

Searcher's Feedback Quality and Effort in Interactive IR: A Simulation based on User Models

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Outline

1. Why simulate interaction?
2. User models
3. Effects of quality and quantity of RFB
4. Conclusion & Future Work

Are system adaptation possibilities identified?

Why Simulate Interaction?

- ❖ Real interactive RFB tests:
 - experimental system + control system
 - 8, 16, 32 ... test searchers (\$\$\$)
 - 4, 8, 16 test topics (hardly more)
 - Latin Square design to fight learning effects
 - e.g. 20 min per searcher & topic
 - rerun = new topics or test persons
 - provides nearly real and rich data
 - but not necessarily recommendations

Why Simulate Interaction?

❖ Simulated RFB tests:

- any number of systems / modifications
- easily any number of test searchers
- easily any number of test topics
- no learning effects
- full test cycle = less than a day
- rerun = just do it
- data: if it only was real ...
 - may gain evidence for recommendation on optimal adaptive behaviour

= what would happen if the users would behave as simulated? Can we advice them suitably?

User Models for RFB

- ❖ Simulation requires a user model that represents assumptions about relevant aspects of searcher behavior w.r.t RFB
- ❖ Obvious candidates:
 - relevance requirement by the searcher
 - value of relevance - tolerance of non-relevance
 - willingness to browse initial results
 - willingness to provide FB
 - level of topic understanding - consistency of FB

A Simple User Model Example

Model $M = \langle R, B, F \rangle$

- ❖ Relevance threshold R to accept a document as FB document: $R \in \{0, 1, 2, 3\}$
- ❖ Browsing window size: at most B top documents are browsed: $B \in \{1, 5, 10, 30\}$
- ❖ Feedback set size: at most F feedback documents are collected: $F \in \{1, 5, 10, 30\}$

All variables \rightarrow yield many *searcher scenarios*

Quality and Quantity of RFB

❖ ECIR'06

❖ Background:

- Users might wish to find especially highly relevant documents (Kekäläinen & Järvelin)
- Users are able to identify highly relevant documents (Sormunen & Vakkari)
- In highly relevant documents ... (Sormunen & al.)
 - a larger share of aspects of the request topic is discussed
 - a larger set of unique expressions is used

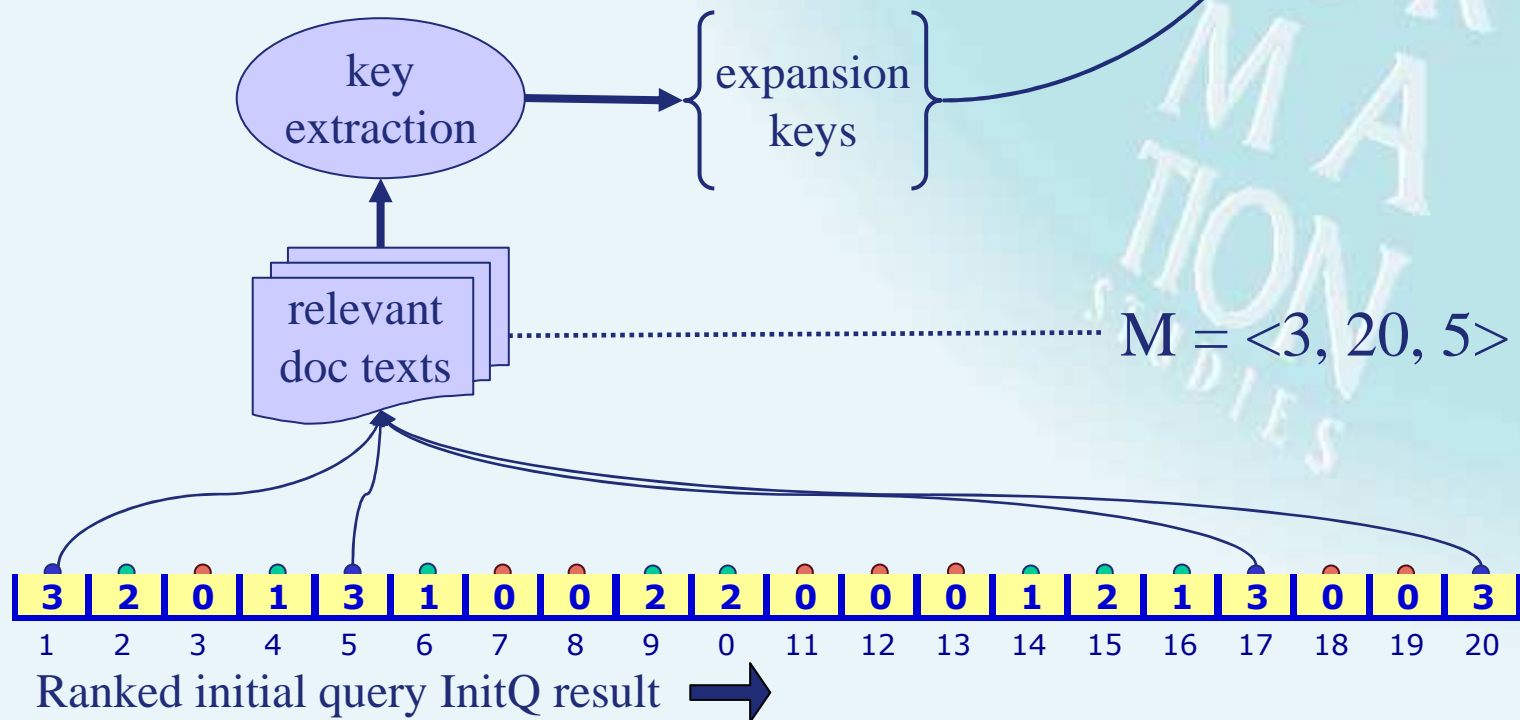
Quality and Quantity of RFB

❖ Research questions:

- How is the quality and quantity of RF related to search effectiveness?
- How effective is RF when we consider relevance levels in evaluation?
- How effective is RF compared to pseudo RF?

Basic Feedback Model Ex

$$FBQ = \#sum(\#sum(InitQKeys) \#sum(ExpansionKeys))$$



Liberal Evaluation (MAP (%), N=41, TREC). Baseline MAP=20.7%

Good RFB not competitive

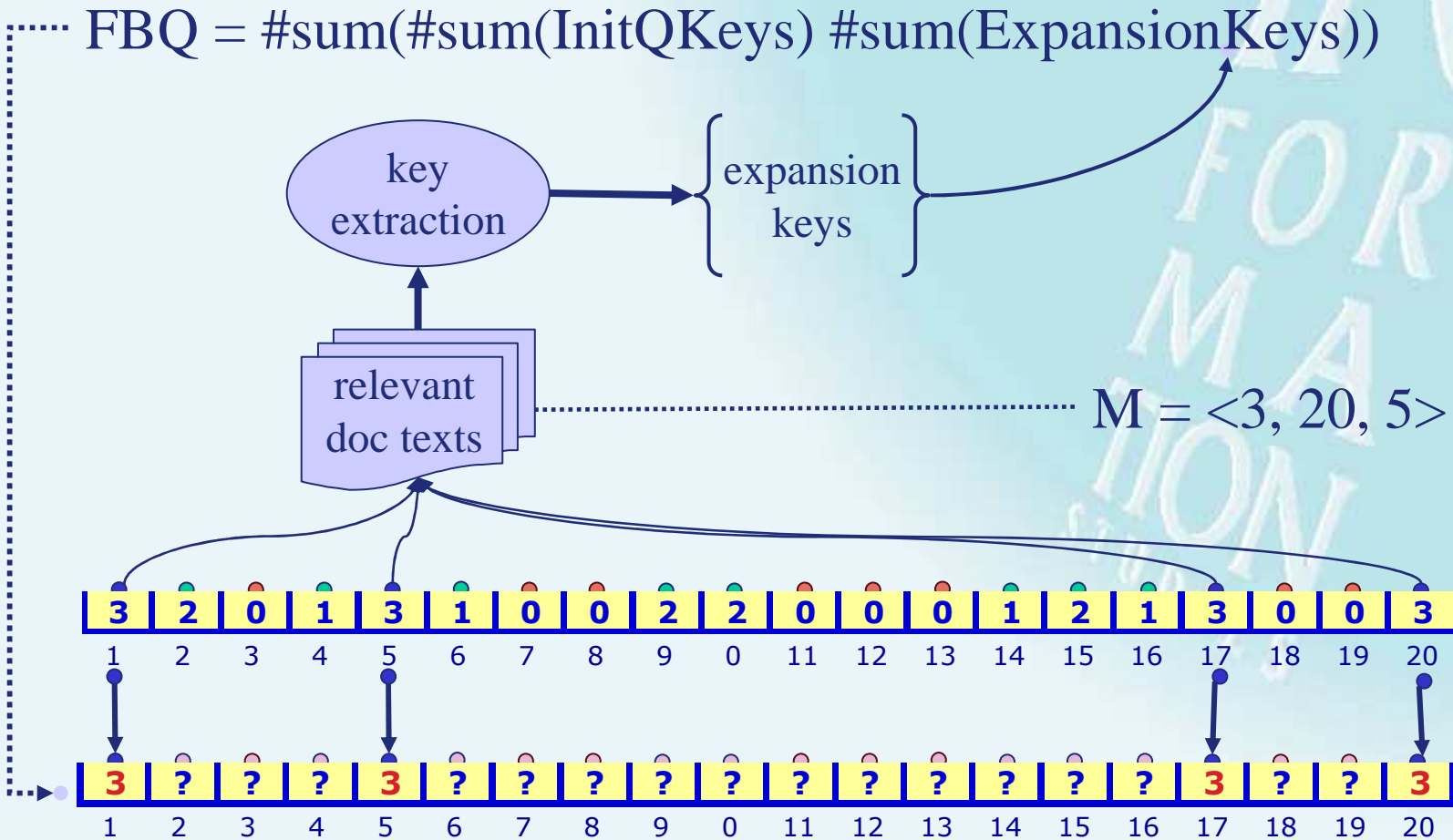
Browse window B	Feed-back set F	Stringent feedback criterion R=3	Diff. to baseline (% units)	Regular feedback criterion R≥2	Diff to baseline (% units)	Liberal feedback criterion R≥1	Diff. to baseline (% units)
30	30	26.5	+5.8	29.5	+8.8	30.2	+9.5
30	10	26.5	+5.8	29.4	+8.7	30.1	+9.4
30	5	26.6	+5.9	28.6	+7.9	28.7	+8.0
30	1	24.4	+3.7	24.2	+3.5	24.0	+3.3
1	1	21.6	+0.9	22.5	+1.8	22.9	+2.2

Stringent Evaluation (MAP (%), N=41, TREC). Baseline MAP=20.2%

Liberal RFB spoils the effect

Browse window B	Feed-back set F	Stringent feedback criterion R=3	Diff. to baseline (% units)	Regular feedback criterion R≥2	Diff to baseline (% units)	Liberal feedback criterion R≥1	Diff. to baseline (% units)
30	30	37.5	+17.3	27.1	+6.9	24.9	+4.7
30	10	37.5	+17.3	27.1	+6.9	24.9	+4.7
30	5	36.9	+16.7	27.5	+7.3	23.9	+3.7
30	1	31.7	+11.5	23.3	+3.1	22.6	+2.4
1	1	20.8	+0.6	21.6	+1.4	22.0	+1.8

Feedback with Freezing Ex.



Ranked RB query result with seen relevant documents frozen to their ranks →

Stringent Evaluation (MAP (%), N=41, TREC). Baseline MAP=20.2%

Browse window B	Feed-back set F	Stringent feedback criterion R=3	Diff. to baseline (% units)	Regular feedback criterion R≥2	Diff to baseline (% units)	Liberal feedback criterion R≥1	Diff. to baseline (% units)
30	30						
30	10						
30	1	27.7	+7.5				
30	1	31.7	+11.5				
1	1						

with freezing

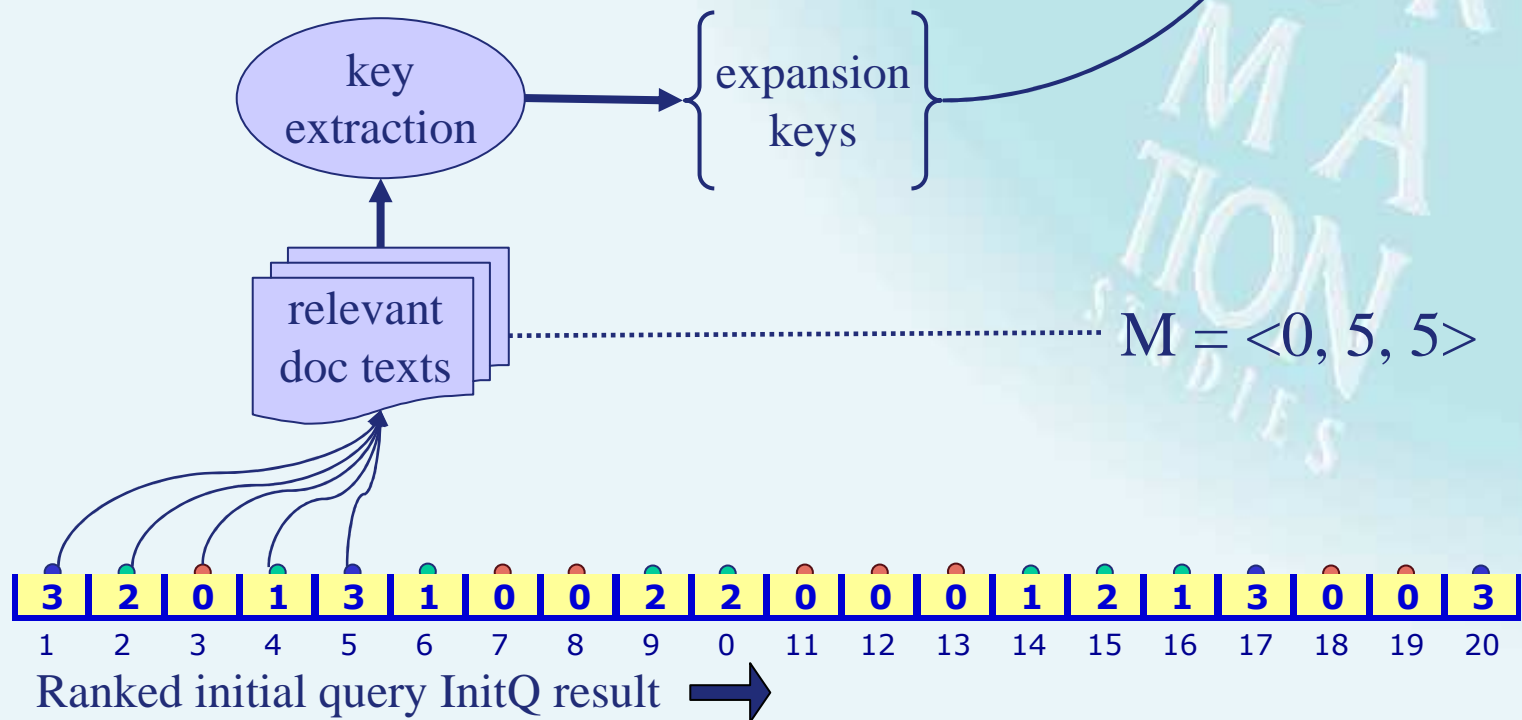
no freezing

Pseudo Relevance Feedback

- ❖ No user interaction after initial search
- ❖ The first N results are assumed relevant
- ❖ Their index features are used to revise the original query
- ❖ Evaluated PRF at three relevance thresholds (stringent, regular, liberal)

Pseudo RFB Model Example

$$\text{FBQ} = \# \text{sum}(\# \text{sum}(\text{InitQKeys}) \# \text{sum}(\text{ExpansionKeys}))$$



Pseudo RFB

- ❖ 1, 5, 10 or 30 top-docs used for feedback; baseline MAP 20.2%
- ❖ Stringent, regular and liberal evaluation levels
- ❖ Results clearly dependent on evaluation stringency

PRF Top B docs	PRF MAP (%) Stringent Eval	Diff. to baseline (% units)	PRF MAP (%) Regular Eval	Diff to baseline (% units)	PRF MAP (%) Liberal Eval	Diff. to baseline (% units)
30	19.8	-0.4	25.1	+2.4	24.2	+3.5
10	19.5	-0.7	25.8	+3.1	24.5	+3.8
5	21.2	+1.0	25.8	+3.1	24.1	+3.4
1	22.0	+1.8	25.3	+2.6	22.8	+2.1

Conclusions

When liberal relevance threshold is used in evaluation:

- ❖ A small number of highly relevant FB documents did not outperform several mixed quality FB documents
- ❖ Even if high-quality FB would be given, its effects remain unseen

Conclusions 2

When stringent evaluation criterion is used in evaluation:

- ❖ relevance threshold for RF documents should be kept high
- ❖ lots of mixed quality RF documents distort the RFB effect of highly relevant documents among them

Conclusions 3

- ❖ PRF improved effectiveness when liberal evaluation criteria were used - by a typical percentage - but not with stringent evaluation
- ❖ PRF adds marginal documents – is this what we want?
- ❖ Are we missing possibilities for useful query/system adaptation?

Further Work

- ❖ 1. How can negative RFB be applied in interactive IR with graded judgments?
- ❖ 2. How effective is negative RFB in a graded assessment environment?
- ❖ 3. How does user's domain knowledge / consistency affect RFB
- ❖ An extended user model developed

Thank you!

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