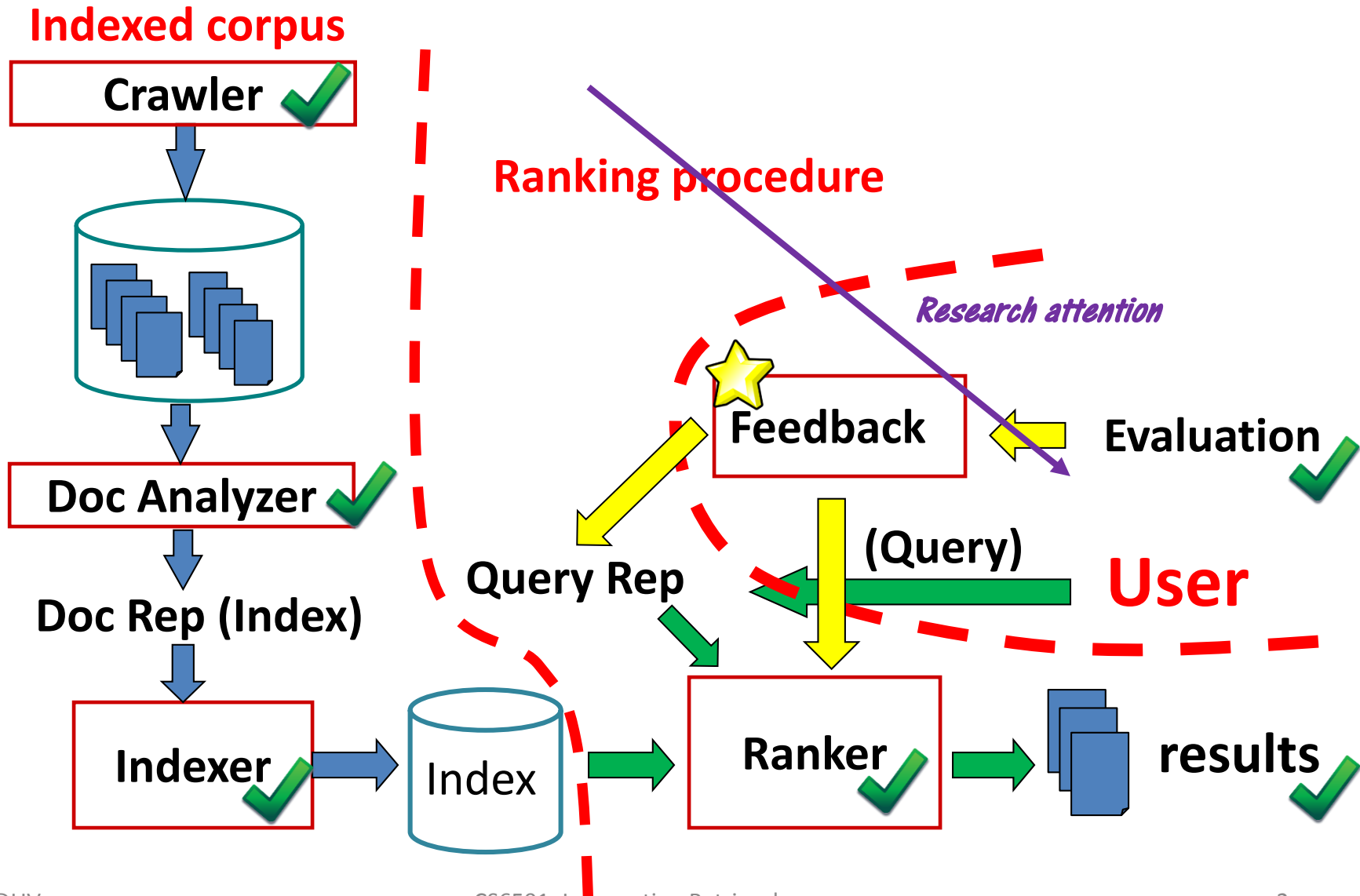


Relevance Feedback

Hongning Wang

CS@UVa

What we have learned so far

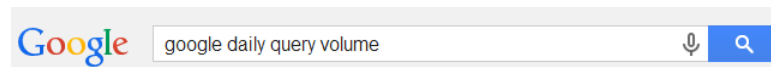


User feedback

should be

- An IR system ~~is~~ an interactive system

Query



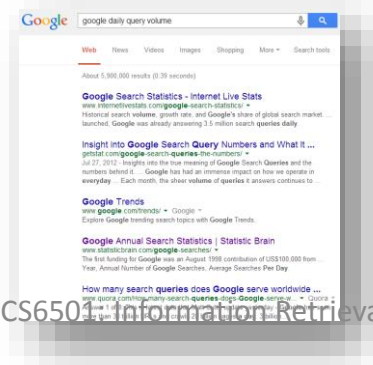
Information need



Feedback

GAP!

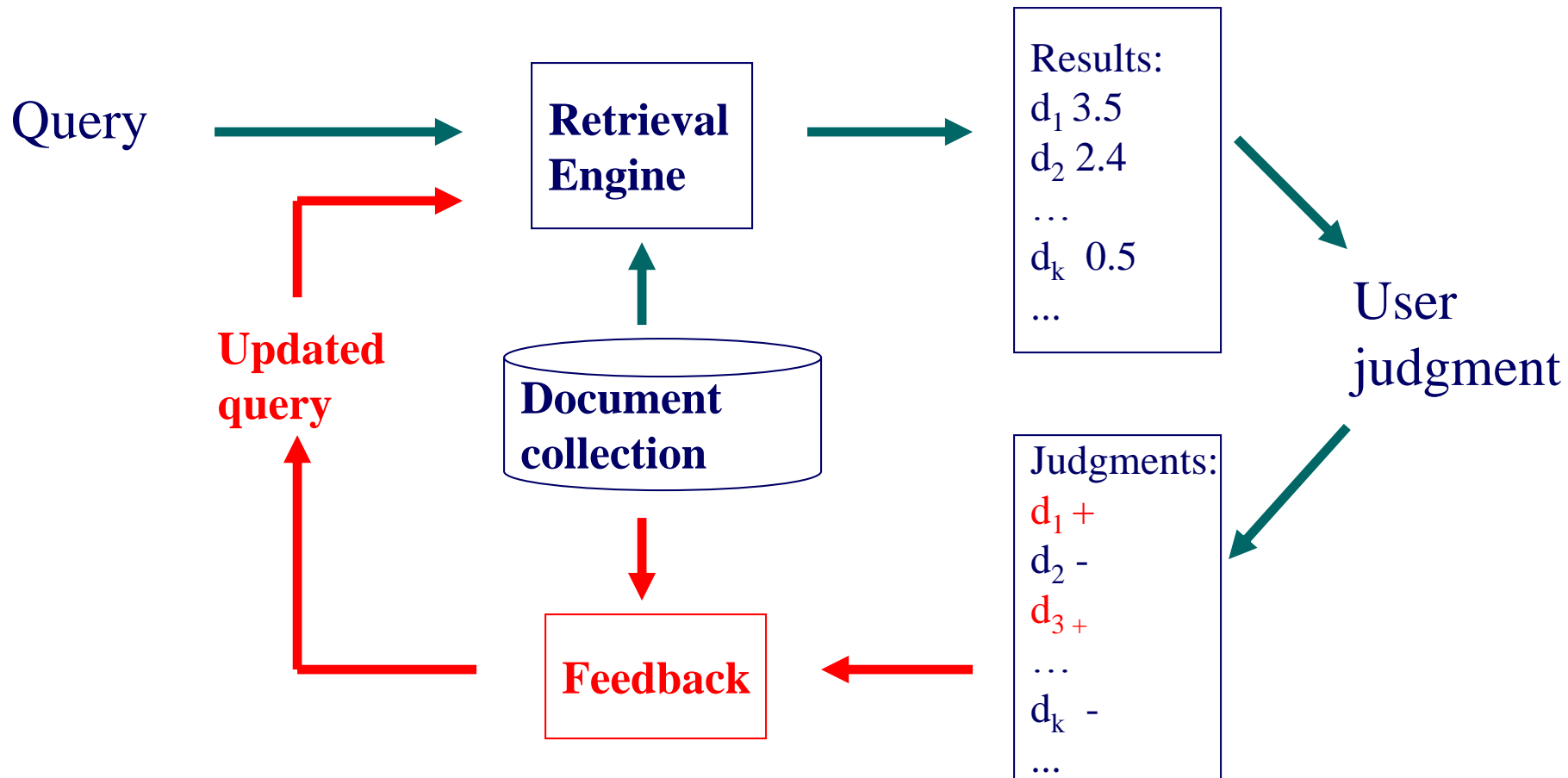
Ranked documents



Inferred information need



Relevance feedback




Relevance feedback in real systems

- Google used to provide such functions

[Personalization](#) - Wikipedia, the free encyclopedia  

Personalization involves using technology to accommodate the differences between individuals. Once confined mainly to the Web, it is increasingly becoming a ...

[en.wikipedia.org/wiki/Personalized](#) - 42k - [Cached](#) - [Similar pages](#) - 

Relevant

[Personalized Gifts from Personalization Mall](#)  

It shows you went out of your way to find the perfect gift and to **personalize** it to make it theirs alone! At PersonalizationMall.com, we design most of our ...

[www.personalizationmall.com/Default.aspx?&did=111028](#) - 47k -

[Cached](#) - [Similar pages](#) - 

Nonrelevant

[What is personalization?](#) - a definition from Whatis.com  

Mar 6, 2007 ... On a Web site, **personalization** is the process of tailoring pages to individual users' characteristics or preferences.

[searchcrm.techtarget.com/sDefinition/0,,sid11_gci532341,00.html](#) - 72k -











[Cached](#) - [Similar pages](#) - 

– Guess why?

Relevance feedback in real systems

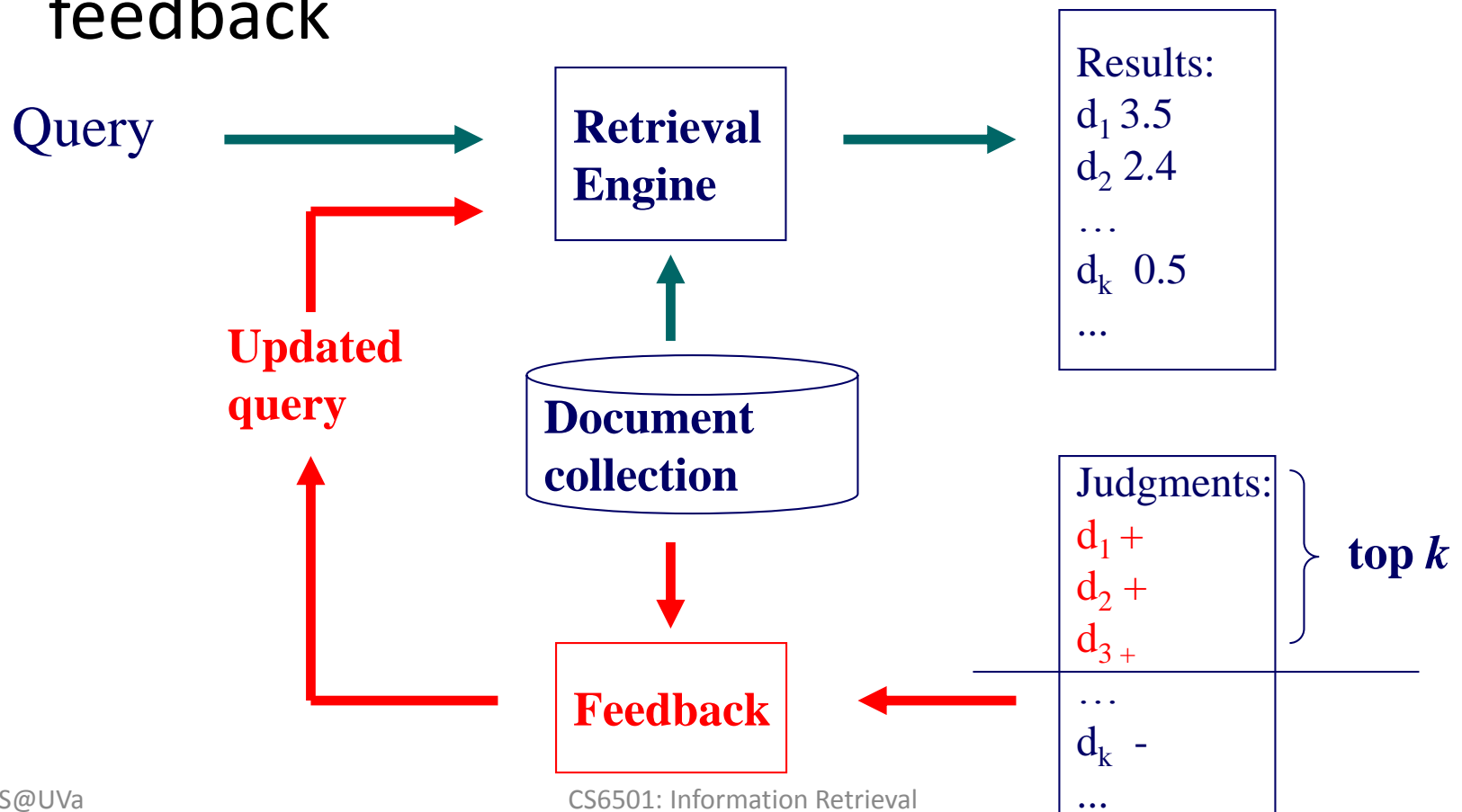
- Popularly used in image search systems

Result:

 Similarity: 1.387633 Query Image top	 Similarity: 0.440483 neutral ▾ top	 Similarity: 0.352732 neutral ▾ top	 Similarity: 0.346222 neutral ▾ top	 Similarity: 0.345664 neutral ▾ top
 Similarity: 0.340732 neutral ▾ top	 Similarity: 0.332161 neutral ▾ top	 Similarity: 0.329942 neutral ▾ top	 Similarity: 0.325042 neutral ▾ top	 Similarity: 0.323497 neutral ▾ top

Pseudo feedback

- What if the users are reluctant to provide any feedback



Basic idea in feedback

- Query expansion
 - Feedback documents can help discover related query terms
 - E.g., query=“information retrieval”
 - Relevant or pseudo-relevant docs may likely share very related words, such as “search”, “search engine”, “ranking”, “query”
 - Expand the original query with such words will increase recall and sometimes also precision

Basic idea in feedback

- Learning-based retrieval
 - Feedback documents can be treated as supervision for ranking model update
 - Will be covered in the lecture of “learning-to-rank”

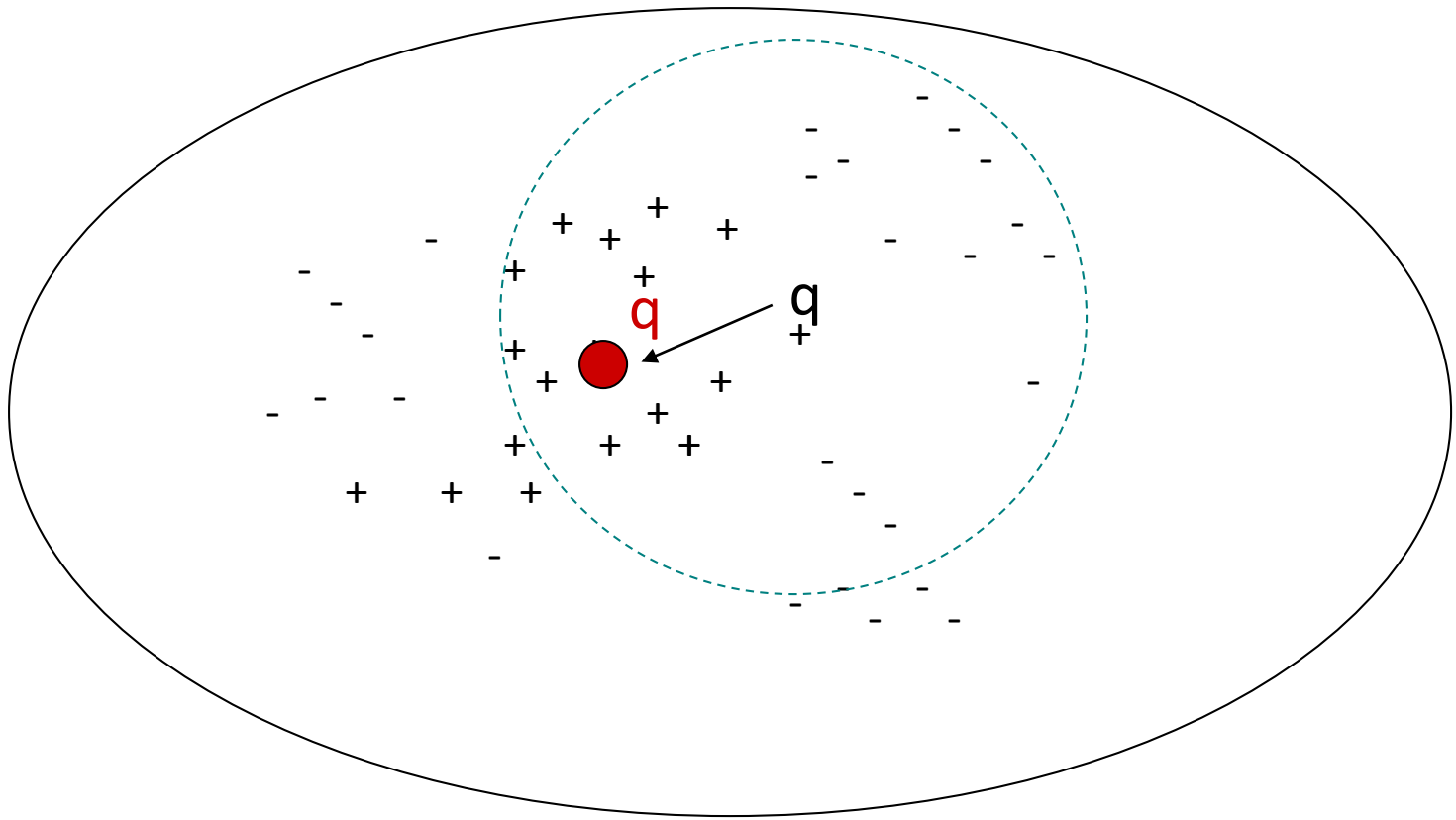
Feedback techniques

- Feedback as query expansion
 - Step 1: Term selection
 - Step 2: Query expansion
 - Step 3: Query term re-weighting
- Feedback as training signal
 - Will be covered later

Relevance feedback in vector space models

- General idea: query modification
 - Adding new (weighted) terms
 - Adjusting weights of old terms
- The most well-known and effective approach is Rocchio [Rocchio 1971]

Illustration of Rocchio feedback



Formula for Rocchio feedback

- Standard operation in vector space

Modified query

Parameters

Original query

Rel docs

Non-rel docs

$$\vec{q}_m = \alpha \vec{q} + \frac{\beta}{|D_r|} \sum_{\forall \vec{d}_i \in D_r} \vec{d}_i - \frac{\gamma}{|D_n|} \sum_{\forall \vec{d}_j \in D_n} \vec{d}_j$$

Rocchio in practice

- Negative (non-relevant) examples are not very important (why?)
- Efficiency concern
 - Restrict the vector onto a lower dimension (i.e., only consider highly weighted words in the centroid vector)
- Avoid “training bias”
 - Keep relatively high weight on the original query weights
- Can be used for relevance feedback and pseudo feedback
- Usually robust and effective

Feedback in probabilistic models

Classic Prob. Model $O(R = 1 | Q, D) \propto \frac{P(D | Q, R = 1)}{P(D | Q, R = 0)}$ ← **Rel. doc model**
 ← **NonRel. doc model**

Language Model $O(R = 1 | Q, D) \propto P(Q | D, R = 1)$ ← **“Rel. query” model**

Parameter Estimation

$\left. \begin{matrix} (q_1, d_1, 1) \\ (q_1, d_2, 1) \\ (q_1, d_3, 1) \end{matrix} \right\} P(D | Q, R = 1)$
 $\left. \begin{matrix} (q_1, d_4, 0) \\ (q_1, d_5, 0) \end{matrix} \right\} P(D | Q, R = 0)$

$\left. \begin{matrix} (q_3, d_1, 1) \\ (q_4, d_1, 1) \\ (q_5, d_1, 1) \\ (q_6, d_2, 1) \\ (q_6, d_3, 0) \end{matrix} \right\} P(Q | D, R = 1)$

Initial retrieval:

- $P(D | Q, R = 1)$: query as rel doc
- $P(Q | D, R = 1)$: doc as rel query

Feedback:

- $P(D | Q, R = 1)$ can be improved for the **current query** and **future doc**
- $P(Q | D, R = 1)$ can be improved for the **current doc** and **future query**

Document generation model

$$Odd(R=1|Q,D) \propto \prod_{i=1}^k \frac{P(A_i = d_i | Q, R=1)}{P(A_i = d_i | Q, R=0)}$$

Terms *occur* in doc (blue dashed box)
 Terms do *not occur* in doc (green dashed box)

$$= \prod_{i=1, d_i=1}^k \frac{P(A_i = 1 | Q, R=1)}{P(A_i = 1 | Q, R=0)} \prod_{i=1, d_i=0}^k \frac{P(A_i = 0 | Q, R=1)}{P(A_i = 0 | Q, R=0)}$$

Important tricks →

$$\approx \prod_{i=1, d_i=q_i=1}^k \frac{p_i}{u_i} \prod_{i=1, d_i=0, q_i=1}^k \frac{1-p_i}{1-u_i}$$
 ← Assumption: terms not occurring in the query are equally likely to occur in relevant and nonrelevant documents, i.e., $p_t = u_t$

$$= \prod_{i=1, d_i=q_i=1}^k \frac{p_i(1-u_i)}{u_i(1-p_i)} \cancel{\prod_{i=1, q_i=1}^k \frac{1-p_i}{1-u_i}}$$

document	relevant(R=1)	nonrelevant(R=0)
term present $A_i=1$	p_i	u_i
term absent $A_i=0$	$1-p_i$	$1-u_i$

Robertson-Sparck Jones Model

(Robertson & Sparck Jones 76)

$$\log O(R=1 | Q, D) \overset{\text{Rank}}{\approx} \sum_{i=1, d_i=q_i=1}^k \log \frac{p_i(1-u_i)}{u_i(1-p_i)} = \sum_{i=1, d_i=q_i=1}^k \log \frac{p_i}{1-p_i} + \log \frac{1-u_i}{u_i} \quad (\text{RSJ model})$$

Two parameters for each term A_i :

$p_i = P(A_i=1 | Q, R=1)$: prob. that term A_i occurs in a relevant doc

$u_i = P(A_i=1 | Q, R=0)$: prob. that term A_i occurs in a non-relevant doc

How to estimate these parameters?

Suppose we have relevance judgments,

$$\hat{p}_i = \frac{\#(\text{rel. doc with } A_i) + 0.5}{\#(\text{rel.doc}) + 1} \quad \hat{u}_i = \frac{\#(\text{nonrel. doc with } A_i) + 0.5}{\#(\text{nonrel.doc}) + 1}$$

“+0.5” and “+1” can be justified by Bayesian estimation as priors

$P(D|Q, R=1)$ can be improved for
the *current query* and *future doc*

Per-query estimation!

Feedback in language models

- Recap of language model
 - Rank documents based on *query likelihood*

$$\log p(q | d) = \sum_{w_i \in q} \log p(w_i | d)$$

where, $q = w_1 w_2 \dots w_n$

Document language model



- Difficulty
 - Documents are given, i.e., $p(w|d)$ is fixed

Feedback in language models

- Approach
 - Introduce a probabilistic query model
 - Ranking: measure distance between query model and document model
 - Feedback: query model update

Q: Back to vector space model?

A: Kind of, but in different perspective.

Kullback-Leibler (KL) divergence based retrieval model

- Probabilistic similarity measure

$$- \text{sim}(q; d) \propto -KL(\theta_q || \theta_d)$$

$$-\sum_w p(w|\theta_q) \log p(w|\theta_q) + \sum_w p(w|\theta_q) \log p(w|\theta_d)$$

Query-specific quality, ignored for ranking

*Query language model,
need to be estimated*

*Document language model,
we know how to estimate*

Background knowledge

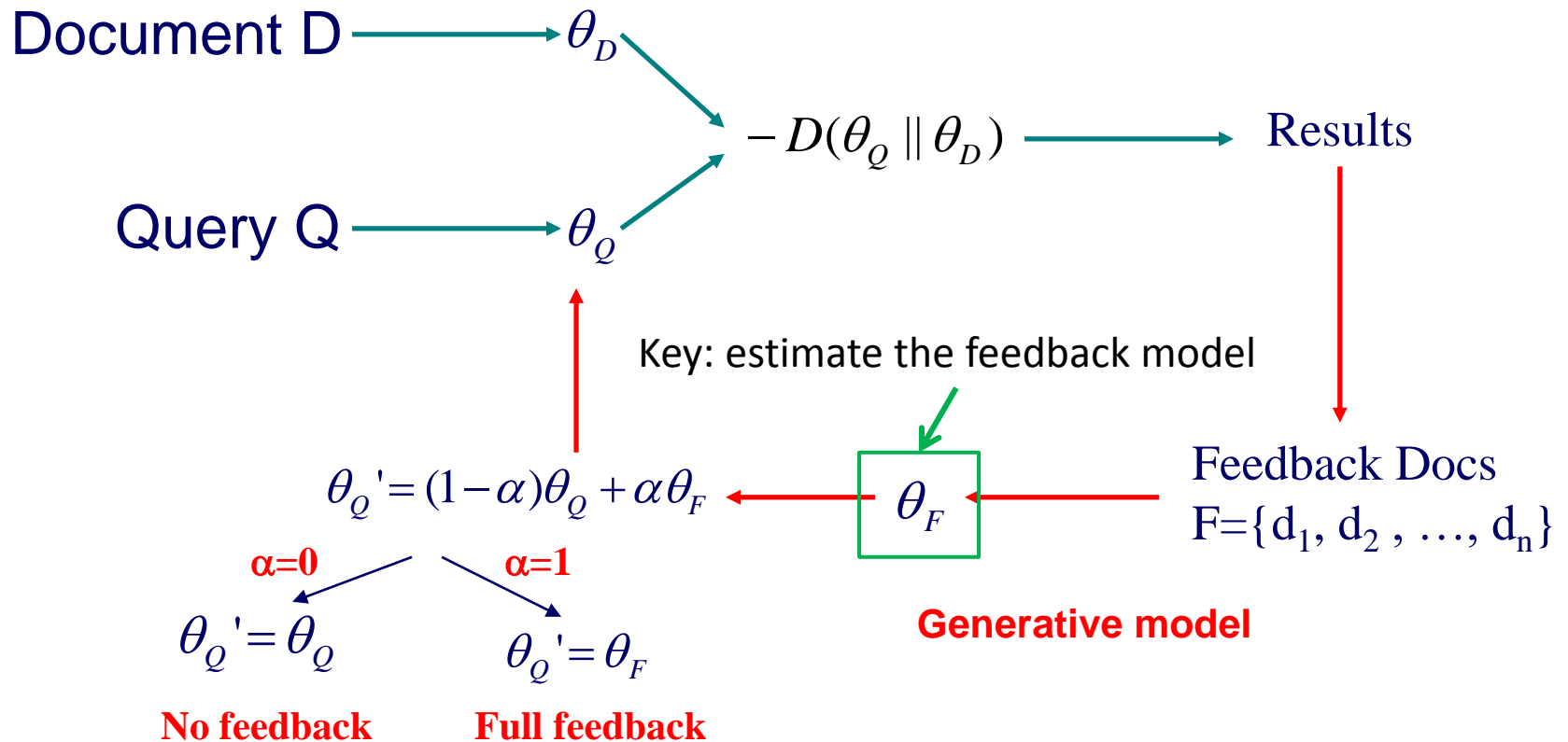
- Kullback-Leibler divergence
 - A non-symmetric measure of the difference between two probability distributions P and Q
 - $KL(P||Q) = \int P(x) \log \frac{P(x)}{Q(x)} dx$
 - It measures the expected number of extra bits required to code samples from P when using a code based on Q
 - P usually refers to the “true” data distribution, Q refers to the “approximated” distribution
 - Properties
 - Non-negative
 - $KL(P||Q) = 0$, iff $P = Q$ almost everywhere

Explains why $\text{sim}(q; d) \propto -D(\theta_q || \theta_d)$

Kullback-Leibler (KL) divergence based retrieval model

- Retrieval \approx estimation of θ_q and θ_d
 - $\text{sim}(q; d) \propto$
 $\sum_{w \in d, p(w|\theta_q) > 0} p(w|\theta_q) \log \frac{p(w|d)}{\alpha_d p(w|C)} + \log \alpha_d$
 - same smoothing strategy* (pointing to α_d)
 - A generalized version of query-likelihood language model
 - $p(w|\theta_q)$ is the empirical distribution of words in a query

Feedback as model interpolation



Q: Rocchio feedback in vector space model?

A: Very similar, but in different interpretation.

Feedback in language models

airport security

Transportation Security Administration - Official Site
www.tsa.gov Official site
Charged with providing effective and efficient security for passenger and freight transportation in the United States. Mission, press releases, employment, milestones ...

Prohibited Items
The My TSA mobile application provides 24/7 access to helpful ...

TSA Precheck Ad
Learn about TSA Pre™ expedited screening! No longer remove ...

Careers
TSA is comprised of nearly 50,000 security officers, inspectors, air ...

See results only from tsa.gov

3-1-1 for Carry-ons
Consolidating these containers in the small bag separate from your ...

Traveler Information
One of the primary goals of the Transportation Security ...

Acceptable IDs
Adult passengers (18 and over) must show a valid U.S. federal or state ...

Airport security - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Airport_security
Airport security refers to the techniques and methods used in protecting passengers, staff and aircraft which use the airports from accidental/malicious harm, crime ...
Airport enforcement ... · Process and equipment · Notable incidents

An Overview of Airport Security Rules - About studenttravel.about.com
Student Transportation Options
Airport security rules are a travel drag: get through airport security and get to the fun part (travel!) faster by knowing what the airport security rules are in advance.

News about Airport Security
bing.com/news
[No need to beef up airport security: govt](http://No%20need%20to%20beef%20up%20airport%20security%20govt)
YahooNews · 1 minute ago
Airport security doesn't need to be strengthened because 30 to 40 New Zealanders are being monitored over links to terrorist groups, the government says. Prime Minister John Key on Wednesday revealed the existence of...

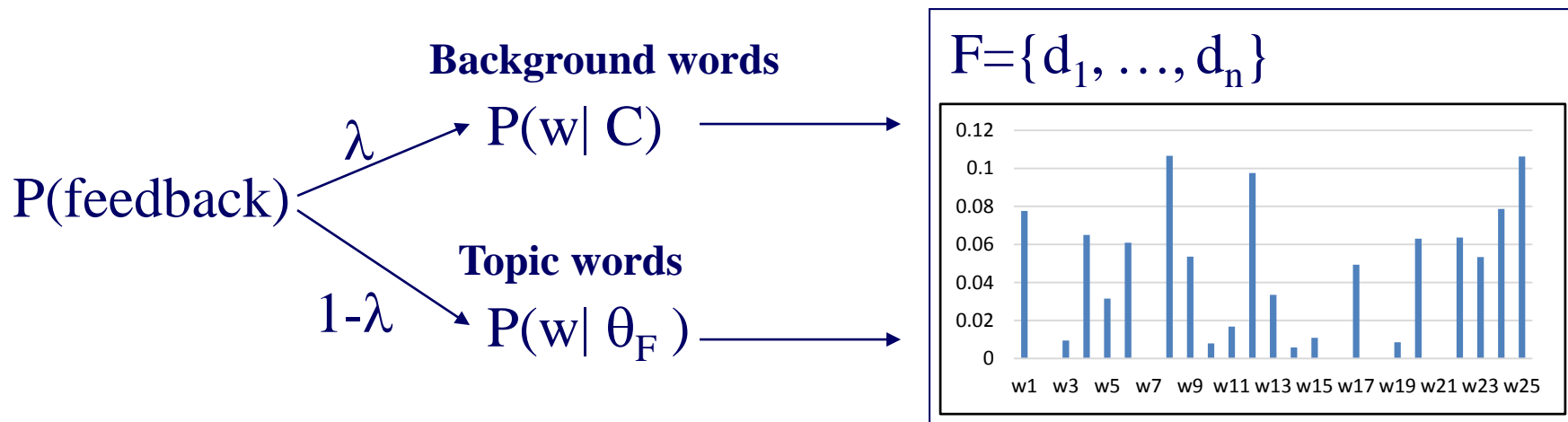
Feedback documents

Airport security - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Airport_security
Airport security refers to the techniques and methods used in protecting passengers, staff and aircraft which use the airports from accidental/malicious harm, crime ...
Airport enforcement ... · Process and equipment · Notable incidents

An Overview of Airport Security Rules - About studenttravel.about.com
Student Transportation Options
Airport security rules are a travel drag: get through airport security and get to the fun part (travel!) faster by knowing what the airport security rules are in advance.

*protect passengers,
accidental/malicious
harm, crime, rules*

Generative mixture model of feedback



$$\log p(d_F) = \sum_{d,w} c(w, d) \log[(1 - \lambda)p(w|\theta_F) + \lambda p(w|C)]$$

λ = Noise ratio in feedback documents

Maximum Likelihood $\bar{\theta}_F = \operatorname{argmax}_{\theta} \log p(d_F)$

How to estimate θ_F ?

Known
Background
 $p(w|C)$

the 0.2
a 0.1
we 0.01
to 0.02
...
flight 0.0001
company
0.00005
...

Unknown
query topic
 $p(w|\theta_F)=?$

“airport security”

...
accident =?
regulation =?
passenger =?
rules =?
...

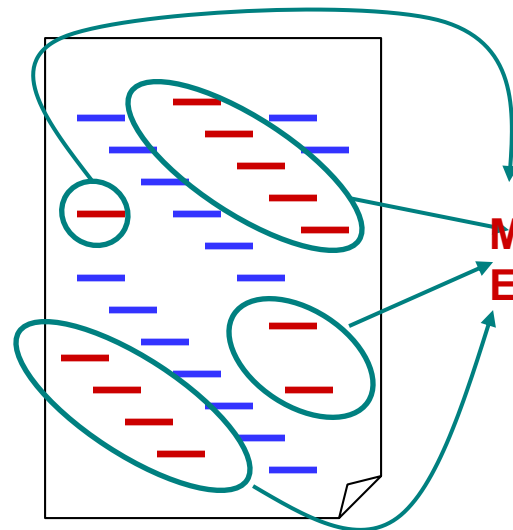
fixed



$\lambda=0.7$



Feedback
Doc(s)



ML
Estimator

$\lambda=0.3$



Suppose, we know the identity
of each word; **but we don't...**

Appeal to EM algorithm

Identity (“hidden”) variable: $z_i \in \{1 \text{ (background)}, 0 \text{ (topic)}\}$

	z_i
the	1
paper	1
presents	1
a	1
text	0
mining	0
algorithm	0
the	1
paper	0
...	...

Suppose the parameters are all known, what's a reasonable guess of z_i ?

- depends on λ (why?)
- depends on $p(w|C)$ and $p(w|\theta_F)$ (how?)

$$p(z_i = 1 | w_i) = \frac{p(z_i = 1)p(w_i | z_i = 1)}{p(z_i = 1)p(w_i | z_i = 1) + p(z_i = 0)p(w_i | z_i = 0)}$$

$$= \frac{\lambda p(w_i | C)}{\lambda p(w_i | C) + (1 - \lambda)p(w_i | \theta_F)} \quad \text{E-step}$$

$$p^{new}(w_i | \theta_F) = \frac{c(w_i, F)(1 - p^{(n)}(z_i = 1 | w_i))}{\sum_{w_j \in \text{vocabulary}} c(w_j, F)(1 - p^{(n)}(z_j = 1 | w_j))} \quad \text{M-step}$$

Why in Rocchio we did not distinguish a word's identity?

A toy example of EM computation

$$p^{(n)}(z_i = 1 | w_i) = \frac{\lambda p(w_i | C)}{\lambda p(w_i | C) + (1 - \lambda) p^{(n)}(w_i | \theta_F)}$$

Expectation-Step:

Augmenting data by guessing hidden variables

$$p^{(n+1)}(w_i | \theta_F) = \frac{c(w_i, F)(1 - p^{(n)}(z_i = 1 | w_i))}{\sum_{w_j \in \text{vocabulary}} c(w_j, F)(1 - p^{(n)}(z_j = 1 | w_j))}$$

Maximization-Step

With the “augmented data”, estimate parameters using maximum likelihood

Assume $\lambda=0.5$

Word	#	P(w C)	Iteration 1		Iteration 2		Iteration 3	
			P(w θ_F)	P(z=1)	P(w θ_F)	P(z=1)	P(w θ_F)	P(z=1)
The	4	0.5	0.25	0.67	0.20	0.71	0.18	0.74
Paper	2	0.3	0.25	0.55	0.14	0.68	0.10	0.75
Text	4	0.1	0.25	0.29	0.44	0.19	0.50	0.17
Mining	2	0.1	0.25	0.29	0.22	0.31	0.22	0.31
Log-Likelihood			-16.96		-16.13		-16.02	

Example of feedback query model

Open question: how do we handle negative feedback?

- Query: “airport security”
 - Pseudo feedback with top 10 documents

$\lambda=0.7$

W	$p(W \theta_F)$
the	0.0405
security	0.0377
airport	0.0342
beverage	0.0305
alcohol	0.0304
to	0.0268
of	0.0241
and	0.0214
author	0.0156
bomb	0.0150
terrorist	0.0137
in	0.0135
license	0.0127
state	0.0127
by	0.0125

$\lambda=0.9$

W	$p(W \theta_F)$
security	0.0558
airport	0.0546
beverage	0.0488
alcohol	0.0474
bomb	0.0236
terrorist	0.0217
author	0.0206
license	0.0188
bond	0.0186
counter-terror	0.0173
terror	0.0142
newsnet	0.0129
attack	0.0124
operation	0.0121
headline	0.0121

Keep this in mind, we will come back

Known
Background
 $p(w|C)$

the 0.2
a 0.1
we 0.01
to 0.02
...
text 0.0001
mining 0.00005
...

Unknown
query topic
 $p(w|\theta_F)=?$

“Text mining”

...
text =?
mining =?
association =?
word =?
...

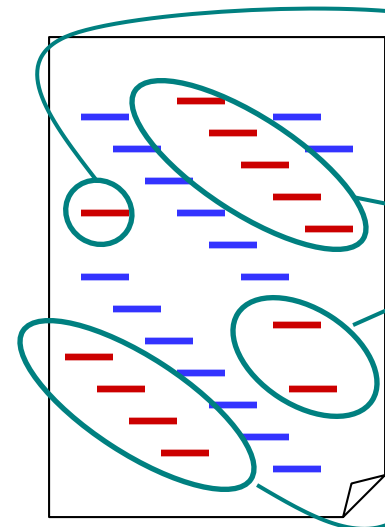
fixed



$\lambda=0.7$



Observed
Doc(s)



ML
Estimator

$\lambda=0.3$



What you should know

- Purpose of relevance feedback
- Rocchio relevance feedback for vector space models
- Query model based feedback for language models