# Chatbot for Elections FAQ for the State of Mississippi

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## 1 PROBLEM

The consumption of election related information is usually through the form of "Frequently Asked Questions" (FAQs) available on the website pertaining to each state. However, it is quite tedious to find the relevant information based on the user question as they need to manually navigate through the available FAQs until a relevant answer is obtained. In order to eliminate this obsolete process, we aim to make use of conversational agents or popularly known as chatbots to allow an interactive interface for user interaction with the content available on the state's election website. In this work, we build ElectionBot using safe chatbot framework built using RASA¹ for the State of Mississippi (MS). The user utterance consisting of an election related question to ElectionBot, and a relevant answer is obtained as output.

#### 2 RELATED WORK

Chatbots have been used for a wide-variety of tasks such as providing information regarding public health [7], assisting in tackling mental health problems [2, 6], or for general purpose chit-chat [8, 9]. In elections, [5] have explored the use of conversational agents for political branding. The authors in [4] study the rise of chatbots in elections and their effects on changing political intention. One of the works closest to the proposed approach in this paper is [3], where the authors have designed a chatbot for providing voting advices. However, the major limitation with this approach is that the information provided is often inconsistent, incorrect, and often polarising for various users owing to the black box nature of the approach. Thus, in our approach, we make sure to use the trusted source of information, i.e., a government website and convey the information captured, and avoiding questions that deviate from the available list of official FAQs.

#### 3 APPROACH

In this section we describe the approach followed in building ElectionBot.

#### 3.1 Safe Chatbot Architecture

Providing safe responses to the user utterances is one of key concerns in our approach to build ElectionBot. We have followed a safe chatbot architecture as shown in Figure 1.

The features that make this architecture safe are:

Logging of user conversation history

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<sup>1</sup>https://rasa.com/

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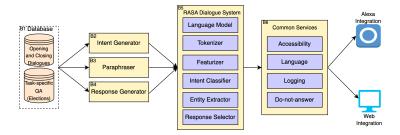


Fig. 1. Safe Chatbot Architecture

Do not answer fallback strategy

The key components mentioned in the architecture are:

- Database (B1): The database is the source from which we extract the training data to train the chatbot. We ensure that the source is reliable and trustworthy. Task-specific QA refers to the data source pertaining to the chosen domain (which is elections, in this case). The opening and closing dialogues are usually generic (like greeting and saying bye).
- Intent Generator (B2): Intent Generation is crucial in building an efficient and functional chatbot. It helps in tagging existing questions to an intent, which can later be utilized to map any new incoming user utterance to the available intent in order to provide desired answers.
- Paraphraser (B3): In order to train a chatbot, it is crucial to show it similar questions that match an answer, rather than having only a single question associated with an answer. However, in any FAQ wesbite, we only obtain a single question tagged with an answer. Thus, in order to create an efficient chatbot, we made use of a paraphrasing tool to generate similar questions as to the one extracted from the election FAQ website.
- **Response Generator (B4)**: We use the response generator that is inherently built-in RASA functionalities. This module helps in fetching and generating relevant answer given a user utterance.
- RASA Dialogue System (B5): We use the RASA chatbot framework [1] to build the chatbot. The dialogue system has an NLU pipeline with different components for understanding human conversation and responding appropriately. Language models like the Spacy language model can be used if one wants to use pre-trained word vectors. Tokenizer converts sentences to tokens. Featurizer creates a vector representation of the user message and response. The intent classifier classifies the intent of the user message. The entity extractor extracts entities that are specified in the training data. The response selector chooses the appropriate response based on the identified intent and entities.
- Common Services (B6): The common services are optional and the user has the flexibility of choosing the services they need. Some of the accessibility options are font settings and Text-to-Speech. The users will be able to converse with the chatbot in the language that is comfortable to them using the language settings. This can be implemented by making use of translators. The conversations can be logged for storage and retrieval using the logging option. This also helps the developers to improve the chatbot conversation by reviewing the stored conversations. We do not want the bot to respond to certain questions (for example, question like 'Do you think the current president is doing a good job?'). These questions are mostly subjective. 'Do-not-answer' option can be used in this case.
- **System Integration**: Web integration and Alexa integration provide an engaging user interface to converse with the chatbot. We integrated the RASA chatbot with Alexa device as

a skill using the Alexa developer console (the skill is still in beta phase). Web integration was done using the RASA webchat package.

# 3.2 Implementation of ElectionBot for MS

In this section, we describe the implementation of ElectionBot to answer FAQs pertaining to the State of MS.

3.2.1 Data. The dataset is scraped from the official government website consisting FAQs for MS<sup>2</sup>. The scraped question and answer pairs are stored in the form of a CSV file which is used to train ElectionBot. Figure 2 shows snapshot of the dataset built for Mississippi. There are a total of 12 Q-A pairs in the dataset, with average question length being 7 words.

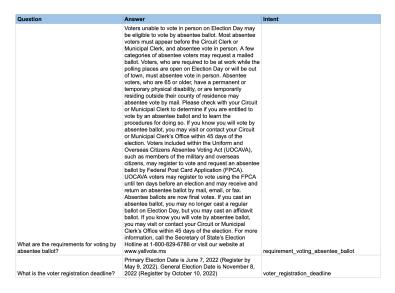


Fig. 2. Snapshot of the dataset for Mississippi

- 3.2.2 Intent Generation. Once we have the dataset, we need to generate the intent for each question present in the dataset. Questions present in the dataset are small, with an average of  $\tilde{7}$  words in a sentence. On further exploration, we identified that most of these words are stop-words, i.e., commonly used words in any language. For example, in English, "the", "is", and "why" qualify as stop-words. In order to obtain important information, it is implicit to remove stop-words, and when we carried out the similar process on the dataset, we identified that there are only a few words left out for every Q-A pair. Thus, in order to obtain the intent for each question, we have used n-gram approach to tag each question with an intent consisting of the important words present in the initially extracted questions. Figure 2 shows the generated intents for the presented questions.
- 3.2.3 Integration with RASA. In order to better train RASA, we need to have multiple similar questions tagged with an answer so that the learning-based framework can better adapt to unseen questions from the user. However, we are limited with having only one question extracted per answer from the government website. Thus, in order to overcome this limitation, we make use of a paraphraser<sup>3</sup> to generate 5 similar questions to each question present in the dataset. With each

<sup>&</sup>lt;sup>2</sup>https://www.sos.ms.gov/elections-voting/faqs

<sup>&</sup>lt;sup>3</sup>https://huggingface.co/eugenesiow/bart-paraphrase

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question in the dataset extended with multiple similar questions, RASA training is performed and the ElectionBot is generated.

3.2.4 Deployment of ElectionBot. We deploy the generated ElectionBot for public usage and testing on a server using the Django<sup>4</sup> framework. ElectionBot for MS can be accessed at - http://casy.cse.sc.edu/ElectionBot-MS-main/Chatbot/. Figurec 3 shows the landing page of the chatbot with user interaction.

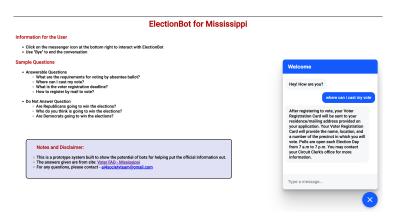


Fig. 3. Deployed ElectionBot with an instance of user interaction

## 4 EVALUATION

The developed chatbot is currently tested among various students and colleagues to perform a check on the functionality and safety. After the initial testing, we are currently working on performing a detailed focus group testing of ElectionBot with a group of 65 years and older people to understand how the elderly would consume information regarding elections using the new-age technologies.

<sup>&</sup>lt;sup>4</sup>https://www.djangoproject.com/

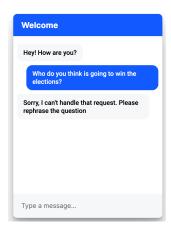


Fig. 4. ElectionBot employing the use of **Do Not Answer** strategy

#### 5 DISCUSSION

Figure 3 shows a user interaction with ElectionBot asking a question that can be answered by the chatbot. However, as mentioned earlier, safety is one of the key aspects in the design of ElectionBot. Thus, in Figure 4, we demonstrate the "Do Not Answer" strategy employed by ElectionBot in deflecting a dubious question posed by the user. After the focus group testing, we would like to add more details on how the group perceived our approach to designing a chatbot for answering election related FAQs.

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