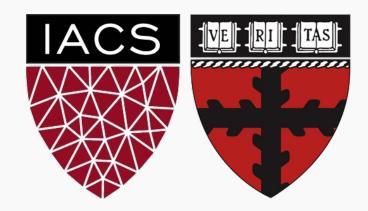
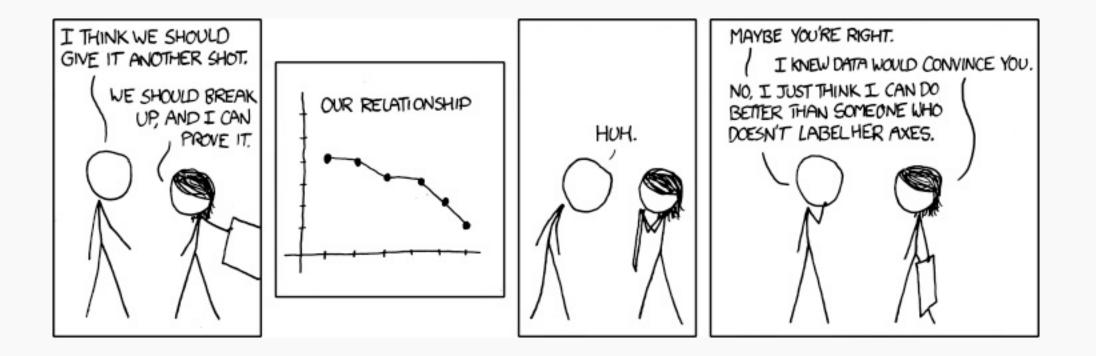
Introduction to Regression Part B: Error Evaluation and Model Comparison

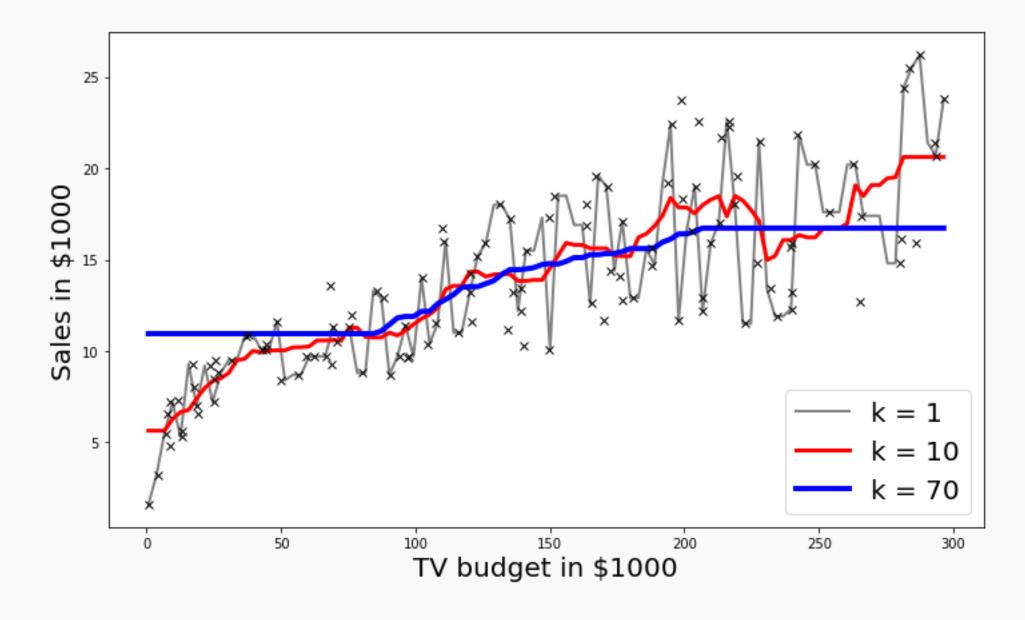
CS109A Introduction to Data Science Pavlos Protopapas, Natesh Pillai





https://xkcd.com/833/

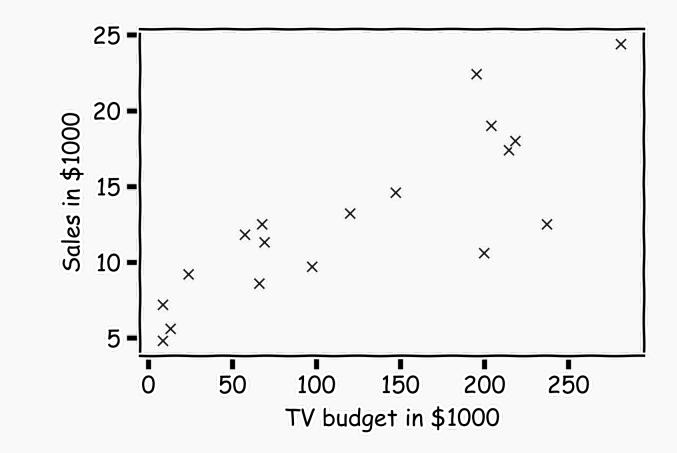






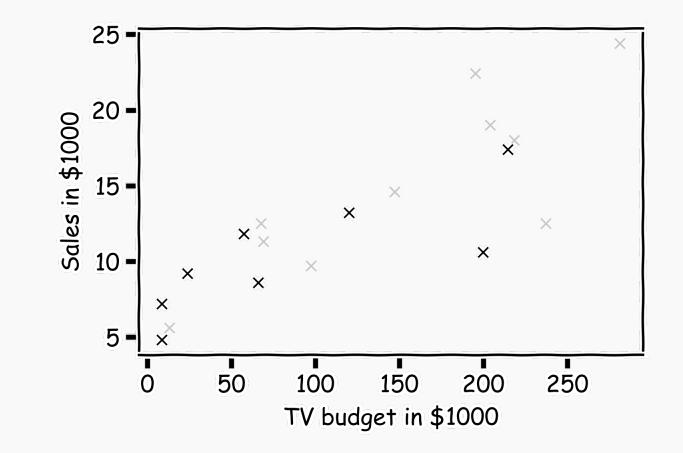


Start with some data.





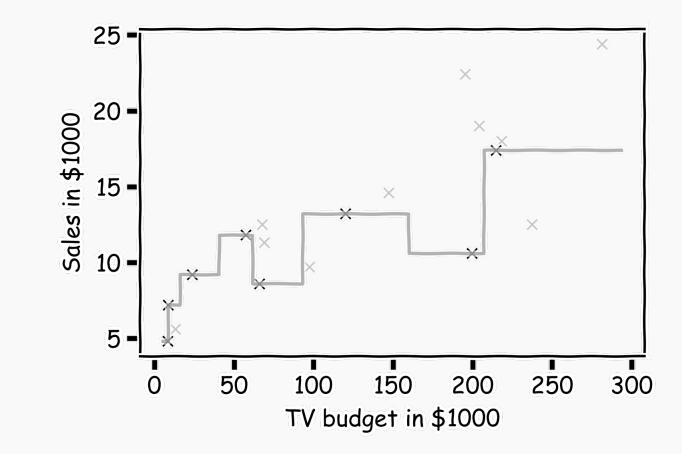
Hide some of the data from the model. This is called **train-test** split.



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

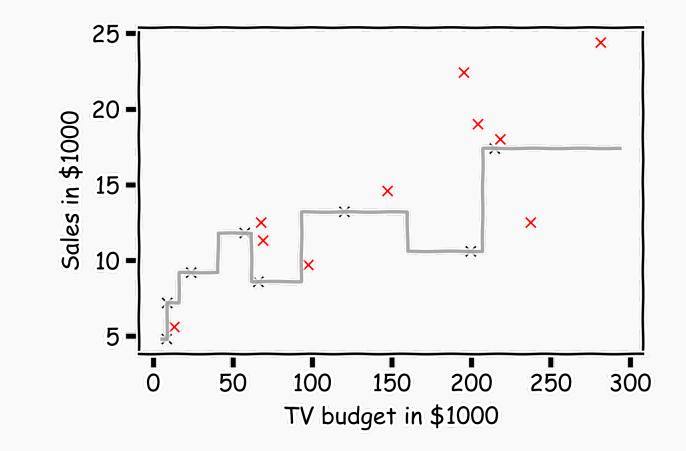


Estimate \hat{y} for k=1.



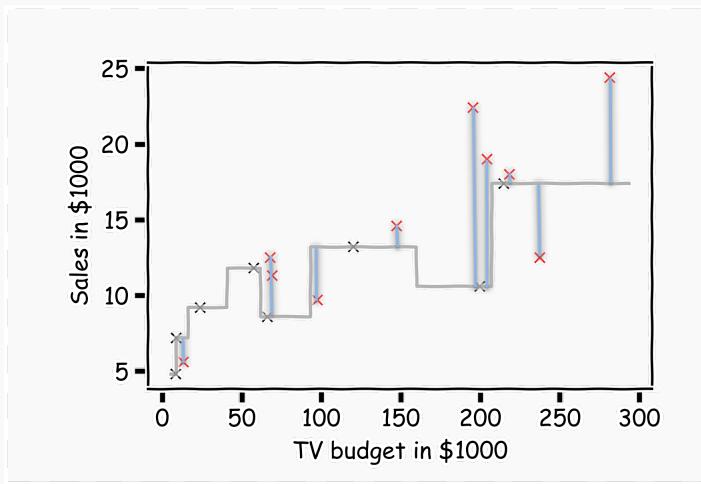


Now, we look at the data we have not used, the **test data** (red crosses).





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



For each observation (x_n, y_n) , the absolute residuals, $r_i = |y_i - \hat{y}_i|$ quantify the error at each observation.

?

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):

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

Note: Loss and cost function refer to the same thing. Cost usually refers 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!

Other choices for loss function:

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

We will motivate MSE when we introduce probabilistic modeling.

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

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



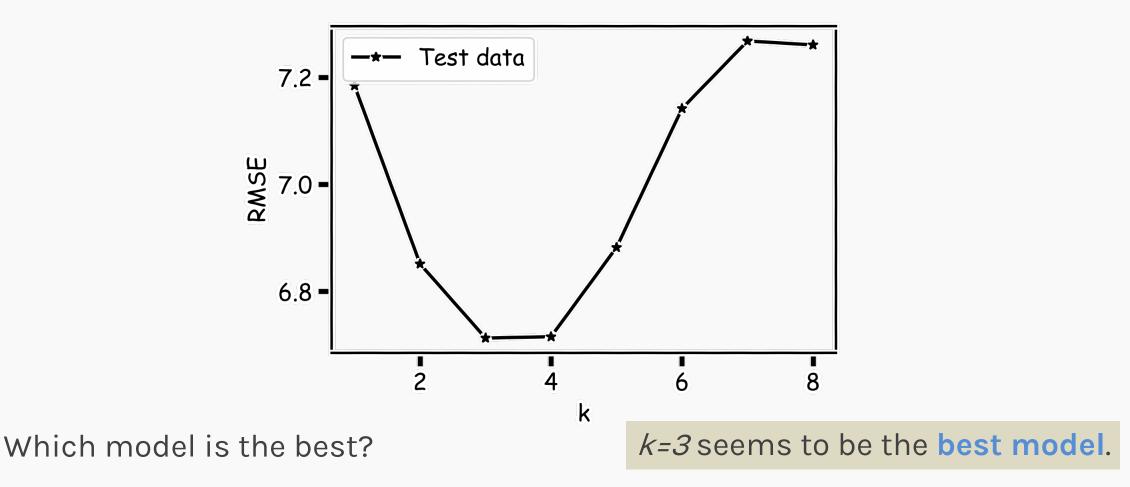
Model Comparison



Model Comparison



Do the same for all *k*'s and compare the RMSEs.





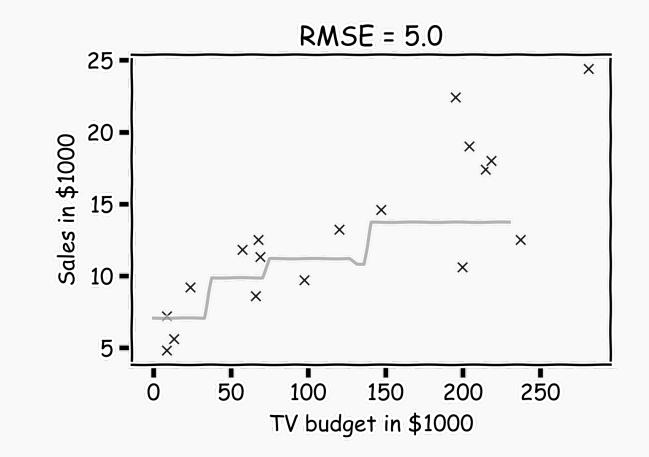
Model Fitness



Model fitness



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

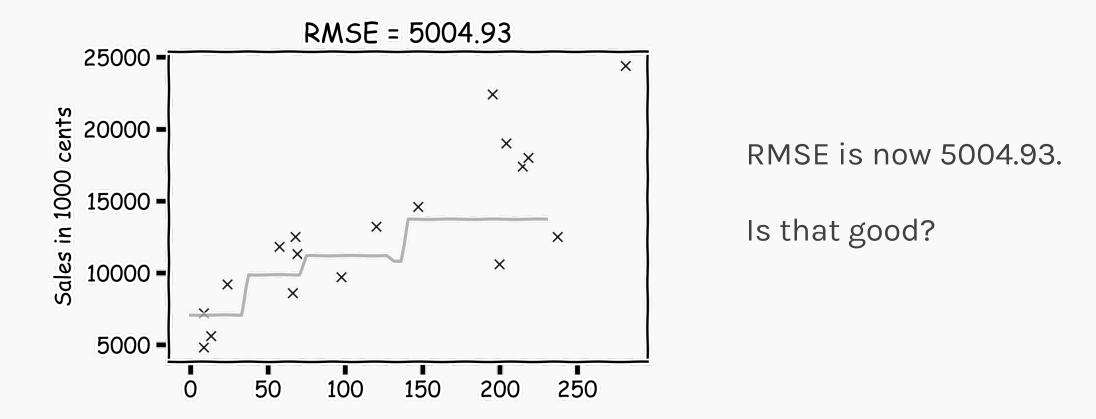


Is RMSE=5.0 good enough?



Model fitness

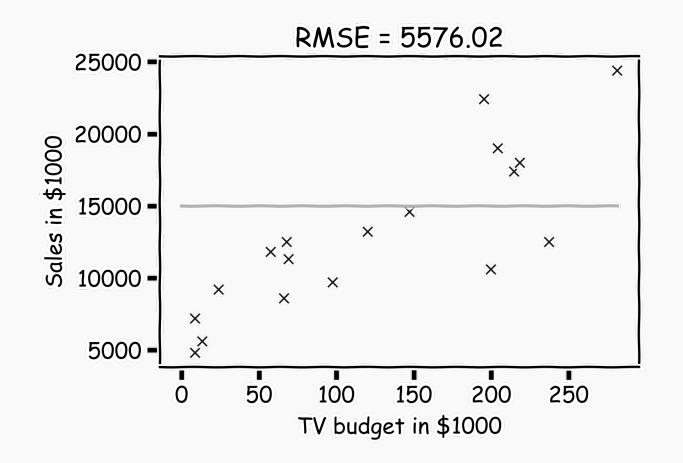
What if we measure the *Sales* in cents instead of dollars?





Model fitness

It is better if we compare it to something.



We will use the simplest model:

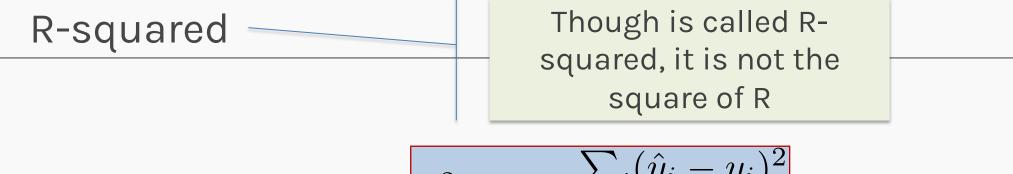
$$\hat{y} = \bar{y} = \frac{1}{n} \sum_{i} y_i$$

as the worst possible model and

$$\widehat{y}_i = y_i$$

as the **best** possible model.

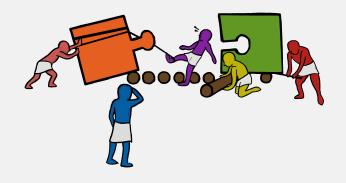




$$R^{2} = 1 - \frac{\sum_{i} (\bar{y}_{i} - y_{i})^{2}}{\sum_{i} (\bar{y} - y_{i})^{2}}$$

- If our model is as good as the mean value, \overline{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.





Use the loss to do model selection (10 min)

Exercise: Finding the Best k in kNN Regression

The goal here is to **find the value of k of the best performing model** based on the test MSE.

