Parsing Speech: A Neural Approach to Integrating Lexical and Acoustic-Prosodic Information

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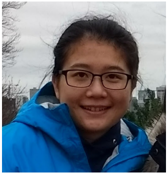
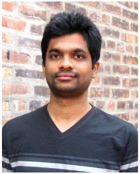
Collaborators



Trang Tran



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Challenges in Parsing Speech

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  - Interjections: hmm, uh, um
  - Speech repair: Why didn't he, why didn't she do it?
  - Parentheticals: I mean, I don't need a car
- Why is conversational speech parsing important?

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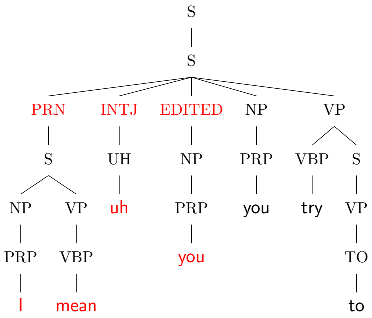
- Why is conversational speech parsing important? Google Duplex!

Utilizing Acoustic-Prosodic Features for Parsing

- Prosodic boundaries found to co-occur with syntactic boundaries (Schepman, 2000)
- Prosodic cues such as, pause length, pitch patterns, intensity etc can be useful
    - Pauses can act like commas
    - Rising pitch at the end of sentence can indicate question
- *Chicago cops arrest man ⟨pause⟩ with knife*
  Chicago cops arrest man with knife

Task

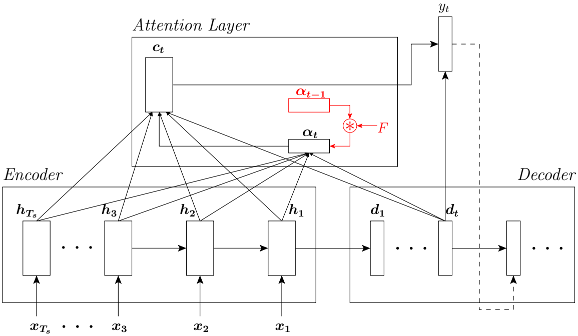
- Constituency parsing of conversational speech
- Assume transcription and word-level alignment of speech signal are given
- Follow the setup of (Vinyals, 2015) to linearize parse tree:



Linearized Parse Tree
(S (S (PRN (S (NP (PRP I)) (VP (VBP mean)))) (INTJ (UH uh)) (EDITED (NP (PRP you))) (NP (PRP you)) (VP (VBP try) (S (VP (TO to))))))

Final POS-normalized linearized parse tree
(S (S (PRN (S (NP XX) (VP XX))) (INTJ XX) (EDITED (NP XX)) (NP XX) (VP XX (S (VP XX)))))

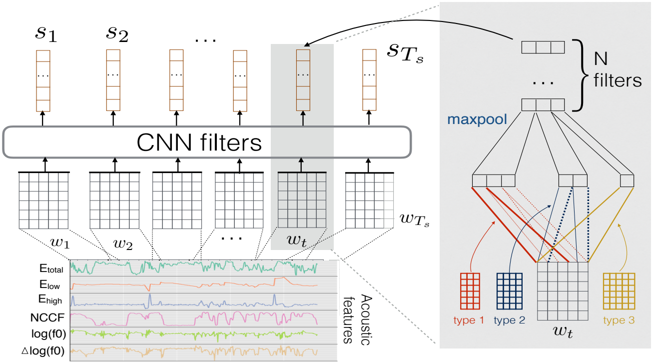
Encoder-Decoder Models



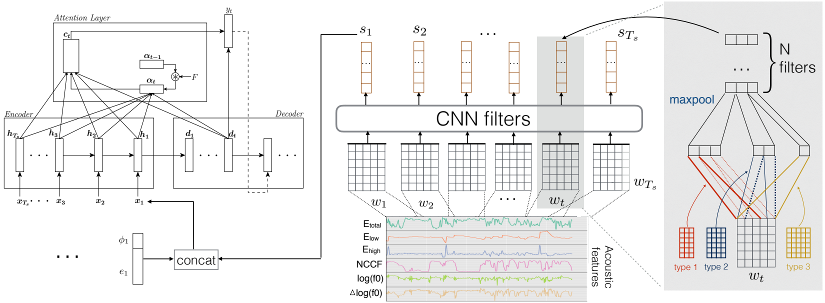
- Use attention-based encoder-decoder model for outputting linearized parsed trees (Vinyals, 2015)
- Also experiment with location-aware attention models (Chorowski, 2015)

Acoustic-Prosodic Features

- Pause (p)
- Word duration (d)
- Fundamental frequency and Energy contours ($f0/E$)



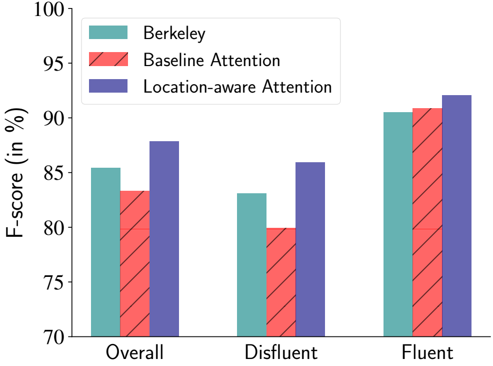
Proposed Model



Experimental Setup

- Switchboard-NXT corpus
- Roughly 100K sentences
- Operate at sentence level - remove punctuation and lowercase words (simulating speech recognition output)
- Baselines:
  - Text-only encoder-decoder model
  - Berkeley parser: Latent-variable probabilistic context-free grammar (PCFG) parser
- Evaluation metric: PARSEVAL F-score

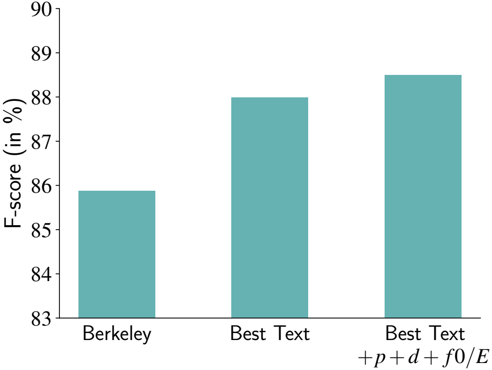
Text-only Models



Dev set results for text-only model

- Refer to the best text-only model, location-aware attention model, referred to as "Best Text" model from hereon.

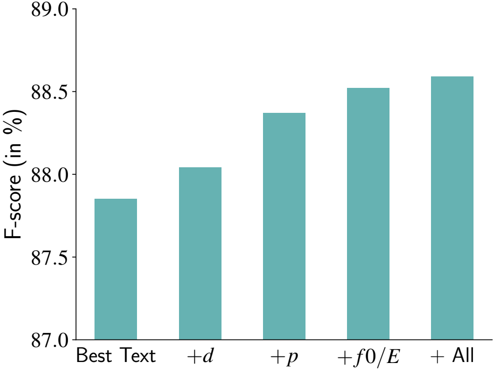
Text + Acoustic-Prosodic feature Models



Test set results

- Acoustic-Prosodic features improve parsing performance, in particular on disfluent sentences

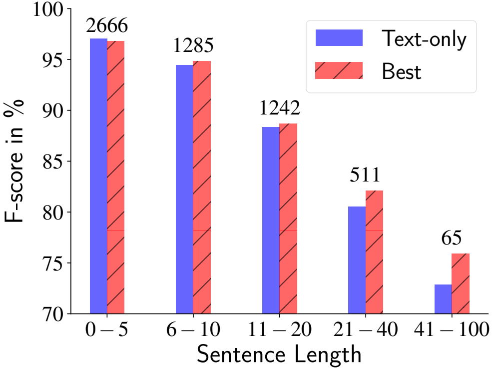
Ablation on Acoustic-Prosodic Features



Ablation on Dev set

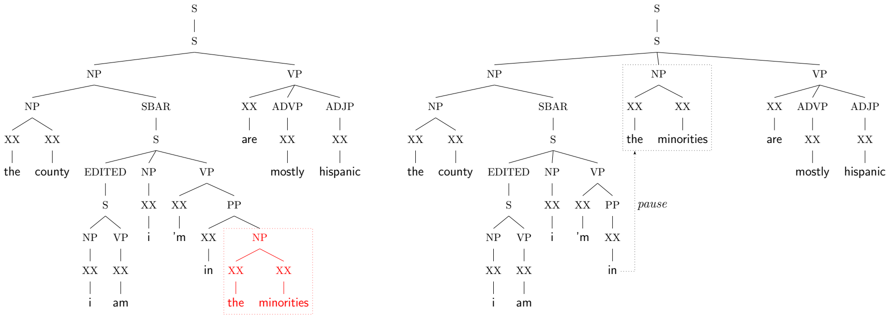
- A combination of all acoustic-prosodic features on top of text features gives the best result

Effect of Sentence Length

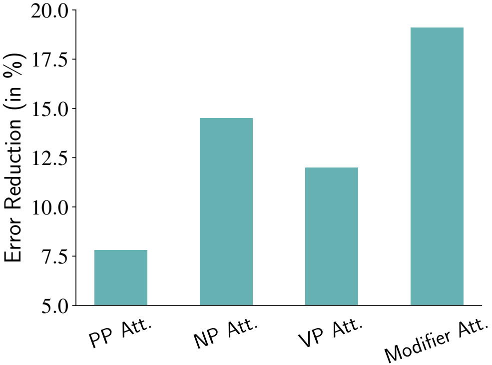


Acoustic-Prosodic features help more on longer sentences

~~Cherrypicked~~ Example



Performance Gain Categorization



Relative error reduction by adding acoustic-prosodic features

- Only analyze disfluent sentences for this analysis
- Analysis done using Berkeley Parser Analyzer (Kummerfeld, 2012)

Conclusion

- Acoustic-prosodic features are useful for constituency parsing
- Particularly useful for disfluent sentences and long sentences
- Future work:
  - Removing the assumption of known sentence boundaries
  - Cleaning up wrong transcriptions in Switchboard
  - Extending this to dependency parsing