Understanding Mention Detector-Linker Interaction for Neural Coreference Resolution

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Abstract
Coreference resolution is an important task for discourse-level natural language understanding. However, despite significant recent progress, the quality of current state-of-the-art systems still considerably trails behind human-level performance. Using the CoNLL-2012 and PreCo datasets, we dissect the best instantiation of the mainstream end-to-end coreference resolution model that underlies most current best-performing coreference systems, and empirically analyze the behavior of its two components: the mention detector and mention linker. While the detector traditionally focuses heavily on recall as a design decision, we demonstrate the importance of precision, calling for their balance. However, we point out the difficulty in building a precise detector due to its inability to make important anaphoricity decisions. We also highlight the enormous room for improving the linker and that the rest of its errors mainly involve pronoun resolution. We hope our findings will help future research in building coreference resolution systems.

1 Introduction
Coreference resolution is the task of identifying mentions in a document that co-refer to the same entity. It is an important task facilitating many applications such as question answering (Morton, 1999) and text summarization (Azzam et al., 1999).

Lee et al. (2017) proposed the first neural end-to-end architecture for coreference resolution. Most recent state-of-the-art systems use it as a backbone while utilizing better scoring functions (Zhang et al., 2018), pruning procedures (Lee et al., 2018), or pre-trained token representations (Joshi et al., 2019, 2020). Despite this usage, to our knowledge, no in-depth analysis has been done to better understand the inner workings of such an influential system. This understanding is important: for example, Kummerfeld and Klein (2013)’s analysis of the then-best classical coreference systems inspired many important follow-up works (Peng et al., 2015; Martschat and Strube, 2015; Wiseman et al., 2016). However, it is unknown if observations on such classical feature-based and often highly pipelined systems extend to the current end-to-end models.

In this paper, we empirically analyze the best instantiation of this model family, SpanBERT (Joshi et al., 2020) + c2f-coref (Lee et al., 2018), by investigating the interaction between its two components: the mention detector and mention linker. Specifically, we study how the errors in each independently or jointly affect the final clustering. Using the CoNLL-2012 (Pradhan et al., 2012) and PreCo (Chen et al., 2018) datasets, we highlight the low-precision, high-recall nature of the detector. While traditionally only recall is emphasized for the detector as a design decision (Lee et al., 2011, 2017), we show huge degradation from noisy mentions and that, perhaps surprisingly, increasing the number of candidates considered by the baseline linker only deteriorates the performance. While some classical coreference pipelines (Uryupina, 2009) focused on detector precision, it is rarely emphasized for modern end-to-end systems. We hence stress the importance of a precision-recall balance for the detector and demonstrate how pruning hyperparameters, in addition to reducing computational complexity, help control this trade-off. However, we show the difficulty of obtaining a high-precision detector by demonstrating the importance of anaphoricity decisions and the inability of the detector to make such decisions. Finally, we highlight the high potential of the linker and that the remaining errors besides anaphoricity decisions mainly involve pronoun resolution. We hope these findings shed light on the internal mechanism of the mainstream coreference system and lay out an empirical foundation for future research.
2 Coarse-to-fine Coreference Resolution

We study the coarse-to-fine coreference system (c2f-coref; Lee et al. 2018). It assigns an antecedent for every span in a document of length \( T \), including a dummy antecedent that indicates non-mentions or non-anaphoric mentions. The final clustering is the transitive closure of connected spans. The system consists of a mention detector and a mention linker. The detector scores all \( O(T^2) \) spans up to length \( L \) and outputs the \( \lambda T \) highest-scoring spans as possibly anaphoric mentions. The linker links each mention candidate with the highest-scoring antecedent among \( K \) ones. Hyperparameters \( L \), \( \lambda \), and \( K \) control the number of considered spans and antecedents, reducing computational complexity.

3 Datasets and Singleton Mentions

CoNLL-2012 is the most common dataset to test coreference models. However, it lacks singleton mention annotation (Pradhan et al., 2012).

Singleton, or non-anaphoric, mentions do not co-reference with other spans, e.g. “The dog” in “[The dog] barks.” However, they may become non-singletons in another context, e.g. “[The dog] barks at [itself].” Being a mention is a span’s inherent property, while anaphoricity, whether or not a mention co-refers, is context-dependent. We use “all mentions” to refer to the union of singletons and non-singletons.

To understand the effect of singleton mentions, we heuristically generate all mentions for CoNLL-12 (§B) for relevant experiments. We also experiment with PreCo, a coreference dataset with annotated singleton mentions. We do all analyses on development sets and report dataset statistics in §A.

4 Experiments

Settings We embed tokens with SpanBERT-large, a pre-trained transformer (Vaswani et al., 2017) with state-of-the-art performance in coreference resolution. We choose the max span width \( L = 30 \), the number of spans considered per word \( \lambda = 0.4 \), and the number of antecedents per span \( K = 50 \). We only keep the first 110 sentences per document during training. To reduce confounding factors, we do not use speaker and genre metadata.

“Original” System refers to a standard SpanBERT + c2f-coref trained baseline. Its F\(_1\) score\(^1\) is reported in Table 1, similar to the results in Joshi et al. (2020) considering we disregard speaker and genre metadata.

|                | CoNLL-12 | PreCo |
|----------------|----------|-------|
| Coref F\(_1\)  | 79.17    | 85.04 |
| NSM P          | 28.37    | 39.23 |
| NSM R          | 96.42    | 98.40 |
| AM P           | 82.04    | 76.55 |
| AM R           | 57.35    | 95.98 |

Table 1: Original system coreference F\(_1\) and precision / recall for non-singleton mentions (NSM) and all mentions (AM) on CoNLL-12 and PreCo development sets.

Oracles We build oracle detectors in which, starting from the original system’s mention candidates (its detector output), we either remove all non-gold mentions (perfect precision), add all missing gold mentions (perfect recall), or both (perfect precision & recall). We give the altered, rather than the original, mention candidates to the linker. We consider both non-singleton mentions and all mentions as gold mentions and modify either in a post-hoc manner or re-train the system with the altered candidates. To control for a non-trainable detector, we train only a linker reusing the original system’s mention candidates, dubbed Fixed Detector. We consider this baseline as the comparison target for the oracles. Besides oracle detectors, we also build an oracle linker that assigns the correct antecedent (including dummy) to every mention candidate.

5 Precision-Recall Trade-Off for the Mention Detector

Traditionally, coreference systems heavily favor recall over precision for the detector (Lee et al., 2011) as the linker cannot recover missed mentions. Similarly, our c2f-coref system gets >96% non-singleton recall yet only <40% precision (Table 1). We therefore explore if detector recall is always more important than its precision. If more spans are considered by increasing the max span width \( L \) or the number of spans considered per word \( \lambda \) in the detector, will the system performance necessarily improve? In the extreme case, if we hypothetically had enough compute that allows the linker to consider all \( O(T^4) \) span-antecedent pairs, should we simply remove the pruning in the detector?

The Aggregated Importance of Precision For all oracles in Table 2, especially the non-singleton ones, fixing precision, compared to recall, yields a much larger improvement. Although the original

\(^1\)We use coreference F\(_1\) to refer to the average F\(_1\) of MUC, B\(^3\), and CEAF\(_{\phi4}\), the most common coreference metric.
Table 2: Baseline and oracle coreference F₁ for non-singleton mentions (NSM) and all mentions (AM) on CoNLL-12 and PreCo development sets. “Fixed Detector” is the baseline with a non-trainable detector. The middle three sections are oracle detectors with perfect candidate precision/recall. The last row is an oracle linker that always makes correct antecedent decisions.

|                   | CoNLL-12 | PreCo |
|-------------------|----------|-------|
| Fixed Detector    | 78.28    | 84.64 |
| NSM               |          |       |
| Perfect P         | 86.02    | 90.31 |
| Post-hoc Oracle   | 79.37    | 85.17 |
| Oracle            | 86.28    | 90.45 |
| Re-train NSM      | 89.98    | 95.09 |
| Perfect R         | 79.65    | 85.22 |
| Oracle            | 92.39    | 96.50 |
| Re-train AM       | 79.48    | 88.37 |
| Perfect P         | 78.52    | 85.23 |
| Oracle            | 80.05    | 89.13 |
| Oracle Linker     | 97.07    | 98.69 |

Table 2: Baseline and oracle coreference F₁ for non-singleton mentions (NSM) and all mentions (AM) on CoNLL-12 and PreCo development sets. “Fixed Detector” is the baseline with a non-trainable detector. The middle three sections are oracle detectors with perfect candidate precision/recall. The last row is an oracle linker that always makes correct antecedent decisions.

precision is low, this highlights the importance of detector precision and the extent to which the linker suffers from noisy mention candidates. These noisy candidates result in extra mention and entity errors in the final clustering (Table 4 in the appendix), accounting for the majority of the ~8 and 6 F₁ difference (CoNLL-12/PreCo) between the post-hoc perfect precision oracle and the baseline (Table 2). Furthermore, re-training the system to leverage the distributional shift of the absence of noise leads to another ~4 and 5 F₁ increase. §C shows that this improvement stems from the linker’s increased confidence in assigning coreference scores when it is not tasked with ignoring non-mentions (or singletons) from noisy candidates.

The Average Importance of Recall The large improvement from fixing precision might be due to it originally having a larger headroom than recall (Table 1). In §D, we compute the average number of operations (span addition/removal) needed for each oracle and the average F₁ improvement from each operation. For non-singleton mentions, recall has 5-8× the average effect of precision. If we control the number of operations by re-training a non-singleton perfect precision oracle removing only as many top-scoring extra spans as missing correct spans, it gets 79.08 and 85.01 F₁ on CoNLL-12 and PreCo, lower than the perfect recall oracles with 79.65 and 85.22. It is therefore only due to the low-precision high-recall nature of the original detector that precision is more significant in aggregate.

Precision-Recall Trade-Off We return to the original question: if we had more computational power, is it always beneficial to consider more spans in the detector? Following our discussion, while recall is important, an imprecise detector has significant adverse effects by increasing the linker’s learning burden. Indeed, increasing the max span width by up to 33% or the spans considered per word by up to 38% only degrades the performance (§E Table 6). As these additionally considered low-scoring spans are mostly noise, we only slightly increase recall but more heavily decrease precision, causing more harm than benefit. Therefore, besides saving computation, these hyperparameters also help balance the precision-recall trade-off. Future work should hence put more emphasis on precision which is often overlooked for end-to-end systems.

6 Difficulties Facing Each Component

6.1 The Detector’s Difficulty With Anaphoricity Decisions

Despite its large aggregated improvement, i.e. ~11.7 and 10.5 F₁ for CoNLL-12 and PreCo, perfect non-singleton precision requires perfect anaphoricity decisions that distinguish non-singletons from singletons. These decisions in fact account for most of the improvement, ~10.5 and 6.7 F₁ (Table 2, non-singleton v.s. all mentions perfect precision).² However, the detector, as a span classifier, does not explicitly model inter-span anaphoric relationships. To test the detector’s ability to distinguish non-singletons from singletons, we build two span classifiers with the same structure as the detector and sigmoid loss that respectively recognize all mentions and non-singleton mentions in PreCo. The former achieves 79.89 classification F₁ while the latter only 54.32, showing the inability of a span classifier to make anaphoricity decisions.

To better understand this difficulty, we define a confusion index as singleton recall divided by non-singleton recall. It correlates with the classifier’s inability to make anaphoricity decisions. We want this value closer to 0, recalling more non-singleton mentions and fewer singleton mentions. A random classifier incapable of distinguishing between the two has an expected confusion index of 1.

The non-singleton mention classifier has a confu-
Table 3: Examples of categorized conflated entity errors in CoNLL-12 development set with a perfect detector. Following past studies (Kummerfeld and Klein, 2013; Joshi et al., 2019), we refer to all deictic terms as pronouns. Each example contains two incorrectly linked entities in bold. Square brackets are added to separate mentions.

| Error Type                  | Example                                                                 | #   |
|-----------------------------|--------------------------------------------------------------------------|-----|
| Pronoun                     | ... a cross-sea bridge connecting Hong Kong, Zhuhai, and Macao.           | 109 |
|                             | ... after their return, Macao, and Hong Kong, the two special ... regions ... |     |
| Exact Match                 | The most important thing about Disney is that it is a global brand.       | 6   |
|                             | The subway to Disney has already been constructed.                       |     |
| Head Match                  | Ten landmark buildings located on Hong Kong Island reveal themselves ...   | 11  |
|                             | ... those private, er, buildings, that is ..., is willing to invest ...    |     |
| Otherwise Match             | And Dr. Andy Henry notices something else ...                            | 7   |
|                             | ... Dr. Mann says they’ve narrowed it down ...                           |     |
| Semantic Proximity          | ... Hong Kong cinema has nurtured many internationally renowned directors ... | 12  |
|                             | ... memorializing Hong Kong’s 100-year film history.                     |     |
| Others                      | But [Paul Kelly] [Steve Sodbury] and Mel Anderson ... had no idea ...    | 5   |

6.2 The Linker’s Errors

While the detector struggles to make anaphoricity decisions, the linker does have explicit anaphoric modeling by assigning the dummy antecedent $\epsilon$ when the detector proposes extra mentions (which it will as it always outputs $\lambda T$ spans). It is therefore also viable to address anaphoricity decisions in the linker. Indeed, the current detector would suffice if the linker were strong enough. In Table 2, the oracle linker achieves near-perfect scores with the original mention candidates, demonstrating the enormous potential of the linker. The oracle linker with coarse-pruned antecedents (Lee et al., 2018) shows similar results (§G).

To understand the remaining linker errors besides imperfect anaphoricity decisions, we analyze the linker assuming a perfect non-singleton detector. In this setting, conflated entities is the single major error source (last row of Table 4 in the appendix). We manually categorized 150 conflated entities in the CoNLL-12 development set and show examples and aggregated counts in Table 3. Sub-optimal pronoun resolution is the biggest issue, and the linker also tends to link spans with various degrees of text match or mere semantic proximity.

Within pronoun errors, the most common error case is a pronoun being linked with an incorrect nominal (e.g. the example in Table 3), occurring 43 times. Sometimes two pronouns, often identical, are incorrectly linked, a case that necessitates improving higher-order inference. They might be third person pronouns that refer to different entities, appearing 29 times. When they are first or second person pronouns, it is usually an artifact of speaker switching in conversations, occurring 37 times.

Among all these conflated errors, better representing span-internal information might be useful for errors such as semantic proximity, but the lack of discerning span-internal content for the more major error types including pronoun resolution and exact match calls for better contextual reasoning.

7 Conclusion

We analyzed the complex interaction between the mention detector and linker in the mainstream coarse-to-fine coreference system. Using oracle experiments, we showed that, while detector recall is important, higher non-singleton mention precision would lead to dramatically better linker performance, though achieving this is difficult. We also demonstrated that the oracle linker performance is near perfect and that the vast majority of remaining linker errors besides anaphoricity decisions are about pronoun resolution. We hope these discoveries will help future research in coreference systems.
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### Table 4: The $F_1$ score improvement after fixing different types of errors on the CoNLL-12 development set. The errors are independently fixed after span errors are fixed. The categorization is from Kummerfeld and Klein (2013).

|                  | Span Error | Conflated Entities | Extra Mention | Extra Entity | Divided Entity | Missing Mention | Missing Entity |
|------------------|------------|-------------------|---------------|--------------|----------------|-----------------|----------------|
| **Original**     | 1.6        | 3.1               | 1.3           | 3.1          | 2.6            | 2.1             | 4.5            |
| **Fixed Detector** | 1.7        | 3.1               | 1.7           | 3.3          | 2.8            | 2.1             | 4.7            |
| NSM              | 0.0        | 2.4               | 0.0           | 0.0          | 2.0            | 2.6             | 5.7            |
| Post-hoc Oracle  | 1.6        | 3.1               | 1.4           | 3.1          | 2.6            | 2.0             | 4.4            |
| Oracle           | 0.0        | 2.3               | 0.0           | 0.0          | 1.9            | 2.5             | 5.5            |
| NSM              | 0.0        | 3.4               | 0.0           | 0.0          | 0.9            | 1.5             | 1.4            |
| Re-train Oracle  | 0.7        | 3.1               | 2.0           | 3.4          | 2.6            | 1.5             | 4.4            |
| Oracle           | 0.0        | 3.0               | 0.0           | 0.0          | 1.0            | 0.4             | 0.3            |

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**A Dataset Statistics**

We use the English portion of the CoNLL-12 shared task (Pradhan et al., 2012) and the PreCo (Chen et al., 2018) dataset. The former contains 2,802/343/348 training/development/testing documents and the latter has 36.6K training documents and 500 each for development and testing.

**B Heuristically Generated CoNLL-12 All Mentions**

We heuristically generate the set of all mentions for CoNLL-12 in a recall-oriented manner. We use the gold syntactic information as a proxy and consider the union of all phrases tagged with NP or NML and all words tagged with PRP, PRPS, WP, WDT, WRB, NNP, VB, VBD, VBN, VBG, VBZ, or VBP. This set includes 99.63% non-singleton mentions which constitute 20.89% of this set. We obtain the set of all mentions by merging this set with the non-singleton mentions to ensure all mentions are a superset of non-singleton mentions.

**C How Does Detector Precision Help Concretely?**

In this section, we further analyze how higher detector precision helps linker decisions. We examine the coreference score the linker assigns to every span-antecedent pair representing the likelihood of a link between them. On CoNLL-12, the non-singleton re-trained perfect precision oracle has an average coreference score of −13.0, which is higher than −15.1 in the perfect recall oracle. Among only the correct span-antecedent pairs, these scores are 11.7 and 7.1 in the two oracles, exhibiting the same pattern. These results indicate that the noise in the perfect recall oracle prevents the system from reliably assigning high coreference scores even for correct links. This can also be shown by observing that, compared to the perfect recall oracle, the perfect precision oracle produces on average larger (4.44 vs. 4.26 entities) and longer-distance (154 vs. 152 spanning distance) clusters, an effect of higher coreference scores.

We also see this effect by examining the amount of potential improvement from having less noise using Table 4. It shows the $F_1$ improvement after fixing categorized errors, following Kummerfeld and Klein (2013) and independently fixing each error type after fixing span (boundary) errors.\(^3\)

In the non-singleton post-hoc oracles, as expected, fixing precision results in fewer extra mention/entity errors and more missing errors, while the perfect recall oracle behaves conversely. However, when re-trained, the perfect precision oracle produces much fewer missing entity errors, even fewer than its perfect recall counterpart. This is likely because the linker in this system learns to leverage the absence of noise and reliably assigns high coreference scores. Despite some incorrect links leading to more conflated entities, the many correct ones drastically reduce missing mention/entity errors. On the other hand, the noise in the perfect recall or the original system prevents such consistent high scores, resulting in more missing mentions and entities.

**D Controlling the Number of Operations in Oracles**

For the perfect precision and perfect recall oracles, we show the average number of operation (span addition/removal) needed to achieve the target can-

\(^3\)The numbers do not add up to the performance gap due to error type interactions.
|                | CoNLL-12 | PreCo |
|----------------|----------|-------|
|                | # op     | Op effect | # op | Op effect |
| NSM P          | 135.9    | 0.086   | 79.2 | 0.132     |
| NSM R          | 1.9      | **0.715** | 0.8  | **0.709**  |
| AM P           | 34.1     | **0.035** | 30.6 | 0.122     |
| AM R           | 115.3    | 0.002   | 4.1  | **0.143**  |

Table 5: The average number of addition/removal operations required for the oracle candidate sets. The average operation effect, in F₁, is the difference between the re-trained oracles and the fixed detector baseline divided by the average number of operations. Boldface indicates the higher per-operation effect between perfect precision and recall in each category.

Table 6: CoNLL-12 development F₁ with increased max span width L or the number of spans considered per word λ. The first column is the original setting. Boldface indicates the best performance for each hyperparameter.

In Table 5, we also compute the average operation effect: the difference between the oracles and the fixed detector baseline divided by the average number of operations. In general, recall has a higher per-operation effect except for CoNLL-12 all mentions which are heuristically generated in a recall-oriented way. This noisy nature makes its perfect recall oracle not very helpful, hence the marginal effect and the reversed pattern.

E System Performance Considering More Spans in the Detector

In Table 6 we show the system performance if we increase the max span width L or the number of spans considered per word λ. Neither improves the performance, with the original performance still marginally performing the best.

F The Confusion Index’s Variation With Span Width

In Figure 1 we plot how the confusion index of the PreCo non-singleton mention classifier (§6.1) changes with span widths. The classifier’s inability to make anaphoricity decisions is the most pronounced for short phrases, possibly because these phrases are also more likely to appear as both singleton and non-singleton mentions whose anaphoricity status is especially hard to determine, discussed in §6.1.

G The Oracle Linker Under Coarse-To-Fine Pruning

In Table 2, the oracle linker achieves 97.07 and 98.69 F₁ on CoNLL-12 and PreCo. It takes the mention candidates produced by the detector and makes the perfect antecedent assignment for each span. The possible antecedent choices for each span are all preceding candidates and the dummy ϵ. Alternatively, we consider only antecedents surviving the coarse pruning (Lee et al., 2018). This oracle linker gets 96.61 and 98.65 F₁ on CoNLL-12 and PreCo, a < 0.4 degradation. This confirms the significance of a strong linker, and that, with a good enough linker, the coarse-to-fine technique only has a negligible performance impact while significantly reducing the decision space.