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Prediction and Analysis of Bus Adherence to Scheduled Times: San Antonio Transit System

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Completed Research

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Abstract

Citizens in large and modern cities heavily rely on smart and efficient public transportation as an alternative to private cars. Public transportation options are expected to be efficient, consistent, and reliable. For example, users of public buses should be able to use their smart phones to reserve and plan their trip at any time. They should also be able to track in real time their routes and any possible delays or issues. Bus adherence to their schedule in public transportation can be modeled as an NP-hard problem. This is due to the many unpredictable factors that can impact such adherence. In this paper, we used deep neural network and regression models to predict bus adherence to scheduled times. We selected San Antonio Transit system as a problem domain and used a dataset containing a snapshot of the adherence of VIA buses from February 2019. We focused on analyzing the significant routes in the dataset and explored the percentage of buses were on time in these routes. Results revealed better performance of neural network models as compared to regression models.

Keywords

Metropolitan transit system, bus adherence, arrival time, neural network, regression.

Introduction

A reliable transit system is a major distinguished criterion of major modern cities. Such systems provide a reliable alternative to individual or personal cars and support the ability of citizens to live in the suburb while daily commuting to their jobs. A major factor of reliability of such systems is related to adherence despite the several different obstacles and in many cases, unforeseeable factors.

One more evolving and important quality criteria in transit systems is the ability of users to see real time information related to bus routes and schedules. This criterion can offset some of the problems related to unforeseen delays or problems. Time adherence and providing accurate and real-time bus location information reduce riders' wait times and thus the length of their daily commutes, leaving more time for vocational, educational, and leisure activities. Survey results, however, revealed that publicly available apps like commonly used Google Maps do not provide specific and accurate real-time information for metropolitan bus routes (Romero et al. 2020). Such information on specific lines and routes is crucial for daily commuters to estimate the arrival time of buses.

The San Antonio public transit system is used by hundreds of thousands of San Antonians a year. VIA Metropolitan Transit system provides regional multimodal transportation options that connect San Antonio community to opportunity, support economic vitality and enhance quality of life throughout the San Antonio region. For example, connecting students to educational opportunities, workers to jobs and workforce training, and residents to social and leisure activities. The transit system provides a "Trip Planner" that helps riders plan their trip and get directions from A to B as shown in Figure 1.

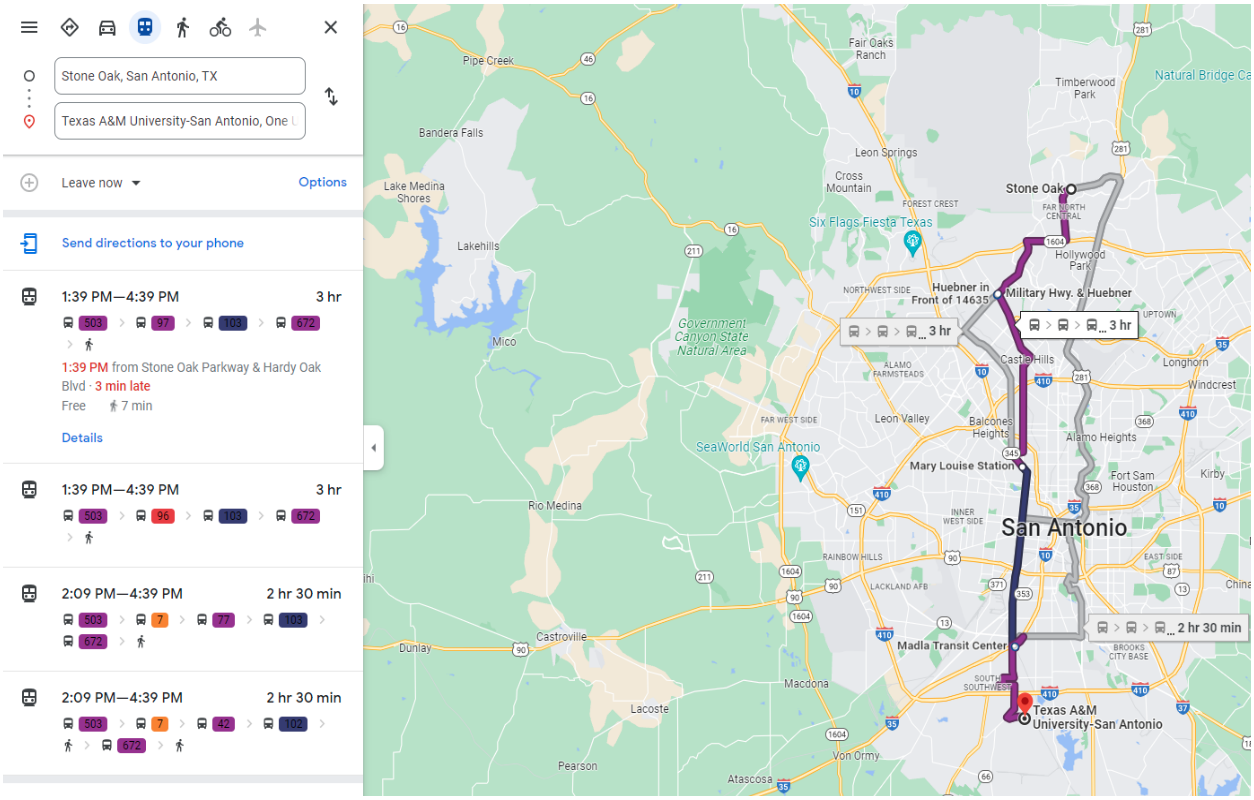

Figure 1: VIA Trip Planner

San Antonio has invested hundreds of thousands of dollars to build an efficient and easy experience for its transportation customers. However, according to a study conducted by the CATO institute (O'Toole 2018), the ridership data reveal that San Antonio transit system in 2018 lost 3 percent of its riders in the previous year and 17 percent in the last 4 years. In the last 50 years, resident trips have fallen from 57 to 38 by the average urban residents. Results also revealed that more low-income citizens are able to get cars on their own and don't really need to use the transit system. In fact, the report indicated a drastic increase in ridership among people who earn more than $75,000.

Despite this, San Antonio has pumped more investment into the system hoping to increase utilization. It would still be beneficial to see if there was a way to make the transit system more efficient and in a way that is cost-effective. Hence, San Antonio Transit service first conducted studies to find out whether the buses were consistently late. If the buses are always on time or already efficient, then there would not be much to look at. They needed to find out not only if the buses were late or not but also how late the buses were. Were the buses a few minutes late or were they late for an extended period of time? It is also important to know those routes that are more often late and how to improve efficiency in those routes.

In this study, we used a dataset containing a snapshot of the adherence of VIA buses from February, 2019. We developed deep learning (DL) models to predict bus adherence to their schedule. The remainder of the study is structured as the following: Section 2 focuses on evaluating a selection of related work. Section 3 covers the main experiments, discussion about the dataset and the state of art prediction models developed. This is then followed by section 4, results, and analysis. Finally, the paper is concluded in section 5 while also exploring possible future directions.

Related Work

Our subject involves aspects related to public transportation time adherence in relation with using machine learning to evaluate and investigate such adherence. It should be mentioned that transportation systems witnessed a significant evolution in the last few decades. Distinguished characteristics of that evolution are related to making those systems smarter and more intelligence, through utilizing the Internet, telecommunication and mobile networks. Existing research (e.g., Chan et al. 2020; Romero et al. 2020) reported that the current transportation systems still do not fully satisfy rider needs, especially as riders' need may continuously evolve. Many countries reported low ridership and tried to investigate reasons and eventually methods to encourage citizens to utilize more those public transportation. One of the reasons that could deter from using the public transport is dissatisfaction due to lack of information on arrival and departure times (Azmi et al. 2018; Brohi et al. 2018). Few publications indicated that popular GPS applications such as Google maps, do not provide information about metropolitan bus routes, which makes bus riders dissatisfied (Romero et al. 2020). Improving the multimodal information passengers receive through transit apps could ease their trips and help materialize some of the potential bus demand in metropolitan areas (Romero et al. 2021).

To improve the prediction of the arrival time, existing research propose different models. For example, Zhang et al. (2009) provided a real-time dynamic model for each component of time, location, stops, and distance between stops to get more accurate prediction results. Further, Zhang et al. (2013) utilized GPS data to propose a dynamic model to predict bus arrival time at each bus stop with acceptable accuracy. The model considered the different dates and different time intervals within the day. Maiti et al. (2014) developed a historical data-based model to predict vehicle arrival time. The results of the proposed model outperform baseline models such as Support Vector Machine (SVM), regression and Artificial Neural Networks (ANNs). Sun et al. (2010) developed a prediction model of bus arrival time using Auto-regressive model. Authors compared the actual arrival time against the predicted one with error rate achieved that was less than 20%. Sinn et al. (2012) proposed an algorithm based on Kernel regression model. The model shows better performance compared to classical linear regression.

Several other researchers used the state of art Artificial Neural Networks (ANN) to predict bus arrival time and the results show promising results. Lin et al. (2013) propose real-time prediction models using artificial neural network (ANN) based on GPS data and automatic fare collection (AFC) system data. Results show that the proposed models outpace the Kalman filter model. Amita et al. (2015) adopted ANN for real time bus arrival time prediction. The model used dwell time, delays and distance between the bus stops features as input data. The ANN model reported better performance than the regression model in terms of accuracy and robustness. More recently, Shoman et al. (2020) proposed a framework based on ANN to predict bus delay on multiple routes using various data sets. Results revealed that the proposed framework can predict bus delays at multiple stops with about 6% mean absolute percentage error (MAPE).

Time series analysis is used by many papers to study and predict transportation adherence over a period of time, (e.g., Altinkaya and Zontul 2013; Bin et al. 2006; Bing et al. 2019; Bradley 1999; Chidlovskii 2017; Chien et al. 2002; Comi et al. 2017; Gong et al. 2020; Handley et al. 2019; Imam 2019; Jeong and Rilett 2004; Li et al. 2020; Mahdavilayen et al. 2020; Ranjitkar et al. 2019; Rashidi et al. 2022; Shalaik 2012; Wang et al. 2018; Williams 2020; Yu et al. 2010). The purpose of time series analysis is: (1) to understand or model the stochastic mechanisms that give rise to an observed series and (2) to predict or forecast the future values of a series based on the history of that series (Bradley 1999). In those relevant research papers, in addition to bus adherence, researchers investigated related issues such as: the estimation of the number of travelers entering the network at any period of time (Chidlovskii 2017), the evaluation of the software applications controlling transportation systems, (e.g. Shalaik (2012), bus dispatching irregularity, Comi et al. (2017), bus dwell time, impact of weather, Wang et al. (2018), Mahdavilayen et al. (2020), Rashidi et al. (2022) and bus bunching prediction (Gong et al. 2020).

San Antonio VIA: Bus Adherence Experiments

San Antonio VIA Dataset

The dataset we used in this project is a snapshot of the adherence of VIA buses from February 19, 2019, "VIA_Adherence"[1]. The dataset contains 37,832 records and 16 columns/attributes. The dataset was

[1]https://gitlab.com/hooli-datathon/civtechsa-datathon/blob/master/Data_Sources/VIA_Adherence.csv

broken down as shown in Table 1. The data contains duplicated time attributes (i.e., ScheduledTime(s), ScheduledTime(HHMMSS), ArrivalTime(s), ArrivalTime(HHMMSS), DepartureTime(s) and DepartureTime(HHMMSS)). These time attributes are further broken down into two different formats. One column is in seconds while the other column is in hours/minutes format.

Attribute	**Description**
ServiceDate	The service date. Is not useful since it simply showed one date (Feb 19, 2019)
Routes	The different routes taken
Block	The Block numbers for each route
RouteDirectionName	The direction of routes (for example, South, North, East etc.)
StopNumber	The number assigned to each bus stop
Location	The actual address of each stop location
Latitude/Longitude	Latitude/Longitude of the bus location
ScheduledTime(s)	The time the bus was scheduled to arrive (expected arrival time) (in seconds format)
ScheduledTime(HHMMSS)	The time the bus was scheduled to arrive (expected arrival time) (in Hour, Minute and seconds format HHMMSS)
ArrivalTime(s)	The actual arrival time (in seconds format)
ArrivalTime(HHMMSS)	The actual arrival time (in Hour, Minute and seconds format HHMMSS)
DepartureTime(s)	The time when the bus left the stop (in seconds format)
DepartureTime(HHMMSS)	The time when the bus left the stop (in Hour, Minute, and seconds format HHMMSS)
Odometer	The vehicle odometer for the trip distance between stops
VehicleNumber	The vehicle number

Table 1: Variables Description

Data Pre-processing and Analysis

We performed the following pre-processing steps to prepare data for analysis.

- First, we dropped duplicate attributes like time variables (i.e., Scheduled Time(s), Arrival Time(s), and Departure Time(s)), in addition to unnecessary/unwanted attributes such as Service Date and Vehicle Number.
- Second, we conducted missing value imputations.
- Third, convert the string attributes into appropriate data type. For example, convert the latitude (Lat) and longitude (Long) attributes to numeric and time attributes such as Arrival Time(s) to data time.
- Fourth, troubleshooting arrival time by adding one to the day if it's after midnight.
- Fifth, compute bus adherence by subtracting arrival time from scheduled time as shown in the following formula, :

$$AD = S_t - A_t \text{ --- } (1)$$

Where:

– AD represents the adherence computed in minutes with positive values indicating bus arriving early and negative values indicating a late arrival to the stop.

– St represents the scheduled arrival time of bus and,

– At represents the actual arrival time of bus.

- Sixth, we obtained bus address from Latitude and Longitude of the bus location.
- Seventh, we extracted the part of day (i.e., Early Morning (EM), Rush Hour (RH), Morning (M), Noon (No), Evening(E), Night(Ni), and Late Night (LN) as shown in Figure 2.

```
if (TIME_HOUR >= 4) and (TIME_HOUR <= 7):
  return 'Early Morning'
elif (TIME_HOUR > 7) and (TIME_HOUR <= 9 ):
  return 'Rush Hour'
elif (TIME_HOUR > 9) and (TIME_HOUR < 12 ):
  return 'Morning'
elif (TIME_HOUR >= 12) and (TIME_HOUR <= 16):
  return'Noon'
elif (TIME_HOUR > 16) and (TIME_HOUR <= 18) :
  return 'Evening'
elif (TIME_HOUR > 18) and (TIME_HOUR <= 24):
  return'Night'
elif (TIME_HOUR < 4):
  return'Late Night'
```

Figure 2: Getting part of the day algorithm

Predicting Bus Adherence to Scheduled Time

To predict bus adherence, we applied deep neural network models (DNN) against a baseline of several regression models such Random Forest, XGB, Decision Tree, and 3-Nearest Neighbors regression models. For the network model, we created a sequential model, Table 2, with three dense layers (input, hidden and output layers) (see Table 3), let $L_i = \{L_1, L_2, L_3\}$. The hidden layer in the model transforms the input data into a deferent output dimension as shown in (equation 2):

$$L_i = y_i = \varphi\,(w_i \otimes x_i + b) \text{ --} (2)$$

where at each forward pass at layer L_i, the weight or the kernel parameter is represented with w_i, the input vector is represented with x_i, and the bias is represented with b.

The projection function to transform input to output is represented with $\otimes$. Lastly, φ represents the deferent activation functions. In our model, we used 'ReLU' as the activation function for the hidden layer, a 'Normal' initializer as the kernal_intializer, mean_absolute_error as a loss function, and 'Linear 'as the activation function for the output layer. To train the model, we used 85% of the dataset as training data and divided it to training and validation data. 10% of the training data was used as validation data. We used 10 epochs in the training process.

To evaluate the DNN and baseline models, we used 15% of the dataset as testing data.

Layer (type)	Output Shape	Param #
dense_38 (Dense)	(None, 10)	2850
dense_39 (Dense)	(None, 10)	110
dense_40 (Dense)	(None, 1)	11

Total params: 2,971

Trainable params: 2,971

Non-trainable params: 0

Table 2: Neural Network Model: "sequential"

The performance of the developed DNN model is compared with the other baseline regression models using the Mean Absolute Error (MAE) measure. MAE is defined as the average difference between the predicted and actual bust arrival time as shown in equation 3.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - y_0|}{n} \qquad (3)$$

Where:

MAE is the mean absolute error

y_i is the predicted value of bust arrival time

y_0 is the actual bus arrival time

n is the number of records (i.e., data points) in the dataset.

Analysis of Significant Routes

To explore the variables that are significant with the target variable (i.e., bus adherence), we run a multiple linear regression model. We use multiple regression to include multiple predictors in the model. To achieve that, we use the ordinary least squares (OLS) function, which computes the ordinary least squares value. OLS is one method to estimate parameters in a linear regression. As shown below, we evaluated different models with different predictors and formulas. Each formula notation has two parts, separated by a tilde, ~. To the left of the tilde is the dependent or target variable, and to the right of the tilde are the predictors or independent variables. We used the analysis of variance (ANOVA) method to calculate models' performance and compare them. The ANOVA shows sum of squared residuals (SSR), which is one way to measure performance, where when values are lower, this indicates a better model.

Model 1: *adherence ~ RouteDirectionName + Road + PartofDay----------------------(4)*

Model 2: *adherence ~ RouteDirectionName + Road * PartofDay----------------------(5)*

Model 3: *adherence ~ Road * PartofDay--(6)*

Model 4: *adherence ~ RouteDirectionName + Road + PartofDay + Postcode-------(7)*

Results and Analysis

Prediction Results

Table 3 shows the Mean Absolute Error (MAE) measure of the deep neural network model (DNN) and the regression models. The results show better performance of the DNN model with better accuracy (i.e., less prediction error) as compared to the regression models.

Model	**Mean Absolute Error (MAE)**
Deep Neural Network	27.79
Random Forest Regressor	39.11
XGB Regressor	39.77
Decision Tree Regressor	46.49
3-Nearest Neighbors regression model	48.86

Table 3: Results of Predicting adherence, using Mean Absolute Error (MAE)

Analysis of Significant Routes

Table 4 shows the results of ANOVA analysis of four models. Based on the sum of squared residuals (SSR) values, the best model was model 2 (very slightly better than model 3).

Model	**SSR (sum of squared residuals)**
Model1	4.062387e+08
Model2	3.652038e+08
Model3	3.653260e+08
Model4	4.009981e+08

Table 4: Models' performance according to ANOVA analysis

Table 5 shows some of the relevant significant variables at the .05 level in model 2. The table also shows the percentage that buses on these significant roads that were on time. The bus was considered on time (not late) if the difference between its arrival and schedule times was less than 5 minutes (<5min). Otherwise, the bus was considered late. We found four routes with below 50 percent on-time arrival rate, two routes with zero percent, especially at night.

Variable	**P>|t|**	**Percentage of buses that were on time**
Road[T.Austin Highway]:PartofDay[T.Night]	0.000	90%
Road[T.Austin Highway]:PartofDay[T.Noon]	0.000	80%
Road[T.Austin Highway]:PartofDay[T.Eve]	0.000	75%
Road[T.Austin Highway]:PartofDay[T.Morning]	0.020	94%
Road[T.Eads Avenue]:PartofDay[T.Eve]	0.000	94%
Road[T.Eads Avenue]:PartofDay[T.Morning]	0.002	100%
Road[T.Eads Avenue]:PartofDay[T.Night]	0.000	92%
Road[T.Eads Avenue]:PartofDay[T.Noon]	0.000	100%

Road[T.South Zarzamora Street]	0.046	84%
Road[T.Babcock Road]:PartofDay[T.Eve]	0.000	83%
Road[T.Babcock Road]:PartofDay[T.Night]	0.000	90%
Road[T.Babcock Road]:PartofDay[T.Noon]	0.003	93%
Road[T.Bandera Road]:PartofDay[T.Eve]	0.001	100%
Road[T.Bandera Road]:PartofDay[T.Night]	0.005	94%
Road[T.Callaghan Road]:PartofDay[T.Eve]	**0.007**	**71%**
Road[T.East César E. Chávez Boulevard]:PartofDay[T.Night]	0.000	100%
Road[T.La Cantera Parkway]:PartofDay[T.Eve]	0.018	76%
Road[T.La Cantera Parkway]:PartofDay[T.Night]	0.010	84%
Road[T.La Cantera Parkway]:PartofDay[T.Noon]	0.017	86%
Road[T.North Ellison Drive]:PartofDay[T.Eve]	**0.002**	**24%**
Road[T.North Ellison Drive]:PartofDay[T.Morning]	0.025	83%
Road[T.North Ellison Drive]:PartofDay[T.Night]	**0.000**	**50%**
Road[T.North Ellison Drive]:PartofDay[T.Noon]	0.000	74%
Road[T.North Loop 1604 East]:PartofDay[T.Eve]	0.000	92%
Road[T.North Loop 1604 East]:PartofDay[T.Night]	0.000	100%
Road[T.Poss Road]:PartofDay[T.Eve]	0.000	75%
Road[T.Poss Road]:PartofDay[T.Night]	0.002	100%
Road[T.Poss Road]:PartofDay[T.Noon]	0.014	95%
Road[T.Potranco Road]:PartofDay[T.Eve]	**0.003**	**57%**
Road[T.Potranco Road]:PartofDay[T.Night]	0.007	81%
Road[T.Potranco Road]:PartofDay[T.Noon]	0.011	86%
Road[T.West Broadview Drive]:PartofDay[T.Night]	0.000	75%
Road[T.West Broadview Drive]:PartofDay[T.Noon]	0.000	100%
Road[T.West Travis Street]:PartofDay[T.Eve]	0.003	78%
Road[T.West Travis Street]:PartofDay[T.Night]	0.017	70%
Road[T.Old Corpus Christi Road]:PartofDay[T.Noon]	0.000	100%
Road[T.US 181]:PartofDay[T.Noon]	0.000	100%
PartofDay[T.Night]	**0.013**	

Table 5: Significant variables with bus adherence at the .05 level

Conclusion

Large modern cities invest to keep and encourage public transportation options. To maximize utilization for those systems, they must be reliable and consistent. Using machine learning and historical data of such systems can help in improving services and reducing problems related to delays, irregularities, etc. In this scope, we studied a public dataset of San Antonio public buses to evaluate their adherence to schedule. We employed and compared classical versus deep learning models and their ability to accurately predict bus adherence. Results indicated that there are few characteristics that can significantly influence delays in bus arrivals and departure times. Those include for example, part of the day, the direction of the bus as well as its location. Predicting consistently variables that can influence the delay, imply the need to include such delays to ensure providing accurate information to bus users. As practical implications, our findings can guide traffic management. In essence, the results show that some routes that are not on time while other routes have less issue when time of day is factored in, so perhaps time of day coupled with infrastructure issues. Our findings can also guide future research of qualitative evaluation such as gathering riders' feedback for those routes with below 50 percent on-time arrival rate.

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