

# An introduction to linear regression

## Topics we'll cover

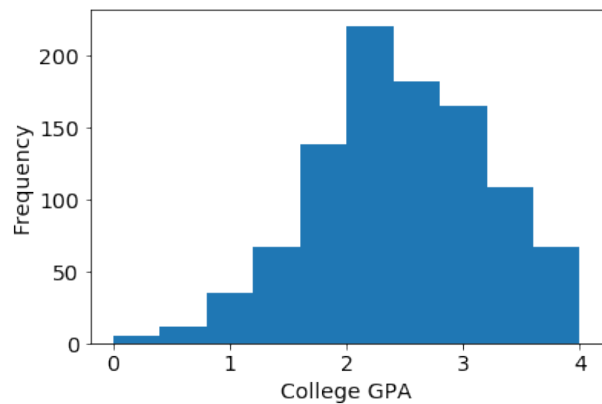
- ① The regression problem in one dimension
- ② Predictor and response variables
- ③ A loss function formulation
- ④ Deriving the optimal solution

# Linear regression

Fitting a line to a bunch of points.

## Example: college GPAs

Distribution of GPAs of students at a certain Ivy League university.

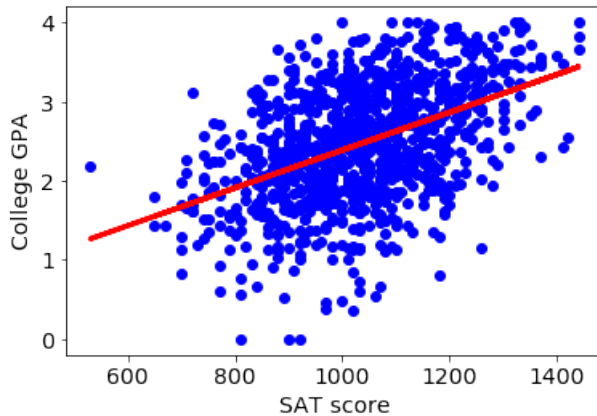


What GPA to predict for a random student from this group?

- Without further information, predict the **mean**, 2.47.
- What is the average squared error of this prediction?  
That is,  $\mathbb{E}[(\text{student's GPA}) - (\text{predicted GPA})]^2$ ?  
The **variance** of the distribution, 0.55.

## Better predictions with more information

We also have SAT scores of all students.



Mean squared error  
(MSE) drops to 0.43.

This is a **regression** problem with:

- **Predictor variable:** SAT score
- **Response variable:** College GPA

## Parametrizing a line

A line can be parameterized as  $y = ax + b$  ( $a$ : slope,  $b$ : intercept).

## The line fitting problem

Pick a line (parameters  $a, b$ ) suited to the data,  $(x^{(1)}, y^{(1)}), \dots, (x^{(n)}, y^{(n)}) \in \mathbb{R} \times \mathbb{R}$

- $x^{(i)}, y^{(i)}$  are predictor and response variables, e.g. SAT score, GPA of  $i$ th student.
- Minimize the mean squared error,

$$\text{MSE}(a, b) = \frac{1}{n} \sum_{i=1}^n (y^{(i)} - (ax^{(i)} + b))^2.$$

This is the **loss function**.

## Minimizing the loss function

Given  $(x^{(1)}, y^{(1)}), \dots, (x^{(n)}, y^{(n)})$ , minimize

$$L(a, b) = \sum_{i=1}^n (y^{(i)} - (ax^{(i)} + b))^2.$$