Developing an Intelligent Chatbot: the First Interim Report

Group xx: Daniel Willis, Charlotte Anderson and Brandon Gous

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Abstract

The report shall introduce some background to the subject as well as the groups motivations for creating the chatbot. It then discusses the group's aims, objectives and difficulties for both part 1 and 2 of the brief. In section 2, similar systems are discusses and evaluated by their relevance to the project. In part REF methods, tools and frameworks used for this project are stated and explained. The design 4 and implementation 5 are then outlined in subsections of the different areas of work. Testing for this project is then covered briefly in section 6. Finally, the groups work is evaluated in section 7 and then a conclusion to the project is made in the closing section 8.

1 Introduction

For this coursework (Wang 2018) the group is developing an intelligent chatbot for customers to use which will find them the cheapest train ticket for a specified journey. The service shall also provide users with information on train delays, for a specified journey, to improve customer service. The chatbot will be able to recognise which service the user wishes to use, using Natural Language Processing techniques. The chatbot will respond appropriately until it has gathered all information needed to answer the user's query.

1.1 Background and Motivation

Increasingly chatbots are used for customer service by companies and businesses. The first wave of chatbot systems could only recognise questions posed to them if they were written exactly as it was programmed to understand **?**ebi). Artificial intelligence is a hot topic at the moment, and has been used to develop seriously intelligent chatbots. Using AI chatbots are able to understand and answer customer questions, which can be asked in a huge variation of ways. As chatbots these days are so capable, many companies favour using AI for customer service over an employee as it can save money and time as **?**Sintef) found in his study than many users understand that chatbots work best when asked direct and precise queries.

1.2 Aim and Objectives of this coursework

The aim of the group is to develop a prototype intelligent chatbot system that can be extended to handle a large variation of queries. The chatbot will have two functions

1. Finding a user the cheapest ticket for a specified journey.
2. Reporting to a user the predicted train delay when prompted with their journey and their current delay.

Our objectives are:

1. To keep to our outlined project plan in the Gantt Chart.
2. Have bi-weekly meetings on Microsoft Team to update the group on progress made.

Have all set separate work completed for the chatbot, ready to be integrated with each other, by the 10th of January. This will give the group a week to integrate their systems together and iron out any issues, ready for the demonstration and video.

1.2.1 MoSCoW

Must

- The chatbot must be able to handle single-way tickets.
- The chatbot must prompt the user until enough information is obtained to complete their query.
- The system must be able to use the gathered information to complete the request.
  - In the case of a cheapest ticket query, it must return the cheapest ticket found and a hyperlink to a page where the customer may purchase it.
  - In the case of prediction, it must return the predicted train delay in minutes at the users destination station
- Once the chatbot has received all the information it needs to search, it must check with the user it has understood the query correctly, so changes can be made if needed.

Should

- The chatbot should be able to handle return tickets.
- The chatbot should be able to handle a large query with multiple pieces of information within it.
- The chatbot should be able to handle misspelt station names.
- That chatbot should return the user an answer to their question, once all the information is obtained, within 15 seconds.

Could

- The chatbot could be able to handle multiple date and time formats.
- The chatbot could be able to ask the user if there is anything more they can help with.
- The chatbot could have an attractive user interface.
- The chatbot could search for multiple adults or children.

Won't

- The chatbot won't be able to handle all query formats.
- The chatbot won't be able to recognise badly spelt station names.
- The chatbot won't be able to use railcards in its search for the cheapest tickets.

1.3 Difficulties and Risks

A risk with this task could be poor project management. To try and reduce this risk, in our first group meeting we decided upon a group leader, Dan. Dan ensured that we had weekly meetings in which he encouraged us to all share what we'd been working on. A large portion of this work had to be completed over the Christmas break. It was important that the team continued to work together despite not being on campus at university. Our group continued to have regular meetings on teams during this time, with the intention that this would reduce the risk of slippage in the project. Another risk is that deadlines will not be met. A member of the group not meeting a specific deadline could mean that the next piece of work cannot be started. To reduce the risk of this happening, the work was divided in such a way that each member could get on with a specific part of the brief. The work was delegated as follows:

Dan:

- Project manager
- Create the database
- Research predictive models
- Programme a few of these models and report back the most successful model
- Work with Brandon to get this work integrated with the chatbot.

Charlotte:

- Write the webscraper for the cheapest ticket
- Decided on the flow of conversation for the chatbot
- Write the NLPU component and work with Brandon to get this integrated with the chatbot.

Brandon:

- Write the Knowledge-Base
- Reasoning Engine and User Interface.
- Worked with the other team members to get their contributions integrated with the chatbot.

Working this way meant that each member could begin programming without having to wait for another member of the group to have already finished a task. In the weekly meetings everyone shared what they had been working on since the last.

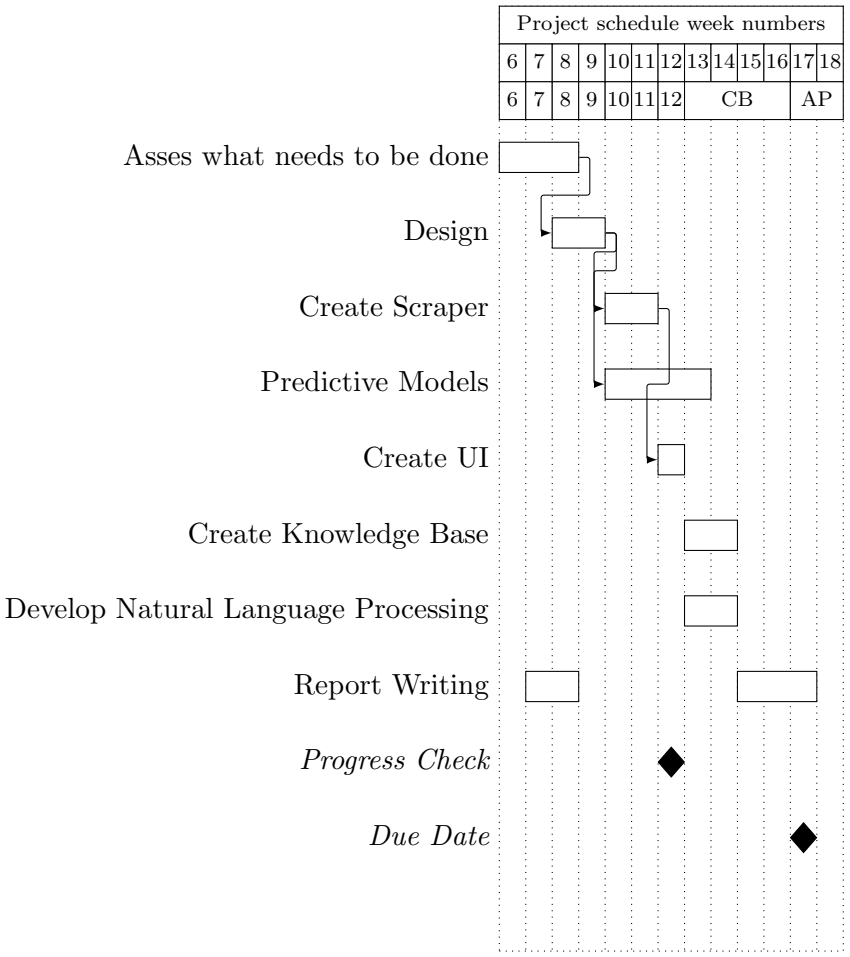
Once the individual work was complete the final risk was that our work would not be integrated together in time. This is a large and integral task, if all elements work separately but cannot work together the brief has not been met, for this reason one of the objectives was to begin integrating work by at least the 10th of January.

1.4 Work Plan

2 Related Work

2.1 TFL chatbot

The TFL chatbot was very friendly and said "You're welcome" (or equivalent) when you thanked it TFL (2020). It seemed to understand what I meant most of the time very well even when I wasn't being very specific. It was functionally useful as it could give me live information about the next few buses if I know



Project Gantt chart

the stop code for the bus stop that I am standing by And was fully integrated with facebook messenger so it is as easy as sending a facebook message.

Unfortunately it had very limited functionality especially for the tubes. I couldn't select my station properly and it took me a few attempts to get the correct station for where there are two called similarly as it did not offer me to pick from suggestions. I couldn't plan as there was no way to enter the time of the journey; it always had to be right then and you couldn't plan ahead of time. And it couldn't understand when you said everything in one message, you had to separate the too and from stations.

Overall I would say the chatbot worked well but needed more functionality as it would only occasionally misunderstand but for tubes it could only tell the user what line the closures are on so that the user can decide if they want to see in more detail when/where they are. But a lot of the time when trying to extract information, especially when talking about cost, it would just send me a link to the TFL website.

2.2 BlenderBot

Blenderbot or parlai is a open source, highly customisable chatbot developed by Facebook Stephen Roller (2020). Its relatively easy to install and use in the terminal, and if you desired its comes with integration into Facebook messager.

You can have it be assigned a random persona or set one for it or just have a general conversation. This was very interesting to play around with giving the AI different characters to play and seeing how well it did.

You can load up models from the "zoo" or create your own built off a base. The 80million data points model is a little clunky and not as fluent. There is a definite pattern to its responses. But the top level 9billion data point weights is very impressive, it could almost pass as a human.

It's very factual too, it will attempt to slip in facts in a "normal" manner rather than just blurting them out robotically.

It comes with a lot of documentation and a paper about how to build a good model.

Overall it was very entertaining and enjoyable speaking to it. If we had longer time on our project I would have liked to incorporate it and perhaps build our own model for it.

2.3 Google Assistant

Google assistant is arguably a chatbot, it just commonly has a speech to text and text to speech software alongside **?**. However there is the option on phones to just type text to it and reply but this conversation would be the same as if you were speaking to it.

Personally I like google assistant and find it very useful to perform tasks such as switching lights on and off, playing media, setting timers for cooking etc. But that is all it is, it is designed to be a tool and to be as useful and functional as possible. It isn't designed to have a proper conversation with it.

This is where it is lacking, its responses are very robotic, blunt and to the point. No human speaks like that. You can ask it all the questions that you like and it always has an answer from crawling the web or doing the maths. You can get it to tell you a joke or the weather or how the traffic looks on your morning commute but it isn't having a real conversation. It is being used as a tool to solve your problem.

Its natural language processing is near perfect and in real time from audio which is incredible. It really understands what you are saying so long as it is a command. Overall a very useful thing to have around but not the best chatbot.

3 Methods, Tools and Frameworks

In this section, you should describe the methods, programming languages, packages, tools and framework you plan to use. for this report, you can list some you have identified and intend to use. No need to give any details.

3.1 Methods

You may list some methods you will use for developing your chatbot, including
Such as what type of user interface (graphical, text, or voice, etc) you intend to use.
What Natural Language Processing and understanding methods you intend use,
What referring or reasoning methods
What prediction methods, such as kNN, neural networks etc.

3.2 Languages, Packages, Tools

On programming language: using Python or Java, or others.
Packages: for NLP, use NLTK(Bird & Klein 2009), or others,
For KnowledgeBase and Engine: PyKE or PyKnow, or others.
For Database: e.g, Postgres, or MongoDB

3.3 Development Framework

4 Design of the Chatbot

4.1 The Architecture of the chatbot

In an early group meeting we decided to conduct the work for this project modularly. This meant creating contracts with one another on what work would be completed by each member, by when and detailing exactly what we expected from each piece of work. This meant we could work separately, which was necessary as much of this work was completed away from university. It was decided that Dan would create a database, as well as writing predictive models, Brandon would write the knowledge-base and inferring engine, and Charlie would write the scraper and NLPU. Once all this work was completed, the group could come together and integrate the various pieces of work.

The chatot is responsible for handling questions from a user and responding to these. It uses the NLPU to understand what a user has inputted as well as to see if all fields have been filled for a search. If all fields have not been inputted, the chatbot will reply to the user asking for the information it is missing. Once the NPLU has all the information it needs to make a search, it delivers this to the scraper or the prediction model depending on the task. If the task is for find the cheapest ticket, once this has been found the chatbot will relay this information to the user with a price and a link to buy the ticket. Similarly, for predicting train delays, once the predicted delay has been predicted, it is relayed through the chatbot to the user.

4.2 User Interface

4.3 Scraper

The implementation of the scraper has been designed to complete the task of finding a cheapest ticket for a train booking. Trainline's website *Search, Compare and Buy Cheap Train Tickets* (n.d.) was chosen to be scraped, this was because when inspecting the page when a search was completed there was a clear tag which indicated the cheapest ticket which could then be used to return to the user. The package 'selenium' (n.d.) was used to webscrape as it was found to be the most useful for what was trying to be achieved. The TrainLine class has many functions which find different elements within TrainLine's page, which are then filled once the chatbot has retrieved information from the user.

The scraper clears all field boxes before entering data. This is because if a field was pre-filled by the website, i.e. defaulting to today's date, when the scraper tried to enter the date which has been specified by the user, it cannot do so as it is already full and throws an error. The scraper uses selenium to find specific elements within the page that will be filled with the users query. For example if a user wants a

single ticket, it is capable of choosing between the radio buttons for a 'single' or 'return' journey. This is done by using TrainLine's element ID's, for example the radio button for a single tickets element ID is 'single', and therefore can be found and clicked.

Once a full search has been made, the scraper waits for an element with an 'aria-label' that has the value 'the cheapest fare'. The price which belongs to this value is the cheapest ticket for the specified journey, and this price and the link to the page is given as a reply to the user through the chatbot.

4.4 NLP

The NLPU is essential to the scraper. TraineLine's website only works for certain date formats, 24 hour times, full and correctly spelt train stations, and will only complete a search successfully if it has all of the information. The NLPU works with the chatbot to ensure all fields are full before passing this information to the scraper so it doesn't fail. Not only this, but the chatbot has to be able to understand what a user is asking it to do. The NLPU can identify, using SpaCy's *Doc · spacy API documentation* (n.d.) parts of speech, when a user is inputting a cheapest ticket query or prediction query. It does this by looking for specific words in the sentence. To identify whether it is a cheapest ticket query it looks for words in the stems.json file, which matches similar words. If a query contains the a words, once stemmed, 'book', 'ticket', 'cheap' or 'buy', it infers that the user is wanted to find the cheapest ticket, rather than asking about a delay prediction. The same goes for the prediction query.

One of the most important parts of the NLPU for this project was the chatbot recognising train station names that were spelt incorrectly, or missing parts of the station name, as when these stations are inputted into the scraper they must be exact or the search will not run. To do this a package called 'fuzzywuzzy' was used, which does a 'fuzzy match' on station names and finds percentage matches to the station names inputted. If a station is not a 100% 'fuzzy match', the chatbot suggests any station that has an 80% match or higher. The unit also handles multiple different date formats, times and understands words like 'today' and 'tomorrow'.

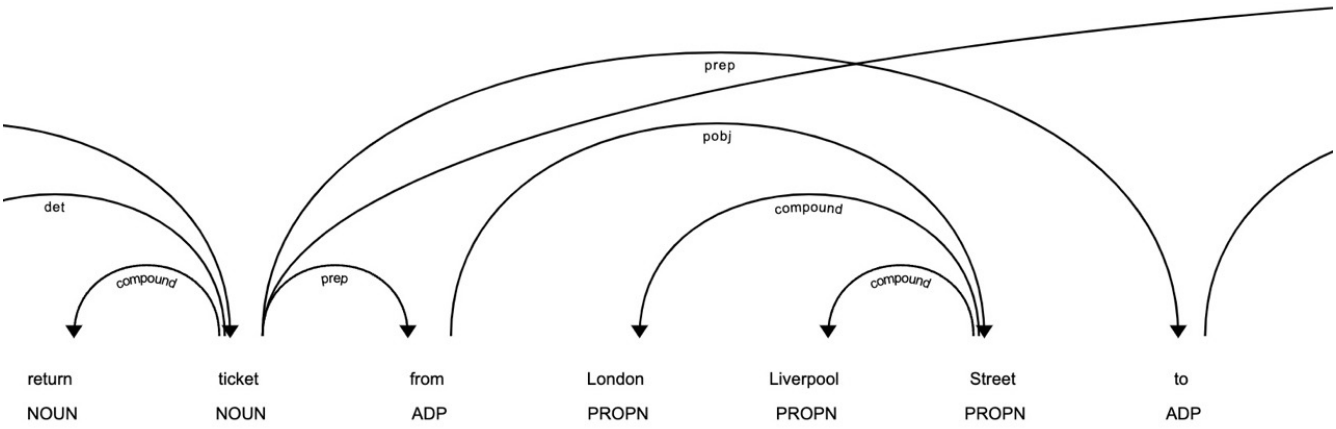


Figure 1: Example of SpaCy's parts of speech tagging on a cheapest ticket query

For sentence queries, like the one in figure 1, the NLPU works by using SpaCy, looking at parts of speech tags like 'NOUN' or 'VERB' or for words within the stems.json file. For example, if the parts of speech tag is 'ADP' and one of the relating 'from_station' words in the stems.json file, the program extracts the following station name and sets it to the origin station.

4.5 Knowledgebase

4.6 Inferring Engine

4.7 Delay Prediction Models

For our prediction models we plan to use three. A Bayesian model that calculated the probability of the train being late to the second station given that the train is delayed to the first station. A neural network that uses the delay and the normal time a train takes between the stations to predict how late the train will be. And K nearest neighbour which predicts how late the train will be to the second station using similar data.

4.7.1 Bayesian

Bayesian Theorem is that the probability of event A happened given that B happened can be calculated by the probability of event B happening given that event A happened multiplied by the probability of event A happening all divided by the probability of event B happening.

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Additionally this can be expanded so that the probability of event B happening doesn't need to be known. The probability of event B happening is equal to the probability of event B happening given event A happened multiplied by the probability of event A occurring plus the probability of event B happening given that event A does not multiplied by the probability that event A does not happen.

$$P(B) = P(B|A) * P(A) + P(B|'A) * P('A)$$

This means that you can calculate the probability of event A happening given that B happened from the probability of event A happening, the probability of event B happening given event A happened and the probability of event B happening given that event A didnt happen.

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B|A) * P(A) + P(B|'A) * (1 - P(A))}$$

We can apply this to the prediction of trains being late by letting event A be the train being late to the second station and event B the train being late by delay or more to the first station.

4.7.2 Neural Network

A neural network is a collection of layers of neurons, each neuron holds a value known as activation of that neuron. There can be an unlimited number of layers and neurons and they can be used to solve very complex problems such as object recognition.

Each neuron is connected to all the neurons of the previous layer through numbers called weights (W) and a bias (b). The weights are organized in the form of a matrix of shape (no of units in current layer, no of units in previous layer). This means that to calculate a neuron on the next layer you need all the previous values.

If this is applied to our problem we chose to have two input nodes of the delay at the first station and the normal time taken between the stations. And we obviously have the output node for the prediction time that the train is late. So these two layers we cannot change, but any of the hidden layers can be altered to still produce a neural network to accomplish the same goal. This is shown in figure 2 it shows all the neurons in the simple neural network we designed to solve the problem with two hidden layers of three neurons each.

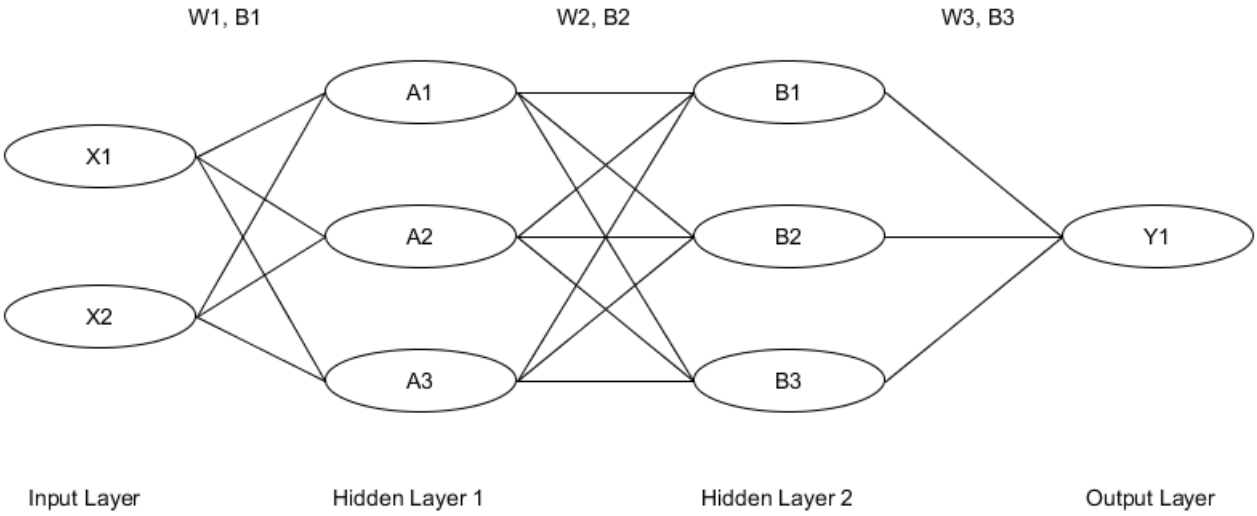


Figure 2: Diagram showing the neural network

For the maths behind the forward and backward propagation, $\mathrm{Wk_{ij}}$ refers to the weight of the connection from i'th neuron in k'th layer to j'th neuron in k-1 layer. The biases are organized in the shape of (no of units in current layer, 1) so $\mathrm{Bk_i}$ corresponds to the bias of the i'th neuron in k'th layer.

Each neurons value can be calculated by:

$$A1 = g(f(X1, X2)) = g(W1_{11} * X1 + W1_{12} * X2 + b1_1)$$

$$A2 = g(f(X1, X2)) = g(W1_{21} * X1 + W1_{22} * X2 + b1_2)$$

$$A3 = g(f(X1, X2)) = g(W1_{31} * X1 + W1_{32} * X2 + b1_3)$$

$$B1 = g(f(A1, A2, A3)) = g(W2_{11} * A1 + W2_{12} * A2 + W2_{13} * A3 + b2_1)$$

$$B2 = g(f(A1, A2, A3)) = g(W2_{21} * A1 + W2_{22} * A2 + W2_{23} * A3 + b2_2)$$

$$B3 = g(f(A1, A2, A3)) = g(W2_{31} * A1 + W2_{32} * A2 + W2_{33} * A3 + b2_3)$$

$$Y = f(B1, B2, B3) = W3_{11} * B1 + W3_{12} * B2 + W3_{13} * B3 + b3_1$$

Where $g(x)$ is the activation function. Being as this is a regression problem and not classification I will use $g(x) = max(0, x)$ more commonly called the ReLU. This returns 0 when x is negative and x when positive. Due to it's low saturation region, it is highly trainable.

The equations above can be vectorised using the dot product of the matrices:

$$A = g(W1.X + b1)$$

$$B = g(W2.A + b2)$$

$$Y = W3.B + b3$$

However for the neural network to become more accurate it has to learn by adjusting the weights an bias to bring the output closer to the target. This is done using a back propagation algorithm to calculate the gradients. These are the vectorized equations:

$$dY = \frac{1}{m} * (Y - T)$$

$$dW3 = \frac{1}{m} * (dY.W3^T)$$

$$db3 = \frac{1}{m} * \sum dY$$

$$dB = W3^T.dY$$

$$dW2 = \frac{1}{m} * (dB.W2^T)$$

$$db2 = \frac{1}{m} * \sum dB$$

$$dA = W2^T.dB * g'(W2.A + b2)$$

$$dW1 = \frac{1}{m} * (dA.W1^T)$$

$$db1 = \frac{1}{m} * \sum dA$$

Where T is the true value, m is the number of datapoints, $*$ is multiplication, $x.y$ is dot product of the matrices x and y and x^T is the transpose of matrix x. We do not need gradients with respect to the input layer neurons because we are not going to change them.

Now using these gradients calculated we can modify our weights and bias getting us closer to the true result.

$$W1 = W1 - lr * dW1$$

$$b1 = b1 - lr * db1$$

$$W2 = W2 - lr * dW2$$

$$b2 = b2 - lr * db2$$

$$W3 = W3 - lr * dW3$$

$$b3 = b3 - lr * db3$$

Where lr is the learning rate which is a configurable hyperparameter that is in the range between 0.0 and 1.0. The learning rate controls how quickly the model adapts to the problem.

4.7.3 K Nearest Neighbors

For the K nearest neighbour model we have to use loads of data extracted from the database for each query. For this we will have to use a stored procedure.

The amount the train was late to the first station is then compared to the amount of delay that the user had at the first station using a distance function, in our case we picked euclidean.

These distances are then sorted and you get the mean of the delay at the second station for the closest K nodes in the dataset. This is simple algorithm but heavily dependant on finding the correct K value. Too small and you wont get the correct number because it will be skewed by having not enough data, too large and the result will be skewed by nodes that are not close enough.

4.8 Conversation Control

5 Implementation

5.1 Predictive Models

5.1.1 Bayes

To get the probabilities we can use stored procedures to extract the frequencies from the database.

Firstly the probability of A (the train being late to the second station). This was easy enough to calculate I simply extracted the frequency count of all times it arrived at the second station late. Totalled up the number of times the train was late and divided by the total pieces of data I had.

Secondly I calculated the probability of B given A (the probability the train was late to the first station by delay given it was late to the second station). To do this I extracted the frequencies of delays at the first station if the train arrived late to the second station. From here I summed all the frequencies that the train was late to the first station by at least the delay.

Next I calculated the probability of B given not A (the probability the train was late to the first station by delay given it was on time to the second station). To do this I extracted the frequencies of delays at the first station if the train arrived on-time or early to the second station. From here I summed all the frequencies that the train was late to the first station by at least the delay.

From here it was just a case of doing the calculation and returning the result as a probability.

5.1.2 Neural Network

We thought that the best way to implement all the weights and values being stored was through dictionaries with string keys eg: "W1" with multidimensional arrays as the value.

This meant that I could implement a solution which has the capacity to expand the number of layers and neurons per layer easily with simple for loops, making the solution highly customizable.

To keep track of how well the network was learning we would test every single data point through it every 1000 iterations and get the root mean squared error for them all. This was then plotted on a graph seen in figure **??**. This shows how quickly it could correct itself at the start and then converge to 0 with a shape similar to $y = x^{-1}$ graph. This was the shape that we expected to see.

We would also graph every hundred thousand iterations as seen in figure 3 to be able to see more clearly that is learning still. However this quickly has a very small range on the Y axis showing it is learning slower.

5.1.3 K Nearest Neighbour

Once you have the data for the KNN it is a very simple algorithm but still heavily depends on the correct K value. So to find the best K value we set up a test to run one thousand iterations of selecting random data points from the data. Then for each piece of data I would create a KNN object with a different value of K ranging 1 to 100 (inclusive). Get a prediction from each object and compare it to the target outcome. From this I calculated the root mean square error for each value of K over the iterations.

The results plotted on a graph is in figure 4 and the top ranking results are included in the table in figure 5. The shape of the graph is exactly what I expected to see with very few neighbours having a very high RMSE and then having a dip where the ideal K value is with the RMSE gradually increasing again as the more neighbours are used.

From these results I concluded that 9 was the best value for K not only because it ranks at the top but because 10 and 8 rank 3rd and 4th in the list. However any value from 5 - 15 would still be accurate.

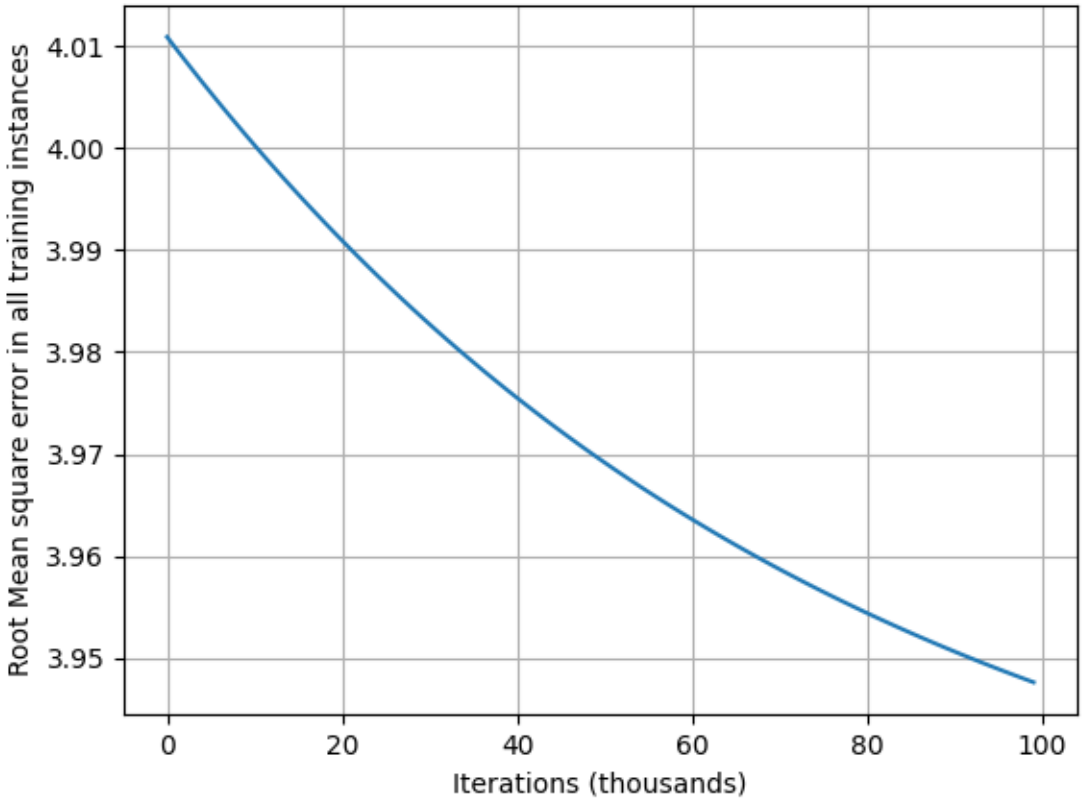


Figure 3: Comparison of neural network and K nearest neighbour

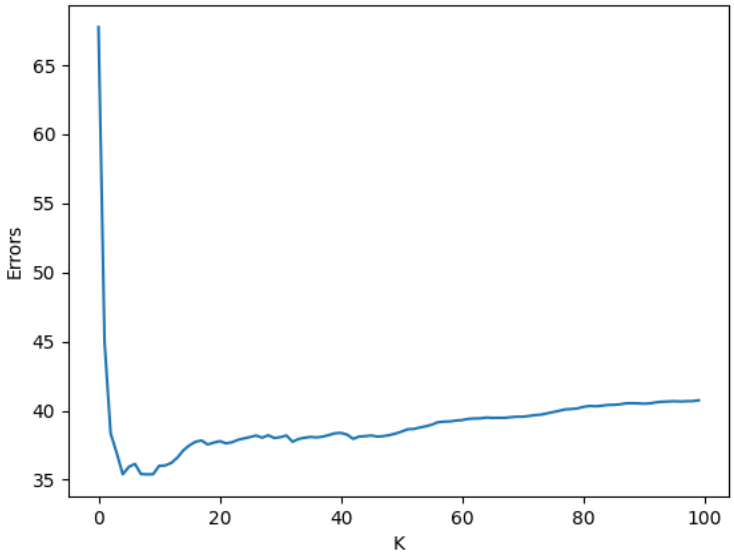


Figure 4: Searching for the correct K value

K	RMSE
9	3.538776543
5	3.539336
10	3.539625
8	3.54108125
6	3.592727778
11	3.600159504
12	3.60323125
7	3.614691837
13	3.620826627
14	3.659637245
4	3.6941
15	3.712949778
16	3.748832031
19	3.75489446
22	3.763205165

Figure 5: Sorted RMSE of K values

5.1.4 Comparison

We didn't think that the Bayesian model was very good as it is a classification model not a regression therefore not particularly useful to the user as they would want to know their expected time of arrival.

In figure **??** we compare the neural network and k nearest neighbours over two million iterations of training the neural network.

This was accomplished by randomly selecting a thousand data sets, running these datasets through both the models and comparing the predictions to the targets. Then train the neural network on the same dataset for a hundred thousand iterations and repeat.

As you can see the K nearest neighbour algorithm is consistently better than the neural network despite the improvements made so we decided to use that as our final predictive model.

6 Testing

6.1 Unit Testing

For the predictive models and NLP, unit tests were used to check that each function achieved its intended purpose; this approach is known as test driven development. Unit tests were written first, then code was developed to pass these tests. This meant the group was able to monitor which parts of development needed more work, and which were complete. Before each merge on GitHub, these tests were run to check that the code being pushed hadn't broken the previous commit. For the NLP, as the scope of what the chatbot could understand is massive, specific tests were written for what the group had outlined as chatflows it should accept.

6.2 Integration Testing

6.3 System Testing

6.4 Userbility Testing

7 Evaluation and Discussion

8 Conclusion or Summary

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