



**SENTIMENT ANALYSIS OF ARABIC STUDENTS FEEDBACK
THROUGHOUT THE SEMESTER**

ALI HADI KHUDHAIR

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**SENTIMENT ANALYSIS OF ARABIC STUDENTS FEEDBACK
THROUGHOUT THE SEMESTER**

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Submitted by **Ali HADI KHUDHAIR**

Approval of the Graduate School of Natural and Applied Sciences, Çankaya University.



Prof. Dr. Halil Tarık EYYUBOĞLU
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.



Assoc. Prof. Dr. Jabd JARAD
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.



Assoc. Prof. Dr. James Little
Supervisor

Examination Date:

Examining Committee Members

Assoc. Prof. Dr. James Little

(Çankaya Univ.)

Prof. Dr. S. Armagan TARIM

(Çankaya Univ.)

Asst. Prof. Dr. Buskay Genç

(Hacettepe Univ.)



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Name, Last Name : Ali HADI KHUDHAIR

Signature



Date

: 13.12.2016

ABSTRACT

SENTIMENT ANALYSIS OF ARABIC STUDENTS FEEDBACK THROUGHOUT THE SEMESTER

KHUDHAIR, Ali

M.Sc., Department of Mathematics

Supervisor: Assoc. Prof. Dr. James Little

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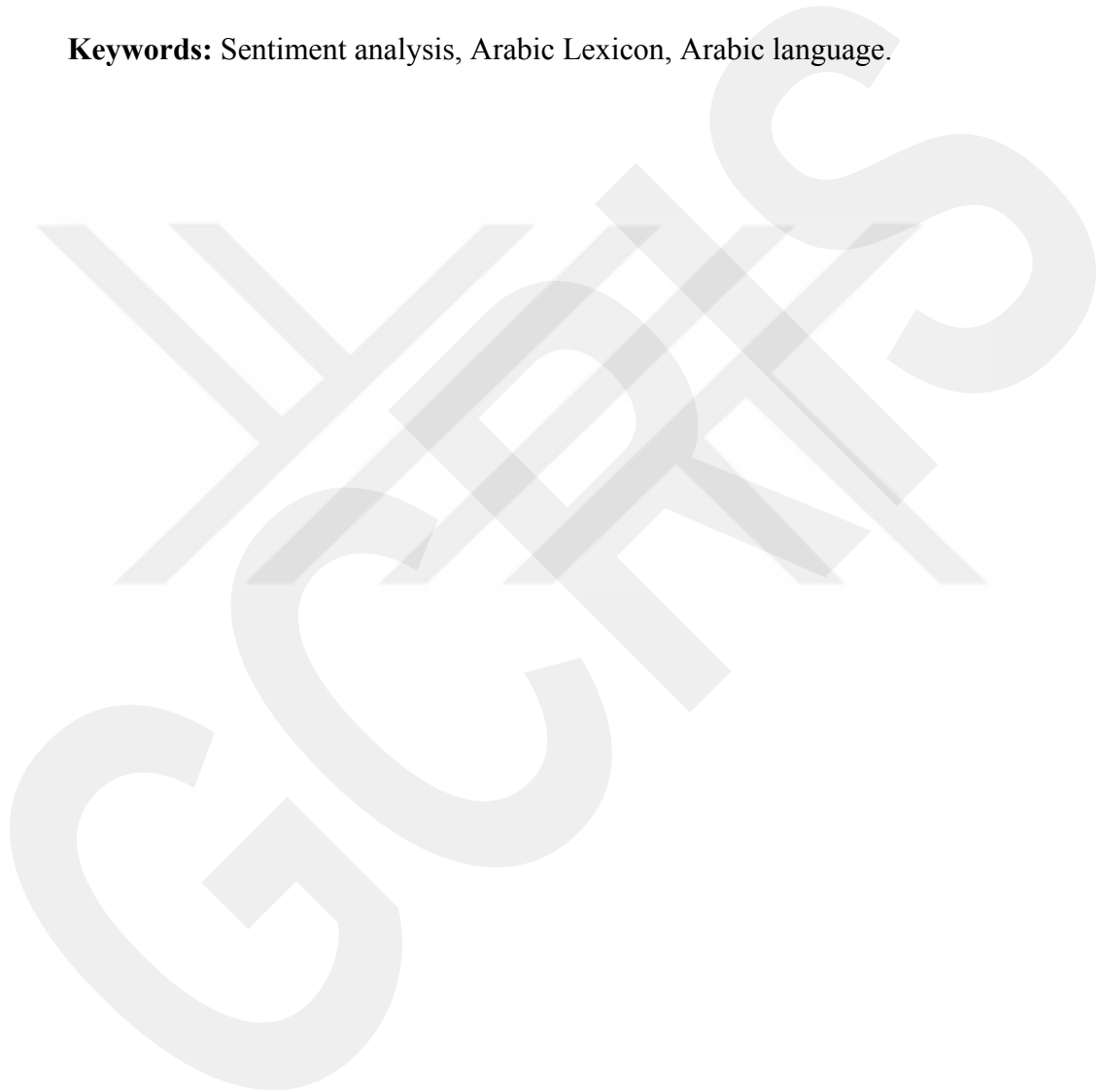
Nowadays, sentiment analysis has become a significant area of research related to machine learning and natural language processing, where sentiments and opinions about several topics are available on the Internet. This allows many parties such as companies, customers or governments to gauge and assess thousands of online opinions automatically. Sentiment on Arabic text is still some way behind that of English, mainly due to the inherent challenges in the language.

We apply sentiment analysis to higher level education, by taking feedback from Arabic-speaking students every week during the semester in the form of 'Tweet'-like comments. This also has the benefit of allowing the students to express their opinion in their mother language to obtain a good quality feedback and alert the lecturer to any issues.

The research shows that using sentiment analysis gives realistic sentiment values for the students' feedback, mainly due to the high accuracy of the Arabic sentiment

lexicon. Over time the sentiment fluctuated in a plausible manner given the order of content presented.

Keywords: Sentiment analysis, Arabic Lexicon, Arabic language.



ÖZ

SÖMESTRE BOYUNCA ÖĞRENCİLERİN ARAPÇA GERİBİLDİRİMLERİNİN DUYGU ANALİZİ

KHUDHAIR, Ali

Yüksek Lisans,

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Günümüzde, duygu analizi, çeşitli konular hakkındaki duygu ve görüşlerin internet üzerinden ulaşılabildiği, özdevimli öğrenme ve doğal dil işlemine ilişkin önemli bir araştırma alanı haline gelmiştir. Bu durum şirketler, müşteriler veya hükümetler gibi birçok ilgili tarafın online olarak mevcut olan binlerce görüşü otomatik olarak ölçmesini ve değerlendirmesini sağlamaktadır. Arapça metinler hakkındaki duygu analizi halen İngilizcenin çok gerisindedir, bunun ana sebebi dilin yapısından gelen zorluklardır.

Sömestre süresince her hafta Arapça konuşan öğrencilerden ‘Tweet’ benzeri yorumlar halinde geribildirimler almak suretiyle, duygu analizini yüksek seviyede eğitime uyguluyoruz. Bunun ayrıca öğrencilerin görüşlerini kendi ana dillerinde ifade etmelerini sağlama, yüksek kalitede geribildirimler alma ve herhangi bir sorun hakkında öğretim üyesini uyarma gibi faydaları vardır.

Araştırma göstermektedir ki, esas olarak Arapça duygu veri sözlüğünün yüksek doğruluk oranı sebebiyle, duygu analizini kullanmak öğrencilerin geribildirimleri

için gerçekçi duygu deęerleri vermektedir. Zamanla, sunulan içerięin sıralaması dikkate alındığında, duygular akla yatkın bir şekilde dalgalanmaktadır.

Anahtar Kelimeler: Duygu Analizi, Arapça veri sözlüęü, Arapça dili.

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LIST OF ABBREVIATIONS

SA	Sentiment Analysis
EWN	English WordNet
SVM	Support Vector Machines Classifiers
NLTK	Natural Language Toolkit
ArSenL	Arabic Sentiment Lexicon
AWN	Arabic WordNet
SAMA	Standard Arabic Morphological Analyzer
ESWN	English SentiWordNet

CHAPTER 1

INTRODUCTION

1.1 Background

With the rapid growth of social media and web applications, feedback in the form of comments, reviews and ratings are now commonly generated by users. Each user can express his/her opinion about many things, including politics, services, people, events, products and education. These require analyzing and processing to get a general estimation of what users feel and think. In the past, obtaining users' opinions was difficult, as it takes a long time to examine manually each review. Therefore, marketing people and managers became interested in providing automatic sentiment analysis tools to speed up the process.

There are two main approaches to making a sentiment analysis. The first approach is using machine learning (ML) techniques and the second approach is using lexicon-based approach, which has been chosen for our thesis.

Our approach depends on a dictionary that it uses to calculate the sentiment of each word.

Many of the studies conducted on sentiment analysis have been in English, Indian and Chinese languages [1]. However, few studies have been conducted using the Arabic language, which is the mother language for more than 300 million speakers. The reason may be that each word in the Arabic language can have a lot of morphological forms. Therefore, applying sentiment analysis becomes a challenge due to this.

One of the application areas for sentiment analysis is in Education. Analysing student feedback is an obvious, although unexplored idea. We can categorize student feedback into [2]:

1- Lecturer to student, which is for self-improvement of the students.

2- Student to lecturer feedback, which guides the lecturer into teaching the courses in ways the students understand better.

We propose a method to obtain the sentiment analysis score for students' feedback in Arabic. In this approach we use a large-scale sentiment lexicon called ArSenL. It contains all or most of the Arabic sentiment words. Each record (word or phrase) in the lexicon has three scores obtained from the mapping with English sentiment WordNet (ESWN): positive, negative, and neutral. For example, ["good" 0.9, 0.1, 0], ["bad" 0.1,0.9,0] and ["lecture" 0,0,1]. Many words in the same domain can have different polarity in different contexts, this is why 'good' has both a positive and negative scores [3]. The total of the three scores is 1.

After collecting the text from students, we process this data and attempt a match between the word and ArSenL to calculate the sentiment score. Each sentence (collection of words) has two scores (positive and negative). We take the largest of these scores to identify its polarity. We also compare two other methods (the Indicoio¹ and Repustate²) that are already built to calculate the sentiment and compare these results with our results to verify our results.

1.2 Hypothesis and Research Questions

The following is main hypothesis of this research:

Students feedback in the form of "tweet" like statements can be measured with sentiment analysis.

In order to test this hypothesis, a number of major research questions were addressed.

1. How well does the sentiment score match reality?
2. Do fluctuations over time reflect difficulty of lectures?
3. Are the software sentiment packages consistent with our results?

1 <https://indico.io/>

2 <https://www.repustate.com/>

1.3 Research Contributions

The research contribution of our work is to build a new model that measures the feeling of foreign students towards each lecture they attend. It allows students write in their mother language, rather than in English and be assessed automatically. It provides the universities with a tool to keep better informed in real time on the sentiments of their foreign students.

1.4 Thesis Structure

This thesis is organized as follows: Chapter two, gives an overview of sentiment analysis in general and sentiment analysis for students feedback in particular, reviewing the relevant literature across the range of topics addressed in the thesis. Chapter three, describes how to collect datasets used in this work and how our methodology. It also shows how to analyse students feedback in terms of sentiment and how to calculate the results. Chapter four, presents the results of the sentiment analysis feedback for two courses and discusses the results in terms of patterns. The last chapter, concludes our work in terms of its applicability and suggests some directions for future research.

CHAPTER 2

SENTIMENT ANALYSIS

2.1 Fundamental Concepts

Nowadays sentiment analysis is a significant technology in determining human reaction to specific topics, usually through social media. Sentiment analysis is the “field of study that analyses people’s opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes” [4].

There is another term, opinion mining, which is equivalent to sentiment analysis.

Liu [5], defines opinions as “subjective expressions that describe people’s sentiment, appraisals or feelings towards entities, events and their properties”. He differentiates between an explicit opinion which grants a positive or negative statement about a theme, with a comparative opinion which explains the positivity or negativity of an item by a match to another item.

Kim and Hovy [6], define an opinion as a combination of four principles: topic, holder, claim, and sentiment, while Liu, defines five principles of an explicit opinion: object, features, orientation, holder and time. In the first case the opinion holder has a claim about a certain topic and associates this claim with a certain sentiment. In the second case, the opinion holder finds some features of a certain object, and associates a certain orientation about them at a specific time.

In computational linguistics, sentiment analysis is considered as a classification problem; texts are labelled either positive or negative. If the text does not contain any opinion, it is then classified as neutral.

In this thesis, we will use as the sentiment items, student feedback, in the form of ‘Tweet-like’ statements that focus on students’ weekly opinion on two courses. We stipulate that the feedback is delivered in the students’ native language, that of

Arabic. In general, the case of sentiment analysis can be branched into four major aspects, as shown in Figure 1 and summarized below.

1. Tasks - sentiment analysis tasks can be classified into wide range polar detection and fine-grained task. Such as sentiment strength detection and emotion detection.
2. Level - the sentiment analysis level is based on the granularity of text used, word-level, phrase-level or sentence-level, document-level.
3. Approaches – there three approaches used in sentiment analysis, lexicon-based approaches, supervised approaches or hybrid approaches.
4. Data type -Sentiment data can be obtained from microblogging sites (e.g. Facebook status updates, tweet messages, SMS) as well as conventional text (e.g., product reviews, news articles).

Next, we will discuss all four branches in detail.

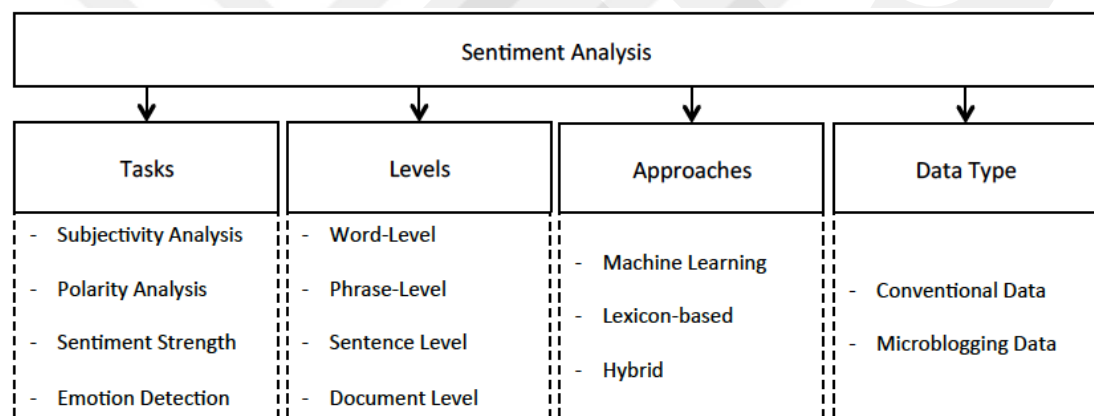


Figure 1 Four dimensions of the sentiment analysis research problem.

We will use an example³ to clarify the various aspects for sentiment analysis. This example is part of a review about the iPhone 7.

"(1) I get a new iPhone every year.(2) This one is disappointing.(3) Yes there are important internal improvements.(4) but considering the price Apple should have done more".

³ https://www.amazon.com/Apple-Plus-Unlocked-128-GB/product-reviews/B01LY5U0EY/ref=cm_cr_dp_qt_hist_three?ie=UTF8&filterByStar=three_star&reviewerType=all_reviews&showViepoints=0. The last access in 7.NOV.2016

2.2 Sentiment analysis tasks

We can determine whether a given text has a positive or negative sentiment by detecting the polarity (positive, negative or neutral) from the sentiment analysis. This is a basic task of sentiment analysis we will focus on the polarity detection. In our example, sentence (2) and (4) have a negative opinion, while sentence (3) has a positive opinion. If there is no sentiment in the sentence that mean neutral (1)

2.3 Sentiment analysis levels

Broadly speaking, there are three levels of text granularity which can be analysed.

1. **Phrase-level sentiment analysis:** Given a multi-word expression in a sentence, the task is to detect sentiment, whether positive or negative (e).
2. **Sentence-level sentiment analysis:** Sentence (s) consist of multiple words and phrases, the task at this level is to identify sentiment whether positive or negative over the whole sentence (s). For instance, sentence (3) has a positive sentiment while sentence (2) has a negative sentiment, but both are in the same single review
3. **Document-level sentiment analysis:** We can determine the general opinion of the overall document through averaging the opinion for each sentence in the document .

2.4 Sentiment classification techniques

Sentiment analysis has three major approaches. They are machine learning, lexicon-based, and hybrid. Machine learning approaches use machine learning algorithms based on linguistic features. The lexicon-based approach depends on a sentiment lexicon. The lexicon is a set of identified and precompiled sentiment terms. The lexicon-based approach can be divided into two main approaches, dictionary-based and corpus-based. In order to determine the polarity of sentiment it uses a semantic or statistical method. The hybrid approach combines machine learning with lexicon-based approach. We can illustrate sentiment classification approaches in Figure 2.

Machine-learning-based approaches require that there is training data to build a model and perform classification. Unfortunately, this data is labelled manually one by one, so requires a high effort.

In machine learning, there are two approaches, supervised and unsupervised learning techniques. The supervised technique can be used when there exists a large number of training documents already labelled (as positive or negative sentiment). The unsupervised techniques are applied by looking for similarities in sentence structure with other known sentiment sentences.

In the lexicon-based approach, the most important step is to find or identify a sentiment lexicon for the domain or language you are using. The lexicon-based approach is divided into two main methods, the dictionary-based approach and the corpus-based approach. In the dictionary-based approach of the most important steps is to find or identify the seeds of opinion words, and then looking for these seeds, such as positive words or negative words like happiness, sadness and love, in a dictionary of antonyms and synonyms. The corpus-based approach starts with the list of seeds opinion words, and then finds other sentiment words in a big corpus to aid in determining sentiment words with context particular orientations. We will explain in detail both approaches and algorithms used in the next section.

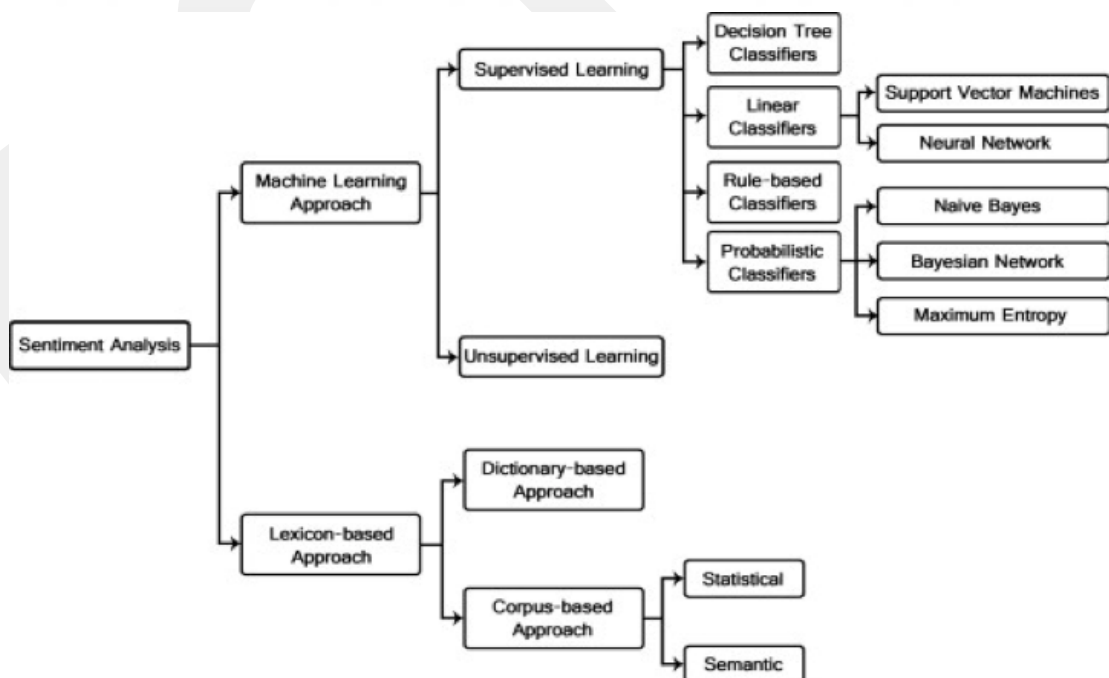


Figure 2 Sentiment classification approaches

2.4.1 Lexicon-based approach

Many sentiment classification approaches are based on opinion words. Positive opinion words are used to convey positive sentiment, while conversely negative words are taken for negative sentiment.

An opinion lexicon consists of opinion phrases, sentiment value and idioms. In order to collect the opinion word list there are three main approaches. The manual approach can be used, but is not used alone, as it is very time-consuming. It is usually used in the final steps to check and avoid mistakes resulting from automated methods. The two automated approaches are presented in the following subsections.

2.4.1.1 Dictionary-based approach

In this approach, opinion words are gathered manually with knowing their positive or negative opinion these words are [7]. This set is then grown by searching in the well known corpora thesaurus or WordNet for their antonyms and synonyms. After the completion of the process, an inspection can be executed manually to correct or remove errors.

This approach has a main disadvantage in the inability to find opinion words with domain and context specific orientations. This approach was used by Qiu and He [8] to identify sentences of sentiment in contextual advertising. Their proposal allowed advertising strategy to improve user experience and increase relevance.

2.4.1.2 Corpus-based approach

The Corpus-based approach relies on syntactic patterns or patterns of words that happen together. Many of these patterns or words can be discovered by starting from a small set of ‘seed terms’. To develop these sets, the Corpus-based approach exploits the relationships between terms [9].

For example, sets can be extended to conjoining adjectives based on "but", "and" connectives where "and" refers to alike polarities and "but" refers to contrasting polarities among the conjoining adjectives. For example, in the following sentence "This car is beautiful and spacious" the word "beautiful" is positive, and that leads to make "spacious" positive as well. This is called sentiment consistency. The phrase "beautiful but dangerous" indicates that dangerous should be negative.

2.4.2 Machine learning approach

To solve the problem of classification of regular text in sentiment analysis, we use the common algorithms in machine learning based on syntactic and/or linguistic features. We have a set of training records $D = \{X_1, X_2, \dots, X_n\}$ where each record may have an outcome called Class associated with it. Given a text with unknown sentiment, a machine learning model will determine it for sentiment.

2.4.2.1 Supervised learning

For supervised learning, we start in the same way as our lexicon approach with a tokenisation of the sentence followed by removed stop word, stemming, normalization. However, instead of checking the sentiment value of each word, we build array where each row contains two elements, a review text and the sentiment label for that review. This method is based on pre-labelled training data. The goal of the classification model is to predict the class for each record of the test dataset. There are various types of supervised classifiers. In the following sections, we present some of the most commonly used classifiers in sentiment analysis.

- **Support Vector Machines Classifiers (SVM)**

A Support Vector Machine performs classification by finding the hyperplane that maximizes the margin between the two classes. The vectors (cases) that define the hyperplane are the support vectors

- **Naïve Bayes Classifier**

The Naive Bayesian classifier is based on Bayes' theorem with independence assumptions between predictors. A Naive Bayesian model is easy to build, with no complicated iterative parameter estimation which makes it particularly useful for very large datasets

- **Decision tree classifier**

Decision tree builds classification or regression models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes.

2.4.2.2 Unsupervised learning

Sometimes in the classification of text, it is difficult to create labelled training data, but easier to collect this unlabelled data. Many researchers have work in this area, such as, Ko and Seo [10] who suggest a method to convert documents into sentences and classify each sentence using a sentence similarity measure and a keyword lists for each sentiment type. Xianghua and Guo [11] also used an unsupervised approach to automatically find the aspects discussed of social reviews in China and the sentiments associated. They tested social reviews that were based on a Chinese lexicon (300-SINA Hownet) and extracted from a blog data set. They discovered that the approach they used obtained a good subject partitioning and improved SA accuracy. It also helped to find out multi-aspect, fine-grained subjects and their related sentiment.

There are other types of unsupervised approaches based on semantic spaces, lexical association using PMI [12], and distributional similarity that measures the similarity between polarity and words [13].

2.5 Microblogging Data

Clearly, the development of microblogging and social networking services in the last eight years, has created new add-on services. These services have imposed a big requirement from the field of sentiment analysis. This new area is known as Sentiment Analysis of Microblogs [14].

Unlike conventional content, microblogging content is generally short (e.g., tweet messages are restricted to 140 characters), contains some abbreviations, ill-formed irregular phrases and words, emoticons and lacks of correct and complete sentence structures. Most of the present work on sentiment analysis for microblogging concentrates on the Twitter data sentiment analysis. Research has also been carried out on sentiment analysis with other social media platforms such as Facebook, MySpace, Sina Weibo.

2.6 Sentiment analysis of Twitter

We refer to Twitter because the student feedback is similar in length to what Twitter allows. Twitter is one of the most popular applications in social networking. It was created in March 2006 and provides micro-blogging services that allows users to send “tweets” about their condition or about the events in their lives and opinions, up to a maximum of 140 characters per message.

With the rapid growth of Twitter users to about 500 million worldwide and with millions of messages every day, it became necessary for organizations to monitor their reputation by analysing the views of Twitter users. This can be done by extracting the sentiment of Tweets about the products and services of their own company and also competitors.

Many Twitter users use abbreviations (because of short tweets no more than 140 characters), have spelling mistakes, poor grammar and sentences are irregular. Therefore, it can be difficult to use sentiment analysis methods designed for conventional texts. However, tweets provide useful indicators for many different purposes. We can classify tweet sentiment into two classes, which are positive and negative polarity [15].

We can extract the sentiment automatically by using the two main approaches, which are lexicon-based approach and machine-learning-based approach.

2.7 Sentiment Analysis Tools and Applications

Sentiment analysis can be applied commercially in many different fields to extract the opinion of the user and the level of satisfaction with the product or service. In this section, we will discuss some of the common Tools and applications and will give brief descriptions of each.

2.7.1 Tools

There are commercial sentiment analysis tools such as Lexalytics, socialmention and text-processing.com. There are some online services available such as, Viralheat⁴, Radiant⁵, Sysomos⁶, etc which provide sentiment values for a sentence.

Lexalytics is one of the major players in the field. It was the first seller to produce a commercial sentiment engine, in 2003. Lexalytics provides two methods of measuring sentiment. The first one is called phrase-based sentiment and the second one is called model-based sentiment. In short, the first method uses a very large dictionary with a score for every word starting from -1 very bad words and ranging to 1 very good words. This method works well and is easy to use for a non-expert. The second method, in short, requires to train the machine learning model on a set of texts, labeled (positive or negative) by humans.

Lexalytics supports many languages, for example, English, French, Chinese and Arabic . However, it does not support the Arabic language completely, such as the sentiment of the Arabic language,.

4 <https://www.viralheat.com/>

5 <https://www.marketingcloud.com/>

6 <https://sysomos.com/>

2.7.2 Applications

Sentiment analysis can be applied in many applications. In the following sections, we will explain some of them.

2.7.2.1 Online Commerce

E-commerce allows users or customers to provide their opinions about the product or services online. These opinions, for instance, can help in providing a summary about a product or a service and from that, identify common issues. Web sites can display previous opinions and recommendations easily for new customers in order to help in their decision-making. Common websites like "amazon.com" provide reviews from customers and also with rating information. These sites contain 75 million opinions from all over the world. Sentiment analysis can assist these sites by converting dissatisfied customers into promoters by analysis of sentiment [16].

2.7.2.2 Voice of the Market (VOM)

Voice of the Market determines what customers feel about your or your competitors' services and products. Convenient and accurate information from the Voice of the Market can help in directing new product development and gaining competitive advantage. Detecting such information early also helps in targeting and directing key marketing campaigns. Management can get customer real-time opinion by using Sentiment Analysis. Zhang et al. [17] proposed a weakness finder system that helps manufacturers discover the weakness of their product from Chinese reviews.

2.7.2.3 Politics

Sentiment analysis can help politics to assess their weaknesses and strength of parties and policies through an opinion analysis process across the population. In figure 3 we see three politicians in 2 hours tv debate in how the public tweet against each politician. We note the varying sentiment level ratios between positive to negative

over time and across the three politicians. This allows each politician to understand the reactions of the public to what they say

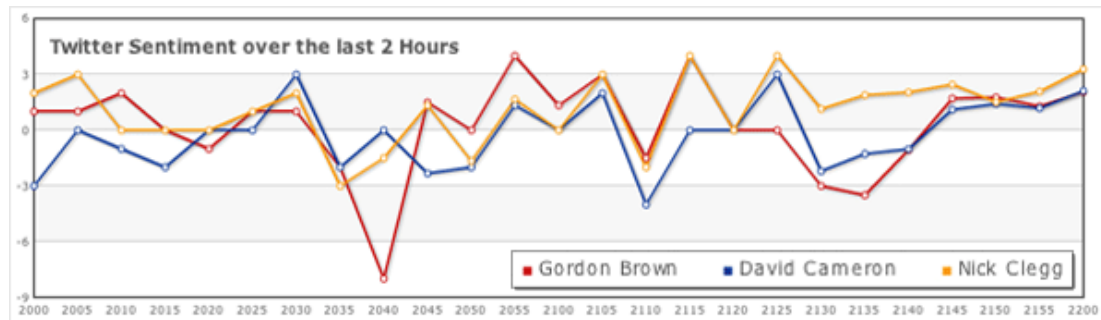


Figure 3 Sentiment level through time⁷

2.7.2.4 Brand Reputation Management

Reputation can be improved or damaged by customers' opinions. This creates an opportunity for companies to manage and strengthen its brand reputation. If, for example, there was negative feedback on the keyboard being faulty, an early recall could be made and a modification issued. Sentiment analysis helps identify the customer's perspective on the brand of the company as well as its products and services [16].

2.8 Arabic Language

Arabic, as a language, comprises 28 letters made up of 25 consonants and 3 long vowels. Arabic can be best described as a cursive, joined-up and longhand language. Cursive means that the letters in an Arabic word are connected to one another in a continuous flowing line, unlike English which is non-cursive. In fact, the letter shape in the Arabic language depends on its position in the word. Note that the writing in Arabic runs in the direction of right to left. Arabic has no capitalization, similar to other languages, such as Korean and Japanese.

Arabic letters have various shapes, depending on their communicative position in the word. This is also unlike English, which has designated letters to represent short vowels. Arabic has diacritics (marks) that play the same unique role as the short

⁷ http://www.bbc.co.uk/blogs/thereporters/rorycellanjones/2010/04/the_tv_debate_what_did_twitter.html

vowels in English and determine the sound or the pronunciation of the letter. In Arabic, it is interesting to note that almost all words are derived from a specific root which is a composition of constants. Roots are generally categorized into three or four major letters called radicals [18].

These basic specific characteristics introduce challenges in the Natural Language perspective; therefore, it needs different techniques by researchers to accomplish a better comparable performance level to what has been accomplished in other languages, such as English.

There are three main kinds of Arabic, these are Classical Arabic (CA), Modern Standard Arabic (MSA) and Dialect Arabic (DA). The oldest version of Arabic is the CA, which has been used since the earliest ages of the Arab nation. The MSA is regarded as the formal and academic Arabic language, which is used nowadays in written books and intellectual materials. The DA is a kind of colloquial language (street form) which differs from region to region, based on the culture in that region [19].

The reason behind choosing Arabic over English in students' feedback in DA within this research, is to make them comfortable in expressing their opinion by using full meaning of feeling explanation. Using English in our sentiment may cause our students to utilize trivial or inappropriate words.

However, Arabic language has many additional challenges for natural language processing, as illustrated by these points:

- A given root can take a few forms relying upon the context, for example (لجُؤون) (أحبو، تحب)

- Arabic has a variety of diacritics; depending on absence or presence of such diacritics, words can have totally different meanings. For example, "school" "مدوينة" and "teacher" "مدرسة", both, when written without diacritics "مدرسة", can be read as the same word.

- Words of negation, which can be used to negate present or past tense verbs, change the verb meaning to the exact opposite. e.g. لم اعجب بهذا الكتاب . "I didn't like this book."

2.9 Sentiment Analysis in student feedback

Sentiment analysis has been carried out in the education domain. Typically, this approach has gathered the opinions of students through social networking, to improve the level of feedback and hence education. Models have been applied to monitor the performance of students, as well as trying to understand how students benefit from the lecturer [20]. When you combine education and sentiment analysis together, education can be improved by saving time to analyse feedback in real-time, rather than at the end of the semester. Students can use any method (e.g. open-ended text responses to questionnaires, SMS, and social media) to express their opinion about the lecturer or some topic in the lecture, e.g. if it is difficult to understand. By finding out students' opinions over time periods, the lecturer can change teaching technique according to the results.

In general, by analysing the sentiment in the text, it can help the teacher to also understanding the student more deeply. The student can express his/her opinions in short phrases or words. The student's feedback can be taken at any time in the lecture, but there will also be time points chosen by the lecturer as he moves from one topic to another.

The lecturer can change the way the lectures are presented depending on the sentiment levels and trends. For example, if students have a negative average sentiment towards a lecture, then after deeper analysis, changes can be made. It is possible for the lecturer to put more examples in the next lesson to make students understand better. However, it may be a one off and the lecturer does not have to respond to every negative review. Some parts of a course are hard, but over time a fuller understanding will hopefully emerge.

After obtaining the results, they can be verified with discussions to make sure sentiment analysis has reflected reality and achieved success in the education area.

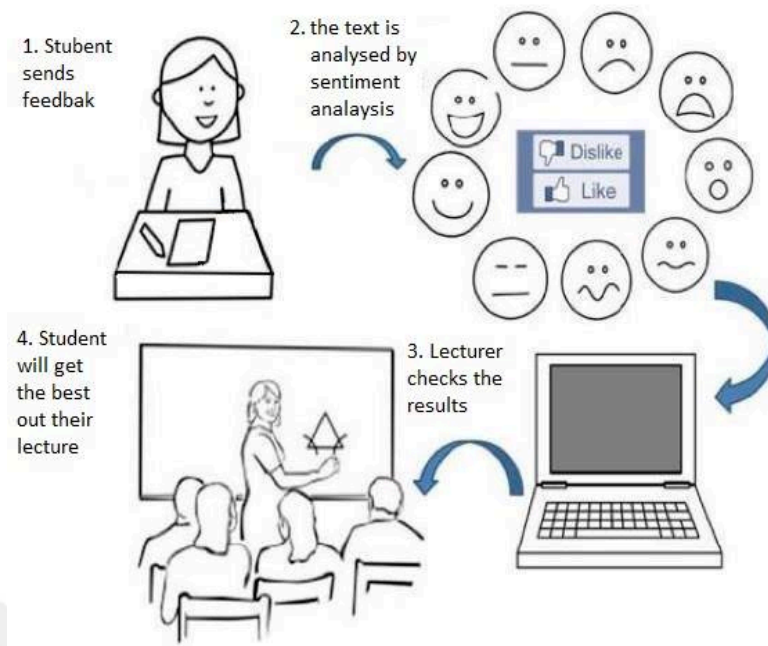


Figure 4 SA students feedback system

CHAPTER 3

THE EMPIRICAL WORK

3.1 Implementation

In this section, we will show how to apply the text processing and lexicon based approach. The diagram of our system architecture is shown in Figure 5.

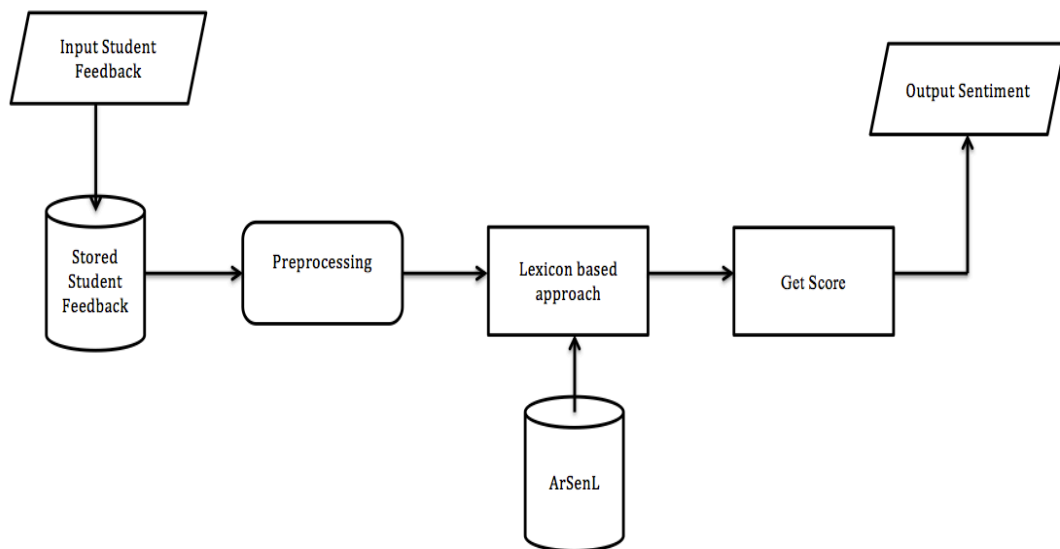


Figure 5 System Architecture

3.2 Programming Frameworks

This section is intended to give a brief overview of the programming languages, principle libraries and environments that used to implement this research.

3.2.1 Hardware Platform

All processes have been implemented on the Mac OS version 10.11.3 (15D21) with processor core i5 and ram 6GB.

3.2.2 RapidMiner

RapidMiner is one of the best tools in data mining. “RapidMiner is the world wide leading open source and business source⁸ data mining solution. It is a java-based data mining library and environment[21]. RapidMiner has a graphical user interface (GUI) which allows access to the algorithms and results, where the user can design his/her model through drag-and-drop operations, without writing any code. Text mining is one of the most important extensions that has been added to RapidMiner, so there are operations for tokenization, remove stopwords, and stemming, etc. The main reason for our choice of RapidMiner is that it supports the Arabic language.

3.2.3 Python

After considering all the possible options, we decided to choose Python 3⁹, because Python can handle natural languages well and in particular strings. Python supports libraries that provide natural language processing tools, which we need in this thesis

3.2.4 NLTK and Scikit

The NLTK¹⁰ and Scikit-learn¹¹ are the most important tools used in the implementation of this project, and worth mentioning when using these tools to write the code, it will facilitate and shorten the time of writing code. We used these libraries for preprocessing, in particular NumPy¹² and Pandas¹³.

3.3 The Data

8 <https://rapidminer.com/the-core-of-rapidminer-is-open-source/>

9 <http://www.python.org/>

10 <http://nltk.org>

11 <http://scikit-learn.org/stable/index.html>

12 <http://www.numpy.org/>

13 <http://pandas.org/>

In this project, we generated our dataset by collecting students' feedback using the FluidSurvey¹⁴ website. FluidSurvey questionnaire is a system designed to interact with people, whose views are sought, without the need for installing software on their PC. It performs the following tasks: feedback forms, building questionnaires directly through the Internet, evaluations and calculating survey results.

We collected data from two courses in one semester, by posting the questionnaire link to students via email. We have to ask two questions in the survey about students satisfaction about the lecture and lecturer, students wrote their comments and opinions in the text box. As shown in Figure 6.

دراسة MIS

ما هي نسبة فهمك للموضوع بشكل عام؟

★ ★ ★ ★ ★

ما هو مدى الرضا عن تقديم المحاضرة؟

★ ★ ★ ★ ★

تعليق حول مدى الرضا

Type here

Submit

Figure 6. FluidSurvey questionnaire

We also collected data manually from the students by distributing a paper questionnaire at the end of each lecture.

3.4 The Preprocessing

¹⁴ <http://fluidsurveys.com/>

After collecting the data from the students, it must be preprocessed before starting the sentiment analysis.

We will explain in detail all steps at this process, as shown in Figure 7.

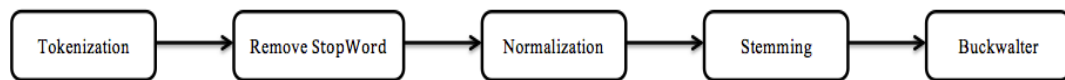


Figure 7. Preprocessing operation

3.4.1 Tokenization

The NLTK libraries offer a number of tokenization functions such as `TrebankWordTokenizer`, `WordPunctTokenizer`, `PunctWordTokenizer` and `WhitespaceTokenizer`. These divide documents into sentences and divide sentences into words and divide words into letters depending on tokenization functions type [1]. In our project, we used `word_tokenize` for dividing the sentences to words, because the data type is a sentence, as shown in this example.

```
>>> from nltk.tokenize import word_tokenize
>>> word_tokenize('Hello World.')
```

The output is <<<<“Hello” , “World”.

3.4.2 Remove StopWords

StopWords is a set of words that are excluded during the preprocessing of data (texts). These words appear in the text repeatedly, such as (in, from, to, ...) and it is advisable that they are ignored and not indexed, in order to improve the accuracy. It is important to note that when you delete stop-words, it does not affect the sentiment of the sentence. The Arabic stop words list is (من ، في ، على ، و ، يا ، عن ، مع ، هو ، ما ، ، اللبي ، كل ، بعد ، ده ، اليوم ، أن ، يوم انا ، إلى ، كان ، ايه ، اللبي ، دي ، بين ، انت ، أنا ، حتى ، لما ، فيه ، اللبي ، هذا ، واحد ، احنا ، اي ، كده ، او ، عليه ، ف ، مين ، الي ، كانت ، أمام ، يكون ، خلال ,etc....)

In our project we used function `get_stop_words ('arabic')` and `stopword.remove()` from the nltk library to remove the Arabic stopwords.

3.4.3 Normalization

Normalization is important for the Arabic language because it contains a lot of diacritics, unlike the English language. Normalization is the process of replacing similar letters (letters interchangeable) with one of these letters, as well as deleting the symbols from the sentences. In our project we put these conditions to work on the normalization of our data.

1. Remove any punctuation from the string such as (. “” ; ').
2. Remove any diacritics (short vowels) such as (َ ِ ُ).
3. Remove non-letters from the word such as (+ = ~ \$).
4. Replace “ َ ”, “ ِ ”, and “ ُ ” with bare alif “ ا ” regardless of position in the word.
5. Remove Tatweel “ ّ ” (for example, using Tatweel the word “ ّأْتَب ” may look like “ ّأْتَب ”).
6. Replace final “ ى ” with “ ى ”.
7. Replace final “ ة ” with “ ة ”.
8. If a word starts with “ ء ” then replace it with “ ء ”.
9. Replace “ ُو ” and “ ُو ” with “ ُو ”.
10. Replace “ ى ” and “ ىء ” with “ ى [15] ”.

3.4.4 Stemming

Stemming is the process of removing all prefixes and/or suffixes of the words to produce their root. Table 1 and 2 [21] show the Arabic prefixes and suffixes. It reduces the impact of the pattern difference and the shape difference of the Arabic words. It also contributes in decreasing the required size to store the words in indexes. Stemming is a mathematical method of gathering all the words that share the same origin and have some semantic relations. Arabic stemming algorithms are classified according to the required level of analysis: based on origin or based on the root [22]. In our project we used the Information Science Research Institute's (ISRI) Arabic stemmer. The reason for our choice of ISRI stemmer is that the design of ArSneL (Arabic Sentiment Lexicon) uses ISRI to get the root of the words, so we used it to facilitate the matching process between ArSneL and our data.

Prefixes	Meaning	Example
ب	with, in, by	بالسيارة
ك	same as	كالدخان
س	will	سأذهب
و	and	ورجالهم
ال	the	والنساء
أ	question mark	أأكلتم
ف	then	فذهبوا
ل	because, to	لنتنام

Table 1 Arabic prefixes

Suffix	Derivative Meaning	Example
ين	Singular female	تلعبين
ان	male dual	يلعبان
و	Plural male	ينمو
ه	Singular female	ضربته
ك	Addresser singular masculine	ضربك
ا	male dual	أكلا
ي	Singular female	أكلتي
ن	Plural	أكلن
ت	Singular female	أكلت
ات	Female plural	لأعبات
ون	absent male plural	يلعبون
وا	absent male plural	أكلوا
تم	addresser male	أكلتم
هم	absent male plural	ضربهم

كم	addresser male	ضريكم
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Table 2 Selected Arabic suffixes

3.4.5 Buckwalter

Buckwalter ¹⁵[23] is a system designed to represent the Arabic language characters on the computer, in standard encoding. The Buckwalter transliteration has been used in many applications for natural language processing for the academic and commercial purposes. It is designed and developed by the Linguistic Data Consortium¹⁶. The Buckwalter transliteration is a strict conversion tool for Arabic characters (one-to-one) to ASCII characters.

In our research, we have built a script in Python to convert the Arabic characters into ASCII symbols following the buckwalter method (see Table 3 [23]). We did this because Python neither supports Arabic characters nor handles it like English characters. The other reason is that the ArSenL dictionary is written in Buckwalter translation.

Letter	Description	Buckwalter
ء	Letter Hamza	,
آ	Letter Alef, Madda above	
أ	Letter Alef, Hamza above	>
ؤ	Letter Waw, Hamza above	&
إ	Letter Alef, Hamza Below	<
ئ	Letter Yeh, Hamza above	}
ا	Letter Alef	A
ب	Letter Beh	b
ة	Letter Teh Marbuta	p
ت	Letter Teh	t

¹⁵ <http://www.qamus.org/transliteration.htm>

¹⁶ <https://catalog ldc.upenn.edu/LDC2010L01>

ث	Letter Theh	v
ج	Letter Jeem	j
ح	Letter Hah	H
خ	Letter Khah	x
د	Letter Dal	d
ذ	Letter Thal	*
ر	Letter Reh	r
ز	Letter Zain	z
س	Letter Seen	s
ش	Letter Sheen	\$

Table 3 A selection of Arabic language characters and their Buckwalter correspondence

3.5 Arabic Sentiment Lexicon (ArSenL)

The main resources to build the ArSenL are Arabic Word-Net (AWN), English WordNet (EWN), SAMA and English SentiWordNet (ESWN), shown in Table 4. There is no direct Arabic Sentiment lexicon. There are however English Sentiment lexicons. For this reason ArSenL gets its sentiment from the English version, but ArSenL obtains the sentiment of Arabic words from the English lexicon that corresponding to Arabic words. We will explain each resource as follows.

Lexicon	Language	Sentiment	#Lemmas
AWN	Arabic	No	~7K
EWN	English	No	~120K
SAMA	Arabic-English	No	~40K
ESWN	English	Yes	~120K
ArSenL	Arabic	Yes	28,760

Table 4 The main resources contributing to the ArSenL database

3.5.1 English WordNet (EWN)

WordNet is a classified and categorized database of words. The parts of speech such as: nouns, verbs, adjectives and adverbs are logically grouped into sets of synonyms, antonyms and part of speech tags.. English version of WordNet is one of the most important tools used in the natural language processing (NLP) for the English Language.

3.5.2 Arabic WordNet (AWN)

Arabic WordNet (AWN) [24] is a collection of Arabic words that is built on English WordNet.

3.5.3 Standard Arabic Morphological Analyzer (SAMA)

Standard Arabic Morphological Analyzer (SAMA) [25] considers each Arabic word token in all possible prefix-stem-suffix segmentations, and lists all known/possible annotation solutions, with assignment of all diacritic marks, and all Part-of-Speech (POS) labels and glosses for each morpheme segment. As shown in Table 5.

Orginal	Buckwalter translation	Segmentaion	Part-of-speech	Synonym
مثال	mivAl	mivAl + u	NOUN+ CASE_DEF_NOM	example/model
لبعض	libaEoDi	li + baEoD + i	PREP + NOUN_QUANT + CASE_DEF_GEN	for/to + some, a few, little, part
حرف	Harof	Harof	NOUN	Latter

Table 5 The SAMA examples

3.5.4 English SentiWordNet (ESWN)

English SentiWordNet (ESWN) is a large-scale sentiment lexicon for English language. Each word in EWN appears in ESWN. All the words in ESWN have three sentiment scores : positive, negative, and neutral, whose sum is equal to 1, for example, the word (love) has sentiment score (1, 0, 0) [26]. Other words are not so definite such as ‘well’ which has a score (0.7,0.1,0.2)

3.5.5 Arabic WordNet-based Approach

For Arabic, the approach follows two steps: mapping SAMA to AWN and mapping AWN to ESWN. The mapping between AWN and SAMA gives us the correct lemma forms for the words in AWN and the mapping between AWN to EWSN gives us the sentiment scores. We can refer to the resulted lexicon as ArSenL-AWN. In this way, we show how the ArSenL is built. More details are in Barado et al [27].

In our research, we added some normalization to the ArSneL, such as removing all the diacritics (marks on the base letter) from the dictionary. The reason for this is that all the students’ feedback was written without diacritical marks. To make a matching between the ArSneL and the students feedback, after implemented the preprocessing operation on it .

3.6 Calculating the Sentiment Score

After executing the previous operations, we want to find the sentiment of an input sentence. The system sends word by word to the ArSenl where a matching process takes place against its list of words. If the matching hits, then we retrieve the positive and the negative value and store these values. This is repeated for each word in the sentence. In the case where there is no match, we ignore the word. After fetching the positive and negative values for all the words in the sentence and storing them, we sum the positive values across all the words to get the score, and likewise for the negative ones. Eventually, if the total score of the positives is greater than the negatives, the sentiment is considered positive and vice versa. We have also stored the negation constructs in the Arabic language such as (ليس، لا ، لم). If one of the negation constructs shows in the sentence, we will invert the positive and negative

values (replace the positive instead of the negative and the negative instead of the positive) for the word that comes after the negation.

3.7 The summary of empirical work

- Input the students' feedback.
- Split sentences to words by tokenization and remove stop words.
- Implemented the normalization and stemming on texts.
- Applied the Buckwalter method.
- Get word polarity score from ArSenL.
- Compute sentence polarity from word polarities.
- Obtain results for students' feedback.

CHAPTER 4

RESULTS

In this chapter, we present the Arabic sentiment analysis results for student feedback using Python language built in the RapidMiner platform. Due to the difficulty of the Arabic language that was collected from students, we used Buckwalter translation to convert to ASCII characters from Arabic ones. Also, we utilized ArSenL to calculate the score of sentiment as mention previously.

We also sent our data to the Indicoio and Repustate companies to compare our results with these companies.

We divided our experiment into four parts as follows.

1. Apply Preprocessing operations on our data.
2. Obtain sentiment score.
3. Compare our results and the companies' results.
4. Display final results for two courses on excel graph.

4.1 Apply Preprocessing operations

At the first stage, we loaded our data into RapidMiner and then this data was passed to a Python library to apply the operations Tokenization, Remove stopwords, Normalization, Stemming and Buckwalter.

Tokenization splits the sentence to words, while Remove stopwords removes any word that has no effecton on the meaning of the sentence like prepositions as in the Table 6 below:

Row No.	Text	Translation	Tokenization & Remove StopWords
1	المحاضرة جيدة جدا وبذل الدكتور جيمس جهودا كبيرة لعرض إيصال المعلومات النبا	The lecture was very good, and Dr james has put efforts in order to deliver the information to us.	المحاضرة، جيدة، جدا، وبذل، الدكتور، جيمس، جهودا، كبيرة، لعرض، إيصال، المعلومات، النبا
2	المحاضرة جيدة جدا وممتعة والدكتور بذل جهودا مضنية في سبيل إيصال المعلومة لنا وإعطائنا معلومات مفيدة وجديدة وفتح آفاق علمية ومساحة من التفكير شكرا جزيلاً للدكتور جيمس	The lecture was very good, joyful and Dr James has made appreciated efforts to deliver the information to us, given us useful fresh information, opened new scientific horizons and a space of thinking thanks a lot Dr. James.	المحاضرة، جيدة، جدا، وممتعة، والدكتور، بذل، جهودا، مضنية، في سبيل، إيصال، المعلومة، لنا، وإعطائنا، معلومات، مفيدة، وجديدة، وفتح، آفاق، علمية، ومساحة، من التفكير، شكرا، جزيلاً، للدكتور، جيمس
3	المحاضرة شيقة وممتعة وجيدة جدا والإستاذ قد بذل مجهود جيد جدا في إيصال المعلومات ونتمنى الحصول على نتائج جيدة مع دكتور جيمس شكرا دكتور جيمس	The lecture was joyful, interesting and very good, the lecturer has made very good efforts in delivering the information to us, we wish we get high grades with Dr. James, thank you Dr. James	المحاضرة، شيقة، وممتعة، وجيدة، جدا، والإستاذ، قد، بذل، مجهود، جيد، جدا، في، إيصال، المعلومات، ونتمنى، الحصول، على، نتائج، جيدة، مع، دكتور، جيمس، شكرا، دكتور، جيمس
4	محاضرة اليوم كانت رائعة و سهلة جدا حيث كانت ذات فائدة كبيرة	Today's lecture was a great and very easy to where it was of interest to big.	محاضرة، اليوم، كانت، رائعة، و، سهلة، جدا، حيث، كانت، ذات، فائدة، كبيرة
5	المحاضرة كانت مفهومة وكان الطلاب مندمجين مع الدكتور بشكل كبير	The lecture was understandable and the students were highly concentrated with the instructor.	المحاضرة، كانت، مفهومة، وكان، الطلاب، مندمجين، مع، الدكتور، بشكل، كبير
6	المحاضرة كانت جدا صعبة و لم افهم الموضوع بشكل كبير	The lecture was very difficult and I didnt understand the topic very well.	المحاضرة، كانت، جدا، صعبة، و، لم، افهم، الموضوع، بشكل، كبير
7	المحاضرة كانت سهلة و الموضوع كان سهل	The lecture was easy and the topic was quite understandable.	المحاضرة، كانت، سهلة، و، الموضوع، كان، سهل
8	الموضوع كان صعب بعض الشيء لكن تم تغطية من قبل المحاضر وفهمه الى حد قليل	The topic was hard to understand somehow, however it was been covered by the lecturer and I understood very few things.	الموضوع، كان، صعب، الشيء، لكن، تم، تغطية، من، قبل، المحاضر، وفهمه، الى، حد، قليل

Table 6 Results of Tokenization and Remove stopwords

On one hand, the diacritics are removed by the Normalization, on the other hand, Stemming returns the word to its root. Table 7 shows the results of the Normalization and Stemming:

Row No.	Text	Translation	Normalization & Stemming
1	المحاضرة جيدة جدا وبذل الدكتور جيمس جهودا كبيرة لعرض إيصال المعلومات النبا	The lecture was very good, and Dr james has put efforts in order to deliver the information to us.	احضر، اجيد، اجدا، ابذل، ادكتور، اجيمس، اجهدا، اكبر، اعرض، ايصل، اعلم، ابنا
2	المحاضرة جيدة جدا وممتعة والدكتور بذل جهودا مضنية في سبيل إيصال المعلومة لنا وإعطائنا معلومات مفيدة وجديدة وفتح آفاق علمية ومساحة من التفكير شكرا جزيلاً للدكتور جيمس	The lecture was very good, joyful and Dr James has made appreciated efforts to deliver the information to us, given us useful fresh information, opened new scientific horizons and a space of thinking thanks a lot Dr. James.	احضر، اجيد، اجدا، امع، ادكتور، ابذل، اجهدا، امضنة، اسبل، ايصل، اعلم، ابنا، اعطاء، اعلم، افيد، اجدا، افح، افق، اعلم، اساح، افكر، اشكر، اجزل، ادكتور، اجيمس
3	المحاضرة شيقة وممتعة وجيدة جدا والإستاذ قد بذل مجهود جيد جدا في إيصال المعلومات ونتمنى الحصول على نتائج جيدة مع دكتور جيمس شكرا دكتور جيمس	The lecture was joyful, interesting and very good, the lecturer has made very good efforts in delivering the information to us, we wish we get high grades with Dr. James, thank you Dr. James	احضر، اشيق، امع، اوجد، اجدا، اساذ، ابذل، اجهدا، اجيد، اجدا، ايصل، اعلم، امنى، احصل، نتج، اجيد، ادكتور، اجيمس، اشكر، ادكتور، اجيمس
4	محاضرة اليوم كانت رائعة و سهلة جدا حيث كانت ذات فائدة كبيرة	Today's lecture was a great and very easy to where it was of interest to big.	احظر، اكانت، ارع، اسهل، اجدا، اكانت، ذات، افندا، اكبر
5	المحاضرة كانت مفهومة وكان الطلاب مندمجين مع الدكتور بشكل كبير	The lecture was understandable and the students were highly concentrated with the instructor.	احظر، افهم، امطلب، ادمع، ادكتور، اكبر
6	المحاضرة كانت جدا صعبة و لم افهم الموضوع بشكل كبير	The lecture was very difficult and I didnt understand the topic very well.	احظر، اجدا، اصعب، لم، افهم، وضع، اكبر
7	المحاضرة كانت سهلة و الموضوع كان سهل	The lecture was easy and the topic was quite understandable.	اشرح، احظر، ادعم، امثل، افهم، اطرق، امقر
8	الموضوع كان صعب بعض الشيء لكن تم تغطية من قبل المحاضر وفهمه الى حد قليل	The topic was hard to understand somehow, however it was been covered by the lecturer and I understood very few things.	وضع، اصعب، الشيء، تم، اعطي، قبل، احظر، افهم، احدا، اقل

Table 7 Results of Normalization and Stemming

Buckwalter literally translates each Arabic letter to its mapping English alphabet. This is shown in Table 8.

Row No.	Text	Translation	buckwalterMode
1	المحاضرة جيدة جدا ويذل الدكتور جيمس جهودا كبيرة لغرض إيصال المعلومات اليها	The lecture was very good, and Dr James has put efforts in order to deliver the information to us.	['HDr', 'jyd', 'jdA', 'b*1', 'dktwr', 'jyms', 'jhd', 'kbr', 'grD', 'y' 'Elm', 'ynA']
2	المحاضرة جيدة جدا وممتعة والدكتور بذل جهودا مضنية في سبيل إيصال المعلومة لنا وإعطينا معلومات مفيدة وجديدة وفتح آفاق علمية ومساحة من التفكير شكرا جزيلاً للدكتور جيمس	The lecture was very good, joyful and Dr James has made appreciated efforts to deliver the information to us, given us useful fresh information, opened new scientific horizons and a space of thinking thanks a lot Dr. James.	['HDr', 'jyd', 'jdA', 'mtE', 'dktwr', 'b*1', 'jhd', 'Dnp', 'sbl', 'ys 'Elm', 'InA', '<ETA}', 'Elm', 'fyd', 'jdd', 'fH', 'Afq', 'Elm', 'sAH', 'fkr', '\$kr', 'jzl', 'dktwr', 'jyms']
3	المحاضرة شيقة وممتعة وجيدة جدا والاستاذ قد بذل مجهود جيد جدا في إيصال المعلومات وتتمني الحصول على نتائج جيدة مع دكتور جيمس شكرا دكتور جيمس	The lecture was joyful, interesting and very good, the lecturer has made very good efforts in delivering the information to us, we wish we get high grades with Dr. James, thank you Dr. James	['HDr', '\$yq', 'mtE', 'wjd', 'jdA', 'sA*', 'b*1', 'jhd', 'jyd', 'jdA 'ysl', 'Elm', 'mnY', 'Hsl', 'ntj', 'jyd', 'dktwr', 'jyms', '\$kr', 'dktwr', 'jyms']
4	محاضرة اليوم كانت رائعة و سهلة جدا حيث كانت ذات فائدة كبيرة	Today's lecture was a great and very easy to where it was of interest to big.	['HZr', 'kAnt', 'r}E', 'shl', 'jdA', 'kAnt', '*At', 'f]d', 'kbr']
5	المحاضرته كانت مفهومه وكان الطلاب مندمجين مع الدكتور بشكل كبير	The lecture was understandable and the students were highly concentrated with the instructor.	['HZr', 'fhm', 'Tlb', 'dmj', 'dktwr', 'kbr']
6	المحاضرة كانت جدا صعبة و لم افهم الموضوع بشكل كبير	The lecture was very difficult and I didnt understand the topic very well.	['HZr', 'jdA', 'sEb', 'lm', 'fhm', 'wDE', 'kbr']
7	المحاضرة كانت سهلة و الموضوع كان سهل	The lecture was easy and the topic was quite understandable.	['\$rH', 'HZr', 'dEm', 'mvl', 'fhm', 'Trq', 'mtz']
8	الموضوع كان صعب بعض الشيء لكن تم تغطية من قبل المحاضر وفهمه الى حد قليل	The topic was hard to understand somehow, however it was been covered by the lecturer and I understood very few things.	['wDE', 'sEb', 'lS}', 'tm', 'gTy', 'qbl', 'HZr', 'fhm', 'Hd', 'qll']

Table 8 Results of Buckwalter

4.2 Obtain sentiment score

We applied our method to calculate the sentiment score. There are two scores positive and negative for each sentence. The sentence appears as positive if the positive score is greater than the negative score and vice versa. As we can see in Tables (9) and (10)

Row No.	Text
1	المحاضرة جيدة جدا وبذل الدكتور جيمس جهودا كبيرة لغرض إيصال المعلومات إلينا
2	المحاضرة جيدة جدا وممتعة والدكتور بذل جهودا مضافية في سبيل إيصال المعلومة لنا وإعطائنا معلومات مفيدة وجديدة وفتح آفاق علمية ومساحة من التفكير شكرا جزيلاً للدكتور جيمس
3	المحاضرة شيقية وممتعة وجيدة جدا والاستاذ قد بذل مجهود جيد جدا في إيصال المعلومات ونتمنى الحصول على نتائج جيدة مع دكتور جيمس شكرا دكتور جيمس
4	محاضرة اليوم كانت رائعة و سهله جدا حيث كانت ذات فائده كبيره
5	المحاضرته كانت مفهومه وكان الطلاب مندمجين مع الدكتور بشكل كبير
6	المحاضرة كانت جدا صعبة و لم افهم الموضوع بشكل كبير
7	المحاضرة كانت سهلة و الموضوع كان سهل
8	الموضوع كان صعب بعض الشيء لكن تم تغطية من قبل المحاضر وفهمه الى حد قليل

Table 9 Sentiment scores

Translation	Pos_score	Neg_score	Sentiment
The lecture was very good, and Dr james has put efforts in order to deliver the information to us.	1,59940883	0,386772643	positive
The lecture was very good, joyful and Dr James has made appreciated efforts to deliver the information to us, given us useful fresh information, opened new scientific horizons and a space of thinking thanks a lot Dr. James.	2,334613352	0,760431135	positive
The lecture was joyful, interesting and very good, the lecturer has made very good efforts in delivering the information to us, we wish we get high grades with Dr. James, thank you Dr. James	2,925804663	0,817222048	positive
Today's lecture was a great and very easy to where it was of interest to big.	0,72928338	0,37307423	positive
The lecture was understandable and the students were highly concentrated with the instructor.	0,394570229	0,092980296	positive
The lecture was very difficult and I didnt understand the topic very well.	0,438690476	0,904761905	negative
The lecture was easy and the topic was quite understandable.	0,35452381	0,139440267	positive
The topic was hard to understand somehow, however it was been covered by the lecturer and I understood very few things.	0,43156682	0,599071941	negative

Table 10 Sentiment scores

4.3 Compare our results with the Indico and Repustate companies

We also sent our data to Indico and Repustate companies that are interested in the text analysis. Indico and Repustate companies have a function called Sentiment, this function has three arguments (data, api_key and language). The output of the Indico system returns a number between 0 and 1, if a value greater than 0.5 indicate to positive sentiment, if the value less than 0.5 indicate to negative sentiment. The output of the Repustate system returns a score range from -1 (negative) to 1 (positive) with a score of 0 being "neutral". When we compare our results with the companys' results, we can see our results are more realistic. We determine ground truth by manual inspection of the sentence and just reading them to determine sentiment. Sentences such as 6 and 10 appeared in our results positive and negative respectively while the same sentences appeared in these companies opposite way, as shown in Table 11.

Translation	Indico	Repustate
The lecture was very good, and Dr james has put efforts in order to deliver the information to us.	0,91949042	{'score': -0.5611798493101557, 'status': 'OK'}
The lecture was very good, joyful and Dr James has made appreciated efforts to deliver the information to us, given us useful fresh information, opened new scientific horizons and a space of thinking thanks a lot Dr. James.	0,873723544	{'score': 0.47977399901215406, 'status': 'OK'}
The lecture was joyful, interesting and very good, the lecturer has made very good efforts in delivering the information to us, we wish we get high grades with Dr. James, thank you Dr. James	0,734921341	{'score': 0.4134663047161541, 'status': 'OK'}
Today's lecture was a great and very easy to where it was of interest to big.	0,588983641	{'score': 0.3319971466928432, 'status': 'OK'}
The lecture was understandable and the students were highly concentrated with the instructor.	0,764796942	{'score': 0.95, 'status': 'OK'}
The lecture was very difficult and I didnt understand the topic very well.	0,059373301	{'score': -0.3983965760314119, 'status': 'OK'}
The lecture was easy and the topic was quite understandable.	0,791520521	{'score': 0.95, 'status': 'OK'}
The topic was hard to understand somehow, however it was been covered by the lecturer and I understood very few things.	0,343847957	{'score': -0.95, 'status': 'OK'}

Table 11 Indico and Repustate results

4.4 Display final results for two courses in Excel

Our data consisted of two courses, Web Analytic (WA) and Management Information System (MIS) in one semester. The WA had four students and the MIS had five students. We reported the maximum and minimum scores for each week and calculated the average also. These three points (maximum, minimum and average)

were inserted into an Excel sheet and each course was plotted over time, as in the figures below.

	Max	Min	Average			
02/02/16	0,805	-0,228	0,157			
09/02/16	0,712	-0,296	0,272			
16/02/16	0,466	-0,432	-0,009			
23/02/16	0,406	-0,298	0,036			
01/03/16	0,746	-0,023	0,318			
08/03/16	1,000	0,000	0,247			

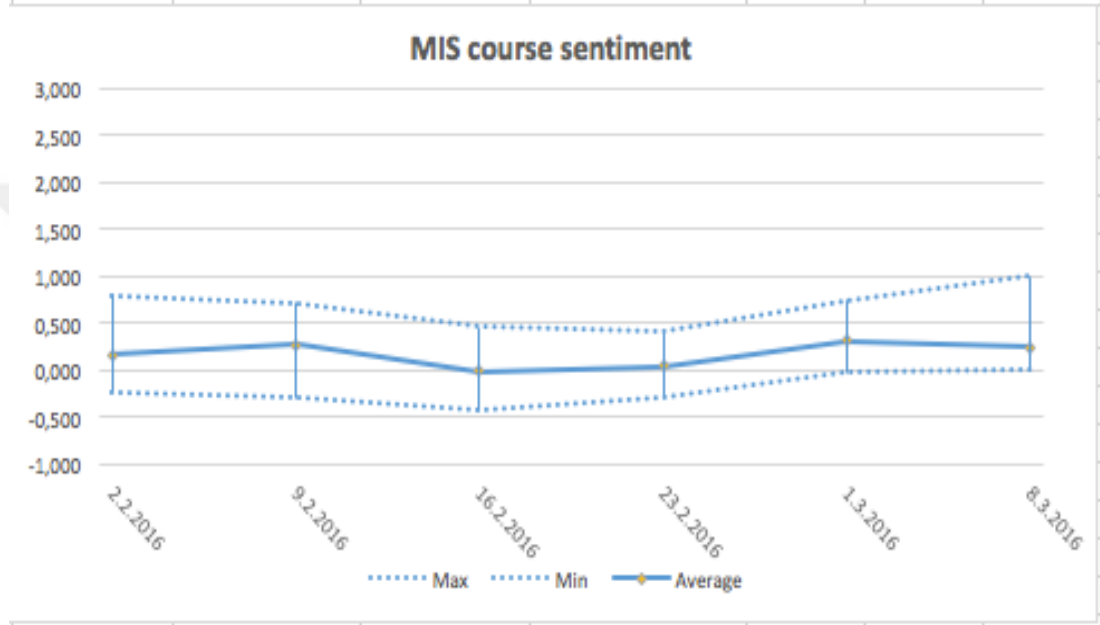


Figure 8 Final results for MIS course

As we saw in the previous figure, we got one average value for just one week that equals to -0.009. this avrage can be considered as a neutral score because it is so close to the value of 0 (neutral value). This is also applied to the week number four (23/2/2016) in the next figure.

	Max	Min	Average					
02/02/16	1,000	0,169	0,623					
09/02/16	0,693	-0,079	0,215					
16/02/16	0,646	-0,079	0,203					
23/02/16	0,379	-0,432	-0,024					
01/03/16	0,253	-0,495	-0,201					
08/03/16	0,545	-0,134	0,147					
15/03/16	0,805	0,142	0,486					
22/03/16	0,547	-0,300	0,068					

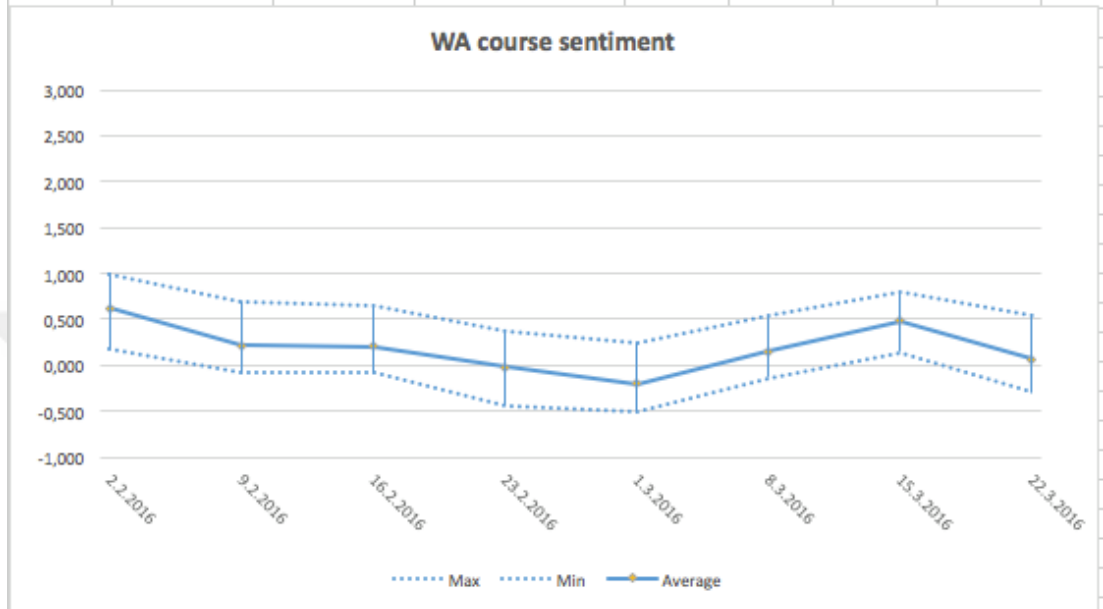


Figure 9 Final results for Web Analytic course

CHAPTER 5

CONCLUSIONS

Based on the outcome of system tests and analysis, it can be concluded that the sentiment results using a lexicon-based approach for the Arabic language, is able to classify sentiment into positive and negative.

Our results are very realistic. We used the ArSenL dictionary to find the sentiment score. We conclude from the sentiment graphs that variations in the curve during the course, is as a result of the different level of difficulty or ease of lecture and lecturer. The graphs are plausible because there is no curve out of range over time of every week of the semester. We found for example that the curve during a midterm exam or some difficult lectures moved down and during some periods of time increased. Our data that was collected from students seemed normal because it ranged between the positive and negative depending on the level of the lecture.

We compared our results with two tools the Indicoio and Repustate to verify results. We found the Indicoio and Repustate accuracy is not always accurate as we have seen Arabic sentences positive, but in Indicoio and Repustate they showed the opposite. The system could be improved in many ways. (1) Making our work as a website instead of installing the application on the computer we can reach it online to make it available for everyone as well as to get results in real time. (2) Using supervised learning we can make comparison between these two approaches. (3) Designing a Web page that has some audio recording tools that allow students to recording their voice to express their opinion and translate this audio to text. (4) We can address repeating the letter more than ones to Identifying the meaning or feeling (A typical style found in casual channels) for instance, جددد in MSA can be written as جدا. Extremely or too much is its meaning

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APPENDICES

APPENDIX A

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Khudhair, Ali Hadi Khudhair

Date and Place of Birth: 28 April. 1990, Babylon, Iraq

Marital Status: Single

Phone: +9647823456178

Email: algeboorya@gmail.com

EDUCATION

Degree	Institution	Year of Graduation
M.Sc.	Çankaya Univ.,	2016
B.Sc.	University of Babylon	2014
High School	Al-Mahaweel School	2010

FOREIN LANGUAGES

Advanced English, Beginner Turkish

HOBBIES

Travel, Books, Swimming.