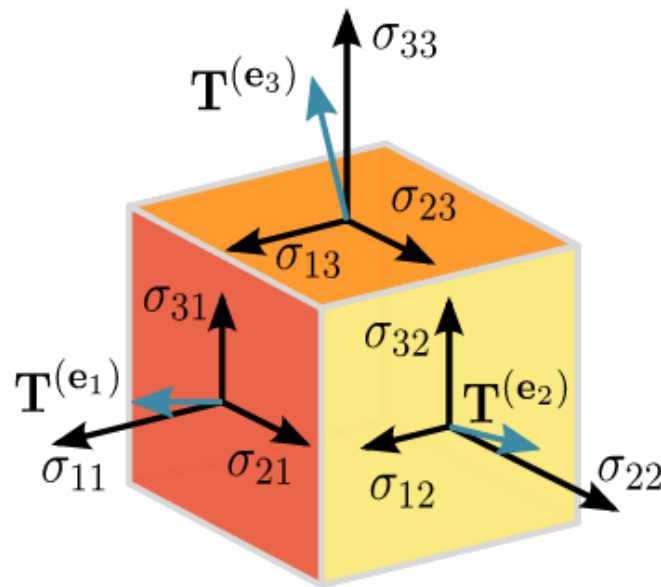


Tensor Discriminant Analysis

Image Processing - II

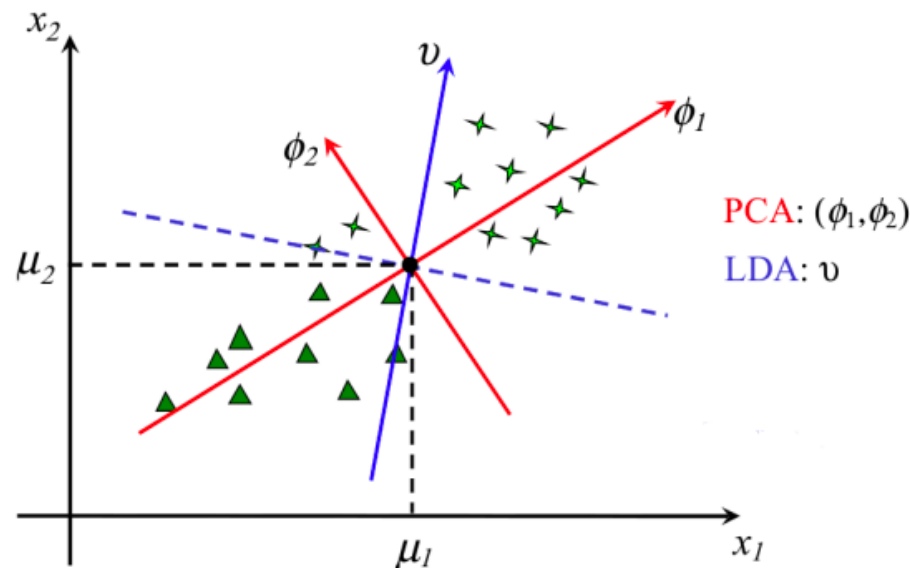
Tensor?

- Generalized linear quantity or geometrical entity that can be expressed as multi-dimensional array



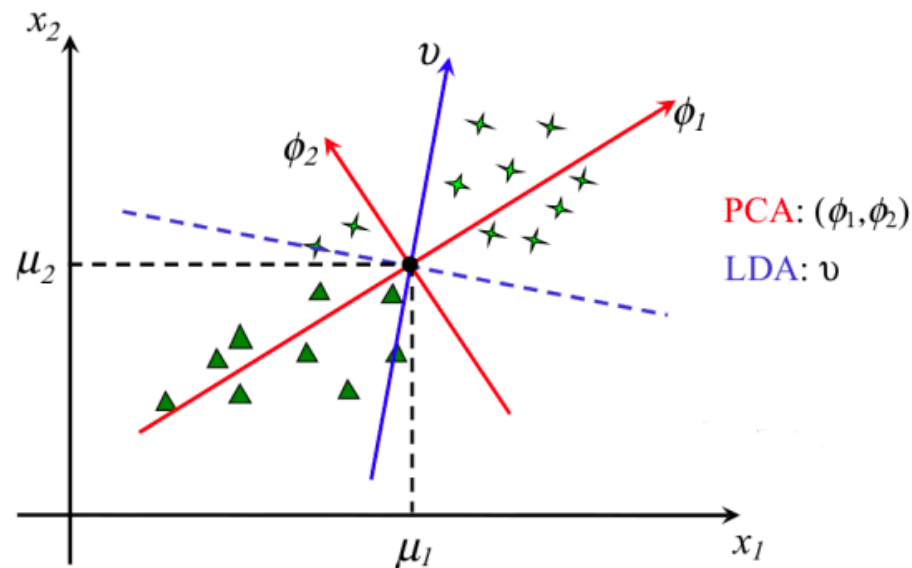
LDA?

- Finds linear combination of features which characterize two or more different objects/classes.
- Closely related to PCA

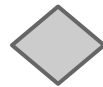
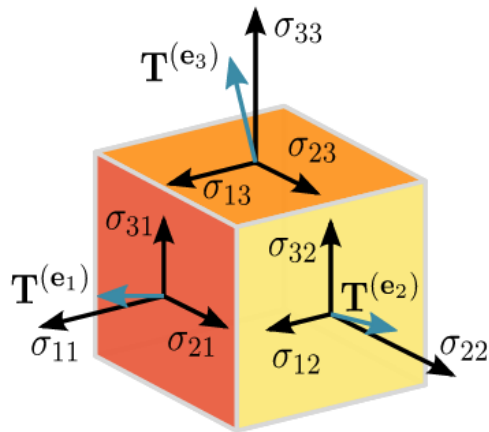


LDA?

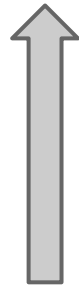
- Following graph shows the difference between LDA and PCA



Enough about LDA!



LDA = Tensor Discriminant Analysis



Magic!!!

Separable Tensor Discriminant Analysis?

- Treat images as images not as vectors!
- Loss of features when converting to vectors
- Projection matrices are learned quickly
- Tackles small sample size problems
- Performs well in visual object detection and recognition

Algorithm:

Input: a training set $\{(\mathcal{X}^\alpha, y^\alpha)\}_{\alpha=1,\dots,N}$ of image patches

$\mathcal{X}^\alpha \in \mathbb{R}^{m \times n}$ with class labels $y^\alpha \in \{-1, +1\}$

Output: a R -term solution of a second-order projection

tensor $\mathcal{W} = \sum_r \mathbf{u}_r \otimes \mathbf{v}_r$

for $r = 1, \dots, R$

$t = 0$

randomly initialize $\mathbf{u}_r(t)$

orthogonalize $\mathbf{u}_r(t)$ w.r.t. $\{\mathbf{u}_1, \dots, \mathbf{u}_{r-1}\}$

repeat

$t \leftarrow t + 1$

contract $x_k^\alpha = \mathcal{X}_{kl}^\alpha u_{r_k}(t)$

compute $\mathbf{v}_r(t) = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$

orthogonalize $\mathbf{v}_r(t)$ w.r.t. $\{\mathbf{v}_1, \dots, \mathbf{v}_{r-1}\}$

contract $x_l^\alpha = \mathcal{X}_{kl}^\alpha v_{r_l}(t)$

compute $\mathbf{u}_r(t) = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$

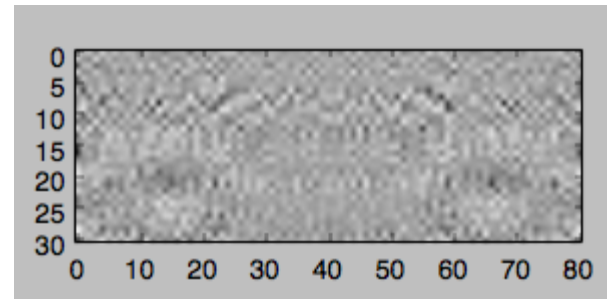
orthogonalize $\mathbf{u}_r(t)$ w.r.t. $\{\mathbf{u}_1, \dots, \mathbf{u}_{r-1}\}$

until $\|\mathbf{u}_r(t) - \mathbf{u}_r(t-1)\| \leq \epsilon \vee t > t_{\max}$

endfor

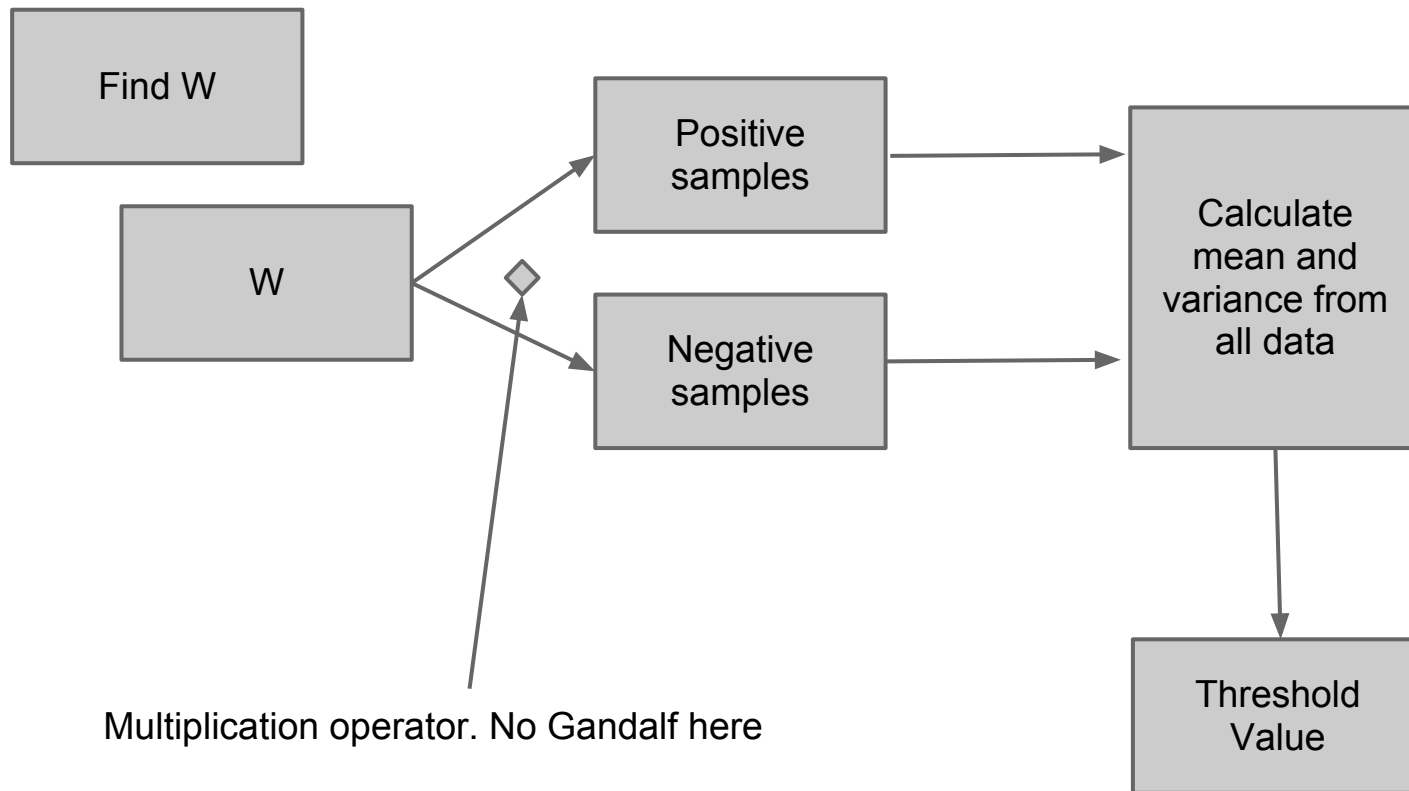
W and Threshold

- W looks like:
($k = 9$, $\text{eps} = 0.0001$)

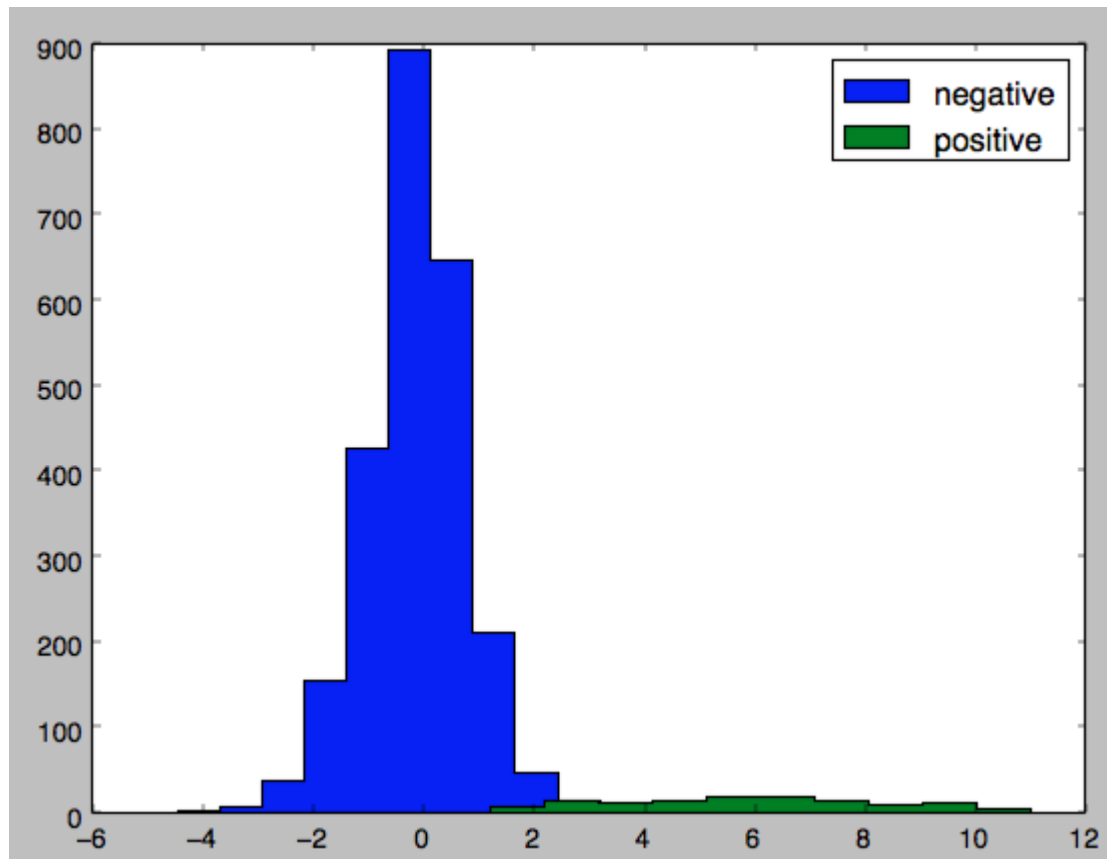


- Threshold, θ , is calculated by computing the mean and variance of the projections of positive samples onto discriminant direction. (Original Paper)

What We Did?

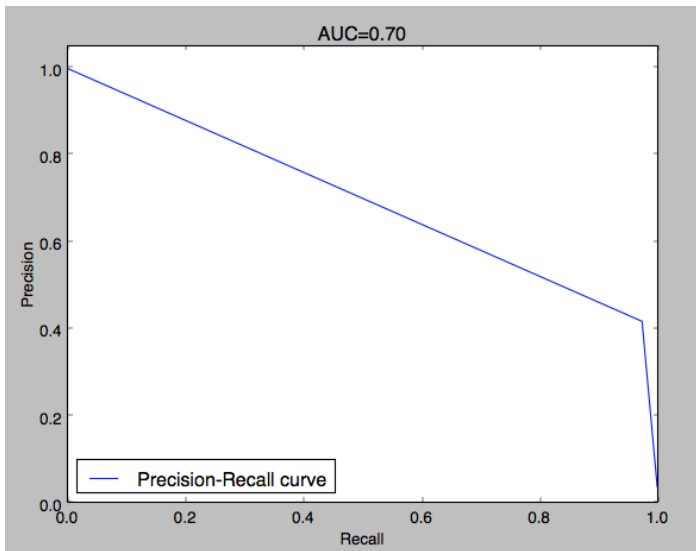


Histogram

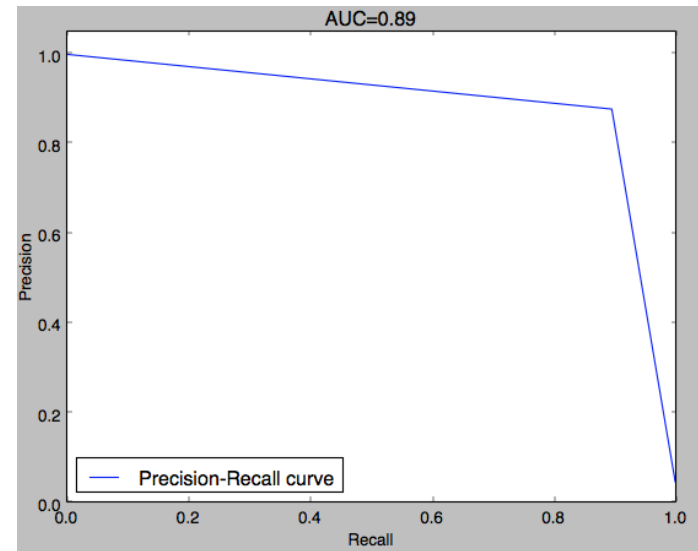


Precision, recall and accuracy

- $k = 6$, $\theta = 1.0$

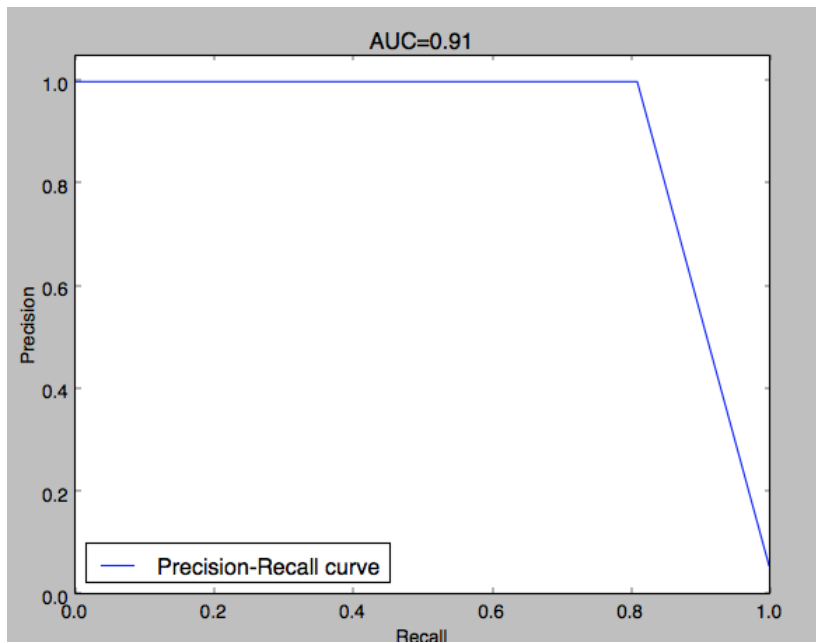


- $k = 6$, $\theta = 2.0$

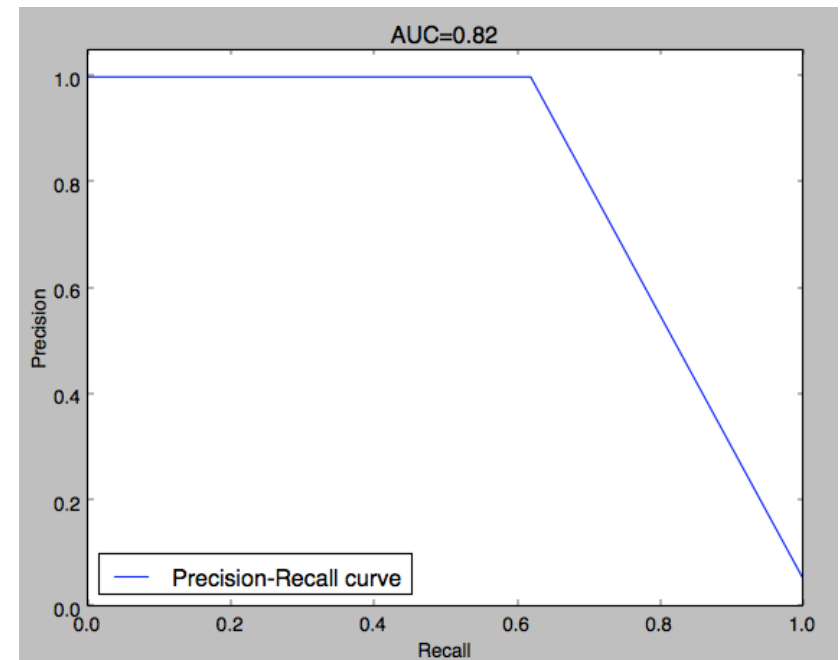


Precision, recall and accuracy

- $k = 6$, $\theta = 3.0$

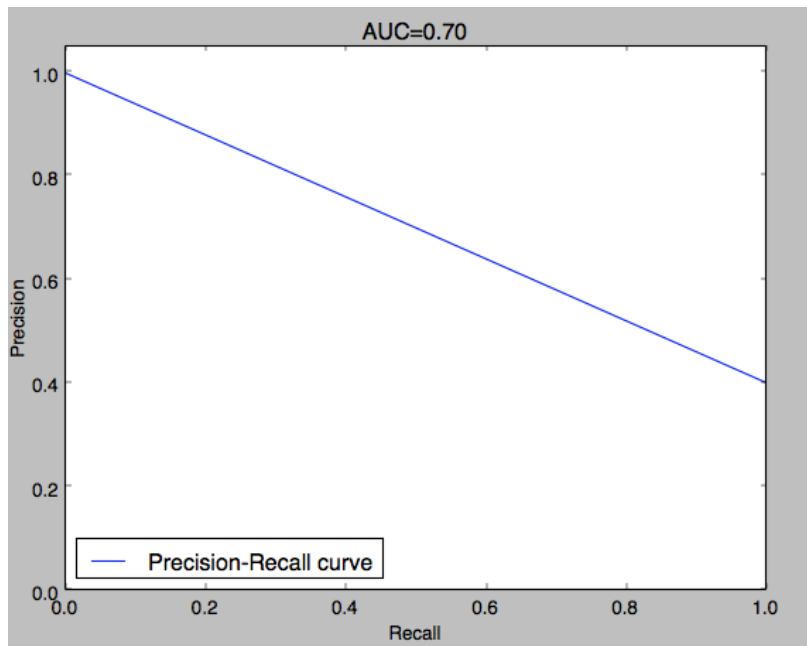


- $k = 6$, $\theta = 4.0$

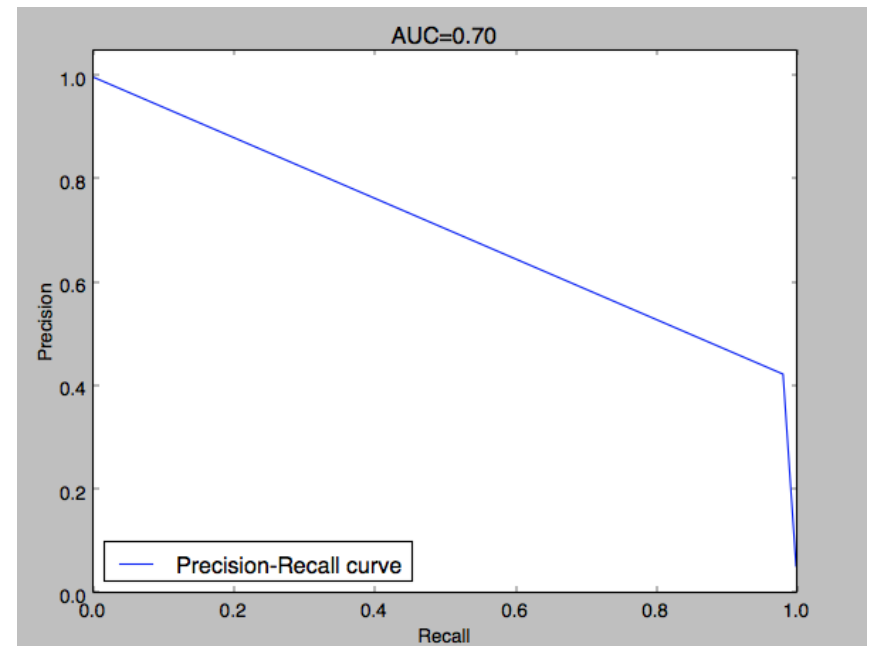


Precision, recall and accuracy

- $k = 7$, $\theta = 1.0$

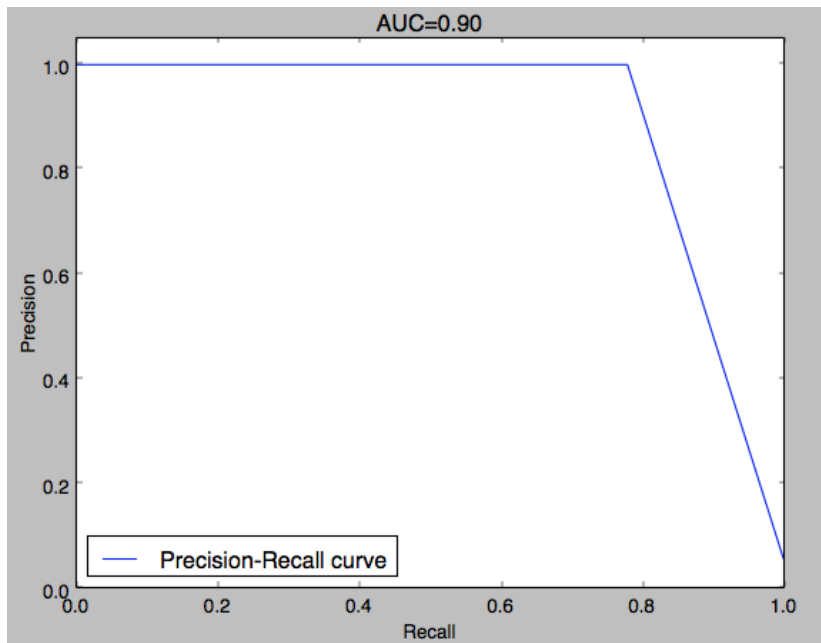


- $k = 8$, $\theta = 1.0$

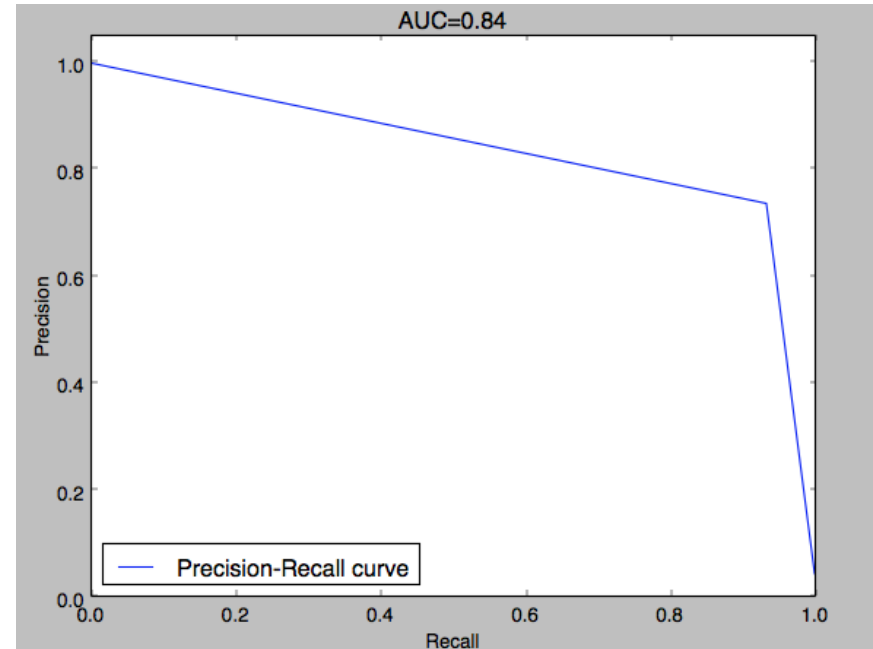


Precision, recall and accuracy

- $k = 9$, $\theta = 1.0$

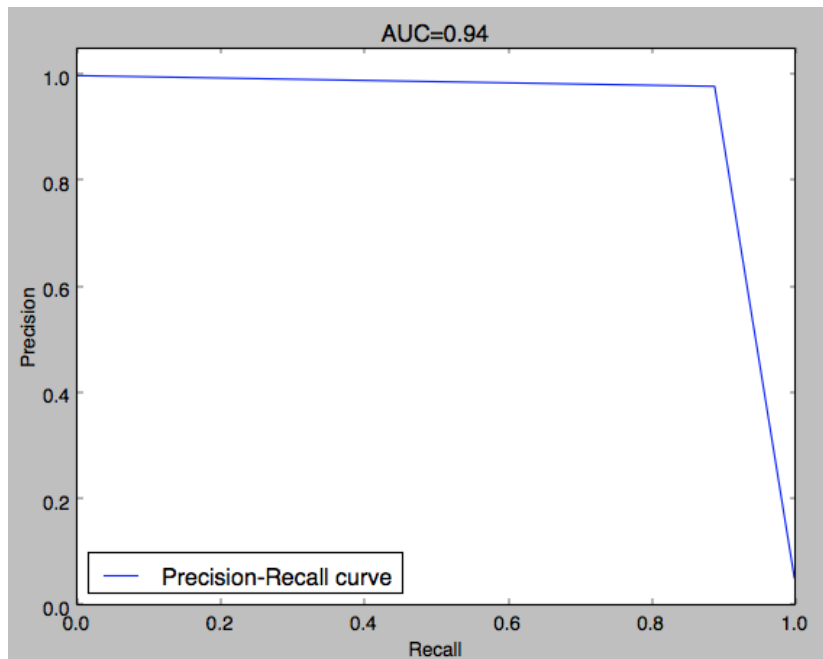


- $k = 9$, $\theta = 2.0$

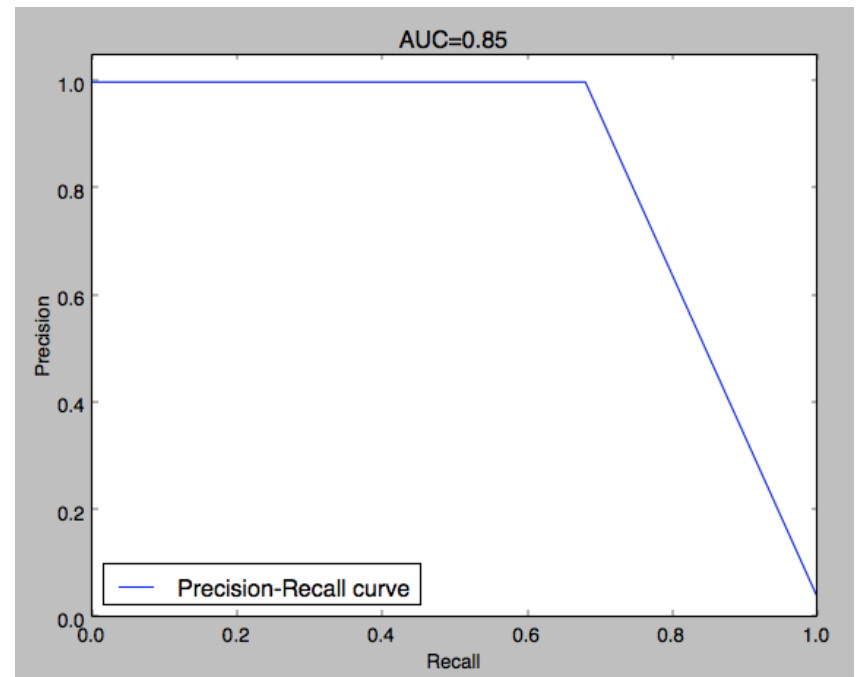


Precision, recall and accuracy

- $k = 9$, $\theta = 3.0$



- $k = 9$, $\theta = 4.0$



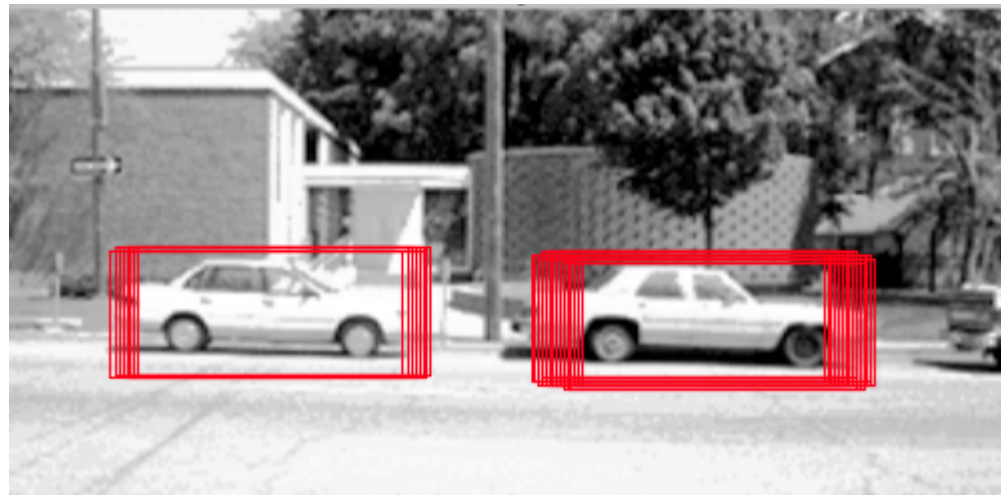
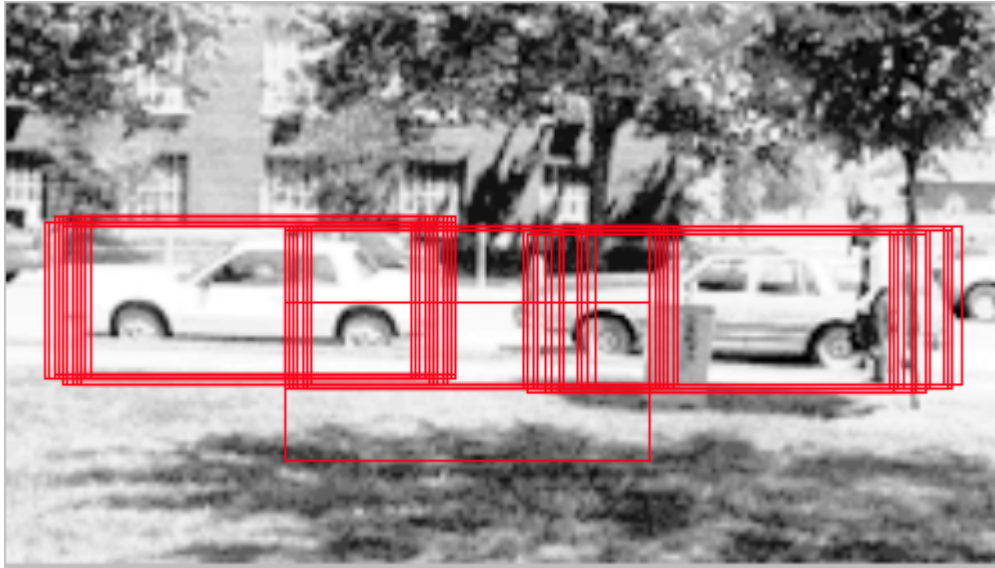
k = ?, theta = ?

- K was chosen to be 9
- theta = 3.0
- Accuracy measure = AUC

Results on Test data

- No convolution while creating patch
- So no convolution here
- Sliding Window
- Image was multiplied by patch
- Thresholded
- Results...

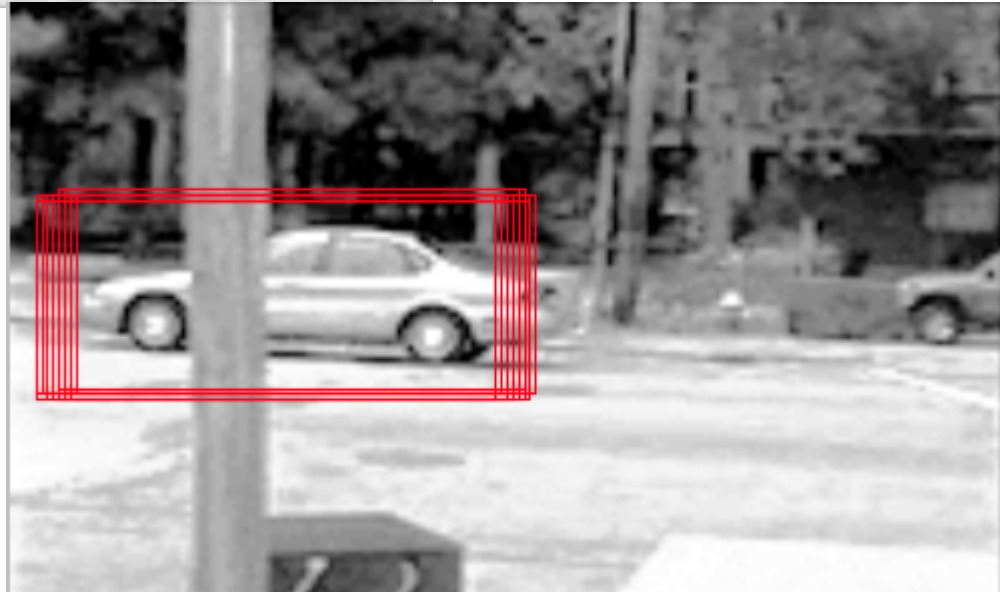
Results on Test data



Results on Test data



Pretty Good huh! :D



Results on Test data

