CS231A TA SESSION

PROBLEM SET 4

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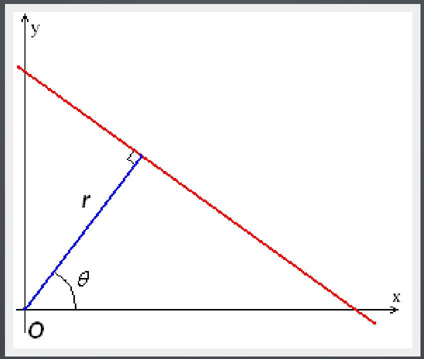
QUESTION 1

HOUGH TRANSFORM

- Transform a point in a cartesian coordinate to
- all lines (line parameters) that pass the point in the polar coordinate

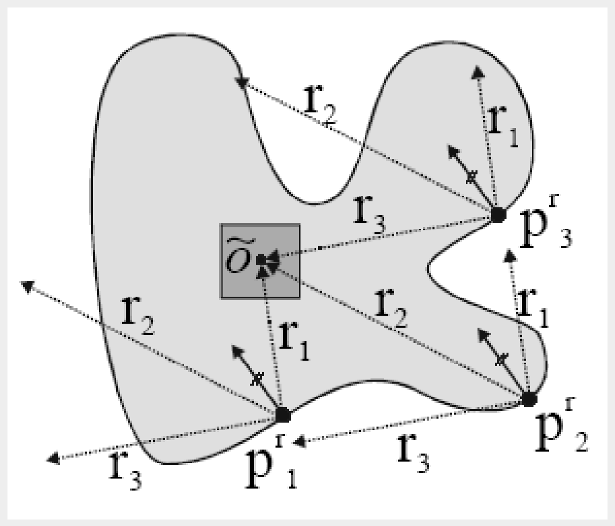
$$H : (x, y) \rightarrow \{(r, \theta) | r(\theta) = x \cos\theta + y \sin\theta\}$$



$$y = -\frac{\cos\theta}{\sin\theta} x + \frac{r}{\sin\theta} \rightarrow r(\theta) = x \cos\theta + y \sin\theta$$

GENERALIZED HOUGH TRANSFORM

- feature $\Phi(x)$ to points in the 2D Hough space $S = \{\vec{a}\}$
  - $\vec{a}$ is the reference origin of the shape
- For points $\vec{x}$ on the boundary, store $\vec{r} = \vec{a} - \vec{x}$: R-Table
  - As a function of the gradient $\Phi(\vec{x})$
  - Rotation and scale : 4D Hough Space



D.H. Ballard, "Generalizing the Hough Transform to Detect Arbitrary Shapes", Pattern Recognition, Vol.13, No.2, p.111-122, 1981

IMPLICIT SHAPE MODEL

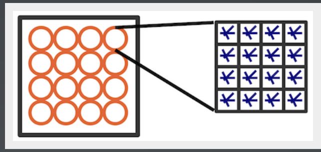
- R-Table as a function of an image patch
- transform an image patch to object centers

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV 2004

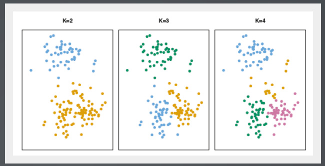
QUESTION 2

BAG OF VISUAL WORDS

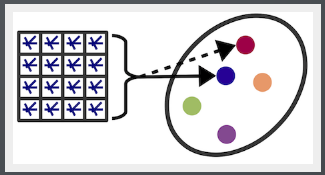
Feature Extraction



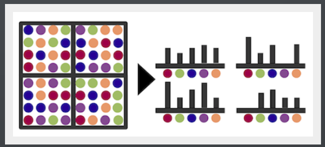
Clustering



Encoding



Spatial Binning

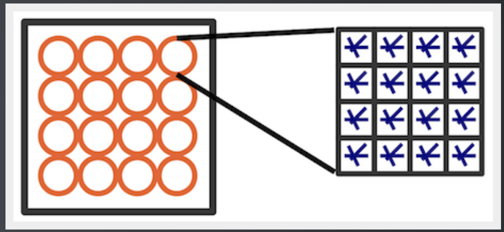


Kernel SVM

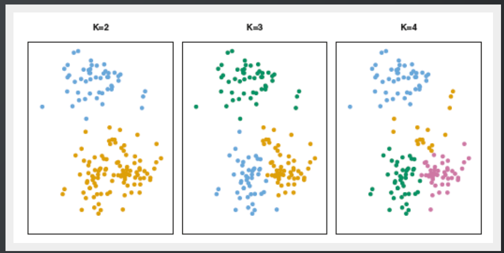
$$k(x, y) = \langle \Psi(x), \Psi(y) \rangle$$

BAG OF VISUAL WORDS

- Feature Extraction
  - Local image feature
  - Robust to typical image transformations
    - Dense SIFT
      - SIFT at every location vs a key point
    - Interest points might not correspond to foreground

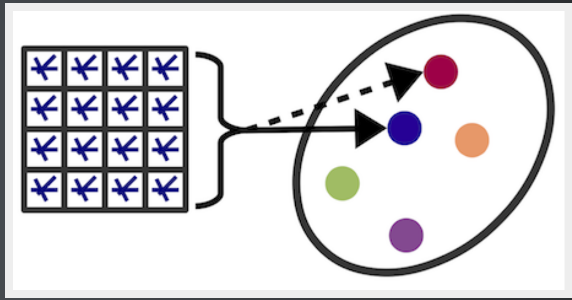


- Clustering (Dictionary)
  - Visual words should be distinctive and diverse
  - Common visual words (wheel) will form a cluster
    - K-means clustering

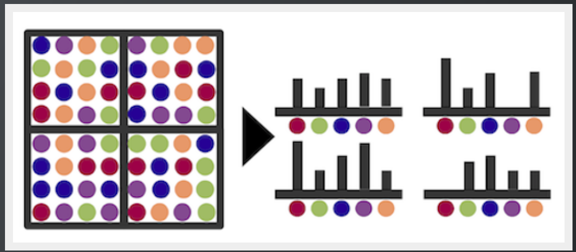


BAG OF VISUAL WORDS

- Encoding
  - Maps local features to visual words
  - Hard quantization
    - assign to the NN



- Spatial Pyramid
  - Encode spatial information
  - Divide the image into subsections
  - For each subsection, create a VW histogram



SIMILARITY METRIC FOR DISTRIBUTIONS

Train a linear SVM on features (distribution): Distance metric??

How similar is a distribution P from a distribution Q: f -divergence!

$$\mathrm{f} : (0, \infty) \rightarrow \mathrm{R}$$, convex

$$\mathrm{D_f}(\mathrm{P}||\mathrm{Q}) = \int \mathrm{f}\left(\frac{\mathrm{dP}}{\mathrm{dQ}}\right) \mathrm{dQ}$$

- Kullback-Leibler Divergence

$$\mathrm{f}(\mathrm{x}) = \mathrm{x} \log \mathrm{x}$$

- χ^2 Divergence

$$\mathrm{f}(\mathrm{x}) = (\mathrm{x} - 1)^2$$

FOR A DISCRETE CASE

- Intersection kernel : $k(x, y) = \sum \min(x_i, y_i)$
- χ^2 kernel : $k(x, y) = \frac{1}{2} \sum \frac{(x_i - y_i)^2}{x_i + y_i}$

In the problem 2, we will use χ^2 kernel for the similarity metric

HOMOGENEOUS KERNEL AND FINITE APPROXIMATION

$K(x, y)$ expensive, non linear!

But in the feature space $\Psi(\cdot)$ it becomes linear (∞dimension)

- Feature map $\Psi(x)$ using the Homogeneous Kernel
- Generic histogram kernel is $K(x, y) = \sum_i k(x_i, y_i)$

  Homogeneous if $k(cx, cy) = ck(x, y)$
  - intersection, χ^2, Hellinger's, Jensen-Shannon's
- Find a finite feature map $\hat{\Psi}(\cdot)$ that

$$k(x, y) = \langle \Psi(x), \Psi(y) \rangle \approx \langle \hat{\Psi}(x), \hat{\Psi}(y) \rangle$$

- Map distributions using $\hat{\Psi}(\cdot)$ then it becomes a linear classification problem in the feature space!

HOMOGENEOUS KERNEL

- Use the homogeneity,
  $k(x, y) = \sqrt{xy}\, k(\sqrt{x/y}, \sqrt{y/x}) = \sqrt{xy}\, K(\log(y/x))$
- Ex, intersection kernel
  - $k(x, y) = \min(x, y) = \sqrt{xy}\, K(\log \frac{y}{x})$
  - $K(w) = e^{-|w|/2}$
- Define $\kappa(\lambda)$ as the Fourier transformation of $K(w)$
- $\Psi(x) = e^{-i\lambda \log x} \sqrt{x\kappa(\lambda)}$
  - Continuous, infinite dimensional feature
- Sample at points $\lambda = -nL, (-n+1)L, \ldots, nL$

  ^
- $\Psi(x) \in R^{2n+1}$

  ^ ^
  - $k(x, y) \approx \langle \Psi(x), \Psi(y) \rangle$
- In the problem 2, we use $n = 1$
- vl_homkermap()

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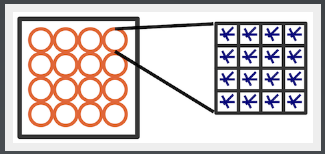

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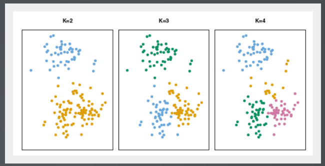

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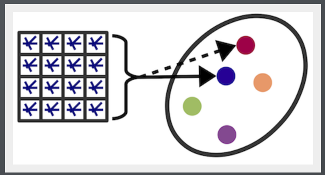

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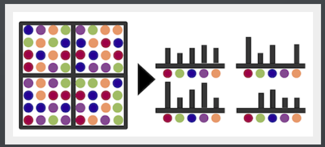

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BAG OF VISUAL WORDS

- Install VL Feat, an extensive CV library
  - http://www.vlfeat.org/
  - Set up the path correctly in the starter code p2.m
- Vary options and see how it affects the performance

- **Code** extract_dense_sift.m
  - Image feature extraction
    - Dense SIFT features
    - use vl_dsift()
  - randomly select 10,000 features
- **Code** create_dictionary.m
  - Create dictionary of visual words
    - Use k-means to find the centroid of clusters.
    - use vl_kmeans()
- **Code** create_histograms.m
  - Represent images as histograms
  - Spatial pyramid