Introduction to Information Retrieval
http://informationretrieval.org

IIR 15-2: Learning to Rank

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Models and Methods

1. Boolean model and its limitations (30)
2. Vector space model (30)
3. Probabilistic models (30)
4. Language model-based retrieval (30)
5. Latent semantic indexing (30)
6. Learning to rank (30)

Take-away

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- Machine-learned relevance: We use machine learning to learn the relevance score (retrieval status value) of a document with respect to a query.

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- Learning to rank: A machine-learning method that directly optimizes the ranking (as opposed to classification or regression accuracy)

Outline

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- Learn weights from this training set, so that the learned scores approximate the relevance judgments in the training set

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- We learn a single classifier or ranker.
- We can then rank documents for a query that we don't have any relevance judgments for.

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  - one feature (ω) that captures query term proximity (often indicative of topical relevance) □

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Training set

Example	DocID	Query	α	ω	Judgment
Φ_1	37	linux ...	0.032	3	relevant
Φ_2	37	penguin ...	0.02	4	nonrelevant
Φ_3	238	operating system	0.043	2	relevant
Φ_4	238	runtime ...	0.004	2	nonrelevant
Φ_5	1741	kernel layer	0.022	3	relevant
Φ_6	2094	device driver	0.03	2	relevant
Φ_7	3191	device driver	0.027	5	nonrelevant

α is the cosine score. ω is the window width.

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- We wish this function to be in agreement with our set of training examples as much as possible.
- The simplest classifier is a linear classifier, defined by an equation of the form:

$$Score(d, q) = Score(\alpha, \omega) = a\alpha + b\omega + c,$$

where we learn the coefficients a, b, c from training data. □

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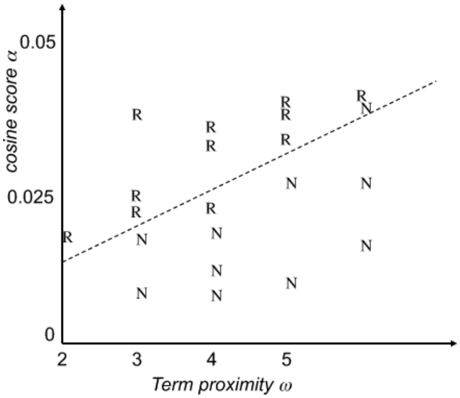

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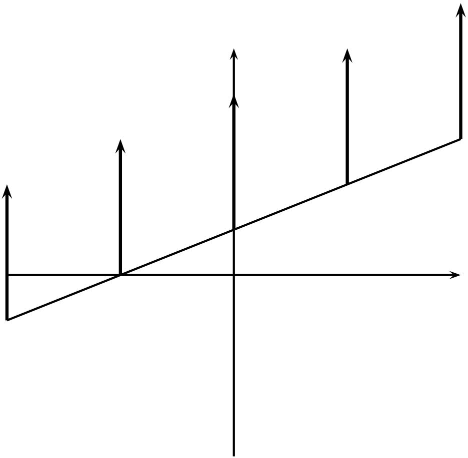

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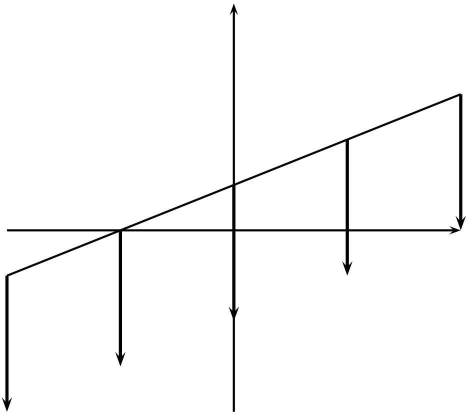

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- In principle, any classification/regression method can be used.
- Big advantage: we avoid hand-tuning scoring functions and simply learn them from training data.
- Bottleneck: we need to maintain a representative set of training examples whose relevance assessments must be made by humans.

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- Any measure that can be calculated for a query-document pair is fair game for this approach.

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- Features derived from standard IR models: query term number, query term ratio, length, idf, sum/min/max/mean/variance of term frequency, sum/min/max/mean/variance of length normalized term frequency, sum/min/max/mean/variance of tf-idf weight, boolean model, BM25, LM-absolute-discounting, LM-dirichlet, LM-jelinek-mercer

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- Most of these features can be computed for different zones: body, anchor, title, url, whole document

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- Spam features: QualityScore
- Usage-based features: query-url click count, url click count, url dwell time
- All of these features can be assembled into a big feature vector and then fed into the machine learning algorithm. □

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- Next up: ranking SVMs, a machine learning method that learns an ordering directly.

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- For two documents d_i and d_j, we then form the vector of feature differences:

$$\Phi(d_i, d_j, q) = \psi(d_i, q) - \psi(d_j, q)$$

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- We can then train an SVM on this training set with the goal of obtaining a classifier that returns

$$\vec{w}^{\mathsf{T}}\Phi(d_i, d_j, q) > 0 \quad \text{iff} \quad d_i \prec d_j$$

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- . . . rather than having to be mapped to a global scale of goodness.
- This often is an easier problem to solve since just a ranking is required rather than an absolute measure of relevance.

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- In most IR settings, getting the order of the top documents right is key.
  - In the simple setting we have described, top and bottom ranks will not be treated differently.
- $\rightarrow$ Learning-to-rank frameworks actually used in IR are more complicated than what we have presented here. □

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Learning-to-rank clearly better than non-machine-learning approaches

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  - Web search engines use a large number of features → web search engines need some form of learning to rank.

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  - Use Latent Semantic Indexing

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Resources

- Chapter 15 of Introduction to Information Retrieval
- Resources at http://informationretrieval.org/essir2011
    - References to learning to rank literature
    - Microsoft learning to rank datasets
    - How Google tweaks ranking

Exercise

Exercise

Write down the training set from the last exercise as a training set for a ranking SVM.