

# Deep Learning for NLP

Sorokin Semen

**Based on MS DL Course of Boris Zubarev @bobazooba**

# Grading system

**Three labs (each 0.17)**  
**Three / five (not decided yet) test**

**50% of cumulative assessment**  
**50% of cumulative assessment**

**If cumulative assessment  $\geq 6$ :**  
free to go or increase your score on the exam  
**else:**  
pass the exam (a result of the exam  $\geq$  cumulative assessment)

**Exam - two topics from different lectures or**  
**(Mb, if you are lucky) questions like "What is the name of the lecturer?" or**  
**"Classify (manually) this image"**



# Framework

Simple

Hard



# Deep Learning

## Classic Machine Learning



## Deep Learning



# Prompt Engineering



**Stellantis South America**

Posted on: 13 September, 2023

- Full Time

Apply

## Prompt Engineer

As Prompt Engineer / Generative AI Engineer, your role is to design, develop, refining and optimize AI-generated text prompts to ensure they are accurate, engaging, and relevant for various applications.

It includes natural language processing (NLP) models and prompts that drive the performance and effectiveness of language models and conversational AI systems.

Generative AI Engineer, you will work with generative models and doing prompt engineering to create new and innovative AI products. You should possess experience in working with Large Language Models (LLMs), utilizing external models, and have the ability to fine-tune open-source models according to the specific requirements of our company.

Collaboration with data scientists, machine learning engineers, and cross-functional teams will be crucial as you focus on creating high-quality prompts, refining model outputs, and enhancing the overall user experience.

Your expertise in NLP algorithms, model engineering, and prompt engineering techniques will play a vital role in shaping the capabilities and performance of AI language models.

PLEASE SHARE YOUR CV IN ENGLISH  
Key Responsibilities:

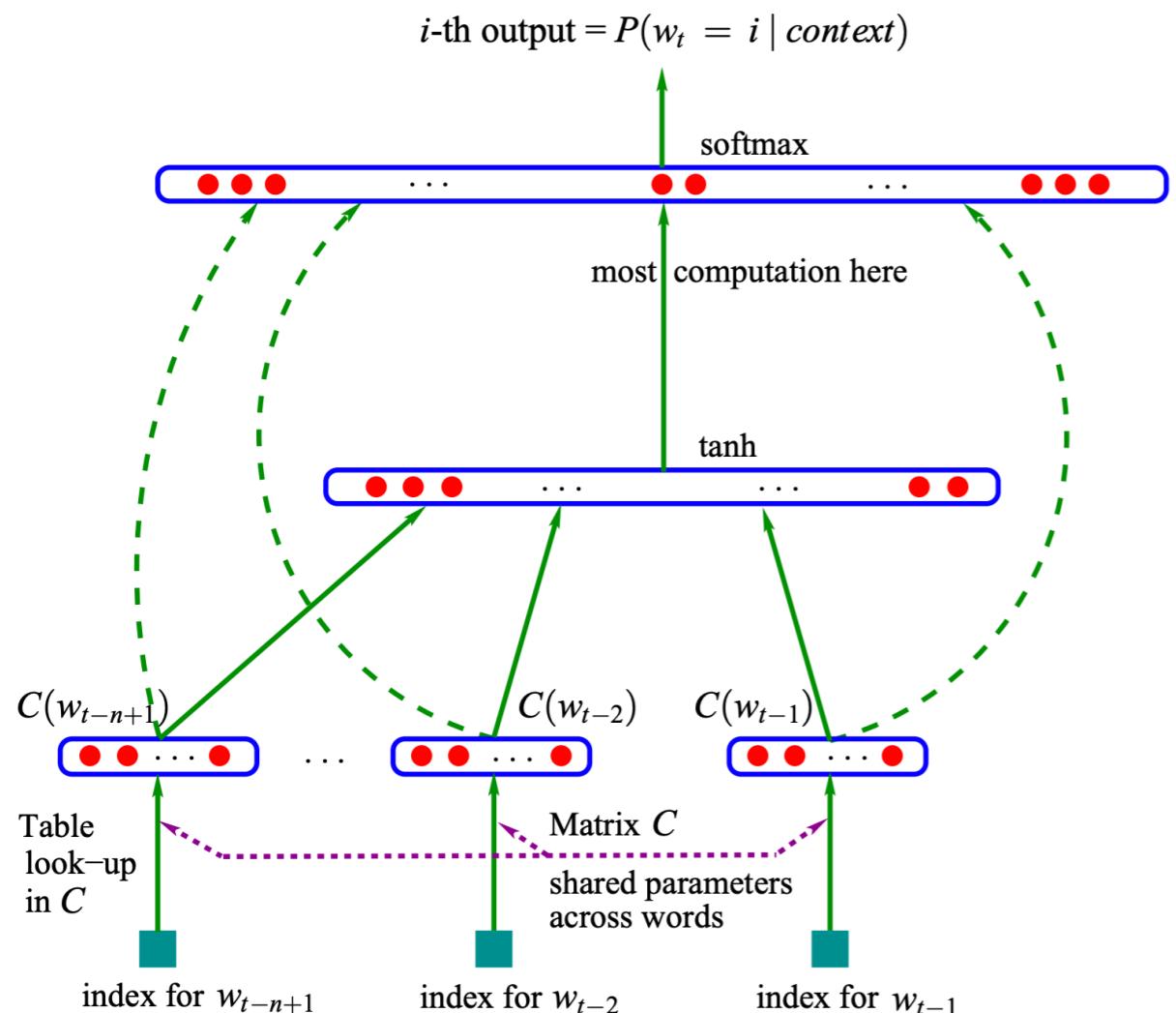
**Prompt Engineering-** Design and develop high-quality prompts and templates that guide the behavior and responses of language models. Craft prompts to elicit specific information or control the model's output, ensuring desired accuracy, relevance, and language fluency. Optimize prompts to improve user interactions and system performance.

**NLP Model Development-** Design and develop NLP models, algorithms, and architectures to solve complex language understanding and generation problems.

# Deep Learning

## Neural Probabilistic Language Model

2003



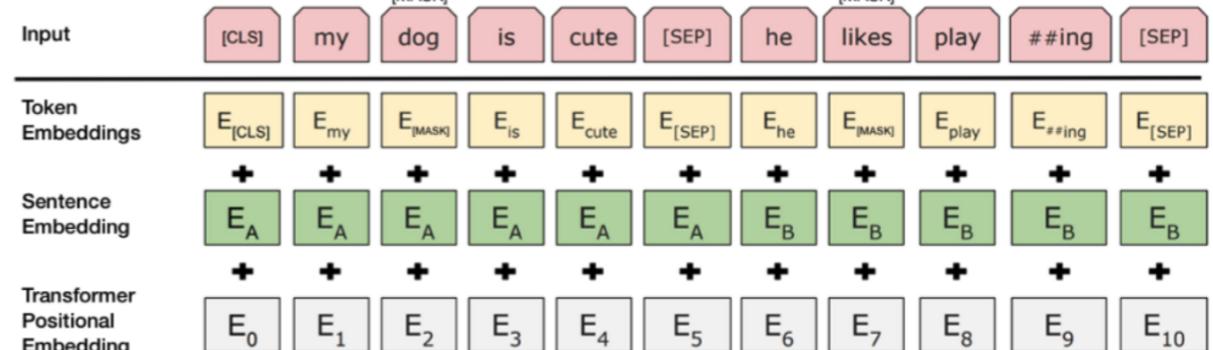
BERT

Q4 2018

Transformer Encoder

24 Layers

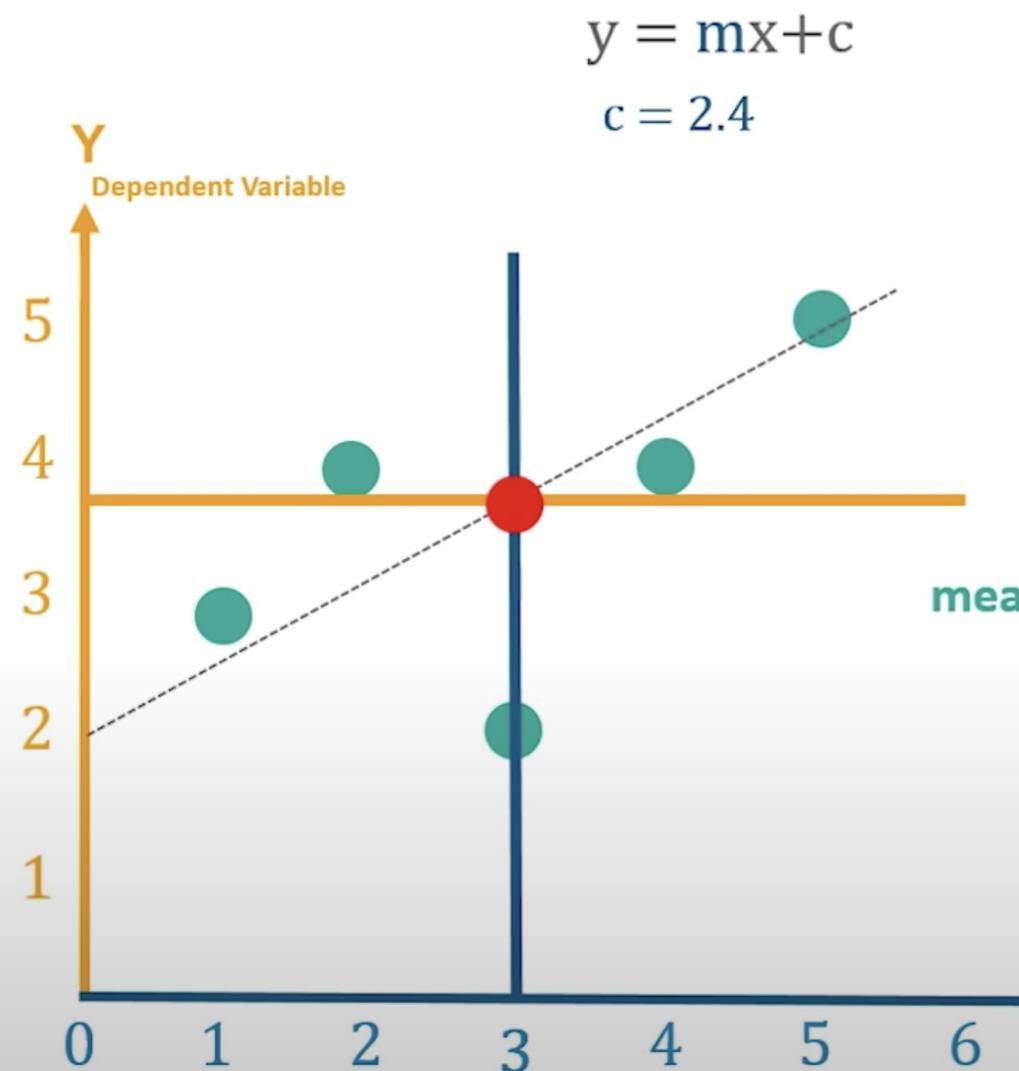
Transformer Encoder



All you need is ~~Love~~ access to GPT-4 API

# ML Recap

# Understanding Linear Regression Algorithm



$x$	$y$	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
1	3	-2	-0.6	4	1.2
2	4	-1	0.4	1	-0.4
3	2	0	-1.6	0	0
4	4	1	0.4	1	0.4
5	5	2	1.4	4	2.8

$$\Sigma = 10 \quad \Sigma = 4$$

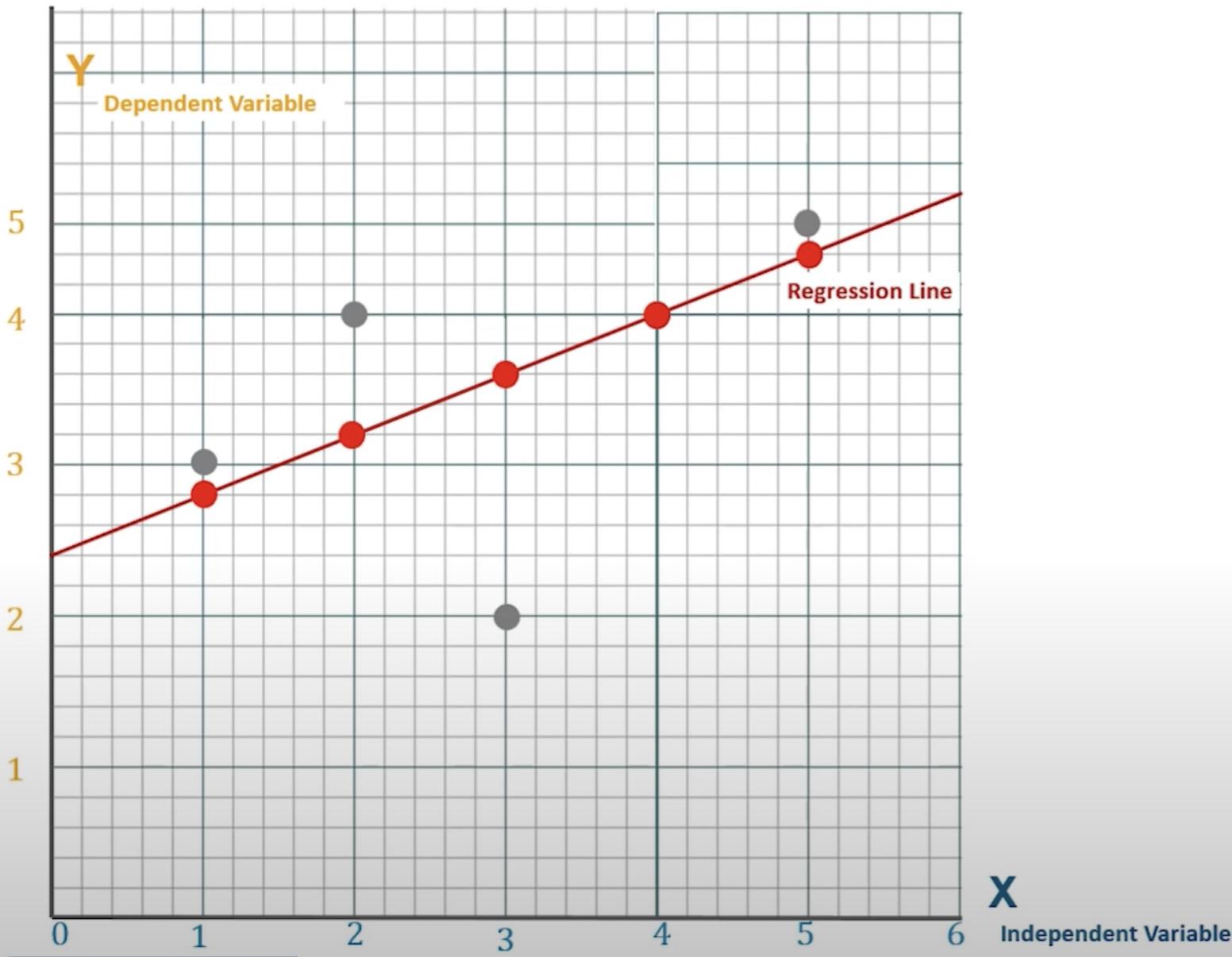
$$m = \sum \frac{(x - \bar{x})(y - \bar{y})}{(x - \bar{x})^2} = \frac{4}{10}$$

$$m = 0.4$$

$$c = 2.4$$

$$y = 0.4x + 2.4$$

# Mean Square Error

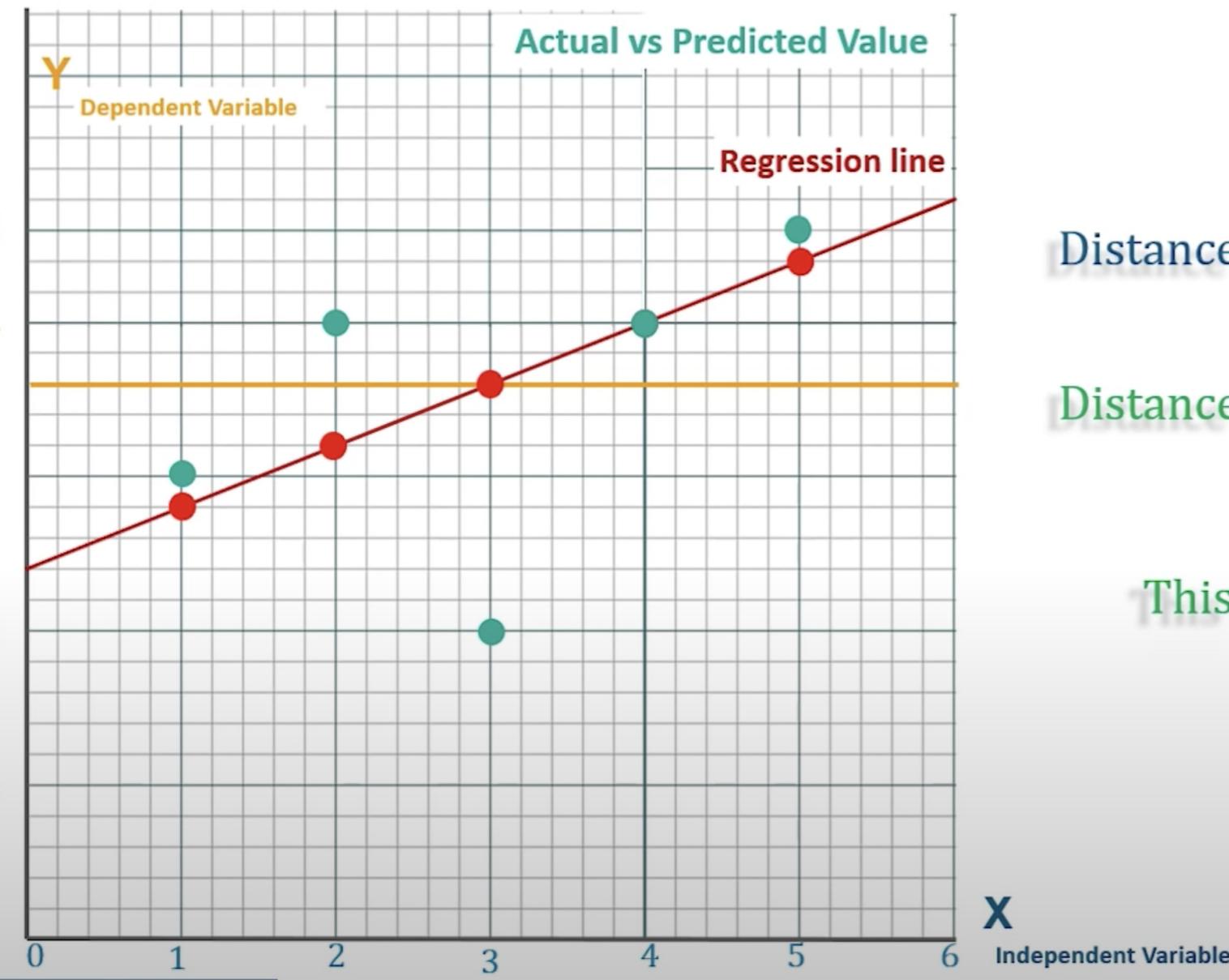


$$\begin{aligned}m &= 0.4 \\c &= 2.4 \\y &= 0.4x + 2.4\end{aligned}$$

For given  $m = 0.4$  &  $c = 2.4$ , lets predict values for  $y$  for  $x = \{1,2,3,4,5\}$

$$\begin{aligned}y &= 0.4 \times 1 + 2.4 = 2.8 \\y &= 0.4 \times 2 + 2.4 = 3.2 \\y &= 0.4 \times 3 + 2.4 = 3.6 \\y &= 0.4 \times 4 + 2.4 = 4.0 \\y &= 0.4 \times 5 + 2.4 = 4.4\end{aligned}$$

# Calculation of $R^2$



Distance actual - mean

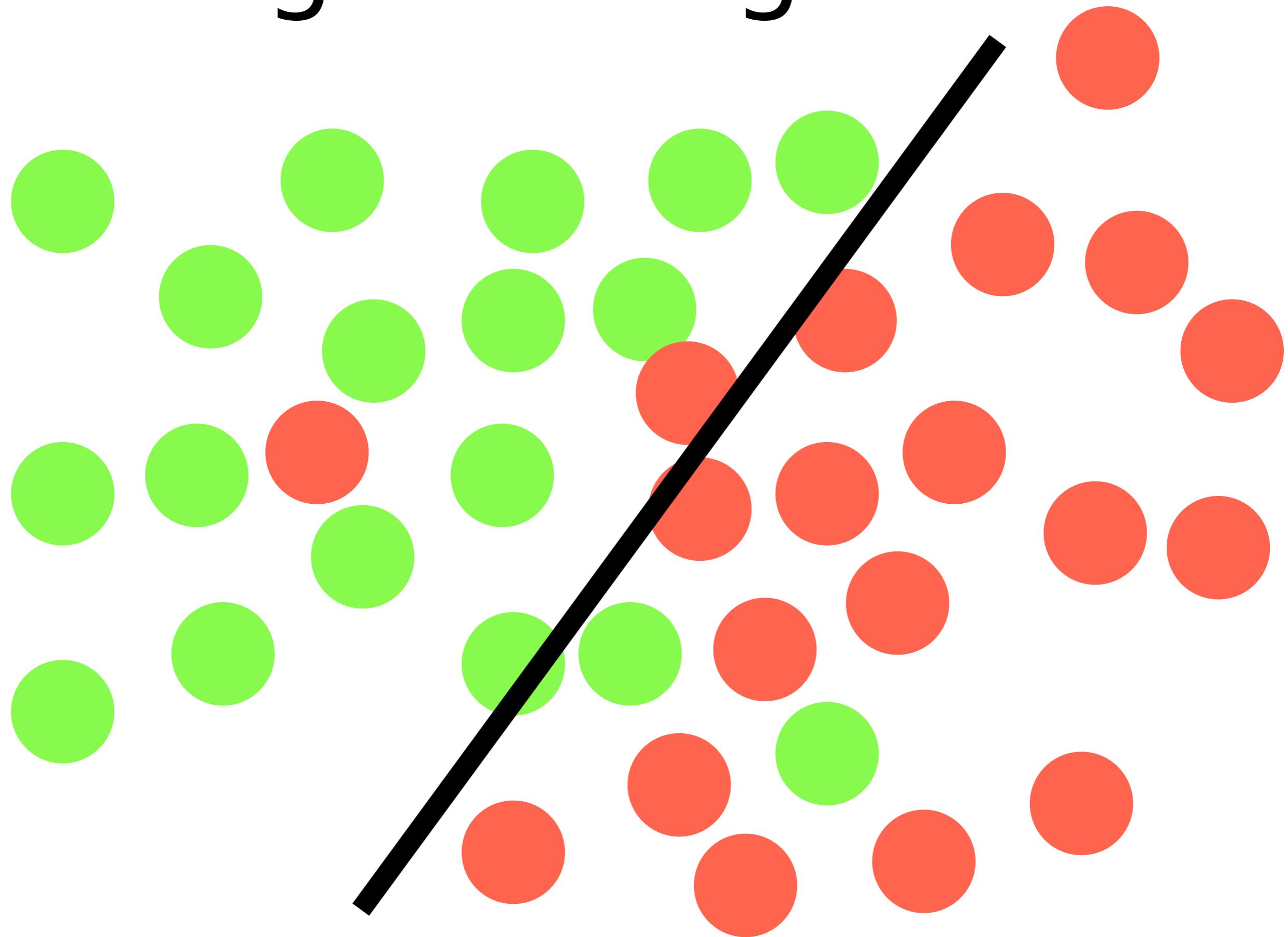
vs

Distance predicted - mean

This is nothing but  $R^2 =$

$$R^2 = \frac{\sum (y_p - \bar{y})^2}{\sum (y - \bar{y})^2}$$

# Logistic Regression



# Logistic Regression

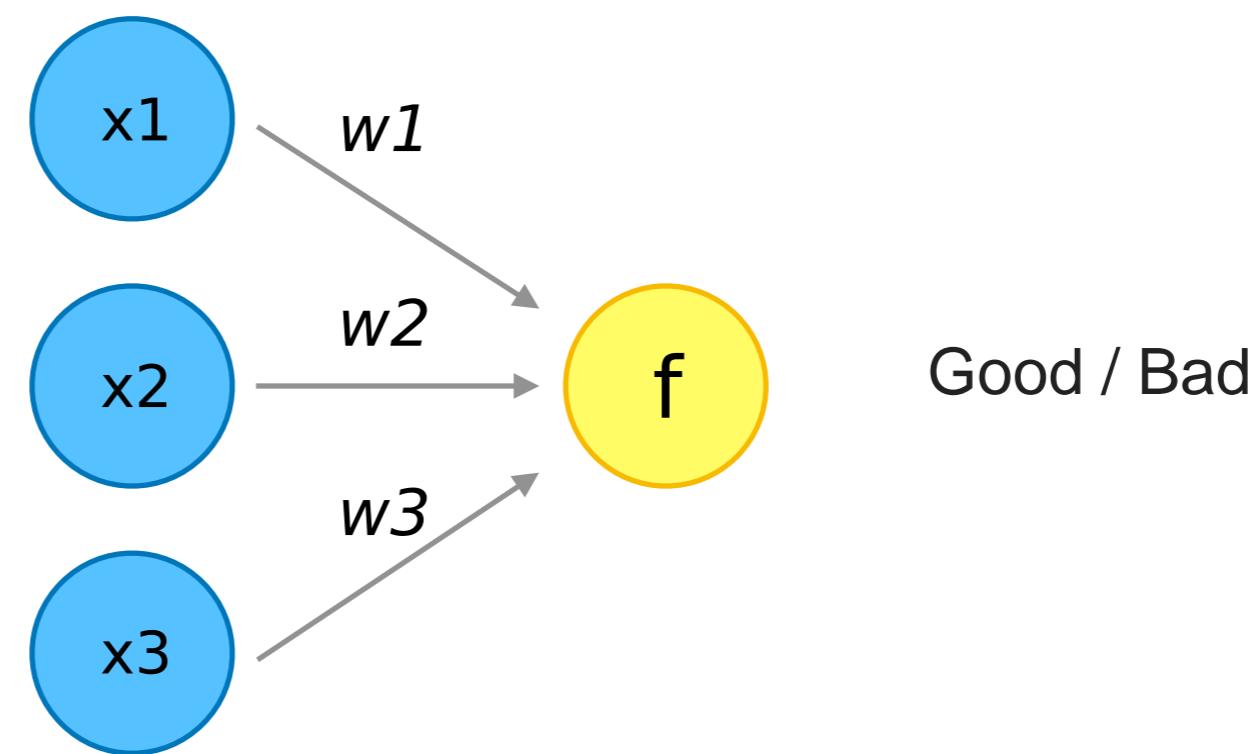
## Inference

House Price

Location

Total building area

$(\text{len}(\text{data}), 3)$



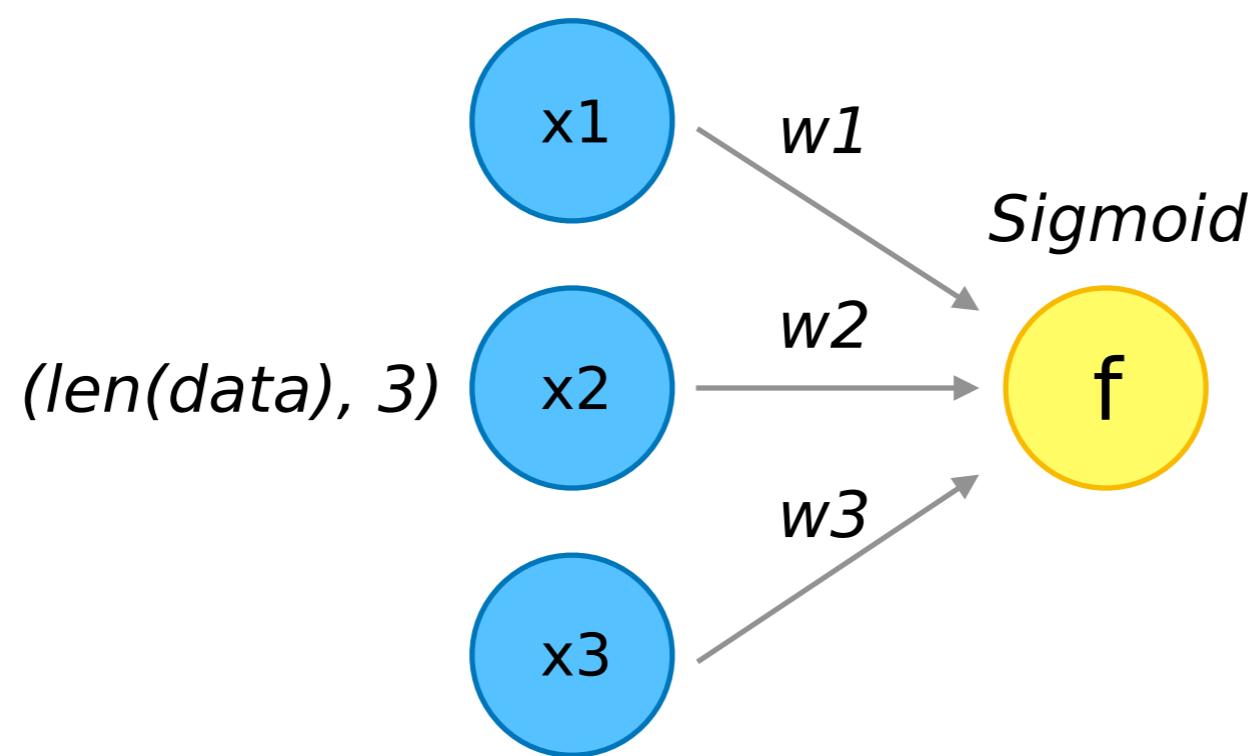
# Logistic Regression

## Inference

$$f = \mathbf{x} * \mathbf{w} + b$$

# Logistic Regression

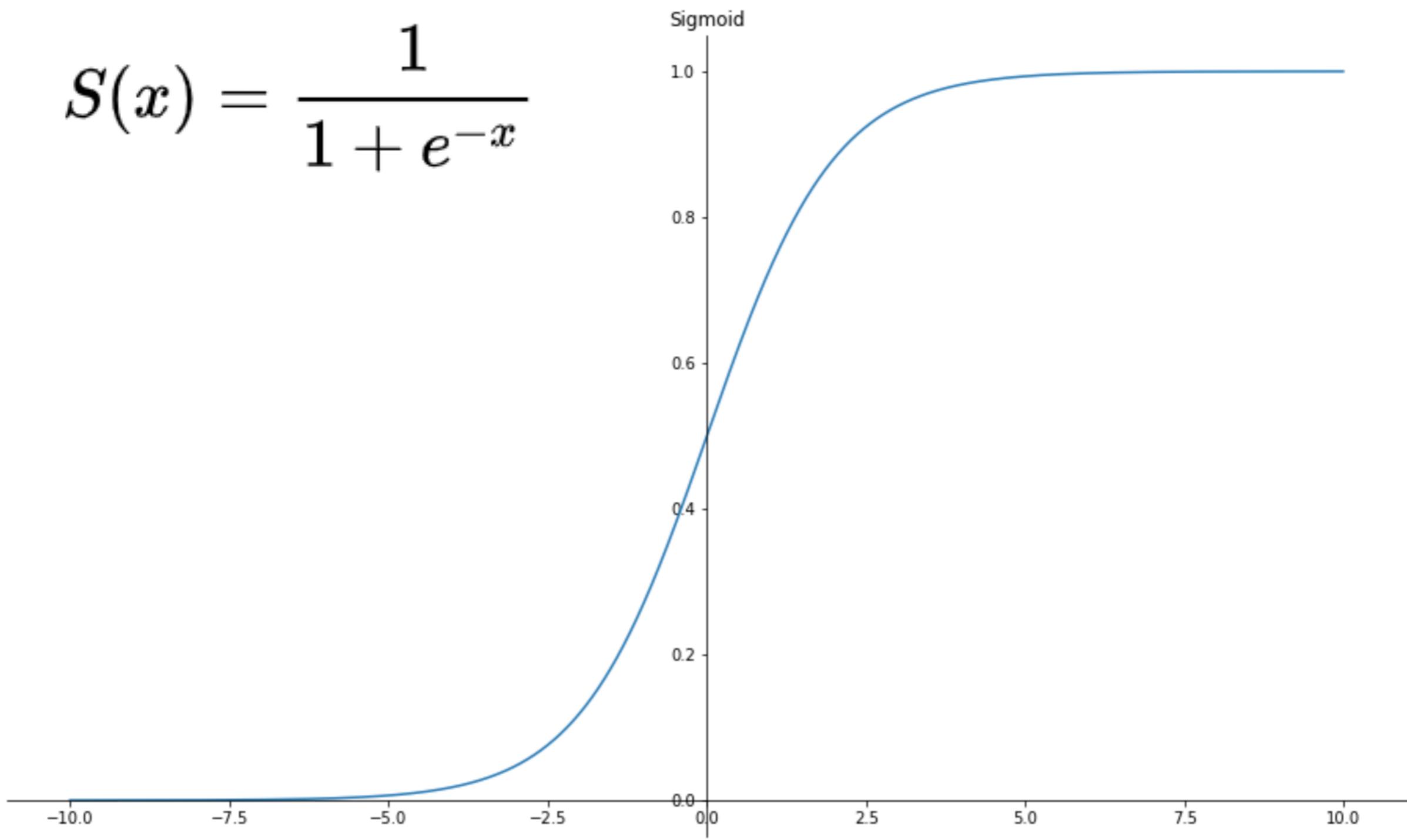
## Inference



# Logistic Regression

## Sigmoid

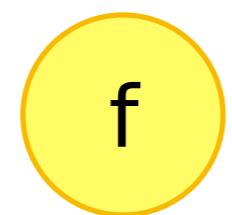
$$S(x) = \frac{1}{1 + e^{-x}}$$



# Logistic Regression

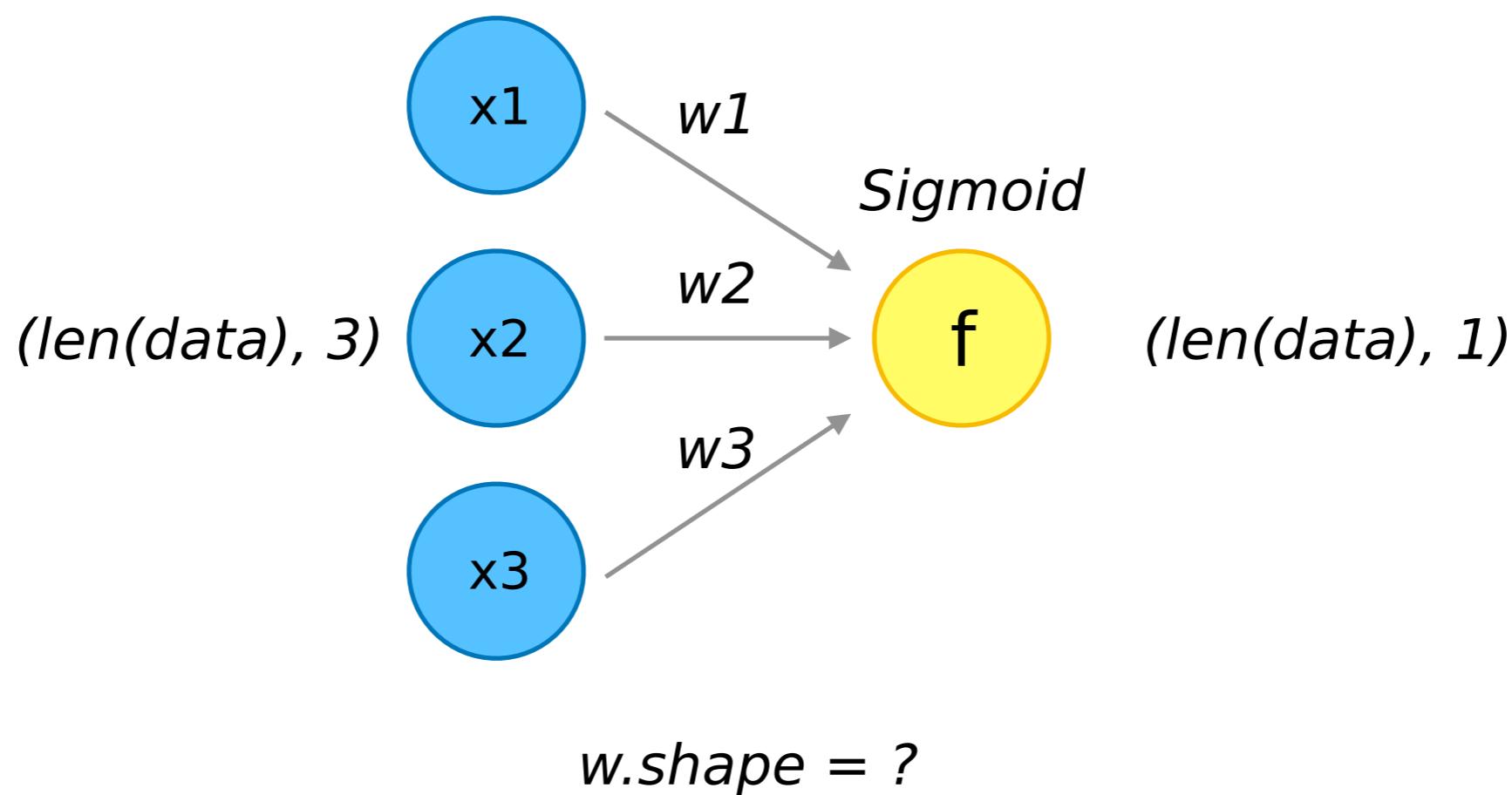
## Inference

$$S(x) = \frac{1}{1 + e^{-x}}$$


$$f = 1 / (1 + \exp(-(\mathbf{x} * \mathbf{w} + b)))$$

# Logistic Regression

## Inference



# Logistic Regression

## Dot Product

$$c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \dots + a_{in}b_{nj} = \sum_{s=1}^n a_{sn}b_{sj}$$

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix}$$


$$f = \mathbf{np.dot(x, w)} + \mathbf{b}$$

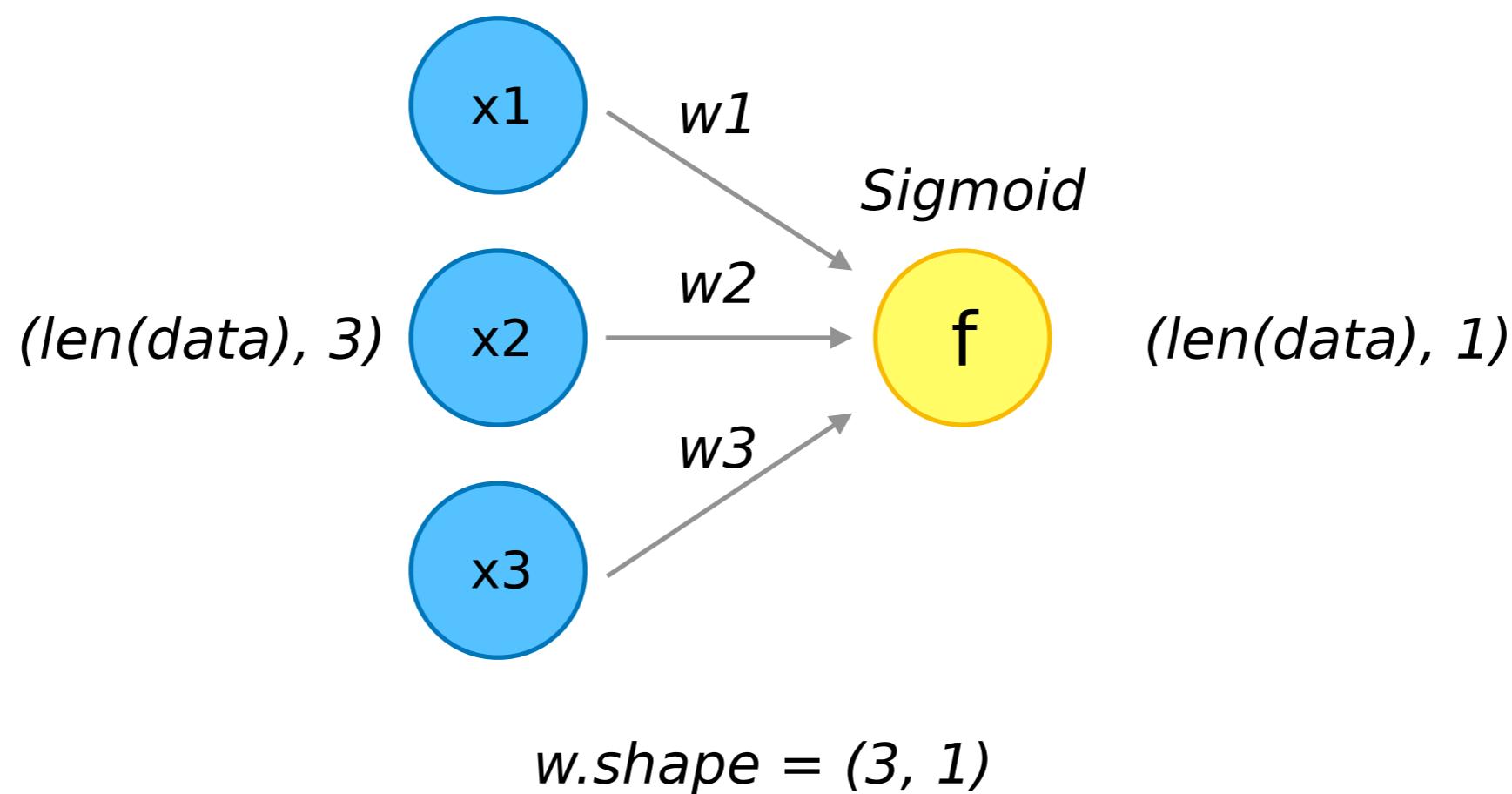
$$AB = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{pmatrix} = \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} & a_{11}b_{13} + a_{12}b_{23} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} & a_{21}b_{13} + a_{22}b_{23} \\ a_{31}b_{11} + a_{32}b_{21} & a_{31}b_{12} + a_{32}b_{22} & a_{31}b_{13} + a_{32}b_{23} \end{pmatrix}$$

**A.shape = (p, m)**

**B.shape = (n, k)**      **np.dot(A, B).shape = (p, k) if m == n**

# Logistic Regression

## Inference



# Difference between classification and regression task

**Classification predictive modeling problems are different from regression predictive modeling problems.**

- Classification is the task of predicting a discrete class label.
- Regression is the task of predicting a continuous quantity.

**There is some overlap between the algorithms for classification and regression; for example:**

- A classification algorithm may predict a continuous value, but the continuous value is in the form of a probability for a class label.
- A regression algorithm may predict a discrete value, but the discrete value in the form of an integer quantity.

[More info](#)