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Admission Query Resolver Chatbot

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ABSTRACT

This project aims to develop an intelligent Admission Query Resolver Chatbot designed to assist prospective students willing to take admission in Maharashtra with inquiries regarding university admissions. The university admission process is often plagued by delays and inefficiencies, resulting in frustration for prospective students and staff. To address this, we propose the development of an Admission Query Resolver Chatbot, leveraging conversational AI to provide timely and accurate responses to admission-related queries. The chatbot will automate query resolution by integrating natural language processing (NLP) and machine learning algorithms, reducing response times and workload for admission staff. This project aims to improve the overall student experience, and student satisfaction, increase staff efficiency, and enhance the effectiveness of the admission process. The ultimate goal is to create a reliable virtual assistant that ensures seamless communication between the university and prospective students, facilitating a smoother admissions process. The chatbot can understand and respond to questions about admission requirements, application procedures, and deadlines. The chatbot can guide users through the application process, ensuring they complete each section correctly. Users can ask questions in natural language, and the chatbot can direct them to relevant answers or provide detailed explanations. The NLP component is crucial for understanding user queries. Techniques like tokenization, entity recognition, and sentiment analysis enable the chatbot to parse and comprehend complex sentences and questions. By automating routine queries, the chatbot reduces the workload on administrative staff, allowing them to focus on more complex tasks and personalized interactions. and university administration. and university administration.

Keywords: NLP, ML Algorithm, Conversational AI, Automated Query Resolution.

Introduction

In recent years, there has been a noticeable shift in how students interact with educational institutions, especially regarding inquiries and the admission process. With the proliferation of online platforms and digital communication, the expectation for immediate responses has grown. Engineering colleges, particularly in densely populated academic hubs like Pune, handle thousands of queries from prospective students annually. Traditional responses to these inquiries, such as emails, phone calls, or in-person visits, are often time-consuming and inefficient, leading to student delays and frustration. At the same time, institutions need help managing these queries efficiently, as administrative staff usually need help to balance routine admission tasks with personalized responses to repetitive questions. This adds operational stress and can result in prospective students receiving inconsistent or delayed information, potentially impacting their decisions to join the college. This problem is further exacerbated during peak admission seasons when inquiries increase dramatically.

To address these challenges, there is a need to develop an admission query resolver chatbot that can provide instant, accurate, and personalized responses to prospective students' queries. This would reduce the workload for admission staff, allowing them to focus on more complex tasks while enhancing the overall student experience by providing 24/7 support and quick resolution of queries. With the introduction of conversational AI and natural language processing (NLP) technologies, a significant opportunity exists to transform how students engage with educational institutions. A chatbot tailored for engineering admissions can streamline communication by providing instant, accurate answers to common queries such as eligibility criteria, application deadlines, course details, fee structures, and entrance exam requirements. This would substantially reduce the burden on administrative staff, ensuring prospective students are well-informed promptly.

However, while education has used chatbots for administrative tasks, they often need more domain-specific knowledge to handle complex academic inquiries. For example, the Pragati chatbot, developed by the CET Cell in Maharashtra, addresses common queries related to CET exams and counseling. While effective for basic questions, it mainly offers predefined responses and lacks deeper integration with university databases to provide real-time updates or personalized answers. This limits its effectiveness for more complex admission-related questions. Developing an intelligent, context-aware Admission Query Resolver Chatbot is crucial to address these gaps, ensuring that it delivers accurate, personalized, and up-to-date information, ultimately transforming the admission process for both students and institutions.

LITERATURE REVIEW

1. Chatbot for Admissions

By Nikolaos Polatidis suggests that the project developed a chatbot using keyword matching and string similarity to assist university admissions. An algorithm that combines keyword matching with string similarity has been developed. A usable system using the proposed algorithm has been implemented. The system was evaluated by keeping logs of questions and answers and by feedback received by potential students who used it. [1].

2. College Enquiry Chatbot

Shubhanshu Bhardwaj, Snehil Khatri, and Swati Khare have created a College Enquiry Chatbot in a simple Python web application that aims to provide college information, asked the user. In the earlier days, students had to visit the college to enquire about courses, fee structure, admission process and other information about the college, which is a tiresome and lengthy process. This is where we thought of using an intelligent bot to deliver the information. [2].

3. An Interactive Chatbot for College Enquiry

Mina Rafik and Ahmed Ashraf. This paper presents a Chatbot system in an educational domain. A system was created to assist university students in their inquiries. The primary goal was to develop a specific architecture, build a model for managing communication, and provide the proper responses to the students. For this purpose, a system has been designed to recognize queries and provide answers to students using artificial intelligence techniques and natural language processing. Finally, an experimental campaign was run when the planned model was implemented to verify its enforceability and efficiency [3].

4. An Intelligent College Enquiry Bot using NLP and Deep Learning based techniques

The chatbot uses NLP and deep learning techniques like RNNs or LSTMs to understand user queries, focusing on intent recognition and entity extraction for accurate responses. It incorporates pattern matching, a structured training dataset, and a feedback mechanism for continuous improvement.

Advantages: Deep Learning Efficiency, Intelligent Responses

Limitations: Initial Data Dependency, Limited Emotional Understanding [4]

5. AI And Web-Based Interactive College Enquiry Chatbot

Rohan Parkar and Jaya Gupta describes an AI and web-based chatbot that uses NLP and AI to answer student inquiries. Built with Flask and SocketIO, it enables real-time chat, processes queries effectively, and improves accuracy with machine learning.

Advantages: Error Reduction, Productivity Boost

Limitations: Rule-Based Limitations, Lack of Personalized Experience [5]

METHODOLOGY

1. Definition of Model Selection Criteria:

In the intricate landscape of the admitEase chatbot project, the criteria for model selection were meticulously crafted to align with its distinctive requirements and overarching objectives. These criteria span a spectrum of essential dimensions, including but not limited to accuracy, latency, language support, and ethical considerations. Each was carefully delineated to ensure that the chosen models not only meet but excel in fulfilling the project's multifaceted needs.

2. Evaluation of Natural Language Understanding (NLU) Models:

The evaluation of NLU models, including Rasa's DIET (Dual Intent and Entity Transformer) classifier, embarked on a journey of meticulous scrutiny. It delved into performance metrics, extracting insights from accuracy rates derived through exhaustive testing against a diverse array of user queries. The evaluation ecosystem thrived on metrics such as intent classification accuracy and entity recognition precision, ensuring a nuanced understanding of model efficacy.

3. Assessment of Dialogue Management Models:

In the realm of dialogue management, a labyrinth of evaluations unfolded, encompassing Rasa Core's TED (Transformer Embedding Dialogue) policy. Rigorous testing protocols were meticulously orchestrated to ascertain response accuracy and contextual consistency across a spectrum of conversation flows. The assessment mosaic was enriched through comparisons with predefined dialogue structures, complemented by subjective evaluations meticulously crafted to discern the chatbot's ability to maintain coherent and contextually relevant interactions.

4. Testing of Backend Integration and Data Retrieval Mechanisms:

The evaluation odyssey extended to backend integration, ensuring seamless data retrieval from MySQL databases and external APIs. A diverse repertoire of queries served as the crucible for assessing the accuracy and efficiency of data-fetching mechanisms. The evaluative prism was further enriched through latency analysis and query success rates, unraveling the intricacies of backend responsiveness with precision and finesse.

5. Evaluation of Response Generation Techniques:

The accuracy and efficiency of response generation mechanisms emerged as the focal point in the realm of chatbot interactions. Against the backdrop of user queries, a symphony of performance metrics such as precision, recall, and response coherence orchestrated a meticulous dance, illuminating the efficacy and effectiveness of the chatbot's response formulation with unparalleled clarity.

6. Training and Optimization of the Chatbot:

The admitEase chatbot underwent a rigorous training process, leveraging a diverse dataset comprising CAP admission FAQs, historical cutoff scores, and seat matrices. The training regimen encompassed fine-tuning the DIET classifier, optimizing TED policy configurations, and implementing rule-based fallback mechanisms. Continuous performance evaluation and iterative refinements ensured the chatbot's adaptability and robustness in handling complex admission-related queries with accuracy and efficient.

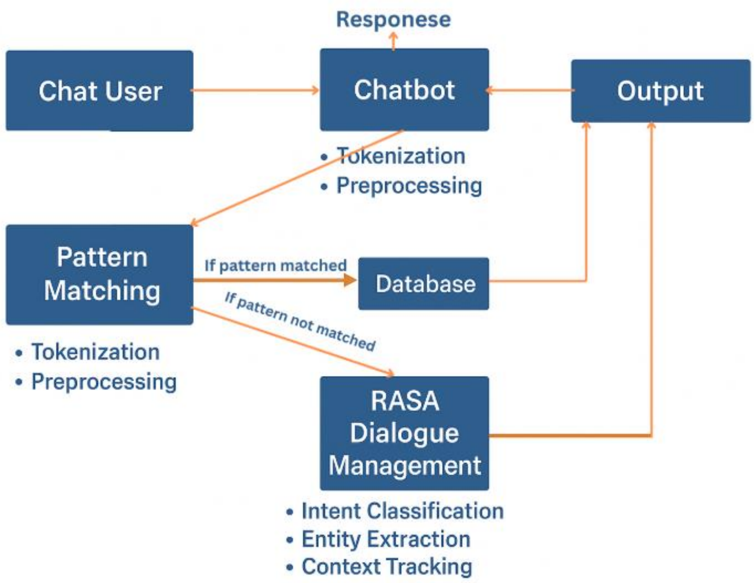

Figure 1

The Admission Query Resolver Chatbot is built to assist users—primarily students—in resolving admission-related queries through intelligent, context-aware conversations. The architecture combines Natural Language Processing (NLP), pattern matching, machine learning, and backend data services to provide real-time, reliable responses.

A. User Input and Preprocessing

1. Chat User Interaction

The process begins when a Chat User sends a message. This message is received by the Chatbot, initiating the processing pipeline.

2. Tokenization and Preprocessing

Both Pattern Matching and the Chatbot apply tokenization and preprocessing:

- Tokenization splits the user input into tokens (words or phrases).
- Preprocessing includes lowercasing, removing special characters, and normalization, which help standardize input for further analysis.

B. Pattern Matching

1. The system first attempts Pattern Matching:

- If the input matches a predefined pattern (e.g., "What is the cutoff for CS?"), the response is directly fetched from a Database without involving complex logic.
- This step ensures faster response time for FAQs and reduces system load.

2. If Pattern is Not Matched

If no match is found:

- The request is forwarded to RASA Dialogue Management, which handles dynamic conversations using NLP and ML.

C. RASA Dialogue Management

This component manages conversations when user queries are more complex or do not match existing patterns.

1. Intent Classification

- The system identifies what the user wants (e.g., asking a cutoff, inquiring about eligibility).
- This is done using RASA's DIET Classifier, a transformer-based model optimized for intent prediction.

2. Entity Extraction

- Important details (entities) like department, year, or score are extracted.
- These entities provide context for the query and guide further processing.

3. Context Tracking

- Rasa tracks the dialogue history, helping the system understand follow-up questions like "What about Electronics?"
- This is managed using Rasa's TED Policy, which predicts the next action based on conversation flow.

D. Backend Integration and Data Services

1. Database Access

- If data is needed, Rasa queries a Database (e.g., MySQL) to retrieve answers like cutoff scores, seat matrix, eligibility criteria, etc.

3. Caching for Performance

- Frequently accessed data (e.g., "cutoff for CS 2024") is cached to reduce database load and improve response time.

E. Response Generation

1. Output Creation

- The Output block receives the final response and delivers it to the chatbot interface.
- The response is formatted for clarity—lists, tables, or direct messages—depending on query type.

2. Custom Actions

Rasa executes Custom Python Actions for:

- Querying databases
- Formatting output
- Generating responses dynamically

F. Feedback Loop

- Every user query, whether handled by pattern matching or Rasa, is processed and responded to in real-time.
- Rasa continuously improves intent prediction and dialogue handling via training and feedback.

MODEL AND ANALYSIS

NLU (Natural Language Understanding) Model

Purpose: This model is responsible for understanding user queries. It classifies the intent (e.g., "ask_admission_process") and extracts key entities (e.g., "course name," "admission year").

Stored in: The .tar files contain this trained NLU model. Example component inside the model:

DIETClassifier or tensorflow_embedding → Classifies user intents.

RegexFeaturizer → Recognizes patterns in text (e.g., phone numbers, email IDs).

EntityExtractor (like CRFEntityExtractor or Duckling) → Extracts names, dates, etc.

Core (Dialogue Management) Model

Purpose: Determines the chatbot's response based on user inputs and conversation history.

Stored in: The same .tar files.

Example component inside the model:

TEDPolicy → Predicts the next action based on conversation context. RulePolicy → Manages fixed responses (e.g., FAQs about admissions). MemoizationPolicy → Remembers past conversation turns.

RESULT AND DISCUSSION

Results

The chatbot has demonstrated a strong ability to understand and classify user intents accurately. With an 91% intent classification accuracy, it effectively recognizes what users are asking and provides relevant responses.

The model consistently identifies user intents with high precision and recall, meaning it can understand a wide range of queries, even when phrased differently. This ensures that conversations feel natural, seamless, and intuitive for users.

Despite the complexity of human language, the chatbot maintains reliable and consistent intent detection, making interactions smooth and engaging. Its strong performance highlights how well it can handle real-world conversations with minimal misinterpretation.

Discussion

An 87.14% accuracy in intent classification means the chatbot is doing an excellent job of understanding users and responding correctly. This level of performance makes it highly dependable for assisting users across different topics and inquiries.

The chatbot's ability to recognize diverse user inputs ensures a smooth and engaging conversation flow, reducing frustration and enhancing user satisfaction. Its performance shows that it can effectively interpret queries and provide meaningful responses, making interactions feel more human-like and natural.

Overall, the chatbot is intelligent, responsive, and well-equipped to handle real-world interactions, making it a reliable digital assistant for users.

CONCLUSION

The development of the Admission Query Resolver Chatbot represents a promising step toward automating and enhancing the admission process for engineering students. Although the chatbot is still under development, it aims to integrate Rasa for natural language understanding and dialogue management, with a responsive frontend designed in Visual Studio Code (VS Code).

Once complete, it will effectively address various admission-related queries, providing students with real-time information about admission criteria, deadlines, application status, and more. This project highlights the potential of conversational AI to streamline university admissions, reduce the workload on administrative staff, and improve the user experience for prospective students.

As the chatbot continues to evolve, leveraging machine learning and natural language processing (NLP), it is expected to offer increasingly accurate and personalized responses with further testing and refinement.

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