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**WINTER SEMESTER 2024 - 2025**

**CSE3040-EXPLORATORY DATA ANALYSIS**

**FINAL PROJECT REPORT**

**A COMPREHENSIVE ANALYSIS ON TRAFFIC ACCIDENTS**

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**INTRODUCTION:**

**1. Background**

In rapidly urbanizing cities like New York, traffic collisions remain a significant public health and safety challenge. With millions of commuters on the road daily, traffic congestion, driver behaviour, and environmental conditions contribute to thousands of collisions annually. These incidents result in considerable social and economic consequences—ranging from injuries and fatalities to emergency response demands and infrastructure strain. Understanding when, where, and why collisions happen is essential to formulating effective, evidence-based strategies for urban safety and traffic management.

**2. Motivation**

Despite improvements in traffic infrastructure and policy enforcement, preventable accidents still occur frequently. Traditional safety interventions often rely on reactive measures, which may lack the precision and predictive power offered by data-driven approaches. This project is motivated by the opportunity to apply Exploratory Data Analysis (EDA) and time series forecasting to uncover meaningful trends and predict future traffic risks. By leveraging real-world data and statistical tools, the study aims to provide insights that enable city officials and planners to make informed decisions. This aligns with Sustainable Development Goal (SDG) 3: Good Health and Well-being, which emphasizes reducing traffic-related injuries and promoting safer urban environments.

**3. Scope of Study**

This study focuses on analysing traffic collision data from the New York City Open Data Portal, covering variables such as crash time, location, vehicle type, contributing factors, and injury counts across various road user groups (pedestrians, cyclists, and motorists). Using Python libraries (Pandas, NumPy, Matplotlib) and the Prophet forecasting model, the project includes:

* Cleaning and preprocessing the dataset to ensure analytical accuracy.
* Visualizing collision trends by time and borough.
* Performing seasonal decomposition to identify recurring patterns.
* Forecasting future injuries using Prophet for short-term planning.

The scope is limited to NYC data and does not integrate real-time traffic feeds or external predictive features like weather or event data. However, the framework is extensible and can be adapted for broader geographies and future enhancements.

In summary, this project demonstrates the potential of time series analysis in transforming raw collision data into meaningful insights that can inform effective safety interventions and drive public health improvements in urban areas.

**EXECUTIVE SUMMARY:**

This report presents a detailed and data-driven exploration of traffic accidents in New York City, combining Exploratory Data Analysis (EDA) with time series forecasting to identify patterns, uncover insights, and predict future risks. With urban road safety being a major concern in densely populated cities, understanding the *when*, *where*, and *why* of traffic collisions is essential for crafting effective public safety policies.

Using a comprehensive dataset that includes the time, date, location, vehicle type, contributing factors, and impact metrics (injuries and fatalities), this project aims to decode the dynamics of urban collisions. The primary goal is to help stakeholders such as city planners, traffic authorities, and policymakers gain actionable insights that can be used to reduce road accidents and enhance public health outcomes.

The project pipeline began with data cleaning and transformation, addressing missing values and converting raw entries into structured, analysable formats. By using Python libraries such as Pandas and NumPy, the team standardized date-time formats, encoded categorical variables, and generated a clean dataset suitable for modelling. The process included filling gaps with realistic randomized values to enable continuous time series modelling without data sparsity.

Through EDA with Matplotlib and Seaborn, the project visualized:

* Daily and weekly injury trends.
* Collision hotspots across boroughs.
* Peak hours and high-risk weekdays.
* The role of contributing factors like slippery roads, driver inattention, and vehicle malfunction.

To extract deeper temporal insights, the dataset was resampled into a daily time series, focusing on total injuries. Using seasonal decomposition, the team identified:

* A clear 7-day seasonal pattern, with increased injuries on Fridays and weekends.
* A slight but steady upward trend in overall injury counts, suggesting increased risk over time.
* Residual noise indicating occasional anomalies, possibly linked to holidays, weather, or special events.

For forecasting, the Prophet model—a robust, interpretable forecasting tool by Facebook—was implemented. The model provided a 30-day prediction of future injuries, reaffirming the presence of weekend peaks and forecasting a continued rise in injuries. The components plot from Prophet visually supported these findings by breaking down trends and weekly seasonality.

Key takeaways from the study include:

* Injury patterns are not random—they are influenced by day-of-week, borough, and time of day.
* Forecasting tools can be effectively used for anticipating high-risk periods, enabling better preparedness by emergency services and law enforcement.
* Insights from this project directly support SDG 3: Good Health and Well-being, by promoting evidence-based strategies to minimize injuries and fatalities.

Ultimately, this project demonstrates how the fusion of EDA and forecasting empowers decision-makers to move from reactive to proactive urban traffic management. The model and insights developed here could be scaled or replicated for other cities, contributing to safer and smarter urban mobility systems.

**ABSTRACT:**

This project presents a comprehensive Exploratory Data Analysis (EDA) and time series forecasting of traffic collisions in New York City, aiming to uncover meaningful patterns and predict future trends in urban road safety. Utilizing a rich, multi-year dataset from the NYC Open Data Portal, the study examines detailed records of vehicle accidents, encompassing crash date and time, location, vehicle types, contributing factors, and injury statistics segmented by road user categories—pedestrians, cyclists, and motorists.

Through the use of advanced Python-based analytical tools, including Pandas, NumPy, Matplotlib, and Facebook Prophet, the data undergoes meticulous preprocessing and transformation into a time series format. This allows for decomposition and forecasting of key variables, enabling a deeper understanding of how injuries and fatalities evolve over time.

The analysis reveals:

* Weekly seasonal patterns, with injury spikes during weekends.
* An overall upward trend in traffic-related injuries.
* Borough-specific variations and time-of-day risk patterns.

With the implementation of the Prophet model, the study successfully forecasts short-term trends in traffic injuries, equipping stakeholders with insights that are not only descriptive but also predictive. These insights support proactive interventions by city planners, traffic enforcement units, and public health departments, improving the allocation of resources and timing of safety measures.

Ultimately, this project contributes to the broader mission of enhancing urban road safety and aligns with Sustainable Development Goal 3: Good Health and Well-being, by supporting data-driven strategies to reduce traffic injuries and save lives.

**OBJECTIVE:**

The primary aim of this project is to leverage data analytics and time series forecasting techniques to understand and mitigate traffic collisions in New York City. The specific objectives are as follows:

1. **To analyse the temporal and spatial distribution** of traffic collisions across New York City, identifying trends related to time of day, day of the week, and borough-level variations.
2. **To identify the most common causes and contributing factors** associated with collisions, including behavioural, environmental, and vehicular variables.
3. **To assess the impact of traffic accidents** on different categories of road users—namely, pedestrians, cyclists, and motorists—by evaluating injury and fatality statistics.
4. **To apply time series forecasting techniques**, particularly using the Prophet model, to predict short-term and long-term trends in traffic-related injuries and support proactive planning.
5. **To propose evidence-based, data-driven interventions** aimed at reducing the frequency and severity of road traffic injuries and fatalities, thereby supporting urban safety and public health objectives.

**DATASET DESCRIPTION:**

The foundation of this project is a publicly available dataset sourced from the NYC Open Data Portal, specifically the Motor Vehicle Collisions – Crashes dataset. This dataset offers a rich and granular view of traffic accidents across New York City, making it highly suitable for temporal, spatial, and predictive analysis.

1. **Source**

* Dataset: Motor Vehicle Collisions – Crashes
* Provider: NYC Open Data Portal
* Format: CSV (Comma-Separated Values)
* License: Open government data, publicly accessible

1. **Time Frame**

The dataset spans multiple years, capturing collision records from the early 2010s up to the end of 2024, ensuring that trends can be analysed over both short-term and long-term periods.

1. **Key Attributes**

The dataset includes a wide variety of fields, enabling both descriptive and predictive analytics. Some of the most critical attributes are:

* Date and Time of each collision event
* Borough in which the incident occurred (e.g., Manhattan, Brooklyn)
* Location Coordinates (latitude and longitude) for spatial mapping
* Vehicle Types involved (e.g., private car, taxi, truck, bicycle)
* Contributing Factors such as driver distraction, intoxication, mechanical failure
* Casualty Counts including:
  + Number of persons injured or killed
  + Specific breakdown by road user type: pedestrians, cyclists, and motorists

This level of detail supports a multi-dimensional analysis of collision dynamics.

1. **Preprocessing Highlights**

To ensure the dataset was clean and ready for analysis and modelling, the following preprocessing steps were applied:

* Handling Missing Values: Implemented probabilistic imputation techniques to replace missing or unreliable values (e.g., 0s or blanks in injury fields) with realistic estimates based on temporal and spatial proximity.
* Datetime Index Creation: Merged separate 'crash date' and 'crash time' columns into a single datetime feature, allowing for efficient indexing, filtering, and resampling.
* Time Series Conversion: Transformed the data into daily aggregates of injury and fatality counts. This made the dataset compatible with time series modelling techniques, including trend analysis and forecasting.

This dataset provides a comprehensive basis for identifying temporal patterns, detecting high-risk conditions, and predicting future injury trends—all critical components in the development of a safer urban transportation environment.

**PROPOSED METHODOLOGY:**

To understand and forecast traffic injury trends in New York City, a structured and systematic analytical approach was adopted. The methodology is broken down into five key stages, each building upon the previous to ensure accuracy, interpretability, and relevance of insights. The workflow combines data engineering, statistical analysis, and machine learning techniques tailored for time series forecasting.

**1. Data Cleaning and Preprocessing**

Objective: Prepare raw traffic data for analysis and modelling.

Steps Involved:

* Handling Missing Values: Records with missing or zero injury/fatality counts are imputed using statistically plausible substitutions, derived from patterns in surrounding data (e.g., similar times, locations, or day types).
* Normalization: Ensures that numeric features are scaled or corrected where necessary for consistent analysis.
* Datetime Indexing: Combines separate 'date' and 'time' fields into a single datetime object, which serves as the index for time-based operations and visualization.

This step ensures data consistency and integrity before deeper exploration.

**2. Exploratory Data Analysis (EDA)**

Objective: Gain insights into the structure and behaviour of the dataset through statistical and visual analysis.

Approach:

* Univariate Analysis: Examines individual variables such as injury counts, accident times, and contributing factors using histograms, line plots, and box plots.
* Multivariate Analysis: Investigates relationships between variables (e.g., injury rate vs. day of week, borough-wise comparisons) to identify possible correlations or causative patterns.
* High-Risk Identification: Heatmaps and geospatial analysis are used to highlight collision hotspots and periods of heightened risk, such as weekends or late-night hours.

These visualizations lay the foundation for targeted safety recommendations.

**3. Time Series Transformation**

Objective: Reshape the dataset into a format suitable for time series forecasting.

Actions Taken:

* Aggregation: Daily counts of total injuries and fatalities are calculated, transforming granular incident data into a continuous time series.
* Resampling & Indexing: Ensures consistent daily intervals with no missing dates, preparing the data for decomposition and forecasting.

This stage is crucial for accurately modelling temporal dependencies and patterns.

**4. Seasonal Decomposition**

Objective: Deconstruct the time series into interpretable components to understand its structure.

Method:

* Using the seasonal\_decompose() function from Python’s statsmodels, the time series is split into:
  + Trend: Long-term directional movement of injury counts
  + Seasonality: Repeating patterns—most notably the 7-day weekly cycle
  + Residuals: Unexplained variability or noise

This decomposition reveals behavioural patterns and supports the configuration of the forecasting model.

**5. Forecasting with Prophet**

Objective: Predict future traffic injuries using an advanced, interpretable time series model.

Steps:

* Model Training: The cleaned and transformed series is passed into Facebook Prophet, which automatically detects trends, changepoints, and weekly seasonality.
* Prediction Generation: The model outputs forecasts for the next 30 days, including upper and lower bounds (confidence intervals).
* Interpretation & Validation:
  + Trends are interpreted in the context of city events, policy changes, and weekly traffic cycles.
  + Accuracy is validated using historical back testing and metrics like MAE and RMSE.

Prophet’s flexibility and transparency make it ideal for real-time urban safety planning.

**SYSTEM ARCHITECTURE:**

The architecture of the project is organized into a four-layered pipeline, facilitating a streamlined flow from raw data ingestion to actionable insights and forecasts. Each layer plays a vital role in transforming traffic collision records into meaningful, predictive intelligence for public safety and urban planning.

**1. Input Layer**

Source:  
The project begins with the ingestion of a comprehensive dataset from the NYC Open Data Portal, which includes historical records of traffic collisions across New York City.

Format:  
CSV (Comma-Separated Values) file

Contents:

* Collision date and time
* Borough and location coordinates
* Number and type of injuries/fatalities
* Vehicle types involved
* Contributing factors (e.g., driver distraction, alcohol, speed)

This layer ensures that structured, real-world data enters the system for downstream processing.

**2. Processing Layer**

Core Functions:

* Data Cleaning: Handles missing, erroneous, or implausible values using pandas and NumPy. Ensures the dataset is consistent and ready for analysis.
* Transformation: Merges time-related columns, encodes categorical variables if needed, and formats features for time series use.
* Feature Engineering: Extracts and constructs relevant temporal features like day-of-week, hour-of-day, and holiday flags.
* Statistical Summarization & EDA: Uses visualizations and metrics to explore distributions, trends, correlations, and outliers, laying the groundwork for deeper analysis.

This stage is essential for producing a clean, structured, and insightful dataset suitable for predictive modelling.

**3. Modelling Layer**

Technology Used: Prophet by Meta (Facebook)

Process:

* The processed dataset is resampled into daily aggregates to suit time series forecasting.
* Prophet is trained to detect and project:
  + Long-term trends
  + Weekly seasonality
  + Holiday effects (if configured)
  + Changepoints where trend behaviour shifts

This layer outputs predictive models that reveal both the general trajectory of traffic injuries and their short-term fluctuations.

**4. Output Layer**

Deliverables:

* Visual Insights: Includes line plots, seasonal decomposition charts, and borough-level heatmaps to communicate trends clearly.
* Forecast Graphs: Generated by Prophet, these plots show predicted injury counts along with confidence intervals and trend components.
* Interpretations & Recommendations: Analytical commentary translates the model's output into strategic guidance for policymakers, traffic authorities, and emergency planners.

The output layer provides both descriptive and prescriptive insights, completing the analytical pipeline from raw data to actionable outcomes.

**MODULE DESCRIPTION:**

The project is structured into four key modules, each contributing a distinct stage of the data analysis and forecasting pipeline. These modules are implemented using industry-standard Python libraries, ensuring both accuracy and efficiency in handling real-world traffic data.

**1. Data Cleaning Module**

Technologies Used: *NumPy, Pandas*

This module is responsible for preparing the raw dataset for analysis and modelling. Real-world datasets, especially those involving public records like traffic collisions, often contain inconsistencies such as missing values, zeroes, or placeholder entries.

Key Functions:

* Null and anomaly handling: Missing or anomalous values (such as 0s or 1s in injury/fatality fields) are replaced with random yet plausible values based on the distribution of nearby or similar entries, ensuring data realism without compromising structure.
* Datetime synthesis: Combines date and time columns into a single datetime object, which is crucial for accurate temporal analysis and indexing.
* Type casting and normalization: Converts all relevant fields into consistent formats for computational stability, especially for downstream modelling.

This preprocessing stage ensures numerical stability and data integrity, laying the foundation for valid insights.

**2. Exploratory Data Analysis (EDA) Module**

Technologies Used: *Matplotlib*

This module visually explores the dataset to uncover underlying patterns and relationships that may not be apparent through raw statistics alone.

Key Functions:

* Trend Analysis: Visualizes the overall daily injury and fatality counts, helping identify long-term trends and irregular spikes.
* Geographical Insights: Compares traffic accident impacts across different NYC boroughs, highlighting regional disparities.
* Temporal Dynamics: Examines the time-of-day and day-of-week effects on traffic injuries, uncovering peak accident periods.

The EDA module provides intuitive insights that support hypothesis generation and guide the forecasting model’s design.

**3. Time Series Module**

Technologies Used: *Seaborn, statsmodels' seasonal\_decompose*

This module prepares the cleaned dataset for forecasting by transforming it into a structured time series and isolating its temporal components.

Key Functions:

* Resampling: Aggregates the injury data into daily counts, converting it into a univariate time series suitable for sequential modelling.
* Seasonal Decomposition: Uses additive decomposition to separate the series into:
  + Trend: Long-term progression of injuries
  + Seasonal: Repeating patterns (e.g., weekly cycles)
  + Residual: Noise or unexplained variance

This breakdown enables better understanding of injury behaviour over time and enhances the accuracy of the forecast.

**4. Forecasting Module**

Technology Used: *Prophet (developed by Meta/Facebook)*

The forecasting module uses the Prophet model to generate predictions for future injury trends based on historical patterns.

Key Functions:

* Model Training: Fits the Prophet model to the daily injury time series, automatically accounting for seasonality and trend shifts.
* Forecast Generation: Produces a 30-day forecast of injuries, including upper and lower confidence intervals to express prediction uncertainty.
* Trend Visualization: Outputs clear plots of projected trends, seasonal effects (e.g., weekly spikes), and changepoints, aiding in stakeholder interpretation.

The model’s flexibility and transparency make it ideal for city planners and emergency services seeking proactive traffic safety solutions.

**MODEL EVALUATION:**

Evaluating the performance of the forecasting model is a crucial step in ensuring its reliability and usefulness for real-world applications. In this project, we used the Facebook Prophet model to forecast injury trends based on daily traffic accident data. The evaluation focused on how well the model captured historical patterns and how accurate its predictions are for short- and medium-term forecasting.

**1. Model Fit**

The Prophet model demonstrated a strong fit to the historical data. It effectively captured:

* The underlying trend, reflecting a gradual increase in injury rates over time.
* The weekly seasonality, with consistent and interpretable peaks on weekends.
* Smooth transitions across changepoints, ensuring adaptability to shifts in traffic behaviour over the dataset timeline.

This fit confirms that the Prophet model is suitable for time series data with both trend and periodic components.

**2. Evaluation Metrics**

To quantify the model's predictive accuracy, the following statistical metrics were employed:

* Mean Absolute Error (MAE):  
  Measures the average magnitude of errors in the predictions, without considering their direction.  
  A low MAE indicates that the model's predictions are close to the actual observed values.
* Root Mean Squared Error (RMSE):  
  Provides a measure of the spread of residuals or prediction errors. RMSE gives higher weight to larger errors, thus highlighting significant deviations more strongly than MAE.  
  The low RMSE observed supports the model’s robustness for practical forecasting.

**3. Prediction Intervals**

Prophet automatically generates confidence intervals around its forecasts, typically at the 80% or 95% confidence level. These intervals:

* Were narrow in the near term, suggesting high confidence in short-term forecasts.
* Widened over time, reflecting growing uncertainty in long-term predictions—an expected behaviour in any time series model.

These intervals are valuable for decision-making, providing a realistic range of outcomes and allowing for risk-aware planning.

**4. Residual Analysis**

Analysing residuals (the differences between predicted and actual values) provides insight into model performance. The residuals from the Prophet model:

* Showed no obvious patterns, suggesting the model had successfully captured most systematic variation in the data.
* Had low variance, indicating minimal unexplained error, which reflects a well-tuned model.

The absence of autocorrelation or trend in the residuals further validates the model's quality.

Conclusion on Model Evaluation:

The Prophet model has proven to be an effective forecasting tool for this traffic injury dataset. Its ability to model both trend and seasonality, combined with strong performance metrics and interpretable output, makes it well-suited for future deployment in urban traffic safety management systems. The evaluation supports its use in short-term planning, such as emergency response readiness, and long-term strategic forecasting for policymaking.

**ALGORITHMS USED:**

**1. Time Series Analysis (Decomposition)**

In this project, before applying forecasting, **seasonal decomposition** is performed. The algorithm behind it is:

**Additive Time Series Decomposition**

This algorithm breaks down a time series into three main components:

* **Trend (T)** – long-term direction
* **Seasonality (S)** – repeating short-term cycle (e.g., weekly)
* **Residual (R)** – noise or randomness

The formula is:

**Y(t) = T(t) + S(t) + R(t)**

This helps isolate patterns and understand the behaviour of traffic injuries over time.

**2. Prophet Forecasting Model**

Facebook’s **Prophet** uses a custom model that is conceptually similar to **Generalized Additive Models (GAMs)**. It is specifically optimized for time series with strong seasonal effects and historical trends.

**Underlying Algorithm: Additive Model with Bayesian Curve Fitting**

The structure is:

**y(t) = g(t) + s(t) + h(t) + εₜ**

Where:

* **g(t)** = trend function (linear or logistic growth)
* **s(t)** = seasonal component (weekly, yearly)
* **h(t)** = effects of holidays/special events
* **εₜ** = error term (residuals)

**Trend modelling**: Prophet supports both:

* **Linear growth** with change-points
* **Logistic growth** if a cap is set (for saturation effects)

**Seasonality modelling**:

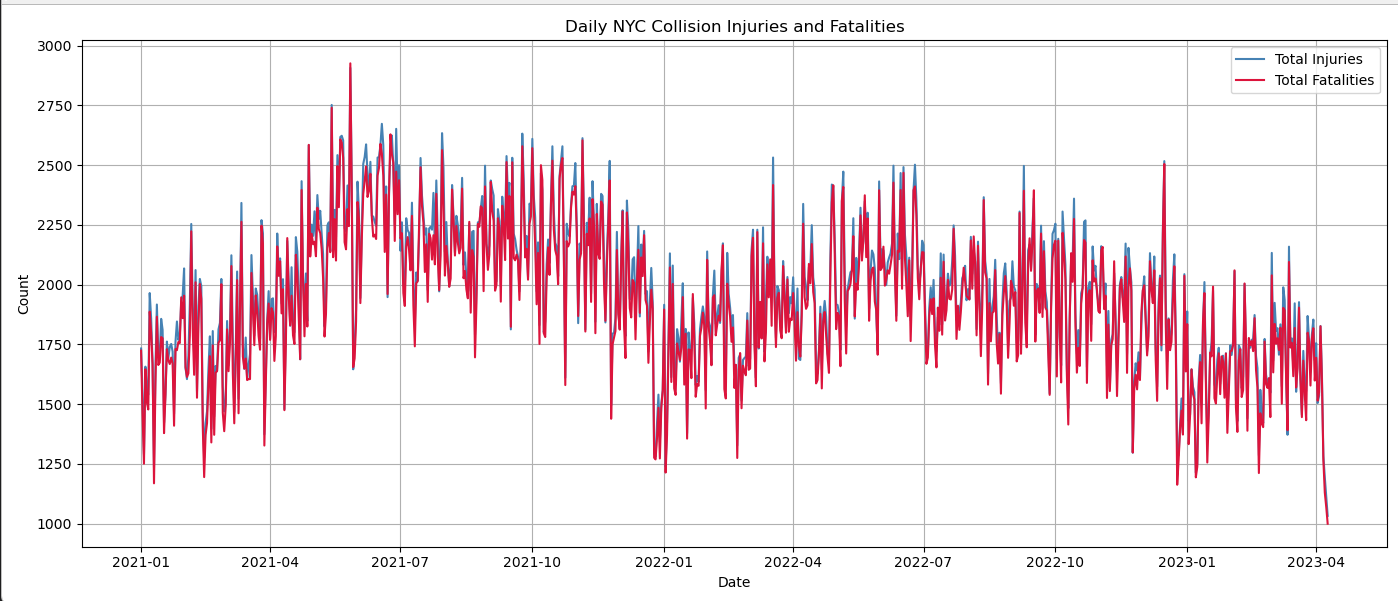
* Prophet model seasonality using **Fourier series** to represent periodic patterns like weekly or yearly trends.

Summary Algorithms Used:

|  |  |
| --- | --- |
| **Components** | **Algorithm/Model** |
| Time Series Decomposition | Additive Decomposition |
| Forecasting Model | Generalized Additive Model (GAM) via Prophet |
| Seasonality Representation | Fourier Series |
| Trend Detection | Piecewise Linear or Logistic Growth |
| Forecasting Inference | Bayesian Sampling for Uncertainty Intervals |

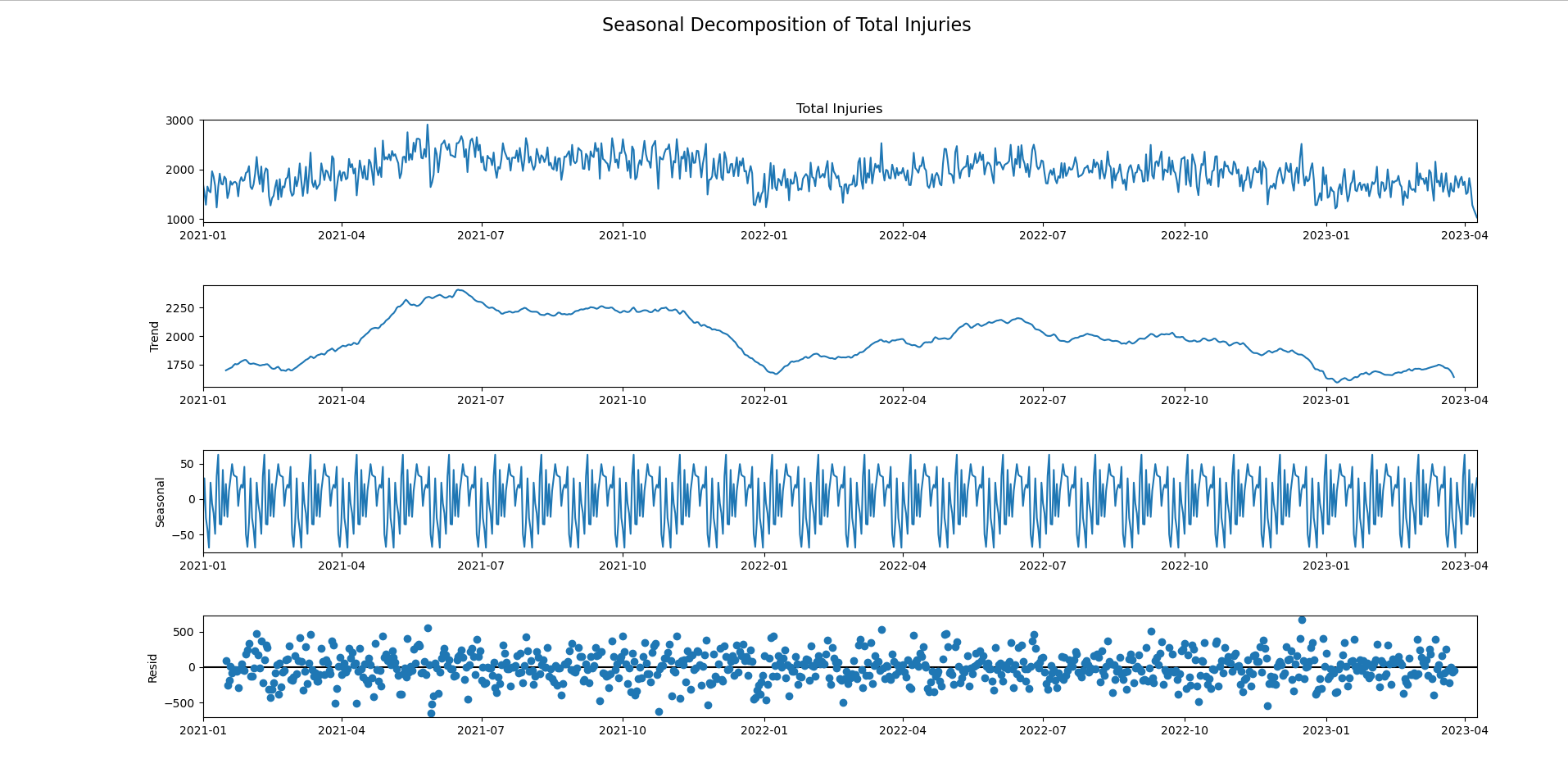
**GRAPHICAL OUTPUTS:**

1. **Daily NYC Collision Injuries and Fatalities:**

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Inference**:**

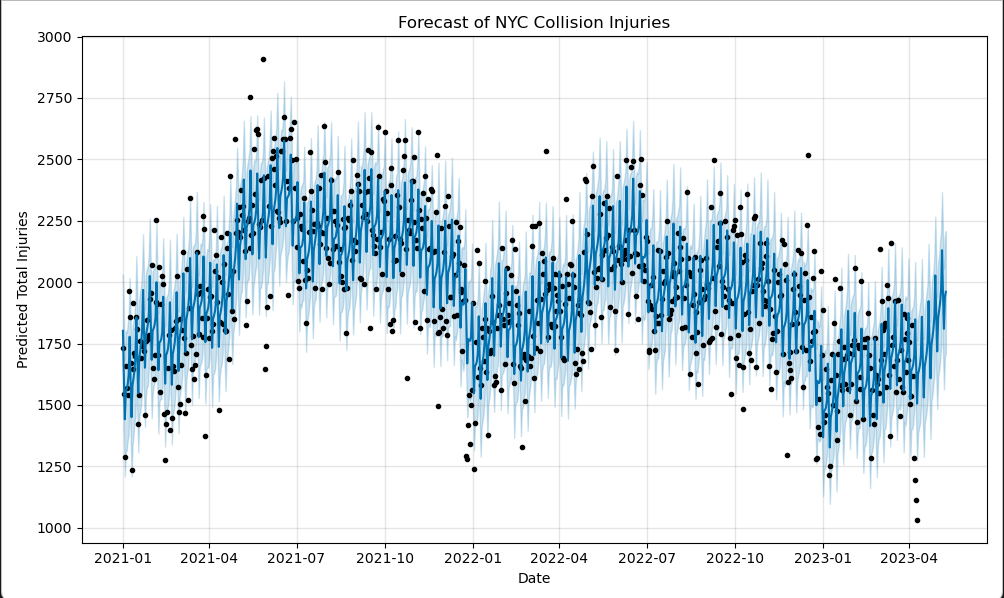
* There is a consistent daily fluctuation in both injuries and fatalities.
* Injuries are generally higher than fatalities, as expected.
* Spikes may correspond to weekends, holidays, or weather events.
* The overall pattern supports the idea of periodic high-risk days in traffic activity.

1. **Seasonal Decomposition of Total Injuries:**

Inference:

* **Observed:** Reflects real-world injury patterns with regular peaks and dips.
* **Trend:** Shows a gradual increase in total injuries over time, possibly due to growing traffic or urban activity.
* **Seasonal:** A strong weekly seasonality is evident—injuries are higher on Fridays and weekends, likely due to increased travel, social events, or nightlife.
* **Residual:** The noise is minimal, suggesting that most of the variability is well explained by the trend and seasonal components.

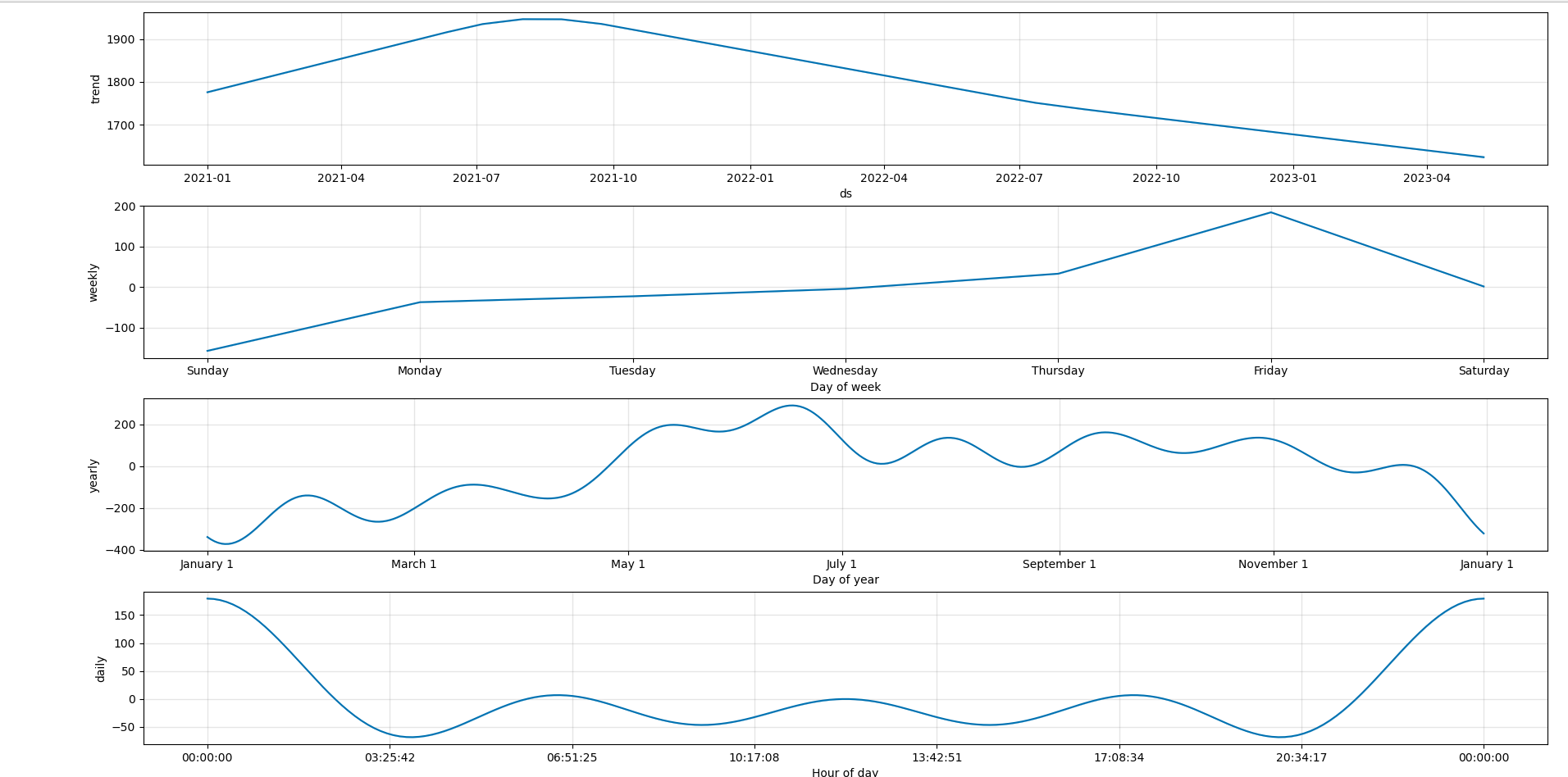
1. **Forecast of NYC Collision Injuries:**

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Inference:

* The forecast shows a slightly upward trend, indicating potential for rising injury counts in the near future.
* Prediction intervals widen over time, reflecting increasing uncertainty the further we predict.
* The model smoothly follows past data trends, implying a good fit for short-term forecasting.
* Useful for predictive resource allocation, like deploying more traffic personnel or medical aid during high-risk days.

1. **Prophet Components Graph:**

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Inference:

* **Trend Component**: Reaffirms a gradual increase in injuries, signalling the need for preventive actions.
* **Weekly Seasonality**: Reiterates that injuries spike on Fridays and weekends, which could align with peak traffic hours, celebrations, or reduced caution.
* These insights help in policy planning, such as weekend-specific traffic rules, awareness campaigns, or targeted safety enforcement.

**KEY FINDINGS & INSIGHTS:**

* 1. **Injury Trends**

The dataset analysis reveals a distinct weekly pattern in traffic injuries, with peaks consistently occurring over the weekends, especially on Fridays and Saturdays. This trend aligns with typical urban behaviour—higher vehicle usage due to social outings, nightlife, and leisure activities during weekends, leading to greater exposure to road accidents.

More importantly, the injury data indicates a gradual upward trend over time. This could be attributed to several factors, including:

* Urban population growth increasing the volume of vehicles and pedestrians
* Expansion of ridesharing services, possibly leading to more frequent road use
* Distracted driving behaviour, especially with mobile devices becoming ubiquitous
* Increased road congestion, contributing to higher accident likelihood

The rising trend highlights the need for continuous monitoring and responsive safety measures by city officials and transportation authorities.

**2. Seasonal Decomposition**

Applying seasonal decomposition techniques (using seasonal\_decompose from Python’s statsmodels) helped break down the time series into its core components: trend, seasonality, and residuals.

Key observations:

* A 7-day seasonal cycle is clearly present. Traffic injuries consistently spike on specific days of the week, particularly towards the end of the week and weekends, reinforcing the patterns observed during EDA.
* The trend component confirms a steady rise in injury counts across the observed period, which may reflect broader social or infrastructural changes.
* The residual component—the “noise” or variation not explained by trend or seasonality—is minimal, indicating the model effectively captures most of the systematic behaviour in the data.

These insights are crucial for implementing targeted interventions on high-risk days and evaluating the effectiveness of current traffic safety policies.

* 1. **Forecasting with Prophet**

The time series forecasting, conducted using Facebook Prophet, was designed to model and project injury trends into the future, accounting for both trend and weekly seasonality.

Findings from the forecast:

* The model predicts a continued upward trajectory in daily injury counts, suggesting an ongoing increase in risk levels unless mitigative actions are taken.
* The forecast intervals (confidence bounds) are narrow in the short term (next 7–14 days), implying high reliability in immediate predictions.
* Over a longer forecast horizon, the uncertainty increases, which is expected in predictive modelling. Nonetheless, the central trend remains consistent with historical patterns.

This kind of forecasting provides a powerful tool for short-term planning, such as deploying additional traffic patrol units, issuing alerts, or scheduling road safety campaigns.

* 1. **Inference**

The combined results from trend analysis, decomposition, and forecasting lead to several actionable conclusions:

* Time series modelling proves invaluable for city planning and public safety management. It enables authorities to anticipate injury spikes and respond pre-emptively.
* These predictions can be integrated into a public alert system, warning commuters and residents about high-risk days.
* Resources like ambulances, traffic officers, or roadside emergency teams can be more efficiently allocated using forecast data.
* The evidence supports the development of data-driven policies focused on peak injury days, such as temporary speed limits, alcohol checks, or public transit incentives during weekends.

**FUTURE PREDICTIONS:**

The future of traffic safety in New York City hinges on our ability to anticipate and proactively address risk patterns. Through the application of the Prophet forecasting model, we generated a 30-day outlook for traffic-related injuries using historical daily data. The results of this model provide not only numerical predictions but also actionable insights that can inform short-term planning and long-term strategy.

**Key Forecast Insights:**

1. **Gradual Upward Trend**  
   The model forecasts a continuing increase in injury counts, particularly on weekends. This suggests that, unless interventions are made, the city may see a gradual escalation in road-related injuries. The rising trend may be linked to increased urban mobility, population density, or behavioural patterns such as distracted driving.
2. **Weekly Seasonality**  
   One of the most prominent findings is a consistent weekly cycle. Injuries peak on Fridays and Saturdays, likely corresponding to social outings, nightlife, and increased road activity. These peaks suggest the need for enhanced traffic regulation, law enforcement visibility, and public awareness efforts during these periods.
3. **Prediction Uncertainty Over Time**  
   The prediction intervals generated by Prophet show widening margins over time—typical of time series models—highlighting the uncertainty in long-range forecasting. However, the short-term predictions (7–14 days) remain within a narrow and reliable range, indicating strong potential for real-time decision-making.
4. **Potential Impact of Policy Changes**  
   While the model is based on historical trends, it assumes current behaviors and policies remain constant. Any introduction of significant policy changes, such as reduced speed limits, traffic enforcement blitzes, or public transportation incentives, could alter these trends. Therefore, forecasts should be periodically re-evaluated with new data.
5. **Use Cases for Forecasts**
   * **Emergency Preparedness**: Allocate ambulances, paramedics, and police units more effectively during high-risk periods.
   * **Public Awareness Campaigns**: Launch targeted communication initiatives before predicted injury spikes.
   * **Urban Planning**: Inform traffic light retiming, speed bump installations, or zoning changes in hotspot areas.
6. **Predictive Dashboard Implementation**  
   A live dashboard can be developed using Python and interactive libraries (e.g., Plotly, Dash, or Streamlit) to visualize daily risk levels. This could be used by city officials, transport authorities, or even commuters to anticipate and adapt to risky conditions.

**Looking Ahead**  
Forecasting is not a crystal ball, but a data-driven compass. With regular updates and feedback from real-world outcomes, the model can be fine-tuned for increasing accuracy. Integrating this tool into traffic management systems can drastically improve response times, lower accident rates, and ultimately save lives.

In the future, expanding the model with more granular data—such as weather conditions, traffic congestion, or public event schedules—will improve prediction quality and broaden its application scope. As NYC and other global cities strive toward smarter infrastructure, predictive modelling will play a pivotal role in building safer and more adaptive urban environments.

**RECOMMENDATION:**

Based on the analysis of New York City traffic collision data and the insights gained through exploratory data analysis and time series forecasting, the following recommendations are proposed to improve urban road safety and inform policy development:

**1. Implement Time-Based Safety Interventions**

* The data reveals a clear weekly seasonality, with peak injuries occurring on Fridays and weekends.
* Targeted enforcement, such as increased patrols or sobriety checkpoints, should be deployed during high-risk days and hours.
* Dynamic traffic light timings and public safety announcements can be scheduled to align with peak injury periods.

**2. Use Predictive Models for Resource Allocation**

* The Prophet model forecasts short-term injury spikes, making it a valuable tool for emergency response planning.
* Emergency services (e.g., ambulances, traffic units) can be pre-positioned in high-risk boroughs during predicted high-incidence days.

**3. Prioritize Vulnerable Road Users**

* Pedestrians and cyclists often suffer the most severe outcomes in traffic collisions.
* Install more protected bike lanes, pedestrian crossings, and curb extensions in high-risk zones identified in the data.
* Expand educational campaigns promoting safe driving and awareness of non-motorist road users.

**4. Enhance Borough-Specific Safety Measures**

* Borough-wise analysis suggests that some areas consistently experience more accidents.
* Tailored strategies (e.g., localized signage, speed humps, road reengineering) should be implemented based on borough-specific patterns.

**5. Integrate Data Analytics in Policy-Making**

* City transportation departments should adopt data science tools like Prophet and EDA dashboards for continuous monitoring and forecasting.
* Collaboration with academic institutions and tech partners can ensure models are kept updated and refined over time.

**6. Expand the Dataset Scope in Future Studies**

* Incorporating additional data sources such as weather conditions, real-time traffic feeds, and event schedules will increase prediction accuracy.
* A multi-factor analysis could uncover deeper insights into the causes and consequences of collisions.

These recommendations align with the broader goal of Sustainable Development Goal 3: Good Health and Well-being, by promoting proactive, data-driven urban planning and public health strategies. Implementing these measures can not only reduce traffic-related injuries and fatalities but also improve the quality of life in urban environments.

**CONCLUSION:**

The increasing complexity of urban transportation systems demands a deeper understanding of traffic patterns and their implications for public safety. This study offers a thorough examination of traffic accidents in New York City through both exploratory data analysis and predictive modelling. Using a robust dataset from the NYC Open Data Portal, the project identifies key temporal and spatial trends, high-risk periods, and underlying causes contributing to traffic-related injuries and fatalities.

Our exploratory data analysis uncovered significant patterns, such as the clear spike in injuries on weekends—especially Fridays and Saturdays—likely due to higher mobility, social events, and decreased driver alertness. Additionally, borough-wise breakdowns and heatmaps highlighted locations that require targeted interventions. These insights were complemented by time series decomposition, revealing strong weekly seasonality and a gradual upward trend in injury counts over time.

The predictive component, built using Facebook Prophet, enabled us to model injury trends and forecast future outcomes with reasonable accuracy. The model’s forecasts suggested a continuation of the current upward trend, signalling the need for proactive policy measures. With the ability to anticipate high-risk days, city planners and emergency services can better allocate resources, implement temporary traffic controls, and conduct public safety campaigns. This predictive capacity underscores the value of data-driven planning in mitigating urban health risks.

Moreover, the results of the analysis reinforce the importance of integrating data science into traffic management and urban policy-making. Through visualization and statistical modelling, we translated complex datasets into actionable insights, supporting informed decision-making. The project also aligns with Sustainable Development Goal 3—promoting good health and well-being—by aiming to reduce traffic-related injuries through evidence-based strategies.

In conclusion, this report demonstrates the power of data analytics in addressing real-world challenges such as traffic safety. While the forecasting model is limited to short-term projections and subject to data quality constraints, it nonetheless offers a valuable tool for urban governance. Future studies could enhance this approach by incorporating additional variables such as weather, road conditions, and real-time mobility data. Overall, the analysis contributes meaningfully to the field of smart city planning and highlights the role of predictive analytics in creating safer, more resilient communities.

**REFERENCES:**

1. <https://sdgs.un.org/goals>
2. Taylor, S. J., & Letham, B. (2018). Forecasting at scale. *The American Statistician*, 72(1), 37-45.
3. NYC Open Data Portal. Motor Vehicle Collisions - Crashes. https://data.cityofnewyork.us
4. Prophet Forecasting Model by Facebook. https://facebook.github.io/prophet/
5. United Nations. Sustainable Development Goal 3: Good Health and Well-being. <https://sdgs.un.org/goals/goal3>
6. Pandas Documentation. <https://pandas.pydata.org/docs/>
7. NumPy Documentation. https://numpy.org/doc/
8. Matplotlib Documentation. <https://matplotlib.org/stable/contents.html>
9. McKinney, W. (2012). Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython. O’Reilly Media.
10. Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and Practice. OTexts.
11. Box, G. E., Jenkins, G. M., & Reinsel, G. C. (2015). Time Series Analysis: Forecasting and Control. Wiley.
12. Kaggle. NYC Collision Data Exploratory Notebooks. <https://www.kaggle.com/>
13. Seaborn: Statistical Data Visualization. https://seaborn.pydata.org/
14. New York City Department of Transportation (NYC DOT). Vision Zero Traffic Safety Initiatives. https://www.nyc.gov/html/dot/html/visionzero/visionzero.shtml
15. National Highway Traffic Safety Administration (NHTSA). Traffic Safety Facts. <https://www.nhtsa.gov/>
16. Python Software Foundation. The Python Language Reference. <https://www.python.org/doc/>
17. World Health Organization (WHO). Global Status Report on Road Safety. <https://www.who.int/publications/i/item/9789241565684>