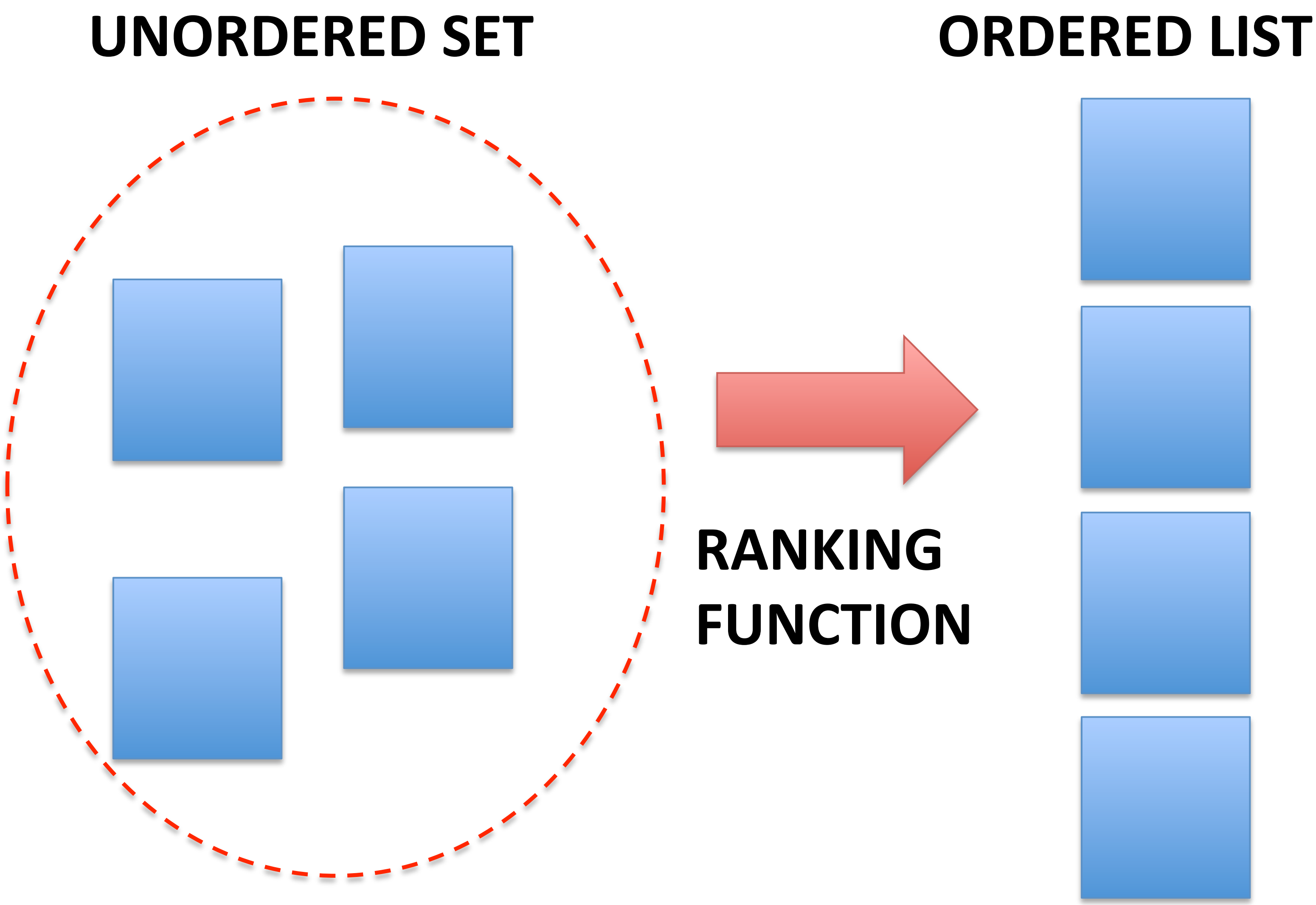
Learning to Rank

Kevin Duh
kevinduh@cs.jhu.edu
June 2018

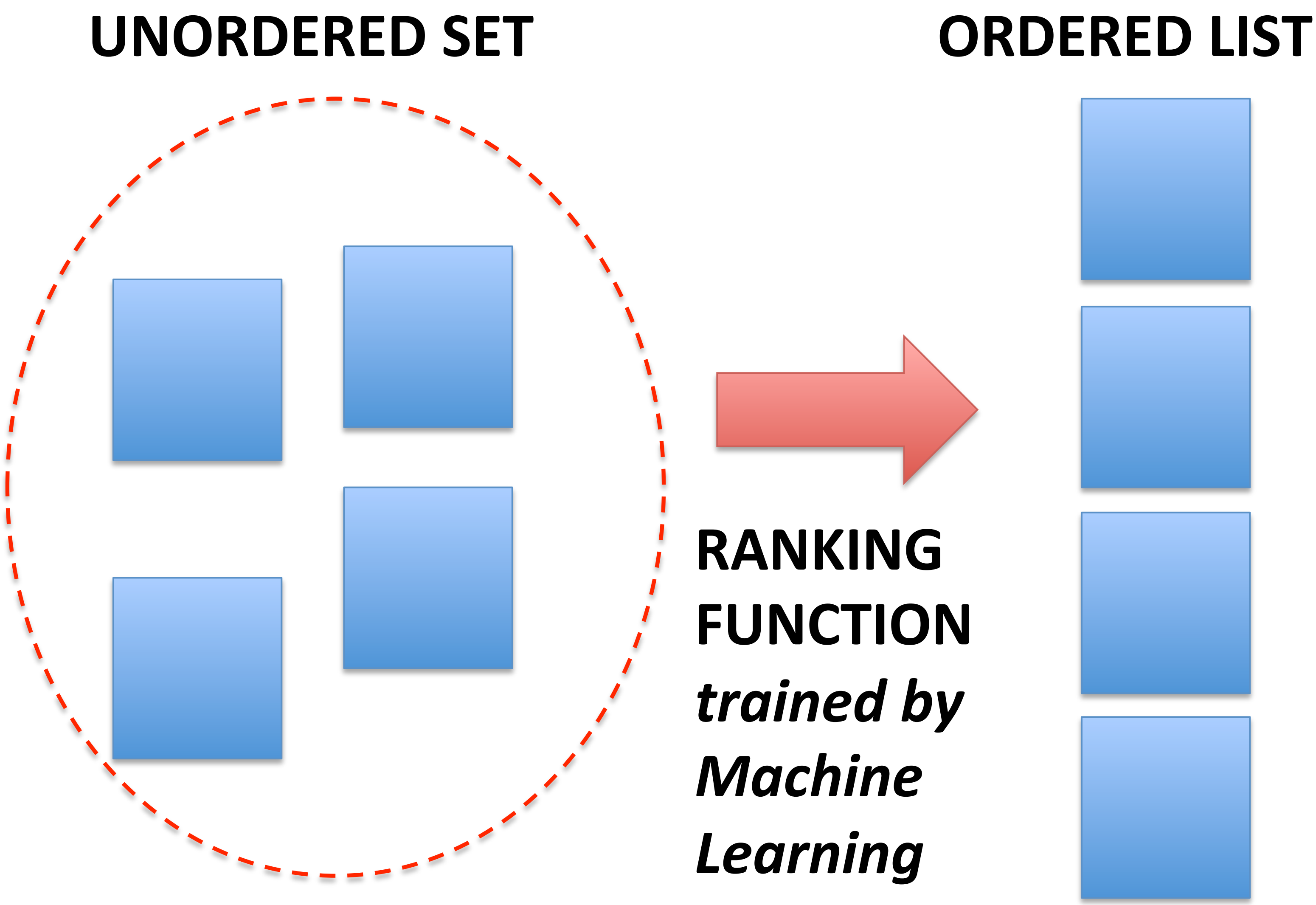
Slides are online @

http://www.cs.jhu.edu/~kevinduh/t/ltr.pdf

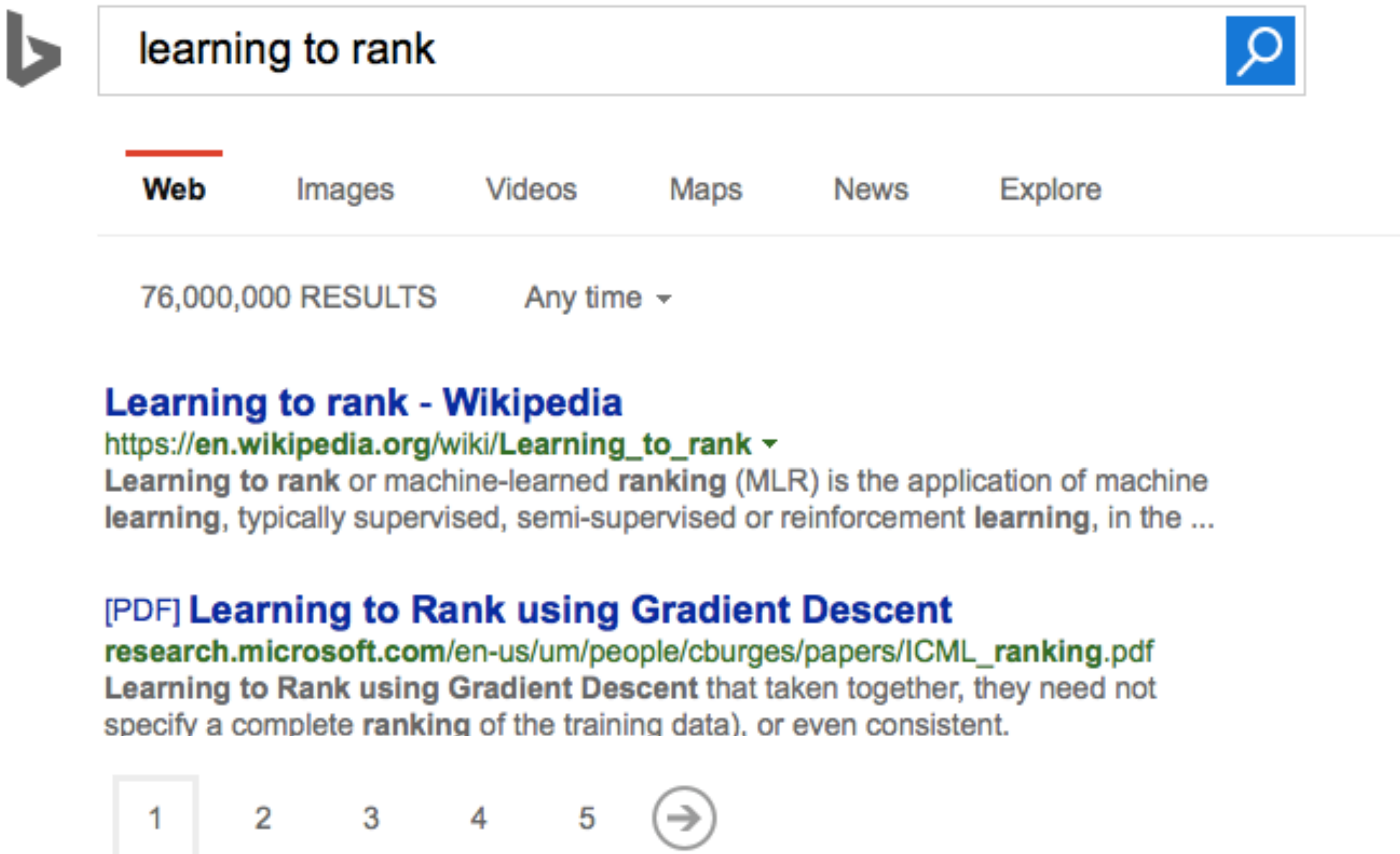
What is Ranking?



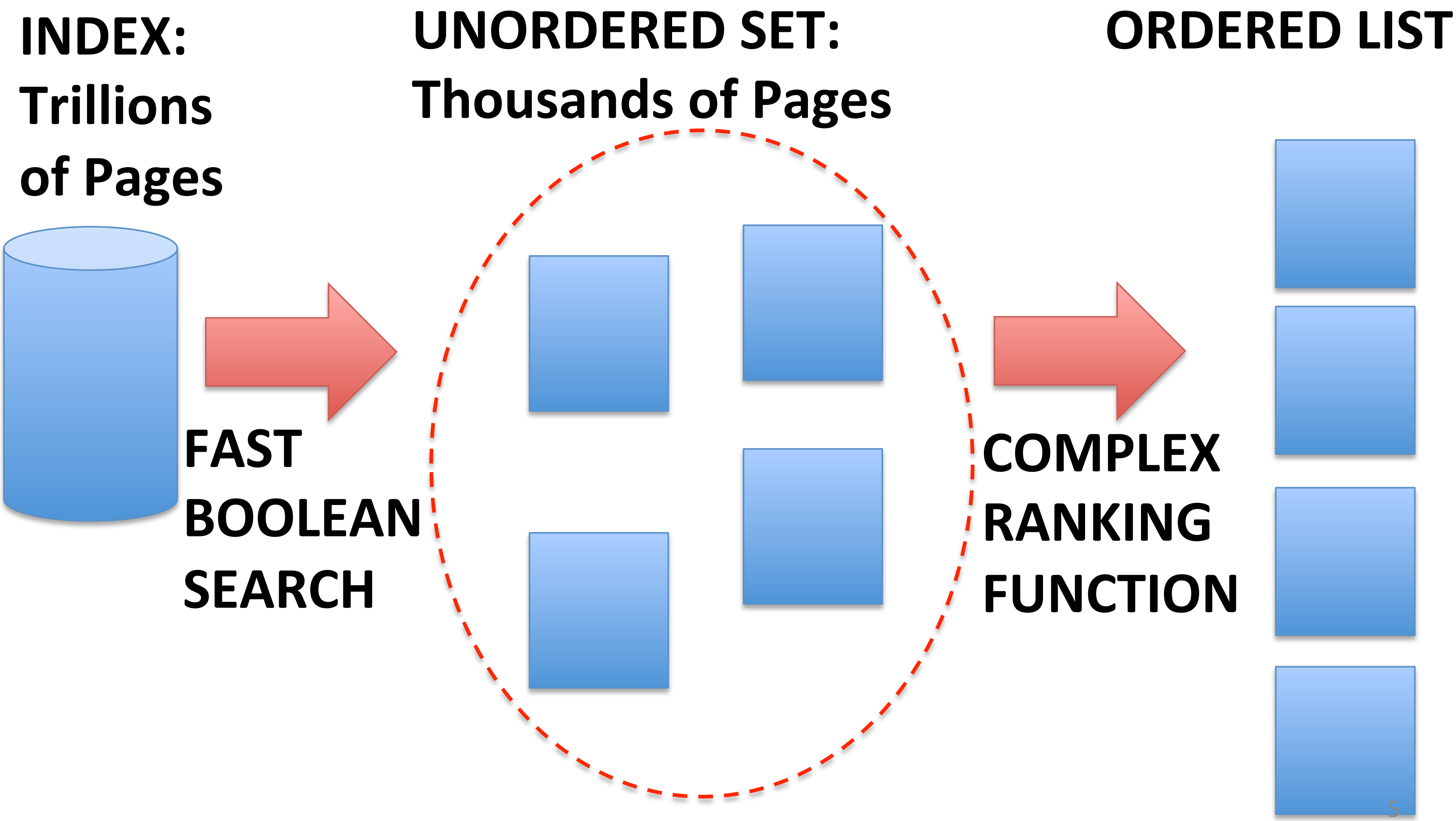
What is Learning to Rank?



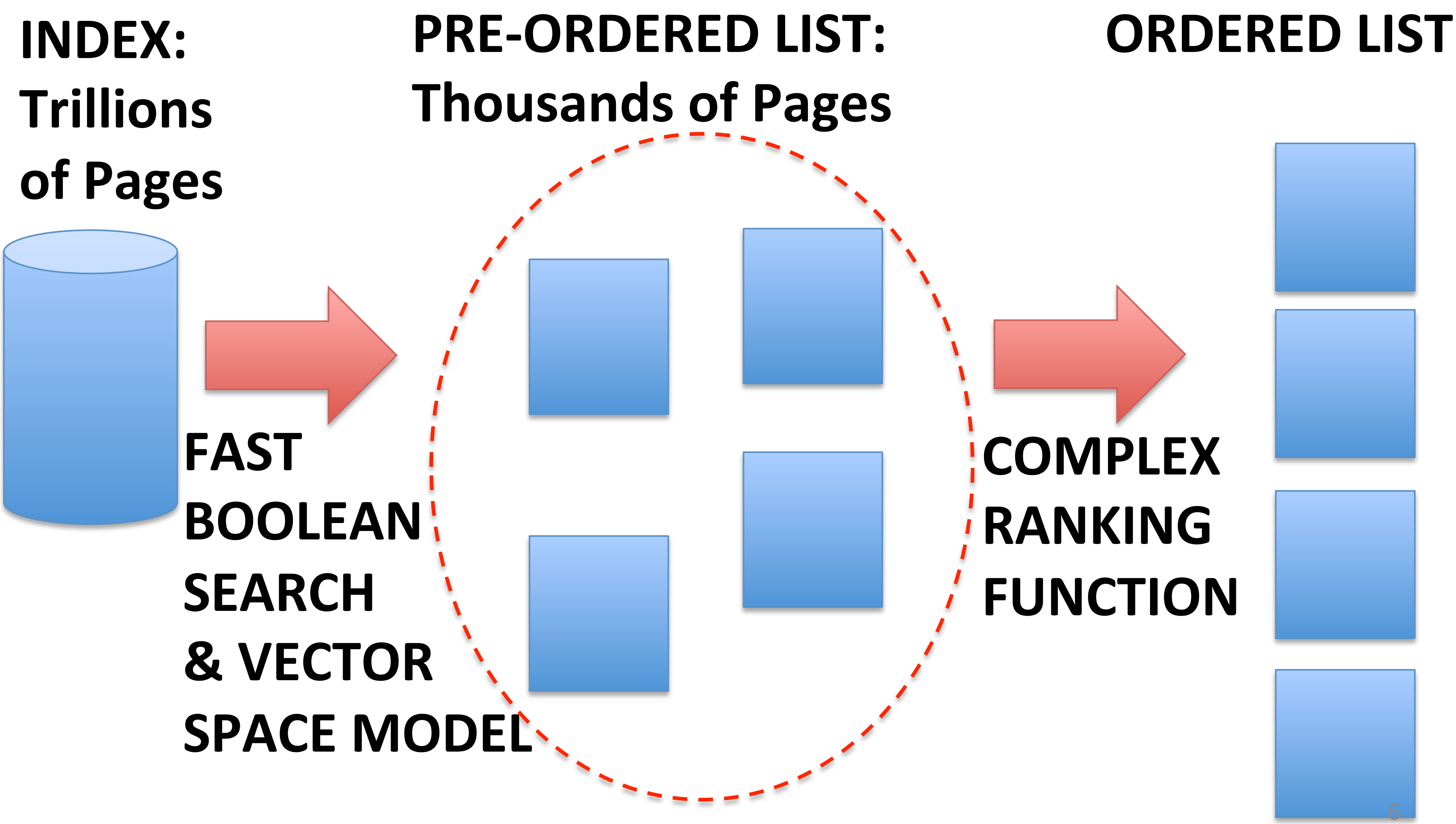
Common in Search Engines



Anatomy of a Search Engine



Anatomy of a Search Engine



Motivation

- In search engines, only the top results matter

- Machine learning approach:
  - Enables more **features** (signal sources)
  - Improves over Boolean search, vector space models like tf-idf

Features of a top search result?

jhu cs courses 2016

Word match?

URL match?

Popular page?

Recently updated?

User intention match?

Not spam?

Clickthrough log?

Johns Hopkins University Computer Science | Facebook
https://www.facebook.com/compscijhu
Johns Hopkins University Computer Science, Baltimore. 407 likes · 5 talking about this. Computer Science at Johns Hopkins University (CS@JHU) is a...

600.318/418: Operating Systems - Johns Hopkins University
srl.cs.jhu.edu/courses/600.418/index.html
Computer science majors and graduate students will be admitted regardless of enrollment limits. ... This course provides an introduction to operating systems.

Department of Computer Science | Course Information
www.cs.jhu.edu/course-info
CS Course Catalog – complete list of departmental courses with descriptions. Note that not all courses are offered every year. Course Area Designators – a chart ...

Johns Hopkins University • Free Online Courses and ...
www.class-central.com › Universities › Johns Hopkins University
Discover free online courses taught by Johns Hopkins University. Watch videos, do assignments, earn a certificate while learning from some of the best Professors.

Useful Features

- Based on Query (q) and Document (d)
  - Various Boolean search and vector space model results, applied to document text, URL, title
  - Click-through: e.g. How many times d is clicked given q vs. How many times d is skipped
  - Results after Query-expansion
- Based on Document only (static)
  - Popularity of page: #Likes, #inlinks, Pagerank
  - Domain structure: main page or subpage
- Many, many more

Re-cap: Goal is to improve top ranked results via many features

jhu cs courses 2016

Word match?

URL match?

Popular page?

Recently updated?

User intention match?

Not spam?

Clickthrough log?

Johns Hopkins University Computer Science | Facebook
https://www.facebook.com/compscijhu
Johns Hopkins University Computer Science, Baltimore. 407 likes · 5 talking about this. **Computer Science** at **Johns Hopkins University** (**CS@JHU**) is a...

600.318/418: Operating Systems - **Johns Hopkins University**
srl.**cs.jhu**.edu/**courses**/600.418/index.html
Computer science majors and graduate students will be admitted regardless of enrollment limits. ... This **course** provides an introduction to operating systems.

Department of **Computer Science** | **Course Information**
www.**cs.jhu**.edu/**course**-info
CS Course Catalog – complete list of departmental **courses** with descriptions. Note that not all **courses** are offered every year. **Course** Area Designators – a chart ...

Johns Hopkins University • Free Online Courses and ...
www.class-central.com › Universities › **Johns Hopkins University**
Discover free online **courses** taught by **Johns Hopkins University**. Watch videos, do assignments, earn a certificate while learning from some of the best Professors.

Challenge: How to weight features?

- If there's only a few, we can manually tune.

  e.g. score = 3 x #wordmatch + 1 x #inlink

- If there are many, we rely on machine learning (i.e. Learning to Rank)

Summary so far

1. Ranking: Unordered set → Ordered list
2. Search engines: only top results matter
3. Good ranking requires many features
4. Next: how to weight features

Problem Formulation

<u>1. Feature extraction</u>

<query, doc_1> → vector x_1

<query, doc_2> → vector x_2

<query, doc_3> → vector x_3

<u>2. Apply ranking function & sort</u>

$F(x_1) = 3$ → Rank 2

$F(x_2) = 1$ → Rank 3 (worst)

$F(x_3) = 4$ → Rank 1 (best)

<u>What function class for F()?</u>

Assume linear weights: $F(x_i) = w^T x_i$

Learn weights w that replicate ranking on training set

Training Set

Query 1	Labels for each query-doc pair
<query, doc$_1$> $\rightarrow$ vector x_1	$\text{label}(x_1) = 3$
<query, doc$_2$> $\rightarrow$ vector x_2	$\text{label}(x_2) = 1$
<query, doc$_3$> $\rightarrow$ vector x_3	$\text{label}(x_3) = 4$

Query 2	Labels for each query-doc pair
<query, doc$_1$> $\rightarrow$ vector x_1	$\text{label}(x_1) = 3$ (Very relevant)
<query, doc$_2$> $\rightarrow$ vector x_2	$\text{label}(x_2) = 2$ (Relevant)
<query, doc$_3$> $\rightarrow$ vector x_3	$\text{label}(x_3) = 1$ (Slightly relevant)
<query, doc$_4$> $\rightarrow$ vector x_4	$\text{label}(x_4) = 0$ (Irrelevant)

Where does the label come from?

- Human annotation
  - High quality, but expensive

- Click-through logs
  - Noisy, but cheap/abundant

Notation

query: $q^{(n)} \qquad n = 1, \ldots, N$

document for query n: $d_i^{(n)} \qquad i = 1, \ldots, I_n$

vector of D features per query-doc: $x_i^{(n)} \in \mathcal{R}^D$

label for each query-doc pair: $l_i^{(n)} \in \mathcal{Z}$

Training set: $\{q^{(n)}, \{x_i^{(n)}, l_i^{(n)}\}\}$

Ranking Function: $F(x_i^{(n)}) = w^T x_i^{(n)}$

Different training approaches

- How to optimize something on a set with a sort operation? Reduce to traditional regression/classification problems

Training Approach	Reduction
Point-wise	Document
Pair-wise	Two Documents
List-wise	All Documents per query

Point-wise Approach

Training set: $\{q^{(n)}, \{x_i^{(n)}, l_i^{(n)}\}\}$

Ranking Function: $F(x_i^{(n)}) = w^T x_i^{(n)}$

Find w that makes each F(x) equal to its label

Training Objective: $\sum_n \sum_i (F(x_i^{(n)}) - l_i^{(n)})^2$

$$\text{Training Objective: } \sum_n \sum_i (F(x_i^{(n)}) - l_i^{(n)})^2$$

$$\rightarrow \sum_z (F(x_z) - l_z)^2 \quad \text{where z ranges over all i, n}$$

Solve with linear regression!

Pair-wise Approach

Training set: $\{q^{(n)}, \{x_i^{(n)}, l_i^{(n)}\}\}$

Ranking Function: $F(x_i^{(n)}) = w^T x_i^{(n)}$

Find w that gives every pair the correct ranking

Training Objective:

$$F(x_i^{(n)}) > F(x_j^{(n)}) \quad \forall \quad i, j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

Training Objective:

$$F(x_i^{(n)}) > F(x_j^{(n)}) \quad \forall \quad i,j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$
$$\rightarrow F(x_i^{(n)}) - F(x_j^{(n)}) > 0 \quad \forall \quad i,j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$
$$\rightarrow w^T x_i^{(n)} - w^T x_j^{(n)} > 0 \quad \forall \quad i,j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$
$$\rightarrow w^T (x_i^{(n)} - x_j^{(n)}) > 0 \quad \forall \quad i,j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$
$$\rightarrow w^T (\delta_{ij}^{(n)}) > 0 \quad \forall \quad i,j \quad \text{s.t.} \quad l_i^{(n)} > l_j^{(n)}$$

Solve with binary classification!

Make a new sample out of every pair

Give new label: Positive for i,j pairs

Negative for j,i pairs

Disclaimer

- We've focused on very simple ranking functions (linear) for simplicity
- In practice, more complex functions (e.g. decision trees, neural nets) are common
- Recommend further reading:
  - Dawei Yin, et. al. "Ranking Relevance in Yahoo Search", Proceedings of KDD2016

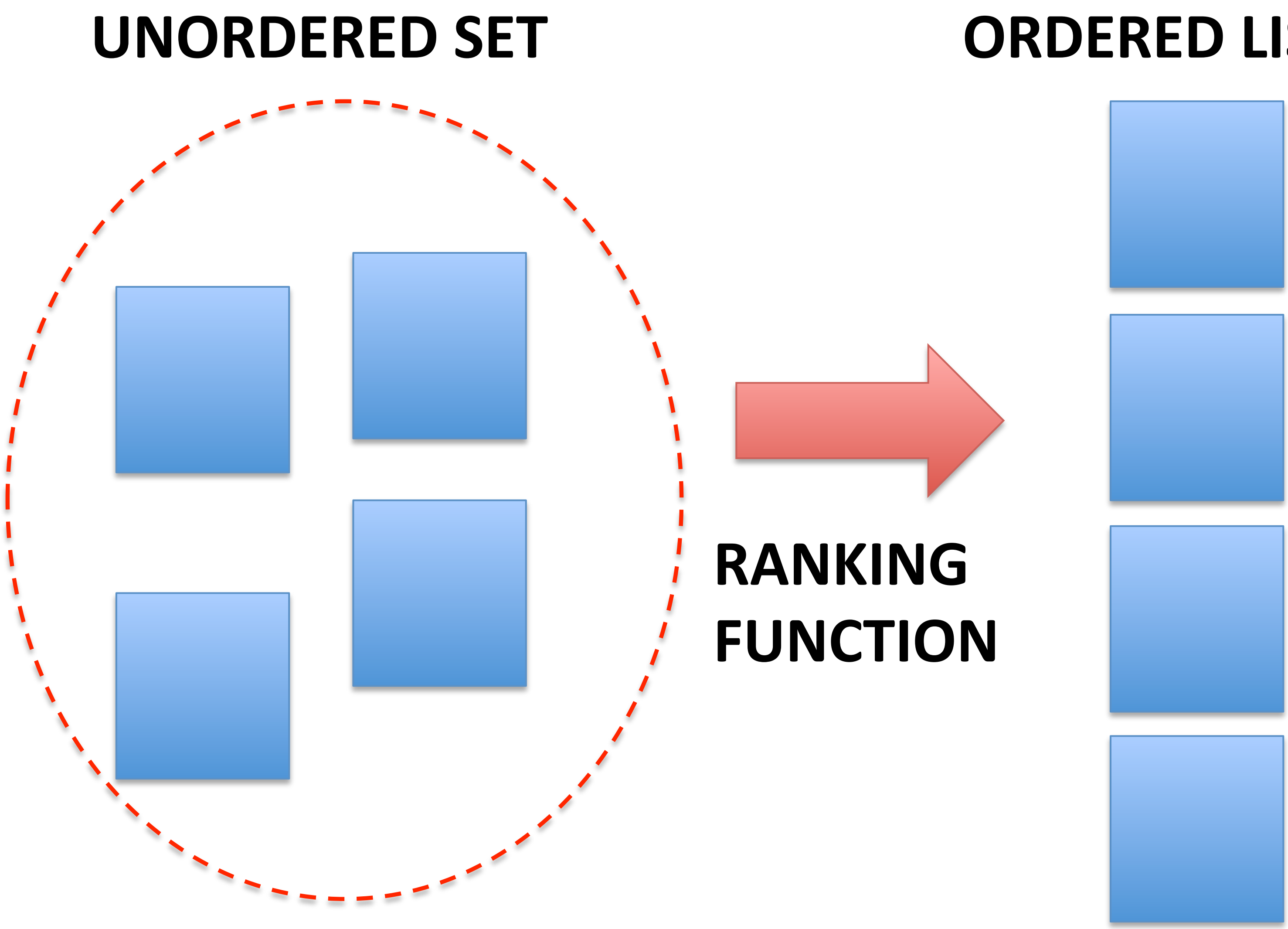
Ranking Relevance in Yahoo Search

Dawei Yin[†], Yuening Hu[†], Jiliang Tang[†], Tim Daly Jr., Mianwei Zhou, Hua Ouyang, Jianhui Chen,
Changsung Kang, Hongbo Deng, Chikashi Nobata, Jean-Marc Langlois, Yi Chang[†]
Relevance Science, Yahoo! Inc.
[†]{daweiy,ynhu,jlt,yichang}@yahoo-inc.com

query	methods	DCG1	DCG3	DCG5
all	LogisticRank	4.31	7.74	9.78
	GBRank	4.26 (-1.19%)	7.52 (-2.81%)*	9.51 (-2.81%)*
	LambdaMart	4.24 (-1.60%)	7.36 (-4.84%)*	9.21 (-5.83%)*
top	LogisticRank	5.69	9.67	12.08
	GBRank	5.56 (-2.22%)	9.25 (-4.29%)*	11.51 (-4.67%)*
	LambdaMart	5.59 (-1.72%)	9.08 (-6.04%)*	11.02 (-8.75%)*
torso	LogisticRank	3.88	7.23	9.26
	GBRank	3.88 (-1.77%)	7.065 (-2.30%)*	9.08 (-2.03%)*
	LambdaMart	3.81 (-1.88%)	6.97 (-3.64%)†	8.92 (-3.64%)*
tail	LogisticRank	2.91	5.65	7.16
	GBRank	2.99 (3.06%)	5.65 (0.01%)	7.19 (0.37%)
	LambdaMart	2.88 (-0.71%)	5.42 (-4.15%)†	6.91 (-2.78%)†

Table 1: Performance comparison of models using different learning algorithms. * denotes p-value<=0.01; † denotes p-value<=0.05.

Other applications of Learning to Rank



Other applications: Protein structure prediction

Amino Acid Sequence:
MMKLKSNQTRTYDGDGYKKRAACLCFSE

various protein folding simulations

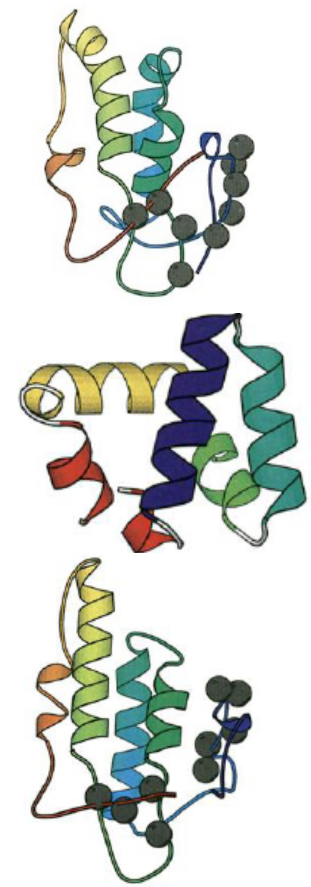
Candidate 3-D Structures

Ranking Function

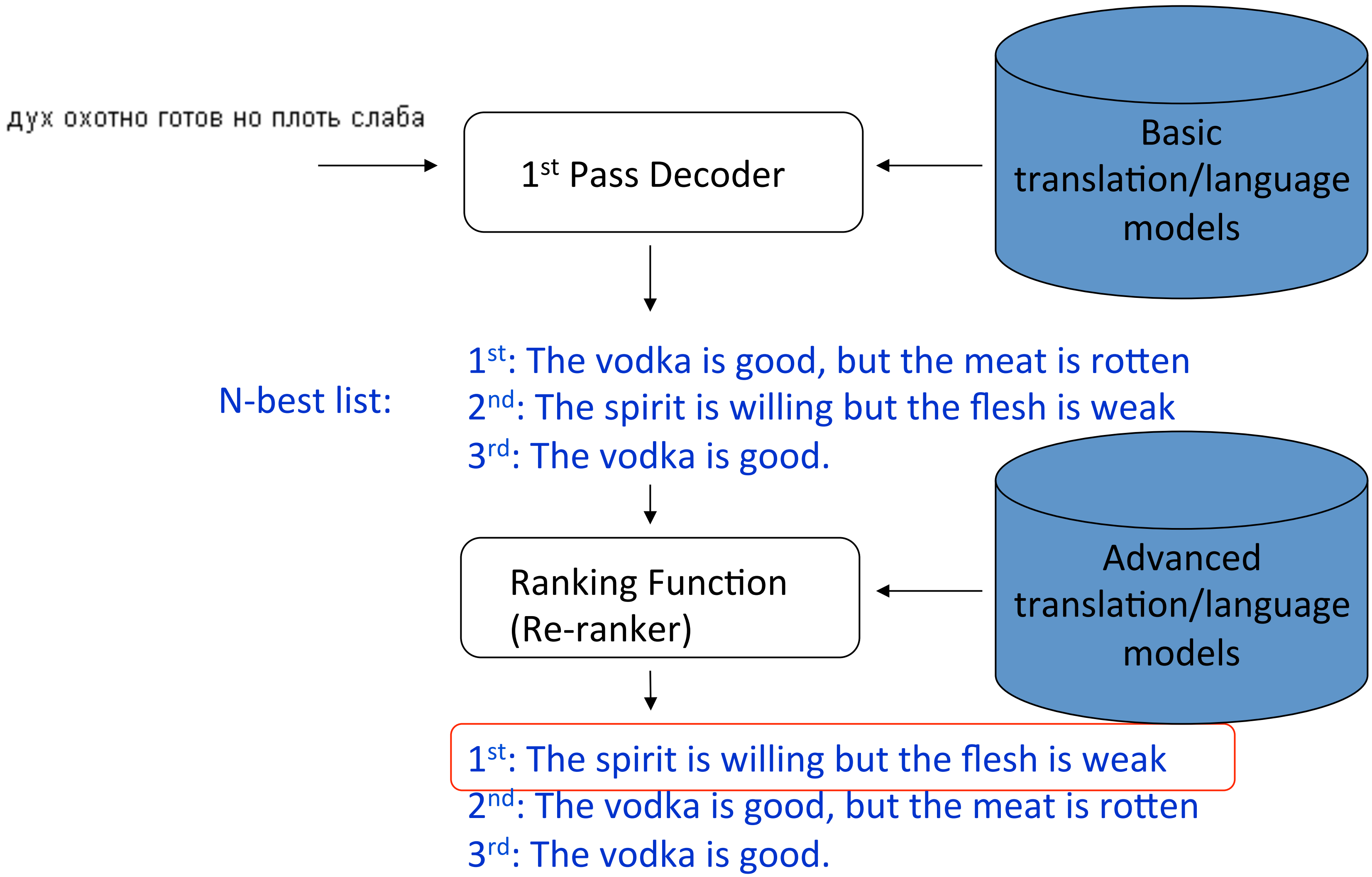
1st

2nd

3rd



Other applications: Machine Translation



Summary

1. Ranking: Unordered set → Ordered list
2. Search engines: only top results matter
3. Good ranking requires many features
4. Approaches to learn weights of features (reduction to classification/regression)

Lab: Build a learning-to-rank system

- Step 0: Download a Learning to Rank dataset
  - http://www.cs.jhu.edu/~kevinduh/t/letor.tgz
  - Source: (OHSUMED in LETOR3.0) http://research.microsoft.com/en-us/um/beijing/projects/letor/letor3download.aspx

```
kduh@a14:~$ mkdir ltr; cd ltr
kduh@a14:~/ltr$ wget http://www.cs.jhu.edu/~kevinduh/t/letor.tgz
kduh@a14:~/ltr$ tar -xvf letor.tgz
```

Step 1: Understand the data format

Format: relevance label, query id, features+

```
0 qid:1 1:1.000000 2:1.000000 3:0.833333 4:0.871264 5:0 6:0 7:0 8:0.941842 9:1.000000 10:1.000000 11:1.0
000 14:1.000000 15:1.000000 16:1.000000 17:1.000000 18:0.719697 19:0.729351 20:0 21:0 22:0 23:0.811565 2
1.000000 27:1.000000 28:0.922374 29:0.946654 30:0.938888 31:1.000000 32:1.000000 33:0.711276 34:0.722202
2 39:1.000000 40:1.000000 41:1.000000 42:1.000000 43:0.959134 44:0.963919 45:0.971425 #docid = 244338
2 qid:1 1:0.600000 2:0.600000 3:1.000000 4:1.000000 5:0 6:0 7:0 8:1.000000 9:0.624834 10:0.767301 11:0.8
685 14:0.680222 15:0.686762 16:0.421053 17:0.680904 18:1.000000 19:1.000000 20:0 21:0 22:0 23:1.000000 2
0.949446 27:0.984769 28:0.955266 29:1.000000 30:0.997786 31:0.441860 32:0.687033 33:1.000000 34:1.000000
0 39:0.425450 40:0.975968 41:0.928785 42:0.978524 43:0.979553 44:1.000000 45:1.000000 #docid = 143821
```

- Questions:
  - How many documents in train.txt?
  - How many queries?
  - How many documents/query?

Step 2: Try out existing ranker

- SVMrank: https://www.cs.cornell.edu/people/tj/svm_light/svm_rank.html

```
kduh@a14:~/ltr$ mkdir svm_rank
kduh@a14:~/ltr$ cd svm_rank/
kduh@a14:~/ltr/svm_rank$ wget http://download.joachims.org/svm_rank/current/svm_rank.tar.gz
```

```
kduh@a14:~/ltr/svm_rank$ tar -xvf svm_rank.tar.gz
```

```
kduh@a14:~/ltr/svm_rank$ make
```

- HELP: svm_rank_learn -?
- TRAIN: svm_rank_learn –c 20 data model

```
kduh@a14:~/ltr$ ./svm_rank/svm_rank_learn -c 20 letor/train.txt model1
```

Step 3. Evaluate

INFERENCE: svm_rank_classify data model output

```
kduh@a14:~/ltr$ ./svm_rank/svm_rank_classify letor/vali.txt model1 vali.pred
Reading model...done.
Reading test examples...done.
Classifying test examples...done
Runtime (without IO) in cpu-seconds: 0.00
Average loss on test set: 0.3840
Zero/one-error on test set: 100.00% (0 correct, 21 incorrect, 21 total)
NOTE: The loss reported above is the fraction of swapped pairs averaged over
      all rankings. The zero/one-error is fraction of perfectly correct
      rankings!
Total Num Swappedpairs  :  51224
Avg Swappedpairs Percent:  38.40
```

Eval script

```
kduh@a14:~/ltr$ perl letor/Eval-Score-3.0.pl letor/vali.txt  vali.pred vali.pred.result 1
kduh@a14:~/ltr$ grep MAP vali.pred.result
MAP:    0.458439033060933
```

Step 4

- Implement your own:
  - point-wise method with linear regression, using sklearn.linear_model.LinearRegression
  - Implement pair-wise method with binary classification, using sklearn.linear_model.LogisticRegression
- Learn more about existing toolkits:
  - SVMrank: https://www.cs.cornell.edu/people/tj/svm_light/svm_rank.html
  - RankLib: https://people.cs.umass.edu/~vdang/ranklib.html
- Evaluate and compare MAP results