

# Foundations of Machine Learning (CS 725)

**FALL 2024** 

#### Lecture 2:

- Introduction to Linear Regression

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### Question 1a

Say you have a continuous random variable X with pdf g(x).

True or False? 
$$\int_{-\infty}^{\infty} g(x)dx = 1$$

### **Question 1b**

Say you have a continuous random variable X with pdf g(x).

True or False? g(x) can be greater than 1

### **Question 1c**

Say you have a continuous random variable X with pdf g(x).

True or Fig. 
$$\int_{a}^{b} g(x)dx$$
 can be greater than 1

### Question 2

We are given two random variables X and Y. X is discrete and can take values -2, -1,0,1,2, with probability  $\frac{1}{5}$  each. Let  $Y = X^2$ . What is the covariance of X and Y, Cov[X, Y]?

Ans: 0

# Recap: Learning a Predictor Function

Consider a target/true function  $f: \mathcal{X} \to \mathcal{Y}$  that holds over a training dataset  $\mathcal{D} = \{(\mathbf{x}_1, y_1), ..., (\mathbf{x}_n, y_n)\}, \mathbf{x}_i \in \mathcal{X}, y_i \in \mathcal{Y}$ . Our goal is to find a predictor function or hypothesis  $h: \mathcal{X} \to \mathcal{Y}$  that closely approximates f.

1. What functions are permissible for the hypothesis h? [Hypothesis Class]

2. How can we quantify the performance of the hypothesis? [Loss/Error Function]

3. How do we find the best hypothesis? [Optimization]

# **Linear Regression**

1. What functions are permissible for the hypothesis h? [Hypothesis Class]

Hypothesis class 
$$\mathcal{H}$$
 is:  $\{h_{\mathbf{w}}: h_{\mathbf{w}}(\mathbf{x}) = \mathbf{w}^T \mathbf{x}, \mathbf{w} \in \mathbb{R}^{d+1}\}$ 

2. How can we quantify the performance of the hypothesis? [Loss/Error Function]

Least squares (or mean squared) loss: 
$$\mathcal{L}_{\text{MSE}} = \sum_{i=1}^{N} (y_i - \mathbf{w}^T \mathbf{x}_i)^2$$

3. How do we find the best hypothesis? [Optimization]

$$\mathbf{w}_{\mathrm{MSE}} = \mathrm{argmin}_{\mathbf{w}} \sum_{i=1}^{N} (y_i - \mathbf{w}^T \mathbf{x}_i)^2 = \mathrm{argmin}_{\mathbf{w}} ||\mathbf{y} - \mathbf{X} \mathbf{w}||_2^2$$

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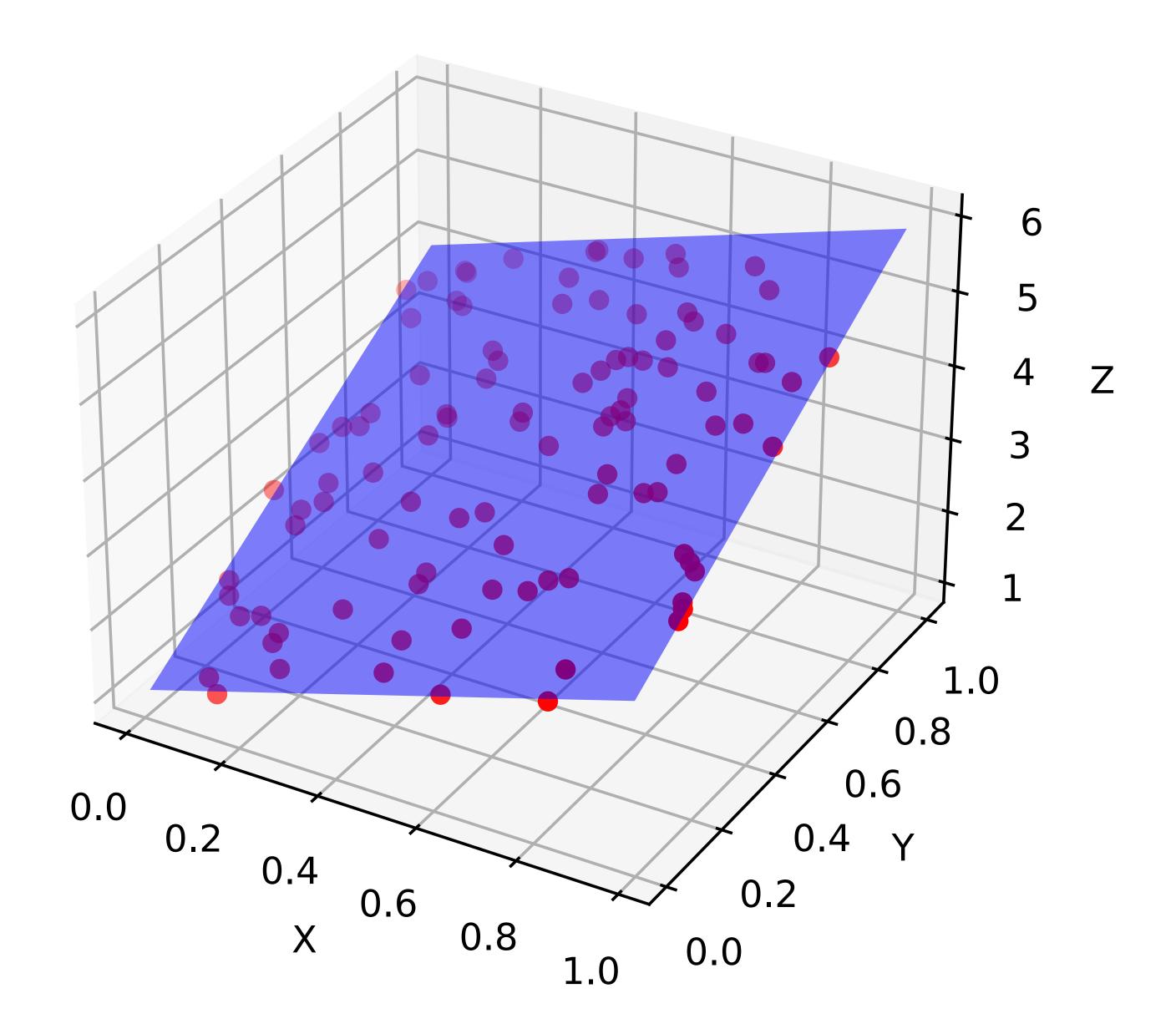
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$$\mathbf{w}_{\mathrm{MSE}} = \mathrm{argmin}_{\mathbf{w}} ||_2^2$$

# **Linear Regression: Linear Functions**

Fitting a plane to 2D points



## **Linear Regression**

Consider a set of predictor (*independent*) variables  $x_1, ..., x_d$  corresponding to an outcome (*dependent*) variable y. Regression is the problem of estimating y as a function of  $x_1, ..., x_d$ . In *Linear Regression*, the relationship between y and  $x_1, ..., x_d$  uses a linear model, that is it is linear in its parameters:

