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Sentiment Analysis of Arabic Tweets: Detecting Revilement

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Abstract: Social media systems play an necessary function in shaping public opinion and reflecting societal sentiments. This study focuses on sentiment analysis in Arabic tweets with a particular focus on offensive or offensive content. The aim of this research is to boost a dependable sentiment evaluationmodel that can accurately classify Arabic tweets as positive or negative, with a particular focus on identifying offensive language.

A multinomial Naive Bayes classifier is trained on pre-processed data to perform sentiment classification. The classifier is fine-tuned to differentiate between positive and negative emotions, with a particular focus on identifying offensive or swearing language. The model is evaluated the usage of a complete set of metrics along with precision, precision, recall, and F1 score.Experimental consequences point out promising overall performance of the developed sentiment evaluation model.The model achieved an accuracy of 93%, effectively classifying Arabic tweets into effective and bad sentiments. The precision, recall, and F1-score metrics similarly validate the model's capacity to precisely become aware of revilement and offensive language.These outcomes spotlight the conceivable of the proposed strategy in successfully examining Arabic tweets for sentiment and offensive content, contributing to higher grasp on line behaviors and sentiments in the context of revilement.

Introduction

Social media systems have end up a phase of communication, enabling individuals to express their thoughts and opinions. Among the diverse content shared on these platforms, the sentiment of users' messages, especially in the context of offensive or cursing language, is of great importance. Sentiment analysis, a department of natural language processing, performs a vital position in understanding and classifying the emotional tone of textdata.

The process begins with a comprehensive data preprocessing pipeline, where the raw text data undergoes cleaning steps. These steps include removing stop words, emojis, punctuation, and diacritics to make certain that the textual content information is in an suitable structure for analysis.Then, the pre-processed textual data is converted into digital features using the Term-

Frequency Inverse Document Frequency (TF-IDF) vectorization technique. This transformation facilitates the extraction of meaningful patterns and features from text, forming the basis for sentiment classification.

To achieve sentiment classification, a multinomial Naive Bayes classifier was used. This machine learning algorithm has been trained to distinguish between positive and negative sentiment in Arabic tweets. Particular emphasis should be placed on identifying cursing language. The model used to be evaluated the use of a complete set of metrics, inclusiveof precision, precision, recall, and F1 score, to accurately evaluate its performance in detecting offensive content.

The experimental results of the study are good, and this indicates the effectiveness of thedeveloped sentiment evaluation model. The model executed an accuracy of up to 93%, which demonstrates its ability to accurately classify Arabic tweets into positive or negative. Precision, recall, and F1-score metrics validate the model's efficiency in detecting instances of swearing, highlighting its usefulness in monitoring and remediating offensive language in social media networking.

This research makes a contributes to sentiment analysis by addressing the specific challenge of identifying offensive or cursing language in Arabic tweets. The developed model provides a valuable tool to better understand and manage emotion dynamics in online interactions, with potential applications in promoting positive online behavior and strengthening digital communities.

Related Work

Sentiment analysis, commonly known as opinion mining, is an area of natural language processing that has acquired sizable interest in latest years due to the growing occurrence of user-generated content material on social media platforms. Researchers have focused on analyzing emotions in different languages and contexts, seeking to understand and classify emotionsexpressed in textual data. In the context of analyzing Arab sentiment, there is a growing interest in analyzing the sentiment conveyed by Arabic tweets, especially those containing insults.

Most of the work associated to sentiment analysis can be grouped into three categories: machine learning, semantic instruction and deep learning. [1]. There are few research that center of attention on detecting offensive Arabic tweets to pick out obscene Twitter accounts. [2] A study by Abdeen, Mohammad AR, et al. [3] The study presented a comprehensive review on the classification of Arabic text. The authors included in their reviewmore than 50 studies, which spanned from 2000 to 2019. The primary focus of this study is to map several issues such as techniques used, effective techniques, new techniques, most commonly used datasets, techniques adopted for feature selection, and the impact of TEM methods. On the classification results. Most of the work on classifying the Arabic language took area in the previous decade (2000-2010), with the exception of a few cases.

They utilized prevailing classification strategies such as SVM, NB, k-NN, Decision Trees, and ANN. Few instances have proposed blended classifiers such as most entropy, master-slave, and BSO-SVM. The datasets used in the introduced work are by and large constructed in-house from Arabic information websites. A few research have used

are no well-known Arab bodies used by most researchers. Abdel Latif Ghallab and others. [4] Proposing a systematic evaluation of the accessible literature intently associated to Arabic sentiment analysis. The major targets of this assessment are to grant the required research effort,

raise additional areas for further research on Arabic sentiment analysis, and reduce difficulties related to the scope of studies. The review results indicate a taxonomy of classification approaches. In addition, the limitations of existing pre-processing methods, feature analysis, and sentiment classification technology are examined. The extracted opinions can be classified as goal or subjective text. In 2016 Berger and Morgan [5].

The intention used to be to create a demographic picture of Twitter supporters of ISIS (Islamic State of Iraq and Syria) and set up a methodology for figuring out pro-ISIS accounts. It started out with a dataset of 454 core accounts, which had
been constantly increased via filtering primarily based on account availability and figuring out bots, amongst different criteria. They received a ultimate listing of 20,000 pro-ISIS accounts for analysis, estimating that at least 46,000 pro-ISIS accounts had been active.

They created subsets of manually categorized accounts, consisting of 6,000 accounts labeled as both pro-ISIS or non-pro-ISIS. The authors concluded that pro-ISIS sympathizers ought to be recognized via descriptions in their profiles, such as the use of phrases like "caliphate," "steadfastness," "Islamic State," "Islamic Caliphate," or references to Iraq. When checking out this classifier with 1,574 manually annotated accounts, they executed a classification accuracy of up to 94%. However, profile data used to be solely reachable for round 70% of the accounts. In 2015 Agarwal [6] The goal is to look into strategies for mechanically figuring out tweets that promote hatred and extremism. Starting with a Twitter information crawling process, they used a semi-supervised mastering strategy based totally on a listing of classification tags (#Terrorism, #Islamophobia, #Extremist) to filter out hate and extremism-related tweets. The coaching dataset consisted of 10,486 tweets. They used random samples to create a validation dataset (one million tweets). The tweets have been in English and manually annotated through 4 students.

They created two specific classifiers (KNN and SVM) and validated their accuracy based on the created datasets for classifying tweets as promoting hatred or being unknown. The resultsshowed a relationship between these tweets and features such as war references, religious sentiments, negativity, and offensive terms.They created two specific classifiers (KNN and SVM) They trained SVM and KNN classifiers on 10,486 positively labeled tweetsand determined F-scores of 0.83 and 0.60, respectively. They applied a leave-one- out approach and examined the effect of every one-of-a-kind characteristic on the typical accuracy of the classifiers. Based on the accuracy results, they concluded that non secular and war-related phrases had been offensive words. Negative sentiments havebeen sturdy warning signs that a tweet promotes hatred. Unlike the KNN classifier, the presence of colloquial language and net query marks performed a sizeable position in the LibSVM classifier.Cheong and Lee [7] Exploiting sentiment analysis of Twitter data to provide visual representations of potential terrorism scenarios. Atika and Ram [8] addressed the challenges dealing with classification strategies in sentiment analysis. In this section, themost frequent troubles such as spam, polarity phase, evaluation quality, sarcasm and area dependency are discussed.In [9], Araque et. al. affords groundbreaking advances in deep getting to know for SA through proposing sentiment models that mix numerous sentiment

classifiers to produce a aggregate of classifiers and a aggregate of floor and depth features. Refaei et al.[10] Creating and publishing a set of annotated Arabic tweets for sentiment analysis, reachable in the LREC shared useful resource repository. It consists of 6,894 tweets: 833 positive, 1,848 negative, 3,685 neutral, and 528 mixed. It is interpreted through morphological features, easy syntactic features, stylistic features, and semantic features. One of the oldest datasets in sentiment evaluation for Arabic tweets used to be the Arabic Sentiment

Tweets Dataset (ASTD)[11]. which is an Arabic tweet corpus written in the Egyptian Dialect. It consists of about 10,000 tweets that are labeled as objective, positive, negative, and mixed. It gives baseline fashions in order to grant benchmarks for future work[12].

Asifetal. [13] The proposed strategy for classifying extremism entails 4 categories: excessive extremism, low extremism, moderate, and neutral, based on the stage of extremism. They created a lexicon the use of density weights to validate it with area experts, ensuing in an accuracy of up to 88% for validation. Later on, MNB (Multinomial Naive Bayes) and SVM (Support Vector Machine) algorithms had been used for classification purposes. Overall, in the multi-language base dataset, SVM outperformed with an accuracy of 82%. Aldarwish et al. [14] The first dataset was once gathered from three social networking websites (Facebook, Live Journal, Twitter). It consisted of 2,073 depressed posts and 2,073 non-depressed posts, manually labeled to classify the posts into one of the 9 detailed signs and symptoms of despair in accordance to the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) by using the American Psychiatric Association. The 2nd dataset contained all the social networking web page posts of the patients. They proposed a machine the use of Rapid Miner to check SVM and NB models. When the use of the supervised NB model, the effects confirmed an accuracy of 100%, a recall of 57%, and a precision of 63%.

De Choudhury et al. [15] They accumulated authenticated tweets from the timeline of476 users who replied to the CES-D questionnaire. They discovered that individuals with depression have interaction in fewer activities, express extra terrible emotions, and have greater scientific and relationship issues shared on line in contrast to these besides the condition. Using SVM, the authors constructed a model that finished its fine overall performance with an RBF kernel, attaining an accuracy of 70%.

Farra et al [16] A set of dictionaries storing positive, negative, and impartial phrase roots used to be used. To decide the sentiment or class of a sentence, a stemming technique used to be utilized to convert phrases to their roots. If the ensuing root is determined in the positive/negative/neutral root dictionary, the sentence is regarded positive/negative/neutral,

respectively. If the phrase is now not located in the dictionary, the consumer is triggered to specify its polarity, and then its root is introduced to the corresponding dictionary. Hamouda and F. E.-z. El-taher [17] The authors accumulated 2,400 remarks from 220 Egyptian Facebook poststo construct their dataset. The dataset used to be manually annotated as offensive, supportive, or impartial primarily based on the textual content content. The comments havebeen preprocessed by using undesirable data such as punctuation marks and stop words. Long feedback exceeding one hundred fifty phrases have been additionally excluded. To extract features, the center of attention was once on the similarity between posts and directed comments. Three classifiers had been used for sentiment classification: SVM, NB, and DT. The SVM classifier executed the satisfactory outcomes in terms of the extracted features. However, this paper solely highlights the MSA model.

Description of the Methodology

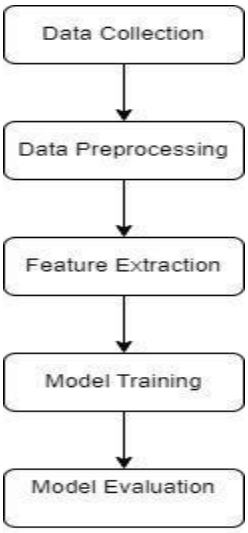
This section will talk about the: Dataset collection, dataset-preprocessing, facets extraction and producing the models.

Dataset Collection

The dataset for this sentiment analysis mission used to be acquired via a inclusive

data series system using the Gephi platform in conjunction with the Twitter API. The main goal was once to acquire a various and representative series of Arabic tweets encompassing each terrible and nice sentiments. A complete of 40,000 tweets had been collected, evenly dispensed into two categories: 20,000 terrible and 20,000 effective tweets.

The data collection process involved several key steps. First, using Gephi's data scraping capabilities, a wide range of Arabic tweets were harvested from the Twitter platform. To make certain diversity, tweets have been accumulated from a number of time periods, regions, and



user profiles.Additionally, specific keywords and hashtags associated with revilement were utilized to target tweets that contained offensive or emotionally charged content.

To achieve a balanced dataset, the collected tweets were meticulously labeled as either negative or positive sentiments. A team of human annotators reviewed and categorized each tweet based on the emotional tone and language used. This labeling process used to be indispensable to make certain the accuracy of the sentiment analysis model and allow sturdy training and evaluation.

Sentiment	Tweets
Positive	20000
Negative	20000

Table 1: Number of tweets for each class

Data Preprocessing

The collected dataset comprises 40,000 Arabic tweets obtained from Twitter through the Gephi platform. The dataset is evenly partitioned, with 20,000 tweets labeled as negative sentiment and an equivalent number labeled as positive sentiment.

Concatenation

The negative and positive sentiment tweets are concatenated to form the training dataset (X_train) for the sentiment analysis model.

Text Preprocessing

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The raw text undergoes a series of preprocessing steps to cleanse and prepare it for analysis:

Removing Stop Words

Arabic stop words, which include common linguistic terms such as prepositions and articles, are eliminated from the text using the stopwords corpus from the Natural Language Toolkit (NLTK) [18].

Removing Emojis

Emojis and emoticons are eliminated from the text using regular expressions to exclude non-textual symbols that do not contribute to sentiment analysis[19].

Removing Punctuation

Punctuation marks and special characters are removed from the text using regular expressions to enhance text cleanliness[20].

Sentiment Labeling

Sentiment labels are converted to numerical values, with positive sentiment assigned a label of 1 and negative sentiment assigned a label of 0.

Tokenization

The preprocessed text is tokenized into individual words using the word_tokenize function fromthe NLTK library [21].

Features Extraction

We aimed to discover the excellent strategies to attain our goal, which was once to detect depression within Arabic tweets the use of computer learning. We achieved this via discovering the high-quality model aspects that gave the very best overall performance accuracy. Different N-gram degrees and TF-IDF strategies have been used to extract therequired features. Six supervised computers gaining knowledge of models have been used to train the dataset, including: SVM, RF, LR, KNN, AdaBoost, and NB. As a result, we determined the function aggregate that gave greatest accuracy.

Term Frequency–Inverse Document Frequency (TF-IDF)

Term frequency-inverse file frequency (TF-IDF) is frequently used for textual content classification. Term-frequency is the range of instances a phrase seems inside a report (Eq.(1)). Inverse document frequency is a weight time period scheme that offers tokens that show up greater often in archives a lower impact, or weight, and offers tokens that appear muchless often a greater weight [19] (Eq. (2)).

$$TF - IDF(t, d) = TF(t, d) * IDF(t) \quad (1)$$

the place "TF(t, d)" is the variety of instances the phrase "t" seems in the record "d" and,

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$$IDF(t) = \log\left(\frac{n}{DF(t)}\right) + 1 \quad (2)$$

the place "n" is the whole variety of documents, and "DF(t)" is the wide variety of archives that comprise the phrase "t".

Generating the Model

Naive Bayes Classifier for Sentiment Analysis

The Naive Bayes (NB) classifier is a probabilistic model that operates on the foundational principles of the Bayes theorem. It is extensively employed in more than a few herbal language processing tasks, inclusive of sentiment analysis. The core assumption of the NB classifier is the "naive" assumption of function independence, which means that all aspects (or attributes) are viewed to be impartial of every different given the category label [21].
The model objectives to calculate the posterior chance of a class given a set of predictor features, which can be expressed the usage of Bayes theorem as follows:

$$P(C\backslash X) = \frac{P(C\backslash X)P(C)}{P(X)} \quad (3)$$

Where:

$P(C|X)$ is the posterior probability of the class given the predictor features.

$P(X)$ is the prior probability of the predictor features.

$P(C)$ is the prior probability of the class.

$P(X|C)$ is the likelihood of the predictor features given the class.

In the context of sentiment analysis, the NB classifier employs this framework to estimate the likelihood of a particular sentiment class (e.g., positive or negative) given the features extracted from the text. By leveraging the calculated probabilities, the NB classifier assigns a sentiment label to the input text.

The simplicity of the NB classifier, coupled with its ability to handle high-dimensional data, makes it a popular choice for text classification tasks. It effectively captures and models the relationships between features and class labels, making it particularly well-suited for sentiment analysis.

4 Performance Measurement

The evaluation of classifiers was once measured with accuracy, precision, recall, and the use of an F1- score. We calculated the overall performance measurement for the classifiers with the following equations, the place "TP"represents a true positive,"TN"represents a authentic negative, "FP"represents a false positive, and "FN" represents a false negative:

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (4)$$

Precision was once measured through calculating the false positives of the classifier.

$$Precision = \frac{TP}{(TP+FP)} \quad (5)$$

Recall used to be measured by means of calculating the false negatives of the classifier.

$$Recall = \frac{TP}{(TP+FN)} \quad (6)$$

The F1-score used to be calculated through taking the weighted harmonic common of the recalland precision measurements.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \quad (7)$$

5 Experimental Results

5.1 Model Performance:

The sentiment analysis model based on the Naive Bayes classifier demonstrated remarkable performance on the collected dataset. With an accuracy of 93%, the model exhibited high precision and recall charges for each advantageous and negative sentiment classes. The precision-recall trade-off was once efficaciously managed, ensuing in an overall F1-score of 0.93. These consequences underscore the robustness of the developed model in precisely classifying sentiments in Arabic tweets.

5.2 Average Tweet Length:

An interesting observation emerged from the analysis of the average tweet length. The average tweet length was calculated to be 89.12 characters, highlighting the concise nature of Arabic tweets. This insight underscores the importance of efficient feature extraction techniques, such as TF-IDF, which enable the model to capture sentiment nuances despite the brevity of individual tweets.

5.3 Word Frequency Analysis:

An good sized word frequency evaluation used to be performed to achieve insights into the most often happening phrases in the dataset.The analysis revealed common words and phrases that contribute to sentiment expression. Notably, words such as "من" and "@" appeared frequently, suggesting their significance in conveying sentiment in Arabic tweets. This analysis aids in understanding the linguistic patterns and expressions prevalent in the dataset.

6 Discussion

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The acquired outcomes validate the efficacy of the employed sentiment analysis methodology on Arabic tweets.The high accuracy and well-balanced precision-recall metrics signify the model's ability to accurately categorize sentiments, which holds immense value in various applications, including social media monitoring and opinion analysis.

The average tweet length provides valuable context for interpreting the model's accuracy. Despite the succinct nature of Arabic tweets, the model successfully leverages the informative features extracted through TF-IDF, showcasing its adaptability to the unique characteristics of the language.

word frequency analysis serves as a linguistically insightful exercise, uncovering the vocabulary that carries sentiment in Arabic tweets. Understanding these prevalent expressions enhances the interpretability of the model's predictions and aids in identifying trends and themes within the dataset.

The experimental results collectively underscore the applicability and efficacy of the sentiment analysis approach on Arabic tweets. These findings make contributions to the broader field of natural language processing and sentiment analysis, offering precious insights for researchers, practitioners, and stakeholders in Arabic-speaking regions

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