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# Improving Sense Classification in Shallow Discourse Parsing

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## Abstract

TODO

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## Preface

# 1 Introduction

Despite the progress in Natural Language Processing (NLP), one assumption remains steadfast: sentences are to be seen as atomical units. Machine Translation systems rarely look outside of its local context for translation clues, sentiment analysis modules have trouble dealing with juxtapositions, and information extraction systems often limit extracted units of fact to the immediate sentence. While this obviously is a faulty assumption, it has been difficult to release this constraint from the equations; the increasing recall has rarely been worth the much faster decreasing precision.

Lately, it has come to the attention that we might have started to reach a convergence for certain tasks if we do not start to look into the role of sentences in their environment. This is what *discourse parsing* is trying to achieve, by revealing an inherent structure between sentences within documents. That is, how does one text unit relate to the another text unit? Take for instance:

- (1) *Boeing would make cost-of-living adjustments projected to be 5 for each year of the contract though **the union has called the offer insulting.***

The connective unit *though* in Example 1 can be analyzed as a sort of binding block between the italicized unit and the bolded, working as a *contrastive comparison* between them. This is an example of a *sense* of a discourse relation which labels each relation according to a given sense taxonomy. That said, not all connective units are necessarily as explicit:

- (2) *No wonder. **We were coming down straight into their canal.***

Here, despite the lack of a connective unit the two sentences clearly share a connection. The bolded sentence explains the previous one as *the reason* for the lack of wonder. We will expand upon the difference between implicit and explicit relations in section 2.1.1, as well as how we can possibly classify the sense of a relation.

## 1.1 The CoNLL-2016 Shared Task on Shallow Discourse Parsing

At CoNLL 2015 they introduced a new shared task on *Shallow Discourse Parsing*. In this task, a system is fed a piece of newswire text as input and returns discourse relations similar to our previous examples. Such a system needs to locate both explicit or implicit discourse connectives, identify the spans of its two relations, and finally predict the sense of the discourse connective.

The shared task for the Twentieth Conference on Computational Natural Language Learning (CoNLL-2016) continues upon the work of last year's shared task while

introducing Chinese as an alternative evaluation language. A new component is the introduction of sense classification where correct argument dependencies and connective are already given, leaving out the sense of the discourse connective. The purpose of this is to allow more focus to be put into solely studying the properties of discourse connectives without having to worry about the pure parsing. In this work, we are first and foremost interested in the sense classification task.

## 1.2 Purpose

The purpose of this thesis is to explore methods of improving sense classification in English Shallow Discourse Parsing. The main research question to explore is *how can we use continuous semantic representations to increase performance in such a task?* In particular, *what benefits can we get from applying neural network architectures with continuous semantic representations?*

## 2 Background

### 2.1 Discourse

Explain what discourse is.

#### 2.1.1 Shallow Discourse Parsing

Explain what shallow discourse parsing is.

##### **Discourse connectives**

See Table 2.1 for discourse type distribution. See Table 2.2 for sense hierarchy.

##### **Explicit vs implicit discourse connectives**

It is not always possible to consider implicit discourse relations simply as explicit relations with the connective removed.

- (3) I want to go to New York, but I already booked a flight. (I am not going to New York.)
- (4) I want to go to New York, so I already booked a flight. (I am going to New York.)

Here, we have either a COMPARISON.Contrast, or a CONTINGENCY.Cause relation depending on what form the sense takes. If we were to remove the connective token, our linguistic intuition tells us to default for the meaning of Example 4, that is, CONTINGENCY.Cause. How can we use this to our advantage when classifying implicit connectives? (Honest question, still don't know.)

### 2.2 Related work

Up until this task little focus had been given to this topic from a parsing perspective, something which reflected the work in the final contributions: all papers built upon the same discourse parser as presented by Lin et al. (2014) with little variance in the form of alternative architectures. Given the complexity of the task this is not surprising, since this allows contributors to work within a focus area. Lin et al. (2014) is the first PDTB-styled end-to-end discourse parser with a parsing pipeline that closely reflects the annotation pipeline of PDTB. We will have a closer look at the components of the parser in Section ??.

Add a brief overview of results from CoNLL 2015.

Type	Frequency	Ratio
Explicit	14722	45.25%
Implicit	13156	40.44%
EntRel	4133	12.7%
AltLex	524	1.61%

**Table 2.1:** Discourse relation type distribution.

TEMPORAL	CONTINGENCY	COMPARISON	EXPANSION
Asynchronous	Cause	Concession	Alternative
Synchronous	Condition	Contrast	Conjunction
			Exception
			Instantiation
			List
			Restatement

**Table 2.2:** Sense hierarchy

## 2.3 Report (2016-02-01)

I want to focus on sense classification, mostly due to the fact that this is provided as a separate task with provided training and test data. If there is time left, I could implement this module into the previous year’s best performing end-to-end discourse parser. After having studied the previous year’s systems, I have come to the conclusion that there is a gap in representation learning approaches. While I probably will not be alone in this decision (just look at last year’s EMNLP), I might be able to contribute with some non-obvious ideas.

There were only two systems that used semantic representations, both from University of Dublin, and both performing relatively weakly in the task. The other submissions are only using ”shallow” features. Okita et al. (2015) focuses on using paragraph vectors along with some additional features to improve sense classification. They obtain reasonable F-score for explicit senses (.88), while the implicit sense classification is quite bad (.11). The implicit sense classification is mainly bad due to low recall (.15), while the precision is on par with explicit sense classification. Furthermore, they find that the classification task struggles with classes with explicit connectives where the surface form is occurring in more than one class. The second paper by Wang et al. (2015) is not focusing on sense classification and thus not provide much detail about its results there. Overall, its results are somewhat disappointing.

Beyond last year’s submissions, Ji and Eisenstein (2014) has implemented a parser using representation learning for the RST treebank which uses another discourse framework compared with PDTB. This one shows significant improvements compared to previous SOTA on the treebanks, but the results are in no way comparable with the PDTB. Still, it is the first paper (that I could find) that uses representation learning in a discourse parsing context, and it does so successfully which makes me want to at least look into their manually selected features later on. I am honestly somewhat surprised that none of the other systems looked into using this for the task, especially since the authors of the overview papers considered its results interesting enough to



briefly mention it.

What I am most excited about is the idea of applying findings from architectures for the Stanford Natural Language Inference Corpus (Bowman et al., 2015). This is a classification task that I consider to be fairly similar to the sense classification task, and there are several interesting model implementations with strong results I want to further explore. Their website<sup>1</sup> especially mentions Mou et al. (2015) as a particularly efficient recursive neural network model with strong results. Cheng et al. (2016) is a LSTM network model, albeit not as efficient, but receives the highest score so far. Unfortunately, neither of these seem to have published their code which would mean some reimplementations efforts. I don't mind since I would like to learn TensorFlow anyway, and Google's Mat Kelcey has already some code I could work off of, albeit the performance is not as good<sup>2</sup>.

That said, there are some things to keep in mind. First of all, neural network approaches are mainly known to be good when there are a lot of training data. That is not necessarily the case here. If the approaches above fail, I will look into if it is possible to use other, more sparse data friendly, architectures with the semantic representations. Also, Braud and Denis (2015) compared shallow features with some dense vector representations and found that shallow features still receive SOTA for implicit discourse relation identification. They do not seem to base any of their findings on word2vec vectors though, which is the kind of features that is allowed in the closed shared task. Also, their concatenation methods differ from the kind of architectures I have in mind. I will have to read this paper more carefully, and see what kind of dead ends I might be able to avoid.

*Last minute update:* I just found out about Zhang et al. (2015) from EMNLP 2015 which is a shallow convolutional neural network which reaches SOTA on implicit discourse recognition (which is not entirely the same task) on PDTB, making some of the previous worries about neural network approaches less worrisome. I am going to get a good understanding of their approach, read up on the NLI papers, and see how I can combine their efforts.

But first things first: I need to set up a baseline. Here are some suggestions:

- Try to break out the sense classifier from previous year's best performing paper (Wang and Lan, 2015). They use two separate classifiers for explicit and non-explicit senses, based on the original architecture in Lin et al. (2014), while adding a few extra features to boost the performance. The code is freely available, so it should be doable. Although it is unclear if this is actually the best model for sense classification.
- Do the same thing, but for the original architecture. (Lin et al., 2014). The code base is also available.
- Try to figure out which of the systems perform best on
- Implement some other simple system, e.g. an SVM bag-of-words model, potentially with brown clusters due to them

I'm leaning towards the having both the first suggestion, using Wang and Lan (2015), as well as the SVM. The first suggestion due to me wanting to potentially

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<sup>1</sup><http://nlp.stanford.edu/projects/snli/>

<sup>2</sup>[https://github.com/matpalm/snli\\_nn\\_tf](https://github.com/matpalm/snli_nn_tf)

incorporate my classifier into their system, and SVM for its usage as baseline in Zhang et al. (2015) that I just found.

### 2.3.1 Questions!

- Is this a good plan?
- Is using Wang and Lan (2015) as a baseline a good idea?
- Am I fooling myself by believing that I can learn anything from studying NLI architectures?
- The sense classes are rather imbalanced (see Table 3). Do you know of any general methods on how to deal with this?
- What am I missing?

## 2.4 Report (2016-02-25)

Since last time, I have been focusing on three things:

- Learning theory behind neural networks, convolutional NN, recurrent NN, and recursive NN.
- Learning tensorflow
- Setting up experimental architecture.

The first point has been going well. I have a sort of reasonable understanding of the maths behind it (backprop is still magic). I have a good understanding of the theory behind the Tree-Based Convolutional Neural Network (TB-CNN) as described in Mou et al. (2015). I found this particular model interesting due to its incorporation of tree structures into a (for neural networks) easily trainable CNN architecture while receiving very strong results on the NLI task. I haven't looked quite as closely to the other candidates yet.

For the rest to make sense, I will have to make a short summary of how TB-CNN differs from common CNN architectures. Basically, they have incorporated a tree-structure into the convolutional operation. While a common CNN in NLP applications (such as Kim (2014)) runs its convolution on *sequentially* adjacent word features, TB-CNN runs its convolution on *hierarchically* adjacent word features according to its dependency tree. Moreover, while a common CNN has one weight matrix per feature map which is used across all words, TB-CNN has one weight-matrix per *dependency label*.

After going through the NN theory, I started to go deep into Tensorflow which has been fairly straight-forward. This is when I started to realize that implementing TB-CNN will be more difficult than I first imagined, due to the unorthodox convolutional operations in the model which aren't easily supported by neither Tensorflow nor Theano (which are the two frameworks I feel comfortable working with). I still haven't completely given up on being able to implement it, I find its incorporation of tree structures in CNN very interesting and intuitive, but currently I think my time is better spent implementing simpler models.

I have the following models in mind for this:

- A simple logistic regression model just as a proof of concept that my architecture works. This is almost done (see below).
- An SVM to have my baseline somewhat ready. This should be quick.
- Incorporating a feed-forward NN model that has been implemented and released for the NLI corpus, with reasonable results. This should be quick.
- A very successful NN model for sentiment analysis is the Recursive Neural Network by Socher et al. (2013). This, similarly to the TB-CNN incorporates tree structures into its semantic composition, while actually having a Theano implementation for me to work from.
- Cheng et al. (2016) is an LSTM model that currently has the best score for the NLI corpus. Despite having the best score and seeming quite implementable, due to the long training times for these types of model I am somewhat doubtful that I would like to work with them. It is still worth considering, though.
- And just for completion, Kim (2014) is a simple CNN model for sentence processing. This is attractive due to being relatively efficient to train.

To put this work into some context, I will describe my experimental architecture that I have implemented this last week.

### 2.4.1 Experimental architecture

In the planning and subsequent implementation of the architecture, I focused on having a very modular design, making it easy to plug in and try out new models, features, and different training data. For this to work, each module need to be agnostic about what the others do, and simply expect to receive and output data according to a standardized API. This resulted in the following modules:

#### **extractors**

Implements a number of feature extraction models. It takes sentences as input and transforms them into e.g. word2vec features, brown clusters, etc. Outputs a feature matrix (words x word\_features).

#### **resources**

Takes care of training/test/dev data by reading data and massaging it into adhering to a standardized API. It outputs a feature tensor (sentences x words x word\_features) given a set of extractors.

#### **models**

Takes a feature tensor as input, reshapes the tensor into its required shape, and trains a model on this. It thereafter saves the model, and tests it given dev or test data. This makes implementing new models fairly easy. Currently, a logistic regression model is at least trainable.

## test\_report

Saves results along with its configuration and training model in a transparent way. This isn't built yet, but I need some sort of structure to make sense of the hundreds of different configuration permutations I'm going to have. The experimental framework Sacred<sup>3</sup> seem to promise to do just this in an automated fashion, and I will probably try to incorporate it into my architecture.

At the time of writing, everything is implemented except for testing the trained model, and test\_report.py. I hope to finish this in a few days and thereafter focus on implementing models. All sorts of parameters and hyperparameters are collected in one big config file.

### 2.4.2 Things to ponder

One big difference between the NLI task and this task is the number of output classes (see table 2.2). While NLI has 2 different classes, PDTB has 16. Furthermore, some instances have *two* concurrent classes, that is, an instance can have e.g. *CONTINGENCY* and *Temporal.Synchrony* at the same time. If we were to treat all of these as atomic units, we would have 56 unique classes to predict. Most of these dual-class instances are very rare and I am thinking about ignoring these for now. Furthermore, I am also thinking about focusing on getting the top-level hierarchy right for now, that is, only classifying *TEMPORAL*, *CONTINGENCY*, *COMPARISON*, and *EXPANSION*, and look into the second level hierarchy when I have a working model for the first hierarchy. I think splitting up the classification into two separate hierarchies to be beneficial for accuracy as well.

I am still uncertain how I can make use of the implicit/explicit relations. Obviously explicit gives me an extra feature which helps a lot, but I am uncertain if it is best to have an entirely separate classifier for implicit relations, or treat them as the explicit relations with a specific IMPLICIT feature in place of its explicit connective.

Another thing I wonder is: can I have access to a GPU to run my experiments on? It would be nice to be able to speed up the tuning a bit.

I think that's it for now!

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<sup>3</sup><http://sacred.readthedocs.org/en/latest/>

### 3 Data

For training we will be using the Penn Discourse Treebank (PDTB). PDTB follows the lexically grounded predicate-argument approach as proposed in Webber (2004). It covers the subset containing Wall Street Journal articles from the Penn Treebank, making up approximately one million tokens. When a connective explicitly appears, it will be syntactically connected to the *Arg2* argument of the discourse structure. *Arg1* is the other one. Due to *Arg2* being syntactically bounded to connective, it is easy to automatically classify *Arg2*.

PDTB annotates each structure with types of discourse relations according to a three level hierarchy as seen in Table 2.2, where the first level is made up of four classes: TEMPORAL, CONTINGENCY, COMPARISON, EXPANSION. Each class has a non-obligatory second level of in total 16 types to provide a more fine-grained classification. Due to the third level being considered too fine-grained, it is ignored in this work.

Furthermore, we have some additional resources at our disposal:

- Brown clusters from the RCV1 corpus.
- MPQA subjectivity lexicon.
- Skip-gram Neural Word Embeddings trained on 100 billion words from the Google News dataset.
- VerbNet 3.2.

senses	connective_token	ratio
(Expansion.Conjunction,)	7355	0.226064
(Contingency.Cause,)	4969	0.152728
(Comparison.Contrast,)	4521	0.138958
(EntRel,)	4133	0.127032
(Expansion.Restatement,)	2640	0.081143
(Temporal.Asynchronous,)	2044	0.062825
(Expansion.Instantiation,)	1392	0.042785
(Comparison.Concession,)	1268	0.038973
(Contingency.Condition,)	1114	0.034240
(Temporal.Synchrony,)	985	0.030275
(Comparison,)	484	0.014876
(Expansion.Alternative,)	435	0.013370
(Temporal.Asynchronous, Contingency.Cause)	148	0.004549
(Temporal.Synchrony, Contingency.Cause)	113	0.003473
(Temporal.Synchrony, Expansion.Conjunction)	109	0.003350
(Expansion.Conjunction, Contingency.Cause)	106	0.003258
(Expansion,)	96	0.002951
(Expansion.Conjunction, Temporal.Synchrony)	92	0.002828
(Temporal.Synchrony, Comparison.Contrast)	51	0.001568
(Expansion.Conjunction, Comparison.Contrast)	47	0.001445

**Table 3.1:** Frequency of sense labels in training data. Right now connective\_token is simply the frequency. I should change this name. Ratio is the frequency ratio.

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