IN4325
Query refinement

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The big picture

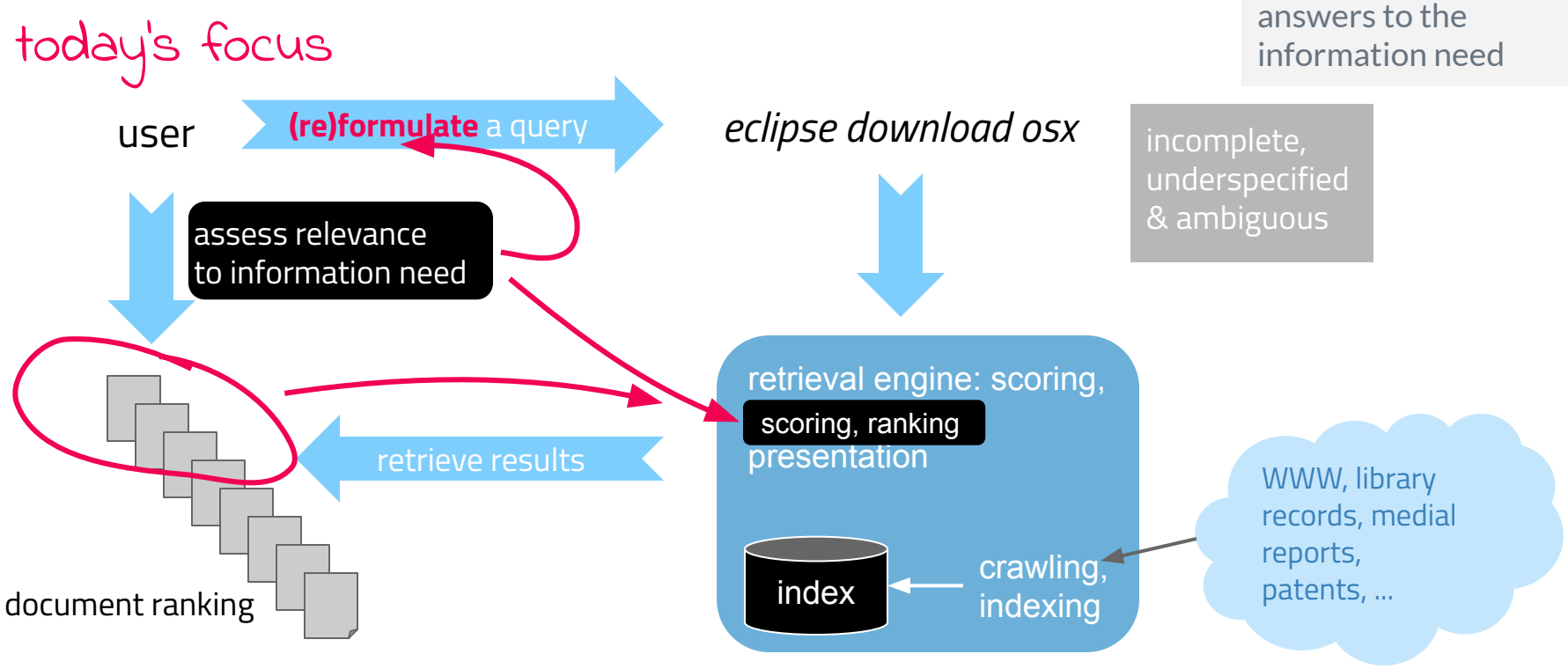
The essence of IR

Information need
Topic the user wants to know more about

Query
Translation of need into an input for the search engine

Relevance
A document is relevant if it (partially) provides answers to the information need

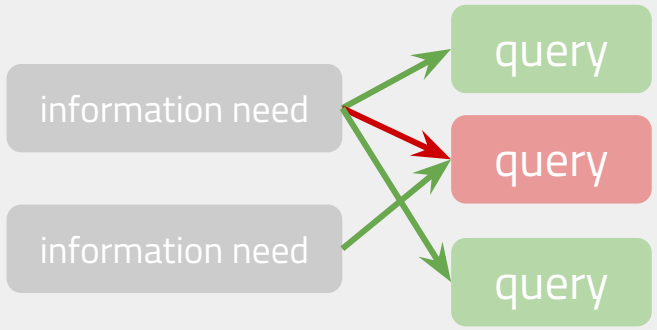
Information need: *Looks like I need Eclipse for this job. Where can I download the latest beta version for macOS Sierra?*



Information needs

- Different categorizations exist:
  - **Informational** vs. **transactional** vs. **navigational**
  - Number of relevant documents wanted
  - Tasks underlying the information need (IN)

- Belkin's **Anomalous State of Knowledge hypothesis**: users recognize anomaly in their knowledge state but cannot precisely specify their IN



Queries are short, ambiguous, imprecise. They can be a poor representation of the IN.

Query refinement techniques

- Either automatically or through user interactions
  - Query expansion
  - Spelling correction
  - Query autocompletion
  - Query suggestions

- Goal: produce a query that is a **better representation** of the information need (this *should* lead to a better ranked list of retrieved documents)

Query expansion


Semantic gap

Query expansion (QE)

- **Idea**: instead of a user manually adding e.g. *synonyms* to her query, let the system help (semi-)automatically in order to decrease the **semantic gap**

- **Global** approaches are *independent* of the query
  - QE with a domain-specific thesaurus is common and successful *for domain-specific corpora*
  - A generic lexical database such as WordNet is ineffective

Query expansion (QE)

- **Idea**: instead of a user manually adding e.g. *synonyms* to he
  (semi-)automa
  semantic gap

- **Global** approac
  - QE with a doma
    for domain-spec
  - A generic lexica

Alzheimer Disease MeSH Descriptor Data 2018

Details | Qualifiers | MeSH Tree Structures | Concepts

MeSH Heading	Alzheimer Disease
Tree Number(s)	C10.228.140.380.100 C10.574.945.249 F03.615.400.100
Unique ID	D000544
Scope Note	A degenerative disease of the BRAIN characterized by the insidious onset of DEMENTIA. Impairment of MEMORY, judgment, attention span, and problem solving skills are followed by severe APRAXIAS and a global loss of cognitive abilities. The condition primarily occurs after age 60, and is marked pathologically by severe cortical atrophy and the triad of SENILE PLAQUES; NEUROFIBRILLARY TANGLES; and NEUROPIL THREADS. (From Adams et al., Principles of Neurology, 6th ed, pp1049-57)
Entry Version	ALZHEIMER DIS
Entry Term(s)	Acute Confusional Senile Dementia Alzheimer Dementia Alzheimer Disease, Early Onset Alzheimer Disease, Late Onset Alzheimer Sclerosis Alzheimer Syndrome Alzheimer Type Senile Dementia Alzheimer's Disease Alzheimer's Disease, Focal Onset Alzheimer-Type Dementia (ATD) Dementia, Alzheimer Type

Query expansion (QE)

- **Idea**: instead of a user manually adding e.g. *synonyms* to her query, let the system help (semi-)automatically in order to decrease the **semantic gap**

- **Global** approaches are *independent* of the query
  - QE with a domain-specific thesaurus is common and successful *for domain-specific corpora*
  - A generic "thesaurus" such as WordNet has not shown to be effective

- **Local** approaches are relative to the retrieved docs.
  - Relevance feedback
  - Pseudo-relevance feedback
  - Implicit feedback (relevance feedback obtained by monitoring search behaviour)

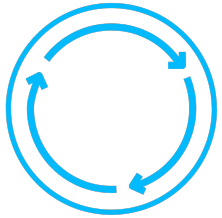
Relevance feedback

PRF: we assume the top-ranked documents are relevant
RF: user indicates which top-ranked documents are relevant

Overview

Search session
A set of searches conducted by a user to solve a (complex) search task within a limited amount of time.

- Approach:
  a. User issues a short query
  b. System returns an initial set/ranked list of results
  c. User marks some of the results relevant or non-relevant
  d. System computes a **better representation** of the information need based on the feedback
  e. System displays revised set/ranked list of results



training data of a search session

machine learning with very limited data

- Insight: it is difficult to formulate a good query based on a complex information need, but it is relatively easy to **decide** whether the returned documents match the information need

- Strategy: words that occur more frequently in relevant than non-relevant documents are added to the query or increased in weight

RF builds on the cluster hypothesis

"*Closely associated documents tend to be relevant to the same requests*." (Keith van Rijsbergen, 1970s)

Common assumption of IR systems: relevant documents are more similar to each other than to non-relevant documents

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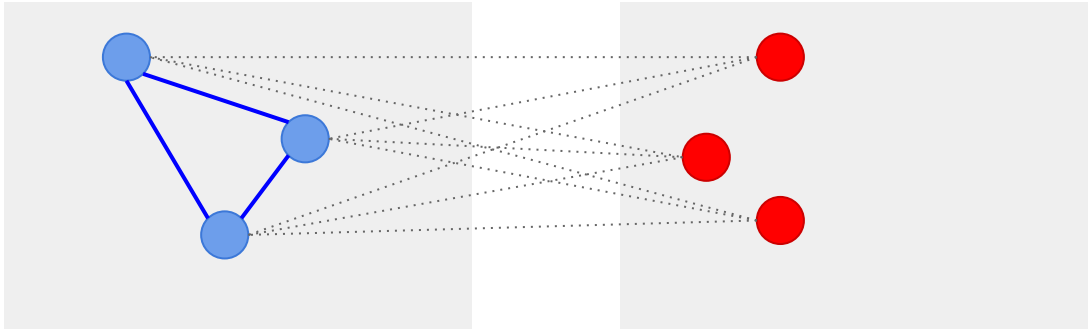
association between all document pairs (R-R), (R-NR)



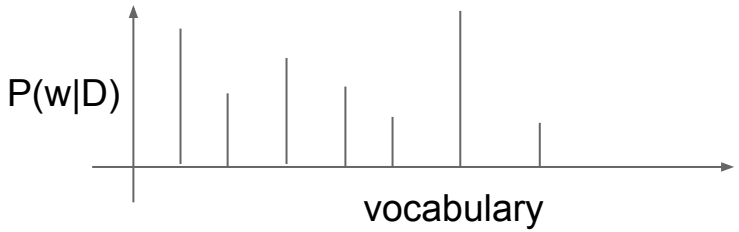
relevant documents (R)

non-relevant documents (NR)

Pseudo-relevance feedback in language models

Language models

- **Unigram language model**: probability distribution over the words (the *vocabulary*) in a language (the *collection* or *document*)
- In IR, unigram LMs represent the *topical content*



- A LM representation of a document can be used to *generate* new text by sampling terms from the distribution (the text won't have a syntactic structure, but that's fine)

Language models

Smoothing

General idea: discount probabilities of **seen words**, assign extra probability mass to **unseen words** with a fallback model (the *collection language model*)

$$P(w \mid D) = \begin{cases} P_{smoothed}(w \mid D) & if\ word\ w\ is\ seen \\ \alpha_d P(w \mid \mathbb{C}) & otherwise \end{cases}$$

Jelineck-Mercer (JM) smoothing: linear interpolation (amount of smoothing controlled) between ML and collection LM

$$P_\lambda(w \mid D) = (1-\lambda) P_{ml}(w \mid D) + \lambda P(w \mid \mathbb{C}), \quad \lambda \in (0,1)$$

Language models

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$$P(w \mid D) = \begin{cases} P_{smoothed}(w \mid D) & if\ word\ w\ is\ seen \\ \alpha_d P(w \mid \mathbb{C}) & otherwise \end{cases}$$

Dirichlet smoothing: longer documents receive less smoothing

"count" of term w in D

$$P_\mu(w \mid D) = \frac{c(w; D) + \mu P(w \mid \mathbb{C})}{\sum_w c(w; D) + \mu}, \quad usually\ \mu > 100$$

Model generalization: create a model/framework that contains existing models as special cases

Relevance models

- Query is a **fixed sample** in LM, with documents being ranked according to their prob. of generating the sample

- Relevance feedback does not come naturally to LM
  - BIM: adjust the weights of the relevance set
  - VSM: Rocchio

- Idea: instead of a fixed sample, consider the query to be a language model (the **relevance model**); it represents the topic covered by relevant documents
  - RF is now principled!

query text now a very small sample generated from the relevance model;
relevant documents are larger samples from the same model

Relevance models

Two options to use our relevance model R

- Option 1: Rank documents by $P(D|R)$
- Option 2: Rank documents according to their *similarity* between the document LM and the query (relevance) LM

Difficult for diverse (wrt. length, vocabulary) sets of documents.

not symmetric

Kullback-Leibler divergence ("KL divergence") measures the difference between two probability distributions P and Q:

$$KL(P||Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)}$$

"true distribution"; usually R

always positive (larger the more apart two distributions are); we use the **negative KL divergence** to rank

Relevance models

$$\log \frac{M}{N} = \log M - \log N$$

$$-KL(P||Q) = -\sum_x P(x) \log \frac{P(x)}{Q(x)}$$

relevance model

$$= \sum_{w \in V} P(w|R) \log P(w|D) - \sum_{w \in V} P(w|R) \log P(w|R)$$

independent of the document, ignore for ranking purposes

Maximum likelihood estimate of $P(w|R)$

$$= \sum_{w \in V} \frac{f_{w,Q}}{|Q|} \log P(w|D)$$

We can ignore terms not in Q.

Isn't this rank equivalent to query likelihood? Yes!

However: we have a **more general model**, we can estimate the relevance model in many ways!

Relevance models

$$= \sum_{w \in V} P(w|R) \log P(w|D) - \sum_{w \in V} P(w|R) \log P(w|R)$$

$$P(w|R) \approx P(w|q_1, q_2, .., q_n)$$

$$P(w|R) \approx \frac{P(w, q_1, q_2, .., q_n)}{P(q_1, q_2, .., q_n)}$$

if query terms are samples from the relevance model, an unseen word's probability should depend on the query terms

$$P(w, q_1, q_2, .., q_n) = \sum_{D \in \mathcal{C}} p(D) P(w, q_1, q_2, .., q_n|D)$$

set of language models

term independence assumption

$$P(w, q_1, q_2, .., q_n|D) = P(w|D) \prod_{I=1}^{n} P(q_i|D)$$

Relevance models

$$= \sum_{w \in V} P(w|R) \log P(w|D) - \sum_{w \in V} P(w|R) \log P(w|R)$$

$$P(w|R) \approx P(w|q_1, q_2, .., q_n)$$

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$$P(w, q_1, q_2, .., q_n) = \sum_{D \in \mathcal{C}} P(D) P(w|D) \prod_{i=1}^{n} P(q_i|D)$$

prior probability of a document

query likelihood score of a document

Requires **two passes for ranking**:

1. Rank documents using query likelihood to obtain the weights needed
2. Use KL-divergence to rank documents by comparing the relevance model and document model

i.e. pseudo-relevance feedback (formally in LM)

Relevance models

In the literature often referred to as RM1, RM2, **RM3**, RM4.

Query drift
The presence of aspects/topics not related to the query in the top-retrieved documents.

Once more …

1. Rank documents using the query likelihood score for query Q.
2. Select some number of the top-ranked documents to be the set C.
3. Calculate the relevance model probabilities $P(w|R)$ using the estimate for $P(w, q_1 \ldots q_n)$.
4. Rank documents again using the KL-divergence score:[13]

The whole collection? Just the top 10-50 ranked ones?

$$\sum_w P(w|R) \log P(w|D)$$

All vocabulary terms? Just the 10-25 that have the highest probabilities?

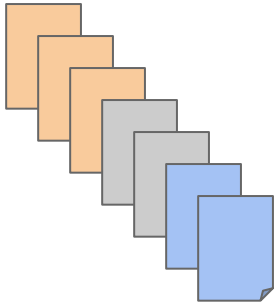
Actually, this model is well motivated but in practice a slight adaptation has turned out to give the best results (=RM3):

Interpolate the relevance model with the original query model to avoid **query drift**.

Source: Search Engines - IR in Practice, Croft et al. (p. 264)

Pseudo-relevance feedback in language models … extensions

Relevance models and clustering



Nothing stops us from smoothing the document language model with **document clusters**:

$$P(w|D) = \lambda P_{ML}(w|D) + (1-\lambda)P(w|Cluster)$$
$$= \lambda P_{ML}(w|D) + (1-\lambda)[\beta P_{ML}(w|Cluster) + (1-\beta)P_{ML}(w|Coll)]$$

Many decisions: which clustering algorithm? How many clusters? Clustering (in)dependent of the queries?

Negative relevance feedback

Another common way of denoting a language model of the **Q**uery and **D**ocument

$$S(Q,D) = -D(\theta_Q||\theta_D) = -\sum_{w \in V} p(w|\theta_Q) \log \frac{p(w|\theta_Q)}{p(w|\theta_D)}$$

KL-divergence

Negative feedback is easy to integrate into the vector space model (remember Rocchio).

In language modeling, it is less natural to directly modify the relevance model (neg. probabilities are not possible).

Idea: $S(Q,D) = -D(\theta_Q||\theta_D) + \beta \cdot D(\theta_N||\theta_D)$

Create a single negative topic model and penalize the document score if it is similar to it..

Estimating relevance models based on external corpora

Idea: mixture of relevance models drawn from different corpora:

$$P(w|\hat{\theta}_Q) = \sum_{c \in \mathcal{C}} P(c) P(w|\theta_Q, c)$$

External corpus only

Mixture of external corpus and target corpus

			BIGNEWS		GOV2		WEB	
	QL	RM3	EE	MoRM	EE	MoRM	EE	MoRM
trec12	0.2502	0.3201	0.3204	0.3319	0.2709	0.3215	0.3092	0.3324
robust	0.2649	0.3214	0.3501	0.3530	0.2748	0.3207	0.3301	0.3352
wt10g	0.1982	0.2030	0.2256	0.2331	0.1999	0.1958	0.2452	0.2429

Mean average precision

collection	docs	terms
BIGNEWS	6,422,629	2,417,464
GOV2	25,205,179	49,917,419
WEB	19,200,000,000	-

Diaz, Fernando, and Donald Metzler. "Improving the estimation of relevance models using large external corpora." Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, 2006.

Last words on query expansion

Has not been taken up by Web search engines

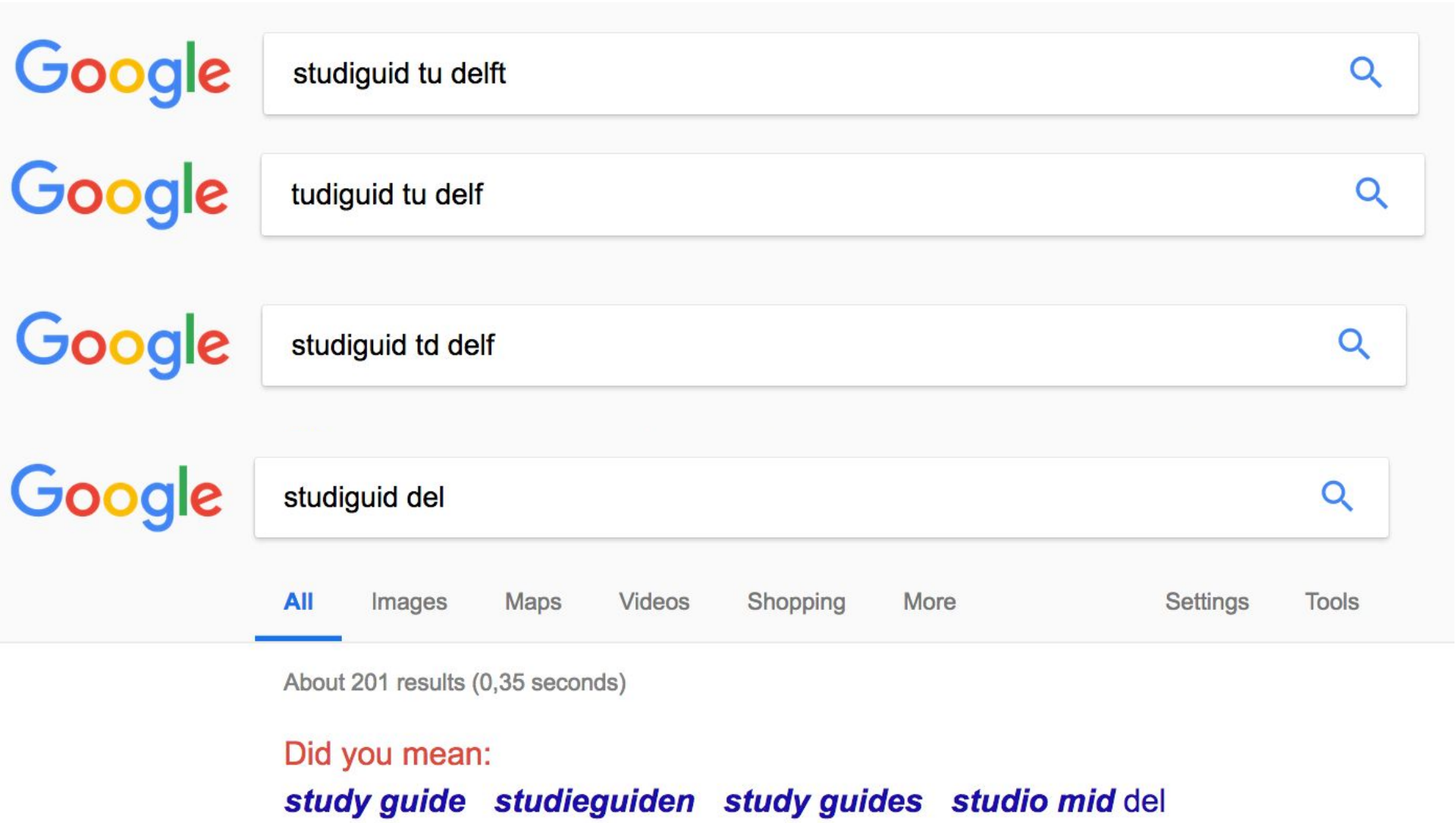
- WSEs cannot afford **computationally expensive** AQE techniques (millisecond response times)

- AQE techniques **perform well on average**, but can cause severe degradation for some queries
- AQE tends to improve **recall** (instead of guaranteeing high precision), often less important for WSE

- **Users** may get confused (their query does not match the returned results)

Spell checking

Web search: “Did you mean …”



`extenssions` → `extensions` (insertion error)
`poiner` → `pointer` (deletion error)
`marshmellow` → `marshmallow` (substitution error)
`brimingham` → `birmingham` (transposition error)
`doceration` → `decoration` (2 substitution errors)

Overview

- **10-15% of Web search queries** contain spelling errors; most are single-character errors

- Challenges:
  a. Variety in type and severity of possible spelling errors in queries (little context available);
  b. No definite lexicon (remember **Heap's law**)

- Generic spell checker:
  a. Create a spelling dictionary and suggest corrections for any word w not in it
  b. Suggestions based on similarity between dictionary words and w (e.g. Levenshtein edit distance, Soundex)

Assumptions in practice:
- first letter is correct
- correct term has similar length

A hundred years old ...

Soundex

- **Homophone**: word that is pronounced the same way as another word but differs in meaning (e.g. *raise* vs. *rays*)
- Soundex is a **phonetic encoding** originally employed for name matching

```
extenssions → E235
extensions → E235
```

use the edit distance of the soundex codes!

1. Keep the first letter (in uppercase).
2. Replace these letters with hyphens: a, e, i, o, u, y, h, w.
3. Replace the other letters by numbers as follows:
   1: b, f, p, v
   2: c, g, j, k, q, s, x, z
   3: d, t
   4: l
   5: m, n
   6: r
4. Delete adjacent repeats of a number.
5. Delete the hyphens.
6. Keep the first three numbers or pad out with zeros.

Source: Search Engines - IR in Practice, Croft et al. (p. 195)

Picking a spelling correction

A misspelled word can several possible corrections

```
lawers → lowers, lawyers, layers, lasers
```

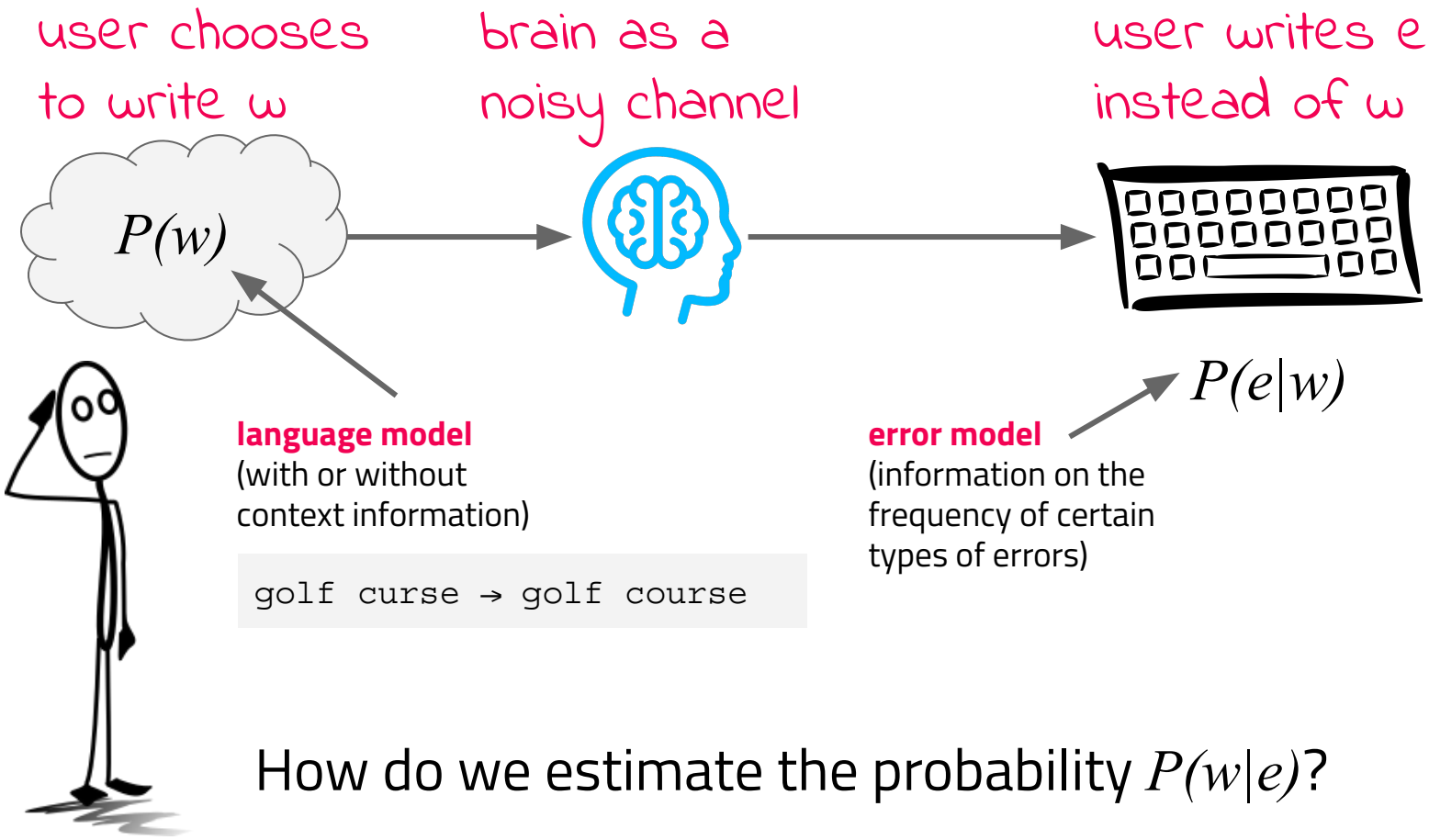
```
trial lawers → trial lowers, trial lawyers, ...
```

Ranking of spelling corrections:

- Use of word frequency of occurrence in the language (**context** independent)
- Use of context and word frequencies leads to better results

This looks pretty ad hoc. Can we make it more principled?

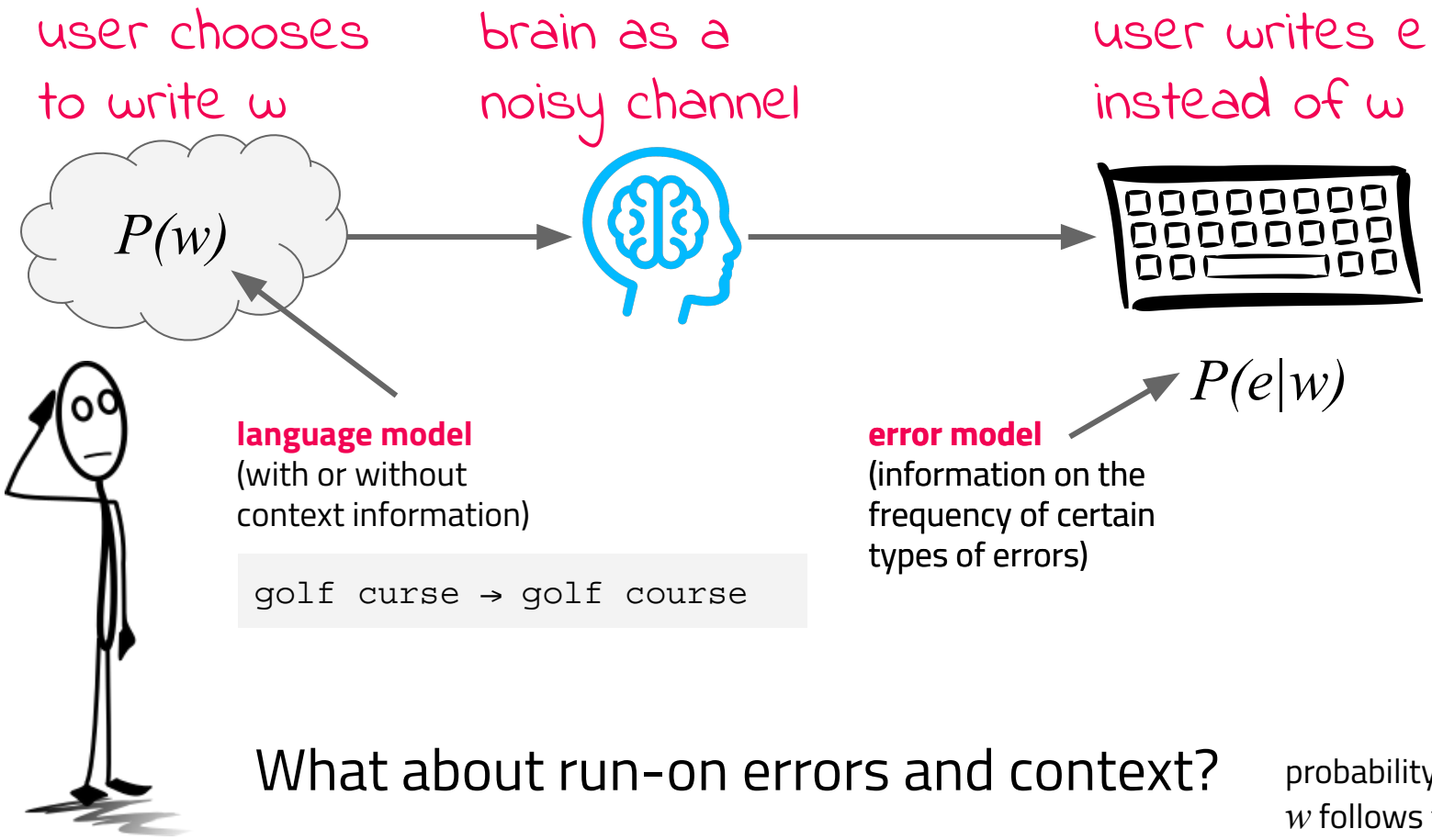
Noisy channel model



How do we estimate the probability $P(w|e)$?

$$P(w|e) \propto P(e|w) \times P(w)$$

Noisy channel model



What about run-on errors and context?

probability that w follows w_p

$$P^{context}(w) = \lambda P(w) + (1-\lambda)P(w|w_p)$$

Source of probabilities

$P(w)$

- **Query log** (mostly for Web search), though frequency alone is not enough (e.g. britny spears)
- High-quality **document corpus** (e.g. news corpus)
- **Wikipedia history diffs** (small edits are often corrections)
- Trusted **lexicon**

$P(e|w)$

- Simple: all errors with the same edit distance have the same probability
- Complex: some errors are more likely than others, e.g. based on keyboard layout, source language, phonetics, cognitive misconceptions

Iterative spelling correction based on query logs

Recall or precision: which metric is more important for a Web search query spell checker?

1. Tokenize the query.
2. For each token, a set of alternative words and pairs of words is found using an edit distance modified by weighting certain types of errors, as described earlier. The data structure that is searched for the alternatives contains words and pairs from both the query log and the trusted dictionary.
3. The noisy channel model is then used to select the best correction.
4. The process of looking for alternatives and finding the best correction is repeated until no better correction is found.

albert einstein	4834
albert einstien	525
albert einstine	149
albert einsten	27
albert einsteins	25
albert einstain	11
albert einstin	10
albert eintein	9
albeart einstein	6
aolbert einstein	6
alber einstein	4
albert einseint	3
albert einsteirn	3
albert einsterin	3
albert eintien	3
alberto einstein	3
albrecht einstein	3
alvert einstein	3

Any string appearing in the query log can be a valid correction, even if misspelled.

Correct spellings tend to be more correct than misspellings. Small mistakes are more common than large mistakes.

Sources: Search Engines - IR in Practice, Croft et al. (p. 198), Cucerzan, Silviu, and Eric Brill. "Spelling correction as an iterative process that exploits the collective knowledge of web users." Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing. 2004.

Iterative spelling correction based on query logs

Ablation study
remove some feature(s) and determine the system effectiveness compared to the compete setup.

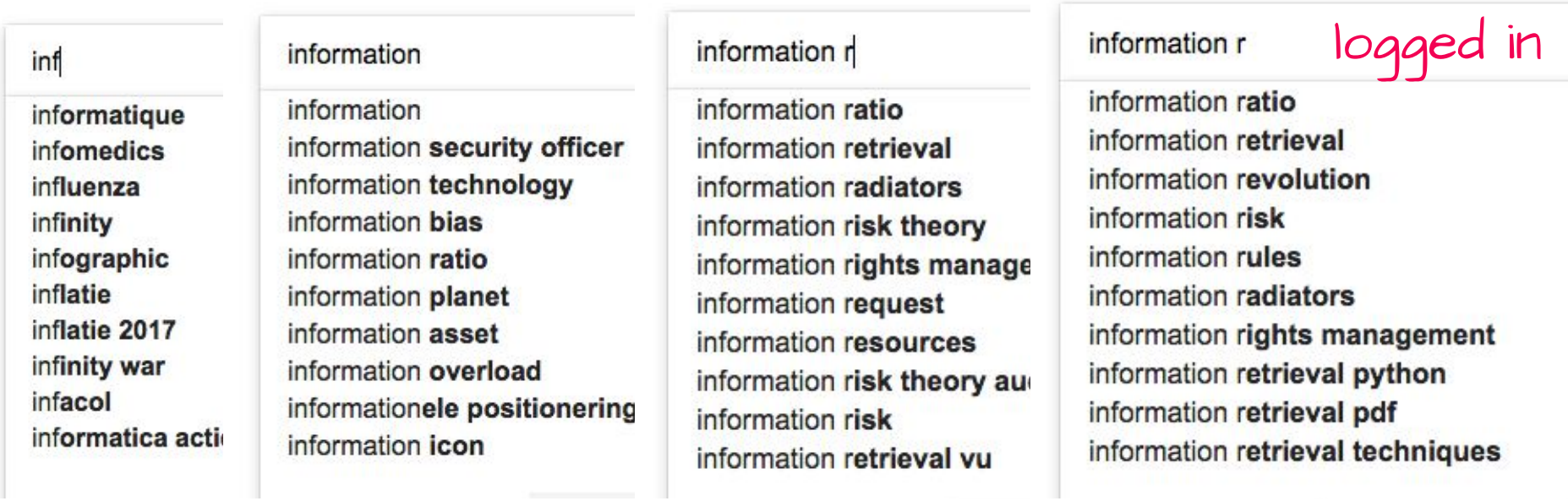
Accuracy

	All queries	Valid	Misspelled
Nr. queries	1044	864	180
Full system	**81.8**	**84.8**	**67.2**
No lexicon	70.3	72.2	61.1
No query log	77.0	82.1	52.8
All edits equal	80.4	83.3	66.1
Unigrams only	54.7	57.4	41.7
1 iteration only	80.9	88.0	47.2
2 iterations only	81.3	84.4	66.7

Source: "Spelling correction as an iterative process that exploits the collective knowledge of web users." Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing. 2004.

Query autocompletion

Overview



Goals:

1. Reduce query entry time
2. Prepare results in advance of query submission
3. Help users formulate a more precise query

Task

- Given the current prefix (=query string the user has typed in so far), rank all possible candidates* (=complete queries)

- Display the top ranked candidates to the user

*assume that we have that list available

Two strong baselines

Assumptions:

1. Access to a query log and document clicks
2. Access to a corpus
3. Access to a user's past queries

Most popular ranker

Query candidates are ranked according to their past popularity

Clicked documents ranker

Cosine similarity between a user's profile (previously clicked docs by that user) and the candidate query profile (previously clicked docs across all users for that query)

Source: Di Santo, Giovanni, et al. "Comparing approaches for query autocompletion." Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, 2015.

Task

Mean reciprocal rank

Prefix length

Approaches			MRR				
Ranking	Query-log Evidence	Personalized	2	4	6	8	10
Sentence occurrence ranker (SO)	No	No	0.005▼	0.0456▼	0.0696▼	0.1003▼	0.1546▼
Most Popular ranker (MP)	Yes	No	0.0964	0.2146	0.2851	0.3248	0.3641
Time Ranker (TR)	Yes	No	0.0324▼	0.1236▼	0.1995▼	0.2707▼	0.3281▼
Most Popular Time ranker (MT)	Yes	No	0.0961	0.2249▲	0.3112▲	0.3684▲	0.4153▲
Terms occurrence ranker (TO)	Yes	No	0.0021▼	0.0326▼	0.0773▼	0.1163▼	0.1617▼
Near Words Ranker (NW)	Yes	No	0.0611▼	0.1576▼	0.2347▼	0.2972▼	0.3611
String Similarity Ranker (SS)	No	Yes	0.0137▼	0.0711▼	0.1628▼	0.1149▼	0.2069▼
WordNet Similarity Ranker (WR)	Yes	Yes	0.089▼	0.0302▼	0.0711▼	0.0908▼	0.1055▼
N-Gram Similarity Ranker (NR)	Yes	Yes	0.0837	0.2927▲	**0.3693▲**	**0.4207▲**	**0.4602▲**
Kernel Similarity Ranker (KR)	Yes	Yes	0.907	0.2876▲	0.3356▲	0.3923▲	0.4121▲
Clicked Documents Ranker (CR)	Yes	Yes	**0.1442▲**	**0.2952▲**	0.3462▲	0.3938▲	0.4183▲

Table 1: Query auto-completion performance over the queries issued during the month of April '13 in our dataset, using the 11 presented ranking approaches. Statistically significant improvements/reductions in performance over the Most Popular ranker (MP) ($p<0.05$ paired t-test) are denoted ▲ and ▼, respectively.

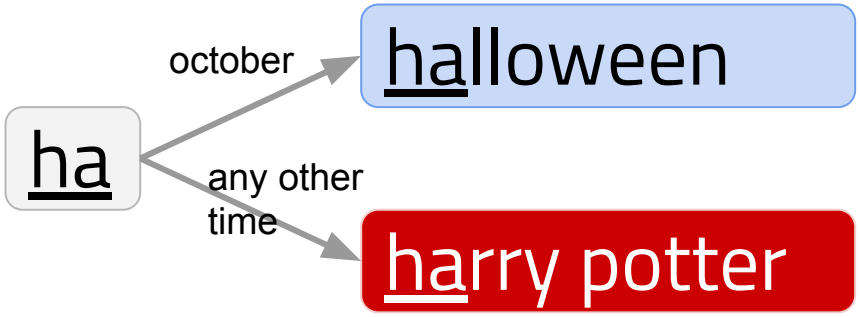
1,417,880 unique queries

November 2010 - March/April 2013

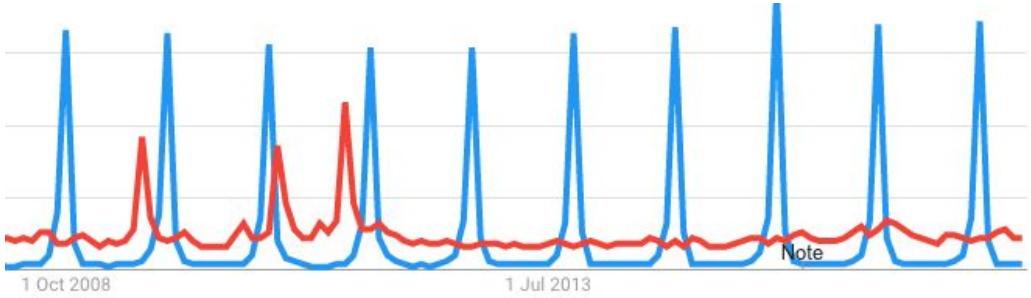
37,806 unique users

Medical search engine with 1.5M articles

Time-sensitive query autocompletion



Approach: apply time-series modeling and rank candidates according to their forecasted frequencies



Rare prefixes

- Query logs are a good source for *frequent* query prefixes

- Pool of candidate queries is usually drawn from a **pre-built prefix trie** (exact matching)

What happens if that does not yield any query candidates?

- Idea: mine popular **query candidate suffixes** (popular n-grams) and generate **synthetic suggestion candidates** (prefix+suffix)that have never been observed in the log

Mitra, Bhaskar, and Nick Craswell. "Query auto-completion for rare prefixes." Proceedings of the 24th ACM international on conference on information and knowledge management. 2015.

Rare prefixes

- Query logs are a go
  prefixes

- Pool of candidate q
  pre-built prefix trie

What happens if that do

- Idea: mine popular
  (popular n-grams) a
  suggestion candida
  never been observe

what to cook with chicken and broccoli and
what to cook with chicken and broccoli *and bacon*
what to cook with chicken and broccoli *and noodles*
what to cook with chicken and broccoli *and brown sugar*
what to cook with chicken and broccoli *and garlic*
what to cook with chicken and broccoli *and orange juice*
what to cook with chicken and broccoli *and beans*
what to cook with chicken and broccoli *and onions*
what to cook with chicken and broccoli *and ham soup*

cheapest flights from seattle to
cheapest flights from seattle *to dc*
cheapest flights from seattle *to washington dc*
cheapest flights from seattle *to bermuda*
cheapest flights from seattle *to bahamas*
cheapest flights from seattle *to aruba*
cheapest flights from seattle *to punta cana*
cheapest flights from seattle *to airport*
cheapest flights from seattle *to miami*

Mitra, Bhaskar, and Nick Craswell. "Query auto-completion for rare prefixes." Proceedings of the 24th ACM international on conference on information and knowledge management. 2015.

Rare prefixes: candidates generation

1. For each query in the query log, generate all possible n-grams from the end of the query

   amsterdam schiphol airport → airport, schiphol airport, amsterdam schiphol airport

2. Aggregate the n-grams across all queries and keep the most popular ones (precomputed)

3. For a given query prefix, extract the end-term

   +most popular ranker candidates

4. Match all suffixes that start with the end-term and create

AOL query log

Top suffixes	Top 2-word suffixes	Top 3-word suffixes
com	for sale	federal credit union
org	yahoo com	new york city
net	myspace com	in new york
gov	google com	or no deal
pictures	new york	disney channel com
lyrics	real estate	my space com
edu	of america	in new jersey
sale	high school	homes for sale
games	new jersey	department of corrections
florida	space com	chamber of commerce
for sale	aol com	bath and beyond
us	s com	in las vegas

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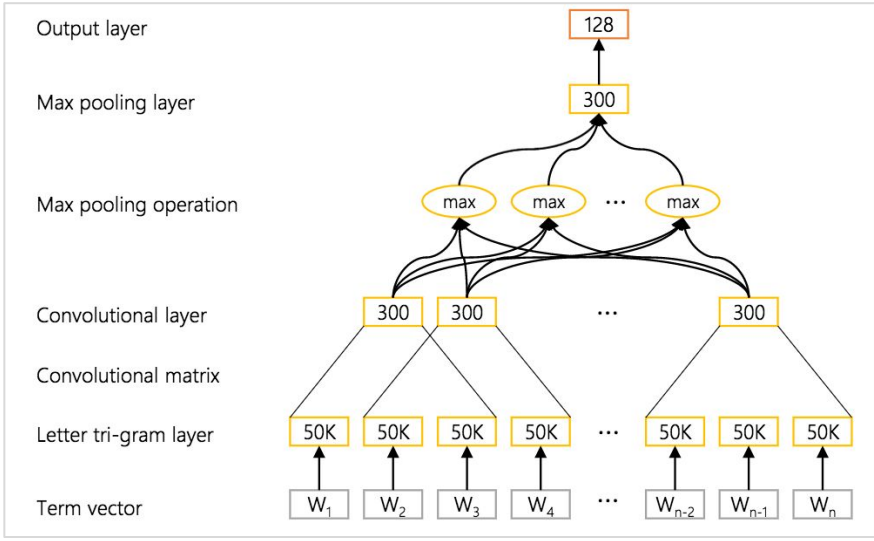
Rare prefixes: ranking features

Supervised ranking model: features are computed for every query prefix and suggestion candidate (synthetic or previously observed)

Main features for **LambdaMART**:

- Query log frequencies of N-grams appearing in a candidate suggestion
- **Convolutional latent semantic model** (training on prefix/suffix pairs generated from sampled queries)

$$clsmsim(\bar{p}, \bar{s}) = cosine(y_1, y_2) = \frac{y_1^\top y_2}{\|y_1\| \|y_2\|}$$



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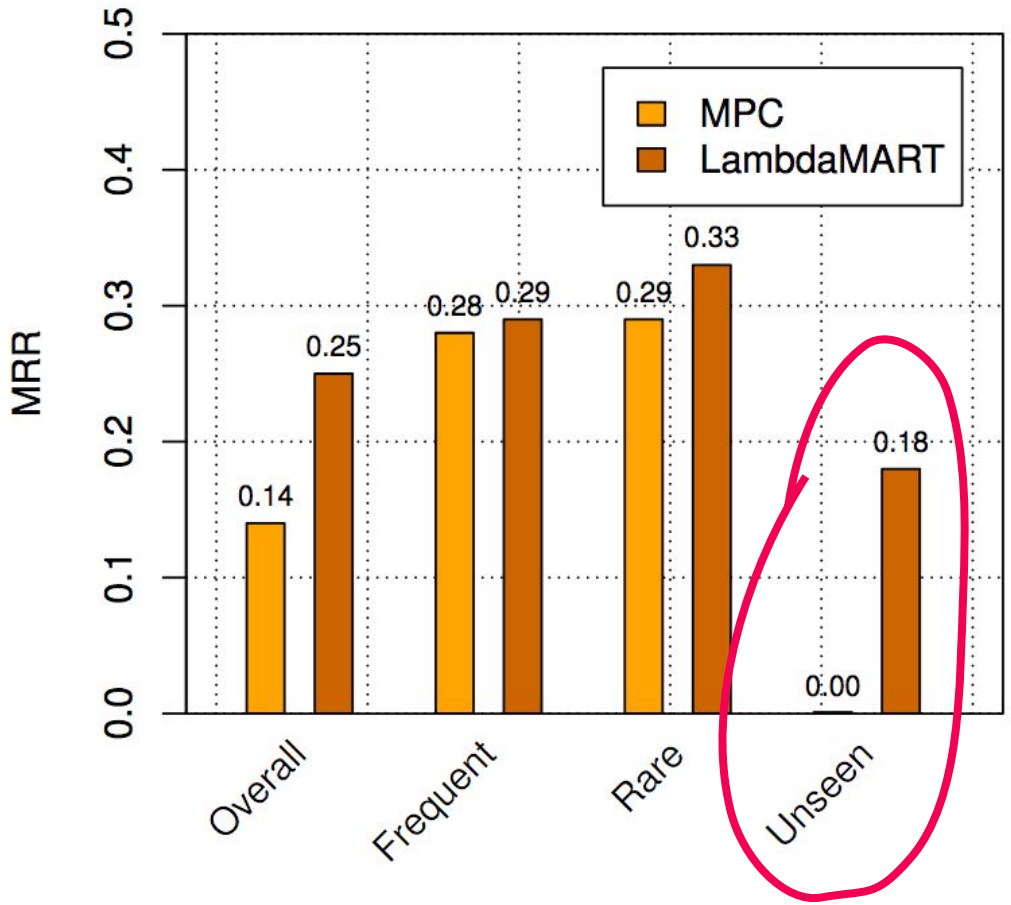
Rare prefixes: results



Baseline: most popular Completion (MPC)

time

background	train	validate	test

Rare prefixes: results

Bing trade secrets

Models	AOL MRR	AOL % Improv.	Bing % Improv.
Full-query based candidates only			
MostPopularCompletion	0.1446	-	-
LambdaMART Model (n-gram features = no, CLSM feature = no)	0.1445	-0.1	-1.7*
LambdaMART Model (n-gram features = yes, CLSM feature = no)	0.1427	-1.4*	-1.2*
LambdaMART Model (n-gram features = no, CLSM feature = yes)	0.1445	-0.1	-1.2*
LambdaMART Model (n-gram features = yes, CLSM feature = yes)	0.1432	-1.0*	-1.5*
Full-query based candidates + Suffix based candidates (Top 10K suffixes)			
MostPopularCompletion	0.1446	-	-
LambdaMART Model (n-gram features = no, CLSM feature = no)	0.2116	+46.3*	+32.8*
LambdaMART Model (n-gram features = yes, CLSM feature = no)	0.2326	+60.8*	+42.6*
LambdaMART Model (n-gram features = no, CLSM feature = yes)	0.2249	+55.5*	+40.1*
LambdaMART Model (n-gram features = yes, CLSM feature = yes)	0.2339	**+61.7***	+43.8*

An **example** that shows how hard we (the IR community) have to work to yield significant gains from deep learning approaches. Gains are possible, but not guaranteed.

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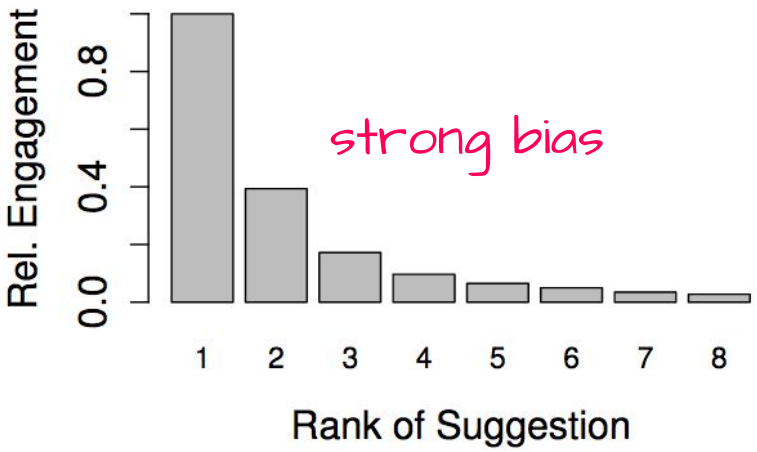
User engagement with query autocompletion

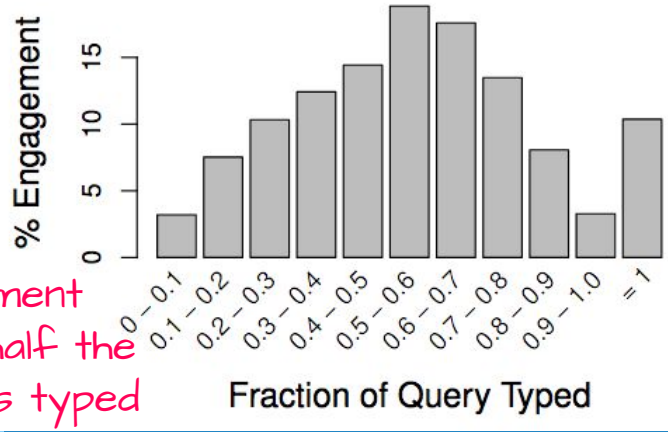
1.6M queries from Bing's search log



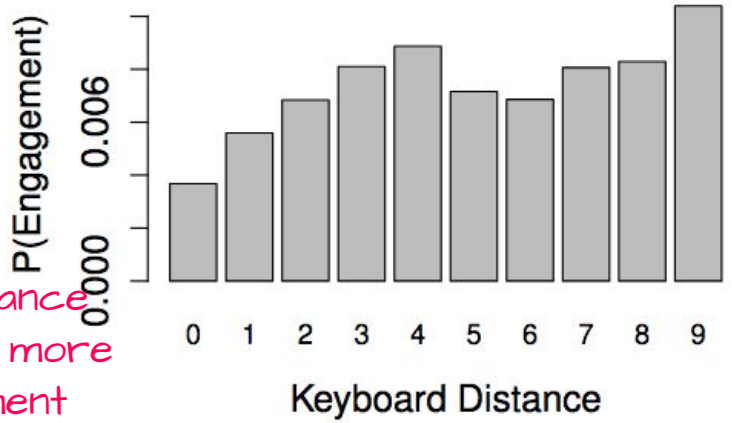
strong bias

Most engagement at word boundaries and after 3 chars of typing a word

Most engagement after half the query is typed



Larger key distance leads to more engagement



That's it for query refinement!

Don't forget that milestone M4 (March 20) **is coming up tonight.**

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