# FUNCTIONS AND WAYS OF HANDLING DATA

## Importing and Exporting data:

Importing and exporting data in python is done by using pandas library

Import pandas as pd

df = pd.read_csv("path of file")

pd.to_csv("path of new file and location)

## Getting insights into data

To get insights into data we can use

df.head()  //to see first 10 rows

df.tail()  //to see last 10 rows

df.describe()  //to get insight into  data as average and other mathematical factors.

df.describe(include="all")  //for all data

df.info()  //can also be use to get info about top 30 and bottom 30 rows.

Df.shape  //will tell you about the shape of the data.

## Connecting to the database

```
from dbmodule import connect

#Create connection object
connection = connect('databasename','username','pswd')

#Create a cursor object
cursor = connection.cursor()

#Run queries
cursor.execute('select * from mytable')
results = cursor.fetchall()

#Free resources
Cursor.close()
connection.close()
```

## Cleaning Data, Removing and replacing missing Values

To remove NA values we use

**df.dropna(subset = "[column_name]", axis = 0, inplace = True)**

Axis 0 — x axis – means dropping rows

Axis 1 — y axis – means dropping columns

Inplace = true —means keep the other data intact and just drop the column or row

**For replacing values**

**df.replace("old val","new val")  // new val can be anything (mean,median,mode)**

Simple calculations can be easily done on data frames

**Df[“column name”] = df[“column name”]*255**

Also we can change column name using

**df.rename(columns = {“original”:”new”}, inplace= true)**

To check datatype of column

**df.dtypes()**

To change datatype of column we use

**df.astype(“data type”)**

## Numpy linspace

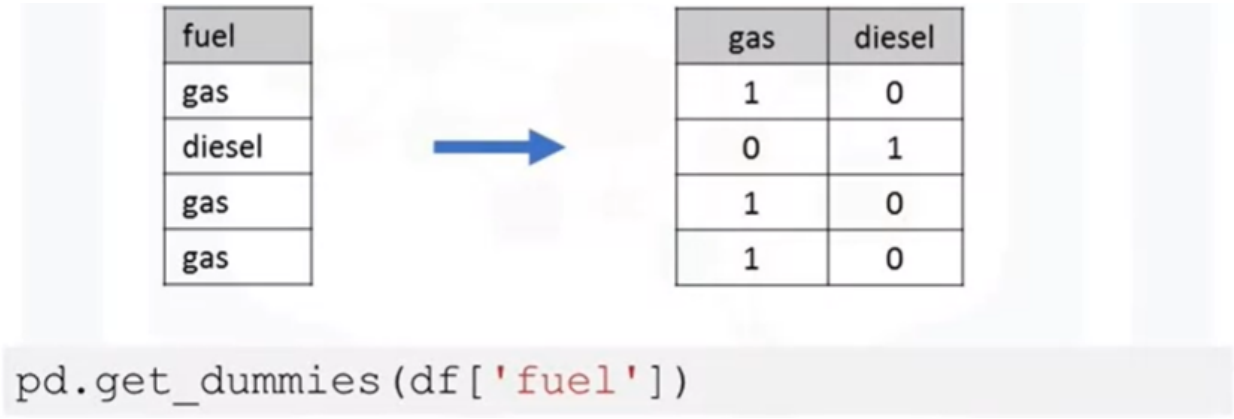
Numpy linspace gives you equally spaced integers in a specified range

np.linspace(start, end, ”HOW MANY NUMBERS YOU WANT”)

```
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 )
```

pd.cut() is used to divide the data as per the bins and labels is used to label them after dividing.

## Turning categorical variables into numerical variables



| fuel |
|---|
| gas |
| diesel |
| gas |
| gas |

| gas | diesel |
|---|---|
| 1 | 0 |
| 0 | 1 |
| 1 | 0 |
| 1 | 0 |

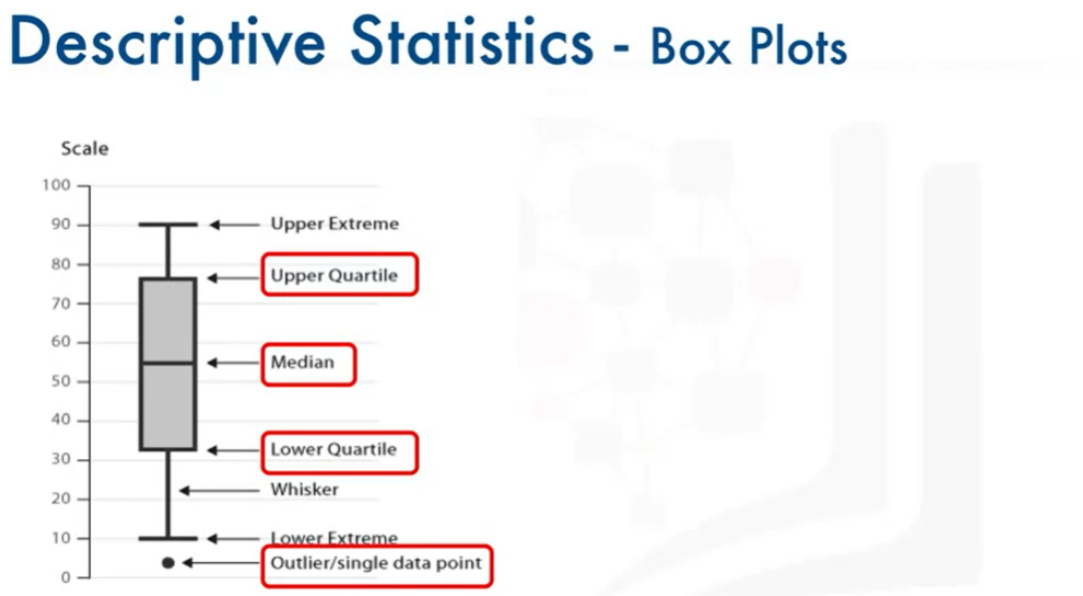
```
pd.get_dummies(df['fuel'])
```

Pd.get_dummies will create dummy variables in the dataset with values as 0 and 1 as false and true respectively.

**VALUE COUNTS is used to count the frequency**

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

drive_wheels_counts.rename(columns={'drive-wheels':'value_counts'}, inplace=True)
drive_wheels_counts
```

## BOX PLOTS —- DATA VISUALIZATION



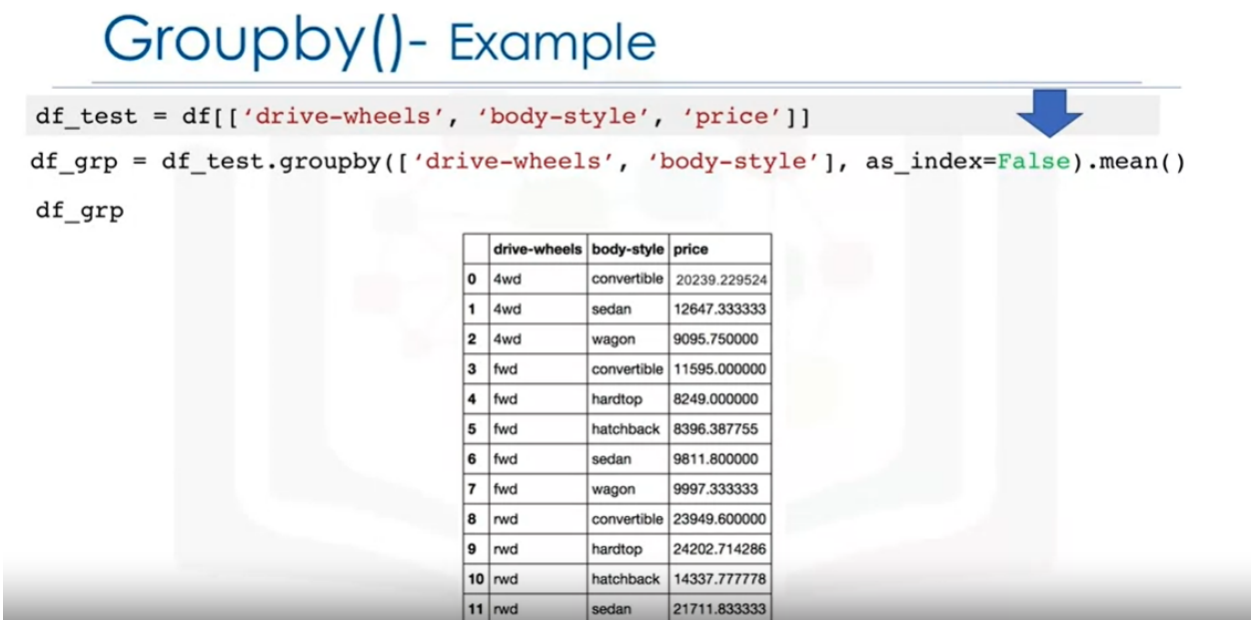

sns.boxplot(x = 'waterfront', y = 'price', data = df)

## SCATTER PLOTS —-- DATA VISUALIZATION

```
y=df["price"]
x=df["engine-size"]
plt.scatter(x,y)

plt.title("Scatterplot of Engine Size vs Price")
plt.xlabel("Engine Size")
plt.ylabel("Price")
```

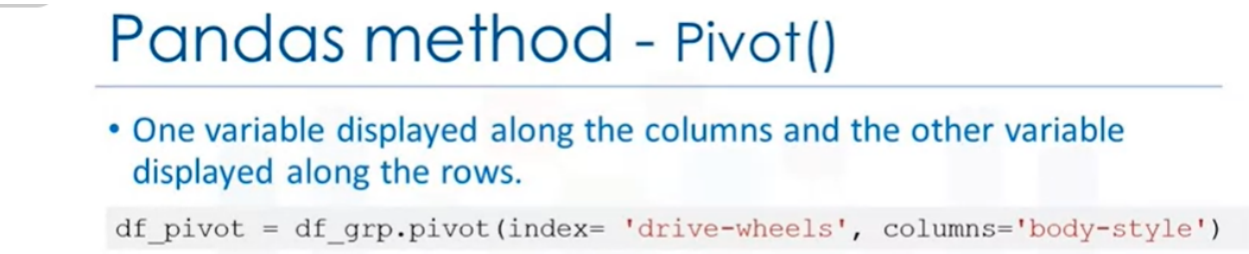
## GROUP BY

Group by is used to group data into categorical variables.



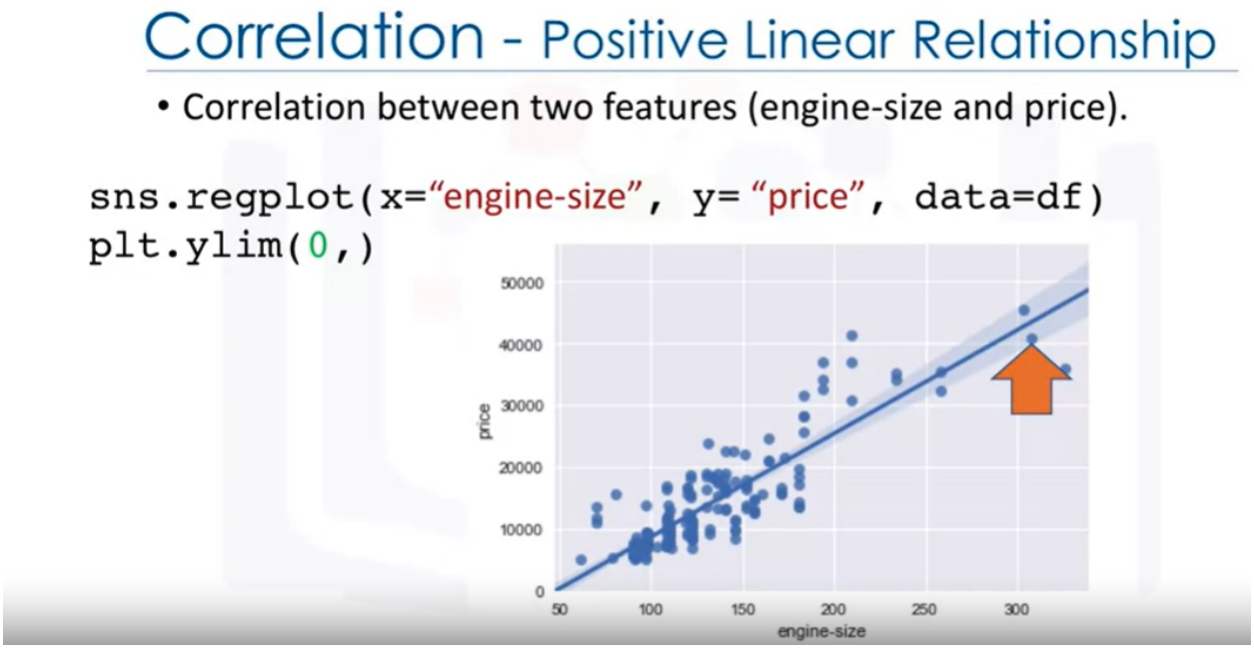

| | drive-wheels | body-style | price |
|---|---|---|---|
| 0 | 4wd | convertible | 20239.229524 |
| 1 | 4wd | sedan | 12647.333333 |
| 2 | 4wd | wagon | 9095.750000 |
| 3 | fwd | convertible | 11595.000000 |
| 4 | fwd | hardtop | 8249.000000 |
| 5 | fwd | hatchback | 8396.387755 |
| 6 | fwd | sedan | 9811.800000 |
| 7 | fwd | wagon | 9997.333333 |
| 8 | rwd | convertible | 23949.600000 |
| 9 | rwd | hardtop | 24202.714286 |
| 10 | rwd | hatchback | 14337.777778 |
| 11 | rwd | sedan | 21711.833333 |

## PIVOT TO BEAUTIFY GROUP BY




| | price | | | | |
|---|---|---|---|---|---|
| **body-style** | **convertible** | **hardtop** | **hatchback** | **sedan** | **wagon** |
| **drive-wheels** | | | | | |
| **4wd** | 20239.229524 | 20239.229524 | 7603.000000 | 12647.333333 | 9095.750000 |
| **fwd** | 11595.000000 | 8249.000000 | 8396.387755 | 9811.800000 | 9997.333333 |
| **rwd** | 23949.600000 | 24202.714286 | 14337.777778 | 21711.833333 | 16994.222222 |

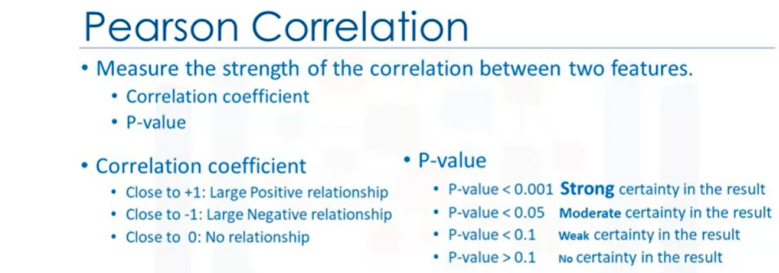
## SEABORN IS MORE STATISTICAL THAN MATPLOTLIB




**Sns.regplot() is used in the same manner as scatter plot and gives more insight into data by drawing the slope lines.**

**PEARSON CORRELATION COEFFICIENT**

**df.corr()>https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.corr.html**




```
pearson_coef, p_value = stats.pearsonr(df['horsepower'], df[ 'price'])
```

- Pearson correlation: 0.81
- P-value : 9.35 e-48

# MODEL DEVELOPMENT

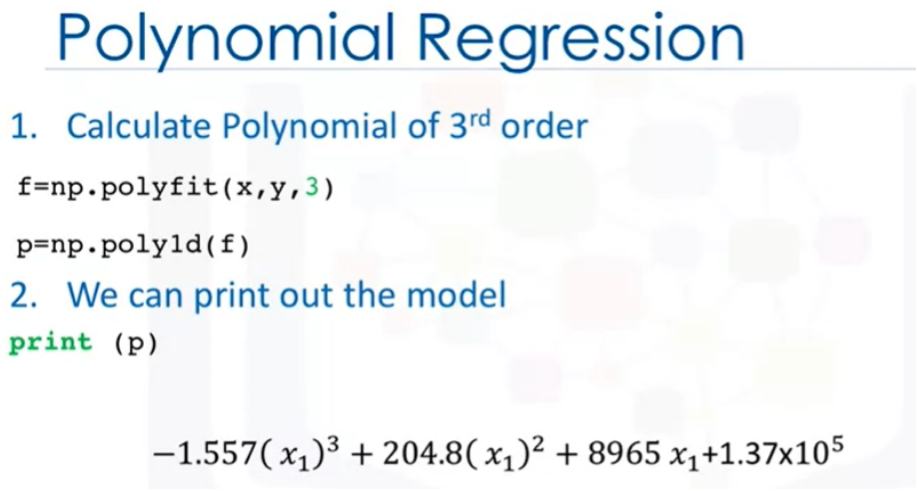
Linear Regression Model

```
from sklearn.linear_model import LinearRegression

lm=LinearRegression()

X = df[['highway-mpg']]

Y = df['price']

lm.fit(X, Y)

Yhat=lm.predict(X)
```

**DISTRIBUTION PLOT**

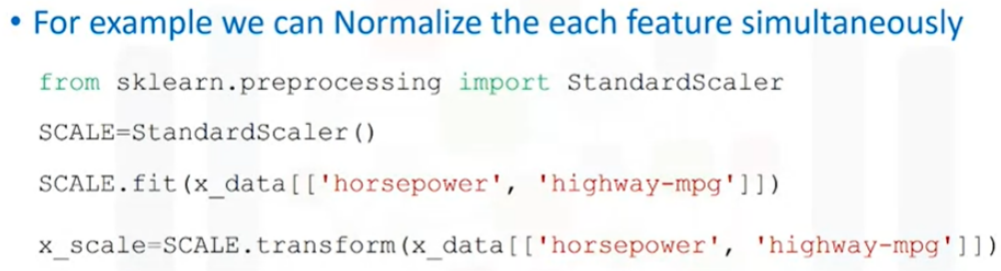
**POLYNOMIAL DISTRIBUTION**

**See sometimes linear regression isnt able to fit all the data points correctly here we require polynomials modes.**




As the linear regression is not very suitable with the polynomials we use sklearn preprocessing library.


We can normalize each feature using



# PIPELINE

Pipelines are very important in machine learning as they reduce your task of applying separate models one by one.

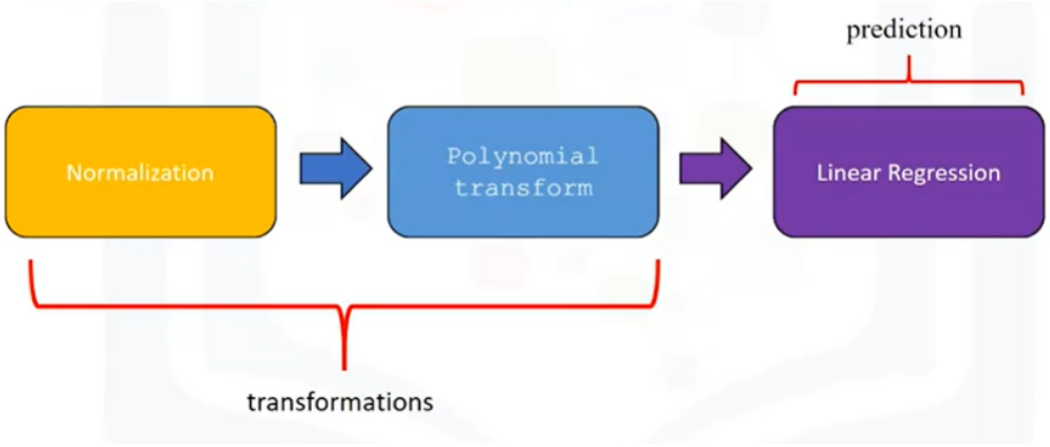
Instead you can create a single pipeline that goes through each model and produces a result.

HOW?

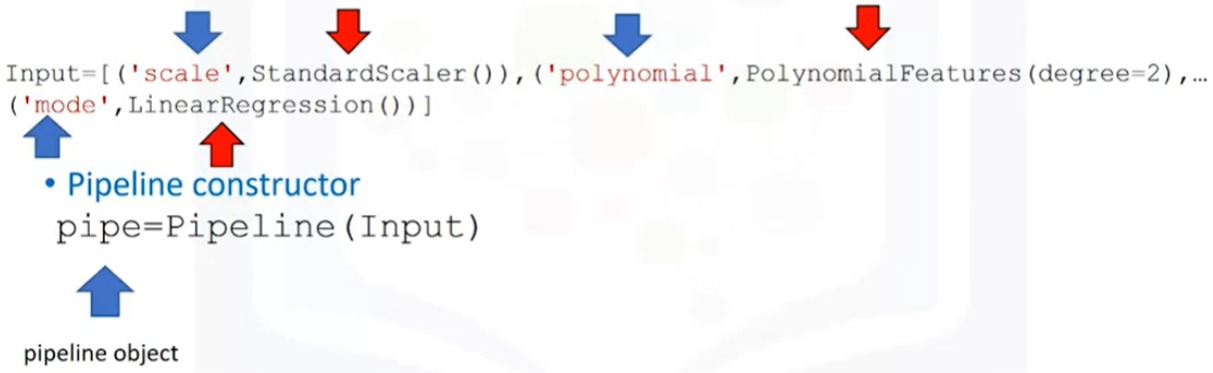
First we need to import the libraries required

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
```

Here the three processes are combined



Creating a pipeline object

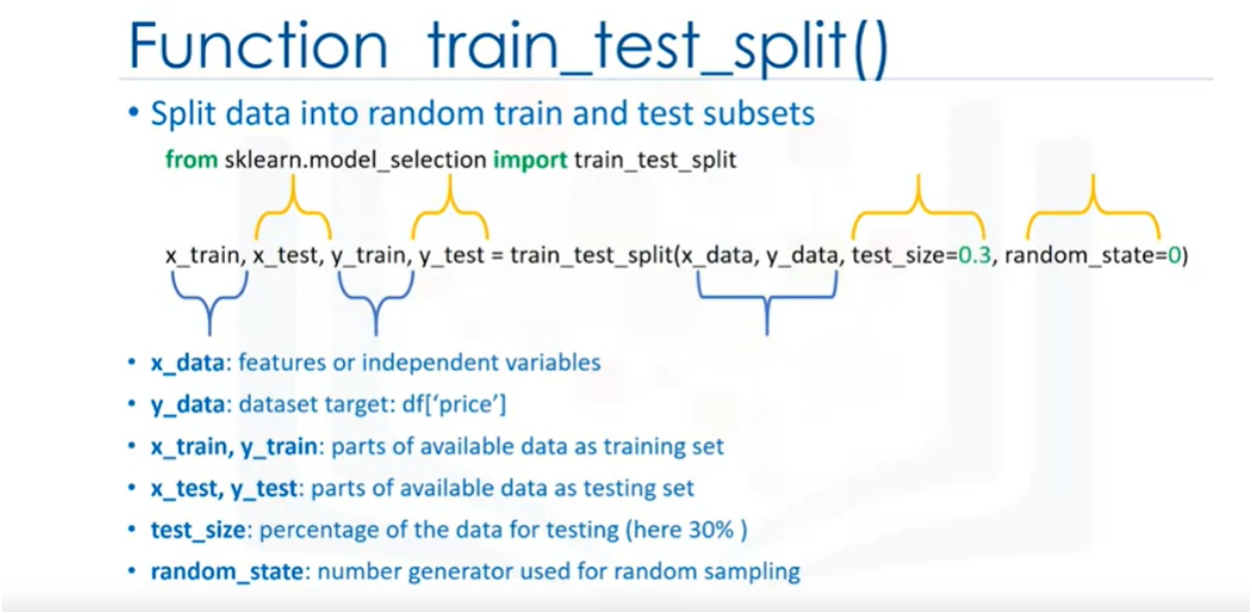



Now after creating a pipeline object we can train and predict using this model

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

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

## Mean Squared Approach and R squared approach?

## Train Test Split




CROSS VALIDATION

Cross-validation is **a technique for evaluating ML models by training several ML models on subsets of the available input data and evaluating them on the complementary subset of the data**. Use cross-validation to detect overfitting, ie, failing to generalize a pattern.

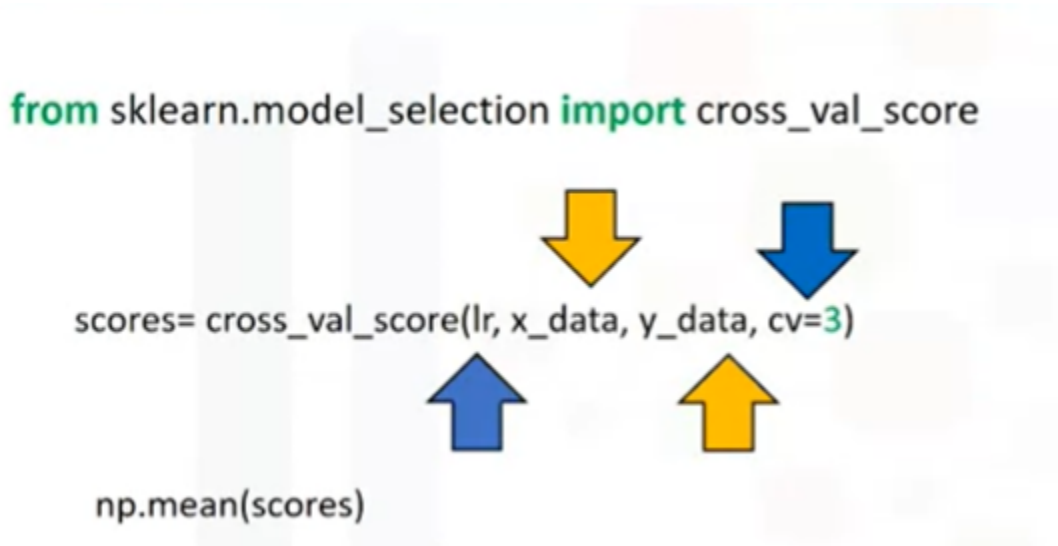
```
from sklearn.model_selection import cross_val_sc

scores= cross_val_score(lr, x_data, y_data, cv=10)
```

cv is used to divide the dataset into parts here cv=10 means dividing the dataset into 10 parts.

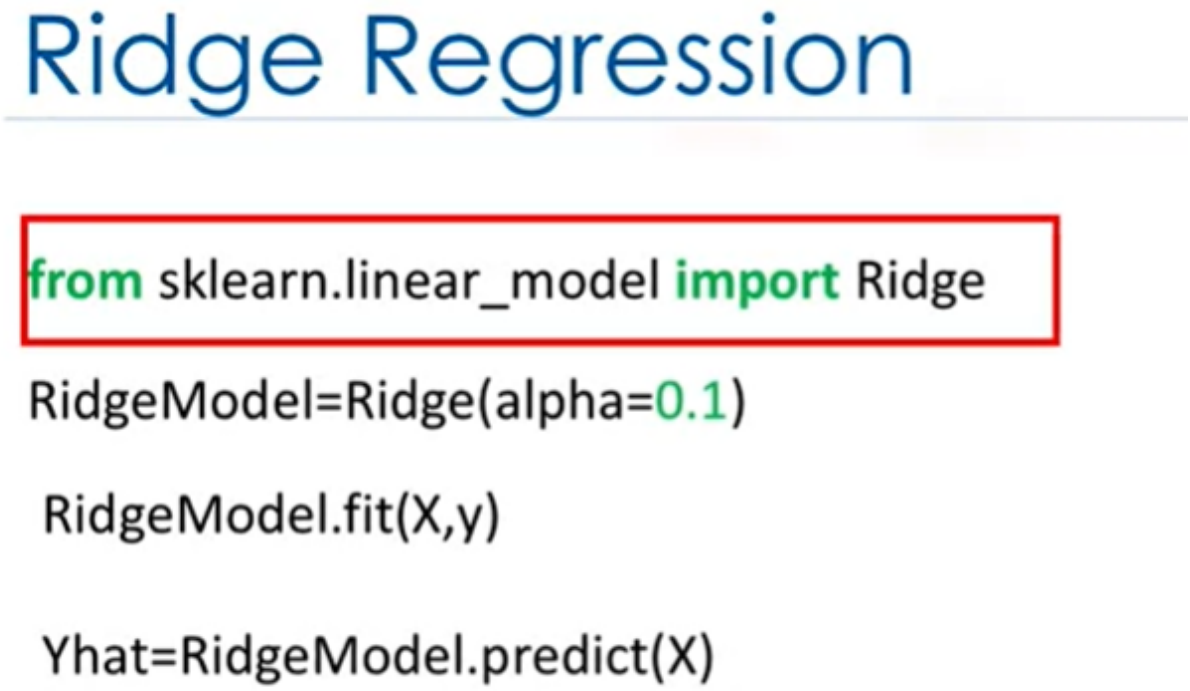
Lr – linear regression model.

X_data is the data/independent variables.

Y_data is the dependent variable or the target variable.




**RIDGE REGRESSION**



## GRID SEARCH

```
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV

parameters1= [{'alpha': [0.001,0.1,1, 10, 100, 1000,10000,100000,100000]}]

RR=Ridge()

Grid1 = GridSearchCV(RR, parameters1,cv=4)

Grid1.fit(x_data[['horsepower', 'curb-weight', 'engine-size', 'highway-mpg']],y_data)

Grid1.best_estimator_

scores  = Grid1.cv_results_
scores['mean_test_score']
```