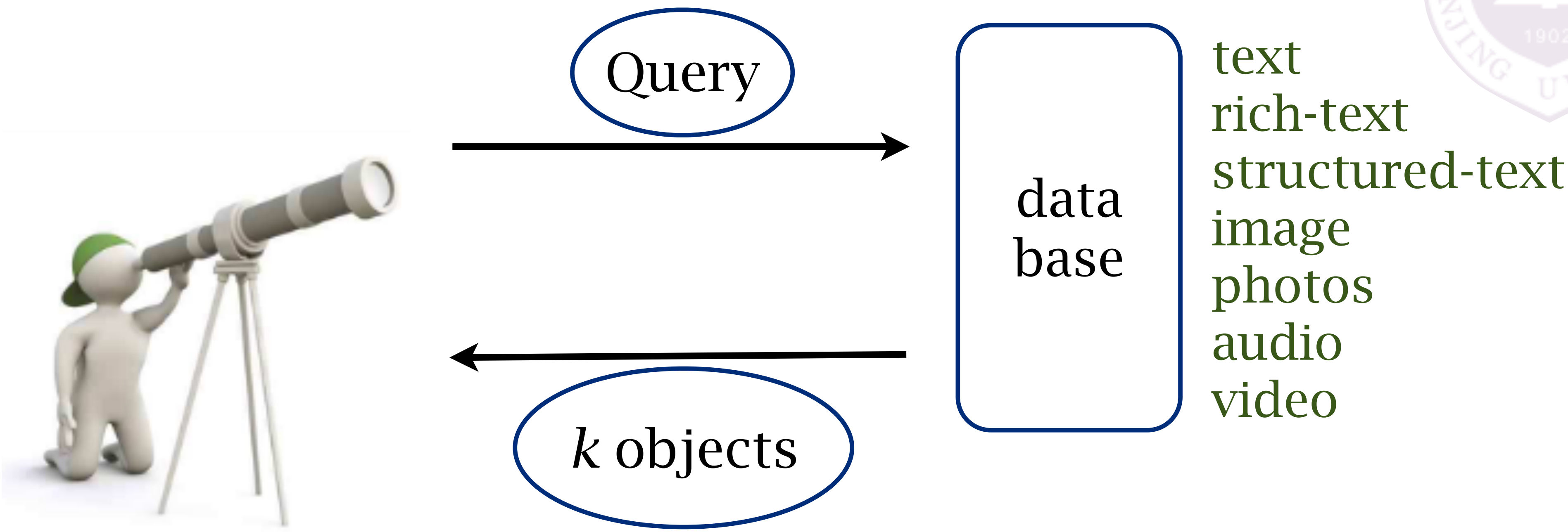
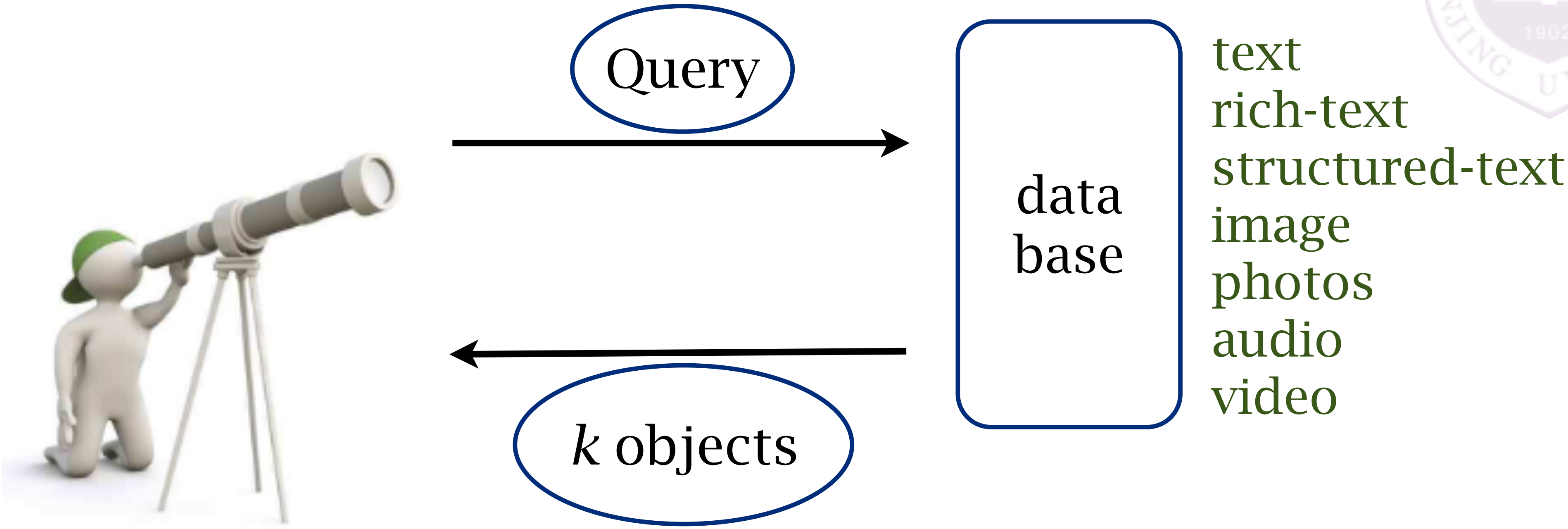
Lecture 12: Data Mining V
Information Retrieval Systems

http://cs.nju.edu.cn/yuy/course_dm14ms.ashx

Information retrieval systems

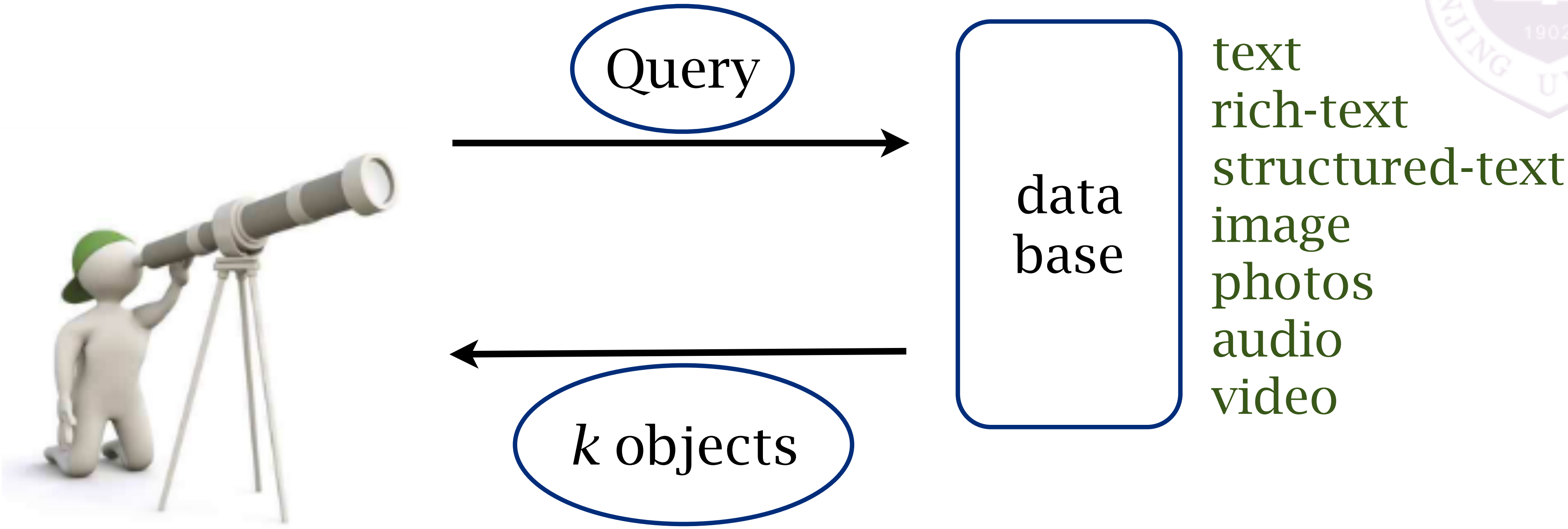


Information retrieval systems



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

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?

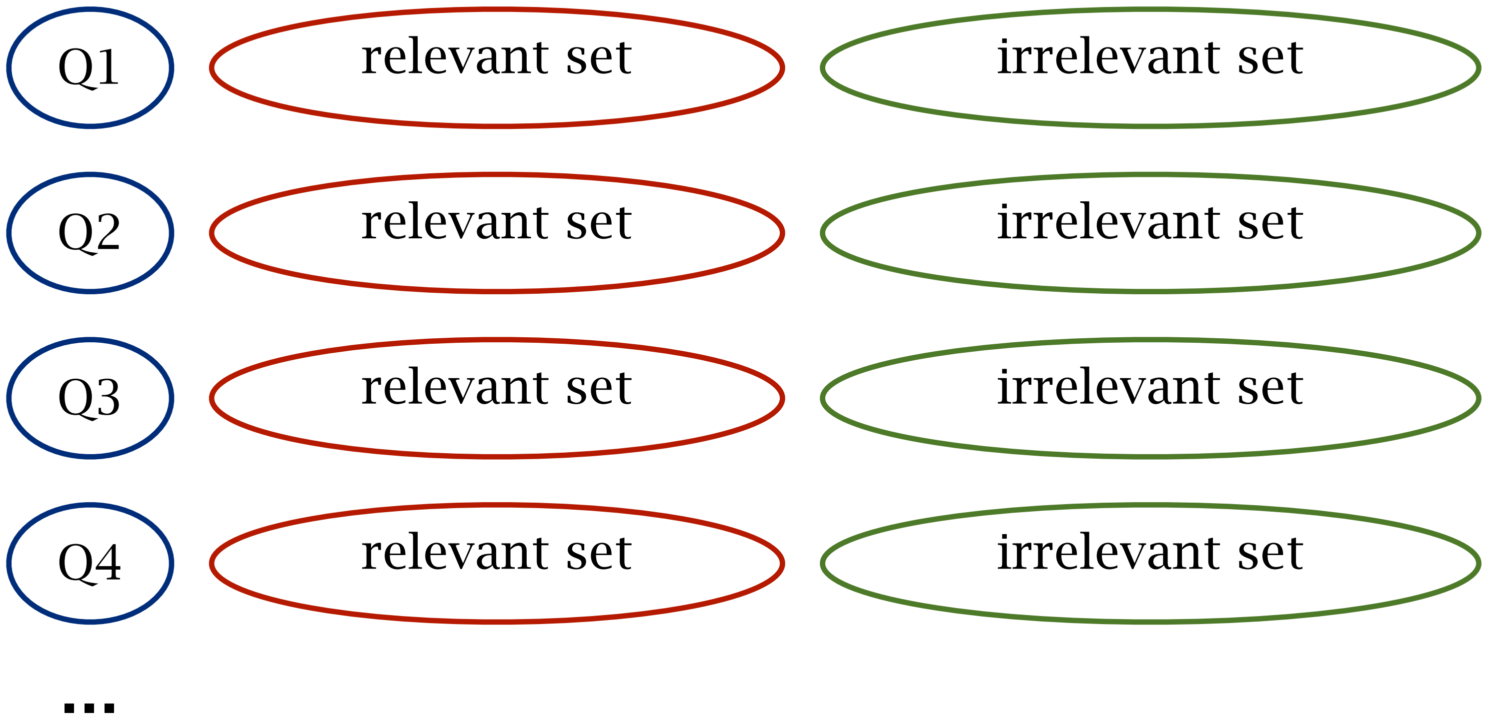
QUERY

N/R R

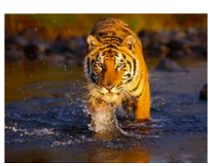
for a particular query, objects can be categorized into "relevant" and "irrelevant"

Evaluation

a set queries and pre-labeled relevant/ irrelevant objects

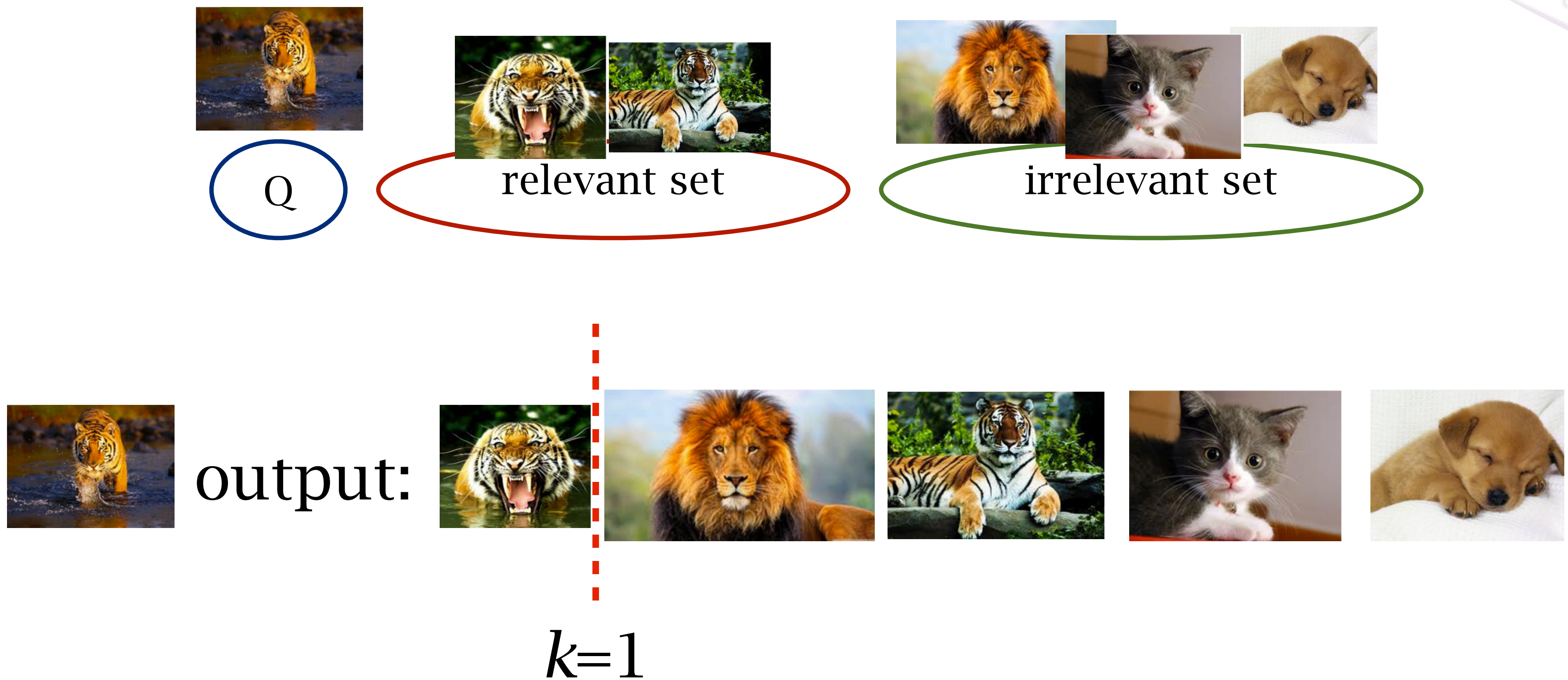


Configurable output

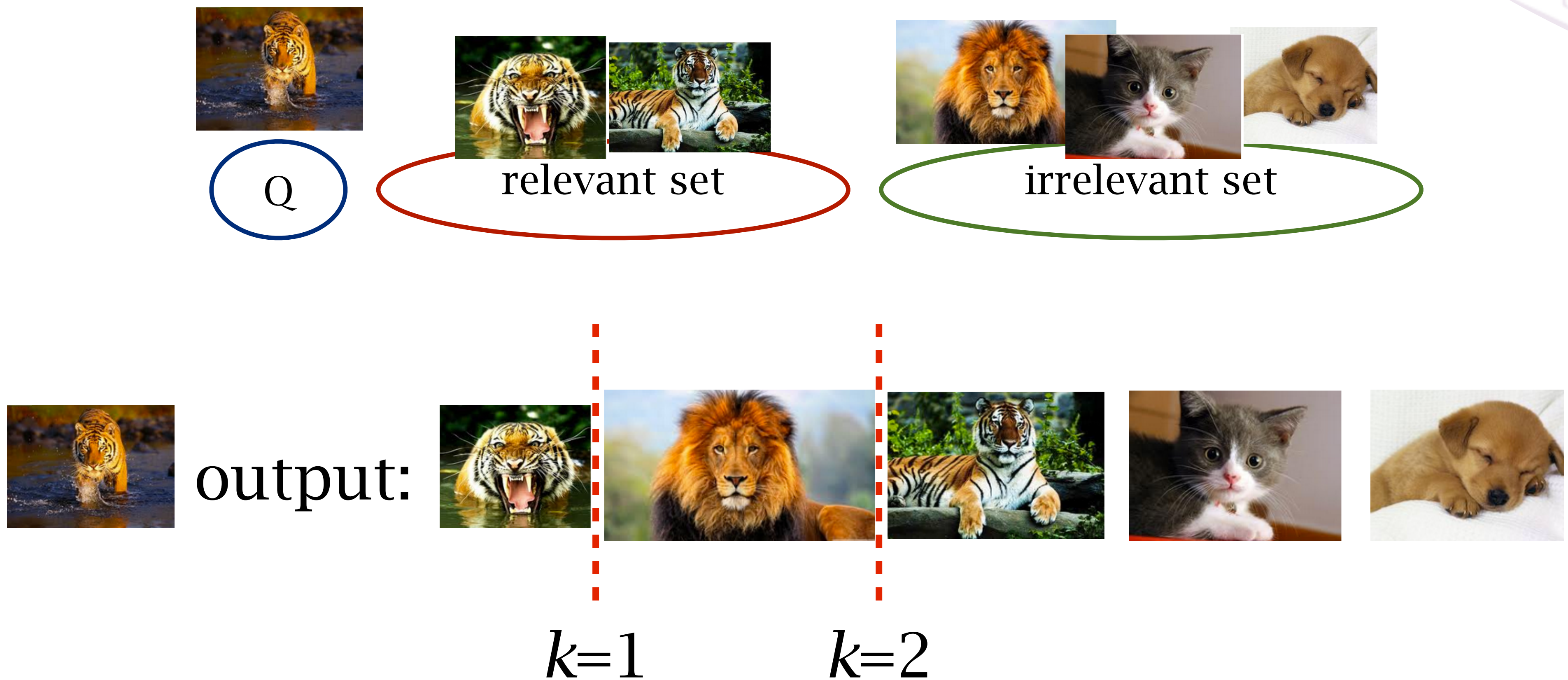


output:

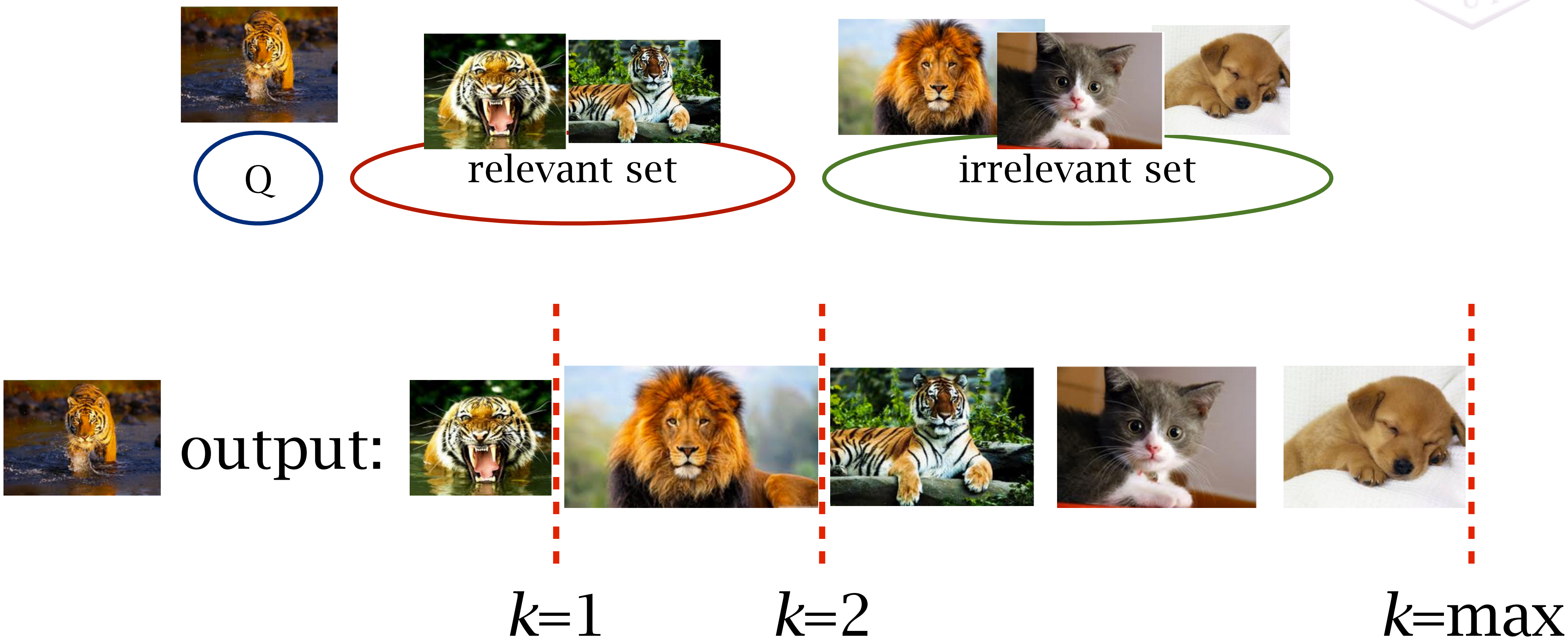
Configurable output



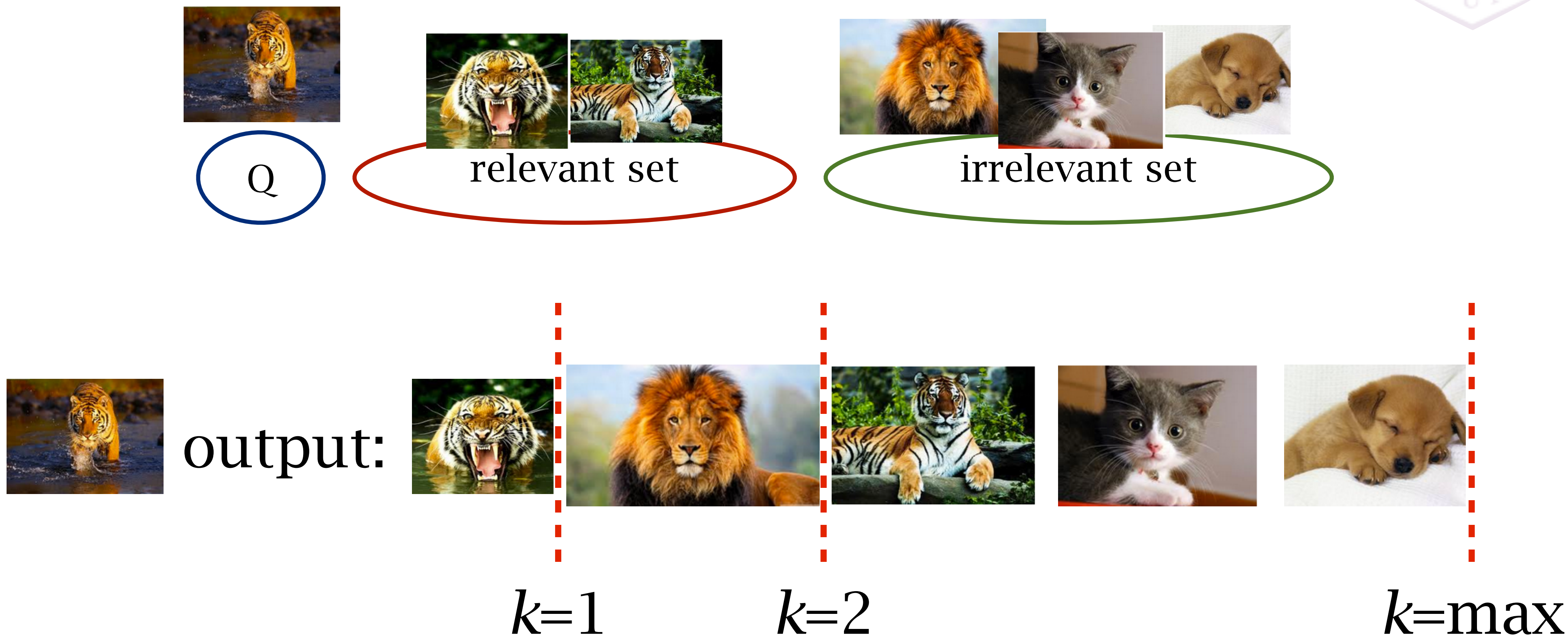
Configurable output



Configurable output



Configurable output



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

output:

+

−

+

−

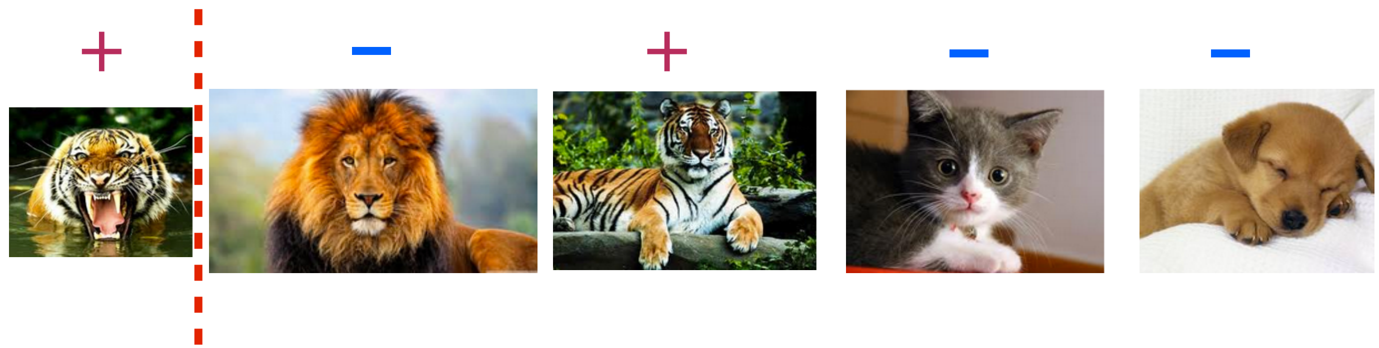
−

should be averaged over all test queries

Precision and recall

Precision: relevant outputs / all outputs
Recall: relevant outputs / all relevant objects

output:



k=1

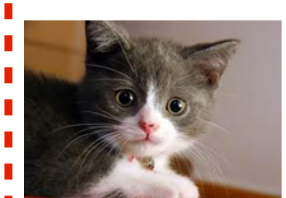
P: 1
R: 0.5

should be averaged over all test queries

Precision and recall

Precision: relevant outputs / all outputs
Recall: relevant outputs / all relevant objects

output:

+	−	+	−	−
				

k=1

P: 1
R: 0.5

k=3

P: 0.66
R: 1

should be averaged over all test queries

Precision and recall

Precision: relevant outputs / all outputs
Recall: relevant outputs / all relevant objects

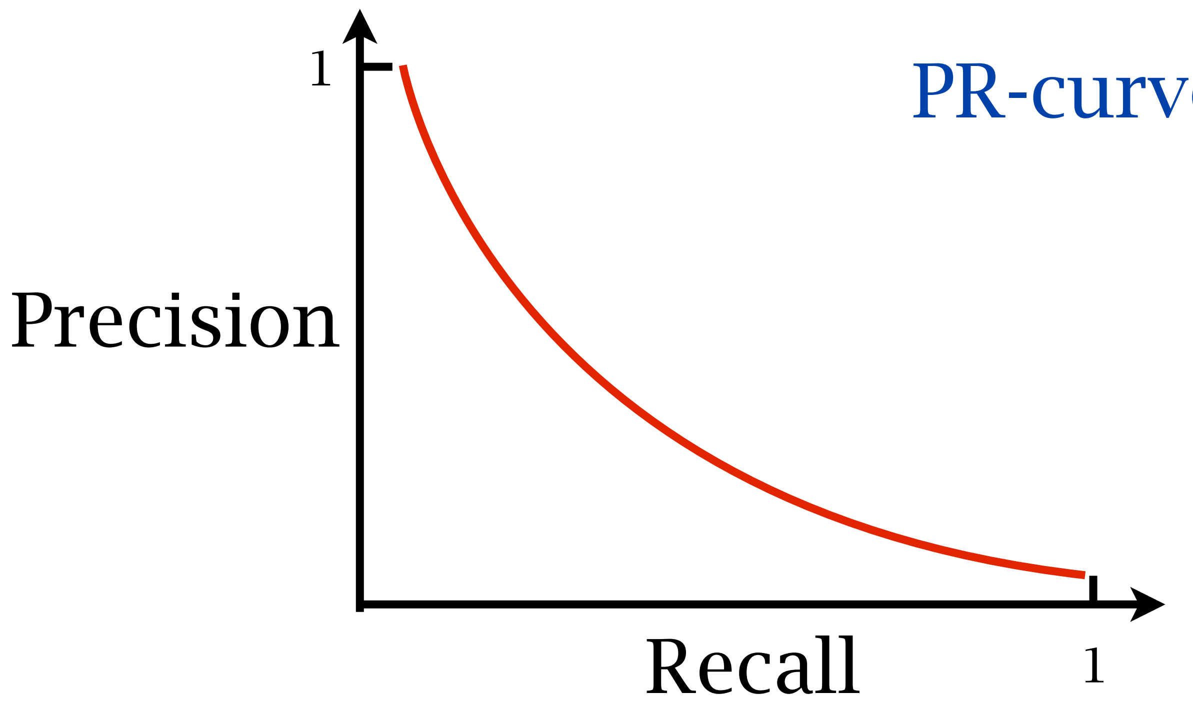
output:

k=1	k=3	k=max
P: 1	P: 0.66	P: 0.4
R: 0.5	R: 1	R: 1

should be averaged over all test queries

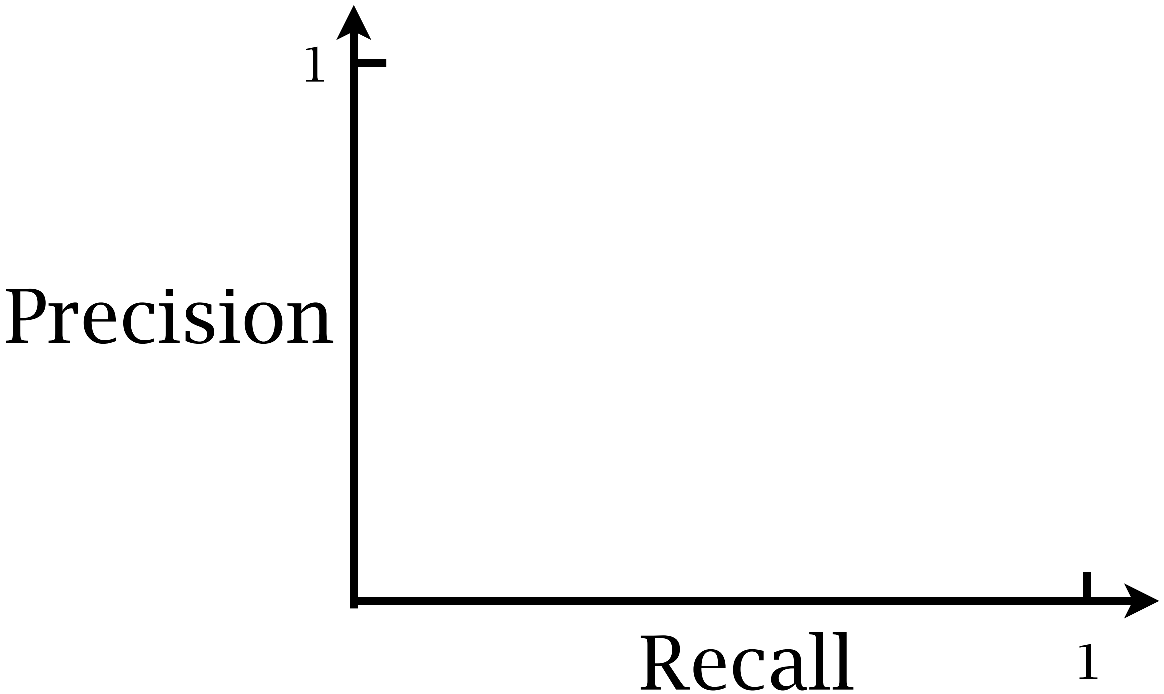
Precision and recall

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



Precision and recall

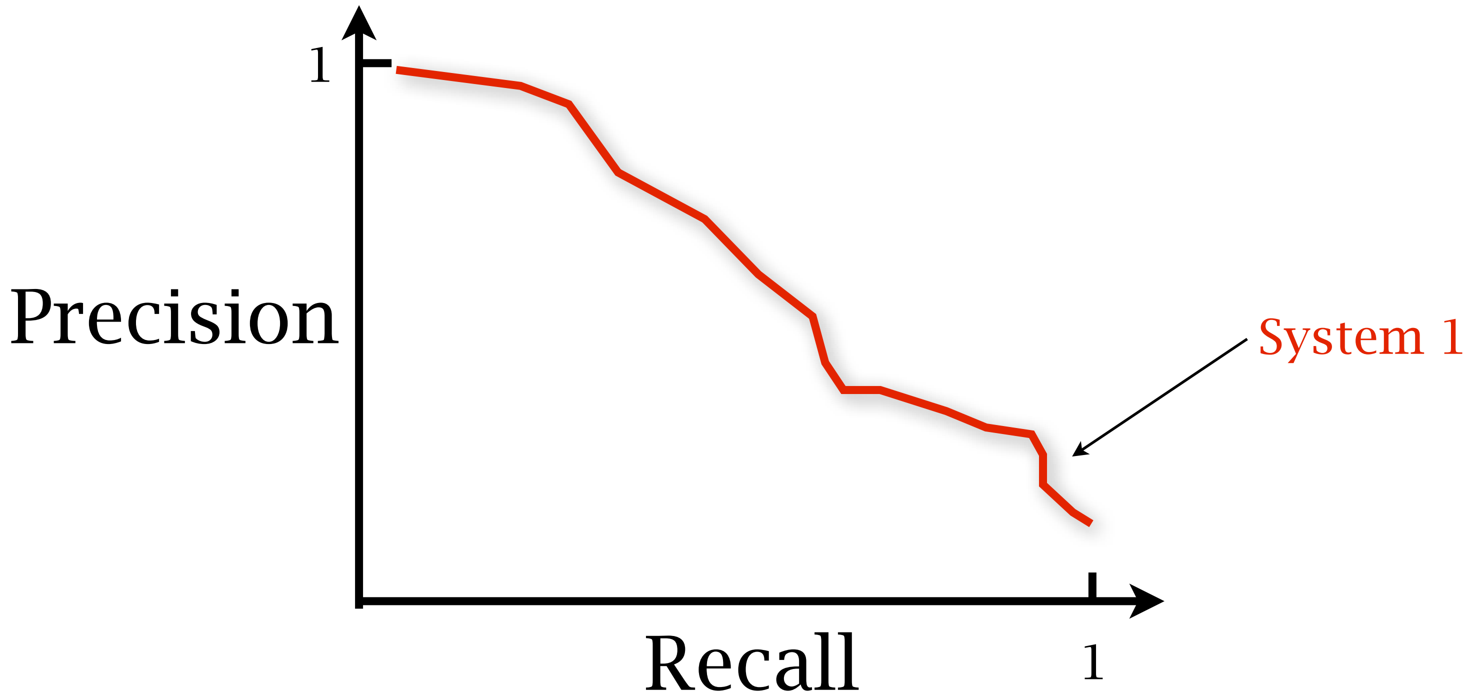
Compare retrieval systems



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

Precision and recall

Compare retrieval systems



System 1 is better than System 2
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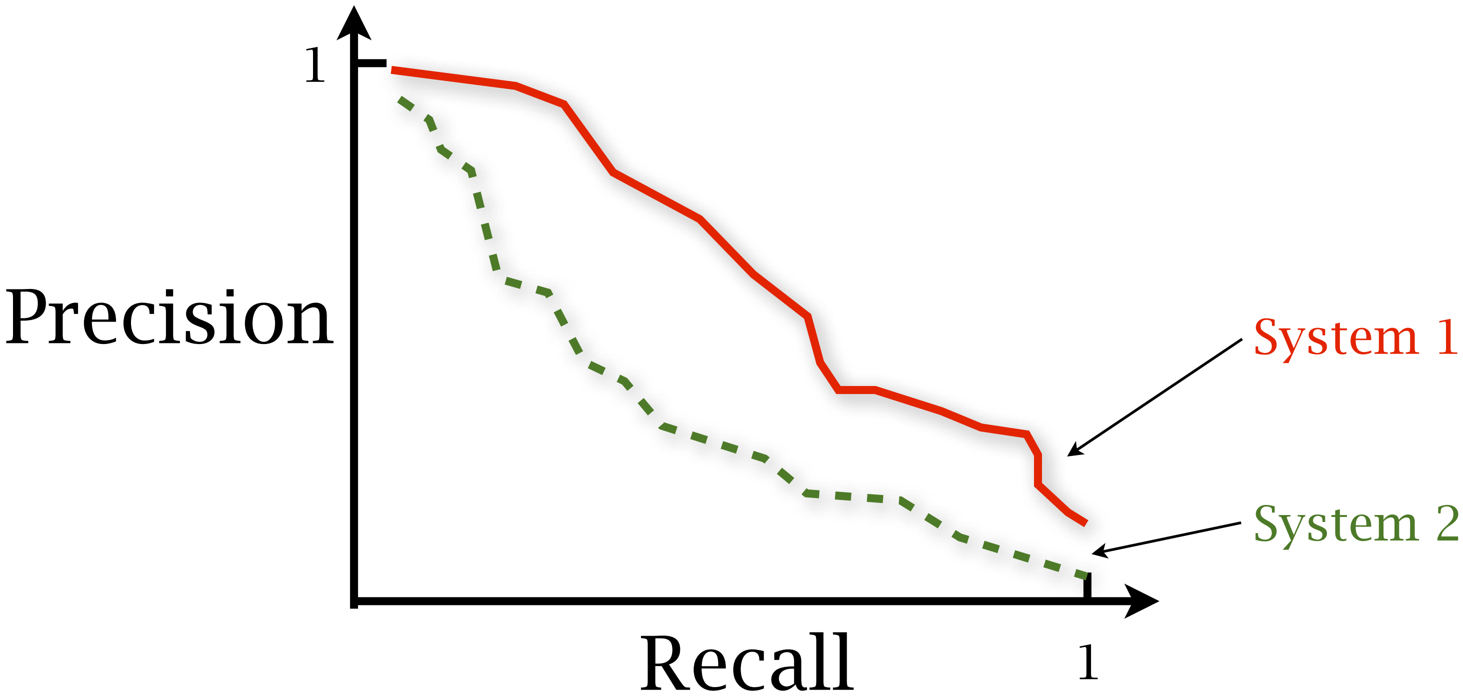
Precision and recall

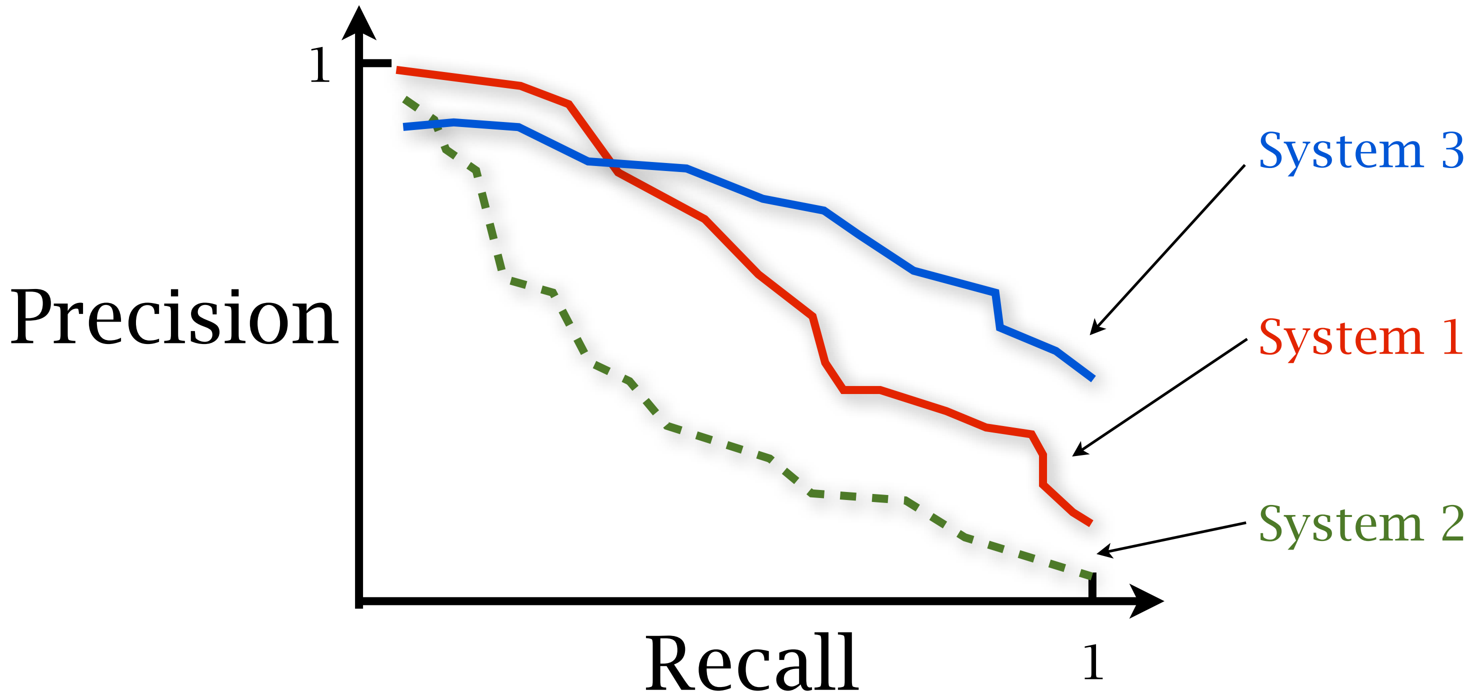
Compare retrieval systems



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

Precision and recall

Compare retrieval systems



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

Precision and recall

Compare retrieval systems

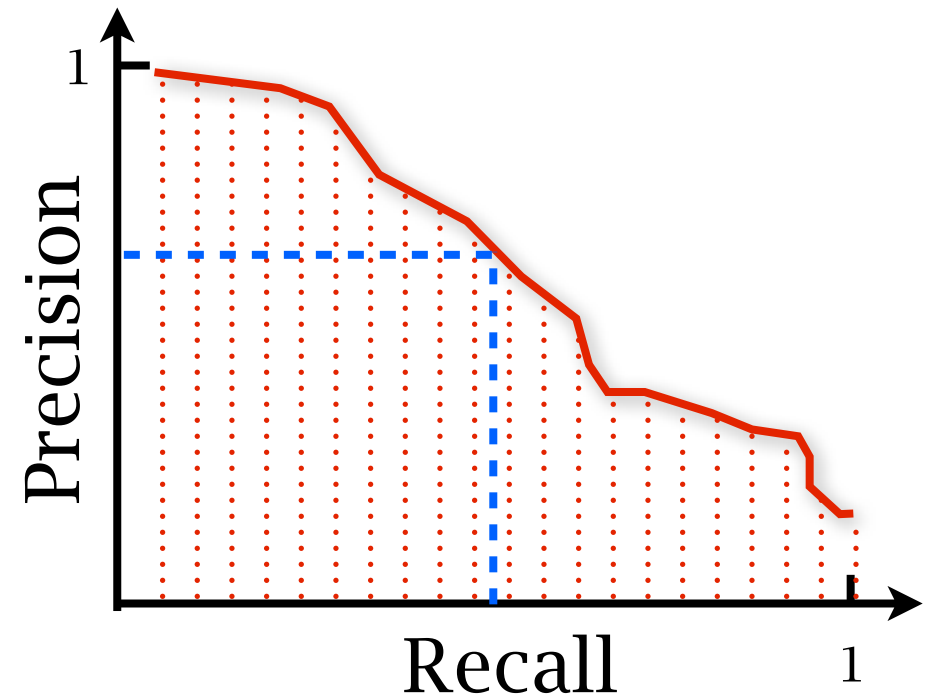
Precision/recall at a fixed k

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

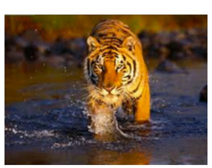
Precision v.s. recall

application dependent

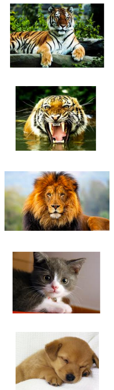
Criminal face retrieval: high recall

 output: 

Recommendation in social network: high precision

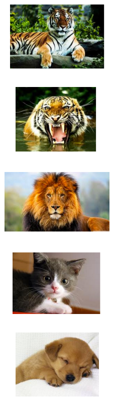
 output: 

IR Systems

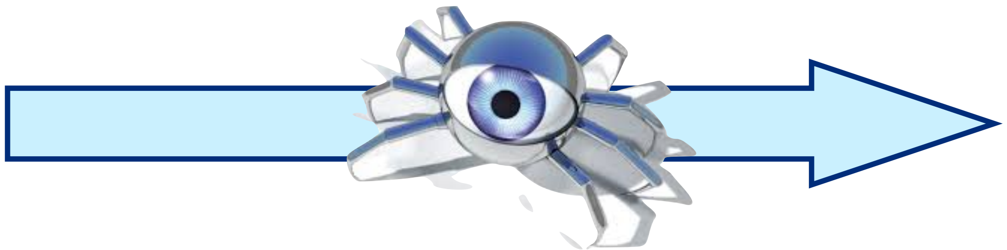


data source

IR Systems

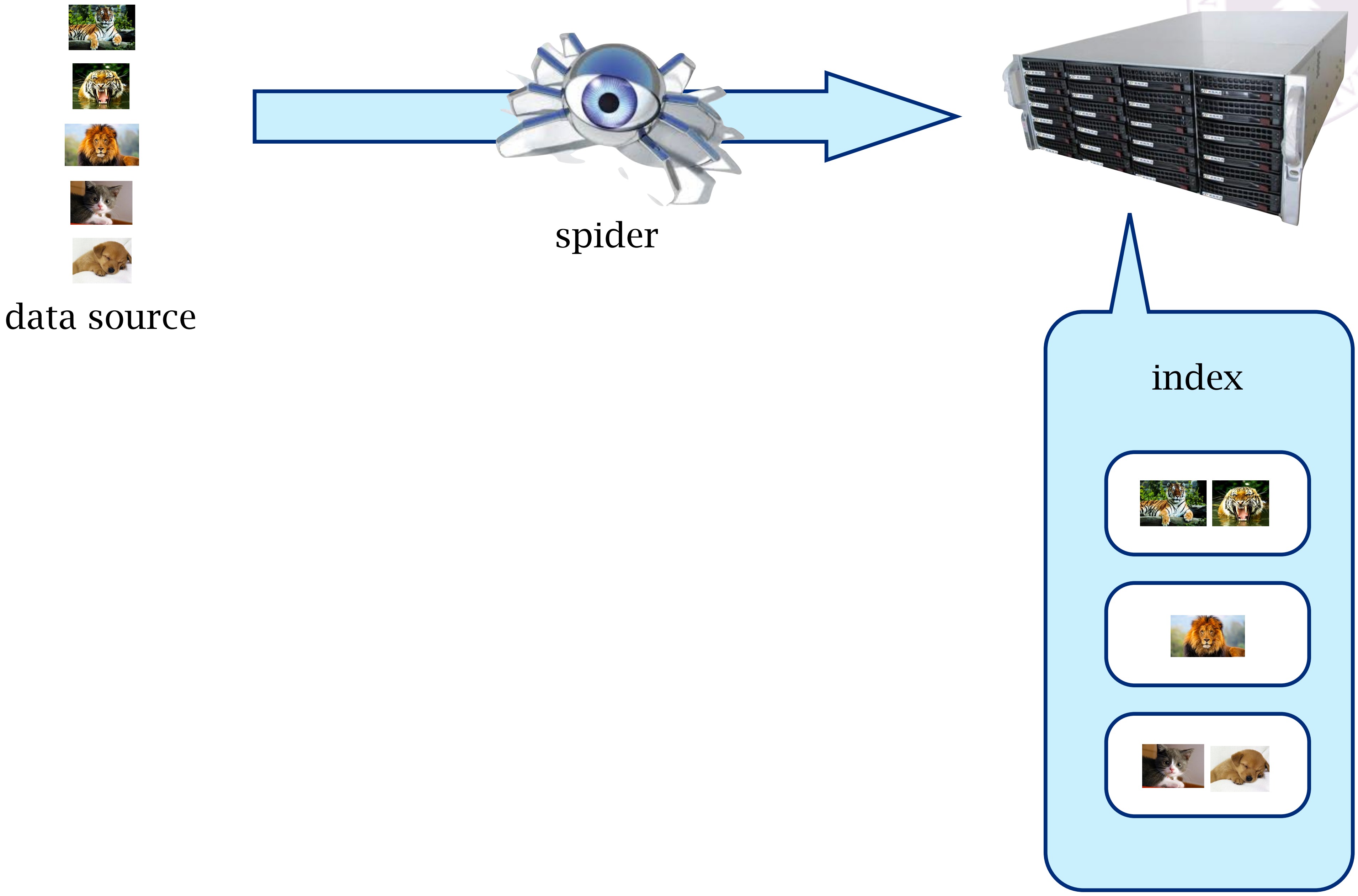


data source

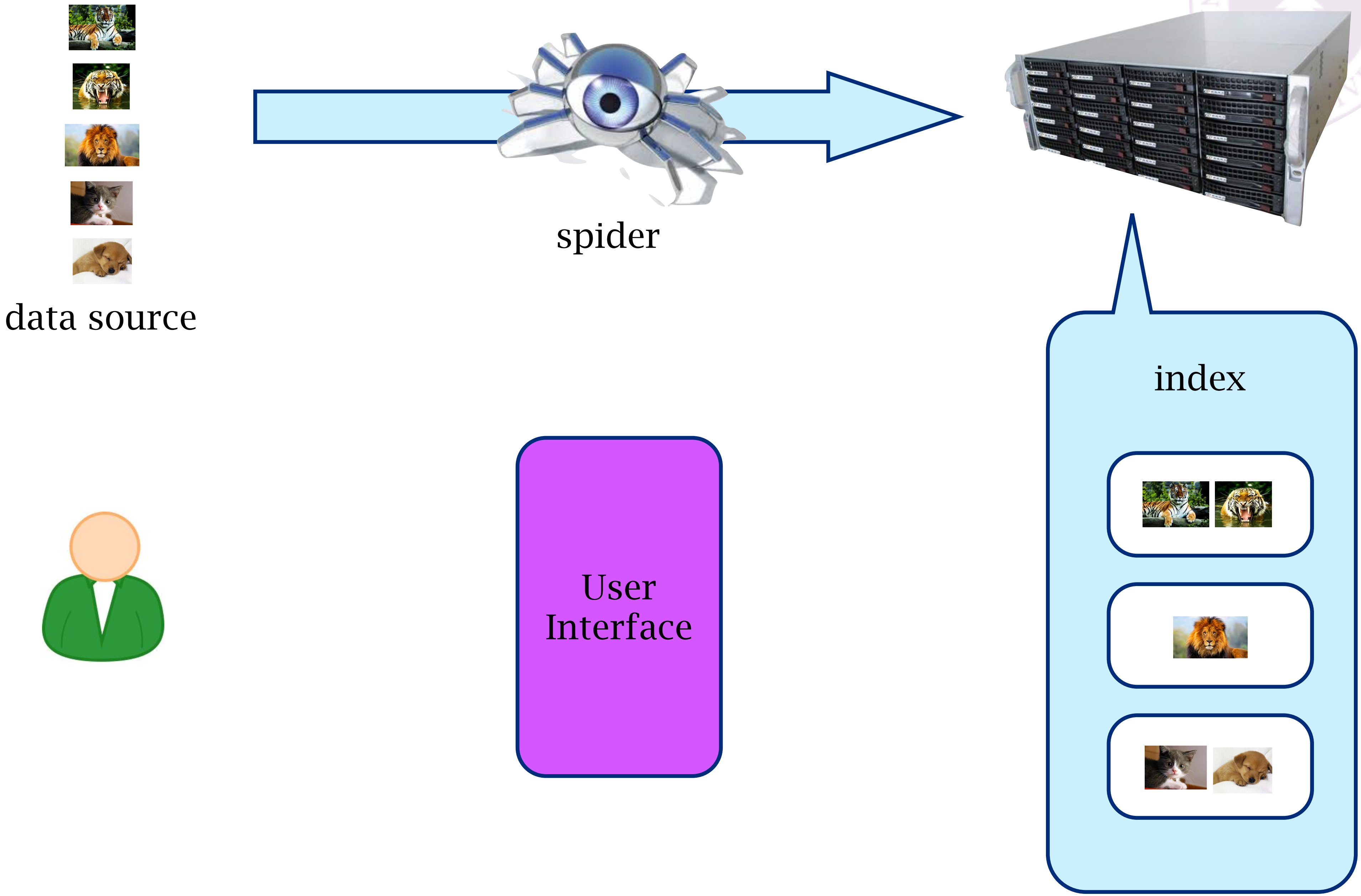


spider

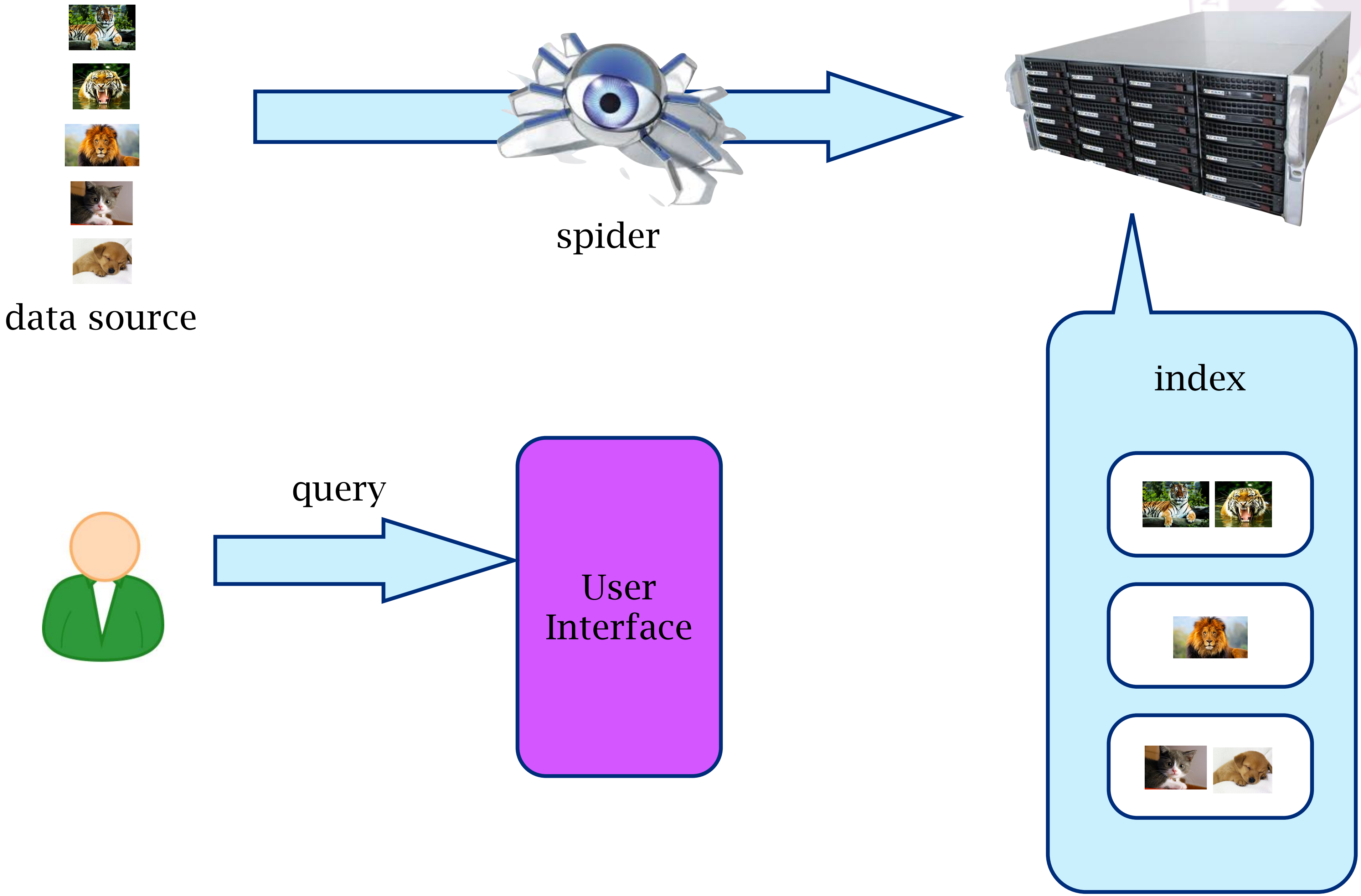
IR Systems



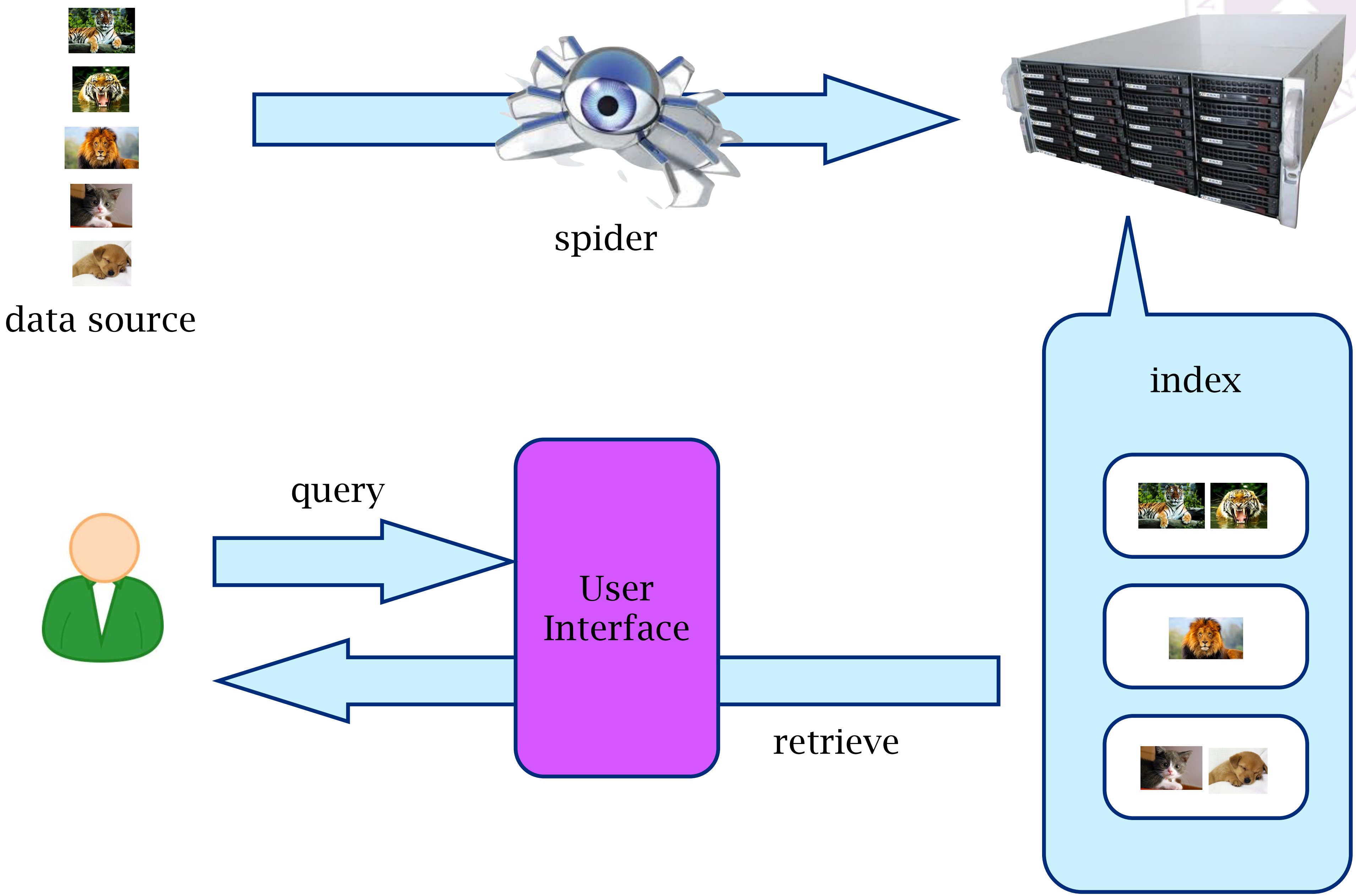
IR Systems



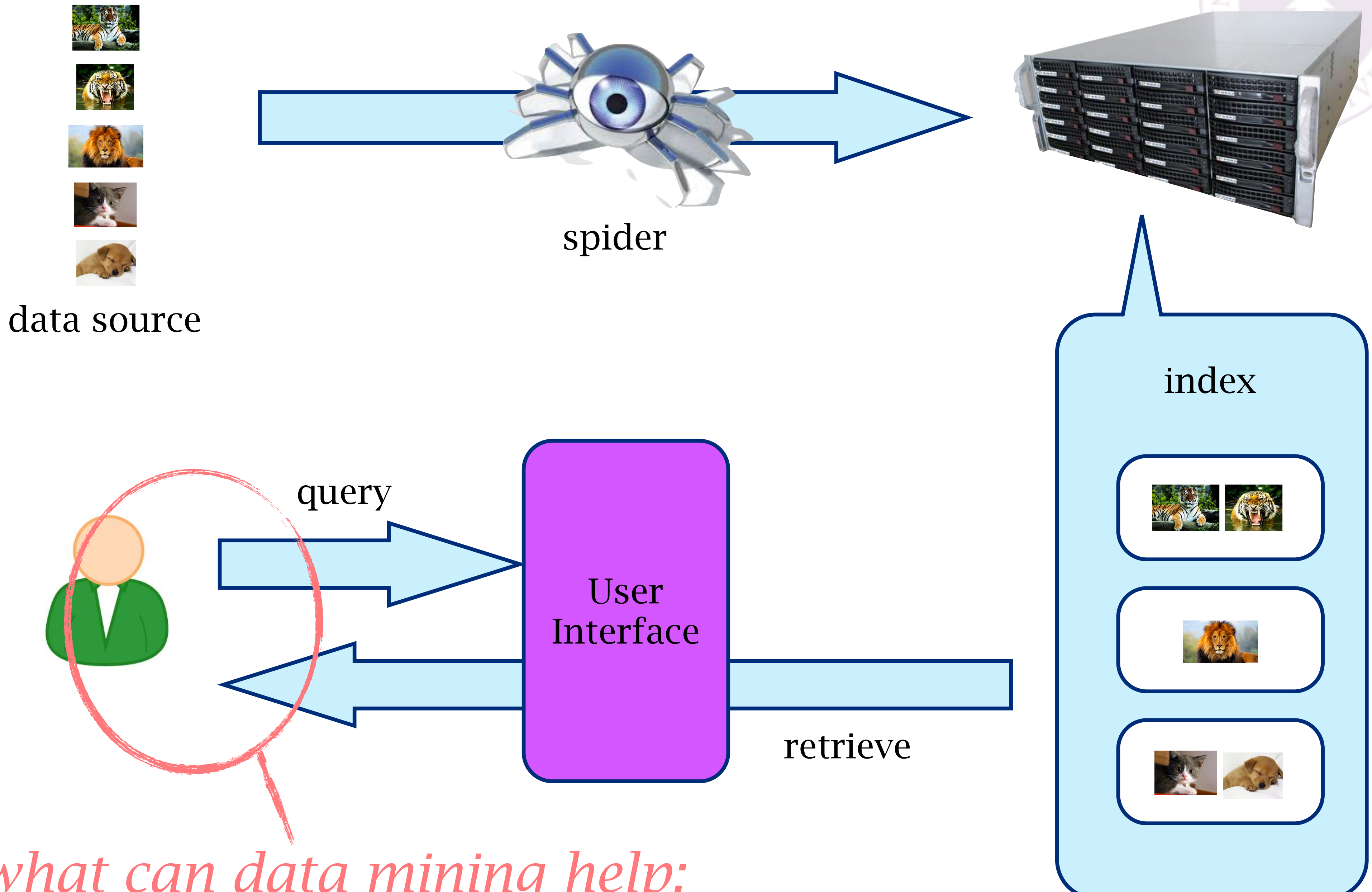
IR Systems



IR Systems

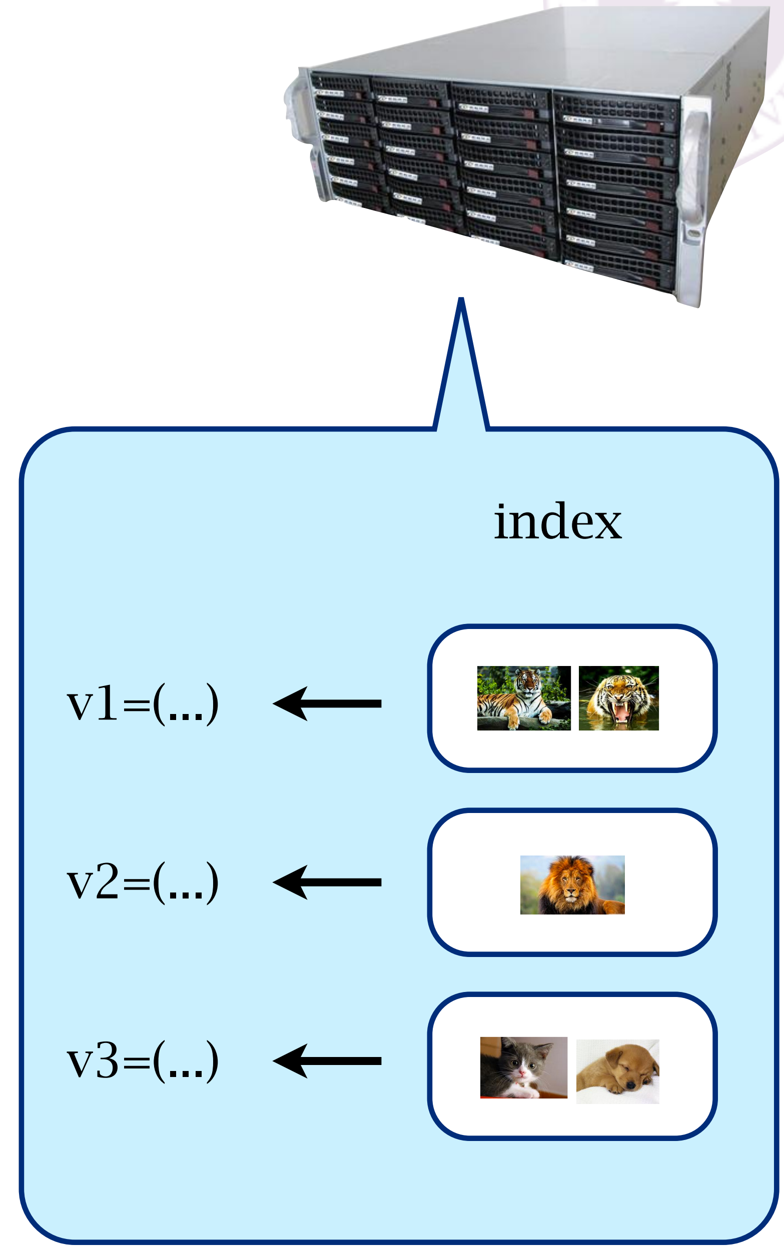


IR Systems



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:

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

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

[Salton and Buckley, 88]

Text: vector representation

the vector representation usually results high dimensional features

Text: vector representation

the vector representation usually results high dimensional features

TF-IDF + PCA

Text: vector representation

the vector representation usually results high dimensional features

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

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

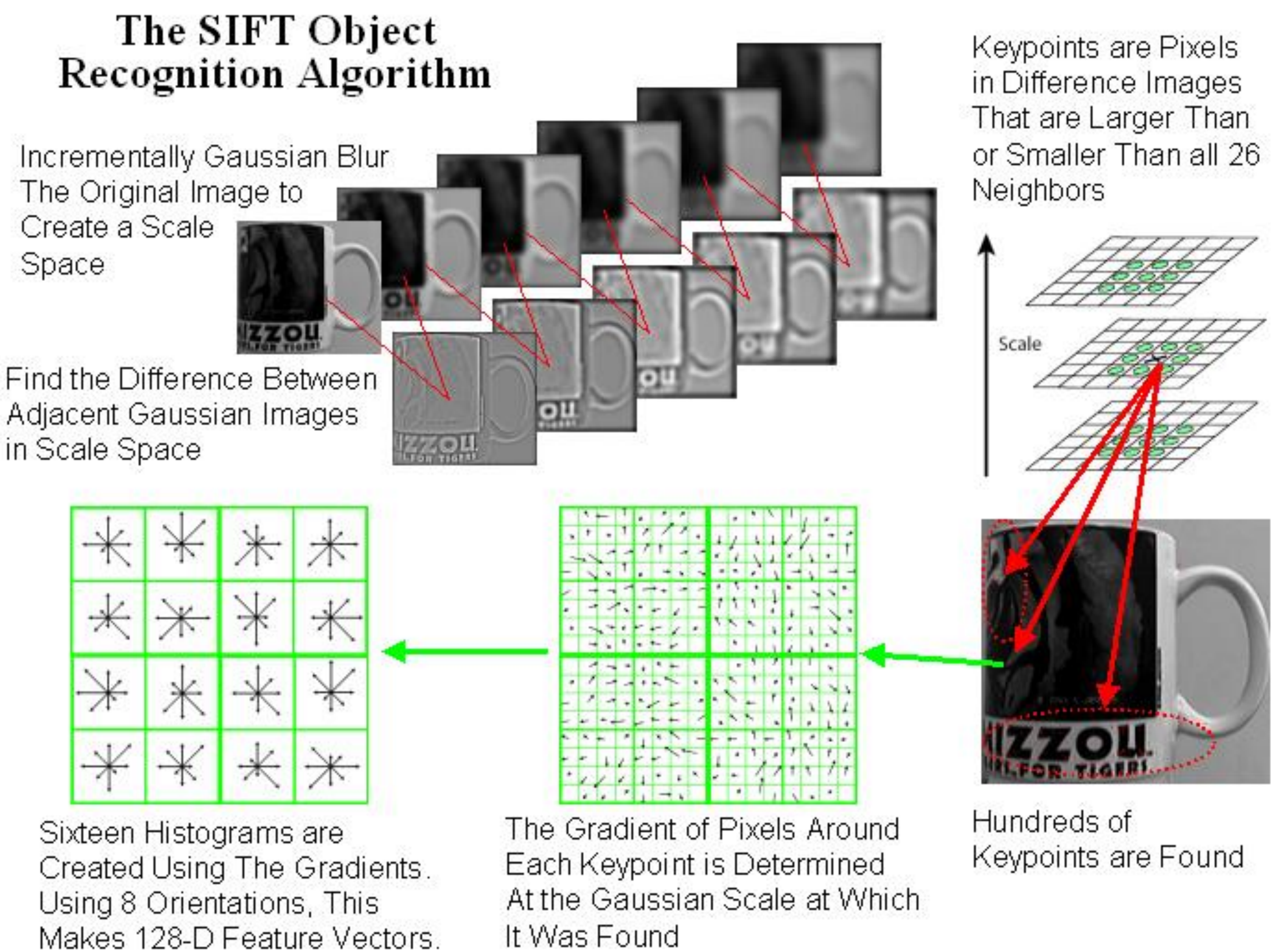
Local features

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

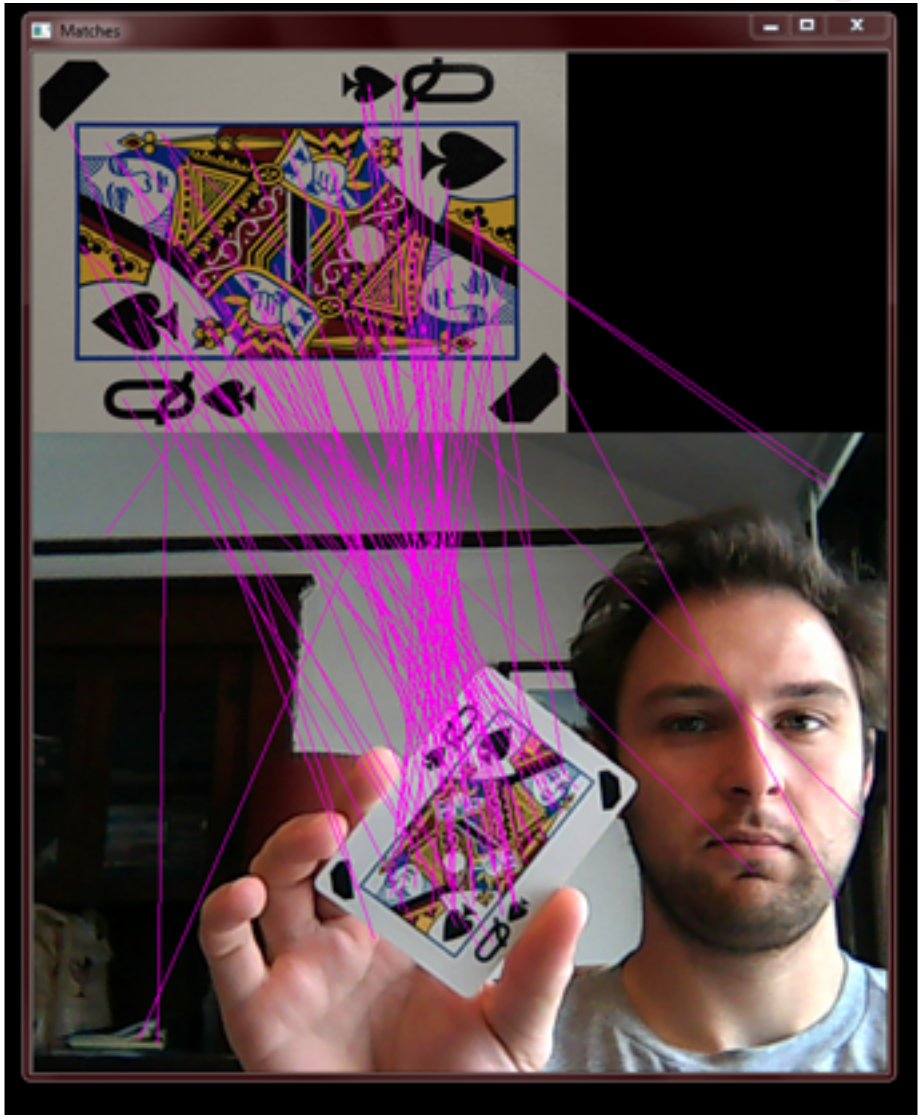
Local features



Pic from http://eecs.vanderbilt.edu/CIS/CRL/wm.shtml

Image: features

- Local features
  - Bag of words of SIFT vectors



Pic from http://blogs.oregonstate.edu/hess/sift-library-places-2nd-in-acm-mm-10-ossc/

Audio: features

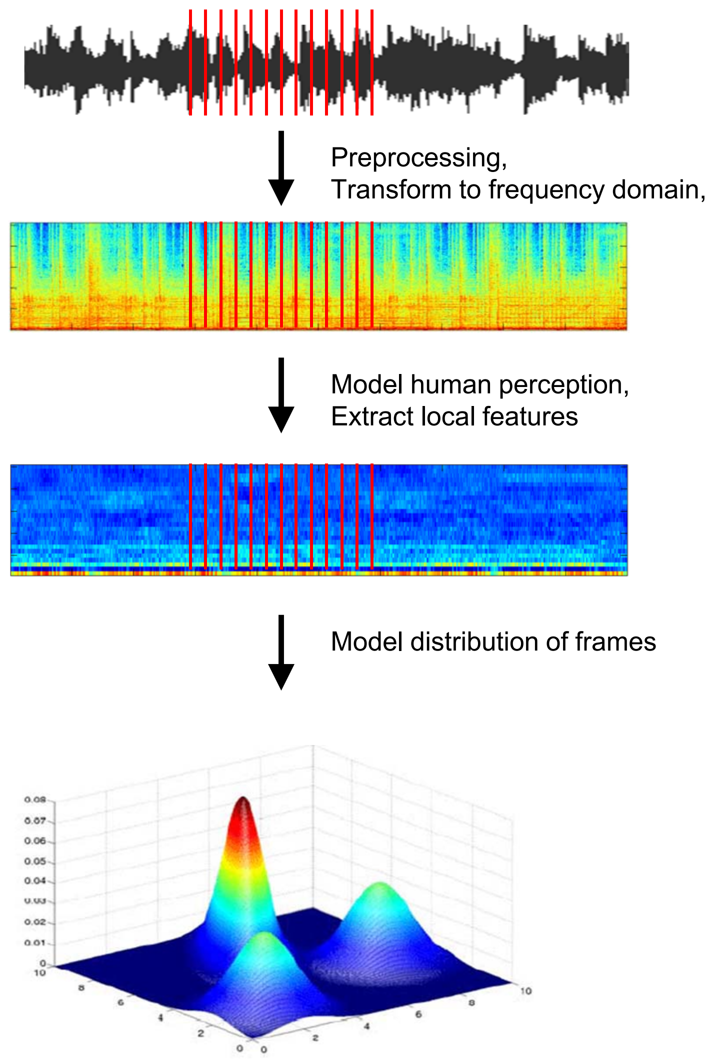
voice audio: speech-to-text transformation

music audio: extract semantic features

Music: features

frame-level processing

- cut frames out
- extract frame features
- bag-of-frame distribution



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

[from Markus Schedl and Peter Knees: Music Information Retrieval 2.0, ECIR'12 Tutorial.]

Music: features

Root-Mean-Square (RMS) Energy

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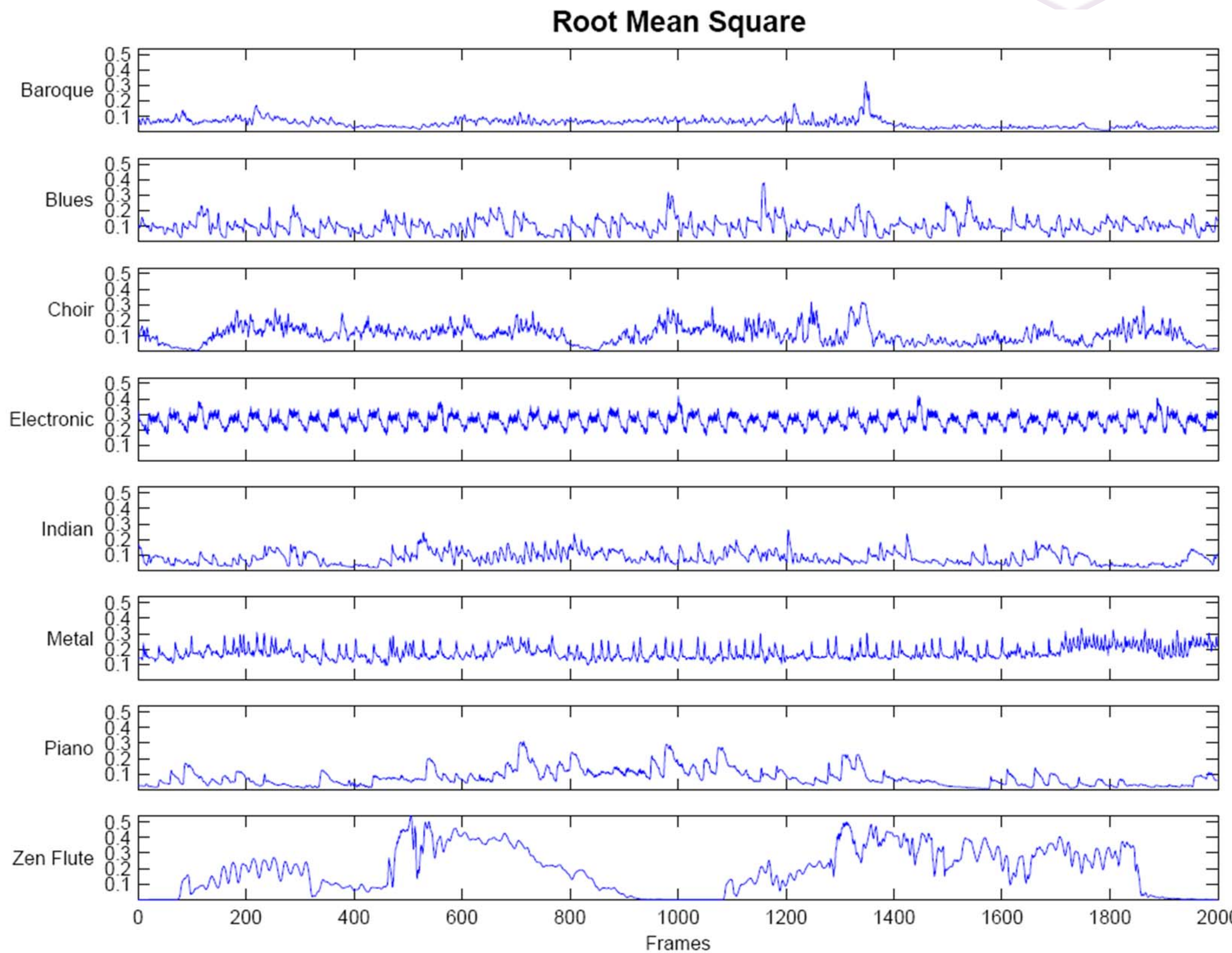


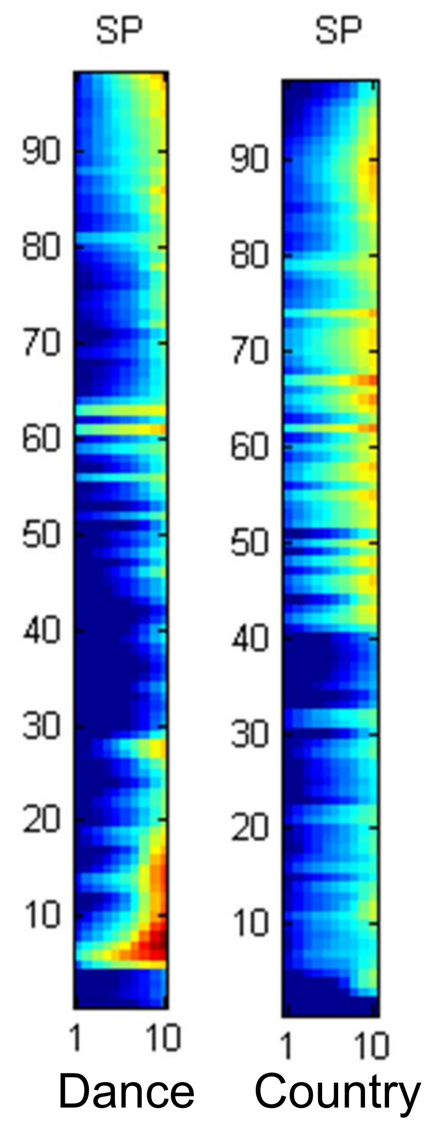
[from Markus Schedl and Peter Knees: Music Information Retrieval 2.0, ECIR'12 Tutorial.]

Music: features

Spectral Pattern

transform into spectrum domain

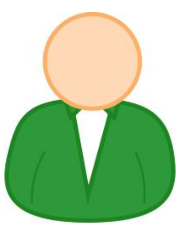
sort the energy in each frequency band of a block of frames

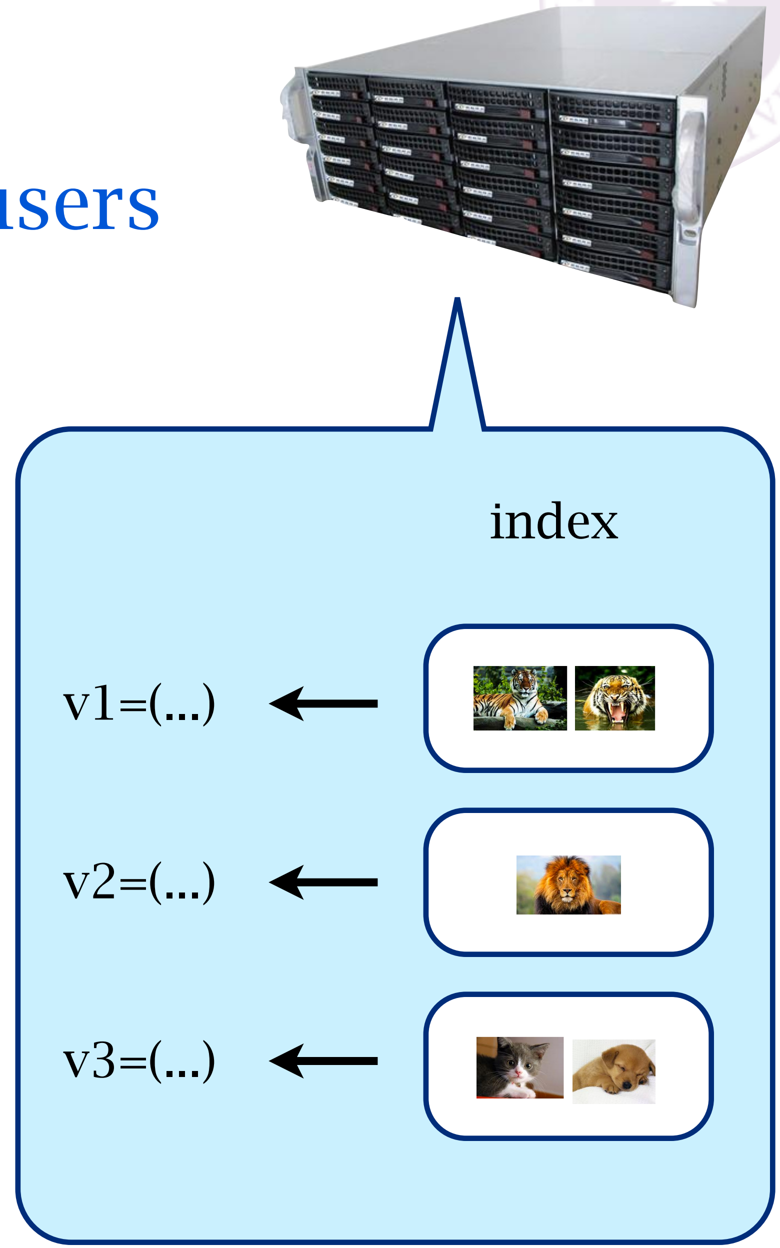


[from Markus Schedl and Peter Knees: Music Information Retrieval 2.0, ECIR'12 Tutorial.]

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

output:

\+ − + − −

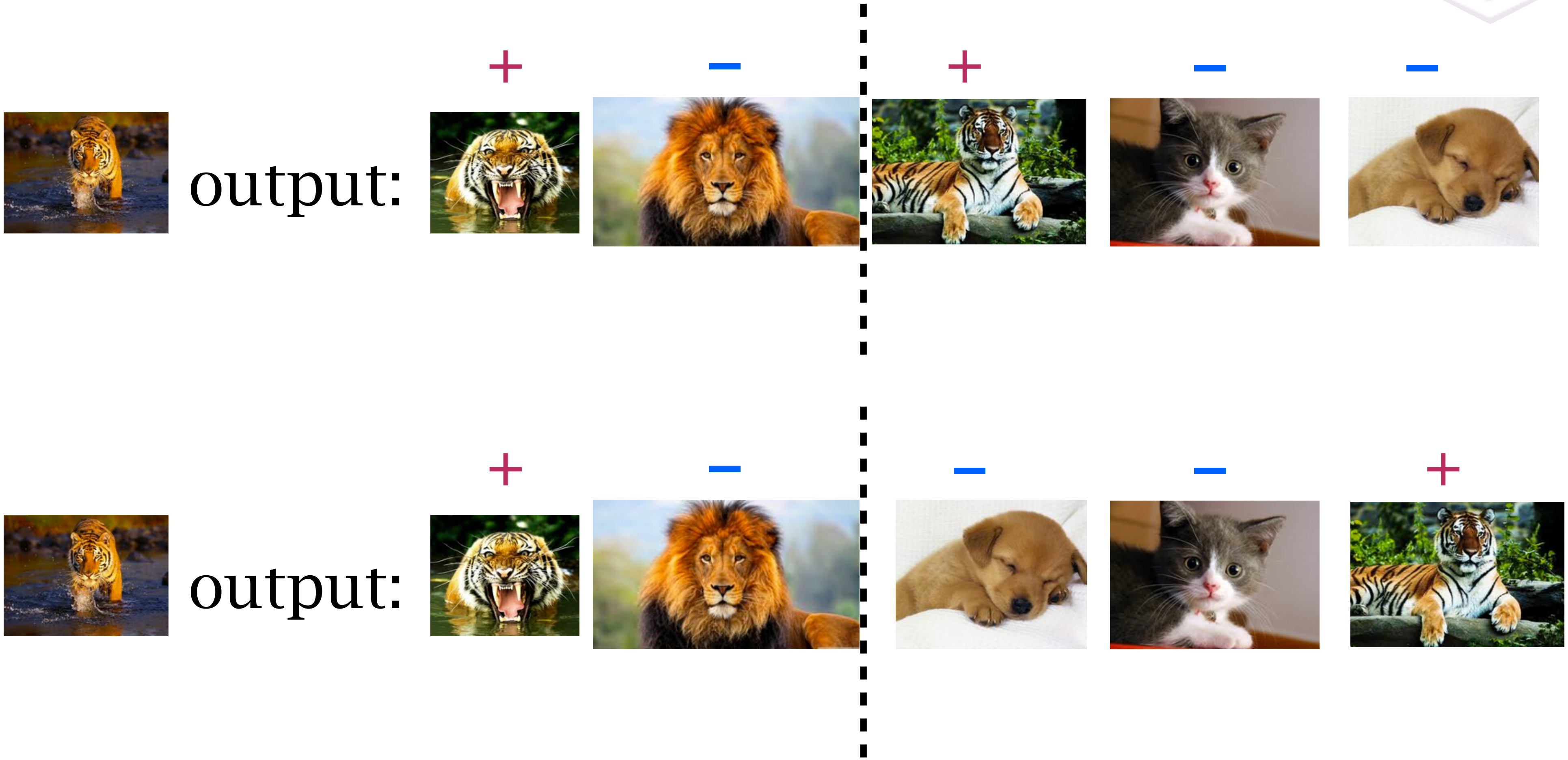
\+ −

learn a binary classifier

weight items by the confidence of the classifier

Learning to rank

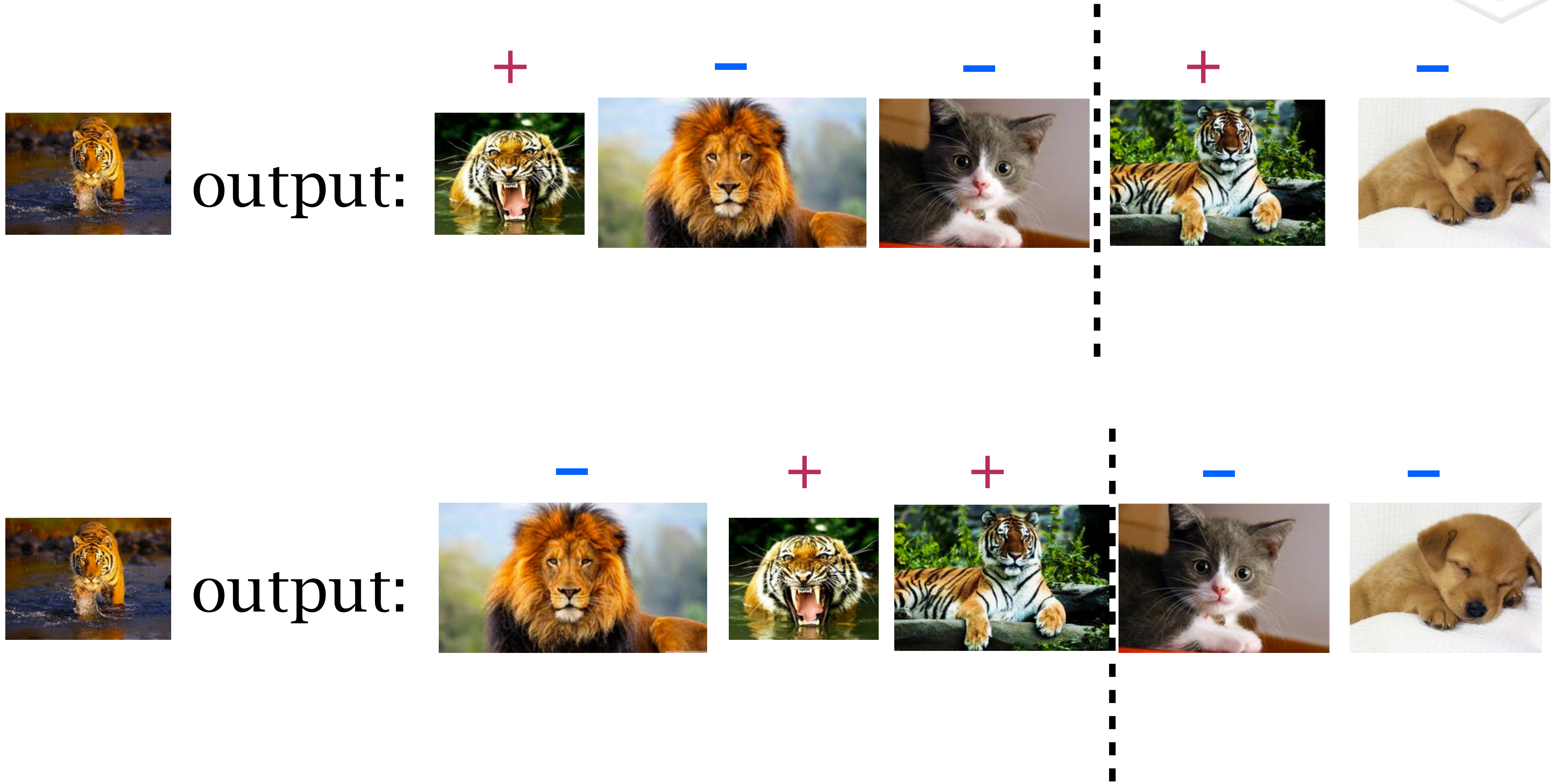
Binary classification ≠ ranking



same classification error
different ranking error

Learning to rank

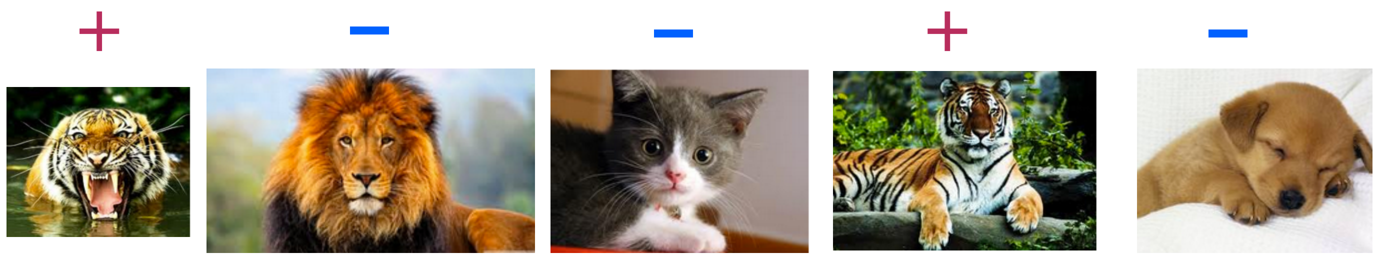
Binary classification ≠ ranking



same ranking error (certain criterion)
different classification error

Learning to rank

Learning with ranking loss



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

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 $t = 1, \ldots, T$:

- Train weak learner using distribution D_t.
- Get weak ranking $h_t : \mathcal{X} \to \mathbb{R}$.
- Choose $\alpha_t \in \mathbb{R}$.
- Update: $D_{t+1}(x_0, x_1) = \dfrac{D_t(x_0, x_1)\exp(\alpha_t(h_t(x_0) - h_t(x_1)))}{Z_t}$
  where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

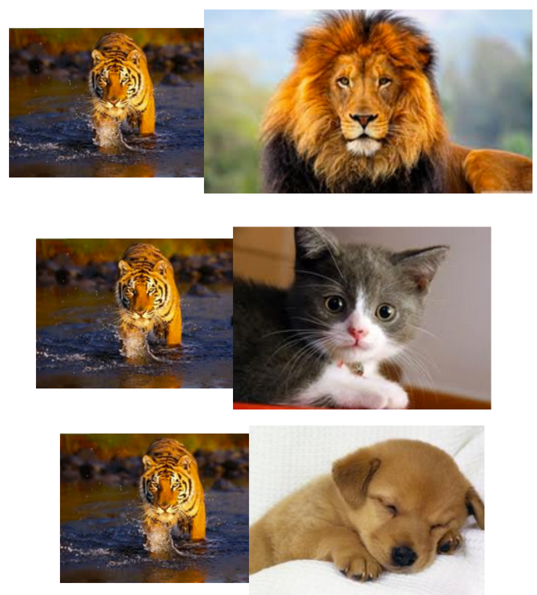
Output the final ranking: $H(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$

Learning to rank

Learning with ranking loss

output:

\+ − + − −



\+ −

learn a ranker

weight items by the ranker output value

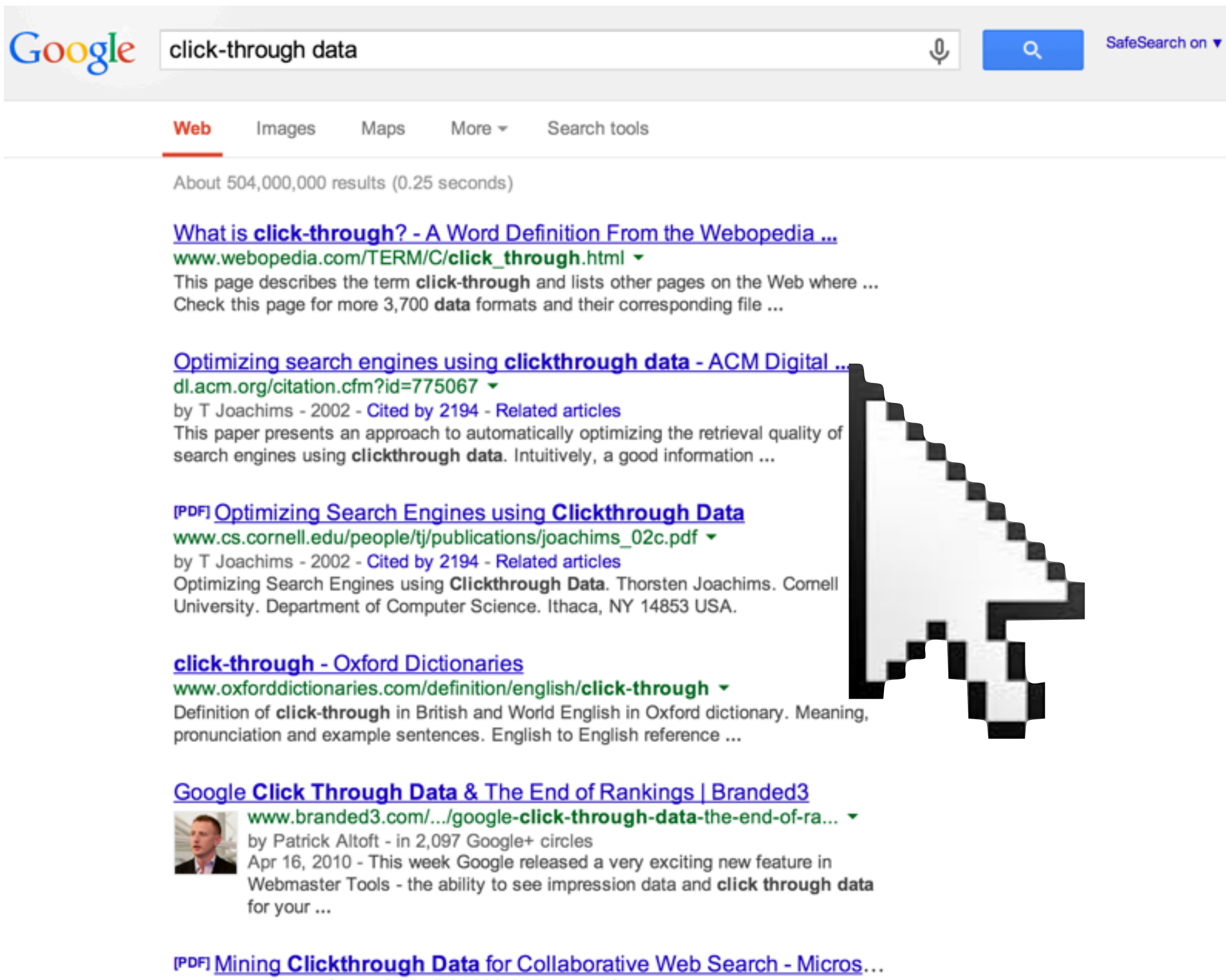
Relevance feedback

The lack of labels

a) traditional Web search *b) WebSIS*

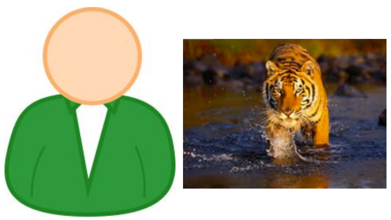
Implicit feedback

Click-through data



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?