Learned Prioritization for Trading Off Accuracy and Speed

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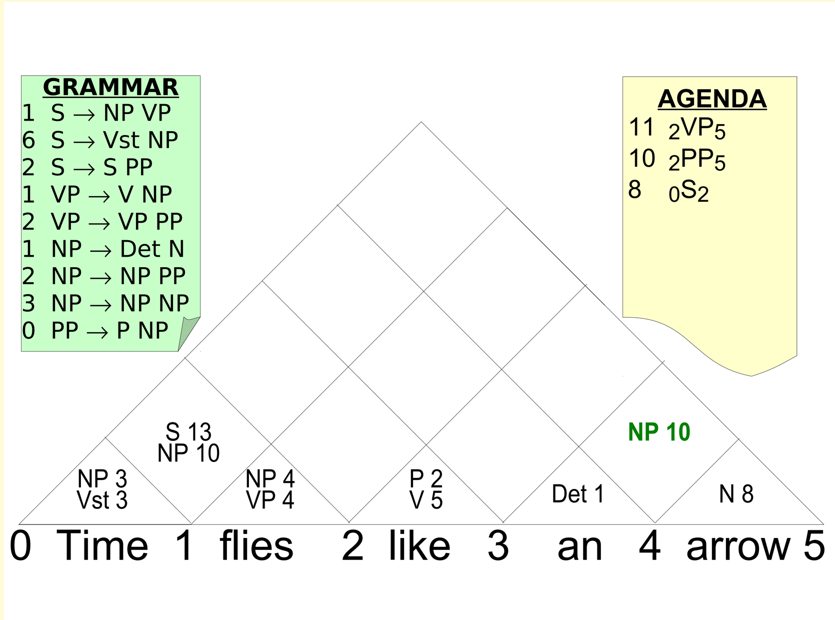
Take Home Summary

- **Main Objective:** fast and accurate structured prediction (search)
- **Search Method:** agenda based dynamic programming
- **Knob To Tune:** prioritization heuristic
- **Bad:** try different known heuristics by hand :(
- **Good:** **learn** a heuristic for your input distribution, grammar, and speed/accuracy needs
- **How?:** hybrid reinforcement/apprenticeship learning!

Agenda Based Parsing

- Goal: find lightest weight parse
- Extend already built partial parses
- Reuse work via dynamic programming
- Extend most promising partial solutions first via agenda



Speed/Accuracy in Agenda Based Parsing

- All experiments on Penn Treebank WSJ (sentence length $\leq$ 15)
- *Preliminary Results* Setup:
  - Berkeley latent variable PCFG trained on sections 2-20
  - RL (if any) trained on 100 sentences from section 21
  - Evaluated on same 100 sentences

Method	Recall	Relative # of Pops
(B1): Exhaustive Search (CKY order)	93.3	3.0x
(B2): Uniform Cost Search (UC)	93.3	1.0x
(B3): Pruned Uniform Cost Search (UC_p)	92.0	0.33x

Agenda Based Parsing as a Markov Decision Process

- State Space: full current chart and agenda
- Action: choose a partial parse from agenda
- Transitions: given the chosen action, deterministically updates chart and builds and pushes other partial (or full) parses to agenda
- Policy: deterministically pops highest-priority available action

$$\pi_\theta(s) = \arg\max_a \ \theta \cdot \phi(a, s) \qquad (1)$$

learning a policy = learning the priority function

- Reward: **accuracy** $- \lambda \cdot$ **time**
  - Accuracy = labeled span recall
  - Time = # of pops from agenda

Attempt 1: Policy Gradient with Boltzmann Exploration

$$\nabla_\theta \mathbb{E}_\tau[R(\tau)] = \mathbb{E}_\tau\left[R(\tau)\nabla_\theta \log p_\theta(\tau)\right] = \mathbb{E}_\tau\left[R(\tau)\sum_{t=0}^{T}\nabla_\theta \log \pi(a_t|s_t)\right] \qquad (2)$$

- *Preliminary Results*: Recall = 56.4, Relative # of pops = 0.46x
- **Main difficulty**: no attempt to determine which actions were "responsible" for a trajectory's reward (i.e. reward outside of sum)

Attempt 2: Policy Gradient With Reward Shaping

- Push back reward to actions:

$$\tilde{r}(s,a) = \begin{cases} \delta(a) - \lambda & \text{if } a \text{ is a full parse tree} \\ 1 - \lambda & \text{if } a \text{ is in the true parse} \\ -\lambda & \text{otherwise} \end{cases} \qquad (3)$$

$\delta(s)$: a negative reward for actions which received early reward for constituents that were not in the final parse. $R(\tau) = \sum_{t=0}^{T} \tilde{r}(s,a)$.

- Gradient step:

$$\nabla_\theta \mathbb{E}_\tau[R(\tau)] = \nabla_\theta \mathbb{E}_\tau[\tilde{R}(\tau)] = \mathbb{E}_\tau\left[\sum_{t=0}^{T}\left(\sum_{t'=t}^{T}\gamma^{t'-t}\tilde{r}_{t'}\right)\nabla_\theta \log \pi(a_t \mid s_t)\right] \qquad (4)$$

- *Preliminary Results*: Recall = 76.5, Relative # of pops = 0.13x
- **Main difficulty**: state space (still) too big compared to number of reasonable trajectories

Attempt 3: Apprenticeship Learning

- Oracle action: actions that leads to a maximum-reward tree (break ties by current policy)
- Apprenticeship learning via classification:
  - train a maximum entropy classifier
  - one example per state observed on an oracle trajectory
  - classifier objective: maximize number of time policy matches oracle action
- *Preliminary Results*: Recall = 84.2, Relative # of pops = 0.85x
- **Main difficulty**: too hard to imitate oracle with our features (e.g. oracle trajectory length ≈ 40, policy trajectory length $\approx 30,000$)

Attempt 4: Oracle-Infused Policy Gradient (I+)

- Let π be an arbitrary policy and let $\delta \in [0, 1]$.
- Define the oracle infused policy π_δ^+ as

$$\pi_\delta^+(a \mid s) = \delta\pi^*(a \mid s) + (1-\delta)\pi(a \mid s) \qquad (5)$$

where $\delta = 0.8^{\text{epoch}}$.
epoch: the total number of passes made through the training set at that point.

- *Preliminary Results*: Recall = 91.2, Relative # of pops = 0.46x

Features

1. Width of partial parse
2. Viterbi inside score
3. Touches start of sentence?
4. Touches end of sentence?
5. Ratio of width to sentence length
6. log p(label | prev POS) and log p(label | next POS) (statistics extracted from labeled trees, word POS assumed to be most frequent)
7. Case pattern of first word in partial parse and previous/next word
8. Punctuation pattern in partial parse (five most frequent)

Final Experiments

- **Final Results** Setup:
  - Berkeley latent variable PCFG trained on sections 2-21
  - RL (if any) trained on section 22
  - evaluated on section 23
- Baselines:
  - **(HA*)** a Hierarchical A*parser [3] with same pruning threshold at each hierarchy level
  - **(UC)** an A*parser with a 0 heuristic function and pruning
  - **(UC_p^*)** an A*variant, on which we decrease the pruning threshold if no tree is returned
  - **(CTF)** an agenda-based coarse-to-fine parser [4].
- Note: CTF and HA* perform much better when evaluated on number of pushes; also, adapting the pruning threshold among grammar levels might further help; future work includes adding coarse-to-fine features to our set

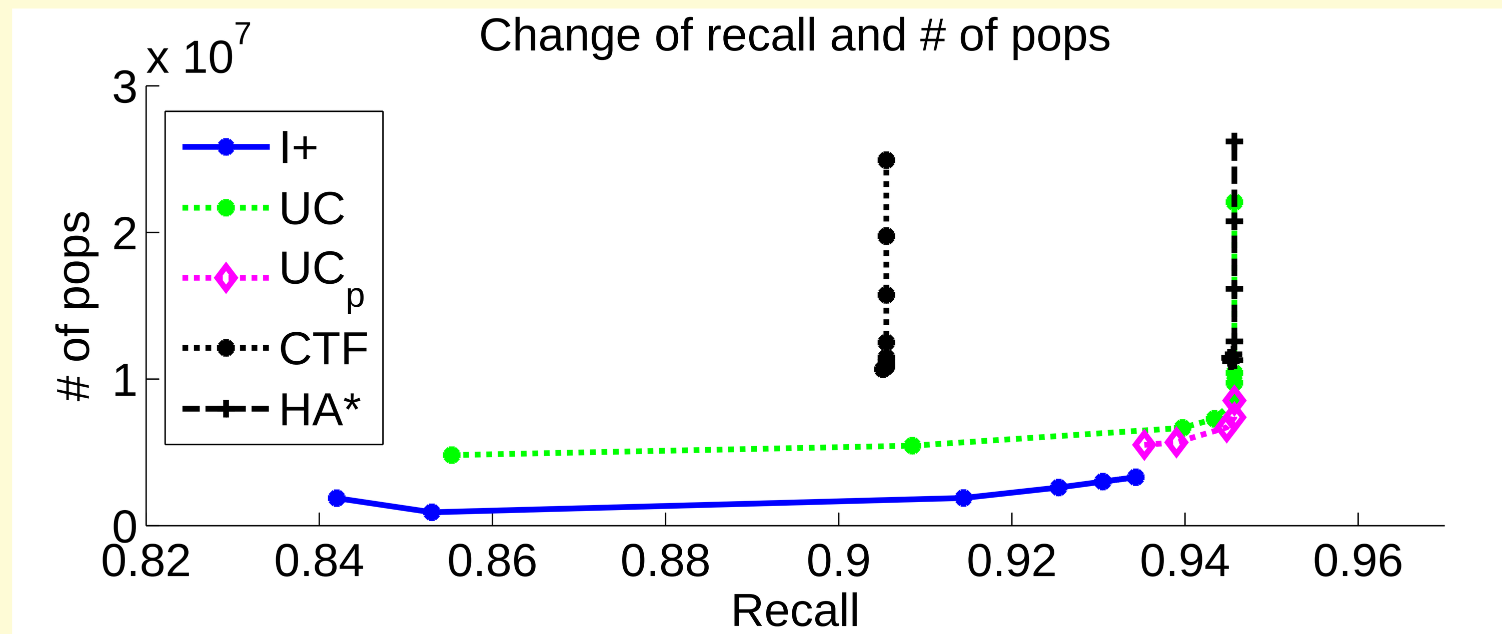


Figure: Pareto frontiers: Our **I+** parser at different values of λ, against the baselines at different pruning levels.

Related Work

1. H. Daumé III, J. Langford, and D. Marcu. 2009. Search-based structured prediction. Machine Learning, 75(3):297—C325.
2. V. Gullapalli and A. G. Barto. 1992. Shaping as a method for accelerating reinforcement learning. In Proceedings of the IEEE International Symposium on Intelligent Control.
3. A. Pauls and D. Klein. 2009. Hierarchical search for parsing. In NAACL/HLT.
4. S. Petrov and D. Klein. 2007. Improved inference for unlexicalized parsing. In NAACL/HLT.
5. S. Ross, G. J. Gordon, and J. A. Bagnell. 2011. A reduction of imitation learning and structured prediction to no-regret online learning. In AI-Stats.