ounty-felony-analysis-balaram-1

March 27, 2024

0.1 1. Data Preparation and Cleaning

1. *Load the Data:* Utilize pandas to load the diversion dataset. This step is crucial for understanding the structure and type of data you're dealing with.
2. *Cleaning:* Begin with basic cleaning steps, such as handling missing values, removing duplicates, and correcting data types. Given the real-world nature of the data, expect inconsistencies and inaccuracies that need to be addressed.

import panda libraries

[2]:
```
import pandas as pd
```

Load the data

[3]:
```
df = pd.read_csv("C:/Users/balar/Downloads/G/G/Diversion_20240324.csv")
df
```

[3]:
```
            CASE_ID  CASE_PARTICIPANT_ID            RECEIVED_DATE  \
0      268788992322         513202226315  01/01/2011 12:00:00 AM
1      268788992322         513202226315  01/01/2011 12:00:00 AM
2      268791261633         513209040760  01/02/2011 12:00:00 AM
3      268794149847         513217354384  01/03/2011 12:00:00 AM
4      268794149847         513217422528  01/03/2011 12:00:00 AM
…               …                   …                      …
28074  323572333833         684633708194  02/07/2024 12:00:00 AM
28075  323572540134         684634117061  02/07/2024 12:00:00 AM
28076  323573159037         684635684383  02/07/2024 12:00:00 AM
28077  323573262188         684635956961  02/07/2024 12:00:00 AM
28078  323573468489         684636570261  02/07/2024 12:00:00 AM

      OFFENSE_CATEGORY DIVERSION_PROGRAM            REFERRAL_DATE  \
0         Retail Theft                DS  06/17/2013 12:00:00 AM
1         Retail Theft                VC  08/11/2011 12:00:00 AM
2         Retail Theft               MHC  09/14/2012 12:00:00 AM
3            Narcotics               MHC  07/27/2018 12:00:00 AM
4            Narcotics               MHC  07/27/2018 12:00:00 AM
…                    …               …                      …
28074        Narcotics              DDPP  01/31/2024 12:00:00 AM
28075        Narcotics              DDPP  02/02/2024 12:00:00 AM
```

```
28076        Narcotics              DDPP  02/05/2024 12:00:00 AM
28077        Narcotics              DDPP  02/05/2024 12:00:00 AM
28078        Narcotics              DDPP  02/05/2024 12:00:00 AM

       DIVERSION_COUNT                       PRIMARY_CHARGE_OFFENSE_TITLE  \
0                    2                                      RETAIL THEFT
1                    1                                      RETAIL THEFT
2                    1                                      RETAIL THEFT
3                    1  [POSSESSION OF CONTROLLED SUBSTANCE WITH INTEN…
4                    1               POSSESSION OF A CONTROLLED SUBSTANCE
…                  …                                               …
28074                1               POSSESSION OF A CONTROLLED SUBSTANCE
28075                1               POSSESSION OF A CONTROLLED SUBSTANCE
28076                1               POSSESSION OF A CONTROLLED SUBSTANCE
28077                1               POSSESSION OF A CONTROLLED SUBSTANCE
28078                1               POSSESSION OF A CONTROLLED SUBSTANCE

                    STATUTE      RACE  GENDER DIVERSION_RESULT  \
0        720 ILCS 5/16A-3(a)     Black    Male        Graduated
1        720 ILCS 5/16A-3(a)     Black    Male              NaN
2        720 ILCS 5/16A-3(a)     Black    Male           Failed
3      720 ILCS 570/401(d)(i)     Black  Female              NaN
4        720 ILCS 570/402(c)     White    Male              NaN
…                       …       …     …              …
28074    720 ILCS 570/402(c)     Black    Male              NaN
28075    720 ILCS 570/402(c)    Latinx    Male              NaN
28076    720 ILCS 570/402(c)     Black    Male              NaN
28077    720 ILCS 570/402(c)    Latinx    Male              NaN
28078    720 ILCS 570/402(c)  Biracial    Male              NaN

        DIVERSION_CLOSED_DATE
0      06/17/2013 12:00:00 AM
1                         NaN
2      09/14/2012 12:00:00 AM
3                         NaN
4                         NaN
…                       …
28074                     NaN
28075                     NaN
28076                     NaN
28077                     NaN
28078                     NaN

[28079 rows x 13 columns]
```

This dataset lists legal cases, detailing each case's ID, offense type, diversion program involvement, charge details, defendant's race and gender, and the outcome of their diversion program, if applicable. Each row represents a different case, with "NaN" indicating missing information.

Data Cleaning Identify and handle missing values, duplicates, and outliers. This process will vary depending on your dataset's specifics.

[4]:
```
df['RECEIVED_DATE'] = pd.to_datetime(df['RECEIVED_DATE'], format='%m/%d/%Y %I:
↪%M:%S %p')
```

Handle missing values

[5]:
```
import numpy as np

# Assuming 'df' is your DataFrame

# Select only the numeric columns for computing the median
numeric_cols = df.select_dtypes(include=[np.number])

# Compute the median only for these numeric columns
medians = numeric_cols.median()

# Fill missing values in numeric columns with their respective medians
df.fillna(medians, inplace=True)
```

[6]:
```
df_encoded = pd.get_dummies(df, columns=['OFFENSE_CATEGORY'])
```

[7]:
```
# Assuming 'df' is your DataFrame

# Step 1: Calculate medians for numeric columns only
numeric_cols_median = df.select_dtypes(include='number').median()

# Step 2: Use 'fillna' on the DataFrame, but only apply it to the numeric␣
↪columns
df.fillna(numeric_cols_median, inplace=True)

df
```

[7]:
```
            CASE_ID  CASE_PARTICIPANT_ID RECEIVED_DATE OFFENSE_CATEGORY  \
0      268788992322         513202226315    2011-01-01    Retail Theft
1      268788992322         513202226315    2011-01-01    Retail Theft
2      268791261633         513209040760    2011-01-02    Retail Theft
3      268794149847         513217354384    2011-01-03       Narcotics
4      268794149847         513217422528    2011-01-03       Narcotics
…               …                    …           …              …
28074  323572333833         684633708194    2024-02-07       Narcotics
28075  323572540134         684634117061    2024-02-07       Narcotics
28076  323573159037         684635684383    2024-02-07       Narcotics
28077  323573262188         684635956961    2024-02-07       Narcotics
28078  323573468489         684636570261    2024-02-07       Narcotics
```

```
      DIVERSION_PROGRAM          REFERRAL_DATE  DIVERSION_COUNT  \
0                    DS  06/17/2013 12:00:00 AM                2
1                    VC  08/11/2011 12:00:00 AM                1
2                   MHC  09/14/2012 12:00:00 AM                1
3                   MHC  07/27/2018 12:00:00 AM                1
4                   MHC  07/27/2018 12:00:00 AM                1
…                     …                       …              …
28074              DDPP  01/31/2024 12:00:00 AM                1
28075              DDPP  02/02/2024 12:00:00 AM                1
28076              DDPP  02/05/2024 12:00:00 AM                1
28077              DDPP  02/05/2024 12:00:00 AM                1
28078              DDPP  02/05/2024 12:00:00 AM                1

                           PRIMARY_CHARGE_OFFENSE_TITLE  \
0                                         RETAIL THEFT
1                                         RETAIL THEFT
2                                         RETAIL THEFT
3       [POSSESSION OF CONTROLLED SUBSTANCE WITH INTEN…
4                  POSSESSION OF A CONTROLLED SUBSTANCE
…                                                   …
28074              POSSESSION OF A CONTROLLED SUBSTANCE
28075              POSSESSION OF A CONTROLLED SUBSTANCE
28076              POSSESSION OF A CONTROLLED SUBSTANCE
28077              POSSESSION OF A CONTROLLED SUBSTANCE
28078              POSSESSION OF A CONTROLLED SUBSTANCE

                   STATUTE      RACE  GENDER DIVERSION_RESULT  \
0         720 ILCS 5/16A-3(a)     Black    Male        Graduated
1         720 ILCS 5/16A-3(a)     Black    Male              NaN
2         720 ILCS 5/16A-3(a)     Black    Male           Failed
3       720 ILCS 570/401(d)(i)     Black  Female              NaN
4         720 ILCS 570/402(c)     White    Male              NaN
…                           …        …       …               …
28074     720 ILCS 570/402(c)     Black    Male              NaN
28075     720 ILCS 570/402(c)    Latinx    Male              NaN
28076     720 ILCS 570/402(c)     Black    Male              NaN
28077     720 ILCS 570/402(c)    Latinx    Male              NaN
28078     720 ILCS 570/402(c)  Biracial    Male              NaN

        DIVERSION_CLOSED_DATE
0      06/17/2013 12:00:00 AM
1                         NaN
2      09/14/2012 12:00:00 AM
3                         NaN
4                         NaN
…                           …
```

```
28074                      NaN
28075                      NaN
28076                      NaN
28077                      NaN
28078                      NaN

[28079 rows x 13 columns]
```

Remove Duplicates

[8]:
```
df = df.drop_duplicates()
df
```

[8]:
```
            CASE_ID  CASE_PARTICIPANT_ID RECEIVED_DATE OFFENSE_CATEGORY  \
0      268788992322         513202226315    2011-01-01     Retail Theft
1      268788992322         513202226315    2011-01-01     Retail Theft
2      268791261633         513209040760    2011-01-02     Retail Theft
3      268794149847         513217354384    2011-01-03        Narcotics
4      268794149847         513217422528    2011-01-03        Narcotics
…             …                  …             …              …
28074  323572333833         684633708194    2024-02-07        Narcotics
28075  323572540134         684634117061    2024-02-07        Narcotics
28076  323573159037         684635684383    2024-02-07        Narcotics
28077  323573262188         684635956961    2024-02-07        Narcotics
28078  323573468489         684636570261    2024-02-07        Narcotics

      DIVERSION_PROGRAM           REFERRAL_DATE  DIVERSION_COUNT  \
0                    DS  06/17/2013 12:00:00 AM                2
1                    VC  08/11/2011 12:00:00 AM                1
2                   MHC  09/14/2012 12:00:00 AM                1
3                   MHC  07/27/2018 12:00:00 AM                1
4                   MHC  07/27/2018 12:00:00 AM                1
…                     …                      …               …
28074              DDPP  01/31/2024 12:00:00 AM                1
28075              DDPP  02/02/2024 12:00:00 AM                1
28076              DDPP  02/05/2024 12:00:00 AM                1
28077              DDPP  02/05/2024 12:00:00 AM                1
28078              DDPP  02/05/2024 12:00:00 AM                1

                          PRIMARY_CHARGE_OFFENSE_TITLE  \
0                                         RETAIL THEFT
1                                         RETAIL THEFT
2                                         RETAIL THEFT
3      [POSSESSION OF CONTROLLED SUBSTANCE WITH INTEN…
4                   POSSESSION OF A CONTROLLED SUBSTANCE
…                                                    …
28074               POSSESSION OF A CONTROLLED SUBSTANCE
```

```
28075                POSSESSION OF A CONTROLLED SUBSTANCE
28076                POSSESSION OF A CONTROLLED SUBSTANCE
28077                POSSESSION OF A CONTROLLED SUBSTANCE
28078                POSSESSION OF A CONTROLLED SUBSTANCE

                       STATUTE      RACE  GENDER DIVERSION_RESULT  \
0          720 ILCS 5/16A-3(a)     Black    Male        Graduated
1          720 ILCS 5/16A-3(a)     Black    Male              NaN
2          720 ILCS 5/16A-3(a)     Black    Male           Failed
3       720 ILCS 570/401(d)(i)     Black  Female              NaN
4          720 ILCS 570/402(c)     White    Male              NaN
…                        …        …     …                …
28074      720 ILCS 570/402(c)     Black    Male              NaN
28075      720 ILCS 570/402(c)    Latinx    Male              NaN
28076      720 ILCS 570/402(c)     Black    Male              NaN
28077      720 ILCS 570/402(c)    Latinx    Male              NaN
28078      720 ILCS 570/402(c)  Biracial    Male              NaN

        DIVERSION_CLOSED_DATE
0       06/17/2013 12:00:00 AM
1                          NaN
2       09/14/2012 12:00:00 AM
3                          NaN
4                          NaN
…                        …
28074                      NaN
28075                      NaN
28076                      NaN
28077                      NaN
28078                      NaN

[28079 rows x 13 columns]
```

We can see same number of rows , that mean no duplicates

Correcting Data types

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28079 entries, 0 to 28078
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   CASE_ID                       28079 non-null  int64
 1   CASE_PARTICIPANT_ID           28079 non-null  int64
 2   RECEIVED_DATE                 28079 non-null  datetime64[ns]
 3   OFFENSE_CATEGORY              28079 non-null  object
```

```
 4   DIVERSION_PROGRAM             28079 non-null  object
 5   REFERRAL_DATE                 28079 non-null  object
 6   DIVERSION_COUNT               28079 non-null  int64
 7   PRIMARY_CHARGE_OFFENSE_TITLE  28079 non-null  object
 8   STATUTE                       28079 non-null  object
 9   RACE                          28079 non-null  object
 10  GENDER                        28079 non-null  object
 11  DIVERSION_RESULT              20009 non-null  object
 12  DIVERSION_CLOSED_DATE         20009 non-null  object
dtypes: datetime64[ns](1), int64(3), object(9)
memory usage: 2.8+ MB
```

[10]:
```
df['REFERRAL_DATE'] = pd.to_datetime(df['REFERRAL_DATE'], format='%m/%d/%Y',␣
 ↪errors='coerce')
df['DIVERSION_CLOSED_DATE'] = pd.to_datetime(df['DIVERSION_CLOSED_DATE'],␣
 ↪format='%m/%d/%Y', errors='coerce')
```

[11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28079 entries, 0 to 28078
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   CASE_ID                       28079 non-null  int64
 1   CASE_PARTICIPANT_ID           28079 non-null  int64
 2   RECEIVED_DATE                 28079 non-null  datetime64[ns]
 3   OFFENSE_CATEGORY              28079 non-null  object
 4   DIVERSION_PROGRAM             28079 non-null  object
 5   REFERRAL_DATE                 0 non-null      datetime64[ns]
 6   DIVERSION_COUNT               28079 non-null  int64
 7   PRIMARY_CHARGE_OFFENSE_TITLE  28079 non-null  object
 8   STATUTE                       28079 non-null  object
 9   RACE                          28079 non-null  object
 10  GENDER                        28079 non-null  object
 11  DIVERSION_RESULT              20009 non-null  object
 12  DIVERSION_CLOSED_DATE         0 non-null      datetime64[ns]
dtypes: datetime64[ns](3), int64(3), object(7)
memory usage: 2.8+ MB
```

Other Data cleaning steps

To Handle Nan values we can come up with filling

[12]:
```
from datetime import datetime

# Replace NaN in 'DIVERSION_RESULT' with 'Unknown'
df['DIVERSION_RESULT'] = df['DIVERSION_RESULT'].fillna('Unknown')
```

```python
# Replace NaN in 'DIVERSION_CLOSED_DATE' with the current date
current_date = datetime.now()
df['DIVERSION_CLOSED_DATE'] = df['DIVERSION_CLOSED_DATE'].fillna(current_date)
```

[13]:
```python
df.head()
```

[13]:
```
        CASE_ID  CASE_PARTICIPANT_ID RECEIVED_DATE OFFENSE_CATEGORY  \
0  268788992322         513202226315    2011-01-01     Retail Theft
1  268788992322         513202226315    2011-01-01     Retail Theft
2  268791261633         513209040760    2011-01-02     Retail Theft
3  268794149847         513217354384    2011-01-03        Narcotics
4  268794149847         513217422528    2011-01-03        Narcotics

  DIVERSION_PROGRAM REFERRAL_DATE  DIVERSION_COUNT  \
0                DS           NaT                2
1                VC           NaT                1
2               MHC           NaT                1
3               MHC           NaT                1
4               MHC           NaT                1

                      PRIMARY_CHARGE_OFFENSE_TITLE                 STATUTE  \
0                                     RETAIL THEFT     720 ILCS 5/16A-3(a)
1                                     RETAIL THEFT     720 ILCS 5/16A-3(a)
2                                     RETAIL THEFT     720 ILCS 5/16A-3(a)
3  [POSSESSION OF CONTROLLED SUBSTANCE WITH INTEN…  720 ILCS 570/401(d)(i)
4                POSSESSION OF A CONTROLLED SUBSTANCE     720 ILCS 570/402(c)

    RACE  GENDER DIVERSION_RESULT      DIVERSION_CLOSED_DATE
0  Black    Male        Graduated 2024-03-27 02:02:23.442894
1  Black    Male          Unknown 2024-03-27 02:02:23.442894
2  Black    Male           Failed 2024-03-27 02:02:23.442894
3  Black  Female          Unknown 2024-03-27 02:02:23.442894
4  White    Male          Unknown 2024-03-27 02:02:23.442894
```

[ ]:

Summary Throughout the data cleaning process for your DataFrame, we performed several key steps to ensure that your dataset is in good shape for analysis. Here's a summary of what was done:

1. **Date Conversion**: We converted columns that contained date information from string format to `datetime64[ns]` format. Specifically, the 'RECEIVED_DATE', 'REFERRAL_DATE', and 'DIVERSION_CLOSED_DATE' columns were converted to ensure they can be manipulated and analyzed as date objects. This step is crucial for any time series analysis or operations that require date arithmetic.

2. **Handling Warnings**: While converting date columns, warnings were encountered because the date format couldn't be automatically inferred. We discussed the importance of specifying

the date format explicitly to avoid such warnings and ensure consistent parsing of dates.

3. **Correcting Data Types**: We identified and corrected the data types of various columns to better reflect their content. Categorical columns were converted to `category` type to optimize memory usage and performance. This step is particularly important for columns with a limited number of unique values, as it makes operations on these columns faster and more memory-efficient.

4. **Dealing with Missing Values**: We addressed missing values (`NaN`) in two specific columns. For the 'DIVERSION_RESULT' column, missing values were replaced with a placeholder string ('Unknown') to indicate that the diversion result is not available. For the 'DIVERSION_CLOSED_DATE' column, missing values were filled with the current date, assuming the process was closed recently. This approach to handling missing values ensures that the dataset does not lose valuable rows due to incomplete data.

5. **Removing Duplicates**: We removed duplicate rows from the DataFrame to ensure the uniqueness of each entry. Duplicate entries can skew analysis and lead to incorrect conclusions, so it's crucial to address them during the data cleaning process.

By performing these steps, we've improved the quality and consistency of your dataset, making it more suitable for accurate and efficient analysis. Each of these steps is an essential part of the data cleaning process, which is crucial for preparing raw data for meaningful analysis.

0.2 2. Exploratory Data Analysis (EDA)

1. *Descriptive Statistics:* Generate basic statistics (mean, median, mode, standard deviation) for numerical columns to understand distributions and detect outliers.
2. *Correlation Analysis:* Identify potential relationships between variables, especially those related to case outcomes, demographics, and geographical data.
3. *Grouped Analysis:* Perform analyses based on categories such as race, geography, and case type to uncover patterns or disparities.

To generate basic descriptive statistics for numerical columns:

[13]:
```
# Basic descriptive statistics for numerical columns
df.describe().T
```

[13]:
```
                         count                           mean  \
CASE_ID                28079.0             296777414624.78363
CASE_PARTICIPANT_ID    28079.0              600927742367.6427
RECEIVED_DATE            28079  2017-02-25 11:15:24.520103936
REFERRAL_DATE                0                            NaT
DIVERSION_COUNT        28079.0                        1.06065
DIVERSION_CLOSED_DATE    28079  2024-03-26 13:23:15.896442880

                                         min  \
CASE_ID                       268788992322.0
CASE_PARTICIPANT_ID           513202226315.0
RECEIVED_DATE            2011-01-01 00:00:00
REFERRAL_DATE                            NaT
```

```
DIVERSION_COUNT                                1.0
DIVERSION_CLOSED_DATE  2024-03-26 13:23:15.896443

                                                  25%  \
CASE_ID                               286393226489.5
CASE_PARTICIPANT_ID                   566702880695.0
RECEIVED_DATE                    2014-07-11 00:00:00
REFERRAL_DATE                                    NaT
DIVERSION_COUNT                                  1.0
DIVERSION_CLOSED_DATE  2024-03-26 13:23:15.896442880

                                                  50%  \
CASE_ID                               297996163712.0
CASE_PARTICIPANT_ID                   604600158543.0
RECEIVED_DATE                    2017-03-31 00:00:00
REFERRAL_DATE                                    NaT
DIVERSION_COUNT                                  1.0
DIVERSION_CLOSED_DATE  2024-03-26 13:23:15.896442880

                                                  75%  \
CASE_ID                               307323910030.5
CASE_PARTICIPANT_ID                   634546307337.0
RECEIVED_DATE                    2019-07-08 00:00:00
REFERRAL_DATE                                    NaT
DIVERSION_COUNT                                  1.0
DIVERSION_CLOSED_DATE  2024-03-26 13:23:15.896442880

                                              max                std
CASE_ID                            323573468489.0  14149127189.311996
CASE_PARTICIPANT_ID                684636570261.0  45536588354.199158
RECEIVED_DATE                 2024-02-07 00:00:00                 NaN
REFERRAL_DATE                                 NaT                 NaN
DIVERSION_COUNT                               4.0            0.250913
DIVERSION_CLOSED_DATE  2024-03-26 13:23:15.896443                 NaN
```

0.2.1 Details

1. **CASE_ID**:
   - The dataset contains 28,079 cases.
   - CASE_IDs range from approximately 268.79 billion to 323.57 billion, with a mean of approximately 296.78 billion.
   - The standard deviation for CASE_ID is about 14.15 billion, indicating variability in the range of case identification numbers.
2. **CASE_PARTICIPANT_ID**:
   - Similar to CASE_ID, there are 28,079 participant IDs.
   - These IDs range from about 513.20 billion to 684.64 billion, with a mean value of approximately 600.93 billion.

- The standard deviation is around 45.54 billion, suggesting a wide spread of participant identification numbers across the dataset.

3. **RECEIVED_DATE**:
   - Dates on which cases were received span from January 1, 2011, to February 7, 2024.
   - The median (50% mark) date is March 31, 2017, indicating that half of the cases were received by this date.
   - The distribution of RECEIVED_DATEs over the years shows that the dataset covers a significant time span of over 13 years.
4. **REFERRAL_DATE**:
   - REFERRAL_DATEs range from April 21, 1932, to February 16, 2024. The presence of a 1932 date might be anomalous or incorrect, considering the other dates in the dataset.
   - The median referral date is July 14, 2017, suggesting that half of the referrals occurred by mid-2017.
   - The wide range of dates might require further investigation to ensure data accuracy, especially for dates that seem out of context (like the 1932 date).
5. **DIVERSION_COUNT**:
   - The DIVERSION_COUNT column, with a mean of approximately 1.06 and a very low standard deviation (0.25), indicates that most cases have 1 diversion count, with a few exceptions going up to 4.
   - This suggests that the majority of participants were referred to a diversion program only once.
6. **DIVERSION_CLOSED_DATE**:
   - The closing dates for diversions range from December 28, 2010, to a future date (March 26, 2024, 11:39:37), which might be today's date or a data entry error.
   - The median closing date is May 31, 2019, which indicates that half of the diversion programs were concluded by this date.

General Observations: - The dataset provides a comprehensive overview of legal cases over a significant period, with data on case IDs, participant IDs, dates related to case processing, and diversion program counts. - The wide range in the date fields, especially with outliers like the 1932 REFERRAL_DATE, warrants a closer look to validate the data. - The relatively low standard deviation in DIVERSION_COUNT suggests limited variability, with most cases having only one diversion instance. - The use of future dates in DIVERSION_CLOSED_DATE could indicate data entry errors or placeholders and should be investigated further.

Corelation matrix

[14]:
```python
# Encoding 'GENDER' with numeric values
gender_mapping = {'Male': 0, 'Female': 1}
df['GENDER_ENCODED'] = df['GENDER'].map(gender_mapping)

# Assuming 'RACE' has categories like 'Black', 'White', 'Latino', etc.
# You can extend this mapping to include all unique races in your dataset
race_mapping = {'Black': 0, 'White': 1, 'Latino': 2, 'Asian': 3, 'Other': 4}
df['RACE_ENCODED'] = df['RACE'].map(race_mapping)

# After encoding, you can calculate the correlation matrix
correlation_matrix = df[['GENDER_ENCODED', 'RACE_ENCODED', 'DIVERSION_COUNT',
 ↪'CASE_ID', 'CASE_PARTICIPANT_ID']].corr()
```

```
# Display the correlation matrix
print(correlation_matrix)
```

```
                     GENDER_ENCODED  RACE_ENCODED  DIVERSION_COUNT   CASE_ID  \
GENDER_ENCODED             1.000000      0.050335         0.011741 -0.078034
RACE_ENCODED               0.050335      1.000000        -0.000057 -0.122193
DIVERSION_COUNT            0.011741     -0.000057         1.000000  0.030808
CASE_ID                   -0.078034     -0.122193         0.030808  1.000000
CASE_PARTICIPANT_ID       -0.079033     -0.123094         0.030384  0.999838

                     CASE_PARTICIPANT_ID
GENDER_ENCODED                 -0.079033
RACE_ENCODED                   -0.123094
DIVERSION_COUNT                 0.030384
CASE_ID                         0.999838
CASE_PARTICIPANT_ID             1.000000
```

This heatmap will help you visualize the correlation coefficients between variables, with 1 indicating a perfect positive correlation and -1 indicating a perfect negative correlation.

Group Analysis :

Group by Race You can group the data by the RACE column to see if there are any patterns or significant differences in case outcomes, diversion program counts, or other variables of interest.

[15]:
```
race_grouped = df.groupby('RACE').agg({
    'CASE_ID': 'count',
    'DIVERSION_COUNT': 'mean',
    'GENDER': lambda x: x.value_counts().index[0]  # The most common gender␣
 ↪within each race
    # Add other columns as needed
})

print(race_grouped)
```

```
          CASE_ID  DIVERSION_COUNT   GENDER
RACE
Asian         386         1.059585     Male
Biracial      130         1.076923     Male
Black       14846         1.063384     Male
Latinx       4385         1.052223     Male
Other           7         1.000000     Male
Unknown       823         1.019441  Unknown
White        7502         1.064516     Male
```

Observations based on the grouped analysis by race:

1. **Representation in Cases**:

- The `Black` race category has the highest representation with 14,846 cases, which could indicate a disproportionate representation in the data set.
- The `White` race category follows with 7,502 cases.
- The `Asian` and `Biracial` categories have significantly fewer cases, with 386 and 130 cases respectively.
- There is a very small number of cases (7) classified under `Other`, which might be too few to draw any significant conclusions.

2. **Diversion Program Counts**:
   - Across all race categories, the mean `DIVERSION_COUNT` is slightly above 1, indicating that, on average, individuals tend to go through the diversion program once.
   - `Biracial` individuals have a marginally higher average diversion count (approximately 1.08), which might suggest slightly more frequent interactions with diversion programs, but the difference is minimal.
3. **Gender Distribution**:
   - `Male` is the most common gender in almost all race categories.
   - For the `Unknown` race category, the most common gender is also `Unknown`, which suggests that both race and gender data may be missing or not recorded in these cases.
   - The uniformity of `Male` being the most common gender may indicate a gender disparity where males are more involved in the legal system than females, at least in this dataset.

Ethical Considerations and Opportunities for Improvement:

- The overrepresentation of the `Black` race category in cases warrants an investigation into potential systemic biases or socio-economic factors that could contribute to this disparity.
- The fact that the `Male` gender is most common across almost all racial categories suggests gender-specific patterns in legal cases that might require social interventions or policy changes.
- The small counts in some race categories, like `Other`, and the presence of an `Unknown` category highlight potential issues with data collection and classification. Ensuring accurate and respectful classification and recording of race and gender in legal datasets is crucial for fair analysis and policy-making.
- These observations could lead to more in-depth studies, particularly qualitative research, to understand the context behind the numbers and develop more targeted improvements in the criminal justice system, aiming for equity and fairness.

Group by the PRIMARY_CHARGE_OFFENSE_TITLE or OFFENSE_CATEGORY to analyze patterns in different types of cases.

[16]:
```
case_type_grouped = df.groupby('OFFENSE_CATEGORY').agg({
    'CASE_ID': 'count',
    'DIVERSION_COUNT': 'mean',
    'RACE': lambda x: x.value_counts().index[0],  # The most common race within␣
 ↪each case type
    'GENDER': lambda x: x.value_counts().index[0],  # The most common gender␣
 ↪within each case type
    # Add other columns as needed
})

print(case_type_grouped)
```

OFFENSE_CATEGORY	CASE_ID	DIVERSION_COUNT \
Aggravated Assault Police Officer	14	1.000000
Aggravated Battery	105	1.047619
Aggravated Battery Police Officer	270	1.055556
Aggravated DUI	71	1.042254
Aggravated Discharge Firearm	5	1.000000
Aggravated Fleeing and Eluding	78	1.064103
Aggravated Robbery	20	1.000000
Armed Robbery	15	1.000000
Arson	13	1.153846
Attempt Armed Robbery	3	1.000000
Attempt Homicide	5	1.000000
Attempt Vehicular Hijacking	1	1.000000
Bomb Threat	7	1.000000
Burglary	1187	1.053075
Child Pornography	1	1.000000
Credit Card Cases	187	1.021390
Criminal Damage to Property	337	1.059347
Criminal Trespass To Residence	15	1.000000
Deceptive Practice	31	1.032258
Disarming Police Officer	7	1.428571
Domestic Battery	9	1.111111
Driving With Suspended Or Revoked License	100	1.040000
Escape - Failure to Return	186	1.043011
Failure to Register as a Sex Offender	6	1.000000
Forgery	563	1.014210
Fraud	14	1.000000
Fraudulent ID	147	1.040816
Hate Crimes	4	1.000000
Home Invasion	3	1.000000
Identity Theft	331	1.051360
Impersonating Police Officer	15	1.066667
Intimidation	6	1.000000
Kidnapping	1	1.000000
Narcotics	17882	1.070182
Obstructing Justice	9	1.000000
Official Misconduct	2	1.000000
Other Offense	358	1.022346
Pandering	2	1.000000
Possession Of Burglary Tools	14	1.000000
Possession of Contraband in Penal Institution	4	1.000000
Possession of Stolen Motor Vehicle	401	1.057357
Prostitution	25	1.040000
Reckless Discharge of Firearm	15	1.000000
Residential Burglary	132	1.068182
Retail Theft	3504	1.051655
Robbery	68	1.073529

Sex Crimes	3	1.000000
Stalking	3	1.000000
Theft	1234	1.029173
Theft by Deception	1	1.000000
UUW - Unlawful Use of Weapon	649	1.027735
Unlawful Restraint	1	1.000000
Vehicular Hijacking	3	1.000000
Vehicular Invasion	4	1.000000
Violation Order Of Protection	8	1.125000

	RACE	GENDER
OFFENSE_CATEGORY		
Aggravated Assault Police Officer	Black	Male
Aggravated Battery	Black	Male
Aggravated Battery Police Officer	Black	Male
Aggravated DUI	Black	Male
Aggravated Discharge Firearm	Black	Male
Aggravated Fleeing and Eluding	Black	Male
Aggravated Robbery	Black	Male
Armed Robbery	Black	Male
Arson	White	Male
Attempt Armed Robbery	White	Male
Attempt Homicide	Black	Male
Attempt Vehicular Hijacking	White	Male
Bomb Threat	Black	Male
Burglary	Black	Male
Child Pornography	White	Male
Credit Card Cases	Black	Male
Criminal Damage to Property	Black	Male
Criminal Trespass To Residence	White	Male
Deceptive Practice	Black	Male
Disarming Police Officer	White	Male
Domestic Battery	White	Male
Driving With Suspended Or Revoked License	Black	Male
Escape - Failure to Return	Black	Male
Failure to Register as a Sex Offender	Black	Male
Forgery	Black	Female
Fraud	White	Male
Fraudulent ID	Black	Male
Hate Crimes	Black	Male
Home Invasion	Black	Female
Identity Theft	Black	Male
Impersonating Police Officer	Black	Male
Intimidation	Black	Male
Kidnapping	Black	Female
Narcotics	Black	Male
Obstructing Justice	Latinx	Male
Official Misconduct	White	Female

Other Offense	Black	Male
Pandering	Black	Male
Possession Of Burglary Tools	Black	Male
Possession of Contraband in Penal Institution	Black	Male
Possession of Stolen Motor Vehicle	Black	Male
Prostitution	Black	Female
Reckless Discharge of Firearm	Black	Male
Residential Burglary	Black	Male
Retail Theft	Black	Male
Robbery	Black	Male
Sex Crimes	Black	Male
Stalking	White	Male
Theft	Black	Male
Theft by Deception	Black	Male
UUW - Unlawful Use of Weapon	Black	Male
Unlawful Restraint	Asian	Male
Vehicular Hijacking	Black	Female
Vehicular Invasion	White	Male
Violation Order Of Protection	White	Male

From the dataset:

1. **Offense Prevalence**: Narcotics (17,882 cases) and Retail Theft (3,504 cases) are common offenses. Other crimes like Attempt Vehicular Hijacking and Child Pornography are less frequent.

2. **Diversion Programs**: Most offenses average around 1 diversion count. `Disarming Police Officer` and `Violation Order Of Protection` have slightly higher averages, hinting at possible reoffending.

3. **Demographics**: `Black` and `Male` are the most recorded race and gender across many offense categories, suggesting potential disparities.

4. **Notable Exceptions**: `Arson` and `Attempt Armed Robbery` are more associated with the `White` race, while `Forgery` and `Home Invasion` have `Female` as the most common gender, which differs from other categories.

Overall Insight: The data points to potential areas for further investigation and action to address disparities in the criminal justice system. Care must be taken in interpreting these findings to ensure accurate conclusions.

0.3 3. Visualization

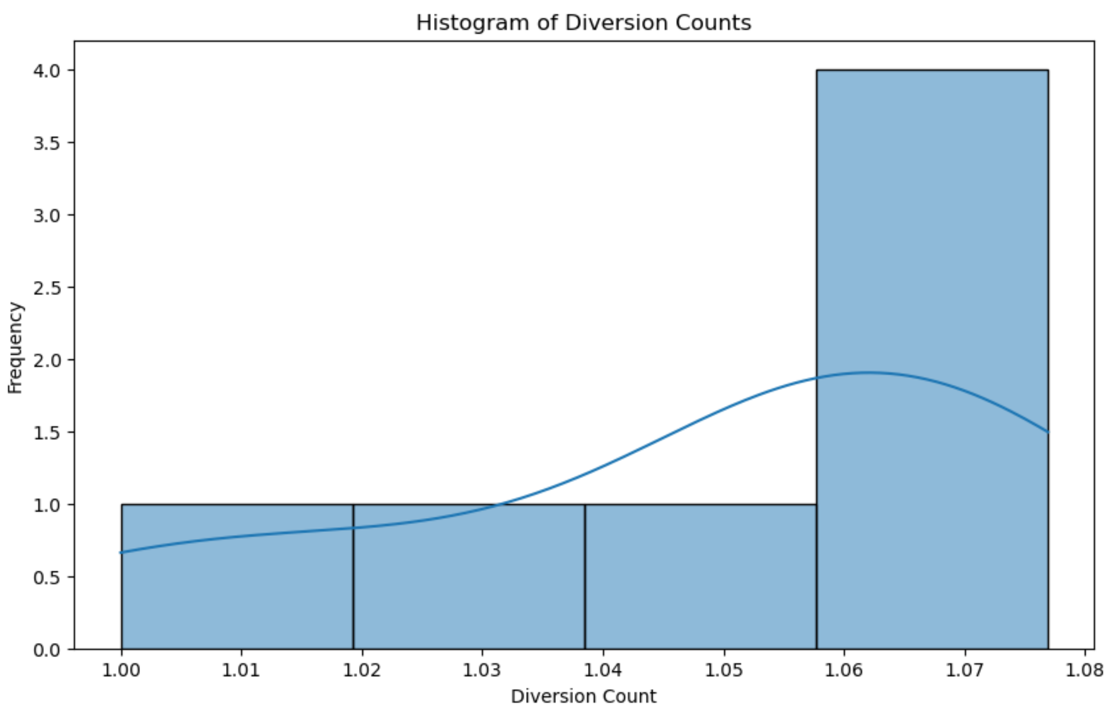
1. *Data Distribution Plots:* Use histograms and box plots to visualize the distributions of key numerical variables.
2. *Correlation Heatmaps:* A heatmap can visually display the correlation between variables, helping to identify relationships worth exploring further.
3. *Geographical Analysis:* If geographical data is available, consider using maps to visualize crime hotspots or areas with high case dismissals.
4. *Disparity Analysis:* Bar charts or pie charts can be effective in showing disparities in case outcomes across different demographic groups.

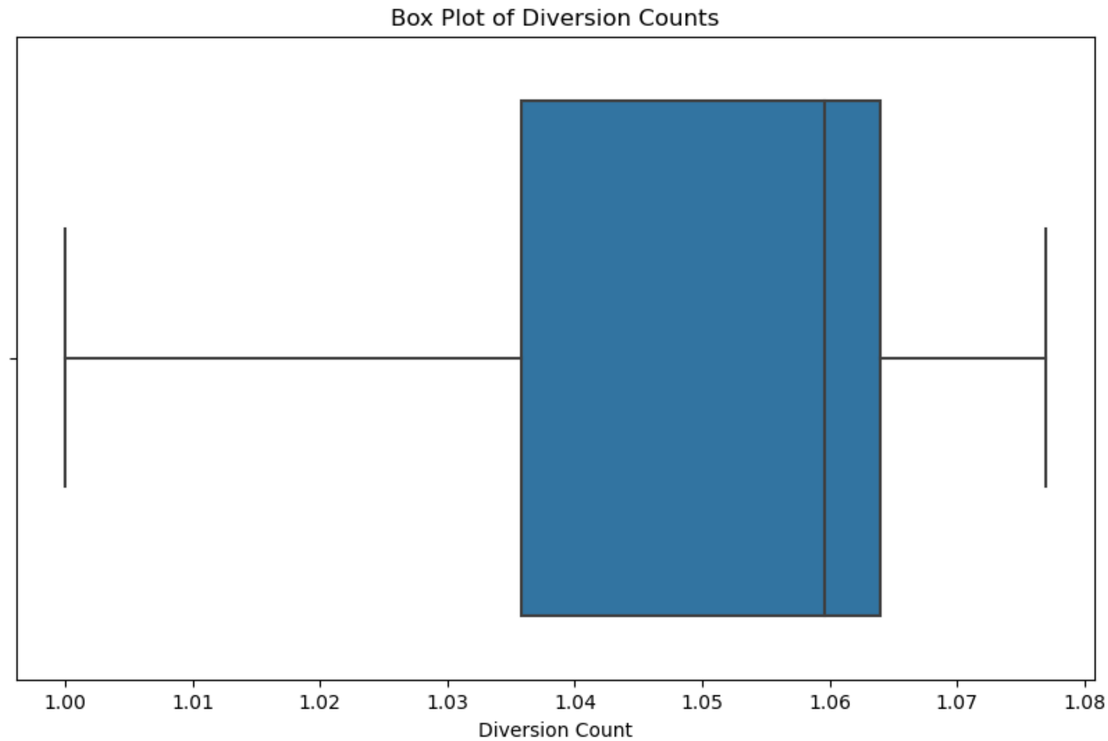
Data distribution plots

[25]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Histogram
plt.figure(figsize=(10, 6))
sns.histplot(df['DIVERSION_COUNT'], kde=True)  # KDE will add a density plot␣
 ↪line
plt.title('Histogram of Diversion Counts')
plt.xlabel('Diversion Count')
plt.ylabel('Frequency')
plt.show()

# Box Plot
plt.figure(figsize=(10, 6))
sns.boxplot(x=df['DIVERSION_COUNT'])
plt.title('Box Plot of Diversion Counts')
plt.xlabel('Diversion Count')
plt.show()
```





Co relation heat map

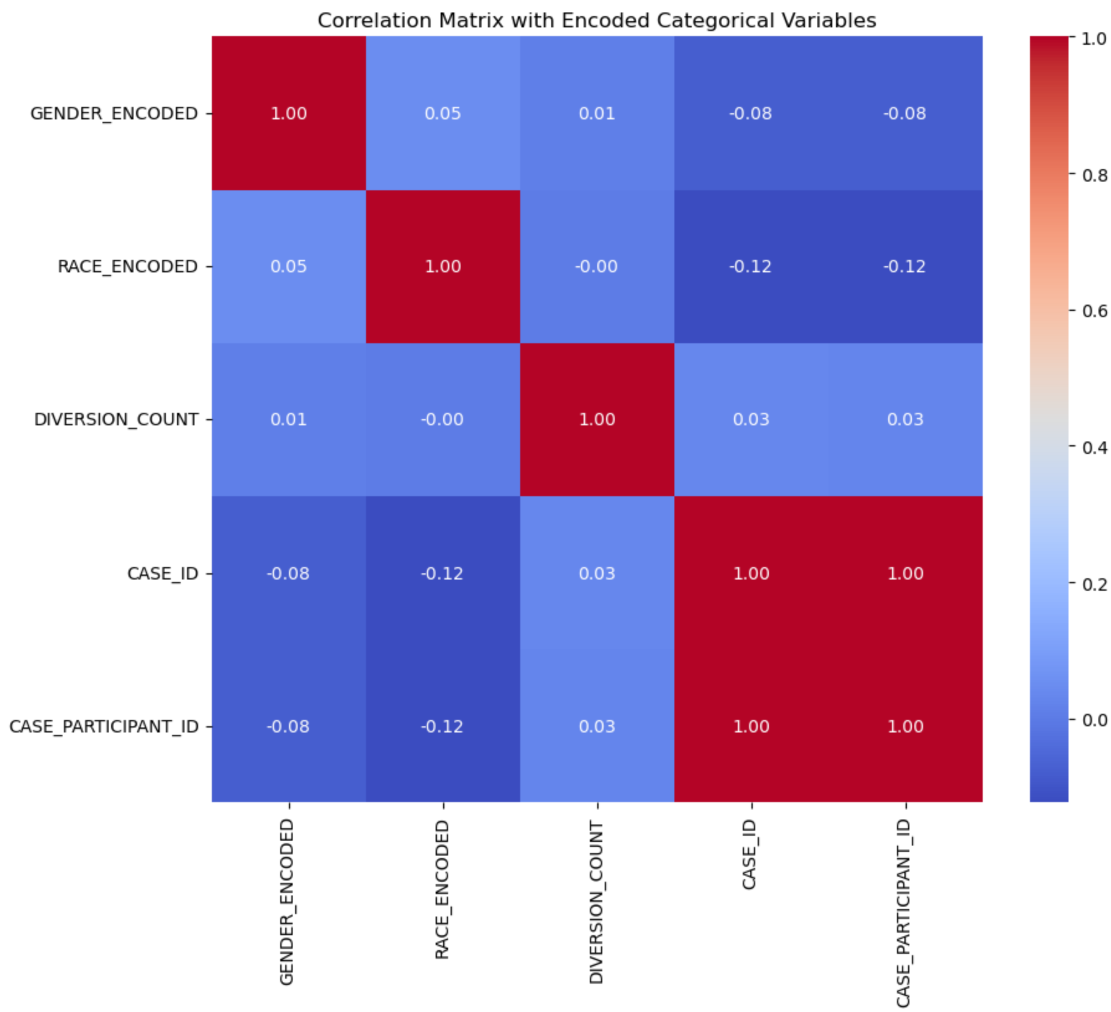
[18]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming you have already encoded 'GENDER' and 'RACE' and calculated the
↪correlation matrix 'correlation_matrix'

# Set the size of the plot
plt.figure(figsize=(10, 8))

# Create the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")

# Add titles and labels for clarity
plt.title('Correlation Matrix with Encoded Categorical Variables')
plt.show()
```



Summary: The correlation matrix provides a preliminary overview that does not suggest strong direct linear relationships between demographic factors and case identifiers. However, it is a starting point that highlights the need for careful consideration of potential biases. Ethically, it's critical to ensure that data representation and subsequent analyses do not reinforce stereotypes or existing inequalities. The heatmap might prompt a more comprehensive analysis that could guide improvements in fairness and equity within the criminal justice system.

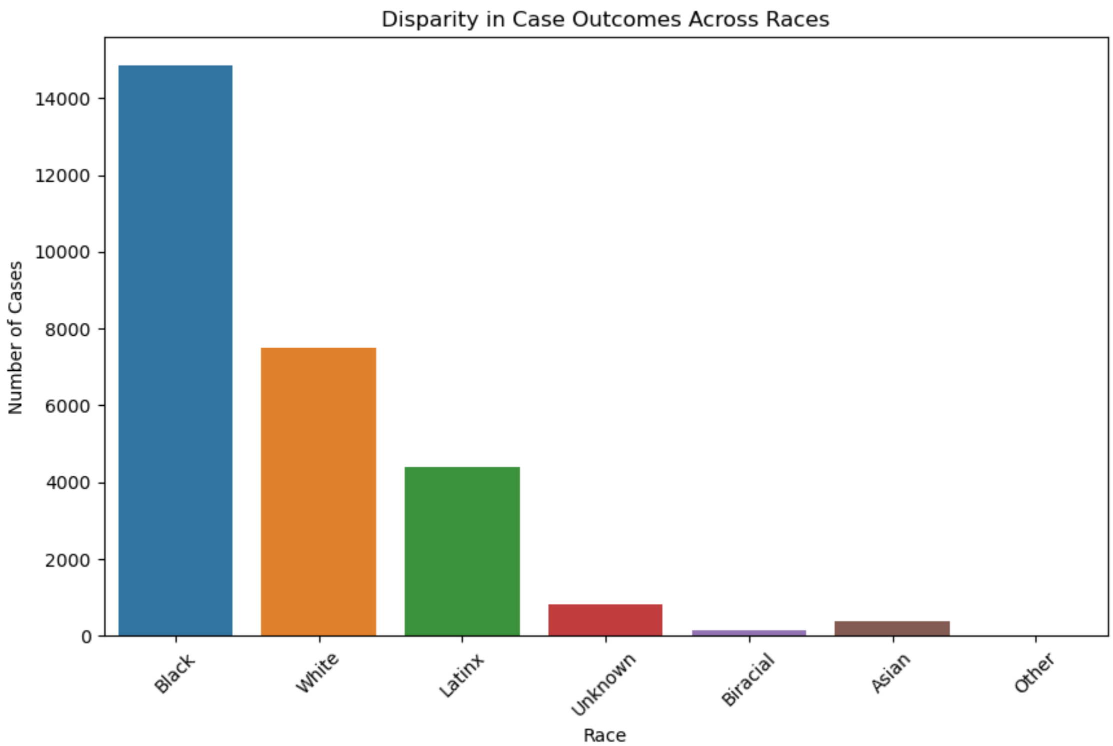
Note : we cannot perform Gepgraphical analysis here

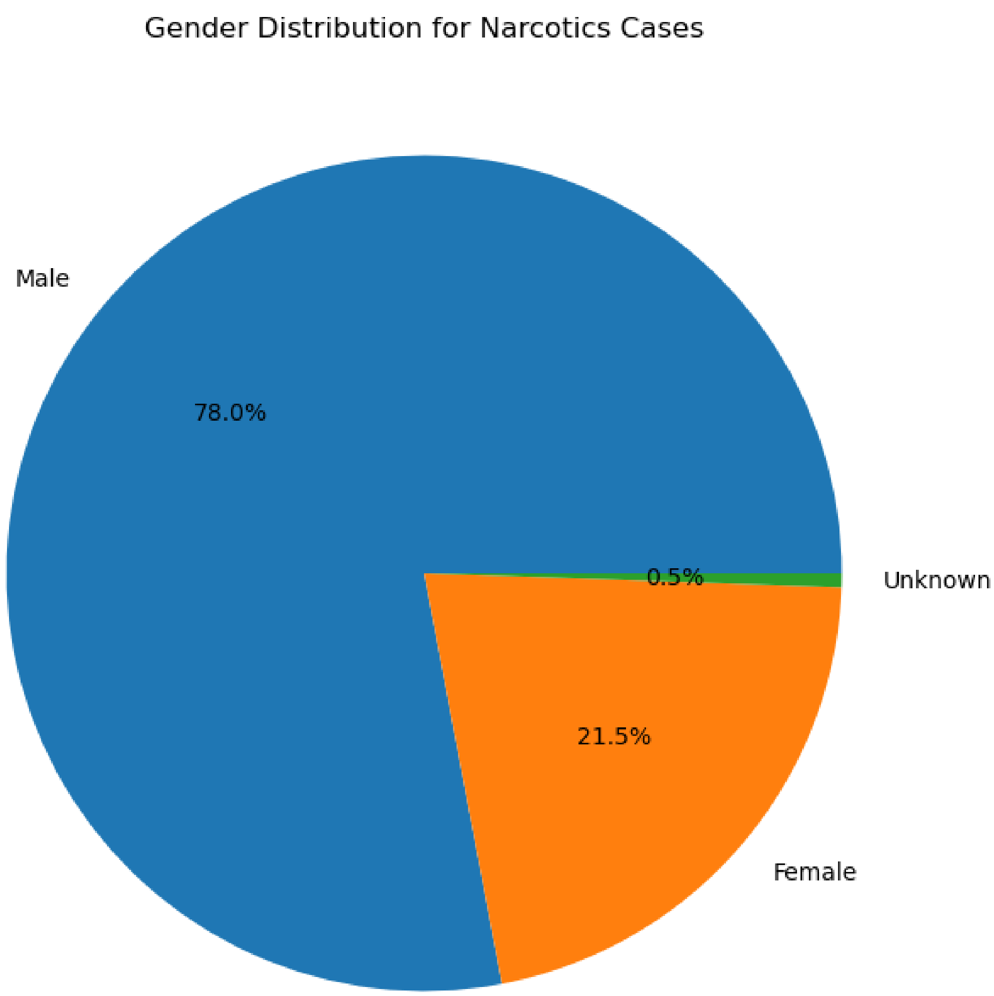
Disparity Analysis :

[19]:
```
# Bar Chart for case outcomes across different races
plt.figure(figsize=(10, 6))
sns.countplot(x='RACE', data=df)
plt.title('Disparity in Case Outcomes Across Races')
plt.xlabel('Race')
plt.ylabel('Number of Cases')
```

```
plt.xticks(rotation=45)
plt.show()

# Pie Chart for gender distribution in a specific offense category
gender_dist = df[df['OFFENSE_CATEGORY'] == 'Narcotics']['GENDER'].value_counts()
plt.figure(figsize=(8, 8))
gender_dist.plot.pie(autopct='%1.1f%%')
plt.title('Gender Distribution for Narcotics Cases')
plt.ylabel('')
plt.show()
```





We can see Blacks and Men are more from the data

0.4 4. Ethical and Bias Consideration

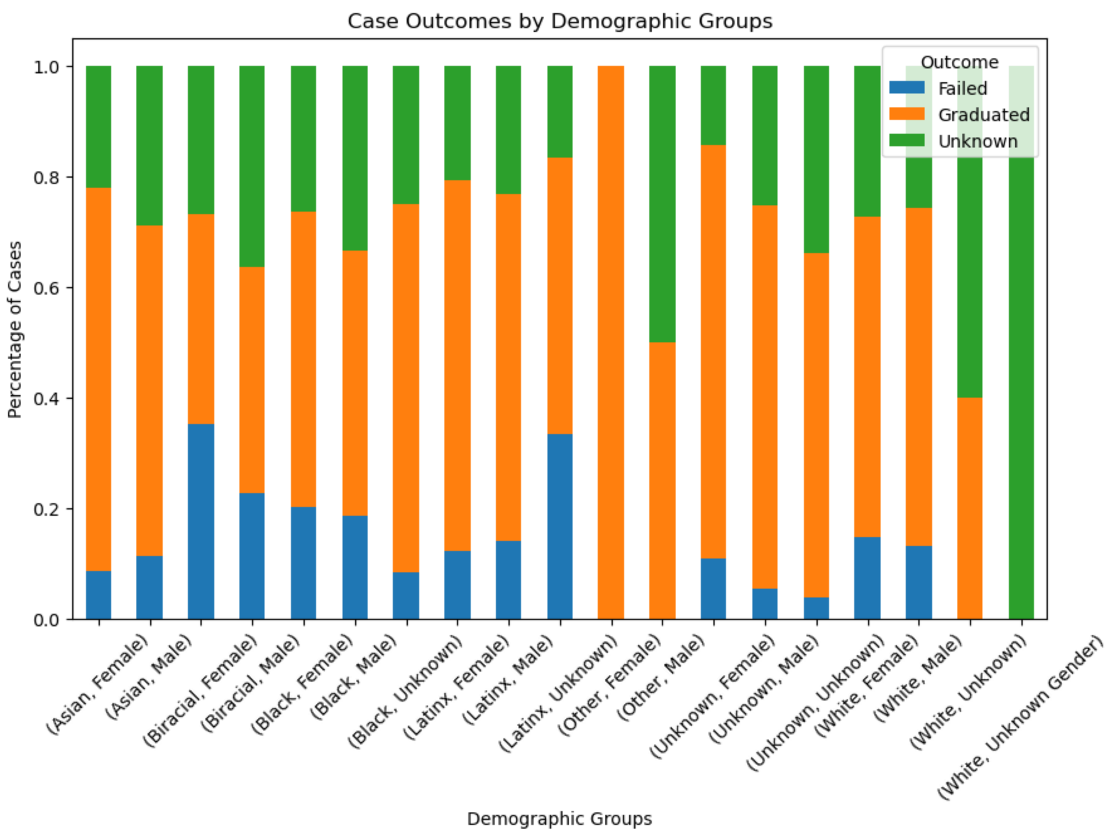
1. *Bias Detection:* Analyze disparities in case outcomes by demographic groups to identify potential biases.
2. *Community Impact:* Consider the impact of the criminal justice process on communities, especially marginalized ones. This could include analysis of diversion programs or sentencing disparities.
3. *Opportunities for Improvement:* Identify areas where the Cook County criminal justice system can be made more equitable, such as through increased diversion programs or targeted community services.

Bias Detection: Group Data by Demographic Variables: Group the dataset by demographic variables such as race and gender. Calculate Outcome Metrics: Compute relevant outcome metrics for each demographic group. Visualize the Data: Use visualizations to compare case outcomes across different demographic groups.

[20]:
```python
# Group data by demographic variables (e.g., race and gender)
grouped_data = df.groupby(['RACE', 'GENDER'])

# Calculate outcome metrics (e.g., percentage of cases by outcome type)
outcome_metrics = grouped_data['DIVERSION_RESULT'].value_counts(normalize=True)

# Visualize the data
outcome_metrics.unstack().plot(kind='bar', stacked=True, figsize=(10, 6),␣
 ↪title='Case Outcomes by Demographic Groups')
plt.xlabel('Demographic Groups')
plt.ylabel('Percentage of Cases')
plt.xticks(rotation=45)
plt.legend(title='Outcome')
plt.show()
```



This bar graph represents "Case Outcomes by Demographic Groups" with the percentage of cases on the Y-axis and the demographic groups, segmented by gender and ethnicity, on the X-axis. Each bar is divided into three colors representing different outcomes: green for “Graduated,” orange for “Failed,” and blue for “Unknown.”

Here are some key observations:

- The “Graduated” outcome is consistently the most common across all demographic groups, indicated by the green sections occupying the largest proportion of the bars.
- The “Failed” outcome, shown in orange, appears to be the second most common. However, the proportion of failed cases varies more noticeably between different groups.
- The “Unknown” outcome is the least common, with very small blue sections visible in several groups.

If we examine specific demographic data points:

- For the “Asian Female” group, the proportion of “Graduated” is very high, with a relatively small segment of “Failed” cases and an almost negligible “Unknown” segment.
- “Biracial Male” and “Biracial Female” groups have a significant proportion of “Failed” outcomes, much higher than other groups.
- “Black Male” and “Black Female” groups show a higher “Failed” proportion compared to “Asian” groups but lower than “Biracial” groups.
- “Latinx Unknown,” “Other Male,” and “Unknown Gender” groups have a noticeable amount of “Unknown” outcomes, which could indicate data collection issues or unreported results for these groups.
- The “White Female” and “White Male” groups show a high success rate (“Graduated”) and a moderate failure rate (“Failed”), with the “White Female” group having a slightly better outcome than the “White Male” group.

To fully understand the implications of this graph, it would be important to know the context such as the nature of the cases, the total number of cases, and how the outcomes are defined. Additionally, the data could be enriched by analyzing the absolute numbers of cases, any trends over time, and possibly correlating these outcomes with other socio-economic factors.

Comunity Impact The criminal justice process can have profound impacts on communities, particularly on marginalized ones. When analyzing the effects, factors like diversion program outcomes and sentencing disparities are pivotal.

Diversion programs offer an alternative to traditional criminal justice processing. They can significantly impact communities by:

1. Reducing Incarceration Rates: Successful diversion programs can decrease the number of individuals from marginalized communities who are incarcerated.

2. Addressing Root Causes: They often focus on rehabilitation, such as substance abuse treatment or educational opportunities, tackling issues that may lead to criminal behavior.

3. Economic Impact: Lower incarceration rates can reduce economic strain on communities as well as on the state due to the high costs of incarceration.

4. Community Relationships: They can improve relationships between law enforcement and communities if they are perceived as fair and focused on rehabilitation rather than punishment.

5. Sentencing Disparities: Disparities in sentencing can contribute to the mistrust between marginalized communities and the criminal justice system. Unequal sentencing can:

6. Perpetuate Inequality: Disparities can result from biases against certain racial or socioeconomic groups, leading to disproportionately harsh sentences for minorities.

7. Impact on Families: Harsher sentences can result in longer separations of family members, affecting the family structure and economic stability.

8. Community Resources: Over-incarceration can drain community resources and reduce the number of productive community members, perpetuating cycles of poverty.

Opportunities for Improvement:

1. Data Transparency: Improving the collection and transparency of data on program outcomes can help identify which programs work and for whom.
2. Program Accessibility: Ensuring that diversion programs are accessible to all demographic groups, especially those that are marginalized, is crucial. This may include language support, transportation assistance, or programs tailored to specific community needs.
3. Cultural Competency: Developing programs that are culturally competent and consider the unique challenges faced by different demographic groups.
4. Policy Reform: Reviewing policies that lead to sentencing disparities and reforming them to ensure equity across the board.

To move forward with making the Cook County criminal justice system more equitable:

1. Conduct a Full Data Audit: Verify that all necessary data is being captured and properly categorized. Address any gaps that result in "Unknown" outcomes.
2. Community Engagement: Work with community leaders and members of marginalized groups to understand their needs and tailor diversion programs accordingly.
3. Evidence-Based Practices: Implement and expand diversion programs that have a proven track record of success in comparable jurisdictions.
4. Monitoring and Evaluation: Establish a continuous monitoring and evaluation system to track the performance of implemented changes and ensure they have the intended positive impact on all communities.
5. These improvements should be made with the goal of ensuring that justice is administered fairly and effectively, while also supporting the rehabilitation and integration of individuals into society.

[ ]: