Model Selection with Cross Validation

CS109A Introduction to Data Science Pavlos Protopapas, Natesh Pillai



COUNTY STATS FOR TEXAS

County	7-day average cases	 ↑ 7-day average deaths 	Cases	Deaths
Glasscock County	-1	0	134	3
Borden County	0	0	34	2
Goliad County	0	0	568	19



Using a single validation set to select amongst multiple models can be problematic - **there is the possibility of overfitting to the validation set**.



It is obvious that degree=3 is the correct model but the validation set by chance favors the linear model.

3

Using a single validation set to select amongst multiple models can be problematic - **there is the possibility of overfitting to the validation set**.

One solution to the problems raised by using a single validation set is to evaluate each model on **multiple** validation sets and average the validation performance.

One can randomly split the training set into training and validation multiple times **but** randomly creating these sets can create the scenario where important features of the data never appear in our random draws.





Train-Validation-Test The test set should never be touched for model training or We introduce a different sub-set, which we called validat selection. to select the model. Validation Train Test We use this to We use this to We use this to report model train a model select model performance







Train	Test	

Train	Train	Train	Train	Valid.	Test



Train	Test





Train	Test











Train	Test	











K-Fold Cross Validation

Given a data set $\{X_1, \dots, X_n\}$, where each $\{X_1, \dots, X_n\}$ contains J features.

To ensure that every observation in the dataset is included in at least one training set and at least one validation set we use the **K-fold validation**:

- split the data into K uniformly sized chunks, $\{C_1, \dots, C_K\}$
- we create K number of training/validation splits, using one of the K chunks for validation and the rest for training.

We fit the model on each training set, denoted $\hat{f}_{C_{-i}}$, and evaluate it on the corresponding validation set, $\hat{f}_{C_{-i}}$ (C_i). The cross validation is the performance of the model averaged across all validation sets:

$$CV(\text{Model}) = \frac{1}{K} \sum_{i=1}^{K} L(\hat{f}_{C_{-i}}(C_i))$$

ere *L* is a loss function.

Leave-One-Out

Or using the *leave one out* method:

- validation set: $\{X_i\}$
- training set: $X_{-i} = \{X_1, ..., X_{i-1}, X_{i+1}, ..., X_n\}$

for *i* = 1, ..., *n*:

We fit the model on each training set, denoted $\hat{f}_{X_{-i}}$, and evaluate it on the corresponding validation set, $\hat{f}_{X_{-i}}(X_i)$.

The *cross validation score* is the performance of the model averaged across all validation sets: $1\sum_{n=1}^{n}$

$$CV(\text{Model}) = \frac{1}{n} \sum_{i=1}^{n} L(\hat{f}_{X_{-i}}(X_i))$$

where *L* is a loss function.









Description

X Exercise: Best Degree of Polynomial using Cross-validation

The aim of this exercise is to find the **best degree** of polynomial based on the MSE values. Further, plot the train and cross-validation error graphs as shown below.



Instructions:

- · Read the dataset and split into train and validation sets.
- · Select a max degree value for the polynomial model.
- For each degree:
 - · Perform k-fold cross validation
 - Fit a polynomial regression model for each degree on the training data and predict on the validation data
- · Compute the train, validation and cross-validation error as MSE values and





When to use CV and when to use Validation only?

Choosing number of folds?







Scaling: Revisited

