The Challenges of Persian User-generated Textual Content: A Machine Learning-Based Approach

Mohammad Kasra Habib
Stuttgart University
ISTE/Empirical Software Engineering
E-mail: kasra.habib@iste.uni-stuttgart.de

Abstract—Over recent years a lot of research papers and studies have been published on the development of effective approaches that benefit from a large amount of user-generated content and build intelligent predictive models on top of them. This research applies machine learning-based approaches to tackle the hurdles that come with Persian user-generated textual content. Unfortunately, there is still inadequate research in exploiting machine learning approaches to classify/cluster Persian text. Further, analyzing Persian text suffers from a lack of resources; specifically from datasets and text manipulation tools. Since the syntax and semantics of the Persian language is different from English and other languages, the available resources from these languages are not instantly usable for Persian. In addition, recognition of nouns and pronouns, parts of speech tagging, finding words’ boundary, stemming or character manipulations for Persian language are still unsolved issues that require further studying. Therefore, efforts have been made in this research to address some of the challenges. This presented approach uses a machine-translated datasets to conduct sentiment analysis for the Persian language. Finally, the dataset has been rehearsed with different classifiers and feature engineering approaches. The results of the experiments have shown promising state-of-the-art performance in contrast to the previous efforts; the best classifier was Support Vector Machines which achieved a precision of 91.22%, recall of 91.71%, and $F_1$ score of 91.46%.

Index Terms—Machine Learning, User-generated Content, Sentiment Analysis, Feature Engineering, Support Vector Machine (SVM), Logistic Regression (LR), Random Forest Classifier (RND), Linear Discriminant Analysis (LDA), Naive Bayes, K-Means and Ensemble Learning

1 INTRODUCTION

Recently, structured and unstructured user-generated content throughout the internet has been dramatically increased. Unstructured data can be easily perceived and analyzed by humans but are very hard for machines to understand. Likewise, extracting what other people think out of the generated content is an important task for decision-making [1] in business, politics, or beyond these domains.

Utilizing and analyzing raw user-generated content and deriving models based on them makes it more valuable, as per the The-Guardian [2]: “Derivatives of data (from user-generated content), which includes predictive models, or clusters of the population in psychological groupings, can be highly valuable to companies involved in micro-targeting advertisements to voters”; involving politics is beyond the scope of this research.

All types of data (i.e., including images, text, or videos), which is created by users of an unknown system or service on the internet, is called to be user-generated content [3], [4]. After all, users have different languages, and the textual contents can be generated with different syntax and semantics. A huge amount of researches has been conducted for analyzing languages such as English [5] and is still actively continuing.
Moreover, this research targets analysis of Persian user-generated textual content and the challenges that come with it, regrettably, there is an inadequate number of researches in exploiting machine learning approaches for the Persian language. On the other hand, analyzing Persian textual content also suffers from a lack of resources [6], [7] such as datasets and text manipulation tools.

Since the syntax and semantics of Persian are different from languages such as English, recognition of nouns and pronouns, parts of speech tagging, finding words’ boundaries, stemming, or character manipulations are also different and are still unsolved issues that require further studying.

Therefore, efforts have been made in this research to address the main challenges. This presented approach conducts a case study of sentiment analysis for the Persian language. The results of this empirical approach have shown promising state-of-the-art performance in contrast to the previous efforts. Assuredly, this research makes the following contributions:

1) A dataset
2) In-depth identification of the main challenges in applying machine learning to Persian text
3) Presenting a state-of-the-art performance for Persian text classification
4) Demonstrates tools impotence for pre-processing Persian text
5) Exhibits that classical machine learning approaches can proffer similar or sometimes even better performance to neural networks at the presence of an ideal dataset

As of related work, this work picks the most relevant ones to its case study for comparison, since some effort have been devoted to other applications of machine learning to Persian.

Elham et al. [5] question whether they can automatically analyze the sentiment of individual tweets in Persian. Their goal is to determine the individual tweets changing sentiment over time concerning the number of trending political topics. They conclude the challenges of their work in three cases:

1) lack of a sentiment lexicon and part-of-speech taggers,
2) frequent use of colloquial words,
3) and, unique orthography and morphology characteristics.

For this work, they have collected over 1 million tweets of political domains in the Persian language, with an annotated dataset of over 3,000 tweets. They deployed Naive Bayes and Support Vector Machines. Based on their finding, SVM outperformed Naive Bayes with an average accuracy of 56% and as higher as 70%.

Ehsan Basiri et al. [8] addresses the problems that come with sentiment analysis and builds three new resources, SPerSent, which contains customers’ comments from the Web, CNRC, a lexicon corpus, and a new stop-word list.

Finally, they evaluate the resources with Naive Bayes. They conclude, “the performance, with regard to all evaluation measures, are better when CNRC is used as the lexicon for labeling the SPerSent”. The best-observed precision, recall, and $F_1$ score are 92%, 87%, and 89% respectively.

An important step for any machine learning related task is feature engineering. The following papers took a step forward to investigate the impact of different feature engineering methodologies for Persian text.

2 RELATED WORKS

Although the applicability of machine learning in natural language processing is extensively studied by scholars for some languages such as English, nevertheless, some suffer lacking it.
Ayoub Bagheri et al. [9], investigated four feature selection approaches for sentiment classification; Document Frequency; Term Frequency Variance; Mutual Information; and Modified Mutual Information. Next, Naive Bayes is fit to evaluate features’ performance. The highest score is attained with Modified Mutual Information features. The final precision, recall, and $F_1$ score are 90.72%, 85.26%, and 87.84% each respectively.

Kia Dashtipour et al. [10], proposes a novel sentiment analysis framework for the Persian language. Different feature engineering and their combinations are evaluated. As a result, the combination of unigram, bigram, and trigram presented the best performance with succeeding 88.36% accuracy.

Besides traditional machine learning algorithms for natural language processing, one can apply neural networks to Persian text.

Kia Dashtipour et al. [11], tend to exploit Deep Learning for Persian sentiment classification. They compared, state-of-the-art shallow MLP based machine learning model with deep autoencoders and deep CNNs. Finally, the proposed CNNs model presents better performance than MLP and autoencoders with an achieved precision, recall, and $F_1$ score of 84%, 83%, and 83% respectively.

Behnam Roshanfekr et al. [12], studies neural networks to accomplish sentiment analysis for Persian text. They conclude that deep learning models outperform other models with a precision of 59.1%, recall of 52.2%, and $F_1$ score of 55.4%.

### 3 The Challenges of Processing the Persian User-generated Textual Content

Before discussing the challenges that come with Persian user-generated textual content, it is better to establish a basic understanding of the language.

Farsi-e-Dari [13] is known as Dari in Afghanistan; one of two official languages [14], Farsi in Iran; the only official language [15], Tajiki in Tajikistan; the only official language [16] and called Persian in the English language; which all refers to Farsi-e-Dari [17]. Each of these names (Dari, Farsi, or Tajiki) refer to a different accent of Persian, it is important to notice its vocabulary is shaped by its environment and broader culture. Yet still, a purer (less influenced) form is spoken by Afghans than other speakers [17].

This beautiful language belongs to the Indo-European language family [17]. Historically, the extent this language spoken ranges from the borders of India in the east, Russia in the north, southern shores of the Persian Gulf to Egypt, and the Mediterranean in the west [17]. Currently, Persian also understood in parts of Armenia, Azerbaijan, India, Iraq, Kazakhstan, Pakistan, Turkmenistan, Uzbekistan, China, and Turkey [18]. Persian originates from the Great Khorasan [19] (which Afghanistan’s major current Persian speaking territories formed the major portion of Khorasan [19]).

#### 3.1 Challenges in Adopting Tools Build for English and Arabic Language Processing

Over recent years plenty of text processing tools are built for English [5]. One might think exploiting them for Persian would be an advantage. Unfortunately, these tools are not adoptable due to the variance in their grammar, syntax, and semantics;
- one can notice the syntax as the biggest difference, e.g., Persian is right-to-left, where English is left-to-right;
- next, parts of speech tagging is another;
- and ambiguity in word morphology and character manipulation are another barrier to be considered.

1. Dari means “Darbari” (which in English means the language of the royal court) [13].
On the other hand, applying tools build for Arabic appears a good option, since this language adopts the Arabic character set and add four more to it [20]. However, both languages might look similar when it comes to writing, yet they are two different languages, and the syntax and semantics of both languages are different.

Hence, the Persian language vocabulary is exposed by Arabic grammar. For example, the words with the Arabic root bring irregular plural forms, while Persian uses a suffix to build plural forms [15]. Thereupon, not to forget Arabic language suffers from lack of tools and research like Persian. Besides, the influence do not imply that the tools built for Arabic text processing are instantly usable for Persian. Even they add-up to the complexity of the language, which will be discussed in the forthcoming sections.

All in all, the differences between Dari, Arabic, and English languages cause to engineer or develop new tools from scratch.

### 3.2 Challenges in Persian Text Processing

The written structure of Persian itself is complex than the languages like English. For instance, the appearance of the homographic word (the once which look alike, but have different meanings) and use of irregular (which comes from Arabic) and with-suffix plural form which needs to be addressed [7], [21].

Moreover, there are many suffixes, prefixes, pronouns, and other parts that can be written separately or connected, which all are open to further research [15]. However, there are some research conducted to apply machine learning to Persian text, which are not adequate.

The main challenges to exploit machine learning models to process Persian text are concluded in lack of resources, ambiguities in character manipulation, morphology, identifying words boundary, and syntax analysis.

#### 3.2.1 The Challenges of Character Encoding

Frequently one can think that Persian is a variant of the Arabic language. It is explicit that Persian and Arabic are two distinct languages, even they belong to different language families. Therefore, it is natural that they have some similarities in terms of syntax by the cause of alphabet adoption.

Fundamentally, computers deal with numbers. They store letters and other characters by assigning a number to each of them [22]. Before the invention of Unicode, there were hundreds of systems and finding a unique way to represent information was relatively difficult [23]. Resuscitation of Unicode is an effort to software internationalization, especially on the Web. Unicode system is designed to assign one unique code for each character even if the character is used in multiple languages [24]. Persian scripts are written based on Arabic characters (⟨U+0600—U+06FF⟩ block) with some extra and modified characters [22], [24]. The current Unicode framework for Persian is insufficient [25].

It is important to know that the design principle in Unicode to represent the relevant shapes are characters not glyphs [24]. In Persian or Arabic a character can take four different shapes (glyph) depending on their position in the sequence (Table 1).

| Character | Beginning | Middle | End | Stand-alone |
|-----------|-----------|--------|-----|-------------|
| شانه‌ | ش‌ه‌ | ش‌ه‌ | ش‌ه‌ | ش‌ه‌ |
| چهین | چ‌ه‌ن | چ‌ه‌ن | چ‌ه‌ن | چ‌ه‌ن |
| قیف | ق‌ی‌ف | ق‌ی‌ف | ق‌ی‌ف | ق‌ی‌ف |

It is noteworthy that for each four visual form (glyph) of a character there is only one single code. Therefore, an algorithm is charged

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2. The word “شانه” —/Shána/ can mean “Shoulder” or “Comb” depending its usage at the sentence, there are many examples of this condition.
to handle four visual form of a character in a sequence \[26, \] \[27\]. This algorithm attaches special characters such as Zero Width Joiner (ZWJ), Zero Width Non-Joiner (ZWNJ) and Right- to-Left Override (RLO) \[25\].

Take ZWNJ for instance. Using it after a code means that the character before ZWNJ must appear in one of its final forms (glyph), a character after ZWNJ forces the character to appear in one of its initial forms (glyph), and similarly characters after RLO should be represented as strong right-to-left character \[23\]. There are also other standards proposed to use for character representation, e.g., ISIRI 6219:2002 (usual in Iran). Despite these standards, Persian keyboard layout is using different codes and many of Persian users do not use the same encoding standards \[23\]. In addition, using different encodings paves the way for more challenges.

Furthermore, if one is asked to write the plural form of "\(بَنَّا\)" (which means "Section" in English), a suffix "\(هَا\)" —/hā/ will be added at the end of the word. Therefore, the plural forms based on different standards representing the words deferentially as follow:

\[
\begin{align*}
(1) & \quad بَنَّا + هَا = بَنَّهَا \\
(2) & \quad بَنَّا + زَمَّنِ + هَا = بَنَّهَا \\
(3) & \quad بَنَّا + هَا = بَنَّهَا
\end{align*}
\]

Another character which causes the same problem is short vowels. A short vowel in Persian transcriptions never appears alone \[15\]. If one is used, then they will be coded independently \[23\], which can also raise the problem of same appearing word width different Unicode.

Moreover, other problem of this kind can happen in regards to using TATWEEL character; a visual character which helps Persian and Arabic words to appear in different widths \[29\]. To tackle this challenge, \[23\] proposes to build a standardized procedure such us using a mapping between Persian and Arabic characters.

3.2.3 Ambiguity at Words’ Boundary

Tokenization as part of preprocessing for text classification or clustering directly affects on the performance of machine learning algorithm. To convert documents into tokens one should simply find the word boundaries.

Tokenization of Persian documents are challenging due to different usage of delimitations; for example, Persian compound and light words are written in delimited form with ZWNJ. Besides, one can use the space character to form these words, which is not respected by users; even by the official organizations \[23\]. Furthermore, to tokenize defining space or ZWNJ as a boundary are not adequate.

Basically, one can think of using four visual forms (beginning, middle, end, stand-alone) as word boundaries, which the final form is a...
strong indication to end of a word. However, [30], [31] shows that this technique with the Unicode system is not applicable.

3.2.4 Ambiguity in Morphology

Morphological ambiguities can arise based on two reasons [23], (1) homograph words, and (2) word boundaries.

Take (1) for instance. The word “م‌ر” can have different pronunciation and meanings with respect to the usage of short vowels which does not appear in the written text: with one usage of short vowels the word “م‌ر” means Love, with another means to Seal and is used to indicate Mahr.

For (2) remember the example from section 3.2.1; that how a word can be treated as 3 (more than 3 are possible) different words due to Unicode mix-ups.

Therefore, similar problems can arise when lexical elements such as preposition, postposition or conjunctions appear separately or attached [23], [35]. A solution to this challenge would be to follow the official Persian’s orthography which recommends writing them separately, which is hard to guarantee. Therefore, a promising solution is to build a text normalizer.

3.2.5 Ambiguity While Detecting Proper Nouns

Importance of using part-of-speech tagging in text analytics is obvious. To tag nouns and pronouns, Arabic transcripts do not enjoy capitalization like English. Therefore, this characteristic is inherited by Persian’s Arabic character adoption.

To solve this challenge, [36] offers some heuristics to distinguishes proper-nouns from nouns.

3.2.6 Ambiguity Syntax Analysis

Another important ambiguity arises when one wants to construct possessives [23]. To construct possessives a short vowel /e/ is used, which does not appear in the writing text. [23] recommends to add this short vowel in writing scripts; for this regards as it is discussed in subsection 3.2.2, adding this short vowel can cause challenges for character manipulation.

Mainly the problems which may occur while Persian text analytics can be summarized to the inconsistency in its character representation and special orthography.

Furthermore, if one does not consider the mentioned challenges while applying machine learning to Persian transcripts it is quite possible to achieve unsatisfied results, which are far away from the expected performance. To remove the ambiguities, [7] proposes to use a combination of orthography and use standards which are defined in [23]. Handling the challenges laid in Persian scripts are the major obstacles of this research.

3.2.7 FEnglish

Another challenge to apply machine learning to Persian transcripts is that one can use English alphabets to write Persian words pronunciation. This style of writing is called FEnglish which became very usual in social networking platforms. There are some tools to convert the written pronunciations from English to Persian alphabet. This conversion is insufficient for textual analysis since it is just a mapping between English to Persian characters. For example, there are two or more characters which can generate almost the same phoneme (e.g., “e” and “a”) and can be used to write a Persian word with it. Since it is not an officially writing standard; writing a word with different selected characters can differ from one to another.

3. In Islam, Mahr is an arbitrary payment, in the form of money or possessions paid by groom, to the bride at the time of marriage to appreciate her [32], [33], [34].

4. The following links are the tools for mapping FEnglish to Persian text: http://www.dictionary-farsi.com/pinglish.asp, http://syavash.com/portal/pinglish2farsi/convertor-en, https://lingojam.com/FarsitoFinglish
Therefore, this can cause to form a high dimension feature space. Yet still, this is considered an open challenge and needs further attention.

From the aforementioned sections, it is now clear that Persian has a complex orthography structure. This complex structure attaches more challenges to the generally available and the laid challenges in social networking platforms. Therefore, to achieve better performance one must consider these challenges.

4 Experiments and Results

This research uses a machine translated dataset, i.e., observations are originally written in English language which each is an assortment of reviews form Rotten Tomatoes. This dataset is originally collected by Pang and Lee [37], for their work on sentiment treebanks, and likewise utilized by Socher et al. [38] for Amazon’s Mechanical Turk to create fine-grained labels for all parsed phrases into corpus. This research considers a bulk of only positive and negative observations. Therefore, the dataset size is shrunken to 16278 instances which 3256 are kept for test purpose.

4.1 Preprocessing and Feature Engineering

Each instance form the culled dataset is applied a four step cleaning; unnecessary characters removal; normalization and stemming; TF-IDF is applied to assign equal weight to more frequent tokens; PCA is used for dimension reduction to keep 0.99% of explained variance ratio to boost the training process.

Once the preprocessing step is satisfied, vector features are built based on word n-gram (i.e., where $n = 1, 2$ and $3$) and character n-gram (i.e., $n = 1$) feature extraction methods. Furthermore, word n-gram models are famous for preserving order which a word appears in a document and if one is required to capture a deeper meaning, i.e., morphological makeups [39], [40], [41] shall go with character n-gram model.

Subsequently, Logistic Regression (LG) is fit to apprehend a baseline. Clearly, it can be inferred that the trained model with unigram features (word n-gram = 1) has imperceptibly higher performance than the rest (TABLE 1).

| Feature Extraction Method | Precision (%) | Recall (%) | $F_1$ Score (%) |
|---------------------------|--------------|------------|-----------------|
| Word 1-gram               | 88.12        | 90.69      | 89.39           |
| Word 2-gram               | 80.46        | 94.63      | 86.98           |
| Word 3-gram               | 70.51        | 98.45      | 82.17           |
| Char 1-gram               | 64.87        | 76.41      | 70.17           |

Since the model’s score comes from training set they hold suspect to be likely to overfitting. Additionally, unigram and bigram features have approximately similar performance. To make sure which feature set to select learning curves for all features are plotted (Fig. 1).

From Fig. 1, it easy to construe that word bigram and trigram features have a high variance (overfitting); there is a gap between each’ two curves. It means the models are significantly admirable on the training set than the validation set. The model with character unigram is prone to underfitting. Therefore, the winner is the word unigram model.

Fig. 1: Learning Curves
Eventually, Random Forest Classifier is trained to select features; each feature is selected based on its mean weight, where each node’s weight is equal to the number of training samples associated with it [42]. It transpires that the feature selection step did not improve the performance, which is dropped from the preprocessing pipeline.

Finally, KMeans is fitted as a preprocessing step, and to extract new features. To achieve the best number of related clusters, the Basian Gaussian Mixture model was used, which resulted in 37 clusters. Three new feature sets are built;

1) **Distances**: replaced instance with their distances to these 37 clusters;
2) **Centers**: instances replaced with their cluster centers;
3) **Combined**: the combination of two previous feature assortments and word unigram features (TABLE 2).

| TABLE 3: Logistic Regression’s performance measurement on extracted features |
|---------------------------------|-----------------|-----------------|-----------------|
| Precision (%) | Recall (%) | F1 Score (%) |
| Distances | 68.54 | 86.98 | 76.67 |
| Cluster Centers | 64.82 | 86.71 | 74.19 |
| Combined | 87.77 | 90.58 | 89.15 |

From Table 2, it can be closed that the new features and even the combination of them with word unigram did not improved the performance; nothing astounding. Therefore, this research will remain with word unigram features.

**4.2 Classifiers’ Performance Study**

From the previous section, Logistic Regression with word unigram features showed a better performance. Hereabouts, this research will advance with training more models and fine-tuning the models’ hyperparameters.

The chosen models are Logistic Regression (LG), SVM with a Stochastic Gradient Descent implementation (SGD SVM), Random Forest Classifier (RND), Linear Discriminant Analysis (LDA), and Multinomial Naive Bayes (MNB) which is suitable for classification with discrete features [42].

Once classifiers’ hyperparameter is fine-tuned with 10 fold of cross-validation (to save time, LDA was applied 3 fold cross-validation), it resembles that SVM (with SGD implementation and l2 regularization) shown a promising performance (Table 4).

Consequently, since the number of positive instances in the dataset is not scarce, plus an equivalent balance of precision and recall are required, this study presents ROC curve instead of precision and recall curves.

![Fig. 2: Classifiers’ ROC Curves](image)

Eventually, this research ought to attempt ensemble learning; Soft Voting, Pasting, and AdaBoost classification models are studied.

First, all the previous algorithms are included for the Voting Classifier except a Gaussian Naive Bayes (GNB) is succeeded LDA considering it to wreck the performance. Second, an ensemble of Voting Classifiers are fitted; each is trained on 200 instances randomly sampled from the training set without replacement (Pasting). Finally, 100 Decision Tree Classifier (where max_depth = 1) is trained to perform AdaBoost (Table 5).

Usually, training ensemble models provide better performance than training a single
classifiers. Nevertheless, even with ensemble learning, better performance is not always guaranteed.

Of Fig. 2, it is evident that SVM, LG, and MNB are the authoritative classifiers and are proffering a comparable performance. Thus, they are influencing the Voting Classifier’s decisions.

Table 4: Classifiers’ performance measurement

|                  | Train Score                  | Test Score                  |
|------------------|-----------------------------|----------------------------|
|                  | Precision (%) | Recall (%) | F₁ Score (%) | ROC AUC (%) | Precision (%) | Recall (%) | F₁ Score (%) | ROC AUC (%) |
| SVM              | 90.01          | 90.49      | 90.25        | 95.30       | 91.22         | 91.71      | 91.46        | 95.69       |
| LG               | 88.12          | 90.69      | 89.39        | 94.68       | 89.06         | 92.20      | 90.60        | 95.11       |
| RND              | 86.79          | 83.76      | 85.25        | 91.34       | 89.09         | 84.45      | 86.71        | 92.64       |
| LDA              | 83.46          | 86.79      | 85.09        | 87.82       | 86.70         | 90.09      | 88.36        | 91.72       |
| MNB              | 84.76          | 93.85      | 89.07        | 95.11       | 86.51         | 94.47      | 90.32        | 95.62       |

Moreover, among the applied ensemble classifiers, the Voting classifier’s scores are comparable with SVM (Fig. 3).

One can trade-off between precision and recall scores for the Voting Classifier to achieve nearly identical once to SVM (Fig. 3). Setting the decision threshold for recall to 0.91 will boost the precision to 90% for the Voting classifier.

Yet, it is not enough, therefore supplementary (with respect to new threshold) ROC and AUC are calculated for this classifier, to make sure this model functions as good as SVM.

Fig. 3: ROC curves for SVM and Ensemble Learning

Fig. 4: SVM and Tweaked Voting Classifier’s ROC curves

From Fig. 4, it is understandable that the curve is engineered and the tweaked model is not as shiny as SVM. Plus, contrasting its performance and its complexity, it does not deserve to replace SVM with it.

This research studied different feature engineering methods, classification algorithms, and ensemble learning. To sum up, SVM with word unigram features outperformed the rest, with an/a achieved/balanced precision, recall, and F₁ score of 90% on the train and 91% on the test set.

5 Evaluation and Future Work

The achievement form the section 4, shown promising state-of-the-art performance in con-
trast to the previous efforts [5], [8], [9], [10], [11], [12] (Table 6).

**TABLE 6: Performance measurement comparison among this work and the related works**

| References            | Model | Precision (%) | Recall (%) | $F_1$ Score (%) |
|-----------------------|-------|---------------|------------|-----------------|
| This Study            | SGD SVM | 91.22         | 91.71      | 91.46           |
| E. Basiri et al. [8]  | NB    | 92.00         | 87.00      | 89.00           |
| A. Bagheri et al. [9] | NB    | 90.72         | 85.26      | 87.84           |
| Kia D. et al. [11]    | CNN   | 84.00         | 83.00      | 83.00           |
| Behnam R. et al. [12] | NN    | 59.10         | 52.20      | 55.40           |

E. Basiri et al. [8], confers a precision score of 0.92; a slight difference of 0.0078 in contrast to this work. On the other hand, it presents a lower recall score, which is 0.87 (i.e., it can not detect 13% of positive instance) in contrast to this work, which is 0.91. A convenient method to compare two classifiers is to embed their precision and recall scores in one metric called $F_1$ score (the harmonic mean). Therefore, looking at the $F_1$ score of both studies, it is clear that this research outperforms E. Basiri et al. [8] with a difference of 2.46% while trading-off between the precision and recall.

Differently, Elham et al. [5] and Kia Dashtipour et al. [10] provides only the Accuracy score instead of precision, recall and $F_1$ score, which is not the preferred metric of evaluation. Thus, this work exhibits a higher (i.e., 93%) accuracy than the previous efforts.

Eventually, this research assumes that better performance can be reached if the following recommendations are satisfied:

1) Existence of an ideal dataset rather than (this) machine-translated one; mistakes in translation were observed in the dataset, as machine translation itself requires further study [43].

2) The existence of sophisticated tools for preprocessing is required; this research applied Hazm for stemming. Hence, Hamz is the state-of-the-art preprocessing tool for the Persian language it needs further improvements. Take for instance, the word “آرام” (—which in English it means “Quiet”) was wrong stemmed to “آرم” (—which in English it means “Vote”) or the word “نظر” (—نظیر) was miss tokenized in two tokens “نظر” and “نظیر”.

From the conducted research it is understandable that wielding the Persian text is a challenging responsibility. Furthermore, ensuing potential research for the future is to work on building rich resources and efficient preprocessing tools. The current solutions are based on traditional machine learning approaches, as well as conducting sentiment classification of Persian text with deep learning will be further fascinating to work in the future.

### 6 Conclusion

This work started by addressing the open challenges to apply machine learning to handle Persian user-generated textual content. Though there is plenty of support for English, unfortunately, adapting these resources is not a solution due to complexity in the syntactical and semantical structure of Persian language. Notwithstanding, several efforts are accomplished to develop preprocessing tools and employ machine learning to classify Persian sentiments, which are not adequate, therefore, in-depth studies are demanding.

First, this study applied a four-step preprocessing, features vectors are constructed based on word and character n-gram techniques. Later, Random Forest Trees are utilized for feature selection. Then KMeans is applied to create three new feature sets. From the results, it was apprehended that word unigram features without feature selection outperformed the rest. Second, five classifiers (Support Vector Machines, Logistic Regression, Random Forest Classifier, Linear Discriminant Analysis, and Multinomial Naive Bayes) and three ensemble learning methods (Voting, Pasting and AdaBoost) are trained and evaluated.

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5. Naive Bayes  
6. Convolutional Neural Networks  
7. Neural Networks
Finally, word unigram features and SVM with gradient descent implementation outperformed the rest, with an achieved precision, recall, and $F_1$ score of 90% on the train and 91% on the test set.

REFERENCES

[1] B. Pang and L. Lee, “Opinion mining and sentiment analysis,” Found. Trends Inf. Retr., vol. 2, no. 1-2, pp. 1–135, Jan. 2008. [Online]. Available: http://dx.doi.org/10.1561/1.50000001.

[2] P. Lewis, D. Pegg, and A. Hern, “Cambridge analytica kept facebook data models through us election,” 2018. [Online]. Available: https://www.theguardian.com/uk-news/2018/may/06/cambridge_analytica_kept_facebook_data_models_through_us_election.

[3] M.-F. Moens, J. Li, and T.-S. Chua, Mining user generated content. CRC Press, 2014.

[4] R.-H. Chen and S.-C. Chang, “Modeling content and membership growth dynamics of user-generated content sharing networks with two case studies,” IEEE Access, vol. 6, pp. 4779–4796, 2018.

[5] E. Vaziripour, C. G. Giraud-Carrier, and D. Zappala, “Analyzing the political sentiment of tweets in farsi.” in ICWSM, 2016, pp. 699–702.

[6] B. Sarrafzadeh, N. Yakovets, N. Cercone, and A. An, “Cross-lingual word sense disambiguation for languages with scarce resources,” in Canadian Conference on Artificial Intelligence. Springer, 2011, pp. 347–358.

[7] M. Shamsfard, “Challenges and open problems in persian text processing,” Proceedings of LTC, vol. 11, 2011.

[8] M. E. Basiri and A. Kabiri, “Sentence-level sentiment analysis in persian,” in 2017 3rd International Conference on Pattern Recognition and Image Analysis (IPRIA). IEEE, 2017, pp. 84–89.

[9] A. Bagheri and M. Saraei, “Persian sentiment analyzer: A framework based on a novel feature selection method,” arXiv preprint arXiv:1412.8079, 2014.

[10] K. Dashtipour, M. Gogate, A. Adeel, A. Hussain, A. Alqarafi, and T. Durrani, “A comparative study of persian sentiment analysis based on different feature combinations,” in International Conference in Communications, Signal Processing, and Systems. Springer, 2017, pp. 2288–2294.

[11] K. Dashtipour, M. Gogate, A. Adeel, C. Ieracitano, H. Larijani, and A. Hussain, “Exploiting deep learning for persian sentiment analysis,” in International Conference on Brain Inspired Cognitive Systems. Springer, 2018, pp. 597–604.

[12] B. Roshanfekr, S. Khadivi, and M. Rahmati, “Sentiment analysis using deep learning on persian texts,” in 2017 Iranian Conference on Electrical Engineering (ICCEE). IEEE, 2017, pp. 1503–1508.

[13] C. Nolle-Karimi. (2018, jun) No differences between farsi and dari. [Online]. Available: https://derstandard.at/130868077512/Landessprache_als_Politikum_Keine_Unterschiede_zwischen_Farsi_und_Dari.

[14] CIA. (2018, jun) The world fact book. [Online]. Available: https://www.cia.gov/library/publications/the-world-factbook/geos/af.html.

[15] M. Zanjani, A. Baraani-Dastjerdi, E. Asgarian, A. Shahriyari, and A. Akhavan Khorazian, “A new experience in persian text clustering using farsnet ontology,” vol. 31, pp. 315–330, 01 2015.

[16] CIA. (2018, jun) The world fact book. [Online]. Available: https://www.cia.gov/library/publications/the-world-factbook/geos/ti.html.

[17] B. Spooner et al., “Persian, farsi, dari, tajiki: Language names and language policies,” Language Policy and Language Conflict in Afghanistan and Its Neighbors: The Changing Politics of Language Choice, pp. 89–120, 2012.

[18] BBC. (2018, jun) A guide to persian. [Online]. Available: http://www.bbc.co.uk/languages/other/persian/guide/facts.shtml.

[19] H. W. Alikuzai, From Aryana-Khorasan to Afghanistan: Afghanistan History in 25 Volumes. Trafford Publishing, 2011.

[20] M. H. Shirali-Shahreza and M. Shirali-Shahreza, “Arabic/persian text steganography utilizing similar letters with different codes,” The Arabian Journal For Science And Engineering, vol. 35, no. 1, 2010.

[21] B. Baluch, “Persian orthography and its relation to literacy,” Handbook of orthography and literacy, pp. 365–376, 2006.

[22] “Unicode consortium.” [Online]. Available: https://unicode.org/.

[23] B. QasemiZadeh, S. Rahimi, and M. S. Ghalati, “Challenges and open problems in persian text processing,” Proceedings of LTC, vol. 11, 2011.

[24] R. Freeland, “The islamic institution of mahr and american court: interpreting mahr agreements as prenuptials and their effect on muslim women,” Wake Forest L. Rev., vol. 76, p. 579, 2010.

[25] H. M. Alshahrani and G. Weir, “Hybrid arabic text steganography,” International Journal of Computer and Information Technology, vol. 6, no. 6, pp. 329–338, 2017.

[26] A. Odoh and K. Elleithy, “Steganography in arabic text using zero width and kashidha letters,” International Journal of Computer Science & Information Technology, vol. 4, no. 3, p. 322, 2002.

[27] L. E. Blenkhorn, “Islamic marriage contracts in american courts: interpreting mahr agreements as prenuptials and their effect on muslim women,” S. Cal. L. Rev., vol. 76, p. 189, 2002.

[28] M. Hassel and N. Mazdak, “Farsism: a persian text summarizer,” in Proceedings of the Workshop on Computational Approaches to Arabic Script-based Languages. Association for Computational Linguistics, 2004, pp. 82–84.

[29] B. Qasemizadeh, “Farsi e-orthography: An example of e-orthography concept,” in Improving Non-English Web Searching (iNEWS07) SIGIR07 Workshop, 2007, pp. 62–64.

[30] R. Ibrahim, Z. Eviatar, and J. Aharon-Peretz, “The characteristics of arabic orthography slow its processing,” Neuropsychology, vol. 16, no. 3, p. 322, 2002.

[31] K. Megerdoomian and R. Zajac, Processing Persian text: Tokenization in the Shiraz project. Computing Research Laboratory, New Mexico State University, 2000.

[32] M. Steinbach, G. Karypis, V. Kumar et al., “A comparison of document clustering techniques,” in KDD workshop on text mining, vol. 400, no. 1. Boston, 2000, pp. 525–526.
[37] L. PaNgB, “Exploiting class relationships for sentiment categorization with respect to ratings and sales,” in Proceedings of ACL 2005.

[38] R. Socher, A. Perelygin, J. Wu, J. Chuang, C. D. Manning, A. Ng, and C. Potts, “Recursive deep models for semantic compositionality over a sentiment treebank,” in Proceedings of the 2013 conference on empirical methods in natural language processing, 2013, pp. 1631–1642.

[39] A. Kulmizev, B. Blankers, J. Bjerva, M. Nissim, G. van Noord, B. Plank, and M. Wieling, “The power of character n-grams in native language identification,” in Proceedings of the 12th Workshop on Innovative Use of NLP for Building Educational Applications, 2017, pp. 382–389.

[40] G. W. Lesher, B. J. Moulton, D. J. Higginbotham et al., “Effects of n-gram order and training text size on word prediction,” in Proceedings of the RESNA'99 Annual Conference. Citeseer, 1999, pp. 52–54.

[41] M. K. Habib, “Machine learning-based text classification and clustering: The challenges of user-generated content,” Master’s thesis, 09 2018.

[42] L. Buitinck, G. Louppe, M. Blondel, F. Pedregosa, A. Mueller, O. Grisel, V. Niculae, P. Prettenhofer, A. Gramfort, J. Grobler, R. Layton, J. VanderPlas, A. Joly, B. Holt, and G. Varoquaux, “API design for machine learning software: experiences from the scikit-learn project,” in ECML PKDD Workshop: Languages for Data Mining and Machine Learning, 2013, pp. 108–122.

[43] J. Slocum, “A survey of machine translation: its history, current status, and future prospects,” Computational linguistics, vol. 11, no. 1, pp. 1–17, 1985.