Building Blocks for Semantic Search Engines: Ranking and Compact Indexing for Entity-Relation Graphs

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(In fewer words)
Ranking and Indexing for Semantic Search

with
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Supported by
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Working notion of semantic search

- Exploiting in conjunction
  - “Strings with meaning” – entities and relations
  - “Uninterpreted strings” – as in IR
- “Is-a” and other relations
- Proximity
- Conductance
- Can approximate many info needs
- “Warehousing” not enough

Type-annotated corpus and query e.g.

Name a physicist who searched for intelligent life in the cosmos
→ type=physicist NEAR “cosmos”…

Where was Sagan born?
→ type=region NEAR “Sagan”

When was Sagan born?
→ type=time
pattern=isDDDD NEAR “Sagan” “born”

Born in New York in 1934, Sagan was a noted astronomer whose lifelong passion was searching for intelligent life in the cosmos.
The query class we address

- Find a token span $w$ (in context) such that
  - $w$ is a mention of entity $e$
    - “Carl Sagan” or “Sagan” is a mention of the concept of that specific physicist
  - $e$ is an instance of atype $a$ given in the query
    - Which $a=$physicist …
  - $w$ is “NEAR” a set of selector strings
    - “searched”, “intelligent”, “life”, “cosmos”

- All uncertain/imprecise; we focus on #3
- Yet surprisingly powerful: correct answer within top 3—4 $w$’s for TREC QA benchmark

Contribution 1: What is “NEAR”?

- XQuery and XPath full text support
  - (distance at most|window) 10 words [ordered] – hard proximity clause, not learnt
  - ftcontains … with thesaurus at … relationship "narrower terms" at most $\ell$ levels

- No implementation combining “narrower terms” and “soft” proximity ranking
- Search engines favor proximity in proprietary ways
-💡A learning framework for graph proximity
Contribution 2: Indexing annotations

- `type=person` NEAR theory relativity → type in `{physicist, politician, cricketer,…}` NEAR theory relativity
  - Large fanout at query time, impractical

- Complex annotation indexes tend to be large
  - Binding Engine (WWW 2005): 10x index size blowup with only a handful of entity types
  - Our target: 18000 atypes today, more later

💡 Workload-driven index and query optimization
  - Exploit skew in query atype workload

Part 1: Scoring and Ranking Nodes in Graphs
Two flavors of ranking problems

- The restricted query class we just discussed
  - 0/1 type membership via “perfect” taxonomy
  - NEAR captured via token rareness and distance between match tokens and candidate token

- General typed entity-relationship (ER) graph
  - Typed edges and nodes with text
  - Random walk biased by
    - Query matching node text
    - Semantics of edge types
  - Learn walk parameters, don’t guess them

Learning to score token spans

- \text{type}=\text{person} \text{ NEAR} “\text{television}” “\text{invent}**”
- Rarity of selectors
- Distance from candidate position to selectors
- Many occurrences of one selector
  - Closest is good
- Combining scores from many selectors
  - Sum is good
Learning the shape of the decay function

- For simplicity assume left-right symmetry
- Parameters \((\beta_1, \ldots, \beta_W)\), \(W=\)max gap window
- Candidate position characterized by a feature vector \(f = (f[1], \ldots, f[W])\)
  - If there is a matched selector \(s\) at distance \(j\) and
  - This is the closest occurrence of \(s\)
  - Then set \(f[j]\) to \(\text{energy}(s)\), ... else 0
- Score of candidate position is \(\beta \cdot f\)
- If we like candidate \(u\) less than \(v\) ("\(u < v\)"")
  - We want \(\beta \cdot f_u \leq \beta \cdot f_v\)

Ranking feature vectors

- "Hard margin" version

\[
\min_{\beta \in \mathbb{R}^d} \beta^t \beta \text{ subject to } \beta^t f_i - \beta^t f_j \leq -1 \text{ for all } i < j
\]

- "Soft margin" version

\[
\min_{\beta \in \mathbb{R}^d, s \geq 0} \beta^t \beta + B \sum_{i < j} s_{ij} \text{ subject to } \beta^t f_i - \beta^t f_j \leq -1 + s_{ij} \text{ for all } i < j
\]

- Quadratic program, slow (watch KDD 2006)
- By eliminating slack vars, can be rewritten as

\[
\min_{\beta \in \mathbb{R}^d} \beta^t \beta + B \sum_{i < j} \max\{0, 1 + \beta^t f_i - \beta^t f_j\}
\]

Approximate with a smooth function
Benign loss functions for scoring

- Replace hinge with
  \[ \min_{\beta \in \mathbb{R}^d} \beta' \beta + B \sum_{i<j} \text{smoothLoss}(0,1 + \beta_i f_i - \beta_j f_j) \]

- Differentiable everywhere, use Newton’s method
  - Minutes instead of hours
- Can shift and scale \( \beta \) without changing rank
- Can set \( \beta_{w+1} = 0 \) and discourage adjacent \( \beta \)'s from differing too much
- Force monotonic decrease (not good)

Learning decay function—results

\[ \min_{\beta} \sum_{j=1}^{W} (\beta_j - \beta_{j+1})^2 + B \sum_{u<v} \text{smoothLoss}(\beta \cdot f_u - \beta \cdot f_v) \]

Discourage adjacent \( \beta \)'s from differing a lot
Penalize violations of preference order

- Roughly unimodal around gap = 4 and 5

Mean reciprocal rank: Average over questions, reciprocal of the first rank where an answer token was found (large good)
Searching personal information networks

PINDB

PINSchema

Company

Person

Email

sent

is-reply-to

wrote

cited

from

to

CC

Affiliation

Author

Paper

Citation

Adapter Registry

Email Adapter

Paper Adapter

PDF, PS, DOC

MBOX, IMAP

Text Index

Graph Index

Searching and Browsing Interface

Free-form keyword Query

Type-near-predicate Query

Activated-twig Query

Graph Browser

Reconciliation Registry

Person-to-person

Paper-to-paper

Email-mentions-person

works -for

Top-ranking persons

Gerhard Weikum

Why is Gerhard the best?

type=person NEAR paper={xml AND index}
Ranking nodes in ER graphs

- Nodes have entity types: Person, Paper, Email, Company
- Edges have relation types: wrote, sent, cited, in-reply-to; edge \( e \) has type \( t(e) \in \{1, \ldots, T\} \)
- Edge \( i \rightarrow j \) of type \( t \) has weight \( \beta(t) \) and conductance \( C(i \rightarrow j) \)

Probability of following blue edge out of \( i \) is \( 2/(2+3+3) \)

Edge conductance

\[
C(j, i) = \begin{cases} 
0, & i \neq d, j \neq d, i \in \text{leaf}(V) \\
\alpha \frac{\beta(t(i,j))}{\sum_{j'} \beta(t(i,j'))}, & i \neq d, j \neq d, i \notin \text{leaf}(V) \\
1, & i \neq d, j = d, i \in \text{leaf}(V) \\
1 - \alpha, & i \neq d, j = d, i \notin \text{leaf}(V) \\
r_{j}, & i = d, j \neq d \\
0, & i = d, j = d 
\end{cases}
\]

Teleport from dummy node to ordinary nodes

Teleport from ordinary nodes to dummy node
Constrained design of conductance

- Hard constraints
  Scaling all $\beta$ preserves $p$, so we can demand all $\beta(t) \geq 1$

$$\begin{align*}
\min_{\beta \geq 1} \text{ModelCost}(\beta) \\
\text{subject to:} \\
p = C(\beta) p \\
p_i \leq p_j \text{ for all } i < j
\end{align*}$$

- Most parsimonious model?
  - All $\beta(t) = 1$:
    $$\text{ModelCost}(\beta) = \sum_t (\beta(t) - 1)^2$$
  - All $\beta(t)$ equal:
    $$\text{ModelCost}(\beta) = \sum_{t \neq t'} (\beta(t) - \beta(t'))^2$$

No margin!? –Because an arbitrary margin (say 1) may never be attainable by deviating from the parsimonious model and scaling $\beta$ (unlike RankSVM)

Breaking the $p = Cp$ recurrence

- Pagerank is usually approximated by the Power Method: $p \approx C^H p^0$ where
  - $H$ is a large enough horizon to give convergence
  - $p^0$ is an initial distribution over nodes, usually uniform

- Compute alongside Pagerank (chain rule):

$$\frac{\partial}{\partial \beta_t} (C^0 p^0)_i = 0 \text{ for all } t \text{ and } i,$$

and for $h = 1, \ldots, H$:

$$\frac{\partial}{\partial \beta_t} (C^h p^0)_i = \sum_j \left[ \frac{\partial C(i, j)}{\partial \beta_t} (C^{h-1} p^0)_j + C(i, j) \frac{\partial}{\partial \beta_t} (C^{h-1} p^0)_j \right]$$
Setting up the optimization

- **Objective**
  \[
  \min_{\beta \geq 1} \sum_{t \neq t'} (\beta(t) - \beta(t'))^2 + B \sum_{i < j} \text{huber} \left( (C^H p^0)_i - (C^H p^0)_j \right)
  \]

- **Gradient of the loss part**
  \[
  \sum_{i < j} \text{huber}' \left( (C^H p^0)_i - (C^H p^0)_j \right) \left( \frac{\partial (C^H p^0)_i}{\partial \beta(t)} - \frac{\partial (C^H p^0)_j}{\partial \beta(t)} \right)
  \]

- Polynomial ratios and products—surface not monotonic or unimodal, need some grid search

The effect of a limited horizon

- Gradients also converge, residuals decrease exponentially
  - Not surprising
  - Can perhaps prove assuming some properties of graph

- As \( H \) increases
  - More CPU time needed
  - Gradient is more accurate, low test error
  - Fewer Newton iterations needed
 Appropriateness of loss approximation

- Less reliable than true error (as usual)
- Hinge loss is even worse than Huber
- “In practice”…
  - $\beta$ optimization never seems to get trapped in local minima
  - $\alpha$ optimization is started from a 0:0.1:1 grid
- Need better understanding of the optimization surface

![Graph showing comparison of true error, hinge loss, and Huber loss](image)

 Learning rate and robustness

- 20000-node, 120000-edge graph
  - 100 pairwise training preferences enough to cut down test error to 11 out of 2000
  - Careful! Training and test preferences were made node-disjoint
- 20% random reversal of train pairs $\rightarrow$ 5% increase in test error
  - Model cost reduces

![Graph showing test error and model cost](image)
Discovering hidden edge weights

- Assign hidden edge weights to edge types
- Compute weighted Pagerank and sample <
- See if our algorithm can recover hidden weights
- Likewise with $\alpha$

Part 1 summary

- Inner product of weights with feature vector
  - A very simple scoring model
  - Still, TFIDF and BM25 evolved over decades
  - Learning weights: very recent, still evolving

- Ranking in graphs increasingly important
  - Pagerank and friends are just version 0.1

- Next step: entity-relationship graphs
  - Nodes and edges have associated types
  - Nodes (possibly edges) have associated text
  - Bootstrap ranking wisdom via learning
Part 2: Indexing for Proximity Search

Part-2: Workload-driven indexing

- Type hierarchies are large and deep
  - 18000 internal and 80000 leaf types in WordNet
- Runtime atype expansion time-intensive
  - Even WordNet knows 650 scientists, 860 cities…
- Index each token as all generalizations
  - Sagan → physicist, scientist, person, living thing
  - Large index space bloat

💡 Index a subset of atypes

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<thead>
<tr>
<th>Corpus/Index</th>
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<tbody>
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Pre-generalize (and post-filter)

- Full set of “atypes” (answer types) is $A$
- Index only a “registered” subset $R$ of $A$
- Say query has atype $a$; want $k$ answers
- Find $a$’s “best” generalization $g \in R$
- Get best $(k') > k$ spans that are instances of $g$
  - Given index on $R$, this is standard IR (see paper)

“Which scientist studied whales?

(Pre-generalize and) post-filter

- Fetch each high-scoring span $w$
- Check if $w$ is-a $a$
  - Fast compact “forward index” (doc,offset) $\rightarrow$ token
  - Fast small “reachability index”, common in XML
- If fewer than $k$ survive, restart with larger $k'$
  - Expensive
  - Pick conservative $k'$
Estimates needed by optimizer

- If we index token ancestors in \( R \) as against ancestors in all of \( A \), how much index space will we save?
  - Cannot afford to try out and see for many \( Rs \)

- If query atype \( a \) is not found in \( R \) and we must generalize to \( g \), what will be the bloat factor in query processing time?
  - Need to average over a representative workload

Index space estimate given \( R \)

- Each token occurrence leads to one posting entry
- Assume index compression is a constant factor
- Then total estimated index size is proportional to

\[
\sum_{r \in R} \text{corpusCount}(r)
\]

- Surprisingly accurate!
Processing time bloat for one query

- If \( R = A \), query takes time approximated by
  \[ t_{\text{scan}} \text{corpusCount}(a) \]
  
  Time to score one candidate position while scanning postings
  Number of occurrences of descendants of type \( a \)

- If \( a \) cannot be found in \( R \), the price paid for generalization to \( g \) consists of
  - Scanning more posting entries: \( t_{\text{scan}} \text{corpusCount}(g) \)
  - Post-filtering \( k' \) responses: \( k' t_{\text{filter}} \)

- Therefore, overall bloat factor is
  \[
  \text{queryBloat}(a, R) = \frac{t_{\text{scan}} \text{corpusCount}(g) + k' t_{\text{filter}}}{t_{\text{scan}} \text{corpusCount}(a)}
  \]

Query time bloat—results

- Observed bloat fit not as good as index space estimate
- Per-query noisy (disk seek etc.)
- While observed::estimated ratio for one query is noisy, average over many queries is much better
Expected bloat over many queries

Prob of new query having atype $a$

$\sum_{a \in A} \text{queryProb}(a) \cdot \text{queryBloat}(a, R)$

- Maximum likelihood estimate
  \[
  \text{queryProb}_\text{Train}(a) = \frac{\text{queryCount}_\text{Train}(a)}{\sum_{a' \in A} \text{queryCount}_\text{Train}(a')}
  \]
- Many $a$’s get zero training probability
  $\Rightarrow$ Optimizer does not register $g$ close to $a$
- Low-prob atypes appear in test $\Rightarrow$ huge bloat
- Collectively matter a lot (heavy-tailed distrib)

Smoothing low-probability atypes

- Lidstone smoothing:
  \[
  \text{queryProb}_\text{Train}(a) = \frac{\text{queryCount}_\text{Train}(a) + \ell}{\sum_{a' \in A} (\text{queryCount}_\text{Train}(a') + \ell)}
  \]
- Smoothing param $\ell$ fit by maximizing log-likelihood of held-out data:
  \[
  \sum_{a \in \text{HeldOut}} \text{queryCount}_\text{HeldOut}(a) \log(\text{queryProb}_\text{Train}(a))
  \]
- Clear range of good fits for $\ell$
- Can probably do better
The \( R \) selection algorithm

- \( R \leftarrow \) roots of \( A \)
- Greedily add the “most profitable” atype \( a^* \)
- Profit = ratio of
  - reduction in bloat of \( a^* \) and its descendants to
  - increase in index space
- Downward and upward traversals and updates
- Gives a tradeoff between index space and query bloat

1. When scientist is included...
2. Bloat of physicist goes down
3. reducing the profit of person

\[ \ell \text{ too small; “improbable” test queries } \Rightarrow \text{large bloat} \]

Optimized space-time tradeoff

With only 520MB, only 1.9 avg bloat
### Optimized index sizes

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<td>Forward index</td>
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</tr>
<tr>
<td>Atype subset index</td>
<td>0.52</td>
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### Part 2 summary

- Working prototype around Lucene and UIMA
  - Annotators attach tokens to type taxonomy
  - Query atype workload help compact index
  - Ranking function learnt from preference data
  - NL queries translated into atype+selectors
- Ongoing work
  - Indexing and searching relations other than is-a
  - More general notions of graph proximity
- Email [soumen@cse.iitb.ac.in](mailto:soumen@cse.iitb.ac.in) for code access
Conclusion

- Perform limited pre-structuring of corpus
  - Difficult to anticipate all query needs
  - Attach graph structure where possible
  - Do not insist on specific schema
  - Partial structure and raw text coexist

- Statistical learning on graph models
  - Models of influence along links getting clearer
  - What is a query? What is a response?
  - Ranking in graphs still under-explored
  - Scalable indexing and “top-k” query execution are major challenges