Facial Feature Detection with Optimal Pixel Reduction SVM

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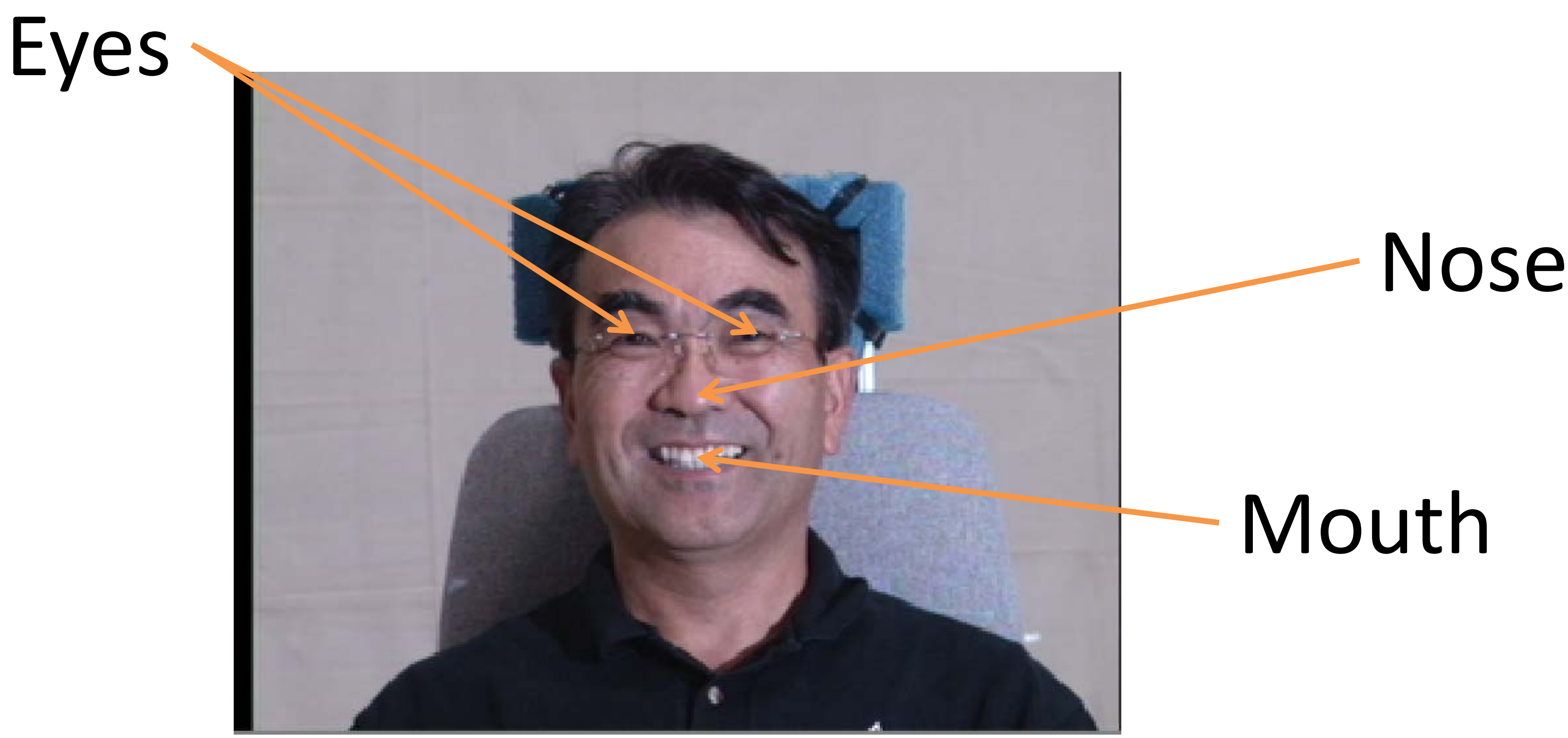
Facial Feature Detection

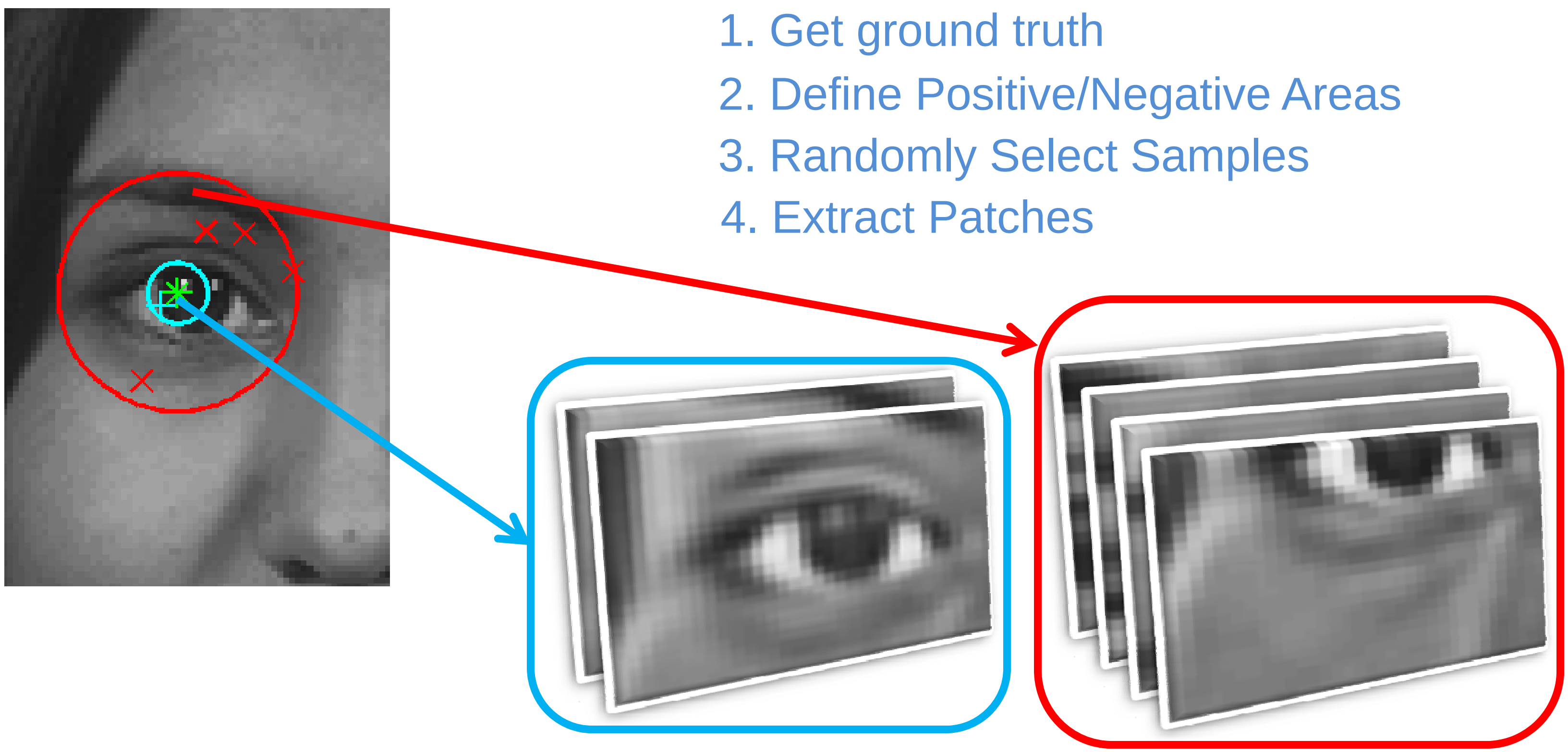


Facial feature detection – previous work

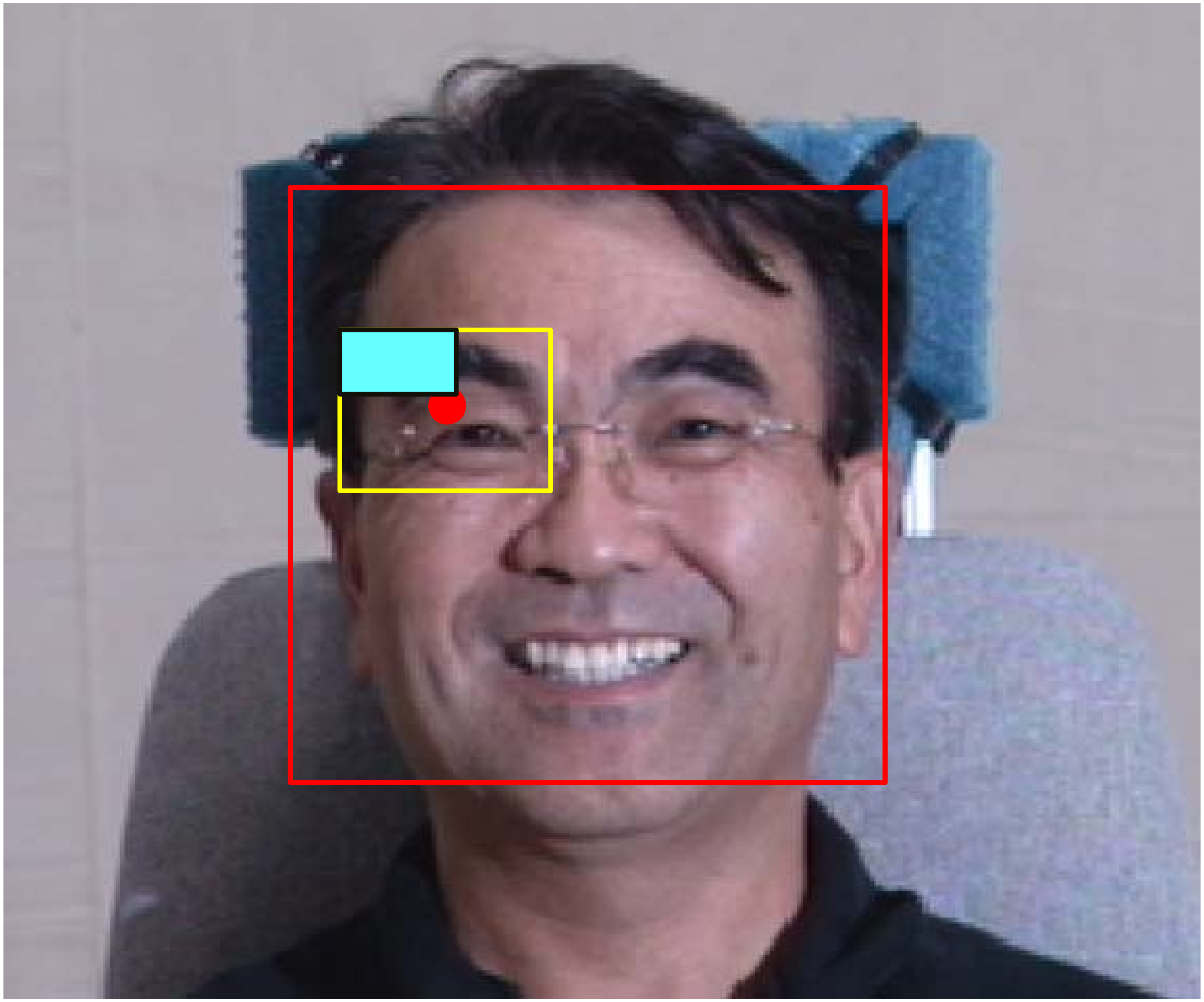
- **Representation:**
  - Intensity
  - Gradient [Kothari & Mitchell 96]
  - Wavelets [Huang & Wechsler 99]
  - Gabor filters [Fasel et al 02]
  - Active infrared [Zhu & Zhi 05]
- **Classifiers:**
  - Neural Network [Reinders et al 96, Huang & Wechsler 99]
  - Boosting [Cristiancce & Cootes 03, Everingham & Zisserman 06, Ma et al 04, Wang et al 05, Niu et al 06]
  - Bayesian/Regression[Zhou & Jiang 04, Everingham & Zisserman 06]
  - SVM [Jee et al 04, Tang et al 05, Jin et al 06, Campadelli et al 06]
- **Multiple facial features**
  - Active shape models [Cootes et al 98, Cristiancce & Cootes 03-06]
  - Pair of eyes [Ma et al 04, Jee et al 04, Tang et al 05, Jin et al 06]

Training an SVM for eye detection

1. Get ground truth
2. Define Positive/Negative Areas
3. Randomly Select Samples
4. Extract Patches

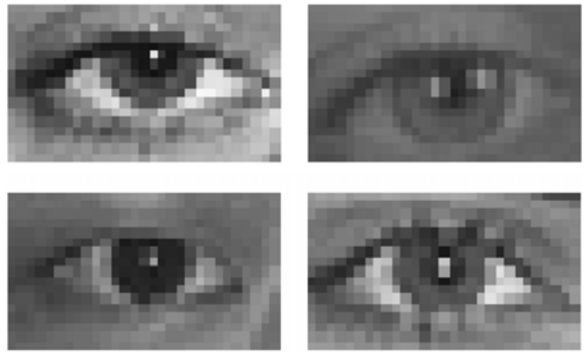


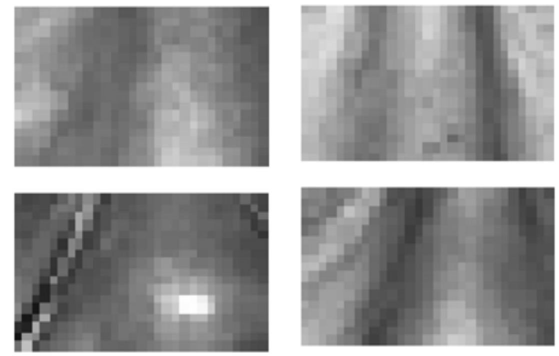
Eye detection with SVM

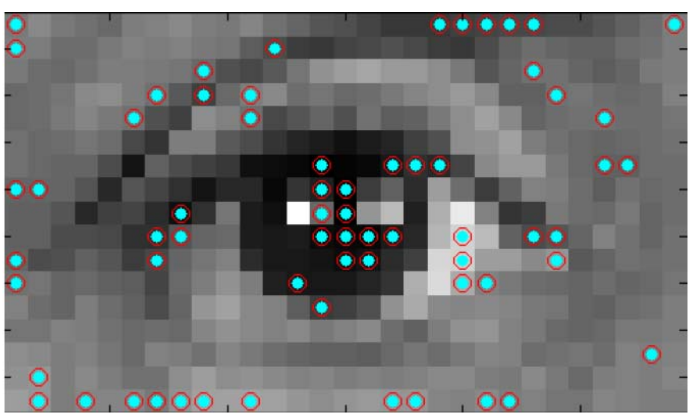


Increasing speed while maintaining accuracy

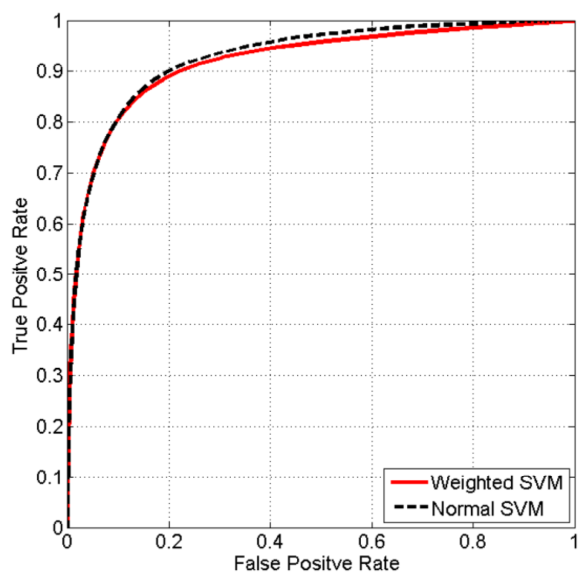
- Reduce #pixels
- Reduce #SVs





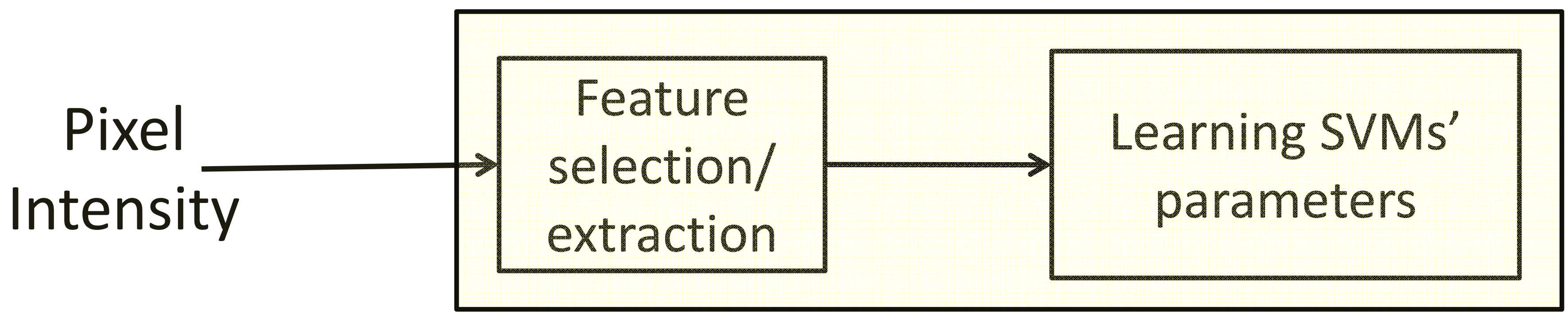


64 pixels (13%) used

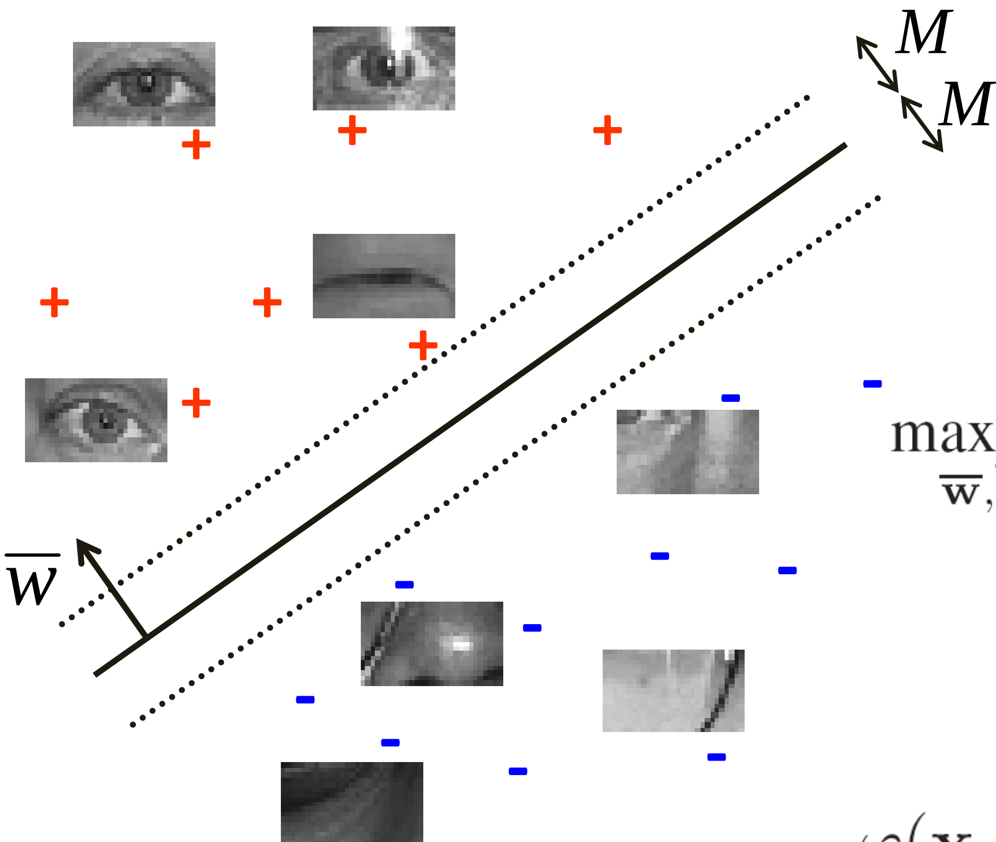


Feature construction in SVM

- Using LOOCV bounds [Weston et al 01, Chapelle et al 02]
- Learning kernel matrix [Cristianini et al 01 , Lanckriet et al 04, Hoi et al 06, de la Torre & Vinyals 07]
- Greedy Selection [Hermes & Buhmann 00, Avidan 04, Mangasarian & Wild 07]
- RELIEF [Kira & Rendell 92, Sun & Li 06]
- Adding Regularization [Stoeckel & Fung 05, Dundar et al 06, Chan et al 07]
- Weighting features in kernel space [Cao et al 07]



SVM & parameterized kernel



$$\mathbf{x}_1, \ldots, \mathbf{x}_n \in \Re^{d \times 1}$$

$$y_1, \ldots, y_n \in \{-1, 1\}$$

Mapping to kernel space

$$\underset{\overline{\mathbf{w}}, \overline{b}, M}{\text{maximize}} \quad M$$

$$\text{s.t.} \quad y_i(\overline{\mathbf{w}}^T \varphi(\mathbf{x}_i) + \overline{b}) \geq M \;\; \forall i$$

$$||\overline{\mathbf{w}}||_2 = 1.$$

$$\varphi(\mathbf{x}_i) = \varphi(\mathbf{x}_i, \mathbf{p})$$

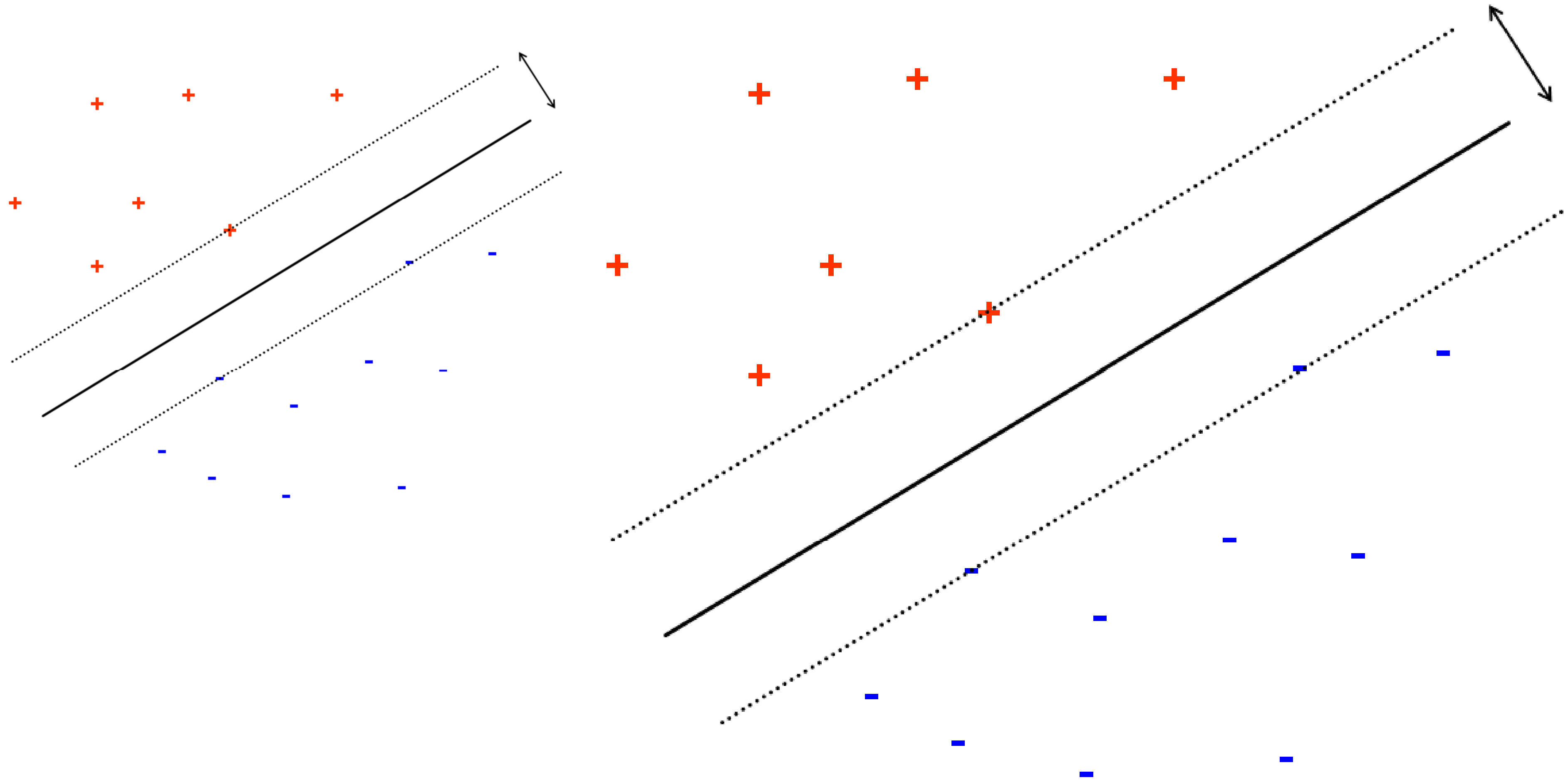
$$\underset{\overline{\mathbf{w}}, \overline{b}, M, \mathbf{p}}{\text{maximize}} \quad M$$

$$\text{s.t.} \quad y_i(\overline{\mathbf{w}}^T \varphi(\mathbf{x}_i, \mathbf{p}) + \overline{b}) \geq M \;\; \forall i$$

$$||\overline{\mathbf{w}}||_2 = 1.$$

?

Comparison of two feature spaces



$$\varphi(\mathbf{x}_i, \mathbf{p}_1) = \frac{1}{2} \times \varphi(\mathbf{x}_i, \mathbf{p}_2)$$

Normalized Margin

$$\underset{\overline{\mathbf{w}}, \overline{b}, M, \mathbf{p}}{\text{maximize}} \quad \frac{M}{\sqrt{\sum_{i,j} \frac{1+y_i y_j}{2} ||\varphi(\mathbf{x}_i, \mathbf{p}) - \varphi(\mathbf{x}_j, \mathbf{p})||_2^2}}$$

$$\text{s.t.} \quad y_i(\overline{\mathbf{w}}^T \varphi(\mathbf{x}_i, \mathbf{p}) + \overline{b}) \geq M \;\; \forall i$$

$$||\overline{\mathbf{w}}||_2 = 1.$$

Scale, translation, rotation invariant!

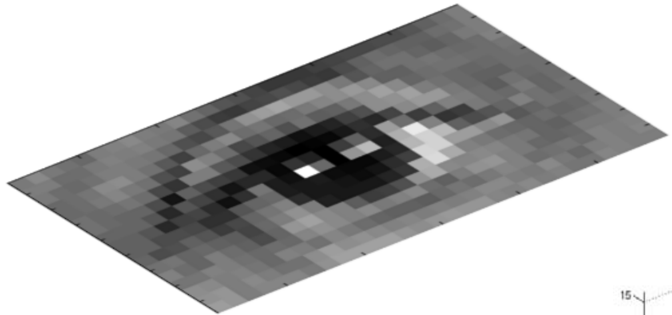
Let $\mathbf{w} = \overline{\mathbf{w}}/M,\, b = \overline{b}/M$

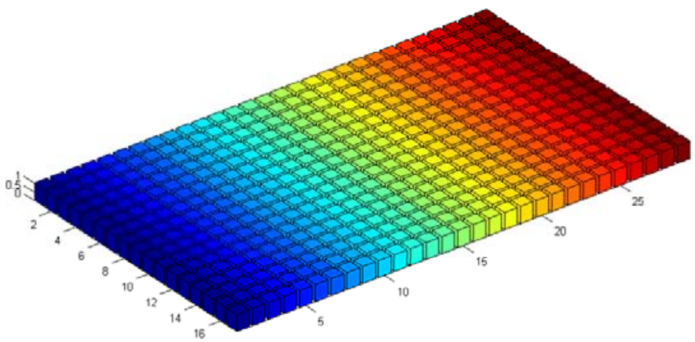
$$\underset{\mathbf{w}, b, \mathbf{p}, \xi}{\text{minimize}} \quad \frac{1}{2} \phi(\mathbf{p}) ||\mathbf{w}||_2^2 \quad + C \sum_i \xi_i$$

$$\text{s.t.} \quad y_i(\mathbf{w}^T \varphi(\mathbf{x}_i, \mathbf{p}) + b) \geq 1 - \xi_i \;\; \forall i$$

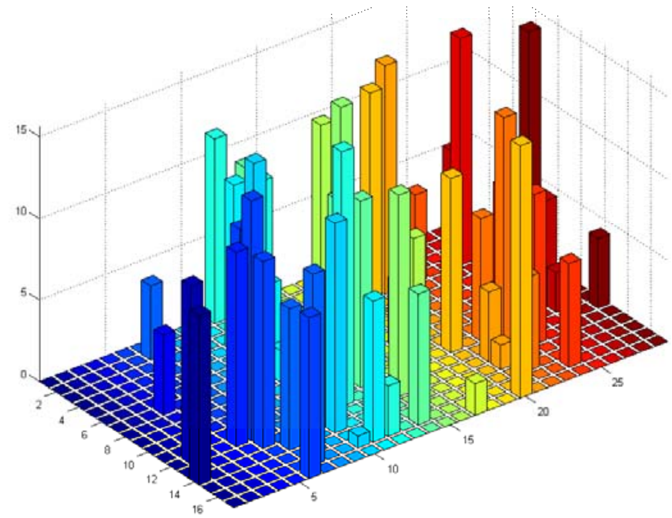
$$\xi_i \geq 0 \;\; \forall i$$

Weighting the pixels





Uniform weights



Non-uniform weights

$$\varphi(, \mathbf{p}) = diag(\mathbf{p})^{1/2}$$

$$p_i \geq 0 \;\; \forall i$$

Learning feature weights

$$\underset{\mathbf{v},b,\mathbf{p},\boldsymbol{\xi}}{\text{minimize}} \quad \frac{1}{2}\sum_{k=1}^{d}\frac{v_k^2}{p_k} + C\sum_{i=1}^{n}\xi_i$$

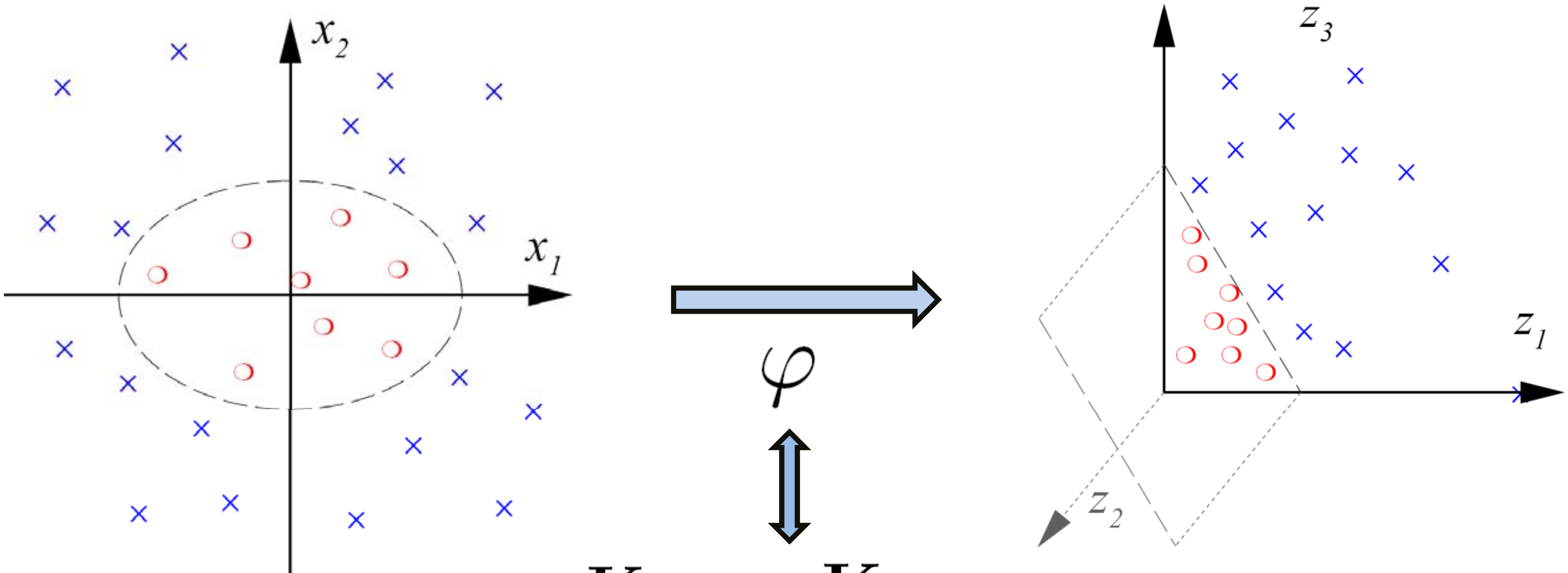
$$\text{s.t.} \quad y_i(\mathbf{v}^T\mathbf{x}_i + b) \geq 1 - \xi_i \;\; \forall i$$

$$\sum_{k=1}^{d} p_k \sum_{i,j} \frac{1 + y_i y_j}{2}(x_{ik} - x_{jk})^2 = 1$$

$$\xi_i \geq 0 \;\; \forall i, p_k \geq 0 \;\; \forall k.$$

Convex!

Feature weighting in feature space



$$\mathbf{K}_{train} \quad \mathbf{K}_{test}$$

$$\widetilde{\varphi} : \Re^d \rightarrow \Re^n, \widetilde{\varphi}(\mathbf{x}) = \mathbf{K}_{train}^{-\frac{1}{2}} \varphi(\mathbf{X})^T \varphi(\mathbf{x})$$

$$\widetilde{\mathbf{K}}_{train} = \mathbf{K}_{train} \qquad \widetilde{\mathbf{K}}_{test} = \mathbf{K}_{test}$$

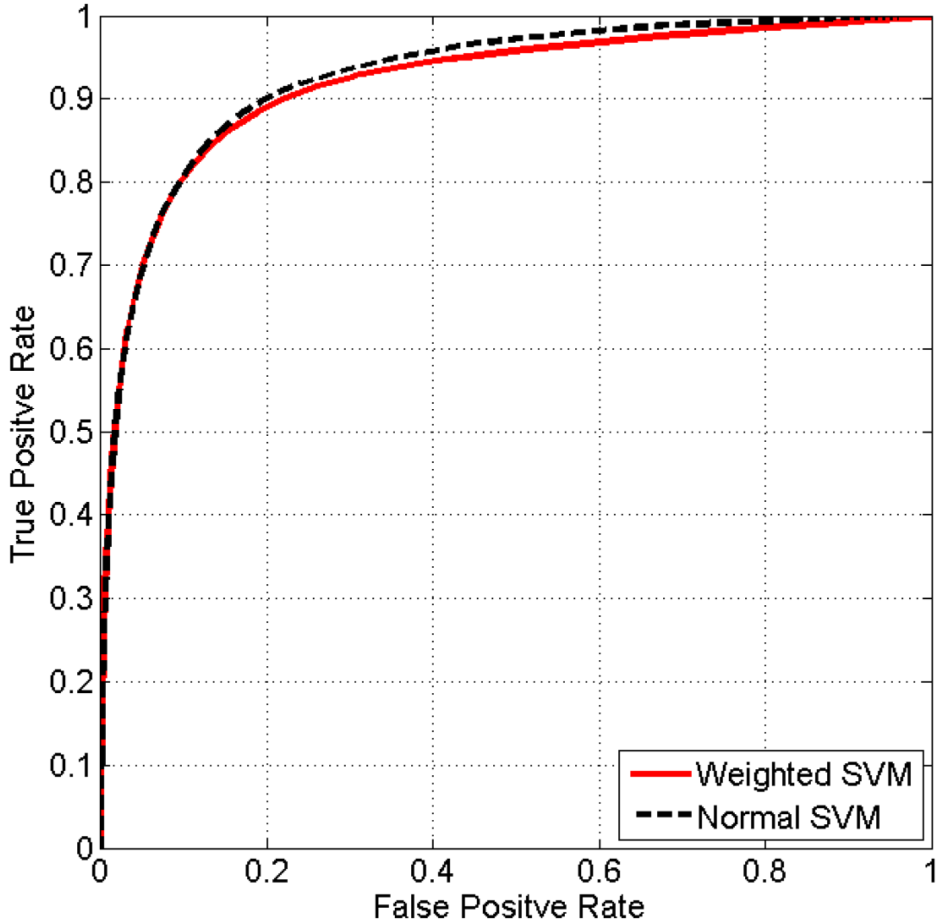
$$\widetilde{\varphi}, \mathbf{p}) = diag(\mathbf{p})^{1/2})^T \varphi(\mathbf{x})$$

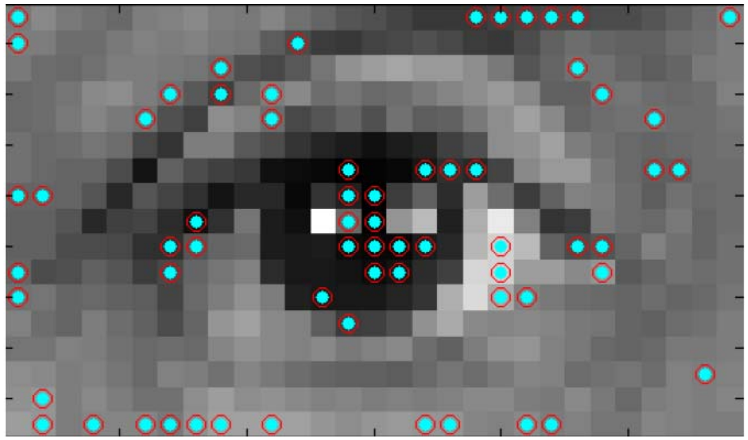
$$p_i \geq 0 \ \forall i$$

Experiment 1 – Eye Detection

- **Task:**
  - Detect left eye position
- **Data:**
  - FERET
  - 2963 frontal faces
  - 4 hand-labeled landmarks
  - 256*384 pixel
  - Training: 60%, testing: 40%

ROCs





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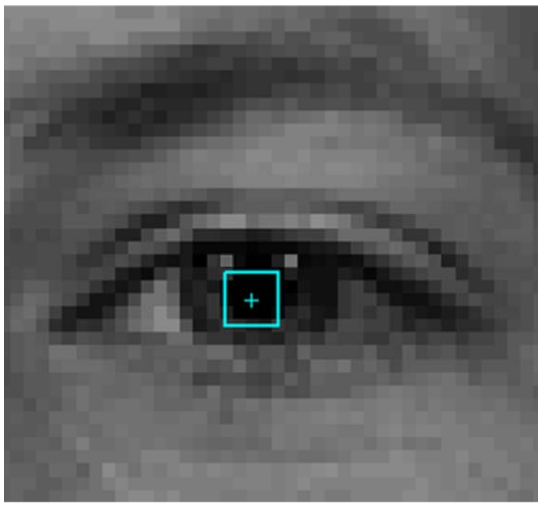
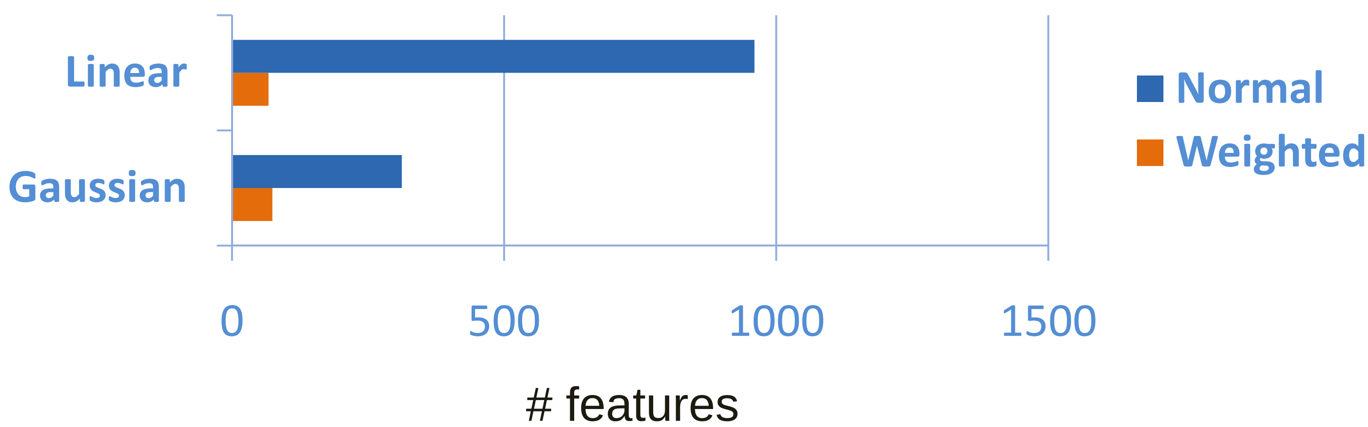


Experiment 2 - Pose classification

- **Task:** pose classification
- **Data:**
  - – CMU face images from UCI ML repository
  - – 312 faces, resolution: 30*32
  - – 20 subjects, at various expressions and poses

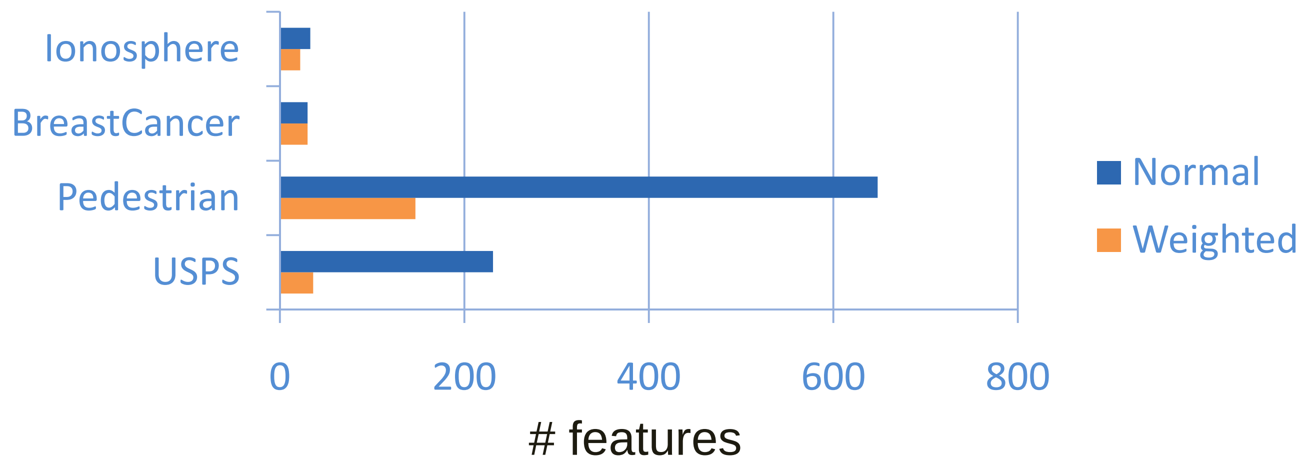
Pose classification

Data	Method	Accuracy		# features used		# Support Vectors	
		Normal	Weighted	Normal	Weighted	Normal	Weighted
CMU Face	Linear SVM	95.5%	95.5%	960	67	120	85
CMU Face	Gaussian SVM	97.48%	98.06%	312	74	186	73



Other standard datasets

Data	Method	Accuracy		# features used		# SVs	
		Normal	Weighted	Normal	Weighted	Normal	Weighted
Ionosphere	Linear SVM	86.89%	88.50%	33	22	79	65
Breast Cancer	Linear SVM	95.43%	96.31%	30	30	40	28
Pedestrian	Linear SVM	72.83%	74.9%	648	147	1291	1159
USPS	Linear SVM	97.75%	97.5%	231	36	50	40



Conclusions

- Learning a subset of pixels optimal for SVM
- Extended to the feature space
- Learning is a JOINT CONVEX optimization problem
- Maintain the classification performance using less support vectors and less features
- More complex features, but convexity will not be preserved