Dynamic Ranked Retrieval

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Handling Query Ambiguity

Max DCG

Support vector machine - Wikipedia, the free encyclopedia
Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. Since an SVM is a classifier, then given a set of training data, SVM minimizes a cost function with a margin maximization rule. The main features of the program are the following: fast optimization algorithm
www.cs.cornell.edu/People/tj/svm_light

LIBSVM — A Library for Support Vector Machines
An integrated and easy-to-use tool for support vector classification and regression
www.csie.ntu.edu.tw/~cjlin/libsvm

SVM-Light Support Vector Machine
Overview. SVM light is an implementation of Support Vector Machines (SVMs) in C. The main features of the program are the following: fast optimization algorithm
www.cs.cornell.edu/People/tj/svm_light

SVM-Struct Support Vector Machine for Complex Outputs
Overview. SVM struct is a Support Vector Machine (SVM) algorithm for predicting multivariate or structured outputs. It performs supervised learning by approximating the Bayes rule of SVM.
www.cs.cornell.edu/People/tj/svm_light/svm_struct.html

SVM-Light FAQ
Overview. SVMlight is an implementation of Vapnik's Support Vector Machine [Vapnik,... if the system does not compile properly, check this FAQ.
www.cs.cornell.edu/People/tj/svm_light/faq.html

SVM and Kernel Methods Matlab toolbox
Overview. Yes, this is another SVM Toolbox but the thing new is that it is fully written in Matlab (even the QP solver).
au.insa-rouen.fr/~arakotom/toolbox/index.html

Diversified

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www.svm.com

School of Volunteering Management | School of Volunteer Management
School of Volunteering Management. The role of the School of Volunteer Management (SVM) is to enhance the development of volunteering in the community by assisting organisations...
www.svm.edu.au

Society for Vascular Medicine - About SVM - Home
Mark Your Calendar. SVM 22nd Scientific Sessions June 2-4, 2011 Seaport Hotel Boston, Mass. Thanks to all who made the 2010 SVM Annual Meeting a huge success.
svm.org

SVM E Business Solutions - Online Marketing Bottom-line Results
SVM helps B-to-B companies leverage the Web to increase sales, strengthen relationships with customers and measure the return on marketing investments
svmsolutions.com

SVM (company) - Wikipedia, the free encyclopedia
SVM LP began as Stored Value Marketing in 1997. SVM is based in the Des Plaines, Illinois and provider of gasoline, restaurant, and other retail gift cards (also known as ...
Dynamic Ranking
Dynamic Ranking: Model

- Users: \( u_1 \ldots u_k \) with \( P(u) \)
- User behavior: \( \pi: u \notin \Psi \rightarrow \sigma \) \rightarrow \text{paths: } \sigma_1 \ldots \sigma_k
- Utility of \( \sigma \) for user \( u \): \( U(u, \sigma) \)
- Overall utility: \( U(\Psi) = \sum_u P(u) \cdot U(u, \pi(u, \Psi)) \)

"Intent-Aware" Measure [Agrawal et al. 2009]
Measure: \( U(u, \sigma) = \sum_i \frac{1}{\log(i+1)} U(u, \sigma[i]) \)

User behavior \( \pi \): Expand if doc is relevant, else skip.

- **User 1**: \( U(u_1, \sigma) = 2.13 \)
- **User 2**: \( U(u_2, \sigma) = 1.93 \)
- **User 3**: \( U(u_3, \sigma) = 1.06 \)
- **User 4**: \( U(u_4, \sigma) = 1.56 \)
- **User 5**: \( U(u_5, \sigma) = 0.93 \)

\[ U(\Psi) = 1.52 \]

Best static ranking \( \sigma^* \): \( U(\sigma^*) = 0.84 \)
Assumption

• **Definition: Modular Utility Functions**

A utility function $U(u, \sigma)$ is modular, if

$$U(u, \sigma) = \sum_i \gamma[i] \, U(u, \sigma[i])$$

with $\gamma[i] \geq 0$ and decreasing, and $U(u, \sigma[i]) \geq 0$.

(e.g. DCG, nDCG, Prec@k)
Algorithm for Static Ranking

• **Algorithm 3: StatMyopic**\( (q, D, P(u)) \)
  – sort documents by expected doc utility
  – \( P(r_d | q) = \sum_u P(r_d | q, u) P(u) \)

• **Theorem: Optimality of StatMyopic**
  For modular utility functions, StatMyopic is optimal for constructing static rankings.

... but it is **not** optimal for general utility functions, for example Average Precision.
Algorithms for Dynamic Ranking

• Algorithm 1: \textit{DynMyopic}(q,D,\pi,P(u))
  – Select d to maximize utility for user distribution that is conditioned on past actions
  – recurse on left and right subtree with user distribution updated according to \pi
Algorithms for Dynamic Ranking

• Algorithm 2: \textit{DynLookahead}(q, D, \pi, P(u))
  
  – Select \(d\) to maximize conditional utility plus utility of static ranking for left and right subtree
  – recurse on left and right subtree with user distribution updated according to \(\pi\)
Adaptivity Gain

• **Definition: Adaptivity Gain**
  The adaptivity gain of a dynamic ranking algorithm $A$ is
  
  $$U(A) - U(\text{StatMyopic}).$$

• **Theorem: Non-Negative Adaptivity Gain**
  For modular utility functions and any (known) user behavior policy $\pi$, both DynMyopic and DynLookahead have a non-negative adaptivity gain.

  ... it is possible to construct examples where adaptivity gain is 0, but where the best possible adaptivity gain > 0.
Related Work

• Interactive Information Retrieval
  – Interface like SurfCanyon.com [Cramer et al., 2009]
  – Simple interaction, like menu browsing
  – Decision-theoretic model [Fuhr, 2008]

• Relevance Feedback
  – Use feedback to refine query, see [Ruthven & Lalmas, 2003]
  – Integrating feedback and result presentation; users “keep state”
  – Exploration, not just exploitation

• Diversified Retrieval
  – Novelty vs. relevance [Carbonell & Goldstein, 1998] [Zhai et al., 2003]
  – Left branch of DynMyopic similar to [Chen & Karger, 2006]
Experiments

• Data:
  – TREC 18 Web Track (WEB)
    • 50 queries
    • 2-8 profiles (i.e. user types) for each query.
    • $P(u)$ uniform.
    • Binary relevance judgments
  – TREC 6-8 Interactive Track (INTERACTIVE)
    • 20 queries
    • 7-56 profiles (i.e. user types) for each query.
    • $P(u)$ proportional to number of relevant documents in profile.
    • Binary relevance judgments
How Large is the Adaptivity Gain?

- Relevance profiles
  - known to the algorithm
- User Behavior
  - $\pi_{\text{det}}$: users expand relevant docs, skip non-relevant docs.
Noisy User Behavior

• Relevance profiles
  – known to the algorithm
• User Behavior
  – $\pi_\varepsilon$: users
    • skip relevant documents with probability $\varepsilon$,
    • exp non-relevant documents with probability $\varepsilon$. 
Learning the Relevance Function

- Relevance profiles
  - Learned $P(\text{rel}|d,q,\pi,a_1...a_i)$
  - Logistic regression
    - Features relating doc and query
    - Features relating doc and expanded
    - Features relating doc and skipped
  - Training data from simulated users
    - $\pi_{\text{det}}$: deterministic users
    - Training examples: ((q,d,a_1...a_i) $\rightarrow$ rel)
    - Sampled a_1...a_i “appropriately”

- Leave-one-query-out cross validation
Conclusions

• Simple interactive ranked retrieval model
  – Combines diversity and recall
  – Evolution, not revolution of user interface; menu browsing

• Theoretical model
  – Provides evaluation measures
  – Guides algorithm design

• Algorithms
  – Two efficient algorithms with non-negative adaptivity gain
  – http://dynamicranking.joachims.org

• Directions for Research
  – Approximation algorithms for constructing dynamic ranking trees
  – Using click data for learning $P(r_d|q,\pi,a_1,...,a_{i-1})$
  – More sophisticated user behavior policies $\pi$
  – More actions than skip and expand
  – Usability (layout, clicking vs. mousing)
Directions for Research

• Approximation algorithms for constructing dynamic ranking trees
  – Approximation guarantees
  – Partial-information online learning problem
• Learning dynamic ranking models from real data
  – Using observational click data for learning $P(r_d|q, \pi, a_1, \ldots, a_{i-1})$
• More sophisticated user behavior policies $\pi$
  – Asymmetric costs for skip and expand / limited depth
  – Verify policy against real user behavior
  – Policies that are not static throughout search
• More actions than skip and expand
  – Backing out of tree
  – Reformulation recommendations
• Usability
  – Result layout
  – Clicking vs. mousing