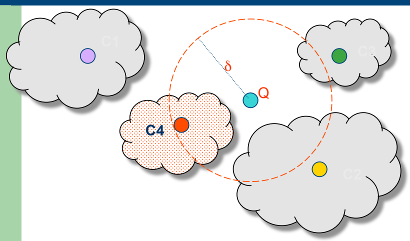
Use of clusters (prune search space)



- …eliminate clusters based on their representatives

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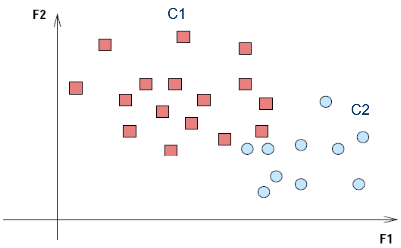
Evaluation of clustering methods



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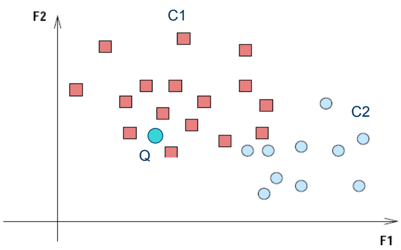
Evaluation of clustering methods



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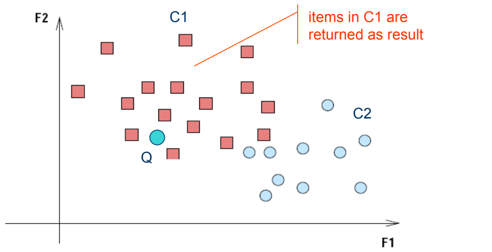
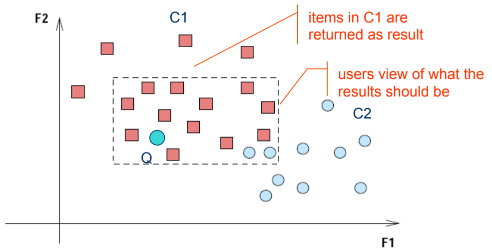
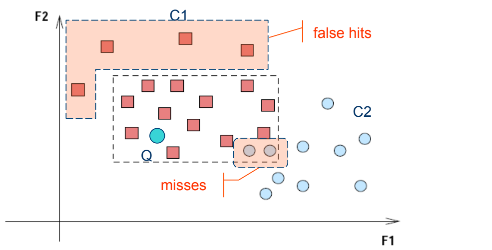
Evaluation of clustering methods



Evaluation of clustering methods

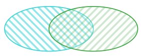


Evaluation of clustering methods



Precision

- Precision



Retrieved and Relevant / Retrieved — measures the effect of false hits

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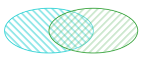
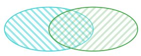
Precision and recall

- Precision



Retrieved and Relevant / Retrieved — measures the effect of false hits

- Recall



Retrieved and Relevant / Relevant — measures the effect of misses

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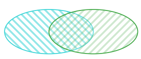
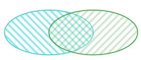
Precision and recall

- Precision



Retrieved and Relevant / Retrieved — measures the effect of false hits

- Recall



Retrieved and Relevant / Relevant — measures the effect of misses

. Both should be closer to 1!!!!

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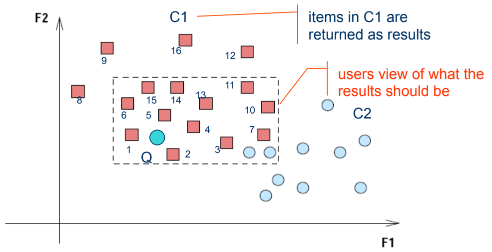
What if we also have rankings in the result???



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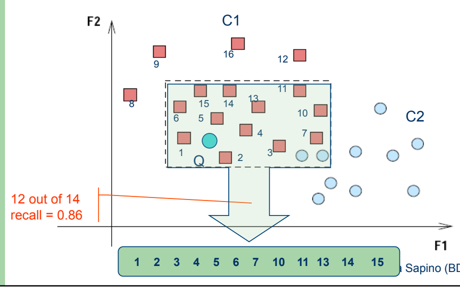

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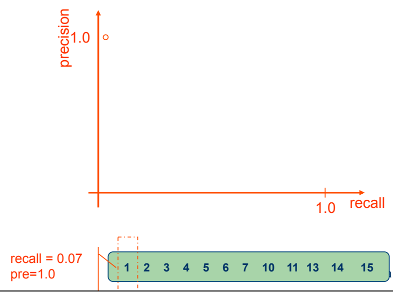

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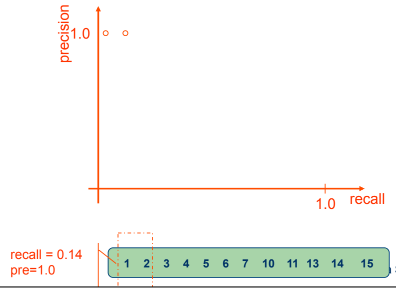

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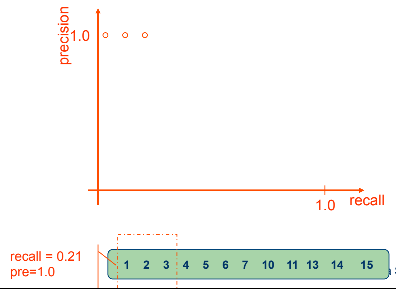

Sapino (BDM 2018)

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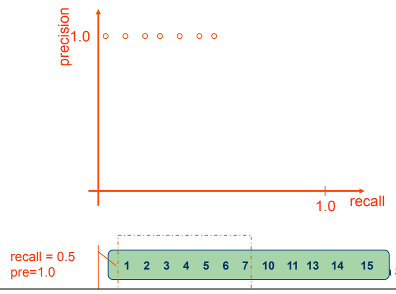

Sapino (BDM 2018)

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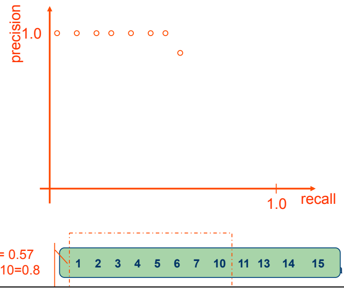

recall = 0.57
pre=8/10=0.8

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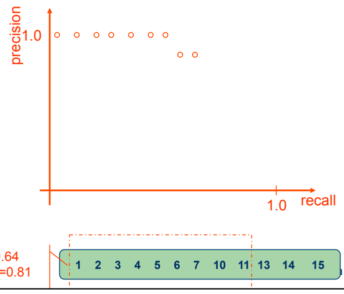
What if we also have rankings in the result???



recall = 0.64
pre=9/11=0.81

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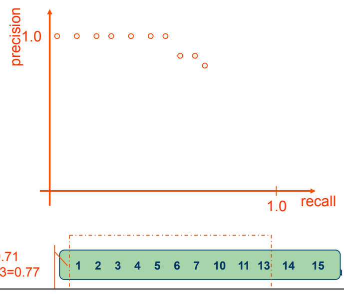
What if we also have rankings in the result???



recall = 0.71
pre=10/13=0.77

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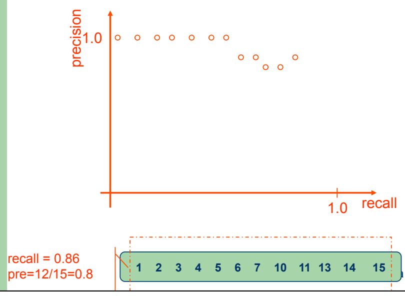
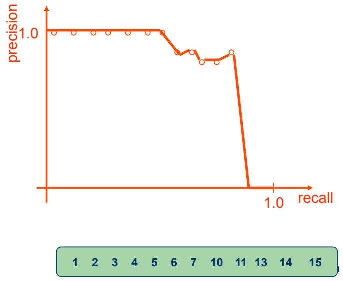
What if we also have rankings in the result???



Precision/recall curve



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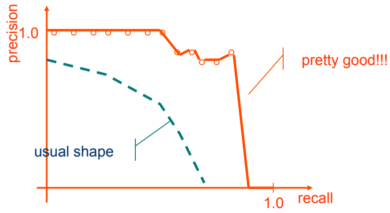

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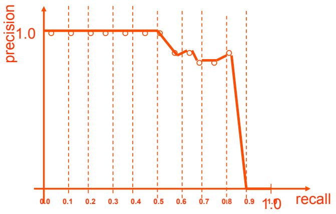

Standard description is with 0.1 increments

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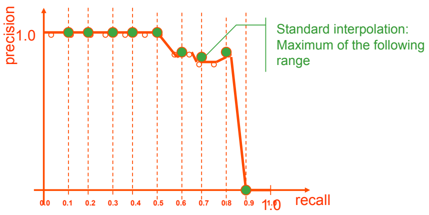
Precision/recall curve



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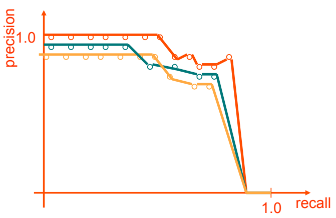
Precision/recall curve



Given multiple queries: we need to take the average behavior!

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Single-value summaries

- R-precision
  - # of relevant documents within first R
  - R is the total number of relevant documents in the result

Single-value summaries

- R-precision
  - # of relevant documents within first R
  - R is the total number of relevant documents in the result
- Example:
  - R = 14
  - # of relevant document in the first 14 is 11

    1 2 3 4 5 6 7 10 11 13 14 15

  - R-precision for this query is 11/14 = 0.876

Harmonic mean

- The harmonic mean of *n* numbers (where *i* = 1, ..., *n*) is

$$\frac{1}{H} \equiv \frac{1}{n} \sum_{i=1}^{n} \frac{1}{x_i}.$$

- Therefore, harmonic mean of x= P and y= R

H(P,R) = 2PR/ (P+R)

Harmonic mean

- The harmonic mean of n numbers (where i = 1, ..., n) is

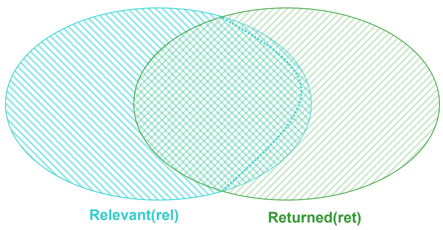
$$\frac{1}{H} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{x_i}.$$

- Therefore, harmonic mean of x= P and y= R

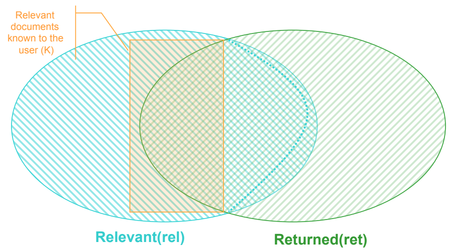
$H(P,R) = 2PR/ (P+R)$

High only when both P and R are high

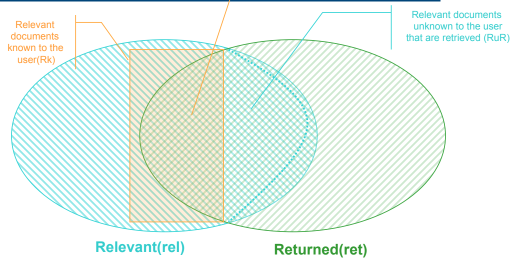
Coverage and Novelty



Coverage and Novelty

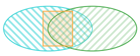


Coverage and Novelty



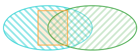
Coverage and novelty

- Coverage



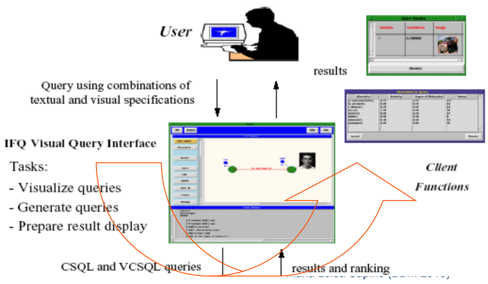
$$\frac{RkR}{Rk}$$

- Novelty

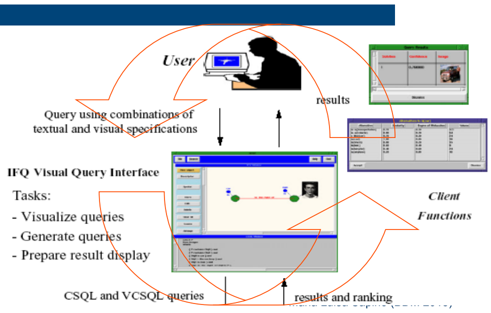


$$\frac{RuR}{RuR + RkR}$$

Relevance feedback



Relevance feedback



Relevance feedback (?)

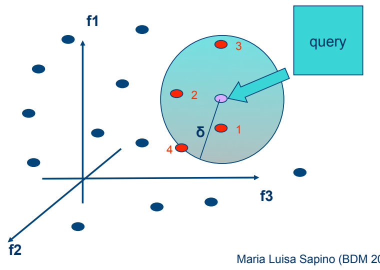
- User submits a query, Q
- System retrieves and ranks a set of objects, S
- User selects a set of relevant (R) and irrelevant (I) objects from S or provides a new ranking
- How can the system improve retrieval results?
  - relevance is subjective
  - distance is objective

Subjectivity vs. objectivity

- *Q*: query
- *R*: event that a document is relevant to the user
- *P(R|Oi)*: given features and weights, the probability that object Oi is relevant to the user
- …then, retrieval is effective iff

$$p(R \mid O_i) > p(R \mid O_j) \Leftrightarrow sim(Q, O_i) > sim(Q, O_j)$$

Query and results



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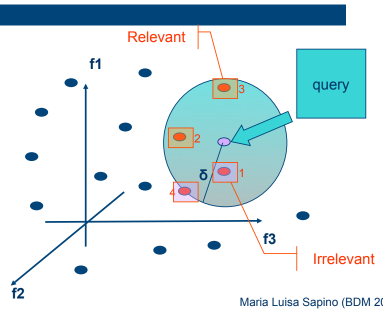
Query and results



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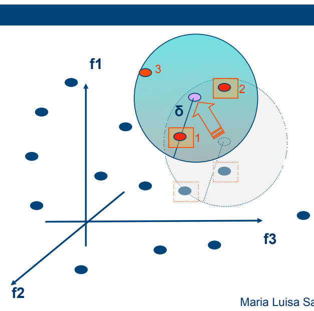
..modify query



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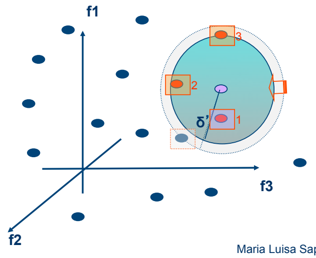
…modify radius



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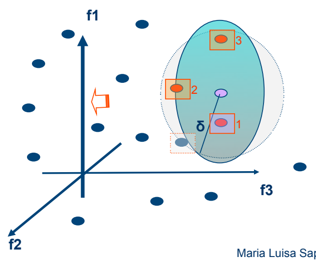
…modify importance (weight) of the features



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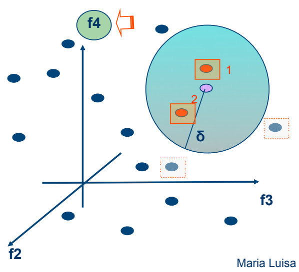
..remove add features



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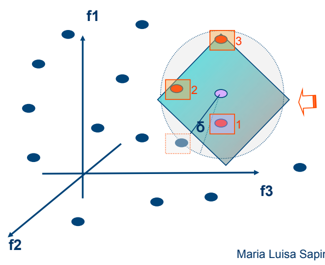
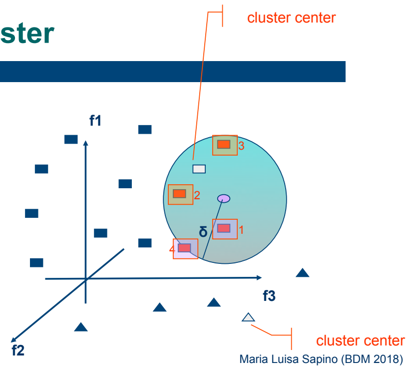
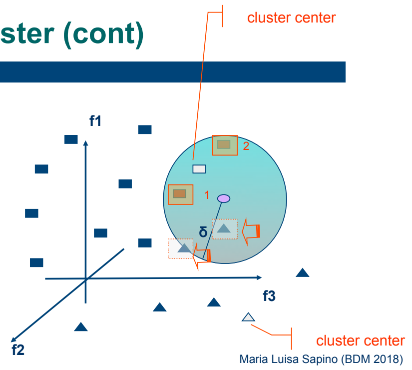
..change the distance measure



..recluster



..recluster (cont)



Basic approach

- An ideal query should separate relevant objects from irrelevant ones

$$sep = \left(\sum_{o_i \in \mathbf{Ir}} dist(Q, o_i) \right) - \left(\sum_{o_i \in \mathbf{Rel}} dist(Q, o_i) \right)$$

should be maximum

Basic approach

- ..assuming linear distance function

$$sep = dist\left(Q, \sum_{o_i \in \mathbf{Ir}} o_i - \sum_{o_i \in \mathbf{Rel}} o_i \right)$$

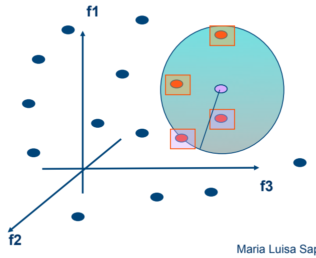
should be maximum

Basic approach

- Move the query
  - closer to the relevant documents and
  - away from irrelevant documents

$$Q' = Q + \left(c_{rel} \times \sum_{o_i \in \mathbf{Rel}} o_i \right) + \left(c_{ir} \times \sum_{o_i \in \mathbf{Ir}} o_i \right)$$

Basic Approach



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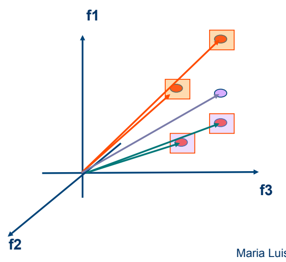
Basic Approach



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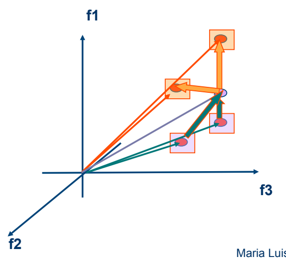
Basic Approach



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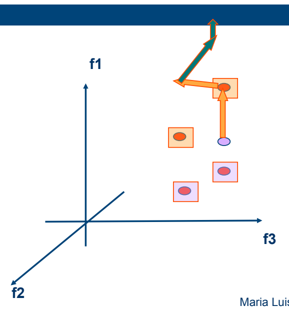

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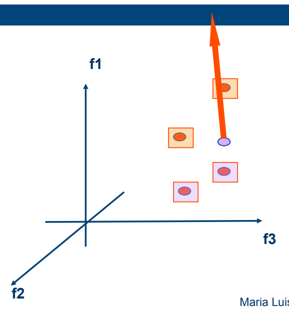
Basic Approach



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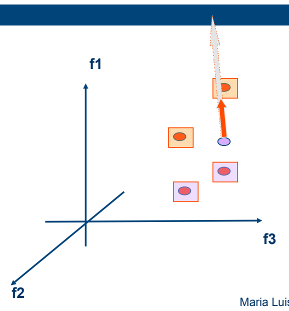
Basic Approach



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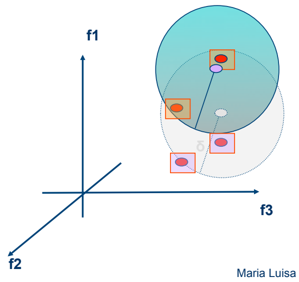
Basic Approach



Feature (term) readjustment

- *Q*: query
- *R*: event that a document is relevant to the user
- *P(R|Oi):* given features and weights, the probability that object o_i is relevant to the user
- Significance of a feature f_k is

$$sig(f_k) = \frac{\log\left(\frac{p(f_k \mid R)}{1 - p(f_k \mid R)}\right)}{\log\left(\frac{p(f_k \mid I)}{1 - p(f_k \mid I)}\right)}$$

Feature (term) readjustment

- *Q*: query
- *R*: event that a document is relevant to the user
- *P(R|Oi):* given features and weights, the probability that object o_i is relevant to the user
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How do we estimate these probabilities

Feature (term) readjustment

- Case I
  - If f_k is not a query term (not used in retrieval)

$$p(f_k \mid R) = p(f_k \mid Retrieved \;\&\; Relevant)$$

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Feature (term) readjustment

- Case II
  - If f_k is a query term (used in retrieval)

$$p(f_k \mid R) \neq p(f_k \mid Retrieved \;\&\; Relevant)$$

  - There would be bias
    - Most retrieved objects will have f_k

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Feature (term) readjustment

- Let us assume binary feature and query
  - $o = \langle f_1, f_2, \ldots f_n \rangle$ f_i = 0 or 1
  - $q = \langle w_1, w_2, \ldots w_n \rangle$ w_i = 0 or 1
- Let us assume dot product as the similarity

$$sim(o,q) = \sum_{i=1}^{n} w_i f_i$$

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Feature (term) readjustment

- If a document is returned, then

$$sim(o,q) = \sum_{i=1}^{n} w_i f_i > T$$

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Feature (term) readjustment

- Let's focus on a specific feature

$$sim(o,q) = w_j f_j + \sum_{i \in \{1..n\} - \{j\}} w_i f_i > T$$

or

$$sim(o,q) = w_j f_j + sim_{(-j)}(o,q) > T$$

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Feature (term) readjustment

$$sim(o,q) = w_j f_j + sim_{(-j)}(o,q) > T$$

	fj=1	fj=0
$sim_{(-j)}(o,q) \leq T$	a	0
$sim_{(-j)}(o,q) > T$	b	c

$$|relevant \,\&\, retrieved| = a + b + c$$

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Feature (term) readjustment

$$p(f_k \mid \text{Ret} \,\&\, \text{Rel}) = \frac{p\big((f_k = 1) \wedge (sim_{(-k)}(o,q) > T)\big)}{p\big(sim_{(-k)}(o,q) > T\big)}$$

Without bias of fk

Feature (term) readjustment

independent

$$p(f_k \mid \text{Ret} \,\&\, \text{Rel}) = \frac{p\big((f_k = 1) \wedge (sim_{(-k)}(o,q) > T)\big)}{p\big(sim_{(-k)}(o,q) > T\big)}$$

⇓

$$p(f_k \mid \text{Ret} \,\&\text{Rel}) = p(f_k = 1)$$

Feature (term) readjustment

independent

$$p(f_k \mid \text{Ret} \,\&\, \text{Rel}) = \frac{p\big((f_k = 1) \wedge (sim_{(-k)}(o,q) > T)\big)}{p\big(sim_{(-k)}(o,q) > T\big)}$$

⇓

$$p(f_k \mid \text{Ret} \,\&\, \text{Rel}) = p(f_k = 1) = p\big(f_k = 1 \mid sim_{(-k)}(o,q) > T\big)$$

Feature (term) readjustment

$$p(f_k \mid \text{Ret \& Rel}) = \frac{p\left((f_k = 1) \wedge \left(sim_{(-k)}(o,q) > T\right)\right)}{p\left(sim_{(-k)}(o,q) > T\right)}$$

$$p(f_k \mid R) = \frac{b}{b+c}$$

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Ranking

- *Q*: query
- *R*: event that a document is relevant to the user
- *P(R|Oi)*: given features and weights, the probability that object oi is relevant to the user
- …then, retrieval is effective iff

$$p(R \mid O_i) > p(R \mid O_j) \Leftrightarrow sim(Q, O_i) > sim(Q, O_j)$$

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Ranking

$$p(R \mid O_i) > p(R \mid O_j) \Leftrightarrow sim(Q, O_i) > sim(Q, O_j)$$

- Let's try to rewrite the first half of the equation using Bayes theorem

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Bayes Theorem

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B)}$$

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Bayes Theorem

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B)}$$

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B \mid A)\, p(A) + p(B \mid \neg A)\, p(\neg A)}$$

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Relevance of two objects

$$p(R \mid O_i) = \frac{p(O_i \mid R)\, p(R)}{p(O_i \mid R)\, p(R) + p(O_i \mid I)\, p(I)}$$

>

$$p(R \mid O_j) = \frac{p(O_j \mid R)\, p(R)}{p(O_j \mid R)\, p(R) + p(O_j \mid I)\, p(I)}$$

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Relevance of two objects

$$\frac{p(O_i \mid R)}{p(O_i \mid I)} > \frac{p(O_j \mid R)}{p(O_j \mid I)}$$

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…so we have

$$\frac{p(O_i \mid R)}{p(O_i \mid I)} > \frac{p(O_j \mid R)}{p(O_j \mid I)} \Leftrightarrow sim(Q,O_i) > sim(Q,O_j)$$

How do we compute these probabilities???

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…so we have

- Let us assume features are independent
  - *o= <f1,f2,…..fn>*
  - *q= <w1,w2,…..wn>*

$$p(O_i \mid R) = \prod_{k=1}^{n} p(f_{i,k} \mid R) \qquad p(O_i \mid I) = \prod_{k=1}^{n} p(f_{i,k} \mid I)$$

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…so we have

- Let us assume features are independent

$$p(O_i \mid R) = \prod_{k=1}^{n} p(f_{i,k} \mid R) \qquad p(O_i \mid I) = \prod_{k=1}^{n} p(f_{i,k} \mid I)$$

$$\frac{p(O_i \mid R)}{p(O_i \mid I)} > \frac{p(O_j \mid R)}{p(O_j \mid I)} \Leftrightarrow \frac{\prod_{k=1}^{n} p(f_{i,k} \mid R)}{\prod_{k=1}^{n} p(f_{i,k} \mid I)} > \frac{\prod_{k=1}^{n} p(f_{j,k} \mid R)}{\prod_{k=1}^{n} p(f_{j,k} \mid I)}$$

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…so we have

- Let us assume features are independent

$$p(O_i \mid R) = \prod_{k=1}^{n} p(f_{i,k} \mid R) \qquad p(O_i \mid I) = \prod_{k=1}^{n} p(f_{i,k} \mid I)$$

$$\frac{p(O_i \mid R)}{p(O_i \mid I)} > \frac{p(O_j \mid R)}{p(O_j \mid I)} \Leftrightarrow \sum_{k=1}^{n} \log \frac{p(f_{i,k} \mid R)}{p(f_{i,k} \mid I)} > \sum_{k=1}^{n} \log \frac{p(f_{j,k} \mid R)}{p(f_{j,k} \mid I)}$$

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…so we have

- Let us assume features are independent
  - use dot product as the similarity measure
  - use $\log \frac{p(f_{i,k} \mid R)}{p(f_{i,k} \mid I)}$ as the weight of the k^{th} feature
  - use *<1,1,1,…,1>* as the query!!!

$$\frac{p(O_i \mid R)}{p(O_i \mid I)} > \frac{p(O_j \mid R)}{p(O_j \mid I)} \Leftrightarrow \sum_{k=1}^{n} \log \frac{p(f_{i,k} \mid R)}{p(f_{i,k} \mid I)} > \sum_{k=1}^{n} \log \frac{p(f_{j,k} \mid R)}{p(f_{j,k} \mid I)}$$

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…what if features are not independent?

- Let us assume features are not independent
  - o= <f1,f2,…..fn>
  - q= <w1,w2,…..wn>

$$p(O_i \mid R) \neq \prod_{k=1}^{n} p(f_{i,k} \mid R) \qquad p(O_i \mid I) \neq \prod_{k=1}^{n} p(f_{i,k} \mid I)$$

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…what if features are not independent?

- Let us assume features are not independent
  - o= <f1,f2,…..fn>
  - q= <w1,w2,…..wn>
- How can we incorporate term dependence???

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…so we have

- Let us assume features are not independent
  - o= <f1,f2,…..fn>
  - q= <w1,w2,…..wn>
- How can we incorporate term dependence???
- Degree of approximation…..

$$I(p1, p2) = \sum_x p1(x) \log \frac{p1(x)}{p2(x)}$$

  - *p1=p2* implies that *I=0*
  - *p1<>p2* implies that *I>0*

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…so we have

- Degree of approximation…..

$$I(p1, p2) = \sum_x p1(x) \log \frac{p1(x)}{p2(x)}$$

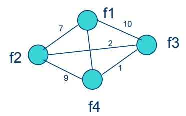
  - *p1=p2* implies that *I=0; p1<>p2* implies that *I>0*

- Degree of dependence between f_i and f_j

$$D_{ij} = I\left(p(f_i \wedge f_j), p(f_i)p(f_j)\right)$$

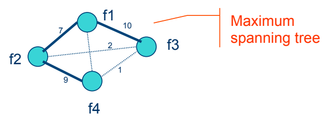
If the two terms are independent, then *Dij* will be 0!!!

Dependence graph



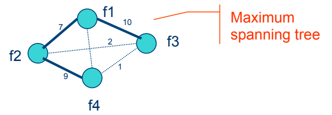
If the two terms are independent, then *Dij* will be 0!!!

Dependence graph



If the two terms are independent, then *Dij* will be 0!!!

Dependence graph



$$p(f_1 \wedge f_2 \wedge f_3 \wedge f_r) = p(f_1)p(f_2 | f_1)p(f_3 | f_1)p(f_4 | f_2)$$

If the two terms are independent, then *Dij* will be 0!!!

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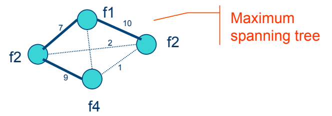
Dependence graph



$$p(f_1 \wedge f_2 \wedge f_3 \wedge f_r) = p(f_1)p(f_2 | f_1)p(f_3 | f_1)p(f_4 | f_2)$$

$p(O_i | R)$ can be computed using the distribution of the features in *R*!!!

$p(O_i | I)$ can be computed using the distribution of the features in *I*!!!

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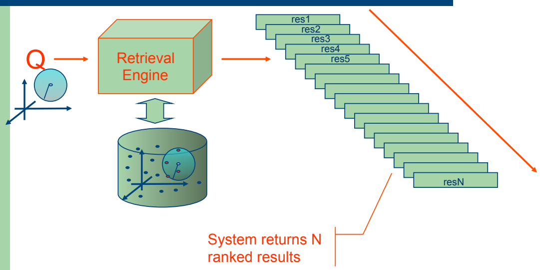
Feedback without user's help..



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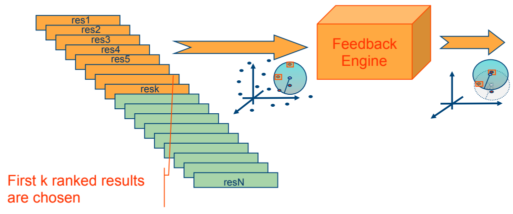
Feedback without user's help..



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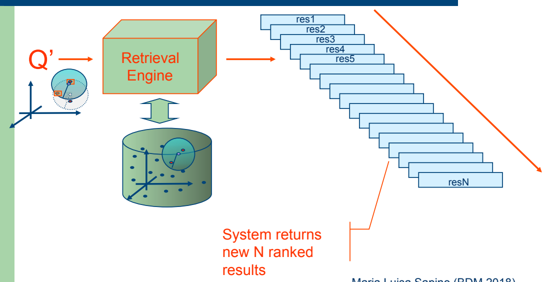
Feedback without user's help..



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