A Neural Entity Coreference Resolution Review

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Abstract Entity Coreference Resolution is the task of resolving all the mentions in a document that refer to the same real world entity and is considered as one of the most difficult tasks in natural language understanding. While in it is not an end task, it has been proved to improve downstream natural language processing tasks such as entity linking, machine translation, summarization and chatbots. We conducted a systematic a review of neural-based approached and provide a detailed appraisal of the datasets and evaluation metrics in the field. Emphasis is given on Pronoun Resolution, a subtask of Coreference Resolution, which has seen various improvements in the recent years. We conclude the study by highlight the lack of agreed upon standards and propose a way to expand the task even further.

Keywords Coreference resolution · Deep Learning · Discourse · Gender Bias · Pronoun resolution · Natural language processing · Neural Networks

1 Introduction

In everyday life we use language in many shapes and forms so as to express our thoughts and communicate. In order to be successful and transferring our train of thought to another person, we have to be coherent. These coherent structures, which can be represented by a set of sentences when in writing, are commonly referred to as Discourse.

Coherence is not always present in a linear way, when describing events as they took place. Therefore, a structure can be coherent even if it does not follow the order of the events that took place. In order to make such structures coherent, we have to make sure that they are cohesive, i.e. the way they are linked is meaningful.

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There are many different forms of discourse. Texts, much like this one, are identified as monologues, while conversations are by definition dialogues of two or more participants. With the advancements in technology we also have Human-Computer Interaction (HCI), usually in the form of a human interacting with a bot (e.g. Siri on iOS devices).

A very common linguistic phenomenon that we identify in all forms of language communication is when two expressions are used to refer to the same entity. We call this phenomenon an anaphora and the terms used to express this phenomenon as anaphoric. The term anaphora originates from the Greek word “αναφορά”, the etymology of which comes from the two words “ανα” and “φορά”. The first term is a preposition indicating a timely phenomenon, something that happened in the past, while the second term means to carry something, together forming a word which indicates that one is carrying something from before, a past term.

The complete set of the phenomena described above is called “Discourse parsing” ([Soricut and Marcu 2004] and is comprised by two distinct subtasks in computational linguistics, Coreference Resolution and Anaphora Resolution, aimed to resolve anaphoric phenomenons. Coreference Resolution is the task of identifying different terms that refer to the same real world entity (corefer). Anaphora Resolution aims towards identifying the antecedent of an anaphoric pronoun or noun phrase in a text. The antecedent is also called a referent while the anaphoric pronoun is called a referring expression ([van Deemter and Kibble 2000]. In this context, Anaphora Resolution can be viewed as a subtask of Coreference Resolution, especially in the case of pronominal Anaphora Resolution which focuses on finding the antecedent of a pronoun to the nominal entity it points back. However, there are cases where anaphora exists but not corefence ([Kibble and van Deemter 2000].

In order to fully understand this field and analyze deep learning approaches towards solving these tasks we need to explore the different types of referring expressions that exist as well as the constrains that identify when two referring expressions can be linked. For that it is crucial to identify what is considered as Coreference Resolution and what Anaphora Resolution in computational linguistics.

In this review, we aim toward presenting in detail the field of Entity Coreference Resolution from a Deep Learning perspective as well as identifying the difficulties and innovations that past literature has. In the field of Anaphora Resolution, [Mitkov 1999] provides a detailed review of the state-of-the-art methods to that date, as well as an in depth explanation of the types of anaphora. A review on Coreference Resolution by [Ng 2010] captures the first fifteen years of research on the field, explaining the variety of approaches that were implemented to date. The most recent review on the field of both Coreference and Anaphora resolution is by [Sukthanker et al. 2018] which aims to capture the gap between last 8 years in the machine learning approaches. Although it touches on deep learning approaches briefly, it does not seem to provide a deep analysis of the methodologies applied in the field.

We successfully bridge the gap by providing a detailed review on neural Entity Coreference Resolution and also provide a review of Pronoun Resolution, a subtask of Coreference Resolution, that has been separated due to it’s importance to downstream tasks such as Machine Translation, Entity Linking, Summarization,
Chatbots, etc. We also highlight the work that has been done towards gender bias in Pronoun Resolution.

In the following sections we describe in detail the anaphoric types (Section 2) that can be found in the English language as well as the constraints that apply on each mention in order to be matched with antecedent (Section 3). We then provide an apposition of the available datasets (Section 4) and an overview of the evaluation metrics (Section 5) for the tasks with focus on the advantages and disadvantages of each. Section 6 provides a brief history of the non-neural approaches on Coreference Resolution, followed by section 7 which provides a detailed insight in the advancements in the task, enabled by neural networks. We separate the approaches based on the methodologies and model types that were developed for Entity Coreference Resolution and for Pronoun Resolution we focus on general and gender bias oriented works. In sections 8, 9, 10 we present the results of the described approaches and provide the final remarks of this study.

2 Anaphoric Types

A variety of anaphoric types have been described in (Hirst, 1981) and (Lappin and Leass, 1994). In the latter those anaphoric types have been further expanded to more distinct cases (Mitkov, 1999; Ng, 2010; Jurafsky and Martin, 2009). Different types of anaphora are resolved in the process of Coreference Resolution and different on Anaphora Resolution, while some are overlapping between the two.

Therefore the difference in the tasks of Coreference Resolution and Anaphora Resolution can be described by the anaphoric types that each one handles and their approach to resolve them. Many deep learning approaches are handling specific anaphoric types, or excel in a certain anaphoric set, while struggle to resolve others. This can also be attributed to datasets that have not been well designed or do not hold a lot of anaphoric examples of some categories, as described in section 4, which leads to the need for more targeted approaches.

In this section, we list the different anaphoric types in the English language, give a brief explanation of their unique characteristics and we differentiate in terms of their information types. We first start with the anaphoric types that point back to a certain antecedent.

Zero Anaphora: This type of anaphora makes use of the gap in a phrase or clause to point back to the antecedent. In most cases, the meaning of such an anaphora can only be understood by the extralinguistic context.

One Anaphora: The type of anaphora realised by the use of the word “one” in a noun phrase.

Pronominal Anaphora: Considered to be the most widespread type, it is realised by the use of anaphoric pronouns and can be divided in three types, definite, indefinite and adjectival. The types of pronominal anaphora identify the type of the antecedent. In the case of definite, it refers to a single entity. Indefinite refers

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1 Extralinguistic context refers to factors that could affect the meaning based on parameters outside the text, such as the historical period, world knowledge or a certain event.
to an entity that is not well defined (e.g. "group of people"). Adjectival refers to an entity that is described with the use of an adjective (e.g. "good person"). The common factor in all of the pronominal anaphoras is that they refer to unique entities in the world, using a different approach of identifying it.

**Demonstratives**: This is the type of anaphora that is used, as the name suggests, to demonstrate a certain entity in a comparative. Pronouns that express such behaviour are “this” and “that”. These pronoun are further divided as proximal (for “this”) and distal (for “that”) as in their use they tend to showcase a certain distance; either literal or in time.

**Presuppositions**: Refers to the ambiguous anaphoric pronouns such as someone, something, anyone, anything, etc.

**Discontinuous Sets (Split Anaphora)**: This type refers to the anaphora in which the pronoun points back to more than one antecedent.

The anaphoric types can be further divided in categories based on the information structure they adhere to. [Haviland and Clark, 1974] [Prince, 1981] [Nissim et al., 2004]

**Inferrable Anaphora (Bridging Anaphora)**: Also called bridging anaphora is a very specific anaphoric type that points back to another anaphoric phrase or clause, which in turn points to an entity mentioned further back in the document.

**Generics**: It refers to the case where a certain anaphoric terms and its antecedent are not referring to the same real world entity. This behaviour makes such anaphoras to be more suitable members for the field of Coreference Resolution than Anaphora Resolution.

**Non referential terms**: It is very important in all the approaches of either Anaphora or Coreference Resolution to identify the anaphoric terms that are not pointing back to any antecedent. The pronoun “it” being the most common referring term that exhibits such behaviour. When found in syntactic phenomenons such as clefts and extrapositions it serves to suggest a certain behaviour while in other cases it is just pleonastic.

There is also a special anaphoric case, called cataphora, in which the anaphoric term proceed the antecedent. All cataphora cases belong to one of the aforementioned anaphoric types with the antecedent coming before the anaphoric noun phrase, hence pointing forward.

### 3 Anaphoric Constrains

In order to identify the right antecedent for each anaphoric noun phrase in a machine learning approach, certain syntactic and semantic features that are meant to limit the possible referents have to be considered. While these features have been
implemented in different variations, they all serve the purpose of enforcing certain constrains that need to be satisfied before a link between a referent and a referring expression can be made.

*Gender agreement:* Referents must agree with the gender of the referring expression to be considered as candidates

*Person agreement:* This constraint refers to the English form of person, which is split in three categories: first, second and third person. The third person is then identified as male, female or nonpersonal (“it”) gender. Referents and referring expressions must also match in this aspect to be linked.

*Number agreement:* Referents and referring expressing must agree in numbers, meaning that the expressions must distinguished in singular and plural expressions

*Binding theory:* Refers to the syntactic relationships that exist in English between the referential expressions and the possible antecedents when they appear in the same sentence, as identified by Chomsky (1981). One way to interpret this binding theory is to identify that reflexive pronouns (i.e. “himself”, “herself”, “themselves”) co-refer with the immediate clause that contains them, whereas the opposite happens for non reflexive pronouns.

*Selectional Restrictions:* This constrain refers to the elimination of a certain antecedent based on the properties a verb places on it.

*Recency:* The referent of a pronoun is more likely to be introduced in statements that are closer to it. Therefore, we consider those clauses closer to the anaphoric pronouns more important.

Apart from the English syntactic constrains, a lot of earlier research has identified some not as strict constraints that set a priority of some antecedents over others (Jurafsky and Martin, 2009).

*Discourse structure:* Limitations to the referent of an entity can be applied due to structural characteristics.

The grammatical role of entities in subject position are more important than those in object position and as a result this behaviour translates to the mentions in subsequent positions. This is based on the salience hierarchy theory by Hajiova and Vrbova (1982).

Entities that have been repeatedly mentioned in the document or have been the focused on in prior discourse are more likely to be continue to be treated in the same way and therefore have a higher priority of being the referent.

However, entities that appear in a parallelism phenomenon are more likely to ignore the grammatical role hierarchy constrains that were described above.

The implicit causality of the verbs, as studied by Caramazza et al (1977), changes the properties of what is considered to be a subject and what an object. This, called verb semantics, differs from Selectional Restrictions as both possibilities are viable even after the restrictions a verb can place on it’s arguments.
Consider the following example:

George borrowed his car and his phone to Nick. He drove it to work.

In this example, the selectional restrictions apply limit the “it” only being able to refer to the car, instead of the phone as well. Similarly, verb semantics limit the antecedent selections from “He” to Nick instead of George based on the semantic emphasis the verb “borrow” applies.

World Knowledge: This constrain is especially true in the task of Coreference Resolution, where terms refer to real world entities. This being the hardest constrain to incorporate to systems as it is beyond syntactical and semantical constrain previously mentioned. As an example, if we consider the referring term “the President”, in a current article about the United States, we have to have prior knowledge that Donald Trump is the current president in order to make the necessary referring term - referent clustering. If the article was, however, a decade old, the term would be referring to Barack Obama, the U.S. President at the time.

4 Standard Datasets for Coreference Resolution

A plethora of datasets have been developed for the tasks of Coreference Resolution through the years. In this survey we will explore the CoNLL 2012 dataset [Pradhan et al., 2012] which is predominantly used as the benchmark dataset in all state-of-the-art implementations for Entity Coreference Resolution as well as the GAP dataset [Webster et al., 2013] that was developed towards Gender Ambiguous Pronoun Coreference Resolution and briefly compare their key factors with the other datasets, created to counter issues within the CoNLL dataset.

Historically, the first datasets are the MUC 6 (Grishman and Sundheim, 1996) and the MUC 7 (Chinchor, 1998), developed for the 6th and 7th Message Understanding Conference respectively, being the ones that defined the task of Coreference Resolution. The dataset focuses more on identity Coreference Resolution while it does not contain annotations for binding theory coreference for example. The MUC datasets are very small in size, available only for the English language and are homogeneous (all the documents are domain specific - in this case news articles). In the following decade, the ACE datasets (Doddington et al., 2004) were developed as part of the Automatic Content Extraction program to deal with the shortcomings of the MUC. However, due to the many years of the program running, four different versions of the ACE dataset have been developed (ACE-2, ACE03, ACE04 and ACE05), starting with only news articles like the MUC datasets and then extending to other domains such as telephonic speech and broadcast conversations as well as other languages (Chinese and Arabic). ACE datasets are also restricted in the semantic types that they identified for this task. As a result, system evaluations and comparisons using the ACE datasets becomes difficult. To make things worse, the ACE dataset does not have a specified train-test split as the program organisers have not released the official test split, making results on the ACE datasets even less trustworthy.

The CoNLL 2011 (Pradhan et al., 2011) and 2012 (Pradhan et al., 2012) shared tasks were tasks on English Coreference Resolution and Multilingual Coreference...
Resolution respectively. The CoNLL 2011 dataset is based on OntoNotes 2.0, while the CoNLL 2012 dataset is based on the OntoNotes 5.0 corpus (Hovy et al., 2006) and is aimed towards unrestricted Coreference Resolution. This resulted in the dataset having significantly more documents in the training and testing splits and being more robust than its predecessors. Principally this made it the benchmark dataset for all state-of-the-art research to this date. Research showcases that a high amount of overlap of previously seen mentions exists between the described splits (Moosavi and Strube, 2017) which leads to overfitting problems.

In the following years, datasets were created to target for task-specific resolution of Coreference and Anaphora. The ECB+ (Cybulska and Vossen, 2014) dataset was introduced to handle topic-based event Coreference Resolution, while the ParCor (Guillon et al., 2014) dataset was aimed towards parallel pronoun Coreference Resolution to be later used for Machine Translation. Also, the CIC (Chen and Choi, 2016) dataset had annotated multi-party conversations and was aimed to improve Coreference Resolution on Chatbots.

In the more recent years, datasets have been created to tackle specific areas of Coreference Resolution as well, since the CoNLL 2012 dataset was lacking either variety or was missing a coreferring type completely. WikiCoref (Ghaddar and Langlais, 2016) has been proposed which provides an unrestricted Coreference Resolution corpus, GUM (Zeldes, 2017) was designed to handle domain adaptation, HardCore (Emami et al., 2018) was designed to test world knowledge while PreCo (Chen et al., 2018) strives to improve error handling by providing separated analysis of mention detection and mention clustering.

Mind the GAP (Webster et al., 2018) a dataset aimed towards Gender Ambiguous Pronoun identification, which was created by the need to disambiguate and de-bias the current implementations that seems to favour masculine over feminine predictions. The issue of gender bias is not only apparent in the CR datasets, but also in modern text representation approaches. As a result it was recently used by Kaggle’s Gender Pronoun Resolution competition and is considered to be the benchmark for the task. In comparison to the CoNLL 2012 dataset, as it targets only gender specific pronoun resolution, the annotations scheme is very different - effectively shifting the clustering problem to a binary classification prediction. During the course of the competition it was also discovered that a small amount of the entries have been miss-labelled which are, to our best of knowledge, not fixed as of yet in the available version.

However, all of aforementioned datasets created prior to 2017, are either very small in size like the ParCor dataset or aim towards a very specific Coreference Resolution task and are therefore an unsuitable replacement of the CoNLL 2012 as the benchmark dataset. Also, due to the recency of the newer datasets, created post 2017, they have not been thoroughly tested and they do not appear in modern research. As a result, none has been able to replace the CoNLL 2012 as the benchmark for the task of CR. The WikiCoref dataset represents an exception as it is being utilized for out of domain evaluation experiments.

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2 https://www.kaggle.com/c/gendered-pronoun-resolution
3 https://www.kaggle.com/c/gendered-pronoun-resolution/discussion/81331
5 Entity Coreference Resolution evaluation metrics

This section describes in detail the three used metrics in research for the evaluation of Entity Coreference Resolution tasks models (MUC, B-cube d and CEAF), briefly touch on alternative metrics and discusses their advantages and disadvantages. These three metrics are important as they provide comparison bases with the previous research. Each metric is going to be described in terms of how it calculates the Precision and Recall. The F1-score is defined as the harmonic mean between the two in all metrics.

Within the scope of this section we will use a global notation for all metrics. We denote a coreference chain as \( C \) and the number of mentions in the chain as \(|C|\). The term key chains refer to gold coreference chains, while system chains refers to system generated (or predicted) chains. \( K(d) \) and \( S(d) \) identify the set of gold coreference chains and predicted coreference chains respectively and can be represented as:

\[
K(d) = \{K_i : i = 1, 2, \ldots, |K(d)|\},
S(d) = \{S_j : j = 1, 2, \ldots, |S(d)|\},
\]

Where \( K_i \) and \( S_j \) represent chains in \( K(d) \) and \( S(d) \) respectively and \(|K(d)|\) and \(|S(d)|\) represent the number of chains in the sets.

5.1 MUC

The MUC score was the first scoring metric introduced to the task of Coreference Resolution by Vilain et al. (1995) for the 6th Message Understanding Conference for the task of Coreference Resolution. It identifies references as linked references, where each can be linked to a maximum of two other references. This is achieved by counting the changes (insertions and deletes) required in the predicted (system) set to make it identical to the gold standard key set. In order to express Precision and Recall we first identify a partition as:

\[
P(S_j) = \{C_j^i : i = 1, 2, \ldots, |K(d)|\}, \text{ where } C_j^i \text{ is } S_j \cap K_i, \quad (1)
\]

Then we can use the subset \( C_j^i \) to calculate the number of common links as :

\[
c(K(d), S(d)) = \sum_{j=1}^{\left|S(d)\right|} \sum_{i=1}^{\left|K(d)\right|} w_c(C_j^i),
\]

where \( w_c(C_j^i) = \begin{cases} 0 & \text{if } |C_j^i| = 0; \\ |C_j^i| - 1 & \text{if } |C_j^i| > 0. \end{cases} \quad (2)
\]

In Eq. (2) \( w_c(C_j^i) \) is commonly identified as “weight” of \( C_j^i \), which represents the minimum number of links needed to create the cluster. Similarly, the number of links in the Key \( k(K(d)) \) and the number of links in the system chain \( s(S(d)) \) are
calculated as:

\[ k(K(d)) = \sum_{i=1}^{|K(d)|} w_k(K_i), \text{ where } w_k(K_i) = |K_i| - 1 \]

and:

\[ s(S(d)) = \sum_{j=1}^{|S(d)|} w_s(S_j), \text{ where } w_s(S_j) = |S_j| - 1 \]

Finally, Precision and Recall are defined using Eqs. \{2 & 3\} as:

\[ Precision = \frac{c(K(d), S(d))}{s(S(d))}, \]

\[ Recall = \frac{c(K(d), S(d))}{k(K(d))} \]

From this we can interpret that the MUC score cannot be used to identify singleton entities (i.e. entities only mentioned once) and therefore cannot be trusted to score datasets like the ACE dataset \cite{Doddington2004}. 

5.2 B-cubed

The B-cubed is a metric introduced by Bagga and Baldwin \cite{Bagga1998} and designed to overcome the problems of MUC score. It does not take into account of the links but calculated Precision and Recall for each mention in the document and uses a weighted sum to calculate the final Precision and Recall. With \( m_n \) as the \( n \)th mention in a document \( d \) and \( C^i_j = S_j \cap K_i \) where \( S_j \) and \( K_i \) are the key and system chains respectively, we define:

\[ Precision(m_n) = \frac{w_c(C^i_j)}{w_k(K_i)} \]

\[ Recall(m_n) = \frac{w_s(S_j)}{w_s(S_j)} \]

where \( w_c(C^i_j) = |C^i_j|, w_k(K_i) = |K_i| \& w_s(S_j) = |S_j| \). Then, Final Precision and Final Recall are calculated as:

\[ FinalPrecision = \sum_{n=1}^{N} Precision(m_n) \]

\[ FinalRecall = \sum_{n=1}^{N} Recall(m_n) \]

where \( N \) represents the number of entities in the documents.

The B-cubed implementation has a significant flaw. The approach metrics, both precision and recall, are computed by comparing if the entities are containing the mention leading to entities being used more than once causing inaccurate results.
5.3 CEAF

CEAF, which stands for Constrained Entity Aligntment F-measure, is introduced by Luo (2005) and was designed to fix the drawbacks of the B-cub ed scoring metric. It aims to find a one-to-one mapping \( g^* \) between the \( K(d) \) and \( S(d) \) chains using the Kuhn-Munkres algorithm (Kuhn, 1955) and a similarity measure \( \phi \) to evaluate the similarity between the entities. The mapping function is defined as \( g \) with a scoring function \( \Phi \) as:

\[
\Phi(g) = \sum_{K_i \in K_{\min}(D)} \phi(K_i, g(K_i)),
\]

where \( g(K_i) = S_j, K_i \in K_{\min}(d) \)

and \( S_j \in S_{\min}(d) \) (8)

with \( \phi \) being the function that calculates the similarity the gold and system chains. With the use of the scoring function in eq. (8) we can identify the optimal mapping \( g^* \) and with it define Precision and Recall as:

\[
\text{Precision} = \frac{\Phi(g^*)}{\sum_{i=1}^{\vert K(d) \vert} \phi(K_i, K_i)} \tag{9}
\]

and

\[
\text{Recall} = \frac{\Phi(g^*)}{\sum_{j=1}^{\vert S(d) \vert} \phi(S_j, S_j)} \tag{10}
\]

In Luo (2005) four different similarity functions are considered:

\[
\phi_1(K_i, S_j) = \begin{cases} 
1 & \text{if } K_i = S_j \\
0 & \text{otherwise} 
\end{cases}
\]

(11)

\[
\phi_2(K_i, S_j) = \begin{cases} 
1 & \text{if } K_i \cap S_j \neq \emptyset \\
0 & \text{otherwise} 
\end{cases}
\]

(12)

\[
\phi_3(K_i, S_j) = |K_i \cap S_j| = w_e(C^i_j)
\]

(13)

\[
\phi_4(K_i, S_j) = \frac{2 \times |K_i \cap S_j|}{|K_i| + |S_j|} = \frac{2 \times w_e(C^i_j)}{w_k(K_i) + w_s(S_j)}
\]

(14)

Out of the 4 different similarity functions only the functions in Eqs. (13 and 14) are used and are considered the two variations of CEAF metric as CEAF\(_m\) for mention-based CEAF and CEAF\(_e\) for entity-based CEAF respectively.

Apart from the three metrics described in detail, which are being used in parallel in all recent research, more metrics have been introduced through the years to solve issues that are not covered in these sections. This is because of the use of the CoNLL 2012 dataset and the CoNLL metric that was proposed along with the dataset (Pradhan et al., 2012), which is the unweighted average of the F1-scores of the MUC, B-Cubed and CEAF metrics. Another argument for the constant use of the CoNLL metric is the replicability and comparability of the results between works and the ability to define the state-of-the-art. Detailed
studies, highlighting the advantages and disadvantages of these metrics have been conducted (Cai and Strube, 2010; Pradhan et al., 2014; Martschat et al., 2013).

Other metrics for Coreference Resolution include B-cubed extensions by Stoyanov et al. (2009) to handle twinless mentions and the ACE evaluation scoring (Doddington et al., 2004) which was introduced to accommodate the ACE conference. In the recent years the BLANC metric (Recasens and Hovy, 2011) which is a Rand-Index based metric was proposed, to solve the issue of high scoring in the MUC and B-Cubed scores from singletons.

Further metrics in the form of the LEA metric (Moosavi and Strube, 2016) have been proposed, which takes into account the importance of each entity and an entity resolution score - leading to higher scores by resolving entities with more mentions. However, as coreference resolution is not an end task, the importance of resolving named entities is important for downstream tasks (Chen and Ng, 2013).

Very recently the NEC evaluation metric has been proposed (Agarwal et al., 2019), giving emphasis on resolving the named entities and its importance on downstream tasks such as Entity Linking.

For the subtask of Pronoun Resolution, there are no special evaluation metrics introduced as it is described and developed as a binary classification task of different pronoun types (e.g. Third Personal, Possessive, etc.). Gendered Pronoun Resolution is treated as a multi-class classification between Masculine and Feminine and Neither, and the results for each class are calculated by convention multi-class Precision and Recall metrics.

6 Brief history of Entity Coreference Resolution approaches

Through the many years of research, CR has been approached with four different techniques. This attests to the difficulty of the problem as the techniques used were built on top of each other in a hierarchical way.

We identify the following approaches deployed to solve CR with chronological order of appearance: Mention-Pair models, Mention-Ranking models, Entity-Based models, Latent Structured models.

Mention-Pair models form the simplest and purest form attempted in CR, examining a pair of mentions at a time, along with the features of each mention, and assigning a binary outcome (Soon et al., 2001; Ng and Cardie, 2002; Denis and Baldridge, 2007).

Mention-Ranking models come to solve the most obvious disadvantage of the Mention-Pair models, not considering dependency with the other candidate antecedents, by simultaneous ranking and making a connection only with the highest ranking antecedent (Yang et al., 2003; Rahman and Ng, 2009).

While the Mention-Ranking models set the new state of the art at the time, they lacked the ability to determine when clusters should not be merged. As transitivity plays a big role in CR, without the ability to take it into account, decisions to pair mention clusters together would inevitably yield mistakes. Entity-Based models offered a means to classify the information required to enable informed merge decisions (Luo et al., 2003; Yang et al., 2004; Ratnoin and Roth, 2012; Stoyanov and Eisner, 2012). This was implemented in Entity-Mention models and Cluster-Mention models, with the later showing significant improvements.
Following on the steps of making previous models that attempted to map entities, Latent-Structure models have made an appearance, shifting the focus from creating agglomerative clustering iteratively to creating a tree-like structure that coreference partitions can be extracted from it (Fernandes et al., 2012; Durrett and Klein, 2013; Björkelund and Kuhn, 2014).

We notice that essentially, Mention-Pair and Mention-Ranking models set the foundation required for the Entity-Based and Latent-Structure models as they represent core components for their functionality. A detailed review of the approaches described above can be found in Ng (2010). In the next section we analyze the advances in that DL approaches that have been introduced, in which we see a similar trend to conventional approaches with DL models implementing mention-ranking approaches and gradually moving to Entity-Based and Latent-structure approaches, iteratively setting the state-of-the-art bar higher.

7 Deep Learning Coreference Resolution

In the recent years, most applications are traversing from simple machine learning techniques to deep learning. This is because of a combination of advancements in hardware that enable complex neural models and advancements in architectures and methodologies that are capable to generalizing better and effectively utilizing vast data. A significant milestone that signalled the start of the DL era is the word embeddings (Mikolov et al., 2013) followed by the more advanced language representation methodologies (Peters et al., 2018; Devlin et al., 2018). However, these advancements have also introduced new challenges in the form of gender bias. Kurita et al. (2019) provides a comprehensive methodology into measuring gender bias in ELMo, while Zhao et al. (2019) also discusses the error and provides two different methodologies to mitigate the bias in the representations via data augmentation and neutralization. As a result, Pronoun Resolution, a subtask of Entity CR has been distinctly identified and tackled to solve the bias in CR resolvers. We make a distinction between the approaches of the two tasks with the former describing a clustering problem while the later describing a binary classification problem.

7.1 Entity Coreference Resolution

At the first stages of DL approaches, the mentions from the documents were extracted using either the Berkeley Coreference System (BCS) (Durrett and Klein, 2013) or the Stanford Deterministic Coref System rules (Lee et al., 2011) while the later was used to extract animacy features in the implementations up to 2017. At early 2017, the first end-to-end CR systems made their appearance. As a result, the implementations are very different as the input transitions from mentions to spans of text.

Following the methodologies used in early CR, neural approaches can be identified in similar categories. We identify four major categories for neural CR: Mention-Ranking models, Entity-Based models, Latent-Structure models and Language-Modeling models. We notice that while mention-pair are very simplistic and have been proven useful in the past, they also have a lot of downfalls that the are solved
through Mention-Ranking. Hence, such approaches were never attempted in neural implementation. However, as Mention-Ranking models are at the core of Entity-based models that utilize the scoring functions to prune possible antecedents, implementations of the first were central to implementation of the later. Neural networks have however allowed for effective implementation of Latent-structure models with a combination of graphs and clusters, further extending past approaches. Finally, approaches that excelled in CR have been identified through Language-Modeling models that are not directly aimed for CR. We analyze each of those approaches separately in the sections below.

7.1.1 Mention-Ranking models

The first neural approach to solve CR, introduced by Wiseman et al. (2015), expands the mention-ranking scoring function described in Chang et al. (2013) to a piece-wise scoring function that distinguishes between the mention being anaphoric or not.

They define their neural network model as an adaptation of the piece-wise scoring function via a feed-forward neural network. It makes use of both the BCS to extract mentions and the Stanford Deterministic Coref System rules to extract two set of features, BASIC (Durrett and Klein, 2013) and BASIC+ which extends them with features utilized in Recasens et al. (2013), and create the feature representations. However, in comparison to past approaches they use the raw, un-conjoined features extracted via BCS and pretrain on the subtasks of anaphoricity and antecedent ranking to initialize the weights of the feature representations before training directly on CR. The model is trained to minimize the regularized, slack-rescaled, latent-variable loss defined as:

$$L_p(\theta_p) = \sum_{n=1}^{N} \max_{\hat{y} \in Y(x_n)} \Delta_p(x_n, \hat{y})(1 + s(x_n, \hat{y}) - s(x_n, y^\ell_n)) + \lambda\|\theta\|_1$$

which makes use of a mistake-specific cost function $\Delta$ of the three mistakes, “false link” (FL), “false new” (FN), “wrong link” (WL) that are individually defined. The subtasks use directly analogous loss functions for the pretrained tasks too.

Shifting from mention parsers and tools to extract mentions, in Lee et al. (2017), the first end-to-end CR approach is described that instead of mentions considers all possible spans of text and learns to identify mention and how to pair them into clusters. The model uses a pairwise scoring function that takes into account a unary mention score of each span and a pairwise score of the two spans in questions. The scoring functions are implemented via two layer FFNNs while the span representations are being computed using bidirectional LSTMs (biLSTMs) to capture lexical information from the whole text. The system also uses an attention mechanism (Bahdanau et al., 2014) to identify the head words in span representations. As the antecedents are not predefined, the loss of the system is defined as:

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

as it uses only the gold mention clusters. However, the system has to apply significant hard limitation to span sizes and distance between the spans and candidate
spans. The latter is done with constraining the spans based on the scores produced via the scoring function.

In Zhang et al. (2018), a different antecedent scoring mechanism is proposed, using the end-to-end span ranking system described in Lee et al. (2017) as the baseline. With the use of biaffine attention to calculate clustering scores, it allows the scoring function to directly model the compatibility of the two mentions and the prior likelihood of being connected. Furthermore, the system extends the loss function (eq. 16) to optimize not only the clustering but clustering and mention detection performance jointly, making use of the biaffine scoring mechanism.

To attempt and solve the common problem of globally inconsistent decisions amongst the mention-ranking models, without using global features or entities, a clustering algorithm is proposed in Gu et al. (2018). Using the span ranking model as a baseline (Lee et al., 2017), they propose the use of indirect links via the scoring function and create sets that are considered during inference to dismiss clustering decisions during inference.

7.1.2 Entity-Based models

Neural Entity-Based models are adaptations or extensions of the previous Mention-Ranking models that attempt to incorporate global features with different methodologies. At the core of the entity-based approaches, they are using adaptation of the Mention-Ranking functions to allow for the cluster-mention ranking.

In Wiseman et al. (2016), a cluster based approach is defined, with clusters holding features of the individual mentions in each cluster in a global representation. The cluster features are then used in a global scoring function between the cluster assigned to each possible antecedent and the mention, along with a local scoring function of the mention and each possible antecedent. The systems uses a specific type of Recursive Neural Networks (RNNs), Long-Short Term Memory (LSTM) networks, to embed cluster features and the same representation for individual mentions and mention-pairs as in Wiseman et al. (2015). The states of the RNNs before a decision is made for current mention are utilized in the global scoring function to make an effective map of the previous decisions. As the model is trained directly on the task of CR, the slack-rescaled loss function described in eq. 15 is optimized to reflect cluster information, while adopting the same mistake-specific cost function.

A similar approach has been used in Clark and Manning (2016b) where they also use clusters to capture global information and use cluster ranking to make merging decisions. In comparison to Wiseman et al. (2016), they define each mention a single entity cluster and combine them during inference. The system is comprised by three different components that work together to feed the respective representations to a single layer cluster ranking model that makes merging decisions.

The mention-pair encoder is a three layer fully connected Feed-Forward Neural Network (FFNN) with a ReLU activation (Nair and Hinton, 2010) on each layer that takes the embeddings and features for each mention and candidate antecedent and produces a high level representation. The cluster-pair encoder produces a distributed representation for a pair of clusters by applying max-pooling and average pooling and concatenating the results for all mention-pairs in each clusters. The mention-ranking model is an adaptation of Wiseman et al. (2015), that scores all
mention pairs produced by the mention-pair encoder. It uses the same loss function described in eq. 15 with the same mistake-specific function. However, the pretraining is done to the two objectives described in Clark and Manning (2013) (All-Pairs Classification and Top-Pairs Classification).

Finally, the Cluster Ranking model is a single layer network that utilizes the cluster-pair encoder and a anaphorocity score to assign cluster scores. The decision to combine or not the cluster is made by the policy network $\pi$ that takes into account cluster ranking and anaphoricity scores of the cluster ranking model and makes a decision of MERGER or PASS. However, as future decisions are based on previous ones, the system is utilizing a learn-to-search algorithm (Chang et al., 2015) to project all possible actions taken by the policy network and is trained to minimize the risk associated with each action, while also sorting the mentions in a descending order using the scores produces by the mention-ranking process.

As the policy network is very hard to optimize correctly and is also directly related with the coreference evaluation metric B-cubed, an extension is described in Clark and Manning (2016a) using Reinforcement Learning (RL). Specifically, two different RL algorithms are used to replace the learn-to-search approach that optimizes the merging policy. This is possible due to the distinct actions of the policy that can be translated into an action-reward system. The Reward Rescaling and REINFORCE algorithm described are attempting two different approaches to optimize the policy, the first by training the agent to be able to map the reward of each individual action and the second by attempting to maximize the expected reward by calculating the probabilistic distribution of an action use the mention-ranking model. Both approaches outperformed the learn-to-search approach in different metrics.

Building on top of Clark and Manning (2016b), the Sanaphor++ system is proposed (Plu et al., 2018). It utilizes semantic knowledge from external data source, specifically Wikipedia, and ontologies from DBPedia and YAGO. The system is applying ADEL and Sanaphor (Plu, 2016; Prokofyev et al., 2015) to provide entity links to mentions, the entities of which are known and utilize the NER tags for entities that are unknown, in order to provide some knowledge. The annotated information is used along the mentions of the system and utilized by an optimized mention-pair ranking model that takes into account the entity information by optimizing the mistake-specific function during training (eq. 15).

7.1.3 Latent-Structure models

An extension of the work in Lee et al. (2017) is described in Lee et al. (2018), which improves the baseline on two aspects. First, it allows for a refined span representation, through iterations, with the use of a gated attention mechanism. As a result, the span-ranking mechanism is predicting latent antecedent trees, with each parent of a span and each tree representing a cluster. Secondly, as the complexity is increasing dramatically on long documents, an antecedent pruning mechanism is applied that is based on an altered scoring mechanism. The altered scoring function uses a less accurate and less computationally expensive score for antecedent and cluster score functions that are leveraged in a beam three-stage beam search during final inference. This, along with the use of the refined spans, effectively alleviates the need for a priori knowledge and heuristics of distance of antecedents in a document, which was used in the baseline model.
In an approach aiming towards better generalization, an adversarial training technique has been proposed in Subramanian and Roth (2019). The system, which is based on the model of Lee et al. (2018), calculates a loss gradient for each span based on the span representations, and modifies the loss function to take into account the adversarial loss using the fast-gradient-sign-method (Miyato et al., 2016). Focusing on the named-entity problem, described by Chen and Ng (2013), they create adversarial examples by replacing named-entities in the test set and ensuring that no data overlap exists.

### 7.1.4 Language-Modelling models

We refer to Language-Modelling models for CR to the models that are not built to solve CR, but to represent tasks of modelling linguistic phenomenon, that are thereafter used to enhance CR and other NLP tasks. As a result, the majority of the models have been implemented and tested with fine-tuning on CR tasks.

A way to use syntactic information, in a treebank format, to infuse spans of text is proposed in Swayamdipta et al. (2018). While using multitask learning to create syntactic information, the systems is unrestrained into creating valid parse trees and does not assume the use of overlapping datasets for the syntactic learner and the primary task. The syntactic scaffolds are only used to bias the decisions of the primary task, which is done by jointly learning to minimize the loss of both tasks simultaneously using a shared set of tuneable parameters. As a result the syntactically-aware span representations can be directly used during inference on any end task that uses spans representations. In the case of CR, the syntactic scaffolds are applied on the implementation of Lee et al. (2017). By enhancing the span representations with syntactic information and altering the loss function described in eq 16 to minimize the loss by taking into account the treebank to enable joint learning, the system boosted the performance of the baseline. What is more, syntactic scaffolds could be implemented to further push the performance of other implementations (Lee et al., 2017, Zhang et al., 2018).

Following the same idea, the effective use of linguistic features in early neural approaches (Clark and Manning, 2016a, 2015; Lee et al., 2017) is questioned in Moosavi and Strube (2018). It builds on the generalization problem due to high mention overlap in the CoNLL dataset train, development and test splits (Moosavi and Strube, 2017). Alternatively, the authors propose a discriminative mining algorithm, that mines patterns in string-matching, syntactic, shallow semantic and discourse features using Frequent-Pattern Tree structure to represent them. The mining algorithm then prunes the tree by measuring the discriminative power, information novelty and frequency of the patterns that arise and enhances the results of the base approaches.

Further attempts have been made for the model to consider information that exceeds the spans. This was implemented either by using cross-sentence dependency in the word representations or considering more than two mentions at a time.

In the case of cross-sentence dependency, two different approaches were proposed in Luo and Glass (2018) which are based on the Lee et al. (2017) system and improves on span representations. First, the linear sentence linking (LSL) uses biLSTMs to initialize the states of the biLSTM of the second sentence using the
hidden states of the first sentence to achieve information cross. Second, they proposed an attention sentence linking (ASL) methodology in which they infuse the memory modules of LSTMs with attention - based on all the previous words of the previous sentence - and apply a gated selection mechanism. As these implementations are both targeted towards changing the span representations in the original systems, the rest of the model is as described in Lee et al. (2017).

Another way to model mutual dependencies between mentions is described in Meng and Rumshisky (2018). Moving from dyad systems (consider only two mentions or two spans of texts at a time) to triad systems that consider three mentions at a time. As this is not an end-to-end system, the mentions are the gold mentions of the dataset and the distance between mentions as well as a binary feature to indicate speaker information are applied. The proposed methodology is described by two models, one that computes mutual dependency between the triads and one that performs the clustering. The first system uses LSTMs to represent the words and the Part-of-Speech (POS) tags and creates a mention-pair representation for each pairwise. The triad representation is created by FFNN applying element-wise vector summations on the pair representations and a decoder function that is used to measure if the representations belong to the same entity. The second system used the probability scores created by the decoders over a pair and calculates the average of their scores in all triads to make a clustering decision.

7.2 Pronoun Resolution

Pronoun Resolution has been a part of Entity CR and was therefore not handled individually until recently. However, the importance of resolving pronouns for downstream tasks along with gender bias both within the CoNLL dataset and sentence representation techniques has made it popular. In comparison to the more difficult problem of Entity Coreference Resolution, the majority of the approaches attempting to solve Pronoun Resolution are not following clustering techniques. The approaches employed for this task are either span-ranking or binary classification (in the case of gender specific pronoun resolution).

Two different approaches to incorporate knowledge have been implemented in Zhang et al. (2019a,b) for pronoun resolution. Both approaches are built with a span representation approach based on the methodology described by Lee et al. (2017) and applying an inter-span attention before computing the final input representation. Zhang et al. (2019a) uses a simple FFNN and Softmax pruning to remove complexity before applying a knowledge attention mechanism. The attention mechanism uses external knowledge sources to weight and score the pruned inputs, resulting in the highest scored pair to be selected. Zhang et al. (2019b) uses the same baseline but instead of the knowledge attention mechanism, it uses knowledge from knowledge graphs in the form of triplets to create a knowledge representation for each mention and calculate a score for that pronoun pair.

In a different approach Tenney et al. (2019) utilizes sentence representation models such as ELMo and BERT with a two-layer MultiLayer Perceptron (MLP) and a sigmoid activation function. The model, although simplistic, utilizes the contextual information of the span representations which are calculated using the attention-pooling mechanism in Lee et al. (2017). The methodology described as
Edge Probing, proved that the sentence representation models hold contextual information outside the sentence that is leveraged towards informed decisions.

At the same time, an in-depth study of BERT has been conducted by Clark et al. (2019), which showcases the distinct linguistic phenomena that are represented by the attention heads and evaluates them in classifying syntactic relations. As a result of attention probing on the attention heads it proves that given a coreferent mention BERT can predict a correct antecedent.

A series of methodologies have been deployed as part of the Kaggle Gendered Pronoun Resolution task. However, despite that a lot of these approaches stem from past implementations, there are some innovations that were introduced. All of the approaches are using ensembles of models or predictions from entity CR systems (Lee et al., 2017; Webster et al., 2018; Lee et al., 2018) and BERT for sentence representation (Tenney et al., 2019). The winning approach of the competition (Attree, 2019) introduced novelty in creating an attention pooling mechanism on the cluster predictions of CR models along with a fine-tuned and a pronoun pooling methodology.

Instead, Ionita et al. (2019) extracted BERT embeddings from specific layers of BERT and used an array of coreference predictions and hand crafted features on their implementation. Liu (2019) introduced a data augmentation technique in which he replaced all names in the dataset to inject anonymity and make the model less biased towards the names themselves. Finally, Xu and Yang (2019) did not use any external predictions used the BERT representations and applied a Recurrent Graph Convolutional Network architecture to capture syntax from the embeddings.

### 8 Coreference Resolution Performance

In this section we present the best results achieved by the methodologies described in sec. 7, discuss the improvements on performance on the approaches and set the state-of-the-art on CR to this date.

#### 8.1 Entity Coreference Resolution results

| Approach                           | MUC Prec | MUC Rec | MUC F1  | B Prec | B Rec | B F1  | CEAF Prec | CEAF Rec | CEAF F1 | CoNLL Prec | CoNLL Rec | CoNLL F1  |
|------------------------------------|----------|---------|---------|--------|-------|-------|-----------|----------|---------|------------|----------|----------|
| Luo and Glass (2018)              | 79.2%    | 73.7%   | 76.4%   | 69.4%  | 62.4% | 66.6% | 72.2%     | 66.6%    | 70.1%   | 64.4%      | 54.0%    | 58.7%    |
| Swayamdipta et al. (2018)         | 78.4%    | 74.3%   | 76.3%   | 68.5%  | 62.9% | 64.7% | 64.6%     | 62.9%    | 64.7%   | 64.7%      | 58.7%    | 58.7%    |
| Moosavi and Strube (2018)         | 71.2%    | 79.4%   | 75.0%   | 59.3%  | 69.7% | 64.1% | 56.5%     | 64.4%    | 60.3%   | 66.4%      | 54.4%    | 54.4%    |
| Meneer and Rishinsky (2015)       | 84.4%    | 87.1%   | 85.8%   | 80.4%  | 77.8% | 87.1% | 84.4%     | 77.8%    | 87.1%   | 87.1%      | 77.8%    | 77.8%    |
| Alshehri and Sarker (2019)         | 74.3%    | 79.1%   | 76.7%   | 68.9%  | 69.8% | 70.0% | 74.3%     | 69.8%    | 71.9%   | 74.3%      | 69.8%    | 71.9%    |
| Luo and Glass (2018)              | 84.9%    | 77.3%   | 81.0%   | 60.7%  | 67.9% | 68.6% | 84.9%     | 77.3%    | 81.0%   | 84.9%      | 77.3%    | 81.0%    |
| Luo and Glass (2018)              | 77.5%    | 79.9%   | 78.7%   | 68.7%  | 70.0% | 68.9% | 77.5%     | 70.0%    | 78.2%   | 77.5%      | 70.0%    | 78.2%    |
| Swayamdipta et al. (2018)         | 77.5%    | 79.9%   | 78.7%   | 68.7%  | 70.0% | 68.9% | 77.5%     | 70.0%    | 78.2%   | 77.5%      | 70.0%    | 78.2%    |
| Moosavi and Strube (2018)         | 77.5%    | 79.9%   | 78.7%   | 68.7%  | 70.0% | 68.9% | 77.5%     | 70.0%    | 78.2%   | 77.5%      | 70.0%    | 78.2%    |
| Meneer and Rishinsky (2015)       | 84.9%    | 77.3%   | 81.0%   | 60.7%  | 67.9% | 68.6% | 84.9%     | 77.3%    | 81.0%   | 84.9%      | 77.3%    | 81.0%    |
| Alshehri and Sarker (2019)         | 84.9%    | 77.3%   | 81.0%   | 60.7%  | 67.9% | 68.6% | 84.9%     | 77.3%    | 81.0%   | 84.9%      | 77.3%    | 81.0%    |

Table 1: Neural Entity Coreference Resolution Results
The results presented in Table 1 are only referring to the best results of each implementation previously described, under the best set of parameters, including ensembles. We consider best results the ones that have achieved the highest CoNLL score, regardless of cases where experiments show higher Precision or Recall in one of the individual scores of one of the metrics. As the results are organised in a per model-type basis, the bold results are the best overall in a per score basis and underline the best results in a per model-type basis.

From the results it is apparent that the best overall results are from either language modelling approaches or latent entity approaches, with a balance between high recall and precision between the methodologies, respectively. In the results showcased in Table 1 [Gu et al. (2018)] appears to be performing worse than his baseline [Lee et al. (2017)]. This is because the results reported for the approach presented in [Lee et al. (2017)] are based on a 5-model ensemble.

A lot of the proposed models are building on top of previous baseline models and hence the results are directly related, with cases where the change in scores comes from a parameter fine tuning, e.g. in [Clark and Manning (2016a)] the fine tuning is done with the use of reinforcement learning. Furthermore, all of the approaches - with the exception of [Wiseman et al. (2015)] and [Wiseman et al. (2016)] - are using dropout to avoid overfitting, and one or more type of word embeddings. Specifically, in [Clark and Manning (2016b)] they are pretraining word2vec embeddings [Mikolov et al. (2013)] on the Gigaword corpus and Polyglot embeddings [Al-Rfou’ et al. (2013)]. In [Lee et al. (2017)] and all the implementations that are based on this are using a combination of Glove [Pennington et al. (2014)] and CNN character embeddings which are extended by the use of ELMo embeddings [Peters et al. (2018)] in [Lee et al. (2018)]. Similarly, [Clark and Manning (2016b)] used RMSprop [Tieleman and Hinton (2012)] for the parameter optimization during learning, while all other approaches in the majority of the implementations are using Adam [Kingma and Ba (2014)].

It is important to note that while FFNN remains the same in all of the implementations, in [Lee et al. (2018)] the authors use Highway BiLSTMs instead of simple BiLSTMs.

### 8.2 Pronoun Resolution

Recently the subtask of Pronoun Resolution has been trending due to the effects of the Kaggle competition\(^4\) and gender bias in both the CoNLL 2012 dataset and the sentence representation methodologies. As a result, due to the recency of the subject, no clear benchmark exists and not all approaches to Pronoun Resolution are evaluated in the same dataset. We present the results in Table 2 in terms of F1 score on CoNLL 2012 datasets for the approaches that were evaluated Pronoun Resolution and the results for the described implementations of the competition on the GAP dataset for Gender Pronoun Resolution in Table 3.

\(^4\) We would like to thank the authors for providing the detailed results of their research as well as a github repository to cross-reference the implementation and provide us with the ability to check the results.

\(^5\) Results from Stanford CoreNLP Framework, which is based on the approach described in [Clark and Manning (2016a)] without the limitations that exist in the CoNLL dataset.

\(^6\) [https://www.kaggle.com/c/gendered-pronoun-resolution/](https://www.kaggle.com/c/gendered-pronoun-resolution/)
Table 2 Pronoun Resolution on CoNLL 2012

|               | M  | F  | B  | O  |
|---------------|----|----|----|----|
| Tenney et al. (2019) | 94.0% | 91.1% | 0.97% | 92.5% |
| Ionita et al. (2019)   | 92.7% | 90.0% | 0.97% | 91.4% |
| Liu (2019)           | 91.6% | 90.8% | 0.99% | 89.26% |
| Xu and Yang (2019)    | 79.9% | 81.1% | 1.01% | 80.3% |
| Webster et al. (2018) | 72.8% | 71.4% | 0.98% | 72.1% |
| Lee et al. (2017)     | 67.7% | 60.0% | 0.89% | 64.0% |

Table 3 Gender Pronoun Resolution on GAP

|               | M  | F  | B  | O  | logloss |
|---------------|----|----|----|----|---------|
| Attree (2019) | 94.0% | 91.1% | 0.97% | 92.5% | .3117   |
| Ionita et al. (2019) | 92.7% | 90.0% | 0.97% | 91.4% | .346    |
| Liu (2019)*   | 91.6% | 90.8% | 0.99% | 89.26%| .179    |
| Xu and Yang (2019)* | 79.9% | 81.1% | 1.01% | 80.3% | .493    |
| Webster et al. (2018) | 72.8% | 71.4% | 0.98% | 72.1% | -       |
| Lee et al. (2017) | 67.7% | 60.0% | 0.89% | 64.0% | -       |

We notice that Tenney et al. (2019) manages - using a simple model - to get very high scores, while the use of external knowledge has improved the baseline in Zhang et al. (2019a). While the approach by Clark et al. (2019) has the worst performance, it is important to note that it is coming out of a sentence representation model with attention probing and is not actually a model designed for the task of pronoun resolution, or even fine-tuned for it.

9 Discussion

Coreference Resolution has taken significant leaps in performance in the recent years, boosted by the use of deep neural networks, word embeddings and language modelling. At the first stages of the NN approaches, the focus was to build good foundation for the task - neural pairwise scoring function, neural modelling of the problem and establishing a training objective. That enabled later implementation of entity based approaches, following a similar timeline as non-neural approaches. In the same time, the task shifted from using the words in their surface forms and feature extraction to using embeddings and end-to-end neural approaches. What significantly boosted performance and has seen the greatest advancements in CR is the language modelling approaches.

In the early approaches, the use of the word surface forms and feature extraction has been very beneficial, but a problem in generalization was present. All implementations that adopted such approaches have found that the pairwise features (distance and head matching in particular) have contributed the most to the performance boost. Similarly, techniques for mapping linguistic features, such as the one presented in Moosavi and Strube (2018) have also greatly helped such approaches, even though they are limited in scope and require a lot of human effort. Also, these techniques were hindered by the cascading errors introduced by the mention detection tools that were required to extract all the mentions and candidate antecedents. With the use of word embeddings and span representation,

* We would like to thank the author for providing gender scores after direct contact.
* We would like to thank the authors for providing gender scores after direct contact.
these approaches were translated into neural functions to learn to identify mentions and pair them together. However, while better generalization was achieved through embeddings, the use of embeddings increased FP links because they confuse paraphrasing with relatedness. The addition of ELMo and BERT embeddings mitigate the issue and provide word representations with semantic context.

Going past the limits of the underlying methodologies, the approaches introduced limits as well.

The mention-ranking models that use mention detection tools (Wiseman et al., 2015) improved on identifying non-anaphoric mentions while in models that use spans of text as input (Lee et al., 2017; Zhang et al., 2018) this is replaced by attention mechanisms which increases precision scores. However, they fail to make global decisions and as a result are prone to errors in transitivity. While the transitivity issue is partially dealt in by a novel clustering methodology during inference which solves incompatible clusters (Gu et al., 2018), these models are unable to make decisions that require world knowledge.

The entity-based models have generally implemented the task as a agglomerative clustering problem, predicting clusters directly. As such they improve on several aspects over the mention-ranking models, although they are also using mention detection tools which makes them prone to cascading errors. The have fewer FL mistakes, which is the main improvement over the previous approaches, leading to better identification of pleonastic pronouns, non-anaphoric pronouns and non-anaphoric nominal mentions. Since as all of the approaches use word embeddings, they also achieved a significant improvement over linking nominals with no head match over previous approaches.

The latent structure models are converting the task of Coreference Resolution into a task of predicting latent tree structures and inferring the clusters from the resulting structures. As a result the required iterations to create such structures increase complexity, making the process very computationally expensive. As they attempt to solve the same issues faced by mention-ranking problems, in a similar manner as entity-based models, they outperform both in terms of precision and recall as they are able to model very distant connections successfully.

The language modelling approaches are attempting to map different language aspects, in order to enhance the CR task and face the issues of the mention-ranking models. The approach described in Swayamdipta et al. (2018) is boosting the performance by better defining pronominal mentions due to the syntactic information, which is also improved by the cross-sentence dependencies that are built in word representations in Luo and Glass (2018). Meng and Rumshisky (2018) improves on the problem of transitivity and salience by explicitly predicting triads instead of dyads while Moosavi and Strube (2018) is using linguistic features to better improve generalization of the models.

Generalization is a big issue in the task of CR, and the performance of the systems is not reflecting the reality. The flaws of the CoNLL dataset, which is used as the benchmark for the task, along with the bias in the scoring metrics (discussed in Section 5) is hindering the improvement. In section 4 we highlighted the issue with lexical features in the CoNLL dataset, where all the systems that are using surface form of mentions instead of spans are affected by it. While, there is also an issue of gender bias (Rudinger et al., 2018; Chen and Ng, 2013). While dealing with this issue, the performance of Lee et al. (2018) decreases rapidly in terms of recall across all the scores as reported in Subramanian and Roth (2019).
It was also discovered that not only the data is biased but also ELMo and BERT
Kurita et al. (2019); Zhao et al. (2019); Clark et al. (2019).

Due to the results of the Kaggle competition in Gendered Pronoun Resolution,
advancements have been achieved in removing bias via various techniques.
Although the results seem promising, most of the approaches are not reflecting
realistic improvement to the task of Entity Coreference Resolution as resolver
predictions from the general task were used in the training process. The work
on Pronoun resolution on the other hand provides insightful results towards
the better use of sentence representation models to the task and the use of external
knowledge features.

What is more, Moosavi and Strube (2018) developed a novel algorithm to
automatically extract the minimum span in a variety of datasets to solve this issue
and boost performance of the current CR resolvers. As the majority of the implementa-
tions discussed are using span, this contribution is very important and can
boost their performance.

It is apparent that most of the approaches, while novel in various aspects, when
published around the same time period. As a result, the improvements that have
been introduced are not adopted to the best possible baseline. The majority of the
language modelling methods are infused using Lee et al. (2017) as their baseline,
which was significantly outperformed by (Lee et al., 2018) and can be modified to
work with that as a baseline.

The task and its subtasks are also being set back by the lack of an agreed-
on standard for both the datasets and the evaluation metrics (Poesio et al.,
2016). The CoNLL 2012 dataset has clear flaws and while it has served as the
benchmark to define the state of the art, the issues hinder improvement. Singletons
are not explicitly labelled, there is a big overlap between the standardized test,
development and train splits and there is also the issue of gender bias. The use
and reliability of the performance metrics used in Entity Coreference Resolution is
also questioned. There is also no benchmark for out-of-domain performance where
we see the majority of Entity CR systems to struggle. From the replacements that
have been proposed in the recent years, due to identifying the same problems in
the dataset, the majority are other task specific of very small in size.

As a result, in the lack of a better alternative, we propose the continued
use of CoNLL 2012 dataset for entity CR to provide a sense continuity, in the
lack of better suited replacement. We encourage the in parallel use of Wiki-
Coref (Ghaddar and Langlais, 2016) for out-of-domain evaluation of the systems
trained on CoNLL data and the GAP (Webster et al., 2018) for gender bias eval-
uation. We also suggest the use of a unifying coreference annotation scheme,
such as the one proposed in Prange et al. (2019), and annotation methodology
Aralikatte and Søgaard (2019) to ensure consistency of the annotations.

10 Conclusions and future work

Coreference Resolution is a very important part of discourse and by extension
of language modelling and language understanding. Although it has seen great
progress through the use of neural networks, it is far from solved and it is consid-
ered as one of the most difficult tasks due to the required world knowledge and
inference problems that surround it.
In order for the task to improve, the immediate need of a better way of measuring the performance is required. Agreed-upon metrics and a better benchmark dataset for the evaluation of the task are sought after, as the performance of current approaches changes dramatically in out-of-domain evaluation. Furthermore, the lack of a clear baseline model needs addressing as approaches are built on top of sub-par models.

The importance of improvements in the task can be found in its use in state-of-the-art approaches of other tasks such as Entity Linking (Kundu et al., 2018; Ling et al., 2015), Machine Translation (Popescu-Belis, 2019; Urbizu et al., 2019; Voita et al., 2018), Summarization (Song et al., 2019; Barros et al., 2019) and Chat Bots (Zhu et al., 2018; Jonell et al., 2018). As a result, we believe that the best approach is to enhance the current language modelling approaches, utilized by all the majority of the tasks, with coreference information.
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