Global Inference for Bridging Anaphora Resolution

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Abstract

We present the first work on antecedent selection for bridging resolution without restrictions on anaphor or relation types. Our model integrates global constraints on top of a rich local feature set in the framework of Markov logic networks. The global model improves over the local one and both strongly outperform a reimplementation of prior work.

1 Introduction

Identity coreference is a relatively well understood and well-studied instance of entity coherence. However, entity coherence can rely on more complex, lexico-semantic, frame or encyclopedic relations than identity. Anaphora linking distinct entities or events this way are called bridging or associative anaphora and have been widely discussed in the linguistic literature (Clark, 1975; Prince, 1981; Gundel et al., 1993).¹ In Example 1, the phrases the windows, the carpets and walls can be felicitously used because they are semantically related via a part-of relation to their antecedent the Polish center.²

(1) . . . as much as possible of the Polish center will be made from aluminum, steel and glass recycled from Warsaw’s abundant rubble. . . . The windows will open. The carpets won’t be glued down and walls will be coated with non-toxic finishes.

¹Poesio and Vieira (1998) include cases where antecedent and anaphor are coreferent but do not share the same head noun. We restrict bridging to non-coreferential cases. We also exclude comparative anaphora (Modjeska et al., 2003)
²Examples are from OntoNotes (Weischedel et al., 2011). Bridging anaphora are typed in boldface; antecedents in italics.

Bridging is frequent amounting to between 5% (Gardent and Manuelian, 2005) and 20% (Caselli and Prodanof, 2006) of definite descriptions (both studies limited to NPs starting with the or non-English equivalents). Bridging resolution is needed to fill gaps in entity grids based on coreference only (Barzilay and Lapata, 2008). Example 1 does not exhibit any coreferential entity coherence. Coherence can only be established when the bridging anaphora are resolved. Bridging resolution may also be important for textual entailment (Mirkin et al., 2010).

Bridging resolution can be divided into two tasks, recognizing that a bridging anaphor is present and finding the correct antecedent among a list of candidates. These two tasks have frequently been handled in a pipeline with most research concentrating on antecedent selection only. We also handle only the task of antecedent selection.

Previous work on antecedent selection for bridging anaphora is restricted. It makes strong untested assumptions about bridging anaphora types or relations, limiting it to definite NPs (Poesio and Vieira, 1998; Poesio et al., 2004; Lassalle and Denis, 2011) or to part-of relations between anaphor and antecedent (Poesio et al., 2004; Markert et al., 2003; Lassalle and Denis, 2011). We break new ground by considering all relations and anaphora/antecedent types and show that the variety of bridging anaphora is much higher than reported previously.

Following work on coreference resolution, we apply a local pairwise model (Soon et al., 2001) for antecedent selection. We then develop novel semantic, syntactic and salience features for this task, showing strong improvements over one of the best known
prior models (Poesio et al., 2004).
However, this local model classifies each
anaphor-antecedent candidate pair in isolation.
Thus, it neglects that bridging anaphora referring to
a single antecedent often occur in clusters (see Ex-
ample 1). It also neglects that once an entity is an
antecedent for a bridging anaphor it is more likely to
be used again as antecedent. In addition, such local
models construct the list of possible antecedent can-
didates normally relying on a window size constraint
to restrict the set of candidates: is the window too
small, we miss too many correct antecedents; is it
too large, we include so many incorrect antecedents
as to lead to severe data imbalance in learning.
To remedy these flaws we change to a global
Markov logic model that allows us to:
• model constraints that certain anaphora are
likely to share the same antecedent;
• model the global semantic connectivity of a
salient potential antecedent to all anaphora in a
text;
• consider the union of potential antecedents for
all anaphora instead of a static window-sized
constraint.
We show that this global model with the same lo-
cal features but enhanced with global constraints im-
proves significantly over the local model.

2 Related Work
Prior corpus-linguistic studies on bridging are be-
set by three main problems. First, reliability is not
measured or low (Fraurud, 1990; Poesio, 2003; Gar-
dent and Manu´ elian, 2005; Riester et al., 2010).3
Second, annotated corpora are small (Poesio et al.,
2004; Korzen and Buch-Kromann, 2011). Third,
they are often based on strong untested assumptions
about bridging anaphora types, antecedent types or
relations, such as limiting it to definite NP anaphora
(Poesio and Vieira, 1998; Poesio et al., 2004; Gar-
dent and Manu´ elian, 2005; Caselli and Prodanof,
2006; Riester et al., 2010; Lassalle and Denis,
2011), to NP antecedents (all prior work) or to part-

3 Although the overall information status scheme in Riester
et al. (2010) achieved high agreement, their confusion matrix
shows that the anaphoric bridging category (BRI) is frequently
confused with other categories so that the two annotators agreed
on only less than a third of bridging anaphors.

of relations between anaphor and antecedent (Mark-
ert et al., 2003; Poesio et al., 2004). In our own
work (Markert et al., 2012) we established a corpus
that circumvents these problems, i.e. human bridg-
ing recognition was reliable, it contains a medium
number of bridging cases that allows generalisable
statistics and we did not limit bridging anaphora or
antecedents according to their syntactic type or re-
lations between them. However, we only discussed
human agreement on bridging recognition in Mark-
ert et al. (2012), disregarding antecedent annotation.
We also did not discuss the different types of bridg-
ing in the corpus. We will remedy this in Section 3.
Automatic work on bridging distinguishes be-
tween recognition (Vieira and Poesio, 2000; Rah-
man and Ng, 2012; Cahill and Riester, 2012; Mark-
ert et al., 2012) and antecedent selection. Work on
antecedent selection suffers from focusing on sub-
problems, e.g. only part-of bridging (Poesio et al.,
2004; Markert et al., 2003) or definite NP anaphora
(Lassalle and Denis, 2011). Most relevant for us is
Lassalle and Denis (2011) who restrict anaphora to
definite descriptions but have no other restrictions
on relations or antecedent NPs (in a French corpus)
with an accuracy of 23%. Also the evaluation set-
up is sometimes not clear: The high results in Poe-
sio et al. (2004) cannot be used for comparison as
they test unrealistically: they distinguish only be-
tween the correct antecedent and one or three false
candidates (baseline of 50% for the former). They
also restrict the phenomenon to part-of relations.
There is a partial overlap between bridging and
implicit noun roles (Ruppenhofer et al., 2010). How-
ever, work on implicit noun roles is mostly focused on few predicates (e.g. Gerber and Chai
(2012)). We consider all bridging anaphors in run-
ning text. The closest work to ours interpreting im-
PLICIT role filling as anaphora resolution is Silberer
and Frank (2012).

3 Corpus for Bridging: An Overview
We use the dataset we created in Markert et al.
(2012) with almost 11,000 NPs annotated for infor-
mation status including 663 bridging NPs and their
antecedents in 50 texts taken from the WSJ portion
of the OntoNotes corpus (Weischedel et al., 2011).
Bridging anaphora can be any noun phrase.
are not limited to definite NPs as in previous work. In contrast to Nissim et al. (2004), antecedents are annotated and can be noun phrases, verb phrases or even clauses. Our bridging annotation is also not limited with regards to semantic relations between anaphor and antecedent.

In Markert et al. (2012) we achieved high agreement for the overall information status annotation scheme between three annotators (κ between 75 and 80, dependent on annotator pairs) as well as for all subcategories, including bridging (κ over 60 for all annotator pairings, over 70 for two expert annotators). Here, we add the following new results:

- Agreement for selecting bridging antecedents was around 80% for all annotator pairings.
- Surprisingly, only 255 of the 663 (38%) bridging anaphors are definite NPs, which calls into question the strategy of prior approaches to limit themselves to these types of bridging.
- NPs are the most frequent antecedents by far with only 42 of 663 (6%) bridging anaphors having a non-NP antecedent (mostly verb phrases).
- Bridging is a relatively local phenomenon with 71% of NP antecedents occurring in the same or up to 2 sentences prior to the anaphor. However, farther away antecedents are common when the antecedent is the global focus of a document.
- The semantic relations between anaphor and antecedent are extremely diverse with only 92 of 663 (14%) anaphors having a part-of/attribute of antecedent (see Example 1) and only 45 (7%) anaphors standing in a set relationship to the antecedent (see Example 2). This contrasts with Gardent and Manuelian’s (2005) finding that 52% of bridging cases had meronymic relations. We find many different types of relations in our corpus, including encyclopedic relations such as restaurant — the waiter as well as, frequently, relational person nouns as bridging anaphors such as friend, husband, president.
- There are only a few cases of bridging where surface cues may indicate the antecedent. First, some bridging anaphors are modified by a small number of adjectives that have more than one role filler, with the bridging relation often being temporal or spatial sequence between two entities of the same semantic type as in Example 3 (see also Lassalle and Denis (2011) for a discussion of such cases). Second, some anaphors are compounds where the nominal premodifier matches the antecedent head as in Example 4.

(2) Still employees do occasionally try to smuggle out a gem or two. One man wrapped several diamonds in the knot of his tie. Another poked a hole in the heel of his shoe. None made it past the body searches . . .

(3) His truck is parked across the field . . . The farmer at the next truck shouts . . .

(4) . . . it doesn’t make the equipment needed to produce those chips. And IBM worries that the Japanese will take over that equipment market.

4 Models for Bridging Resolution

4.1 Pairwise mention-entity model

The pairwise model is widely used in coreference resolution (Soon et al., 2001). We adapt it for bridging resolution4: Given an anaphor mention m and the set of antecedent candidate entities E_m which appear before m, we create a pairwise instance (m, e) for every e ∈ E_m. A binary decision whether m is bridged to e is made for each instance (m, e) separately. A post-processing step to choose one antecedent is necessary (closest first or best first are common strategies). This model causes three problems for bridging resolution: First, the ratio between positive and negative instances is 1 to 17 even if only antecedent candidates from the current and the immediately preceding two sentences are considered. The ratio will be even worse with a larger window size. Therefore, usually a fixed window size is used restricting the set of candidates. This, however, causes a second problem: antecedents which are beyond the window cannot be found. In our data, only 81% of NP antecedents appear within the previous 5 sentences, and only 71% of NP antecedents appear within the previous 2 sentences. The third problem is a shortcoming of the pairwise model itself: decisions are made for each instance separately, ignoring

4Different from coreference, we treat an anaphor as a mention and an antecedent as an entity. The anaphor is the first mention of the corresponding entity in the document.
relations between instances. We resolve these problems by employing a global model based on Markov logic networks.

4.2 Markov Logic Networks

Bridging can be considered a document global phenomenon, where globally salient entities are preferred as antecedents and two or more anaphors having the same antecedent should be related or similar. Motivated by this observation, we explore Markov logic networks (Domingos and Lowd, 2009, MLNs) to model bridging resolution on the global discourse level.

MLNs are a powerful representation for joint inference with uncertainty. An MLN consists of a set of pairs \((F_i, w_i)\), where \(F_i\) is a formula in first-order logic and \(w_i\) is its associated real numbered weight. It can be viewed as a template for constructing Markov networks. Given different sets of constants, an MLN will produce different ground Markov networks which may vary in size but have the same structure and parameters. For a ground Markov network, the probability distribution over possible worlds \(x\) is given by

\[
P(X = x) = \frac{1}{Z} \exp \left( \sum_i w_i n_i(x) \right)
\]

where \(n_i(x)\) is the number of true groundings of \(F_i\) in \(x\). The normalization factor \(Z\) is the partition function.

MLNs have been applied to many NLP tasks and achieved good performance by leveraging rich relations among objects (Poon and Domingos, 2008; Meza-Ruiz and Riedel, 2009; Fahrdi and Strube, 2012, inter alia). We use \textit{thebeast}\textsuperscript{5} to learn weights for the formulas and to perform inference. \textit{thebeast} employs cutting plane inference (Riedel, 2008) to improve the accuracy and efficiency of MAP inference for Markov logic.

With MLNs, we model bridging resolution globally on the discourse level: given the set \(M\) of all anaphors and sets of local antecedent candidates \(E_m\) for each anaphor \(m \in M\), we select antecedents for all anaphors from \(E = \bigcup_{m \in M} E_m\) at the same time. Table 1 shows the hidden predicates and formulas used. Each formula is associated with a weight. The polarity of the weights is indicated by the leading + or −. The weight value (except for hard constraints) is learned from training data. For some formulas the final weight consists of a learned weight \(w\) multiplied by a score \(d\) (e.g. inverse distance between antecedent and anaphor). In these cases the final weight for a formula in a ground Markov network does not just depend on the respective formula, but also on the specific constants. We indicate such combined weights by the term \(w \cdot d\).

We tackle the previously mentioned problems of the pairwise model: (1) We construct hard constraints to specify that each anaphor has at most one antecedent entity (Table 1: f1) and that the antecedent must precede the anaphor (f2). This eliminates the need for the post-processing step in the pairwise model. (2) We select the antecedent entity for each anaphor from the antecedent candidate entities pool \(E\) which alleviates the missing true antecedent problem in the pairwise model. Based on (1) and (2), MLNs allow us to express relations between anaphor-anaphor and anaphor-antecedent pairs ((\(m,n\)) or (\(m,e\))) on the global discourse level improving accuracy by performing joint inference.

5 Features

5.1 Local features

5.1.1 Poesio et al.’s feature set

Table 2 shows the feature set proposed by Poesio et al. (2004) for part-of bridging. Google distance is the inverse value of Google hit counts for the \textit{offPattern} query (e.g. \textit{the windows of the center}). WordNet distance is the inverse value of the shortest path length between an anaphor and an antecedent candidate among all synset combinations. These features are supposed to capture the meronymy relation between anaphor and antecedent. The other ones measure the salience of the antecedent candidate.

| Group     | Feature               | Value     |
|-----------|-----------------------|-----------|
| lexical   | Google distance       | numeric   |
|           | WordNet distance      | numeric   |
| salience  | utterance distance    | numeric   |
|           | local first mention   | boolean   |
|           | global first mention  | boolean   |

Table 2: Poesio et al.’s feature set

\textsuperscript{5}http://code.google.com/p/thebeast
### Hidden predicates

- \( p_1 \) \( \text{isBridging}(m, e) \)
- \( p_2 \) \( \text{hasSameAntecedent}(m, n) \)

### Formulas

#### Hard constraints

- \( f_1 \) \( \forall m \in M : |e \in E : \text{isBridging}(m, e)| \leq 1 \)
- \( f_2 \) \( \forall m \in M \forall e \in E : \text{hasPairDistance}(e, m, d) \land d < 0 \rightarrow \neg \text{isBridging}(m, e) \)
- \( f_3 \) \( \forall m, n \in M : m \neq n \land \text{hasSameAntecedent}(m, n) \rightarrow \text{hasSameAntecedent}(n, m) \)
- \( f_4 \) \( \forall m, n, l \in M : m \neq n \land m \neq l \land n \neq l \land \text{hasSameAntecedent}(m, n) \land \text{hasSameAntecedent}(n, l) \rightarrow \text{hasSameAntecedent}(m, l) \)
- \( f_5 \) \( \forall m, n \in M \forall e \in E : m \neq n \land \text{hasSameAntecedent}(m, n) \land \text{isBridging}(m, e) \rightarrow \text{isBridging}(n, e) \)
- \( f_6 \) \( \forall m, n \in M \forall e \in E : m \neq n \land \text{isBridging}(m, e) \land \text{isBridging}(n, e) \rightarrow \text{hasSameAntecedent}(m, n) \)

#### Discourse level formulas

- \( f_7 \) \( \forall m \in M \forall e \in E : \text{predictedGlobalAnte}(e) \land \text{hasPairDistance}(e, m, d) \land d > 0 \rightarrow \text{isBridging}(m, e) \)
- \( f_8 \) \( \forall m, n \in M \) \( \text{conjunction}(m, n) \rightarrow \text{hasSameAntecedent}(m, n) \)
- \( f_9 \) \( \forall m, n \in M \) \( \text{sameHead}(m, n) \rightarrow \text{hasSameAntecedent}(m, n) \)
- \( f_{10} \) \( \forall m, n \in M \) \( \text{similarTo}(m, n) \rightarrow \text{hasSameAntecedent}(m, n) \)
- \( f_{11} \) \( \forall m \in M \forall e \in E : \text{hasSemanticClass}(m, \text{"rolePerson"}) \land \text{hasSemanticClass}(e, \text{"org|gpe"}) \land \text{hasPairDistance}(e, m, d) \land d > 0 \rightarrow \text{isBridging}(m, e) \)
- \( f_{12} \) \( \forall m \in M \forall e \in E : \text{hasSemanticClass}(m, \text{"relativePerson"}) \land \text{hasSemanticClass}(e, \text{"otherPerson"}) \land \text{hasPairDistanceInverse}(e, m, d) \rightarrow \text{isBridging}(m, e) \)
- \( f_{13} \) \( \forall m \in M \forall e \in E : \text{hasSemanticClass}(m, \text{"date"}) \land \text{hasSemanticClass}(e, \text{"date"}) \land \text{hasPairDistanceInverse}(e, m, d) \rightarrow \text{isBridging}(m, e) \)

#### Local formulas

- \( f_{14} \) \( \forall m \in M \forall e \in E_m : \text{isTopRelativeRankPrepPattern}(m, e) \rightarrow \text{isBridging}(m, e) \)
- \( f_{15} \) \( \forall m \in M \forall e \in E_m : \text{isTopRelativeRankVerbPattern}(m, e) \rightarrow \text{isBridging}(m, e) \)
- \( f_{16} \) \( \forall m \in M \forall e \in E_m : \text{isPartOf}(m, e) \land \text{hasPairDistanceInverse}(e, m, d) \rightarrow \text{isBridging}(m, e) \)
- \( f_{17} \) \( \forall m \in M \forall e \in E_m : \text{isTopRelativeRankDocSpan}(m, e) \rightarrow \text{isBridging}(m, e) \)
- \( f_{18} \) \( \forall m \in M \forall e \in E_m : \text{isSameHead}(m, e) \rightarrow \text{isBridging}(m, e) \)
- \( f_{19} \) \( \forall m \in M \forall e \in E_m : \text{isPremodOverlap}(m, e) \rightarrow \text{isBridging}(m, e) \)
- \( f_{20} \) \( \forall m \in M \forall e \in E_m : \text{isCoArgument}(m, e) \rightarrow \text{isBridging}(m, e) \)

Table 1: Hidden predicates and formulas used for bridging resolution \((m, n, l)\) represent mentions, \(M\) the set of bridging anaphora mentions in the whole document, \(e\) the antecedent candidate entity, \(E_m\) the set of local antecedent candidate entities for \(m\), and \(E = \bigcup_{m \in M} E_m\).
5.1.2 Other features

Since Poesio et al. (2004) deal exclusively with meronymy bridging, we have to extend the feature set to capture more diverse relations between anaphor and antecedent. All numeric features in Table 3 are normalized among all antecedent candidates of one anaphor. For anaphor $m_i$ and its antecedent candidates $E_{m_i}$ ($e_{ij} \in E_{m_i}$), the numeric score for pair $\{m_i, e_{ik}\}$ is $S_{ik}$. Then the value $NormS_{ik}$ for this pair is normalized (set to values between 0 and 1) as below:

$$NormS_{ik} = \frac{S_{ik} - \min_j S_{ij}}{\max_j S_{ij} - \min_j S_{ij}} \quad (2)$$

A second variant of numeric features tells whether the score of an anaphor-antecedent candidate pair is the highest among all pairs for this anaphor.

| Group       | Feature        | Value         |
|-------------|----------------|---------------|
| semantic    | $feat1$        | preposition pattern | numeric      |
|             | $feat2$        | verb pattern   | numeric      |
|             | $feat3$        | WordNet partOf | boolean      |
|             | $feat4$        | semantic class | nominal      |
| salience    | $feat5$        | document span  | numeric      |
| surface     | $feat6$        | isSameHead     | boolean      |
|             | $feat7$        | isPremodOverlap| boolean      |
| syntactic   | $feat8$        | isCoArgument   | boolean      |

Table 3: Local features we developed

Preposition pattern ($feat1$). The $of$Pattern proposed by Poesio et al. (2004) is useful for part-of and attribute-of relations but cannot cover all bridging relations (such as sanctions against a country). We extend the $of$Pattern to a generalised preposition pattern by using the Gigaword (Parker et al., 2011) and the Tipster (Harman and Liberman, 1993) corpora (both automatically POS tagged and NP chunked for improving query match precision).

First, we extract the three most highly associated prepositions for each anaphor. Then for each anaphor-antecedent candidate pair, we use their head words to create the query “anaphor preposition antecedent”. To improve recall, we take lowercase, uppercase, singular and plural forms of the head word into account, and replace proper names by fine-grained named entity types (using a gazetteer). All raw hit counts are converted into the Dunning Root Loglikelihood association measure, then normalized using Formula 2 within all antecedent candidates of one anaphor.

Verb pattern ($feat2$). A set-membership relation between anaphor and antecedent is often hard to capture by the preposition pattern because the anaphor often has no common noun head (see Example 2 in Section 3). Hence, we measure the compatibility of the antecedent candidates with the verb the anaphor depends on.

First, we hypothesise that anaphors whose lexical head is a pronoun or a number are potential set bridging cases and then extract the verb the anaphor depends on. In example 2, for the set anaphor Another, poked is the verb. Then for each antecedent candidate, subject-verb or verb-object queries are applied to the Web 1T 5-gram corpus (Brants and Franz, 2006). In this case, employees poked and diamonds poked are example queries. The hit counts are transformed into PMI and all pairs for one anaphor are normalized as described in Formula 2.

WordNet partOf relation ($feat3$). To capture part-of bridging, we extract whether the anaphor is part of the antecedent candidate in WordNet. To improve recall, we use hyponym information of the antecedent. If an antecedent $e$ is a hypernym of $x$ and an anaphor $m$ is a meronym of $x$, then $m$ is a meronym of $e$.

Semantic class ($feat4$). The anaphor and the antecedent candidate are assigned one of 16 coarse-grained semantic classes, e.g. location, organization, GPE, roleperson, relativePerson, otherPerson, product, language, NORP (nationalities, religious or political groups) and several classes for numbers (such as date, money or percent).

Salience feature ($feat5$). Salient entities are preferred as antecedents. We capture salience superficially by computing the “antecedent document span” of an antecedent candidate. We compute the

6http://tdunning.blogspot.de/2008/03/surprise-and-coincidence.html

7We use WordNet to extract lists for rolePerson (persons like president or teacher playing a role in an organization) and relativePerson (persons like father or son indicating that they have a relation with another person). Persons not in these two lists are counted as otherPerson.
span of text (measured in sentences) in which the antecedent candidate entity is mentioned. This is divided by the number of sentences in the whole document. This score is normalized using Formula 2 for all antecedent candidates of one anaphor.

**Surface features** (feat6-feat7). isSameHead (feat6) checks whether antecedent candidates have the same head as the anaphor: this is rarely the case in bridging anaphora (except in some cases of set bridging and spatial/temporal sequence, see Example 3) and can therefore be used to exclude antecedent candidates. isPremodOverlap (feat7) determines the antecedent for compound noun anaphors whose head is prenominally modified by the antecedent head (see Example 4).

**Syntactic feature** (feat8) The isCoArgument feature is based on the intuition that the subject cannot be the bridging antecedent of the object in the same clause. This feature excludes (some) close antecedent candidates. In Example 4, the antecedent candidate the Japanese isCoArgument with the anaphor that equipment market.

5.2 Global features for MLNs

f1-f13 in Table 1 are discourse level constraints. All antecedent candidates come from the antecedent candidates pool E in the whole document.

**Global salience** (Table 1: f3-f10). The salience feature in the pairwise model only measures the salience for candidates within the local window. However, globally salient antecedents are preferred even if they are far away from the anaphor. We model this from two perspectives:

f7 models the preference for globally salient antecedents, which we derive for each document. For \( m \in M \) and \( e \in E \), let \( \text{score}(m, e) \) be the preposition pattern score for pair \((m, e)\). Calculate pattern semantic salience score \( e_{sal} \) for each \( e \in E \) as

\[
e_{sal} = \sum_{m \in M} \text{score}(m, e)
\]

(3)

If \( e \) appears in the title and also has the highest pattern semantic salience score \( e_{sal} \) among all \( e \) in \( E \), then \( e \) is the predicted globally salient antecedent for this document. Note that global salience here is based on semantic connectivity to all anaphors in the document and that not every document has a globally salient antecedent.

f3-f6 and f8-f10 model that similar or related anaphors in one document are likely to have the same antecedent. To make the ground Markov network more sparse for more efficient inference, we add the hidden predicate \((p2)\) and hard constraints \((f3-f6)\) specifying relations among similar/related anaphors \( m \), \( n \) and \( l \) (reflexivity and transitivity). Formulas f8-f10 explore three different ways (syntactic and semantic) to compute the similarity between two anaphors. In f10, we use SVM\( ^{light} \) (similarity scores from WordNet plus sentence distance as features) to predict whether two anaphors not sharing the same head are similar or not.

**Frequent bridging relations** (Table 1: f11-f13). Three common bridging relations are restricted by semantic class of anaphor and antecedent (see also Section 3). It is worth noting that in formula f11 (modeling that a role person mention like president or chairman prefers organization or GPE antecedents), we do not penalize the antecedents far away from the anaphor. In formula f12 (modeling that a relativePerson mention such as mother or husband prefers close person antecedents) and f13, we prefer close antecedents by including the distance between antecedent and anaphor into the weights.

**MLN formulation of local features** (Table 1: f14-f20). Corresponding to features of the pairwise model (Table 3) – we exclude only semantic class as this is modelled globally via features f11-f13. These local features are only used for an anaphor \( m \) and its local antecedent candidate \( e \) from \( E_m \).

6 Experiments and Results

6.1 Experimental setup

We perform experiments on our gold standard corpus via 10-fold cross-validation on documents. We use gold standard mentions, true coreference information, and the OntoNotes named entity and syntactic annotation layers for feature extraction.

6.2 Improved baseline

We reimplement the algorithm from Poesio et al. (2004) as baseline. Since they did not explain
whether they used the mention-mention or mention-entity model, we assume they treated antecedents as entities and use a 2 and 5 sentence window for candidates. Since the Google API is not available anymore, we use the Web 1T 5-gram corpus (Brants and Franz, 2006) to extract the Google distance feature. We improve it by taking all information about entities via coreference into account as well as by replacing proper names. All other features (Table 2 in Section 5.1.1) are extracted as Poesio et al. did. A Naive Bayes classifier with standard settings in WEKA (Witten and Frank, 2005) is used. In order to evaluate their model in the more realistic setting of our experiment, we apply the best first strategy to select the antecedent for each anaphor.

6.3 Pairwise models

**Pairwise model I**: We use the preposition pattern feature ($feat1$) plus Poesio et al.'s salience features (Table 2). We use a 2 sentence window as it performed on a par with the 5 sentence window in the baseline. We replace Naive Bayes with SVM$_{tight}$ because it can deal better with imbalanced data.

**Pairwise model II**: Based on Pairwise model I. Local features $feat2-feat8$ from Table 2 are added.

**Pairwise model III**: Based on Pairwise model II. We apply a more advanced antecedent candidate selection strategy, which allows to include 77% of NP antecedents compared to 71% in Pairwise model II. For each anaphor, we add the top $k$ salient entities measured through the length of the coreference chains ($k$ is set to 10%) as additional antecedent candidates. For potential set anaphors (as automatically determined by pronoun or number heads), singular antecedent candidates are filtered out. We compiled a small set of adjectives (using FrameNet and thesauri) that indicate spatial or temporal sequences (see Example 3). For anaphors modified by such adjectives we consider only antecedent candidates that have the same semantic class as the anaphor.

6.4 MLN models

**MLN model I**: MLN system using local formulas $f_{1-2}$ and $f_{14-20}$. The same strategy as in Pairwise model III is used to select local antecedent candidates $E_{km}$ for each anaphor $m$.

**MLN model II**: Based on MLN model I, all formulas in Table 1 are used.

6.5 Results

Table 4 shows the comparison of our models to baselines. Significance tests are conducted using McNemar’s test on overall accuracy at the level of 1%.

|                      | acc   |
|----------------------|-------|
| improved baseline    | 18.85 |
| 2 sent. + NB         | 18.40 |
| 5 sent. + NB         |       |
| pairwise model       | 29.11 |
| pairwise model I     | 33.94 |
| pairwise model II    | 36.35 |
| pairwise model III   | 35.60 |
| MLN model            | 35.60 |
| MLN model I          | 41.32 |

Table 4: Results for MLN models compared to pairwise models and baselines.

MLN model II, which is inspired by the linguistic observation that globally salient entities are preferred as antecedents, performs significantly better than all other systems. The gains come from three aspects. First, by selecting the antecedent for each anaphor from the antecedent candidate pool $E$ in the whole document 91% of NP antecedents are accessible compared to 77% in pairwise model III. Second, we leverage semantics and salience by using local formulas and discourse level formulas. Local formulas are used to capture semantic relations for bridging pairs as well as surface and syntactic constraints. Global formulas resolve several bridging anaphors together, often to a globally salient antecedent beyond the local window. Third, the model allows us to express specific relations among bridging anaphors and their antecedents ($f_{11-20}$).

However, our pairwise model II already outperforms improved baselines by about 10%, which suggests that our preposition pattern feature can capture more diverse semantic relations. The continuous improvements shown in pairwise model II and pairwise model III verify the contribution of our other

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8They use a 5 sentence window, because all antecedents in their corpus are within the previous 5 sentences.

9The SVM$_{tight}$ parameter is set according to the ratio between positive and negative instances in the training set.
features and advanced antecedent candidate selection strategy. pairwise model III would become too complex if we tried to integrate discourse level formulas $f_7$, $f_{11}$-$f_{13}$ into antecedent candidate selection. MLN model II solves this task elegantly.

6.6 Discussion and error analysis

We analyse our best model (MLN model II) and compare it to the best local one (pairwise model III).

Anaphors with long distance antecedents are harder to resolve. Table 5 shows the comparison of correctly resolved anaphors with regard to anaphor-antecedent distance. We can see that the global model is equal or better to the local model for all anaphor types but that the difference is especially large for anaphors with antecedents that are 3 or more sentences away due to the use of global salience and accessibility of possible antecedents beyond a fixed window-size.

| sent. distance | # pairs | MLN II | pairwise III |
|---------------|---------|--------|--------------|
| 0             | 175     | 48.57  | 45.14        |
| 1             | 260     | 34.62  | 35           |
| 2             | 90      | 47.78  | 43.33        |
| $\geq$3       | 158     | 35.44  | 16.46        |

Table 5: Comparison of the percentage of correctly resolved anaphors with regard to anaphor-antecedent distance. Significance tests are conducted using McNemar’s test at the level of 1%.

We now distinguish between “sibling anaphors” (anaphors that share an antecedent with other bridging anaphors) and “non-siblings” (anaphors that do not share an antecedent with any other anaphor). The performance of our MLN model II is 54% on sibling anaphors but only 24% on non-sibling anaphors. This shows that our use of global salience and links between related anaphors does indeed help to capture the behaviour of sibling anaphors.

However, our global model is good at predicting the right antecedent for sibling anaphors where the antecedent is globally salient but not as good for sibling anaphors where the (shared) antecedent is a locally salient subtopic. Thus, in the future we need to model equivalent constraints for local salience of antecedents, taking into account topic segmentation/shifting to improve over the 54% for sibling anaphors.

The semantic knowledge we employ is still insufficient. Typical cases where we have problems are: (i) cases with very context-specific bridging relations. For example, in one text about the stealing of Sago Palms in California we found the thieves as a bridging anaphor with the antecedent palms, which is not a very usual semantic link. (ii) more frequently, we have cases where several good antecedents from a semantic perspective can be found. For example, two laws are discussed and a later anaphor the veto could be the veto of either bills. Integration of the wider context apart from the two NPs is necessary in these cases. This includes the semantics of modification, whereas we currently consider only head noun knowledge. An example is that the anaphor the local council would preferably be interpreted as the council of a village instead of the council of a state due to the occurrence of local.

Finally, 6% of the anaphors in our corpus have a non-NP antecedent. These cases are not correctly resolved in our current model as we only extract NP phrases as potential candidate antecedents.

7 Conclusions

We provide the first reasonably sized and reliably annotated English corpus for bridging resolution. It covers a diverse set of relations between anaphor and antecedent as well as all anaphor/antecedent types. We developed novel semantic, syntactic and salience features based on linguistic intuition. Inspired by the observation that salient entities are preferred as antecedents, we implemented a global model for antecedent selection within the framework of Markov logic networks. We show that our global model significantly outperforms other local models and baselines. This work is – to our knowledge – the first bridging resolution algorithm that tackles the unrestricted phenomenon in a real setting.

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