

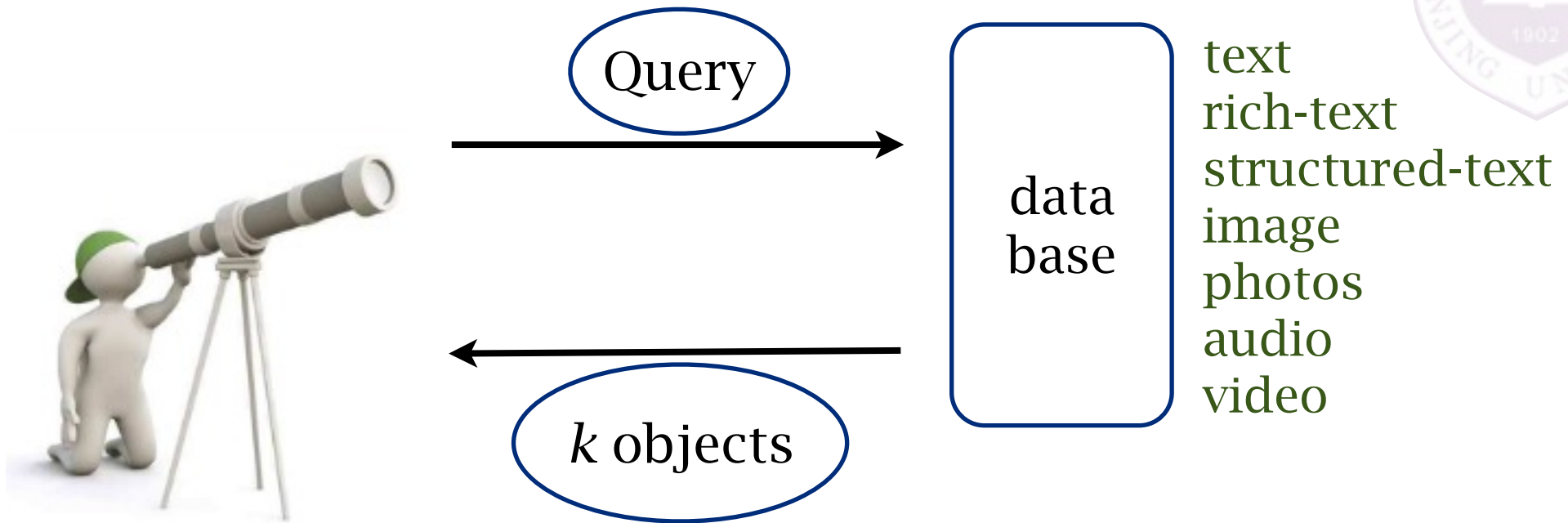
Lecture 13: Data Mining IV

Information Retrieval Systems

http://cs.nju.edu.cn/yuy/course_dm13ms.ashx



Information retrieval systems



Content-based information retrieval:
for objects with rich semantics
find top k objects most similar to the query

- ▶ searching historical records of the Dow Jones index for past occurrences of a particular time series pattern
- ▶ searching a database of satellite images for any images which contain evidence of recent volcano eruptions in Central America
- ▶ searching the Internet for online documents that provide reviews of restaurants in Helsinki

Evaluation

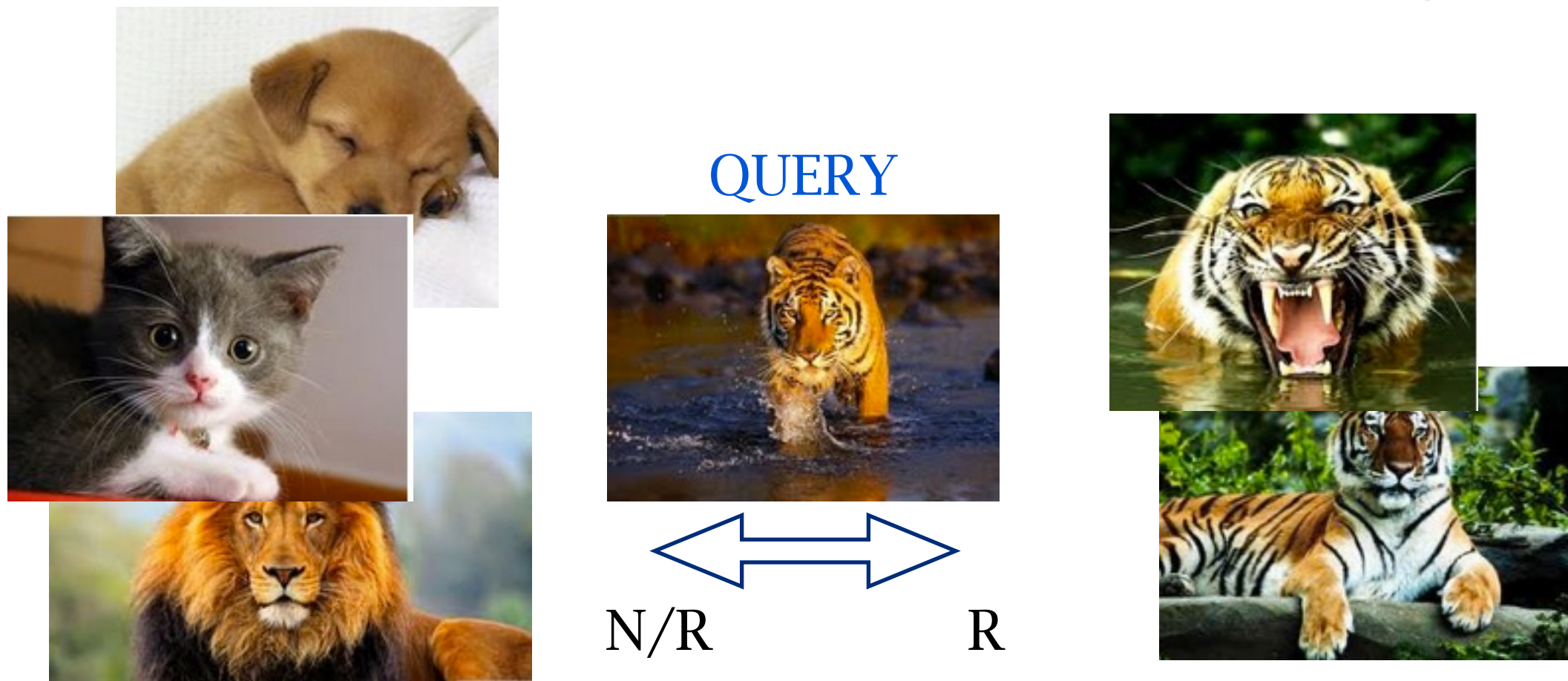
how good is an retrieval system?



unlike classification where labels are given

Evaluation

how good is an retrieval system?

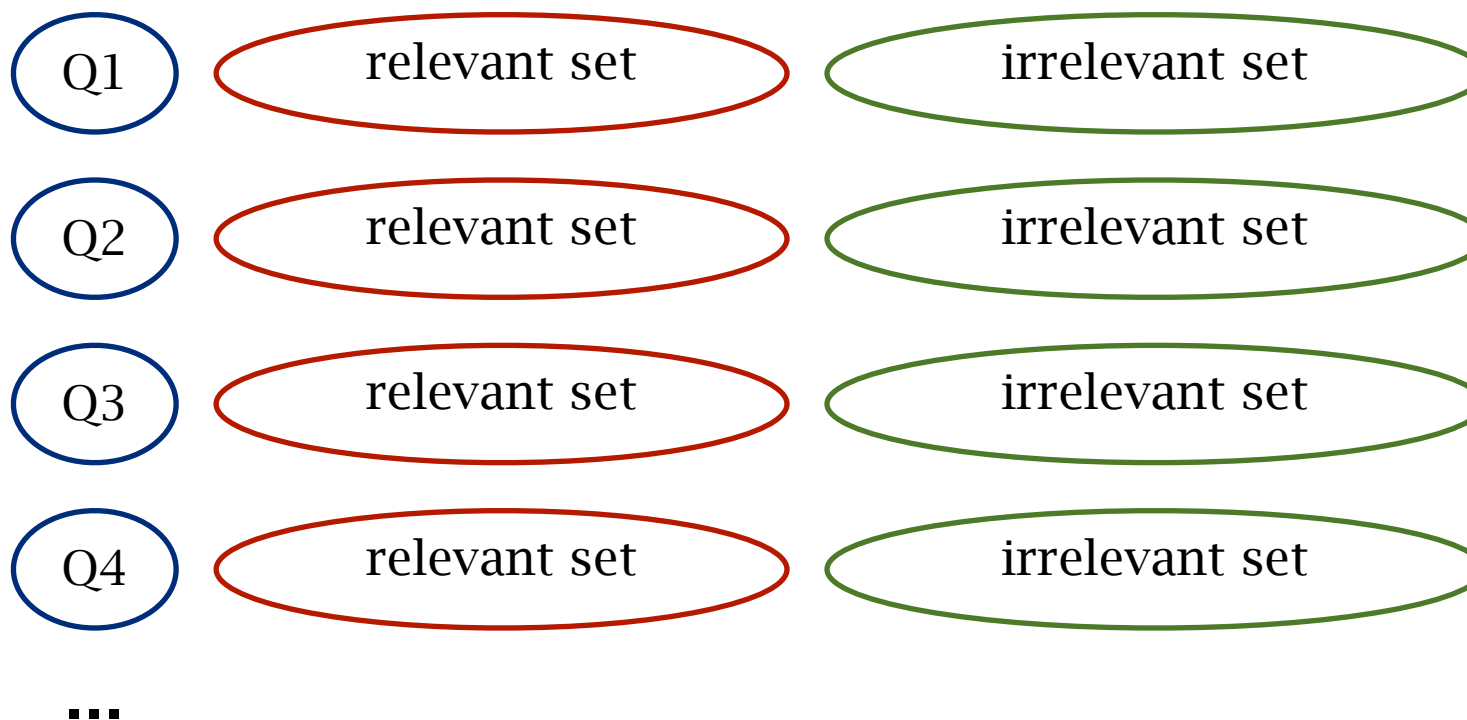


for a particular query, objects can be categorized into “relevant” and “irrelevant”

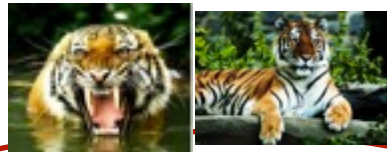
Evaluation



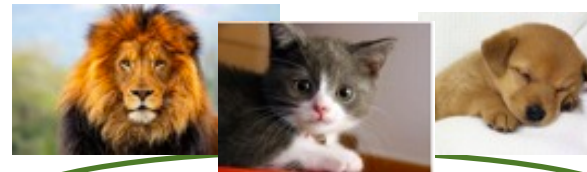
a set queries and pre-labeled relevant/
irrelevant objects



Configurable output



relevant set



irrelevant set



output:



$k=1$



$k=2$



$k=\max$

usually a retrieval system evaluates all objects and rank them according to the similarity

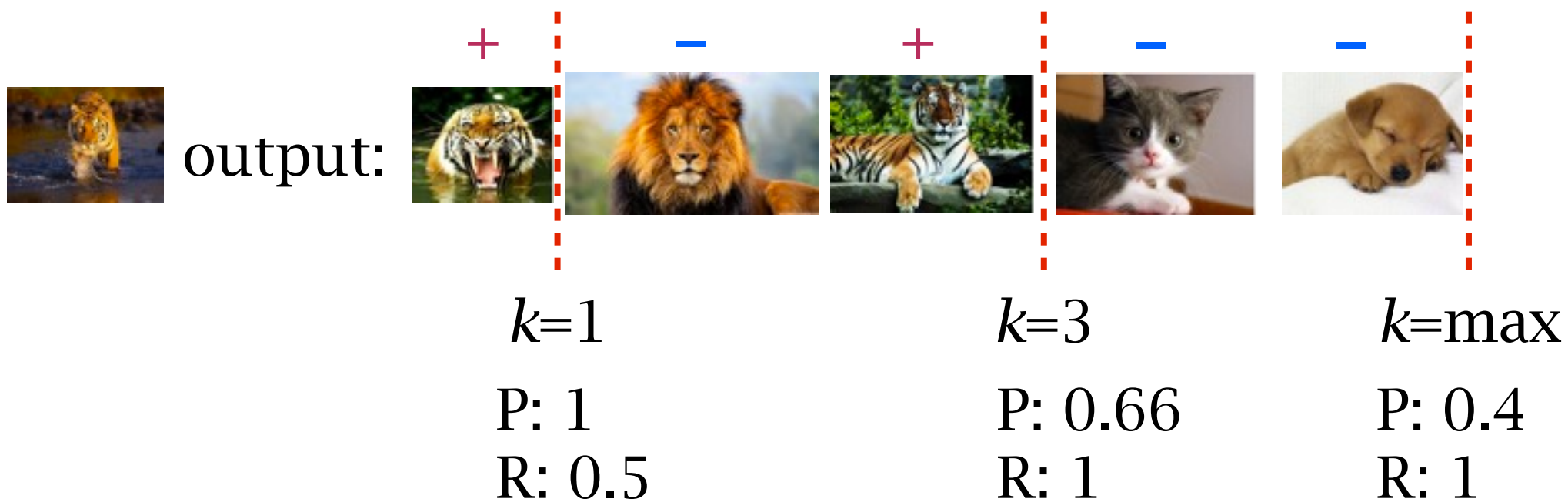
classification error?

Precision and recall



Precision: relevant outputs / all outputs

Recall: relevant outputs / all relevant objects

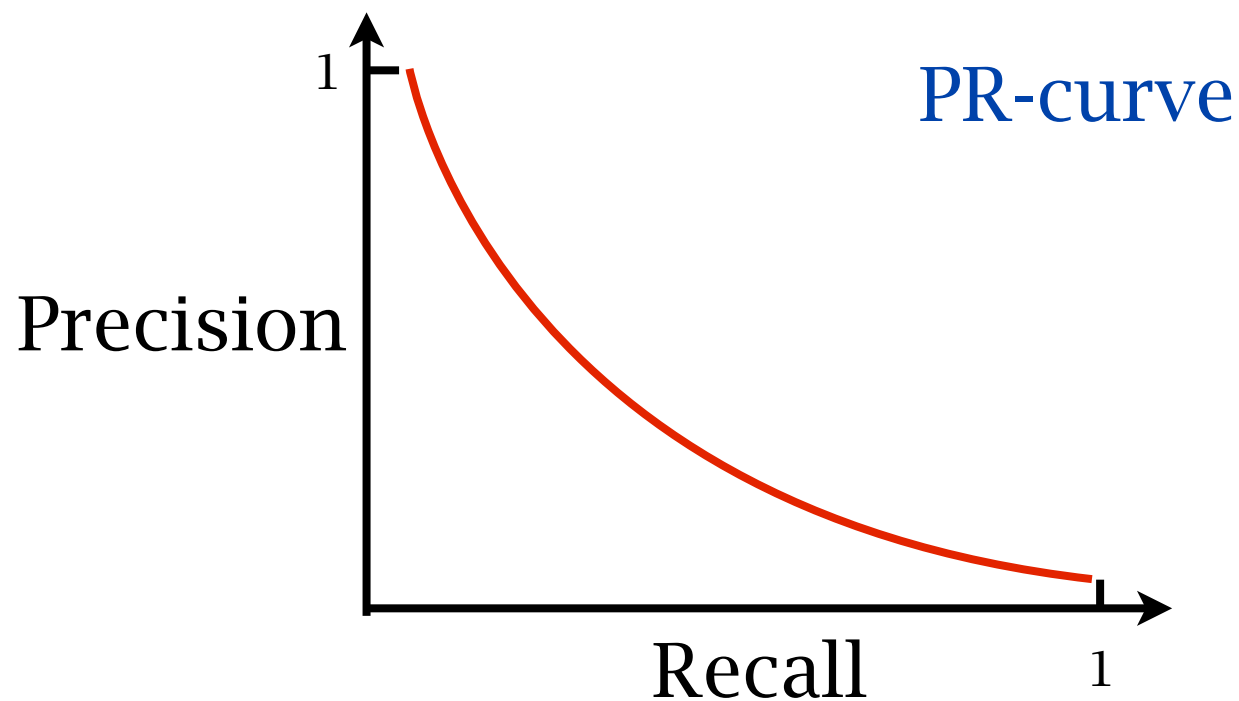


should be averaged over all test queries

Precision and recall



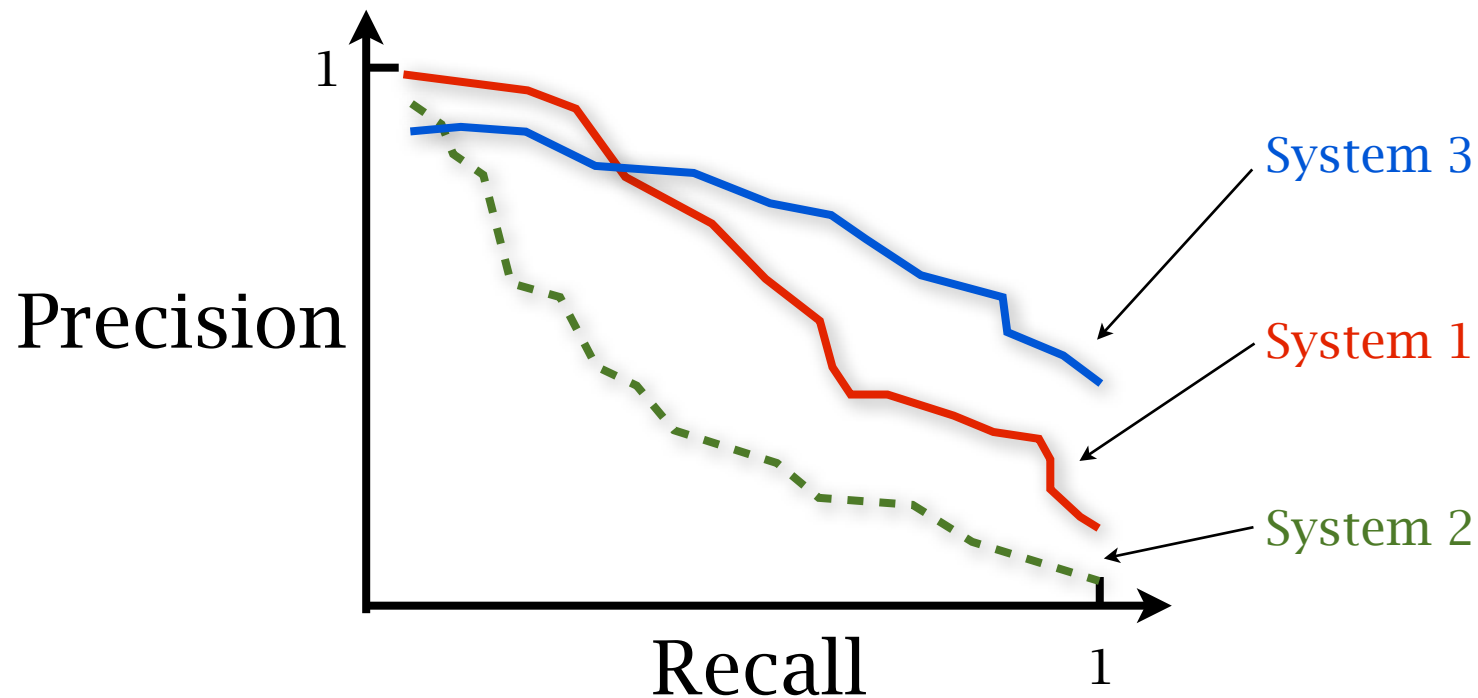
Enumerate all k to produce a set of (P,R) pairs



Precision and recall



Compare retrieval systems



System 1 is better than System 2
System 1 v.s. System 3?

Precision and recall



Compare retrieval systems

Precision/recall at a fixed k

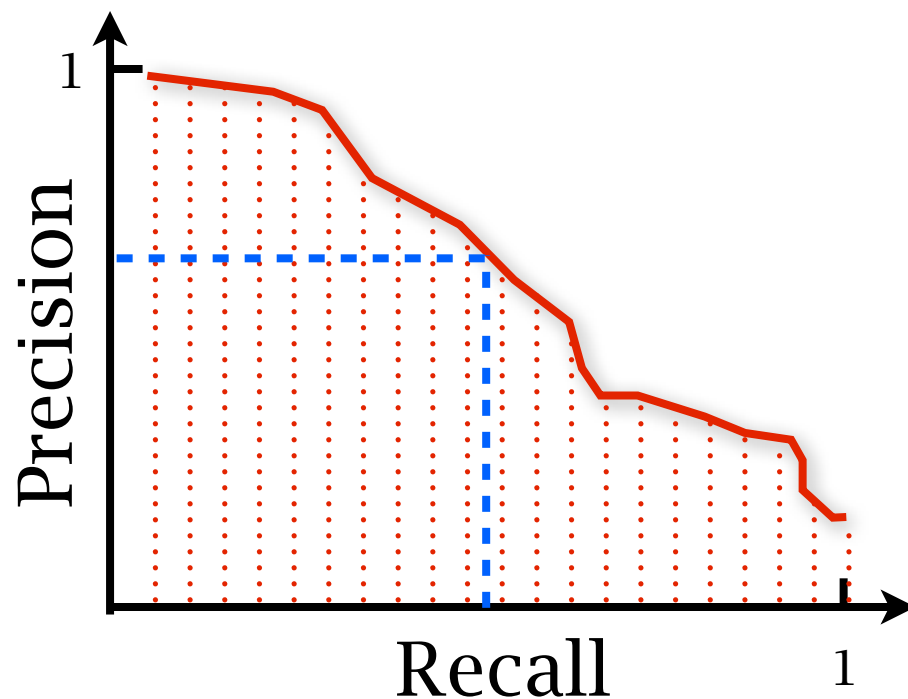
Area under PR-Curve:

Position where $P=R$

F-measure:

for arbitrary cut-point

$$F = \frac{1}{\frac{1}{2} \left(\frac{1}{P} + \frac{1}{R} \right)}$$



Harmonic mean: the probability of the binary random variable whose expectation equals the average expectation of two binary random variables

Precision v.s. recall



application dependent

Criminal face retrieval: high recall



output:



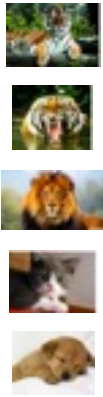
Recommendation in social network: high precision



output:



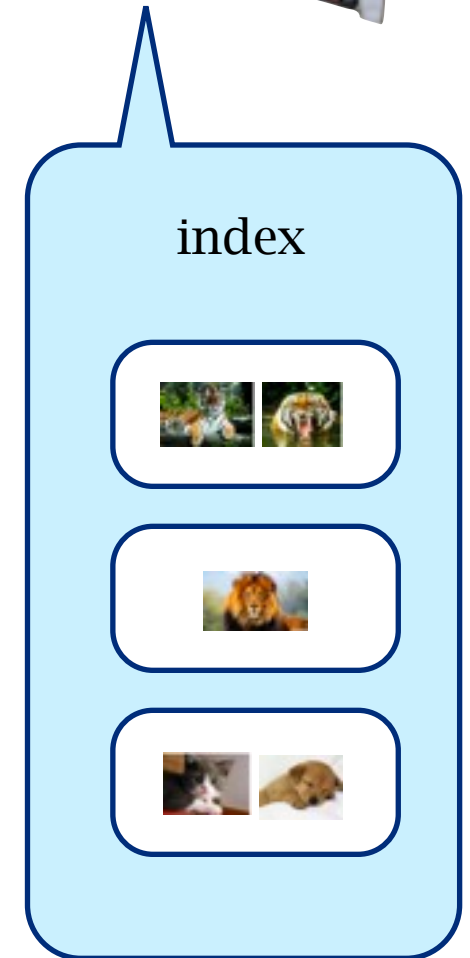
IR Systems



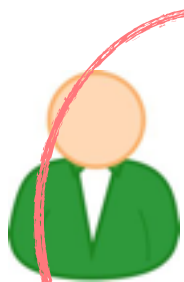
data source



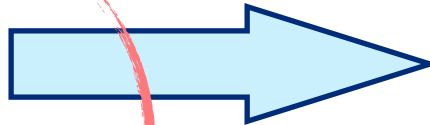
spider



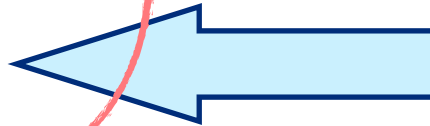
index



query



User Interface

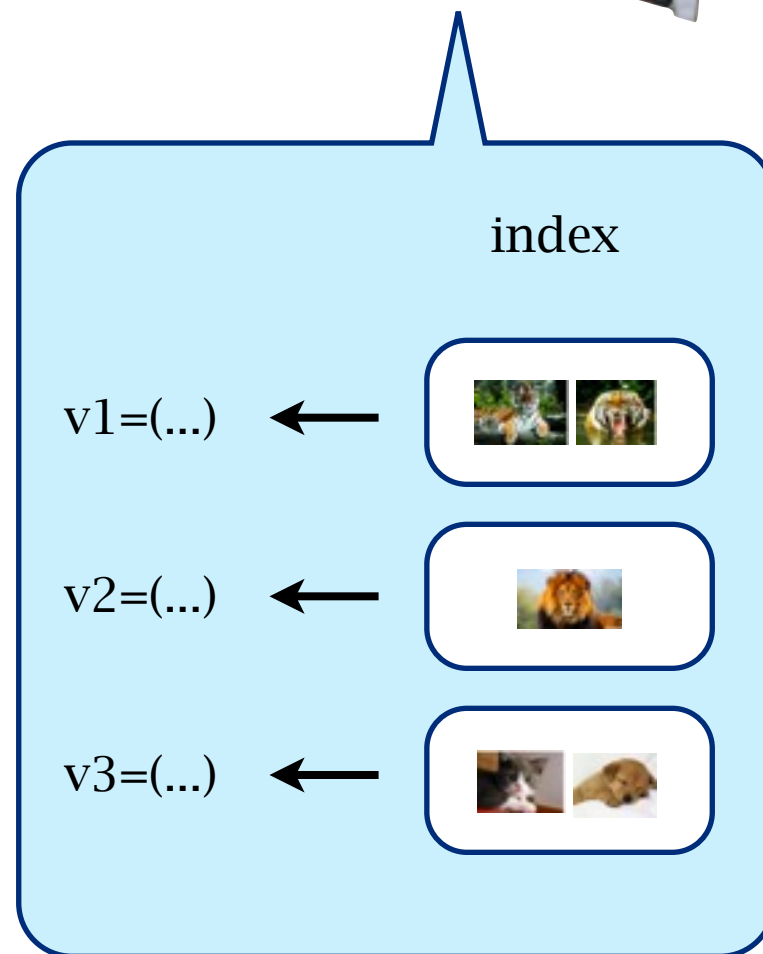


retrieve



*what can data mining help:
find better match*

Understand the content: feature extraction



Text: vector representation



Dictionary: (1, 苏州) (2, 南京) (3, 孔子) (4, 老子)...

苏州老子雕塑卖萌 背对裤衩楼 “吐舌扮鬼脸” (图)

老子雕像继裸女座椅雕塑之后，苏州金鸡湖畔的一尊老子雕塑再度引发争议。道家创始人老子以朴素辩证法思想和无为而治的政治主张，润泽千年，成为中华文化不可或缺的瑰宝。然而，就是这样一个万民敬仰的圣贤，在这尊雕塑上却眼睛紧闭，舌头伸出，露出嘴中一个大门牙，作出一副“龇牙吐舌”的怪状，雷倒了许多路过的市民和游客。昨日，这尊老子“龇牙吐舌”的雕塑在微博上被众多网友转发，一度引起广泛关注。

↓
⇒ (2, 0, 0, 3 ...)

Text: vector representation



Document-term frequency matrix

	t1	t2	t3	t4	t5
D1	24	21	9	0	0
D2	32	10	5	0	3
D3	12	16	5	0	0
D4	6	7	2	0	0
D5	43	31	20	0	3
D6	2	0	0	18	7
D7	0	0	1	32	12
D8	3	0	0	22	4
D9	1	0	0	34	27

cosine similarity:

$$\cos(q, x) = \frac{q^T x}{\|q\| \cdot \|x\|}$$

Query:

(0,0,1,1,0)

features are important to the performance of a retrieval system



Text: vector representation

Inverse Document Frequency

$$IDF(t) = \log \left(\frac{\text{Number of total documents}}{\text{Number of documents containing } t} \right)$$

Document-term frequency (TF)

	t1	t2	t3	t4	t5	t6
D1	24	21	9	0	0	3
D2	32	10	5	0	3	0
D3	12	16	5	0	0	0
D4	6	7	2	0	0	0
D5	43	31	20	0	3	0
D6	2	0	0	18	7	16
D7	0	0	1	32	12	0
D8	3	0	0	22	4	2
D9	1	0	0	34	27	25
D10	6	0	0	17	4	23

$$IDF(t1) = \log \frac{10}{9} = 0.1520$$

$$IDF(t6) = \log_2 \frac{10}{5} = 1$$

multiply

Document-term TF-IDF matrix

	t1	t2	t3	t4	t5	t6
D1	3.7	21	6.6	0	0	3
D2	4.9	10	3.7	0	1.5	0
D3	1.8	16	3.7	0	0	0
D4	0.9	7	1.5	0	0	0
D5	6.5	31	15	0	1.5	0
D6	0.3	0	0	18	3.6	16
D7	0	0	0.7	32	6.2	0
D8	0.5	0	0	22	2.1	2
D9	0.2	0	0	34	14	25
D10	0.9	0	0	17	2.1	23

Text: vector representation



Many ways to form features

Table 4. Performance results for eight term-weighting methods averaged over 5 collections

Term-weighting methods	Rank of method and ave. precision	CACM 3204 docs 64 queries	CISI 1460 docs 112 queries	CRAN 1397 docs 225 queries	INSPEC 12,684 docs 84 queries	MED 1033 docs 30 queries	Averages for 5 collections
1. Best fully weighted ($tf \cdot nfx$)	Rank P	1 0.3630	14 0.2189	19 0.3841	3 0.2626	19 0.5628	11.2
2. Weighted with inverse frequency f not used for docs ($txc \cdot nfx$)	Rank P	25 0.3252	14 0.2189	7 0.3950	4 0.2626	32 0.5542	16.4
3. Classical $tf \times idf$ No normalization ($tfx \cdot tfx$)	Rank P	29 0.3248	22 0.2166	219 0.2991	45 0.2365	132 0.5177	84.4
4. Best weighted probabilistic ($nxx \cdot bpx$)	Rank P	55 0.3090	208 0.1441	11 0.3899	97 0.2093	60 0.5449	86.2
5. Classical idf without normalization ($bfx \cdot bfx$)	Rank P	143 0.2535	247 0.1410	183 0.3184	160 0.1781	178 0.5062	182
6. Binary independence probabilistic ($bxx \cdot bpx$)	Rank P	166 0.2376	262 0.1233	154 0.3266	195 0.1563	147 0.5116	159
7. Standard weights cosine normalization (original Smart) ($txc \cdot txx$)	Rank P	178 0.2102	173 0.1539	137 0.3408	187 0.1620	246 0.4641	184
8. Coordination level binary vectors ($bxx \cdot bxx$)	Rank P	196 0.1848	284 0.1033	280 0.2414	258 0.0944	281 0.4132	260

[Salton and Buckley, 88]

Text: vector representation



the vector representation usually results high dimensional features

TF-IDF + PCA = LSA (Latent Semantic Analysis)

a dimension in LSA is a weighted combination of words

indexing using LSA implicitly involves more key words

Image: features



common ingredient:

colors

RGB, HSV, LIB...

texture

Fourier transformation, wavelets

gradients

edges, descriptors



Image: features



Global features

1. 3-D color feature vector
 - Spatially averaged over the whole image
 - Euclidean distance
2. k-dimensional color histogram
 - bins selected by partition based-based clustering algorithm such as k means
 - k is application dependent
 - Mahanalobis distance using inverse variances
3. 3-D Texture Vector
 - coarseness/scale, directionality, contrast
4. shape feature based on area, circularity, eccentricity, axis orientation, moments

Image: features



Local features

bag-of-words

split the images into small pieces
extract a feature vector per piece
clustering to find centers of feature vectors
each image by a vector of frequency of centers



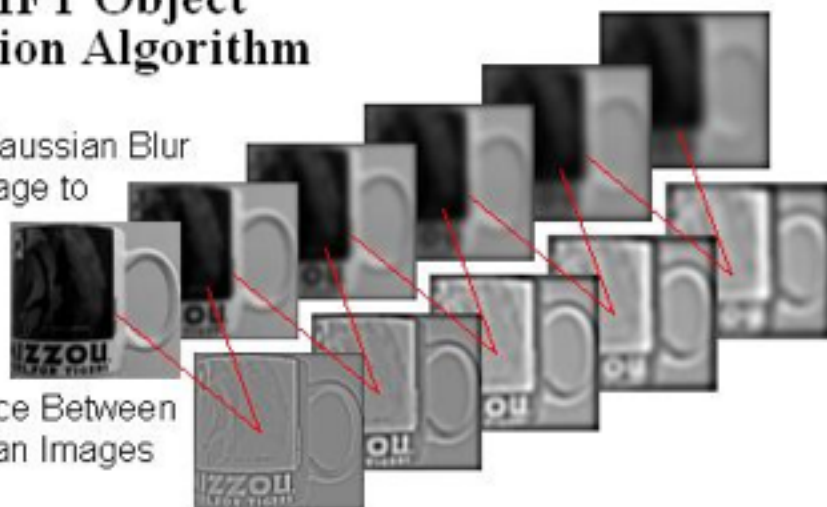
Image: features



Local features

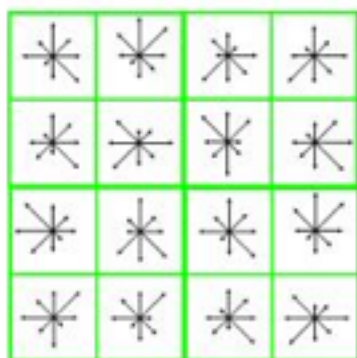
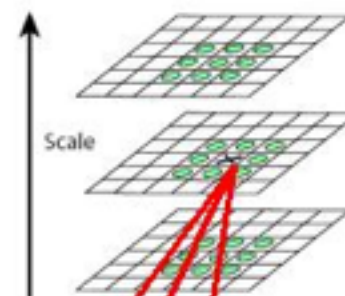
The SIFT Object Recognition Algorithm

Incrementally Gaussian Blur
The Original Image to
Create a Scale
Space

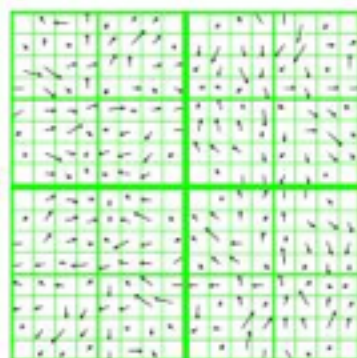


Find the Difference Between
Adjacent Gaussian Images
in Scale Space

Keypoints are Pixels
in Difference Images
That are Larger Than
or Smaller Than all 26
Neighbors



Sixteen Histograms are
Created Using The Gradients.
Using 8 Orientations, This
Makes 128-D Feature Vectors.



The Gradient of Pixels Around
Each Keypoint is Determined
At the Gaussian Scale at Which
It Was Found



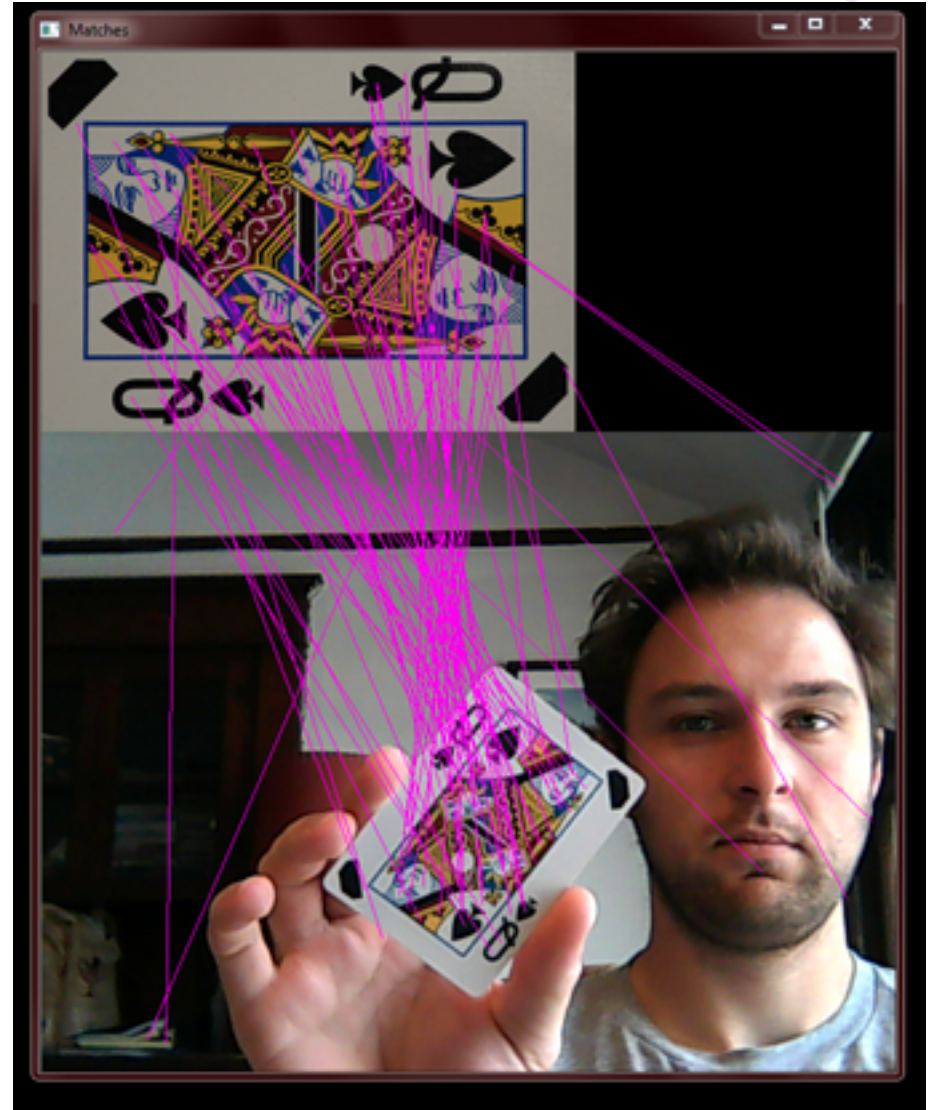
Hundreds of
Keypoints are Found

Image: features



Local features

Bag of words of SIFT vectors



Audio: features



voice audio: speech-to-text transformation

music audio: extract semantic features

Music: features

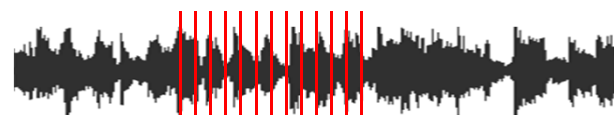


frame-level processing

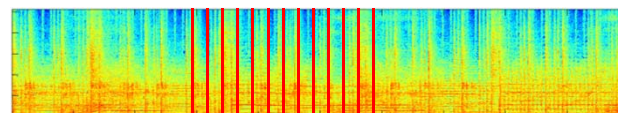
cut frames out

extract frame features

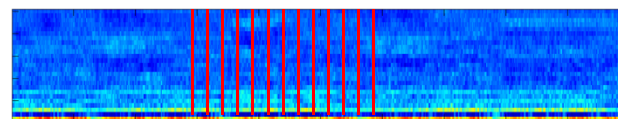
bag-of-frame distribution



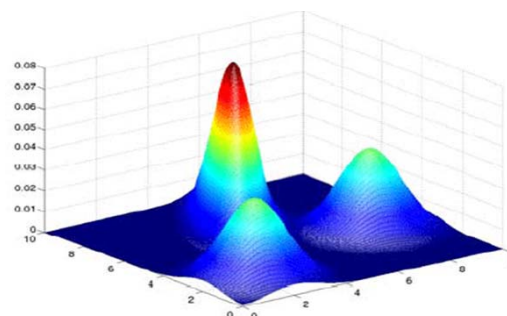
↓ Preprocessing,
Transform to frequency domain,



↓ Model human perception,
Extract local features



↓ Model distribution of frames



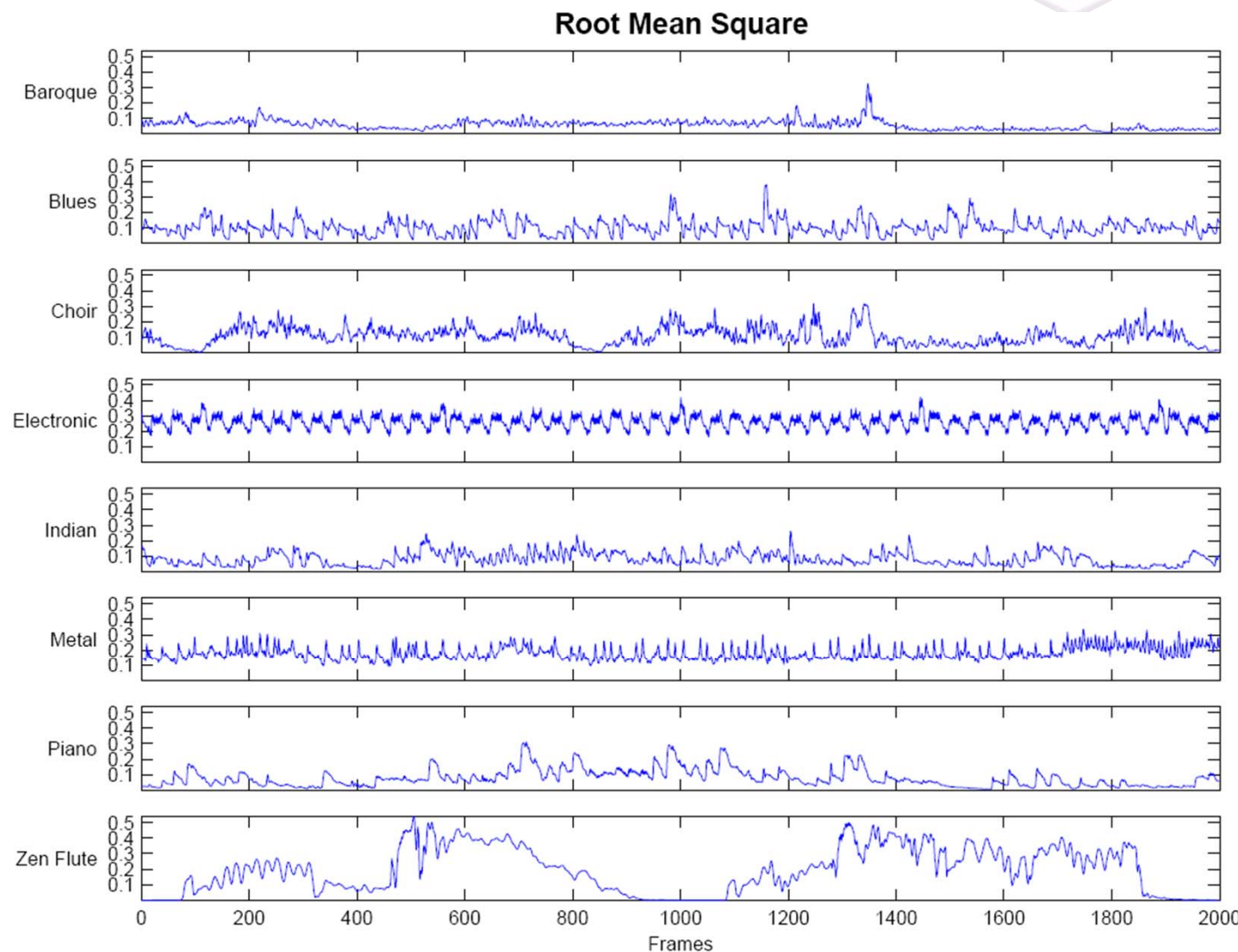
Music: features



Root-Mean-Square (RMS) Energy

$$RMS_t = \sqrt{\frac{1}{K} \cdot \sum_{k=t \cdot K}^{(t+1) \cdot K - 1} s(k)^2}$$

$s(k)$ is the signal value in time domain

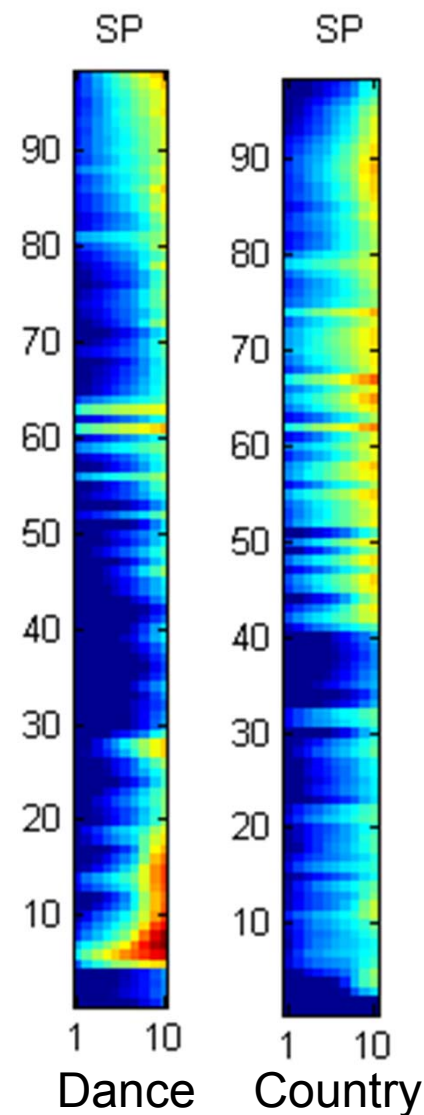


Music: features

Spectral Pattern

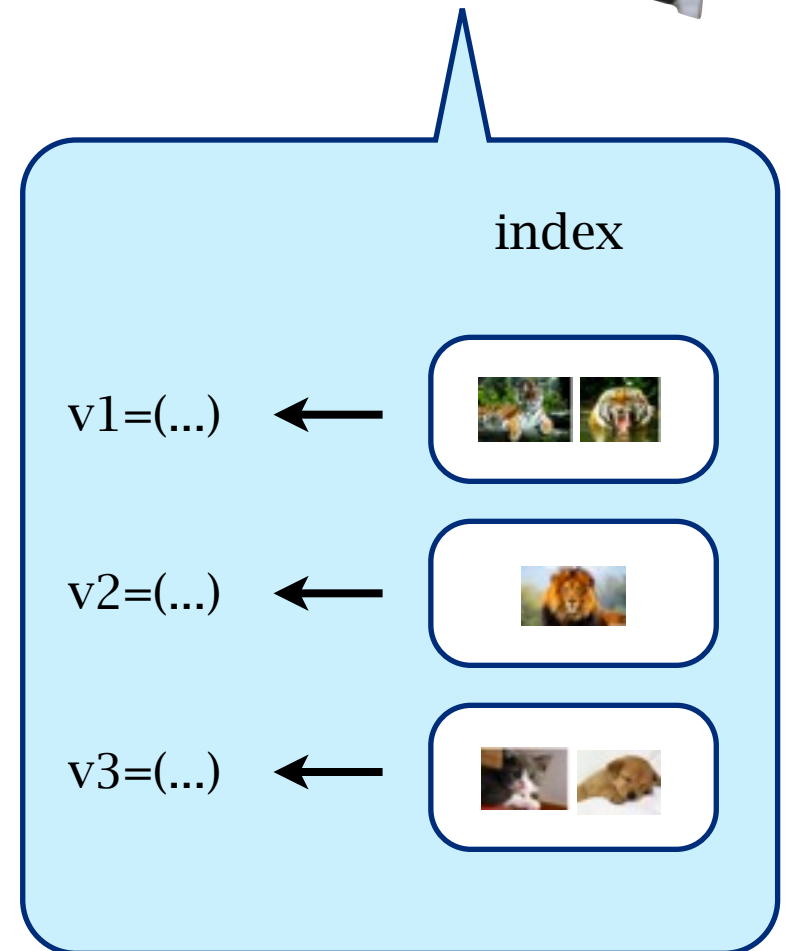
transform into spectrum domain

sort the energy in each frequency band of a block of frames



Understand the user

PageRank is a heuristic,
data reflect the real needs of users



Learning to rank



Transform to binary classification



output:



+



-



+



-

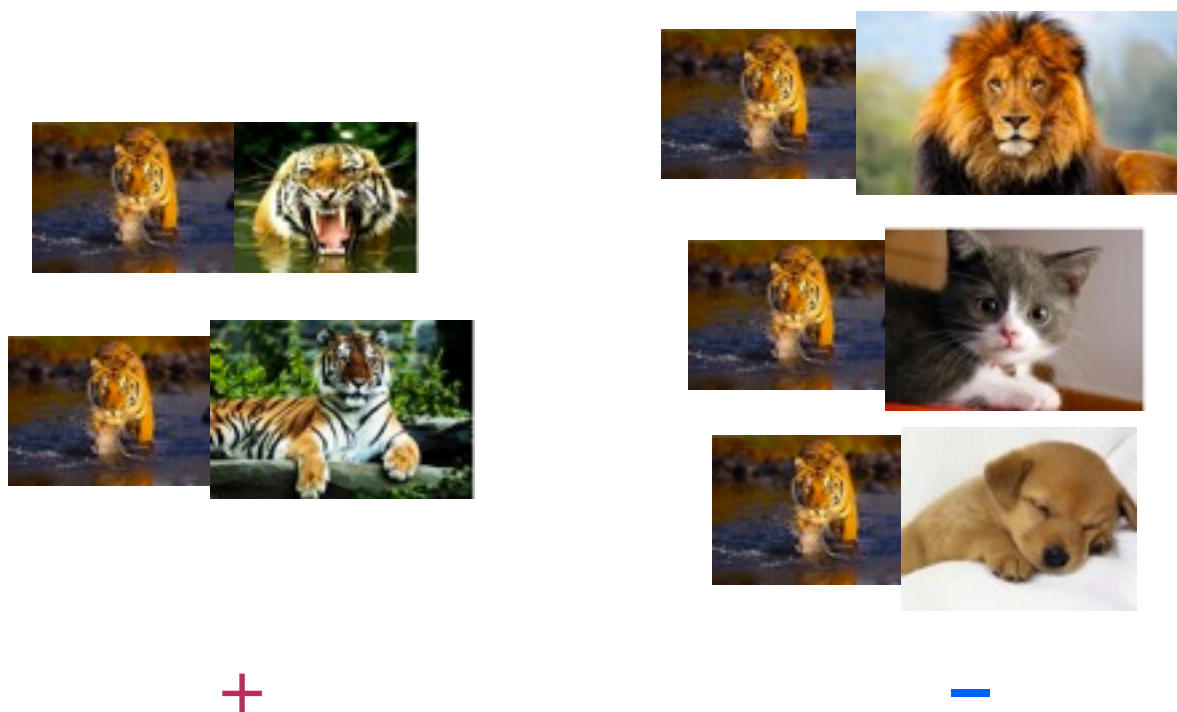


-

Learning to rank



Transform to binary classification



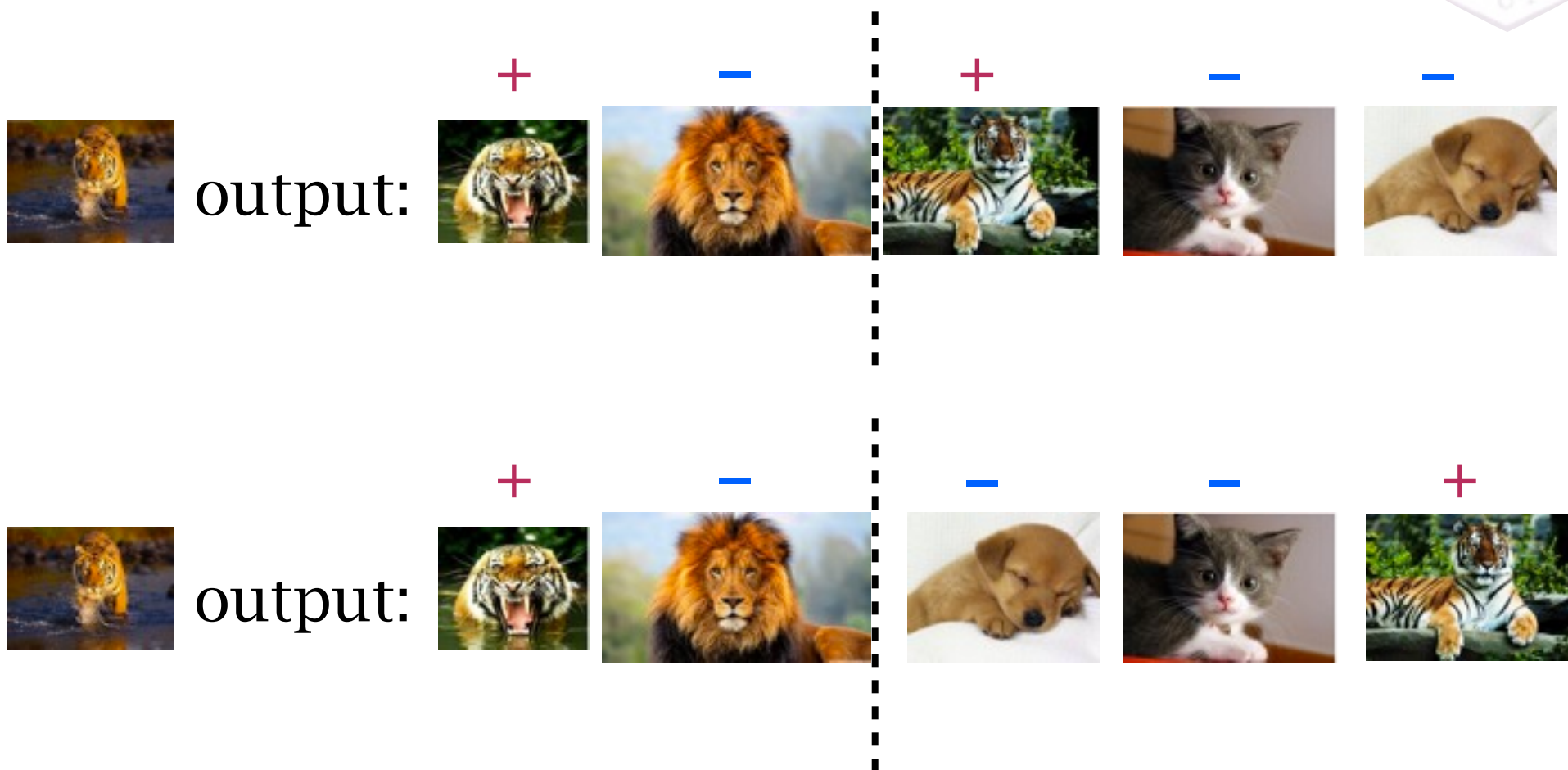
learn a binary classifier

weight items by the confidence of the classifier

Learning to rank



Binary classification \neq ranking

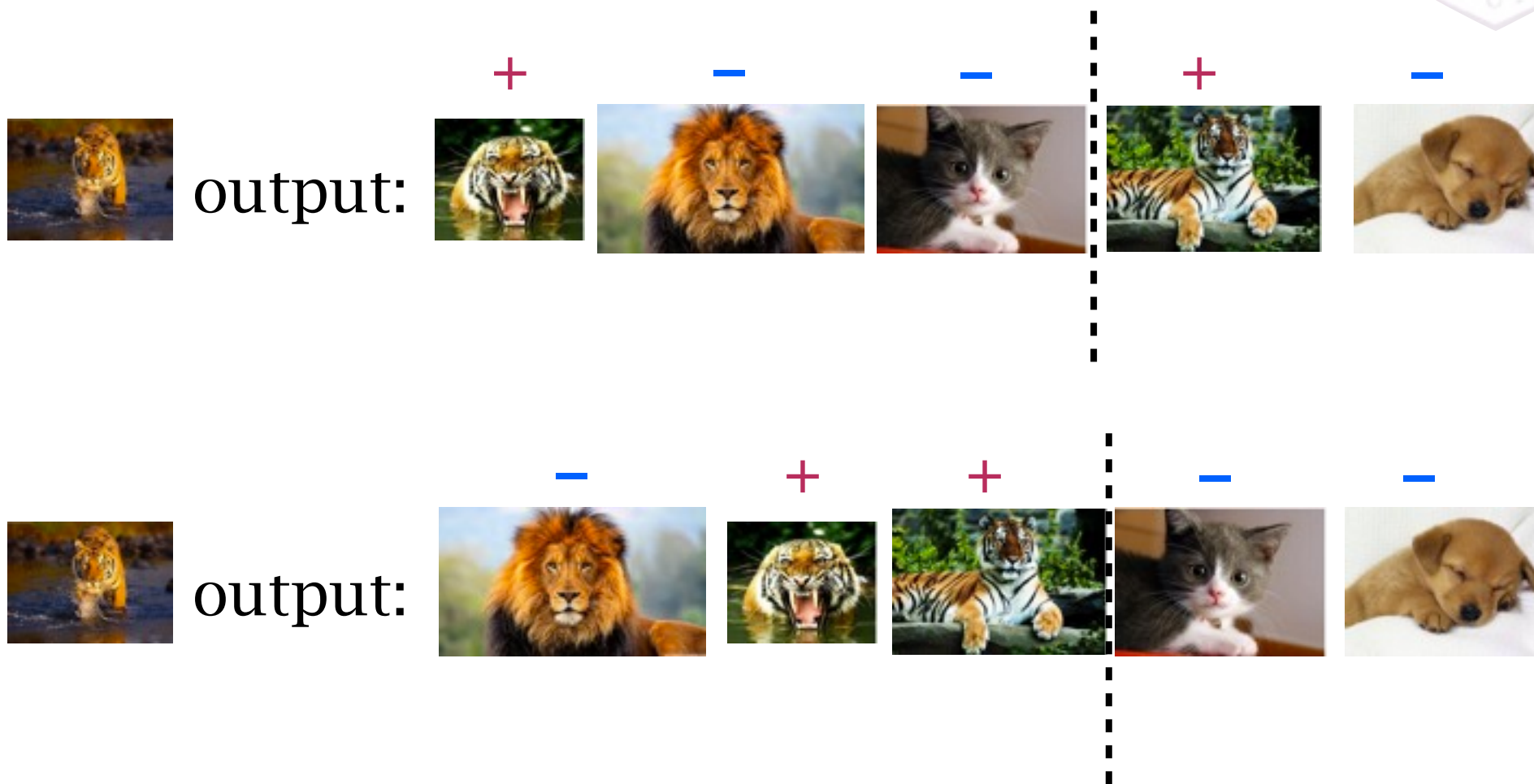


same classification error
different ranking error

Learning to rank



Binary classification \neq ranking

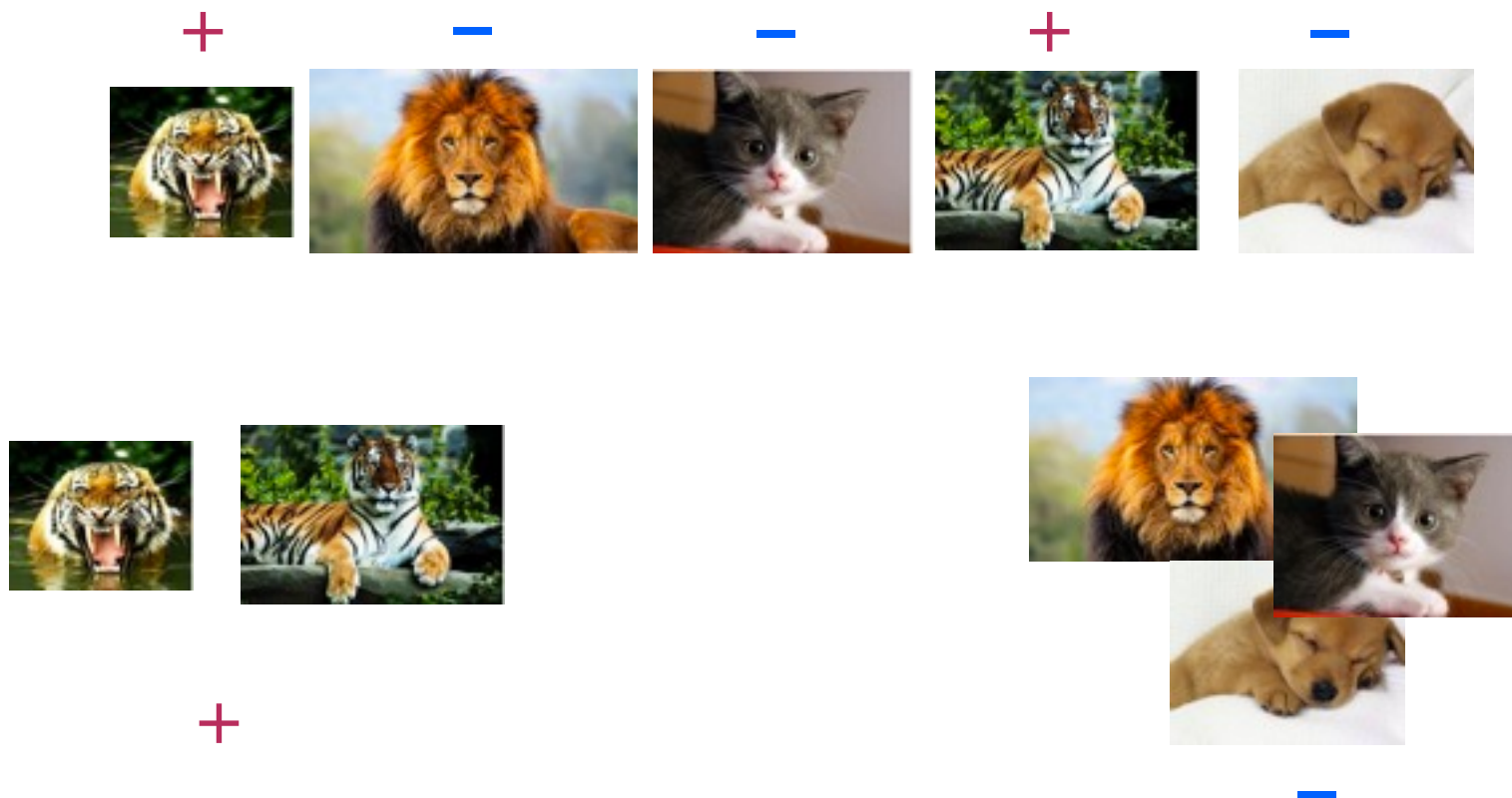


same ranking error (certain criterion)
different classification error

Learning to rank



Learning with ranking loss



$$\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n I[f(x_i^+) < f(x_j^-)]$$

Learning to rank



Learning with ranking loss:

$$\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n I[f(x_i^+) < f(x_i^-)]$$

RankSVM: using hinge loss [Herbrich et al, 2000; Joachims, 2002; Rakotomamonjy, 2004]

$$\min_w \left(\|w\|_2 + C \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n \max\{0, 1 - (f(x_i^+) - f(x_i^-))\} \right)$$

Learning to rank



Learning with ranking loss:

$$\frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n I[f(x_i^+) < f(x_i^-)]$$

RankBoost: using exp-loss [Freund et al, 2003]

Algorithm **RankBoost**

Given: initial distribution D over $\mathcal{X} \times \mathcal{X}$.

Initialize: $D_1 = D$.

For $t = 1, \dots, T$:

- Train weak learner using distribution D_t .
- Get weak ranking $h_t : \mathcal{X} \rightarrow \mathbb{R}$.
- Choose $\alpha_t \in \mathbb{R}$.
- Update: $D_{t+1}(x_0, x_1) = \frac{D_t(x_0, x_1) \exp(\alpha_t(h_t(x_0) - h_t(x_1)))}{Z_t}$

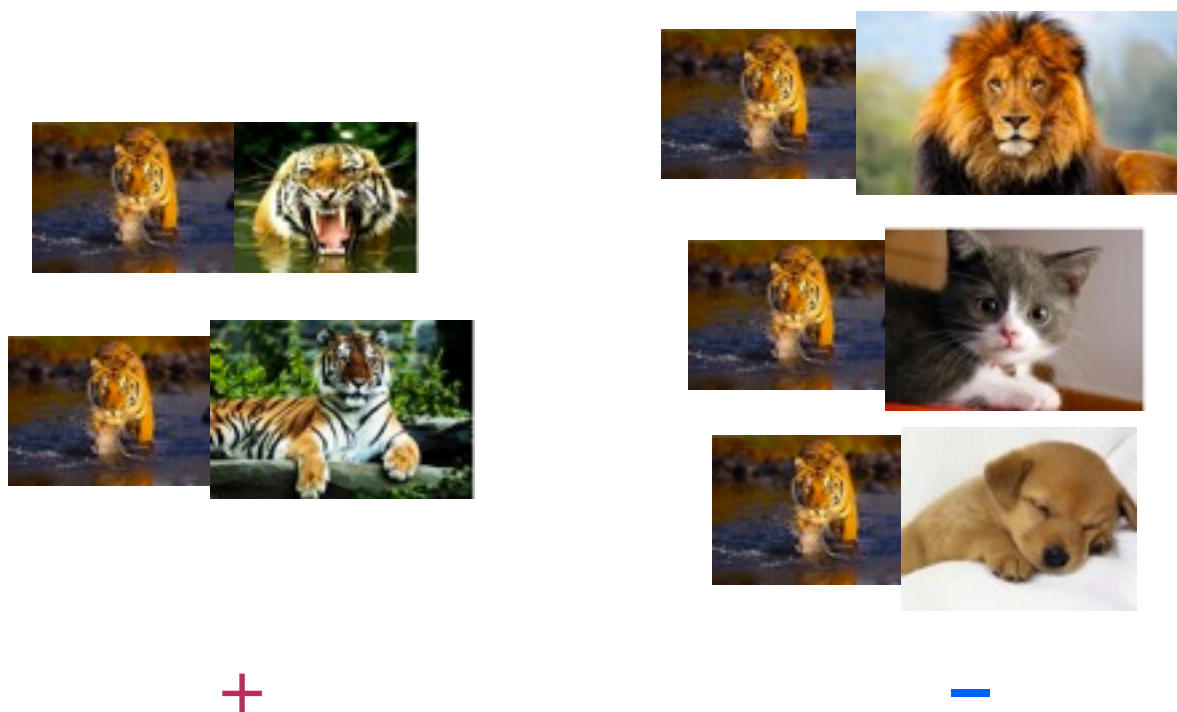
where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final ranking: $H(x) = \sum_{t=1}^T \alpha_t h_t(x)$

Learning to rank



Learning with ranking loss



learn a ranker

weight items by
the ranker
output value

Relevance feedback



The lack of labels

Search

Part 1

[Ares : God of War](#)

The Romans identified Ares with Mars, also a god of war. Agressive and ...

relevance irrelevance

[Ares Unlimited Free Music Downloads](#)

Ares is a nice p2p program for Windows. There are many features to Ares that you ...

relevance irrelevance

a) traditional Web search

Search

     **Part 2**

[Ares : God of War](#) **Part 1**

The Romans identified Ares with Mars, also a god of war.  Agressive and ...

relevance irrelevance

[Ares Unlimited Free Music Downloads](#)

Ares is a nice p2p program for Windows. There are many features to Ares that you ... 

relevance irrelevance

b) WebSIS

Implicit feedback



Click-through data

A screenshot of a Google search results page for the query "click-through data". The search bar at the top shows the query and the Google logo. Below the search bar, there are tabs for "Web", "Images", "Maps", "More", and "Search tools". The search results are displayed below, with a mouse cursor pointing to the second result. The results include a Wikipedia definition, an ACM paper, a Cornell University paper, an Oxford Dictionary entry, a Branded3 article, and a Microsoft article.

Google click-through data

About 504,000,000 results (0.25 seconds)

What is click-through? - A Word Definition From the Webopedia ...
www.webopedia.com/TERM/C/click_through.html ▾
This page describes the term **click-through** and lists other pages on the Web where ...
Check this page for more 3,700 **data** formats and their corresponding file ...

Optimizing search engines using clickthrough data - ACM.Digital ...
dl.acm.org/citation.cfm?id=775067 ▾
by T Joachims - 2002 - Cited by 2194 - Related articles
This paper presents an approach to automatically optimizing the retrieval quality of search engines using **clickthrough data**. Intuitively, a good information ...

Optimizing Search Engines using Clickthrough Data
www.cs.cornell.edu/people/tj/publications/joachims_02c.pdf ▾
by T Joachims - 2002 - Cited by 2194 - Related articles
Optimizing Search Engines using **Clickthrough Data**. Thorsten Joachims. Cornell University. Department of Computer Science. Ithaca, NY 14853 USA.

click-through - Oxford Dictionaries
www.oxforddictionaries.com/definition/english/click-through ▾
Definition of **click-through** in British and World English in Oxford dictionary. Meaning, pronunciation and example sentences. English to English reference ...

Google Click Through Data & The End of Rankings | Branded3
www.branded3.com/.../google-click-through-data-the-end-of-ra... ▾
by Patrick Altoft - in 2,097 Google+ circles
Apr 16, 2010 - This week Google released a very exciting new feature in Webmaster Tools - the ability to see impression data and **click through data** for your ...

Mining Clickthrough Data for Collaborative Web Search - Micros...

Involve user features



different users may use the same keywords for different purpose



output:



geographic data

computer configurations

sites visited

习题



对于用户的一条查询，数据库中总共有100个相关对象，系统返回了10个对象，其中不相关的有3个，请问对于这一条查询，系统的查准率 (Precision) 和查全率 (Recall) 各是多少？