of the words that are close to the meaning in negative values, but it is still needed to be as low as possible because the successful retrieval process should have the exact original words not words close to the meaning.

From this chart, we can see that Google Translate's best performance was in retrieving the second song because it is a new song written in MSA. Also, the rates of foreign words, words that are opposite of the meaning, and the words that are close to the meaning are the lowest in this song; consequently, Google translated the song lyrics correctly as the words are new and easy for Google Translate to understand. In contrast, the lowest performance was in the third song in which the rates of foreign words, words that are opposite of the meaning, and the words that are close to the meaning are more than in the second song because it is written in dialectic Arabic and that affected the translation (Appendix C). Furthermore, the least accurate performance was in retrieving the first song because it is an old song written in formal Arabic and because of the complexity of the words and the lack of using them in the Arab world.

In the next section I will examine whether Google Translate will have the same performance for the sentences’ structures and the meanings in the poems.

Sentences’ Structures and Meanings Retrieval

In this section, I conclude that Google gives better performance in retrieving the meanings and the structures of new songs that were written in formal Arabic as compared to old songs or songs that were written in dialectic Arabic. The poems are divided into verses, and I considered each one of those verses as a sentence structure. In addition, each structure has its own meaning. So, the number of meanings is the same number of verses or sentences' structures. According to this division, the first poem contains 12 verses, and the second poem has 17 verses, while the third poem contains 27 verses. After that, I applied the equations I referred to before to calculate the percentages of successful structures and meaning retrieval. So, we can calculate the total retrieval percentage by summing all vocabularies, structures, and meanings successfully retrieving percentages and divide the result by three as in the equation above. The results are shown in the following table:

	Old + formal Arabic Song	New + Formal Arabic Song	New + Dialectic Arabic Song
Structures' Retrieval Percentage	$\frac{1 \times 100}{12} = 8.33\%$	$\frac{9\times 100}{17} = 52.94\%$	$\frac{10\times 100}{27} =37.03\ \%$
Meanings Retrieval Percentage	$\frac{2 \times 100}{12} = 16.66\%$	$\frac{10\times 100}{17} = 58.82\%$	$\frac{10\times 100}{27} = 37.03\%$
Total Retrieval Percentage	$\frac{53.44+8.33+16.66}{3} =$ 26.14	$\frac{74.32+52.94+58.82}{3} =$ 62.02%	$\frac{65+37.03+37.03}{3} =$ 34.67%

Table 11: Percentages of structures retrieval, meanings retrieval, and total retrieval.

From this table, we can see that the best performance of Google Translate was in the second song which is a new song that was written in formal Arabic. A poorer performance was in the third song which was written in dialectic Arabic. Finally, the lowest performance was when retrieving the first song which is an old song that contain many complex words that are not used in the Arab world anymore.

- **Results Analysis**

In this section, I analyze why I got the previous percentages. The following chart gives a better idea in comparison between the vocabularies, structures, meanings, and total retrieving percentages.

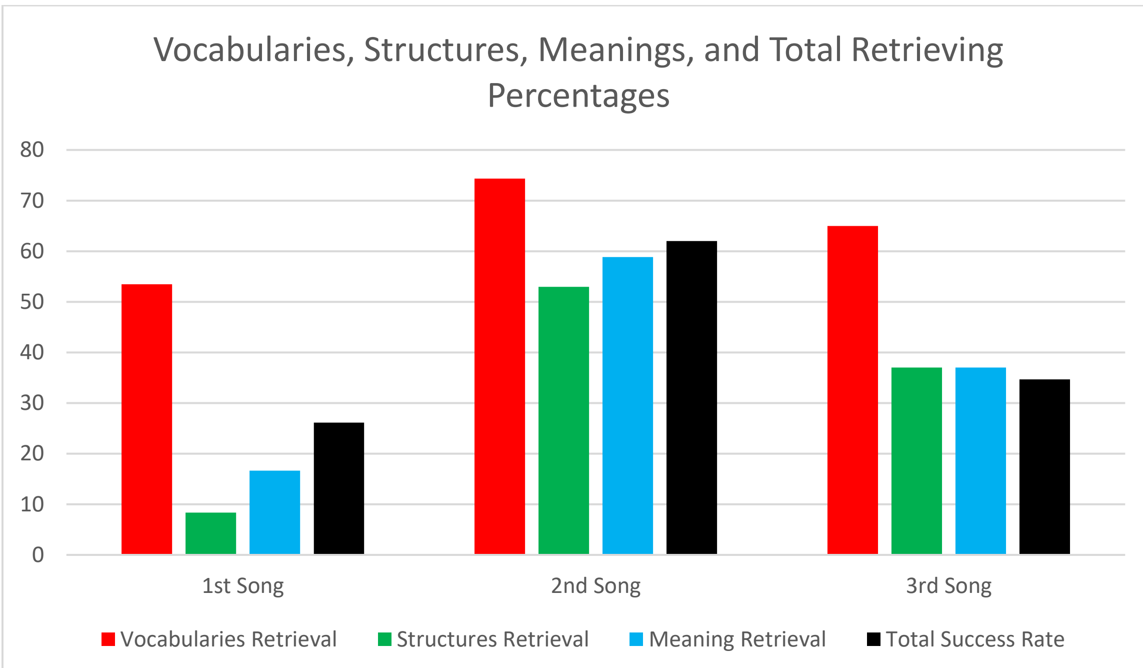

Figure 8: Vocabularies, structures, meanings, and total retrieval percentages

As we can see in the previous chart, the lowest percentage of success retrieval was in analyzing old poems that are written in formal Arabic (like the first song) because they contain difficult words which are not used in the Arab countries anymore. In addition, the users of Google Translate typically translate formal texts or official documents that do not contain difficult and complicated words. The second-lowest success rate was in the analysis of new poems that are written in dialect Arabic (the third song) because most of the Arabic texts that get translated by Google translation are scientific or official texts that are written in MSA. In addition, if there was an error in the translation, usually Arab people suggest corrections in formal Arabic not in their dialect Arabic. So, we can say that Google Translate deals successfully with formal Arabic text and this explains why I got the highest success rate when analyzing new poems that are written in formal Arabic (second song).

Google Translate's failure to translate poetry was obvious in most of the results because Google was unable to understand the structures of the Arabic poems. The highest structure retrieval rate was when retrieving new poems written in formal Arabic (52.94%) because Google Translate was able to translate it correctly into English at the beginning as it does not have difficult old words or dialectic words, and thus Google Translate was able to retrieve the lyrics successfully. But when retrieving the structures of new poems written in dialectic Arabic, Google Translate retrieved them but into formal Arabic structures, and the structure retrieval rate was 37.03% which is an unsatisfactory percentage. On the other hand, retrieving formal Arabic structures of old poems rate was 8.33% which is an unacceptable rate and it is the lowest retrieval rate because Google Translate could not retrieve those structures as they are complex and difficult to rebuild.

Google Translate relied on literal translation and that distorts the semantic meanings of the verses, meanings that reflect the cultures and moral values of Arab people. The highest rate of meaning retrieval was when retrieving meanings of new poems written in formal Arabic (second song) because the Arabic stored words and structures in Google Translate's servers are in formal Arabic, and that helped to understand the meaning of the verses. So, the English translation was correct and then, the meaning retrieval was correct. In contrast, complex old words, and structures of old poems (first song) are not stored in Google Translate's databases, so the meanings of these poems are not understandable for Google Translate. So, the retrieval rate was 16.66% which is considered as a low rate. In addition to that, meaning retrieval of the new poems written in dialectic Arabic (third song) is not satisfied because Google Translate could not understand it where it was reading them as if they are written in formal Arabic, so the retrieval rate was (37.03%) and it is inadequate rate.

From the analysis above, we can see that old complex Arabic words affect Google Translate's performance more than dialectic Arabic words do. The reason for this is that old words are not used anymore in the Arab world, so it is not used in the translation. In addition, in case of an error in translation, each correction is done in MSA so the new translated words will be added to Google Translate's databases and this will make the new added translated words more used than the old difficult words.

- **Implications and Discussion**

Google Translate's databases lack the ability to differentiate between affixes and original letters where we need to break down the word into its components to translate any word between languages. For example, in the Arabic language, a word can have prefixes or suffixes added to the same word. Those prefixes and suffixes can be prepositions, pronouns, etc. By applying semantic rules to those words, we can identify their parts of speech — whether they are nouns, verbs, adjectives, etc. Sometimes, the diacritical marks added to the words can indicate the presence of an affix, but it is rare to see the diacritics in formal Arabic nowadays especially on social media because native Arabic speakers can read the words without them. So, due to the absence of diacritics, the task of breaking down the words into its components can be more complicated. Sometimes it is difficult to decide if the letter in the word is a prefix or suffix, or it is an original letter. In addition, diacritics can indicate presence of another letter which means stressing when pronouncing a letter in the word, and this can change the meaning.

Google Translate is affected by linguistic ambiguity resulting from multiple meanings of one word, leaving the target text out of context and losing its semantic meaning. For example, the word "ودعتني" which we can pronounce as "Waddatani" can mean "you said goodbye", "She said goodbye", or "and she invited me".

When translating to a specific language, the translation must be in accordance with the requirements of this target language where there are rules by which the words in any sentence are ordered and these rules come from grammatical knowledge. For example, the verbs in English do not show the gender of the subject if it is feminine or masculine while in Arabic, verbs indicate the gender of the subject. This is considered a problem in translation between English and Arabic, which is a language that is highly sensitive to the type of verbs, adjectives, and nouns. For example, the verb "Faala" means "he did", the verb "Faalat" means "She did", the verb "Faalu" means "they did", and the verb "Faalaa" means "they both did". From this example, we can see that in the Arabic language, verbs, nouns, or adjectives can describe individuality, pluralism, femininity, and masculinity. Therefore, the automated translator can extract the information we need from the source language. For example, if we consider the original language is English and the target language is Arabic, the number and the gender must be known in some vocabulary, especially the names of people, things, and places. For example, the automated translator should know that John is male, Carol is female, the table is feminine, television is masculine, and any city is considered as feminine.

Most of the translation tasks in the world are texts that do not belong to the most sophisticated and complex type of literary and cultural production. Most professional translators work to meet the huge and rapidly growing demand for the translation of scientific documents, news reports, transactions, administrative notes, diplomacy, technological products, and medical books.

Statistical translation depends on storing words and structures, but there is a severe lack of Arabic stored words and structures, and therefore translation between the Arabic language and other languages is still limited. In addition, Google Translate lacks techniques that allow it to store the texts presented to it without changing it later, especially fixed texts that do not change over time such as Arabic poems, the Holy Quran, or proverbs.

- **Conclusion**

I have tried through this research to reach the core of the problem in which Google Translate fails during the translation process of Arabic texts, especially the literal ones. Some researchers acknowledge that it is impossible to avoid these errors, which is evident through the results that we got in our research. It is important to admit that there is a difficult part of the translation task that needs intellectual efforts from the translator that cannot be ignored.

Finally, with all the improvement attempts, the machine translation in which the human does not interfere remains limited in many areas of knowledge in terms of accuracy and reliability. So, the best translation we can get is when we have interaction and cooperation between human beings and machine translation which is called Human Aided Machine Translation (HAMT).

Chapter 5: Sentiment Analysis

- **Introduction**

In this chapter, I analyze Arabic songs' lyrics which are written in MSA or dialect Arabic. This chapter aims to propose a tool that can extract sentiments of Arabic texts and can evaluate the translation systems in determining the polarity of the lyrics. In addition, this chapter answers the following research questions: How accurate is the sentiment analysis when we apply it to Arabic texts? And how does machine translation from Arabic to English affect the result of the sentiment analysis of the translated text?

Before answering these questions, we need to have an overview of sentiment analysis and its steps when we apply them to any text in any language and to Arabic texts in particular. Any sentiment analysis in any language other than English is called multilingual sentiment analysis.

Implementing lexicon-based sentiment analysis needs four steps to be done. The first step is collecting data and creating datasets. The second step is processing the datasets which means deleting unwanted symbols, numbers, or other language letters like %, ##, $, @, ** symbols. The third step is filtering the data, which means correcting the misspellings, deleting unnecessary repeated letters and stop words, and normalization, which means to convert all forms of a given word into one form such as stemming and lemmatization so we can get the root of the words. And the last step is classification which means deciding whether the texts are positive or negative. In this chapter, I will create two lists of positive and negative words in Arabic and in English to help in the classification "but coming up with the right set of keywords might be less trivial than one might initially think" (Pang & Lee, 2008).

➢ **Multilingual Sentiment analysis**

Researchers are seeking to develop multilingual opinion analysis systems to expand the field of research and meet the market's need to analyze feelings and opinions in more than one language. To develop these systems, researchers are using a variety of methods including using local language grammar, word strings, and word position learning which means learning the word order in a sentence. For example, in Arabic, researchers should know the position of verbs which are put before the subjects and the objects in a sentence, while in English, the subject should be put before.

Sentiment analysis works and research were done on English texts more than texts in other languages (Balahur & Turchi, 2012), but people express their feelings in their language. So, performing sentiment analysis in many languages is important not to miss any fundamental information in texts written in languages other than English (Dashtipour et al., 2016). But the problem in multilingual sentiment analysis is the lack of resources (Balahur & Turchi, 2012). Some of those resources are available online like positive and negative word lists, while others need to be established like suggested translation by a human translator or adding more words to those positive and negative word lists.

Most sentiment analysis experiences of languages other than English use translation into English methods first and then apply the sentiment analysis procedures used in English. The problem in this method is that, as we have seen, some essential information will be missed in translation and that will affect the sentiment analysis's efficiency. This is what I will demonstrate by using my methodology later in this chapter. Despite that problem, multilingual sentiment analysis approaches are developing very fast (Dashtipour et al., 2016), but most of these approaches cannot be used in other languages than the language they were applied in.

"Further, optimizing models for each language is very time consuming and labor-intensive especially for recurrent neural network models" (Can et al. 2018) because we will need to create new datasets for each language to be trained. For example, as I mentioned above, I created positive and negative word lists in Arabic manually. That has taken a long time because there are not libraries and functions in any NLP programming language that deal with the Arabic language.

The main motivation for the experiments I present in this paper is the lack of resources and approaches for sentiment analysis in languages other than English like the Arabic language. Besides, some researchers have used the translation from these languages into English and they have focused only on the issue of classification of feelings and ignored the impact of translation quality and the difference that can be made using these translation systems. My main contribution in this chapter is an assessment of the performance of multilingual sentiment analysis using machine translation systems.

- **Arabic Sentiment Analysis**

As I have mentioned above, opinion mining is a new research field in which a lot of problems need to be solved and most of the work related to it is done in Indo-European languages, especially English. However, there are a few articles analyzing feelings using languages other than English, but they are considered as relatively recent work compared to the research done in English (Rushdi-Saleh et al., 2011). There are some sentiment analysis approaches that focus on Arabic language social media's texts (Hammad & Al-awadi, 2016).

Although the Arabic language is considered one of the most used languages on the Internet and it is spoken by hundreds of millions of people, there are limited resources for sentiment analysis in Arabic. There are few positive and negative datasets, or polarity lexicons. These are the main reasons why I wanted to create an opinion corpus for Arabic in this thesis.

Choosing to implement sentiment analysis in the Arabic language is important for several reasons. First, Arabic sentiment analysis is important because of its large-scale Arab audience. Second, the Arabic language is both challenging and interesting because of its history, its cultural and literary heritage. And finally, Arab people express their feelings on social media and the internet using their own language. Therefore, this opinion mining should be done using this language due to important information that might be missed when the Arabic opinions of Arab people are neglected.

- **Arabic Sentiment Analysis Challenges**

At the present time, Arab people use their dialect to write their opinion about something on the internet or social media, and the dialects are different than Modern Standard Arabic (MSA). "So, we end with many written accents instead of one formal language" (El-Halees, 2011). Sometimes, specific dialects cannot be understood by other people who do not speak it. Syrian people, for example, do not understand Moroccan dialect because it has different words than Syrian words. This can be a problem because we will need to create positive and negative word lists for each dialect and each list will not work with another dialect.

Sometimes, people use MSA in their writings, but they do not write with diacritical marks because Arabic native speakers can read it correctly without them, but for sentiment analysis, this might be a problem. As I mentioned in previous chapters, each diacritical mark can indicate a subject or an object and this will affect the opinion mining efficiency.

The challenges presented above in this section suggest that we need to clean the Arabic data before we start performing sentiment analysis on Arabic texts. The cleaning of Arabic texts is different than cleaning English texts and that will be presented in my methodology section.

The rest of this chapter is structured as follows: the next section presents the methodology that I used here. Section three gives the results of the experiment I did in the methodology. Section four discusses the implications and section five concludes the chapter.

- **Methodology**

Python is one of the top programming languages for data science and it has a strong community and a large set of options to implement NLP models. I wrote code in the Python programming language because it is one of the most used programming languages to implement NLP models. I used Anaconda distribution, which includes many useful Python modules.

In the beginning, I chose 20 random Arabic songs on purpose to explore the different strengths and weaknesses of sentiment analysis. Those songs differ from each other in terms of the country and the period in which they were sung. In addition, those songs differ in terms of words that might be written in formal or dialectic Arabic. I used the Arabic song website "https://www.esm3.com/" to choose those songs. This website classifies songs according to their nationality like Syrian, Lebanese, etc. songs, or according to their type like romantic, sad, or patriotic songs. I chose four Syrian songs and they are "Min Aia Kawkab Jaeey", "Ouhebu Biladi", "La Yushtara", "Kan Ya Ma Kan"; four Lebanese Songs and they are "Watani", "Krehtak", "Oumen", and "Takkabar"; four Gulph Songs and they are "Ya Man Hawahu", "Ya Tayeb", "Etdalaa Ya Kayedhum", and " Ana Nater"; four Iraqi songs and they are "Sabahuki Sukkar", "Ishreen Aam", "Mhajer", and "Ayaratni Bil Shaybie"; and four Egyptian songs and they are “Touba”, “Anta Omri”, “Yalli Taeebna”, Betigi Sertak”. After choosing this list of 20 songs, I wrote Python code to choose five out of them randomly. The code will look as follows:

```
SongsList=['Min Aia Kawkab Jaeey', 'Ouhebu Biladi', 'La Yushtara', 'Kan Ya Ma Kan',
'Watani', 'Krehtak',  'Oumen', 'Takkabar', 'Ya Man Hawahu', 'Ya Tayeb', 'Etdalaa Ya
Kayedhum', 'Ana Nater', 'Sabahuki Sukkar',  'Ishreen Aam', 'Mhajer', 'Ayaratni Bil
Shaybie', 'Touba', 'Anta Omri', 'Yalli Taeebna', 'Betigi Sertak']
print (" random 5 songs we choose to analyze are:", random.sample(SongsList, 5))
```

Figure 9: Python code to choose 5 songs to apply sentiment analysis on them

With this code I got the following five songs to analyze: ['Krehtak', 'Oumen', 'Ana Nater', 'Anta Omri', 'Ya Man Hawahu'].

I translated these songs by Google Translate and then provided my translation so I can compare between the two translations to show how the translation can affect the sentiment analysis of the text. Appendix D includes the songs’ lyrics, their Google translation, and my translation.

In this methodology, I downloaded Arabic positive words and Arabic negative words documents that were written by Amira Magdy Shoukry in her master’s thesis in 2013 and were used in a GitHub project by Alex Rutherford in 2014. These documents did not have enough positive and negative words as they did not have all the polarity words in the lyrics I have. This lack of polarity lexicon affected my analysis and gave different inaccurate results where the number of the positive and negative words in the lyrics was higher than the number I got when I used these lists. So, I added some new positive and negative words in addition to the ones that existed in these documents. Furthermore, I downloaded the English positive and negative word lists from a GitHub project by Marcin Kulakowski (2013). They contained words with positive or negative sentiments in English.

After I translated each song twice, once by Google Translate and once by me, I applied sentiment analysis approaches to them. To do that, I used the following files[2]:

- Arabic Sentiment Analysis Jupyter file with "ipynb" extension to analyze Arabic songs' lyrics sentimentally.
- English Sentiment Analysis Jupyter File with "ipynb" extension to analyze Arabic song's lyrics translations.
- Arabic Song Lyrics text file with "txt" extension.
- English Translation text file of the Arabic song with "txt" extension. This file will have my translation of the Arabic song lyrics.
- Google English Translation text file with "txt" extension. This file will have Google translation of the Arabic song lyrics.
- Arabic Positive Words text file.
- Arabic Negative Words text file.
- English Positive Words Text file.
- English Negative Words text file.

I analyzed the songs one by one where I copied the first song's lyrics and pasted it in the ArabicSong.txt file, then I copied its Google translation and pasted it in the GoogleTranslation.txt file, and finally, I copied the suggested translation and pasted it in the MyTranslation.txt file.

[2] For more information and for the code in those documents, see my GitHub page: https://github.com/ZeinaAizouky/Sentiment-analysis-of-Arabic-song-s-lyrics

After reading those Arabic and English translation files, I cleaned the texts by deleting numbers and non-alphabetical characters like apostrophes, @, #, etc. symbols. Furthermore, I removed the English and Arabic stop words which are commonly used meaningless words such as the, a, an, with, etc. in English. After this cleaning, I split the texts into words to count how frequently each word existed in the text as following:

anymore	made	done	eyes	whole	life	never	spend	evening	lonely
4	**3**	**3**	**2**	**2**	**2**	**2**	**2**	**2**	**2**

Figure 10: the most 10 frequent words with the number of how frequently they existed

I also drew a graph for the most frequent words as following:

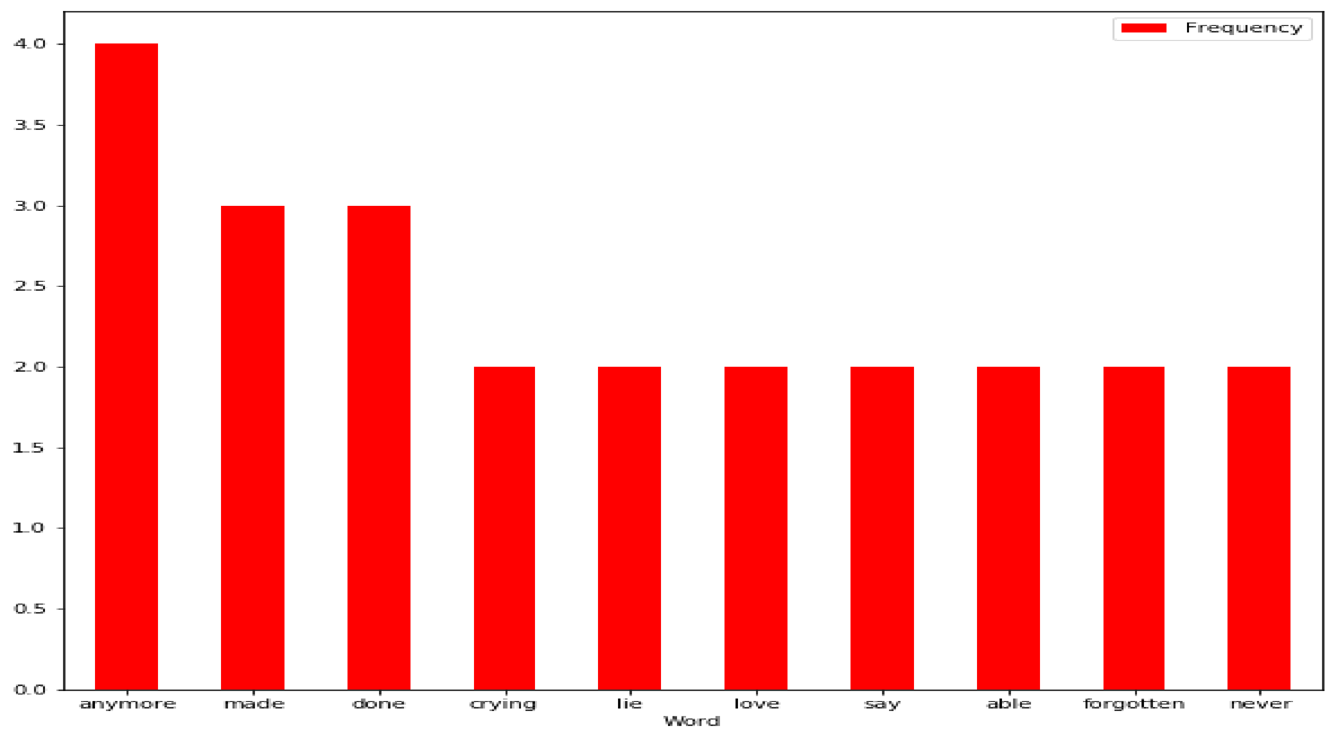

Figure 11: Top frequency word tokens in the translated text

I counted the number of positive and negative words and calculated their percentage in the text (Appendix E which has the English sentiment analysis code). After, I calculated the polarity score of the text by subtracting the percentage of the negative words from the percentage of the positive words after changing those percentages to their equivalent raw number. For example, (8%) is equal to (0.08), and (16%) is equal to (0.16). The result of this subtraction is a raw number also and it expresses the degree of polarity in the text. I will call this number the sentiment score (Table 12). If this number is "0", the text is neutral because it has the same number of negative and positive words. Otherwise, if this number is more than zero, then the sentiment of the text is positive, and if it is less than zero, then the sentiment of the text is negative (Appendix E).

In the next section, I will discuss the results of the sentiment analysis of all Arabic songs' lyrics, their Google translation, and their suggested translation.

- **Results and discussions**

I used a table to view all the results of the sentiment analysis of each song, its Google translation, and my suggested translation. By using the following table, I organized the results, and this made it easier to check the differences between the results of the sentiment analysis of each song and its English translations.

Songs' Name	The Type of the Analyzed text	Number of Positive Words	Number of Negative Words	Positive Percentage	Negative Percentage	Sentiment Score
Krehtak	Arabic Lyrics	19	33	16%	%28	-0.1176
	My Translation	9	25	3%	9%	-0.0606
	Google Translation	10	19	5%	9%	-0.0437
Omen	Arabic Lyrics	26	6	46%	11%	0.35088
	My Translation	20	3	19%	3%	0.16505
	Google Translation	13	3	14%	3%	0.10989
Ana Nater	Arabic Lyrics	23	38	17%	28%	-0.1087

	My Translation	21	22	7%	8%	-0.0034
	Google Translation	23	20	9%	8%	0.01172
Anta Omri	Arabic Lyrics	48	27	27%	15%	0.11602
	My Translation	33	26	10%	8%	0.02154
	Google Translation	28	18	10%	6%	0.03484
Ya man Hawahu	Arabic Lyrics	8	11	15%	19%	-0.0339
	My Translation	7	11	5%	9%	-0.031
	Google Translation	8	6	8%	6%	0.0198

Table 12: Number of positive and negative words, their percentages, and total sentiment percentage

As noticed from this table, the sentiment score is a raw number.

I used the results of Arabic sentiment analysis as a reference because the Arabic language is the original language of the songs and I compared the results of Google translation and the suggested translation sentiment analysis to the Arabic result.

As it was noted in the table above, the results of the sentiment analysis of words in the Arabic language, the Google translation, and the proposed translation differ among each other. Sometimes, the polarity of the results may also change, especially the polarity of Google Translate's results. For example, in the third song "Ana Nater", the sentiments of the Arabic text and my suggested translation are negative, even though the sentiment of the Arabic text is more negative than the sentiment of my suggestion, while the sentiment of Google translation of this song is positive. This change in polarity explains why it is difficult to translate Arabic poetry into English, as many meanings and feelings may be lost or changed when translating.

In this paragraph, I evaluated Google translation by subtracting the polarity percentage of Google translation from the Arabic polarity percentage. Google translation has changed the polarity in two songs: “Ya man Hawahu” and “Ana Nater”. This change in the polarity in the song “Ana Nater” was 0.1203 which was higher than the change in the “Ya Man Hawahu” song’s polarity which was 0.0536. The reason for this is that the song “Ya man Hawahu” is written in formal Arabic and the song “Ana Nater is written in Gulph dialect Arabic and Google Translate works better with texts that are written in MSA. So, Google Translate was not able to translate "Ana Nater" correctly. In contrast, Google’s translation did not change the polarity of the rest of the songs and the best performance was when translating the song “Krehtak”, where the change in polarity was 0.074, even though this song is written in Lebanese dialectic Arabic. The reason for this quality of performance is that Google Translate was able to translate most of the positive Arabic words into positive English words, and negative Arabic words into negative English words even though the translation might not be correct. For example, the word صدق “Saddek” means “to believe” and it is a positive word, but Google has translated it into “my honesty” and it is still a positive word even though it is not a correct translation. The second-best performance of the Google translation is with the “Anta Omri” song, which is written in the Egyptian dialectic Arabic, where the change in polarity was 0.0812. The reason for this good performance is because the Egyptian dialect is common, and the words of this song can be used in the MSA. For example, the word عمري “omri” which mean “my life” and the word انت “Anta” which means “you” are Egyptian words and they exist in the MSA. So, Google Translate was able to translate those words correctly because they are the same in the MSA. The least accurate translation was in the song “Omen” even though it is written in the MSA, where the change in polarity was 0.241. The reason for this low accuracy is that the lyrics of the songs contain complex words and the structures of the phrases are complex and it is difficult for the algorithm to find the subject, object, and verb. So, Google Translate could not translate them correctly.

Next, I evaluated my own translation performance in terms of the polarity of the texts. The polarity of my translated texts was not as good as the Arabic texts' polarity percentage, but my translation did not change the polarity of any song. In addition, I had better results than Google translation did because my translated texts were revised to be identical to the Arabic text and I considered cultural differences, idioms, and metaphors. To evaluate the performance of my translations, for each song, I calculated the differences between Arabic text's sentiment scores and my suggested translation's sentiment scores. The results are shown in the following table:

The Song	The difference between both English and Arabic texts' polarity scores
Krehtak	0.057
Omen	0.18
Ana Nater	0.1052
Anta Omri	0.0945
Ya Man Hawahu	0.0028

Table 13: the differences between my suggested translations' and Arabic texts' polarity scores

From the table above, in terms of being close to the Arabic polarity score, the best performance of my translation was with the song "Ya Man Hawahu" where the difference between both polarity scores was the lowest. The second top performance was with the song "Krehtak". The third top performance was when translating the song "Anta Omri". The fourth top performance was with the song "Ana Nater". The lowest performance was with the song "Omen". The reasons for these differences between polarities is because the positive words in

Arabic might not be positive in English. For example, the word غيرتني "Ghayartni" which means "you have changed me" is a negative word in Arabic but it is neither negative nor positive in English. So, the translation loses one of the polarized words.

As it was noticed, not every translation gave the right polarity of an Arabic text, but a human translation is usually better than Google's translation. So, I used my suggested translation as a baseline to evaluate how much Google Translate's performance was close to it. The differences between both my translations' and Google translations' polarity scores are shown in the following table:

The Song	The difference between my translations' and Google translations' polarity scores
Krehtak	0.17
Omen	0.055
Ana Nater	0.0151
Anta Omri	0.0133
Ya Man Hawahu	0.0508

Table 14: The difference between my translations' and Google translations' polarity scores

The best performance of Google Translate as with the song "Anta Omri" where the difference between both translations' polarity scores was the lowest. The second top performance is with the "Omen" song, and the third is with "Krehtak" song. For the rest of the songs, the Google Translate has changed the polarity of them from negative to positive. The difference of polarity in the song "Ana Nater" between Google translation and my translation is 0.0151 and it is lower than the difference in polarity between both translations of the song "Ya Man Hawahu" which is 0.0508.

As it was noticed, the sentiment analysis of Arabic songs' lyrics did not give the same results when the lyrics were translated into English. Also, Google Translate was not consistent in having the same polarity degree because the words might be written in dialectic Arabic or they might be old words and it is difficult to translate them. While personal translation can give the right meaning, it cannot always give the correct positivity or negativity degree of the text.

- **Implications**

As I demonstrated previously, I used ready-made lists of positive and negative Arabic and English words from a pre-existing project on GitHub. The Arabic positive and negative lists were not sufficient for my project because they did not have all the negative and positive words present in the lyrics, so I added some words. The following table shows the different results between the polarity of each song when we used GitHub lists without adding new words (Rutherford, 2014/2019). The GitHub version of the lexicon lists are the least accurate results and my version of the polarity word lists produced the most accurate results.

Song	the positive and negative lists	Number of positive words	Number of negative words	Positive words percentage	Negative words percentage	Sentiment Score
Krehtak	GitHub version	1	4	1%	3%	-0.0252
	My version	19	23	16%	28%	-0.1176
Omen	GitHub version	0	1	0%	2%	-0.0175
	My version	26	6	46%	11%	0.35088
Ana Nater	GitHub version	2	3	1%	2%	-0.0072
	My version	23	38	17%	28%	-0.1087

Anta Omri	GitHub version	1	2	1%	1%	-0.0055
	My version	48	27	27%	15%	0.11602
Ya Man Hawahu	GitHub version	1	0	2%	0%	0.01695
	My version	8	11	15%	19%	-0.0339

Table 15: Comparing between the number of positive and negative words, their percentages, and the sentiment percentage after adding more words to the sentiment lexicon lists

As it was noticed form the table above, the number of positive and negative words differ a lot in each song when using the GitHub version of the lists versus my version after having added more positive and negative words. This addition took a lot of time because when adding any positive or negative word, we must add all forms that this word might have due to different suffixes, affixes and prefixes, numerous forms for one word with completely different meanings. For example, I added the negative word “ضيع” which means “lost” and all the forms it might have are “أضاع”, “يضيع”, “أضاعت”, “تضيع”, “ضيعتني” which mean “He lost”, “He is losing”, “She lost”, “You lost me”.

In addition to that, Arab people use their dialect rather than MSA. As mentioned, there are about 30 different Arabic dialects and they differ from MSA and each other in terms of vocabularies, structures, and pronunciation (Habash, 2010). So, using the same sentiment analysis approaches used in MSA for these dialects will create low efficiency in sentiment analysis results. So, I have added negative and positive colloquial words that existed in the songs’ lyrics to the lists of positive and negative Arabic words. Recently, some researchers used new sentiment analysis approaches in specific dialects, like the Egyptian dialect CALIMA (Boudad et al., 2018), but this parser will not work for other dialects. So, we need to fill these gaps, covering more Arab dialects to have better opinion mining results for social media data.

As I have mentioned above, Arabs do not use diacritical marks when they write on social media because they can read and understand the meaning without those diacritics. But sometimes, one might notice a text written with full or some diacritics added. This will affect the results of the opinion mining because the parser might not identify this word with diacritics. For example, in our case the word “حب” which means “love” is positive and it exists in our positive list, but when we add any diacritic like “حُبّ”, the parser will not find it in our positive list and this will affect the results of our analysis. I solved this problem by having only lyrics written without diacritics. This is still a problem in the methodology whenever we want to apply it on lyrics written with diacritics.

- **Conclusion**

In this chapter, I have presented an approach for mining opinions on Arabic documents by counting the number of existing positive and negative words in the documents. By adding new words to positive and negative word list lexicons, I also evaluated the quality of sentiment analysis on Arabic-English Google translations and on my translations. The findings showed that applying English sentiment analysis steps on the translated version will give different results than applying Arabic opinion mining steps of the Arabic original version. The results of English sentiment analysis on the translated text are far from reaching the polarity results of Arabic sentiment analysis because the translation of any text might change the rate of the positive or negative words in the text. So, the results of the sentiment analysis on the translated text are less accurate than the results of performing sentiment analysis on the original Arabic texts. In this case, human translation gave better results than Google translation. So, we cannot trust only the Google translation without human interaction and must try to make the translation as identical to the Arabic text as possible. In addition, by adding more positive and negative words with all their possible forms to the lists, we can get more accurate results. In the long term, this can be done by cooperating between many researchers to create big lists of positive and negative words and make them available as references for future works on more songs' lyrics. In addition, those lists could be used for sentiment analysis of people's social media reviews.

Chapter 6: Conclusion

In this thesis, I examined the efficiency and accuracy of Google Translate when performing translation and sentiment analysis in both Arabic and English languages, and I examined the factors that may lower its performance in Arabic- English translation. In addition, I showed how accurate is Arabic sentiment analysis when it is applied it to Arabic songs' lyrics, and what errors we get when we apply English sentiment analysis approaches to text translated from Arabic into English.

The results of the evaluation of Google Translate show that Google Translate has failed to achieve adequate translations in terms of meaning and structure building in the target language. However, there is a huge demand for translation works at a rate that far exceeds the capabilities and energies of the human translation profession. So, the best translation we can get is when we have interaction and cooperation between human beings and machine translation which is called Human Aided Machine Translation (HAMT) where the human beings can be editors who check the correctness of MT and change the literal translation to a better translation which gives more precise meanings, especially to idiomatic expressions.

The results of applying sentiment analysis to Arabic texts showed that old and informal texts lower the performance of sentiment analysis because the old words and informal words are not all in the contemporary word lists. Also, applying English sentiment analysis steps on the translated version will give different results than applying Arabic opinion mining steps on the Arabic original version. Furthermore, Google translation lowers the accuracy of the English sentiment analysis compared to the results we get when we apply the English sentiment analysis to the suggested translation of the lyrics. So, we should improve MT approaches first by having more translation attempts which will enrich MT databases and that will give better results later.

Given my entire thesis research, I suggest that the solution to Arabic translation problem lies in the cooperation between the Arab countries in uniting their efforts and strengthening them to improve the translation of the machine translation to and from the Arabic language, through:

- The cooperation in the field of Arabic computational linguistics between linguistic and computer people in any scientific project at programming, analyzing, and processing the Arabic language. In this regard, I believe that any independent effort not coordinated between these scientific categories is a wasted effort and is useless.
- Translation of all scientific works in the field of Arabic computational linguistics, written in English and other languages by Arab or foreign researchers to the Arabic language.
- Creating a unified dictionary for computer terminology in Arabic and English, according to scientifically accepted terms in this type of idiomatic or terminological dictionaries.
- Creating a special section for computational linguistics in Arab colleges and universities.
- Encouraging universities and scientific research centers to start developing machine translation into Arabic by allocating budgets for scientific research, especially those dealing with this field.

As I mentioned above, to improve Arabic sentiment analysis, we need to have more Arabic positive and negative words in the Arabic opinion lexicon lists, which also means adding all the forms that an Arabic word can have. This is a time-consuming process but, with the collaborating efforts of many governmental societies and people, we can get comprehensive and extensive lists that can be used in all the Middle Eastern countries. In addition, defining a new machine learning method that works with the Arabic language will be essential to get better results in Arabic sentiment analysis.

In future works, I plan to expand the number of songs and other types of texts like scientific articles or a social media conversation and posts to analyze and investigate different document representations. My goal for my future work is to expand the positive and negative word lists and get all the opinion lists that exist in Arabic resources and combine them in one document for use later. I will try also to create a machine learning approach that can work with the Arabic language and compare it to the English performance.

References

Abdul-Mageed, M., Diab, M., & Kübler, S. (2014). *SAMAR: Subjectivity and sentiment analysis for Arabic social media*. Computer Speech & Language, 28, 20–37. https://doi.org/10.1016/j.csl.2013.03.001

Abdul-Mageed, M., & Diab, M. (2014). *SANA: A Large-Scale Multi-Genre, Multi-Dialect Lexicon for Arabic Subjectivity and Sentiment Analysis.* 8. http://www.lrec-conf.org/proceedings/lrec2014/pdf/919_Paper.pdf

Adileh, M. (2011). *Arabic music between the hammer of technological creativity and the anvil of cultural identity (A critical study)*. International Review of the Aesthetics and Sociology of Music, 42(1), 145–163.

Aisha Hamza. (2014). *Machine Translation from and to Arabic (reality and hope)*. Digital content in Arabic and software, Linguistic Studies Center. Algeria.

Adonis. (2011). *مقدمة للشعر العربي An Introduction To Arab Poetics*. Dar al Saqi.Appendixes

Al-Dabbagh, U. (2010). *Free Online Machine Translation Services as Providers of Gist Translation: A Fiction or a Reality.* Paper presented at the 2nd Jordan International Conference on Translation. Amman, Jordan: Petra University.

Al-Dabbagh, U. (2013). *Assessing the Quality of Free Online Machine Translation Services.* International Journal of Translation-IJT, 25(2).

Alfadi Albaridi. (2015). *Musical Instruments from The Arab World.* https://destinationksa.com/musical-instruments-arab-world/

Alhindi, W., Talha, M., & Sulong, G. (2012). *The Role of Modern Technology in Arab Spring.* Archives Des Sciences 1661-464X, 65, 1661–464.

Al-Jawhari, Ismail. (1990). *Al-Sehah Jaj Al-Lugha Wa Sihah A-Arabiya*. Dar Al-Ilm for Millions. https://ia802706.us.archive.org/12/items/FP10502/10502.pdf

Al-Kharabsheh, A., & Yassin, O. (2017). *Translation of Colloquialisms in the Arabic-into-English Subtitled Film, The Dupes.* International Journal of Comparative Literature and Translation Studies*, 5*(3), 18–27. https://doi.org/10.7575/aiac.ijclts.v.5n.3p.18

Alqinai, J. (2010). *Mediating Punctuation in English Arabic Translation*. Journal of Applied Linguistics, 5. https://doi.org/10.1558/japl.v5i1.5

Al-Qudsi, A., Omar, N., & Shaker, K. (2012). *Arabic Machine Translation: A survey*. Artificial Intelligence Review. 42. 10.1007/s10462-012-9351-1.

Al-Sonati B. (2013). *Risk and challenges in translating old texts. An attempt to present a general translation strategy in the light of knowledge theory.* Al-Basra network. http://www.albasrah.net/ar_articles_2013/0613/bhnam_250613.htm

Al-Subaihin, A. A., Al-Khalifa, H. S., & Al-Salman, A. S. (2011). *A proposed sentiment analysis tool for modern Arabic using human-based computing*. Proceedings of the 13th International Conference on Information Integration and Web-Based Applications and Services, 543–546. https://doi.org/10.1145/2095536.2095651

Alwakid, G., Osman, T., & Hughes-Roberts, T. (2017). *Challenges in Sentiment Analysis for Arabic Social Networks.* Procedia Computer Science, 117, 89–100. https://doi.org/10.1016/j.procs.2017.10.097

Alyasin R., Al-Khalil T. (2018). *Asymmetry in translation between English and Arabic*. Al-Baath university, Syria, 26. 127-154

Amenah Fatima Alzahraa. (2008*). The problem of machine translation limits, the translation of the (Systran) verbal syndrome system (English / Arabic).* Mentouri University, Constantine.

Arabic Music Overview. (n.d.). Retrieved April 16, 2018, from http://www.traditionalarabicmusic.com/arabic_music_overview.html

Asharman, A. (2005). Retrieved December 25, 2018, from https://journals.ju.edu.jo/DirasatHum/article/viewFile/1482/1472

Assiri, A., Emam, A., & Aldossari, H. (2015). *Arabic Sentiment Analysis: A Survey*. International Journal of Advanced Computer Science and Applications (IJACSA), 6(12), Article 12. https://doi.org/10.14569/IJACSA.2015.061211

Bailey, J. (2011). The Problem with Detecting Translated Plagiarism. *Plagiarism Today*. https://www.plagiarismtoday.com/2011/02/24/the-problem-with-detecting-translated-plagiarism/

Balahur, Alexandra & Turchi, Marco. (2012). *Multilingual sentiment analysis using machine translation?*. Proceedings of the 3rd Workshop in Computational Approaches to Subjectivity and Sentiment Analysis. 52

60. https://dl.acm.org/doi/pdf/10.5555/2392963.2392976?download=true

Bellos, D. (2012). *Is that a fish in your ear?* London: Penguin.

Bessou, S. (2016, March 14). *المعالجة الالية للغة العربية في الإدارة الالكترونية.* https://www.researchgate.net/publication/315546813_almaljt_alalyt_llght_alrbyt_fy_aladart_alalktrwnyt

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. (2002). *Thumbs up? Sentiment classification using machine learning techniques*. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), 79–86.

Boudad, N., Faizi, R., Oulad Haj Thami, R., & Chiheb, R. (2018). *Sentiment analysis in Arabic: A review of the literature*. Ain Shams Engineering Journal, 9(4), 2479–2490. https://doi.org/10.1016/j.asej.2017.04.007

Cambridge international dictionary of English. (1995). Cambridge: Cambridge University Press

Can, E.F., Ezen-Can, A., & Can, F. (2018). *Multilingual Sentiment Analysis: An RNN-Based Framework for Limited Data*. ArXiv, abs/1806.04511.

Chloe Gilholy. (2017). *Google Translate with Shakespeare*. Poets. https://vocal.media/poets/google-translate-with-shakespeare

Currey, N. E. (2002). *History in contemporary practice: Syria's music canon*. Middle East studies association bulletin, 36(01), 9–19. https://doi.org/10.1017/S0026318400044023

Danielson, V. (1996). *New Nightingales of the Nile: Popular Music in Egypt Since the 1970s*. Popular Music, 15(3), 299–312.

Darin Flynn. (2012). *Phonology: The distinctive features of speech sounds*. University of Calgary. https://www.ucalgary.ca/dflynn/files/dflynn/flynn12_distinctive_features.pdf

Dashtipour, K., Poria, S., Hussain, A., Cambria, E., Hawalah, A. Y. A., Gelbukh, A., & Zhou, Q. (2016). *Multilingual Sentiment Analysis: State of the Art and Independent Comparison of Techniques*. Cognitive Computation, 8, 757–771. https://doi.org/10.1007/s12559-016-9415-7

Deep, M. (2014, June 20). *Translation Plagiarism: A Modern Day Concern*. Plagramme Plagiarism Checker. https://www.plagramme.com/translation-plagiarism-modern-day-concern

Ding, X., Liu, B., & Yu, P. S. (2008). *A holistic lexicon-based approach to opinion mining.* Proceedings of the International Conference on Web Search and Web Data Mining - WSDM '08, 231. https://doi.org/10.1145/1341531.1341561

Ding, X., Liu, B., & Zhang, L. (2009). *Entity discovery and assignment for opinion mining applications*. Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '09, 1125. https://doi.org/10.1145/1557019.1557141

El-Beltagy, S., Khalil, T., Halaby, A., & Hammad, M. (2016, April 8). *Combining Lexical Features and a Supervised Learning Approach for Arabic Sentiment Analysis.*

El-Halees, A. M. (2011). *Arabic opinion mining using combined classification approach*. Arabic Opinion Mining Using Combined Classification Approach. https://iugspace.iugaza.edu.ps/handle/20.500.12358/25202

Eugene P. (2020). *What Are the Most Common Speech Recognition Problems?* WiseGEEK. http://www.wisegeek.com/what-are-the-most-common-speech-recognition-problems.htm

Farghaly, A. (2010). *Arabic Machine Translation: A Developmental Perspective*. https://www.academia.edu/2676492/Arabic_Machine_Translation_A_Developmental_Perspective

Farghaly, A., & Shaalan, K. (2009). *Arabic Natural Language Processing*. ACM Transactions on Asian Language Information Processing, 8, 1–22. https://doi.org/10.1145/1644879.1644881

Farmer, H. G. (1929). *A history of Arabian music to the XIIIth century*. London: Luzac.

Farmer, Henry George. (1965). *An annotated bibliography of Arabic manuscripts with deal with the theory, practice, and history of Arabian music from the eighth to the seventeenth century.*

Fatima, M. (2015*). Machine translation errors*. Abdol-Rahman Mira "Bijaya" University.

Ferrell, T. (n.d.). *Issues in the machine translation of one language to another language—A case study of Google Translator*. 5. https://www.ijmrnd.com/assets/pdf/information-security/Issues-in-the-machine-translation.pdf

Fox, E. (2012). *Saudi Aramco World : Um Kulthum: The Lady's Cairo*. Retrieved November 20, 2018, from http://archive.aramcoworld.com/issue/201201/um.kulthum.the.lady.s.cairo.htm

García-Arenal, M., & Rodríguez Mediano, F. (2017). *Sacred History, Sacred Languages: The Question of Arabic in Early Modern Spain.* In J. Loop, A. Hamilton, & C. Burnett (Eds.), The Teaching and Learning of Arabic in Early Modern Europe (pp. 133–162). Brill. https://doi.org/10.1163/9789004338623_007

Gaule, M., & Josan, G. (2012). *Machine Translation of Idioms from English to Hindi*. International Journal of Computational Engineering and Research ISSN: 2250-3005, 2.

Groves, M., & Mundt, K. (2015). *Friend or foe? Google Translate in language for academic purposes*. English for Specific Purposes, 37, 112–121. https://doi.org/10.1016/j.esp.2014.09.001

Habash, N. Y. (2010*). Introduction to Arabic natural language processing*. San Rafael, Calif.: Morgan & Claypool Publishers.

Hadla, L., Hailat, T., & Al-Kabi, M. (2014). *Evaluating Arabic to English Machine Translation*.

Haines, J. (2001). *The Arabic Style of Performing Medieval Music*. Early Music, 29(3), 369–378.

Hammad, M., & Al-awadi, M. (2016). *Sentiment Analysis for Arabic Reviews in Social Networks Using Machine Learning*. In S. Latifi (Ed.), Information Technology: New Generations (pp. 131–139). Springer International Publishing. https://doi.org/10.1007/978-3-319-32467-8_13

Harmon, J. (2016, October 14). *Why don't we just use Google Translate for the Bible*? Jessica Harmon. http://jlharmon.com/2016/10/14/why-dont-we-just-use-google-translate-for-the-bible/

Henschen, D. (2015, July 7). *Sentiment Analysis: The New State Of The Art*. Constellation Research Inc. https://www.constellationr.com/blog-news/sentiment-analysis-new-state-art

History of the Arabic language at UNESCO | United Nations Educational, Scientific and Cultural Organization. (2017). http://www.unesco.org/new/en/unesco/resources/history-of-the-arabic-language-at-unesco/

Hutchins W.John. (1995*). Machine Translation: A Brief History*. Concise history of the language sciences: from the Sumerians to the cognitivists. Edited by E.F.K. Koerner and R.E.Asher. Oxford: Pergamon Press.

International Journal of Advanced Computer Science and Applications, *5*, 68–73. https://doi.org/10.14569/IJACSA.2014.051112#sthash.NW2l6vl5.dpf

Izwaini, S. (2006). *Problems of Arabic machine translation: Evaluation of three systems*. Proceedings of the International Conference on the challenge of Arabic for NLP/MT, the British Computer Society (BSC), London, UK. Retrieved from: http://www.mt-archive.info/BCS-2006-Izwaini.pdf

Jabak, D. O. (2019). *Assessment of Arabic-English translation produced by Google Translate*. Assessment of Arabic-English Translation Produced by Google Translate. https://www.academia.edu/39973068/Assessment_of_Arabic-English_translation_produced_by_Google_Translate

Jonathan H. Shannon. (2003). Sultans of Spin: Syrian Sacred Music on the World Stage. American Anthropologist, (2), 266.

Jones, K. (2018, March 12). *Why music not a universal language – and what that means for care*. Retrieved December 12, 2018, from http://www.homeandlongtermcare.ca/why-music-not-a-universal-language-and-what-that-means-for-care/

Kaila, K. (2018). *What emotions do different musical keys evoke for you?* Quora. Retrieved December 25, 2018, from https://www.quora.com/What-emotions-do-different-musical-keys-evoke-for-you

Kaltenbacher, M. (2000). *Aspects of universal grammar in human versus machine translation.* In A. Chesterman, N. San Savador, & Y. Gambier (Eds.), Translation in context (pp. 221-230). Amsterdam: John Benjamins.

Kirchhoff, K., Turner, A. M., Axelrod, A., & Saavedra, F. (2011). Application of statistical machine translation to public health information: A feasibility study. *Journal of the American Medical Informatics Association: JAMIA*, *18*(4), 473–478. https://doi.org/10.1136/amiajnl-2011-000176

Kozłowski, S. (2002). *Co to jest tłumaczenie maszynowe?.* Retrieved from: http://kf.mish.uw.edu.pl/kog/kog_seb.pdf, pp. 63-93.

Li, H., Graesser, A., & Cai, Z. (2014). *Comparison of Google Translation with Human Translation*. In Florida Artificial Intelligence Research Society Conference. Retrieved from: https://www.aaai.org/ocs/index.php/FLAIRS/FLAIRS14/paper/view/7864/7823

Liddy, E.D. (2001*). Natural Language Processing*. In Encyclopedia of Library and Information Science, 2nd Ed. NY. Marcel Decker, Inc. https://surface.syr.edu/cgi/viewcontent.cgi?article=1043&context=istpub

Liu, B. (2012). *Sentiment Analysis and Opinion Mining. Synthesis Lectures on Human Language Technologies*, 5(1), 1–167. https://doi.org/10.2200/S00416ED1V01Y201204HLT016

Ludden, D. (2015). *Is Music a Universal Language?* Retrieved December 13, 2018, from https://www.psychologytoday.com/blog/talking-apes/201507/is-music-universal-language

Marcin Kulakowski. (2013). Mkulakowski2's gists. Gist. https://gist.github.com/mkulakowski2

McMullan, T. (2018). Music really is a universal language, study suggests. Retrieved December 12, 2018, from https://www.alphr.com/go/1008294

Michael Denkowski, & Alon Lavie. (2010*). The METEOR Automatic MT Evaluation Metric.* http://www.cs.cmu.edu/~alavie/METEOR/

Michaela Panter. (n.d.). *Translating Academic Writing: Human vs. Machine | AJE*. Retrieved July 4, 2020, from https://www.aje.com/arc/translating-academic-writing-human-vs-machine/

Michele Rousseau. (2013, January 13). *Mercan Dede*. https://www.sufijournal.org/mercan-dede-turns-the-tables-on-sufism/

Mourad, A., & Darwish, K. (2013). *Subjectivity and Sentiment Analysis of Modern Standard Arabic and Arabic Microblogs.* Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, 55–64. https://www.aclweb.org/anthology/W13-1608

Music (Ottoman Empire/Middle East) | International Encyclopedia of the First World War (WW1). (n.d.). Retrieved April 16, 2018, from https://encyclopedia.1914-1918-online.net/article/music_ottoman_empiremiddle_east

Musical Trends in Middle Eastern Music. (n.d.). Retrieved April 15, 2018, from http://www.middleeasterndance.net/Music/AboutMEMusic/Trends.html

n, d. (2018). *Python random.choice() to choose random element from list, String, array*. PYnative. https://pynative.com/python-random-choice/

Nabeel Ali. (1988). *The Arabic language and the computer.*

Nour Aldeen G, Yasin G. (2019). *Modeling and designing a semantic coding system for machine translation (English-Arabic).* Hemma Lekhder-Alwadi University.

Nur, Y. (2015). *The Quietus | Features | Electro Chaabi | Umm Kulthum: Queen Of The Nile.* Retrieved November 20, 2018, from http://thequietus.com/articles/17255-umm-kulthum-queen-of-the-nile

Othman, Waleed. (2004). *Subordination and Coordination in English-Arabic Translation.* Al- Basaer, 8 (2):12 – 33. https://www.translationdirectory.com/article899.htm

Othman M., & Abu Bakr O. B. (n. d.).*بين اللغة العربية والحاسوب يمكن تطبيق اللسانية الحاسوبية لخدمة اللغة العربية*

Oueslati, O., Cambria, E., HajHmida, M. B., & Ounelli, H. (2020). *A review of sentiment analysis research in Arabic language*. Future Generation Computer Systems, 112, 408–430. https://doi.org/10.1016/j.future.2020.05.034

Pang, B., Lee, L., & Vaithyanathan, S. (2002). *Thumbs up? Sentiment Classification using Machine Learning Techniques.* Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (EMNLP 2002), 79–86. https://doi.org/10.3115/1118693.1118704

Pang, B., & Lee, L. (2008). *Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval*. 2 (1-2) (pp. 1-135).

Papineni, K., Roukos, S., Ward, T., & Zhu, W. J. (2002). *BLEU: A Method for Automatic Evaluation of Machine Translation*. https://doi.org/10.3115/1073083.1073135

Petzinger, J., & Petzinger, J. (2016, November 26). *Syrian refugees are the latest artists to light up Berlin's creative scene*. Retrieved April 15, 2018, from https://qz.com/838864/syrian-refugees-are-the-latest-artists-to-light-up-berlins-creative-scene/

Pozzi, F. A., Fersini, E., Messina, E., & Liu, B. (2017). *Chapter 1 - Challenges of Sentiment Analysis in Social Networks: An Overview*. In Sentiment Analysis in Social Networks (pp. 1–11). Morgan Kaufmann. https://doi.org/10.1016/B978-0-12-804412-4.00001-2

Puchała-Ladzińska, K. (2016). *Machine translation: A threat or an opportunity for human translators?* https://doi.org/10.15584/sar.2016.13.9

Racy, A. J. (1986). *Words and Music in Beirut: A Study of Attitudes.* Ethnomusicology, 30(3), 413–427. https://doi.org/10.2307/851587

Rebecca Ray. (2004). *Implementing Machine Translation, The Localization Industry Standards Association*. Route du Monastère, Switzerland.

Rick Noack & Lazaro Gamio. (2015). *The world's languages, in 7 maps and charts.* The Washington Post. https://www.washingtonpost.com/news/worldviews/wp/2015/04/23/the-worlds-languages-in-7-maps-and-charts/

Riloff, E., & Wiebe, J. (2003). *Learning extraction patterns for subjective expressions*. Proceedings of the 2003 Conference on Empirical Methods in Natural Language Processing, 10, 105–112. https://doi.org/10.3115/1119355.1119369

Rushdi-Saleh, M., Martín-Valdivia, M. T., Ureña-López, L. A., & Perea-Ortega, J. M. (2011). *Bilingual Experiments with an Arabic-English Corpus for Opinion Mining.* Proceedings of the International Conference Recent Advances in Natural Language Processing 2011, 740–745. https://www.aclweb.org/anthology/R11-1108

Sakar Alkereyf. (2015). *Natural Languages Processing NLP*. Colombia university. http://sakhar.co/?p=268&lang=ar

Rutherford, A. (2019). Alexrutherford/arabic_nlp [Python]. Retrieved from https://github.com/alexrutherford/arabic_nlp (Original work published 2014)

Salameh, M., Mohammad, S., & Kiritchenko, S. (2015). *Sentiment after Translation: A Case-Study on Arabic Social Media Posts.* Proceedings of the 2015 Conference of the North American

Chapter of the Association for Computational Linguistics: Human Language Technologies, 767–777. https://doi.org/10.3115/v1/N15-1078

Saldaña, S. (2017, June 29). *Syrian Kurdish Musicians Ferhad Feyssal and Hozan Peyal are Preserving Joy*. Retrieved November 2, 2018, from http://www.mosaicstories.org/2017/06/29/syrian-kurdish-musicians-ferhad-feyssal-hozan-peyal-preserving-joy/

Saldaña, S. (2017, September 28). *Reflections on Music and Exile in Syria*. Retrieved April 15, 2018, from http://www.mosaicstories.org/2017/09/28/reflections-music-exile-syria/

Scherf, W. (1992). *Training, talent, and technology*. Teaching Translation and Interpreting, 153.

Shannon, J. H. (2006.). *Among the jasmine trees music and modernity in contemporary Syria*. Middletown, Conn.: Wesleyan University Press,

Shannon, J. H. (2016). *There and Back Again: Rhetorics of Al-Andalus in Modern Syrian Popular Culture*. International Journal of Middle East Studies, 48(1), 5–24.

Sheppard, F. (2011). *Medical writing in English: The problem with Google Translate.* La Presse Médicale, 40(6), 565-566. Retrieved from: http://www.em-consulte.com/en/article/293595

Shoeeb G. (2015). *Arabic Machine Translation.* Abd-Alhammed Ibn Badis University, Algeria.

Shoukry A., Rafea A. (2013*). Arabic Sentence Level Sentiment Analysis*. American University in Cairo. Retrieved from http://dar.aucegypt.edu/bitstream/handle/10526/3536/Arabic_Sentence_Level_Sentiment_Analysis.pdf?sequence=1

Sian Jones. (2020, April 15). *Google Translate: The Unwitting Confidentiality Flaw*. Imperial Blog. https://www.imperialcrs.com/blog/2020/04/google-translate-the-unwitting-confidentiality-flaw/

Suttie, J. (2015). *Four Ways Music Strengthens Social Bonds*. Retrieved April 15, 2018, from https://greatergood.berkeley.edu/article/item/four_ways_music_strengthens_social_bonds

Tagwa Abd Elatif Mohammad. (2016). *Review of Sentiment Analysis for Classification Arabic Tweets.* International Journal of Emerging Technology and Advanced Engineering.

Taufiq, S. (2018). *Fikrun wa Fann - Topics - Music between cultures* - Goethe-Institute. Retrieved April 16, 2018, from http://www.goethe.de/ges/phi/prj/ffs/the/a96/en8626486.htm

T. D. Hedden. (2010*). Machine Translation: A Brief Introduction*. Retrieved from: http://www.hedden.org/intro_mt.html

Thames, J. (2019, June 7). *Machine Translation and Confidentiality*. Language Solutions Inc. https://langsolinc.com/machine-translation-and-confidentiality/

Translating Slang Terms and Colloquialisms: Part 2. (2013, June 19). Matinee Multilingual. https://matinee.co.uk/blog/translating-slang-terms-and-colloquialisms-part-2/

Vitali, R. (2013). *ما هو الفرق بين الموسيقى العربية والموسيقى الغربية؟ / مدونة رامي فيتالي*. Retrieved December 25, 2018, from http://www.ramivitale.com/?p=366

Washington Post. https://www.washingtonpost.com/news/worldviews/wp/2015/04/23/the-worlds-languages-in-7-maps-and-charts/

Watson, J. C. E. (2002). *The Phonology and Morphology of Arabic*. Oxford University Press. Retrieved from: http://ebookcentral.proquest.com/lib/ualberta/detail.action?docID=415941

Westerski, A. (n.d.). *Sentiment Analysis: Introduction and the State-of-the-Art overview*. 9. http://www.adamwesterski.com/wp-content/files/docsCursos/sentimentA_doc_TLAW.pdf

Wood, S. (2020). *All in The Language Family: The Semitic Languages*. Babbel Magazine. https://www.babbel.com/en/magazine/semitic-languages

Appedixes

- **Appendix A**

➢ **Lexical and Semantic Analysis of the 1st song (Old song + Formal Arabic Lyrics)**

Word	Lexical Meaning	Semantic Meaning	Google Translation	Notes	Suggested translation
أعزه "A'Azaho"	Powered him and made him honored	In the verse, it meant honored him	Dearest	Not acceptable because it does not express the meaning at all	Honored
أذلني "Athalani"	Degrade, demean, Humiliate	In the verse, it meant humiliated me	Humiliated	Acceptable translation	Humiliated
وصالك "Wisaloka"	An association, relationship, bond between people	In the verse, it meant reach you	Reach me	Acceptable translation, but it does not accurately express the meaning.	Reach you
دلني "Dollani"	Show, point out, or indicate	In the verse, it meant show or indicate me	Show me	Acceptable translation	Show me
حلفتني "Hallaftani"	Take an oath, swear	In the verse, it meant you made me swear to you	swore on me	Not acceptable because the meaning is different	you made me swear to you

حلفت لي “Halafta Li”	Take an oath, swear.	In the verse, it meant you swore to me	swore to me	Acceptable translation	swore to me
تخون “Takhon”	Cheating, treachery.	In the verse, it meant cheat	betray me	Acceptable translation	Betray or cheat
فخنتني “Fa Khontani”	Cheating, treachery.	In the verse, it meant cheated on me	guessed me	Not Acceptable translation	Cheated on me or betrayed me
تميل “Tamil”	Turning around, deflection.	In the verse, it meant inclined	Inclined	Acceptable translation	Inclined
الهوى “Al-Hawa”	Passion, love.	In the verse, it meant passion	fancy	Not Acceptable translation	Passion
اليمين “Al-Yamin”	Right side, oath	In the verse, it meant oath	Right	Not Acceptable translation	Oath
عاهدتني “A`hadani”	Promise, pledge	In the verse, it meant promised me	pledge to me	Acceptable translation	Promised me
تركتني “Taraktani”	Leave, quit, let go	In the verse, it meant left me	Left me	Acceptable translation	Left me

حيران "Hairan"	Confused, confounded, puzzled	In the verse, it meant confused	Hiran	Not acceptable translation because the same word was repeated, but with the letters of the target language (English)	Confused
صباً "Sabban"	Yearning, longing, nostalgia	In the verse, it meant feel nostalgic	It has not been translated	It has not been translated	Feel nostalgic
هائماً "Haiman"	Enamored, Confused, drifter	In the verse, it meant feel wanderer	Wandering	Acceptable translation	wanderer
أرعى "Araa"	Protect, take care	In the verse, it meant take care	Take care	Acceptable translation	Take care
النجوم "Al-Nojom"	Stars	In the verse, it meant the stars	the stars	Acceptable translation	The stars
عيش "Aish"	Living	In the verse, it meant living	Live	Acceptable translation	Living
هني "Hani"	Carefree, relived	In the verse, it meant carefree	Easy	Acceptable translation but the word carefree is more precise	carefree
لاقعدن "La Akedan"	Sit, take a seat	In the verse, it meant I swear I will sit	To sit	Not Acceptable translation because it has a swear in it	I swear I will sit

الطريق "Al-Tarik"	The road	In the verse, it meant the road	road	Acceptable translation	The road
اشتكي "Ashtaki"	Complain, nag, grumble	In the verse, it meant carefree	Complain	Acceptable translation	Complain
اقول"Aqul"	Say, tell, speak	In the verse, it meant to say	Say	Acceptable translation	Say
مظلوم "Mazlom"	Subject to harsh treatment.	In the verse, it meant wronged	Wronged	Acceptable translation	Wronged, Oppressed, maltreated, tyrannized,
ظلمتني "Zalamtani"	Treat someone despotically or cruelly.	In the verse, it meant carefree	Wronged me	Acceptable translation	Wronged me
لادعون "La Adoan"	Say a prayer, supplicate	In the verse, it meant say a prayer	to pray	Not Acceptable translation because it has a swear in it	I swear I will pray
غسق "Ghasaq"	The beginning of the darkness of the night	In the verse, it meant twilight	twilight	Acceptable translation	Twilight
الدجى "Al-Doja"	The darkness of the night	In the verse, it meant carefree	Dja	Not acceptable translation because the same word was repeated, but with the letters of the target language (English)	Dark night

يبليك Youbleka”	To curse, take offense	In the verse, it meant offense	bless you	Not acceptable translation	Offense you
ربي “Rabbi”	God, lord	In the verse, it meant God	God	Acceptable translation	My God
ابليتني “Ablaitani”	Offended	In the verse, it meant offended	did me	Not Acceptable translation	Offended me

Table 16: Lexical and Semantic Analysis of the 1st song (Old song + Formal Arabic Lyrics)

- **Syntactic and Grammatical Analysis of the 1st Song (Old song + Formal Arabic Lyrics)**

Verse	Google translation	Notes/ analyzation	Suggested translation
يا من هواه أعزه وأذلني كيف السبيل الى وصالك دلني	O dearest and humiliated me How to reach me and show me	First verse: the meaning is different in Google translation than the one Second verse: the translator has incorrectly translated the pronoun in the word “وصالك” where it was translated to “reach me” instead of “reach you”.	You, whose love humiliated me and elevated you Show me how to reach you

انت الذي حلّفتني وحلفت لي وحلفت أنك لا تخون فخنتني	It was you who swore on me and swore to me I swore that you did not betray me, you guessed me	First verse: the word "حلفتني" means "made me swear to you" not "swore on me". So, the pronoun and the meaning here are different from what it was intended. Second verse: the word "حلفت" was translated differently because the diacritic is not there, so the pronoun will be translated differently. this word can be read as "Halafta" and translated to "you swore". Or "Halfatu" which means "I swore". In addition, the verb "فخنتني" means "you betrayed me" not "guessed me".	You are the one who made me swear to, and you swore to me You swore that you do not betray, and you betrayed me
وحلفت أنك لا تميل مع الهوى أين اليمين وأين ما عاهدتني	You swore that you are not inclined to fancy Where is the right and where do you pledge to me?	First verse: the noun "الهوى" was not translated correctly, because it means love not fancy. Second verse: the word "اليمين" can mean "the right side" or "the swearing", and here it means "the swearing". This means that google Translate does not differ between different meanings for the same word, so it translates literally.	You swore that you will not incline to another love Where is that swearing, and where is what you promised me

تركتني حيران صباً هائماً أرعى النجوم وأنت في عيشٍ هني	Hiran left me wandering Take care of the stars while you live easy	First verse: The translation failed here to give the right meaning, and it returned some words in English letters and did not translate them like "Hiran" which means confused. Also, it did not translate the word "صباً" at all, which means "feeling nostalgic" Second verse: Google translation seems as the poet is asking his beloved to take care of the stars while she is living easy, which is not the right meaning. It is a kind of comparison between the poet's situation and his lover's status.	You left me confused, wanderer, and missing you I count the stars while you are living happily
لأقعدنّ على الطريق وأشتكي وأقول مظلوم وأنت ظلمتني	To sit on the road and complain I say wronged and you wronged me	First verse: the first letter in the first word "لاقعدنّ" means "I swear" and it is not the preposition "to". Second verse: the translation is good here as it has expressed the right meaning	I swear, I will sit on the road and complain to God I will say I am oppressed, and you wronged me

ولأدعونّ عليك في غسق الدجى يبليك ربي مثلما أبليتني	And to pray for you in the twilight of Dja God bless you just as you did me	First verse: the first two letters in the first word "ولأدعونّ" means "and I swear" and they don't mean "and to". In addition, the translation returned some words in English letters and did not translate them like "Dja" which means dark night. Second verse: the meaning here is completely different where the word "يبليك" means "offend" not "bless".	And I swear, I will pray in a very dark night For God to offend you as you did to me

Table 17: Syntactic and Grammatical Analysis of the 1st Song (Old song + Formal Arabic Lyrics)

- **Appendix B**

➢ **Lexical and Semantic Analysis of the 2nd Song (New song +Formal Arabic Lyrics)**

Word	Lexical Meaning	Semantic Meaning	Google Translation	Notes	Suggested translation
عيناك "Aynaka"	Vision body organ, eyes	In the verse, it meant your eyes	Your eyes	Acceptable translation	Your eyes
حلمي "Holmi"	What a sleeper sees in his sleep, dream	In the verse, it meant my dream	My dream	Acceptable translation	My dream
سيكون "Sayakon"	Verb to be	In the verse, it meant will be	Will be	Acceptable translation	Will be
كبيرا "Kabeeran"	Large, big, great	In the verse, it meant big	Big	Acceptable translation	Big

يحلم "Yahlomu"	What a sleeper sees in his sleep, dream	In the verse, it meant dream	Dreams	Acceptable translation	Dream
المتعبون "Al-Motaaboon"	Exhausted, tired	In the verse, it meant exhausted people	Tired	Not acceptable translation, because it described the dreams while in the verse it describes people	Tired people
خير "Khair"	Greatness, Wealth, Generosity	In the verse, it meant generosity	It has not been translated	It has not been translated	Generosity
بلادي "Biladi"	The vast land which is inhabited by a group of people. It has cities, villages, and borders	In the verse, it meant my country	My Country	Acceptable translation	My Country
يداك "Yadaka"	A body organ, from the shoulder to the tips of the fingers	In the verse, it meant your hands	Your hands	Acceptable translation	Your hands
تلوح "Tolawihu"	A gesture or signal made by moving one's hand to and from.	In the verse, it meant to wave	Are waving	Acceptable translation	Are waving
للعائدين "Lilaaiedeen"	Action of coming or going back to a place or activity.	In the verse, it meant returners	Returnees	Acceptable translation	Returners

تحمل “Tahmilu”	Carry something by hands	In the verse, it meant carry	Carry	Acceptable translation	Carry
خبزا “Khobzan”	Food made of flour, water, and yeast or another leavening agent, mixed and baked.	In the verse, it meant bread	Bread	Acceptable translation	Bread
الجائعين “Al-Jaieen”	The person who is feeling or the need for food	In the verse, it meant hungry people	Hungry	Not acceptable translation because it didn’t specify who is hungry	Hungry people
أحب “Ohibu”	An intense feeling of deep affection	In the verse, it meant I love	I love	Acceptable translation	I love
يديك “Yadaika”	A body organ, from the shoulder to the tips of the fingers	In the verse, it meant your hands	Your hands	Acceptable translation	Your hands
أكثر “Akthar”	To a greater extent	In the verse, it meant more	More	Acceptable translation	More
ستكون “Satakoonu”	Verb to be	In the verse, it meant will be	It would be	Not Acceptable translation because the subject and the verb tense are not correct	You will be
تعشق “Taashaku”	Love and respect someone deeply.	In the verse, it meant adore	Love	Acceptable translation	Adore

الأوطان “Al-Awtana”	A person's or people's native land.	In the verse, it meant homelands	homelands	Acceptable translation	Homelands
مثلي “Mithli”	Like, such as	In the verse, it meant like me	Like me	Acceptable translation	Like me
سأكون “Sa Akoonu”	Verb to be	In the verse, it meant I will be	I will be	Acceptable translation	I will be
عاد “Aada”	Get back, return	In the verse, it meant came back	Return	Acceptable translation	Return
أهلي “Ahli”	People	In the verse, it meant my people	My family	Acceptable translation	My people
عرسي “Oursi”	Marriage ceremony	In the verse, it meant my wedding	My wedding	Acceptable translation	My wedding
هنالك “Hunalika”	There	In the verse, it meant there	It has not been translated	It has not been translated	There
يحملني “Yahmiluni”	Carry, take, load	In the verse, it meant carry me	Holds me	Acceptable translation	Carry me
فؤادي “Fouaadi”	Heart	In the verse, it meant my heart	My heart	Acceptable translation	My heart
اموت “Amoutu”	Stop living	In the verse, it meant I die	I die	Acceptable translation	I die

فيك "Fika"	For you	In the verse, it meant for you	In you	Not acceptable translation because with different preposition, the meaning is different	For you
متى "Mata"	When	In the verse, it meant when	When	Acceptable translation	When
تموت "Tamoutu"	Stop living	In the verse, it meant you die	Will you die	Acceptable translation	You die
ندوس "Nadousu"	Tread, step, crush by feet	In the verse, it meant crush	Step	Acceptable translation	Crush
المدافع "Al-Madafie"	A large, heavy piece of artillery, typically mounted on wheels, formerly used in warfare.	In the verse, it meant cannon, gun	Guns	Acceptable translation	Cannons
تضيق "Tadika"	Become less wide	In the verse, it meant narrow down	Narrowed	Acceptable translation	Narrow down
بالاطفال "Bil Atfali"	Children	In the verse, it meant children	Children	Acceptable translation	Children
ساحات "Sahatu"	A piece of ground adjoining a	In the verse, it meant yards	It has not been translated	It has not been translated	Squares

	building or house.				
الشوارع "Al-Shawarie"	Streets	In the verse, it meant streets	Streets	Acceptable translation	Streets
يعود "Yaoudu"	Return, come back	In the verse, it meant return	Returns	Acceptable translation	Returns
الصبح "Al-Subhu"	Morning	In the verse, it meant morning	The morning	Acceptable translation	The morning
الرماد "Al-Ramadi"	The powdery residue left after the burning of a substance.	In the verse, it meant ashes	Ashes	Acceptable translation	Ashes
اخونك "Akhunuka"	Betray	In the verse, it meant betray	Your brother	Not Acceptable translation because the meaning is totally different	Betray on you

Table 18: Lexical and Semantic Analysis of the 2nd Song (New song +Formal Arabic Lyrics)

- **Syntactic and Grammatical Analysis of the 2nd Song (New song + Formal Arabic Lyrics)**

Verse	Google translation	Notes/ analyzation	Suggested translation
عيناك حلمي الذي سيكون كبيراً كما يحلم المتعبون كبيراً كخير بلادي	Your eyes are my dream which will be As big as tired dreams	First verse: the translation is very good grammatically and syntactically.	Your eyes are my dream which will be

	As big as my country	Second verse: the word "tired" is an adjective of people not the dreams as in Google translation. Despite of that, it is correct grammatically. Third verse: the word "big" is describing the generosity of the country not the size of the country. So, the meaning is not completely true, but it is correct grammatically.	As big as tired people's dreams As big as the generosity of my country
يداك تلوّح للعائدين وتحمل خبزاً إلى الجائعين	Your hands are waving to the returnees And carry bread to the hungry	First verse: the translation here was able to give the right meaning. Second verse: the translation here was correct partially because it didn't specify who is hungry.	Your hands wave to the people returning home And carry bread to the hungry ones
أحبُ يديكَ... وأكثر أكثر أحب بلادي	I love your hands ... And more the more I love my country	First verse: correct translation grammatically and syntactically. Second verse: from this translation, we can get the idea of the verse, but the sentence structure is not correct syntactically.	I love your hands But I love my country more and more
ستكون لي لو تعشق الأوطان مثلي سأكون لك لو عاد للأوطان أهلي	It would be for me to love homelands like me I will be yours if you return home my family	First verse: The translation failed here to give the right meaning.	You will be mine if you adore homelands like I do I will be yours if my people get home back

عرسي هنالك حيث يحملني فؤادي	My wedding is where my heart holds me	Second verse: the meaning in google translation is different than the original meaning. Third Verse: grammatically, the translation is correct but syntactically and in term of meaning, it is not correct.	There my wedding will be, where my heart carries me
وأموت فيك أموت فيك متى تموت على بلادي	I die in you I die in you When will you die on my own	First verse: Google Translate failed to translate the prepositions here, so the meaning is different, but the grammar here are correct. Second verse: grammatically, the translation here is correct, but syntactically, the context is not correct.	And I die for you, die for you When you're ready to die for my country
وأنا أحبك كي ندوس على المدافع وتضيق بالأطفال ساحات الشوارع ومتى يعود الصبح من بين الرماد	And I love you to step on the guns Street children narrowed children And when the morning returns from the ashes	First verse: the translation is correct grammatically and syntactically. Second verse: the translation failed to give the right meaning and the grammar here are not correct. Third verse: the translation is correct grammatically and in term of context.	And me... I love you so that we together could step on cannons And the streets get over-crowded with kids And when the morning arises from the ashes

سأموت فيك أموت فيك وقد أخونك مع بلادي	I will die in you I will die in you Your brother has been with my country	First verse: Google Translate failed to translate the prepositions here, so the meaning is different, but the grammar here are correct. Second verse: the translation failed to give the right meaning because the word "أخونك" means betray or cheat on you. The grammar here are correct.	I will die for you, I will die for you And I might cheat on you with my country

Table 19: Syntactic and Grammatical Analysis of the 2nd Song (New song + Formal Arabic Lyrics)

- **Appendix C**

➢ **Lexical and Semantic Analysis of the 3rd Song (New song + Lebanese Dialect Lyrics)**

Word	Lexical Meaning	Semantic Meaning	Google Translation	Notes	Suggested translation
علمتني "Alamtni"	Show or explain to someone how to do something	In the verse, it meant you taught me	Taught me	Acceptable translation	Taught me
كيف "Keef"	How	In the verse, it meant how	How to	Acceptable translation	How to
الكره "Al-Kereh"	Feel intense dislike for someone or something	In the verse, it meant hate	Hate	Acceptable translation	Hate

بيكون "Beecon"	Verb to be	In the verse, it meant to be	Bacon	Not acceptable translation. It is a word in dialect Arabic so Google Translate repeated it with English letters without translating it	To be
حرمتني "Haramtni"	refuse to allow something	In the verse, it meant you forbid me	Denied	Not acceptable translation because denying someone is different from banning them from doing something.	You banned me
صدق "Saddek"	Accept something as true	In the verse, it meant to believe	My honesty	Not acceptable translation. This word does not have diacritics, so the translator could not identify the word type and it translated it as a noun while it is a verb.	To believe
بعمري "Bi Omri"	The length of time that a person has lived, or a thing has existed.	In the verse, it meant my life	My life	Acceptable translation	My life

عيون "Oyoun"	Eyes	In the verse, it meant eyes	It has not been translated	It has not been translated	Eyes
ضيعتني "Dayaatni"	Become unable to find something or someone	In the verse, it meant you lost me	You lost me	Acceptable translation	You lost me
و يا ريت "wa Ya Rait"	Wish to do something	In the verse, it meant I wish	And I wish	Acceptable translation	And I wish
عرفتك "Eriftak"	Be Aware of something or someone	In the verse, it meant to know you	Had not known you	Acceptable translation	Had not known you
شجعتني "Shajaatni"	Give support, confidence, or hope to someone	In the verse, it meant you encouraged me	Encouraged	Acceptable translation	Encouraged
عالدنيا "Aldeniya"	Life	In the verse, it meant lifetime	My life	Acceptable translation	My life
قلت "Elt"	Say words to convey information, an opinion, a feeling or intention, or an instruction.	In the verse, it meant I Said	Said	Acceptable translation	Said
قويت "Eweet"	Having great power or strength.	In the verse, it meant I got stronger	Stronger	Not acceptable translation.	I got stronger

سمعتني “Samaatni”	Listen	In the verse, it meant you made me listen	Heard me	Not acceptable translation because it meant you told me not you heard me.	you made me listen to, you told me
احلى “Ahla”	Pleasant; agreeable; satisfactory.	In the verse, it meant the most beautiful	The best	Acceptable translation	The best, the most beautiful
حكي “Hakii”	Conversation, discussion, talk	In the verse, it meant talking	Story	Not Acceptable translation because it did not mean stories, but it meant love talking.	Talking
ومشيت “Wamsheet”	Walk	In the verse, it meant you left	Walked	Acceptable translation	Walked, left
ودعتني “Wadaatni”	Say goodbye	In the verse, it meant you said goodbye	She invited me	Not acceptable translation. Google Translate was not able to translate it because it does not have diacritics.	you said goodbye
شفتك “Sheftak”	See	In the verse, it meant saw you	See you	Acceptable translation	See you
شو “Shou”	What	In the verse, it meant what	What	Acceptable translation	What

عملت "Amalt"	Action, doing something	In the verse, it meant you did	Did you do	Acceptable translation	Did you do
عارف "Aarif"	Being aware or informed.	In the verse, it meant you know	Know	Acceptable translation	Know
انجرح "Enjarah"	Injure, harm, damage	In the verse, it meant got hurt	Get hurt	Acceptable translation	Get hurt
قدام "Edam"	In front of	In the verse, it meant in front of	In front of	Acceptable translation	In front of
عينك "Aynak"	Eyes	In the verse, it meant your eyes	Your eyes	Acceptable translation	Your eyes
قلبي "Albi"	Heart	In the verse, it meant my heart	My heart	Acceptable translation	My heart
بيندبح "Beendabah"	Kill in a violent way	In the verse, it meant got hurt	Is barking	Not acceptable translation because it has a different meaning	Got hurt
فيي "Fie e"	Can	In the verse, it meant I can	What remains	Not acceptable translation because it has a different meaning.	I can
اسهر "Eshar"	Stay up late	In the verse, it meant stay up late	Staying up	Acceptable translation	Staying up late night

لحالي "Lahali"	Alone	In the verse, it meant alone	My current	Not acceptable translation because it meant me being alone and not my current situation.	Alone
ابكي "Ebki"	Cry	In the verse, it meant to cry	Crying	Acceptable translation	Crying
ع حالي "A Hali"	Self	In the verse, it meant on myself	It has not been translated	It has not been translated	On myself
نسيتك "Nesetak"	Forget	In the verse, it meant I forgot you	I forgot you	Acceptable translation	I forgot you
قلك "Ellak"	Tell someone something	In the verse, it meant tell you	It has not been translated	It has not been translated	Squares
حبيبي "Habibi"	A person having a romantic relationship with someone	In the verse, it meant my lover	Darling	Acceptable translation	Darling
كذب "Kazeb"	Not telling the truth	In the verse, it meant to lie	Lie	Acceptable translation	Lie
كرهتك "Kerehtak"	Intense dislike.	In the verse, it meant I hated you	I hate you	Acceptable translation	I hate you

غيرتني "Ghayartni"	Make or become different.	In the verse, it meant you changed me	Changed me	Acceptable translation	Changed me
غيرت "Ghayart"	Make or become different.	In the verse, it meant you changed	Changed me	Acceptable translation	Changed me
كتير "Kteer"	A great deal, much, a lot	In the verse, it meant a lot	A lot	Acceptable translation	A lot
عودتني "Awadetni"	Used to do something	In the verse, it meant you got me used to	It brought me back	Not acceptable translation. It doesn't have diacritics, so the translator could not translate it correctly.	You got me used to
عيش "Eish"	Live	In the verse, it meant live	Live	Acceptable translation	Live
الاسى "Al Asa"	Feel or display deep distress.	In the verse, it meant sorrow	Distress	Not acceptable translation because it has a different meaning.	Sorrow, grief, sadness
بكير "Bakeer"	Before the usual or expected time	In the verse, it meant early	It has not been translated	It has not been translated	Early
غيرتك "Ghayartak"	Make or become different	In the verse, it meant changed you	Your jealousy	Not acceptable translation because it has a different meaning	I changed you

قسيتني “Asaytni”	Tough	In the verse, it meant you made me stronger	You divided me	Not acceptable translation because it has a different meaning	you made me stronger
قسيت “Eseet”	Tough	In the verse, it meant I got stronger	It has not been translated	It has not been translated	I got stronger
بكيتني “Bakaytni”	Cry	In the verse, it meant you made me cry	I cried	Not acceptable translation because I cried by myself is different from crying because of someone.	You made me cry
قبلك “Ablak”	Before	In the verse, it meant before you	Before you	Acceptable translation	Before you
بكيت “Bekeet”	Cry	In the verse, it meant I cried	I did not cry	Acceptable translation	I did not cry
موتتني “Mawatetni”	Die	In the verse, it meant you killed	You died me	Not acceptable translation, because this phrase does not mean anything.	You killed me
عيشتك “Ayashtak”	Live	In the verse, it meant I got you to live	I lived	Not acceptable translation because living on your own is different	I got you to live

				than living because of somebody.	

Table 20: Lexical and Semantic Analysis of the 3rd Song (New song + Lebanese Dialect Lyrics)

- **Syntactic and Grammatical Analysis of the 2nd Song (New song + Lebanese Dialect Lyrics)**

Verse	Google translation	Notes/ analyzation	Suggested translation
علمتني كيف الكره بيكون	She taught me how to hate Bacon	The context in the translated text is totally different form the intended meaning. Grammatically, it is correct.	You taught me to hate.
حرمتني صدق بعمري عيون	My honesty has denied me my life	The meaning in the original text is different from the translated text.	You deprived me from believing in eyes for the whole of my life
ضيعتني وياريت ما عرفتك	You lost me and I wish you did not know you	The translation of this versed correct syntactically and grammatically.	You lost me, and I wish I have never known you
شجعتني ع الدني قلت قويت	I was encouraged by my life, I said strong	The reader might be able to get an approximate meaning, but the order of words will not help for better understanding	You encouraged me to live, so I thought I got stronger.
سمعتني احلى حكي ومشيت	You heard me the best story and I walked	The meaning here between the original verse and the translated one is totally different	You made me listen to the most beautiful words and then you went away.

ودعتني وياريت ما شفتك	She invited me and I wish I did not see you	The meaning in the original text is different from the translated text. The translation is correct grammatically.	You left me, and I would like I have never seen you.
شو عملت فيي	What did you do?	Correct translation syntactically and grammatically.	What have you done to me?
وانت اللي عارف اني مافيي منك انجرح	And you who know that I cannot get hurt	The meaning is predictable in the translated text, but the words order did not help in giving the correct meaning.	And you are the one, who knows that I can't get hurt from you.
شو عملت فيي	What did you do?	Correct translation	What have you done to me?
قدام عينك انتى قلبي قلبي بيندبح	In front of your eyes, you are my heart, my heart is barking	There were no punctuations in the original text, but the translated text has commas which changed the meaning	And my heart hurts in front of your eyes.
ما بقى فيي	What remains in me	Google Translate translated the text as if it is in the formal Arabic because it does not have diacritics to indicate that it was written in dialect Arabic. So, the meaning is different.	I can't stand that anymore.
ما بقى فيي اسهر لحالي ابكي ع حالي	I am not staying up to my current crying	The meaning is completely different.	I can't spend the evening lonely crying about myself.
نسيتك انا	I forgot you	Correct translation	I have forgotten you.
ما بقى فيي قلك حبيبي كذب ع حالي	What is left in you, my beloved, is a lie	The translation did not give the right meaning.	I am not able to say my love to you anymore and lie to myself.

كرهتك انا	I hate you	Correct translation	I hated you
ما بقى فيي اسهر لحالي ابكي ع حالي	I am not staying up to my current crying	The meaning is not correct, and the translated text does not mean anything	I cannt spend the evening lonely crying about myself.
نسيتك انا	I forgot you	Correct translation	I have forgotten you.
ما بقى فيي قلك حبيبي كذب ع حالي	What is left in you, my beloved, is a lie	The translation did not give the right meaning.	I am not able to say my love to you anymore and lie to myself.
كرهتك انا	I hate you	Correct translation	I hated you
ما بقى فيي	What remains in me	The meaning is different.	I cannt do it anymore.
غيرتني غيرت فيي كتير	It changed me, it changed me a lot	the translation was not correct in term of subject. The subject is "you" and not "it". This happened because there are no diacritics to identify the subject	You changed me a lot
عودتني عيش الاسى بكير	It brought me back to live in distress	The meaning is totally different from what was intended	You made me used to the sorrow early.
غيرتني وما عرفت غيرتك	You changed me and I did not know your jealousy	There were no diacritics to decide the meaning of the word "غيرتك" which can mean "your jealousy" and "changed you".	You changed me and I could not change you.
قسيتني ع الدني كلها قسيت	You divided me all over the world	The meaning is totally different.	You harden me, so I became cruel about the whole life
بكيتني وقبلك انا ما بكيت	I cried and before you I did not cry	The meaning is partially correct because the subject of the verb cry is you not I and this did not give	You made me cry and I did not cry before you.

		the completely correct meaning.	
موتتني مع اني عيشتك	You died me while I lived	The translated text has no meaning. So, the translation here is not correct.	You killed me, even though I lived for you.
شو عملت فيي	What did you do?	Correct translation	What have you done to me?

Table 21: Syntactic and Grammatical Analysis of the 2nd Song (New song + Lebanese Dialect Lyrics)

- **Appendix D (Songs' lyrics and their translations)**

The first song "Krehtak" was sung by Elissa in 2012 and it is written in Lebanese dialect Arabic. The second song "Omen" was sung by Fairuz and is written in formal Arabic. The third songs "Ana Nater" was sung by Nabeel Shoeel and is written in Gulph dialect Arabic. The fourth song "Anta Omri" is a romantic song and was sung by Umm Kulthum and was written in Egyptian dialect Arabic. The fifth song "Ya Man Hawahu" is an old song written in formal Arabic and was sung by Mohammad Abdol Rahman.

Song's Name	Song's Arabic Lyrics	Google Translation	My Translation
كرهتك Krehtak I hated you	علمتني كيف الكره بيكون حرمتني صدق بعمري عيون ضيعتني وياريت ما عرفتك	She taught me how to hate Bacon My honesty has denied me my life You lost me and I wish you did not	You taught me to hate. You deprived me from believing in eyes for the whole of my life

	شجعتني ع الدني قلت قويت سمعتني احلى حكي ومشيت ودعتني وياريت ما شفتك شو عملت فيي وانت اللي عارف اني مافيي منك انجرح شو عملت فيي قدام عينك انتى قلبي قلبي بيندبح ما بقى فيي ما بقى فيي اسهر لحالي ابكي ع حالي نسيتك انا ما بقى فيي قلك حبيبي كذب ع حالي كرهتك انا ما بقى فيي اسهر لحالي ابكي ع حالي نسيتك انا ما بقى فيي قلك حبيبي كذب ع حالي كرهتك انا ما بقى فيي غيرتني غيرت فيي كتير عودتني عيش الاسى بكير غيرتني وما عرفت غيرتك قسيتني ع الدني كلها قسيت بكيتني وقبلك انا ما بكيت موتتني مع اني عيشتك شو عملت فيي	know you I was encouraged by my life, I said strong You heard me the best story and I walked She invited me and I wish I did not see you What did you do? And you who know that I cannot get hurt What did you do? In front of your eyes, you are my heart, my heart is barking What remains in me I am not staying up to my current crying I forgot you What is left in you, my beloved, is a lie I hate you I am not staying up to my current crying I forgot you What is left in you, my beloved, is a lie I hate you What remains in me It changed me, it changed me a lot It brought me back to live in distress You changed me and I did not know your jealousy You divided me all over the world I cried and before you I did not cry You died me while I lived What did you do?	You lost me, and I wish I have never known you. You encouraged me, so I thought I got stronger. You made me listen to the most beautiful words and then you went away. You left me, and I would like I have never seen you. What have you done to me? And you are the one, who knows that I cannot get hurt from you. What have you done to me? And my heart hurts in front of your eyes. I cannot stand that anymore. I cannot spend the evening lonely crying about myself. I have forgotten you. I am not able to say my love to you anymore and lie to myself. I hated you. I cannot spend the evening lonely crying about myself. I have forgotten you. I am not able to say my love to you anymore and lie to myself. I hated you I cannot do it anymore. You changed me a lot

			You made me used to the sorrow early. You changed me and I could not change you. You harden me, so I became cruel about the whole life You made me cry and I did not cry before you You killed me, even though I lived for you. What have you done to me?
أؤمن Oumen I believe	أومن أن خلف الحبات الوادعات تزهو جنات أومن أن خلف الليل العاتي الأمواج يعلو سراج أومن أن القلب الملقى في الأحزان يلقى الحنان كلي إيمان إيمان إيمان أومن أن خلف الريح الهوجاء شفاه تتلو الصلاة أومن أن في صمت الكون المقفل من يصغي لي أني إذ ترنو عيناي للسماء تصفو الأضواء تعلو الألحان كلي إيمان إيمان إيمان	I believe that behind the bugs, the brags are proud of paradise I believe that behind the strong night, the waves rise above the siraj I believe that the heart in sadness is getting affectionate I am all Iman Iman Iman I believe that behind the blazing wind, lips recite the prayer I believe that in the silence of the closed universe, he will listen to me As my eyes look up at the sky, the lights clear the melodies I am all Iman Iman Iman	I believe that behind the superfine seeds, there are blooming paradise I believe that behind the very dark nights, there is a bright light I believe that someone is caring for sad hearts

			All of me is in faith, faith, faith I believe that behind the strong winds, there are lips reciting prayers I believe that in the silence of the closed universe, there is someone listening to me And when my eyes look up at the sky, the lights shine, and the melodies rise All of me is in faith, faith, faith

- **Appendix E (English Sentiment Analysis Code)**

```
# check the files in the directory we are in

%ls
```

➢ **Opening and Reading a Text File**

```
import matplotlib.pyplot as plt
import nltk
import re

# make sure that graphs are embedded into our notebook output
%matplotlib inline
with open("GoogleTranslation.txt", "r") as file:
    script = file.read()

# And we can check what we got.
print(script)
```

```
script # Read the script (without existing of new line).
```

You should change the name of the file you want to open according to the name of the text file you saved.

➢ **Cleaning the Script**

```
nltk.download('stopwords') # Download the English stopwords like I, and, now...etc.
```

```
from nltk.tokenize import sent_tokenize, word_tokenize

script = script.lower() # Lower all words.

script=re.sub(r'\n'," ", script) # Remove all new lines

script=re.sub(r'\d'," ", script) # Remove all numbers

# now we will remove all apostrophes " ' "
script = script. replace ("â€™", "'"). replace("can't", "cannot").replace("n't", " not").\
replace("'d", " would").replace("'ve", " have")\
.replace("'ll", " will").replace("'", " ")

tokensLow = nltk.word_tokenize(script) # Split the script into words.

wordTokensLow = [word for word in tokensLow if word[0].isalpha()] # Check if these words
are English words.

stopwords = nltk.corpus.stopwords.words("English") # Get a list of English stop words.

contentWordTokensLow = [word for word in wordTokensLow if word not in stopwords] #
Check if the word is not in stop words list

contentWordTokensLow # print the result
```

- **Word Frequencies**

```
contentWordTokensLowFreq = nltk.FreqDist(contentWordTokensLow) # Frequency
Distribution
contentWordTokensLowFreq # Show the words with their frequencies
```

```
contentWordTokensLowFreq.tabulate(10) # the top 10 high frequency words
```

```
table = pd.DataFrame(list(contentWordTokensLowFreq.items()), columns =
["Word","Frequency"])
# Save the words with their frequencies as a list (array) with row title "Word", and column title
"Frequency"
test = table.sort_values(['Frequency'], ascending=[False])
# Order the frequency from high value to low value
top= test.head (10) # Display the top 10 words
top.plot.bar(x="Word", y= "Frequency", rot=0, color=['r'], figsize=(10,10))
# plot the results in a bar char with size (10×10)
```

- **Open and Read Positive and Negative words Files**

```
with open("EnglishPositive.txt", "r") as file:
    posText = file.read()

with open("EnglishNegative.txt", "r") as file:
    negText = file.read()

posWords = nltk.word_tokenize(posText.lower())
negWords = nltk.word_tokenize(negText.lower())

print(posWords[1:5])
print(negWords[1:10])
```

- **Calculating positive and negative words**

```
# Function that counts how many target words are in a list of tokens
def countSentimentalTokens(listOfTokens,listOfTargetWords):
    numTargetWords = 0
    matchedWords = []
    for token in listOfTokens: # Goes through the tokens in the list
        if token in listOfTargetWords: # For each one it checks if it is in the target list
            numTargetWords += 1
            matchedWords.append(token)
    return numTargetWords, matchedWords # Note that we are returning a tuple (2 values)

thePositive = countSentimentalTokens(contentWordTokensLow,posWords)
print("The number of positive words are " + str(thePositive[0]) + " and the positive words are:
\n\n " + str(thePositive[1]))

theNegative = countSentimentalTokens(contentWordTokensLow,negWords)
print("\n\n The number of negativetive words are " + str(theNegative[0]) + " and the negative
words are: \n\n " + str(theNegative[1]))
```

- **Calculating percentage of positive and negative words**

```
def calculatePercent(listOfTokens,positiveList,negativeList):
    numWords = len(listOfTokens) # How many words in the English translation

    # We call the function to count the tokens from the positive words exist in the text
    positiveMatches = countSentimentalTokens(listOfTokens,positiveList)
    percntPos = positiveMatches[0] / numWords # We divide by the total number of words
for percentage

    # We call the function to count the tokens from the negative words exist in the text
    negativeMatches = countSentimentalTokens(listOfTokens,negativeList)
```

```
    percntNeg = negativeMatches[0] / numWords # We divide by the total number of words for percentage

    return percntPos, percntNeg # We return the percentage of positive and negative words

# We test the function on the first sentence
results = calculatePercent(tokensLow,posWords,negWords)
print("Positive: " + "{:.0%}".format(results[0]) + "  Negative: " +
"{:.0%}".format(results[1]))
```

- **Calculate sentiment**

```
def calculateSentiment(percntPos,percntNeg):
    sentiment = percntPos - percntNeg # Subtract the percentage of negative words from positive words
    return sentiment

# Test what we get
calculateSentiment(results[0],results[1])
# If the result is 0, then the text is neutral
# If the result is more than 0, then the text is positive
# If the result is less than 0, then the text is negative
```

- **Appendix F (Arabic Sentiment Analysis Python Code)**

```
# check the files in the directory we are in
```

```
%ls
```

➢ Opening and Reading a Text File

```
import matplotlib.pyplot as plt
import nltk
import re
import pandas as pd

# make sure that graphs are embedded into our notebook output
%matplotlib inline
with open("arabicSong.txt", "r", encoding = "utf-8") as file: # To read Arabic file, we should use the encoding style "utf-8"
    script = file.read()

# And we can check what we got.
print(script)
```

```
script # Read the script as a whole (without existing of a new line).
```

➢ Cleaning the Script

```
nltk.download('stopwords') # Download the Arabic Stop words.
```

```
from nltk.tokenize import sent_tokenize, word_tokenize

# We do not need to lower the capital letters because Arabic alphabet doesn't have capital and small letters

script=re.sub(r'\n'," ", script) # Remove all new lines

script=re.sub(r'\d'," ", script) # Remove all numbers

tokensLow = nltk.word_tokenize(script) # Split the script into words.

wordTokensLow = [word for word in tokensLow if word[0].isalpha()] # Check if these words are English words.

stopwords = nltk.corpus.stopwords.words("Arabic") # Get a list of Arabic stop words.

contentWordTokensLow = [word for word in wordTokensLow if word not in stopwords] # Check if the word is not in stop words list

contentWordTokensLow [1:20]# print the result
```

- **Word Frequencies**

```
contentWordTokensLowFreq = nltk.FreqDist(contentWordTokensLow) # Frequency Distribution
contentWordTokensLowFreq # Show the words with their frequencies
```

```
contentWordTokensLowFreq.tabulate(10) # the top 10 high frequency words
```

```
table = pd.DataFrame(list(contentWordTokensLowFreq.items()), columns =

["Word","Frequency"])

# Save the words with their frequencies as a list (array) with row title "Word", and column title

"Frequency"
```

```
test = table.sort_values(['Frequency'], ascending=[False])

# Order the frequency from high value to low value

top= test.head (10) # Display the top 10 words

top.plot.bar(x="Word", y= "Frequency", rot=0, color=['r'], figsize=(10,10))

# plot the results in a bar char with size (10×10)
```

- **Open and Read Positive and Negative words Files**

```
with open("arabicPositive.txt", "r", encoding = "utf-8") as file:
    posText = file.read()

with open("arabicNegative.txt", "r", encoding = "utf-8") as file:
    negText = file.read()

posWords = nltk.word_tokenize(posText.lower())
negWords = nltk.word_tokenize(negText.lower())

print(negWords[1:10])
print(posWords[1:10])
```

- **Calculating positive and negative words**

```
# Function that counts how many target words are in a list of tokens
def countSentimentalTokens(listOfTokens,listOfTargetWords):
    numTargetWords = 0
    matchedWords = []
    for token in listOfTokens: # Goes through the tokens in the list
        if token in listOfTargetWords: # For each one it checks if it is in the target list
            numTargetWords += 1
            matchedWords.append(token)
    return numTargetWords, matchedWords # Note that we are returning a tuple (2 values)

thePositive = countSentimentalTokens(contentWordTokensLow,posWords)
print("The number of positive words are " + str(thePositive[0]) + " and the positive words are:
\n\n " + str(thePositive[1]))

theNegative = countSentimentalTokens(contentWordTokensLow,negWords)
print("\n\n The number of negativetive words are " + str(theNegative[0]) + " and the negative
words are: \n\n " + str(theNegative[1]))
```

- **Calculating percentage of positive and negative words**

```
def calculatePercent(listOfTokens,positiveList,negativeList):
   numWords = len(listOfTokens) # How many words total

   # We call the function to count the tokens from the positive list in the sentence
   positiveMatches = countSentimentalTokens(listOfTokens,positiveList)
   percntPos = positiveMatches[0] / numWords # We divide by the total number of words for
percentage

   # We call the function to count the tokens from the negative list in the sentence
   negativeMatches = countSentimentalTokens(listOfTokens,negativeList)
   percntNeg = negativeMatches[0] / numWords # We divide by the total number of words for
percentage

   return percntPos, percntNeg # We return the percentage of positive and negative words

# We test the function on the first sentence
results = calculatePercent(tokensLow,posWords,negWords)
print("Positive: " + "{:.0%}".format(results[0]) + "  Negative: " + "{:.0%}".format(results[1]))
```

- **Calculate sentiment**

```
def calculateSentiment(percntPos,percntNeg):
   sentiment = percntPos - percntNeg # Subtract the percentage of negative words from
positive words
   return sentiment

# Test what we get
calculateSentiment(results[0],results[1])
# If the result is 0, then the text is neutral
# If the result is more than 0, then the text is positive
# If the result is less than 0, then the text is negative
```