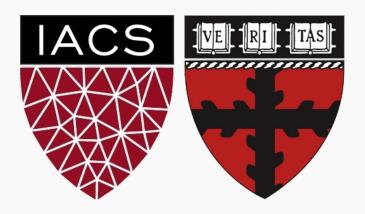
# Introduction to Regression

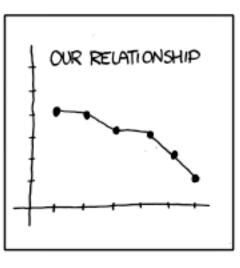
Part B: Error Evaluation and Model Comparison

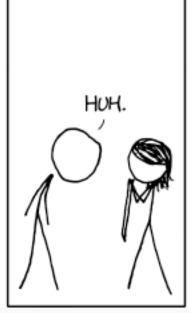
CS109A Introduction to Data Science

Pavlos Protopapas, Kevin Rader and Chris Tanner



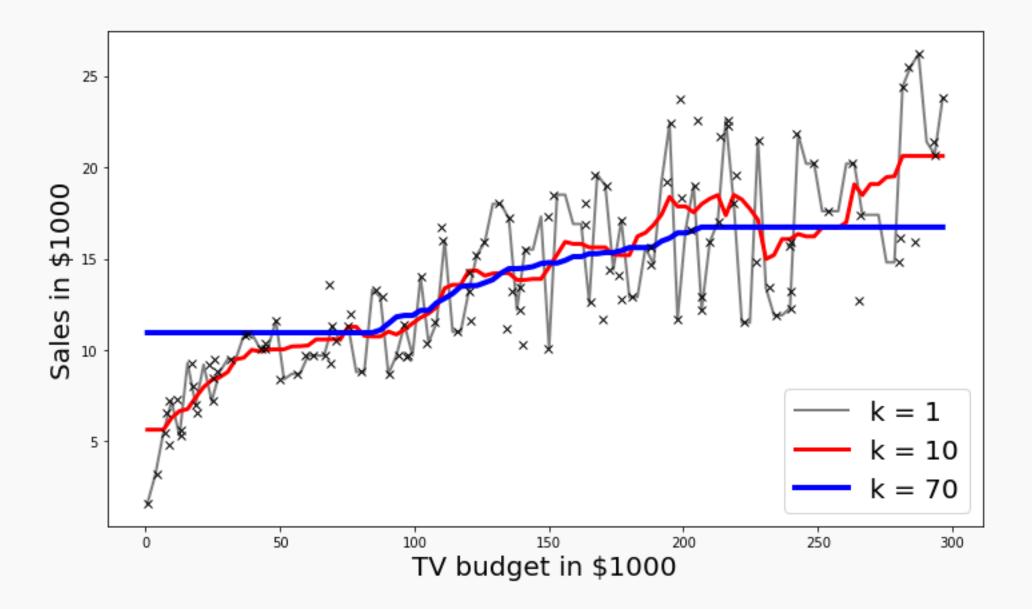








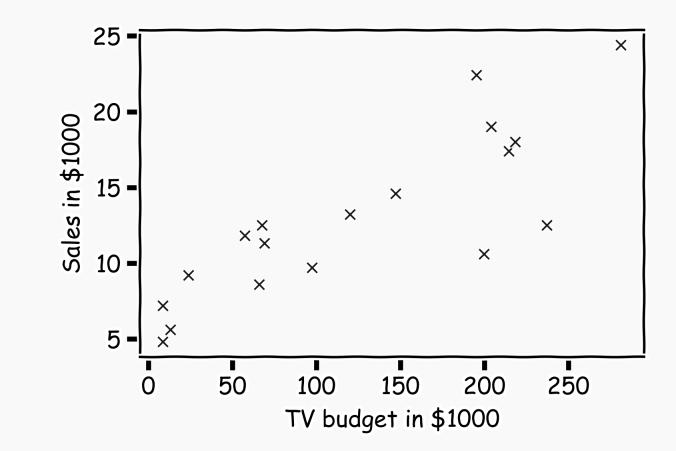






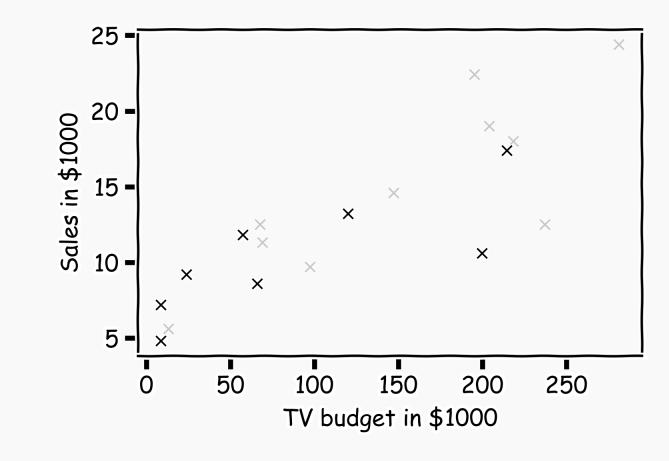


Start with some data.





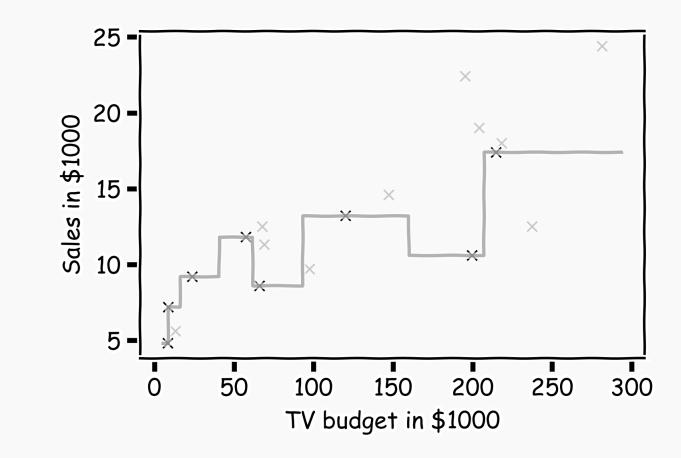
Hide some of the data from the model. This is called train-test split.



We use the train set to estimate  $\hat{y}$ , and the test set to evaluate the model.

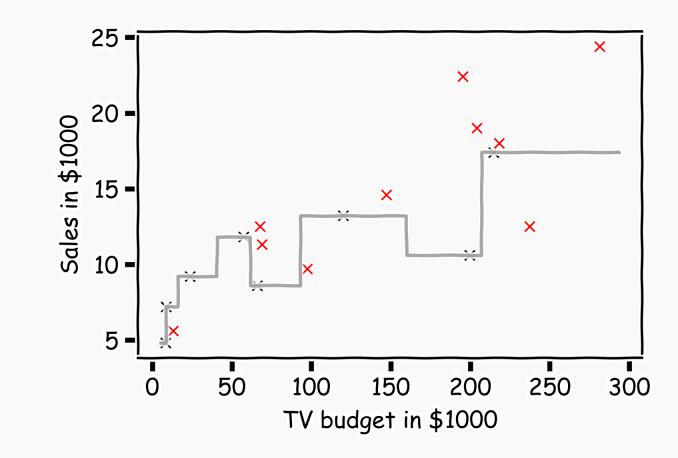


Estimate  $\hat{y}$  for k=1.



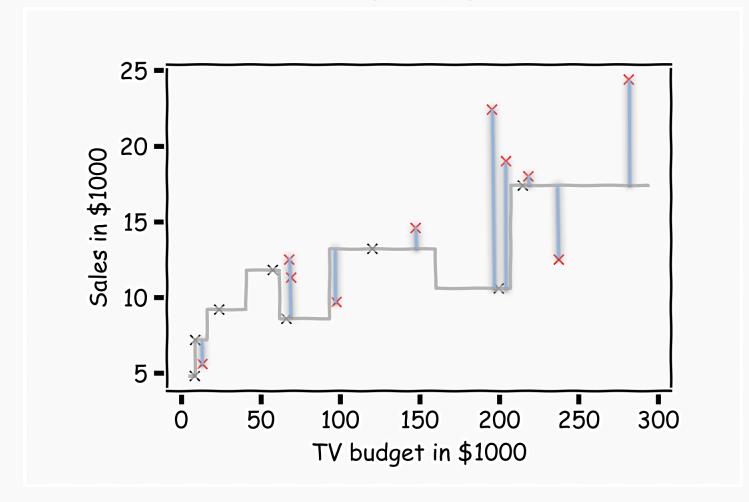


Now, we look at the data we have not used, the test data (red crosses).





Calculate the **residuals**  $(y_i - \hat{y}_i)$ .





In order to quantify how well a model performs, we aggregate the errors and we call that the *loss* or *error* or *cost function*.

A common loss function for quantitative outcomes is the **Mean Squared Error (MSE):** 

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Note: Loss and cost function refer to the same thing. Cost usually refer to the total loss where loss refers to a single training point.

Caution: The MSE is by no means the only valid (or the best) loss function!

- 1. Max Absolute Error
- 2. Mean Absolute Error
- 3. Mean Squared Error

**Note:** The square **R**oot of the **M**ean of the **S**quared **E**rrors (RMSE) is also commonly used.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}$$

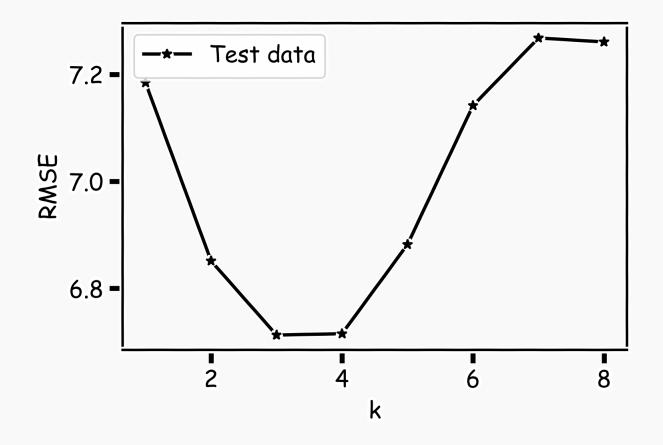


# Model Comparison



# Model Comparison

Do the same for all k's and compare the RMSEs. k=3 seems to be the best model.



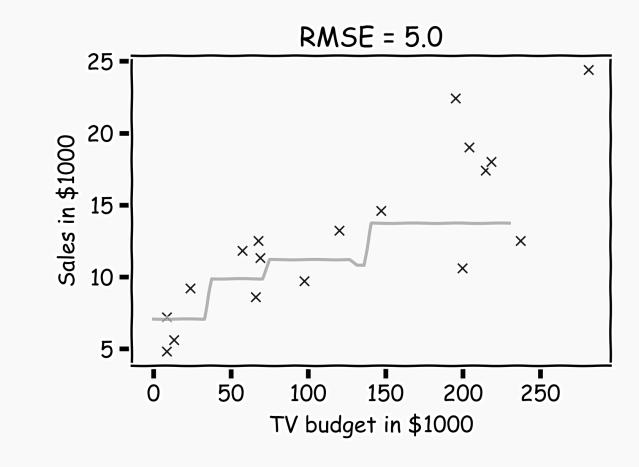


# Model Fitness



#### Model fitness

For a subset of the data, calculate the RMSE for k=3.

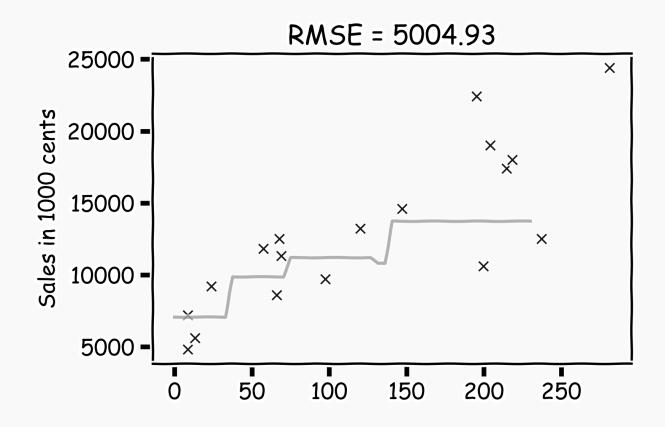


Is RMSE=5.0 good enough?



#### Model fitness

What if we measure the Sales in cents instead of dollars?



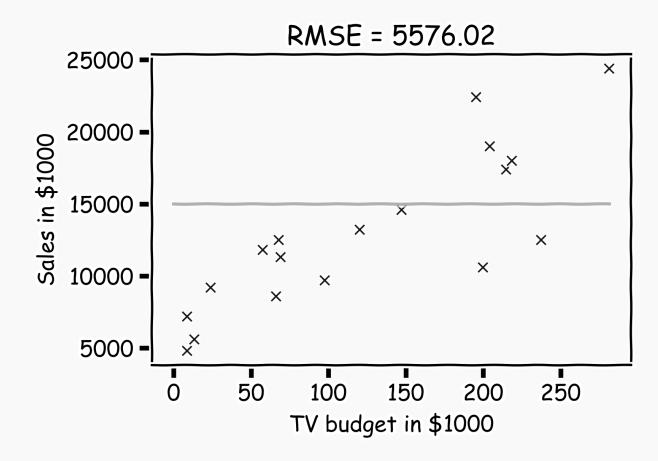
RMSE is now 5004.93.

Is that good?



#### Model fitness

It is better if we compare it to something.



We will use the simplest model:

$$\hat{y} = \bar{y} = \frac{1}{n} \sum_{i} y_{i}$$

as the worst possible model and

$$\widehat{y_i} = y_i$$

as the best possible model.

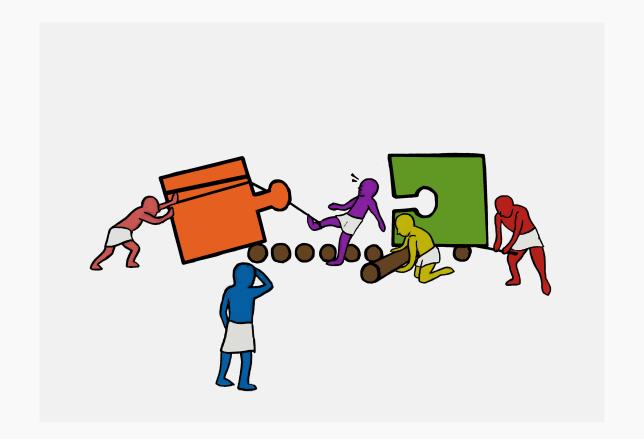


# R-squared

$$R^{2} = 1 - \frac{\sum_{i} (\hat{y}_{i} - y_{i})^{2}}{\sum_{i} (\bar{y} - y_{i})^{2}}$$

- If our model is as good as the mean value,  $\bar{y}$ , then  $R^2=0$
- If our model is perfect then  $R^2 = 1$
- $R^2$  can be negative if the model is worst than the average. This can happen when we evaluate the model in the test set.





Ex B.1



