



CMPS 460 – Spring 2022

MACHINE LEARNING

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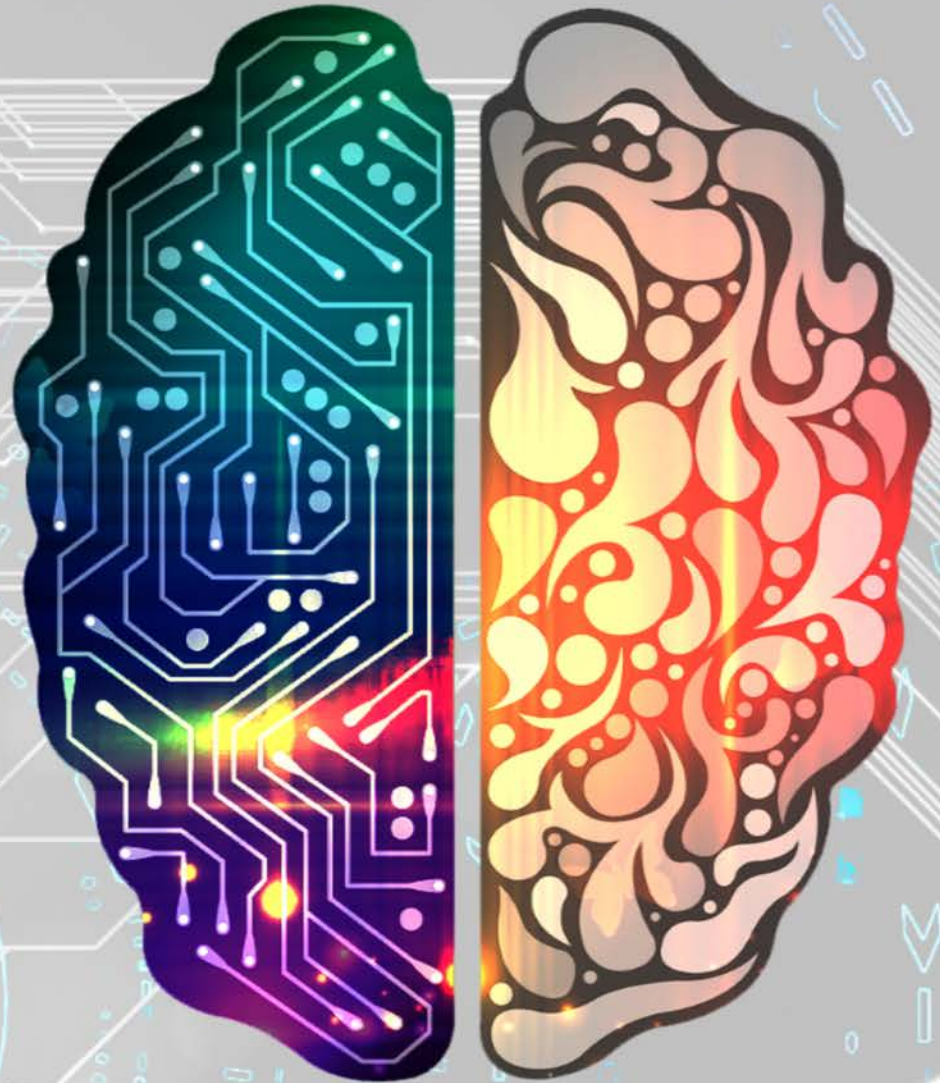


Image hosted by: WittySparks.com | Image source: Pixabay.com

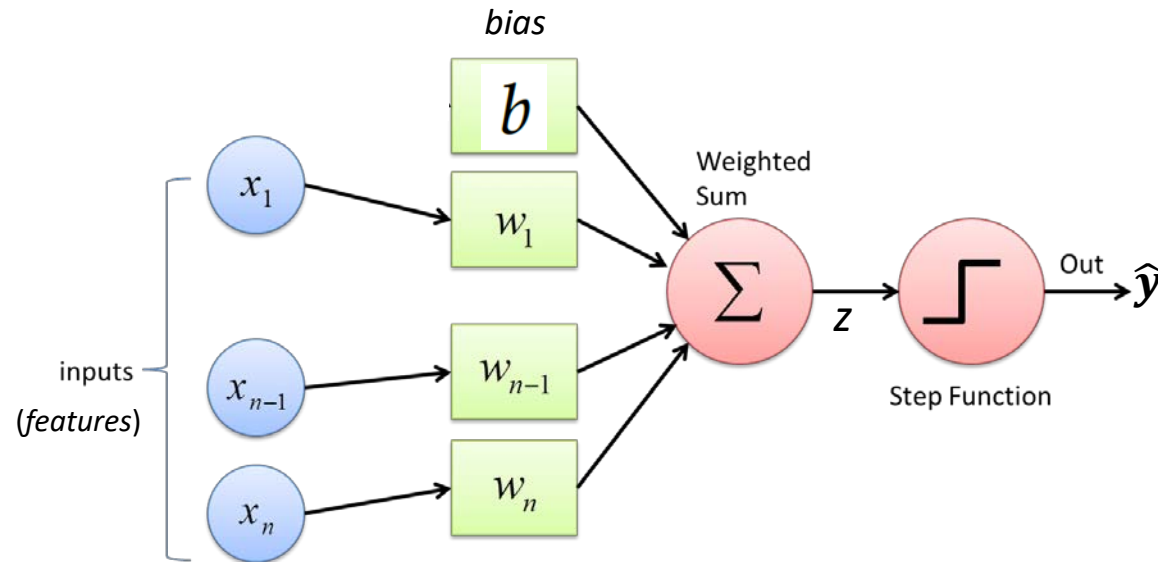
8.c

Prob. Modeling: Logistic Regression



Handout:
Intro, 5.1,
5.2.1, 5.4,
5.5, 5.6.1

Perceptron

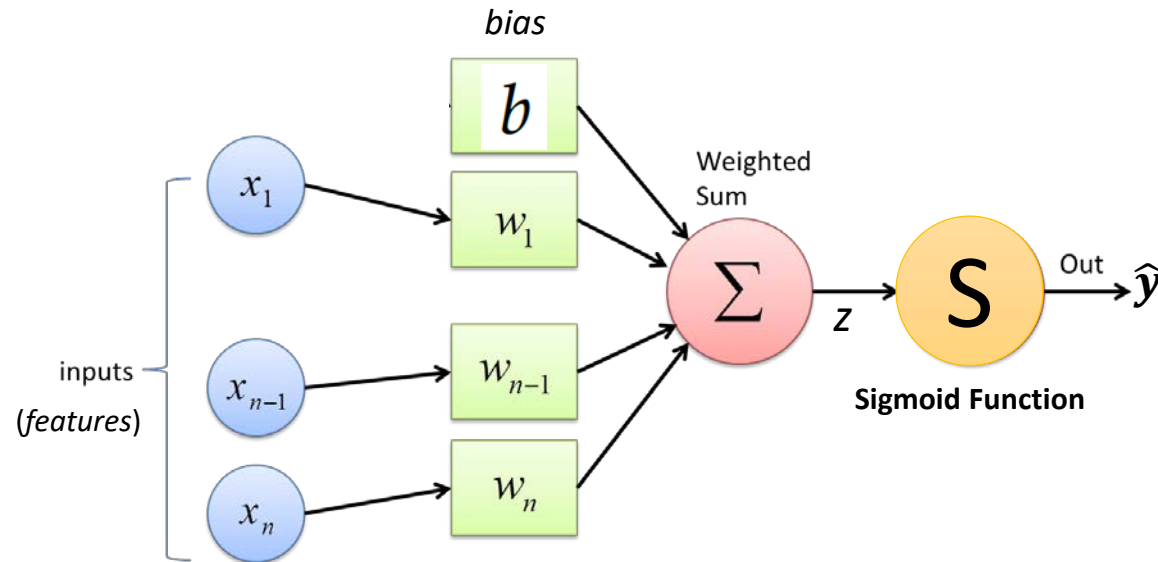


$$z = \left[\sum_{i=1}^n w_i x_i \right] + b$$

$$\hat{y} = \mathbb{I}(z > 0)$$

Probability?

Logistic Regression



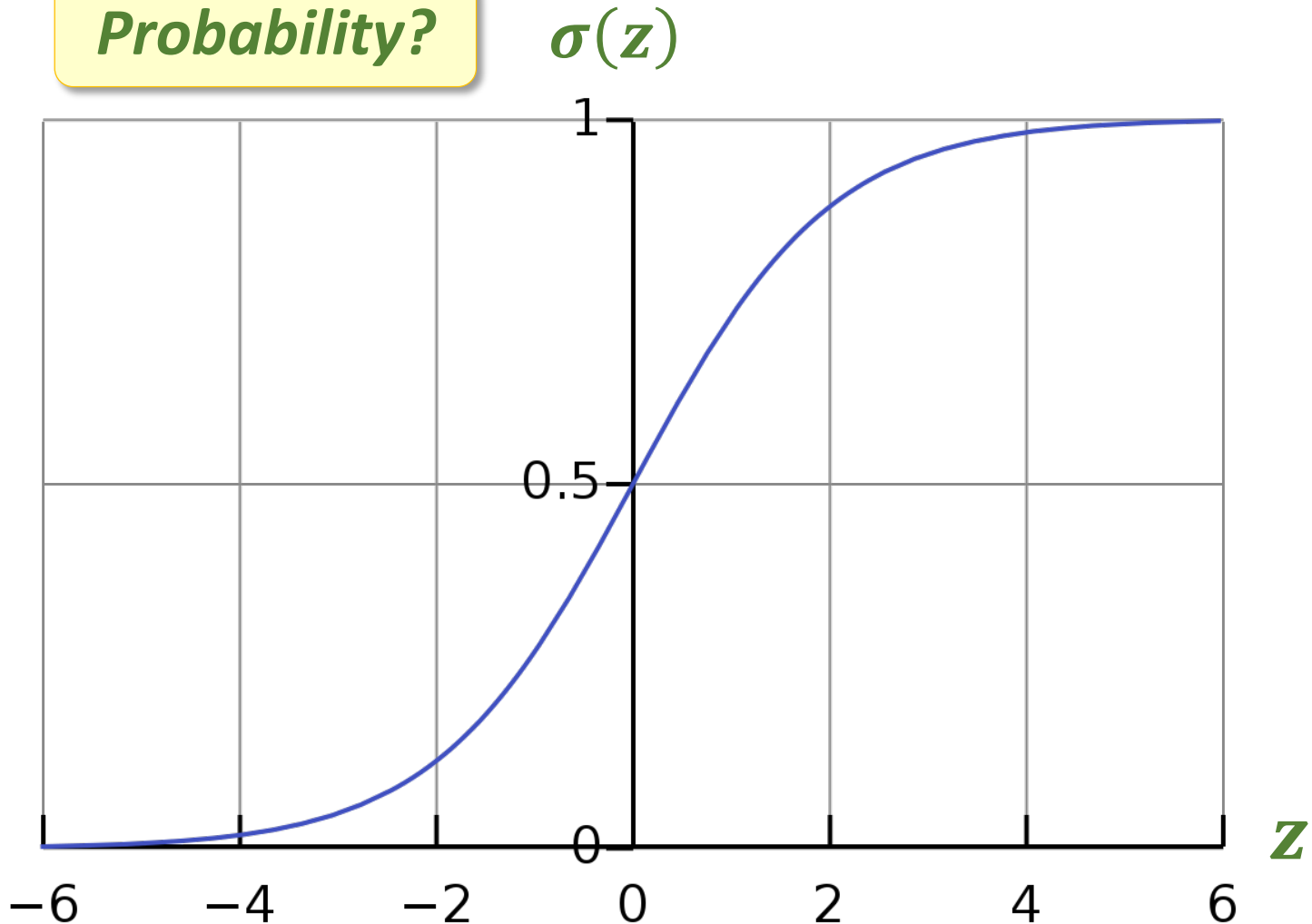
$$z = \left[\sum_{i=1}^n w_i x_i \right] + b$$

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

Sigmoid Function

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

Probability?



LR Prediction

$$\hat{y} = p(y = 1|x) = \sigma(z) = \sigma(wx + b) = \frac{1}{1 + e^{-(wx+b)}}$$

$$1 - \hat{y} = p(y = 0|x) = 1 - \sigma(z) = 1 - \sigma(wx + b) = \frac{e^{-(wx+b)}}{1 + e^{-(wx+b)}}$$

$$\text{BTW: } 1 - \sigma(z) = \sigma(-z)$$

$$\textit{Predicted Label}(x) = \begin{cases} 1 & \text{if } \hat{y} > 0.5 \\ 0 & \text{otherwise} \end{cases}$$

Example

$$n = 3$$

$$x_1 = 1, x_2 = -1, x_3 = 3$$

$$w_1 = -1, w_2 = 2, w_3 = 3, b = 0$$

$$z = ? \quad \hat{y} = ?$$

$$\text{if } b = -7?$$



Learning

Choosing Parameters ...

- Goal: Maximize probability of the correct label
- Remember that

$$\hat{y} = p(y = 1|x)$$

- ➔ Goal: Maximize \hat{y} when $y = 1$, and $1 - \hat{y}$ when $y = 0$
- ➔ maximize the following function:

$$p(y|x) = \hat{y}^y (1 - \hat{y})^{1-y}$$

noting:

if $y = 1$, this simplifies to \hat{y}

if $y = 0$, this simplifies to $1 - \hat{y}$

Choose w and b that maximize the probability of the correct labels in the training data

Cross-Entropy Loss

- **Goal:** maximize probability of the correct label $p(y|x)$
- Maximize: $p(y|x) = \hat{y}^y (1 - \hat{y})^{1-y}$
- Maximize: $\log p(y|x) = \log [\hat{y}^y (1 - \hat{y})^{1-y}]$
 $= y \log \hat{y} + (1 - y) \log(1 - \hat{y})$
- Minimize:

$$L_{\text{CE}}(\hat{y}, y) = -\log p(y|x) = -[y \log \hat{y} + (1 - y) \log(1 - \hat{y})]$$

Cross-Entropy loss

Parameters?

- Minimize:

$$L_{\text{CE}}(\hat{y}, y) = -\log p(y|x) = -[y \log \hat{y} + (1 - y) \log(1 - \hat{y})]$$

- Minimize: **How?**

$$L_{\text{CE}}(\hat{y}, y) = -[y \log \sigma(w \cdot x + b) + (1 - y) \log(1 - \sigma(w \cdot x + b))]$$

By Gradient Descent

- Convex and has a unique global minimum
- No closed formula, but solved by gradient descent.



Generative vs. Discriminative Models

Example!

Suppose we're distinguishing cat from dog images



imagenet



imagenet

Generative Classifier

- Build a model of what's in a cat image
 - Knows about whiskers, ears, eyes
 - Assigns a probability to any image:
 - how cat-y is this image?



- Also build a model for dog images

- Now given a new image:

Run both models and see which one fits better

Discriminative Classifier

- Just try to distinguish dogs from cats

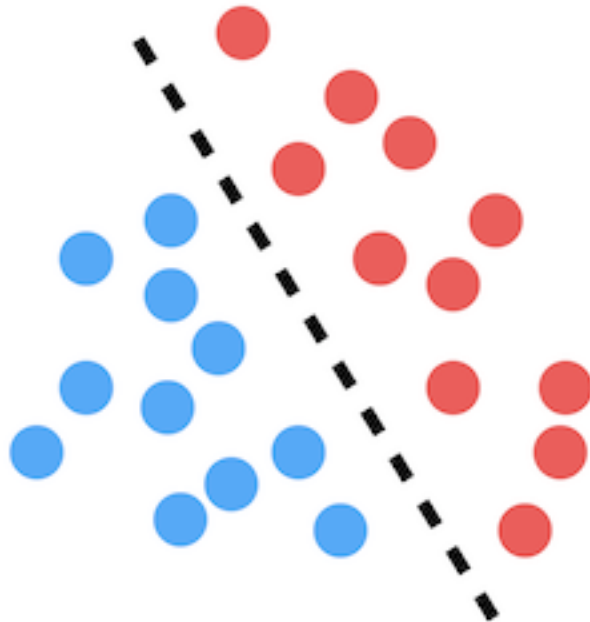


Oh look, dogs have collars!
Let's ignore everything else

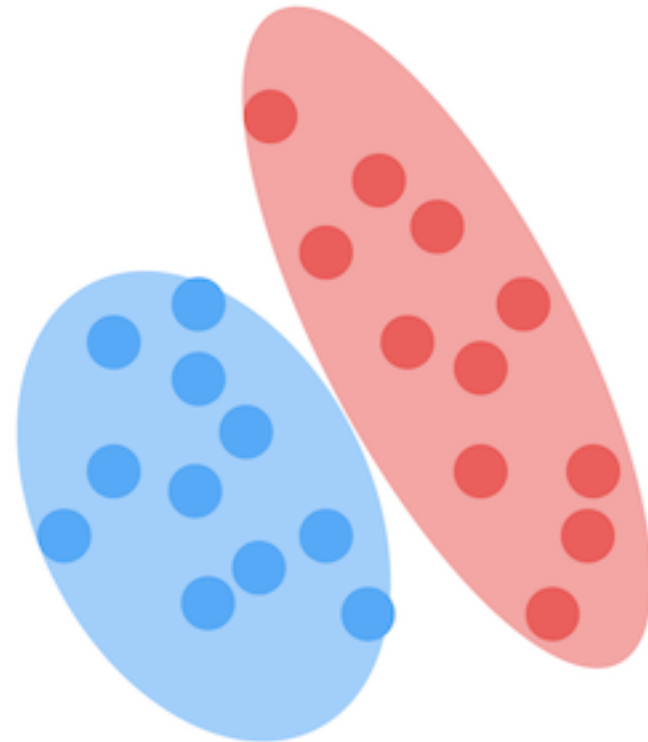


Generative vs Discriminative Classifier

Discriminative



Generative



<https://www.analyticsvidhya.com/blog/2021/07/deep-understanding-of-discriminative-and-generative-models-in-machine-learning/>

Example Classifiers

- Naïve Bayes

$$\hat{c} = \operatorname{argmax}_{c \in C} \underbrace{P(x/y)}_{\text{likelihood}} \underbrace{P(y)}_{\text{prior}}$$

- Logistic Regression

$$\hat{c} = \operatorname{argmax}_{c \in C} \underbrace{P(y/x)}_{\text{posterior}}$$