DisSent: Sentence Representation Learning from Explicit Discourse Relations

Allen Nie∗  Erin D. Bennett∗  Noah D. Goodman
1Department of Computer Science  2Department of Psychology
Stanford University
anie@cs.stanford.edu  {erindb,ngoodman}@stanford.edu

Abstract

Sentence vectors represent an appealing approach to meaning: learn an embedding that encompasses the meaning of a sentence in a single vector, that can be used for a variety of semantic tasks. Existing models for learning sentence embeddings either require extensive computational resources to train on large corpora, or are trained on costly, manually curated datasets of sentence relations. We observe that humans naturally annotate the relations between their sentences with discourse markers like “but” and “because”. These words are deeply linked to the meanings of the sentences they connect. Using this natural signal, we automatically collect a classification dataset from unannotated text. Training a model to predict these discourse markers yields high quality sentence embeddings. Our model captures complementary information to existing models and achieves comparable generalization performance to state of the art models.

1 Introduction

When humans read a sentence they extract a flexible representation of meaning that can be used for many tasks. Developing wide-coverage models to represent the meaning of a sentence is thus a key task in natural language understanding. The applications of such general-purpose representations of sentence meaning are many — paraphrase detection, summarization, knowledge-base population, question-answering, automatic message forwarding, and metaphorical language, to name a few.

Learning flexible meaning representations requires a sufficiently demanding, yet tractable, training task. We propose to leverage a high-level relationship between sentences that is both frequently and systematically marked in natural language: the discourse relations between sentences. Human writers naturally use a small set of very common transition words between sentences1 to identify the relations between adjacent ideas. These words, such as because, but, although, which mark the relationship between two sentences on the highest level, have been widely studied in linguistics, both formally and computationally, and have many different names. We use the name “discourse markers”. Because discourse markers annotate deep conceptual relations between sentences, similar to entailment, they may permit learning from much less data; because discourse markers are produced in natural text, unlike entailment, they don’t require hand annotation.

We thus propose the DisSent model and Discourse Prediction Task to train sentence embeddings. We choose pairs of sentences linked with common discourse markers, and, using a simple data preprocessing scheme, we are able to automatically curate a sizable training set. We then train a sentence encoding model to learn embeddings for each sentence in a pair such that a classifier can identify, based on the embeddings, which discourse marker was used to link the sentences. Conneau et al. (2017) published an evaluation framework, SentEval2, to evaluate sentence embeddings. They compile a set of pre-defined sentence classification tasks on which a good sentence representation should perform well. They used these tasks to evaluate their InferSent model

1We will use “sentences” to mean either whole sentences or the main clauses of a compound sentence.
2https://github.com/facebookresearch/SentEval
which they trained on a natural language inference task (Bowman et al., 2015). We use the SentEval to evaluate our models. Using a model architecture similar to InferSent, but trained on our new discourse classification task, our DisSent embeddings achieve comparable results on many evaluation tasks. Combining our embeddings and those from InferSent achieves state of the art performance, superior to either embedding alone.

2 Discourse Prediction Task

We propose a new task for natural language understanding: discourse marker prediction. Given two sentences in a corpus, the model must predict which discourse marker was used by the author to link the two ideas. Without a semantic understanding of the sentence, it is difficult to predict the discourse connectives. For example, “She’s late ____ she missed the bus” would likely be completed with because, but “She’s sick ____ she missed the class” would likely be completed with so, and “She’s skilled ____ she missed the goal” would likely be completed with but. All of these example pairs have similar syntactic structures and more than half their words in common. But the meanings of the component sentences lead to strong intuitions about which discourse marker makes the most sense. Success at choosing the correct discourse marker likely requires the learned representation to reflect the meaning of a sentence.

Hobbs (1990) argues that discourse relations are always present, and that they fall under a small set of categories. Given this assumption, researchers have attempted to identify the correct relation for a given pair of sentences (Marcu and Echihabi, 2002), or to determine when and why a discourse relation will be made explicit with a discourse marker (Patterson and Kehler, 2013; Yung et al., 2017). Such studies make use of corpora like the Penn Discourse Treebank (PDTB) (Robaldo et al., 2008), where each sentence is annotated with its relation. However, determining the correct relations can be an unnatural and difficult task for annotators, requiring extensive training. In addition, there has been disagreement among researchers and annotators about what exactly is the correct categorization of discourse relations (e.g. Hobbs, 1990; Jasinskaja and Karagjosova, 2015). While sometimes overlapping and ambiguous in the relations they represent, discourse markers in general map onto specific discourse relations (Pitler et al., 2008). We can therefore use explicit discourse markers as proxies for true relations between sentences, without relying on costly and debated annotations of implicit discourse relations.

This task leverages the intrinsic nature of a discourse marker and how it is commonly used, without curation. For instance, because common discourse markers appear in similar distributions across a range of genres (See e.g. Altenberg, 1984, for causal discourse markers), the representations necessary to do well at this task should be less sensitive to style than to content. This is a desirable feature for a sentence embedding that aims to reflect the sentence’s meaning.

| marker      | BookCorpus |
|-------------|------------|
| but         | 51.56      |
| so          | 28.57      |
| if          | 26.32      |
| when        | 22.56      |
| before      | 13.08      |
| still       | 10.41      |
| after       | 9.45       |
| because     | 8.64       |
| while       | 6.02       |
| although    | 1.17       |
| however     | 1.15       |
| meanwhile   | 0.11       |
| for example | 0.07       |
| total       | 179.11 (1.82%) |

Table 1: Frequencies (in 100K) of discourse markers within BookCorpus and percent within the full corpus.

3 Model

DisSent Model We adapt the best architecture from Conneau et al. (2017) as our sentence encoder. This architecture uses a standard bidirectional LSTM (Graves et al., 2013), followed by temporal max-pooling to create sentence vectors. We parameterize the BiLSTM with the same weight $\theta$ for both forward and backward processing to control the parameter growth.

$$\vec{h_t} = \text{LSTM}_f(w_1, ..., w_T | \theta)$$

$$\rvec{h_t} = \text{LSTM}_b(w_T, ..., w_1 | \theta)$$

(1)

We apply temporal max pooling on the resulting sequences of hidden vectors to construct the forward and backward encodings for each sentence. Temporal max pooling builds a sentence representation from all time steps in the processing of a
sentence (Collobert and Weston, 2008; Conneau et al., 2017), providing regularization and shorter back-propagation paths.

\[
\begin{align*}
\vec{H} &= [\vec{h}_1, \ldots, \vec{h}_T] \\
\vec{H} &= [\vec{h}_1, \ldots, \vec{h}_T] \\
\vec{s}_i &= \text{MaxPool}(\vec{H}) \\
\vec{s}_i &= \text{MaxPool}(\vec{H})
\end{align*}
\] (2)

After pooling, we combine the final forward and backward encodings into a single encoding for each sentence via addition, \(s_i = \vec{s}_i^f + \vec{s}_i^b\).

Our objective is to predict the discourse relations between two sentences from their vectors, \(s_1\) and \(s_2\). To do so we must combine the vectors, and some non-linear interactions are likely to be needed. However, because we want generally useful sentence vectors after training, the learned computation should happen before the sentences are combined. To achieve this, we include a fixed set of common pair-wise vector operations: subtraction, multiplication, and average.

\[
\begin{align*}
\vec{s}_{\text{avg}} &= \frac{1}{2}(s_1 + s_2) \\
\vec{s}_{\text{sub}} &= s_1 - s_2 \\
\vec{s}_{\text{mul}} &= s_1 \ast s_2 \\
\vec{s} &= [s_1, s_2, \vec{s}_{\text{avg}}, \vec{s}_{\text{sub}}, \vec{s}_{\text{mul}}]
\end{align*}
\] (3)

Finally we project the concatenated vector \(s\) down to a vector of label size (the number of discourse markers), and use softmax to compute the probability distribution over discourse relations.

4 Data Collection

We describe below a simple, automatic way to collect a large corpus of sentence pairs and the relations between them. We collected such sentence pairs from BookCorpus (Zhu et al., 2015), a dataset of text from unpublished novels (Romance, Fantasy, Science fiction, and Teen genres), which was used by (Kiros et al., 2015) to train their SkipThought model. We use this dataset to train our model.

4.1 Discourse Markers

We chose relatively frequent discourse markers (accounting for at least 1% of discourse markers in the overall corpus) from a large set of discourse markers identified in the manual for the preparation of the Penn Discourse TreeBank (PDTB) (Prasad et al., 2007). We excluded a few discourse markers (and, then, and as) that were very difficult to systematically separate from the sentences they connect or very ambiguous with usages other than as a discourse marker. We present our final set of discourse markers and their frequencies in Table 1.

| method                      | markers                                      |
|-----------------------------|----------------------------------------------|
| string only                 | but, for example, when, meanwhile             |
| string + dep-parse          | because, although, while, if                 |
| dep-parse only              | before, after, however, so, still, though     |

Table 2: Collection method used for each discourse marker.

4.2 Sentence Collection

We processed and collected discourse markers from the BookCorpus dataset (Zhu et al., 2015). We used the same tokenization as used to train SkipThought (Kiros et al., 2015). While discourse markers are quite separable from the sentences they link, there are some complications in extracting sentence pairs from raw text.

Many discourse markers in English occur almost exclusively between the two sentences they connect, and for these discourse markers we simply split on the discourse marker such that the first sentence in the pair (S1) was the part of the sentence before the discourse marker and the second (S2) was the part after.

For other discourse markers, their position in the sentence relative to S1 and S2 is less systematic, and for these markers, we ran Stanford CoreNLP dependency parser (Schuster and Manning, 2016). For discourse markers with consistent patterns, we simply used this parse to exclude pairs that were obviously not linked by that discourse marker. For other discourse markers, we collected pairs by extracting subphrases of the appropriate dependency relation from the dependency parse. The method used for each discourse marker is shown in Table 2.

Using a dependency parse had the added benefit of filtering out many uses of these words that are not discourse markers at all. For example, some discourse markers, (e.g. so) are ambiguous between their discourse marker usage and other usages (e.g. “that’s so cool!”).

Despite these advantages, this method also introduces some problems. The dependency parser
her profile picture was cute, none of these thoughts amounted to much, she could move into town as a full-time witch, myrtle had just decided to give georgias cognitive skills a go, the rush of energy hit us before the sound. complications are to be expected. “tomorrow, i need to go in front of them. “ she looked tired and battered.

| S1 | marker | S2 |
|----|--------|----|
| but | you couldn’t trust those. | because she had no choice in the matter. |
| because | she could make enough money | if there was a sudden, piercing shriek. |
| if | when we had a moment of being hit. | so |
| when | before | for example |
| so | still | i can not be allowed to encounter myself. |
| for example | before | the search party starts out. |
| she had no choice in the matter. | still | i had never in my life seen someone more beautiful.

Table 3: Example pairs from our Books 8 dataset.

produces some incorrect parses, which can result in unrelated pairs., e.g. “I won’t tell him that I didn’t actually buy them so you can’t tell him either.” was parsed as [“that i didnt actually buy them”, so, “you cant tell him either”]. Incorrect parses also introduced errors in extracting sub-phrases, when the discourse marker was embedded within S2, e.g. given the sentence “Okay, so it was what you said, too.” S1 was extracted as “okay,, too.”

4.3 Length-based Filtering
As a way to exclude extremely uninformative sentence pairs and standardize lengths of sentences, we filtered pairs based on several criteria on the lengths of the two sentences. We excluded any pair where one of the two sentences was less than 5 or more than 50 words long. We additionally excluded any pairs where one of the two sentences was more than 5 times the length of the other.

4.4 Training Dataset
Using these methods, we curated a dataset of 9,297,461 pairs of sentences for 13 discourse markers. Examples are shown in Table 3. We then randomly divide the dataset into train/validation/test set with 0.9, 0.1, 0.1 split. The dataset is inherently unbalanced but in our experiments the model is still able to learn rarer classes quite well.

We will also consider smaller sets of discourse markers, resulting in smaller data sets. For our experiment on 8 discourse markers, we have 8,396,747 sentence pairs in total, and for our experiment on 5 discourse markers, we have 7,442,573 sentence pairs in total. Selected markers are displayed in Table 4.

5 Related Work
Current state of the art models summarize the meaning of a sentence via a sentence vector, relying on completely unsupervised learning or supervised learning through high-level classification tasks.

Skipthought (Kiros et al., 2015) is an unsupervised sequence model that has proven to generate useful sentence embeddings. However, it requires large amounts of training data and long training time to perform well. In SkipThought, each word in the previous sentence is used to generate each word in the next sentence. In DisSent, each word in both sentences is used to classify the discourse marker, which is often extracted from the second sentence.

InferSent (Conneau et al., 2017) explores the idea that sentence embeddings can be learned from by capitalizing on sentence relationships. They trained a classifier to predict entailment relations in the Stanford Natural Language Inference (SNLI) (Bowman et al., 2015) and MultiNLI (Williams et al., 2017) corpora, achieving comparable performance to SkipThought on generalization tasks, but with much less data and shorter training time. However, the training set used was built using human annotation, and is therefore laborious and expensive to collect. The InferSent model is therefore limited in the size and variety of dataset it can be trained on. In contrast, while DisSent also leverages sentence relationships, it can be trained on automatically collected data.

Jernite et al. (2017) have proposed a model that leverages discourse relations. They manually put discourse markers into several categories based on human interpretations of discourse marker similarity, and the model predicts the category instead the individual discourse marker. Their model also trains on sentence ordering and ranking of the following sentence. Their data collection methods only allow them to look at paragraphs longer than 8 sentences, and they only obtained 1.4M sentence pairs that contain discourse markers from a much larger corpus. Our proposed model achieves com-
parable results to Jernite et al. (2017) without any auxiliary tasks or manual categorization of discourse markers.

6 Experiments

For all our models, we tuned the hyperparameters on the validation set, and report results from the test set. We use stochastic gradient descent with initial learning rate 0.1, and we anneal by half each time the validation accuracy is lower than previous epoch. We train our models for 10 epochs. We set the feedforward dropout rate to be 0.2 and did not explicitly tune dropout rate. We also clip the gradient norm to 5.0. Parameters were initialized uniformly from [-0.1, 0.1]. We experimented with both temporal mean pooling and temporal max pooling and found the later to perform much better at transfer tasks.

| Label | Discourse Markers |
|-------|-------------------|
| Books 5 | but, because, if, when, so |
| Books 8 | but, because, if, when, so, for example, before, still |

Table 4: Discourse marker sets used in our experiments.

**Discourse Marker Set** To investigate the qualitative relations among the ALL marker set, we build a confusion matrix based on predictions on the test set (Figure 4). We see that many discourse markers are misclassified as the most common marker but (likely an effect of the unbalanced data set). Different markers are misclassified as but to different degrees. The most common such confusion is when the synonymous marker although is mistakenly classified as but.

The temporal relation markers before and after, two intuitively very similar discourse markers, are almost never confused for anything but each other. The fact that they are indeed confusable may reflect the tendency of authors to mark temporal relation primarily when it is ambiguous.

The discourse marker while is an interesting case, since it can be used to express either contrasting or temporal relationships between two sentences. When the model misclassifies while, it is usually either misclassified as the temporal discourse marker when or the contrast classifier but.

Because there appear to be intrinsic conceptual overlap in the set of ALL markers, we experimented on different subsets of discourse markers.

We choose sets of 5 and 8 discourse markers that seemed non-overlapping and frequent, both intuitively and with respect to confusions in Figure 1. The set of sentence pairs for each smaller dataset is a strict subset of those in any larger dataset. Our chosen sets are shown in Table 4.

**Transfer Tasks** We evaluate the performance of our generated sentence embeddings on a series of natural language understanding benchmark tests provided by Conneau et al. (2017). The tasks we chose include sentiment analysis (MR, SST), question-type (TREC), product reviews (CR), subjectivity-objectivity (SUBJ), opinion polarity (MPQA), entailment (SICK-E) and relatedness (SICK-R). These tasks are all classification tasks with 2-6 classes, except for relatedness, for which the model predicts human similarity judgements.

6.1 Results

**Training task** On the discourse marker prediction task that our model is trained for, we achieve high levels of test performance for all discourse markers. (Though it is interesting that because, perhaps the conceptually deepest relation, is also systematically the hardest for our model.) The larger the set, the more difficult the task becomes and we see lower test accuracy overall when the size of the discourse marker set increases. Training task performance for each of our models is shown in Table 6.
Our approach performs similarly to or better than InferSent on four tasks, while doing slightly worse on the remaining four. Some of these differences may be due to small differences in model or training, while the remaining differences may be due to the different task and very different source of data (human curated vs natural corpus).

### Combining embeddings from different tasks

It may be that models trained to predict discourse markers learn complementary information compared to models trained for natural language inference. This idea suggests that better performance can be achieved by combining the embedding vectors. Indeed, we found that by combining sentence representations from our model and InferSent, the concatenated model in Table 7 outperforms either one of the individual models on most tasks (InferSent still outperforms the combined model on two tasks).

### 7 Discussion

The ability of discourse marker prediction as a training task to shape sentence embeddings into a useful, roughly state of the art, form for generalization tasks is encouraging. Yet a number of issues for future research are apparent.

---

### Discourse marker set

Varying the set of discourse markers doesn’t seem to help or hinder the model’s performance on generalization tasks. Generalization performance on the three sets of discourse markers for embedding size 2048 is shown in Table 5. Similar generalization performance was achieved when training on 5, 8, and all 13 discourse markers. The lack of improvement when training on more discourse markers may reflect the overlap in meaning and usage across many discourse markers. It may also simply reflect the fact that the top 5 discourse markers capture most of the relationships in the training data.

### Comparison to previous approaches

In comparing to previous work, we used the Books 8 and Books 5 datasets and trained a model with 4096 embedding size.

Results of our top performing models, and comparison to other approaches, are shown in Table 7. Despite being a much simpler task, with faster training, than SkipThought, the DisSent embeddings outperforms SkipThought embeddings on 5 tasks.

---

**Table 5:** Discourse marker set: Generalization task results for DisSent model using SentEval framework on three different discourse marker sets, holding embedding size constant at 2048 dimensions.

| Training data | Embedding size | MR   | CR   | SUBJ  | MPQA | SST | TREC | SICK-R | SICK-E |
|---------------|----------------|------|------|-------|------|-----|------|--------|--------|
| Books 5       | 2048           | 83.1 | 81.6 | 92.7  | 89.7 | 81.1| 86.4 | 0.803  | 81.7   |
| Books 8       | 2048           | 82.8 | 81.7 | 92.5  | 89.7 | 78.5| 86.8 | 0.808  | 81.9   |
| Books ALL     | 2048           | 82.5 | 80.2 | 92.4  | 89.6 | 82.9| 84.6 | 0.791  | 80.3   |

---

**Table 6:** Training task performance: Test recall for each discourse marker on the classification task.

| Marker       | All (2048) | Books 8 (2048) | Books 8 (4096) | Books 5 (2048) | Books 5 (4096) |
|--------------|------------|----------------|----------------|----------------|----------------|
| but          | 0.90       | 0.95           | 0.94           | 0.97           | 0.97           |
| because      | 0.45       | 0.57           | 0.60           | 0.53           | 0.55           |
| if           | 0.90       | 0.88           | 0.90           | 0.87           | 0.86           |
| when         | 0.71       | 0.89           | 0.90           | 0.89           | 0.91           |
| so           | 0.75       | 0.83           | 0.82           | 0.86           | 0.88           |
| for example  | 0.37       | 0.55           | 0.63           | —              | —              |
| before       | 0.83       | 0.83           | 0.88           | —              | —              |
| still        | 0.84       | 0.79           | 0.84           | —              | —              |
| after        | 0.53       | —              | —              | —              | —              |
| although      | 0.09       | —              | —              | —              | —              |
| however      | 0.66       | —              | —              | —              | —              |
| meanwhile    | 0.49       | —              | —              | —              | —              |
| though       | 0.73       | —              | —              | —              | —              |
| while        | 0.71       | —              | —              | —              | —              |
| Overall      | 0.84       | 0.88           | 0.89           | 0.90           | 0.91           |

---

3Conneau et al. (2017) showed that model generalization performance improved as sentence embedding size increased. We found the same to be true in our experiments. We chose to present the same embedding size as InferSent for comparison.
| model | MR | CR | SUBJ | MPQA | SST | TREC | SICK-R | SICK-E |
|-------|----|----|------|------|-----|------|--------|--------|
| DisSent Books 5 (4096) | 83.4 | 81.8 | 93.4 | 90.0 | 82.5 | 87.0 | 0.821 | 82.6 |
| DisSent Books 8 (4096) | 82.9 | 81.4 | 93.2 | 90.0 | 80.2 | 87.2 | 0.817 | 81.5 |
| Discourse BiGRU (512) (Jernite et al., 2017) | — | — | 88.6 | — | — | 81.0 | — | — |
| **Concatenated model** | | | | | | | | |
| DisSent Books 5 (4096) + InferSent (4096) | 84.3 | 84.6 | 94.0 | 90.6 | 83.7 | 90.4 | 0.885 | 87.1 |
| DisSent Books 8 (4096) + InferSent (4096) | 84.3 | 85.0 | 93.9 | 90.1 | 83.6 | 89.4 | 0.886 | 87.7 |
| **Unsupervised training methods** | | | | | | | | |
| FastSent (Hill et al., 2016) | 70.8 | 78.4 | 88.7 | 80.6 | — | 76.8 | — | — |
| FastSent + AE (Hill et al., 2016) | 71.8 | 76.7 | 88.8 | 81.5 | — | 80.4 | — | — |
| Skipthought (Kiros et al., 2015) | 76.5 | 80.1 | 93.6 | 87.1 | 82.0 | 92.2 | 0.858 | 82.3 |
| Skipthought-LN (Conneau et al., 2017) | 79.4 | 83.1 | 93.7 | 89.3 | 82.9 | 88.4 | 0.858 | 79.5 |
| **Supervised training methods** | | | | | | | | |
| DictRep (bow) (Conneau et al., 2017) | 76.7 | 78.7 | 90.7 | 87.2 | — | 81.0 | — | — |
| InferSent (4096) (Conneau et al., 2017) | 81.1 | 86.3 | 92.4 | 90.2 | 84.6 | 88.2 | 0.884 | 86.1 |

Table 7: Generalization task results using SentEval. InferSent sentence embedding size is 4096 dimensions. SkipThought-LN model trained on 600-dimension word embeddings and produced 2400-dimension sentence embeddings.

**Limitations of evaluation** The generalization tasks that we (following (Conneau et al., 2017)) use to compare models focus on sentiment, entailment, and similarity. These are narrow operational definitions of semantic meaning. A model that generates meaningful sentence embeddings should excel at these tasks. However, success at these tasks does not necessarily imply that a model has learned a deep semantic understanding of a sentence.

Sentiment classification, for example, in many cases only requires the model to understand local structures. Text similarity can be computed with various textual distances (e.g., Levenshtein or Jaro distance) on bag-of-words, without a compositional representation of the sentence. Thus, the ability of our, and other, models to achieve high performance on these metrics may reflect a competent representation sentence meaning; but more rigorous tests are needed to understand whether these embeddings capture sentence meaning in general.

**Shallow or deep features** Different discourse markers appear in different syntactic frames. Our extraction method maintained punctuation and capitalization, which may have provided the model with surface-level syntactic cues that could make the task of classifying discourse markers easier without a semantic understanding of the sentence. These same cues, if encoded in our embedding, may be useful in some generalization tasks. For example, for TREC, punctuation and syntactic structure may be indicative of question type. It seems unlikely that the same surface level cues are useful for all the tasks — DisSent’s high performance on a range of tasks does suggest it is capturing at least some deeper semantic understanding of a sentence.

**Implicit and explicit discourse relation** We focus on explicit discourse relations for training our embeddings. Another meaningful way to exploit discourse relations in training is to predict sentence ordering. Jernite et al. (2017) showed the power of such a method in generating meaningful sentence embeddings.

This approach makes the assumption that adjacent sentences are closer together in meaning space (or generated from similar latent topics). This may be true of many adjacent sentences, especially those whose relation is unmarked. But adjacent sentences can be related to one another in many different, complicated ways. For example, sentences linked by contrastive markers, like but or however are likely expressing different or opposite ideas.

Combining explicit and implicit signals about discourse for training embedding models is an appealing direction for future research.
Conclusion

We present a discourse marker prediction task for training sentence embeddings to reflect the meaning of a sentence. We train our model on this task and show that the resulting embeddings lead to high generalization performance on a number of established tasks for sentence embeddings.

This type of training task can use large amounts of unannotated text, since it relies only on the kinds of annotations (sentence boundaries and discourse markers) that humans naturally mark in their communications with each other. A dataset for this task is therefore easy to collect relative to other supervised tasks. Compared to unsupervised methods that train on a full corpus, our method yields more targeted and faster training. Encouragingly a model trained on discourse marker prediction achieves comparable generalization performance to other state of the art models.

References

Bengt Altenberg. 1984. Causal linking in spoken and written english. Studia linguistica 38(1):20–69.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics.

Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In Proceedings of the 25th international conference on Machine learning. ACM, pages 160–167.

Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. 2017. Supervised learning of universal sentence representations from natural language inference data. arXiv preprint arXiv:1705.02364.

Alex Graves, Navdeep Jaitly, and Abdel-rahman Mohamed. 2013. Hybrid speech recognition with deep bidirectional lstm. In Automatic Speech Recognition and Understanding (ASRU), 2013 IEEE Workshop on. IEEE, pages 273–278.

Felix Hill, Kyunghyun Cho, and Anna Korhonen. 2016. Learning distributed representations of sentences from unlabelled data. arXiv preprint arXiv:1602.03483.

Jerry R Hobbs. 1990. Literature and cognition. 21. Center for the Study of Language (CSLI).

Katja Jasinskaja and Elena Karagjosova. 2015. Rhetorical relations.

Yacine Jernite, Samuel R. Bowman, and David Sonntag. 2017. Discourse-Based Objectives for Fast Unsupervised Sentence Representation Learning. arXiv:1705.00557 [cs, stat] ArXiv: 1705.00557. http://arxiv.org/abs/1705.00557.

Ryan Kiros, Yukun Zhu, Russlan R Salakhutdinov, Richard Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Skip-thought vectors. In Advances in neural information processing systems. pages 3294–3302.

Daniel Marcu and Abdessamad Echihabi. 2002. An unsupervised approach to recognizing discourse relations. In Proceedings of the 40th Annual Meeting on Association for Computational Linguistics. Association for Computational Linguistics, pages 368–375.

Gary Patterson and Andrew Kehler. 2013. Predicting the presence of discourse connectives. In EMNLP. pages 914–923.

Emily Pitler, Mridhula Raghupathy, Hena Mehta, Ani Nenkova, Alan Lee, and Aravind K Joshi. 2008. Easily identifiable discourse relations.

Rashmi Prasad, Eleni Miltsakaki, Nikhil Dinesh, Alan Lee, Aravind Joshi, Livio Robaldo, and Bonnie L Webber. 2007. The penn discourse treebank 2.0 annotation manual.

Alan Lee Eleni Miltsakaki Livio Robaldo, Aravind Joshi Rashmi Prasad, Nikhil Dinesh, and Bonnie Webber. 2008. The penn discourse treebank 2.0. In Proceedings of the Sixth International Conference on Language Resources and Evaluation (LREC08), Marrakech, Morocco, may. European Language Resources Association (ELRA). http://www.lrec-conf.org/proceedings/lrec2008.

Sebastian Schuster and Christopher D Manning. 2016. Enhanced english universal dependencies: An improved representation for natural language understanding tasks. In LREC.

Adina Williams, Nikita Nangia, and Samuel R Bowman. 2017. A broad-coverage challenge corpus for sentence understanding through inference. arXiv preprint arXiv:1704.05426.

Frances Yung, Kevin Duh, Taku Komura, and Yuji Matsumoto. 2017. A psycholinguistic model for the marking of discourse relations. Dialogue & Discourse 8(1):106–131.

Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In Proceedings of the IEEE international conference on computer vision. pages 19–27.