

# Learning Ranking Functions with SVMs

CS4780/5780 – Machine Learning  
Fall 2013

Thorsten Joachims  
Cornell University

T. Joachims, Optimizing Search Engines Using Clickthrough Data, Proceedings of the ACM Conference on Knowledge Discovery and Data Mining (KDD), ACM, 2002  
[http://www.cs.cornell.edu/People/tj/publications/joachims\\_02c.pdf](http://www.cs.cornell.edu/People/tj/publications/joachims_02c.pdf)

## Final Course Projects

- Now
  - Start thinking of project ideas, anything relevant to the course goes
  - Start recruiting team members
- Oct 22
  - Submit project proposal as group of 3-4 students
- Oct 24
  - Submit peer feedback for proposals
- Nov 21
  - Submit status report
- Dec 5
  - Project poster presentations (evening)
- Dec 11
  - Submit final project report
- Dec 18
  - Submit peer reviews of reports

## Adaptive Search Engines

- Traditional 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.freeseervers.com/>
3. SVM4Light Support Vector Machine  
<http://svm.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. Lucern Technologies, SVM1 demo applet  
<http://svm.research.bell-labs.com/SV1SVMst.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 Judgments
  - Ask relevance judges to explicitly judge the relevance of all pages encountered
  - Compare implicit feedback from clicks to explicit judgments

Who discovered the first modern antibiotic?  
 Find the homepage of Emmet - the chef who has a TV cooking program.  
 What actor starred as the main character in the original Time Machine movie?  
 Find the page displaying the routemap for Greyhound buses.  
 You are excited to cast your vote in the democratic presidential primary - What city do you go to in NY?  
 Find the homepage of Michael Jordan, the stationer.  
 Where is the tallest mountain in NY located?  
 Find the homepage for graduate housing at Carnegie Mellon University.  
 A friend told you that Mr. Cornell used to live close to campus - between University and Stewart Area - Does anyone live in his house now; if so, who?  
 Find the homepage of the 1,000 Acres Dude Ranch.

## What is Eye-Tracking?

Eye tracking device

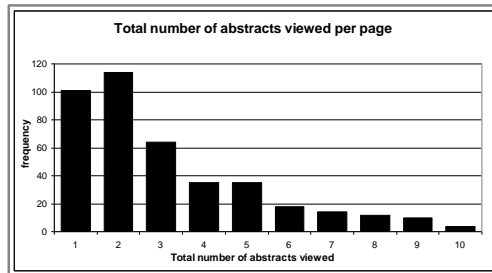


Device to detect and record where and what people look at

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

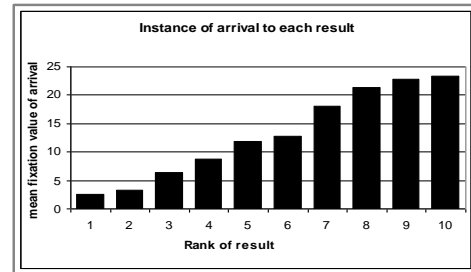
"Scanpath" output depicts pattern of movement throughout screen. Black markers represent fixations.

## How Many Links do Users View?



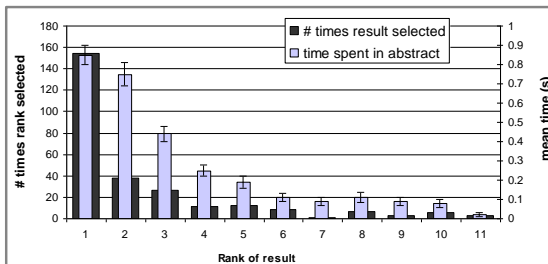
Mean: 3.07 Median/Mode: 2.00

## In Which Order are the Results Viewed?



=> Users tend to read the results in order

## Looking vs. Clicking



- => Users view links one and two more thoroughly / often
- => Users click most frequently on link one

## Do Users Look Below the Clicked Link?

Viewed Rank	Clicked Rank					
	1	2	3	4	5	6
1	90.6%	76.2%	73.9%	60.0%	54.5%	45.5%
2	56.8%	90.5%	82.6%	53.3%	63.6%	54.5%
3	30.2%	47.6%	95.7%	80.0%	81.8%	45.5%
4	17.3%	19.0%	47.8%	93.3%	63.6%	45.5%
5	8.6%	14.3%	21.7%	53.3%	100.0%	72.7%
6	4.3%	4.8%	8.7%	33.3%	18.2%	81.8%

- => Users typically do not look at links below before they click (except maybe the next link)

## How do Clicks Relate to Relevance?

- Experiment (Phase II)
  - Additional 16 subjects
  - Manually judged relevance
    - Abstract
    - Page
- Manipulated Rankings
  - Normal:** Google's ordering
  - Swapped:** Top Two Swapped
  - Reversed:** Ranking reversed
- Experiment Setup
  - Same as Phase I
  - Manipulations not detectable

- Kernel Machines  
<http://www.kernel-machines.org/>
- Support Vector Machine  
<http://jbolivar.freeseversons.com/>
- SVM-light Support Vector Machine  
<http://svmlight.jku.at/svmlight.html>
- An Introduction to SVMs  
<http://www.support-vector.net/>
- Support Vector Machine and ...  
<http://svm.bell-labs.com/SVMrefs.html>
- Archives of SUPPORT-VECTOR...  
<http://www.jisc.ac.uk/lists/SUPPORT...>
- Lucent Technologies: SVM demo applet  
<http://svm.bell-labs.com/SVMdemo.html>
- Royal Holloway SVM  
<http://svm.dcs.rhnc.ac.uk>
- SVM World  
<http://www.svmworld.com>
- Fraunhofer FIRST SVM page  
<http://svm.first.gmd.de>

## Presentation Bias

~~Hypothesis: Order of presentation influences where users look, but not where they click!~~

"normal"	$l_1^-, l_2^-$	$l_1^+, l_2^-$	$l_1^-, l_2^+$	$l_1^+, l_2^+$	total
rel( $l_1$ ) > rel( $l_2$ )	15	19	1	1	36
rel( $l_1$ ) < rel( $l_2$ )	11	5	2	2	20
rel( $l_1$ ) = rel( $l_2$ )	19	9	1	0	29
total	45	33	4	3	85

"swapped"	$l_1^-, l_2^-$	$l_1^+, l_2^-$	$l_1^-, l_2^+$	$l_1^+, l_2^+$	total
rel( $l_1$ ) > rel( $l_2$ )	11	15	1	1	28
rel( $l_1$ ) < rel( $l_2$ )	17	10	7	2	36
rel( $l_1$ ) = rel( $l_2$ )	36	11	3	0	50
total	64	36	11	3	114

## Quality-of-Context Bias

~~Hypothesis: Clicking depends only on the link itself, but not on other links.~~

	Rank of clicked link as sorted by relevance judges
Normal + Swapped	2.67
Reversed	3.27

=> Users click on less relevant links, if they are embedded between irrelevant links.

## 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)

- Kernel Machines  
<http://www.kernel-machines.org/>
- Support Vector Machine  
<http://jbolivar.freeseversons.com/>
- SVM-light Support Vector Machine  
<http://svmlight.jku.at/svmlight.html>
- An Introduction to SVMs  
<http://www.support-vector.net/>
- Support Vector Machine and ...  
<http://svm.bell-labs.com/SVMrefs.html>
- Archives of SUPPORT-VECTOR...  
<http://www.jisc.ac.uk/lists/SUPPORT...>
- Lucent Technologies: SVM demo applet  
<http://svm.bell-labs.com/SVMsvt.html>
- Royal Holloway SVM  
<http://svm.dcs.rhnc.ac.uk>
- SVM World  
<http://www.svmworld.com>
- 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

## Is Relative Feedback Affected by Bias?

Explicit Feedback Data Strategy	Abstracts Phase II		
	"normal"	"swapped"	"reversed"
Click > Skip Above	88.0 ± 9.5	79.6 ± 8.9	83.0 ± 6.7
Last Click > Skip Above	89.7 ± 9.8	77.9 ± 9.9	84.6 ± 6.9
Click > Earlier Click	75.0 ± 25.8	36.8 ± 22.9	28.6 ± 27.5
Click > Skip Previous	88.9 ± 24.1	80.0 ± 18.0	79.5 ± 15.4
Click > No Click Next	75.6 ± 14.5	66.7 ± 13.1	70.0 ± 15.7

⇒ Significantly better than random in all conditions, except "Click > Earlier Click"

## How Well Do Users Judge Relevance Based on Abstract?

Explicit Feedback Data Strategy	Abstracts	Pages
	Phase II all	Phase II all
Inter-Judge Agreement	82.5	86.4
Click > Skip Above	83.1 ± 4.4	78.2 ± 5.6
Last Click > Skip Above	83.8 ± 4.6	80.9 ± 5.1
Click > Earlier Click	46.9 ± 13.9	64.3 ± 15.4
Click > Skip Previous	81.6 ± 9.5	80.7 ± 9.6
Click > No Click Next	70.4 ± 8.0	67.4 ± 8.2

⇒ clicks based on abstracts reflect relevance of the page well

## 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
 
$$U(q, d_i) = w_1 * (\text{\#of query words in title of } d_i) + w_2 * (\text{\#of query words in anchor}) + \dots + w_n * (\text{page-rank of } d_i) = w * \Phi(q, d_i)$$
- Training: Select  $w$  so that

if user prefers  $d_j$  to  $d_i$  for query  $q$ , then  
 $U(q, d_j) > U(q, d_i)$

## Ranking Support Vector Machine

- Find ranking function with low error and large margin

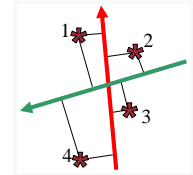
$$\min \frac{1}{2} \bar{w} \cdot \bar{w} + C \sum_{i,j,k} \xi_{kij}$$

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

$$\dots$$

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

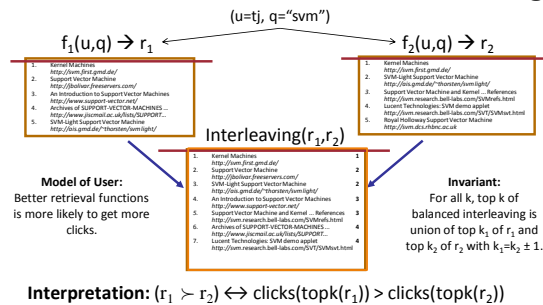
- Properties
  - Convex quadratic program
  - Non-linear functions using Kernels
  - Implemented as part of SVM-light
  - <http://svmlight.joachims.org>



## 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? Balanced Interleaving



[Joachims, 2001][Radlinski et al., 2008]

## 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
  - 0.60
  - 0.48
  - 0.24
  - 0.24
  - ...
  - 0.22
  - ...
  - 0.17
  - 0.16
  - ...
  - -0.15
  - -0.17
  - -0.32
  - -0.38
- Feature
- cosine between query and abstract
  - ranked in top 10 from Google
  - cosine between query and the words in the URL
  - doc ranked at rank 1 by exactly one of the 5 engines
  - host has the name "citeseer"
  - country code of URL is ".de"
  - ranked top 1 by HotBot
  - country code of URL is ".fi"
  - length of URL in characters
  - not ranked in top 10 by any of the 5 search engines
  - 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
  - Other implicit feedback signals
  - Adapting intranet search for ArXiv.org
  - Recommendation
  - Robustness to "click-spam"
  - Learning and micro-economic theory for interactive learning with preference
  - Further user studies to get better models of user behavior

## Feedback across Query Chains

