Imperial College London

Department of Computing

MEng Individual Project Interim Report

Active Delay Warning Transport Application

Author:
Yangfan Zhang

Supervisor:
Dr. Peter McBrien

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Abstract

abstract

¡Abstract here¿ The abstract is a very brief summary of the report's contents. It should be about half a page long. Somebody unfamiliar with your project should have a good idea of what it's about having read the abstract alone and will know whether it will be of interest to them. Note that the abstract is a summary of the entire project including its conclusions. A common mistake is to provide only introductory elements in the abstract without saying what has been achieved.

Acknowledgments

I would like to thank the following people for their support on this project:

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Contents

Chapter 1

Introduction

The London bus network carries 2.4 billion passengers a year [1]. On average, the buses come about 1 minute later than scheduled [6].

Transport for London (TfL) publishes the live expected bus arrival times. It is currently widely available on digital live bus arrivals signs at more than 2,500 bus stops [2]. Passengers can also access this information via SMS, the web, or mobile applications.

Passengers chose travel mode based on travel time and convenience. Find evidence for this assumption. How do people choose travel mode / whether to take bus?

Passengers use the bus arrival times to plan their journey, by factoring in the waiting time when choosing the buses to take. Current London journey planning software takes the journey start time, start location, and destination as input, and recommends routes consisting of a variety of travel mode, with an estimate travel time for each suggested journey. Such popular planners include Google maps [3], Citymapper [4] and TfL Journey Planner [5].

However, the accuracy of the bus arrival times published is affected by many external factors. For example, when there is heavy traffic, the buses are likely to be delayed by a difference significant enough for a change in passengers' route picking. Yet, this delay information is not reflected in the arrival time data or the estimated journey time early enough for the passengers to make a decision to choose an alternate route. As a result, passengers waste time waiting for buses that come much later than expected, or choose to board a bus that will take much longer than the estimated journey time to reach the destination. Although the average bus delay is 1 minute, there was a 16.6 chance of waiting for more than 10 minutes [16].

Scenario, a passenger chose to take a bus, then only realises delay at the end of the journey. Would have chosen another mode of travel should he know of the delay earlier.

What is the problem? what are the objectives? what are the data? What is my approach? What are my contributions and results?

This can be avoided if passengers are informed of the delays in bus arrival times and estimated travel time in advance. Currently, there are no available data services or applications that generate predictions potential delays.

For exemple, a passenger chose to take a bus from point A to point b Such delays can predicted by analysing the historical delays. This is achieved by collecting data from the TfL live bus arrivals Application Program Interface (API) stream feed[2], and estimate the average journey time required between two locations on a given time of the day. Next, a bus arrival time table with delays during various time windows over a week can be crafted and fine tuned incrementally. We compared the travel times in this timetable with the official travel times published by the TfL Open Data to find out the delays in bus arrival times.

Chapter 2

Background

2.1 London Bus Network

The bus network in London is one of the largest and most accessible in the world. It is carrying a staggering number of passengers, with more than 2.4 billion journeys in 2013/14, which was more than any year since 1959 [1].

On an average day between 2005 and 2010, about 14% of the trips made by London residents were by bus [9]. They spent on average 14 minutes per day on these bus trips.

There are currently 19,345 bus stops, and 680 routes served by 8,765 buses daily in London[10].

produce graph for this, number of stops, routes and buses

2.1.1 Bus Network Performance

TfL published the following figures in the second quarter 2014/2015 buses performance data [6].

For the high frequency services, the average scheduled wait was 4.86 minutes, the average excess wait was 0.94 minutes, and the average actual wait was 5.80 minutes. While passengers could expect the buses to come within 10 minutes 83.4% of the time, there was 15.1% chance of waiting for 10-20 minutes, 1.3% chance of waiting for 20-30 minutes, and 0.2% chance of waiting for more than 30 minutes.

For the low frequency services, 87% of the buses services were on time, and 11.4% were 5-15 minutes late.

For the night buses, 84.5% of the services were on time. The average excess wait was 0.68 minutes.

produce graph here

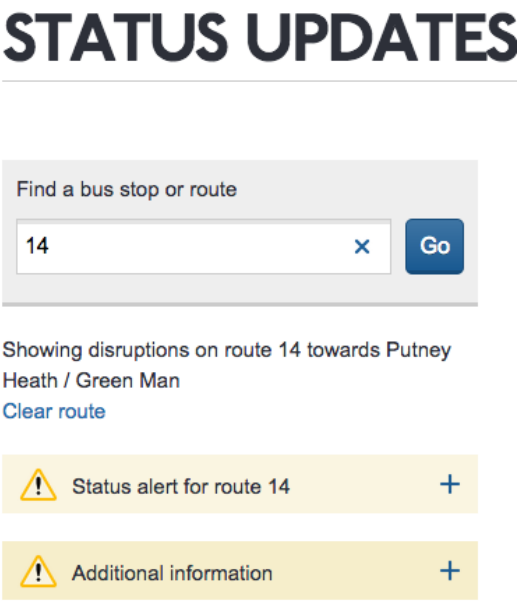


Figure 2.1: Tfl Buses Status Update Service

The bus arrivals might be affected by traffic congestion, staff availability, engineering problems, or mechanical breakdown [16].

2.2 Buses Status Updates

To inform passengers of the bus service disruptions or diversions, TfL provides a bus status updates service online [7]. Passengers can retrieve relevant bus service status for a given bus stop or route (Figure 2.1).

The textual information include service disruptions, diversion, suspensions, and delays due to heavy traffic.

While this service informs passengers of current abnormal bus schedules, it requires passengers to visit the site to check for specific information, and does not provide an estimation on the travel time under the special conditions.

TfL also publishes live status news and updates on Twitter[8], but it is not convenient for passengers to search specific information relevant to their journeys.

Many current popular journey planners such as Google Maps[3], Citymapper London[4], and TfL Journey Planner incorporate the bus delay information in the suggested journeys as a textual alert. However, these apps do not recompute the estimated journey time for passengers to make an informed

decision.

As a result, the lack of data service on bus delay predictions and travel times estimations presents a significant barrier to bus passengers who wish to plan their bus journeys for specific appointments.

2.3 Transport for London Open Data

Open data is defined as data which can be used, re-used and re-distributed freely by anyone - subject only at most to the requirement to attribute and share-alike. There may be some charge, usually no more than the cost of reproduction [11].

It is TfL's strategy to provide free and open data. It began in 2007 using embedded widgets[12]. In 2015, there are around 30 feeds and APIs available [13].

There are 3 forms of data:

- static data files which rarely change,
- feeds that refreshed at regular intervals,
- and APIs that enable a query to receive a bespoke response, depending on the parameters supplied.

Over 5,000 developers have registered for the open data[13], and around 200 travel apps are powered by it [1].

2.3.1 Live Bus Arrivals API Stream

The Live Bus Arrivals API Stream provides the predicted time until a bus is expected to arrive at a stop. This API is designed to enable application developers to subscribe to live bus information and use this data to develop innovative services[15].

The predictions are generated from London buses locations, tracked using a combination of Global Positioning System (GPS), roadside transponders, gyrometers to recognise orientation and turns, and software to match all of the information accurately to a point on a street. Next, the bus location information is transmitted back to a control centre which then works out the predicted bus journey time to reach each downstream stop, given typical journey times at that time of the day [14].

These arrival predictions are available for the next 30 minutes at any point in time. For example, at 9am, the stream will provide predicted bus arrivals up to 9.30am on the same day. This data is refreshed every 30 seconds [15].

This API is controlled via a number of different HTTP requests and parameters. A request is structured as follows:
`http://server/virtualDirectory/type/version?HTTPparameters`

Data Types

This API service provides two types of request to users:

- **instant** The instant requests are made by the client and the server will respond with a single message.
- **stream** The streaming requests are made by the client, in response the server will continually serve data to satisfy the request until the connection is terminated.

The data source for both instant and streaming requests is consistent, ensuring that the data provided to the public remains the same.

We used this API as a source for bus arrival times. See details in Section 5.3.1.

2.3.2 Bus Stop Locations and Routes

The TfL Open Data provides network information on the location of all bus stops in London, and the sequence of bus stops in every bus route.

This data is in the Comma Separated Values (CSV) format. Every entry in the bus sequence file consists of information on the route number, the route direction, the sequence at which the given bus stop is positioned in the route. There is also information on the bus stop name, and bus stop codes for identification purposes.

We used the bus sequences as a reference when calculating the bus journey tiem. See Section 5.3.2 for details.

2.3.3 Journey Planner Bus Timetables

The Journey Planner Bus Timetables[22] contians information on official bus schedules including stops, routes, departures times, departure frequencies, operational notes, as well as the days on which the services run.

The timetables uses the Extensible Markup Language (XML) [18] format, with the schema defined in TransXChange [17], the UK nationwide standard for exchanging bus schedules and related data. For this project, we used the General schema version 2.1[19][20], the latest available version for download. Each XML file contains the bus timetables for one route.

Data Structure

The TransXChange timetable model has the following seven basic concepts[21]:

1. **Service** contains one or more **JourneyPattern** elements and one or more **VehicleJourney** elements. This is the basic concept that brings together the information about a registered bus service.

2. **Registration** specifies the registration details for a service.

3. **Operator** indicates the entity who runs the service.

4. **Route** describes the physical path taken by buses on the service as an ordered list of **StopPoints**.

5. **StopPoint** contains reusable declarations of the stops used by the routes and journey patterns of the schedule. All StopPointRef instances elsewhere in a document are resolved against the contents of the StopPoints element. All stops are defined as being NaPTAN points.

6. **JourneyPattern** specifies an ordered list of links between the **StopPoints**, giving the *relative travel times* between each pair of neighbouring stops.

7. **VehicleJourney** specifies the individual scheduled journey *at a specific absolute time*.

These elements give a complete official bus schedule for each route with the departure time for each bus journey, the relative bus travel time between stops, and the days on which the service operates on. We extracted the offical bus timetables from these XML files, as discussed in Section 5.2.1.

2.3.4 Summary on Available Data

While there is sufficient data on London bus network, official bus timetables, and live arrival times, there is no data service offering real-time predictions on bus delays. There is no reliable predictions estimating the travel times between any two downstream stops and the arrival times at each downstream stop from the point of real-time observation. Hence, we used these available data to create predictions for bus travel timetables, as discussed in Chapter 5.

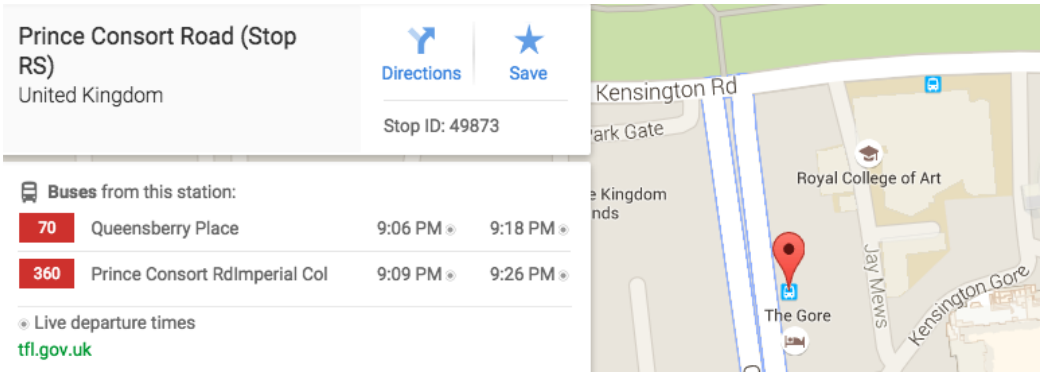


Figure 2.2: Google Maps Using TfL Bus Arrival Data

2.4 Current Travel Applications

Currently, the most popular travel applications powered by the TfL Open Data include TfL Journey Planner, Google Maps (Figure 2.2), and Citymapper London.

Given the departing location, destination, as well as departure time, these applications can provide suggested routes and travel times. Users can further customise their desired journey by specifying the desired walking distance, and accessibility requirements. Moreover, the TfL Journey Planner and homepage status board were redesigned and integrated so customers planning their trip can see immediately if their route is likely to be affected by upgrade work or other disruptions [1], with a textual warning message shown.

However, currently, there are no applications that give predictions on travel times and warnings on potential delays. The estimated travel time shown in apps is extracted from the TfL Journey Planner Bus Timetables. This information does not capture the real time delays according to instant traffic conditions.

Chapter 3

Literature

3.1 Overview

Conventional methods used to predict bus arrival times include regression models, Kalman filters models, Artificial Neural Network (ANN) models, K-nearest neighbours models, and analytical approaches.

3.2 Regression

Regression estimates the relationship between a dependent variable and one or more independent variables. It was used by Patnaik et al. (2004) to predict bus arrival times to downstream stops with data collected by the Automatic Passenger Counting System (APC System) [23].

The regression models require the independent variables to be uncorrelated to each other. It is difficult to provide such a set of variables in the context of bus arrivals predictions. This is because most of the independent variables are correlated (e.g. the number of intermediate bus stops and the number of signalised intersections). Therefore, defining a set of uncorrelated independent variables is the main challenge of building regression models.

3.3 Artificial Neural Network

ANN models are used to estimate functions that can depend of a large number of inputs by adjusting their parameters through message passing between neuron layers. Building an ANN model involve a training process where dependent variables and prediction results are fed in. The advantage of ANN is that the variables can be correlated, whereas the main disadvantage

is that the model training process can take very long (more than 10 hours). Mazloumi (2009) build an artificial neural network with data collected by the Sydney Coordinated Adaptive Traffic System at intermediate signalised intersections and schedule adherence to predict bus travel time[24].

3.4 Kalman Filters

The Kalman filter, also known as linear quadratic estimation(LQE), is a linear recursive predictive algorithm. It starts with a primary estimate and allows parameters to be tuned with each new measurement, in order to find the optimal estimates of unknown variables [25]. It can respond to dynamic conditions of a modelled process, and has been used for dynamic travel time prediction models. Chen et al. (2005) used Kalman filters to predict arrival time with taking into account the effect of schedule recovery impact [26].

3.5 K-Nearest Neighbours Regression

K-Neareast Neighbours (KNN) regression algorithm takes in the k closest training exmaples and produces an output of the property value based of the average of the values of its neighbours. Baker C. M. and Nied A. C. (2013) created models to predict arrival times using KNN, Kernel Regression and seven sets of features[27].

3.6 Analytical Approaches

Analytical approaches were usually developed based on specific available data sets or special conditions. For example, Sun et al.(2007) proposed an algorithm that firsly tracks the bus to obtain the distance to each bus stop, and then predicts bus arrival time using the average speed in various temporal and spatial segmentations [28].

3.7 Summary

While there are many available methods, we have not seen any implementations for London in specific. Additionally, since the TfL makes bus arrival times predictions public, we decided to develop an analytical approach that targets at predicting bus travel time for the city of London only.

Chapter 4

Concept Design

4.1 Objectives

We aim to improve the prediction of bus travel time downstream from location of last observation in mixed traffic operations. We achieve this by providing an API data service of bus travel time predictions, and a demonstrative web application to show case the use of such a data service.

4.2 Bus Travel Times

The bus travel time between 2 neighbouring stops depends on many unpredictable external factors. These include weather conditions, passenger flow, temporary lane closures, as well as the time of the bus trip. Predicting bus travel times by discovering and analysing these contributing factors is complicated.

We decided to bypass looking at these factors, and examine the historical and current bus travel times instead. We assumed that for a specific short time frame, the external factors remain largely unchanged. In this case, the bus travel time between the given 2 neighbouring stops is similar to the previous trips performed in the same time frame.

For bus travel time between every pair of neighbouring stop at each hour of the day, we provide estimations for the following:

- **Reference Timtable** How long does TfL says it take?
- **Current Timetable** How long does it currently take?
- **Historical Timetable** How long does it usually take?

Since the reference timetable shows the typical bus travel time, the historical timetable should converge to the reference timetable over time.

The current timetable shows the most relevant bus travel time at the observation point, a significant increase in travel time compared to the historical or refernece timetables would indicate a bus delay.

4.2.1 Reference Timetable

We extracted the average bus travel time between every pair of neighbouring stops for every route during every hour of the day for every day of the week from the TfL Journey Planner Bus Timetables. This is discussed in Section 5.2.1.

4.2.2 Current Timetable

We collect the live bus arrival times for the past 1 hour, and store the final bus arrival times for each bus at each stop. We then find out the travel time of each bus between every pair of neighbouring stops for the given hour. Next, we calculate the average travel time between each pair of neighbouring bus stops. This serves as a prediction for how long the bus currently takes to travel between two neighbouring stops. See implementation details in Section 5.3.

4.2.3 Historical Timetable

We store the current timetable generated at each hour, and group them by the hour of the day for the same day of the week. We then calculate the average bus travel time between each pair of neighbouring stops for each hour of the day in each day of the week. For example, the average bus travel time between stop A and stop B for 3pm on Wednesday is the average travel time for all the bus trips between these two stops between 2pm to 3pm in the past Wednesdays. More details cound be found in Section 5.4.

4.3 API Data Service and Delay Warning

We provided the above mentioned three timetables as an API data service (Chapter 6) and designed a demostrative mbile application that warns users of current bus delays from a given bus stop (Chapter 7).

Chapter 5

Data Collection and Generation

5.1 Development Environment

5.1.1 Virtual Machine

5.1.2 MySQL Databases

We chose to use MySQL to store the data for the following benefits it offers:

- **User Interface** MySQL has convenient database management tools such as phpMyAdmin[36] and Sequel Pro[37] for easy data browsing.
- **Scalability** MySQL can handle memory heavy computation efficiently, given the correct configuration.

5.2 Generating Reference Timetable

5.2.1 Journey Planner Bus Timetables

Need more detailed explanation. Walk through an example with xml code

In order to calculate the delays in bus arrival times, we need the official bus travel times between stops for reference. This data was extracted from the Journey Planner Bus Timetables[22] as part of the TfL Open Data.

Each xml file contains bus schedule information for a route. For each day of the week, there are predefined number of VehicleJourneys running the give route throughout the day. We used the VehicleJourneys as a starting point to retrieve the departure time of the actual vehicle from the terminal. We then retrieve the corresponding JourneyPattern, and obtained the travel time

between each neighbouring stops on the route for the given vehicle journey, to compute the cumulative travel times throughout the route.

The above computation was performed on each xml file to generate the actual arrival time and travel time for each vehicle trip at each stop in the route throughout the day. The results of this computation was stored in the delay_tfl_timetable table(Table 5.1).

5.3 Generating Current Timetable

- data collection
- data storing
- data processing
- DB optimisation
- python scripts and SQLs
- resulting table name and schema

5.3.1 Collecting Bus Arrival Times

We collect bus arrival data for analysis from the live bus arrivals API. The base URL used in this project was `http://countdown.api.tfl.gov.uk/interfaces/ura/stream_V1`.

We supplied the following parameters which specify the fields returned by the API.

- *StopID* This is the alphanumeric identifier of a bus stop. It is also known as stop_code_lbsl.
- *LineName* This is the route number that is displayed on the front of the bus on any publicity advertising the route.
- *VehicleID* The unique identifier of the vehicle.
- *TripID* The identifer of the specific trip that the prediction is for.
- *EstimatedTime* This is the predicted time of arrival for the vehicle at a specific stop.
- *ExpireTime* This is the time at which the corresponding prediction is no longer valid and should stop being displayed.

Column Name	Type	Comments
id(Primary Key)	int(11)	Auto Increment
route	varchar(64)	The bus route
day	varchar(32)	The day of week for the vehicle journey
run	int(11)	The route direction
sequence	int (11)	The sequence of the bus stop in the route
stop_name	varchar(64)	The name of the bus stop
naptan_atco	varchar(64)	The national identifier of the bus stop
arrival_time	datetime(6)	The expected arrival time for the given vehicle at the current bus stop
travel_time	int(11)	The travel time in seconds from the previous stop in the route to the current stop
cumulative_travel_time	int(11)	The travel time in seconds from the terminal to the current stop
departure_time_from_origin	datetime(6)	The departure time of the given vehicle from the terminal

Table 5.1: delay_tfl_timetable Table Schema

Column Name	Type	Default
id(Primary)	int(11)	Auto Increment
stop_code_lbsl	varchar(64)	
route	varchar(64)	
vehicle_id	varchar(64)	
trip_id	varchar(64)	
arrival_date	date	
arrival_time	timestamp	NULL
expire_time	timestamp	NULL
recorded_time	timestamp	Current Timestamp

Table 5.2: delay_arrivals Table Schema

The resulting query URL is `http://countdown.api.tfl.gov.uk/interfaces/ura/stream_V1?ReturnList=StopID,LineName,VehicleID,TripID,EstimatedTime,ExpireTime`.

Each data entry contains an estimated arrival time for each bus journey at a given bus stop. This estimated arrival time is stored in the database via an UPDATE statement, which ensures that only the latest estimated arrival times per journey per bus stop are stored. To avoid having data being overwritten, only the entries that have been changed in the recent 10 minutes can be updated. This has been achieved through running a daemon process written in python on a virtual host. Table 5.2 shows the schema for arrivals table.

Assumption

We assume that the actual bus arrival time is the midpoint between the last estimated arrival time, and the system time when the clear signal ($ExpireTime = 0$) is received.

5.3.2 Neighbouring Stops

We imported the bus sequences into the delay_bus_sequences table (Table 5.3)

Question: Can I skip some columns of the table schema, as those columns have not been used in the project, but just storing as reference for now?

Additionally, we extracted information on all pairs of neighbouring bus stops and the routes that serve between them. We save this information in

Column Name	Type	Comments
id(Primary Key)	int(11)	Auto Increment
route	varchar(64)	The route name
run	int(11)	The route direction
sequence	int(11)	The sequence of the bus stop in the route
stop_code_lbsl	varchar(64)	The internal bus stop identifier
bus_stop_code	varcher(64)	The public code for the bus stop
naptan_atco	varchar(64)	The national identifier of the bus stop
stop_name	varchar(64)	The name of the bus stop

Table 5.3: delay_bus_sequences Table Schema

Column Name	Type	Comments
id(Primary Key)	int(11)	Auto Increment
route	varchar(64)	The bus route
start_stop	varchar(64)	The stop_code_lbsl for the start stop
end_stop	varcher(64)	The stop_code_lbsl for the end stop

Table 5.4: delay_neighbours Table Schema

the delay_neighbours table (Table 5.4). See sample data in Table 5.5.

5.3.3 Finding the average travel time between neighbouring stops

update this part

To experiment with the queries, we selected one pair of the neighbouring stops (10002, 11469), and listed the time required to travel from stop 10002 to stop 11469 by finding the difference in arrival times for each journey. Sample entries of this list is shown in Figure 5.1.

id	route	start_stop	end_stop
18433	30	10002	11469
44878	N19	10002	11469
47128	N41	10002	29772
8653	19	10002	11469

Table 5.5: Sample data in delay_neighbours Table

start_stop	end_stop	route	trip_id	day	start_time	end_time	length_in_secs
10002	11469	19	346930	Monday	1/12/2015 12:34:16	1/12/2015 12:35:28	72
10002	11469	4	547334	Monday	1/12/2015 12:39:55	1/12/2015 12:41:14	79
10002	11469	19	346961	Monday	1/12/2015 12:40:04	1/12/2015 12:41:53	109
10002	11469	30	226765	Monday	1/12/2015 12:45:07	1/12/2015 12:47:11	124
10002	11469	4	547676	Monday	1/12/2015 12:47:17	1/12/2015 12:49:12	115
10002	11469	19	346976	Monday	1/12/2015 12:48:21	1/12/2015 12:50:09	108
10002	11469	30	276872	Monday	1/12/2015 12:54:05	1/12/2015 12:55:08	63

Figure 5.1: List of journey time from stop 10002 to stop 11469

hour	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
0	NULL	NULL	75.1	56	63.5	62.5	NULL
1	NULL	NULL	68.4	60.6	69.6	54	NULL
2	NULL	NULL	50.5	32.5	58.5	86.5	NULL
3	NULL	NULL	NULL	64	69	51.5	NULL
4	NULL	NULL	NULL	88.5	62	46	NULL
5	NULL	NULL	NULL	61	73	59.3	NULL
6	NULL	NULL	NULL	69	79.4	75.1	NULL
7	NULL	NULL	NULL	88.1	81.7	84.3	NULL
8	NULL	NULL	NULL	90.2	118.8	116.7	NULL
9	NULL	NULL	NULL	82	90.9	101.7	NULL
10	NULL	NULL	NULL	74.4	90.8	145.6	NULL
11	NULL	NULL	NULL	111.2	97.9	124.2	NULL
12	NULL	95.5	267.3	169.9	146.5	114.7	NULL
13	NULL	125.4	245.3	168.2	104.7	NULL	NULL
14	NULL	90.4	NULL	123.8	85.7	NULL	NULL
15	NULL	120.7	113	153.1	87.2	NULL	NULL
16	NULL	168.1	125.1	134.1	100.5	NULL	NULL
17	NULL	113	110.4	124.6	126.5	NULL	NULL
18	NULL	127.1	110.9	179.8	148.6	NULL	NULL
19	NULL	115.5	149.3	243.7	160	NULL	NULL
20	NULL	87.7	96	140.5	85.2	NULL	NULL
21	NULL	80.1	94	94.5	85	NULL	NULL
22	NULL	75	93.3	80.4	100.7	NULL	NULL
23	NULL	54.6	75.6	78	73.7	NULL	NULL

Figure 5.2: Average journey time in seconds from stop 10002 to stop 11469 for each hour of each day of week

We then calculated the average journey time required to travel from 10002 to 11469 for each hour in each week of the day. This information is stored as a timetable, which would be used for further analysis.

Figure5.2 shows the timetable generated. Each cell indicates the average journey time required to travel from stop 10002 to stop 11469 at a give hour of a give week of day. The **NULL** values are due to a current databases performance issue. This will be resolved later.

We plan to construct a timetable this way for each pair of the neighbouring bus stop.

Start Stop	End Stop	Route	Start Time	End Time	Travel Time(sec)
9326	15552	W13	14:53:18	14:52:14	-64

Table 5.6: Travel Time Log Entry with Negative Travel Time

Stop Code	Route	Vehicle ID	Trip ID	Arrival Time	Recorded Time
9326	W13	18685	135229	14:53:18	14:48:25
15552	W13	18685	135229	14:52:14	14:44:02

Table 5.7: Arrivals Entries to Explain Negative Travel Time

5.3.4 Negative Travel Time Filter

In the travel_time_log generated, there were trips between two neighbouring stops with negative travel times, such as the entry shown in Table 5.6.

This was because when we performed the join of the arrivals table, there was a more recent update on the arrival times for the start stop, whereas the arrival times of end stop had not been updated. In Table 5.7, we observed that the Recorded Time for the end stop 9326 was more recent than that of the end stop. As a result, the arrival time for the end stop was earlier than the start stop, causing the travel time to be negative.

We filtered out these negative values before calculating the average travel time between neighbouring stops.

5.4 Generating Historical Timetable

Chapter 6

Delay Data Service

6.1 Overview

To enable structured query of the predictions generated, we created a REST API service for the prediction data. We hope to make these endpoints freely available for other developers to use.

6.2 Django Framework

We used Django Framework[29] for the backend of this project. It is a high-level Python Web framework that encourages rapid development and clean, pragmatic design. We chose it for the following advantages:

- It stores databases schema as data models[30], and allows for quick database migration. This makes deployment to the production server easy by using the given migration command [31].
- Django handles user authentication securely [32], which saves work for development on this part.
- It has a nice compatible REST framework[33], which supports REST API routing[34] and query parameter parsing. Additionally, it offers a built-in user interface that displays the query result with pagination[35].
- Django has a Debug mode that display constructive error messages, make the development much easier.
- It is written in Python, which is a preferred language for its simple and short syntax.

6.3 API Endpoints

- address of the endpoint
- parameters supplied
- return result format

6.3.1 Historical & Current

6.3.2 Reference

6.3.3 Arrival

6.4 Summary of data service

Met the first objective by supplying data on bus travel time predictions

Chapter 7

Mobile Application for Active Delay Warning

7.1 Motivation

Demo App to use the data for effective delay warning
Write from the user point of view
to demonstrate what the predictions can be used for non-technical users
easy to use interface
easy to understand data presentation
personalised warning feature

7.1.1 AngularJS

7.2 Contribution

save users time make informed decisions when choosing travel mode

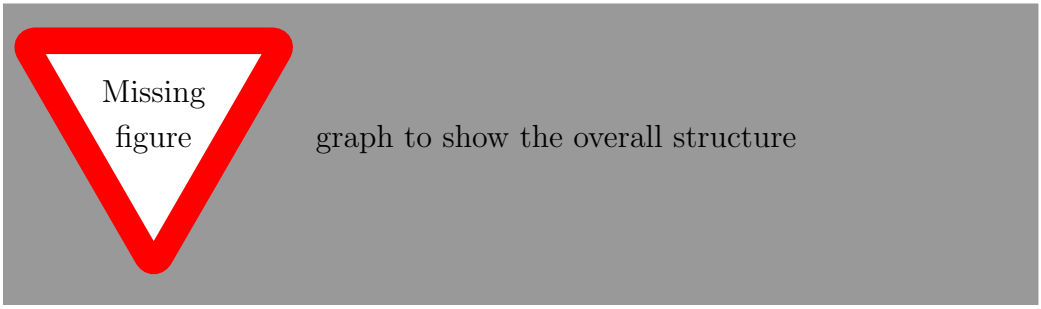
Chapter 8

Technical Details

Missing Testing section

8.1 Overview

- Used Django Framework to build the backend that retrieves data from a MySQL database.
- Used AngularJS with Twitter Bootstrap for frontend development



graph to show the overall structure

8.2 Daemen Script Management

8.3 Backend Deployment

8.4 Frontend Deployment

8.5 Software Project Management

8.5.1 Jenkins

8.5.2 Trello

Chapter 9

Evaluation

9.1 Compare predictions to real data

We can compare the predictions generated to the live bus arrivals data stored in the arrivals table. We can calculate the standard deviation of the difference in the predicted time and actual arrival time. This value will be the direct indicator of the accuracy of the predictions.

9.2 User feedback

We can get students that take buses regularly to use the mobile application to test the accuracy of the delay predictions. The user feedback gathered will be the second input for evaluation.

9.3 Accuracy

How accurate are the predictions?

9.4 Performance

How reliable is the service?

9.5 User feedback on UI

How effective is it at warning delay? ¿¿¿¿¿¿¿ Stashed changes

Chapter 10

Future Work

¡Future work here¿

Chapter 11

Conclusion

¡Conclusion here¿

Acronyms

API Application Program Interface. 2, 4

CSV Comma Separated Values. 4

TfL Transport for London. 1, 2, 4

XML Extensible Markup Language. 4

Glossary

TransXChange the UK nationwide standard for exchanging bus schedules and related data. 4, 5

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