Indexing, Searching, and Ranking in Entity-Relationship Networks with Associated Text

Soumen Chakrabarti
IIT Bombay
http://www.cse.iitb.ac.in/~soumen

(In fewer words)
Ranking and Indexing for Semantic Search

Soumen Chakrabarti
IIT Bombay
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Working notion of "semantic search"

- Extractors and annotators associate structured knowledge with strings
- Neither complete nor perfect
- No complete schema (despite CYC and WordNet)
- Noisy structure must coexist with source text
- Must exploit structured info and uninterpreted strings in conjunction

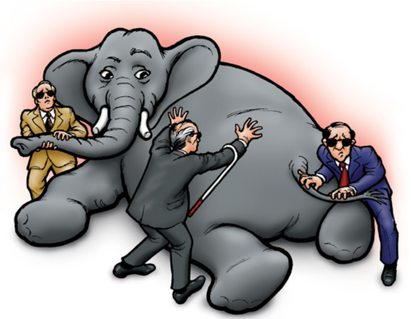


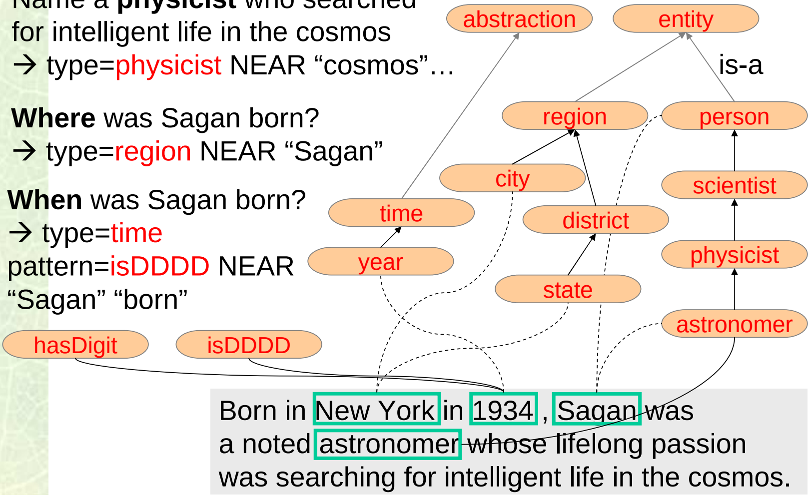
Figure: Artist's impression of "semantic search"

Annotated corpus and query examples

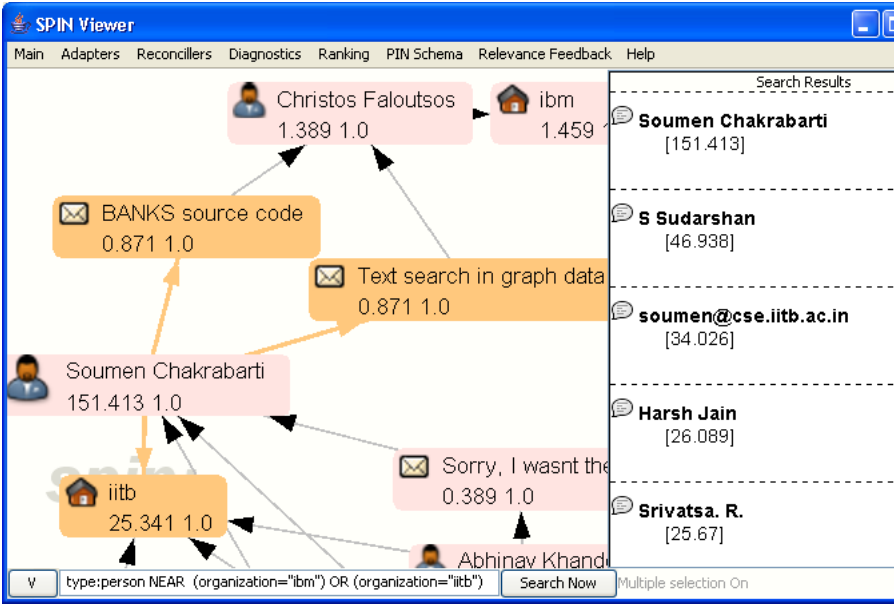
Name a **physicist** who searched for intelligent life in the cosmos
→ type=physicist NEAR "cosmos"…

Where was Sagan born?
→ type=region NEAR "Sagan"

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



Search in entity-relationship graphs



Talk outline

Ranking problems: what is "NEAR"?

- Typed proximity search in text + is-a graphs
- Proximity search in typed graphs
- Discovering hidden favorite communities

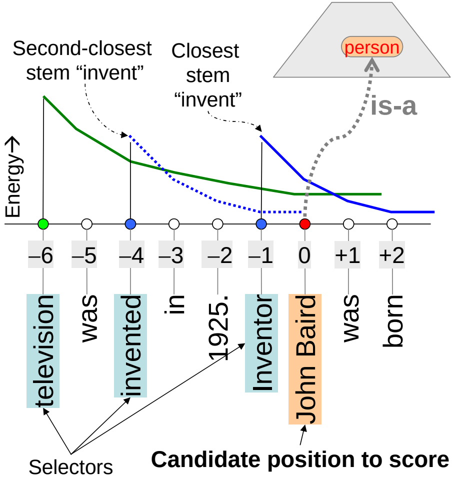
Indexing and query processing problems

- Typed proximity search in text + is-a graphs
- Dynamic (query-sensitive) Pageranking on typed graphs

Learning proximity scores of token spans

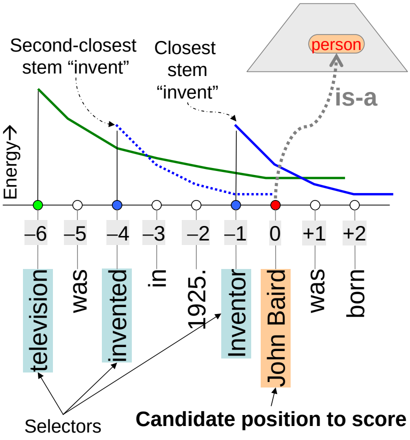
`type=person NEAR "television" "invent*"`

- Rarity of selectors
- Distance from candidate position to selectors
- Many occurrences of one selector (closest)
- Combining scores from many selectors (sum)



Making up a feature vector x for position 0

- Limit to $\pm W$ window
- $x(-4) = 0;$
  $x(-1) = \text{IDF}(\text{invent*});$
  $x(-6) = \text{IDF}(\text{television})$
- $\text{IDF}(w) = \text{numDocs}/\text{numDocsWith}(w)$, or perhaps $\text{IDF}(w) = \log(1 + \text{numDocs}/\text{numDocsWith}(w))$
- Other features, e.g., is selector noun? candidate has digits?
  - If in doubt, throw everything into the kitchen sink



The model vector β

- Score of candidate position is βx
- $\beta(j)$ is the value of the decay function at offset j
- TREC gives us correct i and incorrect j token spans
- $i \prec j$ means we want $\beta x_i + \text{margin} \leq \beta x_j$
- Want β to be smooth with $\beta(-W-1) = \beta(W+1) = 0$

$$\min_{\beta} \sum_{j=-W}^{W+1} (\beta_{j-1} - \beta_j)^2 + B \sum_{i \prec j} \text{SmoothLoss}(\beta x_i + 1 - \beta x_j)$$

$$\min_{\beta} \sum_{j=-W}^{W+1} (\beta_{j-1} - \beta_j)^2 + B \sum_{i \prec j} \log\Big(1 + \exp(\beta x_i + 1 - \beta x_j)\Big)$$

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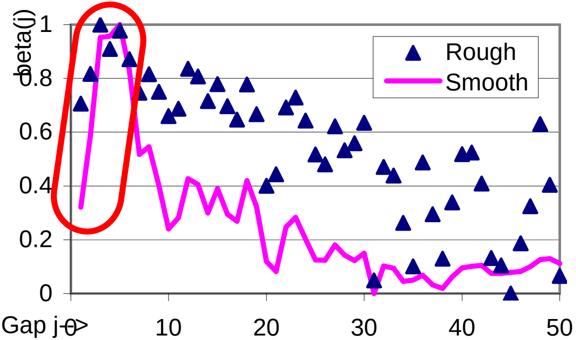
β fit to TREC QA



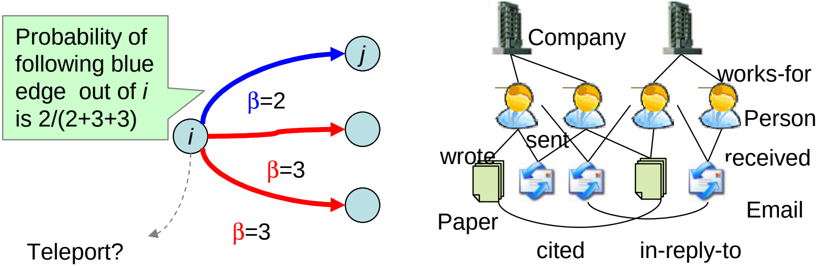
Train	Test	MRR
IR	2000	0.16
2001	2000	0.29

'2001'='TREC 2001'; 'MRR'=Mean reciprocal rank

- Only positive offsets shown
- Unexpected decay shape!
- Smooth function slightly better than rough function
- Improves beyond flat scoring function with only IDF

Next: Extending beyond chain graphs

Typed entity-relationship 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 (u, v) of type $t(u, v)$ has weight $\beta(t(u, v))$ and conductance $C(v, u)$

Conductance, teleport, Pagerank

- Create dummy node d
- Create edges (d, u) and (u, d) for each u
- Let $0 < \alpha < 1$ be the teleport probability
- Let r_v be the probability of teleport to v

$$C_{\{\alpha,\beta\}}(v, u) = \begin{cases} \alpha \frac{\beta(t(u,v))}{\sum_{(u,w)\in E} \beta(t(u,w))}, & u \neq d, v \neq d \\ 1 - \alpha, & u \neq d, u \in V_o, v = d \\ 1, & u \neq d, u \in V \setminus V_o, v = d \\ r_v, & u = d, v \neq d \\ 0, \text{otherwise} \end{cases}$$

C is a function of α and β

Dodging complicated constraints

$$\min_{\substack{0<\alpha<1 \\ \beta\geq\mathbf{0},p}} \text{ModelCost}(\beta) + B\sum_{i\prec j} \text{SmoothLoss}(p_u - p_v)$$

$$\text{subject to} \quad \boxed{p = C_{\{\alpha,\beta\}}\, p}$$

- Both C and p are variables $\Rightarrow$ complicated constraints
- Following power iterations, approximate $p \approx C^H p_0$ where H is a (possibly adaptive) horizon and p_0 is the initial Pagerank vector (say uniform)
- Also, $C_{\{\alpha,\beta\}}$ does not change if all β are scaled

$$\min_{\substack{0<\alpha<1 \\ \boxed{\beta\geq\mathbb{1}}}} \text{ModelCost}(\beta) + B\sum_{i\prec j} \text{SmoothLoss}\Big((C^H p_0)_u - (C^H p_0)_v\Big)$$

ModelCost and SmoothLoss

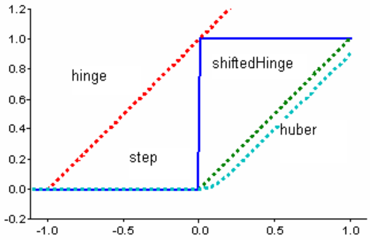
Parsimonious model: all $\beta(t)$s equal

$$\text{ModelCost}(\beta) = \sum_{t \neq t'} \Big(\beta(t) - \beta(t')\Big)^2$$

If β and $\kappa\beta$ (some multiple $\kappa > 1$) are both solutions, optimizer should prefer β

Use SmoothLoss(z) = huber(z), where

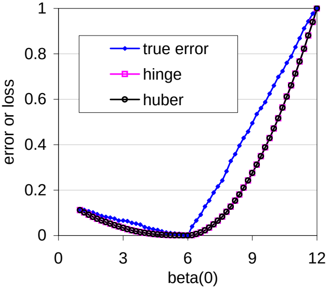
$$\text{huber}(z) = \begin{cases} 0, & z < 0 \\ z^2/(2W), & z \in (0, W] \\ z - W/2, & z > W \end{cases}$$

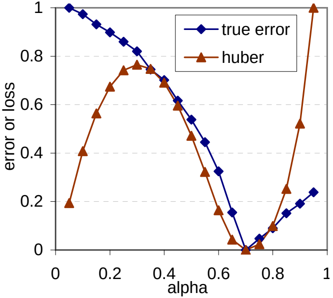


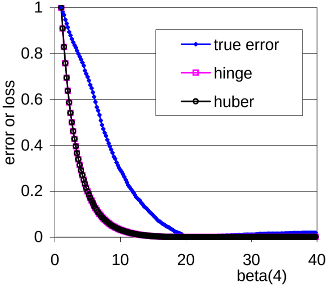
Can compute approximate ∇_β, $\partial/\partial\alpha$, and use gradient descent

Is SmoothLoss approximation good?

- Hinge and Huber essentially identical
- Empirically, wrt $\beta(t)$, true and Huber error have same minima
- Wrt α Huber has spurious minima, but basic grid search adequate

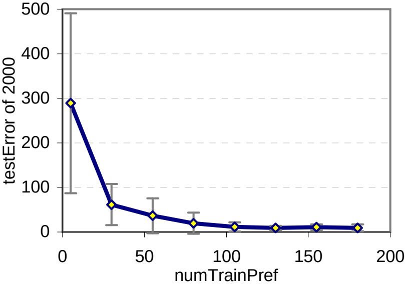


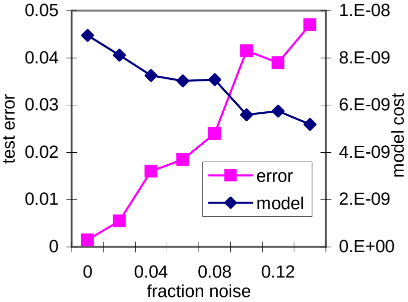




Learning rate and robustness

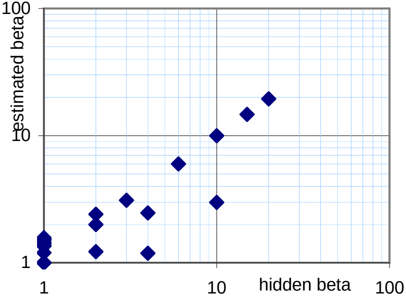
- 20000-node, 120000-edge graph
- 100 pairwise training preferences enough to cut down test error to 11 out of 2000
- 20% random reversal of train pairs leads to 5% increase in test error
- Model cost reduces as noise increases — makes sense

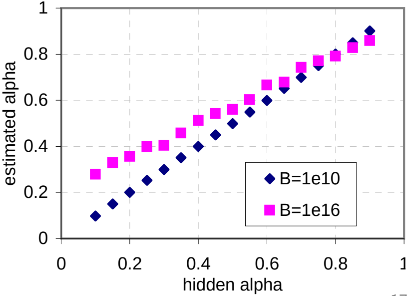




Accuracy of estimating β and α

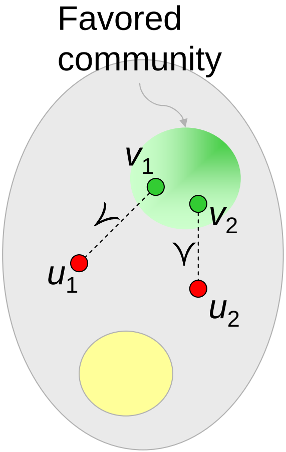
- Assign hidden β, α
- Compute weighted Pagerank and sample $\prec$
- See if algorithm can recover hidden weights
- Upward (downward) pressure on small (large) β thanks to $\sum_{t,t'}(\beta(t) - \beta(t'))^2$ regularizer
- Large patches of β lead to same Pagerank ordering
- α sensitive to B setting





Learning a hidden favored community

- Unlike the random surfer, humans are very selective about following links
- Links in some communities matter, other links do not
- Also preferential teleport
- $\prec$ expresses this indirectly, as in $u_1 \prec v_1$, $u_2 \prec v_2$ etc.
- Goal is to generalize and find the boundaries of favored community
- Unlike global $\beta(t)$ here info is local; does not extend beyond the "teleport radius"



A constrained flow formulation

- Directly estimate p_{uv} instead of $C(v, u) = \Pr(v|u)$
- q_{uv} is a "parsimonious" reference flow (unweighted Pagerank)

$$\min_{\substack{\{0 \le p_{uv} \le 1\} \\ \{0 \le s_{uv} : u \prec v\}}} \sum_{(u,v)\in E'} p_{uv} \log \frac{p_{uv}}{q_{uv}} + B \sum_{u \prec v} s_{uv} \qquad \text{(SoftObj)}$$

subject to

$$\sum_{(u,v)\in E'} p_{uv} = 1 \qquad \text{(Total)}$$

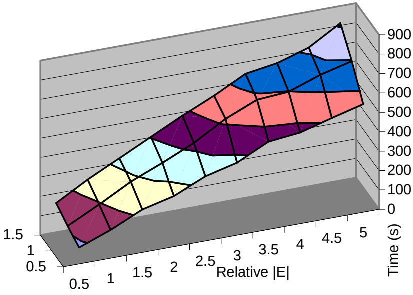
$$\forall v \in V' \quad \sum_{(u,v)\in E'} p_{uv} = \sum_{(v,w)\in E'} p_{vw} \qquad \text{(Balance)}$$

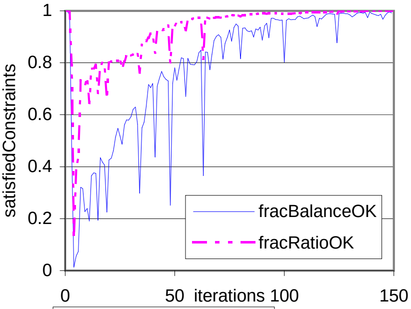
$$\forall v \in V_o \quad (1-\alpha) \sum_{(v,w)\in E} p_{vw} = \alpha p_{vd} \qquad \text{(Teleport)}$$

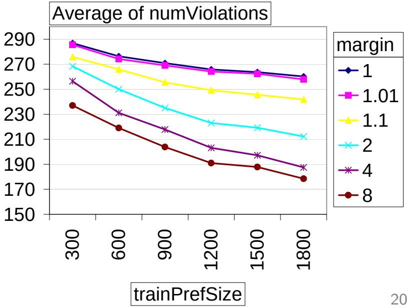
$$\forall u \prec v \quad (1+\epsilon) \sum_{(w,u)\in E'} p_{wu} \le s_{uv} + \sum_{(w,v)\in E'} p_{wv} \qquad \text{(SoftPref)}$$

Experimental results

- We solve the dual via cutting-plane approach
- Time is linear in $|\prec|$, $|V| + |E|$
- Generalization improves with margin $1 + \epsilon$







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Indexing for is-a proximity search

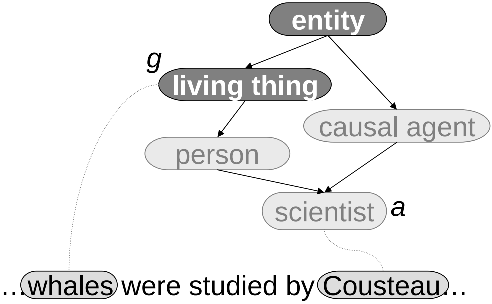
"Which scientist studied whales?" $\longrightarrow$

`type=scientist NEAR study|studied whale*`

- Open-domain type hierarchies very large: 15000 internal and 80000 leaf types in WordNet (full set A)
- Runtime type expansion too expensive: even WordNet knows 650 scientist, 860 cities, ...

Pre-generalize

- Index a subset $R \subset A$
- Query atype $a \notin R$, want k answers
- Probe index with g, ask for $k' > k$

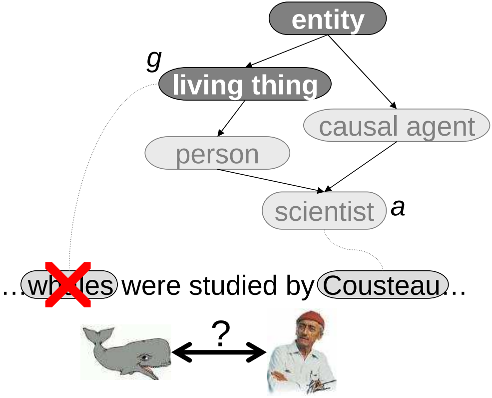


Cost models

- How much space saved by indexing R instead of A? (Cannot afford to try out many Rs, need quick estimate)
- What is the average query time bloat owing to $a \to g$ pre-generalize and post-filter?

Post-filter

- Fetch k' high-scoring spans w for g
- Check if w is-a a as well (using forward and reachability index); if not, discard
- If fewer than k survive, restart with larger k' (expensive!)



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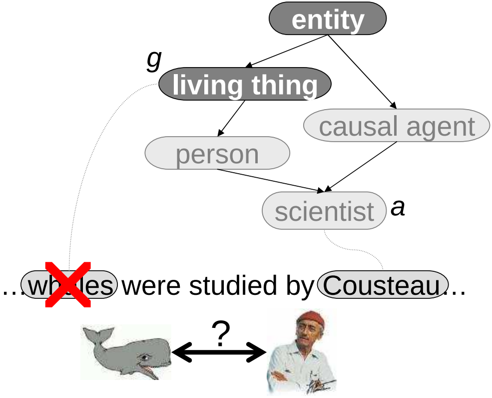
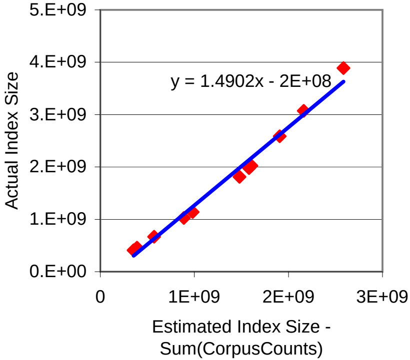


Index space estimate

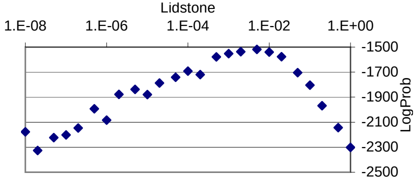
- Let corpusCount(a) be the count of tokens w in the corpus such that w is-a a
- One posting entry for each count of each type a
- Therefore our space estimate is (proportional to) $\sum_{a \in R}$ corpusCount(a)
- Surprisingly accurate despite index compression



Characterizing a query workload

$$\widetilde{\Pr}(a) = \frac{\text{queryLogCount}(a) + \lambda}{\sum_{a' \in A} \left(\text{queryLogCount}(a) + \lambda \right)}$$

- Heavy-tailed type distribution in queries
- Many test types never seen in training types and vice versa
  - $\lambda = 0$ would give these types zero probability
  - Danger of allocating no g close to these as
  - Build multinomial model over a with positive λ
  - Cross-validate likelihood of held-out test log



Query time bloat estimate

- t_{scan} time to scan one candidate position while merging postings
- t_{filter} time to check if w is-a a
- If $R = A$ (all types indexed), query takes time roughly $t_{\text{scan}}\,\text{corpusCount}(a)$
- If $a \notin R$, the price paid for generalization to g consists of
  - Longer scans: $t_{\text{scan}}\,\text{corpusCount}(g)$
  - Post-filtering k' responses: $k'\,t_{\text{filter}}$

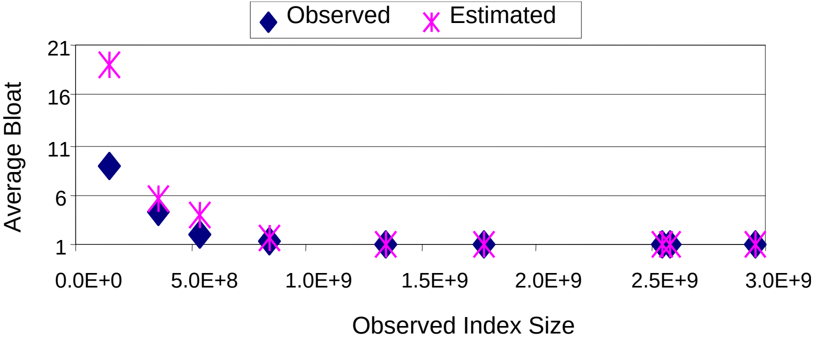
$$\text{expected bloat} = \sum_{a \in A} \widetilde{\Pr}(a) \frac{t_{\text{scan}}\,\text{corpusCount}(g) + k'\,t_{\text{filter}}}{t_{\text{scan}}\,\text{corpusCount}(a)}$$

Now we have a greedy cost-benefit analysis of every type a

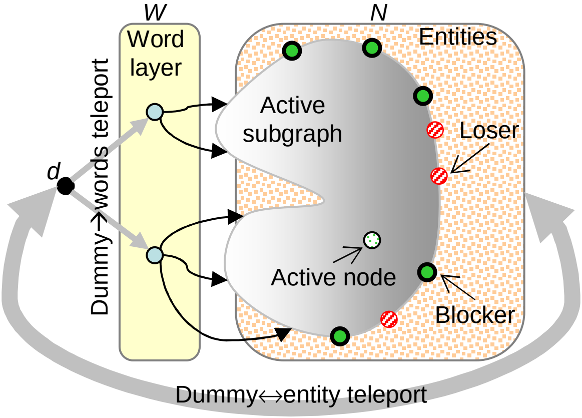
Result of greedy knapsack

- Estimated query bloat reasonably accurate
- With only 520 MB index, only 1.9 average bloat
- Space comparable to inverted index on stems

Corpus/Index	GBytes
Original corpus	5.72
Gzipped corpus	1.33
Stem index	0.91
Full type *A* index	4.30
Type subset *R* index	0.52
Query Bloat	1.90
Reachability index	0.01
Forward index	1.16



Searching a TypedWordGraph



- Attach query words W to preloaded entities N
- Set teleport $r > 0$ only for word nodes
- Compute personalized Pagerank vector (PPV) p_r — slow!

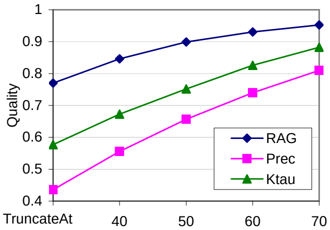
Options to date

Query-time Pagerank

- For $\sim$ 75000 nodes, $\sim$ 200000 edges, $\sim$ 11 sec/query
- Impractical except for very small graphs

Combine per-word PPVs

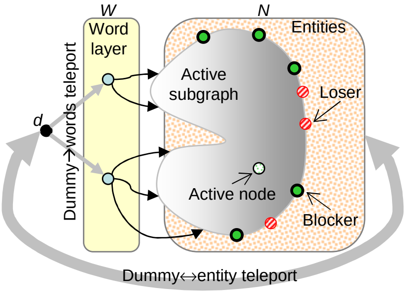
- Proposed by OBJECTRANK
- For $\sim$ 75000 nodes, $\sim$ 175000 words, $\sim$ 526 CPU-hours
- Full PPV index has size 102 GB
- Compare with text index: 56 MB
- Truncating down to 56 MB leads to serious loss of accuracy



RAG=Relative average goodness, Prec=Precision, KTau=Kendall's Tau

HubRank query execution

- Input: query words W, abandon/trim threshold δ
- Max priority queue, priority of node u is estimate of path conductance from d to u
- Grow active set A



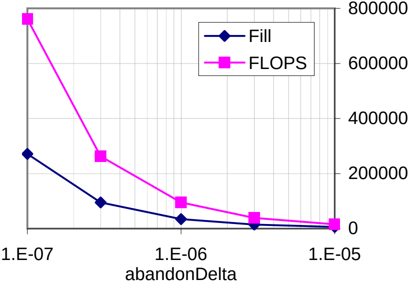
A is bordered with

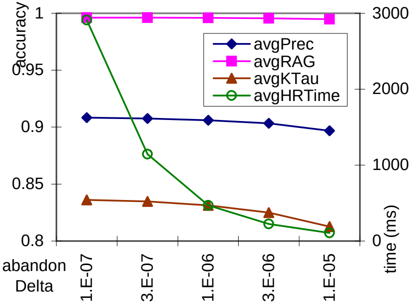
Blockers: Hub nodes with indexed (approx) PPVs

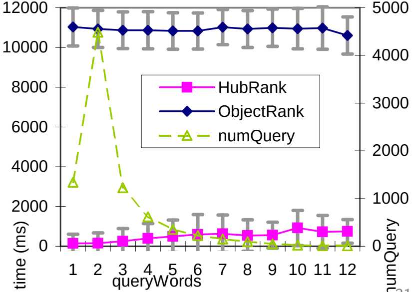
Losers ℓ: Conductance from d to ℓ is too small to matter

- Load trimmed PPV for blockers, trivial PPV for losers
- Iteratively compute PPVs of all active nodes including d
- Sort PPV of d and return results

HubRank results







- Indexing 10 CPU-hours (vs. 526, ObjectRank)
- 63 MB index (vs. 102 GB)
- δ-trim cuts CPU, fill
- Negligible accuracy loss
- Query in 250 ms (vs. 11 s)

Conclusion

- Searching typed entity-relationship graphs
- Perhaps attached to mentions in unstructured text
- Many interesting challenges, surprisingly unexplored
- Architecture for flexible space-time-accuracy tradeoffs
- Ranking
  - Far from vector-space territory, no guidance
  - Learning linear proximity functions
  - Learning edge conductance parameters
- Indexing and query processing
  - Combining large is-a graphs with linear proximity
  - Dynamic personalized Pageranking
  - Anytime preprocessing, anytime query processing