Learning to Rank from Relevance Feedback

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- We improve search result ordering beyond that achieved when using only query expansion
- Success depends on how we extract features
- And on how we request document judgements

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- Background
- Method
- Experiments and Results
- Conclusions

Motivation: Learn from Users

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Search is interactive, let's learn from this

- Interaction is especially useful for difficult search tasks
- But providing explicit feedback is costly for the user
- We must use the feedback we receive well

Overarching Research Question

How can a system that is aware of the interactive nature of search exploit this interactivity to better serve the user's needs?

Background: Learning to Rank from *Relevance Feedback*

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The Rocchio Algorithm and its Discontents

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- Combines an initial query, a positive contribution from relevant documents, and a negative contribution from non-relevant documents
- Judged documents only affect ordering through the expanded query
- Negative feedback is often ignored because it is hard to use
- But negative feedback is found to be especially beneficial for difficult queries (Wang and Wang et al.)

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- To make better use of judged documents
- We use feedback in both learning to rank and query expansion
- To avoid the problems of negative feedback
- We use non-relevant documents in learning to rank, not query expansion

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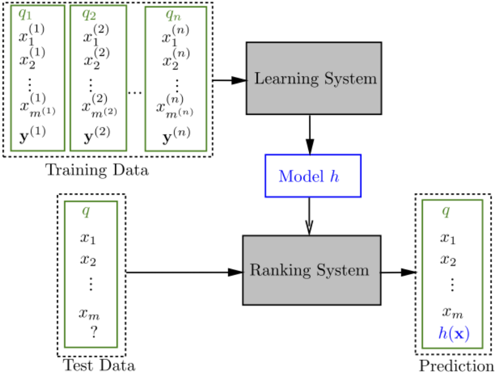

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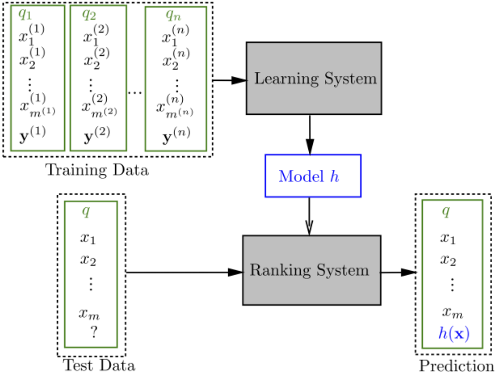

- Extract feature vectors from data

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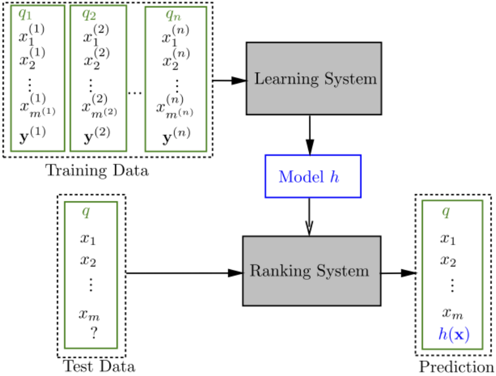

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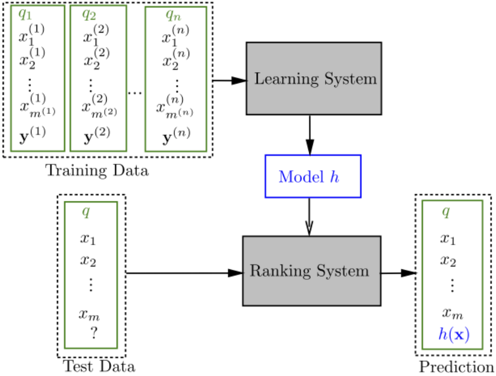

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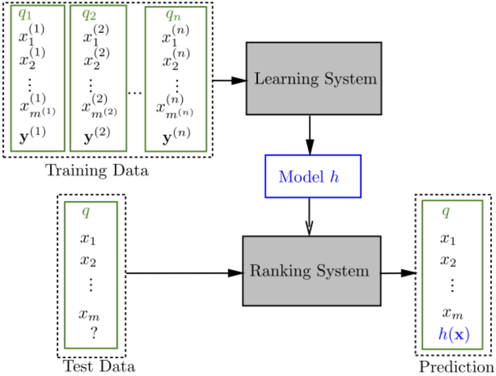

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- Use this model to predict the relevance of unlabeled test data
- Sort documents by their predicted relevance

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Minimize Incorrectly Ordered Pairs

- Using feature vectors for documents in the preference pair set
- Calculate a weight vector over features
- Score unlabeled documents using this weight vector

Background: A Difficult Recall Oriented Task

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e-Discovery and TREC Legal

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- Learning is important, previous TREC Legal participants' systems benefit substantially from incorporating feedback
- We can simulate feedback by using already judged documents

Method Overview

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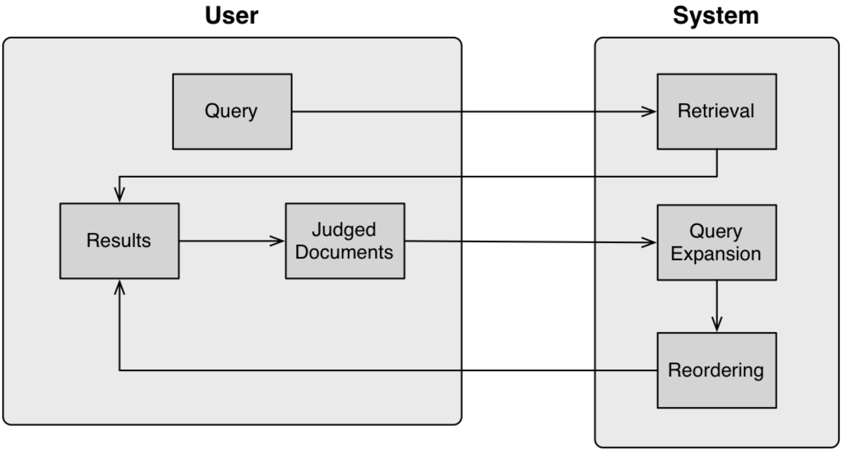

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- Close to the way documents are judged in a real-life search system
- Biases judged documents towards those ranked higher

How to Request Judgements: Random Seeds

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- Randomly sample from the set of informative documents
- Same document set as in exploitative sampling
- No rank based bias

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The input to the *cumulative* feature extractor $\mathbf{\Phi}$ will be:

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Features are the retrieval scores for the same set of judged documents but using different numbers of expansion terms

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- How do we represent documents for learning?
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  2. Constant: retrieval scores with different numbers of expansion terms
  3. Term frequency: vector space model

Learning to Rank improves Query Expansion

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Random Seeds and Constant Features

Metric	Baseline	Expansion	Learning
MAP	0.0674	$^{\triangle}$0.130	$^{\triangle}$**0.137**
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Learning to Rank improves Query Expansion

*By combining traditional query expansion with learning to rank,
a search system can use the interactive nature of search
to better serve the user's needs.*

How to Best Learn from Documents

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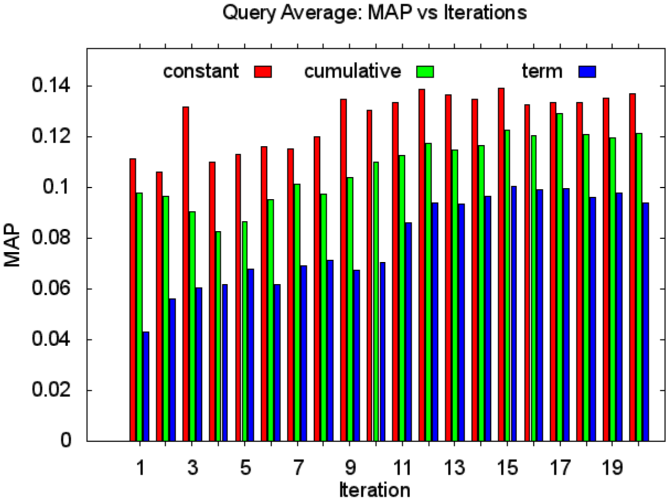
Experiment

- Compare evaluation scores when using different feature spaces
- Compare evaluation scores when using different strategies to choose documents for judgement

Retrieval score features outperform term frequency features when using random sampling



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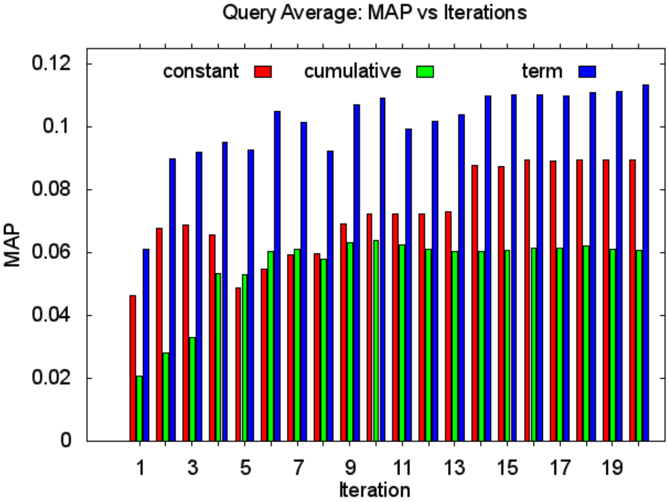
- Content of low ranked documents may be uninformative

Term frequency features outperform retrieval score features for exploitative sampling



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- *frequency*(top five terms in exploitative sampled documents) $= 5 \times$ *frequency*(top five terms in random sampled documents)

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- Our method combines learning to rank and query expansion
- This improves search result ordering beyond no expansion and beyond using only query expansion
- Both constant and term frequency features can improve ordering
- TREC Legal is not significantly different from other search task, such as ad-hoc web page search
- Our method's improvement in scores may be a general result that will apply to other corpuses

Future Work

- Design a better hybrid method

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- Design a better hybrid method
- Apply to additional corpora

Questions?