Toward Search Engines Optimized for Human Learning

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Abstract

While there is strong evidence of people using Web search for learning new topics, most popular Web search engines optimize for relevance, not learning intents. This can result in irrelevant documents and inefficient learning process.

We develop the first framework for learning-oriented information retrieval through general Web search. Through a two-stage process, we greedily select a set of documents specifically geared towards improving learning efficiency in search.

We demonstrate significant improvement over a commercial search baseline through crowdsourced user study: **over 200% more** learning gains per word read. We further show improvements in non-normalized learning gains **of about 15%.**

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Introduction

Most existing Web search engines are still optimizing results for generic relevance, but there is very strong evidence that many people use Web search for learning. As such, a model is needed to optimize document selection with learning utility as the success criteria.

In this study, we developed a framework for learning-oriented Web search. Document selection was done through a two-step optimization problem and we ran a user study to evaluate its effectiveness.

We address three fundamental Research Questions:

- **RQ 1.** Does learning-optimized retrieval framework offer higher learning effectiveness or efficiency compared to traditional retrieval results of a baseline commercial Web search engine?
- **RQ 2.** Do personalized search results that account for a user's prior knowledge improve learning effectiveness or efficiency?
- **RQ 3.** How do learning effectiveness and efficiency vary across different topics (information needs) in different domains?

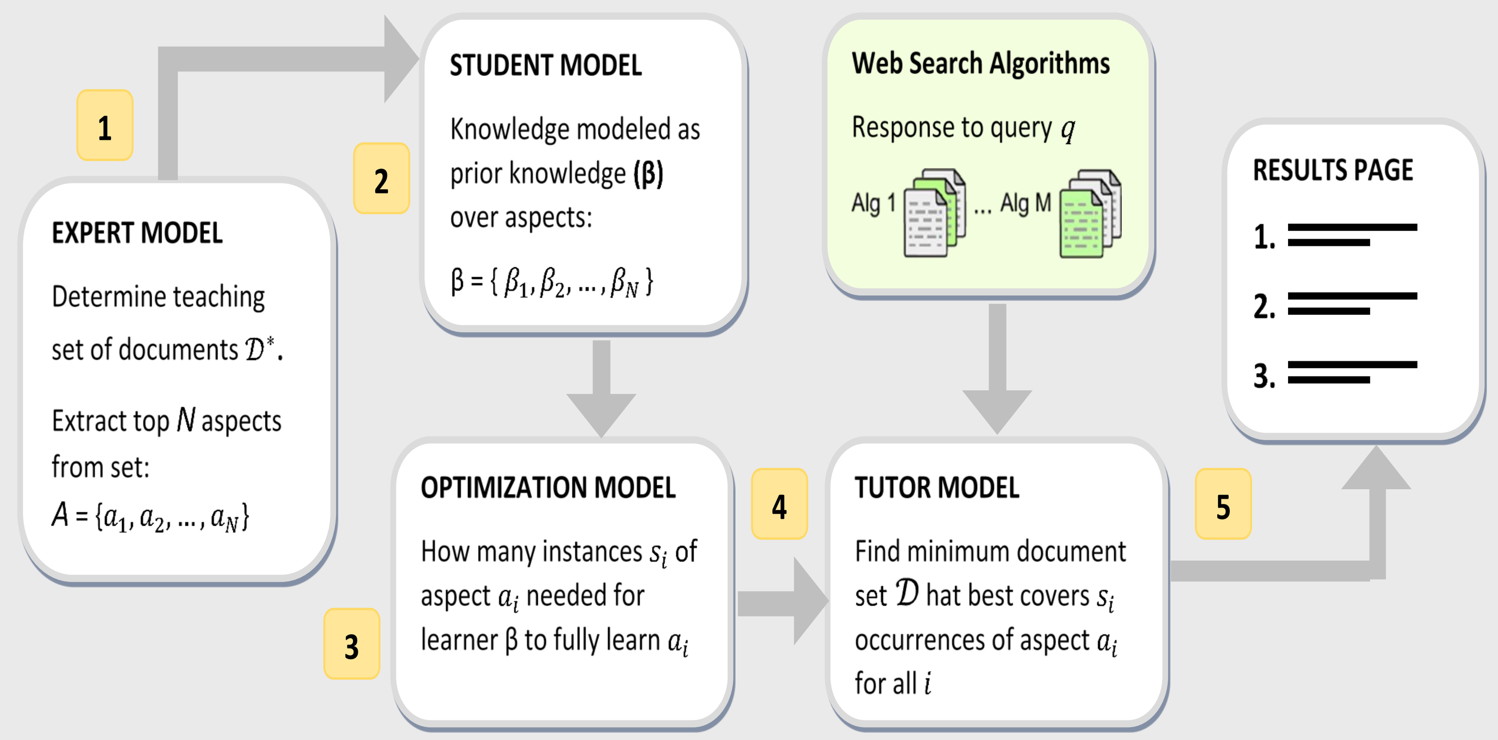
Methodology

We used a multi-stage sequential framework to select the set of documents. The framework has the following four stages:

1. **Expert model.** In this stage, we determine the top N keywords that are most relevant to a particular topic and select these as keywords that the user needs to learn.
2. **Student model.** In this stage, we assess the user's prior knowledge of each of those N keywords. We use a binary representation (i.e. 1 if keyword is known, 0 otherwise).
3. **Optimization Phase 1.** Now, we estimate what the user's knowledge state will be for each keyword after seeing S_k # of instances of keyword k. Given a finite effort penalty, we determine how many total S_k instances user should see for each k to have efficiently learned the definition.
4. **Optimization Phase 2.** Iteratively add documents to the result set, giving preference to those with higher coverage of keyword terms and easier vocabulary difficulty. Terminate when all S_k instances have been covered.

Model Framework

Solve: $$\arg\max_{\mathcal{D}} U(\mathcal{D}) = H(\mathcal{D}) - \lambda E(\mathcal{D})$$



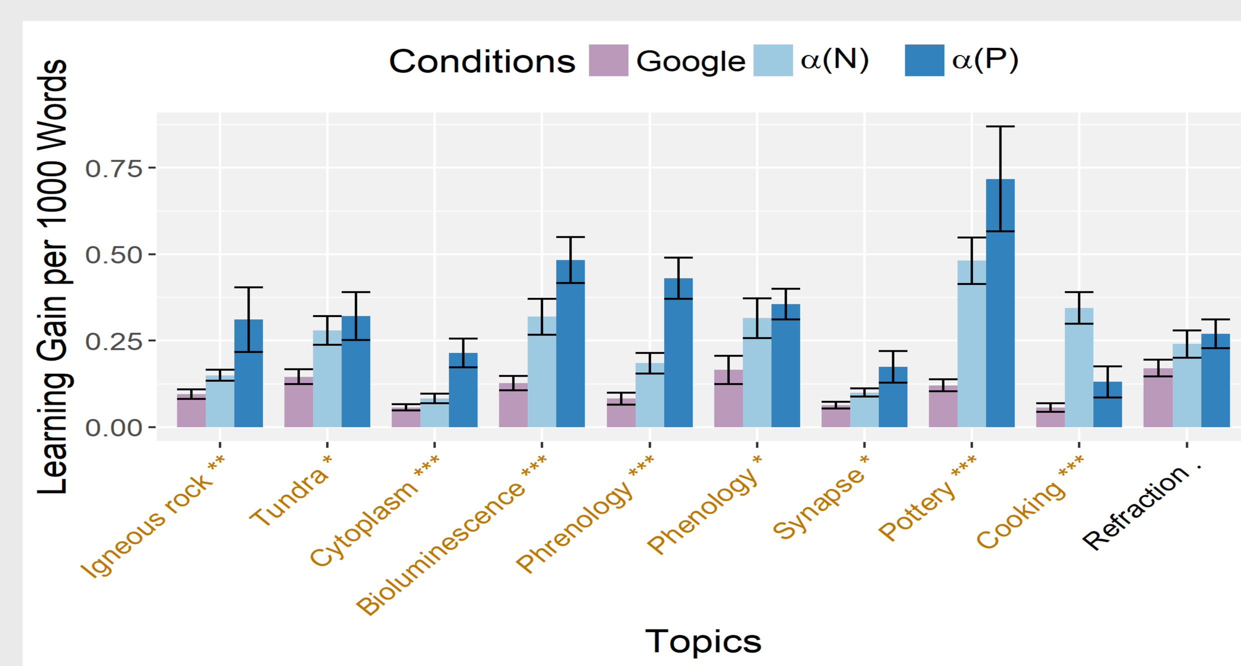
Results

Evaluated learning outcomes from three retrieval models through a crowdsourced user study. There were 10 topics total, each with 10 keywords to learn and 40 participants per <topic, model> combination.

Personalized model showed substantial improvement over commercial search baseline:

- Over 15% higher overall Learning gains.
- Over 200% higher Learning gains per word seen

Measure	Web (n=290)	Non-Personalized (n=290)	Personalized (n=283)	p-value
Absolute Learning Gains	1.72	1.83	**1.98**	p=.046
Realized Potential Learning	0.38	0.43	**0.47**	p=.008
Learning Gains/ 1000 Words	0.11	0.25	**0.35**	p<.001



Discussion

In evaluating our three Research Questions, we found the following general results:

RQ 1 Supported: We found strong evidence that our approach outperformed a commercial baseline.

RQ 2 Supported: On average, personalization improved learning gains and efficiency more than non-personalized.

RQ 3 Partially Supported: We found consistent evidence of better learning *efficiency* across topics but not learning *effectiveness.*

Applications

- Learning-to-rank systems for educational query intents
- Personalized search under effort constraints
- Extend beyond vocabulary learning to other forms.

Conclusions

1. Introduced novel retrieval framework to optimize search as learning
2. Demonstrated improvements in learning effectiveness and efficiency through user study
3. Many possible directions for extensions and improvements

References

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