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# Welcome to Week 6 Lecture 2!

Data Science in Python &  
Machine Learning



# Announcements

## 1. Belt Exam for Stack 2

- a. March 11th - March 13th
- b. Must have attended 80% of classes
- c. Must have passed 90% of assignments
- d. All assignments & resubmits from weeks 1 & 2 are due by Friday at 9am PST (March 11th)

## 2. Final Project

- a. Have at least 5 slides with 2 visualizations.
- b. 1 slide should state the problem.
- c. 2 slides should include visualizations with analyses.
- d. 1 slide should include trends or insights you gained from the data.
- e. 1 slide should include recommendations for stakeholders.

# Learning Goals

**After this lesson you will be able to:**

1. Explain bias, variance, and the bias/variance tradeoff.
2. Visualize how a Tree Based model makes predictions
3. Use regularization to reduce variance (overfitting) in a Tree Based model.

## Introducing the Bias/Variance Tradeoff

Imagine you have a study guide for an upcoming test.

How are you going to use that study guide?

- a) Memorize the study guide?
- b) Focus on just on big ideas?

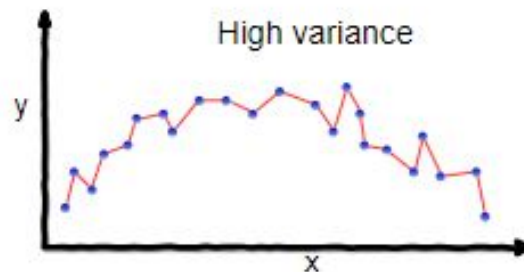
The effectiveness of your approach will only be known on  
**TEST DAY!**

## High Variance = OVERfitting

Study approach A (memorize every detail) corresponds to a model with high variance.

You would do perfect on a test that was exactly the same as your study guide.

But what if there is a question not specifically addressed on your study guide? You have no ability to recognize big ideas to make a valid guess.



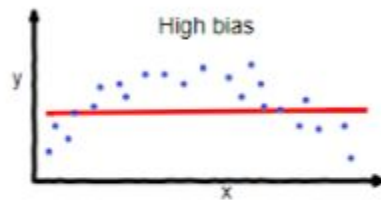
Notice how this model perfectly predicts each data point IF the “test” is the same as the “study guide”.

## High Bias = UNDERfitting

Approach B (only big ideas and no detail) corresponds to a model with high bias

You would miss any question on the test that involved knowing details.

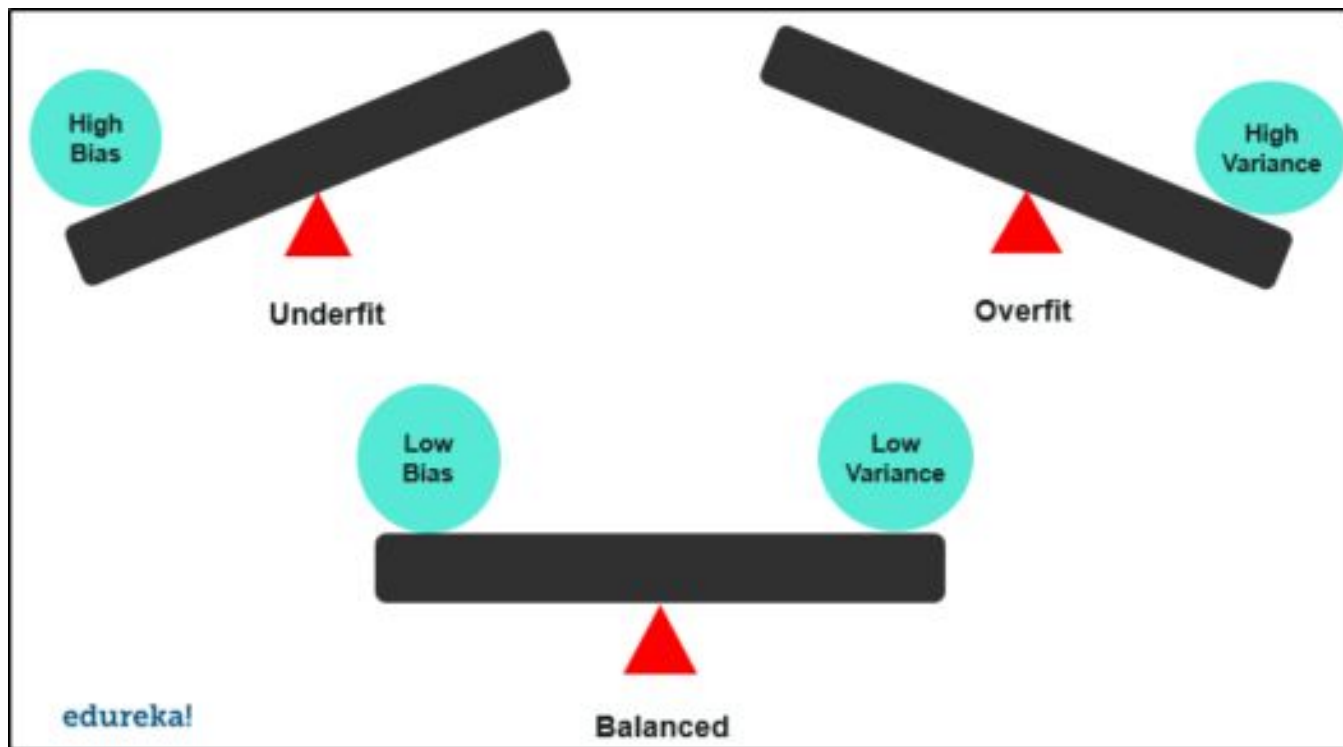
But what if there is a question from the study guide that goes into more detail? You could potentially miss this question because you did not focus on the details.



underfitting

This model is in a reasonable range of the data.  
Notice how this model is so simple that it misses details.

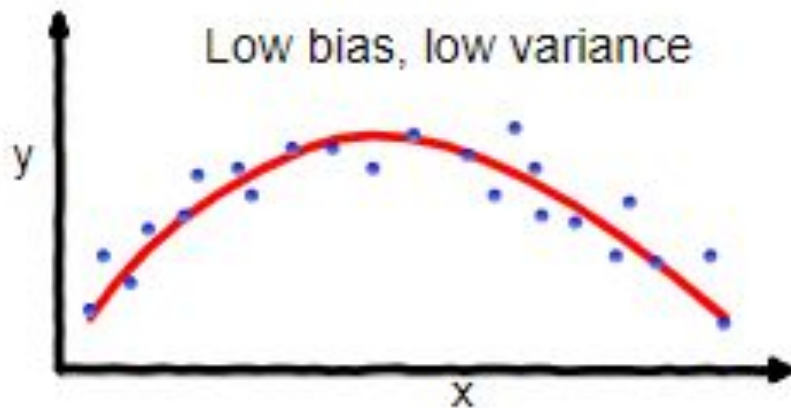
# We want a balance!



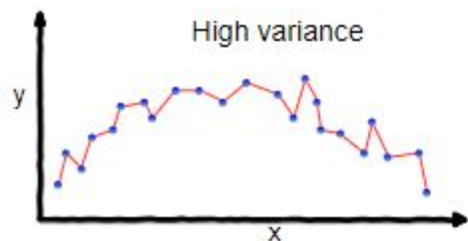
[Source](#)



This is a nice balance between the big pattern and the details. The model found the FUNCTION, but did not fit on the NOISE!

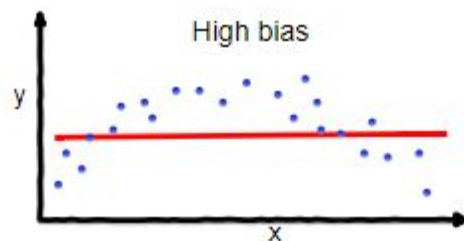


Good balance



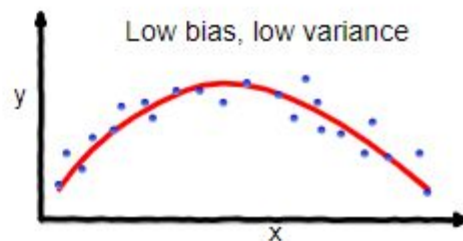
**overfitting**

Model is too complex  
and fits on **random  
noise** in the data



**underfitting**

Model is too simple



**Good balance**

Model is just right  
and fits on the  
**general function**

# Bias/Variance Tradeoff:



Decreasing the **variance** tends to increase the **bias** of the model



# How to identify overfitting?

Train R2 Score	Test R2 Score	Bias/Variance
.30	.29	High Bias (underfit)

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Train R2 Score	Test R2 Score	Bias/Variance
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.45	.14	High Bias AND Variance

# How to identify overfitting?

Train R2 Score	Test R2 Score	Bias/Variance
.30	.29	High Bias (underfit)
.99	.54	High Variance (overfit)
.45	.14	High Bias AND Variance
.95	.94	Good Fit

# Regularization

Regularization prevents a model from overfitting.

We need to find the RIGHT amount of regularization to balance the bias and variance.

[We call this 'tuning' a model](#)



[Image Source](#)



# Regularization

So your model has high variance, now what?

**Regularization** prevents a model from memorizing the data and forces it to find the general function instead.

- Done differently for different model types, for example:
  - **Decision Trees**: Adjust *max\_depth*, *min\_sample\_split*, *min\_sample\_leaf* or other hyperparameters. Check the documentation for more options.
  - **Random Forests**: Adjust *n\_estimators*, *max\_depth*, *min\_sample\_split*, *min\_sample\_leaf* or other hyperparameters. Check the documentation for more options.
  - **K Nearest Neighbors**: Adjust *n\_neighbors*, *weights* or other hyperparameters. Check the documentation for more options.
- Each model type has different ways to regularize it and combat overfitting. Check the documentation for each model type.

# The Goal?

**Maximize the Testing Metrics!!!**

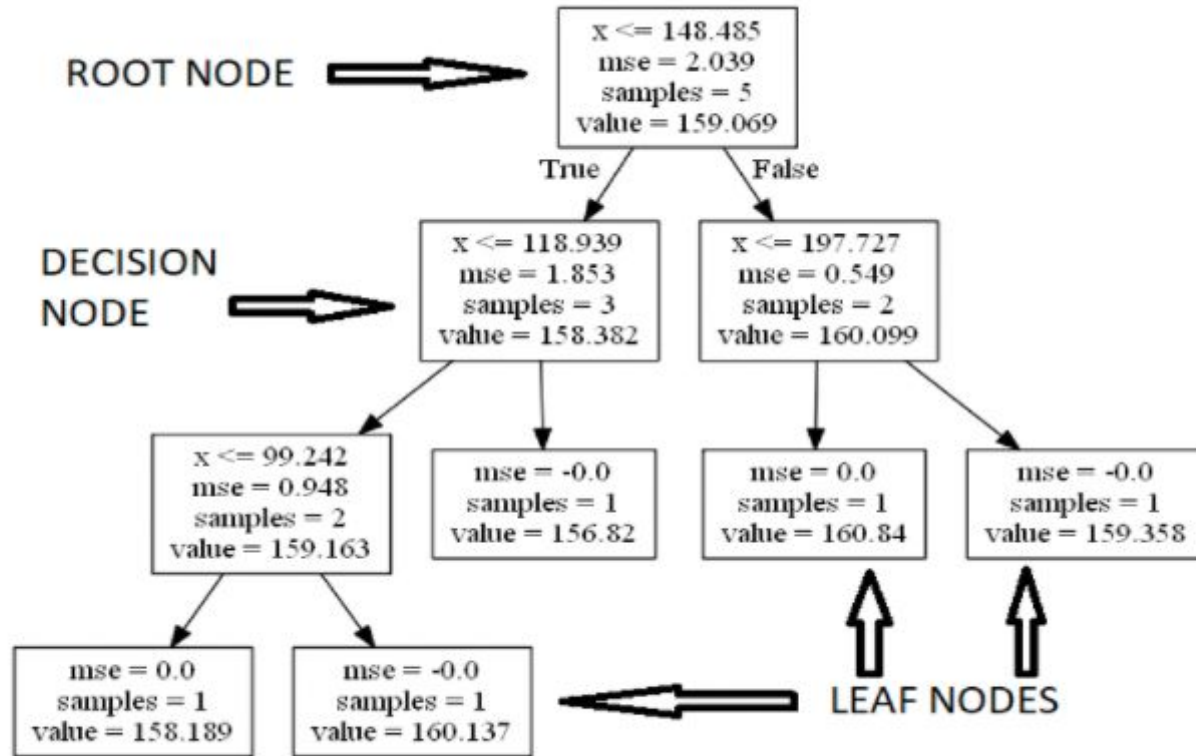
Don't sacrifice test metrics to decrease variance

High variance means you might be able to do better on the test set if you use regularization.

# Implementing Decision Trees

- A predictive modeling approach that separates data into classes using a top down approach
- Can be used for classification and regression
- Regression Trees predict a continuous quantity or numeric output such as \$35.98 or 11.41 inches
- The `sklearn.tree.DecisionTreeRegressor` uses mean squared error, friedman mse and mean absolute error.

# A Simple Decision Tree



# Decision Tree Based Models

## **Advantages**

- Easy to Interpret
- Prediction is fast
- Can be used for classification or regression
- Doesn't require scaling
- Can be used for multiclass classification problems (more than 2 classes)

## **Disadvantages**

- Worse performance than other supervised learning methods
- Prone to overfitting
- Small variations in the data can result in a completely different tree

```
1 # Imports
2 import pandas as pd
3 import numpy as np
4 import matplotlib.pyplot as plt
5 from sklearn.model_selection import train_test_split
6 from sklearn.preprocessing import OneHotEncoder
7 from sklearn.compose import make_column_selector, make_column_transformer
8 from sklearn.pipeline import make_pipeline
9 from sklearn.dummy import DummyRegressor
10 from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

```
6 cat_selector = make_column_selector(dtype_include='object')
7
8 ohe = OneHotEncoder(sparse=False, handle_unknown='ignore')
9
10 ohe_tuple = (ohe, cat_selector)
11
12 transformer = make_column_transformer(ohe_tuple, remainder='passthrough')
```

# Decision Trees in Python

```
1 from sklearn.tree import DecisionTreeRegressor
```

```
1 dec_tree = DecisionTreeRegressor()  
2  
3 dec_tree_pipe = make_pipeline(transformer, dec_tree)  
4  
5 dec_tree_pipe.fit(X_train, y_train)
```

# Bias/Variance Code Along

[CodeAlong Notebook](#)



# Challenge Notebook