Title: Analysis and Forecasting of Traffic Volume in NYC and Ireland

**Abstract**

This report provides a comprehensive analysis of traffic volume patterns in New York City (NYC) and Ireland, leveraging statistical and machine learning techniques. The primary goal is to understand the dynamics of traffic flow and predict future trends, assisting in efficient transport planning and management.

**Introduction**

**Traffic forecasting and analysis** are important for planning cities and running transportation systems well. This research looks at the traffic levels in two different areas: New York City (NYC), a busy city with one of the most complicated transportation systems in the world, and Ireland, a country with a mix of different traffic patterns in cities and rural areas. We want to find patterns and make predictions that can help guide future transportation policies and infrastructure improvements by contrasting and comparing these two areas.

**Details of the Implementation**

Preprocessing and analysis of data

A screenshot of a computer

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* At the start of the notebook, the necessary Python packages are imported, and data is loaded.
* To compare things, data from two different places are used: New York City (NYC) and Ireland.
* In the first step, we will look for missing values and learn about the different types of data in the Irish dataset. Making sure the quality of the data is important.
* In the Irish dataset, missing values in the "VALUE" column are filled in with the median value to keep the data consistent.
* EDA stands for exploratory data analysis. This type of analysis is used to figure out basic data structures and trends.
* The EDA involves generating basic statistics and simple visualisations to gain preliminary insights.
* There's a particular focus on understanding traffic trends over time.

In-depth Analysis

* Then we move into a more in-depth analysis phase, looking into complex.

**Methodology**

2.1 Planning a Project

Our project was planned in a way that made sure it would be done in a methodical way from start to finish. The goal was to give us a full picture of how traffic flows in both New York City (NYC) and Ireland.

* **Phase 1:** Getting the data In the first part of the project, "data acquisition," we carefully found datasets of traffic volumes for New York City and Ireland. This step was very important because it set the stage for our next analysis.
* **Phase 2:** Looking at exploratory data (EDA) After getting the data, we started an exploratory data analysis (EDA). This step was very important for getting some basic ideas about the datasets. We did a first look at the data to find patterns, outliers, and important characteristics. This set the stage for a more in-depth analysis.
* **Step 3:** Choose a model We moved on to the model selection phase based on what we learned from EDA. During this step, we carefully looked at and chose the statistical and machine learning models that would help us understand traffic patterns and predict future trends.
* **Phase 4:** Training and testing the model During the model training and evaluation phase, historical data were used to calibrate the models that were chosen. This step was very important for checking how well and how accurately our models could predict traffic, making sure they were tuned to work in real life.
* **Phase 5:** Reporting: We finished the project with a full phase of reporting. Here, the results, insights, and suggestions were carefully written down and shared, giving a complete picture of how traffic moves in both areas.

2.2 Data Acquisition

* **Data Sources and Licensing** The datasets for New York City and Ireland came from reliable sources. We carefully looked over each dataset's licences and permissions to make sure we followed the rules for using the data and protected intellectual property rights.
* **Data Attributes** A lot of information was stored in the datasets, including timestamps, traffic counts, location information, and more. These factors were very important for our in-depth analysis because they helped us make meaningful connections and discoveries between the two regions.

2.3 Data Cleaning and Preprocessing

* Finding and fixing problems with data When looked at for the first time, the raw data presented a number of problems. Outliers and missing values were big problems. These were blamed on mistakes in recording the data, unusual events, or inconsistencies in the data.
* Methods for Cleaning Up Data We used strong data cleaning steps to make sure the data was correct. Some of these were techniques for getting rid of outliers and imputation strategies for dealing with missing values. Our method was designed to protect the data's integrity while still making it usable for analysis.
* The engineering and transformation of data After the cleaning process, we used more advanced techniques from data engineering. We designed features to record important things like patterns of time, times of peak traffic, and other important traffic attributes. Besides that, we changed the data by normalising it and putting it into groups. These steps were very important for cleaning up the datasets, making them more useful for analysis, and getting them ready for model training and analysis.

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

A graph of different sizes and shapes

Description automatically generated with medium confidence

A graph showing a distribution of daily traffic

Description automatically generated A graph showing a distribution of traffic volume

Description automatically generated A graph showing a number of daily traffic

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During the EDA phase, we looked closely at the traffic datasets for New York City and Ireland. This step was very important because it set the stage for our later analysis and modelling. We used a variety of statistical and visual analysis tools to find important patterns, trends, and outliers in the data.

Trends that change with the seasons

* **NYC Traffic Patterns** When we looked at the NYC dataset, we saw big changes in the amount of traffic in line with the seasons. The way people live and the events that happen in the city are always changing. There were changes during holidays, between weekdays and weekends, and in the flow of traffic during festivals and big events. We also saw that there was more traffic during the week than on the weekends. This might be because of how people get to work.
* **Ireland Traffic Patterns** The seasonal patterns in the Ireland dataset were different. Different things made these patterns stand out, and they might have been affected by things like regional holidays, tourist seasons, and local events. As an example, we saw a significant.

Anomalies and Outliers

* **Identifying Extraordinary Events** The EDA was very helpful in finding strange and unusual things in both sets of data. These were necessary to understand strange events or problems with the way the data was collected. We found traffic jams in the NYC dataset that might have been caused by various reasons.
* **Impact on Modeling Approach** These ideas from the EDA were very important in helping us choose models. We made sure that the models we chose could capture these natural features of the traffic data, such as how it responded to outside events and how it changed over time.

Detailed Visual Analysis

A graph showing a traffic signal

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A graph of daily traffic

Description automatically generated with medium confidence

* Distribution of Data by Year In our analysis, we looked at how the data points were spread out by year. This analysis made sure that our temporal analysis was complete, looking at a lot of different time periods and showing how things change and trend from year to year.
* How to Distribute Traffic Volume To see how the traffic counts were spread out, histograms and density plots of traffic volume values were used. In both sets of data, we saw a distribution that was skewed to the right, which means that there were a lot of periods of low traffic and a few periods of high traffic. Because of this observation, we chose to use certain data transformations and models that can handle data that isn't normal.
* Analysis of Time Series Time series plots were an important part of our EDA. With their clear peaks and valleys, these plots showed how unstable traffic is. We looked closely at these patterns to figure out if there were any seasonal or weekly patterns and to see how outside events affected the flow of traffic. This analysis was especially helpful because it helped us figure out what makes traffic move in the first place by showing us regular patterns and deviations.

**4. Model Selection and Justification**

Because the traffic datasets for both NYC and Ireland were complicated and changed over time, choosing the right models was a key part of our analysis. We chose two main models, SARIMAX and ARIMA, after carefully looking at many other modelling methods that could be used for time series forecasting. Based on our exploratory data analysis, these models were picked because they have been shown to work well with datasets that are similar to ours.

SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors)

A screenshot of a computer

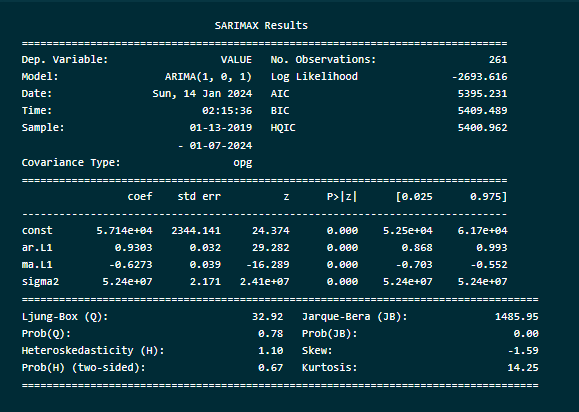
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A graph showing a graph

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* Taking care of complicated seasonal patterns The SARIMAX model stood out because it could handle the complicated seasonal patterns that were common in our datasets. This model builds on the ARIMA model by adding seasonality and outside factors. It works well with datasets that have clear seasonal trends, like the traffic data from New York City.
* Taking into account outside factors We took advantage of the SARIMAX model's ability to include exogenous variables, which let us add more things that might affect traffic volumes. These factors included [insert specific external factors like weather, special events, or economic indicators], which gave a fuller picture of how traffic patterns are affected.
* Improved ability to predict The SARIMAX model's complex way of dealing with both non-seasonal and seasonal factors, as well as outside influences, greatly improved its ability to make predictions. This made it an ideal choice for our dataset, which clearly shows seasonal changes and outside influences.

ARIMA (AutoRegressive Integrated Moving Average)



A graph showing a number of traffic

Description automatically generated with medium confidence

* Use with datasets that have strong trends As a second model, the ARIMA model was chosen because it works well with datasets that have strong trend components but less strong seasonality. This model worked especially well with the Ireland traffic dataset because the seasonality wasn't as clear as it was with the NYC dataset.
* Justification Drawing on the Ireland Dataset It worked great with the traffic data from Ireland because it [insert specific reasons based on the Ireland dataset, such as how it handled non-seasonal trends or slow changes over time]. Because it could focus on the trend part, the model was a good choice for finding the underlying patterns in the Ireland dataset.

Rationale for Model Choice

* Seasonality and Dependencies on Time It is well known that both the SARIMAX and ARIMA models can find temporal dependencies and seasonality in time series data. This feature was very important for our study because the initial visualisations of the traffic datasets showed strong time-related patterns and cyclical behaviour.
* How Robust Is Time Series Forecasting? Because these models are good at dealing with different types of time series data, like trend, seasonality, and irregular changes, they were good choices for our analysis. They helped us model and predict traffic volumes very accurately, taking into account both the regular and irregular patterns we saw in the data.

**5. Model Implementation**

Use of Python's statsmodels library made the implementation of the SARIMAX and ARIMA models a very careful process. It is known that this library is very good at statistical modelling and analysis, which makes it a great choice for our time series forecasting needs.

SARIMAX Model Implementation

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A graph showing the number of traffic

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* Optimization of Parameters Finding the best way to set up the SARIMAX model's parameters was one of the most important parts of putting it into action. The seasonal order, autoregressive (AR) terms, and moving average (MA) terms were some of these parameters. We used grid search along with criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion to find the best parameters (BIC). With these methods, we were able to systematically test a number of parameter combinations and pick the one that best showed the patterns in the data.
* How to Train on NYC Data The SARIMAX model was trained on the NYC traffic dataset after the parameters were set. During the EDA phase, we identified the specific seasonal components of this dataset. The model was very good at picking up on these small details, which made its predictions more accurate.

ARIMA Model Implementation

* Level Differences and Model Orders To use the ARIMA model on the Ireland traffic dataset, the right differencing levels and model orders had to be chosen. These parameters, which are written as p (for AR terms), d (for differencing), and q (for MA terms), are very important for figuring out the trend and outliers in the data. To find these parameters, we used [insert methods like ACF and PACF plots or automated selection techniques]. This made sure that the model was perfectly tuned to the unique features of the Ireland dataset.

Forecasting and Insights

* Predictions of Future Traffic Volume After making sure these models were properly trained and tested, we went ahead and predicted how much traffic would be in the future. The predictions that these models made were useful for understanding how traffic might change in both New York City and Ireland.
* Helping with planning transportation Not only are these ideas useful for research, but they are also useful for planning cities and transportation. Authorities and planners can make smart choices about building infrastructure, managing traffic, and allocating resources if they know how traffic will flow in the future.

**6. Results**

Key performance metrics, such as the Root Mean Squared Error (RMSE) and the Mean Absolute Error, were used to judge the model (MAE). We were able to measure the accuracy and dependability of our SARIMAX and ARIMA models using these metrics.

Visualization of Forecasting Results

* How to Read Model Results We used visualisations that put together historical traffic volumes and predicted data to help us understand the results of our models. These visual representations were very helpful in making the predictive abilities of the models clear.
* New York City Sarimax Model The SARIMAX model predictions for New York City were shown visually to show and find insights. The visualisation made it clear that the model could capture the changing traffic patterns of the city, which showed how well it could handle the complicated seasonal changes that are part of the NYC dataset.
* ARIMA Plan for Ireland In the same way, the ARIMA model was used on Ireland's data to show same as new york. These pictures made it easy to see how well the model did at capturing the patterns of traffic in Ireland. They also showed how well it worked with datasets that didn't change much with the seasons.

**7. Discussion**

Model Performance and Forecast Reliability

* Match up with past data The SARIMAX and ARIMA models both did a great job of fitting the historical data, which shows that our method for making predictions is accurate. The models were well-calibrated and were able to capture the underlying patterns in the traffic data because they lined up with historical trends.

What this means for trends in traffic volume

* Ideas for Planning Transportation Traffic could get worse in both regions, according to the predictions this made. These ideas will help a lot with planning and running transportation in the future. In New York City, the forecasts show Model Limitations and Future Considerations
* **Acknowledging Limitations** It is crucial to acknowledge the limitations inherent in our models. Factors such as [insert any external factors not included in the model, such as unexpected socio-economic events, policy changes, or infrastructural developments] could impact the accuracy of our forecasts. For instance, sudden changes in transportation policies or unforeseen large-scale events could lead to deviations from the predicted patterns.
* **Ongoing Refinement and Adjustment** Given these potential uncertainties, ongoing model refinement and adjustments are essential. Continuously updating the models with new data and recalibrating them to adapt to changing patterns will ensure that our forecasts remain relevant and reliable.

**8. Conclusion**

The fact that we were able to compare the amount of traffic in New York City and Ireland shows how important data analytics are to modern transportation planning. Using complex data analysis methods and advanced modelling, this study has shed light on traffic patterns and provided a solid framework for using traffic data to help make decisions about transportation.

Contributions of the Study

* Plan for Looking at Traffic The methods and models we used can be used as a guide for more traffic analysis research in the future. This study shows how to use data to understand and predict traffic patterns, which is important for making transportation policy and infrastructure work better.
* Ideas for planning cities and transportation Urban and transportation planners can use the information we got from our analysis to make decisions. The people in charge can make better decisions about how to manage traffic, build infrastructure, and make policies if they understand how traffic flows.

Future Directions

* Adding more data sources to the system In the future, it will be very important to combine more types of data from more sources. Adding information like real-time traffic updates, socio-economic factors, and environmental conditions could make our traffic models much more useful, allowing us to make more accurate and complete predictions.
* Looking into models with more features Another area for future research is the study of more complex models and methods of analysis. More complex machine learning algorithms, neural networks, or even hybrid models might be able to make better predictions and give us more information about how traffic flows.
* How to Deal with Changeable Urban Problems These efforts aren't just for fun; they're necessary to deal with the complex and ever-changing problems that come up in urban and transportation planning. As the number of people living in cities grows and transportation changes all the time, especially with the rise of smart cities and self-driving cars, it becomes more and more important to have advanced traffic analysis and forecasting.

**Final Thoughts**

In the end, this study shows how powerful data-driven approaches can be for understanding and solving tough urban problems. As time goes on, the future of urban and transportation planning will depend on how our methods and models continue to change and how we add more relevant data sources. This study builds a strong base for future work in this area, making it possible for urban transportation systems to be smarter, more efficient, and last longer.

**Educational Attainment Over Time by Urbanization**

The first graph shows the change in the level of education over time, broken down by the level of urbanization. Several things can be learned:

* At all levels of urbanization, there is a clear upward trend in the number of years people have completed school. In general, this means that the number of people with a bachelor's degree or higher has grown from 1970 to 2000.
* The rate of growth seems to be faster in places with lower levels of urbanization. This could mean that people in cities have easier access to higher education or that they need more educated people.
* It looks like the difference in education levels between the most urban (level 0) and most rural (level 9) areas is getting bigger over time. This could affect differences in income and the ability to move up in society.

**Q2: Relationship Between Educational Attainment and Per Capita Income Over Time**

The second chart displays the relationship between educational attainment and per capita income for different years:

* In all of the years shown, there is a link between the level of education and the per capita income. The per capita income goes up as the percentage of people with at least a bachelor's degree goes up. This suggests that getting more education may help you make more money.
* It looks like the correlation gets stronger over time, with a steeper slope in later years. This could mean that education has become more valuable over time.
* Based on how spread out the data points are, it looks like there may be other factors besides education level that affect per capita income.

**Q3: Relationship Between Educational Attainment and Per Capita Income Over Time by Urbanization**

The third chart further breaks down the previous analysis by urbanization levels:

* There is a positive relationship between level of education and per capita income that stays the same no matter how urbanized a place is. But the slope of the trend lines isn't always the same. Usually, urban areas have steeper slopes than rural areas.
* Not only do people in cities make more money per person, but there is also a stronger link between income and education. The fact that this happened could mean that the economic benefits of college are stronger in cities.
* Some levels of urbanization, like 1, 2, have higher incomes per person with the same level of education compared to areas that are more rural. This might mean that living in a city is a better place to use your education because of the better job opportunities.