Multi-task Learning Based Neural Bridging Reference Resolution

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Abstract

We propose a multi task learning-based neural model for bridging reference resolution tackling two key challenges faced by bridging reference resolution. The first challenge is the lack of large corpora annotated with bridging references. To address this, we use multi-task learning to help bridging reference resolution with coreference resolution. We show that substantial improvements of up to 8 p.p. can be achieved on full bridging resolution with this architecture. The second challenge is the different definitions of bridging used in different corpora, meaning that hand-coded systems or systems using special features designed for one corpus do not work well with other corpora. Our neural model only uses a small number of corpus independent features, thus can be applied easily to different corpora. Evaluations with very different bridging corpora (ARRAU, ISNOTES, BASHI and SCICORP) suggest that our architecture works equally well on all corpora, and achieves the SoTA results on full bridging resolution for all corpora, outperforming the best reported results by up to 34.9 percentage points.

1 Introduction

Anaphora resolution (Karttunen, 1976; Webber, 1979; Kamp and Reyle, 1993; Garnham, 2001; Poesio et al., 2016) is linking nominal expressions to the entities in the context of interpretation (or discourse model). As illustrated by (1) (adapted from (Hou et al., 2018)), nominal expressions can be linked to the context in several ways: coreference (linking [The Bakersfield Supermarket], [The business], and [its]), bridging or associative reference (linking [the customers] to the supermarket) (Clark, 1975; Poesio et al., 2004; Hou et al., 2018), and discourse deixis (linking [the murder] to the event of murdering in the previous sentence) (Webber, 1991; Kolhatkar et al., 2018).

(1) [The Bakersfield Supermarket] went bankrupt last May. [The business] closed when [[its] old owner] was murdered by [robbers]. [The murder] saddened [the customers].

Bridging reference resolution is the sub-task of anaphora resolution concerned with identifying and resolving bridging references, i.e., anaphoric references to non-identical associated antecedents. Bridging resolution is much less studied than the closely related sub-task of coreference resolution, which has received a lot of attention ((Pradhan et al., 2012; Wiseman et al., 2015; Lee et al., 2017; Lee et al., 2018), to mention just a few recent proposals). One reason for this is the lack of training data. Several corpora have been annotated with bridging reference, including e.g. GNOME (Poesio, 2004), ISNOTES (Markert et al., 2012), SCICORP (Rössiger, 2016) and BASHI (Rössiger, 2018a), but they are all rather small, with at most around 1k examples of bridging reference. ARRAU (Poesio and Artstein, 2008; Uryupina et al., 2019) is much larger, but still contains only 5.5k bridging pairs. It is challenging to train a learning based system on that amount of data, particularly the new neural models. As a result, the current SoTA systems for full bridging resolution are still rule-based, employing a number of heuristic rules many of which are corpus-dependent (Hou et al., 2014; Rössiger et al., 2018). This is problematic at the light of the second challenge for work in this area: namely, that the definitions of bridging are different in these different corpora (Rössiger et al., 2018). Existing corpora differ in whether they attempt to annotate only what Roesiger et al call referential bridging, as in the case of ISNOTES, or also lexical bridging, as
in ARRAU. 1 The ISNOTES, BASHI and SCICORP corpora consist mostly of referential bridging examples, while the ARRAU corpus contains both types of bridging references. As a consequence, a system designed for one corpus (e.g. ISNOTES) works poorly when applied to other corpora (e.g. ARRAU), and significant modifications are needed in order to make the system works equally well on different corpora (Rösiger, 2018b).

To tackle these challenges, we introduce a multi task learning-based neural model that learns bridging resolution together with coreference resolution2. Multi task architectures have proven effective at exploiting the synergies between distinct but related tasks to in cases when only limited amounts of data are available for one or more of the tasks (Clark et al., 2019). Such an architecture should therefore be especially suited for our context, given that, linguistically, bridging reference resolution and coreference resolution are two distinct but closely related aspects of anaphora resolution, and indeed were often tackled together in early ML-based systems (Vieira and Poesio, 2000). Using a neural network-based approach that minimises feature engineering enables the system to be more flexible on the choices of corpora. We mainly evaluate our system on the RST portion of the ARRAU corpus since it is the largest available resource, but we additionally evaluate it on the TRAINS and PEAR portion of the ARRAU corpus, ISNOTES, BASHI and SCICORP corpus to demonstrate its tolerance of diversity.

We start with a strong baseline for bridging adapted from the SoTA coreference architecture (Lee et al., 2018; Kantor and Globerson, 2019) enhanced by BERT embeddings (Devlin et al., 2019). We extend the system to multi-task learning by adding a coreference classifier that shares part of the network with the bridging classifier. In this way, we improve full bridging resolution and its subtasks (anaphor recognition and antecedent selection) by 6.5-7.3% respectively. But because the number of coreference examples is much larger than the number of bridging pairs, the dataset is highly imbalanced. We achieve further improvements of 1.7% and 6.6% on full bridging resolution and anaphor recognition by using undersampling during the training. This final system achieves SoTA results on both full bridging resolution and its subtasks, i.e. 4.5%, 6% and 9.5% higher than the best reported results (Rösiger, 2018b) on full bridging resolution, anaphor recognition and antecedent selection respectively. Evaluation on TRAINS, PEAR, ISNOTES, BASHI and SCICORP shows the same trend. Although the datasets are much smaller and the annotation schemes for ISNOTES, BASHI and SCICORP are different from ARRAU, our system works equally well, achieving the new SoTA results on full bridging resolution for all five corpora.

2 Related Work

2.1 Bridging Reference Resolution

Bridging reference resolution involves two subtasks: anaphor recognition and antecedent selection (Hou et al., 2018). Early work on bridging resolution mostly focused on definite bridging anaphors (Sidner, 1979; Vieira and Poesio, 2000; Lassalle and Denis, 2011), but later systems covered unrestricted antecedent selection (Poesio et al., 2004; Hou et al., 2013). Hou et al. (2013) introduced a model based on Markov logic networks and using an extensive set of features and constraints. They evaluated the system with both local and global features on ISNOTES, and showed that global features can greatly improve performance. The system was later extended in (Hou, 2018b; Hou, 2018a; Hou et al., 2018) to explore additional features from embeddings tailored for bridging resolution to advanced antecedent candidate selection using discourse structure extracted from the Penn Discourse Treebank (d-scope-salience). The Hou et al. (2018) system using d-scope-salience is the current SoTA on antecedent selection for ISNOTES. The anaphor recognition subtask is usually solved as a part of the information status task (Markert et al., 2012; Hou, 2016; Hou et al., 2018).

Recently, systems for full bridging resolution were introduced (Hou et al., 2014; Hou et al., 2018;

1Roesiger et al use ‘referential bridging’ for the cases in which the bridging reference needs an antecedent in order to be interpretable, such as the door in John walked towards the house. The door was open. ‘Lexical bridging’ is when the bridging reference could also be interpreted autonomously, such as Madrid in I went to Spain last year. I particularly liked Madrid. See (Poesio, 2004; Baumann and Riester, 2012; Markert et al., 2012; Hou et al., 2016; Hou et al., 2018; Uryupina et al., 2019) for a detailed discussion of the annotation schemes and their motivations, and (Rösiger et al., 2018; Rösiger, 2018b) for a discussion of the implications.

2The code is available at https://github.com/juntaoy/dali-birdging
Rösiger et al., 2018; Rösiger, 2018b). Hou et al. (2014) proposed a rule-based system for full bridging resolution with the ISNOTES corpus, consisting of a rich system of rules motivated by linguistic knowledge. They also evaluated a learning-based system that uses the rules as features, but the learning-based system only outperforms the rule-based system’s F1 score by 0.1 percentage points. The rule-based system was later adapted by Rösiger et al. (2018; Rösiger (2018b) for full bridging resolution on ARRAU. But since ARRAU follows a different definition of bridging, most of the rules had to be changed. Hou et al. (2018) is the current state of the art on full bridging resolution, but it was only evaluated on ISNOTES.

2.2 Multi-task Learning for Under-Resourced Tasks

Multi-task learning has been successfully used in several NLP applications (Collobert and Weston, 2008; Luong et al., 2016; Kiperwasser and Ballesteros, 2018; Clark et al., 2019). Normally, the goal of multi-task learning is to improve performance on all tasks; but in an under-resourced setting, the aim often is only to improve performance on the low resource task/language/domains (the target task). This is sometimes known as shared representation based transfer learning. Yang et al. (2017) applied transfer learning to sequence labelling tasks; the deep hierarchical recurrent neural network used in their work is fully/partially shared between the source and the target tasks. They demonstrated that SoTA performance can be achieved by using models trained on multi-tasks. Cotterell and Duh (2017) trained a neural NER system on a combination of high-/low-resource languages to improve NER for the low-resource languages. In their work, character-based embeddings are shared across the languages. Recently, Zhou et al. (2019) introduced a multi-task network together with adversarial learning for under-resourced NER. The evaluation on both cross-language and cross-domain settings shows that partially sharing the BiLSTM works better for cross-language transfer, while for cross-domain setting, the system performs better when the LSTM layers are fully shared.

2.3 Neural Coreference Resolution

By contrast with bridging reference, coreference resolution has been extensively studied. Wiseman et al. (2015; Wiseman et al. (2016) first introduced a neural network-based approach to solving coreference in a non-linear way. Clark and Manning (2016) integrated reinforcement learning to let the model, optimized directly on the B3 scores. Lee et al. (2017) proposed a neural joint approach for mention detection and coreference resolution. Their model does not rely on parse trees; instead, the system learns to detect mentions by exploring the outputs of a BiLSTM. After the introduction of context dependent word embeddings such as ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019), the Lee et al. (2017) system has been greatly improved by those embeddings (Lee et al., 2018; Kantor and Globerson, 2019) to achieve SoTA results. We use a simplified version of the model by (Lee et al., 2018; Kantor and Globerson, 2019) as baseline.

3 Methods

3.1 The Single-Task Baseline System

We use as our single-task baseline for bridging reference a simplified version of the SoTA coreference systems by Lee et al. (2018; Kantor and Globerson (2019), since bridging resolution is closely related to coreference: like coreference it requires establishing a link to an entity in the discourse model, but through a non-identity relation. The Kantor and Globerson (2019) model is an extended version of (Lee et al., 2018); the main difference is that Kantor et al use BERT embeddings (Devlin et al., 2019) instead of the ELMo embeddings (Peters et al., 2018) used by Lee et al. These systems have similar architecture and both do mention detection and coreference jointly. We only use the coreference part of the system, since for bridging resolution evaluation is usually on gold mentions.

Our baseline system first creates representations for mentions using the output of a BiLSTM. The sentences of a document are encoded from both directions to obtain a representation for each token in the sentence. The BiLSTM takes as input the concatenated embeddings $\left(\text{emb}_{t}^{T}\right)_{t=1}^{T}$ of both word and character levels. For word embeddings, GloVe (Pennington et al., 2014) and BERT (Devlin et al., 2019) embeddings are used. Character embeddings are learned from a convolution neural network (CNN)
during training. The tokens are represented by concatenated outputs from the forward and the backward LSTMs. The token representations $(x_t^T)_{t=1}^T$ are used together with head representations $(h_t)$ to represent mentions $(M_i)$. The head representation of a mention is obtained by applying attention over its token representations $(\{x_b, \ldots, x_e\})$, where $b_i$ and $e_i$ are the indices of the start and the end of the mention respectively.

Formally, we compute $h_i, M_i$ as follows:

$$
\alpha_t = \text{FFNN}_a(x_t)
$$

$$
a_{i,t} = \frac{\exp(\alpha_t)}{\sum_{k=b_i}^{e_t} \exp(\alpha_k)}
$$

$$
h_t = \sum_{t=b_i}^{e_t} a_{i,t} \cdot x_t
$$

$$
M_i = [x_b, x_e, h_i, \phi(i)]
$$

where $\phi(i)$ is the mention width feature embeddings. Next, we pair the mentions with candidate antecedents to create a pair representation $(P_{(i,j)})$:

$$
P_{(i,j)} = [M_i, M_j, M_i \circ M_j, \phi(i,j)]
$$

where $M_i, M_j$ is the representation of the antecedent and anaphor respectively, $\circ$ denotes element-wise product, and $\phi(i,j)$ is the distance feature between a mention pair. To make the model computationally tractable, we consider for each mention a maximum 150 candidate antecedents.\(^3\)

The next step is to compute the pairwise score $(s(i,j))$. Following Lee et al. (2018), we add an artificial antecedent $\epsilon$ to deal with cases of non-bridging anaphor mentions or cases when the antecedent does not appear in the candidate list. We compute $s(i,j)$ as follows:

$$
s(i,j) = \begin{cases} 
0 & i = \epsilon \\
\text{FFNN}(P_{(i,j)}) & i \neq \epsilon
\end{cases}
$$

For each mention the predicted antecedent is the one has the highest $s(i,j)$, a bridging link will be only created if the predicted antecedent is not $\epsilon$.

### 3.2 Our Multi-task Learning Architecture

Choosing a source task that is closely related to bridging resolution is crucial to the success of our multi-task learning model. In this work, we use coreference as the source task. The key intuitions behind this choice are: (i) from a language interpretation point of view, resolving anaphoric coreference and anaphoric bridging reference are closely related tasks in that they both involve trying to identify relations between anaphors and antecedents (Poesio, 2016)—indeed, the two tasks were typically tackled jointly by non ML-based anaphora resolution systems (Sidner, 1979; Hobbs et al., 1993; Vieira and Poesio, 2000); (ii) from the point of view of the model, both tasks rely on a good mention representations and can be solved by neural mention pair models.

We turn our model into a multi-task model by adding to the architecture an additional classifier for coreference, and jointly predicting coreference and bridging (Figure 1). We use the same candidate antecedents for both bridging and coreference tasks. As shown in Figure 1, our model uses shared mention representations (i.e. the word embeddings and the BiLSTM) with additional options to share some/all hidden layers of the FFNN. By sharing most of the network structure, the mention representations learned by the coreference task become accessible by bridging resolution.

### 3.3 Learning with Imbalanced Data

Following Lee et al. (2018) we optimise our system on the marginal log-likelihood of all correct antecedents. For bridging, we consider an bridging antecedent correct if it is from the same gold coreference cluster $\text{GOLD}(i)$ of the gold bridging antecedent. For coreference, the correct antecedents is implied from the gold coreference cluster $\text{GOLD}(j)$ the mention belongs to. We compute both bridging and coreference losses as follows:

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

\(^3\)The number of maximum antecedents was tuned on the dev set.
in case mention \( i \) is not a bridging/coreference anaphor or \( Y(j) \) (the candidate antecedents) does not contain mentions from \( \text{GOLD}(i) \) for bridging or \( \text{GOLD}(j) \) for coreference, we set \( \text{GOLD}(i/j) = \{\epsilon\} \).

When training with coreference one of the problem we need to face is class imbalance. Consider the RST portion of ARRAU as an example (mostly WSJ text). The corpus contains 72k mentions in total: of these, 45k (63%) are discourse-new (DN), 24k (33%) are discourse-old (DO), and the remaining 3k (4%) are bridging anaphors. Training the model on such an imbalanced corpus may significantly harm recall with bridging anaphors.

To reduce the negative effect of this imbalance, we use undersampling during to training by randomly removing DN and DO examples to make the corpus more balanced. More precisely, we use a heuristic negative example ratio \( \gamma \) to control the total number of negative examples during the training, so that, e.g., \( \gamma = 2 \) means we keep 6k DN and 6k DO examples during training. We set a value for \( \gamma \) by trying a few small values in preliminary experiments; they all gave very similar results, hence we set \( \gamma = 2 \) in the experiments below.

### 4 Experiments

**Datasets** We evaluated our systems on ARRAU (Poesio and Artstein, 2008; Uryupina et al., 2019), ISNOTES (Markert et al., 2012), BASHI (Rösig, 2018a) and SCICORP (Rösig, 2016) with ARRAU RST as our primary dataset as it’s substantially larger.

Bridging references are annotated in ARRAU according to the scheme in (Uryupina et al., 2019), which covers both what Rösig (2018b) call ‘lexical’ and ‘referential’ bridging. The corpus was used for Task 2 of the CRAC 2018 shared task (Poesio et al., 2018), focused on bridging resolution. As done in the CRAC shared task, we evaluate our system on all three subcorpus: RST, TRAINS and PEAR stories. The RST portion of the corpus, consisting of 413 news documents (1/3 of the WSJ section of the Penn Treebank). We used the default train/dev and test subdivisions. The TRAINS and PEAR portion of the corpus contains 114 dialogues and 20 fictions respectively. Since the TRAINS and PEAR are much smaller we use 10-fold cross validation and report the results on test set to compare with previous work.

The ISNOTES corpus consists of 50 documents from the WSJ portion of ONTONOTES, with 663 bridging pairs annotated as well as fine-grained information status according to the scheme in (Markert et al., 2012). Bridging is annotated as one of the information status subclasses. Like ISNOTES, the BASHI corpus contains 50 documents from the WSJ portion of ONTONOTES. The dataset has 459 bridging pairs annotated according to a novel annotation scheme focused on referential bridging (Rösig, 2018a). The SCICORP corpus uses text from a very different domain of scientific texts. The corpus has in total 1366 bridging pairs annotated, again according to its own annotation scheme (Rösig, 2016). Since those corpora are rather small, we used 10-fold cross-validation to evaluate on them.

**Evaluation metrics** We evaluate our system on both full bridging resolution and its subtasks (anaphor recognition/antecedent selection). For full bridging resolution and anaphor recognition we report F1 scores\(^4\). For antecedent selection we report accuracy as it uses gold bridging anaphors.

\(^4\)Following (Rösig, 2018b) we consider a predicted bridging antecedent is correct when it belongs to the same gold coreference cluster as the gold bridging antecedent.
Hyperparameters Apart from the two parameters introduced by our model (maximum number of antecedents and negative example ratio $\lambda$), we use mostly the default settings from Lee et al. (2018), but replace their ELMo settings with the BERT settings from Kantor and Globerson (2019). We train the models evaluated on the ARRAU RST corpus for 200 epochs, and for 50 epochs the models trained on the other corpora.

5 Results and Discussions

5.1 Evaluation on the ARRAU RST corpus

We first evaluated our multi-task learning based system on the antecedent selection subtask, to assess the suitability of our model on bridging. The antecedent selection subtask uses gold bridging anaphors, hence it is simpler than full bridging resolution which additionally involves identifying the bridging references. Focusing on a simpler task allows us to have a clearer view of the effects of multi-task learning. In this experiment, we configured the system to share only the mention representations (the word embeddings and BiLSTM). As illustrated in Table 1a, the baseline system already achieved a pretty good accuracy for this type of task. Although starting from a strong baseline, our multi-task learning based system achieved an improvement of 3.5 percentage points, confirming our hypothesis that coreference is a good source task for bridging.

Sharing The Feed-forward Layers We further extended our model to share the FFNN layers in addition to the mention representations. The FFNN layers have access to pairwise representations to learn the relations between the anaphors and the antecedents, hence contain useful information regarding how likely two mentions are to be related. As expected, this additional sharing of the FFNN layers resulted in additional improvements. The largest improvement of 3.8 percentage points was achieved by sharing 1 additional FFNN layer. The accuracy drops when both hidden layers are shared between coreference and bridging, but the performance is still higher when compared with the model that only shares mention representations. Overall, the multi-task model achieved a substantial gain of 7.3 percentage points when compared with the system only carrying out bridging reference resolution (see Table 1a).

Full Bridging Resolution Having ascertained the benefits of our multi-task model for antecedent selection, we applied the best settings (sharing mention representations and the 1st hidden layer of the FFNN) to full bridging resolution as well. We also report the F1 scores for bridging anaphor recognition, a byproduct of full bridging resolution. Table 1b shows a comparison between the single-task baseline and the multi-task models. The baseline model trained without multi-task learning achieved F1 scores of 13.8% and 20% on full bridging resolution and anaphor recognition, respectively. The low F1 scores are mainly due to a poor recall in both tasks, a well known problem with bridging reference resolution. When applying multi-task learning, the F1 scores improve substantially (6.5% and 7.1% for full bridging

| System               | Shared Network | RST  | ISNOTES |
|----------------------|----------------|------|---------|
| bridging only        |                | 47.4 | 33.8    |
| multi-task           | embeddings, LSTM | 50.9 | 38.7 |
| multi-task           | + 1 FFNN Layer | 54.7 | 43.7 |
| multi-task           | + 2 FFNN Layer | 51.7 | 40.1 |

(a) Antecedent selection

Table 1: Parameter tuning on the dev set of ARRAU RST and ISNOTES.
| Corpus       | Gold Coreference Models | Anaphor rec. | full bridging res. |
|-------------|------------------------|-------------|--------------------|
|             |                        | P | R | F1 | P | R | F1 |                  |
| RST         | Keep                   |   |   |    |   |   |    |                    |
|             | Hou et al. (2013) MLN model I | - | - | - | 35.6 | - | - | - |                    |
|             | Hou et al. (2013) MLN model II | - | - | - | 41.3 | - | - | - |                    |
|             | Hou (2018a)            | 32.4 | - | - | 46.5 | 27.4 | - | - |                    |
|             | Hou et al. (2018)      | - | - | - | 50.7 | - | - | - |                    |
|             | Rösiger (2018b)       | 39.8 | 48.9 | 28.2 | - | - | - | - |                    |
|             | Our model              | **49.3** | **50.9** | **61.2** | 40.7 | **34.0** | 33.4 |                  |
| TRAINS      | Keep                   |   |   |    |   |   |    |                    |
|             | Rösiger et al. (2018)  | 45.9 | 18.3 | 32.0 | 12.8 | 18.3 | - | - |                    |
|             | Our model              | 61.5 | 30.6 | **40.9** | 33.0 | 16.4 | **22.0** |                  |
|             | Rösiger (2018b)       | 39.3 | 21.8 | 24.2 | 27.1 | 21.8 | 24.2 |                  |
|             | Our model              | 62.2 | 40.4 | **48.9** | 39.2 | 25.4 | **30.9** |                  |
| PEAR        | Keep                   |   |   |    |   |   |    |                    |
|             | Hou et al. (2014)      | 65.9 | 14.1 | 23.2 | 57.7 | 10.1 | 17.2 |                  |
|             | Hou et al. (2018)      | 45.9 | 18.3 | 26.2 | 32.0 | 12.8 | 18.3 |                  |
|             | Our model              | 61.5 | 30.6 | **40.9** | 33.0 | 16.4 | **22.0** |                  |
|             | Rösiger et al. (2018)  | 71.6 | 18.3 | 29.2 | 50.0 | 12.8 | 20.4 |                  |
|             | Hou et al. (2018)      | - | - | - | 20.6 | 22.6 | 21.6 |                  |
|             | Our model              | 68.4 | 32.0 | **43.6** | 36.5 | 17.0 | **23.2** |                  |
| ISNOTES     | Keep                   |   |   |    |   |   |    |                    |
|             | Rösiger et al. (2018)  | 49.4 | 20.2 | **28.7** | 24.3 | 10.0 | 14.1 |                  |
|             | Hou et al. (2018)      | - | - | - | 20.6 | 22.6 | 21.6 |                  |
|             | Our model              | 44.6 | 19.6 | 27.2 | 23.6 | 10.4 | **14.4** |                  |
| BASHI       | Keep                   |   |   |    |   |   |    |                    |
|             | Rösiger et al. (2018)  | 49.4 | 20.2 | **28.7** | 24.3 | 10.0 | 14.1 |                  |
|             | Our model              | 44.6 | 19.6 | 27.2 | 23.6 | 10.4 | **14.4** |                  |
| SCICORP     | Keep                   |   |   |    |   |   |    |                    |
|             | Rösiger et al. (2018)  | 17.7 | 0.9 | 8.1 | 3.2 | 0.9 | 1.5 |                  |
|             | Our model              | 52.9 | 41.2 | **46.3** | 25.0 | 19.4 | **21.9** |                  |

Table 2: Comparing our model with the SoTA for antecedent selection.

Table 3: Comparing our model with the SoTA for full bridging resolution.

resolution and anaphor recognition respectively). These F1 improvements are mainly a result of better recall; the precisions of the two models are similar. This suggests that learning with coreference does help the model to capture more correct bridging pairs. However, recall is still much lower than precision. As this might result from data imbalance, we applied undersampling during training, to train the model on a more balanced dataset. As shown in Table 1b, with undersampling the model has a more balanced precision and recall, and also achieves better F1 scores on both full bridging resolution and anaphor recognition. The new model achieved improvements of 6.6% and 1.7% on anaphor recognition and full bridging resolution, respectively, when compared with the model without undersampling. Overall, our multi-task models showed their merit on both tasks and achieved considerable gains of 8.2% and 13.7% when compared with the single-task system.

Comparison with the State of the Art We then evaluated our model on the test set of ARRAU RST to compare it with the previously reported state of the art on the same dataset. Table 2 shows the comparison

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5The Hou et al. (2018) system used additional gold information for feature extraction, see section 5.3 for more details.

6The results of Hou et al. (2014) are from Rösiger et al. (2018), as they were obtained on an unknown subset of the corpus.

7The Hou et al. (2018) result is evaluated on a different setting, i.e. instead of filtering out gold coreference anaphors, they use an IS classifier to assign mentions IS classes and exclude mentions belongs to IS classes other than bridging (including predicted coreference anaphors).
on antecedent selection. The best reported system on this task, (Rösiger, 2018b), is a modified version
of the original rule-based system designed for ISNOTES by Hou et al. (2014). Our system outperforms
the current state of the art by nearly 10 percentage points. Table 3 presents the comparison on the full
bridging resolution and anaphor recognition. Since the only reported full bridging resolution results on
ARRAU (Rösiger, 2018b) are evaluated with coreferent anaphors removed, we follow the same method
to remove gold coreferent anaphors from the evaluation, but we also report the results with coreferent
anaphors included for future reference. Filtering out the gold coreferent anaphors the task is easier,
resulting in better F1 scores. After filtering out gold coreferent anaphors, our system achieved F1 scores
of 24% and 36.7% on full bridging resolution and anaphor recognition respectively, which is 4.5% and
6% higher than the scores reported in Rösiger (2018b). Overall, our model achieved the new SoTA
results on both full bridging resolution and its subtasks.

5.2 Evaluation on the ARRAU TRAINS and PEAR corpus

We then evaluate our system on the TRAINS and PEAR portion of the ARRAU corpus. For both corpora,
the only reported results are by Rösiger (2018b). For antecedent selection our system achieved scores 2%
and 33% better than theirs on TRAINS and PEAR respectively (see Table 2). For the other two tasks, they
only report scores after filtering out the gold coreference anaphors, when evaluate in the same setting,
our system achieved substantial improvements of up to 36.3% and 34.9% for anaphor recognition and
full bridging resolution respectively. Overall, our system is substantially better than the Rösiger (2018b)
system on both TRAINS and PEAR corpora.

5.3 Evaluation on the ISNOTES corpus

Most recent work on bridging reference resolution was evaluated on ISNOTES; a number of systems were
developed for both full bridging resolution (Hou et al., 2014; Rösiger et al., 2018; Hou et al., 2018) and
antecedent selection (Hou et al., 2013; Hou, 2018b; Hou, 2018a; Hou et al., 2018). Since the ISNOTES
follows a very different annotation scheme than that of the ARRAU, to confirm the suitability of our
best setting for ARRAU on corpora only containing referential bridging examples (ISNOTES, BASHI and
SCICORP) we run additional parameter tuning on the ISNOTES corpus. For parameter tuning we use the
same 10 documents as used in Rösiger et al. (2018) as a development set and use the rest 40 documents
for training. As shown in Table 1a and Table 1b the results on ISNOTES follows the same trend as for
ARRAU RST, the best settings for two corpora remain the same.

To compare with the SoTA systems, we use 10-fold cross-validation to obtain predictions for the whole
corpus. On the full bridging resolution task, our system outperforms all the previous results both when
coreferent anaphors are included (3.7%) and when they are excluded (1.6%). The improvements on
anaphor recognition are larger, and our system is more than 14% better in both settings.

For antecedent selection, however, our system achieved a result broadly comparable with that of the
model called MLN model II in (Hou et al., 2013), but lower than those obtained with subsequent devel-
opments of this model (Hou, 2018b; Hou, 2018a; Hou et al., 2018). We can see three main reasons for the
lower performance. (i) The Hou et al systems rely on hand-annotated gold information from OntoNotes
to compute their features, including named entity annotation and syntactic annotation. In addition, the
top performing system from the lab, (Hou et al., 2018), also uses discourse structure annotations from
the Penn Discourse Treebank to define the set of antecedents in the ‘discourse scope’. By contrast, our
system does not rely on any hand-coded annotations at test time. We would argue that this setup is more
realistic than in particular the setup in (Hou et al., 2018)\(^8\). (ii) The models in (Hou, 2018b; Hou, 2018a;
Hou et al., 2018) include, in addition to pairwise features, a number of ‘global’ features designed for
bridging references to globally salient entities and for bridging references that share the same antecedent
(‘siblings’). However, the versions of such features we have tested in our model do not appear to improve
its performance. (iii) The Hou et al systems are evaluated in a mention-entity setting that assumes that
gold coreference chains are available at test time, while our system is based on a mention pair architec-
ture. The use of a mention-entity setting results in a much smaller pool of candidate antecedents;\(^9\) hence

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\(^8\)The Hou et al. (2018) system is not publicly available.

\(^9\)In their system each bridging anaphor only has less than 20 candidate, in contrast with our 150 candidates
the task becomes easier, but less realistic. (iv) The Hou et al systems are heavily tuned on the ISNOTES corpus, the results on other corpora are either not reported or much lower.

Overall, on the ISNOTES corpus our system achieved a competitive result on antecedent selection and the SoTA on full bridging resolution and anaphor recognition.

5.4 Evaluation on the BASHI corpus

We next compare our system with previous models on the BASHI corpus. Since gold mentions are not annotated in BASHI, we use NPs as our predicted mentions without filtering. For antecedent selection the only reported result on BASHI corpus is from Hou (2018a) (see Table 2). Our system achieved a lower than that of Hou (2018a). Rösiger et al. (2018) reported the only results for full bridging resolution and anaphor recognition. Our system achieves an F1 that is 1.5% lower than their result on anaphor recognition, but a better F1 on full bridging resolution (see Table 3). Overall, our models achieves new SoTA on full bridging resolution and antecedent selection.

5.5 Evaluation on the SCICORP corpus

Finally, we evaluated our system on SCICORP corpus, in which, like in the BASHI corpus, gold mentions are not annotated, so again we used NPs as our predicted mentions. SCICORP consists of scientific documents that are very different from the BASHI (news). As a result, the only reported result on SCICORP, (Rösiger et al., 2018), is rather poor. Roesiger et al.’s rule-based system only achieved 1.5% and 8.1% (F1) for full bridging resolution and anaphor recognition respectively. The poor result is mainly due to the system only recognizing less than 1% of the bridging anaphors, which is another example of the sensitivity of rule-based systems to domain shifting. By contrast, our system achieved on this corpus F1 scores of 21.8% and 46.3% for full bridging resolution and anaphor recognition, respectively (Table 3). These scores on SCICORP are broadly in the same range to the scores achieved by our system on the other three corpora, which indicates that our system’s performance doesn’t deteriorate so badly with domain shifting. In terms of the antecedent selection task, our system achieved an accuracy of 33.4%; to the best of our knowledge, this is the first result for antecedent selection on SCICORP.

6 Conclusions

In this paper we proposed a multi-task neural architecture tackling two major challenges for bridging reference resolution. The first challenge is the lack of very large training datasets, as the largest corpus for bridging reference, ARRAU (Uryupina et al., 2019), only contains 5.5k examples, and other corpora are much smaller (the most used corpus for bridging, ISNOTES, (Markert et al., 2012) only contains 663 bridging pairs). The second challenge is that different annotation schemes for bridging are used in different corpora (referential and lexical bridging), so designing a system that can be applied to different corpora is complicated. Our results on the ARRAU RST corpus demonstrate that the performance on full bridging resolution and its subtasks can be significantly improved by learning with additional coreference annotations. Our multi-task model achieved substantial improvements of 7.3%-13.7% for full bridging resolution and its subtasks when compared with the single task baseline that learns solely on bridging annotations. As a result, our final system achieved SoTA results in all three tasks. Further evaluation on TRAINS, PEAR, ISNOTES, BASHI and SCICORP demonstrates the robustness of our system under changes of annotation scheme and domain. The very same architecture used for ARRAU again achieved SoTA results on full bridging resolution for all three corpus.

Overall, our results suggest that coreference is a useful source task for bridging reference resolution, and our neural bridging architecture is applicable to bridging corpora based on different domain or definitions of bridging.

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10We also tried to combine ISNOTES and BASHI for training as suggested by Roesiger, since they both mainly focus on referential bridging; however concatenating the corpora does not improve the performance on either corpus.

11The NPs do not belong to coreference clusters or bridging relations are treated as non-mention during training.
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