Parsing and Speech Research at Brown University

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Talk outline

- Language models for speech recognition
  - Dynamic programming for language modeling
- Prosody and parsing
- Disfluencies and parsing
  - Do disfluencies help parsing?
  - Recognizing and correcting speech repairs
- Conclusions and future work

Applications of (statistical) parsers

Two different ways of using statistical parsers:

1. Applications that use syntactic *parse trees*
   - information extraction
   - (short answer) question answering
   - summarization
   - machine translation
2. Applications that use the *probability distribution* over strings or trees (parser-based language models)
   - *speech recognition and related applications*
   - machine translation

Language modeling with parsers

The *noisy channel model* consists of two parts:

The language model: $\mathrm{P}(x)$, where x is a sentence

The acoustic model: $\mathrm{P}(y|x)$, where y is the acoustic signal

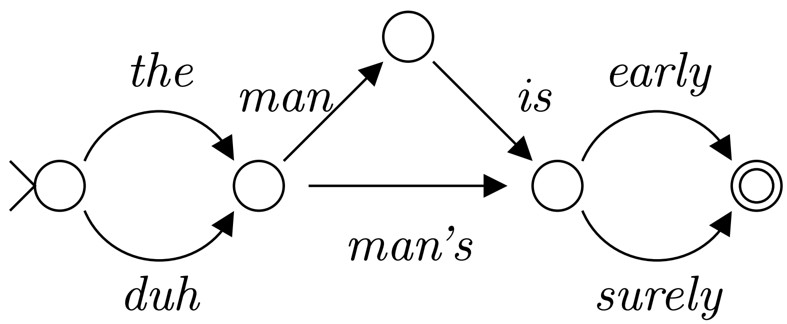
$$\begin{aligned} \mathrm{P}(x|y) &= \frac{\mathrm{P}(y|x)\mathrm{P}(x)}{\mathrm{P}(y)} \qquad \textit{(Bayes Rule)} \\ x^\star(y) &= \operatorname*{argmax}_x \mathrm{P}(x|y) = \operatorname*{argmax}_x \mathrm{P}(y|x)\mathrm{P}(x) \end{aligned}$$

Syntactic parsing models now provide state-of-the-art performance in language modeling $\mathrm{P}(x)$ (Chelba, Roark, Charniak).

Parsing vs language modeling

- A language model models the *marginal distribution* $\mathrm{P}(X)$ over strings X
- A parser models the *conditional distribution* $\mathrm{P}(Y|X)$ of parses Y given a string X
- Different kinds of features seem to be useful for these tasks (Charniak 01)
  - Tri-head features (the syntactic analog of trigrams) are useful for language modeling, but not for parsing
  - EM(-like) training on unparsed data helps language modeling, but not parsing

n-best list approaches



1. the man is early

2. duh man is early

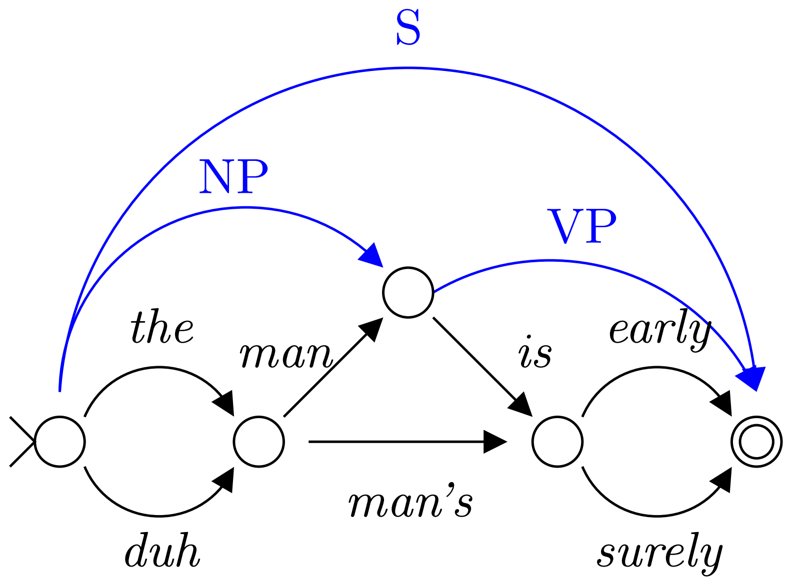
3. the man's early

4. the man is surely

$\ldots$

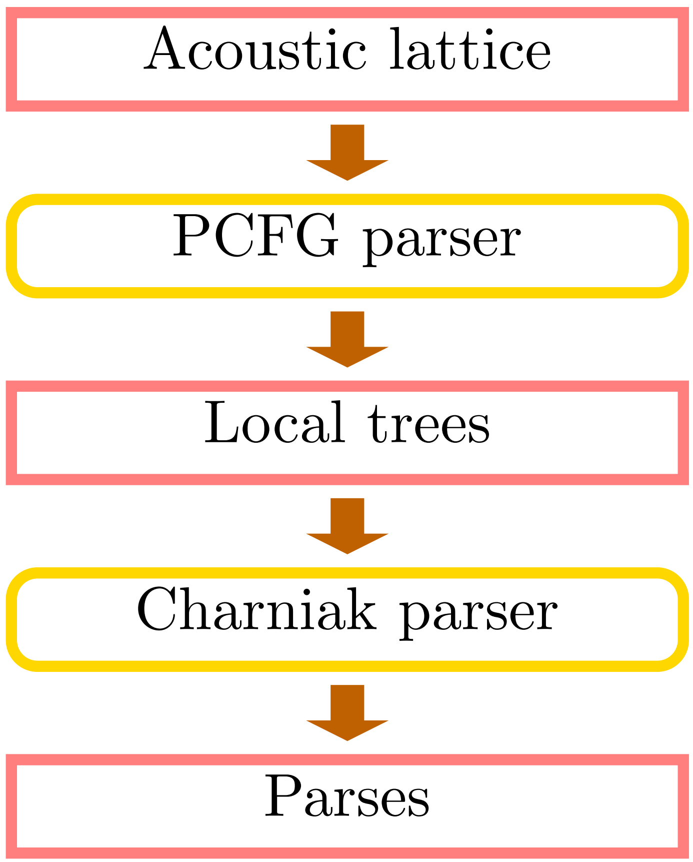
- Roark (p.c.) reports WER improvements with 1,000-best lists
- Can we improve search efficiency and WER by parsing from the lattice? (Chelba, Roark)

Lattices and Charts (IEEE ASRU '03)



- Lattices and charts are the same *dynamic programming* data structure
- Best-first chart parsing works well on strings
- Can we adapt *best-first coarse-to-fine chart-parsing techniques* to lattices?

Coarse to fine architecture



- Use a “coarse-grained” analysis to identify where a “fine-grained” analysis should be applied

Coarse to fine parsing

- Parsing with the full "fine-grained" grammar is slow and takes a lot of memory (Charniak 2001 parser)
- Use a "coarse-grained" grammar to indicate location of likely constituents (PCFG)
- Fine-grained grammar splits each coarse constituent into many fine constituents
- Works well for string parsing:
  - Posits $\approx$ 100 edges to first parse
  - A very good parse is included in $10\times$ overparsing
- Will it work on speech lattices?

Coarse to fine on speech lattices

- PCFG and Charniak Language Model WER:

	WER
trigram (40million words)	13.7
Roark01 (n-best list)	12.7
Chelba02	12.3
Charniak (n-best list)	11.8
100x overparsing on n-best lattices	12.0
100x overparsing on acoustic lattices	13.0

Summary and current work

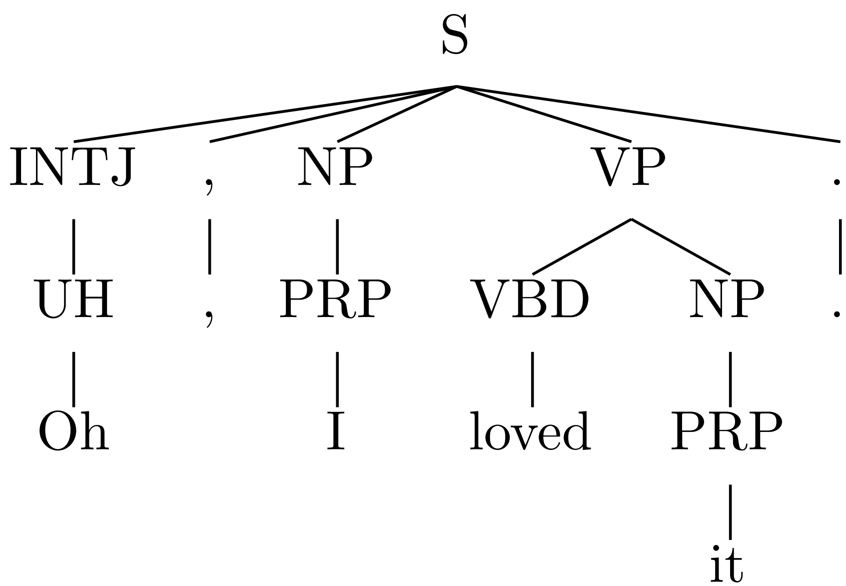
- The coarse-grained model doesn't seem to include enough good parts of the lattice
- If we open the beam further, the *fine-grained model runs out of memory*
- Current difficulties probably stem from *defective nature* of coarse-grained PCFG model

$\Rightarrow$ improve coarse-grained model

$\Rightarrow$ *lexicalization* will probably be necessary
(we are competing with trigrams, which are lexicalized)

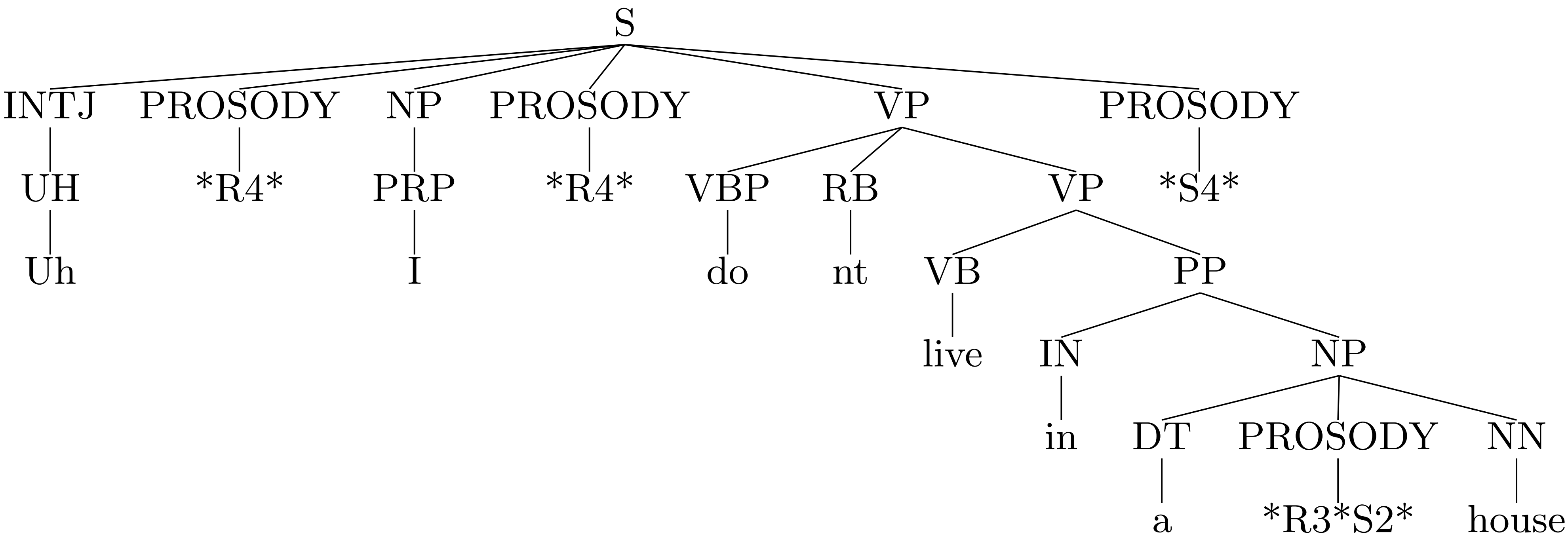
- Can we parse efficiently from a lattice with a lexicalized PCFG?
- Will a three-stage model work better?

Prosody and parsing (NAACL'04)



- Selectively removing punctuation from the WSJ significantly decreases parsing performance
- When parsing speech transcripts, would prosody enhance parsing performance also?

Prosody as punctuation



- Extract prosodic features from acoustic signal (Ferrer 02)
- Use a *forced aligner* to align Switchboard transcript with acoustic signal
- Extract prosodic features from acoustic signal and associate them with a word in transcript
- Bin prosodic features, and attach them in syntactic tree much as punctuation is

Prosodic features we tried

PAU_DUR_N: pause duration normalized by the speaker's mean sentence-internal pause duration,

NORM_LAST_RHYME_DUR: duration of the phone minus the mean phone duration normalized by the standard deviation of the phone duration for each phone in the rhyme,

FOK_WRD_DIFF_MNMN_NG: log of the mean f0 of the current word, divided by the log mean f0 of the following word, normalized by the speakers mean range,

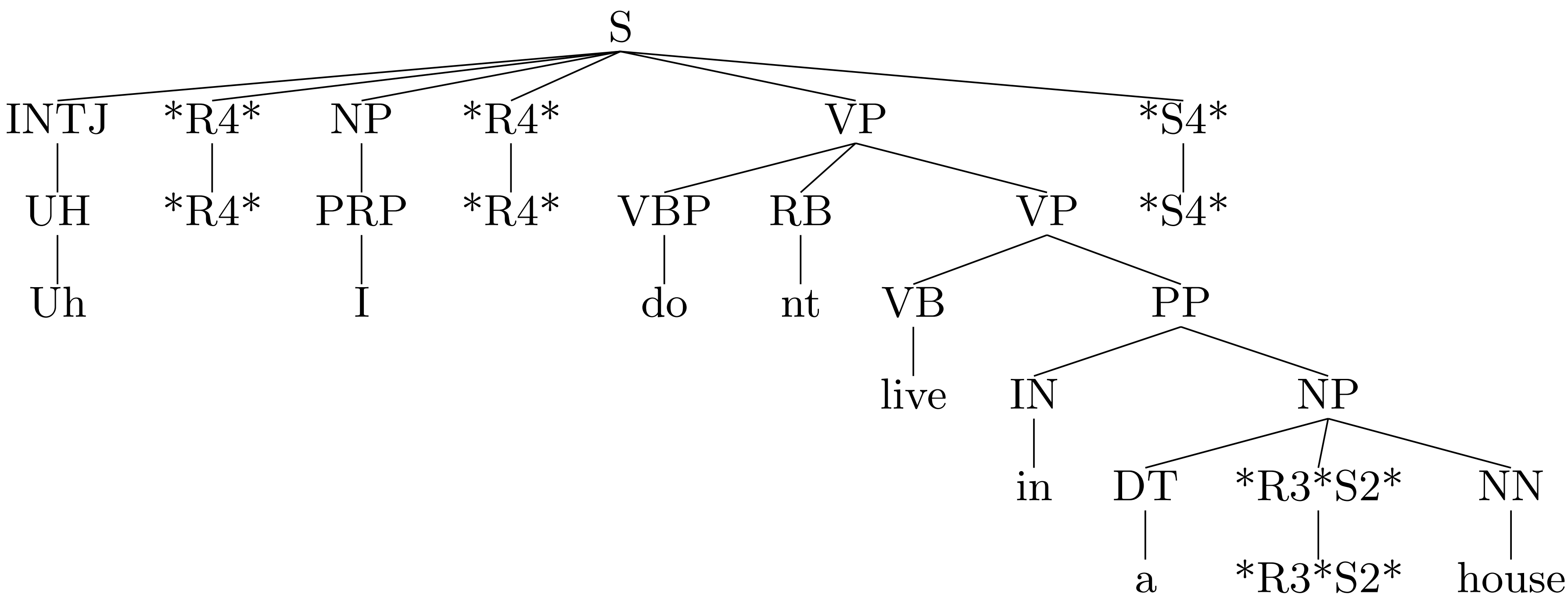
FOK_LR_MEAN_KBASELN: log of the mean f0 of the word normalized by speaker's baseline, and

SLOPE_MEAN_DIFF_N: difference in the f0 slope normalized by the speaker's mean f0 slope.

Binning the prosodic features

- Modern statistic parsers take categorical input, our prosodic features are continuous
- We experimented with many ways of *binning the prosodic feature values*:
  - construct a histogram for all features used
  - divide feature values into 2/5/10 equal sized bins
  - only introduce pseudo-punctuation for the most extreme 40% of bins
  - conjoin binned features
- When *all features* are used:
  - 89 distinct types of pseudo-punctuation symbols
  - 54% of words are followed by pseudo-punctuation

Prosody as punctuation



- Different types of punctuation have different POS tags in WSJ
- POS tags and lexical items are used in different ways in Charniak parsing model

⇒ Also evaluate with "raised" prosodic features

Prosodic parsing results

Annotation	unraised	raised
punctuation	88.212	
none	86.891	
L	85.632	85.361
NP	86.633	86.633
P	86.754	86.594
R	86.407	86.288
S	86.424	85.75
W	86.031	85.681
P R	86.405	86.282
P W	86.175	85.713
P S	86.328	85.922
P R S	85.64	84.832

- Punctuation improves parsing accuracy
- All combinations of prosodic features decrease parsing accuracy
- The more features we used, the more accuracy decreased

Discussion

- Wrong features? Wrong model? (But why does the "wrong model" work so well with punctuation?)
- Why did performance go down?
  - Charniak parser backs off to a bigram model
  - Prosodic punctuation pushes preceding word out of window
  - A manually identified word is probably more useful than an automatically extracted prosodic feature
- *Punctuation is annotated by humans* (who presumably understood each sentence)
- Prosody was annotated by machine (which presumably did not understand)
- *Prosody may prove more useful when parsing from speech lattices*

A TAG-based noisy channel model of speech repairs

- Goal: Apply parsing technology and "deeper" linguistic analysis to (transcribed) speech
- Identifying and correcting speech errors
  - Types of speech errors
  - Speech repairs and "rough copies"
  - Noisy channel model

Speech errors in (transcribed) speech

- Filled pauses

  I think it's, *uh*, refreshing to see the, *uh*, support . . .

- Frequent use of parentheticals

  But, *you know*, I was reading the other day . . .

- Speech repairs

  Why didn't he, why didn't she stay at home?

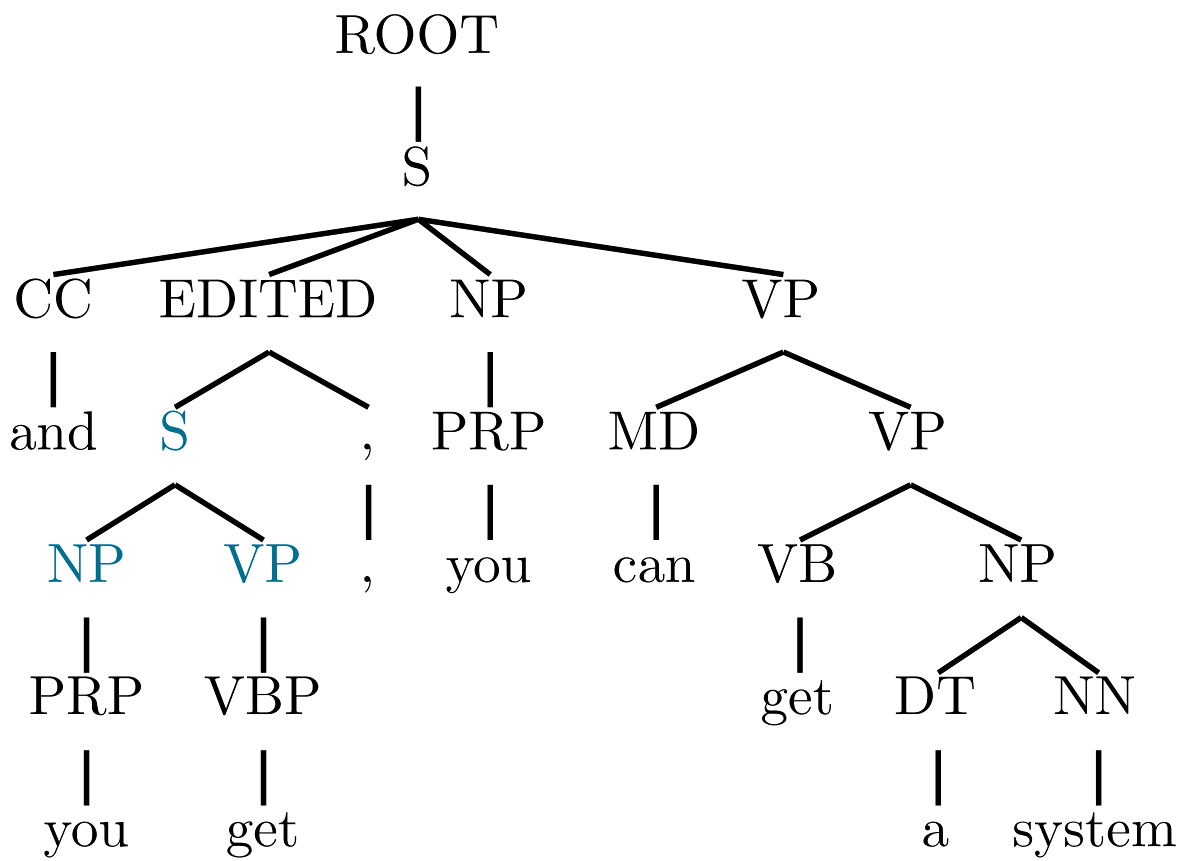
- Ungrammatical constructions

Bear, Dowding and Schriberg (1992), Charniak and Johnson (2001), Heeman and Allen (1997, 1999), Nakatani and Hirschberg (1994), Stolcke and Schriberg (1996)

Special treatment of speech repairs

- *Filled pauses* are easy to recognize (in transcripts)
- *Parentheticals* appear in WSJ, and current parsers identify them fairly well
- *Filled pauses* and *parentheticals* are useful for identifying constituent boundaries (just as punctuation is)
  - Charniak's parser performs slightly better with parentheticals and filled pauses than with them removed
- *Ungrammatical constructions* aren't necessarily fatal
  - Statistical parsers learn mapping of sentences to parses in training corpus
- …but *speech repairs* warrant special treatment, since Charniak's parser doesn't recognize them …

Representation of repairs in Switchboard treebank



- Speech repairs are indicated by EDITED nodes in corpus

Speech repairs and interpretation

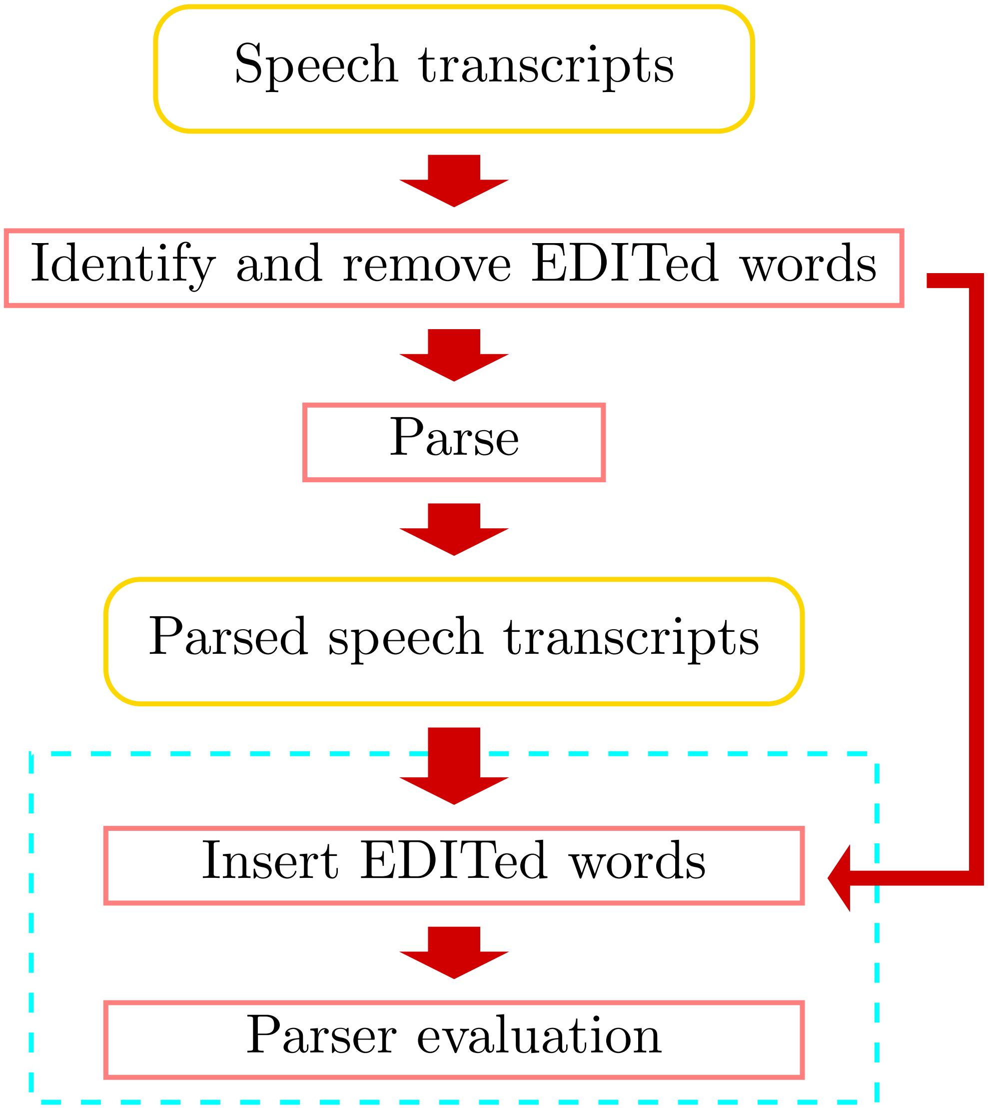
- Speech repairs are indicated by EDITED nodes in corpus
- The unadorned parser does not posit any EDITED nodes even though the training corpus contains them
  - Parser is based on context-free headed trees and head-to-argument dependencies
  - Repairs involve context-sensitive "rough copy" dependencies that cross constituent boundaries

Why didn't he, uh, why didn't she stay at home?

- The interpretation of a sentence with a speech repair is (usually) the same as with the repair excised

⇒ Identify and remove EDITED words (Charniak and Johnson, 2001)

Parser architecture



The noisy channel model

Source model $\mathrm{P}(X)$
Bigram/Parsing LM

Source signal x
a flight to Denver on Friday

Noisy channel $\mathrm{P}(U|X)$
TAG transducer

Noisy signal u
a flight to Boston uh I mean to Denver on Friday

$$\mathrm{P}(x|u) = \frac{\mathrm{P}(u|x)\mathrm{P}(x)}{\mathrm{P}(u)} \qquad \textit{(Bayes Rule)}$$

$$\operatorname*{argmax}_x \mathrm{P}(x|u) = \operatorname*{argmax}_x \mathrm{P}(u|x)\mathrm{P}(x)$$

The structure of a repair

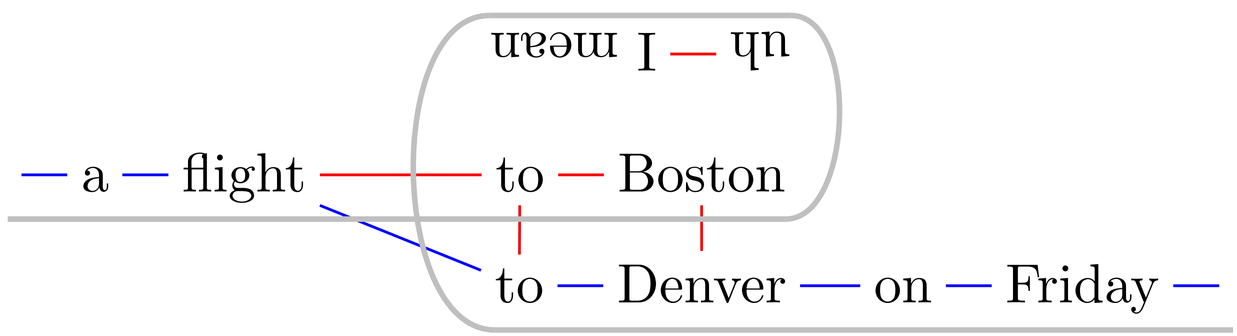
$$\ldots\text{a flight }\underbrace{\text{to Boston,}}_{\text{Reparandum}}\ \underbrace{\text{uh, I mean,}}_{\text{Interregnum}}\ \underbrace{\text{to Denver}}_{\text{Repair}}\text{ on Friday}\ldots$$

- The Interregnum is usually lexically (and prosodically marked), but can be empty
- The Repair is often "roughly" a copy of the Reparandum
  - Finite state and context free grammars cannot generate ww "copy languages" *but Tree Adjoining Grammars can*
  - Repairs are typically short
  - Repairs are not always copies

Shriberg 1994 "Preliminaries to a Theory of Speech Disfluencies"

“Helical structure” of speech repairs

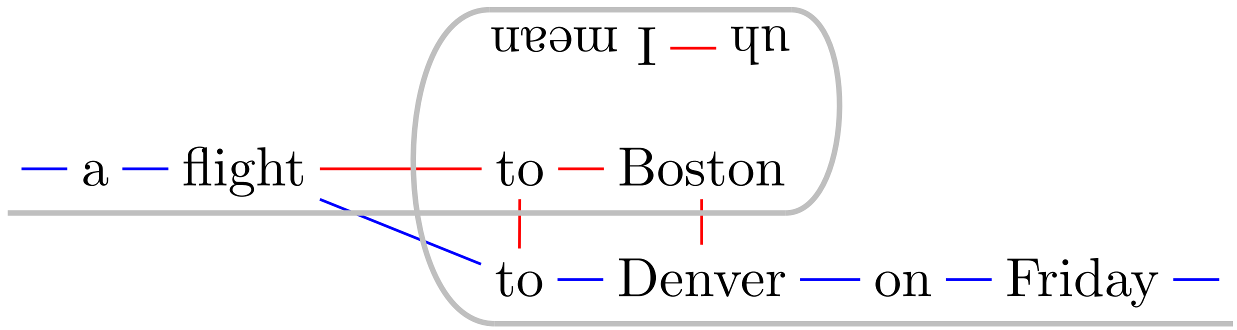
$$\ldots \text{a flight } \underbrace{\text{to Boston,}}_{\text{Reparandum}} \ \underbrace{\text{uh, I mean,}}_{\text{Interregnum}} \ \underbrace{\text{to Denver}}_{\text{Repair}} \text{ on Friday} \ldots$$



- *Language model* generates *repaired string*
- *TAG transducer* generates *reparandum* from repair
- *Interregnum* is generated by specialized finite state grammar in TAG transducer

Joshi (2002), ACL Lifetime achievement award talk

TAG transducer models speech repairs



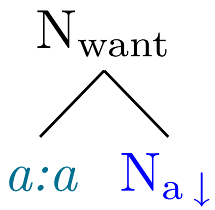
- Source (bigram) language model: *a flight to Denver on Friday*
- TAG generates string of $u{:}x$ pairs, where u is a speech stream word and x is either $\emptyset$ or a source word:
  a:a flight:flight to:$\emptyset$ *Boston:*$\emptyset$ *uh:*$\emptyset$ *I:*$\emptyset$ *mean:*$\emptyset$ *to:to Denver:Denver on:on Friday:Friday*
  - TAG does not reflect grammatical structure (but LM can)
  - right branching finite state model of non-repairs and interregnum
  - adjunction used to describe copy dependencies in repair

Sample TAG derivation (simplified)

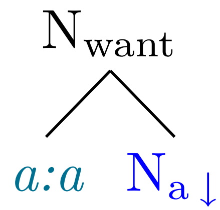
(I want) a flight to Boston uh I mean a flight to Denver on Friday ...

Start state: $\mathrm{N}_{\mathrm{want}\downarrow}$

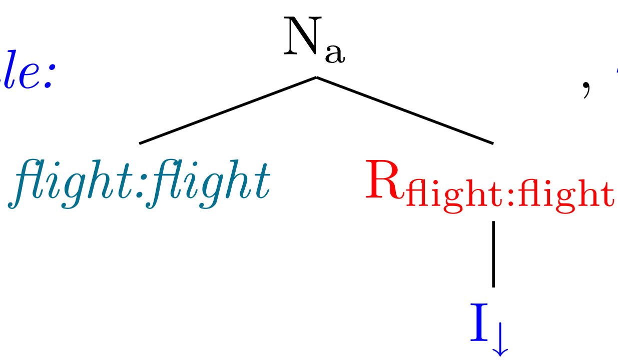
TAG rule:



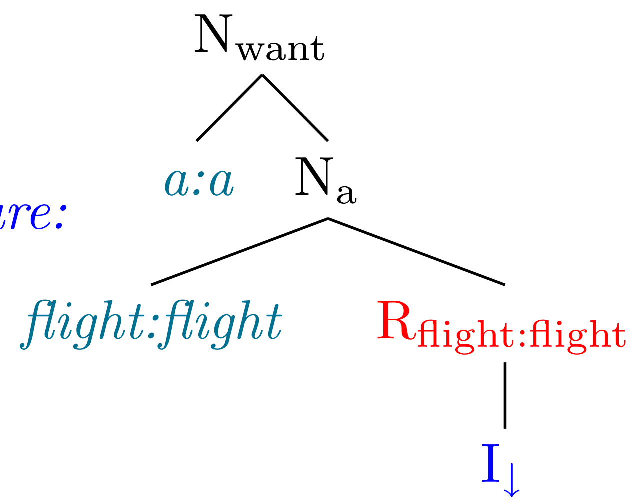
, *resulting structure:*



TAG rule:

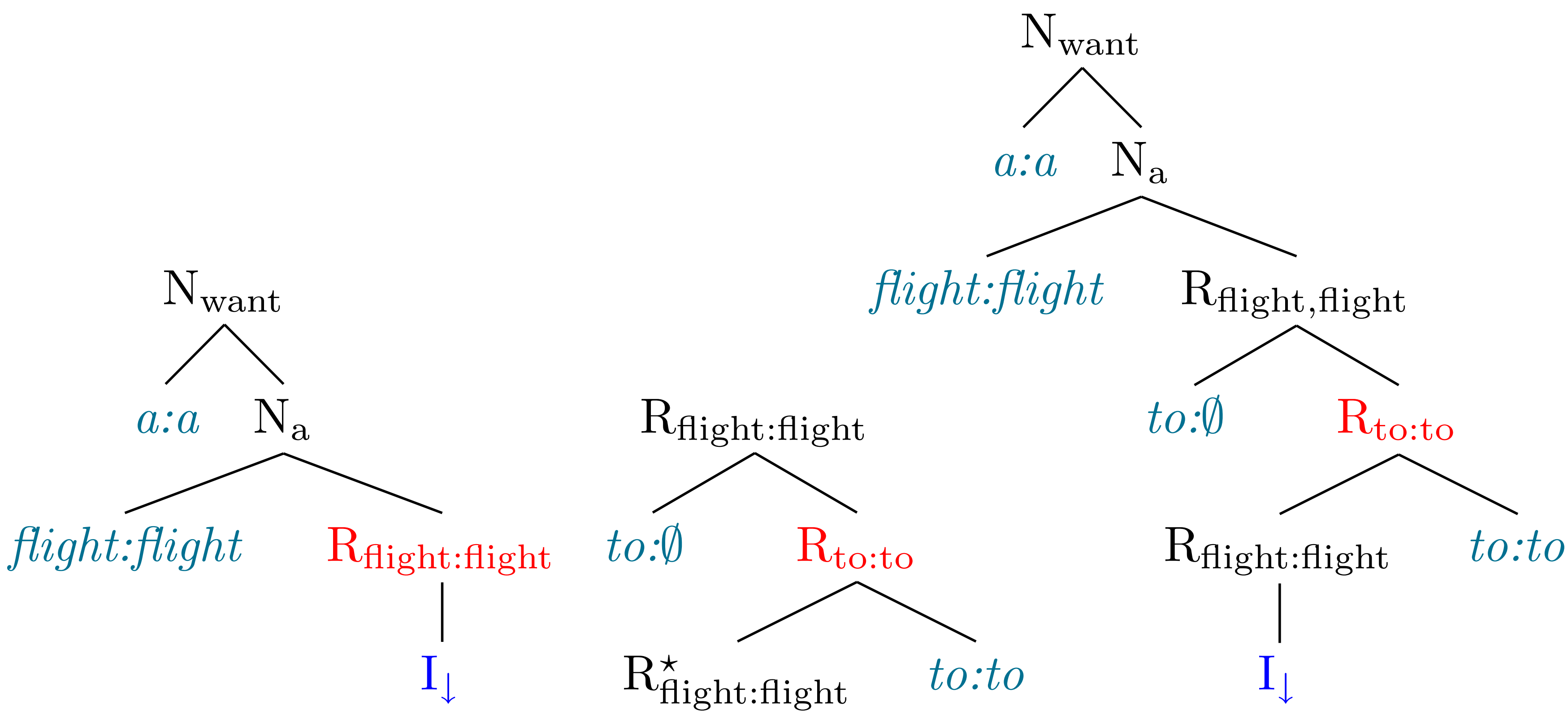


, *resulting structure:*



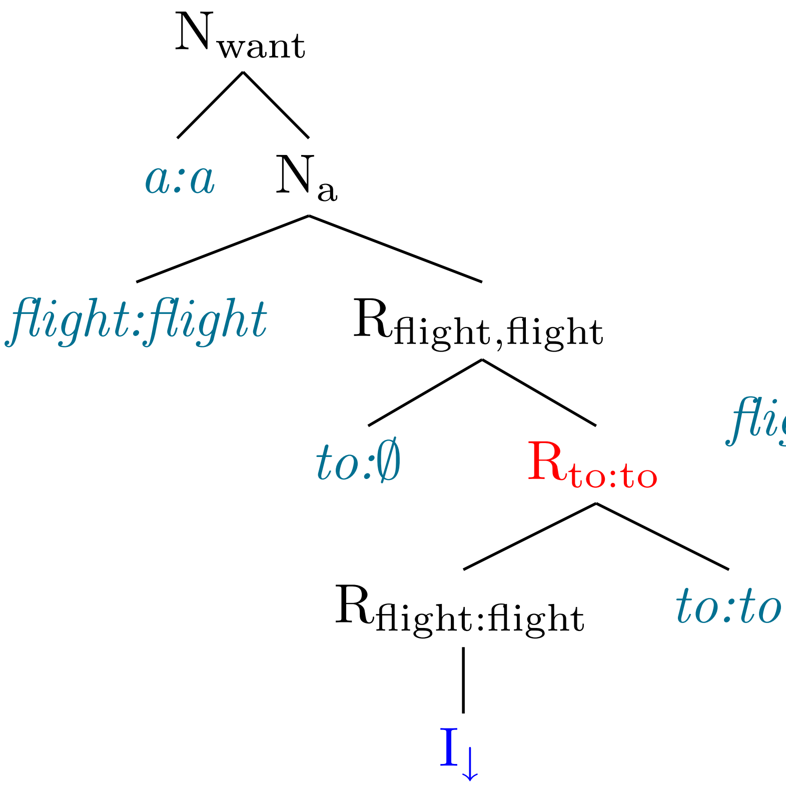
Sample TAG derivation (cont)

(I want) a flight to Boston uh I mean to Denver on Friday . . .

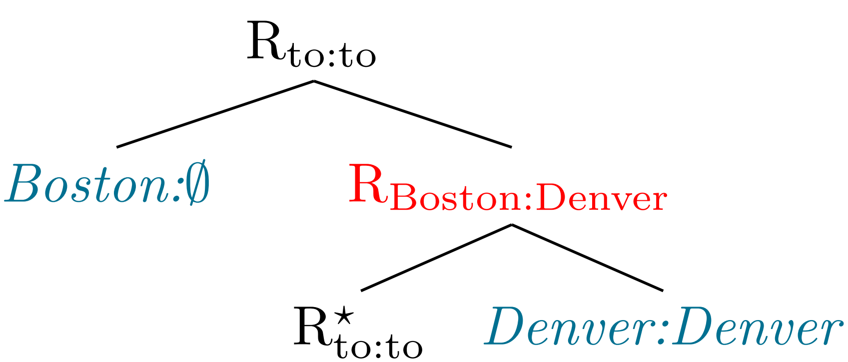


previous structure *TAG rule* *resulting structure*

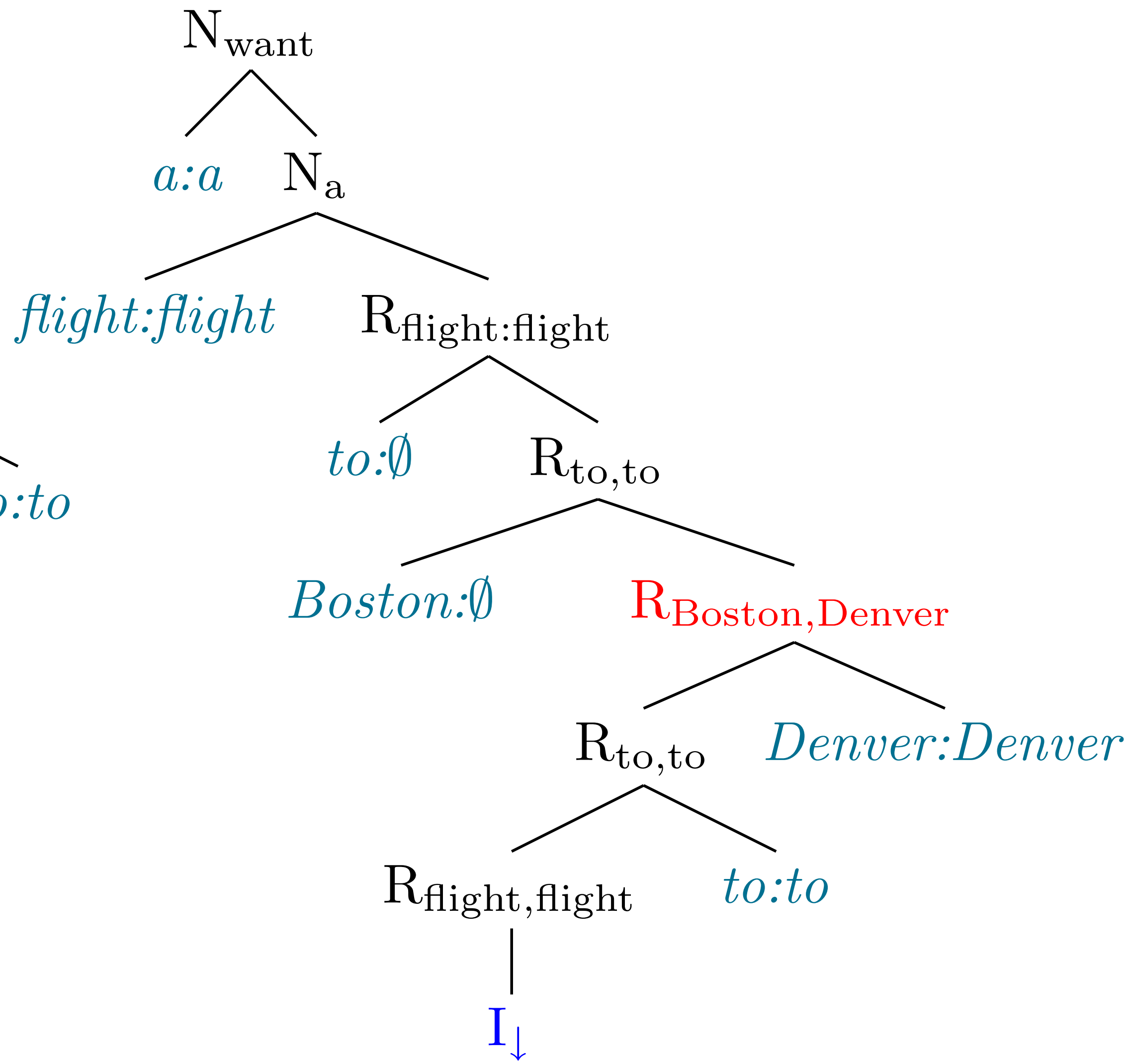
(I want) a flight to Boston uh I mean *to* Denver on Friday . . .



previous structure

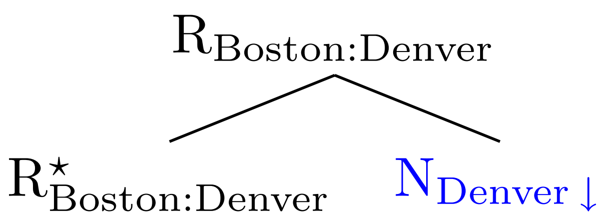


TAG rule

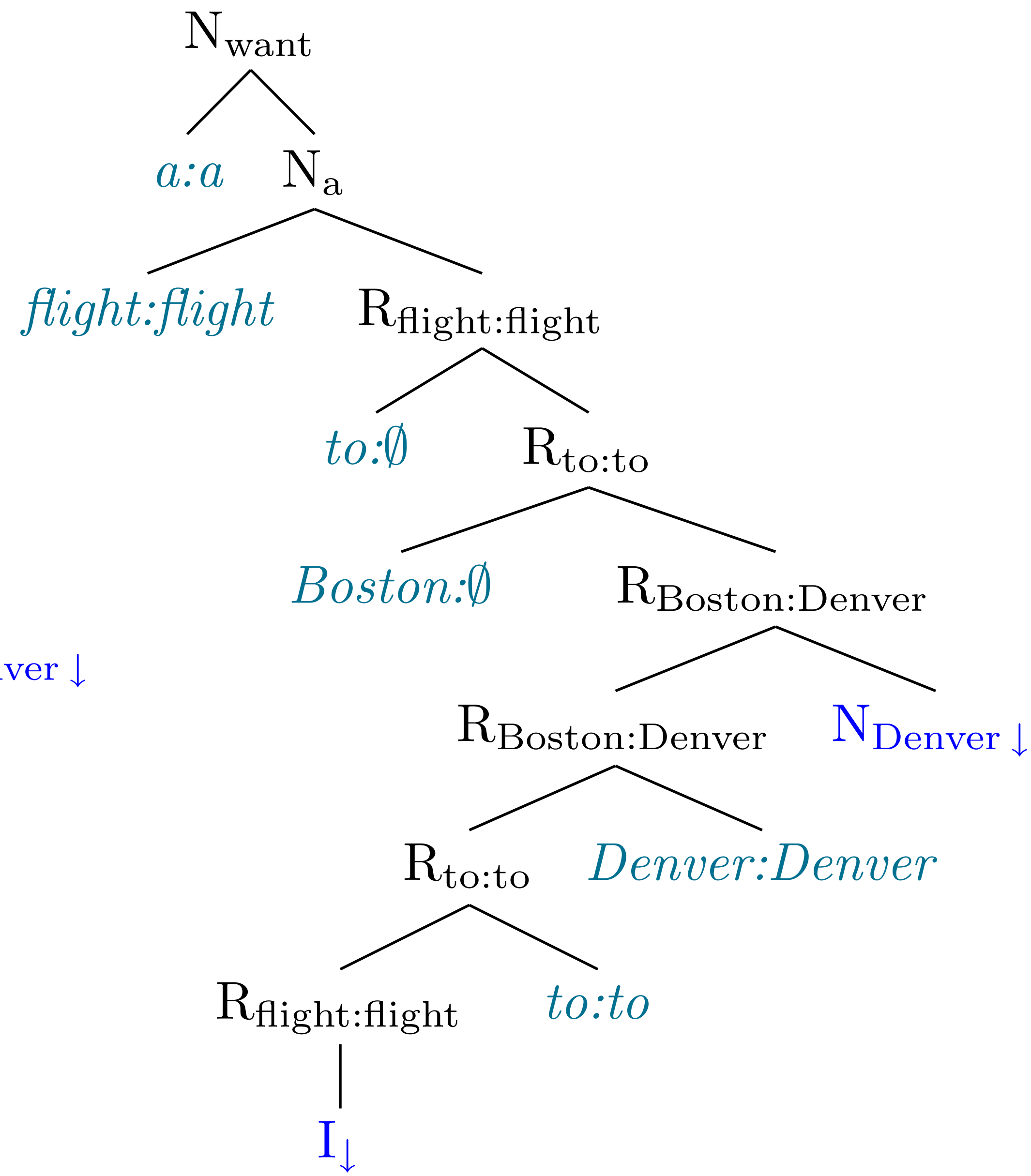


resulting structure

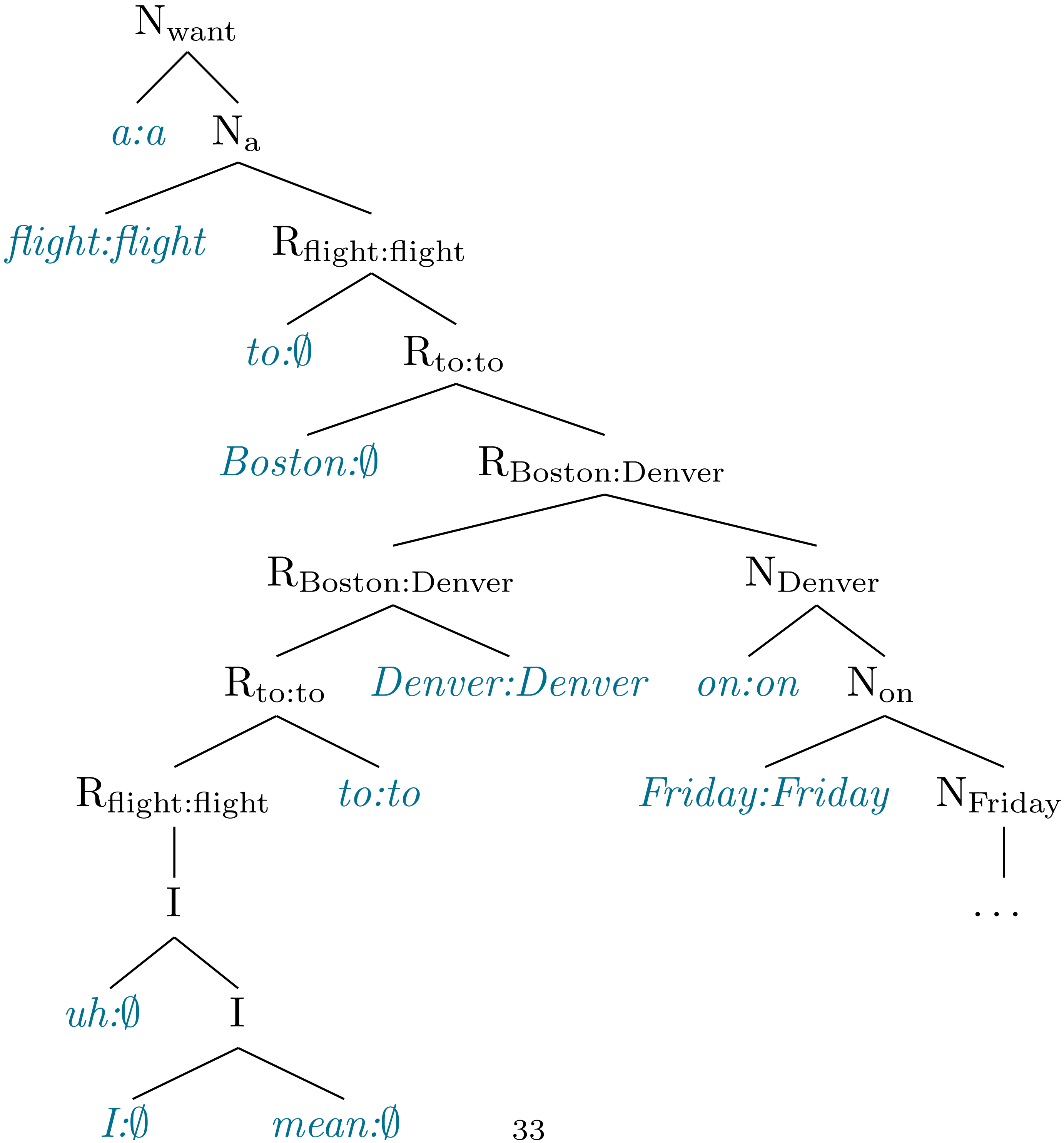
(I want) a flight to Boston uh I mean *to Denver* on Friday . . .



TAG rule



resulting structure


N_want
a:a
N_a
flight:flight
R_flight:flight
to:∅
R_to:to
Boston:∅
R_Boston:Denver
R_Boston:Denver
N_Denver
R_to:to
Denver:Denver
on:on
N_on
R_flight:flight
to:to
Friday:Friday
N_Friday
I
. . .
uh:∅
I
I:∅
mean:∅

Disfluencies in Switchboard

. . . a flight $\underbrace{\text{to Boston,}}_{\text{Reparandum}}$ $\underbrace{\text{uh, I mean,}}_{\text{Interregnum}}$ $\underbrace{\text{to Denver}}_{\text{Repair}}$ on Friday . . .

- Penn Switchboard corpus annotates reparandum, interregnum and repair
- Trained on the disfluency and POS tagged Switchboard files sw[23]*.dps (1.3M words)
- Tested on Switchboard files sw4[5-9]*.dps (65K words)
- Punctuation and partial words ignored
- 5.4% of words are in a reparandum
- 31K repairs, average repair length 1.6 words
- Number of training words: reparandum 50K (3.8%), interregnum 10K (0.8%), repair 53K (4%), unclassified 24K (1.8%)

Training data for the model

$$\ldots\text{a flight }\underbrace{\text{to Boston,}}_{\text{Reparandum}}\ \underbrace{\text{uh, I mean,}}_{\text{Interregnum}}\ \underbrace{\text{to Denver}}_{\text{Repair}}\text{ on Friday }\ldots$$

- Minimum edit distance aligner used to align reparandum and repair words
  - Prefers identity, POS identity, similar POS alignments
- Of the 57K alignments in the training data:
  - 35K (62%) are identities
  - 7K (12%) are insertions
  - 9K (16%) are deletions
  - 5.6K (10%) are substitutions
    - 2.9K (5%) are substitutions with same POS
    - 148 of the 352 substitutions (42%) in heldout data were not seen in training

Estimating the model from data

$$\ldots \text{a flight } \underbrace{\text{to Boston,}}_{\text{Reparandum}} \; \underbrace{\text{uh, I mean,}}_{\text{Interregnum}} \; \underbrace{\text{to Denver}}_{\text{Repair}} \text{ on Friday} \ldots$$

$P_n(\mathsf{repair}|\mathit{flight})$ The probability of a repair beginning after *flight*

$P(m|\mathit{Boston}, \mathit{Denver})$, where $m \in \{\mathsf{copy}, \mathsf{substitute}, \mathsf{insert}, \mathsf{delete}, \mathsf{nonrepair}\}$:
The probability of repair type m when the last reparandum word was *Boston* and the last repair word was *Denver*

$P_w(\mathit{tomorrow}|\mathit{Boston}, \mathit{Denver})$ The probability that the next reparandum word is *tomorrow* when the last reparandum word was *Boston* and last repair word was *Denver*

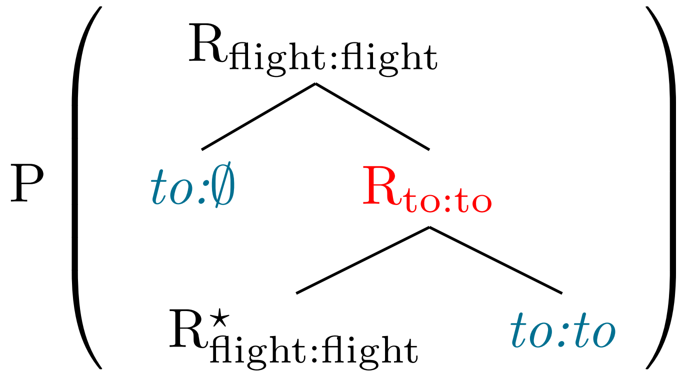
The TAG rules and their probabilities

$$P\left(\begin{array}{c}\mathrm{N}_{\mathrm{want}}\\ \diagup\;\diagdown\\ \color{teal}{a{:}a}\quad \color{blue}{\mathrm{N}_{\mathrm{a}}\downarrow}\end{array}\right) \quad = \quad (1 - \mathrm{P}_n(\mathsf{repair}|a))$$

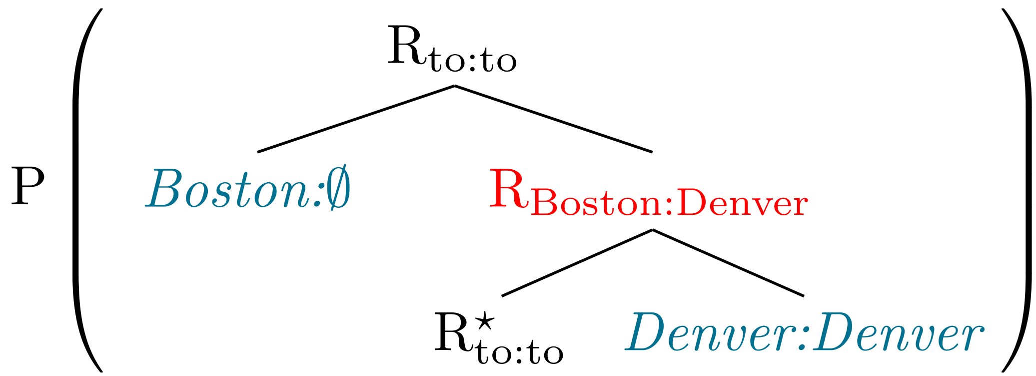
$$P\left(\begin{array}{c}\mathrm{N}_{\mathrm{a}}\\ \diagup\qquad\diagdown\\ \color{teal}{\mathit{flight{:}flight}}\qquad \color{red}{\mathrm{R}_{\mathrm{flight:flight}}}\\ \qquad\qquad\qquad |\\ \qquad\qquad\qquad \color{blue}{\mathrm{I}_\downarrow}\end{array}\right) \quad = \quad \mathrm{P}_n(\mathsf{repair}|\mathit{flight})$$

- These rules are just the TAG formulation of a HMM.

The TAG rules and their probabilities (cont.)



$$= \mathrm{P}_r(\mathsf{copy} \mid \mathit{flight}, \mathit{flight})$$



$$= \mathrm{P}_r(\mathsf{substitute} \mid to, to)$$
$$\mathrm{P}_w(\mathit{Boston} \mid to, to)$$

- Copies generally have higher probability than substitutions

The TAG rules and their probabilities (cont.)

$$\mathrm{P}\left(\begin{array}{ccc} & \mathrm{R}_{\mathrm{Boston,Denver}} & \\ \diagup & & \diagdown \\ \mathit{tomorrow}{:}\emptyset & & \mathrm{R}_{\mathrm{tomorrow,Denver}} \\ & & | \\ & & \mathrm{R}^{\star}_{\mathrm{Boston,Denver}} \end{array}\right) = \begin{array}{l} \mathrm{P}_r(\textsf{insert}|\mathit{Boston}, \mathit{Denver}) \\ \mathrm{P}_w(\mathit{tomorrow}|\mathit{Boston}, \mathit{Denver}) \end{array}$$

$$\mathrm{P}\left(\begin{array}{ccc} & \mathrm{R}_{\mathrm{Boston,Denver}} & \\ & | & \\ & \mathrm{R}_{\mathrm{Boston,tomorrow}} & \\ \diagup & & \diagdown \\ \mathrm{R}^{\star}_{\mathrm{Boston,Denver}} & & \mathit{tomorrow}{:}\mathit{tomorrow} \end{array}\right) = \mathrm{P}_r(\textsf{delete}|\mathit{Boston}, \mathit{Denver})$$

$$\mathrm{P}\left(\begin{array}{ccc} & \mathrm{R}_{\mathrm{Boston:Denver}} & \\ \diagup & & \diagdown \\ \mathrm{R}^{\star}_{\mathrm{Boston:Denver}} & & \mathrm{N}_{\mathrm{Denver}}\downarrow \end{array}\right) = \mathrm{P}_r(\textsf{nonrepair}|\mathit{Boston}, \mathit{Denver})$$

Decoding speech repairs

- We could find the most likely analysis of a sentence
- or alternatively:
  1. compute the probability that each triple of adjacent substrings can be analysed as a reparandum/interregnum/repair
  2. divide by the probability that the substrings do not contain a repair
  3. if the *odds* is greater than a fixed threshold, declare that there is a repair
- Advantages of the more complex approach:
  - Doesn't require parsing the whole sentence (rather, only look for repairs up to some maximum size)
  - Adjusting the odds threshold trades precision for recall
  - Handles *overlapping repairs* (where the repair is itself repaired)

[[What did + what does he] + what does she] want?

Empirical results

- Training and testing data has *partial words and punctuation removed*
- CJ01′ is the Charniak and Johnson 2001 word-by-word classifier trained on new training and testing data

	CJ01′	Bigram	Trigram	Parser
Precision	0.951	0.776	0.774	0.820
Recall	0.631	0.736	0.763	0.778
F-score	0.759	0.756	0.768	0.797

Conclusion and future work

- There are lots of interesting ways of combining speech and parsing
- Some of them don't work better than existing techniques (yet)
- *Syntactic parsers make very good language models*
- (Discriminative models might also be a good thing to try).