

# On the Role of Style in Parsing Speech with Neural Models



Trang Tran, Mari Ostendorf – University of Washington  
Jiahong Yuan, Yang Liu – LAIX Inc.



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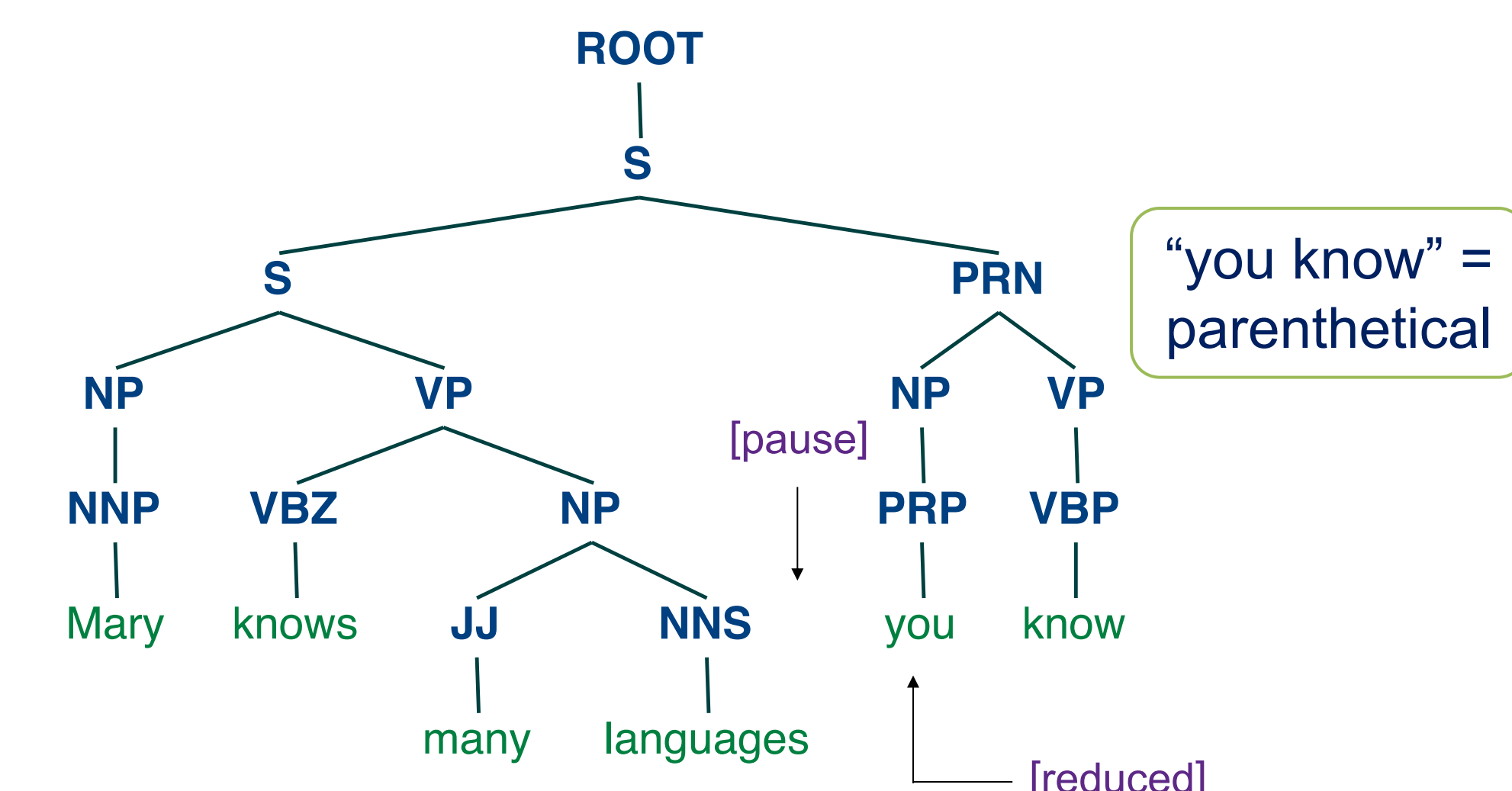
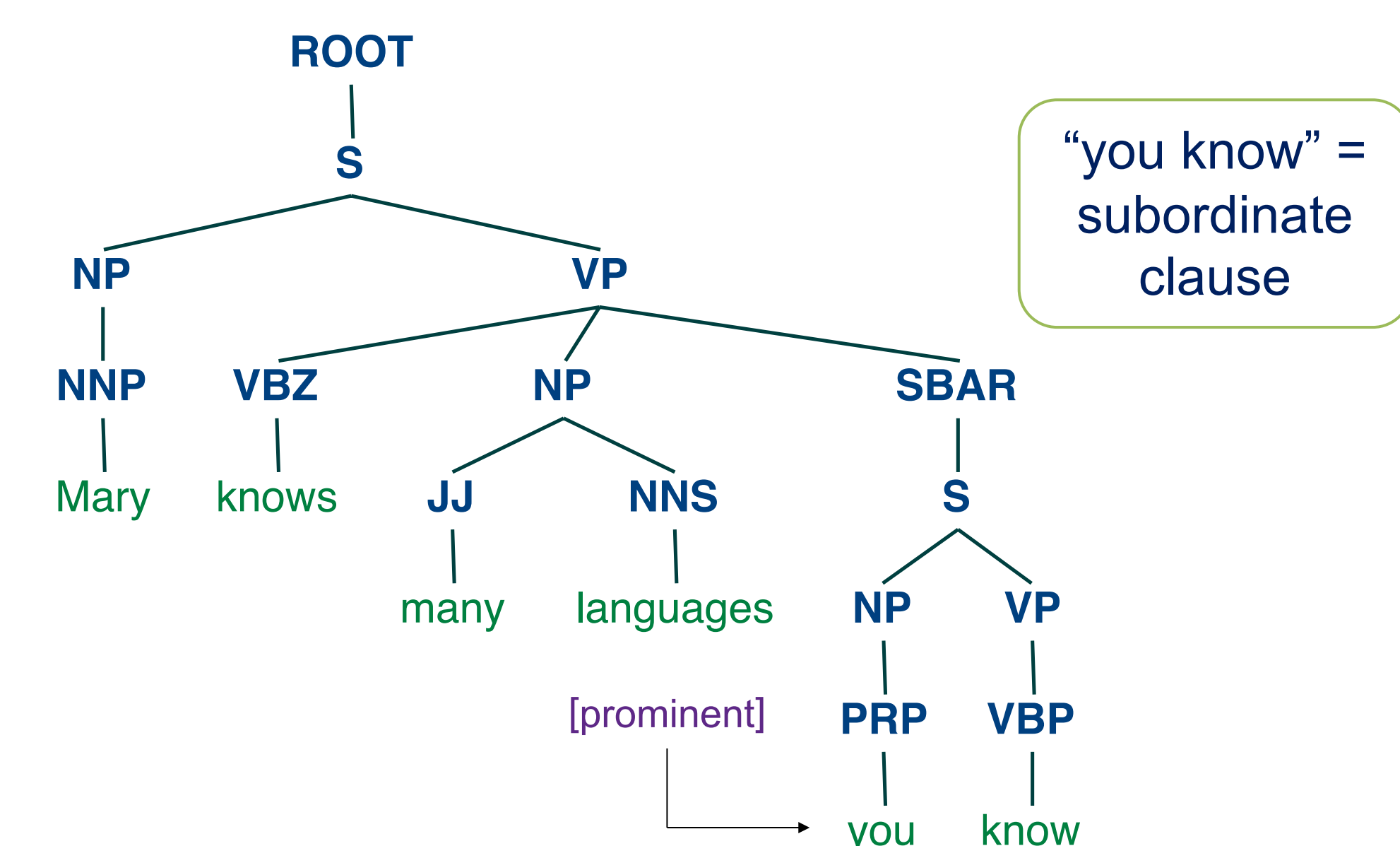
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## Overview

- Parsing: core technology for intermediate language understanding
- Focus of parsing research & resources: written text
- Problem: many applications (dialog systems, assistive devices, translation, ...) involve spoken language
- This work studies impact of **style** difference
  - Written text  $\neq$  spontaneous speech (wording)
  - Spontaneous speech  $\neq$  Read speech (prosody)

## Background

- Parsing: identify syntactic structure
- Speech vs. text:
  - lacks conventional written cues (case, punctuations); has disfluent components
  - has prosody: characteristics beyond words; acoustic correlates (intonation, energy, timing) signal structure



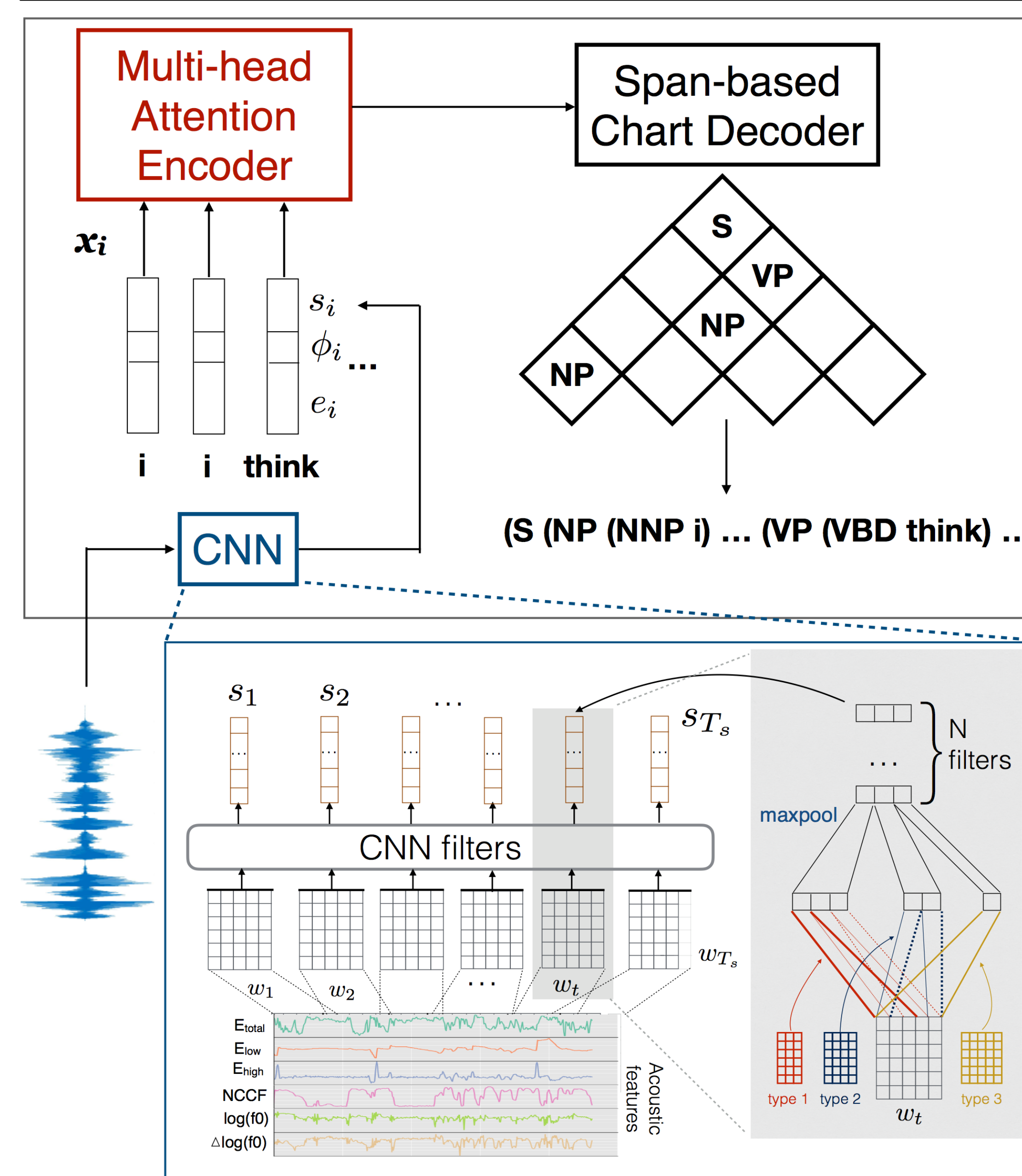
- Recent advances:
  - 2018: prosody benefits neural parsing on spontaneous speech
  - 2018, 2019: contextual embeddings give significant benefit in neural text parsers (SOTA on WSJ Treebank)

## Questions

- Do contextualized word representations learned for written text also benefit spontaneous speech parsers? [Yes!]
- Does prosody improve further on top of the rich text information in neural parsers for spontaneous speech? [Yes!]
- How is the use of prosody affected by mismatch between read and spontaneous speech styles? [Read on...]

## Approach

- Input representation
  - word-level features  $[x_1, x_2, \dots]$
  - $x_i = [e_i, s_i, \phi_i]$
  - $e_i$ : word embeddings
  - $s_i$ : acoustic feature embeddings
  - $\phi_i$ : pause, duration features
- Output:
  - Set of labeled spans  $[(a_i, b_i, l_i), \dots]$
  - $(a_i, b_i, l_i) = (\text{start\_idx}, \text{end\_idx}, \text{label})$
- Self-attentive encoder + chart decoder (self-attn) (Kitaev & Klein, 2018)
- Integrate prosody into via a convolutional neural network (CNN) (Tran et al., 2018)
- Metric: Parseval F1 (label and span)



## Data

| Data  | Style                     | Available Material     | Split             | # Sentences    | Used in    |
|-------|---------------------------|------------------------|-------------------|----------------|------------|
| WSJ   | news text                 | (gold) parses          | train, dev        | 40k            | Q1         |
| SWBD  | conversational speech (C) | audio, (gold) parses   | train, dev, test  | 96k            | Q1, Q2, Q3 |
| CSR   | read news (R)             | audio, (silver) parses | train (tune), dev | 8k             | Q2, Q3     |
| GT-N  | read news/article (R)     | audio, (gold) parses   | test              | 6k (3k unique) | Q3         |
| GT-SW | read version of SWBD (RC) | audio, (gold) parses   | test, analysis    | 31 (13 unique) | Q3         |

## Q1

| Train    | Embedding      | F1   |
|----------|----------------|------|
| WSJ (W)  | BERT           | 77.5 |
|          | Learned        | 91.0 |
|          | GloVe (Fisher) | 91.0 |
| SWBD (S) | GloVe (Gword)  | 91.2 |
|          | ELMo           | 92.7 |
|          | BERT           | 93.2 |
| S+W      | BERT           | 93.4 |

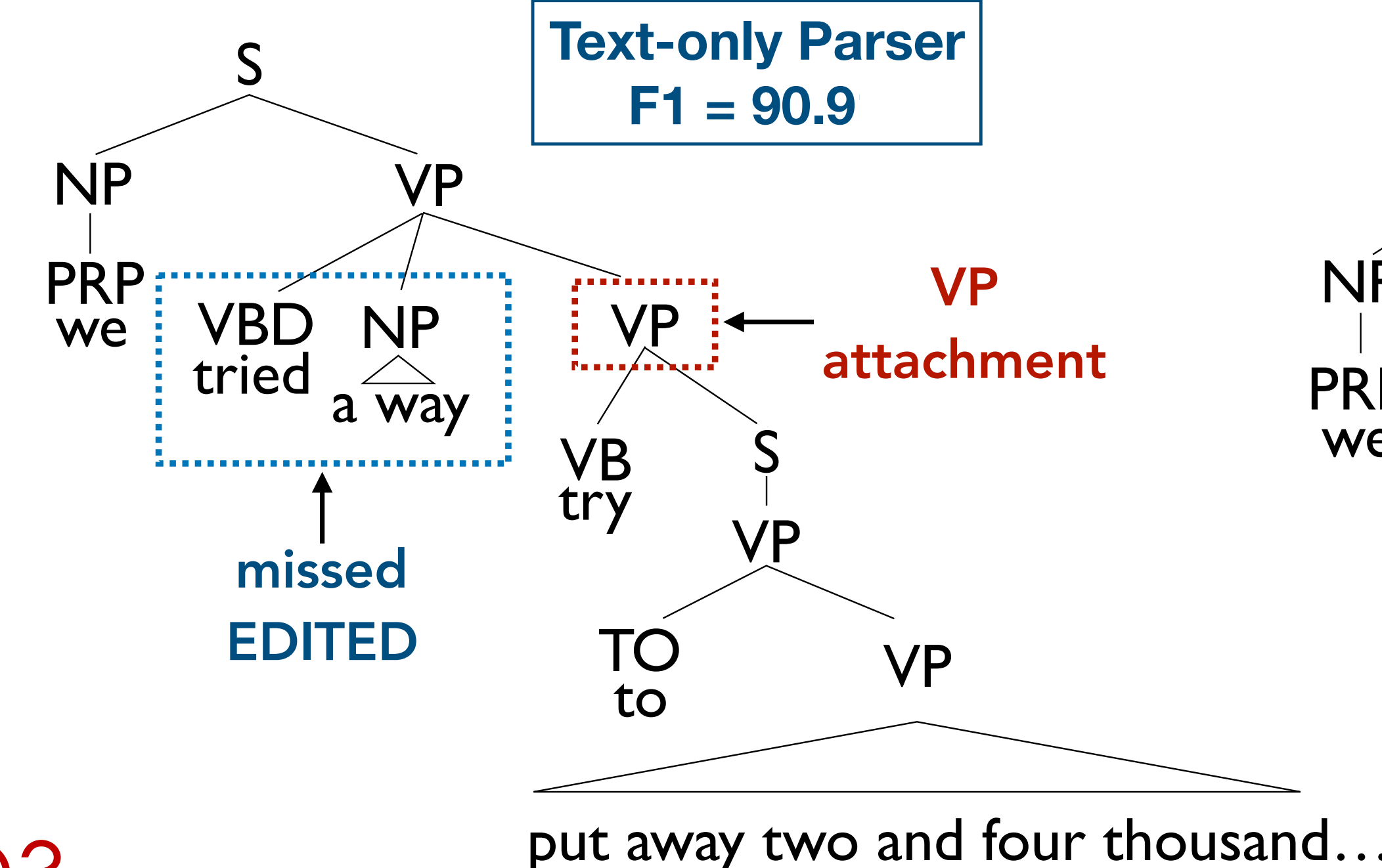
- Training with text alone doesn't work, even with BERT embeddings
- Pretraining on large written text benefits parsing speech
- Training on both (SWBD+WSJ) gives marginal gain

## Results

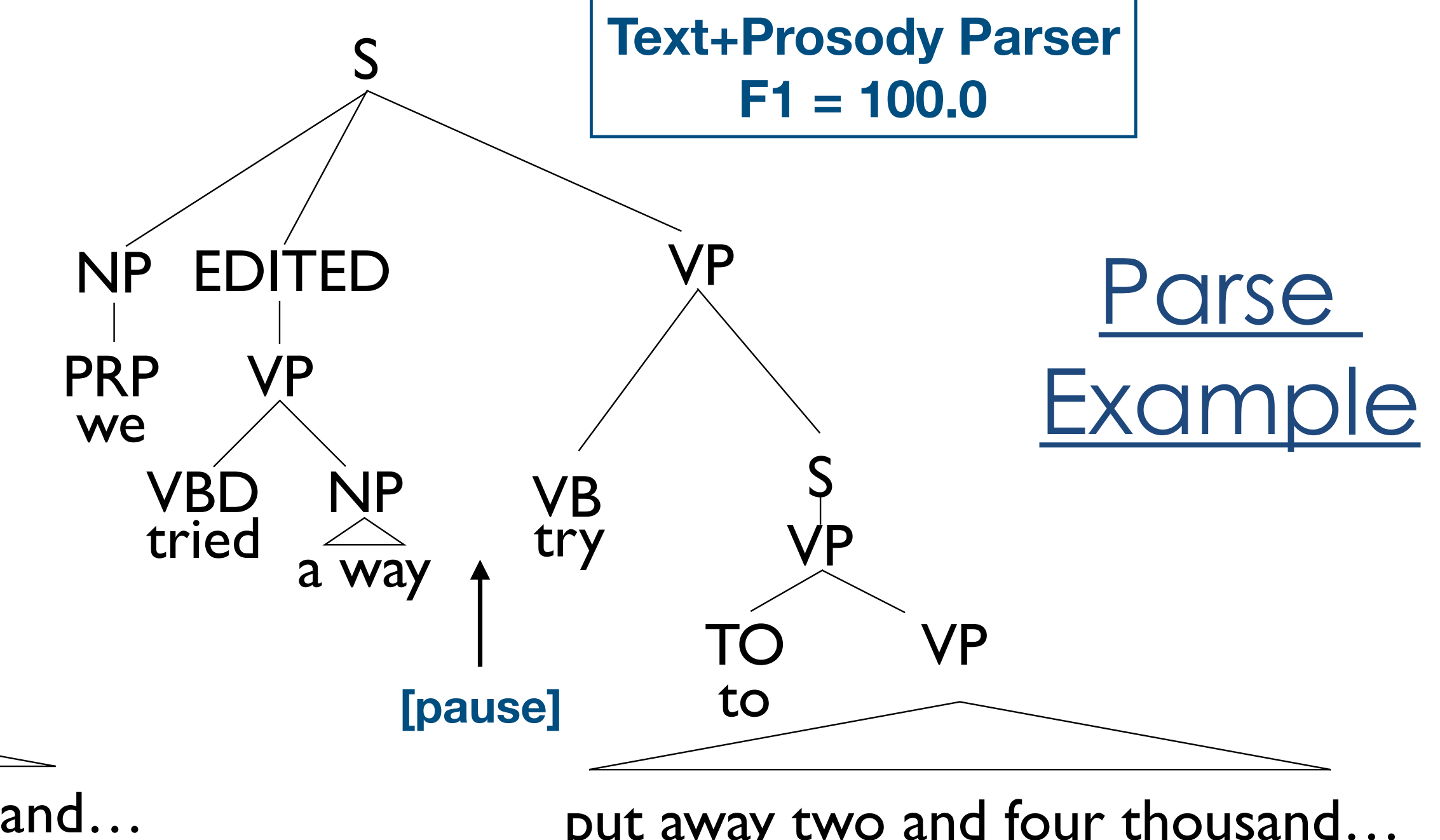
| Model    | all        | disfluent | fluent |
|----------|------------|-----------|--------|
| text     | ELMo 92.5  | 91.5      | 94.6   |
|          | BERT 92.9  | 91.9      | 94.9   |
| +prosody | ELMo 92.7* | 91.7*     | 94.9*  |
|          | BERT 93.0* | 92.1      | 95.2*  |

- SWBD test sentences: 3823 disfluent (with EDITED, INTJ), 2078 fluent
- (\*): statistically significant at  $p < 0.05$
- Using prosody:
  - helps in disfluent and long sentences
  - further improves performance over strong text-only parsers: current best SWBD parsing result
  - reduces edit errors, 19% fewer VP attachment errors

## Text-only Parser F1 = 90.9



## Text+Prosody Parser F1 = 100.0



## Parse Example

## Q3

| Train/Tune | Model    | SWBD (C) | GT-N (R) | GT-SW (RC) |
|------------|----------|----------|----------|------------|
| SWBD (C)   | text     | 92.9     | 92.4     | 98.0       |
| CSR (R)    | text     | 80.6     | 93.9     | 91.4       |
| SWBD (C)   | +prosody | 93.0*    | 92.6*    | 98.0       |
| CSR (R)    | +prosody | 80.4     | 94.2*    | 90.3       |

- Training on conversational (C) speech: minimal degradation on read (R) speech
- Training on (R): significant degradation on (C)  $\rightarrow$  (C) more useful for general training
- Use of prosody differs in (R) vs. (C): style mismatch is both in terms of words and acoustic cues

## Conclusion

- Pretrained contextualized word embeddings on text helps constituency parsing of speech
- Using prosody gives further gains, especially in long and disfluent sentences; reducing attachment errors
- Conversational prosody  $\neq$  read prosody
- Conversational prosody is more general, better for training

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Code: [github.com/trangham283/prosody\\_nlp/tree/master/code/self\\_attn\\_speech\\_parser](https://github.com/trangham283/prosody_nlp/tree/master/code/self_attn_speech_parser)