Coreference Reasoning in Machine Reading Comprehension

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Abstract

The ability to reason about multiple references to a given entity is essential for natural language understanding and has been long studied in NLP. In recent years, as the format of Question Answering (QA) became a standard for machine reading comprehension (MRC), there have been data collection efforts, e.g., (Dasigi et al., 2019), that attempt to evaluate the ability of MRC models to reason about coreference. However, as we show, coreference reasoning in MRC is a greater challenge than was earlier thought; MRC datasets do not reflect the natural distribution and, consequently, the challenges of coreference reasoning. Specifically, success on these datasets does not reflect a model's proficiency in coreference reasoning. We propose a methodology for creating reading comprehension datasets that better reflect the challenges of coreference reasoning and use it to show that state-of-the-art models still struggle with these phenomena. Furthermore, we develop an effective way to use naturally occurring coreference phenomena from annotated coreference resolution datasets when training MRC models. This allows us to show an improvement in the coreference reasoning abilities of state-of-the-art models across various MRC datasets. We will release all the code and the resulting dataset at https://github.com/UKPLab/coref-reasoning-in-qa.

1 Introduction

Given a question and a passage, the task of machine reading comprehension[1] is to select the answer to the question from the passage. Coreference resolution is the task of finding different expressions that refer to the same real-world entity. The tasks of coreference resolution and machine reading comprehension have moved closer to each other. Converting coreference-related datasets into an MRC format improves the performance on some coreference-related datasets (Wu et al., 2020b; Aralikatte et al., 2019). There are also various datasets for the task of reading comprehension on which the model requires to perform coreference reasoning, e.g., DROP (Dua et al., 2019), DuoRC (Saha et al., 2018), MultiRC (Khashabi et al., 2018), etc. Quoref (Dasigi et al., 2019) is a dataset that is particularly designed for evaluating coreference understanding of MRC models. Figure 1 shows a QA sample from Quoref in which the model needs to resolve the coreference relation between "his" and "John Motteux" to answer the question.

context: "In 1834, Henry Hoste Henley died without issue, and the estate was bought at auction by John Motteux, a London merchant. Motteux was also without heirs and bequeathed Sandringham, together with another Norfolk estate and a property in Surrey, to the third son of his close friend, Emily Lamb, the wife of Lord Palmerston..."
question: "What is the first name of the person who was close friends with Lamb?"
gold answer: "John"

Figure 1: A sample from the Quoref dataset. "John Motteux", "Motteux" and "his" are coreferent mentions in the context. In order to answer the question, a model need to understand the coreference relations.

Quoref is created using an adversarial data collection method to discard examples that can be solved using simple lexical cues. Yet, recent large pre-trained language models reached high performance on Quoref. Our analysis shows that high performances on Quoref can still be attributed to annotation artifacts (see Section 3) and that this dataset does not reflect the natural distribution and, therefore, the challenges of coreference reasoning. Our analysis suggests that results on Quoref do not necessarily reflect the coreference reasoning capabilities of the examined models, and answering questions that require coreference reasoning might be a greater challenge than current scores suggest.

[1]This task is also commonly referred to as Question Answering (QA). We use the two terms interchangeably.

In this paper, we propose two solutions to address this issue. First, we propose a methodology for creating MRC datasets that better reflect the coreference reasoning challenge. We release a sample challenging evaluation set containing 200 examples by asking an annotator to create new question-answer pairs using our methodology and based on existing passages in Quoref. We show that this dataset contains fewer artifacts, its distribution of biases is closer to a coreference resolution dataset, and the performance of state-of-the-art models on Quoref considerably drops on this evaluation set. The results on this evaluation set indicate that (1) performing MRC based on coreference reasoning is still an open problem, and (2) our methodology opens a promising direction to create future challenging MRC datasets.

Second, to improve the coreference reasoning of MRC models, we propose to use naturally occurring coreference phenomena from annotated coreference resolution datasets during training. Given two coreferring expressions m_1 and m_2 from a coreference dataset, we create a question whose answer is m_2 using the BART model (Lewis et al., 2020) and consider this question, m_1, and the corresponding document as a new (question, answer, context) tuple. This data helps the model to learn to resolve the coreference relation between m_1 and m_2 to answer the question. We investigate the effectiveness of our proposed solution using two state-of-the-art MRC models. We show that incorporating these additional QA data improves the performance on our new evaluation set as well as other MRC evaluation sets that require coreference reasoning.

Our main contributions are as follows:

- We show that Quoref does not reflect the natural challenges of coreference reasoning and propose a methodology for creating MRC datasets that better reflect this challenge.
- We release a sample challenging dataset that is manually created by an annotator using our methodology. The results of state-of-the-art MRC models on our evaluation set show that, despite the high performance of MRC models on Quoref, answering questions based on coreference reasoning is still an open challenge.
- We propose an effective method to incorporate naturally occurring coreference relations from existing coreference resolution datasets for training MRC models. We show that incorporating this data improves the coreference reasoning of state-of-the-art MRC models across various evaluation sets.

2 Related Work

2.1 Artifacts in NLP datasets

One of the known drawbacks of many NLP datasets is that they contain artifacts.[2] Models tend to exploit these easy-to-learn patterns in the early stages of training (Arpit et al., 2017; Liu et al., 2020; Utama et al., 2020b), and therefore, they may not focus on learning harder patterns of the data that are useful for solving the underlying task. As a result, overfitting to dataset-specific artifacts limits the robustness and generalization of NLP models.

There are two general approaches to tackle such artifacts: (1) adversarial filtering of biased examples, i.e., examples that contain artifacts, and (2) debiasing methods. In the first approach, potentially biased examples are discarded from the dataset, either after the dataset creation (Zellers et al., 2018; Yang et al., 2018a; Le Bras et al., 2020), or while creating the dataset (Dua et al., 2019; Chen et al., 2019; Nie et al., 2020). Bartolo et al. (2020) investigate various model-in-the-loop adversarial filtering methods. They show that adversarially collected datasets result in better generalization to non-adversarially collected datasets. However, the effectiveness of this data collection decreases as we use a stronger model-in-the-loop as they discard more training examples.

In the second approach, they first recognize examples that contain artifacts, and use this knowledge in the training objective to either skip or downweight biased examples (He et al., 2019; Clark et al., 2019a), or to regularize the confidence of the model on those examples (Utama et al., 2020a). The use of this information in the training objective improves the robustness of the model on adversarial datasets (He et al., 2019; Clark et al., 2019a; Utama et al., 2020a), i.e., datasets that contain counterexamples in which relying on the bias results in an incorrect prediction. In addition, it can also improve in-domain performances as well as generalization across various datasets that represent the same task (Wu et al., 2020a; Utama et al., 2020b).

While there is an emerging trend of including adversarial models in data collection, their effec-

[2] I.e., the conditional distribution of the target label based on specific attributes of the training domain diverges while testing on other domains.

tiveness is not yet compared with using debiasing methods, e.g., whether they are still beneficial when we use debiasing methods or vice versa.

2.2 Joint QA and Coreference Reasoning

There are a few studies on the joint understanding of coreference relations and reading comprehension. Wu et al. (2020b) propose to formulate coreference resolution as a span-prediction task by generating a query for each mention using the surrounding context, thus converting coreference resolution to a reading comprehension problem. They leverage the plethora of existing MRC datasets for data augmentation and improve the generalization of the coreference model. In parallel to Wu et al. (2020b), Aralikatte et al. (2019) also cast ellipsis and coreference resolution as reading comprehension tasks. They leverage the existing neural architectures designed for MRC for ellipsis resolution and outperform the previous best results. In a similar direction, Hou (2020) propose to cast bridging anaphora resolution as question answering and present a question answering framework for this task. However, none of the above works investigate the impact of using coreference data on QA.

Dua et al. (2020) use Amazon Mechanical Turkers to annotate the corresponding coreference chains of the answers in the passages of Quoref for 2,000 QA pairs. They then use this additional coreference annotation for training a model on Quoref. They show that including these additional coreference annotations improves the overall performance on Quoref. The proposed method by Dua et al. (2020) requires annotating additional coreference relations on every new coreference-aware QA dataset. Contrary to this, our approach uses existing coreference resolution datasets, and therefore, applies to any new QA dataset without introducing any additional cost.

3 How strong are the artifacts in Quoref?

For creating the Quoref dataset, annotators first identify coreferring expressions and then ask questions that connect two coreferring expressions. Dasigi et al. (2019) use a BERT-base model (Devlin et al., 2019) that is fine-tuned on the SQuAD dataset (Rajpurkar et al., 2016) as an adversarial model to exclude QA samples that the adversarial model can already answer. The goal of using this adversarial model is to avoid including question-answer pairs that can be solved using surface cues. They claim that most examples in Quoref cannot be answered without coreference reasoning.

If we fine-tune a RoBERTa-large model on Quoref, it achieves 78 F1 score while the estimated human performance is around 93 F1 score (Dasigi et al., 2019). This high performance, given that RoBERTa can only predict continuous span answers and Quoref also contains discontinuous answers, indicates that either (1) Quoref presents coreference-aware QA very well so that the model can properly learn coreference reasoning from the training data, (2) pretrained transformer-based models have already learned coreference reasoning during their pre-training, e.g., as suggested by **?** and Clark et al. (2019b), or (3) coreference reasoning is not necessarily required for solving most examples.

In this section, we investigate whether Quoref contains the known artifacts of QA datasets, and therefore, models can solve some of the QA pairs without performing coreference reasoning. Figure 2 shows such an example where simple lexical cues are enough to answer the question despite the fact that coreference expressions “Frankie” and “his” were included in the corresponding context.

context: "...In turn, Frankie stalks Ralph back to his tenement and strangles him to death following a violent brawl between the two. Losing his nerve, Frankie calls up his employers to tell them he wants to quit the job. Unsympathetic, the supervisor tells him he has until New Year's Eve to perform the hit...."
question: "What is the first name of the person who wants to quit their job?"
gold answer: "Frankie"

Figure 2: A QA example that relies on simple lexical overlap without requiring coreference reasoning.

To do so, we train several bias models, which are models that are trained to solve the task only using a targeted artifact. Bias models are then used for detecting biased examples in the dataset, i.e., examples that can be solved using the targeted artifacts.

We investigate five bias models as follows:

- Random named entity: the majority of answers in the Quoref datasets are person names. Therefore, we evaluate a random named entity baseline that randomly selects a PERSON named entity from the context as the answer.[3]
- Wh-word (Weissenborn et al., 2017): according to this artifact, the model can answer the question by only using the interrogative adverbs from the question. For recognizing this bias,

[3] We use spaCy (Honnibal and Johnson, 2015) for NER.

we only train the model on a variation of the dataset in which questions only contain interrogative adverbs.

- Empty question (Sugawara et al., 2020): based on this artifact, the model can select the answer without considering the question.[4] The corresponding bias model is trained only using the contexts and without questions.
- Semantic overlap (Jia and Liang, 2017): based on this artifact, the answer lies in the sentence of the context that has the highest semantic similarity to the question. We use sentence-BERT (Reimers and Gurevych, 2019) to find the most similar sentence.
- Short distance reasoning: we train the bias model only using the most similar sentence of the context instead of the whole context. We exclude the question-answer pairs in which the most similar sentence does not contain the answer. This model will not learn to perform coreference reasoning when the related corefering pairs are not in the same sentence.

For wh-word, empty question, and short distance reasoning, we use the TASE model (Segal et al., 2020) to learn the bias. We do not change the development set for any of the biases.

The *Quoref* column in Table 1 reports the proportion of examples in the Quoref development set that are solved correctly using the bias models.

We also investigate whether these biases have similar ratios in a coreference resolution dataset. We use the CoNLL-2012 coreference resolution dataset (Pradhan et al., 2012a) and convert it to a reading comprehension format, i.e., CoNLL$_{bart}$ in Section 5. This data contains question-answer pairs in which the question is created based on a coreferring expression in CoNLL-2012, and the answer is its closest antecedent. We split this data into training and test sets and train bias models on the training split. The *CoNLL* column in Table 1 shows the bias proportions on this data.

As we see, the short distance reasoning bias model can correctly predict the answer of half of the examples in the Quoref dataset. However, the ratio of such examples is only around 10% in CoNLL-2012. Therefore, apart from the examples that can be solved without coreference reasoning,[5] the difficulty of the required coreference reasoning in the remaining examples is also not comparable with naturally occurring coreference relations in a coreference resolution dataset.

As a result, high performance on Quoref does not necessarily indicate that the model is adept at performing coreference reasoning.

Bias Model	**Quoref**	**CoNLL**
random named entity	9.39	1.52
wh-word	22.99	13.12
empty question	21.51	11.60
semantic overlap	28.66	21.38
short-distance reasoning	**50.70**	9.86

Table 1: The proportion of examples in the Quoref development set and CoNLL-2012 coreference resolution dataset that contain each of the examined biases.

4 Creating an MRQ Dataset that Better Reflects Coreference Reasoning

As mentioned, there is a growing trend in using adversarial models for data creation to make the dataset more challenging or discard examples that can be solved using surface cues (Bartolo et al., 2020; Nie et al., 2020; Yang et al., 2018a; Zellers et al., 2018; Yang et al., 2018b; Dua et al., 2019; Chen et al., 2019; Dasigi et al., 2019).

The assumption for using an adversarial model in Quoref is that it is hard to avoid simple lexical cues by which the model can answer questions without coreference reasoning. Therefore, an adversarial model (A) is used to discard examples that contain such lexical cues. While this adversarial filtering removes examples that are easy to solve by A, it does not ensure that the remaining examples do not contain shortcuts that are not explored by A. First, the adversarial model in Quoref is trained on another dataset, i.e., SQuAD. Thus, the failure of A on Quoref examples may be due to (1) Quoref having different lexical cues than those in SQuAD, or (2) domain shift. Second, , and more importantly, as argued by Dunietz et al. (2020), making the task challenging by focusing on examples that are more difficult for existing models is not a solution for more useful reading comprehension.[6]

In this paper, we instead propose a more systematic methodology for creating question-answer pairs as follows:

[4] E.g., this can indicate the bias of the model to select the most frequent named entity in the context as the answer.

[5] E.g., about 20% of examples can be answered without considering the question.

[6] As put by them: "the dominant MRC research paradigm is like trying to become a professional sprinter by glancing around the gym and adopting any exercises that look hard".

Context Snippet	Question	Gold Answer
"Diamonds" was certified sextuple platinum by the Recording Industry Association of America (RIAA).In Canada, the song debuted at number nine on the Canadian Hot 100 for the issue dated October 13, 2012 [...] It remained atop of it for four consecutive weeks [...]	What is the full name of the chart of which Diamonds remained atop for four consecutive weeks?	Canadian Hot 10
The ever-winding path of John Frusciante's solo career is a confusing one to say the least [...] The album of the same name is Frusciante's first experimenting with the acid house genre. He previously released an EP, Sect In Sgt under this alias in 2012.	Who did release an EP called Sect In Sgt?	John Frusciante

Table 2: Examples from our dataset. The context is cropped to only show the relevant parts.

- Annotators should create a question whose answer is a referring expression m_1, if (1) m_1 has a more informative antecedent m_2 in the text.[7], and (2) m_1 and m_2 reside in a different sentence. The span of m_2 is then annotated as the answer. This ensures that answering the question requires resolving the coreference relation between the m_1 and m_2.
- Candidate passages for creating QA pairs are selected according to their number of named entities. The number of distinct named entities is an indicator of the number of entities in the text. Therefore, there would be more candidate entities for resolving referring expressions.

We provide this guideline to a student from the Computer Science department for generating new QA pairs from the existing passages in the Quoref development set. We select Quoref passages to ensure that the source of performance differences on our dataset vs. Quoref is not due to domain differences. This results in 200 new QA pairs. Table 2 presents examples from our dataset.

Table 3 shows the results of the examined bias models on our dataset. By comparing the results of Table 3 and Table 1, we observe that our dataset contains fewer biases compared to Quoref, and the distribution of the examined biases in this dataset is closer to those in CoNLL-2012. As we will see in Table 6, the performance of state-of-the-art models on Quoref drops more than 10 points, i.e., 13-18 points, on our challenge dataset. We examine 50 randomly selected examples from our challenge set, and they were all answerable by a human.

Bias Model	Ours
random named entity	3.03
wh-word	13.64
empty question	11.62
semantic overlap	24.50
short-distance reasoning	35.35

Table 3: The proportion of examples in our dataset that are correctly answered by bias models.

5 Improving Coreference Reasoning

In this section, we propose to use the annotated data from coreference resolution corpora to improve the coreference reasoning of MRC models. We propose an effective approach to convert coreference annotations into QA pairs so that models learn to perform coreference resolution by answerng those questions. Coreference resolution datasets contain the annotation of expressions that refer to the same entity. In our experiments, we use the CoNLL-2012 dataset (Pradhan et al., 2012b) that is the largest annotated dataset with coreference information.

5.1 Coreference-to-QA Conversion

The existing approach to convert coreference annotations into (question, context, answer) tuples, which is used to improve coreference resolution performance (Wu et al., 2020b; Aralikatte et al., 2019), is to use the sentence of the anaphor as a declarative query, and its closest antecedent as the answer. In this work, we instead generate questions from those declarative queries sing an automatic question generation model. We use the BART model (Lewis et al., 2020) that is one of the state-of-the-art text generation models. Below we explain the details of each of these two approaches for creating QA data from CoNLL-2012. Table 4 shows examples from both approaches.

CoNLL$_{dec}$: Wu et al. (2020b) and Aralikatte et al. (2019) choose a sentence that contains an anaphor as a declarative query, the closest non-pronominal antecedent of that anaphor as the answer, and the corresponding document of the ex-

[7]Proper names are more informative than common nouns, and they are more informative than pronouns (Lee et al., 2013).

Passage in CoNLL	Mention Cluster	CoNLL$_{dec}$ Quesion	CoNLL$_{bart}$ Question	Gold Answer
My mother was Thelma Wahl...She was a very good mother. She was at Huntingdon because she needed care...	[My mother, She, She, she]	She was at Huntingdon because <ref> she </ref> needed care.	who was at huntingdon because she needed care?	My mother
The angel also held a large chain in his hand...The angel tied the dragon with the chain for 1000 years.	[a large chain, the chain]	The angel tied the dragon with <ref> the chain </ref> for 1000 years.	what did the angel tie the dragon with for 1000 years?	a large chain

Table 4: Coreference-to-QA conversion examples using CoNLL$_{dec}$ and CoNLL$_{bart}$ approaches.

pressions as the context.[8] We remove the tuples in which the anaphor and its antecedent are identical.

CoNLL$_{bart}$: we use a fine-tuned BART model (Lewis et al., 2020) released by Durmus et al. (2020) for question generation and apply it on the declarative queries in CoNLL$_{dec}$. It specifies potential answers by masking noun phrases or named entities in the query and then generates questions for each masked text span. We only keep questions whose answer is a coreferring expression and replace that answer with its closest non-pronominal antecedent. We only keep questions in which the masked expression and its antecedent are not identical. Such pairs enforce the model to resolve the coreference relation between these two coreferring expressions to answer the generated question.

5.2 Experimental Setups

To examine the impact of using coreference resolution corpora in improving the coreference reasoning of QA models, we use two state-of-the-art models from the Quoref leaderboard: RoBERTa (Liu et al., 2019) and TASE (Segal et al., 2020). TASE casts the reading comprehension task as a sequence tagging problem to handle questions with multi-span answers. It assigns a tag to every token of the context indicating whether the token is a part of the answer. We use RoBERTa-large from HuggingFace (Wolf et al., 2020) for the RoBERTa baseline. For the TASE model, we use their TASE$_{IO}$+SSE setup that is a combination of their multi-span architecture and single-span extraction with IO tagging.We use the same configuration and hyper-parameters for TASE$_{IO}$+SSE as described in Segal et al. (2020). We train all models for two epochs in all experiments.[9]

[8] We use the code provided by Aralikatte et al. (2019).

[9] The only difference of TASE in our experiments and the reported results in Segal et al. (2020) is the number of training epochs. For a fair comparison, we train all models for the same number of iterations.

Training Strategies. To include the additional training data that we create from CoNLL-2012 using coreference-to-CoNLL conversion methods, we use two different strategies:

- *Joint*: we concatenate the training examples from Quoref and CoNLL-to-QA converted datasets. Therefore, the model is jointly trained on the examples from both datasets.
- *Transfer*: Since the CoNLL-to-QA data is automatically created and is therefore noisy, we also examine a sequential fine-tuning setting in which we first train the model on the CoNLL-to-QA converted data, and then fine-tune it on the Quoref data.

5.3 Data

We evaluate all the models on four QA datasets.

- *Quoref*: the official development and test sets of Quoref, i.e., Quoref$_{dev}$ and Quoref$_{test}$, respectively.
- *Contrast set*: the contrast set (Gardner et al., 2020) that is created based on the official Quoref test set. For creating this evaluation set, the authors manually performed small but meaningful perturbations to the test examples in a way that it changes the gold label. This dataset is constructed to evaluate whether models' decision boundaries align to true decision boundaries when they are measured around the same point. Therefore, it is not constructed to contain more challenging coreference reasoning cases. However, we hypothesize that if a model learns a better coreference reasoning for QA, and therefore, relies less on lexical cues, it will also perform better on the contrast set.
- *MultiRC*: Multi-Sentence Reading Comprehension set (Khashabi et al., 2018) is created in a way that answering questions requires a more complex understanding from multiple

sentences. Coreference reasoning is therefore one of the sources that can improve the performance on this dataset. To use the MultiRC development set, which is in a multi-choice answer selection format, we convert it to a reading comprehension format by removing QA pairs whose answers cannot be extracted from the context.

- *Our challenge set*: our new evaluation set for coreference reasoning in QA described in Section 4.

Dataset	examples
Quoref train	19399
Quoref dev	2418
Contrast set	700
MultiRC	389
Ours	200
CoNLL$_{dec}$	89403
CoNLL$_{bart}$	18906

Table 5: Number of examples in each dataset.

Table 5 reports the statistics of these QA datasets. In addition, it reports the number of examples in CoNLL$_{dec}$ and CoNLL$_{bart}$ datasets that we create by converting CoNLL-2012 training data into QA examples. Since the question generation model cannot generate a standard question for every declarative sentence, CoNLL$_{bart}$ contains a smaller number of examples compared to CoNLL$_{dec}$. The language of all the above datasets is English.

5.4 Evaluation Metric

We use the F1 score that calculates the number of shared words between predictions and gold answers for evaluation.

5.5 Results

Table 6 presents our results for evaluating the impact of using coreference annotations to improve coreference reasoning in QA models. We have reported the results for both of the examined state-of-the-art models, i.e., TASE and RoBERTa-large. We examined both training settings, i.e., (1) training the model jointly on Quoref and converted CoNLL data (Joint), and (2) pre-training the model on the CoNLL data first and fine-tuning it on Quoref (Transfer). *Baseline* represents the results of the examined models that are only trained on Quoref. *CoNLL$_{bart}$* represents the results of the models that are only trained on the CoNLL$_{bart}$ data.

Based on the results of Table 6, we can answer the following questions:

Can incorporating coreference annotations improve coreference reasoning in QA systems? The results of Transfer-CoNLL$_{bart}$ for both RoBERTa and TASE models show that incorporating the generated QA examples from coreference annotations in training QA models improves the results on almost all the examined evaluation sets. These evaluation sets are either explicitly designed to evaluate coreference reasoning, i.e., *Quoref* and *Ours* or a better coreference reasoning improves the performance on them, i.e., *Contrast*. Therefore, better performance on these datasets indicates improved coreference reasoning. Note that *MultiRC* contains QA pairs from a different domain than those in Quoref, while the rest of the evaluation sets are from a similar text-domain. Therefore, the lower results on *MultiRC* can be attributed to domain shift.

Does the choice of coreference-to-QA conversion method impact the results? Using the sentence of coreferring mentions as a declarative query (CONLL$_{dec}$) is the common method for converting coreference resolution datasets into QA format in previous studies. However, since queries in CONLL$_{dec}$ consist of a different format than those in standard QA datasets, their incorporation is not necessarily effective for improving the performance of QA models. Using the question-answer pairs that are created by CoNLL$_{bart}$, on the other hand, has the most positive impact on the overall results for both of the examined models.

Which one of the training settings is better to incorporate coreference annotations? The best scores on our evaluation set are achieved using the transfer training setting in which the model is first trained on the coreference data and is then fine-tuned on the QA dataset. In particular, when the coreference data is noisier, as it is the case for CONLL$_{dec}$, training the model using the transfer setting results in overall better scores compared to the joint setting.

5.6 Analysis

In order to analyze what kind of examples benefit more from incorporating the CoNLL data, we split Quoref$_{dev}$ and our dataset into different subsets based on the *semantic overlap* and *short distance reasoning* biases reported in Table 1, which are

Model	Training setup	Quoref$_{dev}$	Quoref$_{test}$	Ours	Contrast set	MultiRC
TASE	Baseline	84.05	84.71	66.48	73.44	51.83
	CoNLL$_{bart}$	34.95	35.76	39.55	26.24	26.51
	Joint-CoNLL$_{dec}$	84.36	85.14	65.92	74.88	44.71
	Transfer-CoNLL$_{dec}$	85.00	85.88	**73.07**	75.69	50.18
	Joint-CoNLL$_{bart}$	84.30	85.93	69.37	74.00	48.26
	Transfer-CoNLL$_{bart}$	**85.13**	**85.98**	73.01	**77.40**	**51.96**
RoBERTa	Baseline	78.17	78.07	64.72	65.65	36.14
	CoNLL$_{bart}$	28.82	29.10	29.00	17.36	14.81
	Joint-CoNLL$_{dec}$	75.15	74.83	56.94	57.78	29.97
	Transfer-CoNLL$_{dec}$	74.10	73.65	60.09	58.95	30.93
	Joint-CoNLL$_{bart}$	**78.70**	**79.59**	**67.07**	**66.78**	35.43
	Transfer-CoNLL$_{bart}$	78.22	78.33	66.62	66.58	**36.84**

Table 6: Impact of incorporating coreference annotations using different coreference-to-QA conversion methods: (1) CoNLL sentences as declarative queries (CONLL$_{dec}$) and (2) CoNLL-to-QA using the BART question generation model (CoNLL$_{bart}$). Results are reported for the RoBERTa-large and TASE models. The *Baseline* and *CoNLL$_{bart}$* rows show the results of the models when they are trained on the Quoref training data and the CoNLL$_{bart}$ data, respectively. *Joint* refers to the setting in which the model is jointly trained on Quoref and the converted CoNLL data. *Transfer* refers to the setting in which the model is first trained on the converted CoNLL data and fine-tuned on Quoref. Results are reported based on F1 scores. The highest F1 scores for each model are boldfaced and scores lower than the *Baseline* are marked in gray.

Model	Semantic overlap		¬Semantic overlap		Short reasoning		¬Short reasoning	
	dev	Ours	dev	Ours	dev	Ours	dev	Ours
Baseline	81.69	77.2	84.86	62.96	94.84	89.04	72.95	54.15
Joint-CoNLL$_{dec}$	**+2.07**	-5.80	-0.30	+1.19	+0.94	-1.65	-0.34	+0.03
Joint-CoNLL$_{bart}$	+0.86	-3.00	+0.03	+4.82	+0.64	+1.20	-0.16	+3.80
Transfer-CoNLL$_{dec}$	+1.29	**+8.56**	+0.83	+5.94	+1.07	**+8.82**	**+0.83**	+5.37
Transfer-CoNLL$_{bart}$	+1.74	+1.23	**+0.85**	**+8.26**	**+1.54**	+4.70	+0.60	**+7.51**

Table 7: F1 score differences of various TASE models on the Quoref$_{dev}$'s and our dataset splits that are created based on the semantic overlap and short distance reasoning biases. For instance, *Ours* in the ¬Semantic overlap column show the performance differences of the examined TASE models on the split of our dataset in which examples do not contain the semantic overlap bias.

the most common types of biases in both of these datasets.

The *semantic overlap* column in Table 7 represents the results on the subset of Quoref$_{dev}$ or our dataset in which answers reside in the most similar sentence of the context, and the ¬*semantic overlap* column contain the rest of examples in each of these datasets. Similarly, the *short reasoning* column presents the results on the subset of the data in which the examples can be solved by the short distance reasoning bias model, and ¬ *short reasoning* presents the results on the rest of the examples.

Table 7 show the performance differences of the TASE model on these four subsets for each of the two datasets. We observe that (1) surprisingly, the performance of the baseline model is lower on the *semantic overlap* subset compared to ¬*semantic overlap* on Quoref$_{dev}$, (2) the addition of the coreference resolution annotations in all four training settings bridges the performance gap on the *semantic overlap* and ¬*semantic overlap* subsets for both datasets, (3) Transfer-CoNLL$_{bart}$ and Transfer-CoNLL$_{dec}$ improve the performance across all four subsets, and (4) there is still a large performance gap between *short reasoning* and ¬ *short reasoning* subsets. In our coreference-to-QA conversion methods, we consider the closest antecedent of each anaphor as the answer. A promising direction for future work is to also create QA pairs based on longer distance coreferring expressions, e.g., to create two QA pairs based on each anaphor, one in which the answer is the closest antecedent, and the other with the first mention of the entity in the text as the answer.

6 Conclusions

In this paper, we show the high performance of recent models on the Quoref dataset does not necessarily indicate that they are adept at performing coreference reasoning and QA based on coreference reasoning is a greater challenge than current scores suggest.

We first propose a methodology for creating a dataset that better presents the coreference reasoning challenge for MRC. We provide our methodology to an annotator and create a sample dataset. Our analysis shows that our dataset contains fewer biases compared to Quoref, and the performance of state-of-the-art models on Quoref drops considerably on this evaluation set. The most challenging part of this annotation process is to determine coreferring expressions, in particular, if they are far apart. In our dataset, we use existing passages in the Quoref dataset to ensure that the resulting differences are not due to a different text-domain. For future work, we suggest using our methodology to create MRC datasets based on available coreference resolution dataset, in which all coreference relations are already annotated.

To improve the coreference reasoning of QA models, we propose to use naturally occurring coreference phenomena from coreference resolution datasets to train MRC models. We show that our approach improves the performance of two state-of-the-art models on various MRC evaluation sets that require coreference reasoning, including our new evaluation set. The results on our evaluation set suggest that there is still room for improvements, and reading comprehension with coreference understanding remains a challenge for existing QA models, especially if the coreference relation is between to distant expressions.

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A Appendices

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Figure 3: A snippet from the CoNLL-2012 dataset with coreference annotation. In this sentence, "Disney" and "its" are annotated as coreferring mentions.

Passage in CoNLL	**Mention Cluster**	**CoNLL$_{dec}$ Quesion**	**CoNLL$_{bart}$ Question**	**Gold Answer**
After George W. Bush is sworn in, Bill Clinton will head to New York. Mr. Clinton will also spend time at his presidential library in Arkansas. He says he will come to Washington, 'every now and then'.	[Bill Clinton, Mr. Clinton, his, He, he]	He says <ref> he </ref> will come to Washington, 'every now and then.'	who says he will come to washington, 'every now and then'?	Bill Clinton
Paul had already decided not to stop at Ephesus. He did not want to stay too long in Asia. He was hurrying because he wanted to be in Jerusalem on the day of Pentecost if possible.	[Paul, He, He, he]	He was hurrying because <ref> he </ref> wanted to be in Jerusalem on the day of Pentecost if possible.	who was hurrying because they wanted to be in jerusalem on the day of pentecost if possible?	Paul
The KMT vice chairman arrived at party headquarters to meet with KMT Chairman Lien Chan on the afternoon of pw...He said that he will follow Lien Chan as a lifelong volunteer.	[The KMT vice chairman, He, he]	He said that <ref> he </ref> will follow Lien Chan as a lifelong volunteer.	who said that he will follow lien chan as a lifelong volunteer?	The KMT vice chairman
...It also includes a lot of sheep, good clean - living, healthy sheep, and an Italian entrepreneur has an idea about how to make a little money of them...So this guy came up with the idea of having people adopting sheep by an internet.	[an Italian entrepreneur, this guy]	So <ref> this guy </ref> came up with the idea of having people adopting sheep by an internet.	who came up with the idea of having people adopting sheep by an internet?	an Italian entrepreneur
George W. Bush has met with Al Gore in Washington. The two men met for just 15 minutes at the Vice President's official residence...Bush went into the talks with his defeated rival after meeting with President Clinton earlier today.	[Al Gore, his defeated rival]	Bush went into the talks with <ref> his defeated rival </ref> after meeting with President Clinton earlier today.	who did bush go into the talks with after meeting with president clinton earlier today?	Al Gore
Meanwhile Prime Minister Ehud Barak told Israeli television he doubts a peace deal can be reached before Israel's February 6th election. He said he will now focus on suppressing Palestinian violence.	[Prime Minister Ehud Barak, He, he]	He said <ref> he </ref> will now focus on suppressing Palestinian violence.	who said he will now focus on suppressing palestinian violence?	Prime Minister Ehud Barak

Table 8: More examples from coreference-to-QA conversion using CoNLL$_{dec}$ and CoNLL$_{bart}$ approaches.