Aggregation of Word Embedding and Q-learning for Arabic Anaphora Resolution

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Abstract. In many linguistic situations, the repetitions of objects and entities are reduced to the pronoun. The correct interpretation of pronouns plays an important role in the construction of meaning. Thus, the resolution of the pronominal anaphors remains a very important task for most natural language processing applications. This paper presents a novel approach to resolve pronominal anaphora in Arabic texts. At first, we identify non-referential pronouns by using an iterative self-training SVM method. After, we resolve the antecedents by combining a Q-learning method with a Word2Vec based method. The Q-learning method seeks to optimize, for each anaphoric pronoun, a sequence of criteria choice to evaluate the antecedents and look for the best. It uses syntactic criteria as preference factors to favor candidate antecedents over others. The Word2Vec method uses the word embedding model AraVec 3.0. It provides the semantic similarity measures between antecedent word vectors and pronoun context vectors. To combine Q-learning and Word2Vec results, we use a ranking aggregation method. The resolution system is evaluated on literary, journalistic and technical manual texts. Its precision rate reaches until 80.82%.

Keywords: Word2vec · Q-learning · Syntactic · Semantic · Self-training · SVM · Ranking aggregation · Pronominal anaphora · Arabic

1 Introduction

Anaphora is a linguistic phenomenon that plays an important role in the construction of meaning. It implements the different possibilities of resumption of an element in a text. Each anaphoric pronoun depends on another expression, called reference or antecedent, that must be found in the previous (or sometimes the following) part of the text. The pronominal anaphora resolution aims at finding the reference, usually a noun phrase (NP), of an anaphoric pronoun. The implementation of anaphora resolution system can reveal the ambiguity of the text, understand sentences and check the consistency of context. So, such a resolution system has become necessary in many applications of Natural Language Processing (NLP) mainly the applications of information extraction and topics detection.

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Several anaphor resolution works were done for English and other languages, but few works have focused on the Arabic. The lack of NLP resources for Arabic and the specificities of the language can influence the anaphor resolution and make the task more difficult.

The pronominal anaphora resolution that we propose task in this paper includes two main steps: a preliminary step for the identification of non-referential pronouns and a second step for the resolution. The non-referential pronouns identification uses an iterative self-training SVM method. It exploits a set of patterns-based and linguistic-based information as classification features. The resolution step is a combination between a Q-learning based method and word embedding model. For Q-learning method, we considered a set of morpho-syntactic criteria that favor some candidate antecedents over others. The Q-learning algorithm gives the optimal combination of criteria, in order to evaluate the antecedents and choose the best of them. For word embedding method, we used the pre-trained model AraVec 3.0[1]. The word vectors provided by this model allow to calculate the semantic affinity between the pronoun and these candidate antecedents. The combination of the two methods exploits both syntactic and semantic information gives better results.

This article consists of six sections. In Sect. 2 we give the specificities of the Arabic language that influence the task of resolution. In Sect. 3, we conduct a comparative study of the state of the art between the different existing works. In Sect. 3, we describe the method of identifying non-referential pronouns. We explain the steps of our approach, in Sect. 4, and we detail both of the Q-learning and the Word2Vec method. Finally, we present our test corpus, the results of the experiments and their comparisons to the other Arabic works.

2 Impact of Arabic Specificities on Anaphora Resolution

There are several types of anaphora in Arabic. Pronominal anaphora includes personal (subjects and objects), demonstrative and relative pronouns. Personal pronouns can be isolated or suffixed (1). They are generally anaphoric and referential. But they can be non-referential like in the sentence (1). Demonstrative pronouns are generally cataphoric[2] (2). They can also be anaphoric, but in some cases they are non-referential. Relative pronouns are always anaphoric. They refer to the NP (Noun Phrase) that immediately precedes them (3).

(1) إنـــها تمطر (It's raining)
(2) فكه عينيك بتلك البسط الخضراء (Enjoy your eyes from these green valleys)
(3) البسط التي نسجتها يد الطبيعة (The valleys that have been created by nature).

Arabic is a morphologically rich language marked by several distinctive characteristics mainly: the agglutination of clitics[3] to words, the diacritical[4] marks in the

[1] https://github.com/bakrianoo/aravec.

[2] The cataphor is the case where the anaphora precedes its antecedent.

[3] Clitics are elements of grammar attached to the root of a word.

[4] Short vowels in Arabic are replaced by symbols called diacritics.

Arabic texts, and the exceptional case of gender and number agreement. These characteristics influence the anaphora resolution problem. Firstly, the agglutination of clitics to words can induce a problem of ambiguity to determine whether the word contains a pronoun or not. For example, in the word كتابـه (his book) the letter ـه is an enclitic pronoun attached to the root while in the word منتبه (attentive) the letter ـه is a part of the word. Secondly, the lack of diacritical marks in several Arabic texts can produce a morphological ambiguity and even grammatical ambiguity, like the non-vowelized word فهم that can be interpreted like a verb فَهِمَ (understanding) or like a personal pronoun هم attached to coordinating conjunction ف giving the agglutinative form فَهُمْ (so they). In addition, the gender and number agreement in Arabic language poses an exceptional case; this is the case where the anaphoric pronoun in singular feminine form can refer a non-human plural noun, like in the example (4). Moreover, the sentences' length, the frequency of anaphoric expressions and the lack of punctuation make more difficult the segmentation of text. So the range of possible candidates of each anaphora grows wider. The example (5) illustrates the frequency and the diversity of anaphora in one sentence.

(4) ملّت عجول الفلاح ضيق المرابض فجاء وحلـها من معالفـها (The farmer's calves had disliked the tightness of the stable then he came and dissolved them from their mangers)

(5) فكه عينيك بتلك البسط الخضراء التي نسجتـها يد الطبيعة نفسـها فتلك هي السعادة بعينـها (enjoy your eyes to these green valleys that have been created by nature itself, that's all happiness)

3 Previous Work

The anaphor resolution task was the research topic of several NLP works. We can distinguish four types of approaches: rule-based approaches, statistical approaches, learning-based approaches and hybrid approaches. Language-based approaches operates on several sources of knowledge such as Lappin and Leass [1], Mitkov [2], Schmolz et al. [3] for English. Gelain and Sedogbo [4], Bittar [5], Nouioua [6] for the French, Fallahi and Shamsfard [7] for Persian, Ashima and Mohana [8] for India. The work of Mitkov [2] was adapted to the Arabic language in Mitkov et al. [9]. However, linguistic knowledge remains insufficient especially for morphologically rich languages such as Arabic. In fact, linguistic rules alone are unable to resolve semantic ambiguities.

Some works have been based on statistical methods such as the works Seminck and Amsili [10] for English, Elghamry et al. [11] for the Arabic. The work of Elghamry presents a statistical dynamic algorithm. It uses collocational evidence, recency and bands as related features. The bands are used to divide iteratively the search space in order to reduce the number of candidate antecedents. Other works have used machine learning methods to cover the shortcomings of language rules. Most of them considered the resolution as a classification problem and they exploited the characteristic vectors of the pronoun-antecedent pairs, such as the work Aone and Bennett [12] for Japanese, Li et al. [13] for English and Aktas et al. [14] for the German language. However, supervised learning requires large labeled data sources, which is sometimes expensive and difficult for some languages. Approaches based on unsupervised learning, such as the work Charniak and Elsner [15], are fewer.

For hybrid approaches, the authors have combined language rules and learning techniques into a single representation to take advantage of both and to cover one another's shortcomings. Among the works that have opted for this type of approach, we can cite: Weissenbacher and Nazarenko [16], Kamune and Agrawal [17] for English, Dakwale et al. [18], Mujadia et al. [19] for Hindi, Abolohom and Omar [20], Hammami [21] for Arabic. The work of Abolohom and Omar [20] combines 16 rules and a k-Nearest Neighbor classifier. Hammami [21] classifies the pairs (pronoun-antecedent) using a learning algorithm (RIPPER) and a set of morphological features.

4 Identification of Non-referential Pronouns

The main goal of our resolution system is to look for the best antecedent of the anaphoric pronoun in the list of candidate antecedents. Pronouns are identified using their part-of-speech values that are generated by the morphological analyzer of Ben Othman [22]. Then they are filtered to eliminate non-referential pronouns and to avoid the loss of time in the search for non-existent antecedents. To identify the non-referential pronouns, we used a semi-supervised self-training learning method. It exploits an SVM classifier and operates on a set of patterns-based and linguistic-based features. The non-referential pronouns identification is a quite difficult task and needs enough information to have a good result. We achieved a linguistic study in Arabic texts to identify the effective features and the most important constructions of non-referential pronouns.

4.1 Classification Features

The classification features include linguistic-based and pattern-based features. The linguistic-based features are grammatical and syntactical features. Grammatical features indicate the grammatical value, the gender and the number of the current pronoun and of the words surrounding it. Syntactical features concern important syntactical characteristics like the existence of a discriminating delimiter that immediately follows the pronoun, the existence of a specific particle or an impersonal verb after the pronoun.

The pattern-based features test the verification of the non-referential patterns. Non-referential patterns can be grouped into confirmation patterns, time and climate patterns, proverbs and sayings and other constructions of patterns.

Examples of confirmation patterns:

- إنّه مِنَ [غير] (it is [not]) + defined adjective
- إنّه (it is) + Specific delimiter + مِنْ أنْ + verb
- إنّه مَنْ (Whoever) + verb/مَنْ أنّه (qui) + verb/مَنْ لعلّه (maybe who) + verb

The most used time and climate patterns:

- إنّها/إنّه (it is) + specific climate or atmosphere verb
- إنّها (it is) + number [hour/time] + specific words

The other non-referential patterns:

- ما (what) + verb + attached pronoun
- لا يزال/مازال (still) + هناك (There is) + nom

4.2 An Iterative Self-training SVM Method

SVM is a binary classification method based on the use of the functions, called kernel, that allow optimal data separation [23]. In the self-training SVM algorithm, the SVM classifier is first trained on a small set of labeled data (the initial training corpus). Next, it is used to predict labels of unlabeled examples. A subset of unlabeled examples, with their predicted tags, is selected to increase the initial labeled training set. Then, the classifier is newly trained on the recent training data and used to classify other unlabeled examples. This process is repeated several times until all unlabeled data are processed or a maximum number of iterations is reached. At each iteration, the system selects only the most accurate and the most informative instances and then adds them to the set of labeled data. The self-training SVM process includes the flowing steps:

- Training step: the SVM classifier is trained on the labeled data.
- Prediction step: the trained classifier is used to classify the unlabeled data and to predict their labels. Each newly-labeled data has an estimation probability used as a confidence measure.
- Selection step: From the obtained predictions, the system selects only the most accurate and the most informative instances and then adds them to the labeled data. Therefore, we applied two stages of selection:
  - The first stage of selection retains only the instances for which the prediction probability of the class is high.
  - The second stage of selection keeps the most informative data by using similarity measures as Euclidean distance or similarity cosine measures. These methods of measure give more information about the nearest class to each point data.

Selection step handles instance by instance and chooses only instances that check both conditions and verify the two filter stages. For each iteration, the SVM classifier is re-trained on newly-labeled data.

5 Resolution Approach Combining Q-learning and Word2Vec

Our resolution system looks for the best antecedent of each pronoun using syntactic and semantic knowledge in order to favor candidates over others. Syntactic knowledge are preference criteria capable to evaluate and disambiguate candidate antecedents. Semantic knowledge offers the semantic similarity of words. The semantic affinity between the candidate antecedents and the context of the pronoun makes it possible to judge the best antecedent. The syntactic knowledge is used as preference criteria in a

Q-learning method. The semantic knowledge, given by a pre-trained word2Vec model, is used to select the most semantically similar antecedents regarding the context.

The input of our system is the set of pronouns and the candidate antecedents. Our resolution approach combines two methods: a Q-learning method and a word2Vec method. The Q-learning algorithm uses a set of syntactic criteria and interacts with its environment to choose the best combination of criteria, then to evaluate antecedents. The word embedding model uses word vectors, of the pre-trained model AraVec 3.0, to compute similarity measures between the antecedent vector and the mean vector of the pronoun context. Each method provides, for each pronoun, a ranking list of antecedents. To choose the final order of rank, we used a ranking aggregation method. Figure 1 shows the resolution approach process.

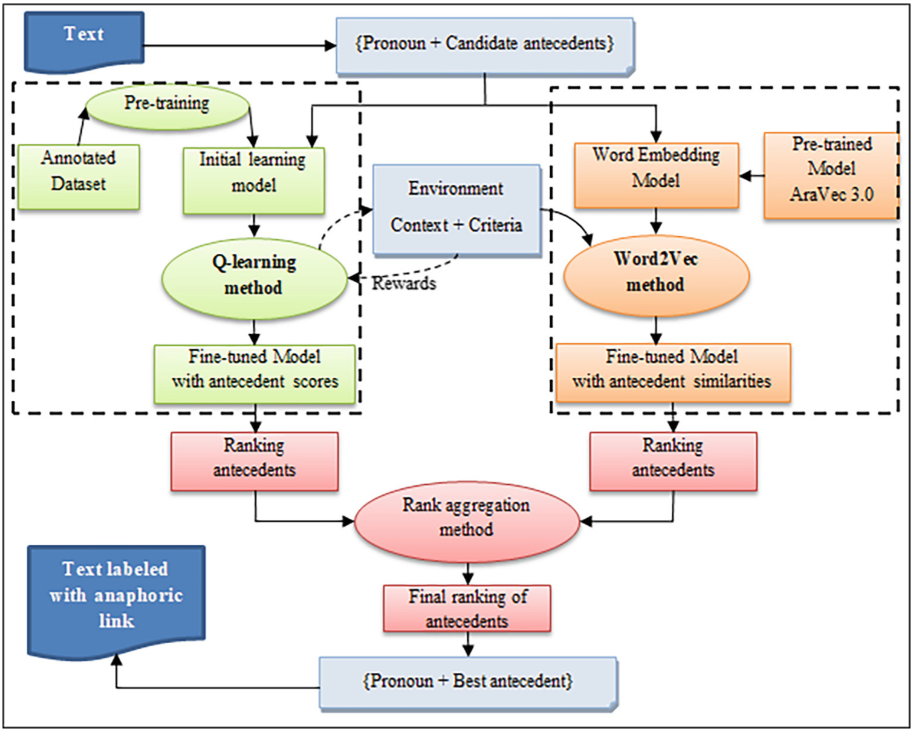

Fig. 1. Resolution approach process

5.1 Q-learning Method

The preference criteria combination for judging the best candidate for each pronoun is unknown in advance and changes according to the context of the pronoun. We have opted for a reinforcement learning approach because it is an effective method for learning in an uncertain and dynamic environment. The environment of our system includes the pronoun, its morpho-syntactic information and the list of linguistic criteria. The choice of reinforcement learning is justified by the following reasons:

- In Arabic, the lack of large data and labeled with anaphoric links makes the use of fully supervised learning quite difficult.
- The environment of the resolution system is dynamic, because on the one hand the list of antecedents is limited to a window of words, and on the other hand, the linguistic criteria and their relevance can change according to the pronoun and the style of the treated text.
- The resolution system seeks to optimize a sequence of decisions (choice of criteria) in order to find the best candidate antecedent.

The anaphora resolution system learns by itself while interacting with its environment. It reinforces the actions that prove to be the best, and this, in order to maximize the rewards obtained at the end. The Q-learning algorithm is one of the most used reinforcement learning techniques. It balances exploration and exploitation processes. The Q-learning algorithm uses a reward matrix R and interacts with its environment containing the context of the pronoun and a list of criteria. This matrix R is initialized during a pre-learning phase that uses some labeled texts.

Syntactic Criteria. The criteria for evaluating antecedents are more or less effective. They represent preferences and not absolute factors. Their relevance depends on the context of the anaphoric pronoun and even on the style of the text, and they are estimates of counts made on some texts tagged with anaphoric link. The set of syntactic criteria is summarized in the Table 1.

Table 1. Syntactic criteria used by Q-learning method

Syntactic criteria	Description
Definiteness	Defined NPs are preferred to those undefined
Topic	The subjects of the current and/or precedent sentences are more favored
Recency	The closest antecedents are the most salient
Paragraph header	The entity ahead of the paragraph is a preferred candidate
Proper noun	The proper noun are important elements of speech and are preferred to others
Repetition	Candidate antecedents whose lemmas are repeated several times in the text are more favored
Precedent pronoun antecedent	The candidate who has already been chosen as antecedent for the preceding pronoun is privileged

Q-learning Process. Our reinforcement learning system is modeled by a Markov Decision Process (MDP). The set of states includes the initial state $S_{\_I}$, the intermediate states representing all possible combinations of criteria and the final state $S_{\_F}$. The initial state $S_{\_I}$ of the PDM contains information about the pronoun Pr. The combination of the criteria (CC) is unknown. The possible actions, from state to other, are the choice of criteria. Each transition from one state S_i to another $S_{\_j}$ has an associated reward value r_{ij}. The final state $S_{\_F}$ contains the optimal sequence of actions that represents the best combination of criteria. Each state S_i can go directly to the final state S_F with a reward r_{iF}. The reward r_{ij} is the participation frequency of the criteria combination of the state S_j, in the resolution of pronoun with similar context. Figure 2 shows an example of the MDP representation for 2 criteria.

The Q-learning [24] algorithm uses two matrices Q and R. The matrix R is a two-dimensional matrix; the lines represent the set of states and the columns are the actions. The actions are the criteria c_x and the final action Φ which makes it possible to go directly to the final state. The contexts of the states contain all combinations of criteria. From each state, there are possible actions (their rewards are r_{ij}) and others not allowed actions (their rewards are equal to −1).

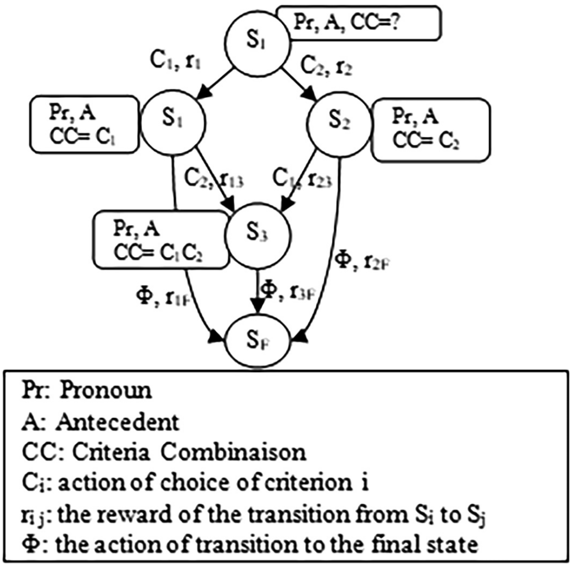

Fig. 2. MDP modeling for choosing the best combination of criteria

The matrix Q is initialized to 0, and it is updated using the reward matrix R. With this matrix Q, the traces are updated according decisions taken in the past. The system learns from experience and explores from one state to another until reaching the goal. In the final matrix Q, the set of optimal actions corresponds to the best combination of criteria capable to evaluate the antecedents of the treated pronoun. The formula (1) is used to update the matrix Q.

$$Q(S_i, a) \leftarrow Q(S_i, a) + \alpha * [R(S_i, a) + \gamma * \mathrm{Max}[Q(\text{next state}, \text{all actions})]] \quad (1)$$

The formula (1) allows to update Q (S_i, a). At each selection of a criterion c, the agent observes the reward R (S_i, action) and the new state S_{i+1} and updates the matrix Q. The parameters alpha (α) and gamma (γ) have a range of 0 to 1; alpha is a learning factor, it controls the update rate, gamma is a discount factor to moderate the impact of future rewards. The Q-learning algorithm goes as follows:

```
1.  Set the alpha (α) and gamma (γ) parameters, set the
    environment rewards in matrix R, initialize matrix Q
    to zero.
2.  For each episode:
        Select a random initial state S_i.
        While final state is not reached Do
          a.  Select a possible action a from S_i
          b.  Consider going to the next state
          c.  Get maximum Q value for this next state
          d.  Compute Q(Si, a) using formula (1)
          e.  Update matrix Q
          f.  Set the next state as the current state.
        End Do
    End For
```

The Q-learning algorithm allows to select the best combination of criteria for each pronoun Pr. Our goal is to give a score to each antecedent in order to evaluate it. The score of an antecedent depends on the relevance of the combination criteria CC. But the criteria of combination CC are not all checked by the antecedent. So, if the antecedent A checks the criterion c (Verif (A, c) = 1) then its score increases by adding the relevance otherwise its score decreases (Verif (A, c) = −1). The evaluation scores allow to judge the best antecedent. The evaluation score calculated for each antecedent is described by the formula (2).

$$score_{Eval} = \sum\nolimits_{\forall c \in CC} Verif(A, c) * relevance(c) \tag{2}$$

5.2 Word2Vec Method

In the last few years, the word embedding model have been illustrated and highlighted in many different NLP tasks. AraVec 3.0 is a distributed word representation open source project which aims to provide the Arabic NLP research community with free to use, powerful word embedding models. The models are built carefully using multiple different Arabic text resources to provide wide domain coverage [25]. The model, that we used, is built using web pages collected from Wikipedia articles in Arabic language.

We exploited the word vectors of the AraVec 3.0 model to extract the semantic affinity between the pronoun and each of these antecedents; we proceeded by calculating the cosine value of these two vectors:

- Vector of antecedent word
- Average vector of the context: it is the average of the word-vectors around the pronoun.

The context of the pronoun contains a number (empirically fixed) of words surrounding the pronouns without considering the particles. For the case of an attached pronoun, the word attached to the pronoun is considered in the context.

The cosine similarity measures of each pair pronoun-antecedent allow to show the most similar antecedents to the pronoun context. We found (experimentally) that the best antecedents must have a cosine value greater than a threshold of 0.2. The antecedent with the best cosine value is considered the first. So, antecedents are ordered by decreasing cosine value except for the case of attached pronouns; for this case of pronouns, we have discarded the antecedents having a cosine value very close to 1 (about 0.9), since the word attached must not be a synonym of the pronoun.

5.3 Combination of Q-learning and Word2Vec

Each of the Q-learning and Word2Vec methods gives an ordered list of antecedents. The values of scores and similarities given by Q-learning and Word2Vec respectively are not compatible and we cannot combine them. In this case, we can only work on the ranking of each method. Several methods have been proposed for this rank aggregation problem.

We tested the kemeny Optimal Aggregation method (using Integer-Programming with Python) and we proposed our own simple but effective method. Our method calculates, for each antecedent, the sum of the votes given by the two methods. It ranks the antecedents in ascending order of the sum of votes. In the case of conflict, ie two antecedents have the same sum of votes; we decide the best based on scores and similarities values, and we choose the antecedent having the highest score (or similarity). Our ranking method favors the antecedent having discriminant values of scores or similarities. The thresholds, that are used to judge the discriminant values, are determined experimentally.

6 Experiments and Results

To measure the efficiency of the proposed approach, we achieved different experiments. Firstly, we evaluated the self-training approach for the identification of non-referential pronouns. Secondly, we conducted experiments for the main resolution approach combining Q-learning and Word2Vec.

6.1 Corpus

To evaluate the identification of non-referential approach, we used a corpus of literary texts extracted from children's stories and a Tunisian basic education textbook. The experimental data set includes the training data and the test data. The training data includes 10877 words and 1525 pronouns. It consists of a small set of labeled data using 68 pronouns (4.5%) and a big set of unlabeled data using 1457 pronouns (95.5%). Usually, the number of referential pronouns is much larger than the number of non-referential pronouns. For labeled data, we tried to use a data set balanced in number of referential and non-referential pronouns; this to provide a better classification of unlabeled instances. For unlabeled data, the size of data set is quite large, and it is difficult to provide a balanced number referential and non-referential pronouns. Then, we proceed to apply the Weka SMOTE[5] filter to create new instances of non-referential data. The test data contains about 440 words and 67 pronouns.

To evaluate the performance of the main resolution approach, we conducted several experiments on a variety of texts. The corpus includes, firstly, literary texts extracted from a Tunisian basic education textbook, and secondly technical manuals and journalistic texts extracted from the web. This corpus contains 4201 words and 436 pronouns of which 409 are referential. The pre-training stage uses training texts containing 5196 words and 638 pronouns. Note that for the Q-learning method, we used training texts just to initialize the model but not for the reinforcement learning process.

6.2 Evaluation of Results

Our system has been able to detect all the anaphoric pronouns and to identify them according to their types. It covers all the anaphors considered in the resolution and generates, for most pronouns, a non-empty list of candidate antecedents.

Evaluation of Non-referential Identification Approach. We performed several tests to show the effectiveness of the semi-supervised self-training SVM approach. Table 2 shows the performance of the proposed approach using the first and the second stage of selection. The first stage retains the most accurate data; the second stage keeps the most informative data based on Euclidean distance or cosine similarity method. The use of the two selection stages keeps the most accurate and most informative data. The following evaluations were performing on the test data.

Table 2. Results of the self-training SVM approach

Selection step		Precision	Precision of non-referential class	Precision of referential class
First selection stage		83.75%	87.5%	80%
Two selection stages	Euclidean distance	**90%**	**96.7%**	83.3%
	Cosine similarity	**90%**	80.6%	**97.2%**

The experiment results showed that the use of the two stages of selection improves the SVM classifier learning and produces better classification model. So, select both the most accurate and the most informative instances filters newly-labeled data and holds the most confident. This approach allowed as to increase the set of labeled training data and to improve classification. It could correctly classified 96.7% of pronouns.

[5] The filter resamples a dataset by applying the Synthetic Minority Oversampling TEchnique (SMOTE). The amount of SMOTE and the number of nearest neighbors may be specified as needed in order to balance the two-class instances size.

Evaluation of Resolution Approach. To show the effectiveness of the proposed approach that combines the Q-learning and Word2Vec methods, we present in Table 3 the precision rate of each method and the final precision of their combination. From this table, we can first deduce that the combination approach outperforms the other methods for all types of texts.

Table 3. Evaluation of the proposed methods

Texts methods	Technical manuals texts	Journalistic texts	Literary texts
Q-learning	72.73%	77.21%	65.43%
Word2Vec	68.53%	75.50%	60.11%
Combination	**80.82%**	**79.77%**	**66.49%**

The proposed approach combines both reinforcement learning method and word embedding method. It benefits from their advantages and exploits the syntactic and semantic knowledge sources. Thus, some occurrences of pronouns, which were not correctly resolved by the first method, have been corrected by the second.

For the evaluation of combination using the rank aggregation methods, we tested the Kemeny Optimal Aggregation method and our discriminant value ranking method. As shown by Fig. 3 the discriminant value method is the best.

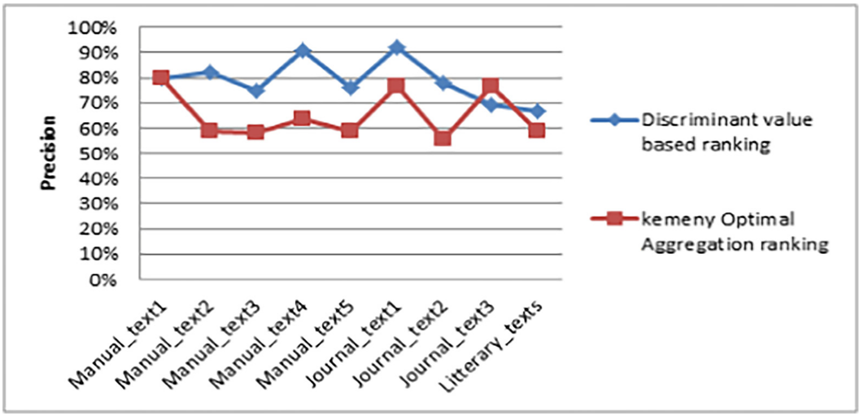

Fig. 3. Results of the combination approach for two aggregation methods

We have noticed that the results of literary texts are worse than those of other types of texts. This can be explained by the complexities of literary texts, where the sentences are much longer and the size of the candidate antecedents list increases and can reach up to 20 candidates. The failed resolutions in literary texts can be explained too, by the presence of a candidate whose identification requires the use of a pragmatic level, ie deduced from the comprehension of the general context of the text. Like in the example

(6), the pronoun **هما** refers to the two distant names ابن عرس et الصبي. Also, by studying this low precision rate, we noticed that a lot of errors came from a reference to proper names. Several pronouns refer to proper names, not all of them are recognized by the pre-trained model AraVec 3.0. By eliminating the resolution of pronouns that refer to a proper name, we could have better results for literary texts. Without considering proper name cases, the Q-learning, the Word2Vec and the combination methods give respectively a precision rate equals to 71.93%, 66.08% and 73.10%, that's why we intend to improve the reference to proper name in the future.

وأغلق **عليهما** البيت فتركه الناسك عند الصبي ولم يجد من يخلفه عند ابنه غير ابن عرس داجن عنده (6)
(and he did not find anyone to keep his son except the weasel who lives with him, he left it with the boy and he closed the house on them).

6.3 Comparison to Arabic Works

As mentioned before, several works have treated the pronominal anaphora resolution in the English language but very few researchers were interested in the Arabic. To have a meaningful comparison, we compared our approach to similar work for Arabic language. To our knowledge the previous Arabic works are: Mitkov et al. [9], Elghamry et al. [11], Abolohom and Omar [20], Hammami [21]. Mitkov et al. [9] proposed a rule-based method. The tests are made on 63 examples of a technical manuals. Their evaluation reached a rate of success equal to 95.2%. The work of Elghamry [11] presented a statistical dynamic algorithm based on "bootstrapping". The evaluation used a corpus including web documents and reached 78% precision. Abolohom et al. [20] proposed a hybrid approach that combines rule-based method and the K-NN supervised learning method. They tested their approach using a corpus extracted from the Holy Quran. They obtained a rate of precision equal to 71.7%. Hammami [21] used a rule-based learner method (RIPPER). It reached 69.2% precision on manual technical texts containing 419 pronouns. Compared to those works, our approach gives encouraging results since it was tested for different types of texts.

7 Conclusion

This article presents a new hybrid method combining Q-learning and Word2Vec for the resolution of pronominal anaphors in Arabic texts. The Q-learning method exploits a set of syntactic criteria. It looks for the optimal combination of criteria with the highest reward values. This combination of criteria is used to evaluate the possible antecedents and calculate their scores. The output of the Q-learning method is an ordered list of antecedents. The Word2Vec based method uses the pre-trained model AraVec 3.0. It exploits the word vectors of this model and calculates the semantic similarity between the antecedent and the pronoun context. The output of the Word2vec method is, also, another ordered list of antecedents. The combination of the two methods exploits the votes of each ordered list and uses a rank aggregation method to select the best antecedent.

As future work, we aim to expand our corpus and perform more experiments. We also plan to improve the semantic representation of words and apply other word embedding models. Finally, we suggest to test our methods for other languages.

References

1. Lappin, S., Leass, H.J.: An algorithm for pronominal anaphora resolution. Computat. Linguist. **20**(4), 535–561 (1994)
2. Mitkov, R.: Robust pronoun resolution with limited knowledge. In: Proceedings of the 18th International Conference on Computational Linguistics (COLING 1998)/ACL 1998, Montreal, Canada (1998)
3. Schmolz, H., Coquil, D., Döller, M.: In-depth analysis of anaphora resolution requirements. In: 2012 23rd International Workshop on Database and Expert Systems Applications, Vienna, Austria (2012)
4. Gelain, B., Sedogbo, C.: La résolution d'anaphore à partir d'un lexique-grammaire des verbes anaphoriques. In: COLING 1992 Proceedings of the 14th Conference on Computational Linguistics, France, vol. 3, pp. 901–905 (1992)
5. Bittar, A.: Un algorithme pour la résolution d'anaphores événementielles. Université Paris 7 Denis Diderot, UFR de Linguistique (2006)
6. Nouioua, F.: Heuristique pour la résolution d'anaphores dans les textes d'accidents de la route. Villetaneuse, Institut Galilée, Université Paris 13, F-93430 (2007)
7. Fallahi, F., Shamsfard, M.: Recognizing anaphora reference in Persian sentences. Int. J. Comput. Sci. **8**, 324–329 (2011)
8. Ashima, A., Mohana, B.: Improving anaphora resolution by resolving gender and number agreement in Hindi language using rule based approach. Indian J. Sci. Technol. **9**(32) (2016)
9. Mitkov, R., Belguith, L., Stys, M.: Multilingual robust anaphora resolution. In: Proceedings of the Third International Conference on Empirical Methods in Natural Language Processing (EMNLP-3), Granada, Spain, pp. 7–16 (1998)
10. Seminck, O., Amsili, P.: A computational model of human preferences for pronoun resolution. In: Proceedings of the Student Research Workshop at the 15th Conference of the European Chapter of the Association for Computational Linguistics, Valencia, Spain, pp. 53–63 (2017)
11. Elghamry, K., Al-Sabbagh, R., El-Zeiny, N.: Arabic anaphora resolution using Web as corpus. In: Proceedings of the Seventh Conference on Language Engineering, Cairo, Egypt, pp. 1–18 (2007)
12. Aone, C., Bennett, S.W.: Applying machine learning to anaphora resolution. In: Wermter, S., Riloff, E., Scheler, G. (eds.) IJCAI 1995. LNCS, vol. 1040, pp. 302–314. Springer, Heidelberg (1996). https://doi.org/10.1007/3-540-60925-3_55
13. Li, D., Miller, T., Schuler, W.: A pronoun anaphora resolution system based on factorial hidden Markov models. In: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics, Portland, Oregon, 19–24 June 2011, pp. 1169–1178 (2011)
14. Aktas, B., Scheffler, T., Stede, M.: Anaphora resolution for Twitter conversations: an exploratory study. In: Proceedings of the Workshop on Computational Models of Reference, Anaphora and Coreference, New Orleans, Louisiana, 6 June 2018, pp. 1–10 (2018)
15. Charniak, E., Elsner, M.: EM works for pronoun anaphora resolution. In: Proceedings of EACL, pp. 48–156 (2009)

16. Weissenbacher, D., Nazarenko, A.: Identifier les pronoms anaphoriques et trouver leurs antécédents: l'intérêt de la classification bayésienne. In: Proceeding of TALN, pp. 145–155 (2007)
17. Kamune, K., Agrawal, A.: Hybrid approach to pronominal anaphora resolution in English newspaper text. Int. J. Intell. Syst. Appl. **02**, 56–64 (2015). https://doi.org/10.5815/ijisa.2015.02.08. Published Online January 2015 in MECS
18. Dakwale, P., Mujadia, V., Sharma, D.M.: A hybrid approach for anaphora resolution in Hindi. In: International Joint Conference on Natural Language Processing, Nagoya, Japan, pp. 977–981 (2013)
19. Mujadia, V., Gupta, P., Sharma, D.M.: Pronominal reference type identification and event anaphora resolution for Hindi. Int. J. Comput. Linguist. Appl. **7**(2), 45–63 (2016)
20. Abolohom, A., Omar, N.: A hybrid approach to pronominal anaphora resolution in Arabic. J. Comput. Sci. **11**(5), 764–771 (2015). https://doi.org/10.3844/jcssp.2015.764.771
21. Hammami, S.: La résolution automatique des anaphores pronominales pour la langue arabe. Thèse de doctorat. Université de Sfax, Faculté des Sciences Economiques et de Gestion, Sfax, Tunisie (2016)
22. Ben-Othmane, C.: De la synthèse lexicographique à la détection et à la correction des graphies fautives arabes. Ph.D. thesis. Université de Paris XI, Orsay (1998)
23. Mohamadally, H., Fomani, B.: SVM: Machines à Vecteurs de Support ou Séparateurs à Vastes Marges. BD Web, ISTY3 Versailles St Quentin, France (2006)
24. Sigaud, O., Garcia, F.: Apprentissage par renforcement Processus décisionnels de Markov en IA. Groupe PDMIA, 27 février 2008
25. Abu Bakr, S., Kareem, E., El-Beltagy, S.R.: AraVec: a set of Arabic word embedding models for use in Arabic NLP. In: 3rd International Conference on Arabic Computational Linguistics, ACLing 2017, Dubai, United Arab Emirates, 5–6 November 2017