Biaffine Modal Dependency Parsing

Anonymous ACL submission

Abstract

A modal dependency structure represents a web of connections in a document describing the source and epistemic strength of statements that helps to establish factuality in a given text. Obtaining such graphs defines the task of modal dependency parsing, which involves event and source identification along with the modal relations between them. In this paper, we propose a simple yet effective biaffine modal dependency parser for English and Chinese that outperforms the previous state of the art.

1 Introduction

At a time when we find ourselves inundated with endless streams of new information and knowledge, being able to identify a source of information and the confidence level with which it is conveyed is often helpful—if not sometimes critical—for better understanding the context behind a text or discourse. Modal dependency structure (MDS) (Vigus et al., 2019) is designed with such representation in mind, where the sources (also known as *concievers*) and events are the nodes of the graph and their edges denote (1) source of factualiy via its direction and (2) level of certainty via its label as a combination of 3 modal strengths (*Full*, *Partial*, and *Neutral*) and 2 polarities (*Affirmative* and *Negative*) based on the annotation scheme from FactBank (Saurí and Pustejovsky, 2009). Recently, MDS has been adopted as a core document-level sub-structure of Uniform Meaning Representation (UMR) (Van Gysel et al., 2021).

Figure 1 shows an example modal dependency tree for a sample document: '`Kim left to join the others. "They are probably eating," she said.`' Rooted by an abstract author (`author`) node whose presence is implied everywhere as the creator of the document, a typical MDS often shows heavy traffic through the author as a principal source of many statements. In the example,

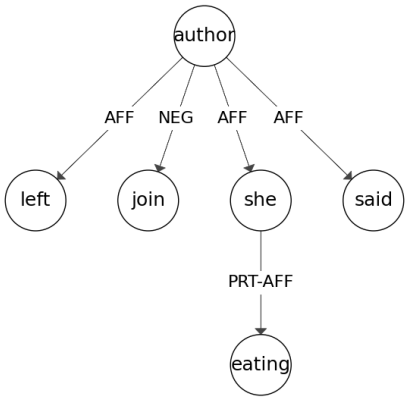

Figure 1: Example of Modal Dependency Graph for "Kim **left** to **join** the others. 'They are *probably* **eating**,' she **said**." `AFF` stands for `full-affirmative`, `NEG` for `full-negative`, and `PRT-AFF` for `partial-affirmative`.

the author is responsible for claiming that the event of *Kim* having *left* and *said* occurred with full certainty; however, the opposite is the case with *join* event, which is best described as a purpose behind *Kim*'s decision to leave[1].

The author also relays a quote from *Kim*, implying that the source of the information within the embedded quotation is attributable not to the author, but rather to *Kim*. Accordingly, the embedded event of *eating* is traced to *she* (coreferent to *Kim*) in the figure. The `partial-affirmative` label reflects Kim's judgment that *eating* **probably** happened. This sub-structure is connected with the rest of the graph thru the `author`-to-`she` edge, indicating that the author is quoting another conceiver.

In order to obtain a modal dependency tree[2] from text, modal dependency parsing (MDP) needs to not only identify the events and conceivers but also

[1] In contrast to MDG-style of annotations, UMR guidlines advises an addition of 'purpose' intermediate node between *left* and *join*.

[2] In general, MDS forms a tree not a graph.

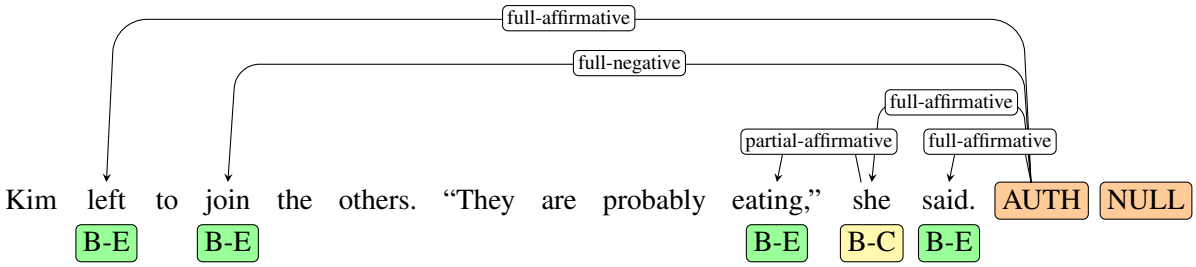

Figure 2: Example of biaffine modal dependency parsing for: 'Kim left to join the others. "They are probably eating," she said.' Orange nodes indicate special abstract nodes `Author` and `Null-Conceiver`. BIO tags below are predicted by the tagger for spans of events and conceivers. Arcs and their labels above are generated by biaffine dependency parser.

predict the modal relations between them. Yao et al. (2022) frames the task as language model priming, in which a prompt with an event in question is provided with context from which its parent, optional grandparent as well as the modal labels are predicted. One shortcoming of this approach is that the context is local in scope as determined by the number of sentences before and after the sentence in which the event in question occurs.

In this work, we present a simple yet effective solution in the form of biaffine modal dependency parsing whose context scope includes the entire document. The model consists of token-level classification for event/conceiver identification paired with biaffine module for arc generation and modal relation labeling. Experiments show that our approach outperforms previous state of the art in English and Chinese MDP.

2 Related Work

Traditionally, event factuality prediction (EFP) was seen as a classification or regression problem that involved rule-based (Nairn et al., 2006; Lotan et al., 2013) or statistical approaches (Diab et al., 2009; Saurí and Pustejovsky, 2012; Lee et al., 2015; Stanovsky et al., 2017). With widespread adoption of deep learning came a surge of neural models for the task, for instance based on LSTMs (Rudinger et al., 2018), GANs (Qian et al., 2018) or GNNs (Pouran Ben Veyseh et al., 2019). Yao et al. (2021) is the first work that casted EFP as modal dependency parsing and reported baseline results along with publicly available annotations in English[3]. This was followed up by prompt-based parser (Yao et al., 2022) with first reported results on Chinese MDP along with an incremental improvement in English. However, its setup assumes that some events be provided for any model execution and it is not clear how these are to be obtained automatically. Our biaffine model has a simpler setup while improving on model performance in both languages. This line of approach based on deep biaffine scoring mainly traces its roots to dependency parsing (Dozat and Manning, 2017, 2018; Zhang et al., 2020) but has also been explored in other areas such as NER tagging (Yu et al., 2020) and constituency parsing (Bai et al., 2021; Chen and Komachi, 2023). With the recent integration of MDS into UMR, improved MDP implies stronger UMR parsing performance (Chun and Xue, 2024), especially as part of the pipeline approach.

3 Approach

Our approach predicts (1) event and conceiver spans via token classification and (2) arcs and relation labels via biaffine dependency parsing in a single step. These modules share a common document encoder which relies on pre-trained language model (PLM) for contextualized embeddings.

The BIO tagger is inherited from Yao et al. (2021) and Yao et al. (2022) where B, I, and O refer to beginning, inside, and outside of a span respectively. The system then attempts to locate their parent via biaffine scoring mechanism in a greedy manner. Once the parent is located, the newly created edge is labeled by a separate biaffine layer.

Figure 2 shows an example of this approach, where the input text is augmented with two special tokens `Author` and `Null Conceiver`[4] at the end. They serve as target index for arc generation as shown by the dependency arcs above. Colored BIO tags below indicate the spans of events and

[3] https://github.com/jryao/modal_dependency

[4] A Null Conceiver is a special case when a conceiver is not specified.

English	Train	Dev	Test
Documents	289	32	32
Sentences	6,825	740	759
Tokens	151,487	17,308	17,177
Conceivers	2,344	298	296
Events	19,541	2,307	2,168
AFF	18,425	2,205	2,077
NEG	800	99	89
PRT-AFF	1,292	165	158
NEUT-AFF	1,368	136	140

Chinese	Train	Dev	Test
Documents	237	30	30
Sentences	3,187	398	366
Tokens	79,809	10,352	10,053
Conceivers	879	136	116
Events	11,679	1,464	1,318
AFF	10,879	1,383	1,257
NEG	331 (298*)	50 (45*)	31
PRT-AFF	919	103	101
PRT-NEG	0 (26*)	0 (5*)	0
NEUT-AFF	429	64	45
NEUT-NEG	0 (7*)	0	0

Table 1: Summary statistics of English and Chinese modal dependency datasets. Conceivers does not include Author which occurs once per document. Labels does not include Depends-on which occurs once per document. AFF stands for Affirmative, NEG stands for Negative, PRT stands for Partial and NEUT stands for Neutral. *Numbers in parenthesis in Chinese statistics denote counts of fine-grained negative values in a 6-way version of the corpus.

conceivers as predicted by the tagger.

The figure also highlights the core difference of our setup against that of conventional dependency parsing, where it is assumed that every token has a parent to point to. Since this approach only focuses on the spans annotated by BIO tagger, it may be described as being comparatively sparse, which is partially offset by the fact that text input in MDP is generally a multi-sentence document.

Model

Formally, a document $\boldsymbol{d}$ is represented as a sequence of tokens $(\boldsymbol{t_0}, ..., \boldsymbol{t_{-1}}, \text{AUTH}, \text{NULL})$, where the surface tokens are followed by two special tokens denoting the Author and Null Conceiver.

Let $\boldsymbol{H} = (\boldsymbol{h_0}, ..., \boldsymbol{h_{-1}}, \boldsymbol{h}_{\text{AUTH}}, \boldsymbol{h}_{\text{NULL}})$ be the contextualized embedding output from PLM for the document $\boldsymbol{d}$. Tag score for $\boldsymbol{i}$th token is obtained by a feedforward layer:

$$\hat{\boldsymbol{y}}_{\boldsymbol{i}}^{\boldsymbol{tag}} = \text{FFN}(\boldsymbol{h_i})$$

Arc and relation scores for $\boldsymbol{i}$th token and $\boldsymbol{j}$th parent candidate token is obtained by two independent biaffine scorers:

$$\hat{\boldsymbol{y}}_{\boldsymbol{i,j}}^{\boldsymbol{arc}} = \text{Biaffine}_{\mathbf{1}}(\boldsymbol{h_i}, \boldsymbol{h_j})$$
$$\hat{\boldsymbol{y}}_{\boldsymbol{i,j}}^{\boldsymbol{rel}} = \text{Biaffine}_{\mathbf{2}}(\boldsymbol{h_i}, \boldsymbol{h_j})$$

Our model attempts to minimize the negative log likelihood which is the sum of cross entropy losses from 3 sub-tasks:

$$\boldsymbol{\mathcal{L}} = \boldsymbol{\mathcal{L}_{tag}} + \boldsymbol{\mathcal{L}_{arc}} + \boldsymbol{\mathcal{L}_{rel}}$$

Inference

Spans of events and conceivers are first identified by the BIO tagger. As we search for parent of each of these entities, non-events and non-conceivers are masked out to guide the decoding process.

For each span, the first token is taken as representative of the whole, and the arc generator produces a score against all of the other spans and the special tokens Author and Null Conceiver. If a parent span consists of multiple tokens as is often the case with conceivers, it is only required that some index within the span be predicted in order to correctly assign the parent. The default fall-back behavior is to attach to the Author node to ensure the graph is connected.

4 Experiments

4.1 Data

The parser is trained and evaluated using the English (Yao et al., 2021) and Chinese (Liu and Xue, 2023) modal dependency corpora, whose statistics are shown in Table 1. We follow previous work on the train/eval/test splits for both languages.

Unlike the English dataset where all of the negative polarity labels are merged into a single full-negative label (Yao et al., 2021), Chinese dataset additionally offers a fine-grained version with partial-negative and neutral-negative annotations, albeit only a few in number. It is not explicitly stated which version is used in the experiments of Yao et al. (2022); we report results using the fine-grained version.

4.2 Setup and Results

Whereas Yao et al. (2022) defines a local scope as determined by the number of sentences before and

Models	Split	English			Chinese		
		Event	Conceiver	Parsing	Event	Conceiver	Parsing
Baseline	Dev	92.8	71.1	71.8*	-	-	61.7*
	Test	90.9	70.4	69.3*	-	-	59.0*
Prompt-based	Dev	93.2	-	72.7	**87.4**	-	65.5
	Test	91.9	-	71.9	**88.6**	-	63.6
Biaffine	Dev	**93.3**	**72.9**	**73.9**	86.7	**88.6**	**68.2**
	Test	**92.0**	**74.8**	**73.0**	87.4	**87.5**	**66.1**

Table 2: Experimental results showing Event and Conceiver identification and Parsing micro-F score. Empty values indicate unreported results. *Baseline parsing results are based on the re-implementation of Yao et al. (2022) rather than from the original publication (Yao et al., 2021).

after the sentence in which the event in question occurs, our approach based on the biaffine attention is global in its context scope. In order to cope with the input length limitation imposed by the pre-trained language models (PLM), long input sequences are split into smaller segments and embedded independently before being merged together (Yao et al., 2021). For English we use `longformer-base` (Beltagy et al., 2020) with 4k context window. For Chinese we use `xlm-roberta-base` (Conneau et al., 2020) with the context window of 512 tokens.

Table 2 shows overall parsing results on English and Chinese MDP in micro F-score as average across 3 different seeds. Our approach outperforms the prompt-based model by about 1% in English, while the gain is even more significant with Chinese at around 3%.

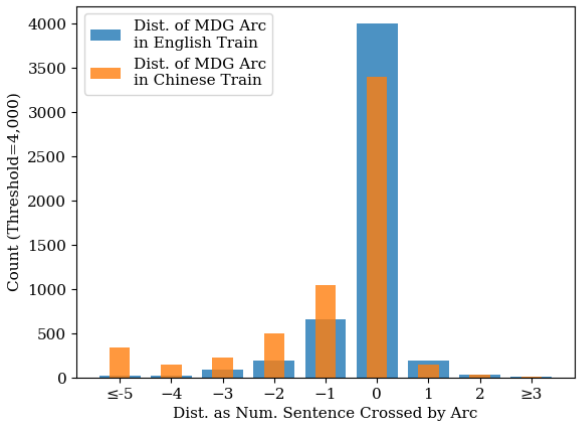

Figure 3: Number of sentences crossed by modal arcs in English and Chinese training corpora, with upper threshold at 4,000. Negative values mean the head is located in some previous sentence, while positive values imply otherwise. 0 means the arc is between spans from the same sentence.

5 Analysis

Our experimental results show marked increase in Chinese MDP despite lower event detection scores. While this may be due to improved conceiver detection, there is no previous reported result for precise comparison. Another explanation is that the biaffine approach is able to predict long-distance edges more easily. As seen with Figure 3 which excludes edges to the abstract nodes such as the `Author`, Chinese modal annotations contain more edges where the parent is located in some previous sentence compared to English[5], despite the fact there are almost twice as many English modal triples. On the development set, the average number of sentences crossed by our approach is -0.22 for English and -0.81 for Chinese. Unfortunately we are unable to reproduce the results of Yao et al. (2022) for comparison due to its setup requiring an enumeration of events whose origin is not clear.

For English MDP, the conceiver identification still remains a major bottleneck especially since it is the first step during decoding with ramifications for the subsequent arc and labeling stage. Furthermore, a conceiver is never a terminal node in MDS; its existence always implies at least one child—another conceiver or, generally speaking, an event. Therefore, detecting conceivers with higher accuracy remains a crucial next step for further improving MDP performance.

6 Conclusion

This work presents a biaffine modal dependency parser that is simple yet effective. The model is evaluated on the English and Chinese datasets and in both instances show improved performance compared to the previous state of the art.

[5]This is due to Chinese being a pro-drop language.

7 Limitations

MDP experiments remain focused on English and Chinese due to the limited availability of modal dependency annotations in other languages. However, with the adoption of MDS into UMR, more and more annotations for low-resource languages such as Arapaho, Cocama-Cocamilla, Navajo, Sanapaná and potentially additional languages may be prepared and released for future model fitting. Another unexplored possibility is to leverage Large Language Models (LLMs) to automatically translate from English or Chinese into another language while retaining the annotations as much as possible.

The fact that the overall loss consists of 3 different signals makes the training potentially unbalanced and slow to converge. We plan to investigate whether tagging could be absorbed as part of arc and label generation, thereby eliminating one of the loss terms at the cost of increased difficulty for the remaining tasks.

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A Corpus Details

The publicly available English dataset (Yao et al., 2021) contains newswire annotations from various news media sources (Yao et al., 2022). The Chinese dataset also consists of newswire data from Xinhua news agency.

B Implementation Details

Hyperparameter	English	Chinese
PLM	`longformer-base`	`xlm-roberta-base`
PLM Dropout	0.1	0.1
Max. Seq. Len.	4096	512
Batch Size	4	1
Grad. Acc. Steps	4	4
Epochs	1,000	1,000
Optim.	AdamW	AdamW
LR	5e-5	5e-5
Weigh Decay	0.01	0.01
Warmup Prop.	0.1	0.1
Arc Hidden Dim.	512	400
Arc Dropout	0.33	0.33
Rel. Hidden Dim.	128	100
Rel. Dropout	0.33	0.33

Table 3: Hyperparameters used in experiments.

We use the Huggingface[6] (Wolf et al., 2020) implementation `longformer-base` (Beltagy et al., 2020), `roberta-large` (Liu et al., 2019) and `xlm-roberta-base` (Conneau et al., 2020). The biaffine layer implementation is based on SuPar[7].

C Experimental Details

All experiments were run on a single NVIDIA RTX A6000 GPU and each run takes about 6 to 8 hours

[6] https://huggingface.co/docs/transformers
[7] https://github.com/yzhangcs/parser

with the hyperparameters in B. The number of parameters for English is 149,386,249; that of Chinese is 278,770,441.