A Speech Act Classifier for Persian Texts and its Application in Identify Speech Act of Rumors

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Abstract. Speech Acts (SAs) are one of the important areas of pragmatics, which give us a better understanding of the state of mind of the people and convey an intended language function. Knowledge of the SA of a text can be helpful in analyzing that text in natural language processing applications. This study presents a dictionary-based statistical technique for Persian SA recognition. The proposed technique classifies a text into seven classes of SA based on four criteria: lexical, syntactic, semantic, and surface features. WordNet as the tool for extracting synonym and enriching features dictionary is utilized. To evaluate the proposed technique, we utilized four classification methods including Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes (NB), and K-Nearest Neighbors (KNN). The experimental results demonstrate that the proposed method using RF and SVM as the best classifiers achieved a state-of-the-art performance with an accuracy of 0.95 for classification of Persian SAs. Our original vision of this work is introducing an application of SA recognition on social media content, especially the common SA in rumors. Therefore, the proposed system utilized to determine the common SAs in rumors. The results showed that Persian rumors are often expressed in three SA classes including narrative, question, and threat, and in some cases with the request SA.

Keywords Speech Act, Persian text classification, Feature extraction, WordNet, Rumor.

1 Introduction

Speech Act (SA) is the performed action by a speaker with an utterance. The theory of SA was first Proposed by Austin [2] and refined by Searle [3]. Searle [4] has introduced five categories of SAs: Assertive (e.g. reciting a creed), Directives (e.g. requests, commands, and advice), Commissives (e.g. promises and oaths), Expressives (e.g. congratulations, excuses, and thanks) and Declarations (e.g. baptisms or pronouncing someone husband and wife). Assertive sentences commit the speaker to something being the case and speaker's purpose for transferring the information to hearer; directives cause the hearer to take a particular action and show the speaker's intention; declarative sentences express the speaker's attitudes and emotions. Searle' classification of SAs is known as basic SA taxonomy that is used in many research.
For example, when you say "I'll be there at six", you are not just speaking, but you seem to be performing the SA of "promising". As functional units, SAs play an important role in effective communication. We use SAs in our conversations every day when greeting, compliment, request, invitation, apology, threaten, and so on. Normally, the SA is a sentence, but it can be a word like “Sorry!” to perform an apology, or a phrase as long as it follows the rules necessary to accomplish the intention like "I'm sorry for my behavior." [1].

Understanding the SAs of a text can help to improve the analysis of texts and give us a better understanding of the state of mind of the people. The automatic recognition of SA (also known as dialogue act) is known as a necessary work in many Natural Language Processing (NLP) systems such as sentiment classification, topic modeling, and Text-To-Speech (TTS) systems and assertion tracking. In this study, the other application of SA classification is represented to identify the common SAs of rumors. The identification of common SA in rumors can be an important step in recognizing rumors. We considered some objectives to enhance the performance of SA classification in the Persian language. These objectives are summarized below.

- **Use feature extraction techniques.** Without using the feature extraction techniques, the length of feature vectors will be very large, and this decreases the accuracy of the classifier. Also, feature selection algorithms are applied to reduce the number of extracted features and increase the overall efficiency of classification algorithms.

- **Use useful features to classify SAs and enriching the Dictionary of Features.** Extracted features are a valuable set of lexical, semantic, syntactic, and surface features in seven SA classes. These features set have a notable impact on performance and thereby increase the accuracy of SAs classifier. To overcome the limitations of words within the dictionary of each SA class, WordNet ontology is used to find synonyms of words that are not in the dictionary.

- **Identify common SAs of rumors.** Rumors are expressed by specific SAs to increase the audience's motivation for rumor distribution. Hence, by analysis of the content of rumor texts and retrieving the type of their SA and determining the common SA in rumors, a preliminary step can be taken to identify rumors.

The rest of the paper is organized as follows: Section 2 discusses related works that have done on SA classification. In Section 3 are introduced applied datasets in this work. Section 4 describes the proposed methodology for identifying the SAs on the Persian language. Then in section 5, the application of SA classification in determining the common SAs of rumors is discussed, and in Section 6 results of our experiments and evaluations and conclusions of paper is shown. In section 7, we conclude with a discussion and directions for future work.

## 2 Related Works

The problem of determining the SA has been a field of interest to researchers from several areas for a long time. There are distinct taxonomies for the different applications of SAs in other languages, especially the English language. The problem of SA classification has been studied not only in English but also in many other languages such as Chinese [25], Korean [26], Arabic [11] and so on. However, in the Persian language is done very little work on automatic SA. As far as we know, the only
published work on Persian SA classification is the work of Soltani-Panah et al. [1]. In following some studies that are relevant to our work are mentioned:

In 1999, Klaus Ries [19] presented an incremental lattice generation approach to detect SA for spontaneous and overlapping speech in telephone conversations (CallHome Spanish). Ries used an HMM algorithm where the states are SAs and the symbols emitted are sentences, and also used neural network based estimates for the output distributions. He showed that how neural networks can be used very effectively in the classification of SAs.

Vosoughi et al. [5] proposed SA recognition on Twitter (English tweets). Vosoughi created a taxonomy of six SAs for Twitter and proposed the set of semantic and syntactic features for labeling tweets manually. Then, the labeled dataset is used to train a logistic regression classifier. In another two work on the English language is done by Zhang et al. for SA classification on Twitter by using supervised [6] and semi-supervised [7] methods. They proposed the set of word-based features and character-based features for creating a labeled dataset.

Qadir and Riloff [18] performed the SA classification on a collection of message board posts in the domain of veterinary medicine. They create a sentence classifier to recognize sentences containing four different SA classes: Commissives, Directives, Expressives, and Representatives. Qadir and Riloff used the collection of features, including lexical and syntactic features, SA word lists from external resources, and domain-specific semantic class features.

Sherkawi et al. [11] presented rule-based and statistical-based techniques for Arabic SA recognition. They represent that advantage of building an expert system is that it did not require a large corpus; instead, from a small set of examples, a core expert system is built. In contrast, using machine-learning methods is a more time-saving task, but it requires a large corpus for training. They evaluated the proposed techniques using three features sets: surface features, cue words, and context features, and found that the cue words feature set is simple and indicative of the SAs when using machine-learning methods. In contrast, the expert system performance has improved significantly when adding context features.

Král et al. [21] used syntactic features derived from a deep parse tree to recognize dialogue acts in the Czech language based on conditional random fields. They considered two types of features, respectively the baseline and syntactic features. The baseline features are: words inflected form, lemmas, part-of-speech tags, pronoun or adverb at the beginning of the sentence, and verb at the beginning of the sentence. The syntactic features rely on a dependency parse tree: dependency label, root position in the utterance, unexpressed subjects, and basic composite pair (subject-verb inversion).

In 2010, Soltani-Panah et al. [1] presented the first work on the automatic categorization of Persian texts based on speech act. They considered seven classes of SAs in Persian language texts and three classification methods including Naïve Bayes (NB), K-Nearest Neighbors (KNN) and Tree learner. Soltani-Panah et al. evaluated three classification algorithm on Persian dataset. They concluded that the KNN with an accuracy of 72% is the most efficient algorithm for classifying Persian SAs. Also, they demonstrated that the amount of labeled training dataset has a high impact on the efficiency of the classification.

Our work is similar to work [5], [6], [18] [11] but what distinguishes our work from them is that in addition to the features presented in previous studies Feature Extraction (FE) techniques are utilized to extract useful features that can distinguish between SA classes. Also, what is notable in our work relative to previous works is that we applied WordNet ontology to enrich the dictionary of the features of each SA class.
3 Data

In this work, the supervised classifiers are utilized to classify SAs, so like any other
supervised classification problem, a large labeled dataset is needed. Also, to analyze
and detect the common SA in Persian rumors, it is necessary to provide a collection of
Persian rumor texts. Due to the lack of such data, we manually collected this dataset in
two classes include, rumor and non-rumor.

3.1 Training Data

To train supervised algorithms and evaluate our proposed SA classifier, we employed
the labeled dataset by Soltani-Panah et al. [1] from multiple subjects and sources. They
labeled the raw corpus that is created by the Research Center of Intelligent Signal
Processing (RCISP).

This dataset contains labeled 9145 Persian sentences in seven SA categories. The
SAs are compiled into a database of 1734 Questions(Que), 928 Requests (Req), 1113
Directives (Dir), 544 Threats (Thr), 850 Quotations (Quo), 2000 Declaratives (Decler),
and 1976 Narratives. The texts of this training dataset are gathered from different
sources such as newspapers, magazines, journals, internet, books, weblogs, itineraries,
diaries, and letters. This data includes various domains such as Economy, Export,
Culture, Sciences, etc. These six SA types alongside the Searle’s SA types are listed in
Table 1.

| Searle’s base SAs types | Our SAs types | Description |
|-------------------------|---------------|-------------|
| Directive               | Questions     | These are usual questions for information or confirmation. |
|                         | Requests      | Politely asks from somebody to do or stop doing something. |
|                         | Directives    | With these SAs we cause the hearer to take a particular action perforce. |
| Commissive              | Threats       | With these SAs we can promise for hurting somebody or doing something if hearer does not do what we want. |
| Expressive Declarations | Quotations    | These are SAs that another person said or wrote before. |
|                         | Declarative   | Transfer information to hearer, these commit the speaker to something being the case. |
| Assertive               | Narratives    | These SAs report connected events, real or imaginary. With these SAs we tell what has happened |

3.2 Annotation

In this study, we intend to detect the common SA in rumors in the Persian language.
Thereby, a dataset of a few thousand Persian posts from Telegram channels in Iran from
May 1, 2017, to March 30, 2018, is collected. For this purpose, we utilized the provided
API by Computerized Intelligent Systems (ComInSys)1 of the University of Tabriz [28].
To verify the rumors, we used several Telegram channels and three websites as

1 www.cominsys.ir
trustworthy sources that document rumors. The reviewed channels and sites for validating rumors are as follows:

- **Checked channels:** Fars News Agency, Iranian Students’ News Agency (ISNA), Tasnim News Agency, Tabnak, Nasim News Agency (NNA), Mehr News Agency (MNA), Islamic Republic News Agency (IRNA).
- **Websites:** gomaneh.com, wikihoax.org, shayaaat.ir.

Four undergraduate students as annotator were asked to check the correctness or falsity of any post collected from the Telegram channels and websites listed above individually. If the authenticity of a Telegram post is confirmed at least in four reliable sources, it is considered as non-rumor. We applied the Fleiss’ Kappa measure to evaluate the degree of agreement and disagreement of annotators with the class of rumors. Fleiss’ Kappa is a way to measure agreement between three or more raters. The kappa score for the four annotators was 0.84, which means that the rate of student agreement in classifying posts based on rumor or non-rumor is relatively high. Since the quality of annotation for a supervised classifier is importance, so we chose the only texts that were labeled by all three annotators. Thereby, 1975 Telegram posts collected, that 882 were rumors and 1093 were non-rumors (i.e. around 74% of all posts).

### 3.3 Features

The effectiveness of speech act classification task depends basically on the features used in training the classification model [11]. We collected a set of 2275 content features as useful features that can distinguish six SA classes in the Persian language. These features can be divided into four categories: Lexical, Semantic, Syntactic and Surface. Table 2 illustrates the number of extracted features from each class separately.

#### Lexical Features

- **Particular words.** Particular words give us valuable information about the type of SAs. So, we collected the particular words in the 6 categories based on SAs categories that these words often appear in texts with specific SAs. To generate this set, we extract N-grams from sequences of the training dataset.
- **Cue words.** There are words that are explicit indicators of the SA also key to understanding, such as, the question mark is a base feature for Ques sentences and next base feature is question words ("چه"/چه/ce/what, "چطور"/cetowr/how, "چرا"/چرا/why, and etc.). The base feature of Req sentences is conditional words ("اگه ممکنه"/age momken/ if possible and etc.).

#### Semantic Features

- **N-grams.** We extract N-grams unigram, bigram phrases from the text. A unigram is a one-word sequence of words like ("بزنو"/borno/Go). A 2-gram (or bigram) is a two-word sequence of words like ("لفتا بزنو"/lotfan boro/Please go).
- **Vulgar words.** Vulgar words are content words that contain the set of slang and obscene (bad words) words. We collect a total of 965 vulgar words from an online collection of vulgar words. Vulgar words mostly appear in the threats SA class. This feature has a binary value that indicates whether vulgar words appear in the text or do not appear.
• **Speech act verbs.** SA verbs are content words which can be used to describe types of SAs. In other words, SA verb is a verb that explicitly conveys the kind of SA being performed, such as promise, apologize, predict, request, warn, insist, and forbid. Also, it is known as the performative verb. Based on SA verbs in English, we collected 910 SA verbs for Farsi in 6 classes.

• **Sentiment.** We believe that sentimental polarity of a text could be an informative factor to identify SAs. For example, texts with Thre SA are usually dominated by negative sentiment. To calculate the sentiment score of the text, we utilized a lexicon-based method. In this method, we obtained the sentiment polarity of Persian words using the NRC Emotion Lexicon. NRC is created by Saif et. al. [21] at the National Research Council Canada, which consists of 14183 words that each word is tagged with one of the following sentiment labels; Positive, Negative, or Neutral. So the sentiment score of the text is calculated based on the polarity of the words using formula 1. In this formula, \( PSntm \) is the number of words with positive polarity in the text \( T \) and \( NSntm \) is the number of words with negative polarity in the text \( T \).

\[
Score_{Sent}(T) = \frac{|PSntm(T)| - |NSntm(T)|}{|PSntm(T)| + |NSntm(T)|}
\]

Syntactic Features

• **Part-of-Speech (POS) tags.** The Parts-of-Speech (POS) is syntactic categories for words. We applied an HMM-based POS tagger for Persian POS tagging. Interjections are mostly used in expressing the requested sentences. Also, Words with the tag "IF" usually appear in the requested sentences. Similarly, adjectives can appear in Declarative and Narrative texts.

• **Punctuations.** We consider three punctuations: '?', '!', and ':'. Punctuations can be predictive of the SA in a sentence. For example, the punctuation '?' appears in Ques or Req sentences, while punctuation '!' appears in "Dir", Req, or Thre sentences, and punctuation ':' appears in the "quotation" sentences. These punctuations are binary features that this binary value indicates to presence or absence of these symbols. Previous work such as Mendoza et al. [27] has shown that only one third of tweets with question marks are real questions, and not all questions are related to rumors. Also, in Persian language, the question mark is not specific to question sentences, but rather often appearing in request sentences and, in limited cases, in threat sentences.

Surface features

• **Token position.** We have defined an assumption similar to the assumption of Moldovan et al. [22]. Based on this assumption, the first and last words in a sentence can be valuable indicators in determining the SA of texts. One argument in favor of this assumption is the evidence that hearers start responding immediately (within milliseconds) or sometimes before speakers finish their utterances [23].
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Table 2. Number of features from each class along with example.

| Feature                  | # of features | Example (Unigram/Bigram)                                                                 |
|--------------------------|---------------|---------------------------------------------------------------------------------------|
| Particular words         | 120           | "تقاضا" ("Tagâzâ/Demand), "خواهش" ("Khâhesh/Request), "لطفا" ("Lotfan/Please),         |
| -Request                 |               | "آی خد" ("Al khodâ/O God), "ترور" ("Toro khodâ/for God's sake)                      |
| SA verbs - Request       | 185           | "بخشید" ("Bebakhshid/Sorry), "خواهشمندم" ("Khâheshmandam/please), "بپرهیز" ("Beparhiz/Avoid) |
| Particular words         | 46            | "میادا" ("Miyâda/Lest), "خواهش" ("Hey/Request"), "بگو" ("Boro/Go)                   |
| -Directives              |               | "خوب" ("Bad jens/Wicked), "وحشتناک" ("Vahshatnâk/Terrible), "هرسنگاک" ("Harânsangka/Horrible) |
| SA verbs - Threats       | 255           | "کشتی" ("Koshtan/Kill"), "مردن" ("Mordan/Die"), "ترسیدن" ("Tarsidan/Fear")          |
| Particular words         | 99            | "بیانیه" ("Bayânie/Statement"), "گزارش" ("Gozâresh/Report"), "سخنرانی" ("Sokhanrâni/Lecture") |
| -Quotations              |               | "توصیه کردن" ("Tosieh kardan/Recommend"), "علامت کردن" ("Elâm kardan/Declare")      |
| SA verbs - Quotations    | 50            | "بدین منظور" ("Bedin manzor/For this purpose"), "بعلت" ("Bale/Love"), "حکاکی" ("Hâkaki/Indicative") |
| Particular words         | 359           | "شامل" ("Shâmel/Include"), "تشکیل دادن" ("Tashkil dadan/Constitute")                |
| -Declarative             |               | "شامل" ("Shâmel/Include"), "تشکیل دادن" ("Tashkil dadan/Constitute")                |
| SA verbs - Declarative   | 200           | "شامل" ("Shâmel/Include"), "تشکیل دادن" ("Tashkil dadan/Constitute")                |
| Vulgar words             | 965           | The presence/absence of vulgar words in the text.                                    |
| Question words           | 63            | "چند" ("Chand/How many"), "چرا" ("Chera/why"), "چیه" ("Chieh/what"), "چه" ("Che/When"), |
|                          |               | "چگونه" ("Chegoneh/How"), "چگونه/چگونه" ("Chegoneh/How/How")                      |
| Conditional words        | 19            | "بگم" ("Bgam/agar/if"), "بگم" ("Bgam/agar/if")                                      |
| Question mark            | 2             | ? , !                                                                                 |
| Exclamation mark         | 1             | !                                                                                   |
| Colon                    | 1             | :                                                                                   |

4 Proposed Methodology

In this study, we used supervised algorithms to categorize texts based on speech acts. The effectiveness of speech act classification task depends basically on the features and a large labeled dataset used in training the classification model [11]. So we focused on the features of the text that can give valuable information about the SA of the text to the classifier. These features are used to construct feature vectors with informative elements and lower dimensional. Then, the classifier is fed by these vectors, which leads to the
creation of a robust system to identify the SAs of Persian texts. Below, each of the steps of the proposed method is explained in detail.

4.1 Text Pre-processing

At this stage, useless information of the text is eliminated. Pre-processing reduces the noise in text and hence makes the data more 'clean' and capable of training the classifier more effectively. In this study, we use the three steps of preprocessing include: tokenization, removing stop words, normalization, stemming and lemmatization.

- **Normalization**: Text normalization is the process of transforming text into a single canonical form that it might not have had before. Preprocessing Persian texts has complexities and challenges [15], that these challenges are addressed by normalization. Some of these challenges include:
  - Replace white spaces with short-spaces.
  - Adding short-spaces between different parts of a word, such as: convert "ماشین ها" to "ماشین ها" (cars).
  - Editing all letters in Arabic style with Arabic Unicode characters are edited to Persian style with mapping to Persian Unicode encoding, such as: convert 'ي' to 'ی' (i) and 'ؤ' to 'و' (v).
- **Tokenization**: This is the process of splitting a text into individual words (unigram) or sequences of words (bigram).
- **Removing stop words**: words to don’t give important information about document content, such as prepositions, special characters (such as '@'), rare words and etc.
- **Stemming word**: reducing inflectional forms and sometimes derivationally related forms of a word to a common base form.
- **Lemmatization**: reducing various linguistic forms of a word to their common canonical form.

4.2 Feature Extraction

In text classification, a major problem is the high dimensionality of the feature space. Therefore, using feature extraction methods, a set of most informative and indicative features of the training set are extracted [8]. In this study, four different methods have been used to extract features. These methods are described following.

**Unigram and Bigram Extraction.** In this method, the features of each class are extracted using the concept of N-gram and TF-IDF method. Thereby, 12 members are added to the feature vector of text (that is, six members for unigram features and six another member for bigram features.). The next step is extracting a numerical value for these feature vector elements. For this purpose, for each word in a text, the TF-IDF value is calculated in 6 speech classes. Then for all classes, the total TF-IDF is calculated for all words.
HMM-based Parts-of-Speech Tagging. Hidden Markov Models are suitable for POS tagging in Persian language and quite comparable with best-case results reported from other models. The process of tag extraction by using HMM can be described as follows:

- Input text $T = (W_1, ..., W_T)$; HMM $\lambda$; set of tags $X_1, ..., X_n$ corresponding to target HMM states $S_1, ..., S_n$.
- Generate sequence $O = (O_1, ..., O_T)$ where $O_t$ is a vector containing word $W_t$.
- Call Forward-Backward algorithm and calculate $q_t^* = \max_{s_t} \gamma_t(i), 1 \leq t \leq T$.
- If $q_t^* = S_i \in \{S_1, ..., S_n\}$, then output "$ < X_i > w_i < X_i > "$; else output $w_t$.

In order to, we can consider that a text is a sequence of observations $O = (O_1, ..., O_T)$. The observations $O_t$ correspond to the tokens of the text. Technically, each token is a vector of attributes generated by a collection of NLP tools. We should attach a semantic tag $X_i$ to some of the tokens $O_t$. An extraction algorithm maps an observation sequence $O_1, ..., O_T$ to a single sequence of tags $(\tau_1, ..., \tau_T)$, where $\tau_t \in \{X_1, ..., X_n, \Lambda\}$

An HMM $\lambda = (\pi, A, B)$ consists of finitely many states $\{S_1, ..., S_n\}$ with probabilities $\pi = P(q_1 = S_i)$, the probability of starting in state $S_i$, and $a_{ij} = P(q_{t+1} = S_j | q_t = S_i)$, the probability of a transition from state $S_i$ to $S_j$. Each state is characterized by a probability distribution $b_i(O_t) = P(O_t | q_t = S_i)$ over observations. Given an observation sequence $O = O_1, ..., O_T$, and according to Bayes’ principle, for each observation $O_t$, we have to return the tag $X_i$ that maximizes the probability $P(\tau_t = X_i | O)$, which means that we should identify a sequence of states $q_1, ..., q_T$ which maximize $P(q_T = S_k | O, \lambda)$ and return that tag $X_i$ that corresponds to the state $S_i$ for each token $O_t$. Then the Forward-Backward algorithm of HMM should be described. $\alpha_t(i) = P(q_t = S_i, O_1, ..., O_t | \lambda)$ is the forward variable. It quantifies the probability of reaching state $S_i$ at time $t$ and observing the initial part $O_1, ..., O_t$ of the observation sequence. $\beta_t(i) = P(O_{t+1}, ..., O_T | q_t = S_i, \lambda)$ is the backward variable and quantifies the chance of observing the rest sequence $O_{t+1}, ..., O_T$ when in state $S_i$ at time $t$. Of course, $\alpha_t(i)$ and $\beta_t(i)$ can be computed and then we can express the probability of being in state $S_i$ at time $t$ given observation sequence $O$, it is $\gamma_t(i) = \frac{\alpha_t(i) \beta_t(i)}{P(O | \lambda)}$.

Thus, after POS tagging by HMM as feature extractor, the noisy and less important features are removed and proper tags as powerful features are selected. Therefore, feature vectors with smaller dimensions that contain useful elements are created.

Feature Extraction Based on Word Position. Each word in the text has a specific location that it can be defined as word position. The effect of the words in the different position of the text is often different for the text classification. We used the position information of the words to improve performance. In a class, if a word has appeared in the first and end of sentences, indicating that the word has the strong ability to distinguish between categories.

In the English language, the first few words of a dialog utterance are very informative of that utterances speech act [22]. This principle applies in the Persian language too. For example, in the Persian language, $\text{Req}$ words usually appear at the beginning of the $\text{Req}$ sentences, such as "لطفا در را بدر کن"/ "Please open the door.". and in some cases appear at the end of the sentence, such as "در را بپز کن لطفا"/ "Open the door, please.". The word "please" is a "requested" word and its position in a sentence is mostly at the beginning or end. Therefore, in each text, the first and end words are...
extracted. If any of these words are found in a dictionary (common words) of one of the SA classes, its binary property is set to 1. Also, in Ques sentences, question words appear at the beginning of the sentence.

In another sentence such as "من از دوستم درخواست کردم تا کتابش را به من بدهد / I asked my friend to give me his book", although the word "ask" (as an SA verb of Req class) appears in the sentence, but the sentence's SA is not Req. In such cases, the word position in the text can be helpful, that is, a word is considered as a base word for SA of Req class when that word appears at the beginning or at the end of the sentence. Thus, the "word position" as a binary feature indicating whether these words appear in the first position or end of the text.

**Extraction of Base Features.** In some cases, the identification of an SA is really difficult. For example, to evaluate the category of Ques SA, consider the following statements:

A. "آیا این کاغذ را می بینی؟ / Do you see this paper?
B. "نظرتان درباره تکاملات قرن بیستم چیست؟ / What is your opinion about the developments of the twentieth century?
C. "ممکنه خواهش کنم به من کمی آب بدهی؟ / May I ask you give me some water?
D. "میشه فردا برین؟ / Is it possible to go tomorrow?
E. "لطفا تلفن تیزیون را روشن کن. / Please turn on the TV.

In the Ques sentences usually appear the question words along with question marks. The first three sentences (i.e., A and B) are expressed with the Ques SA and three next sentences (i.e., C, D, and E) with the Req SA. Statement "A" has a question word, but statement B doesn't contain question words. Thus, the SA type of the statement can be identified by the question mark. On the other hand, the sentences "D" and "E" contain a question mark, but their SA is Req.

To solve this problem, we used two features, including the word position and the base features. For example, in the Req sentences, the first word of the sentence is a Req term, such as "ممکنه"/momkene/May, and the sentence ends with a question mark. In the Persian language, the Ques sentences begin with a question word such as "چرا"/cherâ/why and the sentence ends with a question mark. In question sentences, the first base feature is the question words and the second base feature is the question mark. But Req sentences have only one base feature that is, the Req words. So if the Req words appear at the beginning of the sentence, then the question mark is not considered as the base feature (such as sentence D). So we have six binary features for the base features of each of the six SA classes.

4.3 Create Enrich Dictionary of Features

After pre-processing noisy data and extracting valuable features from training dataset, we intend to create an influential classification system by enriching extracted features. To enrich collected features, we used WordNet ontology as a tool. Each Persian word can have several synonyms. WordNet is a lexical database, which groups nouns, verbs, adjectives and adverbs into sets of synonyms, each expressing a distinct concept. We employed WordNet developed in [20], to find synonyms of given Persian words.
In order to, a vector for each text is derived. Vector elements include features that are obtained using the proposed methods for extracting feature. Thus, a subset $F'$ from $F$ is selected to provide a more efficient description of the documents. To calculate the features weight, we used features frequency in the text.

Classification of text documents involves assigning a text document to a set of pre-defined classes. Since these classes are pre-defined, it is a supervised machine learning task. Therefore, a labeled dataset is needed for training classifier. Let $D = \{D_1, D_2, D_3, \ldots, D_n\}$ be the set of 'n' training document of class $C_j: j = 1,2,3,\ldots,k$ (k denotes number of categories, k=6) and let $W_i^j = \{W_{i1}^j, W_{i2}^j, W_{i3}^j, \ldots, W_{im}^j\}$ be the set of $m$ words of the text document $D_i^j$ of the class $C_j$.

we have extracted all $n \times m$ words of $C_j$ class as distinctive features of SAs to construct dependent dictionary $D_i^j$ of class $C_j$. Therefore, we collected the dictionary of words for each SA class based on their contribution to discriminate an SA from other SAs. The items of dictionary $D_i^j$ are extracted using three feature extraction methods from training dataset of class $C_j$. But since different writers may use different words to express their intention, thus only counting the number of occurrence of different words in the document is not a suitable method to classify documents based on this feature vector.

To resolve this problem, we used WordNet ontology for the Persian language to get synonyms of a word. For this purpose, each word of the text text that does not find an equation for it in the Dictionary of SA classes, it is given to the WordNet. WordNet finds the closest synonyms (Synset) to the given Persian word. If related word suggested by the WordNet appears in the dictionary of SA class $C_j$, In this case, the new word will be added to the dictionary $D_i^j$. Then one binary feature indicates that this word has
appeared in $Dic_j$. Hence, whenever the system determines the SA of a new text, the dictionary of features is developed with new words that their synonyms are in the dictionary.

5 Speech Act in Rumors

Identifying speech act of rumors can have the huge influence in social messaging systems. Since, these systems usually involve the transmission of textual information, can be thought of as a special case of information retrieval.

In this section, we will focus on the application of SA classification in determining the common SAs in rumors. Therefore, first, we need to provide a clear definition of rumors. We define a rumor to an unverified information that is arisen in situations of ambiguity, threat and is spread among users in a network, that these users are attempting to manage risk. According to the research of Computer Emergency Response Team/Coordination Center (CERTCC), five common types of rumors in cyberspace in Iran are as follows:

1. **False news of famous figures:** Perhaps one of the most common rumors in the virtual world is the false news of the death of famous persons and well-known figures. This phenomenon has become widespread in the western countries, and unfortunately, in recent years there has been an increasing trend in Iran, such as news of the deaths of artists, actors, footballers, political figures and so on.

2. **Fake messages with emotional content:** These types of rumors have been common in e-mail services, and have recently been published on social networks. Generally, these messages include content such as helping find a missing child with a request to retype a story that they are trying to spread this fake news by stimulating the audience’s emotions.

3. **Rumors of electoral:** Election issues are one of the most important and most sensitive political issues in society. Because of the importance and sensitivity of the subject and the public’s attention to it, news related to the election is spreading at a great rate, especially on social networks, and stimulates political currents and individuals.

4. **False news about social networks:** Recently, one of the most common rumors on social networks is the creation of suspicion about social networks.

5. **Rumors Related to risks:** This can be considered one of the most influential social phenomena derived from social networks. This phenomenon causes widespread social anxiety and disturbs public opinion and even causes widespread insecurity and distrust to state institutions.

The SA of rumors in first and third types are usually declarative or narrative. The second type of rumors is often expressed by the request SA. The third type of rumors are often expressed by declarative SA, and rumors of the fourth type are often expressed by question SA. The fifth type of rumors are expressed by threat SA.

Based on this evaluation, it is clear that people who create rumors try to persuade people to accept their rumors. To this end, they incite fear and anxiety in the audience. Therefore, these people use narrative, question, threat, and request SAs to achieve their goals. Determining the SA of rumors can play a significant role in the auto-rumor

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1 https://www.certcc.ir/
validation system. In the next section, the results of the experiments show that rumors are often expressed by what type of SAs.

6 Experiments and Discussion

To evaluate the performance of the proposed method for SA recognition, we ran experiments on 6 sets of the labeled dataset by using four different supervised classifiers include: RF, SVM, NB, and KNN. Therefore, we trained these classifiers based on our features. To train the supervised methods, the set of powerful features and 9145 sentences containing different SAs is applied. These sentences are extracted from the Persian corpus by Soltani-Panah [1]. We used K-fold cross-validation methods for training and testing classifiers. Also, to evaluate our system, we used the performance metrics such as precision, recall, and F-measure. Also, we utilized FarsNet as a lexical ontology for the Persian language to extract the synonyms of each word within text. FarsNet is developed by the National Language Processing Laboratory as the first Persian WordNet [20].

6.1 Evaluation Results

The proposed techniques are performed on SA classification two times; the first time, without using WordNet ontology and the second time using FE techniques and WordNet ontology by four classifier RF, SVM, NB, and KNN. Based on best experimental results of the second method (Table 4), the accuracy of Random Forest and SVM as the best classifiers were 0.95, NB as a fast classifier showed a performance of 0.93, the accuracy of KNN as the slow classifier was 0.94. The experimental results of the proposed method for enriching dictionary of features for each SA class and classifying Persian texts based on SA show a great improvement. The accuracy of the proposed method based on classifiers RF and SVM is 0.95.

We also compared the performance of our proposed SA classifier to the only done work on Persian text SA classification by Soltani-Panah et al. [1]. Table 5 shows the results accuracy of our proposed method compared to the Soltani-Panah classifiers. Our classifier outperformed the Soltani-Panah classifiers. Soltani-Panah has encoded all the words in a sentence as an element of each feature vector except functional words such as conjunctions, propositions, numbers, and surnames, etc. But, we utilized set useful features as distinctive characteristics for seven SA classes. Also, by extracting synonym words using WordNet, we were able to develop a set of features in the Dictionary of Speech Action Classes. As with the enrichment of the Dictionary of Features, the system can detect the spoken action of new texts.

The speech act classification by the first method was called FE-SA and by the second method, FE-WN-SA. The results prove that the FE-WN-SA method is effective and efficient in speech act classification.

Figure 4 shows that FE-WN-SA method has a better performance than FE-SA. Therefore, it should be noted that the using of WordNet as a tool for extracting synonyms can have a significant effect on the classification improvement.

As it can be understood from Fig 2., FE-WN-SA method generally has better performance than FE-SA, except in Dir class; the reason behind this is that the WordNet does not contain imperative verbs inherently.

http://farsnet.nlp.sbu.ac.ir/
Table 3. Comparison of the proposed method for SA categorization without using WordNet ontology with four different classifiers.

| Method     | Ques  | Req   | Dir   | Thrt  | Quot  | Decler | Narrtv | Avg   |
|------------|-------|-------|-------|-------|-------|--------|--------|-------|
| Random Forest | 0.93  | 0.917 | 0.918 | 0.891 | 0.73  | 0.996  | 0.941  | 0.903 |
| SVM        | 0.931 | 0.917 | 0.916 | 0.894 | 0.728 | 0.996  | 0.942  | 0.903 |
| NB         | 0.916 | 0.916 | 0.905 | 0.878 | 0.749 | 0.997  | 0.93   | 0.899 |
| KNN        | 0.928 | 0.915 | 0.916 | 0.892 | 0.728 | 0.997  | 0.931  | 0.901 |

Table 4. Comparison of the proposed method for SA categorization using FE techniques and WordNet ontology with four different classifiers.

| Method     | Ques  | Req   | Dir   | Thrt  | Quot  | Decler | Narrtv | Avg   |
|------------|-------|-------|-------|-------|-------|--------|--------|-------|
| Random Forest | 0.957 | 0.957 | 0.919 | 0.985 | 0.851 | 1      | 0.971  | 0.949 |
| SVM        | 0.949 | 0.955 | 0.917 | 0.982 | 0.842 | 0.996  | 0.971  | 0.945 |
| NB         | 0.931 | 0.951 | 0.912 | 0.951 | 0.827 | 0.997  | 0.962  | 0.933 |
| KNN        | 0.947 | 0.951 | 0.918 | 0.967 | 0.801 | 0.997  | 0.967  | 0.935 |

Fig 2. Comparison of F-measure of FE-SA and FE-WN-SA in SA classification

Table 5. Results accuracy of our proposed method compared to the Soltani-Panah classifiers.

| Method       | Soltani-Panah | Our proposed method |
|--------------|----------------|---------------------|
| Random Forest| -              | 0.949               |
| SVM          | -              | 0.945               |
| NB           | 0.739          | 0.933               |
| KNN          | 0.72           | 0.935               |

We improved the performance of our classifier by extracting useful features and referencing to the WordNet to find synonyms for new words. In order to, the F_measure score of classification from 74% (Soltani-Panah's result) to 95% (our result) is
increased. This result demonstrates that the use of FE techniques and WordNet ontology for extending the dictionary of common words in each SA class can be effective in improving the classifier performance.

6.2 Identify SA Class of Rumors

In this paper, we intend to apply the proposed SA classifier to identify the common SAs in Persian rumors. To this end, we collected a set of Telegram posts. Of a few thousand collected Telegram posts, 1975 rumors are verified by trustworthy sources: 882 (45%) were rumor and 1093 (55%) were non-rumors. Since rumors spread in the various fields, such as political, economic, sports, and so on, we requested our annotators to manually label the collected rumors in six categories of political, economic, events, sports, cultural, and health and medicine. In the labeled dataset, events news with 205 rumors (23%) has the largest share. Political news with 186 rumors (21%) is in the next place. Within this timeframe, 154 economic news (17%) and 128 sports news (15%) have been denied. Health and medicine news is at the next place with 114 rumors (13%). Finally, cultural news with 95 rumors (11%) has the lowest share. The classification of rumors in these six categories is due to the fact that the SAs of political rumors can be different from the SAs of cultural rumors or other rumors. To identify the common SAs in rumors, we first need to examine rumors in different domains.

**Fig. 3.** distribution of SAs for each of the five categories of rumors.
Therefore, using the presented classifier for SA classification, we identified SA of 882 labeled rumors in six categories of political, economic, sports, events, cultural and, health and medicine classes separately. The results of the distribution of SAs for each of the six categories of rumors is shown in Fig. 3. Then we calculated the average distribution of SAs on six categories of rumors. Fig. 4 shows the distribution results of SA for rumors.

By analyzing SA of various rumors in Persian language and according to five common rumor categories, which are defined by the CERTCC center; it is possible to determine the common SA of rumors in the Persian language. In order to, we can claim that rumors in the Persian language are often expressed in three SA classes including narrative, question, and threat, and in some cases, with the request SA. These results show that people who make and spread rumors try to express rumors in an exciting, attractive, or threatening way. In order to, they increase the audience’s motivation for distributing rumors. Fig. 5 illustrates the distributions of the speech act types in two categories rumor and non-rumor.

7 Conclusion

In this study, the problem of SA classification is investigated in the Persian language in seven classes. To improve the performance of SA classifier, we utilized the feature extraction methods to extract effective features and also used WordNet to extract
synonym words to enrich the features dictionary. Experimental results prove that the FS methods as the basis for text representation and WordNet as a lexical ontology to extract the synonyms of each word within text, as well as RF and SVM as the best classifiers yielded an accuracy improvement of 0.95 in compared to presented work by Soltani-Panah for SA classification on the Persian language.

We also applied the proposed FS_WN_SA classifier to determine the common SAs in Persian rumors. For this purpose, we first examined rumors in political, economic, events, sports, cultural, and health and medicine categories. Then, using the FS_WN_SA classifier, we identified the SAs of each category. Based on the results of classification in the seven SA classes, it was found that rumors are often expressed in three SA classes, including narrative, question, and threat, and in some cases, with the request SA. Since there is no major difference in expressing the declarative and narrative SAs, so rumor texts are expressed with a relatively similar percentage in these two SA classes. Non-rumors texts are also expressed in declarative SA. On the other hand, since we intend to use discriminating SAs between rumors and non-rumors to identify rumors, so we did not consider the declarative as a common SA in rumors.

As future work, we will use this SA classifier as the basis for rumors verification in the Persian language. Since, the volume of training data plays an important role in learning a model. Training data must be labeled and large enough to cover all the upcoming classes. So, another future work is to use semi-supervised methods for classification.

8 References

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