

# GENERALIZING NATURAL LANGUAGE ANALYSIS THROUGH SPAN-RELATION REPRESENTATIONS

**Zhengbao Jiang**  
Language Technologies Institute  
Carnegie Mellon University  
zhengbaj@cs.cmu.edu

**Wei Xu**  
Department of Computer Science and Engineering  
Ohio State University  
xu.1265@osu.edu

**Jun Araki**  
Bosch Research North America  
jun.araki@us.bosch.com

**Graham Neubig**  
Language Technologies Institute  
Carnegie Mellon University  
gneubig@cs.cmu.edu

## ABSTRACT

A large number of natural language processing tasks exist to analyze syntax, semantics, and information content of human language. These seemingly very different tasks are usually solved by specially designed architectures. In this paper, we provide the simple insight that a great variety of tasks can be represented in a single unified format consisting of labeling spans and relations between spans, thus a single task-independent model can be used across different tasks. We perform extensive experiments to test this insight on 10 disparate tasks as broad as dependency parsing (syntax), semantic role labeling (semantics), relation extraction (information content), aspect based sentiment analysis (sentiment), and many others, achieving comparable performance as state-of-the-art specialized models. We further demonstrate benefits in multi-task learning. We convert these datasets into a unified format to build a benchmark, which provides a holistic testbed for evaluating future models for generalized natural language analysis.

## 1 INTRODUCTION

A large number of natural language processing (NLP) tasks exist to analyze various aspects of human language, including syntax (e.g., constituency and dependency parsing), semantics (e.g., semantic role labeling), information content (e.g., named entity recognition and relation extraction), or sentiment (e.g. sentiment analysis). At first glance, these tasks are seemingly very different in both the structure of their output and the variety of information that they try to capture. To handle these different characteristics, researchers usually use specially designed neural network architectures. In this paper we ask the simple questions: are the task-specific architectures really necessary? Or with the appropriate representational methodology, can we devise *a single model that can perform — and achieve state-of-the-art performance on — a large number of natural language analysis tasks?*

Interestingly, in the domain of *efficient human annotation interfaces*, it is already standard to use unified representations for a wide variety of NLP tasks. On the right we show one example of the annotation interface BRAT (Stenetorp et al., 2012), which has been used for annotating data for tasks as broad as part-of-speech tagging, named entity recognition, relation extraction, and many others. Notably, this interface has a single unified format that consists of spans (e.g. the span of an entity), labels on the spans (e.g. the variety of entity such as “person” or “location”), and labeled relations between the spans (e.g. “born-in”). These labeled relations can form a tree or graph structure (e.g., dependency tree), expressing the linguistic structure of sentences. We detail this BRAT format and how it can be used to represent a wide number of natural language analysis tasks in Section 2.

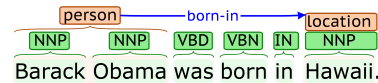


Figure 1: An example from BRAT, consisting of POS, NER, and RE.

	Information Extraction				POS	Parsing		SRL	Sentiment	
	NER	RE	Coref.	OpenIE		Dep.	Consti.		ABSA	ORL
Different Models for Different Tasks										
ELMo (Peters et al., 2018)	✓	×	✓	×	×	×	×	×	✓	×
BERT (Devlin et al., 2019)	✓	×	×	×	×	×	×	×	×	×
BERT baseline (Shi & Lin, 2019)	×	✓	×	×	×	×	×	✓	×	×
SpanBERT (Joshi et al., 2019)	×	✓	✓	×	×	×	×	×	×	×
Single Model for Different Tasks										
Guo et al. (2016)	×	✓	×	×	×	×	×	✓	×	×
Swayamdipta et al. (2018)	×	×	✓	×	×	×	✓	✓	×	×
Strubell et al. (2018)	×	×	×	×	✓	✓	×	✓	×	×
Clark et al. (2018)	✓	×	×	×	✓	✓	×	×	×	×
Luan et al. (2018; 2019)	✓	✓	✓	×	×	×	×	×	×	×
Dixit & Al-Onaizan (2019)	✓	✓	×	×	×	×	×	×	×	×
Marasović & Frank (2018)	×	×	×	×	×	×	×	✓	×	✓
Hashimoto et al. (2017)	×	×	×	×	✓	✓	×	×	×	×
This Work	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 1: The unified span-relation model can work on multiple NLP tasks, in contrast to previous works usually designed for a subset of tasks.

The simple hypothesis behind our paper is: *if humans can perform natural language analysis in a single unified format, then perhaps machines can as well*. Fortunately, there already exist NLP models that perform span prediction and prediction of relations between pairs of spans, such as the end-to-end neural coreference model of Lee et al. (2017). We extend this model with minor architectural modifications (which are *not* our core contributions) and pre-trained contextualized representations (e.g., BERT; Devlin et al. (2019)<sup>1</sup>) then demonstrate the applicability and versatility of this single model on 10 tasks, including named entity recognition (NER), relation extraction (RE), coreference resolution (Coref.), open information extraction (OpenIE), part-of-speech tagging (POS), dependency parsing (Dep.), constituency parsing (Consti.), semantic role labeling (SRL), aspect based sentiment analysis (ABSA), and opinion role labeling (ORL). While previous work has used similar formalisms to *understand* the representations learned by pre-trained embeddings (Tenney et al., 2019a;b), to the best of our knowledge this is the first work that uses such a unified model to actually *perform analysis*. Moreover, despite its simplicity we demonstrate that such a model can achieve comparable performance with special-purpose state-of-the-art models on the tasks above (Table 1). We also demonstrate that this framework allows us to easily perform multi-task learning among different tasks, leading to improvements when there are related tasks to be learned from or data is sparse. In summary, our contributions are:

- We provide the simple insight that a great variety of natural language analysis tasks can be represented and solved in a single unified format, i.e., span-relation representations. This insight may seem obvious in hindsight, but it has not been examined, particularly to this scale, by previous work on model-building for NLP.
- We perform extensive experiments to test this insight on 10 disparate tasks, achieving comparable empirical results as the state-of-the-art, using a single task-independent modeling framework.
- We further use this framework to perform an analysis of the benefits from multi-task learning across all of the tasks above, gleaned various insights about task relatedness and how multi-task learning performs with different token representations.
- In addition, we will release our code and the **General Language Analysis Datasets (GLAD)** benchmark with 8 datasets covering 10 tasks in the BRAT format on <https://github.com/jzbyb/SpanRel>, and provide a leaderboard to facilitate future work on generalized models for NLP. Compared to the full sentence-level tasks in the GLUE leaderboard (Wang et al., 2019a;b), we cover a wide variety of natural language analysis tasks that require analyzing of the finer grained text units (e.g., words, phrases, clauses).

<sup>1</sup>To contrast to work on pre-trained contextualized representations like ELMo (Peters et al., 2018) or BERT (Devlin et al., 2019), these works learn unified *features* to represent the *input* in different tasks, whereas we propose a unified *representational methodology* that represents the *output* of different tasks. Analysis models using BERT still designed special-purpose output predictors for specific tasks or task classes.

Task	Spans annotated with labels
NER	<u>Barack Obama</u> was born in <u>Hawaii</u> . person location
Consti.	And <u>their suspicions</u> of <u>each other</u> <u>run deep</u> . NP NP ADVP PP VP NP S
POS	<u>What kind of memory?</u> WP NN IN NN
ABSA	Great laptop that offers many great <u>features!</u> positive

Table 2a: Span-oriented tasks. Spans are annotated by underlines and their labels.

Task	Spans and (relations) annotated with labels
RE	The <u>burst</u> has been caused by <u>pressure</u> . cause-effect
Coref.	I voted for <u>Tom</u> because <u>he</u> is clever. coref
SRL	<u>We</u> brought <u>you</u> the tale of two cities. ARG0 ARG2 ARG1
OpenIE	<u>The four lawyers</u> climbed out <u>from under a table</u> . ARG0 ARG1
Dep.	<u>The entire division</u> employs <u>about 850 workers</u> . det amod nsubj advmod nummod
ORL	<u>We</u> therefore as MDC <u>do not accept this result</u> . holder target

Table 2b: Relation-oriented tasks. Directed arcs indicate the relations between spans.

## 2 SPAN-RELATION REPRESENTATIONS

In this section, we explain how the BRAT format can be used to represent a large number of tasks. There are two fundamental types of annotations: span annotations and relation annotations. Given a sentence  $\mathbf{x} = [w_1, w_2, \dots, w_n]$  of  $n$  tokens, a span annotation  $(s_i, l_i)$  consists of a contiguous span of tokens  $s_i = [w_{b_i}, w_{b_i+1}, \dots, w_{e_i}]$  and its label  $l_i$  ( $l_i \in \mathcal{L}$ ), where  $b_i/e_i$  are the start/end indices respectively, and  $\mathcal{L}$  is a set of span labels. A relation annotation  $(s_j, s_k, r_{jk})$  refers to a relation  $r_{jk}$  ( $r_{jk} \in \mathcal{R}$ ) between the head span  $s_j$  and the tail span  $s_k$ , where  $\mathcal{R}$  is a set of relation types. This span-relation representation can easily express many tasks by defining different  $\mathcal{L}$  and  $\mathcal{R}$ , as summarized in Table 2a and Table 2b. These tasks fall in two categories: **span-oriented tasks**, where the goal is to predict labeled spans (e.g., named entities in NER) and **relation-oriented tasks**, where the goal is to predict relations between two spans (e.g., relation between two entities in RE).

### • Span-oriented Tasks (Table 2a)

- **Named Entity Recognition** (Sang & Meulder, 2003) NER is traditionally considered as a sequence labeling task. We model named entities as spans over one or more tokens.
- **Constituency Parsing** (Collins, 1997) Constituency parsing aims to produce a syntactic parse tree for each sentence. Each node in the tree is an individual span, and spans are nested.
- **Part-of-speech Tagging** (Ratnaparkhi, 1996; Toutanova et al., 2003) POS tagging is another sequence labeling task, where every single token is an individual span with a POS tag.
- **Aspect-based Sentiment Analysis** (Pontiki et al., 2014) ABSA is a task that consists of identifying certain spans as aspect terms and predicting their associated sentiments.

### • Relation-oriented Tasks (Table 2b)

- **Relation Extraction** (Hendrickx et al., 2010) RE concerns the relation between two entities.
- **Coreference** (Pradhan et al., 2012) Coreference resolution is to link named, nominal, and pronominal mentions that refer to the same concept, within or beyond a single sentence.
- **Semantic Role Labeling** (Gildea & Jurafsky, 2002) SRL aims to identify arguments of a predicate (verb or noun) and classify them with semantic roles in relation to the predicate.
- **Open Information Extraction** (Banko et al., 2007; Niklaus et al., 2018) In contrast to the fixed relation types in RE, OpenIE aims to extract open-domain predicates and their arguments (usually subjects and objects) from a sentence.
- **Dependency Parsing** (Kübler et al., 2009) Spans are single-word tokens and a relation links a word to its syntactic parent with the corresponding dependency type.
- **Opinion Role Labeling** (Yang & Cardie, 2013) ORL detects spans that are opinion expressions, as well as holders and targets related to these opinions.

While the tasks above represent a remarkably broad swath of NLP, it is worth mentioning what we have *not* covered, to properly scope the work. Notably, sentence-level tasks such as text classification and natural language inference are not covered, although they can also be formulated using this span-relation representation by treating the entire sentence as a span. We chose to omit these tasks

because they are already well-represented by previous work on generalized architectures (Lan & Xu, 2018) and multi-task learning (Devlin et al., 2019; Liu et al., 2019), and thus we mainly focus on tasks using phrase-like spans. In addition, the span-relation representations described here are designed for natural language *analysis*, and cannot handle tasks that require *generation* of text, such as machine translation (Bojar et al., 2014), dialog response generation (Lowe et al., 2015), and summarization (Nallapati et al., 2016). There are also a small number of analysis tasks such as semantic parsing to logical forms (Banarescu et al., 2013) where the outputs are not directly associated with spans in the input, and handling these tasks is beyond the scope of this work.

### 3 SPAN-RELATION MODEL

Now that it is clear that a very large number of analysis tasks can be formulated in a single format, we turn to devising a single model that can solve these tasks. We base our model on a span-based model first designed for end-to-end coreference resolution (Lee et al., 2017), which is then adapted for other tasks (He et al., 2018; Luan et al., 2018; 2019; Dixit & Al-Onaizan, 2019; Zhang & Zhao, 2019). At the core of the model is a module to represent each span as a fixed-length vector, which is used to predict labels for spans or span pairs. We first briefly describe the span representation used and proven to be effective in previous works, then highlight some details we introduce to make this model generalize to a wide variety of tasks.

**Span Representation** Given a sentence  $\mathbf{x} = [w_1, w_2, \dots, w_n]$  of  $n$  tokens, a span  $s_i = [w_{b_i}, w_{b_i+1}, \dots, w_{e_i}]$  is represented by concatenating two components: a *content representation*  $\mathbf{z}_i^c$  calculated as the weighted average across all token embeddings in the span, and a *boundary representation*  $\mathbf{z}_i^u$  that concatenates the embeddings at the start/end positions of the span. Specifically,

$$\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_n = \text{TokenRepr}(w_1, w_2, \dots, w_n), \quad (1)$$

$$\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n = \text{BiLSTM}(\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_n), \quad (2)$$

$$\mathbf{z}_i^c = \text{SelfAttn}(\mathbf{c}_{b_i}, \mathbf{c}_{b_i+1}, \dots, \mathbf{c}_{e_i}), \quad \mathbf{z}_i^u = [\mathbf{u}_{b_i}; \mathbf{u}_{e_i}], \quad \mathbf{z}_i = [\mathbf{z}_i^c; \mathbf{z}_i^u], \quad (3)$$

where TokenRepr could be non-contextualized embeddings, such as GloVe (Pennington et al., 2014), or contextualized embeddings, such as ELMo (Peters et al., 2018), BERT (Devlin et al., 2019), and SpanBERT (Joshi et al., 2019). We refer to Lee et al. (2017) for further details.

**Span and Relation Label Prediction** Since we extract spans and relations in an *end-to-end* fashion, we introduce two additional labels NEG\_SPAN and NEG\_REL in  $\mathcal{L}$  and  $\mathcal{R}$  respectively. NEG\_SPAN indicates invalid spans (e.g., spans that are not named entities in NER) and NEG\_REL indicates invalid span pairs without any relation between them (i.e., no relation exists between two arguments in SRL). We first predict labels for *all* spans up to a length of  $l$  words using a multilayer perceptron (MLP):  $\text{softmax}(\text{MLP}^{\text{span}}(\mathbf{z}_i)) \in \Delta^{|\mathcal{L}|}$ , where  $\Delta^{|\mathcal{L}|}$  is a  $|\mathcal{L}|$ -dimensional simplex. Then we keep the top  $K = \tau \cdot n$  spans with the lowest NEG\_SPAN probabilities in relation prediction for efficiency, where smaller pruning threshold  $\tau$  indicates more aggressive pruning. Another MLP is applied to pairs of the remaining spans to produce their relation score:  $\mathbf{o}_{jk} = \text{MLP}^{\text{rel}}([\mathbf{z}_j; \mathbf{z}_k; \mathbf{z}_j \cdot \mathbf{z}_k]) \in \mathbb{R}^{|\mathcal{R}|}$ .<sup>2</sup>

**Application to Disparate Tasks** For most of the tasks, we can simply maximize the probability of the ground truth relation for *all pairs of the remaining spans*. However, some tasks might have different requirements, e.g., coreference resolution aims to cluster spans referring to the same concept and we do not care about which antecedent a span is linked to if there are multiple ones. To accommodate different requirements, we provide two training loss functions:

1. **Pairwise** Maximize the probabilities of the ground truth relations for all pairs of the remaining spans independently:  $\text{softmax}(\mathbf{o}_{jk})_{r_{jk}}$ , where  $r_{jk}$  indexes the ground truth relation.
2. **Head** Maximize the probability of selecting the ground truth head spans for a specific span  $s_j$ :  $\sum_{k \in \text{head}(s_j)} \text{softmax}([o_{j1}, o_{j2}, \dots, o_{jK}])_k$ , where  $\text{head}(\cdot)$  returns indices of one or multiple heads and  $o_j$  is the corresponding scalar from  $\mathbf{o}_j$  indicating how likely two spans are related.

<sup>2</sup>The time complexity of span prediction is  $\mathcal{O}(l \cdot n)$  for a sentence of  $n$  tokens, and the time complexity of relation prediction is  $\mathcal{O}(K^2) = \mathcal{O}(\tau^2 \cdot n^2)$ . Another option for span prediction is to formulate it as a sequence labeling task, as did in previous works on SRL (He et al., 2017) and many others (Lample et al., 2016; Stanovsky et al., 2018), and their time complexity is  $\mathcal{O}(n)$ . Although slower than token-based labeling models, span-based models offer the advantages of being able to model overlapping spans (e.g., overlapping arguments in SRL) and exploring span-level information for span prediction.

Dataset	Domain	#Sent.	Task	#Spans	#Relations	Metric
Wet Lab Protocols (Kulkarni et al., 2018)	biology	14,301	NER	60,745	-	F <sub>1</sub>
			RE	60,745	43,773	F <sub>1</sub>
CoNLL-2003 (Sang & Meulder, 2003)	news	20,744	NER	35,089	-	F <sub>1</sub>
SemEval-2010 Task 8 (Hendrickx et al., 2010)	misc.	10,717	RE	21,437	10,717	Macro F <sub>1</sub> <sup>◦</sup>
OntoNotes 5.0 * (Pradhan et al., 2013)	misc.	94,268	Coref.	194,477	1,166,513	Avg F <sub>1</sub>
			SRL	745,796	543,534	F <sub>1</sub>
			POS	1,631,995	-	Accuracy
			Dep.	1,722,571	1,628,558	LAS
			Consti.	1,320,702	-	Evalb F <sub>1</sub> <sup>†</sup>
Penn Treebank (Marcus et al., 1994)	speech, news	49,208	POS	1,173,766	-	Accuracy
			Dep.	43,948	1,090,777	LAS
			Consti.	43,948	871,264	Evalb F <sub>1</sub> <sup>†</sup>
OIE2016 (Stanovsky & Dagan, 2016)	news, Wiki	2,534	OpenIE	15,717	12,451	F <sub>1</sub>
MPQA 3.0 (Deng & Wiebe, 2015)	news	3,585	ORL	13,841	9,286	F <sub>1</sub>
SemEval-2014 Task 4 (Pontiki et al., 2014)	reviews	4,451	ABSA	7,674	-	Accuracy <sup>◦</sup>

Table 3: Statistics of the GLAD benchmark consisting of 10 tasks from 8 datasets. \* Following He et al. (2018), we use a subset of OntoNotes 5.0 dataset based on CoNLL 2012 splits (Pradhan et al., 2012). <sup>◦</sup> Previous works use gold standard spans in these evaluations. <sup>†</sup> We use standard bracket scoring program Evalb (Collins, 1997) in constituency parsing.

We use option 1 for all tasks except for coreference resolution which uses option 2. Note that the above loss functions *only* differ in how relation scores are normalized and the other parts of the model remain the same across different tasks. At test time, we follow previous inference methods to generate valid outputs. For coreference resolution, we link a span to the antecedent with highest score and build clusters (Lee et al., 2017). For constituency parsing, we use the greedy top-down decoding (Stern et al., 2017) to generate a valid parse tree. For dependency parsing, each word is linked to exactly one parent with the highest relation probability. For other tasks, we predict relations for all span pairs and use those not predicted as NEG\_REL to construct outputs.

Our core insight is that the above formulation is largely *task-agnostic*, meaning that a task can be modeled in this framework as long as it can be formulated as a span-relation prediction problem with properly defined span labels  $\mathcal{L}$  and relation labels  $\mathcal{R}$ . As shown in Table 1, this unified **Span-Relation** (SpanRel) model makes it simple to scale to a large number of language analysis tasks, with breadth far beyond that of previous work.

**Multi-task Learning** The SpanRel model makes it easy to perform multi-task learning (MTL) by sharing all parameters except for the MLPs used for label prediction. With shared span representations, different tasks can learn from each other. However, because different tasks capture different linguistic aspects, they are not equally beneficial to each other. It is expected that jointly training on related tasks is helpful, while forcing the same model to solve unrelated tasks might even hurt the performance (Ruder, 2017). Compared to manually choosing source tasks based on prior knowledge, which might be sub-optimal when the number of tasks is large, SpanRel offers a systematic way to examine relative benefits of source-target task pairs, as we will show in Section 4.3.

## 4 GLAD BENCHMARK AND RESULTS

We first describe our **General Language Analysis Datasets (GLAD)** benchmark and evaluation metrics, then conduct experiments to (1) verify that SpanRel can achieve comparable performance across all tasks (Section 4.2), and (2) demonstrate its benefits in multi-task learning (Section 4.3).

### 4.1 EXPERIMENTAL SETTINGS

**GLAD Benchmark and Evaluation Metrics** As summarized in Table 3, we convert 8 widely used datasets with annotations of 10 tasks into the BRAT format and include them in the GLAD benchmark. It covers diverse domains, spans, and relations, and provides a holistic testbed for natural language analysis evaluation. The major evaluation metric is span-based F<sub>1</sub> (denoted as F<sub>1</sub> unless otherwise noted), a standard metric for SRL. Precision is the proportion of extracted spans (spans not predicted as NEG\_SPAN) that are consistent with the ground truth. Recall is the proportion of ground truth spans that are correctly extracted. F<sub>1</sub> is their harmonic mean. Span F<sub>1</sub>

Category	Task	Metric	Dataset	Setting	SOTA Model	Previous SOTA	Our Model
IE	NER	F <sub>1</sub>	CoNLL03 WLP	BERT	Devlin et al. (2019)	92.8	92.2
				ELMo	Luan et al. (2019)	79.5	79.2
	RE	Macro F <sub>1</sub> F <sub>1</sub>	SemEval10 WLP	BERT, gold	Wu & He (2019)	89.3	87.4
				ELMo	Luan et al. (2019)	64.1	65.5
Coref.	Avg F <sub>1</sub>	OntoNotes	GloVe, CharCNN	Lee et al. (2017) <sup>◦</sup>	62.0	61.1	
OpenIE	F <sub>1</sub>	OIE2016	ELMo	Stanovsky et al. (2018)*	31.1	35.2	
SRL	F <sub>1</sub>	OntoNotes	ELMo	He et al. (2018) <sup>†</sup>	82.9	82.4	
Parsing	Dep.	LAS	PTB	ELMo	Clark et al. (2018)	94.4	94.7
	Consti.	Evalb F <sub>1</sub>	PTB	BERT	Kitaev et al. (2019)	95.6	95.5
Sentiment	ABSA	Accuracy	SemEval14	BERT, gold	Xu et al. (2019) <sup>◊</sup>	85.0/78.1	85.5/76.6
	ORL	F <sub>1</sub>	MPQA 3.0	GloVe, gold	Marasović & Frank (2018)*	56.4	55.6
POS	Accuracy	PTB	ELMo	Clark et al. (2018)	97.7	97.7	

Table 4: Comparison between the SpanRel model and the task-specific state-of-the-art models.<sup>3</sup> Following Luan et al. (2019), we perform NER and RE jointly on WLP dataset. We use gold entities in SemEval-2010 Task 8, gold aspect terms in SemEval-2014 Task 4, and gold opinion expressions in MPQA 3.0 to be consistent with existing works.

is also applicable to the case of relations, where an extracted relation (relations not predicted as NEG\_REL) is correct iff both head and tail spans have correct boundaries and the predicted relation label is correct. To make fair comparisons with existing works, we also compute standard metrics for different tasks, as listed in Table 3. We refer to the corresponding papers for details.

**Implementation Details** We attempted four token representation methods (Equation 1), namely GloVe (Pennington et al., 2014), ELMo (Peters et al., 2018), BERT (Devlin et al., 2019), and SpanBERT (Joshi et al., 2019). We use BERT<sub>base</sub> in our main results and report BERT<sub>large</sub> in Appendix A. A three-layer BiLSTM with 256 hidden units is used (Equation 2). Both span and relation prediction MLPs have two layers with 128 hidden units. Dropout (Srivastava et al., 2014) of 0.5 is applied to all layers. For GloVe and ELMo, we use Adam (Kingma & Ba, 2015) with learning rate of 1e-3 and early stop with patience of 3. For BERT and SpanBERT, we follow standard fine-tuning and use Adam with learning rate of 5e-5,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ , L2 weight decay of 0.01, warmup over the first 10% steps, and number of epochs tuned on development set. Task-specific hyperparameters maximal span length and pruning ratio are tuned on development set and listed in Appendix B.

## 4.2 COMPARISON WITH TASK-SPECIFIC SOTA METHODS

We compare the SpanRel model with state-of-the-art task-specific models by training on data from a single task. By doing so we attempt to answer the research question “can a single model with minimal task-specific engineering achieve competitive or superior performance to other models that have been specifically engineered?” We select competitive SOTA models mainly based on settings, e.g., single-task learning and end-to-end extraction of spans and relations. To make fair comparisons, token embeddings (GloVe, ELMo, BERT) and other hyperparameters (e.g., the number of antecedents in Coref. and the maximal span length in SRL) in our method are set to match those used by SOTA models, to focus on differences brought about by the model architecture.

As shown in Table 4, the SpanRel model achieves comparable performances as the task-specific SOTA methods (regardless of whether the token representation is contextualized or not). This indicates that the span-relation format can generically represent a large number of natural language analysis tasks and it is possible to devise a single unified model that can achieves strong performance on all of them. It provides a strong and generic baseline for natural language analysis tasks and a way to examine the usefulness of task-specific designs.

<sup>3</sup> <sup>◦</sup> The small version of Lee et al. (2017)’s method with 100 antecedents and no speaker features. \* For OpenIE and ORL, we use span-based F<sub>1</sub> instead of syntactic-head-based F<sub>1</sub> and binary coverage F<sub>1</sub> used in the original papers because they are biased towards extracting long spans. <sup>†</sup> For SRL, we choose to compare with He et al. (2018) because they also extract predicates and arguments in an end-to-end way. <sup>◊</sup> We follow Xu et al. (2019) to report accuracy of restaurant and laptop domain separately in ABSA.

Category	Task	Metric	Dataset	GloVe			ELMo			BERT <sub>base</sub>			SpanBERT <sub>base</sub>		
				STL	MTL	+FT	STL	MTL	+FT	STL	MTL	+FT	STL	MTL	+FT
IE	NER	F <sub>1</sub>	CoNLL03 WLP	88.4	86.2↓	87.5↓	91.9	91.6	91.6	91.0	88.6↓	90.2↓	91.3	90.4↓	91.2
				77.6	71.5↓	76.5↓	79.2	77.4↓	78.2↓	78.1	78.2	78.5	77.9	78.6↑	78.5↑
	RE	F <sub>1</sub>	SemEval10 WLP	50.7	15.2↓	33.0↓	61.8	30.6↓	42.9↓	61.7	55.1↓	59.8↓	62.1	54.6↓	61.8
				64.9	38.5↓	53.9↓	65.5	52.0↓	55.1↓	64.7	65.9↑	66.5↑	64.1	67.2↑	67.2↑
	Coref	Avg F <sub>1</sub>	OntoNotes	56.3	50.3↓	53.0↓	62.2	62.9↑	63.3↑	66.2	65.5↓	65.8	70.0	68.9↓	69.7
	OpenIE	F <sub>1</sub>	OIE2016	28.3	6.8↓	19.6↓	35.2	30.0↓	32.9↓	36.7	37.1	38.5↑	36.5	37.3↑	38.6↑
SRL		F <sub>1</sub>	OntoNotes	78.0	77.9	78.6↑	82.4	82.3	82.4	83.3	82.9	83.4	83.1	83.3	83.8↑
Parsing	Dep.	LAS	PTB	92.9	93.2	93.5↑	94.7	94.9	94.9	94.9	94.8	95.0	95.1	95.1	95.1
			OntoNotes	90.4	90.5	90.5	92.3	93.2↑	92.8↑	94.1	93.8	94.0	94.2	94.1	94.2
	Consti.	Evalb F <sub>1</sub>	PTB	93.4	-	93.8	95.3	-	95.3	95.5	-	95.2	95.8	-	95.5
			OntoNotes	91.0	-	91.5↑	93.2	-	93.7↑	93.6	-	93.8	94.3	-	94.2
Sentiment	ABSA	F <sub>1</sub>	SemEval14	63.5	48.5↓	59.0↓	69.2	57.0↓	59.0↓	70.8	63.1↓	67.0↓	70.0	63.5↓	69.5↓
	ORL	F <sub>1</sub>	MPQA 3.0	38.2	18.4↓	31.6↓	42.9	24.7↓	32.4↓	44.5	38.1↓	45.6↑	45.2	40.2↓	47.5↑
POS	Accuracy		PTB	96.8	96.8	96.8	97.7	97.7	97.8	97.6	97.3	97.3	97.6	97.6	97.6
			OntoNotes	97.0	97.0	97.1	98.2	98.2	98.3	97.7	97.8	97.8	98.3	98.3	98.3

Table 5: Comparison between STL and MTL+fine-tuning of the SpanRel model across all tasks. **blue**↑ indicates results better than STL, **red**↓ indicates worse, and black means almost the same (i.e., a difference within 0.5). Constituency parsing requires more memory than other tasks so we restrict its maximal span length as 10 in MTL, thus it cannot form a valid tree.

### 4.3 MULTI-TASK LEARNING WITH SPAN-RELATION REPRESENTATION

To demonstrate the benefit of the SpanRel model in MTL, we perform single-task learning (STL) and MTL across all tasks using end-to-end settings.<sup>4</sup> Following Liu et al. (2019), we perform MTL+fine-tuning and show the results in separate columns of Table 5. Contextualized token representations yield significantly better results than GloVe on all tasks, indicating that pre-training on large corpora is almost universally helpful to NLP tasks. Comparing the results of MTL+fine-tuning with STL, we found that performance with GloVe drops on 8 out of 15 tasks, most of which are tasks with relatively sparse data. It is probably because the capacity of the GloVe-based model is too small to store all the patterns required by different tasks. The results of contextualized representations are mixed, with some tasks being improved and others remaining the same or degrading. We hypothesize that this is because different tasks capture different linguistic aspects, thus are not equally helpful to each other. Reconciling these seemingly different tasks in the same model might be harmful to some tasks. Notably, as the contextualized representations become stronger, the performance of MTL+FT becomes more favorable. 5 out of 15 tasks (NER, RE, OpenIE, SRL, ORL) observe improvements with SpanBERT, a contextualized embedding pre-trained with span-based training objectives, while only one task degrades (ABSA), indicating its superiority in reconciling spans from different tasks. The GLAD benchmark provides a holistic testbed for evaluating natural language analysis capability.

**Task Relatedness Analysis** To further investigate how different tasks interact with each other, we choose five source tasks (POS, NER, Consti., Dep., and SRL) that have been widely used in MTL (Hashimoto et al., 2017; Strubell et al., 2018) and six target tasks (OpenIE, NER, RE, ABSA, ORL, and SRL) to perform pairwise multi-task learning. We hypothesize that although language modeling pre-training is theoretically orthogonal to MTL (Swayamdipta et al., 2018), in practice the benefit of pre-training tends to overlap or even overshadow the benefit of MTL. To analyze these two factors separately, we start with a weak representation GloVe to study task relatedness, then move to BERT to demonstrate how much we can still improve with MTL given strong and contextualized representations. As shown in Table 6 (GloVe), tasks are not equally useful to each other. Notably, (1) for OpenIE and ORL, multi-task learning with SRL improves the performance significantly, while other tasks lead to less or no improvements. (2) Dependency parsing and SRL are generic source tasks that are beneficial to most of the target tasks. (3) ABSA is quite different from the source tasks and no improvement is observed with MTL. This unified SpanRel makes it easy to perform MTL and decide beneficial source tasks.

<sup>4</sup>Span-based F<sub>1</sub> is used as the evaluation metric in SemEval-2010 Task 8 and SemEval-2014 Task 4 as opposed to macro F<sub>1</sub> and accuracy reported in the original papers because we aim at end-to-end extractions.

		GloVe						BERT <sub>base</sub>					
Source \ Target	STL	POS	NER	Consti.	Dep.	SRL	STL	POS	NER	Consti.	Dep.	SRL	
OpenIE	28.3	29.9 <sup>↑</sup>	27.0 <sup>↓</sup>	31.2 <sup>↑</sup>	32.9 <sup>↑</sup>	34.1 <sup>↑</sup>	36.7	34.0 <sup>↓</sup>	34.3 <sup>↓</sup>	35.2 <sup>↓</sup>	37.8 <sup>↑</sup>	38.3 <sup>↑</sup>	
NER (WLP)	77.6	77.8	78.3 <sup>↑</sup>	77.9	78.6 <sup>↑</sup>	78.1 <sup>↑</sup>	78.1	78.0	78.1	78.1	77.7	78.8 <sup>↑</sup>	
RE (WLP)	64.9	65.5 <sup>↑</sup>	65.6 <sup>↑</sup>	64.9	66.5 <sup>↑</sup>	65.9 <sup>↑</sup>	64.7	64.4	64.7	64.3	64.9	65.3 <sup>↑</sup>	
RE (SemEval10)	50.7	52.3 <sup>↑</sup>	52.8 <sup>↑</sup>	49.6 <sup>↓</sup>	52.9 <sup>↑</sup>	52.8 <sup>↑</sup>	61.7	61.9	60.2 <sup>↓</sup>	59.2 <sup>↓</sup>	62.1	59.9 <sup>↓</sup>	
ABSA	63.5	63.4	62.8 <sup>↓</sup>	59.8 <sup>↓</sup>	63.5	60.2 <sup>↓</sup>	70.8	68.9 <sup>↓</sup>	71.4 <sup>↑</sup>	70.4	69.9 <sup>↓</sup>	69.6 <sup>↓</sup>	
ORL	38.2	35.7 <sup>↓</sup>	37.9	36.1 <sup>↓</sup>	38.6	41.0 <sup>↑</sup>	44.5	45.8 <sup>↑</sup>	44.2	44.8	45.1 <sup>↑</sup>	46.6 <sup>↑</sup>	
SRL (10k)	68.8	69.6 <sup>↑</sup>	68.9	70.7 <sup>↑</sup>	71.3 <sup>↑</sup>	-	78.7	79.4 <sup>↑</sup>	79.5 <sup>↑</sup>	79.6 <sup>↑</sup>	79.8 <sup>↑</sup>	-	

Table 6: Performance of pairwise multi-task learning with GloVe and BERT<sub>base</sub>. **blue**<sup>↑</sup> indicates results better than STL, **red**<sup>↓</sup> indicates worse, and black means almost the same (i.e., a difference within 0.5). We show the performance after fine-tuning. Dataset of source tasks POS, Consti., Dep. is PTB and dataset of NER is CoNLL-2003.

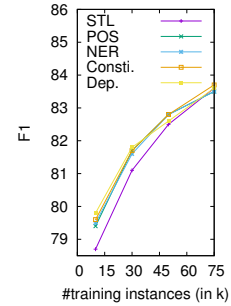


Figure 2: MTL Performance of SRL wrt. the data size.

**MTL under Different Settings** We analyze how token representations and sizes of the target dataset affect the performance of MTL. Comparing BERT and GloVe in Table 6, the improvements of MTL become smaller or vanish as the token representation becomes stronger, e.g., improvement on OpenIE with SRL reduces from 5.8 to 1.6 and improvement on SRL with Dep. reduces from 2.5 to 1.1. This is expected because both large-scale pre-training and MTL aim to learn general representations and their benefits tend to overlap in practice. Interestingly, some helpful source tasks even become harmful when we shift from GloVe to BERT, such as OpenIE paired with Consti. or POS. We conjecture that the gains of MTL might have already been achieved by BERT, but the task-specific characteristics of Consti. and POS hurt the performance of OpenIE. The improvements of MTL shrink as we increase the size of the SRL datasets, as shown in Figure 2, indicating that MTL is more useful when the target data is sparse.

## 5 RELATED WORK

**General Architectures for NLP** There has been a rising interest in developing general architectures for different NLP tasks, with the most prominent examples being sequence labeling framework (Collobert et al., 2011; Ma & Hovy, 2016) used for tagging tasks (e.g., NER, POS) and sequence-to-sequence framework (Sutskever et al., 2014) used for generation tasks (e.g., machine translation). Moreover, researchers typically pick related tasks, motivated by either linguistic insights or empirical results, and create a general framework to perform MTL, several of which are summarized in Table 1. For example, based on the belief that semantic structure of a sentence should conform with syntactic structure, Swayamdipta et al. (2018) and Strubell et al. (2018) use constituency and dependency parsing to improve SRL. Luan et al. (2018; 2019) use a span-based model to jointly solve three information-extraction-related tasks (NER, RE, and Coref.). Compared to existing works, we aim to create an output representation that can solve *nearly every* natural language analysis task in one fell swoop, allowing us to cover a far broader range of tasks with a single model.

In addition, NLP has seen a recent burgeoning of contextualized token embeddings pre-trained on large corpora (e.g., ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019)). These methods focus on learning generic *input* representations, but are agnostic to the *output* representation, requiring different predictors to be designed for different tasks. In contrast, we present a methodology to formulate the output of different tasks in a unified format. Thus our work is orthogonal to those on contextualized embeddings. Indeed, in Section 4.3, we demonstrate that the SpanRel model can benefit from stronger contextualized representation models, and even provide a testbed for their use in natural language analysis.

**Benchmarks for Evaluating Natural Language Understanding** Due to the rapid development of NLP models, large-scale benchmarks, such as SentEval (Conneau & Kiela, 2018), GLUE (Wang et al., 2019b), and SuperGLUE (Wang et al., 2019a) have been proposed to facilitate fast and holistic evaluation of models’ natural language understanding ability. They mainly focus on sentence-level tasks, such as text classification and natural language inference, while our GLAD benchmark focuses on token/phrase-level analysis tasks with diverse coverage of different linguistic structures. With different tasks represented under the same format, a model can be easily evaluated on all our tasks, reflecting various aspects of its natural language analysis capability. New tasks and datasets can be conveniently added to our benchmark as long as they are in the BRAT standoff format, which is one



---

of the most commonly used data format in the NLP community, e.g., it has been used in the BioNLP shared tasks (Kim et al., 2009) and the Universal Dependency project (McDonald et al., 2013).

## 6 CONCLUSION

We provide the simple insight that a large number of natural language analysis tasks can be represented in a single format consisting of spans and relations between spans. As a result, these tasks can be solved in a single modeling framework that first extracts spans and predicts their labels, then predicts relations between extracted spans. We attempted 10 tasks with this SpanRel model under this unified representation and show that this generic task-independent model can achieve competitive performance as state-of-the-art methods tailored for each task. We merge 8 datasets into our GLAD benchmark for evaluating future models for natural language analysis. Future directions include (1) devising hierarchical span representations that can handle spans of different length and diverse content and length more effectively and efficiently. (2) robust multitask learning or meta-learning algorithms that can learn to relate and reconcile very different tasks.

## ACKNOWLEDGMENTS

This work was supported by gifts from Bosch Research. We would like to thank Hiroaki Hayashi, Bohan Li, Pengcheng Yin, Hao Zhu, Paul Michel, Antonios Anastasopoulos for their insightful comments and suggestions.

## REFERENCES

- Laura Banarescu, Claire Bonial, Shu Cai, Madalina Georgescu, Kira Griffitt, Ulf Hermjakob, Kevin Knight, Philipp Koehn, Martha Palmer, and Nathan Schneider. Abstract meaning representation for sembanking. In *Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse, LAW-ID@ACL 2013, August 8-9, 2013, Sofia, Bulgaria*, pp. 178–186, 2013. URL <https://www.aclweb.org/anthology/W13-2322/>.
- Michele Banko, Michael J. Cafarella, Stephen Soderland, Matthew Broadhead, and Oren Etzioni. Open information extraction from the web. In *IJCAI 2007, Proceedings of the 20th International Joint Conference on Artificial Intelligence, Hyderabad, India, January 6-12, 2007*, pp. 2670–2676, 2007. URL <http://ijcai.org/Proceedings/07/Papers/429.pdf>.
- Ondrej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveiling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, Radu Soricut, Lucia Specia, and Ales Tamchyna. Findings of the 2014 workshop on statistical machine translation. In *Proceedings of the Ninth Workshop on Statistical Machine Translation, WMT@ACL 2014, June 26-27, 2014, Baltimore, Maryland, USA*, pp. 12–58, 2014. URL <https://www.aclweb.org/anthology/W14-3302/>.
- Kevin Clark, Minh-Thang Luong, Christopher D. Manning, and Quoc Le. Semi-supervised sequence modeling with cross-view training. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 1914–1925, Brussels, Belgium, October–November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1217. URL <https://www.aclweb.org/anthology/D18-1217>.
- Michael Collins. Three generative, lexicalised models for statistical parsing. In *35th Annual Meeting of the Association for Computational Linguistics and 8th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 16–23, Madrid, Spain, July 1997. Association for Computational Linguistics. doi: 10.3115/976909.979620. URL <https://www.aclweb.org/anthology/P97-1003>.
- Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel P. Kuksa. Natural language processing (almost) from scratch. *J. Mach. Learn. Res.*, 12:2493–2537, 2011. URL <http://dl.acm.org/citation.cfm?id=2078186>.
- Alexis Conneau and Douwe Kiela. SentEval: An evaluation toolkit for universal sentence representations. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC-2018)*, Miyazaki, Japan, May 2018. European Languages Resources Association (ELRA). URL <https://www.aclweb.org/anthology/L18-1269>.

- 
- Lingjia Deng and Janyce Wiebe. MPQA 3.0: An entity/event-level sentiment corpus. In *NAACL HLT 2015, The 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Denver, Colorado, USA, May 31 - June 5, 2015*, pp. 1323–1328, 2015. URL <https://www.aclweb.org/anthology/N15-1146/>.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1423. URL <https://www.aclweb.org/anthology/N19-1423>.
- Kalpit Dixit and Yaser Al-Onaizan. Span-level model for relation extraction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 5308–5314, Florence, Italy, July 2019. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/P19-1525>.
- Daniel Gildea and Daniel Jurafsky. Automatic labeling of semantic roles. *Comput. Linguist.*, 28(3):245–288, September 2002. ISSN 0891-2017. doi: 10.1162/089120102760275983. URL <http://dx.doi.org/10.1162/089120102760275983>.
- Jiang Guo, Wanxiang Che, Haifeng Wang, Ting Liu, and Jun Xu. A unified architecture for semantic role labeling and relation classification. In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pp. 1264–1274, Osaka, Japan, December 2016. The COLING 2016 Organizing Committee. URL <https://www.aclweb.org/anthology/C16-1120>.
- Kazuma Hashimoto, Caiming Xiong, Yoshimasa Tsuruoka, and Richard Socher. A joint many-task model: Growing a neural network for multiple NLP tasks. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017*, pp. 1923–1933, 2017. URL <https://aclanthology.info/papers/D17-1206/d17-1206>.
- Luheng He, Kenton Lee, Mike Lewis, and Luke Zettlemoyer. Deep semantic role labeling: What works and what’s next. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 473–483, Vancouver, Canada, July 2017. Association for Computational Linguistics. doi: 10.18653/v1/P17-1044. URL <https://www.aclweb.org/anthology/P17-1044>.
- Luheng He, Kenton Lee, Omer Levy, and Luke Zettlemoyer. Jointly predicting predicates and arguments in neural semantic role labeling. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 364–369, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi: 10.18653/v1/P18-2058. URL <https://www.aclweb.org/anthology/P18-2058>.
- Iris Hendrickx, Su Nam Kim, Zornitsa Kozareva, Preslav Nakov, Diarmuid Ó Séaghdha, Sebastian Padó, Marco Pennacchiotti, Lorenza Romano, and Stan Szpakowicz. Semeval-2010 task 8: Multi-way classification of semantic relations between pairs of nominals. In *Proceedings of the 5th International Workshop on Semantic Evaluation, SemEval@ACL 2010, Uppsala University, Uppsala, Sweden, July 15-16, 2010*, pp. 33–38, 2010. URL <https://www.aclweb.org/anthology/S10-1006/>.
- Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S. Weld, Luke Zettlemoyer, and Omer Levy. Spanbert: Improving pre-training by representing and predicting spans. *CoRR*, abs/1907.10529, 2019. URL <http://arxiv.org/abs/1907.10529>.
- Jin-Dong Kim, Tomoko Ohta, Sampo Pyysalo, Yoshinobu Kano, and Jun’ichi Tsujii. Overview of bionlp’09 shared task on event extraction. In *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing: Shared Task, BioNLP ’09*, pp. 1–9, Stroudsburg, PA, USA, 2009. Association for Computational Linguistics. ISBN 978-1-932432-44-2. URL <http://dl.acm.org/citation.cfm?id=1572340.1572342>.

- 
- Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015. URL <http://arxiv.org/abs/1412.6980>.
- Nikita Kitaev, Steven Cao, and Dan Klein. Multilingual constituency parsing with self-attention and pre-training. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 3499–3505, Florence, Italy, July 2019. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/P19-1340>.
- Sandra Kübler, Ryan McDonald, and Joakim Nivre. Dependency parsing. *Synthesis Lectures on Human Language Technologies*, 1(1):1–127, 2009.
- Chaitanya Kulkarni, Wei Xu, Alan Ritter, and Raghu Machiraju. An annotated corpus for machine reading of instructions in wet lab protocols. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pp. 97–106, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-2016. URL <https://www.aclweb.org/anthology/N18-2016>.
- Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. Neural architectures for named entity recognition. In *NAACL HLT 2016, The 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego California, USA, June 12-17, 2016*, pp. 260–270, 2016. URL <https://www.aclweb.org/anthology/N16-1030/>.
- Wuwei Lan and Wei Xu. Neural network models for paraphrase identification, semantic textual similarity, natural language inference, and question answering. In *Proceedings of the 27th International Conference on Computational Linguistics*, pp. 3890–3902, Santa Fe, New Mexico, USA, August 2018. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/C18-1328>.
- Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. End-to-end neural coreference resolution. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017*, pp. 188–197, 2017. URL <https://aclanthology.info/papers/D17-1018/d17-1018>.
- Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Multi-task deep neural networks for natural language understanding. In *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers*, pp. 4487–4496, 2019. URL <https://www.aclweb.org/anthology/P19-1441/>.
- Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In *Proceedings of the SIGDIAL 2015 Conference, The 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 2-4 September 2015, Prague, Czech Republic*, pp. 285–294, 2015. URL <https://www.aclweb.org/anthology/W15-4640/>.
- Yi Luan, Luheng He, Mari Ostendorf, and Hannaneh Hajishirzi. Multi-task identification of entities, relations, and coreference for scientific knowledge graph construction. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*, pp. 3219–3232, 2018. URL <https://aclanthology.info/papers/D18-1360/d18-1360>.
- Yi Luan, Dave Wadden, Luheng He, Amy Shah, Mari Ostendorf, and Hannaneh Hajishirzi. A general framework for information extraction using dynamic span graphs. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 3036–3046, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1308. URL <https://www.aclweb.org/anthology/N19-1308>.

- 
- Xuezhe Ma and Eduard H. Hovy. End-to-end sequence labeling via bi-directional lstm-cnns-crf. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers*, 2016. URL <https://www.aclweb.org/anthology/P16-1101/>.
- Ana Marasović and Anette Frank. SRL4ORL: Improving opinion role labeling using multi-task learning with semantic role labeling. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 583–594, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1054. URL <https://www.aclweb.org/anthology/N18-1054>.
- Mitchell P. Marcus, Grace Kim, Mary Ann Marcinkiewicz, Robert MacIntyre, Ann Bies, Mark Ferguson, Karen Katz, and Britta Schasberger. The penn treebank: Annotating predicate argument structure. In *Human Language Technology, Proceedings of a Workshop held at Plainsboro, New Jersey, USA, March 8-11, 1994*, 1994. URL <https://www.aclweb.org/anthology/H94-1020/>.
- Ryan McDonald, Joakim Nivre, Yvonne Quirnbach-Brundage, Yoav Goldberg, Dipanjan Das, Kuzman Ganchev, Keith Hall, Slav Petrov, Hao Zhang, Oscar Täckström, Claudia Bedini, Núria Bertomeu Castelló, and Jungmee Lee. Universal dependency annotation for multilingual parsing. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 92–97, Sofia, Bulgaria, August 2013. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/P13-2017>.
- Ramesh Nallapati, Bowen Zhou, Cicero Nogueira dos Santos, Çağlar Gülçehre, and Bing Xiang. Abstractive text summarization using sequence-to-sequence rnns and beyond. In *Proceedings of the 20th SIGNLL Conference on Computational Natural Language Learning, CoNLL 2016, Berlin, Germany, August 11-12, 2016*, pp. 280–290, 2016. URL <https://www.aclweb.org/anthology/K16-1028/>.
- Christina Niklaus, Matthias Cetto, André Freitas, and Siegfried Handschuh. A survey on open information extraction. In *Proceedings of the 27th International Conference on Computational Linguistics*, pp. 3866–3878, Santa Fe, New Mexico, USA, August 2018. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/C18-1326>.
- Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL*, pp. 1532–1543, 2014. URL <https://www.aclweb.org/anthology/D14-1162/>.
- Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 2227–2237, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1202. URL <https://www.aclweb.org/anthology/N18-1202>.
- Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androutsopoulos, and Suresh Manandhar. Semeval-2014 task 4: Aspect based sentiment analysis. In *Proceedings of the 8th International Workshop on Semantic Evaluation, SemEval@COLING 2014, Dublin, Ireland, August 23-24, 2014.*, pp. 27–35, 2014. URL <https://www.aclweb.org/anthology/S14-2004/>.
- Sameer Pradhan, Alessandro Moschitti, Nianwen Xue, Olga Uryupina, and Yuchen Zhang. Conll-2012 shared task: Modeling multilingual unrestricted coreference in ontonotes. In *Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning - Proceedings of the Shared Task: Modeling Multilingual Unrestricted Coreference in OntoNotes, EMNLP-CoNLL 2012, July 13, 2012, Jeju Island, Korea*, pp. 1–40, 2012. URL <https://www.aclweb.org/anthology/W12-4501/>.

- 
- Sameer Pradhan, Alessandro Moschitti, Nianwen Xue, Hwee Tou Ng, Anders Björkelund, Olga Uryupina, Yuchen Zhang, and Zhi Zhong. Towards robust linguistic analysis using ontonotes. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning, CoNLL 2013, Sofia, Bulgaria, August 8-9, 2013*, pp. 143–152, 2013. URL <https://www.aclweb.org/anthology/W13-3516/>.
- Adwait Ratnaparkhi. A maximum entropy model for part-of-speech tagging. In *Conference on Empirical Methods in Natural Language Processing*, 1996. URL <https://www.aclweb.org/anthology/W96-0213>.
- Sebastian Ruder. An overview of multi-task learning in deep neural networks. *CoRR*, abs/1706.05098, 2017. URL <http://arxiv.org/abs/1706.05098>.
- Erik F. Tjong Kim Sang and Fien De Meulder. Introduction to the conll-2003 shared task: Language-independent named entity recognition. In *Proceedings of the Seventh Conference on Natural Language Learning, CoNLL 2003, Held in cooperation with HLT-NAACL 2003, Edmonton, Canada, May 31 - June 1, 2003*, pp. 142–147, 2003. URL <https://www.aclweb.org/anthology/W03-0419/>.
- Peng Shi and Jimmy Lin. Simple BERT models for relation extraction and semantic role labeling. *CoRR*, abs/1904.05255, 2019. URL <http://arxiv.org/abs/1904.05255>.
- Nitish Srivastava, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *J. Mach. Learn. Res.*, pp. 1929–1958, 2014.
- Gabriel Stanovsky and Ido Dagan. Creating a large benchmark for open information extraction. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pp. 2300–2305, Austin, Texas, November 2016. Association for Computational Linguistics. doi: 10.18653/v1/D16-1252. URL <https://www.aclweb.org/anthology/D16-1252>.
- Gabriel Stanovsky, Julian Michael, Luke Zettlemoyer, and Ido Dagan. Supervised open information extraction. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 885–895, New Orleans, Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1081. URL <https://www.aclweb.org/anthology/N18-1081>.
- Pontus Stenetorp, Sampo Pyysalo, Goran Topić, Tomoko Ohta, Sophia Ananiadou, and Jun’ichi Tsujii. BRAT: a web-based tool for NLP-assisted text annotation. In *Proceedings of the Demonstrations at the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 102–107, Avignon, France, April 2012. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/E12-2021>.
- Mitchell Stern, Jacob Andreas, and Dan Klein. A minimal span-based neural constituency parser. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pp. 818–827, 2017. doi: 10.18653/v1/P17-1076. URL <https://doi.org/10.18653/v1/P17-1076>.
- Emma Strubell, Patrick Verga, Daniel Andor, David Weiss, and Andrew McCallum. Linguistically-informed self-attention for semantic role labeling. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 5027–5038, Brussels, Belgium, October–November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1548. URL <https://www.aclweb.org/anthology/D18-1548>.
- Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pp. 3104–3112, 2014. URL <http://papers.nips.cc/paper/5346-sequence-to-sequence-learning-with-neural-networks>.

- 
- Swabha Swayamdipta, Sam Thomson, Kenton Lee, Luke Zettlemoyer, Chris Dyer, and Noah A. Smith. Syntactic scaffolds for semantic structures. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 3772–3782, Brussels, Belgium, October–November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1412. URL <https://www.aclweb.org/anthology/D18-1412>.
- Ian Tenney, Dipanjan Das, and Ellie Pavlick. BERT rediscovers the classical NLP pipeline. In *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers*, pp. 4593–4601, 2019a. URL <https://www.aclweb.org/anthology/P19-1452/>.
- Ian Tenney, Patrick Xia, Berlin Chen, Alex Wang, Adam Poliak, R. Thomas McCoy, Najoung Kim, Benjamin Van Durme, Samuel R. Bowman, Dipanjan Das, and Ellie Pavlick. What do you learn from context? probing for sentence structure in contextualized word representations. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*, 2019b. URL <https://openreview.net/forum?id=SJzSgnRcKX>.
- Kristina Toutanova, Dan Klein, Christopher D. Manning, and Yoram Singer. Feature-rich part-of-speech tagging with a cyclic dependency network. In *Proceedings of the 2003 Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics*, pp. 252–259, 2003. URL <https://www.aclweb.org/anthology/N03-1033>.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. *CoRR*, abs/1905.00537, 2019a. URL <http://arxiv.org/abs/1905.00537>.
- Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*, 2019b. URL <https://openreview.net/forum?id=rJ4km2R5t7>.
- Shanchuan Wu and Yifan He. Enriching pre-trained language model with entity information for relation classification. *CoRR*, abs/1905.08284, 2019. URL <http://arxiv.org/abs/1905.08284>.
- Hu Xu, Bing Liu, Lei Shu, and Philip Yu. BERT post-training for review reading comprehension and aspect-based sentiment analysis. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 2324–2335, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1242. URL <https://www.aclweb.org/anthology/N19-1242>.
- Bishan Yang and Claire Cardie. Joint inference for fine-grained opinion extraction. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, ACL 2013, 4-9 August 2013, Sofia, Bulgaria, Volume 1: Long Papers*, pp. 1640–1649, 2013. URL <https://www.aclweb.org/anthology/P13-1161/>.
- Junlang Zhang and Hai Zhao. Span based open information extraction. *CoRR*, abs/1901.10879, 2019. URL <http://arxiv.org/abs/1901.10879>.

## A RESULTS OF BERT LARGE MODEL

Category	Task	Metric	Dataset	GloVe	ELMo	BERT <sub>base</sub>	SpanBERT <sub>base</sub>	BERT <sub>large</sub>
IE	NER	F <sub>1</sub>	CoNLL03	88.4	91.9	91.0	91.3	90.9
			WLP	77.6	79.2	78.1	77.9	78.3
	RE	F <sub>1</sub>	SemEval10	50.7	61.8	61.7	62.1	64.7
			WLP	64.9	65.5	64.7	64.1	65.1
	Coref	Avg F <sub>1</sub>	OntoNotes	56.3	62.2	66.3	70.0	-
	OpenIE	F <sub>1</sub>	OIE2016	28.3	35.2	36.7	36.5	36.5
SRL		F <sub>1</sub>	OntoNotes	78.0	82.4	83.3	83.1	84.4
Parsing	Dep.	LAS	PTB	92.9	94.7	94.9	95.1	95.3
			OntoNotes	90.4	92.3	94.1	94.2	94.5
	Consti.	Evalb F <sub>1</sub>	PTB	93.4	95.3	95.5	95.8	95.8
			OntoNotes	91.0	93.2	93.6	94.3	93.9
Sentiment	ABSA	F <sub>1</sub>	SemEval14	63.5	69.2	70.8	70.0	73.8
	ORL	F <sub>1</sub>	MPQA 3.0	38.2	42.9	44.5	45.2	47.1
POS	Accuracy		PTB	96.8	97.7	97.6	97.6	97.4
			OntoNotes	97.0	98.2	97.7	98.3	97.9

Table 7: Single-task learning performance of the SpanRel model with different token representations. BERT<sub>large</sub> requires a large amount of memory so we cannot feed the entire document to the model in coreference resolution.

## B TASK-SPECIFIC HYPERPARAMETERS

As shown in Table 8, a larger maximum span length is used for tasks with longer spans (e.g., OpenIE), and a larger pruning ratio is used for tasks with more spans (e.g., SRL). Constituency parsing does not have span length limit because spans can be as long as the entire sentence. Since relation extraction aims to extract exactly two entities and their relation from a sentence, we keep pruning ratio fixed (top 5 spans in this case) regardless of the length of the sentence.

	Information Extraction				POS	Parsing		SRL	Sentiment	
	NER	RE	Coref.	OpenIE		Dep.	Consti.		ABSA	ORL
max span length $l$	10	5	10	30	1	1	-	30	10	30
pruning ratio $\tau$	-	5	0.4	0.8	-	1.0	-	1.0	-	0.3

Table 8: Task-specific hyperparameters. Span-oriented tasks do not need pruning ratio.