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Comparison of Two Defuzzification Methods of Mean of Max and Central Average in Morphology of Composition Functions in Persian Sentences

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Abstract

Morphology has a special place in any language, including written and spoken applications. Markov method is used to labeling and determine the role of words. Emergence in software sciences has eliminated 0 and 1 computations, putting them within an infinite space of between 0, 1. This characteristic of fuzzy logic has resolved ambiguity in numerous previous problems. The sentence roles in Persian language were specified based on the fuzzy logic's capability to resolve ambiguity. In two defuzzification methods Mean of Max, Central Average, the role of words in the sentence is identified and the success rate of each method is obtained. Finally, Mean of Max with a success rate of 64% proved to be a defuzzifier delivering the best output among two different defuzzification methods.

Keywords: *Role, Defuzzifier, Morphology, Persian Sentences*

1. Introduction

Morphology in any language has a special place according to written applications such as automatic translation and summarization and speech applications such as speech to text conversion, auto responder… Statistical methods are also one of the most widely used morphology methods. In the first stage, different types of sentence structure were extracted by several Persian language and literature experts as well as Persian grammar textbooks studied in Iranian high schools [1]. In the next stage, Microsoft Office Excel 2013 was used for statistical labeling on sentences extracted in the first stage and words derived from Pars Process sentence analyzer software [2], Bijankhan Corpus [3], verb bank of Persian Language Database 3.0, and Encyclopedia of Names and Naming by National Organization for Civil Registration. The results were adopted to train the newly proposed fuzzy system. Markov method is used to labeling and determine the role of words. In this research, using two defuzzification methods, the role of words in the sentence is identified and the results of each method are evaluated together.

2. Literature Review

Morphology is a branch of linguistics that aims to describe the structure of words and the patterns of word formation in a language.

Construction Morphology refers to a theory examining the structure of words through the concepts of "decomposition and composition" [5, 6]. In this paper, the morphological structure of sentences and words was examined based on analysis of the relationships between words and letters [4].The modern methods of semantic analysis have emerged in the USA, including FrameNet by Palmer et al., 2005 [10] and PropBank Baker et al., 1998 [11].

Terminological studies have been conducted in other languages, such as Spanish (Subirats and Petruck, 2003 [12]), Japanese (Ohara et al., 2004 [13]), Dutch (Moortgat et al., 2000 [14]), Urdu (Mukund et al. 2010 [7]) and German (Burchardt et al., 2006 [15]). These studies yielded impressive results, where output products developed in several versions [16]. One of the major projects in this area of research is known as EuroWordNet, involving a multilingual database and several European languages (Dutch, Italian, Spanish, German, French, Czech and Estonian) [17]. Basic works in semantic linguistics were initiated by Fillmore back in 1968 [18, 19]. Despite large lists of specific roles obtained by Fillmore and Ruppenhofer, Baker (2004) [20], and a small set of key roles by Jackendoff (1990) [21], there is still no definitive list of semantic roles [8, 9]. In identification of main semantic roles, only Dowty (1991) [22] studied two roles. However,the most important computational theories about main roles can be found in studies by Fillmore (1968) [18], Jackendoff (1990) [22] and Dowty (1991) [16]. These results have obtain in new search by Ray (2020). Grammar checking is one of the most widely used techniques within natural language processing (NLP) applications. Grammar checkers check the grammatical structure of sentences based on morphological and syntactic processing. These two steps are important parts of any natural language processing systems. Morphological processing is the step where both lexical words (parts-ofspeech) and non-word tokens (punctuation marks, made-up words, acronyms, etc.) are analyzed into their components.[5] Deyoung in 2020 used deep neural networks. State-of-the-art models in NLP are now predominantly based on deep neural networks that are opaque in terms of how they come to make predictions. This limitation has increased interest in designing more interpretable deep models for NLP that reveal the `reasoning' behind model outputs. But work in this direction has been conducted on different datasets and tasks with correspondingly unique aims and metrics; this makes it difficult to track progress. [11]

Upon arrival of the 21st century, medium and large corpora manually adopted semantic roles to develop a statistical method for labeling in FrameNet research by Fillmore, Ruppenhofer and Baker (2004) [20], PropBank by Palmer, Gildea and Kingsbury (2005) [10] and in NomBank by Meyers et al. (2004) [23] [8]. In recent studies, Silva et al. (2016) [24] classified the semantic roles of words, while Rastle et al. (2008) [25] identified roles by splitting words into their original components.

In the scope of Persian language, Web Technology Lab (Ferdowsi University of Mashhad) [26], a summarization system in 2012 known as Ijaz, in addition to several other NLP tools in Persian developed [29]. Dr. Mahmood Bijankhan in 2004 created a text corpus called Bijankhan in Persian. From 1995 until today, Bijankhan has been conducting extensive research in the Persian language corpora, speech recognition and other NLP areas. Dr. Shamsfard et al. developed a new system known as "Hasti", which extracts lexical and semantic data from Persian texts [30]. S. M. Assi and H. Abdolhosseini in 2000 [32], to determine the grammatical categories of words in continuous Persian texts through mathematical and statistical measures generally known as Distributional Partof-Speech Tagging [33]. Najmeh Nouri in 2013 designed a tool for semantic labeling of Persian sentences [34]. Motameni and Peikar in 2016 adopted a fuzzy system to determine the role of words [35].

3. Relevant Literature

This section discusses the definitions of five influential terms in this research including fuzzy system, classification, morphology, independent functions and dependent functions.

3.1 Morphology

Morphology has been given different definitions. One common definition is "a compositional study of morphemes and their functions in words." The science of language study, i.e. linguistics, is a special field of language. Meanwhile, computational linguistics is an important field of linguistics emerging as ICT is introduced in human life. At the same time, computational linguistics is a fundamental element of data mining, which is considered a sub discipline of artificial intelligence. Therefore, the present study can be regarded as an artificial intelligence study. Morphology in every language has its own procedures, because grammar, alphabet, phonemes and discourses vary in each language. For example, linguistics in English is different from those in Persian and Arabic [45–47].

3.2 Markov Approach modeling

In 1906 (Andrei Andreyevich; Markov, 1856–1922) began studies of a new type of random processes. In these processes, the result of one experiment affects the result of the next.
This type of process is called a "Markov chain".

Hidden Markov Model was introduced to the world in the second half of the 1960s in a series of articles by Leonard E. Baum. HMM is also defined as a way to model random processes. It means; Not only can the outcome not be predicted, but also the type of event and the probability of its occurrence must be inferred from the available parameters. HMM was used in terminology in the early 1980s.

3.3 N-gram

One of the methods used in this paper is known as N_gram statistical labeling (Uni_gram and Bi_gram). This labeling method is regarded as one of the most widely adopted statistical terminological methods. The output of N_gram labeling will be matrices used in fuzzy computations [47]. This leading method falls under the category of forward as opposed to backward. This implies that the method was assessed based on the preceding letters of each letter or the preceding words of each word. Equation (1) provides an overview of N_gram labeling computations. Depending on the type of statistical task, Equation (1) may be implemented on letters, words or sentences.

$$P(w_1^n) = \prod_{k=1}^{n} P(w_k \mid w_{k-N+1}^{k-1})$$

Equation 1: N_gram Labeling

In Equation (1), the variable k is the order of N_gram. [27, 28, 30]

3.4 Fuzzy system

In the Oxford dictionary, fuzzy is defined as "ambiguous, blurry, confused, and unclear." This definition can be extended to "fuzzy systems describe unspecified, imprecise and non-deterministic phenomena." And this does not imply that theory itself is imprecise, but as a matter of fact, the fuzzy theory itself is precise [6, 38]. The fuzzy system can be regarded as a convertor of expert knowledge into mathematical formula. Hence, every fuzzy system is based on information, knowledge and rules. This knowledge base can be considered the kernel of fuzzy system. The knowledge base is often made of "if à then" rules. For example, in the Persian sentence ""/ "Hava roz garm ast"/ "Weather is hot today." If the word parts of speech are "noun, noun, adjective, verb", then one of the modes of word functions of the input sentence will be "subject, complement, adverb and verb". [6, 39–41].

Each fuzzy system consists of four components: • Fuzzifier: The fuzzifier module converts the system's numerical inputs into fuzzy sets. • Fuzzy rules base: It stores the "if-then" com- mands created by experts. • Fuzzy inference engine: It simulates the human argumentative process through fuzzy conclusions of inputs and conditional commands. • Defuzzifier: It converts the fuzzy set obtained by inference engine into a numerical value. • In fuzzy logic, the validity of any entity is relative or approximate, i.e. humans are only able to make a decision as an intermediate state [39–44].

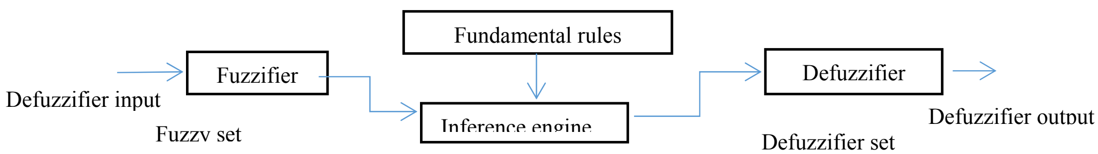

Figure 1- Fuzzy System

In this paper, the two Defuzzifier Mean Of Max and Central Average are evaluated together. [45]

4. Proposed Terminological Method

The input of this system is Persian language sentences. In Persian sentences, words are of two categories: type and role. First, the type, role and symbols used in this research are shown in Table 1.Then, with the Uni_gram and Bi_gram methods of HMM, sentence labeling is performed.

Then the success rate of each Defuzzifier method is calculated to identify the roles.

Table 1 - type, role and symbols used in this research

No.	category	Type /Role	symbol	No.	category	Type /Role	symbol
1	Verb	Type	F	12	Adverb	Role	G
2	name	Type	C	13	adjective	Role	S
3	infinitive	Type	E	14	noun	Role	L
4	Adjective	Type	K	15	apposition	Role	O
5	Pronoun	Type	T	16	governing transducer	Role	P
6	Letter	Type	H	17	Genitive	Role	N
7	Pseudo-sentence	Type	B	18	Governing genitive	Role	M
8	predicate	Role	D	19	Bending	Role	Q
9	subject	Role	A	20	Retroactive	Role	R
10	Object	Role	I	21	exclamation	Role	U
11	complement	Role	J	22	annunciator	Role	V

4.1 State transition matrix

For fuzzy calculations and labeling the roles in this section, two matrices are calculated:

4.1.1 Probability of role substitution in type (Transfer)

This matrix was obtained by initial computations delivering the "probability of occurrence" for each independent/dependent role in each type. At first, we extracted roles and types for 194 types of training phrasing compositions. Then, the total number of role substitutions in types was obtained, followed by examining each specific role in terms of how many roles there are in each type. Finally, the value of each substitution was calculated through Equation (2).

$$P_{\text{transfer}}(\text{Probability of role substitution in type}) = \frac{\text{Number of each role}}{\text{Total number of role presence}}$$

Equation 2: Average presence of each role in each type

The computational output of Equation (2) is a 10×21 matrix. In this regard, 10 is the number of words in decomposition while 21 is the total number of independent + dependent + spacing characters "؛' + "!common roles between decomposition and composition). Given Equation (2), it is clearly understood that the values are fuzzy.

One example for 4 different phrasing modes with inputs "من کتاب را خواندم." , meaning I read the book. This was one input sentence "pronoun, noun, marker, verb" as the type of words, while the other input to the system has been displayed in Table (2).

Table (2): Calculation procedure for each possible phrasing mode according to Equation (2)

No.	Mode	Occurrence value
1	Subject → Object→Marker→Verb.	Pronoun→Subject=0. 78, Noun→Object=0.66, Marker→Marker=1, Verb→Verb=1
2	Predicate→Object→Marker →Verb.	Pronoun→ Predicate =0. 65, Noun→Object=0.66, Marker→Marker=1, Verb→Verb=1
3	Object→Object →Marker→Verb.	Pronoun→ Object =0. 58, Noun→Object=0.66, Marker→Marker=1, Verb→Verb=1
4	Complement→Object→Marker→Verb	Pronoun→ Complement =0. 03, Noun→Object=0.66, Marker→Marker=1, Verb→Verb=1

The values in Table (2) are hypothetical only illustrating the stages and computational procedure. The matrix derived from this stage can somehow be considered Uni_gram because computations are not dependent on previous/next roles.

4.1.2 Additional roles appearing after each role in sentences. (Composition_Role)

This 21×21, 2D matrix is equivalent to the number of sentence roles in Persian + spacing characters. In fact, the statistical computations specified the frequency of a specific role. The total number of presence frequencies for all roles following a specific role were obtained, while calculating average values through Equation (3).

$$1 < i < 21\ ,\ 1 < j < 21$$

$$P_{\text{Composition\_Role}}(\mathrm{i,j}) \;=\; \frac{\text{Possibility of presence for role i after role j}}{\text{Possibility of presence for roles i after 22 roles}}$$

Equation (3): Average presence of each role after another role

In fact, this Bi_gram matrix adopts a forward approach and views roles as forward. Table (3) provides the main roles.

Table (3)- Part Of Composition_Role Matrix For Basic Role

	A	**C**	**D**	**I**	**J**
A	0.14	0	0	0.11	0
C	0	0.03	0.60	0.10	0
D	0	0	0.13	0	0
I	0	0	0	0.27	0.02
J	0	0	0.02	0.04	0.19

As shown in Table (3) and Equation (3), the values of Composition_role matrix are all fuzzy falling within [0, 1].

4.2 Probability distribution of observations (Len_Word)

Firstly, Equation (4) obtained the presence probability of each letter and the next letter in the training sentences and words. The output of this 44×44, 2D matrix to a total of "ضطظعغفقکگلمنوهیئیةؤإأءهٔآ ابپتثجچحخدذرزژسشص" (including the Persian alphabet letters, both isolated and medial) as well as a few characters used in multi-component words including spacing character and other signs and characters in Persian texts.

$$1 < i < 44\ ,\ 1 < i < 44$$

$$P_{\text{char-word}}(\mathrm{i,j}) \;=\; \frac{\text{Possibility of presence for letter j after letter i}}{\text{Possibility of presence for letter i after 44 letters}}$$

Equation (4): Average presence of each role in each type

A 44×44 matrix yields 4 independent roles and 12 dependent roles, a total of 16, to be included in computations of next Stage. After obtaining the values for Bi_gram matrix expressed in Equation (4), we achieved word weights for each input through conversion of Equation (1) to Bi_gram based on Equation (5). Table (5) provides the Bi_gram computation procedure for Equation (5).

$$Len\_Word(w_1^m) = \prod_{k=1}^{n-1} p(\text{letterk followed by letterK} + 1)$$

Equation (5): Bi_gram Labeling for each input word.

In Equation (5), the weight of each word is computed through Bi_gram labeling. It is worth noting that Equation (5) covers only one word. For all words in each input sentence, a matrix was obtained with a length equivalent to the number of words in input sentence × 21). Therefore, the number of words and letters were represented by n and m, respectively. As described above, 21 indicates the total number of the roles in the Persian grammar and spacing characters.

For example, if the input sentence is ".من کتاب را خواندم" and the sentence mode is "subject, object, marker, verb", Table (4) provides the computations with hypothetical values according to Equation (5) and Equation (5).

Table (4): Len_Word computational procedure for a 4-word, 4-role sentence

No.	Word	Role	Computations	Value
1	من	Subject	"م" ← "ن"	0.86
2	کتاب	Object	"ک"←"ت"×"ت"←"ا"×"ا"←"ب"	0.78
3	را	marker		1
4	خواندم	Verb		1

In Table (4), the value of 1 is considered for computations in rows 3 and 4 are not performed since they are shared between type and role.

4.3 Calculate the output and Viterbi algorithm

In the main roles, computations rely on the number of matrices achieved according to input sentence 9 تعداد کلمات جمله ورودی , where 9 drives from 2 common roles of "marker and verb", 5 main roles and 3 spacing characters. In the dependent roles, the number of matrices changes to 17, which is a sum of 11 dependent roles + 1- word role without unknown dependent role + 3 spacing characters + 2 common roles of "marker and verb" shared between decomposition and composition. The number of possible modes is calculated according to the values of state transfer matrices and the probability distribution of observations by Markov's secret modeling method.

The largest value is obtained with the Viterbi algorithm. The Viterbi algorithm (maximum possible state algorithm) is shown in Figure 2. This algorithm has three steps that the main part of this algorithm calculates the largest possible probability.[27,36]

//Given a sentence of length n
//Initialization
$\delta_1(SOS) = 1.0$
$\delta_1(t) = 0.0$ for $t \neq SOS$
//Induction
for i=1 to n do
  for all tags t^j do
    $\delta_{i+1}(t^j) = \max_{1 \le k \le T}\left[\delta_i(t^k) \times P(t^j \mid t^k) \times P(w_{i+1} \mid t^j)\right]$
    $\psi_{i+1}(t^j) = \arg\max_{1 \le k \le T}\left[\delta_i(t^k) \times P(t^j \mid t^k) \times P(w_{i+1} \mid t^j)\right]$
  end
end
//Termination and path extraction
$X_{n+1} = \arg\max_{1 \le j \le T} \delta_{n+1}(t^j)$
for j=n to 1 step -1 do
  $X_j = \psi_{j+1}(X_{j+1})$
end
$P(X_1, \ldots, X_n) = \max_{i \le j \le T} \delta_{n+1}(t^j)$

Fiqure 2. Viterbi Algorithm

4.4 Initial fuzzy computations

The fuzzy computations are implemented after labeling the effective components in adoption of each sentence role in Persian. In this stage, we first achieve the success values for each of three matrices in two defuzzifiers: central average, and mean of max.

Equation (6) is adopted to obtain the average success rate of each role in the initial fuzzy computing section or the main fuzzy computations.

$$\text{Success rate of each role } = \frac{\text{Correct number found in each role}}{\text{Total number of that role}} \times 100$$

Equation 6: Overall success rate/success rate of each role

Equation 6 involves the total number of each role in 73 input sentences previously extracted based on opinions of Persian grammar experts [1]. Moreover, the correct number is obtained based a role in a specific matrix or specific defuzzifier. Equation (7) is employed to extract the total weighted average in the initial fuzzy computation or main fuzzy computation stages.

$$\begin{aligned}&\text{All roles/dependent/intendent roles}\\ &\quad = \frac{\text{Correct number found in all roles/dependent/independent}}{\text{Total number of all roles/dependent/indepen}t}\\ &\quad \times 100\end{aligned}$$

Equation 7: Average or weighted percentage of all roles/independent roles/dependent roles

Equation (7) provides a general formula to obtain the weighted average in independent roles, dependent roles and/or all roles together. In Equation (9), we first achieved the total sum of independent and dependent roles in all 73 input sentences. Then, we obtained the total numbers found in the method in each roles through the specific defuzzification method and in the specific matrix. These were arranged as denominator and numerator of Equation (9), respectively. If the weighted average of dependent/independent roles is considered, then not all roles are included. In the overall set, or the total sum obtained in the specific matrix and defuzzifier, only the sum of those roles is obtained.

4.4.1 Mean Of max

This defuzzifier makes decisions based on the mean of maximums. The generalized computational expression of this defuzzifier can be found Equation (8).

$$h(B') = \{y\epsilon V \mid \mu B'(y) = sup y \epsilon V \mu B'(y)\} \qquad a = (xi + xj)/2$$

Equation (8): How to obtain the average maximums

In the initial line of Equation (13), the maximums are first obtained, and then the maximum with lowest rank as x_j, highest rank as x_j and average of the two in the second line is sent as a solution. Therefore, this defuzzifier operates in occasions different from Largest Max and Smallest Of Max, where there are several maximums for words in the matrix. Prior to deciding on the sequence of matrices according to their importance in Mean Of Max, it is necessary to obtain the weighted average of all roles. According to Equation (9), the overall success rates of each matrix in the defuzzifier with the mean of maximums have been given in Chart (4). [43, 42]

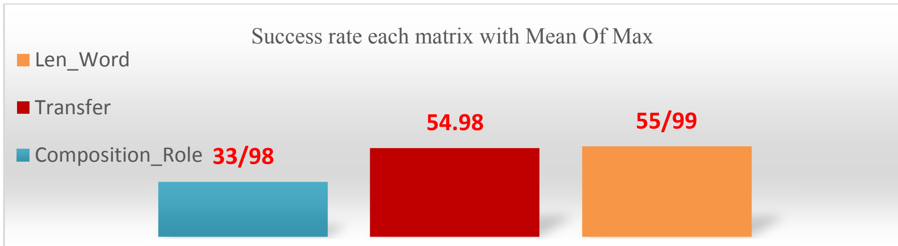

Chart (1): Overall success rate of each matrix in the defuzzifier with mean of maximums

As shown in Chart (1), the sequence of matrices in Mean of Max defuzzifier will be as follows:
1-Len_Word ،2-Transfer ،3-Composition_Role

4.4.2 Central Average (CAVG)

This defuzzifier makes decisions based on the central average of membership elements. The generalized computational expression for this defuzzifier can be found in Equation(9).

$$z_{CAVG}=\frac{\sum_{l=1}^{M} y^{-l} w_l}{\sum_{l=1}^{M} w_l}$$

Equation (9): How to obtain the average of membership elements

In Equation (14), y^{-l} represents the center of fuzzy In Equation (14), y^{-l} represents the center of fuzzy set l'. Moreover, w_l is the height of fuzzy set. For a better understanding of Figure (2), Equation (14) has been given below. This defuzzifier is the most widely used option in fuzzy and fuzzy control systems. The advantages include reasonable operation, easy computations, minimal variations in y^{-l} and w_l, slight variations in the output (i.e. z_{CAVG}), and ultimately good continuity. zy set l'. Moreover, w_l is the height of fuzzy set. For a better understanding of Figure (2), Equation (14) has been given below. This defuzzifier is the most widely used option in fuzzy and fuzzy control systems. The advantages include reasonable operation, easy computations, minimal variations in y^{-l} and w_l, slight variations in the output (i.e. z_{CAVG}), and ultimately good continuity. These three criteria demonstrate that central avg is an ideal defuzzification method. In fuzzy decision-making, it is crucial to decide on every input sentence depending on its decomposition. According to Equation (9), the overall success rates of each matrix in the defuzzifier with the mean degree of membership have been provided in Chart (2). [45, 41, 44]

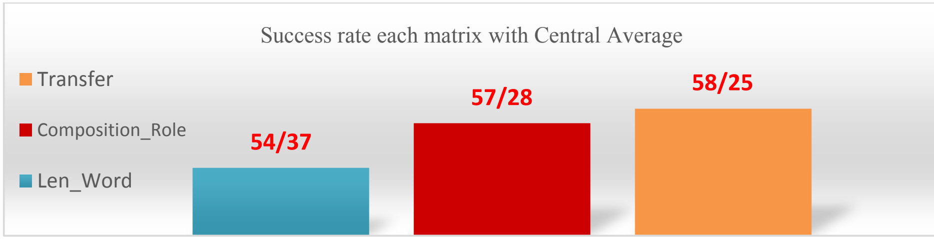

Chart (2): Overall success rate of each matrix in the defuzzifier with the mean degree of membership

As shown in Chart (2), the sequence of matrices in Central Average defuzzifier will be as follows:
1- Transfer,2-Composition_Role, 3-Len_Word

5. Results

After implementing Algorithm Viterbi for every defuzzifier method, we obtained the outputs of each of the two defuzzifiers. Hence, Chart (3) displays the overall success rate of each of the five defuzzifiers.

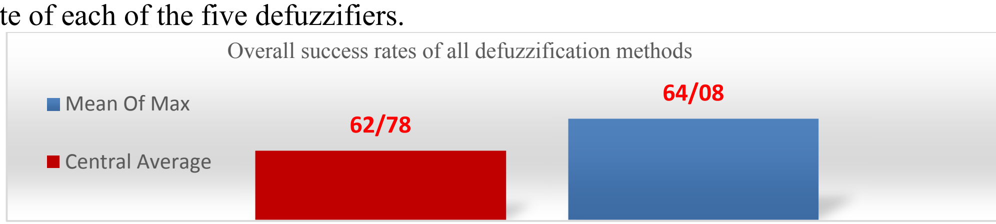

Chart (3): Overall success rate of each of the defuzzifiers with classification of matrices

According to Chart (3), in identification of sentence roles in Persian among two , Mean Of Max defuzzifiers.

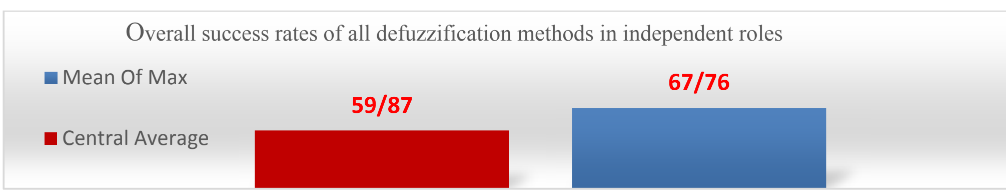

Chart (4): Overall success rate of dependent roles in each defuzzifier with classification of matrices

In each value obtained in Chart (3), two categories of dependent and independent roles are effective. Hence, the success rates of independent roles have been displayed in Chart (4) based on various defuzzification methods and classified fuzzy method.
As shown in Chart (4), the overall sequence is slightly disrupted in independent roles. In the first place, also there is the Mean Of Max defuzzifier, central average is in the second place.

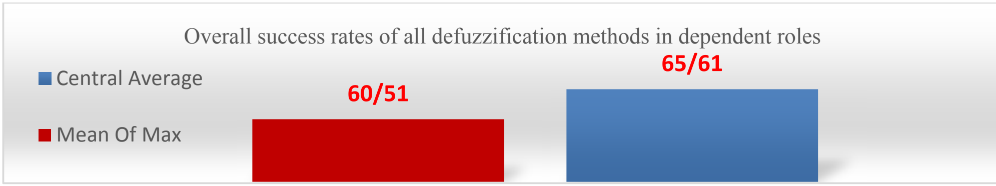

Chart (5): Overall success rate of independent roles in each defuzzifier with classification of matrices

As seen in Chart (5), there is a significant difference in the sequence of success rates in two categories of independent and dependent roles. Therefore, in the category of dependent roles with classified fuzzy, Central Average falls in the first place, Mean of Max in the second place.

6. Conclusions

The results in this study suggested that Mean of Max and Central Average defuzzifiers fell in the first and second places, respectively. Central Average is known as the most ideal defuzzifier in fuzzy systems. However, it achieved the second place in identifying the roles of Persian sentences by a 2% margin.

As seen in independent roles, it also Mean of Max is in the first place and Central Average is in the second place. There is a significant difference in the sequence of success values in the two categories of independent and dependent roles; therefore, in the related categories, Central Average is in the first place and Mean of Max is in the second place.

In future research, Higher N-gram levels can be used, also can use the previous words In N-gram calculations and the results obtained can be checked for better results.

References

[1] The first year of high school, Farsi Book1 - Thirteenth Edition, Tehran: Iran Textbook Printing & Publishing Company, 2009 .

[2] A. Peykar, Pars Process Persian sentence analyzer software, Gorgan: Golestan University, Faculty of Basic Sciences, 2011 .

[3] M. Bijankhan, J. Sheykhzadegan, M. Bahrani and M. Ghayoomi, "Lessons from Building a Persian Written Corpus: Peykare," Language Resources and Evaluation, vol. 45, pp. 143-164, 2011 .

[4] G. Booij, "Construction Morphology," Oxford Research Encyclopedia of Linguistics, http://linguistics.oxfordre.com/view/10.1093/acrefore/9780199384655.001.0001/acrefore-9780199384655-e-254., 2017.

[5] A. K. Ray and V.K. Kaul, "Grammar Checker for Hindi and Other Indian Languages," in International Journal of Scientific & Engineering Research Volume 11, Issue 6, June-2020 .

[6] E. Goldberg, "Constructions at work. The nature of generalization in language.," Oxford: Oxford University Press, 2006 .

[7] S. Mukund , D. Ghosh and R. K. Srihari , "Using Cross-Lingual Projections to Generate Semantic Role Labeled Corpus for Urdu - A Resource Poor Language," in 23rd International Conference on Computational Linguistics (Coling 2010), Beijing, 2010 .

[8] L. M`arquez, X. Carreras, K. C. Litkowski and S. Stevenson, "Semantic Role Labeling: an introduction to special Issue," Computational Linguistics, vol. 34, no. 2, pp. 145-159, 2008 .

[9] A. Kamel Ghalibaf, S., Rahati Ghuchani and A. Estaji, "Labling of Semantic Roles in Persian Sentences through a Memory-based Approach" Symbol and Data Processing, Vol 1, Issue 11, 2009, pp. 13-22

[10] M. Palmer, D. Gildea and P. Kingsbury, "The proposition bank: An annotated corpus of semantic roles," Computational Linguistics, vol. 31, no. 1, 2005 .

[11] J. Deyoung, S. Jain, E. Lehman, N. F. Rajani, R. Socher and B. C. Wallace, "A Benchmark to Evaluate Rationalized NLP Models," in Computation and Language, 2020.

[12] S. Carlos, P. R. L. Miriam, C. Beau, B. F. Collin, E. Michael, F. J. Charles, O. E. Marc, P. E. Sira, R. Josef and S. Petra, "Surprise: Spanish FrameNet!," in Workshop on Frame Semantics at the XVII. International Congress of Linguists, Prague,Czechoslovakia, 2003 .

[13] O. H. Kyoko, F. Seiko, O. Toshio and I. Shun, "The Japanese FrameNet Project: An Introduction," in Proceedings of the Workshop on Building Lexical Resources from Semantically Annotated Corpora at LREC 2004, Lisbon,Portugal, 2004 .

[14] M. Michael, S. Ineke and V. D. W. Ton, "CGN Syntactische Annotatie," Internal report Corpus Gesproken Nederlands, Nederlands, 2000.

[15] Aljoscha, E. Katrin Erk, F. Anette, K. Andrea, P. Sebastian and P. Manfred, "The SALSA Corpus: a German Corpus Resource for Lexical Semantics," in LREC 2006, Genoa, Italy, 2006 .

[16] S. Gerwert, Automatic semantic role labeling in a Dutch corpus, Utrecht: Universiteit Utrecht, Faculty of arts, 2006 .

[17] P. Vossen, Building a multilingual database with wordnets for several European languages., the Human Language Technology sector of the Telematics Applications Programme, 1999 .

[18] F. j. Charles, "The case for case. In E. Bach & R.Harms," Universals in Linguistic Theory, pp. 1-90, 1968 .

[19] J. Fillmore, "Frame semantics and the nature of language," in Annals of the New York Academy of Sciences: Conference on the Origin and Development of Language and Speech, New York, 1976 .

[20] J. Fillmore, J. Ruppenhofer and C. F. Baker, "Framenet and representing the link between semantic and syntactic relations," Frontiers in linguistics, vol. 1, pp. 19-59, 2004 .

[21] R. Jackendoff, "On Larson's Treatment of the Double Object Construction," Linguistic Inquiry, vol. 21, no. 3, pp. 427-456, 1990 .

[22] Dowty, "Thematic Proto-Roles and Argument Selection," Language, vol. 67, no. 3, pp. 547-619, 1991 .

[23] A. Meyers, R. Reeves, C. Macleod, R. Szekely, V. Zielinska, B. Young and R. Grishman, "The NomBank Project:An interim report," in HLT-NAACL 2004 Workshop: Frontiers in Corpus Annotation, Boston, MA, 2004 .

[24] V. S. Silva, S. Handschuh and A. Freitas, "Categorization of Semantic Roles for Dictionary Definitions," in Workshop on Cognitive Aspects of the Lexicon, Osaka, Japan, 2016 .

[25] R. K. D. M. H. McCormick S. F., "Is there a ‘fete’in ‘fetish’? Effects of orthographic opacity on morpho-orthographic segmentation in visual word recognition," J. Mem. Lang, vol. 5, no. 326. 10.1016/j.jml.2007.05.006, p. 307–326, 2008 .

[26] A. F. Web, "Natural Language Processing Software of Ferdowsi University of Mashhad Version 1.3," Web Technology Lab of Ferdowsi University of Mashhad, Mashhad, 2012.

[27] Bijankhan M., "Role of Linguistic Corpora in Formulation of Grammar: Introducing a new Computer Software", Journal of Linguistics, Vol. 2, Issue 19, pp 48-67, 2004.

[28] M. Rouhizadeh, M. Shams fard and M. Arab yarmohammadi, "Building a wordnet for persian verbs," in fourth global wordner conference(GWC 2008), 2008 .

[29] M. K. H. G. M. H. A. Estiri, "An Abstractive Summarization Evaluation Tool using Lexical-Semantic Relations in Farsi Language," in 5th Iranian Conference Electrical and Electronic Engineering (ICEEE 2013), Iran-Gonabad, 2013 .

[30] Hasti Learner System, Shamsfard, 2004, Vol. 1, pp 13-30

[31] Sh. Salami & M. Shamsfard, "Statistical Machine Translation through Syntactic Shallow Labels", 8th International Conference on IT and Knowledge, Bu-Ali Sina University, Hamedan, 2017

[32] S. M. Assi and H. Abdolhosseini, "Grammatical Tagging of a Persian Corpus," International Journal of Corpus Linguistics, vol. 5, no. 1, pp. 69-81, 2000 .

[33] M. Asi, Computer Assisted Syntactic Processing of Persian Language, Humanities Research Center, Academy of Persian Language and Literature, Vol. 1, Issue 1, pp 29-55, 2007.

[34] Nouri, "Developing a Semantic Labeler using FrameNet for Persian Texts" Ferdowsi University of Mashhad, Iran, 2013.

[35] H. Motameni and A. Peykar, "Morphology of Compounds as Standard Words in Persian through Hidden Markov Model and Fuzzy Method, 2015.," Journal of Intelligent & Fuzzy Systems, vol. 30, no. 10.3233/IFS-151865, pp. 1567-1580, 2016 .

[36] M. Surdeanu, S. Harabagiu, J. Williams and P. Aarseth, "Using predicate-argument structures for information extraction.," in ACL-2003, SAPPORO, JAPAN, 2003 .

[37] H. C. Boas, "Bilingual FrameNet Dictionaries for Machine Translation.," in LAS PALMAS, CANARY ISLANDS - SPAIN, LREC 2002, 2002 .

[38] Melli, Y. Wang, Y. Liu, M. M. Kashan, Z. Shi, B. Gu, A. Sarkar and F. Popowi, "Description of squash, the sfu question answering summary handler for the duc-2005 summarization task," safety, vol. 1, p. 14345754, 2005 .

[39] S. Narayanan and S. Harabagiu, "Question answering based on semantic structures," in the 20th international conference on Computational Linguistics, Geneva, Switzerland, 2004 .

[40] L. Zadeh, "Fuzzy sets," Information and Control, vol. 8, no. 3, pp. 338-353, 1965 .

[41] Bloch, "Fuzzy connectivity and Mathematical morphology," Pattern Recognition Letters, vol. 14, pp. 483-488, 1993 .

[42] D. Dubois and H. Prade, "An introduction to fuzzy systems," Clinica Chimica Acta, vol. 270, no. 1, pp. 3-29, 1998 .

[43] M. Moniri, "Fuzzy and Intuitionistic Fuzzy Turing Machines," Fundamenta Informaticae, vol. 123, no. 3, pp. 305-315, 2013 .

[44] A. Krassimir, "Intuitionistic fuzzy logics as tools for evaluation of Data Mining processes," 25th anniversary of Knowledge-Based Systems, vol. 80, pp. 122-130, 2015 .

[45] L.-x. Wang, A Course in Fuzzy Systems and Fuzzy Control, Upper Saddle River: Prentice-Hall International, 1997 .

[46] L.-X. Wang, A Course in Fuzzy Systems and Control, Prentice-Hall International, 1994 .

[47] Al-Sahmsi and A. Guessoum, "A hidden Markov Model – Based POS Tagger for Arabic.," in 8es Journees internationals d'Analyse statistique des Donnees Textuelles, 2006 .

[48] R.Asghari, "Application of N-gram modeling in language statistical modeling," in International Conference on Nonlinear Modeling & Optimization, Amol, Iran, 2012 .

[49] M. Sinane, M. Rammal and K. Zreik, "Arabic documents classification using N-gram," in Conference ICHSL6, Toulouse, 2008 .