

Import Libraries

```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from warnings import filterwarnings
filterwarnings('ignore')
```

Load Data

```
In [11]: from sklearn.datasets import fetch_california_housing
```

```
In [14]: datas = fetch_california_housing()
```

```
In [15]: datas
```

```
Out[15]: {'data': array([[ 8.3252      ,  41.        ,  6.98412698, ...,  2.55555556,
   37.88      , -122.23     ], [ 8.3014      ,  21.        ,  6.23813708, ...,  2.10984183,
   37.86      , -122.22     ], [ 7.2574      ,  52.        ,  8.28813559, ...,  2.80225989,
   37.85      , -122.24     ], ...,
   [ 1.7        ,  17.        ,  5.20554273, ...,  2.3256351 ,
   39.43      , -121.22     ], [ 1.8672      ,  18.        ,  5.32951289, ...,  2.12320917,
   39.43      , -121.32     ], [ 2.3886      ,  16.        ,  5.25471698, ...,  2.61698113,
   39.37      , -121.24     ]]),
'target': array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894]),
'frame': None,
'target_names': ['MedHouseVal'],
'feature_names': ['MedInc',
'HousAge',
'AveRooms',
'AveBedrms',
'Population',
'AveOccup',
'Latitude',
'Longitude'],
'DESCR': '.. _california_housing_dataset:\n\nCalifornia Housing dataset\n-----\n**Data Set Characteristics:**\nNumber of Instances: 20640\nNumber of Attributes: 8 numeric, predictive attributes and the target\nAttribute Information:\n- MedInc median income in block group\n- HouseAge median house age in block group\n- AveRooms average number of rooms per household\n- AveBedrms average number of bedrooms per household\n- Population block group population\n- AveOccup average number of household members\n- Latitude block group latitude\n- Longitude block group longitude\nMissing Attribute Values: None\nThis dataset was obtained from the StatLib repository.\nhttps://www.dcc.fc.up.pt/~ltorgo/Regression/cal\_housing.html\nThe target variable is the median house value for California districts, expressed in hundreds of thousands of dollars ($100,000).\nThis dataset was derived from the 1990 U.S. census, using one row per census block group. A block group is the smallest geographical unit for which the U.S. Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people).\nA household is a group of people residing within a home. Since the average number of rooms and bedrooms in this dataset are provided per household, these columns may take surprisingly large values for block groups with few households and many empty houses, such as vacation resorts.\nIt can be downloaded/loaded using the func:`sklearn.datasets.fetch_california_housing` function.\n.. rubric:: References\n- Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,\n  Statistics and Probability Letters, 33 (1997) 291-297\n'}
```

```
In [22]: df = pd.DataFrame(datas.data,columns=datas.feature_names)
```

```
In [24]: df['target'] = datas.target
```

```
In [25]: df
```

Out[25]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422
...
20635	1.5603	25.0	5.045455	1.133333	845.0	2.560606	39.48	-121.09	0.781
20636	2.5568	18.0	6.114035	1.315789	356.0	3.122807	39.49	-121.21	0.771
20637	1.7000	17.0	5.205543	1.120092	1007.0	2.325635	39.43	-121.22	0.923
20638	1.8672	18.0	5.329513	1.171920	741.0	2.123209	39.43	-121.32	0.847
20639	2.3886	16.0	5.254717	1.162264	1387.0	2.616981	39.37	-121.24	0.894

20640 rows × 9 columns

Clean Data (missing values, outliers)

In [26]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   MedInc      20640 non-null   float64
 1   HouseAge    20640 non-null   float64
 2   AveRooms    20640 non-null   float64
 3   AveBedrms   20640 non-null   float64
 4   Population   20640 non-null   float64
 5   AveOccup    20640 non-null   float64
 6   Latitude     20640 non-null   float64
 7   Longitude    20640 non-null   float64
 8   target       20640 non-null   float64
dtypes: float64(9)
memory usage: 1.4 MB
```

In [53]: df.describe()

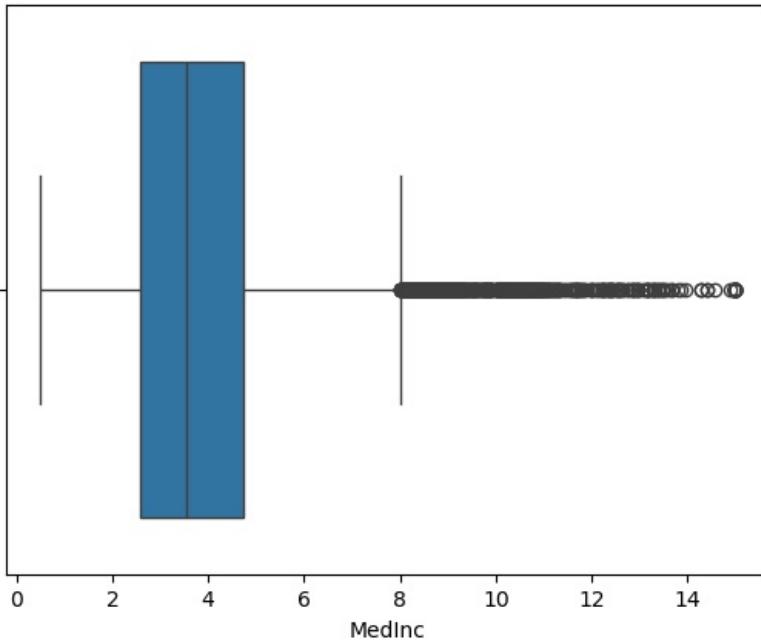
	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	t
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655	35.631861	-119.569704	2.06
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050	2.135952	2.003532	1.15
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308	32.540000	-124.350000	0.14
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741	33.930000	-121.800000	1.19
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116	34.260000	-118.490000	1.79
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261	37.710000	-118.010000	2.64
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333	41.950000	-114.310000	5.00

In [27]: df.isnull().sum()

```
MedInc      0
HouseAge    0
AveRooms    0
AveBedrms   0
Population  0
AveOccup    0
Latitude    0
Longitude   0
target      0
dtype: int64
```

In [28]: sns.boxplot(x=df['MedInc'])

Out[28]: <Axes: xlabel='MedInc'>

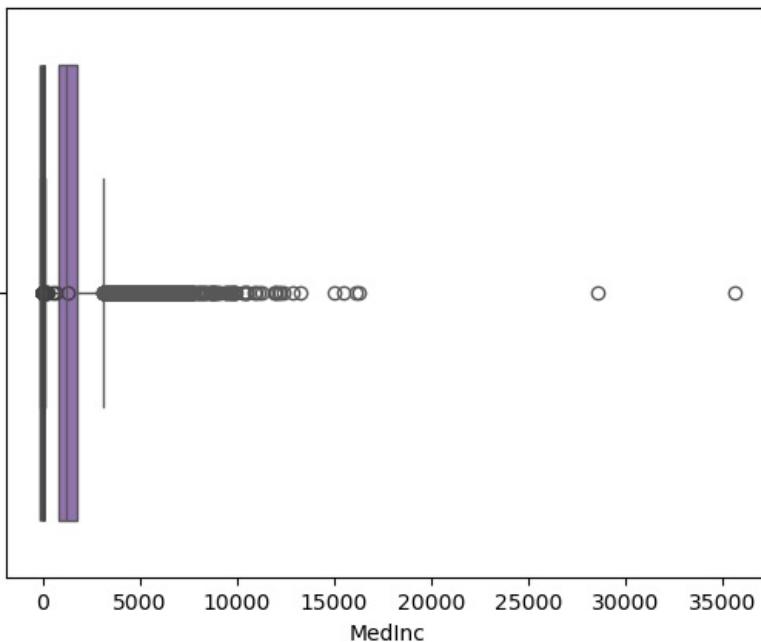


```
In [36]: df.columns
```

```
Out[36]: Index(['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup',
       'Latitude', 'Longitude', 'target'],
       dtype='object')
```

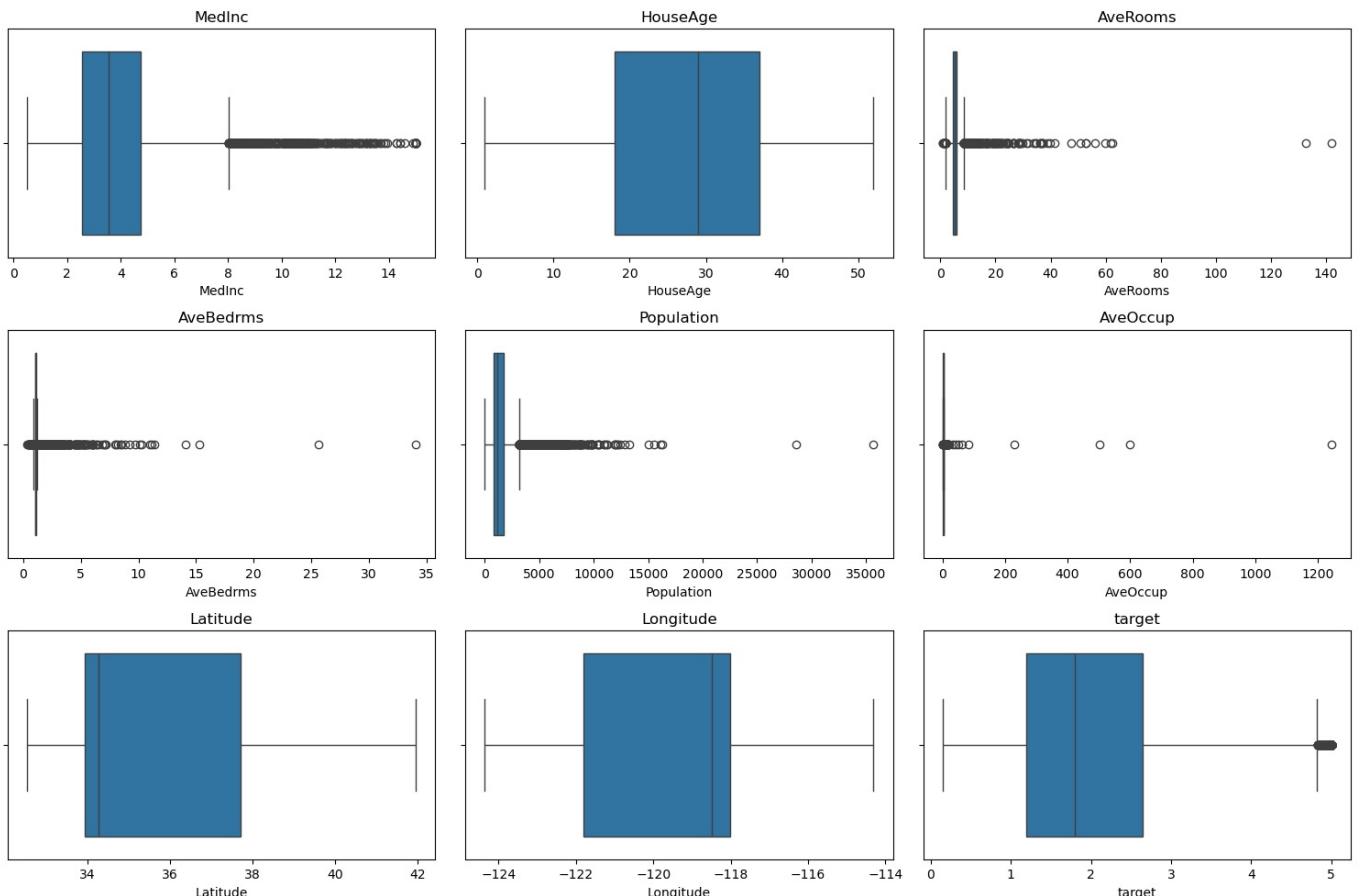
```
In [40]: feature_columns = ['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup','Latitude', 'Longitude']

for cc in feature_columns:
    sns.boxplot(x = df[cc])
```



```
In [46]: feature_columns = ['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup','Latitude', 'Longitude']

plt.figure(figsize=(15, 10)) # Bigger figure
for i, cc in enumerate(feature_columns, 1):
    plt.subplot(3, 3, i)
    sns.boxplot(x=df[cc])
    plt.title(cc)
plt.tight_layout()
plt.show()
```



In []:

Segregate X and y

```
In [49]: X = df.drop('target', axis=1)
y = df.target
```

Split Data (train/test)

```
In [50]: from sklearn.model_selection import train_test_split
In [51]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
In [52]: print("X_train Shape:", X_train.shape)
print("y_train Shape:", y_train.shape)

print("-"*30)

print("X_test Shape:", X_test.shape)
print("y_test Shape:", y_test.shape)

X_train Shape: (16512, 8)
y_train Shape: (16512,)

-----
X_test Shape: (4128, 8)
y_test Shape: (4128,)
```

Preprocess Features (scaling, encoding, etc.)

```
In [55]: from sklearn.preprocessing import StandardScaler
In [57]: scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Train Model (Linear, Logistic, Tree, etc.)

```
In [91]: from sklearn.linear_model import LinearRegression
In [92]: lr = LinearRegression()
lr
```

```
Out[92]: ▾ LinearRegression ⓘ ⓘ  
LinearRegression()
```

```
In [93]: lr.fit(X_train_scaled,y_train)
```

```
Out[93]: ▾ LinearRegression ⓘ ⓘ  
LinearRegression()
```

```
In [94]: y_pred_lr = model.predict(X_test_scaled)
```

```
In [95]: pd.DataFrame(y_pred_lr,columns=['Predicted'])
```

```
Out[95]: Predicted
```

0	0.719123
1	1.764017
2	2.709659
3	2.838926
4	2.604657
...	...
4123	1.991746
4124	2.249839
4125	4.468770
4126	1.187511
4127	2.009403

4128 rows × 1 columns

```
In [96]: pd.DataFrame(y_test)
```

```
Out[96]: target
```

20046	0.47700
3024	0.45800
15663	5.00001
20484	2.18600
9814	2.78000
...	...
15362	2.63300
16623	2.66800
18086	5.00001
2144	0.72300
3665	1.51500

4128 rows × 1 columns

```
In [88]: from sklearn.ensemble import RandomForestRegressor
```

```
In [99]: rf = RandomForestRegressor(n_estimators=100,random_state=42)  
rf
```

```
Out[99]: ▾ RandomForestRegressor ⓘ ⓘ
```

RandomForestRegressor(random_state=42)

```
In [101]: rf.fit(X_train,y_train)
```

```
Out[101]: ▾ RandomForestRegressor ⓘ ⓘ
```

RandomForestRegressor(random_state=42)

```
In [102]: y_pred_rf = rf.predict(X_test)

In [104]: pd.DataFrame(y_pred_rf,columns=['Predicted'])
```

Out[104]:

	Predicted
0	0.509500
1	0.741610
2	4.923257
3	2.529610
4	2.273690
...	...
4123	2.267210
4124	1.993650
4125	4.758219
4126	0.714090
4127	1.650830

4128 rows × 1 columns

```
In [106]: pd.DataFrame(y_test)
```

Out[106]:

	target
20046	0.47700
3024	0.45800
15663	5.00001
20484	2.18600
9814	2.78000
...	...
15362	2.63300
16623	2.66800
18086	5.00001
2144	0.72300
3665	1.51500

4128 rows × 1 columns

Evaluate the model

```
In [72]: from sklearn.metrics import mean_absolute_error,mean_squared_error,root_mean_squared_error,r2_score
```

```
In [121]: print("Linear Regression")
print('*'*30)
print("Mean Squared Error : ",mean_squared_error(y_test,y_pred_lr))
print("Mean Absolute Error : ",mean_absolute_error(y_test,y_pred_lr))
print("Root Mean Squared Error : ",root_mean_squared_error(y_test,y_pred_lr))
print("R Squared : ",r2_score(y_test,y_pred_lr))
```

Linear Regression

Mean Squared Error : 0.5558915986952441
Mean Absolute Error : 0.5332001304956566
Root Mean Squared Error : 0.7455813830127762
R Squared : 0.575787706032451

RandomForest metrics

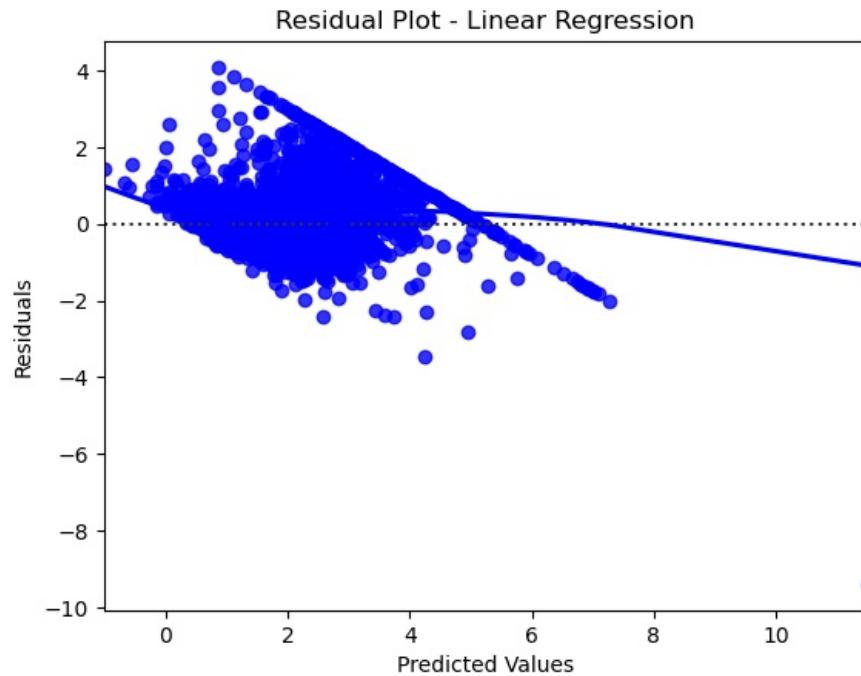
```
In [123]: print("Random Forest")
print('*'*30)
print("Mean Squared Error : ",mean_squared_error(y_test,y_pred_rf))
print("Mean Absolute Error : ",mean_absolute_error(y_test,y_pred_rf))
print("Root Mean Squared Error : ",root_mean_squared_error(y_test,y_pred_rf))
print("R Squared : ",r2_score(y_test,y_pred_rf))
```

Random Forest

```
Mean Squared Error : 0.2553684927247781
Mean Absolute Error : 0.32754256845930246
Root Mean Squared Error : 0.5053399773665033
R Squared : 0.8051230593157366
```

In [108]

```
# 1. Residual Plot for Linear Regression
sns.residplot(x=y_pred_lr, y=y_test - y_pred_lr, lowess=True, color='blue')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot - Linear Regression')
plt.show()
```



In [111]

```
# 2. Feature Importance for Random Forest
feature_importance = pd.Series(rf.feature_importances_, index=data.feature_names)
feature_importance.nlargest(10).plot(kind='barh')
plt.title('Top 10 Feature Importances - Random Forest')
plt.xlabel('Importance Score')
plt.show()
```

