RWTH AACHEN UNIVERSITY

Computer Vision – Lecture 8

Recognition with Global Representations

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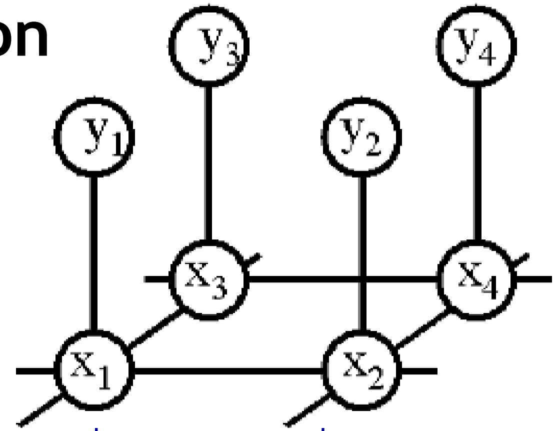
Course Outline

- Image Processing Basics
- Segmentation
  - Segmentation and Grouping
  - Segmentation as Energy Minimization
- Recognition & Categorization
  - Global Representations
  - Sliding-Window Object Detection
  - Image Classification
- Local Features & Matching
- 3D Reconstruction
- Motion and Tracking

Recap: MRFs for Image Segmentation

- **MRF formulation**



Unary potentials
$\phi(x_i, y_i)$

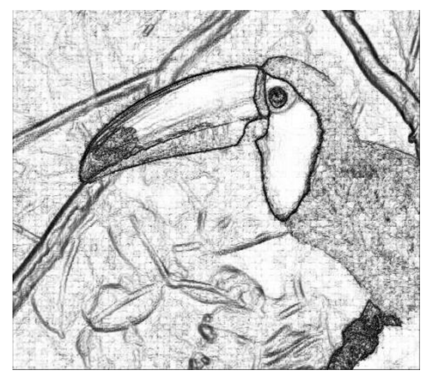
Pairwise potentials
$\psi(x_i, x_j)$

$\Rightarrow$ **Minimize the energy**

$$E(\mathbf{x}, \mathbf{y}) = \sum_i \phi(x_i, y_i) + \sum_{i,j} \psi(x_i, x_j)$$

Data (D)

Unary likelihood

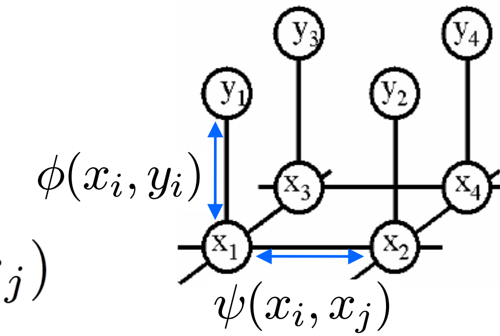


Pair-wise Terms

MAP Solution

Slide adapted from Phil Torr

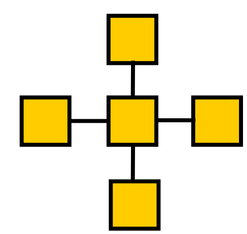
Recap: Energy Formulation



- Energy function

$$E(\mathbf{x}, \mathbf{y}) = \sum_i \underbrace{\phi(x_i, y_i)}_{\text{Unary potentials}} + \sum_{i,j} \underbrace{\psi(x_i, x_j)}_{\text{Pairwise potentials}}$$

- Unary potentials ϕ
  - Encode local information about the given pixel/patch
  - How likely is a pixel/patch to belong to a certain class (e.g. foreground/background)?
- Pairwise potentials ψ
  - Encode neighborhood information
  - How different is a pixel/patch's label from that of its neighbor? (e.g. based on intensity/color/texture difference, edges)

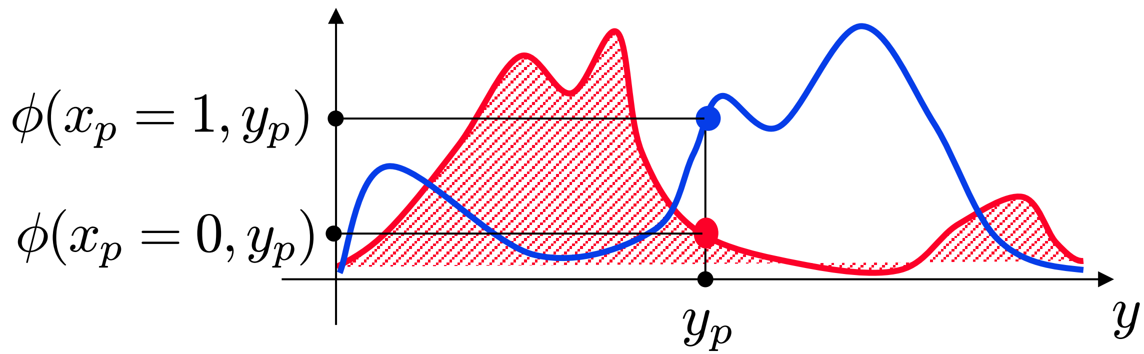


Recap: How to Set the Potentials?

- **Unary potentials**
  - **E.g. color model, modeled with a Mixture of Gaussians**

$$\phi(x_i, y_i; \theta_\phi) = \log \sum_k \theta_\phi(x_i, k) p(k|x_i) \mathcal{N}(y_i; \bar{y}_k, \Sigma_k)$$

$\Rightarrow$ **Learn color distributions for each label**



Recap: How to Set the Potentials?

- Pairwise potentials
  - Potts Model

$$\psi(x_i, x_j; \theta_\psi) = \theta_\psi \delta(x_i \neq x_j)$$

    - Simplest discontinuity preserving model.
    - Discontinuities between any pair of labels are penalized equally.
    - Useful when labels are unordered or number of labels is small.

  - Extension: "Contrast sensitive Potts model"

$$\psi(x_i, x_j, g_{ij}(\mathbf{y}); \theta_\psi) = -\theta_\psi g_{ij}(\mathbf{y}) \delta(x_i \neq x_j)$$

where

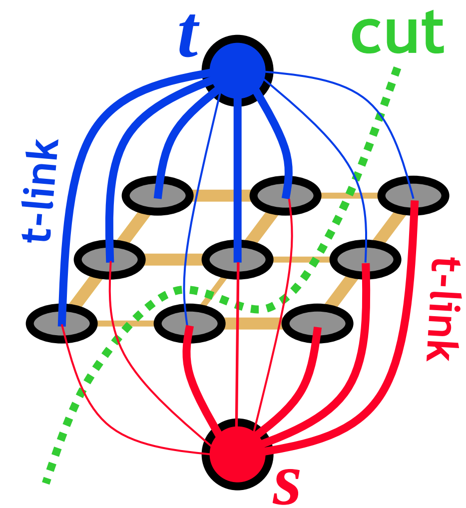
$$g_{ij}(\mathbf{y}) = e^{-\beta \|y_i - y_j\|^2} \qquad \beta = \frac{1}{2}\left(\text{avg}\left(\|y_i - y_j\|^2\right)\right)^{-1}$$

$\Rightarrow$ Discourages label changes except in places where there is also a large change in the observations.

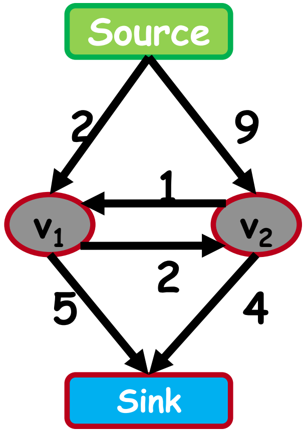
Recap: Graph-Cuts Energy Minimization

- Solve an equivalent graph cut problem
  1. Introduce extra nodes: source and sink
  2. Weight connections to source/sink (t-links) by $\phi(x_i = s)$ and $\phi(x_i = t)$, respectively.
  3. Weight connections between nodes (n-links) by $\psi(x_i, x_j)$.
  4. Find the minimum cost cut that separates source from sink.

  $\Rightarrow$ Solution is equivalent to minimum of the energy.



- s-t Mincut can be solved efficiently
  - Dual to the well-known max flow problem
  - Very efficient algorithms available for regular grid graphs (1-2 MPixels/s)
  - Globally optimal result for 2-class problems



Recap: When Can s-t Graph Cuts Be Applied?

Unary potentials — Pairwise potentials

$$E(L) = \sum_{p} E_p(L_p) + \sum_{pq \in N} E(L_p, L_q)$$

t-links — n-links

$$L_p \in \{s, t\}$$

- s-t graph cuts can only globally minimize **binary energies** that are **submodular**. [Boros & Hummer, 2002, Kolmogorov & Zabih, 2004]

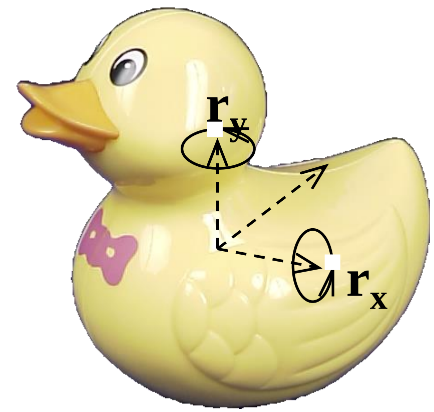
E(L) can be minimized by *s-t* graph cuts $\Leftrightarrow$ $E(s,s) + E(t,t) \leq E(s,t) + E(t,s)$

Submodularity ("convexity")

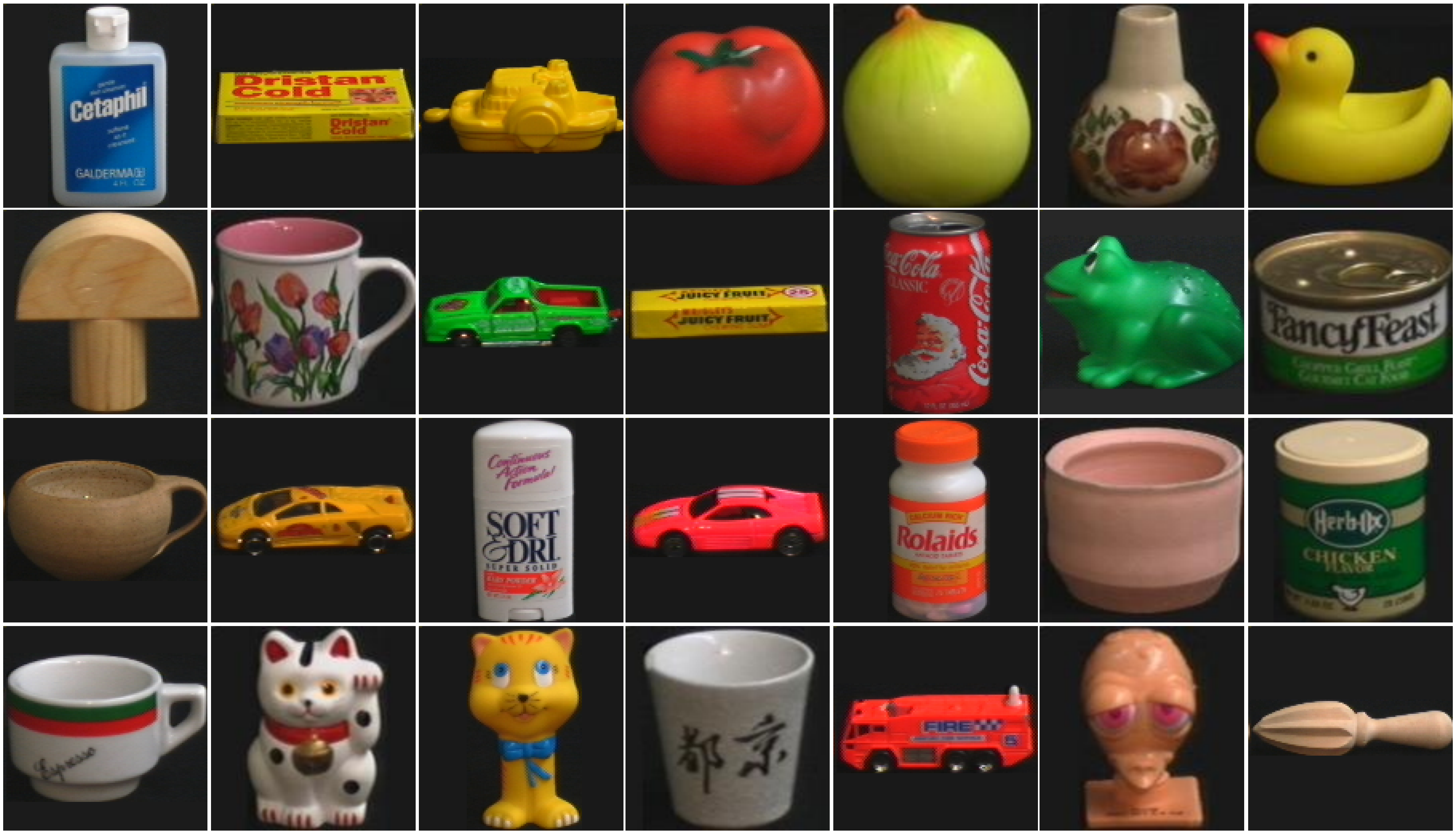
- Submodularity is the discrete equivalent to convexity.
  - Implies that every local energy minimum is a global minimum.
  - $\Rightarrow$ Solution will be globally optimal.

Topics of This Lecture

- Object Recognition
  - Appearance-based recognition
  - Global representations
  - Color histograms
- Recognition using histograms
  - Histogram comparison measures
  - Histogram backprojection
  - Multidimensional histograms
  - Extension: colored derivatives

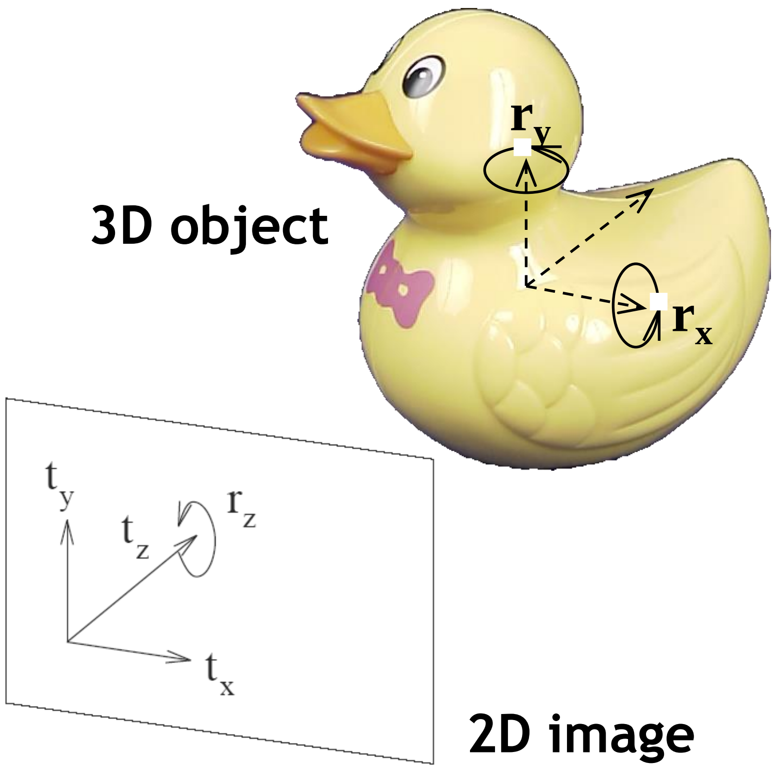


Object Recognition



Challenges

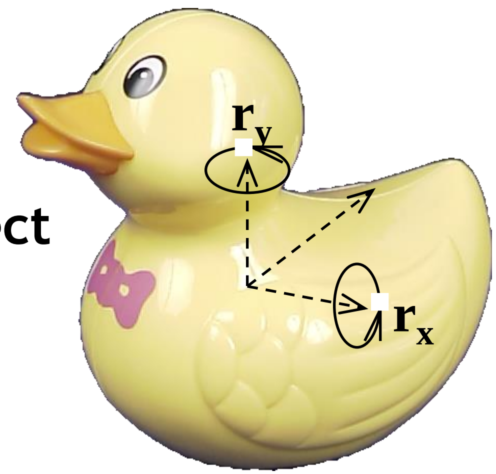
- Viewpoint changes
  - Translation
  - Image-plane rotation
  - Scale changes
  - Out-of-plane rotation
- Illumination
- Noise
- Clutter
- Occlusion



Appearance-Based Recognition

- Basic assumption
  - Objects can be represented by a set of images ("appearances").
  - For recognition, it is sufficient to just compare the 2D appearances.
  - No 3D model is needed.

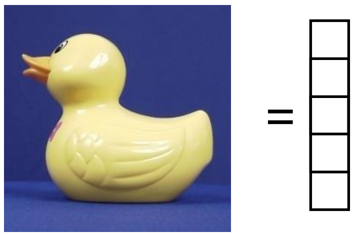
3D object

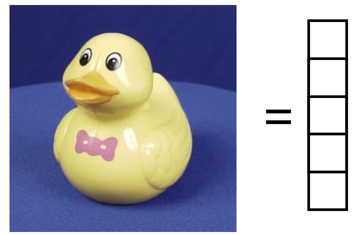


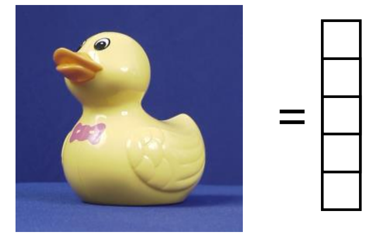
⇒ Fundamental paradigm shift in the 90's

Global Representation

- **Idea**
  - Represent each object (view) by a global descriptor.







  - For recognizing objects, just match the descriptors.
  - Some modes of variation are built into the descriptor, the others have to be incorporated in the training data.
    - E.g., a descriptor can be made invariant to image-plane rotations.
    - Other variations:

Viewpoint changes	Illumination
— Translation	Noise
— Scale changes	Clutter
— Out-of-plane rotation	Occlusion

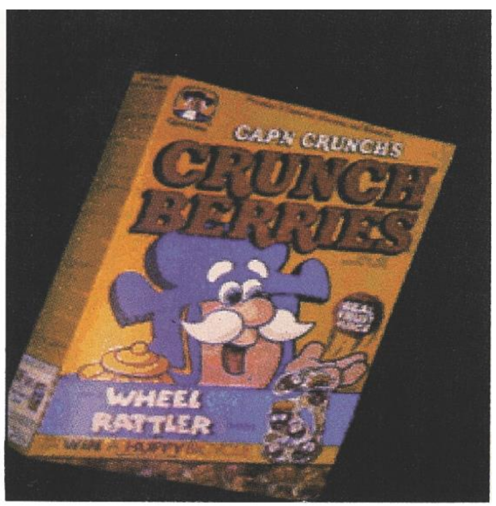
Color: Use for Recognition

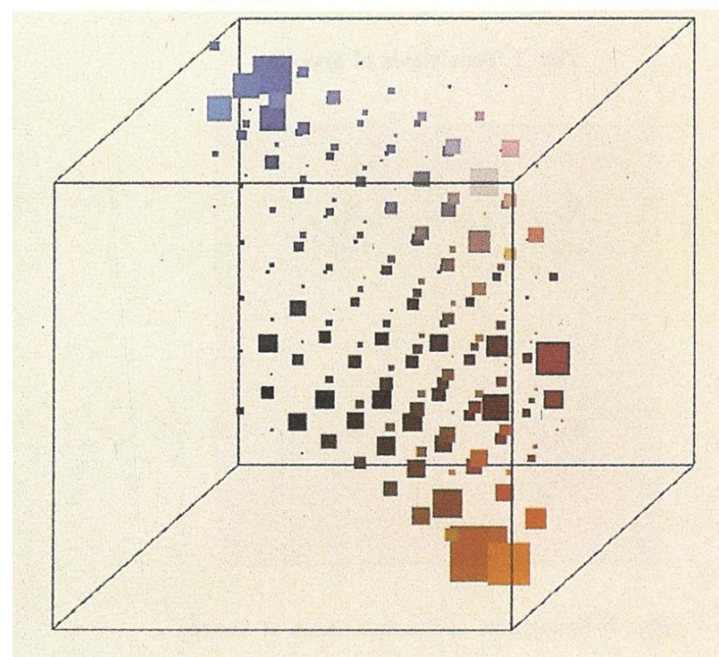
- Color:
  - Color stays constant under geometric transformations
  - Local feature
    - Color is defined for each pixel
    - Robust to partial occlusion

- Idea
  - Directly use object colors for recognition
  - Better: use statistics of object colors

Color Histograms

- Color statistics
  - Here: RGB as an example
  - Given: tristimulus R,G,B for each pixel
  - Compute 3D histogram
    - H(R,G,B) = #(pixels with color (R,G,B))





[Swain & Ballard, 1991]

Color Normalization

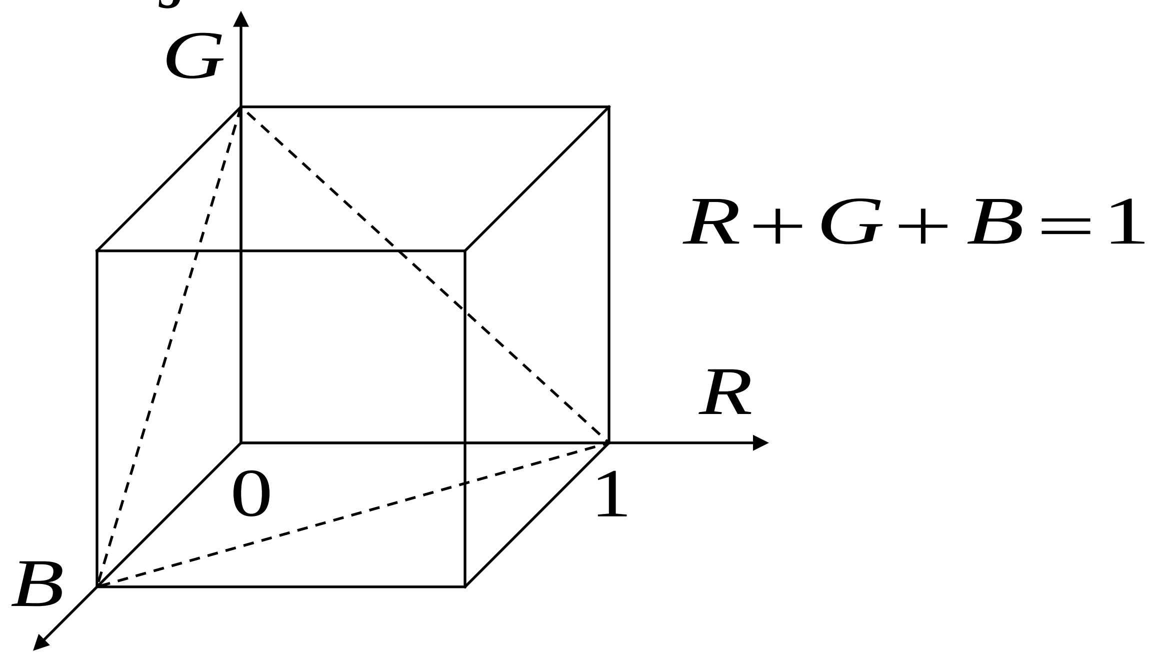
- One component of the 3D color space is intensity
  - If a color vector is multiplied by a scalar, the intensity changes, but not the color itself.
  - This means colors can be normalized by the intensity.
    - Intensity is given by $I = R + G + B$:
  - „Chromatic representation“

$$r = \frac{R}{R+G+B} \qquad g = \frac{G}{R+G+B}$$

$$b = \frac{B}{R+G+B}$$

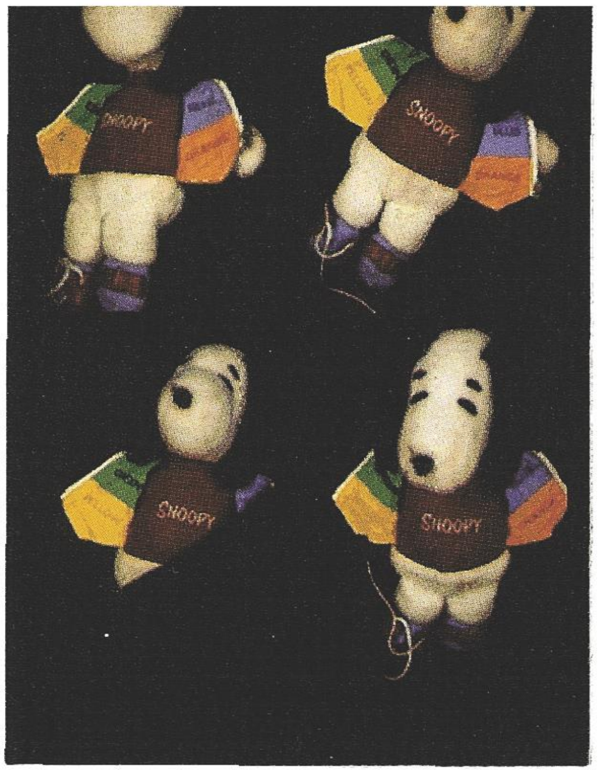
Color Normalization

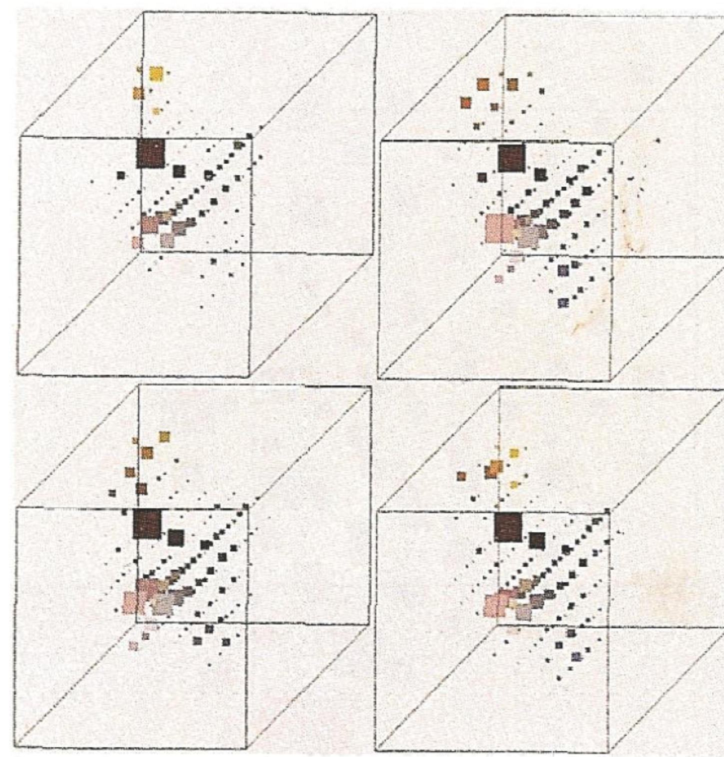
- **Observation:**
  - Since $r + g + b = 1$, only 2 parameters are necessary
  - E.g. one can use r and g
  - and obtains $b = 1 - r - g$



Color Histograms

- **Robust representation**

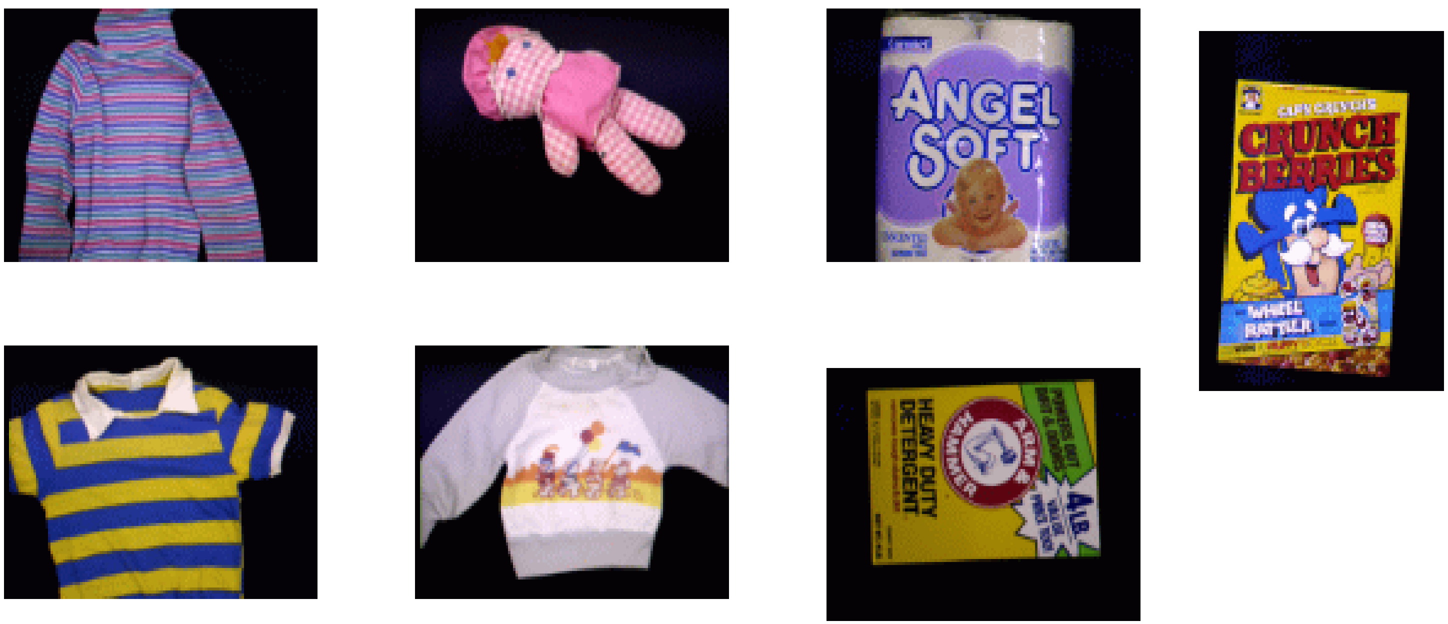




[Swain & Ballard, 1991]

Color Histograms

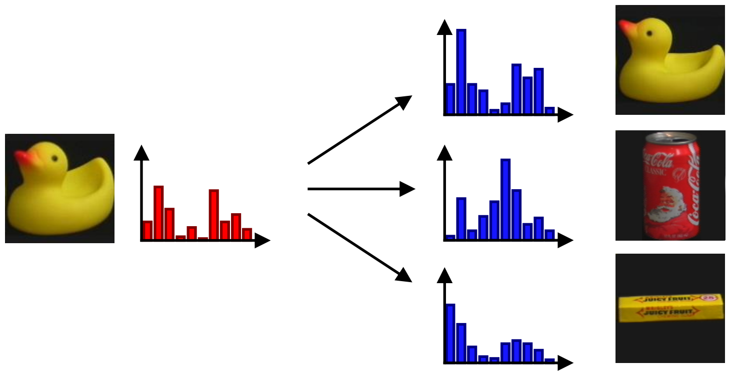
- Use for recognition
  - Works surprisingly well
  - In the first paper (1991), 66 objects could be recognized almost without errors



[Swain & Ballard, 1991]

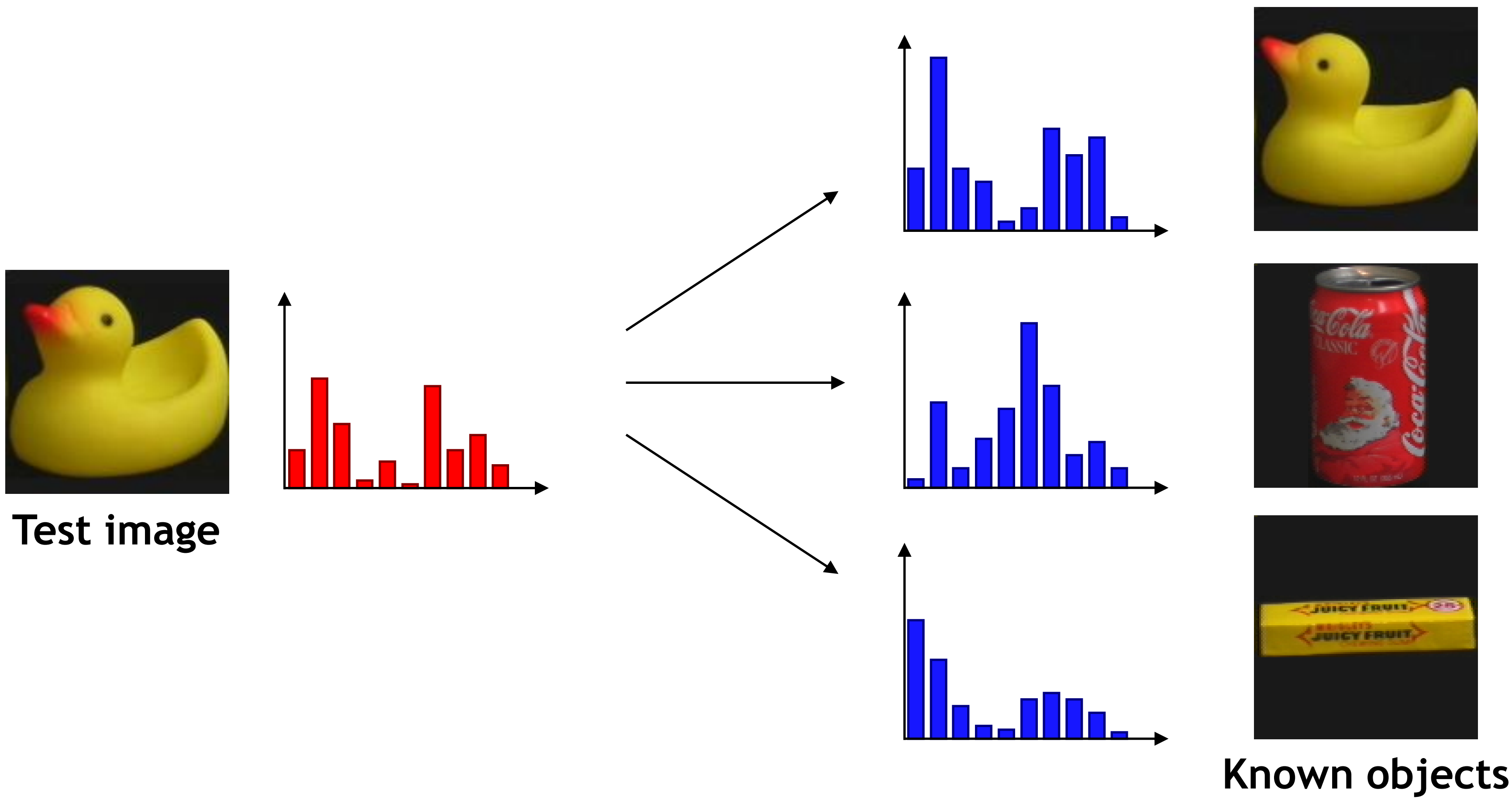
Topics of This Lecture

- Object Recognition
  - Appearance-based recognition
  - Global representations
  - Color histograms
- **Recognition using histograms**
  - Histogram comparison measures
  - Histogram backprojection
  - Multidimensional histograms
  - Extension: colored derivatives



Recognition Using Histograms

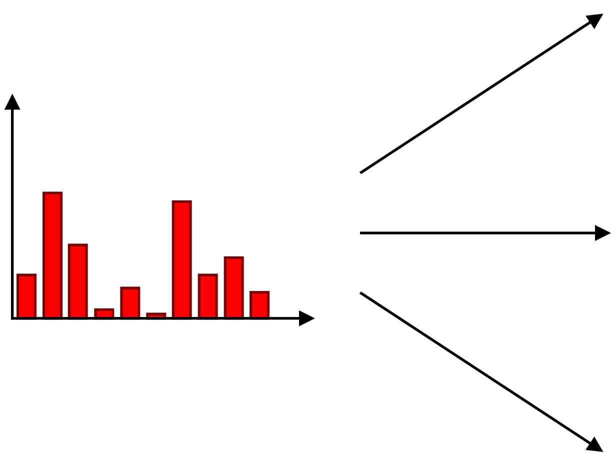
- **Histogram comparison**

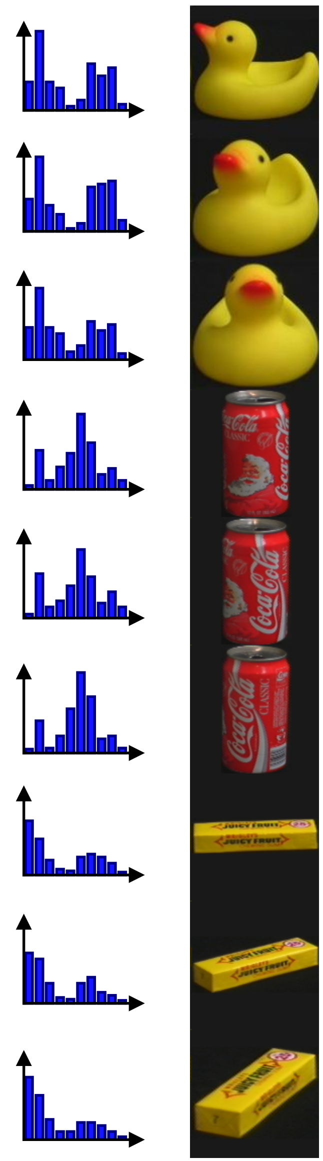


Recognition Using Histograms

- **With multiple training views**

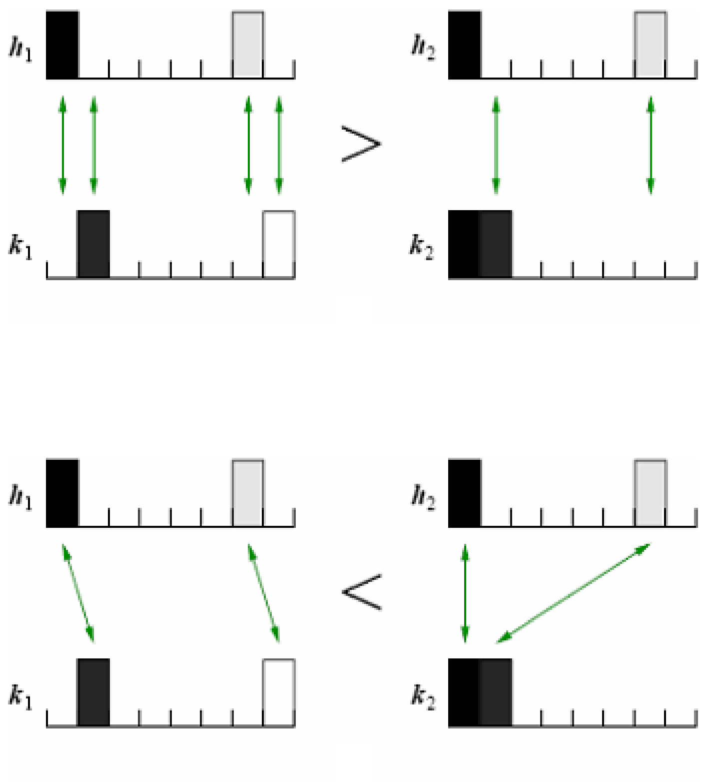
Test image





What Is a Good Comparison Measure?

- **How to define matching cost?**



Bad!

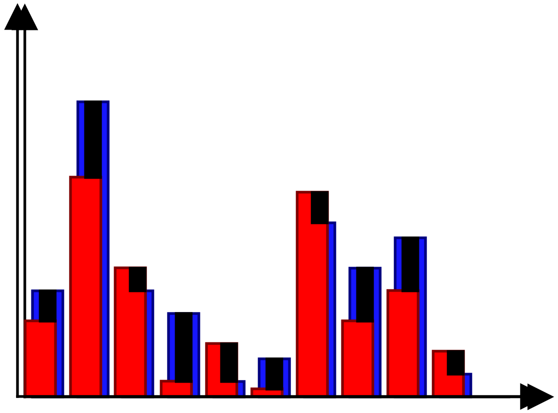
Good!

Slide credit: Pete Barnum

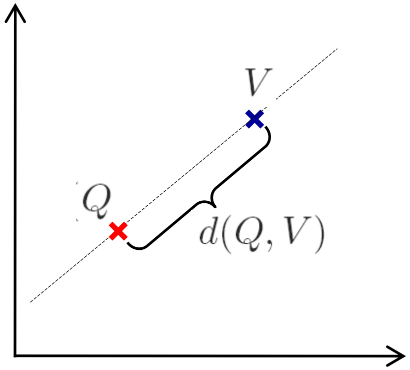
Comparison Measures: Euclidean Distance

- **Definition**
  - Euclidean Distance (=L_2 norm)

$$d(Q,V)=\sum_i (q_i - v_i)^2$$



- **Motivation**
  - Focuses on the differences between the histograms.
  - Interpretation: distance in feature space.
  - Range: [0,∞]
  - All cells are weighted equally.
  - Not very robust to outliers!

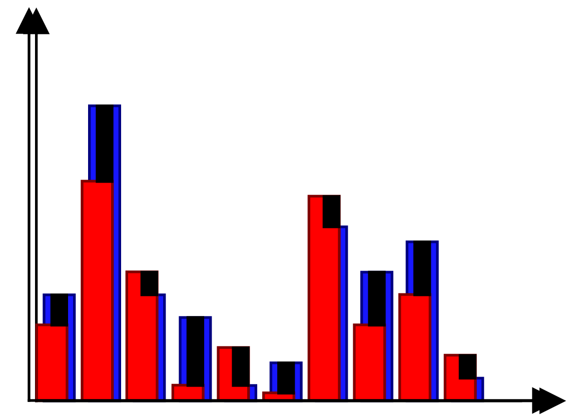


Comparison Measures: Mahalanobis Distance

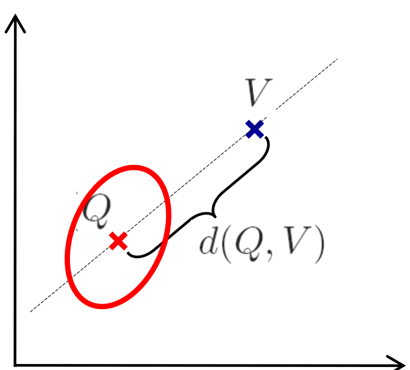
- **Definition**
  - Mahalanobis distance(Quadratic Form)

$$d(Q,V) = (Q-V)^\top \Sigma^{-1} (Q-V)$$

$$= \sum_i \sum_j \frac{(q_i - v_i)(q_j - v_j)}{\sigma_{ij}}$$



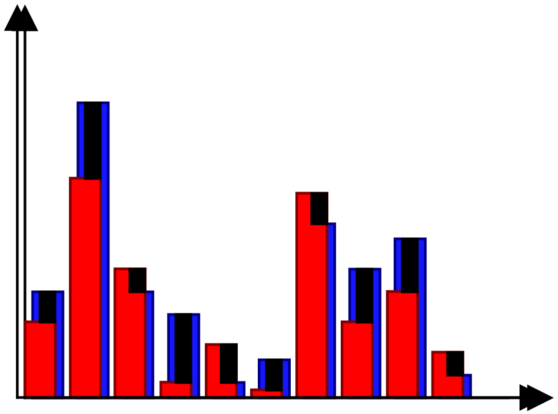
- **Motivation**
  - Interpretation:
    - Weighted distance in feature space.
    - Compensate for correlated data.
  - Range: [0,∞]
  - More robust to certain outliers.



Comparison Measures: Chi-Square

- **Definition**
  - Chi-square

$$\chi^2(Q,V) = \sum_i \frac{(q_i - v_i)^2}{q_i + v_i}$$



- **Motivation**
  - Statistical background:
    - Test if two distributions are different
    - Possible to compute a significance score
  - Range: $[0,\infty]$
  - Cells are not weighted equally!
  - More robust to outliers than Euclidean distance.
    - If the histograms contain enough observations…

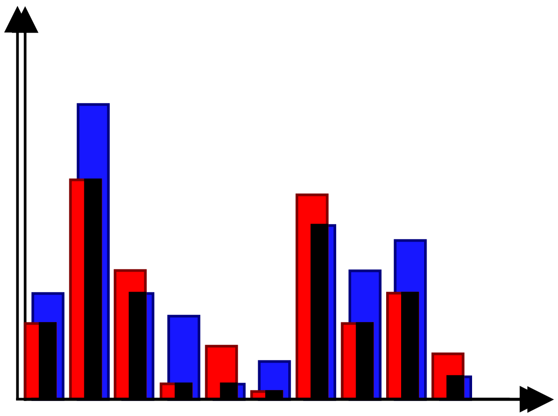
Comp. Measures: Bhattacharyya Distance

- **Definition**
  - Bhattacharyya coefficient

$$BC(Q,V) = \sum_i \sqrt{q_i v_i}$$

  - Common distance measure:

$$d_{BC}(Q,V) = \sqrt{1 - BC(Q,V)}$$

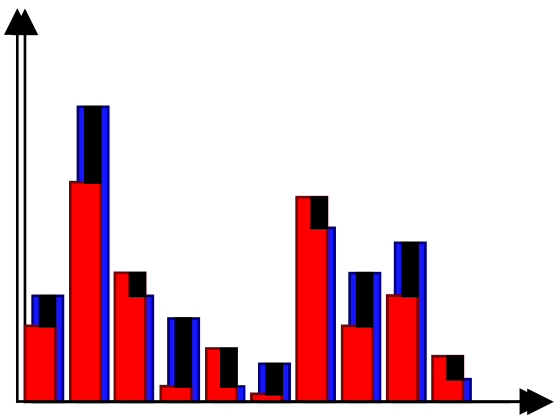


- **Motivation**
  - Statistical background
    - BC measures the statistical separability between two distributions.
  - Range: [0,∞]
  - (Reason for d_{BC}: triangle inequality)

Comparison Measures: Kullback-Leibler

- **Definition**
  - KL-divergence

$$KL(Q,V) = \sum_i q_i \log \frac{q_i}{v_i}$$



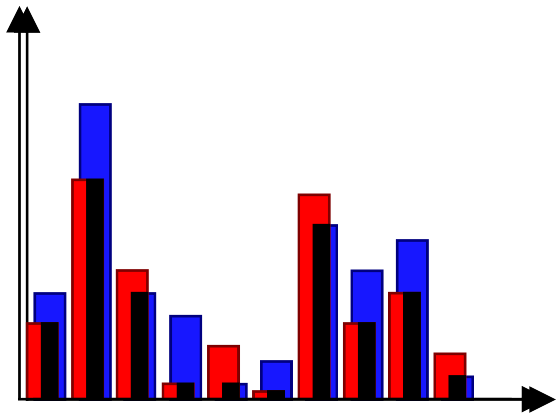
- **Motivation**
  - Information-theoretic background:
    - Measures the expected difference (#bits) required to code samples from distribution Q when using a code based on Q vs. based on V.
    - Also called: *information gain*, *relative entropy*
  - Not symmetric!
  - Symmetric version: *Jeffreys divergence*

$$JD(Q,V) = KL(Q,V) + KL(V,Q)$$

Comp. Measures: Histogram Intersection

- **Definition**
  - **Intersection**

$$\cap(Q,V) = \sum_i \min(q_i, v_i)$$

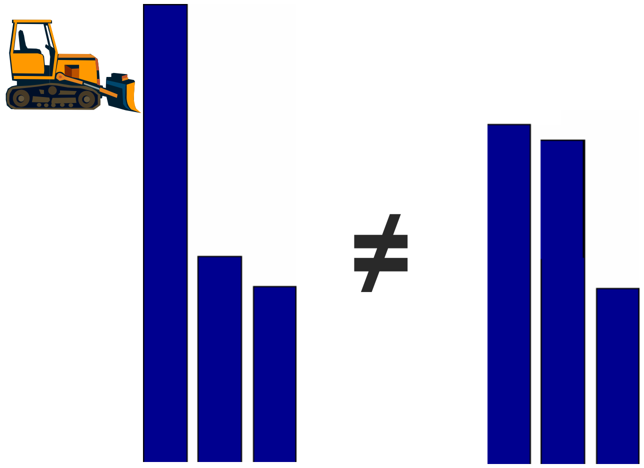


- **Motivation**
  - **Measures the common part of both histograms**
  - **Range: [0,1]**
  - **For unnormalized histograms, use the following formula**

$$\cap(Q,V) = \frac{1}{2}\left(\frac{\sum_i \min(q_i, v_i)}{\sum_i q_i} + \frac{\sum_i \min(q_i, v_i)}{\sum_i v_i}\right)$$

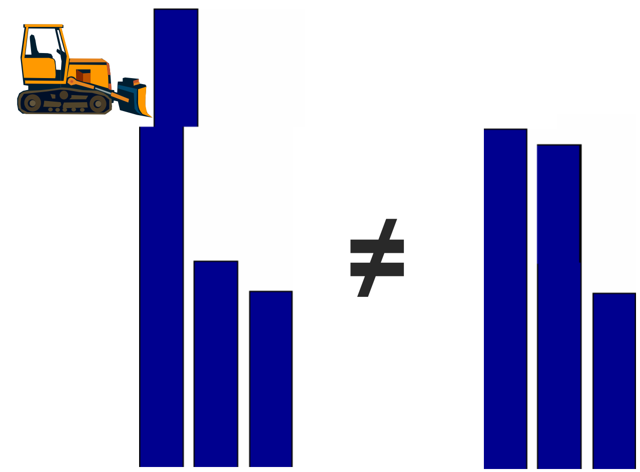
Comp. Measures: Earth Movers Distance

- **Motivation: Moving Earth**



Comp. Measures: Earth Movers Distance

- **Motivation: Moving Earth**



Comp. Measures: Earth Movers Distance

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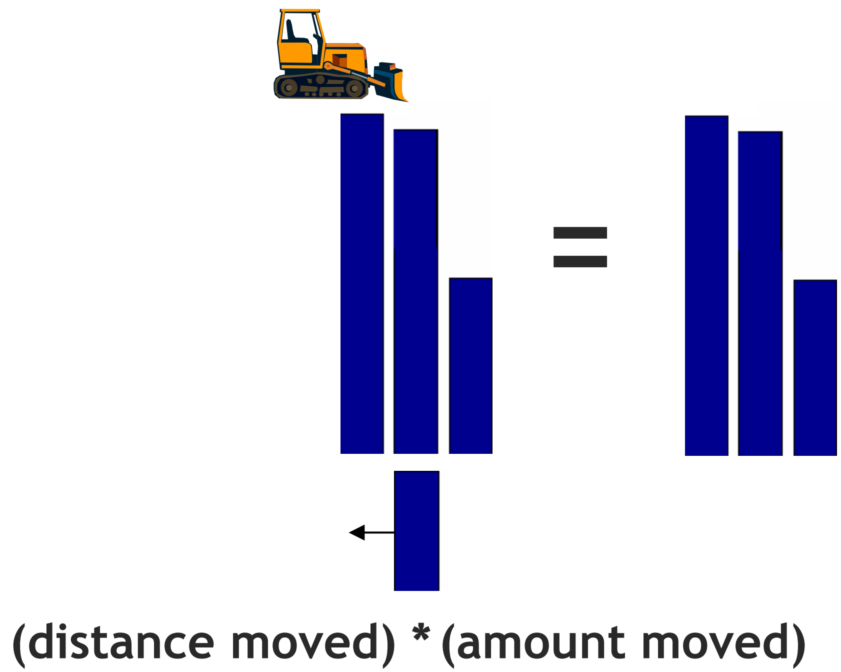
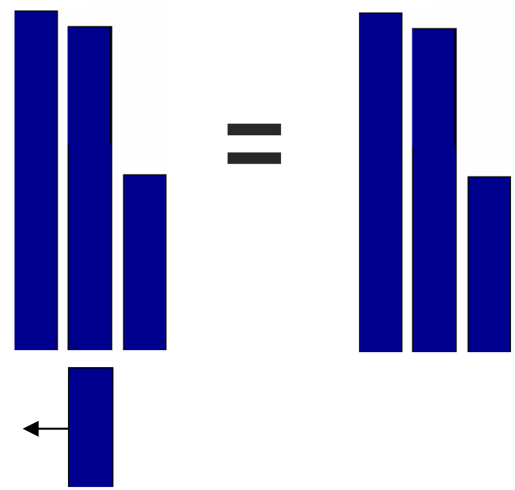
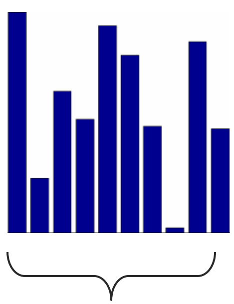


Comp. Measures: Earth Movers Distance

- **Motivation: Moving Earth**
  - Linear Programming Problem



Q

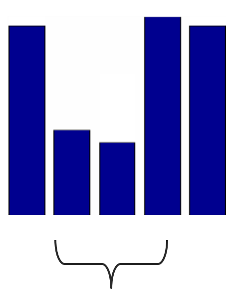


m clusters

$$\sum \text{(distance moved) * (amount moved)}$$

All movements

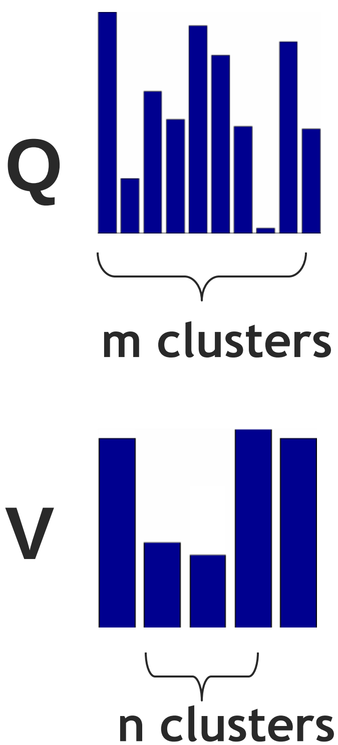
V

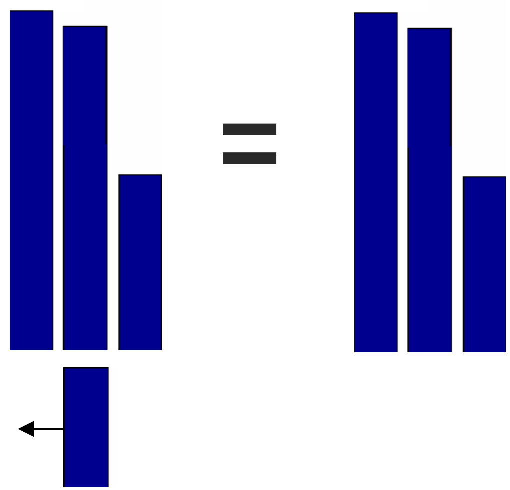


n clusters

Comp. Measures: Earth Movers Distance

- **Motivation: Moving Earth**
  - Linear Programming Problem



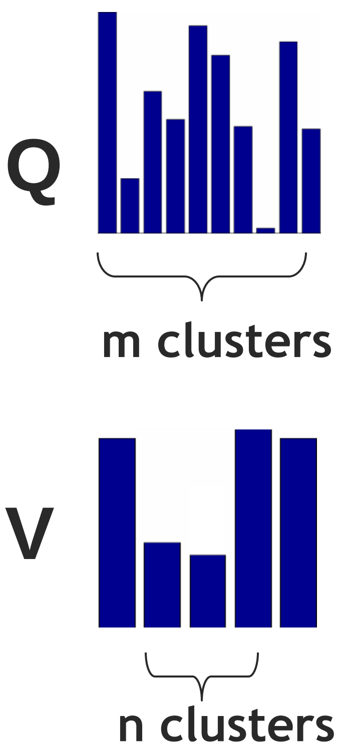


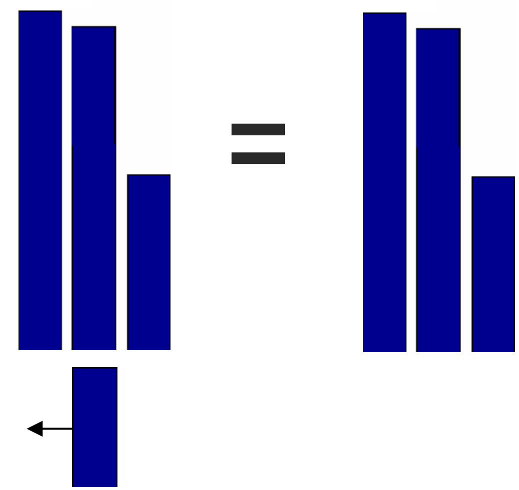
$$\sum_{i=1}^{m}\sum_{j=1}^{n} d_{ij}$$ * (amount moved)

All movements

Comp. Measures: Earth Movers Distance

- **Motivation: Moving Earth**
  - Linear Programming Problem





$$\sum_{i=1}^{m}\sum_{j=1}^{n} d_{ij} f_{ij} = \mathrm{WORK}$$

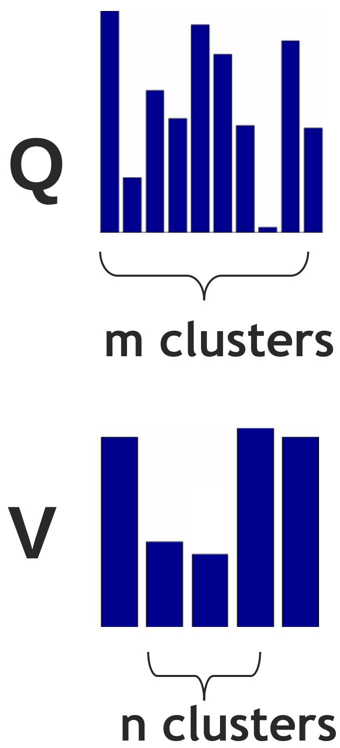
All movements

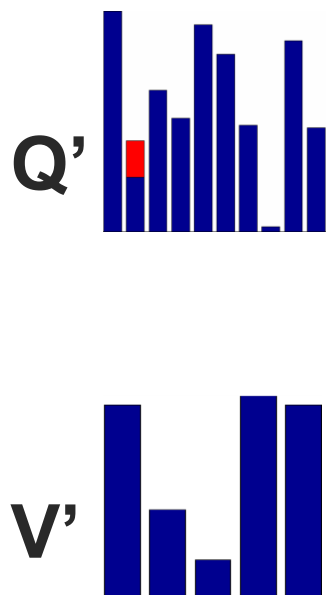
⇒ ***What is the minimum amount of work to convert Q into V?***

EMD Computation

- **Constraints**

1. Move "earth" only from Q to V

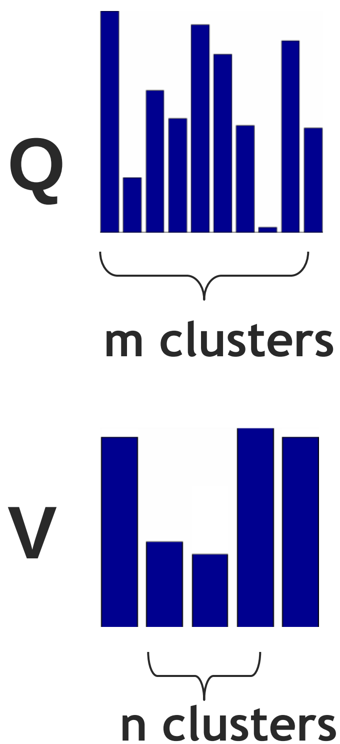




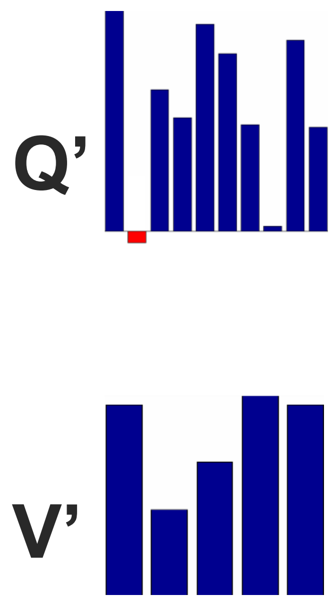
$$f_{ij} \geq 0$$

EMD Computation

- **Constraints**



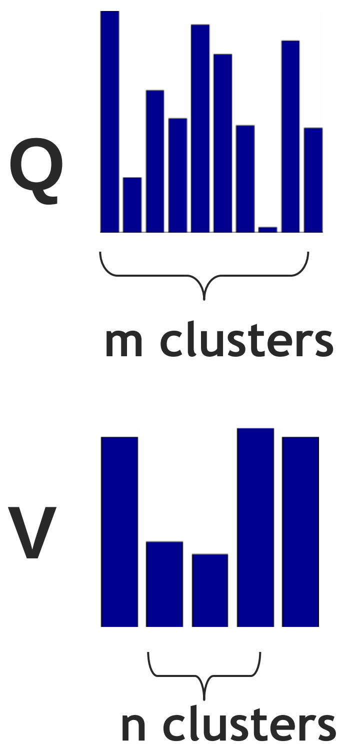
2. Cannot send more “earth” than there is



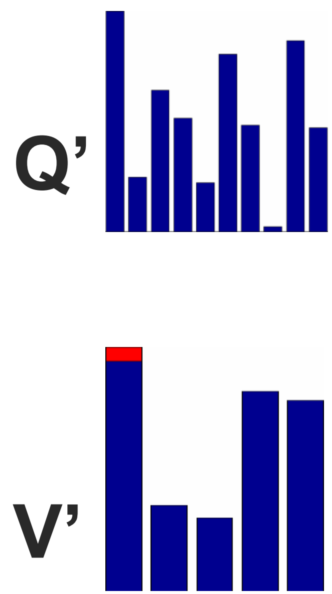
$$\sum_{j=1}^{n} f_{ij} \leq w_{q_i}$$

EMD Computation

- **Constraints**



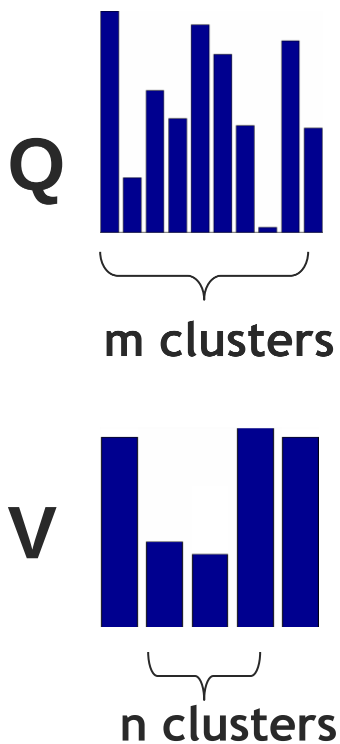
3. V cannot receive more than it can hold



$$\sum_{i=1}^{m} f_{ij} \leq w_{v_j}$$

EMD Computation

- **Constraints**



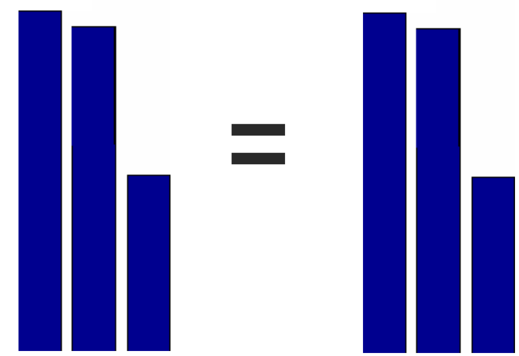
4. As much "earth" as possible must be moved.
   - Either Q must be completely spent or V must be completely filled.

$$\sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij} = \min\left(\sum_{i=1}^{m} w_{q_i}, \sum_{j=1}^{n} w_{v_j}\right)$$

Comp. Measures: Earth Movers Distance

- Motivation: Moving Earth
  - Linear Programming Problem
  - Distance measure

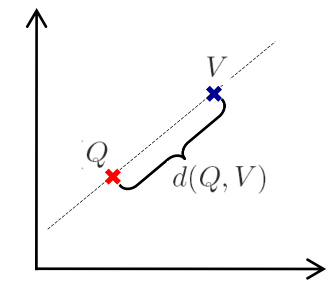
$$D_{EMD}(Q,V) = \frac{\sum_{i,j} d_{ij} f_{ij}}{\sum_{i,j} f_{ij}}$$



$$\sum_{i=1}^{m} \sum_{j=1}^{n} d_{ij} f_{ij} = \text{WORK}$$

- Advantages
  - Nearness measure without quantization
  - Partial matching
  - A true metric
- Disadvantage: expensive computation
  - Efficient algorithms available for 1D
  - Approximations for higher dimensions…

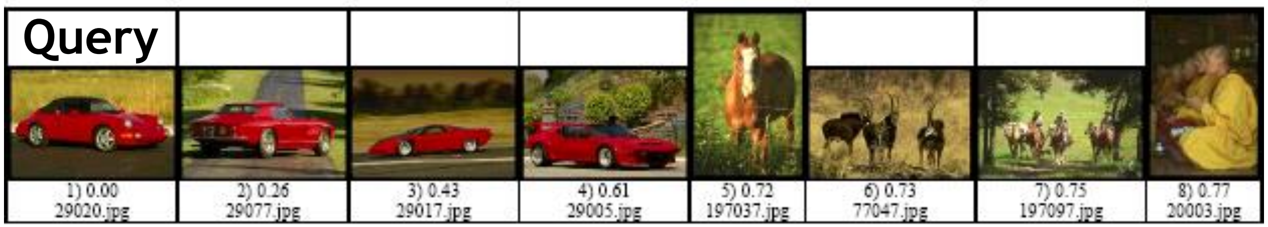
Summary: Comparison Measures



- Vector space interpretation
  - Euclidean distance
  - Mahalanobis distance
- Statistical motivation
  - Chi-square
  - Bhattacharyya
- Information-theoretic motivation
  - Kullback-Leibler divergence, Jeffreys divergence
- Histogram motivation
  - Histogram intersection
- Ground distance
  - Earth Movers Distance (EMD)

Comparison for Image Retrieval

L2 distance



Jeffrey divergence

χ^2 statistics

Earth Movers Distance

Histogram Comparison

- Which measure is best?
  - Depends on the application…
  - Euclidean distance is often not robust enough.
  - Both Intersection and χ^2 give good performance for histograms.
    - Intersection is a bit more robust.
    - χ^2 is a bit more discriminative.
  - KL/Jeffrey works sometimes very well, but is expensive.
  - EMD is most powerful, but also quite expensive

  - There exist many other measures not mentioned here
    - e.g. statistical tests: Kolmogorov-Smirnov
Cramer/Von-Mises
    - …

Summary: Recognition Using Histograms

- Simple algorithm
  1. Build a set of histograms $H=\{h_i\}$ for each known object
     - More exactly, for each *view* of each object
  2. Build a histogram h_t for the test image.
  3. Compare h_t to each $h_i \in H$
     - Using a suitable comparison measure
  4. Select the object with the best matching score
     - Or reject the test image if no object is similar enough.

"Nearest-Neighbor" strategy

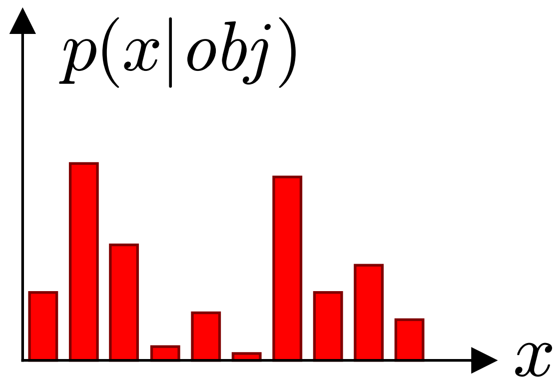
Topics of This Lecture

- Object Recognition
  - Appearance-based recognition
  - Global representations
  - Color histograms

- Recognition using histograms
  - Histogram comparison measures
  - Histogram backprojection
  - Multidimensional histograms
  - Extension: colored derivatives

Localization by Histogram Backprojection

- „Where in the image are the colors we're looking for?"
  - Idea: Normalized histogram represents probability distribution



- Histogram backprojection
  - For each pixel x, compute the **likelihood** that this pixel color was caused by the object: $p(x\,|\,obj)$.
  - This value is projected back into the image (*i.e.* the image values are replaced by the corresponding histogram values).

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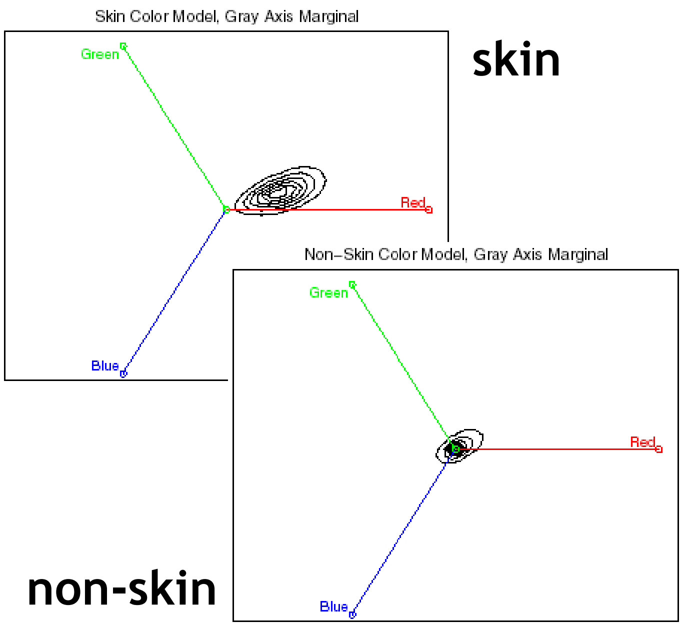
Color-Based Skin Detection

- Used 18,696 images to build a general color model.
- Histogram represen-tation



M. Jones and J. Rehg, Statistical Color Models with Application to Skin Detection, IJCV 2002.

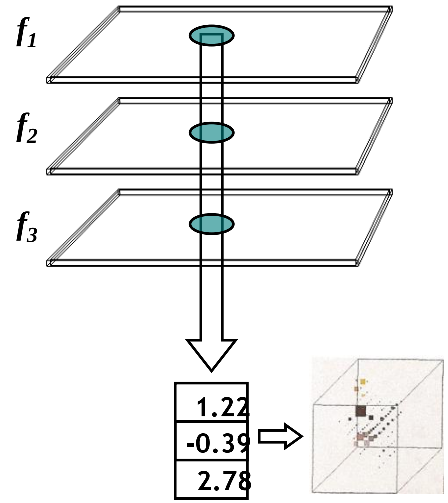
Discussion: Color Histograms

- **Pros**
  - Invariant to object translation & rotation
  - Slowly changing for out-of-plane rotation
  - No perfect segmentation necessary
  - Histograms change gradually when part of the object is occluded
  - Possible to recognize deformable objects
    - E.g., a pullover

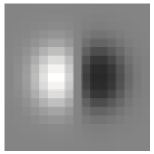
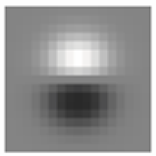
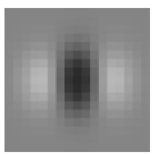
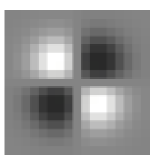
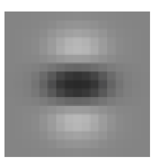
- **Cons**
  - Pixel colors change with the illumination („color constancy problem“)
    - Intensity
    - Spectral composition (illumination color)
  - Not all objects can be identified by their color distribution.

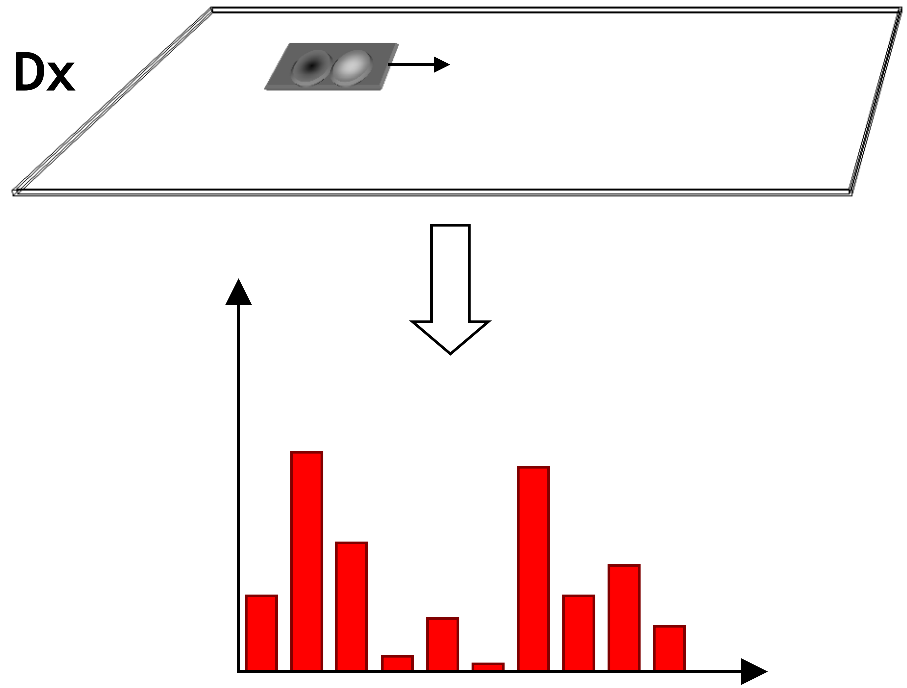
Topics of This Lecture

- Object Recognition
  - Appearance-based recognition
  - Global representations
  - Color histograms
- **Recognition using histograms**
  - **Histogram comparison measures**
  - **Histogram backprojection**
  - **Multidimensional histograms**
  - **Extension: colored derivatives**



Generalization of the Idea

- **Histograms of derivatives**
  - Dx 
  - Dy 
  - Dxx 
  - Dxy 
  - Dyy 



General Filter Response Histograms

- **Any local descriptor (e.g. filter, filter combination) can be used to build a histogram.**

- **Examples:**
  - **Gradient magnitude** $$Mag = \sqrt{D_x^2 + D_y^2}$$
  - **Gradient direction** $$Dir = \arctan \frac{D_y}{D_x}$$
  - **Laplacian** $$Lap = D_{xx} + D_{yy}$$

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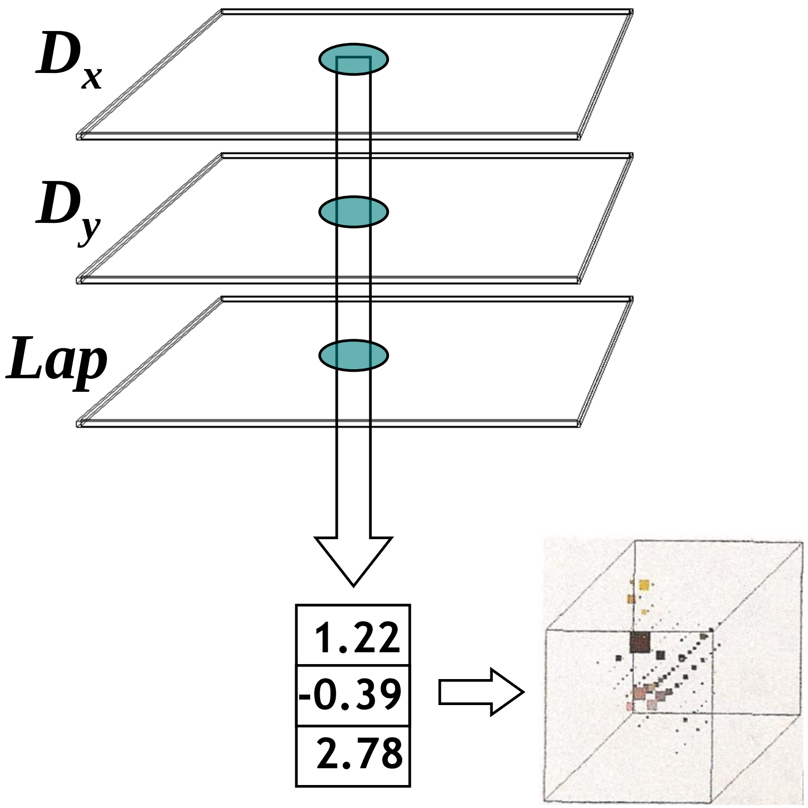
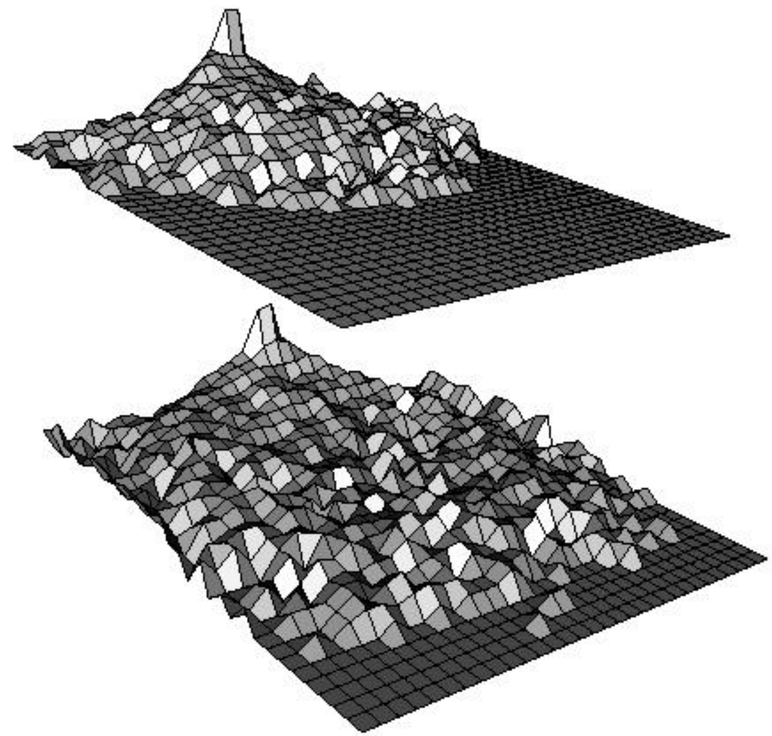
Multidimensional Representations

- Combination of several descriptors
  - Each descriptor is applied to the whole image.
  - Corresponding pixel values are combined into one feature vector.
  - Feature vectors are collected in multidimensional histogram.



Multidimensional Histograms

- **Examples**



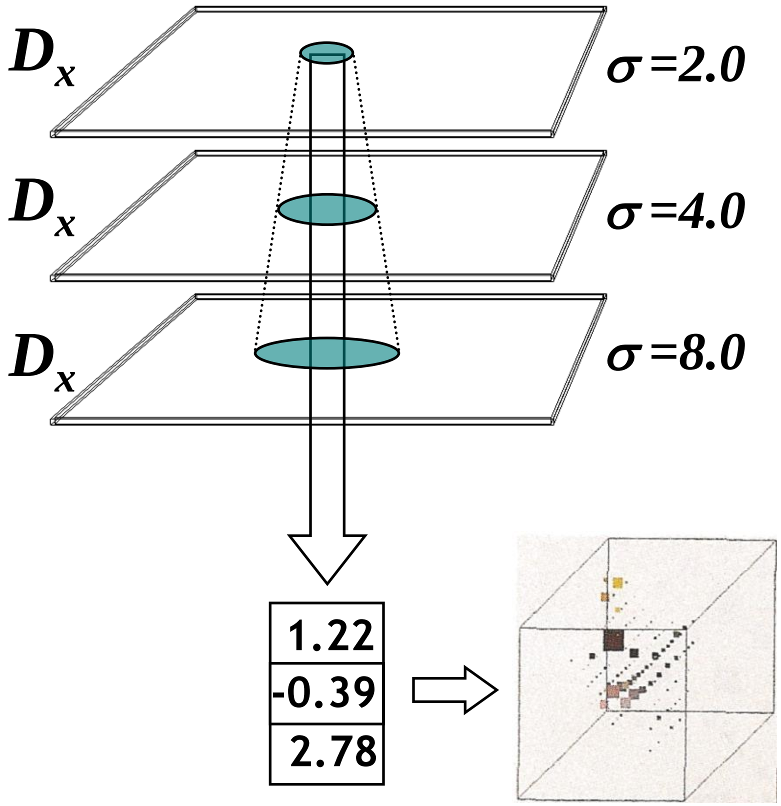
[Schiele & Crowley, 2000]

Multidimensional Representations

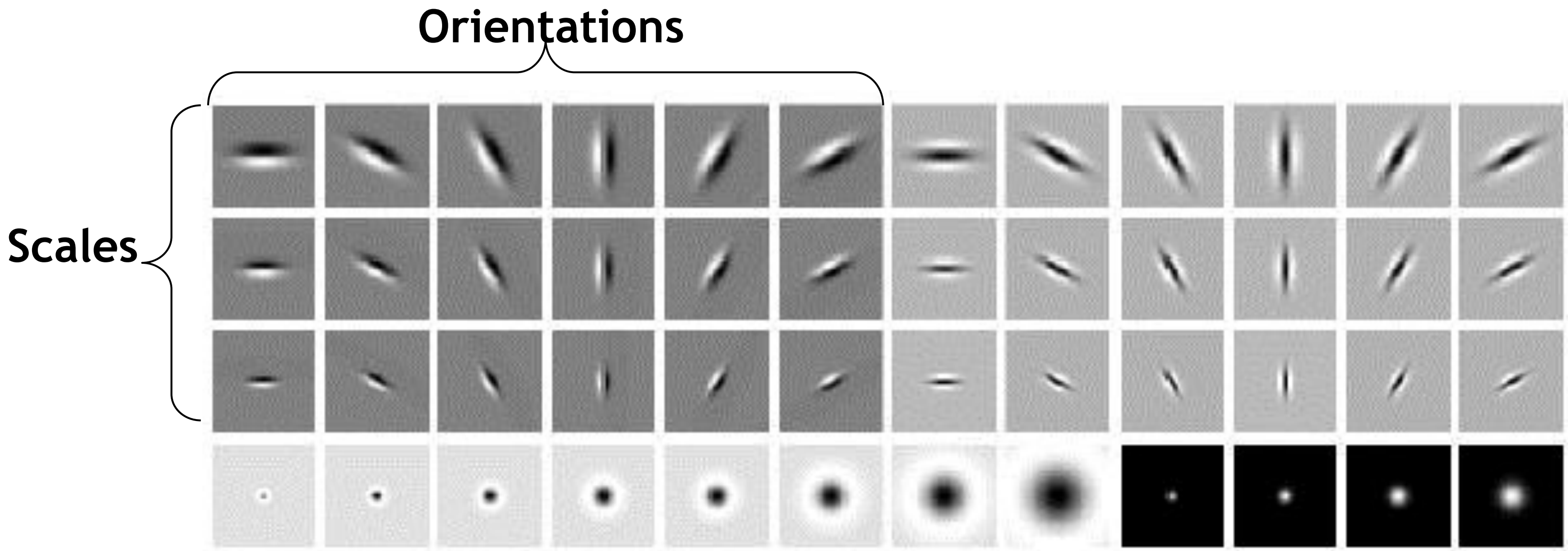
- **Useful simple combinations**
  - D_x-D_y — **Rotation-variant**
    - Descriptor changes when image is rotated.
    - Useful for recognizing oriented structures (e.g. vertical lines)
  - *Mag-Lap* — **Rotation-invariant**
    - Descriptor does *not* change when image is rotated.
    - Can be used to recognize rotated objects.
    - Less discriminant than rotation-variant descriptor.

Special Case: Multiscale Representations

- **Combination of several scales**
  - Descriptors are computed at different scales.
  - Each scale captures different information about the object.
  - Size of the support region grows with increasing σ.
  - Feature vectors capture both local details and larger-scale structures.



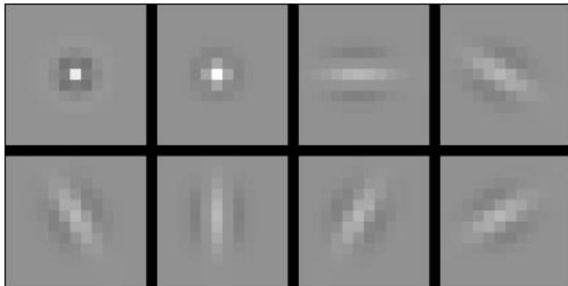
Generalization: Filter Banks



- What filters to put in the bank?
  - Typically we want a combination of scales and orientations, different types of patterns.

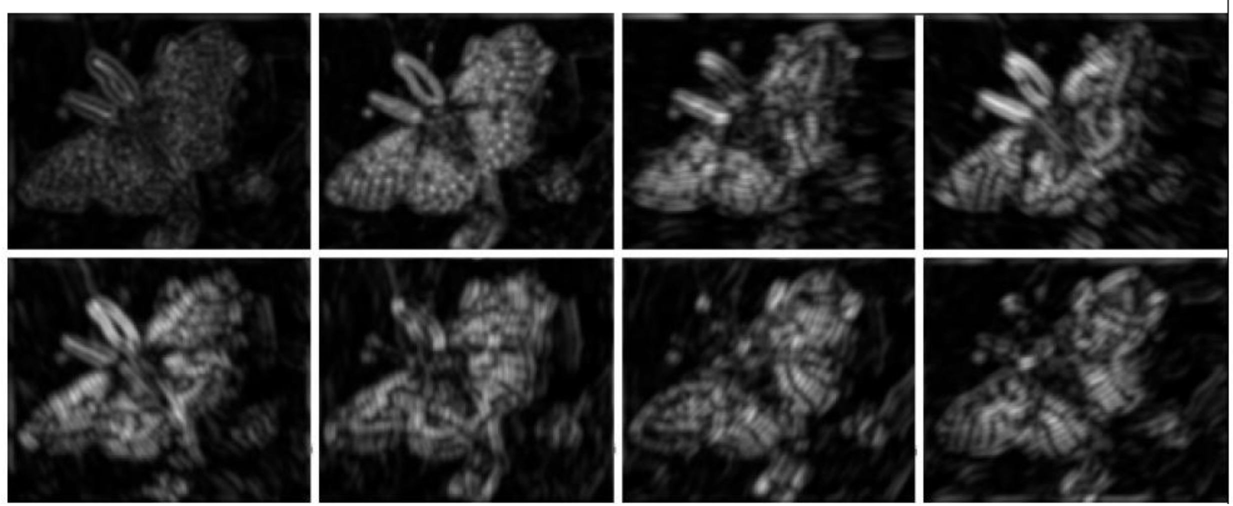
Matlab code available for these examples:
http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

Example Application of a Filter Bank



Filter bank of 8 filters

Input image

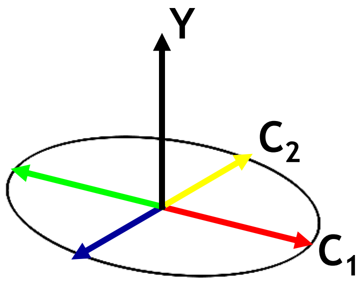


8 response images: magnitude of filtered outputs, per filter

Extension: Colored Derivatives

- YC_1C_2 color space

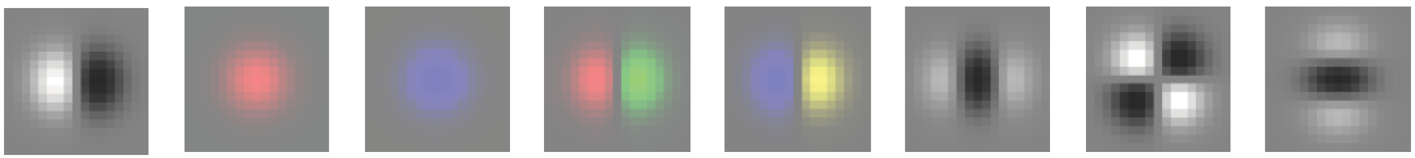
$$\begin{pmatrix} Y \\ C_1 \\ C_2 \end{pmatrix} = \begin{pmatrix} g_r & g_g & g_b \\ \frac{3g_g}{2} & -\frac{3g_r}{2} & 0 \\ \frac{g_b g_r}{g_r^2 + g_g^2} & \frac{g_b g_g}{g_r^2 + g_g^2} & -1 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$



- Color-opponent space
  - Inspired by models of the human visual system
  - Y ≡ intensity
  - C_1 ≡ red-green
  - C_2 ≡ blue-yellow

[Hall & Crowley, 2000]

Extension: Colored Derivatives



- Generalization: derivatives along
  - Y axis → intensity differences
  - C_1 axis → red-green differences
  - C_2 axis → blue-yellow differences
- Feature vector is rotated such that $D_y = 0$
  - Rotation-invariant descriptor

[Hall & Crowley, 2000]

Summary: Multidimensional Representations

- **Pros**
  - Work very well for recognition.
  - Usually, simple combinations are sufficient (e.g. D_x-D_y, Mag-Lap)
  - But multiple scales are very important!
  - Generalization: filter banks
- **Cons**
  - High-dimensional histograms $\Rightarrow$ lots of storage space
  - Global representation $\Rightarrow$ not robust to occlusion

Application: Brand Identification in Video

[Hall, Pellison, Riff, Crowley, 2004]

Application: Brand Identification in Video

[Hall, Pellison, Riff, Crowley, 2004]

Application: Brand Identification in Video

2%

3%

11%

0%

33%

false detection

[Hall, Pellison, Riff, Crowley, 2004]

References and Further Reading

- Background information on histogram-based object recognition can be found in the following paper
  - B. Schiele, J. Crowley, *Recognition without Correspondence using Multidimensional Receptive Field Histograms*. International Journal of Computer Vision, Vol. 36(1), 2000.

- Matlab filterbank code available at
  - http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html