Learning to Rank with Partially-Labeled Data

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(Joint work with Katrin Kirchhoff)
Motivation

- Machine learning can be an effective solution for ranking problems in IR
  - But success depends on quality and size of training data

[Diagram showing labeled and unlabeled data]
Problem Statement

Can we build a better ranker by adding cheap, unlabeled data?
Outline

1. Problem Definition
   1. Ranking as a Supervised Learning Problem
   2. Two kinds of Partially-labeled Data
2. Proposed Method
3. Results and Analysis
Ranking as Supervised Learning Problem

Labels

3 \( x_1^{(1)} = [tfidf, pagerank,...] \)

1 \( x_2^{(1)} = [tfidf, pagerank,...] \)

2 \( x_3^{(1)} = [tfidf, pagerank,...] \)

Query: SIGIR

ACM SIGIR Special Interest Group on Information Retrieval Home Page

"Addresses issues ranging from theory to user demands in the application of computers to the acquisition, organization, storage, retrieval, and distribution..."

www.sigir.org/ - 10k - 頁庫存檔 - 鄰近網頁

SIGIR 2004 -

The 27th Annual International ACM SIGIR Conference will be held at The University of Sheffield, UK, from July 25 to July 29, 2004.

www.sigir.org/sigir2004/ - 9k - 頁庫存檔 - 鄰近網頁

Special Inspector General for Iraq Reconstruction : SIGIR Homepage

Welcome to the Office of the Special Inspector General for Iraq Reconstruction (SIGIR), a temporary federal agency serving the American public as a watchdog...

www.sigir.mil/ - 20k - 頁庫存檔 - 鄰近網頁

Query: Hotels in Singapore

Singapore Hotels | All Hotels in Singapore Reservation Service...

Singapore Hotels - Provides you with complete reservation services for hotels and resorts in Singapore. Sorted according to Price, Location, Class, Name.

hotels.online.com.sg/ - 31k - 頁庫存檔 - 鄰近網頁

The Fullerton Hotel Singapore: Weekend Promotion

Get away for the weekend and bask in the luxury of The Fullerton Hotel Singapore. Relax in your elegant guest room or by the outdoor infinity pool..."
Ranking as Supervised Learning Problem

Query: SIGIR

Train \( f(x) \) such that:
\[
\begin{align*}
    f(x^{(1)}_1) &> f(x^{(1)}_2) > f(x^{(1)}_3) \\
    f(x^{(2)}_1) &> f(x^{(2)}_2)
\end{align*}
\]

Query: Hotels in Singapore

Test Query: Singapore Airport

---

Welcome to Changi Airport [翻譯此頁]
With more than 300 retail outlets and F&B outlets in Changi Airport, indulge yourself ... 2006 Civil Aviation Authority of Singapore. All rights reserved. ... www.changiairport.com/changi/en/index.html?_locale=en - 44k - 

Singapore Changi Airport - Wikipedia, the free encyclopedia [翻譯此頁]
Growth in the global aviation transport was felt in Singapore, where Singapore International Airport at Paya Lebar, Singapore's third main civilian airport ... en.wikipedia.org/wiki/Singapore_Changi_Airport - 292k - 

Up to 70% off Singapore Airport Hotels at Wotif.com [翻譯此頁]
Don't waste money on a taxi – instant confirmation on Singapore Airport Hotels from $165/night. Online bookings. Fast & secure site, and backed by a 24/7 ... www.wotif.com/hotels/singapore-singapore-airport-east-coast-hotels.html - 14k -
Two kinds of Partially-Labeled Data

1. Lack of labels for some documents (depth)

<table>
<thead>
<tr>
<th>Query1</th>
<th>Query2</th>
<th>Query3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doc1 Label</td>
<td>Doc1 Label</td>
<td>Doc1 Label</td>
</tr>
<tr>
<td>Doc2 Label</td>
<td>Doc2 Label</td>
<td>Doc2 Label</td>
</tr>
<tr>
<td>Doc3 ?</td>
<td>Doc3 ?</td>
<td>Doc3 ?</td>
</tr>
</tbody>
</table>

Some references:
Amini+, SIGIR’08
Agarwal, ICML’06
Wang+, MSRA TechRep’05
Zhou+, NIPS’04
He+, ACM Multimedia ‘04

2. Lack of labels for some queries (breadth)

<table>
<thead>
<tr>
<th>Query1</th>
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<th>Query3</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
</tbody>
</table>

This paper
Truong+, ICMIST’06
Focus of this work: Transductive Learning

- Unlabeled data = Test data
  → Transductive Learning

- Main question: How can knowledge of the test list help our learning algorithm?
Why transductive learning?

**Inductive (semi-supervised) learning:**
Need to generalize to new data

<table>
<thead>
<tr>
<th>Query1</th>
<th>Doc1 Label</th>
<th>Doc2 Label</th>
<th>Doc3 Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>All must be predicted</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Query2</th>
<th>Doc1 Label</th>
<th>Doc2 Label</th>
<th>Doc3 Label</th>
</tr>
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<tbody>
<tr>
<td>All must be predicted</td>
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<th>Doc1 ?</th>
<th>Doc2 ?</th>
<th>Doc3 ?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted only for Test Query</td>
<td></td>
<td></td>
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</tbody>
</table>

**Test Query**

<table>
<thead>
<tr>
<th>Doc1 ?</th>
<th>Doc2 ?</th>
<th>Doc3 ?</th>
</tr>
</thead>
<tbody>
<tr>
<td>?</td>
<td>?</td>
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**Transductive learning:**
Test data is fixed and observed during learning; Arguably, transduction is easier than induction

<table>
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<table>
<thead>
<tr>
<th>Test Query</th>
<th>Doc1 ?</th>
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<th>Doc3 ?</th>
</tr>
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*Inductive learning = closed-book exam*
*Transductive learning = open-note exam*
Outline

1. Problem Definition
2. Proposed Method
   1. Intuition
   2. Details of proposed algorithm
3. Results and Analysis
Thought Experiment: What information does unlabeled data provide?

Observation: Direction of variance differs according to query

Implication: Different feature representations are optimal for different queries
Good results can be achieved by:
Ranking Query 1 by BM25 only
Ranking Query 2 by HITS only

Query 1 & Documents
Relevant webpages (high rank)
Irrelevant webpages (low rank)

Query 2 & Documents
Proposed Method: Main Ideas

Main Assumptions:
1. Different queries are best modeled by different features
2. Unlabeled data can help us discover this representation

Two-Step Algorithm:

Requires:
- DISCOVER(): unsupervised method for finding useful features
- LEARN(): supervised method for learning to rank

For each Test List:
- Run DISCOVER()
- Augment Feature Representation
- Run LEARN() and Predict
Proposed Method: Illustration

\[ \mathbf{z} = \mathbf{A}' \mathbf{x} \]: new feature representation

Unsupervised learning outputs projection matrix \( \mathbf{A} \)

Supervised learning of ranking function

\( \mathbf{x} \): initial feature representation
DISCOVER( ) Component

• **Goal of DISCOVER( )**: Find useful patterns on the test list

• **Principal Components Analysis (PCA)**
  - Discovers direction of maximum variance
  - View low variance directions as noise

• **Kernel PCA** [Scholkopf+, Neural Computation 98]
  - Non-linear extension to PCA via the Kernel Trick
    1. Maps inputs non-linearly to high-dimensional space.
    2. Performs PCA in that space
Kernels for Kernel PCA

**Linear**
\[ K(x, x') = \langle x, x' \rangle \]

**Gaussian**
\[ K(x, x') = \exp(-\beta \| x - x' \|) \]

**Polynomial**
\[ K(x, x') = (1 + \langle x, x' \rangle)^d \]

**Diffusion**
\[ K(x, x') = \text{Random walk between } x, x' \text{ on graph} \]
LEARN( ) Component

• Goal of LEARN( ):
  • Optimize some ranking metric on labeled data

• RankBoost [Freund+, JMLR 2003]
  • Inherent Feature Selection
  • Few parameters to tune

• Other supervised ranking methods are possible:
  • RankNet, Rank SVM, ListNet, FRank, SoftRank, etc.
Summary of Proposed Method

• Relies on unlabeled test data to learn good feature representation

• “Adapts” the supervised learning process to each test list

• Caveats:
  • DISCOVER() may not always find features that are helpful for LEARN()
  • Run LEARN() at query time → Computational speedup is needed in practical application
Outline

1. Problem Definition
2. Proposed Method
3. Results and Analysis
   1. Experimental Setup
   2. Main Results
   3. Deeper analysis into where things worked and failed
Experiment Setup (1/2)

- LETOR Dataset [*Liu+, LR4IR 2007]*:

<table>
<thead>
<tr>
<th></th>
<th>TREC03</th>
<th>TREC04</th>
<th>OHSUMED</th>
</tr>
</thead>
<tbody>
<tr>
<td># of queries</td>
<td>50</td>
<td>75</td>
<td>106</td>
</tr>
<tr>
<td>Average # of docs/q</td>
<td>1000</td>
<td>1000</td>
<td>150</td>
</tr>
<tr>
<td># of original features</td>
<td>44</td>
<td>44</td>
<td>25</td>
</tr>
</tbody>
</table>

- Additional features generated by Kernel PCA:
  - 5 kernels: Linear, Polynomial, Gaussian, Diffusion 1, Diffusion 2
  - Extract 5 principal components for each
Experiment Setup (2/2)

- **Comparison of 3 systems:**
  - **Baseline**: Supervised RankBoost
  - **Transductive**: Proposed method: Kernel PCA + Supervised RankBoost
  - **Combined**: Average of Baseline, Transductive outputs

\[
f(x^{(i)}) = \text{sort}\{f_{\text{baseline}}(x_n^{(i)}) + f_{\text{transductive}}(x_n^{(i)})\}
\]

- **Evaluation:**
  - Mean Averaged Precision (MAP)
  - Normalized Discount Cumulative Gain (NDCG) \(\leftarrow\) see the paper
Overall Results (MAP)

- Transductive outperforms Baseline
- Combined give extra improvements (2 datasets)
  - The rankers make complementary mistakes
Did improvements come from Kernel PCA per se, or its transductive use?

Answer: Transductive use
- Running KPCA on the training set (traditional feature extraction) gives little gains
- Gains are a result of test-specific rankers
Do results vary by query?

Answer:
- Yes. For some queries, it is better not to use the transductive method.
What kernels are most useful?

Answer: There is a diversity of kernels that lead to good performance. Different test list have different structure.
Conclusion

• Unlabeled data can be useful for ranking problems

• Two-step transductive algorithm:
  • Adapts the supervised component using a feature representation that better models the test list

• Overall results are positive
  • but results vary at the query-level

• Future work:
  • Computational speed-up
  • Different LEARN() and DISCOVER() components
  • Other ways to exploit unlabeled data
Thanks for your attention!

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• Travel Grant supported by:
  • SIGIR
  • Dr. Amit Singhal (made in honor of Donald B. Crouch)
  • Microsoft Research (in honor of Karen Spark Jones)
The time is ripe for Semi-supervised Ranking!

- Both Semi-supervised Classification and Learning to Rank have become well-established sub-fields with many techniques
Computation Time (OHSUMED)

- On Intel x86-32 (3GHz CPU)
  - Kernel PCA (Matlab/C-Mex): 4.3sec/query
  - Rankboost (C++): 0.7sec/iteration
  - Total time (Assuming 150 iterations): 109sec/query
    (233sec/query for TREC)

- Kernel PCA: $O(n^3)$ for $n$ documents
  - Sparse KPCA: $O(n)$