ENGR 4350:Applied Deep Learning

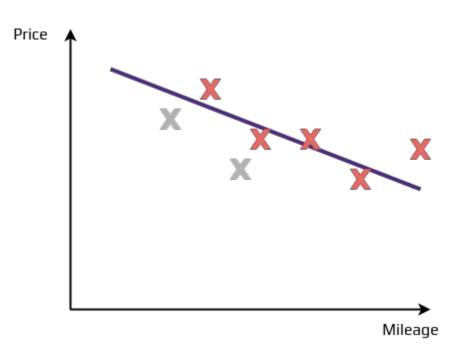
Logistic Regression

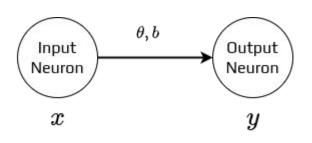


Outline

- An example of neural network
- Logistic Regression
 - Forward Pass
 - Loss Function
 - Gradient Descent

A Neural Network Example

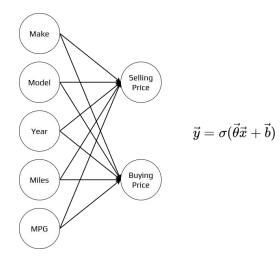




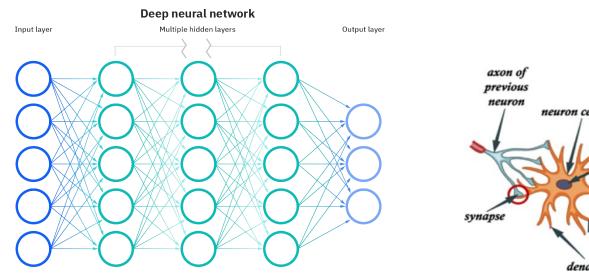
$$y = \sigma(\theta x + b)$$

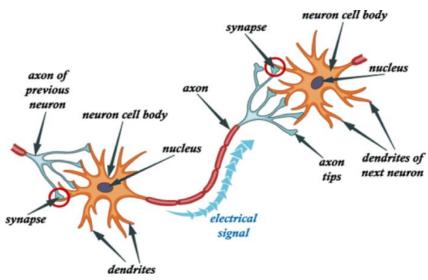
A Neural Network Example

Make	Model	Year	Mileage	MPG	Buying Price	Selling Price
Ford	Edge	2018	50,000	23	\$19,000	\$10,000
Toyota	Land Cruiser	2020	10,000	15	\$80,000	\$50,000
VW	Golf	2010	150,000	36	\$7,000	\$2,000



A Neural Network Example





Binary Classification

- Complex decision makings can be simplified to classification problems.
 - Vehicle control
 - Robotic arm control
 - Gaming
 - 0 ...
- Binary classification works most of the time.
 - Visitor identification
 - Animal protection
 - Farming
 - 0

Logistic Regression

Logistic regression estimates the probability of an event occurring, P(y = 1 | x) such as voted or didn't vote, based on a given dataset of independent variables. Since the outcome is a probability, the dependent variable is bounded between 0 and 1.

- Classification
- Prediction
- Rating

E.g. Given the "make, model, year, mileage, MPG" of vehicles, estimate probabilities of prices of these vehicles under \$20,000.

Problem Settings

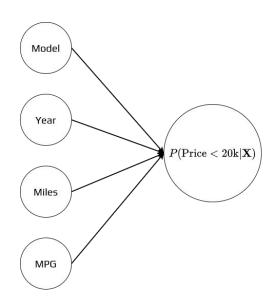
Dataset:
$$\left\{ \left(\mathbf{x}^{(1)}, y^{(1)} \right), \left(\mathbf{x}^{(2)}, y^{(2)} \right), \dots, \left(\mathbf{x}^{(m)}, y^{(m)} \right) \right\}$$

$$\text{Features: } \mathbf{X} = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_n^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \dots & x_n^{(2)} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_1^{(m)} & x_2^{(m)} & \dots & x_n^{(m)} \end{bmatrix} \quad \text{Labels: } \mathbf{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ \vdots \\ y^{(m)} \end{bmatrix}$$

m examples, n independent variables

Forward Pass / Prediction

Id (Model)	Year	Mileage	MPG	Buying Price
5 (Ford Edge)	2018	50,000	23	1 (\$19,000)
105 (Toyota Landcruiser)	2020	10,000	15	0 (\$80,000)
233 (vw Golf)	2010	150,000	36	1 (\$7,000)



Forward Pass / Prediction

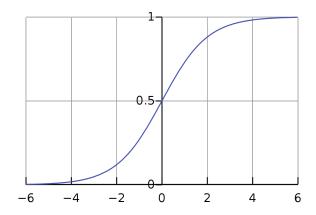
Input: X

Weights:
$$\mathbf{w} \in \mathbb{R}^{n_{\mathbf{x}}}$$
, bias: $b \in \mathbb{R}$

$$\mathbf{w} = [w_1 \quad w_2 \quad . \quad . \quad w_n]$$

Output: $\hat{\mathbf{y}} = \sigma(\mathbf{X}\mathbf{w}^{\mathbf{T}} + b)$

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



Loss Function

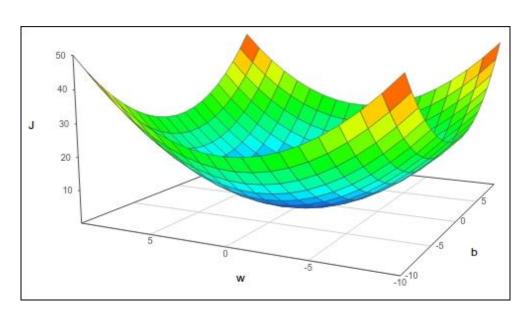
Dataset:
$$\{(\mathbf{x}^{(1)}, y^{(1)}), (\mathbf{x}^{(2)}, y^{(2)}), \dots, (\mathbf{x}^{(m)}, y^{(m)})\}$$

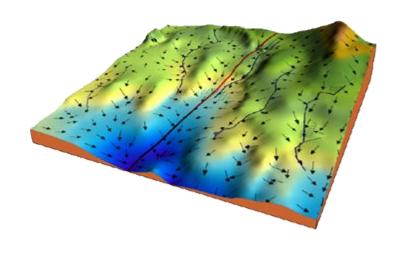
Mean squared error (MSE) loss function:
$$\mathcal{L}(\mathbf{\hat{y}}, \mathbf{y}) = \frac{1}{2}(\mathbf{\hat{y}} - \mathbf{y})^2$$

Cross entropy loss function:
$$\mathcal{L}(\mathbf{\hat{y}}, \mathbf{y}) = -(\mathbf{y} \log \mathbf{\hat{y}} + (1 - \mathbf{y}) \log (1 - \mathbf{\hat{y}}))^2$$

Cost function:
$$J(\mathbf{w}, b) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\mathbf{\hat{y}}, \mathbf{y})$$

Gradient Descent





Find **w** and *b* that minimize $J(\mathbf{w}, b)$

Gradient Descent

repeat until converge {

$$\mathbf{w} := \mathbf{w} - \alpha \frac{\partial J}{\partial \mathbf{w}}$$
 $b := b - \alpha \frac{\partial J}{\partial b}$

$$b:=b-lpharac{\partial J}{\partial b}$$

 α is the learning rate

