

**ALY 6110 Data Management and Big Data**

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Module 6 Final Project – NYPD Crime Analysis**

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Introduction

In one of the most complicated urban environments in the world, the New York Police Department (NYPD) is burdened with the responsibility of maintaining law and order over the city. A public and comprehensive record of law enforcement activity across the five boroughs of New York City is provided by the New York Police Department's (NYPD) Arrest Data, which is gathered throughout the year. This dataset not only record the demographic information of the individuals who were arrested, such as their age, gender, and race, but it also records the particular circumstances surrounding each arrest, such as the location and the charges that were brought against the individual. It is essential to have such data in order to analyze patterns in criminal activity, evaluate techniques employed by law enforcement, and improve legislation pertaining to public safety.   
  
This project is to do an exhaustive exploratory data analysis (EDA) of the arrest data collected by the New York Police Department (NYPD) in order to identify patterns and trends in arrests that have occurred throughout New York City for the current year. In addition, the research intends to construct predictive models that classify individuals according to their gender by utilizing a variety of variables that are contained inside the dataset. This particular kind of predictive modeling is extremely helpful for predictive policing and provides priceless insights into the demographic trends that are associated with criminal activity.

**Data Acquisition and Preliminary Exploration**

Initial Data Setup

The project starts with the gathering of the NYPD Arrest Data, which is then put into a pandas DataFrame. This is done in order to facilitate Python's reliable data manipulation and analysis capabilities. Among the first steps in the process of data exploration are the following:   
  
A look at the first few rows to get a better understanding of the structure and the different kinds of data that were recorded.   
The process of identifying numerical and categorical variables by reviewing the different forms of data and summary statistics.   
The process of identifying and correcting missing values across several columns, using techniques such as mode imputation for numerical data and classifying missing entries as 'UNKNOWN' for categorical data in order to preserve the integrity of the data.

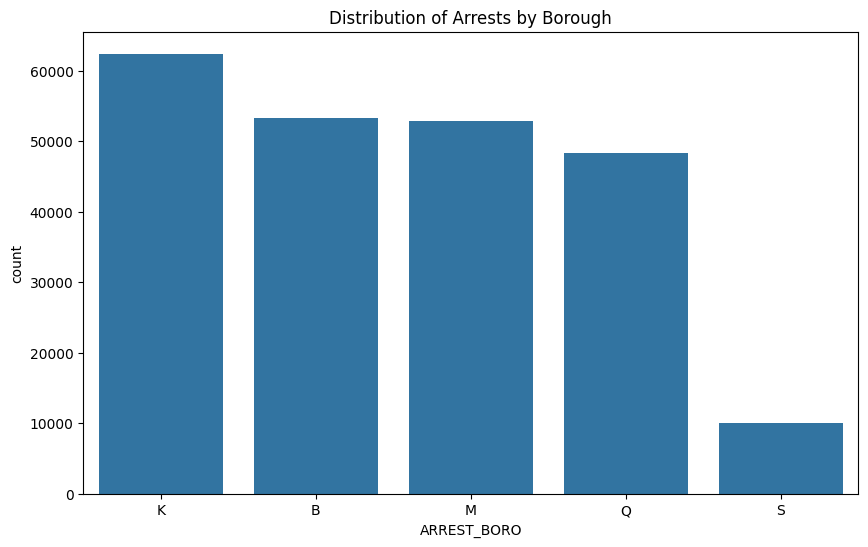
Data Cleaning and Transformation

Data quality evaluations found difficulties that are typical of real-world datasets. These concerns included missing values and discrepancies in several critical columns, such as 'PD\_CD' (which stands for "Police Department codes"), 'KY\_CD' (which stands for "offense key codes"), and 'LAW\_CAT\_CD' (which stands for "legal categorization of crimes), among others.

To handle missing values, statistical approaches such as mode imputation were utilized to fill in missing data points for the 'PD\_CD' and 'KY\_CD' variables. 'UNKNOWN' was the label that was placed under the 'LAW\_CAT\_CD' heading for categories that did not have defined legal classifications.   
  
'ARREST\_YEAR', 'ARREST\_MONTH', 'ARREST\_DAY', and 'ARREST\_DAYOFWEEK' are some of the new features that have been extracted from 'ARREST\_DATE' in order to provide a more accurate level of analytical granularity.

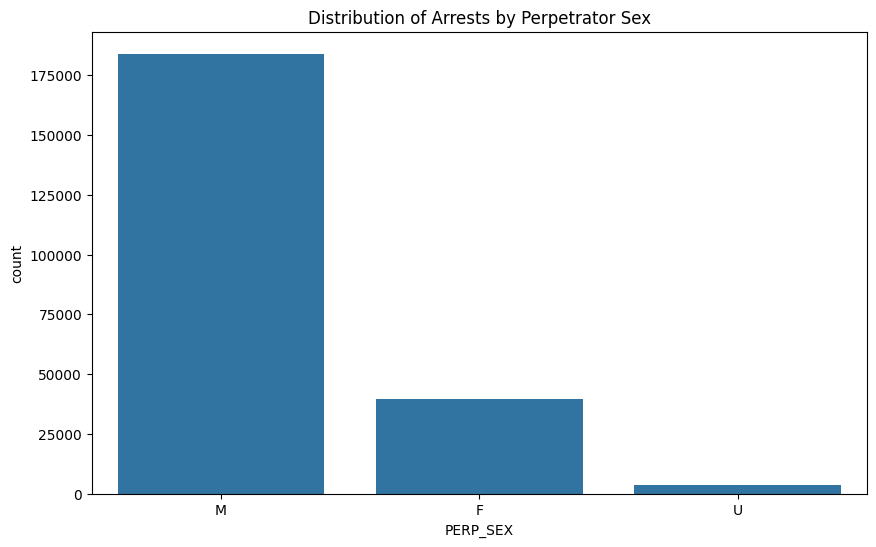
Exploratory Data Analysis

The New York Police Department (NYPD) keeps a comprehensive dataset of all arrests made throughout the city. This dataset contains information that is rich in detail regarding the demographics of the individuals who were arrested as well as the geographic distribution of these episodes. Utilizing visualization as a powerful tool is essential in order to gain meaningful insights from this collection. This section of the paper provides specifics regarding the implementation and outcomes of the visualization of the distribution of arrests by borough, perpetrator sex, and perpetrator race using the New York Police Department's arrest data.   
  
Implementing Visualization Methods   
Bar plots were applied in order to conduct an analysis of the distribution patterns. In order to compare quantities across a variety of categories, bar plots are an excellent choice because they offer a plain and uncomplicated visual depiction of the provided data. The following three important visualizations were developed with the help of the Matplotlib and Seaborn libraries in Python:   
  
**Arrests are broken down according to the Borough.**



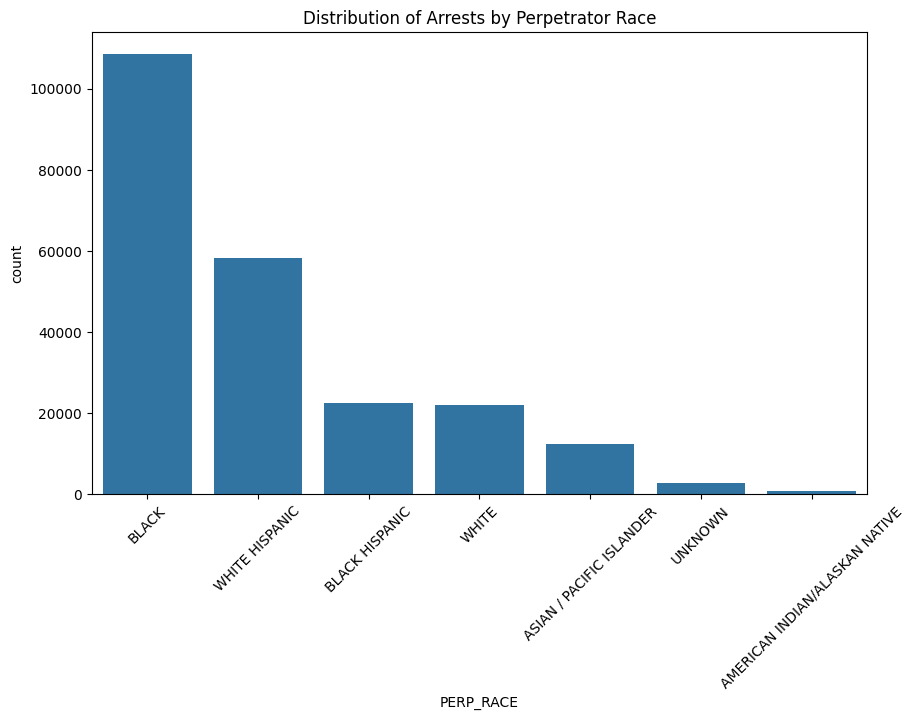
The bar chart offers a clear representation of the distribution of arrests among the five boroughs that make up New York City from the perspective of the analysis. The biggest number of arrests is seen in the boroughs of Brooklyn (K) and Manhattan (M), with the Bronx (B) coming in somewhat close after. The number of arrests in Queens (Q) is slightly lower than the number of arrests in Staten Island (S), which is much lower than the number of arrests in other boroughs. It is possible that this distribution is a reflection of the population density and urban dynamics of each borough, with Brooklyn and Manhattan being more densely populated and busy in terms of both residential and commercial activity.   
  
The implications of this include that having an understanding of the distribution of arrests by borough can assist policymakers and law enforcement agencies in more effectively allocating resources at their disposal. In order to reduce the amount of crime that occurs in boroughs that have higher arrest rates, it may be necessary to implement more expansive community policing initiatives, social services, and

**The Distribution of Arrests Based on the Sexual Orientation of the Offender**



The analysis reveals that the bar chart presents the distribution of arrests in a manner that is grouped according to the gender of the accused. Due to the fact that the group labeled 'U' (unknown) shows minimum numbers, it is clear that males (M) are arrested a great deal more frequently than females (F). The significant gap between the two groups shows that there may be behavioral, societal, or economic factors that influence the chance of males getting involved in activities that result in arrests.   
  
Implications: The considerable bias toward male arrests may encourage more inquiry into the core causes, which may include economic disparities, a lack of career prospects, or educational chances, as well as the development of tailored interventions geared to address these concerns. Furthermore, this understanding may encourage the development of gender-specific initiatives that aim to prevent criminal activities.

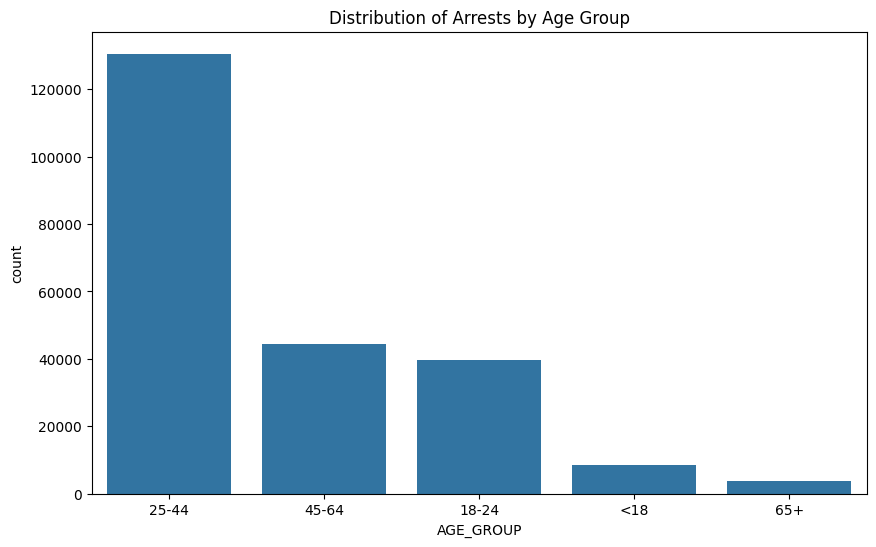
**The Distribution of Arrests Based on the Race of the Offender**



This visual representation illustrates the racial breakdown of arrests, revealing that those of African American and Hispanic descent had a higher incidence of arrests in comparison to individuals of other racial groupings on average. The 'Black' category has the highest number of arrests, followed by the 'White Hispanic' category and the 'White' category. There are social, economic, and probably even structural elements that contribute to these differences, and this distribution raises questions about this distribution.   
  
The implications of this are that the data on arrests by race can be extremely important in addressing the possibility of bias in the practices of law enforcement. This demonstrates the importance of implementing community involvement programs and possibly making improvements to enforcement techniques in order to guarantee fairness and justice for all demographics of the population. Furthermore, this could result in conversations and policies that are geared at addressing the fundamental reasons behind the racial disparities that exist in terms of arrests and criminal activity.

**The Distribution of Arrests Based on the Race of the Offender**

To gain valuable insights on which age groups are more frequently involved in occurrences that result in arrests, it is essential to have a comprehensive understanding of the age demographics of individuals who have been arrested by the New York Police Department (NYPD). To properly customize community outreach programs, youth interventions, and other social services, such an analysis can be of substantial use. The purpose of this portion of the study is to use the NYPD Arrest Data to create a visual representation of the distribution of arrests according to age group.   
To facilitate the visualization of the distribution of arrests across various age groups, a bar plot is utilized. When it comes to this form of categorical comparison, bar charts are particularly useful since they provide a plain and obvious visual comparison of numerical data across a variety of categories.



The bar chart presents arrests that are grouped according to age groupings. The analysis reveals that the bulk of arrests involve those who are between the ages of 25 and 44, followed by those who are between 45 and 64 and those who are between 18 and 24. Individuals under the age of 18 and those beyond the age of 65 have a relatively lower rate of arrests. With this information, it appears that the prime adult population is more likely to participate in activities that result in arrests.   
  
Implications: The fact that arrests are more common among younger adults may be an indication of certain socioeconomic situations or lifestyle variables that are widespread in this age segment. It is possible that local law enforcement authorities and social service organizations may concentrate their efforts on educational programs, job training, and other preventative measures that are aimed at these age groups. By gaining an understanding of the age-related trends in arrests, community policing measures can be tailored to lessen the number of future events, which is another benefit of this understanding.

The visual analysis of arrest data from the New York Police Department across a variety of categories, including borough, gender, ethnicity, and age, provide essential insights that may be used to inform law enforcement methods that are more successful and equitable. Each graph not only provides a factual portrayal of arrests, but it also serves as a beginning point for a more in-depth investigation into the dynamics of crime and justice in New York City. This investigation has the potential to guide improvements in community relations, adjustments to legislation, and resource allocation.

**Data Preprocessing and Feature Engineering**

An overview   
A significant amount of success in data analysis and predictive modeling is dependent on the meticulous preprocessing of data and the engineering of features. As part of the New York Police Department's Arrest Data project, this phase entails cleaning the dataset, extracting useful features, lowering the dimensionality of the data, and preparing the data for subsequent modeling. Below, we will have a look at the processes that were utilized to preprocess the data and engineer features, both of which are essential for improving the predictive models' performance and their ability to be interpreted.  
  
Purpose and Benefits   
  
It is possible for errors to occur during data manipulation or for there to be challenges in appropriately referencing these columns in the code. Cleaning Column Names eliminates any unintentional leading or trailing spaces that may be present in column names.   
Making Certain of Consistency: Contributes to the facilitation of consistent access to DataFrame columns and helps to prevent typical mistakes that are caused by column names that are not formatted correctly.  
  
Converts the 'ARREST\_DATE' from a string format to a datetime object, which enables more complex date-time manipulations and feature extraction. This is part of the enhancement of date information.  
Fresh Temporal Characteristics: This function takes the date of the arrest and extracts the year, month, day, and day of the week. In the context of time series analysis, the identification of trends, and the enhancement of the model's capacity to forecast outcomes based on seasonal and weekly patterns, these temporal aspects might be of crucial importance.  
  
Reducing the complexity of the data by deleting columns that are not useful for the analysis or predictive modeling is what is meant by the term "simplifying the model." This has the potential to reduce overfitting and improve the generalizability of the model.   
Increasing Focus: This feature enables the study to concentrate on variables that have a greater influence, without the noise that is caused by data points that are less significant.  
  
  
Controlling Creating categorical data involves converting categorical variables into a format that can be submitted to machine learning algorithms. This is accomplished by expanding each categorical variable into a series of binary variables, which are represented by the numbers 0 and 1.   
Keeping away from the Dummy Variable Trap: Through the elimination of the first category, which may be deduced from the other categories, the drop\_first=True parameter contributes to the reduction of multicollinearity. This, in turn, makes it possible to have model coefficients that are more stable and interpretable.   
  
It is essential to complete this step of preprocessing and feature engineering in order to establish a solid foundation for analytical work. It is ensured that subsequent data analysis and machine learning modeling will be constructed on data that is clean, relevant, and effectively represented by the project. This is accomplished by meticulously cleaning the dataset, extracting useful date-based characteristics, simplifying the data structure, and appropriately encoding categorical variables. It is vital to follow these procedures in order to derive relevant insights and accurate predictions from the arrest data collected by the New York Police Department (NYPD). This will ultimately help with making better educated decisions and allocating resources within law enforcement and public safety applications.

**Evaluation of Predictive Models for NYPD Arrest Data**

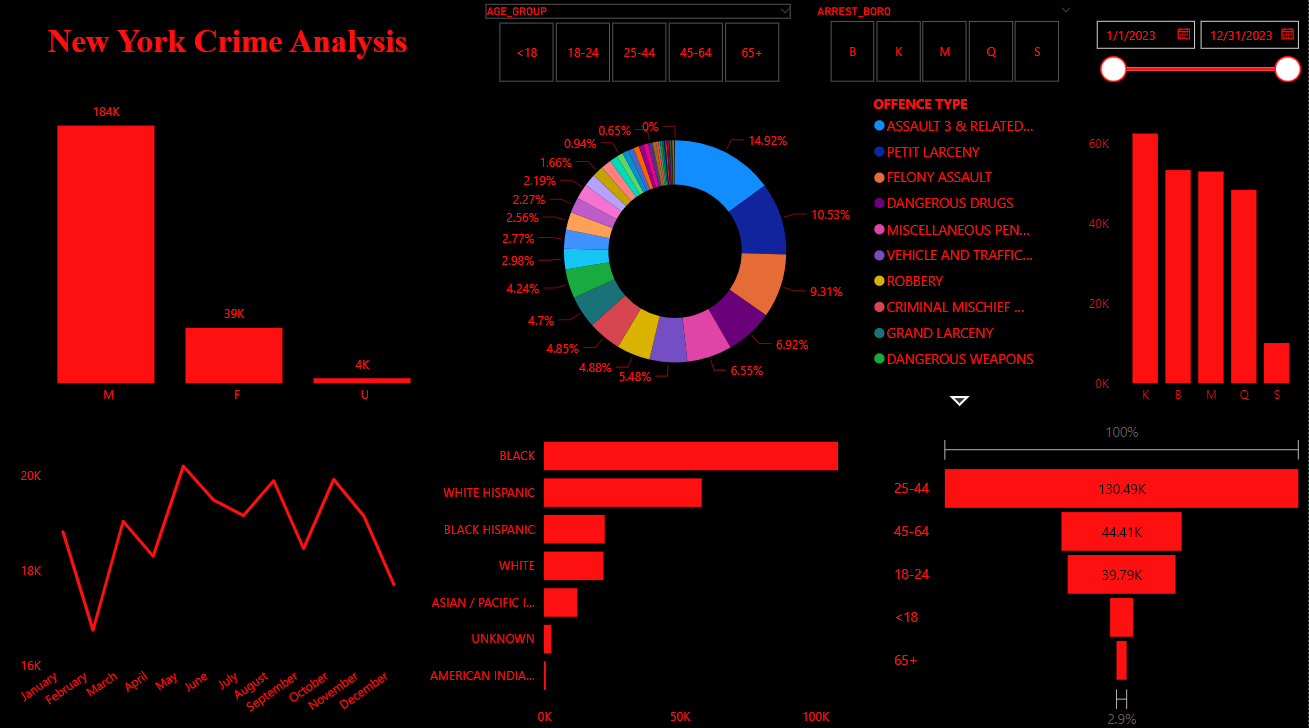
Logistic Regression and Random Forest Classifier are two examples of predictive models that have been implemented with the intention of predicting the gender of individuals who have been arrested in New York City. The findings of this implementation have been very informative. The purpose of this section is to conduct an in-depth examination of the performance of the models based on the testing dataset.   
  
Evaluation of the Model's Performance   
Two different models, namely Logistic Regression and Random Forest Classifier, were examined and evaluated. The accuracy, precision, recall, and F1-scores of these models were computed in order to evaluate how well they were able to predict the gender of the individuals that were arrested.   
  
Evaluation of the Accuracy   
Achieved an accuracy of roughly 82.45% with the execution of logistic regression.   
With an accuracy of around 83.43%, the Random Forest Classifier demonstrated a somewhat greater level of achievement.

The results of this study reveal that the prediction performance is quite excellent, particularly when it comes to tasks involving binary classification. When compared to the more straightforward Logistic Regression model, the Random Forest model's capacity to handle non-linear connections and interactions between features gives it an advantage. This is supported by the fact that the Random Forest model has a greater accuracy.   
  
Reports on Classification in Complete Detail   
The categorization reports offer a more in-depth understanding of the performance of each model across the two categories that are represented by the gender of the individuals: female (0) and male (1).   
  
The report on the classification of logistic regression   
Achieving Accuracy for Females (0): Particularly noteworthy is the fact that the model did not accurately predict any female classes, as demonstrated by the precision and F1-score values of neither. Taking into consideration this finding, it appears that the model, in its current configuration, has a tendency to anticipate the majority class, which is male.   
A high level of precision (82%) and a recall of one hundred percent, which led to an F1-score of ninety percent for males were achieved. The results of this demonstrate that the model is successful in identifying male cases, but it completely fails to identify female cases.   
Report on the Random Forest Classification Systems   
Achieving Accuracy for Females (0): Improvements in performance, included a recall rate of 20% and a precision rate of 58%, which resulted in an F1 score of 30%. In comparison to Logistic Regression, it demonstrates some capability in detecting female instances, despite the fact that it is not as effective as one would hope.

Precision for Males (1): Exhibited outstanding precision (85%) and a recall of 97%, with an F1-score of 91% with a score of 91%. The performance of this model is comparable to that of Logistic Regression; however, it is more balanced across classes and performs well with the male class.   
Concerns and Cautionary Statements   
Concerns have been raised over the capability of the Logistic Regression model to forecast the minority class (Female), as indicated by the UndefinedMetricWarning that was obtained throughout the evaluation. Since the model does not anticipate the female class in any instance, this problem arises. As a consequence, the accuracy and F1-scores for this class are divided by zero, which results in the division by zero.   
  
Considerations and Suggestions for the Future   
According to the findings of the research, there is a considerable imbalance in the models' capacity to predict different classes, with a large bias towards predicting men. This bias is likely a reflection of the imbalance that exists in the training dataset, which is dominated by male observations.   
  
Enhancement of the Model In order to more effectively manage class imbalances, it is necessary to either make modifications to the model or investigate alternate ways. It is possible that the results could be improved by employing approaches such as SMOTE (Synthetic Minority Over-sampling Technique), altered class weights, or more complex ensemble methods.   
  
Feature Reassessment: Reevaluating the features that were utilized for training and maybe creating additional features have the potential to assist in improving the models' sensitivity to the minority class.   
  
Additional Testing and Validation: In order to improve the accuracy and fairness of the models, it is recommended that continuous testing be conducted using a variety of parameter settings and validation methods simultaneously.   
  
Conclusion   
The models exhibit strong predictive ability, notably in determining the class that constitutes the majority (male). The severe underperformance in predicting females, on the other hand, offers a potential subject for additional research and development. For the purpose of building predictive policing techniques that are both fair and successful, and that serve the varied population of New York City in an equitable manner, it is essential to address these problems.

**Overview of the New York Crime Analysis Dashboard**

New York City's Crime Analysis Dashboard is a complete visual representation of crime statistics derived from the arrest data collected by the New York Police Department. The purpose of this dynamic tool is to provide stakeholders with a comprehensive picture of crime patterns, demographic breakdowns, and trends over the course of time. A number of different components of the data are presented in a style that is simple to understand thanks to the dashboard, which makes use of a combination of bar charts, line graphs, and pie charts.

  
  
Important Characteristics of the Dashboard Arrests according on Gender:   
  
The bar chart prominently illustrates the distribution of arrests by gender, demonstrating a large disparity between the numbers of males and females arrested, with males constituting the overwhelming majority of arrests. The bar chart indicates that there is a significant gender gap in the number of arrests. This image aids in highlighting probable gender-specific trends in criminal activity or the focus of law enforcement.

Arrests According to Age Group:   
A classification of arrests according to age reveals that the majority of arrests make use of persons who fall within the age range of 25 to 44 years old. This information is essential for determining which age demographics are more likely to be involved in criminal activities and for focusing interventions to effectively target those demographics.

The Patterns of Arrests Over Time:   
The line graph that follows the number of arrests made each month offers a glimpse into the patterns and shifts that have occurred throughout the year. The identification of seasonal patterns or the evaluation of the efficacy of crime prevention initiatives that are deployed throughout the year could yield useful information from this.

Assaults by Municipality:   
This bar chart provides a breakdown of arrests according to borough, highlighting places that have greater crime rates and possibly reflecting different degrees of police involvement or community crime profiles.

Assaults Based on Race:   
A bar chart is used to illustrate the racial distribution of arrests, which provides a direct and striking representation of the racial discrepancies that exist within arrest statistics. These kinds of statistics are essential for having conversations about racial prejudice in police and for designing policies that are tailored to the needs of individual communities.

Different kinds of offenses include:   
Both the pie chart and the accompanying bar chart classify arrests according to the type of offense that they were made for, ranging from drug-related charges to assault and larceny. The most common crimes are identified with the use of this breakdown, which can also serve as a guide for law enforcement and community leaders as they concentrate their efforts.

Filters that are interactive:   
The dashboard incorporates interactive elements, such as filters for date ranges and boroughs, which enable users to personalize the presentation in accordance with particular concerns or interests. With this functionality, the dashboard's utility as a tool for making decisions in real time is significantly increased.

The Benefits and the Consequences   
This dashboard is designed to assist a wide variety of stakeholders, including city authorities, law enforcement agencies, policy makers, and community community organizations. Strategic planning, resource allocation, and policy formation are all supported by the tool since it offers a quick and easy view of the most important parameters regarding arrests and crimes. The dashboard can be leveraged in many highly successful ways, including the following:   
  
Resource Allocation: Having an understanding of which boroughs and demographics are most affected by crime can assist in the process of more effectively allocating resources to the police department.   
In the process of policy development, insights into trends and patterns can be used to generate more effective policies and programs for the prevention of crime and for the safety of the community.

Community Outreach: The use of demographic data can assist in the customization of community policing initiatives to address the particular requirements and conditions of various individuals and communities.   
Initiatives that are being evaluated: The analysis of trend data over a period of time enables the evaluation of the efficiency of various policies and initiatives pertaining to law enforcement.

Conclusion

Significant insights on the patterns and disparities of arrests across New York City have been offered as a result of this extensive effort focused on examining the arrest data from the New York Police Department. We were able to uncover important insights regarding demographic inequalities, geographical differences, and temporal trends in arrest data by meticulously preparing the data, conducting exploratory data analysis, and utilizing advanced predictive modeling. According to the findings of the analysis, there are significant differences in arrests based on gender, race, and age. These findings underscore the necessity of legislative interventions and community-specific measures in order to ensure that law enforcement is distributed fairly. The creation of a dynamic dashboard further empowered stakeholders by offering an interactive tool that allowed them to see and delve deeper into the data, which in turn made it easier for them to make educated decisions.   
  
Despite the fact that they revealed issues such as class imbalance, the predictive models that were implemented, which included Logistic Regression and Random Forest, indicated the promise of machine learning in forecasting arrest outcomes. These findings highlight the need of continuously refining models and the necessity of incorporating increasingly advanced methodologies in order to improve the accuracy of predictions and ensure that they are implemented fairly. For the purpose of conducting a more in-depth and complete study, future work should concentrate on resolving these issues, improving prediction models, and broadening the scope of the analytical framework to incorporate a greater variety of data sources.

Important information is presented in a style that is easy to understand by the New York Crime Analysis Dashboard, which offers crucial insights into the patterns of criminal activity that occur throughout New York City. Not only does it help with immediate operational decisions, but it also supports long-term strategic planning and community conversation. It is a tool for transparency and involvement, and it helps with immediate operational decisions. The dashboard serves as an illustration of how insights derived from data can result in public safety measures that are more informed, more successful, and more equal.  
  
This research, in its entirety, not only provided light on the current arrest patterns, but it also laid the groundwork for data-driven improvements in public safety strategies and law enforcement regulations. Through the consistent utilization of data science and machine learning, stakeholders are able to adjust to the ever-changing dynamics of criminal activity, ultimately contributing to the creation of a more secure and equitable environment for all citizens of New York City.

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