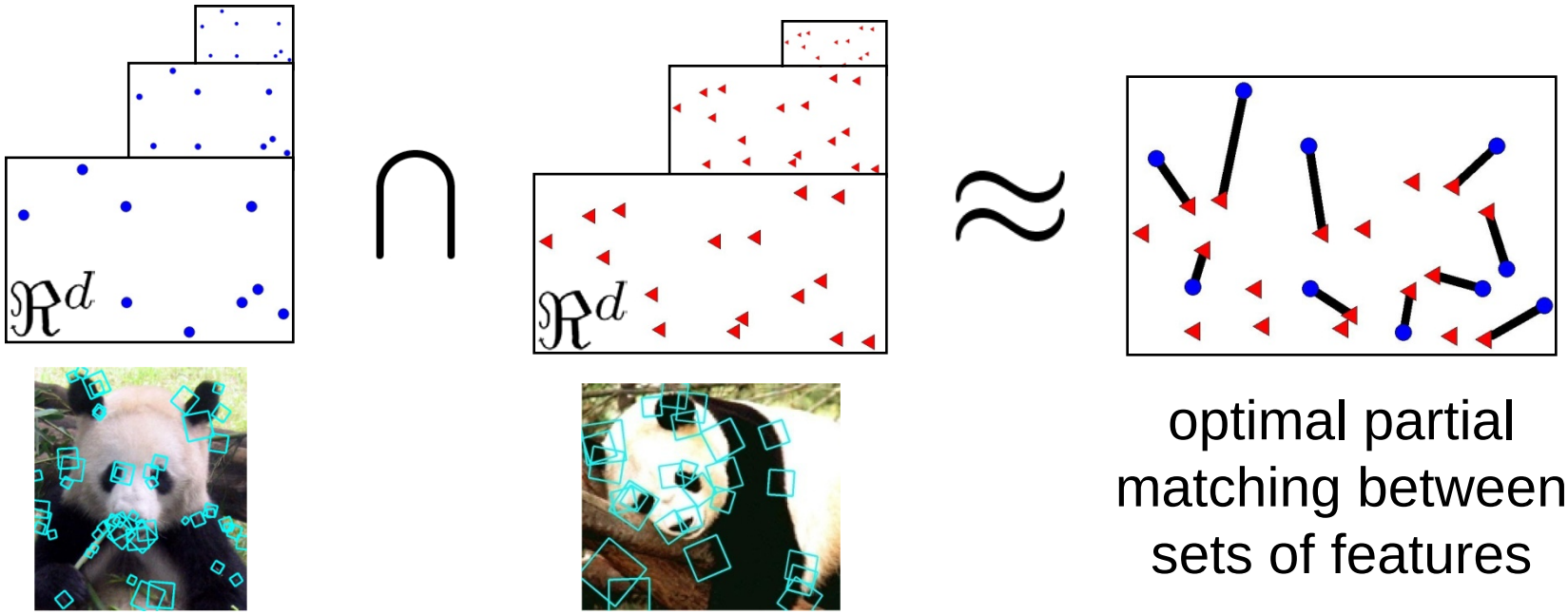
Advanced Representation and Learning

Vinay P. Namboodiri

- Slide Credit to James Hays, Hakan Bilen, Kai Yu and Derek Hoiem

Last class: Pyramid match kernel



optimal partial matching between sets of features

$$K_\Delta\left(\Psi(\mathbf{X}), \Psi(\mathbf{Y})\right) = \sum_{i=0}^{L} \underbrace{\frac{1}{2^i}}_{\text{difficulty of a match at level i}} \underbrace{\left(\mathcal{I}\left(H_i(\mathbf{X}), H_i(\mathbf{Y})\right) - \mathcal{I}\left(H_{i-1}(\mathbf{X}), H_{i-1}(\mathbf{Y})\right)\right)}_{\text{number of new matches at level i}}$$

Last Class: Spatial Pyramid

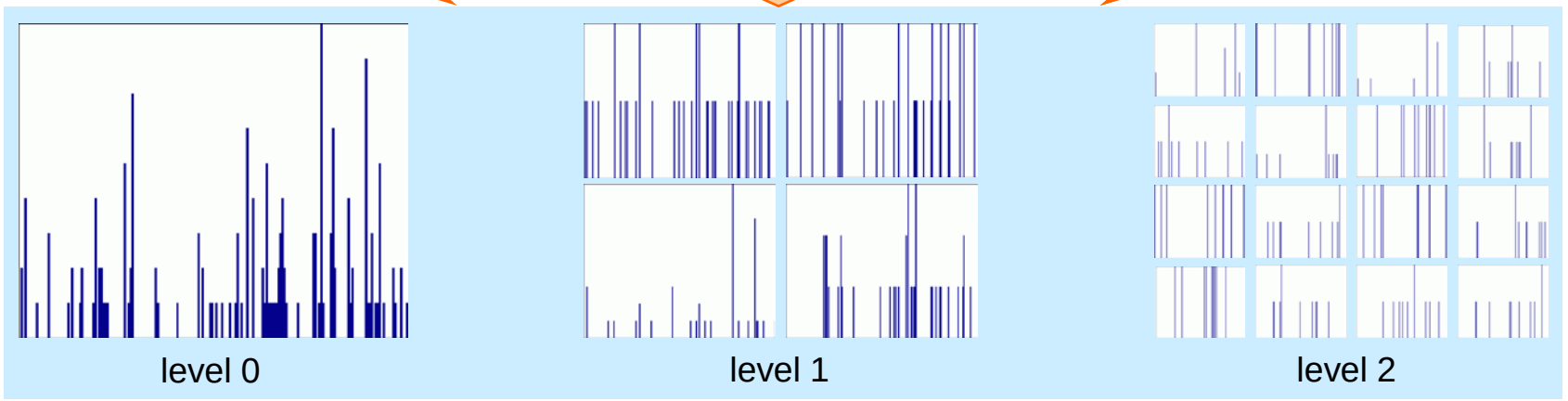


Image Categorization

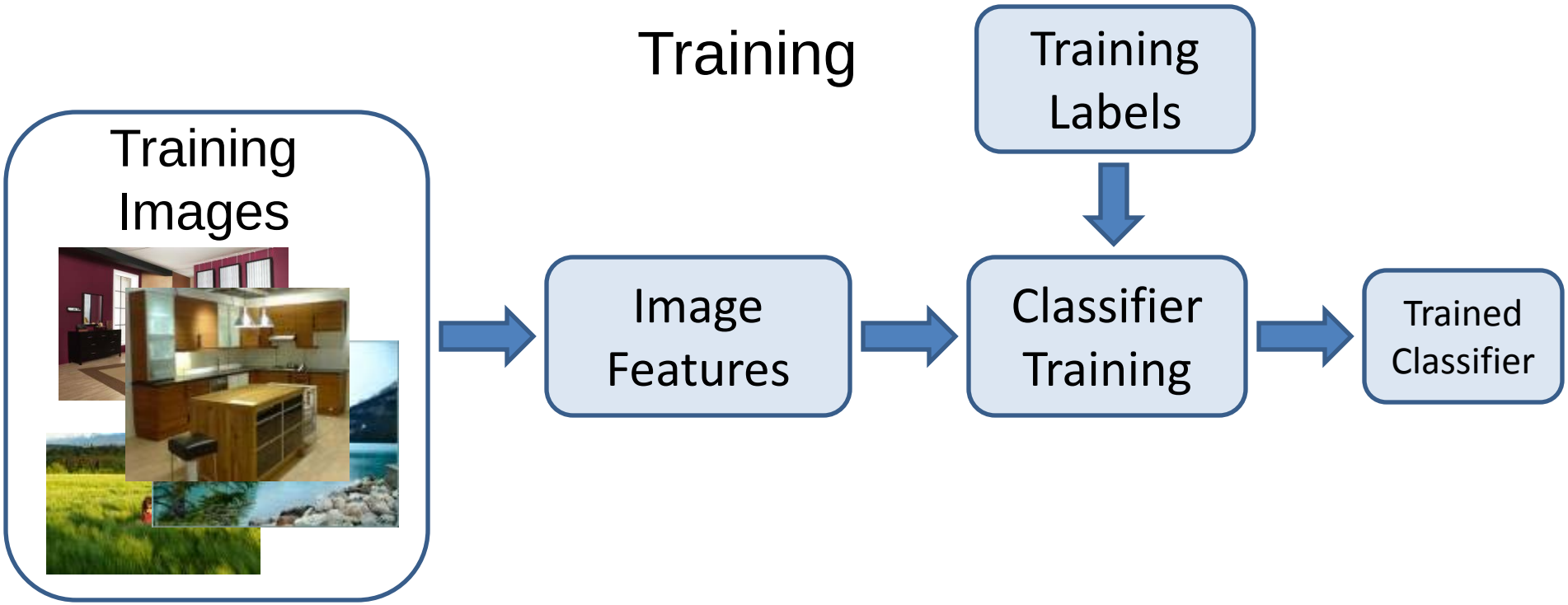


Image Categorization

Training

Training Images

Training Labels

Image Features

Classifier Training

Trained Classifier

Testing

Test Image

Image Features

Trained Classifier

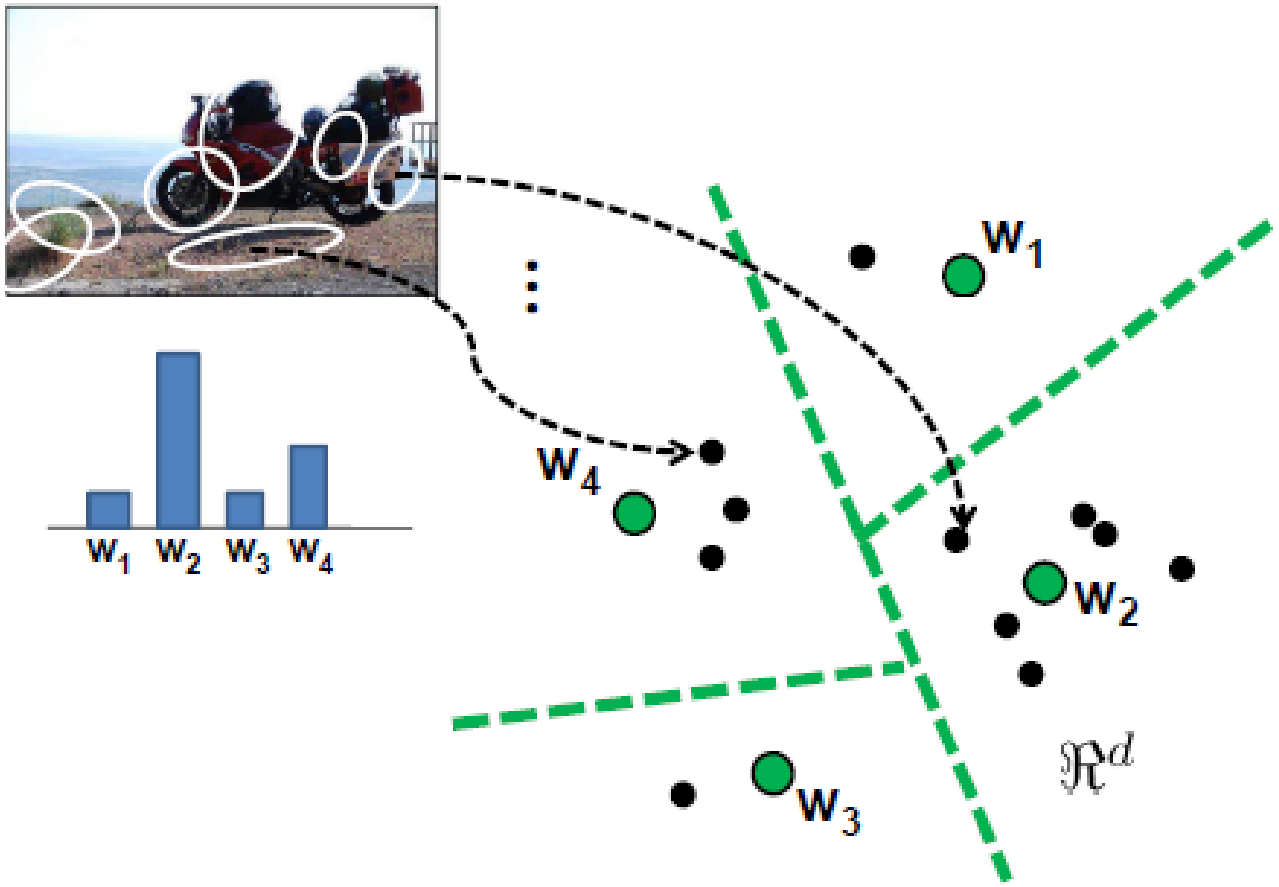
Prediction

Outdoor

Why do good recognition systems go bad?

- E.g. Why isn't our Bag of Words classifier at 90% instead of 70%?
- Training Data
  - Huge issue, but not necessarily a variable you can manipulate.
- Learning method
  - Probably not such a big issue, unless you're learning the representation (e.g. deep learning).
- Representation
  - Are the local features themselves lossy
  - What about feature quantization? That's VERY lossy.

Standard Kmeans Bag of Words



http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Today's Class

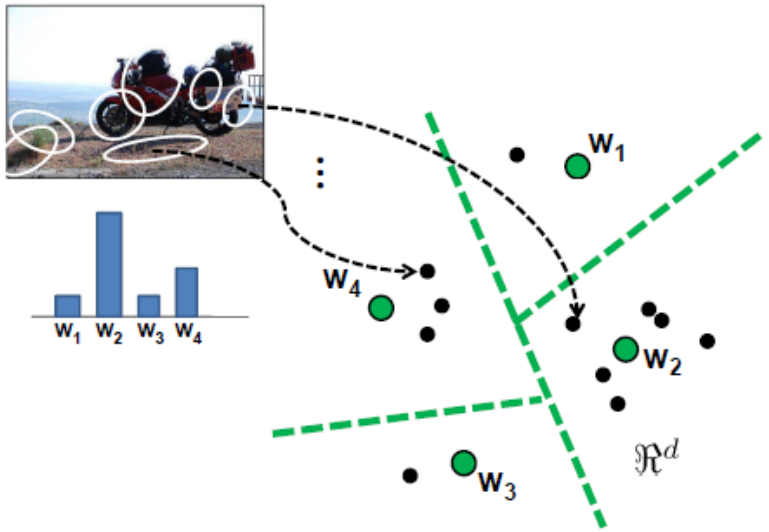
- More advanced quantization / encoding methods that represent the state-of-the-art in image classification and image retrieval.
  - Soft assignment (a.k.a. Kernel Codebook)
  - VLAD
  - Locally Linear Coding

- Classification based on Latent Variables

Motivation

Bag of Visual Words is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**?



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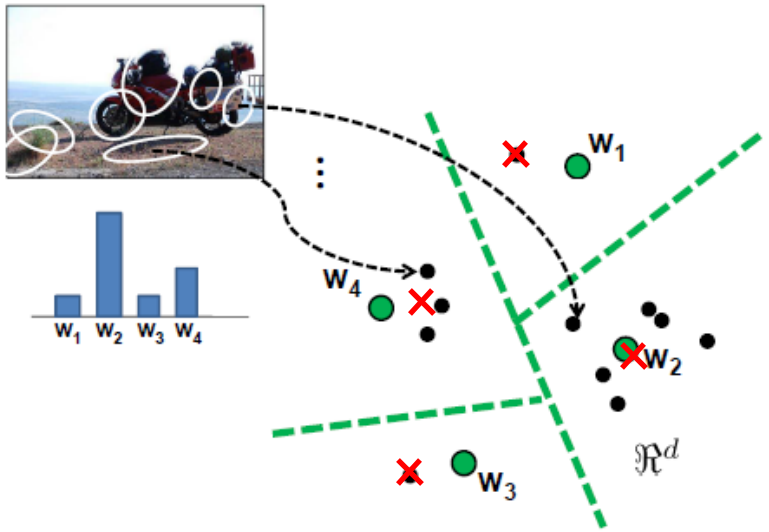

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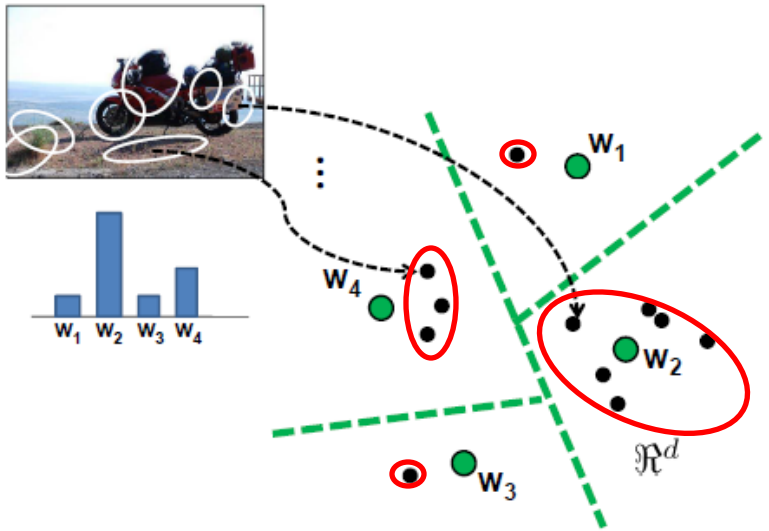
- mean of local descriptors
- (co)variance of local descriptors



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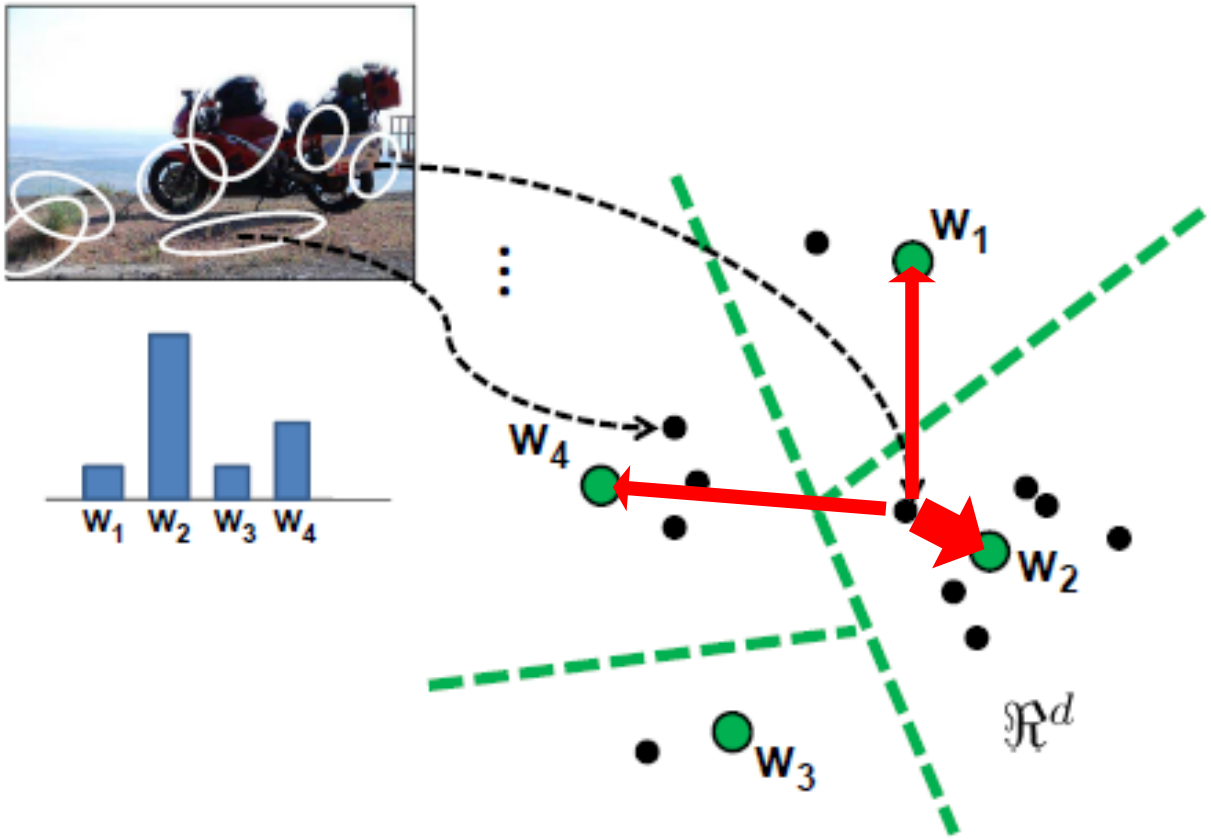
Simple case: Soft Assignment

- Called “Kernel codebook encoding” by Chatfield et al. 2011. Cast a weighted vote into the most similar clusters.

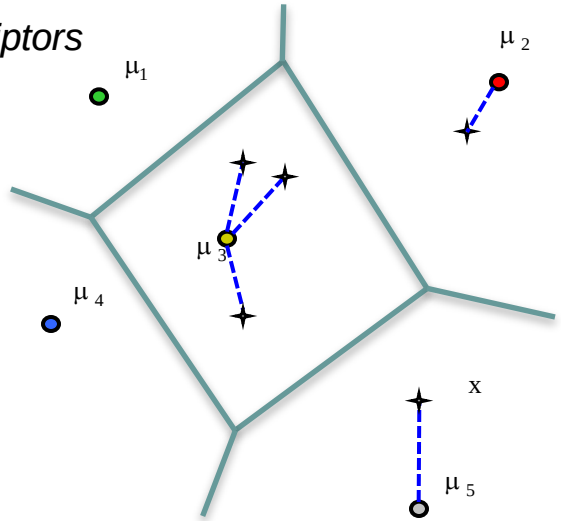


The VLAD representation

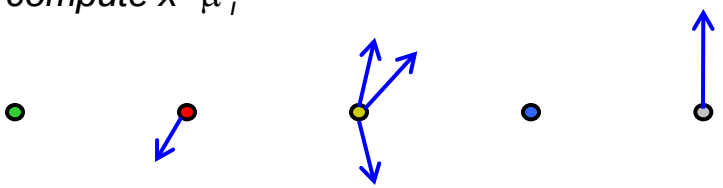
Given a codebook $\{\mu_i, i = 1 \dots N\}$, e.g. learned with K-means, and a set of local descriptors $X = \{x_t, t = 1 \dots T\}$

- ① assign $\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$
- ②③ compute: $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$
- concatenate v_i's + ℓ_2 normalize

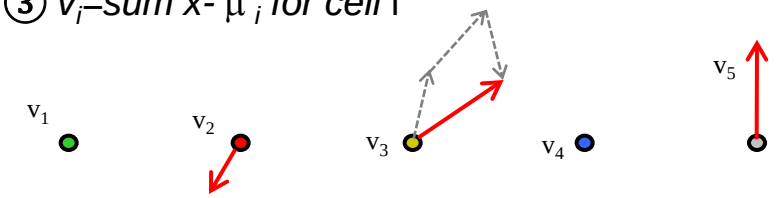
① *assign descriptors* :



② *compute x-* μ_i



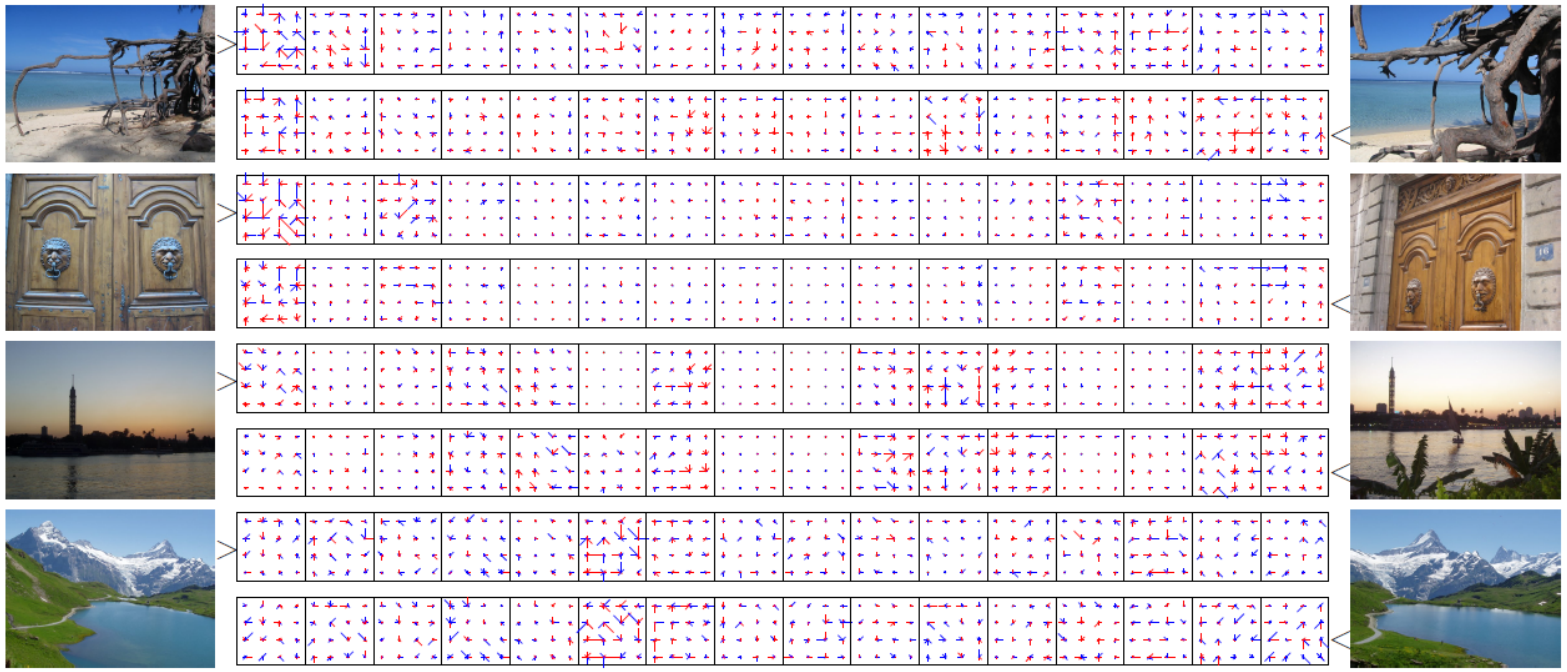
③ *v_i=sum x-* μ_i *for cell* i



Jégou, Douze, Schmid and Pérez, "Aggregating local descriptors into a compact image representation", CVPR'10.

A first example: the VLAD

A graphical representation of $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$



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Local Coordinate Coding (LCC)

Yu, Zhang & Gong, NIPS 09
Wang, Yang, Yu, Lv, Huang CVPR 10

- Dictionary Learning: k-means (or hierarchical k-means)

- Coding for x, to obtain its sparse representation *a*

  Step 1 – ensure locality: find the K nearest bases

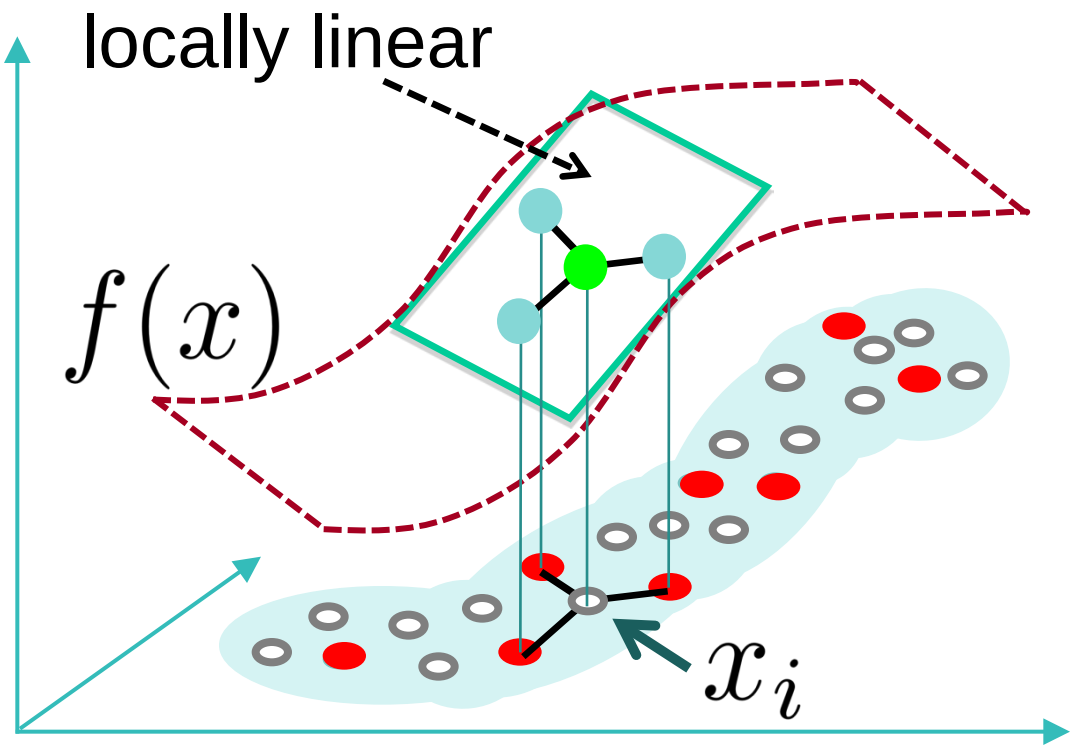
$$[\phi_j]_{j \in J(x)}$$

  Step 2 – ensure low coding error:

$$\min_a \left\| x - \sum_{j \in J(x)} a_{i,j} \phi_j \right\|^2, \quad \text{s.t.} \quad \sum_{j \in J(x)} a_{i,j} = 1$$

Function Approximation based on LCC

Yu, Zhang, Gong, NIPS 10



xerox

KU LEUVEN

PSI VISICS

Object Classification with Latent Variables

IJCV 2013, BMVC 2011

H. Bilen, V.P. Namboodiri and L.V. Gool

VISICS, ESAT, KU Leuven

November 19, 2013

Outline

Visual Object Recognition

?

Visual Object Recognition

?

Visual Object Recognition

observed data

?

Visual Object Recognition

observed data

LABEL

Jean Claude Van Damme

Visual Object Recognition

observed data

LABEL

Jean Claude Van Damme

- instance specific recognition

Visual Object Recognition

observed data

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LABEL

- instance specific recognition
- generic class recognition *e.g.* bicycle, person

What is an object class?

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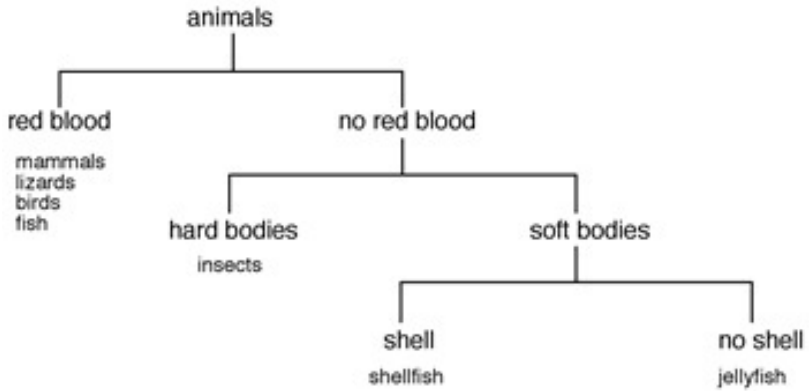
Classical view

- members share a set of properties



What is an object class?

Classical view

- members share a set of properties
- finding the common
- functional or visual?

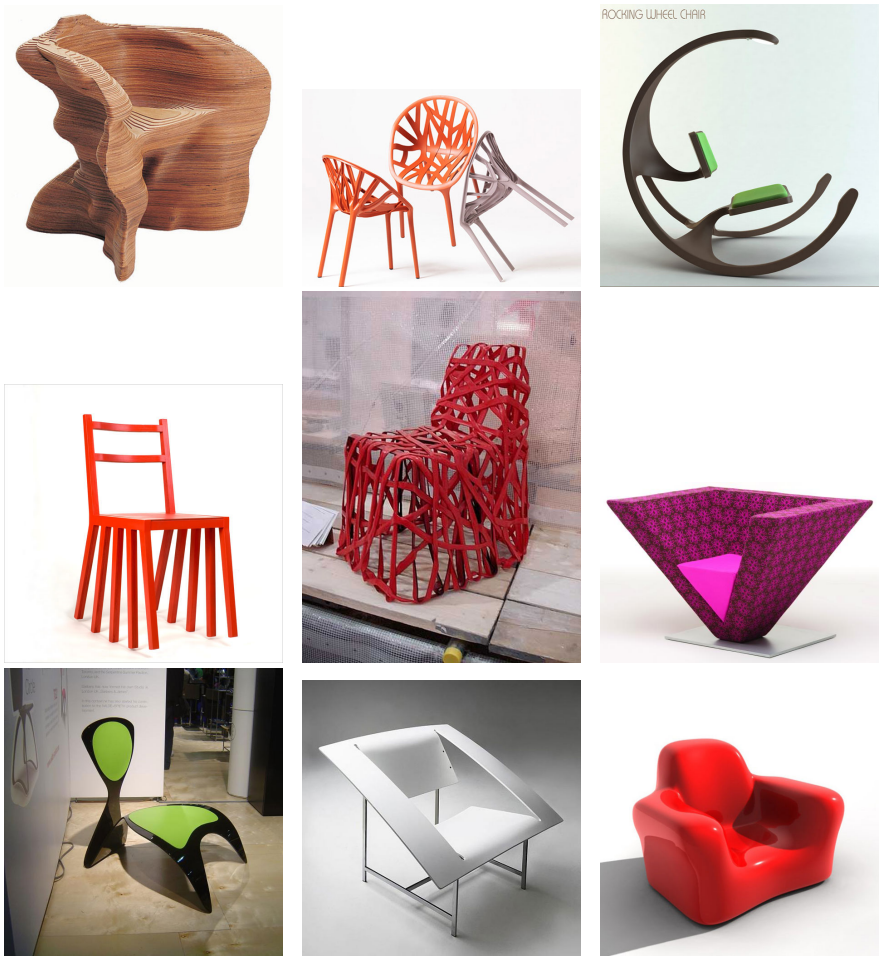


image credits: webdesignerdepot.com

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Exemplar view

- shared properties $\Rightarrow$ *similarity*

image credits: PASCAL VOC 2007 dataset

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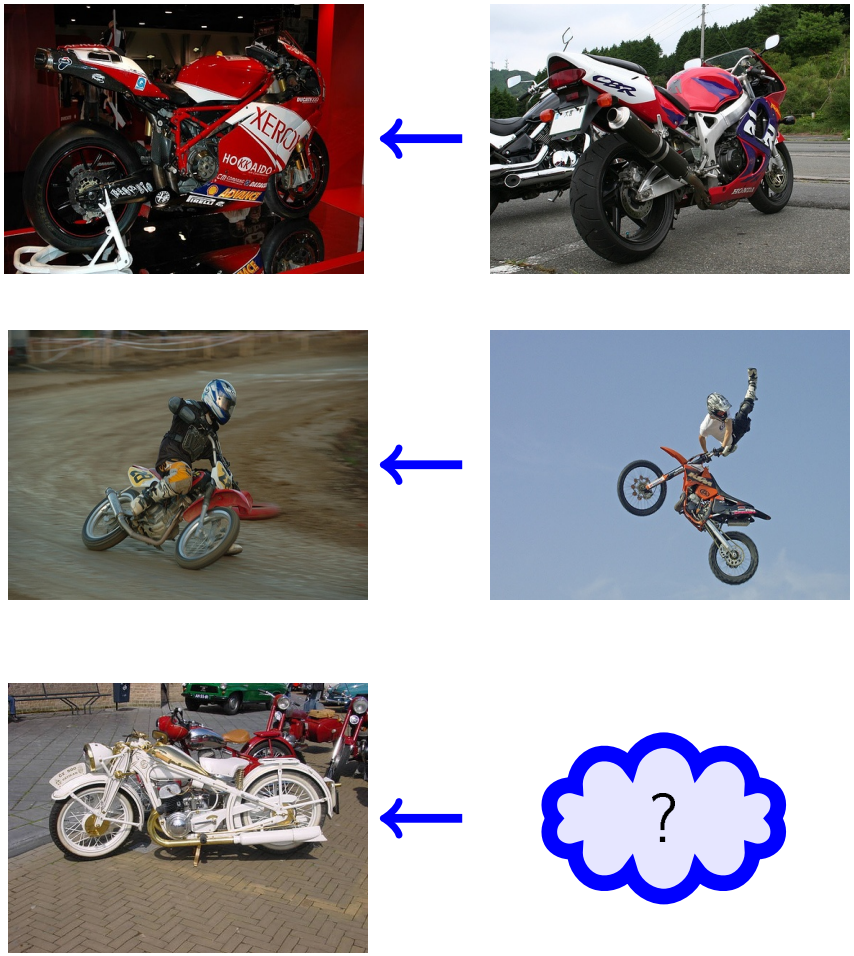

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In practice

- closed, well defined sets
- train and test sets

motorbike

not motorbike

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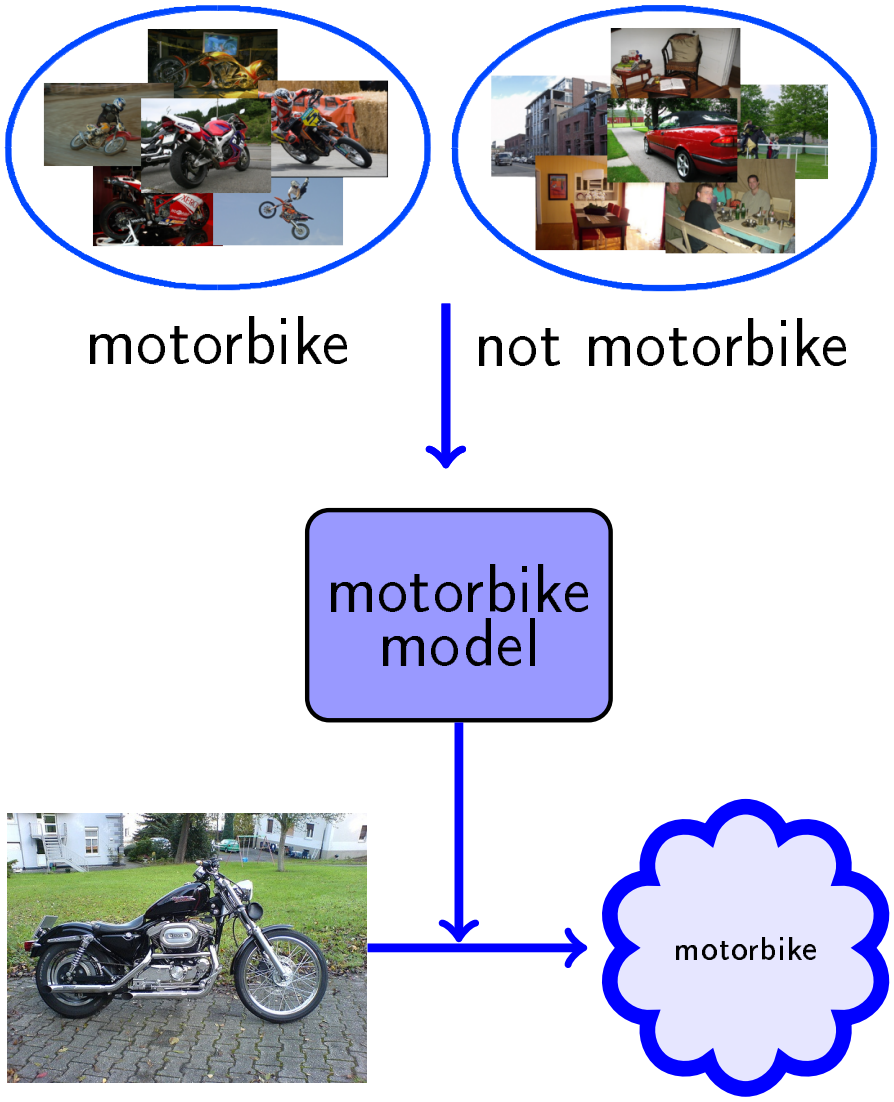
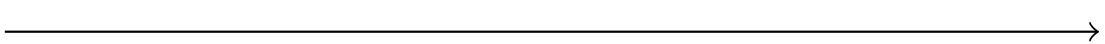
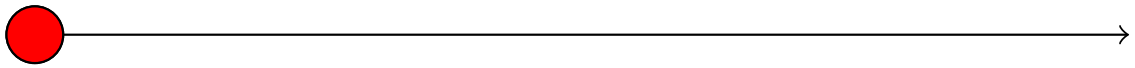


Recognition and Localization



localization

Recognition and Localization

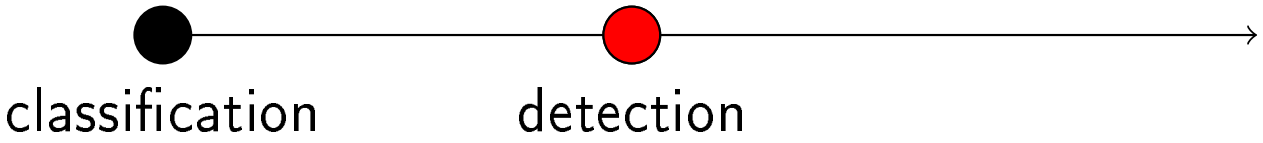


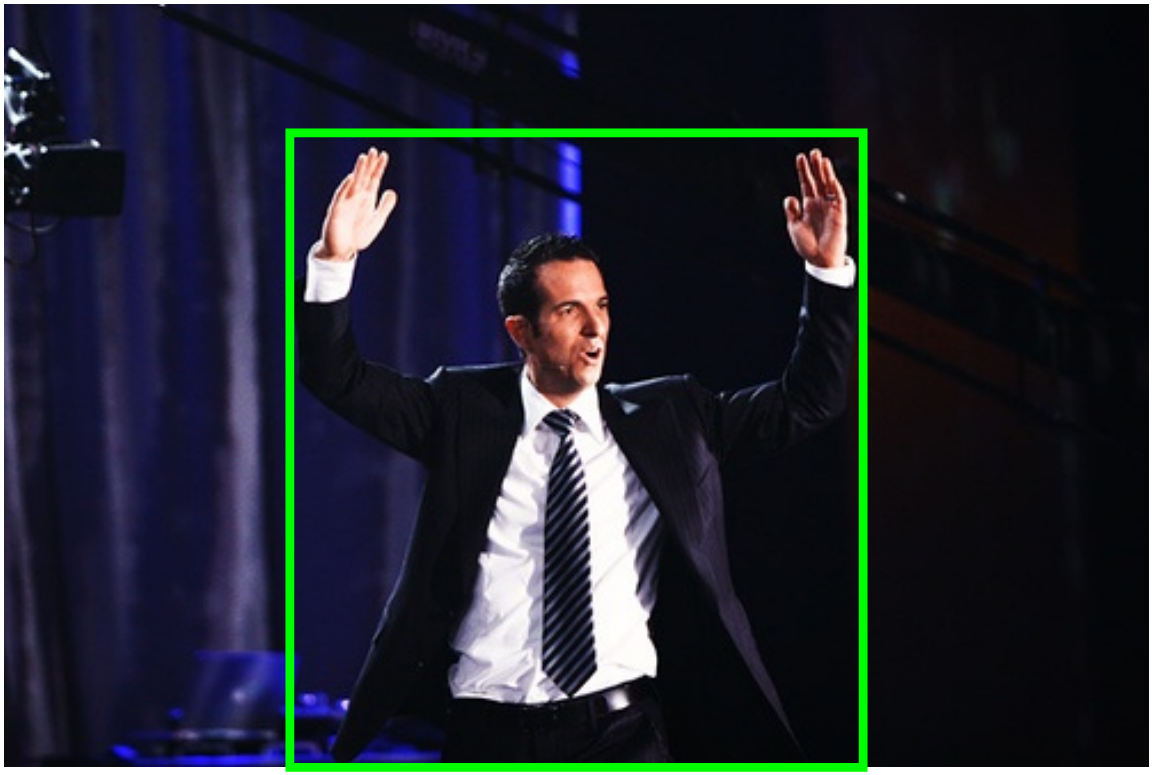
classification

localization

label

Recognition and Localization





bounding box and *label*

Recognition and Localization

label at each pixel

Recognition and Localization

label

Why does it matter?

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Intellectual curiosity

- Can we extract semantic information from a signal?
- Can we make machines see?

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Applications

- Assistive technologies
- Semantic image and video search
- Surveillance
- Medical imaging
- Human-computer interaction
- ...

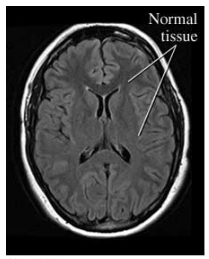

Figure 1

Figure 2

image credits: blog.timesunion.com, renttycoons.com, Intermountain Medical Imaging, digitaltrends.com, iwatchsystems.com

Challenges in Classification

Sources of variation

- illumination
- viewpoint
- background clutter
- occlusion
- intra-class variability
- intra-class vs. inter-class variability

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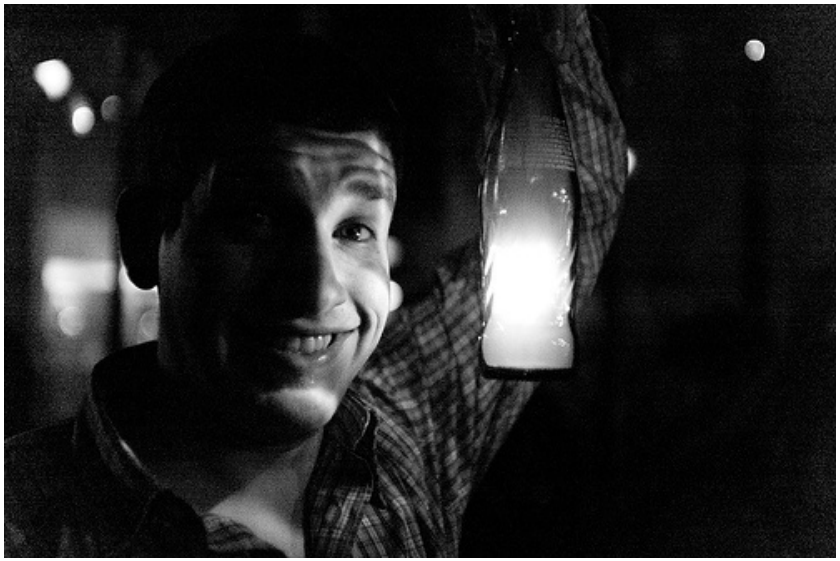

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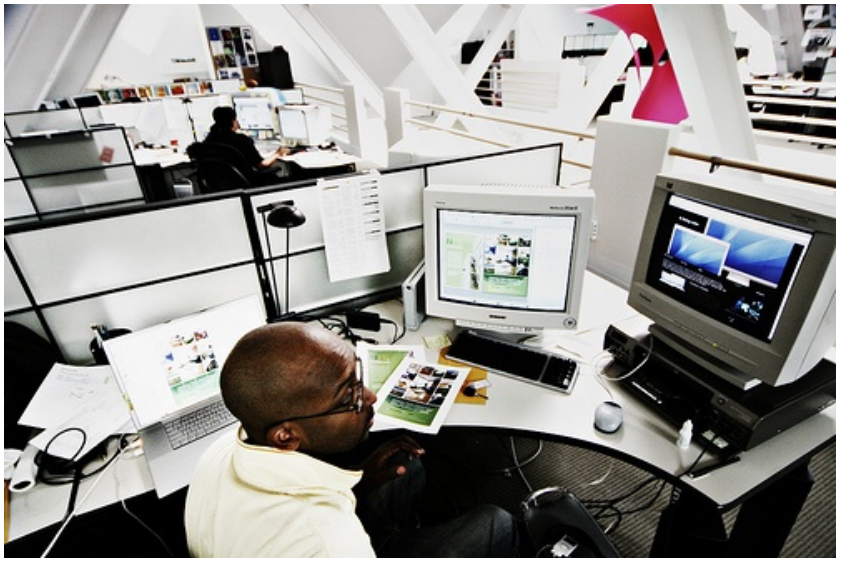

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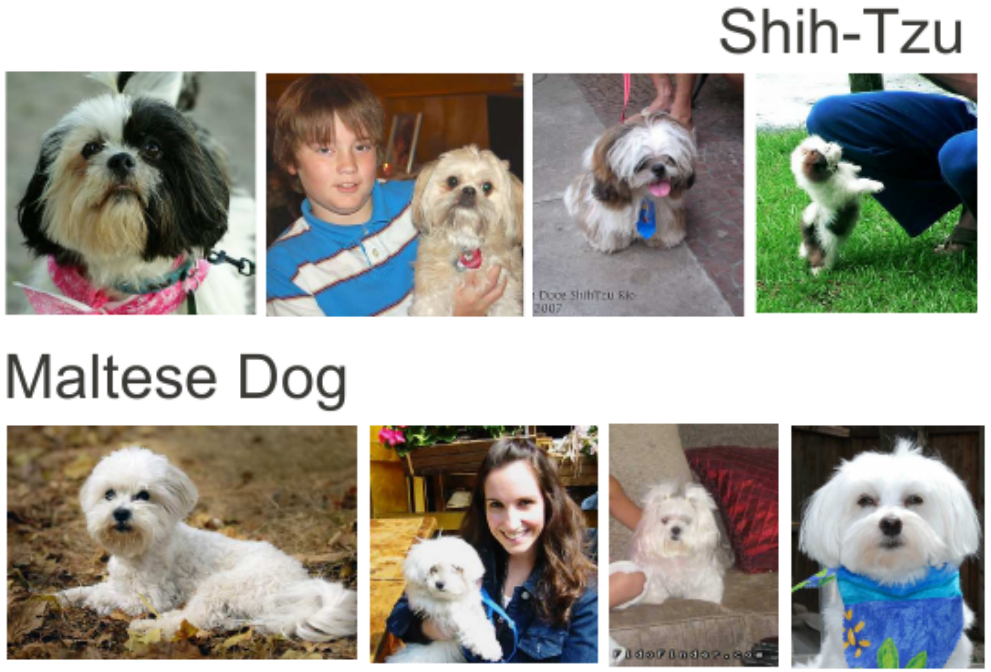

Coping with the challenges

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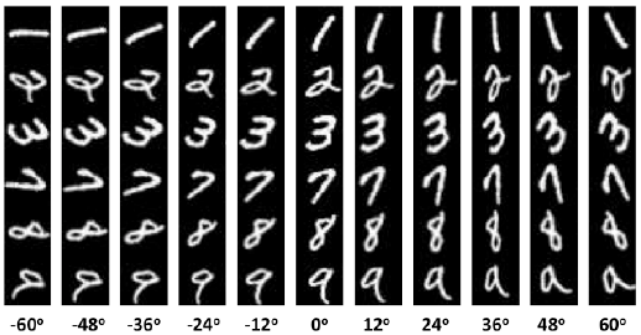

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image credits: Barriosa and Torralba

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- jointly learning both classifier parameters and latent parameters in a discriminative setting

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- state of the art classification methods

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  - EM (generative)
  - CCCP (discriminative)

Learning Spatial Pyramids

Spatial Pyramids [Lazebnik@CVPR06]

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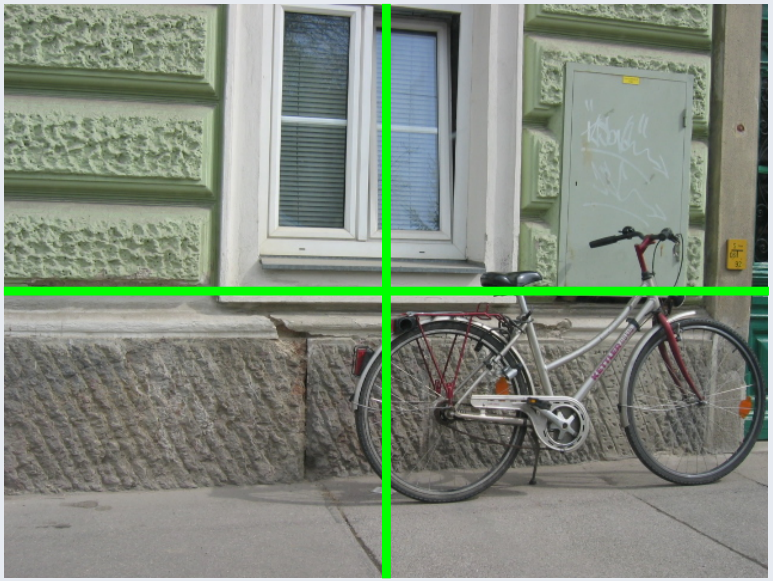
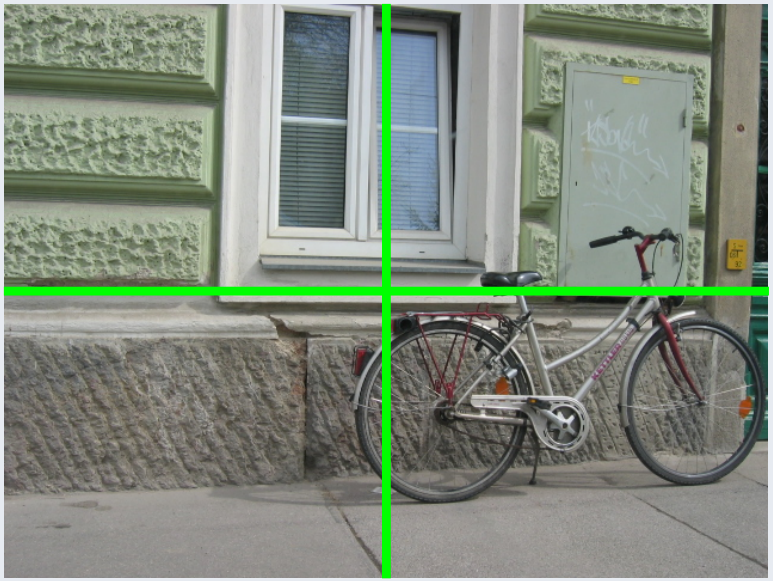


Learning Spatial Pyramids

Spatial Pyramids [Lazebnik@CVPR06]



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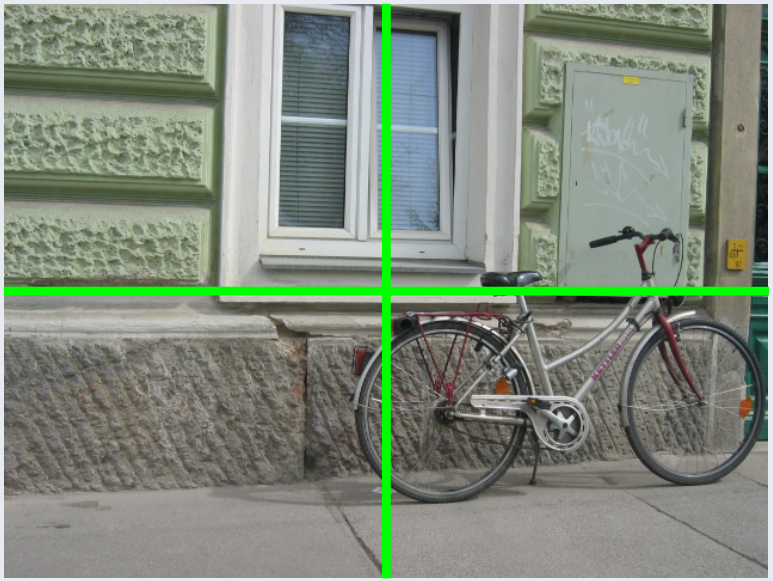

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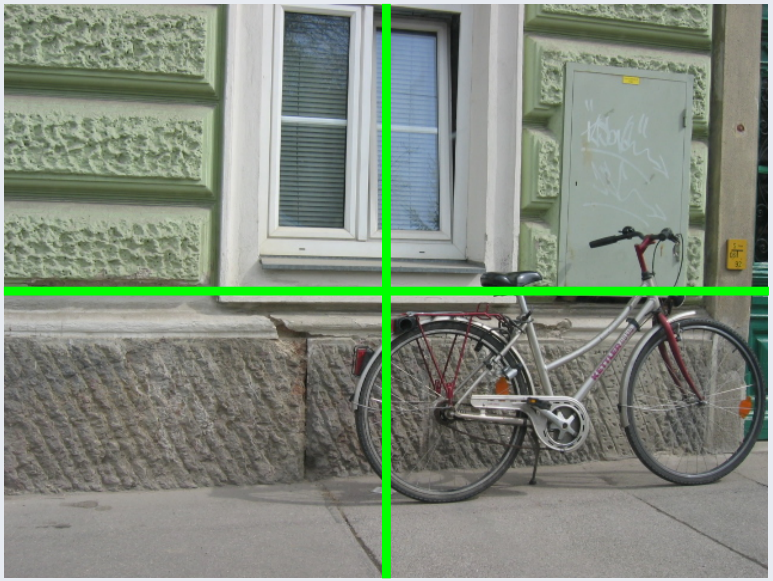

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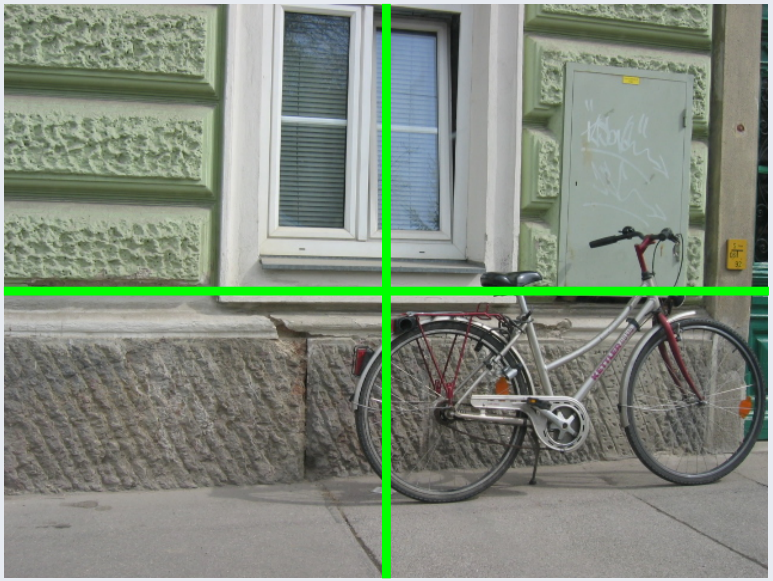

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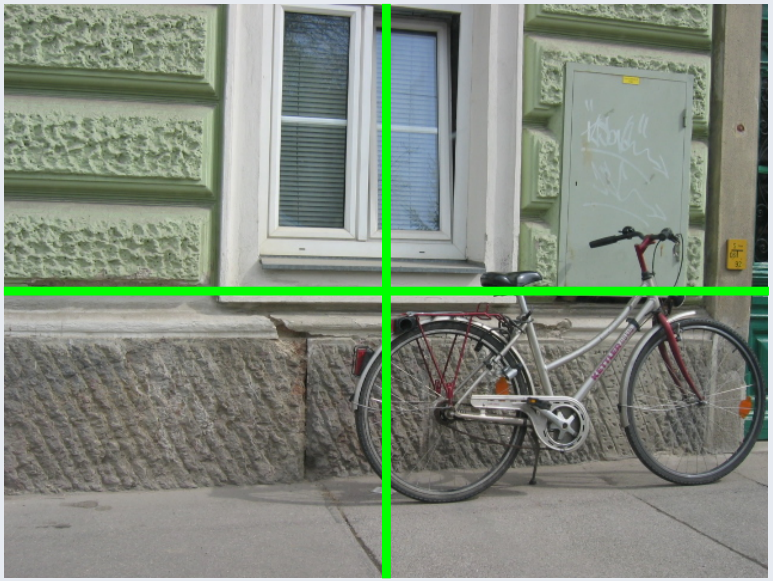

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- cons:
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  - features in cells are not aligned between images
  - includes discriminative and non-representative features

More Flexible Image Representation

Split

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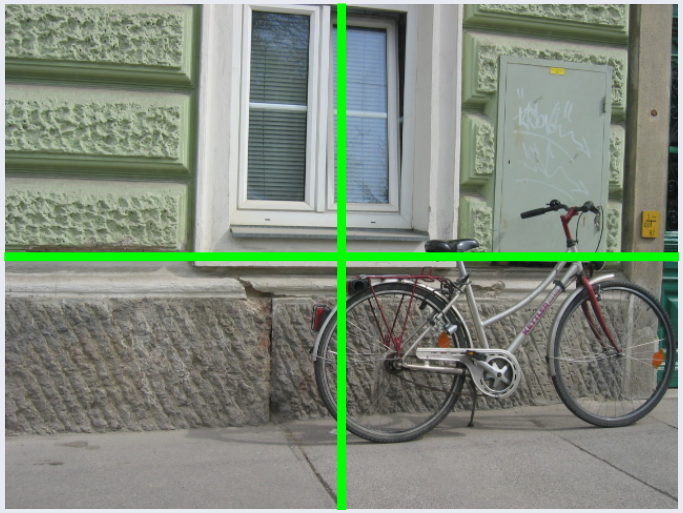

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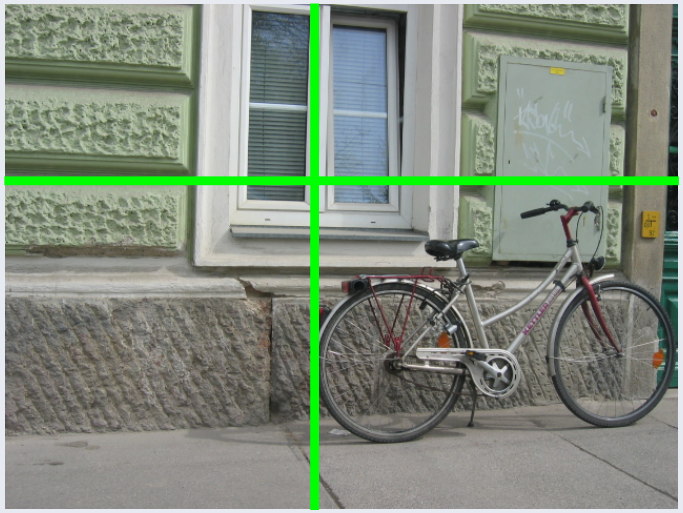

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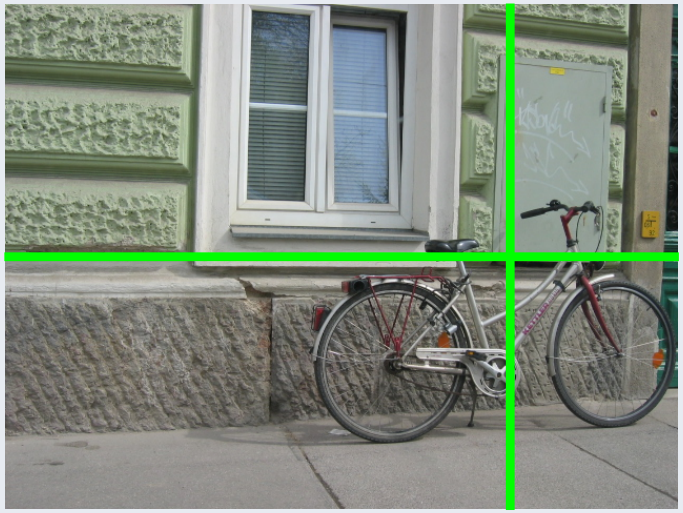

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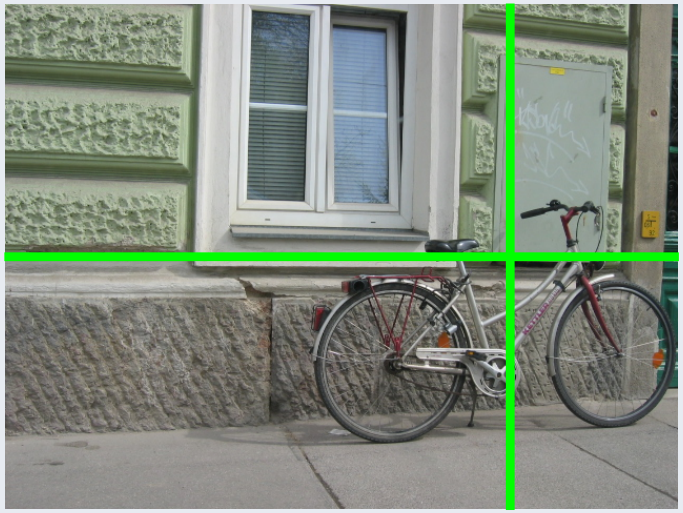
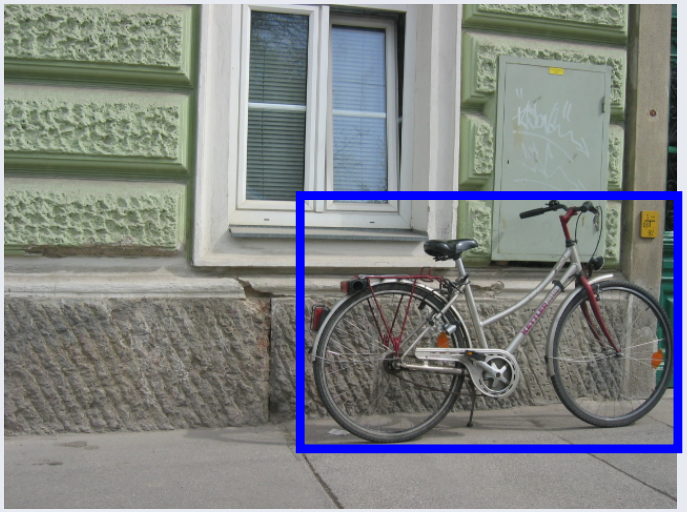


Crop



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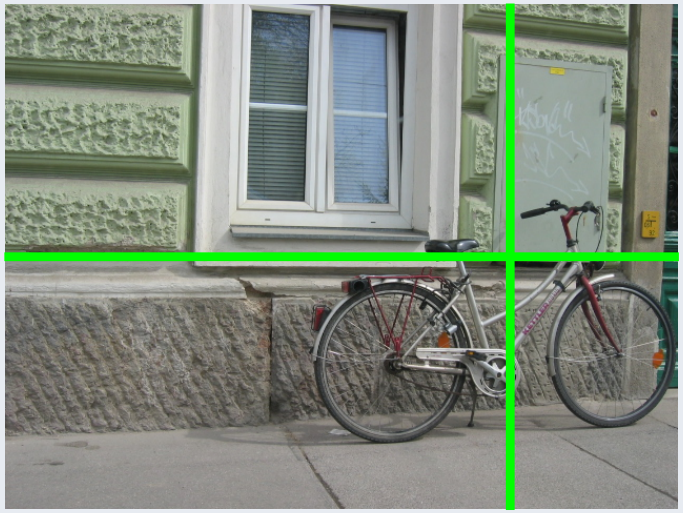

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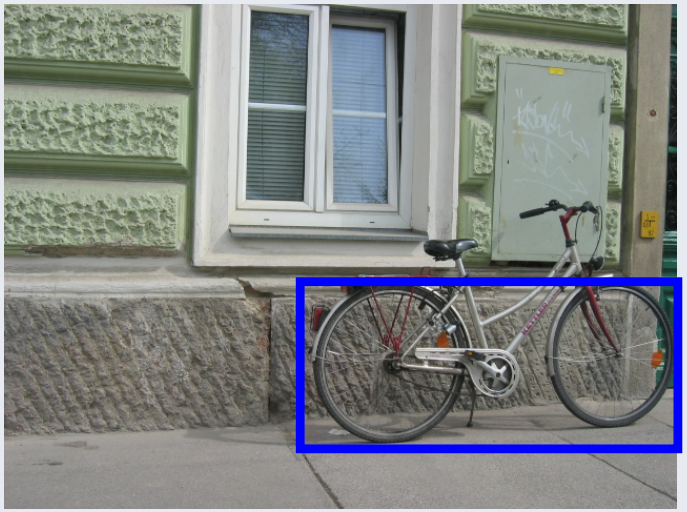

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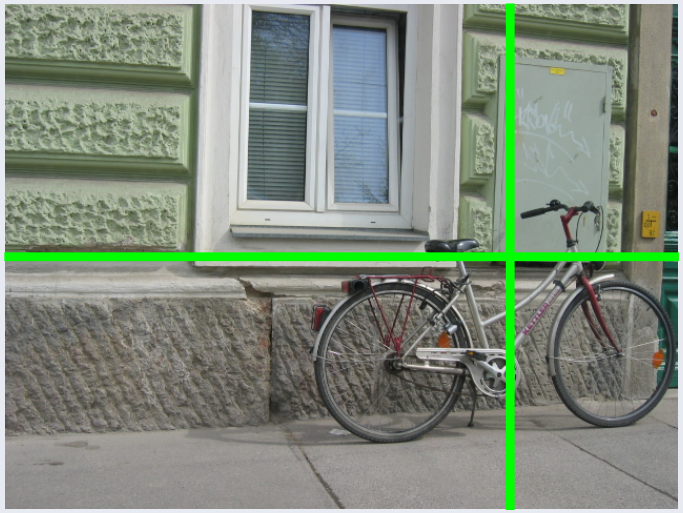

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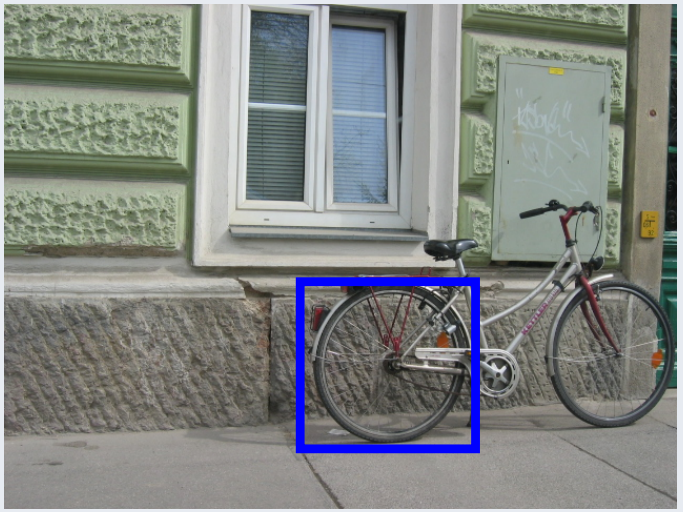

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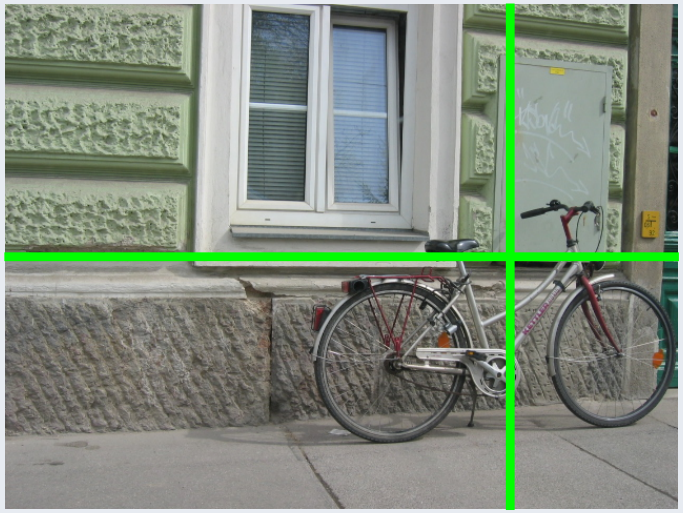

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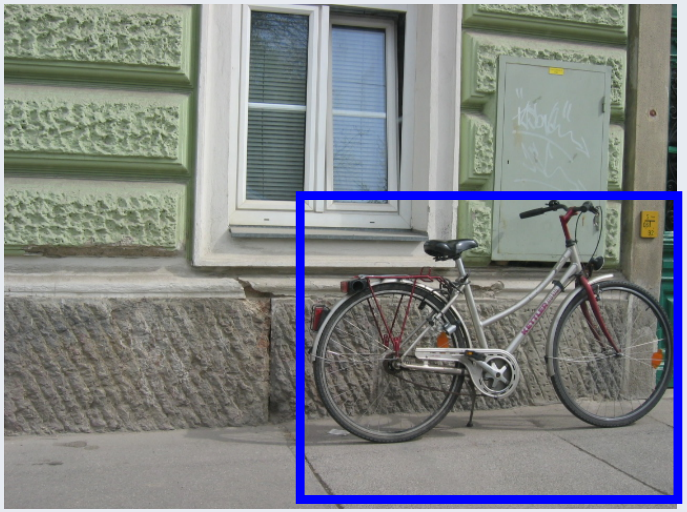

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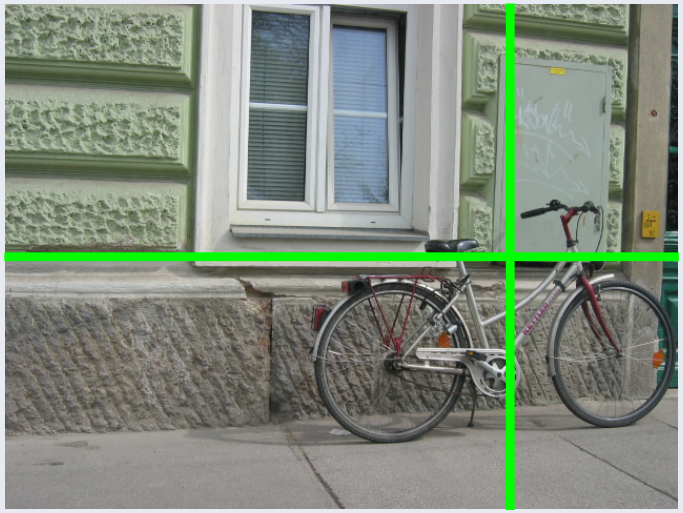

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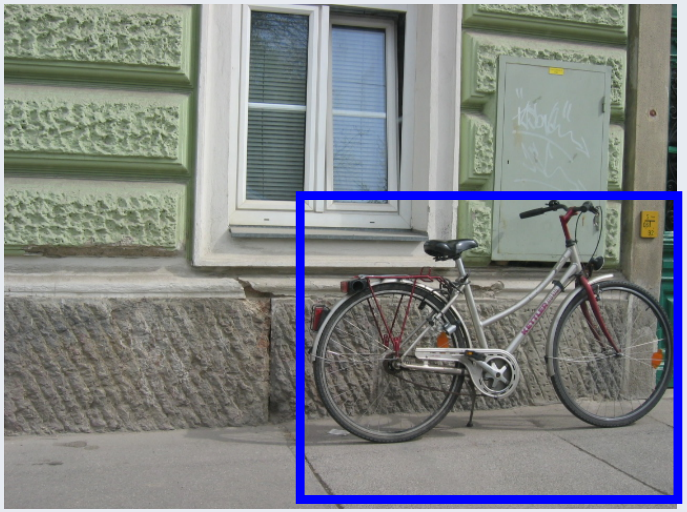

Crop - Uniform Split

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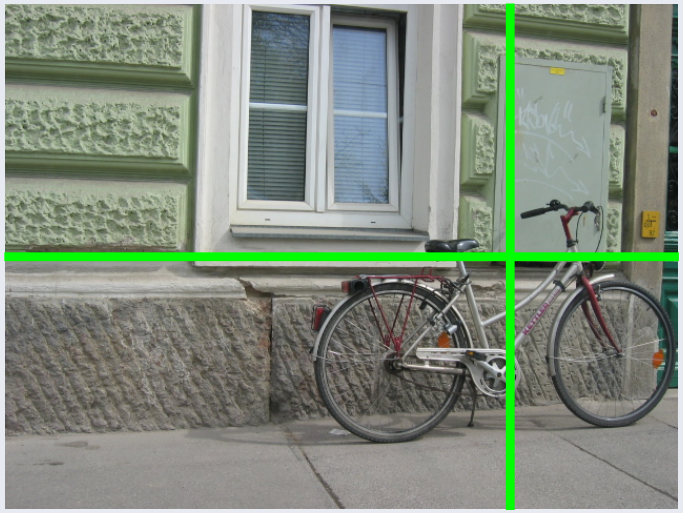

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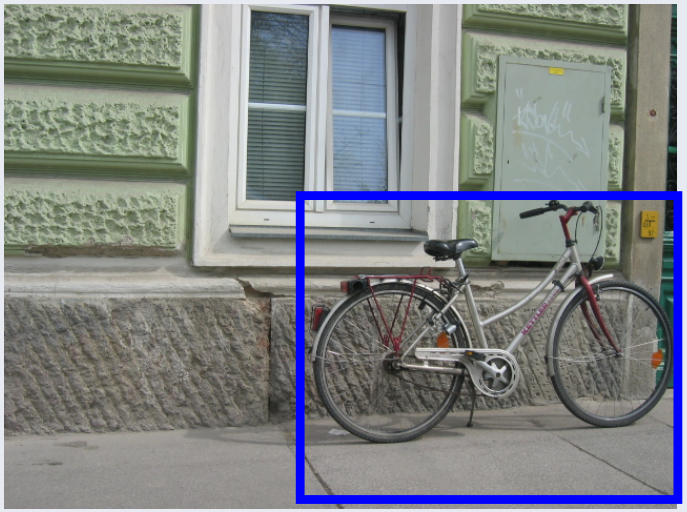

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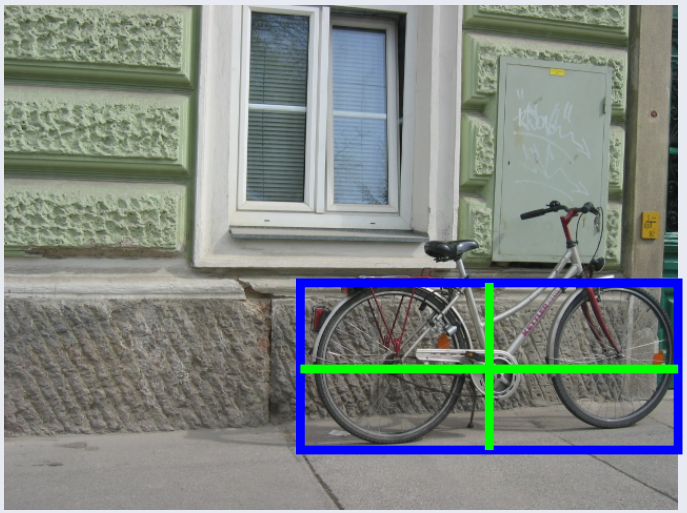

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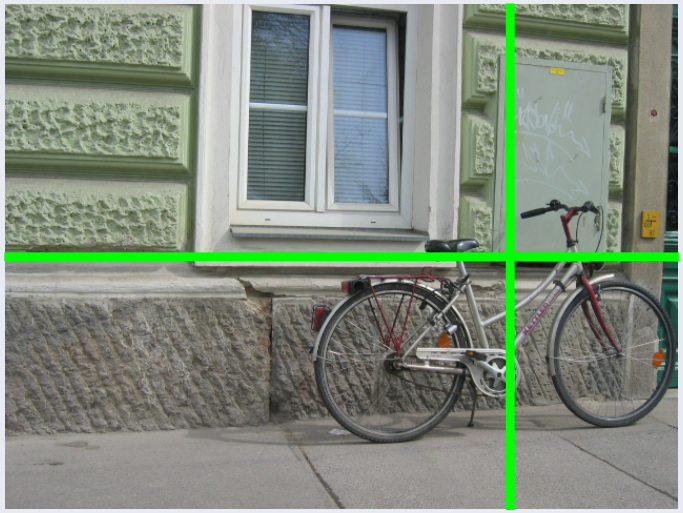

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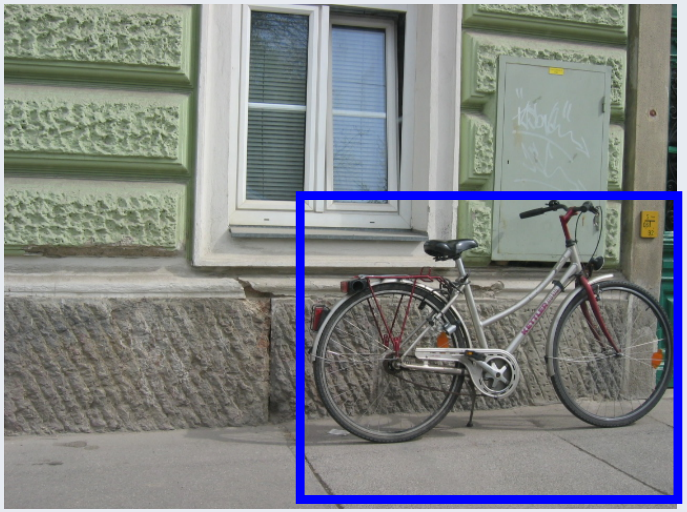

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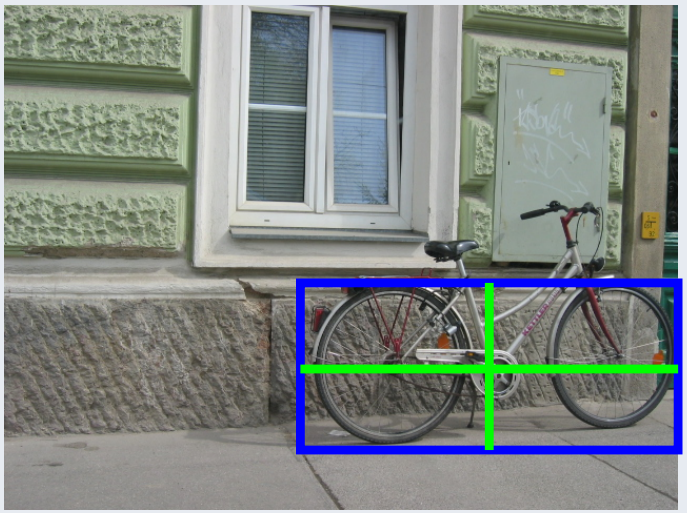

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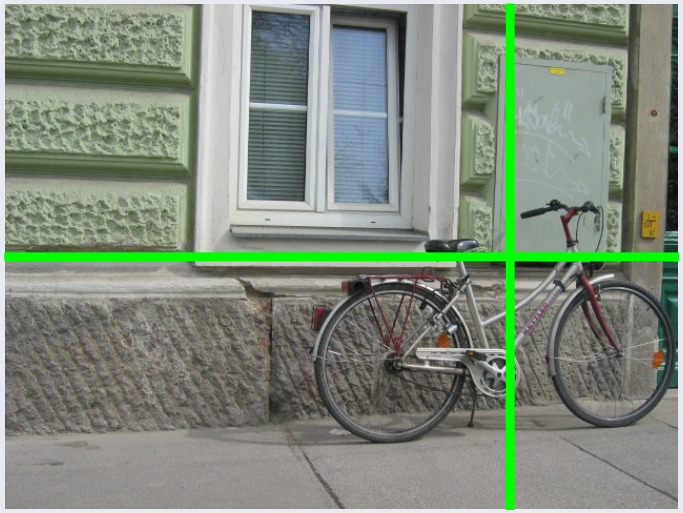

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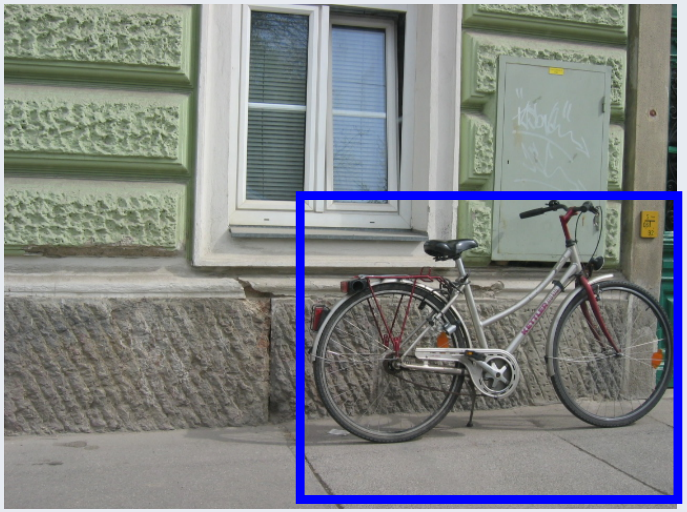

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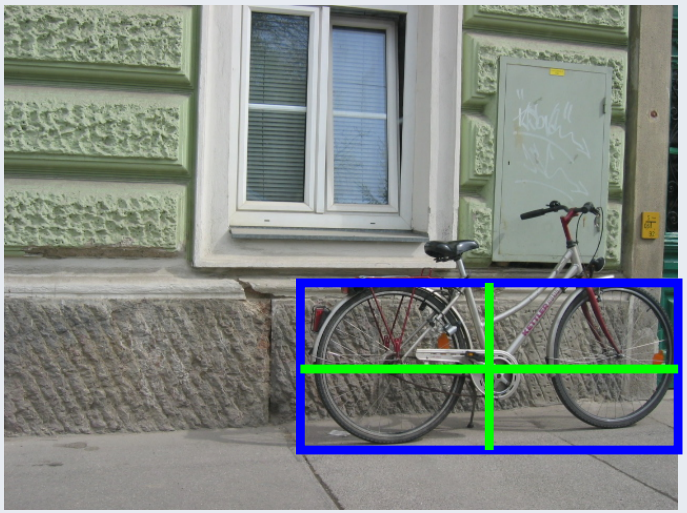

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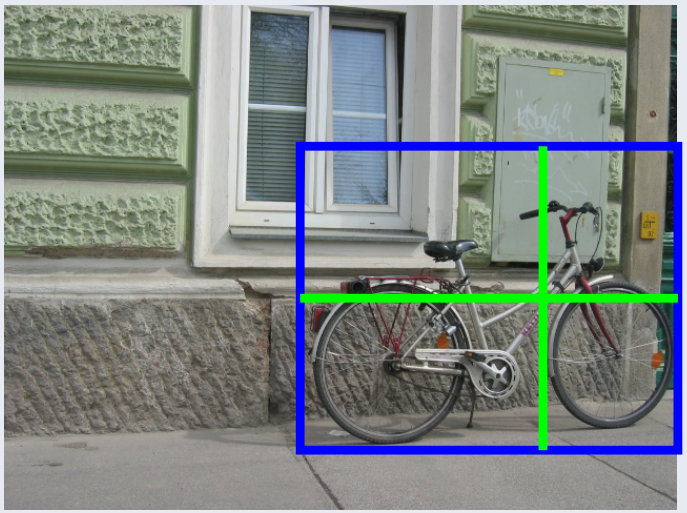

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- We use Latent SVM for learning

Latent Structural SVM Formulation

Training pairs $\{(\mathbf{x_i}, y_i, \mathbf{h_i})\} \in \mathcal{X} \times \mathcal{Y} \times \mathcal{H}$

- $\mathbf{x_i}$ are images/videos, y_i are class labels,
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Discriminant function that measures the matching quality of the triplet:

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- $\boldsymbol{w}$ is the parameter vector of the latent SVM.

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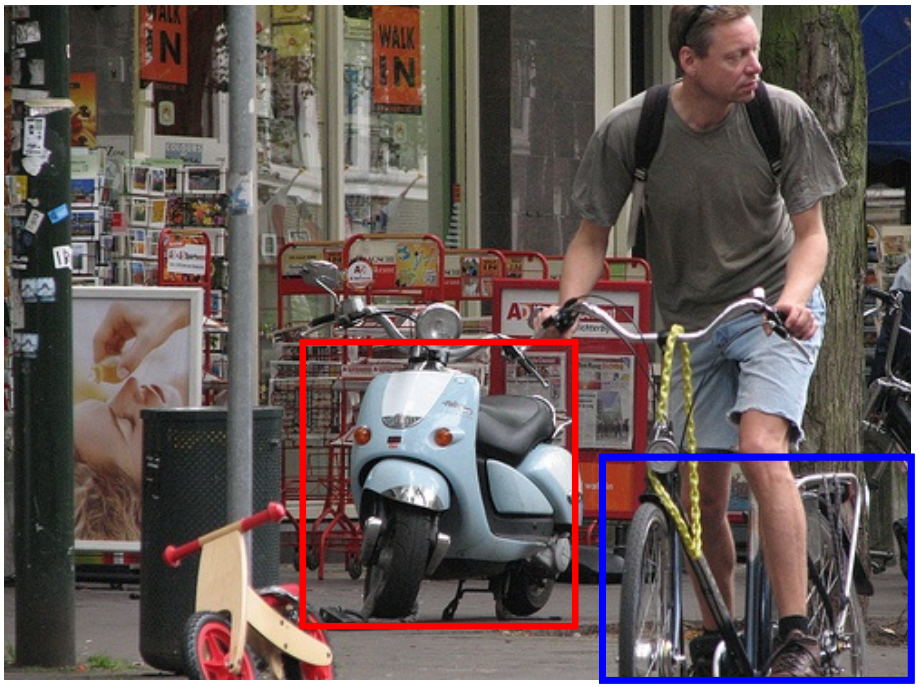

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Prediction & Parameter Learning

$$g_w(x) = \underbrace{\arg\max_{\hat{y}\in\mathcal{Y},\hat{h}\in\mathcal{H}} f_w(x,\hat{y},\hat{h})}_{\text{prediction}}$$

$$\min_w \left\{ \underbrace{\Omega(w)}_{\text{regularization}} + C\sum_{i=1}^{n} \left[\underbrace{\max_{\hat{y}_i,\hat{h}_i} \left[f_w(x_i,\hat{y}_i,\hat{h}_i) + \Delta(y_i,\hat{y}_i) \right]}_{\text{most violated constraint}} - \underbrace{\max_{h_i^*} \left[f_w(x_i,y_i,h_i^*) \right]}_{\text{best latent variable}} \right] \right\}$$

- Loss function $\Delta(y_i,\hat{y}_i)$
- Iterate
  1. ...
  2. ...
- until convergence

Experiments

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		Graz-02	VOC-07	Caltech-101	Activities
Baseline	BoW	86.95 ± 1.4	49.86	61.25 ± 0.9	79.33
	SP	88.05 ± 1.4	54.74	72.68 ± 1.2	88.00
Ours	crop	88.40 ± 1.1	51.82	62.16 ± 1.0	72.00
	split	88.58 ± 1.3	55.32	73.33 ± 1.0	88.00
	crop-uni-split	90.38 ± 1.9	56.26	**75.31 ± 0.7**	**90.67**
	crop-split	**90.62 ± 1.8**	**57.05**	74.93 ± 0.9	88.67

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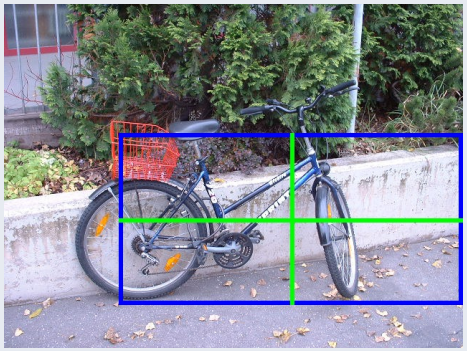
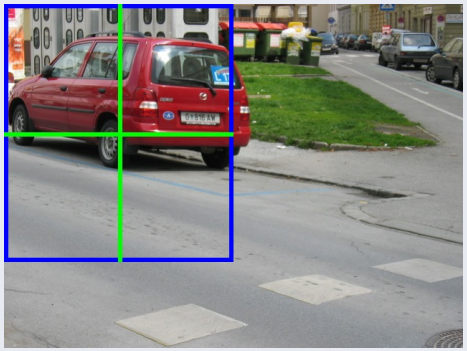
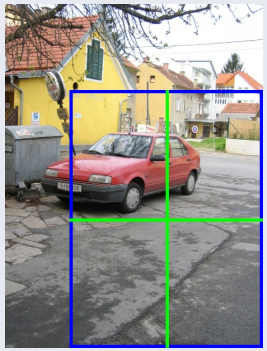
- The best results are obtained with the crop-uni-split or crop-split.
- Both crop-uni-split and crop-split are always better than SP.

Visualization of latent parameters

crop-uniform split examples



crop-split examples