Machine Learning Problems

	Supervised Learning	***Unsupervised Learning***
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

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Machine Learning Problems

	Supervised Learning	***Unsupervised Learning***
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

2

The machine learning framework

- Apply a prediction function to a feature representation of the image to get the desired output:

f() = "apple"

f() = "tomato"

f() = "cow"

Slide credit: L. Lazebnik

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The machine learning framework

$$y = f(\mathbf{x})$$

output | prediction function | Image feature

- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Slide credit: L. Lazebnik

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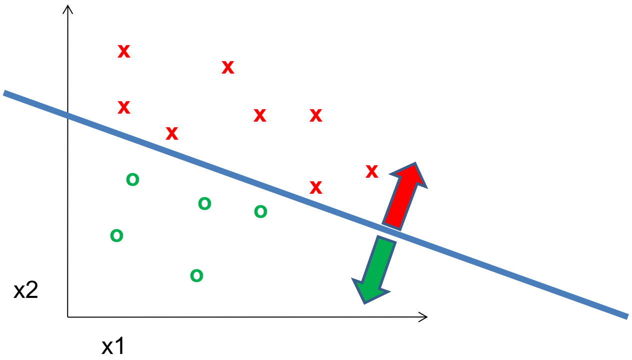
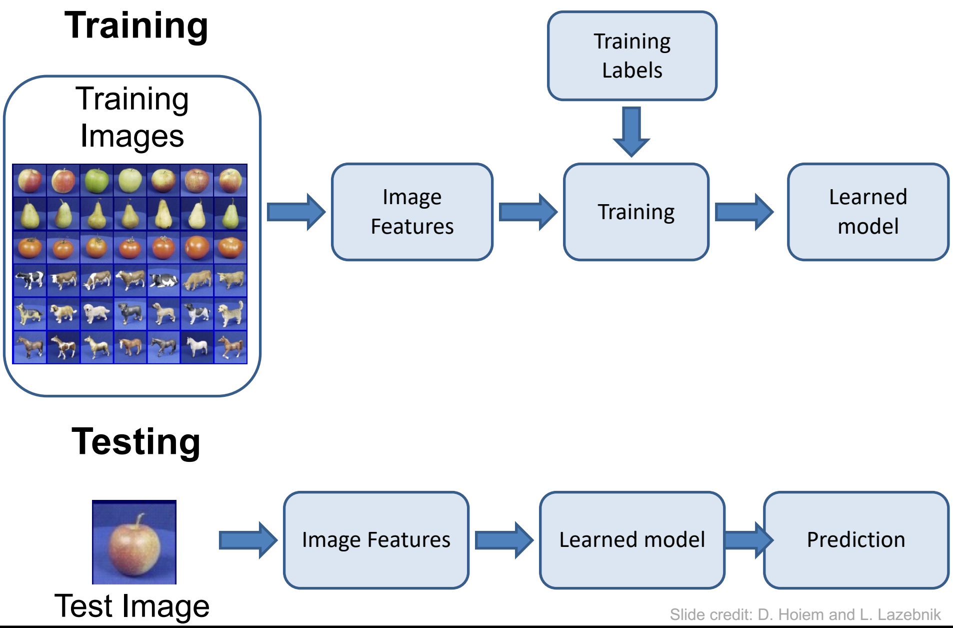
Learning a classifier

Given some set of features with corresponding labels, learn a function to predict the labels from the features



5

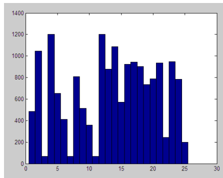
Steps

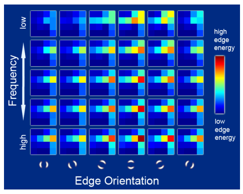


6

Features

- Raw pixels
- Histograms
- GIST descriptors



Slide credit: L. Lazebnik

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One way to think about it…

- Training labels dictate that two examples are the same or different, in some sense
- Features and distance measures define visual similarity
- Classifiers try to learn weights or parameters for features and distance measures so that visual similarity predicts label similarity

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Many classifiers to choose from

- SVM
- Neural networks
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- K-nearest neighbor
- RBMs
- Deep Convolutional Network
- Etc.

Which is the best one?

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Claim:

The decision to *use* machine learning is more important than the choice of a *particular* learning method.

*Deep learning seems to be an exception to this, at the moment, probably because it is learning the feature representation.

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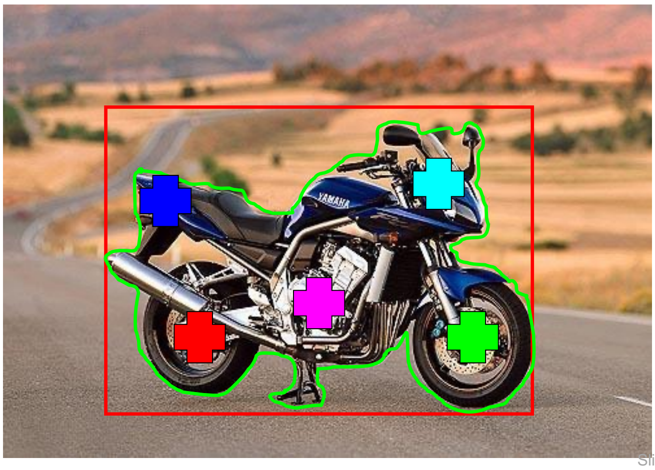
Recognition task and supervision

- Images in the training set must be annotated with the "correct answer" that the model is expected to produce

Contains a motorbike



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Spectrum of supervision

Less **More**

Unsupervised

"Weakly" supervised

Fully supervised

Definition depends on task

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Generalization

Training set (labels known)

Test set (labels unknown)

- How well does a learned model generalize from the data it was trained on to a new test set?

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Generalization

- Components of generalization error
  - **Bias:** how much the average model over all training sets differ from the true model?
    - Error due to inaccurate assumptions/simplifications made by the model.
  - **Variance:** how much models estimated from different training sets differ from each other.
- **Underfitting:** model is too "simple" to represent all the relevant class characteristics
  - High bias (few degrees of freedom) and low variance
  - High training error and high test error
- **Overfitting:** model is too "complex" and fits irrelevant characteristics (noise) in the data
  - Low bias (many degrees of freedom) and high variance
  - Low training error and high test error

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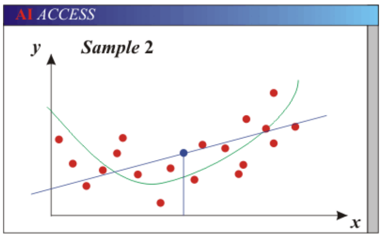
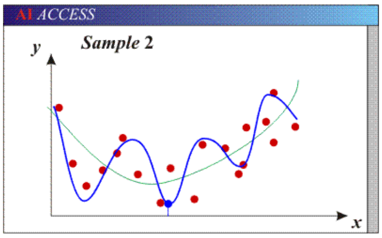
Bias-Variance Trade-off





- Models with too few parameters are inaccurate because of a large bias (not enough flexibility).
- Models with too many parameters are inaccurate because of a large variance (too much sensitivity to the sample).

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Bias-Variance Trade-off

E(MSE) = noise^2 + bias^2 + variance

Unavoidable error

Error due to incorrect assumptions

Error due to variance of training samples

See the following for explanations of bias-variance (also Bishop's "Neural Networks" book):

•http://www.inf.ed.ac.uk/teaching/courses/mlsc/Notes/Lecture4/BiasVariance.pdf

Slide credit: D. Hoiem

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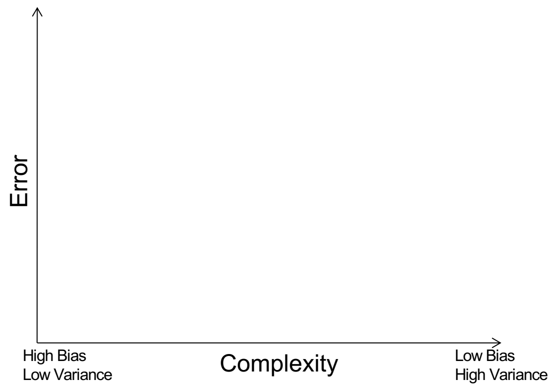
Bias-variance tradeoff

Underfitting **Overfitting**



Slide credit: D. Hoiem

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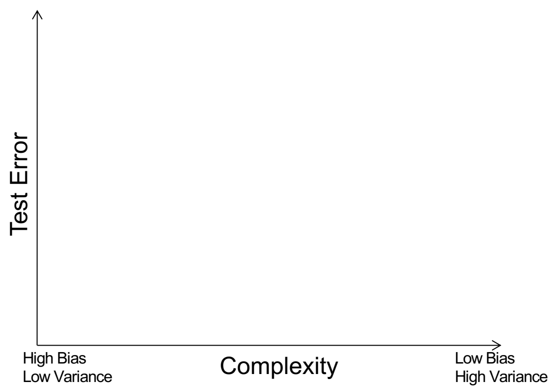
Bias-variance tradeoff



Slide credit: D. Hoiem

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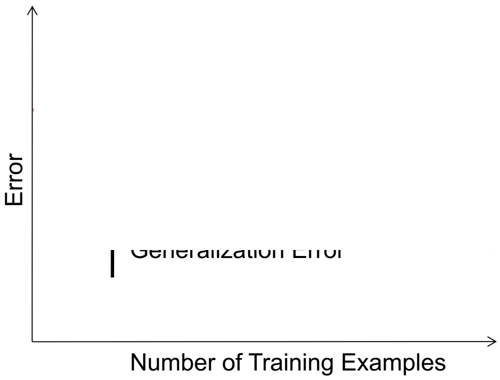
Effect of Training Size

Fixed prediction model



Slide credit: D. Hoiem

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Remember…

- No classifier is inherently better than any other: you need to make assumptions to generalize

- Three kinds of error
  - Inherent: unavoidable
  - Bias: due to over-simplifications
  - Variance: due to inability to perfectly estimate parameters from limited data

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How to reduce variance?

- Choose a simpler classifier
- Regularize the parameters
- Get more training data

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Supervised learning

$$y = f(\mathbf{x})$$

output

prediction function

Image feature

- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

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Image Categorization

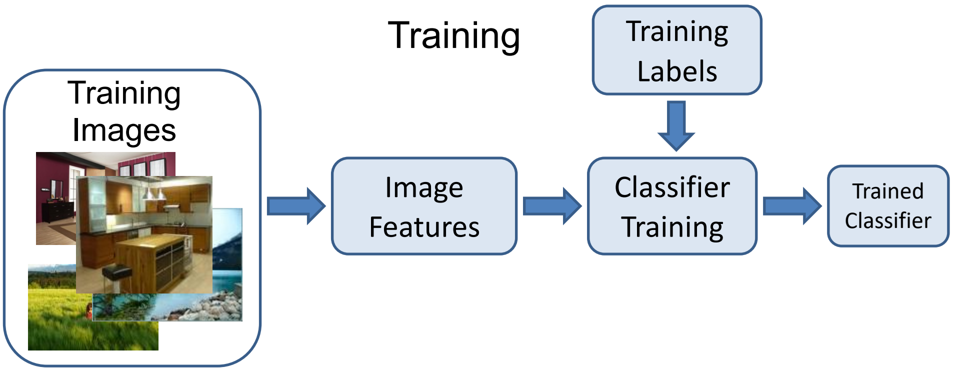

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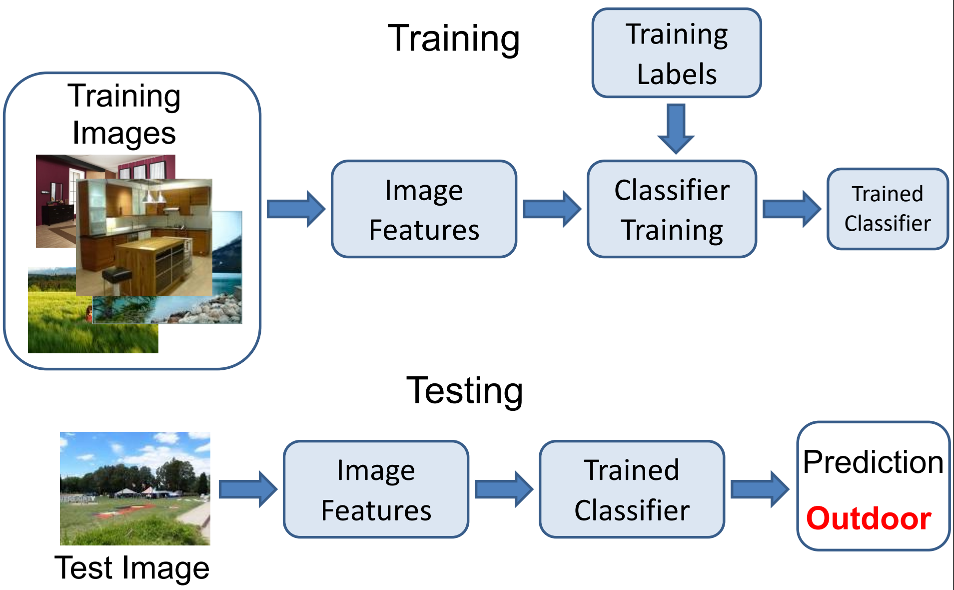
Image Categorization



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Example: Scene Categorization

- Is this a kitchen?



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Image features

Training

Training Labels

Training Images

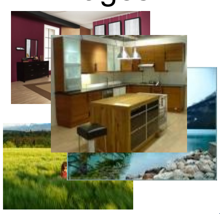

Image Features

Classifier Training

Trained Classifier

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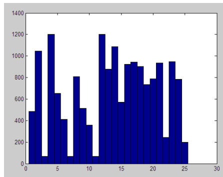
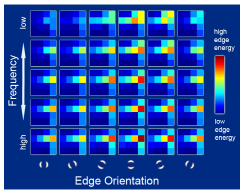
Features

- Raw pixels
- Histograms
- GIST descriptors
- …



Slide credit: L. Lazebnik

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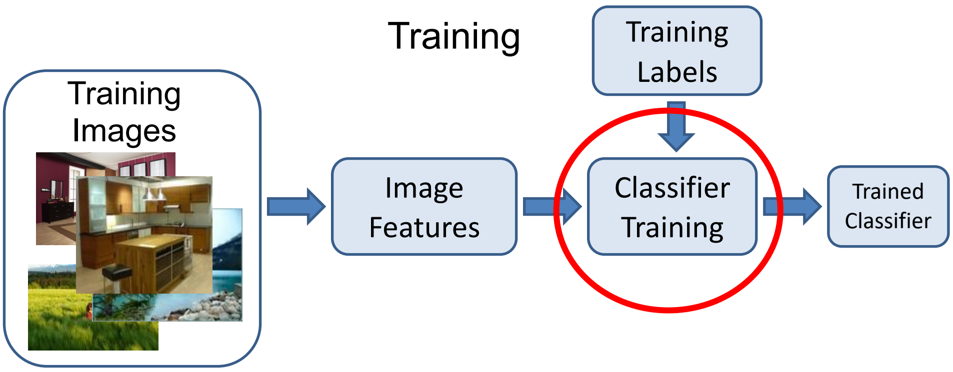
Classifiers



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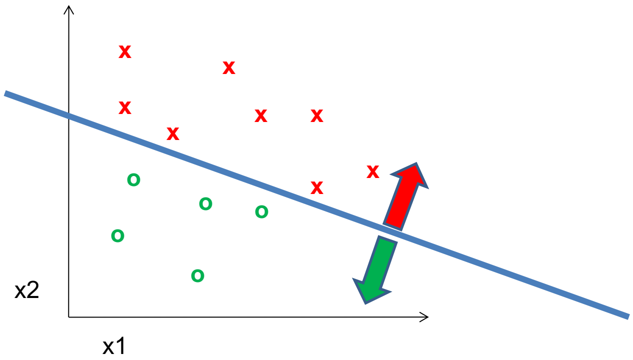
Learning a classifier

Given some set of features with corresponding labels, learn a function to predict the labels from the features



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Very brief tour of some classifiers

- **K-nearest neighbor**
- **SVM**
- Boosted Decision Trees
- Neural networks
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- RBMs
- Etc.

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Generative vs. Discriminative Classifiers

Generative Models

- Represent both the data and the labels
- Often, makes use of conditional independence and priors
- Examples
  - Naïve Bayes classifier
  - Bayesian network
- Models of data may apply to future prediction problems

Discriminative Models

- Learn to directly predict the labels from the data
- Often, assume a simple boundary (e.g., linear)
- Examples
  - Logistic regression
  - SVM
  - Boosted decision trees
- Often easier to predict a label from the data than to model the data

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What to remember about classifiers

- No free lunch: machine learning algorithms are tools, not dogmas
- Try simple classifiers first
- Better to have smart features and simple classifiers than simple features and smart classifiers
- Use increasingly powerful classifiers with more training data (bias-variance tradeoff)

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Making decisions about data

- 3 important design decisions:
  1) What data do I use?
  2) How do I represent my data (what feature)?
  3) What classifier / regressor / machine learning tool do I use?
- These are in decreasing order of importance
- Deep learning addresses 2 and 3 simultaneously (and blurs the boundary between them).
- You can take the representation from deep learning and use it with any classifier.

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Recognition: Overview and History

Slides from Lana Lazebnik, Fei-Fei Li, Rob Fergus, Antonio Torralba, and Jean Ponce

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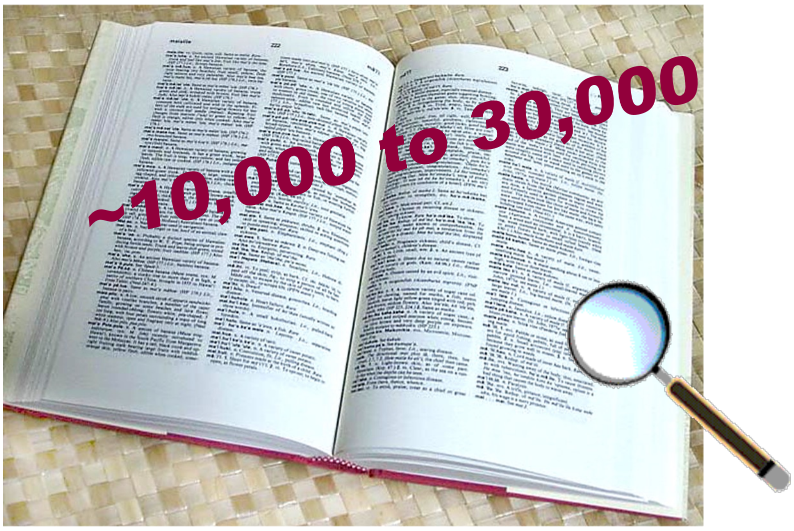
How many visual object categories are there?



Biederman 1987

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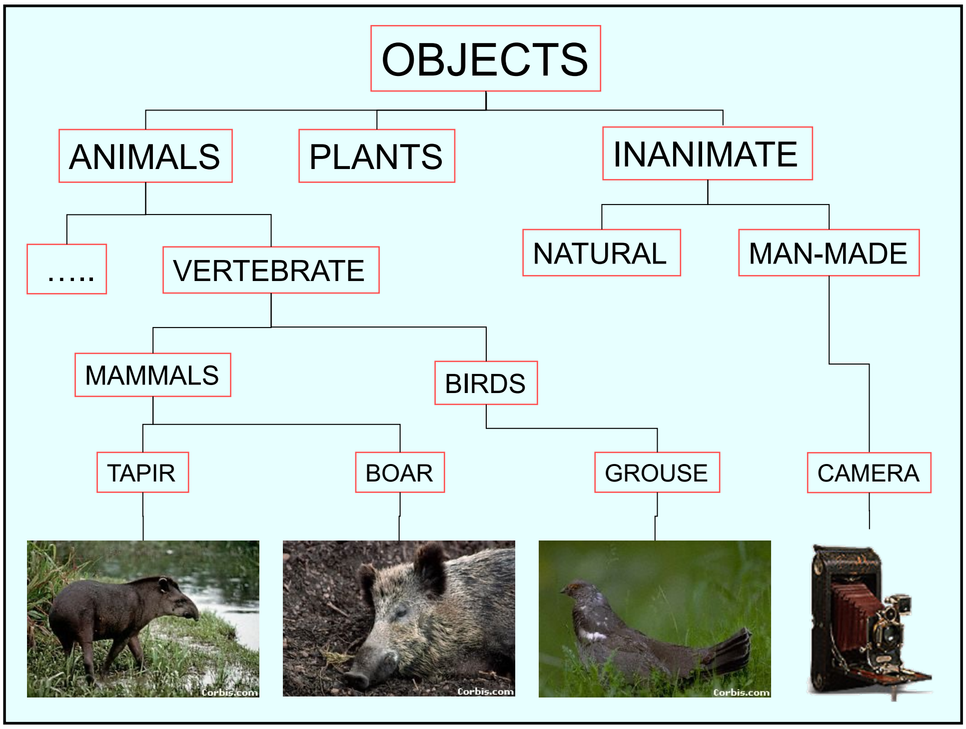

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Specific recognition tasks

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Scene categorization or classification

- outdoor/indoor
- city/forest/factory/etc.

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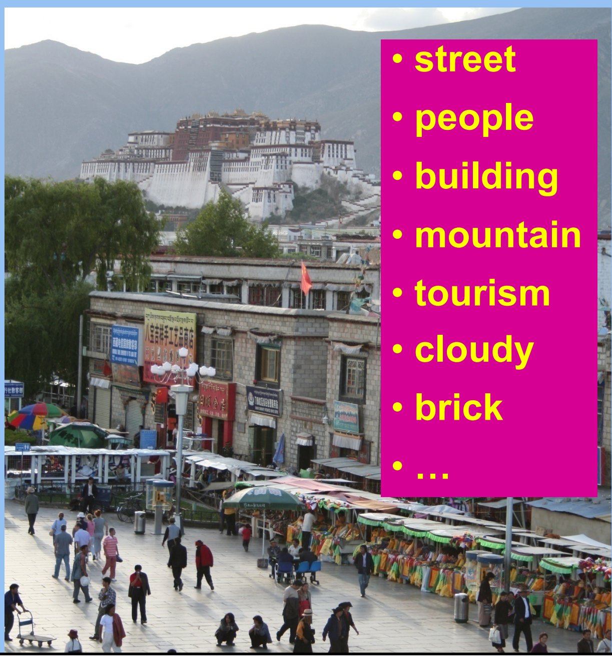
Image annotation / tagging / attributes



- street
- people
- building
- mountain
- tourism
- cloudy
- brick
- …

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Object detection

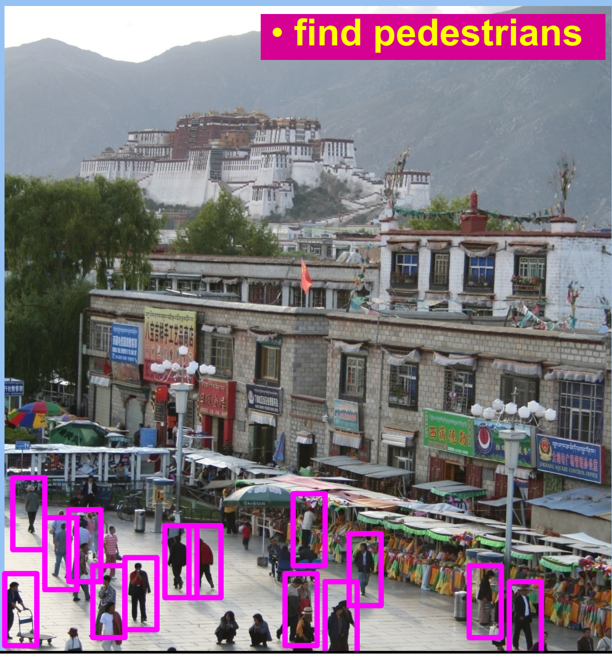

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Image parsing / semantic segmentation

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Scene understanding?

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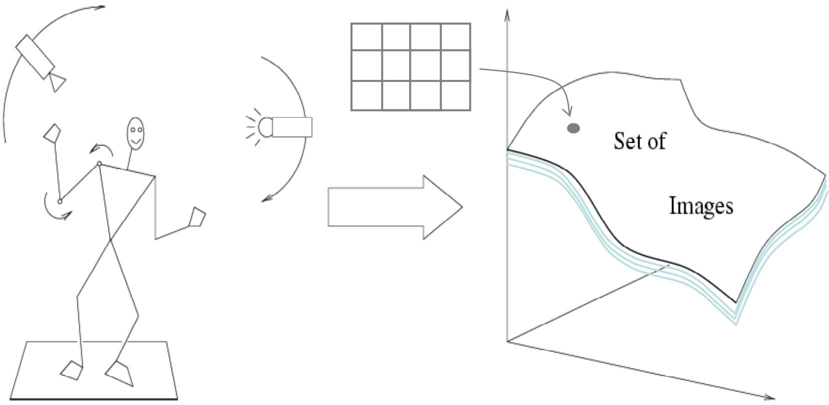
Recognition is all about modeling variability



Variability: Camera position
Illumination
Shape parameters

Within-class variations?

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Within-class variations

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History of ideas in recognition

- 1960s – early 1990s: the geometric era

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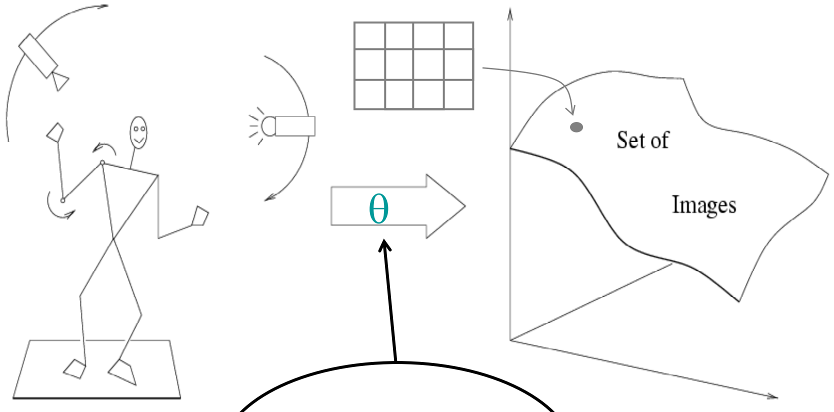

Variability: Camera position
Illumination

Alignment

Shape: assumed known

Roberts (1965); Lowe (1987); Faugeras & Hebert (1986); Grimson & Lozano-Perez (1986); Huttenlocher & Ullman (1987)

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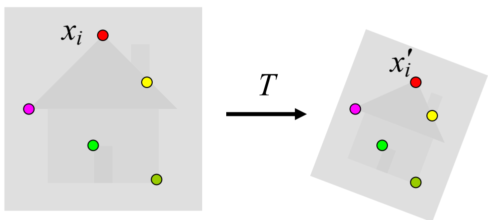
Recall: Alignment

- Alignment: fitting a model to a transformation between pairs of features (*matches*) in two images



Find transformation T that minimizes

$$\sum_i \text{residual}(T(x_i), x_i')$$

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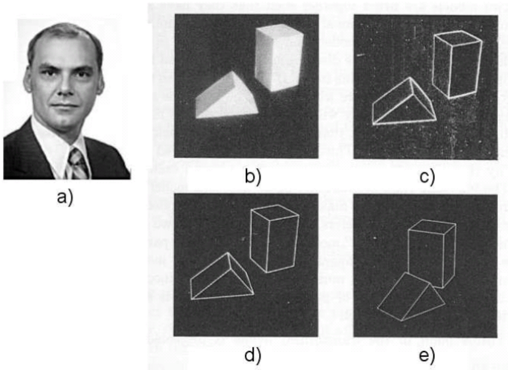
Recognition as an alignment problem: Block world



L. G. Roberts, *Machine Perception of Three Dimensional Solids*, Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

Fig. 1. A system for recognizing 3-d polyhedral scenes. a) L.G. Roberts. b)A blocks world scene. c)Detected edges using a 2x2 gradient operator. d) A 3-d polyhedral description of the scene, formed automatically from the single image. e) The 3-d scene displayed with a viewpoint different from the original image to demonstrate its accuracy and completeness. (b) - e) are taken from [64] with permission MIT Press.)

J. Mundy, Object Recognition in the Geometric Era: a Retrospective, 2006

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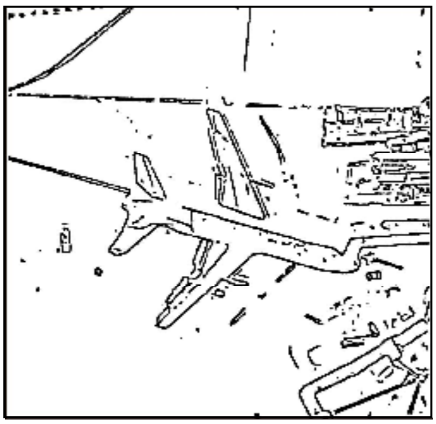
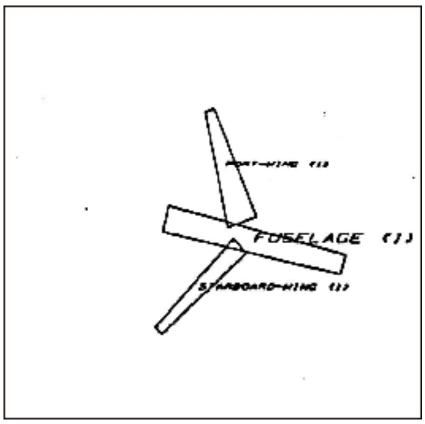
Representing and recognizing object categories is harder...





ACRONYM (Brooks and Binford, 1981)

Binford (1971), Nevatia & Binford (1972), Marr & Nishihara (1978)

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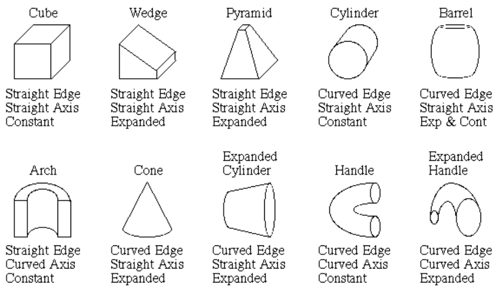
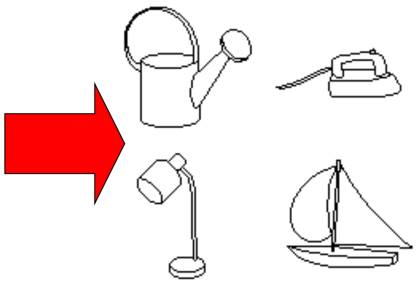
Recognition by components

Biederman (1987)

Primitives (geons)



Objects



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

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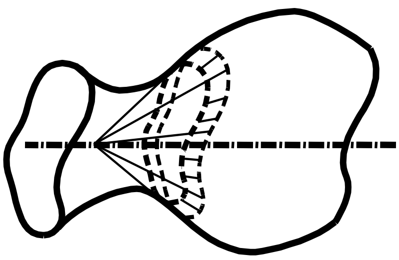
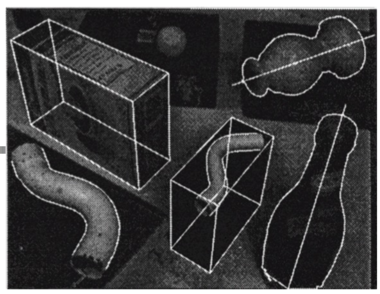
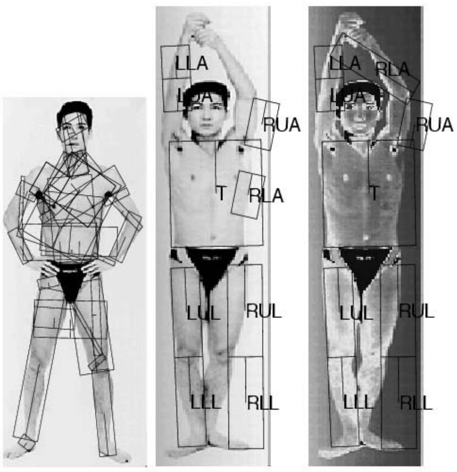
General shape primitives?



Generalized cylinders
Ponce et al. (1989)



Zisserman et al. (1995)



Forsyth (2000)

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History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models

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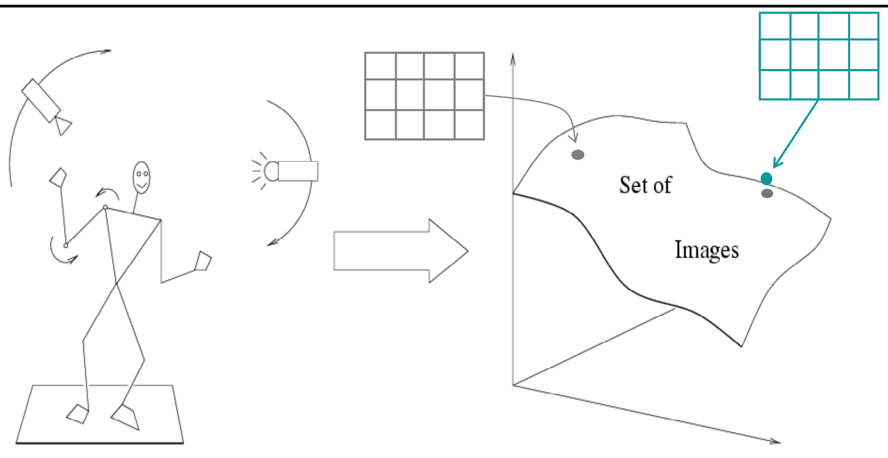

Empirical models of image variability

Appearance-based techniques

Turk & Pentland (1991); Murase & Nayar (1995); etc.

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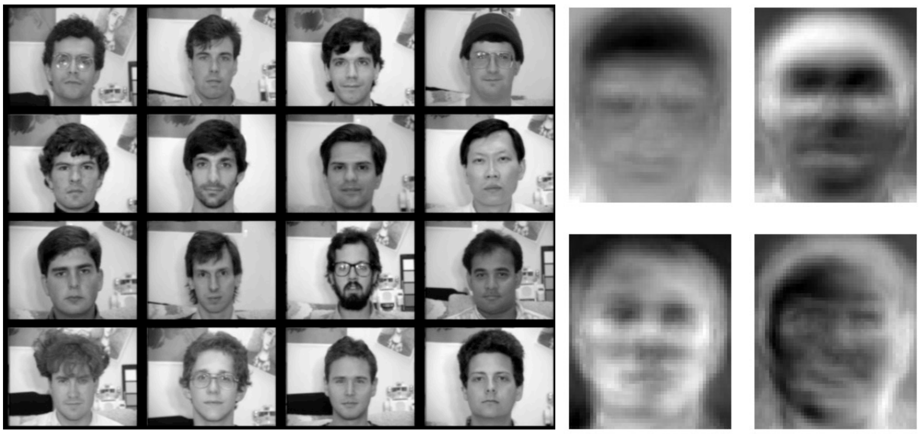
Eigenfaces (Turk & Pentland, 1991)



Experimental	Correct/Unknown Recognition Percentage		
Condition	Lighting	Orientation	Scale
Forced classification	96/0	85/0	64/0
Forced 100% accuracy	100/19	100/39	100/60
Forced 20% unknown rate	100/20	94/20	74/20

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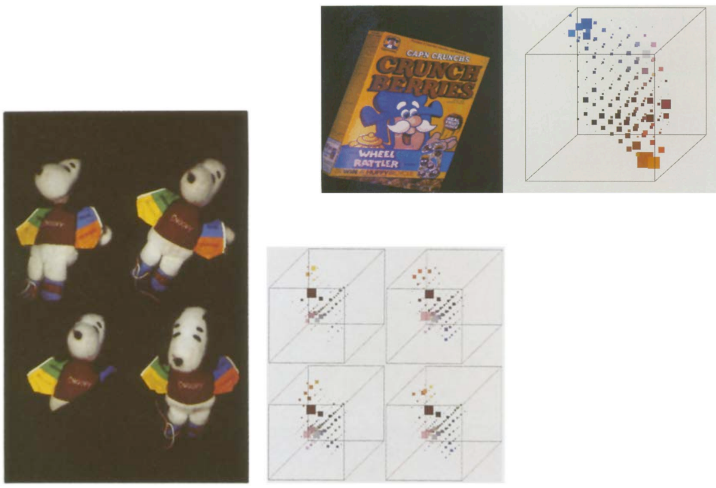
Color Histograms



Swain and Ballard, Color Indexing, IJCV 1991.

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History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- 1990s – present: sliding window approaches

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Sliding window approaches

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Sliding window approaches

- Turk and Pentland, 1991
- Belhumeur, Hespanha, & Kriegman, 1997
- Schneiderman & Kanade 2004
- Viola and Jones, 2000

- Schneiderman & Kanade, 2004
- Argawal and Roth, 2002
- Poggio et al. 1993

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History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features

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Local features for object instance recognition

D. Lowe (1999, 2004)

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Large-scale image search

Combining local features, indexing, and spatial constraints

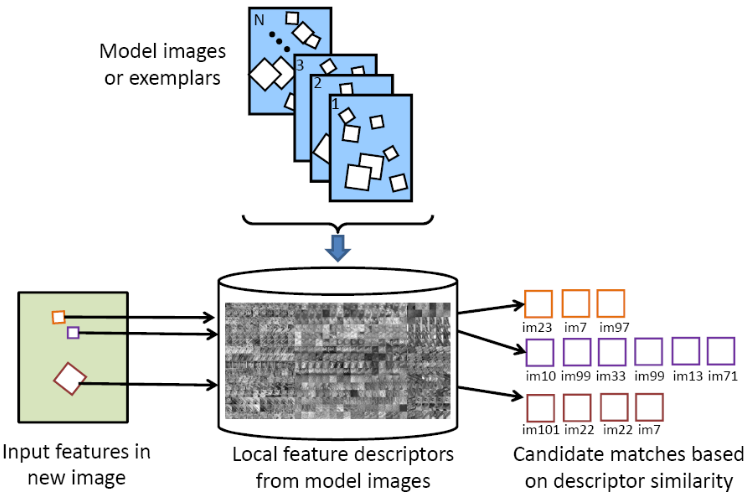

Image credit: K. Grauman and B. Leibe

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Large-scale image search

Combining local features, indexing, and spatial constraints

Philbin et al. '07

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Large-scale image search

Combining local features, indexing, and spatial constraints

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History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models

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Parts-and-shape models

- Model:
  - Object as a set of parts
  - Relative locations between parts
  - Appearance of part

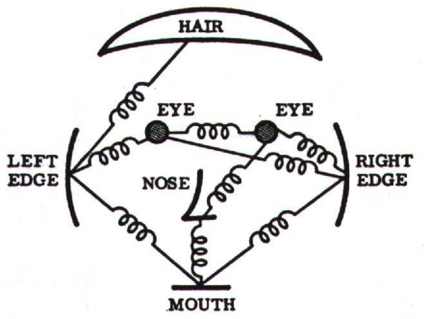

Figure from [Fischler & Elschlager 73]

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Constellation models

Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

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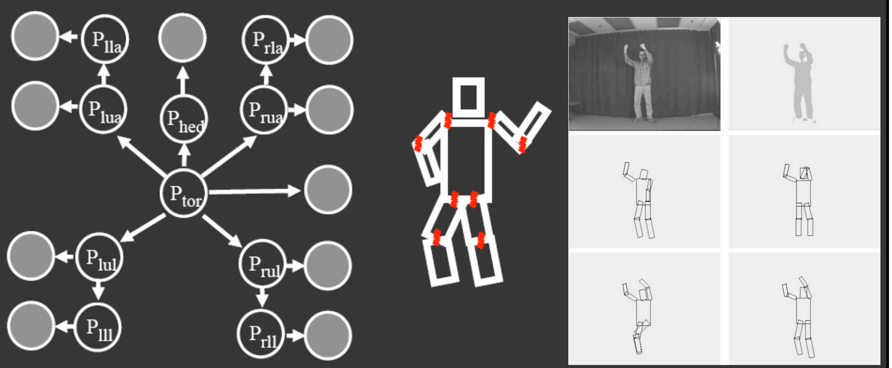
Pictorial structure model

Fischler and Elschlager(73), Felzenszwalb and Huttenlocher(00)



$$\Pr(P_{tor}, P_{arm}, \ldots | Im) \propto \prod_{i,j} \Pr(P_i \mid P_j) \prod_i \Pr(Im(P_i))$$

part geometry

part appearance

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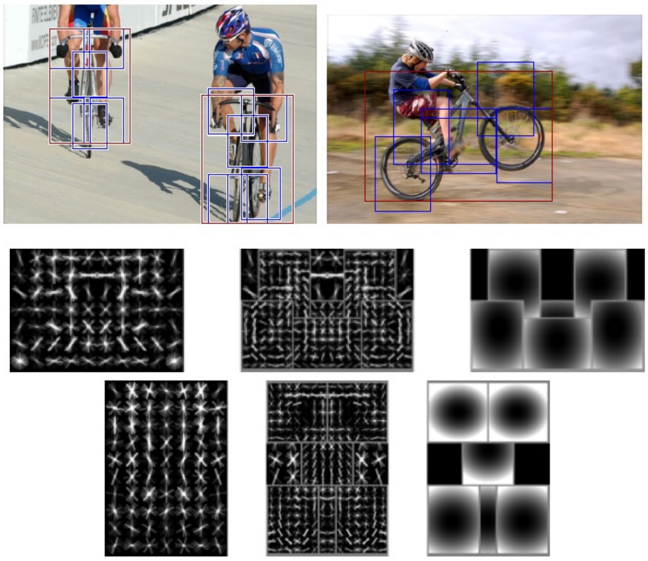
Discriminatively trained part-based models



P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, "Object Detection with Discriminatively Trained Part-Based Models," PAMI 2009

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History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features

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Bag-of-features models

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Bag-of-features models

Object → **Bag of 'words'**

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Objects as texture

- All of these are treated as being the same

- No distinction between foreground and background: scene recognition?

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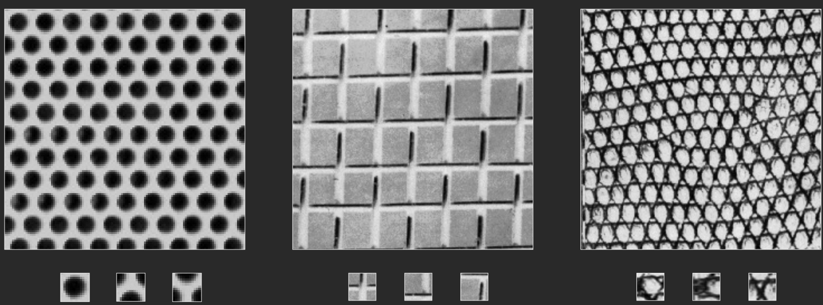
Origin 1: Texture recognition

- Texture is characterized by the repetition of basic elements or *textons*
- For stochastic textures, it is the identity of the textons, not their spatial arrangement, that matters



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

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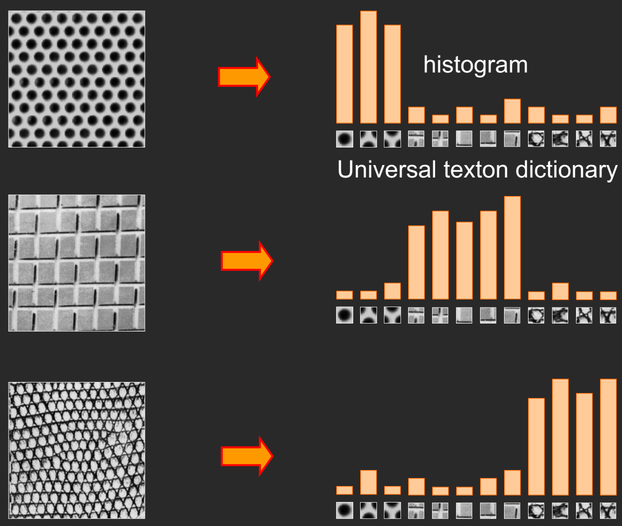
Origin 1: Texture recognition



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

80

Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

81

Origin 2: Bag-of-words models

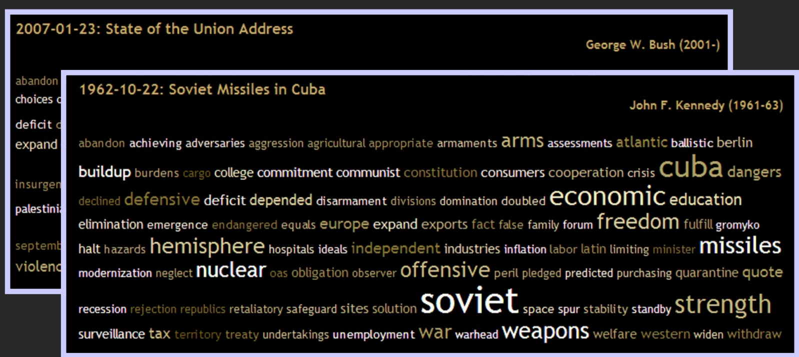
- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

US Presidential Speeches Tag Cloud
http://chir.ag/phernalia/preztags/

82

Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)



US Presidential Speeches Tag Cloud
http://chir.ag/phernalia/preztags/

83

Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

US Presidential Speeches Tag Cloud
`http://chir.ag/phernalia/preztags/`

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History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features
- Early-2010s: CNNs

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