

Introduction to Information Retrieval

<http://informationretrieval.org>

IIR 15-2: Learning to Rank

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2011-06-28

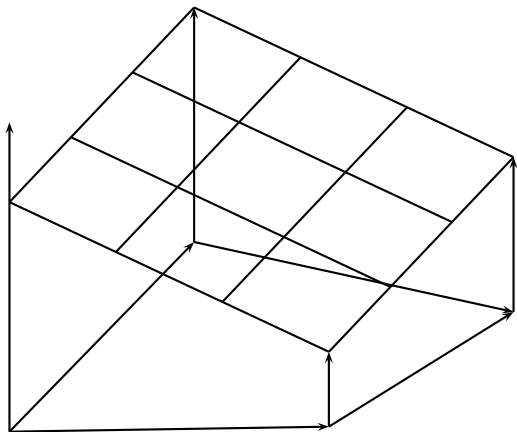
Overview

- 1 Recap
- 2 Zone scoring
- 3 Machine-learned scoring
- 4 Ranking SVMs

Outline

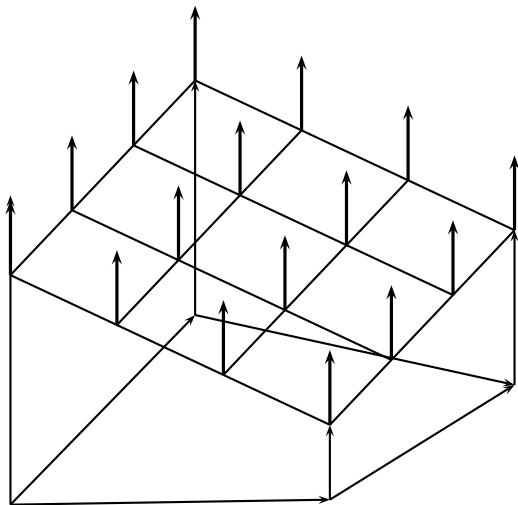
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A linear classifier in 3D



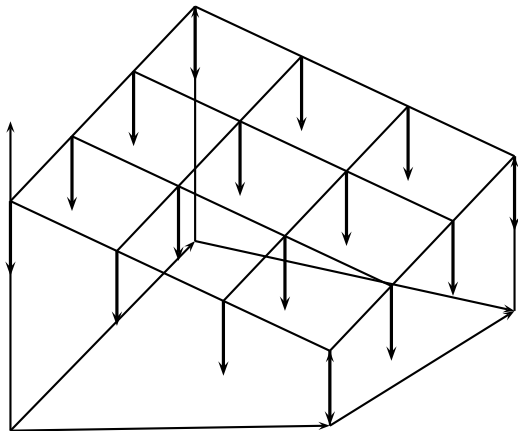
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$$w_1d_1 + w_2d_2 + w_3d_3 = \theta$$
- Example for a 3D linear classifier
- Points $(d_1 \ d_2 \ d_3)$ with $w_1d_1 + w_2d_2 + w_3d_3 \geq \theta$ are in the class c .
- Points $(d_1 \ d_2 \ d_3)$ with $w_1d_1 + w_2d_2 + w_3d_3 < \theta$ are in the complement class \bar{c} .

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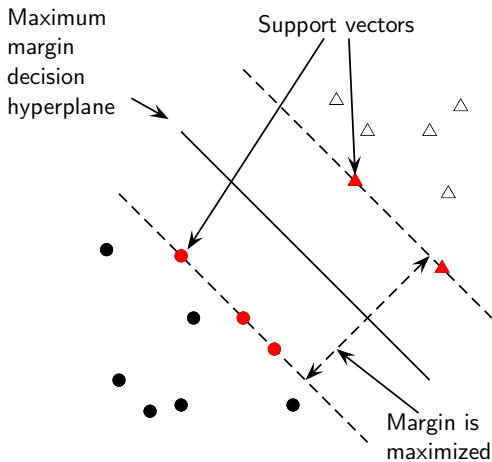
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Linear classifiers

- Many common text classifiers are linear classifiers: Naive Bayes, Rocchio, logistic regression, least squares regression, linear support vector machines etc.
- Each method has a different way of selecting the separating hyperplane
 - Huge differences in performance on test documents

Support vector machines

- Binary classification problem
- Simple SVMs are linear classifiers.
- criterion: being maximally far away from any data point
→ determines classifier **margin**
- linear separator position defined by **support vectors**



Optimization problem solved by SVMs

Find \vec{w} and b such that:

- $\frac{1}{2}\vec{w}^T\vec{w}$ is minimized (because $|\vec{w}| = \sqrt{\vec{w}^T\vec{w}}$), and
- for all $\{(\vec{x}_i, y_i)\}$, $y_i(\vec{w}^T\vec{x}_i + b) \geq 1$

Which machine learning method to choose

- Is there a learning method that is optimal for all text classification problems?
- No, because there is a tradeoff between bias and variance.
- Factors to take into account:
 - How much training data is available?
 - How simple/complex is the problem? (linear vs. nonlinear decision boundary)
 - How noisy is the problem?
 - How stable is the problem over time?
 - For an unstable problem, it's better to use a simple and robust classifier.

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- Machine-learned scoring as a general approach to ranking
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 - Term weights can be learned using training examples that have been judged.
- This methodology falls under a general class of approaches known as [machine learned relevance](#) or [learning to rank](#).

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 - More sophisticated cases: graded relevance judgments
- Learn weights from these examples, so that the learned scores approximate the relevance judgments in the training examples

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 - Rank documents according to probability of relevance

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

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- What features/dimensions would you use to represent a query-document pair?

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Example

Query term appears in `title` and `body` only

Document score: $(0.3 \cdot 1) + (0.5 \cdot 1) = 0.8$.

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Weighted zone score a.k.a **ranked Boolean retrieval**

Rank documents according to $\sum_{i=1}^l g_i s_i$

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- No free lunch: labor-intensive assembly of user-generated relevance judgments from which to learn the weights
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 - Major search engine put considerable resources into creating large training sets for learning to rank.
- Good news: once you have a large enough training set, the problem of learning the weights g_i reduces to a simple optimization problem.

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- Given q, d , $s_T(d, q) = 1$ if a query term occurs in title, 0 otherwise; $s_B(d, q) = 1$ if a query term occurs in body, 0 otherwise
- We compute a score between 0 and 1 for each (d, q) pair using $s_T(d, q)$ and $s_B(d, q)$ by using a constant $g \in [0, 1]$:

$$\text{score}(d, q) = g \cdot s_T(d, q) + (1 - g) \cdot s_B(d, q)$$

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Example

Φ_j	d_j	q_j	s_T	s_B	$r(d_j, q_j)$
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- A given training document d_j and a given training query q_j are assessed by a human who decides $r(d_j, q_j)$ (either relevant or nonrelevant)

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- For each training example Φ_j we have Boolean values $s_T(d_j, q_j)$ and $s_B(d_j, q_j)$ that we use to compute a score:

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- The problem of learning the constant g from the given training examples then reduces to picking the value of g that minimizes the total error.

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$$\epsilon(g, \Phi_j) = (r(d_j, q_j) - \text{score}(d_j, q_j))^2$$
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- Pick the value of g that minimizes the total error

Setting derivative to 0, gives you a minimum of $g = \frac{1}{4}$.

Weight g that minimizes error in the general case

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- Derivation: see book

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- Derivation: see book
- Note that we ignore documents that have 0 match scores for both zones or 1 match scores for both zones – the value of g does not change their final score.

Exercise: Compute g that minimizes the error

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	DocID	Query	s_T	s_B	Judgment
Φ_1	37	linux	0	0	Relevant
Φ_2	37	penguin	1	1	Nonrelevant
Φ_3	238	system	1	0	Relevant
Φ_4	238	penguin	1	1	Nonrelevant
Φ_5	238	redmond	0	1	Nonrelevant
Φ_6	1741	kernel	0	0	Relevant
Φ_7	2094	driver	1	0	Relevant
Φ_8	3194	driver	0	1	Nonrelevant
Φ_9	3194	redmond	0	0	Nonrelevant

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- 1 Recap
- 2 Zone scoring
- 3 Machine-learned scoring**
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More general setup of machine learned scoring

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- Now consider more general factors that go beyond Boolean functions of query term presence in document zones.

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- The vector space cosine similarity between query and document (denoted α)
- The minimum window width within which the query terms lie (denoted ω)
 - Query term proximity is often indicative of topical relevance.
- Thus, we have one feature that captures overall query-document similarity and one features that captures proximity of query terms in the document.

Learning to rank setup for these two features

Learning to rank setup for these two features

Example

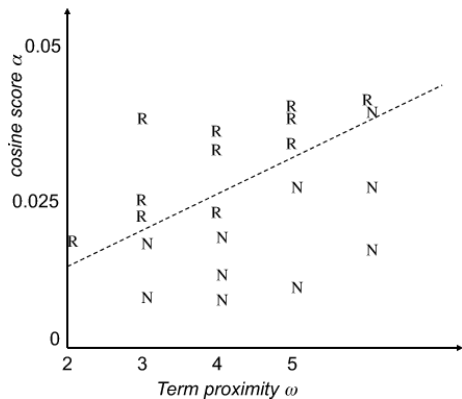
Example	DocID	Query	α	ω	Judgment
Φ_1	37	linux	0.032	3	relevant
Φ_2	37	penguin	0.02	4	nonrelevant
Φ_3	238	operating system	0.043	2	relevant
Φ_4	238	runtime	0.004	2	nonrelevant
Φ_5	1741	kernel layer	0.022	3	relevant
Φ_6	2094	device driver	0.03	2	relevant
Φ_7	3191	device driver	0.027	5	nonrelevant

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

This is exactly the same setup as for zone scoring except we now have more complex features that capture whether a document is relevant to a query.

Graphic representation of the training set

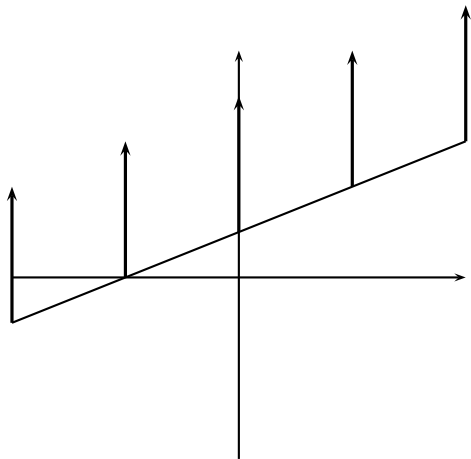
Graphic representation of the training set



This should look familiar.

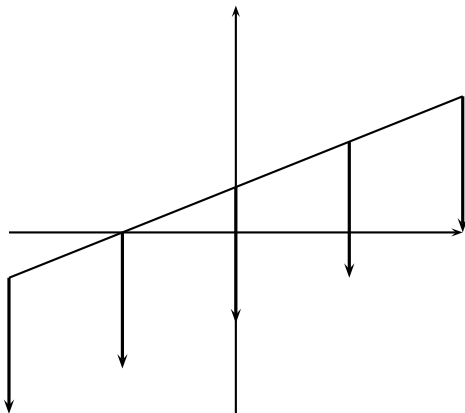
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- Example for a 2D linear classifier
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 - This is what we did for zone scoring just now.

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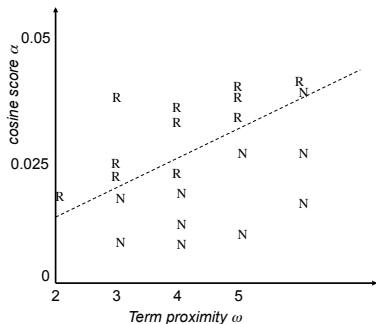
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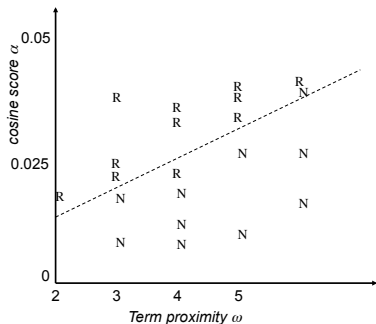
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- Big advantage of learning to rank: we can avoid hand-tuning scoring functions and simply learn them from training data.
- Bottleneck of learning to rank: maintaining a representative set of training examples whose relevance assessments must be made by humans.

Learning to rank for more than two features

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- If these measures can be calculated for a training document collection with relevance judgments, any number of such measures can be used to machine-learn a classifier.

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- Machine learning for ad hoc retrieval is most properly thought of as an ordinal regression problem, where the goal is to rank a set of documents for a query, given training data of the same sort.
- Next up: **ranking SVMs**, a machine learning method that learns an ordering directly.

Exercise

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Give parameters a, b, c of a line $a\alpha + b\omega + c$ that separates relevant from nonrelevant.

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- We again construct a vector of features $\psi_j = \psi(d_j, q)$ for each document-query pair – exactly as we did before.
- For two documents d_i and d_j , we then form the vector of feature differences:

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

Training a ranking SVM

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- This gives us a training set of pairs of vectors and “precedence indicators”. Each of the vectors is computed as the difference of two document-query vectors.
- We can then train an SVM on this training set with the goal of obtaining a classifier that returns

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

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- This often is an easier problem to solve since just a ranking is required rather than an absolute measure of relevance.

Advantages of Ranking SVMs vs. Classification/regression

- Documents can be evaluated **relative** to other candidate documents for the same query, 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.
- Especially germane in web search, where the ranking at the very top of the results list is exceedingly important.

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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.
- → Learning-to-rank frameworks actually used in IR are more complicated than what we have presented here.

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	MAP	W/L	MAP	W/L
SVM_{map}^{Δ}	0.242	–	0.236	–
Best Func.	0.204	39/11 **	0.181	37/13 **
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Learning-to-rank clearly better than non-machine-learning approaches

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- At the present time, machine learning is very good at producing optimal weights for features in a linear combination, but it is not good at coming up with good nonlinear scalings of basic measurements.
- This area remains the domain of human feature engineering.

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- The more features are used in ranking, the more difficult it is to manually integrate them into one ranking function.
- Web search engines use a large number of features → web search engines need some form of learning to rank.

Exercise

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

Take-away today

- Basic idea of learning to rank (LTR): We use machine learning to learn the relevance score (retrieval status value) of a document with respect to a query.
- Zone scoring: a particularly simple instance of LTR
- Machine-learned scoring as a general approach to ranking
- Ranking SVMs

Resources

- Chapters 6 and 15 of IIR
- Resources at <http://ifnlp.org/ir>
 - References to ranking SVM results
 - Microsoft learning to rank datasets