Unsupervised machine learning as acquisition modeling

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Introduction

Unsupervised machine learning as acquisition modeling

- Both humans and computers can learn (aspects of) language
- Human language acquisition is not well understood
- Computer “language acquisition” is well understood
- Can we use machine learning to shed light on human learning?

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Roadmap for this talk

- Motivation
- Modeling lexical acquisition with unsupervised speech segmentation
- Modeling grammar acquisition with unsupervised PCFG induction
- Discussion and future directions

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Motivation

Why model language acquisition computationally?

Of interest to both science and engineering

Why model language acquisition computationally?

- Science:
  - Test predictions of hypotheses about language acquisition
  - Dissect the language learning problem
  - Explore learnability of linguistic phenomena

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- Engineering:
  - Humans are better than computers at learning and using language
  - We learn from cheap and abundant sources of data
  - Low-resource NLP
  - Study and preservation of endangered languages

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But...

NLP is (usually) cognitively implausible

- Normally requires lots of annotated data
  - Microsoft's Bing used 2100 hours of transcribed speech to train its speech recognizer (Dahl et al. 2011)
  - Humans don't have direct access to the right answers
- Unrealistically large memory capacity
  - Humans can't remember every sentence they have ever heard or every word they have ever read
  - Humans can't read billions of words
- Non-incremental processing
  - Humans can't wait until the end of the sentence to start processing it

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- Unrealistically large memory capacity
  - Humans have limited memory capacity, which is reflected in phenomena such as garden path sentences and center embedding
  - Transformers are quadratic
- Non-incremental processing
  - Humans are incremental, NLP is not (or not to the same degree)

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  - Human working memory constraints are severe compared to those of computers (Miller 1956; Cowan 2001; McElree 2001)
- Non-incremental processing
  - Human sentence processing is incremental (Marslen-Wilson 1973; Tanenhaus et al. 1995)

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- Non-incremental processing
  - Humans are incremental, but NLP is not (Tanenhaus et al. 1995)

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- More similar training feedback to that received by humans
- Can still be cognitively implausible in other ways
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This work: Modeling lexical and grammar acquisition

- Models of two related acquisition tasks:
  - **Lexical acquisition:** Learning to segment the speech signal
  - **Grammar acquisition:** Learning to parse

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- Both of these models accept arbitrary naturally-occurring training data in any language
- C.f. computational models that use “toy” input (e.g. Elman 1991; Briscoe 2000; Fodor and Sakas 2004)
- Our approach more accurately represents input to human learners

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Modeling lexical acquisition with unsupervised speech segmentation

Speech segmentation: Cognitive background

- Phonological memory limits may encourage sparse encodings (Baddeley and Hitch 1974)
- Thought to affect learning as well as processing (Baddeley, Gathercole, and Papagno 1998)
- We model this learning pressure by seeking compressible segmentations

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Speech segmentation: Model overview

- Two RNN's:
  - Auto-encoder (AE) network: Reconstructs its input
  - Proposal network: Predicts segmentation points

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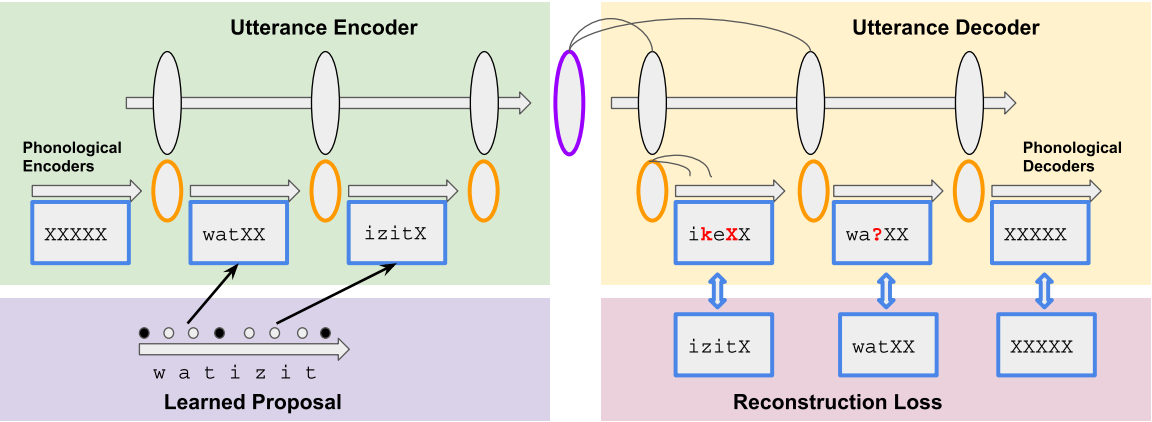
Speech segmentation: Auto-encoder network architecture



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Speech segmentation: Segmenter network architecture

+ LSTM trained to predict segmentation probability at each time step

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Speech segmentation: Model overview

+ Overall segmentation loss is non-differentiable (segmentation decisions are hard)
+ Estimated via importance sampling (e.g. Mnih et al. 2014; Xu et al. 2015), using reconstruction loss for scoring

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Speech segmentation: Model overview

- Memory limits simulated using:
  - Dropout
    - Simulates forgetting
    - Probability of forgetting is p, where $1 - p = 0.5$
  - LSTM hidden state size
    - Controlling capacity of memory
    - Number of hidden units in an LSTM layer (256 and 512 units in this experiment)
    - Hidden units in layer may be regarded as an independent memory cell
    - Bottleneck hearing an input sentence and reproducing it afterwards

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Speech segmentation: Model overview

- Memory limits simulated using:
  - Dropout
    - Simulates forgetting
    - Phonemes drop at rate D_p, words drop at rate D_u
  - LSTM hidden state size
    - Simulates capacity of working memory
    - Phonemes and words are represented as vectors of H real numbers
    - The larger H, the more information can be stored in the LSTM
    - Increasing capacity may be useful, but possibly also lead to overfitting

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    - Simulates capacity of working memory
    - Phonemes or words drop at rate proportional to $\frac{1}{\text{LSTM hidden state size}}$
    - Thus, decreasing memory capacity increases rate of forgetting
    - Assumed capacity of working memory is proportional to LSTM hidden state size

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    - Simulates capacity limitations
    - Larger vs. smaller state is given to decoder, and the encoder is trained to make decoding easier
    - The larger the state, the more the decoder can pay attention to the input
    - Intuition: learning to use larger state is more difficult than using smaller state

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    - Too much memory might not encourage efficient segmentations

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- Acoustic features (MFCC)
- First system to perform unsupervised segmentation of either text or acoustics using same code base

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Speech segmentation: Experiments

- Text: Brent corpus (Brent 1999)
- Acoustics: Zerospeech '15 English (Versteegh et al. 2015)

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Speech segmentation: Results (Brent)

	Bd P	Bd R	Bd F	Wd F
Our system	81	85	83	72

- Examples:
  - yu wanttu si D6bUk
    You wantto see thebook?
  - oke yusIt D* &nd 9I pUty) Suz b&kan
    Okay, yousit there and I'll putyour shoes backon
  - &nd lUk&t WAt D6kItiz pleIN wIT
    And lookat what thekitty's playing with
  - dId yu kQnt OI6v DEm
    Did you count allof them?
  - wan6 lUk&t 6nADR bUk
    Wanna lookat another book?
  - If pApi b9ts pApi gEtss p&Nkt
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System	Bd P	Bd R	Bd F	Wd F
Goldwater 09	90	74	87	74
Johnson 09	-	-	-	88
Berg-Kirkpatrick 10	-	-	-	88
Fleck 08	95	74	83	71
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Speech segmentation: Results (Zerospeech ’15)

System	Bd P	Bd R	Bd F	Wd F
Lyzinski 15	18.8	64.0	29.0	2.4
Räsänen 15	75.7	33.7	46.7	9.6
Räsänen new	61.1	50.1	55.2	12.4
Kamper 16	66.5	58.8	62.4	20.6
Ours	62.4	43.2	51.1	9.3

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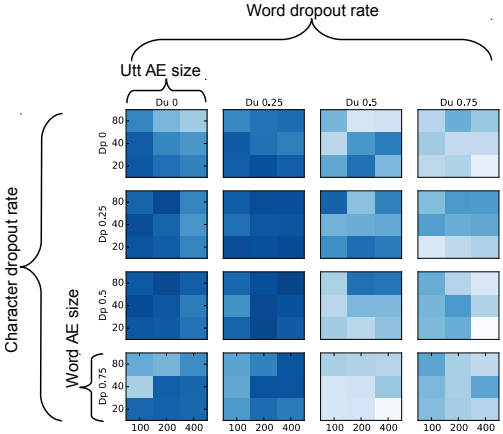
Speech segmentation: Dropout



Dropout and memory limits encourage better segmentations

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Speech segmentation: Conclusion

Our results support the hypothesis that limited phonological memory facilitates lexical acquisition by encouraging efficient segmentation

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Modeling grammar acquisition with unsupervised PCFG induction

Grammar induction: Cognitive background

- Humans have been shown to use distributional statistics in language acquisition (Saffran et al. 1999)
- Cognitively-constrained grammar induction allows us to study:
  - Utility of word distributions to syntax acquisition
  - Acquisition of syntactic structure from raw input (no segmentation, no tags)

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Grammar induction: Cognitive background

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  - Advantages/disadvantages of cognitive constraints

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Grammar induction: Model overview

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Grammar induction: COLING results

	P	R	F_1
Our system	68.83	57.18	62.47
Random baseline (Ours 1st iter)	51.69	38.75	44.30

Unlabeled bracketing accuracy on Eve

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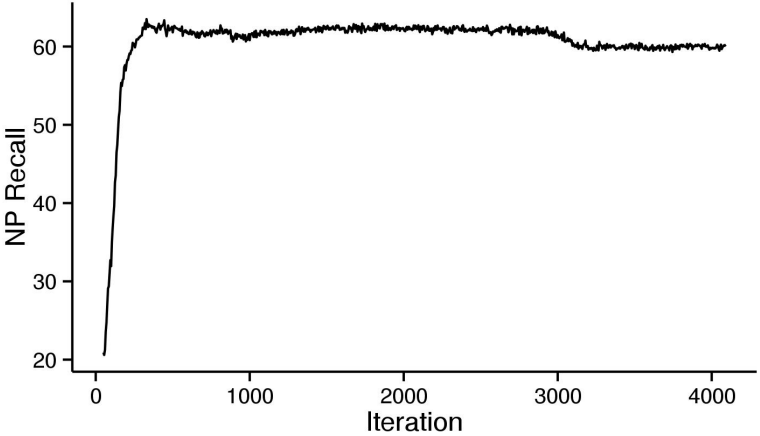
Grammar induction: Error analysis



Percent gold noun phrases (NPs) discovered

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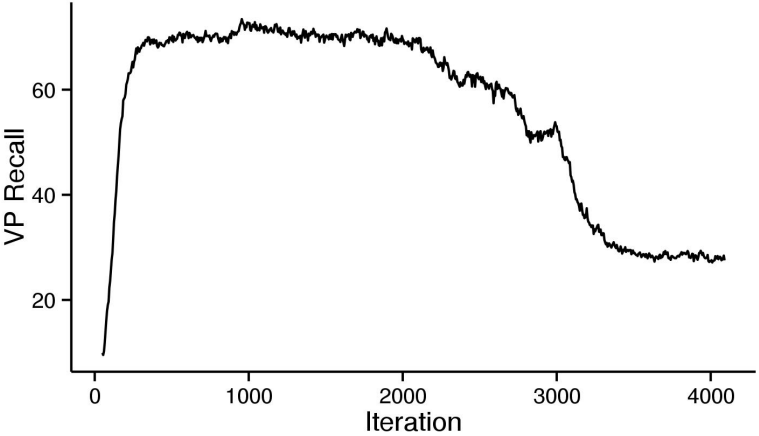

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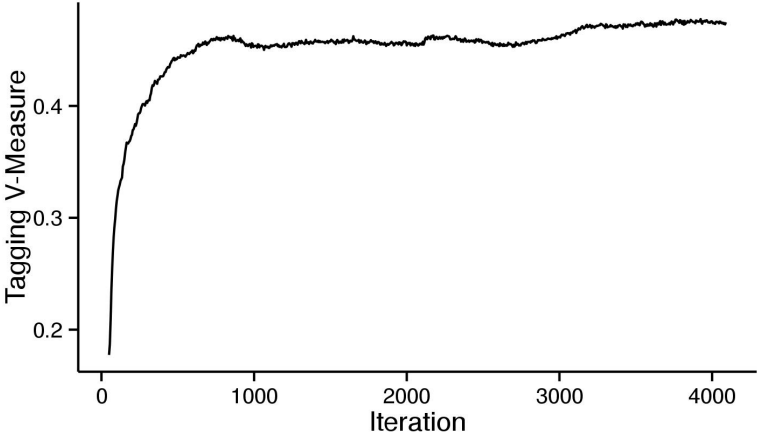
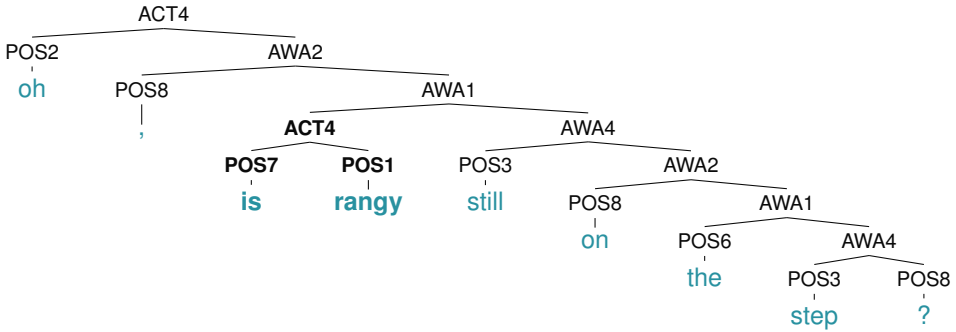


Part-of-speech tagging (V-Measure)

Grammar induction: Constructions of interest

Subject-auxiliary inversion: (c.f. Chomsky 1968)



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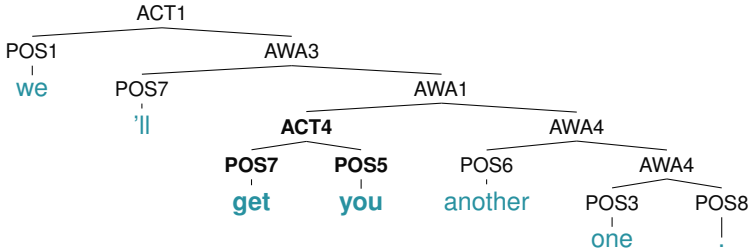

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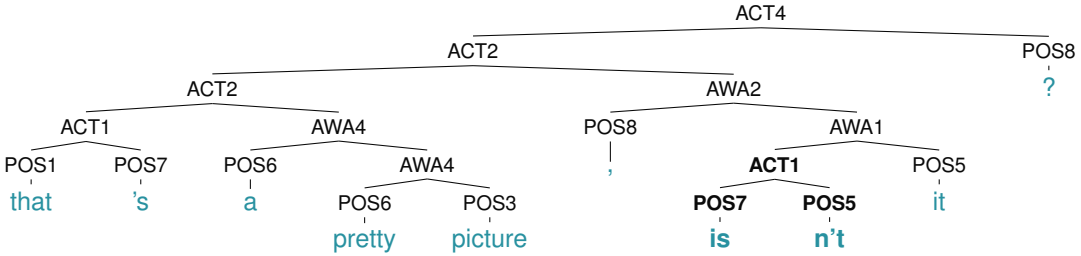
Contraction:



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Grammar induction: Hot off the press

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  - Many of these results are based on English data, which is a fairly easy case

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Thank you!

To you, co-authors, anonymous reviewers of submitted papers, and members of various discussion groups who gave feedback.

Computations for this project were run on a Titan-X GPU donated by the NVIDIA Hardware Grant program and on the Ohio Supercomputer (1987). Funding was provided by NSF #1422987.

This project was sponsored by the Defense Advanced Research Projects Agency award #HR0011-15-2-0022. The content of the information does not necessarily reflect the position or the policy of the Government, and no official endorsement should be inferred.

Segmenter Github:

`https://github.com/melsner/neural-segmentation`

Parser Github:

`https://github.com/tmills/uhhmm/`

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Appendix

Speech segmentation: Algorithm

1. For each training epoch:
   1.1 For each batch of n utterances in the training data
      1.1.1 Generate a proposal distribution (segmenter network output)
      1.1.2 Sample a segmentation from proposal distribution
      1.1.3 Observe reward (normalized negative unit-LSTM segmentation cost) for sampled segmentation
      1.1.4 Update segmenter network parameters using policy gradient

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      1.1.2 Sample *m* segmentations from proposal distribution
      1.1.3 Compute new proposal distribution as normalized sum of segmentations weighted by reconstruction loss
      1.1.4 Train segmenter network on new proposal distribution

Micha Elsner and Cory Shain (to appear). “Speech segmentation with a neural encoder model of working memory”. In: *EMNLP 2017*

Speech segmentation: Algorithm

1. For each training epoch:
   1.1 For each batch of n utterances in the training data
      1.1.1 Generate a proposal distribution (segmenter network output)
      1.1.2 Sample m segmentations from proposal distribution
      1.1.3 Compute new proposal distribution as normalized sum of segmentations weighted by reconstruction loss
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Speech segmentation: Sampling procedure

Given a set of m sampled boundary sequences $B_1..B_m$ with associated reconstruction losses $L_1...L_m$:

$$P(x|B_i) = \frac{P(B_i|x)P(B_i)}{P(x)} \approx \frac{\exp(L_i)}{\sum_j \exp(L_j)} \tag{1}$$

$$w_i^t = \frac{P(x|B_i)}{P_{seg}^t(B_i^t)} \tag{2}$$

$$\mathbb{E}[B(t)] \approx \frac{1}{\sum_i w_i^t} \sum_i w_i^t B_i^t \tag{3}$$

Speech segmentation: Tweaks for acoustics

- Importance sampling caused oversegmentation
- We suspect that this is due to non-independence between samples, exaggerated by longer sequences
- Acoustic results were obtained via 1-best sampling

Speech segmentation: Experiment parameters

- **Brent:**
  - Max characters per utterance: 30
  - Max words per utterance: 10
  - Max characters per word: 7
  - Phonological AE hidden units: 80
  - Utterance AE hidden units: 400
  - Segmenter hidden units: 100
  - Phonological AE dropout probability: 0.5
  - Utterance AE dropout probability: 0.25

Speech segmentation: Experiment parameters

- **Zerospeech:**
  - Max frames per utterance: 400
  - Max words per utterance: 16
  - Max frames per word: 100
  - Phonological AE hidden units: 20
  - Utterance AE hidden units: 400
  - Segmenter hidden units: 1500
  - Phonological AE dropout probability: 0
  - Utterance AE dropout probability: 0.25

Grammar induction: Algorithm

1. **Initalization:** Randomly sample HHMM parameters
2. For each training iteration:
   2.1. **Parsing:** *For each sentence in input:*
   2.2. **Update:** *Update HHMM parameters based on parsed sentence*

Cory Shain et al. (2016). “Memory-bounded left-corner unsupervised grammar induction on child-directed input”. In: *Proceedings of The 26th International Conference on Computational Linguistics*. Osaka, pp. 964–975

Grammar induction: Algorithm

1. **Initalization:** Randomly sample HHMM parameters
2. For each training iteration:
   2.1 **Parsing:** For each sentence in input:
      2.1.1 *Forward pass: Compute posterior over HHMM states left to right*
      2.1.2 *Sample new states from posterior, right to left*
   2.2 Update HHMM parameters from sampled counts

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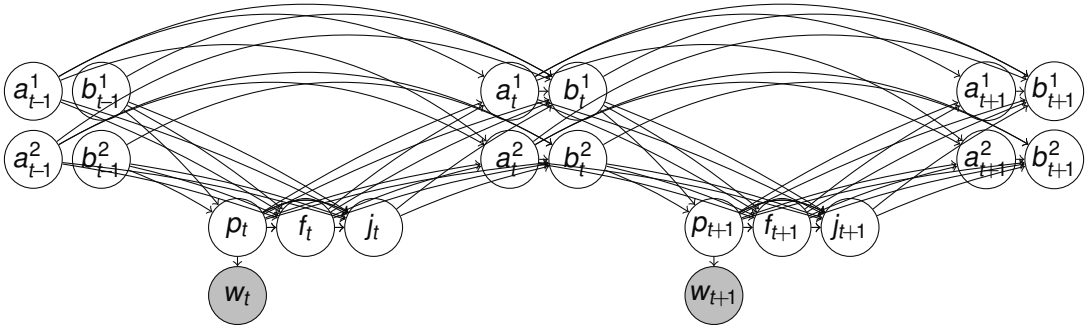
Grammar induction: HHMM Graphical model



Grammar induction: Punctuation

- Punctuation poses a problem — keep or remove?
  - **Remove:** Doesn't exist in input to human learners.
  - **Keep:** Might be proxy for intonational phrasal cues.
- Punctuation was kept in training data in main result presented above.
- We did an additional UHHMM run trained on data with punctuation removed (2000 iterations).

Grammar induction: Full COLING Results

	With punc			No punc		
	P	R	F1	P	R	F1
UPPARSE	60.50	51.96	55.90	38.17	48.38	42.67
CCL	64.70	53.47	58.55	56.87	47.69	51.88
BMMM+DMV (directed)	62.08	62.51	62.30	61.01	59.24	60.14
BMMM+DMV (undirected)	63.63	**64.02**	**63.82**	61.34	**59.33**	**60.32**
UHHMM-4000, binary	46.68	58.28	51.84	37.62	46.97	41.78
UHHMM-4000, flattened	**68.83**	57.18	62.47	**61.78**	45.52	52.42
Right-branching	68.73	**85.81**	**76.33**	**68.73**	**85.81**	**76.33**

Table 1: Parsing accuracy on Eve with and without punctuation (phrasal cues) in the input. The UHHMM systems were given 8 PoS categories while the BMMM+DMV systems were given 45. UPPARSE and CCL do not learn PoS tags. Only the UHHMM systems model limited working memory capacity or incremental left-corner parsing.

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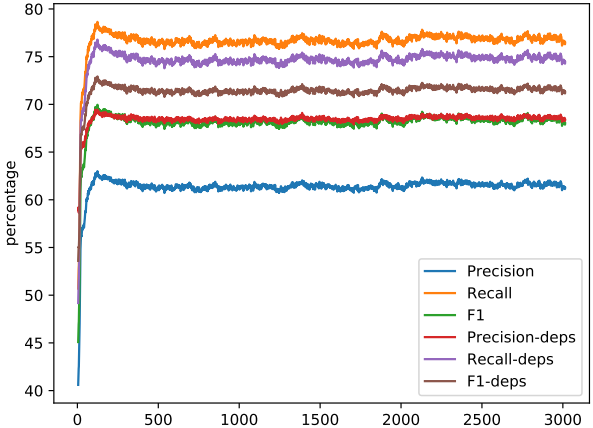
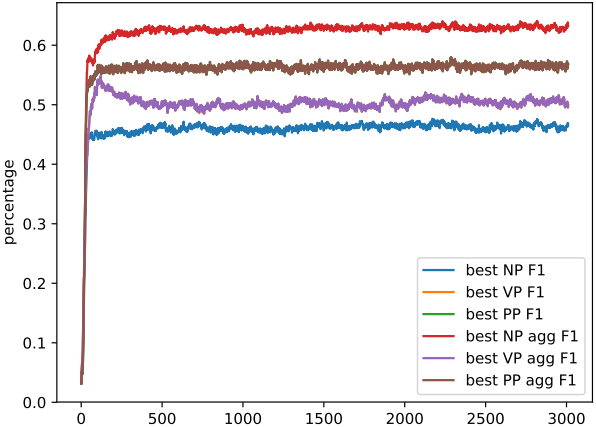
Grammar induction: Newer results



Learning curves on Eve

Grammar induction: Newer results



Category learning on Eve