Toward a Psycholinguistically-Motivated Model of Language Processing

William Schuler[1],
Samir AbdelRahman[2],
Tim Miller[1],
Lane Schwartz[1]

June 24, 2011

[1]University of Minnesota
[2]Cairo University

Background

NSF project: implement interactive model of speech/language processing

- Parsing/speech recognition dep. on semantic interpretation in context (Tanenhaus et al., 1995, 2002)

Background

NSF project: implement interactive model of speech/language processing

- Parsing/speech recognition dep. on semantic interpretation in context (Tanenhaus et al., 1995, 2002)
- Factored time-series model of speech recognition, parsing, interpretation (formal model presented in Computational Linguistics, in press)
- Real-time interactive speech interface: define new objects, then refer (implemented system presented at IUI'08; interp. → vectors of objects)
- This year: interp. vector → head word probabilities / LSA semantics

Background

NSF project: implement interactive model of speech/language processing

- Parsing/speech recognition dep. on semantic interpretation in context (Tanenhaus et al., 1995, 2002)
- Factored time-series model of speech recognition, parsing, interpretation (formal model presented in Computational Linguistics, in press)
- Real-time interactive speech interface: define new objects, then refer (implemented system presented at IUI'08; interp. → vectors of objects)
- This year: interp. vector → head word probabilities / LSA semantics
- Why time-series? composition expensive; time-series simpler than CKY

Background

NSF project: implement interactive model of speech/language processing

- Parsing/speech recognition dep. on semantic interpretation in context (Tanenhaus et al., 1995, 2002)
- Factored time-series model of speech recognition, parsing, interpretation (formal model presented in Computational Linguistics, in press)
- Real-time interactive speech interface: define new objects, then refer (implemented system presented at IUI'08; interp. → vectors of objects)
- This year: interp. vector → head word probabilities / LSA semantics
- Why time-series? composition expensive; time-series simpler than CKY
- Today: is it safe? Human-like memory limits still parse most sentences (evaluated on broad-coverage WSJ Treebank)

Background

NSF project: implement interactive model of speech/language processing

- Parsing/speech recognition dep. on semantic interpretation in context (Tanenhaus et al., 1995, 2002)
- Factored time-series model of speech recognition, parsing, interpretation (formal model presented in Computational Linguistics, in press)
- Real-time interactive speech interface: define new objects, then refer (implemented system presented at IUI'08; interp. → vectors of objects)
- This year: interp. vector → head word probabilities / LSA semantics
- Why time-series? composition expensive; time-series simpler than CKY
- Today: is it safe? Human-like memory limits still parse most sentences (evaluated on broad-coverage WSJ Treebank)
- Friday: model transform also gives nice explanation of speech repair (evaluated on Switchboard Treebank)

Parsing in Short-term Memory

Early work:

Marcus ('80), Abney & Johnson ('91), Gibson ('91), Lewis ('93), ... — Garden pathing, processing difficulties due to memory saturation

- processing difficulties also due to other factors, e.g. similarity (Miller & Chomsky '63; Lewis '93), decay (Gibson '98)
- favor left-corner; but eager/deferred composition? → parallel proc.

Parsing in Short-term Memory

Early work:

Marcus ('80), Abney & Johnson ('91), Gibson ('91), Lewis ('93), ... —
Garden pathing, processing difficulties due to memory saturation

- processing difficulties also due to other factors, e.g. similarity (Miller & Chomsky '63; Lewis '93), decay (Gibson '98)
- favor left-corner; but eager/deferred composition? → parallel proc.

More recently:

Hale (2003), Levy (2008) —
Difficulties due to changing probability/activation of competing hypotheses

- empirical success
- decouples processing difficulty from memory saturation
- but does not explain how/whether parsing fits in short-term memory (and parsing should now be comfortably within STM, not at limit!)

Parsing in Short-term Memory

This model:

Explicit memory elements, compatible w. interactive interpretation

- Bounded store of incomplete referents, constituents over time
  - incomplete referets: individual/group of objects/events ($\sim$ Haddock'89)
  - incomplete constituents: e.g. S/NP (S w/o NP; $\sim$ CCG, Steedman'01)

Parsing in Short-term Memory

This model:

Explicit memory elements, compatible w. interactive interpretation

- Bounded store of incomplete referents, constituents over time
  - incomplete referets: individual/group of objects/events ($\sim$ Haddock'89)
  - incomplete constituents: e.g. S/NP (S w/o NP; $\sim$ CCG, Steedman'01)
- For simplicity, strict complexity limit on memory elements (no chunks):

  one incomplete referent/constituent per memory element

Parsing in Short-term Memory

This model:

Explicit memory elements, compatible w. interactive interpretation

- Bounded store of incomplete referents, constituents over time
  - incomplete referets: individual/group of objects/events ($\sim$ Haddock'89)
  - incomplete constituents: e.g. S/NP (S w/o NP; $\sim$ CCG, Steedman'01)
- For simplicity, strict complexity limit on memory elements (no chunks):

  one incomplete referent/constituent per memory element
- Sequence of stores $\Leftrightarrow$ phrase structure via simple tree transform ($\sim$Johnson'98; system $\sim$Roark'01/Henderson'04 but mem-optimized)

Parsing in Short-term Memory

This model:

Explicit memory elements, compatible w. interactive interpretation

- Bounded store of incomplete referents, constituents over time
  - incomplete referets: individual/group of objects/events ($\sim$ Haddock'89)
  - incomplete constituents: e.g. S/NP (S w/o NP; $\sim$ CCG, Steedman'01)
- For simplicity, strict complexity limit on memory elements (no chunks):
  one incomplete referent/constituent per memory element
- Sequence of stores $\Leftrightarrow$ phrase structure via simple tree transform ($\sim$Johnson'98; system $\sim$Roark'01/Henderson'04 but mem-optimized)
- Alternative stores active in pockets, not monolithic (unbounded beam)
- Essentially, factored HMM-like time-series model

Parsing in Short-term Memory

This model:

Explicit memory elements, compatible w. interactive interpretation

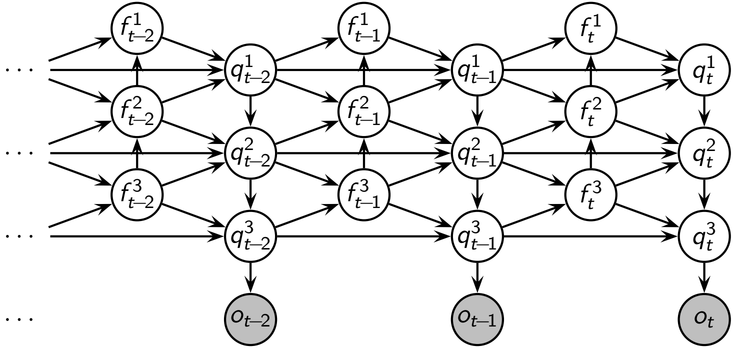
- Bounded store of incomplete referents, constituents over time
  - incomplete referets: individual/group of objects/events ($\sim$ Haddock'89)
  - incomplete constituents: e.g. S/NP (S w/o NP; $\sim$ CCG, Steedman'01)
- For simplicity, strict complexity limit on memory elements (no chunks):
  one incomplete referent/constituent per memory element
- Sequence of stores $\Leftrightarrow$ phrase structure via simple tree transform ($\sim$Johnson'98; system $\sim$Roark'01/Henderson'04 but mem-optimized)
- Alternative stores active in pockets, not monolithic (unbounded beam)
- Essentially, factored HMM-like time-series model

Evaluation of Coverage:

- Can parse nearly 99.96% of WSJ 2–21 using $\leq$ 4 memory elements

Hierarchic Hidden Markov Model

Factored HMM model (Murphy & Paskin '01): bounded probabilistic PDA

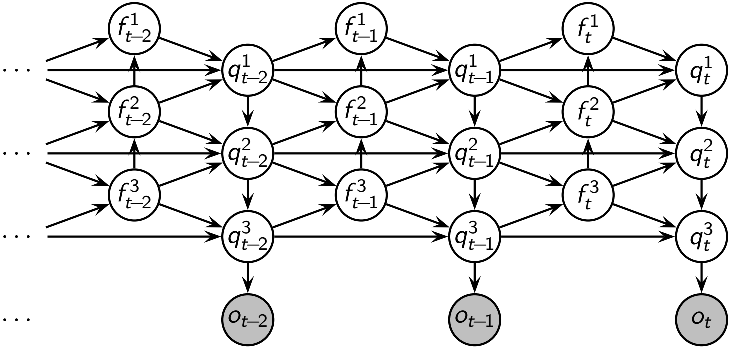


Hidden syntax+ref model, generating observations: words / acoust. features

$$\hat{h}^{1..D}_{1..T} \stackrel{\text{def}}{=} \operatorname*{argmax}_{h^{1..D}_{1..T}} \prod_{t=1}^{T} \mathsf{P}_{\Theta_{\mathrm{LM}}}(h^{1..D}_t \mid h^{1..D}_{t-1}) \cdot \mathsf{P}_{\Theta_{\mathrm{OM}}}(o_t \mid h^{1..D}_t)$$

Hierarchic Hidden Markov Model

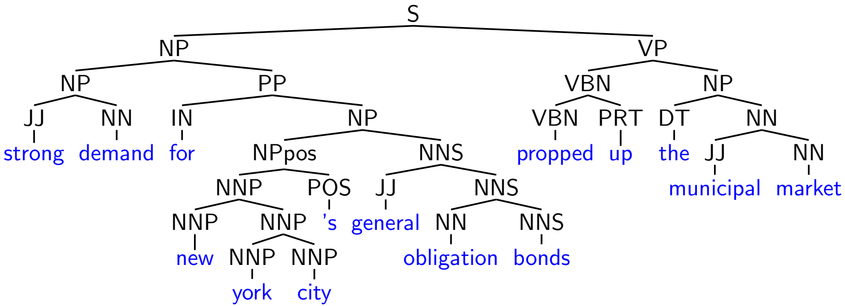
Factored HMM model (Murphy & Paskin '01): bounded probabilistic PDA



$$
\begin{aligned}
\mathsf{P}_{\Theta_{\mathrm{LM}}}(q_t^{1..D} \mid q_{t\text{-}1}^{1..D}) &= \sum_{f_t^{1..D}} \mathsf{P}_{\Theta_{\mathrm{Reduce}}}(f_t^{1..D} \mid q_{t\text{-}1}^{1..D}) \cdot \mathsf{P}_{\Theta_{\mathrm{Shift}}}(q_t^{1..D} \mid f_t^{1..D}\ q_{t\text{-}1}^{1..D}) \\
&\stackrel{\mathrm{def}}{=} \sum_{f_t^{1..D}} \prod_{d=1}^{D} \mathsf{P}_{\Theta_\rho}(f_t^d \mid f_t^{d+1} q_{t\text{-}1}^d q_{t\text{-}1}^{d\text{-}1}) \cdot \mathsf{P}_{\Theta_\sigma}(q_t^d \mid f_t^{d+1} f_t^d\ q_{t\text{-}1}^d q_t^{d\text{-}1})
\end{aligned}
$$

Saving Memory with a Transformed Grammar

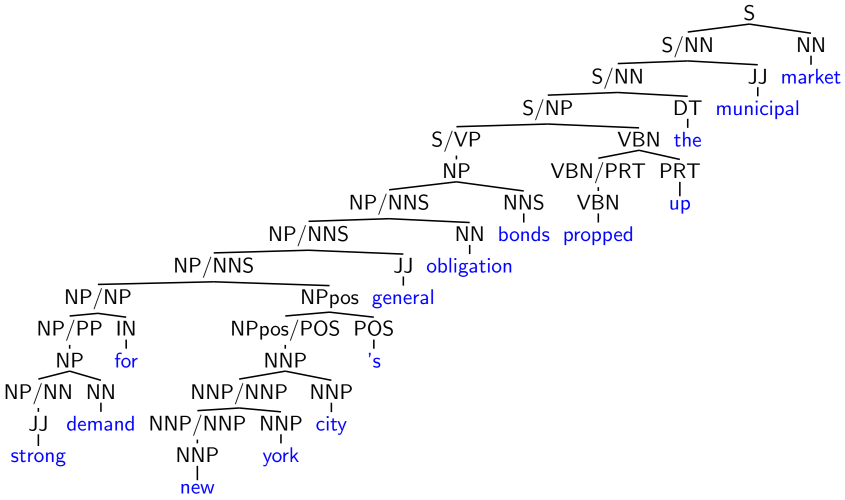
Derive model probabilities from training trees:



Must be transformed into flat, memory-efficient form...

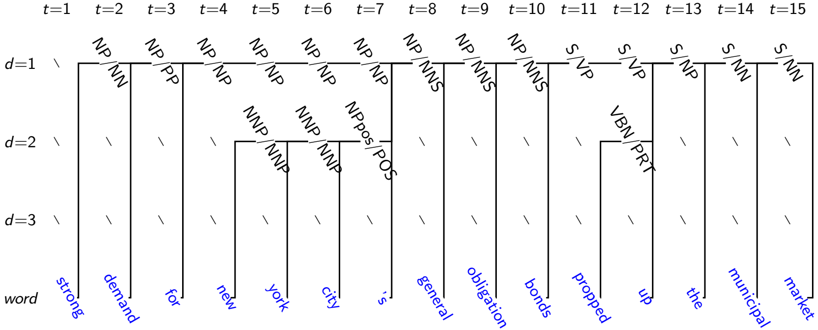
Saving Memory with a Transformed Grammar

'Right-corner transform': $\sim$ left-corner, but reversed so incomplete on right



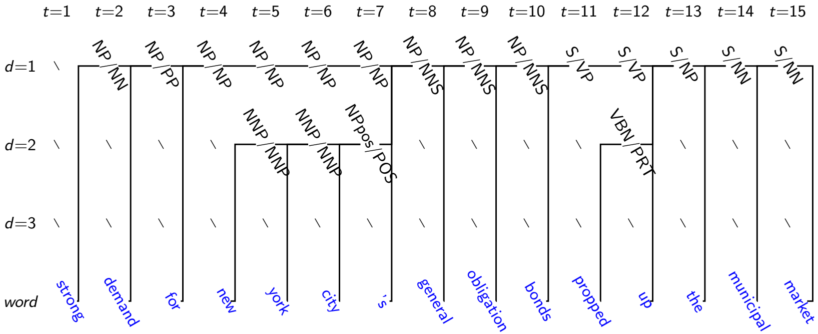
Mapping to HHMM

Align levels to a grid, to train HHMM:



Mapping to HHMM

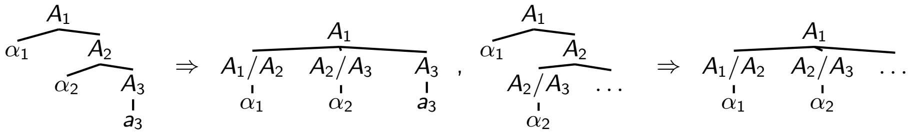
Align levels to a grid, to train HHMM:



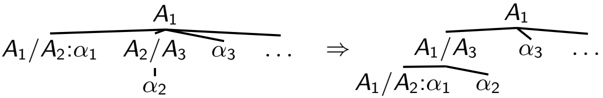
Different than other left-corner models: not all levels open for adjunction
Many configs in parallel; weights depend on learned HHMM probabilities.

Tree Transform

Transform is very simple — first flatten out right-recursive structure:

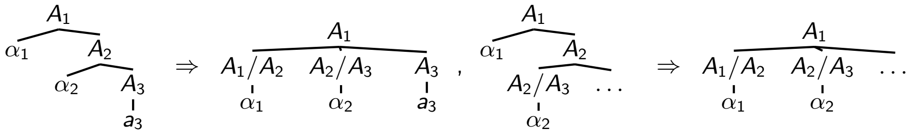


then replace it with left-recursive structure:

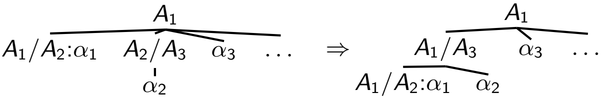


Tree Transform

Transform is very simple — first flatten out right-recursive structure:



then replace it with left-recursive structure:



Only right recursion remaining is center embedding, known to be limited:
"The cart the horse the man bought pulled broke."
(Miller and Chomsky, 1963)

Coverage

How many levels do you need? About four.

stack memory capacity	sentences	coverage
no stack memory	127	0.32%
1 stack element	3,496	8.78%
2 stack elements	25,909	65.05%
3 stack elements	38,902	97.67%
4 stack elements	**39,816**	**99.96%**
5 stack elements	39,832	100.00%
TOTAL	39,832	100.00%

Percent coverage of transformed treebank sections 2–21 w. no punctuation

Good! Because that's supposed to be our limit! (Cowan, 2001)

Coverage

How many levels do you need? About four.

stack memory capacity	sentences	coverage
no stack memory	127	0.32%
1 stack element	3,496	8.78%
2 stack elements	25,909	65.05%
3 stack elements	38,902	97.67%
4 stack elements	**39,816**	**99.96%**
5 stack elements	39,832	100.00%
TOTAL	39,832	100.00%

Percent coverage of transformed treebank sections 2–21 w. no punctuation

Good! Because that's supposed to be our limit! (Cowan, 2001)

Now, a windfall in accuracy due to pruned search space?

Accuracy

No... guessing open adjunction sites to save memory holds back accuracy

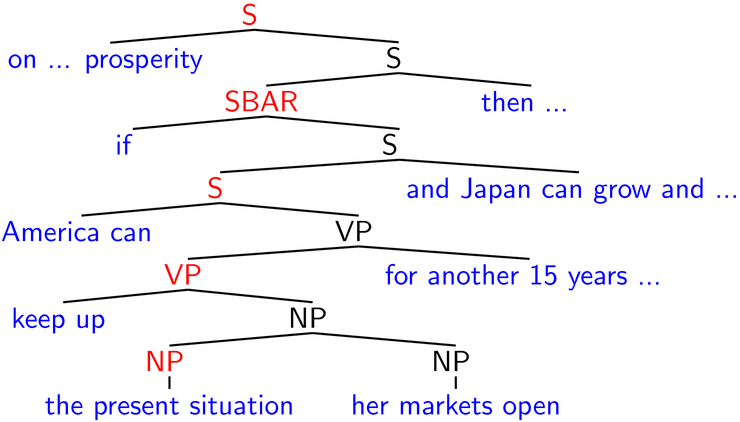
Accuracy results w. no lexicalization or smoothing:

with punctuation: ($\leq$40 wds)	LP	LR	F	fail
KM'03: unmodified, devset	–	–	72.6	0
KM'03: par+sib, devset	–	–	77.4	0
CKY: binarized, devset	72.3	71.1	71.7	0
HHMM: par+sib, devset	**81.4**	**82.9**	**82.1**	**1.4**
CKY: binarized, sect 23	72.0	69.7	70.8	0.3
HHMM: par+sib, sect 23	**79.7**	**80.4**	**80.1**	**0.6**
Henderson'04, non-det., sect 0			89.8	

no punctuation: ($\leq$120 wds)	LP	LR	F	fail
R'01: par+sib, sect 23–24	77.4	75.2	–	0.1
HHMM: par+sib, sect 23–24	**77.6**	**76.8**	**77.2**	**0.4**

Quintuple center-embedding

Here's one of the 16 depth-five sentences in the corpus:



Left-/right-corner won't undo zig-zags. Need them to untangle referents.

Conclusion

Right-corner transform explains parsing w/in human-like memory limits.

Bounded memory HHMM model mostly safe, in terms of coverage.

But, no big windfall in accuracy.

Future work:

- Lexicalization / vector-space semantics
- Smarter strategy for deferring composition if memory not used up
- Smoothing, backoff
- Estimate joint probabilities over entire columns