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APPLICATION OF SENTIMENT ANALYSIS IN SOCIAL NETWORKS: A CASE OF ANALYZING ONLINE HOTEL REVIEWS

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ABSTRACT

In a world where competition is fierce, companies try to acquire a good reputation with their customers. Electronic reputation is a part of this reputation especially in the context of social networks, where everyone can freely express their opinion. Social networks are increasingly being used in the hotel industry. As hotels operate in a competitive and dynamic environment, it is essential that they make effective use of online customer review information to better understand their customers, improve their performance and compete with other hotels. The availability of vast amounts of user-generated data on social networks has led to a growing interest in using automated computational methods such as text mining and sentiment analysis to process large amounts of user-generated data and extract meaningful knowledge and insights.

The objective of this work is to explore the opinions of internet users on a set of hotels in Morocco. Our study will contribute to the literature on social network analysis by uncovering rich new findings and providing actionable insights with implications for hotel managers in Morocco. Studies show remarkable performance gains for companies that seize the opportunities offered by analytics Therefore, the purpose of this paper is to show companies how they can investigate and improve their E-reputation by integrating emerging technologies to analyze unstructured textual data available on social networks using a case study. Our study is divided into several parts: data acquisition allowing to conduct a study based on machine learning, preprocessing, where we filtered this data (eliminate unnecessary words, use tokenization ...) to keep the information needed for better accuracy, the application of Machine Learning algorithms (SVM, Naive Bayes, Decision Tree, Random Forest, and logistic regression) for a supervised classification where the results are binary (positive/negative) and finally the development of an application that allows the realtime E-reputation monitoring. The solution supports two languages: standard Arabic and French.

Keywords: *NLP, Machine learning, Sentiment analysis, Opinion detection, E-reputation*

1. INTRODUCTION

This In today's world, social networks are changing the way people express their views, opinions, and even feelings. Every day, millions of people from different countries, gender, and race share their experiences and opinions on the internet in comfort. Social media platforms generate a huge quantity of data in form of tweets, comments, statuses, reviews, etc. These data should allow us to discover precious information to improve the quality of life and improve the world in which we live. In this context, large companies like Google, Apple, Facebook, and Twitter are starting to explore this data carefully in order to find useful models to improve user needs [1]. Furthermore, people depend mainly on user-generated content online to a large measure for decision-making. For example, if a person wants to buy a product or use a service, he first consults his opinions online and discussions on social networks before making a decision. The amount of user-generated content is too vast to be analyzed by a normal user. It is, therefore, necessary to automate this by using different techniques of sentiment analysis.

The increasing use of social media and ecommerce websites is continually generating a massive amount of data concerning images/videos, sounds, texts, etc. Of this data, text is the most important type of unstructured data, requiring particular attention from researchers in order to obtain meaningful information. Among this data, text is the most important type of unstructured data, requiring special attention from researchers in order to obtain meaningful information. Numerous techniques have recently been proposed for obtaining information from such data. However, the processing of texts of considerable size still poses problems. As a result, accurately detecting the polarity of consumer reviews is an ongoing and exciting challenge [25].

E-reputation is a concept that has emerged as a result of the evolution of Web 2.0 and Internet users' interactions. According to Digimind: The Leading social media Listening and Analytics Solution, a specialist in business intelligence software, ereputation is "the perception that Internet users have of your company, your brand or the people who collaborate with you (managers, employees) and which is potentially visible on many media on the Internet"[23]. 66% of consumers ask for advice before buying a product and 96% of these consumers are influenced by the E-reputation of a brand when making a purchase. As soon as companies became aware of the importance of controlling their EReputation, the construction of a strategy to manage their E-Reputation became a key element of their communication. It is in this context of E-Reputation that our work is inscribed.

In this research, the goal is first to analyze the different opinions that appear in the form of Tweets containing the name of one of the hotels chosen for this study, use machine learning and data mining techniques to detect the strengths of all these hotels, and develop an application to monitor their Ereputation in real-time.

Our document is structured as follows: in section I, we first present the sentiment analysis, the ereputation via social networks, and we will finish by presenting the ML techniques applied to the NLP. In section II, we have reviewed several papers that we have considered in our work, our objective in this section is not to draw up an exhaustive list of the work done in sentiment analysis, but to highlight different trends in order to define the relevant theoretical and operational tools on which the development of our model is based. The third section shows the stages of construction of the analytical model. It presents also the results, the interpretations, the evaluation of the final model, as well as the spreads out the deployment part of the model and the development of the E-reputation application. Finally, we conclude the paper with a conclusion and perspective for our future work.

2. SENTIMENT ANALYSIS AND AREAS OF APPLICATION

2.1 Definition

In the literature, sentiment analysis (also called opinion mining, opinion extraction, sentiment mining, subjectivity analysis, effect analysis, emotion analysis, review mining, appraisal extraction) is a research field that is used to analyze the feelings, attitudes, and emotions of individuals towards entities such as products, services, and economic organizations. Since the early 2000s, sentiment analysis has been one of the busiest research areas in automatic natural language processing, machine learning, statistics and linguistics [14] (B. Liu.2012).

According to [15] (Pozzi et al. 2017), sentiment analysis is about building automatic tools that can extract subjective information from natural language texts, so as to create structured and actionable knowledge that can be used by a decision support system or by a decision-maker.

In the Larousse dictionaries, a feeling is defined as a thought or judgment encouraged by a sensation, while an opinion is defined as a point of view, a judgment, or an evaluation formed in the mind about a particular subject. The difference is quite subtle and each contains elements of the other. The sentence "I am concerned about the current health situation in Morocco" expresses a feeling, while the sentence "I think Morocco was able to handle the situation during the Covid19 period" expresses an opinion.

More formally, as defined in [16], an opinion is a quintuple:

$$(e_i, a_{ij}, s_{ijkl}, h_k, t_l) \quad (1.1)$$

Where:

- e_i: is the entity about which the opinion is given (also called object).
- a_{ij}: the aspect of the entity i which is the target of the opinion (in general, several aspects for the same entity).
- h_k: the opinion holder.
- t_l: the moment when this opinion is expressed. - s_{ijkl}: the feeling towards aspect j of entity i, expressed by person k at time l.

2.2 Categorization Of Sentiments Sentences are either objective or subjective. When a sentence is objective, no other basic task is required. When a sentence is subjective, its polarities (positive, negative, or neutral) must be estimated.

Subjectivity classification [17] (J.M. Wiebe et al. 1999) is the task that distinguishes sentences expressing objective (objective sentences) from sentences expressing subjective views and opinions (subjective sentences). An objective sentence is "This is a book", while an example of a subjective sentence is "This book is interesting". The task of distinguishing between sentences that express positive, negative or neutral polarities is known as polarity classification.

2.3 Types Of Sentiment Analysis

Models of sentiment analysis concentrate on polarity (positive, negative, neutral) as well as on feelings and emotions (anger, joy, sadness, etc.), urgency (urgent, non-urgent) and even intentions (interested vs. not interested).

These categories can be defined and adapted to meet the needs of sentiment analysis. In the following sections, we will discuss the most important types:

2.3.1 Fine-grained sentiment analysis Instead of talking about positive, negative, or neutral sentences, we consider the following categories:

- Very positive
- Positive
- Neutral
- Negative
- Very negative

Some systems also offer different classifications of polarity by identifying whether the positive or negative feeling is associated with a particular feeling, such as anger, sadness or worry (negative feelings), or happiness, love or enthusiasm (positive feelings).

2.3.2 Emotion detection

Emotion detection aims at detecting emotions such as happiness, frustration, anger, sadness, etc. Many emotion recognition systems rely on the use of sentiment lexicons (i.e., lists of emotions) or complex machine learning algorithms. **2.3.3 Aspect-based sentiment analysis (ABSA)** Rather than classifying the overall sentiment of a text as positive or negative, aspect-based sentiment analysis analyzes the text to identify different aspects and determine the corresponding sentiment for each. The results are more accurate, interesting, and detailed because aspect-based analysis examines specifically the information in a text.

3. E-REPUTATION VIA SOCIAL NETWORKS

Reputation is the opinion we have of a company or a brand. In the same way that companies ensure their staff and their assets, it is essential to ensure their image on the Internet because of the risks to which the company or brand is exposed through social media (social networks [18], blogs, web forums [19], website videos, etc.), especially for companies that are unaware of new technologies and do not take seriously the influence of the web and social networks on their representation [20].

With the popularization of the Internet, the advent of smartphones and tablets, and access to 3G, information is spreading exponentially and at high speed [21]. Since then, we talk about the digital reputation that the most "connected" companies consider the most important for their image. Thus, in an economic sector open to competition, the reputation of companies is weakened by the criticisms of Internet users capable of damaging their image. In order to face to compete and to maintain their image, more and more companies are investing in e-reputation through social networks, especially Facebook [20].

4. THE MAIN TASKS IN NLP

This list presents the different research done in the field of automatic language processing:

- Automatic summarization: Provides a comprehensible summary of a set of texts. It is used to provide summaries or detailed information of a text of a known type.
- Coreference resolution: relates the determination of words that refer to the same objects to a sentence or larger set of text, for example by matching pronouns to the nouns to which they are related.
- Discourse analysis: The task is to determine the discourse structure of a connected text, that is, the nature of the discourse relationships between sentences, e.g. elaboration, explanation, contrast. Another possible task is to recognize and classify speech acts in a large set of texts, e.g. yes/no questions, content questions, statements, affirmations, etc.

- Machine Translation: Automatically translates text from one human language to another.
- Morphological segmentation: Separate words into individual morphemes and determine the class of these morphemes. - Named Entity Recognition (NER): Describes a stream of text, determines which elements of the text refer to proper nouns, such as people or places, and what type of each of these nouns or places is being referred to.

4.1 Automatic Natural Language Processing Operations

The fundamental data type used to represent textual content in programming languages (e.g., C, C++, JAVA, Python, etc.) is called string. In this section, we will explore the various operations that can be performed on strings that will be useful for accomplishing various NLP tasks, such as:

- Tokenization (text segmentation).
- Normalization.
- Elimination of empty words (stopwords).
- Rooting (Stemming).
- Lemmatization.
- Morpho-syntactic tagging (part-of-speech tagging).

4.1.1 Tokenization

Tokenization can be defined as the process of segmenting text into smaller parts called tokens. It is considered a crucial step in TALN. Below is an example of tokenization which divides a sentence into individual words, removes punctuation and converts all letters to lower case:

EX: "A swimmer likes swimming thus he swims" Devein: "A" "swimmer" "likes" "swimming" "thus" "he" "swims".

4.1.2 Normalization

Normalization consists of eliminating punctuation, converting the entire text to lower or upper case, eliminating numbers or converting them to words, expanding abbreviations, removing repeated characters, etc.

EX: « I really lovvvvved that movie, The ACTORS were good. . .#GoodDay» becomes: « I really loved that movie the actors were good goodday» **4.1.3 Eliminating empty words** Empty words are words that need to be filtered out during the textual information retrieval task or other natural language tasks, because these words do not contribute much to the overall meaning of the sentence (e.g., words such as, and, or, the ...). There are many search engines that remove empty words to reduce the search space.

EX: "A swimmer likes swimming thus he swims" becomes: "swimmer" "likes" "swimming" "swims". **4.1.4 Rooting and lemmatization of text** Rooting describes the process of transforming a word into its root form. The original rootization algorithm was developed by Martin F. Porter in 1979 and is therefore known as Porter stemmer [22] (MartinFPorter,1980).

EX: "A swimmer likes swimming thus he swims"
Devein: "A" "swimmer" "like" "swim" "thu" "he" "swim"

Rooting can create non-real words, such as "thu" in the example above. Unlike rootization, lemmatization aims to obtain the canonical (grammatically correct) forms of words, called lemmas. Lemmatization is much more difficult and computationally expensive than rootization.

The same example shows: "A" "swimmer" "like" "swimming" "thus" "he" "swim".
4.1.5 Part-of-speech tagging Morpho-syntactic tagging (also called POS taggingpart-of-speech tagging) is one of the many tasks of NLP. It is defined as the process of associating words in a text with the corresponding grammatical information such as part of speech, gender, number, etc. using a computer tool.

EX: "it is a pleasant day to day
Become: ("it", 'PRP') ("is", 'VBZ')) ("a", 'DT') ("pleasant", 'JJ') ("day", 'NN') ("to-day", 'NN') Tq:
- PRP: personal pronoun.
- VBZ: verb, 3rd person singular in the present tense.
- DT: determiner.
- JJ: adjective.
- NN: noun in the present tense.

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5. MACHINE LEARNING APPLIED TO NLP

5.1 Machine Learning

Arthur Samuel defined the term machine learning as "The field of study that gives computers the ability to learn without being explicitly programmed."

Machine learning algorithms are able to successfully learn to perform important tasks by generalizing behaviors from examples. This is often feasible and cost-effective where traditional (procedural) programming is not. As more data becomes available, more challenging problems can be solved. Consequently, machine learning is largely used in computer science and other fields.

5.2 Types of Problems and Tasks

Machine learning tasks are generally classified into two broad categories.
These are:

- Supervised learning

The computer receives examples of desired inputs and outputs, and the objective is to derive a generalized rule that associates inputs with outputs. As example, given an email, we want to predict whether it is "spam" or not.
Supervised learning can in turn be:

- A Classification, when the labels are discrete.
- Regression, when the labels are continuous.

- Unsupervised learning

No label is provided to the learning algorithm. The algorithm has to find by itself a structural relation between input and output.

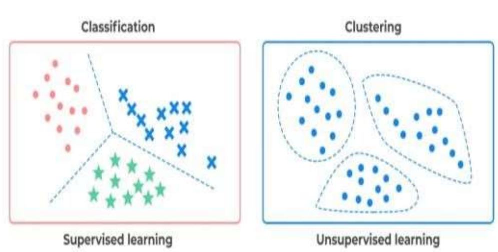

Figure 1: Supervised learning VS Unsupervised learning.

Machine Learning covers several domains:

- Classification: assigns a category (a label) to each object (text classification, speech recognition).
- Regression: previews a real value for each object (prices, stock market values, economic variables, ratings).
- Clustering: dividing (grouping) data into homogeneous groups.
- Ranking: sort objects according to certain criteria (relevant web pages returned by a search engine).
- Dimensionally reduction: find a way to reduce the dimension while preserving some properties of the data (computer vision).

The objective of this research is to explore the opinions of Internet users on a set of hotels in Morocco. It involves identifying, extracting and understanding the attitude or view of these users by analyzing the text. This process usually involves natural language processing, statistical analysis, and machine learning techniques for sentiment analysis.

In the following, we will present the approaches of sentiment analysis, then we expose a reading on related works, and the difficulties encountered during the realization of a sentiment analysis so that we can finally draw some overall conclusions.

6. LITERATURE REVIEW

Sentiment analysis has recently seen many developments and successes in both academic research and industry. This success is favored by the massive growth of data from the web and especially from social networks where users are asked to express their opinion on several objects.

In this context, several works have been carried out with different sub-objectives (corpus construction, opinion detection, feature comparison, ... etc.). We consider two categories namely, Sentiment classification of single polarity and Sentiment classification based on aspects.

6.1 Classification of Single Polarity Sentiments

In their paper (Soukaina MIHI et al. 2020), a new contribution to Arabic resources is presented in the form of a large Moroccan dataset extracted from Twitter and carefully annotated by native speakers. The collected data is provided from

Twitter of users geographically located in Morocco and written only in Arabic. They obtained about 35,000 tweets related to the domains of sports, arts, politics, education and others. The annotators were able to manually annotate over 12,000 tweets with four distinct classes: 6378 objective, 2769 negative, 866 positive, and 2188 sarcastic.

The results of their work are compared for each method by combining the feature extraction methods with the ML classification algorithms. Then, they also try to explain how stemming affects the classification. It is remarkable that for any classification algorithm and whatever the vectorization process, the stemming phase represents an essential and reliable way to improve both performance and accuracy [2].

In the same context, (El Abdouli et Al. 2017) address the problem of sentiment analysis on the Twitter platform. First, they try to classify Moroccan tweets according to the sentiment expressed in them: positive or negative. Second, they discover the topics related to each category, and finally, they locate these "tweets" on the Moroccan map according to their categories (pos, neg) to know the regions where the tweets come from. To this end, they employ a new practical approach that uses sentiment analysis on Moroccan tweets through a combination of tools and methods that are: (1) Apache Hadoop framework (2) Natural Language Processing (NLP) techniques (3) Supervised Machine Learning algorithm "Naive Bayes" (4) Topic modeling using LDA (5) and the interactive map plotting tool called "Folium" [3].

The main contributions in the article by (Elouardighi, A et Al. 2017) are:

- Proposing a set of techniques for preprocessing Facebook comments written in ASM (Arabic standard modern) and ADM (Moroccan Dialectal Arabic) and presenting the proposed process for sentiment analysis.
- Their results show that the best performance was obtained with the [Unigram/TF-IDF] and [Unigram + Bigram/TF-IDF] combinations regardless of the algorithm used [6].

Recently, efforts have been made to provide large-scale Arabic datasets devoted to sentiment analysis, such as LABR and more recently BRAD 1.0, which is regarded as the largest Arabic book review dataset (for sentiment analysis and ML applications). In their work, (Elnagar, A et Al 2018) present BRAD2.0, an extension of BRAD 1.0 with more than 200K additional records to accommodate several Arabic dialects. BRAD 2.0 has a total number of 692586 annotated comments; each represents a single review with a rating ranging from 1 to 5 for a given book. The most interesting property of BRAD2.0 is that it combines both MSA (modern standard Arabic) and DA (dialectal Arabic-Egyptian, Levantine, and Gulf-) [4].

To test and approve the suggested dataset, the authors implemented several supervised and unsupervised classifiers to categorize the book reviews. The SVM model produced the best results among the supervised classifiers. The final accuracies range from 83% to 91%. As for the unsupervised classifiers as a whole, the reported accuracies range from 89% to 91%.

Similarly, HARD is a large dataset of Arabic hotel reviews for sentiment analysis and machine learning applications [5].

To investigate the validity and effectiveness of HARD, (Elnagar, A.et Al 2017) implemented six widely known sentiment classifiers. The classifiers were tested for polarity and classification. Logistic regression and SVM classifiers produced the best results. Reported accuracies ranged from 94% to 97% for polarity classification.

The e-reputation was the subject of the article by (Salhi, Dhai Eddine and Al 2021). This article presents a study of the first mobile operator in Algeria "Djezzy" to detect its e-reputation by analyzing the tweets that mention the company on the social network Twitter.

According to their results, the logistic regression and the SVM give very similar values, with a small superiority for the SVM. For this reason, the authors chose SVM to continue their work. After analyzing the tweets and applying the SVM algorithm, the authors were able to find the ereputation of Djezzy compared to the two competitors in the Algerian market (Ooredoo and Mobilis). The overview of their system is presented as Dashboards [7].

Deep learning methods (DL) have been particularly successful for image and voice

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processing tasks. In recent times, these methods have begun to surpass traditional linear models for natural language processing. Different deep neural network algorithms such as convolutional neural network (CNN), recurrent neural network (RNN), recursive neural network (RecNN), long-term memory (LSTM), and memory network (MemNN) have been used to solve the sentiment analysis task.

In their study (Wu, D. C., Zhong, S., Qiu, R. T. R., & Wu, J. 2022) explore the sentiment information contained in customer comments and their potential for improving hotel demand forecasting. Using an empirical approach, four luxury hotels in Macau were selected and their customer reviews were extracted from two popular online platforms. The authors employed a deep learning method and Long Short-Term Memory model to retrieve sentiment information from costumer's reviews. Also, three sentiment indices, the bullish index, the average index and the variance index were constructed and tested to improve forecast accuracy. The results of this research highlight the importance of textual content for hospitality practitioners in terms of strategy formulation, revenue management and improving competitiveness [24].

However, the research work done in Arabic sentiment analysis using DL is still in its infancy compared to other languages like English. At the level of their paper (Alharbi, A and Al 2019), the focus is on the sentiments expressed in Arabic language due to the growing population of internet users who use Arabic language; it is estimated to be around 5% of the global users. In addition, in recent years, it is considered one of the most emerging languages on the Web. First, the authors highlight the notion of word embedding as most DL models require that the input data be in the form of numerical vectors that represent words and phrases.

The studies mentioned at the level of this paper [8] have considered three main levels of granularity in sentiment analysis: document level, sentence level, entity/aspect level.

Table 1: Sentiment analysis levels [8].

Document level	Sentence level	Entity/Aspect Level
At this level, the problem is whether the entire content of the document expresses a negative or positive opinion.	At this level, sentences are classified taking into account that not all sentences are opinion based. The authors have presented several works at this level, the reported accuracies are between 41% and 80%.	Aspect-level analysis is more refined than document- and sentence-level analysis. The task is to classify the sentiments expressed about a target aspect of an entity. For example, in the sentence "the screen resolution is very good but the size is very small" if the aspect we targeted is
		"screen resolution", the opinion expressed is positive. However, there is a negative opinion if the targeted aspect is "size". Therefore, this task consists of three phases: - Entity extraction. - Aspect extraction. - Aspect sentiment classification.

6.2 Aspect-Based Sentiment Classification

Aspect based sentiment analysis (ABSA), involves extracting aspects from the main entities of the text and identifying the sentiment that the text expresses for each aspect, it is a complicated subtask of sentiment analysis.

In their paper (Huwail J. Alantari, Imran S and Al. 2022) focused on the crucial relationship between a consumer's overall empirical evaluation and the text-based explanation of their evaluation.

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They investigate the tradeoff between predictive and diagnostic capabilities, applying different techniques to estimate this fundamental relationship. For generalization purposes, they analyzed 25,241 products in nine product categories and 260,489 opinions on five review platforms. The results shows that neural network-based machine learning methods, especially pre-trained versions, provide the most accurate predictions, while thematic models like Latent Dirichlet Allocation offer deeper diagnostics [26].

AL-Smadi and Al (2015) promotes the field of Arabic ABSA and provides a reference dataset on manually annotated Arabic (HAAD). HAAD consists of Arabic book notices that have been annotated by humans with aspect terms and their polarities [9].

HAAD has been prepared to cover the following tasks:

- T1: Aspect term extraction: given a sentence (notice), this task consists in extracting all possible aspect terms with respect to the domain of the notice (notice of books in this case), Aspects are extracted regardless of their polarity. For example, conflict and neutral aspect terms must also be extracted.
- T2: Polarity of aspect terms: based on the previous task (T1), this task focuses on assigning the extracted aspects to the polarity class (positive, negative, conflict and neutral). The conflict case occurs when the feelings positive and negative feelings are expressed by the same term or aspect category

(For example, (رواية جميلة و لكنها معقدة بعض الشيء) - T3: Aspect category identification: having predefined aspect categories and a collection of opinion sentences (without annotations), this task examines the ability to assign each opinion sentence to one or more aspect categories. The difference between this task and 1 is that the aspect terms are more fine-grained and should appear in the sentence. - T4: Aspect Category Polarity: having given the aspect categories of the sentences, this task examines the possibilities of assigning a specific polarity (positive, negative, conflicting, and neutral) to each aspect category.

Each opinion sentence in the HAAD dataset is annotated using the following XML tags:

- <aspectTerm term="" polarity="" from="" to=""/>: XML element for each occurrence of an aspect term. In addition to the polarity of the aspect term, its location in the text is provided based on the start and end character index of the text. - <aspectCategory category=" " polarity="/>: XML element for each occurrence of an aspect term category.

In this research AL-Smadi et Al (2018), ML-based approaches are presented to address the challenges of aspect-based sentiment analysis (ABSA) of Arab hotel reviews. Two approaches are implemented and trained: deep recurrent neural network (RNN) and support vector machine (SVM). The proposed approaches are evaluated using a dataset referenced in the paper regarding Arab hotel reviews annotated using an ABSA framework presented at the 2016 Semantic Evaluation Workshop (SemEval-ABSA16).

The dataset was designed to cover the following tasks: - T1: aspect category identification.
- T2: extraction of the aspect Opinion Target Expression (OTE).
- T3: aspect sentiment polarity identification.

Based on the evaluation results of this work [10], it was observed that the supervised machine learning approach using SVM outperforms the other approaches for all three search tasks. This can be explained due to the richness of the feature set extracted to train the SVM model and the ability of SVM to binary classification. In order to show the importance of deep recurrent neural network (RNN) approaches in ABSA, the performance of the two proposed approaches (SVM vs. RNN) were compared in terms of execution time, the deep RNN approach was much too fast for the three tasks.

6.3 Analysis and Discussion

As we have seen, most of the work in the area of Arabic sentiment analysis has focused on the use of supervised learning techniques. The authors of [11] believe that the opportunity space for growth in this area will be driven by the exploration of unsupervised learning techniques, primarily through the hybrid method.

For classifiers, SVM is used in almost all works. And we noticed that it leads to obtain the best results.

In their paper (Adel Assiri, et Al), the authors reviewed the important studies of Arabic sentiment analysis qualitatively and quantitatively. They presented detailed analyses of the methods

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used and the results obtained in the Arabic sentiment analysis studies, as well as a rich discourse on the direction of the current research, which has limitations [11].

Table 2: Qualitative/quantitative assessment of Arab sentiment analysis work [11].

Qualitative evaluation	Quantitative evaluation
- It is clear that supervised learning dominates the other techniques (semisupervised, unsupervised and hybrid techniques). - Dialects are not addressed in most of the surveyed Arabic SA (sentiment analysis) studies, which is a major drawback on the effectiveness of current Arabic SA because most Arabic language texts available in social media and other spaces represent a wide range of distinct, self-contained, morphologically complex Arabic language texts and dialects. - Many of the studies surveyed used the same limited set of classifiers -	The authors applied rigorous modeling of performance data (accuracy, precision, recall and f-score) and statistical procedures to investigate the effectiveness of the methods adopted by the different researchers in the Arab SA works studied. There is only a slight impact of the different methods used on the precision and recall of the results obtained while there was no significant impact on the precision and f-score. This finally leads us to the conclusion that Arab SA researchers should
raising questions about the reasonable value added to the field if each study essentially repeats the same experiment on a different data set. - There is a definite need for more inventiveness and creativity in the design of experiments as well as the development of new classification and analysis techniques beyond established algorithms.	use a more diversified set of techniques and approaches that contribute more to improve scoring on the whole range of performance parameters.

7. OUR APPROACH

Like any supervised machine learning work, our experimentation is mainly done in two steps, learning and testing as illustrated in the figure 2.

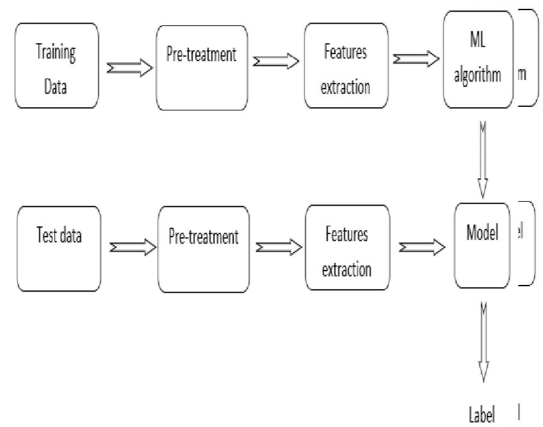

Figure 2: Supervised machine learning process.

7.1 Working Environment

We used the Python programming language which is a portable, dynamic, extensible and free programming language that allows a modular and object-oriented programming approach.

We used the Jupyter development environment, which is an IDE oriented towards a scientific use of Python. It allows to create and share documents containing live code, equations, visualizations and narrative text. To focus on our experiment and take advantage of the power of the Python language, we used the following packages: - Package pandas: a Python package that provides fast, flexible and expressive data structures designed to make working with structured (tabular, multidimensional, potentially heterogeneous) and time-series data both easy and intuitive. It aims to be the fundamental high-level building block for performing practical, real-world data analysis in Python.

- CSV Package: (comma separated value) CSV module for reading and writing data in CSV format. - Package numpy: (NUMeric Python) is a numerical library providing efficient support for large multidimensional arrays, and high-level mathematical routines (linear algebra, statistics, etc.).
- Package re: (Regular expressions) This module provides operations corresponding to regular expressions.
- Package seaborn: is a Python library for data visualization, specialized in statistical analysis. Based on the Matplotlib library, it is fully adapted to

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Pandas data frames. Thus, beyond a visually improved interface, Seaborn allows to produce quickly and intuitively high-quality statistical graphs.

- Matplotlib package: a complete library to create static, animated and interactive visualizations in Python.
- Nltk Package: (Natural Language Toolkit) is a platform for creating Python programs for working with natural language data.
- Package SpaCy: a very advanced Python library for automatic natural language processing. - Package Sklearn: is a Python module for machine learning.
- Package pickle allows to save in a file, in binary format, any Python object and restore it as is without any additional manipulation.
- Package Selenium: is a tool to automate browsers. It is mainly used for testing, but it is also very useful for web scraping.
- Tweepy Package: is an open-source Python package that provides a very convenient way to access the Twitter API with Python. Tweepy includes a set of classes and methods that represent the Twitter API templates and endpoints, and it seamlessly handles various implementation details. - PyMongo package: a python library containing tools for working with MongoDB. - langdetect package: a module for language detection.

The following figure provides an overview of this process. In the following paragraphs we describe the main tasks of each step.

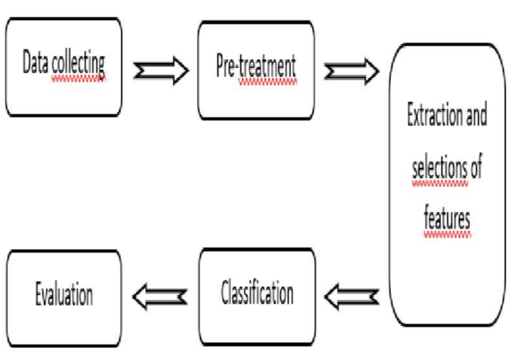

Figure 3: Sentiment analysis process

7.1.1 Data collection and annotation

Since we are looking for reviews of hotels in Morocco, and since the purpose of our research is to analyze Moroccan reviews on social networks, we thought of extracting our data from Twitter, using the Twitter search API where we can retrieve tweets from a user's news feed (i.e., the list of tweets posted by an account). However, it seems that the majority of hotels in Morocco do not have a Twitter account, and even for those that do, the number of reviews we can retrieve does not exceed a dozen, which is not enough to perform sentiment analysis using the machine learning approach. Therefore, we decided to move to the customer/hotel intermediary platforms, which allow customers to leave their review on a specified hotel through their REVIEWS interfaces. On the other hand, we noticed that the most used languages to express a review on hotels in Morocco are standard Arabic and French, so we decided that we will base our sentiment analysis on these two languages. **7.1.1.1 Data collection**

We used Web scraping with Selenium to retrieve the Arabic and French reviews from Booking and TripAdvisor. This allowed us to select 5000 reviews in Arabic and 5290 reviews in French.

The hotels we targeted are located geographically in Morocco in different cities (Marrakech, Casablanca, Fez, Tangier, Agadir, Al-Hoceima).

7.1.1.2 Data Annotation

To follow the supervised learning approach, we need to know the type of sentiment (polarity) of each opinion, which can be done from different tools. We chose the rule-based sentiment analysis tool and the Vader lexicon.

7.1.1.2.1 Vader

Vader (Valence Aware Dictionary and Sentiment Reasoner), more specifically Vader-multi which is a version that supports sentiment detection of texts in different languages (other than the English language which is supported in the original version "Vader Sentiment").

This version integrates the Google Translate API via the Python translate library (which is very slow). It requires an active Internet connection to work. The language of the text is automatically detected and therefore behaves exactly like the original version.

For the results obtained thanks to this tool, we noticed that there were reviews judged neutral by vader, but in reality (judgment of a human being), they express a positive/negative feeling, so we decided to review some reviews and annotate them manually.

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So, the annotation process is done by combining the Vader tool and manual annotation.

7.1.1.2.2 Datasets

The two datasets consist of the following attributes:

- Hotel_name: The name of the hotel.
- Hotel_location: The city where the hotel is located.
- Client_name: The name of the evaluator.
- Client_country: The evaluator's country.
- Date: The date of stay.
- Client_type: The category to which the client belongs (Individual traveler, family, couple, group). - Room_type: The type of the room. - Review: The reviewer's opinion written in Arabic or French.
- Rating: A number from 1 to 10 indicating the degree of satisfaction of the evaluator.
- Polarity: The sentiment of the review (positive/negative).

Dataset Arabic Language:

Table 3: Arabic Dataset Characteristics.

Property	Number
Number of hotels	68
Number of positive reviews	2713
Number of negative reviews	2287

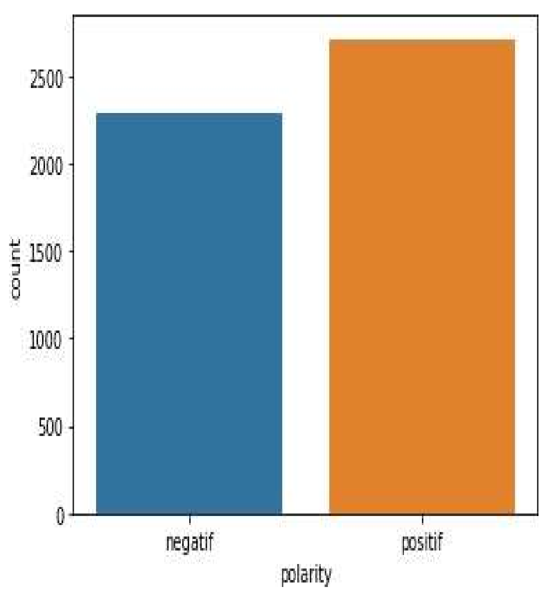

Figure 4: Label distribution (pos/neg) Arabic Dataset.

French Language Dataset:

Table 4: French Dataset Characteristics.

Property	Number
Number of hotels	68
Number of positive reviews	2995
Number of negative reviews	2295

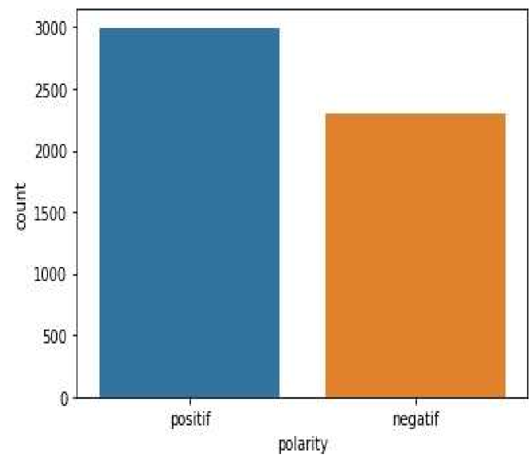

Figure 5: Label distribution (pos/neg) Dataset French.

7.1.2 Data preprocessing

In the following, we present the preprocessing procedure followed in our work. The objective of this step is to clean up the notice texts and bring them as close as possible to a formal language.

We performed cleaning by the following steps:

- Remove emoticons.
- Remove @ user IDs: using regular expressions.
- Delete the #keyword hashtags.
- Delete web links (URL).
- Delete punctuation and special characters, for each language (French/Arabic).
- Delete repeated characters.
- Delete numbers.
- Delete stopwords specific to each language: using the Nltk package.
- Rooting and Lemmatization of the text: using the Spacy package for the French language and Farasa for the Arabic language. **7.1.3 Extraction and selection of features** We have identified 5525 features for the notices written in Arabic and 5834 for those in French. These descriptors play an important role in the classification of sentiments. Studies such as [12] (Pangetal.2008) have shown that the quality of classification models depends on

the specificities of the data used. Therefore, we tested several combinations of extraction schemes to ensure the best quality of the developed models. We proposed the representation: TF-IDF with the N-gram model.

7.1.4 Classification

Many machine learning algorithms have been developed to solve different problems. Each algorithm has its own peculiarities and is based on certain assumptions. No classifier works best in all possible scenarios. In practice, it is always recommended to compare the performance of at least a few machine learning algorithms in order to select the best model for the given problem. These may differ by the number of descriptors or samples, the amount of noise in a dataset, and whether the classes are linearly separable or not [13] (S.Raschka 2015).

In this context, we applied the most widely used classifiers in the sentiment analysis literature. In particular, many classifiers have been applied on our dataset. Regarding the implementation, we used the Sklearn package implementation of the five classifiers.

7.2 Testing and Evaluation Phase

After the learning phase, we move to the testing phase to evaluate our classifier. For performance validation, we use the 80% to 20% rule to validate our model, such that 80% corresponds to the learning phase and 20% for the testing phase.

The combination of the extraction and weighting schemes allowed us to test different configurations. The tables summarize the results of the experiments conducted:

7.2.1 Testing and evaluation of the model for the Arabic language

Table 5: Accuracy for tested configurations (Arabic Model).

Classifier	Configuration TF-IDF	Without lemmatization	Descriptor number	With lemmatization	Descriptor number
SVM	Unigram	0.909	11739	0.919	5525
	Bigram	0.782	41623	0.848	32728
	Unigram + Bigram	0.917	53362	0.910	38253
Naive Bayes	Unigram	0.802	11739	0.763	5525
	Bigram	0.809	41623	0.889	32728
	Unigram + Bigram	0.873	53362	0.910	38253
Decision Tree	Unigram	0.889	11739	0.861	5525
	Bigram	0.729	41623	0.753	32728
	Unigram + Bigram	0.884	53362	0.858	38253
Random Forest	Unigram	0.911	11739	0.917	5525
	Bigram	0.739	41623	0.773	32728
	Unigram +Bigram	0.894	53362	0.909	38253
Logistic-Regression	Unigram	0.928	11739	*0.936*	5525
	Bigram	0.800	41623	0.867	32728
	Unigram + Bigram	0.927	53362	0.929	38253

For each configuration, we have presented the accuracy obtained on the basis of the test sample. In general, these results show that the best performances were obtained with the combination [Logistic Regression - Lemmatization - TF-IDF unigram].

The table below shows the performance parameters results of the classifiers for the TF-IDF unigram representation model with lemmatization:

Table 6: Classification results in Accuracy, Recall and F1-score (Arabic model).

Classifier	Accuracy (%)	Recall (%)	F1-score (%)
SVM	92%	92%	92%
Naive Bayes	81%	94%	81%
Decision Tree	87%	89%	87%
Random Forest	92%	93%	92%
Logistic Regression	94%	93%	94%

The results reported in the table above show that the best performances are obtained in precision (94%), recall (93%) and F1-score (94%) with the Logistic Regression + TF-IDF unigram configuration with lemmatization.

7.2.2 Testing and evaluation of the model for the French language

Table 7: Accuracy for tested configurations (French model).

Classifier	Configuration TF-IDF	Without lemmatization	Descriptor number	With lemmatization	Descriptor number
SVM	Unigram	0.870	7019	0.864	5834
	Bigram	0.759	34160	0.761	32762
	Unigram + Bigram	0.861	41179	0.855	38596

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Naive Bayes	Unigram	0.736	7019	0.714	5834
	Bigram	0.773	34160	0.770	32762
	Unigram + Bigram	0.818	41179	0.798	38596
Decision Tree	Unigram	0.779	7019	0.800	5834
	Bigram	0.694	34160	0.712	32762
	Unigram + Bigram	0.792	41179	0.794	38596
Random Forest	Unigram	0.866	7019	0.863	5834
	Bigram	0.705	34160	0.726	32762
	Unigram + Bigram	0.861	41179	0.862	38596
Logistic-Regression	Unigram	0.885	7019	0.887	5834
	Bigram	0.707	34160	0.802	32762
	Unigram + Bigram	0.880	41179	0.878	38596

For each configuration, we have presented the accuracy obtained on the basis of the test sample. In general, these results show that the best performances were obtained with the combination [Logistic Regression - Lemmatization - TF - IDF unigram].

The table below shows the results of the classifiers for the TF-IDF unigram representation model with lemmatization:

Table 8: Classification results in Accuracy, Recall and F1-score (French model).

Classifier	Accuracy (%)	Recall (%)	F1-score (%)
SVM	88%	90%	88%
Naive Bayes	78%	90%	78%
Decision Tree	83%	87%	83%
Random Forest	88%	91%	88%
Logistic Regression	90%	88%	90%

The results reported in the above table show that the best performances are obtained in precision (90%), recall (88%) and F1-score (90%) with the Logistic Regression + TF-IDF unigram configuration with lemmatization.

The results obtained can be interpreted by the positive influence of the semantic aspect on the quality of the classifier, thus lemmatization represented a reliable way to improve the performance of the classifier. We believe that the involvement of other linguistic aspects, type of words (subject, verb, adjectives. . .) can improve the sentiment analysis process.

7.3 Integrating a Machine Learning Model in a Web Application

In this section, we will show how to incorporate a machine learning model into a web application for tracking satisfaction on real-time hotels.

7.3.1 Recording the current state of the machine learning model

Training a machine learning model can be quite expensive. Of course, we don't want to train our model every time we close our Python interpreter and want to make a new prediction or reload our web application. One option for model persistence is Python's built-in Pickle package. This allows us to serialize and deserialize Python objects to compact the bytecode, so that we can save our classifier in its current state and reload it if we want to classify new samples without needing to train the model from the training data again.

7.3.2 Using MongoDB databases for data storage

We created a MongoDB database called App_Ereputation to store the results of each prediction. We then created a new database document: Reviews. We used it to store and access the entries in the database.

7.3.3 Developing the Web Application with Flask

For the development of our web application with REST API, we used the Flask micro-framework on the server side (backend).

Flask is a web micro-framework written in Python. It is classified as a micro-framework because it does not require any special tools or libraries. It has no database abstraction layer, no form validation, and no other components for which third-party libraries provide common functions. However, Flask supports extensions that can add application functionality as if they were implemented in Flask itself.

7.3.4 Retrieving new tweets using the Twitter Search API (APIREST)

The tweets on which we have applied our models are tweets retrieved through the Twitter Search API and containing the name of one of the hotels in our database.

The Twitter Search API is the public API format offered by Twitter that allows to perform automatic queries within the tweets in a similar way to the query that can be done manually on the web or mobile version of Twitter.

The Twitter Search API can be used to perform social network monitoring as we have done. **7.3.5 An overview of the application** Here is an overview of the global architecture of our application.

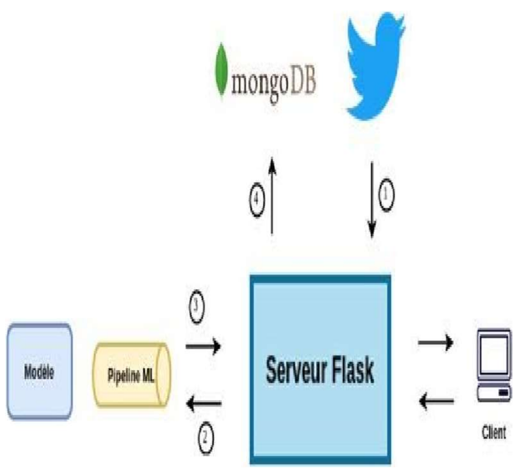

Figure 6: The global architecture of our application.

The different elements of the application are:

- The model: This is the model that we have trained. In fact, it is the state of the model. Which is nothing else than a .pkl file, which is in fact a dictionary containing all the parameters of the trained model.
- The ML pipeline: This is a set of functions that allow to do processing on the raw data in order to predict with the model. The pipeline will be used as an interface between the raw data and the input format of the model.
- The web server: Flask server which exposes the application and thus gives the possibility to the client to make requests.

The flow of use of our application is quite simple: - Step 1: Once the client calls the backend, the backend calls the Twitter search API to collect new tweets containing the name of one of the existing hotels in our database. - Step 2 - Prediction: The server detects the language of the tweet and calls the predict function of the pipeline providing the text of the tweet as a parameter. The pipeline will encode this text and pass it to the corresponding model input (Arabic/French).

- Step 3 - Sending the prediction to the server:
  The pipeline decodes the vectors returned by the model. The intelligible result is then sent to the server.
- Step 4 - Sending the result:
  The server saves the result ("positive" or "negative") in the database (we store the analysis results plus the text of the tweets with its date).

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Home page:

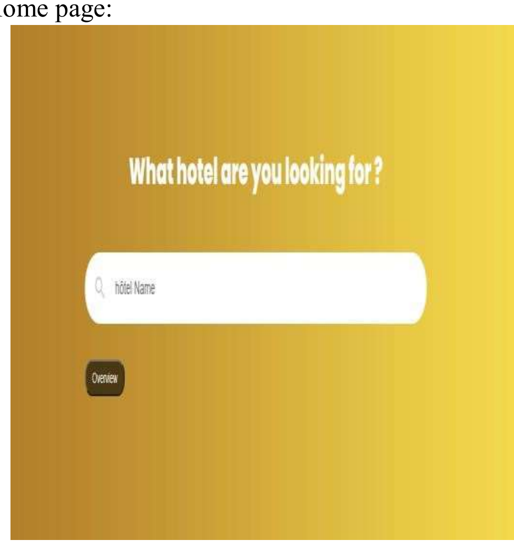

Figure 7: Home page.

Overview:

Dashboards containing information about all hotels.

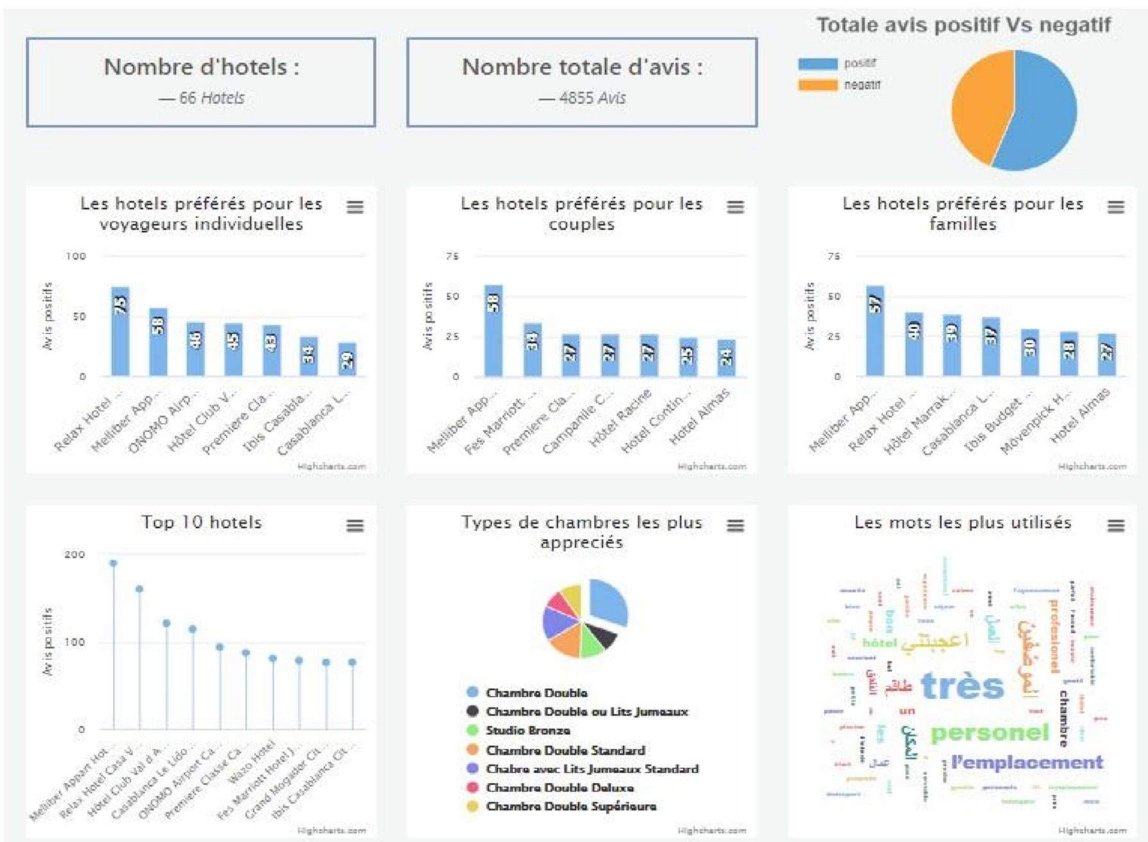

Figure 8: Overview.

Page corresponding to the searched hotel: contains reviews on this hotel, with percentage of positive and Dashboards allowing to have: The total number of negative reviews and other information.

Figure 9: Page Corresponding To The Searched Hotel.

8. DISCUSSION AND IMPLICATIONS

Recent years have witnessed an explosion in social media data. Many internet users share their experiences and opinions about products or services they have experienced on social media such as online forums. Companies now need to adapt new methods and analysis tools to develop better business intelligence and insights. This article presents a workable approach and a case study to show businesses how to analyze online customer reviews to uncover deeper insights and gain a more in-depth understanding of customer opinions on social media. Analyzing online guest reviews could provide valuable information to hotel managers and help them identify the strengths and weaknesses of their establishments. For example, hotel managers can use our approach to monitor categories with low sentiment scores and take action to respond immediately to negative reviews to reduce the potential impact. Alternatively, they can explore the attributes of the hotel that guests have mentioned in their reviews, in addition to their accommodation experience. Hotel managers can also compare evaluation results over time to see if their actions are having a real impact on guest satisfaction and experience. Word co-occurrence analysis can help hotel managers identify key concerns or mentions so that they know what aspect of their hotel needs more attention.

Berezina et al (2016) [27], from a managerial perspective, suggest looking at and monitoring the categories that have emerged from online customer reviews to not only understand the voice of each individual customer, but also to see a broader picture that all these voices would collectively form. At the final stage of text mining, an evaluation of the results is required to see if any insights have been uncovered and to determine their importance using visualization techniques and representation tools such as graphs and association rules.

Figure 7 is the home page. This interface allows users of our platform to search for any hotel in Morocco by name. This search will take them to the next interface, figure 9, where they can find a detailed analysis of the chosen hotel. Below the search bar in figure 7 is a small button (Overview) which takes us to figure 8. This presents a global view, in real time, of the customer experience at hotels in Morocco. This interface can be divided into 3 important parts:

- Distribution of pos/neg sentiments across hotels in Morocco.
- Suggestion of the most preferred hotels in Morocco
- Classification by category (rooms, hotels, services, costs, etc.) of the most frequently used articles and words describing customer satisfaction with hotels in Morocco.

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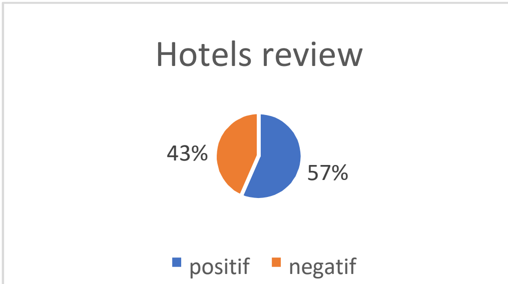

Figure 10: Distribution Of Pos/Neg Sentiments

We analyzed about 66 hotels with more than 4855 reviews. The result of our data set shows that about 57% comments are positive and 43% comments are negative, as shown in Figure 10. This gives us a basic idea of the hotel industry.

Figure 11: Classification By Category (Rooms, Hotels, Services, Costs, Etc.) For Extremely Satisfied Customers

The word clouds generated for extremely satisfied and extremely dissatisfied customers are shown in Figure 11. The word clouds reveal some common categories that are frequently mentioned in both positive and negative reviews, including food, location, rooms, service and staff (see Table 9).

Table 9: The Most Frequently Mentioned Categories In Reviews

	Categories
Extremely Satisfied Customers	food, location, rooms, service, staff,
Extremely Dissatisfied Customers	Rooms, food, check-in, service, staff

As certain categories, such as location, may be considered uncontrollable by hotel managers, they may choose to focus their efforts on controllable categories in order to have a concrete impact. For example, they can train staff to be friendly or helpful, improve the quality and variety of the food offered by the hotel, improve the check-in service, and so on. The graphs we generated from this case study, such as sentiment by rating and category correlation network, show not only the ability of social network analytics to produce business insights, but also its potential to understand how different hotel properties are related and perceived in the minds of consumers (Krawczyk & Xiang, 2016) [28]. The results confirm the findings of Kim, Lim and Brymer (2015) [29] that overall ratings are the strongest predictor of hotel performance.

This case study also provides empirical findings to help hotel managers understand the thoughts or opinions of extremely satisfied and extremely dissatisfied hotel guests. We noticed that satisfied and dissatisfied guests share a common interest in the following categories: food, location, rooms, service and staff. This finding has clear managerial implications for managers to consider these five categories and suggest that the categories that make customers happy can also make them unhappy if they are not provided or if there are problems with these categories (Berezina et al., 2016) [27]. Efforts should be made to improve customers' positive perception of these five categories. Hotels that score well in any of these five categories are recommended to highlight them as a competitive advantage in their marketing and advertising activities.

9. CONCLUSIONS AND PERSPECTIVES

More and more people are publicly expressing their private thoughts and feelings on social networking platforms such as online forums and Twitter on a scale never seen before. It is vital that companies have a workable framework or approaches that help them not only to make sense of the vast amount of accumulated text, but also to do so effectively.

The aim of this study was to explore the usefulness of online reviews in understanding how hotels in Morrocco are perceived by consumers. This paper seeks to show companies how social network analysis can identify insights from online reviews through a case study. The main contribution of this study is the presentation of a tested approach using natural language pre-processing, text mining, sentiment analysis and machine learning techniques to analyze online textual content. The results generated are particularly helpful for the rapid monitoring, diagnosis and evaluation of services. For example, hotel managers can use the results to develop customer strategies and evaluate staff performance, including identifying the strengths and weaknesses of current services. The value of the recommended approach was illustrated by a case study of hotel online reviews.

In the case study, we first sought to determine a reliable classifier for the classification of reviews about a hotel. We focused on the task of binary classification (positive/negative), for this reason we used a dataset consisting of reviews on hotels, collected from Booking and TripAdvisor, on the other hand, we noticed that the languages most used to express a review on hotels in Morocco; are the standard Arabic language and the French language, so we decided that we will base our sentiment analysis on these two languages. After preparing the data, we implemented machine learning methods frequently used in classification with a TF-IDF text representation. The measures we used to evaluate our methods are accuracy, precision, recall, and F1score. Our experiments showed that the Logistic Regression machine learning model was able to produce higher precision, F1-score and accuracy than the other models used, and lemmatization also increased the accuracy of all the models tested. After training our machine learning model, we deployed it in our application which is used to classify the tweets bearing the name of one of the hotels chosen for this study, and consequently track their E-reputation in real time.

In summary, the results demonstrate the value of using natural language pre-processing, text mining and sentiment analysis to categorize textual content, discover new insights and derive information from large amounts of textual data. Companies can follow our approach to guide their efforts in tracking, collecting and analysing various user-generated textual content on the Internet and improve hotel guest experiences and reputation management

This work could be improved and extended to include reviews from Facebook and / or Instagram or other social networks. We will also be able to compare the responses of hotel management in Morocco and other European countries to online reviews and identify their respective styles of online reputation management. Technically, it is also planned to improve the proposed approach by evaluating other deep learning algorithms such as Long Short-Term Memory Networks (LSTM) and using different text representations.

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