Ввод [1]:
```python
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
from sklearn.svm import SVR, SVC
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.neural_network import MLPRegressor, MLPClassifier
from xgboost import XGBRegressor, XGBClassifier
from catboost import CatBoostRegressor, CatBoostClassifier
from sklearn.utils import resample
```

Ввод [4]:
```python
# Load and prepare the regression data
# California Housing dataset
california = fetch_california_housing()
X_reg = pd.DataFrame(california.data, columns=california.feature_names)
y_reg = pd.Series(california.target, name='MEDV')
```

Ввод [5]:
```python
# Load and prepare the classification data
# Credit Card Fraud Detection dataset (from Kaggle)
df_fraud = pd.read_csv("https://storage.googleapis.com/download.tensorflow.org/

df_fraud.head()
```

Out[5]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739

5 rows × 31 columns

Ввод [6]:
```python
# Resample the dataset to handle imbalance
df_majority = df_fraud[df_fraud.Class == 0]
df_minority = df_fraud[df_fraud.Class == 1]

df_minority_upsampled = resample(df_minority, replace=True, n_samples=len(df_ma
df_balanced = pd.concat([df_majority, df_minority_upsampled])

X_clf = df_balanced.drop("Class", axis=1)
y_clf = df_balanced["Class"]
```

Ввод [7]:
```
# Split data into training and testing sets
X_reg_train, X_reg_test, y_reg_train, y_reg_test = train_test_split(X_reg, y_re
X_clf_train, X_clf_test, y_clf_train, y_clf_test = train_test_split(X_clf, y_cl

# Standardize the data
scaler_reg = StandardScaler()
X_reg_train = scaler_reg.fit_transform(X_reg_train)
X_reg_test = scaler_reg.transform(X_reg_test)

scaler_clf = StandardScaler()
X_clf_train = scaler_clf.fit_transform(X_clf_train)
X_clf_test = scaler_clf.transform(X_clf_test)
```

Ввод [8]:
```
# Define models
reg_models = {
    "Linear Regression": LinearRegression(),
    "Random Forest Regressor": RandomForestRegressor(random_state=42),
    "SVR": SVR(),
    "MLP Regressor": MLPRegressor(random_state=42),
    "XGBoost Regressor": XGBRegressor(random_state=42),
    "CatBoost Regressor": CatBoostRegressor(random_state=42, verbose=0)
}

clf_models = {
    "Logistic Regression": LogisticRegression(max_iter=200, random_state=42),
    "Random Forest Classifier": RandomForestClassifier(random_state=42),
    "SVC": SVC(probability=True, random_state=42),
    "MLP Classifier": MLPClassifier(max_iter=500, random_state=42),
    "XGBoost Classifier": XGBClassifier(random_state=42),
    "CatBoost Classifier": CatBoostClassifier(random_state=42, verbose=0)
}
```

Ввод [9]:
```python
# Function to evaluate regression models
def evaluate_regression(model, X_train, X_test, y_train, y_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)
    return {"MAE": mae, "MSE": mse, "RMSE": rmse, "R^2": r2}

# Function to evaluate classification models
def evaluate_classification(model, X_train, X_test, y_train, y_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Check if the model supports predict_proba before calculating AUC-ROC
    if hasattr(model, "predict_proba"):
        y_proba = model.predict_proba(X_test)
        auc = roc_auc_score(y_test, y_proba[:, 1])
    else:
        auc = None

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    return {"Accuracy": accuracy, "Precision": precision, "Recall": recall, "F1
```

Ввод [10]:
```python
# Evaluate all regression models
reg_results = {}
for name, model in reg_models.items():
    reg_results[name] = evaluate_regression(model, X_reg_train, X_reg_test, y_

reg_results
```

Out[10]:
```
{'Linear Regression': {'MAE': 0.5332001304956565,
  'MSE': 0.555891598695244,
  'RMSE': 0.7455813830127761,
  'R^2': 0.5757877060324511},
 'Random Forest Regressor': {'MAE': 0.3274252027374032,
  'MSE': 0.255169737347244,
  'RMSE': 0.5051432839771741,
  'R^2': 0.8052747336256919},
 'SVR': {'MAE': 0.3985990769520539,
  'MSE': 0.3570040319338641,
  'RMSE': 0.5974981438748276,
  'R^2': 0.7275628923016779},
 'MLP Regressor': {'MAE': 0.36877316473912425,
  'MSE': 0.29240885643712883,
  'RMSE': 0.5407484225008232,
  'R^2': 0.7768567971583497},
 'XGBoost Regressor': {'MAE': 0.30957335413783094,
  'MSE': 0.2225899267544737,
  'RMSE': 0.4717943691423984,
  'R^2': 0.8301370561019205},
 'CatBoost Regressor': {'MAE': 0.2929549181997955,
  'MSE': 0.19892244594277952,
  'RMSE': 0.4460072263347081,
  'R^2': 0.8481981967112175}}
```

Ввод [11]:
```
# Evaluate all classification models
clf_results = {}
for name, model in clf_models.items():
    clf_results[name] = evaluate_classification(model, X_clf_train, X_clf_test

clf_results
```

Out[11]:
```
{'Logistic Regression': {'Accuracy': 0.9494574679492817,
  'Precision': 0.9771448794844093,
  'Recall': 0.9206563706563706,
  'F1 Score': 0.9480599280718558,
  'AUC-ROC': 0.9871691028715313},
 'Random Forest Classifier': {'Accuracy': 0.9999384485517824,
  'Precision': 0.9998771649674487,
  'Recall': 1.0,
  'F1 Score': 0.9999385787113814,
  'AUC-ROC': 1.0},
 'SVC': {'Accuracy': 0.9945131280445985,
  'Precision': 0.9931569183380587,
  'Recall': 0.9959108459108459,
  'F1 Score': 0.9945319756743022,
  'AUC-ROC': 0.999504184633533},
 'MLP Classifier': {'Accuracy': 0.9995867259905387,
  'Precision': 0.9991758289932838,
  'Recall': 1.0,
  'F1 Score': 0.9995877446121728,
  'AUC-ROC': 0.999983543572519},
 'XGBoost Classifier': {'Accuracy': 0.9999384485517824,
  'Precision': 0.9998771649674487,
  'Recall': 1.0,
  'F1 Score': 0.9999385787113814,
  'AUC-ROC': 1.0},
 'CatBoost Classifier': {'Accuracy': 0.9997537942071294,
  'Precision': 0.99950884086444,
  'Recall': 1.0,
  'F1 Score': 0.9997543601080816,
  'AUC-ROC': 0.9999595003639341}}
```

Ввод [12]:
```
# Convert results to DataFrames for easy visualization
reg_results_df = pd.DataFrame(reg_results).T
clf_results_df = pd.DataFrame(clf_results).T
```

Ввод [13]:
```
# Display results
print("Regression Model Performance:")
display(reg_results_df)

print("\nClassification Model Performance:")
display(clf_results_df)
```

```
Regression Model Performance:
```

	MAE	MSE	RMSE	R^2
Linear Regression	0.533200	0.555892	0.745581	0.575788
Random Forest Regressor	0.327425	0.255170	0.505143	0.805275
SVR	0.398599	0.357004	0.597498	0.727563
MLP Regressor	0.368773	0.292409	0.540748	0.776857
XGBoost Regressor	0.309573	0.222590	0.471794	0.830137
CatBoost Regressor	0.292955	0.198922	0.446007	0.848198

```
Classification Model Performance:
```

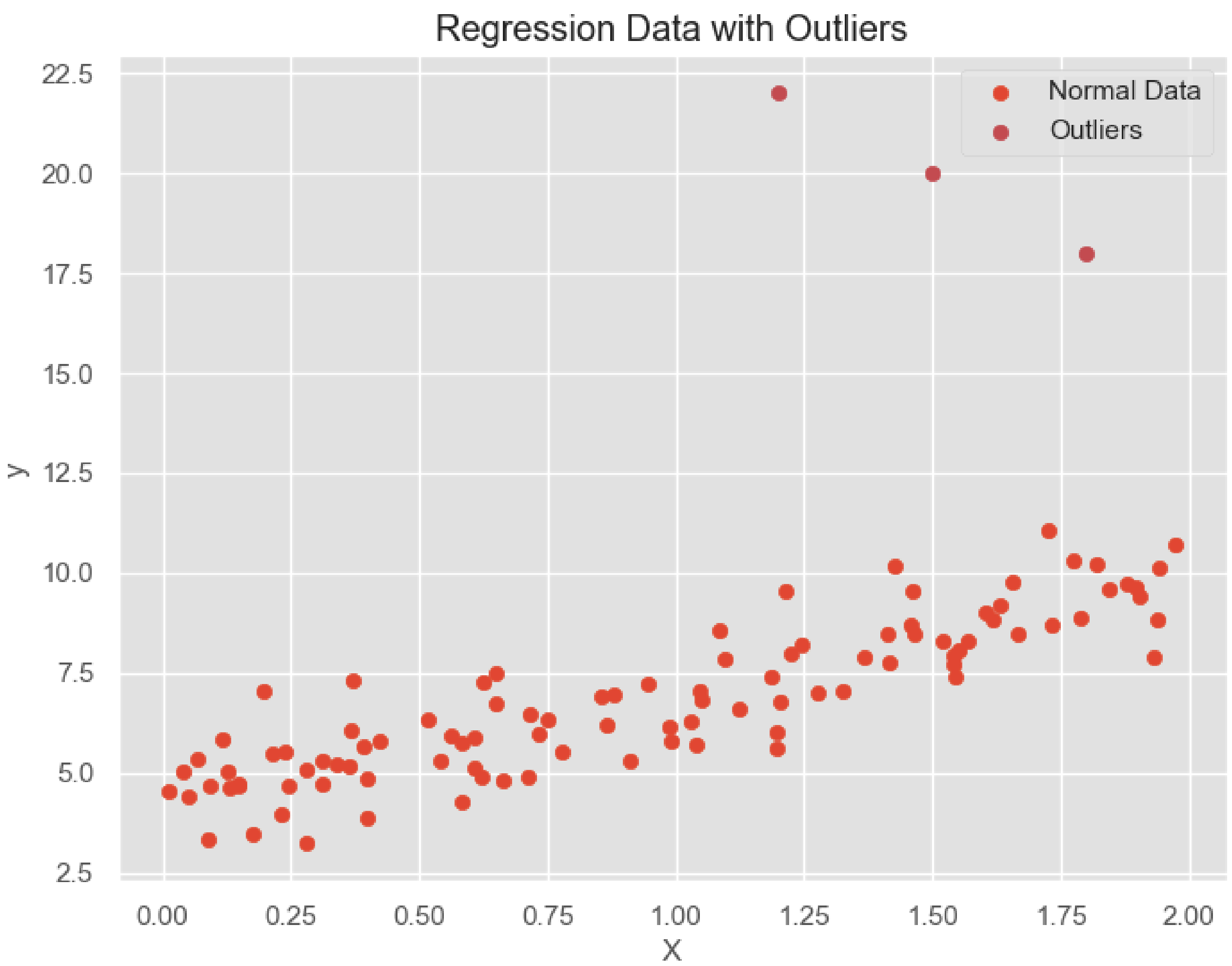
	Accuracy	Precision	Recall	F1 Score	AUC-ROC
Logistic Regression	0.949457	0.977145	0.920656	0.948060	0.987169
Random Forest Classifier	0.999938	0.999877	1.000000	0.999939	1.000000
SVC	0.994513	0.993157	0.995911	0.994532	0.999504
MLP Classifier	0.999587	0.999176	1.000000	0.999588	0.999984
XGBoost Classifier	0.999938	0.999877	1.000000	0.999939	1.000000
CatBoost Classifier	0.999754	0.999509	1.000000	0.999754	0.999960

Ввод [ ]:

Ввод [ ]:

Ввод [34]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.model_selection import train_test_split

# Generate synthetic data for regression
np.random.seed(42)
X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)

# Introduce outliers
X_outliers = np.append(X, [[1.5], [1.8], [1.2]])
y_outliers = np.append(y, [[20], [18], [22]])

# Plot the data with outliers
plt.figure(figsize=(8, 6))
plt.scatter(X, y, label="Normal Data")
plt.scatter([1.5, 1.8, 1.2], [20, 18, 22], color='r', label="Outliers")
plt.title("Regression Data with Outliers")
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
plt.show()

# Split the data with outliers and without outliers
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
X_train_outliers, X_test_outliers, y_train_outliers, y_test_outliers = train_t



# Fit linear regression model without outliers
model_no_outliers = LinearRegression()
model_no_outliers.fit(X_train, y_train)
y_pred_no_outliers = model_no_outliers.predict(X_test)

# Fit linear regression model with outliers
model_with_outliers = LinearRegression()
model_with_outliers.fit(X_train_outliers, y_train_outliers)
y_pred_with_outliers = model_with_outliers.predict(X_test_outliers)

# Evaluate model performance without outliers
mse_no_outliers = mean_squared_error(y_test, y_pred_no_outliers)
mae_no_outliers = mean_absolute_error(y_test, y_pred_no_outliers)
r2_no_outliers = r2_score(y_test, y_pred_no_outliers)

# Evaluate model performance with outliers
mse_with_outliers = mean_squared_error(y_test_outliers, y_pred_with_outliers)
mae_with_outliers = mean_absolute_error(y_test_outliers, y_pred_with_outliers)
r2_with_outliers = r2_score(y_test_outliers, y_pred_with_outliers)

# Print model performance metrics
print(f"Performance without Outliers:\nMSE: {mse_no_outliers:.4f}, MAE: {mae_n
print(f"Performance with Outliers:\nMSE: {mse_with_outliers:.4f}, MAE: {mae_wi

# Plot regression lines with and without outliers
plt.figure(figsize=(8, 6))
plt.scatter(X, y, label="Normal Data")
plt.scatter([1.5, 1.8, 1.2], [20, 18, 22], color='r', label="Outliers")
plt.plot(X_test, y_pred_no_outliers, color='blue', label="Regression Line (No
plt.plot(X_test_outliers, y_pred_with_outliers, color='green', linestyle='dash
plt.title("Regression Lines with and without Outliers")
plt.xlabel("X")
plt.ylabel("y")
```

```
plt.legend()
plt.show()
```




```
Performance without Outliers:
MSE: 0.6537, MAE: 0.5913, R²: 0.8072
Performance with Outliers:
MSE: 6.5629, MAE: 1.1686, R²: 0.4123
```

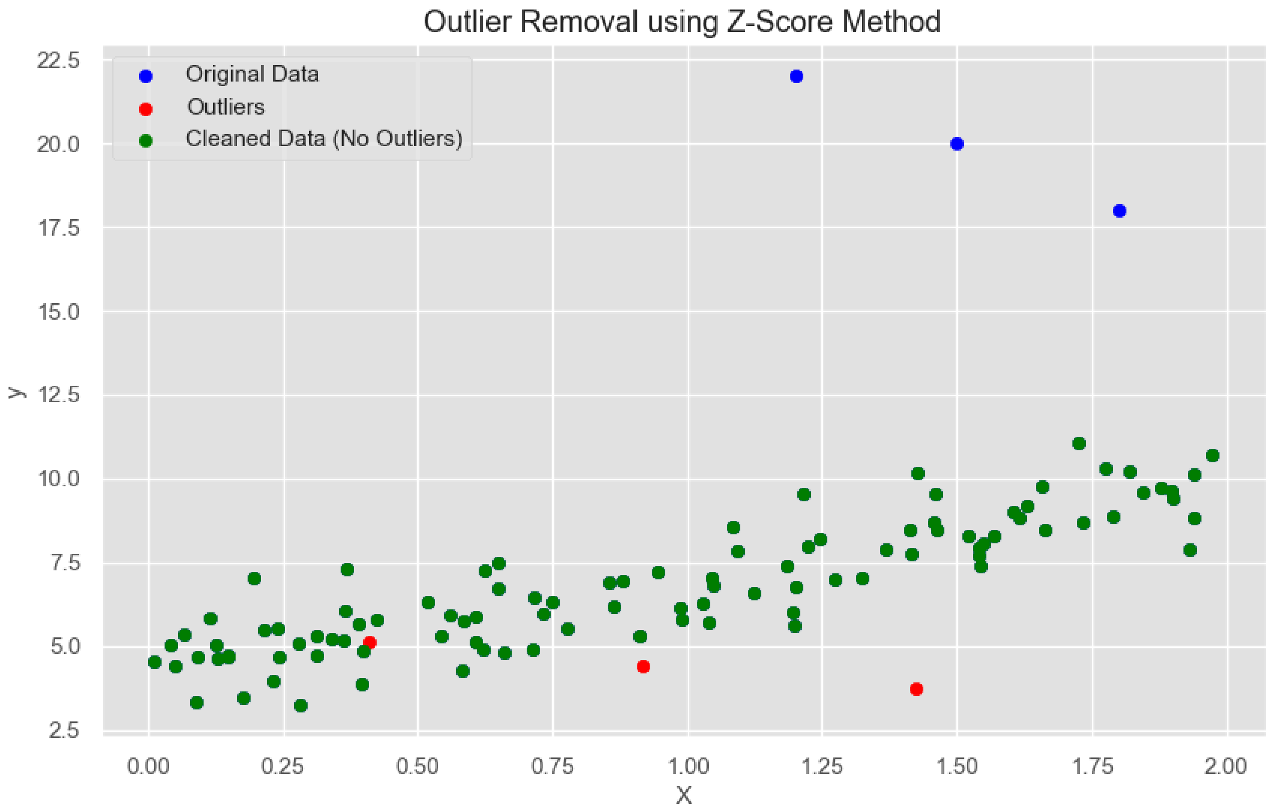
Regression Lines with and without Outliers
Normal Data
Outliers
Regression Line (No Outliers)
Regression Line (With Outliers)
y
X
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

Ввод [ ]:

Ввод [26]:

```
import numpy as np
import pandas as pd
from scipy.stats import zscore

# Generate synthetic data for regression
np.random.seed(42)
X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)

# Introduce outliers
X_outliers = np.append(X, [[1.5], [1.8], [1.2]])
y_outliers = np.append(y, [[20], [18], [22]])

# Combine X and y into a DataFrame
df = pd.DataFrame(np.hstack([X_outliers.reshape(-1, 1), y_outliers.reshape(-1,

# Compute Z-scores for each column
df_zscores = df.apply(zscore)

# Set a threshold for identifying outliers
z_threshold = 3

# Identify rows where any z-score exceeds the threshold
outliers = df_zscores[(np.abs(df_zscores) > z_threshold).any(axis=1)]

# Remove the outliers
df_no_outliers = df[(np.abs(df_zscores) <= z_threshold).all(axis=1)]

print(f"Original data size: {df.shape[0]}")
print(f"Data size after outlier removal (Z-Score method): {df_no_outliers.shap

# Plot original data and cleaned data
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.scatter(df["X"], df["y"], label="Original Data", color='blue')
plt.scatter(outliers["X"], outliers["y"], label="Outliers", color='red')
plt.scatter(df_no_outliers["X"], df_no_outliers["y"], label="Cleaned Data (No
plt.title("Outlier Removal using Z-Score Method")
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
plt.show()
```

```
Original data size: 103
Data size after outlier removal (Z-Score method): 100
```

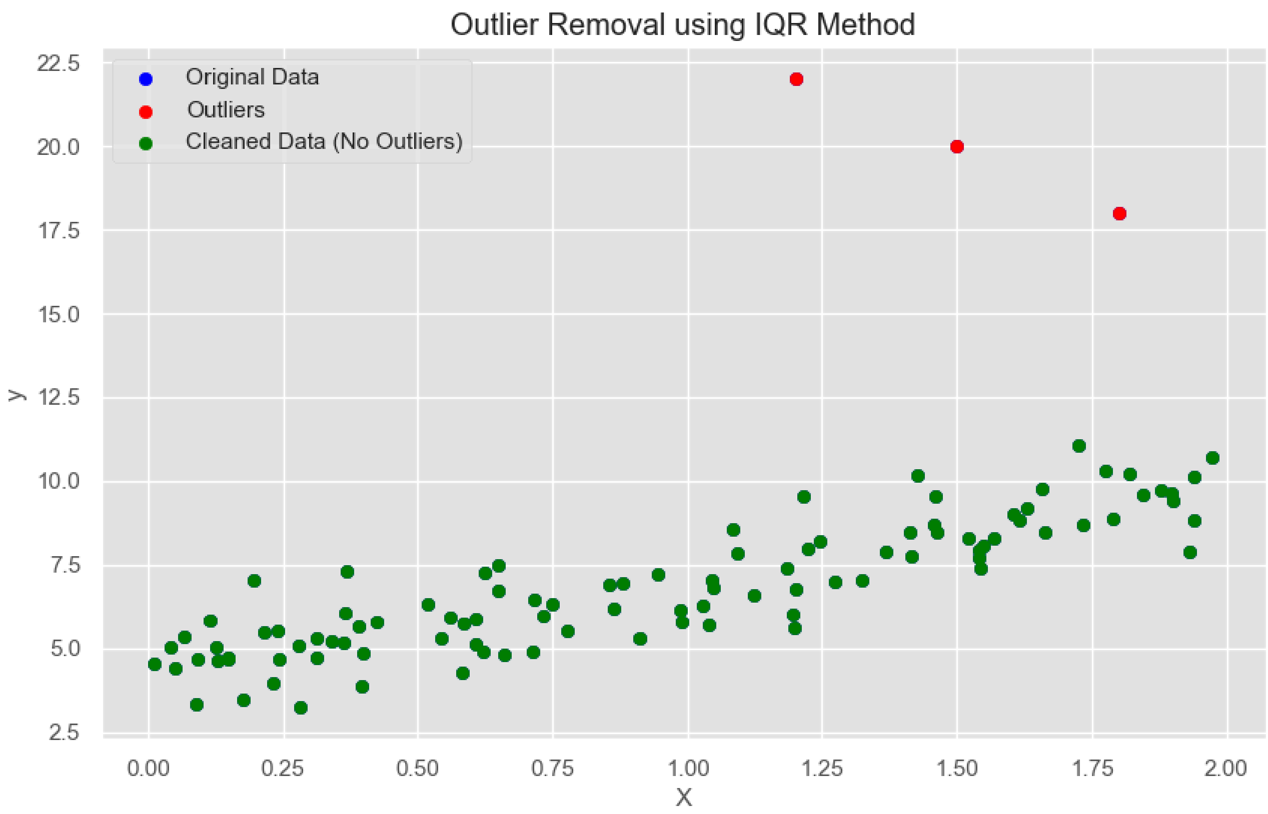

Outlier Removal using Z-Score Method
Original Data
Outliers
Cleaned Data (No Outliers)
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
y
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
X

Ввод [ ]:

Ввод [27]:

```
import numpy as np
import pandas as pd

# Generate synthetic data for regression (as before)
np.random.seed(42)
X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)

# Introduce outliers (as before)
X_outliers = np.append(X, [[1.5], [1.8], [1.2]])
y_outliers = np.append(y, [[20], [18], [22]])

# Combine X and y into a DataFrame
df = pd.DataFrame(np.hstack([X_outliers.reshape(-1, 1), y_outliers.reshape(-1,

# Compute IQR for the y column
Q1 = df["y"].quantile(0.25)
Q3 = df["y"].quantile(0.75)
IQR = Q3 - Q1

# Define lower and upper bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Identify outliers
outliers = df[(df["y"] < lower_bound) | (df["y"] > upper_bound)]

# Remove outliers
df_no_outliers = df[(df["y"] >= lower_bound) & (df["y"] <= upper_bound)]

print(f"Original data size: {df.shape[0]}")
print(f"Data size after outlier removal (IQR method): {df_no_outliers.shape[0]

# Plot original data and cleaned data
plt.figure(figsize=(10, 6))
plt.scatter(df["X"], df["y"], label="Original Data", color='blue')
plt.scatter(outliers["X"], outliers["y"], label="Outliers", color='red')
plt.scatter(df_no_outliers["X"], df_no_outliers["y"], label="Cleaned Data (No
plt.title("Outlier Removal using IQR Method")
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
plt.show()
```

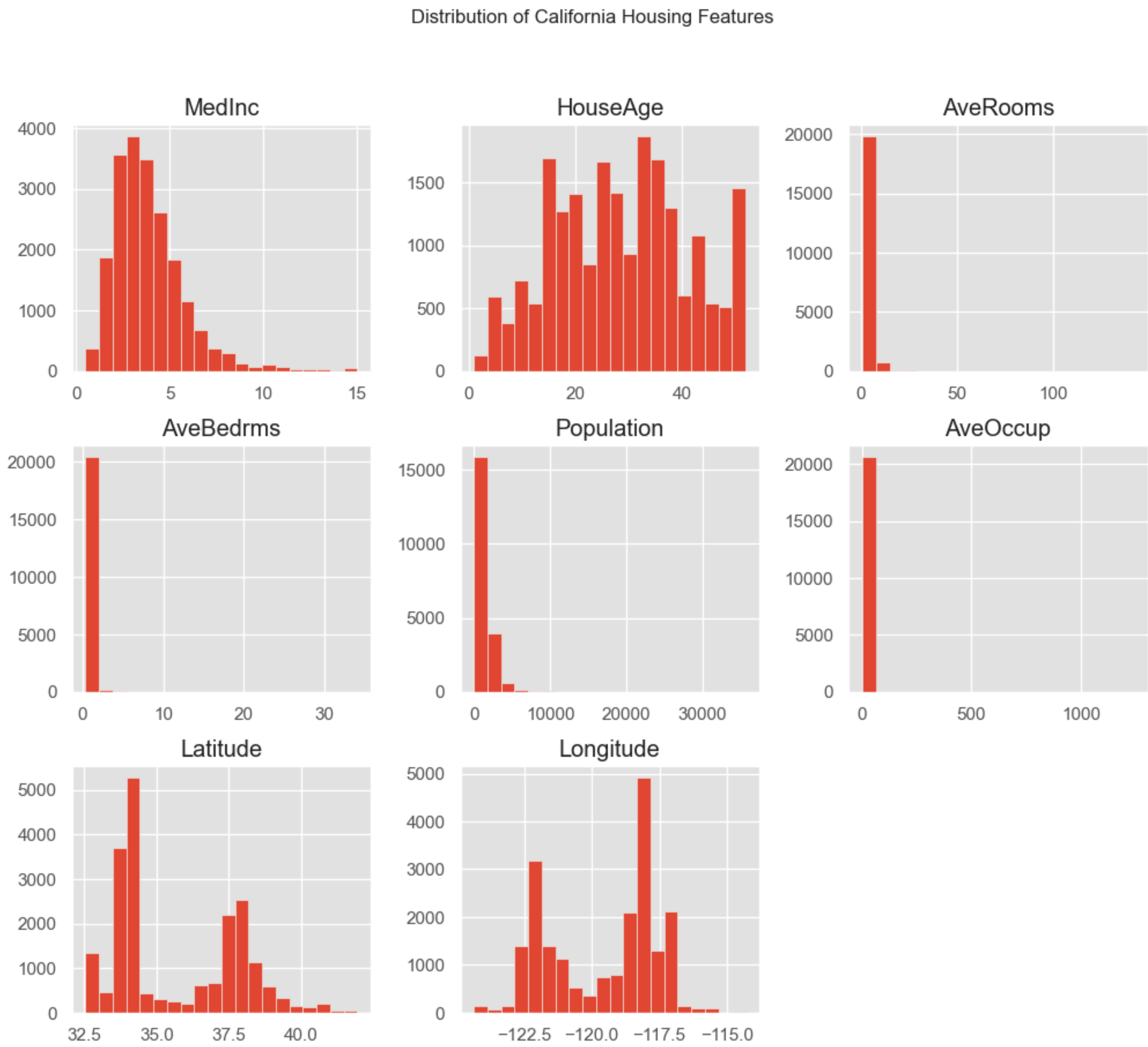
```
Original data size: 103
Data size after outlier removal (IQR method): 100
```

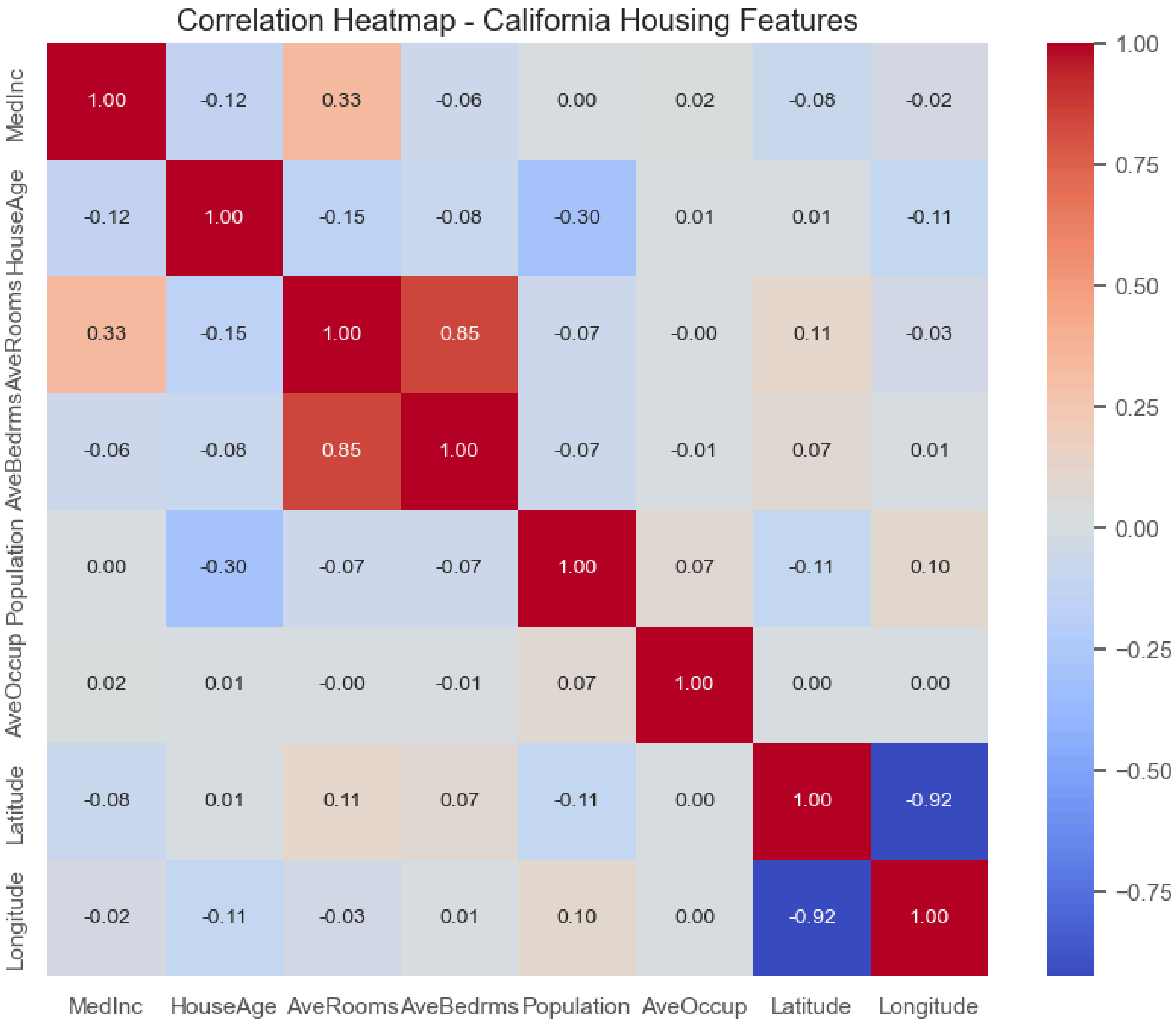


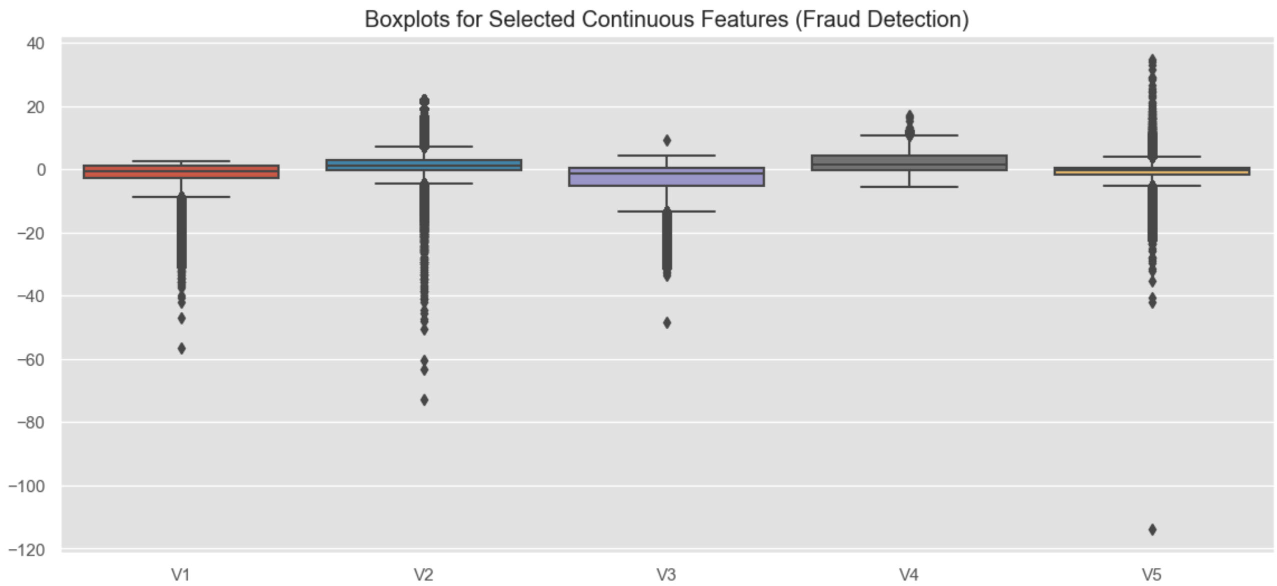
Outlier Removal using IQR Method
Original Data
Outliers
Cleaned Data (No Outliers)
y
X
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

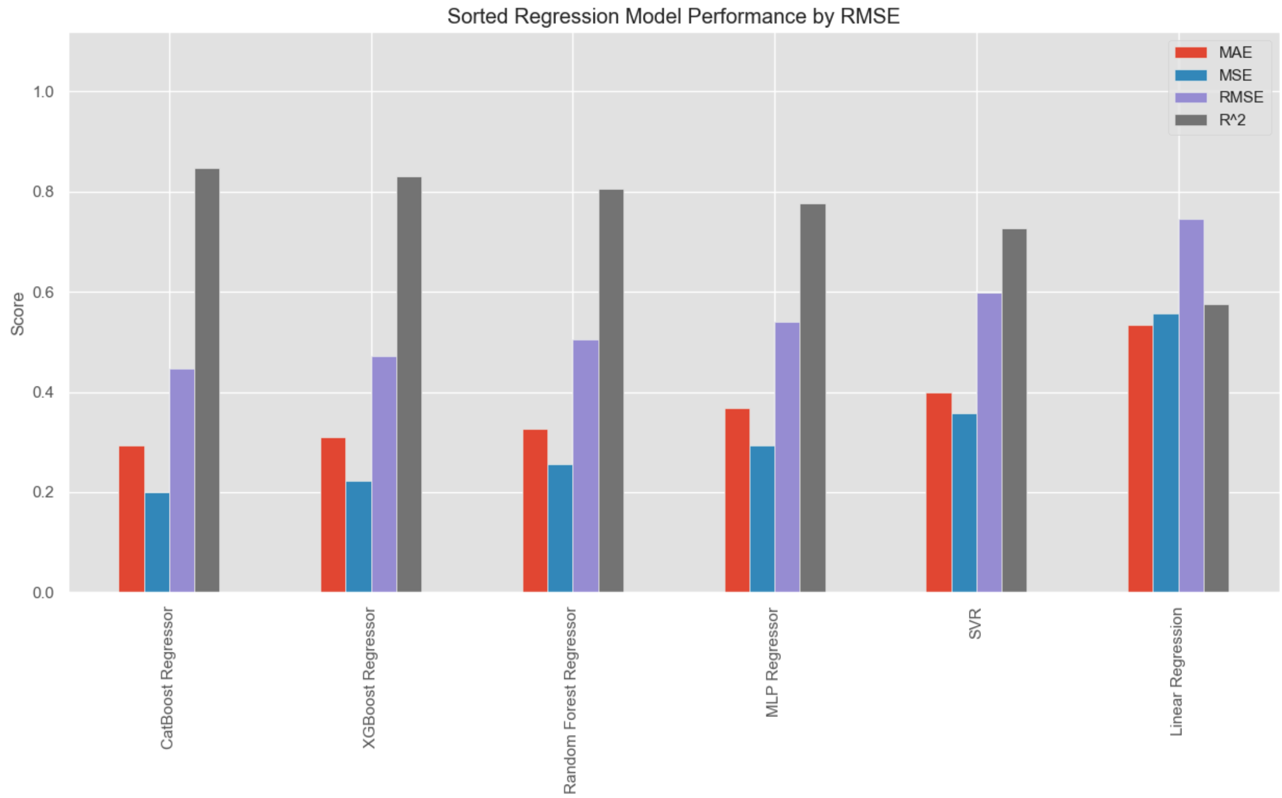
Ввод [33]:

```
# Import necessary libraries for visualization
import seaborn as sns
import matplotlib.pyplot as plt

# Set plot style
sns.set(style="whitegrid")
plt.style.use("ggplot")

### EDA Visualizations for Regression Data (California Housing Dataset)

# Plot histograms for regression features
X_reg.hist(figsize=(12, 10), bins=20)
plt.suptitle("Distribution of California Housing Features")
plt.show()

# Correlation heatmap for regression features
plt.figure(figsize=(10, 8))
sns.heatmap(X_reg.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Heatmap - California Housing Features")
plt.show()


# Boxplots for continuous features (selected few) in the fraud detection datas
plt.figure(figsize=(14, 6))
sns.boxplot(data=df_balanced[['V1', 'V2', 'V3', 'V4', 'V5']])
plt.title("Boxplots for Selected Continuous Features (Fraud Detection)")
plt.show()

### Sorted Model Performance Comparison Visualizations

# Sort regression results by RMSE (example metric) and plot
reg_results_df_sorted = reg_results_df.sort_values(by='RMSE', ascending=True)
reg_results_df_sorted.plot(kind='bar', figsize=(15, 7), title="Sorted Regressi
plt.ylim(0, reg_results_df_sorted['RMSE'].max() * 1.5)  # Adjust vertical axis
plt.show()

# Sort classification results by F1 Score (example metric) and plot
clf_results_df_sorted = clf_results_df.sort_values(by='F1 Score', ascending=Tr
clf_results_df_sorted.plot(kind='bar', figsize=(15, 7), title="Sorted Classifi
plt.ylim(0.9, clf_results_df_sorted['F1 Score'].max() * 1.01)  # Adjust vertic
plt.show()
```

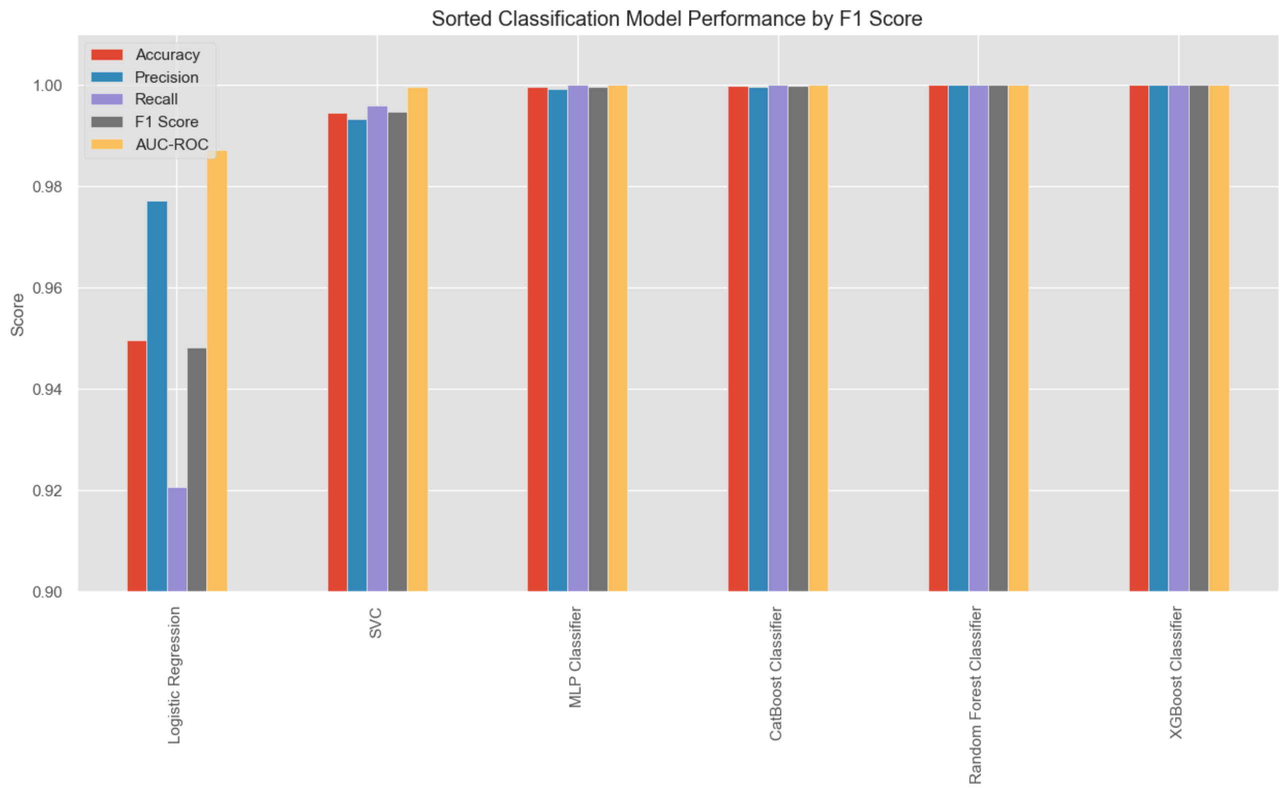

Distribution of California Housing Features
MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude


Correlation Heatmap - California Housing Features
MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75


Boxplots for Selected Continuous Features (Fraud Detection)
V1
V2
V3
V4
V5



Sorted Regression Model Performance by RMSE
MAE
MSE
RMSE
R^2
Score
1.0
0.8
0.6
0.4
0.2
0.0
CatBoost Regressor
XGBoost Regressor
Random Forest Regressor
MLP Regressor
SVR
Linear Regression



Sorted Classification Model Performance by F1 Score
Accuracy
Precision
Recall
F1 Score
AUC-ROC
Score
1.00
0.98
0.96
0.94
0.92
0.90
Logistic Regression
SVC
MLP Classifier
CatBoost Classifier
Random Forest Classifier
XGBoost Classifier