Social Recommendation and External Resources for Book Search

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Introduction

- new book search task this year
 - searching books with social information and opinion instead of book content

- whole new collection
 - amazon.com and Library Thing documents
 - topics extracted from LT forums

Introduction (2)

3 different approaches experimented this year

- weighted query expansion with Wikipedia
 - performed well last year
 - new thematic graph approach
 - #fail

Introduction (3)

- recommendation systems
 - using user reviews and ratings
 - good performances

baselines

- modeling unigrams and bigrams occurrences
- using user tags and Amazon/LT browse nodes
- best results (at least with crowdsourcing judgements)

Outline

- Introduction
- Baselines
- Query Expansion with Wikipedia
- Social Recommendation
- Conclusions and future work

Baselines

language modeling approach to retrieval

modeling unigrams and bigrams of the query

- Sequential Dependance Model
 - special case of the Markov Random Field [Metzler2005]
 - Dirichlet smoothing with default value (μ = 2500)

Baselines (2)

- weighting query terms
 - unigram matches $f_T(q,D) = log P(q_i|D)$
 - bigram exact matches $f_O(q_i, q_{i+k}, D) = log P(\#1(q_i, ..., q_{i+k})|D)$
 - bigram matches within an unordered window of 8 tokens $f_U(q_i,q_{i+k},D) = log \ P(\#uw8(q_i,...,q_{i+k})|D)$

$$score_{SDM}(Q, D) = \lambda_T \sum_{q \in Q} f_T(q, D) + \lambda_O \sum_{i=1}^{|Q|-1} f_O(q_i, q_{i+1}, D) + \lambda_U \sum_{i=1}^{|Q|-1} f_U(q_i, q_{i+1}, D)$$

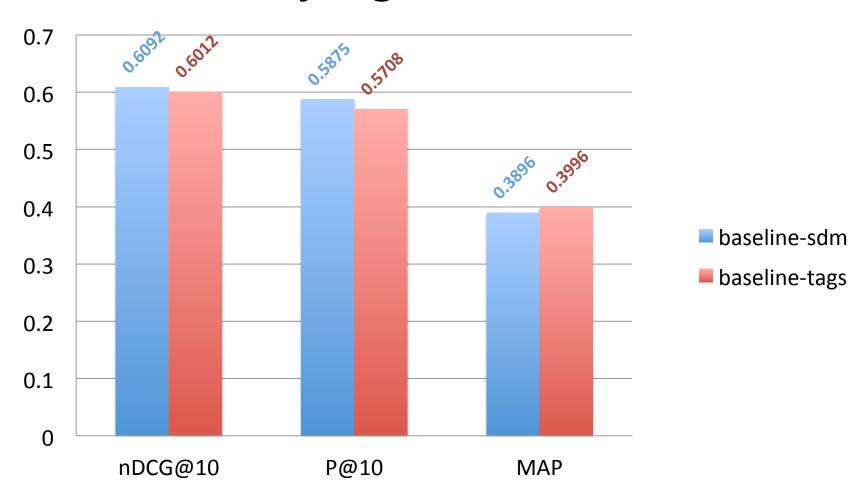
- $-\lambda_{T} = 0.85, \lambda_{O} = 0.10, \lambda_{U} = 0.05$
- best run overall using Amazon MT judgements

Baselines (3)

- using classification information?
 - user tags, Amazon/LT category labels

```
<book><isbn>0673993280</isbn><title>Microeconomics (6th Edition)</title>
<tags>
    <tag count="1">Paperback</tag>
    <tag count="1">textbook</tag>
    <tag count="1">economics</tag>
</tags>
<bre>browseNodes>
    <browseNode id="3">Business & Investing
    <bre><bre>de id="53">Nonfiction</brewseNode>
    <browseNode id="1000">Subjects
    <bre>browseNode id="2581">Economics/browseNode>
</browseNodes>
             Social Recommendation and External Resources for Book Search - Deveaud et al.
</book>
```

Evaluation using amazon mechanical turk Artificial Artificial Intelligence judgements



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Query Expansion with Wikipedia

- few « real » text in the documents
 - mainly reviews or blurbs
 - very different from last year!

- expanding queries with terms from Wikipedia
 - expect to retrieve well-known books relevant to the query and extract useful terms

Query Expansion with Wikipedia (2)

 terms must be weighted in order to reflect their relative importance inside the expansion

using entropy as a measure of informativeness

$$H_{\mathcal{W}}(w) = -\sum_{w \in \mathcal{W}} p_{\mathcal{W}}(w) \cdot \log p_{\mathcal{W}}(w)$$

combining expansion terms with SDM

$$score(Q, D) = score_{SDM}(Q, D) + \lambda_{W} \sum_{w \in W} H_{W}(w) \cdot f_{T}(w, D)$$

Query Expansion with Wikipedia (3)

- terms are extracted from the best ranked
 Wikipedia article for a given query
- using Wikipedia API for retrieving articles
 - stopwords removal with a 429 terms list, including HTML-related elements (nbsp, amp, http...)
- selecting the 20 words with best *entropy* for the expansion
 - performed well last year on Book and Ad Hoc tracks

Query Expansion with Wikipedia (4)

 problem: not enough « good » informative terms are selected

- possible solutions:
 - selecting more terms from pages: can introduce even more noise
 - using more pages: can cause some « topic drift »
 - using more pages thematically related to the best ranked page

Query Expansion with Wikipedia (5)

- Wikipedia hyperlinks and their anchor texts are defined by (expert) users
 - an hyperlink between two Wikipedia articles often models a thematic link
 - e.g. Heineken article have a link to the Beer article
- if an anchor text contains expansion terms, the linked article may be a good expansion document
 - beer is an expansion term from the Heineken article
 - more expansion terms can be extracted from the Beer article

Query Expansion with Wikipedia (6)

- can be viewed as an oriented graph
 - represents thematic hyperlinks from an article to another
 - query-driven tree

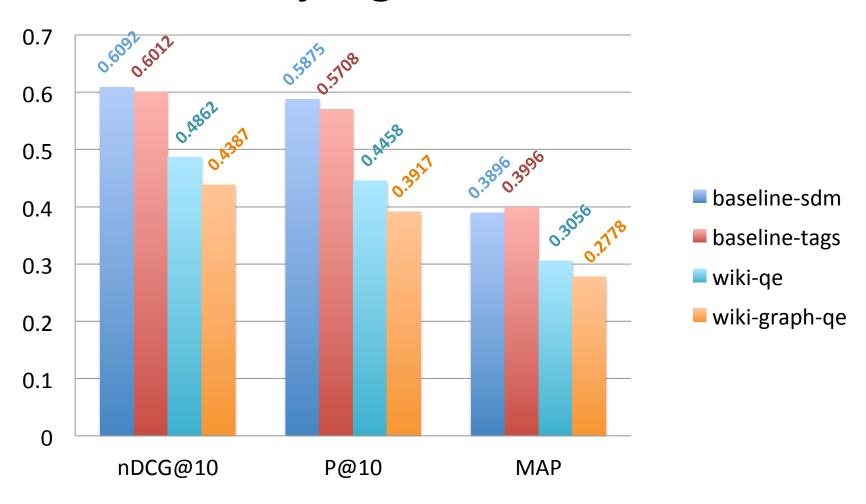


Query Expansion with Wikipedia (7)

- relies on the good selection of the first article
 - P@1 must be 1.0

- can cause topic drifts
 - down-weighting sub-articles (w = 0.5)
 - limiting the number of sub-articles $(N_{sub} = 5)$

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Social Recommendation

- documents are Amazon pages
 - users comment and review and rate products
- intuition #1: a high reviewed product must be relevant
 - or at least popular...
 - PageRank-like [Bao2007]
- intuition #2: a high rated product must be relevant

Social Recommendation (2)



THE PROBLEM WITH AVERAGING STAR RATINGS

source: xkcd.com

Social Recommendation (3)

- often a small amount of ratings for a book
 - how significant is the contribution of each rating?
 - $-X_R$ a random set of « bad » ratings in [1,3]
 - $-X_U$ the set of user ratings for a given book
- evaluate significant differences between X_R and $X_R + X_U (X_{R+U})$
 - small |X_U| but very good ratings
 - average ratings but large $|X_U|$

Social Recommendation (4)

- using Welch's t-test
 - test whether the population means are different
 - i.e. whether user ratings are useful
- popularity and quality in a single estimate
 - probability that users do not displease a book

- combining it with SDM (baseline) estimate
 - probability that a book is relevant to a query

Social Recommendation (5)

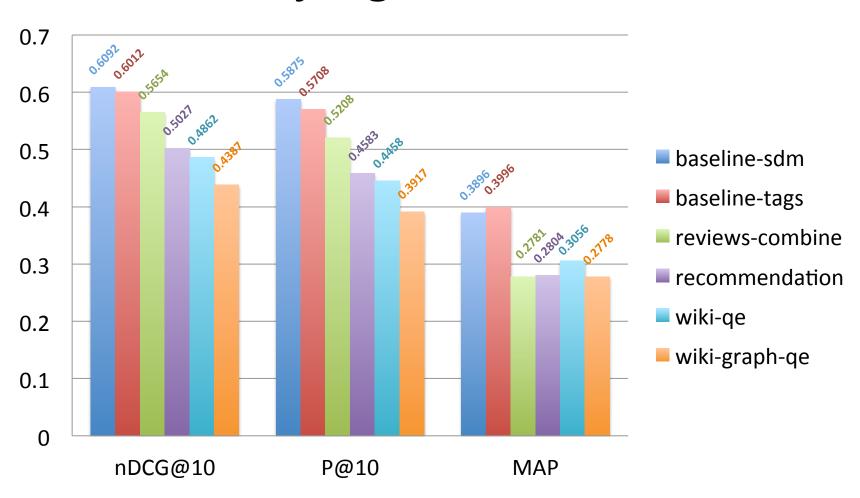
$$s_{recomm}(Q, D) = \lambda \ score_{SDM}(Q, D) + (1 - \lambda) \ \frac{X_{R+U} - X_{U}}{s_{\bar{X}_{R+U} - \bar{X}_{U}}}$$

based on observations over test topics:

$$\lambda = 1 - \frac{SDM_{MAX} - SDM_{100}}{N_{Results}}$$

- experiments with field retrieval
 - only <title> and <content> instead of all the text
 - field retricted smoothing
 - 6 for the title, 157 for the content of the reviews

Evaluation using amazon mechanical turk Martificial Artificial Intelligence judgements



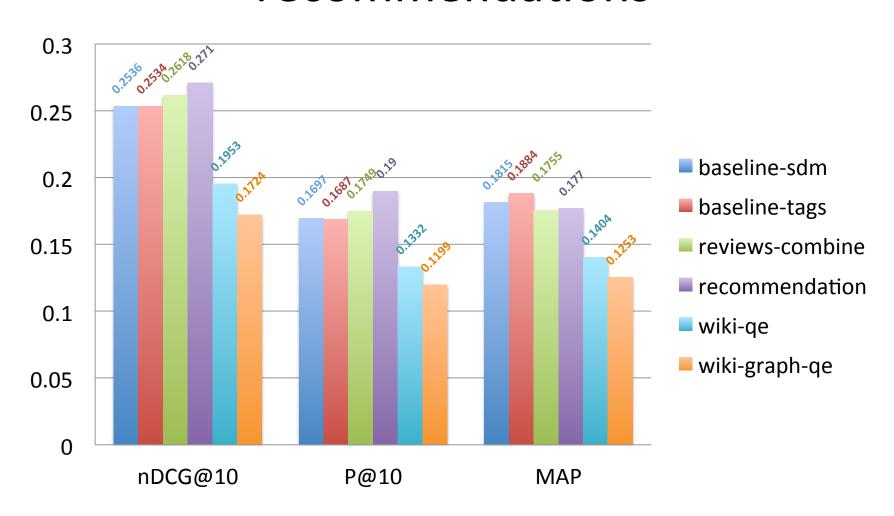
LibraryThing vs AMT judgements?

- LibraryThing
 - derived from LT forums
 - 2377 judgements for 211 topics
 - 67 topics have less than 5 judgements
 - 74 topics have 10 or more judgements

amazon mechanical turk™ Artificial Artificial Intelligence

- 1426 judgements for 24 (mixed) topics
- 601 documents judged relevant

Evaluation using LibraryThing recommendations



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Conclusions and future work

 query expansion with weighted words extracted from Wikipedia does not work

- recommendation systems based on social ratings performs well
 - depending on the relevance judgements set
- LM approach with a SDM on the entire text of the Amazon pages achieves best results

Conclusions and future work (2)

- extending the relevance judgements?
 - concatenation?
 - more crowdsourcing?

- using more resources
 - social and opinion-oriented
 - combining several sources of user reviews

apply to a general product search system

thank you for your attention