# Large Scale Exam Grading Using Cloud

### Presented by:

Sharwin Neema

Saket Nerurkar

Yash Aditya

Ashmit Khandelwal

Hardav Raval

### <u>Github</u>:

https://github.com/SaketNer/RCAzureGradert

# PROJECT OVERVIEW

- The project is to create a scalable paper grading system using Cloud and OpenAi.
- We have used Azure Kubernetes, Azure Web App, Openai, and Pinecone.
- The answers, student ID, paper number, and question number are stored in an Azure SQL database. The official answers to the exam questions are also uploaded to the database.

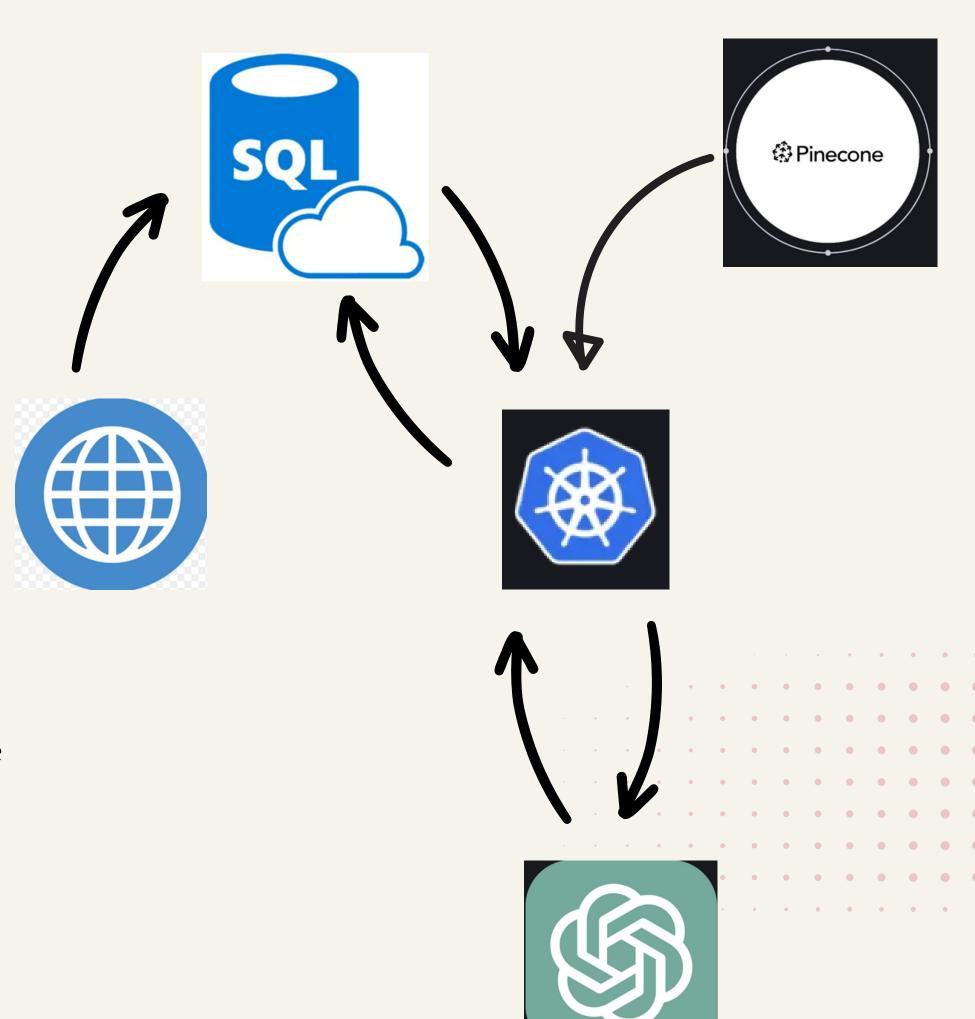
### Check Answers Using open.ai

Paper No:			
Student ID:			
Question No:			
Question No.			
Answer:			
	Upload		

• Utilizes a subject-related book uploaded to Pinecone for reference during evaluation.

• Kubernetes manages retrieval of student answers and official answers from the database.

- Kubernetes also fetches relevant context from the Pinecone book.
- ChatGPT is invoked by Kubernetes to evaluate student answers using the collected data.
- Marks assigned by ChatGPT are stored in the Azure SQL database.



# SYSTEMARCHITECTURE

The system architecture consists of the following components:

- 1. Website: A website that allows students to submit their descriptive answers to exam questions. The website also collects the student ID, paper number, and question number for each answer.
- 2. Azure SQL Database: A relational database in Azure that stores the student answers, official answers, and other relevant data.
- 3. Pinecone: A vector database that stores the book related to the exam subject. The context from the book is retrieved using Pinecone.
- 4. Kubernetes: A container orchestration system that pulls requests from the Azure SQL database and calls ChatGPT to evaluate the student answers.
- 5. ChatGPT: A language model developed by OpenAI that is used to evaluate the student answers and assign marks.

# Azure Functions Vs Kubernetes

We chose Kubernetes for our model due to several key benefits:

- Flexibility: Kubernetes provides more flexibility and control over the deployment and scaling of the application compared to Azure Functions. With Kubernetes, we can easily configure and manage the resources required for the application, such as CPU, memory, and storage.
- Scalability: Kubernetes is designed to handle large-scale, distributed applications, making it a better choice for our project, which involves evaluating a large number of student answers.



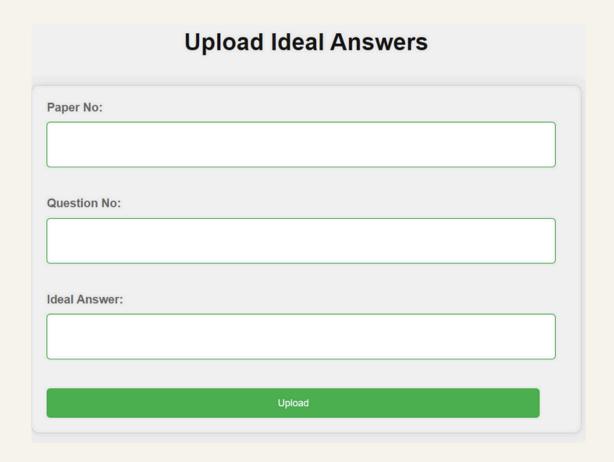
Feature	Azure Functions	Kubernetes
Deployment	Easy	Complex
Management	Simple	Advanced
Customization	Limited	High
Scalability	Automatic	Manual
Cost	Pay-per-use	Upfront costs
Integration	Azure-focused	Multi-cloud

- Integration: Kubernetes provides a rich ecosystem of tools and integrations, making it easier to connect with other services and systems.
- **Portability:** Kubernetes is a cloud-native platform that can run on any cloud provider or on-premises infrastructure, providing greater portability and flexibility for the application.



We've developed two user-friendly websites to streamline the exam process: **one for students** to upload their answers and **another for professors** to submit official answers.

These platforms were crafted with HTML, CSS, and Flask, ensuring intuitive navigation and seamless functionality for both students and professors.



Check Answers Using open.ai								
Paper No:								
	•	•	•	•	•	•	•	•
Student ID:		•	•	•	•	•	•	
	•	•	•	•	•	•	•	
Question No:	•	•	•	•	•	•	•	
Question No:		•	•	•	•	•	•	
	•	•	•	•	•	•	•	
Answer:	٠	•	•	•	•	•	•	•
Upload								

The data collected from these
 websites is stored in separate tables
 within the Azure SQL database:

• one table for student answers and another for the ideal answers.

10	student_id	question_no	answer
	1	1	cookie technology
	2	1	Cookie technology
	1	2	three-way handsha
	2	2	In the "three-way h

Student answers

paper_no	question_no	answer
1	1	cookie technology h
1	2	three-way handshak
	Ideal answers	

Executing **Kubernetes** code orchestrates the invocation of **ChatGPT**, which is provided with **student answers**, **ideal answers**, and the **grading scheme**.

Subsequently, ChatGPT
autonomously assigns grades to
students along with detailed
explanations for each assessment.

```
upload_marks(paper_no,student_id,quesntion_no,marks,reason):
    cursor = conn.cursor()
    print("uploading")
    cursor.execute("INSERT INTO final_marks (paper_no,student_id,question_no,marks,reason) VALUES
def check_ans(ideal_answer, student_answer):
    context = get_context(ideal_answer)
    text = f"You are a highly experienced professor in the field of computer science, tasked wit
    #print(text)
    client = OpenAI(api_key="sk-proj-W0lHK8EgUiZY00xMtYc8T3BlbkFJFD0iSZnoED53RX4pf14N")
    completion = client.chat.completions.create(
        model="gpt-3.5-turbo",
        messages=[
            {"role": "system", "content": "You are a professor grading answer papers of college
            {"role": "user", "content":text}
        temperature= 0
    print(completion.choices[0].message.content)
    split_text = completion.choices[0].message.content.split(',', 1)
    marks_split = split_text[0].split(' ') Kubernetes code
    marks = marks_split[1]
    print("marks give are ", int(marks))
```

Utilizing Python scripts, we fetch and compute grades for each professor, meticulously storing them in designated SQL tables.

Getting marks from the sql databse for each proff

student_id	question_no	marks	reason
1	1	6	Reasons: The studen
2	1	8	Reasons: The studen
1	2	8	Reasons: The studen
2	2	8	Reasons: The studen

```
Attempting Connection connection done student_id marks
0 1 104
1 2 106
(.venv) saket@Sakets-MacBook
```

## Alternative Approach using LangChain

### We alternatively tried 2 more approaches:

- 1. Using a simple retriever for RAG, the context is derived from the ideal answer as reference. Then making a call to chatGPT to return us a score and explaination behind the score. This we tested out however the results were not very satisfactory. Much more work was needed on the prompt.
- 2. Creating a Sequential chain which would perform RAG in the first chain and then using that context call the second chain along with the ideal and student answer as the input to then return a score and explanation for the same. We ran into a roadblock here as we were unable to figure out how to pass in the context from the first chain along with the student and ideal answers that we were passing when the whole chain was first called to the second chain.

#### Link for the colab notebook:

https://colab.research.google.com/drive/1EZD9HaJBCR8LzjrDw0iTXO-3xoIk4TJj?authuser=0#scrollTo=ZOsNsdrGMrPd

```
ARAG.ipynb 
File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text
```

#### FINAL FUNCTION

```
▶ import warnings
    warnings.filterwarnings('ignore')
    openai_api_key="sk-proj-W0lHK8EgUiZY0QxMtYc8T3BlbkFJFD0iSZnoED53RX4pf14N"
    #!pip install langchain
    #!pip install faiss-cpu
    #!pip install -U langchain-openai
    #from dotenv import load_dotenv, find_dotenv
    #_ = load_dotenv(find_dotenv()) # read local .env file
    from langchain_openai import ChatOpenAI
    llm_model = "gpt-3.5-turbo"
    llm = ChatOpenAI(temperature=0.9, model=llm_model, openai_api_key=openai_api_key)
    from langchain.chains.combine_documents import create_stuff_documents_chain
    from langchain.embeddings import OpenAIEmbeddings
    from langchain.prompts import PromptTemplate
    from langchain.chat_models import ChatOpenAI
    from langchain.prompts import ChatPromptTemplate
    from langchain.chains import LLMChain , SequentialChain
    from langchain_community.vectorstores import FAISS
    from langchain.schema import Document
    from langchain_core.messages import HumanMessage
    #text_splitter = RecursiveCharacterTextSplitter(chunk_size=1000, chunk_overlap=200)
    #splits = text_splitter.split_documents(docs)
    #vectorstore = Chroma.from_documents(documents=splits, embedding=OpenAIEmbeddings())
```

```
document = Document(page_content="The Indian Independence Movement, was a series of historic events in South Asia with the u
 get answers from sql
ideal_answer = "India became independent in 1947 from British Rule. "
student_answer = "India became independent in 1962 from Chinese Rule. The Nationalistic movement started in Uttar Pradesh"
# Embed the document
documents = [document]
embeddings = OpenAIEmbeddings(openai_api_key=openai_api_key)
vectorstore = FAISS.from_documents(documents=documents, embedding=embeddings)
#embed = embeddings.embed_query(ideal_answer)
retriever = vectorstore.as_retriever()
llm = ChatOpenAI(temperature=0.9, model=llm_model,openai_api_key=openai_api_key)
context = retriever.invoke(ideal_answer)
print(context)
qa_template = PromptTemplate(
   template=""" You are an answer evaluation agent. \
    Evaluate the student's answer :{student_answer} based on the \
    ideal answer: {ideal_answer} and {context}.
   Return a JSON object with a score (integer between 0 and 5) and an explanation (string).
    input_variables=["student_answer", "ideal_answer", "context"]
 Format the prompt with specific input values
qa_prompt = qa_template.format(student_answer=student_answer, ideal_answer=ideal_answer, context=context)
messages = [
   HumanMessage(content=qa_prompt),
output = llm(messages)
print(output)
```

# THANKYOU