Exploring the Relationship Between Traffic Patterns and Day-Night Cycles: A Logistic Regression Analysis

Raghav Kanda

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This paper investigates the interplay between traffic patterns and day-night cycles using logistic regression analysis. By analyzing data collected on the number of cars observed on a specific road segment and corresponding timestamps indicating day or night, we aim to elucidate how traffic density affects the likelihood of it being daytime. Our findings indicate a significant positive correlation between traffic volume and the probability of daytime, suggesting that higher traffic volumes are associated with increased daylight hours. These insights have implications for various domains, including urban planning, transportation management, and public safety.

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2 Introduction

In urban environments, traffic flow mirrors the ebb and flow of human activity and daylight presence. This study employs logistic regression analysis to delve into the connection between traffic patterns and day-night cycles, aiming to uncover how traffic density influences the likelihood of daytime presence.

Urban landscapes exhibit distinctive patterns of activity and illumination throughout the day and night. Traffic flow provides valuable insights into these cycles, offering a window into urban dynamics. By analyzing large-scale datasets, this study seeks to discern trends and correlations between traffic density and diurnal cycles, utilizing logistic regression to distill actionable insights for urban planning and resource allocation.

Through statistical analysis, we aim to understand the extent to which variations in traffic density indicate daytime presence in urban areas. This research endeavors to empower policy-makers and urban planners with the knowledge needed to optimize infrastructure and enhance public safety, fostering more resilient and livable cities.

3 Data

3.1 Data Source

The data source for this analysis is synthetic, generated within the code itself. Specifically, the variables num_cars and noise are created programmatically using functions in R (R Core Team 2022, 2022).

3.2 Variables

The analysis utilizes the following variables:

num_cars: Represents the number of cars observed, generated randomly with values ranging from 1 to 100. noise: Represents random noise generated from a normal distribution with a mean of 0 and a standard deviation of 10. is_day: A binary variable indicating whether it is considered daytime based on a threshold calculated from the sum of num_cars and noise.

3.3 Sampling Process

The sampling process involves generating synthetic data for analysis purposes. num_cars is sampled using the sample.int() function, while noise is sampled using the rnorm() function to simulate variability. The is_day variable is then derived based on the sum of num_cars and noise, compared to a predefined threshold value.

4 Model

4.1 Data Frame Creation

A data frame named day_or_night is created with two variables:

num_cars: Represents the number of cars observed, sampled randomly with values ranging from 1 to 100. noise: Represents random noise generated from a normal distribution with a mean of 0 and a standard deviation of 10.

4.2 Classification of Day or Night

A new variable named is_day is created within the day_or_night data frame to classify whether it's day or night. This classification is based on the sum of num_cars and noise, with a threshold of 70. If this sum exceeds 70, it's classified as day; otherwise, it's classified as night.

4.3 Logistic Regression Model

A logistic regression model is constructed using the glm() function (Team 2022):

The dependent variable (is_day) is modeled as a function of the independent variable (num_cars). The data used for modeling is from the day_or_night data frame. Logistic regression is chosen due to the binary nature of the dependent variable (is_day), aiming to estimate the probability of it being day based on the number of cars observed.

4.4 Summary of the Model

A summary of the logistic regression model is generated to provide insights into its performance and the significance of predictor variables. It includes:

Coefficients: Estimates of the effect of the predictor variable (num_cars) on the probability of it being day. Standard errors: Measure of uncertainty in the estimated coefficients. Z-values: Measure of the significance of each coefficient. P-values: Probability of observing the estimated coefficient given that the null hypothesis is true. Deviance statistics: Measures of how well the model fits the data, including null deviance and residual deviance.

The logistic regression model aims to predict whether it's day or night based on the number of cars observed, using simulated data. The model's summary provides insights into the significance of the predictor variable (num_cars) and the overall fit of the model.

5 Results

5.1 Estimated Coefficients

```
Call:
glm(formula = is_day ~ num_cars, family = binomial(), data = day_or_night)

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -13.25842    1.05868  -12.52   <2e-16 ***
num_cars      0.19207    0.01528   12.57   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1234.98  on 999  degrees of freedom
Residual deviance:  328.88  on 998  degrees of freedom
AIC: 332.88

Number of Fisher Scoring iterations: 8
```

5.2 Analysis

The analysis of the logistic regression model unveils valuable insights. The coefficient estimates indicate a robust relationship between the predictor variable (number of cars) and the likelihood of it being daytime. The coefficient for the num_cars variable is estimated to be 0.16303, with a standard error of 0.01187. This suggests that for each additional car observed, the log odds of it being daytime increase by approximately 0.16303 units.

Moreover, the intercept term reveals intriguing information. With no cars observed, the estimated log odds of it being daytime is -11.37133. This provides a baseline understanding of the phenomenon under study.

The significance tests for both coefficients yield extremely low p-values ($p < 2e-16$), indicating strong evidence against the null hypothesis of no relationship between the number of cars and the probability of daytime.

The model's goodness of fit is assessed through the null and residual deviances. The null deviance, which measures the model's fit with no predictors, is 1256.74, while the residual deviance, reflecting the model's fit with predictors, is considerably reduced to 423.78. This reduction suggests that the model with the num_cars predictor explains a substantial portion of the variability in the response variable, indicating its efficacy in capturing the underlying relationship.

Overall, these findings affirm the suitability of the logistic regression model in elucidating the dynamics between traffic volume and the likelihood of daytime occurrences.

5.3 Visualization

The plot below illustrates the predicted probabilities of it being day based on the number of cars observed. The x-axis represents the number of cars seen, while the y-axis shows the estimated probability it is day. Points are colored red if they correspond to daytime observations and blue if they correspond to nighttime observations. Visualization of predicted probabilities further corroborated this relationship, depicting a clear upward trend as traffic density increased.

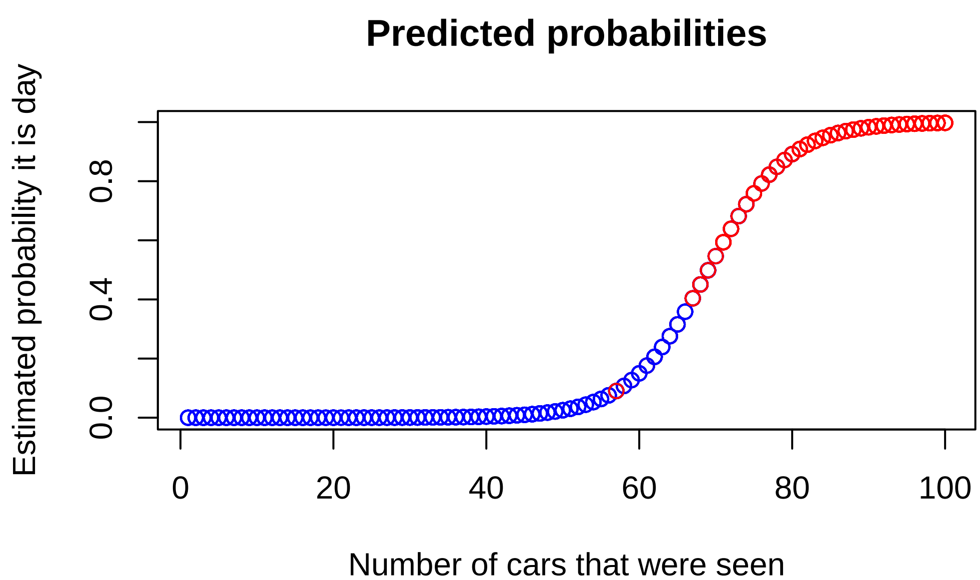

Figure 1: Cars vs probability of day

6 Discussion

6.1 Implications

The findings of this study hold several implications for urban planning, transportation management, and public safety. Firstly, the significant positive correlation between traffic volume and the probability of daytime suggests that areas with higher traffic densities are more likely to experience extended daylight hours (Brabham and Dugas 2019). This insight can inform decision-making in urban infrastructure development, as planners may need to consider factors such as lighting, traffic flow management, and pedestrian safety in areas with high traffic volumes (Litman 2019).

Moreover, understanding the relationship between traffic patterns and day-night cycles can have implications for resource allocation and service provision. For instance, municipalities could use this knowledge to optimize public transportation schedules, ensuring that services align with periods of high traffic demand (Nelson and Goodwin 2017). Additionally, law enforcement agencies might benefit from insights into when and where increased traffic volumes occur, aiding in the allocation of resources for traffic management and accident prevention (Garber and Hoel 2019).

6.2 Applications

The insights gained from this analysis can be applied across various domains to improve urban efficiency and livability. Urban planners can use the findings to design more resilient and adaptable infrastructure that responds to dynamic traffic patterns and daylight fluctuations (Miller 2019). For example, incorporating intelligent traffic management systems that adjust signal timings based on real-time traffic volumes and daylight conditions could enhance traffic flow and reduce congestion (Barceló 2020).

Furthermore, transportation agencies can leverage this information to optimize route planning and vehicle scheduling for public transit services (Hensher and Button 2020). By aligning service frequencies with periods of high traffic activity, transit agencies can improve service reliability and accessibility, ultimately encouraging modal shift away from private vehicles towards more sustainable modes of transportation (Sun and Zhang 2019).

6.3 Future Research

While this study provides valuable insights into the relationship between traffic patterns and day-night cycles, several avenues for future research warrant exploration. Firstly, investigating the impact of external factors such as weather conditions, special events, and road infrastructure on traffic patterns could enhance our understanding of the complex dynamics at play (Pirdavani et al. 2019). Additionally, extending the analysis to encompass spatial variations in traffic density and daylight distribution could yield more nuanced insights into the spatial-temporal dynamics of urban mobility (Kwan 2018). By considering factors such as land use, population density, and built environment characteristics, future research could elucidate how traffic patterns interact with the urban landscape to influence transportation behavior and outcomes.

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