Collecting, err, Correcting Speech Errors

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Talk outline

- What are speech repairs, and why are they interesting?
- A *noisy channel model* of speech repairs
  - combines two very different kinds of structures
  - a novel model of *interpreting ill-formed input*
- "Rough copy" dependencies, context free and *tree adjoining grammars*
- Reranking using machine-learning techniques
- Training and evaluating the model of speech errors
- RT04F evaluation

Speech errors in (transcribed) speech

- Restarts and repairs

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

  I want a flight *to Boston, uh,* to Denver on Friday

- Filled pauses

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

- Parentheticals

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

- "Ungrammatical" constructions

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

Why focus on speech repairs?

- *Filled pauses* are easy to recognize (in transcripts at least)
- *Parentheticals* are handled by current parsers fairly well
- *Ungrammatical constructions* aren't necessarily fatal
  - Statistical parsers *learn constructions in training corpus*
- . . . but *speech repairs* warrant special treatment, since the best parsers badly misanalyse them . . .

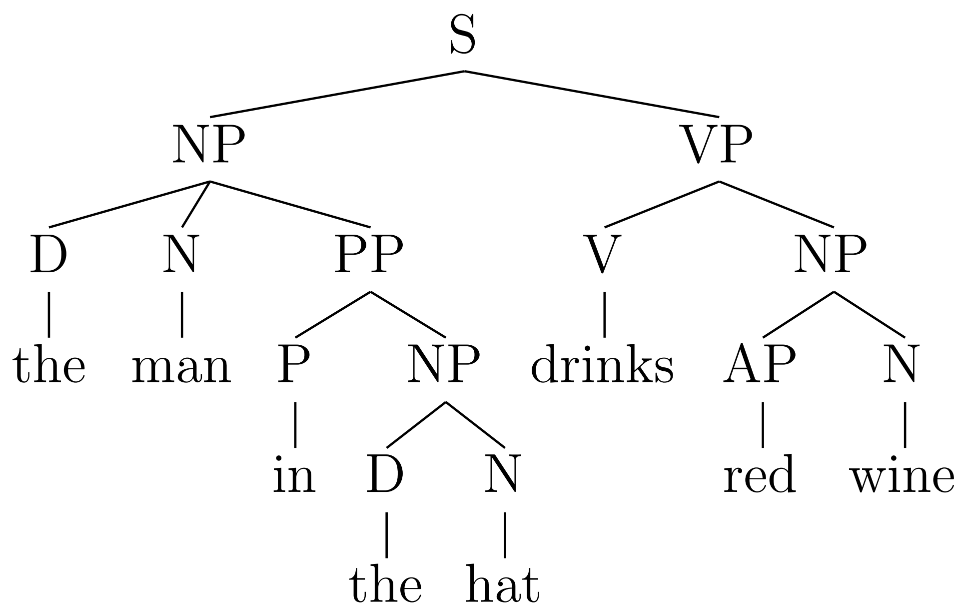
Statistical models of language

- Statistical regularities are incredibly useful!
- Early statistical models focused on dependencies between n adjacent words (*n-gram models*)

$$\$ \rightarrow \textit{the} \rightarrow \textit{man} \rightarrow \textit{in} \rightarrow \textit{the} \rightarrow \textit{hat} \rightarrow \textit{drinks} \rightarrow \textit{red} \rightarrow \textit{wine} \rightarrow \$$$

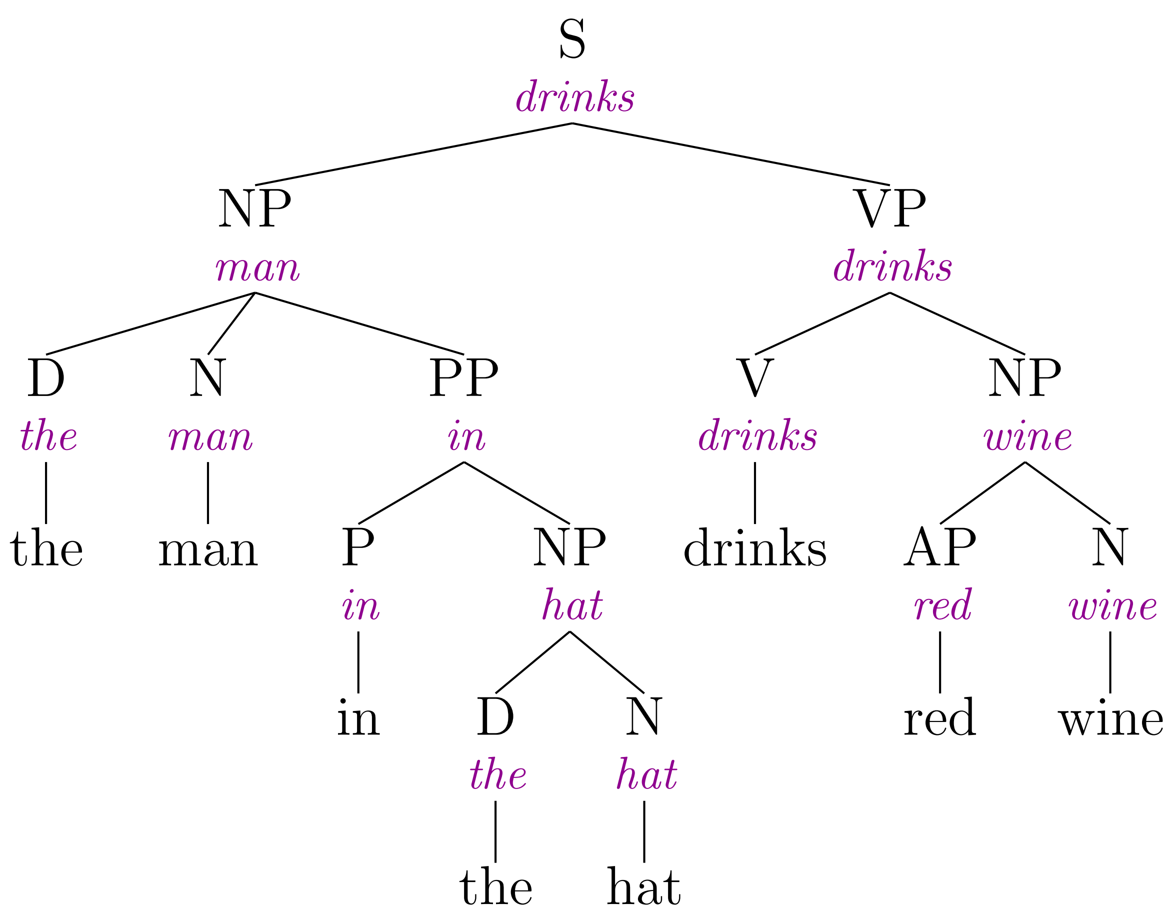
- Probabilities estimated from real *corpora*
- If model permits every word sequence to occur with non-zero probability $\Rightarrow$ model is *robust*
- Probability distinguishes "good" from "bad" sentences
- These simple models work surprisingly well because *they are lexicalized* (capture some semantic dependencies) and *most dependencies are local*

Probabilistic Context Free Grammars



- Rules are associated with *probabilities*
- Probability of a tree is the product of the probabilities of its rules
- *Most probable tree* is "best guess" at correct syntactic structure

Head to head dependencies



Rules:

$$\underset{drinks}{\mathrm{S}} \rightarrow \underset{man}{\mathrm{NP}} \;\; \underset{drinks}{\mathrm{VP}}$$

$$\underset{drinks}{\mathrm{VP}} \rightarrow \underset{drinks}{\mathrm{V}} \;\; \underset{wine}{\mathrm{NP}}$$

$$\underset{wine}{\mathrm{NP}} \rightarrow \underset{red}{\mathrm{AP}} \;\; \underset{wine}{\mathrm{N}}$$

...

- *Lexicalization* captures a wide variety of syntactic (and semantic!) dependencies
- Backoff and smoothing are central issues

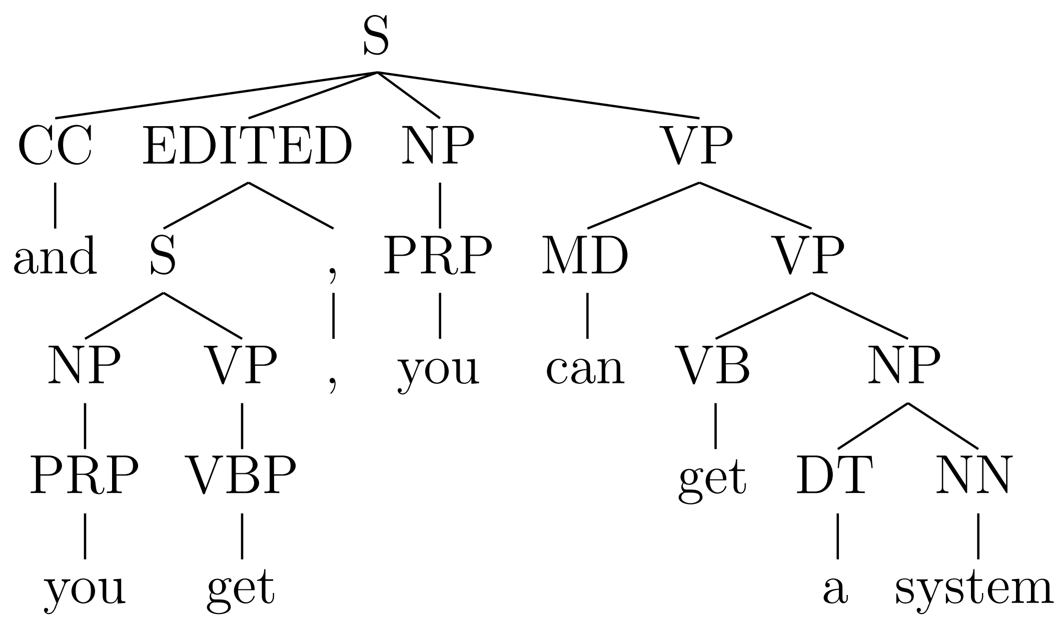
The structure of repairs

$$\ldots \text{and } \underbrace{\text{you get,}}_{\text{Reparandum}} \ \underbrace{\text{uh,}}_{\text{Interregnum}} \ \underbrace{\text{you can get}}_{\text{Repair}} \text{ a system} \ldots$$

- The Reparandum is *often not a syntactic phrase*
- The Interregnum is usually lexically and prosodically marked, but can be empty
- The Reparandum is often a *"rough copy"* of the Repair
  - Repairs are typically short
  - Repairs are not always copies

Shriberg 1994 "Preliminaries to a Theory of Speech Disfluencies"

Treebank representation of repairs



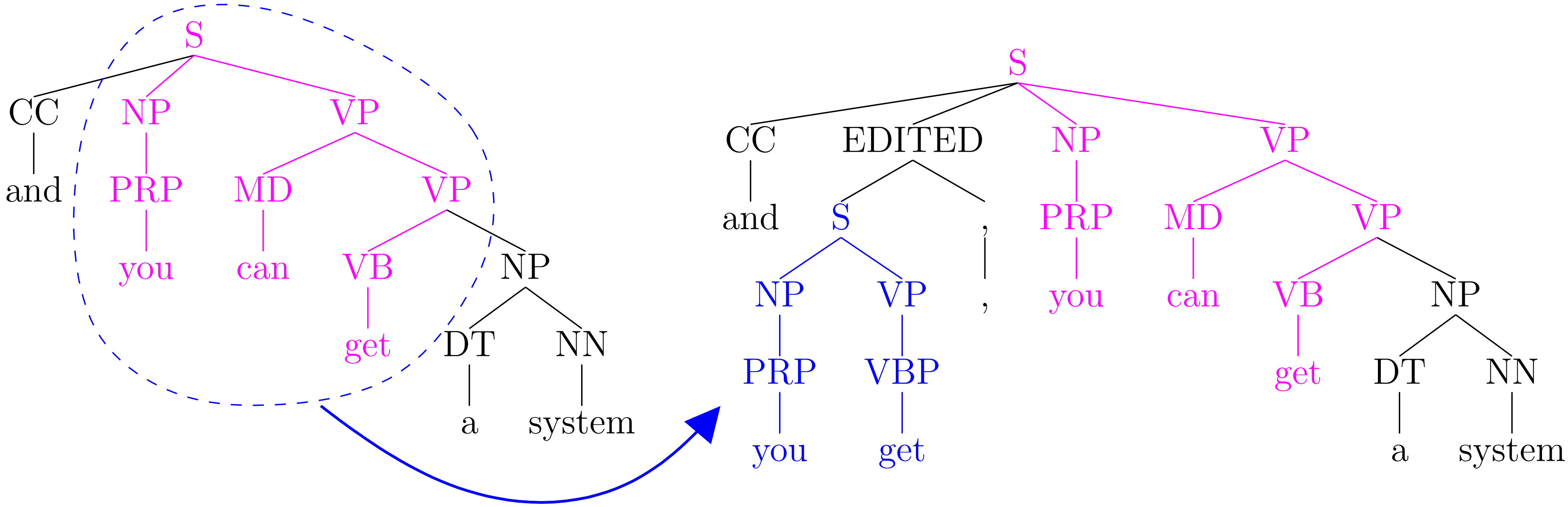
- The *Switchboard treebank* contains the parse trees for 1M words of spontaneous telephone conversations
- Each reparandum is indicated by an EDITED node (interregnum and repair are also annotated)
- But Charniak's parser never finds any EDITED nodes!

The "true model" of repairs (?)

… and $\underbrace{\text{you get,}}_{\text{Reparandum}}$ $\underbrace{\text{uh,}}_{\text{Interregnum}}$ $\underbrace{\text{you can get}}_{\text{Repair}}$ a system …

- Speaker generates intended "conceptual representation"
- Speaker incrementally generates syntax and phonology,
  - recognizes that what is said doesn't mean what was intended,
  - "backs up", i.e., partially deconstructs syntax and phonology, and
  - starts incrementally generating syntax and phonology again
- but without a good model of "conceptual representation", this may be hard to formalize …

Approximating the "true model" (1)



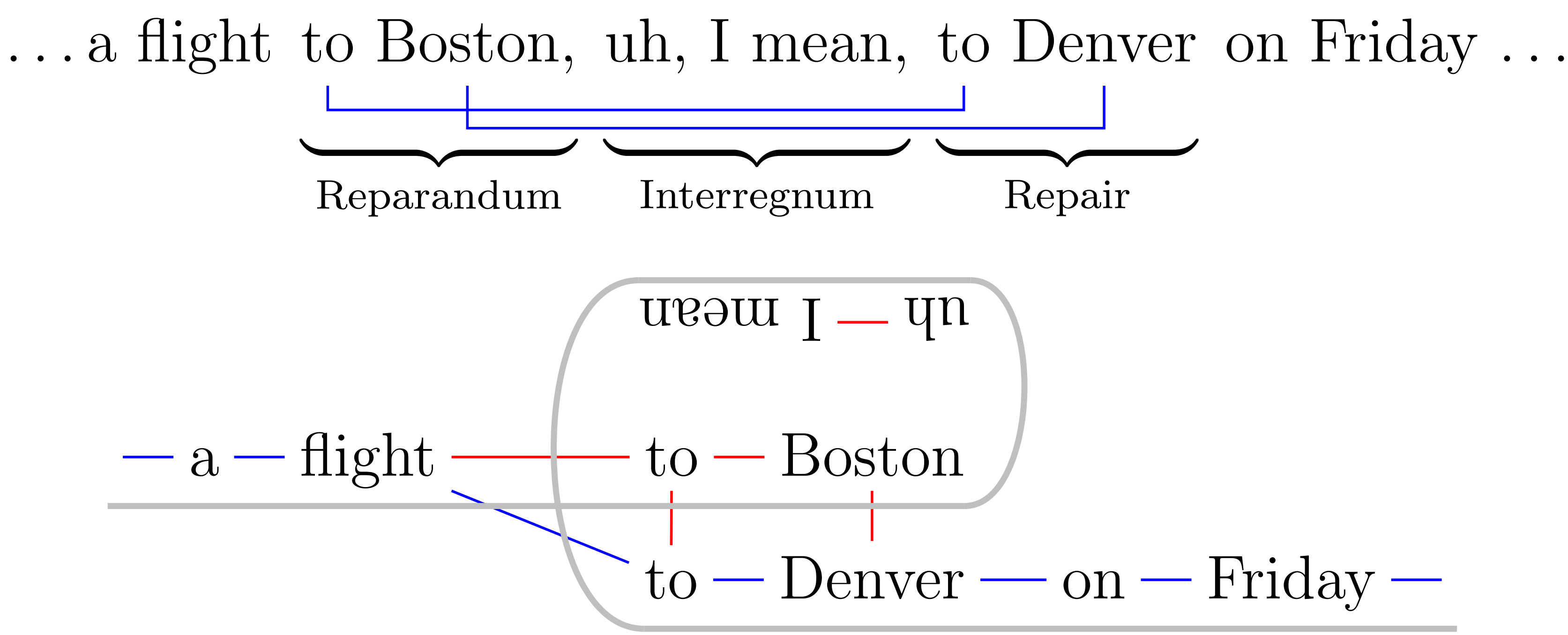
- Approximate semantic representation by *syntactic structure*
- Tree with reparandum and interregnum excised is what speaker intended to say
- Reparandum results from attempt to generate Repair structure
- Dependencies are *very different to those in "normal" language!*

Approximating the “true model” (2)

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

- Use Repair string as approximation to intended meaning
- Reparandum string is “rough copy” of Repair string
  - involves *crossing* (rather than *nested*) dependencies
- String with reparandum and interregnum excised is well-formed
  - after correcting the error, what’s left should have high probability
  - *uses model of normal language to interpret ill-formed input*

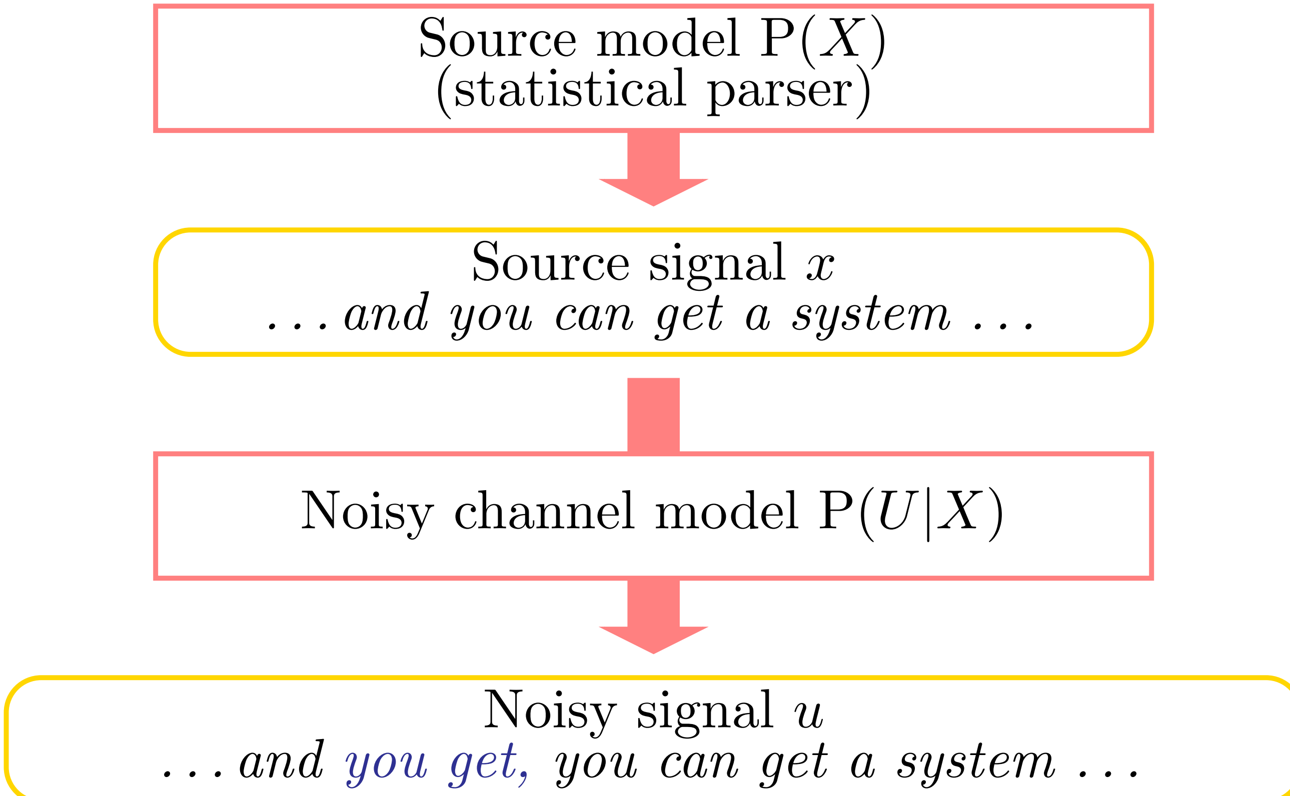
Helical structure of speech repairs



- Backup and Repair nature of speech repairs generates a dependency structure unusual in language
- These dependencies seem *incompatible with standard syntactic structures*

Joshi (2002), ACL Lifetime achievement award talk

The Noisy Channel Model



- Noisy channel models combines two different submodels
- *Bayes rule* describes how to invert the channel

$$\mathrm{P}(x|u) = \frac{\mathrm{P}(u|x)\mathrm{P}(x)}{\mathrm{P}(u)}$$

The channel model

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

- Channel model is a *transducer* producing *source:output pairs*

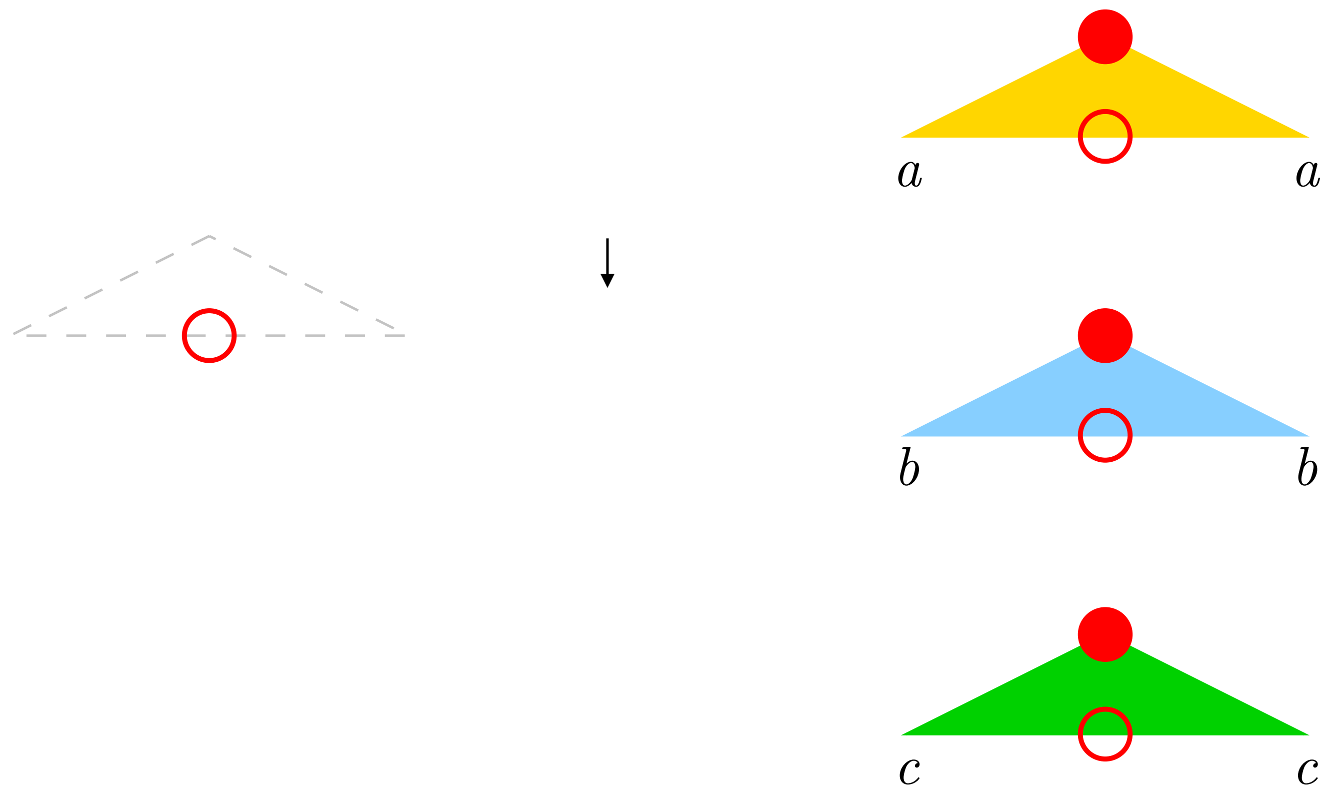
  . . . a:a flight:flight ∅:to ∅:Boston ∅:uh ∅:I ∅:mean to:to Denver:Denver . . .

- only 62 different phrases appear in *interregnum* (*uh, I mean*)

  ⇒ *unigram model* of interregnum phrases

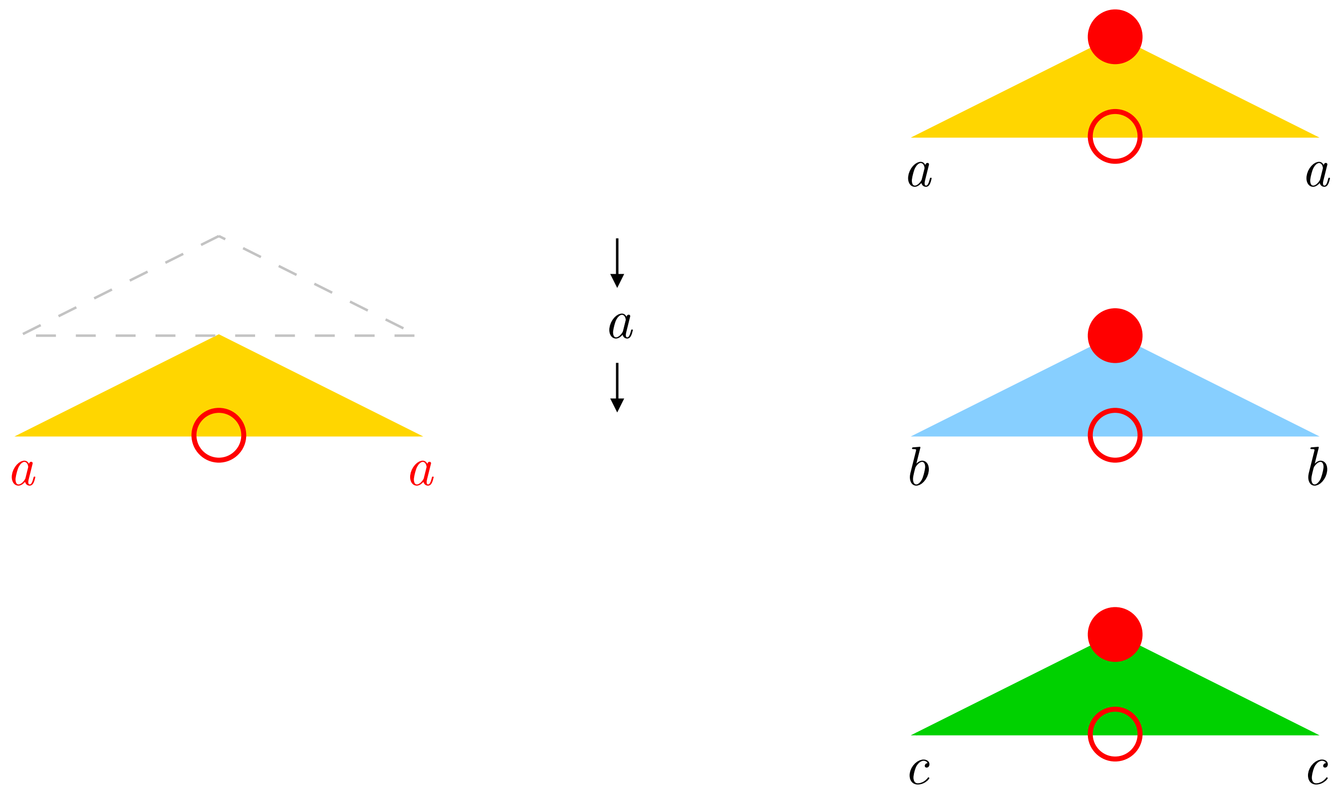
- *Reparandum* is "rough copy" of repair
  - We need a probabilistic model of rough copies
  - FSMs and CFGs *can't generate copy dependencies* . . .
  - but *Tree Adjoining Grammars* can

CFGs generate ww^R dependencies (1)



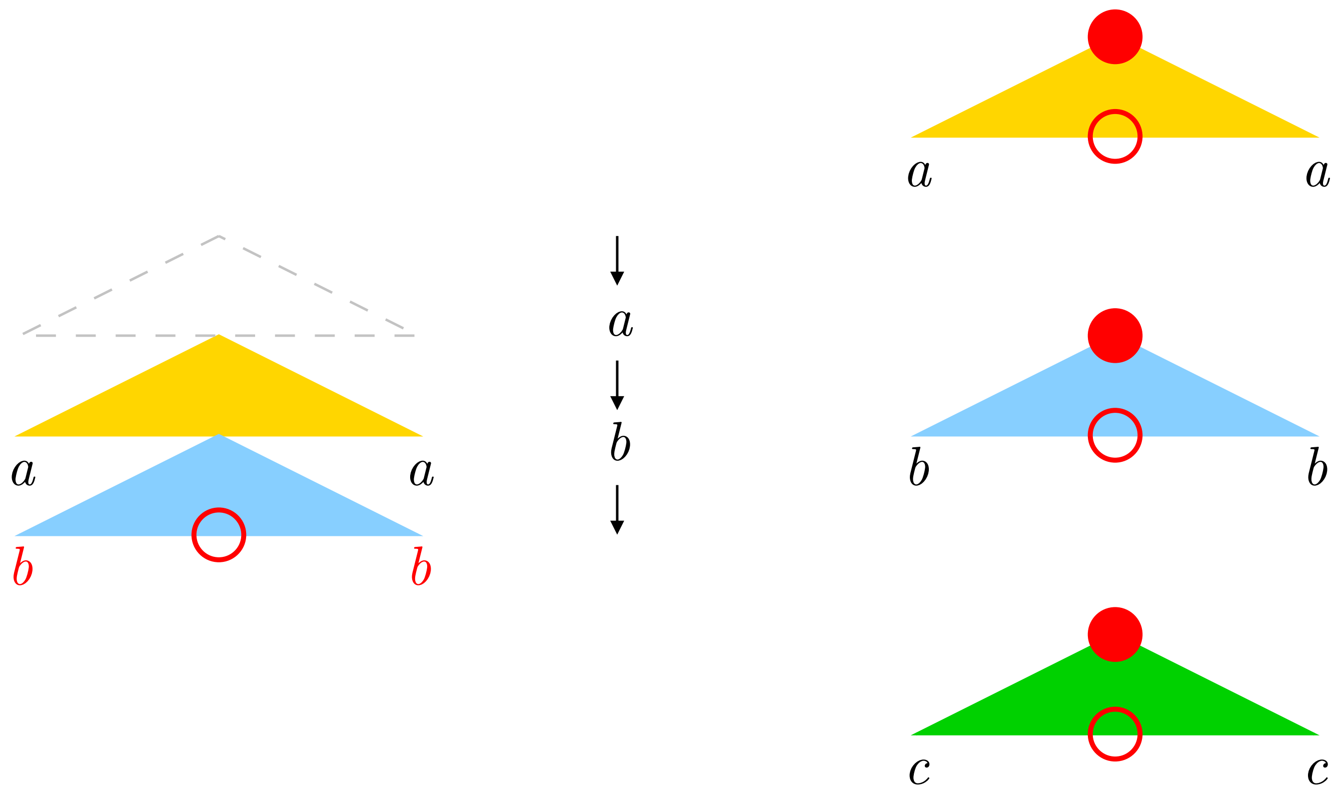
- CFGs generate *nested dependencies* between a string w and its reverse w^R

CFGs generate ww^R dependencies (2)



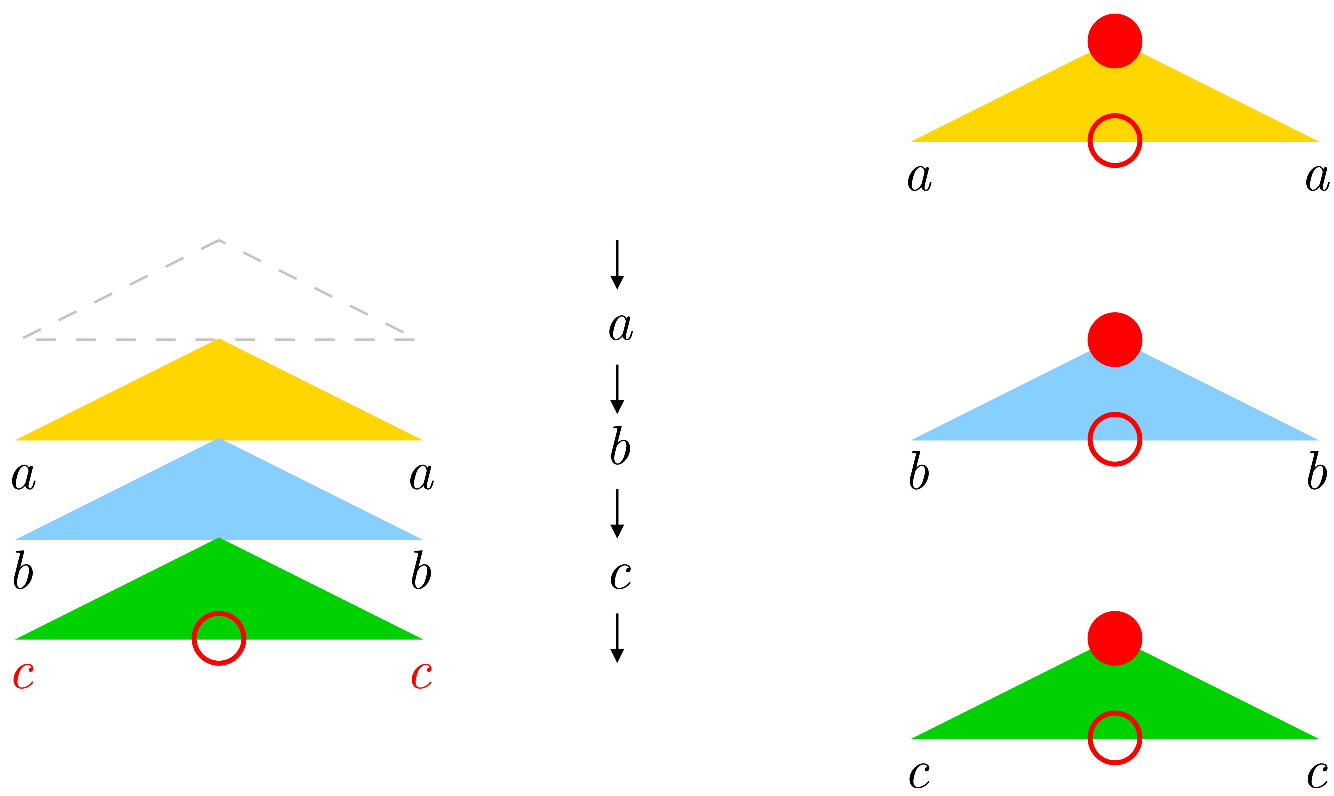
- CFGs generate *nested dependencies* between a string w and its reverse w^R

CFGs generate ww^R dependencies (3)



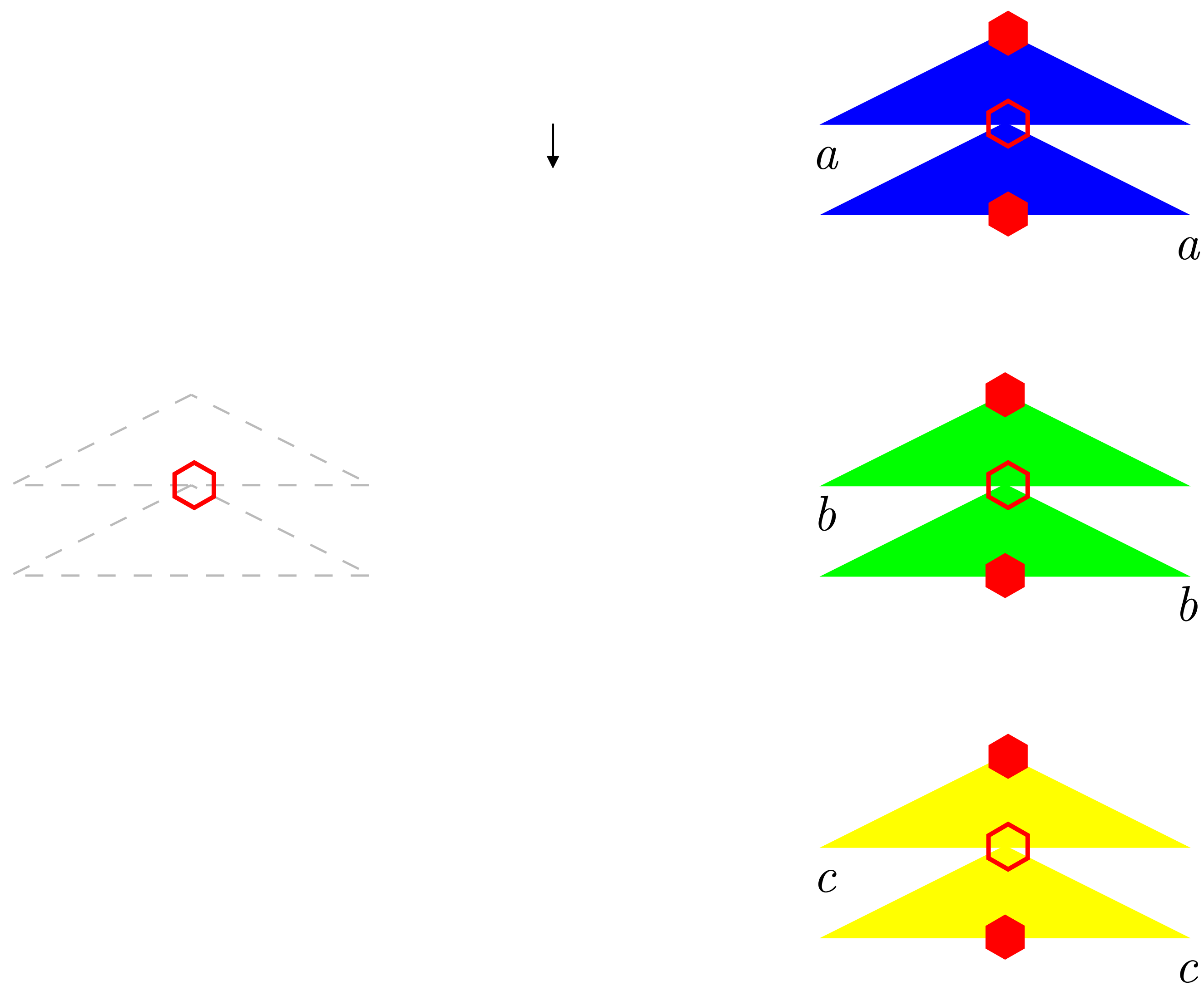
- CFGs generate *nested dependencies* between a string w and its reverse w^R

CFGs generate ww^R dependencies (4)

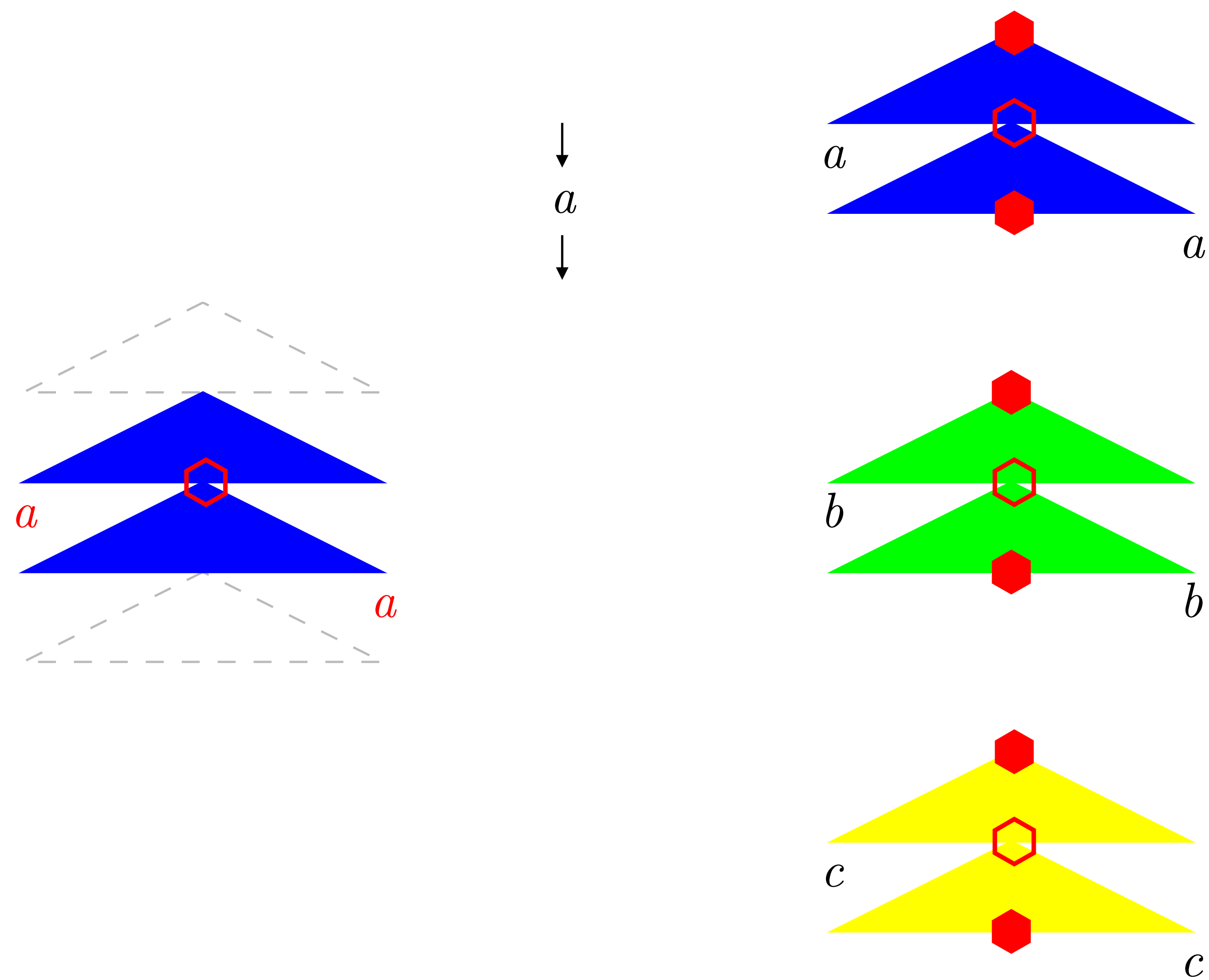


- CFGs generate *nested dependencies* between a string w and its reverse w^R

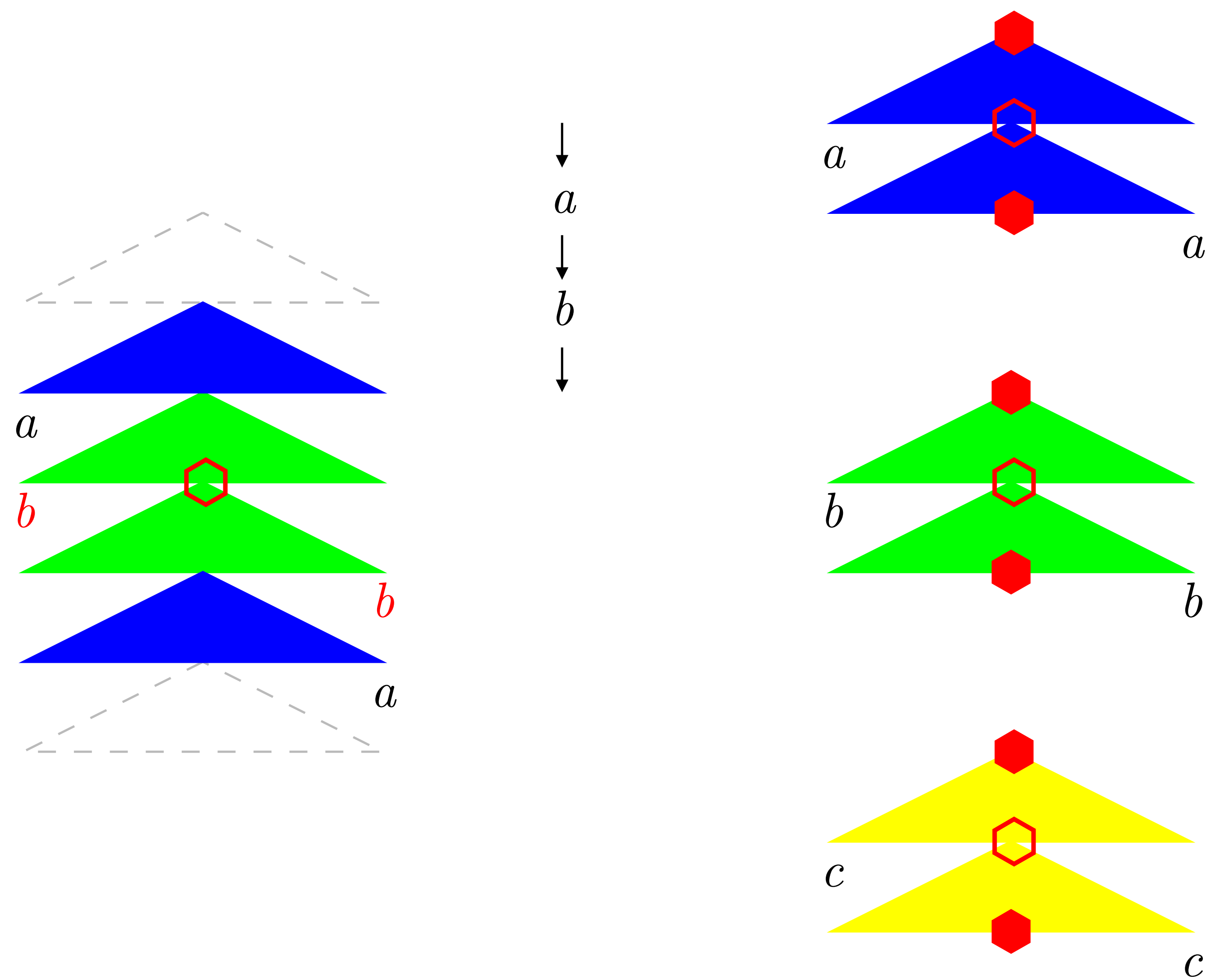
TAGs generate ww dependencies (1)



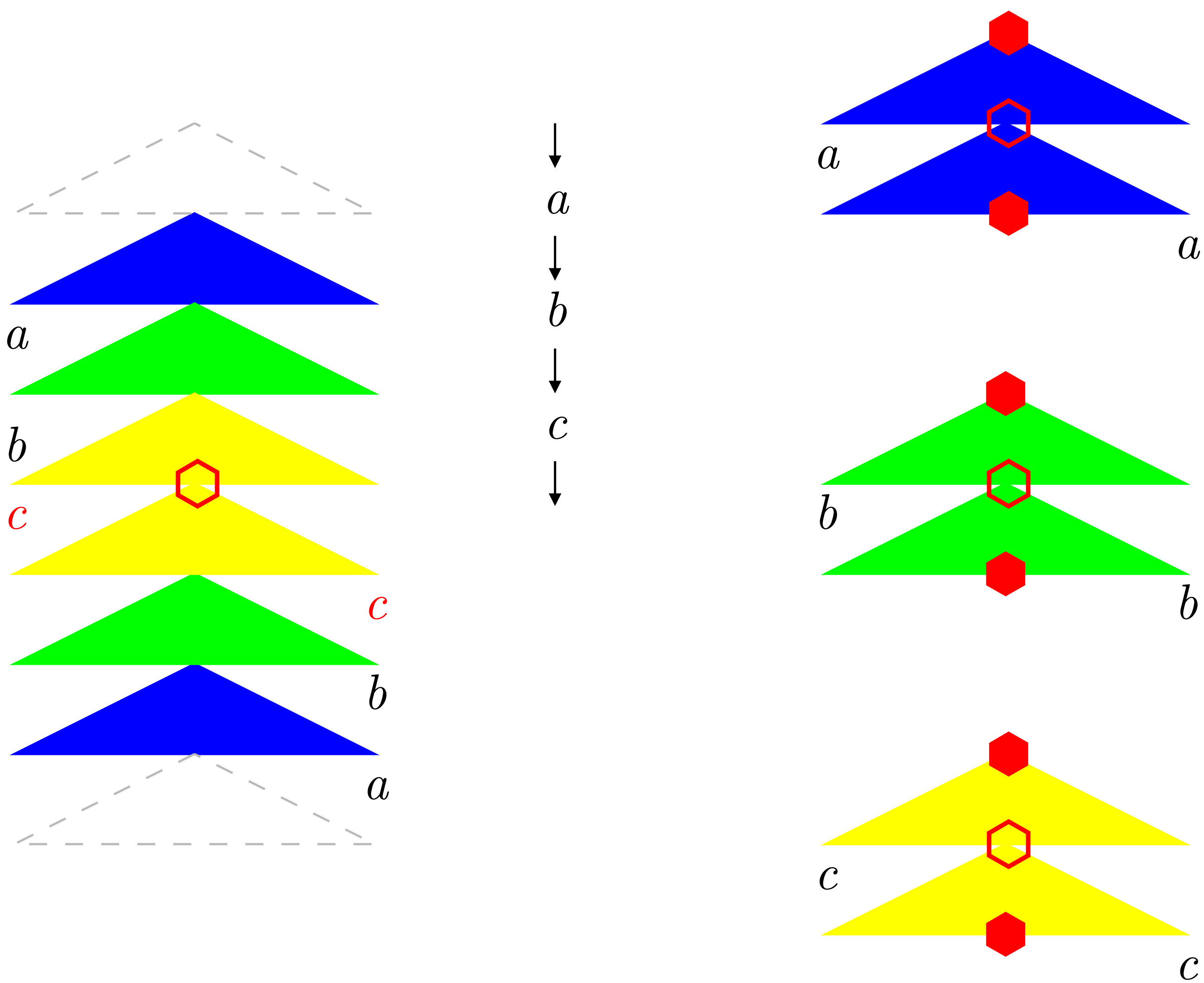
TAGs generate ww dependencies (2)



TAGs generate ww dependencies (3)



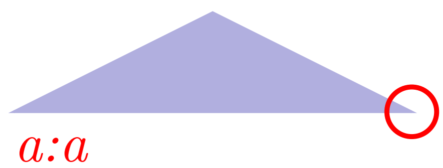
TAGs generate ww dependencies (4)



Derivation of *a flight* . . . (1)

a:a flight:flight 0:to 0:Boston 0:uh 0:I 0:mean to:to Denver:Denver on:on Friday:Friday

Derivation of *a flight* . . . (2)



a:a flight:flight 0:to 0:Boston 0:uh 0:I 0:mean to:to Denver:Denver on:on Friday:Friday

$\downarrow$

a

Derivation of *a flight* ... (3)

a:a *flight:flight* *0:to 0:Boston 0:uh 0:I 0:mean to:to Denver:Denver on:on Friday:Friday*

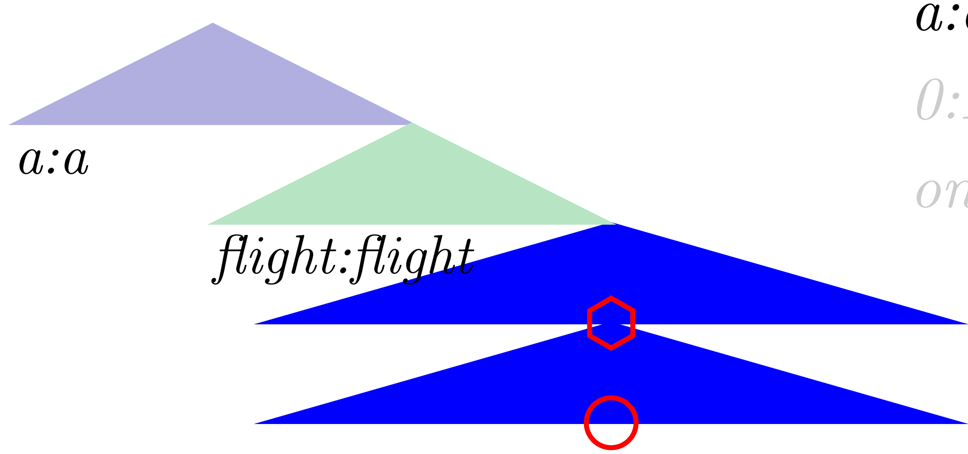
$\downarrow$

a

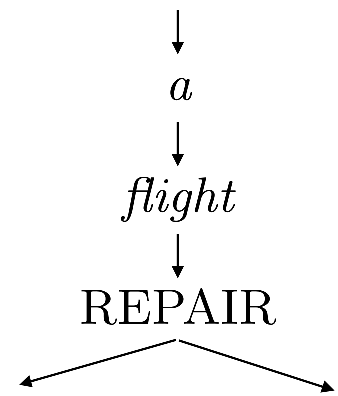
$\downarrow$

flight

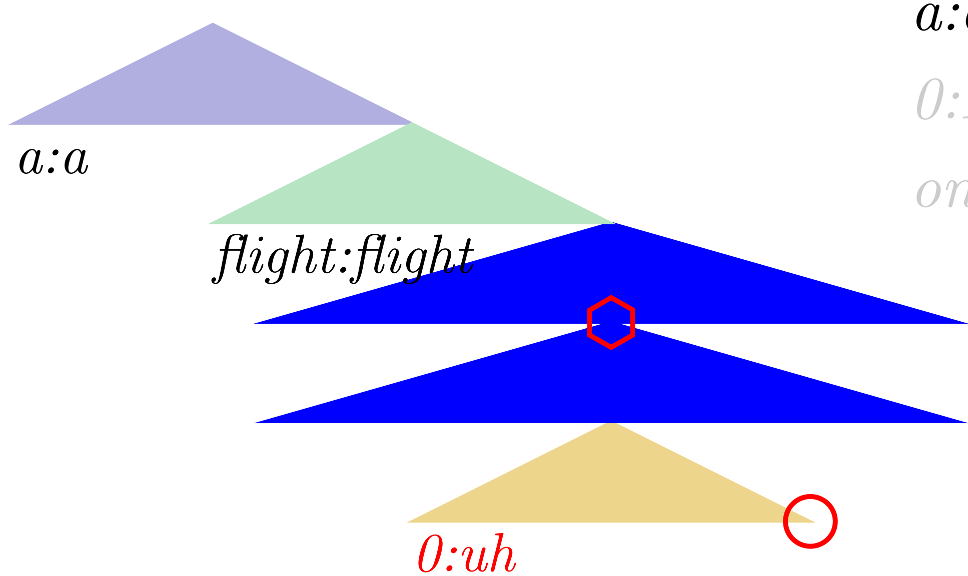
Derivation of *a flight* . . . (4)



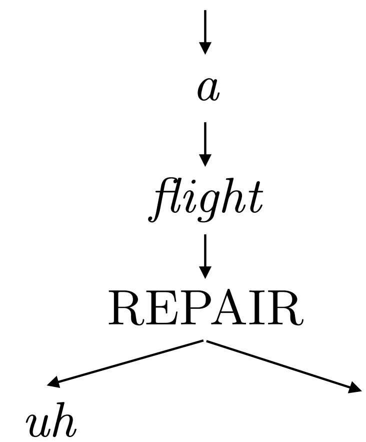
a:a flight:flight *0:to 0:Boston 0:uh 0:I 0:mean to:to Denver:Denver on:on Friday:Friday*



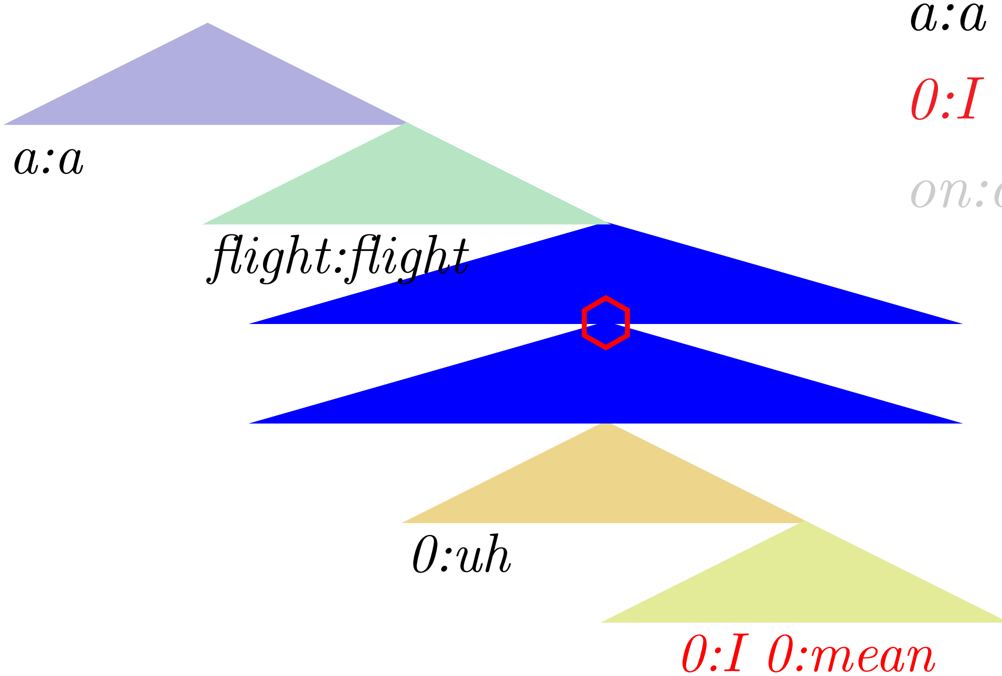
Derivation of *a flight* . . . (5)



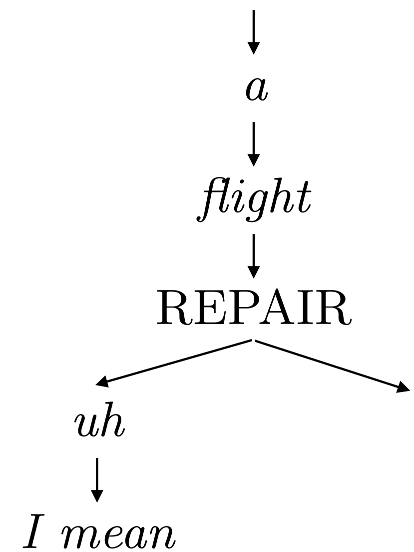
a:a flight:flight 0:to 0:Boston 0:uh 0:I 0:mean to:to Denver:Denver on:on Friday:Friday



Derivation of *a flight* . . . (6)

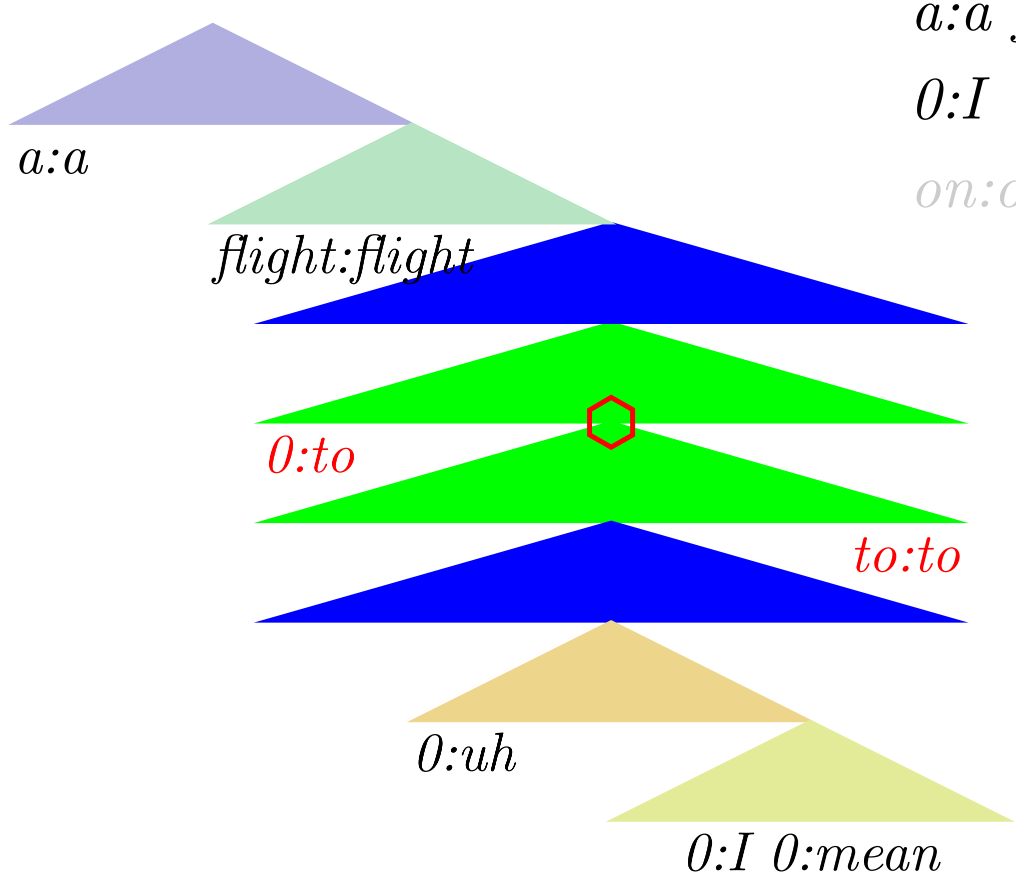


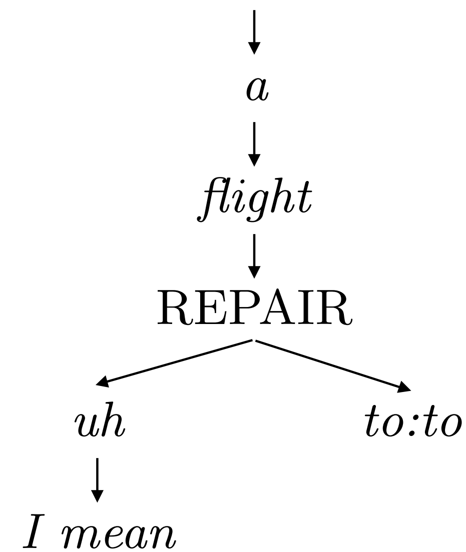
a:a flight:flight 0:to 0:Boston 0:uh
0:I 0:mean to:to Denver:Denver
on:on Friday:Friday



Derivation of *a flight* . . . (7)

a:a flight:flight 0:to 0:Boston 0:uh
0:I 0:mean to:to Denver:Denver
on:on Friday:Friday



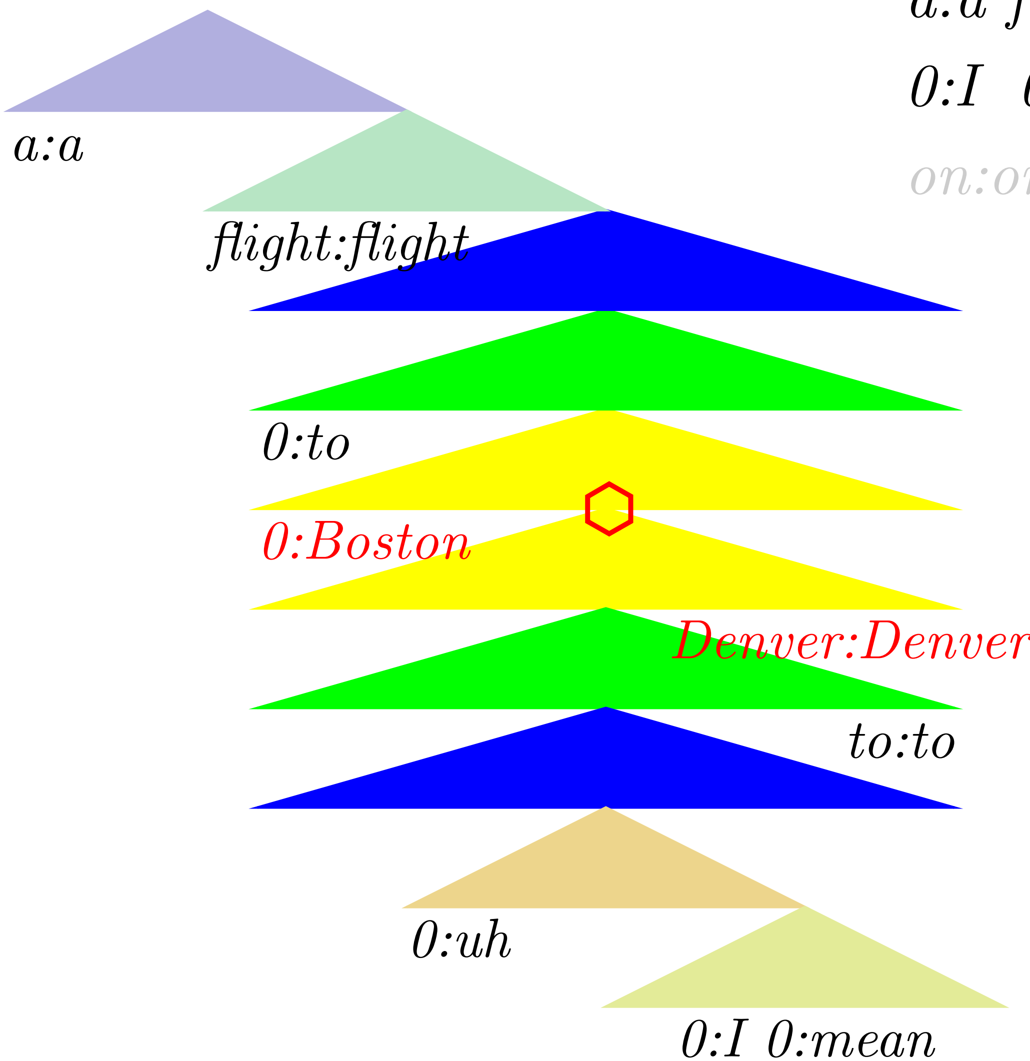


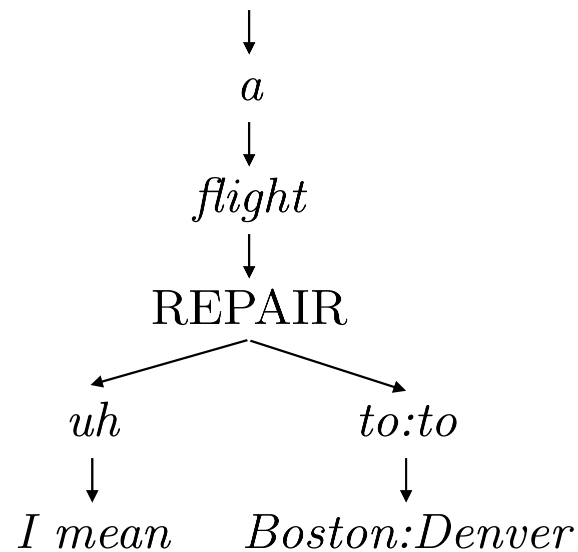
Derivation of *a flight . . .* (8)

a:a flight:flight 0:to 0:Boston 0:uh

0:I 0:mean to:to Denver:Denver

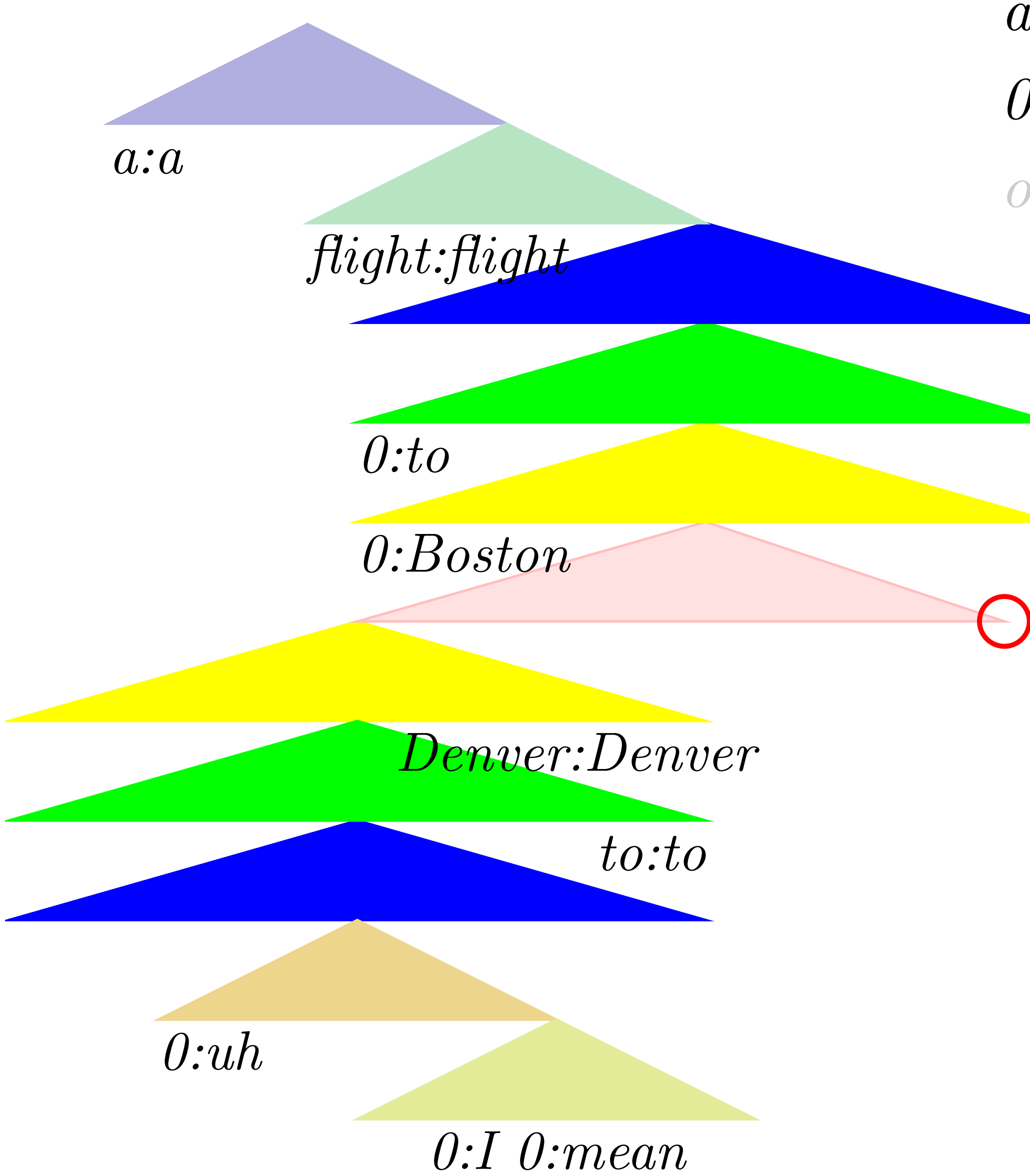
on:on Friday:Friday

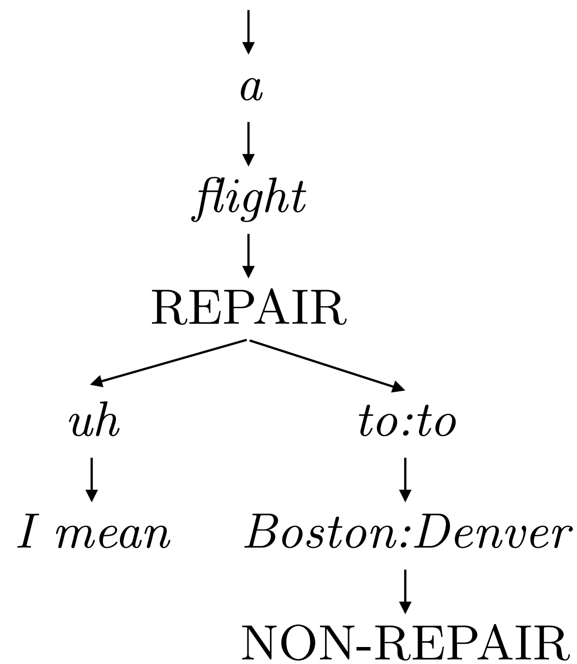




Derivation of *a flight . . .* (9)

a:a flight:flight 0:to 0:Boston 0:uh
0:I 0:mean to:to Denver:Denver
on:on Friday:Friday



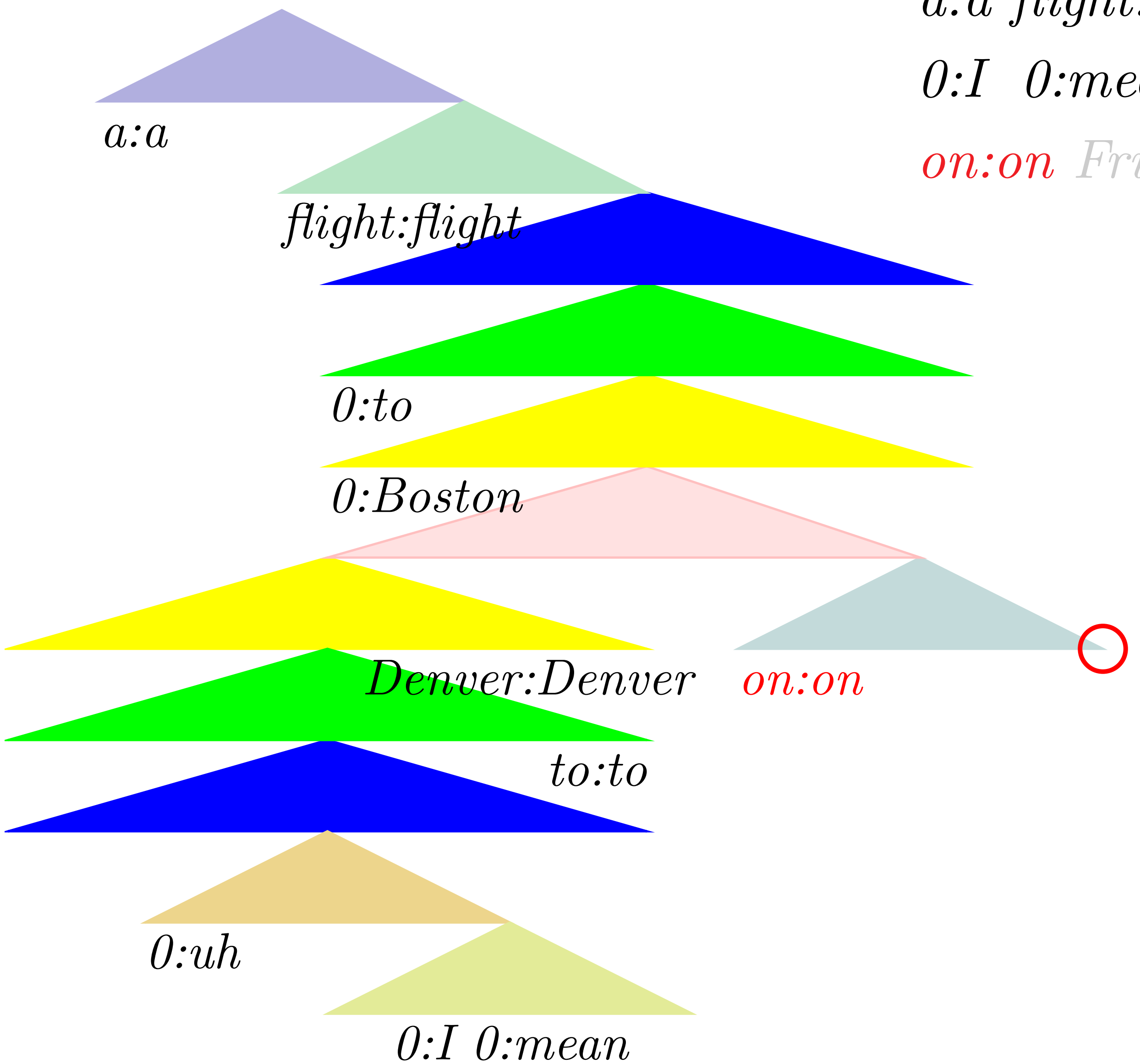


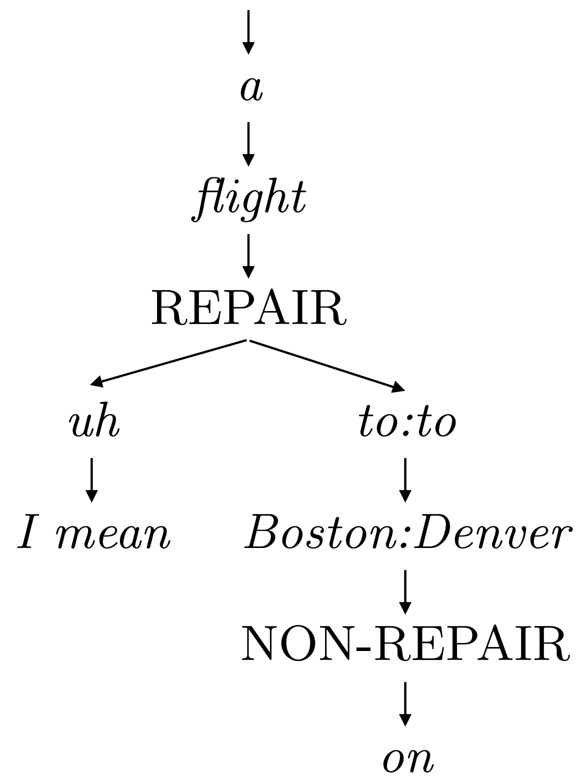
Derivation of *a flight* . . . (10)

a:a flight:flight 0:to 0:Boston 0:uh

0:I 0:mean to:to Denver:Denver

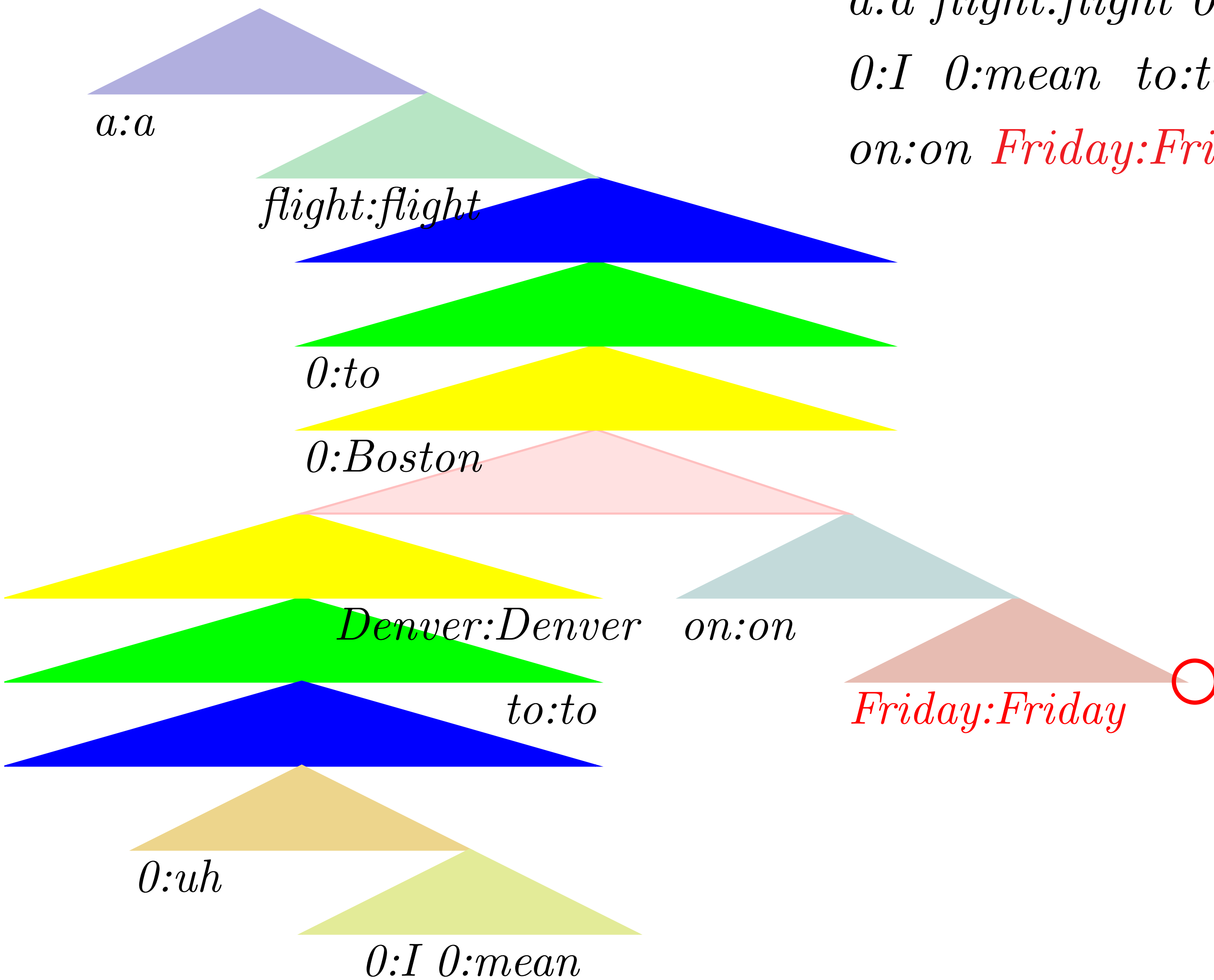
on:on Friday:Friday

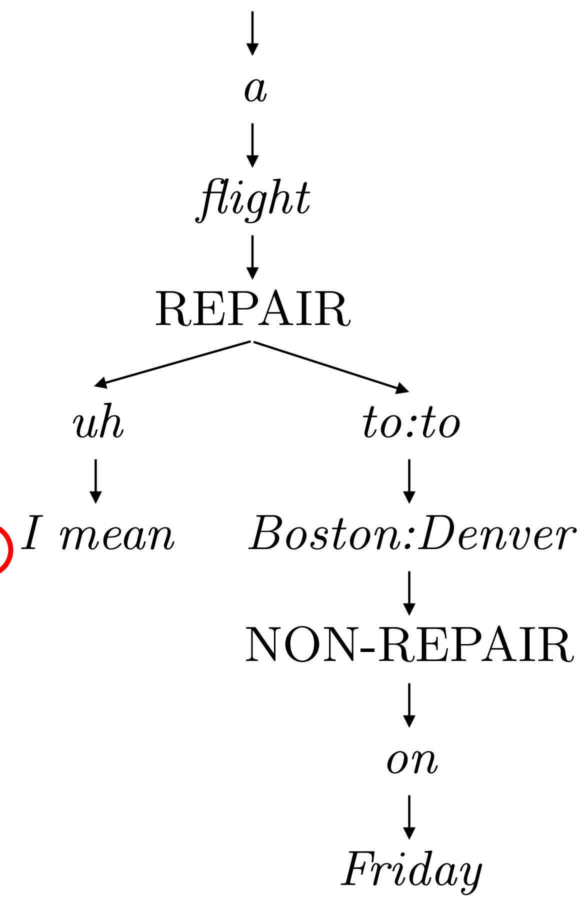




Derivation of *a flight* . . . (11)

a:a flight:flight 0:to 0:Boston 0:uh 0:I 0:mean to:to Denver:Denver on:on Friday:Friday





Training data (1)

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

- Switchboard corpus annotates *reparandum, interregnum and repair*
- Trained on Switchboard files sw[23]*.dps (1.3M 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%), too complicated 24K (1.8%)

Training data (2)

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

- Reparandum and repair word-aligned by *minimum edit distance*
  - 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 352 substitutions (42%) in heldout are not in training

Estimating the channel model

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

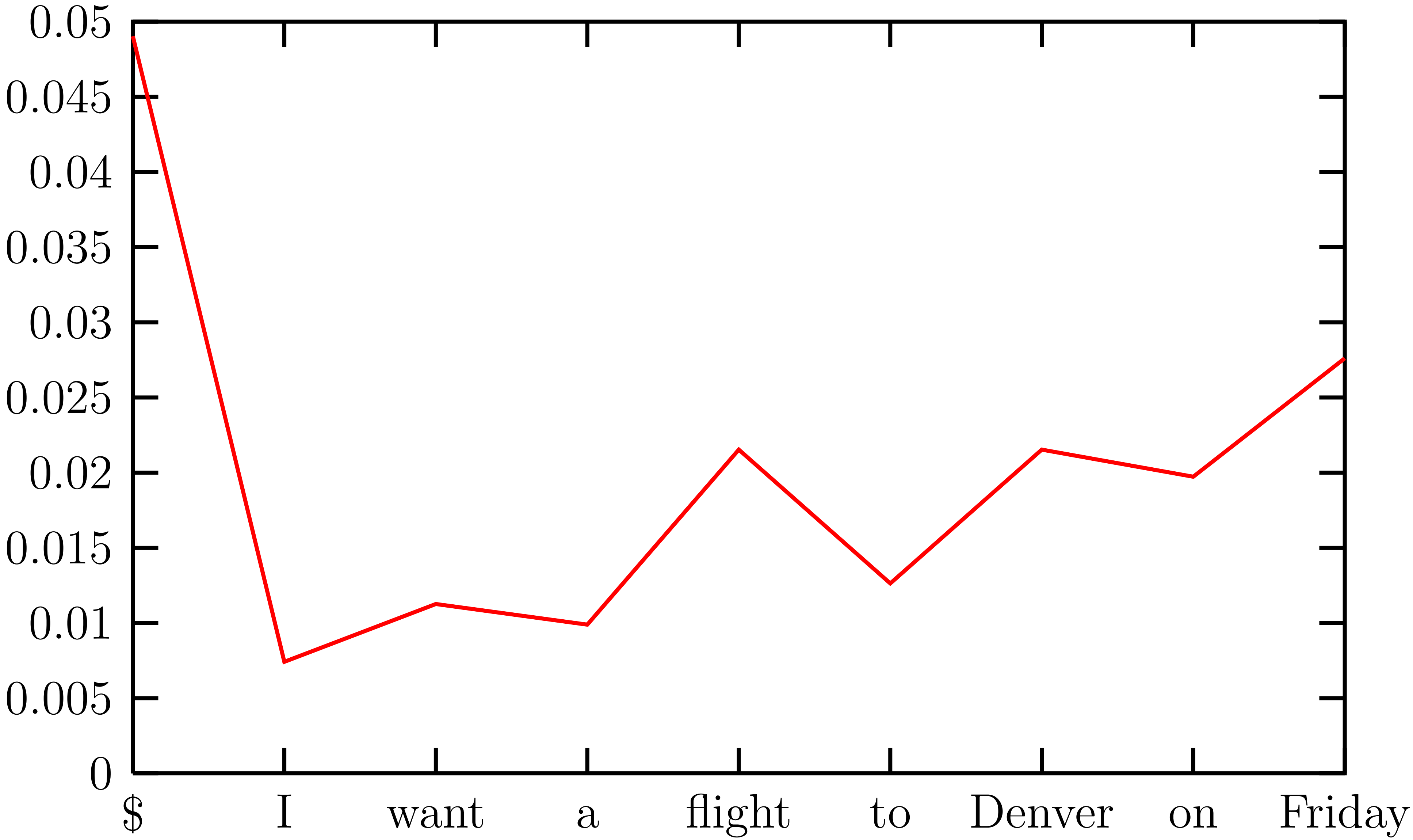
- Channel model is defined in terms of several simpler distributions:

  $\mathrm{P}_r(\mathsf{repair}|\mathit{flight})$: Probability of a repair starting after *flight*

  $\mathrm{P}_t(m|\mathit{Boston}, \mathit{Denver})$, where $m \in \{\mathsf{copy}, \mathsf{substitute}, \mathsf{insert}, \mathsf{delete}, \mathsf{end}\}$
  Probability of m after reparandum *Boston* and repair *Denver*

  $\mathrm{P}_m(\mathit{tomorrow}|\mathit{Boston}, \mathit{Denver})$: Probability that next reparandum word is *tomorrow*

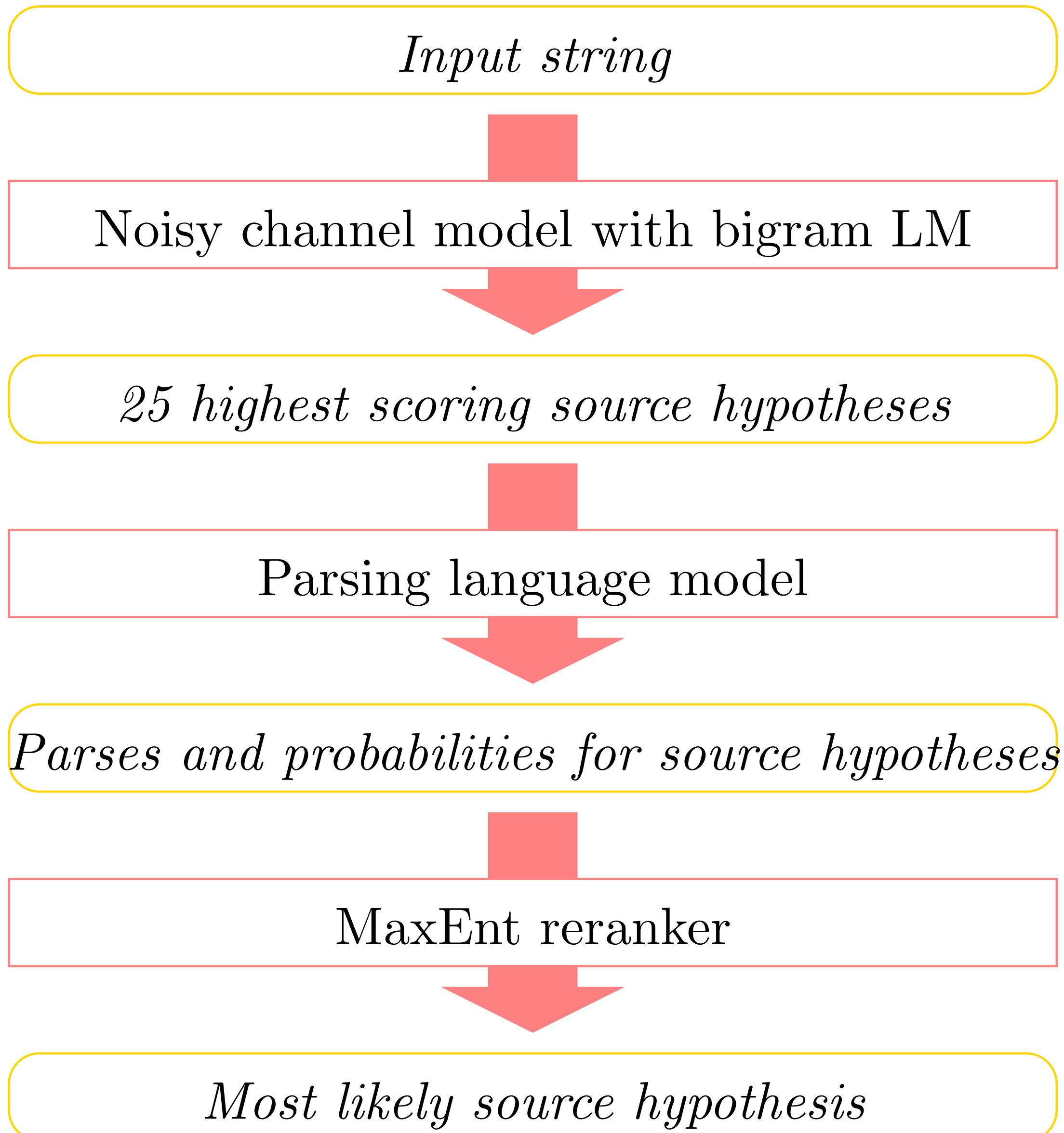
Estimated repair start probabilities



Implementation details (1)

- Don't know how to efficiently *search* for best analysis using parser LM
  $\Rightarrow$ find 25-best hypothesized sources for each sentence using a simpler *bigram* LM
- Calculate probability of each hypothesized source using parsing LM
- Two ways of combining channel and language model log probabilities
  - Add them (noisy channel model)
  - Use them as *features* in a machine learning algorithm
    $\Rightarrow$ a *reranking* approach to finding best hypothesis

Implementation details (2)

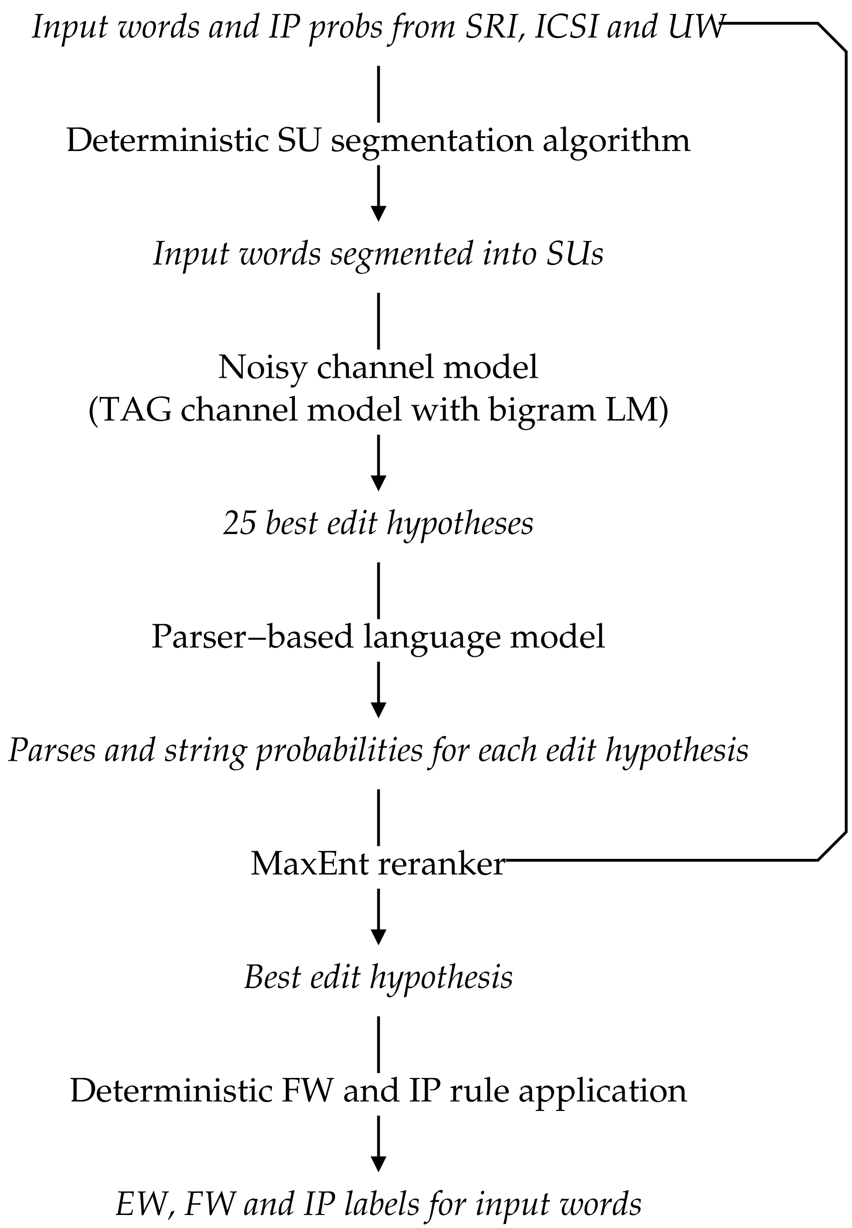


Evaluation of model's performance

	f-score	error rate
NCM + bigram LM	0.75	0.45
NCM + parser LM	0.81	0.35
MaxEnt reranker using NCM + parser LM	0.87	0.25
MaxEnt reranker alone	0.78	0.38

- Evaluated on an unseen portion of Switchboard corpus
- *f-score* is a geometric average of EDITED words precision and recall (bigger is better)
- *error rate* is the number of EDITED word errors made divided by number of true edited words (smaller is better)

RT04F competition



- RT04F evaluated *meta-data extraction*
- Test material was unsegmented speech
- ICSI, SRI and UW supplied us with ASR output, SU boundaries and acoustic IP probabilities

RT04F evaluation results

Task/error rate	Oracle words	ASR words
EDITED word detection	46.1	76.3
Filler word detection	23.7	40.0
Interruption point detection	28.6	55.9

- EDITED word detection used noisy channel reranker
- Filler word detection used *deterministic rules*
- Interruption point detection combined these two models

Evaluation of model's performance

Error rate on dev2 data	Oracle words	ASR words
Full model	0.525	0.773
– parsing model	0.55	0.790
– repair model	0.567	0.805
– prosodic features	0.541	0.772

- DARPA runs a competitive evaluation (RT04) of speech understanding systems
- EDITED word detection was one task in this evaluation
- Our system was not designed to deal with the RT04 data
  - our system assumes input is segmented into sentences

Conclusion and future work

- *Syntactic parsers make good language models*
- Grammars are useful for lots of things besides syntax!
- *Noisy channel model* can *combine very different kinds of models*
  - a lexicalized CFG model of syntactic structure
  - a TAG model of "rough copy" dependencies in speech repairs
- Modern *machine learning techniques* are very useful
  - can exploit *prosodic* and other kinds of information
- Novel way of modeling *robust language comprehension*
- Performs well in practice