

Capstone Midterm Presentation

Nexteer (AI Bots) Team

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Introduction of the Team

Project Manager



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Database Management,
NLP, UI/UX



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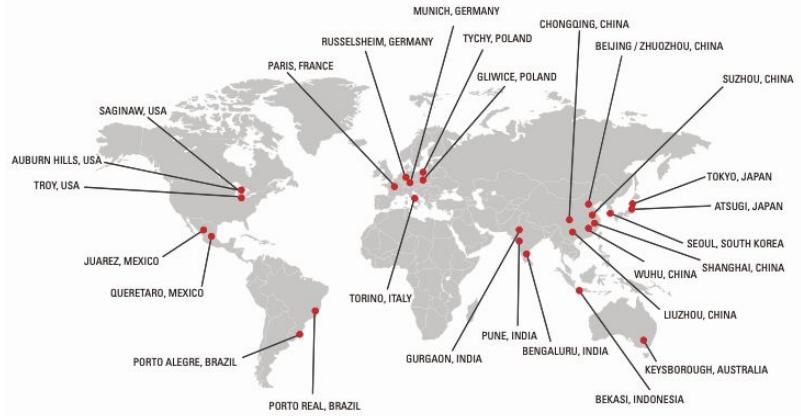
Deep Learning,
NLP, RAG,
LLMs



Louis Leng

Full-stack
Development

Background: Nexteer Automotive



- Global leading motion control technology company that specializes in automotive steering and driveline systems
- Aims to accelerate mobility that is safe, green, and exciting through innovative motion control technologies

Problem Statement

Nexteer's internal organization currently has multiple individual chatbots that each take care of a particular domain.

Pain points:

- Current chatbots lack the capability to accurately identify the domain of a question
- Query is not always redirected to the appropriate bot/expert
- Inefficiencies in process
- Decreased user satisfaction

Objectives/Outcomes

- Develop a chatbot dispatcher that can streamline the process of directing queries to the most appropriate chatbot based on their skills and access
 - Understanding the domain of user queries
 - Redirection logic
 - Metadata structure
 - Mechanism to validate user permission
- Our solution will work alongside existing chatbots — not replacing them

Deliverables

Proof of Concept (POC):

- A model that understands user query domain

- Redirection logic/demo of redirecting user to specialized chatbots

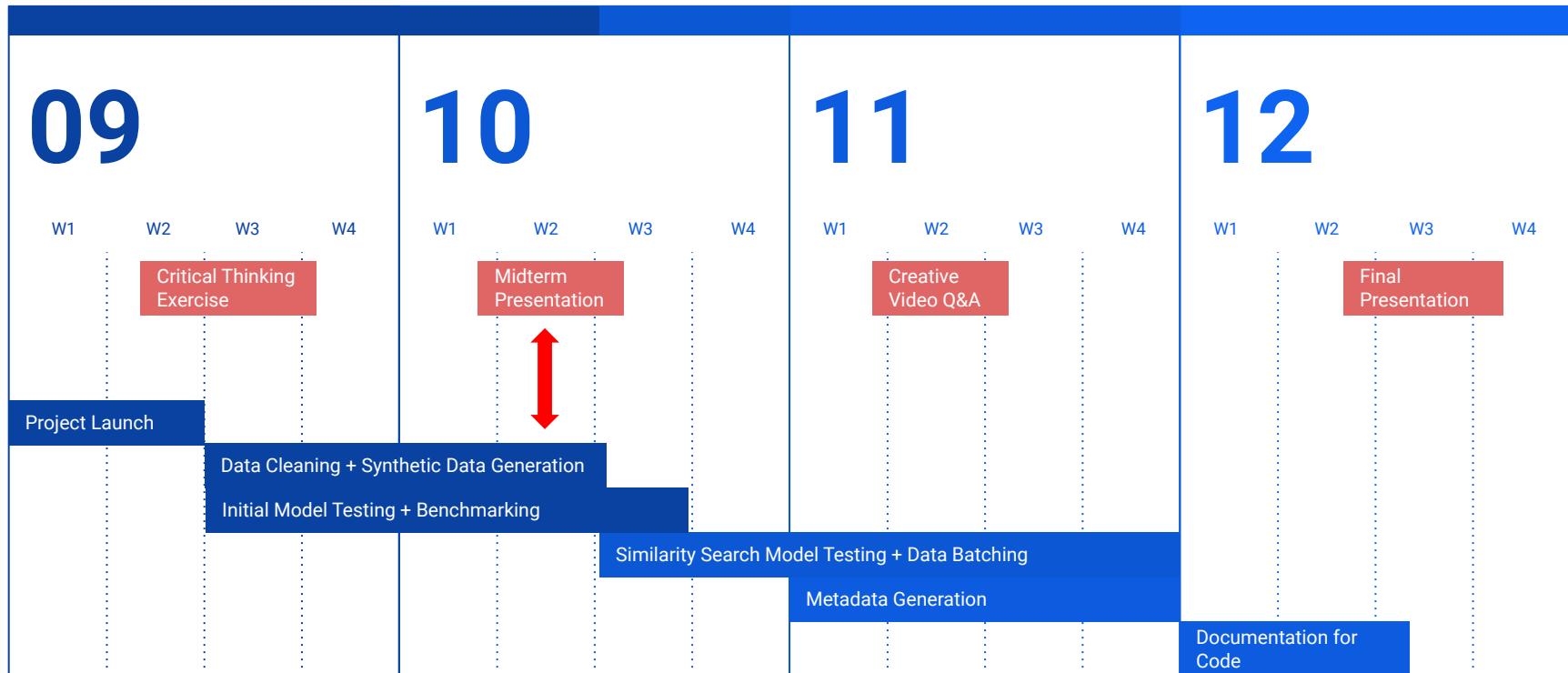
Specific items:

- Code (for testing model/redirection logic)

- Documentation

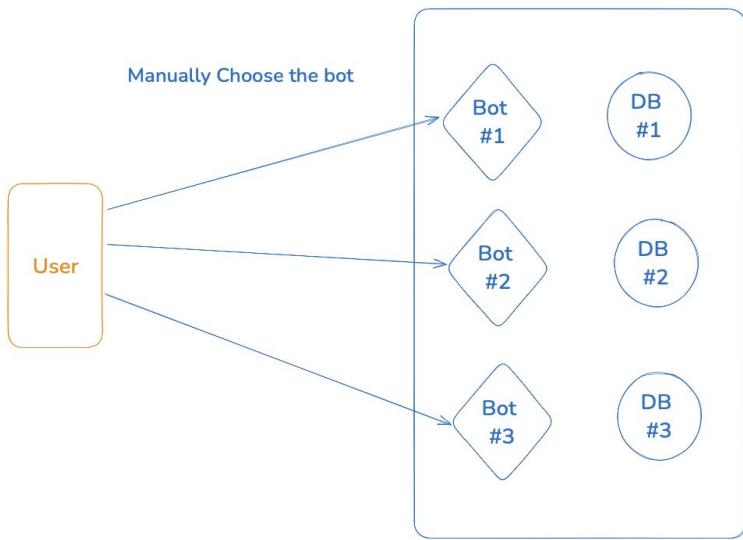
- Final Presentation

Project Schedule

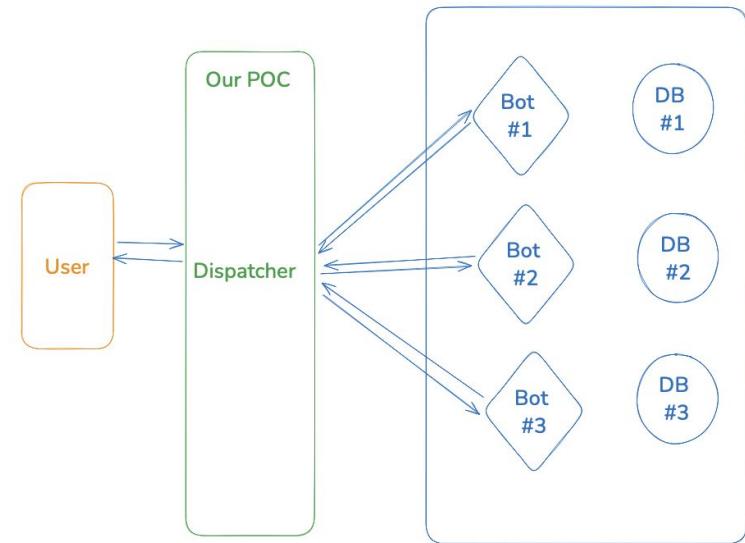


Before vs After

Current Situation



After POC



Types of Data and potential problems for the POC



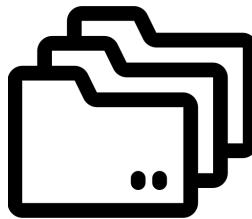
Chat History

Existing conversation history & user queries

Problem: Not easy-to-use format

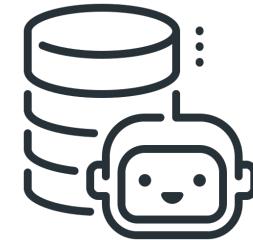
Solution:

- Clean the data for testing
- Generate Synthetic Data



Company Files

Files which chatbots use - like HR databases and financial documents



Chatbot Metadata

Information about the chatbots themselves

Problem: Not enough information stored

Solution:

- Propose a new schema for the metadata
- Generate 'dummy' metadata structure for testing

Cleaning Existing Conversation History

Problem: How do we *evaluate* the dispatcher we made?

- Difficult to assess key metrics like response relevance, satisfaction, or engagement
- Lack of clear data for analyzing chatbot behavior
- Inefficiency in comparing user needs vs. bot responses

Solution: *Use the existing data* of how the users are talking to the chatbots

- Extensive scripting to clean and make dataset of conversation history for testing after the POC is ready

The Conversation History Dataset

```
{  
  "_id": {  
    "$oid": "66612be4a416d8266c96157d"  
  },  
  "SessionId": "e0f8e343-101a-1861-1339-a50e83123127",  
  "History": "{\"type\": \"human\", \"data\": {\"content\": \"what is NSR\"},  
  \"AgentGuid\": \"GSM\",  
  \"AgentName\": \"GSM\",  
  \"EpochTime\": 1717658660.691448,  
  \"UserUPN\": \"b6167420-49db-4d6d-9280-009e0288fe46\",  
  \"QuestionGuid\": \"82444764-00eb-4562-9fe6-c74eb5ec0dc1\",  
  \"ResponseGuid\": \"8b148338-31ff-4836-951c-803bf9334b34\"}  
},  
{  
  "_id": {  
    "$oid": "66612be4a416d8266c96157e"  
  },  
  "SessionId": "e0f8e343-101a-1861-1339-a50e83123127",  
  "History": "{\"type\": \"ai\", \"data\": {\"content\": \"NSR st\"},  
  \"AgentGuid\": \"GSM\",  
  \"AgentName\": \"GSM\",  
  \"EpochTime\": 1717658660.758014,  
  \"UserUPN\": \"b6167420-49db-4d6d-9280-009e0288fe46\",  
  \"QuestionGuid\": \"82444764-00eb-4562-9fe6-c74eb5ec0dc1\",  
  \"ResponseGuid\": \"8b148338-31ff-4836-951c-803bf9334b34\"}  
},  
{  
  "_id": {  
    "$oid": "66619bc8613dc8bb428c9c23"  
  },  
  "SessionId": "ae5f3acd-06f6-0bb7-1f4e-f78cb92fe88e",  
  "History": "{\"type\": \"human\", \"data\": {\"content\": \"what is NSR\"},  
  \"AgentGuid\": \"GSM\",  
  \"AgentName\": \"GSM\",  
  \"EpochTime\": 171768304.88501,  
  \"UserUPN\": \"b6167420-49db-4d6d-9280-009e0288fe46\",  
  \"QuestionGuid\": \"2d69b667-5013-c1a8-e139-72db97cd231\",  
  \"ResponseGuid\": \"2f6a9d2e-9a79-4e12-b5f6-29920e180446\"}  
},
```

~100 lines of code

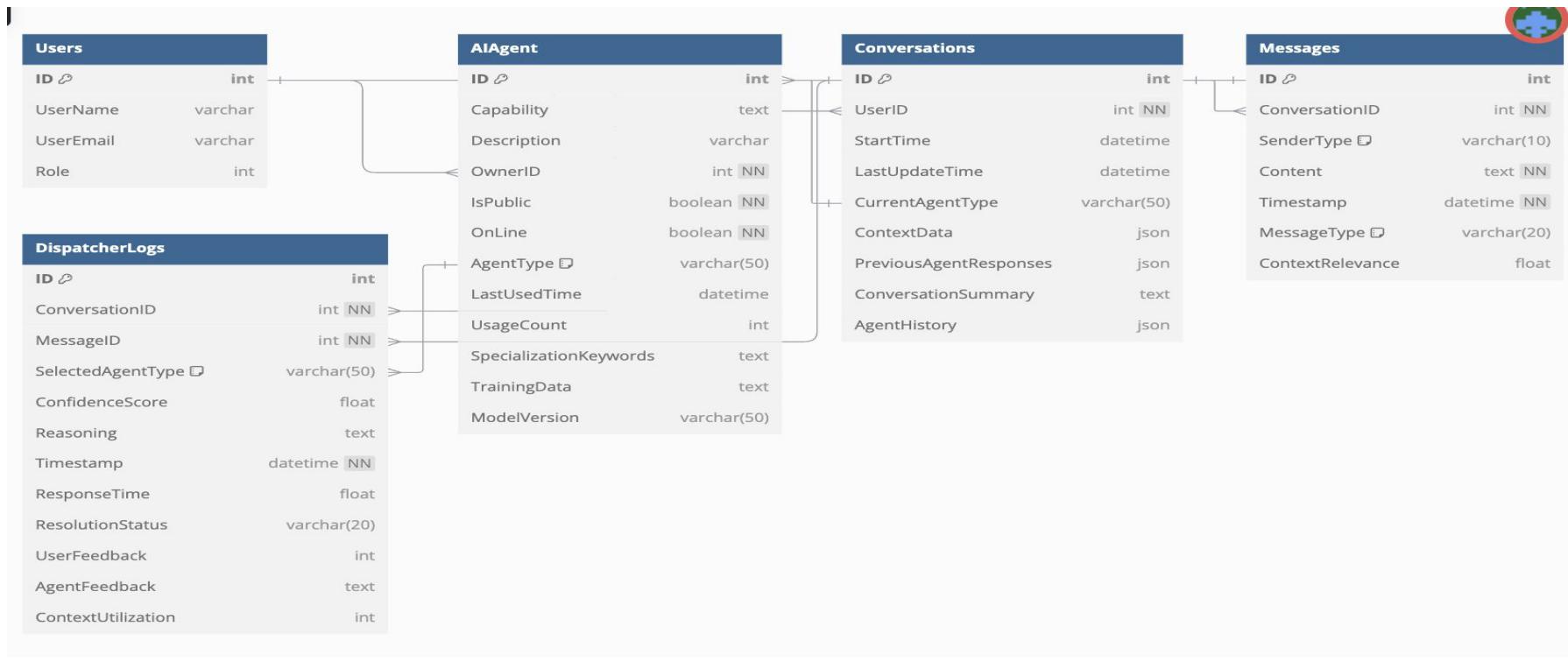
| Responding Agent | Question |
|--------------------------|---|
| GSM | what is NSR |
| GSM | what is NSR |
| GSM | what is NSR |
| GSM | What if I want to sell motor to Nexteer, how can I process? |
| GSM | What if I want to sell motor to Nexteer, how can I process? |
| CN-HR | 列出公司的福利政策? |
| CustomerRequirementAgent | Decompose customer requirement: "prevent steering lock in a high speed drive" |
| CustomerRequirementAgent | Decompose customer requirement: "prevent steering lock in a high speed drive" |
| CustomerRequirementAgent | i mean "steering lock" |
| CustomerRequirementAgent | Decompose customer requirement: "prevent steering lock in a high speed drive" |
| CN-HR | 工作10年以后，可以享受几天年假? |
| CN-HR | 列出公司的福利政策? |
| GSM | What if I want to sell motor to Nexteer, how can I process? |

Why create a new schema structure for the metadata?

- **Simplified Schema:** A well-structured data schema categorizes chat data for efficient management.
- **Quick Searches:** Metadata enables fast and precise searches within the chat history.
- **Accurate Modeling:** Metadata supports more accurate modeling of user interactions and AI agent performance.

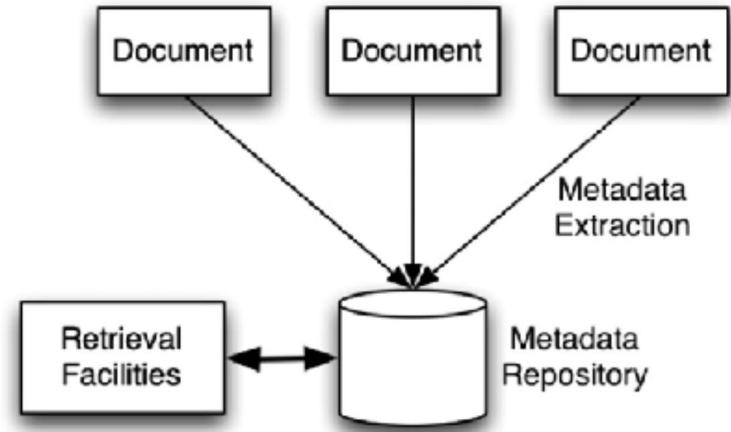
```
CREATE TABLE [dbo].[Users] (
    [ID] [int] IDENTITY(1,1) NOT NULL,
    [UPN] [nvarchar](max) NULL,
    [UserName] [nvarchar](max) NULL,
    [UserEmail] [nvarchar](max) NULL,
    [Role] [int] NOT NULL,
    [ActiveCategoryId] [int] NULL,
    [ActiveCategoryName] [nvarchar](250) NULL,
    [ContextID] [nvarchar](250) NULL,
    CONSTRAINT [PK_Users] PRIMARY KEY CLUSTERED
    (
        [ID] ASC
    )WITH (STATISTICS_NORECOMPUTE = OFF, IGNORE_DUP_KEY = OFF, OPTIMIZE_FOR_SEQUENTIAL_KEY = OFF) ON [PRIMARY]
) ON [PRIMARY] TEXTIMAGE_ON [PRIMARY]
GO
***** Object: Table [dbo].[UserScopes]    Script Date: 9/12/2024 2:43:49 PM *****/
SET ANSI_NULLS ON
GO
SET QUOTED_IDENTIFIER ON
GO
CREATE TABLE [dbo].[UserScopes](
    [ID] [int] IDENTITY(1,1) NOT NULL,
    [CategoryId] [int] NOT NULL,
    [UserID] [int] NOT NULL,
    CONSTRAINT [PK_UserScopes] PRIMARY KEY CLUSTERED
    (
        [ID] ASC
    )WITH (STATISTICS_NORECOMPUTE = OFF, IGNORE_DUP_KEY = OFF, OPTIMIZE_FOR_SEQUENTIAL_KEY = OFF) ON [PRIMARY]
) ON [PRIMARY]
```

Proposed Schema

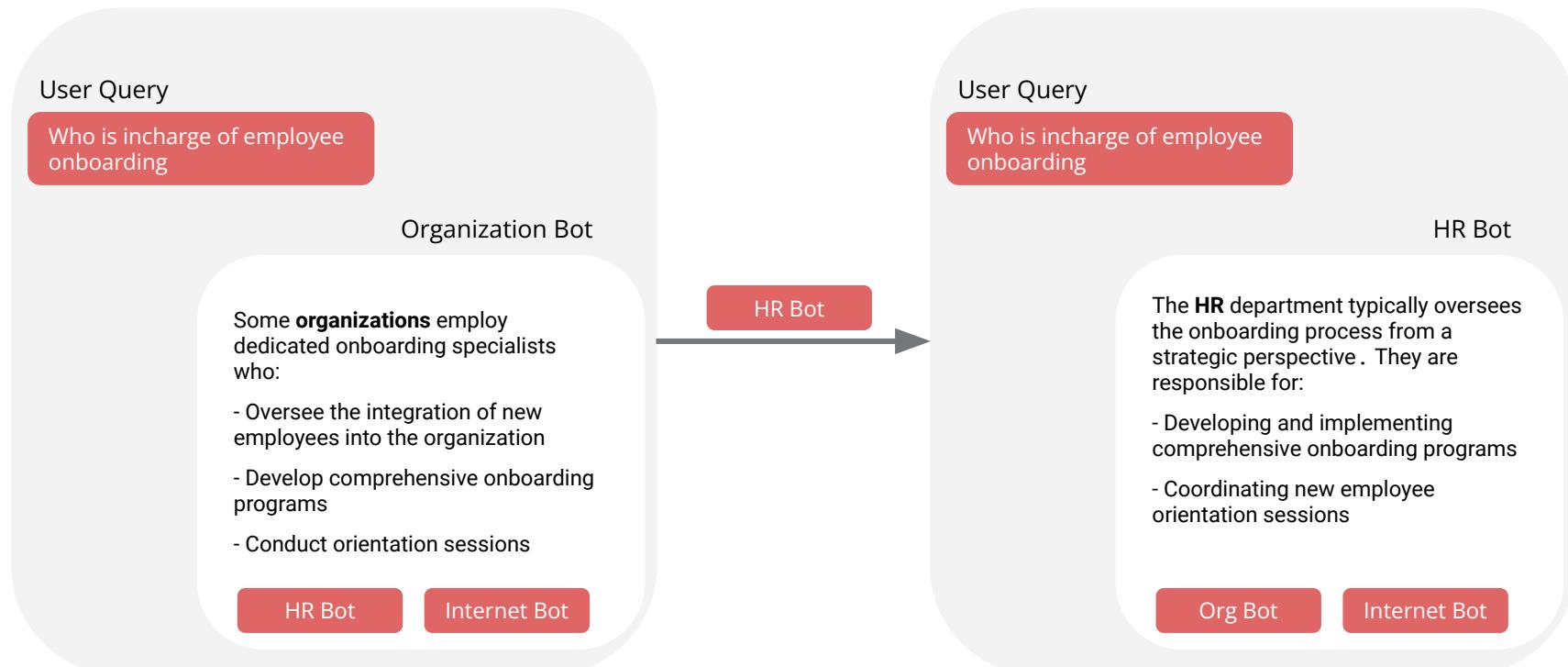


Next Steps: Metadata Generation

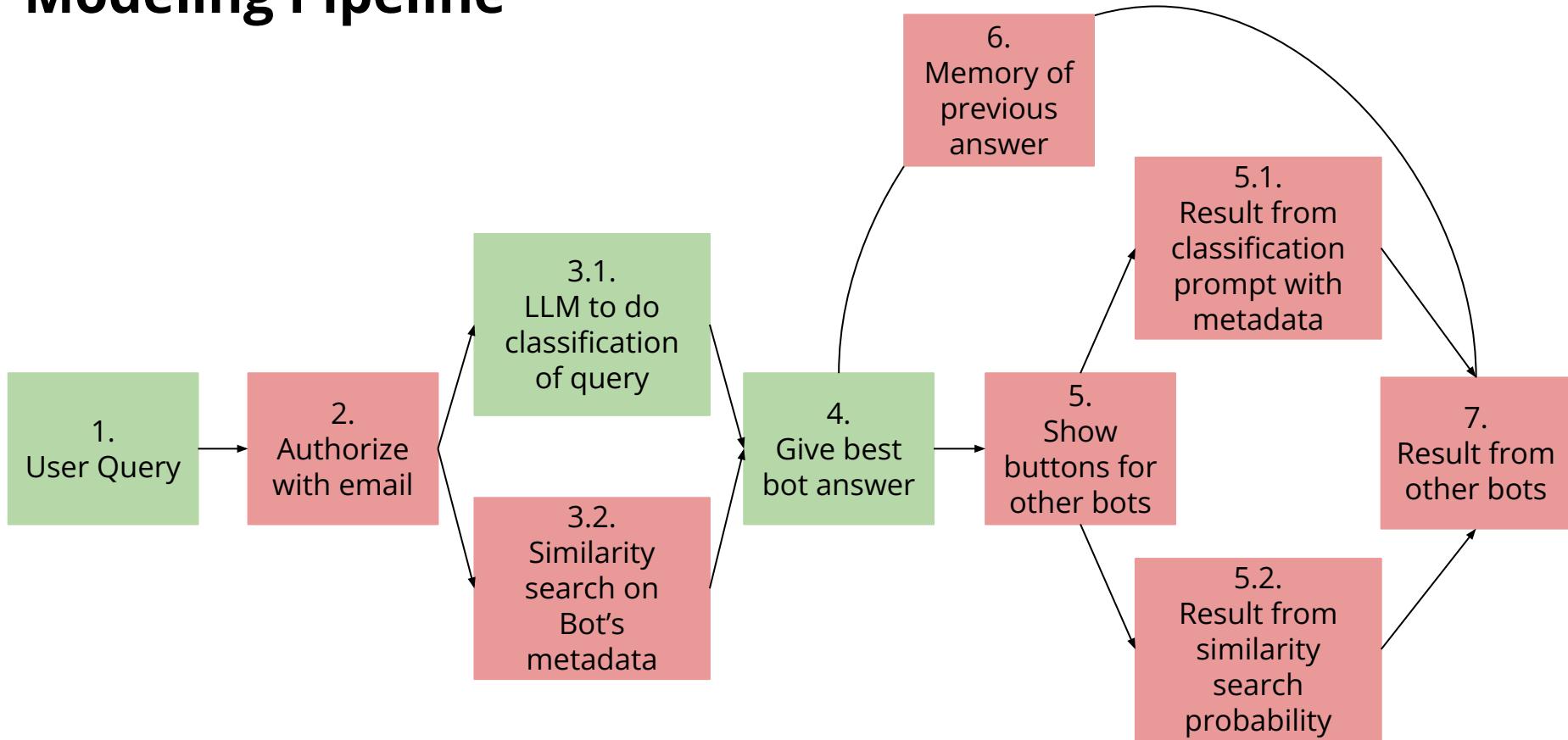
- **Emulate Chatbots:** Create simulated chatbot history.
- **Generate Metadata:** Automatically create metadata.
- **Test and Evaluate:** Assess metadata effectiveness.
- **Develop Documentation:** Write clear documentation for the database schema.



Model Dispatcher Expectations



Modeling Pipeline



Modeling Approach

Prompt with metadata

- Creating JSON of each bot's metadata
- Including that JSON into the prompt
- Let the LLM classify based on metadata

Advantages:

- Language model's understanding of context
- Can handle complex classification criteria
- Easily updatable by modifying the prompt

Disadvantages:

- Potential for hallucinations or misclassification
- More tokens, potentially increasing costs
- Slower for a large number of bots

Similarity search on metadata

- Creating JSON of each bot's metadata
- Doing similarity search of user query on JSON
- Get probability of similarity for each bot

Advantages:

- Very fast, especially with libraries like FAISS
- Scales well to a large number of bots
- Less prone to hallucinations

Disadvantages:

- Miss nuanced relationships that a language model could catch
- Additional infrastructure for vector storage and search

Model Trade Offs

1. Evaluate the trade-offs between accuracy and computational resources for our specific use case
2. Consider the number of bots and the frequency of updates to bot metadata
3. Test both approaches with your actual data to compare performance and accuracy

Synthetic User Query Generation

Real user data: Available sparsely, lots of invalid data and not enough to train/test AI models

| | |
|---|---|
| 1 | User Queries |
| 2 | å~—å‡ºå...¬å, çš,,ç!å~©æ”¿ç--í¼Ý |
| 3 | how can a supplier to meet it? |
| 4 | Which division most have the customers? |

Benefits of using synthetic data:

1. Can create any “x” number of rows of user queries and labels as required
2. Easy to create balanced data for different chatbots.
3. We started with 4 demo classes for the POC: Customer Search, Internet Search, Organizational Information, Generic.

Synthetic User Query Generation



Utilized different AI to generate synthetic user queries to provide correctness and prevent one AI from relying on or repeating previous answers.



Study the files with the actual user data and generate some "actual" user queries and the chat bot these user should be redirected to.

Certainly. I'll generate the first 50 new questions based on the patterns observed in the provided file. Here they are:

1. "What was our customer acquisition cost last quarter?", Customer Database Search
2. "Who is in charge of employee onboarding?", Organizational Information
3. "What are the latest developments in renewable energy?", Internet Search
4. "Can you provide a list of customers who haven't made a purchase in 6 months?", Customer Database Search
5. "What's the procedure for requesting time off?", Organizational Information
6. "Find the top-rated restaurants in my city.", Internet Search
7. "What's the average customer lifetime value for our premium subscribers?", Customer Database Search

OpenAI Bot Demo

≡ Nexteer Redirect AI Bot ▾



Nexteer Redirect AI Bot

By Louis Leng ✎

This AI bot would receive a question from the user and return a which bot it should redirect.

Is our CEO
available for a
meeting today?

Message Nexteer Redirect AI Bot



ChatGPT can make mistakes. Check important info.

Simulating Actual Usage for Nexteer

Replicated real-world scenarios by utilizing both real-world and synthetic data to simulate diverse user interactions, improving categorization accuracy and enhancing the bot's ability to handle various queries effectively.



Test off-the-shelf LLM models for classifying user queries

Testing Criteria: Give the synthetic user queries to GPT and Gemini Model with the same prompt and monitor effectiveness at classification

```
prompt_base = """  
You are an expert at classifying user queries into the following categories:  
'Customer Database Search', 'Organizational Information', 'Internet Search', and 'Generic'.  
Here are some correctly classified examples:
```

1. "How many parts did Ford purchase in 2021?" | Customer Database Search
2. "Who is the manager of the sales department?" | Organizational Information
3. "What is the weather tomorrow?" | Internet Search
4. "Hello, how are you today?" | Generic

Now, classify the following queries.
For each query, provide the label separated by a '|'.
Only output the query and the predicted label.
"""

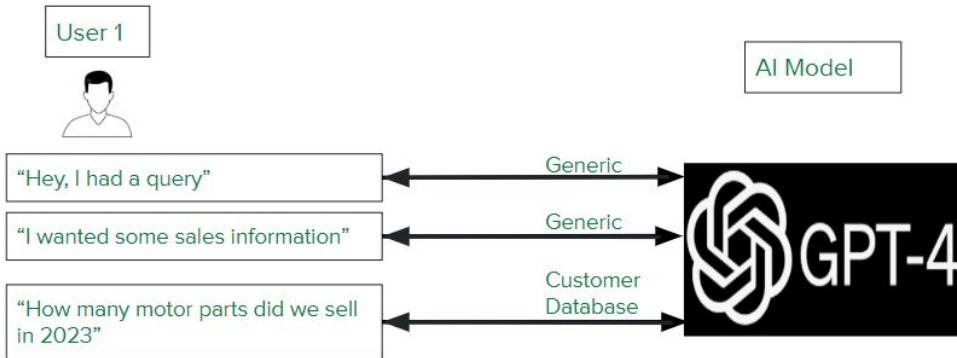
Test off-the-shelf LLM models for classifying user queries

Testing Results: While GPT 4o and Gemini API-based models offer similar accuracy, GPT 4o-mini was **4.5x faster**

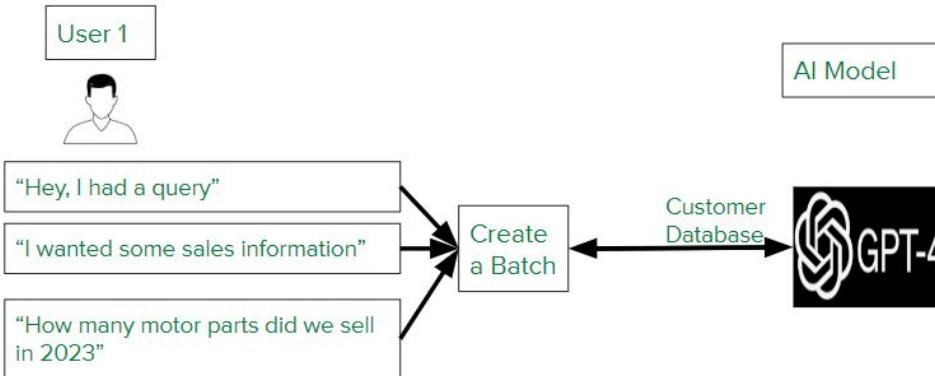
| Model | Accuracy | Inference Time(seconds) |
|--------------|----------|-------------------------|
| Gemini | 97.3% | 3.08 |
| GPT(4o-mini) | 96.7% | 0.67 |

Next Steps: Data Batching

Current Method:



Proposed Method:



Next Steps: Data Batching

Key Idea: Not all user queries are useful in classifying user domain. Batch queries together to improve inference time.

We have started experimenting with batch size=1,2,3 and will monitor its effect on classification accuracy.

Summary of Next Steps

1. Explore automated metadata generation based on proposed schema
2. Conduct data batching experiment
3. User query similarity search with metadata
4. Benchmark open-source Llama 3.2 performance on classification of user queries
5. Test LLM model performance with more metadata in prompts (JSON key-value pairs)

Thank You

Q&A