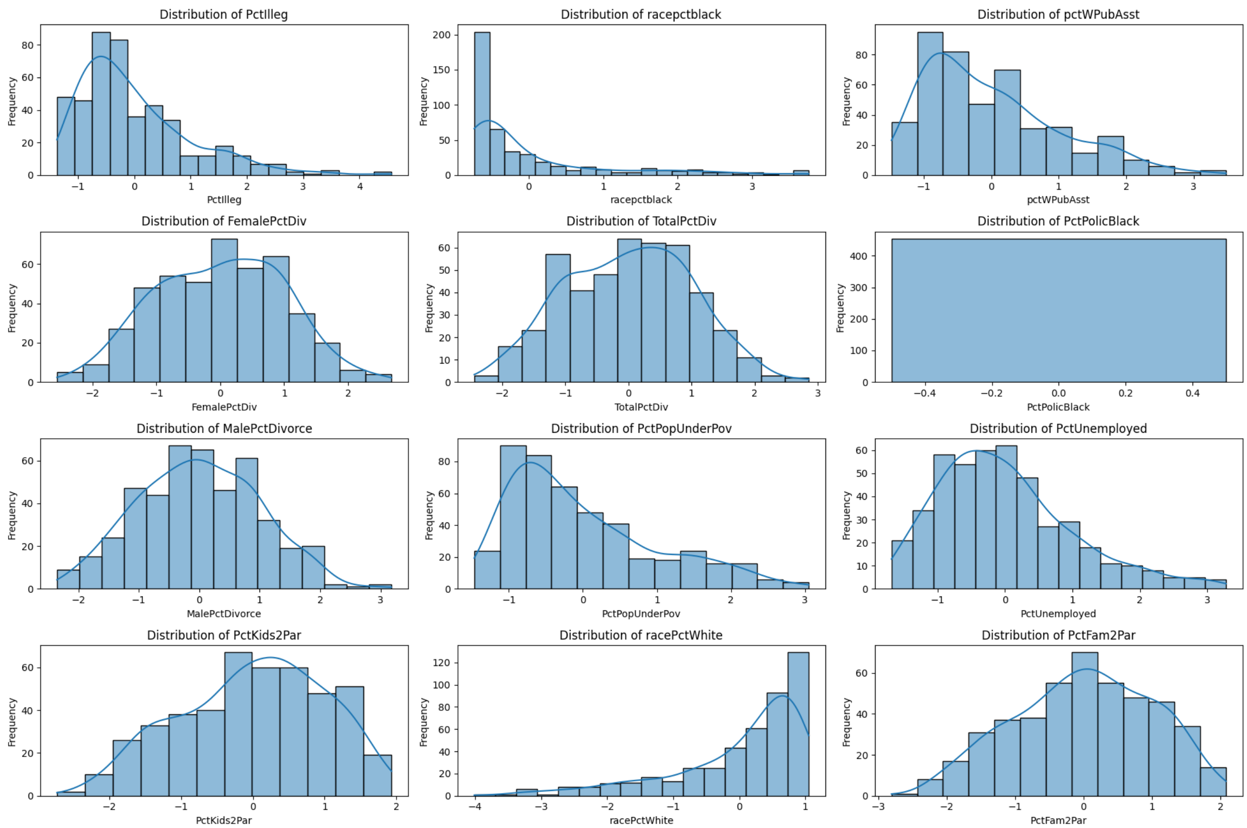
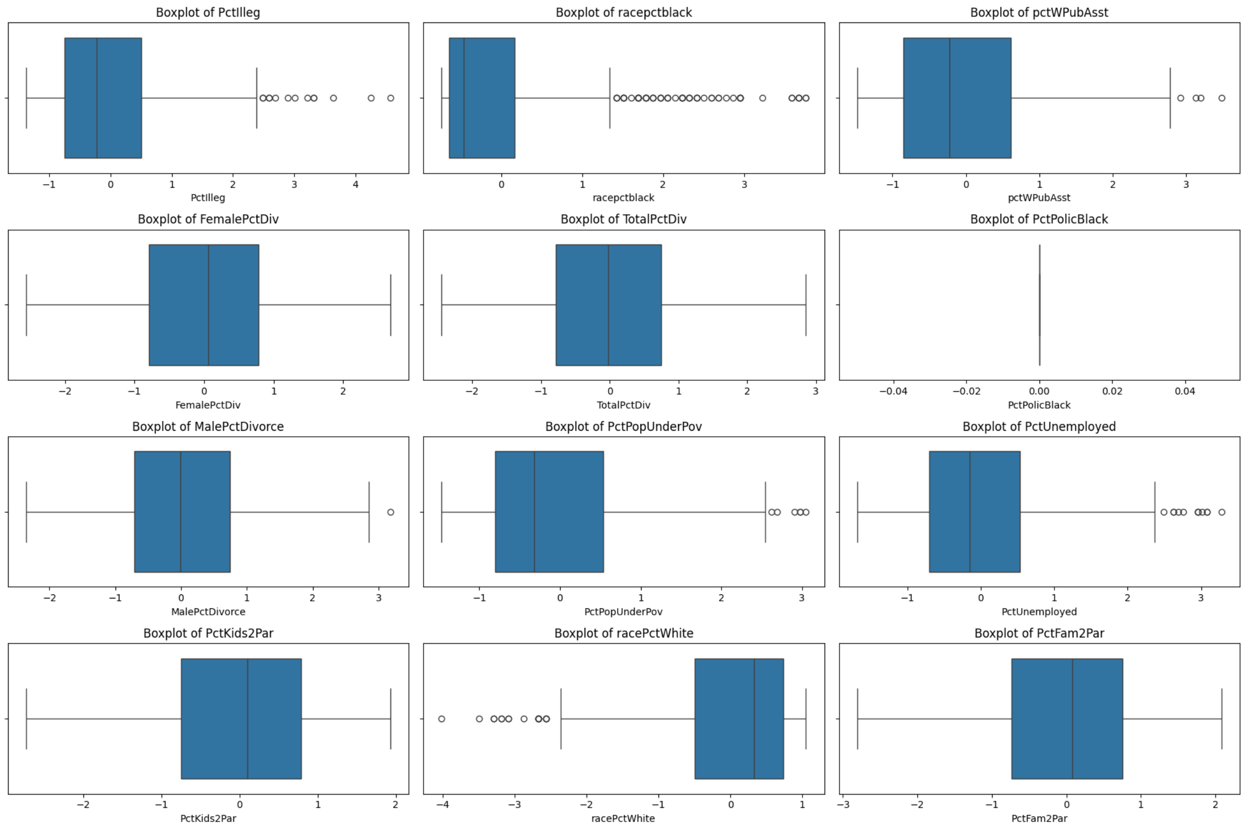
```python
# Exploratory Data Analysis and Model Building

# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score

# Load the cleaned dataset
data = pd.read_csv('cleaned_communities_crime_data.csv')

# Exploratory Data Analysis (EDA)

# 1. Visualizations

# Select a subset of the most relevant features based on correlation
with the target
relevant_features = ['PctIlleg', 'racepctblack', 'pctWPubAsst',
'FemalePctDiv',
                     'TotalPctDiv', 'PctPolicBlack', 'MalePctDivorce',
'PctPopUnderPov',
                     'PctUnemployed', 'PctKids2Par', 'racePctWhite',
'PctFam2Par']

# Distribution plots for relevant features
plt.figure(figsize=(18, 12))
for i, column in enumerate(relevant_features, 1):
    plt.subplot(4, 3, i)
    sns.histplot(data[column], kde=True)
    plt.title(f'Distribution of {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



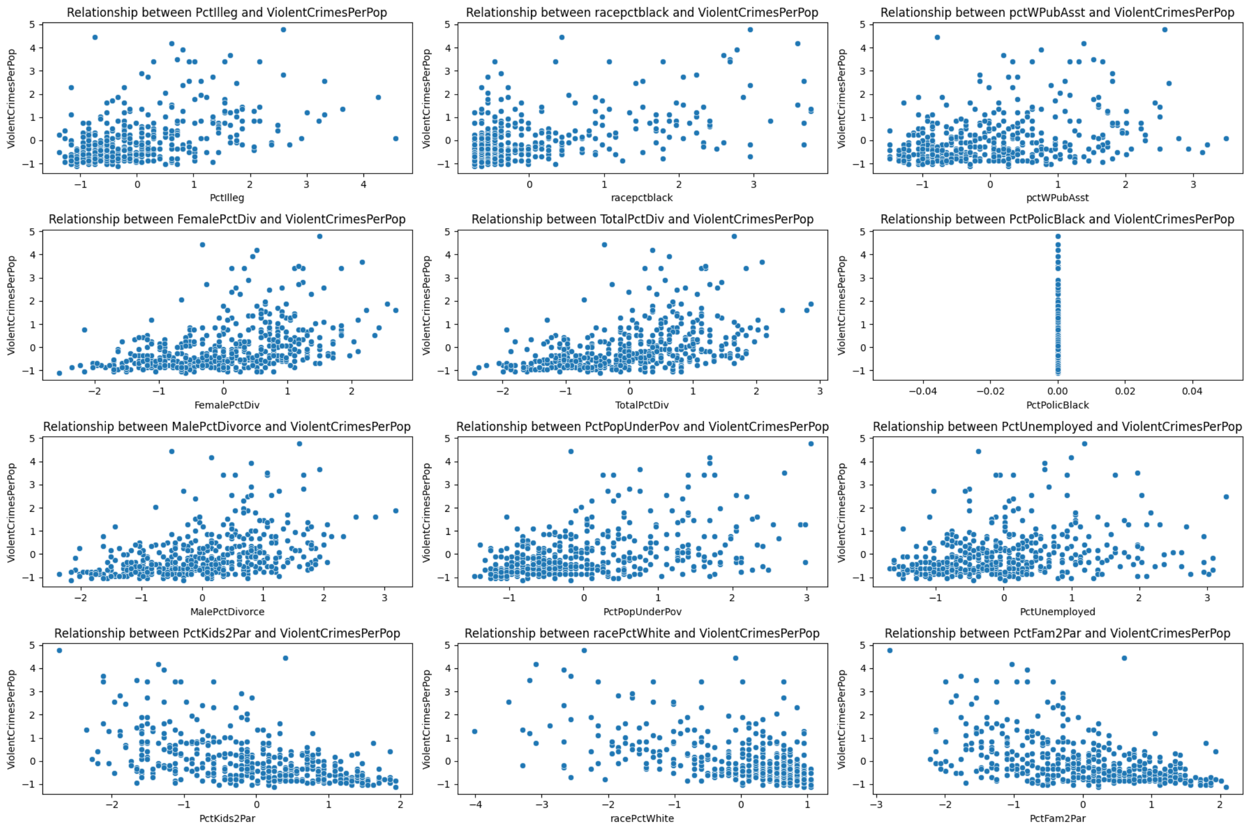
Distribution Plots for Relevant Features The distribution plots show the frequency of values for each relevant feature. Key observations include:

PctIlleg, pctWPubAsst, PctPolicBlack, PctPopUnderPov, and PctUnemployed: These features exhibit skewed distributions, indicating a concentration of values towards one end of the scale. racepctblack and racePctWhite: These features are also skewed, reflecting demographic distributions in the dataset. FemalePctDiv, TotalPctDiv, MalePctDivorce, PctKids2Par, and PctFam2Par: These features show more symmetrical distributions, indicating a more even spread of values. Takeaway: The skewed distributions, particularly for racial and socio-economic features, suggest the need to consider transformations or handling techniques to ensure model robustness and fairness.

```python
# Boxplots for relevant features
plt.figure(figsize=(18, 12))
for i, column in enumerate(relevant_features, 1):
    plt.subplot(4, 3, i)
    sns.boxplot(x=data[column])
    plt.title(f'Boxplot of {column}')
    plt.xlabel(column)
plt.tight_layout()
plt.show()
```



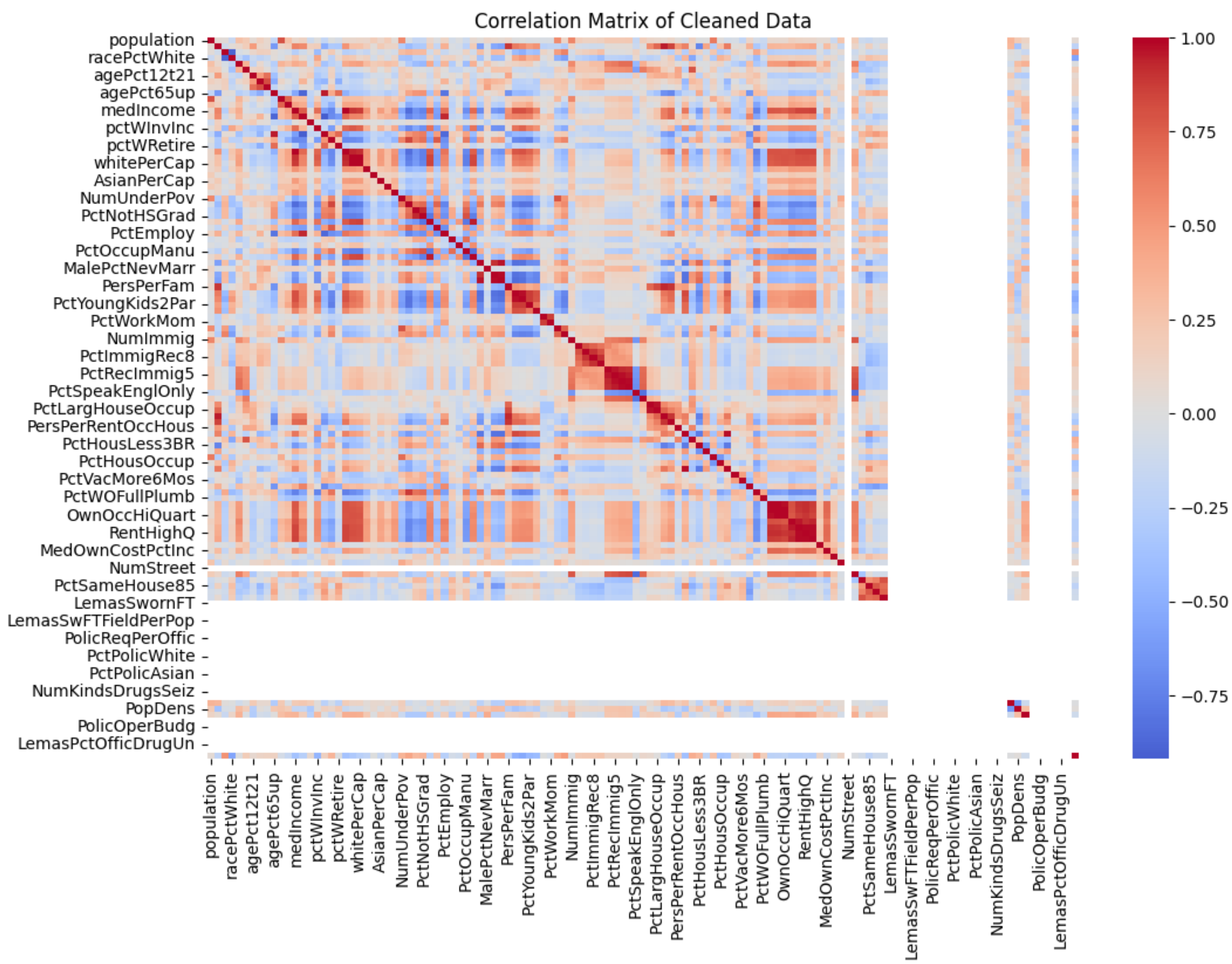

```python
# Scatter plots for relationships between relevant features and target
variable
target = 'ViolentCrimesPerPop'
plt.figure(figsize=(18, 12))
for i, column in enumerate(relevant_features, 1):
    plt.subplot(4, 3, i)
    sns.scatterplot(x=data[column], y=data[target])
    plt.title(f'Relationship between {column} and {target}')
    plt.xlabel(column)
    plt.ylabel(target)
plt.tight_layout()
plt.show()
```



Scatter Plots of Relevant Features vs. Target Variable The scatter plots reveal the relationships between the relevant features and the target variable, ViolentCrimesPerPop:

Positive Correlations: Features like PctIlleg, racepctblack, pctWPubAsst, TotalPctDiv, PctPopUnderPov, and PctUnemployed show positive correlations with ViolentCrimesPerPop. Negative Correlations: Features like PctKids2Par, racePctWhite, and PctFam2Par show negative correlations with ViolentCrimesPerPop. Non-linear Relationships: Some features exhibit non-linear relationships, suggesting the need for non-linear modeling techniques. Takeaway: The identified correlations can guide feature selection and engineering, emphasizing the importance of including socio-economic and demographic factors in the model.

```
# Heatmap for correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(data.corr(), cmap='coolwarm', center=0)
plt.title('Correlation Matrix of Cleaned Data')
plt.show()
```



Correlation Matrix of Cleaned Data The heatmap provides an overview of the correlations between all features:

High Correlations: There are several high correlations between features, such as racePctWhite and racepctblack, indicating potential multicollinearity. Clustered Features: Features like pctWPubAsst, PctIlleg, and socio-economic indicators cluster together, suggesting they capture similar underlying factors. Takeaway: The correlation matrix highlights the need to address multicollinearity, potentially through techniques like PCA or removing highly correlated features.

```
# 2. Descriptive Statistics
print("Summary Statistics for Numerical Features:")
print(data.describe())

Summary Statistics for Numerical Features:
         population  householdsize  racepctblack  racePctWhite
racePctAsian  \
count  4.540000e+02   4.540000e+02  4.540000e+02  4.540000e+02
4.540000e+02
mean   2.738876e-17   1.623762e-16  5.282118e-17 -4.440892e-16 -
5.869020e-17
```

```
std    1.001103e+00   1.001103e+00  1.001103e+00  1.001103e+00
1.001103e+00
min   -9.694131e-01  -2.810767e+00 -7.325109e-01 -4.014492e+00 -
1.102725e+00
25%   -9.694131e-01  -7.339849e-01 -6.426298e-01 -4.999900e-01 -
6.537233e-01
50%   -4.652739e-01  -7.319056e-02 -4.628677e-01  3.269516e-01 -
2.795549e-01
75%    5.430046e-01   5.876038e-01  1.662998e-01  7.404224e-01
2.442809e-01
max    4.071979e+00   3.136382e+00  3.761542e+00  1.050526e+00
4.135632e+00

        racePctHisp   agePct12t21   agePct12t29   agePct16t24
agePct65up  \
count  4.540000e+02  4.540000e+02  4.540000e+02  4.540000e+02
4.540000e+02
mean   2.347608e-17  3.912680e-16 -9.312179e-16 -8.607897e-17 -
2.504115e-16
std    1.001103e+00  1.001103e+00  1.001103e+00  1.001103e+00
1.001103e+00
min   -7.211009e-01 -2.826862e+00 -2.821513e+00 -2.434949e+00 -
2.459714e+00
25%   -5.744253e-01 -6.409367e-01 -5.986413e-01 -6.602649e-01 -
7.621085e-01
50%   -4.277498e-01  1.982570e-03 -5.875432e-03 -1.762602e-01
1.181317e-01
75%    1.227681e-02  6.449018e-01  5.868904e-01  4.690795e-01
7.468746e-01
max    4.852570e+00  3.345163e+00  4.143485e+00  3.857113e+00
2.695978e+00

       ...      LandArea       PopDens  PctUsePubTrans
PolicCars  \
count  ...  4.540000e+02  4.540000e+02    4.540000e+02  4.540000e+02

mean   ... -3.912680e-17 -1.330311e-16   -5.477752e-17  2.775558e-17

std    ...  1.001103e+00  1.001103e+00    1.001103e+00  0.000000e+00

min    ... -1.425276e+00 -1.406601e+00   -8.651465e-01  2.775558e-17

25%    ... -7.592179e-01 -7.227740e-01   -6.405745e-01  2.775558e-17

50%    ... -2.596745e-01 -2.343260e-01   -3.598594e-01  2.775558e-17

75%    ...  5.728977e-01  6.448806e-01    3.699998e-01  2.775558e-17

max    ...  3.237129e+00  3.380190e+00    4.075439e+00  2.775558e-17
```

```
       PolicOperBudg  LemasPctPolicOnPatr  LemasGangUnitDeploy  \
count   4.540000e+02                454.0         4.540000e+02
mean    1.387779e-17                  0.0         5.551115e-17
std     0.000000e+00                  0.0         0.000000e+00
min     1.387779e-17                  0.0         5.551115e-17
25%     1.387779e-17                  0.0         5.551115e-17
50%     1.387779e-17                  0.0         5.551115e-17
75%     1.387779e-17                  0.0         5.551115e-17
max     1.387779e-17                  0.0         5.551115e-17

       LemasPctOfficDrugUn  PolicBudgPerPop  ViolentCrimesPerPop
count                454.0     4.540000e+02         4.540000e+02
mean                   0.0    -5.551115e-17        -1.017297e-16
std                    0.0     0.000000e+00         1.001103e+00
min                    0.0    -5.551115e-17        -1.120009e+00
25%                    0.0    -5.551115e-17        -6.922080e-01
50%                    0.0    -5.551115e-17        -3.499674e-01
75%                    0.0    -5.551115e-17         3.345138e-01
max                    0.0    -5.551115e-17         4.783641e+00

[8 rows x 123 columns]
```

Descriptive Summary Statistics for Numerical Features The summary statistics offer insights into the distribution and scale of numerical features:

Standardized Values: All features have been standardized, with means close to 0 and standard deviations close to 1. Extreme Values: Min and max values highlight the range of the features, confirming the presence of outliers addressed during preprocessing. Takeaway: Standardization ensures all features contribute equally to the model, preventing dominance by features with larger scales.

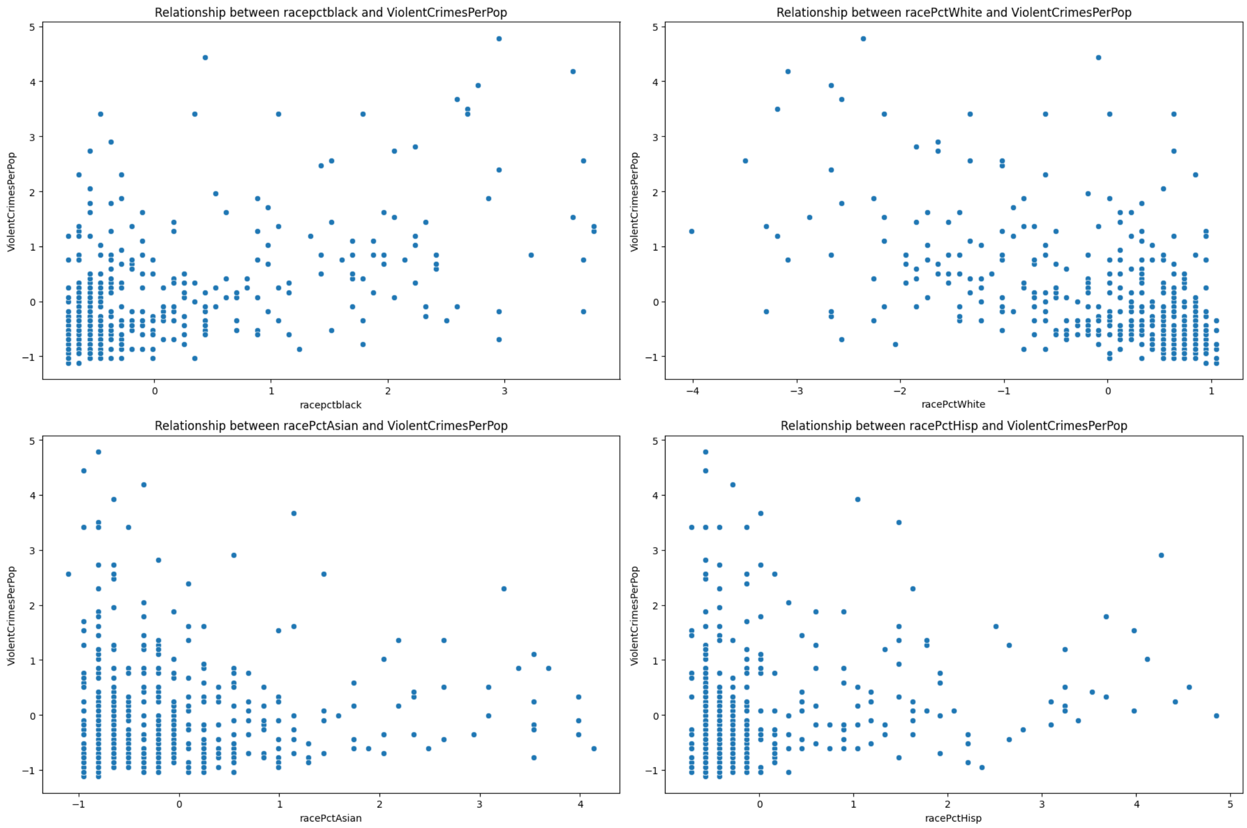
```
# 3. Correlation Analysis
corr_with_target = data.corr()[target].sort_values(ascending=False)
print("Top 10 features positively correlated with
ViolentCrimesPerPop:")
print(corr_with_target.head(10))
print("\nTop 10 features negatively correlated with
ViolentCrimesPerPop:")
print(corr_with_target.tail(10))

Top 10 features positively correlated with ViolentCrimesPerPop:
ViolentCrimesPerPop    1.000000
racepctblack           0.535113
PctIlleg               0.482994
TotalPctDiv            0.444203
PctHousNoPhone         0.442323
PctPopUnderPov         0.440676
FemalePctDiv           0.433663
MalePctDivorce         0.430808
```

```
PctPersDenseHous       0.390105
NumIlleg               0.381966
Name: ViolentCrimesPerPop, dtype: float64

Top 10 features negatively correlated with ViolentCrimesPerPop:
PctPolicMinor         NaN
OfficAssgnDrugUnits   NaN
NumKindsDrugsSeiz     NaN
PolicAveOTWorked      NaN
PolicCars             NaN
PolicOperBudg         NaN
LemasPctPolicOnPatr   NaN
LemasGangUnitDeploy   NaN
LemasPctOfficDrugUn   NaN
PolicBudgPerPop       NaN
Name: ViolentCrimesPerPop, dtype: float64
```

Top 10 Features Correlated with ViolentCrimesPerPop The top positively and negatively correlated features with ViolentCrimesPerPop are identified:

Positive Correlations: Features like racepctblack, PctIlleg, and TotalPctDiv show strong positive correlations with ViolentCrimesPerPop. Negative Correlations: Features related to law enforcement (PctPolicMinor, OfficAssgnDrugUnits) show NaN values, likely due to insufficient data or preprocessing issues or too low values. Takeaway: These correlations can inform feature selection, highlighting the importance of socio-economic and demographic features in predicting violent crime rates.

```python
# 4. Feature Relationships with Sensitive Features
sensitive_features = ['racepctblack', 'racePctWhite', 'racePctAsian',
'racePctHisp']
plt.figure(figsize=(18, 12))
for i, feature in enumerate(sensitive_features, 1):
    plt.subplot(2, 2, i)
    sns.scatterplot(x=data[feature], y=data[target])
    plt.title(f'Relationship between {feature} and {target}')
    plt.xlabel(feature)
    plt.ylabel(target)
plt.tight_layout()
plt.show()
```




```python
# Building and Evaluating Predictive Models

# 1. Model Selection: Linear Regression and Random Forest
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest': RandomForestRegressor(n_estimators=100,
random_state=42)
}

# 2. Split the dataset into training and testing sets
X = data.drop(columns=[target])
y = data[target]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# 3. Train the models
trained_models = {}
for model_name, model in models.items():
    model.fit(X_train, y_train)
    trained_models[model_name] = model
    print(f'{model_name} model trained.')
```

```
Linear Regression model trained.
Random Forest model trained.
```

```python
# 4. Evaluate the models
for model_name, model in trained_models.items():
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    print(f'\n{model_name} Model Evaluation:')
    print(f'Training RMSE: {mean_squared_error(y_train, y_pred_train,
squared=False)}')
    print(f'Testing RMSE: {mean_squared_error(y_test, y_pred_test,
squared=False)}')
    print(f'Training MAE: {mean_absolute_error(y_train,
y_pred_train)}')
    print(f'Testing MAE: {mean_absolute_error(y_test, y_pred_test)}')
    print(f'Training R^2: {r2_score(y_train, y_pred_train)}')
    print(f'Testing R^2: {r2_score(y_test, y_pred_test)}')
```

```
Linear Regression Model Evaluation:
Training RMSE: 0.6699564711927812
Testing RMSE: 0.9292943823689844
Training MAE: 0.4951976466437991
Testing MAE: 0.6270491822826886
Training R^2: 0.5613331157665811
Testing R^2: 0.010942961442030219

Random Forest Model Evaluation:
Training RMSE: 0.31818760679044406
Testing RMSE: 0.8457309858287455
Training MAE: 0.22198732642901106
Testing MAE: 0.5852313869433543
Training R^2: 0.9010517318178832
Testing R^2: 0.18082026647767568

C:\Users\Fujitsu\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\sklearn\metrics\_regression.py:492:
FutureWarning: 'squared' is deprecated in version 1.4 and will be
removed in 1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
C:\Users\Fujitsu\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\sklearn\metrics\_regression.py:492:
FutureWarning: 'squared' is deprecated in version 1.4 and will be
removed in 1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
C:\Users\Fujitsu\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\sklearn\metrics\_regression.py:492:
```

```
FutureWarning: 'squared' is deprecated in version 1.4 and will be
removed in 1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
C:\Users\Fujitsu\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-
packages\Python311\site-packages\sklearn\metrics\_regression.py:492:
FutureWarning: 'squared' is deprecated in version 1.4 and will be
removed in 1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
```

Linear Regression Model Evaluation The linear regression model's performance is evaluated:

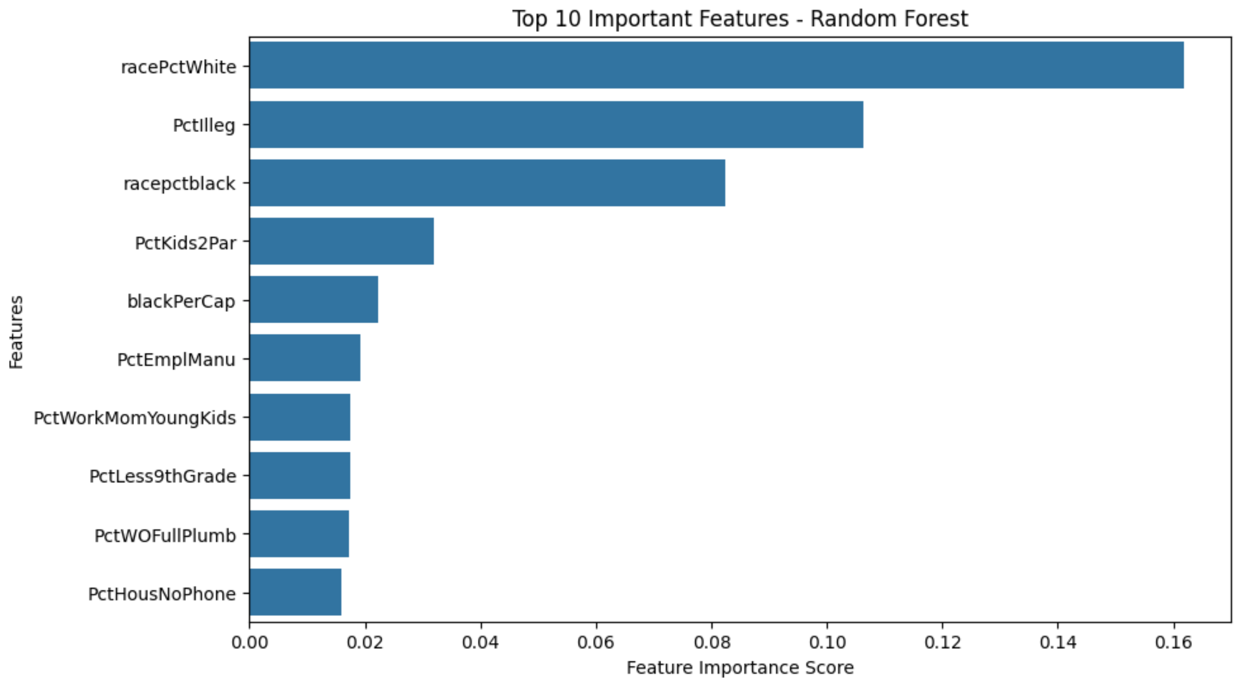
Training RMSE: 0.6699 Testing RMSE: 0.9293 Training R^2: 0.5613 Testing R^2: 0.0109 Takeaway: The linear regression model shows poor generalization, with a significant drop in R^2 from training to testing, indicating potential overfitting.

Random Forest Model Evaluation The random forest model's performance is evaluated:

Training RMSE: 0.3182 Testing RMSE: 0.8457 Training R^2: 0.9011 Testing R^2: 0.1808 Takeaway: The random forest model performs better than linear regression, with improved R^2 and lower RMSE, though it still shows room for improvement in generalization.

```
# 5. Feature Importance Analysis (for Random Forest)
rf_model = trained_models['Random Forest']
feature_importance = pd.Series(rf_model.feature_importances_,
index=X.columns).sort_values(ascending=False)
print("\nTop 10 important features according to Random Forest:")
print(feature_importance.head(10))

# Visualize feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance.head(10),
y=feature_importance.head(10).index)
plt.title('Top 10 Important Features - Random Forest')
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.show()


Top 10 important features according to Random Forest:
racePctWhite           0.161952
PctIlleg               0.106305
racepctblack           0.082461
PctKids2Par            0.032034
blackPerCap            0.022230
PctEmplManu            0.019295
PctWorkMomYoungKids    0.017558
PctLess9thGrade        0.017383
```

```
PctWOFullPlumb        0.017307
PctHousNoPhone        0.015861
dtype: float64
```

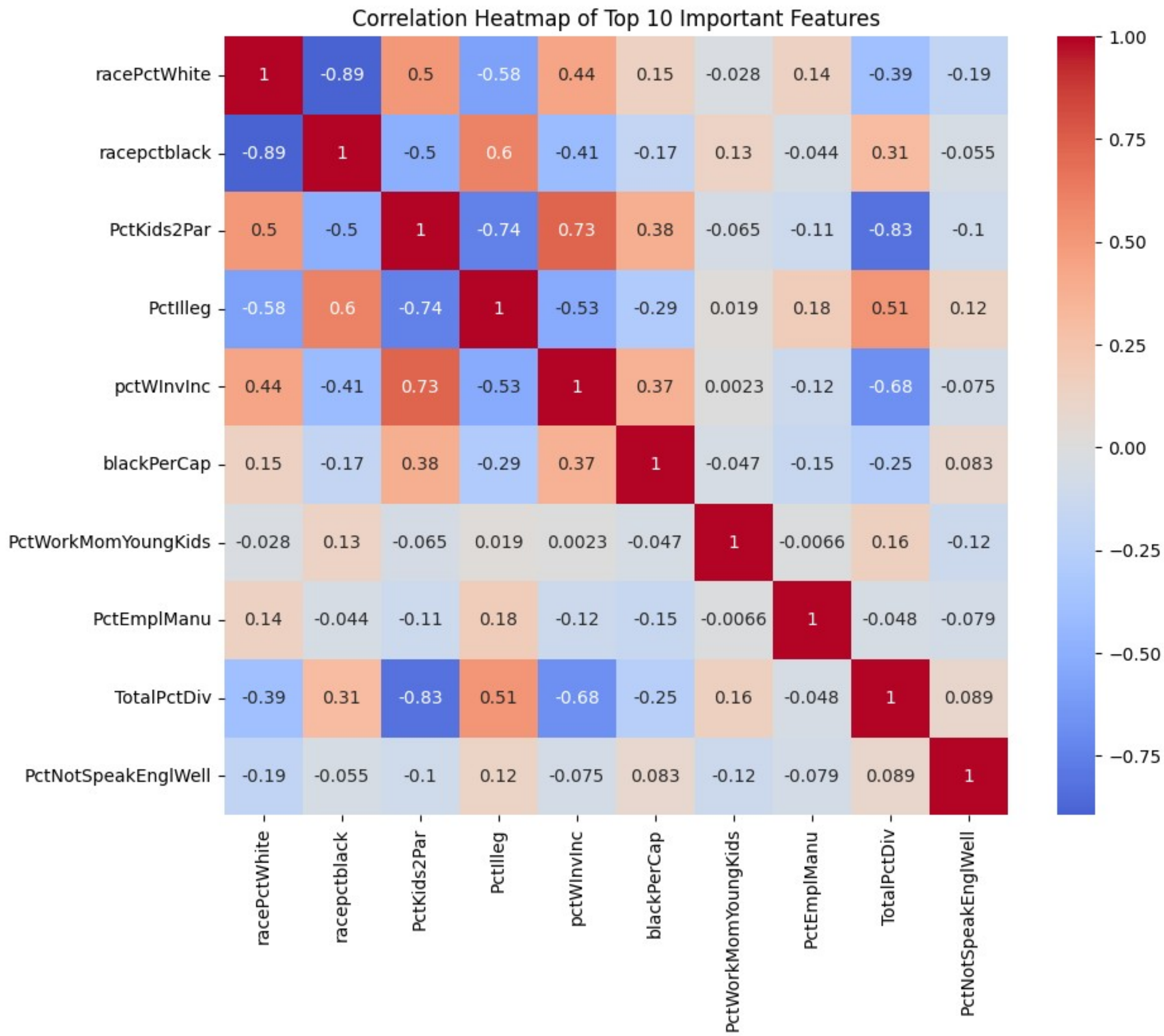


Top 10 Important Features - Random Forest The bar plot visualizes the feature importance scores from the random forest model:

Top Features: racePctWhite, PctIlleg, racepctblack, PctKids2Par, and others are identified as the most important features. Takeaway: These important features should be prioritized in further modeling and analysis, focusing on their relationships with the target variable.

```python
# Define the target variable
target = 'ViolentCrimesPerPop'

# Random Forest Model to determine feature importance
X = data.drop(columns=[target])
y = data[target]

# Train a Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X, y)

# Feature importance
feature_importance = pd.Series(rf_model.feature_importances_,
index=X.columns).sort_values(ascending=False)
top_features = feature_importance.head(10).index

# 1. Correlation Heatmap for Top Features
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(data[top_features].corr(), annot=True, cmap='coolwarm',
center=0)
plt.title('Correlation Heatmap of Top 10 Important Features')
plt.show()
```

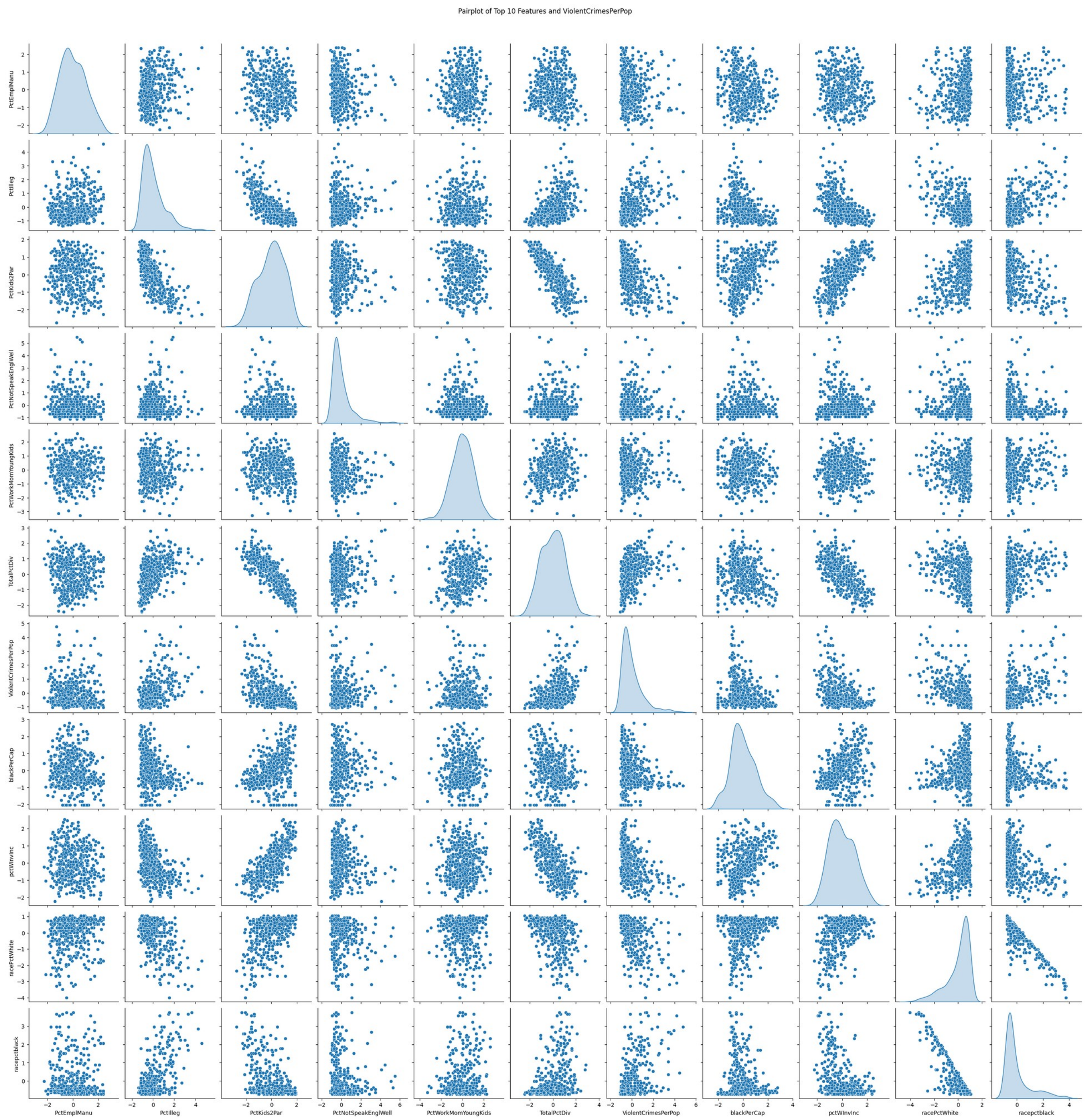


Correlation Heatmap of Top 10 Important Features The heatmap reveals the correlations among the top 10 important features:

High Correlations: Some features show high correlations with each other, such as PctIlleg and NumIlleg. Potential Redundancies: High correlations suggest potential redundancies, indicating the need for dimensionality reduction or feature selection. Takeaway: These correlations help in refining the model, ensuring it captures unique and relevant information without redundancy.

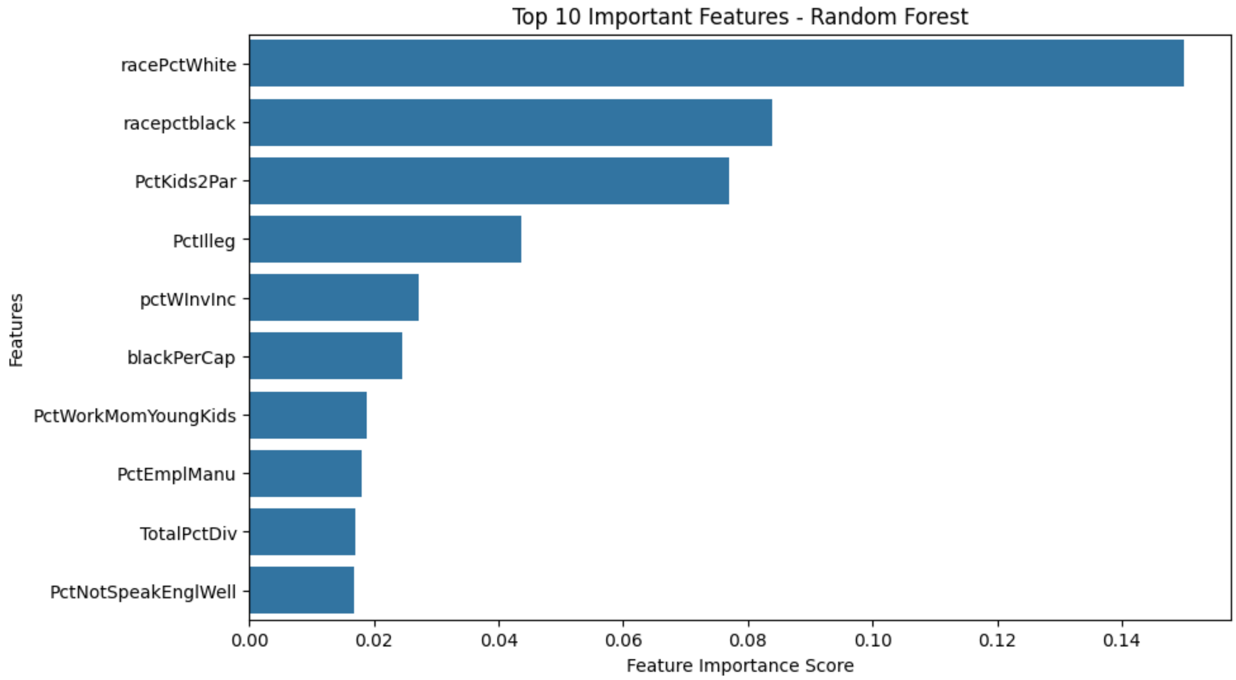
```
# 2. Pairplot for Top Features
sns.pairplot(data[top_features.union([target])], diag_kind='kde',
```

```
kind='scatter')
plt.suptitle('Pairplot of Top 10 Features and ViolentCrimesPerPop',
y=1.02)
plt.show()
```



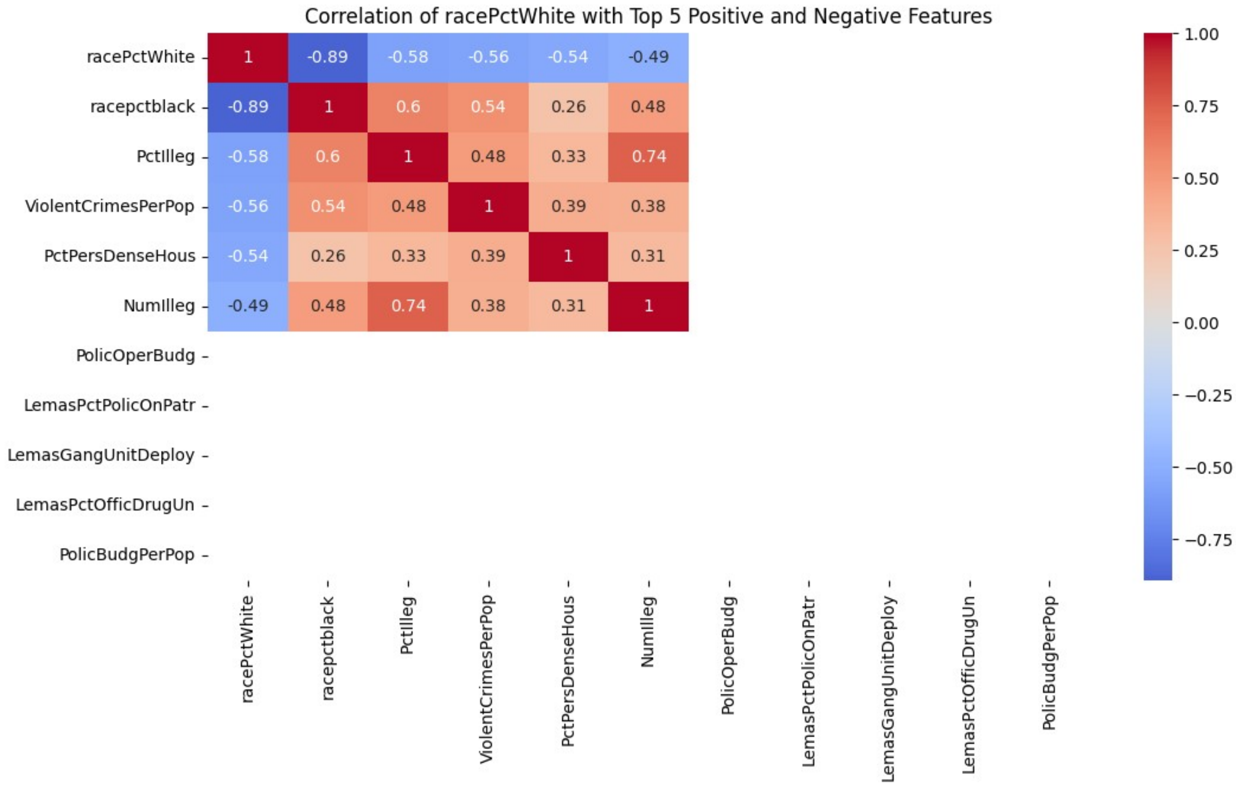

```
# 3. Bar Plot of Feature Importance
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance.head(10),
y=feature_importance.head(10).index)
plt.title('Top 10 Important Features - Random Forest')
```

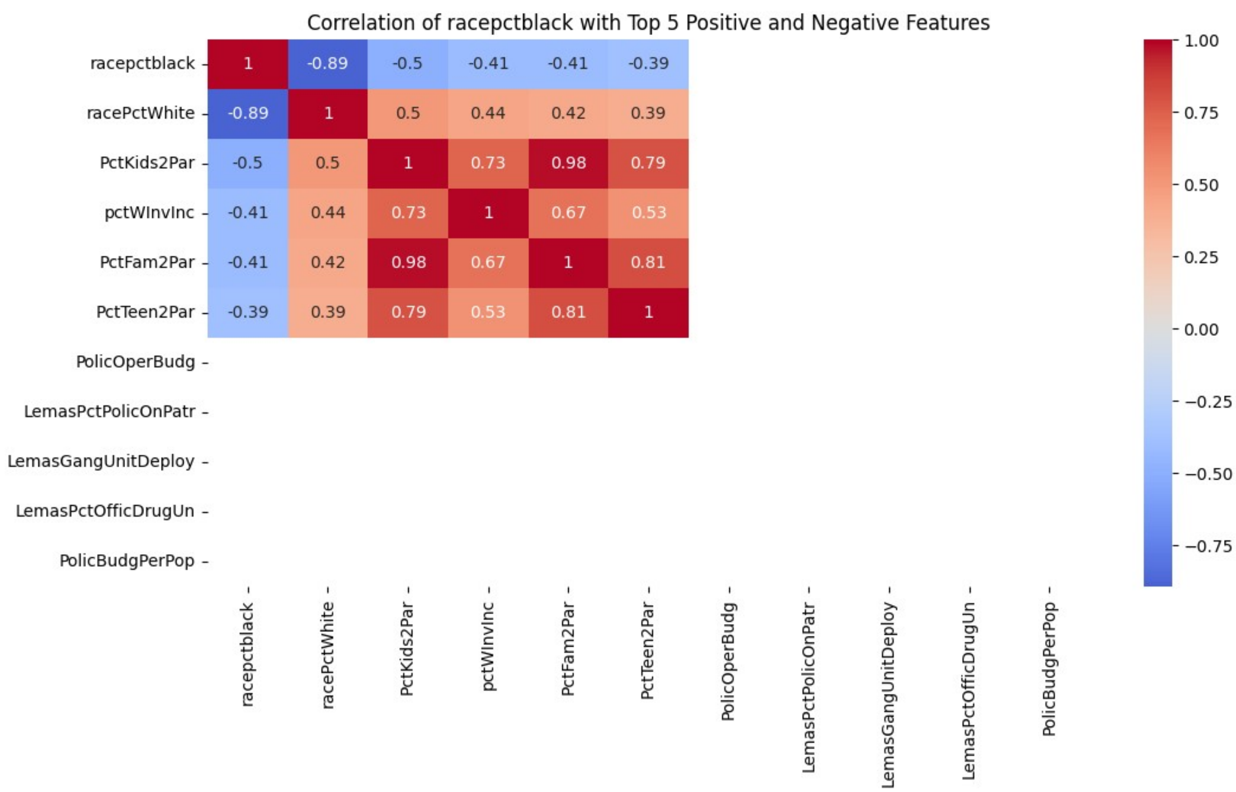
```
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.show()
```

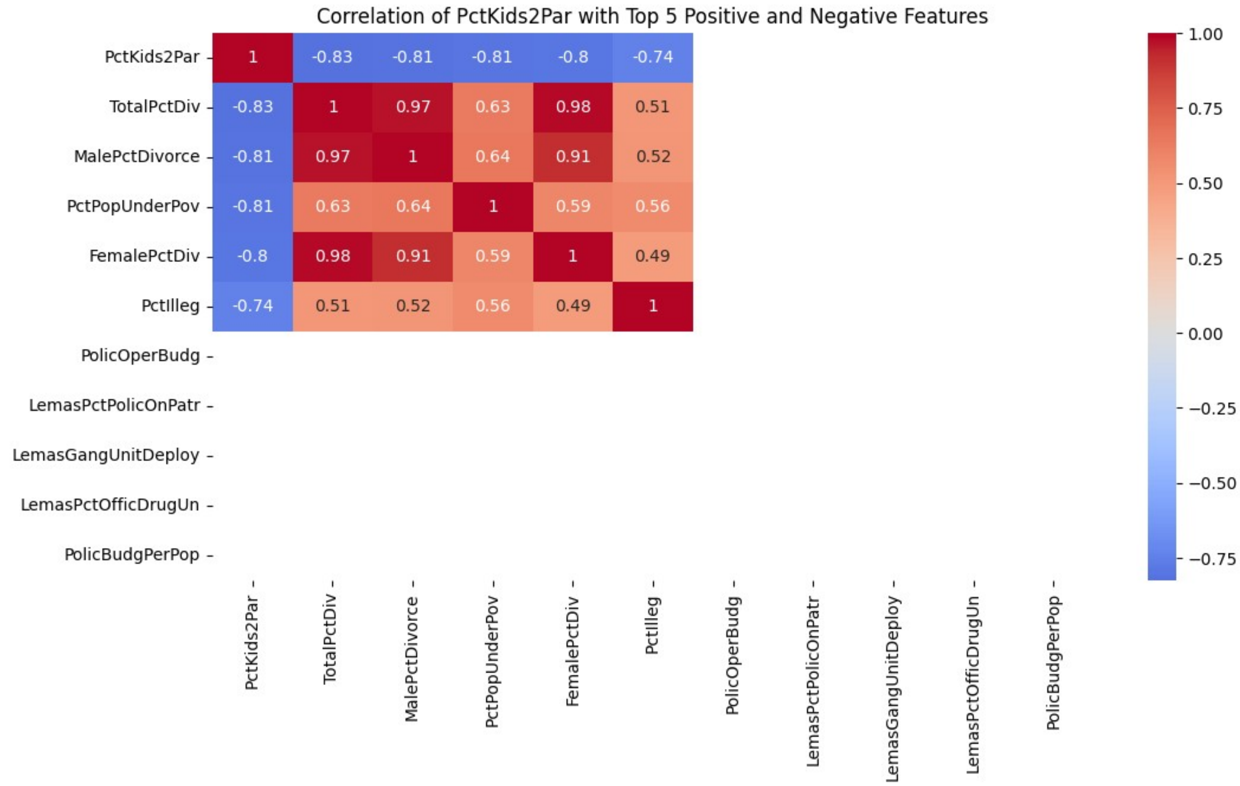


This shows a slight shift between the Top 10 Features but the overall important features stayed the same

```
# 4. Detailed Correlation Analysis for Top 3 Features
top_3_features = feature_importance.head(3).index

for feature in top_3_features:
    corr_feature = data.corr()[feature].sort_values()
    top_5_neg = corr_feature.head(5).index
    top_5_pos = corr_feature.tail(5).index
    top_10_corr_features = top_5_neg.append(top_5_pos)

    plt.figure(figsize=(12, 6))
    sns.heatmap(data[[feature] + list(top_10_corr_features)].corr(), 
annot=True, cmap='coolwarm', center=0)
    plt.title(f'Correlation of {feature} with Top 5 Positive and 
Negative Features')
    plt.show()
```


Correlation of racePctWhite with Top 5 Positive and Negative Features
racePctWhite
racepctblack
PctIlleg
ViolentCrimesPerPop
PctPersDenseHous
NumIlleg
PolicOperBudg
LemasPctPolicOnPatr
LemasGangUnitDeploy
LemasPctOfficDrugUn
PolicBudgPerPop
1 -0.89 -0.58 -0.56 -0.54 -0.49
-0.89 1 0.6 0.54 0.26 0.48
-0.58 0.6 1 0.48 0.33 0.74
-0.56 0.54 0.48 1 0.39 0.38
-0.54 0.26 0.33 0.39 1 0.31
-0.49 0.48 0.74 0.38 0.31 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75


Correlation of racepctblack with Top 5 Positive and Negative Features
racepctblack
racePctWhite
PctKids2Par
pctWInvInc
PctFam2Par
PctTeen2Par
PolicOperBudg
LemasPctPolicOnPatr
LemasGangUnitDeploy
LemasPctOfficDrugUn
PolicBudgPerPop
1 -0.89 -0.5 -0.41 -0.41 -0.39
-0.89 1 0.5 0.44 0.42 0.39
-0.5 0.5 1 0.73 0.98 0.79
-0.41 0.44 0.73 1 0.67 0.53
-0.41 0.42 0.98 0.67 1 0.81
-0.39 0.39 0.79 0.53 0.81 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75



Correlation of racePctWhite with Top 5 Positive and Negative Features The heatmap shows the correlation of racePctWhite with other features:

Strong Negative Correlation: racePctWhite has a strong negative correlation with racepctblack and PctIlleg. Positive Correlations: Some positive correlations are observed with socio-economic features like PctPersDenseHous. Takeaway: These correlations highlight the complex interplay between demographic features and crime rates, informing bias detection and mitigation strategies.

The other 2 graphics also show similar socie-economic trends: racepctblack: Strongly correlated with racePctWhite and socio-economic factors. PctKids2Par: Correlated with TotalPctDiv, MalePctDivorce, and other family-related features. Takeaway: These detailed analyses help identify indirect correlations, guiding feature engineering and bias mitigation efforts.

```
print("Done")
```

```
Done
```