IMPERIAL COLLEGE LONDON

DEPARTMENT OF COMPUTING

MENG INDIVIDUAL PROJECT INTERIM REPORT

Active Delay Warning Transport Application

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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

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Chapter 1

Introduction

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

Transport for London (TfL) publishes live predictions of bus arrival times. This information is available on digital live bus arrivals signs at more than 2,500 bus stops [2]. Commuters can also access this information via SMS, the TfL website, or its mobile applications.

Passengers use 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 employing a variety of travel modes, with an estimated duration for each suggested journey. Popular planners include Google Maps [3], Citymapper [4] and the TfL Journey Planner [5].

However, the accuracy of the bus arrival times published is affected by many external factors beyond the distance travelled. For example, when there is heavy traffic, buses are likely to be delayed significantly enough to cause 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 is a 16.6% chance of waiting for more than 10 minutes [16].

This problem can be avoided if passengers are informed of the delays in bus arrival times and estimated travel time in advance. Currently, the TfL live bus arrivals Application Program Interface (API)feed[2] provides data on immediate bus arrivals at a given stop. We verified the accuracy of this API in Section 9.1, and found that the accuracy of the arrival predictions vary by the projection time in future.The predictions are largely accurate for the next five minutes, with an average of 45 seconds delay. However, there are no available data services or applications that offer projected bus travel times that incorporate predicted delays.

We provided such a data service (Chapter 6) and built a demonstrative mobile application (Chapter 7). The concept plan is presented in Chapter 4.

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.

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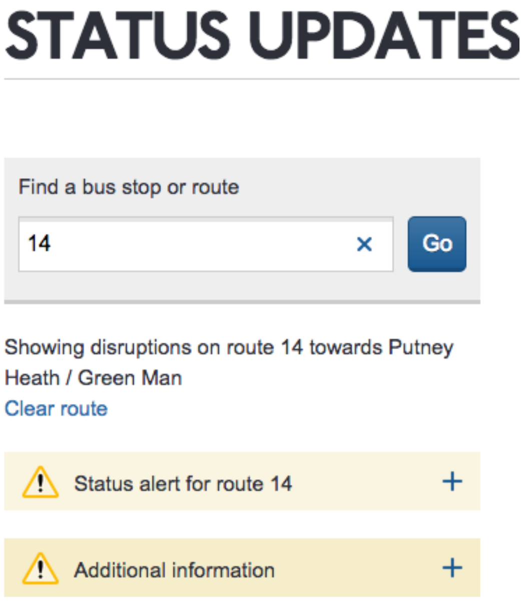

STATUS UPDATES

Find a bus stop or route

14

Go

Showing disruptions on route 14 towards Putney Heath / Green Man

Clear route

Status alert for route 14

Additional information

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.

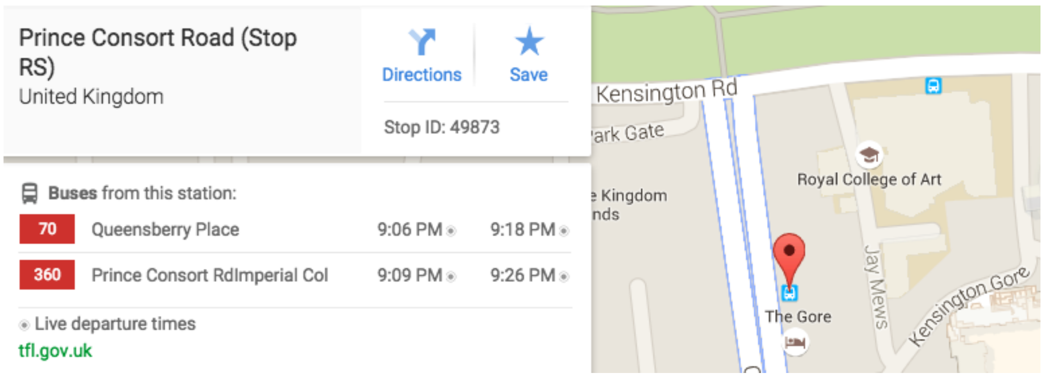
6. **JourneyPattern** specifies an ordered list of links between the **StopPoints**, giving the *relative travel times* between each pair of neighbouring stops.

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.

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.


Prince Consort Road (Stop RS)
United Kingdom

Stop ID: 49873

Buses from this station:

70	Queensberry Place	9:06 PM	9:18 PM
360	Prince Consort RdImperial Col	9:09 PM	9:26 PM

Live departure times
tfl.gov.uk

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.

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 Contributions

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).

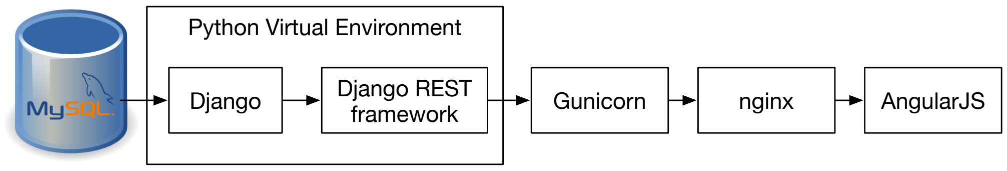


Figure 4.1: Architecture

4.4 Architecture Design

The overall architecture is shown in Figure 4.1. We discuss each component in detail in the following chapters.

Chapter 5

Data Collection and Generation

5.1 Development Environment

5.1.1 Virtual Machine

We set up a Virtual Machine in the Doc's Private Cloud[29] with the specifications shown in Table 5.1. We allocated a large memory for memory intensive Databases operations.

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[30] and Sequel Pro[31] for easy data browsing.
- **Scalability** MySQL can handle memory heavy computation efficiently, given the correct configuration.

Spec	Value
Number of CPU Cores	8
CPU (in MHz)	1000
Memory (in GB)	30

Table 5.1: Virtual Machine Specifications

Databases Optimisation

As some databases operations involve joining large tables, we optimised the Databases with the following settings in file */etc/mysql/my.cnf* to allow MySQL to access more memory in the Virtual Machine[32] [33].

```
[mysqld]
innodb_io_capacity = 2000
innodb_read_io_threads = 64
innodb_thread_concurrency = 0
innodb_write_io_threads = 64
innodb_buffer_pool_size=20G
join_buffer_size=2G
sort_buffer_size=1G
read_buffer_size=1G
read_rnd_buffer_size=1G
max_connection=200
```

5.2 Generating Reference Timetable

For each day of the week, there are a predefined number of VehicleJourneys running the give route. We used the VehicleJourneys as a starting point to retrieve the departure time of the actual vehicle from the terminal. We then retrieved 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. We grouped the bus travel time by the hour that the arrival time falls in, and find the average bus travel time between every pair of the neighbouring stops for the given hour of the given day of the week. The results of this computation was stored in the delay_tfl_timetable table(Table 11.1).

5.2.1 Detailed Steps

We used The ElementTree XML API in Python [34] to extract the official bus travel times between stops from the Journey Planner Bus Timetables[22].

Each XML file contains bus schedule information for one route. We carried out the following steps on each XML file:

1. Obtain the route from **Services** → **Service** → **Lines** → **Line** → **LineName**

2. For each **VehicleJourneys** → **VehicleJourney**, we extract the followings:

   (a) The departure time from **DepartureTime**

   (b) The days of the week that this journey operates on from **OperatingProfile** → **RegularDayType** → **DaysOfWeek**

   (c) The corresponding journey pattern reference from **JourneyPatternRef**

3. Each **JourneyPatternRef** maps to one Journey Pattern Section. This mapping is stored in **Services** → **Service** → **StandardService** → **JourneyPattern**.

   We retrieve the corresponding Journey Pattern Section Reference as such:

   (a) Each **JourneyPattern** element contains an element id, and a subelement **JourneyPatternSectionRefs**.

   (b) We map each Journey Pattern id to its corresponding **JourneyPatternSectionRefs** for reference.

   (c) We consult the above mapping to retrieve the Journey Pattern Section Reference for each Journey Pattern Reference found in Step 2(c).

4. Next, we obtained the bus travel time between every pair of neighbouring stops in the route from the **JourneyPatternSections**. The detailed steps are as the following:

   (a) For each **JourneyPatternSectionRefs**, find the corresponding **JourneyPatternSections** → **JourneyPatternSection** with the same id.

   (b) Each **JourneyPatternSection** contains multiple **JourneyPatternTimingLink** subelements. Each **JourneyPatternTimingLink** contains information for one pair of neighbouring bus stops. We retrieved the following information:

      i. **From SequenceNumber**

      ii. **From** → **StopPointRef**

      iii. **To SequenceNumber**

iv. **To → StopPointRef**
v. **RunTime**

5. At this point, we have the departure time from the terminal stop for each vehicle journey(Step 2(a)), and the bus travel time between every pair of the neighbouring stops (Step 4(b)v.). We calculate the cumulative bus travel time for each stop, and derive the bus arrival time at each stop for the given vehicle journey.

6. We group the bus travel time by the hour that the arrival time falls in, and find the average bus travel time between every pair of the neighbouring stops for the given hour of the given day of the week.

5.3 Generating Current Timetable

5.3.1 Collecting Bus Arrival Times

Building the Query URL

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/instant_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.
- *DirectionID* The direction of the bus.
- *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.

The resulting query URL is `http://countdown.api.tfl.gov.uk/interfaces/ura/instant_V1?ReturnList=StopID,LineName,DirectionID,VehicleID,TripID,EstimatedTime,ExpireTime`.

Storing Arrival Times

The TfL Live Bus Arrival Feed is updated every 30 seconds to give a more accurate predictions of the bus arrival times. We send an HTTP request to the above URL every 30 seconds.

Each data entry in the return result contains an estimated arrival time for each bus journey at a given bus stop. We assume that the actual bus arrival time is the the midpoint between the last estimated arrival time, and the system time when the clear signal ($ExpireTime = 0$) is received.

Since sometimes the clear signal is lost for certain entries, we will assume the actual bus arrival time is the last estimated arrival time, when it is more than 15 minutes after the expire time. This means that we have not received any new updates for the given bus at a given stop 15 minutes after the last estmated arrival time.

As we would like to only store the actual bus arrival times, we keep a local copy of the current query result using the pickle module in Python[35], and only update the Databases when the most arrival time for the given bus at the given stop has expired for more than 15 minutes.

We achieved this by the following steps:

1. Load the local arrivals objects if there exists a copy.
2. Pull the new TfL arrivals predictions.
3. Update the loacl arrivals objects with the new predictions.
4. For arrival entries that have expired for more than 15 minutes, remove these entries from the local copy, and store them in the delay_arrivals table in the Databases.

These steps were implemented in a Python script. Each run of the steps takes approximately 10 to 15 seconds. We re-run the script 15 seconds after the previous run finishes.

5.3.2 Generating Bus Sequences and Neighbouring Stops

We imported the bus routes data introduced in Section 2.3.2 into the delay_bus_sequences table (Table 11.3). Every entry contains information on the route name, route direction, and the sequences of stops in the route. As the sequence information for some routes have gaps, we preprocessed the data by updating the sequence number of the following stops to fill up the

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

Table 5.2: Sample data in delay_neighbours Table

gaps. This preprocessing step was done after a few examples verified with the up-to-date TfL routes in the TfL Journey Planner.

In order to find out the average travel time between any pair of neighbouring stops, we need a list of all the neighbouring stops serving by various routes for reference.

We extracted this information from the bus routes data , and stored it in the delay_neighbours table (Table 11.4). In the sample entries shown in Table 5.2, we can see that there are three different routes serving between stop 10002 and 11469. When calculating the average travel time between these two stops at a given hour, we used all bus trip information for these three routes.

5.3.3 Generating the Current Average Travel Time Between Neighbouring Stops

To generate the current average travel time, we first isolated the arrival times collected in the recent one hour.

We then performed the following steps on the recent arrivals data:

1. For each bus traveling between each pair of the neighbouring bus stop,
   (a) We found out the arrival times for the same bus at the start stop and the end stop of the neighbouring pair.
   (b) We calculated the difference of these two arrival times, and saved it as one entry of the travel time.
2. We computed the the average travel time of all bus trips took place between every pair of neighbouring stops, and saved it in the current timetable.
3. We also saved the current day of week, and hour of the day in the timetable for reference.

We ran the above steps every hour to refresh the current timetable. Before every update, we stored the current timetable into a log for generating the historical timetable.

5.4 Generating Historical Timetable

The current timetable generated every hour is stored in a log. We processed this log by computing the average bus travel time by the start stop, end stop, day of the week, and hour of the day.

This computation is performed weekly on Sunday midnight to update the 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[36] 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[37], and allows for quick database migration. This makes deployment to the production server easy by using the given migration command [38].
- It has a nice compatible REST framework[40], which supports REST API routing[41] and query parameter parsing. Additionally, it offers a built-in user interface that displays the query result with pagination[42].
- Django has a Debug mode that display constructive error messages, make the development much easier.
- It is written in Python, which is our preferred language for its simple and short syntax.

6.3 Deployment Setup

6.3.1 Python Virtual Environment

In order to manage our Python project requirements neatly and make deployment simple, we set up virtual environment[43] [44] to manage the project requirements. This helps to separate the Python packages installed for different projects as well.

6.3.2 Web Server

We chose to use Nginx[46] as the web server and Gunicorn[45] as the Python Web Server Gateway Interface HTTP Server.

Nginx was chosen over Apache Web Server as it was more widely used with Django and Gunicorn setup, therefore there was more support articles available online for reference [47].

6.4 API Endpoints

We built the backend using Django framework and Django REST framework, and exposed the following 3 endpoints for users to access data. The base URL for all endpoints is `http://delay.doc.ic.ac.uk:5000`.

6.4.1 Historical & Current Timetables

This API endpoint is built to provide information on how long the bus on a given route at a given hour of the given day will take to reach the future stops from a given starting stop.

Query URL & Parameters

The base URL to access the historical and current timetables is `http://delay.doc.ic.ac.uk:5000/predictions/?`.

The following parameters are required to obtain a specific set of predictions:

- **day** Day of the week
- **hour** Hour of the day [0 - 23]
- **route** Route

- **run** Route direction
- **naptan_atco** The NaPTAN code for the starting downstream stops in the route

For example, the URL to retrieve historical and current bus travel time predictions for route 360 for downstream stops starting with NaPTAN code 490016263E at hour 15 on Tuesday is `http://delay.doc.ic.ac.uk:5000/predictions/?day=Tuesday&hour=15&route=360&run=2&naptan_atco=490016263E`.

Result Format

The result of the API query is a JSON list of bus stops, following the given route sequences in the given route direction, starting with the given stop.

Each bus stop entry contains information on the bus stop, as well as the bus travel time in seconds. The following four fields are the most important ones:

- **average_travel_time** Historical average bus travel time from the previous stop to the current stop.
- **cumulative_travel_time** Historical average bus travel time from the given starting stop to the current stop.
- **average_travel_time** Current average bus travel time from the previous stop to the current stop.
- **cumulative_travel_time** Current average bus travel time from the given starting stop to the current stop.

Backend Computation

For each request, the Django backend performs the following computation steps to produce the response:

- Search the database for the bus sequence with the given route and run.
- If a NaPTAN code is given, filter out the stops after the given stop.
- For each pair of the neighbouring stops, search the databases for the corresponding historical travel time, and the current travel time values for the give hour of the day, and day of the week.

- Compute the cumulative travel time from the starting stop to each downstream stop.
- Return the result in JSON format.

6.4.2 Reference Timetable

This API endpoint is designed to provide information on the TfL official bus travel time for the buses on a given route at a given hour of the given day of week to reach downstream stops from a given starting stop.

Query URL & Parameters

The base URL to access the reference timetable is `http://delay.doc.ic.ac.uk:5000/tfl_timetable/?`.

The required parameters are the same for the predictions endpoint, described in Section 6.4.1.

For example, the URL to retrieve reference timetable entries for route 360 for downstream stops starting with NaPTAN code 490016263E at hour 15 on Tuesday is `http://delay.doc.ic.ac.uk:5000/tfl_timetable/?day=Tuesday&hour=15&route=360&run=2&naptan_atco=490016263E`.

Result Format

The result of this API query is similar to that of the prediction endpoint. It consists of a JSON list of bus stops, ordered by the given route sequences.

Each bus stop entry contains information on the bus stop. Additionally, the **average_travel_time** field indicates the official bus travel time from the previous stop to the current stop in seconds, whereas the **cumulative_travel_time** field shows the official bus travel time from the givien starting stop to the current stop in seconds.

Backend Computation

The backend processes each request as such:

- Search the tfl timetable in databases for the entries for the given route, run and arrival hour.
- Filter the entries for the given day of the week, and the future stops of the given stop.

- Compute the cumulative travel time for the bus to reach each downstream stop from the given stop.
- Return the result in JSON format.

6.4.3 Arrival

This endpoint serves as a wrapper for the Tfl Live Bus API endpoint. Given a set of Global Positioning System (GPS) coordinates and the radius of circle, this API endpoint returns the arrival times of buses arriving at stops within the circle.

Query URL & Parameters

The base URL for this endpoint is `http://delay.doc.ic.ac.uk:5000/arrivals/?`.

The required parameters include the latitude and the longitue of the GPS coordinates, and the radius in meters.

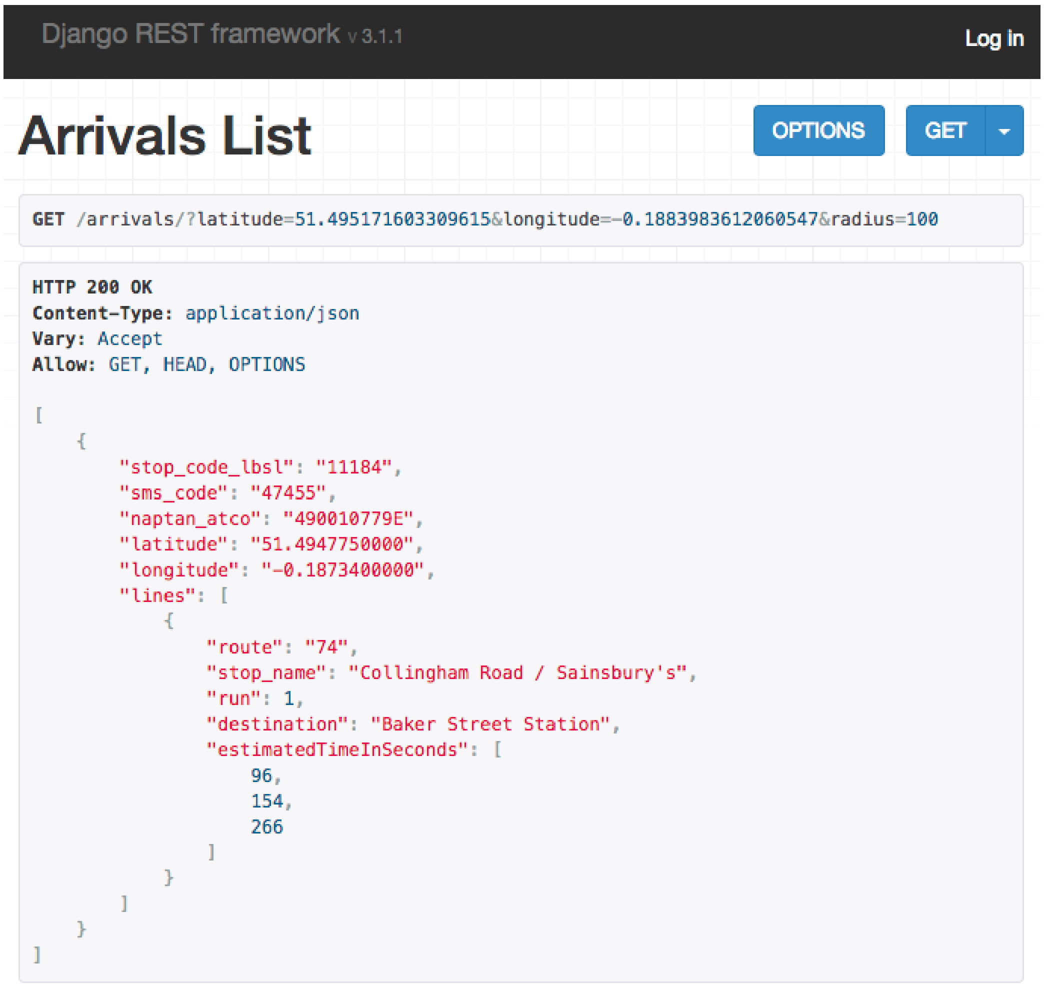
An example query URL would be `http://delay.doc.ic.ac.uk:5000/arrivals/?latitude=51.495171603309615&longitude=-0.1883983612060547&radius=100`.

Result Format

The query result is a list of bus stops within the circle. Each bus stop entry has basic information about the stop, and a list of the buses arriving at the stop in the next 30 minutes, grouped by the bus routes. Within each route, the **estimatedTimeInSeconds** shows the arrival times of the buses arriving at the given stop. See Figure 6.1 for example response.

6.5 Summary of Data Service

Building these three API endpoints helped us meet our first objective by supplying data on bus travel time predictions. We evaluated the accuracy and performance in Chapter 9.



```
GET /arrivals/?latitude=51.495171603309615&longitude=-0.1883983612060547&radius=100
```

```
HTTP 200 OK
Content-Type: application/json
Vary: Accept
Allow: GET, HEAD, OPTIONS

[
    {
        "stop_code_lbsl": "11184",
        "sms_code": "47455",
        "naptan_atco": "490010779E",
        "latitude": "51.4947750000",
        "longitude": "-0.1873400000",
        "lines": [
            {
                "route": "74",
                "stop_name": "Collingham Road / Sainsbury's",
                "run": 1,
                "destination": "Baker Street Station",
                "estimatedTimeInSeconds": [
                    96,
                    154,
                    266
                ]
            }
        ]
    }
]
```

Figure 6.1: Sample Response for Arrivals API

Chapter 7

Mobile Application for Active Delay Warning

We designed a web application to demonstrate the potential use of our API data service. It allows users to search for nearby bus stops, view the available routes and live bus arrival times. For each route, the user can view the historical, current and reference bus travel time to reach each downstream bus stop.

7.1 Implementation

7.1.1 AugularJS Framework

We chose to use the AngularJS Framework [48] with UI Bootstrap [49] to build the frontend of the application. This was because AngularJS employs a clear Model-View-Controller structure, and has a wide range of packages to build extensions with.

7.1.2 Development & Deployment Pipeline

We used Yeoman [50], a web application scaffolding tool, to organise and manage scripts and files. We also used Grunt [51], a Javascript task runner to manage the build and delopment process.

For deployment, we created a Grunt task to run tests, minify the javascript files, and copy the minified version to the production server.

7.2 Frontend Walkthrough

We deployed the frontend web to `http://delay.doc.ic.ac.uk/`.

7.2.1 Landing Page

7.3 Future Extensions

personalised active warning feature
  to demonstrate what the predictions can be used for non-technical users
  easy to use interface
  easy to understand data presentation

7.4 Deployment

7.5 Summary

save users time make informed decisions when choosing travel mode

Chapter 8

Technical Details

8.1 Process Control System - Supervisor

We needed to monitor two daemon tasks. The first task was the script to send requests to TfL Live Bus Arrivals API and save the arrivals to the Databases (Section 5.3.1). The second task was to keep Gunicorn running (Section 6.3.2).

We used Supervisor[52] to monitor these two tasks. It watches the two processes and restart them if they fail, and ensure they start on system boot.

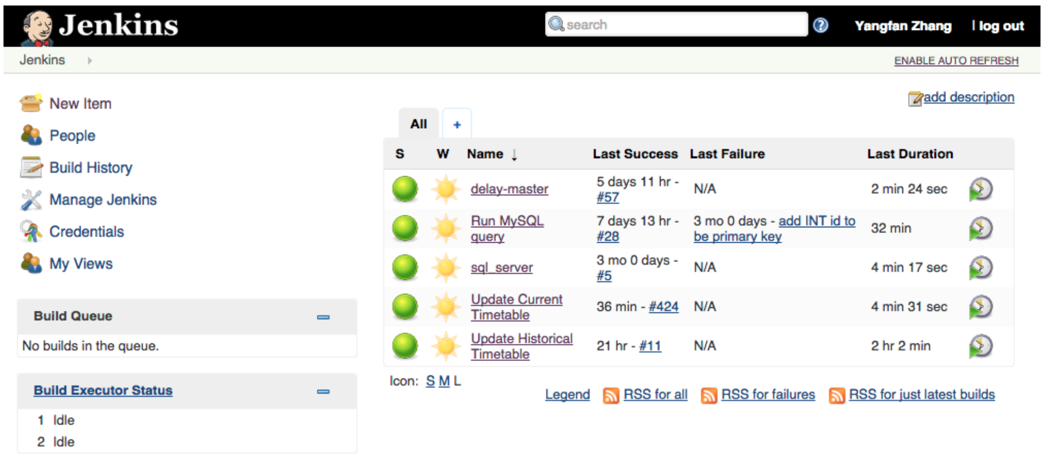
Suervisor was chosen as it matches our requirement exactly, as it is meant to be used to control processes related to a project or a customer, and is meant to start like any other program at boot time.

8.2 Scheduled Tasks Management - Jenkins

We used Jenkins[54] to managed our predictions timetable update schedule. Figure 8.1 shows some of our schedule tasks.

8.2.1 Current Timetable Update

The current timetable is re-generated every hour. We set up a Jenkins job to re-run the relevant current timetable update SQL script every hour, and save the previous timetable into a log for updating the historical timetable at a later time. This job takes less than 10 minutes on average.



Build Queue

No builds in the queue.

Build Executor Status

1 Idle

2 Idle

S	W	Name ↓	Last Success	Last Failure	Last Duration
●	☀	delay-master	5 days 11 hr - #57	N/A	2 min 24 sec
●	☀	Run MySQL query	7 days 13 hr - #28	3 mo 0 days - add INT id to be primary key	32 min
●	☀	sql_server	3 mo 0 days - #5	N/A	4 min 17 sec
●	☀	Update Current Timetable	36 min - #424	N/A	4 min 31 sec
●	☀	Update Historical Timetable	21 hr - #11	N/A	2 hr 2 min

Icon: S M L

Legend RSS for all RSS for failures RSS for just latest builds

Figure 8.1: Jenkins Dashboard

8.2.2 Historical Timetable Update

Similarly, we set up a Jenkins job to update the Historical Timetable daily at 3.30am when the server is less busy.

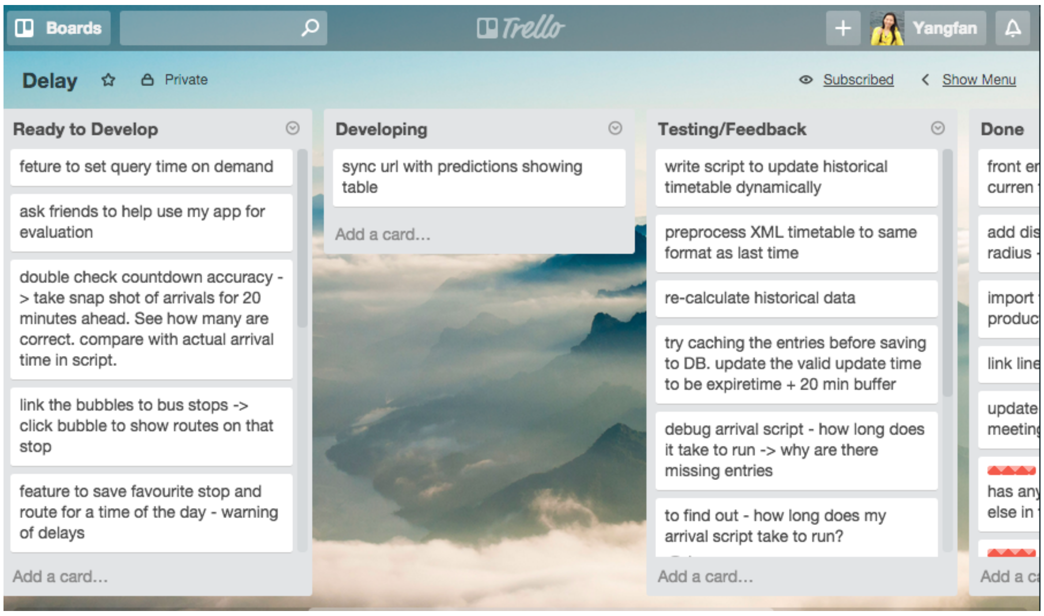
8.2.3 Arrivals Daily Backup

The arrivals table grows rapidly by approximately 150 thousand rows per hour. In order to allow fast access to the arrivals within the past one hour to construct the current timetable, we decided to save the arrivals for the current day in a new table, while keeping the past arrivals entries in an archive table. This required us to backup the arrivals entries daily to the arive.

Again, we created a Jenkins job to run the back up script daily. In order not to affect the historical timetable update, we set this job as a downstream task of the historical timetable update.

8.2.4 Software Project Management - Trello

We used Trello [55] for project management. It was useful to keep track of the tasks backlog, the tasks at hand, and the tasks to be further tested (Figure 8.2).



Ready to Develop

- feture to set query time on demand
- ask friends to help use my app for evaluation
- double check countdown accuracy -> take snap shot of arrivals for 20 minutes ahead. See how many are correct. compare with actual arrival time in script.
- link the bubbles to bus stops -> click bubble to show routes on that stop
- feature to save favourite stop and route for a time of the day - warning of delays

Add a card...

Developing

- sync url with predictions showing table

Add a card...

Testing/Feedback

- write script to update historical timetable dynamically
- preprocess XML timetable to same format as last time
- re-calculate historical data
- try caching the entries before saving to DB. update the valid update time to be expiretime + 20 min buffer
- debug arrival script - how long does it take to run -> why are there missing entries
- to find out - how long does my arrival script take to run?

Add a card...

Done

- front er curren
- add dis radius -
- import produc
- link line
- update meeting
- has any else in

Add a c

Figure 8.2: Project Trello Board

Chapter 9

Evaluation

9.1 Accuracy of Live Bus Arrivals API Stream

The Tfl Live Bus Arrivals API Stream updates the bus arrival times every 30 seconds. This means that the bus arrival predictions for the current stop would get more and more accurate as the bus approaches the stop. This is because any error in earlier predictions would be incrementally corrected at every update as the location of the bus gets refreshed.

9.1.1 Test for Accuracy

We evaluated the accuracy of these predictions by the following steps:

- We took a snapshot of all the bus arrivals predictions for the next 30 minutes at a given recorded time (2015-06-04 11:24:37).
- We grouped these prediciton entries by the difference between the predicted arrival time and the recorded time at a 5-minute interval. For example, the predictions for the buses arriving in the next 5 minutes, next 5 to 10 minutes, and next 10 to 15 minutes, etc. We added an additional group for the next 0 - 3 minutes for reference.
- After 3 hours, we compared each arrival prediction entry in the snapshot table against the actual arrival data we stored for generating the current timetable. The difference between the predicted and the actual arrival time gives an indication of the prediction accuracy. We stored this difference as the delta value. A negative delta indicates the bus came later than the predicted time.

Predictions for	Average Delta (Seconds)
next 0 - 3 mintues	-34.8112
next 0 - 5 mintues	-45.4951
next 5 - 10 mintues	-97.2584
next 10 - 15 mintues	-134.3606
next 15 - 20 mintues	-169.5990
next 20 - 25 mintues	-174.7177
next 25 - 30 minutes	-166.1368

Table 9.1: Live Bus Arrivals API Stream Accuracy - A negative delta indicates the bus came later than the predicted time

- We calcuated the average delta value for each group, and created Table 9.1.

9.1.2 Test Result

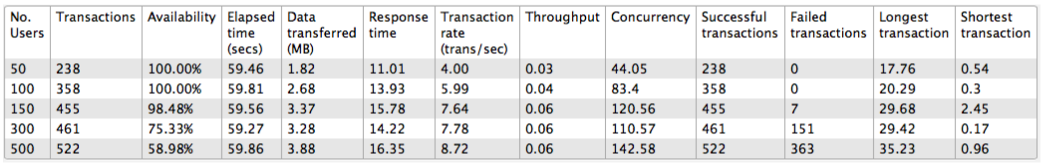
Table 9.1 shows that buses usually came later than the predictions provided by the Live Bus Arrivals API Stream. For the buses that were predicted to due in the next 5 minutes, they usually came less than one minute later than the predicted arrival time. We took this finding into consideration when testing the accuracy of our current and historical timetable by only choosing buses that are due within the next 5 minutes as tracking targets.

9.2 Correctness and Performance of the API

9.2.1 Tool

We used *siege*[53] to conduct the load test of our API endpoints. Our aim was to test the number requests the server could handle reliably at one time, and the response time it took.

Siege takes in the number of users, the delay time between each page load, the test running time, and the list of URLs to send requests to as parameters. It then simulates the user behaviours to fire requests to the list of given URLs. At the end of the test, *Siege* generates a report for the test, including metrics such as the transaction rate, and the response time of the target URLs.



No. Users	Transactions	Availability	Elapsed time (secs)	Data transferred (MB)	Response time	Transaction rate (trans/sec)	Throughput	Concurrency	Successful transactions	Failed transactions	Longest transaction	Shortest transaction
50	238	100.00%	59.46	1.82	11.01	4.00	0.03	44.05	238	0	17.76	0.54
100	358	100.00%	59.81	2.68	13.93	5.99	0.04	83.4	358	0	20.29	0.3
150	455	98.48%	59.56	3.37	15.78	7.64	0.06	120.56	455	7	29.68	2.45
300	461	75.33%	59.27	3.28	14.22	7.78	0.06	110.57	461	151	29.42	0.17
500	522	58.98%	59.86	3.88	16.35	8.72	0.06	142.58	522	363	35.23	0.96

Figure 9.1: Result of Performance Test with Siege

9.2.2 Preparation

We generated a list of API URLs with random parameters for testing. We then ran the siege tests by fixing the test running time to be 1 minute, with 1 second of delay between each page load.

9.2.3 Test for Correctness

We first tested for the correctness of our API endpoints. This involves firing requests with random day of the week and hour of day, route, run, and starting bus stop code to check whether the server can return a response correctly.

At this stage, we found some specific URLs that resulted in a 500 error code, and debugged the backend code to return correct results. For example, this happened when we requested for a reference travel time for a bus route at an hour out of its operating time. As there was no corresponding entry in the databases, we fixed the code by returning an empty list by default.

After we received 200 status code for all requests in a few test runs consistently, we proceeded to perform the load tests by fixing the day of the week and hour of the day to be the current values when the test was run.

9.2.4 Load Test for Performance

We found out that currently, the server could reliably handle about 150 users to send requests concurrently, with an average response time of 15.78 seconds. Figure 9.1 shows the results of our tests.

plot graph from results

```
Transactions is the number of server hits. In the example, 25 simulated users [

Elapsed time is the duration of the entire siege test. This is measured from the

Data transferred is the sum of data transferred to every siege simulated user. I
```

```
Response time is the average time it took to respond to each simulated users req

Transaction rate is the average number of transactions the server was able to ha

Throughput is the average number of bytes transferred every second from the serv

Concurrency is average number of simultaneous connections, a number which rises 

Successful transactions is the number of times the server returned a code less t
```

9.3 Accuracy of Predictions

How accurate are the predictions?

9.3.1 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.

9.4 User feedback on UI

On the How effective is it at warning delay?

Chapter 10

Future Work

- improve the performance of API endpoints by separating the data collection DB from the API request handling DB

Chapter 11

Conclusion

¡Conclusion here¿

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
average_travel_time	datetime(6)	The average travel time in seconds for the bus trips from the previous stop in the route to the current stop during the given arrival hour
cumulative_travel_time	int(11)	The average travel time in seconds from the terminal to the current stop for the bus trips arrived at the current stop in the given arrival hour

Table 11.1: 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 11.2: delay_arrivals Table Schema

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 11.3: 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 11.4: delay_neighbours Table Schema

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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