A Structured Span Selector for Span Prediction Tasks

Anonymous NAACL submission

Abstract

Several natural language processing tasks require selecting text spans and making decisions upon them, e.g. coreference resolution and semantic role labeling. A typical approach for these tasks is to naively score all spans and greedily select spans for downstream processing. This approach ignores any useful linguistic biases such as spans that need to be considered for these problems are typically syntactic constituents. In this paper, we propose a novel linguistically-motivated "structured" span-selection model which learns to make use of the partial span-level annotation provided for such problems. Compared to previous approaches, our approach gets rid of the heuristic greedy span selection scheme, allowing us to model the downstream tasks on an optimal set of spans. We evaluate our model on two popular span prediction tasks: coreference resolution and semantic role labeling; and show improvements on both tasks in terms of performance as well as efficiency.

1 Introduction

Many key NLP problems are often framed as span prediction problems. This include problems such as coreference resolution (Lee et al., 2017, 2018; Joshi et al., 2020), semantic role labeling (He et al., 2017, 2018), question answering (Lee et al., 2016; Izacard and Grave, 2020) and named entity recognition (Yamada et al., 2020). For instance, in coreference resolution, entity spans are extracted from a given document and clustered into equivalence classes in which each cluster contains mention spans that refer to the same entity (Wiseman et al., 2016; Clark and Manning, 2016; Lee et al., 2017). Similarly, in semantic role labeling, textual spans are identified as arguments and their roles with respect to a specific predicate are classified (Gildea and Jurafsky, 2000; He et al., 2017).

In these methods, a neural network is typically used to score a large number of potential spans in the text. As the number of spans to consider can potentially be very large, these spans are greedily selected as potential antecedents, roles or answers. While this span selection approach has become the de-facto choice in many of these systems, it has several issues. First, these approaches typically ignore the inherent structure in the problem. For example, spans of interest in problems such as coreference and SRL are typically syntactic constituents. Furthermore, as these methods score all possible spans, they can be quite inefficient.

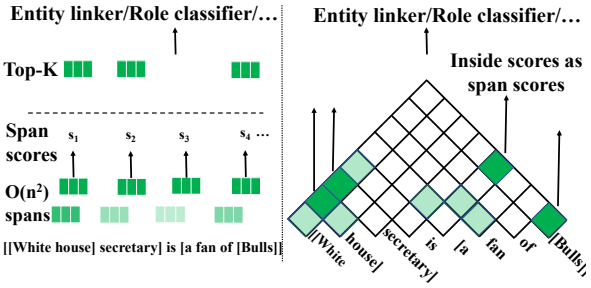

Figure 1: On the left: greedy span selection in previous work (Lee et al., 2018; He et al., 2017). On the right: our structured span selector.

As shown in subsequent works (Zhang et al., 2018; Wu et al., 2020), the quality of the span selector can have a large impact on the overall system performance. Thus, in this paper, we propose a novel structured span selector as a replacement to the existing greedy span selection methods used in the aforementioned works. Our span selector is modeled as a chart parser which learns to score partial, possibly nested, span annotations given in the training corpus. Instead of optimizing the full parse, we directly learn the marginal distribution over spans using the inside scores in the parse. The marginal can be easily computed by backpropagating through the inside score (Eisner, 2016). Fig. 1 illustrates the difference between the traditional greedy approach and our approach.

We apply our span selector on one coreference

(Joshi et al., 2020) and one SRL model (He et al., 2018), and evaluate them on the the CoNLL-2012 coreference resolution and SRL benchmarks. In both cases, we optimize the log-likelihood of the joint distribution defined by the span selection model and the conditional for the downstream tasks as defined in Lee et al. (2017) and He et al. (2018).

In contrast to previous approaches which use a set of heuristics[1] to prune the set of spans to be considered, our model gets rid of these heuristics and directly uses the optimal set of spans proposed by the structured scorer. The number of spans proposed by the scorer are significantly lower than the number of spans previously considered in these models, resulting in considerable reduction in the memory required to train these models. At the same time, the selected spans are also more accurate. We show with quantitative and qualitative analysis that the structured span selection model is able to handle nested spans and longer spans significantly better than the greedy approach.

The new span selector also leads to significant gains in both downstream tasks considered in this work: coreference and SRL. In our experiments, we find that the proposed model improves the performance of the end-to-end coreference model on the OntoNotes English dataset (by 0.4 CoNLL F1 points) and the LitBank dataset (by 0.7 CoNLL F1 points). On the SRL task, our model also achieves consistent gains over previous work.

2 Background and Related Work

We begin by a background on two span selection tasks considered in our work: coreference resolution and SRL. We describe some previous works on these tasks and contrast them to our work.

2.1 Span Selection Task

Span selection models extract a set of textual spans from a given document. These models typically select spans by selecting the start token and the end token in the span. Thus, there are inherently $\binom{N}{2}$ textual spans (the complexity is $\mathcal{O}(n^2)$) within a document with N tokens to choose from. Previous span selection models (Lee et al., 2017; He et al., 2018) enumerate all possible spans in a brute force manner and feed greedily selected top-k span candidates for downstream processing.

[1] Lee et al. (2017) consider spans such that the maximum span width is 10, the number of spans per word is 0.4, etc. Then, the spans are greedily pruned.

However, several span selection tasks require spans that are syntactic constituents, which is a useful but often neglected inductive bias in these works. For instance, in coreference resolution, span selection models are supposed to extract noun phrases, pronouns, and sometimes, verbs. While in semantic role labeling, span selection models are required to extract syntactic constituents that could form semantic arguments of a predicate, such as noun phrases, prepositional phrases, and adverbs. This assumption is also supported by quantitative results. For the OntoNotes dataset, He et al. (2018) reports that 98.7% of the arguments in SRL are constituents. For coreference resolution, we find 99.1% of the mentions are constituents.

Our work uses a context-free parsing formulation to enumerate spans. In context-free grammars, the number of valid syntactic constituents in a sequence of length n is bounded by $\mathcal{O}(n)$, as the constituents can be viewed as the internal nodes of a binary parse tree in Chomsky normal form. Compared with brute-force enumeration and greedy pruning, this inductive bias serves us as a natural pruning strategy to reduce the complexity from $\mathcal{O}(n^2)$ to $\mathcal{O}(n)$ and provides us a more natural and linguistically informed way to model span-based tasks in NLP, through which we can employ parsing techniques and retrieve the optimal span selection for downstream tasks.

2.2 Coreference Resolution

Most coreference resolution models involve two stages: mention detection and mention clustering. Traditional pipeline systems relied on parse trees and hand-engineered rules to extract mentions (Raghunathan et al., 2010). However, this was reversed by Lee et al. (2017) who showed that we can directly detect mentions as well as assign antecedents for them in an end-to-end manner.

Alongside our work, some other works (Zhang et al., 2018; Swayamdipta et al., 2018; Miculicich and Henderson, 2019; Yu et al., 2019) have also explored better mention proposers for coreference. Zhang et al. (2018) use multi-task loss to directly optimize the mention detector. Swayamdipta et al. (2018) also leverage syntactic span classification as an auxiliary task to assist coreference. Miculicich and Henderson (2019) and Yu et al. (2019) both improve the mention detector with better neural network structures. Yet they still need to manually set a threshold to control the number of selected

candidate mentions and non of them could produce an optimal span selection for downstream task. Finkel and Manning (2009) situate NER in a parsing framework by explicitly incorporating named entity types into parse tree labels. In contrast, our work requires neither syntax annotations nor hyperparameter tuning for mention selection.

Zhang et al. (2018) proposed a multi-task style loss to provide direct supervision to mention detection. Yet the seemingly simplistic and heuristic mention detection scheme by greedily taking a fixed top portion of all candidate spans still remains unchanged in the aforementioned work.

Pretrained contextual word representations (Joshi et al., 2019, 2020; Lee et al., 2018) and higher-order inference techniques (Lee et al., 2018; Kantor and Globerson, 2019; Xu and Choi, 2020) have brought major improvements to the original model by Lee et al.. Aside from this line of work, Wu et al. (2020) formulate coreference resolution as a question answering task, and achieve state-of-the-art results on multiple benchmarks.

2.3 Semantic Role labeling

Semantic role labeling (SRL) extracts relations between predicates and their arguments. Two major lines of work in SRL are sequence tagging models (He et al., 2017; Marcheggiani et al., 2017) and span-based models (He et al., 2018; Ouchi et al., 2018; Li et al., 2019).

Sequence tagging models for SRL convert semantic role annotations to BIO sequences. The tagger generates a label sequence for one single predicate at a time. However, span-based models generate the set of all candidate arguments in one forward pass, and classify their semantic roles with regard to each predicate. As discussed in (He et al., 2018), span-based models empirically perform better than sequence tagging models as they incorporate span-level features. Span-based models also do better at long-range dependencies as well as agreement with syntactic boundaries.

Very recently, Zhang et al. (2021) explore a novel direction by reducing semantic role labeling to a dependency parsing task and find promising results.

2.4 Nested and Partial Span Annotations

Nested mentions and partially annotated mentions are the two major concerns of this work. Various datasets contain partial annotations of mentions. For example, singletons are not annotated in Ontonotes (Pradhan et al., 2012). In the following coreference resolution example, the bracketed nested spans are annotated, while the underlined spans are valid mentions that are missed out, since they do not co-refer with any other mention in the same document.

> [The President]$_1$ has said $\big[$[he]$_1$ and [his]$_1$ wife, now a [New York]$_3$ senator$\big]_2$ will spend weekends at [their]$_2$ house in <u>Chappaqua</u>.

The same issues also exist in SRL data. In the example below, there are two predicates (boxed words in the example) in one sentence. Their arguments are nested (i.e. ARG1 and ARG2 of the second predicate locate within ARG2 of the first predicate). Besides, many syntactic constituents that could form valid arguments are unannotated.

> [The most important thing about Disney]$_{1\text{-ARG1}}$ $\boxed{\text{is}_1}$ [that [it]$_{2\text{-ARG1}}$ $\boxed{\text{is}_2}$ [a global brand]$_{2\text{-ARG2}}$]$_{1\text{-ARG2}}$.

3 A Structured Span Selection Model

We first start by giving a formal definition of span selection tasks. We define a **document** to be a sequence of words, e.g. $D = [w_1, \ldots, w_{|D|}]$. A **span** is a contiguous subsequence of words in the document. We write $[i, j]$ to denote the contiguous subsequence of words $w_i \ldots w_j$. Span $[i, j]$ is of interest in the downstream task, e.g. if it is an entity in coreference resolution or if it is an argument in semantic role labeling, denoted as $\mu[i, j]$.

Previous work has mostly considered a greedy procedure for span selection. The approach produces a score $s(\mu_{ij})$ *independently* for each span $\mu[i, j]$ in the document. As the number of spans $\mu[i, j]$ is potentially very large, the set of spans are greedily pruned to a set of size K:

$$S^* = \text{Top-K}\left(\{s(\mu_{ij}) | 1 \leq i < j \leq |D|\}\right) \quad (1)$$

We will see later in our experiments that tuning K can be quite challenging. Moreover, as the greedy approach scores each span independently, it cannot judiciously make use of the provided span annotation.

3.1 A Weighted Context-Free Grammar for Span Selection

To mitigate the issues with greedy span selection used in prior work and to effectively utilize the partial nested span annotations, we propose to train a CFG parser defined by Gaddy et al. (2018) using only partial annotations. The original parser

takes as input the scores $s([i,j],l)$ of assigning constituent label l to span $[i,j]$. We propose to learn a grammar that has only one type of constituents given to us for span selection, that is, is a span of interest in the downstream task or not. Following Gaddy et al. (2018), we eliminate the need for binarization by setting the score of a span not being a mention to 0. Thus, we use $s_p(\mu_{ij})$ as shorthand for the parsing score of span $[i,j]$.

We define the score of an annotation of a sentence as a sum over the scores of all annotated mention spans:

$$s(M) = \sum_{[i,j]\in M} s_p(\mu_{ij}), \tag{2}$$

where M is the set of annotated mention spans. The problem of mention detection is thus to find an optimal annotation tree that maximizes the score:

$$M^* = \arg\max_M s(M), \tag{3}$$

where we employ the CKY algorithm. The recursive function used is:

$$s_{\text{best}}([i,j]) = s_p(\mu_{ij}) + \max_{i\le k<j}\{s_{\text{best}}([i,k]) + s_{\text{best}}([k,j])\},$$

where $s_{\text{best}}[i,j]$ is the score of the optimal annotation over span $[i,j]$.

We use an important property of the inside-outside algorithm (Baker, 1979) to learn the marginal distribution $p(\mu_{ij})$. Borrowing the notations from CFG parsing, let $\mathcal{T}$ be the set of all mention annotations of the input sentence, $\mathcal{T}_{ij}$ be the set of those that contains μ_{ij}, and $Z = \sum_{M\in\mathcal{T}} \exp(s(M))$:

$$p(\mu_{ij}) = \sum_{M\in\mathcal{T}_{ij}} p(M) = \sum_{M\in\mathcal{T}_{ij}} \frac{\exp(s(M))}{Z}$$

We now briefly introduce the inside-outside algorithm and how to efficiently calculate $p(\mu_{ij})$. For a span $[i,j]$, its inside value is defined as

$$\alpha([i,j]) = \exp(s_p(\mu_{ij})) \sum_{k=i}^{j-1} \alpha([i,k]) \cdot \alpha([k,j]),$$

and $\alpha([i,j]) = \exp(s_p(\mu_{ij}))$ when $i = j$. As described by Eisner (2016), we can calculate the marginal probability $p(\mu_{ij})$ by backpropagating through the log-transformed inside value $\log Z = \log \alpha([0,n])$. Finally, we have

$$p(\mu_{ij}) = \frac{\partial \log Z}{\partial s_p(\mu_{ij})}, \tag{4}$$

which can be efficiently computed with the automatic differentiation in modern deep learning tools such as PyTorch. For details of deduction of Eq. (4), we refer the readers to (Eisner, 2016, Sec 4.3).

4 Adaptations to Downstream Tasks

In this section, we introduce how our structured span selector can be applied in end-to-end frameworks for coreference resolution and SRL.

4.1 Coreference Resolution

The goal of coreference resolution is to connect every mention $\mu[i,j]$ to its **antecedent**, which is itself another mention in the same document. Note that in the formulation of coreference discussed in this task, a mention may have a dummy antecedent, denoted as ϵ, if it is not a mention or does not co-refer with any previous span.

The core technical contribution of this paper is a joint model for mention detection and downstream tasks. We write $\mu[i,j] \rightsquigarrow \mu[k,\ell]$ to denote that $\mu[i,j]$ co-refers with $\mu[k,\ell]$; in other words, that $\mu[k,\ell]$ is $\mu[i,j]$'s antecedent. Our paper introduces the following framework for joint modeling mention detection and coreference resolution:

$$\underbrace{p(\mu[i,j])}_{\text{pr. } \mu[i,j] \text{ is a mention}} \times \underbrace{p\left(\mu[i,j] \rightsquigarrow \mu[k,\ell] \mid \mu[i,j]\right)}_{\text{pr. } \mu[i,j]\text{'s antecedent is } \mu[k,\ell]}$$

From now, we use μ_{ij} as a shorthand for $\mu[i,j]$, and $p(\mu_{ij} \rightsquigarrow \mu_{k\ell})$ for $p(\mu_{ij} \rightsquigarrow \mu_{k\ell} \mid \mu_{ij})$. The joint distribution is then $p(\mu_{ij} \rightsquigarrow \mu_{k\ell}, \mu_{ij}) = p(\mu_{ij} \rightsquigarrow \mu_{k\ell})\, p(\mu_{ij})$. In principle, modelers can choose $p(\mu_{ij})$ and $p(\mu_{ij} \rightsquigarrow \mu_{k\ell})$ according to their taste. In this work, we implement $p(\mu_{ij})$ as a weighted context-free grammar, which we describe in §3.1 and $p(\mu_{ij} \rightsquigarrow \mu_{k\ell})$ as Lee et al. (2017)'s popular coreference model, described in §4.1.

Lee et al. (2017) as Mention Linker. We choose $p(\mu_{ij} \rightsquigarrow \mu_{k\ell})$ to be the one from (Lee et al., 2017). In principle, we can use any mention-ranking model that computes a distribution over $\mathcal{Y}([i,j])$, the set of preceding spans of $[i,j]$. But we choose (Lee et al., 2017) because it is very well known and effective. Using $\mathcal{Y}_{ij}$ as a shorthand for $\mathcal{Y}([i,j])$:

$$p(\mu_{ij} \rightsquigarrow \mu_{k\ell}) = \frac{\exp(s(\mu_{ij}, \mu_{k\ell}))}{\sum_{m\in\mathcal{Y}_{ij}} \exp(s(\mu_{ij}, m))},$$

$$s(\mu_{ij}, \mu_{k\ell}) = s_m(\mu_{ij}) + s_m(\mu_{k\ell}) + s_a(\mu_{ij}, \mu_{k\ell}).$$

$s_m(\mu_{ij})$ is a score for span $[i,j]$ being a mention and $s_a(\mu_{ij}, \mu_{k\ell})$ for $[k,\ell]$ to be a coreferent

antecedent of $[i, j]$. Both s_a and s_m are computed by neural networks that take span representations as inputs. The score $s(\mu_{ij}, \epsilon)$ is fixed to 0.

Training, Decoding and Other Concerns. As for mention detection, Lee et al.'s model adopts a naïve greedy algorithm by taking the top $\lambda|D|$ spans with the highest mention scores s_m, where λ is a hyperparameter that has to be manually defined for different datasets. However, finding a proper ratio λ can be very tricky. Since in many coreference datasets such as OntoNotes, only the mentions that are referred to more than once are annotated (as discussed in §3.1), learning a mention detector from such data requires the ability to handle partially annotated examples.

The case that $[i, j]$ is assigned to an antecedent assignment ϵ (i.e. $y_{ij} = \epsilon$) happens when (a) $[i, j]$ is a singleton mention, or (b) $[i, j]$ is the first appearance in a mention cluster, or (c) $[i, j]$ is not a valid mention. To handle the partial annotation and retrieve valid mentions that are not annotated in the dataset, we split the probability into two separate terms corresponding to the above scenarios:

$$p(\mu_{ij} \rightsquigarrow \epsilon, \mu_{ij}) = p(\mu_{ij})p(\mu_{ij} \rightsquigarrow \epsilon) + (1 - p(\mu_{ij})). \tag{5}$$

We expect singleton mentions to have a larger first term and smaller second term, and the opposite for non-mentions. The final objective function is then the negative log-likelihood of the joint distribution defined at the beginning of §4.1:

$$L = -\sum_{[i,j]} \log \sum_{m \in \mathcal{Y}_{ij} \cap \text{GOLD}_{ij}} p(\mu_{ij} \rightsquigarrow m, \mu_{ij}), \tag{6}$$

where GOLD_{ij} is the ground truth mention cluster that span $[i, j]$ belongs to.

For mention detection, the time complexity of training and inference for one sentence is $\mathcal{O}(n)$ with parallel computation. Sentence-level parallelism can also be applied to all the sentences. Thus, the overall time complexity is $\mathcal{O}(n_{\text{max}})$, the length of the longest sentence in the document.

4.2 Semantic Role Labeling

The goal of semantic role labeling is to classify the **semantic role** of every argument $\mu[i, j]$ with respect to a given predicate. Following the notation style of §4.1, we use $\mu[i, j] \overset{l}{\rightsquigarrow} v$ to denote that $\mu[i, j]$ plays the semantic role l in the frame of predicate v. The joint probability can be written as $p\left(\mu_{ij} \overset{\ell}{\rightsquigarrow} v, \mu_{ij}\right) = p\left(\mu_{ij} \overset{\ell}{\rightsquigarrow} v\right) p(\mu_{ij})$. Our joint framework for argument detection and semantic role labeling is then:

$$\underbrace{p(\mu[i, j])}_{\text{pr. } \mu[i,j] \text{ is an argument}} \times \underbrace{p\left(\mu[i, j] \overset{\ell}{\rightsquigarrow} v \mid \mu[i, j]\right)}_{\text{pr. } \mu[i,j]\text{'s role is } \ell \text{ w.r.t. predicate } v}$$

He et al. (2018) as Role Classifier. As this work focuses on span selection, we choose the role classifier to be the popular and effective one from (He et al., 2018), and use gold predicates v during training and evaluation.

The semantic role label l takes value from a discrete label space $\mathcal{L}$. The classifier then models the following probability distribution:

$$p\left(\mu_{ij} \overset{\ell}{\rightsquigarrow} v\right) = \frac{\exp\left(s(\mu_{ij}, v, \ell)\right)}{\sum_{\ell \in \mathcal{L}} \exp\left(s(\mu_{ij}, v, \ell)\right)},$$
$$s(\mu_{ij}, v, \ell) = s_m(\mu_{ij}) + s_r\left(\mu_{ij}, v, \ell\right).$$

Similar to the coreference model of Lee et al. (2017), $s_m(\mu_{ij})$ is the score for span $[i, j]$ to be an argument and $s_r\left(\mu_{ij}, v, \ell\right)$ for $[i, j]$ to play the role l for predicate v. Note that the score for ϵ label (i.e. no relation) $s(\mu_{ij}, v, \epsilon)$ is set to constant 0, similar to the null antecedent case in coreference.

Training Objective. He et al.'s model also suffers from the challenge of tuning the hyperparameter λ and the issue of partial annotation for the span selection model. To deal with these, we use a similar strategy as in §4.1. Again, the probability of null relation is split into two terms:

$$p(\mu_{ij} \overset{\epsilon}{\rightsquigarrow} v, \mu_{ij}) = p(\mu_{ij})p(\mu_{ij} \overset{\epsilon}{\rightsquigarrow} v) + (1 - p(\mu_{ij})). \tag{7}$$

Thus, the training objective for SRL with our structured span selection model is then:

$$L = -\sum_{[i,j]} \sum_{v} \log p(\mu_{ij} \overset{l}{\rightsquigarrow} v, \mu_{ij}), \tag{8}$$

where l is the correct semantic label of $\mu[i, j]$ with regard to predicate v.

5 Experiments

5.1 Datasets

Coreference: We employ the CoNLL-2012 English shared task dataset (OntoNotes) (Pradhan et al., 2012) and LitBank (Bamman et al., 2020)

in our experiments. For OntoNotes, we apply the speaker encoding in (Wu et al., 2020), that is using special tokens (`<speaker>`, `</speaker>`) to denote the speaker's name, as opposed to the original binary features used by Lee et al. (2017). This simple change brings a consistent boost to the performance by 0.2 CoNLL F1. A major difference between these two datasets is that LitBank has singleton mention annotations while OntoNotes does not. For LitBank, we use the standard 10-fold cross-validation setup, as is the standard practice.
SRL: We use the CoNLL-2012 SRL dataset. Gold predicates are provided to the model.

5.2 Coreference Resolution

We report the average precision, recall, and F1 scores of the standard MUC, B^3, and $CEAF_{\phi_4}$ and the average CoNLL F1 score on OntoNotes test set in Tab. 1. The average CoNLL F1 scores on LitBank are shown in Tab. 2. For OntoNotes, we run the experiments with 5 random initializations and the improvements reported are significant under the two-tailed *t*-test.

We compare our models with several representative previous work. In order to focus on comparing the impact of mention detection, we apply no higher-order inference techniques in our models and report the non-higher order result from (Xu and Choi, 2020). Joshi et al. (S) is the major baseline that uses SpanBERT (Joshi et al., 2020) and is trained with the speaker encoding discussed in §5.1. This encoding gives 0.2 F1 score improvement over the result reported in (Xu and Choi, 2020).

Our model with the structured mention detector achieves 80.5 F1 score, a 0.4 F1 improvement over the baseline. While on LitBank, our model achieves 76.3 F1, which is a 0.7 F1 improvement over Joshi et al.. It can also be observed that this gain mainly comes from improved recall, which is because we have a superior mention detector that can retrieve mentions with better accuracy. We further analyze this result in the following section.

5.2.1 Analysis of Mention Detector

Next, we examine the performance of our proposed mention detection scheme. As shown in Fig. 2, compared with Joshi et al. (S), our model predicts a far more accurate set of mentions with a higher recall. In contrast to Joshi et al. (S) who select $0.4|D|$ mention spans, our method only selects $0.26|D|$ mention spans with a slightly higher mention recall. The smaller span set would make the overall coreference model more efficient as well.

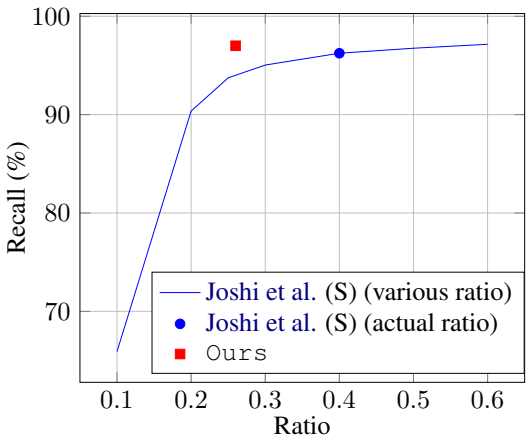

Figure 2: Recall of gold mentions as we vary the ratio of spans kept. Ratio refers to the number of predicted mentions divided by $|D|$. Our mention detector significantly outperforms Joshi et al. (S)'s with a ratio of 0.26 and a recall of 97.0%. Yet Joshi et al. (S) only achieves 96.2% recall with a ratio of 0.40.

5.2.2 Analysis of Structured Modeling

To see how our structured modeling benefits the overall coreference model, we further compare our approach with a baseline `Sigmoid` which replaces the $p(\mu_{ij})$ in Eq. (4) with a simple non-structured estimator:

$$p_\sigma(\mu_{ij}) = \sigma(s_p(\mu_{ij})), \tag{9}$$

where σ is the sigmoid function $\sigma(x) = \frac{1}{1+\exp(-x)}$. The loss function used for `Sigmoid` is identical with our structured model as given in Eq. (6). Through this comparison, we aim to show the effectiveness of structured modeling.

We also build a multi-task learning baseline `MTL` similar to (Swayamdipta et al., 2018). The model performs an auxiliary task which classifies spans into noun phrase, other syntactic constituent, or non-constituent. The coefficient of the multi-task loss is set to 0.1 as in (Swayamdipta et al., 2018).

This comparison is shown in Tab. 3. We find that replacing $P(i)$ with unstructured $P_\sigma(i)$ degrades the performance by 0.3 F1 score. Thus, we conclude that the structured probability function is more expressive than $P_\sigma(i)$ as it models the global annotation for each sentence. In contrast, the mention detector of Joshi et al. (S) and `Sigmoid` models each span independently.

	MUC			B^3			$CEAF_{\phi_4}$			
	P	R	F	P	R	F	P	R	F	Avg. F1
Lee et al. (2017)	78.4	73.4	75.8	68.6	61.8	65.0	62.7	59.0	60.8	67.2
Lee et al. (2018)	81.4	79.5	80.4	72.2	69.5	70.8	68.2	67.1	67.6	73.0
Fei et al.	85.4	77.9	81.4	77.9	66.4	71.7	70.6	66.3	68.4	73.8
Kantor and Globerson	82.6	84.1	83.4	73.3	76.2	74.7	72.4	71.1	71.8	76.6
Joshi et al. (2019)	84.7	82.4	83.5	76.5	74.0	75.3	74.1	69.8	71.9	76.9
Joshi et al. (2020)	85.8	84.8	85.3	78.3	77.9	78.1	76.4	74.2	75.3	79.6
Xu and Choi	85.7	85.3	85.5	78.6	78.6	78.6	76.8	74.8	75.8	79.9
Joshi et al. (S)	86.6	84.5	85.6	80.4	77.3	78.8	77.8	74.0	75.8	80.1
Ours	86.1	85.5	**85.8**	79.8	78.8	**79.3**	77.4	75.4	**76.4**	**80.5**

Table 1: Results on the CoNLL-2012 English shared task test set. Avg. F1 in the last column denotes the average F1 of MUC, B^3, and $CEAF_{\phi_4}$. Joshi et al. (S) refers to the original end-to-end model with SpanBERT and trained with speaker encoding. **The improvements shown in the table are significant under the two-tailed *t*-test.**

	Avg. P	Avg. R	Avg. F1
Bamman et al.	-	-	68.1
LB-MEM	-	-	75.7
U-MEM	-	-	75.9
Joshi et al.	78.7	72.9	75.6
Ours	77.4	75.3	**76.3**

Table 2: Results on the test set of LitBank. The results are averaged over 10 train/dev/test splits. LB-MEM and U-MEM are reported in (Toshniwal et al., 2020).

	Avg. P	Avg. R	Avg. F1
Joshi et al. (S)	81.6	78.6	80.1
Sigmoid	80.8	79.6	80.2
MTL	80.8	78.9	79.8
Ours	81.1	79.9	**80.5**

Table 3: Comparison with three constructed baselines.

5.2.3 Qualitative Analysis

To shed some light on where the gains of our proposed model come from, we also exhibit some qualitative results in this section.

Nested Mentions. We first investigate the capability of our structured model in handling nested mentions. Tab. 4 shows the recall rate of mentions of different nested depth. Here, nested depth refers to the level of nesting in the mentions. E.g. in the first example given in §2.4, *The president* is of depth 1, while *he and his wife, now a New York senator* is of depth 2.

As shown in Tab. 4, the gains of our method are larger for deeply nested mentions, which highlights the capability of our structured span detector to handle harder nested mentions that cannot be handled by the greedy selector.

Nested Depth	1	2	3+
Greedy	96.5	87.1	86.2
Ours	97.8	93.2	93.9

Table 4: Recall rate of mentions of different nested depth on CoNLL-2012 dev set. There are 16873, 2100, and 182 mentions respectively of each nested depth.

Widths of Mentions. We also compare the recall rate for mentions of different widths in Tab. 5. We show that our model can detect longer spans better, which are usually more difficult to detect. For spans with 5-12 words, our structured model still maintains a recall rate of 96.5%, compared to a sharp drop of the greedy unstructured model.

Span Width	1-4	5-12	12+
Greedy	96.2	92.7	82.5
Ours	97.8	96.5	85.2

Table 5: Recall rate of mentions of different width on CoNLL-2012 dev set. There are 16356, 2180, and 619 mentions respectively of each width interval.

5.3 Semantic Role Labeling

For semantic role labeling, we report the precision, recall, and F1 score on the CoNLL-2012 SRL dataset. The gold predicates are provided during

both training and evaluation. Therefore, the model have to focus on extracting the correct arguments and classifying their roles for each predicate. The results are shown in Tab. 6 in comparison with previous span-based models. He et al.$_{\text{SpanBERT}}$ refers to the model of He et al. (2018) with SpanBERT$_{\text{large}}$ (Joshi et al., 2020) as sentence encoder.

5.3.1 Analysis of Argument Detection

	Avg. P	Avg. R	Avg. F1
He et al. (2018)	-	-	85.5
Ouchi et al. (2018)	87.1	85.3	86.2
Li et al. (2019)	85.7	86.3	86.0
Shi and Lin (2019)	85.9	87.0	86.5
He et al.$_{\text{SpanBERT}}$	88.3	85.9	87.1
`Ours`	88.1	86.9	**87.5**

Table 6: Results on the test set of CoNLL-2012 semantic role labeling task. The precision, recall, and F1 scores are averaged over all semantic roles.

Next, we report the performance of our span selector on the SRL task. Following the same trend as coreference resolution, we find that our structured model is able to extract much more accurate arguments and thus, significantly reduce the memory consumption for the downstream task. While keeping a comparable recall rate of gold arguments (96.5% for the greedy selector and 96.2% for `ours`), our span selector reduces the number of enumerated spans by 21.2%.

	P	R	F1
`BIO`	90.2	91.0	90.6
`Greedy`	92.8	90.2	91.5
`Ours`	92.8	91.2	92.0

Table 7: Comparison of unlabeled span accuracy.

We compare the accuracy of retrieving unlabeled argument spans in Tab. 7. `BIO` refers to the tagger-style SRL model using the same text encoder. Our model outperforms the other two baselines.

5.4 Qualitative Examples

In this section, we show a qualitative example to illustrate the grammar learned by our span selector for coreference resolution and SRL.

Two sets of extracted spans for the same input sentence are shown in Tab. 8. For coreference resolution, our model selects maximal NPs (containing all modifiers) and verbs. While in SRL, the parse tree consists of much denser and syntactically heterogeneous spans of NPs, PPs, modal verbs, and adverbs, etc.. This comparison empirically shows that our model is capable and robust enough to learn much more complex underlying grammars from partial annotation.

Input	The world' s fifth Disney park will soon open to the public here .
Coref	[[The world' s] fifth [Disney] park] will soon [open] to [the public] here.
SRL	[The world' s [fifth] [Disney] [park]] [will] [soon] [[open] [to the public]] [here].

Table 8: A qualitative example of the grammar learned by the structured span selector on coreference resolution and SRL.

5.5 Memory Efficiency

We further analyze the memory efficiency of our model. We evaluate the peak GPU memory usage on the development set of OntoNotes. For both tasks, we see a significant reduction in memory usage of 27% for coreference and 24% for SRL.

	Coref	SRL
`Greedy`	11.5	12.2
`Ours`	8.5	9.3

Table 9: Comparison of peak GPU memory usage in GBs at inference time on development set.

6 Conclusion and Future Work

In this paper, we proposed a novel structured model for span selection. In contrast to prior span selection methods, the model is structured, which allows it to model the spans better. Instead of a greedy span selection procedure, the span selector uses partial span annotations provided in data to directly obtain the set of optimal spans. We evaluated our span selector on two typical span prediction tasks, namely coreference resolution and semantic role labeling, and achieved consistent gains in terms of accuracy as well as efficiency. In the future, we plan to generalize the proposed span selection model to other NLP tasks, e.g. extractive question answering (Lee et al., 2016). It would also be interesting to experiment with various pretraining techniques for span selection.

Ethical Considerations

To the best of our knowledge, the datasets used in our work do not contain sensitive information. Although our model has been evaluated under academic settings, it could also be applied in sensitive contexts, e.g. healthcare or legal scenarios. It is essential that necessary anonymization and robustness evaluation is undertaken before using our model in these settings.

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A Experimental Settings

The systems are implemented with PyTorch. We use SpanBERT$_{\text{large}}$ as text encoder. We train the model for 20 epochs and select the best performing model on the development set for testing. The documents are split into 512 word segments to fit in SpanBERT$_{\text{large}}$. Models used for coreference resolution have 402 million learnable parameters, and models for SRL have 382 million learnable parameters.

We closely follow the hyperparameter settings of Joshi et al. (2020) and build our models upon the codebase of Xu and Choi (2020) [2] under Apache License 2.0. The learning rate of SpanBERT$_{\text{large}}$ parameters is set to 1×10^{-5} with 0.01 decay rate, and the learning rate of task parameters is set to 3×10^{-4}. The dropout rate of feedforward neural network scorers is set to 0.3. When training our model, we randomly sample $0.1|D|$ negative spans that are not mentions and add their negative log-likelihood $-\log p(\mu_{ij})$ to the training objective. This is to prevent $p(\mu_{ij})$ from converging to 1.

For SRL task, we use a batch size of 32 for 40 epochs and the same learning rate with coreference resolution. The same negative sampling technique is applied.

Our models are trained on Nvidia Tesla V100 GPUs with 32GB memory. The average training time is around 8 hours for Joshi et al. (S) baseline, and around 9 hours for our model. For SRL models, training takes 25 hours.

B Results on the Development Set

In this section, we report the results that our models get on the development sets of OntoNotes and LitBank.

	Avg. P	Avg. R	Avg. F1
Joshi et al. (S)	82.0	78.8	80.4
`Sigmoid`	81.6	79.4	80.5
`Ours`	81.1	80.2	**80.7**

Table 10: Results on CoNLL-2012 coreference resolution development set.

	Avg. P	Avg. R	Avg. F1
Joshi et al. (S)	78.8	73.7	76.1
`Ours`	77.4	75.6	**76.6**

Table 11: Results on LitBank development set.

	Avg. P	Avg. R	Avg. F1
He et al.$_{\text{SpanBERT}}$	87.9	85.0	86.4
`Ours`	87.8	86.2	**87.0**

Table 12: Results on CoNLL-2012 semantic role labeling development set.

[2] https://github.com/lxucs/coref-hoi