

# Foundations of Machine Learning

## AI2000 and AI5000

FoML-17  
Perceptron

Dr. Konda Reddy Mopuri  
Department of AI, IIT Hyderabad  
July-Nov 2025

# So far in FoML

- Intro to ML and Probability refresher
- MLE, MAP, and fully Bayesian treatment
- Supervised learning
  - a. Linear Regression with basis functions (regularization, model selection)
  - b. Bias-Variance Decomposition (Bayesian Regression)
  - c. Decision Theory - three broad classification strategies
    - Probabilistic Generative Models - Continuous & discrete data
    - (Linear) Discriminant Functions - least squares solution



# The Perceptron



ભારતીય નોંકેટિક વિજ્ઞાન સંસ્કૃત પ્રેરણાખાડ  
ભારતીય પ્રૌદ્યોગિકી સંસ્થાન હૈદરાબાદ  
Indian Institute of Technology Hyderabad



# The Perceptron Algorithm

- Input:  $x \in \mathbb{R}^D$
- Targets (2 classes):  $t \in \{C_1, C_2\}$
- Prediction:  $y(\mathbf{x}) = f(\mathbf{w}^T \phi(\mathbf{x}))$

Activation function  $f(a)$



# The Perceptron Algorithm

- Class decisions:
  - Assign  $x$  to  $C_1$  if:
  - Assign  $x$  to  $C_{-1}$  if:
- Criterion for correct classification:



# The Perceptron Algorithm

- The loss (perceptron criterion):

$$E_P(\mathbf{w}) =$$



# Perceptron learning: SGD

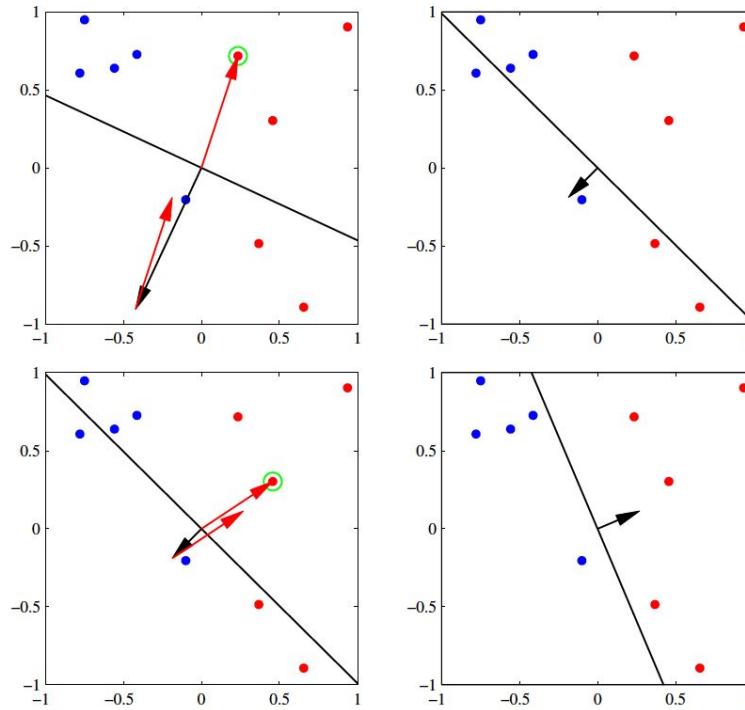
$$\begin{aligned} E_P(\mathbf{w}) &= \sum_{n \in \mathcal{M}} \mathbf{w}^T \phi(\mathbf{x}_n) t_n \\ &= \sum_{n \in \mathcal{M}} E_n(\mathbf{w}) \end{aligned}$$

SGD: for each misclassified sample  $\mathbf{x}_n$ :

$$\mathbf{w}^{t+1} = \mathbf{w}^t -$$



# Perceptron learning: SGD



If data is linearly separable, perceptron converges



# Perceptron - Issues

- Works only for 2 classes
- More than one solutions
  - Initialization and the order in which the data is presented
- Will not converge if the dataset is not linearly separable
- Need to define basis functions
  - This is the case for all the methods that we discussed so far

