

شبكة المعلومات الجامعية التوثيق الإلكتروني والميكروفيلو

# بسم الله الرحمن الرحيم





MONA MAGHRABY



شبكة المعلومات الجامعية التوثيق الإلكتروني والميكروفيلو



شبكة المعلومات الجامعية التوثيق الالكتروني والميكروفيلم



MONA MAGHRABY



شبكة المعلومات الجامعية التوثيق الإلكترونى والميكروفيلم

# جامعة عين شمس التوثيق الإلكتروني والميكروفيلم قسم

نقسم بالله العظيم أن المادة التي تم توثيقها وتسجيلها علي هذه الأقراص المدمجة قد أعدت دون أية تغيرات



يجب أن

تحفظ هذه الأقراص المدمجة بعيدا عن الغبار



MONA MAGHRABY

#### AIN SHAMS UNIVERSITY

Faculty of Computer and Information Sciences Information Systems Department



# Feature-based Approach for Sentiment Analysis of Social Networks

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of M.Sc. in Computer and Information Sciences

To

Information Systems Department, Faculty of Computer and Information Sciences, Ain Shams University

By

#### Nagwa Moustafa Kamal Saeed

Teaching Assistant at Information Systems Department Faculty of Computer and Information Sciences Ain Shams University

#### **Under the Supervision of**

#### Prof. Dr. Tarek Fouad Gharib

Head of Information Systems Department Faculty of Computer and Information Sciences Ain Shams University

#### Prof. Dr. Nagwa Lotfy Badr

Information Systems Department
Dean of the Faculty of Computer and Information Sciences
Ain Shams University

#### **Dr. Nivin Atef Helal**

Information Systems Department
Faculty of Computer and Information Sciences
Ain Shams University

# Acknowledgment

First and foremost, I would like to thank God Almighty for giving me the strength, knowledge, ability and opportunity to undertake this research study and to persevere and complete it satisfactorily.

I wish to express a deep sense of gratitude and appreciation to Prof. Dr. Tarek Gharib, Prof. Dr. Nagwa Badr and Dr. Nivin Atef for their supervision, continuous support, encouragement, invaluable guidance and skillful suggestions which deeply contributed to the completion of this research study.

Finally, I would like to express my deep sense of gratitude towards my beloved family who are the biggest source of my strength and of course my prime source of ideas. They have all made a tremendous contribution in helping me reach this stage in my life. Had it not been for their unflinching insistence and their support to me, my dream of getting this degree would have remained a mere dream. Therefore, I would like to thank all of them for their endless love, continual support, prayers, patience, understanding and encouragement throughout these years and for their believing in me that I can finish my research study in time.

#### **Abstract**

In the last few years, online reviews where individuals express their thoughts, interests, experiences and opinions have majorly spread over the internet. Sentiment analysis field of study has evolved to analyze these online reviews and provide valuable insights for both individuals and organizations that may help them in making decisions. Unfortunately, the performance of sentiment analysis process is affected by the nature of online reviews' content that may contain emoticons and negation words. Moreover, spam reviews have been written for the purpose of deceiving others. These spam reviews may greatly influence online marketing and prevent both individuals and organizations from concluding real ideas about certain services or products. Therefore, there is a need to develop an approach that considers these issues.

In this thesis, an enhanced approach for sentiment analysis is proposed which aims to enhance the performance of classifying reviews based on their features and assigning an accurate sentiment score to each feature. This enhanced approach is achieved by handling negation, detecting emoticons, and detecting spam reviews using a combination of different types of properties which leads to achieving better predictive performance. Moreover, this approach examines the impact of using three different feature extraction methods on the performance of sentiment classification which are extracting all nouns, extracting only the nouns that occur frequently, and extracting frequent nouns by applying Apriori algorithm.

Several experiments have been carried out to validate the effectiveness of the proposed approach. The performance of the proposed approach has been measured using different types of evaluation metrics which are accuracy, precision, recall, and f1 score. The proposed approach has been verified against three datasets of different sizes. The experimental results showed the efficiency of the proposed approach in detecting spam reviews, classifying reviews based on their features and assigning an accurate sentiment score to each feature. The proposed approach achieves a maximum accuracy of about 99.06% in detecting spam reviews and outperforms the existing related works with an average value of 13.35% for accuracy. The proposed approach achieves as well a maximum accuracy of about 97.13% in classifying reviews after considering the three main challenges: negation handling, emoticons detection, and spam reviews detection together and after employing "extracting frequent nouns by applying Apriori algorithm" as a feature extraction method, where there is an improvement in accuracy value of about 29.72%, and a great saving in the feature space by 96.9% versus when not considering these three main challenges together along with this feature extraction method.

## **List of Publications**

- Saeed NMK, Helal NA, Badr NL, Gharib TF (2018) The Impact of Spam Reviews on Feature-based Sentiment Analysis. In: Proc. - 2018 13th Int. Conf. Comput. Eng. Syst. ICCES 2018. IEEE, pp 633–639.
- 2. Saeed NMK, Helal NA, Badr NL, Gharib TF (2020) An enhanced feature-based sentiment analysis approach. Wiley Interdiscip Rev Data Min Knowl Discov 10:1–20.

# **Table of Contents**

| Abstract   |   | I    |
|------------|---|------|
| List of Pu | ublications   | II   |
| Table of   | Contents  | III  |
| List of Fi | gures   | V    |
| List of Ta | ables   | VII  |
| List of A  | bbreviations  | VIII |
| Chapter    | 1: Introduction                                       | 1    |
| 1.1        | Motivation  | 2    |
| 1.2        | Objective   | 3    |
| 1.3        | Thesis Organization                                   | 3    |
| Chapter    | 2: Opinion Mining and Sentiment Analysis Background   | 5    |
| 2.1        | Opinion Mining and Sentiment Analysis                 | 5    |
| 2.2        | Structural Levels of Sentiment Analysis               | 5    |
| 2.3        | Opinion Mining and Sentiment Analysis Challenges      | 7    |
| 2.4        | Summary   | 9    |
| Chapter    | 3: Related Work                                       | 10   |
| 3.1        | Studies Performing Sentiment Analysis                 | 10   |
| 3.2        | Studies Detecting Spam Reviews Only                   | 15   |
| 3.3        | Summary   | 17   |
| Chapter    | 4: Enhanced Feature-based Sentiment Analysis Approach | 18   |
| 4.1        | Preprocessing   | 22   |
| 4.2        | Features and Sentiment Terms Extraction               | 22   |
| 4.         | .2.1 Features Extraction                              | 23   |

|     | 4.2.2   |       | Opinion Words Extraction                        | 23 |
|-----|---------|-------|---|----|
|     | 4.2     | 2.3   | Emoticons Extraction                            | 24 |
|     | 4.3     | Fea   | atures' Sentiment Scores Calculation            | 24 |
|     | 4.3     | 3.1   | Opinion Words' Sentiment Scores Calculation     | 26 |
|     | 4.3.2   |       | Negation Handling                               | 27 |
|     | 4.3     | 3.3   | Emoticons' Sentiment Scores Calculation         | 27 |
|     | 4.4     | Spa   | am Reviews Detection                            | 29 |
|     | 4.4     | 4.1   | Property Processing                             | 29 |
|     | 4.4     | 4.2   | Spam/Truthful Reviews Classification            | 32 |
|     | 4.5     | Po    | larity Classification                           | 37 |
|     | 4.6     | Su    | mmary   | 38 |
| Ch  | apter 5 | 5: Ev | valuation, Experimental Results and Discussions | 39 |
|     | 5.1     | Da    | taset   | 39 |
|     | 5.2     | Eva   | aluation Metrics                                | 40 |
|     | 5.3     | Exp   | perimental Results                              | 42 |
|     | 5.3     | 3.1   | Features Extraction                             | 42 |
|     | 5.3.2   |       | Negation Handling and Emoticons Detection       | 44 |
|     | 5.3     | 3.3   | Spam Reviews Detection                          | 48 |
|     | 5.3     | 3.4   | Enhanced Feature-based Sentiment Analysis       | 61 |
|     | 5.4     | Dis   | scussions                                       | 65 |
|     | 5.5     | Sui   | mmary   | 70 |
| Ch  | apter 6 | 6: Co | onclusion and Future Work                       | 71 |
|     | 6.1     | Co    | nclusion  | 71 |
|     | 6.2     | Fut   | ture Work                                       | 72 |
| Ref | ference | es    |   | 73 |
| Ara | abic Su | ımm   | ary   | 78 |

# **List of Figures**

| Figure 4.1: Graphical illustration for the proposed feature-based sentiment analysis approach  |
|--|
| Figure 4.2: Overview of the proposed approach  |
| <b>Figure 4.3:</b> Enhanced feature-based sentiment analysis algorithm   |
| Figure 4.4: Features' sentiment scores calculation algorithm   |
| <b>Figure 4.5:</b> Overview of the different types of properties used for spam reviews detection                                       |
| <b>Figure 4.6:</b> Spam reviews detection using rule-based classification algorithm 33   |
| <b>Figure 4.7:</b> Spam reviews detection using machine learning classification algorithm  |
| <b>Figure 4.8:</b> Polarity classification algorithm   |
| <b>Figure 5.1:</b> Confusion matrix40  |
| <b>Figure 5.2 (a):</b> Performance of FbSA with and without considering (negation handling + emoticons detection) on "DOSC" dataset    |
| <b>Figure 5.2 (b):</b> Performance of FbSA with and without considering (negation handling + emoticons detection) on "YelpNYC" dataset |
| <b>Figure 5.2 (c):</b> Performance of FbSA with and without considering (negation handling + emoticons detection) on "YelpZIP" dataset |
| <b>Figure 5.3:</b> The impact of using different set of properties on the performance of the rule-based spam reviews detection method  |
| <b>Figure 5.4 (a):</b> Accuracy of the machine learning classification spam reviews detection method on "DOSC" dataset                 |
| <b>Figure 5.4 (b):</b> Accuracy of the machine learning classification spam reviews detection method on "YelpNYC" dataset              |

| <b>Figure 5.4 (c):</b> Accuracy of the machine learning classification spam review detection method on "YelpZIP" dataset                        |
|---|
| Figure 5.5 (a): Performance of spam reviews detection methods on "DOSC dataset  |
| <b>Figure 5.5 (b):</b> Performance of spam reviews detection methods on "YelpNYC dataset  |
| <b>Figure 5.5 (c):</b> Performance of spam reviews detection methods on "YelpZIP dataset  |
| <b>Figure 5.6 (a):</b> Performance of FbSA (negation handling + emotions detection before and after spam reviews detection on "DOSC" dataset    |
| <b>Figure 5.6 (b):</b> Performance of FbSA (negation handling + emotions detection before and after spam reviews detection on "YelpNYC" dataset |
| <b>Figure 5.6 (c):</b> Performance of FbSA (negation handling + emotions detection before and after spam reviews detection on "YelpZIP" dataset |

# **List of Tables**

| Table 4.1: Example of opinion words and their sentiment scores    26   |
|--|
| <b>Table 4.2:</b> Different purposes of using emotions and their influence on enhancing the sentiment classification process       28              |
| <b>Table 5.1:</b> The performance of feature-based sentiment analysis (FbSA) on using different feature extraction methods                         |
| <b>Table 5.2:</b> The impact of considering negation handling and emotions detection on the performance of feature-based sentiment analysis (FbSA) |
| <b>Table 5.3:</b> The impact of using different set of properties on the performance of the rule-based spam reviews detection method               |
| <b>Table 5.4:</b> The performance of spam reviews detection on using different machine learning techniques and properties' set.       55           |
| <b>Table 5.5:</b> Features' sentiment scores before and after detecting spam reviews 57  |
| <b>Table 5.6:</b> Comparison between state-of-the-art spam reviews detection results and our proposed method       61                              |
| <b>Table 5.7:</b> The impact of spam reviews detection on the performance of FbSA while considering negation handling and emoticons detection      |

### List of Abbreviations

**CNN** Convolutional Neural Network

**DOSC** Deceptive Opinion Spam Corpus

**DT** Decision Tree

**Emotion** Emotion Icon

**FbSA** Feature-based Sentiment Analysis

**IDE** Integrated Development Environment

**KNN** K-Nearest Neighbors

LIWC Linguistic Inquiry and Word Count

**LR** Logistic Regression

**LSTM** Long Short-Term Memory

MLP Multi-Layer Perceptron

**NB** Naïve Bayes

**NLP** Natural Language Processing

NN Neural Networks

**NYC** New York City

**POS** Part of Speech

**RF** Random Forest

**SVM** Support Vector Machine

**ZIP** Zone Improvement Plan

## Chapter 1

### Introduction

Nowadays, there is a major increase in the number of people using the internet mainly social networking sites. Social networking sites provide a virtual community which allows people to interact with each other and share their thoughts, interests, experiences and opinions about different topics. This situation has led to the formation of a very huge amount of online reviews which can be exploited in various fields such as healthcare, politics, marketing, sociology, entertainment, etc. These online reviews have become a valuable source of information that people can refer to in order to judge the quality of a certain service or product while making decisions to use or purchase this service or product. Manually processing or analyzing these online reviews would be a very difficult task as it would be time consuming and may lead to inaccurate decisions too. This naturally led to the emergence of the field of study which is known as opinion mining and sentiment analysis [1].

Opinion mining and sentiment analysis are considered as subfields of natural language processing (NLP), information retrieval and text mining. Opinion mining is the process of extracting users' opinions and thoughts expressed on entities or features/aspects of entities from unstructured texts, while sentiment analysis is the process of analyzing the opinionated text and determining its polarity in an automated manner [2].

#### 1.1. Motivation

In these days, the need for automatically tackling and analyzing large volumes of individuals' online reviews is growing day after day. The analysis of these online reviews is performed in order to infer useful information that can be exploited to help both individuals and organizations in concluding real ideas and gaining experiences about certain services or products. Moreover, this information can be helpful in making a decision concerning buying a product or in enhancing the quality of services or products. Unfortunately, the process of automatically analyzing and detecting the sentiment in these online reviews faces several challenges such as (spam reviews detection, emoticons detection, negation handling, etc.) which all affect its overall performance and lead to low accuracy in the classification of the users' sentiments.

Furthermore, previous different studies either have applied sentiment analysis on different structural levels (Document level, Sentence level and Feature level) without considering any of the challenges mentioned above or have applied sentiment analysis with considering only one challenge of the above mentioned ones or detected spam reviews only without considering their influence on the performance of sentiment classification. So, these studies generally handled some of the above mentioned challenges but not all of them together which led to low accuracy in the classification of the users' sentiments. Therefore, there is a need to develop a sentiment analysis approach that considers these challenges.