Natural Language Understanding, Generation, and Machine Translation

Lecture 12: Unsupervised Parsing

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The Story so Far

Unsupervised Parsing

Unsupervised Parsing via Constituency Tests

Grammaticality Model

Results

Co-training for Unsupervised Parsing

Reading: Cao et al. [2020], optional: Maveli and Cohen [2022]

The Story so Far

Neural Parsing

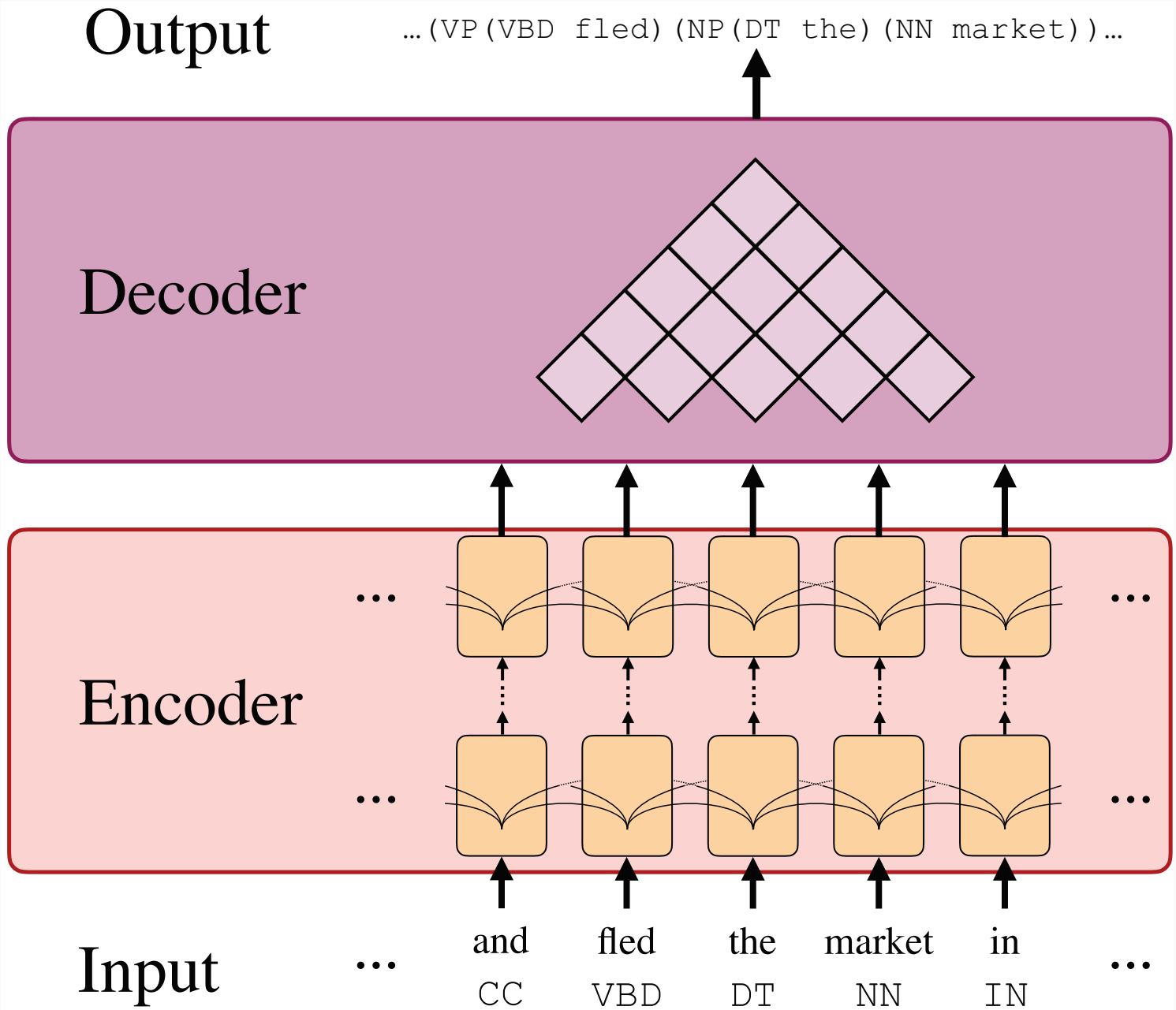
- We have seen how **encoder-decoder models** can be used for syntactic parsing: the input is a sequence of words, the output is a sequence of labeled brackets.
- This approach can use LSTMs or transformers, decoding can use beam search or CYK.
- An alternative is to model **parser transitions,** i.e., the actions that are required to build a syntax tree [Kim et al., 2019]. Not discussed in this course.

Neural Parsing

- We have seen how **encoder-decoder models** can be used for syntactic parsing: the input is a sequence of words, the output is a sequence of labeled brackets.
- This approach can use LSTMs or transformers, decoding can use beam search or CYK.
- An alternative is to model **parser transitions,** i.e., the actions that are required to build a syntax tree [Kim et al., 2019]. Not discussed in this course.

But what if we don't have **syntactically labeled training data?** Can we still infer syntactic structure if we have lots of text?

Neural Encoder-Decoder Parsing



Unsupervised Parsing

Unsupervised Parsing

Goal of unsupervised parsing: induce syntactic structure from **unlabeled text:**

- this is an old problem in the literature on formal grammars (Gold's theorem);
- human children learn the syntax of their native language with little supervision;
- we have treebanks for a few dozen languages (out of the world's around 6,000);
- unsupervised parsing can be used as the first stage in constructing larger treebanks.

But: Unsupervised parsing is hard! SotA F-score is around 60, compared to $>$95 for supervised parsing.

Unsupervised Parsing

Key insights for grammar induction:

- exploit the idea behind linguistic constituency tests;
- a sequence of words is a constituent if it appears in the context specific for this constituent;
- long constituents often have short equivalents (pro-forms), e.g., a noun phrase can be replaced by a pronoun;
- the constituency of pro-forms is easy to discover, they are often single words;
- we will use constituency test to discover which **spans** (sequences of words) should be **phrases.**

Unsupervised Parsing

The insights on the previous page were first used for unsupervised parsing by Klein and Manning [2002].

Their **Constituent Context Model** (CCM) was the first unsupervised parsing model that beat the righ-branching baseline for English.

Today, we will look at a neural incarnation of this idea. Cao et al. [2020] model combines constituency tests with **pre-trained language models** such as BERT.

Unsupervised Parsing via Constituency Tests

Constituency Tests

Example: *by midday , [the london market] was in full retreat*

A: *by midday ,*

B: *the london market*

C: *was in full retreat*

where B is the **span of words being tested for constituency.**

Cao et al. [2020] use the following constituency tests:

Name	Applied to "A [B] C"	Example
Clefting	it {is, was} B that A C	*it {is, was} the london market that by midday , was in full retreat*
Coordination	A B and B C	*by midday , the london market and the london market was in full retreat*
Substitution	A {it, ones, did so} C	*by midday , {it, ones, did so} was in full retreat*
Front Movement	B , A C	*the london market , by midday , was in full retreat*
End Movement	A C B	*by midday , was in full retreat the london market*

Now try this with a non-constitutent (e.g., *market was*)! You will get ungrammatical strings.

Unsupervised Parsing via Constituency Tests

General approach proposed by Cao et al. [2020]:

- **constituency test:** take a sentence, modify it via a transformation (e.g., replace a span with a pronoun);
- check if the result is grammatical using a neural grammaticality model;
- produce a tree for the sentence by aggregating the results of constituency tests over spans;
- select the tree with the highest score;
- add to this **refinement:** alternate between improving the tree and improving the grammaticality model.

Constituency Tests

Transformation function: $c : (\texttt{sent}, i, j) \mapsto \texttt{sent}'$
takes the span i to j of a sentence and outputs a new sentence.

Judgment function: $g : \texttt{sent} \mapsto \{0, 1\}$
judges whether the resulting sentence is grammatical or not.

- Assumption: the span is a constituent if the transformed sentence is grammatical.
- We need a set of transformations (manually specified) and a grammaticality model (learned).
- Constituency tests provide the model with an inductive bias.
- Note that not all constituency tests that linguists use are based on transformations (e.g., semantic preservation).

Parsing Algorithm

Key idea: score each span in the sentence and then choose the tree with the best total score.

Let $g_\theta : \texttt{sent} \mapsto [0, 1]$ be the grammaticality model with parameters θ.

We score each span by averaging the grammaticality judgments over the constituency tests C:

$$s_\theta(\texttt{sent}, i, j) = \frac{1}{|C|} \sum_{c \in C} g_\theta(c(\texttt{sent}, i, j))$$

Then, we score each tree by summing the scores of its spans and choose the highest scoring binary tree via CYK:

$$t^*(\texttt{sent}) = \operatorname*{argmax}_{t \in T(\texttt{len(sent)})} \sum_{(i,j) \in t} s_\theta(\texttt{sent}, i, j)$$

$T(\texttt{len(sent)})$ is the set of binary trees with $\texttt{len(sent)}$ leaves.

Grammaticality Model

Initializing the Grammaticality Model

- To train the grammaticality model, we need a corpus of grammatical and ungrammatical sentences as training data.
- However, this would constitute a form of supervision.
- So instead we train the grammaticality model using a **real/fake task.**
- Given an unlabeled corpus of sentences and a set of **corruptions,** the task is to predict whether a sentence is real or corrupted.
- The grammaticality model is not trained from scratch, but by fine-tuning RoBERTa, a variant of BERT.
- 5 million sentences from English Gigaword serve as a the unlabeled training corpus.

Initializing the Grammaticality Model

Cao et al. use the following set of corruptions:

Name	Description
Shuffle	Choose a random subset of words in the sentence and randomly permute them.
Swap	Choose two words and swap them.
Drop	Choose a random subset of words in the sentence and drop them.
Span Drop	Choose a random contiguous span of words and drop it.
Span Movement	Choose a random contiguous span of words and move it to the front or back.
Bigram	Generate a sentence of the same length using a bigram language model trained

The grammaticality model must determine whether a given sentence is real or corrupted.

Refining the Grammaticality Model

Refinement procedure:

1. Using the span-based algorithm, parse a batch B of sentences.
2. Use these trees as pseudo-gold labels to update the span judgments.
3. Repeat for the next batch of sentences.

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Updating span judgments: For each sentence, minimize binary cross-entropy (included in predicted tree or not):

$$\sum_{(i,j)\in t^*(\texttt{sent})} \log(s_\theta(\texttt{sent}, i, j)) + \sum_{(i,j)\notin t^*(\texttt{sent})} \log(1 - s_\theta(\texttt{sent}, i, j))$$

$s_\theta(\texttt{sent}, i, j)$ only depends on the grammaticality model, so we are optimizing its parameters: increase the grammaticality judgments of constituent, decrease the judgments of non-constituents.

Results

Comparison with other Unsupervised Parsers

Model	PTB F1 Mean	PTB F1 Max
PRPN† (Shen et al., 2018)	37.4	38.1
URNNG (Kim et al., 2019b)	–	45.4
ON† (Shen et al., 2019)	47.7	49.4
Neural PCFG† (Kim et al., 2019a)	50.8	52.6
DIORA (Drozdov et al., 2019)	–	58.9
Compound PCFG† (Kim et al., 2019a)	55.2	60.1
Left Branching	8.7	
Balanced	18.5	
Right Branching	39.5	
Ours (before refinement)	48.2	
Ours (after refinement)	**62.8**	**65.9**
Oracle Binary Trees	84.3	

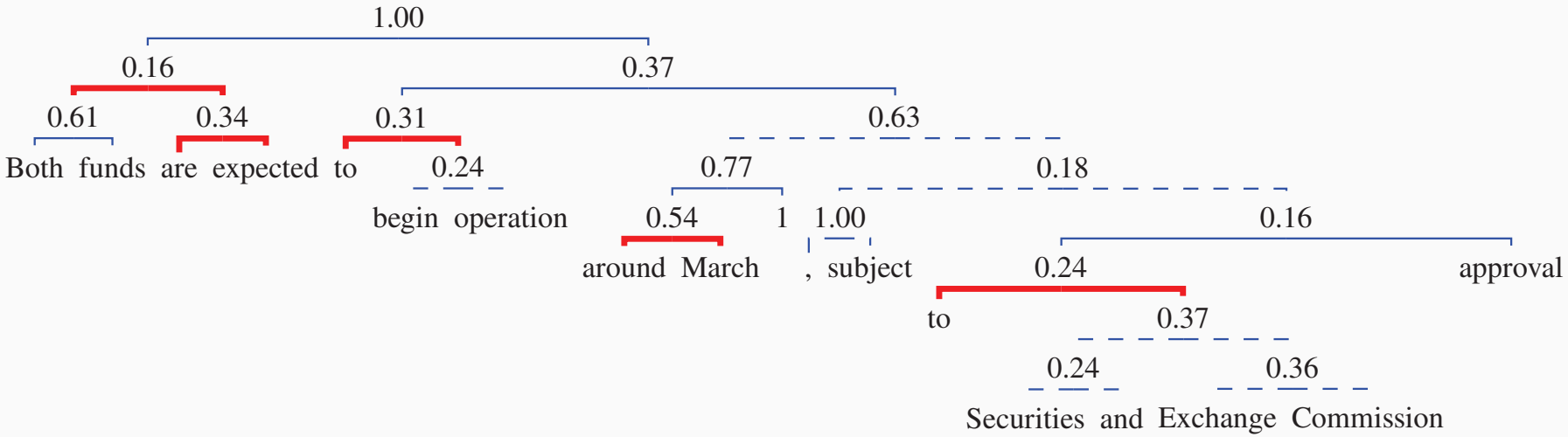
Combination with Unsupervised RNNG

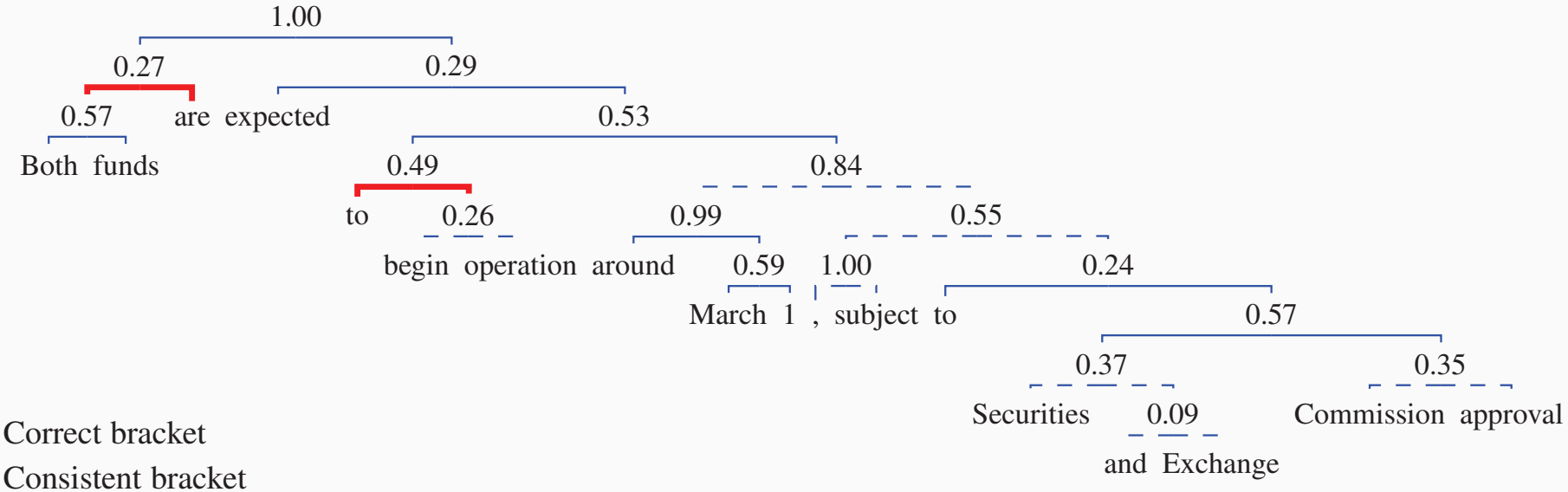
Unsupervised RNNG is a variant of Recurrent Neural Network Grammar proposed by Kim et al. [2019].

URNNG can be trained using the induced trees of another unsupervised parser, followed by fine tuning with an LM objective.

Model	PTB F1	
	Initial (Max)	+URNNG
PRPN	47.9	51.6
ON	50.0	55.1
Neural PCFG	52.6	58.7
Compound PCFG	60.1	66.9
Ours (after refinement)	65.9	**71.3**
Supervised Binary RNNG	71.9	72.8

Analysis of the Output: Before and After Refinement



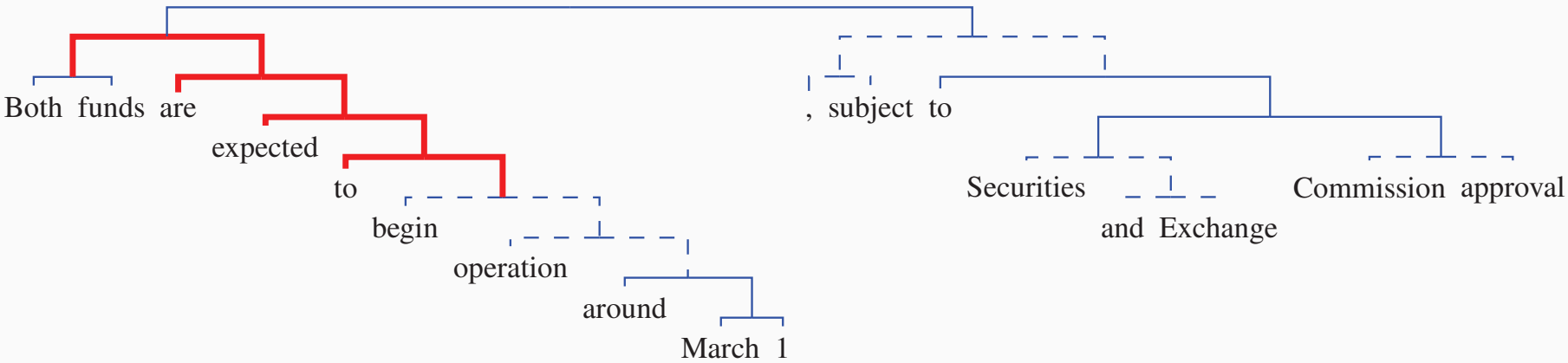


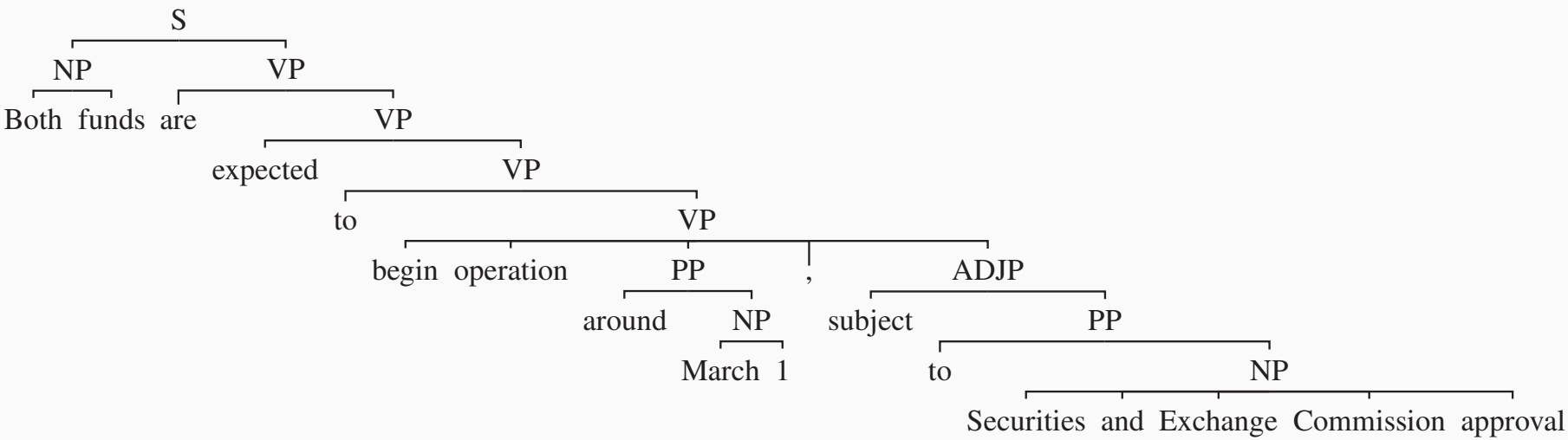
Correct bracket

Consistent bracket

Crossing bracket

Analysis of the Output: After Refinement+URNNG and Gold





Correct bracket

Consistent bracket

Crossing bracket

Analysis of Model Behavior

Cao et al. provide a detailed analysis of the behavior of their model:

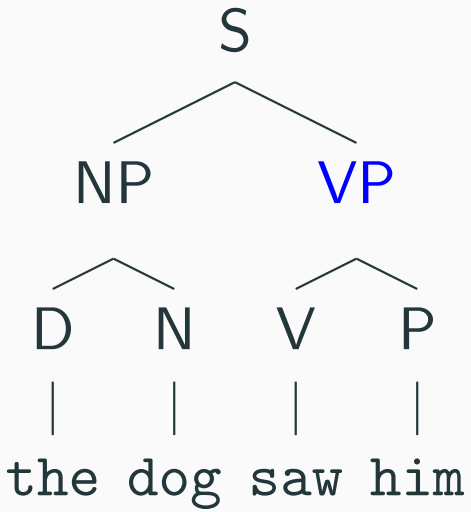
- recall by constituency label
- analysis by constituency test
- common mistakes
- example trees

This is something to emulate!

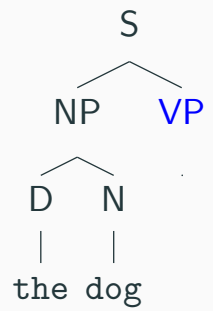
Co-training for Unsupervised Parsing

PCFGs, the Supervised Case

At node VP:



Outside tree o =

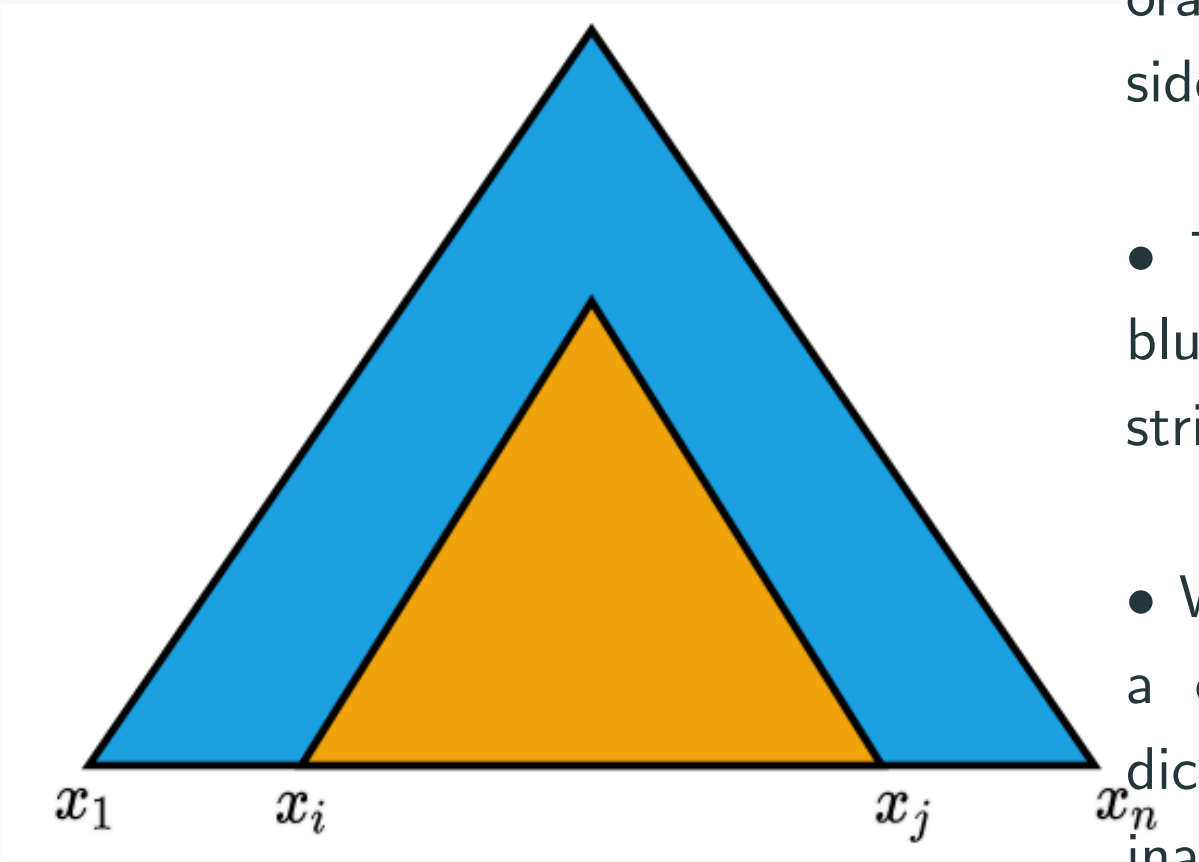


Inside tree t =

Conditionally independent given the label and the connecting nonterminal

$$p(o, t|\text{VP}) = p(o|\text{VP}) \times p(t|\text{VP})$$

Inside Outside Strings



- The yield of the orange part is "inside string"
- The yield of the blue part is "outside string"
- We will bootstrap a classifier to predict if a node dominates a pair of (inside,outside) strings

Co-training (Yarowsky, 1995; Blum and Mitchell, 1998)

Roughly! Repeats the following steps (given unlabeled data U and labeled data L):

- Train a classifier with one "view" on L
- Train a classifier with another "view" on L
- Take some (confident) predictions on U from both classifiers and add to L

Co-training works best when the two views are conditionally independent given the label

And In Our Case...

This leads to:

- Take all sentences, and break them all possible ways into inside/outside strings
- Get neural representations for each pair (i, o) as two "views"
- Take a subset of these L, and label them with some heuristics - the label is whether (i, o) has a node that connects them
- Do co-training

Weak Supervision

What would be the seed dataset to start the co-training process?

- All $(start, end)$ spans for a given sentence have label 1 (are constituents)
- All $(start, end - i)$ for $i = 1, 2, ..., 6$ have label 0
- Another simple heuristic that relies on casing

How Do We Use These Labels?

Let

- $p_i(e)$ be the confidence of the classifier for an inside of span e
- $p_o(e)$ be the confidence of the classifier for an outside of span e

Then, for three different types of scores:

- $score(e) = p_i(e)$
- $score(e) = p_o(e)$
- $score(e) = p_i(e) \cdot p_o(e)$

find the tree $t^* = \arg\max_t \sum_{e \in t} score(e)$

Also referred to as span decoding

Results

Model	WSJ-Full		WSJ-10	
	Mean	Max	Mean	Max
Trivial Baselines:				
Left Branching (LB)	8.7		17.4	
Balanced	18.5			
Right Branching (RB)	39.5		58.5	
Unsupervised Parsing approaches:				
PRPN† (Shen et al., 2018)	37.4	38.1	58.4	–
URNNG⋆ (Kim et al., 2019b)	–	45.4	–	–
ON† (Shen et al., 2019)	47.7	49.4	63.9	–
Tree Transformer†⋆ (Wang et al., 2019)	50.5	52.0	66.2	–
Neural PCFG† (Kim et al., 2019a)	50.8	52.6	64.6	–
DIORA⋆ (Drozdov et al., 2019)	–	58.9	60.5	–
Compound PCFG† (Kim et al., 2019a)	55.2	60.1	70.5	–
S-DIORA†⋆ (Drozdov et al., 2020)	57.6	64.0	71.8	–
Constituency Test⋆ (Cao et al., 2020)	62.8	65.9	68.1	–
Ours⋆ (using inside)	55.9	57.2	66.2	–
Ours⋆ (using inside w/ self-training)	61.4	64.2	71.7	–
Ours⋆ (using inside and outside w/ co-training)	**63.1**	66.8	**74.2**	–
Oracle Binary Trees	84.3		82.1	

Summary

- We don't have treebanks for most of the world's language, so we can't train supervised parsers.
- Instead, use unsupervised parsing models, which learn syntax trees from unlabeled text.
- Use constituency tests from linguistic theory: transformation applied to a sentence span that preserves grammaticality.
- Requires a model to judge grammaticality. Obtained by fine-tuning RoBERTa.
- Select the parse tree that maximizes the grammaticality scores of its spans.
- Performs well, but requires with refinement (self-training); can be combined with Unsupervised RNNG.

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