

```
In [15]: import pandas as pd

df = pd.read_csv(r'C:\Users\humer\Downloads\california.housing.csv')

print(df.head())
print(df.info())
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms
0	-122.23	37.88	41	880	1
1	-122.22	37.86	21	7099	11
2	-122.24	37.85	52	1467	1
3	-122.25	37.85	52	1274	2
4	-122.25	37.85	52	1627	2

	population	households	median_income	median_house_value	ocean_proximity
0	322	126	8.3252	452600	NEAR BAY
1	2401	1138	8.3014	358500	NEAR BAY
2	496	177	7.2574	352100	NEAR BAY
3	558	219	5.6431	341300	NEAR BAY
4	565	259	3.8462	342200	NEAR BAY

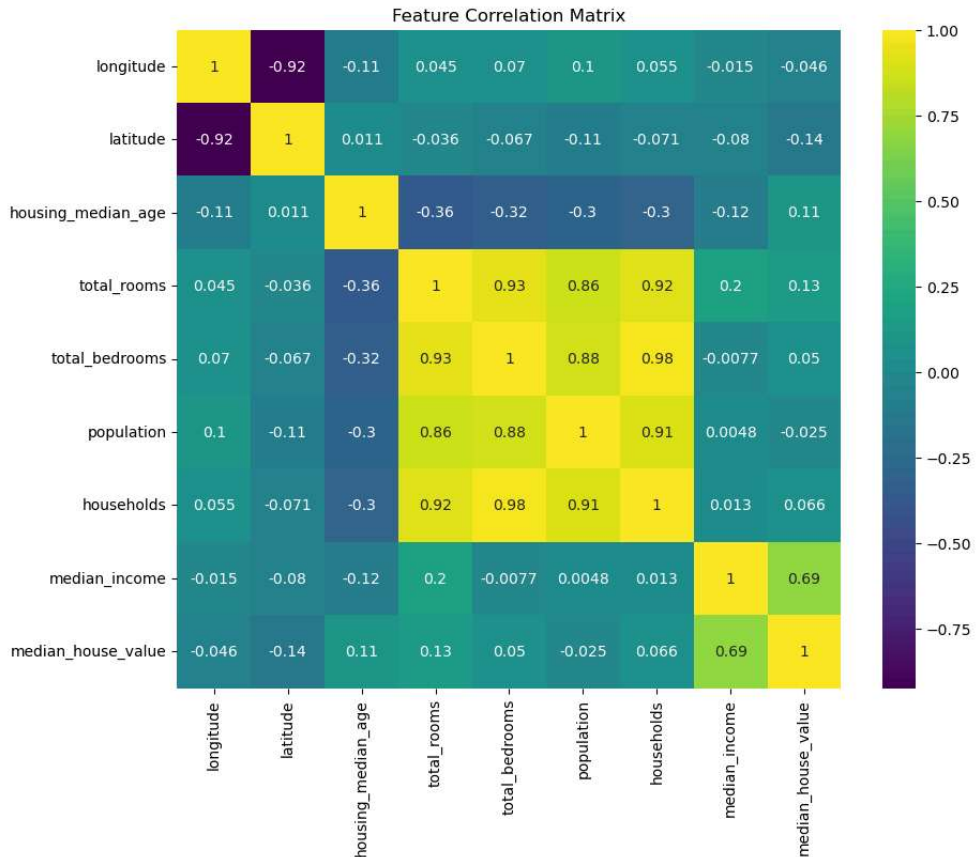
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):

#	Column	Non-Null Count	Dtype
0	longitude	20640 non-null	float64
1	latitude	20640 non-null	float64
2	housing_median_age	20640 non-null	int64
3	total_rooms	20640 non-null	int64
4	total_bedrooms	20433 non-null	float64
5	population	20640 non-null	int64
6	households	20640 non-null	int64
7	median_income	20640 non-null	float64
8	median_house_value	20640 non-null	int64
9	ocean_proximity	20640 non-null	object

dtypes: float64(4), int64(5), object(1)
memory usage: 1.6+ MB
None

```
In [16]: numeric_df = df.select_dtypes(include=['float64', 'int64'])

plt.figure(figsize=(10, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='viridis')
plt.title("Feature Correlation Matrix")
plt.show()
```



```
In [40]: print(df.info())
print(df.describe())

print(df.isnull().sum())

# Correlation heatmap
import seaborn as sns
import matplotlib.pyplot as plt
df_numeric = df.drop(columns=['ocean_proximity'])
sns.heatmap(df_numeric.corr(), annot=True, cmap='coolwarm')
plt.title("Feature Correlation Heatmap (Numeric Only)")
plt.show()
```

```
<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  int64
3   total_rooms                          20640 non-null  int64
4   total_bedrooms                      20640 non-null  float64
5   population                           20640 non-null  int64
6   households                           20640 non-null  int64
7   median_income                       20640 non-null  float64
8   median_house_value                  20640 non-null  int64
9   ocean_proximity                     20640 non-null  object
dtypes: float64(4), int64(5), object(1)
memory usage: 1.6+ MB
None

      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    20640.000000  20640.000000  20640.000000   20640.000000
mean         536.838857   1425.476744    499.539680     3.870671
std         419.391878   1132.462122    382.329753     1.899822
min           1.000000     3.000000     1.000000     0.499900
25%         297.000000    787.000000    280.000000     2.563400
50%         435.000000   1166.000000    409.000000     3.534800
75%         643.250000   1725.000000    605.000000     4.743250
max        6445.000000  35682.000000   6082.000000    15.000100

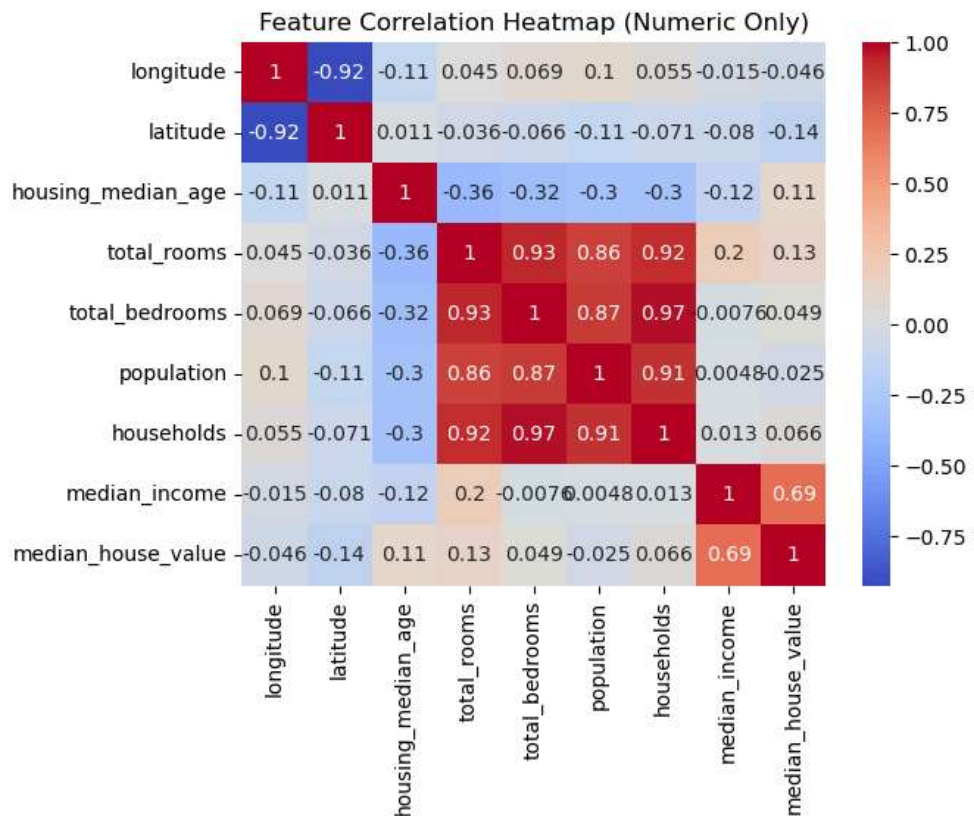
      median_house_value
count    20640.000000
mean     206855.816909
std      115395.615874
min       14999.000000
25%      119600.000000
50%      179700.000000
75%      264725.000000
max       500001.000000

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

```



```
In [25]: from sklearn.linear_model import LinearRegression
```

```

lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

```

```
Out[25]: LinearRegression
```

```
LinearRegression()
```

```
In [35]: # Predict using the trained model
y_pred_lr = lr_model.predict(X_test)
```

```

print("Linear Regression Performance:")
print("R² Score:", r2_score(y_test, y_pred_lr))
print("MAE:", mean_absolute_error(y_test, y_pred_lr))
import numpy as np

```

```
rmse = np.sqrt(mean_squared_error(y_test, y_pred_lr))  
print("RMSE:", rmse)
```

Linear Regression Performance:

R² Score: 0.6254240620553608

MAE: 50670.7382409719

RMSE: 70060.52184473517

```
In [34]: from sklearn.ensemble import RandomForestRegressor  
  
rf_model = RandomForestRegressor(random_state=42)  
rf_model.fit(X_train, y_train)  
y_pred_rf = rf_model.predict(X_test)  
  
print("Random Forest Performance:")  
print("R2 Score:", r2_score(y_test, y_pred_rf))  
print("MAE:", mean_absolute_error(y_test, y_pred_rf))  
import numpy as np  
  
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))  
print("RMSE:", rmse_rf)
```

Random Forest Performance:

R² Score: 0.8169555593071559

MAE: 31643.65566860465

RMSE: 48975.818369986104

```
In [47]: print(X.dtypes)
```

```
longitude      float64  
latitude       float64  
housing_median_age  int64  
total_rooms    int64  
total_bedrooms float64  
population     int64  
households     int64  
median_income  float64  
ocean_proximity object  
dtype: object
```

```
In [ ]:
```