

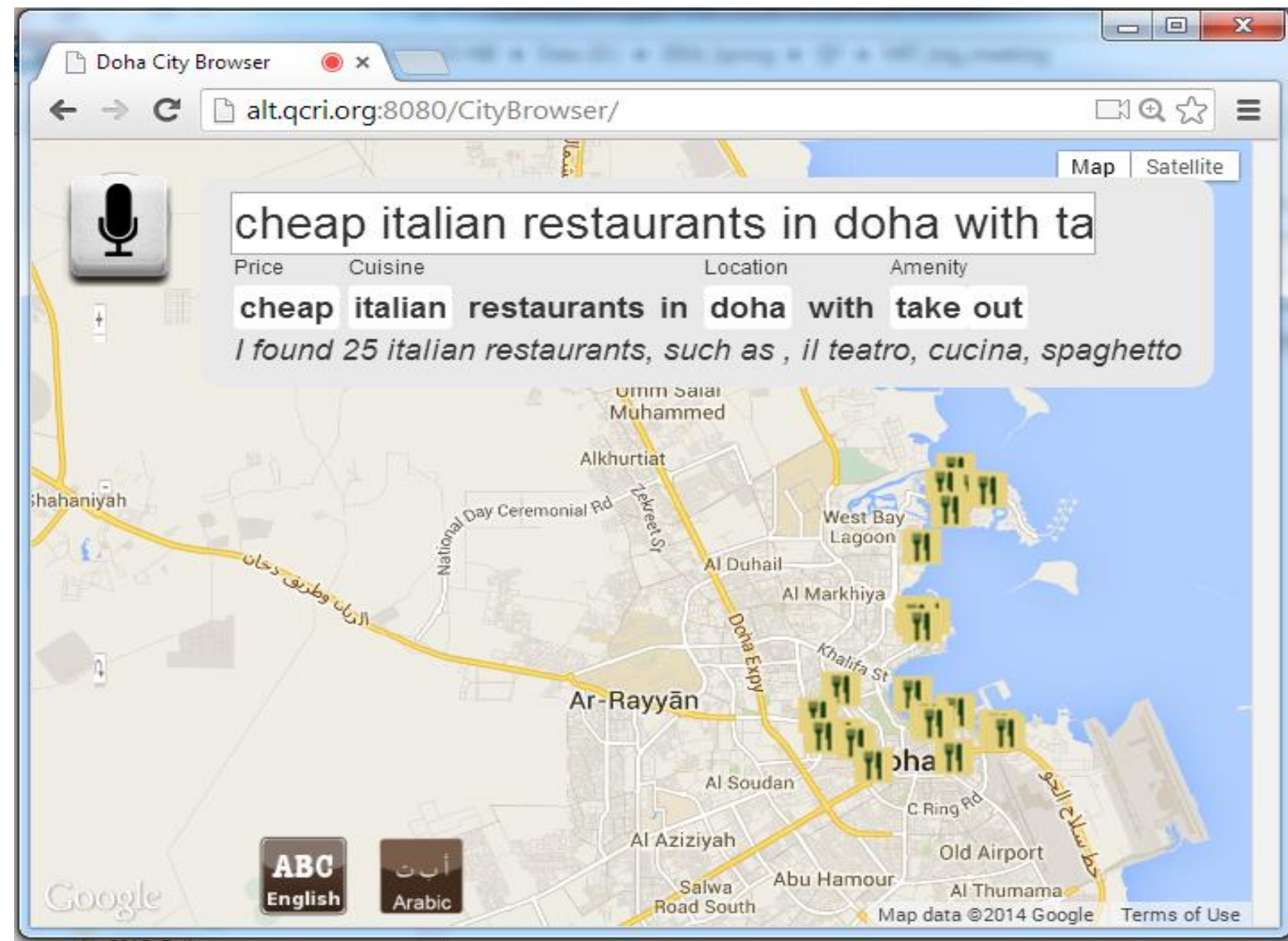


Semantic Kernels for Semantic Parsing

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1. Motivation



How do we convert a spoken request like
"cheap italian restaurants in doha with take out"
into a database query?

Processing Steps

Text/Speech
"cheap italian restaurants in doha with take out"

semantic parser

Semantically segmented text
(cheap) (italian) restaurants in (doha) with (take out)
<Price> <Cuisine> <City> <Amenity>

rule normalizer

Semantic representation
{"Price": "low",
"Amenity": "take out",
"City": "doha",
"Cuisine": "italian"}

query builder

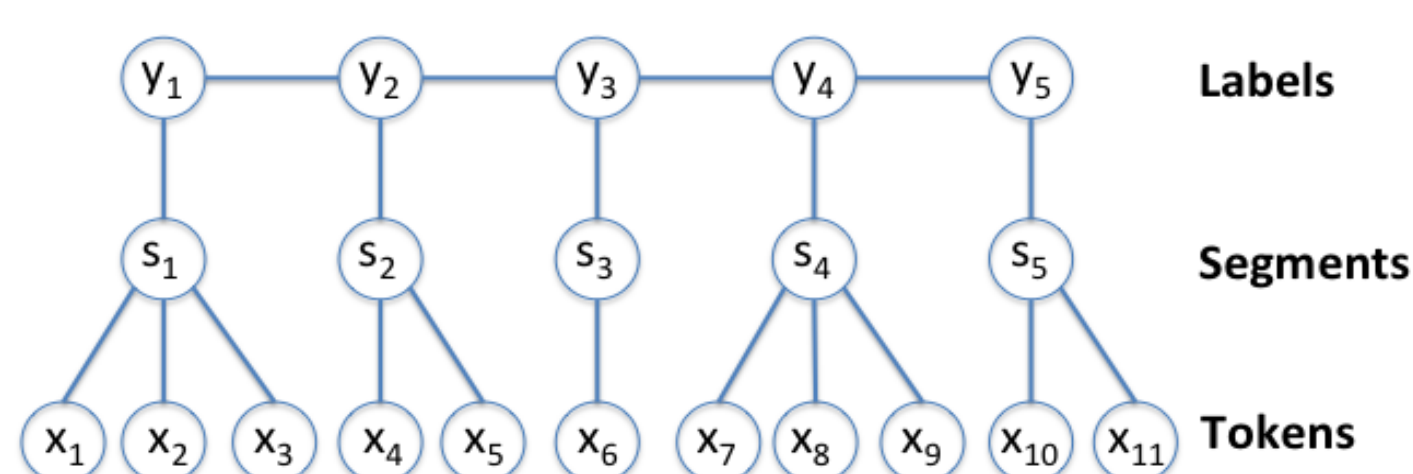
DB query
{ \$and[{ "cuisine": { "\$regex": "italian" } },
{ "city": { "\$regex": "doha" } },
{ "price": { "\$regex": "low" } },
{ "amenity": { "\$regex": "carry out" } }] }

2. State-of-the-art Semantic Parser

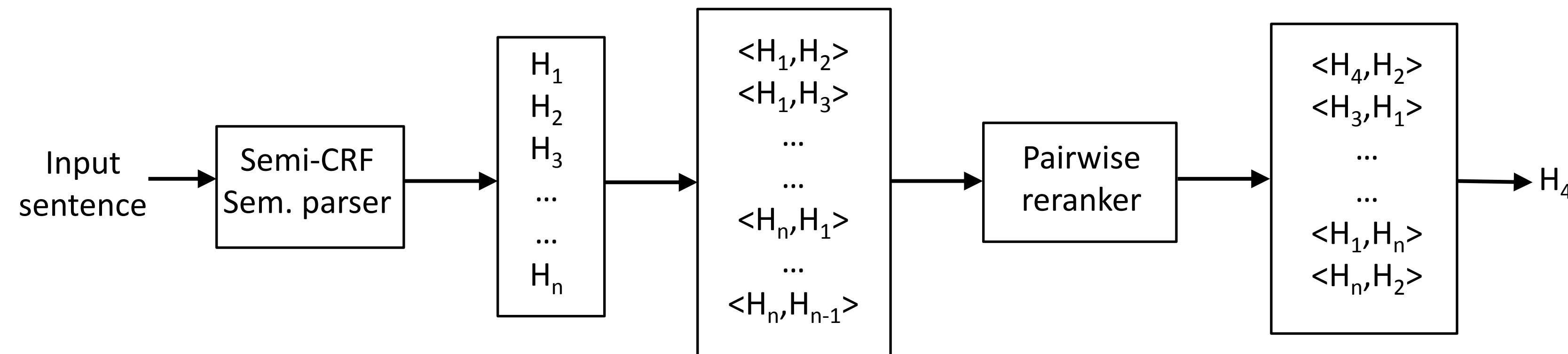
Semi-Markov CRFs (Sarawagi & Cohen 04)

- Joint sequential segmentation/classification
- Discriminative probabilistic sequential model
- Undirected graphical model

$$P(s|x) = \frac{1}{Z_i(x)} \exp\{\sum_j \lambda_j f(y_{j-1}, s_j, x)\}$$

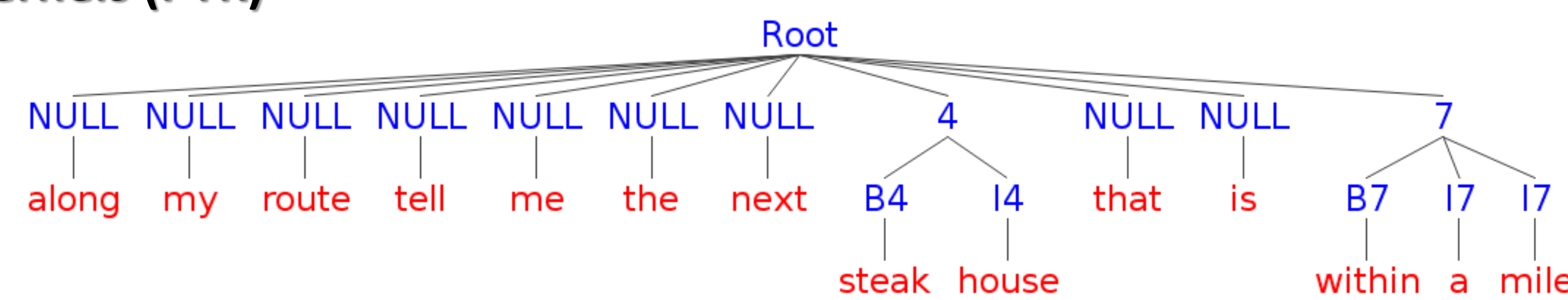


3. Our Approach: Reranking with Semantic Kernels



- Semi-CRF generates n -best hypotheses (H_i)
- Pairwise reranking function trained with SVMs with the preference reranking kernel
- Hypotheses are represented with tree-based structures (tree kernels are applied)
- Focus on kernels using semantics: LSA-based smoothing lexical similarity and Brown clusters

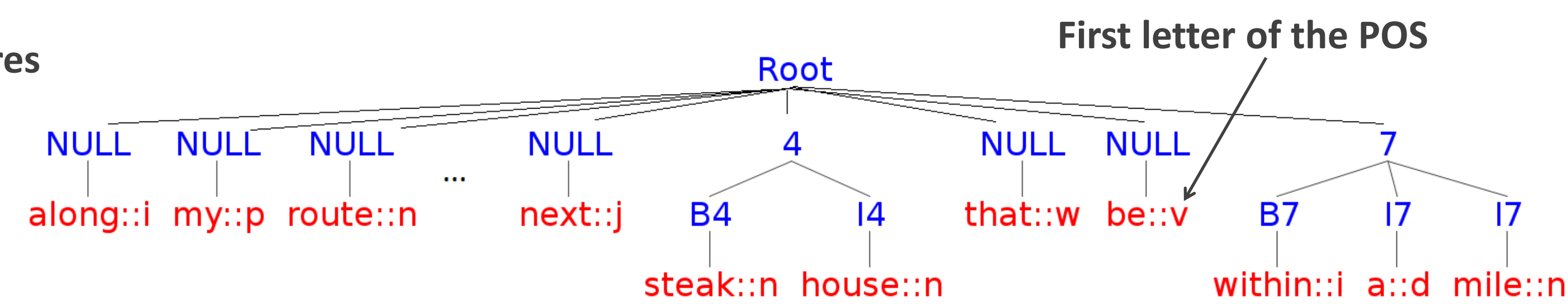
Partial Tree Kernels (PTK)



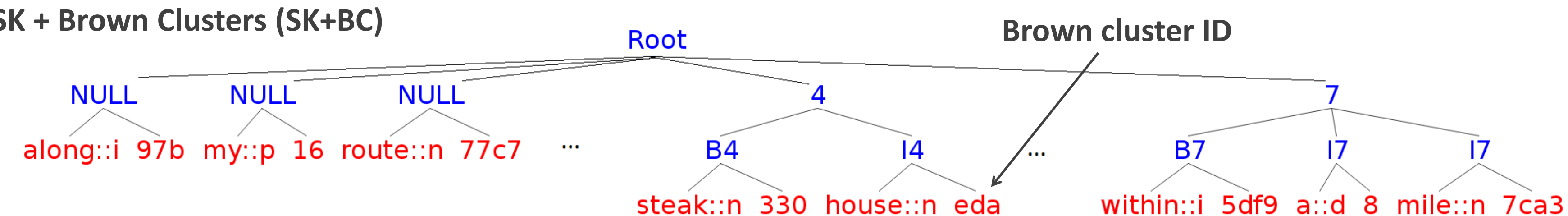
Smoothed PTK or Semantic Kernel (SK)

- Soft matching of tree fragments via similarity
- Node similarity derived using LSA

SK Structures

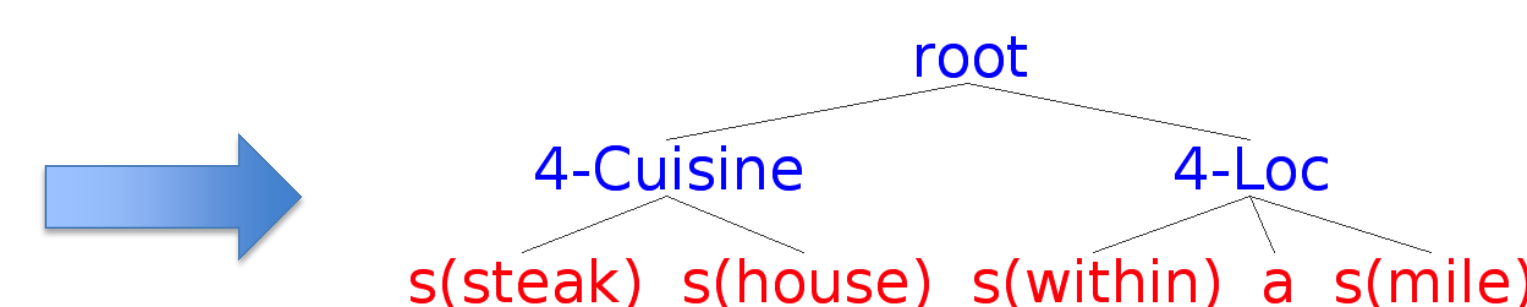


SK + Brown Clusters (SK+BC)



Semantic Structures for CSL Reranking

- Tree Kernels capture structural similarities between trees
- Brown cluster IDs in the structures capture semantic dependencies between labels
- LSA-smoothed SKs enable to measure the similarity between tree fragments (based on LSA word similarity), thus powerful semantic patterns are generated



Extra features in a flat vector (+all)

- From the semi-CRF: probability of label sequences, label sequence n -grams, DB-based, etc.

4. Experiments

- Dataset: human annotations (McGraw et al. 12)

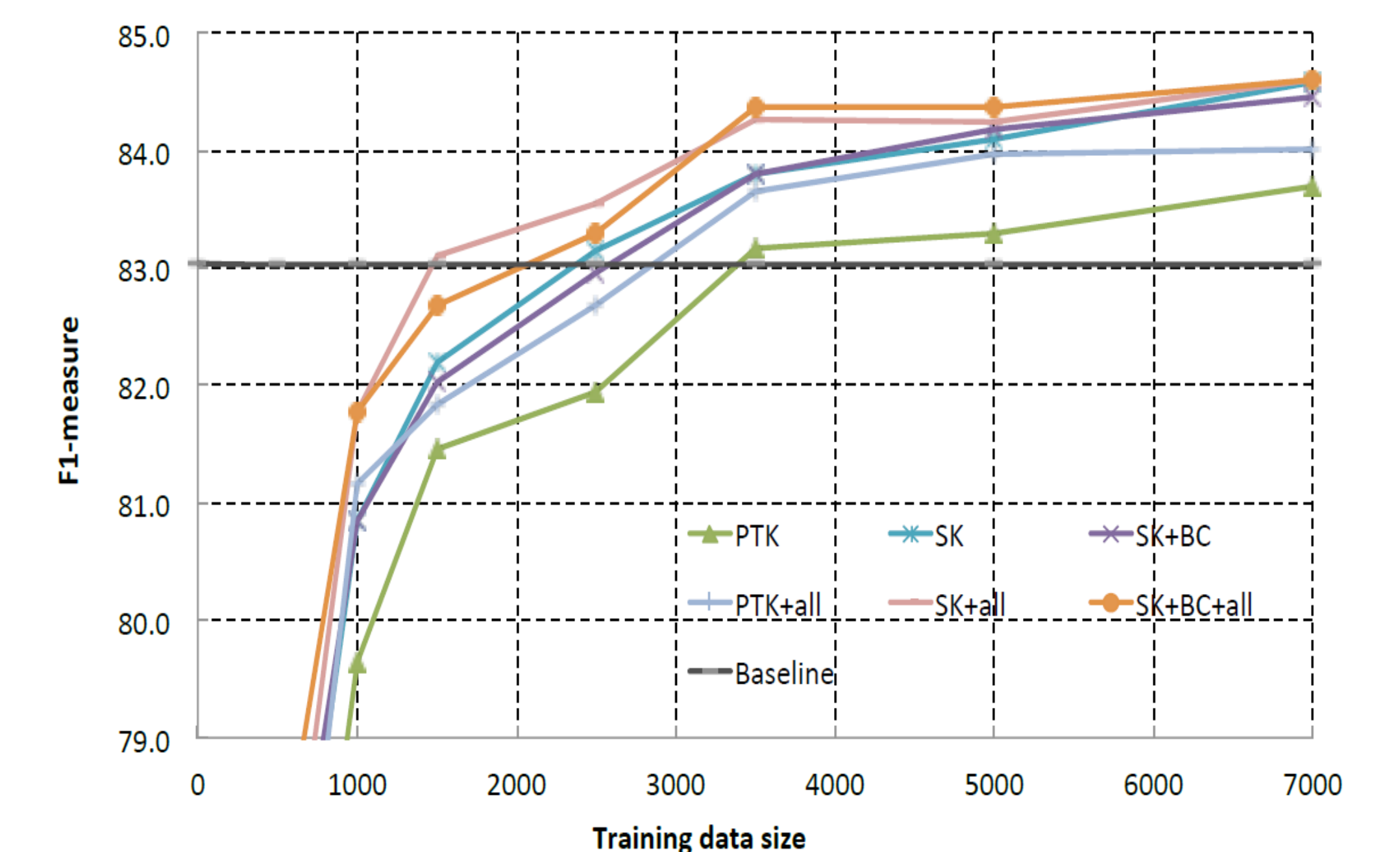
Train	Test	Train Reranker	Test Reranker
6,922	1,521	28,482	7,605

- Oracle: shows large room for improvement

N	1	2	5	10	100
Oracle F1	83.03	87.76	92.63	95.23	98.72

- Brown clusters: from Yelp restaurants reviews
- Lexical similarity for SK: LSA on TripAdvisor reviews

Main results



5. Conclusions

- The LSA-smoothed semantic kernel (SK) improves significantly over the semi-CRF ("baseline") and over our previous state-of-the-art reranker, which uses shallow syntactic patterns and PTK (Saleh et al., COLING-2014; equivalent to PTK+all)
 - ~10% relative improvement
- BCs do not significantly improve any model
- PTK+all is better than PTK but its accuracy is lower than any SK
- +all helps SK only with small sizes of the training set

Note: the state of the art on the task is very hard to beat

6. Future Work

- Explore semantic similarity from distributional and other sources, e.g., Wikipedia, Wiktionary, WordNet, FrameNet, BabelNet, and LSA for different domains.

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