Roll Number:- 22102B2006

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Github Link:- https://github.com/KhushilBhimani2004/Machine-Learning

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error as mse, r2_score
from sklearn.metrics import accuracy_score
import plotly.express as px
```

```
df = pd.read_csv("/content/housing.csv")
```

```
df.head(10)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0
5	-122.25	37.85	52.0	919.0	213.0	413.0	193.0	4.0368	269700.0
6	-122.25	37.84	52.0	2535.0	489.0	1094.0	514.0	3.6591	299200.0
7	-122.25	37.84	52.0	3104.0	687.0	1157.0	647.0	3.1200	241400.0
8	-122.26	37.84	42.0	2555.0	665.0	1206.0	595.0	2.0804	226700.0
9	-122.25	37.84	52.0	3549.0	707.0	1551.0	714.0	3.6912	261100.0

Next steps: Generate code with df View recommended plots

```
# from google.colab import drive
# drive.mount('/content/drive')
```

```
df.shape
```

```
(20640, 10)
```

```
df.columns
```

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

```
df.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
```

```
1 df.describe()
```

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

```
1 df.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
```

```
1 df.duplicated().sum()
```

```
0
```

```
1 # med_value = df['total_bedrooms'].median()
2 # med_value
```

```
1 df =df.dropna(axis=0, how='any')
```

```
1 df.sample(10)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populat
13868	-117.31	34.35	9.0	2404.0	390.0	107
19338	-122.82	38.53	27.0	1823.0	360.0	90
5620	-118.25	33.78	32.0	296.0	139.0	51
4694	-118.37	34.07	52.0	2195.0	435.0	88
2126	-119.71	36.77	11.0	5112.0	1384.0	248
15686	-122.42	37.79	48.0	4506.0	1342.0	198
17892	-121.91	37.36	42.0	3224.0	708.0	194
7441	-118.20	33.94	45.0	1570.0	328.0	132
6629	-118.15	34.16	18.0	1711.0	383.0	147
13279	-117.65	34.10	44.0	1526.0	337.0	83

```
1 df.isnull().sum()
```

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

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 20433 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20433 non-null  float64
 1   latitude            20433 non-null  float64
 2   housing_median_age  20433 non-null  float64
 3   total_rooms         20433 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20433 non-null  float64
 6   households          20433 non-null  float64
 7   median_income       20433 non-null  float64
 8   median_house_value  20433 non-null  float64
 9   ocean_proximity     20433 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.7+ MB
```

```
1 unique_val = df['ocean_proximity'].unique()
2 unique_val
```

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

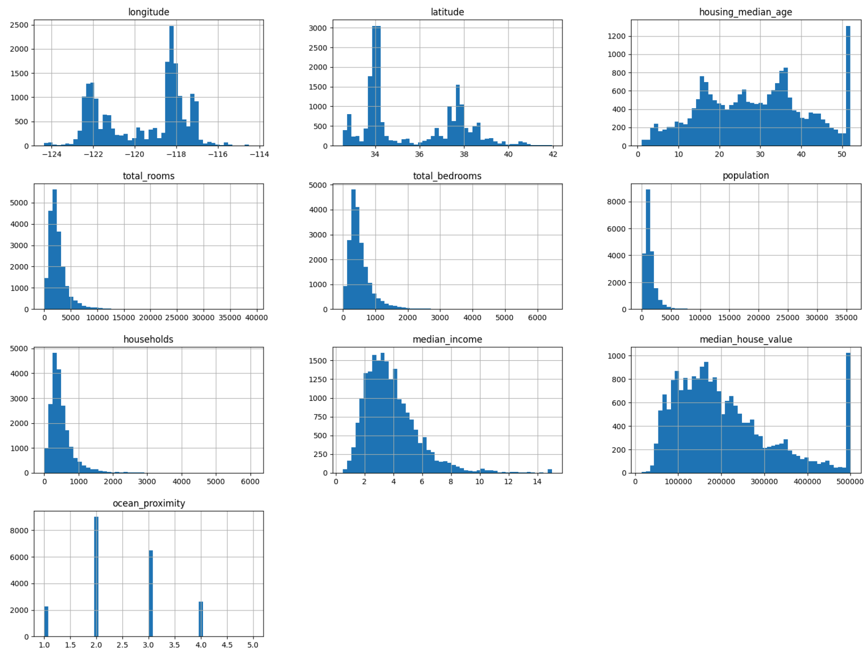
```
1 df['ocean_proximity'] = df['ocean_proximity'].map({'NEAR BAY': 1, '<1H OCEAN': 2, 'INLAND': 3, 'NEAR OCEAN' : 4, 'ISLAND': 5})
2 #
3 #
```

```
1 df.head(10)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
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
5	-122.25	37.85	52.0	919.0	213.0	413.0
6	-122.25	37.84	52.0	2535.0	489.0	1094.0
7	-122.25	37.84	52.0	3104.0	687.0	1157.0
8	-122.26	37.84	42.0	2555.0	665.0	1206.0
9	-122.25	37.84	52.0	3549.0	707.0	1551.0

Next steps: Generate code with df View recommended plots

```
1 df.hist(bins=50, figsize=(20,15))
2 plt.show()
```



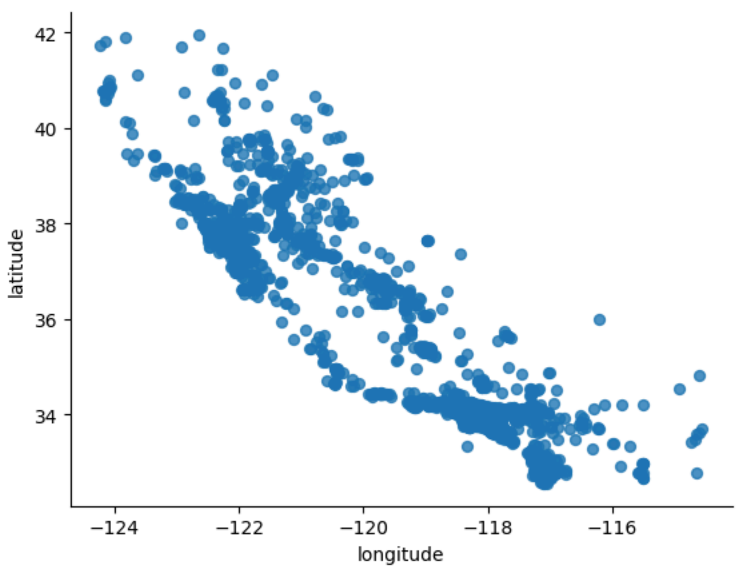

```
1 df.corr()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedr
longitude	1.000000	-0.924616	-0.109357	0.045480	0.06
latitude	-0.924616	1.000000	0.011899	-0.036667	-0.06
housing_median_age	-0.109357	0.011899	1.000000	-0.360628	-0.32
total_rooms	0.045480	-0.036667	-0.360628	1.000000	0.93
total_bedrooms	0.069608	-0.066983	-0.320451	0.930380	1.00
population	0.100270	-0.108997	-0.295787	0.857281	0.87
households	0.056513	-0.071774	-0.302768	0.918992	0.97
median_income	-0.015550	-0.079626	-0.118278	0.197882	-0.00
median_house_value	-0.045398	-0.144638	0.106432	0.133294	0.04
ocean_proximity	0.181198	-0.067980	-0.206178	0.015917	0.00

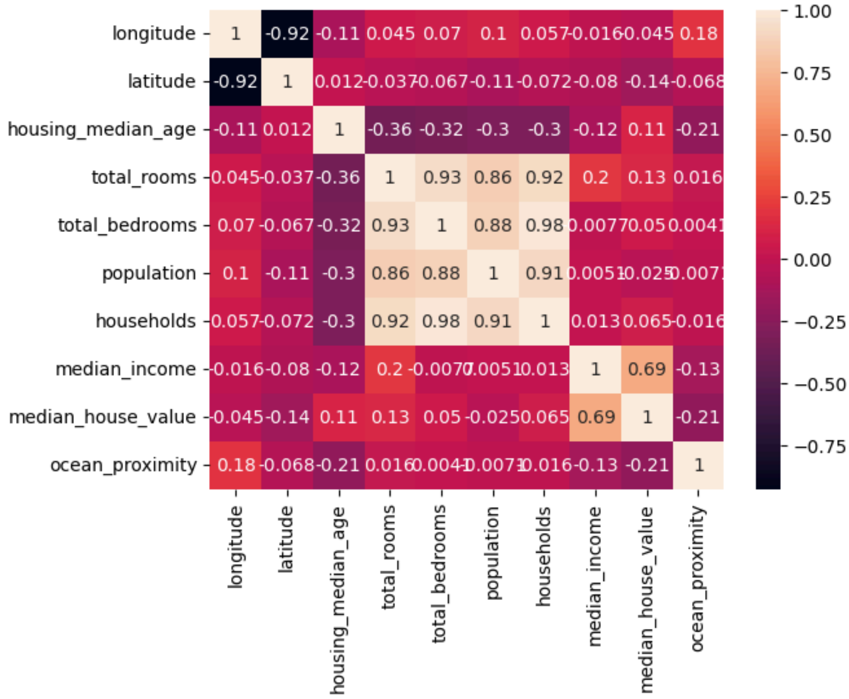
```
1 corrln = df.corr()['median_house_value']
2 round(corrln,2)
```

```
longitude            -0.05
latitude             -0.14
housing_median_age    0.11
total_rooms           0.13
total_bedrooms        0.05
population           -0.03
households            0.06
median_income         0.69
median_house_value    1.00
ocean_proximity      -0.21
Name: median_house_value, dtype: float64
```

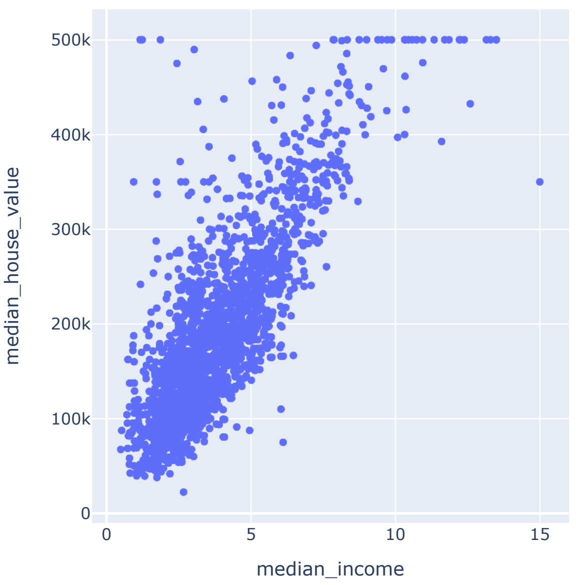
```
df.sample(3000).plot(kind='scatter', x='longitude', y='latitude', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```




```
ax = sns.heatmap(df.corr(), annot = True)
```




```
data = df.head(2000)
px.scatter(data, x='median_income', y='median_house_value')
```




```
1 df.columns
2 housing_df = df[['longitude', 'latitude', 'housing_median_age', 'total_rooms',
3        'total_bedrooms', 'population', 'households', 'median_income',
4        'ocean_proximity',  'median_house_value']]
```

```
1 housing_df.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
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

Next steps: Generate code with housing_df View recommended plots

```
1 train_pd, test_pd, val_pd = housing_df[:18000], housing_df[18000:19217], housing_df[19215:]
2 len(train_pd), len(test_pd), len(val_pd)
```

```
(18000, 1217, 1218)
```

```
1 X_train, y_train = train_pd.drop('median_house_value', axis=1), train_pd.to_numpy()[:, -1]
2 X_train.head(10)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
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
5	-122.25	37.85	52.0	919.0	213.0	413.0
6	-122.25	37.84	52.0	2535.0	489.0	1094.0
7	-122.25	37.84	52.0	3104.0	687.0	1157.0
8	-122.26	37.84	42.0	2555.0	665.0	1206.0
9	-122.25	37.84	52.0	3549.0	707.0	1551.0

Next steps: Generate code with X_train View recommended plots

```
X_val, y_val = val_pd.to_numpy()[:,:-1], val_pd.to_numpy()[:, -1]
X_test, y_test = test_pd.to_numpy()[:,:-1], test_pd.to_numpy()[:, -1]
```

```
X_train.shape, y_train.shape, X_test.shape, y_test.shape, X_val.shape, y_val.shape
```

```
((18000, 9), (18000,), (1217, 9), (1217,), (1218, 9), (1218,))
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_val = scaler.transform(X_val)
```

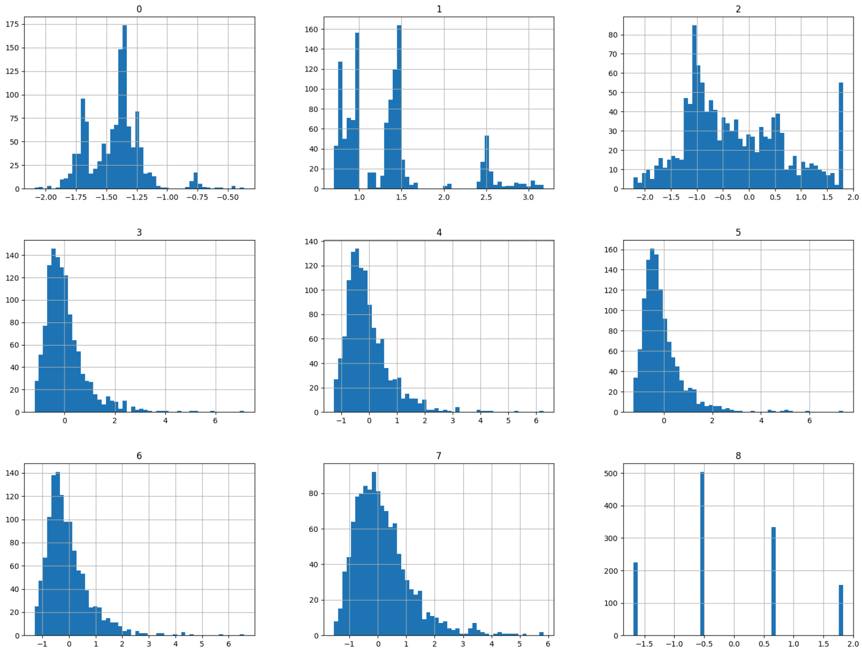
```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning:

X does not have valid feature names, but StandardScaler was fitted with feature names

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning:

X does not have valid feature names, but StandardScaler was fitted with feature names
```

```
pd.DataFrame(X_train)
```

	0	1	2	3	4	5	6	
0	-1.453822	1.204250	0.935040	-0.795703	-0.964371	-0.970876	-0.972988	2.32936
1	-1.448767	1.194570	-0.642170	2.018961	1.315597	0.843015	1.637958	2.31688
2	-1.458876	1.189729	1.802506	-0.530032	-0.822019	-0.819064	-0.841409	1.76947
3	-1.463931	1.189729	1.802506	-0.617382	-0.717005	-0.764970	-0.733049	0.92303
4	-1.463931	1.189729	1.802506	-0.457617	-0.611991	-0.758863	-0.629850	-0.01915
...	...	...	...	...	...	...	...	.
17995	-1.352724	0.947718	-0.799891	0.530841	1.597968	0.432076	1.676658	-0.19260
17996	-1.352724	0.957398	-1.036472	0.345732	1.518624	0.038586	1.392859	-0.15553
17997	-1.347669	0.952558	-0.642170	-0.075631	0.314465	0.044694	0.479544	0.01104
17998	-1.347669	0.952558	-0.326728	-0.255309	-0.362291	-0.141145	-0.309932	0.46045
17999	-1.342614	0.952558	-1.036472	-0.693870	-0.439302	-0.816447	-0.462151	0.16955

18000 rows × 9 columns

```
pd.DataFrame(X_test).hist(bins=50, figsize=(20,15))
plt.show()
```




```
X_train.shape, X_test.shape, X_val.shape,
```

```
((18000, 9), (1217, 9), (1218, 9))
```

```
##Linear Regression Model
```

```
# Preprocessing - scaling the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Train the model
lm = LinearRegression().fit(X_train_scaled, y_train)
```

```
y_train_pred = lm.predict(X_train_scaled)
y_val_pred = lm.predict(X_val_scaled)
```

```
mse_train = mse(y_train, y_train_pred)
rmse_train = mse(y_train, y_train_pred, squared=False)

# Calculate MSE and RMSE for validation set
mse_val = mse(y_val, y_val_pred)
rmse_val = mse(y_val, y_val_pred, squared=False)

# Calculate R² score for training set
r2_train = r2_score(y_train, y_train_pred)

# Calculate R² score for validation set
r2_val = r2_score(y_val, y_val_pred)
```

```
print(f'Training MSE: {mse_train}')
print(f'Training RMSE: {rmse_train}')
print(f'Training R²: {r2_train}')
```

```
Training MSE: 4985623211.241477
```

```
print(f'Validation MSE: {mse_val}')
print(f'Validation RMSE: {rmse_val}')
print(f'Validation R²: {r2_val}')
```

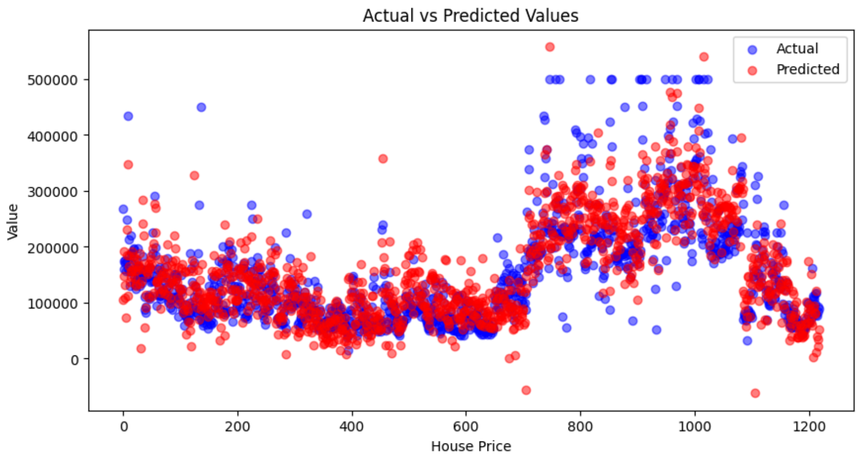
```
Validation MSE: 3021634923.4105325
Validation RMSE: 54969.399882212034
Validation R²: 0.6626316715336671
```

Double-click (or enter) to edit

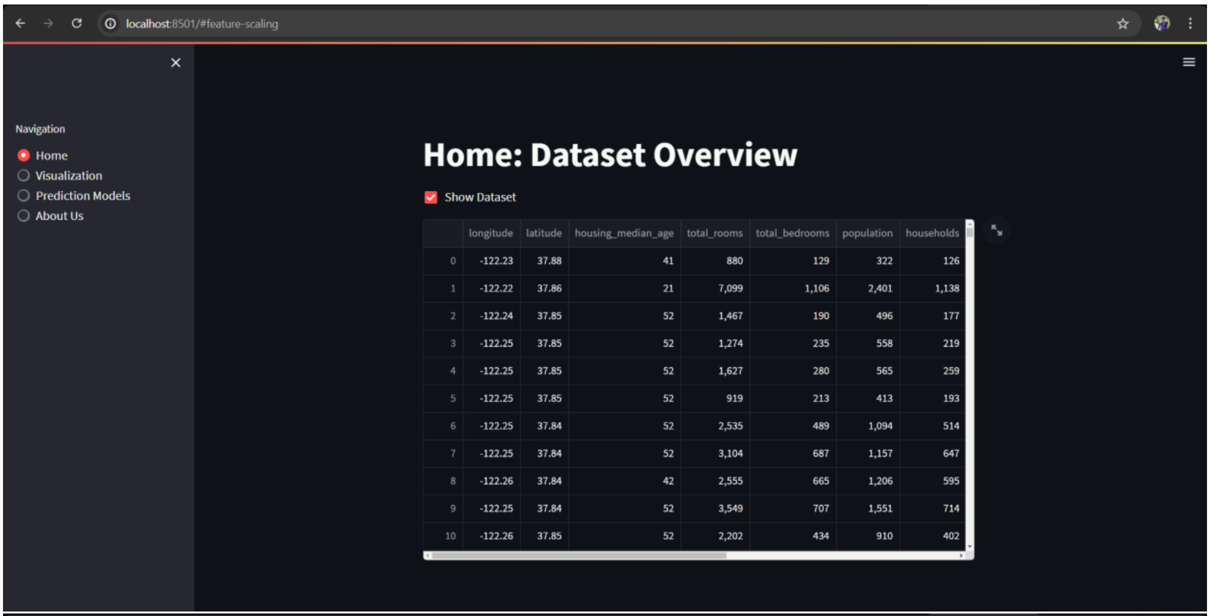
```
print('Some predictions on the validation set:', y_val_pred[:5])
```

```
Some predictions on the validation set: [104479.44966118 192574.74579031 146838.49904684 131771.43881713
 109040.18165488]
```

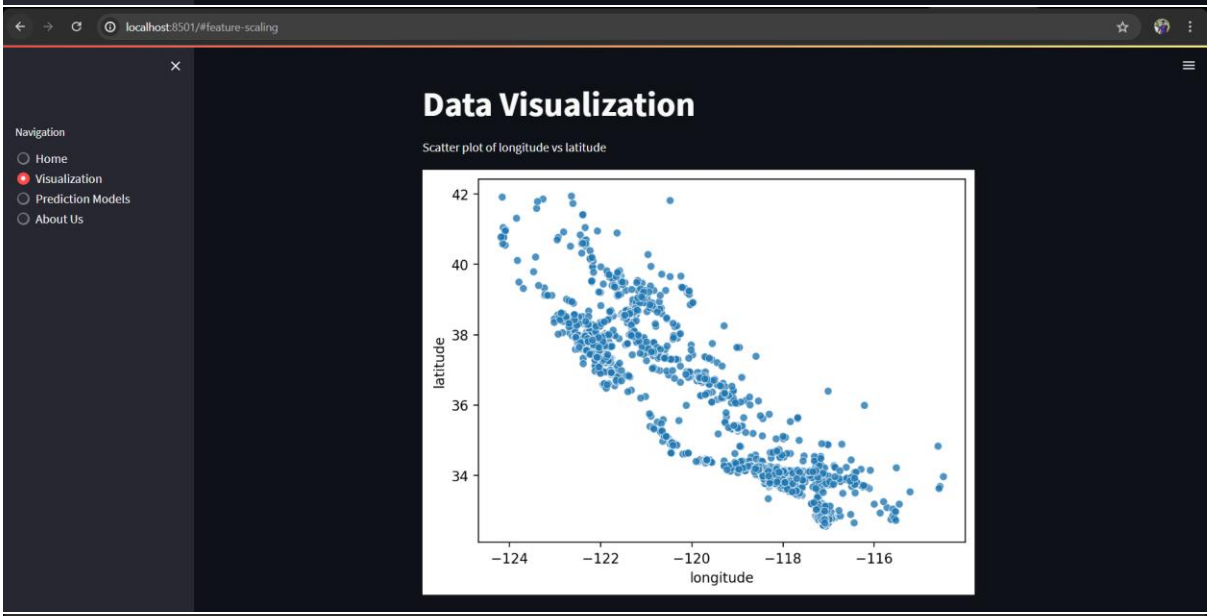
```
plt.figure(figsize=(10, 5))

# Plot actual values
plt.scatter(range(len(y_val)), y_val, color='blue', alpha=0.5, label='Actual')

# Plot predicted values
plt.scatter(range(len(y_val)), y_val_pred, color='red', alpha=0.5, label='Predicted')

plt.xlabel('House Price')
plt.ylabel('Value')
plt.title('Actual vs Predicted Values')
plt.legend()
plt.show()

```

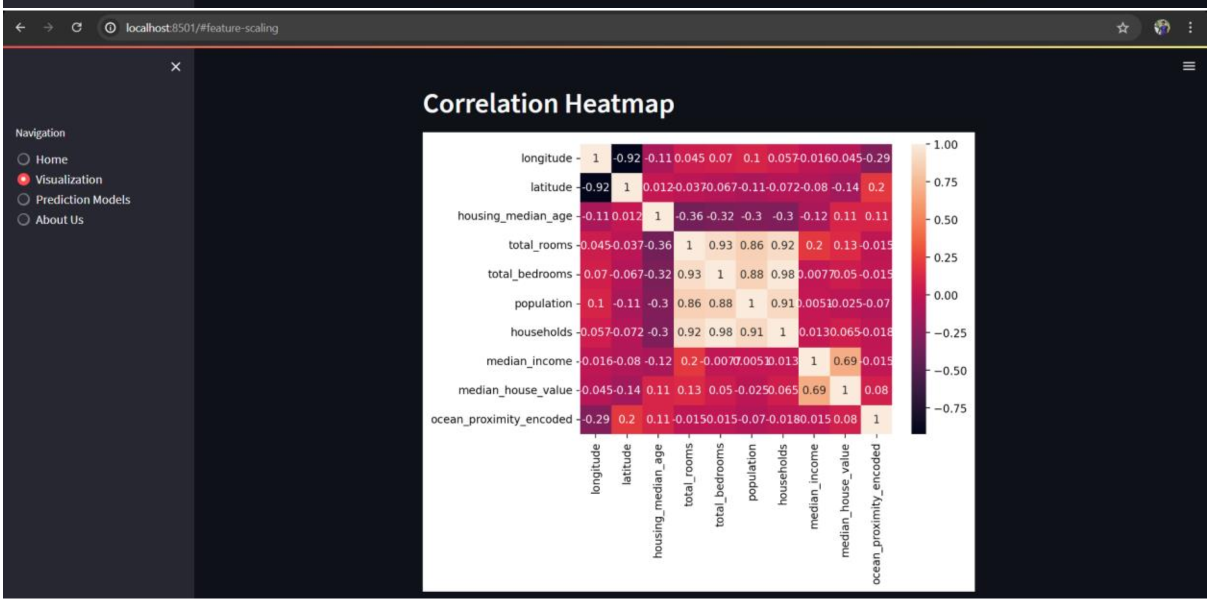


User Interface -



	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41	880	129	322	126
1	-122.22	37.86	21	7,099	1,106	2,401	1,138
2	-122.24	37.85	52	1,467	190	496	177
3	-122.25	37.85	52	1,274	235	558	219
4	-122.25	37.85	52	1,627	280	565	259
5	-122.25	37.85	52	919	213	413	193
6	-122.25	37.84	52	2,535	489	1,094	514
7	-122.25	37.84	52	3,104	687	1,157	647
8	-122.26	37.84	42	2,555	665	1,206	595
9	-122.25	37.84	52	3,549	707	1,551	714
10	-122.26	37.85	52	2,202	434	910	402





User Interface -