Loading the data

Used house prediction because previous dataset of Airplane Crash had most of the values from 0 to 10.

```
# all the libraries
   import os
   import pandas as pd
   import numpy as np
   import matplotlib.pyplot as plt
   import seaborn as sns; sns.set()
   import missingno as msno
   from sklearn import linear_model
   from sklearn.model selection import train test split
   from sklearn.preprocessing import normalize
   from sklearn.linear model import LinearRegression
   from sklearn.metrics import mean squared error
   %matplotlib inline
   import matplotlib.pyplot as plt
   from mpl_toolkits.mplot3d import Axes3D
   import itertools
        /usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
           import pandas.util.testing as tm
   import os
   import tarfile
   from six.moves import urllib
   DOWNLOAD ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/master/"
   HOUSING PATH = os.path.join("datasets", "housing")
   HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"
   def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
       if not os.path.isdir(housing path):
           os.makedirs(housing path)
       tgz_path = os.path.join(housing_path, "housing.tgz")
       urllib.request.urlretrieve(housing url, tgz path)
       housing_tgz = tarfile.open(tgz_path)
       housing tgz.extractall(path=housing path)
       housing_tgz.close()
   fetch housing data()
   impont pandac ac nd
https://colab.research.google.com/drive/1 s5dMSInujp5 ACEgcjTpMzn TDsLJfT#scrollTo=s9XUgyOxR0Do&printMode=true
```

```
def load_housing_data(housing_path=HOUSING_PATH):
    csv_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(csv_path)
```

houseprediction = load_housing_data()
houseprediction.head()

₽		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	hoı
	0	-122.23	37.88	41.0	880.0	129.0	322.0	
	1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	
	2	-122.24	37.85	52.0	1467.0	190.0	496.0	
	3	-122.25	37.85	52.0	1274.0	235.0	558.0	
	4	-122.25	37.85	52.0	1627.0	280.0	565.0	

▼ Data Exploration

houseprediction.shape

[→ (20640, 10)

houseprediction.describe()

₽		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	рс
	count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	206
	mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	14:
	std	2.003532	2.135952	12.585558	2181.615252	421.385070	11:
	min	-124.350000	32.540000	1.000000	2.000000	1.000000	
	25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	7
	50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	110
	75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	17:
	max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	356

houseprediction.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
```

#	Column	Non-Null Count	Dtype
0	longitude	20640 non-null	float64
1	latitude	20640 non-null	float64
2	housing_median_age	20640 non-null	float64
3	total_rooms	20640 non-null	float64
4	total_bedrooms	20433 non-null	float64
5	population	20640 non-null	float64
6	households	20640 non-null	float64
7	median_income	20640 non-null	float64
8	<pre>median_house_value</pre>	20640 non-null	float64
9	ocean proximity	20640 non-null	object

data_drop = houseprediction.drop(['longitude','latitude','total_bedrooms','population','house

data_drop.dtypes

```
housing_median_age float64
total_rooms float64
median_income float64
median_house_value float64
dtype: object
```

Checking if there are any missing value. If true, missing values are present. If false not present

```
houseprediction.isna().values.any()
```

True

data drop.info

Г⇒	<pre><bound method<="" pre=""></bound></pre>	DataFrame.info of		housing_median_age	total_rooms	<pre>median_income</pre>	n
_	0	41.0	880.0	8.3252	452600	.0	
	1	21.0	7099.0	8.3014	358500	.0	
	2	52.0	1467.0	7.2574	352100	.0	
	3	52.0	1274.0	5.6431	341300	.0	
	4	52.0	1627.0	3.8462	342200	.0	
	• • •	• • •		• • •		• •	
	20635	25.0	1665.0	1.5603	78100	.0	
	20636	18.0	697.0	2.5568	77100	.0	
	20637	17.0	2254.0	1.7000	92300	.0	
	20638	18.0	1860.0	1.8672	84700	.0	
	20639	16.0	2785.0	2.3886	89400	.0	

[20640 rows x 4 columns]>

data_drop.isnull().sum()

 Γ_{\rightarrow}

```
housing_median_age 0
total_rooms 0
median_income 0
median_house_value 0
dtype: int64
```

remove_data = houseprediction[houseprediction.isnull().any(axis=1)] # dropping missing values
remove_data.shape

```
[→ (207, 10)
```

```
# Use the sklearn imputer class, select median as method
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
```

```
[(x, y) for x, y in zip(houseprediction.isna().sum(), houseprediction.isna().sum().index) if

□→ [(207, 'total_bedrooms')]
```

Total bedrooms has missing values - fill median values for it

```
average = houseprediction["total_bedrooms"].median()
houseprediction["total_bedrooms"].fillna(average, inplace=True)
houseprediction.isna().values.any()

    False
```

Checking corrolation between the dependent and independent variables

data_drop.corr()

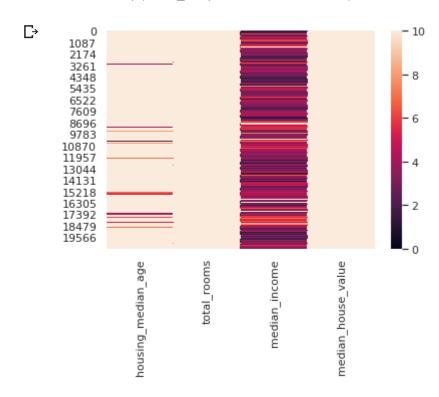
₽		housing_median_age	total_rooms	median_income	median_house_value
	housing_median_age	1.000000	-0.361262	-0.119034	0.105623
	total_rooms	-0.361262	1.000000	0.198050	0.134153
	median_income	-0.119034	0.198050	1.000000	0.688075
	median_house_value	0.105623	0.134153	0.688075	1.000000

```
correlation = data_drop.corr()
correlation.style.background_gradient()
correlation.style.background_gradient().set_precision(3)
#precision(3) is set for 2 decimal palces.
```

housing_median_age total_rooms median_income median_house_value

housing_median_age 1.000	-0.361	-0.119	0.106
total_rooms -0.361	1.000	0.198	0.134
median_income -0.119	0.198	1.000	0.688
median house value 0.106	0.134	0.688	1.000

ax = sns.heatmap(data_drop, vmin=0, vmax=10)



data_drop.describe()

₽		housing_median_age	total_rooms	median_income	median_house_value
	count	20640.000000	20640.000000	20640.000000	20640.000000
	mean	28.639486	2635.763081	3.870671	206855.816909
	std	12.585558	2181.615252	1.899822	115395.615874
	min	1.000000	2.000000	0.499900	14999.000000
	25%	18.000000	1447.750000	2.563400	119600.000000
	50%	29.000000	2127.000000	3.534800	179700.000000
	75%	37.000000	3148.000000	4.743250	264725.000000
	max	52.000000	39320.000000	15.000100	500001.000000

X = data_drop[['housing_median_age','total_rooms','median_income']]

Y = data_drop['median_house_value']

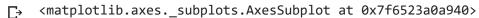
Training and splitting data

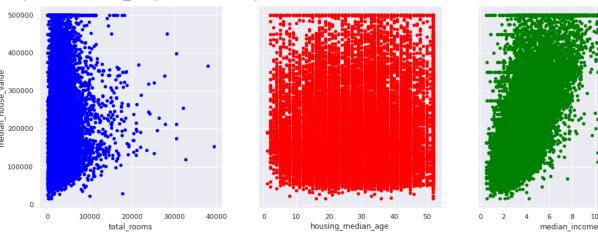
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.3,random_state=42)
x_train.shape, x_test.shape, Y.shape,y_train.shape, y_test.shape

[> ((14448, 3), (6192, 3), (20640,), (14448,), (6192,))
```

▼ Data Visualization

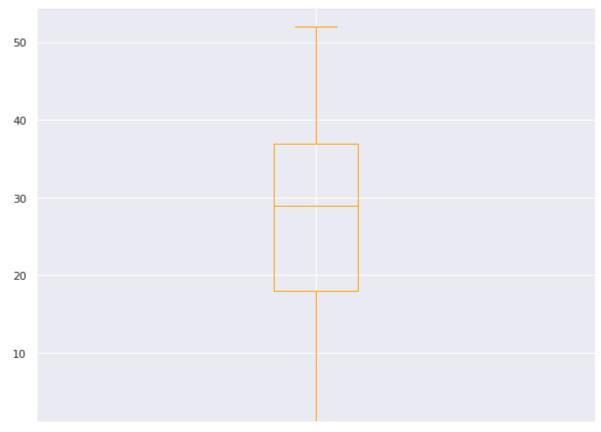
#visualize the relationship between the features and the response using scatterplots
fig, axs = plt.subplots(1, 3, sharey=True)
data_drop.plot(kind='scatter', x='total_rooms', y='median_house_value', ax=axs[0], figsize=(1
data_drop.plot(kind='scatter', x='housing_median_age', y='median_house_value', ax=axs[1], col
data_drop.plot(kind='scatter', x='median_income', y='median_house_value', ax=axs[2], color='g





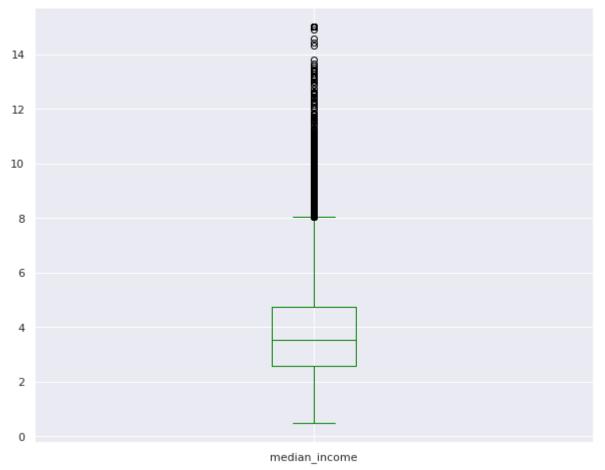
x_train.boxplot('housing_median_age', figsize=(10,8),grid=True, color='orange')

<matplotlib.axes._subplots.AxesSubplot at 0x7f6523897ac8>



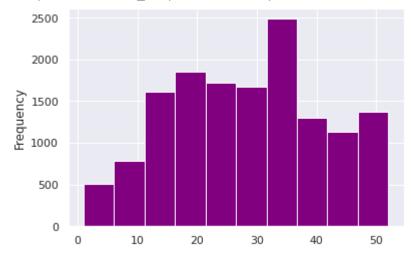
x_train.boxplot('total_rooms', figsize=(10,8),grid=True, color='red')

<matplotlib.axes._subplots.AxesSubplot at 0x7f6521fcb4a8>



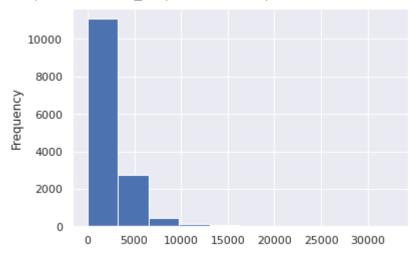
x_train['housing_median_age'].plot(kind='hist',color='purple')



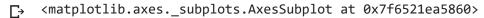


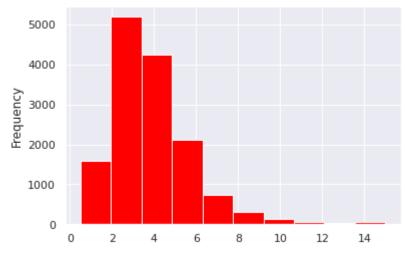
x_train['total_rooms'].plot(kind='hist')

<matplotlib.axes._subplots.AxesSubplot at 0x7f6521f63c88>



x_train['median_income'].plot(kind='hist',color='red') # Distributed normally towards median_





x_train[x_train.isnull().any(axis=1)]

ightharpoonup housing_median_age total_rooms median_income

→ Standardise data

Note that once the data is normalize, we cannot further make a summary statistics. For that reason we have assigned different names for normalised data (norm_train or norm_test)

```
from sklearn.preprocessing import StandardScaler
std = StandardScaler()
norm_train = std.fit_transform(x_train)
norm_test = std.fit_transform(x_test)
```

Transformed data

→ Simple Linear Regression

```
numInstances = (data_drop.shape[0])
print(numInstances)
X = np.random.rand(numInstances,1).reshape(-1,1)
y_true = -3*X + 1
y = y_true + np.random.normal(size=numInstances).reshape(-1,1)
plt.scatter(X, y, color='black')
plt.plot(X, y_true, color='blue', linewidth=3)
plt.title('True function: y = -3X + 1')
plt.xlabel('X')
plt.ylabel('y')
```

```
20640
Text(0, 0.5, 'y')

True function: y = -3X + 1
```

▼ Perform Regression with one Independent Variable

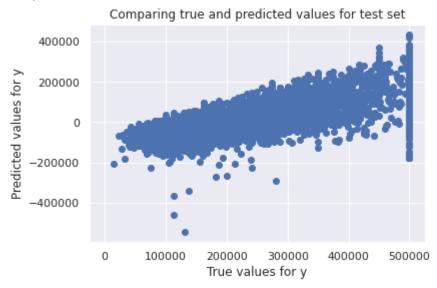
```
slr = data drop.median income.values
slr = slr.reshape(-1,1)
        _2 532...
from sklearn.model selection import train test split
X_train_rp,X_test_rp,Y_train_rp,Y_test_rp = train_test_split(slr,Y,test_size=0.3, random_stat
                                               •
from sklearn.linear_model import LinearRegression
modelslr = LinearRegression()
modelslr.fit(X_train_rp,Y_train_rp) # model fitting for the training set
    LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
R-squared on the training dataset
modelslr.score(X train rp,Y train rp)
    0.48062719927664055
modelslr.score(X_test_rp,Y_test_rp)
# R-squared value on the test set
    0.4564966485656325
Training dataset has slighter better score than Test dataset
Y pred rp = modelslr.predict(X test rp)
Y_pred_rp.mean()
    207389.01699770137
from sklearn.metrics import mean squared error, r2 score
# Comparing true versus predicted values
plt.scatter(Y_test_rp, Y_test_rp - Y_pred_rp, color='b')
x = np.random.rand(30)
plt.plot(x, x*0)
plt.title('Comparing true and predicted values for test set')
```

plt.xlabel('True values for y')

```
plt.ylabel('Predicted values for y')

# Model evaluation
print("Root mean squared error = %.4f" % np.sqrt(mean_squared_error(Y_test_rp, Y_pred_rp)))
print('R-squared = %.4f' % r2_score(Y_test_rp, Y_pred_rp))
```

Root mean squared error = 85124.5362 R-squared = 0.4565



from sklearn.metrics import mean_squared_error
print(np.sqrt(mean_squared_error(Y_test_rp,Y_pred_rp)))

F→ 85124.53624841144

▼ Plotting the Least Squares Line

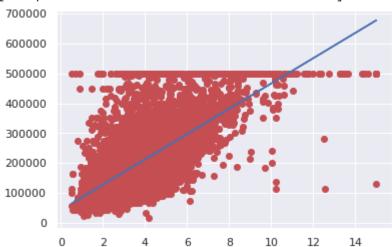
```
#Ploting on train data Set
plt.scatter(X_train_rp,Y_train_rp,color='r')
plt.plot(X_train_rp,modelslr.predict(X_train_rp), color='b')
```

C→

```
[<matplotlib.lines.Line2D at 0x7f768525a978>]
```

```
#Ploting on Test data Set
plt.scatter(X_test_rp,Y_test_rp,color='r')
plt.plot(X_test_rp,modelslr.predict(X_test_rp), color='b')
```





modelslr

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

Multiple Linear Regression

```
#split data
numTrain = 20  # number of training instances
numTest = numInstances - numTrain

X_train = X[:-numTest]
X_test = X[-numTest:]
y_train = y[:-numTest]
y_test = y[-numTest:]
```

Summary of training data set

```
import statsmodels.api as sm
xstat = sm.add_constant(norm_train)
est = sm.OLS(y_train,xstat)
statfit = est.fit()
print(statfit.summary())
```

OLS Regression Results

========	========	======		=====:			=======	
Dep. Variab	le: med:	ian_hoເ	ıse v	alue	R-sa	uared:		0.514
Model:		_	_	OLS		R-squared:		0.514
Method:		Least	Squ	ares	_	atistic:		5096.
Date:	Sı	un, 05			Prob	(F-statistic):	0.00
Time:			01:0	5:43	Log-	Likelihood:		-1.8374e+05
No. Observa	tions:		1	4448	AIC:			3.675e+05
Df Residual	s:		1	4444	BIC:			3.675e+05
Df Model:				3				
Covariance	Type:	r	nonro	bust				
========	========		-===	=====	====	========	=======	
	coef	std	err		t	P> t	[0.025	0.975]
const	2.069e+05	671	. 261	308	.262	0.000	2.06e+05	2.08e+05
x1	2.504e+04	721.	211	34	.715	0.000	2.36e+04	2.65e+04
x2	8834.2420	730.	735	12	.090	0.000	7401.907	1.03e+04
x3	8.085e+04	685	.723	117	.903	0.000	7.95e+04	8.22e+04
Omnibus:	=======	=====	==== 2998	.715	==== Durb	======== in-Watson:	=======	1.975
Prob(Omnibu	s):		0	.000	Jarq	ue-Bera (JB):		7420.517
Skew:	•			.147		(JB):		0.00
Kurtosis:			5	.659		. No.		1.53
========	========	======		=====	====	========	=======	========

Summary of the model on the Test set

```
import statsmodels.api as sm
xstat = sm.add_constant(norm_test)
est = sm.OLS(y_test,xstat)
statfit = est.fit()
print(statfit.summary())
```

OLS Regression Results

______ Dep. Variable: median_house_value R-squared: 0.513 Model: Adi. R-squared: 0.512 Method: F-statistic: 2169. Least Squares Date: Sun. 05 Apr 2020 Proh (F-statistic): a aa

#Defined y_predict

pred_y = reg.predict(norm_test)

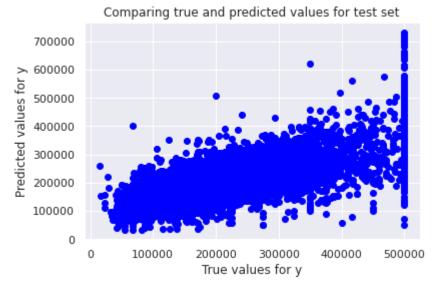
Df Model: 3

Evaluate model on test data set

coet std err t P>|t| [0.025 0.975]

Comparing true versus predicted values
plt.scatter(y_test, pred_y, color='blue')
plt.title('Comparing true and predicted values for test set')
plt.xlabel('True values for y')
plt.ylabel('Predicted values for y')

Text(0, 0.5, 'Predicted values for y')



from sklearn.metrics import mean squared error, r2 score

pred_y

□→ array([101793.6345172 , 153912.1246265 , 242069.08675016, ..., 187843.23022605, 186694.36205061, 159502.22858421])

pred_y.mean()

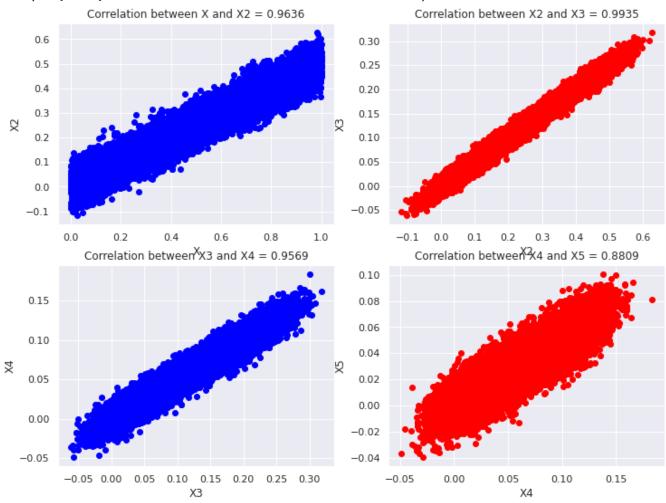
#Score for training dataset
reg.score(norm_train,y_train)

```
\Box
     0.5141931111690983
#Score for testing dataset
reg.score(norm_test, y_test)
     0.5124347436482521
#Model prediction
from sklearn.metrics import mean squared error
print(np.sqrt(mean_squared_error(y_test,pred_y)))
     79996.80957002078
regr = LinearRegression()
regr.fit(norm_train,y_train)
     LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
pred_y = regr.predict(X_test)
numInstances = (houseprediction.shape[0])
                # number of training instances
numTrain = 20
numTest = numInstances - numTrain
seed = 1
np.random.seed(seed)
X2 = 0.5*X + np.random.normal(0, 0.04, size=numInstances).reshape(-1,1)
X3 = 0.5*X2 + np.random.normal(0, 0.01, size=numInstances).reshape(-1,1)
X4 = 0.5*X3 + np.random.normal(0, 0.01, size=numInstances).reshape(-1,1)
X5 = 0.5*X4 + np.random.normal(0, 0.01, size=numInstances).reshape(-1,1)
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(12,9))
ax1.scatter(X, X2, color='blue')
ax1.set xlabel('X')
ax1.set ylabel('X2')
c = np.corrcoef(np.column stack((X[:-numTest],X2[:-numTest])).T)
titlestr = 'Correlation between X and X2 = %.4f' % (c[0,1])
ax1.set title(titlestr)
ax2.scatter(X2, X3, color='red')
ax2.set xlabel('X2')
ax2.set ylabel('X3')
c = np.corrcoef(np.column stack((X2[:-numTest],X3[:-numTest])).T)
titlestr = 'Correlation between X2 and X3 = %.4f' % (c[0,1])
ax2.set title(titlestr)
```

```
ax3.scatter(X3, X4, color='blue')
ax3.set_xlabel('X3')
ax3.set_ylabel('X4')
c = np.corrcoef(np.column_stack((X3[:-numTest],X4[:-numTest])).T)
titlestr = 'Correlation between X3 and X4 = %.4f' % (c[0,1])
ax3.set_title(titlestr)

ax4.scatter(X4, X5, color='red')
ax4.set_xlabel('X4')
ax4.set_ylabel('X5')
c = np.corrcoef(np.column_stack((X4[:-numTest],X5[:-numTest])).T)
titlestr = 'Correlation between X4 and X5 = %.4f' % (c[0,1])
ax4.set_title(titlestr)
```

Γ Text(0.5, 1.0, 'Correlation between X4 and X5 = 0.8809')



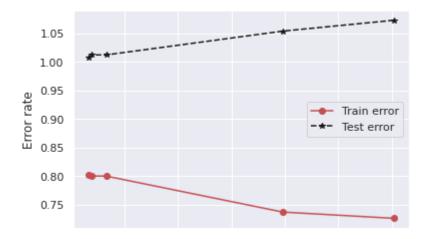
```
X_train2 = np.column_stack((X[:-numTest],X2[:-numTest]))
X_test2 = np.column_stack((X[-numTest:],X2[-numTest:]))
X_train3 = np.column_stack((X[:-numTest],X2[:-numTest],X3[:-numTest]))
X_test3 = np.column_stack((X[-numTest:],X2[-numTest:],X3[-numTest:]))
X_train4 = np.column_stack((X[:-numTest],X2[:-numTest],X3[:-numTest]))
```

```
X test4 = np.column stack((X[-numTest:],X2[-numTest:],X3[-numTest:],X4[-numTest:]))
X_{\text{train5}} = \text{np.column\_stack}((X[:-numTest],X2[:-numTest],X3[:-numTest],X4[:-numTest],X5[:-numTest])
X test5 = np.column stack((X[-numTest:],X2[-numTest:],X3[-numTest:],X4[-numTest:],X5[-numTest
regr2 = linear model.LinearRegression()
regr2.fit(X_train2, y_train)
regr3 = linear_model.LinearRegression()
regr3.fit(X_train3, y_train)
regr4 = linear model.LinearRegression()
regr4.fit(X_train4, y_train)
regr5 = linear model.LinearRegression()
regr5.fit(X_train5, y_train)
   LinearRegression(copy X=True, fit intercept=True, n jobs=None, normalize=False)
y_pred_train = regr.predict(X_train)
y pred test = regr.predict(X test)
y pred train2 = regr2.predict(X train2)
y pred test2 = regr2.predict(X test2)
y pred train3 = regr3.predict(X train3)
y_pred_test3 = regr3.predict(X_test3)
y_pred_train4 = regr4.predict(X_train4)
y_pred_test4 = regr4.predict(X_test4)
y pred train5 = regr5.predict(X train5)
y_pred_test5 = regr5.predict(X_test5)
import pandas as pd
import matplotlib.pyplot as plt
columns = ['Model', 'Train error', 'Test error', 'Sum of Absolute Weights']
model1 = "%.2f X + %.2f" % (regr.coef_[0][0], regr.intercept_[0])
values1 = [ model1, np.sqrt(mean squared error(y train, y pred train)),
           np.sqrt(mean_squared_error(y_test, y_pred_test)),
           np.absolute(regr.coef_[0]).sum() + np.absolute(regr.intercept_[0])]
model2 = "%.2f X + %.2f X2 + %.2f" % (regr2.coef_[0][0], regr2.coef_[0][1], regr2.intercept_[
values2 = [ model2, np.sqrt(mean squared error(y train, y pred train2)),
           np.sqrt(mean_squared_error(y_test, y_pred_test2)),
           np.absolute(regr2.coef_[0]).sum() + np.absolute(regr2.intercept_[0])]
model3 = "%.2f X + %.2f X2 + %.2f X3 + %.2f" % (regr3.coef_[0][0], regr3.coef_[0][1],
                                                 regr3.coef_[0][2], regr3.intercept_[0])
values3 = [ model3, np.sqrt(mean_squared_error(y_train, y_pred_train3)),
           np.sqrt(mean_squared_error(y_test, y_pred_test3)),
           np.absolute(regr3.coef_[0]).sum() + np.absolute(regr3.intercept_[0])]
```

```
regr4.coef_[0][2], regr4.coef_[0][3], regr4.intercept
values4 = [ model4, np.sqrt(mean_squared_error(y_train, y_pred_train4)),
           np.sqrt(mean squared error(y test, y pred test4)),
           np.absolute(regr4.coef_[0]).sum() + np.absolute(regr4.intercept_[0])]
model5 = "%.2f X + %.2f X2 + %.2f X3 + %.2f X4 + %.2f X5 + %.2f" % (regr5.coef_[0][0],
                                        regr5.coef_[0][1], regr5.coef_[0][2],
                                        regr5.coef [0][3], regr5.coef [0][4], regr5.intercept
values5 = [ model5, np.sqrt(mean_squared_error(y_train, y_pred_train5)),
           np.sqrt(mean_squared_error(y_test, y_pred_test5)),
           np.absolute(regr5.coef_[0]).sum() + np.absolute(regr5.intercept_[0])]
results = pd.DataFrame([values1, values2, values3, values4, values5], columns=columns)
plt.plot(results['Sum of Absolute Weights'], results['Train error'], 'ro-')
plt.plot(results['Sum of Absolute Weights'], results['Test error'], 'k*--')
plt.legend(['Train error', 'Test error'])
plt.xlabel('Sum of Absolute Weights')
plt.ylabel('Error rate')
```

results

₽		Model	Train error	Test error	Sum of Absolute Weights
	0	-2.57 X + 0.76	0.802360	1.007736	3.328980
	1	-1.84 X + -1.32 X2 + 0.71	0.800471	1.012590	3.877417
	2	-1.90 X + -2.13 X2 + 1.86 X3 + 0.71	0.800320	1.012596	6.593432
	3	-1.66 X + 0.60 X2 + 9.25 X3 + -27.43 X4 + 0.67	0.737331	1.054231	39.614817
	4	-1.76 X + 3.99 X2 + 3.61 X3 + -35.83 X4 + 14.5	0.726365	1.073214	60.364800



Ridge regression

₽		Model	Train error	Test error	Sum of Absolute Weights
	0	-2.57 X + 0.76	0.802360	1.007736	3.328980
	1	-1.84 X + -1.32 X2 + 0.71	0.800471	1.012590	3.877417
	2	-1.90 X + -2.13 X2 + 1.86 X3 + 0.71	0.800320	1.012596	6.593432
	3	-1.66 X + 0.60 X2 + 9.25 X3 + -27.43 X4 + 0.67	0.737331	1.054231	39.614817
	4	-1.76 X + 3.99 X2 + 3.61 X3 + -35.83 X4 + 14.5	0.726365	1.073214	60.364800

Lasso Regression

	Model	Train error	Test error	Sum of Absolute Weights
0	-2.57 X + 0.76	0.802360	1.007736	3.328980
1	-1.84 X + -1.32 X2 + 0.71	0.800471	1.012590	3.877417
2	-1.90 X + -2.13 X2 + 1.86 X3 + 0.71	0.800320	1.012596	6.593432
3	-1.66 X + 0.60 X2 + 9.25 X3 + -27.43 X4 + 0.67	0.737331	1.054231	39.614817
4	-1.76 X + 3.99 X2 + 3.61 X3 + -35.83 X4 +	N 726365	1 በ73214	<u>ഒ</u> 364800

[#] This is formatted as code