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# OPTIMIZING PERSIAN MULTI-OBJECTIVE QUESTION ANSWERING SYSTEM

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**Abstract-** In recent years, Question Answering Systems (QASs) have been known as one of the most significant tools to access information. QASs are search engines that can return a short and accurate answer for each question in natural languages. The answer to the question that asked in such a system could be a document, a paragraph, a sentence, etc. In this paper, an approach is proposed to optimize the performance of web-based QASs for answering questions in Persian. It has been considered a Persian Multi-Objective QAS that would achieve the most probable answer from the documents that has been retrieved by the standard search engine. Various features can be extracted from the text, through the ranking process. Each of them examines the text from a perspective, but changes in the values of them are not consistent with each other; therefore, it is needed to use a method that considers all these views. In this regard, three different aspects (lexical, contextual and syntactical) of the text are considered.

Because evolutionary algorithms are appropriate for issues that have a large search space and texts can be analyzed from various aspects, the proposed approach uses NSGA-II as a Multi-Objective Evolutionary algorithm (MOEA). We have used a standard dataset and web data for assessing our system. Comparing the obtained results from the proposed approach with other existing systems, reveals that it yields considerable and effective results.

**Keywords:** Question Answering System, NSGA-II, Natural Language Processing, Multi-Objective Problems, Persian Language.

## 1. INTRODUCTION

With the ever-increasing amount of information in the recent decades, finding the needed information from a mass of web data, has been more complex. Therefore, the development of the Internet has made it possible to access information easily and has allowed each user to be an information producer. "Information is power", but it can be confusing if we cannot find the beneficial information [1].

Regarding this purpose, there are automated tools for accessing information. Current information retrieval (IR) systems return a limited number of documents based on one or a few keywords (query) that a user entered. These systems have some big challenges. For instance, users usually do not have the skill of selecting the main keywords of their questions, so they enter them completely. In addition, it is usually not easy for users to convert their questions into the suitable keywords, as they are not expert. Besides, entering a few keywords is not adequate for determining the exact purpose of user, hence sometimes such conversion is not possible [2].

In most cases, the user may not be able to enter the suitable query in the system, even if he/she is sure that the required information exists in a document in the texts collection. Moreover, users are looking for answers to their questions, while these systems return some documents that probably contain the answer. So, the user has to read them completely to find the target answer.

Although there is a steady progress in the efficiency of present search engines, what is not widely known is that a fundamental feature is missed in them, which is deduction capability. This feature can be used to answer a query using information from different parts of the knowledge base. Whereas, QAS is a system that has a deduction capability [1].

Unlike IR systems, the goal of QASs is to communicate directly via natural language. So, they get the users question in natural language and give the accurate response [2] [3]. Accordingly, such systems must deal with more complicated NLP techniques. Furthermore, it is said that QASs are recognized as the improved version of usual search engines [4]. For this purpose, the importance of the linguistic analysis at various levels is undeniable. Generally, these systems can be assessed from different perspectives; e.g., basis of answers, domain, and the interviewers' nature. To select the answer from a set of possible options, you need to rank them, so that the score of each, is calculated based on a set of features. [5]. Since there are many types of features for prioritizing texts, this process can be done for each type separately. Thus, it can be considered as a multi-objective optimization problem, which aims to find the right answer from all of these results.

Evolutionary algorithms can provide solutions which are near to the optimum in reasonable time for large-scale optimization problems [6]. These techniques are intuitive population-based search procedures that include random variability and selection operators. Recently, these approaches are used widely to optimize many engineering systems [7] [8] [9] and also many attempts have been made to introduce new evolutionary algorithms [10] [11].

In this paper, an approach to optimize the performance of Persian multi-objective QAS (PMOQAS) is proposed, which consists of four main stages and analyzes the text from three dimensions. For each of them, the predefined text features are extracted and the objective functions of the NSGA-II algorithm will use the combination of them. Our proposed approach selects the most suitable answer for the user's question from the retrieved documents by the web search engine. The experiments proofs that proposed method has achieved acceptable results in comparison with the existing QASs.

This paper is structured as follows. Section 2 gives an overview of QASs and introduces some related works in this area. In Section 3, the structure of the QAS is described. Section 4 presents evaluation metrics and datasets. Section 5 is about experimental results. Finally, Sections 6 and 7 provides the conclusions and future works, respectively.

## 2. RELATED WORKS

Green et al. and Woods et al. proposed the first QASs which are BASEBALL [12] and LUNAR [13], respectively. Both of them were restricted-domain and using natural language questions, they introduced a structured database and analyzed questions based on a set of patterns, that were expected to happen in the input [14].

Another method which has been used to extract answers are statistical methods, because the web contents include many paraphrases and its multilinguality is constantly increasing. Echihabi et al. proposed a statistical approach that scores a given sentence and a its substring, which is probable to be the answer, according to the query [15].

Rinaldi et al. presented a QAS that was domain-specific, and by using paraphrases, in a collection of technical documents finds answers [16].

Previous efforts on feature engineering task tried to select answers automatically as an alternative to manual rule definition [17] [18] [19]. Severyn et al. defined a method for automatically learning complicated patterns such as relational semantic structures of questions and their related answer texts [18]. This approach derived trees from the questions' syntactic trees, and used automatic classifiers to provide texts connected by relational tags. Severyn et al. proposed a supervised method which learns a model for re-ranking, by exploiting structural relationships between each question and its probable answers [19]. Moschiti et al. tried to re-rank answers using linguistic kernels and supervised discriminative models, which learn the suitable ranking from examples [20]. They defined four features: N-gram, bag-of-words (BoW), syntactic chunks and NP-VP-PP groups. Hele et al. presented a ranking method based on a statistical language model using question type features, keywords and a mathematical model for answer extraction [21].

Moreda et al. examined the influence of using two features: WordNet and semantic roles, in an open-domain system for extracting answers [22]. Khodadi et al. proposed a Genetic Programming-based method for this purpose [5]. In another research Khodadi et al. proposed a method that search among sentences of retrieved documents using Memetic algorithm [23]. Atkinson et al. ranked answers of a specific type of questions (*How-To* questions) using an evolutionary model in a community question answering system [24]. Their method combines clustering techniques and evolutionary algorithms to rank answers from user-generated contents in web. In another study, Figueroa et al. tried to answer factoid questions using Genetic algorithm for finding intended *N*-grams [25].

Tohidi et al. provided a Multi-Objective QAS [26]. In the ranking process, some text features were extracted, that each of them examined the text from a perspective. As changes in the values of their features were not consistent, the approach that consider all these views, was used. Zhang et al. used question features to determine the answer type and answer features intended by the user [27].

Yoon et al. used intent keywords in questions to find similar ones in a question answering database, then the users answer was produced according to the answers of these similar questions [28]. De et al. assigned a topic tag to each keyword in the query and the purpose of the question was inferred using rules based decision on the tags set in it [29]. Both et al. presented an approach driven by a question answering vocabulary core that was provided by domain-specific communities to existing ontologies [30].

Croce et al. merged kernels of dependency tree with lexical similarities to classify questions [31] and Yu et al. used co-training style semi-supervised learning for question classification [32].

Yu et al. defined a medical definitional QAS called MedQA that analyze lots of electronic documents automatically to generate coherent and brief answers for definitional questions [33]. Furthermore, Hazrina et al. showed that out of 13 types of the known ambiguities, less than half of them had been addressed by the previous research successfully [34].

Unfortunately, up to now, very little research has been done on question answering systems for Persian language. So, we hope this research will be one of the first steps in this direction.

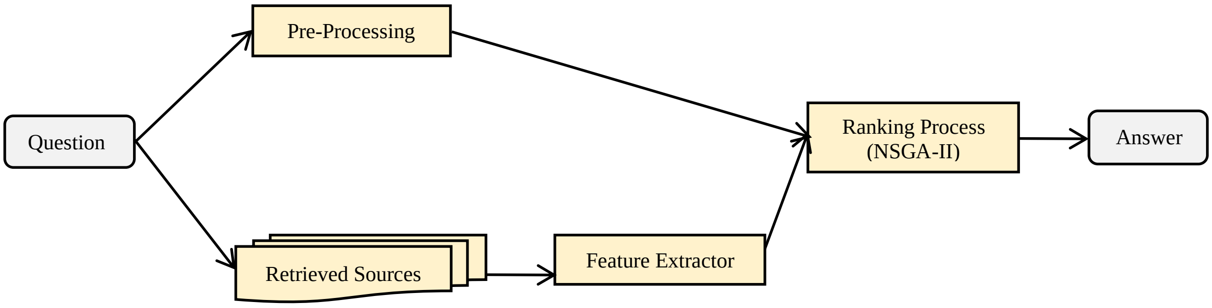


Figure 1. Structure of our proposed approach

## 3. STRUCTURE OF OUR PROPOSED QAS

The main structure of the proposed approach is shown in Figure 1. Although some words (Stop words) such as auxiliary verbs, adverbs and etc. are used frequently, they are of little importance and in *pre-processing* step, we have omitted them using a predefined list of these words. Then, if they occur in the text, they are deleted from the document. This approach improves the processing quality and increase the speed of the process by reducing the computational load.

*Retrieved Sources* is an important step, that extracts a texts set that contain probable answers from retrieved documents. For web-based QAS, it is possible to use the web search for extracting passage, instead of processing the text of all returned documents completely.

It has been considered based on using snippet that search engines generate and process them [35]. Therefore, it can speed up the process.

As, QASs should work real-time, the main goal of this paper is optimizing the performance of QASs without complicating them. Besides, some features have been chosen to analyze text in three levels.

In order to maximize the system performance, three objectives are defined for the multi-objective algorithm that categorize the selected features in three groups which are Lexical, Syntactical and Semantic feature, as shown in Figure 2.

In the *Feature Extractor* step of our proposed approach, these features from text are extracted.

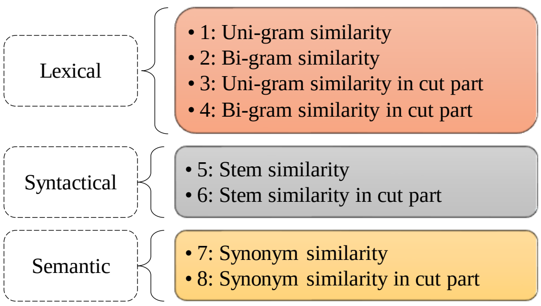


Figure 2. Three groups of features for text ranking [26]

In the *ranking process* step, the most probable answer from retrieved resources is found using NSGA-II and doing a systematic search. The chromosome model which has 3 genes, is presented in Figure 3. They indicate the sentence number $I$ and two cut points $C_1$ and $C_2$ in this sentence, which includes $N$ words.

| $I$ | $C_1$ | $C_2$ |
|---|---|---|

Figure 3. Chromosome model [26]

The initial population size of NSGA-II depends on the retrieved text's size and here it is considered as 10% of the whole search space, which its members are selected randomly. In general, all possible parts of all sentences form the total search space. Further, for each chromosome in implementation, three fitness functions should be calculated as Equations (1), (2) and (3) [26].

$$w_1 f(1)^{\alpha_1} + w_2 f(2)^{\alpha_2} + w_3 f(3)^{\alpha_3} + w_4 f(4)^{\alpha_4} \quad (1)$$

$$w_5 f(5)^{\alpha_5} + w_6 f(6)^{\alpha_6} \quad (2)$$

$$w_7 f(7)^{\alpha_7} + w_8 f(8)^{\alpha_8} \quad (3)$$

where, $f$ is short form of 'feature' and the number in the parentheses is its number in Figure 2. The 1st fitness function analyses a text the lexical view, the next one is for the syntactic perspective, and the last function is related to the text's semantic [26].

As mentioned before, each chromosome is related to a specific part of the text, which its genes address it directly.

If the first Pareto front of the final result contains more than one individual, the one that have the lowest number of words in cut part is selected, as it is more likely to be the correct answer and would be more accurate.

In our proposed approach, operators are used in parallel. It means that two operators separately select their chromosomes from the total population and simultaneously. Here, in the crossover operator, the second and the third genes in one chromosome switch with the same genes in the other one, which means that a new cut part of the selected sentence will be analyzed.

In each execution of the crossover operator, if the generated chromosome does not exist in the search space, the operation is repeated with two other population members. After this replacement, features are re-computed based on the selected sentence of the document.

It is important to note that the three mentioned genes of chromosomes help to identify the related cut part and, in each chromosome, the composition of these three genes is unique. The mutation operator changes the value of the first gene to a random number in the range of the sentences' number in the document, that is equivalent to select a new sentence in the search space. The values of the two other genes, which indicate the cut part, are fixed for the mutation operator. In addition, similar to the crossover operator, if in the search space there is not any member like the generated chromosome, the operation will be performed again to generate another member.

## 4. EVALUATION

For evaluating the performance of the QAS, MRR (mean reciprocal rank) which is a standard metric in this field, is used. Score of each answer is calculated according to its position in ranking, by assigning inverse of its position, as Equation (4). The MRR of a system is the average value for a set $Q_u$ of $Q_n$ questions [3].

$$MRR = \frac{1}{Q_n} \times \sum_{\forall q \in Q_u} \frac{1}{rank\_answer_q} \tag{4}$$

The other standard metric that has been used to evaluate the presented approach, is Top-*n* Accuracy. This metric is one of the most usual ways for measuring a method's accuracy. Setting the value 1 for *n* means the only answer that the system will produce must be exact and correct. Therefore, by considering *n* to have a greater value, we let the system to have more wrong guesses. For instance, by assuming *n*=4, the system must give the correct answer in the top 4 generated responses. The standard formula which calculates the metric (*n*=1) is as Equation (5) [5]:

$$Top1accuracy = \frac{number\,of\,correct\,answers}{number\,of\,questions} \tag{5}$$

In this paper, Rasekhoon question answering dataset (www.rasekhoon.net) is employed to evaluate question matching model. Most of questions and answers in this service is about religion and had been answered by experts. In this paper the Stop-word list that has been used contains 927 Persian words, which occur a lot in documents, however, their semantic effect in texts is very low. Extracting this stop word list is based on: syntactic classes, corpus statistic and expert judgments. Some of the most important challenges that arise in the Persian automatic text processing are outlined as well in [36].

## 5. EXPERIMENTAL RESULTS

Overall, the system user enters his/her question, then the system returns a set of candidate sentences for being its answer. Afterwards, they would be ranked and a sentence with the highest score is selected.

In the following, using NSGA-II as a scoring approach with some objectives is analyzed and the impact of the selected features are compared. NSGA-II results can be different in each execution, so this algorithm was run repeatedly (30 times) and the most repeated response considered as the final result. The effect of each feature in the fitness functions formulas can be different. Assuming the ratio (weight) of feature number *n* as $w_n$, then giving each value to these variables result in different outcomes.

These weights were examined with some values and the most probable value for each of them was found, as shown in Table 1.

Table 1. Evaluation metrics for each set of weights

| $W = < w_1.w_2.\ldots.w_8 >$ | MRR | Top1-Accuracy |
|---|---|---|
| <0, 1, 1, 1, 1, 1, 1, 1> | 0.497 | 0.243 |
| <1, 0, 1, 1, 1, 1, 1, 1> | 0.509 | 0.266 |
| <1, 1, 0, 1, 1, 1, 1, 1> | 0.356 | 0.207 |
| <1, 1, 1, 0, 1, 1, 1, 1> | 0.477 | 0.252 |
| <1, 1, 1, 1, 0, 1, 1, 1> | 0.503 | 0.266 |
| <1, 1, 1, 1, 1, 0, 1, 1> | 0.453 | 0.252 |
| <1, 1, 1, 1, 1, 1, 0, 1> | 0.509 | 0.252 |
| <1, 1, 1, 1, 1, 1, 1, 0> | 0.483 | 0.243 |
| <1, 1, 1, 1, 1, 1, 1, 1> | 0.511 | 0.266 |
| <2, 1, 1, 1, 1, 1, 1, 1> | 0.590 | 0.252 |
| <1, 2, 1, 1, 1, 1, 1, 1> | 0.636 | 0.480 |
| <1, 1, 2, 1, 1, 1, 1, 1> | 0.534 | 0.299 |
| <1, 1, 1, 2, 1, 1, 1, 1> | 0.681 | 0.492 |
| <1, 1, 1, 1, 2, 1, 1, 1> | 0.583 | 0.365 |
| <1, 1, 1, 1, 1, 2, 1, 1> | 0.590 | 0.389 |
| <1, 1, 1, 1, 1, 1, 2, 1> | 0.574 | 0.374 |
| <1, 1, 1, 1, 1, 1, 1, 2> | 0.583 | 0.399 |
| **<1, 2, 1, 2, 1, 1, 1, 1>** | **0.655** | **0.505** |

Table 1 represents that the weight of two features should be 2. It means that these two are more significant in analyzing text than other feature with weight 1.

In addition, in the mentioned formulas the different order for each feature can generate different outcomes. In this regard, given the previous selected weights, we consider $\alpha_n$ as the order of feature number *n*, and we tested these variables with some possible values, as presented in Table 2. Then, again the most suitable values for each of them were selected. By this means, we defined the fitness functions formulas here [26].

Table 2. Evaluation metrics for each set of feature order

| $\alpha = < \alpha_1.\alpha_2.\ldots.\alpha_8 >$ | MRR | Top1-Accuracy |
|---|---|---|
| <1, 1, 1, 1, 1, 1, 1, 1> | 0.605 | 0.485 |
| <2, 1, 1, 1, 1, 1, 1, 1> | 0.579 | 0.439 |
| <1, 2, 1, 1, 1, 1, 1, 1> | 0.614 | 0.480 |
| <1, 1, 2, 1, 1, 1, 1, 1> | 0.623 | 0.435 |
| <1, 1, 1, 2, 1, 1, 1, 1> | 0.635 | 0.463 |
| <1, 1, 1, 1, 2, 1, 1, 1> | 0.583 | 0.439 |
| <1, 1, 1, 1, 1, 2, 1, 1> | 0.640 | 0.458 |
| <1, 1, 1, 1, 1, 1, 2, 1> | 0.645 | 0.433 |
| <1, 1, 1, 1, 1, 1, 1, 2> | 0.623 | 0.474 |
| <1, 2, 1, 2, 1, 1, 1, 1> | 0.640 | 0.463 |
| <1, 2, 1, 2, 1, 2, 1, 1> | 0.646 | 0.485 |
| **<1, 1, 2, 2, 1, 2, 1, 2>** | **0.655** | **0.505** |

As presented in Tables 1 and 2, the value of features related to the chosen cut part has power of 2 in the functions, which shows the greater influence of them. Moreover, in the first fitness function, bigrams' features have the order 2, suggesting their double effect in comparison with the unigram features. Fitness Function final formulas are as Equations (6), (7) and (8).

$$\left[ f(1) + \left( f(3)^2 \right) \right] + 2\left[ f(2) + \left( f(4)^2 \right) \right] \tag{6}$$

$$\left[ f(5) + \left( f(6)^2 \right) \right] \tag{7}$$

$$\left[ f(7) + \left( f(8)^2 \right) \right] \tag{8}$$

Single-objective algorithms are not appropriate solutions for MOEAs, because changes in their objectives are not consistent with each other [26]. Figure 4 shows the behavior of these three fitness functions in each generation (for one question and document). It can be observed that decreasing and increasing in the value of one fitness function will not cause a same change in the other functions necessarily.

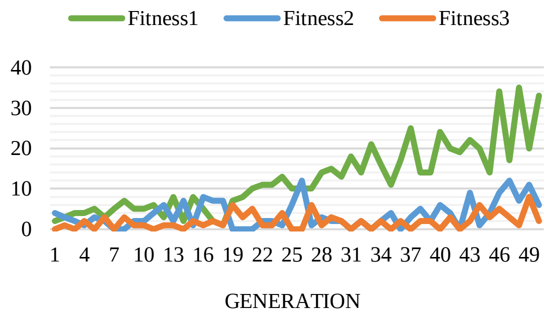


Figure 4. Changes of the fitness functions in 50 generations

In each application, NSGA-II converges to the final result, with different generations numbers [26]. Here for finding the suitable value, NSGA-II was executed with different generations' numbers and the two mentioned metrics was measured each time. The related results are presented in Figure 5.

It can be seen that the algorithm converges to the final result after 50 generations, thus we considered the generations' number for NSGA-II as 50.

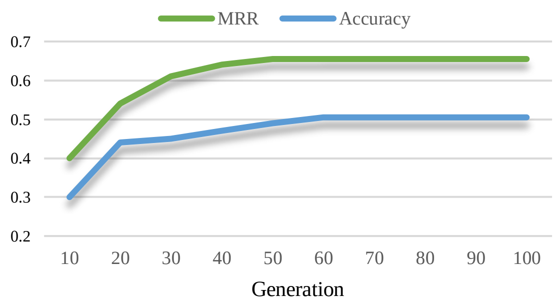


Figure 5. The required number of generations for the NSGA-II

The results according to our evaluation metrics obtained in 30 runs, their average and the best ones are presented in Figures 6 and 7.

Table 3 illustrates that this approach is able to achieve similar Top1-accuracy (using the standard dataset) in comparison with the existing English QASs. Below, in Table 4, our proposed approach has been compared with some related research using the MRR metric.

According to the Table 4, our proposed approach was able to achieve similar MRR rate in comparison with previous studies for English language.

Undoubtedly, the speed of question answering systems is a significant feature for them. Therefore, we analyze the average time that the proposed system spends to answer each entered question, compared with other related systems.

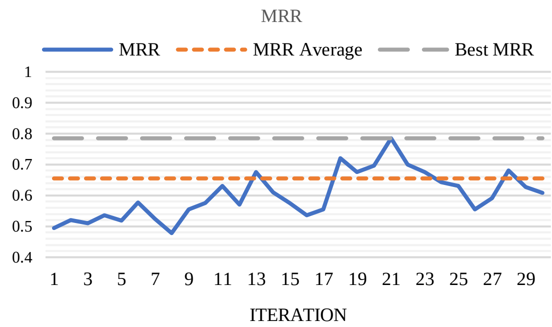


Figure 6. Computed MRR metrics

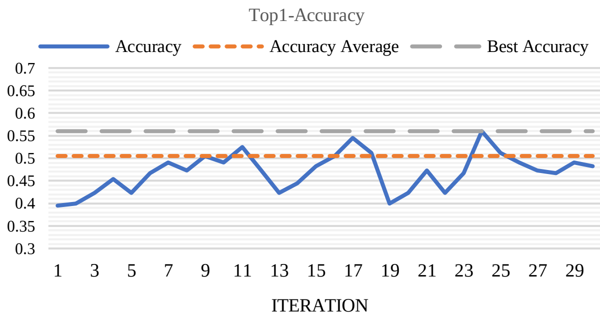


Figure 7. Computed Top1-Accuracy metrics

Table 3. Top1-accuracy of the PMOQAS and similar research

| System | Top1-Accuracy |
|---|---|
| GP-based feature learning QAS [5] | 0.460 |
| sv2007c [5] | 0.289 |
| LymbaPA07 [5] | 0.706 |
| FMIX [37] | 0.290 |
| LCCFerret [5] | 0.494 |
| MOQAS [26] | 0.527 |
| Proposed approach | 0.505 |

Table 4. MRR of the PMOQAS and similar research

| System | MRR |
|---|---|
| web QAS using GA (PreGA) [25] | 0.387 |
| web QAS using GA (GAQA+GASCA) [25] | 0.569 |
| FMIX (Perceptron) [37] | 0.641 |
| FMIX (SVM-rank) [37] | 0.638 |
| MOQAS [26] | 0.711 |
| Proposed approach | 0.655 |

In Table 5, it can be seen that the responsiveness of the proposed model is acceptable in comparison with other systems that use evolutionary algorithms, although, generally the speed of these algorithms is lower than common machine learning methods. So, to reduce computational load of the system and to improve its speed, it is recommended to work with snippets produced by search engines instead of processing the retrieved document completely.

Table 5. The average time of the PMOQAS and similar research

| System | Time (Milliseconds) |
|---|---|
| PreGA [25] | 36671.006 |
| GAQA+GASCA [25] | 185724.634 |
| MOQAS [26] | 56120.769 |
| Proposed approach | 68104.584 |

## 6. CONCLUSIONS

Although available search engines like Google, have a lot of notable and remarkable features, they lack the capability of deduction, that a primary QAS is expected to have; However, we know that search engines are really useful, as skilled users and experts can resolve their information needs. From this perspective of view, a qualified search engine can be considered as a semi-mechanized QAS.

It is very complex to improve a search engine to a QAS. To achieve this goal, creative ideas and new concepts are required to solve problems that arise, when we face an environment which has uncertainty.

This paper illustrates a multi-objective method, that may be considered as a fundamental step in this direction.

Here, NSGA-II is used to optimize the performance of a Persian QAS. It is extracted some general features of text and grouped them in three different categories: Lexical, Syntactical and Semantic features. Afterward, the features' combination in each group was considered as an objective of the problem. So, NSGA-II that have all the three objectives is executed, and using this algorithm answers are ranked in different Pareto fronts. Then, the most likely answer for the user question is found.

The experimental results illustrate that the top1-accuracy and MRR of our proposed approach is acceptable compared to the related works.

Generally, the speed of evolutionary algorithms is lower than other machine learning techniques, and here it is one of the limitations of the approach.

## 7. FUTURE WORKS

In this paper, the main goal was to examine Persian question answering systems, however, other languages can also be processed in future.

A possible future work for optimizing the proposed model is to use frequently asked questions (FAQ) to improve the performance of the system.

Another action could be adding other features to make the *feature extractor* step more accurate, which needs deeper knowledge about Persian language.

As mentioned before, processing the provided snippets (by search engines) instead of analyzing the whole documents, could considerably enhance the system speed. Finally, parallelizing some steps in the proposed structure, will also help reducing the time for answering each entered question.

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