Ranking and Learning

Adapted by Diana Inkpen, 2015,

from Tao Yang, 2014.

Partially based on Manning, Raghavan, and Schütze‘s text book.

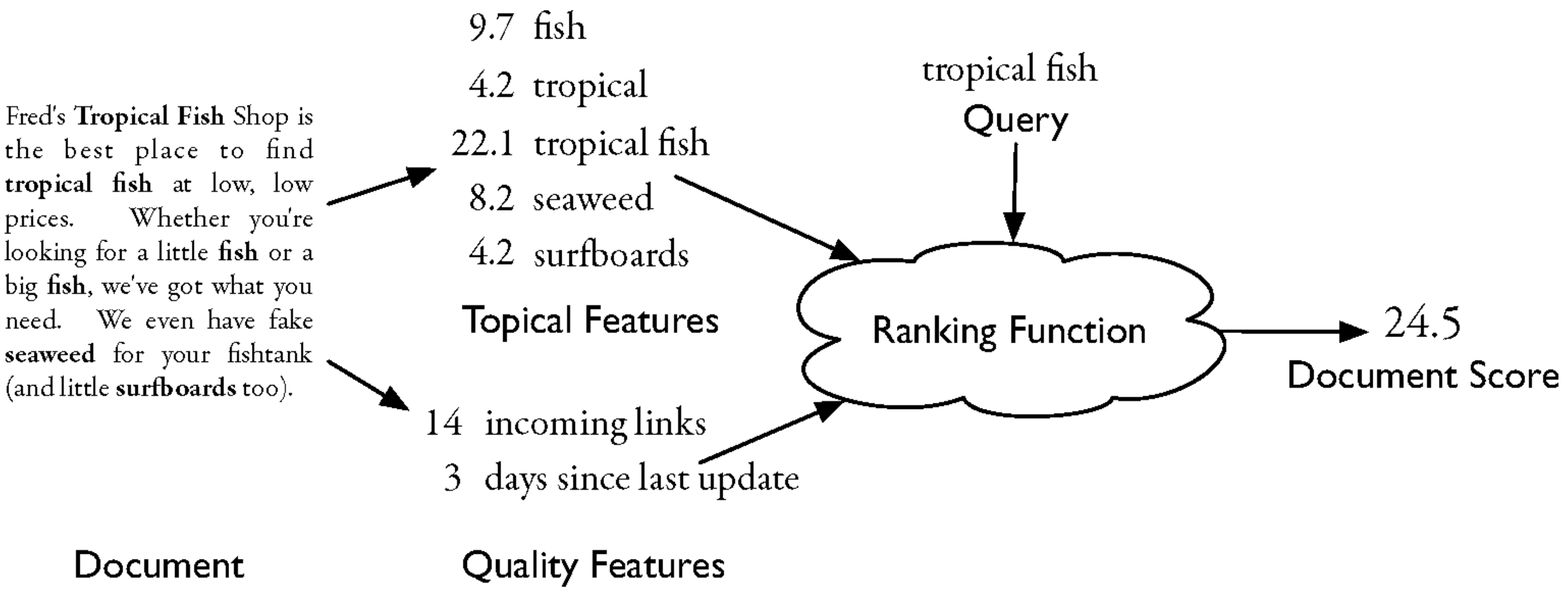
Content

- Weighted scoring for ranking
- Learning to rank: A simple example
- Learning to ranking as classification

Scoring

- **Similarity-based approach**
  - Similarity of query features with document features
- **Weighted approach: Scoring with weighted features**
  - *return in order the documents most likely to be useful to the searcher*
  - Consider each document has subscores in each feature or in each subarea.

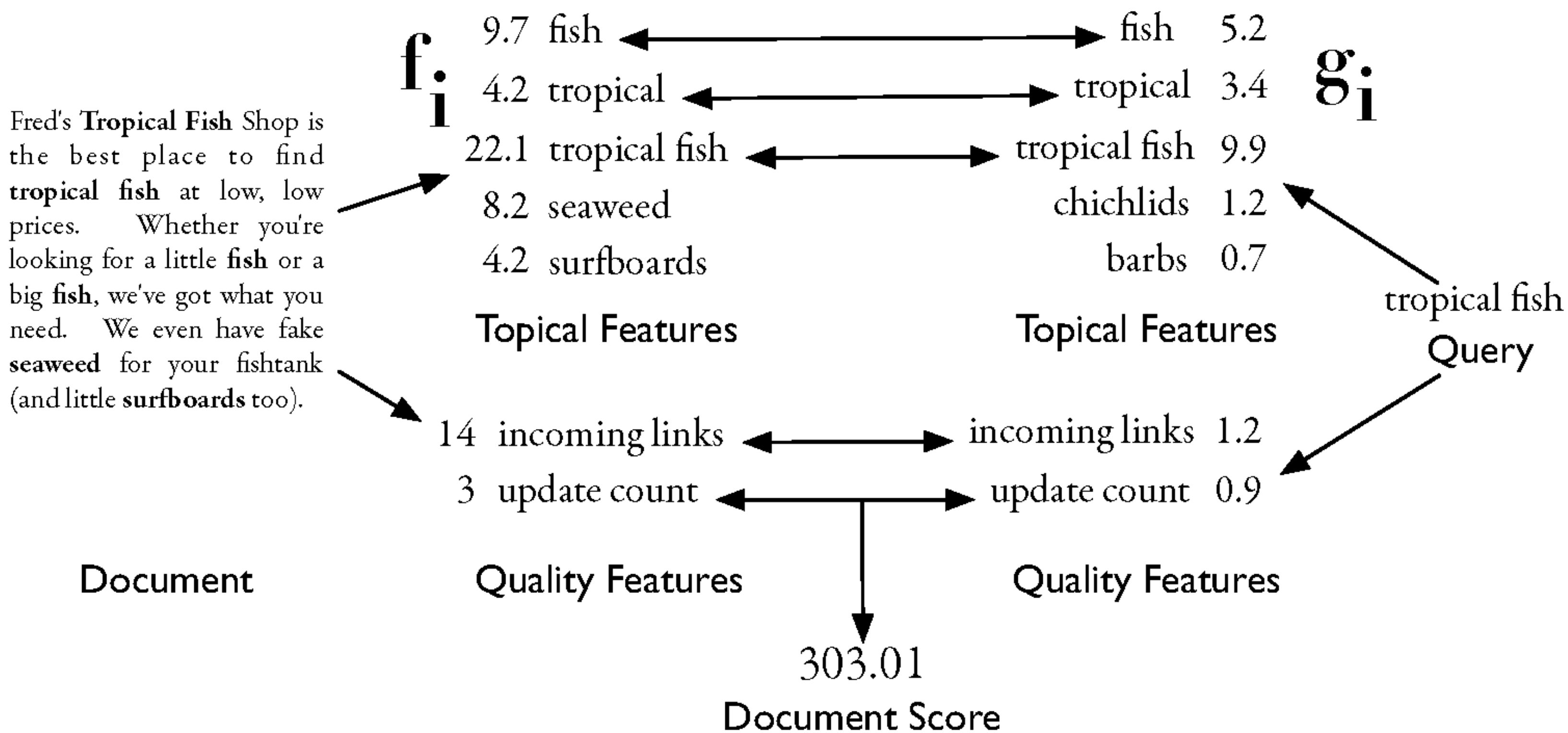
Simple Model of Ranking with Similarity



Similarity ranking: example
[Croft, Metzler, Strohman‘s textbook slides]

$$R(Q, D) = \sum_i g_i(Q) f_i(D)$$

f_i is a document feature function
g_i is a query feature function



Weighted scoring with linear combination

- **A simple weighted scoring method: use a linear combination of subscores:**
  - E.g.,

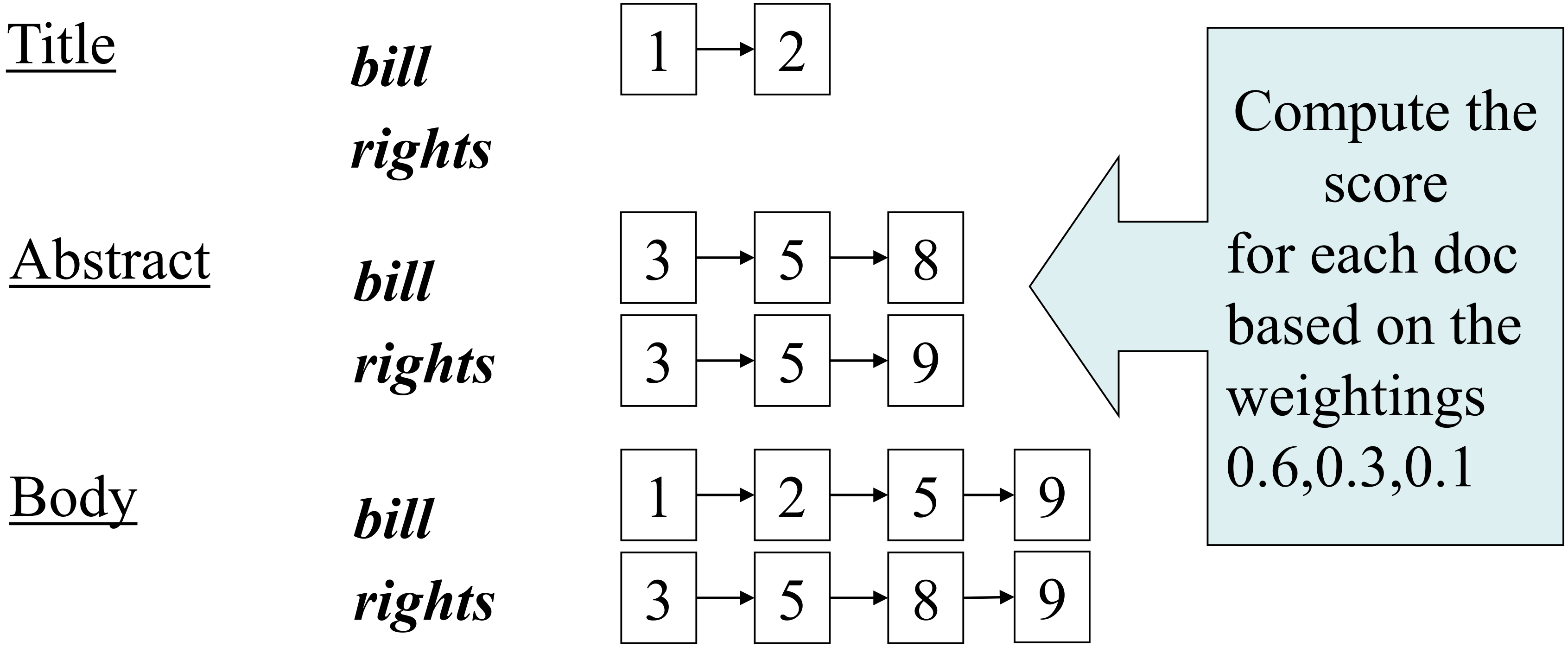
    Score = 0.6*< Title score> + 0.3*<Abstract score> + 0.1*<Body score>

  - The overall score is in [0,1].

Example with binary subscores
Query term appears in title and body only Document score: (0.6 · 1) + (0.1 · 1) = 0.7.

Example

- **On the query “*bill rights*” suppose that we retrieve the following docs from the various zone indexes:**

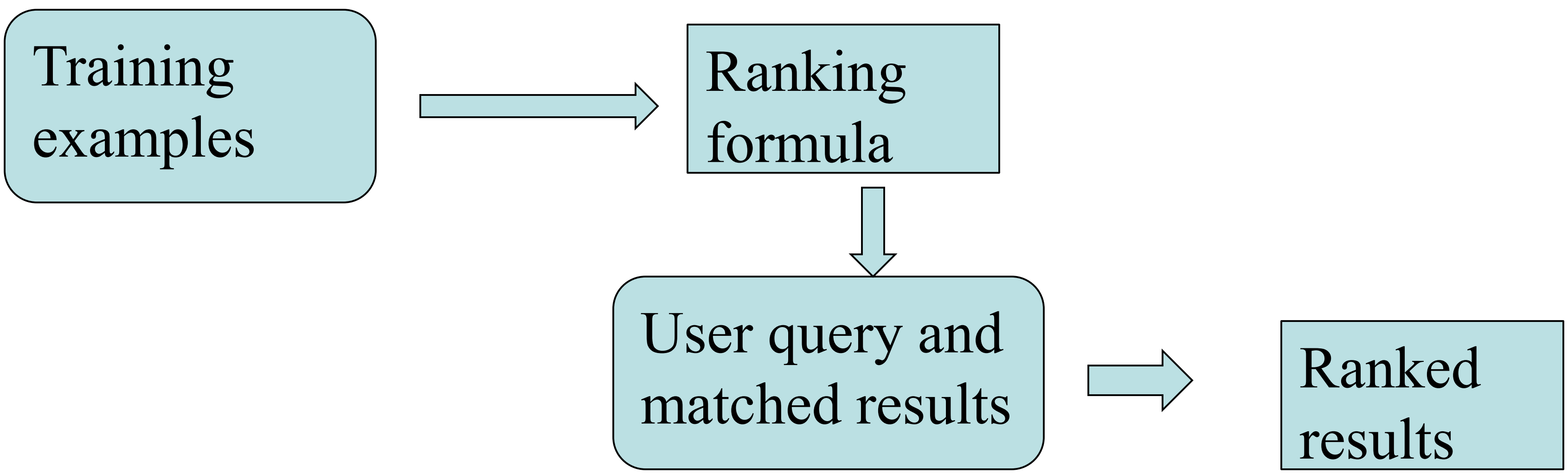


How to determine weights automatically: Motivation

- **Modern systems – especially on the Web – use a great number of features:**
  - Arbitrary useful features – not a single unified model
    - Log frequency of query word in anchor text?
    - Query word highlighted on page?
    - Span of query words on page
    - # of (out) links on page?
    - PageRank of page?
    - URL length?
    - URL contains “~”?
    - Page edit recency?
    - Page length?
- **Major web search engines use “hundreds” of such features – and they keep changing**

Machine learning for computing weights

- **How do we combine these signals into a good ranker?**
  - "machine-learned relevance" or "learning to rank"
- **Learning from examples**
  - These examples are called training data



Learning weights: Methodology

- Given a set of **training examples**,
  - each contains (query *q*, document *d*, relevance score r(d,q)).
  - r(d,q) is relevance judgment for *d* on *q*
    - Simplest scheme
      - relevant (1) or nonrelevant (0)
    - More sophisticated: graded relevance judgments
      - 1 (Bad), 2 (Fair), 3 (Good), 4 (Excellent), 5 (Perfect)

- Learn weights from these examples, so that the learned scores approximate the relevance judgments in the training examples

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Simple example

- **Each doc has two zones, Title and Body**
- **For a chosen $w \in [0,1]$, score for doc *d* on query *q***

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

where:

$s_T(d, q) \in \{0,1\}$ is a Boolean denoting whether *q* matches the Title and

$s_B(d, q) \in \{0,1\}$ is a Boolean denoting whether *q* matches the Body

Examples of Training Data

Example	DocID	Query	s_T	s_B	Judgment
Φ_1	37	linux	1	1	Relevant
Φ_2	37	penguin	0	1	Non-relevant
Φ_3	238	system	0	1	Relevant
Φ_4	238	penguin	0	0	Non-relevant
Φ_5	1741	kernel	1	1	Relevant
Φ_6	2094	driver	0	1	Relevant
Φ_7	3191	driver	1	0	Non-relevant

From these 7 examples, learn the best value of *w*.

How?

- **For each example Φ_t we can compute the score based on** $score(d_t, q_t) = w \cdot s_T(d_t, q_t) + (1 - w)s_B(d_t, q_t)$
- **We quantify Relevant as 1 and Non-relevant as 0**
- **Would like the choice of *w* to be such that the computed scores are as close to these 1/0 judgments as possible**
  - Denote by $r(d_t,q_t)$ the judgment for Φ_t
- **Then minimize total squared error**

$$\sum_{\Phi_t} (r(d_t, q_t) - score(d_t, q_t))^2$$

Optimizing *w*

- **There are 4 kinds of training examples**
- **Thus only four possible values for score**
  - And only 8 possible values for error
- **Let n_{01r} be the number of training examples for which $s_T(d, q)=0$, $s_B(d, q)=1$, judgment = *Relevant*.**
- **Similarly define n_{00r}, n_{10r}, n_{11r}, n_{00i}, n_{01i}, n_{10i}, n_{11i}**

s_T	s_B	Score
0	0	0
0	1	$1-w$
1	0	w
1	1	1

Judgment=1 $\Rightarrow$ Error=w

Judgment=0 $\Rightarrow$ Error=$1-w$

$$\text{Error: } \left[1-(1-\omega)\right]^2 n_{01r} + \left[0-(1-\omega)\right]^2 n_{01i}$$

Total error – then calculus

- **Add up contributions from various cases to get total error**

$$(n_{01r} + n_{10i})w^2 + (n_{10r} + n_{01i})(1 - w)^2 + n_{00r} + n_{11i}$$

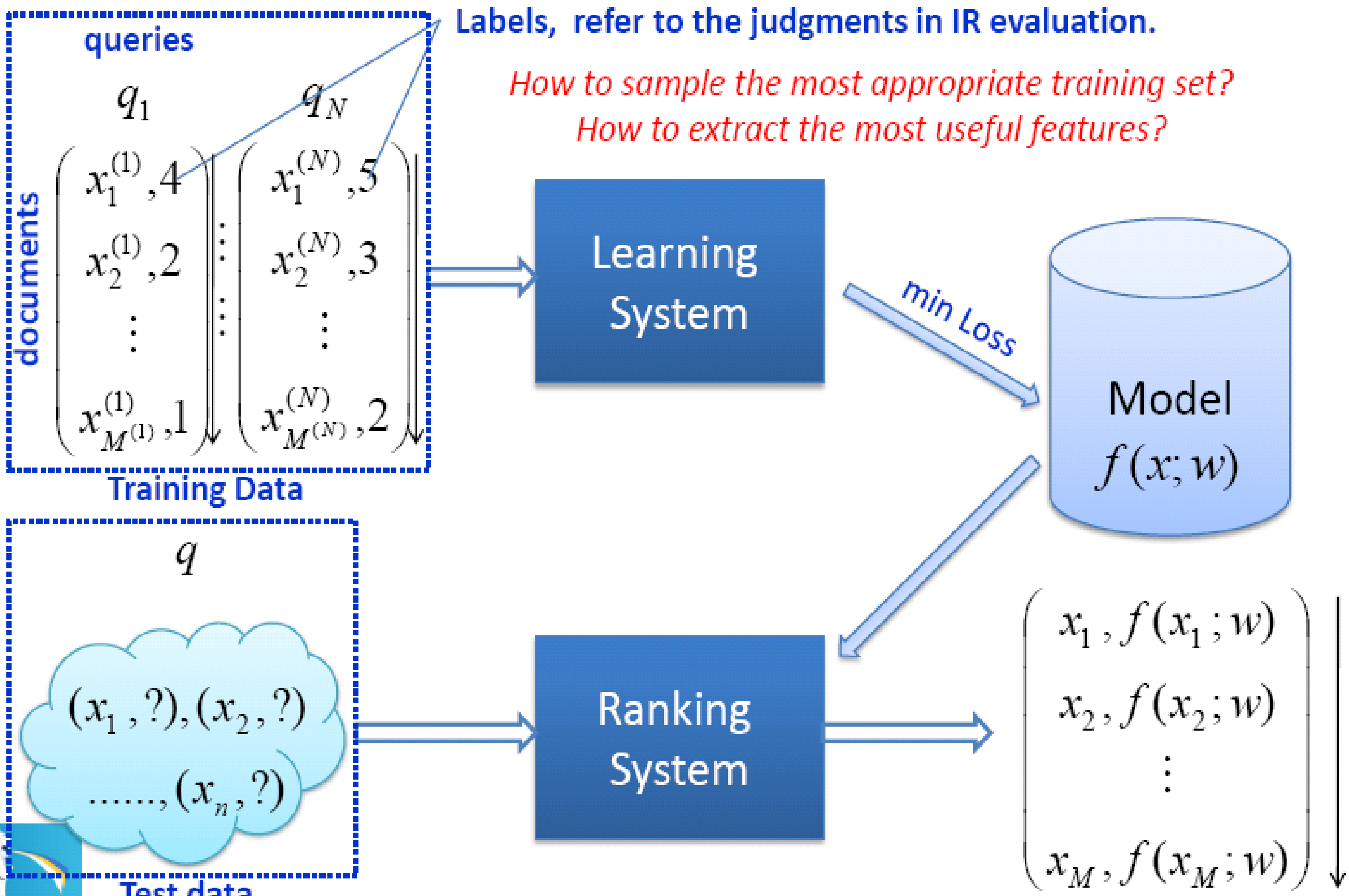
- **Now differentiate with respect to *w* to get optimal value of *w* as:**

$$\frac{n_{10r} + n_{01i}}{n_{10r} + n_{10i} + n_{01r} + n_{01i}}.$$

Generalizing this simple example

- **More (than 2) features**
- **Non-Boolean features**
  - What if the title contains some but not all query terms …
  - Categorical features (query terms occur in plain, boldface, italics, etc)
- **Scores are nonlinear combinations of features**
- **Multilevel relevance judgments (Perfect, Good, Fair, Bad, etc.)**
- **Complex error functions**
- **Not always a unique, easily computable setting of score parameters**

Framework of Learning to Rank



Learning-based Web Search

- **Given features $e_1, e_2, \ldots, e_N$ for each document, learn a ranking function $f(e_1, e_2, \ldots, e_N)$ that minimizes the loss function L under a query**

$$f^* = \min_{f \in F} L\left(f(e_1, e_2, \ldots, e_N), GroundTruth \right)$$

- **Some related issues**
  - The functional space *F*
    - linear/non-linear? continuous? Derivative?
  - The search strategy
  - The loss function

A richer example

- **Collect a training corpus of (*q, d, r*) triples**
  - Relevance *r* is still binary for now
  - Document is represented by a feature vector
    - **x** = (α, ω)   α is cosine similarity, ω is minimum query window size
      - ω is the shortest text span that includes all query words (Query term proximity in the document)
- **Train a machine learning model to predict the class *r* of a document-query pair**

example	docID	query	cosine score	ω	judgment
Φ_1	37	linux operating system	0.032	3	*relevant*
Φ_2	37	penguin logo	0.02	4	*nonrelevant*
Φ_3	238	operating system	0.043	2	*relevant*
Φ_4	238	runtime environment	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*

Using classification for deciding relevance

- A linear score function is

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

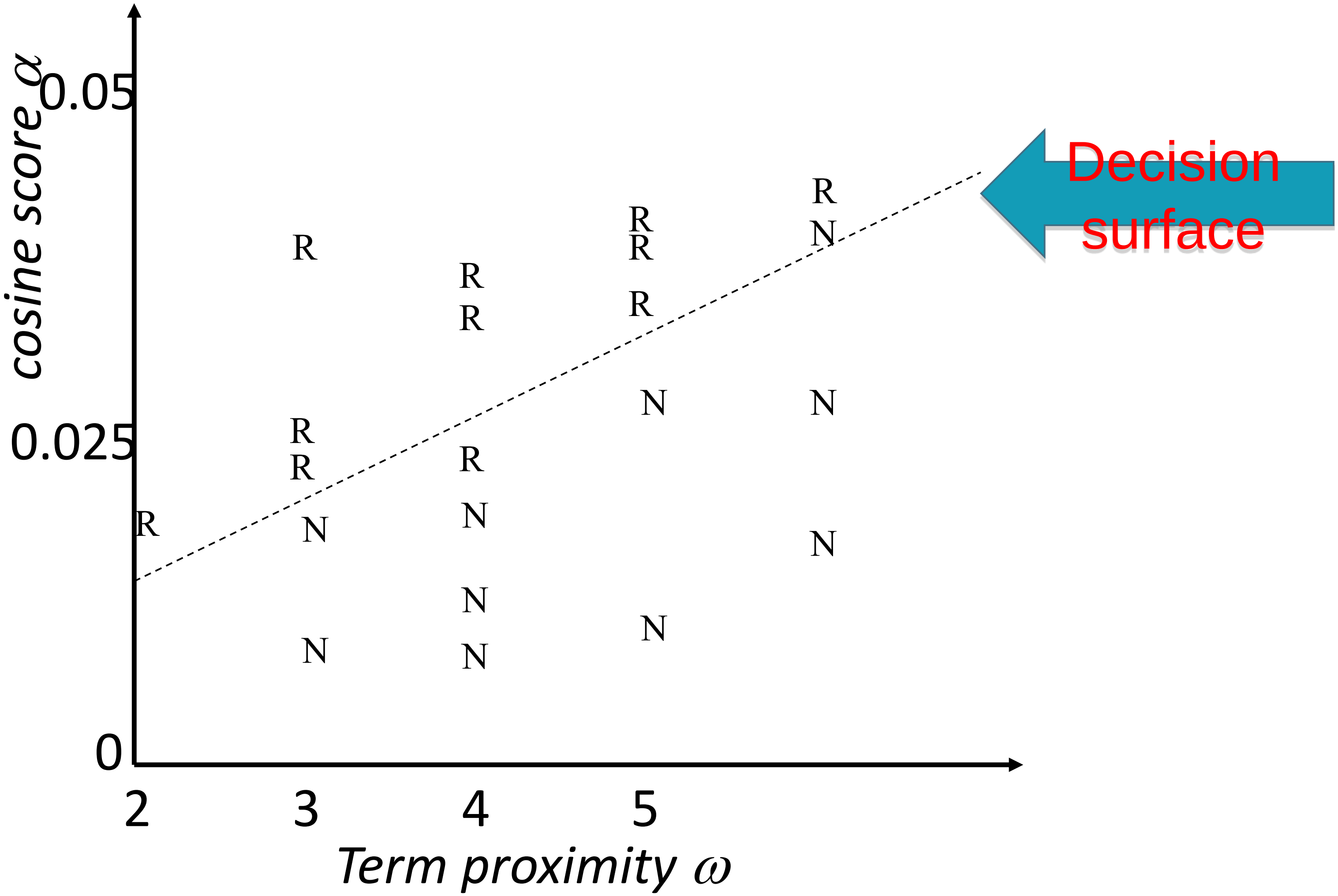
- And the linear classifier is

Decide relevant if $Score(d, q) > \theta$

Otherwise irrelevant

- … just like when we were doing classification

Using classification for deciding relevance



More complex example of using classification for search ranking

[Nallapati SIGIR 2004]

- We can generalize this to classifier functions over more features
- We can use methods we have seen previously for learning the linear classifier weights

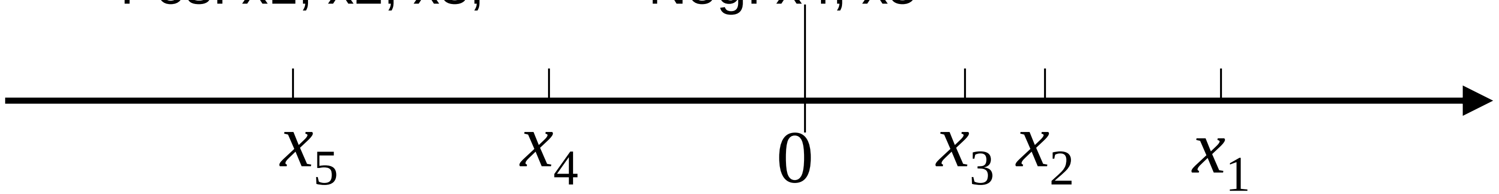
An SVM classifier for relevance

[Nallapati SIGIR 2004]

- Let $g(r|d,q) = \mathbf{w} \bullet f(d,q) + b$
- Derive weights from the training examples:
  - want $g(r|d,q) \leq -1$ for nonrelevant documents
  - $g(r|d,q) \geq 1$ for relevant documents
- Testing:
  - decide relevant iff $g(r|d,q) \geq 0$
- Train a classifier as the ranking function

Ranking vs. Classification

- **Classification**
  - Well studied over 30 years
  - Bayesian, Neural network, Decision tree, SVM, Boosting, …
  - Training data: points
    - Pos: x1, x2, x3,   Neg: x4, x5



- **Ranking**
  - Less studied: only a few works published in recent years
  - Training data: pairs (partial order)
    - Correct order: (x1, x2), (x1, x3), (x1, x4), (x1, x5) (x2, x3), (x2, x4) …
    - Other order is incorrect

Learning to rank: Classification vs. regression

- **Classification probably isn't the right way to think about score learning:**
  - Classification problems: Map to an unordered set of classes
  - Regression problems: Map to a real value
  - Ordinal regression problems: Map to an *ordered* set of classes
- **This formulation gives extra power:**
  - Relations between relevance levels are modeled
  - Some documents are better than other documents for some queries; not an absolute scale of goodness

"Learning to rank"

- **Assume a number of categories *C* of relevance exist**
  - These are totally ordered: $c_1 < c_2 < \ldots < c_J$
  - This is the ordinal regression setup
- **Assume training data is available consisting of document-query pairs represented as feature vectors ψ_i and relevance ranking c_i**

Modified example

- **Collect a training corpus of (*q, d, r*) triples**
  - Relevance label *r* has 4 values
    - Perfect, Relevant, Weak, Nonrelevant
- **Train a machine learning model to predict the class *r* of a document-query pair**

example	docID	query	cosine score	ω	judgment
Φ_1	37	linux operating system	0.032	3	*Perfect*
Φ_2	37	penguin logo	0.02	4	*Nonrelevant*
Φ_3	238	operating system	0.043	2	*Relevant*
Φ_4	238	runtime environment	0.004	2	*Weak*
Φ_5	1741	kernel layer	0.022	3	*Relevant*
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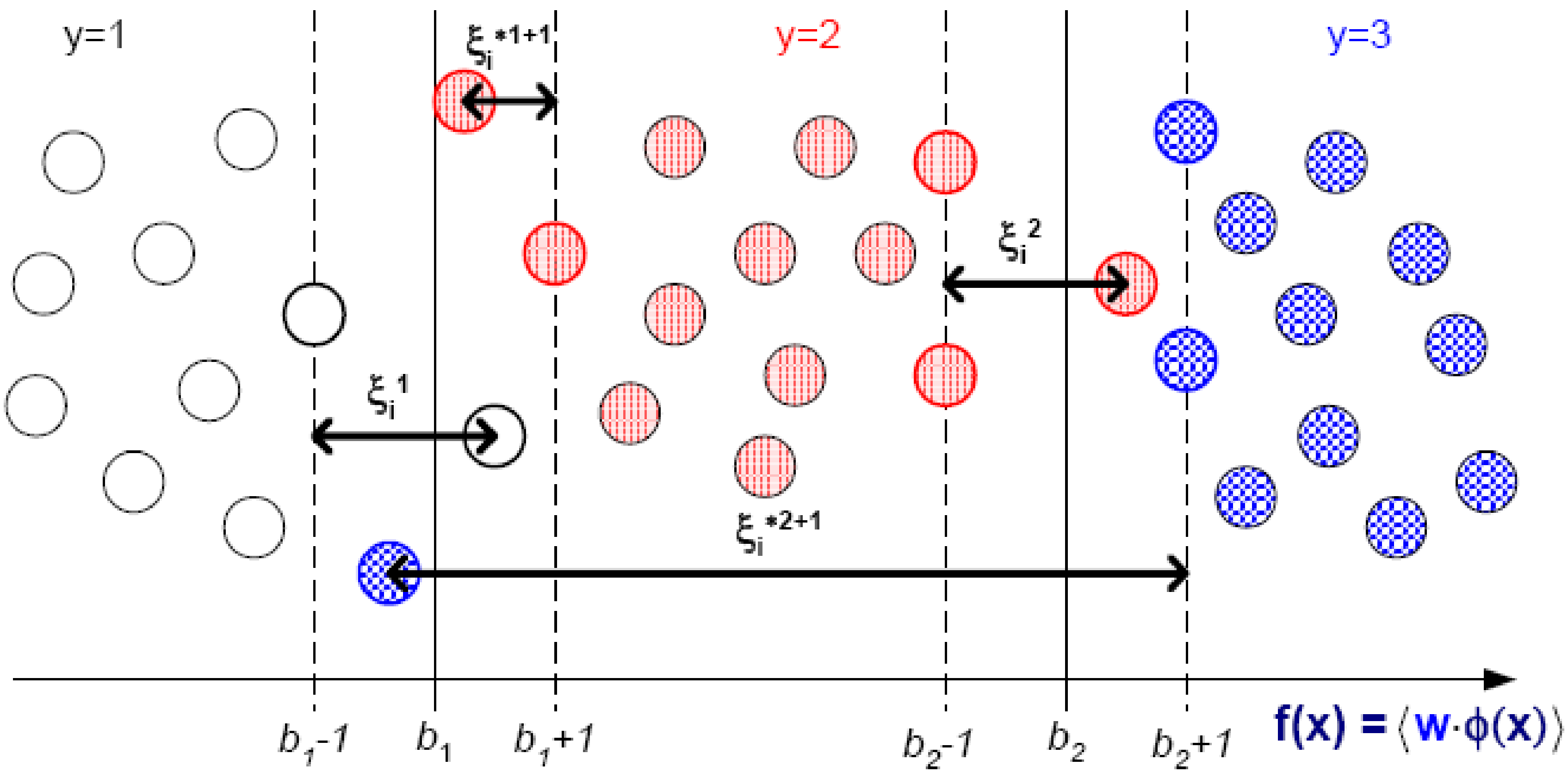
"Learning to rank"

- *Point-wise* learning
  - Given a query-document pair, predict a score (e.g., relevancy score)
- *Pair-wise* learning
  - the input is a pair of results for a query, and the class is the relevance ordering relationship between them
- *List-wise learning*
  - Directly optimize the ranking metric for each query

Point-wise learning: Example

- **Goal is to learn a threshold to separate each rank**



The Ranking SVM : Pairwise Learning

[Herbrich et al. 1999, 2000; Joachims et al. KDD 2002]

- **Aim is to classify instance pairs as**
  - correctly ranked
  - or incorrectly ranked
- **This turns an ordinal regression problem back into a binary classification problem**
- **We want a ranking function *f* such that c_i is ranked before c_k :**

$$c_i < c_k \text{ iff } f(\psi_i) > f(\psi_k)$$

- **Suppose that *f* is a linear function**

$$f(\psi_i) = \mathbf{w} \bullet \psi_i$$

- **Thus**

$$c_i < c_k \text{ iff } w(\psi_i - \psi_k) > 0$$

Ranking SVM

- **Training Set**
  - for each query q, we have a ranked list of documents totally ordered by a person for relevance to the query.
- **Features**
  - vector of features for each document/query pair

$$\psi_j = \psi(d_j, q)$$

  - feature differences for two documents d_i and d_i

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

- **Classification**
  - if d_i is judged more relevant than d_j, denoted $d_i \prec d_j$
  - then assign the vector $\Phi(d_i, d_j, q)$ the class y_{ijq} =+1; otherwise −1.

Ranking SVM

Optimization problem is equivalent to that of a classification SVM on pairwise difference vectors $\Phi(q_k, d_i)$ - $\Phi(q_k, d_j)$