

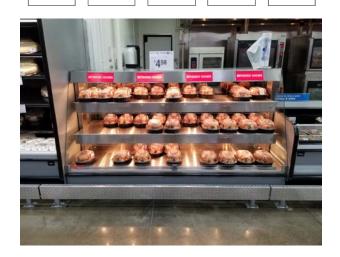
Image Intro

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Patterns in Images

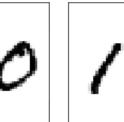
- Obtain
- Scrub
- Explore
- Model
- iNterpret

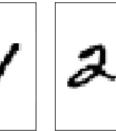


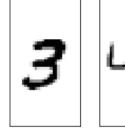


Our Challenge This Week?





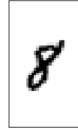






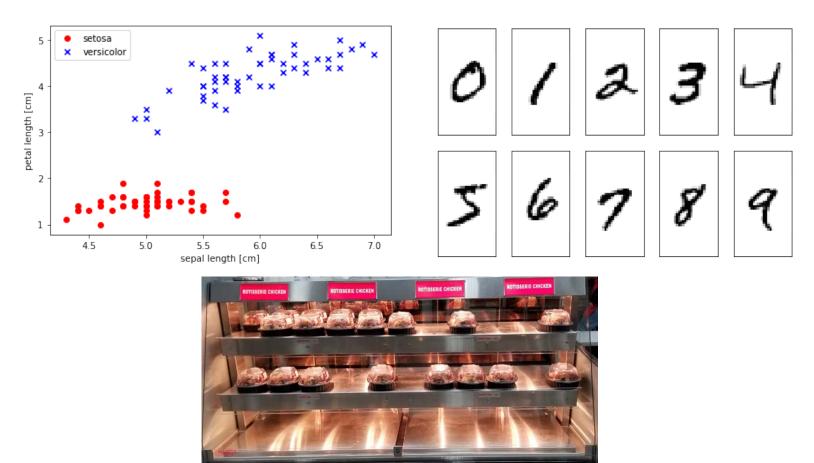




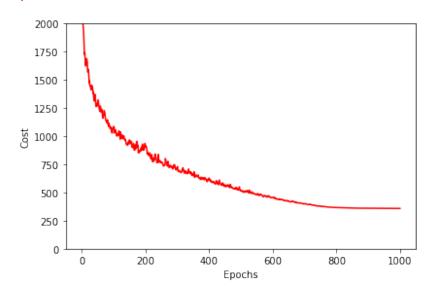


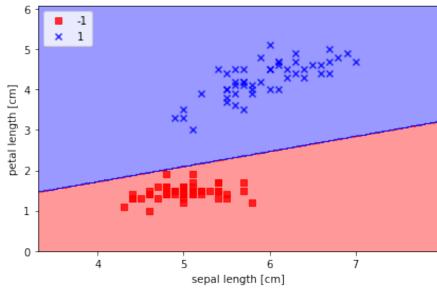


Using Machine Learning for Classification



But How?









Data Review

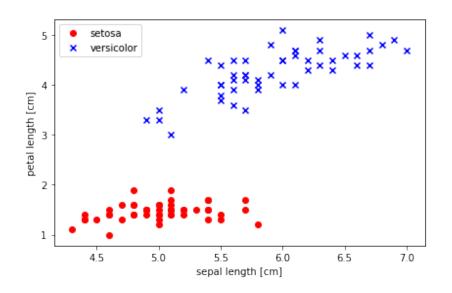
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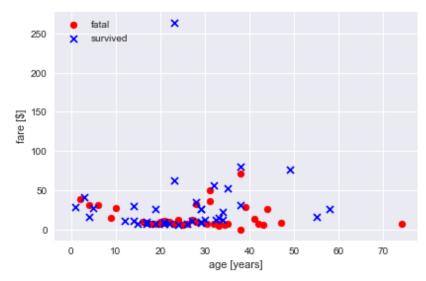
Basic Data



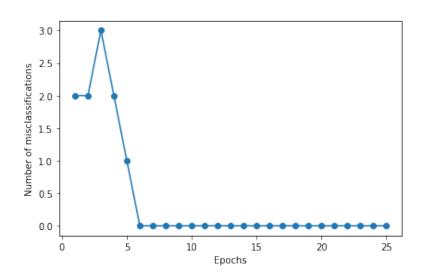
	0	1	2	3	4
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5	3.6	1.4	0.2	Iris-setosa

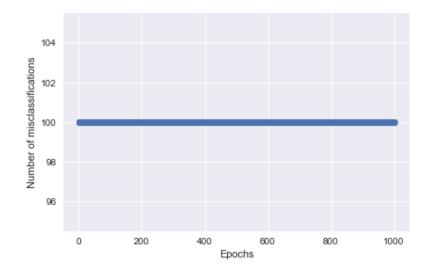
Convergence Limitations





Convergence Limitations (cont.)





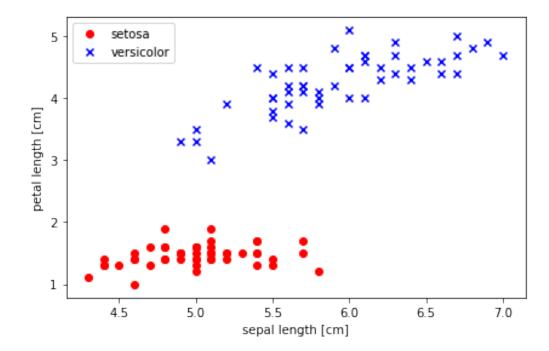


Perceptron

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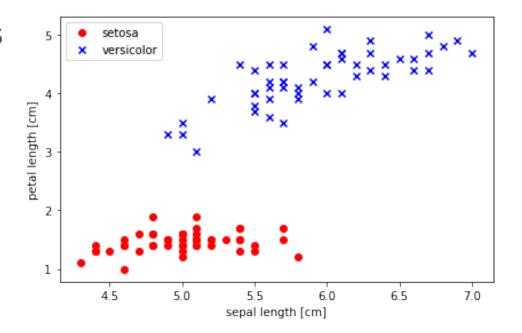
Perceptron Model





Rosenblatt's Model

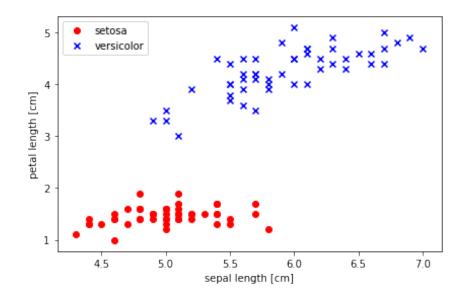
- Initialize the weights
- For each sample:
 - Compute the output
 - Update the weights



Rosenblatt's Model (cont.)

•
$$\mathbf{w} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$$
, $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$

•
$$\varphi(z) = \begin{cases} 1, & \text{if } z \ge \theta \\ -1 & \text{otherwise} \end{cases}$$



Perceptron Learning Rule

•
$$\mathbf{w} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$$
, $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$

$$z = \mathbf{w}^T \mathbf{x}$$

$$\Delta w_j = \eta (y^i - \hat{y}^i) x_j^{(i)}$$

•
$$\varphi(z) = \begin{cases} 1, & \text{if } z \ge \theta \\ -1 & \text{otherwise} \end{cases}$$

Perceptron Learning Rule (cont.)

$$z = \mathbf{w}^T \mathbf{x}$$

$$\Delta w_j = \eta (y^i - \hat{y}^i) x_j^{(i)}$$

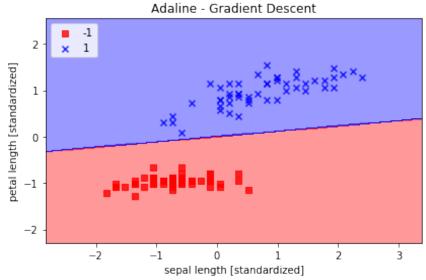


Adaline

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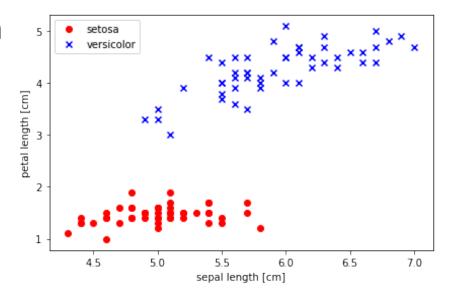
Adaptive Linear Neurons





Adaline Rule

- Linear activation function
- Quantizer for predicting the class



Adaline Rule (cont.)

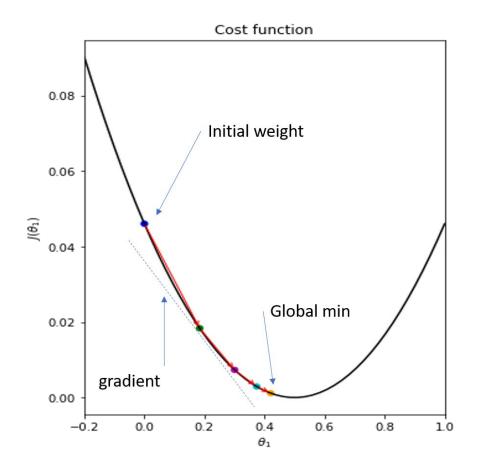
•
$$\mathbf{w} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$$
, $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$

 $\varphi(\mathbf{w}^T\mathbf{x}) = \mathbf{w}^T\mathbf{x}$

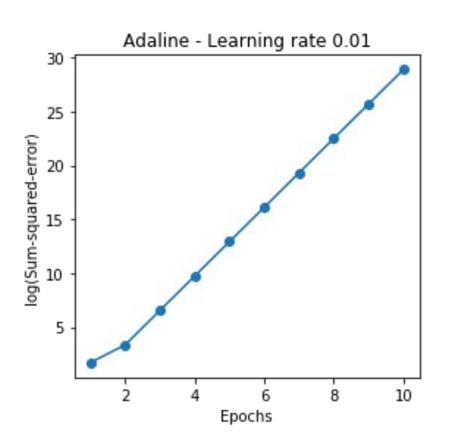
•
$$\varphi(z) = \mathbf{w}^T \mathbf{x}$$

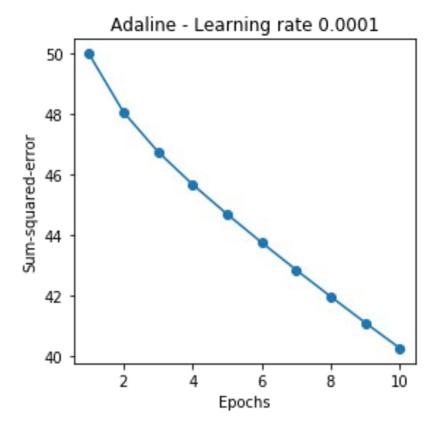
$$\Delta w = -\eta \nabla J(w)$$

Gradient Descent



Learning Rate





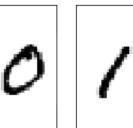


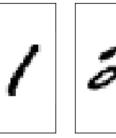
Neural Networks

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Neural Networks















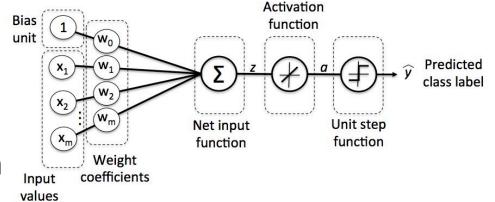




Single Layer Recap

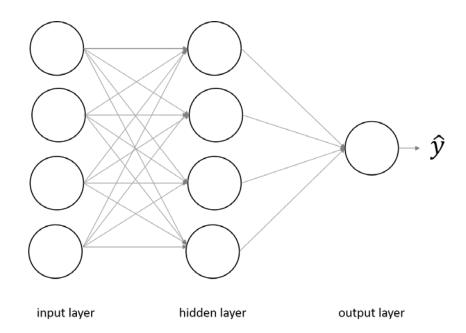
- Perceptron model
 - Unit step function
- Adaptive linear neuron
 - Activation function

 Input layer – output layer



Multilayer Introduction

- Hidden layer fully connected to input layer
- Output layer fully connected to hidden layer

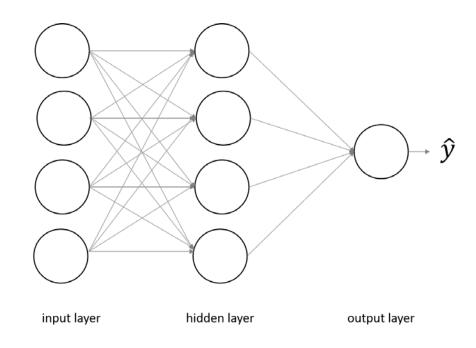


Multiple hidden layers

Multilayer Perceptrons

Feedforward

- Hidden layers
 - Linear units
 - Rectified linear units
 - Logistic sigmoid
 - Softmax



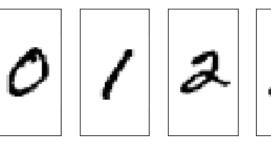


Propagation

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Neural Networks





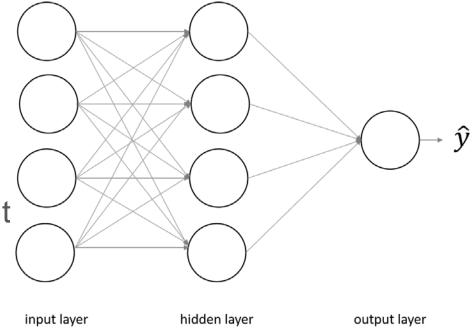






Forward Propagation

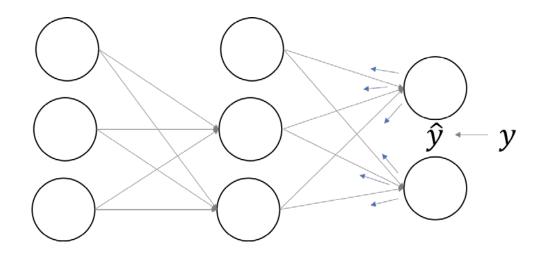
- Start at input layer
- Forward propagate patterns
- Calculate error
- Calculate network output
- Threshold function



Back Propagation

Computationally efficient

Matrix – vector computation





Templating

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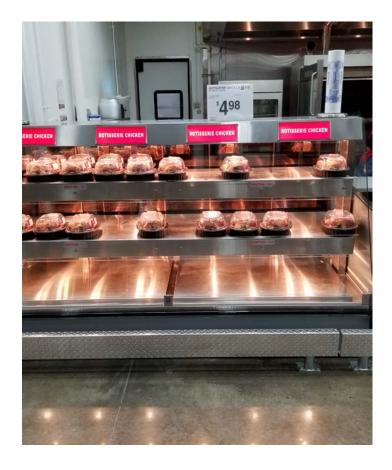
Neural Networks





Template Matching

- Given a template image
- Match within larger image
- OpenCV based



Methods

- CCOEFF
- CCOEFF Normed
- CCORR
- CCORR Normed
- SQDIFF
- SQDIFF Normed

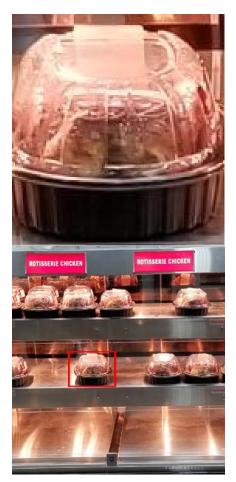


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Limitations

- Requires similar scale
- Requires similar rotation
- Finds area with "most" correlation

Not optimal for counting ©



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