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Random Walk Modeling for Retrieving Information on Semantic Networking

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Abstract

In this article, the famous random walk model is exploited as a model of stochastic processes to retrieve some specific words which are used in social media by users. By spreading activation on semantic networking, this model can predict the probability of the words' activation, including all probabilities in different steps. In fact, the trend of probability in different steps is shown and the result of two different weights, when the steps tend to infinity is compared. In addition, it is shown that the results of the random walk model are aligned with the experimental psychological tests, showing that, as a model for semantic memory, it is a suitable model for retrieving in social media.

Keywords: Semantic networking, retrieval system, random walk model, spreading activation, social media.

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Introduction

Semantic memory is one of the two types of explicit memory that can organize different kinds of information. The idea of semantic memory was introduced by Tulving and his colleagues [27]. They suggested that the semantic and episodic memories are of distinct forms that can organize different types of information. Hence, in their point of view, long-term memory is divided into periodic and semantic memories, where semantic memory contains information, related to each other.

In fact, the semantic memory is made of some conceptual networks that are communicated to each other. Here, words and their connections are the basis of these networks [14]. By activating some of them, the information related to these semantic units can be activated and retrieved. One of the applications of the semantic networking is representing knowledge structures that can be searched in this semantic networking by using diffusion-based models [4].

Basically, information retrieval is one of the most important research topics in computer science that has attracted the attention of the scientific community. The information retrieval has various applications, such as web search, digital library search, information filtering, recommender systems, social researches, etc.

The main duty of retrieving information is finding relevant and needed information, which is done by creating models based on textual data, and then by querying the information to them which is needed by the user [23, 1]. Hence, to achieve this goal, several models are proposed by experts that some of them are mentioned as follows.

One of these models is titled "vector model". In this model, both queries and related documents are presented as vectors in the space. In this method, one calculates the similarities between the two vectors [21]. Next, we can mention the probabilistic model which is based on the estimation of related documents in a series, where the degree of similarity and conformity of the queries and the documents are measured and shown as a probabilistic phenomenon [19]. Another model is a linguistic model, where the probability of the word sequences in each document are calculated based on their queries [18]. Another approach to retrieval is the inference networks, which is used to infer the relevance between documents and queries [25].

The Boolean model is one of the retrieval models subset, where its weight is assigned based on the presence or the absence of keywords in the documents [20]. The existence of the relationship between queries and documents is determined via using a neural network model based on their weights that are assigned to the links between the queries and documents. The weights are calculated based on the similarity coefficients between them [30].

Retrieval models are based on fuzzy sets, and they work in a way where the queries are calculated based on the degrees of connection to documents. The degrees are shown by similarity coefficients and assigned to those relationships. Sometimes the result of these models is presented as the ranking [15]. Basically, some retrieval systems are used to retrieve relevant documents that show their results as ranking. In these systems, the score of the relationship between the queries and the documents are calculated [22].

One type of retrieval models is the graph-based model that includes several different models, such as random walk model that works based on weight for citation analysis, social networking, and connection structure on the web. The random walk is one of the most famous models of stochastic processes which is invented by Pearson [17]. The random walk is used in a variety of fields such as animal nutrition research [29], neuroscience to study of neural firing dynamic [26], brain decision making [28], the polymer sequences [7], behavioral description of financial markets [3], and etc.

In this article, we try to investigate the random walk model in the field of cognitive linguistics. The spreading activation in semantic networking is one of the long-standing issues in the field of language psychology. Basically, these topics are used in constructing theoretical models for investigating semantic memory. Some different models have been created by various algorithms to search for information. these models are mostly built by the spreading activation methods on the network and their result is shown as a ranking [4].

In this method by activating a node, one activates other nodes, having relation with firstly activated node. Because of the strength of association between these connections, activation spreads out in the whole network. Hence, we will use this concept for building a probabilistic model to estimate the probability of words activation in semantic networking. This model can be applied in the psycholinguistic study of users of social media.

In this article, a random walk model based on co-occurrence weight for semantic memory is proposed. In fact, we try to predict the probability of words activation that users used in their sentences, and generally in the social media.

In section 2, some retrieval graph-based models are introduced, and then in the second 3, the way how one can create semantic networking from the users' comments in social media is explained. In section 4, a random walk model is built to estimate the probability of the words activation in semantic networking as a retrieval system. Finally, the performance of the model in retrieving is to investigate, and the results are discussed in section 5.

2. Graph Based Modeling

The theoretical attitude of using graph theories in the information retrieval return to Minsky's works [12]. In the models based on graphs, the keywords, documents, and authors are considered as the nodes, and their links between them are considered as their connections. Thus, one can search and retrieve the information by studying these networks in the same way.

Many different forms of models based on the graph are used by connectionists that we refer to some of them such as neural network, spreading activation models, associative networks, ontologies, and etc. [6]. One of the first networks presented in this way is the Hopfield network. This model is suitable for information processing modeling. In this model, the information is stored in the network layers where neurons are used as the nodes and the weights as the synapses in communication between these neurons. In this method, retrieving is done when the nodes are activated in the parallel mode until the network converges to a steady-state [9].

Another connectionist model which is applicable in the information retrieval is the Belew's model. This model consists of a network with three layers of authors, the term Index, and documents. In this model, users give feedback to the system for making a change in displaying the authors, term Index, and documents in the repeating periods, and the learning process is done according to this procedure [2]. Paggain Brain proposed a computational model for ranking the vectors that use a random walk model to rank the web pages. In this model web, pages are nodes and edges are web page references.

Graph-based algorithms, such as page ranking, are used to reference analytics, social networking, and web structural analysis. In general, graph-based algorithms are used to determine important vectors. They are also used to extract information from the text, e.g. summarizing, classifying, extracting keywords, and determining the sense of words [13, 16].

3. Semantic Networking

To have a random walk model, first of all, semantic networking from users' expressions and sentences is needed. Hence, we extract user's comments randomly from social media such as Instagram, and then we can create semantic networking based on the words that are used in comments by users. To create semantic networking, it is necessary to consider the words in comments as the nodes that are connected by edges together, and then assign weights to the edges based on the frequency of words co-occurrences in a phrase. In fact, the relationship between two nodes depends on the two words were used by users in their comments.

In retrieval models, weights are usually calculated based on the frequency of the co-occurrence words in a window with 2 to 40 words. In this study, a window with two words is determined and a relationship between all of them is created. The weight on the edges is calculated based on the frequency of words co-occurrences in each comment. The calculated weight are assigned to the desired edge via the following relation,

$$W_{ij} = \frac{f(t_i.t_j)}{f(t_i) + f(t_j) - f(t_i.t_j)}, \tag{1}$$

where, W_{ij} is the weight between n_i and n_j, as the nodes that are connected by an edge to each other. $f(t_i.t_j)$ represents the number of times that two words were used together by users in the comments. Also, $f(t_i)$ and $f(t_j)$ represent the number of frequencies of the words i and j in the intended context.

4. Random Walk Model

Among all different types of random walk models, the Markov chain is the most common type which is used in information retrieval. The Markov chain is a mathematical system that is based on the probability of moving on a set of states. In fact, probability of moving on the nodes, based on matrix and numbers inside matrix are the calculated weights which are assigned to the edges that connect the nodes, which is indicated here by $P(i|j)$, as the probability of moving from node i to node j. Considering the vector, $p \in R^n$, one can express $p^{(0)}$ and $p^{(t)}$ as the initial probability distribution and distribution in step t. Thus, the probability distribution of a set of nodes can be calculated in the same way. Equation (2) shows how to calculate the probability distribution in step t [24].

$$p^{(t)} = p^{(t-1)}W = p^{(t)}W^t. \tag{2}$$

Therefore, the weight in the random walk is imposed as a matrix, emphasizing that the weight should be normalized for the corresponding edges between two nodes, which is defined by Craswell and Zsummer as follows [5].

$$P_{t+1(k|j)} = \frac{C_{jk}}{\sum_i C_{ji}}.$$

$p^{(t)}$ is the probability distribution in the step t, that can be calculated by multiplying the matrices for t times. The fundamental theorem of the Markov Chain proves that probability distribution at long term converges to a particular vector, represented by π. In the matrix mode, $\pi p = \pi$, where p is considered as the transition matrix. Since the value of this distribution no longer changes and remains constant, it is called as stationary distribution. In fact, one can say that the stationary distribution is obtained when t tends to infinity [10].

Another kind of weight that is applied to the random walk model is the maximum degree of the neighbor nodes. It means that the activation propagates from the initial node to the node, having the highest degree, compared to the other neighbors. The probability of activation is P_{ij} that is calculated based on $d_{ji}/\sum_{j\in\tau(i)} d_j d_i$, where $\tau(i)$ denotes all connections of the node i, and its stationary distribution calculated when t tends to the infinity [31].

When propagation is happened, by activating a word as an input word, or cue word, or stimulus word, the probability of response words will be achieved. The words which have a direct relationship with input word are activated in the first step, and other words which have an indirect relationship with the input word are activated in the next steps.

One of the goals of this article is to estimate the probability of words, which are used by the users in the social media, where we can propose a recommender system, based on a cognitive concept as semantic networking. In addition, it is intended to estimate the probability of the usage of a word in the verbal context. As a consequence, one can understand that if it is possible to estimate the probability of a word activation in the verbal context, using the connections of the words shows the importance of a word. This can be done by constructing a semantic network and then by using the random walk model according to the co-occurrence weight and the weight of degree.

One should note that this model is based on the semantic networking of the users in the social media, and the word activation predictions are the methods which they used in social media. To achieve this goal, the following procedure is followed. First, 1000 comments of users are extracted, and semantic networking based on the extracted information is made, exploiting the procedures mentioned in part 4. Then, the random walk model which is established according to the mathematical relations in section 5 is applied to semantic networking. Finally, the word activation model in different steps, based on the distribution in the probability network, is obtained, and the final distribution of each word, based on both co-occurrence and degree weights, is also found.

5. Case Study

Here, one word is considered as the input, and the probability of the other words are obtained, as it is shown in table 1. The word "*Sentimental*" was chosen randomly as an input, the probability of activation of the other words as the response is calculated. A few words are selected randomly for analysis, listed in table 1. In this article, the user's comments in Persian are investigated. The reader can find the original Persian equivalent of the words, which all are single words, in table 2 in Appendix A.

In the column titled **Wgt.** (i.e. the weight), words with zero value does not have direct relation to the input word, and the words with the numerical values have directly relation to the input words. Steps of **1**, **2**, **3**, **5**, **20**, and **100** are calculated for each of these words, based on the random walk model, and are listed in table 1, titled as **step**. In addition, the degree of each node that is the number of nodes connection and stationary distribution of those words based on degree and weight are listed with titles of **Degree**, **simple str**, and **str** respectively in Table 1.

Table 1: Numerical values of steps, weight, degree, stationary distribution based on degree and weight. The numbers indicated in the Steps, str. and Simple str. columns are all of the order of 10^{-5}.

SD	Step 1	Step 2	Step 3	Step 5	Step 20	Step 100	Wgt.	Deg.	Simple str.	str.
Permission	0	0	1.71	7.94	44.6	48.5	0	165	209	7.94
Music	0	226.8	332.3	376.9	93.5	48.6	0	11	13.9	1015.86
Violence	0	22.2	35.3	48.6	48.1	48.5	0	59	74.7	1262.85
Your Popularity	0	5.17	11	21.5	48.3	48.5	0	98	124.2	168.05
Married	0	2.48	5.41	11.4	38.8	48.5	0	210	266.1	353.55
Hijab	0	6.03	11	19.2	43.3	48.5	0	120	266.1	353.55
Their Master	0	74.4	124.3	174.6	88.3	48.5	0	10	12.7	597.07
Army	0	0	39.9	124	91.5	48.5	0	2	2.53	14445.31
Gentlemen	3637.7	2760.2	2215.9	1436.2	111.7	48.5	0.33	36	45.6	45.6
They Say	2328.8	1835	1504.5	1012.1	97.6	48.5	0.25	52	65.9	743.94
Iranians	857.2	688.8	562.3	383.2	70.2	48.5	0.25	134	169.8	657.75
You	187.3	172.7	151.3	117.8	53	48.5	0.76	496	624.4	791.11
People	594.5	494.3	408.3	284.2	61.9	48.5	0.14	183	231.8	613.7

Based on the weight, the probability of the words, which are retrieved at the various steps is different. It depends on the issue that the relevant words are directly connected to the input word or not. Figure 1 shows the trend probability of the words that are not related directly to the input word. Hence, all of them are zero in **step 1**, and the probability of retrieving increases in the next step and from one point to the next steps, a decreasing trend is observed. Their value depends on edges' weights, which in some words can be more or less than the others. In **step 100**, all probabilities converge to a number.

Figure 2 shows the probabilities of the words that have a direct connection to the input word. The trend probability of the words is descending. It means that probability based on edges' weight in the first step are high and gradually decrease in the next steps until they converge to a number in **step 100**.

Due to the difference in the weights and subsequent probabilities of the retrieved words, to determine the probability of the trend in a better way, we calculate the average of the probabilities in each step. The probabilistic mean of the words in different steps is shown in Figure 3. In fact, in the first step, the average probability of retrieved words as a response is much higher, and in the next steps, the average probability of retrieved words is decreased.

The mean values of the stationary distribution each word in the semantic networking is based on weight by the title of **M str** are calculated separately and shown in Figure 3. The mean of the stationary distribution, based on degree,

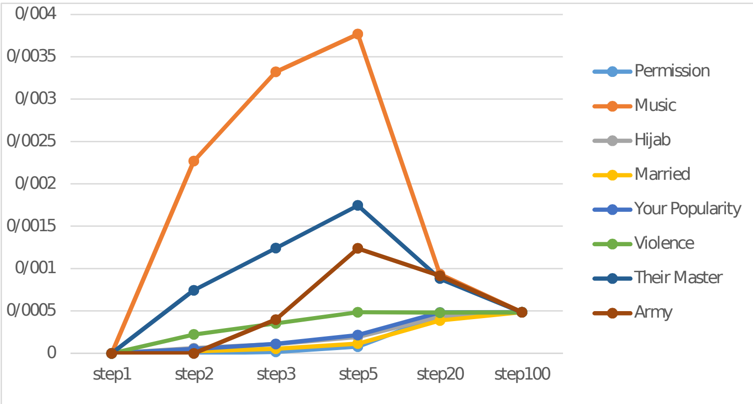

Figure 1: Probability of the words which have indirect connections with the input word.

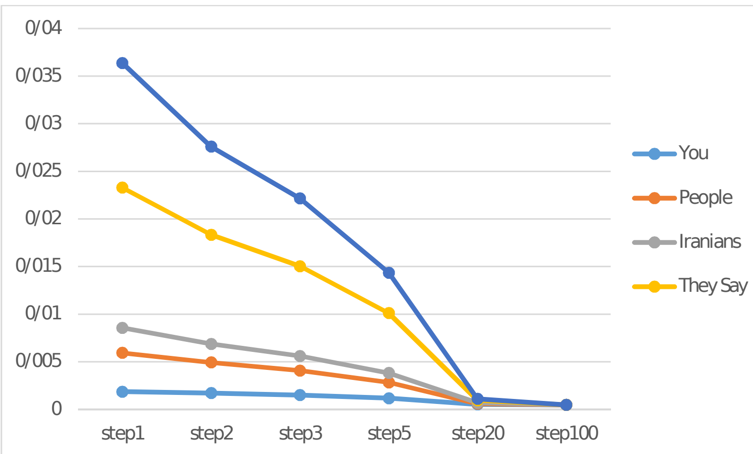

Figure 2: Probability of the words which have direct connections with the input word.

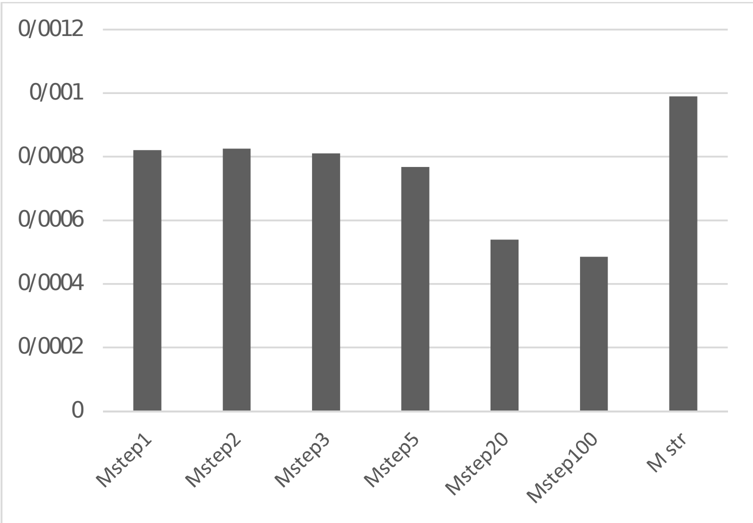

Figure 3: Mean of steps probability.

titled **M s str** is shown in Figure 4, which is a comparison between two probabilistic means of the stationary distribution based on co-occurrence weight and the degree. The figure shows that the mean of the stationary distribution of words based on the degree is higher than the stationary distribution of words based on co-occurrence weight.

To determine the relationship between the retrieval probability of the words with each other in different steps and the weight, we use the correlation matrix, which is shown in Figure 5. p-value $\leqslant 0.01$ is considered significant in this correlation matrix.

According to the Equation (1) which is proposed for weight, it is observed that when the number of steps is increased, the correlation with weight will be decreased. This means that the correlation coefficient with weight in step 1 is higher than step 100. Also, the correlation coefficient of step 1 in comparison to step 2 is higher than the correlation coefficient of step 1 in comparison to step 100. This issue is true for the steps where their step numbers are close to each other.

Regarding the stationary distribution, no correlation between steps and weight is observed. Perhaps, this is due to the enormous change in probability values of stationary distribution, compared to other parameters when the steps tend to infinity. However, a high correlation is observed between the degree of each node and the simple stationary distribution. Another point to mention is that there is a negative correlation between the degree of each node and steps, which is true for

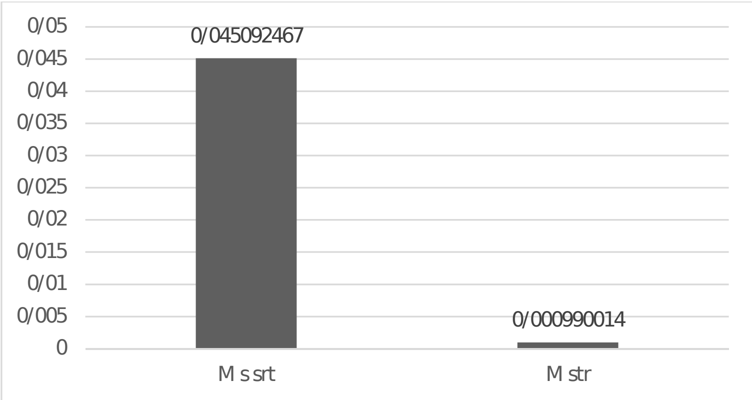

Figure 4: Stationary distribution based on degree vs. co-occurrence weight.

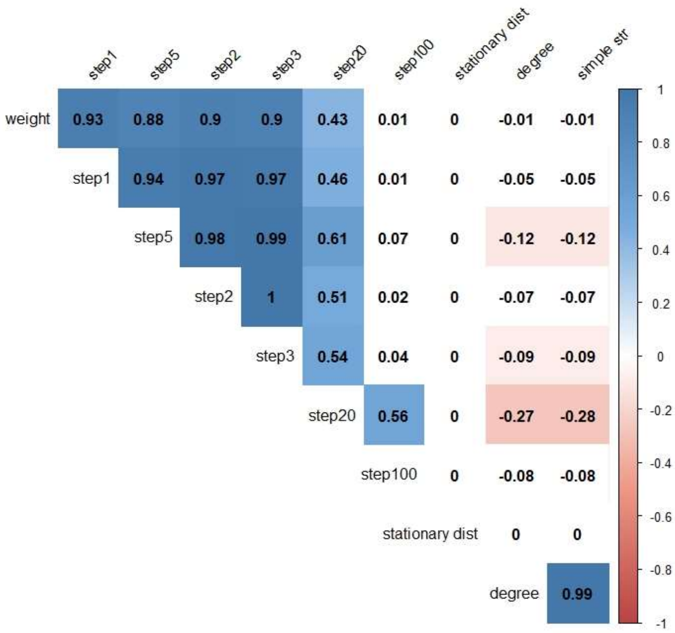

Figure 5: Correlation matrix coefficients.

the stationary distribution based on degree.

6. Discussion

In this article, a random model on semantic associative networking is applied. Then, by activating a word, the probability of retrieving other words in that semantic context is estimated. This is a model of semantic memory to predict the probability of words activation, used in social media. In fact, the semantic networking from expressions and sentences which were used by users in social media is made. Thus, one can say that this semantic networking is a large network, consists of smaller semantic networks, which users have in their semantic memory.

The results show that there are two types of data in this model. One is the words that have a direct connection with the input word. It means that the input word has co-occurrence with them, and another is the group of the other words that do not have a direct connection. In fact, they have a connection to input words via other words.

Another important parameter is the association with the input word, which is expressed by weight. Weight indicates the power of the words association. On the other hand, the weight indicates strength or the weakness of the word's connection in semantic networking.

According to Figure 5 and correlation over of 90% in steps 1 to 100, one can say that the model is achieved to its purpose, i.e. calculating the retrieval probability based on co-occurrence weight. Thus, based on the random walk model one could predict the activation probability of the words in a social media which users used to comment.

Therefore, depending on the type of application one can use different steps of the random walk model to calculate the probability of retrieving the words in the comments of users in social media. For example, if someone wants to calculate the activation probability of the words that are directly related to the input word we can use step 1, and to calculate retrieval probability of the words that have connection with input word by one intermediate one can use step 2, and as the same way, one may use other steps until the probabilities converge to a number.

This model is useful to estimate the activation probabilities of the words that have an indirect relation with input words. Thus, using this model, this question can be answered how many intermediates should be activated before the activation of the specific word, and what would be its probability?

After some steps, the activation probability of the words converges to a number. It means the probability of all words that are activated in the semantic networking will be the same. In this study after 95 steps, the probability of all the words converges to 0.000485. Hence, practically after 95 times of movement across the semantic networking, or after 95 times spreading activation in the semantic networking, the activation probability of all words being the same.

Actually, it can occur in a semantic memory of people. In the memory tasks, such as associative semantic task, after repeating cues and responding sequentially, the probability of retrieving the responses get closer until all of them become equal [11]. This result is matched to the Hebb repetition effect, where retrieval performance is improved when the list is repeated during a serial-recall [8]. Thus, by this model, we can determine that after how many times of repetition, all the words get an equal probability.

Another benefit of this model is that one can predict the activation probability of the different words by a particular word that is used by users in social media after being repeated several times. Perhaps, it could be useful for psycholinguistic studies. Since the probability of neighboring words in a network affects each other, it is possible to calculate the activation probability of specific words, considering this issue that the words have a direct or indirect connection to the input word.

Another point of this model is that in the first step, all of the words are retrieved, where one can say the accuracy of this retrieval system is 100% in the first step. According to figure 3, the mean of probabilities until the fifth step does not have any significant changes, while at the higher steps, this value is reduced. Hence, as the information retrieval system, the initial step is more appropriate to estimate the probability of words in semantic networking.

Another topic, discussed in this article is the probability of words activation based on the number of the links where the words have, or the degree of the nodes in the network. To do this, it is necessary to calculate the weight, based on two nodes that are connected. Then, we created a random walk model and calculated the stationary distribution of each word. Because of the high correlation of degree with simple stationary distribution, one can say that this model can estimate the probability of words activation based on their connection with other words.

7. Conclusion

In this article, it has been shown that the random walk model can estimate the probability of each word based on the input in different steps. Also, it estimates the stationary distribution probability of the words in the semantic networking without considering word-to-word interactions. By random walk model, one could achieve stationary distribution, based on the degree values that show the importance of nodes. One should note that in retrieval systems, different models are represented, and are used for different purposes, such as clustering and similarity determination. But here, we built a random walk model, based on the weights, to predict the activation probability of the words in semantic networking as a suitable approach for social psycholinguistic studies.

Appendix A

As we mentioned before, we used the comments of Iranian users of specific social media. Here, we present the Persian words which are used for this research and their English equivalents. As it is indicated previously, one can see that all Persian words are single words, which is vital for this model.

Table 2. Single words in user's comments in English and their Persian equivalents.

Permission	Music	Violence	Your Popularity	Married	Hijab
اجازه	آهنگ	خشونت	محبوبیتتون	متاهل	حجاب
Their Master	Army	Gentlemen	They Say	Iranians	You
اربابانشون	ارتش	آقایان	میگن	ایرانیان	شما

Confilcts of Interest. The authors declare that there are no conflicts of interest regarding the publication of this paper.

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