

C280, Computer Vision

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Lecture 13: Topic Models for Recognition

Last Lecture

- Scanning window paradigm
- GIST
- HOG
- Boosted Face Detection
- Local-feature Alignment; from Roberts to Lowe...
- BOW Indexing

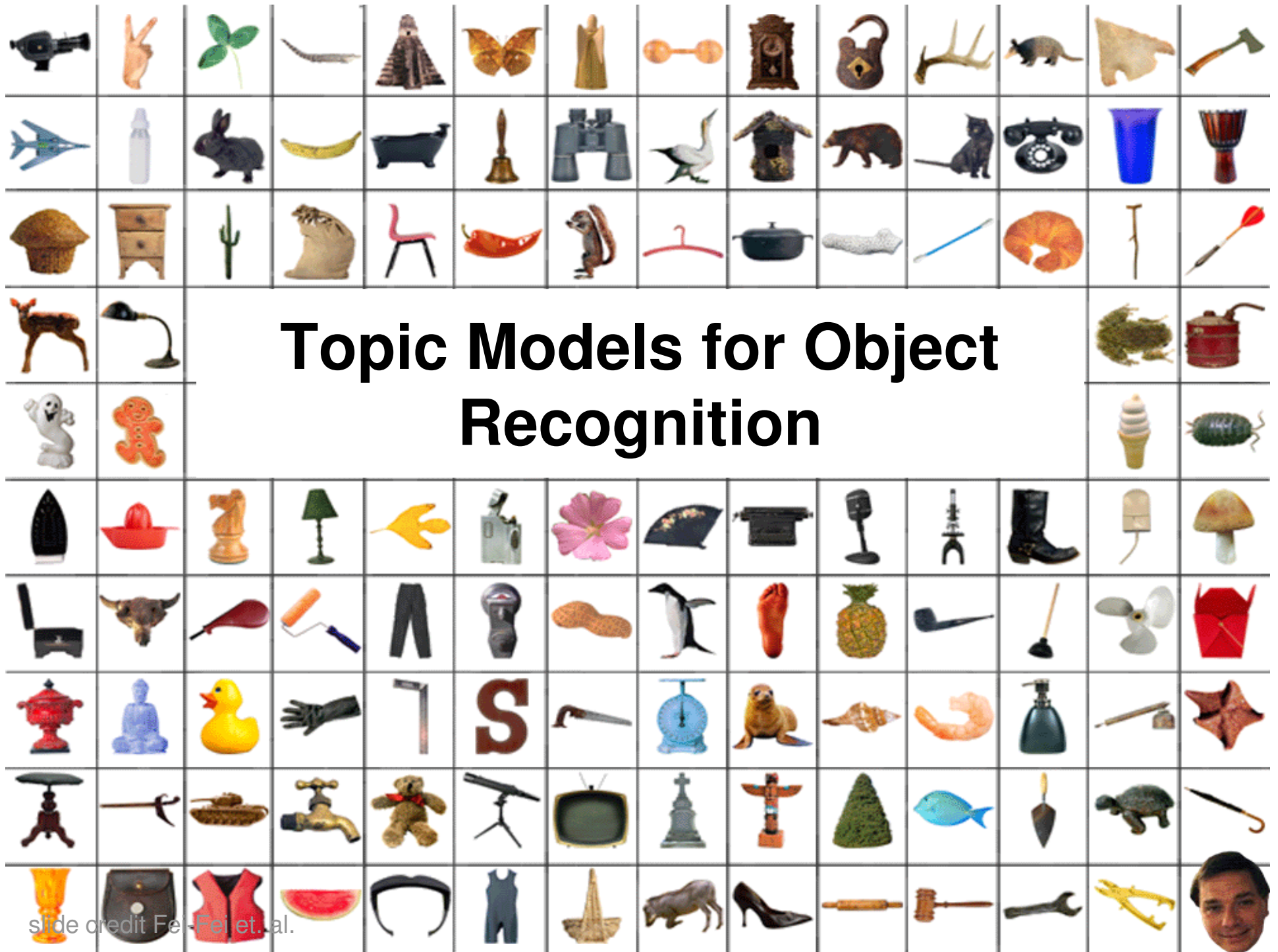
Next three lectures

- Today: learning object categories from the web
 - LSA and LDA models
 - Harvesting training data from the web
 - Exploiting image and text
- Tues. Oct. 20th: Generative models
 - Condensation
 - ISM
 - Transformed-HDPs
 - More Context...
- Thurs. Oct. 22nd: Advanced BOW kernels
 - Pyramid and spatial-pyramid match
 - Multi-kernel learning
 - Latent-part SVM models

Today: Topic Models for Recognition

Guest lecture by Kate Saenko:

- Dataset issues
- Topic models for category discovery [Sivic05]
- Category discovery from web [Fergus05]
- Bootstrapping a category model [Li07]
- Using text in addition to image [Berg06]
- Learning objects from a dictionary [Saenko08]



Topic Models for Object Recognition

slide credit Fei-Fei et. al.

How many object categories are there?



slide credit Fei-Fei et. al.

Biederman 1987

Dataset Issues In Object Recognition

Datasets

Caltech101/256

[Fei-Fei et al, 2004]

[Griffin et al, 2007]



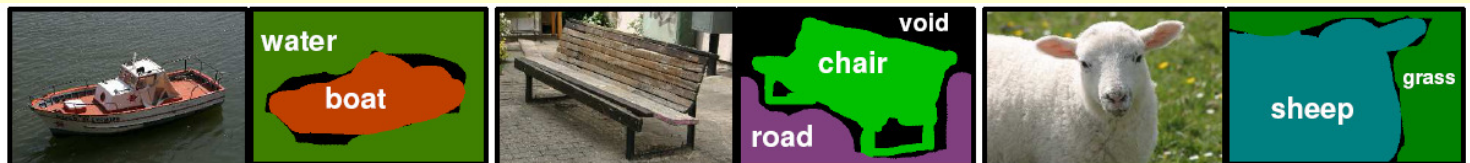
PASCAL

[Everingham et al, 2009]



MSRC

[Shotton et al. 2006]

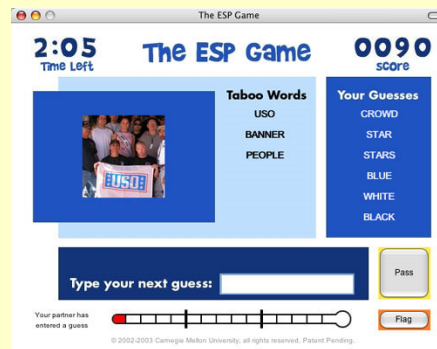


slide credit Fei-Fei et. al.

Datasets

ESP

[Ahn et al, 2006]



Dog
Leash
German
Shepard
Standing
Canine

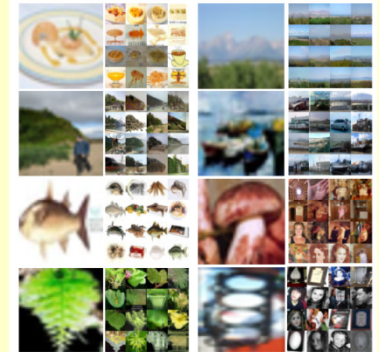
LabelMe

[Russell et al, 2005]



TinyImage

Torralba et al. 2007



Lotus Hill

[Yao et al, 2007]



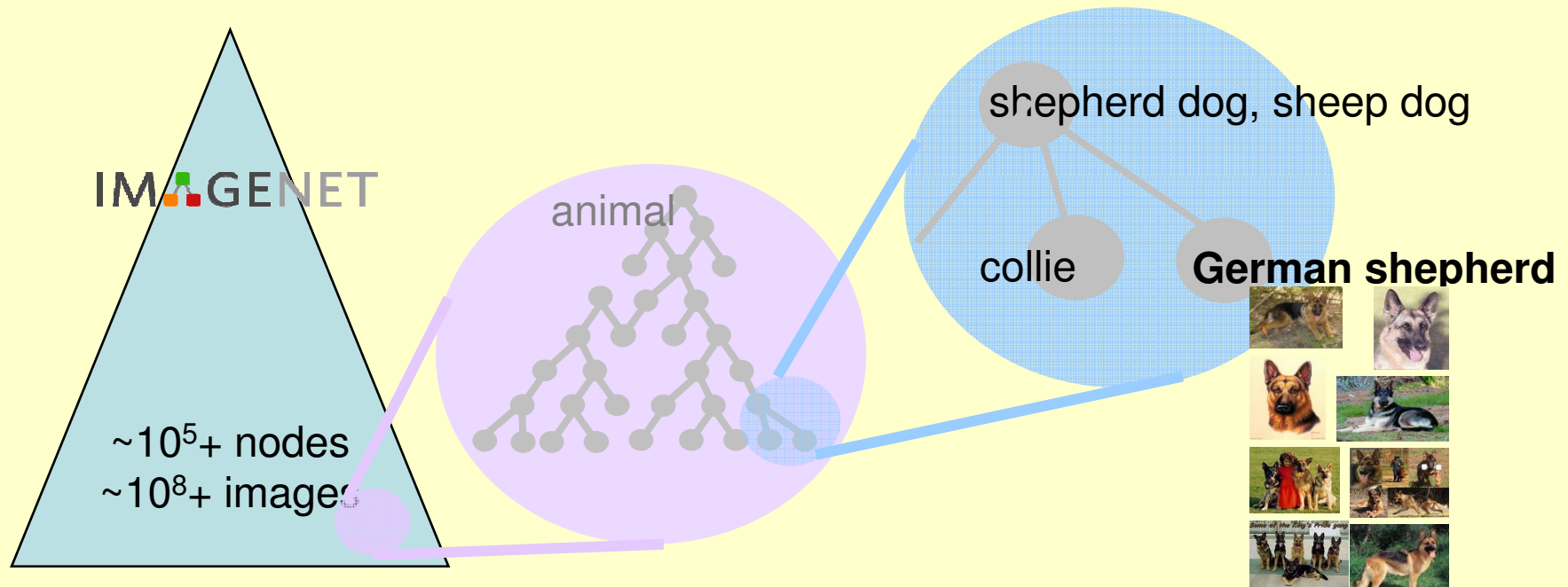
slide credit Fei-Fei et. al.

Size of existing datasets

Datasets	# of categories	# of images per category	# of total images	Collected by
Caltech101	101	~100	~10K	Human
Lotus Hill	~300	~ 500	~150K	Human
LabelMe	183	~200	~30K	Human
Ideal	~30K	>>10²	A LOT	Machine

IMAGENET

- An **ontology of images** based on WordNet
- Collected using Amazon Mechanical Turk



IMAGENET

14,847 categories, 9,349,136 images

- Animals
 - Fish
 - Bird
 - Mammal
 - Invertebrate
- Scenes
 - Indoors
 - Geological formations
- Sport Activities
- Fabric Materials
- Instrumentation
 - Tool
 - Appliances
 - ...
- Plants
 - ...

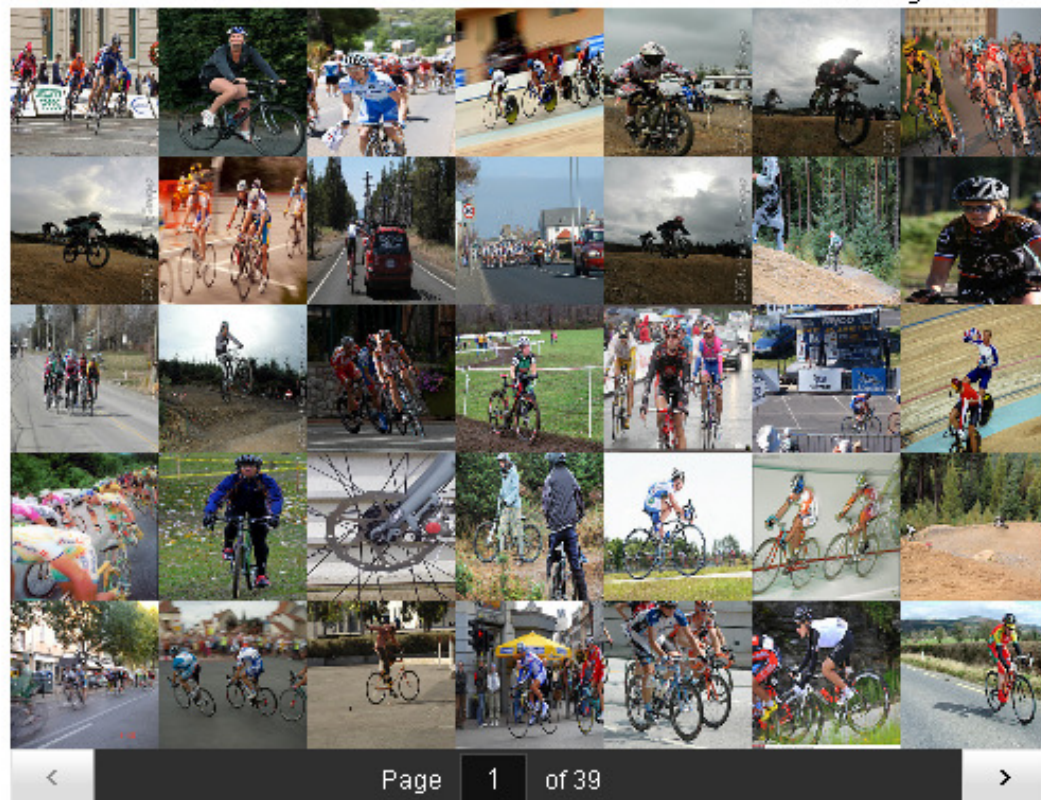
IMAGENET

“Cycling”

The sport of traveling on a bicycle or motorcycle

- [-] ImageNet(14790 children)
 - [+] animal, animate being, beast, brute, creature, fauna(39)
 - [+] fabric, cloth, material, textile(283 children)
 - [-] sport, athletics(176 children)
 - [+] rowing, row(2 children)
 - [+] athletic game(70 children)
 - [+] riding, horseback riding, equitation(8 children)
 - archery(0 children)
 - [+] **cycling(3 children)**
 - [+] sledding(3 children)
 - [+] skating(6 children)
 - rock climbing(0 children)
 - spectator sport(0 children)

1363 Images indexed



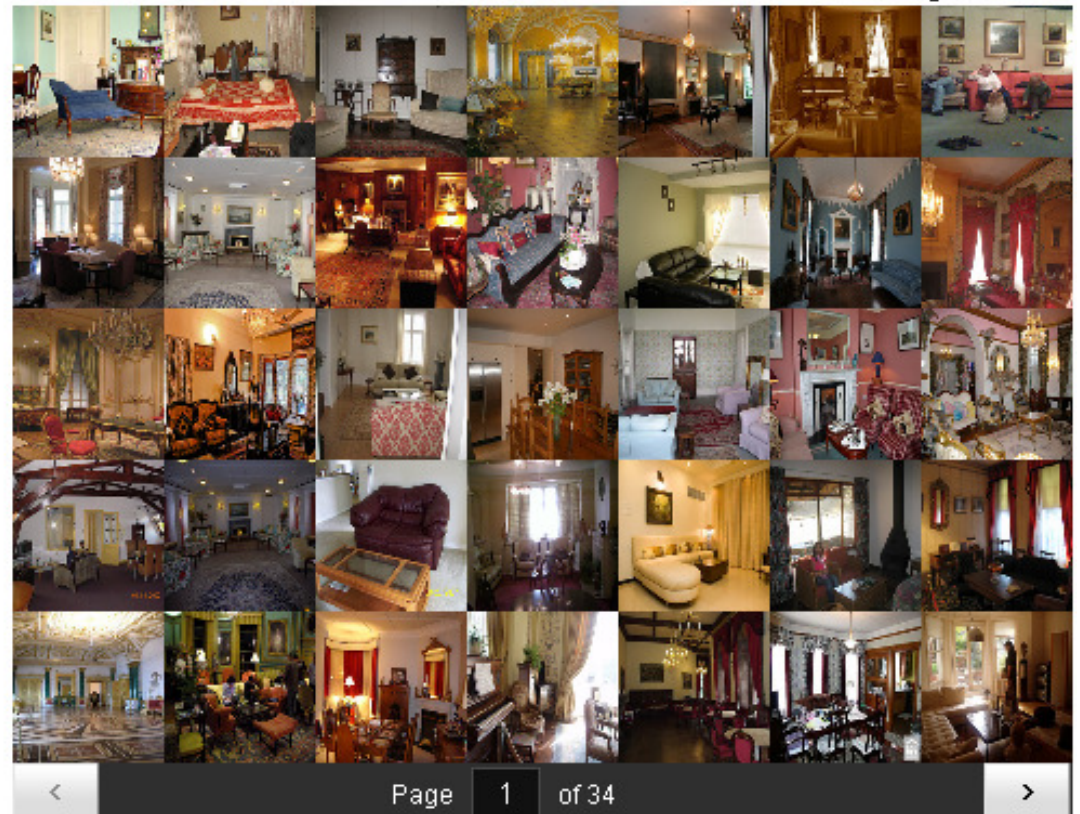
IMAGENET

“Drawing room, withdrawing room”

A formal room where visitors can be received and entertained

1160 Images indexed

- room(195 children)
 - workroom(0 children)
 - scullery(0 children)
 - scriptorium(0 children)
 - rotunda(0 children)
- + recreation room, rec room(3 children)
- reception room(2 children)
 - drawing room, withdrawing room(0 children)**
 - parlor, parlour(0 children)
- + reading room(1 children)
- rathole(0 children)
- presence chamber(0 children)
- poolroom(0 children)
- manor hall, hall(0 children)



*Images of children objects are not included. All images shown are thumbnails. Images may be

How much supervision do you need to learn models of objects?

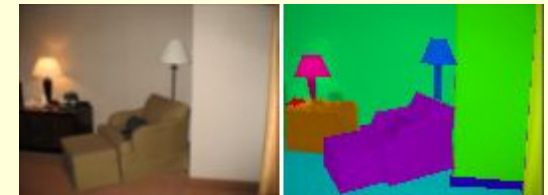
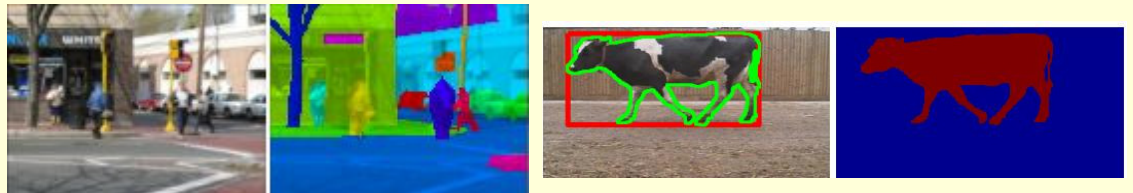
Object label + segmentation

LabelMe, PASCAL, TU Darmstadt,
MIT scenes and objects

MIT+CMU frontal faces



Viola & Jones '01
Rowley et al. '98



Agarwal & Roth '02, Leibe &
Schiele '03, Torralba et al. '05

Object appears somewhere in the image

Caltech 101, PASCAL, MSRC

airplane



motorbike



face



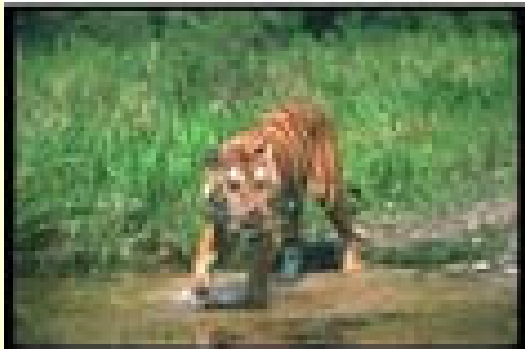
car



Fergus et al. '03, Csurka et al. '04,
Dorko & Schmid '05

Image + text caption

Corel, Flickr, Names+faces, ESP game



TIGER CAT WATER GRASS

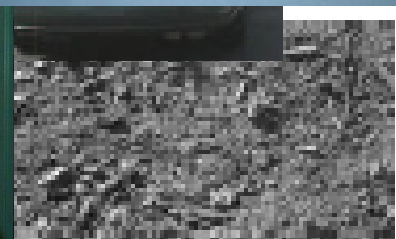
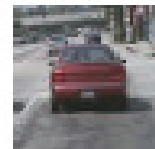


British director **Sam Mendes** and his partner actress **Kate Winslet** arrive at the London premiere of 'The Road to Perdition', September 18, 2002. The film stars **Tom Hanks** as a Chicago hit man who has a separate family life and co-stars **Paul Newman** and Jude Law. REUTERS/Dan Chung

Barnard et al. '03, Berg et al. '04

Images only

Given a collection of unlabeled images, discover visual object categories and their segmentation



- Which images contain the same object(s) ?
- Where is the object in the image?

Discovering Objects and Their Location in Images

J. Sivic, B. C. Russell, A. A. Efros,
A. Zisserman, W. T. Freeman.

Presented at the International Conference on Computer Vision, 2005.

Analogy: Discovering topics in text collections

Text document

The William Randolph Hearst Foundation will give \$1.25 million to Lincoln Center, Metropolitan Opera Co., New York Philharmonic and Juilliard School. "Our board felt that we had a real opportunity to make a mark on the future of the performing arts with these grants an act every bit as important as our traditional areas of support in health, medical research, education and the social services," Hearst Foundation President Randolph A. Hearst said Monday in announcing the grants. Lincoln Center's share will be \$200,000 for its new building, which will house young artists and provide new public facilities. The Metropolitan Opera Co. and New York Philharmonic will receive \$400,000 each. The Juilliard School, where music and the performing arts are taught, will get \$250,000. The Hearst Foundation, a leading supporter of the Lincoln Center Consolidated Corporate Fund, will make its usual annual \$100,000 donation, too.

Discovered topics

"Arts"	"Budgets"	"Children"	"Education"
NEW	MILLION	CHILDREN	SCHOOL
FILM	TAX	WOMEN	STUDENTS
SHOW	PROGRAM	PEOPLE	SCHOOLS
MUSIC	BUDGET	CHILD	EDUCATION
MOVIE	BILLION	YEARS	TEACHERS
PLAY	FEDERAL	FAMILIES	HIGH
MUSICAL	YEAR	WORK	PUBLIC
BEST	SPENDING	PARENTS	TEACHER
ACTOR	NEW	SAYS	BENNETT
FIRST	STATE	FAMILY	MANIGAT
YORK	PLAN	WELFARE	NAMPHY
OPERA	MONEY	MEN	STATE
THEATER	PROGRAMS	PERCENT	PRESIDENT
ACTRESS	GOVERNMENT	CARE	ELEMENTARY
LOVE	CONGRESS	LIFE	HAITI

Blei, et al. 2003

Visual analogy

document - image

word - visual word

topics - objects

System overview



Input image



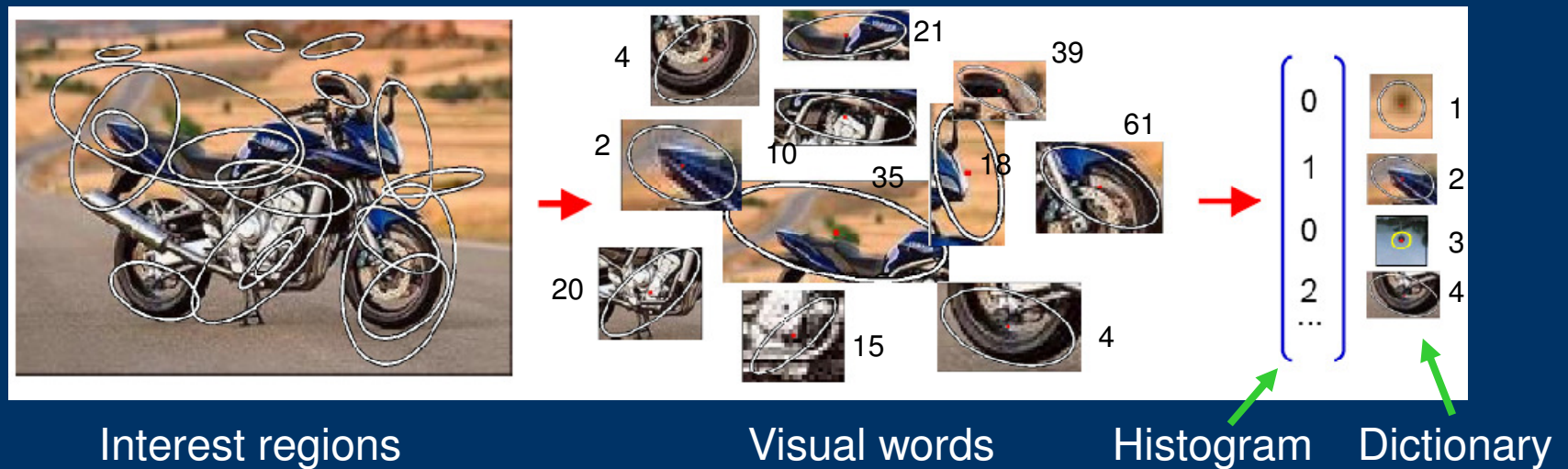
Compute visual words



Discover visual topics

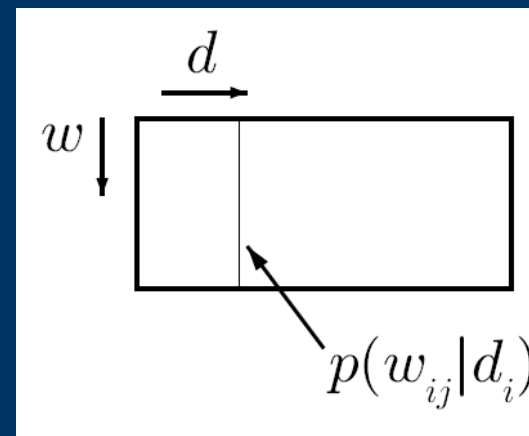
Bag of words

- LDA model assumes exchangeability
- Order of words does not matter

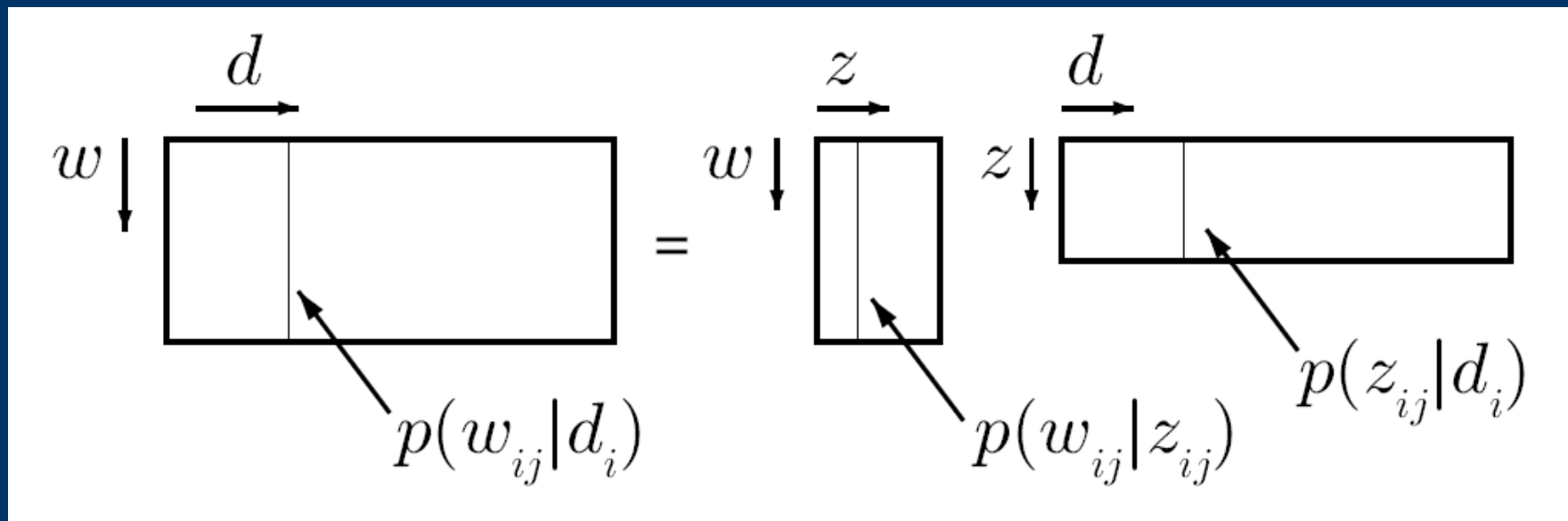


Stack visual word histograms
as columns in matrix

Throw away spatial information!



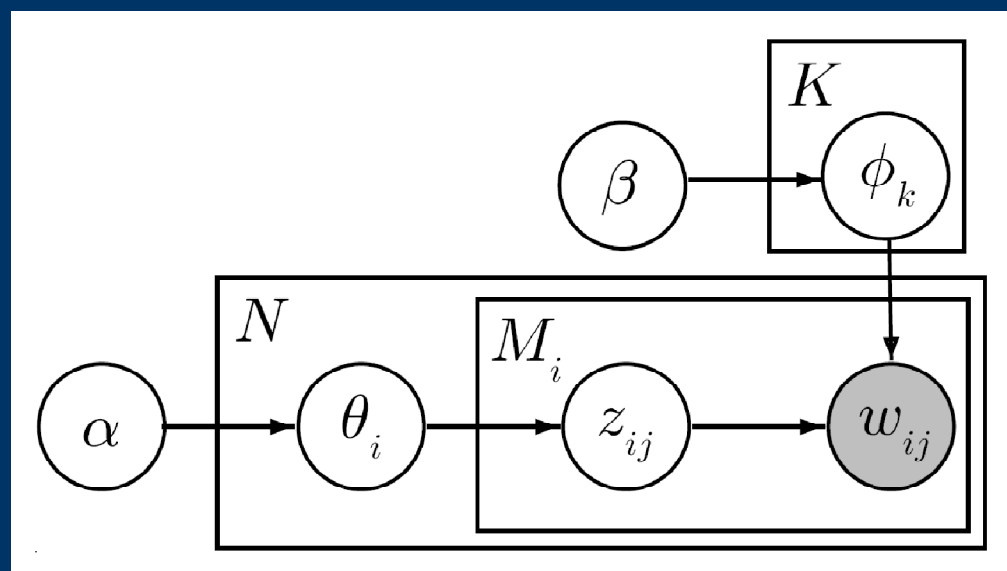
Low-rank matrix factorization



- Latent Semantic Analysis (Deerwester, et al. 1990)
- Probabilistic Latent Semantic Analysis (Hofmann 2001)

Latent Dirichlet Allocation (LDA)

Blei, et al. 2003



w_{ij} - words

z_{ij} - topic assignments

θ_i - topic mixing weights

ϕ_k - word mixing weights

$$z_{ij} | \theta_i \sim \theta_i$$

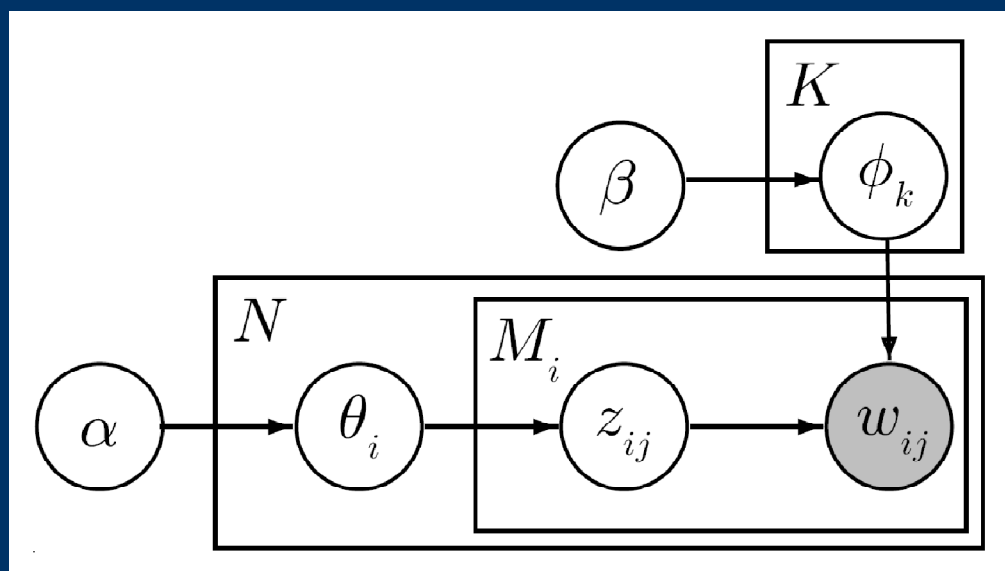
$$w_{ij} | z_{ij} = k, \phi \sim \phi_k$$

$$\theta_i | \alpha \sim \text{Dirichlet}(\alpha)$$

$$\phi_k | \beta \sim \text{Dirichlet}(\beta)$$

Latent Dirichlet Allocation (LDA)

Blei, et al. 2003



w_{ij} - words

z_{ij} - topic assignments

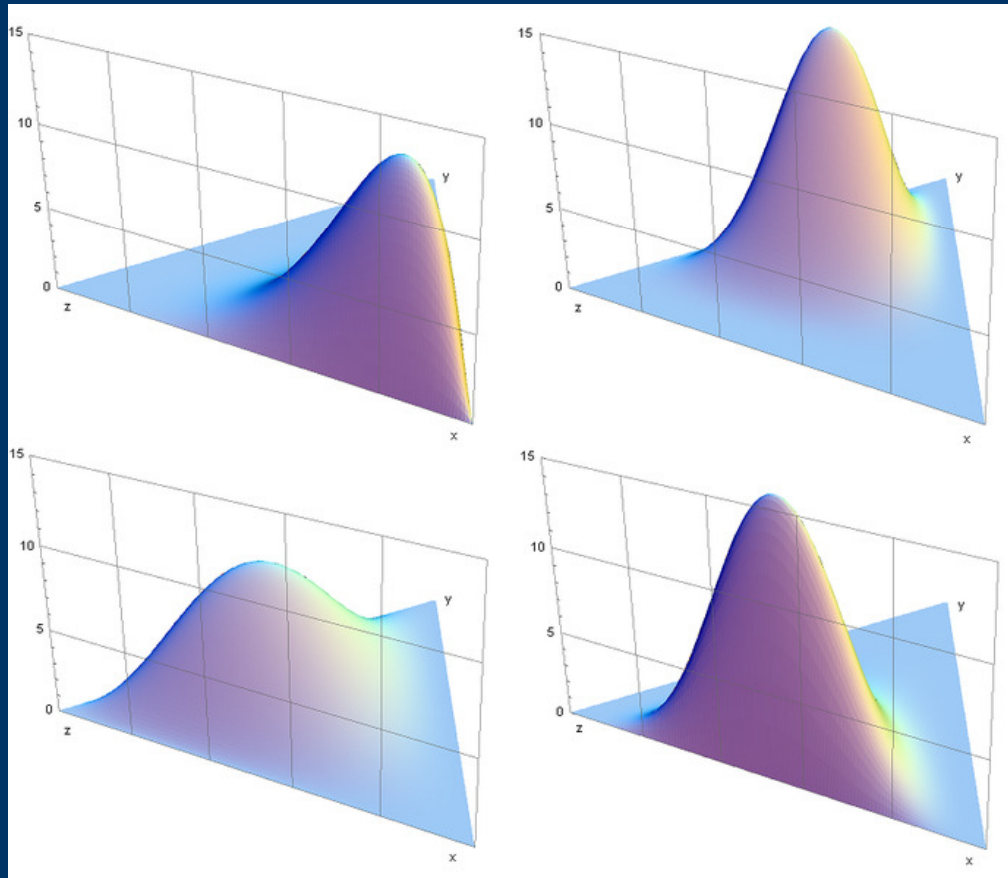
θ_i - topic mixing weights

ϕ_k - word mixing weights

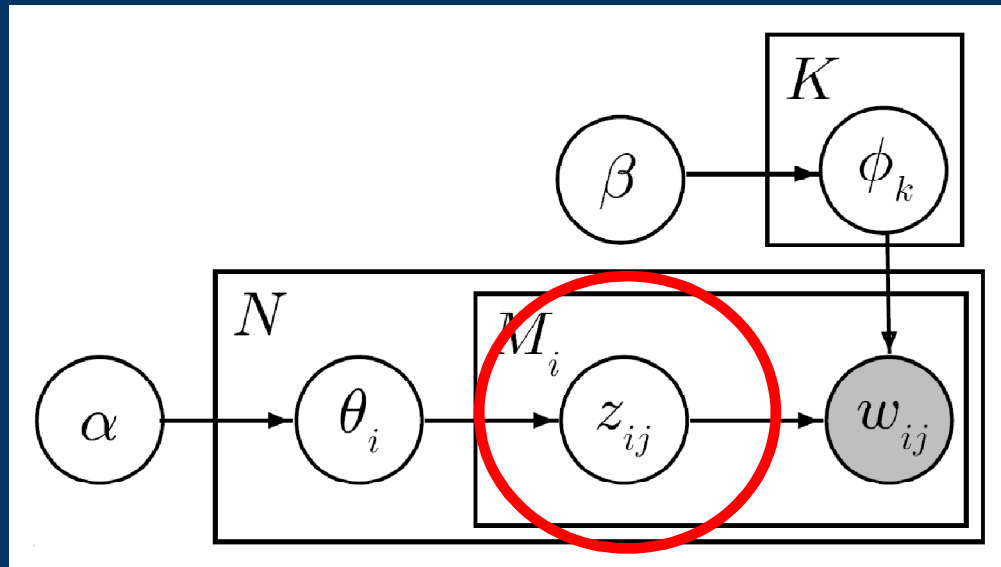
$$p(w_{ij}) \propto \sum_{k=1}^K p(w_{ij} | z_{ij} = k, \phi_k) p(z_{ij} = k | \theta_i)$$

Dirichlet Distribution

$$f(x_1, \dots, x_{K-1}; \alpha_1, \dots, \alpha_K) = \frac{1}{B(\alpha)} \prod_{i=1}^K x_i^{\alpha_i - 1}$$



Inference



w_{ij} - words

z_{ij} - topic assignments

θ_i - topic mixing weights

ϕ_k - word mixing weights

Use Gibbs sampler to sample topic assignments

[Griffiths & Steyvers 2004]

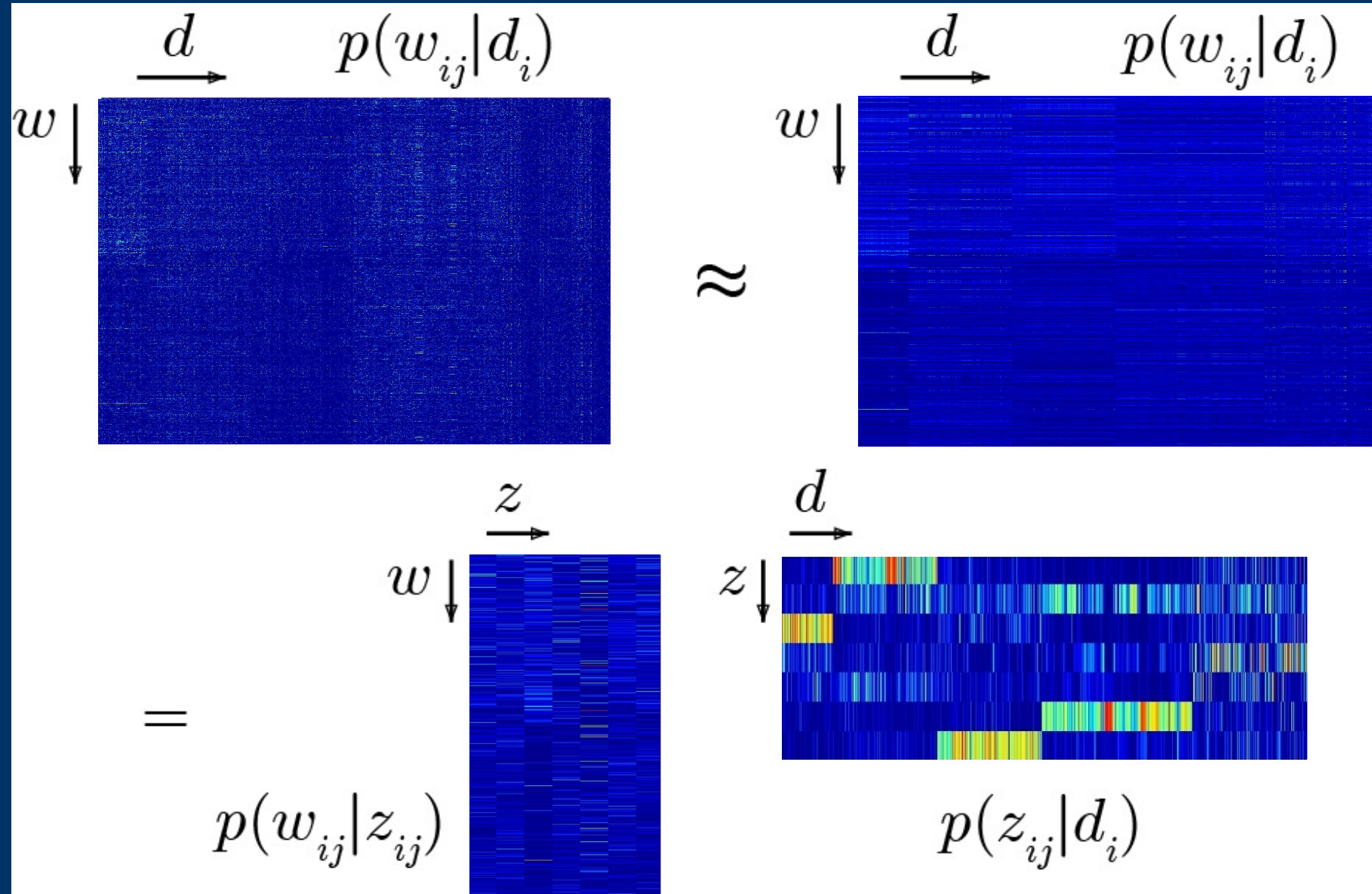
$$z_{ij} \sim p(z_{ij} = k | w_{ij} = v, w_{\setminus(ij)}, z_{\setminus(ij)}, \alpha, \beta)$$

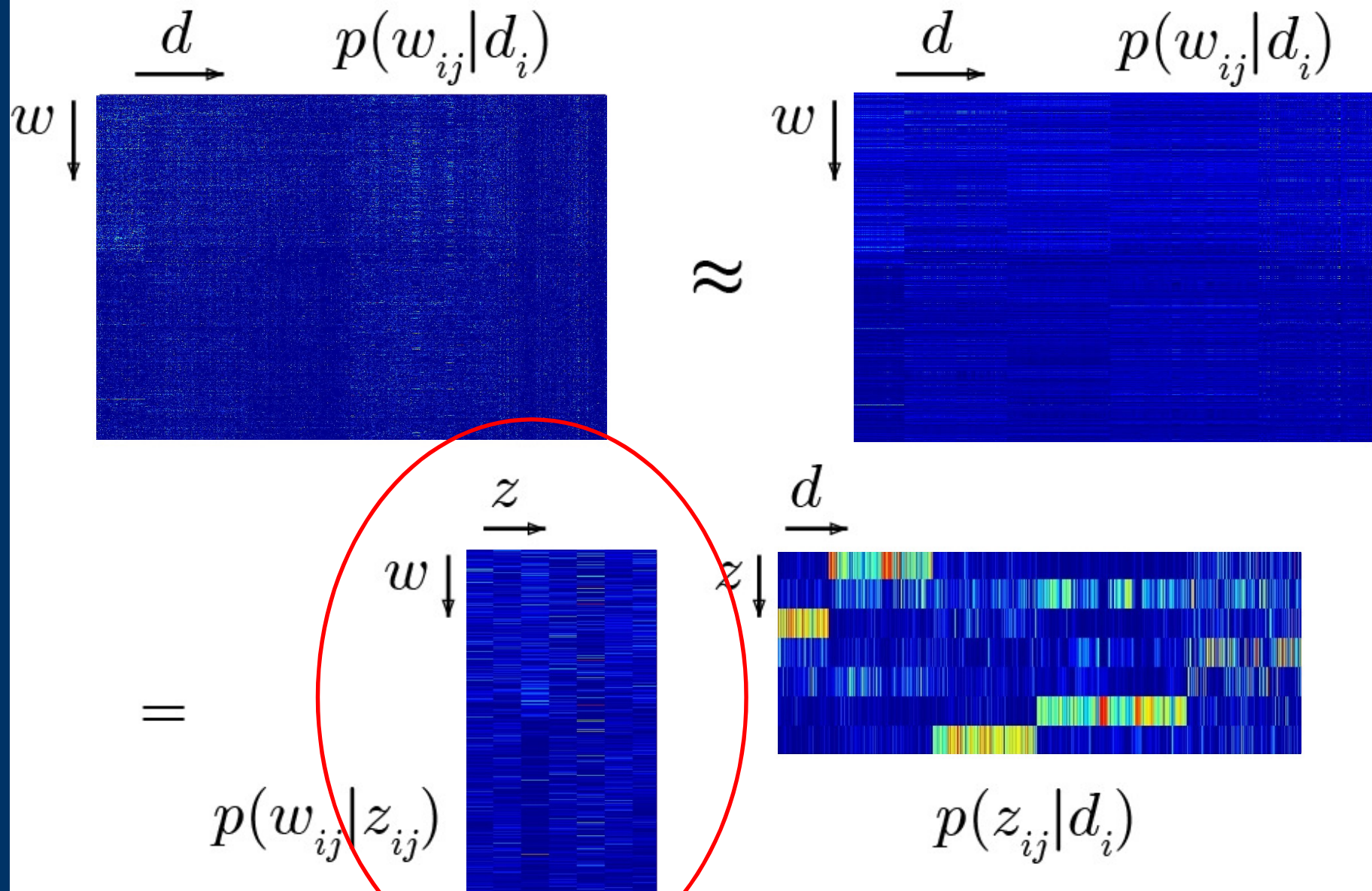
- Only need to maintain counts of topic assignments
- Sampler typically converges in less than 50 iterations
- Run time is less than an hour

Apply to Caltech 4 + background images



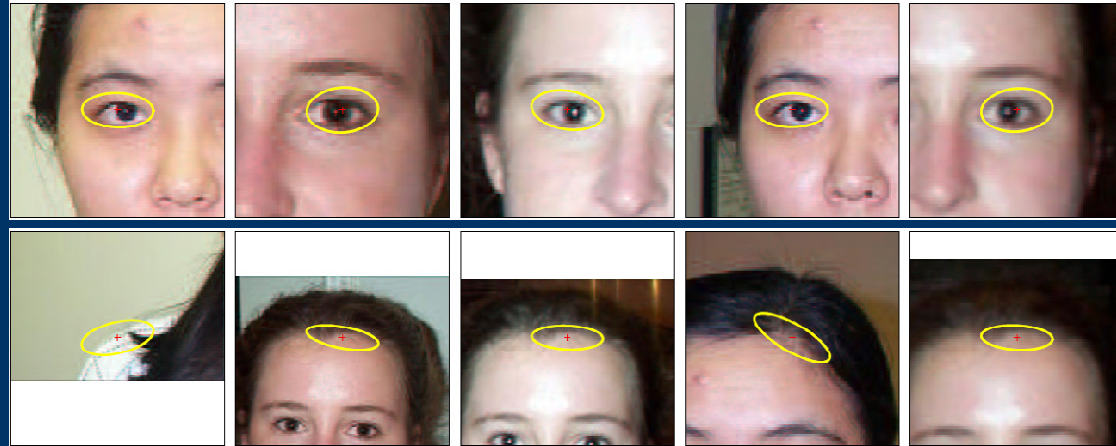
Faces	435
Motorbikes	800
Airplanes	800
Cars (rear)	1155
Background	900
Total:	4090





Most likely words given topic

Topic 1

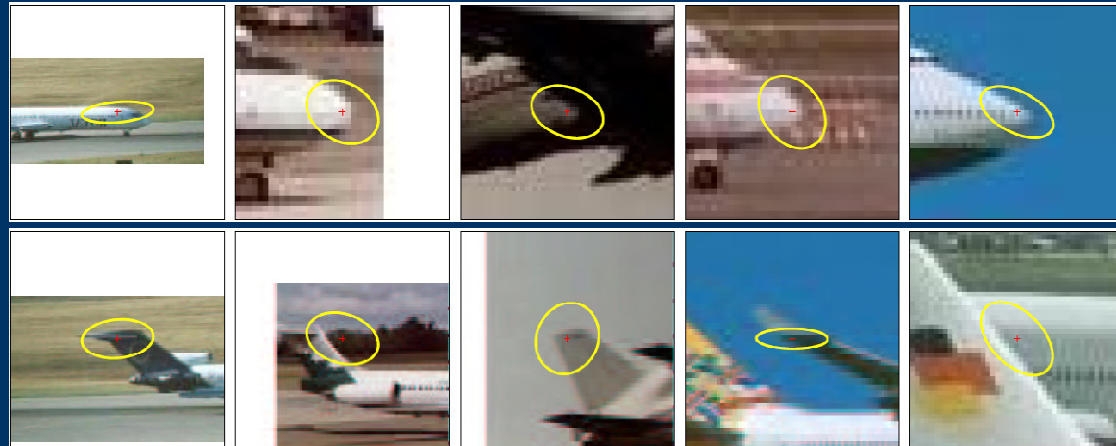


Topic 2



Most likely words given topic

Topic 3



Word 1

Word 2

Topic 4



Word 1

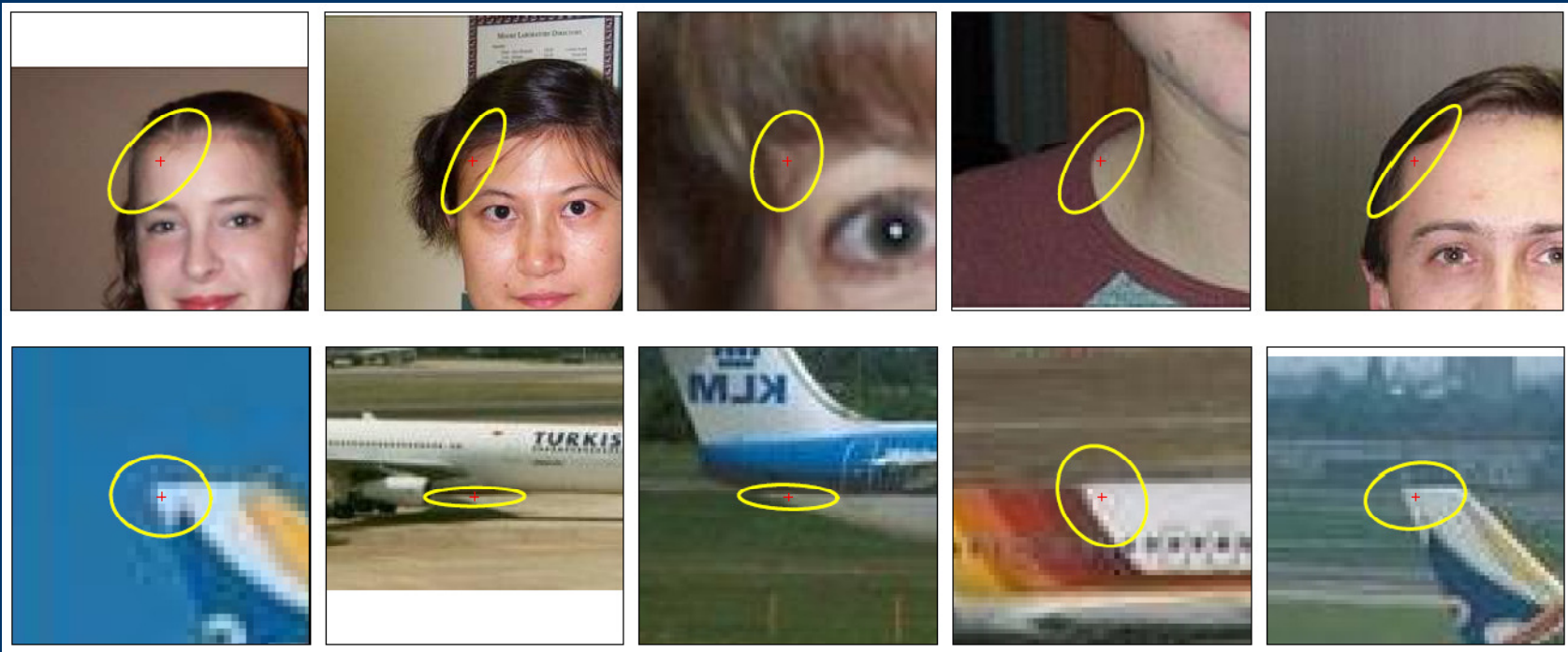
Word 2

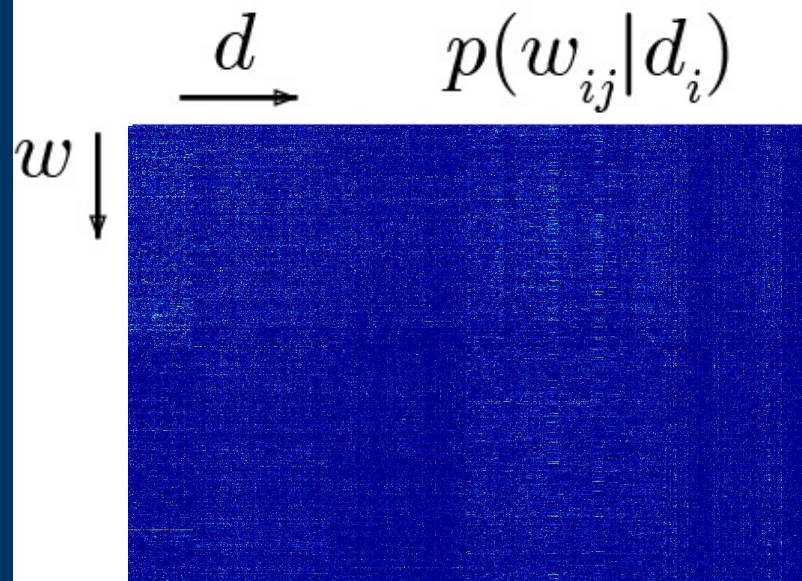
Polysemy

In English, “bank” refers to:

1. a institution that handles money
2. the side of a river

Regions that map to the same visual word:





\approx

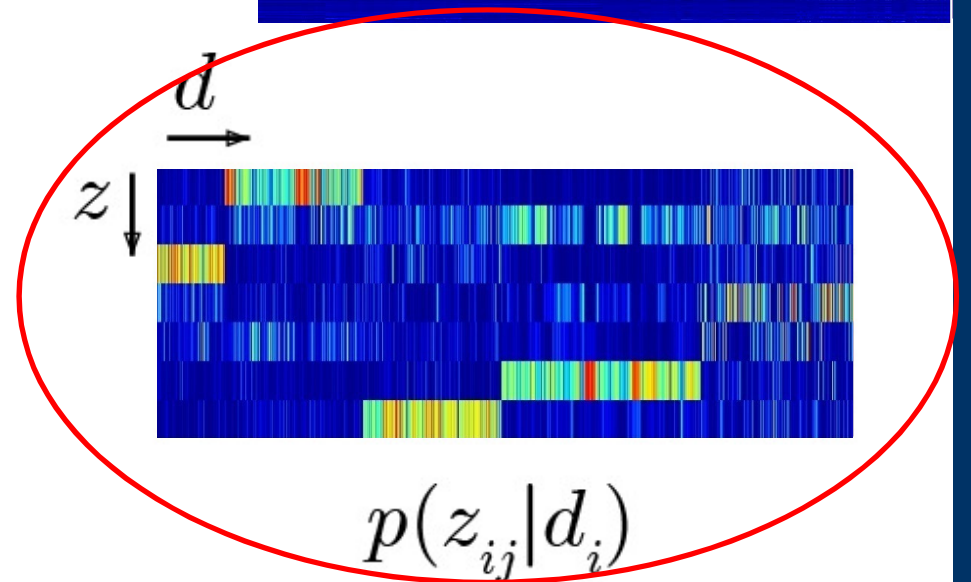
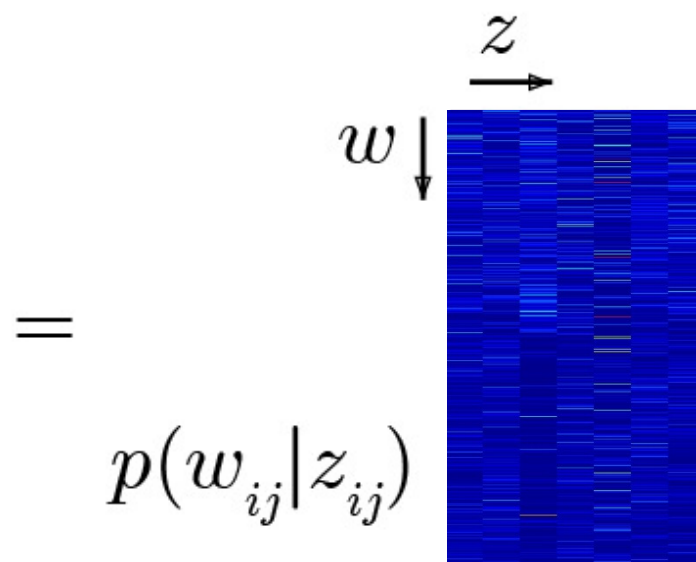
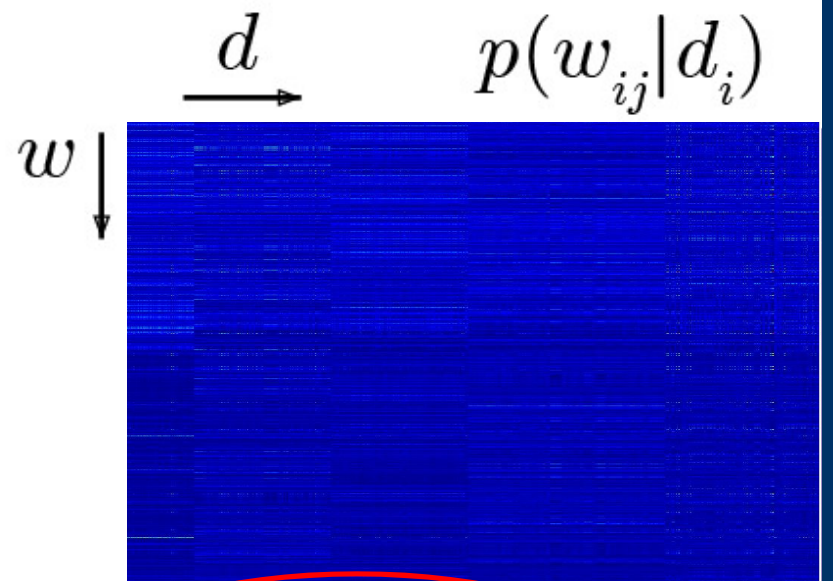
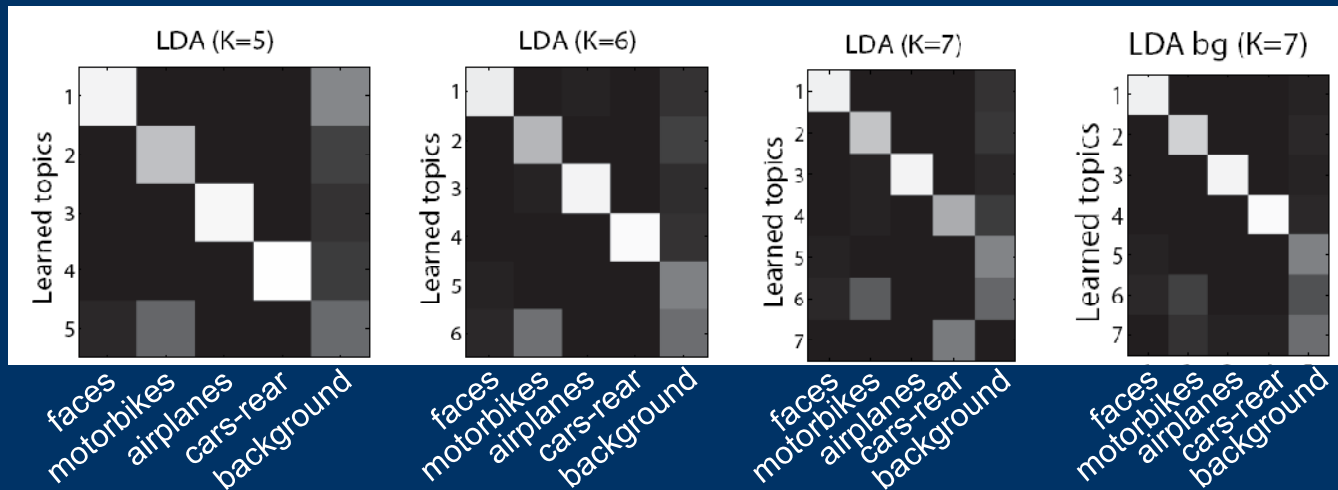


Image clustering

Confusion matrices:



Average confusion:

Expt.	Categories	T	LDA		pLSA		KM baseline	
			%	#	%	#	%	#
(1)	4	4	97	86	98	70	72	908
(2)	4 + bg	5	78	931	78	931	56	1820
(2)*	4 + bg	6	84	656	76	1072	—	—
(2)*	4 + bg	7	78	1007	83	768	—	—
(2)*	4 + bg-fxd	7	90	330	93	238	—	—

Comparison with supervised model

Percent ROC equal error rate

	<u>LDA</u>	<u>Constellation model</u> <u>[Fergus et al. '03]</u>
Faces	7.8	3.6
Motorbikes	9.9	6.7
Airplanes	2.5	7.0
Cars rear	8.5	9.7

- Comparable performance to constellation model
- Level of supervision:
 - LDA: one number (of topics)
 - Constellation model: 400 labels for each category
- Also an indication of the level of difficulty of the Caltech 5 dataset

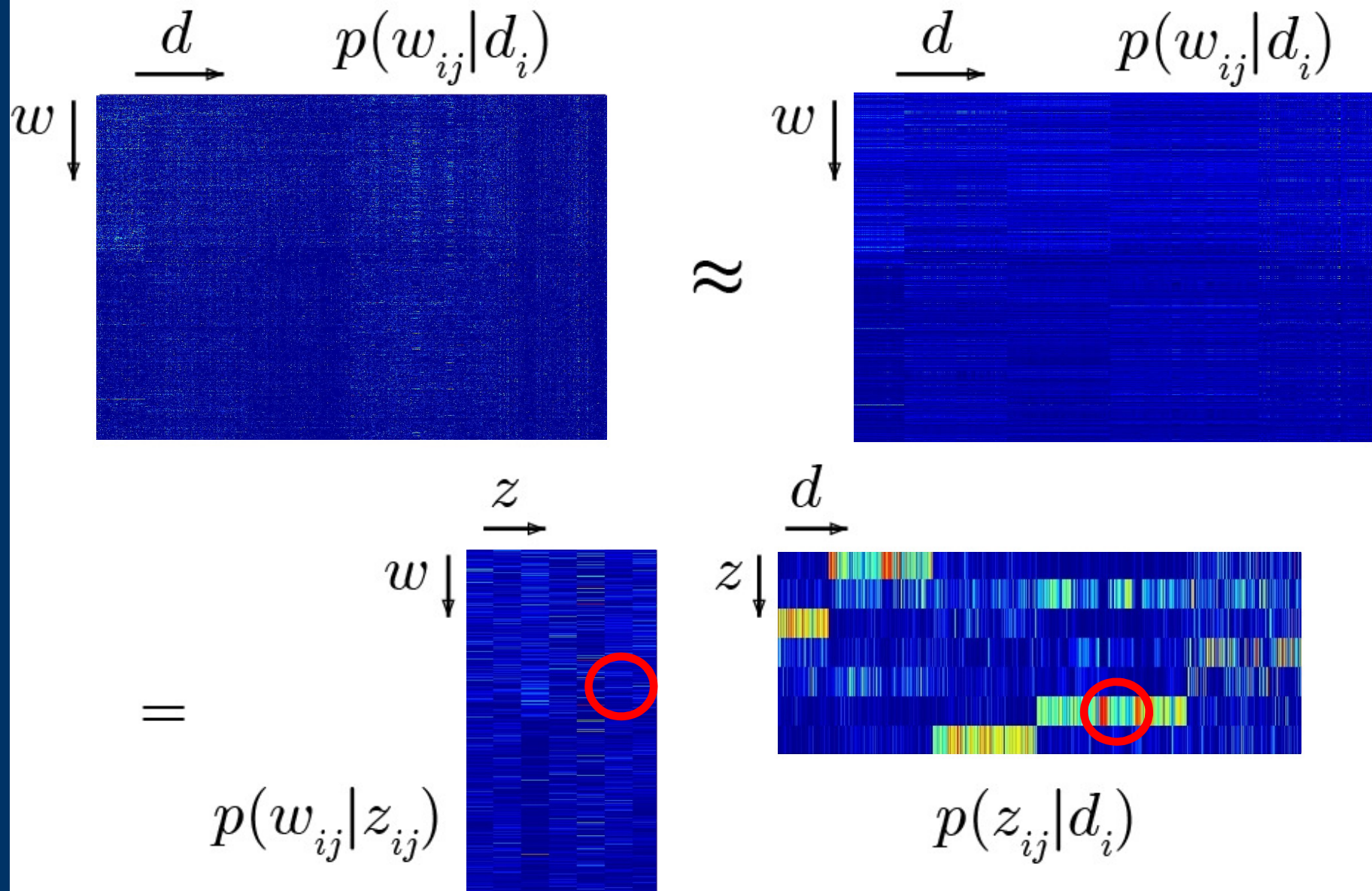
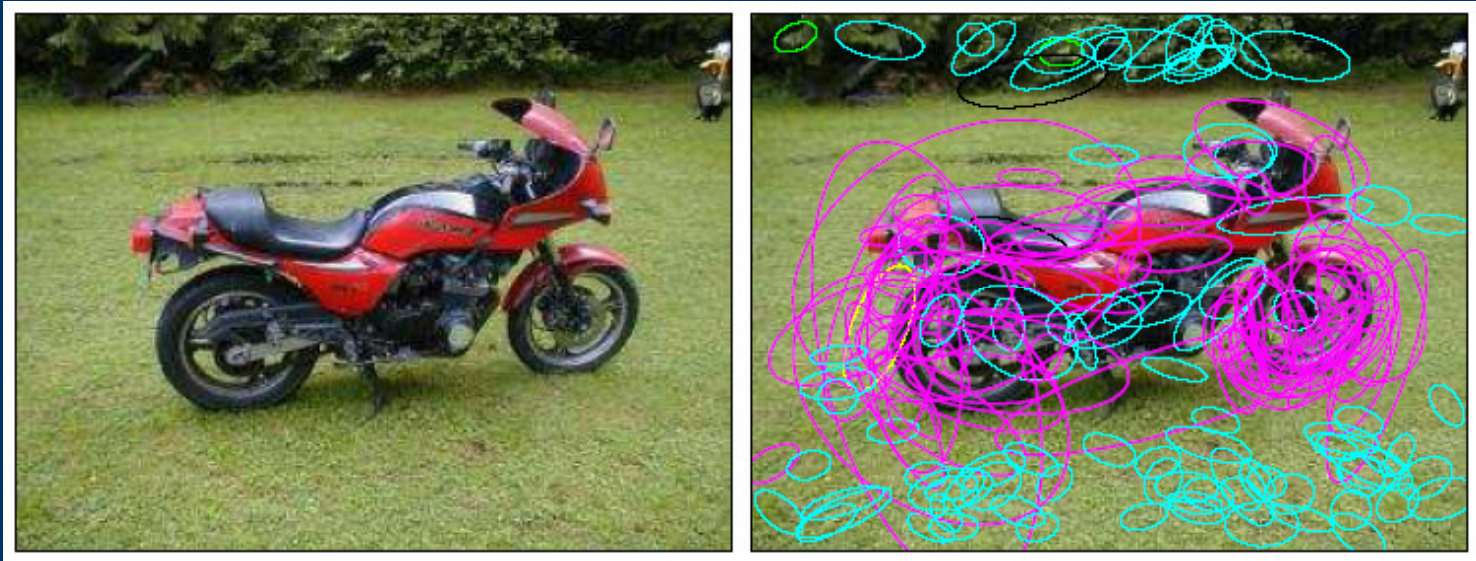
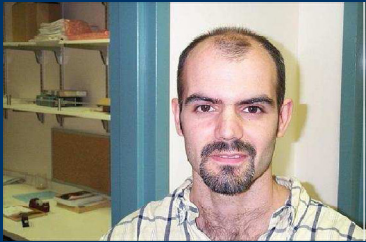


Image as a mixture of topics (objects)





Summary -- Sivic

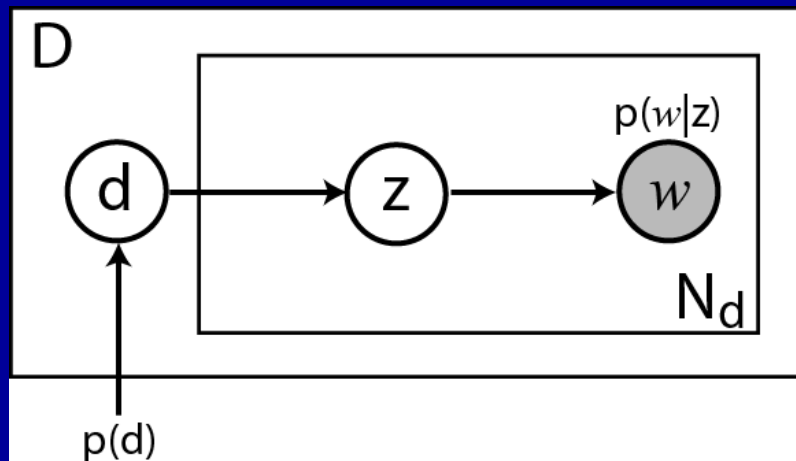
- Discovered visual topics corresponding to object categories from a corpus of unlabeled images
- Used visual words representation and topic discovery models from the text understanding community
- Classification on unseen images is comparable to supervised methods on Caltech 5 dataset
- The discovered categories can be localized within an image

Learning Object Categories from contaminated data

Rob Fergus
Li Fei-Fei
Pietro Perona
Andrew Zisserman

Probabilistic Latent Semantic Analysis (pLSA)

- Introduced by Hofmann in text analysis field
- Latent Dirichlet Allocation (LDA) – Blei and Jordan
- Adapted to visual data by:
 - Sivic, Russell et al. (Unsupervised object category discovery) *ICCV '05*
 - Fei-Fei and Perona (Scene analysis using LDA) *CVPR '05*

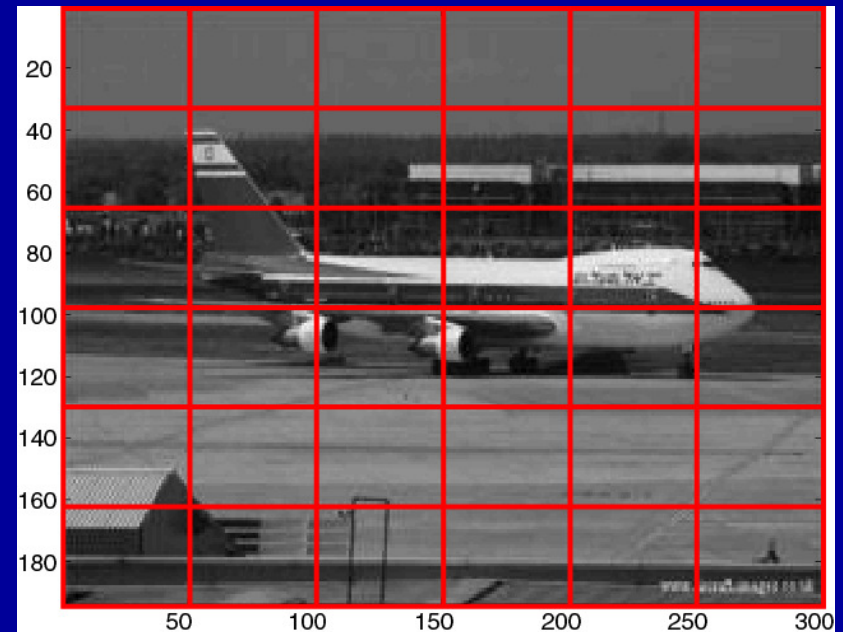
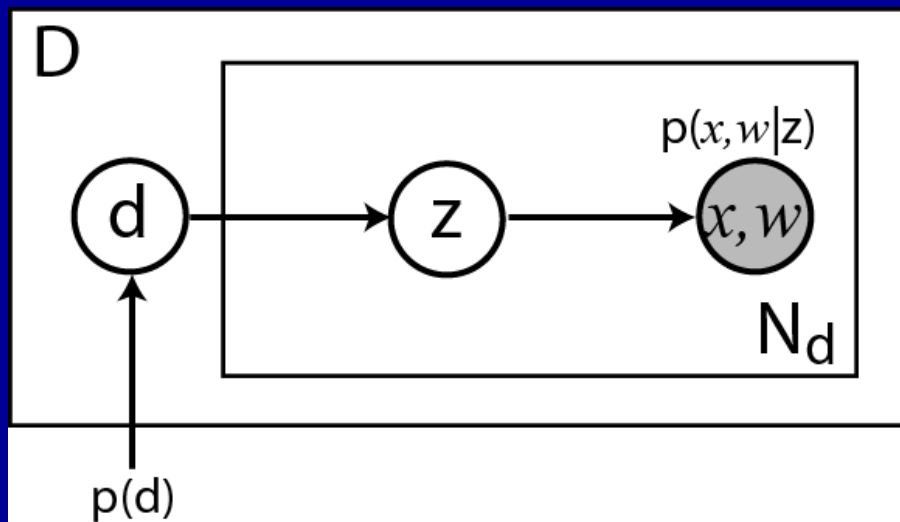


- Need to choose # topics (Z)

	Text domain	Image domain
d	Document	Image
z	Topic	Object
w	Word	VQ'd appearance of region

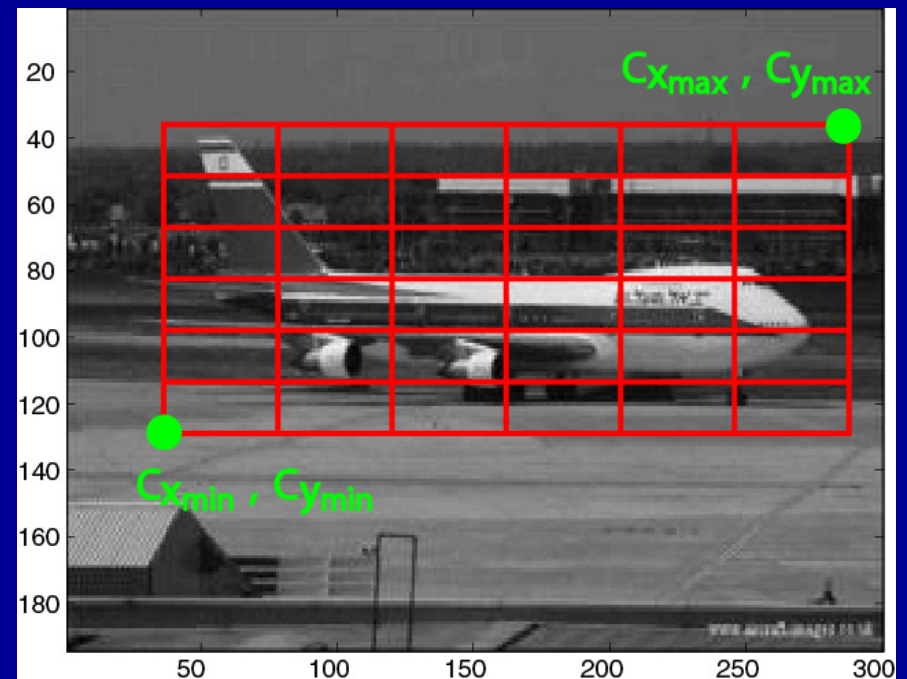
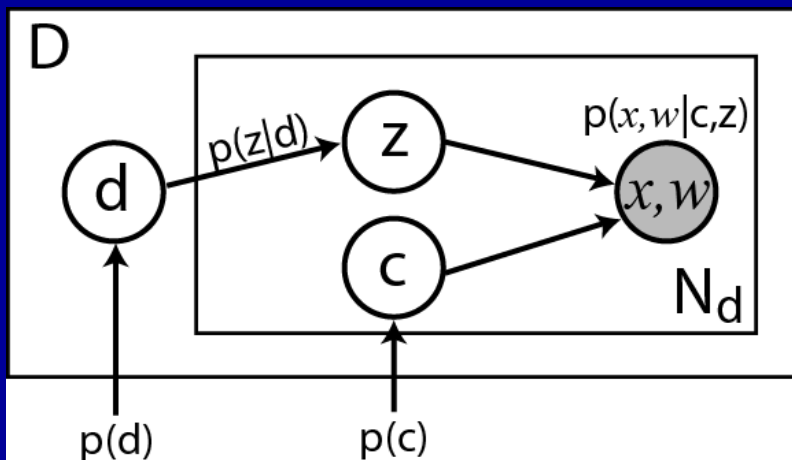
1. Improvements on pLSA: ABS-pLSA

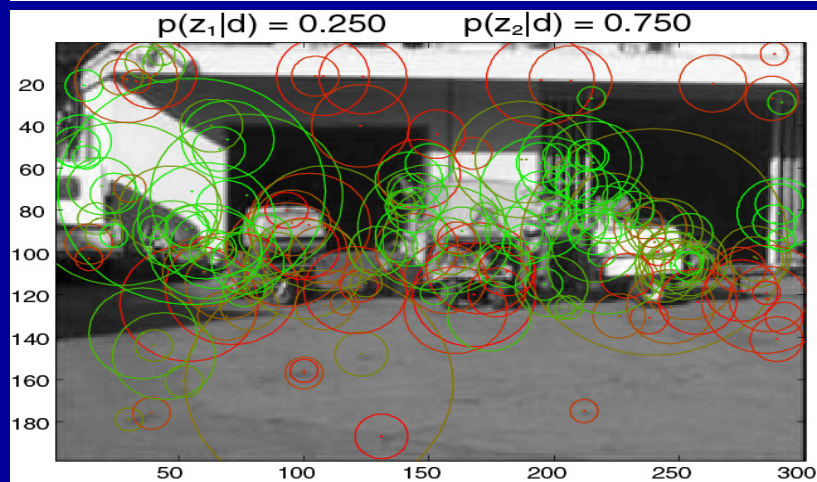
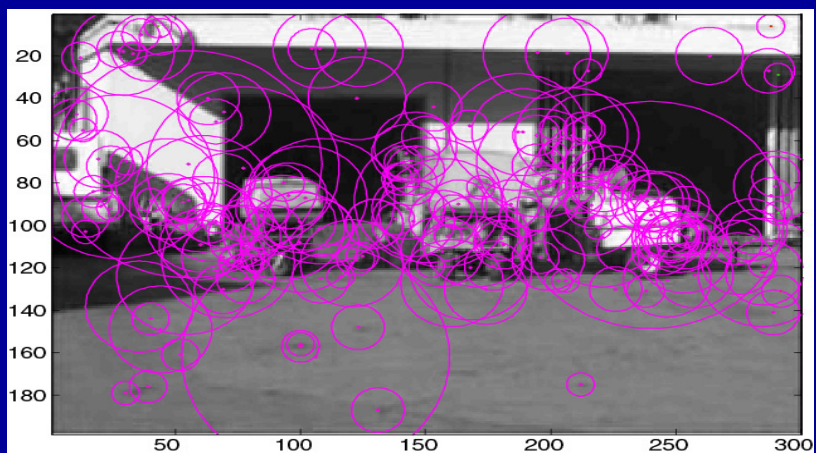
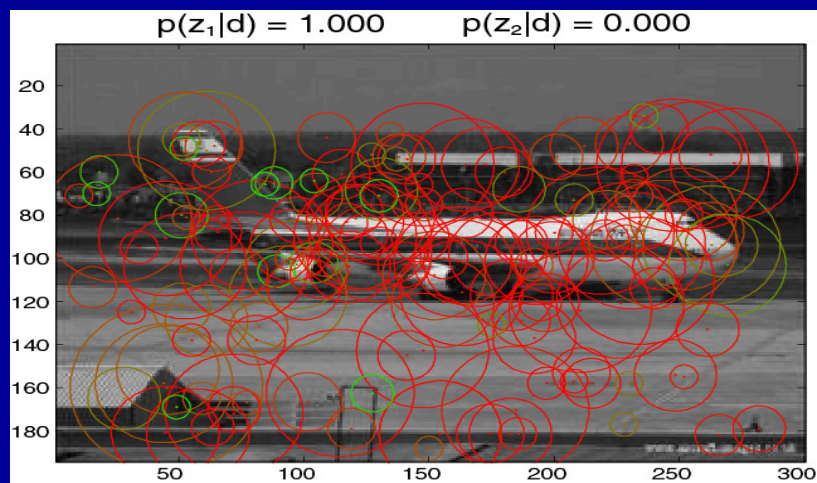
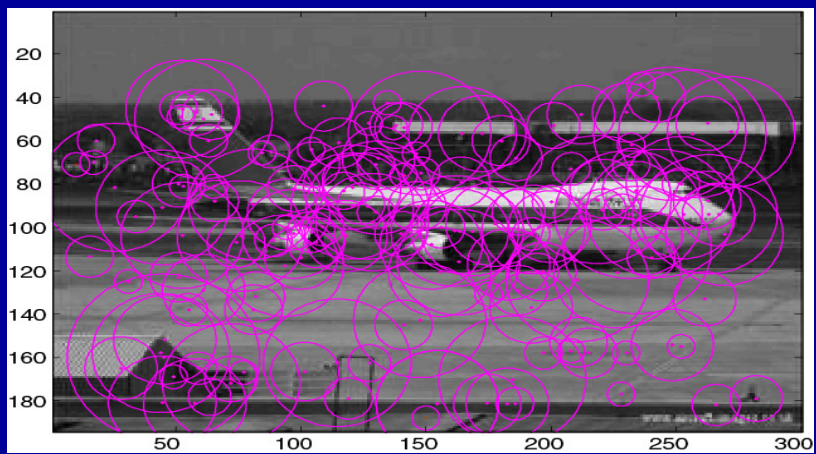
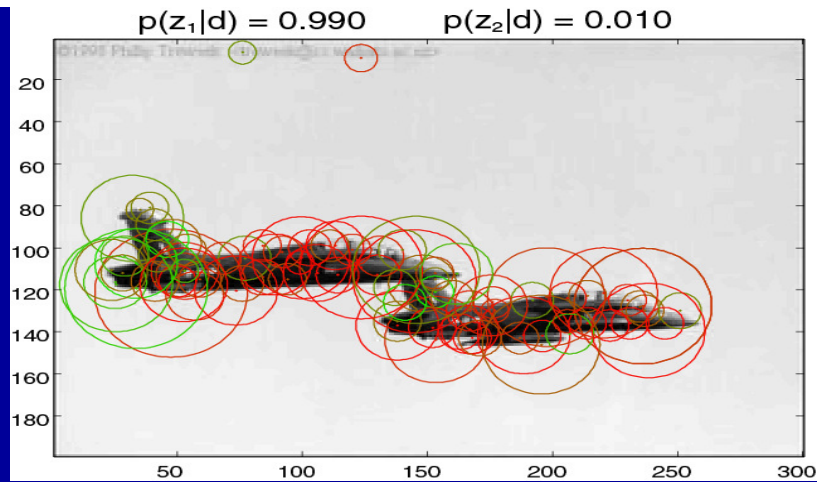
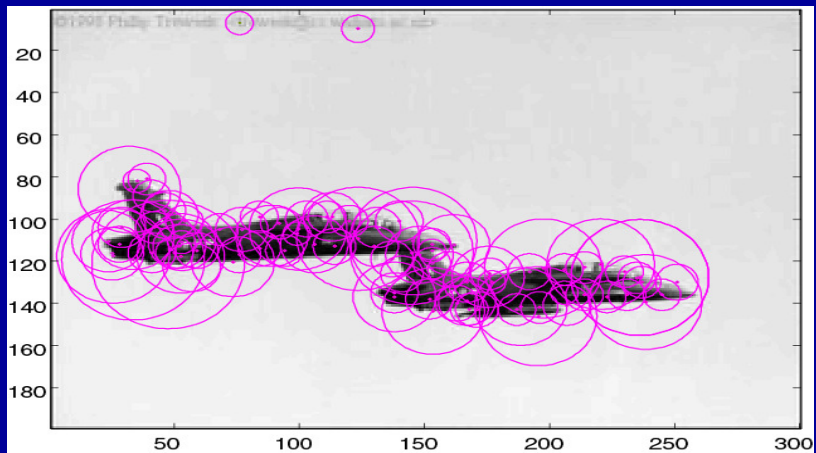
- No spatial information used in pLSA
- Simplest form of spatial model:
- Joint spatial/word model
 - Quantize location of region within image
 - Absolute coordinate frame



2. Improvements on pLSA: TSI-pLSA

- ABS-pLSA uses absolute coordinate frame
 - Cannot handle translation or scaling
- Introduce sub-window conditioned on hidden variable c :
- c is a 4-d vector – gives bounding box of object
- Gives (T)ranslation and (S)cale (I)nvariance.

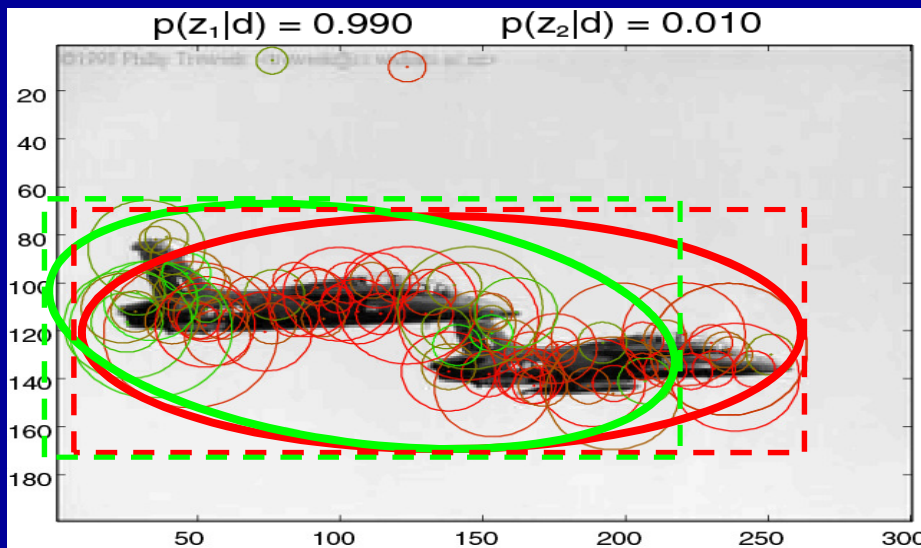




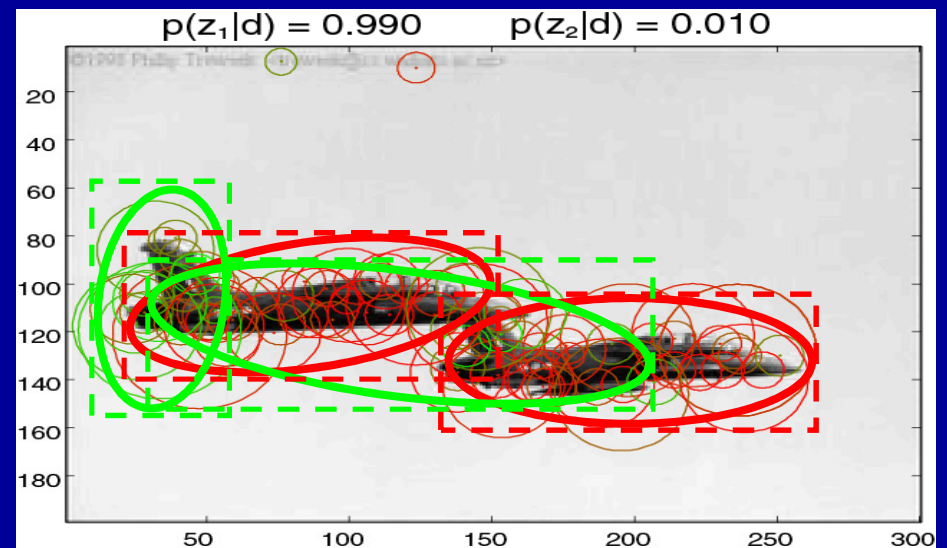
Proposing bounding boxes

- Use pLSA to propose bounding boxes in a bottom-up manner
- Use regions weighted by $P(w|z)$.
- Fit Gaussian mixture model with ($C=1$ & $C=2$) components for each topic:

$C = 1$ component



$C = 2$ components



- Gives us a set of possible bounding boxes

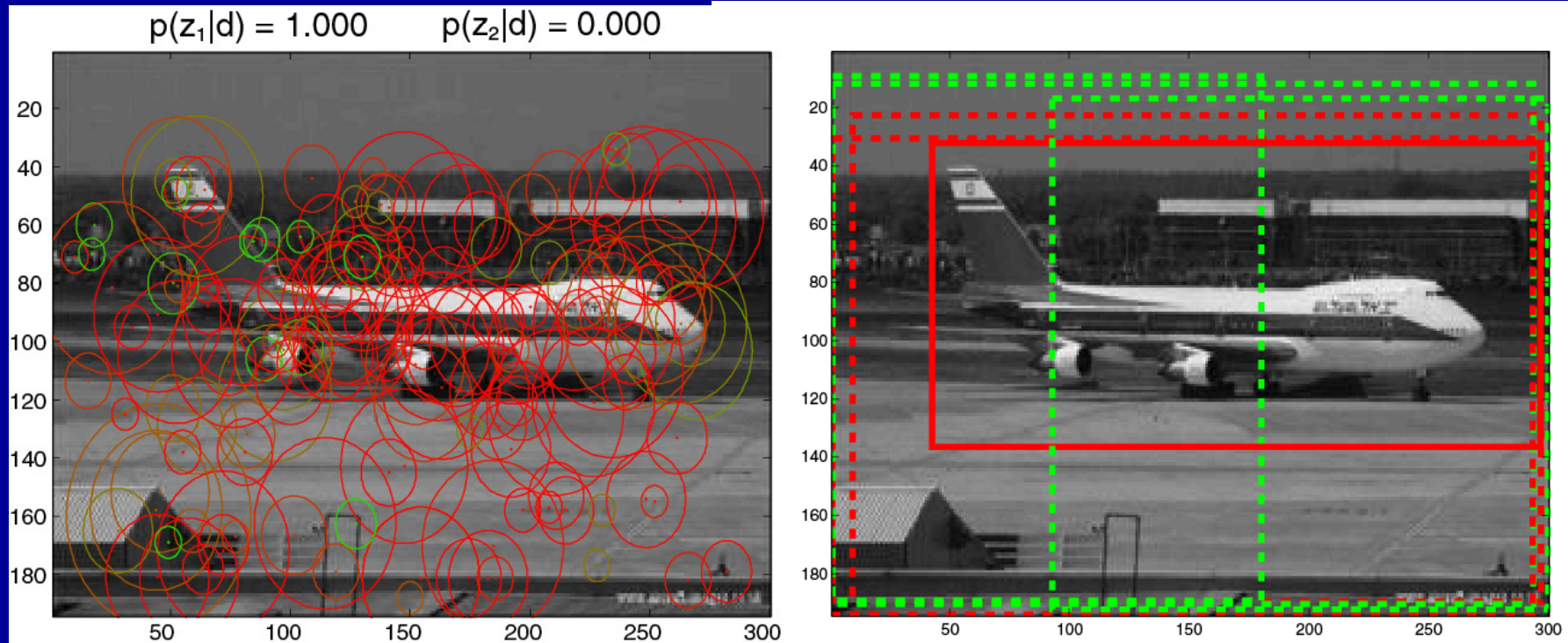
Obtaining bounding box estimates

Learning:

- Use $p(w|z)$ density from plain pLSA model, learn from training data
- Sum over different sub-windows in learning

Recognition:

- Average $p(w|z)$ over sub-window of learnt TSI-pLSA model
- Drawback: Only use appearance information
- Restrict choice of bounding boxes to those belonging to best topic



Comparison between pLSA models

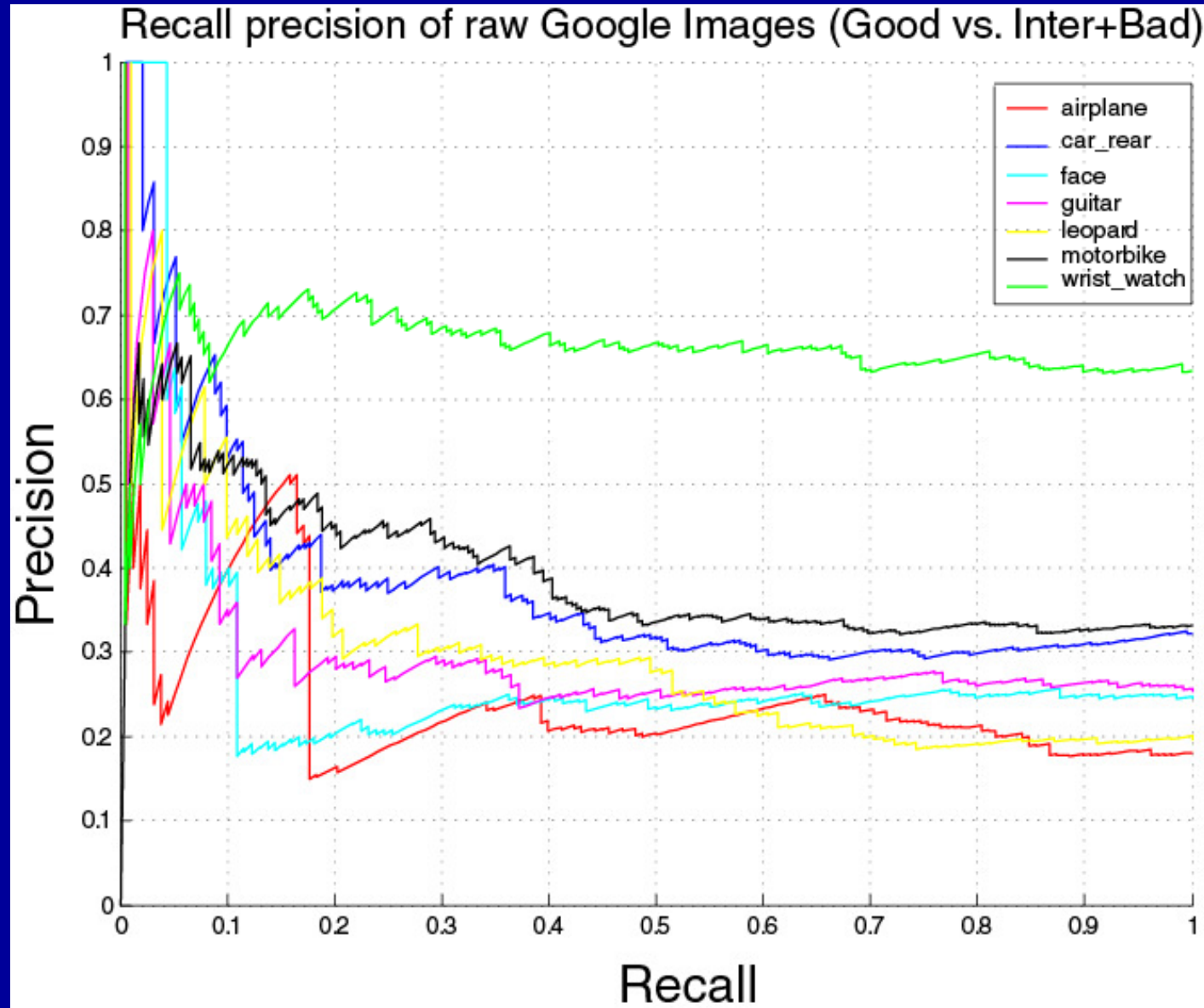
- PASCAL object recognition challenge datasets
- Classification task

	Plain pLSA	ABS – pLSA	TSI-pLSA
PASCAL Cars	31.7	30.8	25.8
PASCAL Motorbikes	33.7	30.2	25.7

Training pLSA models from Google images

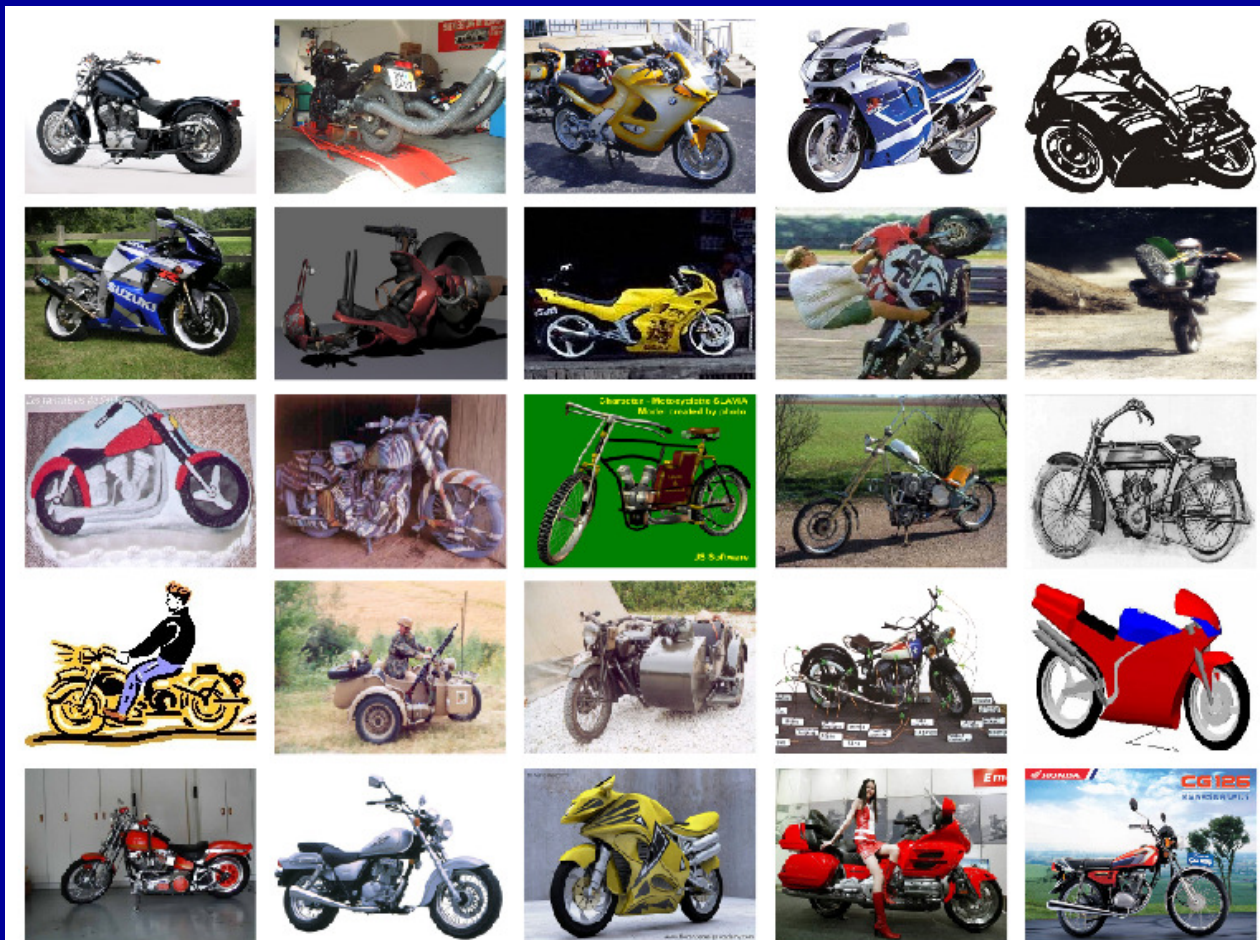
- Multiple topics can handle polluted data
 - Each topic models a visually consistent component of data
- Different aspects handled by
 - Different topics
 - Multimodal nature of densities
- TSI-pLSA can handle translation and scaling of object within image
- Everything automatic except for:
 1. Number of topics to use (Z)? Fix $Z = 8$
 2. How to pick topic belonging to good images?

Google's variable search performance



Picking the best topic

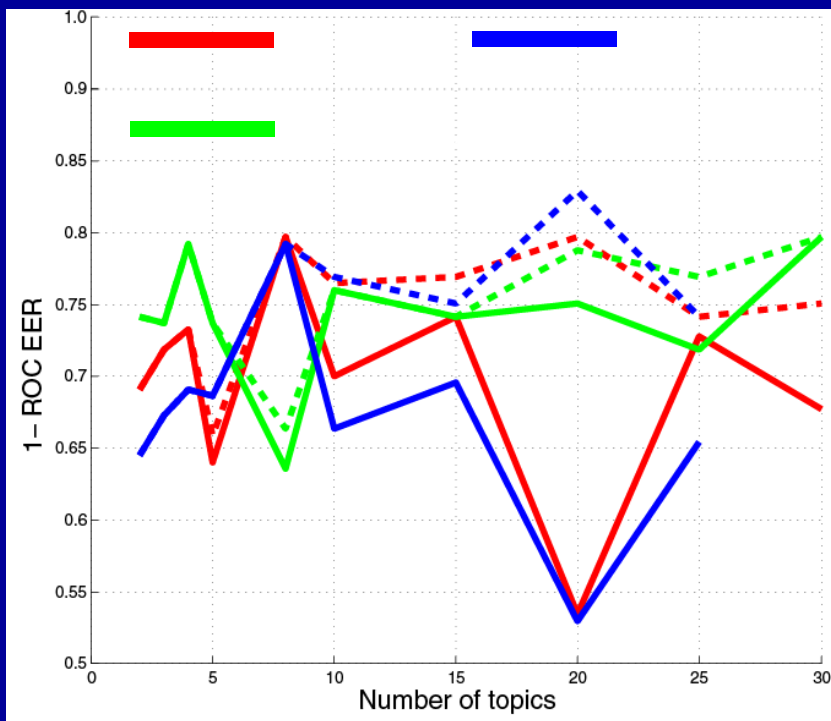
- Use Google's automatic translation tool to translate keyword
- Use: German, French, Italian, Spanish, Chinese, English
- Take first 5 images returned using translated keywords to give validation set



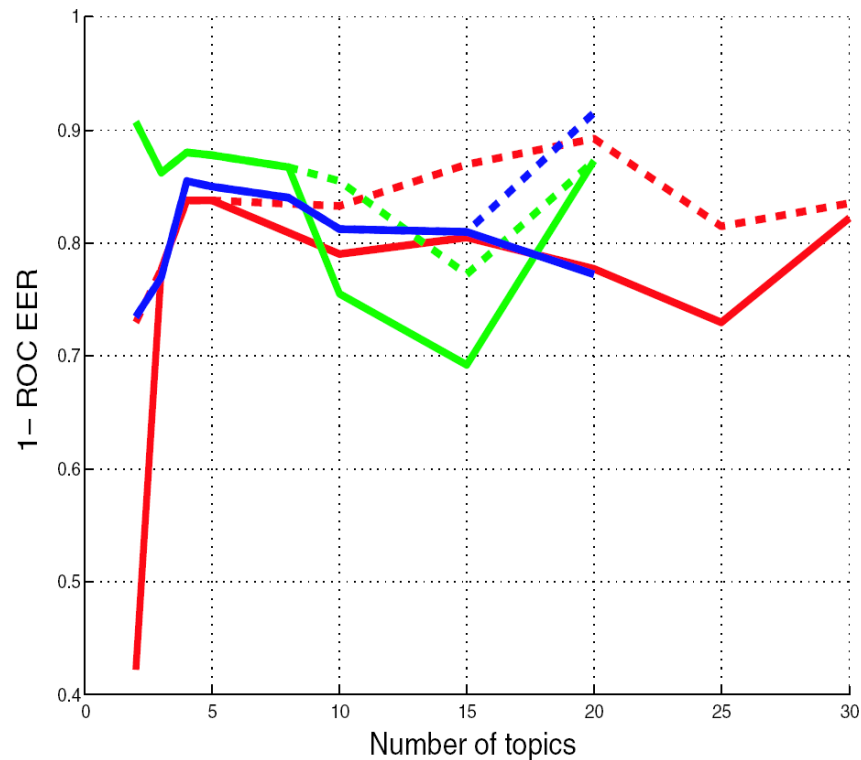
2. Picking the number of topics

- Small number gives very general topics
- Large number gives highly specific topics
 - Overfitting problems
 - Difficult to automatically pick best one
- Use $Z=8$, chosen empirically using face and airplane classes

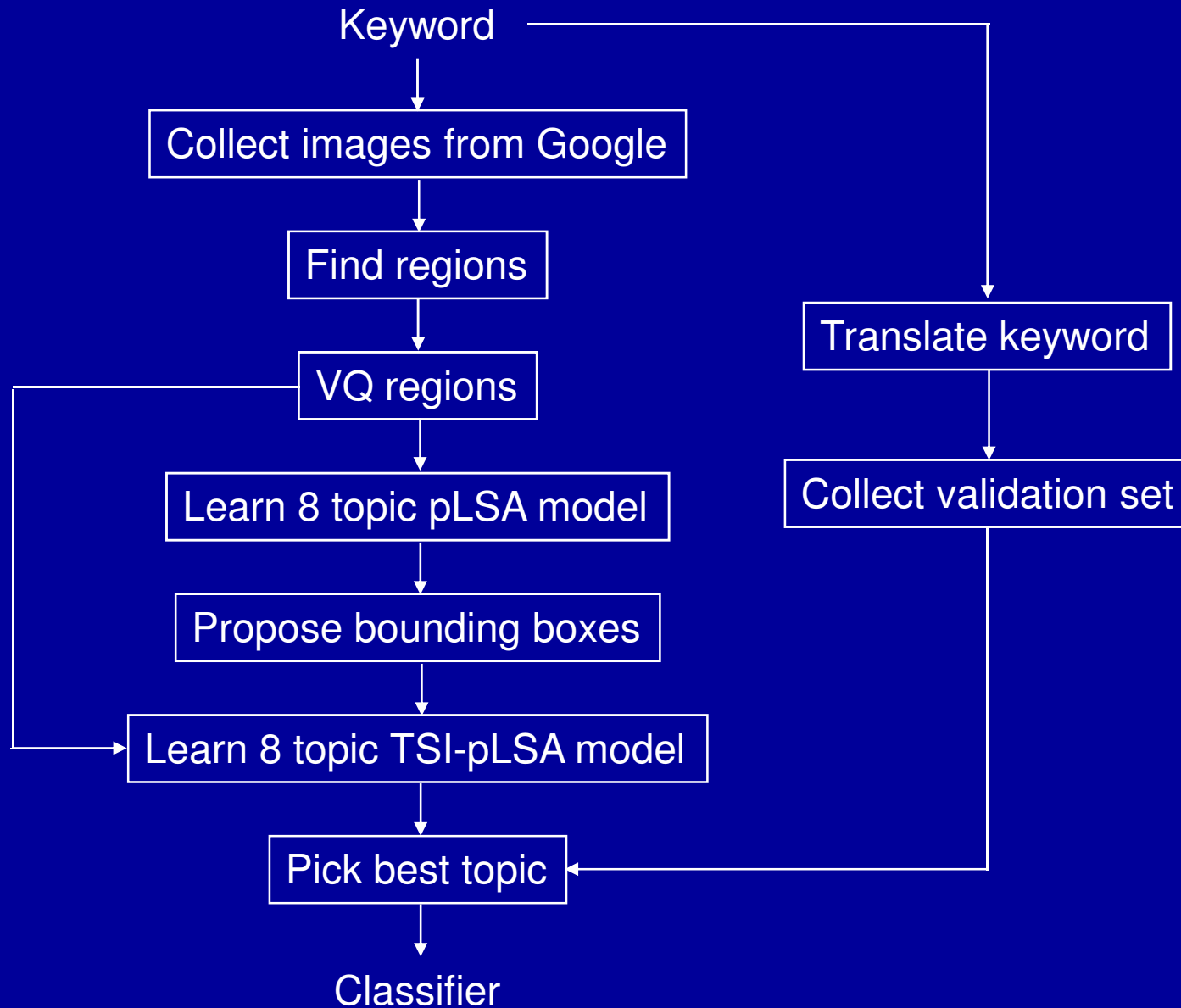
Face



Cars Rear



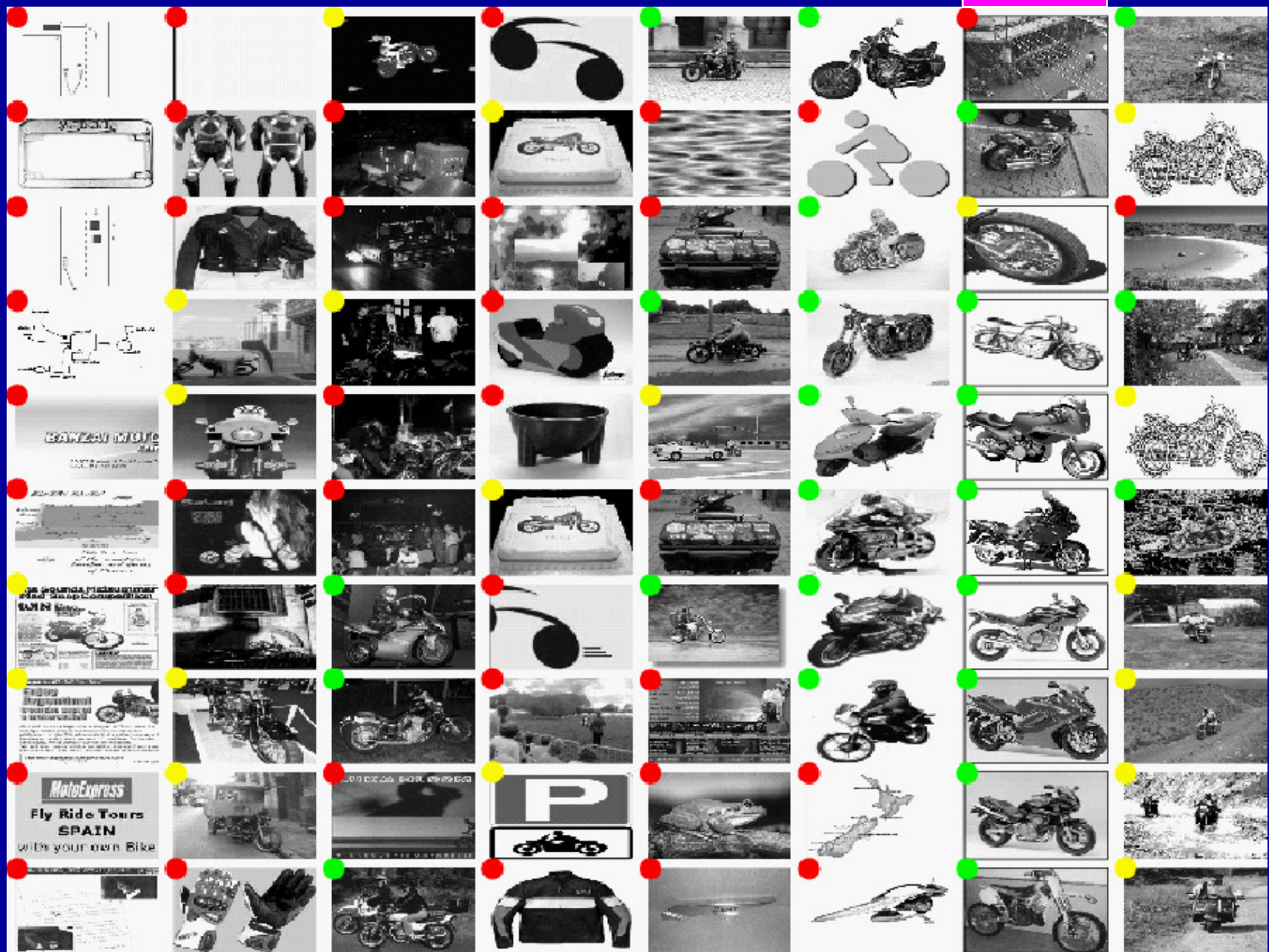
Overall learning scheme



Motorbike – pLSA



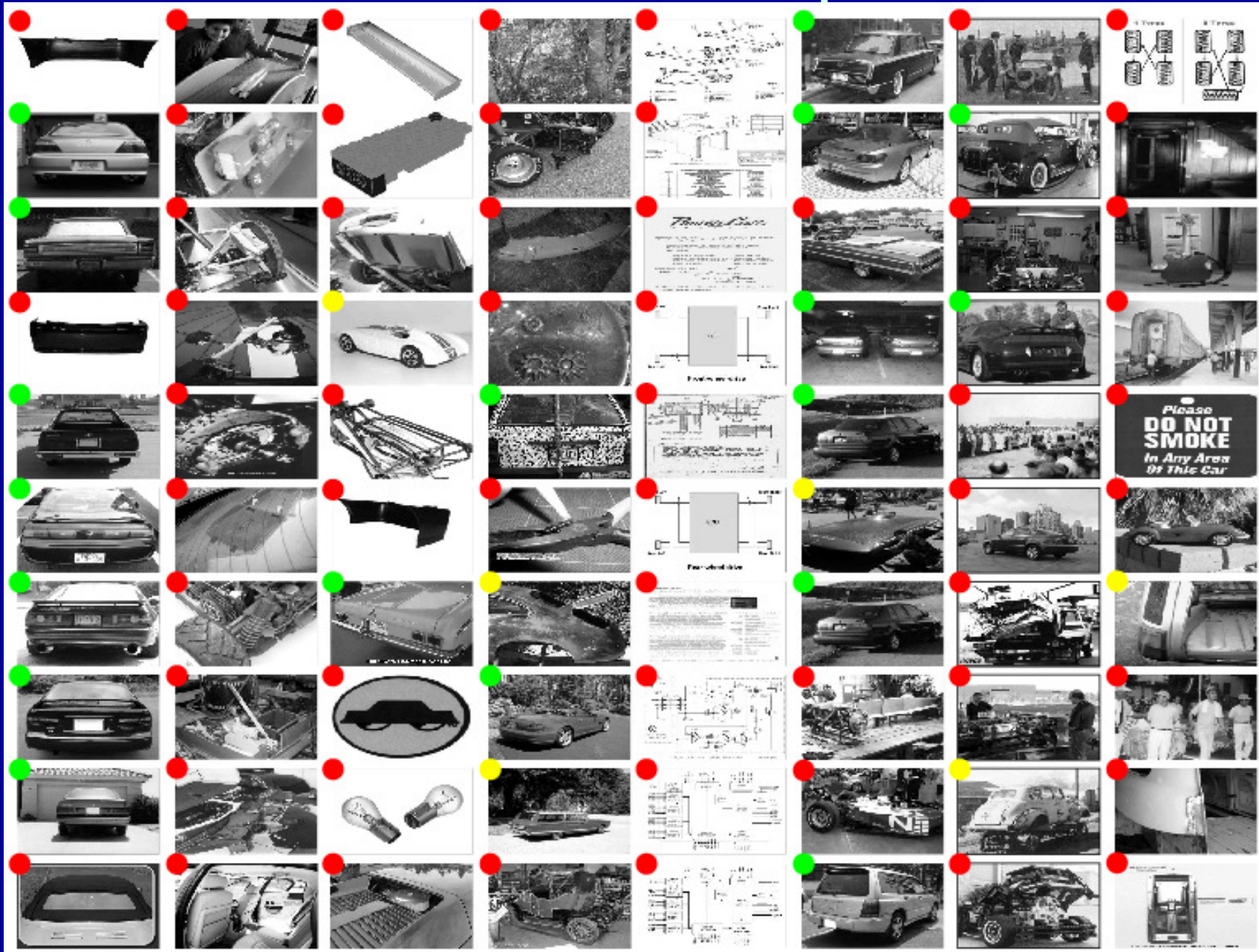
Motorbike – TSI-pLSA



Car Rear – pLSA



Car Rear – TSI-pLSA



OPTIMOL: automatic Object Picture collecTion via Incremental MOdel Learning

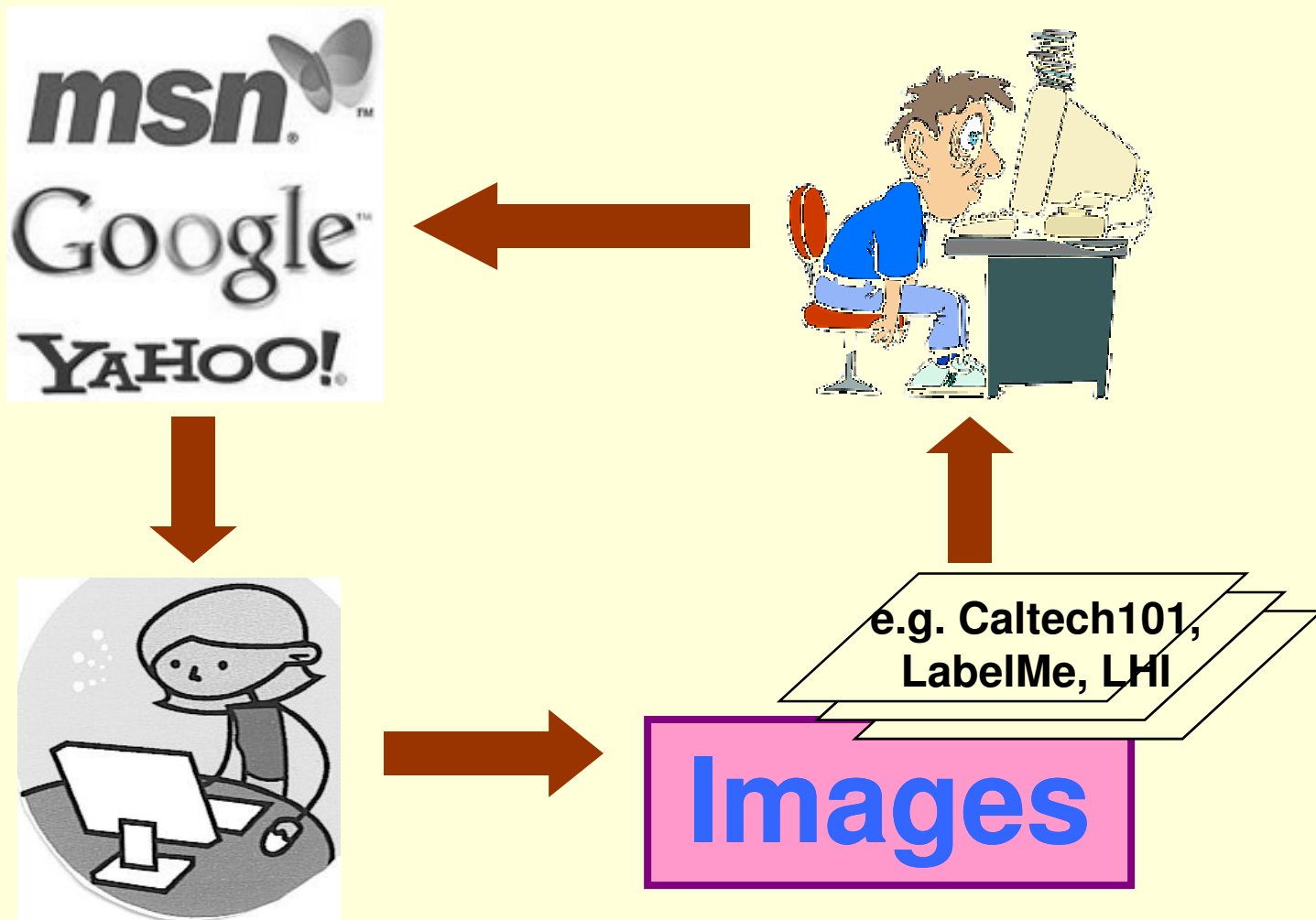
L.-J. Li
G. Wang
L. Fei-Fei

Presented at CVPR '07

a chicken and egg problem...



...among users, researchers, and data



Framework

Dataset



Category model

Classification

Downloaded Web images



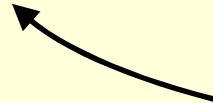
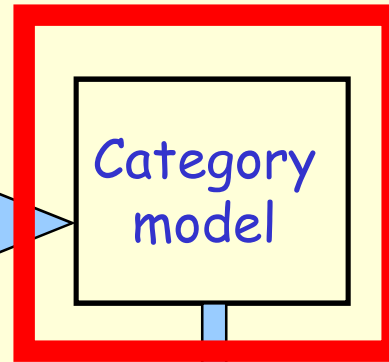
Keyword: accordion

Framework

Dataset



...



Classification

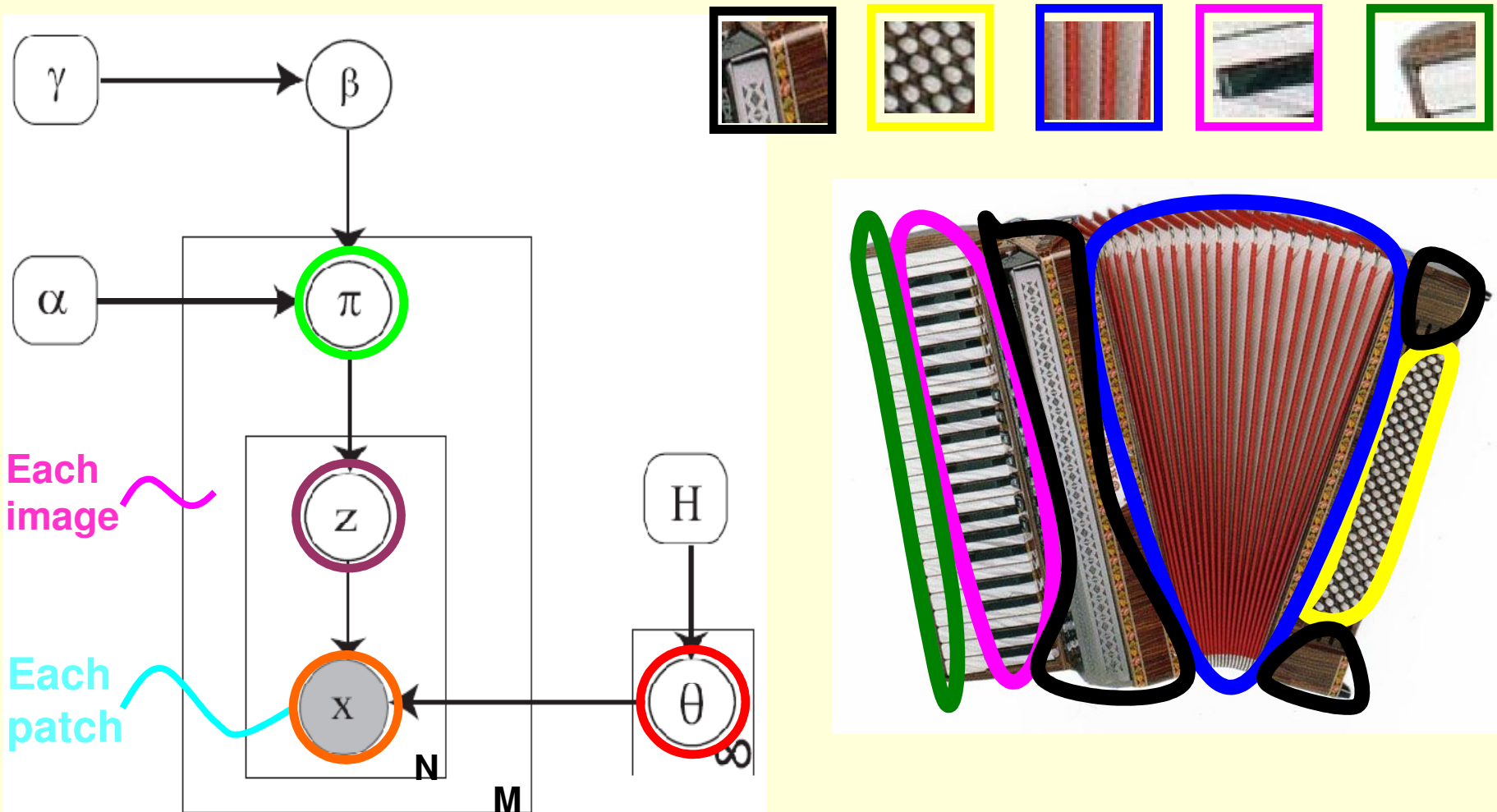
Downloaded Web images



Keyword: accordion

Nonparametric topic model

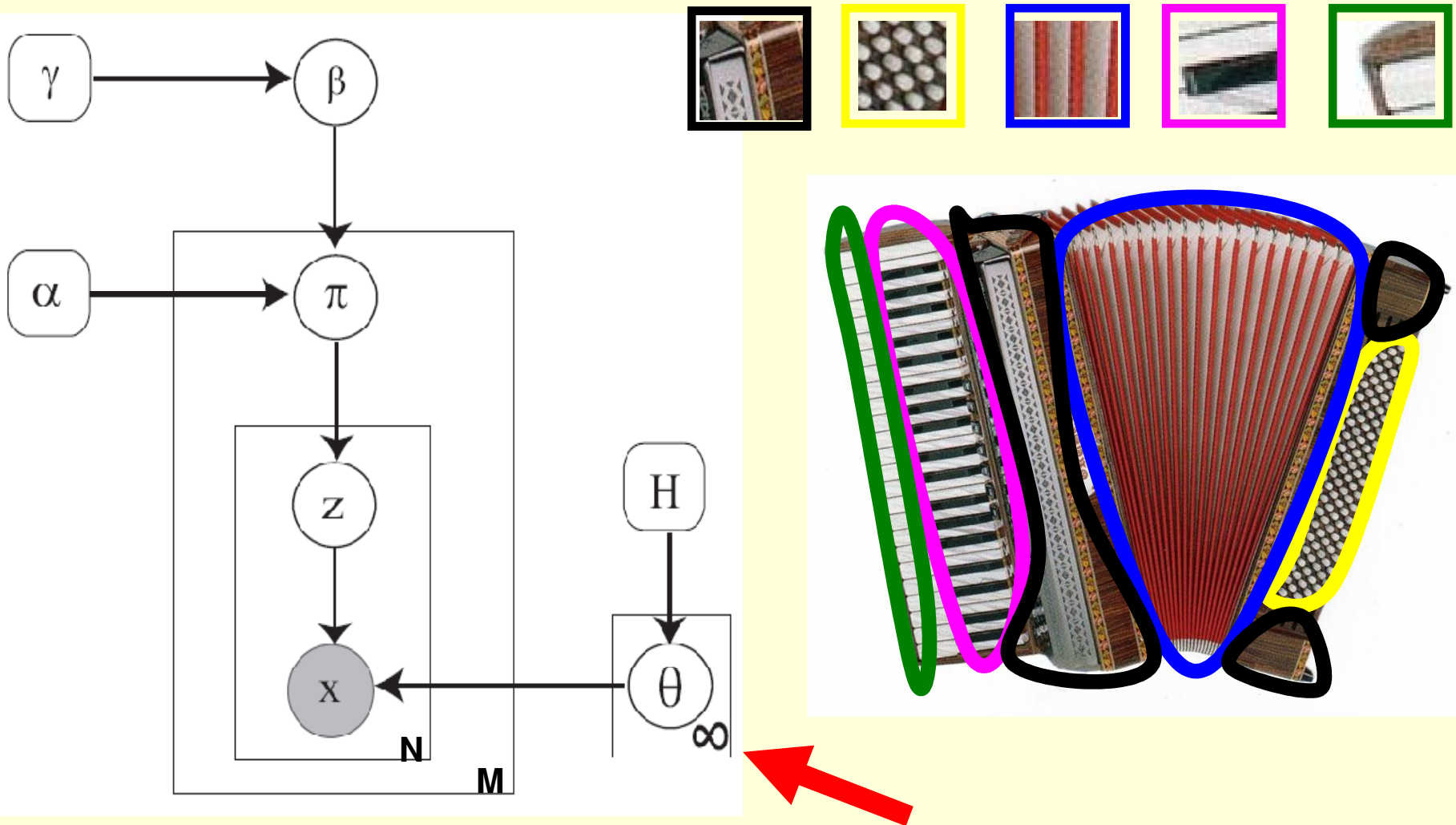
-Hierarchical Dirichlet Process (HDP)



Teh, et al. 2004; Sudderth et al. CVPR 2006; Wang, Zhang & Fei-Fei, CVPR 2006

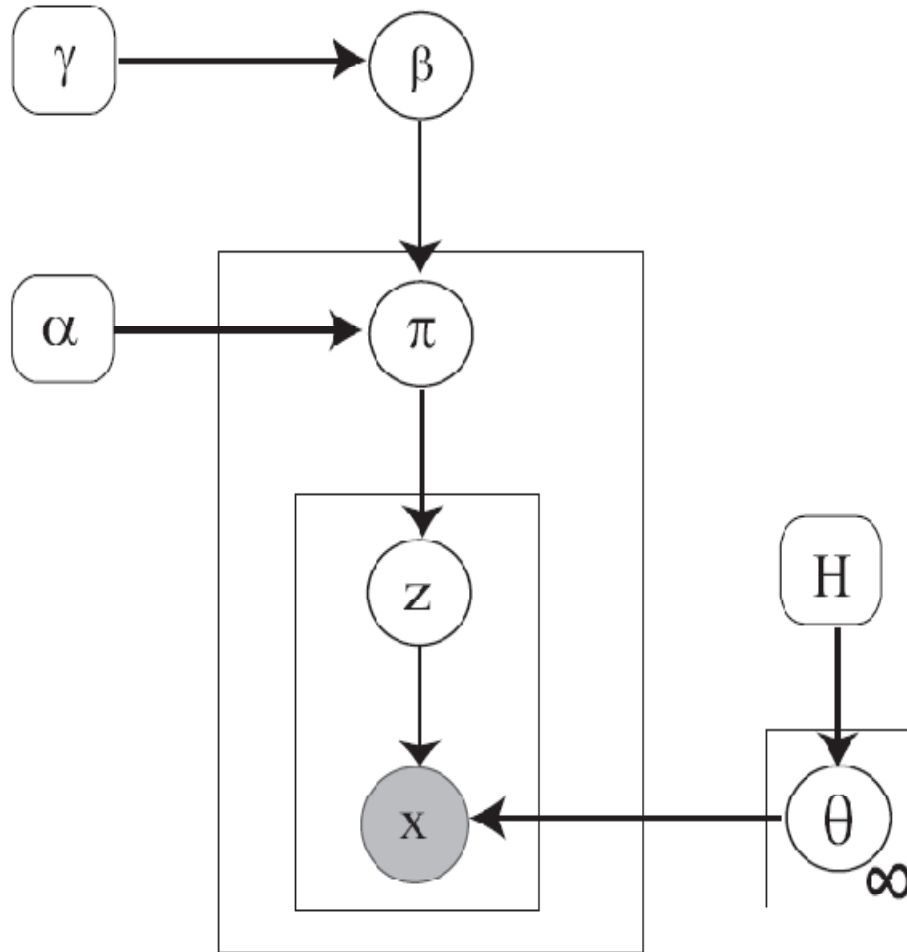
Nonparametric topic model

-Hierarchical Dirichlet Process (HDP)



Teh, et al. 2004; Sudderth et al. CVPR 2006; Wang, Zhang & Fei-Fei, CVPR 2006

Classification



Category likelihood for I :

$$P(I|c) = \prod_i \sum_j P(x_i|z_j, c)P(z_j|c)$$

Likelihood ratio for decision:

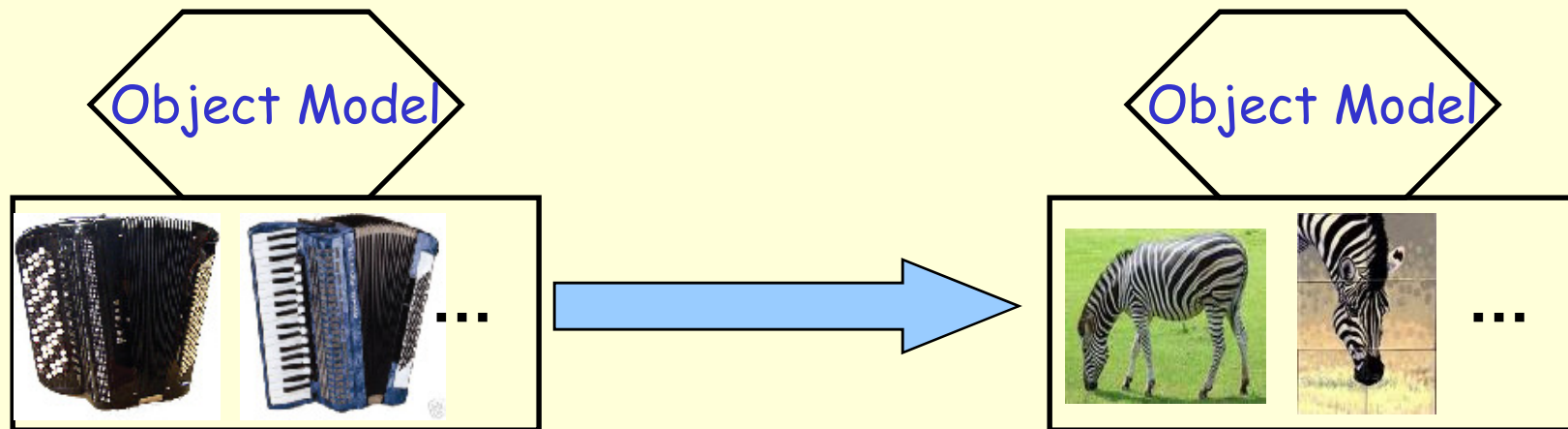
$$\frac{P(I|c_f)}{P(I|c_b)}$$

Annotation

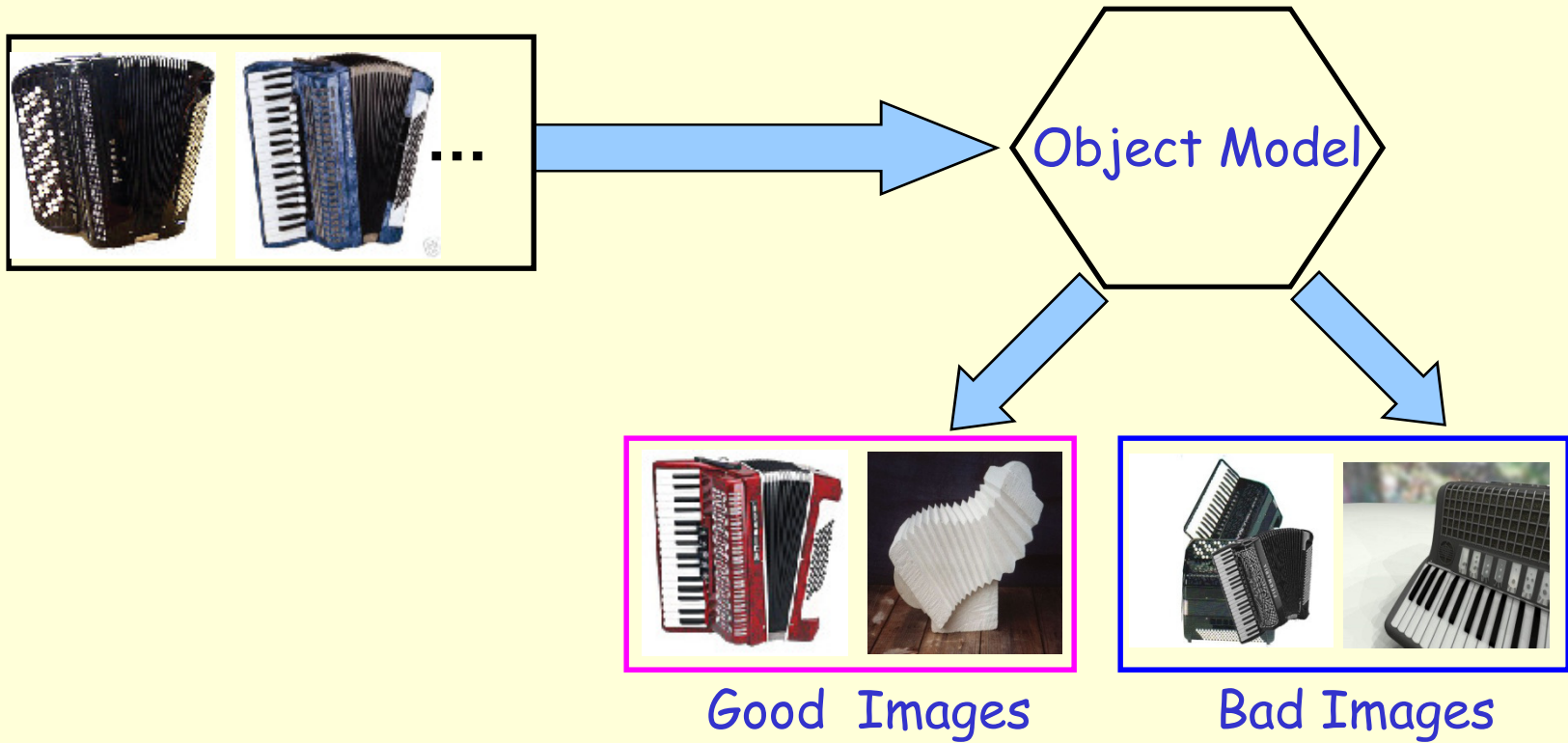


$$p(x|c_f) = \sum_i p(x|z_i, c_f)p(z_i|c_f)$$

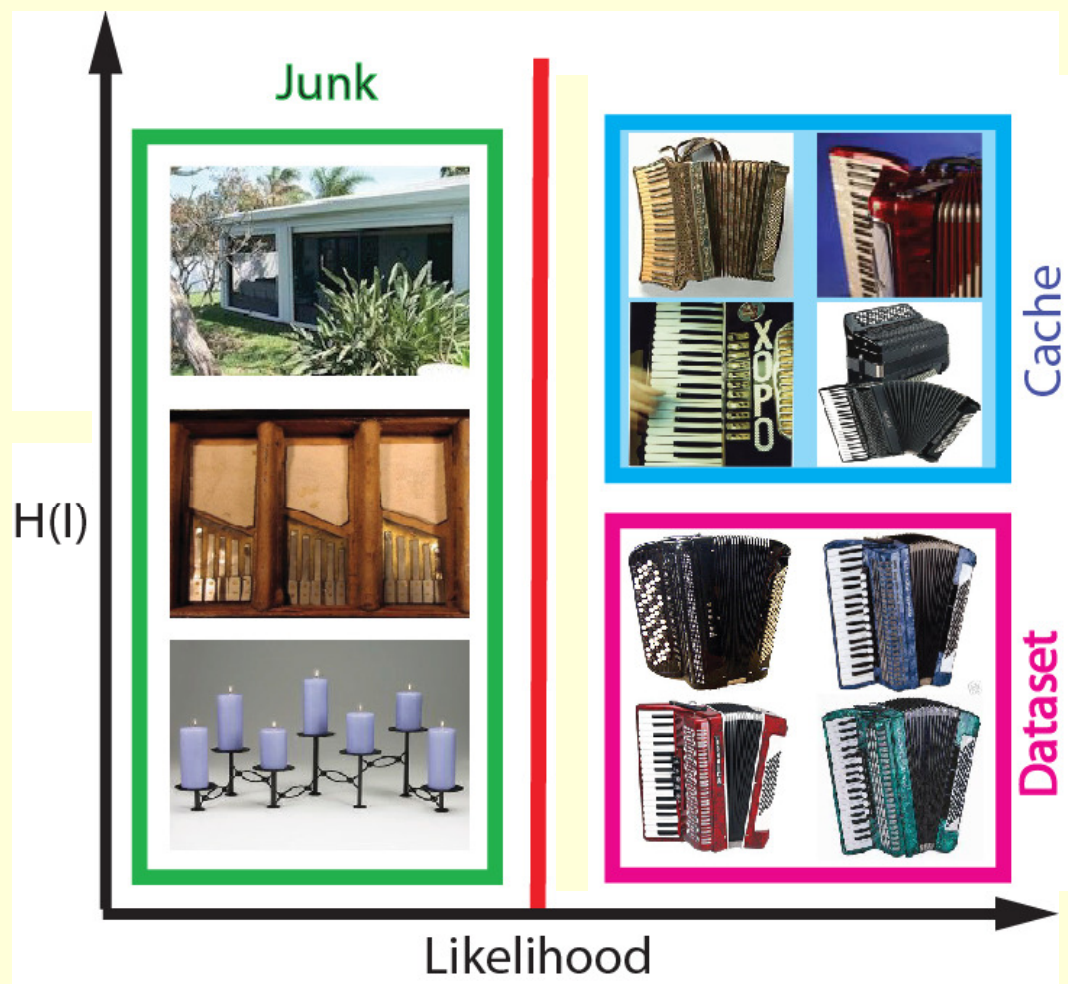
Pitfall #1: model drift



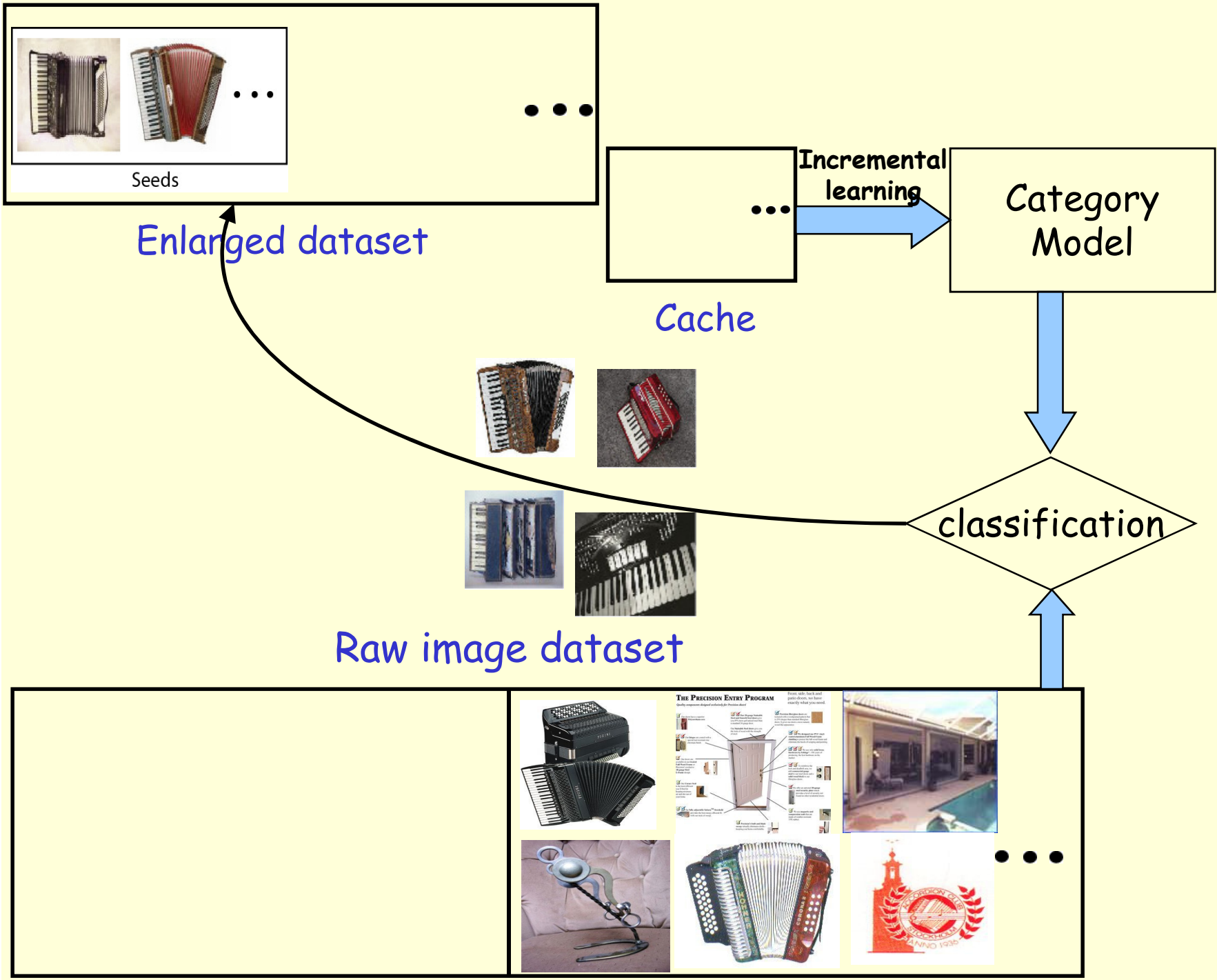
Pitfall #2: model diversity



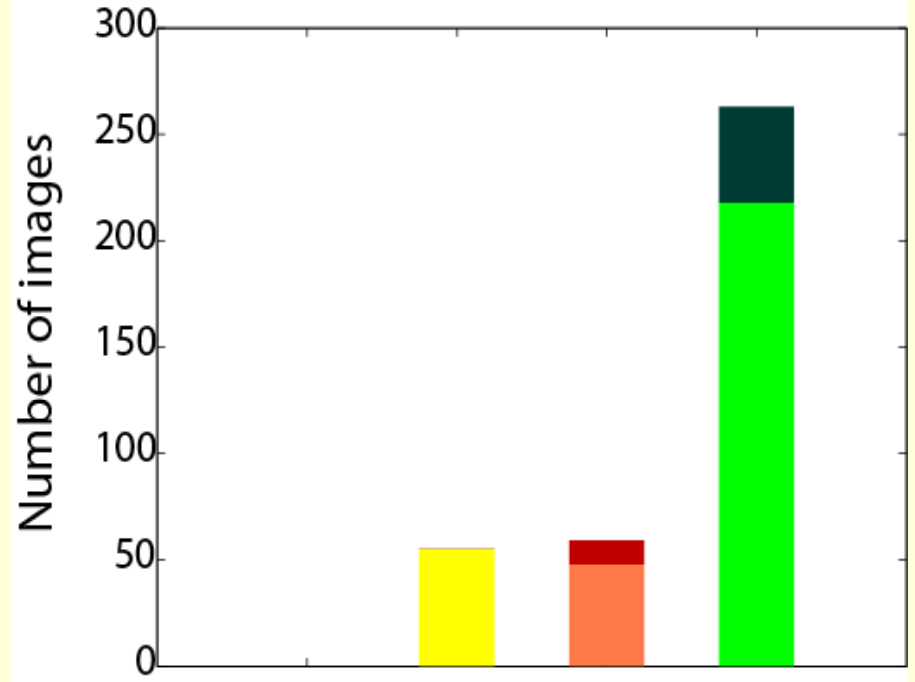
The “cache set”



$$H(I) = - \sum_z p(z|I) \ln p(z|I)$$



Result



Labelme

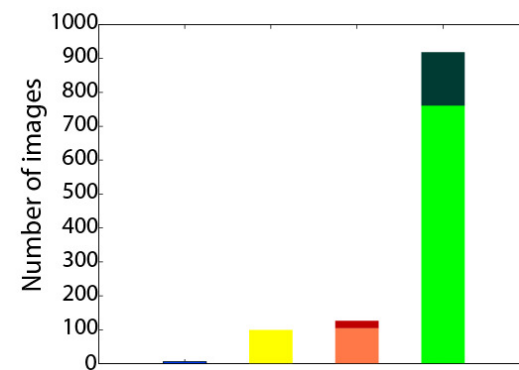
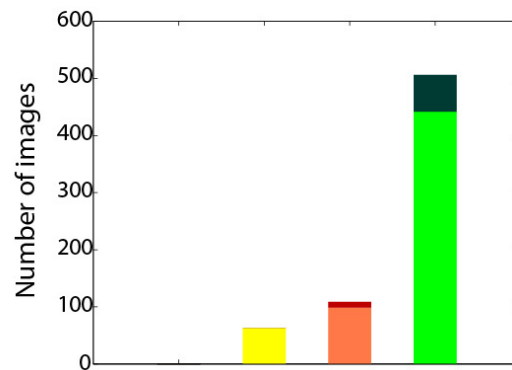
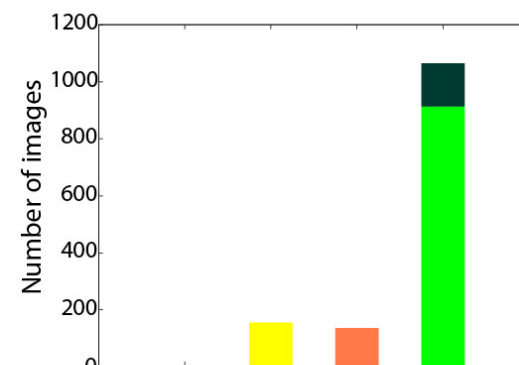
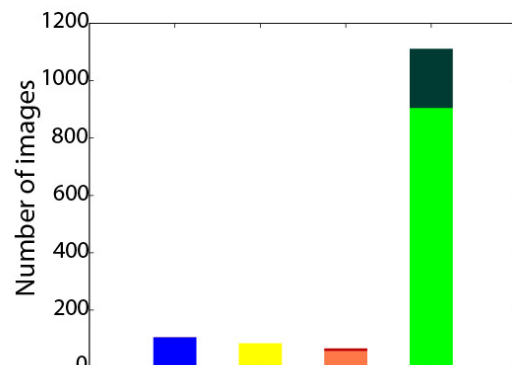
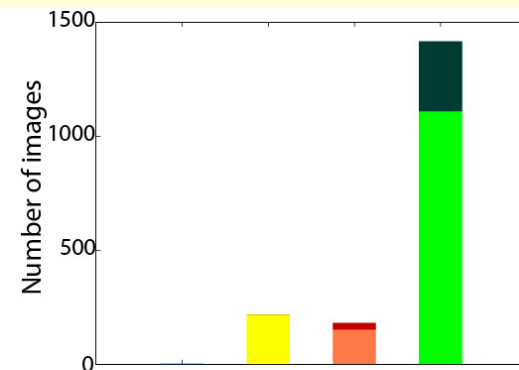
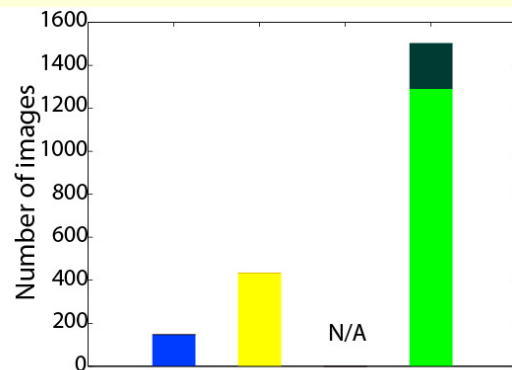
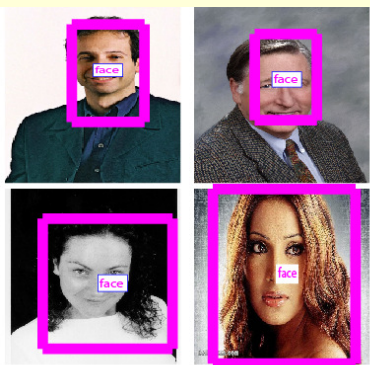
101(Human)

101(OPTIMOL) P

101(OPTIMOL) F

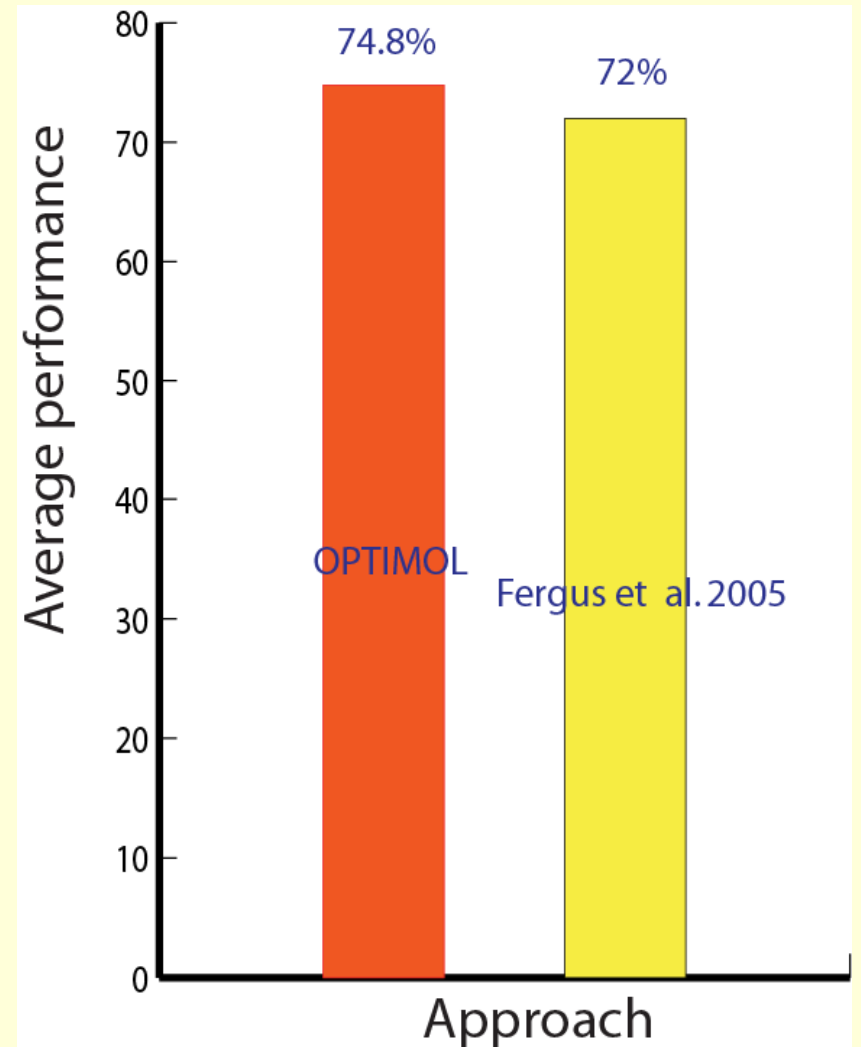
web(OPTIMOL) P

web(OPTIMOL) F



OPTIMOL also learns good models

	p	c	f	b	l	u	w
airplane	76.0	14.0	0.3	5.3	0.3	0.3	4.8
car	1.0	94.5	0.3	4.5	0.3	0.3	0.3
face	0.5	1.4	82.9	3.7	0.5	0.5	11.5
guita	2.2	4.9	5.6	60.4	13.3	0.2	13.3
leopard	1.0	2.0	1.0	5.0	89.0	1.0	2.0
motorbike	0.3	5.5	0.3	5.5	1.0	67.3	20.5
watch	1.7	5.5	17.7	11.0	5.5	5.0	53.6



Animals on the Web

Tamara L. Berg
D. Forsyth

Presented at CVPR '06.

I want to find lots of good pictures of monkeys...

What can I do?

Google Image Search -- monkey

monkey - Google Image Search http://images.google.com/images?hl=en&q=monkey&btnG=Search...













[Sign in](#)

[Google](#) [Web](#) [Images](#) [Video](#) [News](#) [Maps](#) [more »](#)

monkey

Moderate SafeSearch is on

Images Showing: [All image sizes](#) Results 1 - 20 of about 1,060,000 for monkey [\[definition\]](#)

			
monkey 300 x 327 - 24k - jpg plus.maths.org	super code monkey 215 x 161 - 9k - jpg money.cnn.com	singapore-zoo-monkey-65 1044 x 1586 - 453k - jpg photo.net	this is no ordinary monkey 722 x 548 - 90k - jpg www.noordinarymonkey.com
			
this is no ordinary monkey 640 x 480 - 109k - jpg www.noordinarymonkey.com	No Touch Monkey cover 207 x 288 - 24k - jpg www.ayunhalliday.com	angry monkey zoo, south africa ZA ... 258 x 206 - 26k - jpg profile.myspace.com	... Tinta Anti Personal Space Monkey 432 x 576 - 157k - jpg www.bocatinta.com
			
Slide 002032 Lagothrix flavicauda ... 640 x 427 - 199k - gif pin.primat.wisc.edu	News from the Monkey side 1024 x 742 - 57k - png home.gna.org	Mono cubano Cuban monkey 504 x 443 - 30k - jpg pangaea.org	20040925.jpg 550 x 660 - 111k - jpg www.monkey-business.net

1 of 2 3/27/07 4:09 PM

monkey - Google Image Search http://images.google.com/images?q=monkey&gbv=2&svnum=10&h...













[Sign in](#)

[Google](#) [Web](#) [Images](#) [Video](#) [News](#) [Maps](#) [more »](#)

monkey

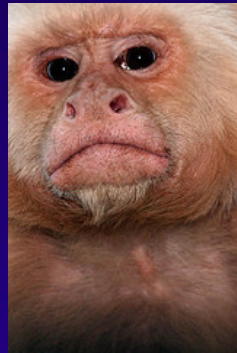
Moderate SafeSearch is on

Images Showing: [All image sizes](#) Results 21 - 40 of about 1,060,000 for monkey [\[definition\]](#)

			
George the monkey 250 x 284 - 13k - jpg www.george.site.btinternet.co.uk	Click to enlarge photo. 300 x 224 - 12k - jpg www.honolulu zoo.org	Japanese Macaque - Macaca fuscata 296 x 320 - 26k - jpg www.blueplanetbiomes.org	Gorilla 374 x 275 - 17k - gif www.citizenlunchbox.com
			
plastique-monkey-SHOP-820.jpg ... 799 x 820 - 124k - jpg www.plastiquemonkey.com	monkey 180 x 240 - 15k - jpg www.answers.com	Super man or is it Superman? 640 x 480 - 66k - jpg www.monkey.net [More from www.monkey.net]	Flaming Monkey 546 x 532 - 62k - jpg members.lycos.nl
			
Monkey Journal 834 x 551 - 51k - png www.gnome.org	Lenin's monkey 1092 x 950 - 1048k - jpg library.uwsp.edu	Lenin's monkey 518 x 676 - 209k - jpg library.uwsp.edu [More from library.uwsp.edu]	Free Monkey Interact 341 x 669 - 90k - jp www.free-monkey.com

1 of 2 3/27/07 4:12 PM

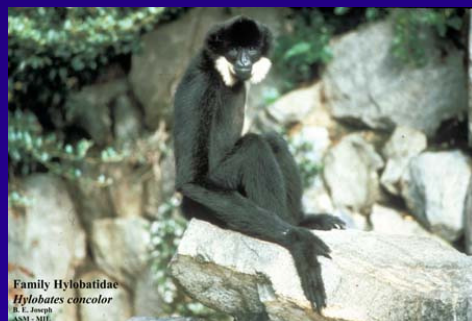
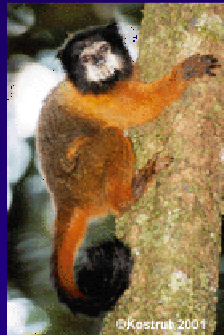
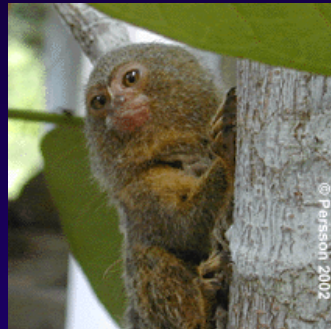
Flickr Search - monkey



Even with humans doing the labeling, the data is extremely noisy -- context, polysemy, photo sets

Words alone still won't work!

“Animals on the Web” Results



General Approach

- Vision alone won't solve the problem.
- Text alone won't solve the problem.
 - > Combine the two!

Consumer Photo Collections

Flickr – 3 billion photographs, several million uploaded per day

Over the hills and far away



Road, Hills, Germany, Hoffenheim, Outstanding Shots, specland, Baden-Wuerttemberg

Heavenly



Peacock, AlbinoPeacock, WhiteBeauty, Birds, Wildlife, FeathredaleWildlifePark, PictureAustralia, ImpressedBeauty

End of the world - Verdens Ende - The lighthouse 1



Verdens ende, end of the world, norway, lighthouse, ABigFave, vippefyr, wood, coal

Museum and Library Collections

Fine Arts Museum of
San Francisco (82,000
images)



bowl stemmed
small Irrescent
glass



Woman of Head
Howard H G Mrs Gift
America North bust
States United Sculpture
marble

New York Public Library Digital
Collection



The new board walk,
Rockaway,
Long Island



Part of New England,
New York, east New
larsey and Long
lland.

Web Collections

Billions of Web Pages

Tree - Wikipedia, the free encyclopedia

http://en.wikipedia.org/wiki/Tree

Tree

From Wikipedia, the free encyclopedia

A **tree** is a large, perennial, woody plant. Though there is no set definition regarding minimum size, the term generally applies to plants at least 6 m (20 ft) high at maturity and having secondary branches supported on a main stem or stems (see shrub for comparison). Most trees exhibit clear apical dominance, though this is not always the case (Mitchell, 1978).^[1] Compared with most other plant forms, trees are long-lived. A few species of trees grow to 115 m (375 ft) tall and some can live for several thousand years.



Trees are an important component of the natural due to their prevention of erosion and significant landscaping and agriculture, both for their aesthetic and their orchard crops (such as apples). Wood a common building material. Trees also play a part in many of the world's mythologies (see trees: Trees have also been found to play an important producing oxygen and reducing carbon dioxide atmosphere, as well as moderating ground temperature increasing albedo. These traits could potentially alleviate Global warming.

Tillamook Rock Lighthouse, Oregon at Lighthousefriends.com

http://www.lighthousefriends.com/light.asp?ID=135



Tillamook Rock, OR



Description: One mile west of Tillamook Head, a rock rises from the ocean. In the shape of a sea monster, it is where old Nor'westers go to die. Where Indians believed under ocean tunnels inhabited by spirits came to the surface. Where sheer cliffs drop straight into the sea to depths of 96 to 240 feet. Where clinging to the top, fighting off the gripping hands of the sea, stands a lighthouse. A symbol of the precarious line between human endeavor and the forces of nature.

An intriguing and powerful testament of the will and determination of the human spirit, the story of Tillamook Rock Lighthouse began in 1879. Originally, it was hoped that a lighthouse could be built at Tillamook Head, a 1,000 foot high headland 20 miles south of the Columbia River. However, with its high elevation, fog often shrouded the top and its sheer face offered no acceptable alternative.

In June 1879, a lighthouse engineer boasted out to the rock to determine if a lighthouse there would be feasible. Though there were monstrous seas, and a landing was impossible, the engineer decided the rock could be conquered. The first surveyors accessed the site by jumping from a rocking boat onto the rock. On one attempt, master mason John R. Trewavas, who had a major role in the construction of a similar lighthouse on Wolf Rock off of Land's End, England, made the trip to the rock with his assistant Cherry. In attempting a landing, Trewavas slipped and was swept into the churning sea. Cherry dove in after him, but couldn't find him. The boat was able to rescue Cherry, but Trewavas was never found.

The locals, skittish of the project to begin with, raised an outcry over the foolhardiness of the endeavor. No local skilled workers could be found willing to work on the construction. Charles A. Ballantyne, who replaced Trewavas, hired men unfamiliar with the area and sequestered them in the Cape Disappointment keepers' quarters until construction could begin, in hopes the locals would not scare them away.

On October 21, 1879, four laborers were put on the rock. The rest of the crew followed five days later. Putting men on the rock entailed strung a 4 1/2" line from the U.S. Revenue Cutter, *Thomas Corwin*, to the rock. The men would then use a "breaches buoy" to cross the line. With the cutter rolling and pitching in the swells, the line was never taut, and the transported fellow was often drug through the icy water.

The first two weeks of construction found the crew totally exposed to the elements. Barren of caves, overhangs or ledges, the rock could not even provide minimal shelter. The workers chipped, chiseled, and blasted away. And then it hit.

Contents

- 1 Classification
- 2 Morphology
- 3 Life stages
- 4 Champion trees
 - 4.1 Tallest trees
 - 4.2 Stoutest trees
 - 4.3 Largest trees
 - 4.4 Oldest trees
- 5 Trees in culture
- 6 Major tree genera
 - 6.1 Flowering plants (Magnolioid angiosperms)
 - 6.1.1 Dicotyledons (Magni broadleaf or hardwood tr
 - 6.1.2 Monocotyledons (L
 - 6.2 Conifers (Pinophyta; softw
 - 6.3 Ginkgos (Ginkgophyta)

1 of 7

1 of 4

3/28/07 9:44 PM

Giant Pandas at the National Zoo - National Zoo/ FONZ

http://nationalzoo.si.edu/Animals/GiantPandas/

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Giant Pandas

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Giant Pandas:
Fujifilm Giant Panda Habitat
Meet the Pandas
Panda Habitat
Mei & Tian's Enrichment
Meet the Panda Staff
Panda Photo Gallery
Cub Photo Gallery
Giant Pandas for Kids
Giant Panda Facts
Conservation & Science
News & Event Archive
Frequently Asked Questions
More Panda Resources

Panda Cam:
Bibliography
Web Resources:
[Panda](#)
[Panda](#)
[Panda](#)
"Learning from Tai Shan" in Chinese
Visit the Prer Gallery of Art and Nur M. Sackler Gallery, the Smithsonian's National Museum of Art
Related Scientific Publications

US Lead Corporate Sponsor:
UJIFILM
Sole Sponsor:
Planet
It's more the latest Animal Planet web site. Sign up for the Animal Planet newsletter from Discovery Communications.
Chase Panda Cam, a book with ages of Tai Shan's first seven births, at the National Zoo Store.

News from the Fujifilm Giant Panda Habitat

We expect that Tai Shan will, at a minimum, be here throughout the summer and early fall. → [more](#)

Coming soon: a photo diary of National Zoo Director John Berry's recent trip to China.

March 27: This Year's Breeding Plans

As part of our giant panda research program and to strengthen genetic variability among zoo pandas, we are planning to artificially inseminate Mei Xiang with semen from Gao Gao, San Diego Zoo's adult male panda, should Mei drop.

Flower Picture Gallery

Moosey Hybrid Dahlias...
Sun 22th Nov 2004
Picture (7 of 1048)

Species Daylily...
Sun 22th Nov 2004
Picture (7 of 1048)

Hemerocallis...
Sun 22th Nov 2004
Picture (7 of 1048)

Close up detail of the pollen laden stamens on a species Hemerocallis.

Flower Picture Gallery

http://www.mooseycountrygarden.com/flower-picture-gallery/flower...

mooseycountrygarden.com » Garden Picture Gallery

Flower Picture Gallery

[Flower pictures](#) - Looking for flower pictures? Flower pictures - Wide variety of flowers - Do-Flower.com/Pictures

[Flower Photo Gallery](#) - Browse our free galleries. Free photos, screen savers & more! Always.com!

[Rose Flower](#) - Need Rose Flower? Save on Plants and Flowers www.smarter.com

[Flower Lily](#) - Looking for Red Flower Lily? Visit our flower Lily guide. LilyHistory.info

[Ads by Google](#)

Flowers are important to [gardeners](#), and we all have our favourite annuals, perennials and flowering shrubs. Sometimes we choose a shrub of plant solely because of the colour or style of its flowers, and can be lamely disappointed with their transient nature. But would we want our plants to flower for ever? The photographs in the Gallery are a mixture of small and big, tidy and messy flowers.

Raindrop on Camellia...
Mon 3rd Oct 2005
Picture (7 of 1048)

Pink petals of my favourite deep pink Camellia, with a few artistic raindrops!

Unknown Lily...
Sat 9th Apr 2005
Picture (7 of 1048)

I don't want to say about this lily - even if it's an Asiatic or an Oriental. My local nursery lady threw it in with a trailer load of bargain bin scruff I was taking home. A gardening friend thinks it could possibly be called Stargazer...

Moosey Hybrid Dahlias...
Wed 10th Mar 2004
Picture (7 of 1048)

This multi-coloured dahlia must have been created by my bees! Only have plain red and plain yellow ones in the garden.

Species Daylily...
Sun 22th Nov 2004
Picture (7 of 1048)

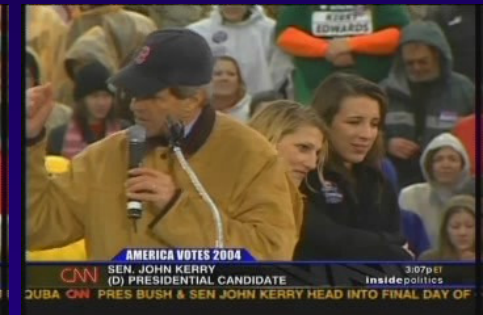
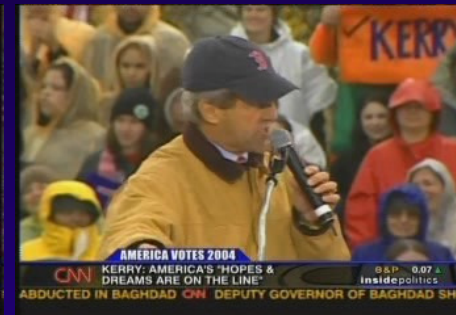
I have several clumps of this rust coloured species daylily.

Natural Flowers & Leaves
Orchids, Roses, Carnations & Leaves Preserved
Forever Wholesale Retail
www.foreverwholesale.com

1 of 3

3/28/07 9:41 PM

Video



OUTSIDE IN THE RAIN THE SENATOR WEARING HIS UH BASEBALL CAP A BOSTON RED SOX CAP AS HE TALKED TO HIS SUPPORTERS HERE IN THE RAIN THE UH SENATOR THEY'RE DOING HIS BEST TO TRY TO MAKE HIS CASE THAT HE WILL BE THE MAN FOR THE MIDDLE CLASS AND UH TRY TO CONVINCHE HIS SUPPORTERS TO EXPRESS THEIR SUPPORT THROUGH A VOTE ON TUESDAY IN THERE WE ARE TWENTY FOUR HOURS FROM THE GREAT MOMENT THAT THE WORLD IN AMERICA IS WAITING FOR IT I NEED TO YOU IN THESE HOURS TO GO OUT AND DO THE HARD WORK NOT ON THOSE DOORS MAKE THOSE PHONE CALLS TO TALK TO FRIENDS TAKE PEOPLE TO THE POLLS HELP US CHANGE THE DIRECTION OF THIS GREAT NATION FOR THE BETTER CAN YOU IMAGINE A UH SENATOR BEGINNING HIS DAY IN FLORIDA TODAY

TrecVid 2006

Consumer Products



Marc by Marc Jacobs
Adorable peep-toe pumps, great for any occasion. Available in an array of uppers. Metallic fabric trim and bow detail. Metallic leather lined footbed. Lined printed design. Leather sole. 3 3/4" heel.

Zappos.com



soft and glassy patent calfskin trimmed with natural vachetta cowhide, open top satchel for daytime and weekends, interior double slide pockets and zip pocket, seersucker stripe cotton twill lining, kate spade leather license plate logo, imported
2.8" drop length
14"h x 14.2"w x 6.9"d

Katespade.com



It's the perfect party dress. With distinctly feminine details such as a wide sash bow around an empire waist and a deep scoopneck, this linen dress will keep you comfortable and feeling elegant all evening long.

* Measures 38" from center back, hits at the knee.

* Scoopneck, full skirt.

* Hidden side zip, fully lined.

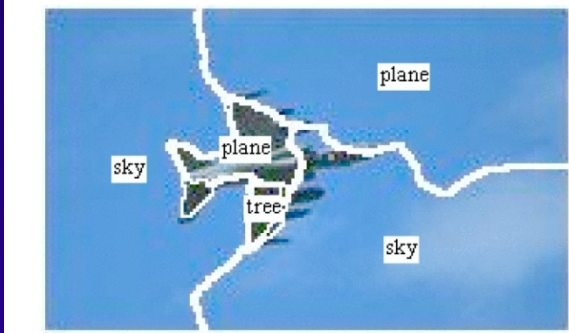
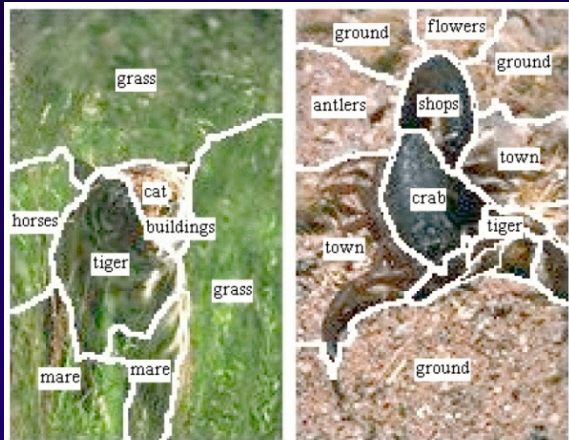
* 100% Linen. Dry clean.

bananarepublic.com

E-commerce transactions in 2004, 2005, 2006 of \$145 billion, \$168 billion, and \$198 billion (Forrester Research).

Previous Work - Words & Pictures

Labeling Regions



Barnard et al,
JMLR 2003

Clustering Art



Barnard et al,
CVPR 2001

Auto-Annotation



Li and Wang, PAMI 2003

Image Classification



Yanai et al, MIR 2005

Animals on the Web Outline:

Harvest pictures of animals from the web using Google Text Search.

Select visual exemplars using text based information.

Use visual and textual cues to extend to similar images.

Harvested Pictures



The Interactive Frog Dissection
An on-line tutorial

1994

The New York Times Magazine

Rethinking, thinking
gellfrog - A Smart Notebook for the Times

Find a LeapPad® Book



What's New

ScienceMatrix

Try the World Summit Award-winning program,
new from Digital Frog International. Cell Structure & Function
Free for a limited time.

University of Michigan Museum of Zoology

Animal Diversity Web

About Us Special Topics Teaching About Animal Names Help



Kit Virtuel de Dissection de Grenouille

Retour à zéro

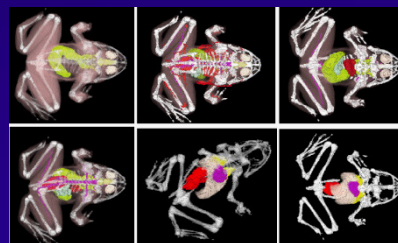
peau squelette cœur intestins paille intestins reins vessie prostate fies gros intestin testis

Langues: Français Albanais Néerlandais Espagnol Italien Portugais

Traduit par Franck Naves

The FROGGY Page

Ribbit.



14,051 images for 10 animal categories.

12,886 additional images for monkey category using related monkey queries (primate, species, old world, science...)

Text Model

Latent Dirichlet Allocation (LDA) on the words in collected web pages to discover 10 latent topics for each category.

Each topic defines a distribution over words. Select the 50 most likely words for each topic.

Example Frog Topics:

1.) frog frogs water tree toad leopard green southern music king irish eggs folk princess river ball range eyes game species legs golden bullfrog session head spring book deep spotted de am free mouse information round poison yellow upon collection nature paper pond re lived center talk buy arrow common prince

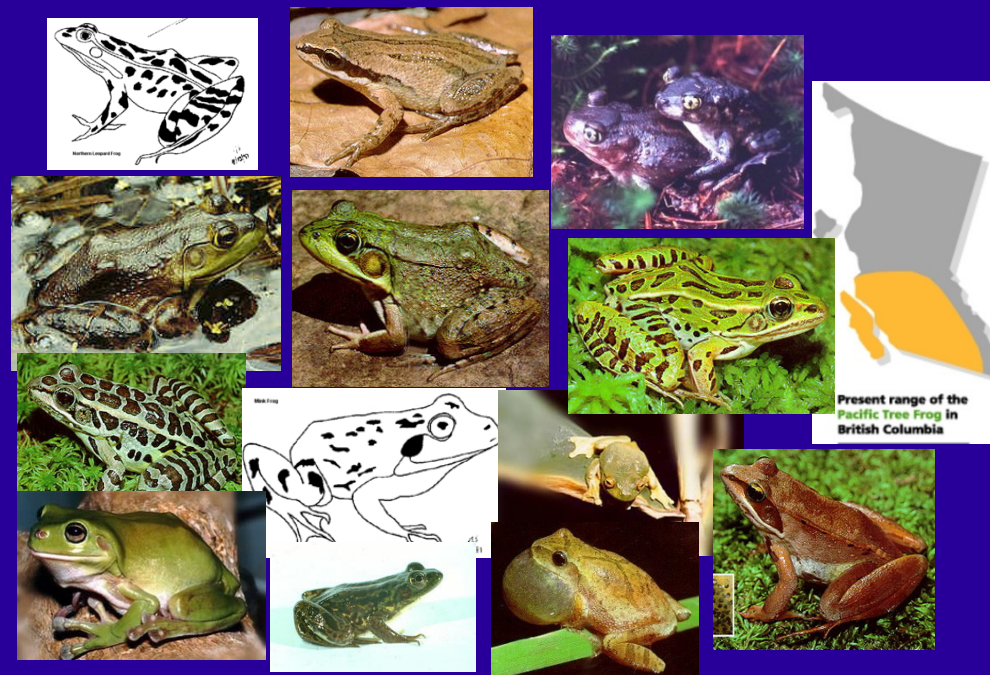
2.) frog information january links common red transparent music king water hop tree pictures pond green people available book call press toad funny pottery toads section eggs bullet photo nature march movies commercial november re clear eyed survey link news boston list frogs bull sites butterfly court legs type dot blue

Select Exemplars

Rank images according to whether they have these likely words near the image in the associated page (word score)

Select up to 30 images per topic as exemplars.

1.) frog frogs water tree toad leopard green southern music king irish eggs folk princess river ball range eyes game species legs golden bullfrog session head ...

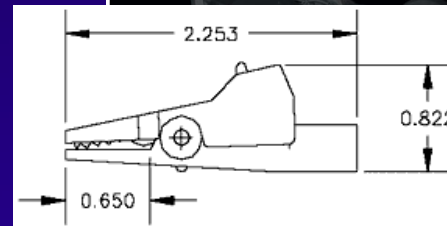
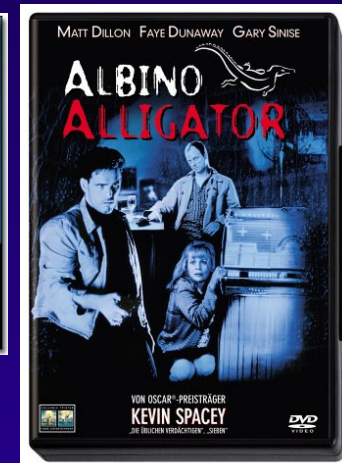


2.) frog information january links common red transparent music king water hop tree pictures pond green people available book call press ...



Senses

There are multiple senses of a category within the Google search results.



Ask the user to identify which of the 10 topics are relevant to their search. Merge.

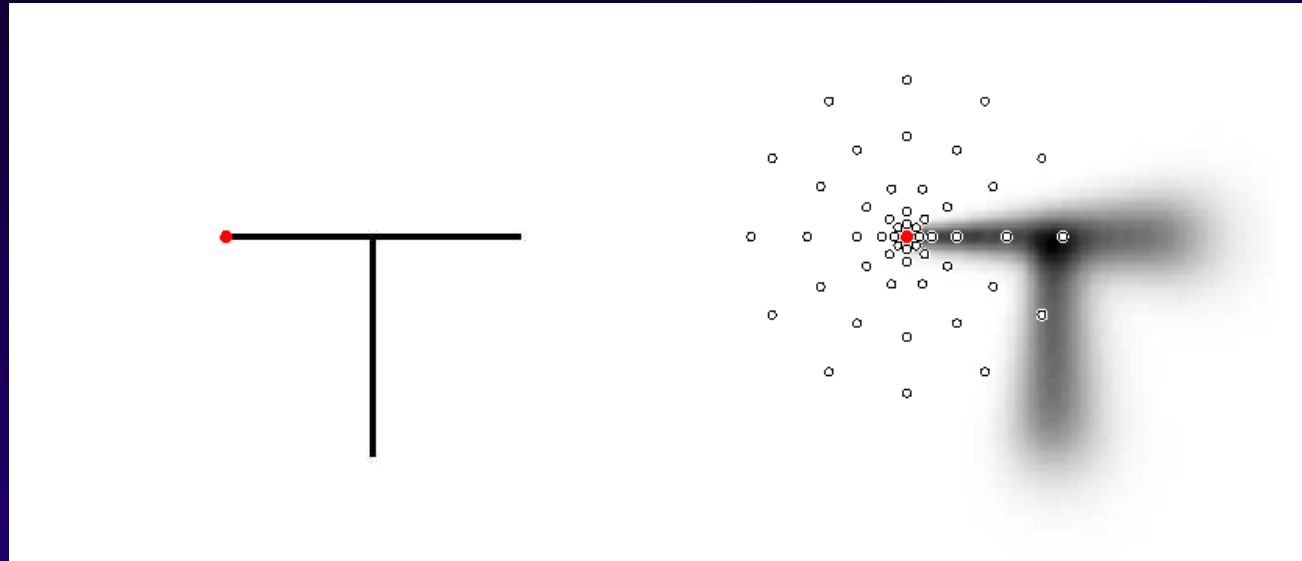
Optional second step of supervision – ask user to mark erroneously labeled exemplars.

Image Model



Match Pictures of a category

Geometric Blur Shape Feature



(A.) Berg & Malik '01

Sparse Signal

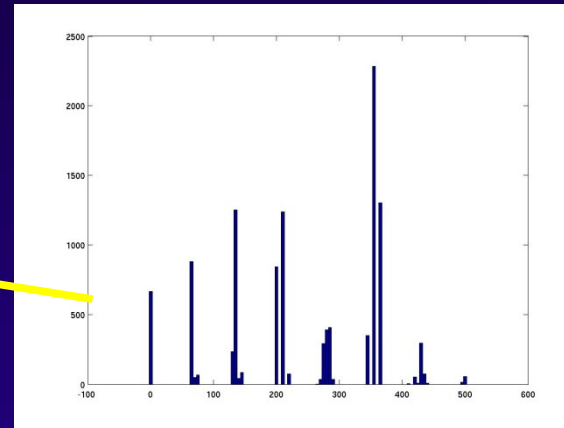
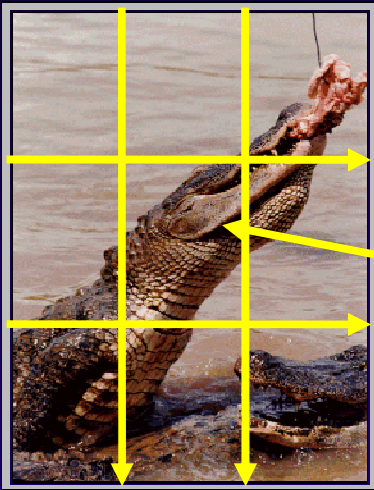
Geometric Blur

Captures local shape, but allows for some deformation.
Robust to differences in intra category object shape.

Used in current best object recognition systems
Zhang et al, CVPR 2006
Frome et al, NIPS 2006

Image Model (cont.)

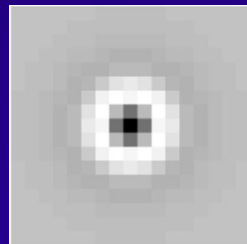
Color Features: Histogram of what colors appear in the image



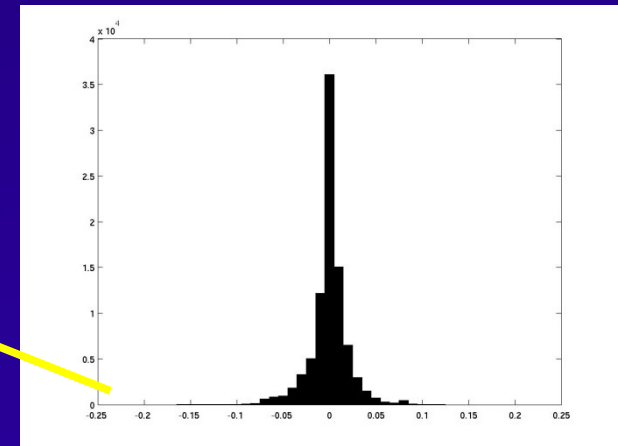
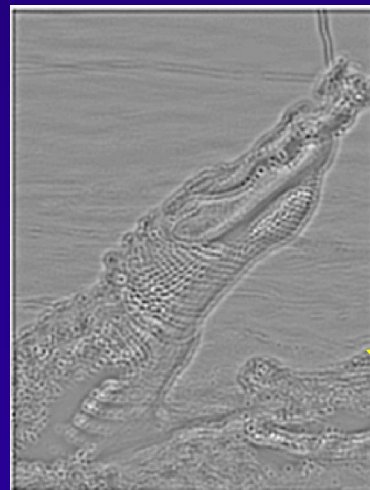
Texture Features: Histograms of 16 filters



*



=



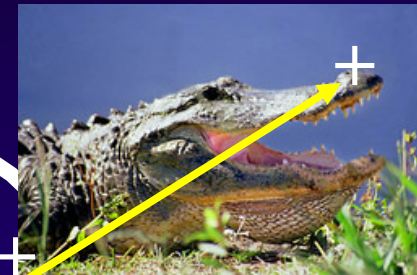
Scoring Images

Irrelevant Features



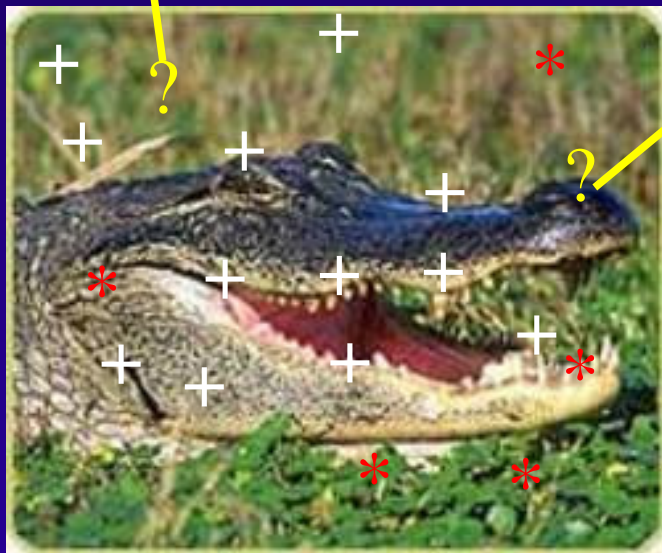
Irrelevant Exemplar

Relevant Features



Relevant Exemplar

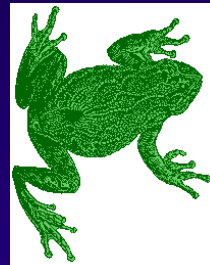
Query



For each query feature apply a 1-nearest neighbor classifier. Sum votes for relevant class. Normalize. Combine 4 cue scores (word, shape, color, texture) using a linear combination.

Classification Comparison

Words

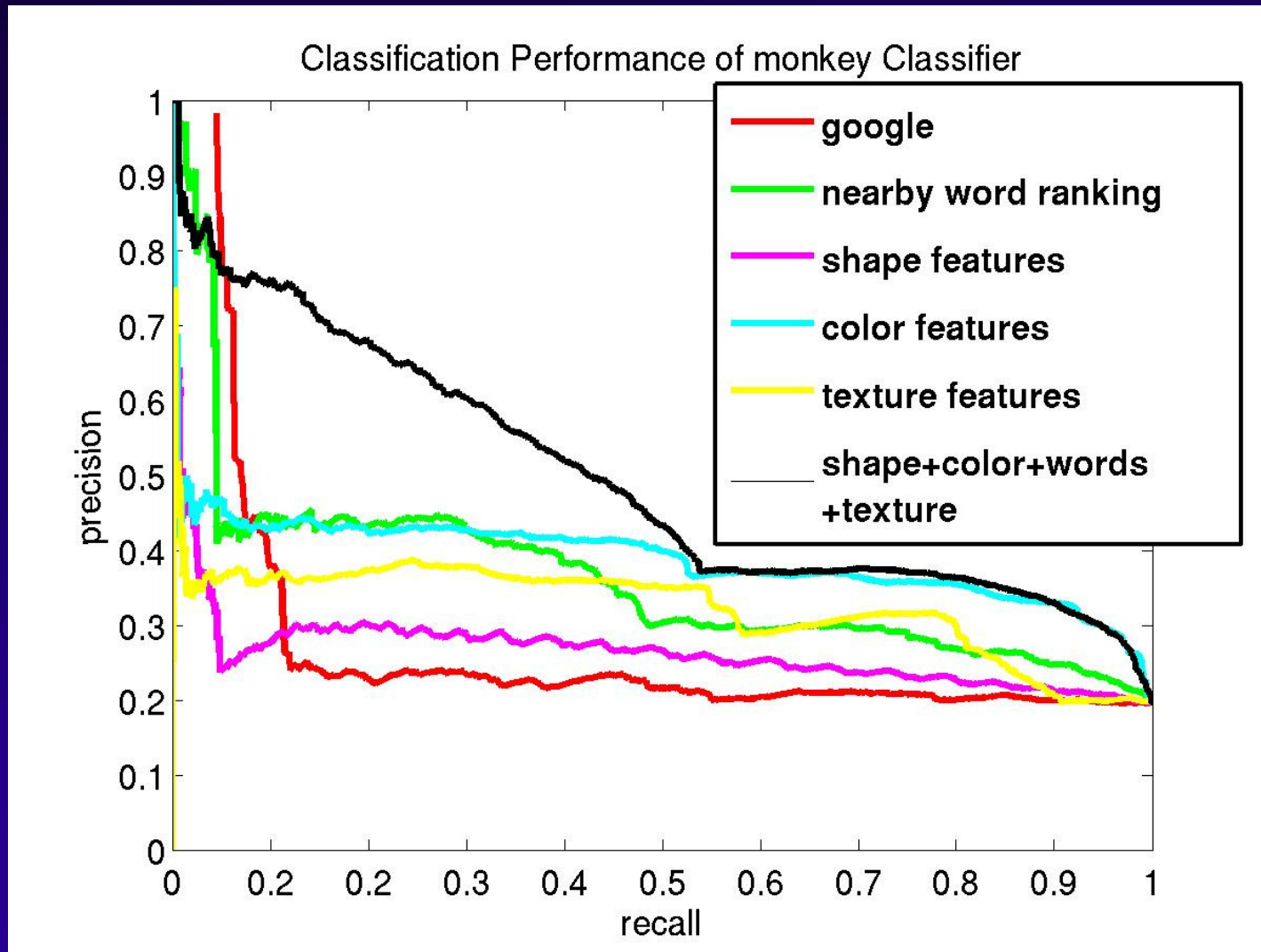


Words + Picture



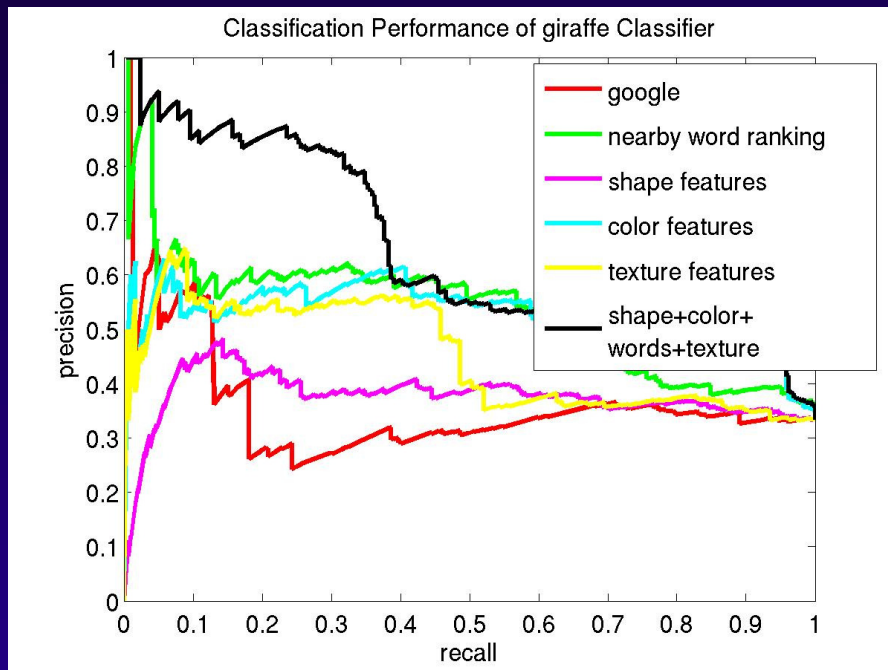
Cue Combination:

Monkey

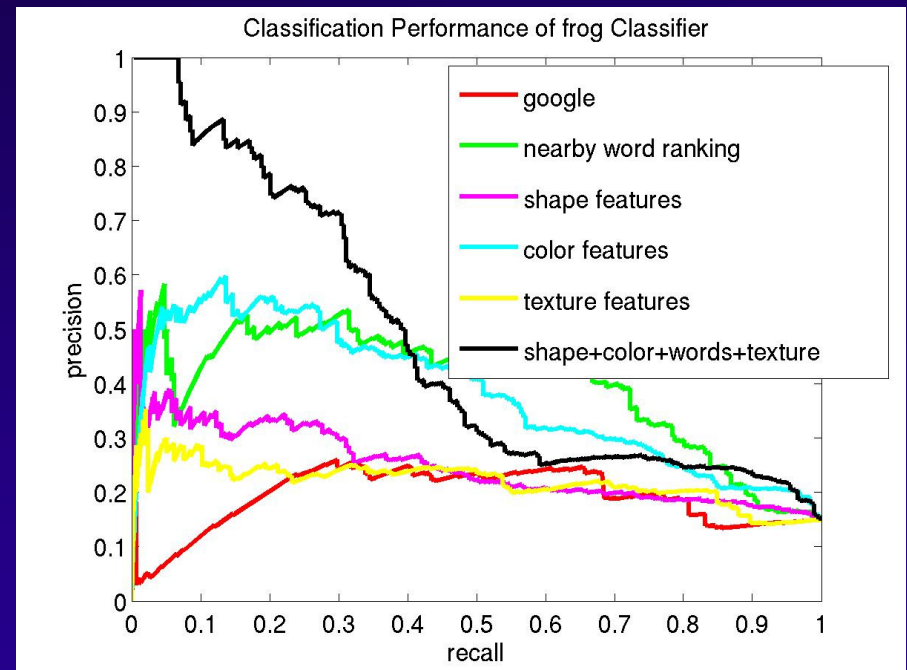


Cue Combination:

Giraffe

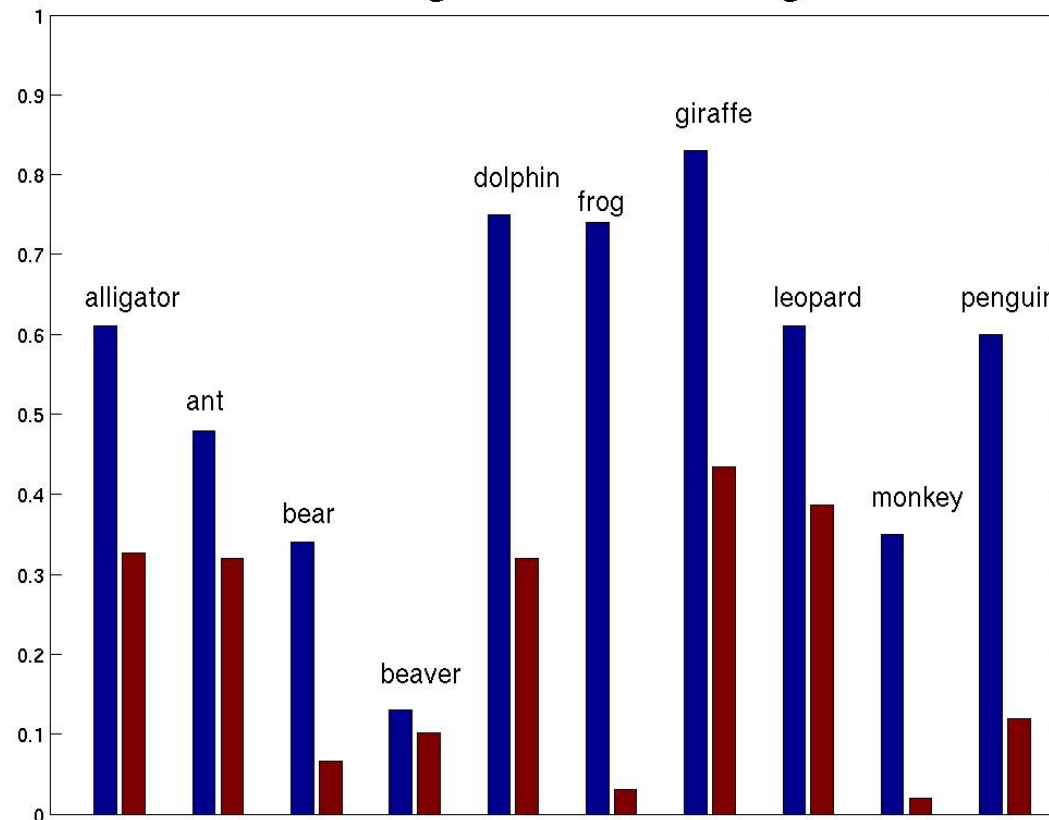


Frog



Re-ranking Precision

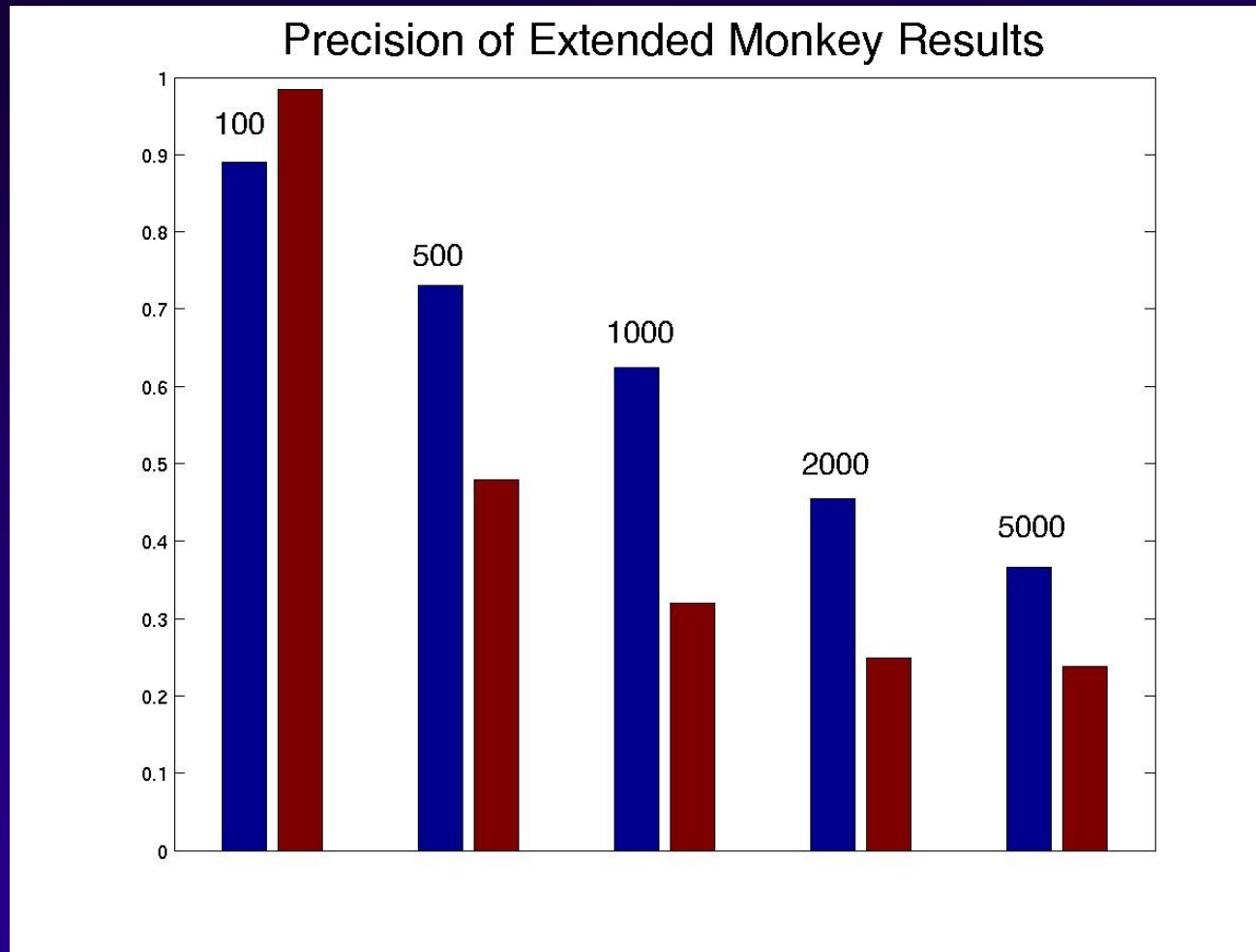
Precision of Categories at 100 images returned



Classification Performance Google

Re-ranking Precision

Monkey



Summary - Berg

Enormous amounts of data.

How to deal with it is still an open question.

We should combine words & pictures

Data opens up lots of new research problems!

WISDOM: An Unsupervised Model of Image Sense

Kate Saenko and Trevor Darrell

*Saenko and Darrell. Unsupervised learning of visual sense models for polysemous words. NIPS 2008,
Saenko and Darrell, Filtering Abstract Senses From Image Search Results, NIPS 2009.*



bag



bag

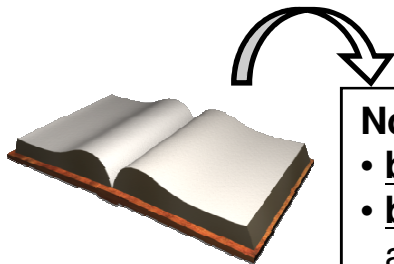


bag



bag

... The **Tote** is the perfect example of two **handbag** design principles that ... The lines of this **tote** are incredibly sleek, but ... The semi **buckles** that form the **handle** attachments are ...



Noun

- **bag, container** (a flexible container with a single opening)
- **bag, handbag, pocketbook, purse** (a container used for carrying money and small personal items or accessories (especially by women))
- **bag, travelling bag, suitcase** (a rectangular container for carrying clothes)

Image Sense Disambiguation

Hurricane,
tornado watch



Celebrity watch



Watch out!

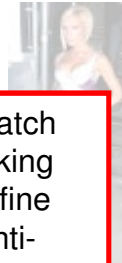
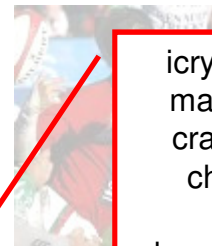


Would rather
watch...

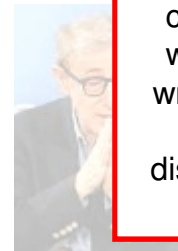


Suicide watch

Text contexts

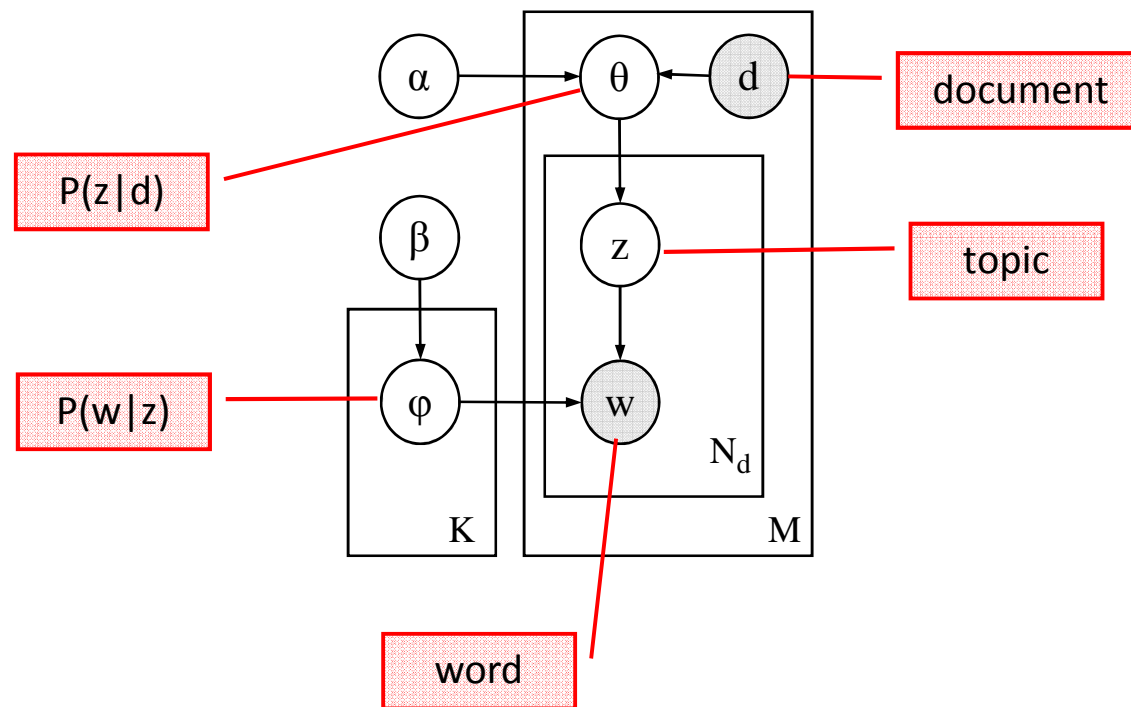


icrystal rfid wrist watch features watch masterpiece innovative watch making craftsmanship absolute precision fine charm high scratch resistance anti-allergenic characteristics make chronometer true jewel s wrist water proof sleek stylish wrist **watch** solar powered available watch ticket key purse identity card special offer place order rfid wrist watch absolutely free rfid watch black wrist strap rfid watch orange wrist strap rfid watch stainless steel privacy disclaimer copyright icrystal pty website



Latent Dirichlet allocation (LDA) (Blei et al. '03)

- One of several techniques for discovering latent dimensions in bag-of-words data

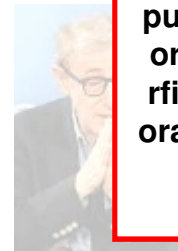
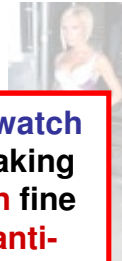


Topic 2

new
world
media
right
said
house
april
obama
islam
march
bush
war
american
time

...

Latent Topics

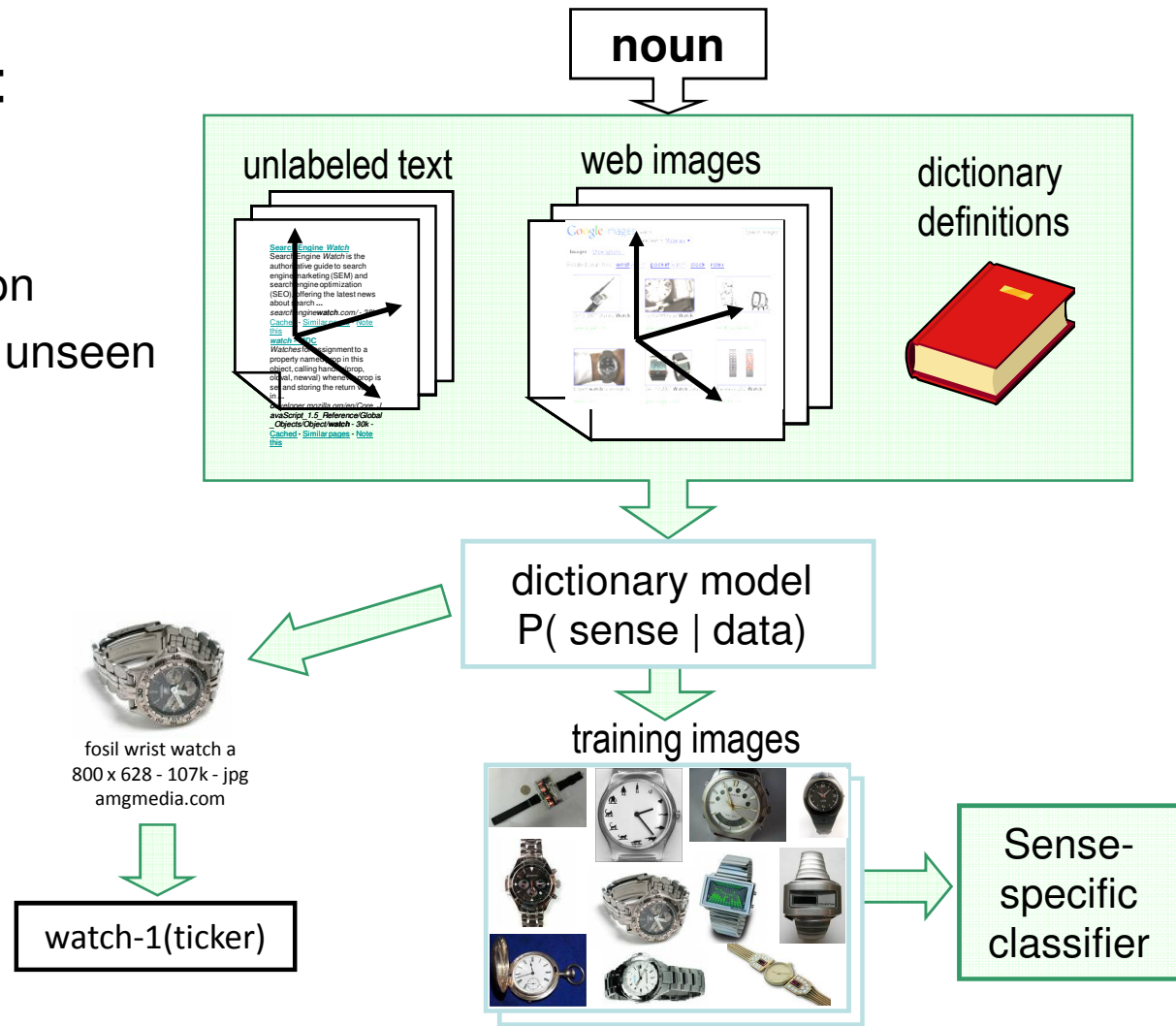


icrystal rfid wrist watch features watch masterpiece innovative watch making craftsmanship absolute precision fine charm high scratch resistance anti-allergenic characteristics make chronometer true jewel wrist water proof sleek stylish wrist watch solar powered available watch ticket key purse identity card special offer place order rfid wrist watch absolutely free rfid watch black wrist strap rfid watch orange wrist strap rfid watch stainless steel privacy disclaimer copyright icrystal pty website

Web Image Sense DictiONary Model

WISDOM does:

1. image sense disambiguation
2. dataset collection
3. classification of unseen images



WISDOM: Using dictionary entries to ground senses

- Use entry text to learn a probability distribution over words for that sense
- Problem: entries contain very little text
 - Expand by adding synonyms, example sentences, etc.
 - Still, very few words are covered!

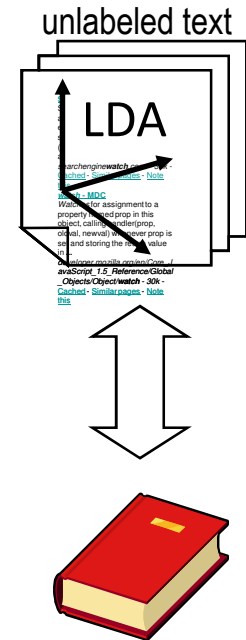
- **S:** (n) **mouse** (any of numerous small rodents typically resembling diminutive rats having pointed snouts and small ears on elongated bodies with slender usually hairless tails)
- *direct hyponym / full hyponym*
 - **S:** (n) [house mouse](#), [Mus musculus](#) (brownish-grey Old World mouse now a common household pest worldwide)
 - **S:** (n) [harvest mouse](#), [Micromyx minutus](#) (small reddish-brown Eurasian mouse inhabiting e.g. cornfields)
 - **S:** (n) [field mouse](#), [fieldmouse](#) (any nocturnal Old World mouse of the genus Apodemus inhabiting woods and fields and gardens)
 - **S:** (n) [nude mouse](#) (a mouse with a genetic defect that prevents them from growing hair and also prevents them from immunologically rejecting human cells and tissues; widely used in preclinical trials)
 - **S:** (n) [wood mouse](#) (any of various New World woodland mice)
- *direct hypernym / inherited hypernym / sister term*
 - **S:** (n) [rodent](#), [gnawer](#) (relatively small placental mammals having a single pair of constantly growing incisor teeth specialized for gnawing)

WISDOM: Probabilistic dictionary-based model

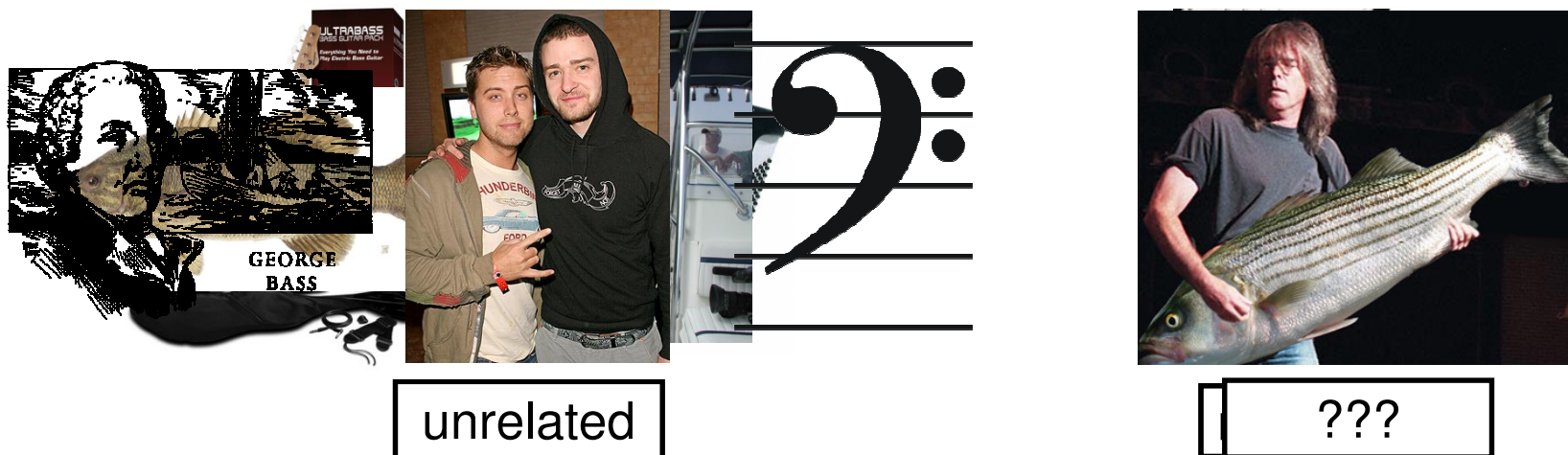


Main idea:

- Using LDA, learn latent sense-like dimensions on a large amount of related text,
- Model dictionary senses in LDA space:
 - Map image contexts to topics
 - Map topics to senses



Evaluation datasets



- Collected by querying **YAHOO!** Image Search
 - MIT-ISD: bass, face, mouse, speaker, watch
 - MIT-OFFICE: cellphone, fork, hammer, keyboard, mug, pliers, scissors, stapler, telephone, watch
 - UIUC-ISD: bass, crane, squash

ISD example results

bass: raw web image data



bass: fish



bass: musical instrument



squash: raw web image data



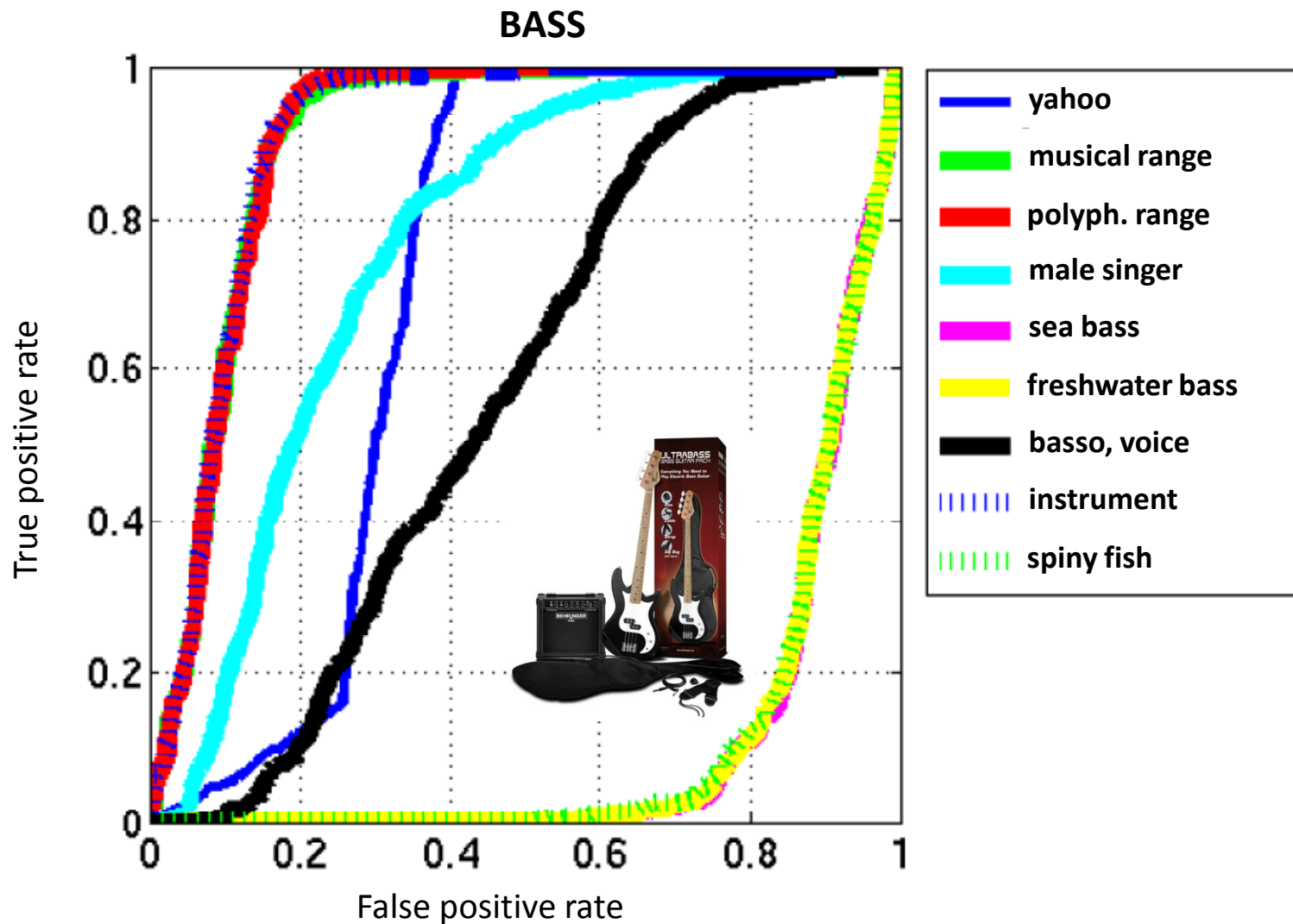
squash: vegetable



squash: sports



ISD Results: ROC using each WordNet sense for BASS



Results: Filtering visual senses

Yahoo Search: “telephone”



DICTIONARY

1: (n) **telephone**, [phone](#), [telephone set](#) (electronic equipment that converts sound into electrical signals that can be transmitted over distances and then converts received signals back into sounds)

2: (n) **telephone**, [telephony](#) (transmitting speech at a distance)

Results: Filtering visual senses

Artifact sense: “telephone”



DICTIONARY

1: (n) **telephone**, [phone](#), [telephone set](#) (electronic equipment that converts sound into electrical signals that can be transmitted over distances and then converts received signals back into sounds)

2: (n) **telephone**, [telephony](#) (transmitting speech at a distance)

Lecture Summary

- The web contains unlimited, but extremely noisy object category data
- The text surrounding the image on the web page is an important recognition cue
- Topic models (pLSA, LDA, HDP, etc.) are useful for discovering objects in images and object senses in text
- Bootstrap model from small amount of labeled or weakly labeled data
- Still an open research problem!

Next Lectures

- Today: learning object categories from the web
 - LSA and LDA models
 - Harvesting training data from the web
 - Exploiting image and text
- Tues. Oct. 20th: Generative models
 - Condensation
 - ISM
 - Transformed-HDPs
 - More Context...
- Thurs. Oct. 22nd: Advanced BOW kernels
 - Pyramid and spatial-pyramid match
 - Multi-kernel learning
 - Latent-part SVM models

Bibliography

- R. Fergus, L. Fei-Fei, P. Perona, and A. Zisserman, "Learning object categories from Google's image search," ICCV vol. 2, 2005, pp.1816-1823 Vol. 2. <http://dx.doi.org/10.1109/ICCV.2005.142>
- Sivic, Russell et al. "Unsupervised object category discovery" ICCV '05
- Fei-Fei and Perona "Scene analysis using LDA" CVPR '05
- T. Berg and D. Forsyth, "Animals on the Web". In Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR). IEEE Computer Society, Washington, DC, 1463-1470. <http://dx.doi.org/10.1109/CVPR.2006.57>
- L.-J. Li, G. Wang, and L. Fei-Fei, "Optimol: automatic online picture collection via incremental model learning," in Computer Vision and Pattern Recognition, 2007. CVPR '07. IEEE Conference on, 2007, pp.1-8. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4270073
- K. Saenko and T. Darrell, "Unsupervised Learning of Visual Sense Models for Polysemous Words". Proc. NIPS, December 2008, Vancouver, Canada. http://people.csail.mit.edu/saenko/saenko_nips08.pdf

Additional reading

- N.Loeff, C.O. Alm, D.A. Forsyth, "Discriminating image senses by clustering with multimodal features". Proceedings of the COLING/ACL 2006 Main Conference Poster Sessions, pages 547–554, Sydney, July 2006 [[PDF](#)]
- G. Wang and D. Forsyth, "Object image retrieval by exploiting online knowledge resources". *IEEE Computer Vision and Pattern Recognition (CVPR)*. 2008. [[PDF](#)]
- F. Schroff, A. Criminisi, and A. Zisserman, "Harvesting image databases from the web," in *Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on*, 2007, pp. 1-8. <http://dx.doi.org/10.1109/ICCV.2007.4409099>
- D. M. Blei and M. I. Jordan, "Modeling annotated data," in *SIGIR '03: Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval*. New York, NY, USA: ACM Press, 2003, pp. 127-134. <http://dx.doi.org/10.1145/860435.860460>
- P. Duygulu, K. Barnard, J. F. G. de Freitas, and D. A. Forsyth, "Object recognition as machine translation: Learning a lexicon for a fixed image vocabulary," in *ECCV '02: Proceedings of the 7th European Conference on Computer Vision-Part IV*. London, UK: Springer-Verlag, 2002, pp. 97-112. <http://portal.acm.org/citation.cfm?id=645318.649254>

Slide Credits

- As attributed...