EEC1509 - Machine Learning

Lesson #06 K-Nearest Neighbors

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Update repository

```
git clone https://github.com/ivanovitchm/EEC1509_MachineLearning.git
```

Ou ....

```
git pull
```

Agenda

- Univariate KNN
  - Euclidean distance for univariate
  - Function to make predictions
  - Error metrics
- Multivariate KNN
  - Normalize columns
  - Euclidean distance for multivariate
- Hyperparameter optimization
- Cross-Validation

Inside Airbnb
Adding data to the debate

About Behind Get the Data

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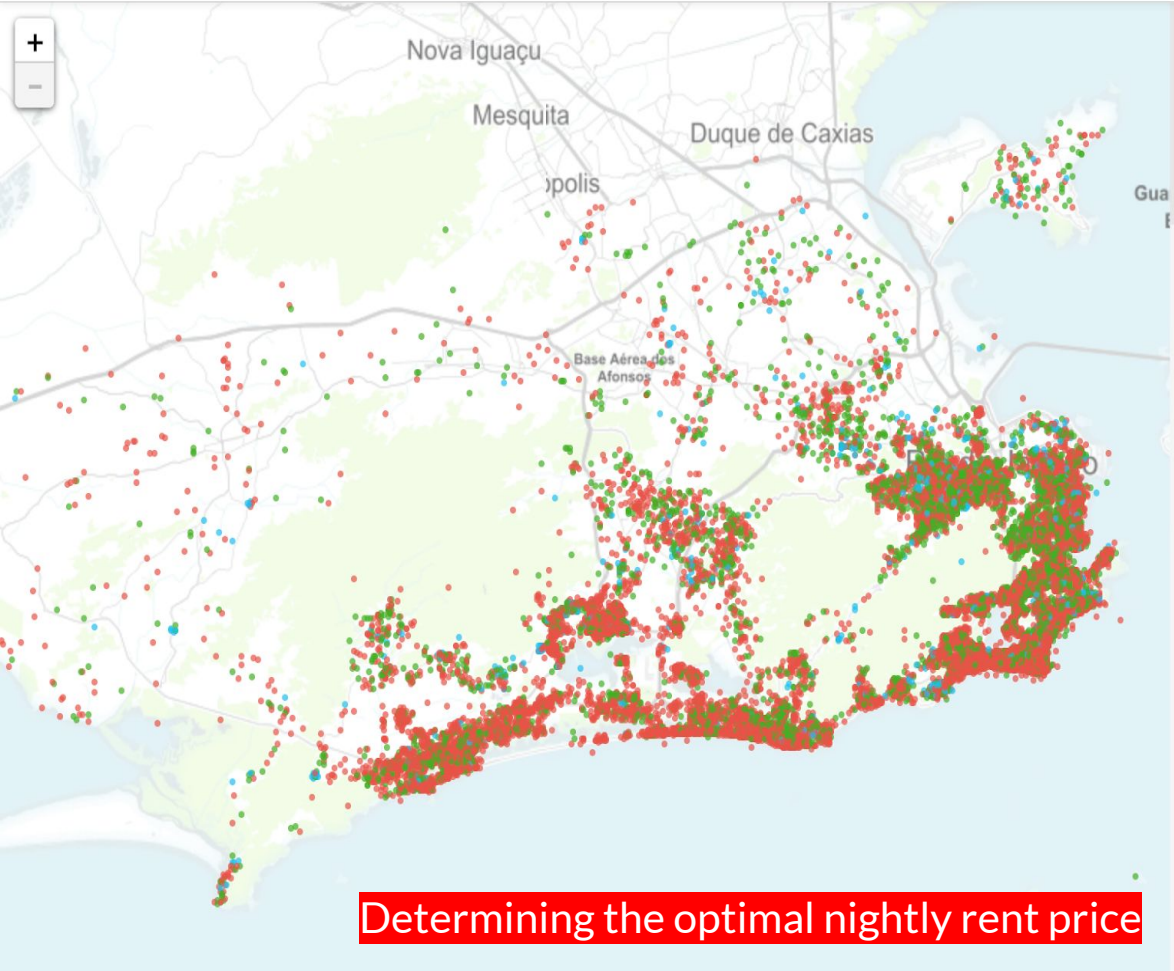


Rio de Janeiro

Filter by:
Rio de Janeiro

32,469
out of **32,469** listings (100%)

About Airbnb in Rio de Janeiro

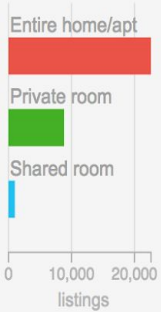
How is Airbnb really being used in and affecting your neighbourhoods?

Room Type

Only entire homes/apartments

Airbnb hosts can list entire homes/apartments, private or shared rooms.

Depending on the room type and activity, an airbnb listing could be more like a hotel, disruptive for neighbours, taking away housing, and illegal.



69.7%
entire homes/apartments

R$682
price/night

22,631 (69.7%)
entire home/apartments

8,822 (27.2%)
private rooms

1,016 (3.1%)
shared rooms

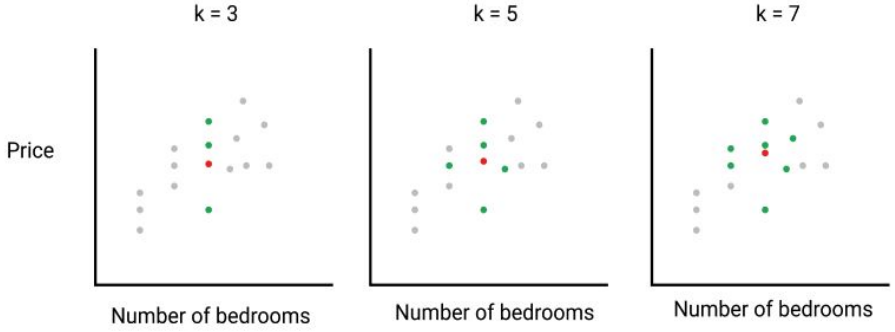
Determining the optimal nightly rent price

- host_response_rate: the response rate of the host
- host_acceptance_rate: number of requests to the host that convert to rentals
- host_listings_count: number of other listings the host has
- latitude: latitude dimension of the geographic coordinates
- longitude: longitude part of the coordinates
- city: the city the living space resides
- zipcode: the zip code the living space resides
- state: the state the living space resides
- accommodates: the number of guests the rental can accommodate
- room_type: the type of living space (Private room, Shared room or Entire home/apt
- bedrooms: number of bedrooms included in the rental
- bathrooms: number of bathrooms included in the rental
- beds: number of beds included in the rental
- price: nightly price for the rental
- cleaning_fee: additional fee used for cleaning the living space after the guest leaves
- security_deposit: refundable security deposit, in case of damages
- minimum_nights: minimum number of nights a guest can stay for the rental
- maximum_nightss: maximum number of nights a guest can stay for the rental
- number_of_reviews: number of reviews that previous guests have left

96 rows

```
total 112M
-rw-r--r-- 1 root root 112M Sep 29 21:46 listings.csv
drwxr-xr-x 2 root root   1M Sep 27 20:32 sample_data
```

Select the number of similar listings, **k**, you want to compare with.



For each listing, calculate how similar it is to our unpriced listing.

For this example, we'll use 3 for our **k** value.

K-Nearest Neighbors

Rank each listing by the similarity metric and select the first **k** listings.

Calculate the mean list price for the **k** similar listings and use as our list price.

Euclidean distance

$$d = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2}$$

index	host_listings_count	accommodates	bedrooms	bathrooms	beds
0	26	4	1	1	2
1	1	6	3	3	3

$(q_1 - p_1) + (q_2 - p_2) + \ldots + (q_n - p_n)$ differences (26 - 1) + (4 - 6) + (1 - 3) + (1 - 3) + (2 - 3)

$(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2$ squared differences $(25)^2 + (-2)^2 + (-2)^2 + (-2)^2 + (-1)^2$

$\sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2}$

Euclidean distance

$= \sqrt{625 + 4 + 4 + 4 + 1}$

$= \sqrt{638}$

$= 25.258661$

Euclidean distance - example

Univariate case

$$d = \sqrt{(q_1 - p_1)^2}$$

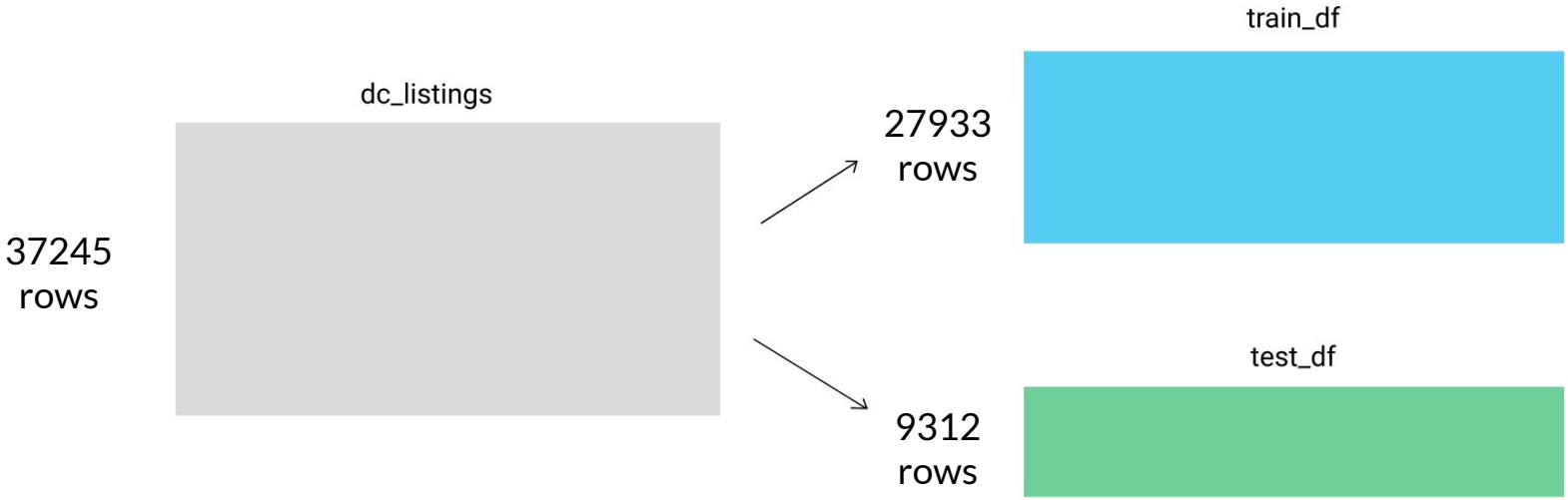
$$d = |q_1 - p_1|$$

	accommodates
our listing	8

	index	accommodates	distance
dc_listings	0	4	$(4 - 8)^2$
	1	6	$(6 - 8)^2$
	2	1	$(1 - 8)^2$
	3	2	$(2 - 8)^2$

Testing quality of predictions

Machine Learning Model



Error metrics

Mean Absolute Error

$$MAE = \frac{|actual_1 - predicted_1| + |actual_2 - predicted_2| + \ \ldots + |actual_n - predicted_n|}{n}$$

Mean Squared Error

$$MSE = \frac{(actual_1 - predicted_1)^2 + (actual_2 - predicted_2)^2 + \ \ldots + (actual_n - predicted_n)^2}{n}$$

Root Mean Squared Error

$$RMSE = \sqrt{MSE}$$

https://medium.com/human-in-a-machine-world/mae-and-rmse-which-metric-is-better-e60ac3bde13d

Improve the accuracy (multivariate knn)

- Increase the number of attributes the model uses to calculate similarity when ranking the closest neighbors
- Increase k, the number of nearby neighbors the model uses when computing the prediction
- We'll focus on more robust techniques for testing a machine learning model's accuracy, namely, cross-validation

Improve the accuracy (multivariate knn)

When selecting more attributes to use in the model, we need to watch out for columns that don't work well with the distance equation.

- non-numerical values (e.g. city or state)
  - Euclidean distance equation expects numerical values
- missing values
  - distance equation expects a value for each observation and attribute
- non-ordinal values (e.g. latitude or longitude)
  - ranking by Euclidean distance doesn't make sense if all attributes aren't ordinal

Removing features

- room_type: e.g. **Private room**
- city: e.g. **Washington**
- state: e.g. **DC**

- host_response_rate
- host_acceptance_rate
- host_listings_count

- latitude: e.g. **38.913458**
- longitude: e.g. **-77.031**
- zipcode: e.g. **20009**

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 37245 entries, 3629 to 33003
Data columns (total 10 columns):
accommodates          37245 non-null int64
bathrooms             37168 non-null float64
bedrooms              37219 non-null float64
beds                  37188 non-null float64
price                 37245 non-null float64
security_deposit      18540 non-null object
cleaning_fee          23159 non-null object
minimum_nights        37245 non-null int64
maximum_nights        37245 non-null int64
number_of_reviews     37245 non-null int64
dtypes: float64(4), int64(4), object(2)
memory usage: 3.1+ MB
```

Normalize columns

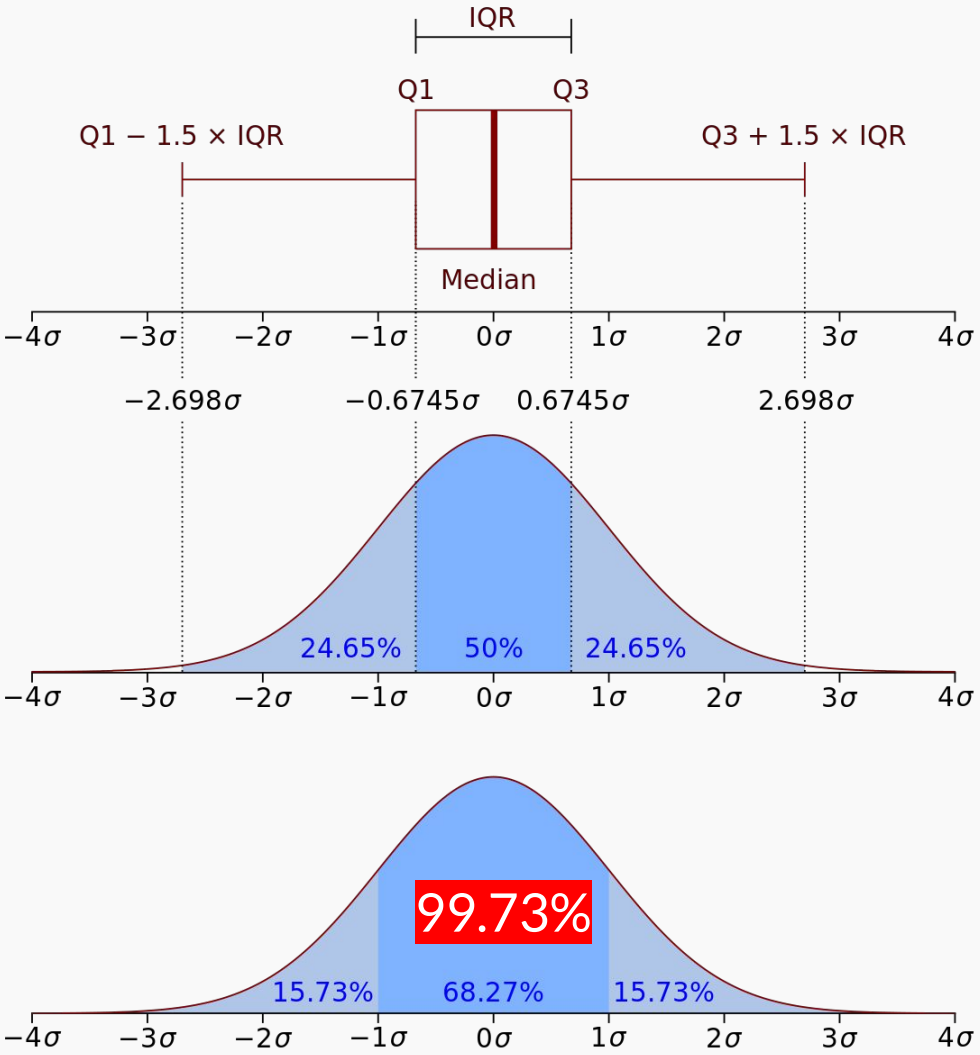
accommodates	bathrooms	bedrooms	beds	price	minimum_nights	maximum_nights	number_of_reviews
8	1.0	1.0	1.0	200.0	2	60	0
6	2.0	3.0	4.0	901.0	10	27	0
2	1.0	1.0	1.0	229.0	2	50	24
2	1.0	1.0	2.0	200.0	3	1125	0
2	2.0	1.0	1.0	75.0	2	30	2

accommodates	bathrooms	bedrooms	beds	price	minimum_nights	maximum_nights	number_of_reviews
1.455750	-0.67557	-0.597149	-0.779645	200.0	-0.121917	-0.008480	-0.337027
0.691698	0.27004	1.229023	0.665006	901.0	0.254259	-0.008483	-0.337027
-0.836405	-0.67557	-0.597149	-0.779645	229.0	-0.121917	-0.008481	0.981934
-0.836405	-0.67557	-0.597149	-0.298095	200.0	-0.074895	-0.008400	-0.337027
-0.836405	0.27004	-0.597149	-0.779645	75.0	-0.121917	-0.008482	-0.227114

Normalize columns (outliers)

```
1 normalized_listings.describe()
```

	accommodates	bathrooms	bedrooms	beds	price	minimum_nights	maximum_nights	number_of_reviews
count	3.712900e+04	3.712900e+04	3.712900e+04	3.712900e+04	37129.000000	3.712900e+04	3.712900e+04	3.712900e+04
mean	-1.314721e-16	-4.592913e-18	-4.822558e-17	-4.478090e-17	645.284872	-2.066811e-17	7.654855e-19	2.387358e-17
std	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1658.580291	1.000000e+00	1.000000e+00	1.000000e+00
min	-1.218415e+00	-1.621158e+00	-1.510215e+00	-1.261178e+00	0.000000	-1.689371e-01	-8.484452e-03	-3.370226e-01
25%	-8.363938e-01	-6.755609e-01	-5.971412e-01	-7.796344e-01	150.000000	-1.689371e-01	-8.482279e-03	-3.370226e-01
50%	-7.235234e-02	-6.755609e-01	-5.971412e-01	-2.980906e-01	296.000000	-1.219157e-01	-8.400222e-03	-3.370226e-01
75%	3.096684e-01	2.700359e-01	3.159325e-01	1.834533e-01	626.000000	-2.787293e-02	-8.400222e-03	-1.721546e-01
max	5.952288e+01	1.729078e+01	3.957810e+01	2.281602e+01	41719.000000	5.733824e+01	1.609190e+02	1.647951e+01


IQR
Q1
Q3
Q1 − 1.5 × IQR
Q3 + 1.5 × IQR
Median
−4σ
−3σ
−2σ
−1σ
0σ
1σ
2σ
3σ
4σ
−2.698σ
−0.6745σ
0.6745σ
2.698σ
24.65%
50%
24.65%
99.73%
15.73%
68.27%
15.73%

Euclidean distance for multivariate case

	accommodates	bathrooms
	-0.596544	-0.439151
	-0.596544	0.412923

$(q_1 - p_1) + (q_2 - p_2) + \ldots + (q_n - p_n)$ differences (-0.596544 + 0.596544) + (-0.439151 - 0.412923)

$(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2$ squared differences $(0)^2$ + $(-0.852074)^2$

$\sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2}$

Euclidean distance $= \sqrt{0 + 0.72603}$

$= 0.852074$

Introduction to scikit-learn

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, … — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, … — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, … — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples

Scikit-learn workflow

The scikit-learn workflow consists of 4 main steps:

- instantiate the specific machine learning model you want to use
- fit the model to the training data
- use the model to make predictions
- evaluate the accuracy of the predictions

Scikit-learn workflow

```
# features
train_columns = ['accommodates', 'bathrooms']

# instantiate a knn object
knn = KNeighborsRegressor(n_neighbors=5, algorithm='brute', metric='euclidean')

# train the model
knn.fit(train_df[train_columns], train_df['price'])

# predict
predictions = knn.predict(test_df[train_columns])

# evaluate
rmse = np.sqrt(mean_squared_error(predictions,test_df.price))
```

Improve the accuracy (multivariate knn)

- We'll focus on the impact of increasing k, the number of nearby neighbors the model uses to make predictions.

Hyperparameters

- When we **vary the feature**s that are used in the model, we're **affecting the data** that the model uses.
- On the other hand, **varying the k value affects the behavior of the model independently of the actual data** that's used when making predictions.
- Values that affect the behavior and performance of a model that are unrelated to the data that's used are referred to as hyperparameters.

Hyperparameter Optimization

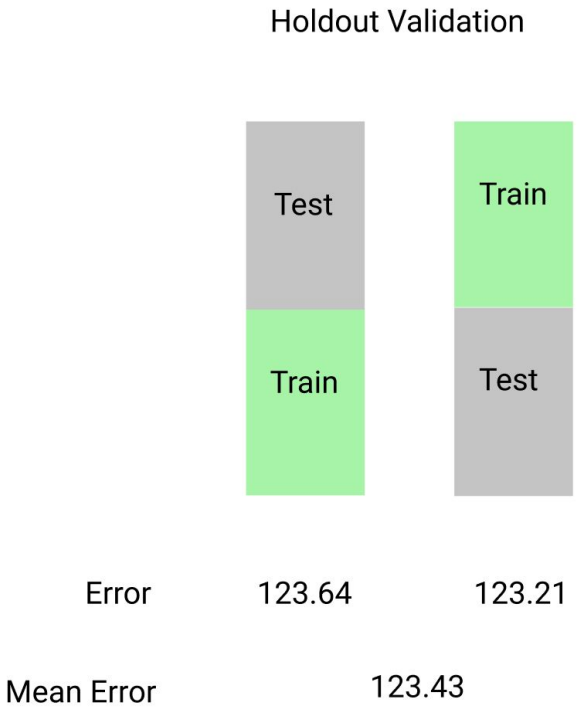
A simple but common hyperparameter optimization technique is known as grid search:

- selecting a subset of the possible hyperparameter values,
- training a model using each of these hyperparameter values,
- evaluating each model's performance,
- selecting the hyperparameter value that resulted in the lowest error value.

Improve the accuracy (multivariate knn)

- We can focus on more robust techniques for testing a machine learning model's accuracy

Holdout Validation



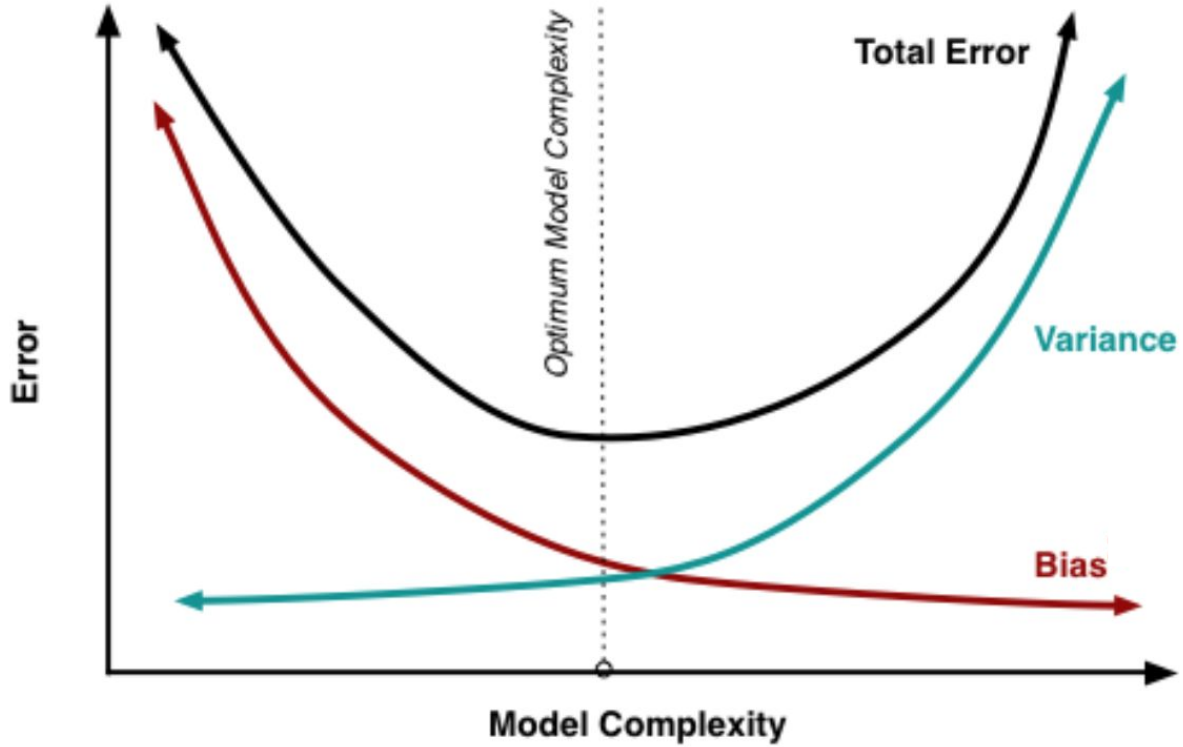
Holdout validation is actually a specific example of a larger class of validation techniques called **k-fold cross-validation.**

K-Fold Cross Validation

Errors	120.55	122.11	125.91	123.41	122.81

Mean Error 122.96

Bias-Variance Tradeoff




MacBook Pro