Assessing Discourse Relations in Language Generation from Pre-trained Language Models

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Abstract
Recent advances in NLP have been attributed to the emergence of large-scale pre-trained language models. GPT-2 (Radford et al., 2019), in particular, is suited for generation tasks given its left-to-right language modeling objective, yet the linguistic quality of its generated text has largely remain unexplored. Our work takes a step in understanding GPT-2’s outputs in terms of discourse coherence. We perform a comprehensive study on the validity of explicit discourse relations in GPT-2’s outputs under both organic generation and fine-tuned scenarios. Results show GPT-2 does not always generate text containing valid discourse relations; nevertheless, its text is more aligned with human expectation in the fine-tuned scenario. We propose a decoupled strategy to mitigate these problems and highlight the importance of explicitly modeling discourse information.

1 Introduction
Recent progress in NLP has been marked with the emergence of large-scale pre-trained models, e.g., ELMo (Peters et al., 2018), BERT (Devlin et al., 2019), and GPT-2 (Radford et al., 2019). Among these, GPT-2 is particularly suitable in natural language generation due to its underlying left-to-right language modeling objective. Indeed, GPT-based language models have shown impressive results for open-domain dialogue generation (Golovanov et al., 2019; Wolf et al., 2019; Zhang et al., 2019). This has motivated investigations into GPT-2’s generated text (See et al., 2019; Wallace et al., 2019).

In this paper, we perform the first discourse analysis of GPT-2’s outputs, under both organic and fine-tuned scenarios, with the goals of understanding model behavior and pointing towards ways of improvement. We chiefly focus on discourse relations, one of the most important linguistic devices for textual coherence. Discourse relations specify the relationships between text spans, for example:

Jazz is good, but my favorite is country music.

The two clauses are connected by a CONTRAST relation, as signaled by the connective but. Discourse relations are central in establishing textual coherence. For example, they create rhetorical connections between spans in the absence of anaphoric entity mentions (Lascarides and Asher, 2008). Cognitive experiments have repeatedly shown discourse relations to be highly influential in the mental processing of text (Meyer and Freedle, 1984; Horowitz, 1987; Millis et al., 1993; Sanders and Noordman, 2000). Spans joined with incorrect discourse connectives can seem logically incoherent although they are independently grammatical:

Jazz is good, because my favorite is country music.

We examine to what extent does GPT-2 generate text that upholds plausible discourse relations, once a discourse connective (usually 1-2 tokens) is generated. We present a comprehensive analysis of discourse connectives in both fine-tuned generation—specifically, open domain dialogue generation—and organic generation directly from GPT-2. We find that GPT-2 generates valid discourse connectives when the relation can be inferred by humans with high agreement, yet struggles to recover less obvious relations. Our manual analysis reveals the most common connective error is that the relation, signaled by the connective, does not hold between the spans they connect. To this end, we propose a simple remedy: train

The two text spans linked via a connective are also called arguments of a discourse relation.
a connective prediction model and replace incorrect connectives in a post-processing step. This method improves agreement between human and machine-generated connectives by 0.03 F1 in the fine-tuned scenario and 0.04 in the organic scenario. Collectively, our results highlight the importance of inferring discourse relations (Xue et al., 2015), and explicitly incorporating discourse information in language models (Ji et al., 2016), to increase their downstream efficacy.

2 Experimental Setup

**Fine-tuned.** We choose open-domain dialog generation as our fine-tuned scenario, given that it is a high entropy task. The model conditions on a prompt (dialog turn) and generates a response (next turn). We use the PERSONAChat (Zhang et al., 2018) data for the ConvAI2 challenge. We use 122,499 prompt-response pairs for training and 4,801 pairs for validation.²

We fine-tune GPT-2 medium (345M parameters). For compatibility with GPT-2’s pre-training, we concatenate the prompt and response (separated by a delimiter) during training. GPT-2 is fine-tuned for 3 epochs using Adam (Kingma and Ba, 2015) and a learning rate of 5e-5. The cross-entropy (language modeling) loss is only calculated for the response. At test-time, the model is conditioned on the prompt (and delimiter) and generates the response. We use top-k sampling (k=10) sampling for decoding (Fan et al., 2018).³ Our approach is similar to Zhang et al. (2019) and we follow Ko et al. (2019) to encourage generation of informative responses.⁴

For quality assurance, we manually evaluate GPT-2’s generated responses against SpaceFusion (Gao et al., 2019), a state-of-the-art RNN-based model, re-trained on PERSONAChat. The evaluation is conducted on Amazon Mechanical Turk, where 5 annotators (per HIT) chose between GPT-2 and SpaceFusion responses. GPT-2 (45.5% chosen) largely outperforms SpaceFusion (16.9% chosen). For the other 37.7%, the two are tied.

**“Organic” generation.** To determine to what extent GPT-2 understands the discourse functions of connectives, without the effects of fine-tuning, we engage an organic scenario. In this case, we give GPT-2 a partial utterance that acts as the first argument of an explicit discourse relation in the training data, and its task is to generate the rest of the utterance. Once again, we use PERSONAChat to ensure that the results are comparable to the conditioned setting.⁵ We use nucleus sampling (Holtzman et al., 2019) (p = 0.9) for decoding.

3 Assessing explicit discourse relations

At a high level, our assessment strategy compares discourse connectives from GPT-2 outputs with human judgment, following existing strategies of discourse relation annotation, which asks annotators to insert connectives between text spans (Prasad et al., 2008; Scholman and Demberg, 2017; Yung et al., 2019). A discourse connective can be considered valid if humans would also insert a connective signaling the same discourse relation when the connective is masked.

**Extracting sentences with discourse connectives.** We follow prior work (Braud and Denis, 2016; Ma et al., 2019) in the use of heuristics to extract sentences with discourse connectives, using a list of 11 connectives most frequently observed in PERSONAChat: after, and, because, before, but, if, since, so, though, when, while. Specifically, a clause (using verbs as approximations) needs to appear before and after the connective; the connective cannot be immediately followed by a punctuation; and only and and but can follow a period. We remove instances of so immediately followed by an adjective or adverb. Upon manual inspection of a random sample of 133 extracted sentences, 100% of them contain an explicit discourse relation.

In the PERSONAChat training set, ~11% of the responses contain one of the connectives. In contrast, the fine-tuned model generates a connective 26% among all responses, and the organic one 15%. The increase in percentage is likely because connectives are frequent words in the corpus. Table 1 shows the relative frequencies of these connectives. Notably, the distribution of connectives is skewed, with and and but appearing much more often than other connectives, a characteristic similar to other collected examples of discourse relations in the conversation domain (Ma et al., 2019).

²Since our focus of this work is on discourse relations, we don’t use the given personas in the dataset, similar to other work in dialogue generation with this data (Cai et al., 2019).

³We experimented with top-k sampling and nucleus sampling for both tasks, and picked the better performing one upon manual inspection of the validation data.

⁴Ko et al. (2019) used a linguistic metric which performed better than mutual information also used in Zhang et al. (2019).

⁵We do not explicitly perform quality assurance for this scenario as we do not fine-tune GPT-2. Details of language modeling performance are discussed in Radford et al. (2019).
Table 1: % of sentences with a particular discourse connective, of all sentences that contain a connective.

| Connective | PERSONA | CHAT |
|------------|---------|------|
| after      | 1.4     | 0.5  |
| and        | 40.7    | 45.7 |
| because    | 4.2     | 1.7  |
| before     | 1.1     | 0.4  |
| but        | 28.5    | 35.9 |
| if         | 4.4     | 1.6  |
| since      | 2.8     | 2.6  |
| so         | 4.8     | 3.7  |
| though     | 1.1     | 0.2  |
| when       | 8.8     | 5.3  |
| while      | 2.1     | 2.4  |

| Fine-tuned | 0.5 | 45.7 |
| Organic    | 0.5 | 51.4 |

Table 2: % of sentences where the discourse relation is agreed by $n \in \{3, 4, 5\}$ annotators.

| Relation   | Fine-tuned | Organic |
|------------|------------|---------|
| contingency | 6.4        | 12.5    |
| temporal   | 5.1        | 6.2     |
| contrast   | 35.1       | 27.1    |
| conjunction | 52.5       | 53.0    |
| no relation | 0.9        | 1.1     |

Table 3: % of annotated majority relations.

Table 4: % of connectives in generated texts that are consistent with human annotation, stratified by the # of annotators agreeing on the relation.

Table 2 shows the percentage of sentences whose discourse relation is agreed upon by 5, 4, and 3 workers; Table 3 shows the frequency distribution of majority relations (one that is agreed by $\geq 3$ workers). For the fine-tuned case, 89.7% of the sentences have a majority relation; inter-annotator agreement measured by Krippendorff’s alpha is 0.508, indicating moderate agreement (Artstein and Poesio, 2008). This shows that in most cases, readers are able to infer a discourse relation between the spans of text given, and they do so consistently. Similarly in the organic case, 83.5% of the sentences have a majority relation. However, relations agreed by $\geq 4$ workers are much fewer; Krippendorff’s alpha is also at a lower value of 0.382. After adjudicating 70 examples with no majority, we find that the cause of lower inter-annotator agreement is likely due to the fact that more than one relation can often hold, and in other cases, the quality of the generated text is low.

**Annotating discourse relations.** To assess if GPT-2 generate valid discourse connectives, we compare relations signaled by these connectives with relations that humans judge to hold given the rest of the sentence, as in a one-word masked language modeling task. Specifically, for each output sentence that contains a discourse connective, we mask the connective and show the rest of the sentence to annotators (in the case of dialogue generation, we also show the prompt). They are asked to fill in the blank with a connective that most naturally expresses the relation between the arguments, or NONE if they think the two segments are not related. This type of insertion is used previously to crowdsource discourse relations (Yung et al., 2019; Scholman and Demberg, 2017). To reduce label sparsity, we group the connectives into the four top-level discourse relations in the Penn Discourse Treebank (Prasad et al., 2008) (contingency, contrast, expansion, temporal), and the annotators are asked to choose a group if it contains the connective they think most appropriately fills the blank. The grouping is shown in Appendix A.

We use Amazon Mechanical Turk to crowdsourc e 1.2K sentences each for the organic and fine-tuned scenarios. Each sentence is annotated by five workers. As quality control, we only allow workers in the US that have completed more than 500 hits with an acceptance rate of $>98%$.

**Assessment results.** Table 4 shows the percentage of sentences where the connective in the generated text agree with the majority relation annotated by humans; we also show the results stratified by how many people agree on the relation. For the connectives since and while which can signal two relations, we count the model as correct if either relation is annotated by humans. Notably, for relations that humans agree more consistently, the models also generate correct relations more often. This hints that GPT-2 captures obvious,

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6If multiple connectives exist, we only consider the first one in this work.

7Adjudication is done by an expert in the Linguistics department.
unambiguous relations better. A confusion matrix contrasting human vs. model connectives is shown in Appendix B.

## 4 Fixing discourse connectives

As a first step to fix erroneous connectives, we propose a post-processing technique that does not require retraining a transformer or modifying model structure: replacing generated discourse connectives with ones from a connective prediction model. This task is related to discourse relation classification (e.g., Xue et al. (2015), Nie et al. (2019)), yet there is no annotated corpora on the dialog domain. While Ma et al. (2019) mined discourse relations in conversations, using their data yielded inferior performance in preliminary experiments.

### Connective prediction model.

We train a model to predict the masked discourse connective given the rest of the sentence, or NONE if no relation. For training, we extract 1 million sentences from Reddit that contain discourse connectives, using the heuristics in Section 3. We restrict the length of sentences to be 7-25 tokens, similar to that in PersonaChat. The model is fine-tuned on the pretrained BERT-base-uncased model (Devlin et al., 2019), where the text before the connective is used as sentence A, and text after the connective is used as sentence B. We add an additional classification layer taking the learned [CLS] representation as input. To obtain training data for the NONE class, we add 300K synthesized examples with sentence A and sentence B sampled from different posts, approximating the absence of discourse relations.

The model is fine-tuned for 3 epochs on Reddit using a learning rate of 5e-6. The classification accuracy on the validation set of PERSONAChat is 0.743 and macro-F1 is 0.649. In the organic setting, we directly apply this model to predict the masked connective. In the fine-tuned setting, to obtain a better model in the domain of PERSONAChat, we fine-tune the model for 1 epoch on the training set of PERSONAChat. The classification accuracy improved by 3% and macro-F1 5%.8

### Post-processing results.

With this connective prediction model, we replace connectives in generated outputs with the predicted ones. We evaluate whether the predicted connectives align better with human judgments, after collapsing to discourse relation types. We see the NONE prediction (4.4% for fine-tuned and 17.5% for organic) as an indicator that the sentence is not coherent, and resample from the model for a new sentence. These cases are not included in the results.

Table 5 shows after post-processing, the macro-f1 consistency between a connective in sentence with its corresponding human labeled discourse relation; we stratify results according to agreement among human annotators. Confusion matrices comparing predicted vs. human labels are in Appendix B, showing that the better performance of the model is not due to simply preferring the most frequent class. For both fine-tuned and organic cases, the predicted connective aligns closer to human labels than those generated by GPT-2. The improvement is notably more substantial for the organic case, an indication that fine-tuning GPT-2 nudges the model very close to what the connective prediction model learns. The overall improvement is likely due the connective prediction model having access to text before and after the connective, while the initial language generation model does not. This finding points to future work on considering stronger discourse-related signals (Ji et al., 2016) and stronger models for inferring relations.

### 5 Conclusion

This work presents an assessment of discourse relations in organic and fine-tuned language generation from GPT-2. We find that the understanding of discourse connectives are present in these models but are limited, especially when the relation requires more inference. We present a post-processing strategy to replace generated connectives, such that they align better with human expectation.

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|               | Fine-tuned | Organic |
|---------------|-----------|---------|
| GPT-2 predicted | 0.781     | 0.828*  |
| GPT-2 predicted | 0.760     | 0.789   |
| ≥ 4            |           |         |
| ≥ 3            | 0.789     | 0.766*  |

Table 5: Consistency between human annotated and predicted discourse relations, measured in macro-f1 of the four relation types. (≥ n): ≥ n annotators agree on a relation. (*): p < 0.05 on a bootstrapping test. Accuracies tabulated in Appendix C.

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8Note that this improvement does not translate to a better model for the organic scenario, since GPT-2’s output without fine-tuning does not fall in the PERSONAChat domain.
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A Connective grouping in crowdsourced annotations.

We group the 11 connectives into discourse relations they most frequently signal, according to the Penn Discourse Treebank (PDTB) (Prasad et al., 2008). To further help annotators, we included unambiguous synonyms of connectives to anchor the relations more. For ambiguous connectives in our list, we put them in all possible relations they signal. The specific groupings are listed below:

- because, therefore, if, so, since (CONTINGENCY)
- but, although, though, however, whereas, while (CONTRAST)
- before, after, when, since, while (TEMPORAL)
- and, in addition (EXPANSION)

We also give the NONE option if the annotator could not find a suitable connective or that the two text spans are not related.

B Confusion Matrices

Figure 1 shows a confusion matrix comparing human labeled relations (where at least 3 annotators agree) with GPT-2 generated ones.

Figure 2 compares the prediction between GPT-2 and the connective predictor for post-processing (Section 4) (subfigure (a)). It illustrates the type of relations that the connective model replaced correctly (subfigure (b)) and incorrectly (subfigure (c)). This shows that the fixing is working properly instead of simply predicting more common relations to improve accuracy.

C Consistency measured by accuracy

Table 6 shows accuracy values of before and after post-processing. We also show cases where ≥ 2 annotators agree to account for the possibility of multiple valid relations.

|            | Fine-tuned | Organic |
|------------|------------|---------|
| ≥ 4        | 86.8       | 89.2*   |
| ≥ 3        | 81.5       | 82.9    |
| ≥ 2        | 84.1       | 85.9*   |

Table 6: Consistency between human annotated and predicted discourse relations, measured in accuracy. (≥ n): calculated on all sentences that ≥ n annotators agree on a relation. (*): p < 0.05 on a binomial test.