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Information Retrieval

Learning to Rank: Fundamentals

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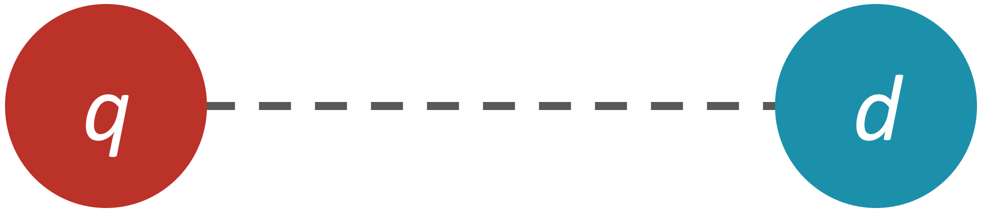
The ranking problem



$$f(q,d)$$

Many solutions

Topicality models

- VSM, BM, LM, DFR, MRF, LSI, DESM, …

Quality models

- PageRank, in-links, spam, …

No silver bullet

- Different models excel at different scenarios

How to combine multiple models?

Ensembling the cues

Linear combination?

- $f(q,d) = \alpha_1 f_{\mathrm{BM25}}(q,d) + \alpha_2 f_{\mathrm{PR}}(q,d)$

How to fit α_1 and $\alpha_2 = (1 - \alpha_1)$?

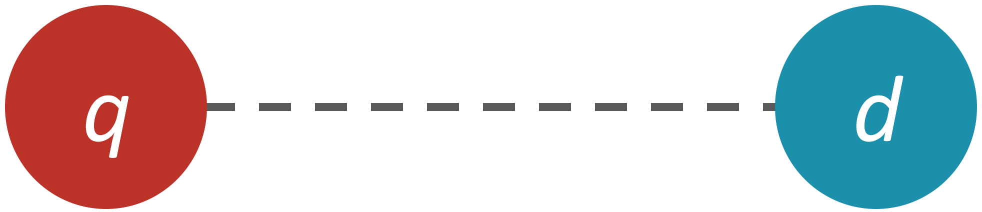
- $\{\alpha_1 = 0.3, \alpha_2 = 0.7\} \rightarrow \{\mathrm{MAP} = 0.2, \mathrm{nDCG} = 0.6\}$
- $\{\alpha_1 = 0.5, \alpha_2 = 0.5\} \rightarrow \{\mathrm{MAP} = 0.1, \mathrm{nDCG} = 0.5\}$
- $\{\alpha_1 = 0.7, \alpha_2 = 0.3\} \rightarrow \{\mathrm{MAP} = 0.4, \mathrm{nDCG} = 0.7\}$ ✓

What if we have thousands of models?

❝ *Mr. Singhal has developed a far more elaborate system for ranking pages, which involves more than 200 types of information, or what Google calls "signals."*

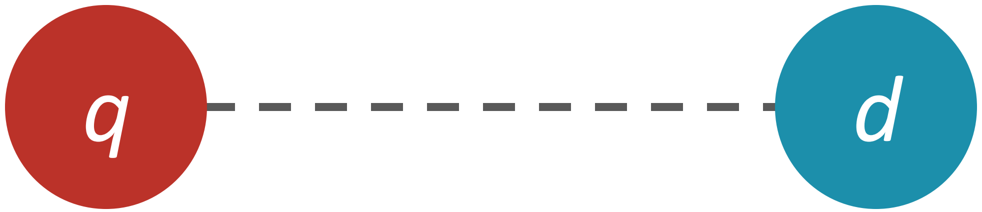
- Saul Hansell, New York Times, June 2007

The ranking problem



$$f(q, d)$$

Learning to rank



$$f(\mathbf{x})$$

Learning to rank

Feature-based representation

- Individual models as ranking ”features”

Discriminative learning

- Effective models learned from data
- Aka machine-learned ranking

Learning to rank

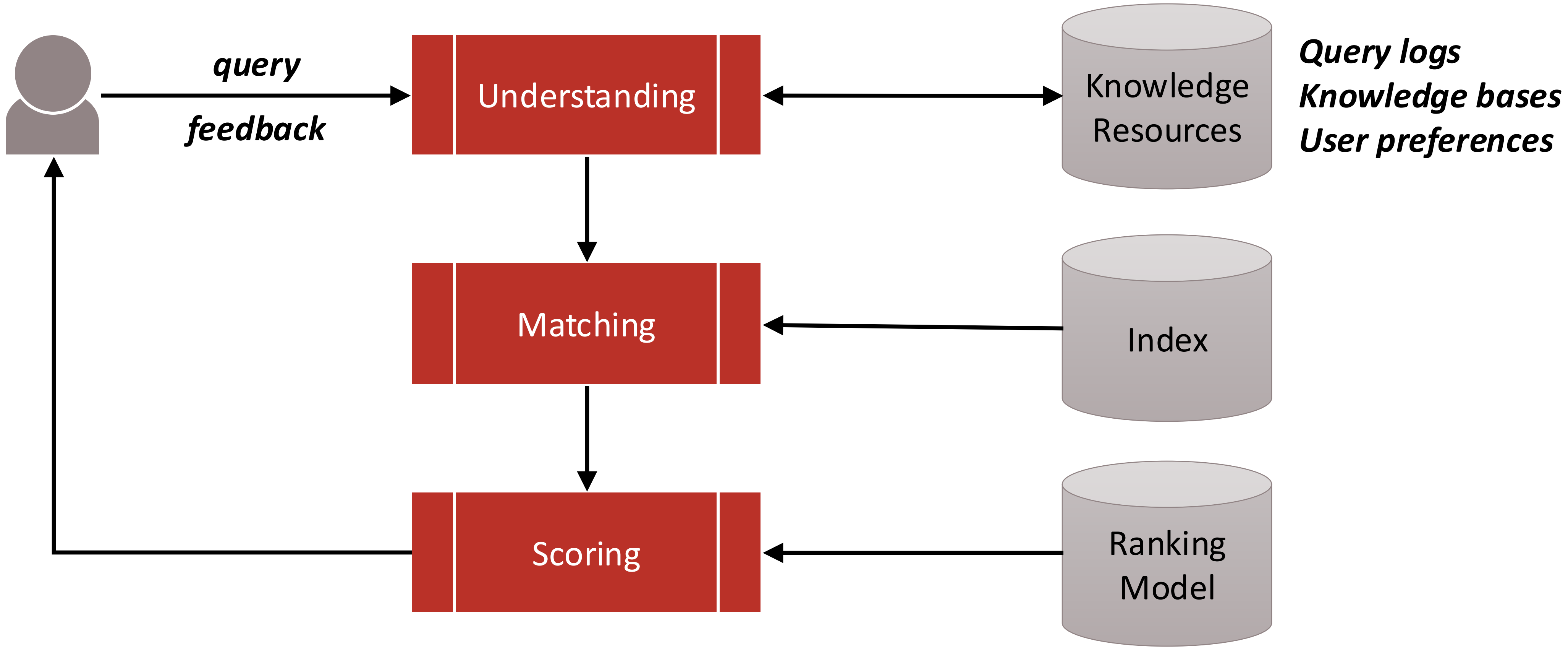
Actively researched over the last couple of decades

- Both by academia as well as industry players

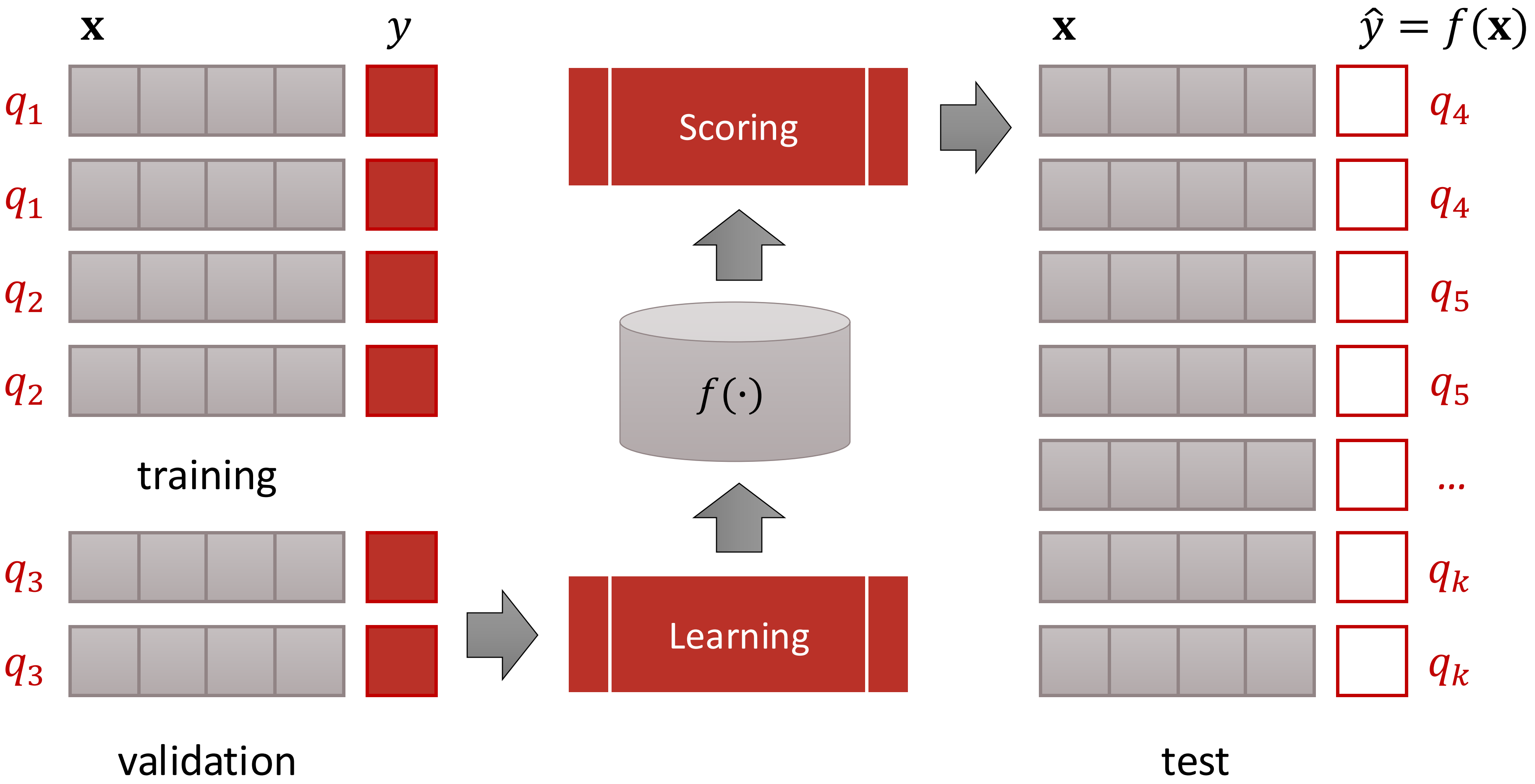
Why didn’t it happen earlier?

- Limited availability of training data
- Poor machine learning techniques
- Too few features to show value

Query processing overview



Discriminative learning framework



Building blocks

Goal is to learn a ranking model

- $f : \mathcal{X} \rightarrow \mathcal{Y}$

That minimizes some loss function

- $\mathcal{L} : f(\mathcal{X}) \times \mathcal{Y} \rightarrow \mathcal{R}$

$\mathcal{X}$: input space

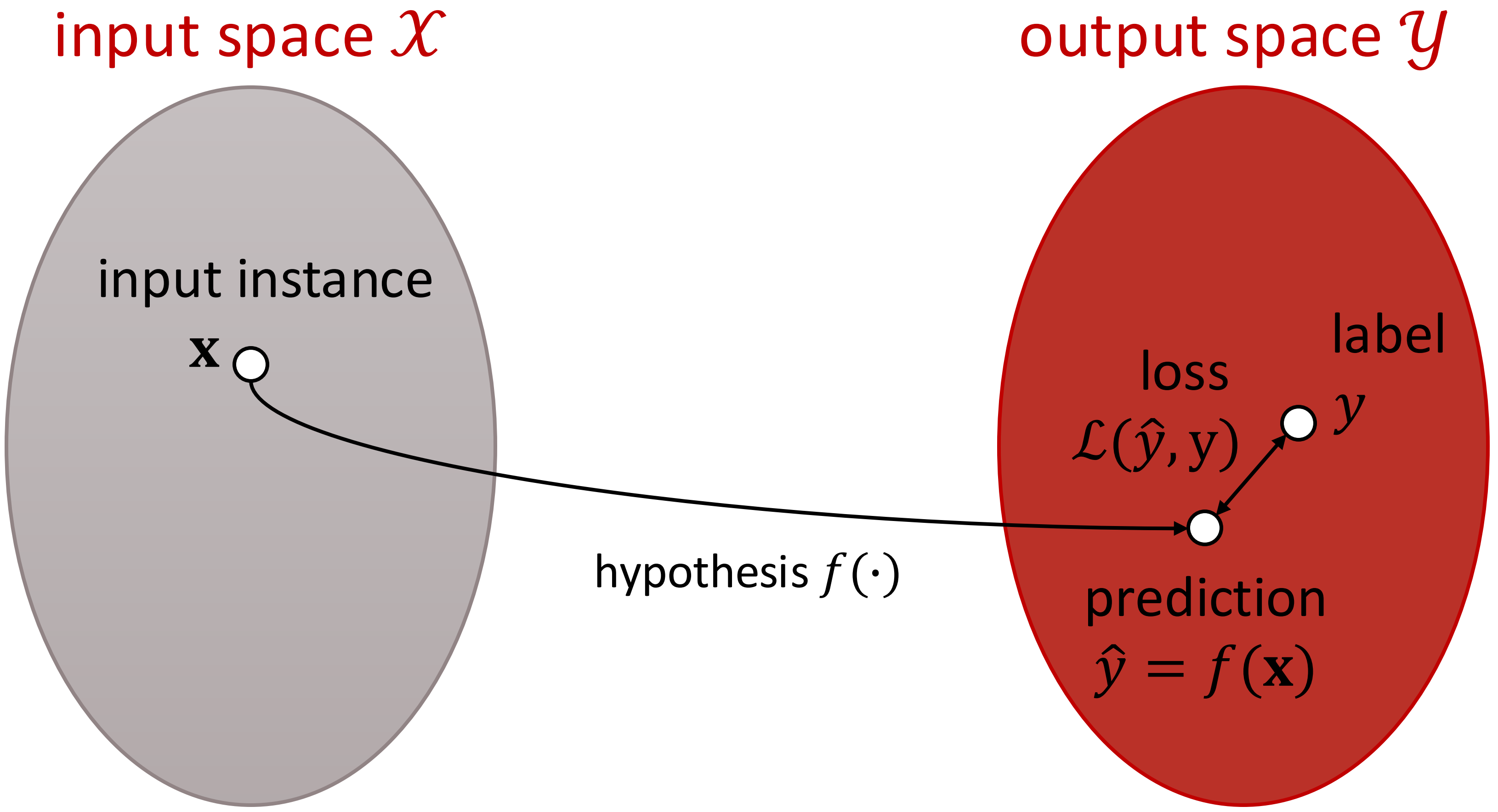
$\mathcal{Y}$: output space

$\mathcal{F}$: hypothesis space

$\mathcal{L}$: loss function

$\mathcal{O}$: optimizer

Building blocks

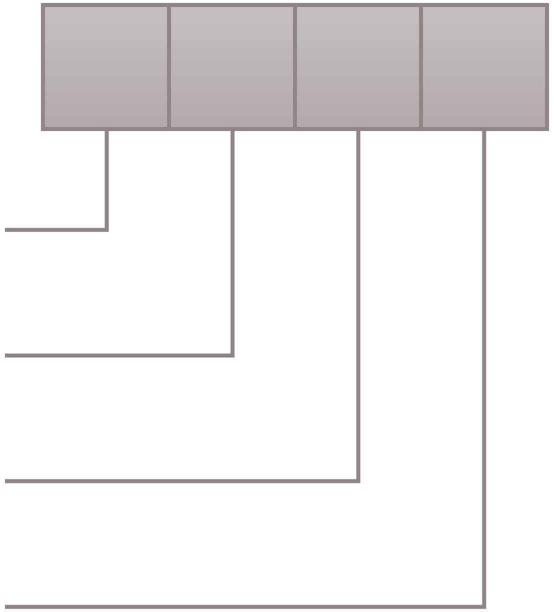


Input space ($\mathcal{X}$)

LTR takes as input feature vectors

- $\mathbf{x} \in \mathcal{X}$

$$\mathbf{x} = \mathbf{\Phi}(q, d)$$



$$f_{\text{BM25.title}}(q, d)$$

$$f_{\text{BM25.body}}(q, d)$$

$$f_{\text{BM25.anchor}}(q, d)$$

$$f_{\text{PageRank}}(q, d)$$

Ranking features

Query-dependent (depend on $\langle \boldsymbol{q}, \boldsymbol{d} \rangle$)

- BM25, LM, PL2, …

Query-independent (depend on $\boldsymbol{d}$)

- PageRank, readability, spaminess, …

Query features (depend on $\boldsymbol{q}$)

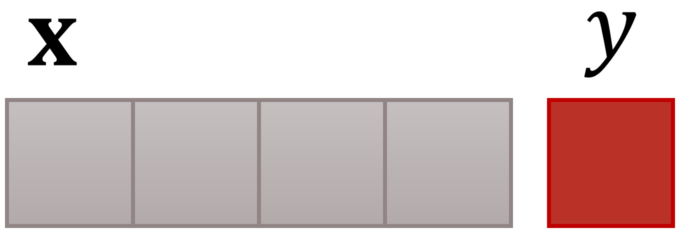
- Query length, query type, …

Output space ($\mathcal{Y}$)

LTR may produce different outputs

- $y \in \mathcal{Y}$

Each scalar y labels a training instance



Data labeling alternatives

Labeling of individual documents

- Binary judgments (non-rel, relevant)
  $y \in \{0,1\}$
- Graded judgments (non-rel, …, perfect)
  $y \in \{0,1,2,3,4,5\}$

Data labeling alternatives

Labeling of pairs of documents

- Implicit judgments

d_1
d_2
d_3 ✓
d_4
d_5

$d_3 \succ d_1$
$d_3 \succ d_2$
$\cancel{d_3 \succ d_4}$
$\cancel{d_3 \succ d_5}$

Data labeling alternatives

Creation of list

- List (or permutation) of items is given
- Ideal, but difficult to implement

Hypothesis space ($\mathcal{F}$)

Goal is to learn a ranking model

- $f : \mathcal{X} \rightarrow \mathcal{Y}$

A hypothesis $f \in \mathcal{F}$ could be any function

- Linear functions
- Non-linear functions (trees, networks)

Hypothesis space ($\mathcal{F}$)

Linear hypotheses

$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + \mathrm{b}$

- $\mathbf{w}$ is a weight vector
- b is a scalar bias

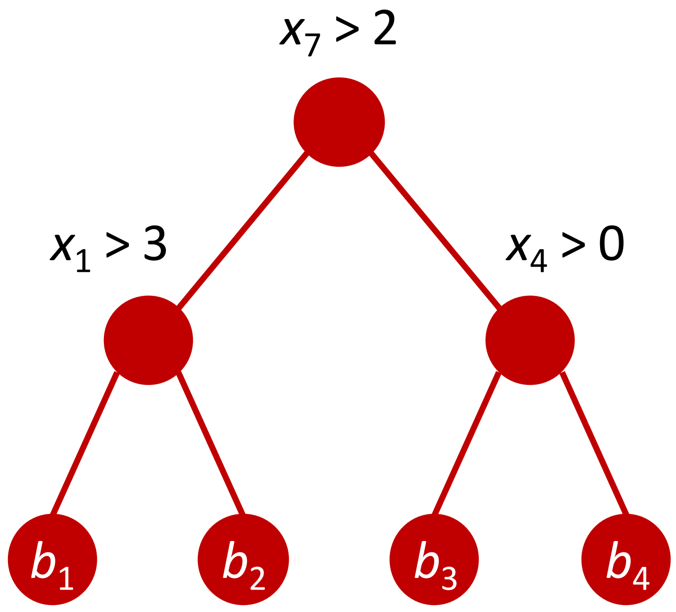
$$\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \end{bmatrix} \times \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b \end{bmatrix}$$

Hypothesis space ($\mathcal{F}$)

Tree-based hypotheses

$f(\mathbf{x}) = \sum_k b_k \mathbf{1}(\mathbf{x} \in R_k)$

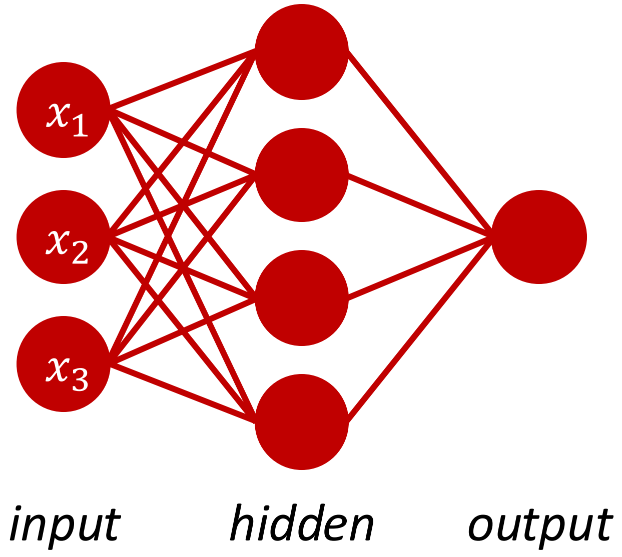
- k is one of the leaves in the tree
- b_k is the value predicted in region R_k
- $\mathbf{1}(\cdot)$ is the indicator function



Hypothesis space ($\mathcal{F}$)

Neural network hypotheses

$$f(\mathbf{x}) = \underbrace{\sigma_2(\mathbf{W}_2 \underbrace{\sigma_1(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1)}_{\textit{1}^{st}\textit{ layer output}} + \mathbf{b}_2)}_{\textit{2}^{nd}\textit{ layer output}}$$



- $\mathbf{W}_k$ is a weight matrix
- $\mathbf{b}_k$ is a bias vector
- σ_k is an activation function

Hypothesis space ($\mathcal{F}$)

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A hypothesis $f \in \mathcal{F}$ could be any function

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- Non-linear functions (trees, networks)

There are infinitely many such functions

How to find the best $f(\mathbf{x})$?

Look for the one with minimum loss

Loss function ($\mathcal{L}$)

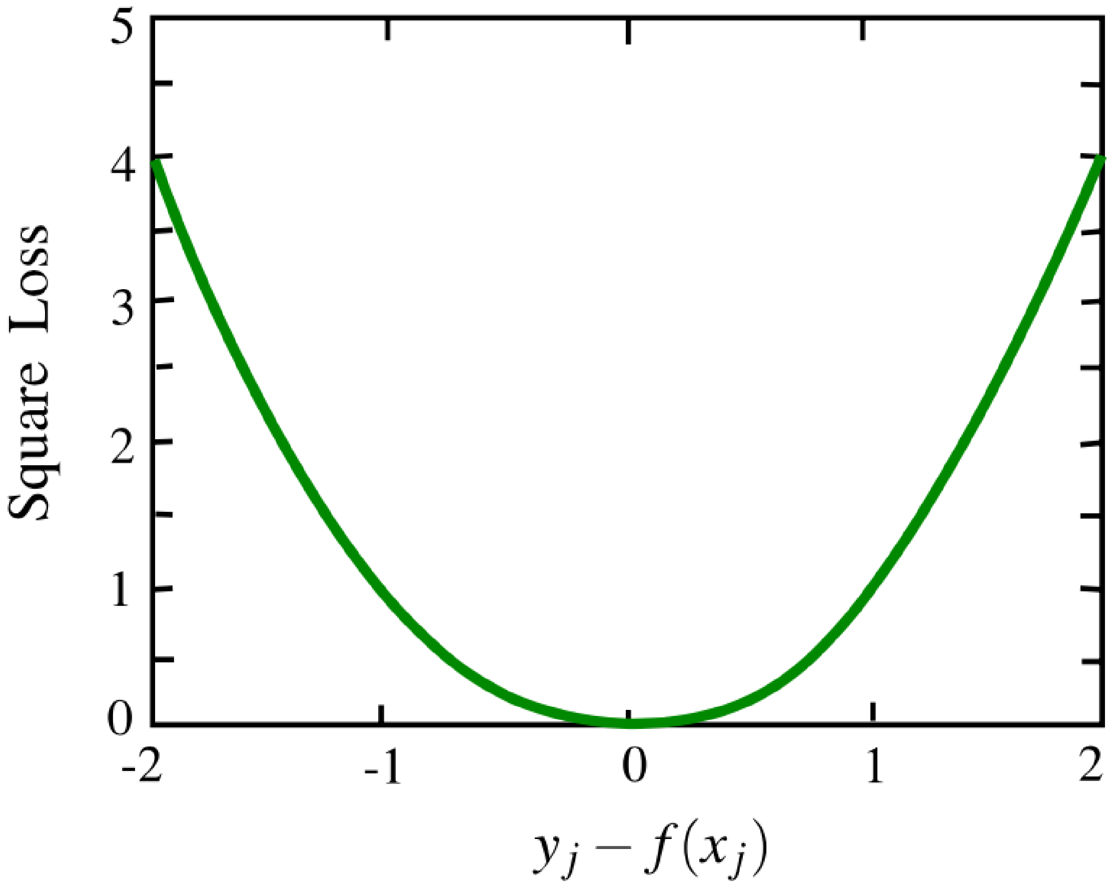
Loss as a measure of error

- $\mathcal{L}(\hat{y}, y) = \mathcal{L}(f(\mathbf{x}), y)$

Many options once again

- 0-1 loss: $\mathcal{L}(\hat{y}, y) = \mathbf{1}(y \neq f(\mathbf{x}))$
- Absolute loss: $\mathcal{L}(\hat{y}, y) = |y - f(\mathbf{x})|$
- Square loss: $\mathcal{L}(\hat{y}, y) = (y - f(\mathbf{x}))^2$

Example: square loss



How to find $f(\mathbf{x})$ that gives the minimum loss?

Hint:

- $f(\mathbf{x}; \mathbf{w})$ is actually parameterized by some $\mathbf{w}$

Optimizer

Coordinate methods

◦ Line search, one coordinate at a time

Gradient methods

◦ Walk downhill, all coordinates together

Boosting methods

◦ Upweight difficult examples

Learning algorithms

Query refinement (WWW 2008)

ListNet (ICML 2007) SVM-MAP (SIGIR 2007) Nested Ranker (SIGIR 2006)

LambdaRank (NIPS 2006) Frank (SIGIR 2007) MPRank (ICML 2007)

MHR (SIGIR 2007) RankBoost (JMLR 2003) LDM (SIGIR 2005)

RankNet (ICML 2005) Ranking SVM (ICANN 1999) IRSVM (SIGIR 2006)

Discriminative model for IR (SIGIR 2004) SVM Structure (JMLR 2005)

GPRank (LR4IR 2007) QBRank (NIPS 2007) GBRank (SIGIR 2007)

AdaRank (SIGIR 2007) McRank (NIPS 2007) SoftRank (LR4IR 2007)

CCA (SIGIR 2007) ListMLE (ICML 2008)

RankCosine (IP&M 2007)

Relational ranking (WWW 2008) Supervised Rank Aggregation (WWW 2007)

Learning algorithms

Pointwise	$\mathcal{X}$: single documents
	$\mathcal{Y}$: scores or class labels
Pairwise	$\mathcal{X}$: document pairs
	$\mathcal{Y}$: partial orders
Listwise	$\mathcal{X}$: document collections
	$\mathcal{Y}$: ranked document list

Pointwise approaches

Reduce ranking to regression or classification

- Assume relevance is query-independent

In practice, relevance is query-dependent

- Utility of a feature may also be query-dependent
- By putting documents associated with different queries together, the training process may be hurt

Pairwise approaches

Reduce ranking to classification on document pairs associated with the same query

- No longer assume independent relevance

Unique properties of ranking not fully covered

- Number of instance pairs varies across queries
- Importance of errors varies across ranking positions

Listwise approaches

Perform learning directly on document list

◦ Treats ranked lists as learning instances

Two major approaches

◦ Define listwise loss functions

◦ Directly optimize IR evaluation measures (current state-of-the-art)

Recap

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Summary

Learning to rank has been around for a few decades, but has only recently become hot

- More data, better resources, better algorithms

Machine learned ranking over many features easily beats traditional hand-designed ranking models

- Lots of open directions

Open directions

Deep learning

- Feature learning (vs. feature engineering)

Online learning

- Incremental, exploration-exploitation models

Structured learning

- Diversity, context-awareness

References

Learning to rank for information retrieval
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Learning to rank for information retrieval
Liu, 2011

Learning to rank for information retrieval and natural language processing
Li, 2014

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Coming next...

Learning to Rank: Pointwise

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