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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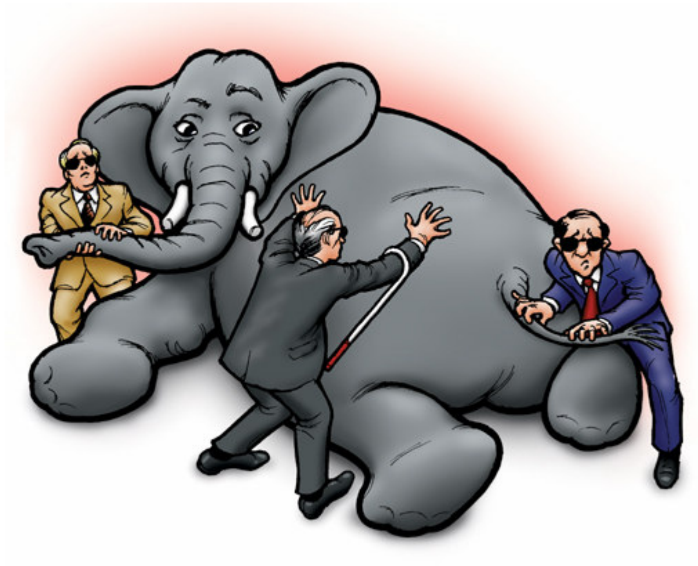
Supported by
IBM, Microsoft, Yahoo!

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

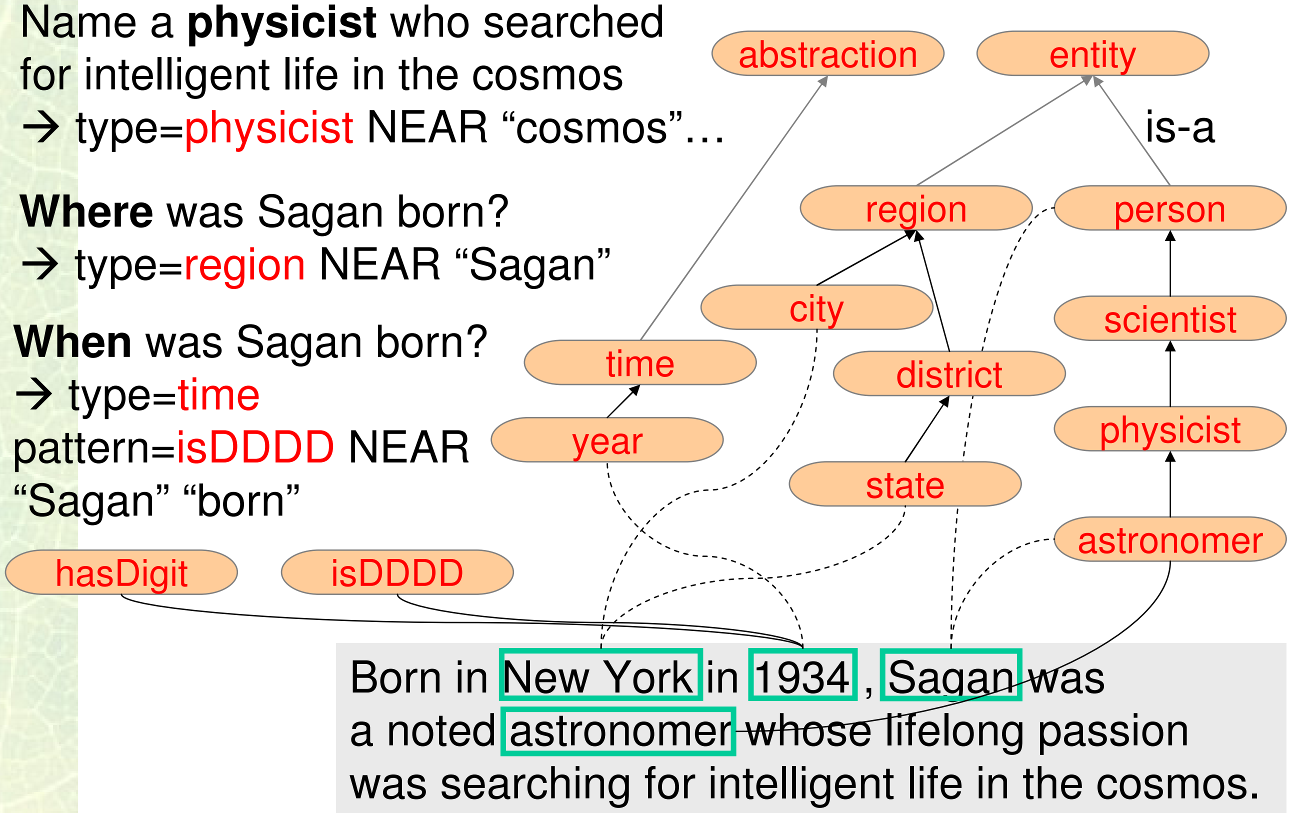


Type-annotated corpus and query e.g.

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”



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 ℓ levels
- No implementation combining "narrower terms" and "soft" proximity ranking
- Search engines favor proximity in proprietary ways

A learning framework for graph proximity

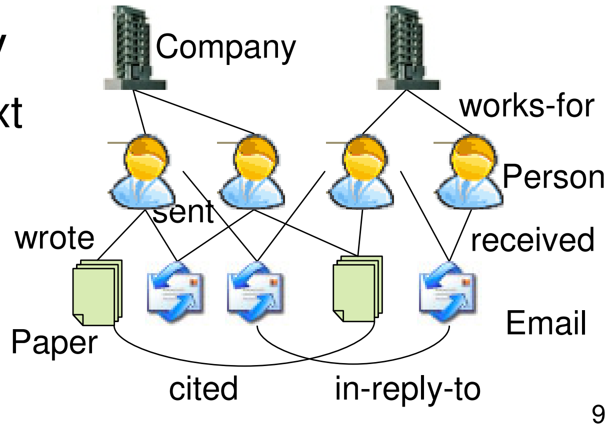
Contribution 2: Indexing annotations

- 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

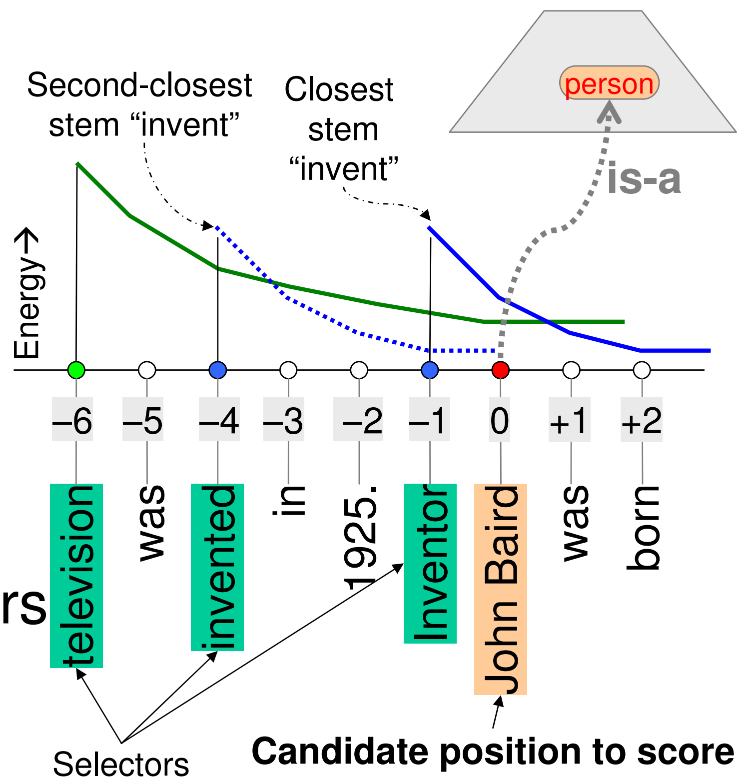
Two flavors of ranking problems

- 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

- type=person NEAR “television” “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 *energy*(s), … else 0
- Score of candidate position is $\beta \cdot f$
- If we like candidate u less than v ("$u \prec v$")
  - We want $\beta \cdot f_u \le \beta \cdot f_v$

Ranking feature vectors

- "Hard margin" version

$$\min_{\beta \in R^d} \underbrace{\beta' \beta}_{\text{Regularizer}} \text{ subject to } \beta' f_i - \beta' f_j \le -1 \text{ for all } i \prec j$$

- "Soft margin" version

$$\min_{\beta \in R^d, s \ge 0} \beta' \beta + B \sum_{i \prec j} s_{ij} \text{ subject to } \beta' f_i - \beta' f_j \le -1 + \underbrace{s_{ij}}_{\text{Slack variable}} \text{ for all } i \prec j$$

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

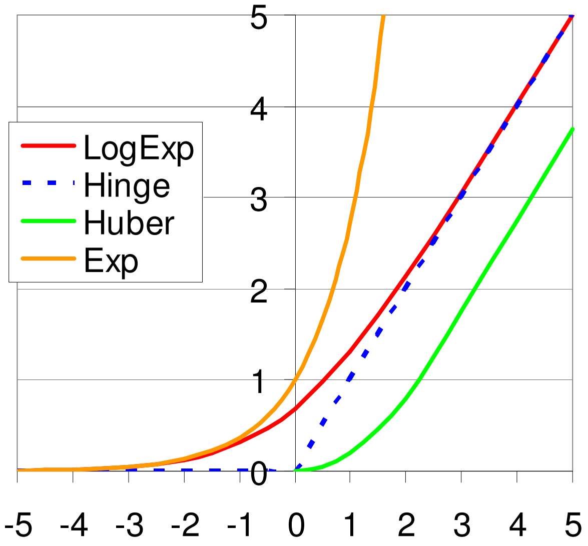
$$\min_{\beta \in R^d} \beta' \beta + B \sum_{i \prec j} \underbrace{\max\{0, 1 + \beta' f_i - \beta' f_j\}}_{\text{Approximate with a smooth function}}$$

Benign loss functions for scoring

- Replace hinge with

$$\min_{\beta \in R^d} \beta' \beta + B \sum_{i \prec j} \boxed{\text{smoothLoss}} \{0, 1 + \beta' f_i - \beta' f_j\}$$

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

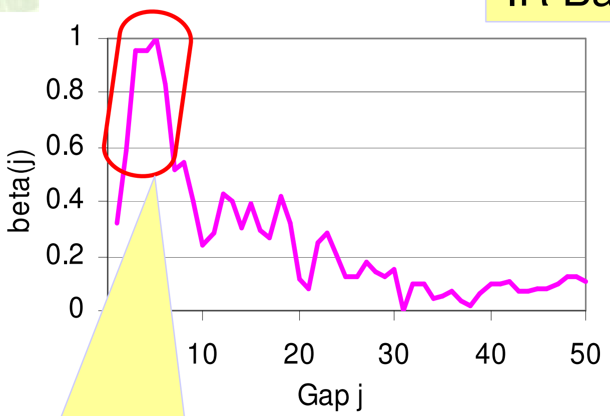


Learning decay function—results

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

Discourage adjacent βs from differing a lot

Penalize violations of preference order



Roughly unimodal around gap = 4 and 5

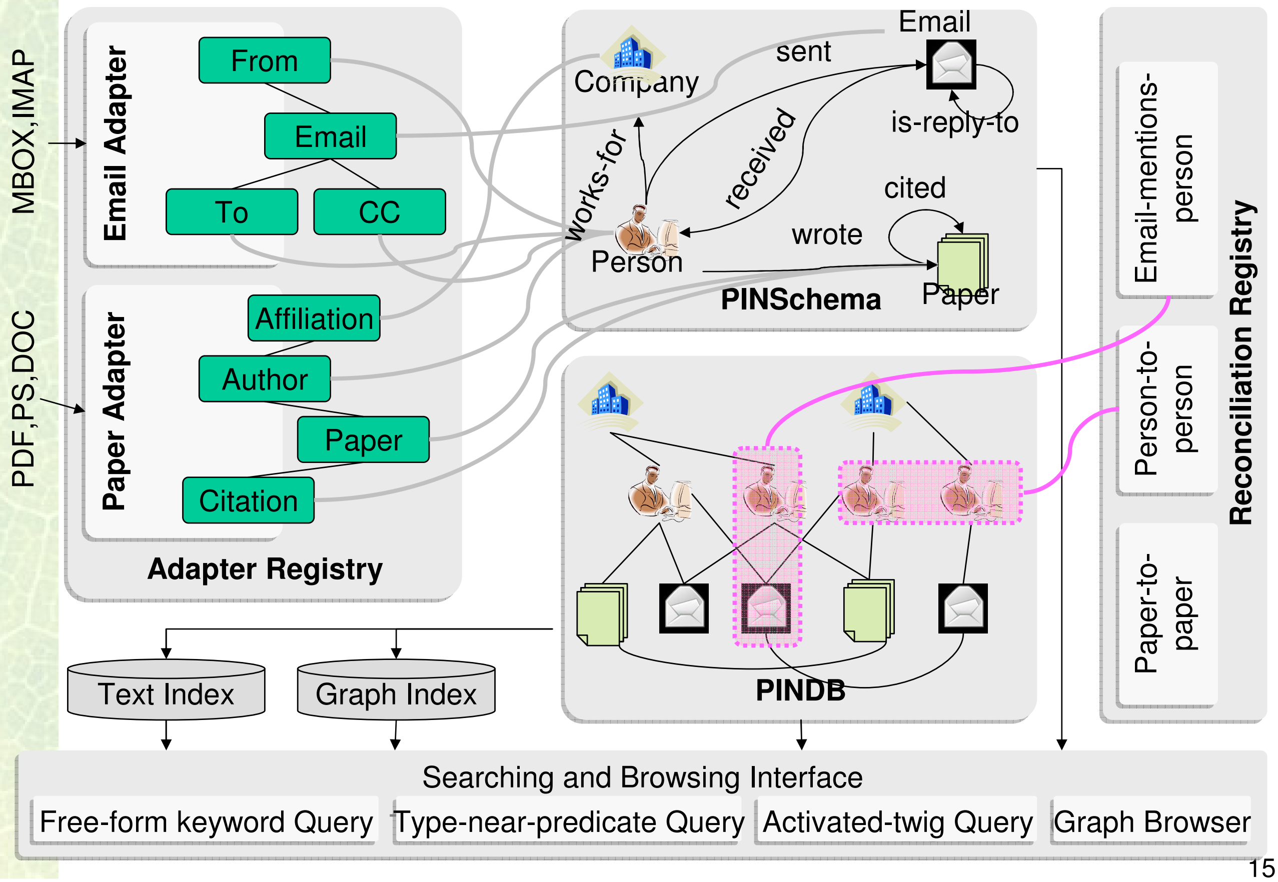
IR Baseline

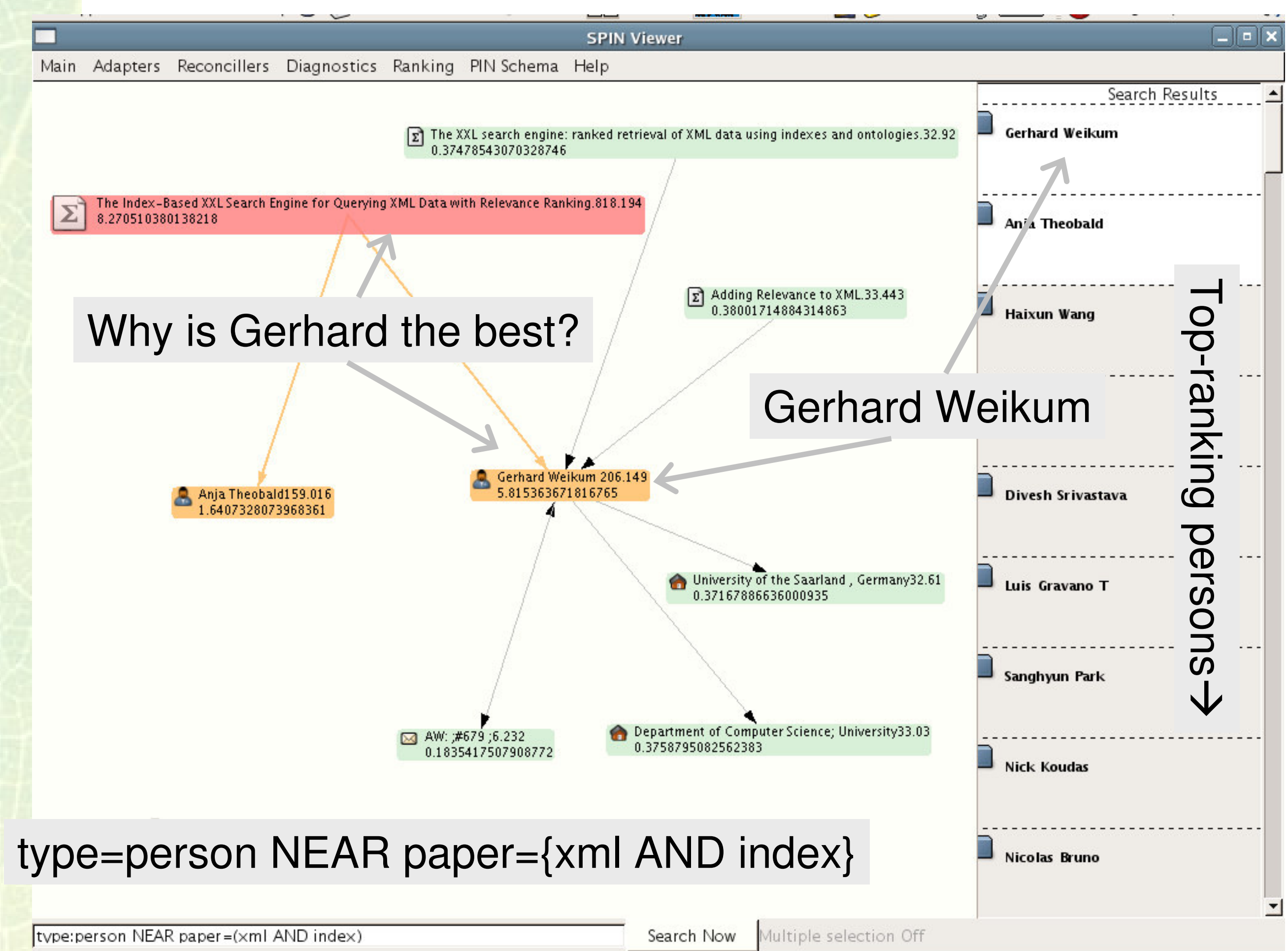
Train	Test	MRR
IR	2000	0.16
2001	2000	**0.29**

TREC year

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

Searching personal information networks

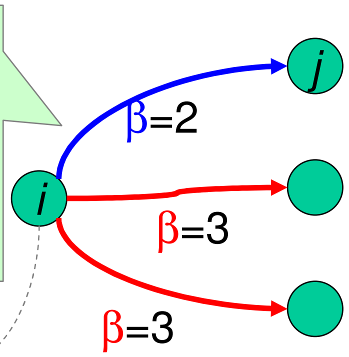




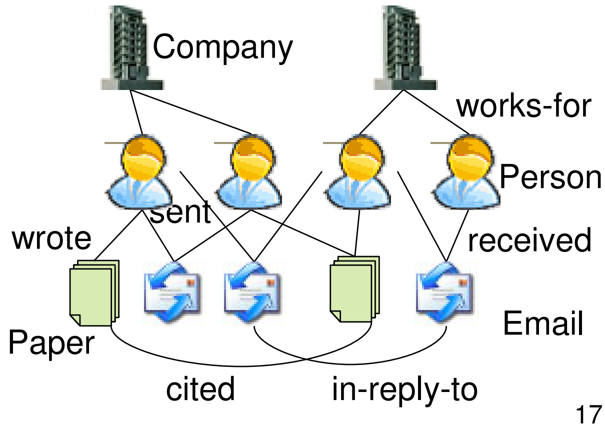
Ranking nodes in ER graphs

- 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*→*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)



Teleport?



Edge conductance

Dead-end

Ordinary walk step

$$C(j,i) = \begin{cases} 0, & i \neq d, j \neq d, i \in \mathrm{leaf}(V) \\ \alpha \frac{\beta(t(i,j))}{\sum_{j'} \beta(t(i,j'))}, & i \neq d, j \neq d, i \notin \mathrm{leaf}(V) \\ 1, & i \neq d, j = d, i \in \mathrm{leaf}(V) \\ 1-\alpha, & i \neq d, j = d, i \notin \mathrm{leaf}(V) \\ \boxed{r_j} & i = d, j \neq d \\ 0, & i = d, j = d \end{cases}$$

Teleport from dummy node to ordinary nodes

Teleport from ordinary nodes to dummy node

Constrained design of conductance

- Hard constraints

Scaling all β preserves **p**, so we can demand all β(t)≥1

$$\min_{\beta \geq \mathbf{1}} \mathrm{ModelCost}(\beta)$$

subject to :

$$\mathbf{p} = \mathbf{C}(\beta)\,\mathbf{p}$$

$$p_i \leq p_j \text{ for all } i \prec j$$

Must break this recurrence between **p** and **p** to solve directly

- Most parsimonious model?
  - All β(*t*)=1:

$$\mathrm{ModelCost}(\beta) = \sum_t (\beta(t) - 1)^2$$

  - All β(*t*) equal:

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

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

Breaking the **p=Cp** recurrence

- Pagerank is usually approximated by the Power Method: $\mathbf{p} \approx \mathbf{C}^H \mathbf{p}^0$ where
  - *H* is a large enough horizon to give convergence
  - $\mathbf{p}^0$ is an initial distribution over nodes, usually uniform
- Compute alongside Pagerank (chain rule):

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

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

$$(C^h p^0)_i = \sum_j C(i,j)\,(C^{h-1} p^0)_j$$

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

Setting up the optimization

- Objective

$$\min_{\beta \geq \mathbf{1}} \sum_{t \neq t'} (\beta(t) - \beta(t'))^2 + B \sum_{i \prec j} \text{huber}\left((C^H p^0)_i - (C^H p^0)_j\right)$$

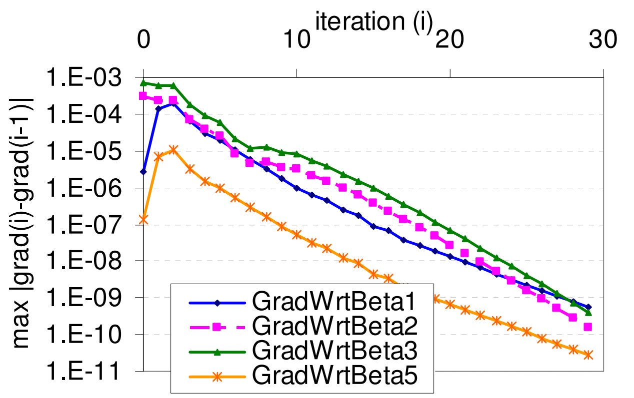
- Gradient of the loss part

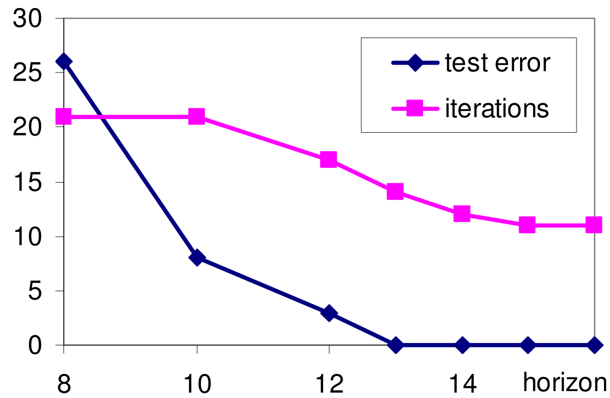
$$\sum_{i \prec j} \text{huber}'\left((C^H p^0)_i - (C^H p^0)_j\right)\left(\frac{\partial (C^H p^0)_i}{\partial \beta(t)} - \frac{\partial (C^H p^0)_j}{\partial \beta(t)}\right)$$

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

The effect of a limited horizon

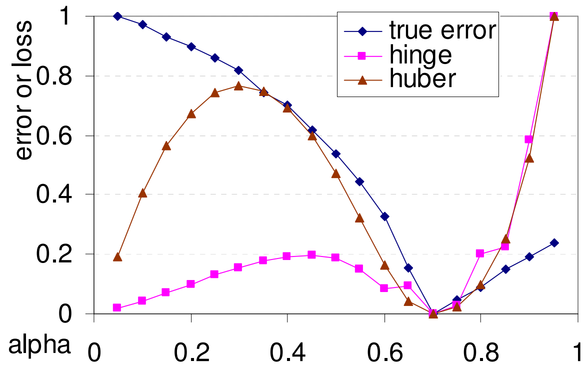
- Gradients also converge, residuals decrease exponentially
  - Not surprising
  - Can perhaps prove given some assumptions
- As H increases
  - More CPU time needed
  - Gradient is more accurate, low test error
  - Fewer Newton iterations needed

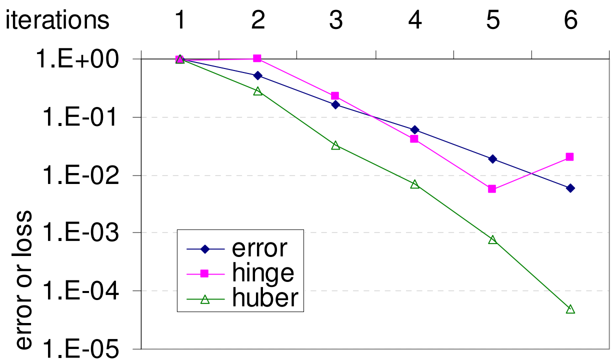




Appropriateness of loss approximation

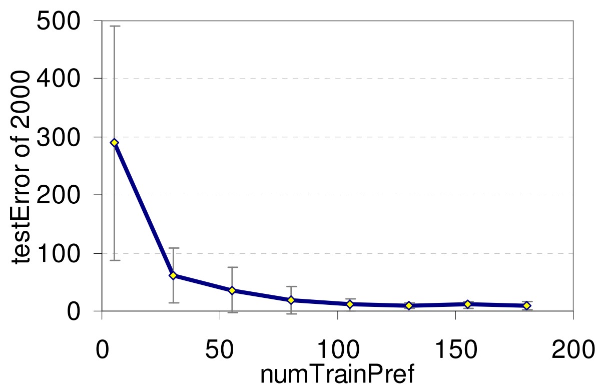
- Less reliable than true error (as usual)
- Hinge loss is even worse than Huber
- "In practice"…
  - β optimization never seems to get trapped in local minima
  - α optimization is started from a 0:0.1:1 grid
- Need better understanding of the optimization surface

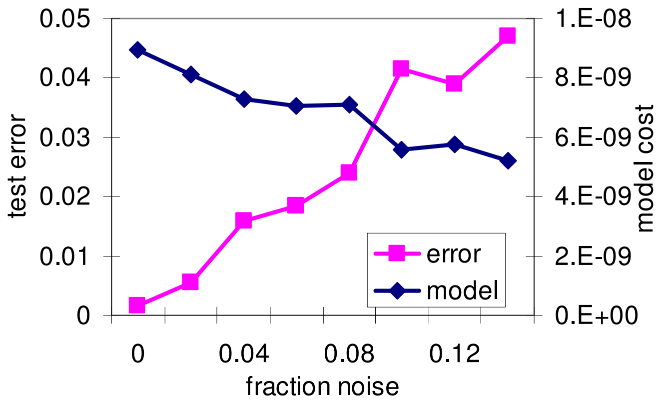




Learning rate and robustness

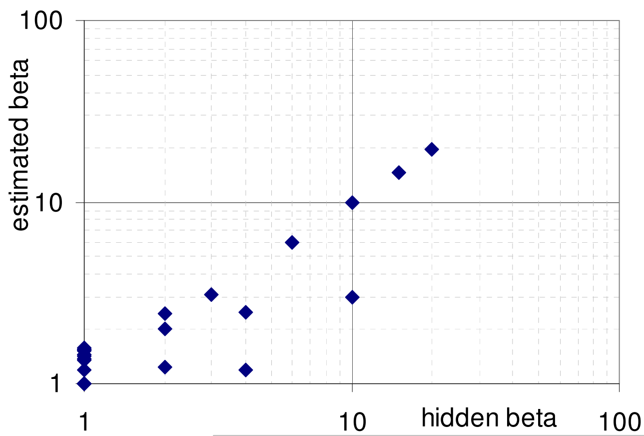
- 20000-node, 120000-edge graph
  - 100 pairwise training preferences enough to cut down test error to 11 out of 2000
  - Careful! Training and test preferences were made node-disjoint
- 20% random reversal of train pairs → 5% increase in test error
  - Model cost reduces

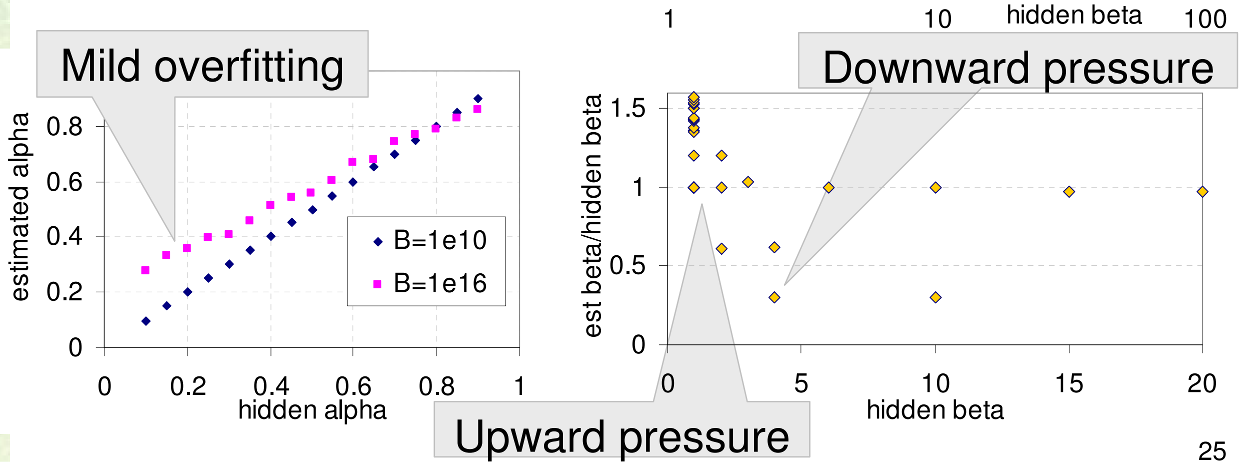




Discovering hidden edge weights

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





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

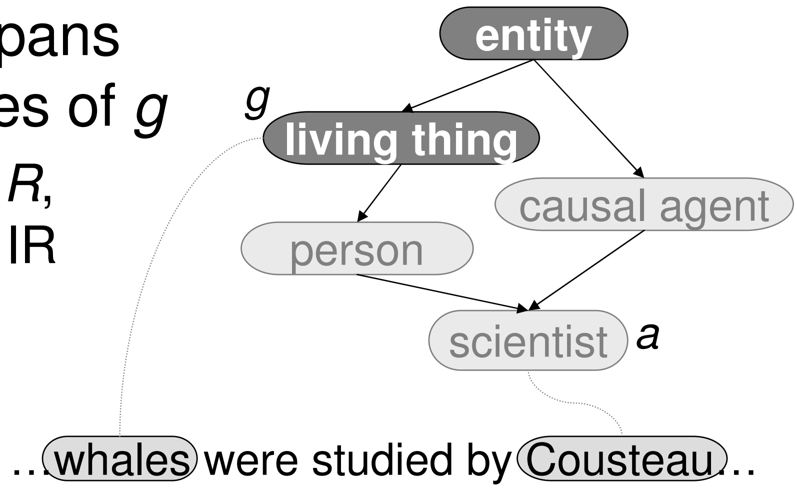
Index a subset of atypes

Corpus/Index	Gbytes
Original corpus	5.72
Gzipped corpus	1.33
Stem index	0.91
Full type index	4.30

Pre-generalize (and post-filter)

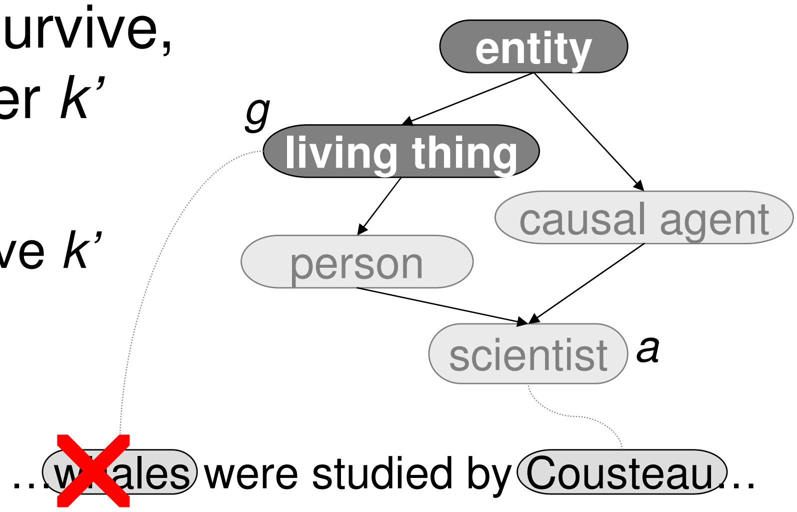
- Full set of "atypes" (answer types) is A
- Index only a "registered" subset R of A
- Say query has atype a; want k answers
- Find a's "best" generalization $g \in R$
- Get best $k' > k$ spans that are instances of g
  - Given index on R, this is standard IR (see paper)

"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)→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 *R*s
- 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

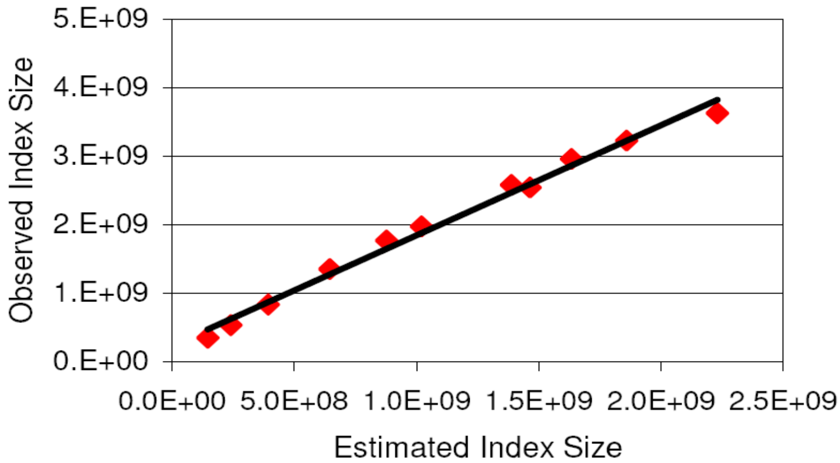
Index space estimate given R

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

$$\sum_{r \in R} corpusCount(r)$$

Number of tokens in corpus that connect up to *r*

- Surprisingly accurate!



Processing time bloat for one query

- If R=A, query takes time approximated by

$$t_{\text{scan}}\ \mathit{corpusCount}(a)$$

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: $t_{\text{scan}}\ \mathit{corpusCount}(g)$
  - Post-filtering k' responses: $k'\,t_{\text{filter}}$

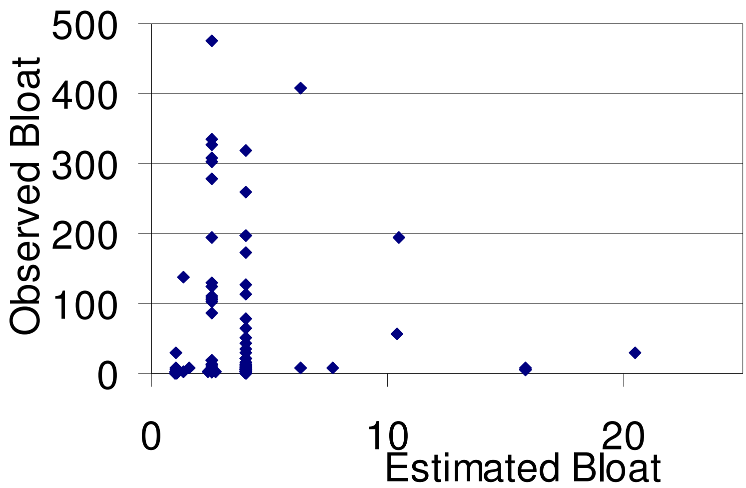
Time to check if answer is instance of a as well

- Therefore, overall bloat factor is

$$\mathit{queryBloat}(a,R) = \frac{t_{\text{scan}}\,\mathit{corpusCount}(g) + k'\,t_{\text{filter}}}{t_{\text{scan}}\,\mathit{corpusCount}(a)}$$

Query time bloat—results

- Observed bloat fit not as good as index space estimate



- While observed::estimated ratio for one query is noisy, average over many queries is much better

Expected bloat over many queries

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

Prob of new query having atype *a*

Already estimated

- Maximum likelihood estimate

$$queryProb_{\text{Train}}(a) = \frac{queryCount_{\text{Train}}(a)}{\sum_{a' \in A} queryCount_{\text{Train}}(a')}$$

- Many *a*'s get zero training probability
→ Optimizer does not register *g* close to *a*
- Low-prob atypes appear in test → huge bloat
- Collectively matter a lot (heavy-tailed distrib)

Smoothing low-probability atypes

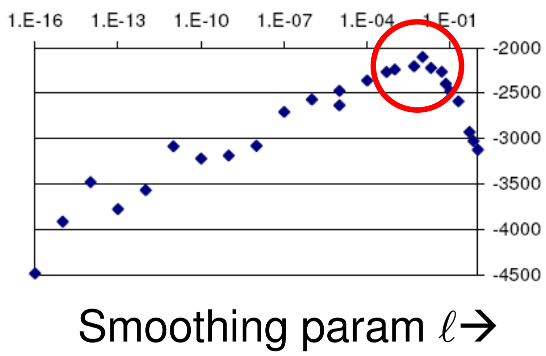
- Lidstone smoothing:

$$queryProb_{\text{Train}}(a) = \frac{queryCount_{\text{Train}}(a) + \ell}{\sum_{a' \in A} \left(queryCount_{\text{Train}}(a') + \ell\right)}$$

- Smoothing param ℓ fit by maximizing log-likelihood of held-out data:

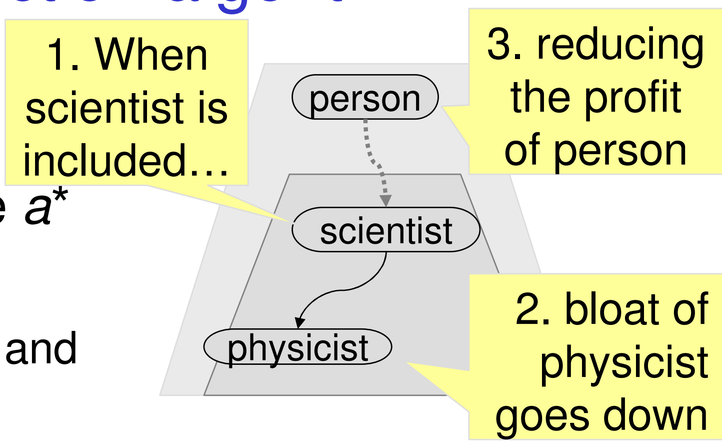
$$\sum_{a \in \text{HeldOut}} queryCount_{\text{HeldOut}}(a)\ \log(queryProb_{\text{Train}}(a))$$

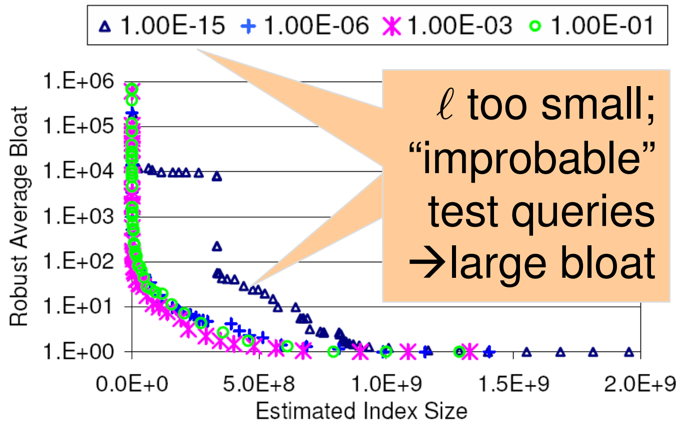
- Clear range of good fits for ℓ
- Can probably do better



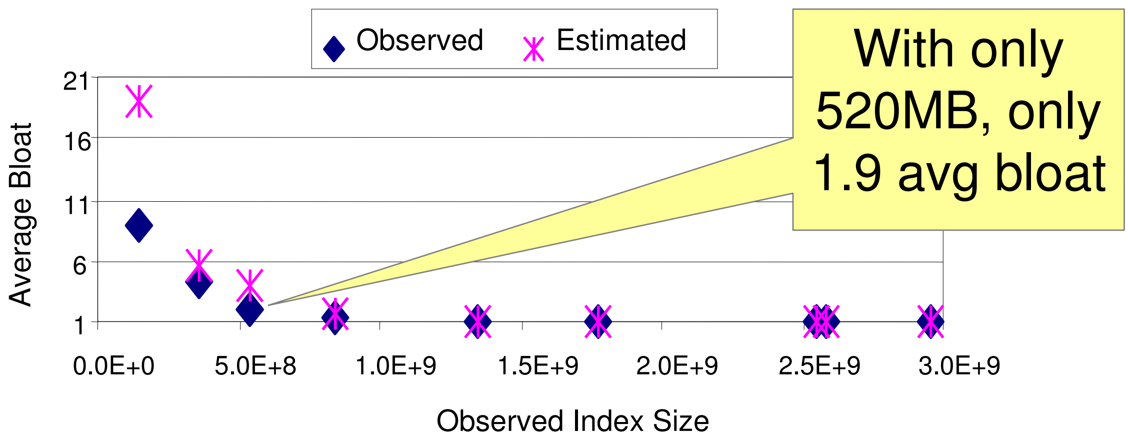
The *R* selection algorithm

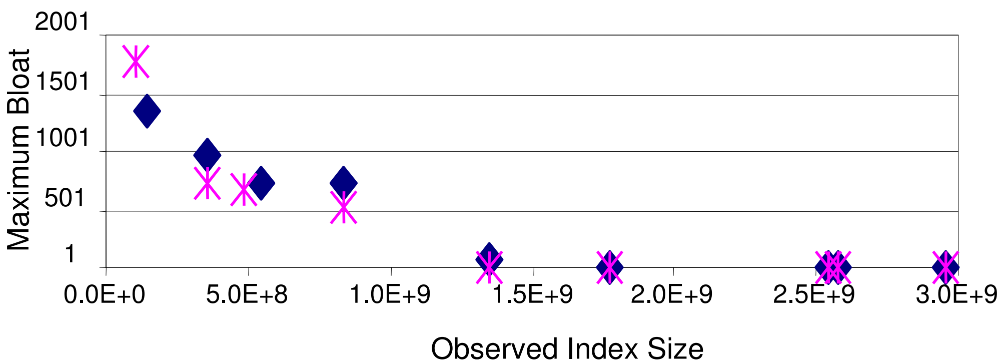
- $R \leftarrow$ roots of A
- Greedily add the "most profitable" atype a^*
- Profit = ratio of
  - reduction in bloat of a^* and its descendants to
  - increase in index space
- Downward and upward traversals and updates
- Gives a tradeoff between index space and query bloat





Optimized space-time tradeoff





Optimized index sizes

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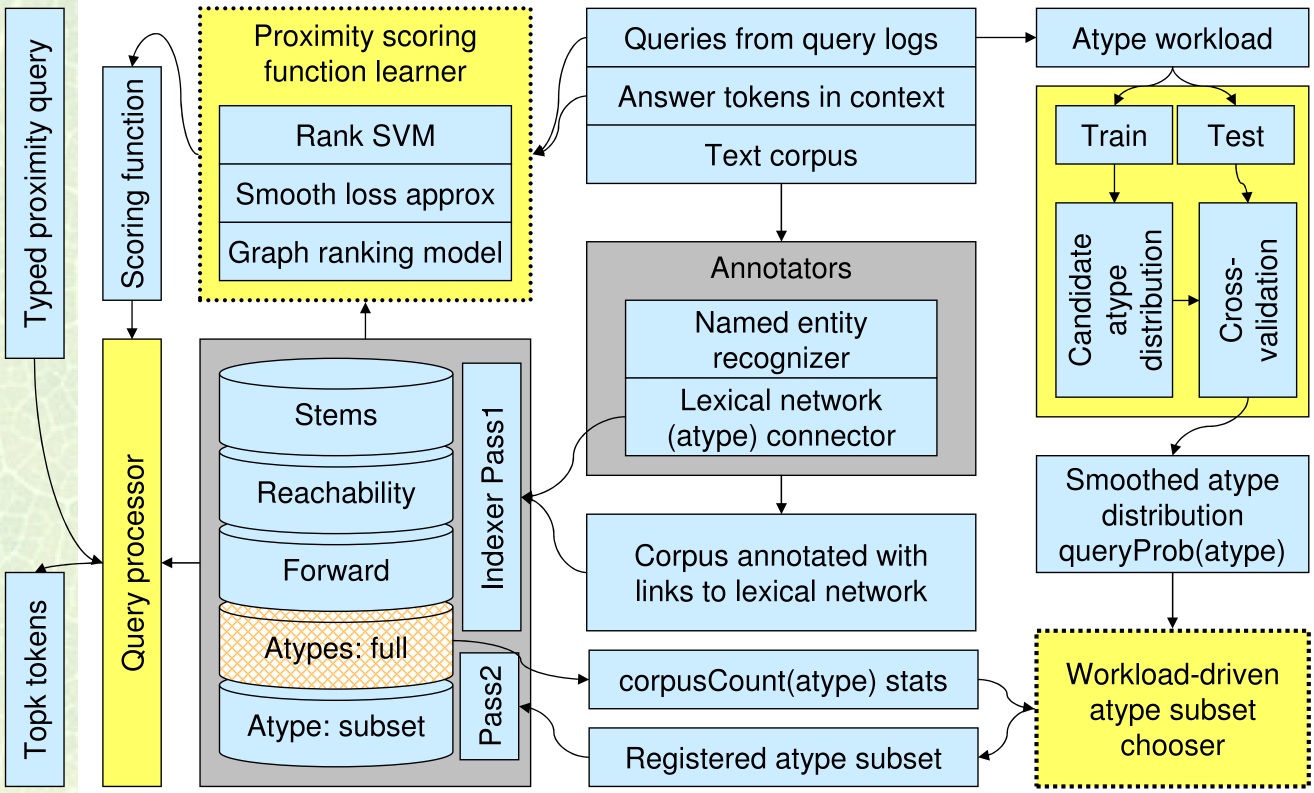
Original corpus	5.72
Gzipped corpus	1.33
Stem index	0.91
Full type index	4.30
Reachability index	0.01
Forward index	1.16
Atype subset index	0.52

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 for code access

The big picture



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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
- Exploit statistical tools 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