Design and Development of an Application for Predicting Bus Travel Times using a Segmentation Approach

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Abstract: Public transportation applications today face a unique challenge: Providing easy-to-use and intuitive design, while at the same time giving the end user the most updated and accurate information possible. Applications often sacrifice one for the other, finding it hard to balance the two. Furthermore, accurately predicting travel times for public transport is a non-trivial task. Taking factors such as traffic, weather, or delays into account is a complex challenge. This paper describes a data driven analysis approach to resolve this problem by using machine learning to estimate the travel time of buses and places the results in a user-friendly application. In particular, this paper discusses a predictive model which estimates the travel time between pairs of bus stops. The approach is validated using data from the bus network in Dublin, Ireland. While the evaluation of the predictive models show that journey segment predictions are less accurate than the prediction of a bus route in full, the segmented approach gives the user more flexibility in planning a journey.

1 INTRODUCTION

Due to its importance in trip and route planning, travel time prediction has a long history and has been considered by several researchers in different domains (Lin et al., 2005). There is no doubt regarding the value of accurate prediction. While travel time prediction is relevant to all transport modes, it is perhaps road transport which receives the most attention. Studies have long shown that passengers are demanding services which are informative and dynamic (Peek and van Hagen, 2002) and provide them with the ability to factor waiting times and delays into their trip planning (Kroes and Daly, 2018). From an operators perspective, the ability to understand travel times is important for scheduling and service provision (Gkiotsalitis and Cats, 2017). Despite much activity in this area, many questions remain unanswered. This is due in part to the difficulties of incorporating the impact of external factors such as demand, time of day, weather conditions or seasonal patterns into prediction algorithms (Cristóbal et al., 2019).

The aim of the work presented in this paper is to provide an effective solution to the problem that Dublin Bus, and other public transportation applications, face in relation to providing accurate estimates of travel and arrival times for trip planning within an easy to use application. Static journey predictions are common. These provide a simple estimated travel time for each route. This can be produced based on a single average of all travel times. Such a time is often unrealistic given the variables that impact travel time such as demand, time of day, weather conditions or seasonal patterns. In this paper we describe a new algorithm for predicting travel times and integrate it into an innovative mobile application. Predictions are made by analysing historical weather and travel time data with a Random Forest machine learning algorithm based on estimating travel time between pairs of adjacent bus stops. Random Forest Classification is an ensemble method in which a collection of individual decision trees are used to produce a classification. The classification which is produced my the majority of trees in the ensemble is the output classification (Breiman, 2001). The approach has shown to outperform individual constituent models.

The remainder of this paper is organised as follows: Section 2 examines related work in the area of machine learning for predicting travel time as well as a review of bus trip planning applications. Section 3 presents our approach for estimating bus travel time between stops and also briefly describes the interface of the accompanying application. Section 4 presents the results of evaluating the accuracy of the travel time prediction. Finally Section 5 concludes the paper with

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a discussion and the identification of some area for future research.

2 RELATED WORK

Due to the importance of trip planning for both operators and end users there are many examples of trip planning application across many domains including commuting and tourism (Jariyasunant et al., 2011), (Huang and Peng, 2002), (Brilhante et al., 2015). The applications all have a user interface which allows the location for origin and destination to be specified and then provides a route recommendation using various modes of transport considering different spatiotemporal constraints. Some utilise real-time data (Liebig et al., 2017) but the majority of applications use static data and provide travel time estimate based on the best or worst case. This section briefly examines applications available before discussing techniques for more robust travel time prediction using machine learning.

2.1 Bus Applications

There are a plethora of bus and transport planning applications available to support travellers and commuters. A review of other transport apps currently available on mobile app stores was carried out. Most allow users to plan routes, view timetables, locate bus stops and find points of interest. In relation to journey time predictions, several apps integrated Google's journey prediction API, rather than building their own model; examples include the *Hit the Road*, *SDMTS & NCTD*, *MuniMobile*, *CityMapper* and *OneBusAway Seattle* apps. It is unclear if any of the apps used any more criteria in their predictions, other than the search terms in the journey planner.

In the Irish context, the Dublin Bus App makes extensive use of real-time information to estimate the arrival time of a bus. The application also includes journey planning, favourites, and fare calculating features; but does not provide journey time predictions. Instead, travel times are given by timetables which give journey estimates for several sections of the journey (for example, the number 4 route is broken into seven journey segments, with an estimate for each). Static predictions like these do not reflect likely traffic conditions for a given journey and are not very useful to the user. Transport for Ireland (TFI) have developed a Real-time Journey Planner application for Dublin. When queried for a particular destination, the application returns a multi-modal journey plan with a travel time prediction for each mode segment in the journey. These estimates are dynamic, and predictions take into account factors such as time of day. It is not clear if weather-related factors are taken into account. This is a stand-alone app for journey planning and does not have a diverse range of features in comparison with other apps analysed such as ticket top up options.

2.2 Estimating Bus Travel Time

Recently, advances in machine learning along with the availability of new data sets have renewed interest in data driven approaches for predicting travel time in transport systems. Several machine learning approaches have been investigated for this problem including Support Vector Machine (SVM) and Artificial Neural Network (ANN) models (Chang et al., 2010). However, both approaches can take a significant time to train which may make them unsuitable for real-time predictions(Lee et al., 2012). Mazloumi et al. (2011) investigated these techniques for bus routes in Melbourne, Australia and decided to prioritise ANN models due to their modelling flexibility, predictive ability and generalization potential. Ensemble methods such as Random Forest models were also explored by several researchers (Gal et al., 2017). These models are generally faster to train and can be optimised relatively easily, and thus have potential to scale (Gal et al., 2017). Hybrid models also appear in the literature, but these models either showed mediocre results or had a significantly long processing time (Peng et al., 2018),(Petersen et al., 2019). Linear Regression models were tested by Jeong and Rilett (2004) and compared to Artificial Neural Network Models and historical averages, with the result that they were worse performing than both and therefore ruled out of consideration. For the interested reader, Cristóbal et al. (2019) provide an excellent review of these approaches applied to bus travel time prediction.

Within travel time prediction, there are different approaches in terms of what time is to be predicted, the whole route or segments. Within this context there are also different approaches to defining segments of routes for analysis. Celan (2017) examined the underlying traffic system to determine optimal segments. This study compared a model "defined by bus stops and crossings of the road network", a model "defined by bus stops", "a data model which addresses the individual parts of the network in relation to the potential barriers that affect the travel speed of buses", and "a data model with fixed-length links of the bus network". Many of these models required a significant amount of contextual information to define bus stop segments which adds additional overhead to the work. Gal et al. (2017) proposes a segmentation technique where a segment is defined by pairs of bus stops. Historical data are used with an approach based on queuing theory to predict journey time. Segments are combined to produce predictions for larger trips. The approach was tested with data with the bus network in Dublin. These segmentation techniques and the need to understand the network influenced our approach which is described in the next section.

While ANN predicted accurate results when compared to more classical approaches such as linear regression, there is a trade off when compared to the computation time. Models built using Random Forest approaches are faster to train and can handle large feature sets while still producing comparable results (Gal et al., 2017). In Section 3 the development of the model is described which uses segments based on pairs of adjacent bus stops. The evaluation metrics used in the literature include root-mean squared error, mean absolute relative error and median absolute relative error. These measures will be also used to assess the effectiveness of our approach.

3 APPROACH

While the Dublin Bus App is widely used across Dublin and is most likely the most used application for checking bus arrival times, it is not built with accurate times in mind. The use of static timetables rather than a predictive model means that a user could be waiting at a bus stop for 10 minutes, while the app claims that a bus is simply 1 minute away. Our approach to the problem relies on an understanding of how Dublin's bus system is designed. Unlike a city like London, where buses have multiple hubs and routes that are centred around various points (for example, Victoria Station, Euston Station, etc.), Dublin relies on the majority of bus routes passing through the city centre. In this sense, it is more of a "star" design rather than a hub design. Of course, the city centre is the area most likely to be congested which adds to the uncertainty in travel time prediction. However, this also means that most buses will pass through the same set of stations at some point, meaning that rather than build a model that tries to specifically target bus routes, our approach is to build a model that uses stop-pairs to predict journey time. For example, bus routes 39a, 46, and 145 all pass through the same set of stops for a significant portion of their respective routes. Therefore, instead of developing three separate models for predicting travel time, one model that handles common element of their routes is proposed. The predictive aspects of the approach are incorporated into a mobile web application which functions for single bus or multi-connection routes, and journeys that utilise the entire route or just a few stops of a route. It is fully scalable and can handle the variety of routes an average user might want to take.

3.1 System Description

The final product is a transportation app which brings together a journey planner with prediction, real-time bus information, the ability to log in and save favorite routes, a game, and route list. The map contains features such as a user finding their nearest stops, and planning a route to a selected location. There are five sections of the app - Home, Journey Planner, Routes, Favourites, and More.

3.1.1 Wire Frame Design

During the early planning stages, wire frames (see Figure 1) were created to show how the app would like and to aid the design. The final product was quite similar to these wire frames and is discussed in the coming sections.

Figure 1: Original Wireframes.

3.1.2 Home Page

The home page, shown in Figure 2, is map-centric and by default shows the user's location and nearby stops.

3.1.3 Real-time Information

As shown in Figure 3, there are markers on the *home* and *journey planner* pages which show where Dublin

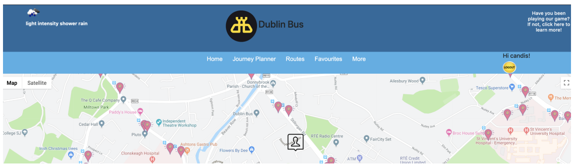


Figure 2: Home Page.

bus stops are located. When a user clicks one of the markers, an information window displays the stop ID, stop name and the routes which stop at that location. There is a real-time button, which when pressed, details bus arrival times at that location - taken from the Real Time Passenger Information (RTPI) API, supplied by Dublin Bus.

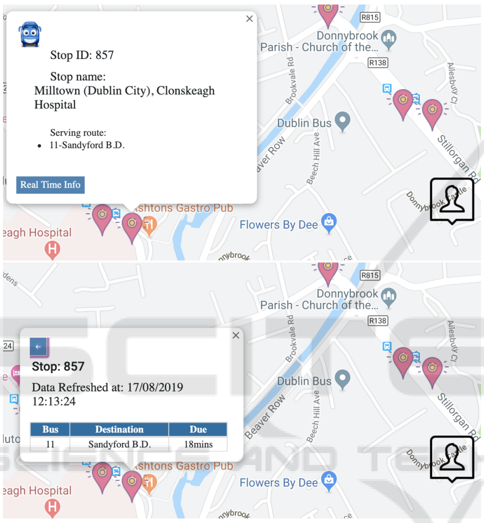


Figure 3: Markers and Real-time Information.

3.1.4 Journey Planner and Search Pages

The journey planner is map-centric and allows for search and planning of journeys. Once a user types in an address or business of their choice and hits "search", pin(s) will appear on the map. These markers change based on the type of business for which they search (restaurant, hotel, school, etc), as presented in Figure 4. Clicking that icon or marker and then "route to here" presents the user with the possible bus routes to that place from the user's current location.

3.1.5 Planning a Journey

The "show journey planner" button allows the user to input an origin and destination, along with a date and time for travel. Once submitted, it displays different possible routes - with the number of connections required – along with an estimated time for the journey

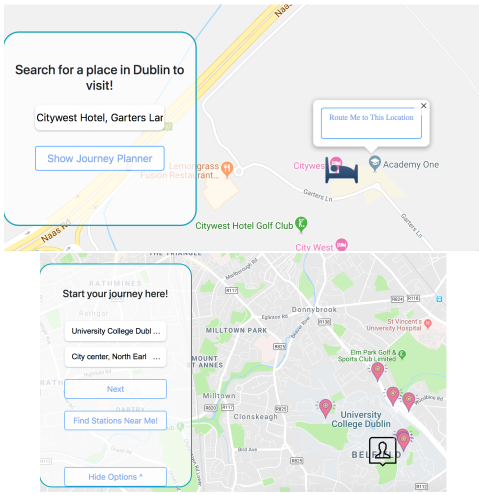


Figure 4: Search and Journey Planning.

(described in Section 3.2. When one of the routes is clicked, the map then displays each stop on the journey along with detailed directions including any connections and estimated walking time. This is demonstrated in Figure 5 for both the desktop and mobile versions.

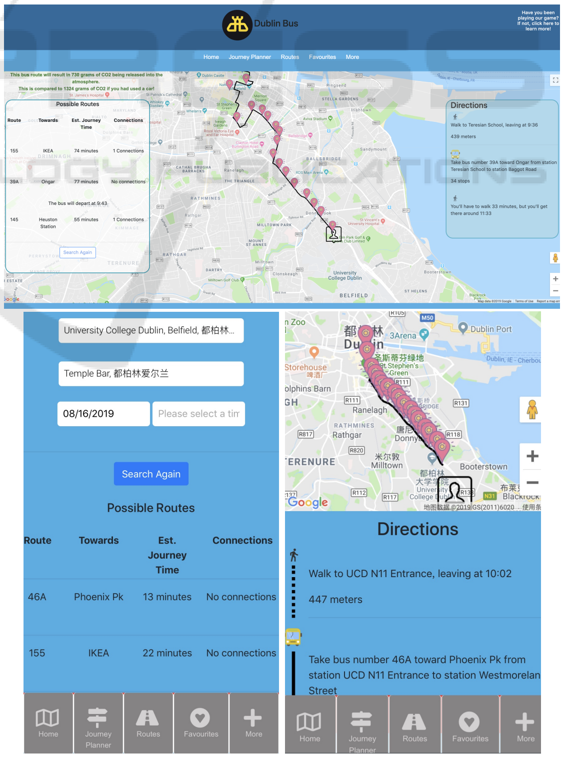


Figure 5: Desktop and Mobile Journey Planner and Prediction.

3.1.6 Routes

The app contains a page which lists all Dublin Bus routes with numbers and destinations. For ease of use, the user may search for their required route by its number. Figure 6 demonstrates that when a user clicks on a particular route, a map appears with all of the route's stops listed, in both directions.

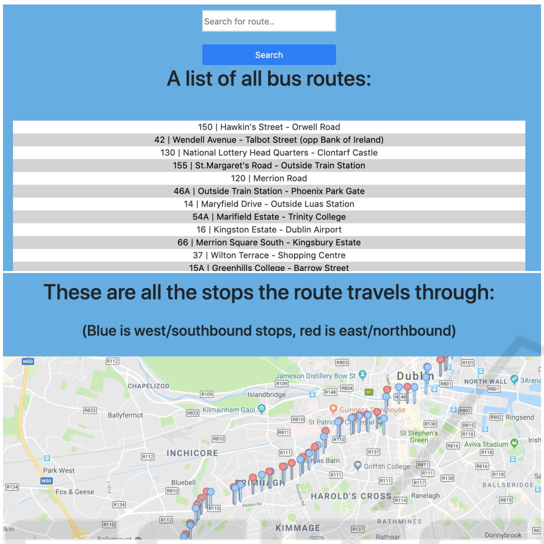


Figure 6: Route Information.

3.1.7 Favourites

As seen in Figure 7, there is login functionality built into the favourites page which allows the user to access favourites (as well as the game) only when logged in. The user is required to provide basic information - username, email, and password - to sign up. On the favourites page, the user is able to create and delete favourite journeys, as well as plan that particular trip.

3.1.8 Additional Functionality

As part of its innovation, the application contains a game (seen in Figure 8) in which twenty Dublin landmarks are marked on a map. The user can click the marker to learn more about the attraction - and if the (logged-in) user visits the attraction they receive points. These points are displayed on the *more* page, along with cumulative calculations of CO_2 savings, a weather forecast, and a news feed from the Dublin Bus website.

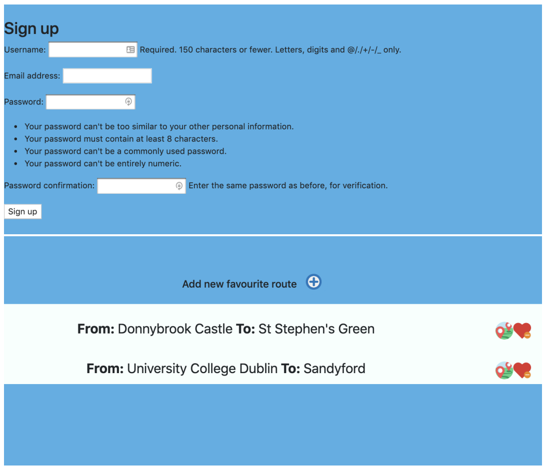


Figure 7: Signing Up and Favourites.

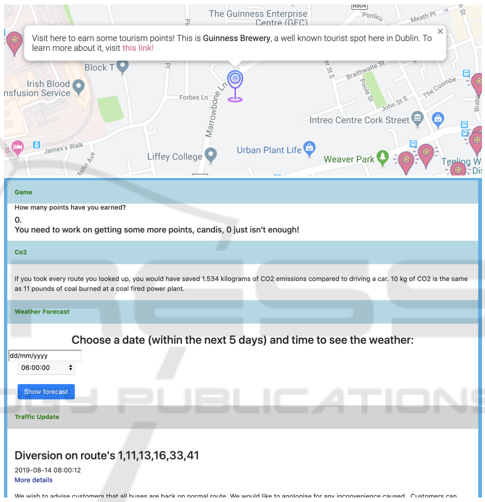
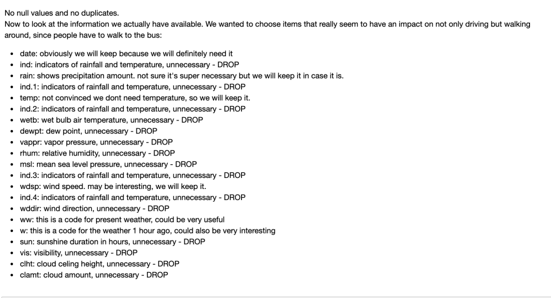


Figure 8: Game Marker and More Page.

3.2 Data Management and Feature Selection

Dublin Bus provided 12 months of historical information on vehicles, individual trips, and GPS data for each stop. Weather information was also gathered from data.gov.ie, which was cross-referenced with the historical bus data. The weather data contained the weather conditions every hour for a multitude of different categories. This included features like the amount of rain (mm), the temperature, and the wind-speed. These were the main three features of the weather information that we felt would impact the general population's use of the public transport system, and were used for our machine learning models. The bus data was more complicated. It was split across two files, each containing a part of the data relating to a specific trip made on a route, the duration of the route, the planned departure and arrival times, and the actual departure and arrival times. There were also columns that contained ID's for various trip parts, stops, etc. The final dataset used in the machine learning contained 50 columns, a mix of data from the Nation Transport Authority, weather data, and columns created by the team to signify certain things, such as whether the trip was during peak times, whether it was heavy rain or light rain, etc.

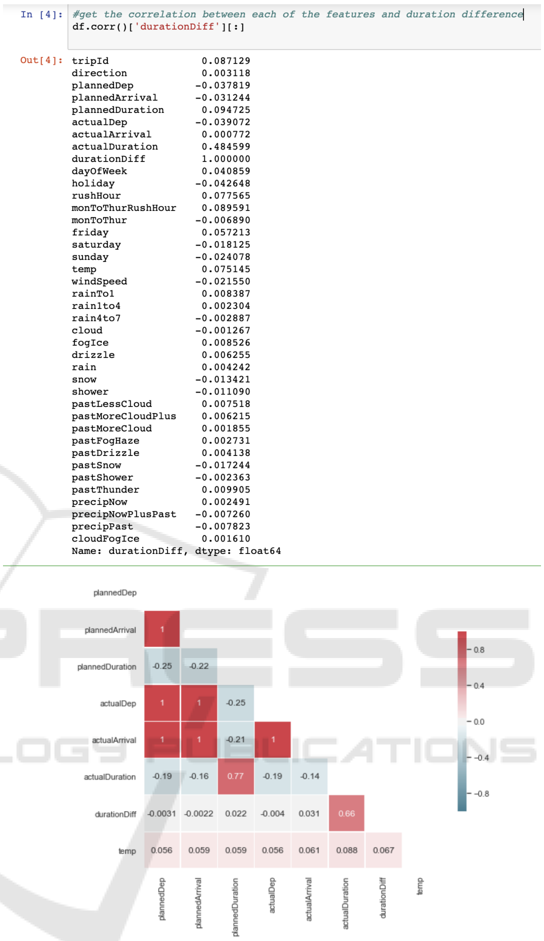
As the data provided by Dublin Bus was large, working with it was a particular challenge. The Pandas suite of data analysis tools [1] was used in conjunction with early filtering and sampling in order to manage the data. To clean the trip data, columns with unusable data were dropped, and null and contradictory values were investigated and dropped. It was necessary to drop rows that had been suppressed so that they wouldn't skew the data set. Many features for the 'Trips' data were built and included day of week (Monday-Sunday), if the day was a holiday, as well as rush hour. For rush hour, the actual departures from 7:00-8:30am and 4:00-6:00pm were used because if trips average between 30 minutes and 1 hour, all of the "rush hour" trips would be included. Columns were added for the journey duration as well as the difference in duration between the actual and planned journeys. To merge the 'Trips' data with the weather data, it was crucial to create a feature to combine the date with the actual time of arrival - so that the hourly weather could be matched with the hour the bus arrived. Dummy variables were created for the rain measurements, including current and past rain. These categories were then binned by type (ex: rain, snow, shower, clouds, etc). Figure 9 shows the original weather columns.


No null values and no duplicates.
Now to look at the information we actually have available. We wanted to choose items that really seem to have an impact on not only driving but walking around, since people have to walk to the bus:

- date: obviously we will keep because we will definitely need it
- ind: indicators of rainfall and temperature, unnecessary - DROP
- rain: shows precipitation amount. not sure it's super necessary but we will keep it in case it is.
- ind.1: indicators of rainfall and temperature, unnecessary - DROP
- temp: not convinced we dont need temperature, so we will keep it.
- ind.2: indicators of rainfall and temperature, unnecessary - DROP
- wetb: wet bulb air temperature, unnecessary - DROP
- dewpt: dew point, unnecessary - DROP
- vappr: vapor pressure, unnecessary - DROP
- rhum: relative humidity, unnecessary - DROP
- msl: mean sea level pressure, unnecessary - DROP
- ind.3: indicators of rainfall and temperature, unnecessary - DROP
- wdsp: wind speed. may be interesting, we will keep it.
- ind.4: indicators of rainfall and temperature, unnecessary - DROP
- wddir: wind direction, unnecessary - DROP
- ww: this is a code for present weather, could be very useful
- w: this is a code for the weather 1 hour ago, could also be very interesting
- sun: sunshine duration in hours, unnecessary - DROP
- vis: visibility, unnecessary - DROP
- clht: cloud celing height, unnecessary - DROP
- clamt: cloud amount, unnecessary - DROP

Figure 9: The Weather Columns in the Weather Dataset.

The analysis showed there was very little correlation on any of the features when plotted against the 'duration difference', as you can see in Figure 10. In order to improve this, additional features on the 'Trips' data frame were created for weekday rush hour, Friday, Saturday, and Sunday. New weather features were also created - precipitation now (combining together rain, snow, drizzle, etc), precipitation in the past hour, and a feature that combined precipitation now with precipitation in the past hour.


```
In [4]: #get the correlation between each of the features and duration difference
        df.corr()['durationDiff'][:]

Out[4]: tripId               0.087129
        direction            0.003118
        plannedDep          -0.037819
        plannedArrival      -0.031244
        plannedDuration      0.094725
        actualDep           -0.039072
        actualArrival        0.000772
        actualDuration       0.484599
        durationDiff         1.000000
        dayOfWeek            0.040859
        holiday             -0.042648
        rushHour             0.077565
        monToThurRushHour    0.089591
        monToThur           -0.006890
        friday               0.057213
        saturday            -0.018125
        sunday              -0.024078
        temp                 0.075145
        windSpeed           -0.021550
        rainTo1              0.008387
        rain1to4             0.002304
        rain4to7            -0.002887
        cloud               -0.001267
        fogIce               0.008526
        drizzle              0.006255
        rain                 0.004242
        snow                -0.013421
        shower              -0.011090
        pastLessCloud        0.007518
        pastMoreCloudPlus    0.006215
        pastMoreCloud        0.001855
        pastFogHaze          0.002731
        pastDrizzle          0.004138
        pastSnow            -0.017244
        pastShower          -0.002363
        pastThunder          0.009905
        precipNow            0.002491
        precipNowPlusPast   -0.007260
        precipPast          -0.007823
        cloudFogIce          0.001610
        Name: durationDiff, dtype: float64
```


Figure 10: Correlation with the 'Duration Difference'.

Each of the features was plotted against the 'duration difference' value. No single feature was identified as a good predictor; but the plots showed that while there are some outliers, there are not many, which is useful information when cleaning the data. As the correlation between features and the 'duration difference' was so poor, pairs of features were examined as shown in Figure 11. Again, this did not lead to a greater insight. Instead of using any of the pairs for modeling, features with the highest correlation were chosen - the final features used were 'dayOfWeek'(with 0-6 being Monday through Sunday), 'friday' (boolean), 'rushHour' (boolean), 'temp' (in degrees C), 'monToThurRushHour' (boolean), 'direction' (either 1 or 2), and 'windSpeed'.

[1] https://pandas.pydata.org/

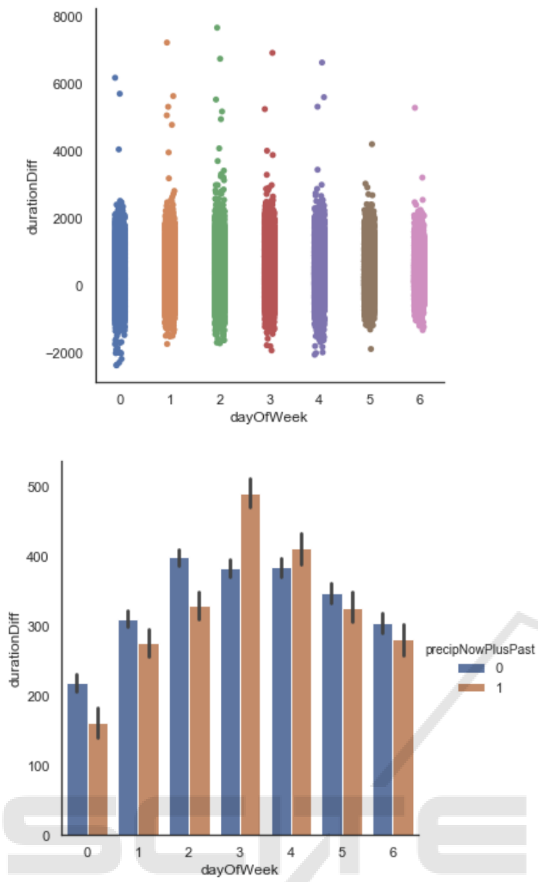


Figure 11: Plots Against ‘Duration Difference’.

3.3 Prediction Algorithm

Two approaches to predicting travel time were implemented. An early approach taken was to predict the travel time for a full route. Tests showed that using a Random Forest classification with the features described above to predict travel time produced a model with a Root Mean Square Error (RMSE) of 600 seconds, or 10 seconds per stop. This was not a satisfactory outcome so a second approach was employed. This strategy involved taking a percentage of that estimated time to present to the user for specified stop segments, but accuracy was severely limited. The next steps were to decrease the RMSE and Mean Absolute Error, increase the R, and create models efficiently.

A study by Jiang (2017) that worked with similar historical bus data concluded that “whole route travel time prediction using segments has better results than the route prediction model using solely bus GPS data”. The potential increase in accuracy paired with the ability to predict segments of trips led to the use of a segmented approach in model creation. This segmentation strategy allowed the data to be turned into a ‘network’ of linked stops, rather than a list of individual stops. This ‘network’ approach meant that full route information for each bus line could be generated easily, including each stop id, its ‘progrnumber’ in the route, and the latitude and longitude of each stop. This information then formed the basis for the app’s **routes** page.

In order to calculate journey segments, as well as the full journey duration time, each journey was divided into ‘stop pairs’. Each row would need to record the time taken to travel from the first to the second stop in the pair, for each stop pair in a specific trip. The ‘progrnumber’ feature allowed the ability to arrange stop pairs in the correct order of the trip. As processing all of the leave times data (over 116 million rows) would have taken several weeks to process, a sample of 12,000 trip IDs was taken, divided evenly across each direction. The goal was to create a new collection of ‘stop pairs’ and their travel time duration, rather than the individual ‘stop’ information that already existed. This enabled the app to return predictions for a segment of a route by adding all stop pair predictions between a specific start point and destination. It also increased the amount of data available, as many stops exist on several routes, and this extra data had the potential to increase the accuracy of the models.

Several routes were not included in the sampling, or had limited amounts of data, and required a more hands-on approach. For roughly twenty routes, additional individual files were created. For a single route, for one direction, the data set held between 3,000 - 7,000 rows of data; however, as previously stated, some data sets were smaller. To increase the accuracy of the models, two different model types were used - Random Forest and linear regression, both implemented using the scikit-learn package[2]. Complex model types are generally not suited to dealing with such small amounts of data, thus the inclusion of a linear regression model, as it is easy to apply and interpret, would give a reasonable baseline accuracy if the more complex Random Forest model did not give suitable results.

Pickle files were created for each direction of each route, containing a dictionary of all stop pairs and their associated trained model. These were then incorporated into the journey planner feature, through which user inputs could be processed and a prediction delivered.

[2]https://scikit-learn.org/stable/

4 EVALUATION

The focus of this section is on evaluating the performance of the machine learning algorithm using the selected features and segmentation approach. While the application predicts travel times for over 100 bus routes, the evaluation focuses on a subset of that number. Evaluation of the accompanying application's functionality and interface is left for future work.

4.1 Predictive Modelling for Accuracy

Multiple strategies were employed to improve the machine learning model to make it more accurate and efficient. These included adding more data, removing outliers and handling missing values, examining the correlation of features to select the most effective, tuning the algorithm by optimising the number of decision trees, and engineering features to examine their effect on the model. A cross validation approach was adopted for evaluations. The sample of data we had available was split into a test set and a training set. The training set was used to build the classifier and the test set was used to determine the accuracy of these classification models. The models were primarily evaluated using Mean Average Error (MAE) and R^2 because they are robust and a simple metrics to apply and interpret.

To evaluate the models, three sample route categories were chosen - 'urban' and 'rural' routes (based on travel through a defined area in city centre), and whether a route was 'frequent' (if there is a period of a headway of fifteen minutes or less on weekdays). Figure 12 shows the accuracy of the Random Forest models for six routes. The 'Whole Journey Prediction' column shows the metrics of an entire journey, trained on 'actualDuration' from the 'Trips' data. The 'Timetable Prediction' contains the static estimated duration of a whole journey on this route, taken from Dublin Bus's timetables. The 'Segmented Journey' adds the predictions of all stop pair segments' duration for the journey.

	Whole Journey Prediction	Timetabled Prediction	Segmented Journey	Training Sample Size
46A (Frequent, Urban)	MAE: 526.09694 RMSE: 728.09346 R2: 0.38957	MAE: 1110.01138 RMSE:1335.65516 R2: -1.05422	MAE:984.50516 RMSE: 1205.37242 R2:-0.67302	48,178 rows
4 (Frequent, Urban)	MAE:484.56538 RMSE: 656.40924 R2: 0.48073	MAE:1005.35872 RMSE:1213.87638 R2: -0.775797	MAE:994.96187 RMSE: 1197.98126 R2: -0.729596	23,807 rows
11 (Infrequent, Urban)	MAE:688.4321433331297 RMSE:989.17755 R2: 0.35386	MAE:957.21614 RMSE: 1232.43097 R2: -0.00301	MAE: 963.43651 RMSE: 1231.86974 R2: -0.002099	17,637 rows
7 (Infrequent, Urban)	MAE: 683.30069 RMSE: 922.52683 R2:0.27701	MAE:918.19022 RMSE: 1168.44994 R2: -0.15984	MAE: 1305.80709 RMSE: 1588.71975 R2: -1.14423	12,505 rows
84A (Infrequent, Rural)	MAE: 497.463201 RMSE: 708.951172 R2:-0.24439	MAE: 1490.27291 RMSE: 1583.079933 R2:-5.20483	MAE: 1929.7546 RMSE: 2034.95115 R2:-9.25255	2,289 rows
31B (Infrequent, Rural)	MAE:468.104503 RMSE:603.52193 R2: 0.32793	MAE:695.06754 RMSE: 812.16415 R2: -0.21708	MAE: 631.04502 RMSE: 753.53043 R2: -0.04769	1,241 rows

Figure 12: Accuracy of Six Representative Random Forest Models.

Figure 12 displays the MAE which shows that on average, the difference between the predicted value and the observed value. The figure also includes RMSE, which is Root Mean Squared Error. It provides a similar metric to MAE, except instead of a linear equation, it uses a quadratic formula to weight large differences more, making it a particularly useful metric when large errors are undesirable. The magnitude of the difference between the MAE and RMSE give an indication of the variance in error.

4.1.1 Results and Critique of Predictive Model Evaluation

The most accurate predictions were the full journey time predictions of the Random Forest models. In comparison with the static timetabled results, the 'whole journey' predictions perform significantly better across all routes. These models still perform well even when there are few rows of data, as in the case of route 31B. In contrast, the aggregated journey segments are often less accurate than the timetabled predictions. Although under-performing when compared to the 'whole journey' predictions, the 'segmented journey' predictions do produce better metrics when they have access to more data, as in the case of the routes 46A and the 4. However, it is important to note that the 'segmented journey' predictions divide each row into stop pairs, so models are based on far less data than 'whole journey' models. It is clear from the table that accuracy steadily declines as less data is available, with the exception of route 31B.

Although the aggregated 'segmented journey' predictions were the least accurate, the approach offers the most flexible planning and is likely to be more accurate in planning a specific journey. The Dublin Bus timetable does offer a breakdown of segments, but these are not detailed (for example, the 46A route has 61 stops, but breaks this into only 5 segments for estimations). On a typical journey, most users will not travel from the first stop of a bus line to its last. In addition, the general data trend is that segmented journey accuracy improves with a larger amount of data.

5 CONCLUSION

While the predictive model that was implemented was not as accurate as hoped, it provides insight on the best approaches to a problem like this. With limited access to hardware, it was not possible to utilize all the data that was provided, instead having to sample from the dataset. The results of the valuation show that providing more data has the potential to improve the results. Furthermore, while segmenting the journey into stop-pairs seemed like the smartest way to approach the problem, especially with the bus system in Dublin, when data was sparse, it provided worse accuracy than the static timetable. In cases where there is more data in the dataset, the segmented journey model does perform better than the static timetable; however, the whole journey model always outperforms the static timetable. In cases with less data, the whole journey model can be about 1000 seconds more accurate. With the right hardware and the ability to analyse the entire dataset, the segmented journey model may have returned better results. The flexibility that the segmented model would provide would be a good fit for a journey planning application, and any opportunity to incorporate that into a public transportation application would allow users to receive better results when trying to estimate the journey time for their bus routes. The next steps of the work are to increase the amount of data to train the model for the segmentation approach. User testing of the application will also be carried out the ascertain the effectiveness of the interface and associated tools described in Section 3.

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REFERENCES

Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

Brilhante, I. R., Macedo, J. A., Nardini, F. M., Perego, R., and Renso, C. (2015). On planning sightseeing tours with tripbuilder. *Information Processing & Management*, 51(2):1–15.

Celan, M., . L. M. (2017). Bus arrival time prediction based on network model. *Procedia Computer Science*, pages 138–145.

Chang, H., Park, D., Lee, S., Lee, H., and Baek, S. (2010). Dynamic multi-interval bus travel time prediction using bus transit data. *Transportmetrica*, 6(1):19–38.

Cristóbal, T., Padrón, G., Quesada-Arencibia, A., Alayón, F., de Blasio, G., and García, C. R. (2019). Bus travel time prediction model based on profile similarity. *Sensors*, 19(13):2869.

Gal, A., Mandelbaum, A., Schnitzler, F., Senderovich, A., and Weidlich, M. (2017). Traveling time prediction in scheduled transportation with journey segments. *Information Systems*, 64:266–280.

Gkiotsalitis, K. and Cats, O. (2017). Exact optimization of bus frequency settings considering demand and trip time variations. In *96th Transportation research board annual meeting*.

Huang, R. and Peng, Z.-R. (2002). Schedule-based pathfinding algorithms for transit trip-planning systems. *Transportation Research Record*, 1783(1):142–148.

Jariyasunant, J., Work, D. B., Kerkez, B., Sengupta, R., Glaser, S., and Bayen, A. (2011). Mobile transit trip planning with real-time data. Technical report, UC Berkeley: University of California Transportation Center.

Jeong, R. and Rilett, R. (2004). Bus arrival time prediction using artificial neural network model. In *Proceedings. The 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No.04TH8749)*, pages 988–993.

Jiang, F. (2017). Bus transit time prediction using gps data with artificial neural networks. https://bit.ly/2wRujmI.

Kroes, E. and Daly, A. (2018). The economic value of timetable changes. *Transportation Research Procedia*, 31:3–17.

Lee, W.-C., Si, W., Chen, L.-J., and Chen, M. C. (2012). A new framework for bus travel time prediction based on historical trajectories. *Proceedings of the 20th International Conference on Advances in Geographic Information Systems*.

Liebig, T., Piatkowski, N., Bockermann, C., and Morik, K. (2017). Dynamic route planning with real-time traffic predictions. *Information Systems*, 64:258–265.

Lin, H.-E., Zito, R., Taylor, M., et al. (2005). A review of travel-time prediction in transport and logistics. In *Proceedings of the Eastern Asia Society for transportation studies*, volume 5, pages 1433–1448.

Mazloumi, E., Rose, G., Currie, G., and Moridpour, S. (2011). Prediction intervals to account for uncertainties in neural network predictions: Methodology and application in bus travel time prediction. *Engineering Applications of Artificial Intelligence*, 24(3):534–542.

Peek, G.-J. and van Hagen, M. (2002). Creating synergy in and around stations. *TRB 81stannualmeeting CD-ROM. Washington, DC*.

Peng, Z., Jiang, Y., Yang, X., Zhao, Z., Zhang, L., and Wang, Y. (2018). Bus arrival time prediction based on pca-ga-svm. *Neural Network World*, 28(1):87–104.

Petersen, N. C., Rodrigues, F., and Pereira, F. C. (2019). Multi-output bus travel time prediction with convolutional lstm neural network. *ArXiv, abs/*, 1903:02791.