House Price Prediction

Importing Libraries

In [1]:

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

Importing Data

In [2]:

```
data = pd.read_csv('Data/housing.csv')
```

Understanding the Data

In [3]:

```
data.head()
```

Out[3]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	householc
0	-122.23	37.88	41	880	129.0	322	12
1	-122.22	37.86	21	7099	1106.0	2401	113
2	-122.24	37.85	52	1467	190.0	496	17
3	-122.25	37.85	52	1274	235.0	558	21
4	-122.25	37.85	52	1627	280.0	565	25

In [4]:

```
print('The number of Records in the data is : ',len(data))
```

```
The number of Records in the data is :  20640
```

In [5]:

```
data.isna().sum()
```

Out[5]:

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

In [6]:

```
data[data['total_bedrooms'].isnull()]
```

Out[6]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	hous
290	-122.16	37.77	47	1256	NaN	570	
341	-122.17	37.75	38	992	NaN	732	
538	-122.28	37.78	29	5154	NaN	3741	
563	-122.24	37.75	45	891	NaN	384	
696	-122.10	37.69	41	746	NaN	387	
...	...	...	...	...	...	...	
20267	-119.19	34.20	18	3620	NaN	3171	
20268	-119.18	34.19	19	2393	NaN	1938	
20372	-118.88	34.17	15	4260	NaN	1701	
20460	-118.75	34.29	17	5512	NaN	2734	
20484	-118.72	34.28	17	3051	NaN	1705	

207 rows × 10 columns

Substituting the NaN values in No_of_Bedroom with any measure of central tendency isn't a clear step to undertake, and since the total number of missing values is within 1% of the total sample size, we can drop the Records with NaN values

Treating Missing Values

In [7]:

```
data.dropna(inplace = True)
```

In [8]:

```
data.shape
```

Out[8]:

```
(20433, 10)
```

Checking for any other Null value

In [9]:

```
data.isnull().sum()
```

Out[9]:

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

In [10]:

```
data.head()
```

Out[10]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househol
0	-122.23	37.88	41	880	129.0	322	12
1	-122.22	37.86	21	7099	1106.0	2401	113
2	-122.24	37.85	52	1467	190.0	496	17
3	-122.25	37.85	52	1274	235.0	558	21
4	-122.25	37.85	52	1627	280.0	565	25

So, we have 9 numeric columns and 1 non-numeric column ('ocean_proximity') in our data
Now, 'median_house_value' is our target variable

Some more insights of the data at hand

In [11]:

```
data.describe()
```

Out[11]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	p
count	20433.000000	20433.000000	20433.000000	20433.000000	20433.000000	204
mean	-119.570689	35.633221	28.633094	2636.504233	537.870553	14
std	2.003578	2.136348	12.591805	2185.269567	421.385070	11
min	-124.350000	32.540000	1.000000	2.000000	1.000000	
25%	-121.800000	33.930000	18.000000	1450.000000	296.000000	7
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	11
75%	-118.010000	37.720000	37.000000	3143.000000	647.000000	17
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	356

The only categorical data in the dataset - ocean_proximity

In [12]:

```
data['ocean_proximity'].unique()
```

Out[12]:

```
array(['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND'],
      dtype=object)
```

Lets see if we can find out some more information from ocean_proximity

In [13]:

```
op = ['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND']
for x in op:
    df = data[data['ocean_proximity'] == x]
    print(x,'   :   ', np.mean(df['median_house_value']))
```

```
NEAR BAY   :   259279.29207048457
<1H OCEAN   :   240267.99081248615
INLAND   :   124896.86314655172
NEAR OCEAN   :   249042.35502283106
ISLAND   :   380440.0
```

In [14]:

```
data['ocean_proximity'].replace(['INLAND','<1H OCEAN','NEAR OCEAN','NEAR BAY','ISLAND'], [1
```

In [15]:

```
data['ocean_proximity'].unique()
```

Out[15]:

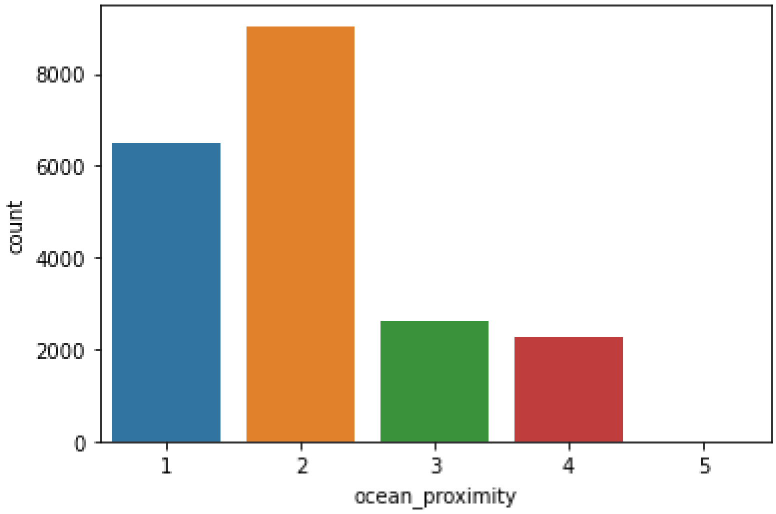
```
array([4, 2, 1, 3, 5], dtype=int64)
```

In [16]:

```
sns.countplot(data['ocean_proximity'])
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2457b3d0>
```



The above plot shows the number of localities of each kind.

Trying to gain some more insights about the data through Visualisation

Latitude and Logitude are geographical features and can not be quantified. Thus I decide to let them be.

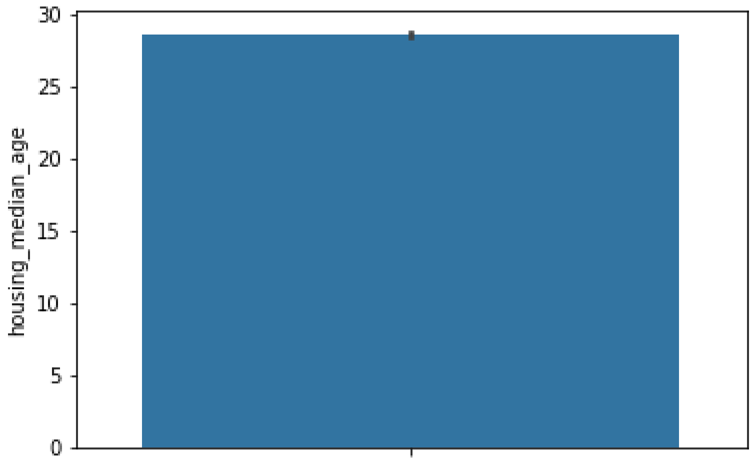
Lets start with housing_median_age

In [17]:

```
sns.barplot(y = data['housing_median_age'])
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xb99a00>
```

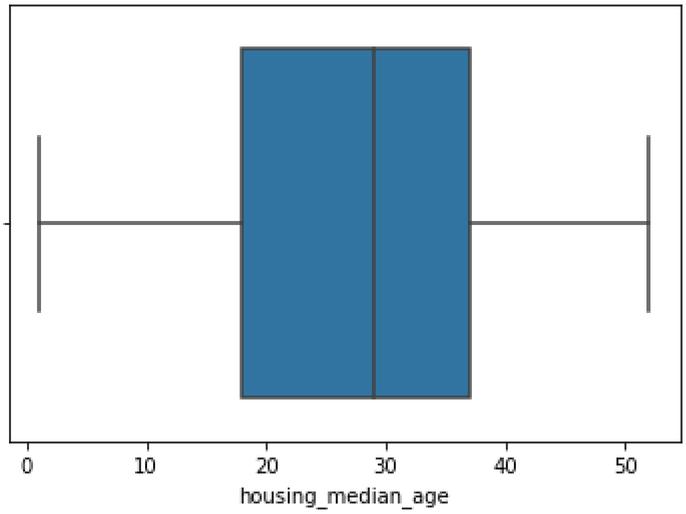


In [18]:

```
sns.boxplot(data['housing_median_age'])
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xf4abe0>
```



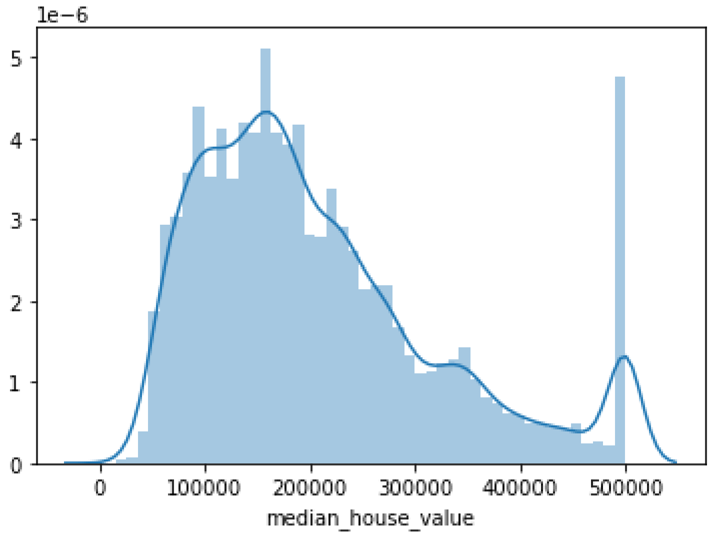
'housing_median_age' seems pretty balanced and requires no further attention

In [19]:

```
sns.distplot(data['median_house_value'])
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xf84430>
```



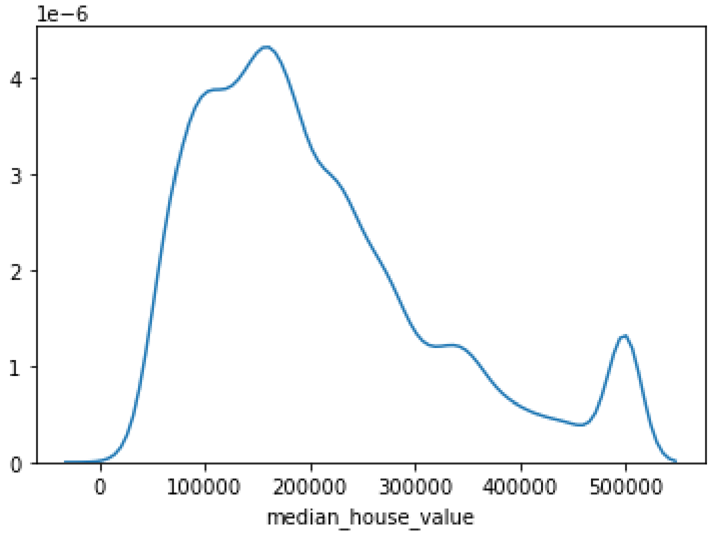
the above plot shows the couunt of records with certain values of median_house_value

In [20]:

```
sns.distplot(data['median_house_value'], hist = False)
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xff5ca0>
```

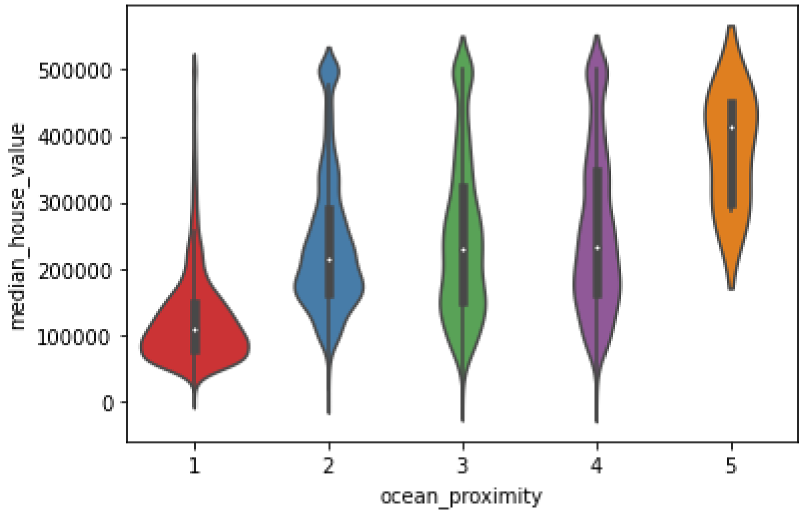


In [23]:

```
# median_house_value vs. Ocean Proximity
sns.violinplot(x = 'ocean_proximity', y = 'median_house_value', data = data, palette = 'Set
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x277a0e38>
```



Understanding Relationship between Data through HeatMap

In [24]:

```
data.corr()
```

Out[24]:

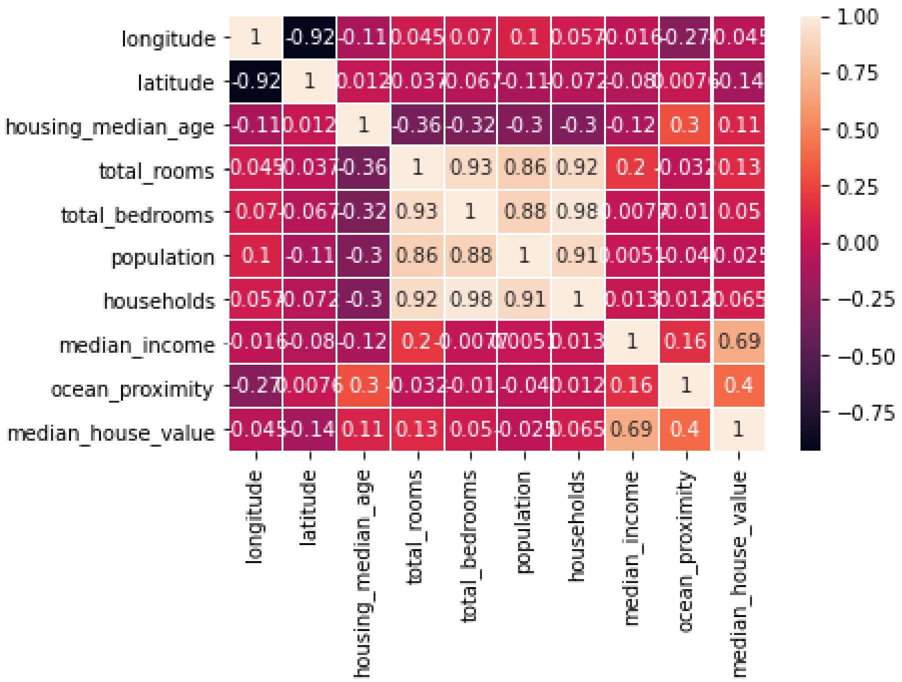
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms
longitude	1.000000	-0.924616	-0.109357	0.045480	0.069608
latitude	-0.924616	1.000000	0.011899	-0.036667	-0.066983
housing_median_age	-0.109357	0.011899	1.000000	-0.360628	-0.320451
total_rooms	0.045480	-0.036667	-0.360628	1.000000	0.930380
total_bedrooms	0.069608	-0.066983	-0.320451	0.930380	1.000000
population	0.100270	-0.108997	-0.295787	0.857281	0.877747
households	0.056513	-0.071774	-0.302768	0.918992	0.979728
median_income	-0.015550	-0.079626	-0.118278	0.197882	-0.007723
ocean_proximity	-0.271779	0.007637	0.295519	-0.032244	-0.010014
median_house_value	-0.045398	-0.144638	0.106432	0.133294	0.049686

In [28]:

```
sns.heatmap(data.corr(), linewidths=0.1, annot = True)
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27c0b3d0>
```



Leaving out any data will make the models biased, so the predictions has to be made with all the data, intact

Prediction Models

Lets partition the data into 2 parts, one - the predictor and the other being the target variable

In [37]:

```
x = data[['longitude', 'latitude', 'housing_median_age', 'total_rooms','total_bedrooms', 'p
y = data['median_house_value']
```

Let's import thetrain_test_split to split the data into training and testing data and LinearRegression Model from the sklearn.linear_model

Linear Regression

In [60]:

```
from sklearn.linear_model import LinearRegression
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 = 3

linear_regressor = LinearRegression()
linear_regressor.fit(x_train, y_train)

y_pred = linear_regressor.predict(x_test)
print('Accuracy of Linear regression on test set: {:.6f}'.format(linear_regressor.score(x_t
```

```
Accuracy of Linear regression on test set: 0.653770
```

The Accuracy of the Linear model turn out to be **65.3770 %**.

Decision-Tree Regressor

In [43]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split


x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state =

regr = DecisionTreeRegressor(max_depth=9)
regr.fit(x_train, y_train)

y_pred = regr.predict(x_test)
print('Accuracy of Decision-Tree Regressor on test set: {:.6f}'.format(regr.score(x_test, y
```

```
Accuracy of Decision-Tree Regressor on test set: 0.736268
```

The Accuracy od the model from Decision-Tree Regressor is **73.6268 %** .

Random Forest Regressor

The Rondom Forest Regressor is seeded with :
n_estimators = **200**
max_depth = **19**
random_state = **2**

In [54]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state =

regr = RandomForestRegressor(n_estimators = 200 , max_depth=19, random_state=2)
regr.fit(x_train, y_train)

y_pred = regr.predict(x_test)
print('Accuracy of Rondom Forest Regressor on test set: {:.6f}'.format(regr.score(x_test, y
```

```
Accuracy of Rondom Forest Regressor on test set: 0.832100
```

Accuracy of Rondom Forest Regressor on test set is **83.2100 %**

Comparision of the Accuracy got on Different Models

In [68]:

```
models = ['Linear Regression', 'Decision Tree Regressor', 'Random Forest Regressor']
accuracies = [65.3770, 73.6268, 83.2100]
conclusion = pd.DataFrame({'Models' : models , 'Accuracies' : accuracies})
conclusion
```

Out[68]:

	Models	Accuracies
0	Linear Regression	65.3770
1	Decision Tree Regressor	73.6268
2	Random Forest Regressor	83.2100

Submitted by : Subham Panigrahi