AlumConnect: Intelligent Alumni Discovery & Insights using RAG and LLM

- MODULE EBA5004 PRACTICAL LANGUAGE PROCESSING
- TEAM GROUP 18
- TEAM MEMBERS :
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INTRODUCTION

Gaps in Career Mapping & Alumni Insights:

1. Difficulty in Mapping Resumes to Job Market Trends

- Job descriptions evolve rapidly with emerging tools, roles, and technologies
- Resumes often lack alignment with real-time industry expectations
- Students and early professionals struggle to understand what skills are truly in demand

2. Alumni Data Underutilized in Career Preparation

- Alumni possess valuable real-world insights, but this data is scattered or hidden
- Traditional career tools do not leverage alumni journeys for personalized guidance
- Missed opportunity to showcase how specific roles and skills connect to actual career paths

3. Need for Automated, Intelligent Matching Systems

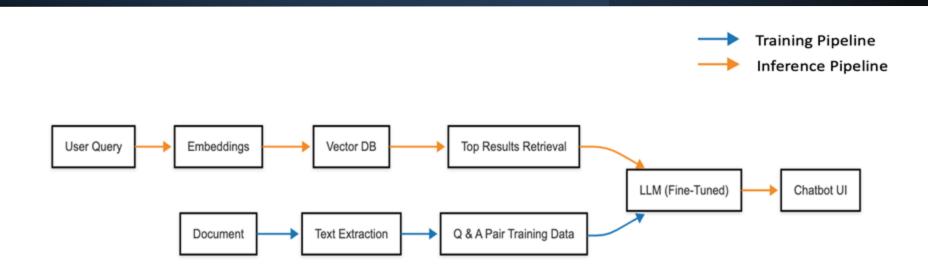
- Manual search is time-consuming and often leads to irrelevant results
- Existing platforms lack contextual understanding of user queries and profiles
- Al can bridge this gap by intelligently linking user intent to relevant alumni data

INTRODUCTION

SOLUTION WE ARE PROPOSING:

• To develop an Al-powered alumni search chatbot that efficiently retrieves and presents alumni profiles based on job titles, companies, industries, and skills.

HIGH LEVEL DIAGRAM



The diagram represents the Al-powered Alumni Search Chatbot architecture, integrating Retrieval-Augmented Generation (RAG) with LLM fine-tuning.

The system operates in two main workflows:

- 1. Retrieval Workflow (Top Row) active during inference
- 2. Fine-Tuning Workflow (Bottom Row) Training pipeline

HIGH LEVEL DIAGRAM

1) Retrieval Workflow (Top Row) – active during inference:

A user query is processed into embeddings using a pre-trained model. The embeddings are stored and searched in a vector database. Relevant alumni profiles are retrieved based on similarity and ranking. The LLM (Fine-Tuned) generates a context-aware response based on the retrieved results. The chatbot UI delivers a natural language response to the user.

2) Fine-Tuning Workflow (Bottom Row) – Training pipeline:

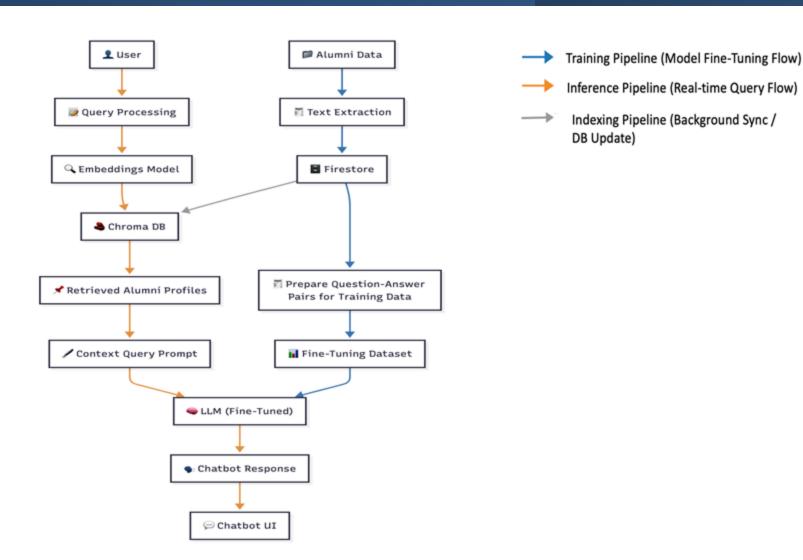
Alumni resumes/documents are extracted for structured data processing.

Extracted text is converted into Q&A pairs to create high-quality training data.

These Q&A pairs are used to fine-tune the LLM for improved alumni-related query responses. The fine-tuned LLM integrates both real-time retrieval (RAG) and fine-tuned knowledge to ensure responses are accurate, contextual, and continuously improving.

This dual approach ensures the chatbot effectively balances retrieval efficiency with deep contextual learning, providing high-quality alumni search results.

FLOWCHART FOR TRAINING AND INFERENCE PIPELINES



PROJECT ROADMAP

- Data Collection & Processing
- Fine-Tuning Llama 3 with QA Pairs
- Backend API Development
- Implementing RAG for Intelligent Search for Gemini & Llama models
- Chatbot UI Development & Integration
- Inference testing
- Performance Comparison of Gemini & Llama models

MODELS AND TOOLS USED

MODELS USED

Llama model:

- Version : Meta-Llama-3-8B-Instruct
- We have fine-tuned this model with our dataset and integrated with RAG during inference.

Gemini model:

- Version : gemini-1.5-flash
- We have used this pretrained model for comparison with the finetuned model.

TOOLS AND FRAMEWORKS

- Coding Environment: Google Collab
- Database Tools: Firestore
- Vector Stores: Qdrant, ChromaDB
- Embedding Models: Sentence Transformers (all-MiniLM-L6-v2), Google Generative Al Embeddings
- LLM Integration Tools:
 - LangChain (chains, memory, prompt templates)
 - Google Generative AI (via langchain-google-genai)
 - Ngrok (for local-to-web LLM API exposure in early prototype)
- Configuration: python-dotenv (for API keys & environment variables)
- Utility Libraries: requests, json, tqdm, shutil, traceback, re
- UI Framework: Gradio

RUNTIME ENVIRONMENT

Component	Value	
Platform	Google Collab Notebooks	
GPU Used	NVIDIA T4 (16GB VRAM)	
Training Strategy (fine tuning Llama)	20 batches × 4 hours = 80 hours total	
Checkpointing	Intermediate checkpoints saved to resume from failures and for inference testing	

IMPLEMENTATION

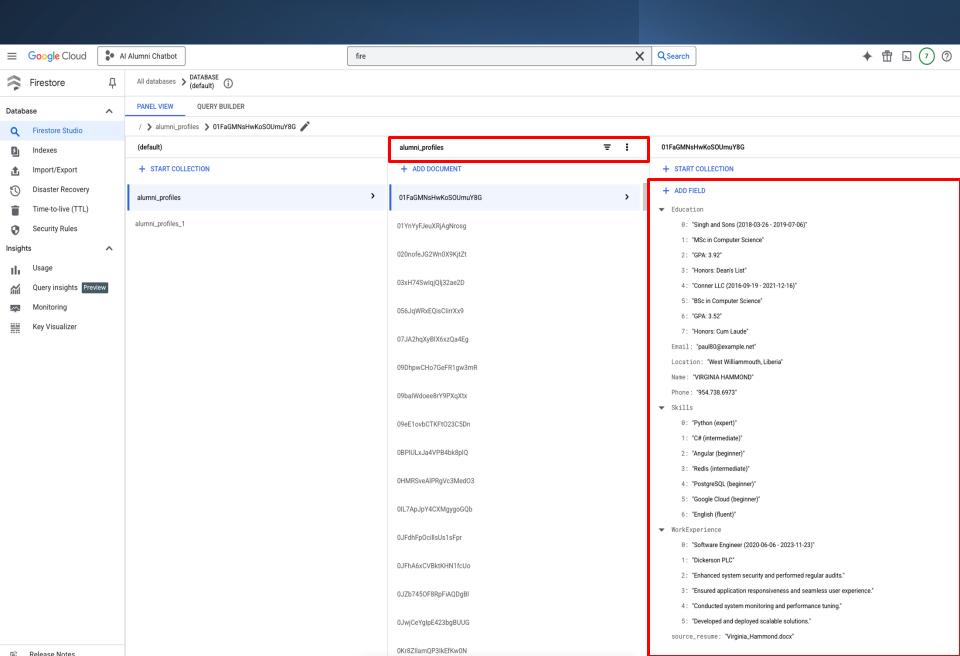
DATASET PREPARATION

Dataset sources : We used synthetic datasets generated from around 3500 resumes in Kaggle.

Resume Text Extraction:

- Notebook: 1_Resume_Text_Extraction_N_To_DB_Firestore.ipynb
- Reads resume records from .json source and .txt source
- Parses fields like: name, email, contact, location, job_title, experience, skills, education, languages, etc.
- Uses simple string manipulation and regex-based heuristics to identify sections from text.
- Each parsed resume is formatted into a Python dict with consistent field keys.
- The cleaned records are uploaded to Google Firestore:
 - Collection name: alumni profiles
 - Each document has a unique Firestore ID.

EXTRACTED DATA STORED IN GOOGLE FIRESTORE DB



DATASET PREPARATION

Q&A Pair Generation

- Notebook: 2_Prepare_Q_&_A_Pairs.ipynb
- Loads the alumni profiles from Firestore.
- For each record, it:
 - Constructs multiple hardcoded questions (e.g., "Who has skills in Python?", "Who worked at DBS?")
 - Builds corresponding answers using the record's fields.
- Formats these into OpenChat-style JSONL pairs:

TRAINING, RAG - INFERENCE USING LLAMA

LLM FINETUNING - QLoRA (LLAMA)

- Fine-tune the LLaMA 3 model on custom alumni Q&A data using QLoRA, optimized for constrained GPU environments (Collab T4).
- Loads the previously generated .jsonl dataset.
- Tokenizes data using a LLaMA-compatible tokenizer.
- Uses transformers, peft, and bitsandbytes to set up QLoRA fine-tuning:
 - Model: meta-llama/Meta-Llama-3-8B-Instruct
 - LoRA Config:
 - r = 32
 - lora_alpha = 64
 - lora_dropout = 0.05
 - Target modules: q proj, v proj, k proj, o proj
 - Quantization: 4-bit via bnb_4bit

LLM FINETUNING - QLoRA (LLAMA)

Training config:

- Optimizer: AdamW
- Learning Rate: 2e-5
- Batch size: 4 × accumulation steps 4 → effective batch = 16
- Precision: fp16 with gradient checkpointing
- Checkpoints: saved every 500 steps
- Total steps: 20230

RAG IMPLEMENTATION (LLAMA)

Embedding Model:

all-MiniLM-L6-v2 via SentenceTransformer

Vector Store:

QdrantClient – hosted remotely

Retrieval Process:

Manually queries Qdrant using vector similarity search

Query Flow:

- User inputs query
- Text converted to embedding
- Qdrant returns top similar documents
- Documents + query passed to custom LLM endpoint via requests.post (Ngrok tunnel)

INFERENCE (LLAMA)

Step 1: User Query

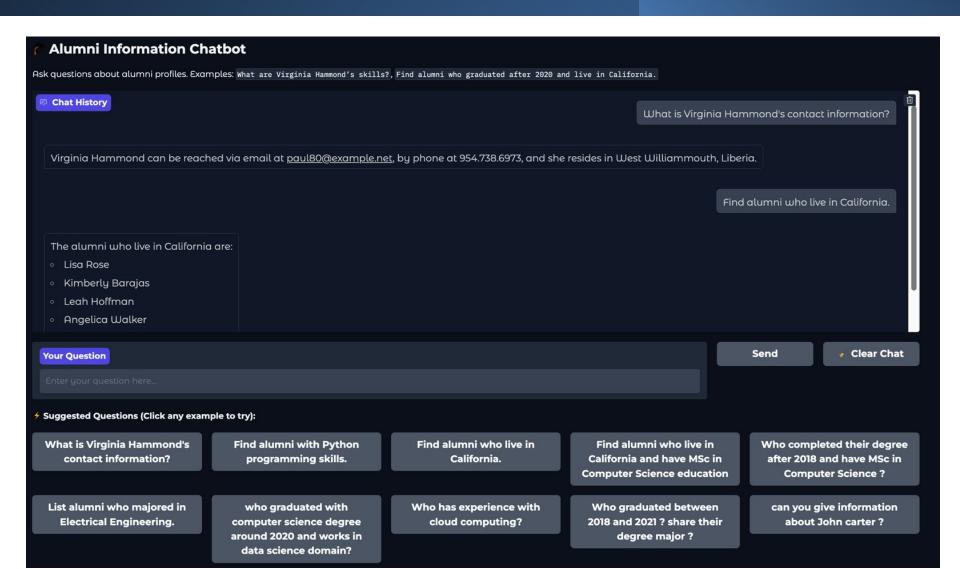
Input query captured via Gradio interface

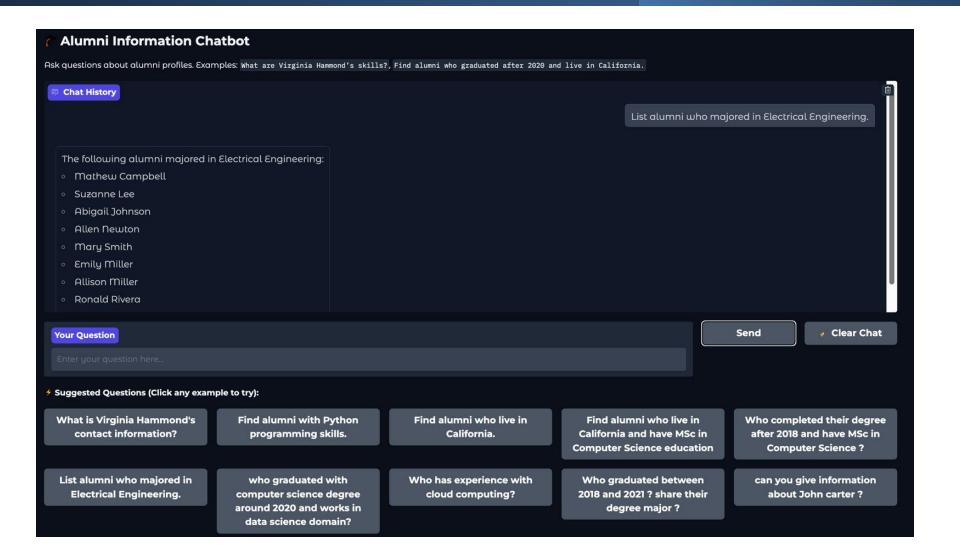
Step 2: Document Retrieval

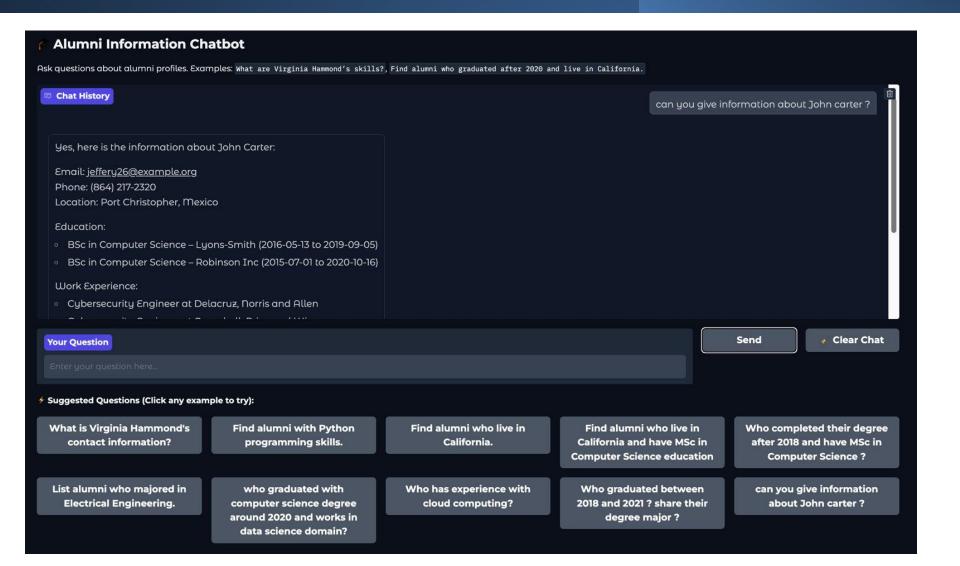
- Query is embedded using SentenceTransformer
- Embedding passed to QdrantClient (RAG DB) for similarity search

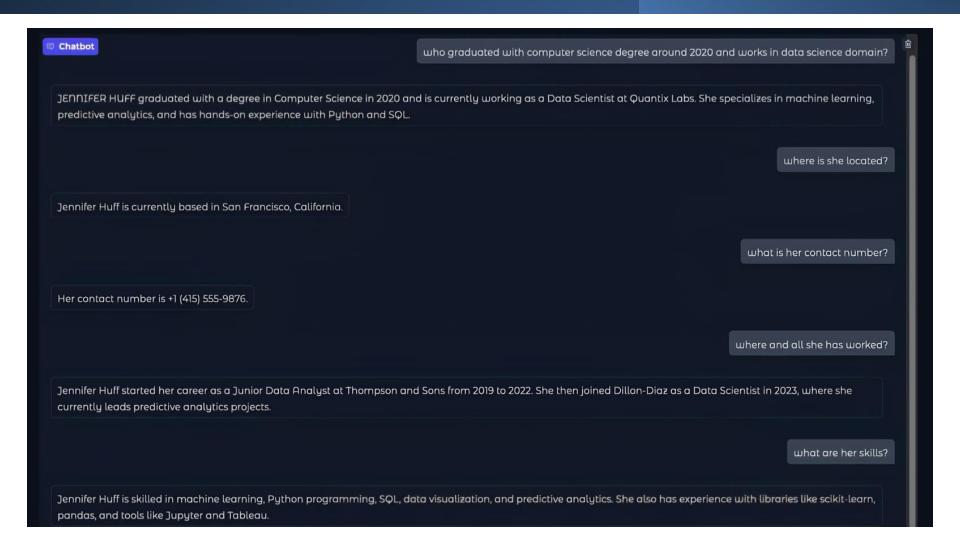
Step 3: LLM Inference

- Retrieved documents + user query are sent via POST request to the fine tuned Llama LLM endpoint exposed using Ngrok.
- Custom API performs text generation using this model.









RAG & INFERENCE USING GEMINI

RAG IMPLEMENTATION (GEMINI)

Data Source:

Extracted resume data is imported from Google Firestore DB.

Embedding Model:

GoogleGenerativeAIEmbeddings via langchain-google-genai embedding-001

Vector Store:

ChromaDB – embedded, fast local storage

Retriever:

.as_retriever() – wraps vector store into a retriever interface

Query Flow:

- User query passed to ConversationalRetrievalChain
- Retriever pulls relevant chunks from ChromaDB
- ChatGoogleGenerativeAI responds using prompt template + context

INFERENCE (GEMINI)

Step 1: User Query

Handled through Gradio chat interface

Step 2: Context Retrieval

- Embedding generated using GoogleGenerativeAIEmbeddings
- Chroma vector store used to fetch relevant chunks

Step 3: LLM Inference with Memory

- Query and retrieved documents passed to LangChain's ConversationalRetrievalChain
- Uses ChatGoogleGenerativeAI to generate responses with context from ConversationBufferMemory (temperature = 0.2)
- retrieved_docs = retrieve_with_reranking(query, metadata_filter, k=kwargs.get('k', 10))
- Prompt templates provide structured guidance

PSEUDO CODE (GEMINI)

// Initialize services

SET API_KEYS and ENDPOINTS for vector_database and language_model

CREATE vector_database_client and sentence_embedder

// Core function to answer queries

```
FUNCTION answer_query(query):
   // Vector search
   query_vector = embed(query)
   profiles = search_vector_database(query_vector,
limit=5)
```

// Format results for context

```
IF profiles exist THEN
  context = format_profiles(profiles)
ELSE
  context = "No relevant profiles found."
```

// Get LLM response

prompt = build_prompt(context, query)
return get_llm_response(prompt)

// UI handler functions

FUNCTION respond(message, history):
 reply = answer_query(message)
 ADD message and reply TO history
 RETURN updated_history

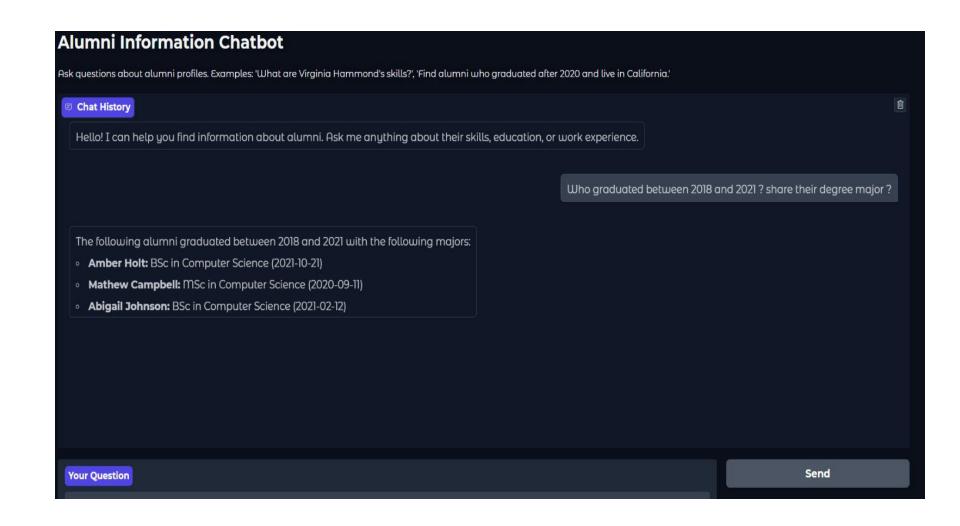
FUNCTION clear():
 RETURN empty_history

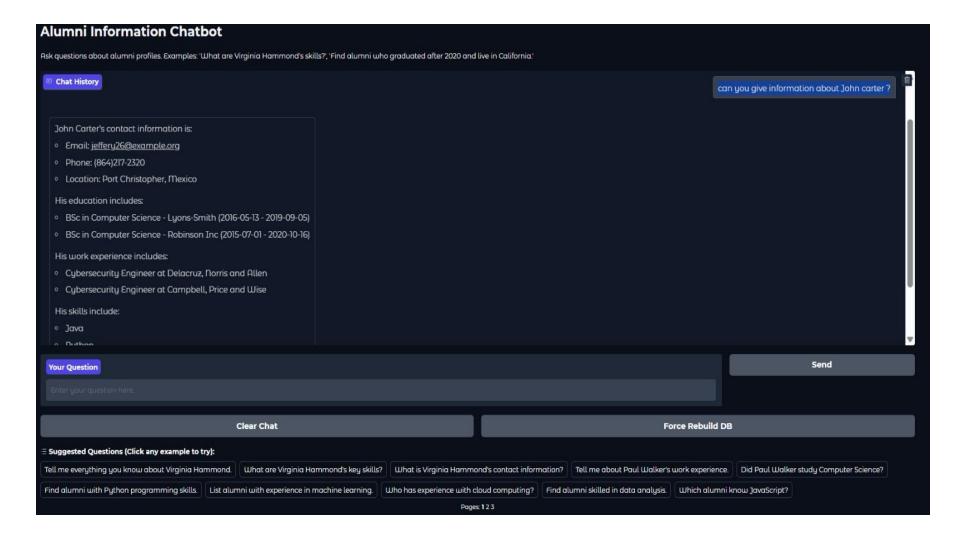
// UI setup

CREATE chat_interface with:

- Chatbot component
- Text input
- Send and Clear buttons

CONNECT buttons to handler functions LAUNCH interface





The following alumni completed an MSc in Computer Science after 2018:

- Lisa Rose (2022-12-13)
- o Kimberly Barajas (2021-09-13)
- Eric Le (2021-06-03)
- Leah Hoffman (2021-06-13)
- Philip Welch (2022-04-04)

Who completed their degree after 2018 and have MSc in Computer Science? Share their contact as well

The following alumni completed their MSc in Computer Science after 2018:

- Lisa Rose: Email: tanya48@example.com, Location: Cathychester, Luxembourg, Phone: 242-468-2730
- o Kimberly Barajas: Email: wellsmichelle@example.net, Location: Carlosberg, Saint Kitts and Nevis, Phone: 960-994-1820
- Leah Hoffman: Email: <u>brian99@example.net</u>, Location: Andrewsbury, Nigeria, Phone: 413-485-1533

e Ford: MSc in Computer Science (2015-09-28 - 2019-03-17) Chat History Christopher Lopez: BSc in Computer Science (2018-11-17 - 2020-11-12), BSc in Computer Science (2015-08-21 - 2021-11-09) Find alumni who live in California and have MSc in Computer Science education The following alumni have an MSc in Computer Science: Lisa Rose: Jones, Villegas and Williamson (2018-08-29 - 2022-12-13) Emily Miller: Johnson PLC (2016-02-21 - 2021-04-26) Kimberly Barajas: Mitchell, Wilson and Diaz (2017-05-15 - 2021-09-13) Melissa Watson: Leon Ltd (2018-12-09 - 2022-08-14) Michelle Owens: Morgan Inc (2017-07-22 - 2022-08-21) Angelica Walker: Henson, Nichols and Lewis (2016-12-05 - 2019-07-17) Lisa Williamson: Kennedy, Scott and Schmidt (2017-03-14 - 2019-08-13) Leah Hoffman: Campos, Doyle and Townsend (2018-04-17 - 2021-06-13) Jacqueline Ford: Rogers, Cortez and Scott (2015-09-28 - 2019-03-17) Send **Your Question**

EVALUATIONS AND RESULTS

EVALUATION: ROUGE SCORES

What is ROUGE?

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is a metric used to evaluate text generation quality by comparing model responses to reference answers. It is widely adopted in tasks like summarization and question answering.

ROUGE-1 F1:

- Measures word-level overlap (unigrams) between the generated answer and the reference.
- The **F1 score** balances precision (accuracy of words used) and recall (coverage of key words).

ROUGE-L F1:

 Based on the Longest Common Subsequence (LCS) — measures how well the sequence and structure of the generated text matches the reference, rewarding coherence.

EVALUATION: ROUGE SCORES

QUESTION	RESPONSE LLAMA	RESPONSE GEMINI	ROUGE-1 F1	ROUGE-L F1
What is Virginia Hammond's contact	Virginia Hammond can be reached via emai	Virginia Hammond's contact informa	0.619047619	0.619047619
Find alumni with Python programming	Alumni skilled in Python for data analysis and	Virginia Hammond: "Perfected data	0.417910448	0.328358209
Find alumni who live in California.	The alumni who live in California and have a	The following alumni studied Comput	0.179245283	0.141509434
Find alumni who live in California and have MSc in Computer Science education ?	The following alumni live in California and ha	The following alumni have an MSc in	0.323529412	0.308823529
Who completed their degree after 2018?	The following alumni completed their degre	The following alumni completed degr	0.99543379	0.99543379
Who completed their degree after 2018 and have MSc in Computer Science ?	The following alumni completed their degre	Lisa Rose (2022-12-13)Kimberly Bara	0.55555556	0.55555556
List alumni who majored in Electrical	The following alumni majored in Electrical E	Mathew CampbellSuzanne LeeAbiga	0.837209302	0.837209302
who graduated with computer science degree around 2020	The following alumni graduated with a Com	The following alumni completed a Co	0.947368421	0.947368421
who graduated with computer science degree around 2020 and works in data	This question cannot be answered definitive	I cannot answer this question. The pr	0.329896907	0.226804124
Who graduated between 2018 and 2021? share their degree major?	The following alumni graduated between 20	The following alumni graduated betv	0.902439024	0.902439024
can you give information about John carter	Yes, here is the information about John Cart	Email: jeffery26@example.orgPhone	0.875912409	0.875912409

EVALUATION: ROUGE SCORES

From the scores, what we see is:

High Scores (ROUGE > 0.9)

- Example: "Who completed their degree after 2018?"
- Both finetuned LLaMA and Gemini scored ~0.995 on ROUGE-1 and ROUGE-L, indicating highly accurate and well-aligned responses.
- Example: "Graduated between 2018 and 2021?"
- Gemini scored 0.90+, reflecting strong understanding of date-based queries.

Mid Scores (ROUGE 0.5-0.8)

- Example: "Majored in Electrical" Gemini reached ~0.83
- Shows partial match with correct names and degrees, but possible variation in wording.

Low Scores (ROUGE < 0.4)

- Example: "Alumni in California" finetuned LLaMA scored 0.17, Gemini slightly better.
- Indicates vague, incomplete, or hallucinated responses likely due to insufficient or noisy context.
- "Graduated around 2020 and works in data" Poor scores reflect inability to handle compound filters in a single query.

EVALUATION: RESPONSE COMPARISON

	QUESTION	RESPONSE LLAMA	RESPONSE GEMINI
		Virginia Hammond can be reached via	Virginia Hammond's contact information is:
	formation?	email at paul80@example.net, by phone at 954.738.6973, and she resides in West Williammouth, Liberia.	Email: paul80@example.net Phone: 954.738.6973 Location: West Williammouth, Liberia
	nd alumni with Python ogramming skills.	Alumni skilled in Python for data analysis and visualization include Virginia Hammond, John Smith, Alice Johnson, and Bob Williams.	Virginia Hammond: "Perfected data analysis and data visualization using Python and Tableau." John Smith: "Perfected data analysis and data visualization using Python and Tableau." Alice Johnson: "Perfected data analysis and data visualization using Python and Tableau." Bob Williams: "Perfected data analysis and data visualization using Python and Tableau."
The alumni who live in California and have an MSc in Computer Science are: Lisa Rose Kimberly Barajas Leah Hoffman Angelica Walker Jacqueline Ford Lisa Williamson		an MSc in Computer Science are: • Lisa Rose • Kimberly Barajas • Leah Hoffman • Angelica Walker • Jacqueline Ford	The following alumni studied Computer Science: Michael Bartlett: BSc in Computer Science (2017-08-18 - 2022-11-28), MSc in Computer Science (2018-09-09 - 2021-07-04) Angelica Walker: BSc in Computer Science (2017-08-12 - 2023-02-03), MSc in Computer Science (2016-12-05 - 2019-07-17) Mathew Campbell: BSc in Computer Science (2015-04-07 - 2021-10-01), MSc in Computer Science (2017-10-10 - 2020-09-11) Lisa Williamson: MSc in Computer Science (2017-03-14 - 2019-08-13), MSc in Computer Science (2015-04-02 - 2022-03-23) Chris Allen: BSc in Computer Science (2016-07-04 - 2022-01-05), BSc in Computer Science (2016-09-09 - 2019-10-12) Lisa Rose: MSc in Computer Science (2018-08-29 - 2022-12-13) Kimberly Barajas: MSc in Computer Science (2017-05-15 - 2021-09-13) Leah Hoffman: MSc in Computer Science (2018-04-17 - 2021-06-13) Jacqueline Ford: MSc in Computer Science (2018-09-28 - 2019-03-17) Christopher Lopez: BSc in Computer Science (2018-11-17 - 2020-11-12), BSc in Computer Science (2015-08-21 - 2021-11-09)

CHALLENGES AND LIMITATIONS

GPU Constraints

- Running embedding models, inference, or fine-tuned LLMs locally or on limited Colab tiers often hits **memory and compute bottlenecks**.
- Real-time inference, especially with context-aware models, demands efficient model selection or offloading to cloud APIs, which adds cost and latency trade-offs.

Hallucinations in LLM Outputs

- Large Language Models sometimes generate plausible-sounding but factually incorrect answers, especially when alumni data is sparse or loosely structured.
- This can mislead users during career planning or alumni research, making it crucial to improve retrieval grounding and control prompt engineering.

CHALLENGES AND LIMITATIONS

ngrok Free Hosting Constraints

Using ngrok's free tier for hosting backend services (e.g., LLMs or APIs) introduces significant performance and availability limitations.

Prompt-Template Instructional Fragility

- Cascade-effect edits Any tweak to the prompt's instruction stack (e.g., adding stricter citation wording) unexpectedly shifted answers for unrelated queries. The template proved brittle: improving one case routinely broke another, so every minor change demanded a full regression sweep.
- Guideline overload vs. clarity Packing tone, length, citation, and safety
 rules into a single template left the LLM juggling too many directions. We
 found that past a certain density, instructions began to blur together,
 reducing response consistency and forcing painful trade-offs between
 coverage and clarity.

CHALLENGES AND LIMITATIONS

Data Privacy & Scraping Limitations

- Public platforms like LinkedIn restrict automated scraping of user profiles due to privacy policies and terms of service.
- Aggregating alumni data at scale requires ethical sourcing, consent, or relying on unstructured datasets manually collected, affecting scalability.
- Due to these concerns, we used only synthetic datasets.

CONCLUSION

- AlumConnect bridges the critical gap between static resumes and the evolving job market by harnessing the power of underutilized alumni data.
- Through a Retrieval-Augmented Generation (RAG) framework and finetuned LLMs, the system tries to intelligently match user queries with relevant alumni career paths, offering actionable, personalized insights.
- Key accomplishments include the development of workflows—retrieval and fine-tuning, integration of advanced models like LLaMA 3 and Gemini, and the creation of an interactive chatbot.
- Looking ahead, the project aims to scale by incorporating real university alumni datasets, deploying to the cloud for wider accessibility, and adding real-time feedback mechanisms to iteratively enhance LLM accuracy and relevance.

REFERENCES

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- Hugging Face Fine-Tuning Guide : https://huggingface.co/docs/transformers/training
- FAISS (Facebook AI Similarity Search): https://faiss.ai/
- FastAPI for AI Chatbot APIs: https://fastapi.tiangolo.com/
- Meta Al's Llama 3: https://huggingface.co/docs/transformers/main/model_doc/llama3
- https://www.kaggle.com/datasets/snehaanbhawal/resume-dataset
- https://ai.google.dev/gemini-api/docs/models#gemini-1.5-flash-8b

DEMO OF THE APP