

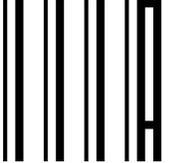
On the Effectiveness of Query Variation in Technology-Assisted Review Systems



UNIVERSITÀ
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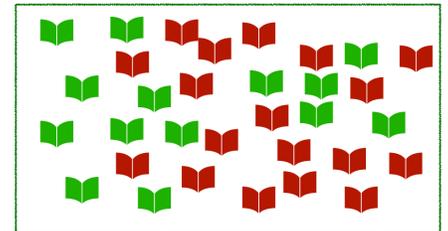
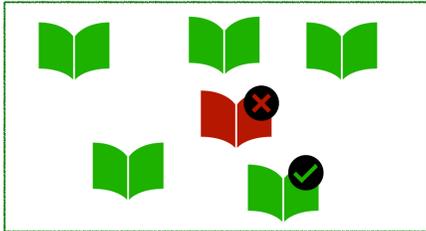
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Problem: Systematic Reviews

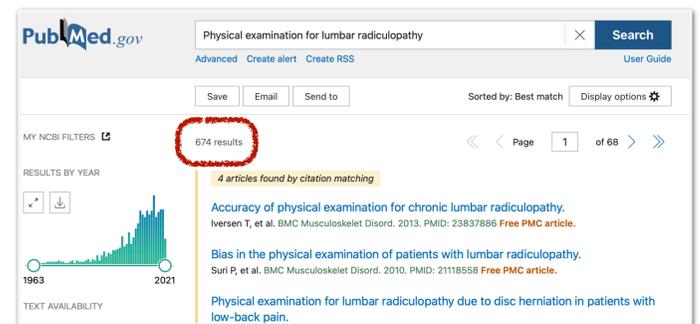
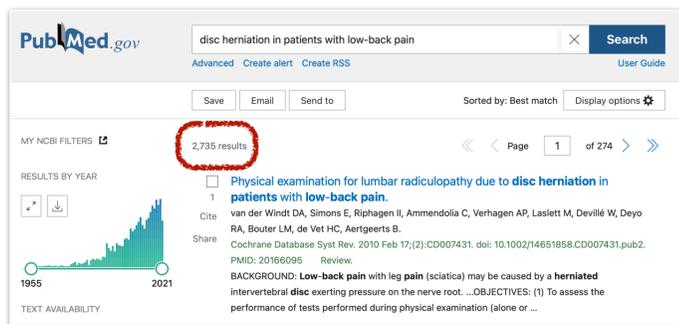
High-recall Information Retrieval systems require the finding of all the relevant pieces of information in a collection.

A few "good" documents

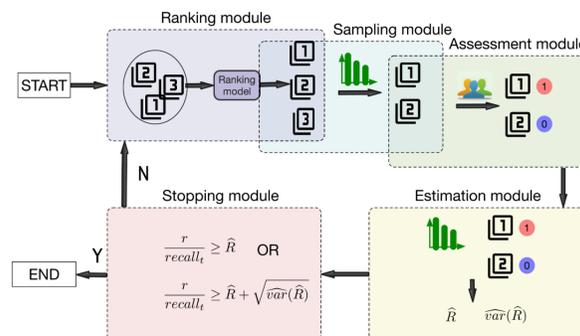
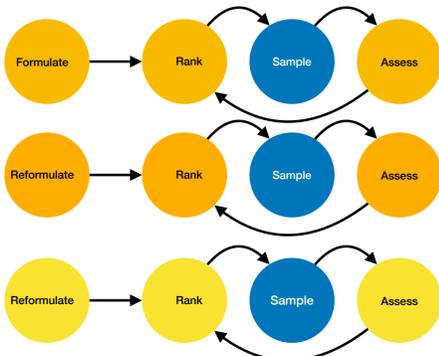


All the good documents with some "bad" ones

Try Query Variants to Find Missed Relevant Document



When to Stop/Continue the Query Reformulation/Review



Li, D., Kanoulas, E. TOIS 2021
When to Stop Reviewing in Technology-Assisted Reviews:
Sampling from an Adaptive Distribution to Retain Residual Relevant Documents

Umemoto, K., Yamamoto, T., Tanak., K. SIGIR 2016
ScentBar: A Query Suggestion Interface Visualizing
the Amount of Missed Relevant Information for Intrinsically Diverse Search

Experimental Results

Automatic Query Reformulations using Knowledge Bases

Table 2: Retrieval performances of the considered models on the TREC PM 2019 Clinical Trials task. Median refers to the average median values of the Scientific Literature task and it is computed considering all the runs submitted to the task. Bold values represent the highest scores among models and median.

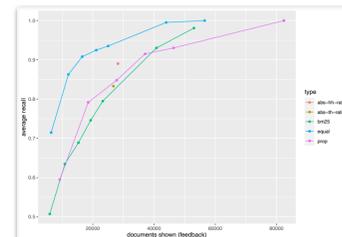
	P@10	infNDCG	Rprec
base	0.5053	0.6186	0.4337
neop/reduced	0.5237	0.5755	0.4135
solid/original	0.5368	0.6239	0.4386
solid/reduced	0.5316	0.5940	0.4264
qrels/combined	0.5342	0.5706	0.4381
median	0.4658	0.5137	0.3477

Table 3: Retrieval performances of the considered models on the TREC PM 2019 Scientific Literature task. Median refers to the average median values of the Scientific Literature task and it is computed considering all the runs submitted to the task. Bold values represent the highest scores among models and median.

	P@10	infNDCG	Rprec
base	0.5125	0.4747	0.2977
neop/original	0.5150	0.4645	0.2982
neop+comd/original	0.5125	0.4636	0.2964
neop+gnm/original	0.5050	0.4740	0.2999
qrels/combined	0.5075	0.4665	0.2986
median	0.5450	0.4559	0.2806

Marchesin, S., Di Nunzio, G. M., Agosti, M. MDPI Information 2021
Simple but Effective Knowledge-Based Query Reformulations
for Precision Medicine Retrieval

Manual Query Reformulation with Continuous Active Learning



run	recall@k	recall doc shown
equal-11000	0.28	0.94
equal-1600	0.28	0.91
abs-hi-ratio	0.46	0.89
prop-1600	0.28	0.85
abs-th-ratio	0.43	0.83
bmg25-11000	0.18	0.79

Table 2: Best performing runs. Averaged recall at k and recall are shown together with the total number of documents shown (for relevance feedback). The two runs by [15], abs-hi-ratio and abs-th-ratio, are reported for comparison.

Di Nunzio, G. M. ECIR 2018
A Study of an Automatic Stopping Strategy for
Technologically Assisted Medical Reviews

Automatic Prediction of Query Variants Performance

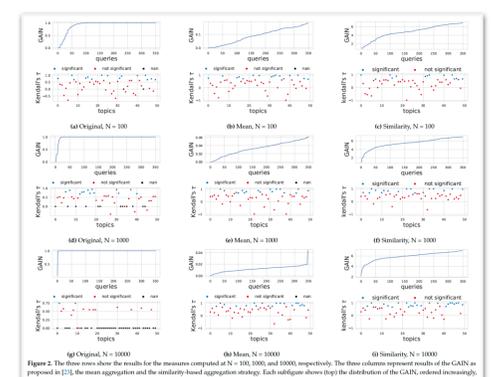


Figure 2: The three rows show the results for the measures computed at N=100, 1000, and 10000, respectively. The three columns represent results of the GAIN as proposed in [15], the mean aggregation and the similarity-based aggregation strategy. Each subfigure shows (top) the distribution of the GAIN, ordered increasingly, of the 100 queries and (bottom) correlation between the information ordered by predicted GAIN (or similarity) and the information ordered by the true recall.

Di Nunzio, G.M., Faggioli, G., MDPI Applied Sciences 2021
A Study of a Gain Based Approach for
Query Aspects in Recall Oriented Tasks