INTRODUCTION

Deep Neural Networks

Session 02

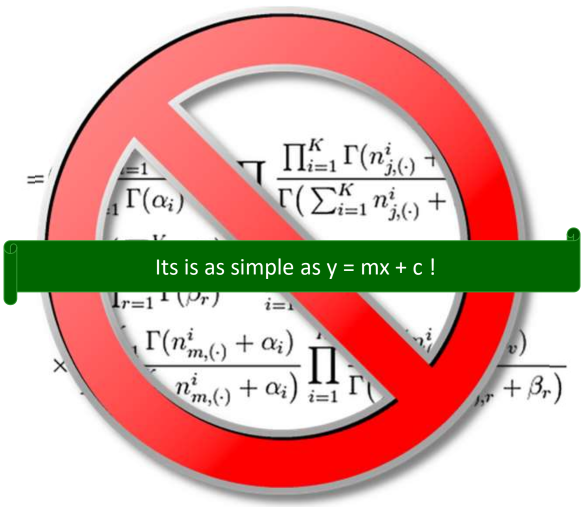
Pramod Sharma
pramod.sharma@prasami.com

Agenda

- Perceptron
- Single Layer Neural Network
- Overview of back propagation of errors

3

Solution to Equation of Perceptron



Its is as simple as y = mx + c !

Frank Rosenblatt

pra-sâmi

4

To play or not to play…

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0	38	1	15	0	600	1
2	0	25	1	15	1	800	1
3	0	26	1	15	1	1000	1
4	5	27	1	10	1	600	0
5	20	23	0	8	1	1800	0
6	30	22	0	6	0	600	0

- Features:
  - Rains in millimeter
  - Temperature in ° C
  - Homework completed? – 0 : No; 1: Yes
  - Team members : How many team members are ready to play?
  - Is cricket equipment available?
  - Ground: per hour rent in Rupees/hour

pra-sâmi

5

Weights

- Each of the feature has different importance
- To assign importance to each of the feature, we use weights!
- Values of each features are in different order of magnitude
  - Summation is not going to work
  - Scale the features between 0 and 1

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0	38	1	15	0	600	1
2	0	25	1	15	1	800	1
3	0	26	1	15	1	1000	1
4	5	27	1	10	1	600	0
5	20	23	0	8	1	1800	0
6	30	22	0	6	0	600	0

- Note:
  - Variation in features have different bearing on the results
  - Team members → higher the better
  - Ground cost → lower the better

5/15/2024

pra-sâmi

6

Perceptron

- In MP Neuron Model,
  - All inputs had same weights
  - Threshold 'w_0' could take limited values
  - Every feature needed to be [0,1]
- Perceptron model introduced different weights to different inputs features
- Real values are also accepted
  - Temperatures are in tens and ground rent is in hundreds.
  - Min – Max – Scaler to compensate for huge difference is values
- Threshold 'w_0' can take any value
- Outputs are still [0, 1]

5/15/2024

pra-sâmi

7

Perceptron

- Loss Function:
  - A correction is applied on the outputs
  - To adjust values of 'w_i' to reach right results
  - It would also give us indications of what weights to be fixed to arrive at the solution

- Activation function g(x) is applied as follows:
  - If $\sum x_i . w_i \geq w_0$ => ŷ = 1
  - If $\sum x_i . w_i < w_0$ => ŷ = 0

5/15/2024

pra-sâmi

8

Perceptron – Data Preprocessing

- Lets consider "Ground" and "Team Members" as features and its associated weights to arrive at the solution.

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0	38	1	15	0	600	1
2	0	25	1	15	1	800	1
3	0	26	1	15	1	1000	1
4	5	27	1	10	1	600	0
5	20	23	0	8	1	1800	0
6	30	22	0	6	0	600	0

5/15/2024

pra-sâmi

Perceptron – Data Preprocessing

9

- Scaled Data (all columns to be between 0 and 1)

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0.00	0.00	1.00	1.00	0.00	1.00	1
2	0.00	0.81	1.00	1.00	1.00	0.83	1
3	0.00	0.75	1.00	1.00	1.00	0.67	1
4	-0.17	0.69	1.00	0.44	1.00	1.00	0
5	-0.67	0.94	0.00	0.22	1.00	0.00	0
6	-1.00	1.00	0.00	0.00	0.00	1.00	0

- What about reverse correlation
- Two option to address reverse correlation
  - Take negative of values
  - Use negative weight

5/15/2024

pra-sâmi

Perceptron – Weights

10

- Weights – consider importance of each of the feature

id	Threshold	Team Members		Ground		Calculations	Likely	Played	Loss
	w0	x1	w1	x2	w2	w0+x1*w1+x2*w2	(y_hat)	(y)	(y-y_hat)^2
1	-1.00	1.00	1.10	1.00	1.00	1.10	1	1	0
2	-1.00	1.00	1.10	0.83	1.00	0.93	1	1	0
3	-1.00	1.00	1.10	0.67	1.00	0.77	1	1	0
4	-1.00	0.44	1.10	1.00	1.00	0.49	1	0	1
5	-1.00	0.22	1.10	0.00	1.00	-0.76	0	0	0
6	-1.00	0.00	1.10	1.00	1.00	0.00	1	0	1

5/15/2024

pra-sâmi

11

Perceptron – Weights and Loss

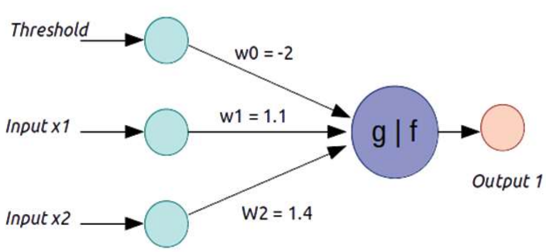
- Our best solution would be where ground truth and predicted values are same
- Loss is some function of ground truth and predicted values
- And we want it to be cumulative, Square of difference looks promising
  - $\ell(\hat{y}, y) = (y - \hat{y})^2$
  - Our overall loss was 2.
- By adjusting weights (w_1, w_2) and threshold (w_0) we can bring the loss to minimum (zero in this case)

id	Threshold	Team Members		Ground		Calculations	Likely	Played	Loss
	w0	x1	w1	x2	w2	w0+x1*w1+x2*w2	(y_hat)	(y)	(y-y_hat)^2
1	-2.00	1.00	1.10	1.00	1.40	0.50	1	1	0
2	-2.00	1.00	1.10	0.83	1.40	0.27	1	1	0
3	-2.00	1.00	1.10	0.67	1.40	0.03	1	1	0
4	-2.00	0.44	1.10	1.00	1.40	-0.11	0	0	0
5	-2.00	0.22	1.10	0.00	1.40	-1.76	0	0	0
6	-2.00	0.00	1.10	1.00	1.40	-0.60	0	0	0

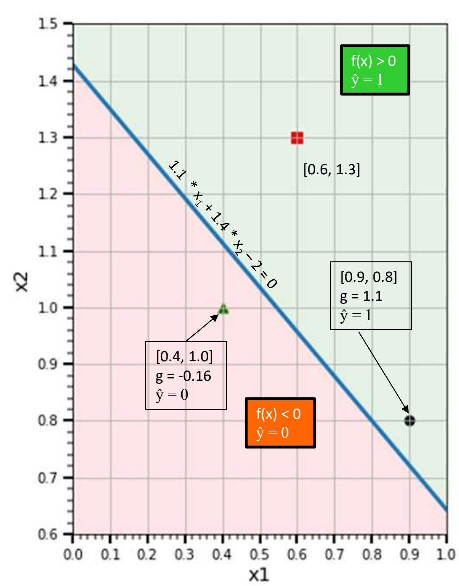
pra-sâmi

13

Perceptron



- We can represent : g = $w_0 + x_1 * w_1 + x_2 * w_2$
  - As g = $[x_1, x_2].\begin{bmatrix}w_1\\w_2\end{bmatrix} + w_0$
- Given: W = $\begin{bmatrix}1.1\\1.4\end{bmatrix}$ and w_0 = -2
  - g = $[x_1, x_2].\begin{bmatrix}1.1\\1.4\end{bmatrix}$ - 2
  - g = 1.1 * x_1, +1.4 $* x_2$ - 2

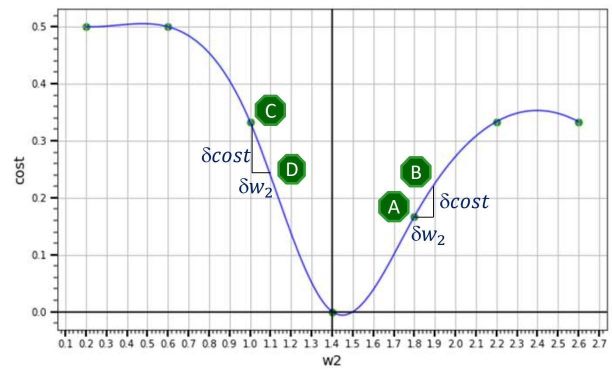


pra-sâmi

14

Perceptron – Gradient Descent

- w_0, w_1, w_2 need to be adjusted to arrive at most optimal solution i.e. lowest point on the graph.
- Assume that w_0 is fixed at -2, and w_1 at 1.1 and w_2 varies from 0 to 3 (only one variable considered to make plotting simple)
- From point A to B, slope is positive hence w_2 value needs to be decreased
- From point C to D slope is negative hence w_2 needs to be increased.



pra-sâmi

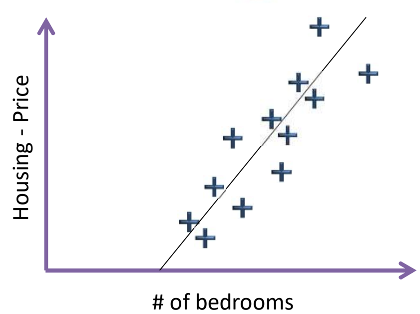
15

Perceptron – Activation Function

- So we based our entire calculations on:

$$z = w_0 + x_1 * w_1 + x_2 * w_2$$

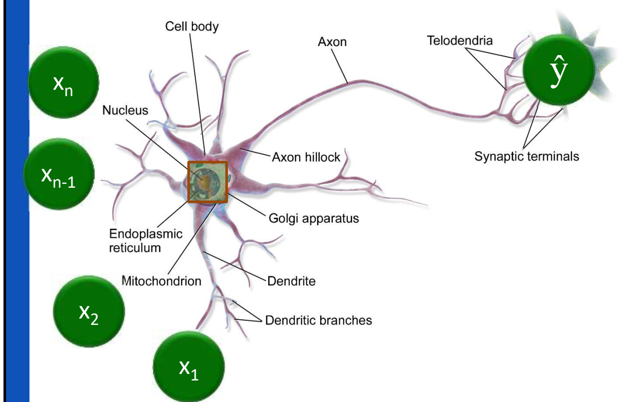
But that's an equation of straight line! ☺
What happened to all those 'inhibitory' features?

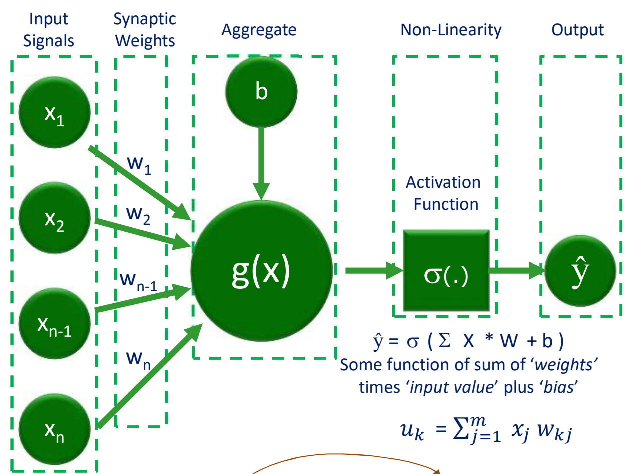


pra-sâmi

16

Non Linear Activation function





ŷ = σ (Σ X * W + b)
Some function of sum of '*weights*' times '*input value*' plus '*bias*'

$$u_k = \sum_{j=1}^{m} x_j \, w_{kj}$$

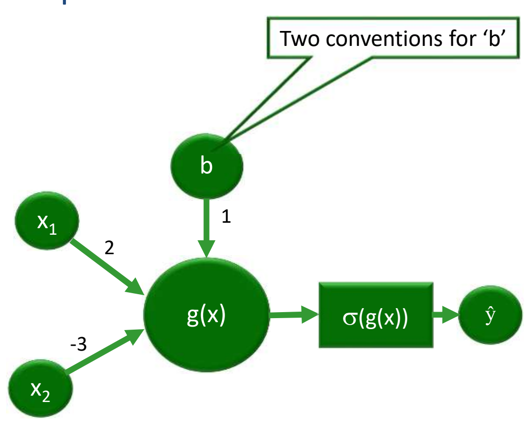
$$y_k = \sigma\,(u_k + b_k)$$

Non-linear Activation function

pra-sâmi

17

Perceptron with non-linear activation function



- Given:
  - W $=\begin{bmatrix} 2 \\ -3 \end{bmatrix}$ and b = 1
  - ŷ = σ ([x1, x2]. $\begin{bmatrix} 2 \\ -3 \end{bmatrix}$ + 1)
  - ŷ = $\sigma\,(\underbrace{1 + 2 * x1 - 3 * x2}_{z})$
- ŷ = σ (z) ;
- Lets use sigmoid function for σ.
  - ŷ = $\frac{1}{(1+e^{-z})}$

pra-sâmi

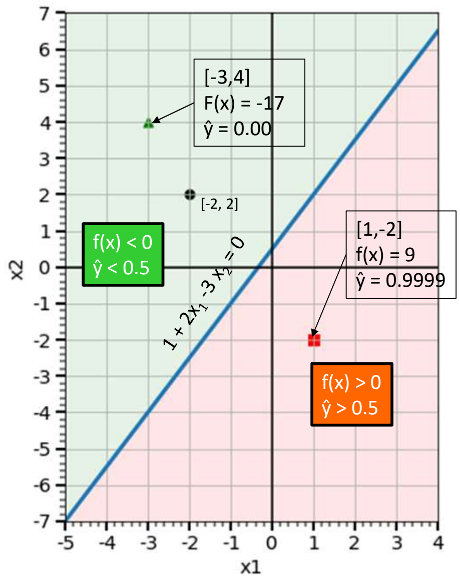
18

Perceptron with non-linear activation function

- $\hat{y} = \sigma\ (1 + 2 * x_1 - 3 * x_2)$

- For X = [-3, 4]
  - $\hat{y} = \sigma\ (1 + 2 * (-3)\ -3 * 4)$
  - $\hat{y} = \sigma\ (1 - 6\ -12)$
  - $\hat{y} = \sigma\ (-17)$
  - $\hat{y} = 0.0$

- Similarly, for X = [1, -2]
  - $\hat{y} = \sigma\ (1 + 2 * 1 - 3 * (-2))$
  - $\hat{y} = \sigma\ (1 + 2\ - 6)$
  - $\hat{y} = \sigma\ (9)$
  - $\hat{y} = 1.0$



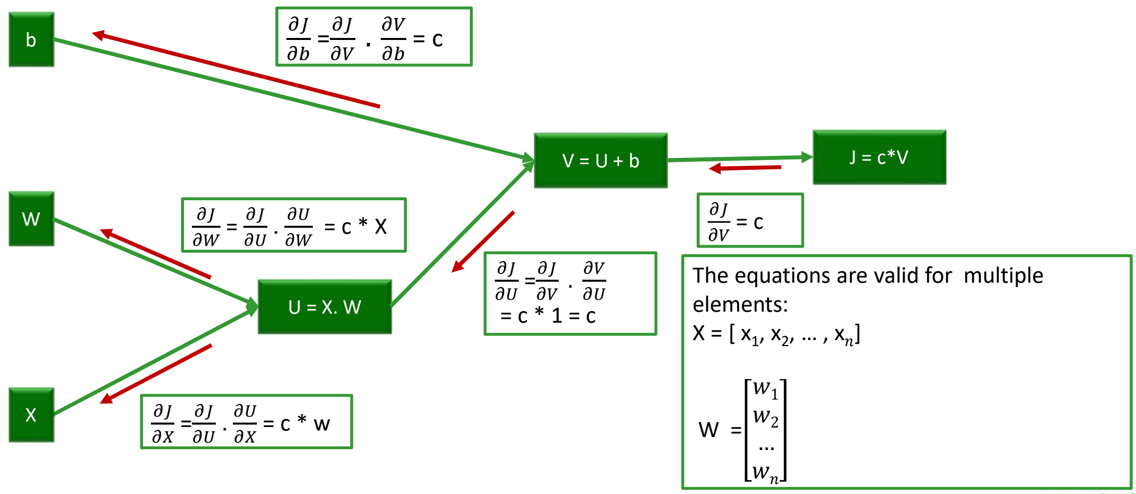
5/15/2024

pra-sâmi

20

Computational Graph

- Consider following hypothetical case, basic equation for single neuron :
  - $\hat{y}$ = X. W + b and Cost is some constant times $\hat{y}$; J = c * $\hat{y}$



5/15/2024

pra-sâmi

21

Exercise 2 : Computational Graph

- Given a Cost Function J
  - J (w, x, b) = 3 *(b + x * w)
- Calculate $\frac{\partial J}{\partial W}$, $\frac{\partial J}{\partial x}$ and $\frac{\partial J}{\partial b}$
- Calculate slope at point :
  - b = 6
  - w = 3
  - x = 2

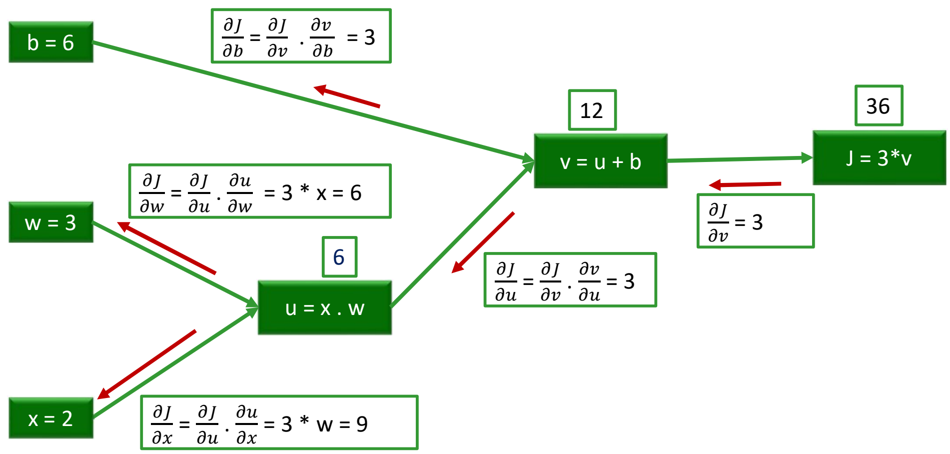
5/15/2024

pra-sâmi

22

Exercise - Solution

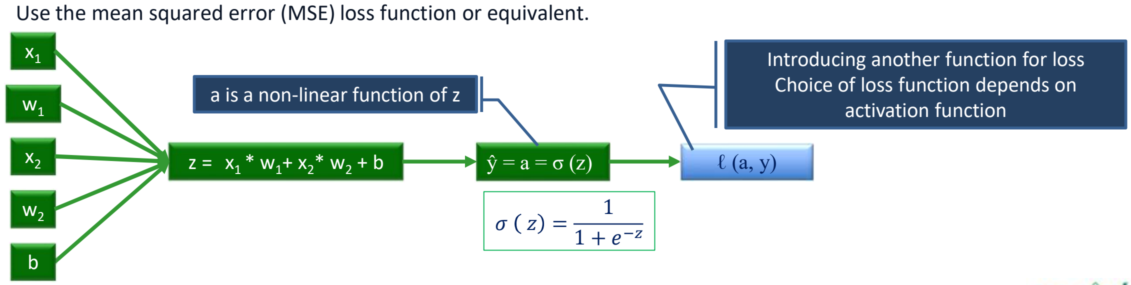
- Given a Cost Function J (w, x, b) = 3 *(b + w*x)



23

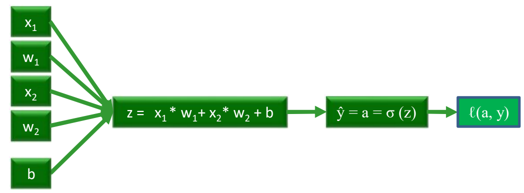
Consider Single Path… MLE

- Maximum likelihood estimation, or MLE, is a framework for inference for finding the best statistical estimates of parameters from historical training data
  - Exactly what we are trying to do with the neural network
- In Classification, output is probability of it belonging to a class
  - Maximum likelihood estimation, seeks a set of model weights that minimize the difference between the predicted probability distribution and the Ground Truth [cross-entropy]
- In Regression problems:
  - Use the mean squared error (MSE) loss function or equivalent.



24

Consider Single Path… Loss Function



- A function used to evaluate a candidate solution
- Helps to maximize or minimize the objective function
- Estimates how closely the distribution of predictions made by a model matches the ground truth (maximum likelihood)
- Under maximum likelihood framework , the error between two probability distributions is measured using cross-entropy
  - Hence $\ell(\hat{y}, y) = -[y * \log(\hat{y}) + (1 - y) * \log(1 - \hat{y})]$

25

Cost Function

- $\hat{y} = \sigma(\Sigma\, W * X + b)$
- Where $\sigma(z) = \frac{1}{1+e^{-z}}$
- Loss function:
  - A parameter which defines how good our outputs are i.e.
  - How far our predicted values 'ŷ' (y hat) were from ground truth 'y'
- For logistic regression
  - $Loss(\hat{y}, y) = -(y . \log \hat{y} + (1 – y) . \log (1 - \hat{y})$
  - Loss function is for an instance
  - In case of binary classification, $Loss(\hat{y}, y) = - y . \log \hat{y}$

- Cost Function: Its a sum of losses for all instances
  - $J(W, b) = \frac{1}{m} (\Sigma\, Loss(\hat{y}, y))$
  - $= - \frac{1}{m} (\Sigma (y . \log \hat{y} + (1 – y) . \log (1 - \hat{y}))$
- For binary classification:
  - $J(W, b) = \frac{1}{m} (\Sigma\, Loss(\hat{y}, y))$
  - $= - \frac{1}{m} (\Sigma (y . \log \hat{y})$

26

Forward and Back Propagation

x1, w1, x2, w2, b → $z = x_1 * w_1 + x_2 * w_2 + b$ → $\hat{y} = a = \sigma(z)$ → $\ell(a, y)$

$\frac{\partial \ell}{\partial z} = \frac{\partial \ell}{\partial a} \cdot \frac{\partial a}{\partial z}$

$= \{ -y/a + (1-y)/(1-a) \} * a * (1-a)$

$= a - y$

$\frac{\partial \sigma(z)}{\partial z} = \sigma(z) \cdot (1 - \sigma(z))$

$\frac{\partial a}{\partial z} = a \cdot (1 - a)$

$\frac{\partial \ell}{\partial a} = -y/a + (1-y)/(1-a)$

$z = X * W + b$

$\hat{y} = a = \sigma(z)$

$\sigma(z) = \frac{1}{1+e^{-z}}$

$\ell(a, y) = -[\, y * \log(a) + (1-y) * \log(1-a) \,]$

For binary classification:

$\ell(a, y) = -y * \log(a)$

$\Longrightarrow$

$\frac{\partial \ell}{\partial w1} = x_1 \cdot \frac{\partial \ell}{\partial z} = x_1 \cdot (a-y)$

$\frac{\partial \ell}{\partial w2} = x_2 \cdot \frac{\partial \ell}{\partial z} = x_2 \cdot (a-y)$

$\frac{\partial \ell}{\partial b} = \frac{\partial \ell}{\partial z} = (a-y)$

$\Longrightarrow$

$w_1 = w_1 - \alpha * \frac{\partial \ell}{\partial w_1} = w_1 - \alpha * x_1 * (a-y)$

$w_2 = w_2 - \alpha * \frac{\partial \ell}{\partial w_2} = w_2 - \alpha * x_2 * (a-y)$

$b = b - \alpha * \frac{\partial \ell}{\partial b} = b - \alpha * (a-y)$

Where α is learning rate. The cost function is

$J(W, b) = \frac{1}{m} * (\Sigma\, \ell(a, y))$

Hence $\frac{\partial J}{\partial w_1} = \frac{1}{m} * (\Sigma \frac{\partial \ell(a, y)}{\partial w_1})$

pra-sâmi

27

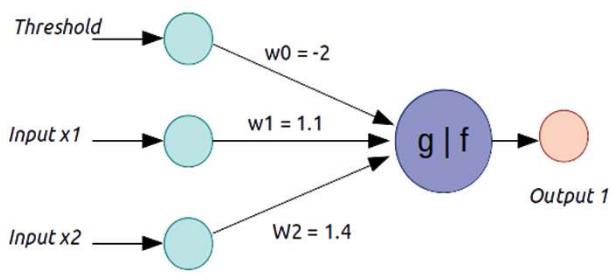
So where are the hidden layers!!!

pra-sâmi

28

Hidden Layers

id	Threshold	Team Members		Ground	
	x0	x1	w1	x2	w2
1	-2.00	1.00	1.10	1.00	1.40
2	-2.00	1.00	1.10	0.83	1.40
3	-2.00	1.00	1.10	0.67	1.40
4	-2.00	0.44	1.10	1.00	1.40
5	-2.00	0.22	1.10	0.00	1.40
6	-2.00	0.00	1.10	1.00	1.40



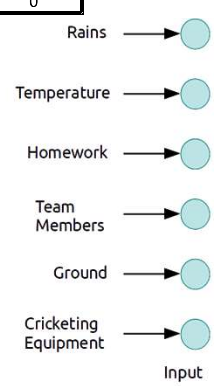
5/15/2024

pra-sâmi

29

Hidden Layers

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0.00	0.00	1.00	1.00	0.00	1.00	1
2	0.00	0.81	1.00	1.00	1.00	0.83	1
3	0.00	0.75	1.00	1.00	1.00	0.67	1
4	-0.17	0.69	1.00	0.44	1.00	1.00	0
5	-0.67	0.94	0.00	0.22	1.00	0.00	0
6	-1.00	1.00	0.00	0.00	0.00	1.00	0



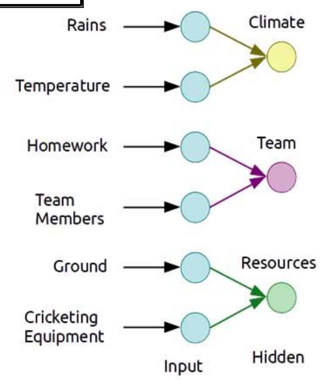
5/15/2024

pra-sâmi

30

Hidden Layers

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0.00	0.00	1.00	1.00	0.00	1.00	1
2	0.00	0.81	1.00	1.00	1.00	0.83	1
3	0.00	0.75	1.00	1.00	1.00	0.67	1
4	-0.17	0.69	1.00	0.44	1.00	1.00	0
5	-0.67	0.94	0.00	0.22	1.00	0.00	0
6	-1.00	1.00	0.00	0.00	0.00	1.00	0



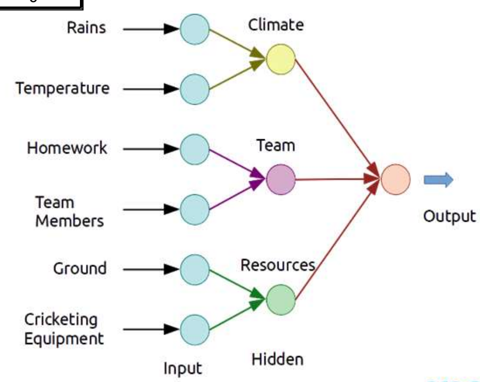
5/15/2024

pra-sâmi

31

Hidden Layers

id	Rains	Temp	Homework	Team Members	Equipment	Ground	Played
1	0.00	0.00	1.00	1.00	0.00	1.00	1
2	0.00	0.81	1.00	1.00	1.00	0.83	1
3	0.00	0.75	1.00	1.00	1.00	0.67	1
4	-0.17	0.69	1.00	0.44	1.00	1.00	0
5	-0.67	0.94	0.00	0.22	1.00	0.00	0
6	-1.00	1.00	0.00	0.00	0.00	1.00	0

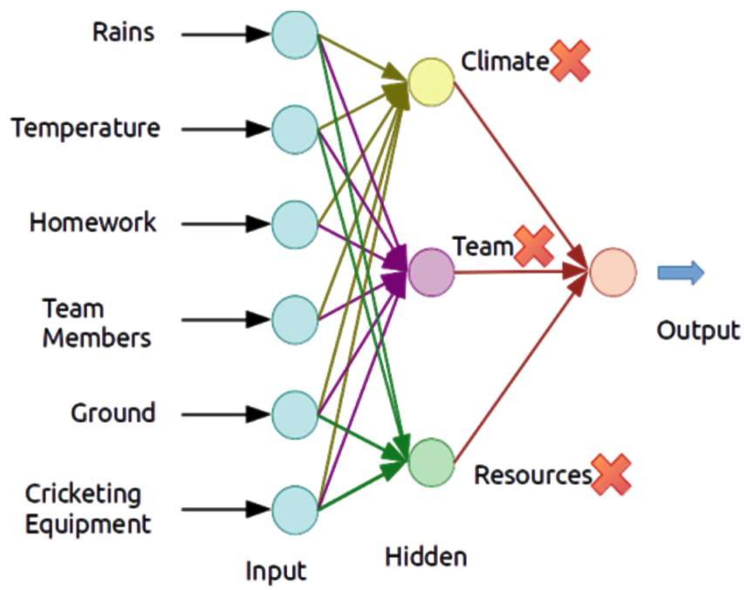


5/15/2024

pra-sâmi

32

Hidden Layers



5/15/2024

pra-sâmi

33

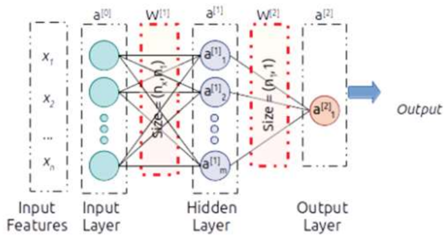
Hidden Layers

5/15/2024

pra-sâmi

34

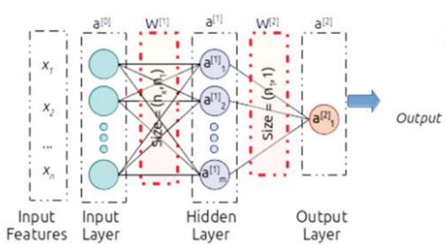
Two Major Conventions

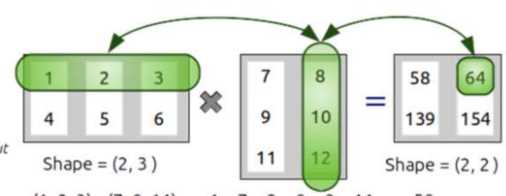


pra-sâmi

35

Two Major Conventions





(1, 2, 3) • (7, 9, 11) = 1 × 7 + 2 × 9 + 3 × 11 = 58

(1, 2, 3) • (8, 10, 12) = 1 × 8 + 2 × 10 + 3 × 12 = 64

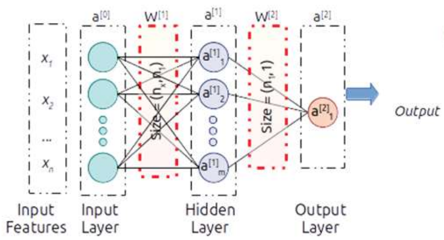
(4, 5, 6) • (7, 9, 11) = 4 × 7 + 5 × 9 + 6 × 11 = 139

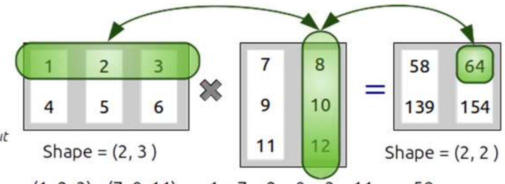
(4, 5, 6) • (8, 10, 12) = 4×8 + 5×10 + 6×12 = 154

pra-sâmi

36

Two Major Conventions



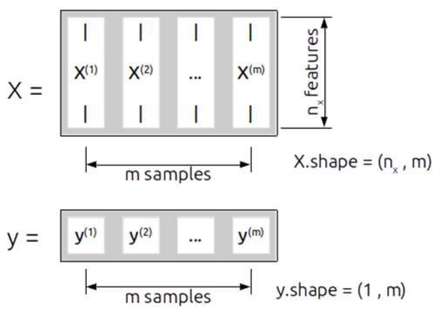


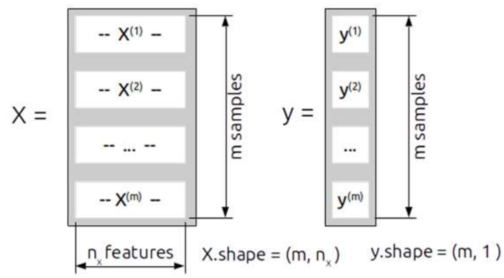
(1, 2, 3) • (7, 9, 11) = 1 × 7 + 2 × 9 + 3 × 11 = 58

(1, 2, 3) • (8, 10, 12) = 1 × 8 + 2 × 10 + 3 × 12 = 64

(4, 5, 6) • (7, 9, 11) = 4 × 7 + 5 × 9 + 6 × 11 = 139

(4, 5, 6) • (8, 10, 12) = 4×8 + 5×10 + 6×12 = 154

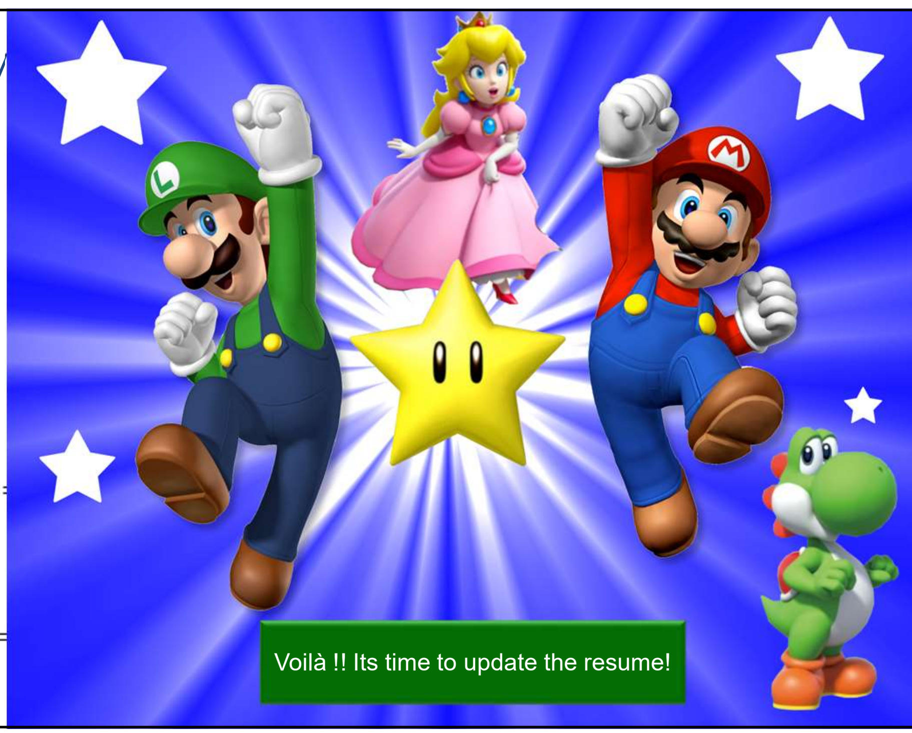




5/15/2024 pra-sâmi

37

Two M



5/15/2024 pra-sâmi

38

Reflect…

- How many type of layers Deep Learning Algorithms have?
  - A. 2
  - B. 3
  - C. 4
  - D. 5
- Answer : B

- The first layer is called the?
  - A. Input Layer
  - B. Output Layer
  - C. Hidden Layer
  - D. None of The Above

- Answer : A

- Which of the following is/are Limitations of deep learning?
  - A. Data labeling
  - B. Obtain huge training datasets
  - C. Both A and B
  - D. None of the above
- Answer : C

- Deep learning algorithms are _______ more accurate than machine learning algorithm in image classification.
  - A. 33%
  - B. 37%
  - C. 40%
  - D. 41%
- Answer : D

5/15/2024

pra-sâmi

39

Reflect…

- In which of the following applications can we use deep learning to solve the problem
  - A. Protein structure prediction
  - B. Prediction of chemical reactions
  - C. Detection of exotic particles
  - D. All of the above

- Answer : D

- The number of nodes in the input layer is 10 and the hidden layer is 5. The maximum number of connections from the input layer to the hidden layer are:
  - A. 50
  - B. less than 50
  - C. more than 50
  - D. It is an arbitrary value

- Answer : A

- What is a perceptron?
  - A. A type of neural network
  - B. A reinforcement learning algorithm
  - C. A clustering algorithm
  - D. A regression algorithm

- Answer : A

- Who is credited with the invention of the perceptron?
  - A. Geoffrey Hinton
  - B. Yann LeCun
  - C. Frank Rosenblatt
  - D. Andrew Ng

- Answer : C

5/15/2024

pra-sâmi

40

Reflect…

- What is the basic building block of a perceptron?
  - A. Neuron
  - B. Weight
  - C. Activation function
  - D. Bias
- Answer: A
- In a perceptron, what is the purpose of the activation function?
  - A. To compute the weighted sum of inputs
  - B. To introduce non-linearity
  - C. To adjust the weights during training
  - D. To add a bias to the output
- Answer: B
- What is the primary purpose of training a perceptron?
  - A. To optimize the activation function
  - B. To minimize the error in the output
  - C. To increase the number of neurons
  - D. To add more layers to the network
- Answer: B
- In a binary classification problem, what is the output of a perceptron?
  - A. Real number
  - B. Probability
  - C. Binary value (0 or 1)
  - D. Vector
- Answer: C

5/15/2024

pra-sâmi

41

Reflect…

- What is the perceptron learning rule used for?
  - A. Updating weights to reduce prediction error
  - B. Adjusting the learning rate during training
  - C. Initializing weights in the network
  - D. Selecting the appropriate activation function
- Answer: A
- What happens if a perceptron is unable to learn a linearly separable function?
  - A. It converges quickly
  - B. It converges slowly
  - C. It never converges
  - D. It always converges
- Answer: C
- Which of the following statements about the perceptron is true?
  - A. It can only be used for linearly separable problems
  - B. It is suitable for any type of problem
  - C. It can only have one layer
  - D. It has no weights
- Answer: A
- What is the main limitation of a single-layer perceptron?
  - A. It cannot learn non-linearly separable functions
  - B. It requires a large amount of training data
  - C. It is computationally expensive
  - D. It is not suitable for classification tasks
- Answer: A

5/15/2024

pra-sâmi

42

Reflect…

- What is a deep neural network?
  - A) A neural network with a single layer
  - B) A neural network with more than one layer
  - C) A neural network with no layers
  - D) A neural network with only input and output layers
- Answer: B
- What is the purpose of the backpropagation algorithm in training deep neural networks?
  - A) To compute the gradient of the loss function with respect to the weights
  - B) To initialize the weights of the network
  - C) To regularize the network
  - D) To activate neurons in the network
- Answer: A
- What is the primary function of the input layer in a deep neural network?
  - A) Extracting features from the input data
  - B) Normalizing the input data
  - C) Propagating the output to the next layer
  - D) Receiving input data and passing it to the hidden layers
- Answer: D) Receiving input data and passing it to the hidden layers
- Which term refers to the number of neurons in the hidden layer of a neural network?
  - A) Depth
  - B) Width
  - C) Length
  - D) Breadth
- Answer: B) Width

5/15/2024

pra-sâmi

43

Reflect…

- What does the term "backpropagation" refer to in the context of neural networks?
  - A) The process of adjusting the weights of the network based on the prediction error
  - B) The process of training the network using labeled data
  - C) The process of selecting the optimal hyperparameters for the network
  - D) The process of initializing the weights of the network
- Answer: A) The process of adjusting the weights of the network based on the prediction error
- What is the primary purpose of using multiple hidden layers in a deep neural network?
  - A) To increase the computational efficiency
  - B) To decrease the complexity of the network
  - C) To learn hierarchical features from the input data
  - D) To reduce the training time
- Answer: C) To learn hierarchical features from the input data
- Which type of neural network architecture is commonly used for image recognition tasks?
  - A) Recurrent Neural Network (RNN)
  - B) Convolutional Neural Network (CNN)
  - C) Feedforward Neural Network (FNN)
  - D) Long Short-Term Memory (LSTM)
- Answer: B) Convolutional Neural Network (CNN)

5/15/2024

pra-sâmi

44

Reflect…

- What is the purpose of regularization techniques in deep neural networks?
  - A) To increase the complexity of the model
  - B) To reduce the computational cost of training
  - C) To prevent overfitting
  - D) To speed up the convergence of the training process
- Answer: C) To prevent overfitting
- Which term describes the process of evaluating the performance of a neural network on unseen data?
  - A) Training
  - B) Testing
  - C) Validation
  - D) Optimization
- Answer: B) Testing
- What is the primary disadvantage of using deep neural networks?
  - A) They require large amounts of labeled data for training
  - B) They are computationally expensive to train
  - C) They are prone to overfitting
  - D) They are difficult to interpret
- Answer: B) They are computationally expensive to train

5/15/2024

pra-sâmi

45

Next Session - Coding Perceptron Model in Python

5/15/2024

pra-sâmi

46

5/15/2024

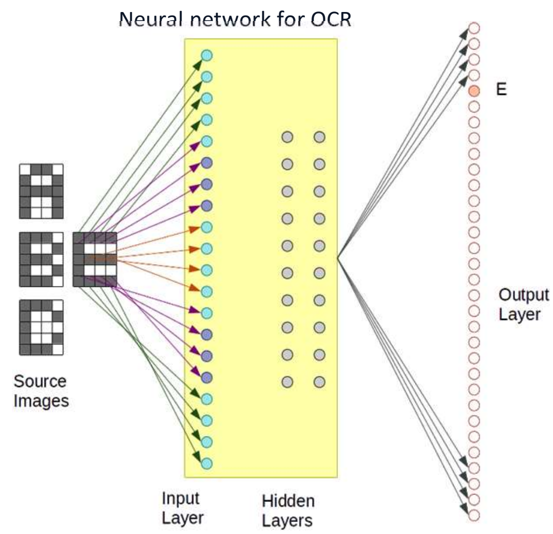
EXTRA MATERIAL

Applications

48

Applications

- The properties of neural networks define where they are useful
- Typical Network
  - Can learn complex mappings from inputs to outputs, based solely on samples
  - Difficult to analyse
  - Firm predictions about neural network behaviour difficult;
    - Unsuitable for safety-critical applications.
  - Require limited understanding from trainer, who can be guided by heuristics



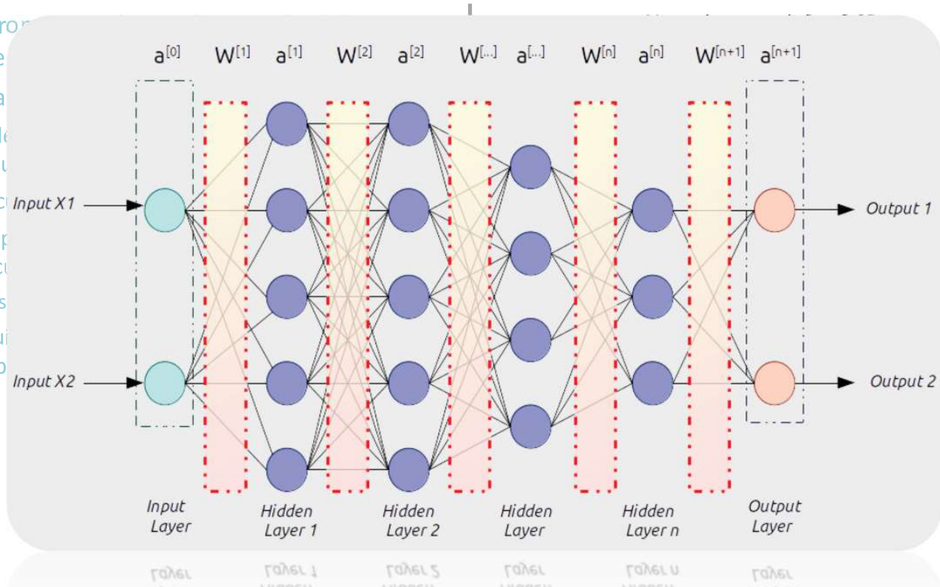
5/15/2024

pra-sâmi

49

Applications

- The pro
  where
- Typica
  - Can l
    outpu
  - Diffic
  - firm p
    diffic
    - Uns
  - Requi
    can b



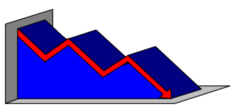
5/15/2024

pra-sâmi

50

Applications

- Stock market prediction
  - "Technical trading" refers to trading based solely on known statistical parameters; e.g. previous price
  - Neural networks have been used to attempt to predict changes in prices.
  - Difficult to assess success or otherwise
    - Since companies using these techniques are reluctant to disclose information.



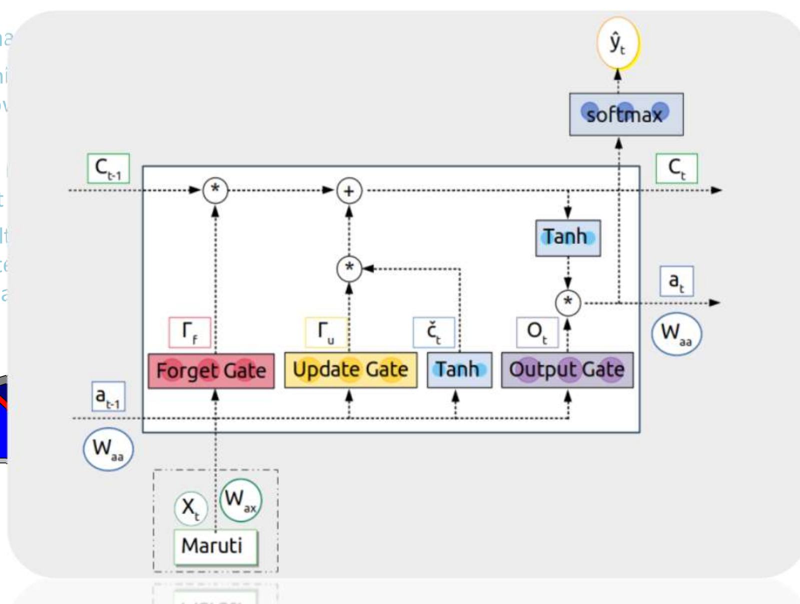
- **Mortgage assessment**
  - Assess risk of lending to an individual
  - Difficult to decide on marginal cases
  - Neural networks have been trained to make decisions, based upon the opinions of expert underwriters
  - Neural network produced a 12% reduction in delinquencies compared with human experts

5/15/2024

pra-sâmi

51

Applications



5/15/2024

pra-sâmi

52

Applications

- ALVINN: Autonomous Land Vehicle In a Neural Network

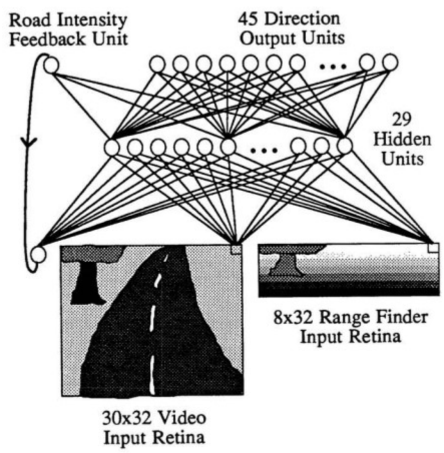
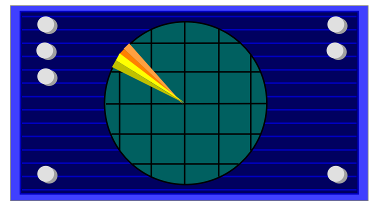


Figure 1: ALVINN Architecture

- **Sonar target recognition**
  - Distinguish mines from rocks on sea-bed
  - The neural network is provided with a large number of parameters which are extracted from the sonar signal.
  - The training set consists of sets of signals from rocks and mines.



5/15/2024 pra-sâmi

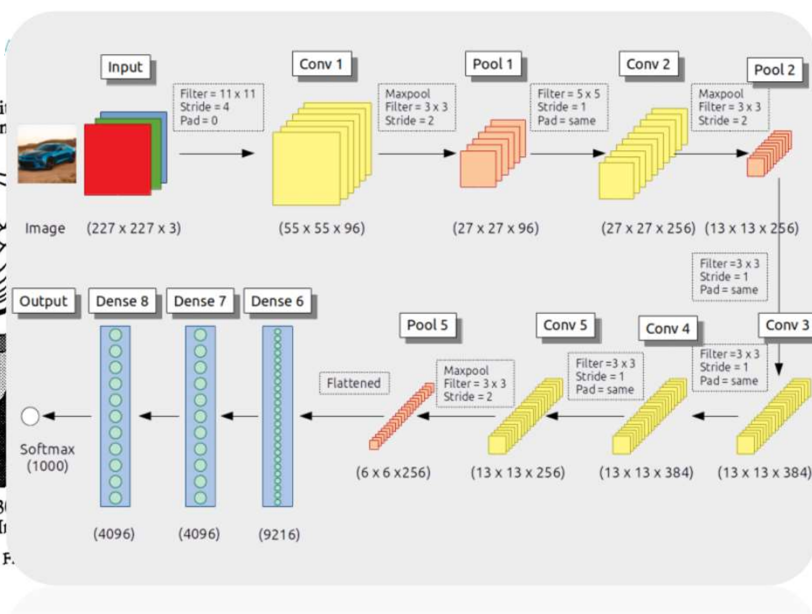
53

Applications

- ALVINN: A
  Network

Road Intensi
Feedback Un

sea-bed
with a large
e extracted from
of signals from



5/15/2024 pra-sâmi

54

Applications

- Engine management
  - The behavior of a car engine is influenced by a large number of parameters
    - temperature at various points
    - fuel/air mixture
    - lubricant viscosity.
  - Major companies have used neural networks to dynamically tune an engine depending on current settings.

- Signature recognition
  - Each person's signature is different.
  - There are structural similarities which are difficult to quantify.
  - Recognizes signatures to a high level of accuracy.
  - Considers speed in addition to gross shape
  - Makes forgery even more difficult.

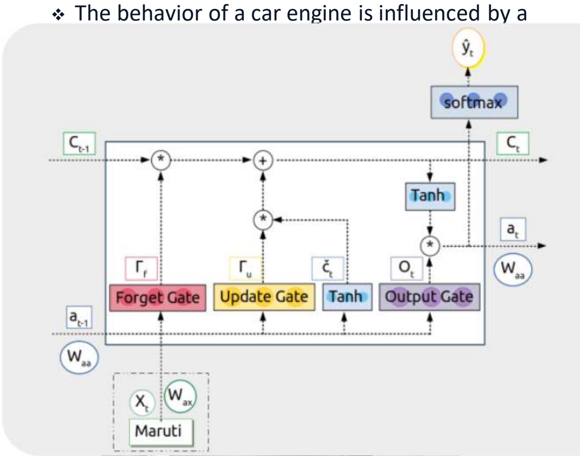
5/15/2024

pra-sâmi

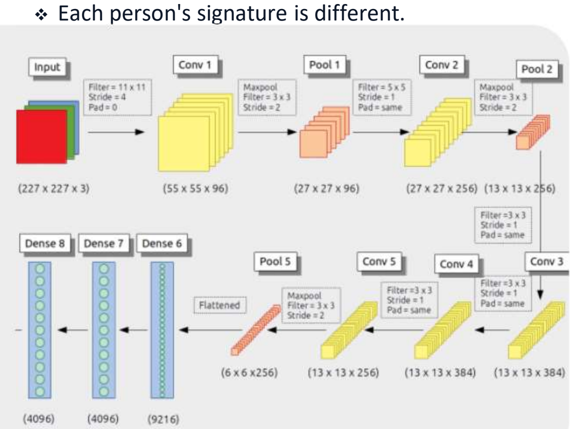
55

Applications

- Engine management
  - The behavior of a car engine is influenced by a



- Signature recognition
  - Each person's signature is different.



5/15/2024

pra-sâmi

56

Derivation of Sigmoid

$$
\begin{aligned}
\partial a &= \partial\sigma(z) \\
&= \frac{\partial}{\partial z}\left[\frac{1}{1+e^{-z}}\right] \\
&= \frac{\partial}{\partial z}\left(1+\mathrm{e}^{-z}\right)^{-1} \\
&= -(1+e^{-z})^{-2}(-e^{-z}) \\
&= \frac{e^{-z}}{(1+e^{-z})^2} \\
&= \frac{1}{1+e^{-z}} \circ \frac{e^{-z}}{1+e^{-z}} \\
&= \frac{1}{1+e^{-z}} \circ \frac{(1+e^{-z})-1}{1+e^{-z}} \\
&= \frac{1}{1+e^{-z}} \circ \left[\frac{1+e^{-z}}{1+e^{-z}} - \frac{1}{1+e^{-z}}\right] \\
&= \frac{1}{1+e^{-z}} \circ \left[1 - \frac{1}{1+e^{-z}}\right] \\
&= \sigma(z) \circ (1-\sigma(z)) \\
&= a \circ (1-a)
\end{aligned}
$$