

Bark Plug: The ChatGPT of the Bagley College of Engineering at Mississippi State University

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Abstract

Higher education has been caught by storm through the advent of Artificial Intelligence (AI) and Large Language Models (LLM) such as ChatGPT. Clearly, there are multiple roles for these sorts of tools to play in higher education, and in particular within engineering and computer science curricula. In this work, we have taken a different approach. At Mississippi State University (MSU) we have formed a multidisciplinary collaboration to utilize the principles behind AI and LLM to develop a chatbot to serve the college of engineering and the university community, including students, staff, faculty, administration, alumni and the community.

As a large, public land grant, doctoral university with a very high research activity, as well as engagement in every county in our state through the MSU Extension service, our chatbot is:

- intended to aid in undergraduate student recruiting and provide guidance for initial student placement in appropriate majors.
- serve as a tool to assist in domestic and international graduate student recruiting in line with the institutional research priorities of autonomy, economic development, addressing disparity and cybersecurity.
- be a resource for the university community to aid in student persistence, retention and graduation through both academic advising and student support services cosponsored by the division of academic affairs and the division of student affairs.
- beyond academic affairs and student life, serve as a gateway for citizens of the state to become connected with university services such as the MSU Extension, Center for Entrepreneurship & Outreach, MSU Small Business Development Center and the Center for Community-Engaged Learning.

In this work, the processes behind the development of the algorithm for this tool and a sample demonstration for the College of Engineering and other university level services will be outlined.

Introduction and Background

Artificial Intelligence (AI) has been a topical research area for decades, but has become mainstream during the last couple of years. The advent of AI tools such as ChatGPT have brought forth dialogues ranging from plagiarism, ownership / copyright and academic integrity to using AI as a tool (similar to a slide rule, calculator or computer) to enhance and further push the boundary of classroom learning and academic research. In fact, many institutions have written or have proposed formal policies on the ethical use of AI. Additionally, faculty hiring trends in STEM fields have brought in faculty who have access to and experience in using “toolboxes” such as AI, machine learning, data science and cybersecurity to enhance their research. Furthermore, to help contextualize academic research needs at comprehensive institutions, many university libraries are adding faculty positions with specific aims including data science, copyright / intellectual property; virtual / extended reality and AI / emerging technologies to support research in critical areas such

as autonomy, advanced materials, big data, cultural geography, linguistics, discovery and digital humanities.

Aside from formulation of the algorithms behind LLM's [1], a great deal of dialogue is occurring about how to best utilize AI tools such as ChatGPT. For example, a recent Chronicle article [2] outlined one student's positive experiences in leveraging ChatGPT to get some specific advice towards an assignment. This work touches on a newly developing field called "prompt engineering." The reader is referred to the article by Lo [3] to provide additional guidance to users of AI tools, pointing to the CLEAR Framework acronym (Concise, Logical, Explicit, Adaptive and Reflective). These concepts have also been discussed in several forums, including the chemical engineering division of ASEE at the 2023 meeting [4], and provide a framework for our model development.

Development of a college-level / university-specific chatbot would be considered the next step forward to providing personalized, inclusive and accurate responses that address each student's questions in an engaging and efficient manner. This information could pertain to course materials and helping as a course tutor [5] or providing insight on university-specific knowledge, ranging from administrative procedures and scholarship opportunities to faculty research areas and campus life insights.

Institutional Support and Other Needs

This project was initiated by the Department Head of Computer Science & Engineering, who was working with faculty in his home department and in the School of Chemical Engineering. Their Predictive Analytics and Technology Integration Laboratory (PATENT) aims to accelerate advances in several interdisciplinary fields by addressing the challenges in data management, integration, and analytics, as well as predictive modeling and simulation. By integrating various technologies and data sources, including artificial intelligence and machine learning, PATENT will contribute to developing next-generation solutions that are data-driven, resilient, and robust in both real-world and theoretical domains across these diverse industrial sectors, such as engineering, social sciences, agriculture and more. PATENT conducts fundamental and applied research in fields including, but not limited to: artificial intelligence, cybersecurity and cyber-physical systems.

The dean of engineering had partnered with the department head to solicit a significant endowment from a private donor to financially support this laboratory. Preliminary work is being supported by PATENT's endowment returns, indirect cost return from funded projects in the PATENT lab and discretionary development & endowment funds managed by the dean's office. This included supporting undergraduate student, graduate student and postdoctoral research, as well as providing a modest computing infrastructure. The PI's received a strong endorsement from the institutional vice presidents, and developed a collaboration with the Department of Marketing, Quantitative Analysis & Business Law and with the Department of Art regarding a branding and marketing campaign to have the most impact to prospective and current students. Furthermore, the team is reviewing quotations for purchasing a larger server with expanded Graphical Processing Unit (GPU) capabilities that can support scaleup of this project to the broader campus community.

The Bagley College of Engineering and the Department of Computer Science and Engineering are planning on purchasing a server configuration that includes 4 state-of-the-art NVIDIA H100 GPUs, 1 TB of RAM, and 16 TB of flash storage. This setup will include high-speed networking to ensure that our LLM developers have access to a high-bandwidth, low-latency connection to the server for handling the most resource-intensive tasks. Additionally, the server will be equipped with RDMA (Remote Direct Memory Access), which will enable its storage capacity to scale into the range of hundreds of terabytes without experiencing bandwidth limitations, thereby ensuring optimal performance.

Brief Formulation of the Large Language Model

There are many different forms of language models in existence, each with different use cases. In theory, these models are no different than other probabilistic models, where the next entry in a sequence is estimated; however, these models are specialized in handling and generating human language. Earlier iterations of these models used Hidden Markov Models (HMM) and were mostly used for speech recognition and natural language processing, and to some extent for grammar check. Other approaches used Long-Short-Term-Memory (LSTM) or even bi-directional LSTM, which introduced advancements in terms of performance and remembering the state of the system. Yet, these models all suffered from their limited capacity in remembering long-term dependencies (often referred to as the issue of “vanishing gradients”) and subpar performance.

The most significant change to this realm came from a seminal paper by Google scientists in 2017 [6] in which they introduced the concept of transformers. This led to the introduction of more recent models, such as Masked Language Models (MLM), that generally use transformers to fill in the gaps (e.g., Bidirectional Encoder Representations from Transformers (BERT) [7]). Among all models, the Generative Pre-Trained Transformer (GPT) models are by far the most capable at managing context over longer text sequences than previous models and predicting the most probable word to follow. These models have seen a massive rise in popularity in recent years, thanks to the exceptional success of OpenAI’s GPT 3.0 in engaging in conversations through its ChatGPT interface. This popular model was later refined into GPT 3.5 and their most recent iteration, GPT 4.0.

While there are many ways to train a language model, the majority of GPTs are trained on a large body of text. This may include using public or private sources, open access repositories, crowd-maintained wikis (such as Wikipedia) or under special circumstances with data generated by another language model. The sheer volume of the text processed by these models, and the number of parameters they use to tune their models, which is typically in the order of several billion parameters, has resulted in them being known as Large Language Models (LLM). The large scale of these models contributes significantly to their capabilities in understanding and generating human language.

As mentioned earlier in this section, the GPTs are probabilistic models and can estimate the next entry (word, in the case of languages) in a sequence. The degree of confidence in estimating the next entry is a factor that plays a crucial role in controlling the behavior of a GPT. This parameter, often referred to as the “Temperature”, can restrict the model to only output the most probable

value, thus resulting in a very predictable behavior, or allow it to come up with values that are not necessarily the first choice, thus becoming more creative. As an example of this behavior, let us consider the following two cases:

Example: Complete the following sentence: "It is a beautiful sunny ____"

Case 1 - GPT with temperature set to 1 (predictable): "day." (This is a common, expected completion for the sentence.)

Case 2 - GPT with temperature set to 0.5 (more creative): "afternoon, perfect for a walk in the park." (This response is more detailed and creative, yet still relevant to the context.)

This behavior of GPTs can also result in their demise, as these models are susceptible to generating sequences that are plausible, but inaccurate or non-existent. This phenomenon, known as the hallucination, is especially important in places where accuracy and factual correctness are important, such as the academic context. For example, in an academic context, a GPT model might reference a study that seems relevant but does not actually exist. To overcome this issue, the models are often instructed to only state factual matters, and be less creative, which counters their vast capabilities.

Another way of overcoming the hallucination problem is to provide detailed context surrounding the prompt or the question that is asked from the model. This process, commonly referred to as Retrieval Augmented Generation (RAG), is a very effective way of enriching the responses generated by the model with a retrieval mechanism that fetches information from a dataset or database, while benefiting from its creativity [8] ensuring that the generated content is based on factual data. In other words, the RAG balances between creativity and accuracy.

Our initial architecture design is shown in Figure 1 below. When we developed a beta-test version of this chatbot, we envisioned inquiries coming from three classifications: current students, prospective students and faculty / staff. However, in conversations with constituencies around campus, it was requested to add a general inquiry classification. These classifications are important as we trained the bot to “think” and to generate responses that are appropriate to those classifications.

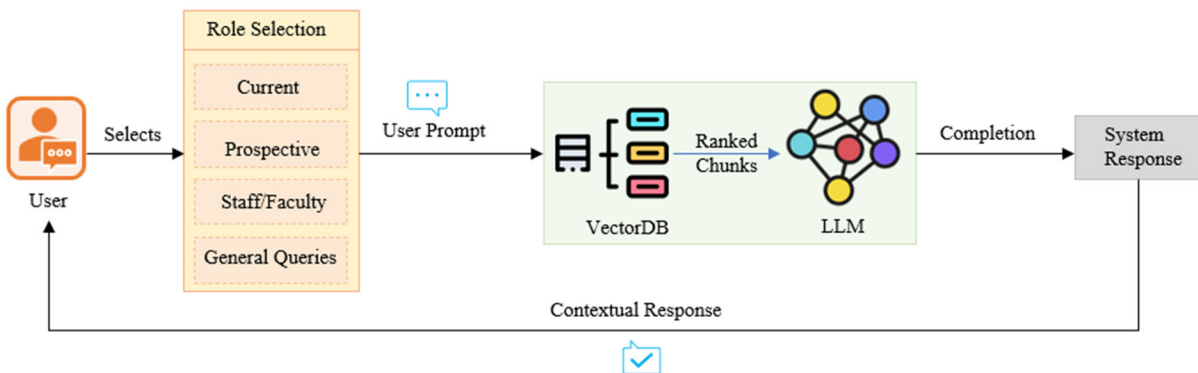


Figure 1 - Initial Architecture of Bark Plug

All initial inquiries need to choose a classification. In the future, we intend to develop an app for mobile devices such as iPhones, iPads and Android devices, for instance. In those situations, and in future online development, we would allow users to establish an account to log in to the system, and the bot would “remember” the conversation with the user, and be better prepared to give more specific information. We are also planning on developing training functionality to teach users some of the basics of “prompt engineering” to better engage with the bot.

After identifying into the four major groups, the user then can ask questions at a prompt. Our initial beta version had limited information covering 4 of the largest engineering departments on campus, but we have now expanded it to cover nearly 50 academic departments. We further trained the model to better respond to student inquiries. The model currently has been trained to give lengthy answers in the form of a numbered list. We plan on refining this to also include links to outside sources (typically these will be websites on our university server, but also intend to include phone numbers so that the user could call when they have determined the campus office that can best help them.

We have also formulated a sentiment analysis [9] as part of the bot’s responsiveness. If the user’s emotional tone is negative or positive, we would like the bot to respond appropriately. Prior versions assumed a neutral tone and responded in a like manner. Keep in mind that the more information we obtain and archive, the bot will be better prepared to gauge the user’s mindset and intent before answering. In essence, we are aiming to extract “body language” from the tone, looking at sentence structure (as an illustrative example, consider perhaps terseness from the user).

A facet added in more recent versions is a guided LLM [10]. In this approach, the model will try to assemble a large prompt, thus increasing the responsiveness and accuracy of the result, by asking the user different pieces of information relevant to the initial question raised by the user. It is important to note that a typical user of the system may not necessarily know how to craft effective prompts, to get the best responses from the model, but a guided model can piece together different pieces of information that can enrich the prompt. As an example, let us consider the case where a prospective student is inquiring about choosing a major. Once the user specifies their interest in getting help choosing a major, the system would use a light weight LLM to start asking about their interests, their ideal job environment, expected salary and other relevant information. Once sufficient preliminary information is gathered, the system would then form a detailed and tailored prompt, then subject it to RAG before being passed to the main LLM. In addition to gathering more relevant information from the user and improving the responsiveness of the results, this approach benefits from a smooth and low latency guide, with the more resource-intensive processes, like the main LLM call and the RAG, reserved for the final, more complex query processing. This tiered approach optimizes both the user experience and system resource utilization.

This allows the model to “think ahead” in its response when searching for appropriate content to match the user tone and query. These result in an improvement of the value of the response and increases user satisfaction with the tool, which will lead to an improved likelihood that the bot will be used again in the future.

The past decade saw a massive expansion of internet utilization as we switch over to cloud-based subscriptions and services, including more emergence into social media, which has fundamentally changed how we communicate, learn, and engage with the world. The pandemic pushed us even further into the digital world, making remote work, virtual meetings and online platforms essential for everyday interactions. This whole trend has significantly boosted reliance on AI, with more and more people looking into AI-driven solutions, to the point that AI was literally the theme of the Consumer Electronics Show [10]. This makes it crucial to pay close attention to the ethical and societal issues surrounding AI (e.g., data privacy and misinformation) and emphasizes the need for some governance on the AI generated materials. We also took into account the concepts of prompt engineering to train our LLM about the characteristics of our anticipated users.

Examples and Impact

In this section, we will briefly illustrate the utility of this tool, from the perspective of a prospective student, a current student with academic affairs needs and a current student with student affairs needs.

We have functionality to handle:

- general queries (meant for alumni, parents and general users external to the university)
- respond to information about scholarships and financial aid
- to interact with prospective students to give more tailored departmental selections
- to handle students considering multiple majors (or deciding between them)

We can also handle undecided students by asking some self-reflection questions. These include:

- "What subjects or topics are you genuinely interested in or excited about?"
- "What are some activities or projects where you feel most confident and capable?"
- "Do you have any specific career goals or aspirations? Are there industries or professions you're drawn to?"
- "Would you like to work remote, at the office or outdoors?"
- "What is your salary expectation?"
- "Outside of academics, what do you enjoy doing in your free time? Are there any hobbies or extracurricular activities that you're passionate about?"
- "What learning environment do you prefer? Some students thrive in small, interactive classes, while others prefer larger lecture-style classes."

The above changes have led to the revised architecture / algorithm shown in figure 2 below.

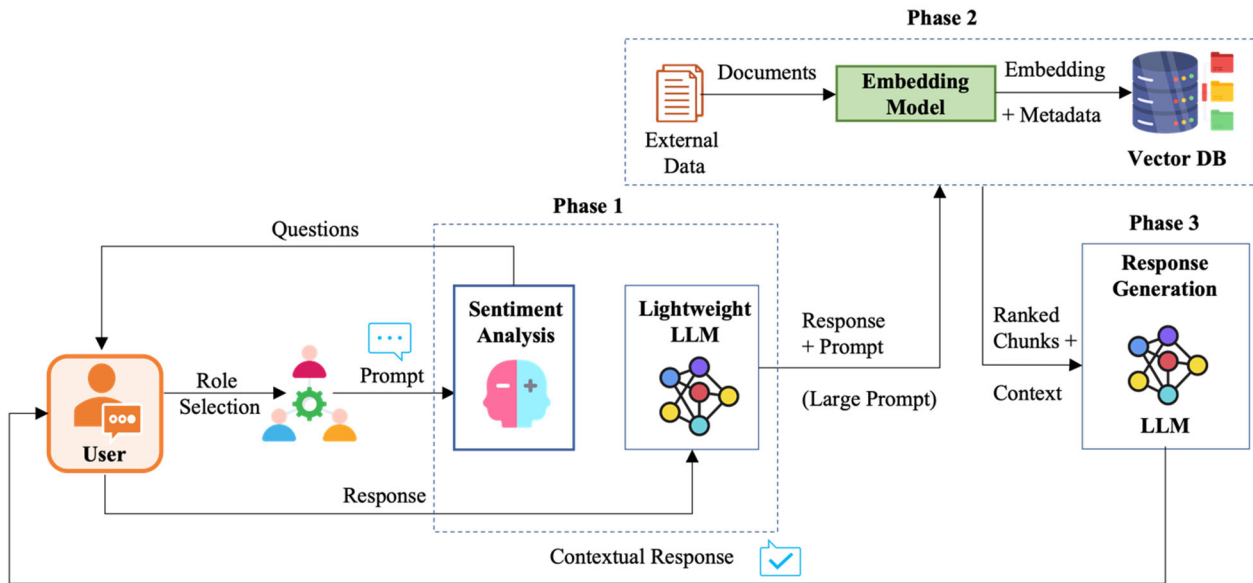


Figure 2 - Current Architecture of Bark Plug

As stated earlier, Bark Plug's system is designed to generate contextual responses based on user prompts, employing Large Language Models (LLMs) augmented with data from our institutional website as an external source. As figure 2 demonstrates, the interaction within Bark Plug begins with users selecting specific roles within the university, such as current student, prospective student, faculty/staff, and general queries. These roles are crafted to elicit tailored responses, acknowledging the diverse informational needs across different user categories. For instance, prospective students may seek guidance on choosing a major, while current students might inquire about specific courses or professors. Meanwhile, faculty and staff may have distinct queries, such as information on parking, accommodation, and employee benefits. General queries are designed to address the needs of alumni, parents, guardians, students, and the wider public, providing information on topics like upcoming athletics events, past events, parking details for game days, and other general information.

The architecture of Bark Plug encompasses three distinct phases: sentiment analysis and large prompt creation, Retrieval Augmented Generation (RAG), and response generation. The process begins with the user prompt serving as the input to the initial phase. Here, the system employs sentiment analysis to discern the emotional tone embedded within the user's input.

To execute sentiment analysis, Bark Plug leverages the "distilbert-base-uncased-finetuned-sst-2-english" model, which is specifically fine-tuned for sentiment analysis tasks. Upon receiving the user prompt, the system employs this model to classify the sentiment expressed within the input as either "positive" or "negative." For instance, let's consider a scenario where a prospective student is undecided about their major. To assist such users in navigating through available majors and career options based on their interests and experiences, sentiment analysis serves as the initial step. Figure 3 offers a detailed schematic overview of how sentiment analysis operates within our application. After obtaining the user's response, the system proceeds to analyze it using a sentiment analysis function. This function evaluates the sentiment conveyed within the response,

categorizing it as either positive or negative. For instance, responses to questions like "Have you decided on a major yet?" could range from affirmative statements like "yes" or "absolutely" to more hesitant expressions like "I am thinking about it" or "I don't know." Rather than exhaustively considering every possible response, Bark Plug utilizes the sentiment analysis function to automatically discern the underlying sentiment of the user's input. If the sentiment is identified as positive, the system proceeds to response generation. However, if the sentiment leans towards the negative spectrum, Bark Plug intervenes to provide additional assistance in aiding the user's decision-making process regarding their major selection.

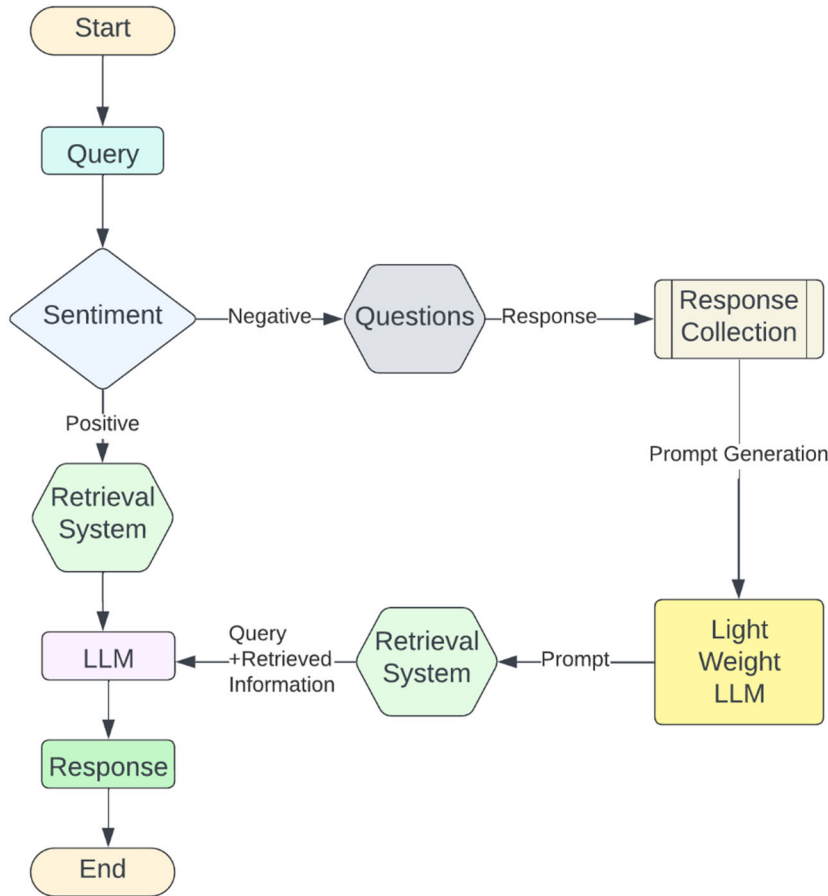


Figure 3 – Workflow of a Bark Plug that uses sentiment analysis and retrieval systems to generate responses

To achieve this, Bark Plug engages the user in a series of follow-up questions designed to delve deeper into their interests, past experiences, academic achievements, preferred work environments, and other relevant factors. These responses are then collected and synthesized to generate a more comprehensive prompt, facilitating further interaction and guidance. To efficiently handle this task, Bark Plug utilizes lightweight LLMs such as the quantized LLMA-2.

The second phase revolves around RAG, where the system leverages an OpenAI embedding model, specifically "text-embedding-ada-002," and ChromaDB to convert the external data into a vector database. The input to this phase is the output of the initial phase i.e., the larger prompt.

This phase entails three steps such as document processing, applying the embedding model and converting it into a vector database. The document processing step involves breaking down documents into smaller chunks, optimizing chunk size and overlap to prevent information loss. In our case, we employ a chunk size of 800 characters with a 100-character overlap. The second step focuses on converting the processed documents into embeddings. To achieve this, we employ the text-embedding-ada-002 model, which effectively captures the semantic nuances of the text. The last step involves the creation of a vector database. The embeddings generated in the previous step are transformed into a vector database using ChromaDB, which serves as the underlying infrastructure for the storage and retrieval of information. The output of this step is the ranked chunks and the context.

In the retrieval process aimed at extracting relevant information from the external dataset based on the user prompt, Bark Plug employs the Max Marginal Relevance (MMR) approach. This method selects chunks that are both like the input and diverse. It identifies chunks with embeddings exhibiting the highest cosine similarity to the input and iteratively adds them, penalizing for closeness to previously chosen examples. This ensures a balanced retrieval, emphasizing relevance and diversity in the retrieved information.

The final phase is response generation with the input being ranked in chunks with the context obtained from the second phase of the Bark Plug architecture. This augmented prompt, crafted using prompt engineering techniques, is then presented to the LLM within Bark Plug. We utilize GPT-3.5 Turbo models for response (text) generation. This tri-phased architecture of sentiment analysis and large prompt creation, RAG, and response generation collectively empowers Bark Plug to deliver sophisticated and context-aware conversational AI experiences.

Demonstration

We utilize this model in our beta version and illustrate sample queries and answers in the appendix as figures A1-A6 at the end of the paper. Although the responses are longer, for the sake of brevity we have truncated the answers to just a handful of paragraphs.

Conclusions and Future Directions

We have illustrated the background and utility of a generative pre-trained transformer at MSU, intended to aid the institution in recruiting prospective students; supporting current students in both academic and student affairs; help guide faculty and staff in advising students more accurately and pointing them to appropriate institutional policies and procedures. We have beta-tested this with smaller sized constituency groups on campus; including our research team; the institutional vice presidents and small student groups from the Bagley College of Engineering; College of Business; and College of Architecture, Art & Design.

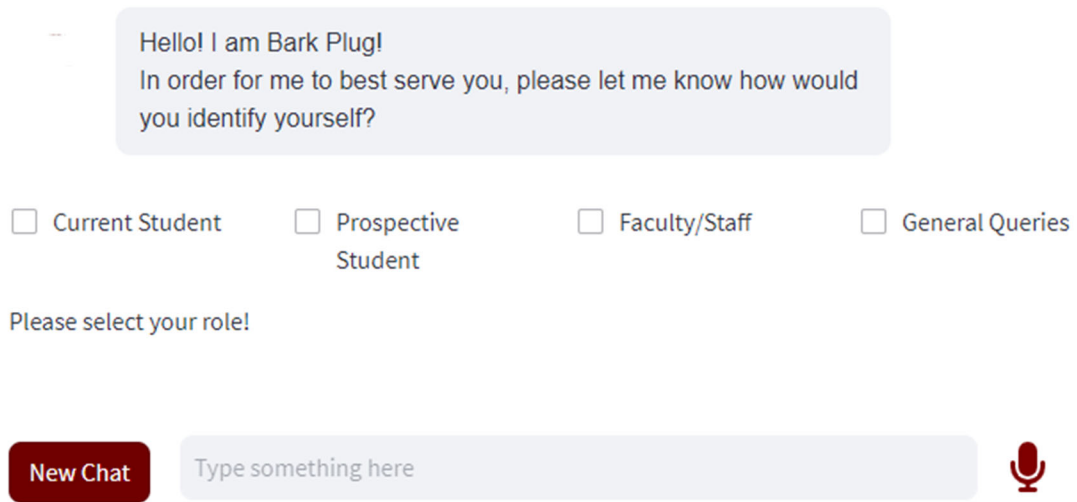
It is our intent in the future to migrate this platform to a more customizable User Interface Design (e.g., using Django) and to consolidate our vector databases to improve the user experience and reduce “thinking time” of our GPT servers. Furthermore, we hope to develop tools to query prospective students in a dialogue with a resulting suggestion of multiple degree programs for the student to consider for their college career. After helping prospective engineering students identify

possible majors (or for current engineering students to choose a different major or a different college), we plan to develop a series of teaching assistants to help with our more difficult courses (traditionally called weed-out courses). A longer-term goal would be to include non-academic and general-purpose data in the database, such as information about institutional athletics programs and the local community (including rental housing, shopping and restaurants).

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Appendix A. Demonstration



Hello! I am Bark Plug!
In order for me to best serve you, please let me know how would you identify yourself?

Current Student Prospective Student Faculty/Staff General Queries

Please select your role!


[New Chat](#) 

Figure A1. Initial Bark Plug screen

what classes do i take as a first year student in computer science



As a first-year student in the Bachelor of Science in Computer Science program at Mississippi State University, you will take a variety of classes to build a strong foundation in computer science. Here is a sample of the classes you may take:

1. CSE 1284: Introduction to Computer Programming
2. CSE 1384: Intermediate Computer Programming
3. CSE 2383: Data Structures
4. CSE 3183: Systems Programming
5. CSE 3724: Computer Organization
6. CSE 4714: Programming Languages
7. CSE 1011: Introduction to CSE
8. CSE 2813: Discrete Structures
9. CSE 2213: Methods & Tools
10. MA 1713: Calculus I
11. MA 1723: Calculus II
12. MA 3113: Linear Algebra
13. EN 1103: English Composition I
14. EN 1113: English Composition II
15. CH 1213: Chemistry I
16. CH 1211: Investigations in Chemistry I

Figure A2. Example dialogue with Bark Plug

what sort of student organizations are in the department of computer science and engineering



The Department of Computer Science and Engineering at Mississippi State University offers several student organizations for students interested in computer science. Here are some of the student organizations available:

1. CSE Ambassadors: The CSE Ambassador Team assists the department head and assistant department head with recruiting and retention events. These students represent the department to prospective students and their parents. Leadership skills and reliability are a must for these volunteer positions. Students interested in becoming a CSE Ambassador should contact Dr. Andy Perkins.

2. Association of Computing Machinery (ACM): The MSU student Chapter of the ACM exists to promote an increased knowledge of the science, design, development, construction, languages, and applications of modern computing machinery. It also aims to promote a greater interest in computing machinery and its applications, and provide a means of communication between persons having an interest in computing machinery. The faculty advisor for ACM is Dr. Shahram Rahimi.

Figure A3. Example dialogue with Bark Plug

i live outside of the state. what sort of scholarships can i obtain?



As a prospective student living outside of the state, there are several scholarships that you may be eligible for at Mississippi State University. One option is the National Science Foundation Scholarship for Service Program. This program provides scholarships that fully fund the typical costs that students pay for books, tuition, and room and board while attending an approved institution of higher learning. These scholarships are funded through grants awarded by the National Science Foundation. However, it's important to note that each year or partial year of scholarship benefits incurs a one-year government service obligation.

Additionally, there may be other scholarships available specifically for students majoring in Computer Science and Engineering. One example is the Susan & Philip Bridges Scholarship in CSE. To be eligible for this scholarship, you must have and maintain a 2.5 or higher GPA, demonstrate financial need, and major in Computer Science or Software Engineering.

Figure A4. Example dialogue with Bark Plug

my sister is a current student in building and construction science. she is interested in transferring to civil engineering. what does she need to do?



If your sister is a current student in Building and Construction Science and is interested in transferring to Civil Engineering at Mississippi State University, she will need to follow a specific process. Here are the steps she should take:

1. Meet with an academic advisor: Your sister should schedule a meeting with an academic advisor in the Department of Civil and Environmental Engineering. The advisor will provide guidance on the transfer process and help her understand the requirements for the Civil Engineering program.
2. Review the transfer requirements: Your sister should carefully review the transfer requirements for the Civil Engineering program. This may include specific GPA requirements, completion of prerequisite courses, and other criteria. It's important for her to understand what is expected in order to successfully transfer.

Figure A5. Example dialogue with Bark Plug

my brother is in mechanical engineering and needs tutoring help with statics. what can he do?



If your brother is in mechanical engineering and needs tutoring help with statics, there are several resources available at Mississippi State University that he can utilize. Here are some options for him:

1. **Tutoring Services:** Mississippi State University offers tutoring services for various subjects, including engineering. The Center for Student Success provides free tutoring services to all MSU students. Your brother can visit their website or contact them directly to inquire about tutoring availability for statics.
2. **Engineering Academic Support Office:** The Bagley College of Engineering at Mississippi State University has an Academic Support Office that provides resources and support for engineering students. They may offer tutoring services specifically for engineering courses, including statics. Your brother can reach out to this office for more information on tutoring options.

Figure A6. Example dialogue with Bark Plug