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Data Analysis with Python

IBM: DA0101EN

LEARNING OBJECTIVES

In this course you will learn about:

```
Data Acquisition
How to Obtain Basic Insight From a Dataset
Data Wrangling
Exploratory Data Analysis
Model Development
Model Evaluation
```

1 Introduction to Data Analysis with Python

- Problem requiring data analysis
- dataset to analyze in python
- overview of packages
- import and export data
- Basic insights

Can we estimate the price of used cars?

The problem

why data analysis? data everywhere, helps discovery of information.

Tom wants to sell his car, but wants the best price. what affects the price?

Understand the data

There are documentation and the .csv file.

The first attribute, "symboling", corresponds to the insurance risk level of a car. Cars are initially assigned a risk factor symbol associated with their price. Then, if an automobile is more risky, this symbol is adjusted by moving it up the scale. A value of +3 indicates that the auto is risky, -3 that it is probably pretty safe. The second attribute "normalized-losses" is the relative average loss payment per insured vehicle year. This value is normalized for all autos within a particular size classification (two-door small, station wagons, sports/speciality, etc...), and represents the average loss per car per year. The values range from 65 to 256. The other attributes are easy to understand.

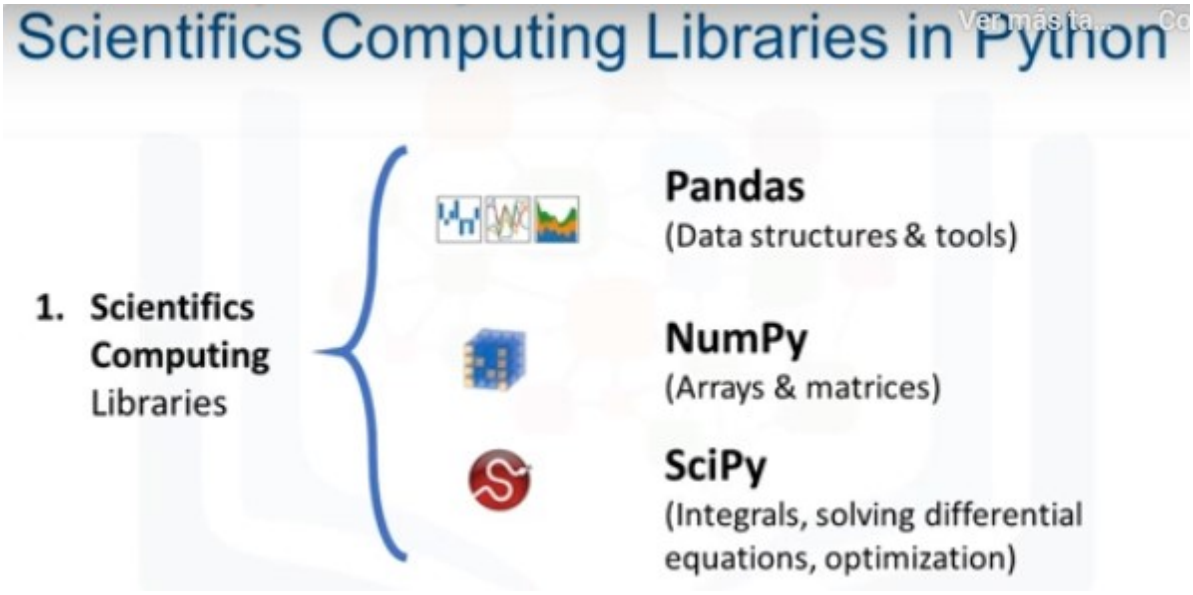
Thus, the goal of this project is to predict "price" in terms of other car features.

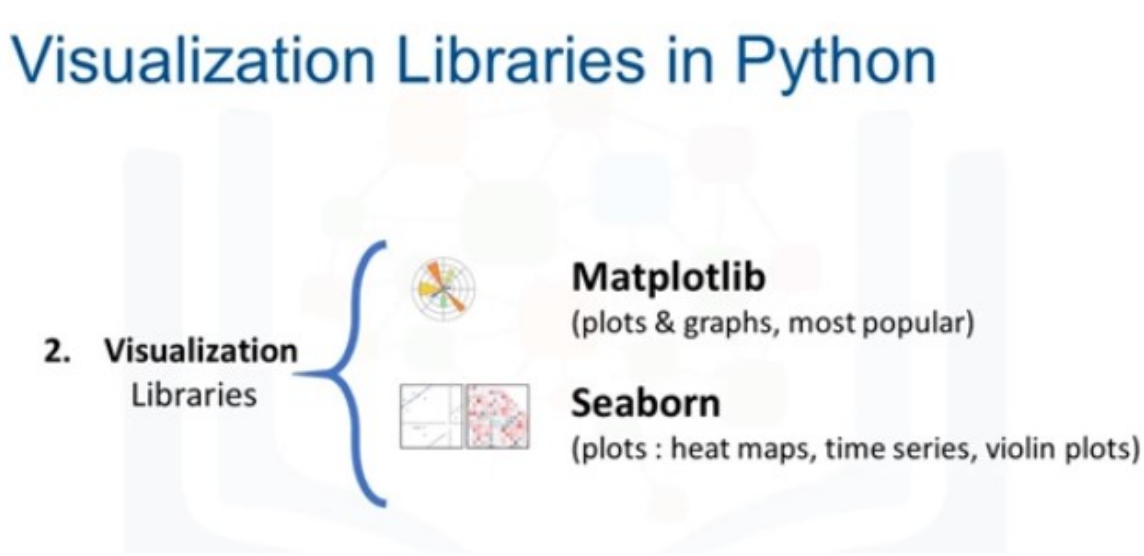
No.	Attribute name	attribute range	No.	Attribute name	attribute range
1	symboling	-3, -2, -1, 0, 1, 2, 3.	14	curb-weight	continuous from 1488 to 4066.
2	normalized-losses	continuous from 65 to 256.	15	engine-type	dohc, dohcv, l, ohc, ohcf, ohcv, rotor.
3	make	audi, bmw, etc.	16	num-of-cylinders	eight, five, four, six, three, twelve, two.
4	fuel-type	diesel, gas.	17	engine-size	continuous from 61 to 326.
5	aspiration	std, turbo.	18	fuel-system	1bbl, 2bbl, 4bbl, idi, mfi, mpfi, spdi, spfi.
6	num-of-doors	four, two.	19	bore	continuous from 2.54 to 3.94.
7	body-style	hardtop, wagon, etc.	20	stroke	continuous from 2.07 to 4.17.
8	drive-wheels	4wd, fwd, rwd.	21	compression-ratio	continuous from 7 to 23.
9	engine-location	front, rear.	22	horsepower	continuous from 48 to 288.
10	wheel-base	continuous from 86.6 120.9.	23	peak-rpm	continuous from 4150 to 6600.
11	length	continuous from 141.1 to 208.1.	24	city-mpg	continuous from 13 to 49.
12	width	continuous from 60.3 to 72.3.	25	highway-mpg	continuous from 16 to 54.
13	height	continuous from 47.8 to 59.8.	26	price	continuous from 5118 to 45400.

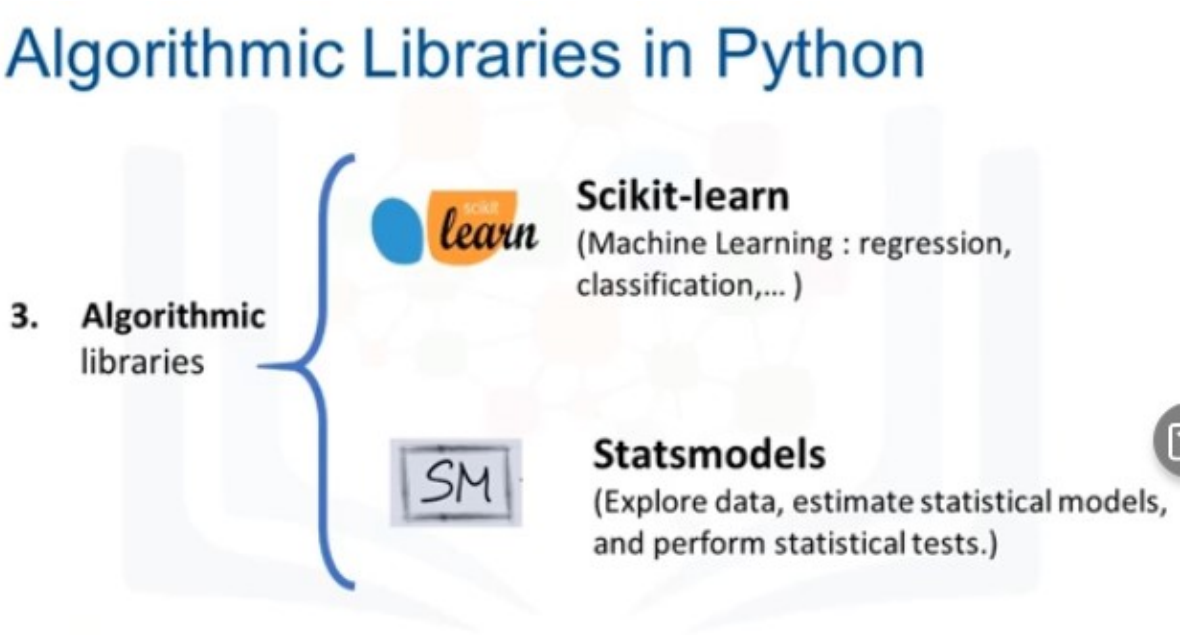
Target (Label)

Python packages

A Python library is a collection of functions and methods that allow you to perform lots of actions without writing any code. The libraries usually contain built-in modules providing different functionalities, which you can use directly. And there are extensive libraries, offering a broad range of facilities.







importing and exporting data

Format and file path. read_csv() df df.head(n) df.tail(n)

Add headers df.columns = headers headers = ["a","b","c"]

export df to csv: df.to_csv(path)

csv, json, excel, sql

Analyzing data

Check data type data distribution

object, float, int y datatime

- potential info and type mismatch
- compatibility with python methods

dataframe.dtypes

df.describe(include="all") -> count, mean, std deviation, min, 25%, 50%, 75%, max all -> UNIQUE, top, freq

Data lab

- Data source: https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data (https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDA0101ENSkillsNetwork20235326-2021-0
- Data type: csv

In [10]:
```
#install specific version of libraries used in  lab
import sys
!{sys.executable} -m pip install pandas
!{sys.executable} -m pip install numpy
!{sys.executable} -m pip install matplotlib
!{sys.executable} -m pip install scipy
!{sys.executable} -m pip install seaborn
!{sys.executable} -m pip install ipywidgets
```

```
Requirement already satisfied: pandas in /home/flynn/anaconda3/lib/python3.9/
site-packages (1.4.2)
Requirement already satisfied: python-dateutil>=2.8.1 in /home/flynn/anaconda
3/lib/python3.9/site-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /home/flynn/anaconda3/lib/pyth
on3.9/site-packages (from pandas) (2021.3)
Requirement already satisfied: numpy>=1.18.5 in /home/flynn/anaconda3/lib/pyt
hon3.9/site-packages (from pandas) (1.21.5)
Requirement already satisfied: six>=1.5 in /home/flynn/anaconda3/lib/python3.
9/site-packages (from python-dateutil>=2.8.1->pandas) (1.16.0)
Requirement already satisfied: numpy in /home/flynn/anaconda3/lib/python3.9/s
ite-packages (1.21.5)
Requirement already satisfied: matplotlib in /home/flynn/anaconda3/lib/python
3.9/site-packages (3.5.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /home/flynn/anaconda3/lib
/python3.9/site-packages (from matplotlib) (1.3.2)
Requirement already satisfied: numpy>=1.17 in /home/flynn/anaconda3/lib/pytho
n3.9/site-packages (from matplotlib) (1.21.5)
Requirement already satisfied: fonttools>=4.22.0 in /home/flynn/anaconda3/lib
```

In [13]:

```
  Input In [13]
    pip install pandas
        ^
SyntaxError: invalid syntax
```

In [11]:

```
# import pandas library
import pandas as pd
import numpy as np
```

In [12]:

```
#This function will download the dataset into your browser

from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Input In [12], in <cell line: 3>()
      1 #This function will download the dataset into your browser
----> 3 from pyodide.http import pyfetch
      5 async def download(url, filename):
      6     response = await pyfetch(url)

ModuleNotFoundError: No module named 'pyodide'
```

Read Data

We use `pandas.read_csv()` function to read the csv file. In the brackets, we put the file path along with a quotation mark so that pandas will read the file into a dataframe from that address. The file path can be either an URL or your local file address.

Because the data does not include headers, we can add an argument `headers = None` inside the `read_csv()` method so that pandas will not automatically set the first row as a header.

You can also assign the dataset to any variable you create.

In [ ]:

```
path = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM
```

In [ ]:

```
#you will need to download the dataset; if you are running locally, please com
await download(path, "auto.csv")
path="auto.csv"
```

This dataset was hosted on IBM Cloud object. Click [HERE (https://cocl.us

/DA101EN_object_storage?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkDA0101ENSkillsNetwork20235326-2021-01-01 for free storage.

Import pandas library

import pandas as pd

Read the online file by the URL provides above, and assign it to variable "df"

df = pd.read_csv(path, header=None)

After reading the dataset, we can use the `dataframe.head(n)` method to check the top n rows of the dataframe, where n is an integer. Contrary to `dataframe.head(n)`, `dataframe.tail(n)` will show you the bottom n rows of the dataframe.

In [ ]:
```
# show the first 5 rows using dataframe.head() method
print("The first 5 rows of the dataframe")
df.head(5)
```

In [ ]:
```
print("The last 10 rows of the dataframe\n")
df.tail(10)
```

In [ ]:
```
# create headers list
headers = ["symboling","normalized-losses","make","fuel-type","aspiration", "n
           "drive-wheels","engine-location","wheel-base", "length","width","heig
           "num-of-cylinders", "engine-size","fuel-system","bore","stroke","comp
           "peak-rpm","city-mpg","highway-mpg","price"]
print("headers\n", headers)
```

In [ ]:
```
df.columns = headers
df.head(10)
```

In [ ]:
```
df1=df.replace('?',np.NaN)
```

In [ ]:
```
df=df1.dropna(subset=["price"], axis=0)
df.head(20)
```

In [ ]:
```
print(df.columns)
```

Save Dataset

Correspondingly, Pandas enables us to save the dataset to csv. By using the `dataframe.to_csv()` method, you can add the file path and name along with quotation marks in the brackets.

For example, if you would save the dataframe **df** as **automobile.csv** to your local machine, you may use the syntax below, where `index = False` means the row names will not be written.

In [ ]:
```
df.to_csv("automobile.csv", index=False)
```

Read/Save Other Data Formats

Data Formate	Read	Save
csv	pd.read_csv()	df.to_csv()
json	pd.read_json()	df.to_json()
excel	pd.read_excel()	df.to_excel()
hdf	pd.read_hdf()	df.to_hdf()
sql	pd.read_sql()	df.to_sql()
...	...	...

In [ ]:
```
df.dtypes
```

In [ ]:
```
# check the data type of data frame "df" by .dtypes
print(df.dtypes)
```

In [ ]:
```
dataframe.describe()
```

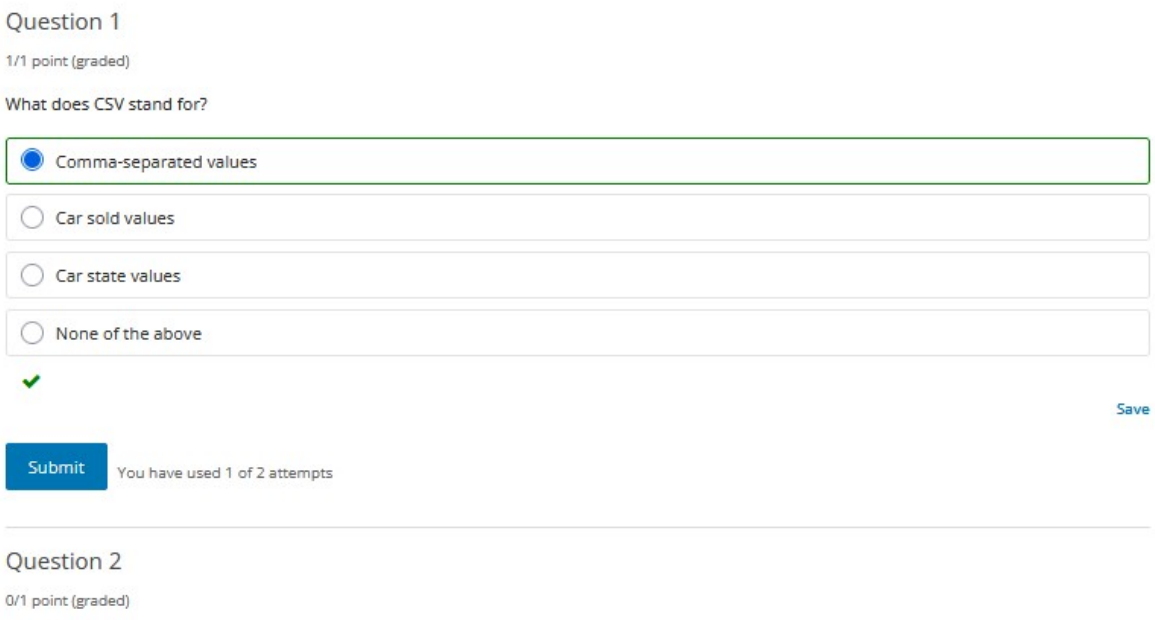
In [ ]:
```
df.describe()
```

In [ ]:
```
# describe all the columns in "df"
df.describe(include = "all")
```

In [ ]:
```
df[['length', 'compression-ratio']].describe()
```

In [ ]:
```
dataframe.info()
```

In [ ]:
```
# look at the info of "df"
df.info()
```



In the data set, which of the following represents an attribute or feature?

- ○ Row
- ○ Column
- ● Each element in the dataset

✖

Submit You have used 2 of 2 attempts

Question 3

1/1 point (graded)

What is the name of what we want to predict?

- ● Target
- ○ Feature
- ○ Dataframe

✔

Save

Submit You have used 1 of 2 attempts

Question 4

1/1 point (graded)

What is the command to display the first five rows of a dataframe `df` ?

- ● `df.head()`
- ○ `df.tail()`

✔

Submit You have used 1 of 1 attempt

Question 5

1/1 point (graded)

What command do you use to get the data type of each row of the dataframe `df` ?

- ● `df.dtypes`
- ○ `df.head()`
- ○ `df.tail()`

✔

Save

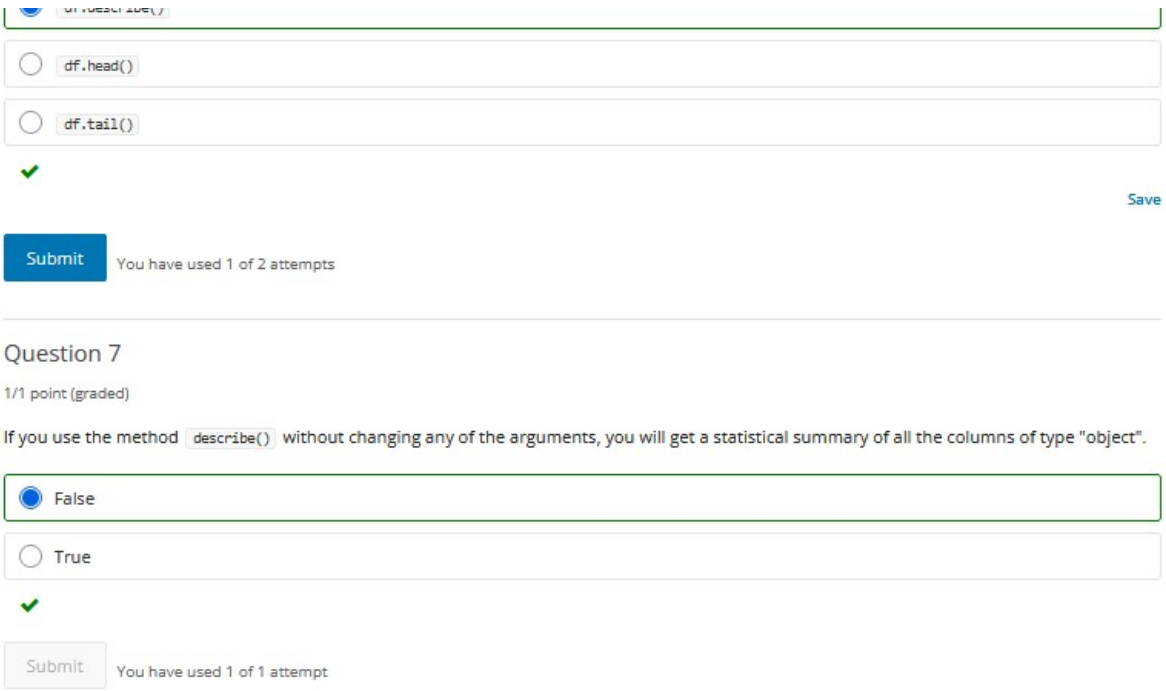
Submit You have used 1 of 2 attempts

Question 6

1/1 point (graded)

How do you get a statistical summary of a dataframe `df` ?

- ● `df.describe()`



Module 2 - Cleaning and Preparing the Data

Pre-Processing Data in Python.- convert raw to for another data.

- identify and handling missing value
- data formatting
- Data normalization
- Data Binning
- Turning categorical values to numerical values

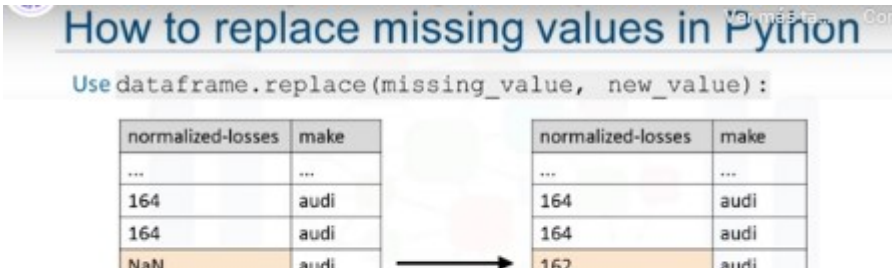
Dealing with a nmissing value

? "N/A", 0

- check with the data collection source
- Drop the missing values: drop variable or data entry
- replace the missing values: with average. by frequency. based on other functions.

dataframes.dropna() axis 0 the entire row, 1 drops the entire column, implace true writes the result back

Replace missing values



158	audi
...	...

158	audi
...	...

```
mean = df["normalized-losses"].mean()
df["normalized-losses"].replace(np.nan, mean)
```

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How to deal with missing data?

Check with the data collection source

Drop the missing values
- drop the variable
- drop the data entry

Replace the missing values
- replace it with an average (of similar datapoints)
- replace it by frequency
- replace it based on other functions

Leave it as missing data

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Data Formatting

- Data are usually collected from different places and stored in different formats.
- Bringing data into a common standard of expression allows users to make meaningful comparison.

Non-formatted:
- confusing
- hard to aggregate
- hard to compare

City
NY
New York
N.Y
N.Y

City
New York
New York
New York
New York

Formatted:
- more clear
- easy to aggregate
- easy to compare

Applying calculations to an entire column

- Convert "mpg" to "L/100km" in Car dataset.

city-mpg
21
21
19
...

city-L/100km
11.2
11.2
12.4
...

```
df["city-mpg"]= 235/df["city-mpg"]

df.rename(columns={"city_mpg": "city-L/100km"}, inplace=True)
```

Incorrect data types

- Sometimes the wrong data type is assigned to a feature.

```
df["price"].tail(5)

200    16845
201    19045
202    21485
203    22470
204    22625
Name: price, dtype: object
```

Correcting data types

To *identify* data types:

- Use **`dataframe.dtypes()`** to identify data type.

To *convert* data types:

- Use **`dataframe.astype()`** to convert data type.

Example: convert data type to integer in column "price"

```
df["price"] = df["price"].astype("int")
```

Binning

- Binning: Grouping of values into "bins"
- Converts numeric into categorical variables
- Group a set of numerical values into a set of "bins"
- "price" is a feature range from 5,000 to 45,500
  (in order to have a **better representation** of price)

price: 5000, 10000,12000,12000, 30000, 31000, 39000, 44000,44500

bins: low Mid High

Binning in Python pandas

price
13495
16500
18920
41315
5151
6295
...

→

price	price-binned
13495	Low
16500	Low
18920	Medium
41315	High
5151	Low
6295	Low
...	...

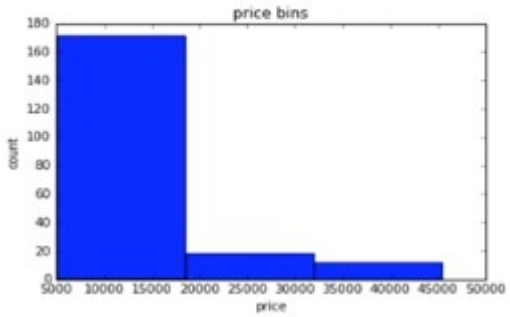
```
bins = np.linspace(min(df["price"]), max(df["price"]), 4)

group_names = ["Low", "Medium", "High"]

df["price-binned"] = pd.cut(df["price"], bins, labels=group_names, include_lowest=True )
```

Visualizing binned data

- E.g., Histograms



Categorical → Numeric

Solution:

- Add dummy variables for each unique category
- Assign 0 or 1 in each category

Car	Fuel	...	gas	diesel
A	gas	...	1	0
B	diesel	...	0	1
C	gas	...	1	0
D	gas	...	1	0

"One-hot encoding"

Dummy variables in Python pandas

- Use pandas.get_dummies() method.
- Convert categorical variables to dummy variables (0 or 1)

fuel
gas
diesel
gas
gas

→

gas	diesel
1	0
0	1
1	0
1	0

```
pd.get_dummies(df['fuel'])
```

LAB

Question #1:

Based on the example above, replace NaN in "stroke" column with the mean value.

avg_stroke = df["stroke"].astype("float").mean(axis = 0) print("Average of stroke:", avg_stroke)

df["stroke"].replace(np.nan, avg_stroke, inplace = True)

Calculate the mean value for the "horsepower" column

Question #2:

According to the example above, transform mpg to L/100km in the column of "highway-mpg" and change the name of column to "highway-L/100km".

df["highway-mpg"] = 235/df["highway-mpg"]

df.rename(columns={'highway-mpg':'highway-L/100km'}, inplace=True)

df.head()

Question #3:

According to the example above, normalize the column "height".

df['height'] = df['height']/df['height'].max()

df[["length","width","height"]].head()

Question #4:

Similar to before, create an indicator variable for the column "aspiration"
dummy_variable_2 = pd.get_dummies(df['aspiration'])

dummy_variable_2.rename(columns={'std':'aspiration-std', 'turbo': 'aspiration-turbo'}, inplace=True)

dummy_variable_2.head()

Question #5:

Merge the new dataframe to the original dataframe, then drop the column 'aspiration'.

df = pd.concat([df, dummy_variable_2], axis=1)

df.drop('aspiration', axis = 1, inplace=True)

Question 1

1/1 point (graded)

Consider the dataframe `df` . What is the result of the following operation: `df['symbolling'] = df['symbolling'] + 1` ?

- (●) Every element in the column "symbolling" will increase by one.
- ( ) Every element in the row "symbolling" will increase by one.
- ( ) Every element in the dataframe will increase by one.

✔

Save | Show answer

Submit You have used 1 of 2 attempts

✔ Correct (1/1 point)

Question 2

1/1 point (graded)

Consider the dataframe `df` . What does the command `df.rename(columns={'a':'b'})` change about the dataframe `df` ?

- ( ) Renames column "a" of the dataframe to "b".
- ( ) Renames row "a" to "b".
- (●) Nothing. You must set the parameter "inplace = True".

✔

Save | Show answer

Question 3

1/1 point (graded)

Consider the dataframe "df". What is the result of the following operation `df['price'] = df['price'].astype(int)` ?

- ( ) Convert or cast the row 'price' to an integer value.
- (●) Convert or cast the column 'price' to an integer value.
- ( ) Convert or cast the entire dataframe to an integer value.

✔

Save | Show answer

Submit You have used 1 of 2 attempts

✔ Correct (1/1 point)

Question 4

1/1 point (graded)

Consider the column of the dataframe `df['a']` . The column has been standardized. What is the standard deviation of the values as a result of applying the following operation: `df['a'].std()` ?

- (●) 1
- ( ) 0

3

Show answer

Submit You have used 2 of 2 attempts

Question 5 a)

1/1 point (graded)

Consider the column of the dataframe, df['Fuel'], with two values: 'gas' and' diesel'. What will be the name of the new columns pd.get_dumies(df['Fuel']) ?

- 1 and 0
- Just 'diesel'
- Just 'gas'
- 'gas' and 'diesel'

Save | Show answer

Submit You have used 1 of 2 attempts

Correct (1/1 point)

Question 5 b)

1/1 point (graded)

What are the values of the new columns from part 5a)?

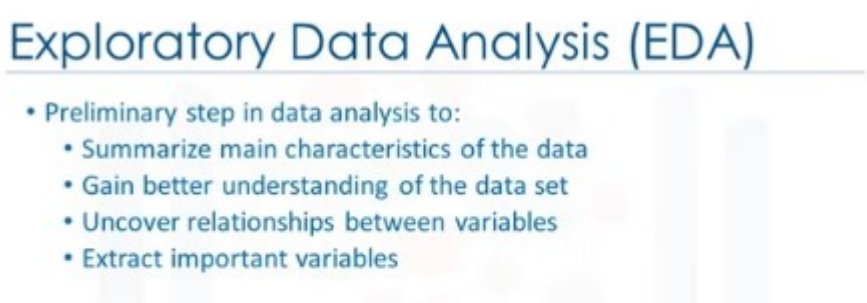
- 1 and 0
- Just 'diesel'
- Just 'gas'
- 'gas' and 'diesel'

Save | Show answer

Submit You have used 1 of 2 attempts

Correct (1/1 point)

Module 3 - Exploratory Data Analysis



- Question:

"What are the characteristics that have the most impact on the car price?"

Learning Objectives

In this module you will learn about:

- Descriptive Statistics
- GroupBy
- ANOVA
- Correlation
- Correlation - Statistics

Descriptive Statistics

- Describe basic features of data
- Giving short summaries about the sample and measures of the data

Descriptive Statistics- Describe()

- Summarize statistics using pandas **describe()** method

```
df.describe()
```

	Unnamed: 0	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bore	stroke
count	201.000000	201.000000	164.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.00000(
mean	100.000000	0.840796	122.000000	98.797015	174.200995	65.889055	53.766667	2555.666667	126.875622	3.319154	3.256766
std	58.167861	1.254802	35.442168	6.066366	12.322175	2.101471	2.447822	517.296727	41.546834	0.280130	0.316049
min	0.000000	-2.000000	65.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	2.540000	2.070000
25%	50.000000	0.000000	NaN	94.500000	166.800000	64.100000	52.000000	2169.000000	98.000000	3.150000	3.110000
50%	100.000000	1.000000	NaN	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	3.310000	3.290000
75%	150.000000	2.000000	NaN	102.400000	183.500000	66.600000	55.500000	2926.000000	141.000000	3.580000	3.410000
max	200.000000	3.000000	256.000000	120.900000	208.100000	72.000000	59.800000	4066.000000	326.000000	3.940000	4.170000

Descriptive Statistics - Value_Counts()

- summarize the categorical data is by using the **value_counts()** method

```
drive_wheels_counts=df["drive-wheels"].value_counts()
```

```
drive_wheels_counts.rename(colunms={'drive-wheels':'value_counts' inplace=True)
drive_wheels_counts.index.name= 'drive-wheels'
```

	value_counts
drive-wheels	
fwd	118
rwd	75
4wd	8

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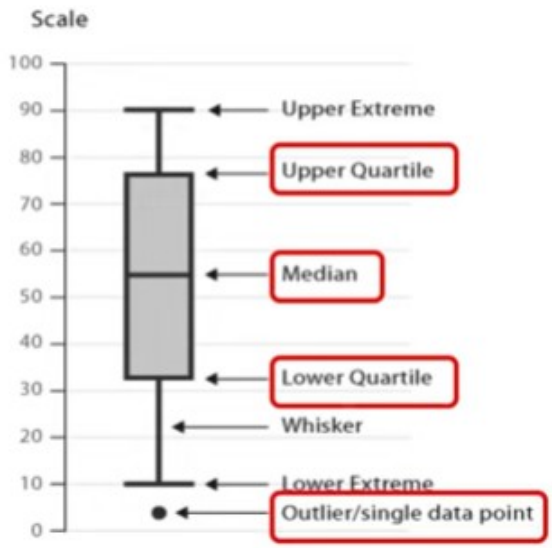
4

Descriptive Statistics - Box Plots



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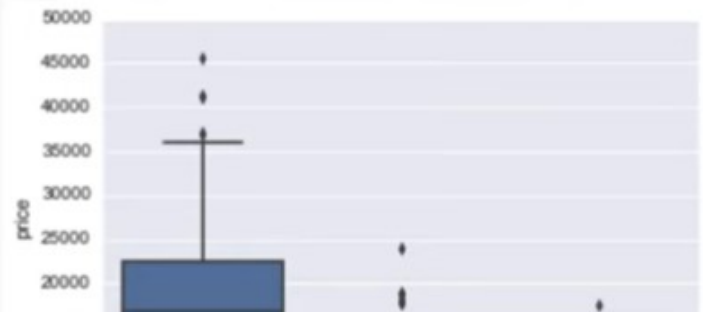
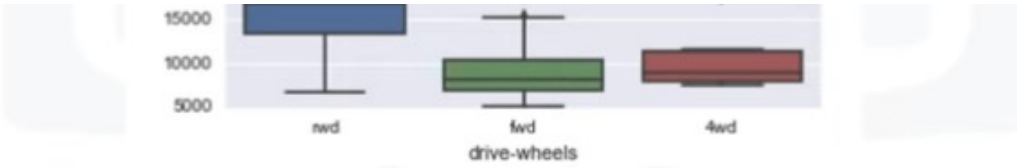
Box Plot - Example

```
sns.boxplot(x= "drive-wheels", y= "price",data=df)
```





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Questions

Question 1

1/1 point (graded)

Consider the dataframe "df". What method provides the summary statistics?

- (●) df.describe()
- ( ) df.head()
- ( ) df.tail()

✔

Save | Show answer

Submit You have used 1 of 2 attempts

✔ Correct (1/1 point)

Question 2

1/1 point (graded)

Consider the following dataframe:

```
df_test = df['body-style', 'price']
```

The following operation is applied:

```
df_grp = df_test.groupby(['body-style'], as_index=False).mean()
```

What are resulting values of `df_grp['price']` ?

- (●) The average price for each body style.
- ( ) The average price.
- ( ) The average body style.

✔

Save | Show answer

Submit You have used 1 of 2 attempts

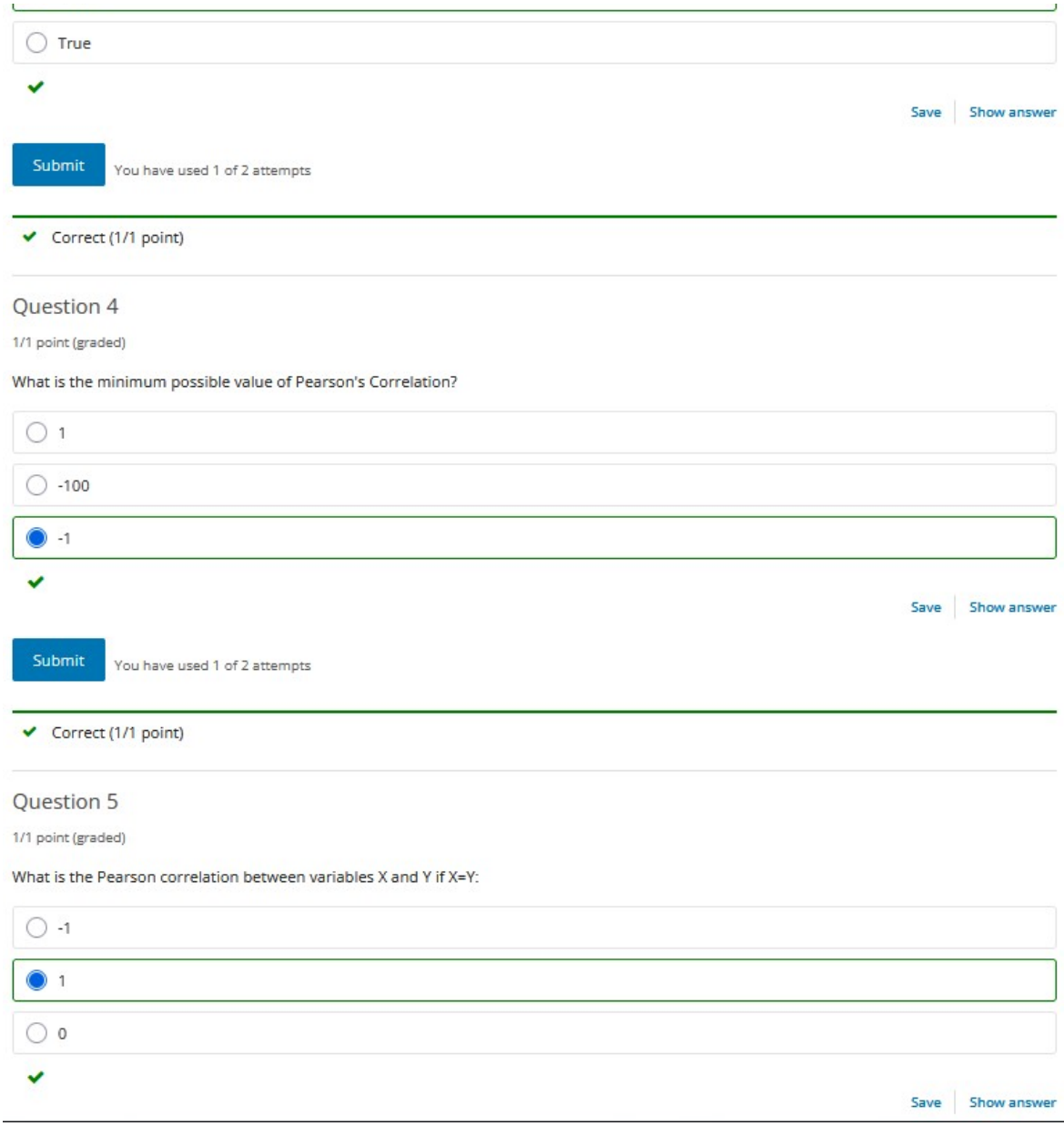
✔ Correct (1/1 point)

Question 3

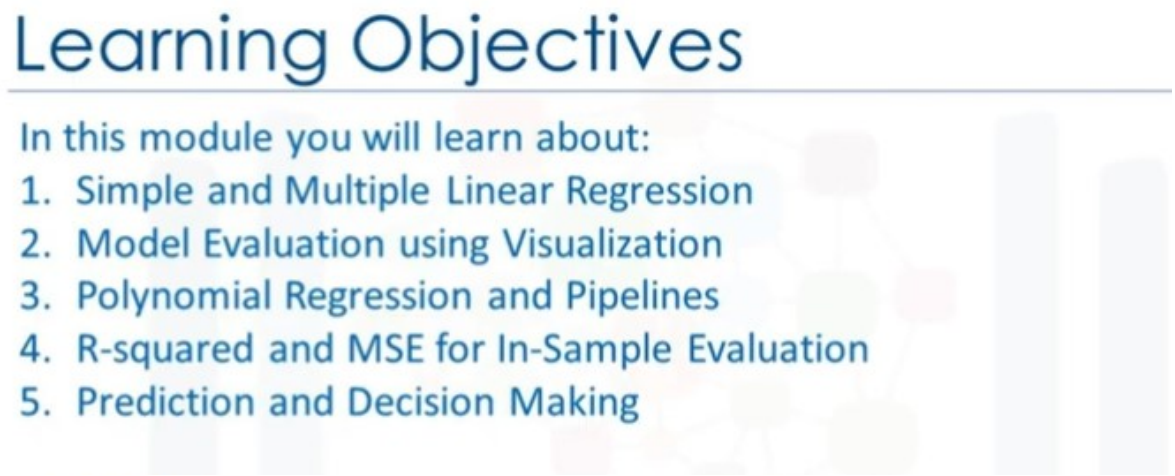
1/1 point (graded)

Correlation implies causation:

- (●) False



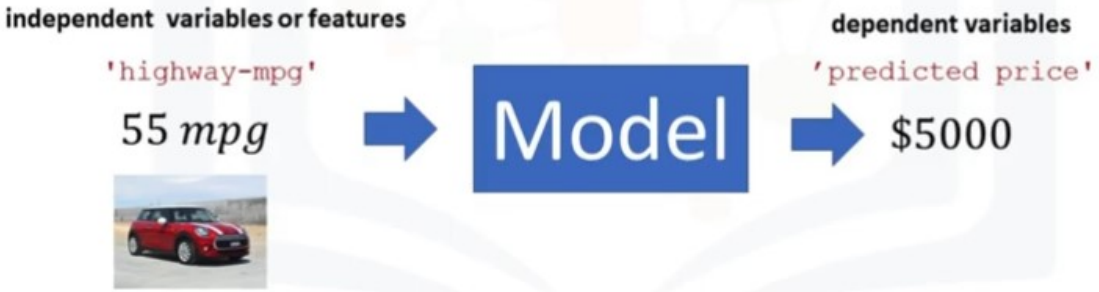
Module 4 - Model Development



- Question
  - **How can you determine a fair value for a used car?**

Model Development

- A model can be thought of as a mathematical equation used to predict a value given one or more other values
- Relating one or more independent variables to dependent variables.



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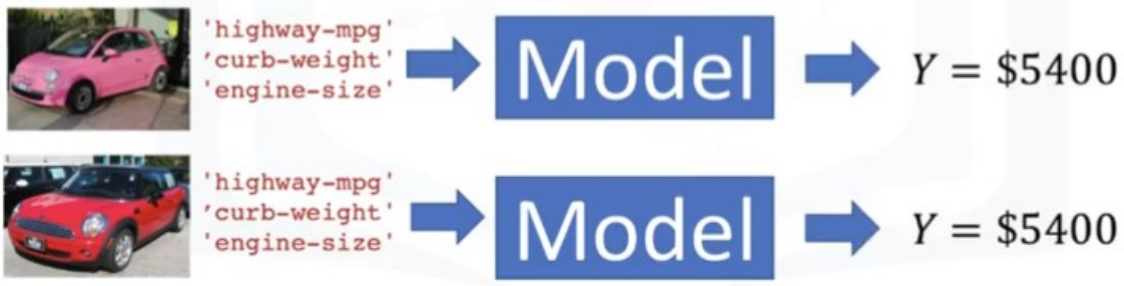
Model Development

- To understand why more data is important consider the following situation:

1. you have two almost identical cars
2. Pink cars sell for significantly less



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Model Development

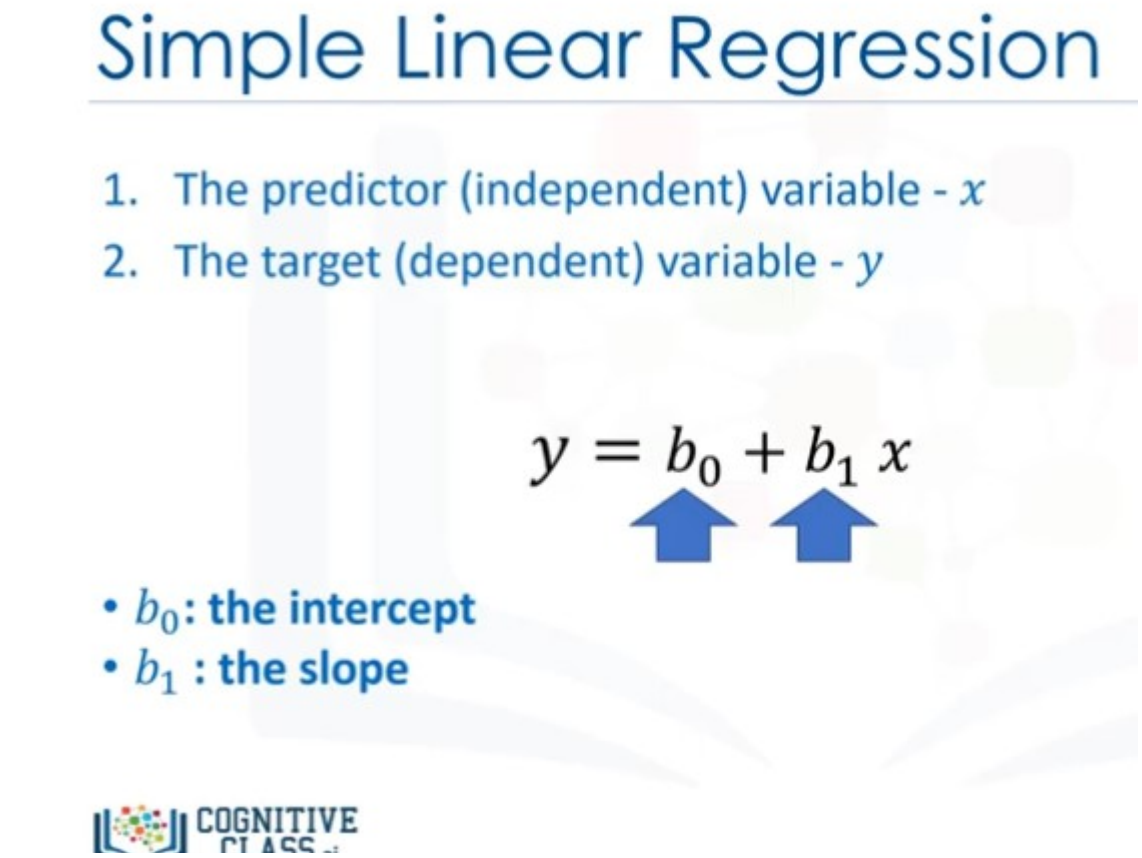
In addition to getting more data you can try different types of models

In addition to getting more data you can try different types of models.

In this course you will learn about:

1. Simple Linear Regression
2. Multiple Linear Regression

Linear and Multiple Linear Regression

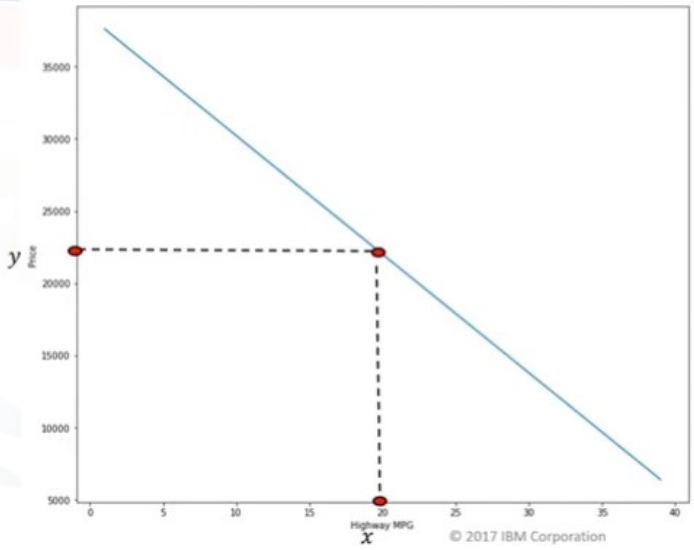


Simple Linear Regression: Prediction

$$y = 38423 - 821x$$

$$= 38423 - 821\,(20)$$

$$= 22\,003$$



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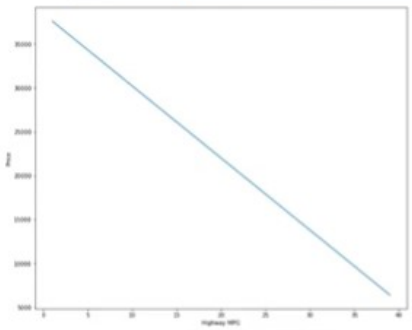
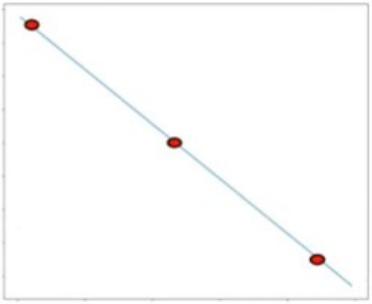
Simple Linear Regression: Fit



Fit

(b_0, b_1)

Simple Linear Regression: Fit



$$X = \begin{bmatrix} 0 \\ 20 \\ 40 \end{bmatrix} \quad Y = \begin{bmatrix} 38423 \\ 22003 \\ 5583 \end{bmatrix}$$

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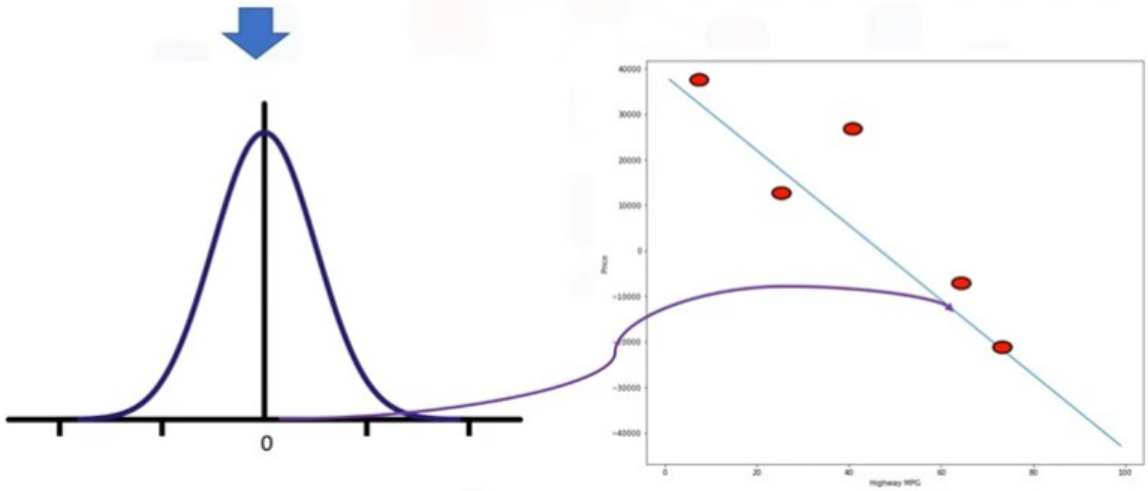
x

 6

Simple Linear Regression: Fit



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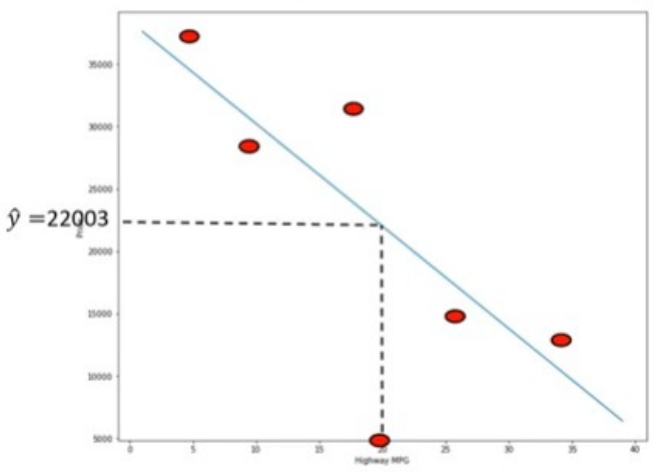
x

 7

Simple Linear Regression



Fit

Predict

$$\hat{y} = b_0 + b_1 x$$

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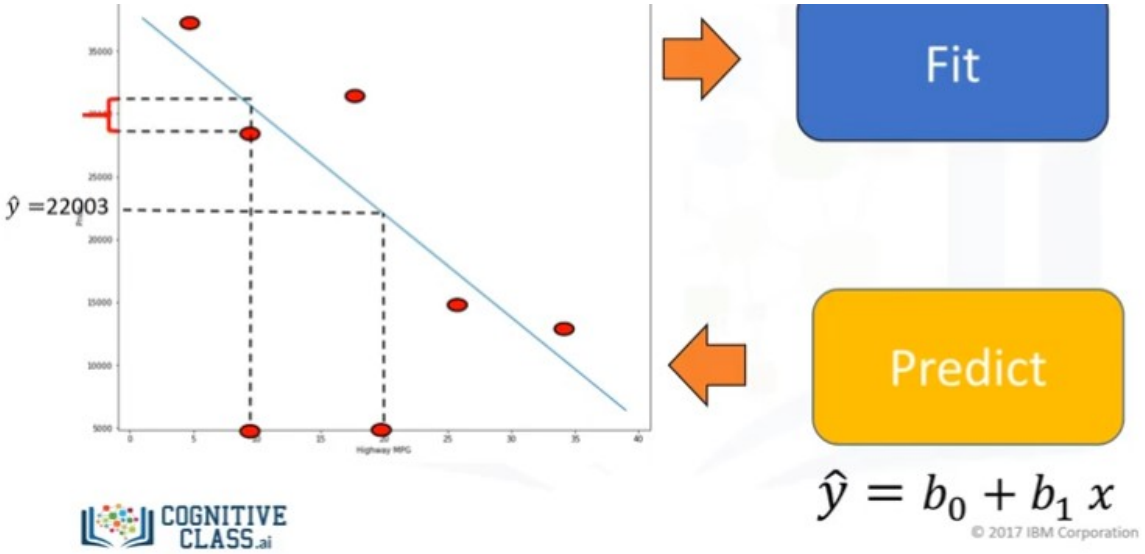
Simple Linear Regression



Fitting a Simple Linear Model Estimator

- X :Predictor variable
- Y: Target variable

1. Import linear_model from scikit-learn

```
from sklearn.linear_model import LinearRegression
```

2. Create a Linear Regression Object using the constructor :

```
lm=LinearRegression()
```

Fitting a Simple Linear Model

- We define the predictor variable and target variable

```
X = df[['highway-mpg']]
Y = df['price']
```

- Then use lm.fit (X, Y) to fit the model , i.e fine the parameters b_0 and b_1

```
lm.fit(X, Y)
```

- We can obtain a prediction

```
Yhat=lm.predict(X)
```

Yhat	X
2	5
:	
3	4

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SLR – Estimated Linear Model

- We can view the intercept (b_0): `lm.intercept_` → `38423.305858`
- We can also view the slope (b_1): `lm.coef_` → `-821.73337832`
- The Relationship between Price and Highway MPG is given by:
- **Price = 38423.31 - 821.73 * highway-mpg**

$$\hat{Y} = b_0 + b_1 x$$

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Multiple Linear Regression (MLR)

This method is used to explain the relationship between:

- One continuous target (Y) variable
- Two or more predictor (X) variables

Multiple Linear Regression (MLR)

$$\hat{Y} = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4$$

- b_0 : **intercept (X=0)**
- b_1: the **coefficient** or **parameter** of x_1
- b_2: the **coefficient** of **parameter** x_2 and so on..

Multiple Linear Regression (MLR)

$$\hat{Y} = 1 + 2x_1 + 3x_2$$

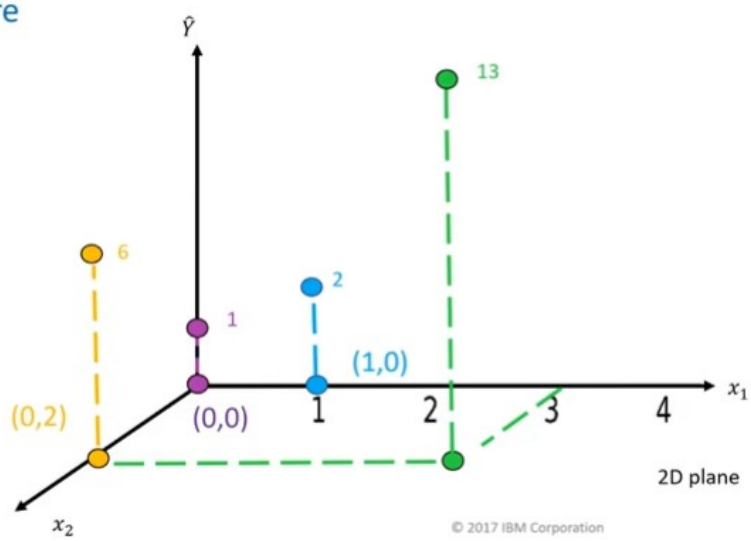
- The variables x_1 and x_2 can be visualized on a 2D plane, lets do an example on the next slide

- This is shown below where

$$\hat{Y} = 1 + 2x_1 + 3x_2$$

n	x_1	x_2
1	0	0
2	0	2
3	1	0
4	3	2

$\hat{Y}$
1
6
2
13



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Fitting a Multiple Linear Model Estimator

1. We can extract the for 4 predictor variables and store them in the variable Z

```
Z = df[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']]
```

2. Then train the model as before:

```
lm.fit(Z, df['price'])
```

3. We can also obtain a prediction

```
Yhat=lm.predict(X)
```

x_1	x_2	x_3	x_4
3	5	-4	3
:	:	:	:
2	4	2	-4

Yhat
2
:
3

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MLR – Estimated Linear Model

1. Find the intercept (b_0)

```
lm.intercept_
-15678.742628061467
```

2. Find the coefficients (b_1, b_2, b_3, b_4)

```
lm.coef_
array([52.65851272 ,4.69878948,81.95906216 , 33.58258185])
```

The Estimated Linear Model:

- **Price** = -15678.74 + (52.66) * **horsepower** + (4.70) * **curb-weight** + (81.96) * **engine-size** + (33.58) * **highway-mpg**

$$\hat{Y} = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4$$

Model Evaluation using Visualization

Regression Plot

Why use regression plot?

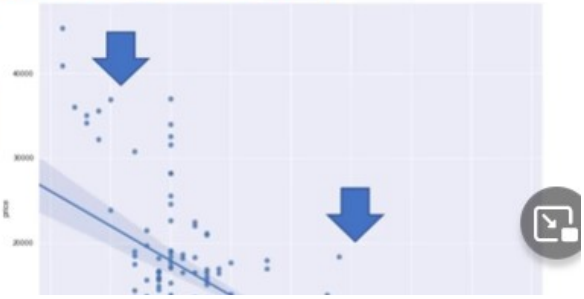
It gives us a good estimate of:

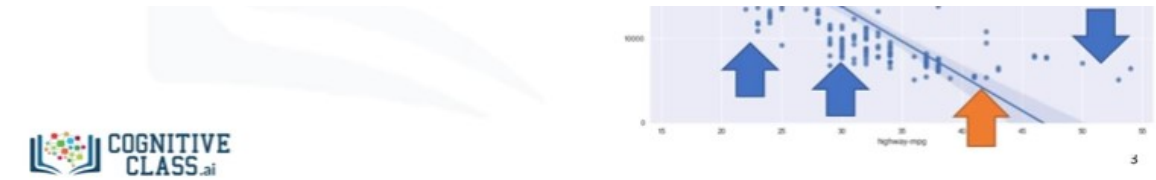
1. The relationship between two variables
2. The strength of the correlation
3. The direction of the relationship (positive or negative)

Regression Plot

Regression Plot shows us a combination of:

- The scatterplot: where each point represents a different y
- The fitted linear regression line (ŷ).



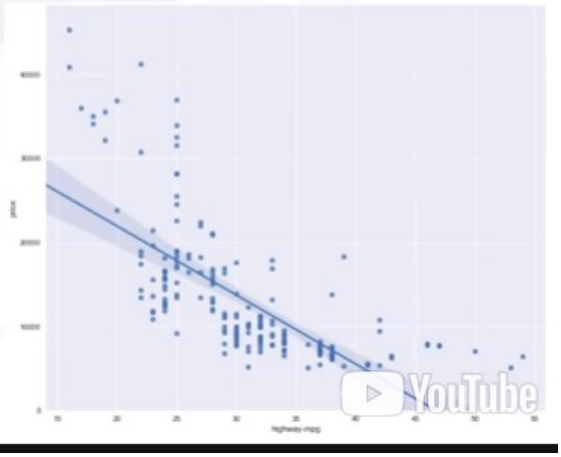


Regression Plot

Ver más ta... Compartir

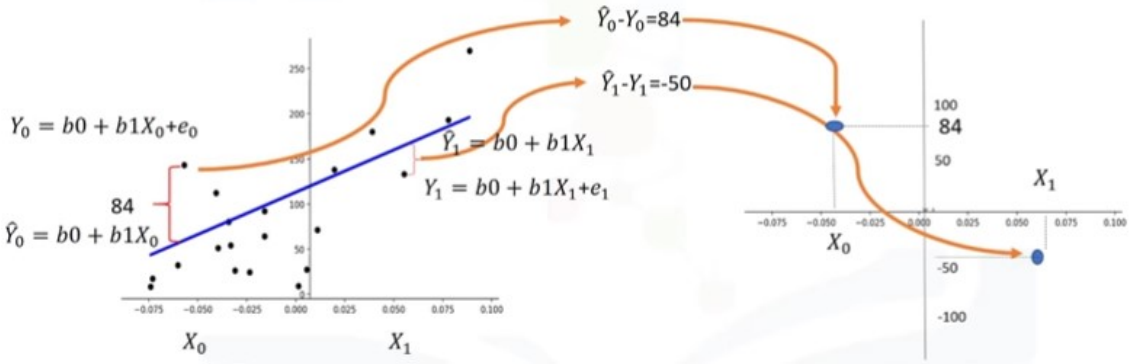
```
import seaborn as sns

sns.regplot(x="highway-mpg", y="price", data=df)
plt.ylim(0,)
```



Residual Plot

Y-axis: residuals



X-axis: the predictor variable or fitted values.

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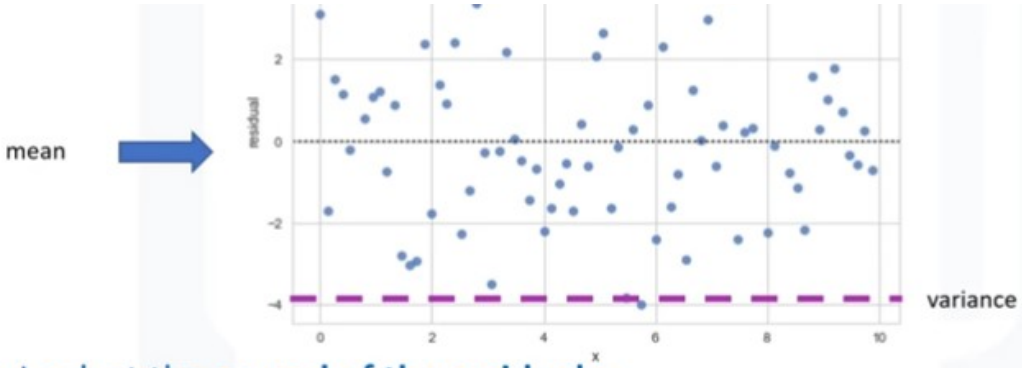
Residual Plot



- Look at the **spread of the residuals**:
  - Randomly spread out around x-axis then a linear model is appropriate.

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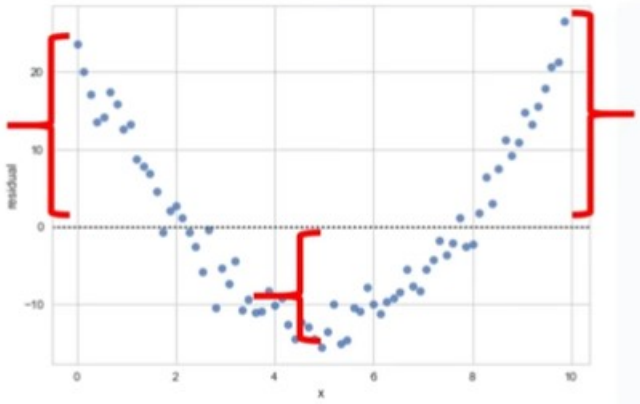
Residual Plot



- Not randomly spread out around the x-axis
- Nonlinear model may be more appropriate

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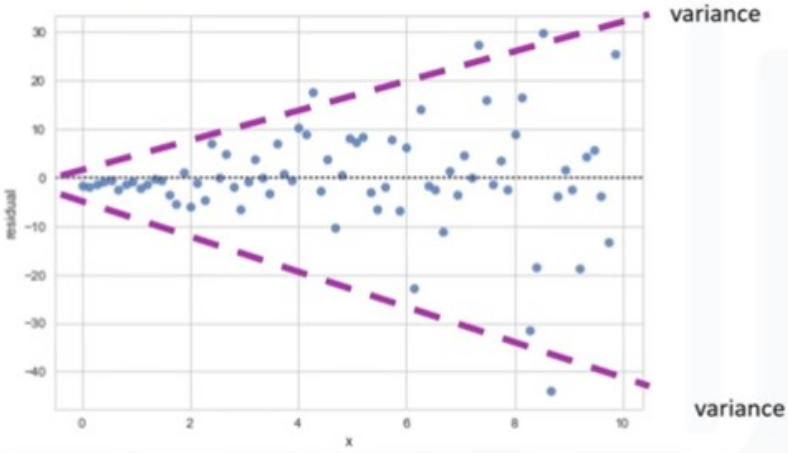
Residual Plot



- Not randomly spread out around the x-axis
- Variance appears to change with x axis

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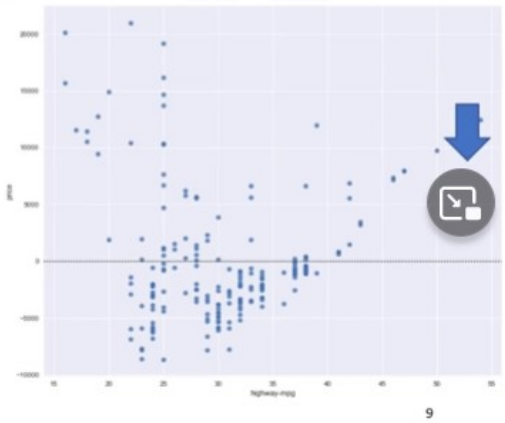
Residual Plot

```
import seaborn as sns
```

```
sns.residplot(df['highway-mpg'], df['price'])
```



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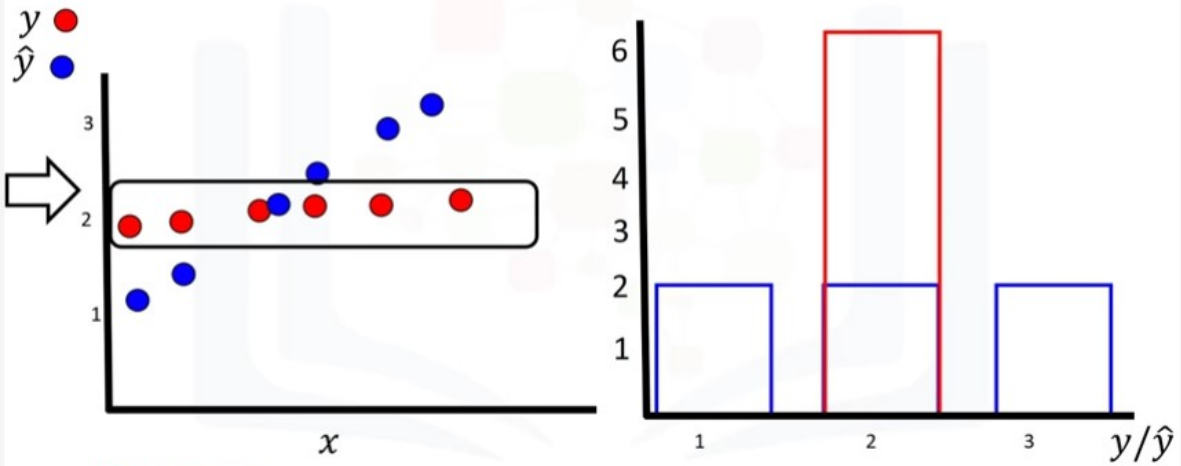
Distribution Plots



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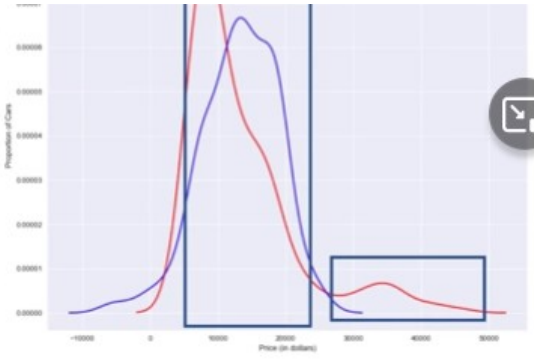
Distribution Plots

Compare the distribution plots:

- The fitted values that result from the model
- The actual values



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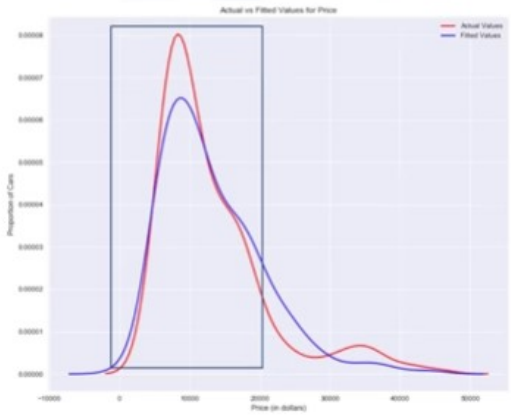
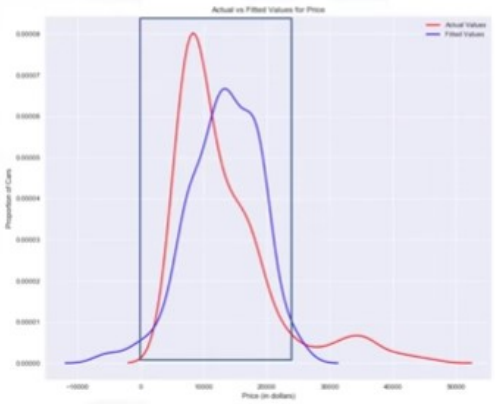
MLR – Distribution Plots





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Distribution Plots

```
import seaborn as sns

ax1 = sns.distplot(df['price'], hist=False, color="r", label="Actual Value")

sns.distplot(Yhat, hist=False, color="b", label="Fitted Values" , ax=ax1)
```

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Polynomial Regression and Pipelines

Distribution Plots

```
import seaborn as sns

ax1 = sns.distplot(df['price'], hist=False, color="r", label="Actual Value")

sns.distplot(Yhat, hist=False, color="b", label="Fitted Values" , ax=ax1)
```

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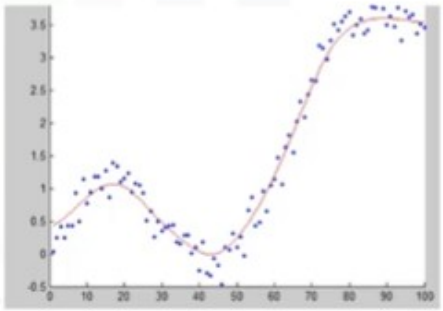
Polynomial Regressions

- A special case of the general linear regression model
- Useful for describing curvilinear relationships.

Curvilinear relationships:
By squaring or setting higher-order terms of the predictor variables.



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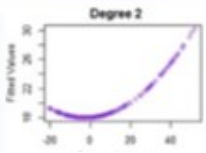
2

Polynomial Regression

- Quadratic – 2nd order

$$\hat{Y} = b_0 + b_1 x_1 + b_2 (x_1)^2$$

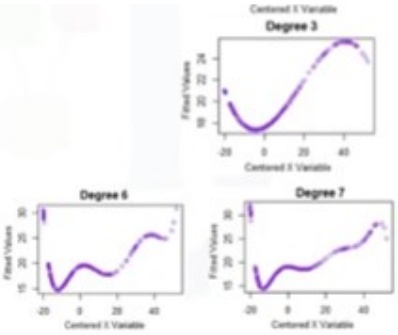


- Cubic – 3rd order

$$\hat{Y} = b_0 + b_1 x_1 + b_2 (x_1)^2 + b_3 (x_1)^3$$

- Higher order

$$\hat{Y} = b_0 + b_1 x_1 + b_2 (x_1)^2 + b_3 (x_1)^3 + ..$$



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3

Polynomial Regression

1. Calculate Polynomial of 3rd order

```
f=np.polyfit(x,y,3)
p=np.poly1d(f)
```

2. We can print out the model

```
print (p)
```

$$-1.557(x_1)^3 + 204.8(x_1)^2 + 8965\, x_1 + 1.37 \times 10^5$$

Polynomial Regression with More the One Dimension

- We can also have multi dimensional polynomial linear regression

$$\hat{Y} = b0 + b1\, X_1 + b2\, X_2 + b3\, X_1 X_2 + b4(X_1)^2 + b5(X_2)^2 + ..$$

Polynomial Regression with More the One Dimension

- The "preprocessing" library in scikit-learn,

```
from sklearn.preprocessing import PolynomialFeatures
```

```
pr=PolynomialFeatures(degree=2, include_bias=False)

x_polly=pr.fit_transform(x[['horsepower', 'curb-weight']])
```

Polynomial Regression with More the One Dimension

```
pr=PolynomialFeatures(degree=2)

pr.fit_transform([1,2], include_bias=False)
```

X_1	X_2
1	2

X_1	X_2	X_1X_2	X_1^2	X_2^2
1	2	(1) 2	1	$(2)^2$
1	2	2	1	4

Pre-processing

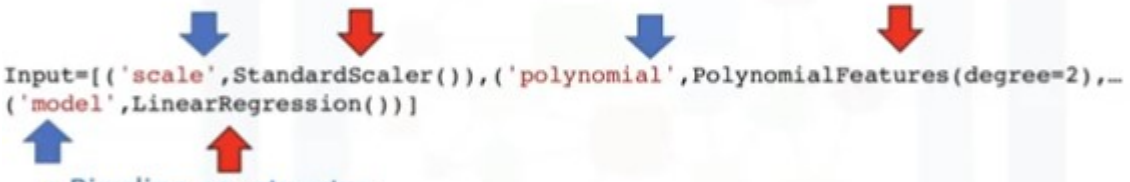
- For example we can Normalize the each feature simultaneously:

```
from sklearn.preprocessing import StandardScaler

SCALE=StandardScaler()
SCALE.fit(x_data[['horsepower', 'highway-mpg']])

x_scale=SCALE.transform(x_data[['horsepower', 'highway-mpg']])
```

Pipelines

- There are many steps to getting a prediction

Pipeline Constructor



- Pipeline constructor

```
pipe=Pipeline(Input)
```

- We can train the pipeline object

```
Pipe.train(X['horsepower', 'curb-weight', 'engine-size', 'highway-mpg'],y)

yhat=Pipe.predict(X[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']])
```

Measures for In-Sample Evaluation

Measures for In-Sample Evaluation

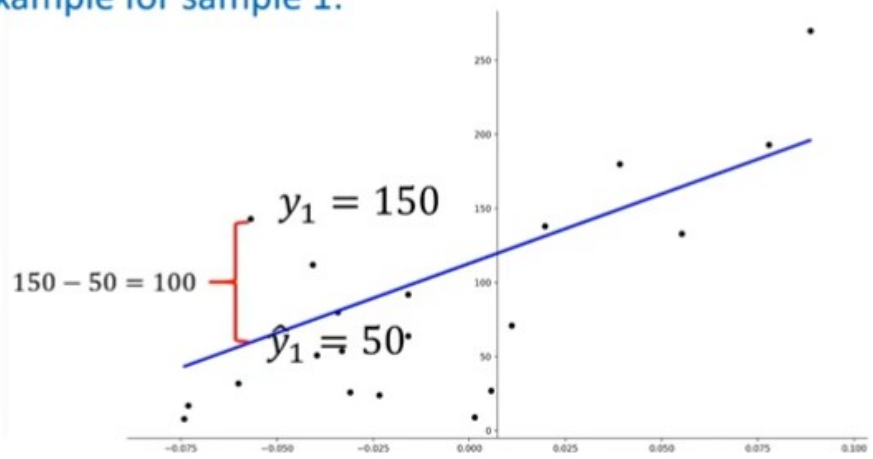
- A way to numerically determine how good the model fits on dataset.

- Two important measures to determine the fit of a model:
  - **Mean Squared Error (MSE)**
  - **R-squared (R^2)**

Mean Squared Error (MSE)

Mean Squared Error (MSE)

- For Example for sample 1:



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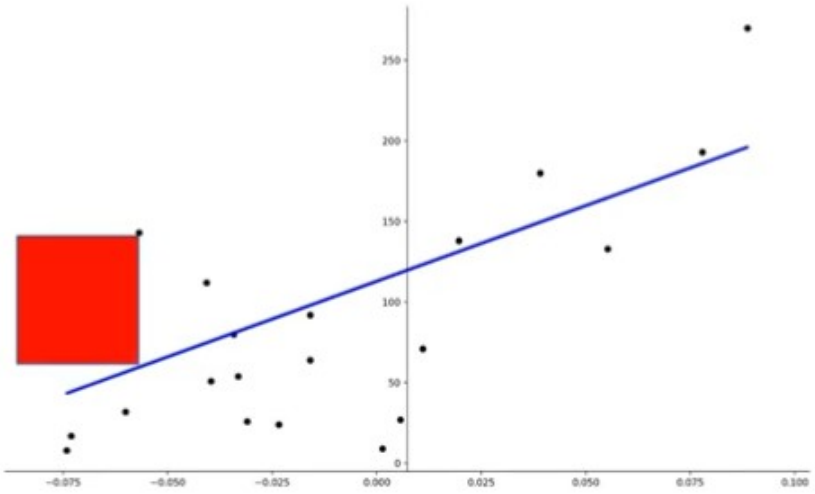
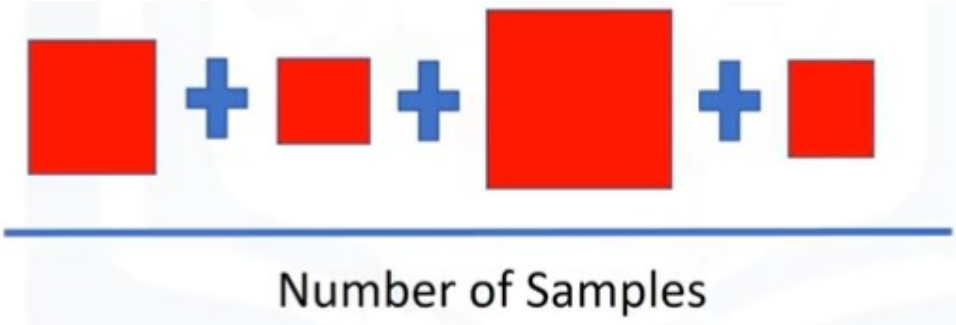
Mean Squared Error (MSE)

- To make all the values positive we square it

$(50)^2$



Mean Squared Error (MSE)



Mean Squared Error (MSE)

- In python we can measure the MSE as follows

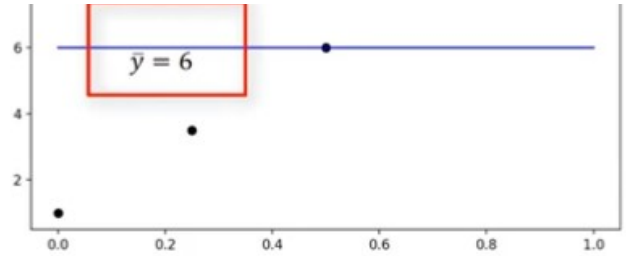
```
from  sklearn.metrics import mean_squared_error

mean_squared_error(df['price'],Y_predict_simple_fit)


3163502.944639888
```

R-squared/ R^2

- The Coefficient of Determination or R squared (R^2)
- Is a measure to determine how close the data is to the fitted regression line.
- R^2: the percentage of variation of the target variable (Y) that is explained by the linear model.
- Think about as comparing a regression model to a simple model i.e the mean of the data points

Coefficient of Determination (R^2)

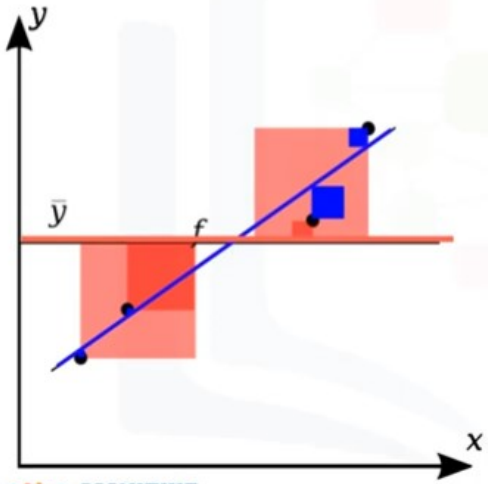
- In this example the average of the data points $\bar{y}$ is 6



Coefficient of Determination (R^2)

$$R^2 = \left(1 - \frac{\text{MSE of regression line}}{\text{MSE of the average of the data}}\right)$$

Coefficient of Determination (R^2)



- The blue line represents the regression line
- The blue squares represents the MSE of the regression line
- The red line represents the average value of the data points
- The red squares represent the MSE of the red line
- We see the area of the blue squares is much smaller then the area of the red squares

COGNITIVE CLASS.ai Source: https://en.wikipedia.org/wiki/Coefficient_of_determination 10

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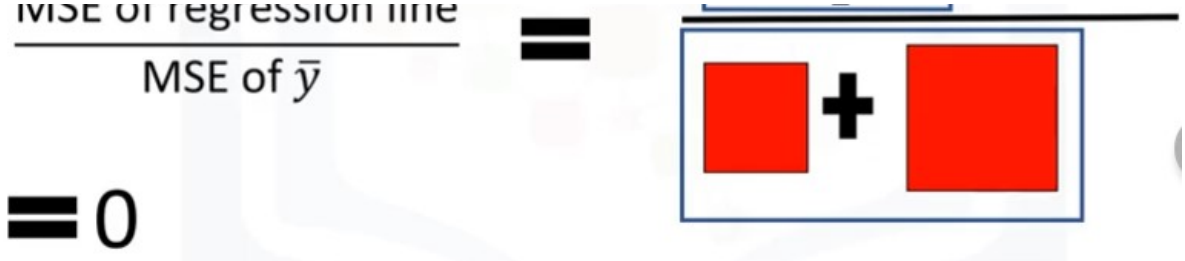
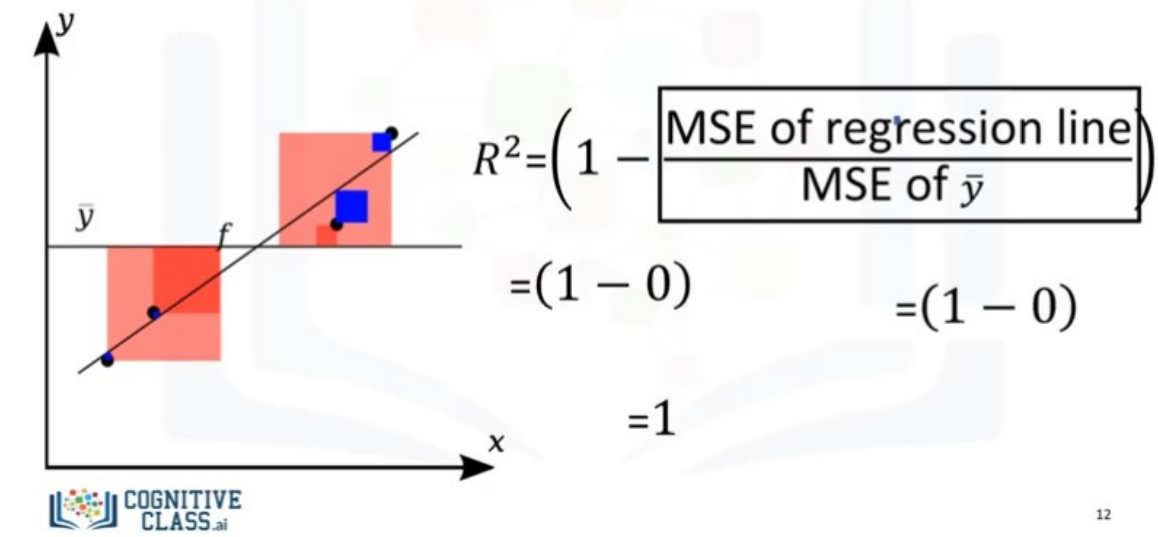
Coefficient of Determination (R^2)

- In this case ratio of the areas of MSE is close to zero

MSE of regression line


MSE of regression line
MSE of $\bar{y}$
= 0
=


Coefficient of Determination (R^2)
y
x
$\bar{y}$
f
$R^2 = \left(1 - \frac{\text{MSE of regression line}}{\text{MSE of } \bar{y}}\right)$
$= (1 - 0)$
$= (1 - 0)$
$= 1$
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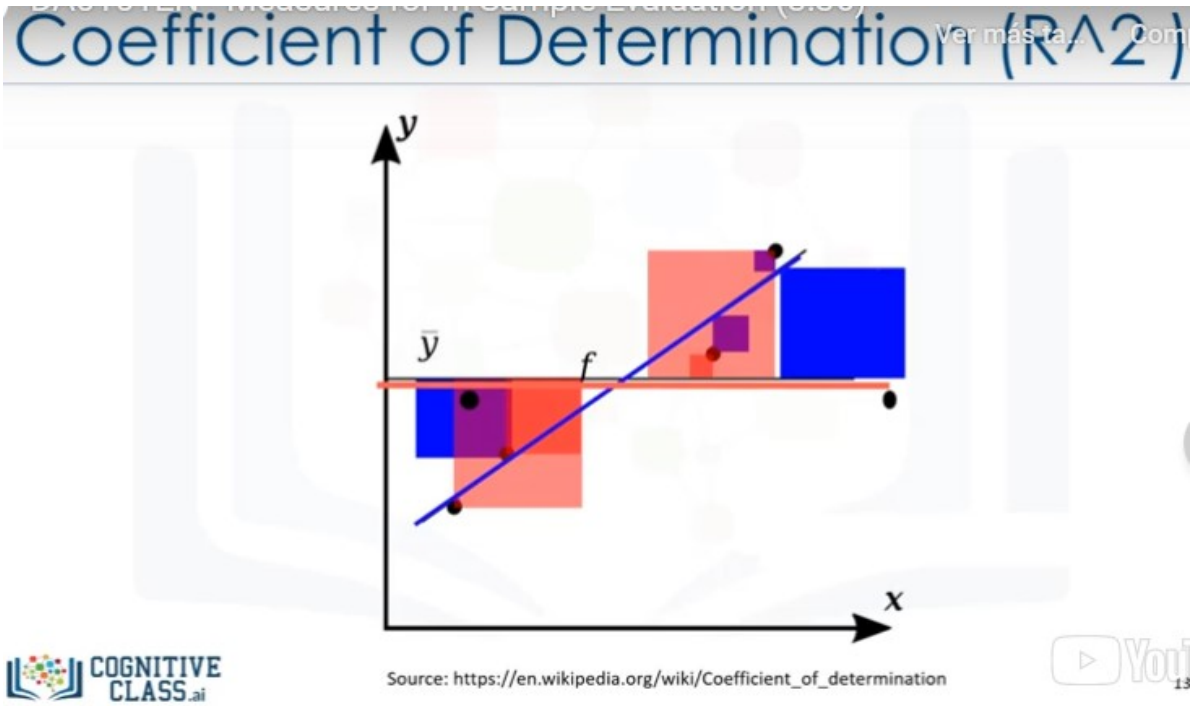
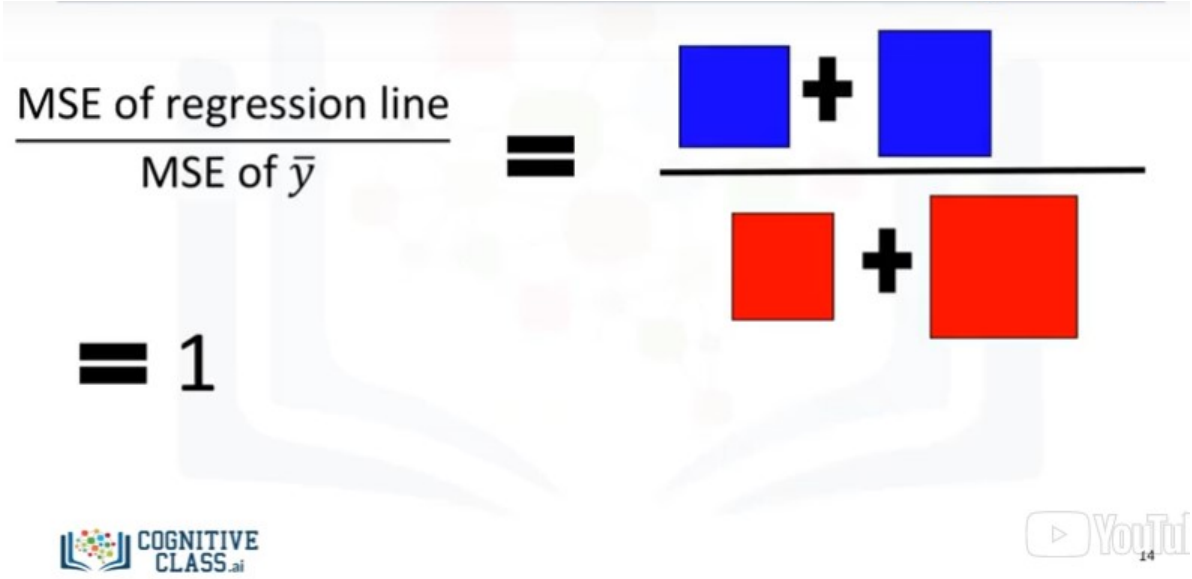
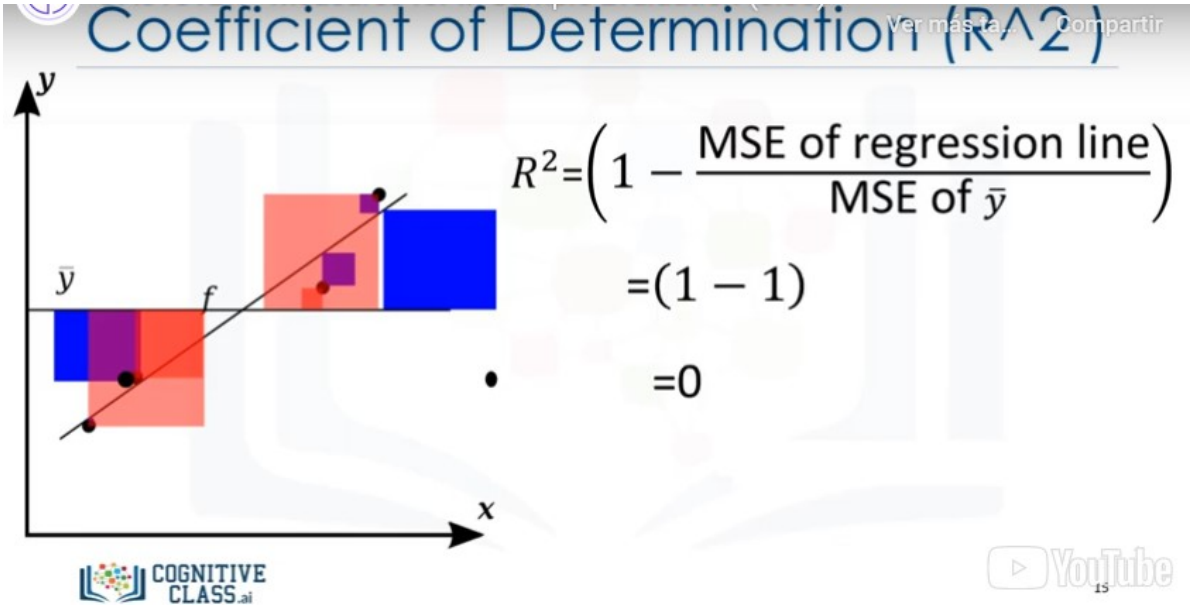
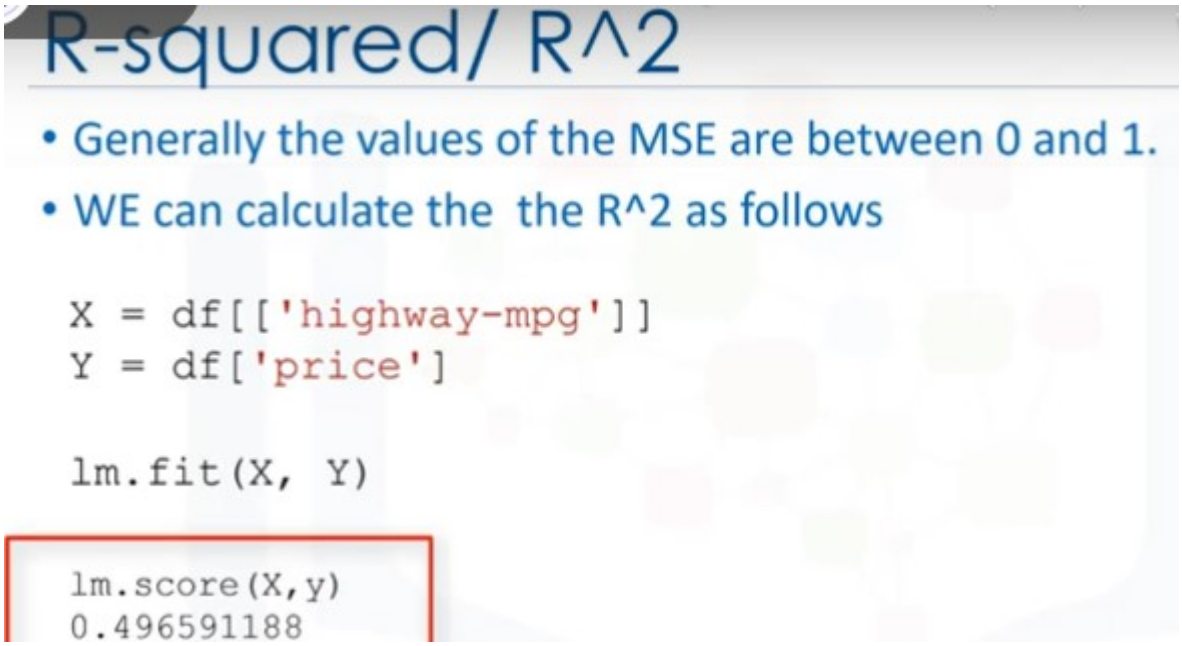
12


Coefficient of Determination (R^2)
y
x
$\bar{y}$
f
COGNITIVE CLASS.ai
Source: https://en.wikipedia.org/wiki/Coefficient_of_determination
13


DA0101EN - Measures for In Sample Evaluation (3:36)
Coefficient of Determination (R^2)


MSE of regression line
MSE of $\bar{y}$
= 1
COGNITIVE CLASS.ai


Coefficient of Determination (R^2)
$R^2 = \left(1 - \frac{\text{MSE of regression line}}{\text{MSE of } \bar{y}}\right)$
$= (1 - 1)$
$= 0$
$\bar{y}$
f
y
x
COGNITIVE CLASS.ai


R-squared/ R^2
• Generally the values of the MSE are between 0 and 1.
• WE can calculate the the R^2 as follows
X = df[['highway-mpg']]
Y = df['price']
lm.fit(X, Y)
lm.score(X,y)
0.496591188

Graded Review Questions

Question 1

1/1 point (graded)

Let `X` be a dataframe with 100 rows and 5 columns. Let `y` be the target with 100 samples. Assuming all the relevant libraries and data have been imported, the following line of code has been executed:

```
LR = LinearRegression()
```

```
LR.fit(X, y)
```

```
yhat = LR.predict(X)
```

How many samples does `yhat` contain?

- ○ 5
- ○ 500
- ◉ 100
- ○ 0

✔

Save | Show answer

Submit You have used 1 of 2 attempts

✔ Correct (1/1 point)

Question 2

1/1 point (graded)

What value of R^2 (coefficient of determination) indicates your model performs best?

- ○ -100
- ○ -1
- ○ 0
- ◉ 1

Question 3

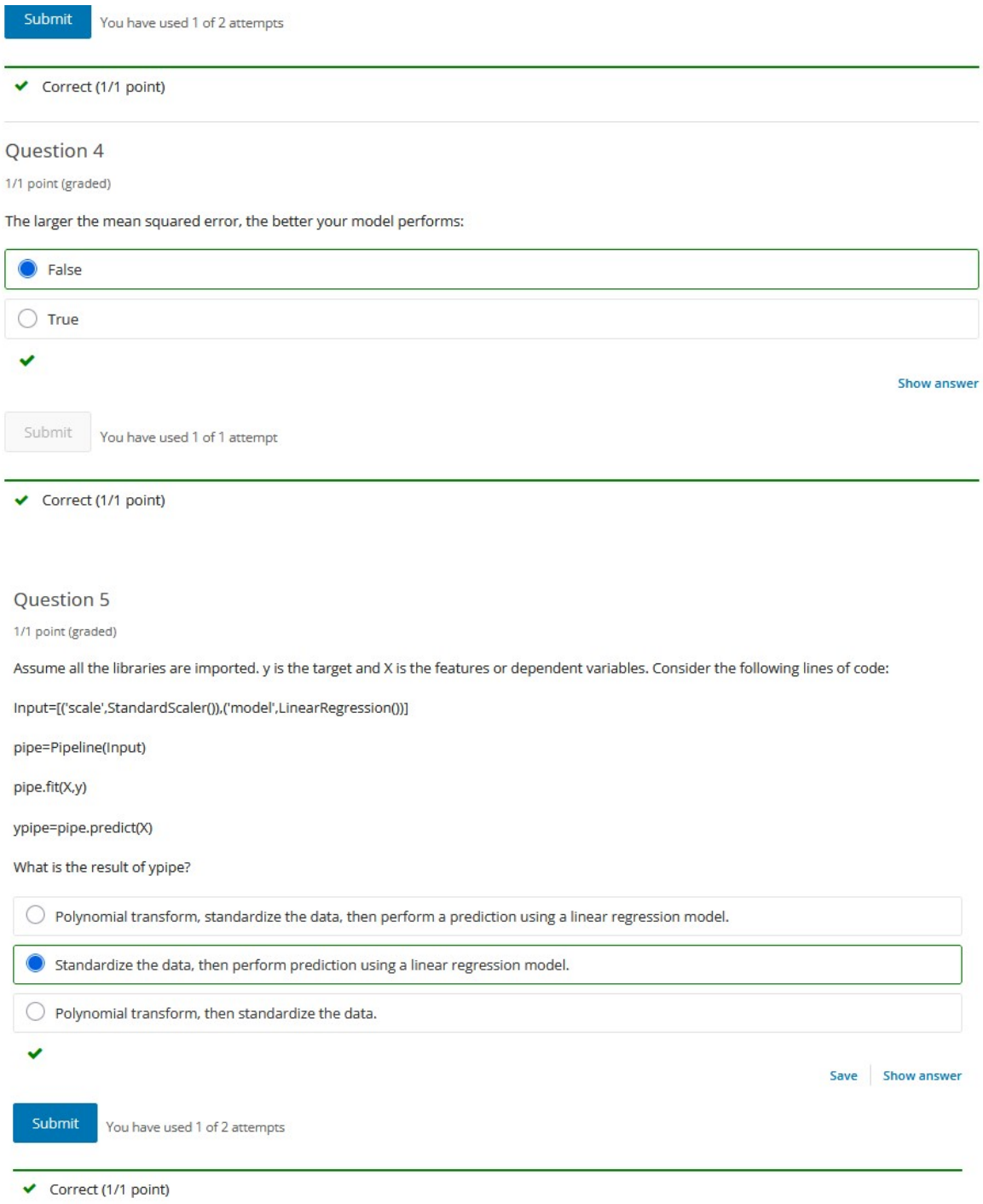
1/1 point (graded)

Which statement is true about polynomial linear regression?

- ○ Polynomial linear regression is not linear in any way.
- ◉ Although the predictor variables of polynomial linear regression are not linear, the relationship between the parameters or coefficients is linear.
- ○ Polynomial linear regression uses wavelets.

✔

Save | Show answer



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