Integrating Conceptual Knowledge into Relevance Models

A Model and an Estimation Method

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Outline

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Vocabulary Gap

- A user has an information need and formulates a query
- But: not all (relevant) documents use the same term(s)
  - Different documents may contain different terms to denote a single *concept*
  - Others may even denote different *concepts* with the same term
- Solution: perform query enrichment/expansion
  - Use *conceptual* knowledge
  - Use terms from an initial result set
- **How can we combine these?**

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Research Questions

1. How can we use a language modeling framework to combine conceptual knowledge with pseudo-relevance feedback in a principled and transparent fashion?
2. Can our model compete with state-of-the-art approaches ?

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Generative Language Models

- Query-likelihood approach:

$$P(d|Q) \propto P(d) \cdot \prod_{q \in Q} P(q|\theta_d)$$
$$\propto \prod_{q \in Q} \frac{c(q,d)}{|d|}$$

- With Dirichlet smoothing:

$$P(d|Q) \propto \prod_{q \in Q} \frac{c(q,d) + \mu P(q|\theta_C)}{|d| + \mu}$$

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Query Models

- Generative language modeling assumes that queries are generated from documents
- Difficult to incorporate relevance feedback information
  - It's unclear how the likelihood of an "expanded query" is to be computed (as well as interpreted)
  - It's even harder to allow different query terms to have different weights
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Query Models

- Ranking then comes down to calculating the *distance* between $P(w|\theta_Q)$ and $P(w|\theta_d)$ for $w \in V$
- E.g. using the KL-divergence

$$D_{kl}(\theta_Q||\theta_d) = \sum_w P(w|\theta_Q) \cdot \log \frac{P(w|\theta_Q)}{P(w|\theta_d)}$$

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Relevance Models

- Relevance modeling assumes both the query and the document are generated from an unseen source—a relevance model
- A set of documents R is used as a model from which terms are "sampled":

$$P(w|\hat{\theta}_Q) \propto P(w) \cdot \prod_{q \in Q} \sum_{d \in R} P(q|\theta_d) \cdot P(\theta_d|w)$$

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Our Algorithm

Our algorithm assumes every document is annotated with one or more *concepts*

- tags
- classifications/classes
- thesaurus terms

Our Algorithm: Three Steps

1. Determine the concepts most closely associated with a query
2. Look at the documents associated with these concepts, in conjunction with the query, to establish a *conceptually-biased* (or thesaurus-biased) relevance model
3. Interpolate the original query model with the found terms

Determining Concepts

For a given query Q, rank the concepts $m \in M$ according to:

$$\begin{aligned} P(m|Q) &= \frac{P(m) \cdot P(Q|m)}{P(Q)} \\ &= P(m) \cdot \sum_{d} P(Q|d) \cdot P(d|m) \end{aligned}$$

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Estimating a Thesaurus-biased Model

- Then, estimate a thesaurus-biased relevance model by incorporating the top-l thesaurus terms
- Assuming the thesaurus terms $m_1, \ldots, m_l$ to be independent, we obtain

$$\begin{aligned}
& P(w|\hat{\theta}_Q) \\
& \quad \propto \quad P(w) \cdot \prod_{q \in Q} \sum_{d \in R} P(q|\theta_d) \cdot P(w|\theta_d) \cdot P(m_1, \ldots, m_l|\theta_d) \\
& \quad \propto \quad P(w) \cdot \prod_{q \in Q} \sum_{d \in R} P(q|\theta_d) \cdot P(w|\theta_d) \cdot \prod_{i=1}^{l} P(d|m_i) \cdot P(m_i)
\end{aligned}$$

Interpolating the Original Query Model

- Finally, the found model is interpolated with the original query (using a mixing weight λ) to yield the final query model

$$P(w|\theta_Q) \quad = \quad \lambda \cdot P(w|\tilde{\theta}_Q) + (1-\lambda) \cdot P(w|\hat{\theta}_Q),$$

where

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Estimating λ

- To find λ, we approximate the query model space using (pseudo-)relevant documents
- The log of the likelihood of observing these terms is:

$$\log P(w_1, \ldots, w_n|\theta_Q, \lambda) = \sum_i \pi_i \prod_{j=1}^{n} \log \left(\lambda P(w_j|\tilde{\theta}_{q_i}) + (1-\lambda)P(w_j|\hat{\theta}_{q_i})\right)$$

- Then, use the EM algorithm to find λ which maximizes this loglikelihood:

$$\lambda^* = \arg\max_{\lambda} \log P(w_1, \ldots, w_n|\theta_Q).$$

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Update formulas:

$$\pi_i^{k+1} = \frac{\pi_i^k \prod_{j=1}^n \left(\lambda^k P(w_j|\tilde{\theta}_{q_i}) + (1-\lambda^k) P(w_j|\hat{\theta}_{q_i}\right)}{\sum_{i'} \pi_{i'}^k \prod_{j=1}^n (\lambda^k P(w_j|\tilde{\theta}_{q_{i'}}) + (1-\lambda^k) P(w_j|\hat{\theta}_{q_{i'}})}$$

$$\lambda^{k+1} = \frac{1}{n} \sum_i \pi_i^{k+1} \sum_{j=1}^n \frac{\lambda^k P(w_j|\tilde{\theta}_{q_i})}{\lambda^k P(w_j|\tilde{\theta}_{q_i}) + (1-\lambda^k) P(w_j|\hat{\theta}_{q_i})}$$

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TREC Genomics

	Size	Vocab. size
trecgen05	4,591,008 **abstracts**	800,477,879
trecgen06	162,259 **full-text docs**	1,090,232,994

- PubMed
  - Bibliographic database maintained by the National Library of Medicine (NLM)
  - Over 15M entries, containing author information, abstracts, etc. etc.
- Medical Subject Headings (MeSH)
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Retrieval Effectiveness

MAP	QL	RM		MM	
trecgen05	0.218	0.220	+2.33%	**0.241**	+12.09%
trecgen06	0.359	0.360	+0.28%	**0.416**	+15.88%

P10	QL	RM		MM	
trecgen05	0.369	**0.374**	+1.36%	0.360	-2.44%
trecgen06	0.450	0.454	+0.89%	**0.465**	+3.33%

Ad-hoc retrieval results of the query-likelihood baseline (QL), Relevance model (RM), and thesaurus-biased model (MM) (best scores in boldface.)

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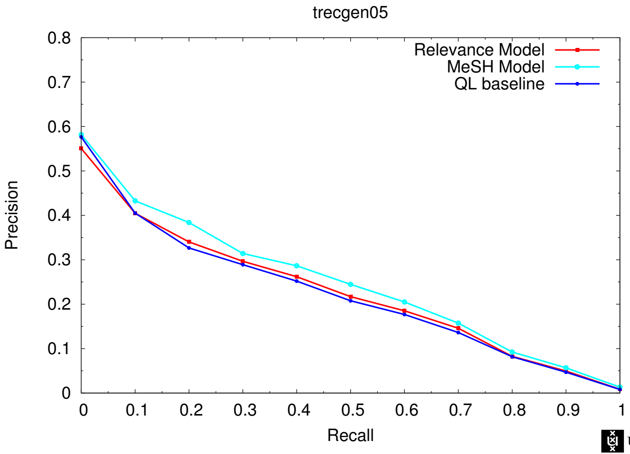

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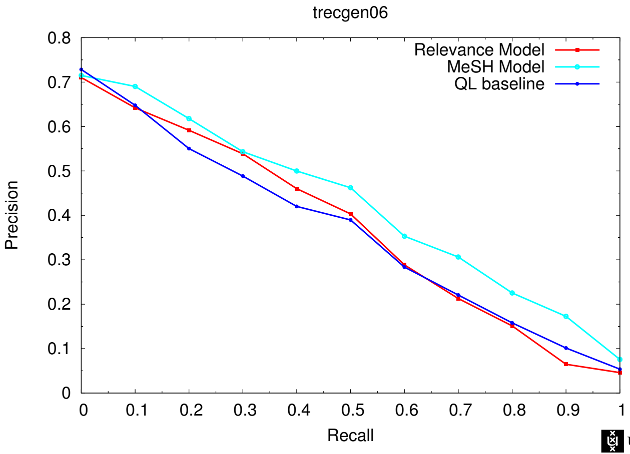

Summary and Future Work

Summary

- We have shown how to incorporate conceptual knowledge into a language modeling framework, through biasing relevance models
- We have used the EM algorithm to estimate λ and, using this approach, our model outperforms both a query-likelihood baseline, as well as state-of-the-art relevance models on two distinct test collections

Future Work

- Incorporate structure/relations between concepts
- Move to different domain(s) with different annotations