

6.S093: Visual Recognition through Machine Learning Competition

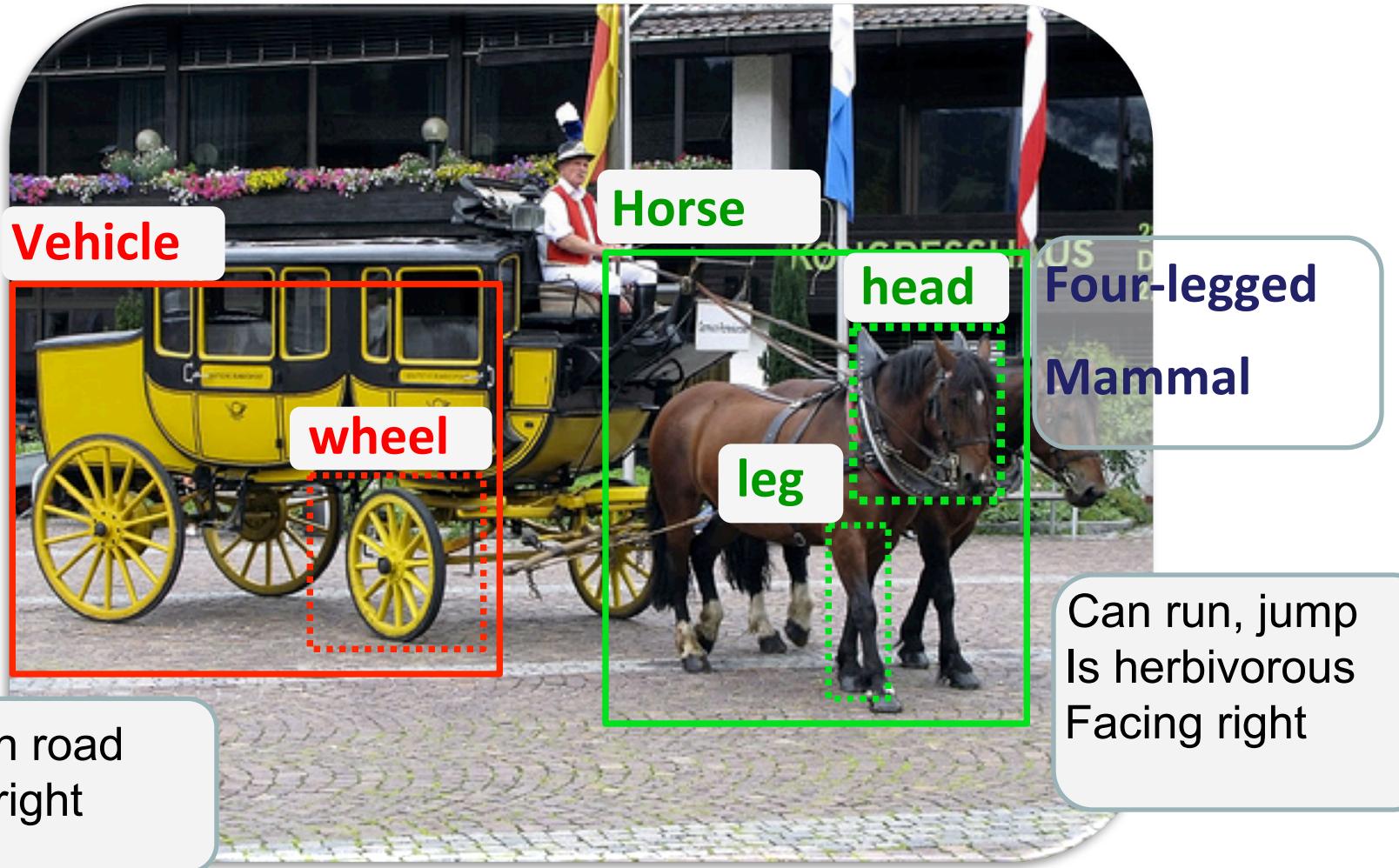
Image Representation

Acknowledgment: Many slides from Antonio Torralba,
James Hays, Derek Hoeim, and Pete Barnum.

Image Recognition



Image Recognition



Our competition



Vehicle

Horse

Our competition



PLEASE FORM A TEAM UPTO 3 MEMBERS



Vehicle

Horse

Image Representation

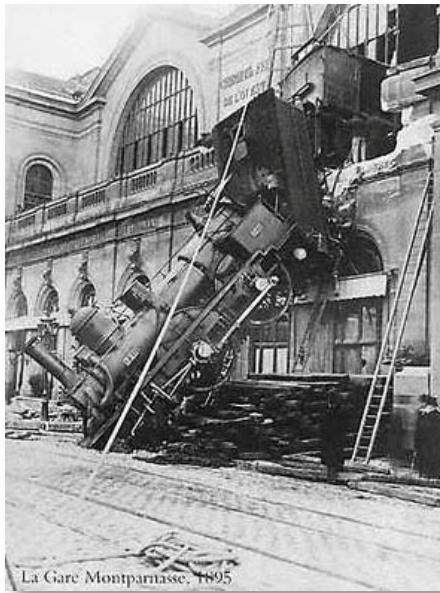
- Image is merely a set of numbers



| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 3 | 2 | 5 | 4 | 7 | 6 | 9 | 8 |
| 3 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2 | 1 | 0 | 3 | 2 | 5 | 4 | 7 | 6 |
| 5 | 2 | 3 | 0 | 1 | 2 | 3 | 4 | 5 |
| 4 | 3 | 2 | 1 | 0 | 3 | 2 | 5 | 4 |
| 7 | 4 | 5 | 2 | 3 | 0 | 1 | 2 | 3 |
| 6 | 5 | 4 | 3 | 2 | 1 | 0 | 3 | 2 |
| 9 | 6 | 7 | 4 | 5 | 2 | 3 | 0 | 1 |
| 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | 0 |

Image Representation

- Image is merely a set of numbers



La Gare Montparnasse, 1895

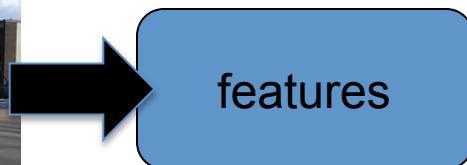
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 3 | 2 | 5 | 4 | 7 | 6 | 9 | 8 |
| 3 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2 | 1 | 0 | 3 | 2 | 5 | 4 | 7 | 6 |
| 5 | 2 | 3 | 0 | 1 | 2 | 3 | 4 | 5 |
| 4 | 3 | 2 | 1 | 0 | 3 | 2 | 5 | 4 |
| 7 | 4 | 5 | 2 | 3 | 0 | 1 | 2 | 3 |
| 6 | 5 | 4 | 3 | 2 | 1 | 0 | 3 | 2 |
| 9 | 6 | 7 | 4 | 5 | 2 | 3 | 0 | 1 |
| 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | 0 |

- Images have to be summarized to be more meaningful for machines to interpret.

Typical Recognition System

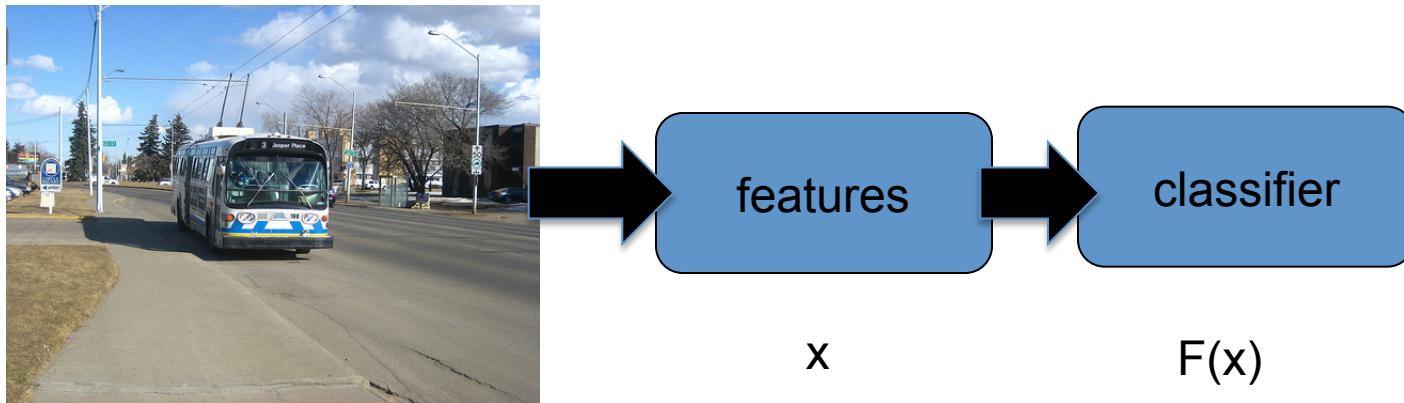


Typical Recognition System



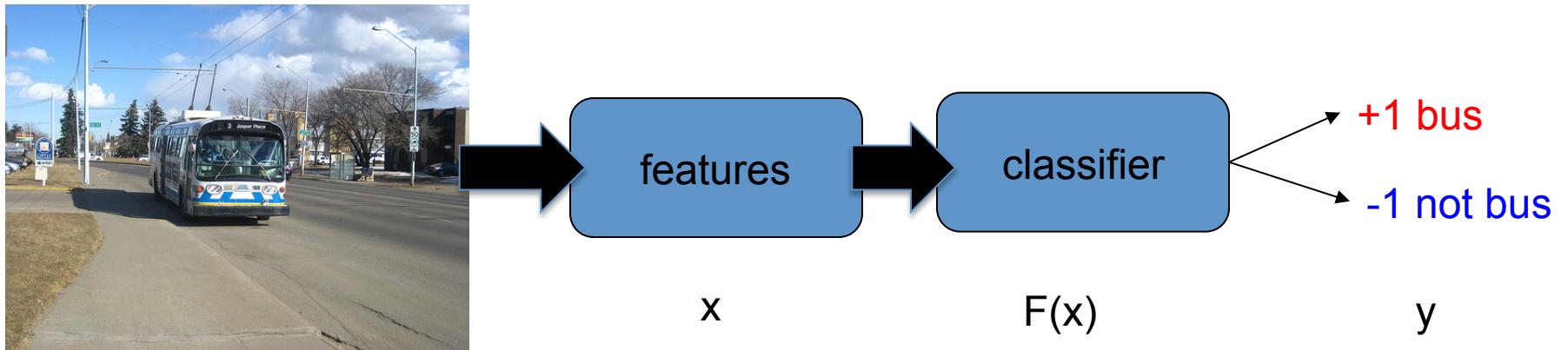
- Extract features from an image

Typical Recognition System



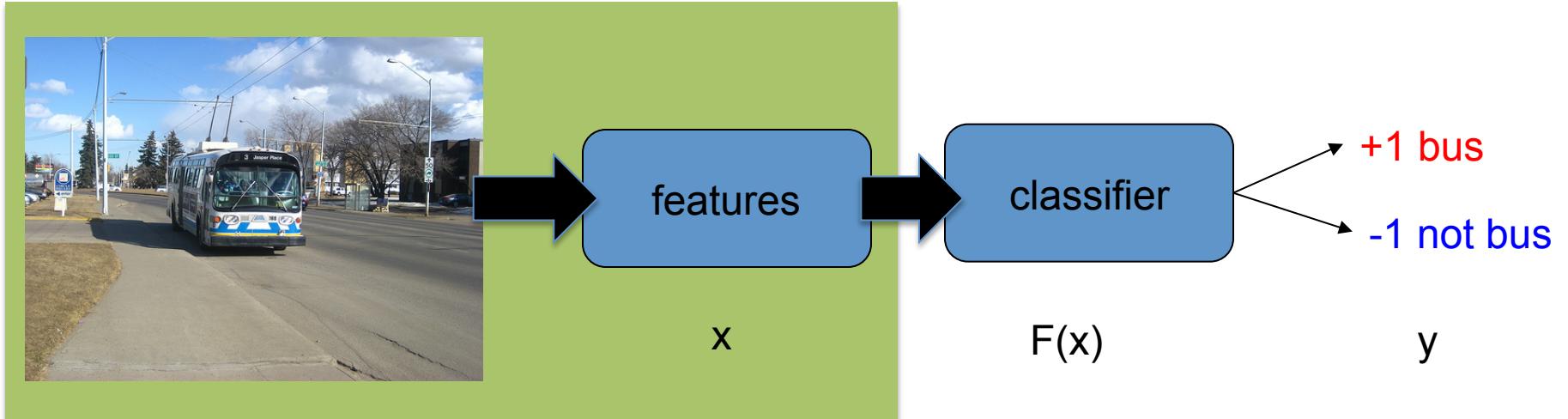
- Extract features from an image
- A classifier will make a decision based on extracted features

Typical Recognition System



- Extract features from an image
- A classifier will make a decision based on extracted features

Typical Recognition System



- Extract features from an image
- A classifier will make a decision based on extracted features

Features



Color histogram

| | | | | | | | | | | |
|-----|-----|-----|--|-----|--|--|-----|-----|-----|-----|
| 0.2 | 0.7 | 0.1 | | ... | | | 0.1 | 0.4 | 0.2 | 0.9 |
|-----|-----|-----|--|-----|--|--|-----|-----|-----|-----|



| | | | | | | | | | | |
|-----|-----|---|--|-----|--|--|-----|-----|-----|-----|
| 0.4 | 0.1 | 0 | | ... | | | 0.9 | 0.7 | 0.2 | 0.4 |
|-----|-----|---|--|-----|--|--|-----|-----|-----|-----|



| | | | | | | | | | | |
|-----|-----|-----|--|-----|--|--|---|---|-----|-----|
| 0.8 | 0.9 | 0.7 | | ... | | | 0 | 0 | 0.1 | 0.7 |
|-----|-----|-----|--|-----|--|--|---|---|-----|-----|

Different types of representation

- Low-level
 - Color, HOG, SIFT
- Mid-level
 - Part-based, Region-based
- High-level
 - Object presence, object relationship, scene class

Image representation is used for

- Object recognition
- Image alignment and building panoramas
- 3D reconstruction
- Motion tracking
- Indexing and database retrieval
- Robot navigation

Right features depend on the goal

- Object
 - Local shape info, shading, shadows, texture
- Scene
 - Linear perspective, gradients
- Material properties
 - Color, texture
- Motion
 - Optical flow, tracked points

General Principles of Representation

- Coverage
 - Ensure that all relevant info is captured
- Concision
 - Minimize number of features without sacrificing coverage
- Directness
 - Ideal features are independently useful for prediction

Image representations

- Templates
 - Intensity, gradients, etc.
- Histograms
 - Color, texture, SIFT descriptors, etc.
- Average of features

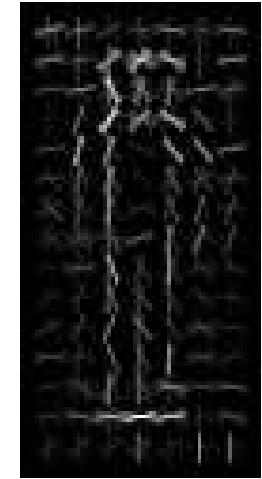
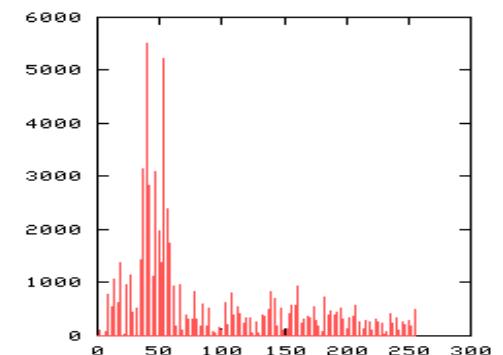
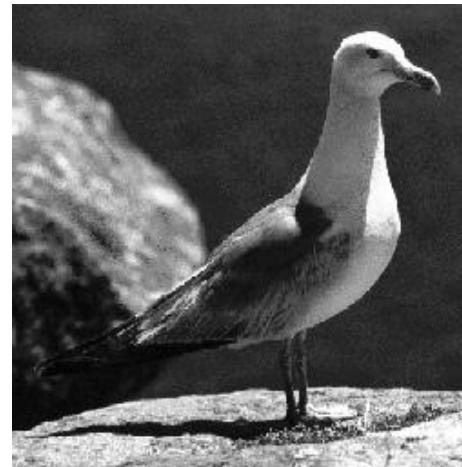
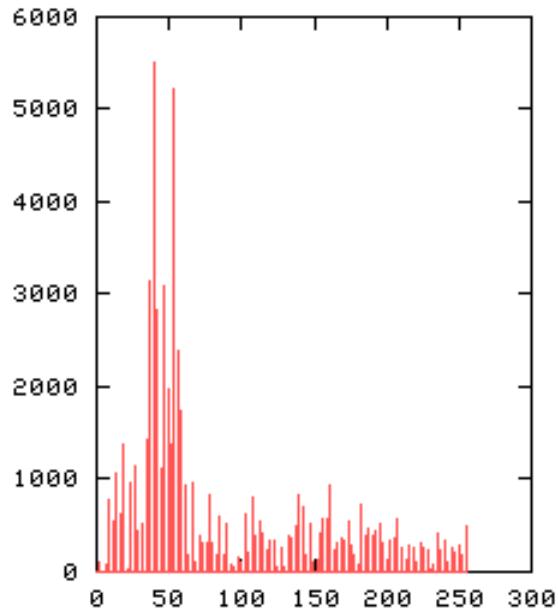


Image
Intensity

Gradient
template



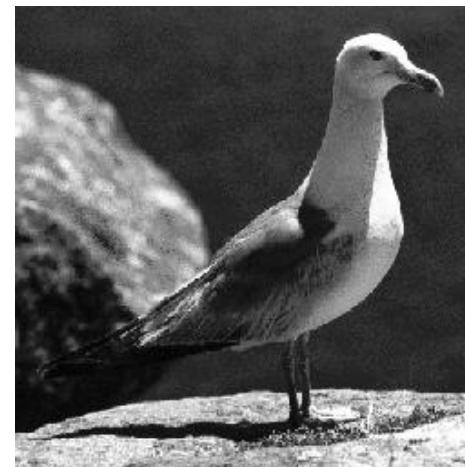
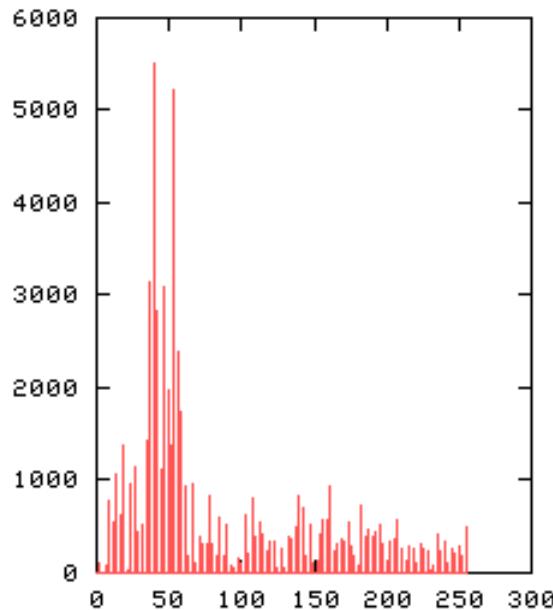
Histograms



Global histogram

- Represent distribution of features
 - Color, texture, depth, ...

Histograms

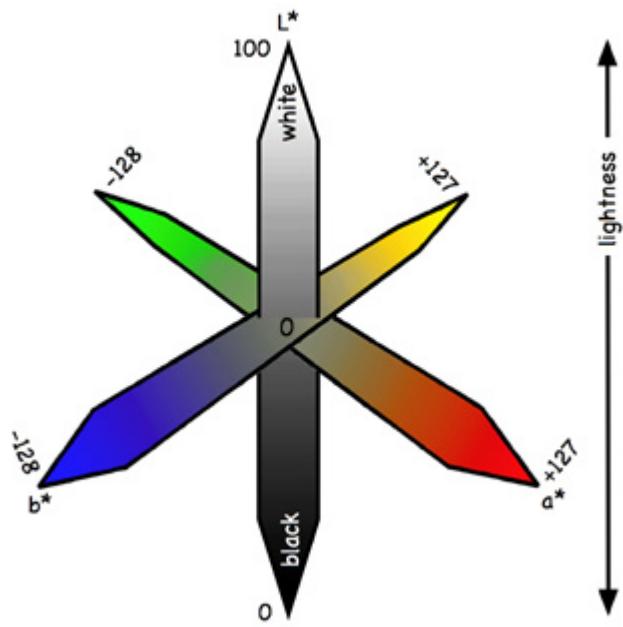


Global histogram

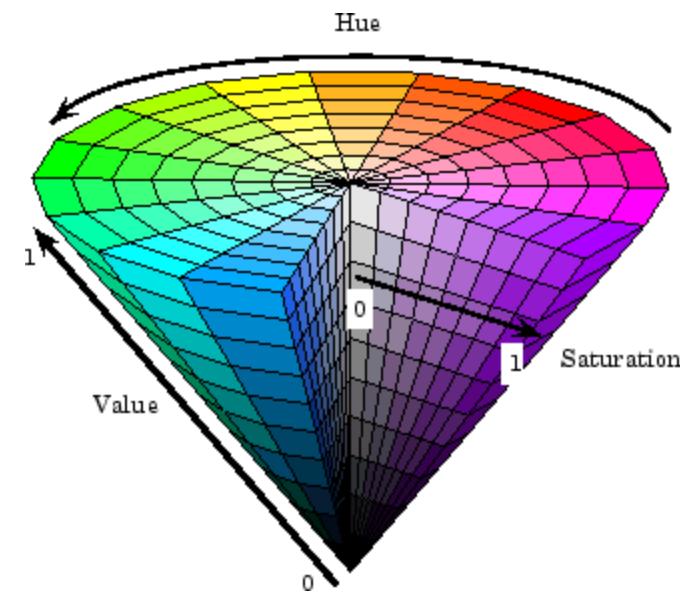
- Represent distribution of features
 - Color, texture, depth, ...
- For example, how many red color pixels are there?

What kind of things do we compute histograms of?

- Color



L^{*}a^{*}b^{*} color space

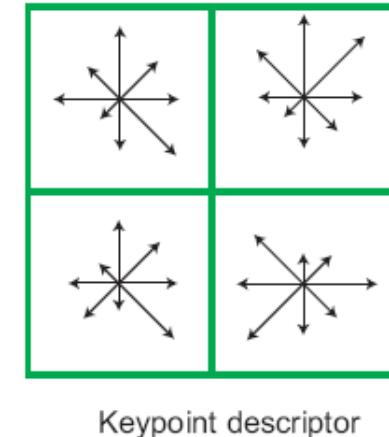
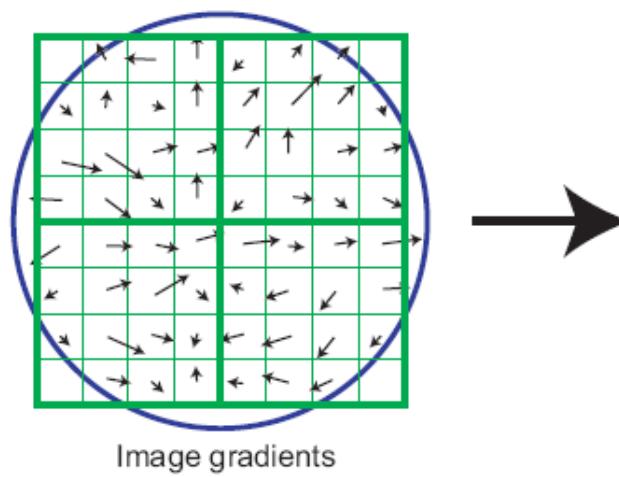


HSV color space

- Texture (filter banks or HOG over regions)

What kind of things do we compute histograms of?

- Histograms of descriptors



SIFT – Lowe IJCV 2004

- “Bag of words”

Histograms



Histograms



Histograms



Histogram of color will do a great job!



Histograms



Histograms



Histograms



Histogram of color will be poor.



Histograms



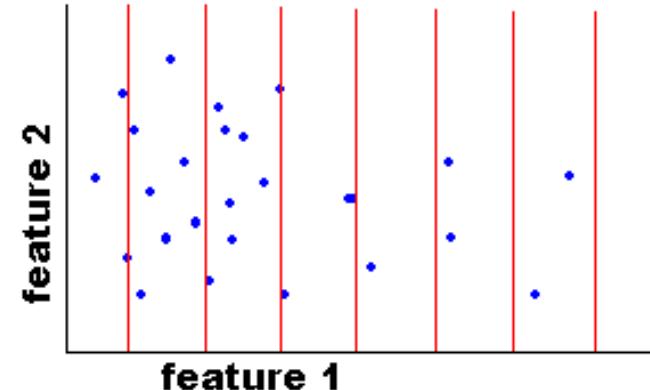
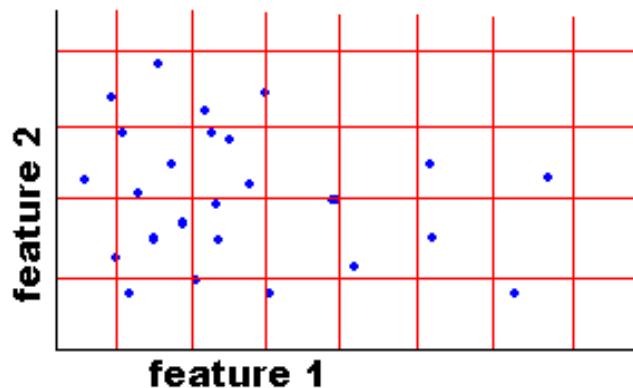
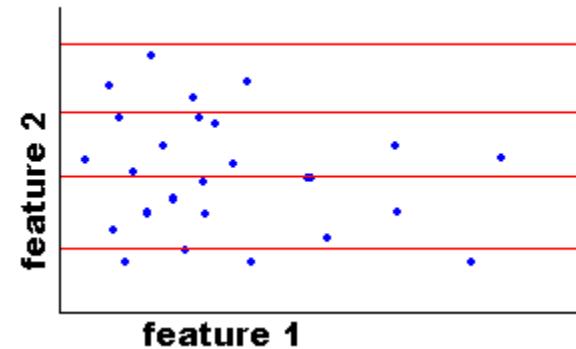
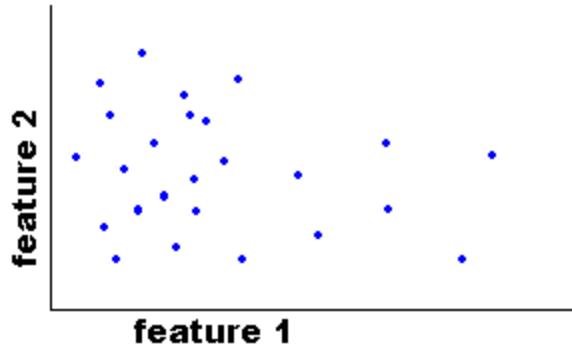
Histogram of color will be poor.

How about histogram of orientation??



Image Representations: Histograms

Histogram: Probability or count of data in each bin



Histograms: Implementation issues

- Quantization
 - Grids: fast but applicable only with few dimensions
 - Clustering: slower but can quantize data in higher dimensions



Few Bins

Need less data

Coarser representation

Many Bins

Need more data

Finer representation

- Matching
 - Histogram intersection or Euclidean may be faster
 - Chi-squared often works better
 - Earth mover's distance is good for when nearby bins represent similar values

Histogram of Oriented Gradient

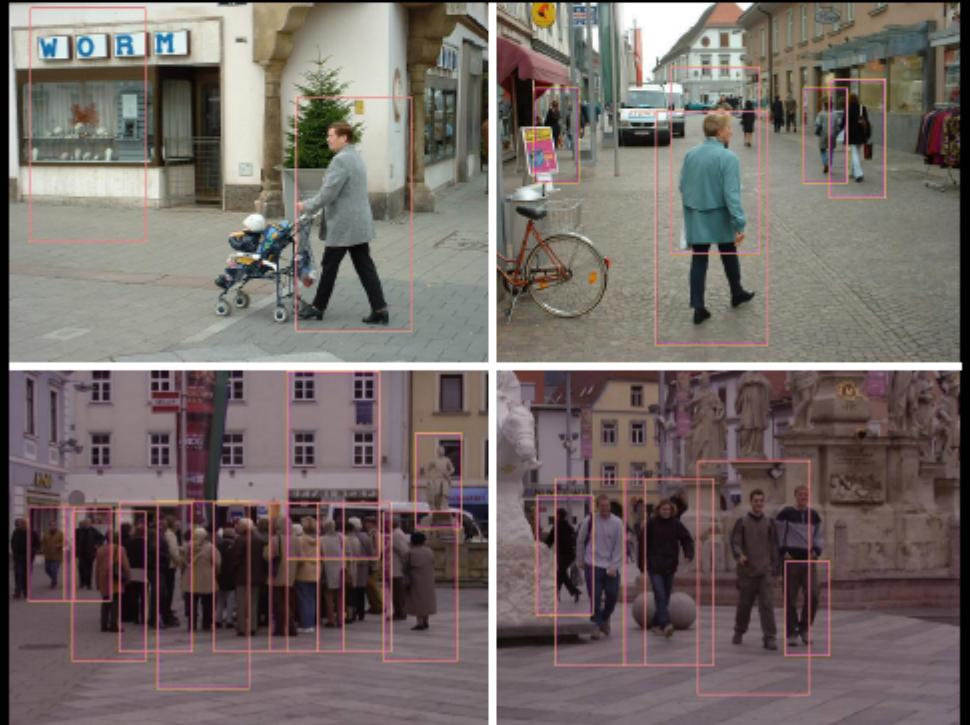
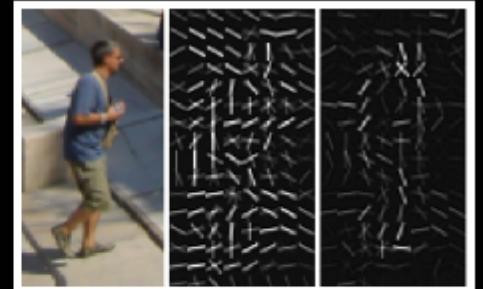
- One of the most successful features for object recognition and detection
- Dalal, N. and Triggs, B. “Histograms of oriented gradients for human detection”

2d Global Detector

Dalal and Triggs, CVPR 2005

- 3-D Histogram of Oriented Gradients (HOG) as descriptors
- Linear SVM for runtime efficiency
- Tolerates different poses, clothing, lighting and background
- Currently works for fully visible upright persons

Importance weight responses



Slides from Sminchisescu

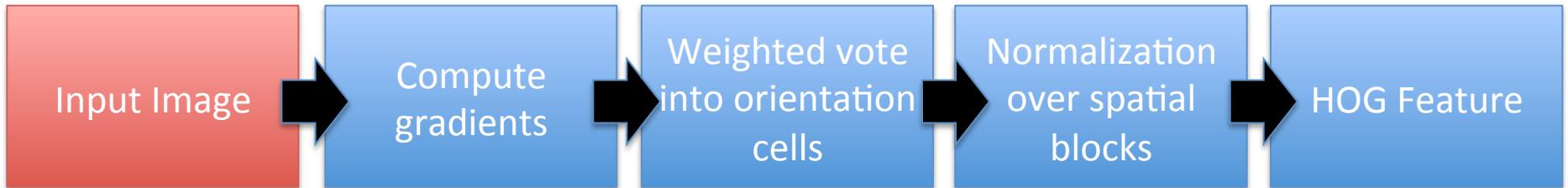
Dynamic Pedestrian Detection

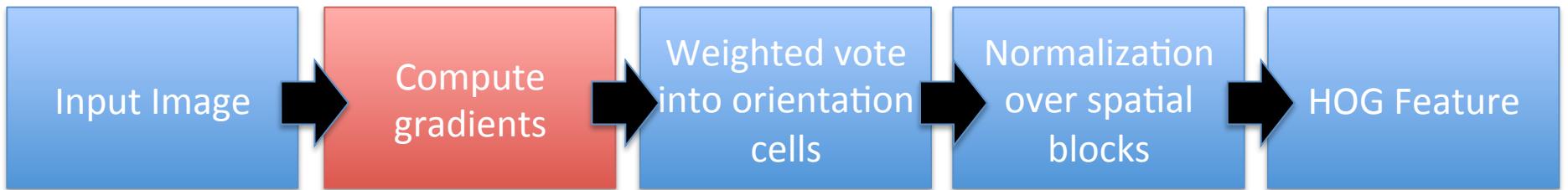
Viola, Jones and Snow, ICCV 2003



- Train using AdaBoost, about 45,000 possible features
- Efficient and reliable for distant detections (20x15), 4fps

Slides from Sminchisescu





Compute gradients

Weighted vote
into orientation
cells

Normalization
over spatial
blocks

HOG Feature

| | | |
|----|---|----|
| +1 | 0 | -1 |
| +2 | 0 | -2 |
| +1 | 0 | -1 |

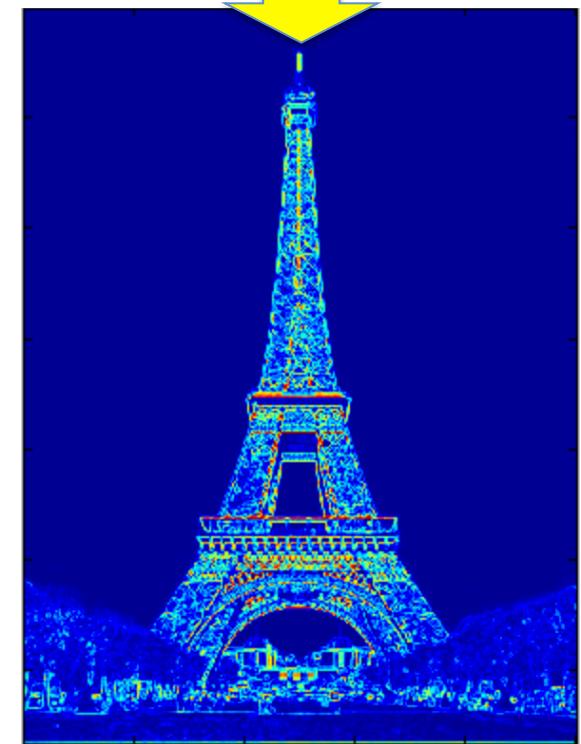
Sobel x

| | | |
|----|----|----|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

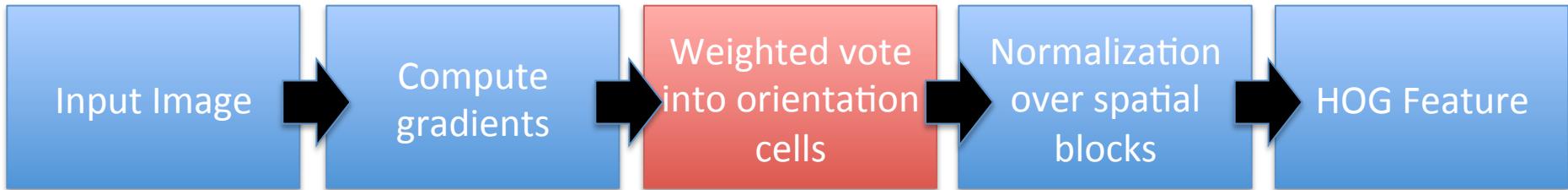
Sobel y

Apply filters to obtain the
gradient

$$G = \sqrt{G_x^2 + G_y^2}$$



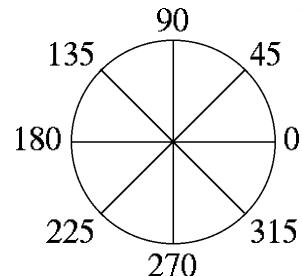
$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * A \quad \text{and} \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$



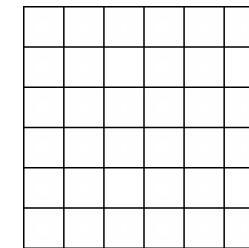
- Histogram of gradient orientations

- Orientation

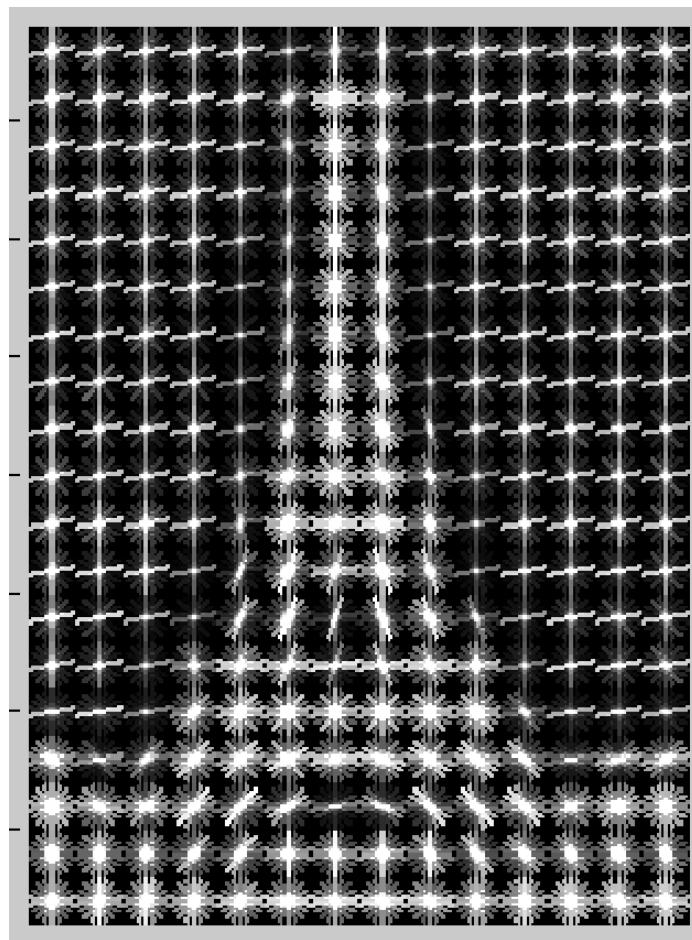
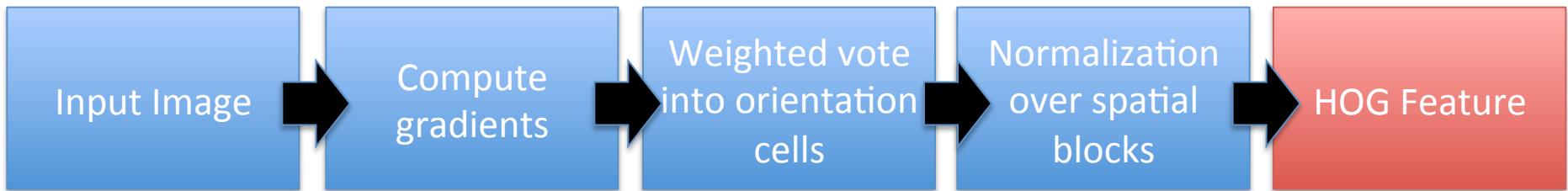
$$\Theta = \text{atan2}(\mathbf{G}_y, \mathbf{G}_x)$$



- Position



- Weighted by magnitude $\mathbf{G} = \sqrt{\mathbf{G}_x^2 + \mathbf{G}_y^2}$



Choosing a descriptor

- Again, need not stick to one
- For object recognition or stitching, HOG or variant (e.g. SIFT) showed a promising result.

Exercise: Simplified HOG

- Exercise 1: Compute gradient orientation and magnitude
- Exercise 2: Compute global histogram of gradient
- Exercise 3: Compute a distance between histograms