

# Learning Ranking Functions with SVMs

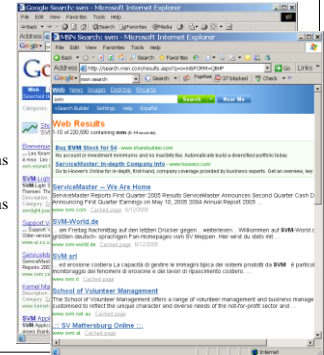
CS4780 – Machine Learning  
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T. Joachims, Optimizing Search Engines Using Clickthrough Data, Proceedings of the ACM Conference on Knowledge Discovery and Data Mining (KDD), ACM, 2002.

## Adaptive Search Engines

- **Current Search Engines**
  - One-size-fits-all
  - Hand-tuned retrieval function
- **Hypothesis**
  - Different users need different retrieval functions
  - Different collections need different retrieval functions
- **Machine Learning**
  - Learn improved retrieval functions
  - User Feedback as training data



## Overview

- **How can we get training data for learning improved retrieval functions?**
  - Explicit vs. implicit feedback
  - Absolute vs. relative feedback
  - User study with eye-tracking and relevance judgments
- **What learning algorithms can use this training data?**
  - Ranking Support Vector Machine
  - User study with meta-search engine

## Sources of Feedback

- ~~**Explicit Feedback**~~
  - Overhead for user
  - Only few users give feedback
  - ⇒ not representative
- **Implicit Feedback**
  - Queries, clicks, time, mousing, scrolling, etc.
  - No Overhead
  - More difficult to interpret



## Feedback from Clickthrough Data

**Relative Feedback:**  
Clicks reflect preference between observed links.

**Absolute Feedback:**  
The clicked links are relevant to the query.

- (3 < 2),
- (7 < 2),
- (7 < 4),
- (7 < 5),
- (7 < 6)

1. Kernel Machines  
<http://svm.first.gmd.de/>
2. Support Vector Machine  
<http://bolivar.freeservers.com/>
3. SVM4light Support Vector Machine  
<http://ais.gmd.de/~thorsten/svm/light/>
4. An Introduction to Support Vector Machines  
<http://www.support-vector.net/>
5. Support Vector Machine and Kernel ... References  
<http://svm.research.bell-labs.com/SVMrefs.html>
6. Archives of SUPPORT-VECTOR-MACHINES ...  
<http://www.jiscmail.ac.uk/lists/SUPPORT...>
7. Lucent Technologies SVM demo applet  
<http://svm.research.bell-labs.com/SV1/SVMsvt.html>
8. Royal Holloway Support Vector Machine  
<http://svm.dcs.rhnc.ac.uk>

- Rel(1),
- NotRel(2),
- Rel(3),
- NotRel(4),
- NotRel(5),
- NotRel(6),
- Rel(7)

## User Study: Eye-Tracking and Relevance

- **Scenario**
  - WWW search
  - Google search engine
  - Subjects were not restricted
  - Answer 10 questions
- **Eye-Tracking**
  - Record the sequence of eye movements
  - Analyze how users scan the results page of Google
- **Relevance Judgements**
  - Ask relevance judges to explicitly judge the relevance of all pages encountered
  - Compare implicit feedback from clicks to explicit judgments



## What is Eye-Tracking?

Eye tracking device



**Device to detect and record where and what people look at**

- **Fixations:** ~200-300ms; information is acquired
- **Saccades:** extremely rapid movements between fixations
- **Pupil dilation:** size of pupil indicates interest, arousal



"Scanpath" output depicts pattern of movement throughout screen. Black markers represent fixations.

## Conclusion: Viewing Behavior

- Users most frequently view two abstracts
- Users typically view results in order from top to bottom
- Users view links one and two more thoroughly and often
- Users click most frequently on link one
- Users typically do not look at links below before they click (except maybe the next link)

=> **Design strategies for interpreting clickthrough data that respect these properties!**

## Are Clicks Absolute Relevance Judgments?

- **Clicks depend not only on relevance of a link, but also**
  - On the position in which the link was presented
  - The quality of the other links

=> **Interpreting Clicks as absolute feedback extremely difficult!**

## Strategies for Generating Relative Feedback

### Strategies

- "Click > Skip Above"
  - (3>2), (5>2), (5>4)
- "Last Click > Skip Above"
  - (5>2), (5>4)
- "Click > Earlier Click"
  - (3>1), (5>1), (5>3)
- "Click > Skip Previous"
  - (3>2), (5>4)
- "Click > Skip Next"
  - (1>2), (3>4), (5>6)

1. Kernel Machines  
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<http://bolivar.freeseervers.com/>
3. SVM-Light Support Vector Machine  
<http://ais.gmd.de/~thorsten/svm-light/>
4. An Introduction to SVMs  
<http://www.support-vector.net/>
5. Support Vector Machine and ...  
<http://svm.bell-labs.com/SVMrefs.html>
6. Archives of SUPPORT-VECTOR...  
<http://www.jisc.ac.uk/lists/SUPPORT...>
7. Lucent Technologies: SVM demo applet  
<http://svm.bell-labs.com/SVMsvt.html>
8. Royal Holloway SVM  
<http://svm.dcs.rhnc.ac.uk>
9. SVM World  
<http://www.svmworld.com>
10. Fraunhofer FIRST SVM page  
<http://svm.first.gmd.de>

## Comparison with Explicit Feedback

Explicit Feedback Data Strategy	Abstracts Phase I "normal"
Inter-Judge Agreement	89.5
Click > Skip Above	80.8 ± 3.6
Last Click > Skip Above	83.1 ± 3.8
Click > Earlier Click	67.2 ± 12.3
Click > Skip Previous	82.3 ± 7.3
Click > No Click Next	84.1 ± 4.9

=> **All but "Click > Earlier Click" appear accurate**

## Learning Retrieval Functions from Pairwise Preferences

**Idea:** Learn a ranking function, so that number of violated pair-wise training preferences is minimized.

**Form of Ranking Function:** sort by

$$\begin{aligned}
 rsv(q, d_i) &= w_1 * (\text{\#of query words in title of } d_i) \\
 &\quad + w_2 * (\text{\#of query words in anchor}) \\
 &\quad + \dots \\
 &\quad + w_n * (\text{page-rank of } d_i) \\
 &= w * \Phi(q, d_i)
 \end{aligned}$$

**Training:** Select  $w$  so that

$$\begin{aligned}
 &\text{if user prefers } d_1 \text{ to } d_2 \text{ for query } q, \\
 &\text{then} \\
 &rsv(q, d_1) > rsv(q, d_2)
 \end{aligned}$$

## Ranking Support Vector Machine

- Find ranking function with low error and large margin

$$\min \frac{1}{2} \bar{w} \cdot \bar{w} + C \sum_{i,j,k} \xi_{kij}$$

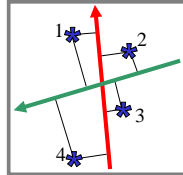
$$\text{s.t. } \bar{w} \cdot \Phi(q_1, d_i) \geq \bar{w} \cdot \Phi(q_1, d_j) + 1 - \xi_{1ij}$$

$$\dots$$

$$\bar{w} \cdot \Phi(q_n, d_i) \geq \bar{w} \cdot \Phi(q_n, d_j) + 1 - \xi_{nij}$$

- Properties**

- Convex quadratic program
- Non-linear functions using Kernels
- Implemented as part of SVM-light
- <http://svmlight.joachims.org>



## Experiment

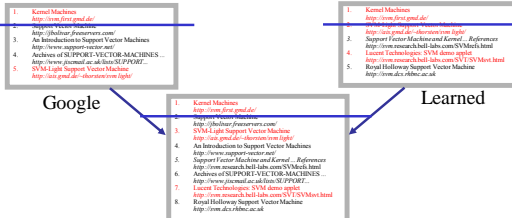
### Meta-Search Engine "Striver"

- Implemented meta-search engine on top of Google, MSNSearch, Altavista, Hotbot, Excite
- Retrieve top 100 results from each search engine
- Re-rank results with learned ranking functions

### Experiment Setup

- User study on group of ~20 German machine learning researchers and students
  - => homogeneous group of users
- Asked users to use the system like any other search engine
- Train ranking SVM on 3 weeks of clickthrough data
- Test on 2 following weeks

## Which Ranking Function is Better?



- Approach**

- Experiment setup generating "unbiased" clicks for fair evaluation.

- Validity**

- Clickthrough in combined ranking gives same results as explicit feedback under mild assumptions [Joachims, 2003].

## Results

Ranking A	Ranking B	A better	B better	Tie	Total
Learned	Google	29	13	27	69
Learned	MSNSearch	18	4	7	29
Learned	Toprank	21	9	11	41

### Result:

- Learned > Google
- Learned > MSNSearch
- Learned > Toprank

**Toprank:** rank by increasing minimum rank over all 5 search engines

## Learned Weights

- | Weight | Feature  |
|--------|--|
| 0.60   | cosine between query and abstract                    |
| 0.48   | ranked in top 10 from Google                         |
| 0.24   | cosine between query and the words in the URL        |
| 0.24   | doc ranked at rank 1 by exactly one of the 5 engines |
| ...    |  |
| 0.22   | host has the name "citeseer"                         |
| ...    |  |
| 0.17   | country code of URL is ".de"                         |
| 0.16   | ranked top 1 by HotBot                               |
| ...    |  |
| -0.15  | country code of URL is ".fi"                         |
| -0.17  | length of URL in characters                          |
| -0.32  | not ranked in top 10 by any of the 5 search engines  |
| -0.38  | not ranked top 1 by any of the 5 search engines      |

## Conclusions

- Clickthrough data can provide accurate feedback**
  - Clickthrough provides relative instead of absolute judgments
- Ranking SVM can learn effectively from relative preferences**
  - Improved retrieval through personalization in meta search
- Current and future work**
  - Exploiting query chains
  - Adapting intranet search for Cornell Library Web Collection and Physics E-Print ArXiv
  - Implementation of methods in Osmot Search Engine
  - Robustness to "click-spam"
  - Learning theory for interactive learning with preference
  - Further user studies to get more operational model of user behavior
- Info and Papers**
  - <http://www.joachims.org>