

بسم الله الرحمن الرحيم

Joint Parsing and Disfluency Detection in Linear Time

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Overview

① Introduction

Speech Disfluency
Parsing Disfluent Sentences

② Joint Dependency Parsing and Disfluency Detection

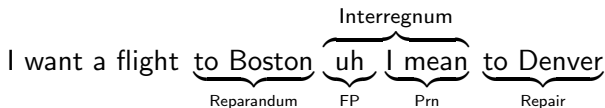
Arc-Eager Parsing
Additional Transitions for Handling Disfluencies
Learning Model

③ Evaluation

Disfluency Detection
Parser Evaluation

Speech Disfluency

- Speech text is mostly disfluent
- Disfluency types:
 - ✓ Filled pauses; e.g. *uh*, *um*
 - ✓ Discourse markers and parentheticals; e.g. *I mean*, *you know*
 - ✓ Reparandum (edited phrase)



Parsing Disfluent Sentences

- Most prior approaches focus solely on disfluency detection.
- Why not parse the disfluent sentence at the same time as disfluency detection?
 - ✓ This has the potential to speed-up spoken language processing in dialogue systems.

Parsing Disfluent Sentences

- Parsing spoken language is harder than written text.
Disfluencies make it much harder
- How about joint parsing?
Studies that only focus on disfluency detection vastly outperform joint model approaches by 20 F score or more.

Our Approach: Joint Parsing and Disfluency Detection

- Parsing and disfluency detection with high accuracy and processing speed.

I want a flight to Boston uh I mean to Denver

I want a flight to Denver



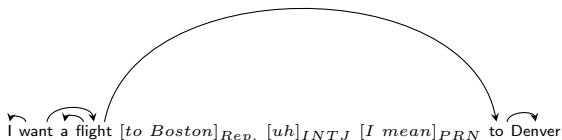
This is the real output of our system!

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Arc-Eager Parsing [Nivre, 2004]

- **Goal:** Finding the best dependency tree
- **Parser State:** Buffer of words, stack of already processed words and set of already made dependency arcs.
- **Initialization:** Buffer with sentence words, stack and arc-set are empty.
- **Final State:** Stack and buffer are empty and arc-set has a set of arcs.

Arc-Eager Parsing

Actions in an arc-eager algorithms are:

- **Shift:** $[... j]_S [i k ...]_B \rightarrow [... j i]_S [k ...]_B$
- **Right-arc:** $[... j]_S [i k ...]_B \rightarrow [... j i]_S [k ...]_B + \text{add-arc}(j,i)$
- **Left-arc:** $[... h j]_S [i k ...]_B \rightarrow [...h]_S [i k ...]_B + \text{add-arc}(i,j)$
- **Reduce:** $[... h j]_S [i k ...]_B \rightarrow [...h]_S [i k ...]_B$
- **Are these actions ENOUGH for disfluency detection?**

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- **Reduce:** $[... h j]_S [i k ...]_B \rightarrow [...h]_S [i k ...]_B$
- **Are these actions ENOUGH for disfluency detection?**

Additional Transitions for Handling Disfluencies

- Three additional actions:

Intj[i]: Remove the first i words from the buffer and tag them as *interjection* (**Intj**).

[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [uh₇, I₈, mean₉, to₁₀, Denver₁₁]_B
→ Next action is Intj[1]
[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [I₈, mean₉, to₁₀, Denver₁₁]_B

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Additional Transitions for Handling Disfluencies

- Three additional actions:

Prn[i]: Remove the first i words from the buffer and tag them as *discourse marker* (**Prn**).

[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [I₈, mean₉, to₁₀, Denver₁₁]_B
→ Next action is Prn[2]
[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [to₁₀, Denver₁₁]_B

Additional Transitions for Handling Disfluencies

- Three additional actions:

Prn[*i*]: Remove the first *i* words from the buffer and tag them as *discourse marker* (**Prn**).

[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [I₈, mean₉, to₁₀, Denver₁₁]_B
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Additional Transitions for Handling Disfluencies

- Three additional actions:
 - ✓ **RP[i:j]**: From the words outside the buffer, remove un-removed words i to j and tag them as *reparandum* (**RP**).

[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [to₁₀, Denver₁₁]_B

Candidates: RP[6:6], RP[5:6], RP[4:6], RP[3:6], ..., Intj[1], Intj[2], ..., Prn[1], Prn[2], ..., Shift, Reduce, Left-arc, Right-arc

→ Next action is RP[5:6]

[ROOT₀, want₂, flight₄]_S [to₁₀, Denver₁₁]_B

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- Three additional actions:

✓ **RP[i:j]**: From the words outside the buffer, remove un-removed words i to j and tag them as *reparandum* (**RP**).

$[\text{ROOT}_0, \text{want}_2, \text{flight}_4, \text{to}_5, \text{Boston}_6]_S \quad [\text{to}_{10}, \text{Denver}_{11}]_B$

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→ **Next action is RP[5:6]**

$[\text{ROOT}_0, \text{want}_2, \text{flight}_4]_S \quad [\text{to}_{10}, \text{Denver}_{11}]_B$

Let's Practice

[ROOT₀, want₂, flight₄]_S [to₅, Boston₆, uh₇, I₈, mean₉, to₁₀, Denver₁₁]_B

Next action is **right-arc:prep**



Let's Practice

[ROOT₀, want₂, flight₄, to₅]_S [Boston₆, uh₇, I₈, mean₉, to₁₀, Denver₁₁]_B

Next action is **right-arc:obj**



Let's Practice

[ROOT₀, want₂, flight₄, to₅, Boston₆]_S [uh₇, I₈, mean₉, to₁₀, Denver₁₁]_B

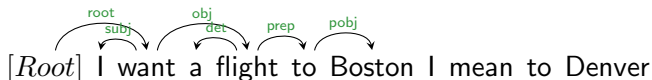
Next action is **Intj[1]**



Let's Practice

$[ROOT_0, want_2, flight_4, to_5, Boston_6]_S \quad [I_8, mean_9, to_{10}, Denver_{11}]_B$

Next action is **Prn[2]**



Let's Practice

$[ROOT_0, want_2, flight_4, to_5, Boston_6]_S \quad [to_{10}, Denver_{11}]_B$

Next action is **RP[5:6]**



Let's Practice

$[ROOT_0, want_2, flight_4, to_5, Boston_6]_S \quad [to_{10}, Denver_{11}]_B$

Deleting words and dependencies



Let's Practice

$[\text{ROOT}_0, \text{want}_2, \text{flight}_4]_S \quad [\text{to}_{10}, \text{Denver}_{11}]_B$

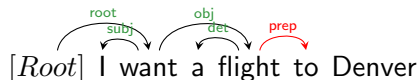
Next action is **right-arc:prep**



Let's Practice

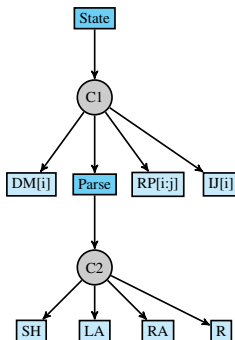
$[ROOT_0, want_2, flight_4, to_{10}]_S \quad [Denver_{11}]_B$

Next action is **right-arc:pobj**



Two Classifiers for Learning the Model

- Instead of having one complete joint model, we have two classifiers that each classifier has its own features and label set.



Features

- We use two kinds of features for the first classifier: *local* and *global*.

Global Features

First n words inside/outside buffer ($n=1:4$)

First n POS i/o buffer ($n=1:6$)

Are n words i/o buffer equal? ($n=1:4$)

Are n POS i/o buffer equal? ($n=1:4$)

n last FG transitions ($n=1:5$)

n last transitions ($n=1:5$)

n last FG transitions + first POS in the buffer ($n=1:5$)

n last transitions + first POS in the buffer ($n=1:5$)

$(n+m)$ -gram of m/n POS i/o buffer ($n,m=1:4$)

Refined $(n+m)$ -gram of m/n POS i/o buffer ($n,m=1:4$)

Are n first words of i/o buffer equal? ($n=1:4$)

Are n first POS of i/o buffer equal? ($n=1:4$)

Number of common words i/o buffer words ($n=1:6$)

Local Features

First n words of the candidate phrase ($n=1:4$)

First n POS of the candidate phrase ($n=1:6$)

Distance between the candidate and first word in the buffer

Learning Algorithm

- We experimented with two learning algorithms [Collins, 2002]:
 - ✓ We use averaged Perceptron [Collins, 2002] with mostly binary features (AP).
 - ✓ Changing weight updates from 1 to 2 for misclassification of reparandum shows improvement (WAP).

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Evaluation Data and Measures

- Data
 - ✓ We use Switchboard parsed section (mrg files) with the same train/dev/test split as [Johnson and Charniak, 2004]
- Metric
 - ✓ **Disfluency detection**: F-score of detecting reparandum.
 - ✓ **Parsing**: F-score of finding correct parents for fluent words.

Disfluency Detection

Model	Model Description	F-Score
[Miller and Schuler, 2008]	Joint + PCFG parsing	30.6
[Lease and Johnson, 2006]	Joint + PCFG parsing	62.4
[Kahn et al., 2005]	TAG + LM rerank.	78.2
[Qian and Liu, 2013]	IOB tagging	81.4
[Qian and Liu, 2013]–Opt.	IOB tagging	82.1
Our Model	AP	80.9
Our Model	WAP	81.4

Parser Evaluation

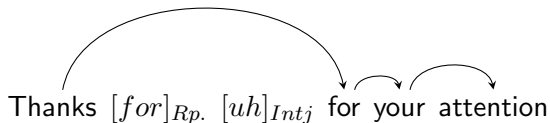
	UAS	LB	UB	Pr.	Rec.	F1
AP	88.6	70.7	90.2	86.8	88.0	87.4
WAP	88.1	70.7	90.2	87.2	88.0	87.6

Table 1: Parsing results. UB = upperbound (parsing clean sentences), LB = lowerbound (parsing disfluent sentences without disfluency correction). UAS is unlabeled attachment score (accuracy), Pr. is precision, Rec. is recall and F1 is f-score.

Conclusion and Future Directions

- Our experiments show that our model is close to the state-of-the-art.
- There are still many avenues of improving accuracy:
 - ✓ Better structure: completely joint model
 - ✓ Better features: prosodic features
 - ✓ K-beam training and decoding
 - ✓ Classifier ensemble

Any Question?



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