Introduction to Information Retrieval
http://informationretrieval.org

IIR 15-2: Learning to Rank

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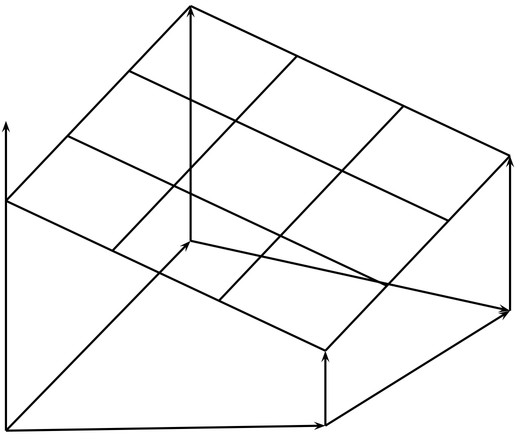
Overview

Outline

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

A linear classifier in 3D



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- Example for a 3D linear classifier
- Points $(d_1\ d_2\ d_3)$ with $w_1 d_1 + w_2 d_2 + w_3 d_3 \geq \theta$ are in the class c.
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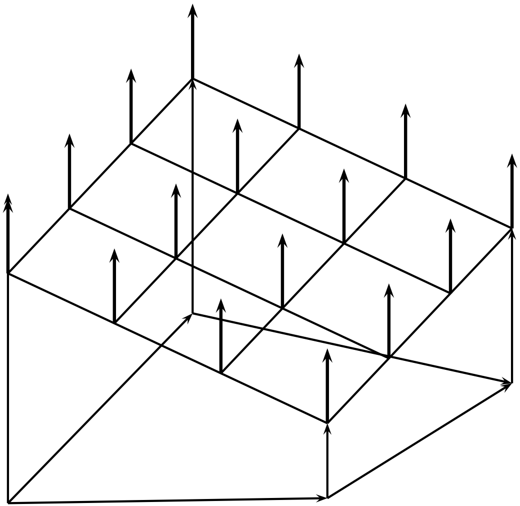

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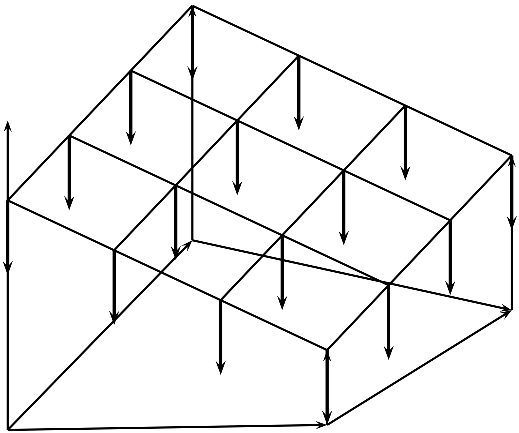

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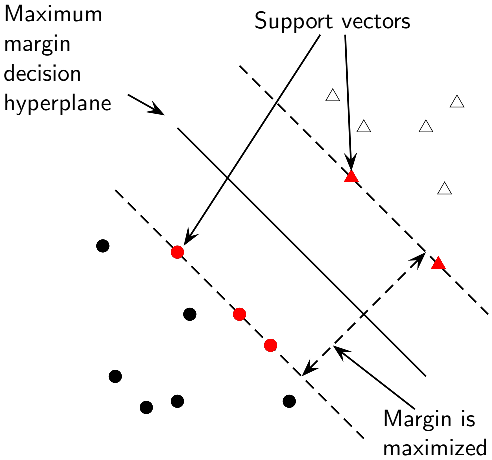
Linear classifiers

- 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 $\rightarrow$ determines classifier **margin**
- linear separator position defined by **support vectors**



Optimization problem solved by SVMs

Find $\vec{w}$ and b such that:

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

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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- Ranking SVMs

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- Now we view this ranking problem as a machine learning problem – we will learn the weighting or, more generally, the ranking.
  - 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
  - Especially in a dynamic collection (such as the Web)
  - Major search engines 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 $g \in [0, 1]$:

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

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Example

Φ_j	d_j	q_j	s_T	s_B	$r(d_j, q_j)$
Φ_1	37	linux	1	1	Relevant
Φ_2	37	penguin	0	1	Nonrelevant
Φ_3	238	system	0	1	Relevant
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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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  $\epsilon(g, \Phi_j) = (r(d_j, q_j) - score(d_j, q_j))^2$
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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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- 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.

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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

Solution

2	n_{10r}	$s_T = 1$	$s_B = 0$	document relevant
0	n_{10n}	$s_T = 1$	$s_B = 0$	document nonrelevant
0	n_{01r}	$s_T = 0$	$s_B = 1$	document relevant
2	n_{01n}	$s_T = 0$	$s_B = 1$	document nonrelevant

$$g = \frac{n_{10r} + n_{01n}}{n_{10r} + n_{10n} + n_{01r} + n_{01n}} = \frac{2+2}{2+0+2+0} = 1$$

Outline

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

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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

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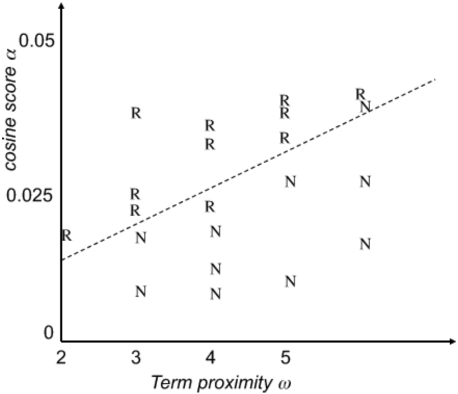

This should look familiar.

In this case: LTR approach learns a linear classifier in 2D

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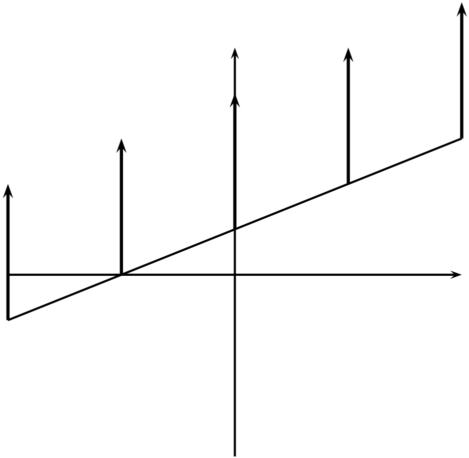

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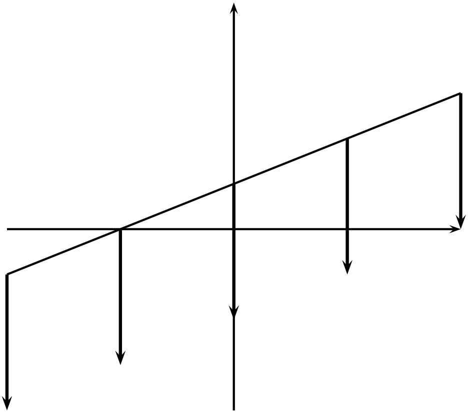

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  - This is what we did for zone scoring just now.

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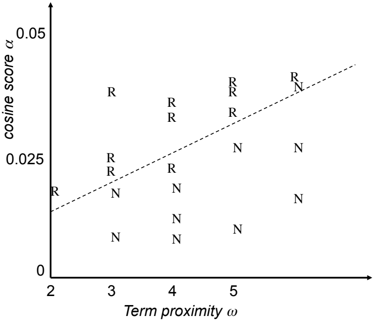

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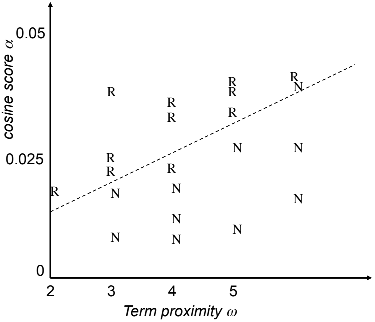

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- Big advantage of learning to rank: we can avoid hand-tuning scoring functions and simply learn them from training data.
- Bottleneck of learning to rank: maintaining a representative set of training examples whose relevance assessments must be made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

Learning to rank for more than two features

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- In addition to cosine similarity and query term window, there are lots of other indicators of relevance: PageRank-style measures, document age, zone contributions, document length, etc.
- 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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Example

Example	DocID	Query	Cosine	ω	Judgment
Φ_1	37	linux	0.051	3	relevant
Φ_2	37	linux	0.04	5	nonrelevant
Φ_3	238	operating system	0.3	2	relevant
Φ_4	238	operating system	0.12	3	relevant
Φ_5	518	runtime	0.04	2	relevant
Φ_6	518	runtime	0.005	10	nonrelevant

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

Outline

Basic setup for ranking SVMs

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- We again construct a vector of features $\psi_j = \psi(d_j, q)$ for each query-document 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 query-document vectors.

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- By hypothesis, one of d_i and d_j has been judged more relevant.
- Notation: We write $d_i \prec d_j$ for "d_i precedes d_j in the results ordering".
- If d_i is judged more relevant than d_j, then we will assign the vector $\Phi(d_i, d_j, q)$ the class $y_{ijq} = +1$; otherwise -1.
- This gives us a training set of pairs of vectors and "precedence indicators". Each of the vectors is computed as the difference of two query-document vectors.
- 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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- 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.
- $\rightarrow$ 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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- 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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- While skilled humans can do a very good job at defining ranking functions by hand, hand tuning is difficult, and it has to be done again for each new document collection and class of users.
- 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 $\rightarrow$ 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.

Recall: Vector of feature differences:
$\Phi(d_i, d_j, q) = \psi(d_i, q) - \psi(d_j, q)$,
$\vec{w}^{\mathsf{T}}\Phi(d_i, d_j, q) > 0 \quad \text{iff} \quad d_i \prec d_j$

Example

Example	DocID	Query	Cosine	ω	Judgment
Φ_1	37	linux	0.03	3	relevant
Φ_2	37	penguin	0.04	5	nonrelevant
Φ_3	238	operating system	0.04	2	relevant
Φ_4	238	runtime	0.02	3	nonrelevant

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://cislmu.org`
  - References to ranking SVM results
  - Microsoft learning to rank datasets