Review of coreference resolution in English and Persian

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Abstract

Coreference resolution (CR) is one of the most challenging areas of natural language processing. This task seeks to identify all textual references to the same real-world entity. Research in this field is divided into coreference resolution and anaphora resolution. Due to its application in textual comprehension and its utility in other tasks such as information extraction systems, document summarization, and machine translation, this field has attracted considerable interest. Consequently, it has a significant effect on the quality of these systems. This article reviews the existing corpora and evaluation metrics in this field. Then, an overview of the coreference algorithms, from rule-based methods to the latest deep learning techniques, is provided. Finally, coreference resolution and pronoun resolution systems in Persian are investigated.

Keywords: Coreference Resolution; Deep Learning; Natural Language Processing; Neural Networks; Anaphora Resolution

1. Introduction

Natural language processing is a research field that deals with the relationship between computers and human language. This task aims to program computers to process vast quantities of natural language knowledge. According to its definition, this field of study encompasses discourse models, syntactic and semantic text analysis, and an accurate understanding of context. However, this research field faces numerous obstacles. This article examines one of these challenges: coreference resolution.

The discourse model consists of a collection of sentences that make sense only when combined. In computational linguistics, anaphora resolution involves finding an antecedent for pronouns and definite expressions whose interpretation depends on a previous contextual expression. Coreference resolution goes one step further and identifies all in-text expressions that refer to the same real-world entity.

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This study reviews coreference resolution as one of the most challenging areas in natural language processing. Coreference resolution is defined as: “The problem of identifying all noun phrases or in-text mentions that refer to the same real-world entity” [1-3].

By slightly modifying the original definition, we can define coreference resolution as: “The task of grouping all the mentions within a document into equivalent classes where all the mentions within the class refer to the same discourse entity”[4, 5]. As an example of coreference, consider the phrase, "The Iranian president attended the meeting of the Persian Gulf Council. He met other members after breakfast. Hassan Rouhani then attended the summit". The mentions outlined below for the entity Hassan Rouhani are coreference.

(“The Iranian president” attended the meeting of the Persian Gulf Council. “He” met other members after breakfast. “Hassan Rouhani” then attended the summit.)

Coreference resolution is a binary problem: two mentions in the text are either coreference or not. CR has numerous applications in other areas of natural language processing, including information extraction [6], text summarization [7-9], question answering [10], machine translation [11], sentiment analysis [12, 13], and machine reading [14].

Coreference resolution has shifted from the hand-crafted features methods [15-17] to deep neural network systems [18-20]. This article compares these two systems. Several rule-based and machine learning algorithms have been proposed in recent years. In addition, different types of models, such as mention-pair [21], cluster-based [22], and ranking models [5], have been developed by various researchers.

Several articles have proposed a review of coreference resolution algorithms, corpora, and tools [23-28]. Mitkov [29] reviewed the most current methods and definitions in this field for the anaphora resolution task.

Ng [24] examined 15 years of efforts in coreference resolution, and the diverse methods have been presented in this field. In another study, Sukthanker et al. [27] reviewed machine learning methods and several deep learning systems. Ferreira et al. [25] examined corpora, introduced evaluation metrics, and the most recent end-to-end deep learning systems in a review article. Stylianou and Vlahavas [28] examined neural network-based coreference resolution systems and new deep neural network pronoun resolution systems. Lastly, Lata et al. [30] provided a detailed review of all kinds of mention detection methods for coreference resolution systems.

Recently, the direction of research has changed from entity-based to event-based coreference resolution in the field of information extraction [31]. The challenges of event coreference resolution are more than entity coreference resolution. Recently, several neural network systems are proposed in the neural event coreference resolution field [32-34]. In this paper, event coreference is not investigated.
The key contributions of the current paper are as follows:

- A total of 171 articles are reviewed concerning coreference resolution models.
- A comprehensive analysis of developed corpora in the domain of coreference resolution is performed.
- Important evaluation metrics in this field are examined with examples.
- A comprehensive review of coreference systems, ranging from fundamental rule-based systems to advanced deep learning systems, is conducted. The implementation results and website addresses are examined for various methods, strengths, and weaknesses.
- The challenges in this area are explored.
- The systems in Persian introduced to this field are briefly reviewed.

Coreference resolution systems generally exhibit a unique architecture, where different parts of this architecture can be changed according to different models. For example, in end-to-end deep learning systems, the preprocessing and extracting of hand-crafted features are removed, and the model learns them from the raw data. As shown in Figure 1, the first section is responsible for data preparation and feature extraction. In the subsequent step, feature selection is attempted. Following this step, the mentions are separated into two classes (i.e., coreference and non-coreference). The mentions are then placed in their respective chains.

![Figure 1. Coreference resolution architecture](image)

The remainder of this article is structured as follows:

In Section 2, the popular coreference corpora are analyzed, and in Section 3, the existing evaluation metrics are described in depth with examples for each metric. Section 4 covers coreference algorithms ranging from basic rule-based systems to the latest deep learning systems. In Section 5, coreference systems in Persian are reviewed. Section 6 summarizes challenges in the field of
coreference resolution and discusses the solutions proposed by various articles. Finally, the paper's conclusion is presented in Section 7.

2. Coreference corpora

For two reasons, research in the field of coreference resolution that examines practical applications necessitates corpora containing coreferential information. The first is to train a machine learning system. The second is testing the developed systems with large amounts of data. Additionally, it is a useful resource for studying language and intertextual relationships.

One of the requirements for comparing supervised systems in natural language processing is the availability of a suitable corpus for comparing the performance of various algorithms on that particular corpus. Over the years, numerous coreference corpora of varying sizes and languages have been developed. These corpora vary based on the domain, annotation scheme, types of annotated relationships, size, and the language under study. This section examines the English coreference corpora. Furthermore, corpora from other languages have been analyzed. Task-specific and other corpora, including medicine coreference, are not examined.

OntoNotes 5.0 is the most extensive coreference corpus in English [35]. In other languages, efforts have been made to compile corpora of this size and standard. For example, the one million-word Persian corpus was developed [36].

The MUC corpus was one of the first ones introduced at the Sixth and Seventh Message Understanding Conferences. For many years, the MUC-6 [37] and the MUC-7 [38] have been the benchmarks for comparing coreference systems in English. However, they are no longer utilized due to developing a suitable large-scale corpus. This corpus contains 318 Wall Street Journal articles developed in SGML with the MUC standard in the annotation and evaluation section. This corpus was too small, so it was divided into two train and test sections. Only the identity relation was labeled, and no other relations were adequately considered. In this corpus, only links are annotated, and singletons are not considered.

The ACE corpus [39] was developed in four different versions between 2002 and 2008. This corpus is annotated in three different languages: English, Chinese, and Arabic. Although this corpus was created to address several issues with the MUC corpus, it also has disadvantages. One of its major drawbacks is that it only considers seven types of entities. In addition, it is difficult to compare different systems when the training and test phases are not explicitly separated. Nonetheless, the authors of the published articles have made this distinction themselves, and other papers have compared their findings to this separation. This corpus contains a greater range of content types than its predecessor.
The MATE project [40] launched a fundamental examination of annotation formulation. Numerous later corpora, such as [35, 41-44] in English and other languages [45-48], have adopted this coding method as a pattern. This guide contains a wider variety of nominal groups and relationships than its predecessors. This corpus is annotated through the MMAX2 annotating tool [49].

The successive corpus in this field is the CoNLL-2011 [50], based on OntoNotes 2.0. This corpus was created exclusively in English. It is comparable to the one introduced at the 2010 Semeval competition [51], followed by introducing the new CoNLL-2012 [52] in multiple languages. The CoNLL-2012 corpus, based on OntoNotes 5.0 [35], has become the standard for comparing different coreference systems. Compared to the previous version, one of the characteristics of this corpus is a significant increase in the number of train and test documents. This corpus has several limitations. The first limitation of this corpus is that singletons are not labeled. The second one states that certain non-referential expressions (such as expletives) are not annotated in this corpus.

The GNOME corpus [40, 53] was one of the first corpora in the cross-domain field that used the annotation method introduced in MATE. This corpus was developed to study centering theory, which evaluates cross-domain algorithms in the coreference domain. This corpus generally includes three areas: museum, office, and Sherlock. The total size of this corpus is approximately 40,000 tokens. The ARRAU [44] corpus was developed with much more complex relationships in the coreference domain (such as resolving multi-reference relationships) with the MMAX2 annotation tool. This corpus, which comprises different categories, was soon adopted by the Italian corpus LiveMemories [48].

In addition to the mentioned corpora, efforts have been made in task-specific coreference resolution. An example is the NP4E corpus [54], which is annotated for event coreference resolution in MMAX2 format. Another corpus in the event domain is the ECB+ corpus [55] annotated with the ECB + format. Furthermore, the ParCor and ParCorFull corpora [56, 57] have been developed for parallel pronoun coreference. These two corpora are labeled in German and English for machine translation purposes and are annotated in MMAX2 format. Moreover, the CIC corpus [58] was developed to improve coreference in Chatbot in CoNLL format.

GUM [59], WikiCoref [60], KnowRef [61], PreCo [62], and LitBank [63] are examples of corpora for specific coreference domains. However, most of these corpora are small or were created to address only a portion of the coreference task. Consequently, they were unable to replace CoNLL-2012 as a benchmark.

The creation of non-English corpora has been attempted, except for the non-English components of ACE and CoNLL. In SEMEVAL evaluation [51], the competition dataset includes a collection of Italian LiveMemories, Spanish and Catalan ANCORA, German Tüba/DZ [45], and English OntoNotes corpus. They were all converted to a standard format and given the same annotation. The University of Barcelona's ANCORA corpus [47, 64] results from years of effort and annotation in Spanish and Catalan in multiple steps. Its annotation standard is formatted in MATE.
The RCDAT corpus [36] in Persian has been annotated with approximately one million tokens using the CoNLL standard. Table 1 lists several significant coreference corpora in various languages.

| Language       | Corpus Name         | Reference | Size   |
|----------------|---------------------|-----------|--------|
| English        | GNOME               | [40]      | 40k    |
|                | ACE-2               | -         | 180k   |
|                | ACE-2005            | [39]      | 400k   |
|                | ACE-2007            | -         | 300k   |
|                | ARRAU 2.0           | [44]      | 300k   |
|                | ONTONOTES 5.0       | [42]      | 1450k  |
|                | CoNLL 2012          | [52]      | 1450k  |
|                | MUC-6               | [37]      | 30k    |
|                | MUC-7               | [38]      | 25k    |
| Italian        | LIVE MEMORIES      | [48]      | 600K   |
|                | I-CAB               | [65]      | 250K   |
|                | Venex               | [41]      | 40k    |
| Spanish        | ANCORA-CO-ES       | [64]      | 400k   |
|                | ACE-2007            | -         | 200k   |
| Hindi-Bengali  | ICON                | [66]      | -      |
| German         | Tüba/DZ             | [45]      | 600k   |
| Dutch          | CUREA               | [46]      | 325k   |
|                | KNACK-2002          | [67]      | 125k   |
| Catalan        | ACORA-CO-CA         | [64]      | 400k   |
| Czech          | PDT 2.0             | [68]      | 800k   |
| Chinese        | ACE-2005            | [39]      | 200k   |
|                | ACE-2007            | -         | 250k   |
|                | ONTONOTES 5.0       | [42]      | 820k   |
| Arabic         | ACE-2005            | [39]      | 200k   |
|                | ACE-2007            | -         | 250k   |
|                | ONTONOTES 5.0       | [42]      | 820k   |
| Persian        | PerCoref            | [69]      | 200K   |
|                | RCDAT               | [36]      | 1000K  |

3. Evaluation metrics

This section reviews well-known metrics for evaluating coreference systems, and the advantages/disadvantages of each metric are reviewed. Each specific coreference metric compares the precision and recall of systems. In other words, the f1-score is computed after these two metrics are obtained.

3.1. MUC metric
This link-based metric was introduced during the Sixth MUC Conference [37]. Its purpose is to compare key and response chain links. In this metric, recall is the number of links that must be removed from the key chain to obtain a response chain.

In contrast to the recall metric, the precision metric is defined as the number of links that must be removed from the response chain to obtain the key chain. For a response partition based on the key defined as a partition \((r, k)\) and a key partition based on the response as a partition \((k, r)\), the precision and recall are calculated according to the following equations.

\[
\text{Precision}(R,K) = \sum_{r \in R} \frac{|r| - |\text{Partition}(r,K)|}{|r| - 1}
\]  

(1)

\[
\text{Recall}(K,R) = \sum_{k \in K} \frac{|k| - |\text{Partition}(k,R)|}{|k| - 1}
\]  

(2)

This metric lacks a solution for identifying singletons, one of its weaknesses. Therefore, it cannot be used to evaluate datasets containing singletons. Also, as per [70, 71], this metric demonstrates the least discrimination power. According to Luo [71], another drawback of this metric is that if all of the key mentions are linked, the system recall based on this metric will equal 100. This metric also has disadvantages for scoring systems that generate fewer chains.

3.2. B³ metric

Bagga and Baldwin [70] introduced this metric to solve the MUC problems. This metric calculates precision and recall for every individual mention separately. Consequently, the weighted sum of this individual precision and recall is calculated to achieve the final precision and recall. In this metric, recall is defined as mapping each mention in the key to one of the response mentions, followed by calculating the number of overlapping mentions in the key and response. The definition of precision is exactly the opposite of recall. The precision and recall for the \(i\)th entity are calculated according to the following expressions.

\[
\text{Precision} = \frac{\text{The number of correct elements in the entity of mention}_i}{\text{The number of mentions in response entity of mention}_i}
\]  

(3)

\[
\text{Recall} = \frac{\text{The number of correct elements in the entity of mention}_i}{\text{The number of mentions in key entity of mention}_i}
\]  

(4)

Final recall and precision are calculated using the following two formulas.

\[
\text{Final precision} = \sum_{i=1}^{N} w_i \times \text{precision}
\]  

(5)

\[
\text{Final recall} = \sum_{i=1}^{N} w_i \times \text{recall}
\]  

(6)
This metric has some flaws as well. For instance, if a system repeats mentions in response, its precision and recall will change for this metric. This is because the $B^3$ metric permits the key or response entity to be repeated multiple times. Then, for every repetition, a recall or precision score is assigned to the response or key.

If a system generates all entities as singletons, it will have a recall rate of 100. In addition, if it connects all entities into a single entity, this system's precision will be 100.

### 3.3. CEAF metric

This metric was proposed by Luo [71]. Its general purpose is to identify entity-based similarities. The mapping function is defined with a scoring function $\varphi (g)$:

$$\varphi (g) = \sum_{k \in k_m} \varphi (k, g(k))$$  \hspace{1cm} (7)

Given document $D$ and the key and response entities, the optimal mapping that maximizes total similarity can be determined as follows.:

$$g^* = \arg \max_{g \in G_m} \phi (g)$$  \hspace{1cm} (8)

Then:

$$\phi (g^*) = \sum_{k_i \in k^*} \varphi (k_i, g^*(k_i))$$  \hspace{1cm} (9)

After calculating $\varphi (k, k)$ and $\varphi (r, r)$, precision and recall are calculated as follows:

$$\text{Precision} = \frac{\varphi(g^*)}{\sum_{r_i \in r^*} \varphi(r_i, r_i)}$$  \hspace{1cm} (10)

$$\text{Recall} = \frac{\varphi(g^*)}{\sum_{k_i \in k} \varphi(k_i, k_i)}$$  \hspace{1cm} (11)

The similarity metric can be calculated using the following four equations. The third is used in $CEAF_m$, and the fourth is used to calculate $CEAF_e$.

$$\varphi_{1}(K, R) = \begin{cases} 1 & \text{if} \ R = K \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (12)

$$\varphi_{2}(K, R) = \begin{cases} 1 & \text{if} \ R \cap K \neq \emptyset \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (13)

$$\varphi_{3}(K, R) = |R \cap K|$$  \hspace{1cm} (14)
\[
\phi_4(K, R) = 2 \cdot \frac{|R \cap K|}{|R| + |K|}
\]  

3.4. CoNLL metric

In 2012, during the CoNLL shared task, a metric that averaged the previous three metrics was introduced and became the standard for comparing coreference systems. The corpus utilized in this competition was OntoNotes [52]. This metric is computed using the formula shown below.

\[
CoNLL = \frac{(MUC_{F1} + B^3_{F1} + CEAF_{F1})}{3}
\]  

3.5. ACE-Value metric

This metric was introduced during the ACE conference [39]. Similar to the CEAF, this metric seeks the optimal mapping between keys and responses, except that precision and recall are not normalized.

3.6. BLANC metric

This link-based metric was introduced by [72]. Additionally, it is an adaptation of the Rand index [73] for coreference.

If \(C_K\), \(C_R\), \(N_K\), and \(N_R\), denote coreference chains in the key, coreference chains in response, non-coreference chains in the key, and non-coreference chains in response, respectively, the precision and recall for this metric can be calculated using the following expressions.

\[
R_C = \frac{|C_K \cap C_R|}{|C_K|}
\]  

\[
R_N = \frac{|N_K \cap N_R|}{|N_K|}
\]  

\[
P_C = \frac{|C_K \cap C_R|}{|C_R|}
\]  

\[
P_N = \frac{|N_K \cap N_R|}{|N|}
\]  

\[
Precision = \frac{P_C + P_N}{2}
\]  

\[
Recall = \frac{R_C + R_N}{2}
\]  

In a baseline system where all mentions are connected and form a single entity, this metric performs poorly against the \(B^3\) and CEAF metrics. It has been observed that the identification effects mentioned above are significant in this metric [74] due to the utilization of non-coreference relations. As a result, it is less prevalent in relevant works.

3.7. LEA metric
This metric was proposed by Moosavi and Strube [74] in 2016 to counteract the previously mentioned identification effect. The mention identification effect for a metric is that if the system finds more mentions, it will increase system performance, regardless of whether they are true or false. The authors artificially added links to their system, which are in the key but not in the response. Consequently, an increase in $B^3$, CEAF, and BLANK metrics is observed. The only metric capable of overcoming this issue is the MUC metric, which has other issues described previously.

This metric is based on two terms of importance and resolution score. The first one depends on the size of the corpus, and the second one is calculated based on the links' similarity. In this metric, chains receiving more mentions will receive higher scores. According to Luo [71], discriminative power and interpretability are two reasonable prerequisites for coreference systems that CoNLL metrics fail to meet.

In this metric, the authors consider an entity's size. To circumvent the problem of the mention identification effect, they evaluate the coreference relationships between entities rather than the resolved mentions. Consequently, duplicate mentions in response entities will not affect this metric. Since it considers all links, its separation power will be greater than MUC's.

Resolution-score for the $k_{ith}$ key entity is calculated as a fraction of correctly co-referenced links.

$$\text{Res\_score}(K_i) = \frac{\sum_{r_j \in R} \text{link}(K_i \cap r_j)}{\sum_{r_j \in R} \text{link}(K_i)}$$  \hspace{1cm} (23)

Precision and recall are calculated as follows:

$$\text{Importance}(e_i) = |e_i|$$  \hspace{1cm} (24)

$$\text{Precision} = \frac{\sum_{r_1 \in R} \text{Importance}(r_1) \cdot \sum_{k_j \in K} \frac{\text{link}(r_1 \cap k_j)}{\text{link}(r_1)}}{\sum_{r_2 \in R} \text{Importance}(r_2)}$$  \hspace{1cm} (25)

$$\text{Recall} = \frac{\sum_{k_i \in K} \text{Importance}(K_i) \cdot \sum_{r_j \in R} \frac{\text{link}(k_i \cap r_j)}{\text{link}(k_i)}}{\sum_{r_2 \in R} \text{Importance}(k_2)}$$  \hspace{1cm} (26)

3.8. NEC metric

Agarwal et al. [75] introduced the Named Entity Coreference (NEC) metric. This metric considers the practical applications of coreference resolution in the subsequent task. In NEC, the type of mentions is considered in the final f1-score. The following is an example from the original article:

**Gold chain** = [John Doe, he1, he2, he3] [Richard Roe, he4, he5]
System output 1 = [John Doe, he1, he2] [Richard Roe, he4, he5]

System output 1 = [he1, he2] [he4, he5]

Because current evaluation metrics do not account for the type of mentions, both outputs receive the same score. The first output receives higher NEC scores. This is because the first system's output refers to a nominal mention. The NEC metric calculation is as follows.

For every \( k_i \in K \), assume \( N_i \) is the set of response mentions with a full name of \( k_i \).

\[
\text{Precision} = \frac{|r_j \cap k_i|}{|r_j|} \quad (27)
\]
\[
\text{Recall} = \frac{|r_j \cap k_i|}{|k_i|} \quad (28)
\]

The f1 value is then calculated for the response and key entities as follows:

\[
f(k_i, r_j) = \frac{2p(k_i, r_j) \cdot r(k_i, r_j)}{p(k_i, r_j) + r(k_i, r_j)} = 2 \cdot \frac{|r_j \cap k_i|}{|k_i| + |r_j|} \quad (29)
\]

Then, the following value is assigned to f1 for the \( k_i \) entity:

\[
F1_i = \max_{r_j \in R: r_j \cap N_i \neq \emptyset} f(k_i, r_j) \quad (30)
\]

Finally, the f1 value for the whole system is as follows:

\[
\frac{1}{|K|} \sum_{k_i \in K} F1_i \quad (31)
\]

3.9. A simple metric comparison example

In this section, we will review an example adopted from Pradhan et al. [76]. Suppose there are two chains in the key “K”: \([a, b, c]\) and \([d, e, f, g]\). In response “R”, there are three chains \([a, b]\), \([c, d]\), and \([f, g, h, i]\).

\[
K = [a, b, c], [d, e, f, g]
\]
\[
R = [a, b], [c, d], [f, g, h, i]
\]

Precision and recall for the metric above are examined below.

3.9.1. MUC metric

Considering the chains above, calculating precision and recall is straightforward.
\[
\text{Precision}(R, K) = \sum_{r \in R} \frac{|r| - |\text{Partition}(r, k)|}{|r| - 1} = \frac{(3 - 2) + (4 - 3)}{(3 - 1) + (4 - 1)} = 0.4
\]

\[
\text{Recall}(K, R) = \sum_{k \in K} \frac{|k| - |\text{Partition}(k, r)|}{|k| - 1} = \frac{(2 - 1) + (2 - 2) + (4 - 3)}{(2 - 1) + (2 - 1) + (4 - 1)} = 0.4
\]

### 3.9.2. \textit{B³} metric

Based on the chains above, precision and recall are as follows:

\[
\text{Recall} = \frac{1}{7} \times \left( \frac{2^2}{3} + \frac{1^2}{3} + \frac{1^2}{4} + \frac{2^2}{4} \right) \approx 0.42
\]

\[
\text{Precision} = \frac{1}{8} \times \left( \frac{2^2}{2} + \frac{1^2}{2} + \frac{1^2}{2} + \frac{2^2}{4} \right) = 0.5
\]

### 3.9.3. CEAF metric

The CEAF\textsubscript{m} is calculated according to the similarity metric in Eq. (14). The value of CEAF\textsubscript{m} \( f_1 \) is 0.53.

\[
\text{Recall} = \frac{|R_1 \cap K_1| + |R_3 \cap K_2|}{|K_1| + |K_2|} = \frac{2 + 2}{3 + 4} = 0.57
\]

\[
\text{Precision} = \frac{|R_1 \cap K_1| + |R_3 \cap K_2|}{|R_1| + |R_2| + |R_3|} = \frac{2 + 2}{2 + 2 + 4} = 0.5
\]

The CEAF\textsubscript{e} metric is then computed. Using Eq. (15), the similarity metric for this metric is as follows.

\[
\phi_4(K, R) = 2 \times \frac{|R \cap K|}{|R| + |K|}
\]

The value of CEAF\textsubscript{e} \( f_1 \) is 0.52.

\[
\text{Recall} = \frac{\phi_4(K_1, R_1) + \phi_4(K_2, R_3)}{N_k} = \frac{\frac{2 \times 2}{3 + 2} + \frac{2 \times 2}{4 + 4}}{2} = 0.65
\]
Precision = \frac{\phi_4(K_1, R_1) + \phi_4(K_2, R_3)}{N_r} = \frac{\frac{2 \times 2}{3} + \frac{2 \times 2}{4}}{4} \approx 0.43

3.9.4. BLANK metric

For this metric, first, the values of \( C_k, N_k, C_r, \) and \( N_r \) are computed according to Eqs. (17-20).

\( C_k = \{ab, ac, bc, de, df, dg, ef, eg, fg\} \)

\( N_k = \{ad, ae, af, ag, bd, be, bf, bg, cd, ce, cf, cg\} \)

\( C_r = \{ab, cd, fg, fh, fi, gh, gi, hi\} \)

\( N_r = \{ac, a, af, ag, ah, ai, bc, bd, bf, bg, bh, bi, cf, cg, ch, ci, df, dg, dh, di\} \)

Precision and recall are as follows for both coreference and non-coreference links:

\[
R_C = \frac{|C_k \cap C_r|}{|C_k|} = \frac{2}{9} \approx 0.22
\]

\[
P_C = \frac{|C_k \cap C_r|}{|C_r|} = \frac{2}{8} = 0.25
\]

\[
R_n = \frac{|N_k \cap N_r|}{|N_k|} = \frac{8}{12} \approx 0.67
\]

\[
P_n = \frac{|N_k \cap N_r|}{|N_r|} = \frac{8}{20} = 0.4
\]

According to Eqs. (21) and (22), \( F_C \) is approximately 0.23, and \( F_n \) is 0.5. The BLANK will be an average of \( F_C \) and \( F_n \).

3.9.5. LEA metric

In this example, the set \( S \) is a key set and consists of two chains \( s_1 = [a, b, c] \) and \( s_2 = [d, e, f, g] \), and the set \( R \) is a response set and comprises three chains \( r_1 = [a, b] \), \( r_2 = [c, d] \) and \( r_3 = [f, g, h, i] \). The importance value of an entity is equal to its size. Therefore, it is 3 for chain \( s_1 \) and 4 for chain \( s_2 \). The set of coreference links in \( s_1 \) and \( s_2 \) are \{ab,ac,bc\}, and \{de,df,dg,ef,eg,fg\}, respectively.

The “\( ab \)” link is the only common connection between \( s_1 \) and \( r_1 \); no common link exists between \( s_1 \) and the other two responses. Cluster \( s_2 \) has a common link with \( r_3 \) and lacks a common link with the other two response sets. The resolution-score value for chains \( s_1 \) and \( s_2 \) is calculated according to Eq. (23).
\[
\text{Res}\_\text{score}(K_1) = \frac{1 + 0 + 0}{3}
\]
\[
\text{Res}\_\text{score}(K_2) = \frac{0 + 0 + 1}{6}
\]

Similar calculations are made for the importance and resolution-score values of the response clusters. Next, the precision and recall values are calculated through Eqs. (25) and (26).

\[
\text{Precision} = \frac{2 \times \frac{1 + 0}{1} + 2 \times \frac{0 + 0}{1} + 4 \times \frac{0 + 1}{6}}{2 + 2 + 4} \approx 0.33
\]
\[
\text{Recall} = \frac{3 \times \frac{1}{3} + 4 \times \frac{1}{6}}{3 + 4} \approx 0.24
\]

4. Coreference algorithms

Several articles and books have comprehensively discussed computational methods for coreferential expressions. Most early coreference systems depended on hand-crafted and knowledge-rich rules.

In the late 1990s, coreference resolution systems shifted from rule-based to machine-learning methods. In recent years, they have shifted to hybrid and deep learning systems. This section begins by examining rule-based systems. Then, machine learning algorithms and deep learning systems are separately investigated. In addition, a separate section examines Persian anaphora and coreference resolution systems.

4.1 Rule-based systems

Rule-based coreference resolution systems were popular in the 1970s and 1980s. These systems were one of the most popular titles for doctoral dissertations at that time [77]. For example, Charniak's doctoral dissertation, "Understanding Children's Stories" [78], focused on complex knowledge and inference mechanisms and analyzed pronoun resolution. This dissertation was only partially implemented and had several significant flaws. However, it was the first system to attempt computational inference in the field of pronoun resolution. The manual evaluation of these rule-based systems on a small scale was a common problem of rule-based systems of the past. Such evaluations are rarely utilized in less than a few hundred words.

Hobbs [15] proposed the pronoun resolution system as one of the first rule-based systems. This system traverses the syntactic parse tree in a backward, left-to-right breadth-first manner. In this system, the author manually examined 100 pronouns from three different textual sources and achieved 88.3% accuracy. Subsequent evaluations by other researchers on large corpora have demonstrated that this algorithm is highly competitive if complete syntactic knowledge is
available. In contrast to most early rule-based systems, this system is less knowledge-intensive and classed as a significant advantage.

A trend in anaphora resolution research was founded on the theory of salience instead of simple recency. Simple recency indicates that the antecedent chosen is the first candidate that matches the anaphora or pronoun. Since it is false, as stated in the Hobbs algorithm, salience theory [79-86] was instead developed.

Sinder [79] failed to provide a self-evaluation of his salience theory; only a few examples of how this theory operates were stated. Later, Carter [87] evaluated Sinder’s theory and modified Sinder’s system in his proposed system. The elimination of the recency rule was among the most significant changes. The Carter system, known as SPAR, was initially evaluated using his own texts in which all anaphors correctly located their antecedents. The author then evaluated the system using 23 texts written by others, which yielded a 93% accuracy rate.

Lappin and Leass [83] reported an 82% accuracy by re-implementing the Hobbs algorithm and checking 360 pronouns on their corpus. Like the primitive rule-based system, their system was pronoun resolution and knowledge-rich. Their algorithm is also founded on the salience principle. In this system, candidates for the antecedent of each pronoun (anaphora) are scored based on several predefined features. In reality, they are penalized or rewarded based on these syntactic features. An antecedent candidate with the highest salience score is ultimately chosen as the winner. Their algorithm’s input is a deep parse tree, and the candidates are filtered based on syntactic constraints. They evaluated 360 pronouns and reported an 86% accuracy rate compared to the 82% accuracy rate of the Hobbs system. Their system employs in-depth linguistic information boundaries, whereas Kennedy and Boguraev [88] reported a 75% accuracy rate on news texts using a constraint grammar parser and identifying noun phrases.

The system proposed by Lappin and Leass [83] is unsuitable for knowledge-poor scenarios due to the use of deep and ambiguous parsers. Using a partial parser, the authors of the ROSNA system [89] proposed a three-step algorithm to address this issue: 1) candidate filtering, 2) ranking and sorting candidates, and 3) candidate selection.

In the 1980s and 1990s, discourse knowledge-based methods and centering algorithms [90] gained popularity among researchers, replacing the salience theory. This theory simplifies the salience model in which only one focus will be maintained. In the field of anaphora resolution, the system [82] is the best-proposed centering algorithm. This algorithm was implemented on only a series of texts and achieved an accuracy of 90% versus 88% compared to the Hobbs system. Indeed, the Hobbs algorithm has been more accurate in some areas, such as news texts.

The algorithm proposed by Tetreault [91] was motivated by the centering theory and has evolved into one of the simplest yet most effective centering algorithms. In this algorithm, the “cf” (center focus) ranking is combined with several ideas from the Hobbs algorithm. They reported an accuracy of 80.4% when applying this algorithm to news articles, compared to 76.8% when using
the Hobbs algorithms. Lately, researchers have used centering theory in their neural model. For example, in the model introduced by Chai and Strube [92], centering transition derived from centering theory is added to the neural coreference model.

In the 1990s, rule-based systems shifted from knowledge-rich to knowledge-poor systems. The ROSNA and the system presented by Kennedy and Boguraev [88] were among the first systems to move toward a knowledge-poor system. One of the characteristics of these systems is that their evaluation is based on large datasets. The other one is using heuristic methods instead of complete syntactic knowledge or world knowledge.

The CogNIAC [93], built on the Hobbs system, uses pos tags, noun phrases, matching, and a complete parse tree. In this system, the pronoun resolution task is performed using six rules. Their system evaluation is based on narrative texts, Wall Street texts, and 30 MUC6 documents. Another knowledge-poor system is the MARS [94]. Like CogNIAC, this system utilizes five heuristic rules. This system has been implemented in English, Arabic, Polish, and Bulgarian and used in the guitar platform [95].

FASTUS [96] is one of the rule-based systems presented at the MUC6 conference; it employs a text chunker with multiple constraints for pronouns, definite noun phrases, and nouns. It is the best MUC6 system, with an F-measure of 65%. The LACIE system at the University of Sheffield, which participated in the MUC6 and MUC7 conferences, was another system. With an f-measure of approximately 59%, the initial version of LACIE [97] was the third-best system in MUC6. The subsequent LACIE system [98] won the MUC7 competition.

The CoNLL-2011 competition winner was a rule-based system later incorporated into the Stanford preprocessing tool. This system [99] introduced a pipeline of 12 coreference sieves. Each sieve contains some handwritten rules, and the output of each step is determined as the input to the next step. A series of coreference chains are formed at each sieve. The chains are then transferred to the subsequent sieve to be combined with the current mentions, and so on.

Contrary to these simple rules, the system won CoNLL-2011. Figure 2 presents the sieve-based architecture. The sieves of this system are as follows.

1. The sieve is preprocessed with high precision and recall.
2. This sieve identifies the text speakers and links the first and second-person pronouns to their speakers.
3. According to this sieve, two mentions are placed in one chain if they have the same string.
4. This sieve places identical strings in a chain after removing the text following their heads.
5. Two mentions are placed in a chain if any of the following conditions are satisfied: appositive, predicative nominative, acronym, demonym, role appositive, and relative pronoun.
6. The strict head match sieve connects noun phrases that meet a series of conditions: entity head match, word inclusion, compatible modifiers only, and not-i-within-i). This sieve comprises three sub-sieves.
7. Proper head word match links two mentions if both of them are headed by a proper noun and satisfy several constraints.
8. This sieve is the same as sieve 6, except it simplifies the matching conditions between the two heads.
9. Placing pronouns in their proper chain is a challenging and ambiguous task. According to this sieve, pronouns are placed in their respective clusters.
10. In the last sieve, post-processing is performed according to the desired corpus.

Table 2 demonstrates the outcomes for rule-based systems.

Figure 3. The architecture of the coreference resolution sieve [100]
Table 2. Comparison of rule-based systems

| Algorithm | Dataset | Evaluation Metric | Metric Score |
|-----------|---------|-------------------|--------------|
| [78]      | Manually on a small scale | Not systematically evaluated | - |
| [15]      | Narrative texts | Hobb’s metric | 88.3 |
| [82]      | Narrative texts | Hobb’s metric | 90 |
| [83]      | Five Computer Science manuals | Hobb’s metric | 89 |
| [88]      | News text | Resolution accuracy | 75 |
| [93]      | MUC-6 | Precision and Recall | P:73, R:75 |
| [96]      | MUC-6 | MUC F₁ | 65 |
| [97]      | MUC-6 | MUC F₁ | 59 |
| [91]      | News articles | Hobb's metric | 80.4 |
| [99]      | MUC-6 | MUC, B₁ | MUC: 77.7, B₁:73.2 |
| [100]     | CoNLL 2012 | CoNLL | 60.13 |

With the emergence and expansion of coreference corpora and the development of machine learning architectures, research in this area has shifted to machine learning methods. Another reason for the shift is the rule-based systems' inability to identify pronoun references correctly. This shortcoming is because accurate context information is difficult to extract for rule-based systems when searching for pronoun references. Hand-crafting complex rules in rule-based systems is a difficult task. Machine learning systems can automatically extract these rules and the interactions between features if sufficient training data is available. The following section describes in detail the machine learning models in the coreference resolution domain.

4.2. Early machine learning models (non-neural systems)

The first machine learning system in coreference resolution was the mention-pair model. Soon et al. [21] developed this model, which became the foundation for developing coreference machine learning systems. Machine learning methods can be categorized into four models: mention-pair, entity-mention, cluster-based, and ranking. In the following section, these models are discussed in detail.

4.2.1. Mention-pair model

This model, introduced by Aone and Bennett [101], is the most prevalent model used for coreference systems. The authors employed the decision tree [102] to learn the coreference model. Soon et al. [21] later finalized this model. A feature of this model is creating a pair of noun phrases and their presentation as a feature vector. The binary classifier then determines whether each pair is a coreference or not. This model consists of three primary components that are distinct from one another. Improving one part does not necessarily improve the following parts. Despite its simplicity, this is one of published articles' most commonly used models.
The first part of this model is used to create training samples. The datasets developed in this stage are usually unbalanced. Therefore, it is necessary to reduce training data skewness. The most common method for creating positive and negative samples is presented by Soon et al. [21]. Then, negative samples consist of all mentions between the anaphora and its closest antecedent. Later modifications to this technique were presented in references [103-106].

The second part of this model is classifier training. Different systems use different classifiers. Examples include the decision tree [21, 104, 105, 107], the maximum entropy classifiers [108-111], the RIPPER rule-based learner [104, 109, 112], the statistical methods [113], the SVM [114, 115].

The third part of this model is the clustering of coreference classes. Various strategies have been used in the clustering section, e.g., link-first strategy[21], best-first strategy [4, 104], correlation clustering strategy [116], Bell tree [108], and graph clustering algorithms [110].

In the link-first strategy, the text for each mention is scrolled from right to left. Then, the first mention that exceeds a certain threshold (for instance) is selected as the antecedent. In contrast, the best-first method examines all probabilities preceding the current mention and identifies the mention with the highest probability as its antecedent.

Despite using only surface features, the mention-pair model has acceptable results compared to rule-based systems. This system has been modified so frequently that most competing systems in CoNLL were based on this design.

This model also has some limitations, such as local optimality. For example, it has three mentions [Bill Clinton], [Clinton] and [She], respectively. According to the pair decisions, if the first pair [Bill Clinton, Clinton] is considered a coreference, and then the second pair [Clinton, She] is created, then the incorrect chain [Bill Clinton, Clinton, She] is generated by the transitive relation.

Another issue with this model is that it can only determine a candidate's suitability for an anaphora, not its suitability relative to other candidates. Entity-based models were created to solve the first model, and ranking models were created to solve the second. A large number of training samples and the problem of unbalanced databases are also issues with this model. Other models have been developed over time to address these issues.

4.2.2. Entity-based model (clustering model)

Unlike the mention-pair model, the entity-based can use prior knowledge (especially partial entity knowledge). Subsequent systems for coreference resolution allowed a mention to be thoroughly compared to an entity and then make coreference decisions. In fact, coreference resolution is modeled as an incremental clustering problem and not a binary classification in these methods.
Cardie and Wagstaff introduced one of the earliest approaches in this field [117]. When two clusters merge, this system performs a crucial operation that verifies the compatibility between all cluster mentions. Their model was not compared to the mention-pair model in this article.

Graph partitioning is another example of cluster-based models [22, 110, 118]. In this model, mentions are stored in the form of graph nodes, and the edges between them express the possible coreference relations between the two mentions. Initially, all names are connected by edges. The edges are given weights based on binary or unary features between two mentions. A graph-cutting algorithm then cuts the edges based on their weights to create coreference partitions. In Figure 3, a cutting algorithm cuts all the edges that connect the two circular clusters. The stop criterion for the cutting algorithm is determined experimentally by machine learning.

![Figure 3](image-url)

**Figure 3**. Graph-based modeling of coreference resolution. The circles within the image represent a concentration of the golden corpus. The image is from Culotta et al. [22]

Nicolae and Nicolae [110] used “the best-cut method” to remove the edges from the graph. In this article, the researchers addressed pronouns separately and omitted them from the graph. They attached them to the graph based on a pairwise determination. Although, in contrast to Cardie and Wagstaff [117], they did not employ cluster-based features and were superior to the entity-mention models introduced by Luo et al. [108]. In 2011, Cai and Strube [118] introduced the concept of hyper-edge, one of the most effective CoNLL-2011 systems.

Culotta et al. [22] used first-order logic to define cluster-based properties. Their model significantly outperformed the mention-pair model. However, they failed to study the effect of cluster features independently. One of the benefits of this model over the mention-pair model is that it resolves coreferences in a single step. In addition, it examines multiple coreference links simultaneously.

A clustering method prevents inconsistencies between coreference chains during the pairing of mention-pair model samples. In this system, an additional component, such as integer linear programming (ILP), ensures uniqueness and Transitive closure when pairing the mention-pairs [1,
As input, the ILP layer receives the weights of the pair decisions and optimizes the clustering operation. However, many engineering mechanisms and computational efforts are required for this method. One of its issues is its continued reliance on the mechanism that generates mention-pairs. ILP systems are NP-hard problems, which is another drawback of this method.

Another method that eliminates the classification is the algorithm proposed by Fernandes et al. [122]. Training examples are a set of mentions within the document and the correct chains in this method. This algorithm was one of the best algorithms presented at CoNLL-2012.

### 4.2.3. Entity-mention model

In the entity-mention model, pairwise decisions are stored and involved in subsequent decisions. Instead of examining a pair of mentions, these algorithms examine the decisions between a mention and a chain. This model is proposed to solve the mention-pair model's first problem. It determines whether or not a mention is a coreference to a prior partial chain. The feature vector is formed between a mention and a chain, and cluster-based features will be added.

Luo et al. [108] presented a model that combines the global optimization of coreference chains. Partial clusters of mentions are represented at one point in the discourse model as a tree (Bell tree). Figure 4 represents this tree for the three mentions $m_i, m_j,$ and $m_k$. This method determines whether each mention should join the current chain or start a new one.

![Figure 4. Example of a Bell tree adopted from Luo et al. for three mentions [108]](image-url)
In this model, each feature's highest pair decision score is calculated by scrolling all the names within the candidate cluster. For example, for the distance feature, the nearest mention is selected from the list of mentions within the chain and is calculated for the feature vector. The leaves of the Bell tree represent the clusters made to that point. Due to the vast search space, the authors employed a series of heuristic and beam search rules for pruning. The results demonstrated no improvement over the mention-pair model; the only benefit of this system was that it utilized fewer features. Another difference in their model is that there are inconsistencies, such as placing the pronoun “he” and "she" in the same chain.

Yang et al. [123] proposed a system for use in medical texts following the previous system. Scrolling from left to right through text incrementally forms coreference chains. Each occurrence is compared to its preceding partial chains. The maximum value of a chain's mention is compared to the value of the mention under study.

Evaluations indicate that the entity-mention model has increased the coreference resolution system's efficacy. Eventually, Yang et al. [124] enhanced the performance of existing systems by using inferential logic programming to learn coreference rules.

Daumé III and Marcu [125] proposed a system simultaneously performing the mention detection and coreference resolution tasks. Their model used a relatively large, diverse, and heavy feature set. However, their system performed poorly in identifying pronoun references.

4.2.4. Ranking systems

This strategy is a compromise between global and local approaches. The ranking model permits the consideration of multiple candidates concurrently and determines which candidate is the most likely choice for anaphora. Connolly et al. [126] proposed the first ranking system, which ranks two mention candidates. This model was subsequently employed by Yang et al. [106] under the name twin candidate model.

Then, Denis and Baldridge created the twin candidate model [5] so that multiple antecedent candidates compete for a mention. This model eliminates the link-first and first-best clustering components, and each mention identifies an antecedent. The mention ranking model proposed by Durrett and Klein [127] also employed only shallow features. This model was more efficient than the Stanford system [99, 100, 128] and the system proposed by Fernandes et al. [122].

This model continues to have the issue of mention-pair local decisions. Since information is not aggregated at the entity level in this model, it will not affect subsequent decisions. This issue prompted the development of the cluster-ranking model. The cluster ranking model combines entity-based and ranking models' beneficial characteristics. Clark and Manning's [129] deep neural network model is an example of a cluster ranking model.
Another issue is that the ranking model does not distinguish between referential and non-referential mentions. Recent ranking-based deep learning techniques [129-131] distinguish referential from non-referential mentions and resolve coreference. Since extracting features for a coreference resolution system is complex, new systems have shifted to deep learning models. Table 3 compares early systems for machine learning.

Table 3. Comparison of early coreference machine learning systems

| Algorithm       | Learning Algorithm | Dataset     | Evaluation Metric | Metric Score |
|-----------------|--------------------|-------------|-------------------|--------------|
| **Mention-Pair model** |                    |             |                   |              |
| [6]            | C4.5               | MUC-6       | MUC               | 47.2         |
| [21]           | C4.5               | MUC-6       | MUC               | 62.6         |
| [104]          | C4.5               | MUC-6       | MUC               | 69.1         |
| [104]          | RIPPER             | MUC-6       | MUC               | 70.4         |
| [106]          | C5.0               | MUC-6       | MUC               | 78.3         |
| [116]          | CRF hidden markov  | MUC-6       | MUC               | 73.42        |
| [4]            | Average perceptron | MUC         | MUC               | 75.8         |
|                |                    |             |                   | B3           |
| [132]          | Max Entropy        | ACE-NPAPER  | MUC               | 80.8         |
| **Entity-Mention model** |                |             |                   |              |
| [108]          | Max Entropy        | ACE         | ACE-val           | 89.9         |
| [123]          | C5.0               | GENIA       | F-measure         | 81.7         |
| [124]          | ILP                | ACE-BNews   | MUC               | 63.5         |
| **Entity-based model (clustering model)** |                |             |                   |              |
| [117]          | C4.5               | MUC-6       | MUC               | 54           |
| [110]          | Maximum Entropy Model | MUC-6       | MUC               | 89.63        |
| [22]           | first-order logic  | ACE         | B3                | 79.3         |
| [1]            | Logistic Classifier | MUC-6       | MUC               | 68.3         |


| Reference | Methodology | Task | ACE | CoNLL | Score |
|-----------|-------------|------|-----|-------|-------|
| [120]     | Integer Linear Programming | ACE | CoNLL | 69.7  |
| [118]     | End to end clustering | MUC-6 | MUC | 64.5  |
| [122]     | Structured Perceptron | CoNLL-2012 | CoNLL | 60.65 |

**Ranking systems**

| Reference | Methodology | Task | ACE | CoNLL | Score |
|-----------|-------------|------|-----|-------|-------|
| [126]     | - | MUC-6 | MUC | 52.2  |
| [106]     | C4.5 | MUC-6 | MUC | 71.3  |
| [5]       | Max Entropy | ACE | CoNLL | 70.4  |
| [127]     | - | CoNLL-2012 | CoNLL | 61.7  |

4.3. Deep learning systems

Like most natural language processing tasks, new coreference resolution systems shifted to new methods based on deep neural networks. This shift is attributed to the development of both hardware and newer architectures. In this section, we will examine deep learning systems in coreference resolution. Early coreference resolution neural network systems developed a nonlinear model for coreference tasks. Feature extraction and mention detection modules are still handcrafted. These modules include a pipeline of NLP preprocessing tools. The end-to-end coreference resolution system was first introduced by Lee et al. [133]. These systems execute mention detection and coreference resolution in a single operation. Eliminating pipeline modules increases efficiency. This section begins by examining the earliest neural network systems. In the second section, the end-to-end systems are examined in depth.

Each proposed deep learning system (early neural networks and end-to-end systems) may fit into one of these four categories. Each is a subset of one or more of these four models. Figure 4 shows the four categories for deep learning models.
4.3.1. Early neural network models

The first nonlinear mention-ranking coreference system was introduced by Wiseman et al. [130]. Pre-training on both subtasks enables it to identify referentiality and resolve coreferences by learning several features. The authors employ a neural network in this system that automatically attempts to learn an intermediate presentation from only the raw and un-conjoined features. Using a neural network to define their model, they developed an extension of previous mention-ranking models. Previous ranking models utilized raw and un-conjoined features, but this paper offers a solution based on neural networks. In this model, any interaction between features will be conducted by feature representation. This system has improved CoNLL points by about 1.5 points (63.39) compared to the optimal systems. One of the strengths of this model compared to its predecessor systems is using local inference. Another advantage of this system is that the feature conjunction is not explicitly defined. The model learns it automatically. One of this method's weaknesses is its inability to use global information when constructing coreference clusters.

A nonlinear cluster-based neural networks method is utilized in the system proposed by Wiseman et al. [131]. It uses long short-term memory networks (LSTM) to embed cluster-based features. It employed the model introduced in Wiseman et al. [130] to represent mentions and mention-pairs. This model changes the mention-ranking function introduced in [130] by adding global concepts. RNN states are used in the global scoring function to map previous decisions correctly before the recent decision. This system has an accuracy of 64.21 CoNLL points. A significant advantage of this model is implicit learning at the cluster level.
The system proposed by Clark and Manning [134] also used a cluster-ranking method with a different strategy. In this system, each mention is considered a cluster incrementally combined with other chains to complete partial chains. The system consists of three distinct components that interact with one another. Then, they serve as the input of a single-layer neural network, completing the cluster-ranking operation. The mention-pair encoder, illustrated in Figure 6, passes the feature pair from a three-layer fully connected FFNN network with a ReLU activator [135] in each layer to create a feature presentation. As shown in Figure 5, the cluster-pair encoder uses pooling around mention-pairs to generate an entity representation.

![Figure 6. Mention-pair encoder derived from Clark and Manning [134]](image)

The cluster-ranking encoder then uses the mention-pre-trained ranking's weights to feed the cluster-pair representation to the input of a fully connected single-layer network. Decisions in this

![Figure 7. Cluster-pair encoder derived from Clark and Manning [134]](image)
section include the decision to merge or reject. Due to the interdependence of decisions, the system uses a training algorithm to map all possible operations. This system scored 65.29 CoNLL points in the English-language CoNLL dataset, surpassing all previous systems.

Until now, conventional coreference systems have employed a heuristic objective function. Consequently, considerable effort is required to tune the parameters. Clark and Manning [129] proposed two reinforcement learning algorithms to optimize a mention-ranking neural network based on evaluation metrics directly. This method demonstrates the importance of independent actions in the mention-ranking model. In their study, the objective function introduced in [130] was modified according to the award applied by each coreference decision. The paper also examined the reinforced policy gradient algorithm [631]. The mention-ranking model introduced by [134] was used in their system. According to the authors, the study was the first to use reinforcement learning to solve coreferential expressions. The system had a CoNLL point of 65.73% in English.

4.3.2. End-to-End Models

Lee et al. [133] proposed the first end-to-end mention-ranking system for coreference resolution without using syntactic parsers or hand-crafted features. The main idea of this model is to consider all the in-text spans as mention candidates and antecedents. The other is to find the right distribution between anaphora and its candidates by eliminating unsuitable candidates. This system aims to select an antecedent for each allowed span. Figure 8 shows the architecture of the end-to-end system.

![Figure 8. End-to-end model architecture derived from Lee et al. [133]](image-url)
In this system, the bidirectional LSTM is used for span representation. The system also uses an attention mechanism [137] to identify the head of words within the span presentation. This span presentation is defined as follows:

\[ g_i = [x_{\text{START}(i)}^*, x_{\text{END}(i)}^*, x_i, \emptyset(i)] \]  

(32)

The model uses a pairwise ranking function implemented by a two-layer FFNN, illustrated in Figure 9. Only a fraction of the best span scores are stored as input for coreference operation. The optimization function uses only gold chains. During the inference, the most probable antecedent candidate for the mention is selected, and the clusters are constructed through the transitive relation. The accuracy of this system is 67.2 CoNLL points in the single setting and 68.8 points in the ensemble setting. The optimization function of the system is defined as:

\[ \log \prod_{i=1}^{N} \sum_{\hat{y} \in Y(i) \cap \text{GOLD}(i)} P(\hat{y}) \]  

(33)

The previous system utilized a massive, computationally intensive, parameter-rich deep neural network. As an extension to this system, reference [138] used the linear sentence link model (LSL) and the attention sentence link (ASL) model to improve the span representation section. Their system accuracy scored 67.8 CoNLL points.

The system proposed by Zhang et al. [139] extends the Lee et al. system’s loss function. It optimizes clustering and combines mention detection and clustering using the biaffine ranking mechanism. The authors optimize mention and antecedent ranking simultaneously within the loss function. This mention-ranking system had an accuracy of 69.2% in the CoNLL metric. The model architecture is shown in Figure 10.
Another issue with the Lee et al. system is that span-pair clustering decisions are not made globally, resulting in incompatible clusters. In the latent-structure-based system proposed by Lee et al. [140], the inferential procedure is introduced to allow the model to infer in higher-order structures and consider the information at the entity level. Two fundamental modifications were made to this system. First, the attention mechanism surrounding predicted chains is used to predict hidden candidate trees. Thus, each span has a single parent, and each tree represents a cluster. In the second change, a mechanism for thinning candidates was implemented to reduce calculations in more important documents. This system receives 73 CoNLL points, significantly more than the baseline system.

A solution to this problem is also provided in the mention-ranking system proposed by Gu et al. [141]. The authors made changes to the clustering section of Lee et al. [133] to eliminate the first-order model. Their model has the advantage of rule-based post-processing, improvement over the baseline output, and simplicity. The accuracy of this system is 68.4 CoNLL points.

Preserving the properties of co-referenced clusters throughout resolution is a significant challenge in coreference resolution. The explanation is that the cluster’s information is scattered across multiple mentions. Kantor and Globerson [142] proposed the Entity Equalization method to solve this problem by displaying each mention within a cluster. This problem is solved by estimating the sum of all cluster mentions. BERT [137], which is more efficient than previous systems, was utilized for the first time for coreference resolution. This system increased CoNLL accuracy to 76.6, resulting in a performance increase of 3.6 points.

For a better generalization, Subramanian and Roth [143] proposed an adversarial technique that increased Lee et al.’s [133] system CoNLL points by approximately 0.23%. The gradient loss is based on each span and its representation in this system. The loss function is changed to incorporate the adversarial loss. In addition, in Joshi et al. [144], the system proposed by Lee et al. [133] is developed and fine-tuned for coreference resolution via BERT. This system outperformed
ELMO and BERT-base in detecting separate but related entities. This system demonstrated 76.9 CoNLL points.

Joshi et al. [145] adjusted the BERT objective function to create a span representation by introducing the spanBERT. This model outperforms previous models in coreference resolution and question answering. Additionally, this system achieves superior CoNLL-2012 results with 79.6% CoNLL points. Their system, despite its simplicity, had an efficiency of 79.9% CoNLL points.

Despite the appropriate performance of neural coreference models, these models add a lot of complexity to the baseline model [133]. Lai et al. [146] proposed an efficient baseline system based on pre-trained transformer language for coreference resolution.

Liu et al. [147] presented a graph neural network (GNN) coreference system, a second-order model. Mention modeling and its relationships using GNN replicate and integrate mention characteristics that refer to an entity, producing global and second-order results. The system achieved 77 CoNLL points. Similarly, Xu and Choi [19] performed the analysis for higher-order inference using spanBERT. The authors used four higher-order inference methods, two of which were their own. Their optimal model scored 80.2% CoNLL points at CoNLL-2012.

Systems developed in references [18, 148] used neural network-based methods to limit using memory while incrementally building clusters. Memory bounding methods are necessary because the system stores entire entities in memory via incremental clustering, which is impractical for large documents. Xia et al. [18], using the model proposed by Joshi et al. [145] as the baseline system, applied two contributions to their system. The first contribution was using online clustering. Memory consumption will be significantly reduced by storing active entity embeddings during inference. Compared to the model proposed in [145], accuracy decreases by only 3%. During incremental testing and cluster construction, the entity space is pruned based on cluster size and distance from candidates. The system by [148] is based on [18], except that their unbound memory method is different.

In the article by Hourali et al. [149], the RoBERTA method [150] was used to apply syntactic and semantic knowledge and extract coreference chains in different text sizes. This paper's coreference was executed using deep neural networks and turning the problem into a multi-criteria decision making (MCDM) model. The alternatives are antecedent candidates with this conversion, and the features are the coreference evaluation metrics. The two-way GRU identifies lengthy word dependencies in spans, resulting in superior performance compared to RNN networks. On the CoNLL standard, this system's accuracy was 80.

Miculicich and Henderson [151] presented a graph structure model (G2GT model) to encode coreference links within documents. This model helps to build the complete coreference graph all at once. Since the construction of higher-order graphs increases the computational complexity, the
authors used two methods to reduce this complexity. The efficiency of this system was 80.5% CoNLL points.

Wu et al. [152] proposed a method for coreference resolution as a Question-Answering task. Their method breaks the coreference resolution task into a query-based span prediction problem. Their model comprises three sub-tasks, the Mention Proposal module, the Mention Linking module, and the Coreference Clustering, shown in Figure 11. The results examined on the CoNLL corpus reported an accuracy of 83.1 CoNLL points.

The system proposed by Kholsa and Rose [153] is an extension of the Lee et al. [133] model, except that it only used the BERT representation and focused on mention linking. In this system, various named entity types are used to reduce the inconsistency of chains in the predicted clusters. Also, due to the improvement of mention representation and examining type consistency between candidate mentions, type information was applied in this model. Finally, an accuracy of 85.8 CoNLL points was reported for this system.

The system proposed by Wang et al. [154] currently has the highest CoNLL value on the CoNLL-2012 corpus using BERT. The authors proposed an actor-critic-based method for mention detection and clustering using reinforcement learning and joint training. This method handles mention diversity better by considering sample training at the mention level rather than the sentence or document level. The CoNLL score attributed to this article is 87.5.

![Figure 11. The overall architecture of the CorefQA model derived from Wu et al. [152]](image)

### 4.4. Coreference resolution results

Table 4 compares the results of the systems described. The table also contains the results of systems with models comparable to those described. The results indicate that neural network-based coreference systems exhibit good long-term performance. Primitive neural network coreference
systems, such as [129-131], rely on parsers and hand-crafted features. Current systems use the model proposed by Lee et al. [133] to perform end-to-end coreference.

Lee et al. [133] introduced a new architecture that independently scores entity-mention pairs and then uses the clustering algorithm to build chains. Later systems used this architecture as a baseline to compare their results. Lee et al. [140] improved the results by developing and introducing higher-order inference. As another example, Wu et al. [152] proposed a mention-ranking transfer learning system to turn the coreference resolution problem into a QA problem.

According to the explored results, the system proposed by Wang et al. [154] demonstrates the highest performance coreference resolution. Based on these results, most high-performance systems have used higher-order inference and have been inferred globally. Thanks to the higher-order mechanism and pre-train language models such as BERT, the end-to-end systems efficiently perform on the CoNLL-2012 corpus.

Using an embedding technique by neural network systems is a further issue. Early systems used Word-to-vec, glove, and other models. Recent models, in contrast, have incorporated contextual representations such as BERT and spanBERT, thereby enhancing the outcomes. Table 4 lists the source code address of papers that made their source code available as a further contribution.

### Table 4. Results of coreference resolution systems

| Deep learning system | Model Type    | MUC   | B1   | CEAF | CoNLL | Implementation address                      |
|----------------------|---------------|-------|------|------|-------|--------------------------------------------|
| [122]                | Entity based  | 70.51 | 57.58| 53.86| 60.65 | No official code was found.                 |
| [127]                | Mention ranking | 70.51 | 58.33| 55.36| 61.4  | No official code was found.                 |
| [155]                | Entity based  | 70.72 | 58.58| 55.61| 61.63 | No official code was found.                 |
| [156]                | Entity based  | 71.24 | 58.71| 55.18| 61.71 | No official code was found.                 |
| [130]                | Mention ranking | 72.0  | 60.5 | 57.1 | 63.4  | https://github.com/swiseman/nn_coref        |
| [131]                | Entity based  | 73.4  | 61.5 | 57.7 | 64.2  | https://github.com/swiseman/nn_coref        |
| [129]                | Entity based  | 74.0  | 62.9 | 59.0 | 65.3  | https://github.com/clarkkev/deep-coref      |
| [134]                | Entity based  | 74.6  | 63.4 | 59.2 | 65.7  | https://github.com/clarkkev/deep-coref      |
| [157]                | Entity based  | 80.9  | 65.7 | 50.8 | 65.8  | https://github.com/text-machine-lab/entity-coref |
| [158]                | Language modelling | 76.3  | 65.7 | 61.5 | 67.8  | https://github.com/swabhs/scaffolding       |
| [138]                | Mention ranking | 76.4  | 65.6 | 61.4 | 67.8  | https://github.com/luohongyin/coatt-coref  |
| [133]                | Mention ranking | 77.2  | 66.6 | 62.6 | 68.8  | https://github.com/kentonl/e2e-coref        |
| [139]                | Mention ranking | 77.6  | 67.1 | 62.9 | 69.2  | No official code was found.                 |
| [140]                | Mention ranking | 80.4  | 70.8 | 67.6 | 73.0  | https://github.com/kentonl/e2e-coref        |
| [143]                | Mention        | 80.7  | 71.1 | 67.9 | 73.2  | No official code was found.                 |
| Reference | Approach            | Mention ranking | PCAC-2008 corpus | Official code |
|-----------|---------------------|-----------------|-----------------|---------------|
| [159]     | Entity based        | 81.4            | 71.7            | 68.4          | 73.8          | No official code was found. |
|           |                     | 83.4            | 74.7            | 71.8          | 76.6          | [https://github.com/bkntr/coref-ee](https://github.com/bkntr/coref-ee) |
| [144]     | Entity based        | 83.5            | 75.3            | 71.9          | 76.9          | [https://github.com/mandarjoshi90/coref](https://github.com/mandarjoshi90/coref) |
| [147]     | Entity based        | 83.8            | 75.1            | 72.2          | 77            | No official code was found. |
| [148]     | Entity based        | 84.7            | 76.8            | 73.2          | 78.2          | [https://github.com/shtoshni92/long-doc-coref](https://github.com/shtoshni92/long-doc-coref) |
| [18]      | Entity based        | 85.3            | 77.8            | 75.2          | 79.4          | [https://github.com/pitrack/incremental-coref](https://github.com/pitrack/incremental-coref) |
| [145]     | Language modeling   | 85.3            | 78.1            | 75.3          | 79.6          | [https://github.com/facebookresearch/SpanBERT](https://github.com/facebookresearch/SpanBERT) |
| [146]     | Mention ranking     | 85.4            | 78.7            | 75.0          | 79.7          | No official code was found. |
| [149]     | Mention ranking     | 86.1            | 79.2            | 74.8          | 80            | No official code was found. |
| [19]      | Entity based        | 85.7            | 79               | 75.9          | 80.2          | [https://github.com/lxucs/coref-hoi](https://github.com/lxucs/coref-hoi) |
| [151]     | Entity based        | 85.9            | 79.3            | 76.4          | 80.5          | No official code was found. |
| [152]     | Mention ranking     | 88              | 82.2            | 79.1          | 83.1          | [https://github.com/ShannonAI/CorefQA](https://github.com/ShannonAI/CorefQA) |
| [153]     | Mention ranking     | 92.2            | 84.4            | 79.9          | 85.5          | No official code was found. |
| [154]     | Mention ranking     | 92.5            | 85.9            | 84.1          | 87.5          | No official code was found. |

5. Persian coreference resolution systems

This section will review research papers on coreference and anaphora resolution in Persian. The Persian language is chosen for study because its lexical, syntactic, and morphological structures are entirely distinct from those of the English language. As an example of the distinction between these two languages, we can mention gendered pronouns, which do not exist in Persian. However, there are some similarities in the definitions of the features between these two languages.

Moosavi and Ghassem-Sani [161] made the initial attempt in Persian. In this paper, the authors evaluate the performance of the feature set proposed by Denis and Baldrige [161] using a variety of algorithms, including decision trees and maximum entropy. The PCAC-2008 corpus was created by labeling the pronoun references in the Bijankhan corpus [162]. As noted by the authors, some aspects of the English system were disregarded, and others were added. However, the low performance reported in this article could be attributable to several factors, including the complexity of the PCAC-2008 corpus and the inadequacy of the feature set. The C4.5 decision tree method has the highest accuracy, with an f1 value of 44.7%.

A new corpus was developed in the system proposed by reference [163]. The feature set presented in this article increased the efficiency by 20% compared to the feature set used in the previous system. The authors implemented models in their new corpus. Later, Nourbakhsh and Bahrani [164] modified Moosavi's system by changing it to the PCAC-2008 corpus and manually
extracting the noun phrases. Their result improved the previous system by achieving an f1 value of 75%, compared to 45%.

Shamsfard and Fallahi [611] proposed the first rule-based system in Persian. In this system, the authors used a series of hand-crafted rules to identify the antecedent of different types of pronouns by using five rules. First, the input text is preprocessed by the tokenizer, stemmer, and part of the speech tagger. The pronoun's antecedents are then determined using these rules. Afterward, they are delivered to the evaluation section to determine the number of missing or incorrectly identified antecedents. Finally, they compared their system with Moosavi and Ghassem-Sani’s pronoun resolution system [160]. The corpus used to evaluate the system was derived from five Persian blogs. A 95% precision and 90% recall were reported on this simple corpus.

The paper by Nazaridoust et al. [166] introduced the first coreference resolution system in Persian. In feature vector construction, positive samples are made between each anaphor and its actual antecedent. Negative samples are created between each anaphor and its previous mentions. The created data set is highly unbalanced. Therefore some processes have been used to balance the data set. A total of 17 features are used in this system. This system has been tested on 20% of the corpus using decision tree algorithms, a support vector machine, and a multilayer neural network. Optimal results are associated with the neural network with an f1 value of 39.4%.

Rahimi and HosseinNejad [36] developed a coreference corpus with approximately one million tokens. All noun phrases, pronouns, and named entities are labeled as mentions. Their corpus contains seven tags for named entities. This paper develops a coreference resolution system using a support vector machine whose average CoNLL value on gold samples is about 60. This is the first Persian system to produce coreference chains and evaluate the output with the CoNLL standard.

In the study by Sahlani et al. [167], a method based on a fully connected neural network was used to improve feature extraction and train a machine learning model for the coreference resolution in Persian. In the feature extraction section, a series of heuristic features, word embedding, and a semantic feature introduced in [168] were used. A fully connected deep neural network is then developed to estimate the probability of mention-pairs.

The third hidden layer’s output is considered the mention-pairs feature vector. Then, in the final section, a hierarchical clustering algorithm is used to generate the coreference chains. The output of this system on the Uppsala test dataset [169] improved over the reimplementation of other systems in Persian. Table 5 compares the evaluation of this system with other systems implemented on test data. The authors found that in re-implementing other systems, some of the features introduced in English have been removed or edited, and some features specific to Persian have been added.
Table 5. The results described in the article (Hourali et al., 2020)

| The system presented in [36] | MUC | B3  | CEAF | CoNLL |
|-------------------------------|-----|-----|------|-------|
| The system presented in [170] | 69.25 | 54.7 | 57.15 | 59.56 |
| The system presented in [133] | 72.14 | 56.71 | 58.95 | 61.69 |
| The system presented in [129] | 72.06 | 56.66 | 59.4 | 61.66 |
| The system presented in [134] | 71.79 | 56.12 | 59 | 61.24 |
| The system presented in [167] | 71.89 | 56.29 | 58.63 | 61.36 |
| The system presented in [145] | 74.92 | 59.73 | 61.75 | 64.54 |

6. Discussion and issues

With the introduction of deep learning systems, the efficiency of coreference resolution systems and other NLP systems has increased significantly over time. Despite the constant improvement of coreference resolution, this field faces the significant obstacles discussed as follows:

- A good performance on coreference systems could not be achieved if only raw features were defined. Early coreference systems used linear models and sophisticated methods for feature conjunction. Hand-crafted feature conjunction is hard to define, and early inferential methods (such as [122]) that did this automatically were challenging to implement. The interaction between features is performed automatically by defining feature representations using deep learning models. The first system which defines feature representation is [130]. This method learns two separate feature representations for anaphoric detection and antecedent ranking. These representations define the interaction between features. Learning these representations increases model adaptability but makes model training more challenging.

- Using word embedding in recent deep learning systems increased the efficiency of these systems. The coreference model is based on each input token representation. For example, the article proposed by Lee et al. [140] used ELMO as word embedding. The article by Kantor and Globerson [142] used BERT [171], which exhibits the highest performance in many NLP areas. Using BERT for coreference resolution is not a simple task. The authors used BERT in their model by introducing a novel method. BERT-large is used in [144]. Using BERT-large representation in the coreference resolution model better distinguishes between separate entities such as (the president and CEO). This representation works better than ELMO and BERT-based representation. The authors of article [145] introduced the span-BERT representation to display better and predict spans. This representation differs from BERT in its masking scheme and training objective.

- Another challenge of coreference systems is using global knowledge in these systems. The primary issue with cluster features is that they are challenging to define. Changing the cluster size can result in a sparse vector of cluster features. In early systems, cluster features are defined by three operators (most, none, and all). Wiseman et al. proposed one of the
first neural network systems to aid this challenge [131]. In this system, learning cluster features is performed implicitly, and hidden RNN states consume a sequence of (partial) clusters. Applying this cluster-level feature to the mention-ranking model increases the accuracy of the ranking model. One of the advantages of global representation is extracting suitable information for complex pronoun resolution.

- Unlike [131], which used RNN to provide a higher-order model, the end-to-end system presented by Lee et al. [140] employed the global structure more efficiently. The system presented by Kantor and Globerson [142] is the first higher-order model that can be derived end-to-end. Consequently, their system is more effective than previous systems. A false cluster may propagate errors in subsequent predictions, which is a problem with the system.

- In the article proposed by Liu et al. [147], entity-centric properties are appropriately captured by GNNs. After that, the authors of the article [19] analyzed the two preceding global systems in their respective articles. In addition, they presented two new global systems and reported the end-to-end model implementation results for these four systems.

- Coreference systems used parsers and other syntactic resources before the emergence of end-to-end models. Extracting information to construct feature vectors was performed manually. One of the challenges in coreference systems was using these parsers and hand-crafted feature extraction. The first challenge of earlier systems was that some features could not be developed in other languages. The second challenge was that the error created in the parser and the manual extraction of features could cause cascading errors. End-to-end systems developed by Lee et al. [133] solved this problem. Only gold chains are used to train end-to-end systems. In these systems, mention detection and clustering are executed concurrently. Because decisions are made locally in the Lee et al. system, irrelevant mentions may be grouped. Subsequent papers have incorporated global terms into this model to address this issue.

- Another challenge in coreference resolution is a generalization in different domains. Many regularization techniques were proposed for neural networks, such as l2 regularization, dropout, and adversarial training. These techniques were used in deep learning coreference resolution systems for generalization. For example, the authors of the end-to-end system [140] used dropout regularization in their article. Subramanian and Roth use the adversarial first-gradient sign method, which improves the model generalization.

- A further challenge is the evaluation metric used to compare systems. Today's standard for comparison is an average of three metrics (MUC, B3, and CEAF) called the CoNLL score. Indeed, these metrics exhibit several flaws. Consequently, some metrics were introduced to address these issues but have not successfully gained acceptance as a standard.

7. Conclusion

Coreference resolution is one of the most important sub-tasks in the natural language processing field. Although this field has successfully employed deep neural networks, it remains one of the
most challenging subtasks in language processing due to the requirement for global knowledge. Despite the necessity of universal knowledge for coreference resolution, current systems have used less global knowledge inference and have focused on entity-level inference.

In this article, we examined both early and new models in coreference resolution. We also examined existing corpora and evaluation metrics for the coreference domain. Since research on coreference systems has shifted from rule-based to deep learning systems, we thoroughly reviewed rule-based systems to current advanced deep learning systems. This review article also discussed Persian systems in coreference and pronoun resolution.

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