Vine Pruning for Efficient Multi-Pass Dependency Parsing

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Dependency Parsing





Styles of Dependency Parsing



Styles of Dependency Parsing



Preview: Coarse-to-Fine Cascades



linear-size dependency representation



















First-Order Feature Calculation







First-Order Feature Calculation

[VERB * IN left 5]



[VERB_11 * left_5]

[VERB 11 IN left 5]

[went] [As, ADP] [went, As] [went, VBD, As] [NNS, *, ADP] [VBD, ADJ, NNP] [As, left, 5] [went, VERB, As] [NOUN, *, IN] [VERB, JJ, NOUN] [As, left, 5] [VBD, ADJ, ADP, NNP] [VBD, ADP, left, 5] [NOUN, VERB, IN, NOUN] [VBD, As, ADP, left, 5] [VBD, *, ADP, left, 5] [NNS, VBD, *, left, 5] [NNS, VBD, NNP, left, 5] [JJ, *, IN, left, 5] [NOUN VERB IN left 5]

went

fans Wild

As

[NOUN * IN left 5]

Arc Length By Part-of-Speech



Arc Length By Part-of-Speech



Arc Length By Part-of-Speech



















Arc Length Heat Map



Arc Length Heat Map



Banded Matrix



Banded Matrix







Outer Arc



Outer Arc





As McGwire neared , fans went wild


Coarse-to-Fine



* As McGwire neared , fans went wild









Coarse-to-Fine



dynamic programs for parsing

Inference Questions

questions:

- How do we reduce inference time to O(n)?
- How do we decide which arcs to prune?

Vine Parsing (Eisner and Smith, 2005)

Eisner First-Order Rules





















Vine Parsing Rules



























Arc Pruning

• Prune arcs based on max-marginals.

$$maxmarginal(a) = \max_{y:a \in y} (y \cdot w)$$

- Can compute using inside-outside algorithm.
- Generic algorithm using hypergraph parsing.

Max-Marginals for First-Order Arcs

maxmarginal(neared \rightarrow fans) > threshold ?



Max-Marginals for Outer Arcs



pruning and training

Max-Marginal Pruning

goal: Define a threshold on max-marginal score.

• Validation parameter α trades off between speed and accuracy.

$$t_{lpha}(w) = lpha \max_{y} (y \cdot w) + (1 - lpha) \frac{1}{|A|} \sum_{a \in A} \mathsf{maxmarginal}(a, w)$$

- Highest scoring parse upper bounds any max-marginal.
- Assume average of max-marginals is lower than gold.






















Structured Cascade Training (Weiss and Taskar, 2011)

- Train a linear model with a loss function for pruning.
- · Regularized risk minimization with loss based on threshold

$$\min_{w} \lambda \|w\|^2 + \frac{1}{P} \sum_{p=1}^{P} [1 - y^{(p)} \cdot w + t^{(p)}_{\alpha}(w)]_+$$

• Can use a simple variant of perceptron/pegasos to train.





feature one







feature one



feature one









feature one



experiments

Implementation

Inference

- Experiments use a highly-optimized C++ implementation.
- Baseline first-order parser processes 2000 tokens/sec.
- Hypergraph parsing framework with shared inference.

Model

- Final models trained with hamming-loss MIRA.
- Full collection of dependency parsing features (Koo, 2010).
- First-, second-, and third-order models match state-of-the-art.

Baselines

NoPrune	exhaustive parsing model with no pruning
LocalShort	unstructured classifier over $O(n)$ short arcs (Bergsma and Cherry, 2010)
Local	unstructured classifier over $O(n^2)$ arcs (Bergsma and Cherry, 2010)
FirstOnly	structured first-order model in cascade (Koo, 2010)
VinePosterior	posterior pruning cascade trained with L-BFGS
ZhangNivre	reimplementation of state-of-the-art, k-best, transition-based parser (Zhang and Nivre, 2011).

Speed/Accuracy Experiments: First-Order Parsing



Speed/Accuracy Experiments: Second-Order Parsing



Speed/Accuracy Experiments: Third-Order Parsing



Empirical Complexity: First-Order Parsing



Empirical Complexity: Second-Order Parsing



Empirical Complexity: Third-Order Parsing



Multilingual Experiments: First-Order Parsing



Multilingual Experiments: Second-Order Parsing



Multilingual Experiments: Third-Order Parsing



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