California House Price Prediction --Shreenav Dhakal 27 March 2022

Importing libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.base import TransformerMixin, BaseEstimator
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer

from sklearn.linear_model import LinearRegression, Lasso,
Ridge,ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor, AdaBoostRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error,r2_score
from sklearn.model_selection import cross_val_score

from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
```

Loading the dataset

```
housing = pd.read_csv(r"D:/python/housing.csv")
```

Exploring the dataset

```
housing.head()

   longitude  latitude  housing_median_age  total_rooms
total_bedrooms  \
0    -122.23     37.88                41.0        880.0
129.0
1    -122.22     37.86                21.0       7099.0
1106.0
2    -122.24     37.85                52.0       1467.0
190.0
3    -122.25     37.85                52.0       1274.0
235.0
```

```
4    -122.25     37.85                 52.0       1627.0
280.0

   population  households  median_income  median_house_value
ocean_proximity
0       322.0       126.0         8.3252            452600.0
NEAR BAY
1      2401.0      1138.0         8.3014            358500.0
NEAR BAY
2       496.0       177.0         7.2574            352100.0
NEAR BAY
3       558.0       219.0         5.6431            341300.0
NEAR BAY
4       565.0       259.0         3.8462            342200.0
NEAR BAY
```

```
housing.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   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

```
housing.isnull().sum()
```

```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

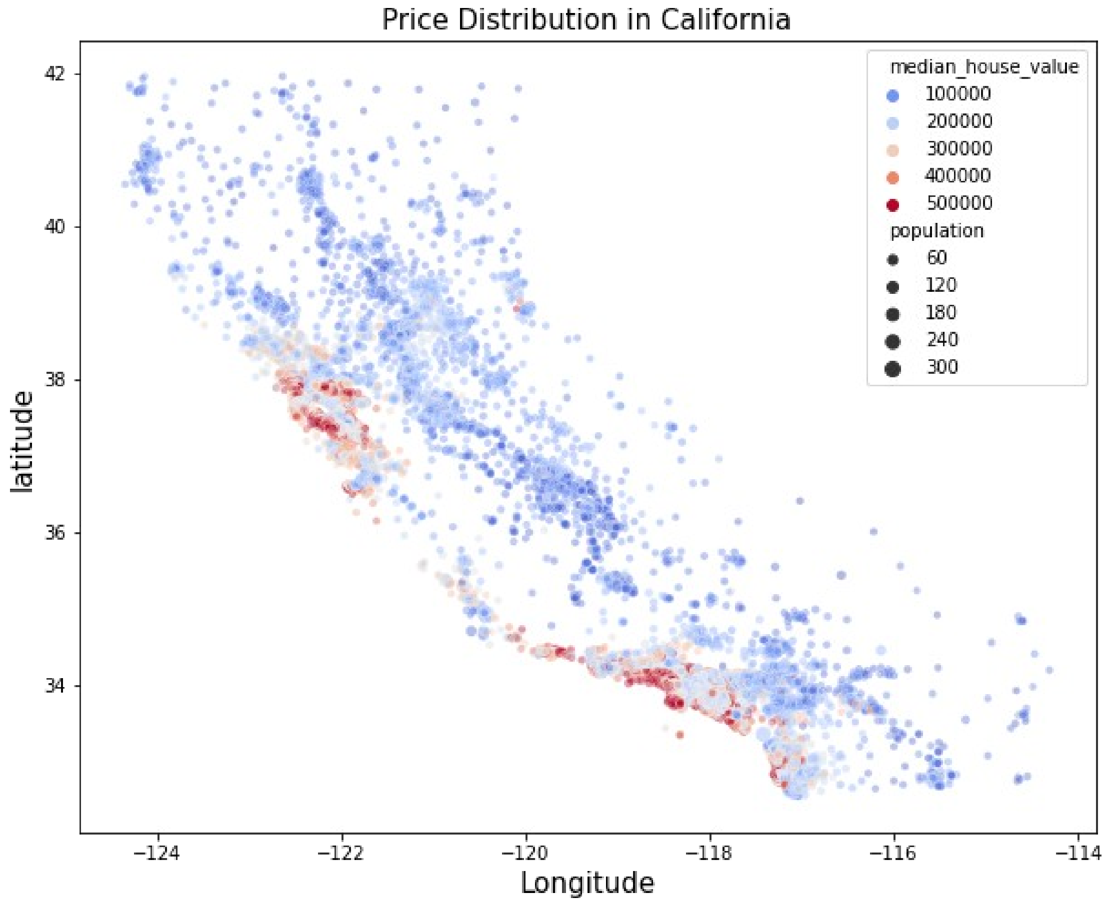
```
housing.describe()
```

```
         longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

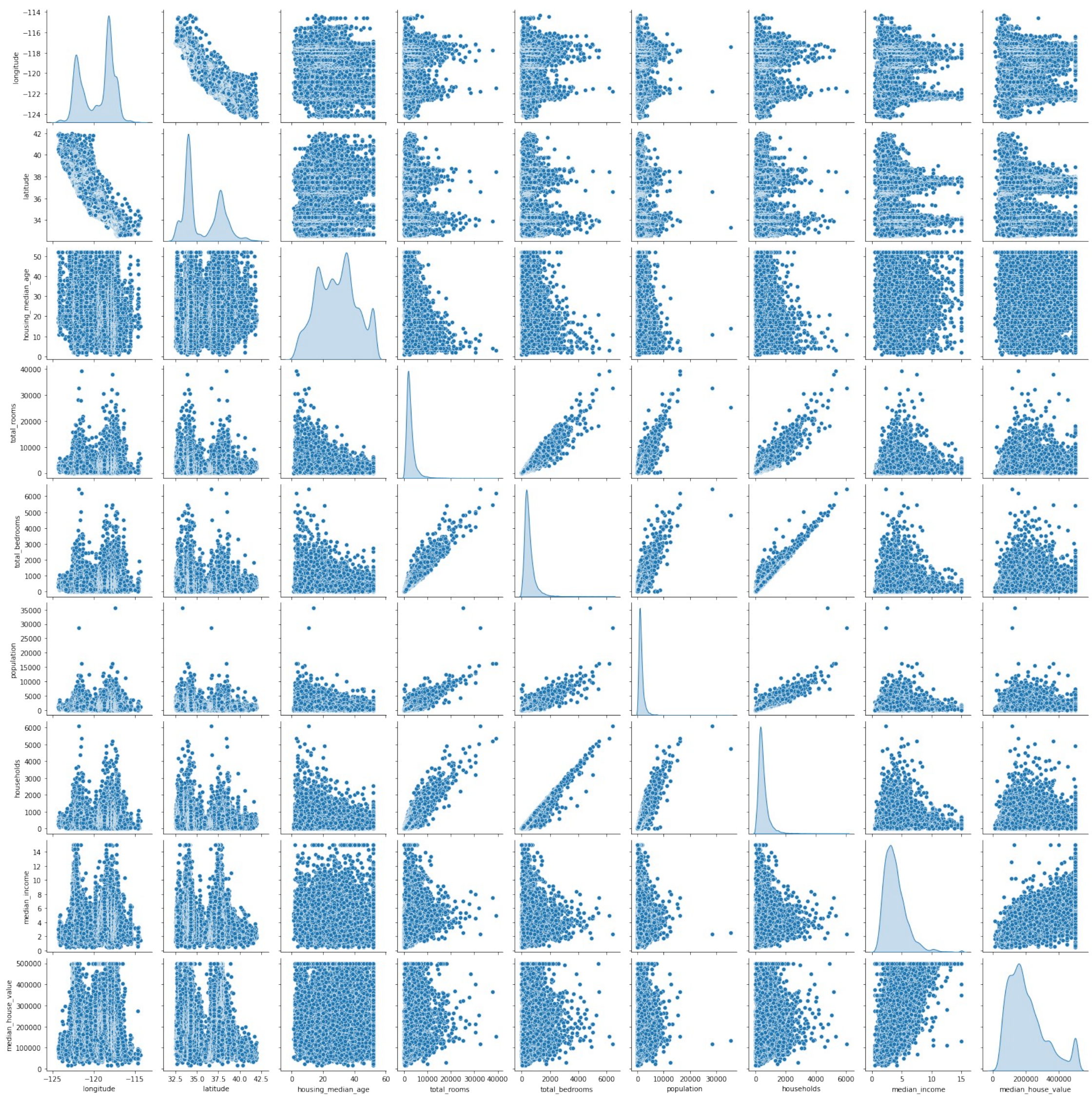
Target Variable: median_house_value already scaled variables: median_income (maybe represented as 1 = 10000$)

Visualizing the dataset

```
fig = plt.figure(figsize=(10,8))
sns.scatterplot(data=housing, x='longitude', y='latitude',
hue='median_house_value',
palette='coolwarm',size=housing['population']/100,alpha=0.4)
plt.title('Price Distribution in California',fontsize=15)
plt.xlabel('Longitude',fontsize=15)
plt.ylabel('latitude',fontsize=15)
plt.show()
```




```
sns.pairplot(housing,diag_kind='kde',kind='scatter')
plt.show()
```




```
## finding the correlations
housing.corr()
```

```
                    longitude  latitude  housing_median_age
total_rooms  \
longitude            1.000000 -0.924664           -0.108197
0.044568
latitude            -0.924664  1.000000            0.011173    -
0.036100
housing_median_age  -0.108197  0.011173            1.000000    -
0.361262
total_rooms          0.044568 -0.036100           -0.361262
1.000000
total_bedrooms       0.069608 -0.066983           -0.320451
0.930380
population           0.099773 -0.108785           -0.296244
0.857126
```

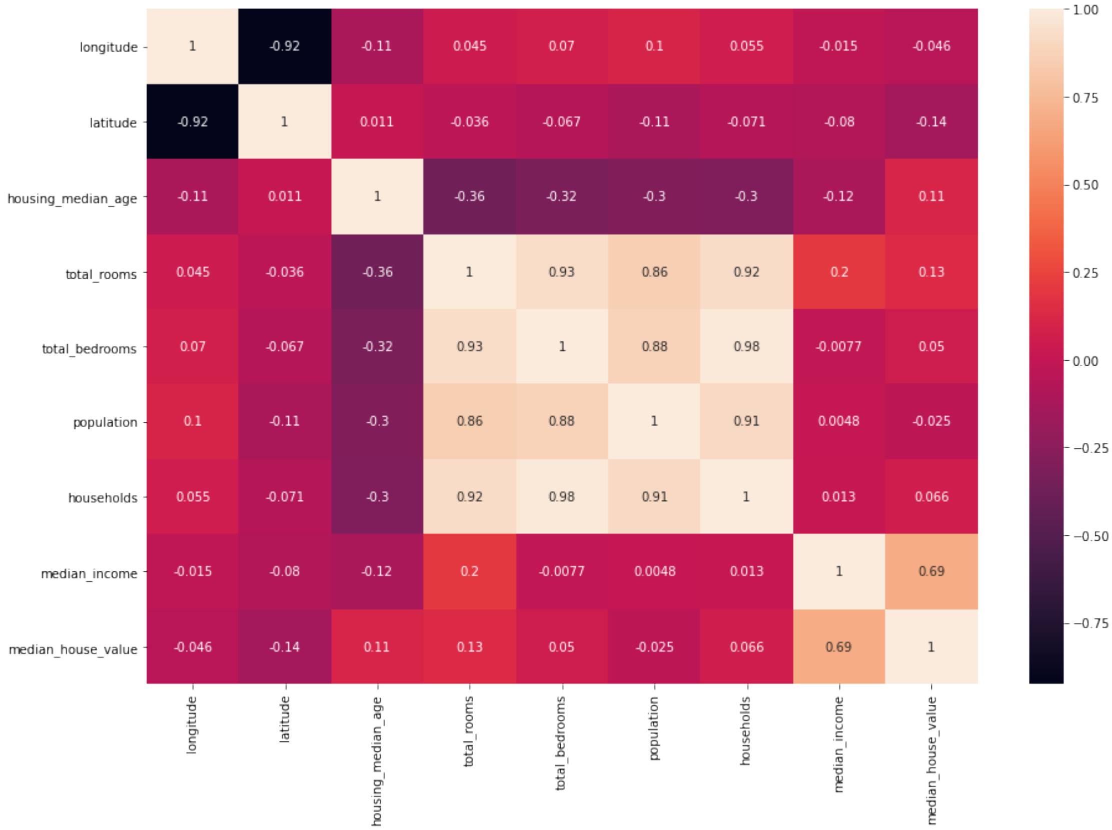
```
households           0.055310 -0.071035           -0.302916
0.918484
median_income       -0.015176 -0.079809           -0.119034
0.198050
median_house_value  -0.045967 -0.144160            0.105623
0.134153

                    total_bedrooms  population  households
median_income  \
longitude                 0.069608    0.099773    0.055310      -
0.015176
latitude                 -0.066983   -0.108785   -0.071035      -
0.079809
housing_median_age       -0.320451   -0.296244   -0.302916      -
0.119034
total_rooms               0.930380    0.857126    0.918484
0.198050
total_bedrooms            1.000000    0.877747    0.979728      -
0.007723
population                0.877747    1.000000    0.907222
0.004834
households                0.979728    0.907222    1.000000
0.013033
median_income            -0.007723    0.004834    0.013033
1.000000
median_house_value        0.049686   -0.024650    0.065843
0.688075

                    median_house_value
longitude                    -0.045967
latitude                     -0.144160
housing_median_age            0.105623
total_rooms                   0.134153
total_bedrooms                0.049686
population                   -0.024650
households                    0.065843
median_income                 0.688075
median_house_value            1.000000
```

```
housing.corr()
['median_house_value'].drop('median_house_value').sort_values(ascendin
g=False)
```

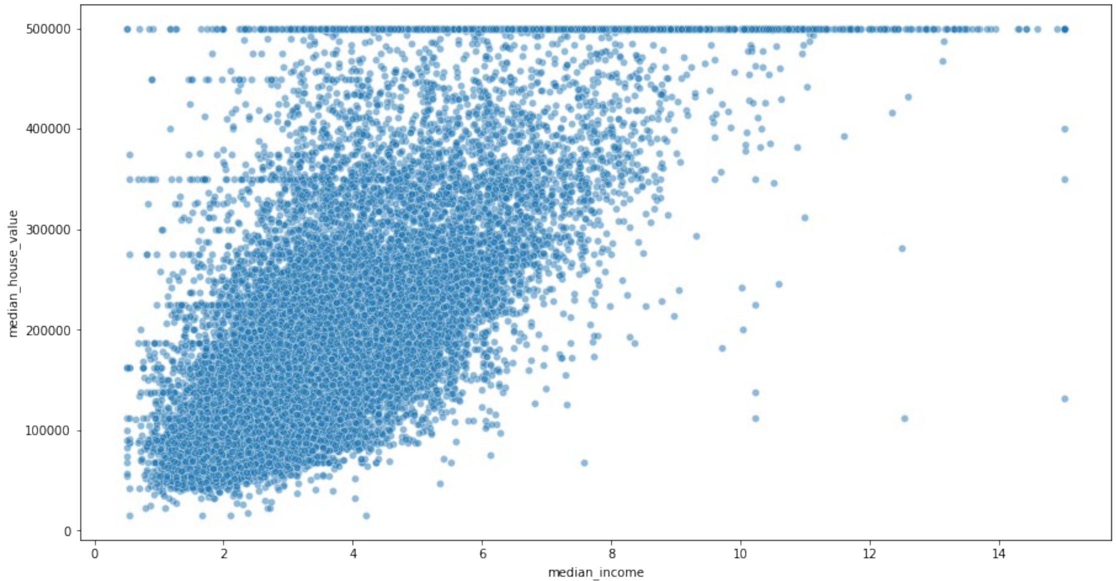
```
median_income         0.688075
total_rooms           0.134153
housing_median_age    0.105623
households            0.065843
total_bedrooms        0.049686
population           -0.024650
longitude            -0.045967
```

```
latitude             -0.144160
Name: median_house_value, dtype: float64
```

```
fig = plt.figure(figsize=(15,10))
sns.heatmap(housing.corr(),annot=True)
plt.show()
```




```
fig = plt.figure(figsize=(15,8))
sns.scatterplot(data=housing, x='median_income',
y='median_house_value',alpha=0.5)
plt.show()
```




```
housing['median_house_value'].max()
```

500001.0

```
housing.loc[housing['median_house_value']==500000].shape
```

(27, 10)

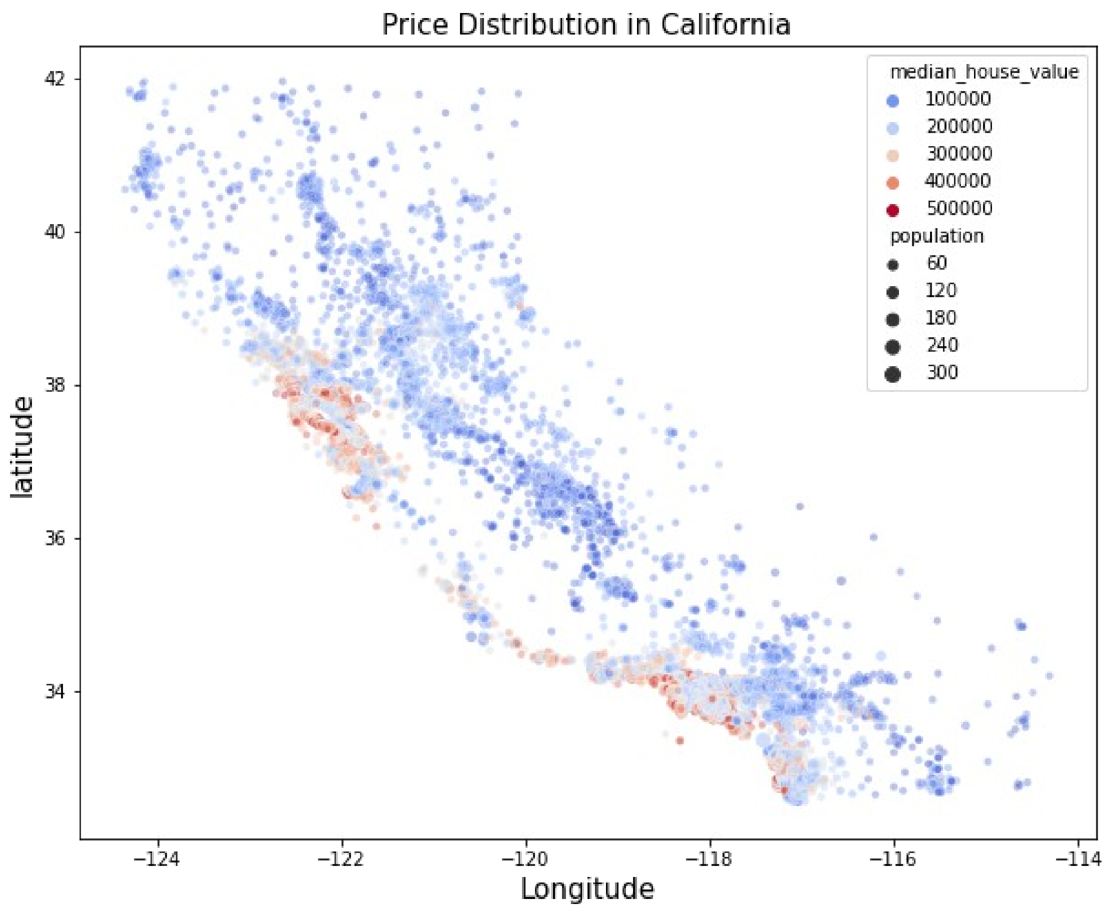
```
housing.loc[housing['median_house_value']>=500001.0].shape
```

(965, 10)

The house prices greater than 500000 are all scaled into 500001.0 which will create a problem while creating a model. So we will create a model that can predict the house prices upto 500000

```
housing = housing.loc[housing['median_house_value']<500001.0]
```

```
fig = plt.figure(figsize=(10,8))
sns.scatterplot(data=housing, x='longitude', y='latitude',
hue='median_house_value',
palette='coolwarm',size=housing['population']/100,alpha=0.4)
plt.title('Price Distribution in California',fontsize=15)
plt.xlabel('Longitude',fontsize=15)
plt.ylabel('latitude',fontsize=15)
plt.show()
```



Splitting the dataset into train and test

```
housing['income_cat'] =
pd.cut(housing['median_income'],bins=[0,1.5,3,4.5,6,np.inf],labels=[1,
2,3,4,5])

housing['income_cat'].value_counts()

3    7103
2    6552
4    3502
5    1704
1     814
Name: income_cat, dtype: int64

housing.index = np.arange(0,19675)

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2,
random_state=42)
for train_idx, test_idx in split.split(housing,housing['income_cat']):
  train_data = housing.loc[train_idx]
  test_data = housing.loc[test_idx]
```

```
for a in (housing,train_data,test_data):
  a.drop(columns=['income_cat'],inplace=True)

y_train = train_data[['median_house_value']]
X_train = train_data.drop(columns=['median_house_value'])

y_test = test_data[['median_house_value']]
X_test = test_data.drop(columns=['median_house_value'])
```

Data preparation

```
X_train.columns
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity'],
      dtype='object')
```

```
class AttributeAdder(TransformerMixin, BaseEstimator):
  def __init__(self,add_bedroom_per_room=True):
    self.add_bedroom_per_room = add_bedroom_per_room

  def fit(self,X,y=None):
    return self

  def transform(self,X,y=None):
    popn_per_household = X[:,5] / X[:,6]
    room_per_household = X[:,3] / X[:,6]
    if self.add_bedroom_per_room:
      bedroom_per_room = X[:,4] / X[:,3]
      return
np.c_[X,popn_per_household,room_per_household,bedroom_per_room]
    else:
      return np.c_[X,popn_per_household,room_per_household]

num_pipeline = Pipeline([
                         ("imputer",SimpleImputer(strategy='median')),
                         ("adder",AttributeAdder(True)),
                         ("scaler",StandardScaler())
])

X_train.columns[:-1]
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income'],
      dtype='object')
```

```
num_attribs = list(X_train.columns[:-1])
cat_attribs = ['ocean_proximity']

full_pipeline = ColumnTransformer([
```

```
                                    ("num", num_pipeline,num_attribs),

("encoder",OneHotEncoder(),cat_attribs)
])

X_train_prepared = full_pipeline.fit_transform(X_train)
```

Model building and testing

1. Trying all Regression algorithm

```
y_train = y_train.values

all_models = [LinearRegression(), Ridge(), Lasso(), ElasticNet(), 
DecisionTreeRegressor(), RandomForestRegressor(), 
KNeighborsRegressor(), GradientBoostingRegressor(),
              AdaBoostRegressor()]
names = ['Linear Regression', 'Ridge Regression', 'Lasso Regression', 
'Elastic Net Regression', 'Decision Tree Regressor', 'Random Forest 
Regressor',
         'K Neigbor Regressor','Gradient Boosting','ADA Boosting 
Regressor']

Model = []
RMSE = []
R2 = []

def input_scores(name,model,x,y):
  Model.append(name)
  RMSE.append(np.sqrt(-1 * 
cross_val_score(model,x,y,scoring='neg_mean_squared_error',cv=10).mean
()))
  R2.append(cross_val_score(model,x,y,scoring='r2',cv=10).mean())

for name, model in zip(names,all_models):
  input_scores(name,model,X_train_prepared, y_train)

Model

['Linear Regression',
 'Ridge Regression',
 'Lasso Regression',
 'Elastic Net Regression',
 'Decision Tree Regressor',
 'Random Forest Regressor',
 'K Neigbor Regressor',
 'Gradient Boosting',
 'ADA Boosting Regressor']

RMSE
```

```
[61199.25356216318,
 61195.9740176221,
 61199.10907219672,
 69342.85669410611,
 65080.06093904587,
 45770.644916993726,
 55920.22274361194,
 48912.93187815943,
 69957.89174434757]
```

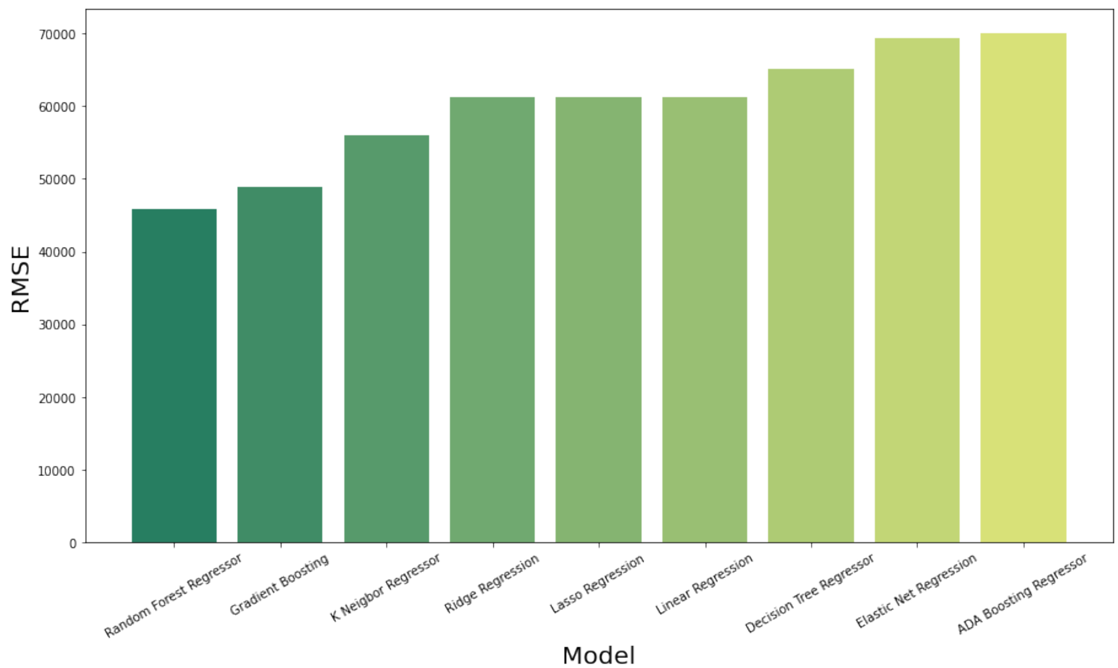
R2

```
[0.6104351489834946,
 0.6104831329312667,
 0.6104383597637165,
 0.4999590103136108,
 0.5654976264091178,
 0.7812830078939901,
 0.6744960046389483,
 0.7511051225085594,
 0.4469811951307312]
```

```
df = pd.DataFrame({'Model':Model, 'RMSE':RMSE, 'R2':R2})
df.sort_values(by=['R2'],ascending=False,inplace=True)
```

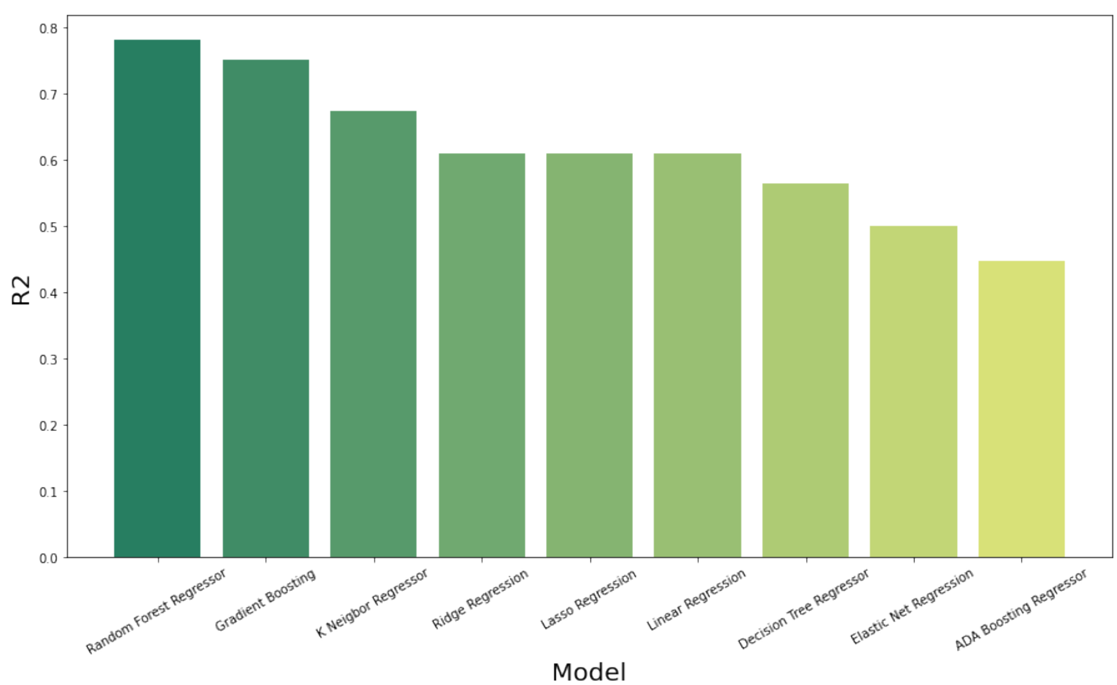
```
fig = plt.figure(figsize=(15,8))
sns.barplot(data=df, x='Model',y='RMSE', palette='summer')
loc,labels = plt.xticks()
plt.setp(labels,rotation=30)
plt.xlabel('Model',fontsize=20)
plt.ylabel('RMSE',fontsize=20)
plt.plot()
```

```
[]
```




```
fig = plt.figure(figsize=(15,8))
sns.barplot(data=df, x='Model',y='R2', palette='summer')
loc,labels = plt.xticks()
plt.setp(labels,rotation=30)
plt.xlabel('Model',fontsize=20)
plt.ylabel('R2',fontsize=20)
plt.plot()
```

```
[]
```



Random Forest Regressor seems to be the suitable model Now we tune the model to find the best hyper-Parameters

Using Randomized Search CV

```
n_estimators = [int(x) for x in np.linspace(start = 20, stop = 200, 
num = 5)]
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(1, 45, num = 3)]
min_samples_split = [5, 10]
bootstrap = [True, False]
forest = RandomForestRegressor()
parameters = {'n_estimators':n_estimators, 
'max_features':max_features, 'max_depth':max_depth, 
'min_samples_split':min_samples_split, 
'min_samples_leaf':min_samples_leaf, 
              'bootstrap':bootstrap}
random = RandomizedSearchCV(forest, parameters, cv=10, n_jobs=-1, 
n_iter=20, 
verbose=2,scoring='neg_mean_squared_error').fit(X_train_prepared, 
y_train)
```

```
Fitting 10 folds for each of 20 candidates, totalling 200 fits
```

```
random.best_params_
```

```
{'n_estimators': 110,
 'min_samples_split': 10,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 23,
 'bootstrap': False}
```

Let's find out the best estimator

```
random.best_estimator_
```

```
RandomForestRegressor(bootstrap=False, max_depth=23, 
max_features='sqrt',
                      min_samples_split=10, n_estimators=110)
```

```
np.sqrt(-1 * random.best_score_)
```

```
44853.88718840359
```

Using Grid Search CV

```
forest = RandomForestRegressor()
param_grid = [
{'n_estimators': [10, 25], 'max_features': [5, 10],
 'max_depth': [10, 50, None], 'bootstrap': [True, False]}
]

grid =
```

```
GridSearchCV(forest,param_grid,cv=10,scoring='neg_mean_squared_error')
.fit(X_train_prepared,y_train)

grid.best_params_

{'bootstrap': False, 'max_depth': None, 'max_features': 5,
'n_estimators': 25}

np.sqrt(-1 * grid.best_score_)

45067.9676678366
```

Finding the best predictor

```
random_predictor = random.best_estimator_
grid_predictor = grid.best_estimator_

random_predicted = random_predictor.predict(X_train_prepared)
grid_predicted = grid_predictor.predict(X_train_prepared)

print(f"RMSE of Random CV predictor for train values:
{np.sqrt(mean_squared_error(y_train, random_predicted))}")
print(f"RMSE of Grid CV predictor for train values:
{np.sqrt(mean_squared_error(y_train, grid_predicted))}")

RMSE of Random CV predictor for train values: 15862.30313657804
RMSE of Grid CV predictor for train values: 0.0

X_test_prepared = full_pipeline.fit_transform(X_test)

random_predicted = random_predictor.predict(X_test_prepared)
grid_predicted = grid_predictor.predict(X_test_prepared)

print(f"RMSE of Random CV predictor for test values:
{np.sqrt(mean_squared_error(y_test, random_predicted))}")
print(f"RMSE of Grid CV predictor for test values:
{np.sqrt(mean_squared_error(y_test, grid_predicted))}")

RMSE of Random CV predictor for test values: 50792.879426015636
RMSE of Grid CV predictor for test values: 54438.683377948786
```

Feature Importance

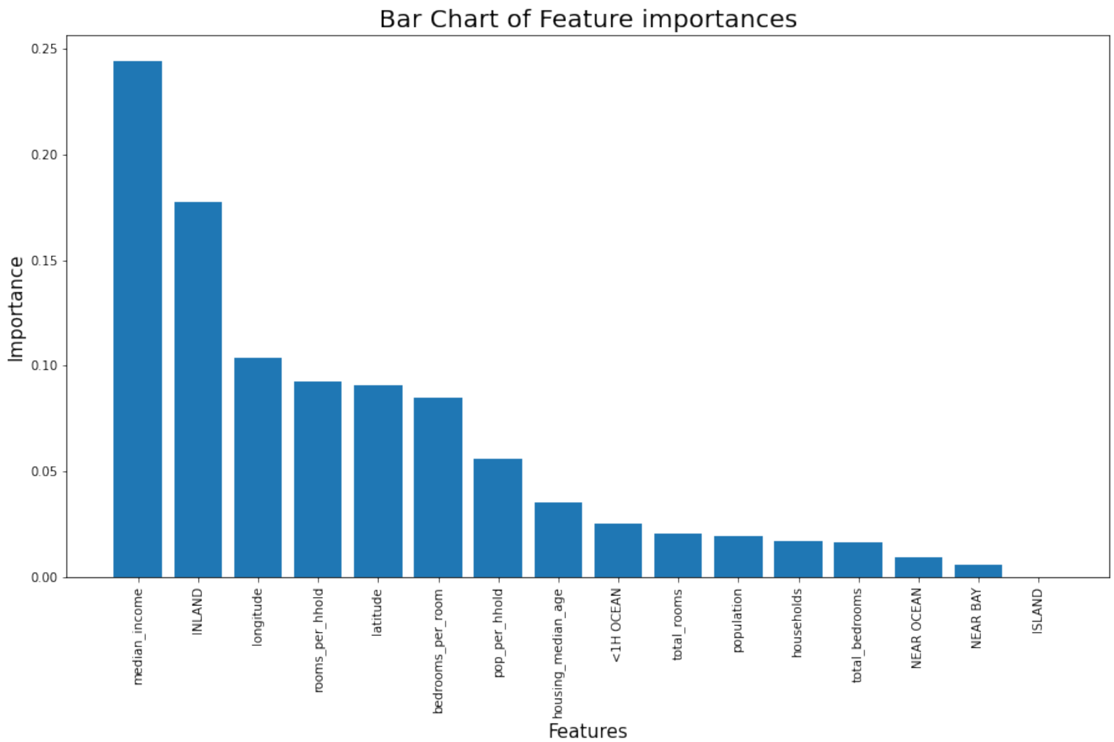
```
importances = random.best_estimator_.feature_importances_

num_attribs = list(housing.columns)
del num_attribs[-2]

del num_attribs[-1]

extra_attribs = ["rooms_per_hhold", "pop_per_hhold",
"bedrooms_per_room"]
cat_encoder = full_pipeline.named_transformers_["encoder"]
```

```
cat_one_hot_attribs = list(cat_encoder.categories_[0])
attributes =  num_attribs + extra_attribs + cat_one_hot_attribs

feature_importance = sorted(zip(importances, attributes),reverse=True)

df = pd.DataFrame(feature_importance, columns=['Importance',
'feature'])

df
```

	Importance	feature
0	0.244187	median_income
1	0.177653	INLAND
2	0.103955	longitude
3	0.092620	rooms_per_hhold
4	0.090588	latitude
5	0.085079	bedrooms_per_room
6	0.056179	pop_per_hhold
7	0.035198	housing_median_age
8	0.025505	<1H OCEAN
9	0.020580	total_rooms
10	0.019274	population
11	0.017067	households
12	0.016426	total_bedrooms
13	0.009624	NEAR OCEAN
14	0.005862	NEAR BAY
15	0.000204	ISLAND

Median_income, INLAND and Longitude seems to have more importance than any other feature in feature a model can be made using only this attributes for faster processing

```
fig = plt.figure(figsize=(15,8))
plt.bar(df['feature'].values, df['Importance'].values)
plt.xticks(range(len(df['feature'])),
df['feature'].values,rotation='vertical')
plt.title('Bar Chart of Feature importances',fontsize=20)
plt.xlabel('Features',fontsize=15)
plt.ylabel('Importance',fontsize=15)
plt.show()
```


Bar Chart of Feature importances
Importance
0.25
0.20
0.15
0.10
0.05
0.00
median_income
INLAND
longitude
rooms_per_hhold
latitude
bedrooms_per_room
pop_per_hhold
housing_median_age
<1H OCEAN
total_rooms
population
households
total_bedrooms
NEAR OCEAN
NEAR BAY
ISLAND
Features