First variable selection

Read clean data

In [1]:
```
import pandas as pd

# Specify the path to your CSV file
file_path = 'Group_2_clean_Data..csv'

# Load the CSV file into a DataFrame
df = pd.read_csv(file_path)

df.head()
```

Out[1]:

	communityname	State	countyCode	communityCode	fold	pop	perHoush	pctBlack	pctWhite	pctAsian	...	burglaries
0	149.0	28.0	55.0	509.0	1.0	11980.0	3.10	1.37	91.78	6.50	...	14.1
1	1034.0	35.0	58.0	424.0	1.0	23123.0	2.82	0.80	95.57	3.44	...	57.0
2	1780.0	34.0	114.0	959.0	1.0	29344.0	2.43	0.74	94.33	3.43	...	274.0
3	664.0	31.0	53.0	213.0	1.0	16656.0	2.40	1.70	97.35	0.50	...	225.0
4	140.0	22.0	82.0	471.0	1.0	11245.0	2.76	0.53	89.16	1.17	...	91.0

5 rows × 125 columns

In [2]:
```
# Assuming `df` is your DataFrame:
df_feature = df.iloc[:, 5:-18]  # Select all rows and columns from index 5 to the 18th-to-last
df_target = df['burglaries']  # Select the 'violentPerPop' column as the target variable


df_feature.head(5)
```

Out[2]:

	pop	perHoush	pctBlack	pctWhite	pctAsian	pctHisp	pct12-21	pct12-29	pct16-24	pct65up	...	persHomeless	pctForeignBo
0	11980.0	3.10	1.37	91.78	6.50	1.88	12.47	21.44	10.93	11.33	...	0.1	10
1	23123.0	2.82	0.80	95.57	3.44	0.85	11.01	21.30	10.48	17.18	...	0.0	8
2	29344.0	2.43	0.74	94.33	3.43	2.35	11.36	25.88	11.01	10.28	...	0.0	5
3	16656.0	2.40	1.70	97.35	0.50	0.70	12.55	25.20	12.19	17.57	...	0.0	2
4	11245.0	2.76	0.53	89.16	1.17	0.52	24.46	40.53	28.69	12.65	...	0.0	1

5 rows × 102 columns

From Random forest model, we can see the most top 10 important features

In [3]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Splitting the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
    df_feature, df_target, test_size=0.2, random_state=42
)

# Initialize the Random Forest Regressor
rf_model = RandomForestRegressor(random_state=42, n_estimators=100)

# Train the model
rf_model.fit(X_train, y_train)

# Predict on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model
```

```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Predict on the training set
y_train_pred = rf_model.predict(X_train)

# Calculate metrics for both train and test sets
train_mse = mean_squared_error(y_train, y_train_pred)
train_r2 = r2_score(y_train, y_train_pred)

# Print the results
print(f"Training Set Metrics:")
print(f"  - Mean Squared Error: {train_mse:.2f}")
print(f"  - R-squared: {train_r2:.2f}")

print(f"Testing Set Metrics:")
print(f"  - Mean Squared Error: {mse:.2f}")
print(f"  - R-squared: {r2:.2f}")
```

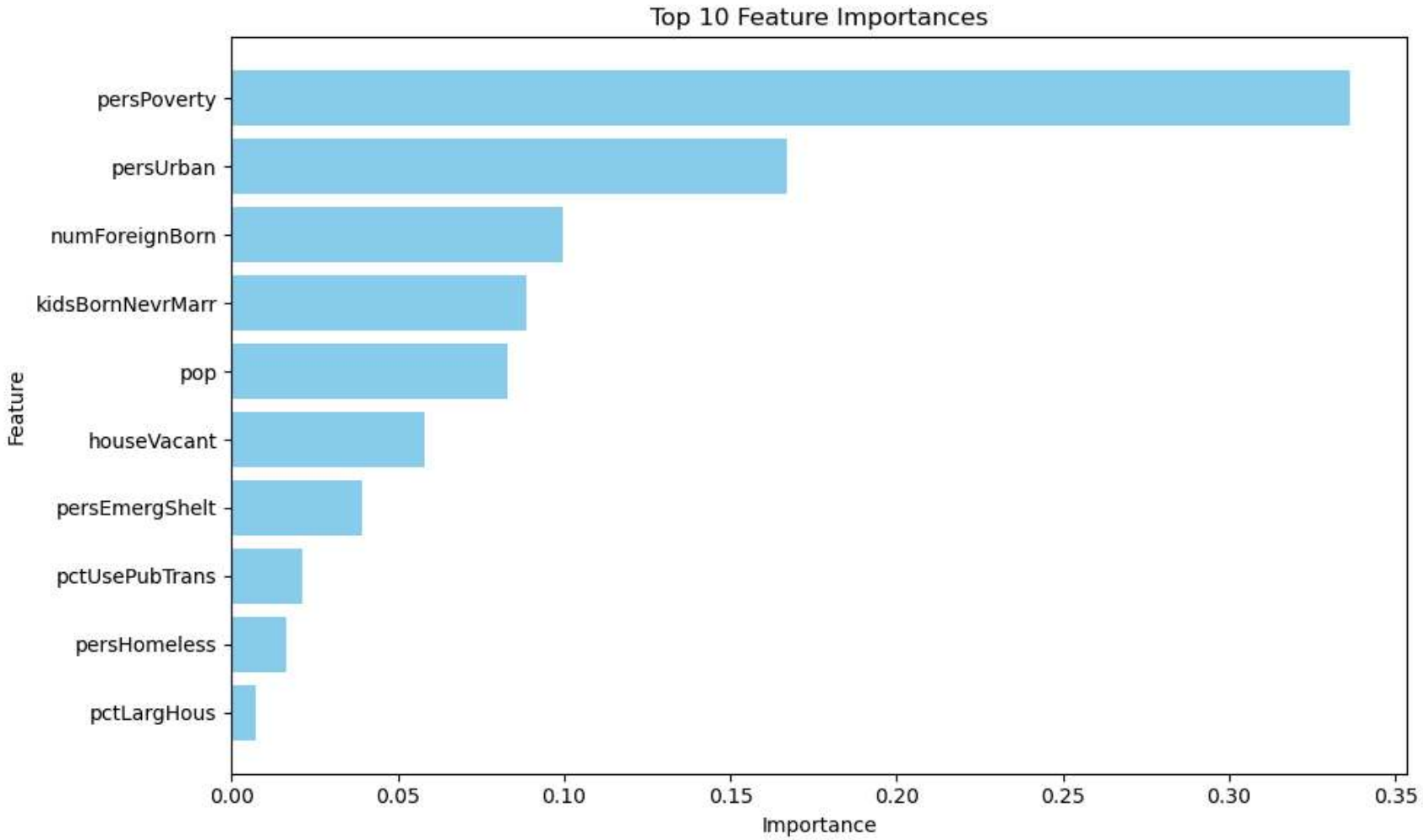
```
Training Set Metrics:
  - Mean Squared Error: 515588.70
  - R-squared: 0.95
Testing Set Metrics:
  - Mean Squared Error: 232487.27
  - R-squared: 0.91
```

In [4]:

```
# Extract and display feature importances
feature_importances = rf_model.feature_importances_

# Create a DataFrame for better visualization
import pandas as pd
importance_df = pd.DataFrame({
    'Feature': df_feature.columns,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

# Display the top 10 features
top_10_features = importance_df.head(10)
print("Top 10 Feature Importances:")
print(top_10_features)

# Visualize the top 10 feature importances
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.barh(top_10_features['Feature'], top_10_features['Importance'], color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top 10 Feature Importances')
plt.gca().invert_yaxis()  # Invert y-axis to show the most important feature at the top
plt.tight_layout()
plt.show()
```

```
Top 10 Feature Importances:
             Feature  Importance
27        persPoverty    0.336468
10          persUrban    0.167081
51     numForeignBorn    0.099657
49   kidsBornNevrMarr    0.088693
0                 pop    0.083006
71        houseVacant    0.057868
91     persEmergShelt    0.039022
100    pctUsePubTrans    0.021161
92       persHomeless    0.016425
63        pctLargHous    0.007318
```



Select our first feature

In [5]:
```
selected_features = ['persPoverty']
```

experimenting with random forest model

In [6]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np

# Subset the dataset with selected features
X_selected = df_feature[selected_features]

# Step 3: Log-transform the target variable
y_log = np.log1p(df_target)  # Apply log(1 + y) transformation

# Step 4: Train-Test Split
X_train, X_test, y_train_log, y_test_log = train_test_split(
    X_selected, y_log, test_size=0.2, random_state=42
)

# Feature scaling is not required for Random Forest

# Step 5: Train the Random Forest Model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train_log)

# Step 6: Predict
y_pred_log = rf_model.predict(X_test)

# Inverse-transform predictions to the original scale
y_pred = np.expm1(y_pred_log)
y_test = np.expm1(y_test_log)

# Step 7: Evaluate
test_mse = mean_squared_error(y_test, y_pred)
test_r2 = r2_score(y_test, y_pred)

# Print the results
print(f"Testing Set Metrics using selected Features, and Log-Transformed Target with Random Forest:")
print(f"  - Mean Squared Error: {test_mse:.2f}")
print(f"  - R-squared: {test_r2:.2f}")
```

```
Testing Set Metrics using selected Features, and Log-Transformed Target with Random Forest:
  - Mean Squared Error: 511192.00
  - R-squared: 0.81
```

experimenting with svr model with only selected first variable

In [7]:
```python
from sklearn.linear_model import ElasticNet
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np

# Subset the dataset with selected features
X_selected = df_feature[selected_features]

# Step 3: Log-transform the target variable
y_log = np.log1p(df_target)  # Apply log(1 + y) transformation

# Step 4: Train-Test Split
X_train, X_test, y_train_log, y_test_log = train_test_split(
    X_selected, y_log, test_size=0.2, random_state=42
)

# Step 5: Feature Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Train the SVR Model
svr_model = SVR(kernel='rbf', C=1.0, epsilon=0.1)
svr_model.fit(X_train_scaled, y_train_log)

# Step 7: Predict and Evaluate
y_pred_log = svr_model.predict(X_test_scaled)

# Inverse-transform predictions to the original scale
y_pred = np.expm1(y_pred_log)
y_test = np.expm1(y_test_log)
```

```
# Calculate metrics on the original scale
test_mse = mean_squared_error(y_test, y_pred)
test_r2 = r2_score(y_test, y_pred)

# Print the results
print(f"Testing Set Metrics using selected Scaled Features, and Log-Transformed Target with SVR:")
print(f"  - Mean Squared Error: {test_mse:.2f}")
print(f"  - R-squared: {test_r2:.2f}")
```

```
Testing Set Metrics using selected Scaled Features, and Log-Transformed Target with SVR:
  - Mean Squared Error: 572918.81
  - R-squared: 0.78
```

experimenting with knn model with only the first select variable

In [8]:

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np


# Subset the dataset with selected features
X_selected = df_feature[selected_features]

# Step 3: Log-transform the target variable
y_log = np.log1p(df_target)  # Apply log(1 + y) transformation

# Step 4: Train-Test Split
X_train, X_test, y_train_log, y_test_log = train_test_split(
    X_selected, y_log, test_size=0.2, random_state=42
)

# Step 5: Feature Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Train the kNN Model
knn_model = KNeighborsRegressor(n_neighbors=5)  # Default n_neighbors=5
knn_model.fit(X_train_scaled, y_train_log)
```

```
# Step 7: Predict and Evaluate
y_pred_log = knn_model.predict(X_test_scaled)

# Inverse-transform predictions to the original scale
y_pred = np.expm1(y_pred_log)
y_test = np.expm1(y_test_log)

# Calculate metrics on the original scale
test_mse = mean_squared_error(y_test, y_pred)
test_r2 = r2_score(y_test, y_pred)

# Print the results
print(f"Testing Set Metrics using Lasso-Selected, Scaled Features, and Log-Transformed Target with kNN:")
print(f"  - Mean Squared Error: {test_mse:.2f}")
print(f"  - R-squared: {test_r2:.2f}")
```

```
Testing Set Metrics using Lasso-Selected, Scaled Features, and Log-Transformed Target with kNN:
  - Mean Squared Error: 524885.78
  - R-squared: 0.80
```

In [17]:

```
from sklearn.linear_model import ElasticNet
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np

# Step 1: Train ElasticNet for feature selection
elastic_net = ElasticNet(alpha=0.2, l1_ratio=0.5, random_state=42)  # Adjust alpha and l1_ratio as needed
elastic_net.fit(df_feature, df_target)

# Step 2: Select features with non-zero coefficients
selected_features = df_feature.columns[np.abs(elastic_net.coef_) > 1e-4]
print(f"Selected Features by ElasticNet: {list(selected_features)}")

# Subset the dataset with selected features
X_selected = df_feature[selected_features]

# Step 3: Log-transform the target variable
y_log = np.log1p(df_target)  # Apply log(1 + y) transformation
```

```python
# Step 4: Train-Test Split
X_train, X_test, y_train_log, y_test_log = train_test_split(
    X_selected, y_log, test_size=0.2, random_state=42
)

# Step 5: Feature Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 6: Train the SVR Model
svr_model = SVR(kernel='rbf', C=1.0, epsilon=0.1)
svr_model.fit(X_train_scaled, y_train_log)

# Step 7: Predict and Evaluate
y_pred_log = svr_model.predict(X_test_scaled)

# Inverse-transform predictions to the original scale
y_pred = np.expm1(y_pred_log)
y_test = np.expm1(y_test_log)

# Calculate metrics on the original scale
test_mse = mean_squared_error(y_test, y_pred)
test_r2 = r2_score(y_test, y_pred)

# Print the results
print(f"Testing Set Metrics using ElasticNet-Selected, Scaled Features, and Log-Transformed Target with SVR:")
print(f"  - Mean Squared Error: {test_mse:.2f}")
print(f"  - R-squared: {test_r2:.2f}")
```

```
C:\Users\hyz20\miniconda3\envs\gpu-env\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:697: Convergence
Warning: Objective did not converge. You might want to increase the number of iterations, check the scale of the feat
ures or consider increasing regularisation. Duality gap: 1.497e+08, tolerance: 7.625e+04
  model = cd_fast.enet_coordinate_descent(
```

```
Selected Features by ElasticNet: ['pop', 'perHoush', 'pctBlack', 'pctWhite', 'pctAsian', 'pctHisp', 'pct12-21', 'pct1
2-29', 'pct16-24', 'pct65up', 'persUrban', 'pctUrban', 'medIncome', 'pctWwage', 'pctWfarm', 'pctWdiv', 'pctWsocsec',
'pctPubAsst', 'pctRetire', 'medFamIncome', 'perCapInc', 'whitePerCap', 'blackPerCap', 'NAperCap', 'asianPerCap', 'oth
erPerCap', 'hispPerCap', 'persPoverty', 'pctPoverty', 'pctLowEdu', 'pctNotHSgrad', 'pctCollGrad', 'pctUnemploy', 'pct
Employ', 'pctEmployMfg', 'pctEmployProfServ', 'pctOccupManu', 'pctOccupMgmt', 'pctMaleDivorc', 'pctMaleNevMar', 'pctF
emDivorc', 'pctAllDivorc', 'persPerFam', 'pct2Par', 'pctKids2Par', 'pctKids-4w2Par', 'pct12-17w2Par', 'pctWorkMom-6',
'pctWorkMom-18', 'kidsBornNevrMarr', 'pctKidsBornNevrMarr', 'numForeignBorn', 'pctFgnImmig-3', 'pctFgnImmig-5', 'pctF
gnImmig-8', 'pctFgnImmig-10', 'pctImmig-3', 'pctImmig-5', 'pctImmig-8', 'pctImmig-10', 'pctSpeakOnlyEng', 'pctNotSpea
kEng', 'pctLargHousFam', 'pctLargHous', 'persPerOccupHous', 'persPerOwnOccup', 'persPerRenterOccup', 'pctPersOwnOccu
p', 'pctPopDenseHous', 'pctSmallHousUnits', 'medNumBedrm', 'houseVacant', 'pctHousOccup', 'pctHousOwnerOccup', 'pctVa
cantBoarded', 'pctVacant6up', 'medYrHousBuilt', 'pctHousWOphone', 'ownHousLowQ', 'ownHousMed', 'ownHousUperQ', 'ownHo
usQrange', 'rentLowQ', 'rentMed', 'rentUpperQ', 'rentQrange', 'medGrossRent', 'medRentpctHousInc', 'medOwnCostpct',
'medOwnCostPctWO', 'persEmergShelt', 'persHomeless', 'pctForeignBorn', 'pctBornStateResid', 'pctSameHouse-5', 'pctSam
eCounty-5', 'pctSameState-5', 'landArea', 'popDensity', 'pctUsePubTrans', 'pctOfficDrugUnit']
Testing Set Metrics using ElasticNet-Selected, Scaled Features, and Log-Transformed Target with SVR:
  - Mean Squared Error: 125342.65
  - R-squared: 0.58
```

In [ ]: