

# Chatbot Assistant For Academic Queries

A Project Report Submitted

for the Course

**MA 499 PROJECT**

in

**Mathematics and Computing**

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# CERTIFICATE

This is to certify that the work contained in this report entitled **Chatbot Assistant For Academic Queries** submitted by **BOJJA SAI PREETHAM** (Roll No: **170123015**) and **MALISSETTI KIRAN KARTHEEK** (Roll No: **170123031**) to Department of Mathematics, Indian Institute of Technology Guwahati towards the requirement of the course **MA 499** has been carried out by them under my supervision.

It is also certified that, along with literature survey, a few new results are established/computational implementations have been carried out/simulation studies have been carried out/empirical analysis has been done by the student under the project.

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April 2021

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## **ABSTRACT**

The main aim of the project is to create a chatbot that can assist students with information regarding the academics such as classes,courses etc.We discuss about the chatbot structure and different technologies used,about dialogflow,django and also evaluate the intent correctness with our survey data using F score.We discuss about the database schema used and the different types of intents and entities used in our chatbot and about the intent confidence score.

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# Chapter 1

## Introduction

Chatbots are computer programs used to conduct an on-line chat conversation via text or text-to-speech, in lieu of providing direct contact with a live human agent. This technology started in the 1960's; the aim was to see if chatbot systems could fool users that they were real humans. However, chatbot systems are not only built to mimic human conversation, and entertain users. In this paper we would like to provide how it is useful for academic purposes[6]. The learning habits and absorbing information is constantly changing with the increasing use of technology in everyday life. It is because of artificial intelligence that the educators today are able to provide a personalized learning environment to the students. Chatbots or artificially intelligent conversational tools, built to improve student interaction and collaboration, are acting as a game changer in the innovative ed-tech

world. The chatbots in education system provides the benefits such as Enhanced student engagement, smart and secure feedback, efficient teaching assistants, better student support, Instant student help, Up to date information for the Institution and many more. Even research has demonstrated that individual help given by professors and departments is exorbitant and nearly impossible, and students can't participate in effective learning. It is revealed that this lack of individual support leads to weak learning outcomes, high dropout rates and dissatisfaction[2].

With the opportunities at hand we wanted to develop a chatbot which can help to resolve some of the issues and increase the effective learning of the students which at the same time decrease the burden on the professors answering the routine questions. Chatbots are domain specific i.e their results depend on the domain in which they are trained to perform. Chatbots have a developing presence in present day society, turning out to be indispensable pieces of everything from the individual assistants on mobile phones to specialized help over phone lines, and in any event, being utilized for well-being mediations[5]. Chatbots decrease the response time by being available 24/7 to resolve the queries increasing the users satisfaction. They can even handle multiple users at the same time doing the routine tasks and assisting in multi-languages.

# Chapter 2

## Chatbot structure

### 2.1 General chatbot overview

Now that we have seen a basic overview of what we are going to do, In this section we would look into the general chatbot structure. All the chatbots have the same purpose i.e they receive messages from the user and generate the answers in a convenient way[4].

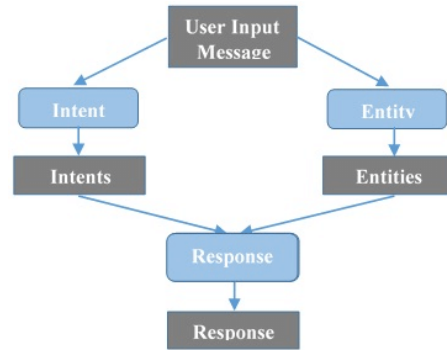


Figure 2.1: General Chatbot structure

## 2.2 User Message Analysis

When the chatbot receives the input from the user, the chatbot should be able to understand what the user is talking about. This can be understood by identifying the user intent. Intent can be thought upon as the goal of the messages. Upon understanding the Users intent, it should also extract the context. This information is used to capture the current situation of the user and generate the appropriate response accordingly.

Intent identification and extraction of context i.e User message Analysis is done using Natural Language processing techniques. The next section presents basics of Natural Language Processing and then we look into the Response Generation component of chatbot.

## 2.3 Natural Language Processing

Natural language refers to the way we, humans, communicate with each other either through speech or text. To answer a question through chatbot first we need to understand the question. There are hundreds of ways to ask a simple question like people use different tenses, vocabulary etc to pose a similar question. With growing social media users no more chat in formal language which is also one of the major concerns. So the computer should understand the questions asked in chatbot.

Pertaining to this there is a major field in the artificial intelligence domain which has been booming in the past few years is Natural language processing (NLP). NLP plays a crucial role in human machine interaction. The ultimate goal of NLP is to make machines understand language as we do. Now it's no longer about trying to interpret a text or speech based on its keywords, but about understanding the meaning behind those words.

NLP is very handy in many industries like healthcare, finance etc. Some examples are we can predict the disease from the speech of the patient using the previous records, identifying fake news, the correction of grammar we see in grammarly is also done through NLP.

Syntactic and semantic analysis are used to understand natural language.

### **2.3.1 Syntactic Analysis**

If the words are arranged such that they follow grammatical rules then the sentence is said to follow a particular syntax. We use some techniques to these groups of words and derive meaning from them.

### **2.3.2 Semantic Analysis**

Semantic analysis is the process of understanding and getting context from the given sentence. This is the toughest part of NLP which is not completely solved yet.

## **2.4 Response Generation**

After getting the User intent and the context of the message, the chatbot generates the response. The following three models help in generating the appropriate response[3].



### **2.4.1 Pattern based model**

It is also known as rule based model. In this model, chatbot generates a response by matching the user messages with the question-answer pattern. These type of models are mostly used to answer the most frequently asked questions in entertainment, business and several other domains.

These are generally coded in AIML language. The main drawback of this model is if we want our chatbot to answer a large set of questions we need to hardcode each and every question .

### **2.4.2 Retrieval based model**

Retrieval-based models are more in use at the moment. The chatbot uses the intent and context of the expression to answer the question by querying the database by using the API's to connect with them.

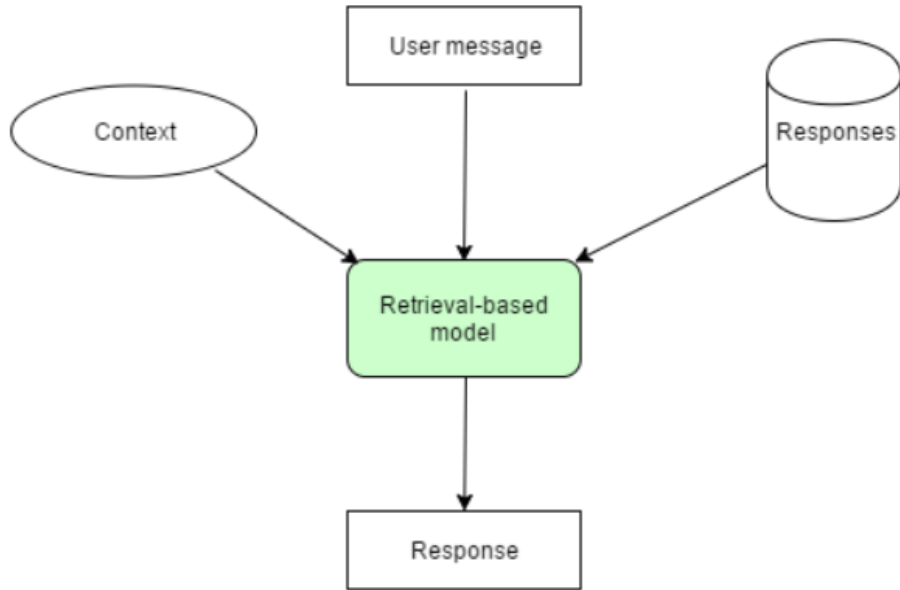


Figure 2.2: Retrieval Based Model

### 2.4.3 Generative model

This is the smartest among these three models i.e it generates the response with much accuracy. But building and training it needs a vary large data set in order to achieve good results. This is why the model has not been used to build a chatbot in reality yet.

Generative models are comparatively difficult to build and develop. Training of this type of bot requires investing a lot of time and effort by giving millions of examples. This is how the deep learning model can engage

in conversation. However, still, you cannot be sure what responses the model will generate.

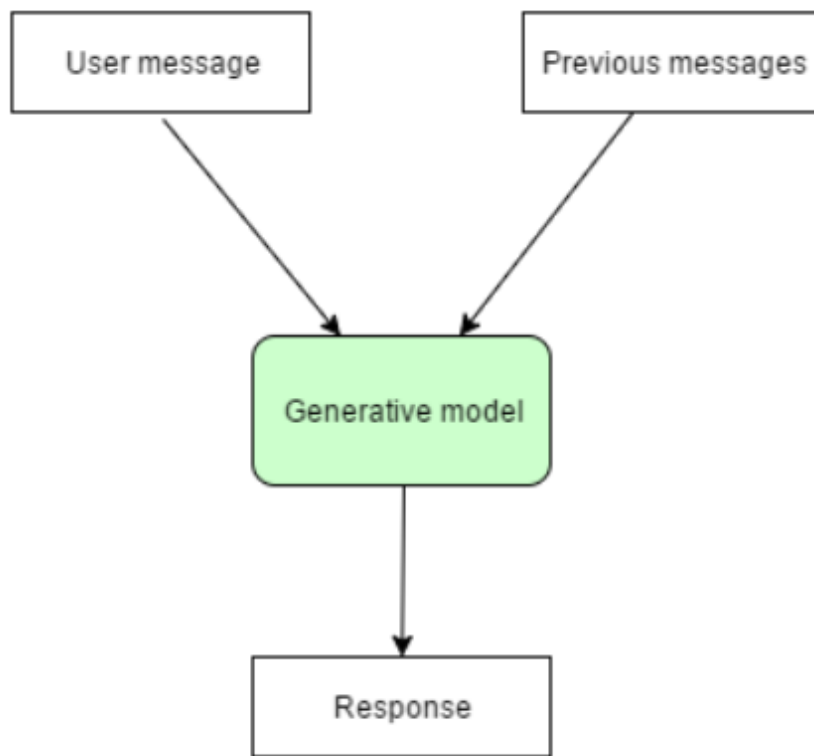


Figure 2.3: Generative Based Model

# **Chapter 3**

## **NLP vs Decision-Tree based**

### **Chatbot**

Why did we choose NLP based chatbot over flow based chatbot? This question is answered in this chapter by first defining what they are and what are their individual advantages and finally what made us to choose NLP based chatbot.

#### **3.1 What is a Decision-Tree Based Chatbot?**

Decision-Tree Based Chatbots, also known as “Rule-Based” chatbots are a very popular type of chatbot. These particularly use a series of pre-defined rules to drive visitor conversation offering them a conditional if/then at each

step. Decision trees can also replace general FAQs.

Decision trees offer visitors accurate and pointed answers to their queries and require a thorough analysis of historical customer service queries and data. Once the frequently asked questions are determined, rule-based chatbots slowly narrow each conversation until the visitor is happy with their answer. Sometimes the bots also navigate them to a Live agent if the person on the other side is not happy with the answer.

For example, if a customer is looking for a user manual for upgrading their software, they'd choose the "user manual" button where they'd be asked for the product type, model number, etc. Of course, this is a highly customizable model, making it a very widely used platform.

### **3.1.1 Advantages of Decision-Tree Based Chatbot**

The conversation flow is highly customizable

The analysis and setup is easy, making it quick to setup

The handover to a human agent is straightforward

Give pointed and more accurate answers with higher customer satisfaction

## **3.2 What is a Natural Language Processing Based Chatbot?**

Natural Language Processing (NLP) based chatbots or simply put – “AI Chatbots” are a powerful variety of chatbots that use machine learning to understand the context of unstructured inputs from the visitor. The bot in this case provides them with a response through pattern interpretation rather than fixed buttons and a flow. To understand the input, these types of questions do not look for keywords but instead dissect the phrases into detecting “intents” – the motive of a visitor. For example, while one might type “Get Pizza”, someone else might input “I am hungry”; in both cases, the bot must provide a way for the user to order a pizza.

NLP backed chatbots require training. Training refers to the process of educating the chatbot on how to guess the most appropriate response to the user’s spoken or typed input. Essentially, the more you train your bot, the more they learn, and the more accurate they get in providing resolution to your customers.

### **3.2.1 Advantage of NLP Based Chatbot**

They save a lot of time and money in the long run due to their self-learning  
They make a strong case for sentiment analysis

They are resource-efficient reducing the human intervention in maintenance, training, etc.

### **3.3 Why NLP based chatbot over Decision-Tree based chatbot**

Now that we have seen how both these models of chatbot works and what their advantages are, we would like to answer why one over the other? The main motive behind choosing NLP based model is in it's ability to provide higher user satisfaction as compared to Decision based model. Decision based model guides the user towards the result by following a path which sometimes might be long. If the user needs answers for a few questions then it's going to take a lot of time which might lead to their discomfort. But in case of NLP based chatbot the user gets the answer directly which gives them the comfort to use them for a considerable time.

The decision based chatbot might take an advantage in providing an accurate results in the starting phases of the deployment but that advantage will soon be nullified as NLP based chatbot can get better as they can use the user questions as their training phrases.

# Chapter 4

## Architecture

In this section, we will see the architecture involved in creating our chatbot and how we get a response from it. There are many chatbot platforms that can be used to build, some of them are wit.AI, API.AI(Dialogflow), IBM Watson, etc. These platforms help us in intent identification, entity extraction, and response generation by using webhook requests.

### 4.1 DialogFlow

Here we will consider 4 chatbot platforms and use the details given in this paper[1]. The platforms are pandorabots, Dialogflow, wit.ai, and luis.ai. Among all of the four chat-bot development platforms, Pandorabots



has been able to match the least number of intents. So, pandorabots is the worst performer among all. Dialogflow.com, Wit.ai and Luis.ai performed nearly the same in terms of true positive cases of intent id matches. But, in the case of false intent id matches, Wit.ai and Luis.ai maintained relatively higher confidence scores in comparison to Dialogflow. In case of false intent id match, the lower confidence score is desirable. Dialogflow also has a feature to add follow-up intent. So, Dialogflow is chosen to develop chatbot to assist students..

Dialogflow is a natural language understanding platform that can be used to integrate conversational user interface to messenger, skype, Twilio, etc. It was initially known as API.AI before Google bought the company. It is a part of the Google Cloud Platform (GCP). Before we dive into Dialogflow we need to learn about some jargon used in NLP and Dialogflow.

#### **4.1.1 Agent**

In Dialogflow, the agent is a virtual being that handles the conversations with end-users. We will train the agent with our intents, entities, and training phrases which we will learn now.

### 4.1.2 Intent

When the end-user asks a question he asks it with a certain intention which the chatbot needs to find. The process of matching the end user's expression to intent is called intent matching. The algorithm's that Dialogflow uses an intent matchings are rule-based grammar matching and ML matching where the latter is inaccurate for small sets of training sets and which is advised to turn off this algorithm when the training phrases are less in number.

So we create a certain set of intents and train them with a good no of training phrases such that whenever a similar question is asked Dialogflow should match the question to the intent and reply accordingly.

### 4.1.3 Entity

Dialogflow identifies and extracts the useful data from the user input and stores them as parameters at run time. These are known as Entities. We can also make an entity a must for a particular intent and prompt a question to extract the entity from the user if the user did not mention that on the expression or the agent is unable to find that entity.

For example, let us talk about the intent weather which we gave an example in the user-defined intent. There we just asked for the temperature but did not provide the time and place for which we are asking for, so we use an entity place and time and make them required for the weather intent and get the data and use some API's to get the temperature.

## 4.2 Webhook

For the response generation in Dialogflow there is a feature called fulfillment, when this is enabled for intent and when this intent is matched Dialogflow calls webhook service with information of the matched intent like parameters, intent name, etc.

A webhook is also called a web callback or HTTP push API. This is used to deliver data to other applications in real-time i.e you get data immediately. Unlike API's where you need to pull data frequently to make it real-time. These are also called Reverse APIs. Majority of webhooks POST data to your URL in JSON format.

The webhook services must take JSON requests and send JSON responses in return. The webhook service must handle HTTP requests. Its URL for requests must be publicly accessible. We used ngrok for tunneling our local address to make it publicly accessible.

We can also write code in an inline editor for dynamic response and deploy the code on google cloud. The inline editor only supports node js and it does not require any webhook request were as to implement a webhook service we can use many web frameworks according to our convenience such as Flask, Django, etc.

## **4.3 Django**

### **4.3.1 Introduction**

Django is a high-level python web framework that uses MTV architectural patterns without all of the dependency problems that you normally will find with other frameworks..Many well-known websites are made using Django some of them are Instagram, Mozilla etc. All the codes of the Django framework are written in Python, which runs on many platforms. This leads to run Django too on many platforms such as Linux, Windows, and Mac OS.

The default database used by Django is SQLite. It is embedded with Django. Its advantages over MySQL are it is a server-less app whereas the latter one requires a server it works in client-server architecture. And also MySQL needs to be installed separately to use it and connect to our app whereas SQLite comes embedded. SQLite can only handle one request at a time and is only efficient for small databases.

### 4.3.2 MVC Architecture

MVC stands for Model-View-Controller. This is a software design i.e is a template on how to solve a problem. Though Django uses MVT architecture, first we will look into MVC architecture and come back to MVT as they are almost similar.

**Controller:** The code that does the thinking and decision making. For example URL routing, what page should be displayed after a particular action etc? It is an interface between model and view components. This can be told as an engine of architecture.

**View:** The HTML, CSS, etc which makes up the look and feel of the application. Everything that is visible on the page is contributed by the views

part.

**Model:** The model component stores data and its related logic. It represents data that is being transferred between controller components or any other related business logic. For example, a Controller object will retrieve the customer info from the database. It manipulates data and send back to the database or use it to render the same data..

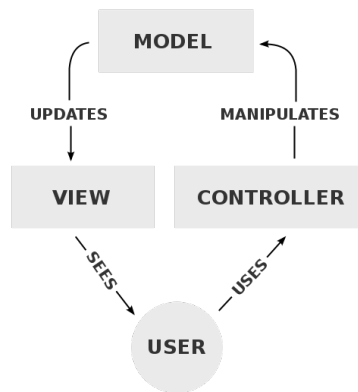


Figure 4.1: MVC Architecture

In the MTV pattern:

**Model:** Just like the Model explanation in the MVC pattern, this also takes the same position as the interface or relationship between the data and

contains everything related to data access and validation.

**Template:** This relates to the View in the MVC pattern as it is the presentation layer that handles the presentation logic in the framework and basically controls what should be displayed and how it should be displayed to the user.

**View:** This part relates to the Controller in the MVC pattern and handles all the business logic that throws down back to the respective templates. It serves as the bridge between the model and the template

### 4.3.3 ORM

One of the most important and useful features of Django is Object Relational Mapper(ORM) which helps us to interact with databases just like we do in SQL. Django's ORM is just a way to create SQL to query and manipulate your database and get results using python.

For every class you create in Django using python ORM converts them to SQL commands and creates tables. Similarly, every object, you create adds data to the table. It creates all of the CRUD operations. This feature helps in shifting between various applications for performing

extraction of data. It increases portability across databases. Migrate command reads the make migration scripts and crates SQL command and runs them

## 4.4 Architecture

Here we will look into the architecture that the chatbot works upon. As we have seen we use Dialogflow for intent identification and entity extraction. For dynamic response, we send an HTTPS request to the webhook service as we discussed in the previous section. The code for the webhook service is written in python and we use Django framework for extraction of data and send back responses to Dialogflow in JSON format which will be converted to text by Dialogflow and will be displayed to the user. We will look into the flow of our chatbot from the architecture diagram below

1. The user types an expression to be answered.
2. Dialogflow matches the end-user expression to an intent using Natural language processing and extracts parameters using named entity recognition.
3. If the compulsory parameters are not identified it replies with a follow-up question and extracts the parameter
4. If the response is static Dialogflow directly replies to the user and the



conversation ends.

5. If the response is dynamic Dialogflow sends a webhook request message to our webhook service i.e Django using JSON format. This message contains information about the matched intent, the action, the parameters, and the response defined for the intent.

6. Django performs actions as needed, like database queries or API calls, and extracts data.

7. Django sends a webhook response message to Dialogflow in JSON format. This message contains the response that should be sent to the end-user.

8. The user sees response in text format which is extracted by the Dialogflow from JSON response.

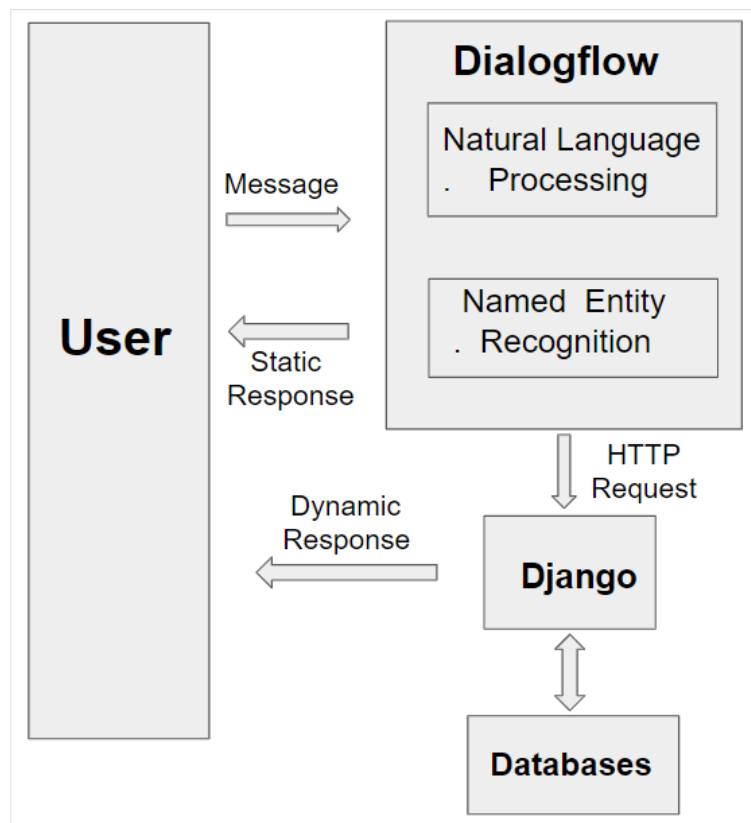


Figure 4.2: Architecture

# Chapter 5

## Implementation

The tools and languages that we are using in this implementation are Django 3.1.1, Dialogflow, SQLite 3.34.1, Python 3.8.5.

### 5.1 Database Schema

Here we will discuss the schema of all the databases used in our chatbot. The schema plays a crucial part because we extract data from databases based on these only. In the following tables, we mentioned the columns in each database table, their datatype. PK and FK are primary and foreign keys respectively.

SLOT	
SLOT(PK)	CharField

Figure 5.1: Schema of Slot

DEPARTMENT	REGISTRATION DETAILS
NAME(PK) CharField	DEPARTMENT(FK)
CODE CharField	VENUE CharField
VENUE CharField	START TIME DateTimeField
	END TIME DateTimeField

Figure 5.2: Schema of Department and Registration Details

TIMETABLE	REGISTERED COURSES
SLOT(FK)	ROLL NO(FK)
DAY CharField	COURSE(FK)
START TIME TimeField	ATTENDANCE IntegerField
END TIME TimeField	

Figure 5.3: Schema of Timetable and Registered Courses

<b>COURSE</b>	
DEPARTMENT(FK)	COURSE NAME CharField
COURSE CODE CharField	INSTRUCTOR(FK)
SLOT(FK)	VENUE CharField
COURSE CONTENT URLField	GRADING SCHEMA CharField
PREREQUISITES CharField	CREDITS IntegerField
REFERENCES CharField	COMPULSORY BooleanField
ELECTIVE BooleanField	LAB BooleanField

Figure 5.4: Database Schema of Course

<b>PROFESSOR</b>	<b>STUDENT</b>
NAME(PK) CharField	ROLL NO(PK) CharField
ROOM NO CharField	NAME CharField
RESEARCH AREA CharField	MAIL EmailField
DEPARTMENT(FK)	DEPARTMENT(FK)
WEBSITE URLField	HOSTEL CharField
	ROOM NO CharField

Figure 5.5: Schema of Professor and Student

## **5.2 Intents**

In this section, we will talk about all the intents that are used in our chatbot.

### **5.2.1 AttendanceByCourse**

If this intent is matched we will reply with attendance for a particular course by using course id and roll no as parameters.

### **5.2.2 AttendanceByRoll**

If this intent is matched we will reply with attendance of courses registered by a particular student using roll no as a parameter.

### **5.2.3 CompulsoryCourses**

If this intent is matched we will reply with all the compulsory courses that a student has to take in a particular semester by using department and semester number as parameters.

### **5.2.4 Course Registration**

If this intent is matched we will reply with the registration details like timing, venue using the department as a parameter.

### **5.2.5 CourseDetails**

If this intent is matched we will reply with all the course details like professor taking that course, no of credits, timetable slot, does it have lab part, and many other things using course code as a parameter for extracting from the database.

We also created some extra intents to answer some other details of a course which were not frequently asked and makes the reply clumsy if we reply with all the details like course website kind of things.

### **5.2.6 CourseReferences**

If this intent is matched we will reply with the references like books and all for a particular course using course id as a parameter.

### **5.2.7 CourseVenue**

If this intent is matched we will reply with the place where is class is conducted for a particular course using course id as a parameter.

### **5.2.8 CourseWebsite**

If this intent is matched we will reply with the website where it has all the course related details of a particular course using course id as a parameter.

### **5.2.9 GradingScheme**

If this intent is matched we will reply with grading schema as a string for a particular course using course id as a parameter.

### **5.2.10 MyCourses**

If this intent is matched we will reply with a list of registered courses in this semester by a particular student by using roll no as a parameter.

### **5.2.11 Prerequisite**

If this intent is matched we will reply if there are any prerequisites to register for a particular course using course id as a parameter.

### **5.2.12 SemesterCourses**

If this intent is matched we will reply with all the courses that are available in this semester which are not compulsory also like electives.



### **5.2.13 Student Details**

If this intent is matched we will reply with details of a particular student using his roll no as a parameter.

### **5.2.14 TimeTable\_RollNo**

If this intent is matched we will reply with the whole timetable for a week of a particular student by using his roll no as a parameter and checking the registered courses in that semester and also using the timetable slots for all that courses.

### **5.2.15 TimeTable\_RollNo\_Course**

If this intent is matched we will reply with a timetable of a particular course using course id as a parameter.

## **5.3 Entities**

In this section, we will check what entities we used in our chatbot. These are the sole of extraction of data from database as they are used as filters to extract data.

- Course Code

- Course Name
- Department
- Roll No
- Semester

# Chapter 6

## Survey Results and Evaluation

### 6.1 Survey

In order to train and test the chatbot we need a dataset that contains the questions that the user asks pertaining to that intent. The total no of intents we have considered for the development of this chatbot are 17 main intents and 2 default intents. The dataset is created by ourself as we observed that all the questions that we are getting from survey are almost similar and the question itself being too trivial. As this is not going to serve our purpose we trained the chatbot by self creating the questions.

The main purpose of this training is to make the chatbot identify the intent of the user. Once the intent identification is done, response generation

is taken care of by django framework. The intents with sample questions are shown below.

User Intent	Sample Question
AttendanceByCourse	What is my attendance in distributed computing?
AttendanceByRoll	what is my attendance?
CompulsoryCourses	What are the compulsory courses in this semester?
Course Registration	Get the registration details for MNC department
CourseDetails	Who is the professor for MA616
CourseReferences	Get me the references for DBMS
CourseVenue	where are the classes for computational finance going to happen?
CourseWebsite	Get me the course website link for distributed computing?
Department	Who is the HOD of MNC department
GradingScheme	How many quizzes do we have for the CS245 course?
Marks	How many marks did i get in MA616?
MyCourses	Get me the list of courses that i registered for?
Prerequisite	what are the prerequisites for Distributed computing?
SemesterCourses	What courses do I have in this semester?
Student Details	Get me the mail id of preetham?
TimeTable for RollNo	when do i have classes?
TimeTable for RollNo and Course	when do i have database classes?

Table 6.1: Sample questions

## 6.2 Performance Metric

In order to measure the performance of the chatbot we would first like to introduce relevant metrics, and use a confusion matrix to detect the areas that need to be taken care of. The Performance of a chatbot depends on how well it is able to identify the intent of the user. Intent identification(Text classification) comes under the field of Information retrieval where performance is measured using the F-score.

### 6.2.1 True/False Positive/Negative

Each data point, after classification belongs to one of these categories. Positive/negative refers to the declared solution for the datapoint. When trying to detect a medical condition, for example, a patient is declared “positive” if the system declares they have the condition. True/false refers to the success or failure of your prediction. For example, true negative means that the data point you want to classify doesn’t belong to the class, and that is exactly what you predicted. Therefore, you can use four terms to qualify data points: true positive, true negative, false positive and false negative. The below example gives an idea on these four categories.

## 6.3 Key Metrics

To measure the performance of bots, we look at three different metrics: precision, recall and F1-score, calculated separately for each intent of the bot. These three metrics give different insights about the performance of each intent of the bot, as well as the bot as a whole. The calculation of these metrics is based upon the four categories of classification we saw above: true positive, true negative, false positive and false negative.

### 6.3.1 Precision

precision is defined as the number of correctly identified positive results divided by the number of all positive results, including those not identified correctly. It can be thought of as the answer to the question “Out of all predictions of A, how many were correct?” where A is the intent under consideration.

$$P = \frac{TP}{TP + FP}$$

### 6.3.2 Recall

Recall is defined as the number of correctly identified positive results divided by the number of all samples that should have been identified as positive. In

short, it answers the question “out of all the examples in A, how many were detected?”

$$R = \frac{TP}{TP + FN}$$

### 6.3.3 F-score

F-score is defined as the harmonic mean of precision and recall. It helps you answer the question “What is the global performance of prediction, with respect to class A?”

$$F = \frac{2.P.R}{P + R}$$

To obtain global scores over the performance of your bot, it is best to provide a weighted average of each of the metrics. This way, the global F1-score serves as a general ‘grade’ of the performance of your bot, while the precision and recall scores can be used to understand the best ways to go about improving the performance of your bot.

# Chapter 7

## Results and Conclusions

We have tested the chatbot with questions and the responses generated(intent matched) are used to calculate the precision,Recall and f-score of each intent. Finally we have taken weighted average of F-score to calculate the global F-score of the chatbot.

From the results obtained,it is observed that chatbot fails to match the correct intent when the queries are almost similar to two or more intents. For example when the query is "how many marks does all the quizzes carry in distributed computing course?". In this case the chatbot identified the intent as Marks instead of Grading scheme because of similarity between marks and grading scheme. These corner and almost similar intents can be differentiated by increasing the chatbot's training.



User Intent	Precision	Recall	F-score
AttendanceByCourse	0.923	1	0.96
AttendanceByRoll	1	0.833	0.909
Compulsory-courses	0.6	0.5	0.545
Course-Registration	0.75	1	0.857
CourseDetails	0.9	0.818	0.857
CourseReferences	0.875	1	0.933
Coursevenue	0.667	0.889	0.7616
CourseWebsite	0.75	0.857	0.8
Department	1	1	1
GradingScheme	0.875	1	0.933
Marks	1	0.667	0.8
MyCourses	0.714	0.833	0.77
Prerequisite	0.75	0.75	0.75
Semester courses	0.5	0.5	0.5
Student Details	1	1	1
TimeTable-RollNo	1	0.833	0.909
TimeTable-RollNo-Course	1	0.33	0.495

Table 7.1: F-score

The Global f-score,i.e by calculating using weighted average of the F-score of each intent, is obtained as 0.8146. From the above table it can be observed that there are intents like student details, Attendance By course, Grading scheme, Time table-RollNo and AttendanceByRoll having the F-score above 90%.There are some intents having F-score in medium range i.e from 75% to 90%. Some of the intents had a very less F-score showing the issues where our chatbot is facing. The higher F-score of some of the intents is mainly due to the fact that there is enough distinction the chatbot could find in them. They are not very similar to other intents which helps the chatbot in identifying the correct intent when the user asks the questions related to those intents.

We can observe that Compulsory courses,semester courses,My courses performs poorly which is because of their very similar nature and also due to ineffecient training of the chatbot which is due to lack of proper dataset. The issue can be better understood by looking the tables in the appendix where the results of the testing of chatbot are shown. The chatbot even faces issues in case of Timetable-RollNo-Course intent. The chatbot is identifying the intent of user as coursevenue when the true intent is timetable-RollNo-Course. These results could get better as the number of training phrases

increases.

# Chapter 8

## Limitations

Even though the chatbot works well there are certain number of limitations it faces. The first limitation is in on the number of intents. In order to give the precise answer the user asks the number of intents must be increased manifold. It is better explained by considering the example of student details intent. This intent gives the details of student which contains 5 fields namely roll number,name, room number, mail id, phone number, hostel. Now if a user asks for the mail id of student by giving his roll number, providing only mail id serves the purpose.In order to do just writing the function that gives mail id will be sufficient. Now if user comes with a question asking about his room number, we must have a function that produces the result with only his room number. So if a user asks a question asking for only one field of the student details then we need 5 functions to handle them. Now implementing

them is not too hard. But what if user asks about both mail id and phone number of the user. Or What if he wants 3 fields of a student details. So implementing all possible combinations takes up 32 functions. These many functions are just for one main intent. Imagine implementing for 10 main intents. The number of functions to be taken care of goes out of reach. So our chatbot provides the answer along with extra information for some of the questions.

The other limitation is on the dataset. The number of phrases used to train and test the chatbot are not too much as there aren't readily available datasets. Still the results are much better because of the dialogflow algorithms along with the training phrases that covered almost all the relevant phrases using which the chatbot can identify the intent of the user and respond with correct answer. But there are some cases that this issue is highlighted. It is in the case of intents being too much similar that it becomes too difficult for chatbot to identify the correct intent among those. For example, if the user asks the question as "whats the marks distribution in Distributed Algorithms course?". Our bot identified the intent as Marks where as the true intent of it being "Grading Scheme". This happened because of the very similar nature between those two intents which is highlighted by that question.

# Chapter 9

## Annexure

### 9.1 Testing Phrases and their Confidence score

The tables in this section shows the intent identification of the chatbot when the user asks a question. The first column represents the user question, the second question shows the intent recognized by the chatbot, the third column shows the true intent of the user and the fourth column shows the intent detection confidence or confidence score of the query.

The confidence score, which lies between 0(completely uncertain) and 1(completely certain), is used for matching the potential intent. If the highest-scoring intent has a value more than the ML classification threshold, it is returned as a match. Otherwise, the default fallback intent is matched if there is any mentioned, else no intent is matched.

User Query	Detected intent	True Intent	Intent Confidence Score
Timing of course registration?	Course Registration	Course Registration	0.9034205
When is the registration for Maths 3rd semester students?	Course Registration	Course Registration	1
Is registration happening in the morning or afternoon?	Course Registration	Course Registration	0.8416123
Details for course registration?	Course Registration	Course Registration	0.9514238
What are the requirements for course registration?	Course Registration	Course Registration	0.92239404
What are the prerequisites for distributed computing	Prerequisite	Prerequisite	1
Systems course prerequisites	Prerequisite	Prerequisite	0.65680426
Courses that i should know before taking Wireless course	CompulsoryCourses	Prerequisite	0.5854
Get the list of courses available	SemesterCourses	SemesterCourses	0.7519893
Get the list of courses available in EEE	SemesterCourses	SemesterCourses	1
Get the list of courses available in 8th semester	SemesterCourses	SemesterCourses	1
Which courses did i register for	MyCourses	MyCourses	0.73470175
My registered courses	MyCourses	MyCourses	0.8309843
Courses that i registered for	MyCourses	MyCourses	0.8768093
170101040's courses	MyCourses	MyCourses	1
When is the compfin course exam	Course Registration	Exam	0.38670826
Computational finance course exam schedule	CourseWebsite	CourseWebsite	0.5973046
Database course page	CourseReferences	CourseWebsite	0.49091852
computational finance course page	CourseWebsite	CourseWebsite	0.6646798
Reference books for compfin	CourseReferences	CourseReferences	0.82944447
Database classroom	CourseVenue	CourseVenue	0.5489467
Marking scheme compfin	GradingScheme	GradingScheme	0.80693907
Database attendance	AttendanceByCourse	AttendanceByCourse	0.61763173
Database attendance minimum	AttendanceByCourse	AttendanceByCourse	0.61763173
What are the compulsory courses for btech mnc 3rd semester	SemesterCourses	CompulsoryCourses	0.5756505
Electives for btech mnc 4th sem	Default Fallback Intent	Default Fallback Intent	1
What is my attendance in this DBMS course?	AttendanceByCourse	AttendanceByCourse	0.7874501
how many classes did I attend in CS245?	AttendanceByCourse	AttendanceByCourse	1
Give my attendance for all courses?	AttendanceByRoll	AttendanceByRoll	0.890381
what courses should i take this semester?	CompulsoryCourses	CompulsoryCourses	0.6061358
courses that i shouldn't miss this semester?	SemesterCourses	CompulsoryCourses	0.57475936
details of my course registration	Course Registration	Course Registration	0.9012199

Table 9.1: Confidence score1

who is teaching ma101?	CourseDetails	CourseDetails	0.7372353
how many credits does ma651 have	CourseDetails	CourseDetails	0.5788352
books to refer for ma101?	CourseReferences	CourseReferences	0.86523527
where is this class happening?	CourseVenue	CourseVenue	0.7627674
Whats my attendance in MA616 course	AttendanceByCourse	AttendanceByCourse	1
In DBMS course, get me my attendance	AttendanceByCourse	AttendanceByCourse	0.5878191
how many classes have i attended in DBMS course	AttendanceByCourse	AttendanceByCourse	0.83774346
What are the prerequisites of the course ma473	prerequisite	prerequisite	0.78020054
What is the attendance of 170123015 in MA 616	AttendanceByCourse	AttendanceByCourse	0.72051877
Get me the attendance of preetham in MA651	AttendanceByCourse	AttendanceByCourse	0.6580585
Do I have more than 75percentage in computer architecture	AttendanceByCourse	AttendanceByCourse	0.6799617
How much attendance do I have in CS221	AttendanceByCourse	AttendanceByCourse	0.8481493
Harsha's attendance in Databases	AttendanceByCourse	AttendanceByCourse	0.78619176
Hema's attendance in every course	AttendanceByRoll	AttendanceByRoll	0.87514937
My attendance	AttendanceByRoll	AttendanceByRoll	0.87514937
What are the attendances of mine in every course i registered	MyCourses	AttendanceByRoll	0.79580384
Do i have any course with less than 75 percentage attendance	AttendanceByRoll	AttendanceByRoll	0.7532813
Tell me the attendances of bharath in every course	AttendanceByRoll	AttendanceByRoll	0.6763563
When do i have database class	CourseVenue	Timetable-RollNo-Course	0.7058976
Where is CS223 class going to happen	CourseVenue	CourseVenue	0.7058976
In which class MA616 happens	CourseVenue	CourseVenue	1
Get me the time table of EE220	TimeTable-RollNo-Course	TimeTable-RollNo-Course	1
Signals and Systems's venue?	CourseVenue	CourseVenue	0.5464499
How many compulsory courses do we have this semester?	CompulsoryCourses	CompulsoryCourses	0.6770798
Is computational finance a compulsory course?	CourseWebsite	CompulsoryCourses	0.54582745
What are the must take courses by me?	CompulsoryCourses	CompulsoryCourses	0.61739737
My marks in quiz2 of Systems course	Marks	Marks	0.6452648
How many marks did i get in MA616 midsem exam	Marks	Marks	0.87230647
How many marks did i get in MA423 mid semester examination	Marks	Marks	0.7636004
My marks in distributed computing end semester examination?	GradingScheme	Marks	0.60399824
What courses do i have on monday	My courses	TimeTable-RollNo	1
All classes schedule of mine	TimeTable-RollNo	TimeTable-RollNo	0.919106
What are the classes i have on Friday	TimeTable-RollNo	TimeTable-RollNo	0.88808733
What are the available courses i have in this semester	CompulsoryCourses	semestercourses	0.67721176
Courses that i could register for in this semester	Course Registration	semestercourses	0.5961772
What are the courses available for a CSE Student in 4th semester	Course Registration	semestercourses	1
Where is MNC department located	Department	Department	0.74536055
CSE Department location	Department	Department	0.8333744

Table 9.2: Confidence score2



Get me the details of CS245	CourseDetails	CourseDetails	0.7433653
Tell the Professor name of database	CourseDetails	CourseDetails	0.7756244
Who is the teaching the comp fin course	CourseDetails	CourseDetails	0.5181792
Who is the teaching the computational finance course	CourseWebsite	CourseDetails	0.6272142
Database course details	CourseDetails	CourseDetails	0.7888293
Wireless Ad hoc professor	CourseDetails	CourseDetails	0.8152237
Wireless Ad hoc teacher	AttendanceByCourse	CourseDetails	0.40056872
In which semester is Database course taught	CourseDetails	CourseDetails	0.72376335
how many students are enrolled in CS245	CourseDetails	CourseDetails	1
References for Database course	CourseReferences	CourseReferences	0.847051
Which sources should i read to follow signals course	CourseReferences	CourseReferences	0.6531927
Which book should be followed for Architecture course	CourseReferences	CourseReferences	0.6887315
Tell me the text books that are followed for Wireless course	CourseReferences	CourseReferences	0.79511935
MA616 text books	CourseReferences	CourseReferences	1
Where are Databases classes held	CourseVenue	CourseVenue	0.7736458
Location of MA 651 class	CourseVenue	CourseVenue	1
Room no of systems class	CourseVenue	CourseVenue	0.39719537
Class for Wireless course is held at	CourseDetails	CourseVenue	0.41208944
What is the website link of database course	CourseWebsite	CourseWebsite	0.76065624
Distributed computing course link	CourseWebsite	CourseWebsite	0.7370919
Link for computer Architecture	CourseWebsite	CourseWebsite	0.7382895
EE220 course website link	CourseWebsite	CourseWebsite	1
What is the grading scheme of Computer Architecture	GradingScheme	GradingScheme	0.7371567
Distributed computing grading scheme	GradingScheme	GradingScheme	0.8374151
What is the marking scheme of Wireless course	GradingScheme	GradingScheme	0.7139865
How are marks distributed for MA651 course	GradingScheme	GradingScheme	1
How many quizzes do we have in Systems course	GradingScheme	GradingScheme	0.6169472
End sem weightage for Distributed computing course	GradingScheme	GradingScheme	0.8271311
Harsha's details	Student Details	Student Details	1
Room no of harsha	Student Details	Student Details	0.8352612
Get me the mail id of kommineni	Student Details	Student Details	1
Which hostel does sri ram stay in	Student Details	Student Details	0.6650547
do You know where kiran stays	Student Details	Student Details	0.7714368
Can i get room no,mail id and hostel of bharath	Student Details	Student Details	0.826228
What's my time table	TimeTable-RollNo	TimeTable-RollNo	0.83699596
When do i have classes	TimeTable-RollNo	TimeTable-RollNo	1
Class schedule for tommorow	TimeTable-RollNo	TimeTable-RollNo	0.8910821
Do i have database class tomorrow	CourseVenue	TimeTable-RollNo-Course	0.6651669
When is Wireless class	CourseVenue	TimeTable-RollNo-Course	0.6625544
Get me the class schedule for DBMS course	TimeTable-RollNo-Course	TimeTable-RollNo-Course	0.64272845
What is the time table for systems course	TimeTable-RollNo-Course	TimeTable-RollNo-Course	0.5737908
When do I have database classes	CourseVenue	TimeTable-RollNo-Course	0.7229005
CS245 classes schedule	CourseVenue	TimeTable-RollNo-Course	1
What are my courses in this semester	SemesterCourses	Mycourses	0.7188647
What courses did preetham register for in this semester	Mycourses	Mycourses	0.5719913
How many marks did i score in DBMS quiz1	Marks	Marks	0.915256
What's my score in computational finance endsem	prerequisite	Marks	0.50702685

Table 9.3: Confidence score3

## 9.2 Screenshots

These are this list of the databases and this is how they look in django's admin interface.

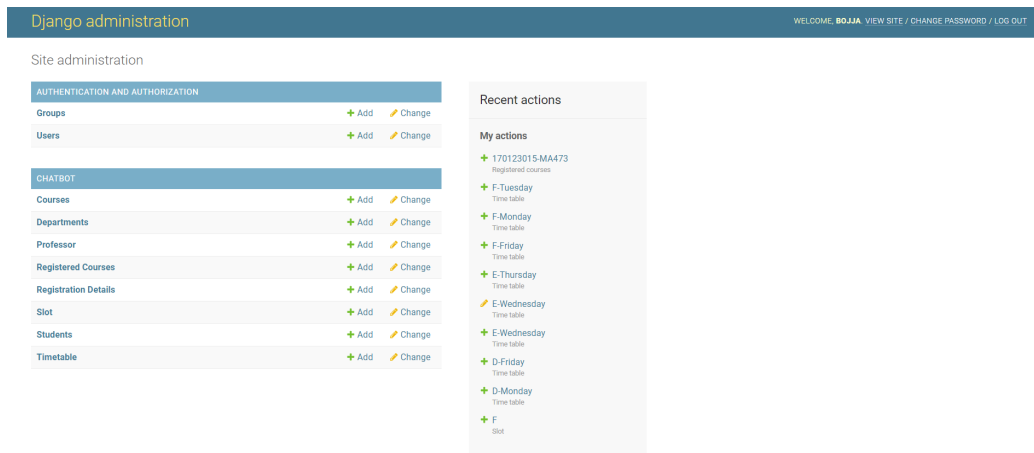


Figure 9.1: Databases

In course database these are the rows with each row being represented by their course id.

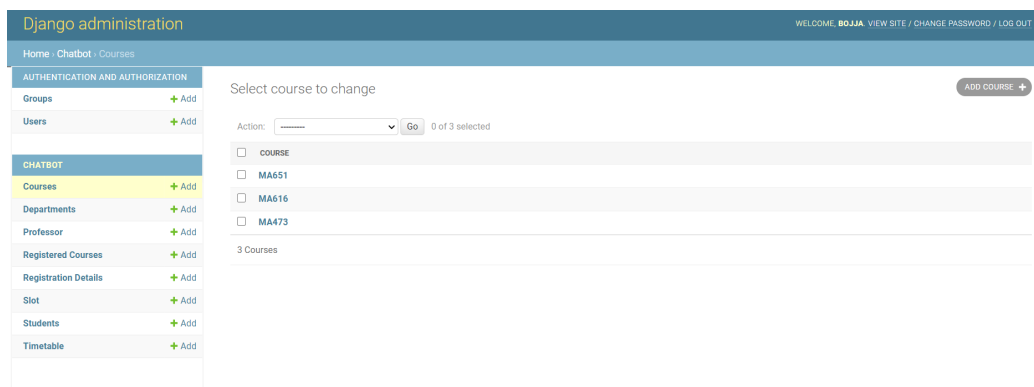


Figure 9.2: Databases Values

If we open one of the row these are the attributes that are stored as columns in databases.

The screenshot shows a 'Change course' form. The sidebar on the left contains links to various database tables: Groups, Users, Courses, Departments, Professor, Registered Courses, Registration Details, Site, Students, and Timetable. The main form fields are as follows:

- Dept name: dropdown menu
- Course name: text input field
- Course code: text input field
- Course instructor: dropdown menu
- Slot: dropdown menu
- Course version: text input field
- Course content: text input field with a link icon
- Grading scheme: text input field
- Prerequisite: text input field
- Course credits: text input field
- References: text input field
- Compulsory: checkbox
- Elective: checkbox
- Leth: checkbox

At the bottom of the form, there are four buttons: 'Cancel', 'Save and add another', 'Save and continue editing', and 'Save'.

Figure 9.3: Databases Columns

If we ask a question for example "course details of MA651", here we need to use the webhook service because we need a dynamic response extracting data from database. So as we discussed the request will be sent in JSON format the following 2 diagrams shows the request which consists of our query, intent, intent detection score etc.

Also, the reply from Django will be in JSON format as we can see below the fulfillment text contains the text that should be displayed to the end-user.

```

{
  "responseId": "b43c96d2-125a-4788-a09d-dbc6f6577b43-d74139ee",
  "queryResult": {
    "queryText": "course details of MA651",
    "parameters": {
      "course-code": "MA651",
      "course_name": ""
    },
    "allRequiredParamsPresent": true,
    "fulfillmentMessages": [
      {
        "text": {
          "text": [
            ""
          ]
        }
      }
    ]
  },
  "intent": {
    "name": "projects/bsp-9sgi/agent/intents/6e06828d-66a6-4d4a-8e33-a4444d2a8be6",
    "displayName": "CourseDetails"
  },
  "intentDetectionConfidence": 0.76488453,
  "languageCode": "en"
},
"originalDetectIntentRequest": {
  "source": "DIALOGFLOW_CONSOLE",
  "payload": {}
},
"session": "projects/bsp-9sgi/agent/sessions/0bc30d24-8931-e3c1-d2cb-ef786afcce29"
}

```

Figure 9.4: Fulfillment Request

```

1 {
2   "fulfillmentText": "course_name : Distributed Algorithms \n course_code : MA651 \n
   course_instructor : Partha Sarathi Mandal \n slot_id : A \n course_venue : 2102 \n
   course_credits : 6 \n "
3 }

```

Figure 9.5: Fulfillment Response

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