Words and Pictures

D.A. Forsyth, UIUC

relevant co-authors are:

Kobus Barnard (U. Arizona), Tamara Berg (SUNY- Stony Brook), Alex Berg (Columbia), David Blei (Princeton), Pinar Duygulu (Bilkent U.), Ian Endres (UIUC), Ali Farhadi (UIUC), Nando de Freitas (UBC), Julia Hockenmaier (UIUC) Derek Hoiem (UIUC), Michael Jordan (UCB), Gang Wang (UIUC)

Conclusions

- The words near pictures are informative
  - learn to recognize objects
  - understand the pictures better
- Expose crucial problems in recognition
  - what is worth recognizing?
  - how should we describe things?
  - what should we say about a picture?

A crowd of young adults in a

A girl in a brown shirt and a blue jean skirt is dancing with a young man dressed in a

A group of people standing in a

A large group of people dancing

Dancing at club and

Annotation results in complementary words and pictures

Query on

“Rose”

Example from Berkeley
Blobworld system







Annotation results in complementary words and pictures

Query on

Example from Berkeley
Blobworld system

Annotation results in complementary words and pictures

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“Rose”

and

Example from Berkeley
Blobworld system

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

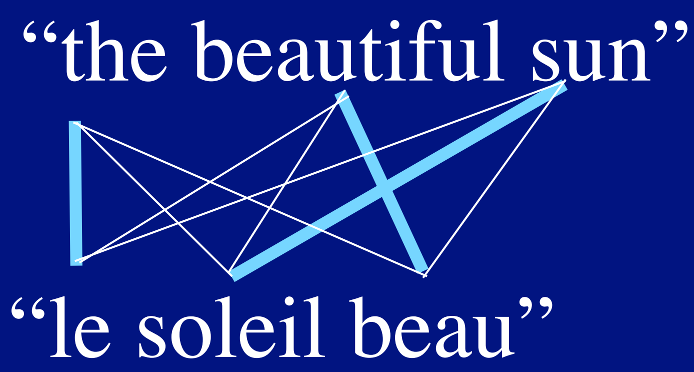
E-commerce transactions in 2004, 2005, 2006 of $145 billion, $168 billion, and $198 billion (Forrester Research).

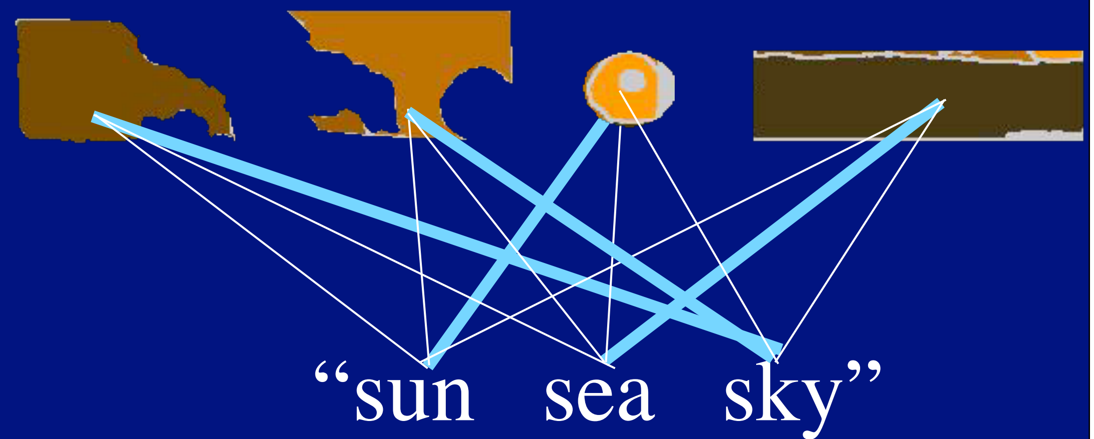
Attaching nouns to regions

tiger cat grass

Quite like object recognition

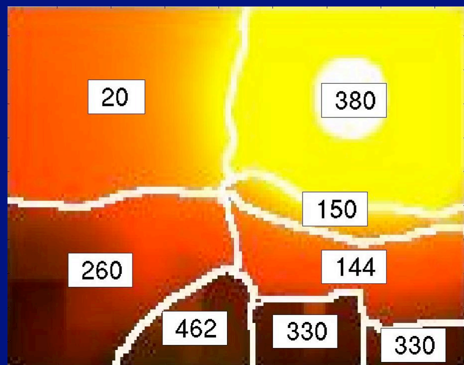
Lexicon building



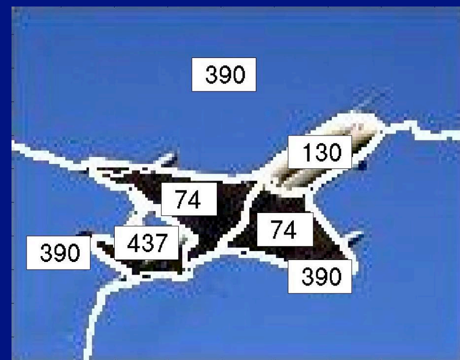


- In its simplest form, missing variable problem
- Pile in with EM
  - given correspondences, conditional probability table is easy (count)
  - given cpt, expected correspondences could be easy
- Caveats
  - might take a lot of data; symmetries, biases in data create issues

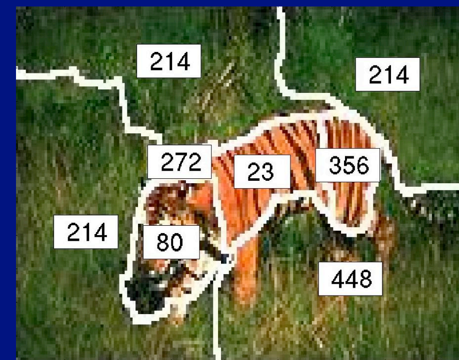
Brown, Della Pietra, Della Pietra & Mercer 93; Melamed 01



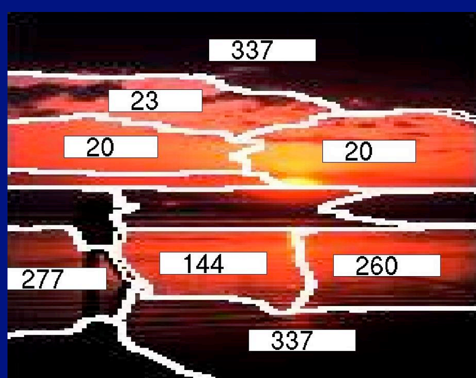
city mountain sky sun



jet plane sky

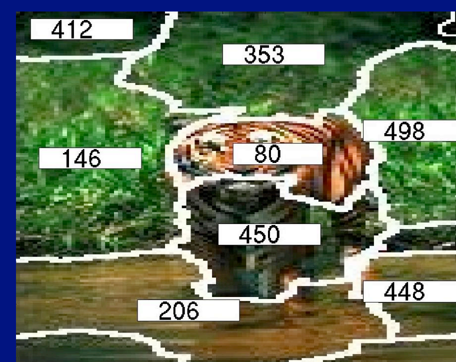


cat forest grass tiger



beach people sun water

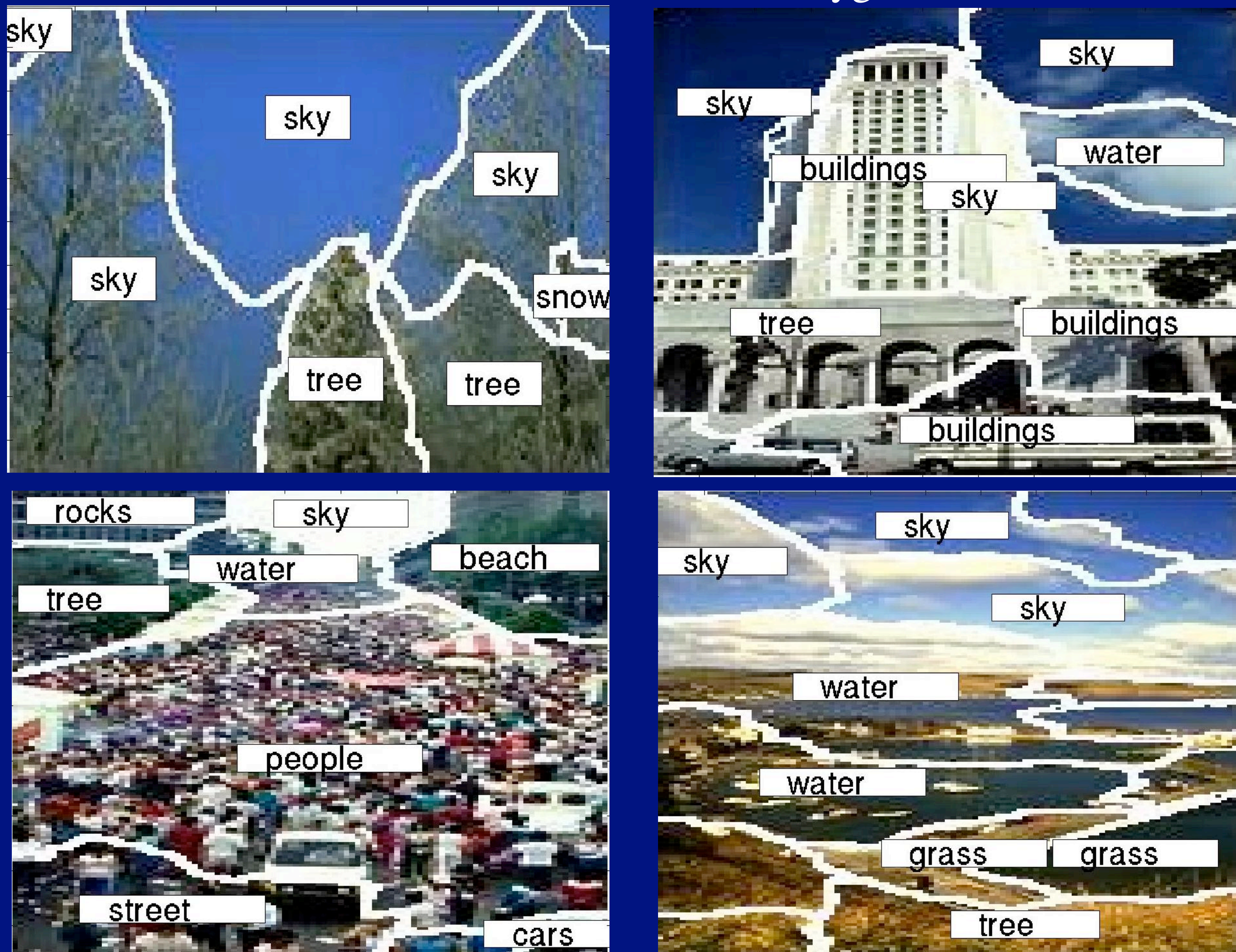
jet plane sky



cat grass tiger water

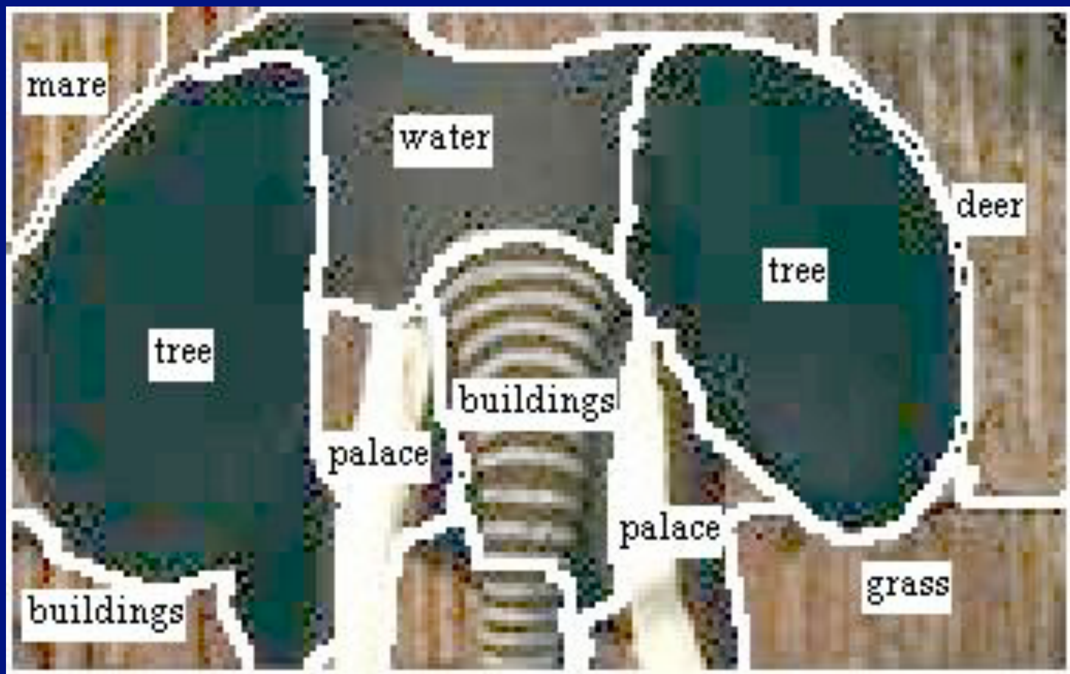
Duygulu et al, 02; Barnard et al 03

Duygulu et al, 02; Barnard et al 03



Method	P	R	F1	Ref
Co-occ	0.03	0.02	0.02	[53]
Trans	0.06	0.04	0.05	[27]

Y. Mori et al 99
Duygulu et al, 02



Duygulu et al, 02; Barnard et al 03

Things have gotten a lot better...

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Co-occ	0.03	0.02	0.02	[53]	Y. Mori et al 99
Trans	0.06	0.04	0.05	[27]	Duygulu et al, 02
CMRM	0.10	0.09	0.10	[37]	Jeon et al 03
TSIS	0.10	0.09	0.10	[19]	Celebi et al 05
MaxEnt	0.09	0.12	0.10	[39]	Jeon et al 04
CRM	0.16	0.19	0.17	[44]	Lavrenko et al 03
CT-3×3	0.18	0.21	0.19	[82]	Yavlinsky et al, 05
CRM-rect	0.22	0.23	0.23	[31]	Feng et al 04
InfNet	0.17	0.24	0.23	[50]	Metzler et al 04
MBRM	0.24	0.25	0.25	[31]	Feng et al 04
MixHier	0.23	0.29	0.26	[17]	Carneiro et al, 05
PicSOM	0.35*	0.35*	0.35*	[73]	Viitaniemi et al 07

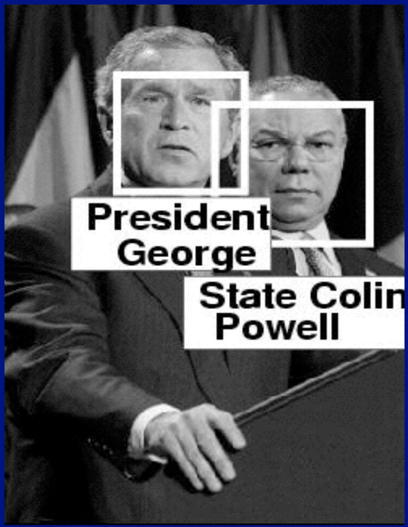
cf Makadia et al 08, P=0.27, R=0.32, nearest neighbours

News dataset

- Approx 5e5 news images, with captions
  - Easily collected by script from Yahoo over the last 18 months or so
- Mainly people
  - politicians, actors, sportsplayers
  - long, long tails distribution
- Face pictures captured “in the wild”
- Correspondence problem
  - some images have many (resp. few) faces, few (resp. many) names (cf. Srihari 95)

Berg et al 04, 05

President George W. Bush makes a statement in the Rose Garden while Secretary of Defense Donald Rumsfeld looks on, July 23, 2003. Rumsfeld said the United States would release graphic photographs of the dead sons of Saddam Hussein to prove they were killed by American troops. Photo by Larry Downing/Reuters



US President George W. Bush (L) makes remarks while Secretary of State Colin Powell (R) listens before signing the US Leadership Against HIV /AIDS , Tuberculosis and Malaria Act of 2003 at the Department of State in Washington, DC. The five-year plan is designed to help prevent and treat AIDS, especially in more than a dozen African and Caribbean nations(AFP/ Luke Frazza)

German supermodel Claudia Schiffer gave birth to a baby boy by Caesarian section January 30, 2003, her spokeswoman said. The baby is the first child for both Schiffer, 32, and her husband, British film producer Matthew Vaughn, who was at her side for the birth. Schiffer is seen on the German television show 'Bet It...?!' ('Wetten Dass...?!') in Braunschweig, on January 26, 2002. (Alexandra Winkler/Reuters)

British director Sam Mendes and his partner actress Kate Winslet arrive at the London premiere of 'The Road to Perdition', September 18, 2002. The films 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

Berg et al 04, 05; see also Everingham et al 06; Sivic et al 09, 09; Pham 08; Ozkan 06, 06a; Guillaimin 08; Mensink 08; etc

Predicting more structure

- Correlated words
  - waves go with beaches not cats
- Adjectives
  - green hat
- Attributes
  - has nose
- Relations
  - cat on mat
- Sentences
  - A dolphin holds a basketball as it swims on its back

A **dolphin** holds a **basketball** as it swims on its **back** .

A **dolphin** swimming upside down while holding a **basketball**

A **dolphin** swims upside down holding a **basketball** between it 's **flippers** .

A **seal** floats on it 's back in the **water** , holding a **basketball** .

The **dolphin** on his **back** holds the **orange** **basketball**

Correlated Words

- Simple method:
  - rack up some features, build a bunch of linear classifiers one per word
  - works poorly
    - few examples per word
    - many features, only some are stable

Learn this

$$\mathcal{D} \approx \mathcal{M}\mathcal{X}$$

Word data (observed)

Image representation (observed)

Correlated words

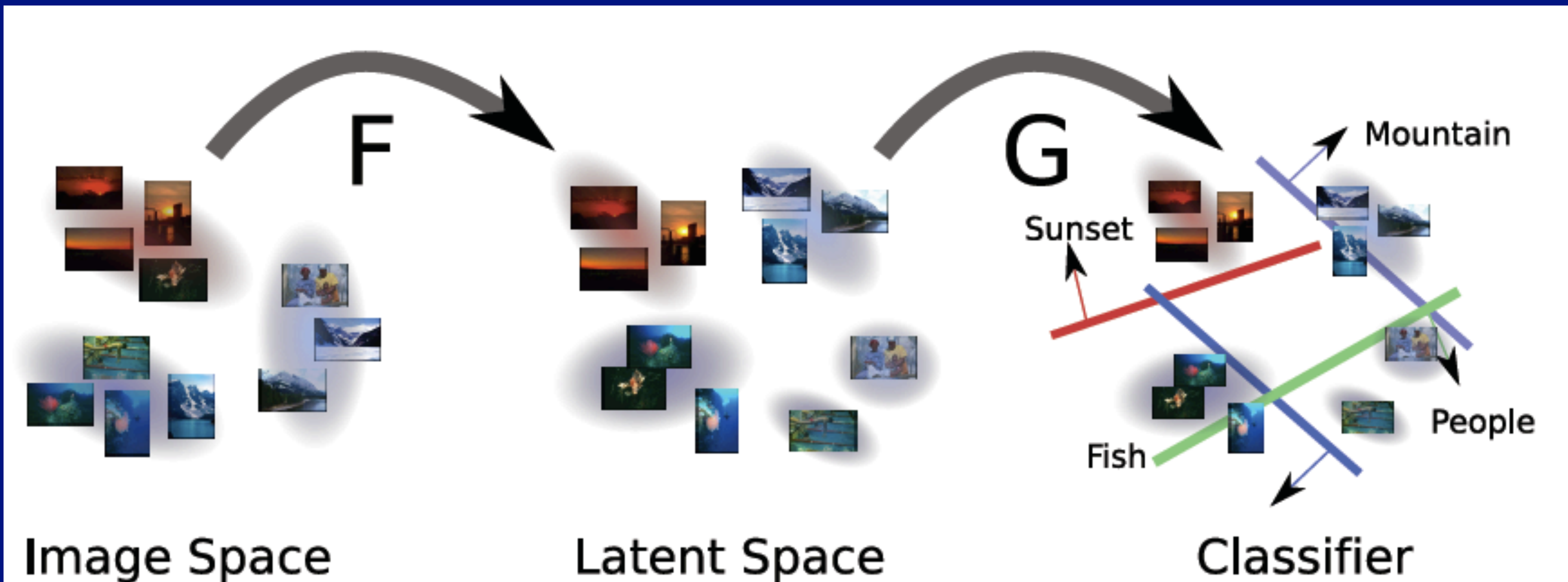
- Idea
  - some features are not helpful
  - a low dimensional subspace is good at predicting most things (Ando +Zhang,)
  - We can find this space by penalizing rank in the matrix of linear classifiers

Learn this

$$\mathcal{D} \approx \mathcal{G}\mathcal{F}\mathcal{X}$$

Word data (observed)

Image representation (observed)



Loeff Farhadi 08; see also Quattoni Darrell 07

It was there and we didn't

It was there and we predicted it

It wasn't and we did

Loeff Farhadi 08; see also Quattoni Darrell 07

Correlated word predictors are quite good

Method	P	R	F1	Ref	
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(section 2.2, kernel)	0.29	0.29	0.29		
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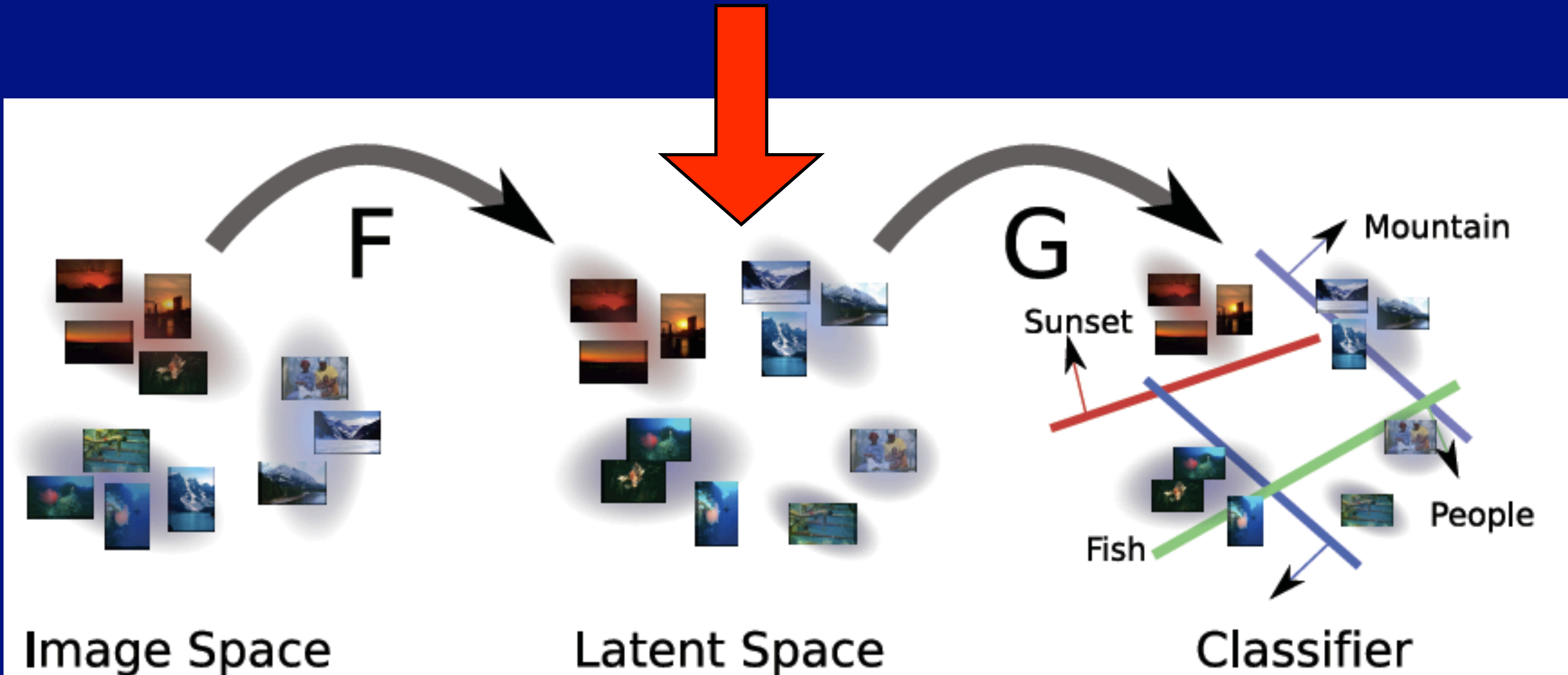
cf Makadia et al 08, P=0.27, R=0.32, nearest neighbours

Scenes as object bags

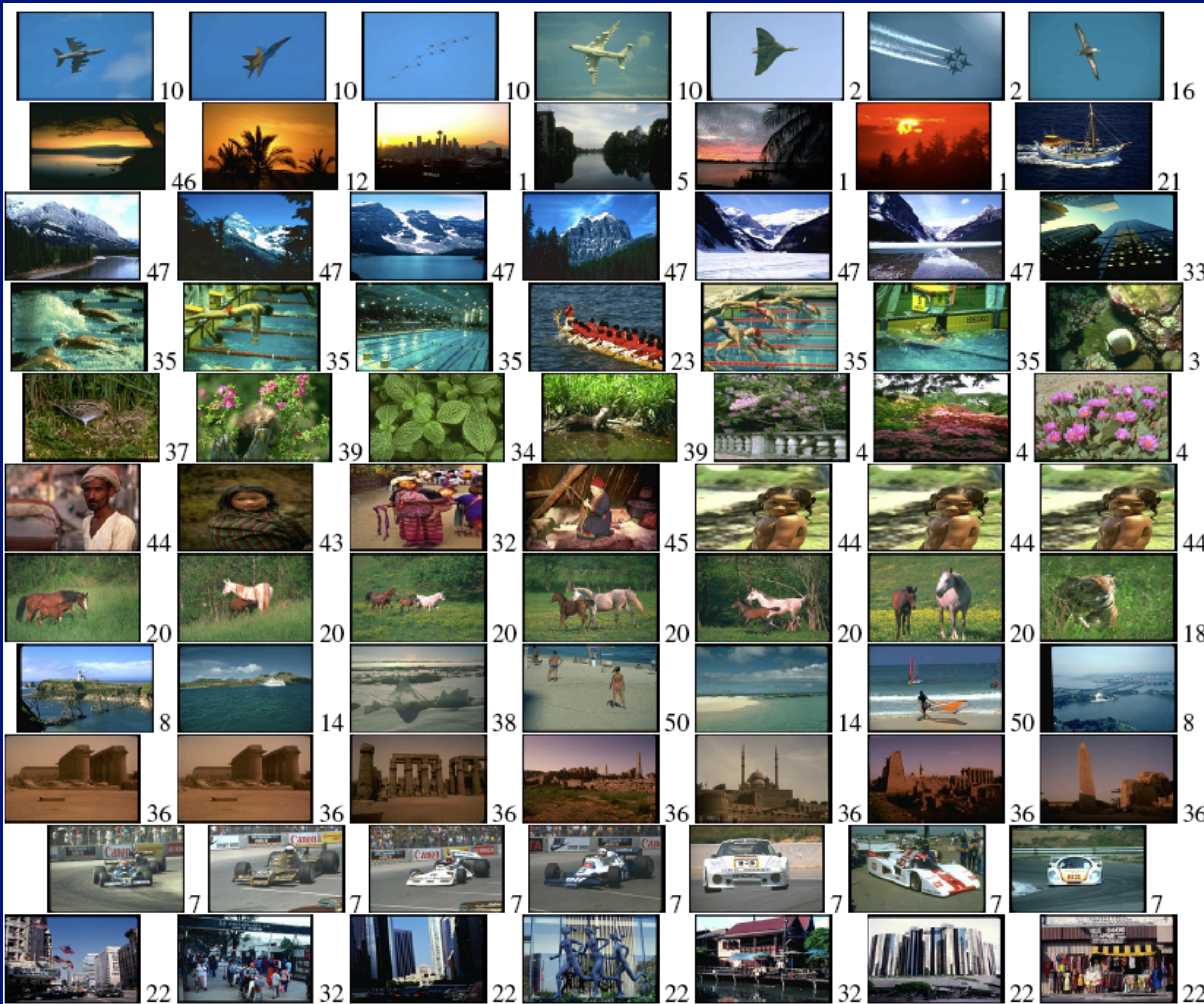
- We could build collections of labelled scene images
  - useful, but..
    - kitchen, bathroom, outdoor, and then?
- We could collect images of similar appearance
  - but...
    - might not really have similar objects in them
- Unsupervised bag discovery
  - Pictures of the same scene tend to contain similar objects
      - i.e. tend to attract the same image annotations

In this space, images are "close" if they "look similar" AND if they predict "similar" words



Loeff Farhadi 08

Scene



CD #
(rough proxy)

Loeff Farhadi 08

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“Pink” from Google

Yanai Barnard 05

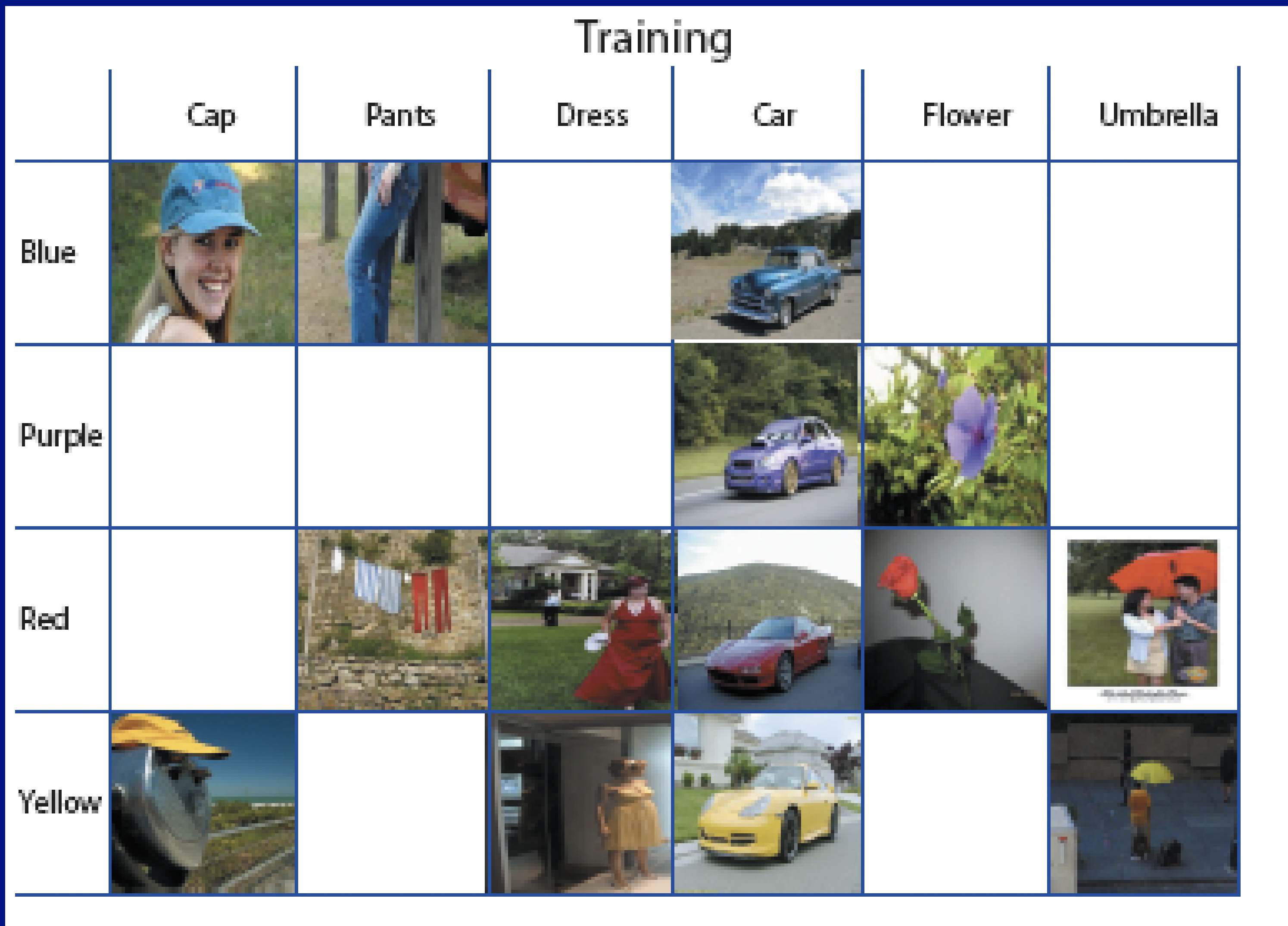
“Pink” after 10 EM iterations

Yanai Barnard 05

Adjectives for localization

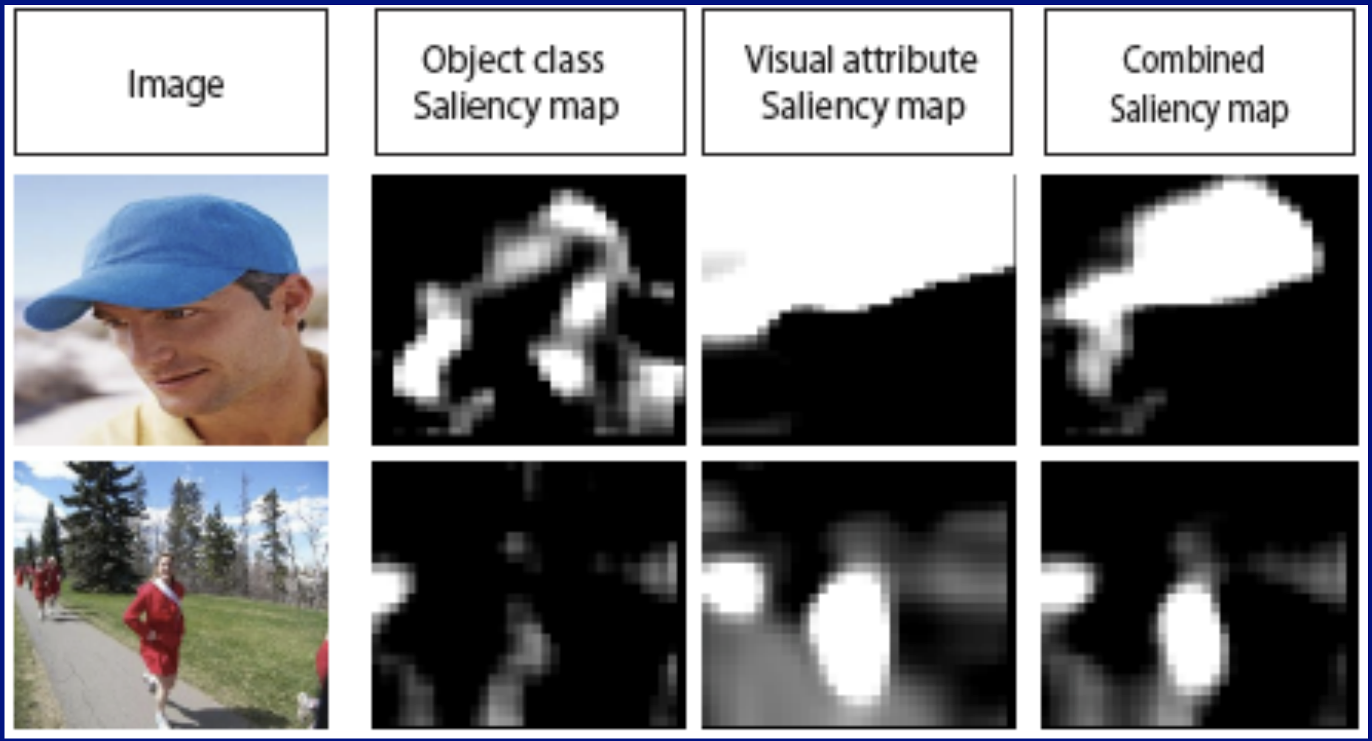
- In partially supervised training
  - we know what is in the image, but not where
  - very usual condition
- But if we have adjectives
  - we can improve location estimates
    - for noun w/ adjective
    - for adjective w/noun
  - and so speed training and improve recognition

Adjectives



Wang et al 09

Adjectives



Wang et al 09

Adjectives

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What is recognition?

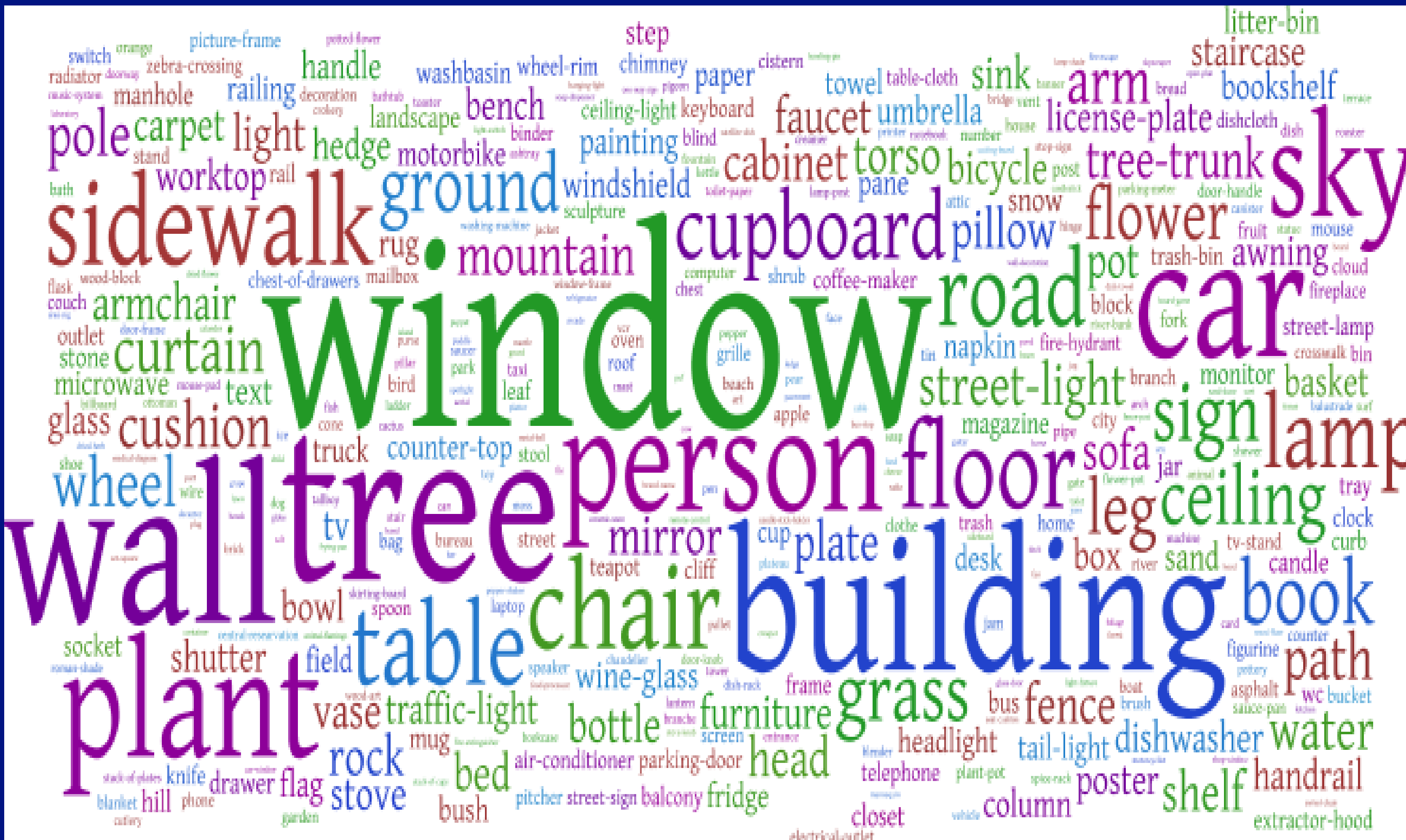
- k-way classification
  - but what about unfamiliar objects?
  - how reliable are names?

Are these monkeys?

Recognition - desirable properties

- Accuracy
  - be good at recognizing known objects
- Unfamiliarity
  - Make useful statements about objects whose name isn't yet known
- Manage deviant objects
  - Say how a detected object is different from the usual
- Learn by X
  - Single picture
  - Reading
    - Description (0 pictures)

Most things are unfamiliar



Wang ea 10; labelme data

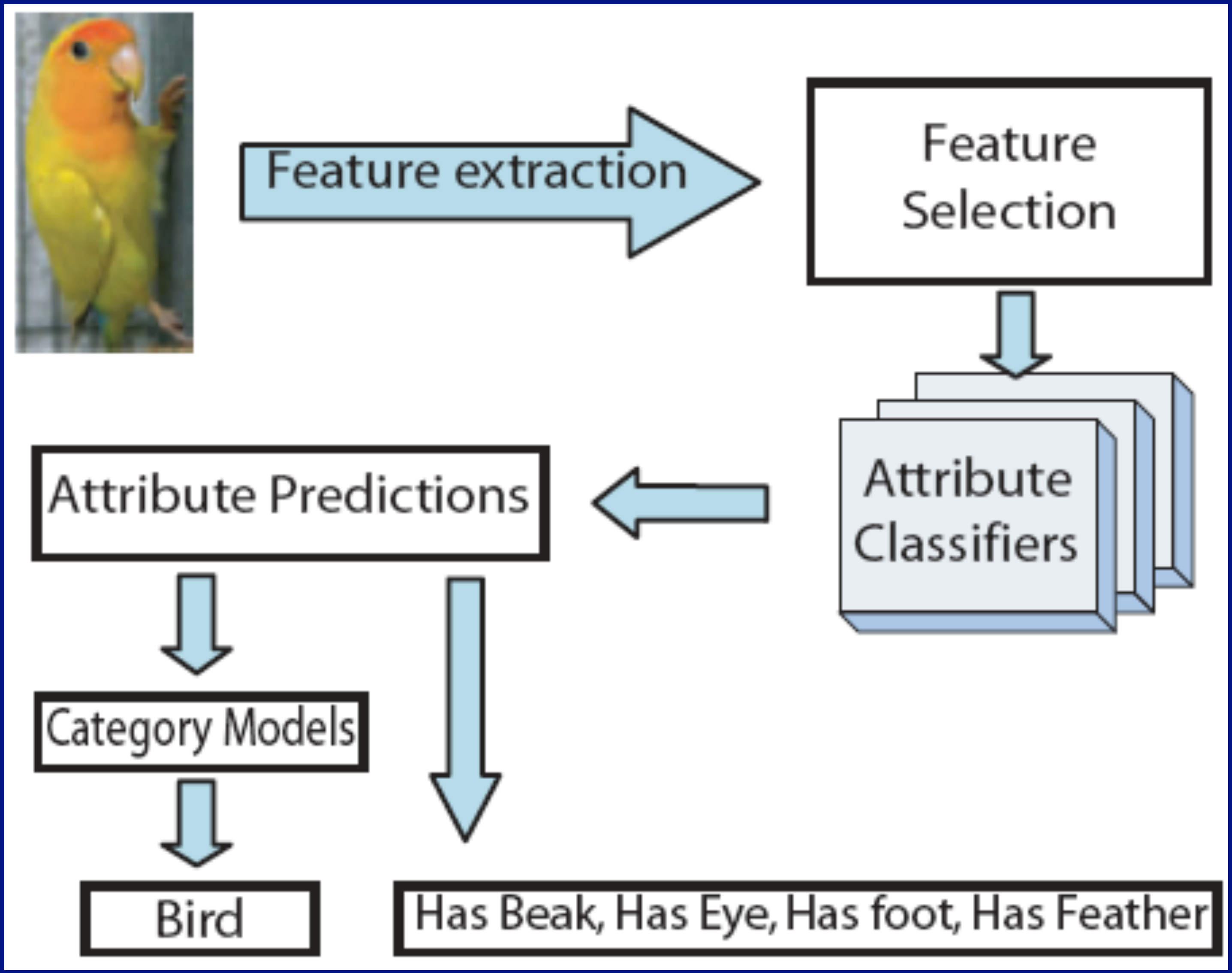
For language people: distributional semantics?

Attributes

- Properties shared by many object categories
- Material (like)
  - glass, wood, furry, red, etc.
- Part (like)
  - has wheel, has head, has tail, etc.
- Shape (like)
  - is 2D Boxy, is cylindrical, etc

cf Ferrari Zisserman 07

General architecture

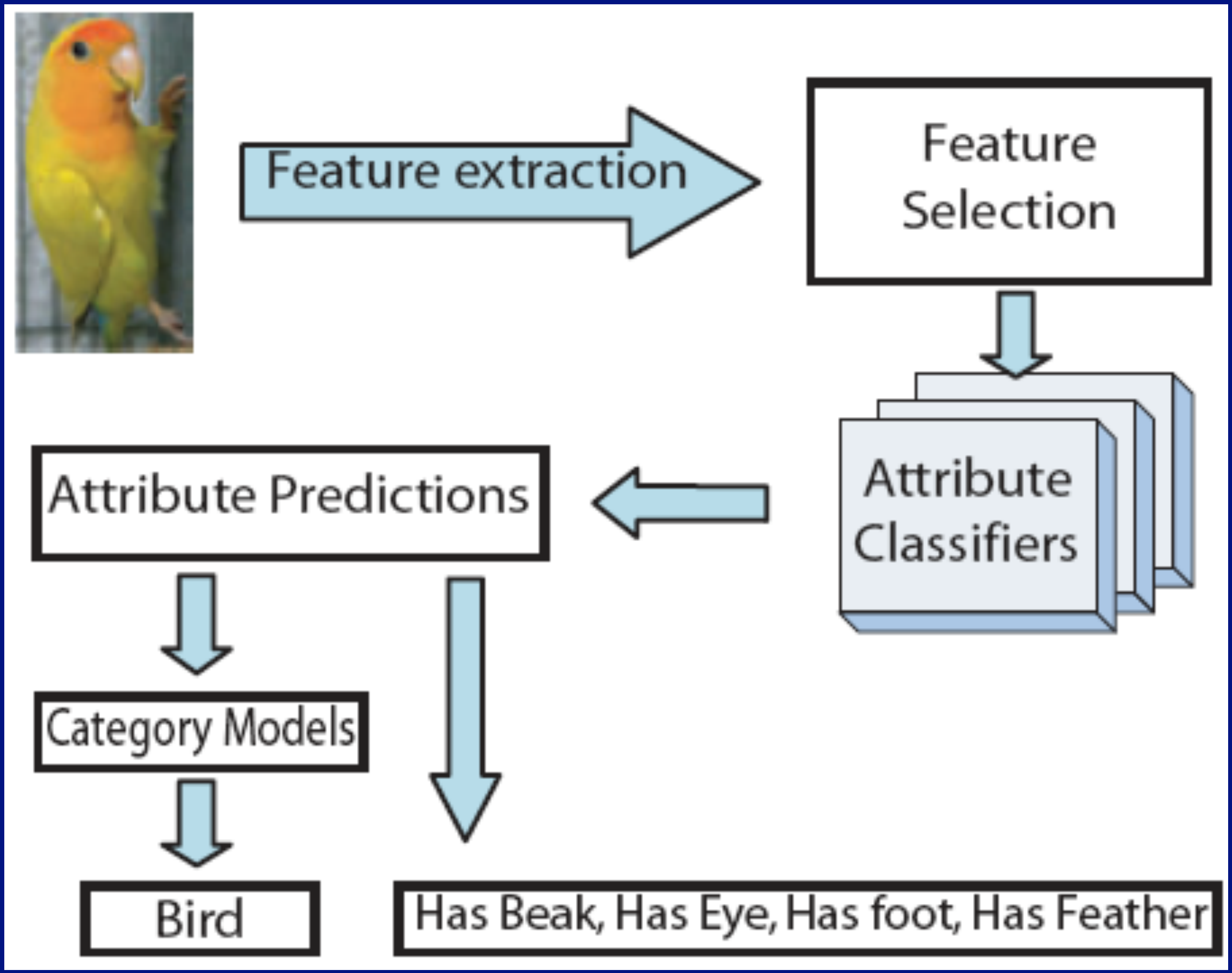


Farhadi et al 09; cf Lampert et al 09

Attribute predictions for unknown objects

Farhadi et al 09; cf Lampert et al 09

General architecture

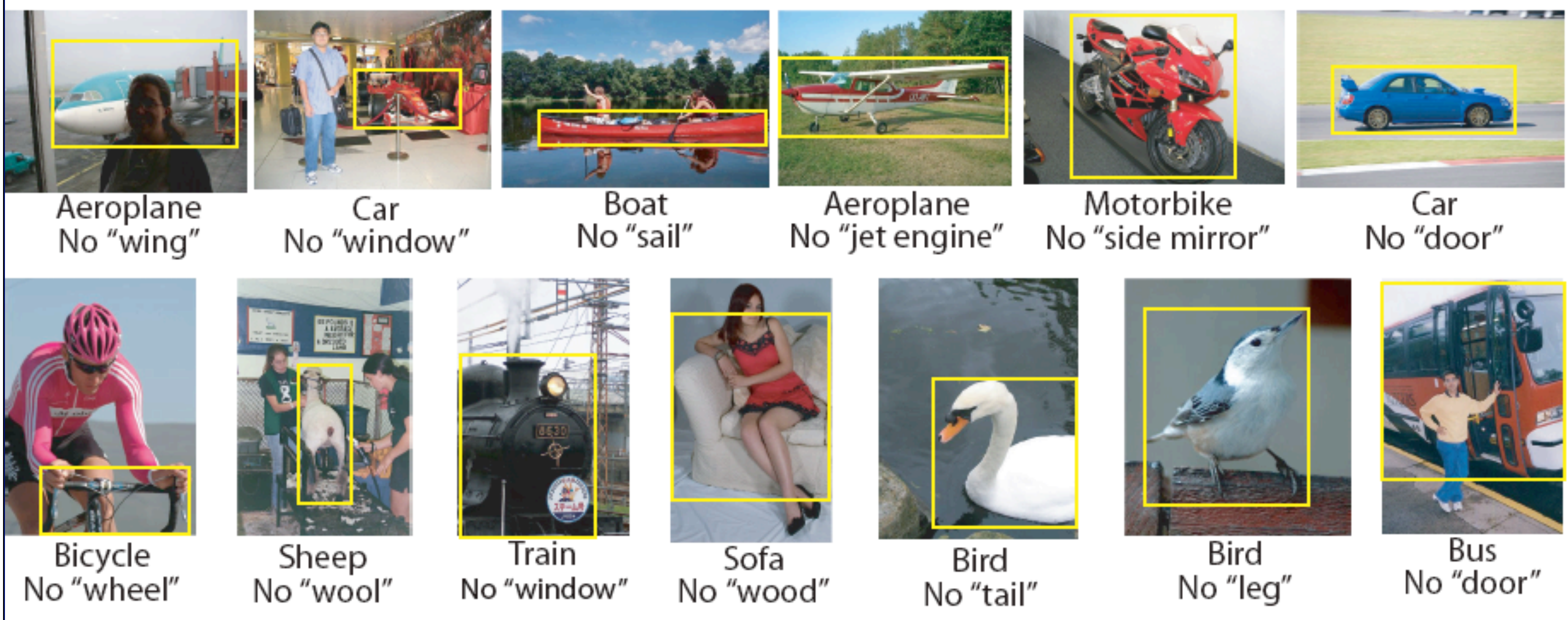


Farhadi et al 09; cf Lampert et al 09

How is an object different from typical?

- Pragmatics suggests this is how adjectives are chosen
  - If we are sure it's a cat, and we know that
    - an attribute is different from normal
    - the detector is usually reliable
  - we should report the missing/extra attribute

Missing attributes



Extra attributes

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Gupta and Davis 08, but there is still a lot here

- Sentences
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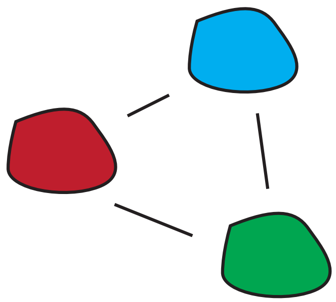
Relations as an MRF

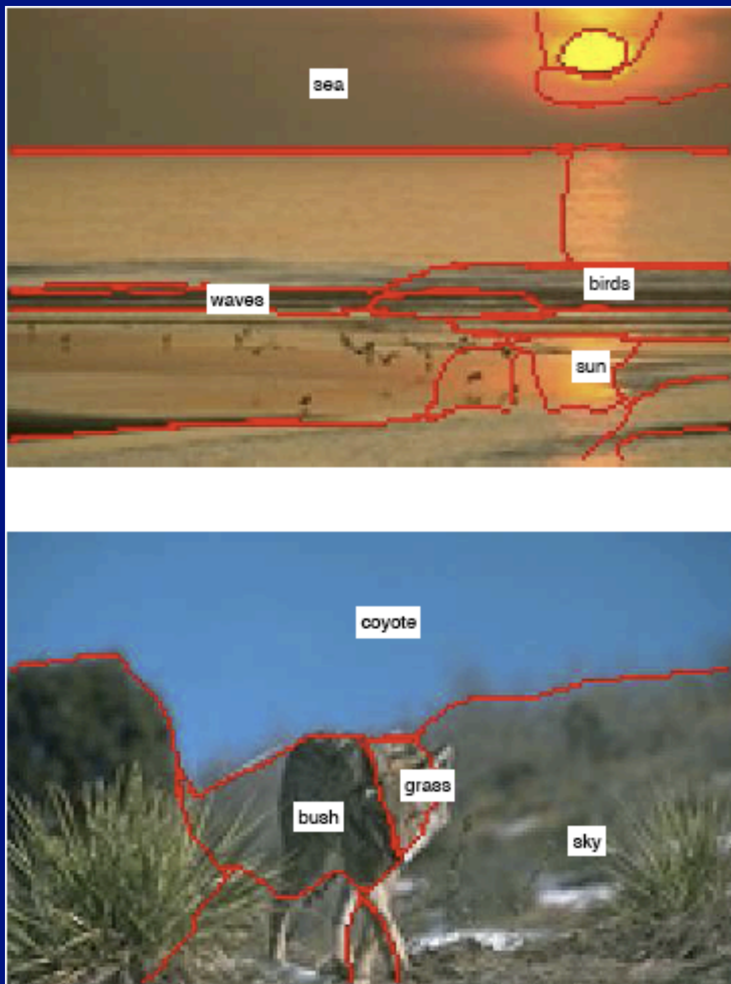


Sun IN Sky

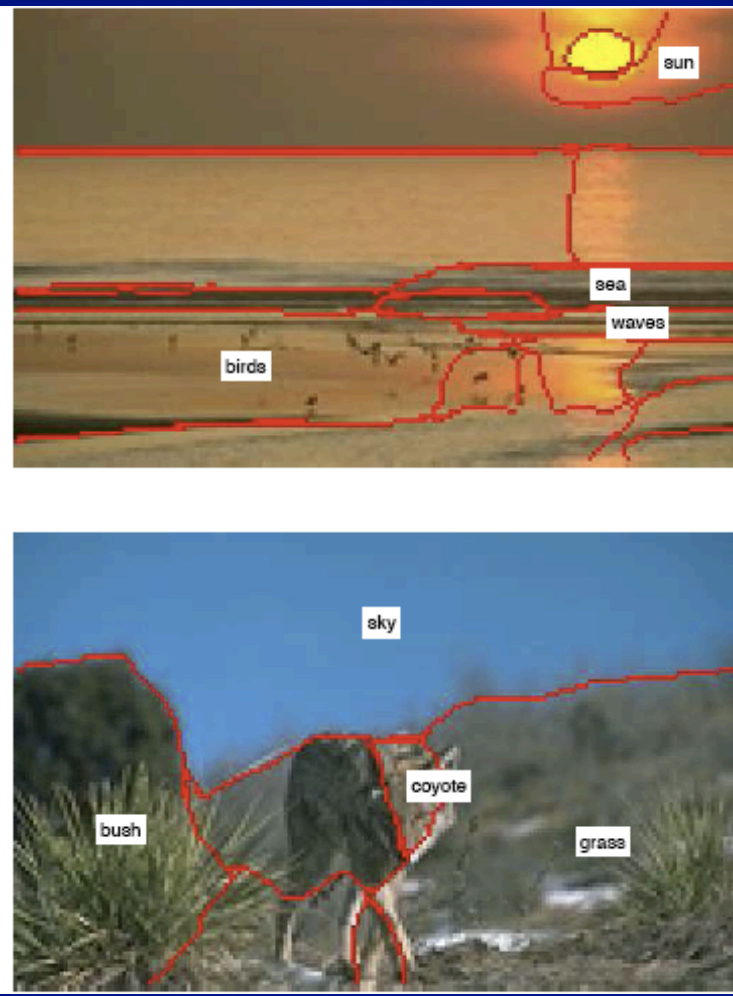
Sky ABOVE Grass

Sun ABOVE Grass

Gupta and Davis 08



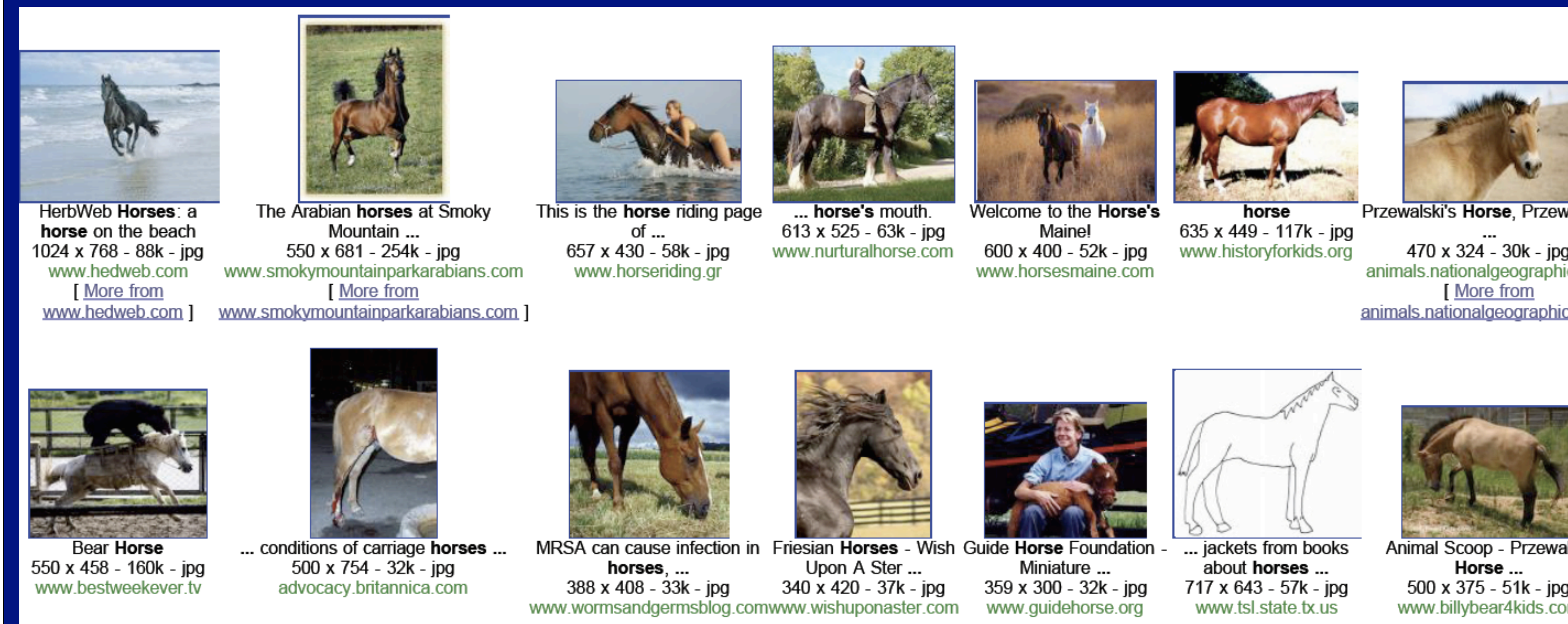
Duygulu et al 02



Gupta and Davis 08

Relations distort participants

Relations distort participants

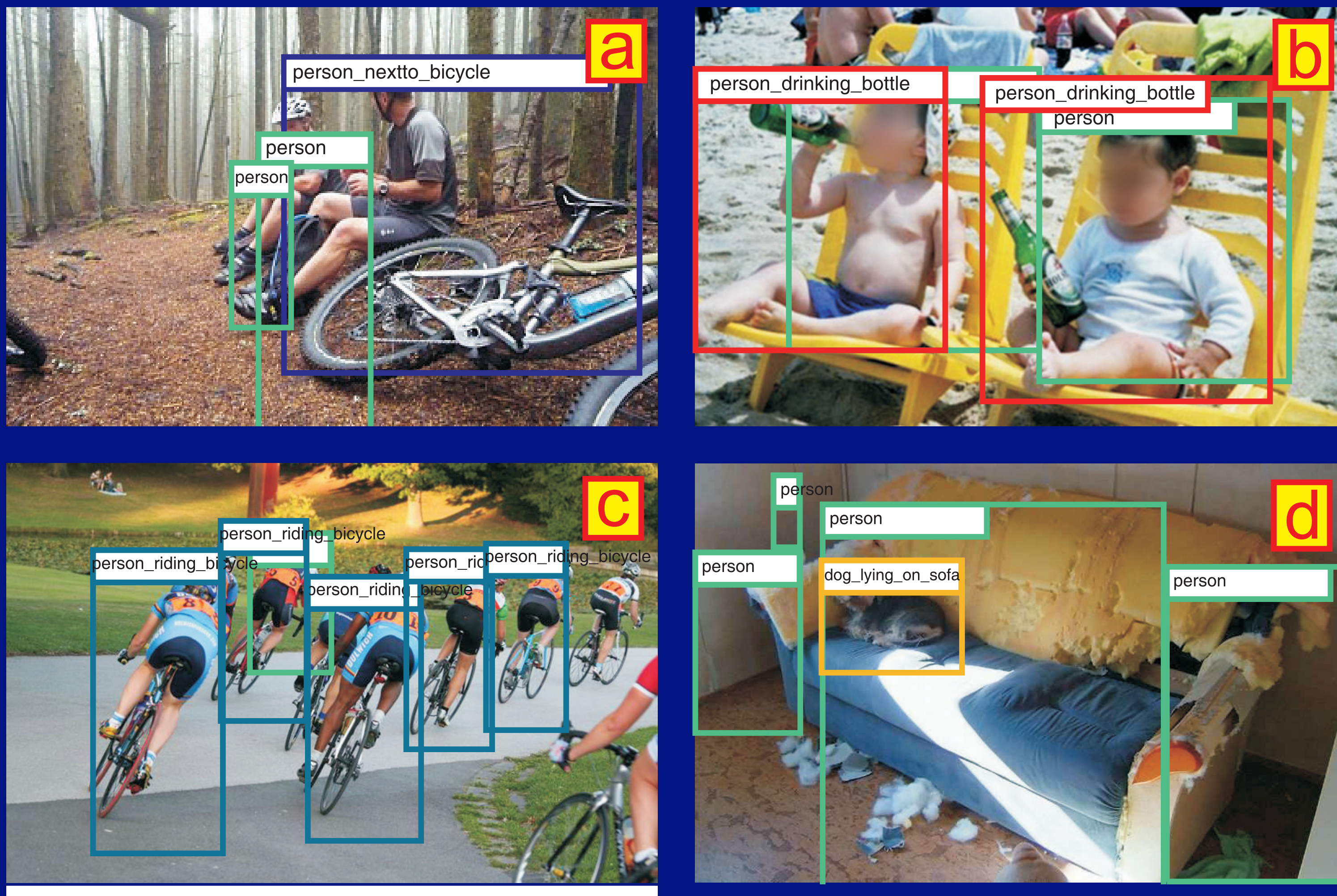


Relations distort participants

Scenes > Visual phrases > Objects

“Sledder”
Is this one thing?
Should we cut her off her sled?

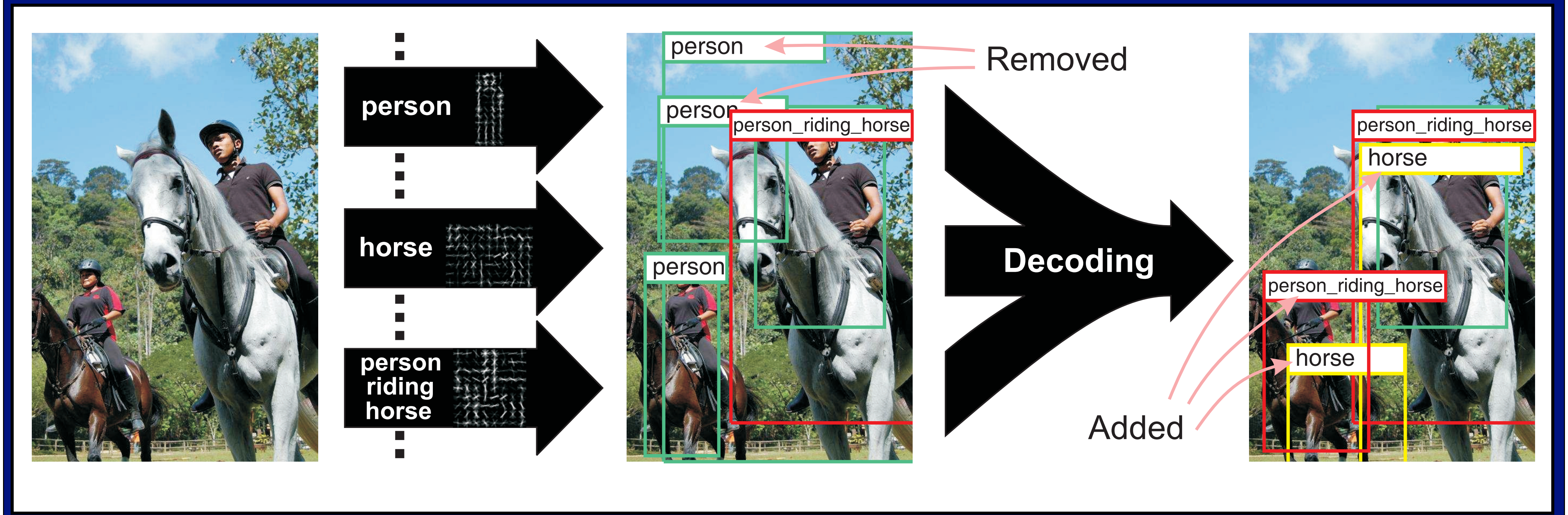
Scenes > Visual phrases > Objects



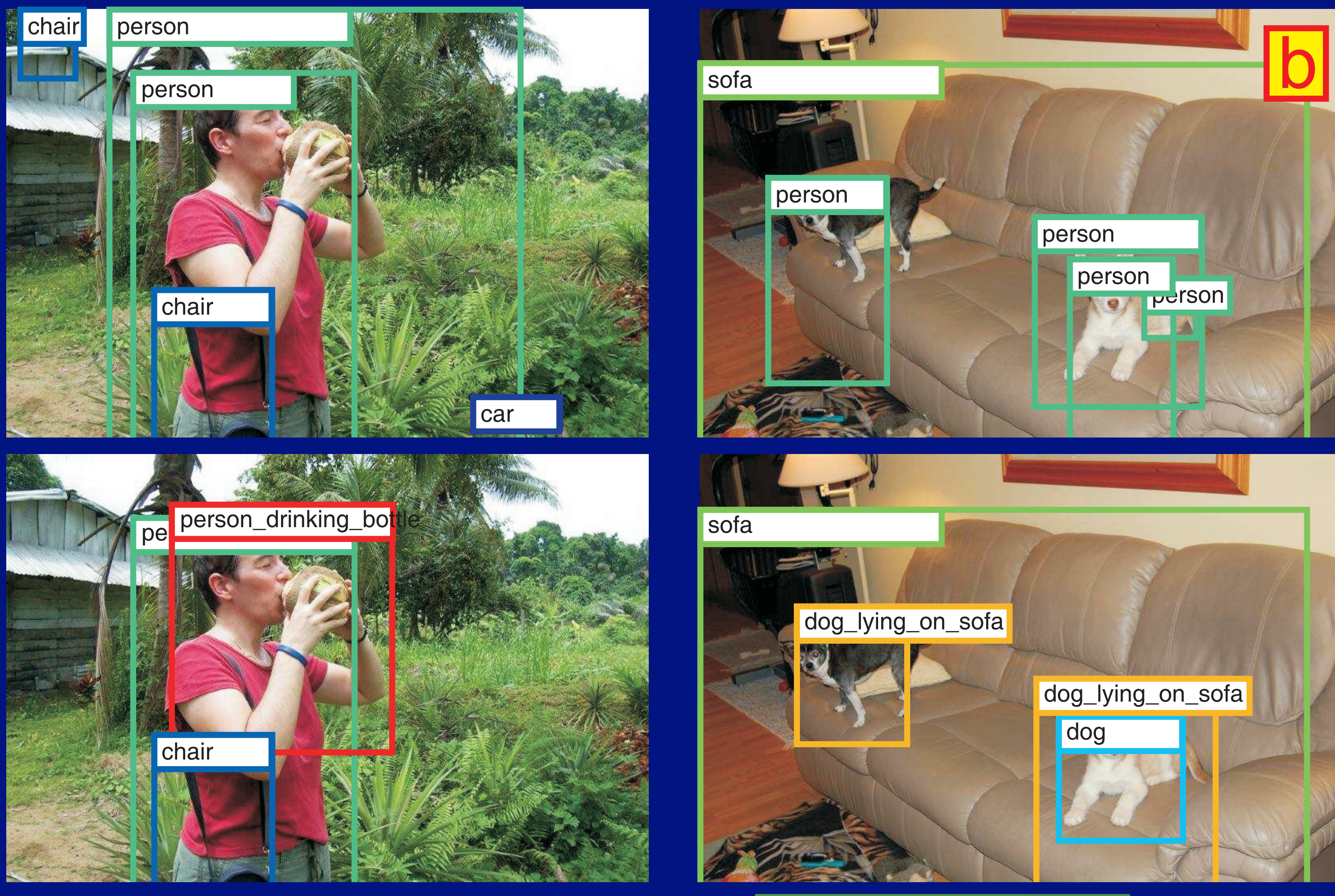
Farhadi 11

For language people: what are units of knowledge?

Decoding


person
horse
person riding horse
person
person
person_riding_horse
person
Removed
Decoding
Added
person_riding_horse
horse
person_riding_horse
horse

Decoding helps



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Two girls take a break to sit and talk .

Two women are sitting , and one of them is holding something .

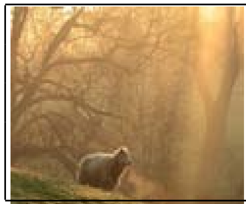
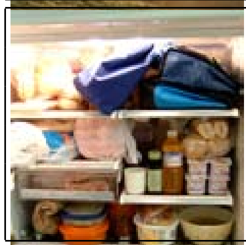
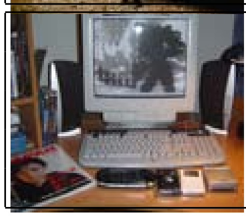
Two women chatting while sitting outside

Two women sitting on a bench talking .

Two women wearing jeans , one with a blue scarf around her head , sit and talk .

Sentences from Julia Hockenmaier's work

Examples

	(pet, sleep, ground) (dog, sleep, ground) (animal, sleep, ground) (animal, stand, ground) (goat, stand, ground)	see something unexpected. Cow in the grassfield. Beautiful scenery surrounds a fluffly sheep. Dog hearding sheep in open terrain. Cattle feeding at a trough.
	(furniture, place, furniture) (furniture, place, room) (furniture, place, home) (bottle, place, table) (display, place, table)	Refrigerator almost empty. Foods and utensils. Eatables in the refrigerator. The inside of a refrigerator apples, cottage cheese, tupperwares and lunch bags. Squash apenny white store with a hand statue, picnic tables in front of the building.
	(transportation, move, track) (bike, ride, track) (transportation, move, road) (pet, sleep, ground) (bike, ride, road)	A man stands next to a train on a cloudy day A backpacker stands beside a green train This is a picture of a man standing next to a green train There are two men standing on a rocky beach, smiling at the camera. This is a person laying down in the grass next to their bike in front of a strange white building.
	(display, place, table) (furniture, place, furniture) (furniture, place, furniture) (bottle, place, table) (furniture, place, home)	This is a lot of technology. Somebody's screensaver of a pumpkin A black laptop is connected to a black Dell monitor This is a dual monitor setup Old school Computer monitor with way to many stickers on it

Farhadi ea 10

Conclusions

- The words near pictures are informative
  - learn to recognize objects
  - understand the pictures better
- Expose crucial problems in recognition
  - what is worth recognizing?
  - how should we describe things?
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