Developing a train booking chatbot: Final report

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1 Introduction

According to Oracle (2019), Chat-bots are computer programmes that can simulate and process natural language conversation with humans. Chatbot has received major increase in popularity for organisations recently due to its capability to resolve tasks using natural language with greater efficiency relative to a human operator. While general (conversational) chatbot exists and are able to respond and process a wide range of conversation and instructions, most chatbots that are developed are specialised in a certain task. The aim of this project is to develop a task-oriented chatbot that can locate the cheapest train ticket given the details, predict train delays for selected train routes and provide contingencies for experts during a train journey.

1.1 Background and Motivation

Chatbots was first introduced in the 1960s. Initially, chatbots were developed with the goal to mimic natural conversation (of a specific group of individual) without any specific goals or tasks to be accomplished. Some notable early chatbots are ELIZA, PARRY which uses simple systems such as response pairing. Another major development was the growth of chatbots that uses pattern matching instead of pairing pre-defined response pairs. The classic example of such chatbot is Jabberwocky, which has been used for academic research. Chatbots grew significantly in popularity in the early 2000s, organisations are developing task-oriented chatbots to handle specific tasks online. General purpose chatbots such as Siri, Google assistant and Alexa became more common this decade. These chatbots have a ability to process and handle large amount of different tasks.

Chatbots provide various advantages to the operations of an organisation, and with the increase of platforms and open-source programs that aids the development of chatbot, the amount of chatbots deployed online has been growing significantly. Unlike human customer support, Chatbots are able to process multiple user request in parallel and are always available any time of the day (EXASTAX 2019). Chatbots can also engage customer proactively to engage with customers, collecting and monitoring customer data during the process. More advanced chatbot can also improve the organisations presence in the global market by providing chatbots in different languages. Some online platforms also allow chatbots to be deployed to other platforms such as social media which would further increase the amount of engagement an organisation has on its market EXASTAX (2019).

There are also certain limitations on chatbots as well. Task-oriented chatbots are usually constrained in the type of conversations it could process, conversation that went out of scope might result in (ECN 2019):

- Default response when chatbots fail to process the conversation
- Inaccurate assumption of users intention, causing problems in communication

Whilst it's possible to develop chatbots that are capable of handling large amount of tasks, it's time consuming and costly to deploy such chatbot that may not be utilised fully. Therefore, an additional objective of this project is to develop a chatbot that is capable of handling most conversation within the scope of the tasks while providing relevant information when the conversation goes out of scope.

1.2 Components of a Chatbot

There are multiple different components in the background that simulates natural language conversation in a task-oriented chatbot.

1.2.1 Natural language processing

Natural language processing (NLP) is a crucial part of a chatbot as it functions as the connection between natural language conversation to the background functionalities. NLP functions to process sentences that user entered and extract the intentions of the user (Garbade 2018). Two of the main method of understanding natural sentences: Syntactic analysis works by applying grammatical rules and grouping words in sentences to derive meaning from the sentence. On the other hand, Semantic analysis aims to derive meaning of words by trying to understand the meaning of words by analysing the sentence, context and grammar (Garbade 2018).

1.2.2 Reasoning engine

While NLP processes and understands the meaning of a sentence, a reasoning engine is responsible mapping the extracted meaning to actions. It uses defined rules or models to discover the aim or intent of the user and provides relevant responses accordingly.

1.2.3 Web Scraping

Web-scraping is the process of extracting structured data from the web for other processes. The module can go through a webpage and extract information that is required. Web scrapers also has the ability to submit and fill in information online as well to request for further information such as automatically filling in a form. Web scraping is an important component for a train booking chatbot as well because information about train tickets has to be obtained online.

1.2.4 Data mining

Data mining is the act of extracting previously unknown information from data and converting into a structured format for other uses. The purpose of data mining is to discover pattern, anomalies or correlations. Data mining is usually done on combination with other aspects of computing such as AI, Statistics and Machine learning and the information obtained would be used for some other operations.

1.2.5 Predictive model

A predictive model provides forecast of certain outcomes. A predictive model is usually trained with existing structured data using a specified method or a combination of different method and makes a forecast based on the data it's trained on. For the train booking chatbot, it will be trained on previous train delay data and provide predictions on delays of new unseen train delays.

1.2.6 Knowledge-base system

Knowledge-base system contains a collection of information that can be accessed using an inference engine. These information is typically used as part of a decision making process and for the chatbot, it will be used to save information regarding actions to take in case of an emergency.

2 Methods, Tools and Frameworks

2.1 Methods

As there as multiple different components for a chatbot, the components will be developed separately with clear requirements set for each of the components to decrease the amount of bugs that may occur during the combination of different components. Team members will be assigned with 1 to 3 components that are linked to develop, with constant updates on the progress

2.1.1 Code management

As components will be developed independently, all codes will be uploaded to GitHub repository. Compilation and error checking will be assigned to one member. Each member will create a separate branch for code development and codes will be merged after a meeting with the full team.

2.2 Languages, Packages, Tools

2.2.1 Language

Following the requirement, the chatbot will be developed mainly in *Python*. *Python* contains a vast library of packages and framework that supports the development of an intelligent system which will significantly reduce the amount of time needed for development. Aside from that, the User interface will be developed using HTML and CSS and supported by *Flask*.

2.2.2 Packages

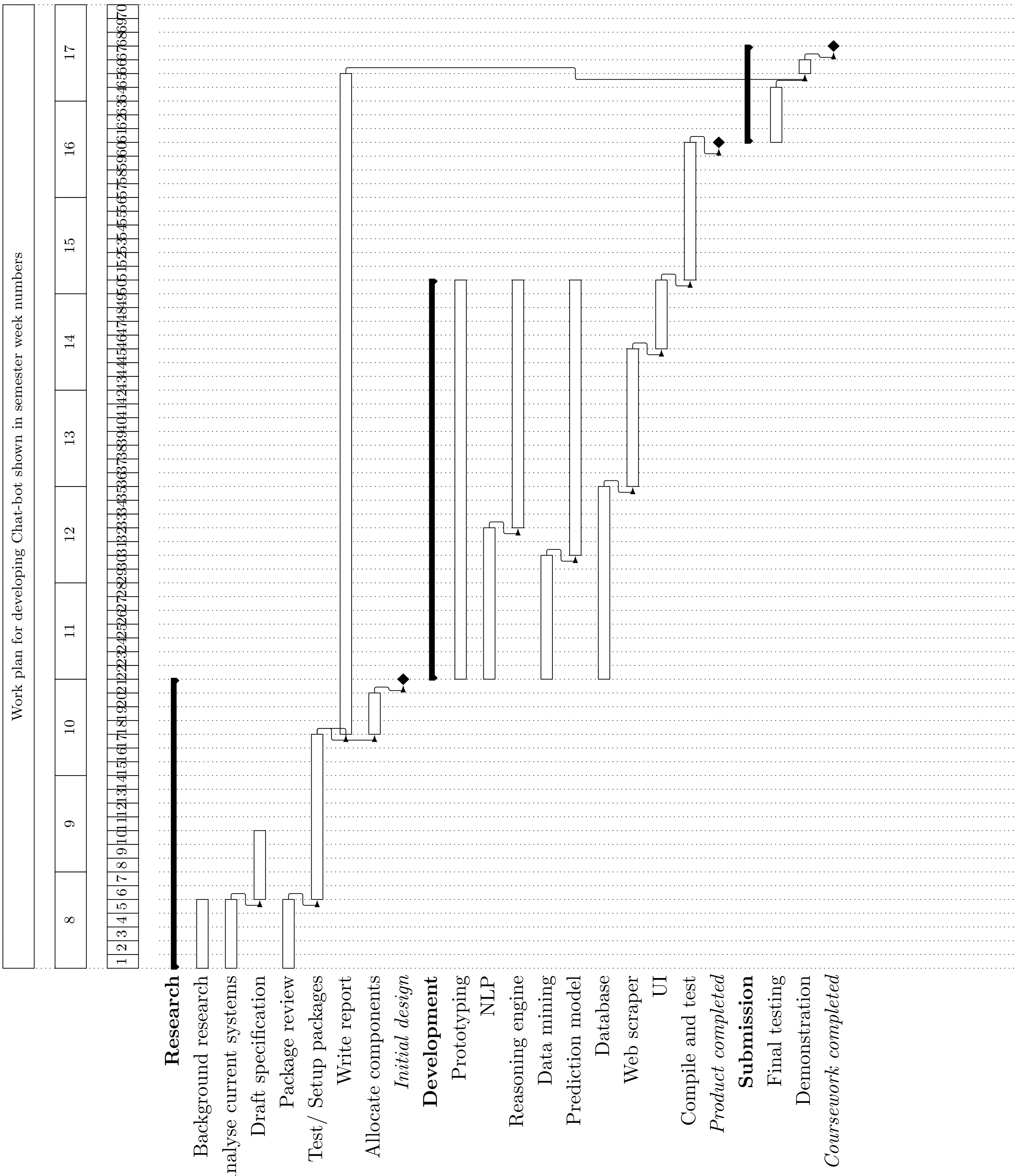
For Natural language processing, there are two packages that can be used to support the development: *SpaCy* and *NLTK*.

SpaCy, NLTK, Scrapy, Selenium, BeautifulSoup, Sci-kit learn, Numpy, SQLite, Joblib, Experta, HSP

2.2.3 Tools

The chatbot will be developed using *Visual Studio Code*, a code editor that allows development of python software and it also includes packages for error checking and syntax highlighting. Visual studio code also allows editing of other file types such as *HTML*, *CSS* and *csv* files all with error checking and syntax highlighting available. In terms of database management, DB Browser is a software that allows viewing and managing of data. Having a database management software allows testing whether if database interaction is successful between modules and also allow manual analysis of collected data.

2.3 Work Plan



Work plan for developing Chat-bot shown in semester week numbers
8
9
10
11
12
13
14
15
16
17
Research
Background research
Analyse current systems
Draft specification
Package review
Test/ Setup packages
Write report
Allocate components
Initial design
Development
Prototyping
NLP
Reasoning engine
Data mining
Prediction model
Database
Web scraper
UI
Compile and test
Product completed
Submission
Final testing
Demonstration
Coursework completed

3 Design of the Chatbot

3.1 The Architecture of the chatbot

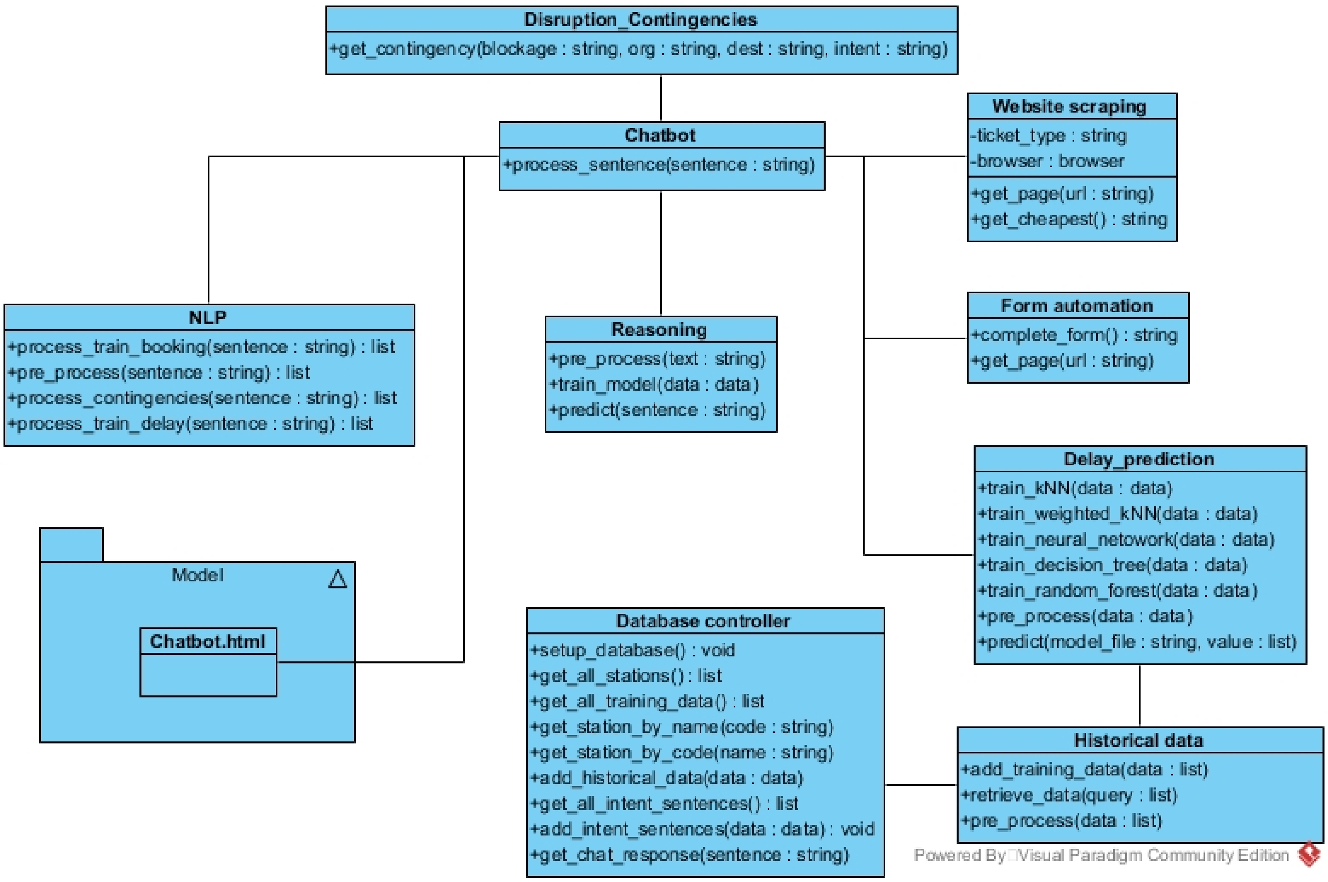


Figure 1: Structure of the chatbot

3.2 User Interface

The user interface is created using *HTML* and *CSS* as it provides portability and flexibility during development ans usage. HTML and CSS provides a simple framework for updating and customising the visuals allowing replication of the chatbot across sites with different designs. The user interface is be connected to the back-end using Python *Flask*. While the current plan is to deploy the chatbot online and embedded within a website, existing frameworks such as *Django* and *PhoneGap* can be used to deploy the chatbot across a wider range of platforms.

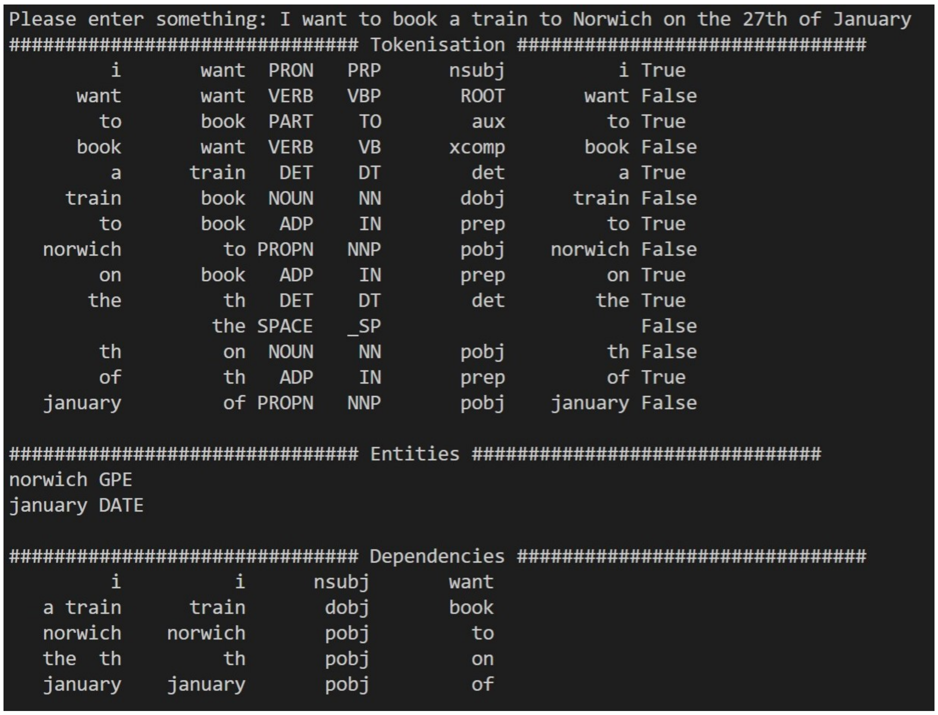
3.3 NLP

Natural language processing mainly rely on the *SpaCy* framework to filter, process and extract required information. The chatbot will also utilise a minor amount of *NLTK* functions to increase the accuracy at which the chatbot picks up the relevant information.

NLP is be the link between the chatbot and background functions that handles train booking, delay prediction and contingency planning. The system extracts information such as location, dates and key words using token tagging and dependencies trained by existing models provided by the framework.

Location and date in the sentences is obtained using the entity tagger present in *SpaCy*. Each function will aim to retrieve a set of pre-defined information.

The NLP module can recognise various form of input for date and time. For dates, the natural language processing unit for it can accept dates in the format of *'dd-mm-yy'*, *xxth of Month* and *Month xx*. All formats will be automatically converted to fit the format needed for web-scraping. Aside from that, the date unit will also accept more abstract inputs like "today" or "tomorrow". For the time unit, it will be able to accept "now" as an input in addition to normal 24-hour input.



```
Please enter something: I want to book a train to Norwich on the 27th of January
############################## Tokenisation ##############################
        i       want   PRON   PRP      nsubj          i True
     want       want   VERB   VBP       ROOT       want False
       to       book   PART    TO        aux         to True
     book       want   VERB    VB      xcomp       book False
        a      train    DET    DT        det          a True
    train       book   NOUN    NN       dobj      train False
       to       book    ADP    IN       prep         to True
  norwich         to  PROPN   NNP       pobj    norwich False
       on       book    ADP    IN       prep         on True
      the         th    DET    DT        det        the True
                 the  SPACE   _SP                       False
       th         on   NOUN    NN       pobj         th False
       of         th    ADP    IN       prep         of True
  january         of  PROPN   NNP       pobj    january False

############################## Entities ##############################
norwich GPE
january DATE

############################## Dependencies ##############################
        i          i      nsubj       want
  a train      train       dobj       book
  norwich    norwich       pobj         to
  the  th         th       pobj         on
  january    january       pobj         of
```

Figure 2: A prototype of Natural language processing. The system tokenises provided sentence and finds the entities and dependencies

Error prevention will also be implemented into the system where spelling mistakes on station names by using trained models to predict the which location is the most likely station that is intended by the user.

3.4 Reasoning engine

The reasoning engine will be trained using K-nearest neighbours with a database of sentences tagged with intention. The model will be used to predict the intent of sentences entered by users. The sentences will be tagged with '**B**', '**C**', '**D**' and '**N**' representing **B**ooking, **C**ontingencies, **D**elays and **N**ormal conversations. Additional training data can potentially be added into the database to improve prediction accuracy in the future. The model is trained by vectorising the sentences. The vectors are then hashed to decrease the size to accommodate future growth. As the model predicts by comparing sentence similarity, sentences that contains different location name will still be classified accurately without the need for the specific sentence to be included in the model.

The decision to utilise kNN is to ensure that majority of inputs can be recognised. The model can be constantly updated to adapt to the way user requests for different services. This will allow the system to continue to function efficiently as communication methods change in the future which pre-defined rules might not be able to achieve. As the model predicts by sentence similarity, additional intents can be added easily in the future to expand functionality of the chatbot.

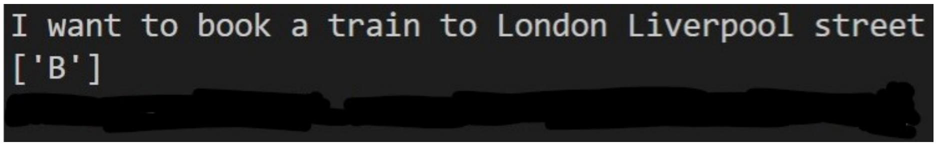


Figure 3: Reasoning engine for the chatbot

3.5 Website scraping

This module will utilise functions from the *Scrapy*, *BeautifulSoup* and *Selenium* to complete the a booking form and scraping ticket data from the link returned from the form submission. The cheapest train ticket will be retrieved from the list of tickets available and along with the web link, returned to the user for booking. Train ticket information is retrieved from the site *Trainline* by entering auto completing the form using the information collected from conversation with the user and scraping info from the link returned from the form submission. *Scrapy* was later removed from and the detailed explanation can be found in section 4.2

3.6 Knowledge-base

The knowledge-base will be used to store contingencies in the case of railroad disruptions. The module will use the package *Experta*, a new branch of *PyKnow* to define a ruled base inference system to retrieve contingencies. The rules will take the type of blockage (e.g. full or partial) the origin and destination pairs and the type of information the user is requesting. Using these information, the module will then return pre-set contingencies to the user.

For the generation of rules, the information is extracted from the actual contingencies document of train service companies provided for this development. Using the simple rule and fact format of *Experta*, extra rules can be potentially added in the future by staff with limited IT-experience.

3.7 Prediction Model

For prediction model, a neural network is used to predict the delays. From analysis of data acquired from *HSP*, we noticed that although the departure delay is available, there isn't a clear connection between the data provided and the delay time therefore a case based reasoning such as kNN might not be able to provide an accurate prediction without the presence of stronger attribute such as delay reason. Additionally, kNN are lazy learners which might significantly increase the prediction time due to the large size of training dataset.

Neural network was considered as the model for delay prediction as multi layer perceptrons aims to create a model that fits the data given instead of finding the training data that fits the unknown data best. Although utilising neural network might result in difficulties when visualising the model however it will produce a better prediction within a shorter time period once the a suitable setting is found.

The model was later modified during implementation to use a heterogeneous ensemble instead of neural network. Details are explained in section 4.2.

3.8 Data Acquisition

Data acquisition is designed into the system in two parts. Firstly, historical train data will be acquired, processed and saved into the local database using the *HSP* API which provides data of previous trains and their delays. Historical data can be acquired by providing parameters such as the start and end date of data needed, time and type of day. 3 years of data for trains travelling from Norwich to London Liverpool street will be extracted as the initial dataset for training but the system will allow further addition of data should it be needed. The historical data will contain the following list of information:

Origin station, Destination station, Departure time, Departure delay, Arrival time, Arrival delay, Month of year, Type of Date, TOC code. By having Data acquisition built into the system, delay prediction can be expanded in the future to increase the coverage of different train routes. Another consideration during the design of data acquisition was the change of train operating companies or train routes in the future. An example can be seen where there was a new route added from Diss to Hatfield Peverel in 2018 which was not available before. Having in-built data acquisition will improve the ability to update the system without reliance on external software.

Aside from acquiring historical data, the chatbot will also record successful predictions of the user intent to reinforce the model for future predictions. The system will save the initial sentence that was used to determine the intention of the user but will not store the follow up sentences when the system is completing a specific task.

3.9 Database

The system database will be created using the package *SQLite*. It will function to store active data that is used by the system which includes: Historical data, Sentence tagged with intent, Responses for normal conversations, Station codes and also a test dataset. These data will be accessed using SQL commands embedded in defined functions within the system. Although using SQL will increase the layers and development work needed for the system, having a database system provides greater flexibility in the way the data can be queried and updated without the need of defining our own methods. It will also provide stronger security as the data saved will not be written in plain files that are easily accessible and understandable by humans which would allow the potential of collecting more personal data in the future if required with a lower level of security concern.

4 Implementation

4.1 Development stages

4.1.1 Stage 1

During design of the chatbot, dependency analysis revealed that the chatbot relies heavily on the database. Most of the function within the system requires access to the database therefore the development of database is prioritised. Stage 1 focused purely on creating the functions for creation, updating and access of the database. Figure 4 shows a summary of dependencies between different modules in the system.

4.1.2 Stage 2

After development of the database, priority is given to systems that are projected to be time consuming. From analysis of the modules, reasoning engine, natural language processing and data acquisition are chosen to be the modules to focus on for the second stage.

For the NLP module, having it developed early will allow discovery of how well SpaCy and NLTK discovers entities and dependencies and come up with contingencies if there was any problems during natural language processing. Reasoning engine for intent will also be developed early to ensure that the reasoning engine can accurately predict the intent of sentences by running test on different sentence types. During research, we found out that there are significant amount of historical train data and it will be take time to collect, process and store the data. The prediction module will also take time to test out different type of models and fine tuning the final model however due to its dependency on the data acquisition module the development needs postponed until Stage 3.

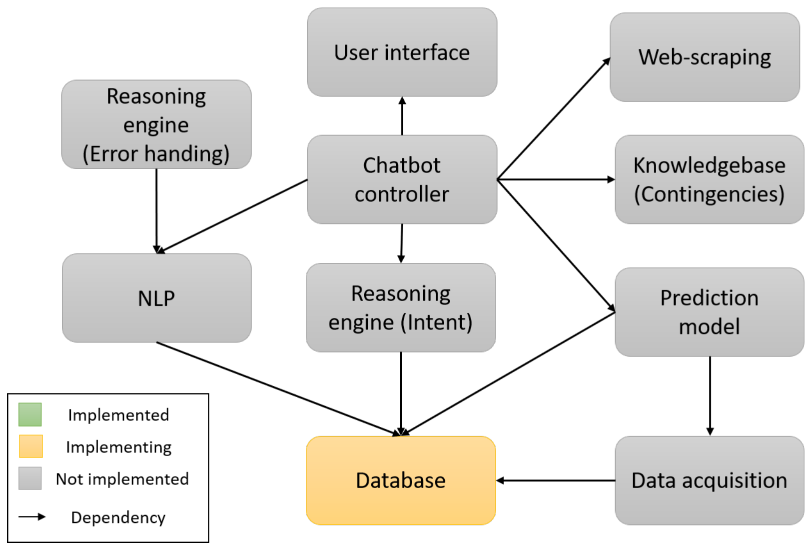


Figure 4: Stage 1 of Development process

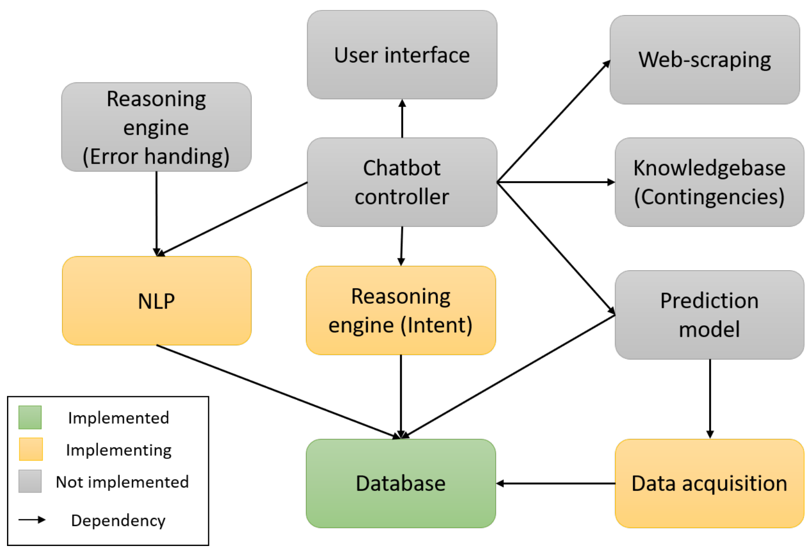


Figure 5: Stage 2 of Development process

4.1.3 Stage 3

Stage 3 will focus on the three main functionalities of the chatbot, obtaining cheapest train ticket, providing contingency plans and predicting train delays. For stage 3, the critical task will be the prediction model where large amount of time will be needed for model training and finding the best model to predict delays.

4.1.4 Stage 4

The focus of stage 4 will be the development of the user interface where the users will be interacting with the chatbot. This stage will also involve the development of basic flask framework that allows communication between the back-end and front-end. During the development of UI, a reasoning engine for error handling in sentences will also be created identify spelling mistakes to improve the usability of the system

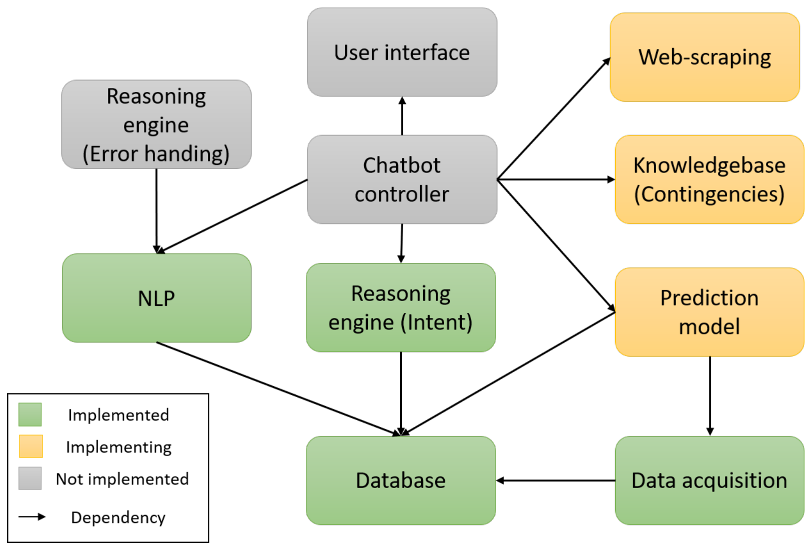


Figure 6: Stage 3 of Development process

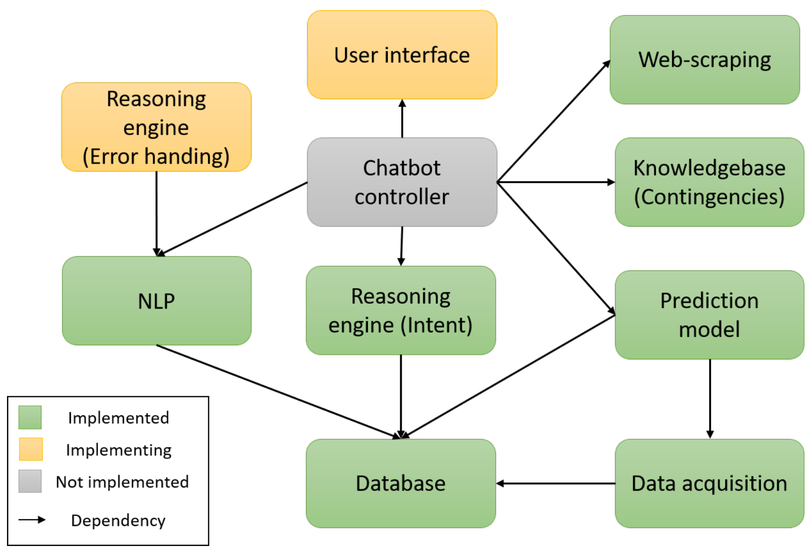


Figure 7: Stage 4 of Development process

4.1.5 Stage 5

The final stage will be development of the chatbot controller that connects the flask framework to the python functionalities. Final testing will also be conducted during the stage to ensure that all modules function as expected.

4.2 Problems and Mitigations

During development of web scraping module, we found that the ticket data was generated dynamically using JavaScript. As a simple *Scrapy Spider* does not retrieve html data generated dynamically, *Selenium* web driver was used instead to retrieve the full web page and scraped using *BeatifulSoup*.

During evaluation of predictive models, most of models trained with the preset values obtained an extremely low R^2 value (< 0.01) and returned highly inaccurate predictions. To improve the accuracy, we defined a list of different values for the settings of the models and by utilising cross validation, obtained the value setting that returns more accurate predictions and a higher R^2 of between 0.55 to 0.4 with the

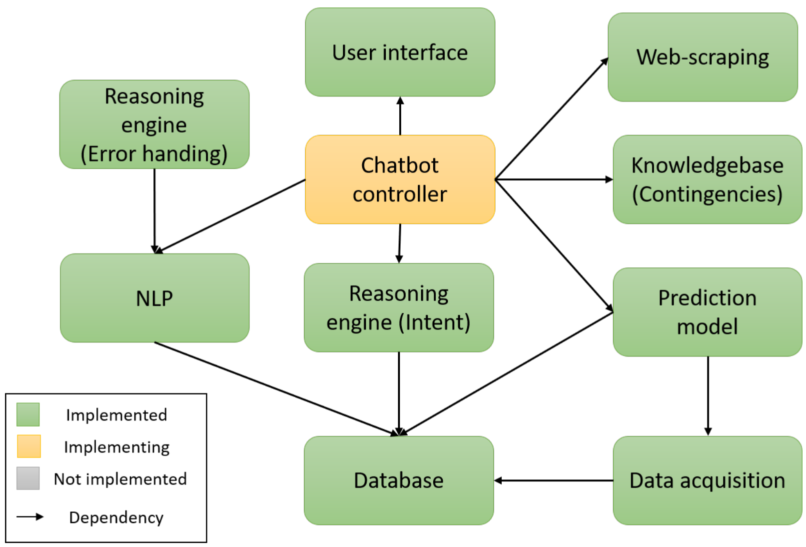


Figure 8: Stage 5 of Development process

prediction accuracy of $+/-0.6$ minutes. The neural network has 20 hidden layers with constant learning rate and it uses the *adam* solver to find the optimum.

To further address the issue, we modified the system to utilise a heterogeneous ensemble that uses a voting regressor to further improve the prediction accuracy.

5 Testing

Testing is done in different levels of implementation. Firstly, unit testing was done to all the individual modules by writing local main methods to test the functionality and check if it executes and behaves as expected. For modules that depends on input from another, dummy values were provided. These tests will also decrease coupling which will increase the portability of individual modules.

Aside from that, integration testing will be conducted with the completion of a development stage detailed in section 4.1. These tests focuses on the methods that depends on input from another modules which were previously tested with dummy values during unit testing. This allows early detection of bugs and inconsistencies which can be addressed in an earlier stage of development.

After the system has been assembled, priority will be placed on white-box testing to test all the internal functionalities implemented alongside minor black-box testing to discover potential errors or mistakes. These tests will be monitored and previous working versions will be saved for recovery in case that the testing creates unforeseen irreversible effects.

6 Evaluation and Discussion

6.1 Contribution

- Alvin -
- Joe -
- YuTing -

7 Conclusion or Summary

Chatbot provides an efficient way to handle common questions and requests and with the introduction of Artificial intelligence and machine learning, The capability of chatbot has significantly improved. Additionally, organisations has begun to put priority in customer engagement which resulted in majority of organisations implementing chatbots on their selected platforms. The opportunity for us to develop a working chatbot prototype allowed to gain insight on the back-end structure of a chatbot which will be incredibly beneficial in this growing industry.

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