Investigating the Role of Centering Theory in the Context of Neural Coreference Resolution Systems

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Abstract

Centering theory (CT; Grosz et al., 1995) provides a linguistic analysis of the structure of discourse. According to the theory, local coherence of discourse arises from the manner and extent to which successive utterances make reference to the same entities. In this paper, we investigate the connection between centering theory and modern coreference resolution systems. We provide an operationalization of centering and systematically investigate if neural coreference solvers adhere to the rules of centering theory by defining various discourse metrics and developing a search-based methodology. Our information-theoretic analysis reveals a positive dependence between coreference and centering; but also shows that high-quality neural coreference resolvers may not benefit much from explicitly modeling centering ideas. Our analysis further shows that contextualized embeddings contain much of the coherence information, which helps explain why CT can only provide little gains to modern neural coreference resolvers which make use of pretrained representations. Finally, we discuss factors that contribute to coreference which are not modeled by CT such as world knowledge and recency bias. We formulate a version of CT that also models recency and show that it captures coreference information better compared to vanilla CT.

1 Introduction

Centering theory (CT; Grosz et al., 1995) is a well-known theory of discourse that provides an account of the coherence of a piece of text through the manner in which successive utterances refer to the same discourse entity. CT has served as a theoretical foundation for many NLP applications such as coreference resolution, machine translation, text generation and summarization. Among them, CT has been most well-studied in the context of coreference, a task of linking referring expressions to the entity they refer to in the text (Sidner, 1979; Brennan et al., 1987; Iida et al., 2003; Beaver, 2004; Kong et al., 2009; Kehler and Rohde, 2013).

Previous work has shown that there are deep connections between CT and coreference. Referring expressions often show preference to certain linguistic forms to indicate a reference relation to their antecedents. For example, pronouns are often used to refer to preceding named entities, but reintroduction of the named entity leads to use of their nominal form. These referring expressions thereby can be seen to connect the various utterances in the text and contribute to the coherence of the overall text. Thus, it has long been believed that coherence can impose constraints on referential accessibility. See fig. 1 for an example.

Old coreference resolution models indeed exploited this connection (Brennan et al., 1987; Sidner, 1979; Iida et al., 2003; Beaver, 2004; Kong et al., 2009), arguing that the constraints proposed by CT can serve as a useful guide for coreference resolution models (Elango, 2005; van Deemter and Kibble, 2000; Chai and Strube, 2022). However, modern coreference systems are primarily based on neural networks and are trained end to end without any explicit linguistic bias. A natural question is, then, whether these neural coreference resolvers work in a similar way as CT suggests and, more
practically, if CT may be a useful inductive bias for neural coreference resolution systems.

In this paper, we attempt to provide an answer to these questions through a careful analysis of neural coreference models using various discourse metrics (referred to as centering metrics) and conducting several statistical tests. Because CT, at its core is a linguistic theory, and not a computational one, we first provide a computational operationalization of CT that we can directly implement (§2). Our operationalization requires us to concretely specify the linguistic notations present in the original work (Grosz et al., 1995; Poesio et al., 2004) and draw conclusions about how well neural coreference resolvers accord with CT.

In a series of systematic analyses (§5), we first show that neural coreference resolution models achieve relatively high scores under centering metrics, indicating they do contain some information about discourse coherence, even though they are not trained by any CT signals. In addition, as shown in Fig. 2, there is a non-trivial relationship between CT and coreference, which we quantify by mutual information, between the performance of a coreference resolver and our various CT operationalizations (Chambers and Smyth, 1998; Gordon and Hendrick, 1998). However, the centering scores taper off as we have more accurate coreference models (i.e., models with higher CoNLL F1): the dependence between CT and coreference performance decreases when CoNLL F1 reaches above 50%. This interval, unfortunately, is where all modern coreference resolution models lie. This indicates that entity coherence information is no longer helpful in improving current neural coreference resolution systems.

Next, we turn to answering the question: Where in their architecture do neural coreference systems capture this CT information? Our experiments on the well-known C2F coreference model with SpanBERT embeddings (Joshi et al., 2020) (§5.3) reveal that the contextualized SpanBERT embeddings contain much of the coherence information, which explains why incorporating elements of CT only yields minor improvements to a neural coreference systems.

Finally, we explore what information required in coreference resolution is not captured by CT? We show that CT does not capture factors such as recency bias and world knowledge (§6) which might be required in the task of coreference resolution.

In order to explore the role of recency bias, we extend our CT formulation to account for this bias by controlling the salience of centers in the CT formulation. We show that this reformulation of CT captures coreference information better compared to vanilla CT at the same centering score level. We end with a summary of takeaways from our work.

2 Coreference and Centering Theory

In this section, we overview the necessary background on coreference and centering theory in our own notation. We define a discourse $\mathcal{D} = [U_1, \ldots, U_N]$ of length $N$ as a sequence of $N$ utterances, each denoted as $U_n$. We take an utterance $U_n$ of length $M$ to be a string of tokens $t_1 \cdots t_M$ where each token $t_n$ is taken from a vocabulary $\mathcal{V}$. Let $\mathcal{M}(U_n) = \{m_{1}, m_{2}, \ldots\}$ be the set of mentions in the utterance $U_n$. A mention is a subsequence of the tokens that comprise $U_n = t_1 \cdots t_M$. Mentions could be pronouns, repeated noun phrases, and so forth, and are often called anaphoric devices in the discourse literature.

2.1 Coreference

Next, let $\mathcal{E}$ be the set of entities in the world. A coreference resolver $f : \mathcal{M}(\mathcal{D}) \rightarrow \mathcal{E}$ implements a function from the set of mentions onto the set of entities (henceforth also referred to as the MENTION ENTITY MAPPING $f$). In Table 1, $f(\cdot)$ denotes $f(\cdot)$ for illustration, i.e., a mention, e.g., Mike, is mapped to the entity [[Mike]]. Here we reuse the notation $\mathcal{M}(\cdot)$, where $\mathcal{M}(\mathcal{D}) \equiv U_n \in \mathcal{D} \mathcal{M}(U_n)$. Rule-based or feature-based coreferences resolvers (Hobbs, 1978; Sidner, 1979; Brennan et al., 1987; Kong et al., 2009) resolve coreference by explicitly combining CT constraints or syntactic constraints. Current state-of-the-art coreference resolvers are end-to-end neural models (Lee et al., 2017; Joshi et al., 2020; Wu et al., 2020).

2.2 Centering Theory

Centering theory (CT) offers a theoretical explanation of local discourse structure that models the interaction of referential continuity and the salience

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1This definition of an utterance could be understood as a textual unit as short as a clause, but it also could be understood as a textual unit as long as multiple paragraphs; we have left it intentionally open-ended and will revisit this point in §4.

2In general, coreference resolution includes a mention detection step. In our analysis, we assume the mentions to be given. Thus, $f$ can essentially be thought of as an implementation of the entity-linking step in coreference resolution.
of discourse entities in the internal organization of a text. It was one of the first formal treatments of discourse, and remains one of the most influential.

As the name suggests, CT revolves around the notion of centering, which is, informally, the shifting of focus from one entity to another during the discourse. A center is then defined as an entity in \( \mathcal{E} \) that is in the focus at a certain point in the discourse. CT describes some preferences on: a) the nature of the shift of the center from one entity to another, and b) linguistic properties of mentions referring to the center (e.g., mentions that attach to the center are typically subjects and are preferentially pronominalized compared to others). We offer a more formal treatment later in the section.

As an example of centering theory in action, consider the discourse given in Table 1: \( \mathcal{D} = [U_1 \ldots U_5] \). Now, consider replacing \( U_4 \) with:

\[
1. U'_4 : \text{He has annoyed John a lot recently.}
\]

Note that the resulting discourses \( \mathcal{D}' = [U_1 \ldots U_4', U_5] \) and \( \mathcal{D}'' = [U_1 \ldots U_4, U_5] \) differ only by one utterance. CT argues that \( \mathcal{D}' \) is not as felicitous as \( \mathcal{D} \). This is because, in the utterance \( U_3 \), the discourse entity \([John]_i\) is the center and not \([Mike]_m\), and given a preference for pronominalizing the center of attention, \([John]_i\) should be pronominalized as well if \([Mike]_m\) is pronominalized. We will now formally define the key notions of centering theory.

### Weighting function over Mentions.

Let \( \text{weight} : U_n \times \mathcal{M}(U_n) \rightarrow \mathbb{R} \) be a weighting function on the set of mentions in utterance \( U_n \). Mentions that are assigned a higher weight are more likely to link to a center, i.e., an entity in focus, in the given context. For example, in \( U_1 \) in Table 1, John is assigned the highest weight since it is the subject of the sentence, thus, is more likely to link to the center.\(^3\)

### Weighting function over Entities.

Now we turn from weighting mentions to weighting entities. Given an utterance \( U_n \), let \( f^{-1}_{U_n}(e) \) be the pre-image of \( e \in \mathcal{E} \):

\[
f^{-1}_{U_n}(e) = \left\{ m \mid m \in \mathcal{M}(U_n), f(m) = e \right\}
\]

which maps an entity \( e \) back to a set of mentions it links to. Now we may lift the weighting function of a weight to an entity by having it take the highest weight attached to the mentions that link to the entity, i.e.,

\[
\text{weight}(U_n, e) = \bigoplus_{m \in f^{-1}_{U_n}(e)} \text{weight}(U_n, m)
\]

where \( \bigoplus \) is a generic aggregator over mentions; obvious choices are \( \bigoplus = \max \) or \( \bigoplus = \sum \).

The weighting function weight is arguably the most important component of centering. Previous

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\(^3\) It is worth noting that the original presentation of Grofz et al. (1995), in contrast, specifies a ranking of the entities.

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| Utterance; mentions (elements of \( \mathcal{M} \)) are underlined | \( C_f \) | \( C_p \) | \( C_b \) | Transition |
|---|---|---|---|---|
| \( U_1 \) John has been having a lot of trouble arranging his vacation. | \([John]_i\) \([trouble]_j\) \([vacation]_k\) | \([John]_i\) | \( e \) | — |
| \( U_2 \) He cannot find anyone to take over his responsibilities. | \([John]_i\) \([responsibilities]_j\) | \([John]_i\) | \([John]_i\) | CONTINUE |
| \( U_3 \) He called up Mike yesterday to work out a plan. | \([John]_i\) \([Mike]_m\) \([plan]_n\) | \([John]_i\) | \([John]_i\) | CONTINUE |
| \( U_4 \) Mike has annoyed John a lot recently. | \([Mike]_m\) \([John]_i\) | \([Mike]_m\) | \([Mike]_m\) | RETAIN |
| \( U_5 \) He called John at 5 AM on Friday last week. | \([Mike]_m\) \([John]_i\) | \([Mike]_m\) \([Mike]_m\) | | SMOOTHSHIFT |

Table 1: An example describing centering theory with the weighting function \( w \) being GRAMMATICALROLE. Here, \([e]_i\) denotes the entity \( e_i \). For each utterance, a set of mentions \( \mathcal{M} \) are detected with weights, then map to a set of entities \( C_f \) (both He and his map to \([John]_i\) in \( U_2 \)). We sort the entities in \( C_f \) by their weights for illustration. \( C_p \) is the most weighted element in \( C_f \) (\([John]_i\) is an important entity than \([responsibilities]_j\) in \( U_2 \)). \( C_b \) is chosen from the \( C_f \) of the previous utterance.
works assume that several factors play a role in determining the weighting. Among them, grammatical roles (Gordon et al., 1993; Walker, 1998; Grosz et al., 1995; Walker et al., 1994; Brennan et al., 1987) and semantic roles (Sidner, 1979; Kong et al., 2009) are two factors that have been used in previous work. Previous work adopts the following orderings to define weight, respectively:

- **GRAMMATICAL ROLE:** Pronoun(Subject) > Pronoun(Object) > Subject > Object > Others.
- **SEMANTIC ROLE:** Pronoun(Agent) > Pronoun(Patient) > Agent > Patient > Others.

Other factors may include, for example, the utterance-level first-mention advantage, i.e. entities mentioned first in an utterance are more accessible than entities mentioned second. One could also expect external world knowledge to play a role in defining the weight. We will revisit this in §6.

Using our weighting function, we now define a set of forward-looking centers \( C_f(U_n) \), the preferred center \( C_p(U_n) \) and the backward-looking center \( C_b(U_n) \) as follows:

**The Forward-Looking Centers.** Each utterance \( U_i \) in a discourse is assigned a set of forward-looking centers. The forward-looking centers depend only on the expressions that constitute that utterance; they do not depend on any previous utterances in the discourse.

\[
C_f(U_n) \overset{\text{def}}{=} \{ f(m) | m \in M(U_n) \} \tag{3}
\]

where, as mentioned earlier, \( f \) is a coreference resolver.

**The Preferred Center.** The preferred center is the most prominent discourse focus in \( U_n \), e.g. \([\text{John}]_1 \) in \( U_1 \) in Table 1.

\[
C_p(U_n) \overset{\text{def}}{=} \arg\max_{e \in C_f(U_n)} \text{weight}(U_n, e) \tag{4}
\]

**The Backward-looking Center.** The backward-looking center, however, depends mainly on the previous utterance, i.e. the most weighted element of \( C_f(U_n-1) \) that appears in \( C_f(U_n) \). In Table 1, \([\text{John}]_4 \) as the highest-weighted element of \( C_f(U_3) \) appears in \( C_f(U_4) \), so \( C_b(U_4) \) is \([\text{John}]_1 \); otherwise, we will look at the second most weighted element of \( C_f(U_3) \) and so on.

| \( \text{TRANSITION} \) | \( C_f(U_n) \) | \( C_p(U_n) \) | \( C_b(U_n) \) |
|-------------------------|-----------------|-----------------|-----------------|
| CONTINUE > RETAIN > SMOOTHSHIFT > ROUGHSHIFT | \( C_f(U_n) \) | \( C_p(U_n) \) | \( C_b(U_n) \) |
| \( C_f(U_n) = C_f(U_{n-1}) \) \text{ or } \( C_f(U_n) \) undefined | CONTINUE | RETAIN | SMOOTHSHIFT |

Table 2: Four Types of Transitions in CT

\[
C_b(U_n) \overset{\text{def}}{=} \arg\max_{e \in C_f(U_{n-1}) \cap C_f(U_n)} \text{weight}(U_{n-1}, e) \tag{5}
\]

The connection between the backward-looking center and the preferred center forms the theory’s key claims about coherence. That is, texts fraught with abrupt center switches from one entity to the next are perceived to be less coherent.

The key difference between CT and coreference resolution is in the design of the decision function \( f \) that maps mentions to entities. While coreference models define a ranking or a classification function, CT defines a set of rules and constraints based on the relationship between the backward-looking center and the preferred center.

2.3 Centering Metrics

Next, we describe some metrics which use CT to assess coherence of a piece of text. We will later use these metrics to define a coherence metric which will let us study the relationship between discourse coherence as evaluated via CT and coreference.

TRANSITION. CT gives a formal account of how discourse involves continuous updates to a local attentional state, which is described in Table 2 as transitions. The transition relations are used to hypothesize that discourses are easier to process when successive utterances are perceived as being “about” a unique discourse entity. Transitions have the descending preference order of CONTINUE > RETAIN > SMOOTHSHIFT > ROUGHSHIFT. This rule captures the essence of the theory aiming to minimize the number of focus shifts. The transition information can be used to determine the extent to which a text conforms with, or violates, the principles of centering theory. Naturally, we can compare the coherence of different discourses by employing the preferences of transitions, i.e. given a set of discourses of the same length, we sort them by the number of CONTINUE transitions first, then use the number of RETAIN, SMOOTHSHIFT, ROUGHSHIFT as tie breakers sequentially.

Following previous literature (Poesio et al., 2004; Karamanis et al., 2004), we also define
four centering metrics: $\neg$NOCB, COHERENCE, SALIENCE and CHEAP.

$\neg$NOCB. The $\neg$NOCB constraint is a predicate that returns true if $C_b(U_n) \neq \varepsilon$. NOCB occurs when $C_b(U_n)$ is undefined. Consider the example in Table 1. If $U_5$ is changed to “Jane called Anna at 5 AM on Friday”, we will observe a NOCB, which implies a very sharp shift of focus since no element in $C_j(U_{n-1})$ is realized in $U_n$.

COHERENCE. The COHERENCE constraint is a predicate that returns true if $C_h(U_n) = C_h(U_{n-1})$, e.g. $U_2$ to $U_3$, since the continuity of $C_h$ is the core concept of local coherence.

SALIENCE. The SALIENCE constraint is a predicate that returns true if $C_b(U_n) = C_b(U_{n-1})$, indicating the maintained focus, i.e. $C_b$ is the most salient entity ($C_p$). For example, the SALIENCE constraint satisfy in $U_2$, $U_3$ and $U_5$ as $C_b$ and $C_p$ denote the same entity.

CHEAP. The CHEAP constraint is a predicate that returns true if $C_b(U_n) = C_p(U_{n-1})$. Qualitatively, this constraint enforces that the transition taken is the easiest, i.e. the transition that causes the least inferential load on the listener (Strube and Hahn, 1999), e.g. $U_4$ to $U_5$. However, if we assign $f$ (He) in $U_5$ to another entity, e.g. [Mary], $C_b(U_5)$ has to be the second most weighted entity in $C_j(U_4)$, i.e. [John], which violates the CHEAP constraint. We measure coherence using the ratio of the transitions that satisfy those constraints to the total amount of transitions in $\mathcal{D}$, e.g. $|\{U_n | U_{n-1} \rightarrow U_n \text{ satisfy } X \}|/(N - 1)$, where $X$ is one of the constraints.

Finally, KP denotes the sum of the four metrics defined above (Kibble and Power, 2000).

3 Assessing Coherence

Although the aforementioned centering metrics are straightforward, they cannot be directly used as a measurement of coherence quality as properties of discourse that are not related to coherence also affect these statistics. For example, discourse that contains more entities and mentions tends to have a higher rate of violations. To alleviate this issue, we adopt a search-based methodology to quantify coherence, which was first brought up in (Karamanis et al., 2004) for text structuring.

The key assumption behind this is that among all the possible permutations of a given discourse, the original permutation should be the most coherent one. We randomly sample a set of permutations from the space of possible permutations of the discourse $\mathcal{D}$ for discourses longer than 5 utterances and take the entire permutation space for short discourses. We then rank all candidate permutations of utterances by a given centering metric $M$ mentioned above. The explored search space is divided into sets of permutations that score better, equal, or worse than the original discourse $\mathcal{D}$ according to the metric $M$. The third step is to calculate the centering score

$$C_h(M, f, \mathcal{D}) = \text{Worse}(M, f, \mathcal{D}) + \frac{\text{Equal}(M, f, \mathcal{D})}{2}$$

where the Worse (or Equal) function denotes the number of permutations that score lower than (or equal to) $\mathcal{D}$ according to $M$ based on the coreference resolver $f$. Intuitively, this function assigns 1 unit of credit if original discourse $\mathcal{D}$ has a higher score than a scrambled (possibly incoherent) discourse and 0.5 unit of credit if the scores are equal. A higher $C_h(M, f, \mathcal{D})$ is indicative of a set of entity clusters $f(\mathcal{D})$ with better coherence quality. Finally, the coherence quality $\overline{C}_b$ on the entire corpus $\mathcal{C}$ is summarized as the average centering score

$$\overline{C}_b(M, f, \mathcal{C}) = \frac{1}{|\mathcal{C}|} \sum_{\mathcal{D} \in \mathcal{C}} C_h(M, f, \mathcal{D})$$

4 Experimental Setup

4.1 Datasets

We experiment on the OntoNotes 5.0 (CoNLL-2012 shared task) dataset (Hovy et al., 2006; Pradhan et al., 2013), which is a popular benchmark dataset in coreference resolution literature. The dataset also contains rich syntactic and semantic annotations such as part of speech, syntax and semantic roles, which is useful in our analysis. There are 2802, 343, and 348 documents in the training, development, and test set, respectively. It is worth noting that all previous work on CT has been based on much smaller datasets with shorter documents as well as fewer documents overall. For example, the Ontonotes dataset has documents that are on average 75 times longer than the GNOME dataset (Poesio et al., 2004) used in several previous CT papers (Poesio et al., 2004; Karamanis et al., 2004).
4.2 Coherence Model Parameters

Centering theory is an abstract theory in that it discusses focality using high-level semantic notions, e.g. the salience of an entity in an utterance. However, to make very specific claims about centering theory using data, we have to make these high-level notions precise. For instance, we have to precisely define what we mean by utterance and there are multiple choices, e.g. a clause, sentence or a paragraph. We describe and justify our choices in the operationalization of CT below.

UTTERANCE. The UTTERANCE parameter is set to SENTENCES. In principle, one could consider other linguistic units in future work.

PREVIOUS UTTERANCE. The PREVIOUS UTTERANCE parameter can be either TRUE or FALSE. This parameter dictates whether we should ignore null utterances, i.e., utterances that do not contain mentions such as one-interjection-utterance “Uh-oh...”. We set this parameter to TRUE.

CF CANDIDATE. The CF CANDIDATE parameter can take on values such as CLUSTERONLY, INCLUDESINGLETON, which stand for only taking into account entities that mentioned more than once or including singletons, respectively. This parameter has never been considered in previous centering literature since entities are always manually annotated in the small-scale datasets they experimented on. However, in real-world datasets, such as Ontonotes 5.0, this parameter must be set appropriately. In our experiments, both CLUSTERONLY and INCLUDESINGLETON are considered.

WEIGHT. As mentioned in §2.2, we consider GRAMMATICAL ROLE and SEMANTIC ROLE in our experiment. For GRAMMATICAL ROLE weighting function, the entire OntoNotes test set is used, while the experiment with SEMANTIC ROLE weighting function is conducted on a subset of the OntoNotes testset where semantic role annotations are available. This subset consists of 61.2% of the documents.

4.3 Coreference Models Parameters

We explore several coreference resolution models with various embedding approaches – SPANBERT (Joshi et al., 2020), GloVe (Pennington et al., 2014), One-hot, using different amounts of training data (10%, 20%, . . . , 100% of the OntoNotes training set). Each model is trained for 40 epochs and 5 independent runs with different seeds. The models and checkpoints we used in our experiments and analysis are: C2F (Lee et al., 2018) (with SPANBERT-base, SPANBERT-large, GLOVE and ONEHOT embeddings), COREFQA (Wu et al., 2020), INCREMENTAL (Xia et al., 2020). In total, there are 8,600 checkpoints. For SPANBERT-large, we set INFER-ENCE_ORDER to 2 with COARSE_TO_FINE being true, while the rest of C2F models adopt INFER-ENCE_ORDER of 1 without COARSE_TO_FINE tuning. ONEHOT models use one-hot word vectors as input and do not leverage any pretrained embeddings. For both GLOVE and ONEHOT, we add another LSTM context layer after the embedding layer as in (Lee et al., 2017) and set the depth of this LSTM layer to be 1. For all the models mentioned above, the ratio of the number of mentions to the total number of words in the document (SPANS_PER_LENGHT) is set to 0.4, the dimension of all feed-forward networks is 1500 and the dimension of the feature fed into feed-forward networks is 20. The upper bound number of spans is MAXAntecedents of 50. We also filtered out spans that are longer than 30 tokens. For COREFQA and INCREMENTAL, we follow the parameter settings specified in their original papers.

5 Experimental Results

We first investigate the relationship between centering and coreference.

5.1 Comparing a Strong and a Weak Coref System on Centering Measures

To start with, we compare the centering scores of MENTION ENTITY MAPPING $f$ being GOLD, STRONG and WEAK in Table 3, where GOLD denotes a “system” where the ground truth annotations are used for MENTION ENTITY MAPPING $f$, STRONG denotes a well-trained C2F-SPANBERT-large coreference model (with a CoNLL F1 of 78.87%), and WEAK denotes a underfitted C2F-SPANBERT-base model (with a CoNLL F1 of 17.51%). Four instantiations of CT are provided and we report statistical significance using the two-tailed permutation test with $p < 0.05$.

The first observation in Table 3 is that no centering scores of the coreference system significantly exceed the upper bound provided by the ground truth annotations, regardless of the instantiations.

\(^4\)STRONG is trained for 40 epochs untill convergence, while WEAK is trained only for 2 epochs.
Table 3: The comparison of different centering metrics by a permutation-based methodology with MENTION ENTITY MAPPING \( f \) being gold annotations and two coreference resolvers. \( CO \) and \( IS \) stand for \( CF \) CANDIDATE being CLUSTERONLY and INCLUDESINGLETON, respectively. \( \dagger \) represents that the current model is significantly outperformed by the corresponding right one; * represents the opposite (\( \alpha = .05 \)).

It appears that ground truth annotations of reference links are more consistent with the centering theory constraints than coreference annotations, which verifies our CT operationalization. It is also worth noting that all the centering metrics of \( \text{GOLD} \) are above 70\%. This, from a coherence assessment perspective (Barzilay and Lapata, 2008; Karamanis et al., 2004), indicates that the CT information is sufficient to distinguish the original discourse from randomly sampled permutations to some extent, supporting the claims about local coherence of the centering theory, particularly the CB existence claim.

On the other hand, despite not having been trained with any CT-related supervision, the \( \text{STRONG} \) model achieves high centering scores (even not being outperformed by \( \text{GOLD} \) on \( \neg \text{NOCB} \), \( \text{COHERENCE} \) and \( \text{SALIENCE} \) when \( \text{CF CANDIDATE} \) is considered to be \( \text{CLUSTERONLY} \)), indicating that it does contain substantial coherence information. In contrast, the \( \text{WEAK} \) performs significantly worse on the centering scores, which suggests that CT can be used as a goal for optimizing coreference performance.

5.2 Scaling Up: Exploring the Relationship between Coreference and Coherence

To further systematically investigate the shape of the relationship between CT and coreference, we scale up our experiment. We compute the centering scores and the CoNLL F1 scores of all 8,600 checkpoints listed in §4.3, with the weighting function being \( \text{GRAMMATICAL ROLE} \) and \( \text{CF CANDIDATE} \) being \( \text{CLUSTERONLY} \). As shown in Fig. 2, there is a monotonic relationship between the centering scores and the CoNLL F1. The centering metrics have high positive correlations (.883) and high mutual information (.451) with CoNLL F1, with significance tested by the t-test (\( p \)-value < .01). As the CoNLL F1 increases, the curve is flattened out, and the centering scores stop growing when the CoNLL F1 reaches a certain level (about 50\%). This suggests that the utilization of CT is more useful for improving coreference models; however, it provides little information gain when the predicted coreference chains are already of high quality. We will explore the mismatch between the CT objective and the coreference objective later in §6.

5.3 Where do Coreference Models Capture Centering Information?

As shown in §5.2, unlike feature-based or rule-based systems which explicitly leverage discourse-level coherence information by combining CT rules, the usefulness of CT for coreference is not guaranteed for modern end-to-end neural coreference systems. These neural models get surprisingly high coreference performance even though they are trained without any coherence signals. A natural question to ask here is why, i.e., which components of the neural models account for coherence modeling? Therefore, in this section, we will be concerned with answering this scientific question; in particular, two components of the neural mod-
els, namely the embedding layer (i.e. pretrained LMs) and the coreference resolver (i.e. coreference training), will be investigated and compared. We analyze these two possible sources of coherence information using 6,000 c2f model checkpoints. For simplicity, we refer the c2f model with SpanBERT-base, GloVe and one-hot embeddings as SPANBERT, GLOVE and ONEHOT, respectively.

**Centering scores vs. CoNLL F1.** Our first objective is to investigate how the performance of coreference and coherence varies as a function of the embedding layer. A version of Fig. 2 where the models are grouped by the types of their embedding layers is shown in Fig. 3. We observe that the centering scores of SPANBERT correlate most closely with its CoNLL F1 scores, that is, SPANBERT achieves greater gains on coherence modeling when training with the coreference objective. This indicates that the coherence information contained in the pretrained contextualized embedding is the most useful for coreference resolution.

**Training epoch.** We further show both the CoNLL F1 and the centering scores as a function of training epoch in Fig. 4. For each epoch, we calculate the mean of five independent runs. While the centering scores of ONEHOT and GLOVE increase smoothly over time, SPANBERT reaches a relatively high level of centering score at a very early training epoch and does not improve thereafter. This result suggests that SPANBERT contains more coherence information than ONEHOT and GLOVE. In addition, the centering score for ONEHOT is initially higher than that of GLOVE. One hypothesis for this observation is that the sparse one hot encoding enables ONEHOT to rapidly learn coherence information from Ontonotes in the early stages of the training process.

**Amount of Training Data.** Fig. 5 shows the CoNLL F1 and centering scores as a function of training data. The best performing models across different training epochs are considered, resulting in 150 checkpoints. As shown in Fig. 5, the centering scores and the CoNLL F1 increase as the amount of coreference training data increases, suggesting that the practice of coreference training does lead to improvements in coherence modeling. There is, however, a smaller growth rate for SPANBERT compared to GLOVE and ONEHOT. It indicates that the coherence information contained in the coreference training may overlap substantially.
with that contained in the pretrained embeddings.

**Mutual Information.** So far, we have shown 1) pretrained contextualized embeddings contain a substantial amount of coherence information that can be utilized for coreference resolution; 2) coreference training further improves the model’s ability to perform coherence modeling. In order to compare the contributions of the embedding layer and coreference training to coherence modeling, we quantify the relationship between coherence and coreference by mutual information (MI). We report the MI between the centering scores and CoNLL F1 for different embeddings in Fig. 6.

The MI between the centering scores and CoNLL F1 is smaller for SPANBERT, especially when trained with fewer coreference annotations, suggesting that implementing the pretrained LM as the embedding layer already provides sufficient information about coherence modeling that overlaps with coreference. Therefore, the model learns mainly information that does not overlap with centering-based coherence modeling from coreference annotations. The ineffectiveness of CT for modern neural coreference systems can be attributed to this finding. This also suggests that coreference resolution needs more than coherence modeling.

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1.a) To express its determination, the Chinese securities regulatory department compares this stock reform to a die that has been cast.
1.b) It takes time to prove whether the stock reform can really meet expectations, and whether any deviant...
1.c) Dear viewers, the China News will end here.
1.d) Thank you everyone for watching.
1.e) Coming up is the Focus Today hosted by Shilin.
1.f) Good-bye, dear viewers.

2.a) Among unanswered questions is what PASOK’s cut was from the $210 million Mr. Koskotas pinched.
2.b) Two former ministers were so heavily implicated in the Koskotas affair that PASOK members of Parliament voted to refer them to the special court.
2.c) But... millions of drachmas Mr. Koskotas funneled into New Democracy coffers.

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Table 4: One linguistic phenomena in coreference resolution that CT does not treat: recency of mentions. $C_p$’s are underlined. Singleton are marked in gray.

6 What’s needed for Coreference and not captured by CT?

As stated earlier, CT is a theory of coherence of a piece of discourse. So far, we have argued why CT should be expected to impinge on the coreference resolution task. At the same time, we have also shown that the inductive bias introduced by CT is not enough for coreference resolution. A natural question to ask then is, are there other linguistic factors that contribute to coreference which are not captured by CT? If so, what are those factors?

In this section, we attempt to answer: What are the factors that contribute to coreference resolution which are not captured by CT? In particular, we examine the predictions made by our operationalization of CT and study various linguistic phenomena, such as recency of mentions, discourse relations and world knowledge.

6.1 Modeling Recency Bias

One aspect of anaphora that CT does not treat directly is recency of mentions, i.e., entities mentioned most recently are more accessible than entities mentioned earlier (Gernsbacher et al., 1989). Inspired by the structure building framework proposed by Gernsbacher (1990), we provide a more refined account of CT that can account for a broader

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$^5$All 6,000 checkpoints are used for MI estimation. We adopt the default bin estimation in infotheo package in R for mutual information estimation. The same trends were observed when we tested other MI estimation techniques, including KDE, KSG, and partitioning.
range of linguistic phenomena, particularly the principle of recency. Formally, we expand the notion of the backward-looking center in §2.2 from a binary distinction to a scalar one.

**Backward-looking Centers.** Given a semiring \( W = (A, \oplus, \otimes, 0, 1) \), the backward-looking centers \( C_b \) are now defined as a set of weighted entities over \( W \). \( C_b \) could now be updated recursively throughout the entire discourse:

\[
C_b(U_n) \overset{\text{def}}{=} C_b(U_{n-1}) \cup C_f(U_{n-1})
\]

(8)

In words, the backward-looking centers of \( U_n \) are now defined as the union of the existing entities in comprehenders’ mental latent representation and the newly appeared entities in \( U_n \). The weights of \( C_f(U_n) \) are defined recursively as:

\[
\mathcal{W}(C_f(U_n)) \overset{\text{def}}{=} \text{forget} \left( \mathcal{W}(C_f(U_{n-1})) \right) \oplus \text{gate} \left( C_f(U_{n-1}), C_b(U_{n-1}) \right) \otimes \text{weight} \left( U_{n-1} \setminus C_f(U_{n-1}) \right)
\]

(9)

where \( \text{forget}(\cdot) \) is a forget function and \( \text{gate}(\cdot, \cdot) \) is a gating function. In (8) and (9), \( C_b \) could be understood, in Gernsbacher (1990)’s structure building framework, as a set of memory nodes, and \( C_f \) could be seen as the incoming stimuli that activates, enhances or suppresses those memory nodes by reweighing \( C_b \).

It is worth noting that \( \mathcal{W} \) mediates the accessibility of centers at the discourse level and thus differs from the weighting function weight that mediates the salience of centers at the utterance level. If we take a closer look at (9), we see that (5) is just a special case of it, where \( \mathcal{W} = \{ \mathbb{R}, +, \times, 0, 1 \} \), \( \text{forget}(x) = 0 \) and \( \text{gate}(x, y) = x \wedge y \). Note that a zero constant forget function forget indicates that the original CT framework does not take into account recency.

\( C_b \) is now defined as the most highly ranked entity in \( C_b \):

\[
C_b(U_n) \overset{\text{def}}{=} \arg\max_{e \in C_b(U_n)} \mathcal{W}(e)
\]

(10)

Table 5:

| Metric          | Cor.     | MI      |
|-----------------|----------|---------|
| KP              | .883     | .451    |
| KP-recency      | .912(+.029)\dag | .632 (+.181)\dag |

Table 5: The correlation and MI between the centering metric KP and CoNLL F1 of both the original CT operationalization and the refined operationalization with the trainable forget gate. \dag denotes \( p < 0.05 \).

**Operationalization.** To provide an operationalization of the principle of recency, we adopt a one layer feed-forward neural network to be a trainable forget function \( \text{forget}(x) \) and discard the gate function, i.e., \( \text{gate}(x, y) = 1 \). Table 5 shows the correlation and mutual information between the centering score KP and CoNLL F1. The same setting as in Fig. 6 in §5.3 is adopted. Fisher’s Z transformation and the corresponding test are conducted for the comparison of correlation coefficients and mutual information. The refined operationalization with the trainable forget gate yields both a higher correlation and a higher MI, indicating that this variation captures more aspects of coreference in its coherence model.

**6.2 Discourse Relations and World Knowledge**

CT, along with our refined framework, only provide accounts for attention. However, discourse relations and world knowledge can also be important for modelling anaphora. Table 6 illustrates via an example the influence that different discourse

\[\text{RESULT} \quad \text{Mitt flew to San Diego this weekend.} \]

\[\text{He was therefore able to visit several campaign donors.} \]

\[\text{PARALLEL} \quad \text{Mitt flew to San Diego this weekend.} \]

\[\text{Rick stayed in Kansas to campaign.} \]

Table 6: Different discourse relations have different demands on coreference for coherence modeling.
President Volodymyr Zelensky on Monday delivered a virtual speech to world leaders attending the World Economic Forum in Davos, Switzerland, urging them to impose "maximum" sanctions on Russia for invading his country.

b) Zelensky said more nations should embargo its oil and block its banks.

Table 7: An example where world knowledge must be taken into account for coreference. The correct choice of antecedent for its requires the understanding of sanction and invading.

relations might have on the relationship between coherence and coreference. While two mentions being coreferent is crucial for the example of RESULT to be coherent, the coherence of the example of PARALLEL has nothing to do with whether the center stays unchanged. Table 6 offers an example where world knowledge must be taken into account for coreference. It is also worth noting that the choice of antecedent for the “it” in utterance (b) has no influence on the CT-based coherence scores.

7 Other Related Work

Some previous works have also explored the connection between CT and coreference. Sidner (1979) investigated the process of focussing in the context of comprehension of anaphoric expressions in English discourse. Brennan et al. (1987) presented a formalization of centering and used it as the basis for an algorithm to track discourse context and bind pronouns, called the BFP algorithm. Then a critical evaluation of CT for pronoun interpretation was proposed by Kehler (1997). Tetreault (2001) then compared pronoun resolution algorithms and introduced a centering algorithm (LeftRight Centering). After that, Beaver (2004) reformulated the centering model of anaphora resolution and discourse coherence. Later, Kong et al. (2009) employed CT in pronoun resolution from a semantic perspective. An interesting review on the connection between centering and anaphora can be found in Joshi et al. (2006). The most recent related work would be (Kibble and Power, 2000), which tries to incorporates CT into neural coreference resolution and improves its performance, especially on pronoun resolution in long documents, formal well-structured text, and clusters with scattered mentions. While these works have attempted to use CT or some modified version of it for coreference, CT itself is not a theory of coreference resolution. The systematic analysis in this paper attempts to address the issue of the under-explored correlation of CT and coreference and provides a further theoretical basis for the use of CT in coreference. Moreover, we explore the relationship in the context of modern coreference systems and a much larger dataset.

8 Conclusion

By building a joint computational framework of CT and coreference, we conclude that although CT itself is not a theory of coreference, there exists a strong dependency between coreference and CT. However, this dependence is not linear. When the coreference quality of a model is high enough, the usefulness of CT is limited. We also confirm that neural coreference models, especially those adopting contextualized embeddings, contain much discourse-level coherence information. Thus, we conclude that CT can only provide minimal gains to modern coreference models. That being said, the low mutual information between coherence and coreference suggests that coherence modeling should still be incorporated into neural models, given that it cannot be learned entirely from coreference annotations. Finally, we explore which linguistic factors contribute to anaphora and may not be captured by CT; and find that recency bias, discourse relations and world knowledge may help explain some of the difference.

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