Abstract

Coreference (‘he eats potatoes’) and many forms of ellipsis (e.g., ‘so does Mary’) are similar in that they make it possible to identify an appropriate text span in the previous discourse. This paper proposes to use a neural architecture developed for question answering to the tasks of ellipsis and coreference resolution. We present both single-task and joint models and evaluate them across standard benchmarks, outperforming the current state of the art for ellipsis by up to 48.5% error reduction – and for coreference by 37.5% error reduction.

1 Introduction

Ellipsis and coreference resolution are hard, open problems in NLP, and important sources of error in machine translation, question answering, and dialogue understanding (Vicedo and Ferrandez, 2000; Dzikovska et al., 2006; Chung and Gildea, 2010; Macketanz et al., 2018). Except for OntoNotes, there are no large annotated corpora for either phenomenon, and for ellipsis resolution, we only have annotations for a subset of the known ellipsis constructions. Since annotation is expensive and cumbersome, any synergies across these tasks, or with other related tasks, could be very useful, enabling us to leverage auxiliary data sources when learning models for ellipsis and coreference resolution.

This paper begins with a simple observation depicted in Figure 1. Coreference (I and Mr. Smith) and ellipsis (where) can be converted to machine comprehension questions, where answering these questions by identifying text spans in context implicitly resolves the original phenomena. In some sense, ellipsis, coreference, and questions (most often) put in focus referentially dependent expressions (Carlson, 2006), or free variables (Partee, 1978), that need to be resolved in order to fully understand the discourse.

This observation leads us to suggest treating ellipsis resolution, coreference resolution, and question answering alike, and to apply a state-of-the-art architecture for question answering (QA) to the tasks of ellipsis and coreference resolution, as well as to experiment with using training data for these tasks, and for QA, as auxiliary data sources for each other.

Contributions We cast ellipsis and coreference as QA problems, enabling us to induce models for these tasks using a neural architecture originally developed for QA. Applying this architecture straight out of the box enables us to establish a new state of the art on 2/2 ellipsis datasets and 1/2 coreference datasets, and competitive performance on the other coreference dataset. Moreover, using the same architecture for these tasks enables us to explore synergies between them, even with QA, and we show that training joint models for multiple tasks leads to even better performance.
2 Ellipsis and Coreference

Linguists have long pointed out deep links among different forms of ellipsis, as well as between ellipsis and pronominal anaphora. For example, Merchant (2001) presents a unified account of ellipsis phenomena within a minimalist syntactic framework, and theorists such as Postal (1966) and Elbourne (2013) go so far as to argue that pronouns are also elliptical forms. The exact nature of the connections between ellipsis and anaphoric constructions remains a subject of controversy among linguists. However it is clear that there are rooted connections, and in our view these connections represent potential areas to be exploited with forms of knowledge transfer among datasets of different types. Typically in NLP, ellipsis and coreference have been treated as distinct tasks.  

2.1 Sluice Ellipsis

Sluices are elliptical questions that leave behind a *wh*-phrase. Normally the elided material is a sentential constituent. Consider the example from Figure 2. There, the phrase *The whole thing worked out* is the antecedent, which is missing after the question word *how*. Sluicing occurs across formal and informal registers, and is widely attested among the languages of the world. Resolving sluice ellipsis is important in tasks like dialogue, where antecedents may be introduced in previous turns.

Evaluation metrics In NLP, sluice resolution has been evaluated in terms of token-level F1-score for predicted antecedent text spans. This is due to the fact that the antecedents usually vary in length, and bracketing agreements between annotators is often low.

State of the art Rønning et al. (2018b) train a four-layer LSTM in a multi-task setting. They use POS tagging, Chunking and CCG super-tagging as the auxiliary tasks for the first, second and third layers respectively. The final layer predicts the antecedents, and the network is optimized only for sluice resolution performance. They report a token level F1-score of 0.67.

2.2 Verb Phrase Ellipsis

Verb Phrase Ellipsis (VPE) elides a verb phrase, leaving an auxiliary verb behind. In Figure 2, the verb phrase *believe Seymour can do it* is elided, leaving the auxiliary verb *don’t* in its place. Like sluicing, VPE occurs in formal as well as informal registers, although it is not nearly as widely attested as sluicing among different languages.

Evaluation metrics As suggested by Bos and Spenader (2011), we evaluate each antecedent prediction by calculating the token level precision and recall. The final evaluation metric is the average F1-score over all antecedents. Note that our method is not directly comparable to end-to-end results for VPE, but to the step referred to as antecedent identification by Liu et al. (2016) and Kenyon-Dean et al. (2016).

State of the art Liu et al. (2016) break VPE resolution into three sub-tasks: (i) target detection, (ii) antecedent head resolution, and (iii) antecedent boundary determination. Step (ii) and (iii) combine into antecedent identification, which is the problem we consider in this paper. They use handcrafted features and train a logistic classifier as well as a ranking model for each sub-task. The top performing system (F1 = 0.65 for antecedent identification) is a ranker which jointly models head resolution and boundary detection. While Kenyon-Dean et al. (2016) report better end-to-end scores for VPE, they perform on par on antecedent identification (F1 = 0.65).

2.3 Coreference Resolution

Coreference resolution is the process of identifying all the mentions in a text which refer to the same entity. In the example passage in Figure 2, the phrases *The world’s fifth Disney park* and *September 12* are referred to later by the phrases *Disney* and *the same day as the park* respectively. Similar to ellipsis resolution, coreference resolution is an important step in many higher level NLP tasks such as information extraction (Sarawagi et al., 2008), dialogue (Banjade et al., 2015), etc.

In general, coreference resolution involves two major sub-tasks: mention detection and linking. Except for the end-to-end model introduced by (Lee et al., 2017), all other coreference resolution systems use syntactic parsers for extracting headword features and as input to hand-engineered
Figure 2: Examples of VPE, Sluice Ellipsis, and Coreference represented as “questions” about their associated contexts. In the ellipsis examples, wh-phrases and auxiliary verbs are marked in red and elided phrases are marked in blue. In coreference examples, the mentions are highlighted in green and their antecedents in orange. Since context sentences can contain multiple mentions, each mention is disambiguated with <ref></ref> tags when input to the model. See Section 4.2 for more information.

Evaluation metrics We evaluate our system’s responses on the official CoNLL 2012 shared task evaluator. Each metric measures a different dimension of the system response quality: (i) MUC: the MUC (Vilain et al., 1995) scores focus on links and counts the number of links to be inserted or deleted between mentions in the response, in comparison with the gold keys. The precision and recall is obtained by dividing the number of common links by the number of links in the response and key respectively (ii) B3: with a focus on mentions, the B3 (Bagga and Baldwin, 1998) metric computes the precision and recall between the mentions in the response entity chain and the gold entity chain. These numbers are then averaged over all chains to get the final values (iii) CEAF_C: The entity variant of CEAF (Luo, 2005) aligns entities in the response and gold key. It applies an entity based similarity metric for each pair of entities and picks the best mapping to calculate the precision and recall.

The average F1-score of these three metrics is used for the final comparison between systems.

State of the art The current state-of-the-art for coreference resolution is the model proposed by Lee et al. (2018), which performs a combination of coarse-to-fine and second-order inference on top of the model proposed in Lee et al. (2017), is briefly described here. Representations of all possible spans $i$ in a document are computed and the top $M$ spans are retained based on a mention score $s_M(i)$. A coref scorer $s_c(i, j)$ is used to identify likely antecedents $j$ for each $i$. For every $i$, the top $K$ antecedent spans are computed by summing the individual mention and coref scores: $s_M(i) + s_n(j) + s_c(i, j)$. Once the mentions and antecedents are pruned in this manner, inference involves refining the span representations iteratively by using the antecedent distributions as an attention mechanism. Their F1-score on the test set of CoNLL-2012 shared task is 0.73.

3 Model Architecture

We now describe the QA architecture employed in our experiments, which is borrowed from Devlin et al. (2018). As depicted in Figure 3, the...
model uses a multilayer perceptron (MLP) to predict answer spans from contextual representations output by a pretrained encoder. Here, given a context and a sentence containing VPE, sluice ellipsis, or a coreferent anaphor, the model is tasked with identifying a span in the context that resolves the phenomenon in question.

**Question and Context Encoding** Recently, contextual representations from Transformer architectures (Vaswani et al., 2017) trained with a language modelling objective have performed well on multiple NLP tasks (Peters et al., 2018; Radford et al., 2018), including QA. BERT (Devlin et al., 2018) is a multi-layer bidirectional Transformer encoder, which currently has state-of-the-art performance on the SQuAD QA task (Rajpurkar et al., 2016).\(^6\) It is trained on a combination of: (i) a masked language modelling objective: 15% of the input tokens are masked, and the model is trained to predict these tokens, and (ii) a next sentence prediction objective: given two sentences, the model is trained to predict whether the second sentence appears immediately after the first. It is trained on a concatenation of the BookCorpus (Zhu et al., 2015) and English Wikipedia.

We use the pre-trained $BERT_{BASE}$ uncased model to encode questions and their contexts. It has 12 Transformer blocks, 12 self-attention heads, and a hidden size of 768. Word piece tokenization (Wu et al., 2016) is performed on the context paragraph and the question. The context and the question are represented in sequence, with boundaries marked by dummy symbols as shown in Figure 3.

**Answer prediction** A one-layer MLP with 2 outputs are the only parameters learned from scratch. The weight matrix of size $H \times 2$ can be thought of as a start vector $S^H$ and an end vector $E^H$ of size $\mathbb{R}^H$. The dot product of each token representation $T_i$ with $S^H$ and $E^H$ is computed, and a softmax over all words gives the probability of $i_s$ and $i_e$ being the start and end indices, respectively. The log-likelihood of $i_s$ and $i_e$ is the training objective. During inference, $i_e > i_s$ is imposed, since $i_e$ is not conditioned on $i_s$ during training. The model is also allowed to refrain from answering a question.

The model is finetuned for 7 epochs with a maximum sequence length of 384 (due to memory constraints) and a maximum question length of 64. A data point is split if its context exceeds the maximum sequence length. The Adam (Kingma and Ba, 2014) optimizer is used with an initial learning rate of $5 \times 10^{-5}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1 \times 10^{-6}$, and L2 weight decay of 0.01 with a linear learning rate warmup of 0.1. All experiments were run on a single NVIDIA Titan X with a batch size of 12.\(^7\)

### 4 Experiments & Results

We start this section by briefly describing the various datasets used for training, and then explain

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\(^6\)As of May 31, 2019.

\(^7\)We use [https://github.com/huggingface/pytorch-transformers](https://github.com/huggingface/pytorch-transformers) for all our experiments.
Table 1: Question-answer pair count and average context lengths (ACL) for different datasets, after converting them into QA format

| Task             | Train | Dev  | Test  | ACL |
|------------------|-------|------|-------|-----|
| Sluice Ellipsis  | 1.4k  | 480  | 992   | 351 |
| VPE              | 264   | 20   | 78    | 984 |
| OntoNotes        | 153k  | 18.8k| 19.5k | 463 |
| WikiCoref        | 5.6k  | 630  | 638   | 2.2k |

how they are converted into QA format. We then present results for different experimental setups and finally provide an ablation study over auxiliary datasets.

4.1 Data

Sluice ellipsis For training and evaluation of sluice ellipsis, we use the corpus introduced by Anand and McCloskey (2015), which contains 3,103 annotated examples of embedded sluices, collected from the New York Times section of the English Gigaword. Since the annotators were free to paraphrase the antecedent, in some cases, a string match on the context did not return antecedent span indices. To ensure a fair comparison, we follow Rønning et al. (2018b) in ignoring these instances, and use their split for training, development and testing.

VPE Bos and Spenader (2011) provide VPE annotations for the WSJ part of the Penn Treebank. All 25 sections were annotated, and we follow them in using sections 0-19 for training, and 20-24 for testing. We further hold out sections 18-19 from the training data for development.

Coreference resolution For coreference resolution, we train and evaluate on two corpora: (i) the English portion of the OntoNotes 5.0 corpus with the standard data split used in the CoNLL-2012 shared task (Pradhan et al., 2012), and (ii) the WikiCoref corpus (Ghaddar and Langlais, 2016), which contains annotations of 30 documents from the English Wikipedia. From this dataset, we use 22 documents for training, 4 documents for development, and 4 for testing.

4.2 Conversion

For converting the various datasets into the QA format of \(<\text{context, question, answer}>\) triples, we perform a simple restructuring as shown in Figure 2. We consider the entire document as the context; the sentence in which the ellipsis/mention is present becomes the question, and the antecedent/entity becomes the answer. In case of coreference resolution, where a single sentence can have \(n\) mentions, we create \(n\) questions where every question is the same sentence with a different mention \(i \in \{1 \ldots n\}\) marked for resolution. In these cases, we use \(<\text{ref}>\) and \(</\text{ref}>\) tags to mark the start and end of the mention spans. Table 1 shows the number of QA pairs created from each dataset and the average number of words in their contexts.

When combining datasets from different tasks, we prepend the context and question with task specific tags. The tags used are \(<\text{coref}>\), \(<\text{sluice}>\) and \(<\text{vpe}>\) for the two coreference, Sluice and VPE datasets respectively.

4.3 Results

We conduct experiments in three main settings: (i) the SINGLE-TASK setting, in which we train and evaluate on the same task; (ii) the JOINT setting, where we augment data for a given task with data from a subset of other tasks, and (iii) the UNIVERSAL setting, in which we train on all datasets, including SQuAD (Rajpurkar et al., 2016). The results of all three settings can be seen in Table 2.

SINGLE-TASK In this setup, we achieve state-of-the-art results in both the ellipsis datasets and one coreference dataset with absolute error reductions of 45.45% (Sluice Ellipsis), 25.71% (VPE) and 29.16% (WikiCoref). On OntoNotes, the end-to-end model proposed by Lee et al. (2018), while not strictly comparable, seemingly performs slightly better and beats our model by 0.01 F1. See Section 6 for a direct comparison.

JOINT In this setup, we improve the performance of our model by exploiting the similarities between ellipsis and coreference. We train our model with different combinations of datasets, as determined by performance on validation data. For Sluice Ellipsis and VPE, the best results are obtained training only on the combination of these two datasets. For OntoNotes, the best score is obtained when the model is trained on the combination of all the datasets. The best result on WikiCoref is obtained when the model is trained on the combination of WikiCoref and OntoNotes.

UNIVERSAL Since we reduce ellipsis and coreference resolution problems to QA, we also experiment with training on a mixture of data annotated...
for ellipsis, coreference, and QA (SQuAD). This
universal model performs as well or better than the
single-task models, except for VPE; see column 5
in Table 2. The model achieves a token-level F1 score of 86.6 on the SQuAD development data.
Performance drops considerably for VPE, be-
cause the 87,500 training QA pairs in SQuAD
completely overwhelm the 264 VPE pairs. To mit-
igate this, a randomly sampled subset of SQuAD
was augmented which did not give statistically sig-
ificant improvement over the single model.

4.4 Ablation on datasets
We performed an exhaustive ablation study when
searching for the optimal task combinations for
our joint models, i.e., by training models on dif-
ferent combinations of datasets. Note that these
datasets vary considerably in size (Table 1). For
each dataset, the variations in its F1-scores when
combined with other datasets are shown in Figure
4. The most interesting findings from these abla-
tions are mentioned below.

When the two ellipsis datasets are combined,
the overall performance of the model increases
for both tasks. The absolute increase is around
1.21% for Sluice Ellipsis and 4% for VPE. This
shows that the two types of ellipsis are very simi-
lar, and that when learning ellipsis resolution mod-
els, there is considerable synergy between the two
resources. The addition of Sluice Ellipsis data
when training a VPE model has a bigger effect
than the other way around, presumably because
the sluice data is bigger and more diverse. If we
add coreference data when training these models,
we see a slight decrease in performance. This
is probably due to the fact that the coreference
datasets are much bigger. Subsampling the coref-
ference datasets, we observed a small but insignifi-
cant performance boost, but we do not report these
experiments here.

When the two coreference datasets are com-
bined, F1-scores increase by 1% for OntoNotes
and by 7.14% for WikiCoref. Interestingly, the
coreference model trained on OntoNotes benefits
further from adding ellipsis training data, lending
support to our initial hypothesis that the two tasks
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We find that prepending task specific tags help
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5 Error Analysis
We now look at some errors made by our systems.
We compare and contrast the ellipsis models in
the SINGLE-TASK and JOINT settings. For coref-
ereference resolution, we showcase some interesting
statistics on referential forms.

VPE The VPE system trained with just VPE
data (SINGLE-TASK VPE) substantially improves
the state-of-the-art, but further improvement is ob-
served when there is joint training with the sluice
data (JOINT VPE). Note that the sluice dataset is
far larger than the VPE dataset.

With respect to selecting an antecedent of the
right syntactic form, the SINGLE-TASK VPE sys-
tem generally does better; it nearly always be-
gins with a verb. The JOINT VPE system is less
good, since sluicing antecedents are not VPs, but
rather, sentences. Consider the examples in Fig-
ure 5. In example (a), the JOINT VPE system in-
correctly includes the subject it, presumably be-
cause the sluice data includes complete sentences
as antecedents. Similarly in example (b)—though
the SINGLE-TASK VPE system correctly chooses
an antecedent beginning with the verb make, it
continues with additional material that does not
form a coherent antecedent. The JOINT VPE re-
sult is also incorrect, but note that it consists of the
complete sentence containing the correct VP an-
tecedent. Example (b) presents the advantages and

| Task         | SoA       | Ref                      | Single-Task | Universal | Joint |
|--------------|-----------|--------------------------|-------------|-----------|-------|
| Sluice Ellipsis | 0.67     | Rønning et al. (2018a) | 0.82        | 0.82     | 0.83  |
| VPE          | 0.65     | Liu et al. (2016)       | 0.74        | 0.58     | 0.77  |
| OntoNotes*   | 0.73     | Lee et al. (2018)       | 0.72        | **0.73** | 0.73  |
| WikiCoref*   | 0.52     | Ghaddar and Langlais (2016) | 0.66     | 0.67     | 0.70  |

Table 2: Main results. Ellipsis resolution scores are token-level F1, whereas coreference resolution scores are
macro-averages of MUC, B3, and CEAFφ scores. *: Coreference results are not fully comparable with the reported
state of the art. See Section 6 for more details.
Then at 10:15, the Dow suddenly started to rebound, and when it shot upward it did so even faster than the early-morning fall.

A 190-point drop isn't likely to make much of a dent; multiply that a few times over, though, and it will.

Then the whole thing will start to collapse, just as it did in the 1970s, and the ghosts and banshees will be howling through the place turning people's hair white.

A 190-point drop isn't likely to make much of a dent; multiply that a few times over, though, and it will.

Sluice Ellipsis  The JOINT Sluice Ellipsis results improve modestly over the SINGLE-TASK Sluice Ellipsis results. This is noteworthy, since the added VPE data is quite small compared to the size of the sluice data. Similar to the VPE systems, the sluice systems consistently select an antecedent of the right syntactic form, which is normally a complete sentence. Many of the errors consist of empty outputs: SINGLE-TASK Sluice Ellipsis produces 58 empty outputs, while JOINT Sluice Ellipsis produces 63. Another source of error is discontiguous antecedents. It is not unusual for the gold antecedent to be a discontiguous span (Donecker, 1996), but our system is not permitted to produce discontiguous antecedents, so these cases will always be a source of error. All the systems have problems when the antecedent follows the ellipsis, as in the following example:  

I don’t know why, but women seem to need a story.

Coreference  The OntoNotes-trained system improves a little when combined with WikiCoref. Here we examine specific referential forms in OntoNotes (WikiCoref has similar traits), as shown in Figure 6. In general, performance is better on frequent pronouns – e.g., ‘he’ over ‘she’, ‘this’ and ‘that’. An exception to this is that ‘it’ is less accurate, but more frequent than ‘he’. It is notable that the possessive pronouns (‘his’, ‘her’, ‘its’) are all more accurate than their nominative counterparts (‘he’, ‘she’, ‘it’), perhaps because they tend to have a closer connection to their antecedents. Overall, the single-word referential forms are less accurate than multiple-word forms. For example, definite descriptions (forms begin-
Figure 6: Exact match percentage (bars) and number of occurrences (dots) of referential forms in OntoNotes

ning with ‘the’) are more accurate than any of the single-word forms, with the exception of ‘its’. We speculate that multi-word forms provide more specific information, thus limiting the set of potential antecedents. Another point of interest is the difference in accuracies of gender specific pronouns. Male pronouns generally tend to be more accurate than their female counterparts. Antecedents of ‘he’ and ‘his’ are matched 20% more frequently than for ‘she’ and ‘her’. This might be due to the fact that female pronouns are 50% rarer than male pronouns in OntoNotes.

6 Discussion & Related Work

Comparability with coreference literature

Converting coreference into QA on the one hand makes the coreference resolution problem harder, in that we require the identification of a specific antecedent span, rather than any mention in the entity chain; on the other hand, our problem becomes easier by providing the bracketing of the mention that needs to be resolved. Due to these differences, it is not possible to directly compare our results with others in literature.

To make our results more comparable with Lee et al. (2018), we provided their model with the bracketing of the mentions and considered the first mention to be the antecedent. This way we can reinterpret their clusters as QA pairs, and we do not penalize them for getting mention brackets wrong by only considering pairs where they correctly identify the mention brackets. Note this gives their model an advantage over ours, as their model considers multiple sources of evidence for inferring the coreference links, and gets to pick the subset of data on which the models are compared.

On OntoNotes, in this setting, and after pruning around 7,358 mentions Lee et al. (2018) bracketed wrongly, their new average F1-score is 0.76. Our performance on the same subset of the data is 0.72. Upon manual inspection, we see the model in Lee et al. (2018) has a strong bias favoring nominal antecedents, whereas our model is more likely to predict clausal antecedents. On WikiCoref, our model remains better than the previous state of the art by some margin, with an F1 of 0.69 over 0.43.

Limitations of our approach One limitation of our approach is that, along with most other work in NLP, we assume ellipsis and coreference resolution amount to finding antecedent text spans that corefer with the target mention. This is not always the case, however. First, the elided material can have extra-linguistic antecedents (1); second, the elided material can refer to something that is contextually implied (2).

(1) [Having passed out test papers] Begin!
(2) I went by Downing Street 10 yesterday, but she wasn’t home.

Other QA-based universal architectures We are not the first to use QA to redefine a set of tasks. Recently, He et al. (2015) showed that semantic role labeling annotations could be solicited by asking simple questions that implicitly target predicate-argument relations in a sentence. In the realm of actually employing QA models to solve other tasks, Levy et al. (2017) reframed relation extraction as a QA problem, yielding models which were better at generalizing in the zero-shot setting. Extending this idea, McCann et al. (2018) introduced the decaNLP challenge, which casts a set of 10 core tasks in NLP as QA problems. Similar to our joint experiments with ellipsis and coreference, their architecture jointly learns across all of these tasks. decaNLP includes pronoun resolution, a subset of coreference resolution, but it does so only on a small, hand-crafted dataset; it does not address ellipsis.

7 Conclusion

We reinterpret ellipsis and coreference resolution as question answering problems, and use a state-of-the-art QA architecture to establish new state of the art for several benchmarks. Furthermore, we show benefits of training joint models for these phenomena.
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