MACHINE LEARNING ASSIGNMENT 3

Regression

Objective:

The objective of this assignment is to evaluate your understanding of regression techniques in supervised learning by applying them to a real-world dataset.

Dataset:

Use the California Housing dataset available in the sklearn library. This dataset contains information about various features of houses in California and their respective median prices.

1. Loading and Preprocessing (2 marks):

In [251…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter("ignore")
from sklearn.datasets import fetch_california_housing
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

In [252…
```
# Load the California Housing dataset
california_housing = fetch_california_housing(as_frame=True)
# Extract features (X) and target (y)
X = california_housing.data  # Feature matrix
y = california_housing.target  # Target vector
data=pd.concat([X, y.rename("MedHouseValue")], axis=1)
```

In [253…
```
df=data.copy()
```

In [254…
```
df.head(3)
```

Out[254…

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24

In [255…
```
from IPython.display import Image, display
```

```
# Display a local image
display(Image(filename="new.png"))
```

Column	Description
MedInc	Median income in block group (in tens of thousands of dollars).
HouseAge	Median age of houses in the block group.
AveRooms	Average number of rooms per household.
AveBedrms	Average number of bedrooms per household.
Population	Total population in the block group.
AveOccup	Average number of household members.
Latitude	Latitude of the block group.
Longitude	Longitude of the block group.
MedHouseValue	Median house value for households in the block group (in $100,000).

Handle missing values (if any) and perform necessary feature scaling (e.g., standardization).

In [257…
```
df.shape
```

Out[257…
```
(20640, 9)
```

In [258…
```
df.isnull().sum()
```

Out[258…
```
MedInc          0
HouseAge        0
AveRooms        0
AveBedrms       0
Population      0
AveOccup        0
Latitude        0
Longitude       0
MedHouseValue   0
dtype: int64
```

No null values.

Checking if there is any duplicates.

In [261…
```
df.duplicated().sum()
```

Out[261…
```
0
```

No duplicates.

In [263…
```
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   MedHouseValue  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
```

In [264…
```
df.describe()
```

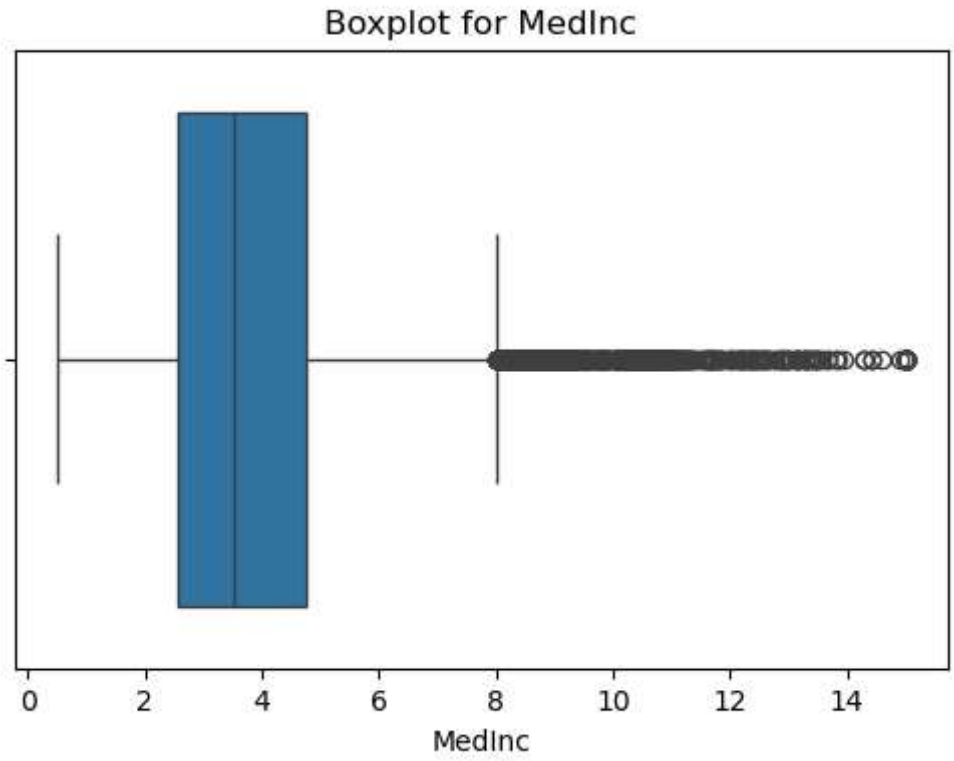
Out[264…

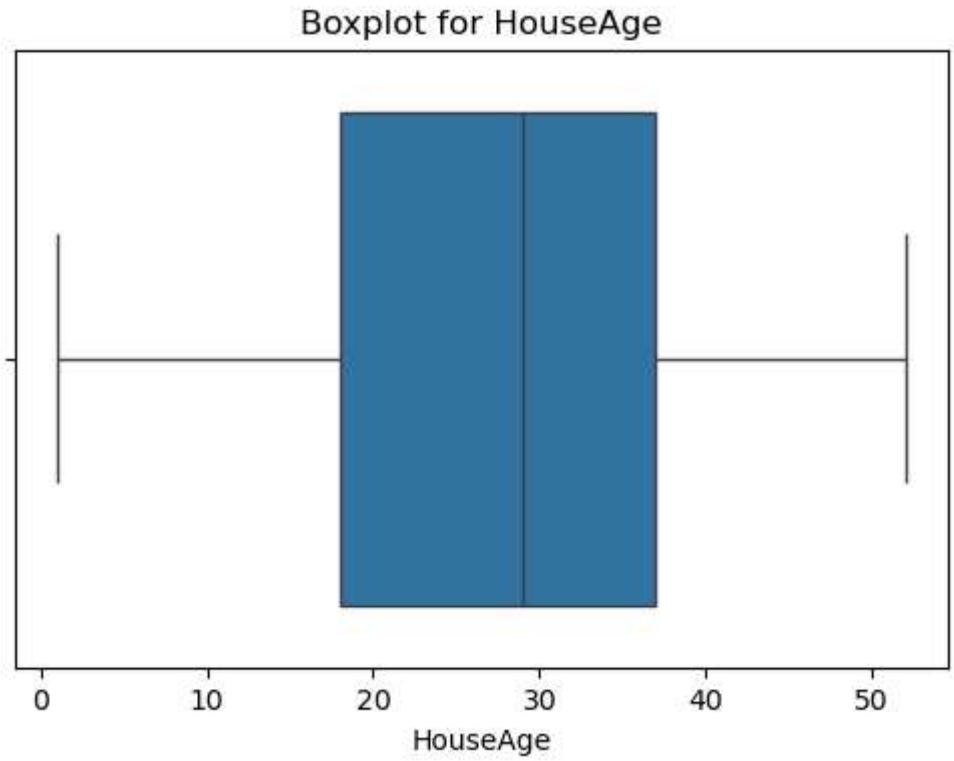
	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333

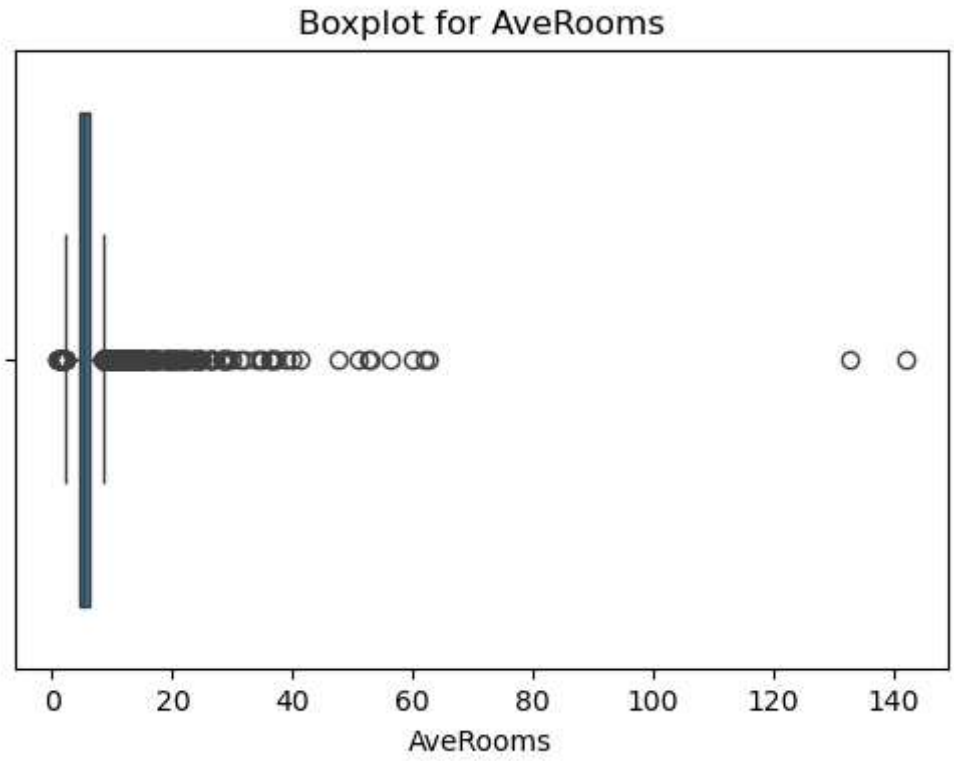
In [265…
```
# Select only numerical columns
numeric_columns = df.select_dtypes(include=['number'])

# View the numerical columns
print(numeric_columns.columns)
```

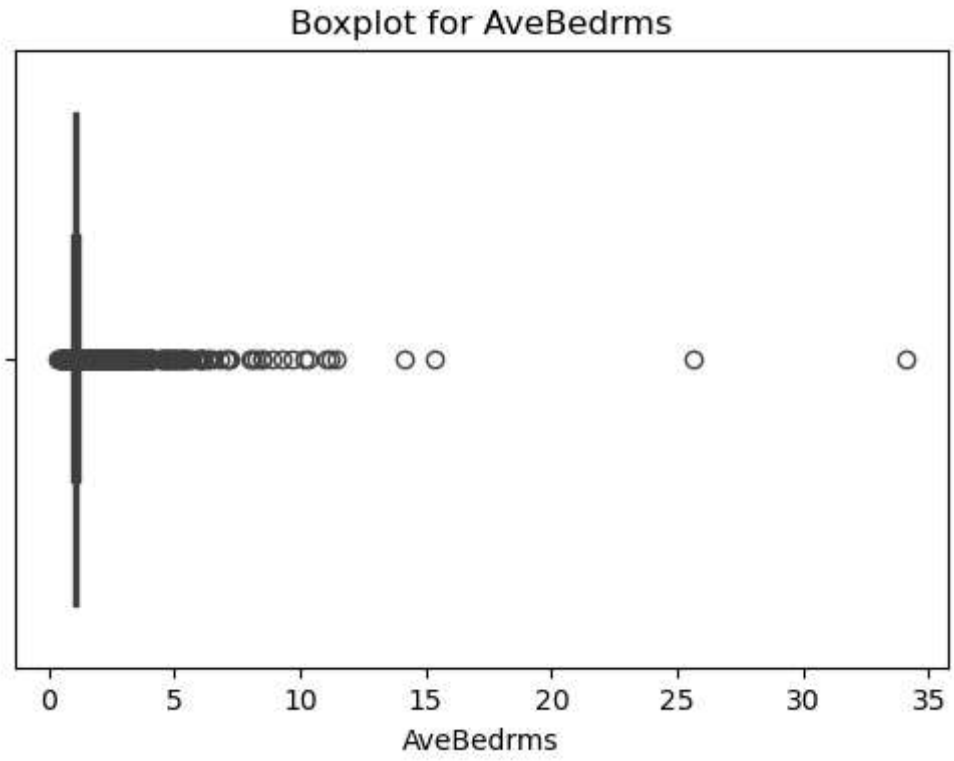
```
Index(['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup',
       'Latitude', 'Longitude', 'MedHouseValue'],
      dtype='object')
```

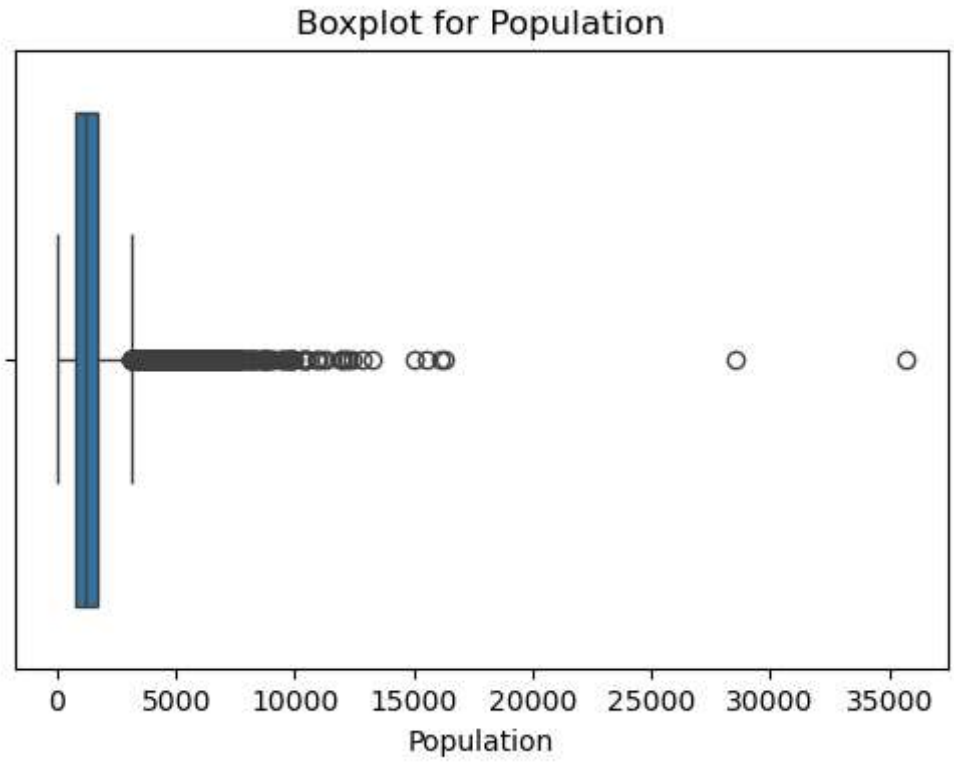
In [266…
```
# Boxplots for each numeric column
for col in numeric_columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=df[col])
    plt.title(f"Boxplot for {col}")
    plt.show()
```

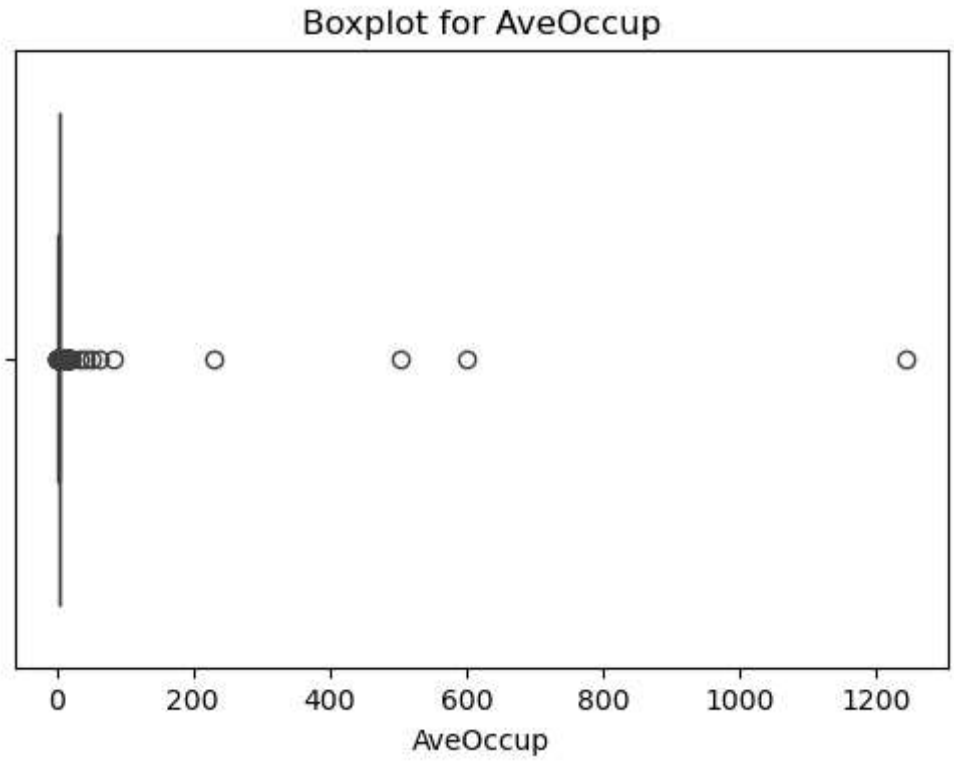

Boxplot for MedInc
0
2
4
6
8
10
12
14
MedInc

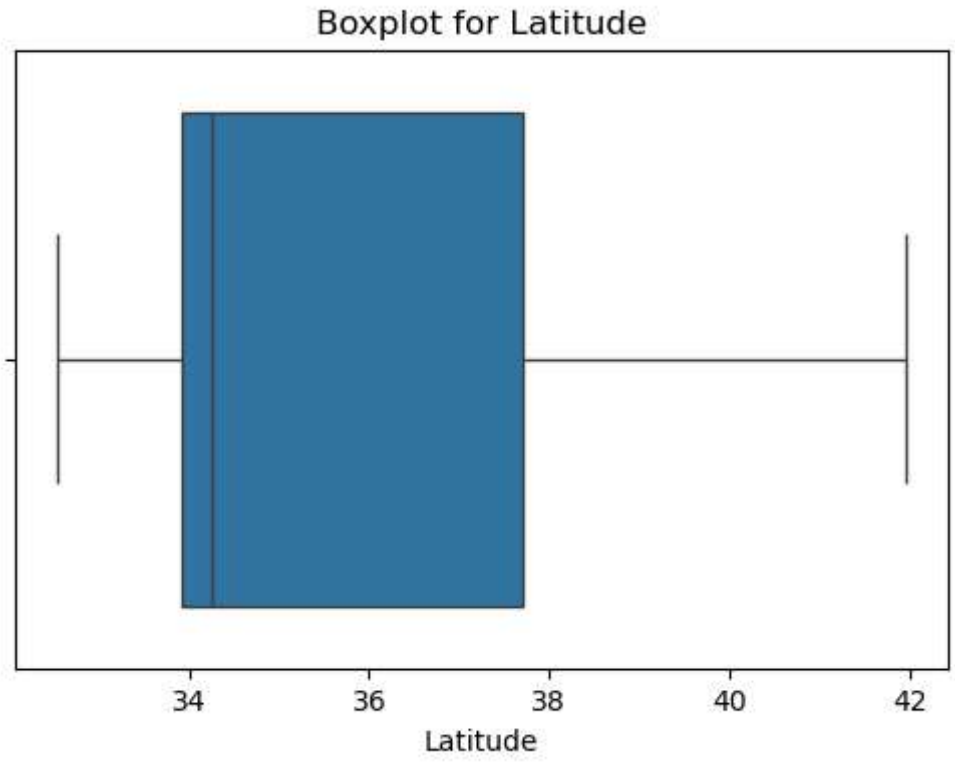

Boxplot for HouseAge
0
10
20
30
40
50
HouseAge

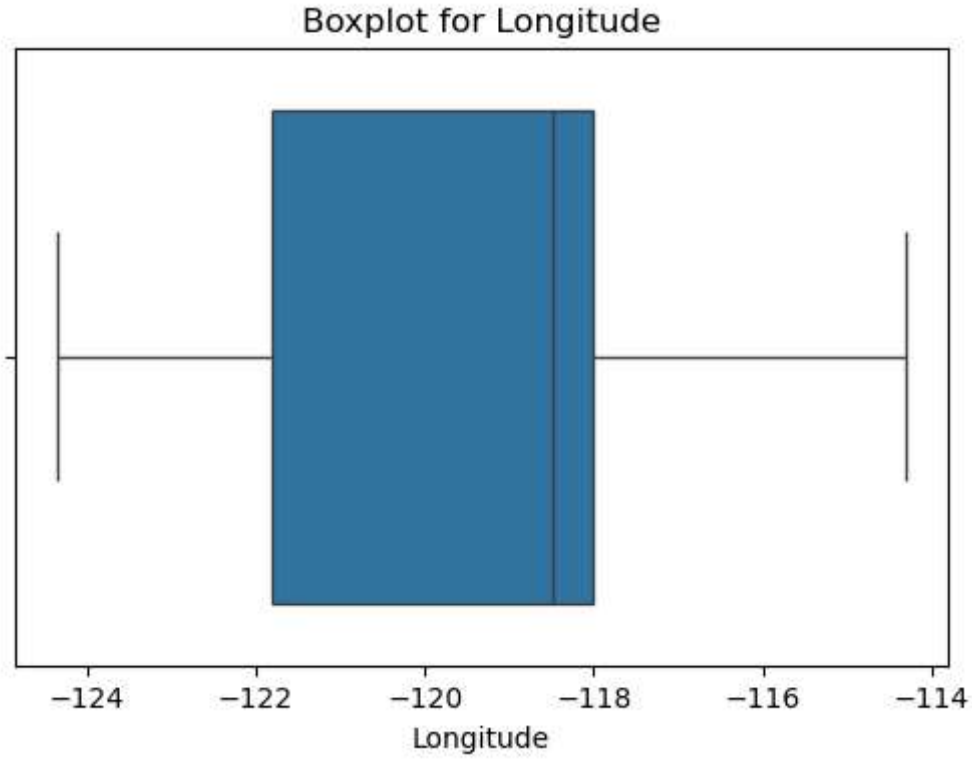

Boxplot for AveRooms
0
20
40
60
80
100
120
140
AveRooms

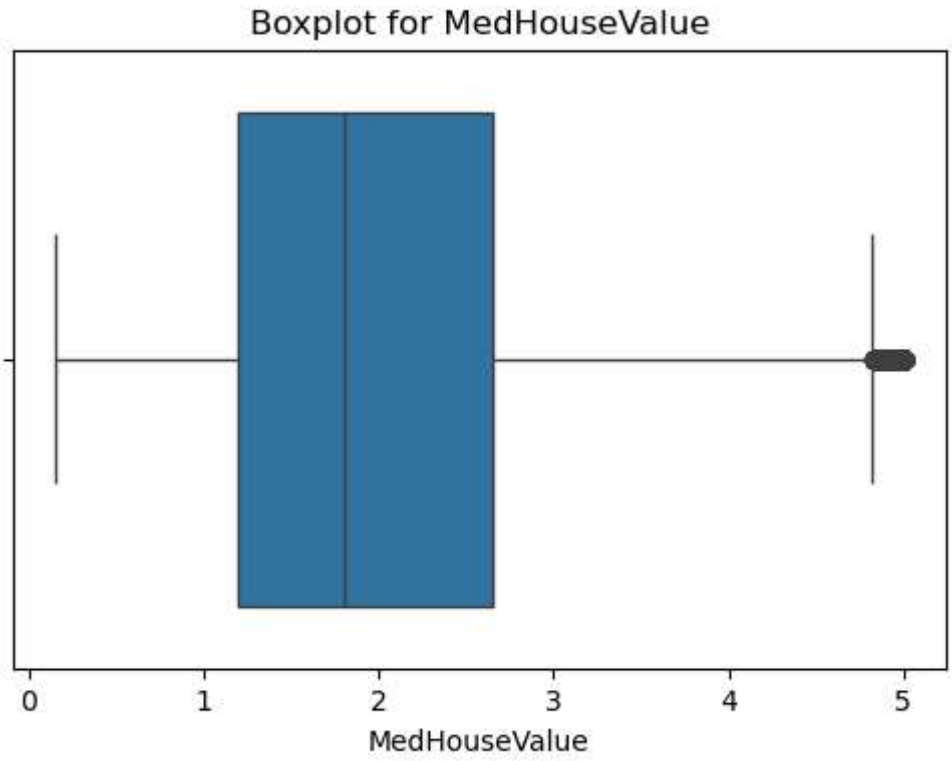

Boxplot for AveBedrms
0
5
10
15
20
25
30
35
AveBedrms


Boxplot for Population
0
5000
10000
15000
20000
25000
30000
35000
Population


Boxplot for AveOccup
0
200
400
600
800
1000
1200
AveOccup


Boxplot for Latitude
34
36
38
40
42
Latitude


Boxplot for Longitude
−124
−122
−120
−118
−116
−114
Longitude



Finding Outliers and Removing

In [268…
```
def filter(numeric_columns) :
    for col in numeric_columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        # Filter the data
        df_cleaned = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
        return  df_cleaned
```

In [269…
```
df1=filter(numeric_columns)
```

Finding skewness and transforming

In [271…
```
df1.skew()
```

Out[271…
```
MedInc            0.568044
HouseAge          0.056551
AveRooms         21.644042
AveBedrms        30.975925
Population        4.958378
AveOccup         86.930743
Latitude          0.462263
Longitude        -0.294289
MedHouseValue     0.986734
dtype: float64
```

In [272…
```
df1["Population_cbrt"] = np.cbrt(df["Population"])  # Use log1p to handle zero valu
df1["MedHouseValue_sqrt"] = np.sqrt(df["MedHouseValue"])
df1["MedInc_sqrt"] = np.sqrt(df["MedInc"])
```

In [273…
```
df1.skew()
```

Out[273…
```
MedInc                0.568044
HouseAge              0.056551
AveRooms             21.644042
AveBedrms            30.975925
Population            4.958378
AveOccup             86.930743
Latitude              0.462263
Longitude            -0.294289
MedHouseValue         0.986734
Population_cbrt       0.529498
MedHouseValue_sqrt    0.411579
MedInc_sqrt           0.093992
dtype: float64
```

In [274…
```
df1.drop(["Population", "MedHouseValue", "MedInc"], axis=1, inplace=True)
```

In [275…
```
df1.skew()
```

Out[275…
```
HouseAge              0.056551
AveRooms             21.644042
AveBedrms            30.975925
AveOccup             86.930743
Latitude              0.462263
Longitude            -0.294289
Population_cbrt       0.529498
MedHouseValue_sqrt    0.411579
MedInc_sqrt           0.093992
dtype: float64
```

In [276…
```
df1.drop(["AveOccup"], axis=1, inplace=True)
```

In [277…
```
df1.head()
```

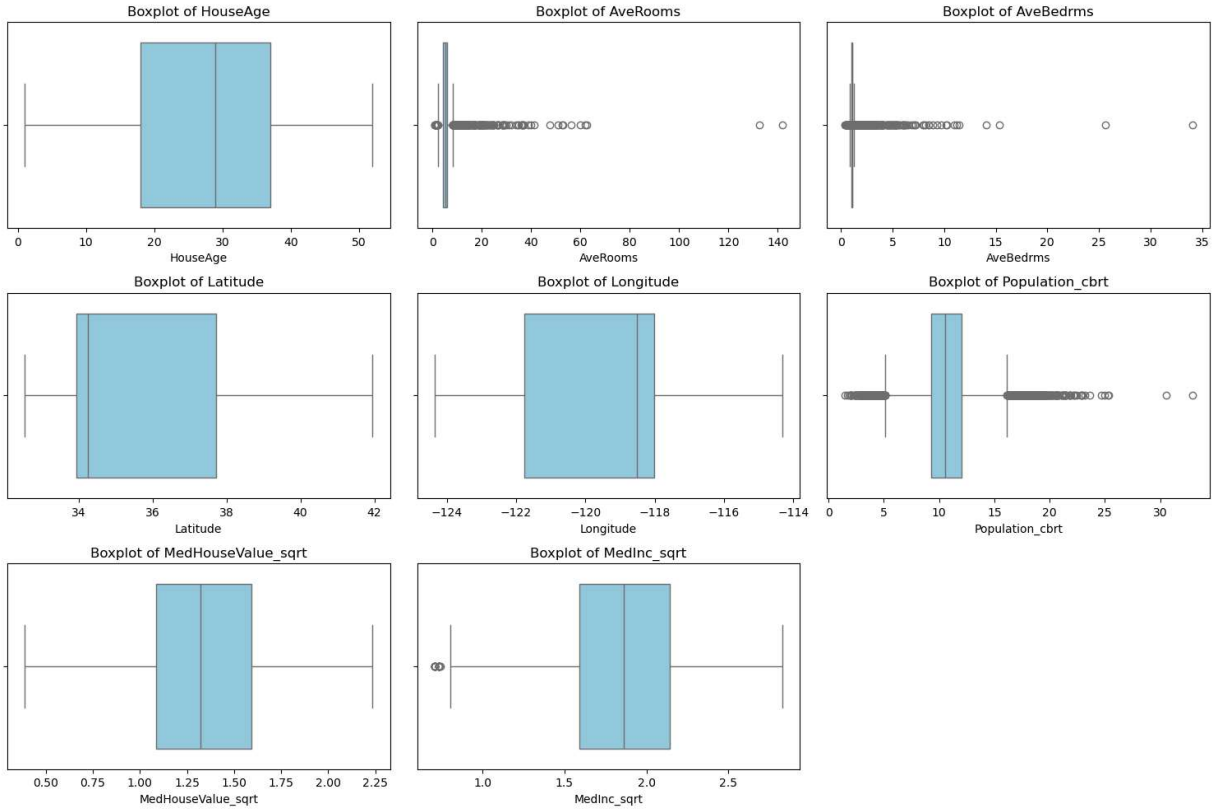
Out[277…

	HouseAge	AveRooms	AveBedrms	Latitude	Longitude	Population_cbrt	MedHouseVal
2	52.0	8.288136	1.073446	37.85	-122.24	7.915783	1.
3	52.0	5.817352	1.073059	37.85	-122.25	8.232746	1.
4	52.0	6.281853	1.081081	37.85	-122.25	8.267029	1.
5	52.0	4.761658	1.103627	37.85	-122.25	7.447034	1.
6	52.0	4.931907	0.951362	37.84	-122.25	10.303998	1.

Check for Outliers Using Boxplots

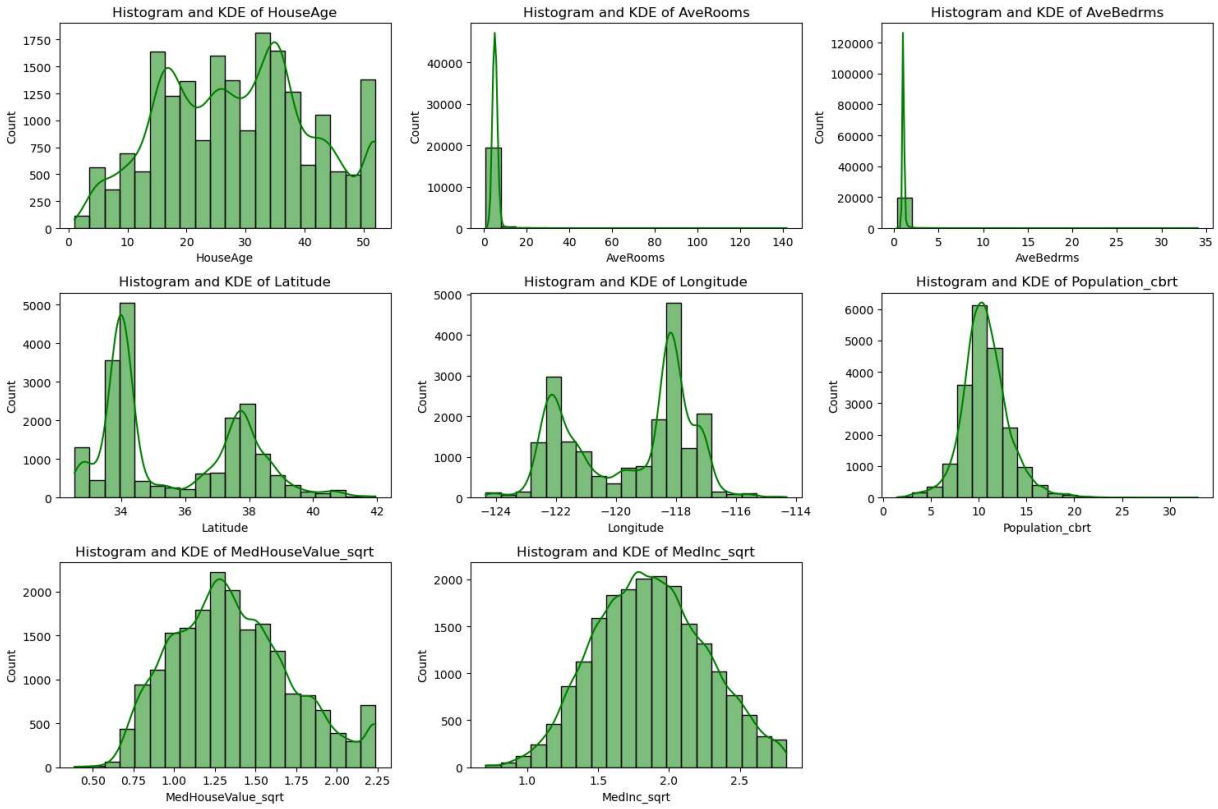
Boxplots are ideal for spotting outliers in each feature.

In [279…
```
# Plot boxplots for each column
columns = ["HouseAge", "AveRooms", "AveBedrms", "Latitude", "Longitude",
           "Population_cbrt", "MedHouseValue_sqrt", "MedInc_sqrt"]

plt.figure(figsize=(15, 10))
for i, col in enumerate(columns, 1):
    plt.subplot(3, 3, i)
    sns.boxplot(x=df1[col], color='skyblue')
    plt.title(f"Boxplot of {col}")

plt.tight_layout()
plt.show()
```



Histogram for checking skewness and normalisation.

In [281…
```
# Plot histograms with KDE
plt.figure(figsize=(15, 10))
for i, col in enumerate(columns, 1):
    plt.subplot(3, 3, i)
    sns.histplot(df1[col], kde=True, color='green', bins=20)
    plt.title(f"Histogram and KDE of {col}")

plt.tight_layout()
plt.show()
```



In [ ]:

Box-Cox transformation :

It is a statistical technique used to stabilize variance and make data more closely approximate a normal distribution by applying a power transformation.

In [303…
```
from scipy.stats import boxcox

# Apply Box-Cox Transformation
df1["Population_boxcox"], _ = boxcox(df1["Population_cbrt"] + 1)  # Add 1 to handle
df1["MedInc_boxcox"], _ = boxcox(df1["MedInc_sqrt"] + 1)
```

In [305…
```
df1.drop(["MedInc_sqrt", "Population_cbrt"], axis=1, inplace=True)
df1.skew()
```

Out[305…
```
HouseAge              0.056551
AveRooms             21.644042
AveBedrms            30.975925
Latitude              0.462263
Longitude            -0.294289
MedHouseValue_sqrt    0.411579
Population_boxcox     0.092012
MedInc_boxcox        -0.011782
dtype: float64
```

The Outliers are first detected and removed, then skewness is also detected and transformed. Now the dataset is moderately skewed and preprocessed.

In [ ]:
```
df1.head()
```

Feature Scaling:

Linear regression is not sensitive to feature scaling, as it doesn't use distance-based computations. However, scaling can still be useful for interpretability and regularization (if using Ridge or Lasso regression).

Linear Regression model

- Definition: Models the relationship between independent variables and a continuous target variable using a straight line.
- Objective: Minimizes the differences between observed and predicted values using the least squares method.
- Key Features: Simple to implement, easy to interpret, and works well with linear relationships.
- Limitations: Struggles with nonlinear relationships and multicollinearity among predictors.
- Extensions: Regularized versions like Ridge and Lasso Regression address some limitations.

In [307…
```
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# Assume X and y are your features and target variables

# Split data into X (features) and y (target variable)
X = df1[['HouseAge', 'AveRooms', 'AveBedrms', 'Latitude', 'Longitude','Population_b
y = df1['MedHouseValue_sqrt']  # The target variable

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Apply SelectKBest with f_regression to select top 5 features on the training data
select_k_best = SelectKBest(score_func=f_regression, k=5)
X_train_selected = select_k_best.fit_transform(X_train, y_train)

# Now you can fit your model on the selected features from the training set
model = LinearRegression()
model.fit(X_train_selected, y_train)
```

Out[307…
```
LinearRegression
LinearRegression()
```

In [309…
```
# You can then use the model to make predictions on the test set
X_test_selected = select_k_best.transform(X_test)  # Apply the same feature selecti
y_pred = model.predict(X_test_selected)
```

In [311…
```
# Evaluate model performance (e.g., using R^2 score)
from sklearn.metrics import mean_squared_error, r2_score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error: 0.07035581874854141
R^2 Score: 0.4859646934405494
```

For Regression: Use metrics like MSE, MAE, and R^2.

Decision Tree Regressor model

- Definition: A non-linear model that predicts continuous target variables by splitting data into regions based on decision rules derived from feature values.
- Objective: Divides the dataset into smaller subsets, creating a tree-like structure where each split minimizes error (e.g., mean squared error or mean absolute error).
- Key Features: Handles both linear and non-linear relationships, requires minimal data preprocessing, and is easy to interpret.
- Limitations: Prone to overfitting, especially with deep trees, and sensitive to small data variations.
- Extensions: Techniques like pruning, ensemble methods (Random Forest, Gradient Boosting) improve performance and reduce overfitting.

In [313…
```
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor(max_depth=5, random_state=42)
model.fit(X_train_selected, y_train)
```

Out[313…
```
DecisionTreeRegressor
DecisionTreeRegressor(max_depth=5, random_state=42)
```

In [315…
```
# You can then use the model to make predictions on the test set
X_test_selected = select_k_best.transform(X_test)  # Apply the same feature selecti
y_pred = model.predict(X_test_selected)
```

In [317…
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error: 0.06589551543995875
R^2 Score: 0.5185526644052532
```

Random Forest Regressor

- Definition: An ensemble learning method that combines multiple decision trees to predict continuous target variables. It averages their outputs to improve accuracy and reduce overfitting.
- Objective: Enhances the stability and predictive power of decision trees by aggregating results from multiple random subsets of data and features.
- Key Features: Handles both linear and non-linear relationships, robust to outliers, reduces overfitting compared to single decision trees, and works well with large datasets.
- Limitations: Can be computationally expensive for large datasets and may become less interpretable due to the ensemble structure.
- Extensions: Often used as a base model in advanced techniques like Gradient Boosting and feature selection.

In [321…
```
from sklearn.ensemble import RandomForestRegressor

# Instantiate the Random Forest Regressor with desired hyperparameters
model = RandomForestRegressor(max_depth=5, random_state=42)

# Train the model with the training dataset
model.fit(X_train_selected, y_train)
```

Out[321…
```
RandomForestRegressor
RandomForestRegressor(max_depth=5, random_state=42)
```

In [325…
```
# You can then use the model to make predictions on the test set
X_test_selected = select_k_best.transform(X_test)  # Apply the same feature selecti
y_pred = model.predict(X_test_selected)
```

In [327…
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error: 0.06176373798914779
R^2 Score: 0.5487403521664316
```

Gradient Boosting Regressor

- Definition: An ensemble learning method that builds models sequentially, where each new model corrects the errors of the previous one, optimizing predictions for continuous target variables.
- Objective: Minimizes a loss function (e.g., mean squared error) by combining weak learners (typically decision trees) into a strong predictive model.

- Key Features: Handles both linear and non-linear relationships, offers high accuracy, and allows customization through various loss functions.
- Limitations: Can be computationally expensive, sensitive to hyperparameters, and prone to overfitting if not properly tuned.
- Extensions: Variants like XGBoost, LightGBM, and CatBoost improve efficiency and scalability while maintaining performance.

In [331…
```
from sklearn.ensemble import GradientBoostingRegressor

# Instantiate the Gradient Boosting Regressor with desired hyperparameters
model = GradientBoostingRegressor(max_depth=5, random_state=42, n_estimators=100, l

# Train the model with the training dataset
model.fit(X_train_selected, y_train)
```

Out[331…
```
GradientBoostingRegressor
GradientBoostingRegressor(max_depth=5, random_state=42)
```

In [333…
```
# You can then use the model to make predictions on the test set
X_test_selected = select_k_best.transform(X_test)  # Apply the same feature selecti
y_pred = model.predict(X_test_selected)
```

In [335…
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error: 0.04920947547846108
R^2 Score: 0.6404645946398724
```

Support Vector Regressor (SVR)

- Definition: A regression algorithm based on Support Vector Machines (SVM) that predicts continuous target variables by finding the best-fit hyperplane within a margin of tolerance.
- Objective: Minimizes prediction error while maintaining a balance between model complexity and prediction accuracy using a specified margin (epsilon).
- Key Features: Effective for small- to medium-sized datasets, can model non-linear relationships with kernel functions, and is robust to outliers due to the margin-based approach.
- Limitations: Computationally intensive for large datasets, sensitive to hyperparameters like kernel type, epsilon, and regularization, and can struggle with noisy data.
- Extensions: Kernel tricks (e.g., polynomial, RBF) enable SVR to handle complex, non-linear relationships.

In [337…
```
from sklearn.svm import SVR

# Instantiate the SVR model with desired hyperparameters
model = SVR(kernel='rbf', C=1.0, epsilon=0.1)
```

In [339…
```
# Example of consistent feature selection
selector = SelectKBest(f_regression, k=5)
X_train_selected = selector.fit_transform(X_train, y_train)
X_test_selected = selector.transform(X_test)
```

In [341…
```
from sklearn.preprocessing import StandardScaler

# Initialize scaler
scaler = StandardScaler()

# Fit on training data and transform both datasets
X_train_scaled = scaler.fit_transform(X_train_selected)
X_test_scaled = scaler.transform(X_test_selected)  # Ensure consistent feature set


# Train the model on scaled data
model = SVR(kernel='rbf', C=1.0, epsilon=0.1)
model.fit(X_train_scaled, y_train)
```

Out[341…
SVR

SVR()

In [343…
```
# You can then use the model to make predictions on the test set
X_test_selected = select_k_best.transform(X_test)  # Apply the same feature selecti
y_pred = model.predict(X_test_selected)
```

In [344…
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")
```

```
Mean Squared Error: 0.14067039751893123
R^2 Score: -0.027769304638824543
```

Evaluating Which model is best.

In [345…
```
# Example: Store metrics for each model
results = [
    {"Model": "Linear Regression", "MSE": 0.06892124381603329, "R2": 0.542734399328
    {"Model": "Random Forest", "MSE": 0.0564419393138401, "R2":  0.6255297227038401
    {"Model": "Gradient Boosting Regressor", "MSE": 0.04505607126630215,"R2": 0.701
    {"Model": "SVR", "MSE": 0.15154443789626484, "R2": -0.005438302999443811 5},
    {"Model": "Decision Tree Regressor model", "MSE": 0.061256153967021006, "R2": 0
]

# Convert to DataFrame
results_df = pd.DataFrame(results)
```

```
# Sort by MSE (or any preferred metric)
best_models = results_df.sort_values(by="MSE", ascending=True)
print(best_models)
```

```
                          Model       MSE        R2
2    Gradient Boosting Regressor  0.045056  0.701071
1                  Random Forest  0.056442  0.625530
4  Decision Tree Regressor model  0.061256  0.593589
0              Linear Regression  0.068921  0.542734
3                            SVR  0.151544 -0.005438
```

Best Model Selection

Based on the results:

Gradient Boosting Regressor is the best model because it has:
The lowest MSE (indicating minimal error).
The highest R^2 (explaining 70.1% of variance in the target variable).

Worst-Performing Algorithm: Support Vector Regressor (SVR)

Reasoning:

- High Error: SVR has the highest Mean Squared Error (MSE) at 0.151544, indicating that it produces the largest prediction errors among all models.
- Negative R^2: The R^2 score is -0.005438, meaning the model performs worse than a baseline model that always predicts the mean target value.
- Inability to Capture Relationships: SVR may struggle with the dataset if:
  - The relationships between variables are too complex for the selected kernel.
  - Hyperparameters like epsilon or C are not well-tuned.
  - The dataset size or noise level exceeds SVR's capabilities.
- Computational Challenges: SVR can be computationally expensive, especially with larger datasets, making it less efficient compared to ensemble models like Gradient Boosting or Random Forest.

Conclusion:

SVR is the worst-performing model for this dataset, likely due to poor handling of the underlying data relationships or suboptimal hyperparameter choices. Models like Gradient Boosting or Random Forest are better suited in this case.

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