Ensemble-based Active Learning for Parse Selection

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Quick summary: 1

- Active learning is concerned with minimising the amount of annotated training material necessary to achieve a given performance level.
- With less training material:
  - We can create trainable speech and language technologies faster.
  - . . . and save money.
- Labelling more training material will also lead to better results.

Quick summary: 2

Active learning results:

- Introduce multiple-model uncertainty sampling.
  - This easily outperforms (single-model) uncertainty sampling.
- Introduce a very simple active learning method – lowest best probability selection (LBP).
  - LBP is competitve with improved uncertainty sampling.

Quick summary: 3

Active learning results:

- Show that an ensemble trained without active learning can beat a single model trained with active learning.

- . . . but that this ensemble can itself be outperformed by an ensemble trained with active learning.

Quick summary: 4

Parse selection results:

- For HPSG, an ensemble of three log-linear models achieves the best reported parse selection performance.
- Ad-hoc selection methods based upon superficial characteristics (sentence length, ambiguity rate etc) perform no better than random selection.
- Annotating sentences in the order they appear in the corpus is much worse than random selection.

Talk outline

- The English Resource Grammar (ERG) and the Redwoods Treebank.
- Parse selection for the ERG.
- Active learning (AL) methods.
- Experimental results.
- Comments

The English Resource Grammar

The ERG:

- . . . is a broad-coverage manually written HPSG grammar.

- . . . also provides semantic analyses of in-coverage sentences.

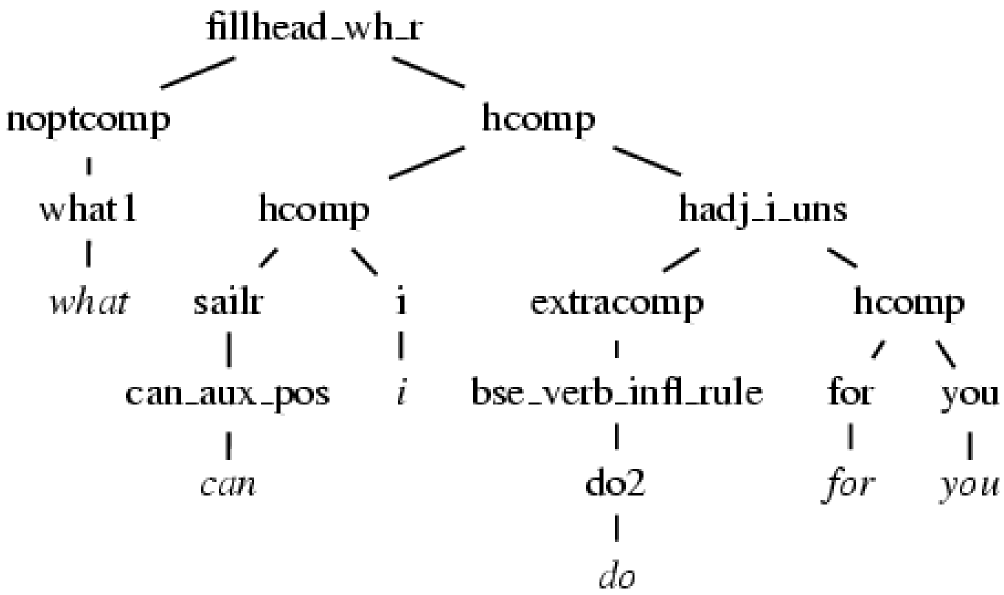
The Redwoods Treebank: 1

- Redwoods is a treebank of derivation trees for in-coverage sentences.
- Each such sentence has a distinguished preferred derivation tree.
- Derivation trees can be used to recover either parse trees or associated semantic interpretations.
- Latest version (3) statistics:

Sentences	Length	Parses
5302	9.3	58.0

- Only ambiguous sentences.

The Redwoods Treebank: 2



An example derivation tree

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Parse selection: 1

- A conditional log-linear model:

$$P(t \mid s, M_k) = \frac{1}{Z(s)} \exp(\sum_{i=1}^{n} f_i w_i)$$

- Weights for model M_k are determined using the LMVM algorithm (Malouf 02).

- (We also use a perceptron model)

Parse selection: 2

- Product model:

$$P(t \mid s, M_1, \ldots, M_n) = \frac{\prod_{1=1}^{n} P(t \mid s, M_i)}{Z}$$

- Based upon a Product of Experts formulation (Hinton 99).
  - . . . averages the contribution of each submodel.
  - . . . is an ensemble of log-linear models.

Parse selection: 3

- We treat the distribution of parses over a sentence in a binary manner.

- Three sets of features over derivations:
  - Configurational: loosely based on (Toutanova and Manning 02) – grandparent, local trees etc.
  - Ngram: derivations are flattened and treated as strings; ngrams are then extracted from these strings.
  - Conglomerate: features over phrase structure and Minimum Recursion Semantics (MRS).

Parse selection results

- Ten-fold cross-validation.
- Exact match evaluation.
- Unambiguous sentences are not counted.

Random	22.7
Log-linear (config)	74.9
Log-linear (ngram)	74.0
Log-linear (conglom)	74.0
Product (all)	77.8

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Active learning

- The error of a model can be decomposed into a sum of:
  - Noise: intrinsic errors in the training set.
  - Bias: systematic errors a learner makes.
  - Variance: how much parameter estimates vary as a function of training set choice.

- Active learning methods generally select examples which reduce the variance of a model.

Active learning methods: 1

- Sample selection is one AL method.
- Basic idea:
  - Putatively automatically label all examples in a pool and select a subset of examples according to some method.
  - Manually label selected examples.
  - Remove labelled examples from the pool.
  - Retrain the model(s) and iterate.

Active learning methods: 2

- Sample selection for parse selection:
  - An example is a sentence.
  - Labelling an example means distinguishing one parse from the other parses for that sentence.

- Annotation cost is in terms of selecting the best parse (and not drawing parses from scratch).

Active learning methods: 3

- Selecting the best parse means navigating through a set of choice points.
- Each choice point (a discriminant) partitions the set of parses.
- A typical sentence requires 5 choices.
- Much more efficient than drawing a parse.
  - . . . implies that the best parse is present.
- Active learning annotation cost is in terms of the number of discriminants per sentence.

Uncertainty sampling: 1

- Tree entropy (Hwa 2000):

$$f_{us}(s,\tau) = -\sum_{t \in \tau} p(t \mid s, M_i) \log p(t \mid s, M_i)$$

- Basic idea: selects examples with parses that are most uniformly distributed.

- Tree entropy has been applied to training CFG treebank parsers.

- We do not need to normalise tree entropy.

Uncertainty sampling: 2

- We can improve uncertainty sampling as follows:

$$f_{us}^{es}(s,\tau) = -\sum_{t\in\tau} p(t \mid s, M_1, \ldots, M_n) \log p(t \mid s, M_1, \ldots, M_n)$$

- The single model has been replaced with a product (ensemble) model.
- We call this Product Uncertainty Sampling.

Lowest best probability selection

- LBP:

$$f_{lbp}(s, \tau) = \mathrm{max}_{t \in \tau}\ p(t \mid s, M_i)$$

- Basic idea: selects examples with least discriminated parse.
- LBP is similar to uncertainty sampling.
- Generalising to an ensemble is trivial.

Query-by-committee

- Select examples when individual models predict different parses as being the preferred analysis.
- Basic idea: labelling uncertainly manifests as labelling disagreement.
- QBC is an ensemble method.

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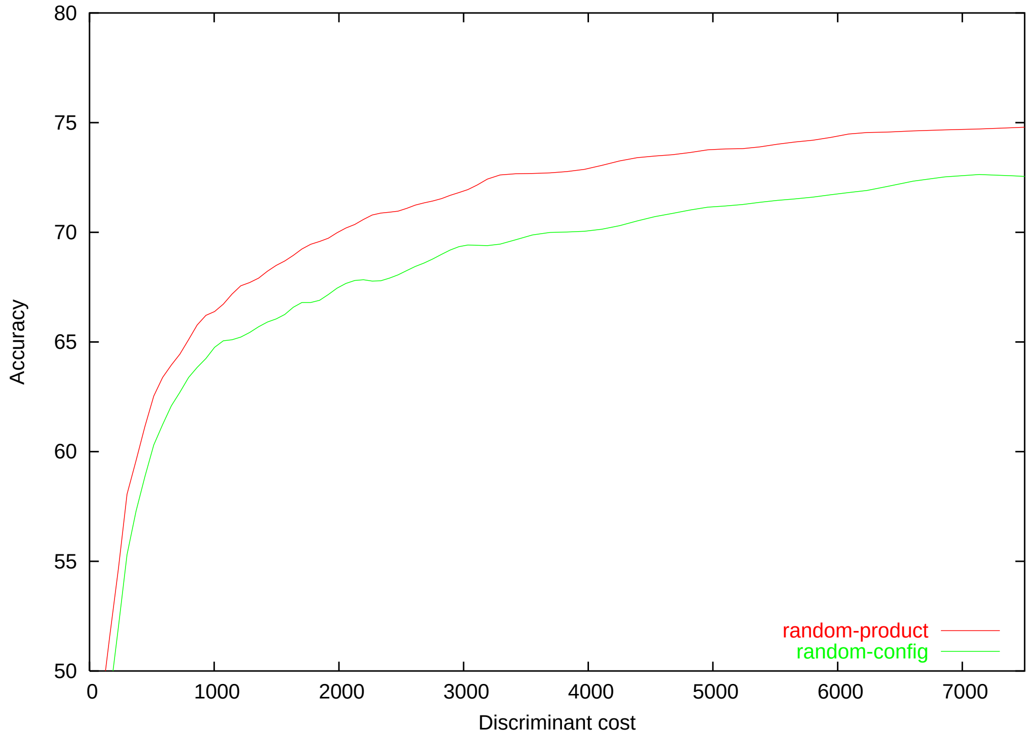
Baselines

- For comparison we used the following baselines:
  - Select n examples randomly.
  - . . . and label using a single model (config-random).
  - . . . and label using a product model (product-random).

- All experiments are averages over 10-fold cross-validation.

- Use $2k$ sentences.

Baseline results: 1



Random selection for a product model, Random selection for a single model

Baseline results: 2

- Random selection for our product model is better than random selection for a single model.

- Shows that improving the model can reduce annotation cost.

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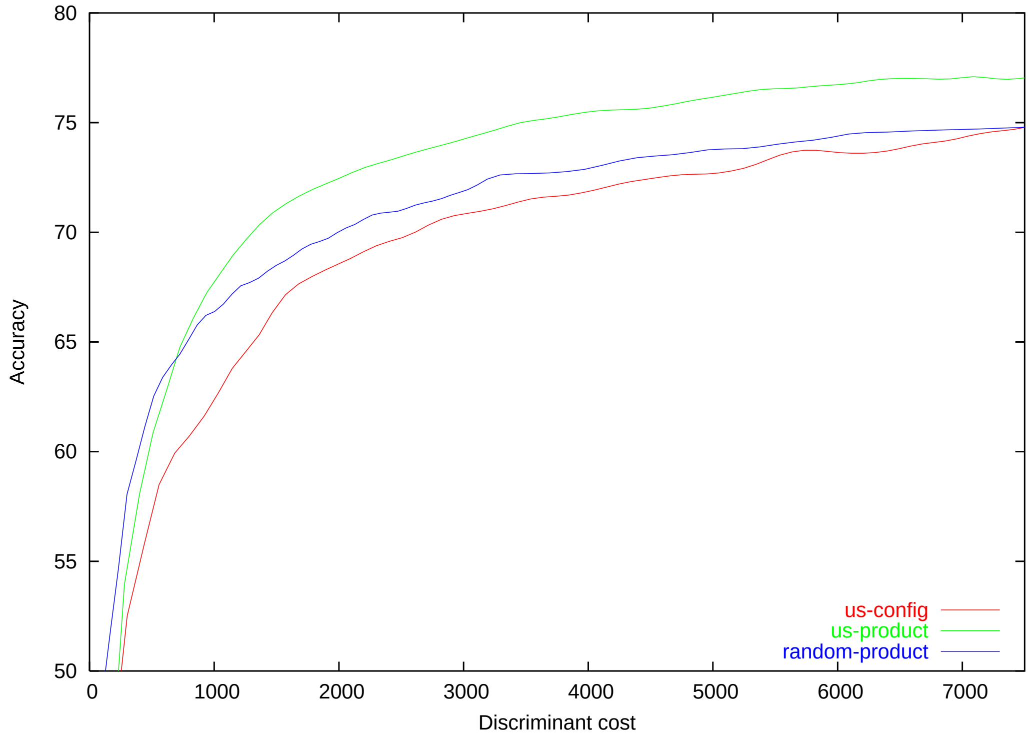
Main result: 1



US using a $\prod$ model, Random selection using a $\prod$ model, US using a single model

Main results: 2

- Random selection for our product model can outperform a single model with examples selected by active learning.
- . . . but ensemble-based active learning, for an ensemble model, outperforms random selection for an ensemble model.
- (A single model active learning method selecting examples for an ensemble model performs worse)

Heuristic selection

- Selecting shortest / longest / least ambiguous / most ambiguous sentences all performed no better than random selection.

- Selecting examples in the order they appeared in the corpus required 45% more labelling decisions than for random selection.
  - Most likely because Redwoods contains two domains.

Cross method comparison: 1

Method	Cost	Reduction	
		rand-config	rand-$\prod$
rand-config	3700	n/a	(46.2%)
rand-$\prod$	1990	46.2%	N/A
US-config	2600	29.7%	(25.2%)
QBC	1300	64.9%	34.7%
LBP-$\prod$	1280	65.4%	35.7%
US-$\prod$	1300	64.9%	34.7%

Annotation cost needed to achieve an average 70% parse selection performance.

Cross method comparison: 2

Method	Cost	Reduction	
		rand-config	rand-$\prod$
rand-config	13000	n/a	(36.2%)
rand-$\prod$	8300	36.2%	N/A
US-config	7700	40.8%	7.2%
QBC	3820	70.6%	54.0%
LBP-$\prod$	3660	71.9%	55.9%
US-$\prod$	3450	73.5%	58.4%

Annotation cost needed to achieve an average 75% parse selection performance.

Cross method comparison: 3

Method	Cost	Reduction rand-$\prod$
rand-config	N/A	N/A
rand-$\prod$	13800	N/A
US-config	N/A	N/A
QBC	6780	50.9%
LBP-$\prod$	7320	47.0%
US-$\prod$	6410	53.6%

Annotation cost needed to achieve an average 77% parse selection performance.

Comments

- Active learning can dramatically reduce the annotation effort involved with training HPSG parse selection mechanisms.

- Ensemble methods can improve both parse selection and active learning.

- Further reductions should follow from only considering n-best parses.

- Ongoing work is concerned with bootstrapping a semantic interpretation system based on the ERG (Rosie Project).