Deep vs shallow NLP for Information Extraction

• DISCLAIMER – Natural Language Processing is a broad field, with many more applications than discussed here
• Broadly speaking, Information Extraction (IE) is concerned with finding entities and facts/relations about these entities in text

Deep vs shallow NLP (for Information Extraction)

• Deep == sophisticated == expensive (e.g., parsing, figuring out dependencies among words)
• Shallow == heuristic == cheap
  • Ex: assume every verb between two entities define a relation
Why shallow methods?

• The difference in computational cost is several orders of magnitude [Christensen et al., K-Cap 2011]
• Shallow methods can be deployed at Web scale
• Probabilistic methods filter out individual mistakes as noise

Where do we draw the line?

• Shallow vs deep depends on many factors, but generally we assume that
  ▪ POS tagging and chunking are shallow
  ▪ Parsing and beyond are considered deep

• Virtually all NLP toolkits out there will handle these tasks
  ▪ GATE (http://gate.ac.uk/)
  ▪ LingPipe (http://alias-i.com/lingpipe)
  ▪ Apache OpenNLP (http://opennlp.apache.org/)
  ▪ Apache UIMA—Unstructured Information Management Applications (http://uima.apache.org/)
  ▪ …

Roadmap—Part I

• Finding entities
  ▪ Shallow “ontology” extraction
  ▪ Entity identification and Co-reference resolution

• Finding (binary) relations
  ▪ One sentence at a time
  ▪ All sentences “at once” with clustering

• Applications
  ▪ Social media aggregation/analytics

Finding entities and classes with Hearst Patterns

• Succinct list of syntactic patterns expressing hyponymy (i.e., subclasses or instances of a class) [Hearst, ACL 1992]
  • Ex:

| NP “such as” NP* cities such as London, Paris, and Rome |
| “such” NP “as” NP* “or” | “and” NP works by such authors as Herrick and Shakespeare |
| NP, NP* “or” | “and” other NP bruises, wounds, broken bones or other injuries |
| NP “especially” | “including” NP* all common-law countries including Canada and England |
**KnowItAll**

- [Etzioni et al., 2005]
- **Multiple classes**: extracting, validating, and generalizing rules. KnowItAll project at U. Washington

Extracts both entities and relations

- Pattern learning: relies on a small number of templates, which are instantiated as good extractions are found
- Subclass extraction: aims at finding (part of) the concept hierarchy (e.g., physicist IS-a scientist)

- **Generate-and-test loop**: apply extraction patterns and test the plausibility of the extracted results—using Point-wise Mutual Information (PMI)

**Generate-and-test loop**

- General idea that has been used over and over again: finding entities, relations, etc.

```plaintext
find occurrences of seed instances
annotate text
extract new instances
patterns
generate new patterns
test
instances
```

**Entity extraction—other pointers**

- **Single class**: expanding a list of known entities using a search engine

- **Single class from multiple sources**: combining extractors

- **Multiple classes**: extracting, validating, and generalizing rules
Finding IS-A relationships

• Iteratively apply Hearst patterns [Kozareva and Hovy, EMNLP 2010]

• Optimization problem: removing redundant edges

```
“animals such as lion and ?” → \{lion, tiger, jaguar\}
“? such as lion and tiger” → feline
“? such as feline” → “Big Predatory Mammals”
“mammals such as felines and ?” → \{felines, bears, wolves\}
```

Adding some depth: [Snow et al., NIPS 2005]

• Corpus: 6 million sentences from several News corpora

• Parsing provides more reliable features, including part of speech tags and structural dependencies, compared to the syntactic features of the Hearts patterns

• The resulting concept hierarchy was shown to be more precise and more detailed than Wordnet
  ▪ Although Wordnet is designed to be general

NER as sequence labeling problem

• Start with annotated example sentences, indicating where the entities are, and their types (e.g., ORG, PER, LOC,...)

```
NP  V  PREP  NP  PREP  NP
Kings  favored  over  Davis  in  Finals
```

• Labeled sequence prediction: sampling from a trained CRF model: Stanford NER tool [Finkel et al., ACL 2005]
  ▪ Uses both local and global information; features include POS tags, previous and following words, n-grams, ...

• Invaluable open source, stand-alone tool
  ▪ Off the shelf, it comes trained for news articles, but can be easily trained for other domains

De-duplication and disambiguation of entities

Mrs. Obama told Ray that the family will likely watch the game …
As for who the first family may be rooting for, President Obama told ABC News’ …
“… I can’t make predictions because I will get into trouble.” Obama said last month…

• Once references to named entities are identified, detect whether any of them refer to the same real world entity and which don’t

• One intra-document co-reference resolution tool provided by the GATE framework: Orthomatcher [Bontcheva et al., TALN 2002]
Orthomatcher [Bontcheva et al., 2002]

- Rule-based: inexpensive, ad-hoc, but shown to perform well in many tasks
  - Gazetteers: known entities, common abbreviations (Ltd., Inc., ...), synonyms (New York = the big apple, ...), and ad-hoc list for the specific domain
- Proper name co-reference resolution
  - Orthographical matches (James Jones = Mr. Jones); Token Re-ordering and abbreviations (University of Sheffield = Sheffield U.)
  - Non-transitivity and exclusion triggers in some rules (BBC News ≠ News);
- Pronominal co-reference resolution
  - Ad-hoc rules from empirical observation (e.g., 80% of all ‘he, his, she, her’ mentions refer to the closest person in the text)
- Fairly accurate on news articles
  - Well-written text

<table>
<thead>
<tr>
<th>Text type</th>
<th>OM precision</th>
<th>recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>broadcast news</td>
<td>94%</td>
<td>92%</td>
</tr>
<tr>
<td>newspaper</td>
<td>98%</td>
<td>92%</td>
</tr>
<tr>
<td>newspapers</td>
<td>98%</td>
<td>95%</td>
</tr>
</tbody>
</table>

Entity identification and linking [Cucerzan, 2007]

- Entity recognition builds on capitalization rules, so the document processing starts with splitting sentences and finding the correct case for all words in each sentence
  - Builds on a large (1B words) corpus of Web documents
- Resolves structural ambiguity (e.g., [[Barnes and Noble]] or [[Barnes]] and [[Noble]]), possessives, and prepositional attachments using the surface forms extracted from Wikipedia (or the Web corpus for entities not in Wikipedia)
- Disambiguation based on vector space model similarity of mentions in the text and mentions in the knowledge base
- Evaluation of 756 surface forms, of which 127 were non-recallable, from news text shows accuracy of 91.4%

Entity identification and linking [Cucerzan, 2007]

- Performs entity identification, in-document co-reference resolution, and cross-document co-reference resolution
  - Instead of relying on heuristics, the disambiguation rules come from statistical analysis of Wikipedia (>1.4 million entities) and a large corpus of Web searches
- Surface forms, entities, tags and context words
  - Mentions to entities are compared against the knowledge base using other terms nearby in the sentence that indicate context
  - Spread-activation like algorithm
- Building the knowledge base
  - Parse Wikipedia’s entity pages, redirecting pages, disambiguation pages, and list pages
  - Courtesy of S. Cucerzan

Entity linking

Mrs. Obama told Ray that the family will likely watch the game …
As for who the first family may be rooting for, President Obama told ABC News’ …
“… I can’t make predictions because I will get into trouble,” Obama said last month…

Mrs. Obama [en.wikipedia.org/wiki/Michelle_Obama]
President Obama [en.wikipedia.org/wiki/Barack_Obama]
Collective entity linking

• Multiple surface forms for the same entity, and multiple entities with the same "canonical" surface form
• Often it is easier to link all named entities at once

Barbosa, Wang, Yu, Shallow Information Extraction for the Knowledge Web. ICDE 2013, Brisbane, Australia

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Open/Closed Relation extraction

<table>
<thead>
<tr>
<th></th>
<th>Closed</th>
<th>Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of target relations</td>
<td>1</td>
<td>All</td>
</tr>
<tr>
<td>Relation-specific training</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Cost</td>
<td>Linear on the number of relations</td>
<td>Constant</td>
</tr>
</tbody>
</table>

• Closed relation extraction == binary classification problem: does the sentence express a relation (YES/NO)?
  ▪ Supervised systems: [Culotta and Sorensen, ACL 2004]; [Bunescu and Mooney, EMNLP 2005]; [Zelenko et al., JMLR 2003]
  ▪ Bootstrapping approaches: DIPRE [Brin, WWW 1998]; Snowball [Agichtein and Gravano, DL 2000]; KnowItAll [Etzioni et al., WWW 2004]
  ▪ Distant supervision: [Mintz et al., ACL 2009]
Open relation extraction

• Term coined by Banko and Etzioni (2008) to mean learning both the relations and the instances from the data

• Some landmark systems/papers
  - TextRunner uses a classifier based on Conditional Random Fields (CRFs) over sentences [Banko and Etzioni, ACL 2008]
  - ReVerb is a manually refined version of TextRunner focusing a subset of relation patterns [Fader et al., ACL 2011]
  - StatSnowBall builds on the SnowBall system [Zhu et al., WWW 2009]
  - [Hasegawa et al., ACL 2004] introduced an unsupervised method based on text clustering

ORE “one sentence at a time”

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Pattern</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>38%</td>
<td>E₁ Verb E₂</td>
<td>X established Y</td>
</tr>
<tr>
<td>23%</td>
<td>E₁ NP Prep E₂</td>
<td>X settlement with Y</td>
</tr>
<tr>
<td>16%</td>
<td>E₁ Verb Prep E₂</td>
<td>X moved to Y</td>
</tr>
<tr>
<td>9%</td>
<td>E₁ Verb to Verb E₂</td>
<td>X plans to acquire Y</td>
</tr>
</tbody>
</table>

• Relation extraction as a sequence prediction task
  - TextRunner: [Banko and Etzioni, 2008] a small list of part-of-speech tag sequences that account for a large number of relations in a large corpus
  - ReVerb: [Fader et al., 2011] use an even shorter list of patterns, extracting verb-based relations

• The ReVerb/TextRunner tools have extracted over one billion facts from the Web

• Efficient: no need to store the whole corpus

• Brittle: multiple synonyms of the the same relation are extracted

ORE on “all sentences” at once

• [Hasegawa et al., 2004] use hierarchical agglomerative clustering of all triples \((E_1, C, E_2)\) in the corpus
  - \(E_1, C, E_2\) where the context \(C\) derives from all sentences connecting the entities
  - The clustering is done on the context vectors (not the entities)

• All triples (and thus, entity pairs) in the same cluster belong to the same relation

SONEX

• Offline (HAC clustering)

• Online (buckshot): cluster a sample and classify the remaining sentences, one at a time
  - No discernible loss in accuracy, but much higher scalability
  - Also allows the same entity pair to belong to multiple relations
SONEX: Clustering features

- Clustering features derived from the words between entities
  - **Unigrams:** stemmed words, excluding stop words.
  - **Bigrams:** sequence of two (unigram) words (e.g., Vice President).
  - **Part of Speech Patterns:** small number of relation-independent linguistics patterns from TextRunner [Banko and Etzioni, 2008]

- Verbal and non-verbal relations

- Weights: Term frequency (tf), inverse document frequency (idf) and **Domain frequency** (df) [Merhav et al., SIGIR 2010]

\[
df_j(t) = \frac{f_j(t)}{\sum_{1 \leq j \leq n} f_j(t)}
\]

SONEX: From Clusters to Relations

- Clusters are sets of entity pairs with similar contexts
  - We find relation names by looking for prominent terms in the context vectors
  - Most frequent term
  - Centroid of cluster

<table>
<thead>
<tr>
<th>Relation</th>
<th>Cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>Campaign Chairman</td>
<td>McCain : Rick Davis</td>
</tr>
<tr>
<td></td>
<td>Obama : David Plouffe</td>
</tr>
<tr>
<td>Strongman President</td>
<td>Zimbabwean : Robert Mugabe</td>
</tr>
<tr>
<td></td>
<td>Mugabe : Hugo Chavez</td>
</tr>
<tr>
<td>Chief Architect</td>
<td>Kia Behnia : BMC Software</td>
</tr>
<tr>
<td></td>
<td>Brendan Eich : Mozilla</td>
</tr>
<tr>
<td>Military Dictator</td>
<td>Pakistan : Pervez Musharraf</td>
</tr>
<tr>
<td></td>
<td>Zimbabwe : Robert Mugabe</td>
</tr>
<tr>
<td>Coach</td>
<td>Tennessee : Rick Neuheisel</td>
</tr>
<tr>
<td></td>
<td>Syracuse : Jim Boeheim</td>
</tr>
</tbody>
</table>

SONEX: importance of domain

- DF works really well except when MISC types are involved
  - **Example:** coach
    - LOC–PER domain: (England, Fabio Capello); (Croatia, Slaven Bilic)
    - MISC–PER domain: (Titans, Jeff Fisher); (Jets, Eric Mangini)

- DF alone improved the f-measure by 12%

SONEX: from clusters to relations

- Evaluate relations by computing the agreement between the Freebase term and the chosen label
  - Scale: 1 (no agreement) to 5 (full agreement)
### SONEX vs ReVerb—clustering analysis

<table>
<thead>
<tr>
<th>Systems</th>
<th>Purity</th>
<th>Inv. Purity</th>
</tr>
</thead>
<tbody>
<tr>
<td>ReVerb</td>
<td>0.97</td>
<td>0.22</td>
</tr>
<tr>
<td>SONEX</td>
<td>0.96</td>
<td>0.77</td>
</tr>
</tbody>
</table>

- **Purity:** homogeneity of clusters  
  - Fraction of instances that belong together
- **Inv. purity:** specificity of clusters  
  - Maximal intersection with the relations
- Also known as overall f-score

### Meta CRF: deep vs shallow cost/benefit

- CRF taking into account structural features of the tree to label direct and indirect (meta) relations [Mesquita and Barbosa, ICWSM 2011]
- Outperformed the baseline by  
  - 190% on meta relations and  
  - 86% on statements with direct relations

### Roadmap—Part I

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- **Applications**  
  - Social media aggregation/analytics

### Popularity/hit counts over time

- **Source:** [http://www.textmap.com](http://www.textmap.com) entry about Barack Obama (around July 2008)
- **Task:** entity recognition  
  - Identifying that the articles mention Barack Obama
- **Task:** entity disambiguation  
  - Figuring out all “surface” forms for the same entity
- **Task:** entity disambiguation  
  - Figuring out which Barack Obama the articles mention
- **Task:** clustering  
  - Grouping the article sources by kind (sports, business, entertainment, ...)

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Social delivery—story centered

- News aggregator building on preferences and your social network

![Wavii Story Centered](http://example.com/wavii.png)

Information networks in Social Media Analysis

- Source: [http://www.silobreaker.com](http://www.silobreaker.com) network around Hilary Clinton
- Integrates news, blogs, audio/video feeds, press releases...

![Silobreaker Network](http://example.com/silobreaker.png)

Social delivery—story centered

- Wavii: [http://wavii.com](http://wavii.com)
- Tasks: news aggregation
  - Identifying topics and related news
- Task: content filtering
  - Identifying preferences
- Task: event extraction
  - Similar to summarization: finding a sentence that captures the news item (e.g., its title?)

![Sample Event Extraction](http://example.com/event-extraction.png)

SILO Breaker

- Extracting information networks from text
- Task: entity recognition
  - Figuring out which entities are mentioned in the corpus (and their kinds), and the relations among entities
- Task: entity disambiguation
  - Figuring out all "surface" forms for the same entity
- Tasks: relation extraction
  - Determining which entities and/or relations are most relevant to the entity on the spotlight

![Sample Entity Recognition](http://example.com/entity-recognition.png)
Summary

• Large-scale open information extraction is an active and exciting area, with many impressive results and ongoing projects
  - YAGO (Max Planck Institute), KnowItAll (U. Washington), NELL (Carnegie Mellon U.), Google’s Knowledge Graph, Microsoft’s Satori, Probase
  - ...

• Challenges/future work:
  - Plug and play NLP
  - Evaluation

Outline

• Motivation
  - Why doing all this in the first place?
  - Define what shallow means – no deep linguistic analysis
  - Emphasizing why the need for shallow extraction techniques

• PART I: shallow extraction techniques
  - Entity extraction
  - Relation extraction
  - Application Social text mining

• Part II: Bring Knowledge to Search

• Part III: Real life knowledge base, scalability and probability

Knowledge is Becoming Part of Search

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Knowledge is Becoming Part of Search

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Knowledge is Becoming Part of Search

- “... a new breed of search experiences ... the user is saved the burden of culling documents from a results list and laboriously extracting information buried within them.”

- Baeza-Yates & Raghavan on Next Generation Web Search

- All major search engines have started incorporating “knowledge” into search results

- Search users do respond, albeit slowly, to the capabilities of search engines → leading to more innovations on integrating knowledge and search.

Leveraging Knowledge for Search

- Improving web search
  - Query enrichment
  - Entity navigation

- Shallow knowledge search
  - Search over knowledge bases
  - Knowledge search over Web

- Al-ish knowledge search
  - Question answering
  - Natural language search
  - Survey by Lopez, Uren, Sabou, Motta, Semantic Web 2(2):125

Improving Web Search via Query Enrichment

- Goal: better query understanding by associating semantics with user queries
  - Complimentary to using query logs to learn classes and attributes

- Case studies:
  - Query tagging
  - Query suggestion

Query Enrichment is Critical for Knowledge Search

- Query tagging is the first step toward knowledge search
- Query suggestion can guide users toward queries they otherwise assume can not be handled

[Example image showing query enrichment in search results]
From Entity to the Information Box, via Knowledge Base

- Industrial focus has been on KB construction
  - Entity navigation is considered to be relatively simple
  - Not true, but KB construction poses more challenges now
- However, some challenges are already hard to ignore:
  - Information selection
  - Information visualization
  - Information freshness

Recent Studies on Query Tagging

- Named entity recognition
  - [Guo et al, SIGIR 2009]
- Rich interpretation
  - [Li, Wang, Acero, SIGIR 2009]
- Template mining:
  - [Agarwal, Kabra, Chang, WWW 2010]

The Query Tagging Problem

- Even simple named entity tagging is not easy

  “first love lyrics”

  ➔ The real entity is “first love” of class “song”

Tagging Named Entities in Queries [Guo et al, SIGIR 2009]

- Challenges:
  - Short text
  - Fewer language features: e.g., no punctuation, no capitalization
- Intuition:
  - Use context to disambiguate
  - Use query logs to learn probabilities
  - Gather class labels on seed entities
Probabilistic Model

- Model the tagging problem as computing the probabilities of all possible triples, (e, t, c), that can represent the query
  - e: entity
  - t: context
  - c: class label for the entity

- “first love lyrics”
  - (“first love”, “# lyrics”, song), or
  - (“first”, “# love lyrics”, album), or
  - (“love” “first # lyrics”, emotions), or
  - (“lyrics”, “first love #”, music)

- The one with the highest probability can be considered as the correct tagging.

Training and Prediction

- Step 1: Gather seed set of (entity, class) pairs
- Step 2: Match the seed set with query log and gather their contexts: (e_{seed}, t)
- Step 3: Use the contexts gathered from step 2, match with the query log again and gather expanded entities: (e_{expanded}, t)

- Conditional probability estimates:
  - Pr(e): occurrence frequency in logs
  - Pr(t|c): learned from Step 2.
  - Pr(c|e): learned from Step 3 with fixed Pr(t|c) from Step 2.

- Prediction: apply to all possible query segmentations

Probabilistic Model

- The learning problem is:

\[
\max_{i=1}^{N} \prod \Pr(e_i, t_i, c_i)
\]

- Pr(e, t, c) can be estimated as:

\[
\Pr(e, t, c) = \Pr(e) \Pr(c|e) \Pr(t|e, c)
= \Pr(e) \Pr(c|e) \Pr(t|c)
\]

  - Simplification: context only depends on the class
    - i.e., “lyrics” is more likely associated with songs, regardless which song

Results

- 12 Million unique queries ➔ tagged 0.15 Million
  - Recall is quite low
- Sampled 400 queries for evaluation
  - 111 movie, 108 game, 82 book, 99 song

![Graph showing accuracy for different categories]
Challenging Queries

• “american beauty company”
  ▪ Highly popular entity that is wrong
• “lyrics for forever by brown”
  ▪ Multiple contexts
• “canon sd350 camera” or “canon vs nikon”
  ▪ Multiple entities

The Query Tagging Problem

• Tagging just the entities is not enough
  “canon powershot sd850 camera silver”

Rich interpretation:
  “canon” ➔ brand
  “powershot sd850” ➔ model
  “camera” ➔ type
  “silver” ➔ attribute

Rich Interpretation [Li et al, SIGIR 2009]

• Fully interpret the query instead of just tagging a single entity
• Handles multi-entity and multi-context queries
• Limited within a specific domain

• Challenges:
  ▪ Which learning model to use:
    • Query is no longer treated as bag of words but a sequence instead
    • Training labels are harder to generate
    • Each query can have multiple labels co-exist

• Sequential learning model is easy to find: Conditional Random Fields (CRF)

Automatically Obtaining Labels (Shopping)

• Target schema
• Leverage click log to find (query, product) pairs
  ▪ Focus on queries that led to clicks on product listing pages
• Extract metadata from those products to produce (query, metadata) events
  ▪ Relatively easy since product pages are well-structured (within MSN shopping)
• Map metadata to target to produce (query, target) pairs
• Conservative automatic labeling
  ▪ Only query tokens mapped to exactly one target field are labeled
• Complementing automatic labels with manual labels
  ▪ E.g., “cheap” ➔ SortOrder
Using Automatic Labels in CRF

- Automatic labels can often be wrong ➔ Adopt them as soft evidences
- The true labels are created as hidden
- The automatic labels on the query terms are created as observed variables to bias the true label selections

Recent Studies on Query Suggestion

- Query to Query
  - [Szpektor, Gionis, Maarek, WWW 2011]
- Entity to Query
  - [Bordino et al, WSDM 2013]

Results

- Training labels
  - Automatic: 50K labels for clothing; 20K labels for electronics
  - Enhanced by 4K manual labels for clothing and 15K manual labels for electronics

The Query Suggestion Problem

- Enormously popular with the users
  - Works very well for head queries
- Approaches
  - Query similarity
    - E.g., Cosine similarity, edit distance
  - Query flow graph
    - Leveraging co-occurrences of queries in the same query session
Query Flow Graph [Boldi et al, CIKM 2008]

- Constructed from query session logs
- Nodes are queries
- Create an edge \( (q_1, q_2) \) if:
  - \( q_2 \) appeared as a reformulation of \( q_1 \) in a session
- Edge weights can be assigned in many ways
  - \( \Pr(q_2 \mid q_1) = \frac{f(q_1, q_2)}{f(q_1)} \)
  - \( \text{PMI}(q_1, q_2) = \log \frac{f(q_1, q_2)}{f(q_1)f(q_2)} \)

Query Flow Graph

- Intuition:
  - If, users often search "new york restaurants" after searching for "new york hotels" and similarly for other popular cities such as "shanghai", "paris", etc.
  - Then, "pkoytong restaurants" can be a good recommendation candidate for "pkoytong hotels" since "pkoytong" is also a city

Query Template Flow Graph [Szpektor et al, WWW 2011]

- Query entity tagging techniques made query template generation possible!
  - "new york restaurants" \( \rightarrow \) "<city> restaurants"
  - Essentially, knowledge can be used to enrich the query to address many issues associated with long tail queries
- Computing edge weights between query and template
  - Assuming a hierarchical ontology
  - \( S(q, t) \) is computed based on where in the hierarchy the query entity in \( q \) is matched

Query to Template Edges

\[
S_{qt}(q, t) = \alpha^d(z, e)
\]
Template-to-Template Edges

- Creating edges between templates
  - A template-to-template edge occurs if and only if a query-to-query edge occurs and the two queries match the two templates, respectively, with the same entity

- Computing edge weights between templates
  - The more supporting query-to-query pairs there are, the higher the weights

\[
S_t(t_1, t_2) = \sum_{(q_1, q_2) \in \text{Sup}(t_1, t_2)} s_{q_1}(q_1, q_2),
\]

\[
s_{tt}(t_1, t_2) = \frac{S_t(t_1, t_2)}{\sum_t S_t(t_1, t)}.\]

Generating Recommendations

- Let \( S(x, y) \) be the probability of reaching \( y \) from \( x \) in the graph
  - E.g., product of all the edge weights on the path from \( x \) to \( y \).

- The score of \( r(q_1, q_2) \) can be computed as
  - \( S(q_1, q_2) \) based on original query flow graph, plus
  - \( \text{SUM}_i [(q_1, t_i), S(t_i, t_j), S(q_2, t_j)] \) based on the query template flow graph

- Tough cases remain
  - E.g., entities that do not appear in the ontology hierarchy, which is much more common in long tail queries

Results

- The query template graph: 95M queries, 60 candidate templates per query
  - Number of edges is linear to the number of nodes

<table>
<thead>
<tr>
<th>pair occurrences</th>
<th>QFG</th>
<th>QTPG</th>
<th>relative increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>total in test-set</td>
<td>3134388</td>
<td>3134388</td>
<td>24.37%</td>
</tr>
<tr>
<td>upper-bound coverage</td>
<td>(23.65%)</td>
<td>(28.17%)</td>
<td>(882851)</td>
</tr>
<tr>
<td># in top-100</td>
<td>(16.97%)</td>
<td>(25.49%)</td>
<td>(799001)</td>
</tr>
<tr>
<td># in top-10</td>
<td>(9.49%)</td>
<td>(20.74%)</td>
<td>(649093)</td>
</tr>
<tr>
<td># ranked highest</td>
<td>(2.86%)</td>
<td>(10.01%)</td>
<td>(313638)</td>
</tr>
<tr>
<td>MAP</td>
<td>0.050</td>
<td>0.137</td>
<td>249.5%</td>
</tr>
<tr>
<td>avg. position</td>
<td>18.35</td>
<td>8.3</td>
<td></td>
</tr>
</tbody>
</table>

The Query Suggestion Problem

- More challenging for long tail queries
  - Query similarity often lead to wrong suggestions
    - By definition, they are very rare in query log

- Proposed approaches:
  - Dropping non-critical terms [Jain, Ozertem, Velipasaoglu, SIGIR 2011]
  - More interestingly, query templates!
Entity Query Graph [Bordino et al WSDM 2013]

- Recommending queries when a user shows interests in an entity, e.g.:
  - When a user is visiting a Wikipedia page
  - When a user searches for an entity
  - When a user’s profile has an entity
- Similar idea to extend query flow graph, but using entities instead of templates
- Again, enabled by query tagging techniques

Entity Query Graph

- Entity-to-query edges
\[ w_{EQ}(e \rightarrow q) = \frac{f(q)}{\sum_{q_i \in X_E(q_i)} f(q_i)} \]
- Entity-to-entity edges
\[ w_{E}(e_u \rightarrow e_v) = 1 - \prod_{i=1, \ldots, r} (1 - p_{q_{t_x} \rightarrow q_{t_y}}(e_u \rightarrow e_v)) \]

Results

- Generate recommendations based on personalized PageRank over the Entity Query Graph
- Data: 200M queries; 100M entities; linear number of edges again

<table>
<thead>
<tr>
<th>Testset</th>
<th>Label</th>
<th>EQGraph</th>
<th>Reverse IR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wikipedia pages</td>
<td>Related and interesting</td>
<td>62.7%</td>
<td>33%</td>
</tr>
<tr>
<td></td>
<td>Related but obvious</td>
<td>3.3%</td>
<td>41.5%</td>
</tr>
<tr>
<td></td>
<td>Unrelated</td>
<td>34%</td>
<td>25.5%</td>
</tr>
<tr>
<td>Yahoo! News + Yahoo! Finance</td>
<td>Related and interesting</td>
<td>52%</td>
<td>40%</td>
</tr>
<tr>
<td></td>
<td>Related but obvious</td>
<td>2.3%</td>
<td>34.3%</td>
</tr>
<tr>
<td></td>
<td>Unrelated</td>
<td>45.7%</td>
<td>25.7%</td>
</tr>
<tr>
<td>Full testset</td>
<td>Related and interesting</td>
<td>58%</td>
<td>36.1%</td>
</tr>
<tr>
<td></td>
<td>Related but obvious</td>
<td>2.9%</td>
<td>38.4%</td>
</tr>
<tr>
<td></td>
<td>Unrelated</td>
<td>39.1%</td>
<td>25.9%</td>
</tr>
</tbody>
</table>

Leveraging Knowledge for Search

- Improving web search
  - Query enrichment
  - Entity navigation
- Shallow knowledge search
  - Search over knowledge bases
  - Knowledge search over Web
- Al-ish knowledge search
  - Question answering
  - Natural language search
**Shallow Knowledge Search**

- **Shallow == Queries are represented as**
  - Simple keywords
  - Shallowly tagged with structural annotations
    - Nothing resembles the full structure-ness of SQL/SPARQL

- **Approaches can be classified on knowledge representation**

- **Search over knowledge bases**
  - Assume the presence of structured knowledge bases
  - Relational databases
  - Semi-structured databases
  - Ontologies such as YAGO [Suchanek, Kasneci, Weikum, WWW 2007]

- **Knowledge search over Web**
  - Assume only structured annotations on Web documents

**Search over Knowledge Bases**

- An “ancient” topic in database community (incomplete list)
  - Relational:
    - DBXplorer [Agrawal, Chaudhuri, Das, ICDE 2002]
    - BANKS [Bhalotia et al, ICDE 2002]
    - DISCOVER [Hristidis, Papakonstantinou, VLDB 2002]
    - ObjectRank [Balmin, Hristidis, Papakonstantinou, VLDB 2004]
  - Semi-structured:
    - XRank [Guo et al, SIGMOD 2003]
    - TX [Al-Khalifa, Yu, Jagadish, SIGMOD 2003]
    - XSearch [Cohen et al, VLDB 2003]
    - PI X [Amer-Yahia et al, VLDB 2003]
    - Schema-Free XQuery [Li, Yu, Jagadish, VLDB 2004]
  - Ontology:
    - NAGA [Kasneci et al, ICDE 2008]

- **Semantic query to semantic search in IR / Semantic Web community**
  - Combining full-text with ontology [Bast et al, SIGIR 2007]
  - Falcon [Cheng, Qu, Int. J. Semantic Web Inf. Syst., 2009]
  - Semplore [Wang et al, J. Web Semantics, 2009]
  - Sig.ma [Tummarello et al, J. Web Semantics, 2010]
  - Search over RDF data [Blanco, Mika, Vigna, ISWC 2011]

**Knowledge Search over Web Documents**

- **Searching for entities and objects (incomplete list)**
  - Object level ranking [Nie et al, WWW 2005]
  - Object finder queries [Chakrabarti et al, SIGMOD 2006]
  - EntityRank [Cheng, Yan, Chang, VLDB 2007]
  - Entity package finder [Angell et al, EDBT 2009]
  - Concept search [Giunchiglia, Kharevich, Zaihrayeu, ESWC 2009]
  - TEXplorer [Zhao et al, CIKM 2011]

- **Searching for tabular data (very few studies so far)**
  - Studies on table annotation with search as a motivating application
    - [Cafarella et al, VLDB 2008] [Venetis et al, VLDB 2011]
    - [Limaye, Sarawagi, Chakrabarti, VLDB 2010]
    - [Wang et al, ER 2012]
  - **Answering table queries** [Pimplikar, Sarawagi, VLDB 2012]
  - Entity enrichment using tabular data: [Yakout et al, SIGMOD 2012]

**Tabular Data Search**

- **Query:** consists of a set of component queries, each correspond to a search for a column
- **Answer:** combining multiple tables

![Tabular Data Search Diagram](image-url)
Focusing on Column Mapping

• Naïve Approach
  ▪ Finding relevant tables based on the whole query
  ▪ Match component queries to columns individually

• Global Approach
  ▪ The more relevant the table, the more likely a column can be matched, and vice versa
  ▪ The more relevant the column, the more likely other columns in the same table can be matched

• Solution: Jointly determining query-table, query-column and column-column associations using a graphical model.
  ▪ Nodes in the graphical model are column variables: assignable to one of the component queries, plus relevant or irrelevant

Some Details

• The graphical model takes care of the global modeling, node and edge potentials are modeled using a feature based framework

• Matching columns to component queries
  ▪ Fuzzy matching between tokens in the component query and column header or table context

• Associating columns
  ▪ Based on column content

• Table-level constraints, e.g.:
  ▪ One component query can only match one column per table
  ▪ Each relevant table must match at least n component queries

• Approximate inference

Results

• 59 queries collected using AMT with column splitting based on Google search
  ▪ Single column: “dog breed”
  ▪ Two columns: “country | currency”
  ▪ Three columns: “fast cars | company | top speed”

• 25 million tables from 500 million pages

Knowledge Search Summary

• Lots of work are happening in knowledge search

• Lots of challenges remain:
  ▪ Knowledge base maintenance
  ▪ Information selection
  ▪ Search beyond simple entities
    ▪ Some of which are being addressed by Q/A and NLP search
Outline

• Motivation
  ▪ Why doing all this in the first place?
  ▪ Define what shallow means – no deep linguistic analysis
  ▪ Emphasizing why the need for shallow extraction techniques

• PART I: shallow extraction techniques
  ▪ Entity extraction
  ▪ Relation extraction
  ▪ Application Social text mining

• Part II: Bring Knowledge to Search

• Part III: Real life knowledge base, scalability and probability

Probase: a probabilistic semantic network

Probase Concepts (2+ millions)

“python” in Probase
# of descendants (WordNet)

![Graph showing the number of descendants over rank for WordNet.]

Transitivity does not always hold

- furniture
- plastic material
- chair
- film

# of descendants (early version of Probase)

![Graph showing the number of descendants over rank for the early version of Probase.]

Probase Scores

- Typicality
- Vagueness
- Representativeness
- Ambiguity
- Similarity

foundation for inferencing
Typicality

"robin" is a more typical bird than a "penguin" \( p(\text{robin} | \text{bird}) > p(\text{penguin} | \text{bird}) \)

Representativeness (basic level of categorization)

software company

\[
\text{max}_c p(c|e) \times p(e|c)
\]

\[
p(\text{company}) \quad \ldots \quad ? \quad \ldots \quad \text{largest OS vendor}
\]

\[
p(\text{c|e}) \quad \text{high typicality}
\]

Microsoft

Ambiguity

- Probase defines 3 levels of ambiguity
  - Level 0 (1 sense): apple juice
  - Level 1 (2 or more related senses): Google
  - Level 2 (2 or more senses): python

- Concepts form clusters, clusters form senses (through isa relation)

Vagueness

key players

factors

items

things

reasons

...
**Similarity**

- microsoft, ibm → 0.933
- google, apple → 0.378

\[ \text{sim}(t_1, t_2) = \max_{X, Y} \cosine(c_x(t_1), c_y(t_2)) \]

**Example: FrameNet**

**Frame: Apply_heat**

- **FE1**: She was **FRYING** eggs and bacon and mushrooms on a camp stove in Woolley’s billet.
- **FE3**: Example:** FrameNet**

| Concept          | P(c|FE) | Instance          | P(w|FE) |
|------------------|--------|-------------------|--------|
| heat source      | 0.19   | Stove             | 0.00019|
| Large metal      | 0.04   | Radiator*         | 0.00015|
| Kitchen appliance| 0.02   | Oven              | 0.00015|
|                  |        | Grill*            | 0.00014|
|                  |        | Heater*           | 0.00013|
|                  |        | Fireplace*        | 0.00013|
|                  |        | Lamp*             | 0.00013|
|                  |        | Hair dryer*       | 0.00012|
|                  |        | Candle*           | 0.00012|

**Applications**

- **Query Understanding**
  - Head/Modifier/Constraint detection
  - ...
  - **SRL (semantic role labeling)** with FrameNet
    - e.g. Tom broke the window.

**Knowledge Bases**

<table>
<thead>
<tr>
<th>WordNet</th>
<th>Wikipedia</th>
<th>Freebase</th>
<th>Probase</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cat</strong></td>
<td>Domesticated animals; Cats; Felidae; Felines; Carnivora; Carnivores; Domesticated animals; Companion animal; Domesticated animal; Exotic pet; Vertibrate; Animal; Pet; Species; Mammal; Small animal; Carnivore; Domesticated animal; Companion animal; Domesticated animal; Small pet; Cat; Felid; Adult male; Man; Gossip; Gossiper; Rumormonger; Newsmonger; Woman; Adult female; Stimulant; Stimulant drug; Excitant; Tracked vehicle; ...</td>
<td>Companies listed on the New York Stock Exchange; IBM; Cloud computing providers; Companies based in Westchester County, New York; Multinational companies; Software companies of the United States; Top 100 US Federal Contractors; ...</td>
<td>Animal; Pet; Species; Mammal; Small animal; Thing; Mammalian species; Small pet; Animal species; Carnivore; Domesticated animal; Companion animal; Exotic pet; Vertibrate; ...</td>
</tr>
<tr>
<td><strong>IBM</strong></td>
<td>N/A</td>
<td>Business operation; Issuer; Literature subject; Venture investor; Competitor; Software developer; Architectural structure owner; Website owner; Programming language designer; Computer manufacturer/brand; Customer; Operating system developer; Processor manufacturer; ...</td>
<td>Company; Vendor; Client; Corporation; Organization; Manufacturer; Industry leader; Firm; Brand; Partner; Large company; Fortune 500 company; Technology company; Supplier; Software vendor; Global company; Technology company; ...</td>
</tr>
<tr>
<td><strong>Language</strong></td>
<td>Communication; Auditory communication; Word; Higher cognitive process; Faculty; Mental faculty; Module; Text; Textual matter; Languages; Linguistics; Human communication; Human skills; Wikipedia articles with ASCII art; ...</td>
<td>Employers; Written work; Musical recording; Musical artist; Musical album; Literature subject; Quotation; Periodical; Type profile; Jovian; Periodical subject; Type/domain equivalent topic; Broadcast genre; Periodical subject; Video game content description; ...</td>
<td>Instance of: Cognitive function; Knowledge; Cultural factor; Cultural barrier; Cognitive process; Cognitive ability; Cultural difference; Ability; Characteristic; Attribute of: Film; Area; Book; Publication; Magazine; Country; Work; Program; Media; City; ...</td>
</tr>
</tbody>
</table>
Knowledge Bases

covers every topic?
contains rich connections?
breadth and density enable understanding

Concept Learning

China  Brazil  India
emerging market

Understanding Web Tables

<table>
<thead>
<tr>
<th>website</th>
<th>president</th>
<th>city</th>
<th>motto</th>
<th>state</th>
<th>type</th>
<th>director</th>
</tr>
</thead>
</table>

body  smell  taste
wine
Bayesian

\[ P(c_k|E) = \frac{P(E|c_k)P(c_k)}{P(E)} \propto P(c_k) \prod_{i=1}^{M} P(t_i|c_k). \]

- For a mixture of instances and properties: Noisy-Or model

\[ P(c|t_i) = 1 - \left(1 - P(c|t_i, z_i = 1)\right)\left(1 - P(c|t_i, z_i = 0)\right) \]

Where \( z_i = 1 \) indicates \( t_i \) is an entity, \( z_i = 0 \) indicates \( t_i \) is a property

- Bayesian rule gives:

\[ P(c|T) \propto P(c) \prod_{i} P(t_i|c) \propto \frac{\prod_{i} P(c|t_i)}{P(E)^{2-1}}. \]
Modeling Co-occurrence

Probase + LDA model

Wikipedia

- Infer topics $z$ from text $s$ using collapsed Gibbs sampling:

$$p(z_i = k | z_{-i}, C) \propto (n_{k} + \alpha) \times \frac{C_{w_{i}k} + n_{w_{i}k} + \beta}{\sum_{w} C_{w_{i}k} + n_{w_{i}k} + |W| \beta}$$

- Estimate the concept distribution for each term $w$ in $s$:

$$p(c | w, z) \propto p(c | w) \sum_{k} \pi_{w,k} \phi_{ck}$$

$$\phi_{ck} = \frac{C_{c,k} + \beta}{\sum_{w} C_{w,k} + |W| \beta}$$

0.028598 0.033760 0.034999 0.036341 0.036651 0.038612 0.048214 0.073715 0.089717 0.122754 0.137297 0.155901 0.177584 0.203856 0.235789 0.273786 0.318607 0.370606 0.429709 0.495908 0.570205 0.642503 0.712800 0.781198 0.847601 0.911904 0.974207 1.034510 1.092813
**CTR and search/ads similarity**

![Graph showing CTR and similarity comparison]

**CTR and search/ads similarity (torso and tail queries)**

![Graph showing CTR and similarity comparison for torso and tail queries]

**FrameNet Sentences**

<table>
<thead>
<tr>
<th></th>
<th>Basic</th>
<th>T100</th>
<th>T200</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fold 1</td>
<td>-4.716</td>
<td>-3.401</td>
<td>-3.385</td>
</tr>
<tr>
<td>Fold 2</td>
<td>-4.728</td>
<td>-3.409</td>
<td>-3.393</td>
</tr>
<tr>
<td>Fold 3</td>
<td>-4.741</td>
<td>-3.432</td>
<td>-3.417</td>
</tr>
<tr>
<td>Fold 4</td>
<td>-4.727</td>
<td>-3.413</td>
<td>-3.399</td>
</tr>
<tr>
<td>Fold 5</td>
<td>-4.740</td>
<td>-3.433</td>
<td>-3.417</td>
</tr>
</tbody>
</table>

Log-likelihood of frame elements with five-fold validation.

**Conclusion**

- Knowledge is needed in learning
- Knowledge is probabilistic
- (Short) Text understanding
  - Syntax (from NLP parser)
  - Dictionary (from an entity store)
  - Probabilistic knowledge