

# SVM for binary classification

## in CIFAR-10 dataset

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# CIFAR-10

## Dimensionality:

- 32\*32 px \* 3 channels per image
- 5000 training images per class
- 10 classes
- 1000 test images

6: frog



9: truck



9: truck



4: deer



1: automobile



1: automobile



2: bird



7: horse



8: ship



3: cat



4: deer



7: horse



7: horse



2: bird



9: truck



9: truck



9: truck



3: cat



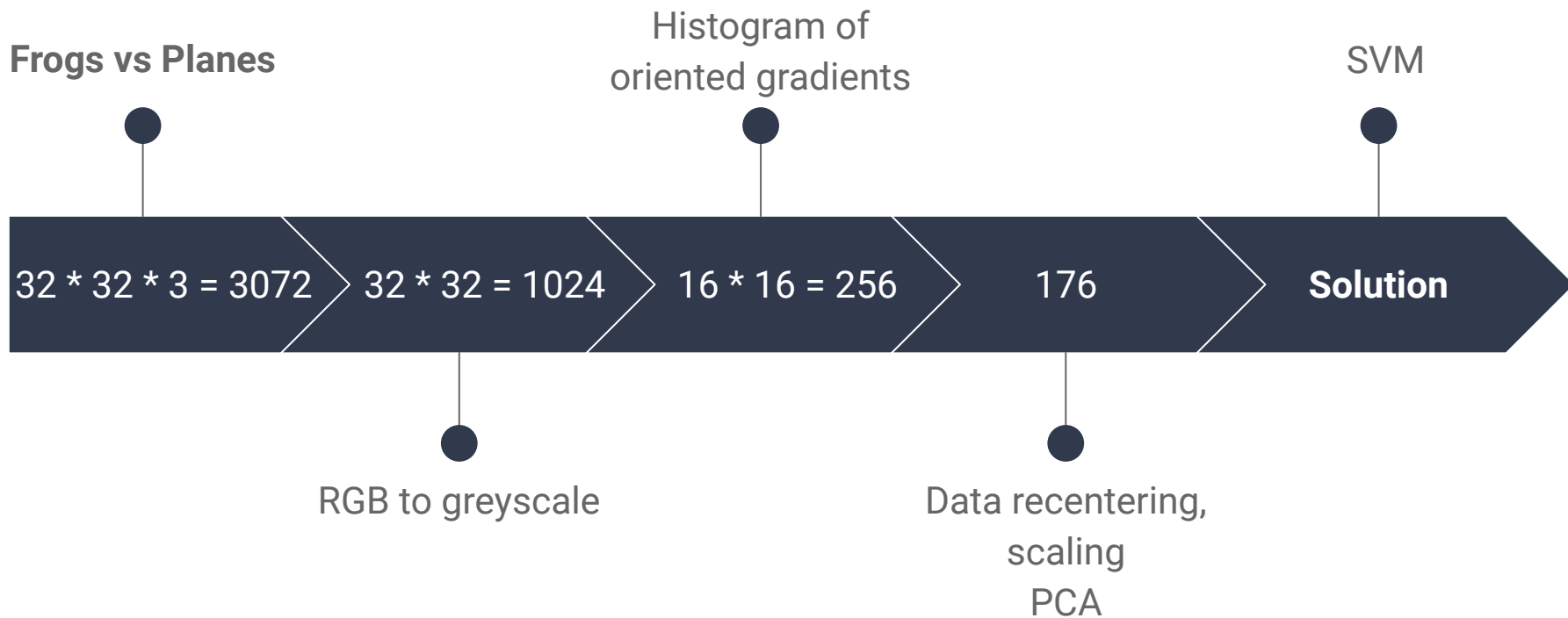
2: bird



6: frog

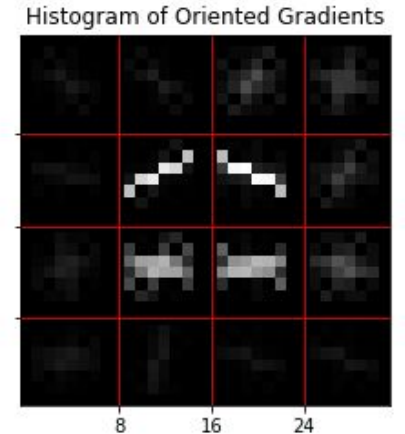
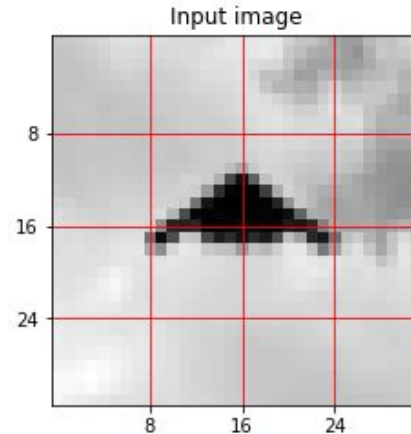
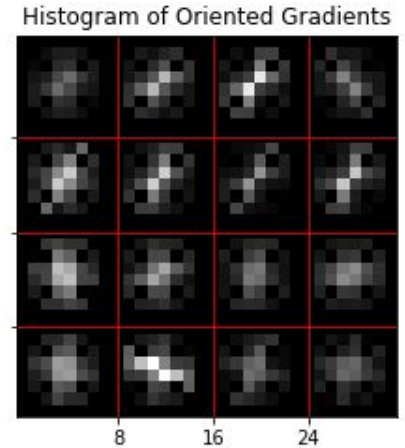
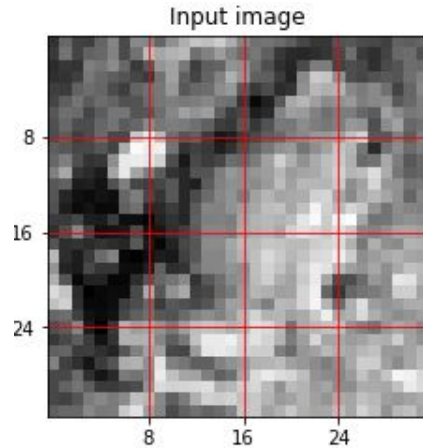


# Dimensionality overview



# Preprocessing: Histogram of oriented gradients

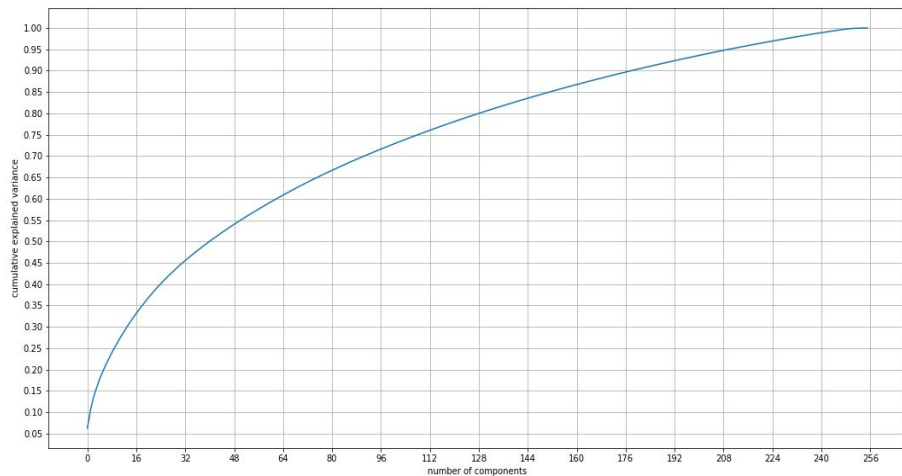
- computing the gradient image in row and col with Sobel filter
- computing gradient histograms
- flattening into a feature vector



# Scaling and PCA

Cumulative explained variance 90%  
with 176 features

**SVM?**



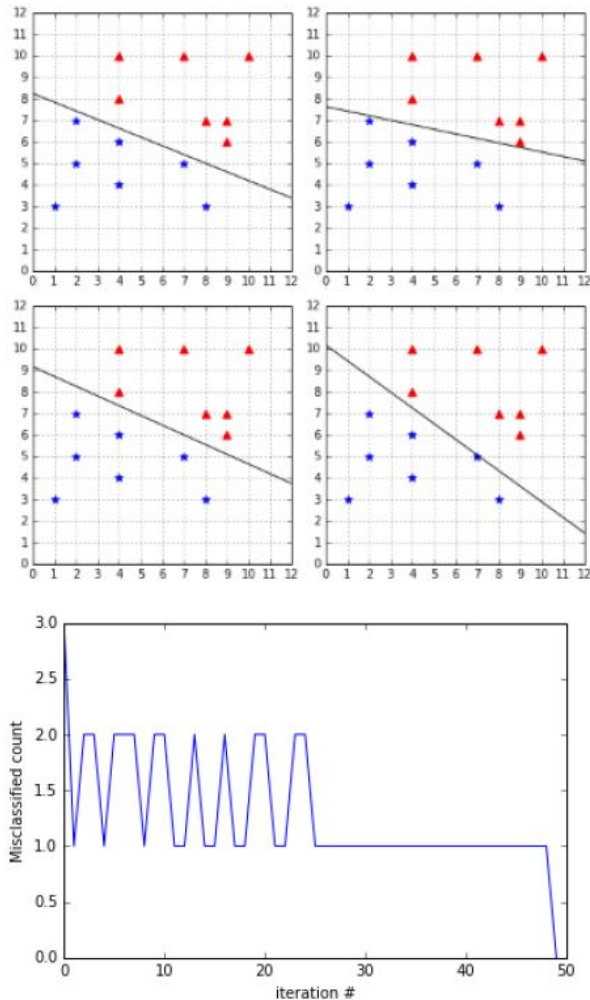
# Perceptron Learning Algorithm

$$\text{sign} f(x), \quad f(x) = x^T w + b$$

$$w_i = w_{i-1} + \gamma y_i x_i, \text{ if } y_i w^T x_i \leq 0$$

Iteratively separates linearly separable data:

- no generalization
- never ends if data are non-separable



# What's the best separating hyperplane?

We need to compute a number that allows us to tell which hyperplane separates the data the best.

$$f = y(\mathbf{w} \cdot \mathbf{x} + b)$$

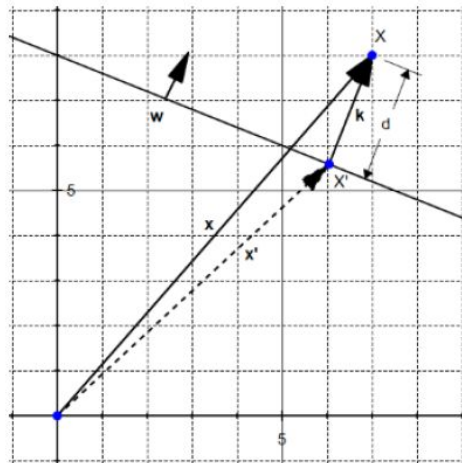
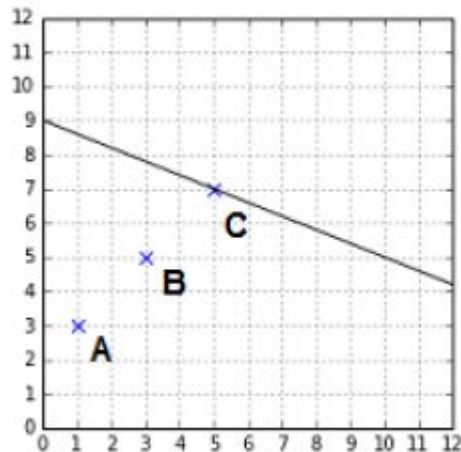
$$\gamma = y\left(\frac{\mathbf{w}}{\|\mathbf{w}\|} \cdot \mathbf{x} + \frac{b}{\|\mathbf{w}\|}\right)$$

$$F = \min_{i=1..m} y_i(\mathbf{w} \cdot \mathbf{x}_i + b)$$

$$M = \min_{i=1..m} y_i\left(\frac{\mathbf{w}}{\|\mathbf{w}\|} \cdot \mathbf{x} + \frac{b}{\|\mathbf{w}\|}\right)$$

Functional Margin

Geometric Margin



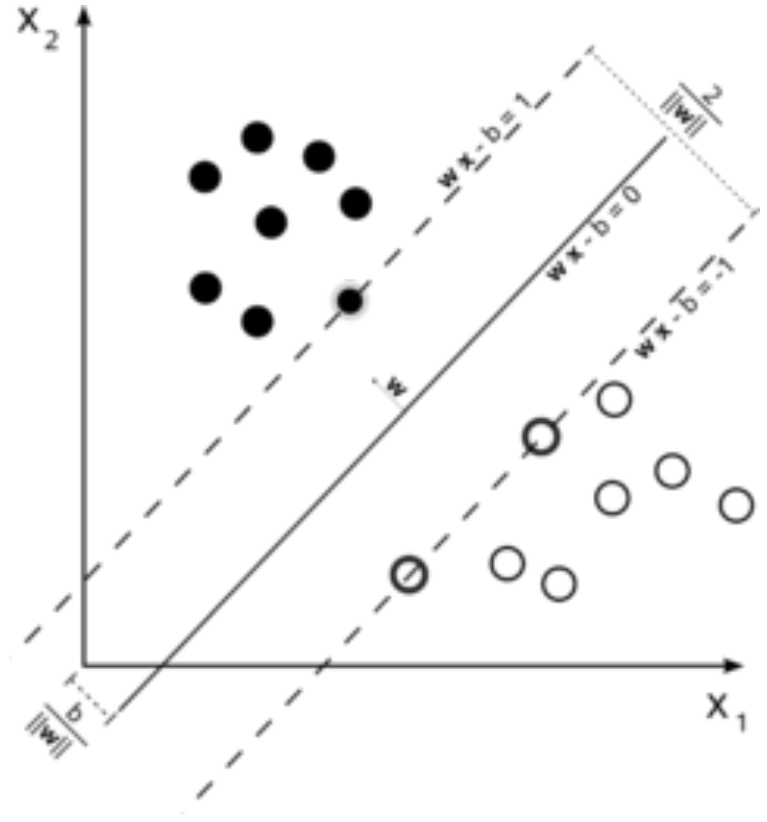
# Support Vector Machines

SVM optimization problem (*hard margin*):

$$\begin{array}{ll}\text{maximize}_{\mathbf{w}, b} & M \\ \text{subject to} & \gamma_i \geq M, \quad i = 1, \dots, m\end{array}$$

$$\begin{array}{ll}\text{maximize}_{\mathbf{w}, b} & \frac{F}{\|\mathbf{w}\|} \\ \text{subject to} & f_i \geq 1, \quad i = 1, \dots, m\end{array}$$

$$\begin{array}{ll}\text{minimize}_{\mathbf{w}, b} & \frac{1}{2} \|\mathbf{w}\|^2 \\ \text{subject to} & y_i(\mathbf{w} \cdot \mathbf{x}_i) + b \geq 1, \quad i = 1, \dots, m\end{array}$$





# Solution

- Lagrange multipliers
- Wolfe dual problem (Slater's condition)
- Karush-Kuhn-Tucker conditions

## CVXOPT QP solver:

Computational complexity:  $O(Dn^3)$

$$\begin{array}{ll}\text{minimize}_x & \frac{1}{2}x^T Px + q^T x \\ \text{subject to} & Gx \leq h \\ & Ax = b\end{array}$$

$$\mathcal{L}(\mathbf{w}, b, \alpha) = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^m \alpha_i [y_i(\mathbf{w} \cdot \mathbf{x}_i + b) - 1]$$

$$\nabla_{\mathbf{w}} \mathcal{L} = \mathbf{w} - \sum_{i=1}^m \alpha_i y_i \mathbf{x}_i = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial b} = - \sum_{i=1}^m \alpha_i y_i = 0$$

$$\text{maximize}_{\alpha} \quad \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j$$

$$\text{subject to} \quad \alpha_i \geq 0, \text{ for any } i = 1, \dots, m$$

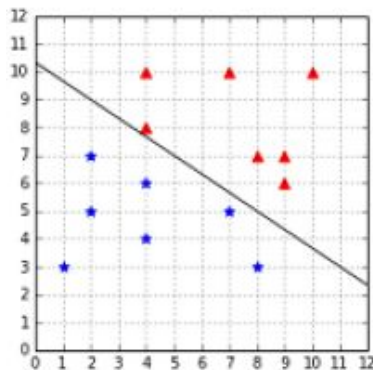
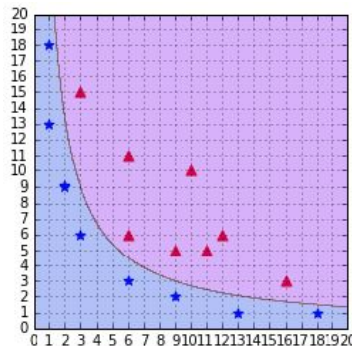
$$\sum_{i=1}^m \alpha_i y_i = 0$$

# Not linearly separable data

## Soft margin SVM

$$\begin{aligned} & \underset{\mathbf{w}, b, \zeta}{\text{minimize}} && \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^m \zeta_i \\ & \text{subject to} && y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \zeta_i \\ & && \zeta_i \geq 0 \quad \text{for any } i = 1, \dots, m \end{aligned}$$

$$\begin{aligned} & \underset{\alpha}{\text{maximize}} && \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j \\ & \text{subject to} && 0 \leq \alpha_i \leq C, \text{ for any } i = 1, \dots, m \\ & && \sum_{i=1}^m \alpha_i y_i = 0 \end{aligned}$$



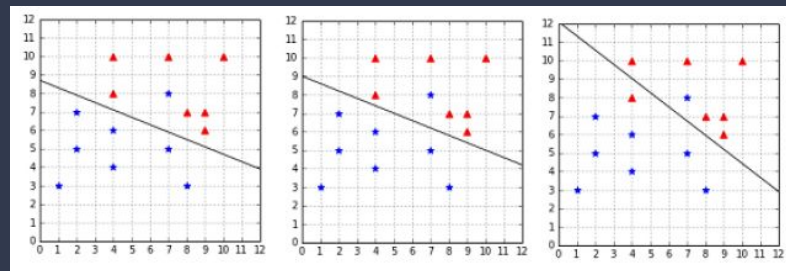
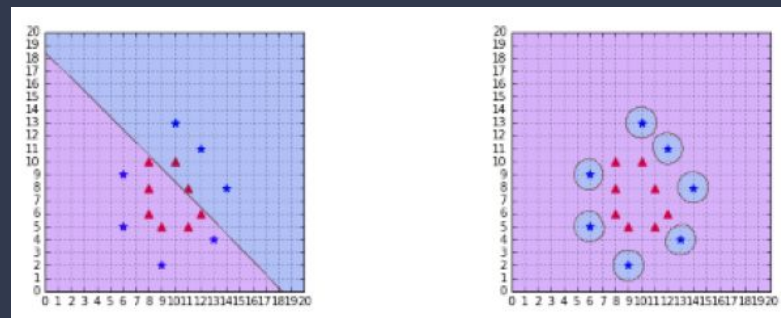
## Kernel

$$\begin{aligned} & \underset{\alpha}{\text{maximize}} && \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \\ & \text{subject to} && 0 \leq \alpha_i \leq C, \text{ for any } i = 1, \dots, m \\ & && \sum_{i=1}^m \alpha_i y_i = 0 \end{aligned}$$

# Cross Validation

#X\_train = 2000 for performance reasons

	linear	$\frac{1}{176+V(x)}$	$5 e^{-5}$	$5 e^{-4}$	$1/176$	$5 e^{-2}$
0.1	0.87	0.88	0.49	0.89	0.87	0.49
1	0.87	<b>0.91</b>	0.87	0.91	0.9	0.63
10	0.86	0.9	0.9	0.9	0.9	0.64



# Final Results

	plane	car	bird	cat	deer	dog	frog	horse	ship	truck
plane	0.0	0.91	0.84	0.89	0.89	0.92	0.92	0.93	0.83	0.9
car	0.91	0.0	0.94	0.92	0.95	0.95	0.93	0.94	0.89	0.84
bird	0.84	0.94	0.0	0.74	0.76	0.77	0.83	0.85	0.91	0.93
cat	0.89	0.92	0.74	0.0	0.78	0.68	0.82	0.83	0.92	0.9
deer	0.89	0.95	0.76	0.78	0.0	0.81	0.86	0.84	0.92	0.94
dog	0.92	0.95	0.77	0.68	0.81	0.0	0.83	0.83	0.95	0.93
frog	0.92	0.93	0.83	0.82	0.86	0.83	0.0	0.92	0.95	0.94
horse	0.93	0.94	0.85	0.83	0.84	0.83	0.92	0.0	0.94	0.91
ship	0.83	0.89	0.91	0.92	0.92	0.95	0.95	0.94	0.0	0.9
truck	0.9	0.84	0.93	0.9	0.94	0.93	0.94	0.91	0.9	0.0