Required Libraries

```
import scipy
import sklearn.svm
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import sklearn.linear_model, sklearn.datasets
from sklearn import kernel_ridge
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.tree import DecisionTreeClassifier
```

Loading the combined test and train datasets for regression

To be able to preprocess the datasets more efficiently, train and test datasets have been combined and will be seperated according to their orginal lengths (800/220) in the model fitting section.

```
#Getting the combined housing_coursework test and training dataset
housingData = pd.read_csv('/housing_coursework_data.csv')

df = pd.DataFrame(data= housingData)

display(df)
```

	No.	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	pop
0	1	-122.21	37.83	34	5065	788.0	
1	2	-122.22	37.77	52	391	128.0	
2	3	-122.23	37.79	30	610	145.0	
3	4	-122.20	37.78	52	2300	443.0	
4	5	-122.19	37.79	50	954	217.0	
...	...	...	...	...	...	...	
1015	1016	-121.70	38.65	22	1360	282.0	

✓ 0s completed at 21:10

1017	1018	-122.00	38.83	26	272	49.0
1018	1019	-122.03	38.69	23	1796	380.0
1019	1020	-121.58	39.14	52	662	160.0

1020 rows × 11 columns

Preprocessing

To be able to get a more accurate result, we must prepare the dataset to fit into our models.

```
df = df.drop(columns=['No.', 'longitude', 'latitude'])
display(df.head())
```

	housing_median_age	total_rooms	total_bedrooms	population	households	median_in
0	34	5065	788.0	1627	766	6.
1	52	391	128.0	520	138	1.
2	30	610	145.0	425	140	1.
3	52	2300	443.0	1225	423	3.
4	50	954	217.0	546	201	2.

```
display(df.select_dtypes(include=np.number).head())
display(df.select_dtypes(exclude=np.number).head())
```

	housing_median_age	total_rooms	total_bedrooms	population	households	median_in
0	34	5065	788.0	1627	766	6.
1	52	391	128.0	520	138	1.
2	30	610	145.0	425	140	1.
3	52	2300	443.0	1225	423	3.
4	50	954	217.0	546	201	2.

	ocean_proximity
0	NEAR BAY

1	NEAR BAY
2	NEAR BAY
3	NEAR BAY

```
display(df.select_dtypes(include=np.number).describe())
```

	housing_median_age	total_rooms	total_bedrooms	population	households	me
count	1020.000000	1020.000000	1011.000000	1020.000000	1020.000000	
mean	27.623529	2732.830392	556.577646	1474.960784	515.614706	
std	12.311122	2168.037719	423.168029	1116.843167	382.273122	
min	2.000000	19.000000	11.000000	34.000000	9.000000	
25%	17.000000	1482.000000	301.500000	807.500000	287.750000	
50%	28.000000	2206.500000	452.000000	1204.000000	427.000000	
75%	36.000000	3260.000000	672.500000	1815.750000	626.500000	
max	52.000000	27700.000000	4386.000000	15037.000000	4072.000000	

Removing lines that have empty data

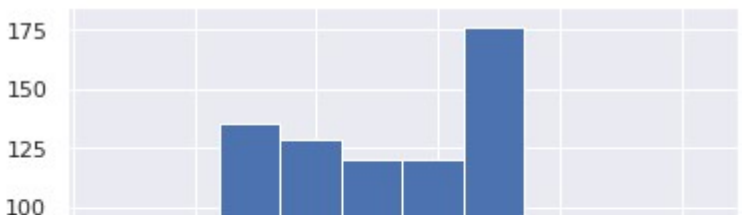
```
print('Original dataset length:')
print(len(df))
df_nl = df.dropna()
print('Dataset length after removing all rows of missing data:')
print(len(df_nl))
```

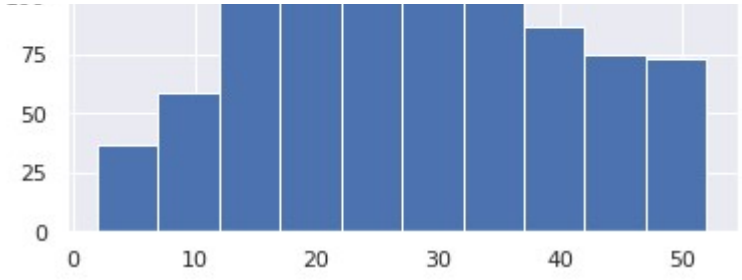
```
Original dataset length:
1020
Dataset length after removing all rows of missing data:
1011
```

Removing outliers

```
df_nl["housing_median_age"].hist()
```

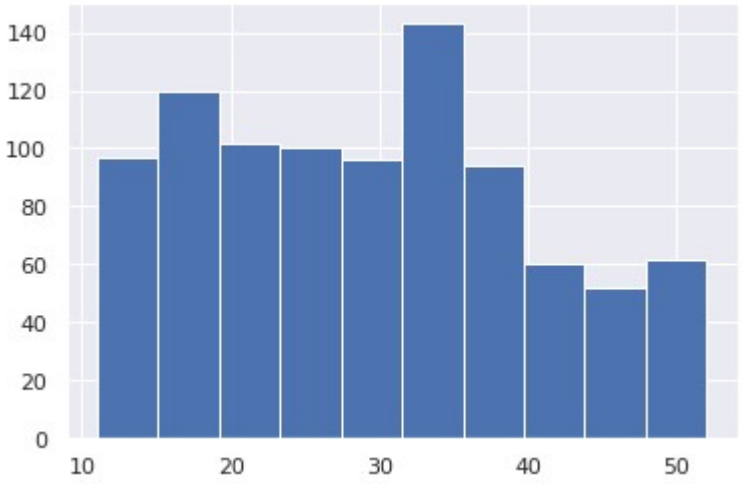
```
<AxesSubplot:>
```





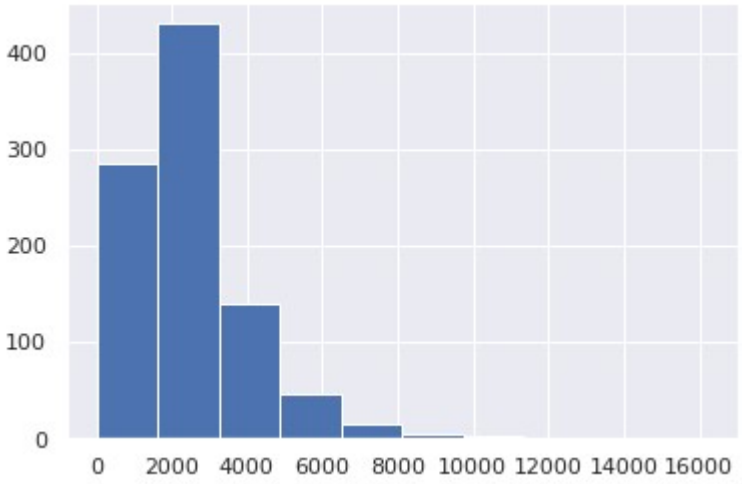

```
df_nl=df_nl[df_nl["housing_median_age"] > 10]
df_nl["housing_median_age"].hist()
```

```
<AxesSubplot:>
```



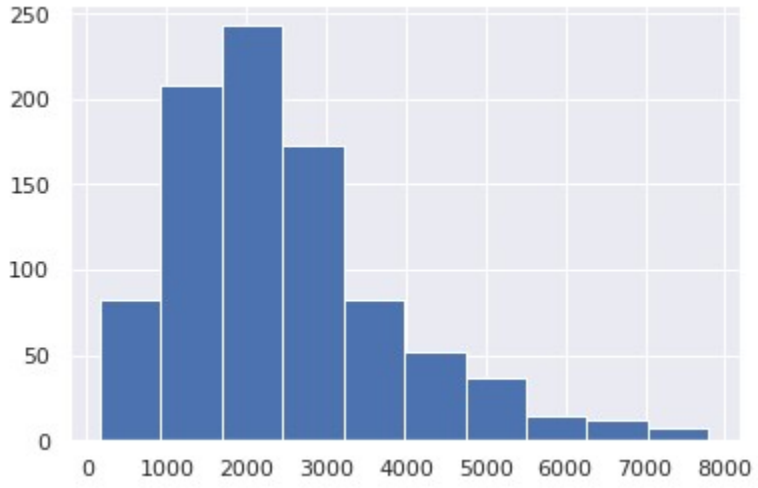

```
df_nl["total_rooms"].hist()
```

```
<AxesSubplot:>
```



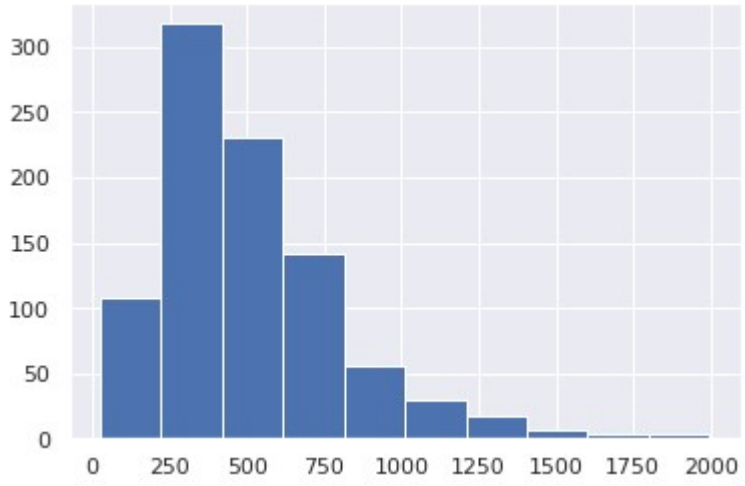

```
df_nl=df_nl[df_nl["total_rooms"] < 8000]
df_nl=df_nl[df_nl["total_rooms"] > 100]
df_nl["total_rooms"].hist()
```

```
<AxesSubplot:>
```



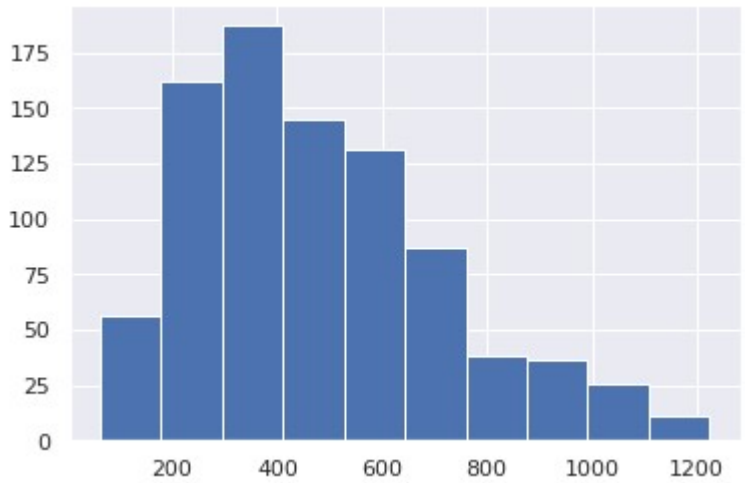

```
df_nl["total_bedrooms"].hist()
```

```
<AxesSubplot:>
```



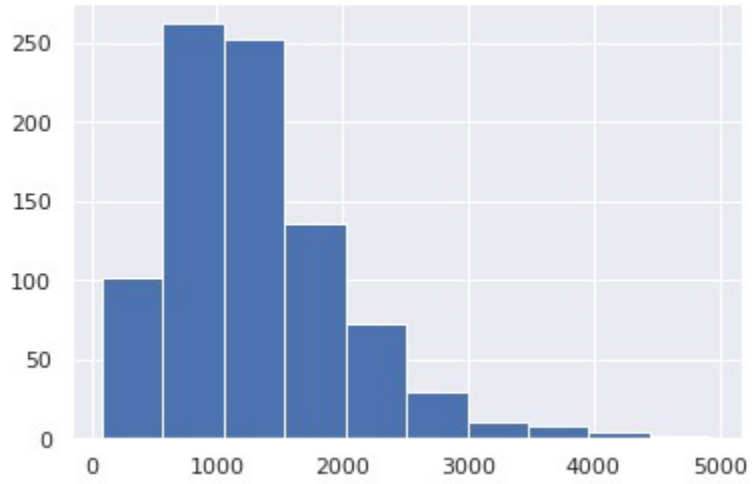

```
df_nl=df_nl[df_nl["total_bedrooms"] < 1250]
df_nl=df_nl[df_nl["total_bedrooms"] > 50]
df_nl["total_bedrooms"].hist()
```

```
<AxesSubplot:>
```



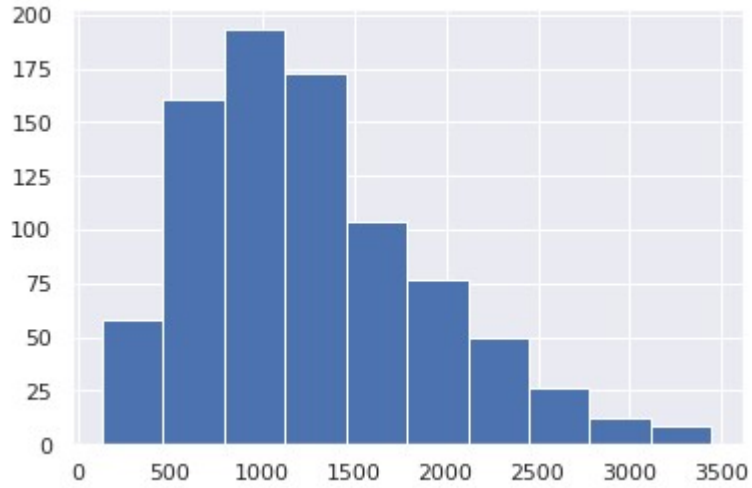
```
df_nl["population"].hist()
```

```
<AxesSubplot:>
```



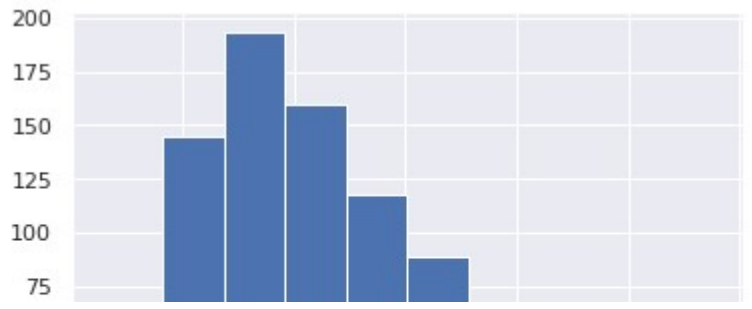

```
df_nl=df_nl[df_nl["population"] < 3500]
df_nl=df_nl[df_nl["population"] > 100]
df_nl["population"].hist()
```

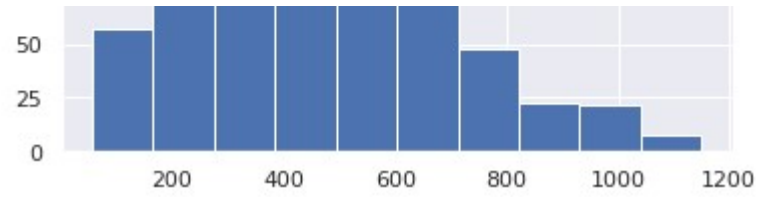
```
<AxesSubplot:>
```




```
df_nl["households"].hist()
```

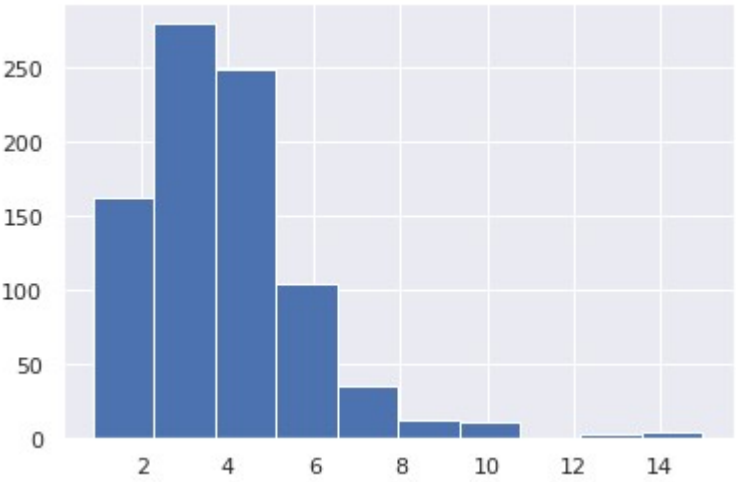
```
<AxesSubplot:>
```





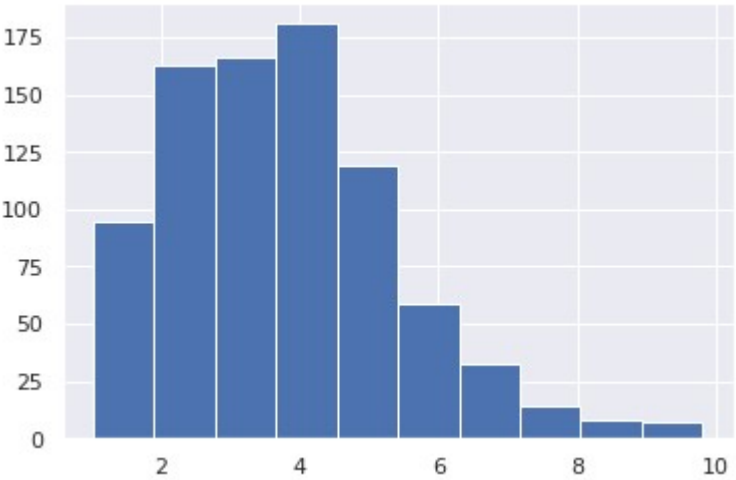

```
df_nl["median_income"].hist()
```

```
<AxesSubplot:>
```




```
df_nl=df_nl[df_nl["median_income"] < 10]
df_nl=df_nl[df_nl["median_income"] > 1]
df_nl["median_income"].hist()
```

```
<AxesSubplot:>
```




```
display(df_nl.select_dtypes(include=np.number).describe())
```

	housing_median_age	total_rooms	total_bedrooms	population	households	medi
count	845.000000	845.000000	845.000000	845.000000	845.000000	
mean	29.000533	2335.127811	474.862722	1272.271006	444.531361	

mean	29.990533	2335.127811	474.862722	1272.271006	444.531361
std	10.893491	1189.606128	229.670442	634.104043	213.169515
min	11.000000	296.000000	62.000000	131.000000	56.000000
25%	21.000000	1456.000000	297.000000	801.000000	284.000000
50%	30.000000	2127.000000	428.000000	1155.000000	411.000000
75%	37.000000	2946.000000	612.000000	1643.000000	573.000000
max	52.000000	7436.000000	1224.000000	3444.000000	1150.000000

```
Xy_df = df_nl[['median_income', 'median_house_value']]

display(Xy_df)
```

	median_income	median_house_value
0	6.8976	333300
1	1.6471	95000
2	1.6198	122700
3	3.5398	158400
4	2.6667	172800
...	...	...
1012	3.9000	146900
1013	1.9510	152500
1014	4.7222	167200
1015	2.4167	225000
1018	2.7955	96300

845 rows × 2 columns

```
display(Xy_df.select_dtypes(include=np.number).describe())
```

	median_income	median_house_value
count	845.000000	845.000000
mean	3.778673	202746.897041
std	1.614736	110577.971892
min	1.011400	14999.000000
25%	2.559200	116500.000000

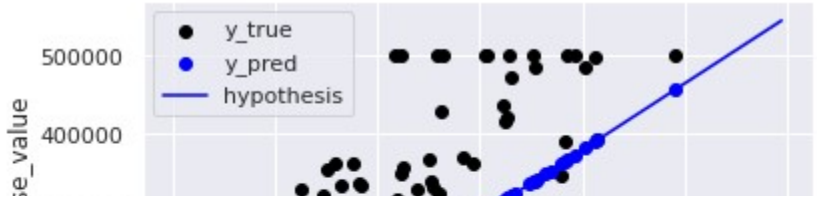
25%	2.559200	116500.000000
50%	3.638900	182100.000000
75%	4.701900	251800.000000
max	9.814400	500001.000000

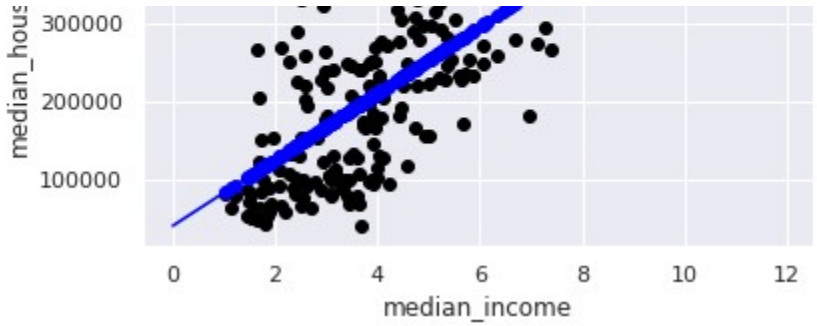
Univariate Linear Regression

```
X = np.array(Xy_df[['median_income']])
y = np.array(Xy_df['median_house_value'])

n_train_points = 645
n_new_points = 200

X_train = X[:n_train_points]
X_new = X[n_train_points:n_train_points+n_new_points]

y_train = y[:n_train_points]
y_true = y[n_train_points:n_train_points+n_new_points]


obj = sklearn.linear_model.LinearRegression(fit_intercept=True)

obj.fit(X_train, y_train)

y_pred = obj.predict(X_new)

print('theta_0:',obj.intercept_)
print('theta_1:',obj.coef_)
```

```
theta_0: 41075.503248247755
theta_1: [42343.37535385]
```

```
plt.scatter(X_new, y_true,  color='black', label='y_true') # Observed y values
plt.scatter(X_new, y_pred, color='blue', label='y_pred') # predicted y values
plt.plot(np.r_[0:12:0.1], obj.predict(np.r_[0:12:0.1][:, np.newaxis]), color='blue', label=
plt.xlabel('median_income')
plt.ylabel('median_house_value')
plt.legend()
plt.show()
```



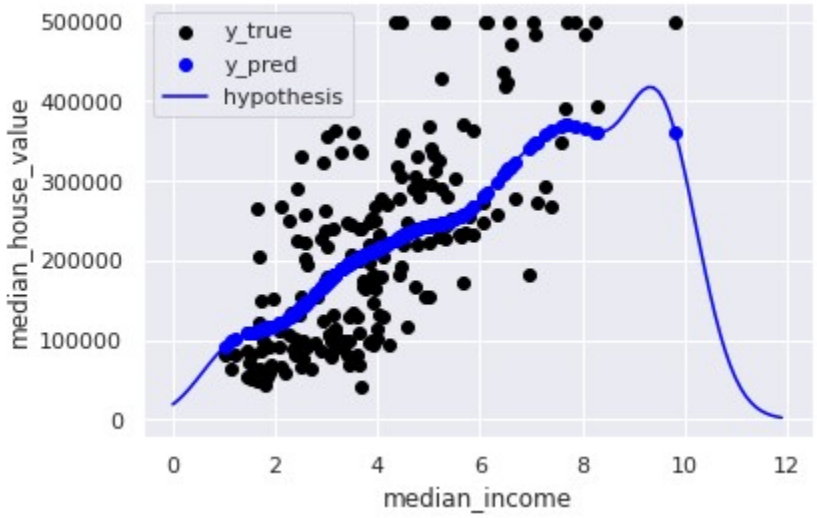



```
#The mean squared error loss
print('Mean squared error loss: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_true, y

#The R2 score
print('R2 score: {:.4f}'.format(sklearn.metrics.r2_score(y_true, y_pred)))
```

```
Mean squared error loss: 7853511232.6919
R2 score: 0.5014
```

Kernal Ridge Regression

```
X = np.array(Xy_df[['median_income']])
y = np.array(Xy_df['median_house_value'])

n_train_points = 645
n_new_points = 200

X_train = X[:n_train_points]
X_new = X[n_train_points:n_train_points+n_new_points]

y_train = y[:n_train_points]
y_true = y[n_train_points:n_train_points+n_new_points]

obj = kernel_ridge.KernelRidge(kernel='rbf')

obj.fit(X_train, y_train)

y_pred = obj.predict(X_new)


plt.scatter(X_new, y_true,  color='black', label='y_true')
plt.scatter(X_new, y_pred, color='blue', label='y_pred')
plt.plot(np.r_[0:12:0.1], obj.predict(np.r_[0:12:0.1][:, np.newaxis]), color='blue', label=
plt.xlabel('median_income')
plt.ylabel('median_house_value')
plt.legend()
plt.show()
```




```
#The mean squared error loss
print('Mean squared error loss: {:.4f}'.format(sklearn.metrics.mean_squared_error(y_true, y

#The R2 score
print('R2 score: {:.4f}'.format(sklearn.metrics.r2_score(y_true, y_pred)))
```

```
Mean squared error loss: 8329636025.7743
R2 score: 0.4712
```

Loading the combined test and train datasets for regression

To be able to preprocess the datasets more efficiently, train and test datasets have been combined and will be seperated according to their orginal lengths (650/241) in the model fitting section.

```
#Getting the combined Titanic test and training dataset
titanicData = pd.read_csv('/Titanic_data.csv')

sf = pd.DataFrame(data= titanicData)

display(sf)
```

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Emb
0	1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	

1	2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000

Preprocessing

To be able to get a more accurate result, we must prepare the dataset to fit into our models.

```
sf = sf.drop(columns=['PassengerId', 'Name', 'SibSp', 'Parch', 'Ticket', 'Fare'])
display(sf.head())
```

	Pclass	Sex	Age	Embarked	Target: Survived
0	3	male	22.0	S	0
1	1	female	38.0	C	1
2	3	female	26.0	S	1
3	1	female	35.0	S	1
4	3	male	35.0	S	0

```
display(sf.select_dtypes(include=np.number).head())
display(sf.select_dtypes(exclude=np.number).head())
```

	Pclass	Age	Target: Survived
0	3	22.0	0
1	1	38.0	1
2	3	26.0	1
3	1	35.0	1

4	3	35.0	0

	Sex	Embarked
0	male	S
1	female	C
2	female	S
3	female	S
4	male	S

Determining if there is any mistypes or empty data

```
print(pd.unique(sf['Pclass']))
print(pd.unique(sf['Target: Survived']))
print(pd.unique(sf['Sex']))
print(pd.unique(sf['Embarked']))
```

```
[3 1 2]
[0 1]
['male' 'female']
['S' 'C' 'Q' nan]
```

```
display(sf.select_dtypes(include=np.number).describe())
```

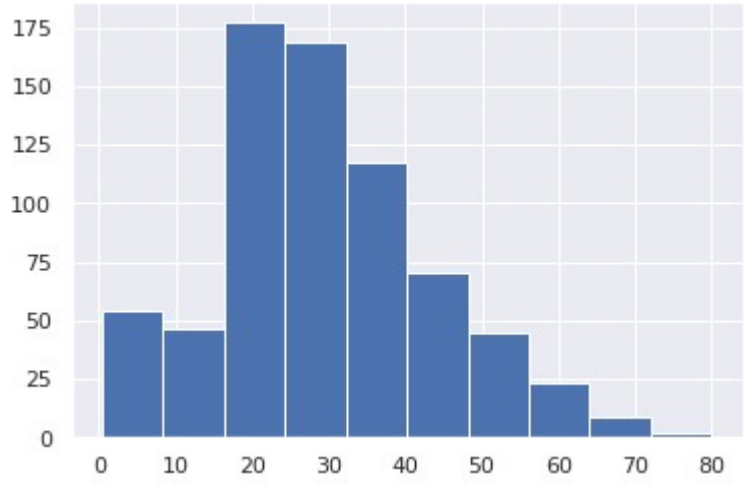
	Pclass	Age	Target: Survived
count	891.000000	714.000000	891.000000
mean	2.308642	29.699118	0.383838
std	0.836071	14.526497	0.486592
min	1.000000	0.420000	0.000000
25%	2.000000	20.125000	0.000000
50%	3.000000	28.000000	0.000000
75%	3.000000	38.000000	1.000000
max	3.000000	80.000000	1.000000

```
print('Original dataset length:')
print(len(sf))
sf_nl = sf.dropna()
print('Dataset length after removing all rows of missing data:')
print(len(sf_nl))
```

```
Original dataset length:
891
Dataset length after removing all rows of missing data:
712
```

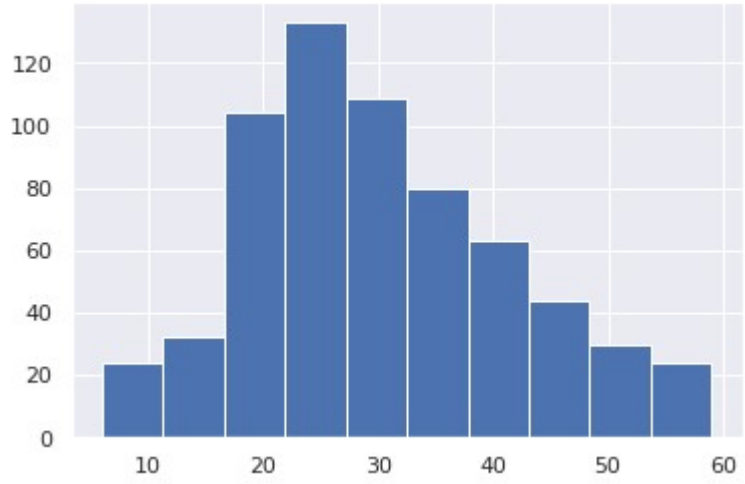
```
sf_nl["Age"].hist()
```

```
<AxesSubplot:>
```




```
sf_nl=sf_nl[sf_nl["Age"] < 60]
sf_nl=sf_nl[sf_nl["Age"] > 5]
sf_nl["Age"].hist()
```

```
<AxesSubplot:>
```




```
display(sf_nl.select_dtypes(include=np.number).describe())
```

	Pclass	Age	Target: Survived
count	643.000000	643.000000	643.000000
mean	2.244168	30.115863	0.390358

std	0.835976	11.466844	0.488210
min	1.000000	6.000000	0.000000
25%	1.000000	22.000000	0.000000
50%	3.000000	29.000000	0.000000
75%	3.000000	37.500000	1.000000
max	3.000000	59.000000	1.000000

```
sf_f = sf_nl.drop(columns=['Sex', 'Embarked'])
display(sf_f)
```

	Pclass	Age	Target: Survived
0	3	22.0	0
1	1	38.0	1
2	3	26.0	1
3	1	35.0	1
4	3	35.0	0
...	...	...	...
885	3	39.0	0
886	2	27.0	0
887	1	19.0	1
889	1	26.0	1
890	3	32.0	0

643 rows × 3 columns

Converting the dataset to arrays

```
dataset = sf_f
raw_X_sf = pd.DataFrame(data=dataset, columns=['Pclass', 'Age'])
raw_y_sf = pd.DataFrame(data=1 - (dataset['Target: Survived']), columns=['Target: Survived
raw_sf = pd.concat([raw_X_sf, raw_y_sf], axis=1)
#Shuffling the dataset
rng = np.random.default_rng(0)
Xy_sf = raw_sf.iloc[rng.permutation(len(raw_sf))].reset_index(drop=True)

display(Xy_sf)
```

	Pclass	Age	Target: Survived
0	3	19.0	1
1	1	22.0	0
2	2	19.0	0
3	2	23.0	1
4	2	23.0	1
...	...	...	...
638	3	19.0	0
639	2	24.0	0
640	1	30.0	0
641	1	42.0	0
642	3	42.0	1

643 rows × 3 columns

Conversion of data to NumPy arrays

```
#Preparing the NumPy ndarrays
Xs = np.array(Xy_sf[sf_f.columns[0:2]])
ys = np.array(Xy_sf['Target: Survived'])

n_train_points = 450
n_new_points = 193

#Splitting the data into training/new data
raw_X_train = Xs[:n_train_points]
raw_X_new = Xs[n_train_points:n_train_points+n_new_points]

#Splitting the targets into training/new data
y_train = ys[:n_train_points]
y_new = ys[n_train_points:n_train_points+n_new_points]
```

Standardization

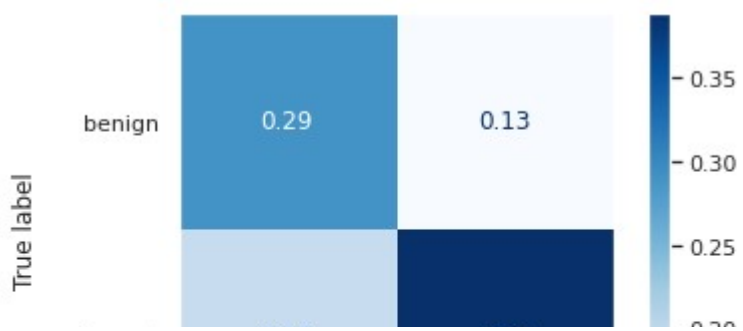
```
scaler = StandardScaler()
scaler.fit(raw_X_train)
```

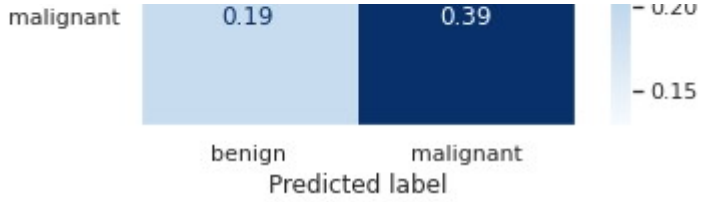
```
X_train = scaler.transform(raw_X_train)
X_new=scaler.transform(raw_X_new)
```

Decision Tree

```
#Creating Decison Tree object
obj = DecisionTreeClassifier(min_samples_split=2, min_samples_leaf=9,random_state=40)

#Training the model using the training sets
obj.fit(X_train, y_train)

#Making predictions using the testing set
y_new_pred = obj.predict(X_new)

#The accuracy score
print('Accuracy: {:.4f}'.format(sklearn.metrics.accuracy_score(y_new, y_new_pred)))

#Confusion matrix
confusion_mat = sklearn.metrics.confusion_matrix(y_new, y_new_pred, normalize='all')
print('Confusion matrix: ', confusion_mat)

#Visualizing the confusion matrix
sklearn.metrics.ConfusionMatrixDisplay(confusion_mat, display_labels=['benign', 'malignant
plt.grid(False)

#The classification report
print(sklearn.metrics.classification_report(y_new, y_new_pred))
```

```
Accuracy: 0.6788
Confusion matrix:  [[0.29015544 0.12953368]
 [0.19170984 0.38860104]]
              precision    recall  f1-score   support

           0       0.60      0.69      0.64        81
           1       0.75      0.67      0.71       112

    accuracy                           0.68       193
   macro avg       0.68      0.68      0.68       193
weighted avg       0.69      0.68      0.68       193
```





SVM

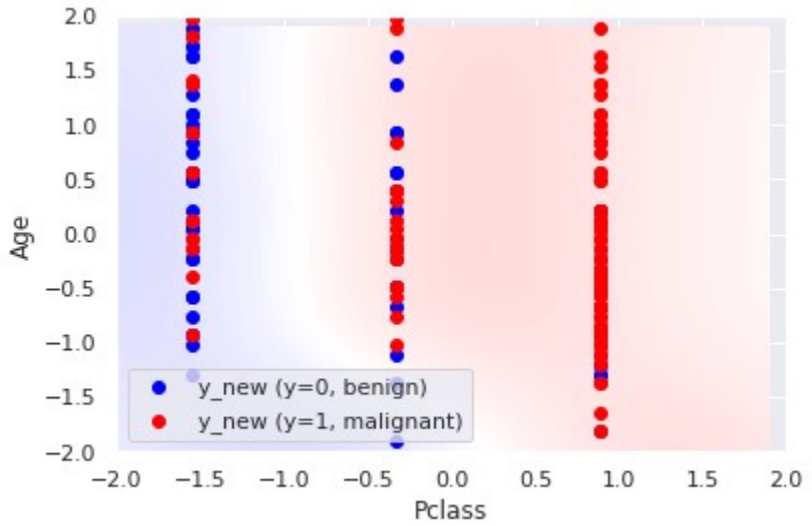
Creation of SVM object and predicting

```
#Creating the support vector classifier object
obj = sklearn.svm.SVC(C=1,kernel='rbf',random_state=40)

#Training the model using the training sets
obj.fit(X_train, y_train)

#Making predictions using the testing set
y_pred = obj.predict(X_new)
```

Plotting SVM results

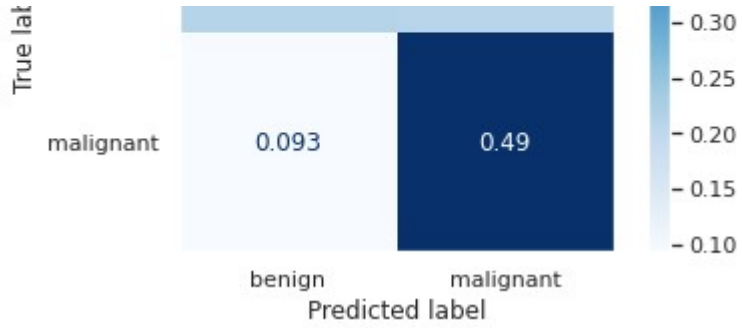
```
# Plotting the outputs
xrange = [-2, 2]
yrange = [-2, 2]
step = 0.1
x = np.arange(xrange[0], xrange[1], step)
y = np.arange(yrange[0], yrange[1], step)
xx, yy = np.meshgrid(x, y)
obj.set_params(decision_function_shape='ovo')
z = obj.decision_function(np.c_[xx.reshape([-1]), yy.reshape([-1])]).reshape(xx.shape)
plt.contourf(xx, yy, z, cmap='bwr', vmin=-10.0, vmax=10.0, levels=200)

X_new_neg = X_new[y_new==0, :]
X_new_pos = X_new[y_new==1, :]
plt.scatter(X_new_neg[:, 0], X_new_neg[:, 1],  color='blue', label='y_new (y=0, benign)')
plt.scatter(X_new_pos[:, 0], X_new_pos[:, 1],  color='red', label='y_new (y=1, malignant)')

plt.xlim(xrange)
plt.ylim(yrange)

plt.xlabel(sf_f.columns[0])
plt.ylabel(sf_f.columns[1])
```

```
plt.legend()

plt.show()
```




```
#The accuracy score
print('Accuracy: {:.4f}'.format(sklearn.metrics.accuracy_score(y_new, y_pred)))

#Confusion matrix
confusion_mat = sklearn.metrics.confusion_matrix(y_new, y_pred, normalize='all')
print('Confusion matrix: ', confusion_mat)

#Visualizing the confusion matrix
sklearn.metrics.ConfusionMatrixDisplay(confusion_mat, display_labels=['benign', 'malignant
plt.grid(False)

#The classification report
print(sklearn.metrics.classification_report(y_new, y_pred))
```

```
Accuracy: 0.6995
Confusion matrix:  [[0.21243523 0.20725389]
 [0.09326425 0.48704663]]
              precision    recall  f1-score   support

           0       0.69      0.51      0.59        81
           1       0.70      0.84      0.76       112

    accuracy                           0.70       193
   macro avg       0.70      0.67      0.67       193
weighted avg       0.70      0.70      0.69       193
```



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