

# SMAI-M20-L22: Introduction to SVM

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- **Quiz 1**

- The same time as last week.
- The same set of topics we planned.
- All objective. (similar to Class Review)

In the context of binary classification and LDA:

- What do we know about the direction of the discriminant vector?
- What do we know about the objective?
- What do we know about the uniqueness of the solution?
- What do we know about the ranks of  $S_w$  and  $S_B$ ?
- How does singularity of  $S_B$  and  $S_w$  affect us?

(

$$\text{obj } w^T A w$$

$$\text{const } \|w\| = 1 \quad / \text{a. 2.}$$

$$\underbrace{w^T S w}_{\text{Fixed}} = \underline{\underline{1/2}}$$

$$\begin{matrix} \downarrow \\ \textcircled{w} \\ w \end{matrix}$$

$$\begin{matrix} \downarrow \text{max} & \downarrow \text{min} \\ \text{I} & \end{matrix}$$

$$\boxed{w^T S w \quad \underline{\underline{w^T S w = 1}}}$$

# Recap:

- **Supervised Learning:** Formulation, Conceptual Issues, Concerns etc.
- **Classifiers:** (i) Nearest Neighbour, (ii) Notion of a Linear Classifier (iii) Perceptrons (iv) Bayesian Optimal Classifier (v) Logistic Regression (vi) Multiclass classification architectures
- **Dimensionality Reduction and Applications:** (i) Feature Selection and Extraction (ii) PCA (iii) LDA (iv) Eigen face
- **Matrix Factorization and Applications:** (i) SVD, (ii) Eigen Decomposition (iii) Matrix Completion (iv) LSI (v) Recommendations
- **Other Topics:**
  - Linear Regression
  - MLE
  - Gradient Descent
  - Stochastic and Batch GD
  - Eigen Vector based optimization
  - Neuron model
  - Loss Functions and Optimization
  - Kernel Functions and Kernel Matrix

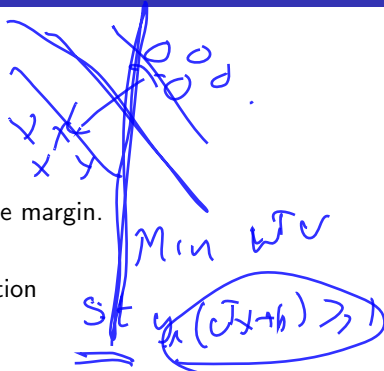
# This Lecture:

- 1 Introduction to SVMs
  - SVM as a classifier that maximizes the margin.
- 2 Solving Logistic Regression as GD
  - From objective to GD and Regularization
- 3 LDA: Extending to Multi-Class

**Questions? Comments?**

$$\boxed{\text{sig}(\omega^T x) \sim y_i}$$

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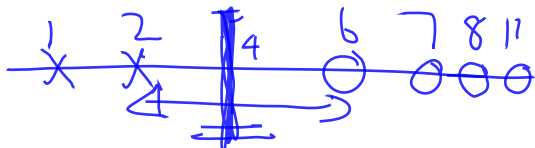






# Discussions Point - I

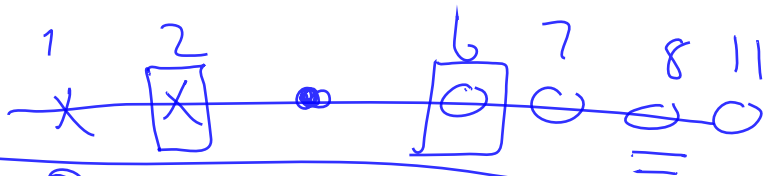
Consider Five 1D samples:



$(1, +)$ ,  $(2, +)$ ,  $(7, -)$ ,  $(6, -)$ ,  $(11, -)$

- 1 Which will be a valid decision boundary with perceptron criteria? (i) 2.5 (ii) 6.5 (iii) 5.00 (iv) 4.00
- 2 What will be the optimal decision boundary with SVM criteria? (i) 2.5 (ii) 6.5 (iii) 5.00 (iv) 4.00 5
- 3 Assume we add a sample  $(8, -)$  to the training set, will SVM decision boundary change? why? what is the new one?
- 4 Assume we add a sample  $(4, -)$  to the training set, will SVM decision boundary change? why? what is the new one?

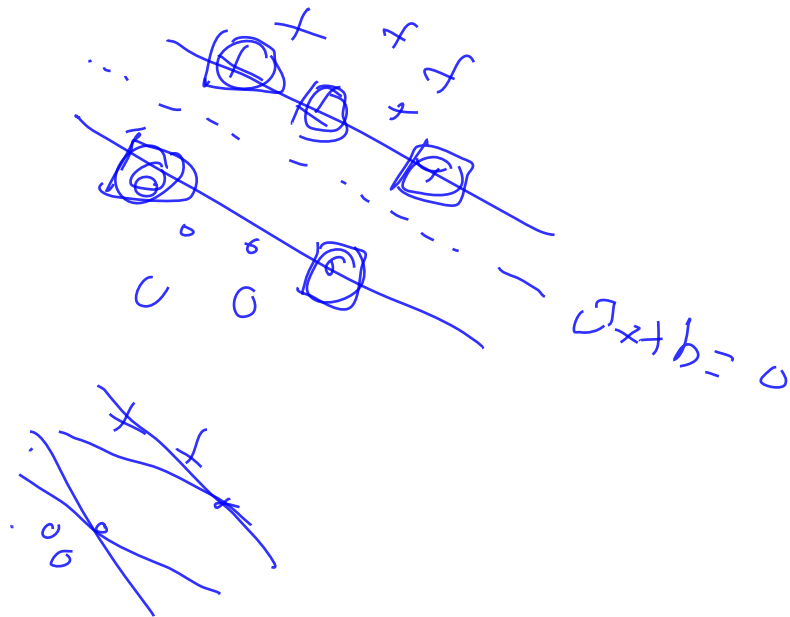
Support vectors



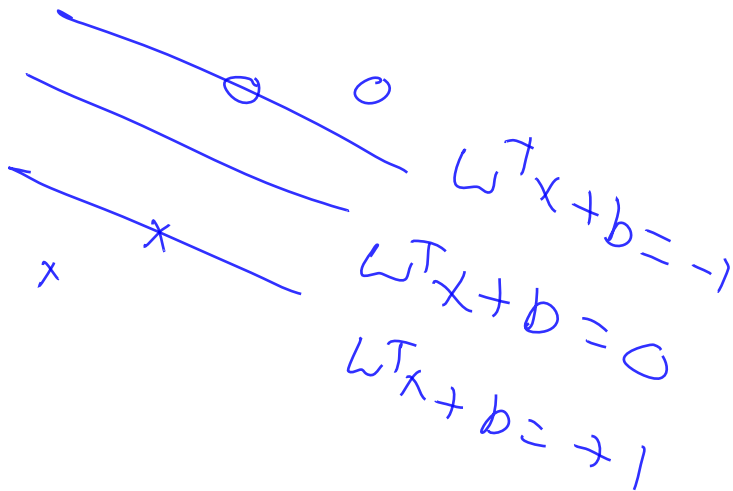
$$w^* = \sum d_i x_i$$

$$w^* = \frac{1}{2}(2) + \frac{1}{2}(6) + \underline{0} \cdot 1 + \underline{0} \cdot 7 + \underline{0} \cdot \dots \cdot \underline{0} \cdot 11$$

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## Discussions Point -II

We know the objective of logistic regression as:

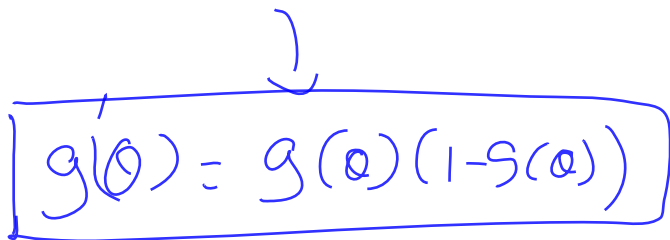
$$y_i = \{0, 1\}$$

$$J = \sum_{i=1}^N y_i \log(g(\mathbf{w}^T \mathbf{x}_i)) + (1 - y_i) \log(1 - g(\mathbf{w}^T \mathbf{x}_i))$$

Derive the gradient ascent update equation

Hint:

$$\mathbf{w}^{k+1} = \mathbf{w}^k + \eta \sum_{i=1}^N (y_i - g(\mathbf{w}^T \mathbf{x}_i)) \mathbf{x}_i$$
$$\mathbf{w}^{k+1} = \mathbf{w}^k + \eta \frac{\partial J}{\partial \mathbf{w}}$$



A handwritten equation  $g'(0) = g(a)(1 - S(a))$  is enclosed in a hand-drawn rectangular box. Above the box, a blue bracket is drawn, spanning the width of the box and pointing downwards towards the equation.

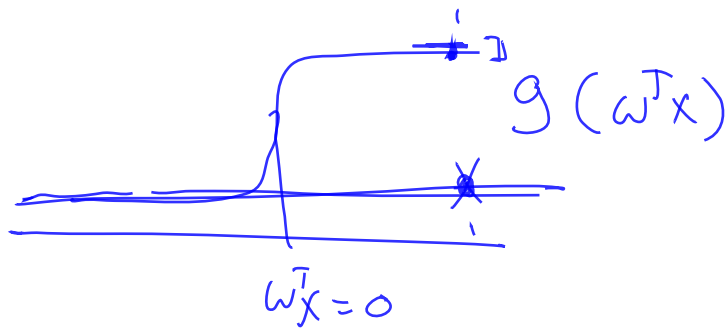
$$g'(0) = g(a)(1 - S(a))$$











$$\frac{1}{N} \sum (y_i - g(\omega^T x_i))^2 \quad | \quad y_i - g(\omega^T x_i)$$

## Discussion Point - III

MLE

X

How do you compare the GD rule with that of if we had used an MSE loss between predicted probabilities and our actual labels (probabilities)?

$$w^{k+1} = w^k + \eta \sum_{i=1}^N (y_i - g(w^T x_i)) x_i$$

$\epsilon_i$

MLF







## What Next:? (next three)

- ① Winding up (i) Logistic Regression (ii) Multi-Class Classification and (iii) LDA
- ② **SVMs and Kernels**