# Course Registration Chatbot

### Overview

This project aims to develop an LLM-powered chatbot to streamline and simplify the course registration process for college students. The chatbot will integrate data from multiple sources, including Banner and Trace, to provide personalised course recommendations, verify program requirements, check prerequisites, and offer insights on professor reviews. The system will be built using Google Cloud Platform (GCP) and will incorporate MLOps best practices, including monitoring and CI/CD pipelines, to ensure robust and efficient operation.

This repository hosts the data pipeline designed to collect, process, and store data related to Northeastern University course offerings and student feedback.

## Data Pipeline - Key Components and Workflow

## 1. Data Collection

The pipeline collects three main types of data:

- **Course Information**: Web scraping scripts fetch details about course offerings from the NEU Banner system, including CRN, title, instructor, etc.
- **Student Feedback**: Extracts student feedback from NEU Trace instructor comments reports, which are available as PDF documents and uploaded to Google Cloud Storage (GCS) for processing.
- **Training Data**: Uses specific seed queries and refined data from BigQuery to generate structured data for training purposes.

#### 2. Data Processing

The collected data undergoes several stages of processing:

- **PDF Data Extraction**: Python-based scripts analyze the PDF files to extract relevant course evaluation comments.
- **Data Cleaning**: Removes irrelevant details and standardizes the data to ensure consistency across different sources.
- Structured Data Creation: Organizes the cleaned data into structured datasets optimized for analysis.

#### 3. Train Data Generation

Using the train\_data\_dag in Airflow, the pipeline generates seed data for training a model. This process involves:

- **Data Retrieval**: Fetches initial data from BigQuery and performs similarity searches to refine the dataset.
- **LLM Response Generation**: Generates responses from a language model (LLM) based on the seed queries and processed data.

• **Data Upload**: The generated data is uploaded to GCS and then loaded back into BigQuery to be used as training data.

This automated DAG enables systematic preparation of data needed for training and ensures consistency in the generation process.

#### 4. Data Storage

The processed data is stored for easy access and analysis:

- Google Cloud Storage (GCS): Intermediate results, final datasets, and training data are stored in designated GCS buckets.
- **BigQuery**: Structured datasets and training data are ingested into BigQuery tables for efficient querying and analysis.

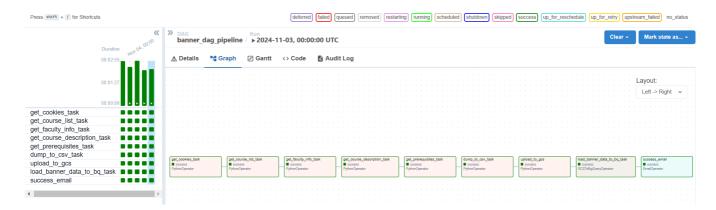
### Airflow DAGs Overview

## 1. Banner Data DAG Pipeline (banner dag pipeline)

This Airflow DAG focuses on fetching data from the NEU Banner system, processing it, and storing it in BigQuery. The steps are as follows:



- **get\_cookies\_task**: Retrieves authentication cookies to access Banner data.
- **get\_course\_list\_task**: Obtains a list of courses from the Banner system.
- get\_faculty\_info\_parallel: Collects faculty information for each course, running tasks in parallel.
- get\_course\_description\_parallel: Fetches course descriptions in parallel for efficiency.
- dump\_to\_csv\_task: Converts the data into a CSV format for easier handling and debugging.
- upload\_to\_gcs: Uploads the CSV file to Google Cloud Storage.
- load\_banner\_data\_to\_bq: Loads the Banner data from GCS into BigQuery.
- Success Email: Sends an email notification upon successful data loading.



This pipeline streamlines the process of gathering and storing course and faculty information from the Banner system.

### 2. PDF Processing Pipeline (pdf processing pipeline)

This Airflow DAG is set up to process NEU Trace course review data. It fetches data, processes it, and then stores it in a BigQuery table. Here's how it works:



- select\_distinct\_crn: Selects unique Course Registration Numbers (CRNs) to identify distinct courses.
- **get\_crn\_list**: Fetches a list of CRNs to be processed.
- get\_unique\_blobs: Retrieves unique PDF files from the data source.
- process\_pdfs: Extracts data from each PDF.
- preprocess\_pdfs: Prepares the extracted data for storage by cleaning and structuring it.
- **upload\_to\_gcs**: Uploads the preprocessed data to Google Cloud Storage.
- **load\_courses\_to\_bigquery** and **load\_to\_bigquery**: Loads processed course and review data into specific BigQuery tables.
- Success Email: Notifies the team upon successful completion of the data processing.
- trigger\_train\_data\_pipeline: Triggers the training data pipeline once PDF processing is complete.



This pipeline is essential for organizing and storing course review data in a structured format for analysis.

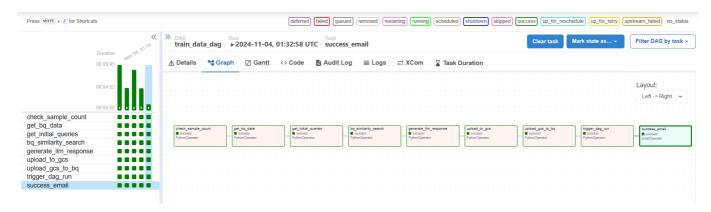
## 3. Train Data DAG (train data dag)



This Airflow Directed Acyclic Graph (DAG) is responsible for generating seed queries to train a model. It involves several steps:

check\_sample\_count: Ensures that there are enough samples available for training.

- get\_bq\_data: Retrieves data from BigQuery to be used for training.
- **get\_initial\_queries**: Generates initial queries based on the data retrieved.
- **bq\_similarity\_search**: Uses BigQuery to perform similarity searches, which help in refining the data for training.
- **generate\_llm\_response**: Generates responses from a language model based on the seed data.
- **upload\_to\_gcs**: Uploads processed data to Google Cloud Storage.
- upload\_gcs\_to\_bq: Loads the data from Google Cloud Storage back into BigQuery.
- trigger\_dag\_run: Triggers additional DAG runs if necessary.
- success email: Sends an email notification upon successful completion of the pipeline.



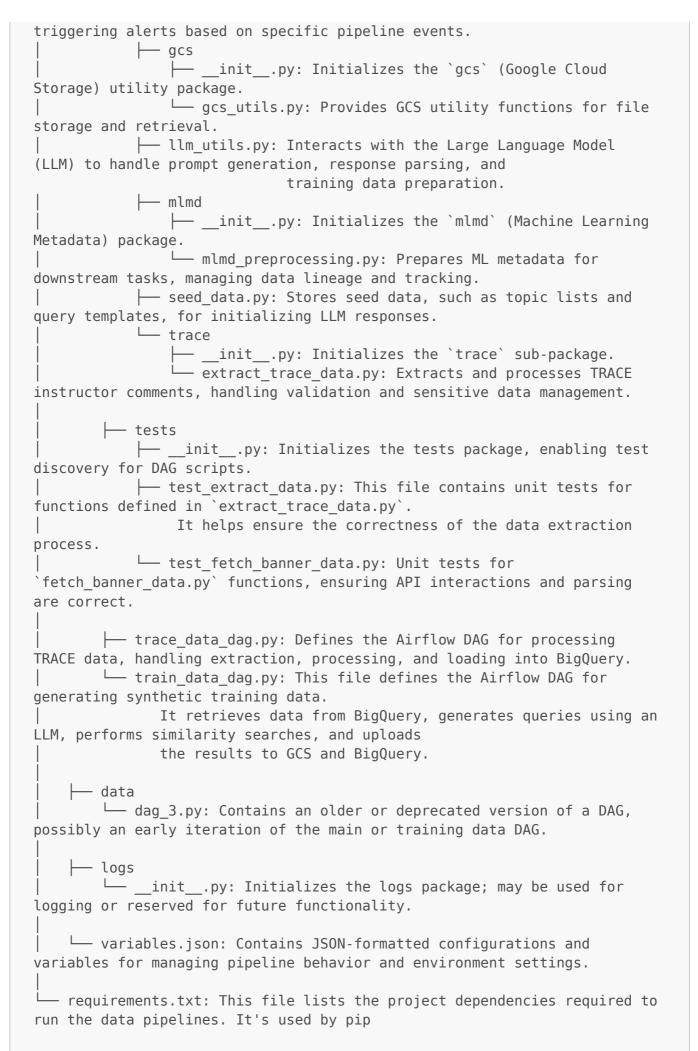
This DAG is designed to automate the preparation and processing of training data in a systematic way.

These DAGs automate and organize different stages of the data pipeline, each targeting a specific dataset (training data, course reviews, or Banner data) for Northeastern University courses.

## Project Directory Structure and Description

```
.github
     workflows
        ├─ gcd-upload.yaml: This workflow defines a CI/CD pipeline to
upload the data pipeline code to Google Cloud Storage.
            It triggers on pushes to the main and workflow-testing
branches and uses gsutil to copy the files.
        python-tests.yaml: This workflow runs Python tests using
pytest. It is triggered by pushes to the main,
            fix-testcases-import-error, and gibran/banner-dag branches
and sets up a Python environment with the
            necessary dependencies.
— .gitignore: This file specifies files and directories that should be
ignored by Git. It includes common Python artifacts,
     build directories, test results, and various IDE configuration files.
README.md: This file provides documentation for the project, including
an overview, architecture diagrams, and instructions
     for contributing. It explains the purpose of the project and its
different components.
   assets
    └─ imqs
```

│ ├── Banner_Data_DAG.png: Visualization of the Banner Data DAG for fetching course data.
workflow.
│ └── Train_Data_DAG.png: Diagram for the training data generation
DAG.
data_pipeline
—initpy: Initializes the `data_pipeline` package, making it
importable and setting up any package-level configurations.
│ │ ├── dags
pipeline.
banner_data_dag.py: This file defines the Airflow DAG for
<pre>fetching course data from the NEU Banner system.   It scrapes course details, faculty information, and</pre>
prerequisites, then uploads the data to GCS and BigQuery.
—initpy: Initializes the `scripts` sub-package within
`dags` for modularized utility scripts.
exponential backoff retry logic. It's used to handle
transient errors during API calls or other operations.
<pre>—initpy: Initializes the `banner` sub-package. — fetch_banner_data.py: This file defines functions for</pre>
fetching course information from the NEU Banner system, including cookies,
course lists, descriptions, and prerequisites. It
interacts with the Banner API and parses the HTML responses.
It uses multithreading to speed up the data retrieval
process.
├──initpy: Initializes the `bq` (BigQuery) utility package.
bigquery_utils.py: This file contains utility
functions for interacting with BigQuery, such as checking sample counts
and retrieving data. It handles tasks such as data
extraction, similarity search, and data loading.  ———————————————————————————————————
project IDs and sample counts used across scripts.
data
initpy: Initializes the `data` sub-package.
$ig $ data_anomalies.py: Provides functions for detecting and handling data anomalies within the pipeline.
data processing.py: This file contains functions for
processing data, specifically for generating initial queries for the LLM.
It prepares data before it is used in other parts of
the pipeline. │                     data_utils.py: Utility functions for data handling,
including cleaning and parsing data.
│



to install the necessary packages.

## Instruction to Reproduce

To reproduce this data pipeline on Google Cloud Platform (GCP), follow these instructions:

### **Prerequisites**

- 1. Google Cloud Account: Make sure you have an active Google Cloud account.
- 2. **Project Setup**: Create a new GCP project or use an existing one. Note down the PROJECT ID.
- 3. Billing Enabled: Ensure billing is enabled for your project.
- 4. Google Cloud SDK: Install the Google Cloud SDK to interact with GCP resources.
- 5. **Python 3.x**: Make sure Python 3.10 is installed.

Step 1: Set Up GCP Services and Resources

#### 1.1. Enable Required APIs

Go to GCP Console -

- 1. BigQuery Enable API
- 2. Cloud Composer Enable API
- 3. VertexAI Enable API

### 1.2. Set Up Cloud Storage Buckets

1. Create a Cloud Storage bucket to store data and pipeline artifacts. Replace BUCKET\_NAME and PROJECT ID with your values.

```
export BUCKET_NAME=<your-bucket-name>
gcloud storage buckets create gs://$BUCKET_NAME --project $PROJECT_ID
--location=<region>
```

Make sure the region is coherent with the composer region, or select multi-region bucket.

2. Create folders inside the bucket for organizing data and other artefacts:

```
gsutil mkdir gs://$BUCKET_NAME/data
```

#### 1.3. Set Up BigQuery Dataset

1. Create a BigQuery dataset to store processed data.

```
export DATASET_NAME=<your-dataset-name>
bq --location=<region> mk --dataset $PROJECT_ID:$DATASET_NAME
```

### Step 2: Configure Airflow with Cloud Composer

#### 1. Create a Cloud Composer Environment:

- Go to the **Cloud Composer** page in the GCP Console.
- Create a new Composer environment, specify Python 3 as the runtime, and select the same region as the other resources.
- Note the Composer Environment Name and GCS Bucket associated with Composer for later steps.

#### 2. Upload DAGs and Scripts:

- Update the github workflows to match your GCP environment (Project, Bucket, etc). The workflow will take care of uploading the files to the bucket.
- 3. **Update Environment Variables** in Composer to reference the GCS bucket, BigQuery dataset, and other configurations. These can be set in the Airflow Variables section within the Composer UI.
  - You can use the environment file provided to setup the composer environment. Go to the
     Composer -> Airflow UI -> Admin -> Variables -> Import Variables
  - Upload the file.

#### 4. Python Package Dependencies:

- Update the requirements.txt file with the necessary dependencies.
- Install the dependencies in Composer by specifying the path to requirements.txt in the Composer environment configuration.

#### Step 3: CI/CD Pipeline Setup with GitHub Actions

#### 1. GitHub Actions Workflow:

- The gcd-upload. yaml file should handle uploading code to GCS on pushes to specific branches.
- The python-tests. yaml file should handle unit tests and linting.

#### Step 4: Testing the Pipeline

#### 1. Trigger the Pipeline:

 You can trigger your pipeline by running the Airflow DAGs through the Composer UI or setting specific schedules for each DAG as defined in the code.

#### 2. Verify Data in BigQuery:

• After successful DAG runs, check your BigQuery dataset for expected tables and data to ensure the pipeline processed and loaded data correctly.

## 3. Logs and Debugging:

• Monitor logs from Airflow in the Composer environment to debug issues. Logs are available for each task within the DAG.

## 4. Alerts and Anomaly Detection:

• Change the environment variable for email in the composer environment to receive alerts regarding any anomaly detected, errors in the code and the status of the DAG run.

## BigQuery Data Schema

1. Table 1 - Course Data Table

Field Name	Туре
crn	STRING
course_code	STRING
course_title	STRING
instructor	STRING
term	STRING

#### 2. Table 2 - Banner Course Data Table

Field Name	Туре
crn	STRING
course_title	STRING
subject_course	STRING
faculty_name	STRING
campus_description	STRING
course_description	STRING
term	STRING
begin_time	STRING
end_time	STRING
days	STRING
prereq	STRING

### 3. Table 3 - Review Data Table

Field Name	Туре
review_id	STRING

Field Name	Туре
crn	STRING
question	STRING
response	STRING

4. Table 4 - Train Data Table

Field Name	Туре
question	STRING
context	STRING
response	STRING

## Data Version Control(DVC)

We store all our data in Google Cloud Storage Bucket and use the versioning capability provided by GCS to maintain data versions.

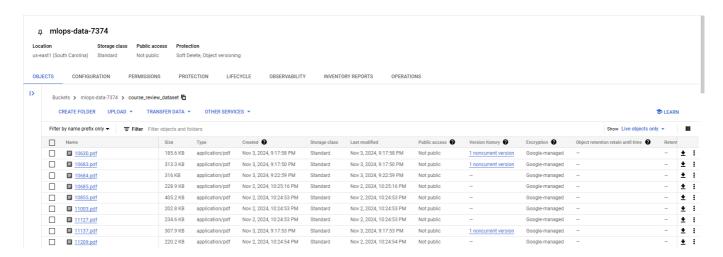
## Object versioning (for data recovery)

With object versioning on, you can restore objects that have been overwritten or deleted. Live and noncurrent versions are stored in the same bucket and storage class by default. To reduce costs, limit the number of versions by adding a lifecycle rule. Learn more



You have 2 lifecycle rules applied to noncurrent versions.

#### MANAGE RULES



## Alerts and Anomaly Detection

- 1. We have written custom code to detect any anomalies in our data pipeline.
- 2. In our PDF processing pipeline, we detect any changes in the PDF's format and validate whether all the fields are getting parsed as we expect them to. If we find any changes to the field names, we

classify the PDF as an anomaly and trigger an alert to the user.

- 3. For banner data, if we do not get any information about the faculty for any course, we send an alert and skip processing that entry.
- 4. This pipeline also acts as our schema validation pipeline as we parse only the fields we want in our database.

## **MLMD**

1. We are capturing all the metadata based on the pre-processing pipeline which parses and processes the PDFs in our database. We store all the metadata in a Cloud SQL DB for proper tracking.

## Pipeline Flow Optimization

- 1. We have tracked the Gantt chart for all the DAGs that we have created, we make sure that every task is modular and consumes minimal time for execution.
- 2. We have also implemented parallelization in some of our pre-processing functions.
- 3. We have optimized our resources to optimise the cost and wait time for each pipeline task.(for example, reducing time from 10min->3.5min for one of the DAGs)



## Tools and Technologies

- **Python**: Core programming language for development.
- Google Cloud Platform (GCP): Provides cloud infrastructure for storage and computation.
- **Cloud Composer**: Managed workflow orchestration tool on Google Cloud that uses Apache Airflow to automate, schedule, and monitor complex data pipelines.
- **Google Cloud Storage:** Cloud-based storage solution used to store, manage, and retrieve large volumes of structured and unstructured data, making it ideal for data warehousing and big data analytics tasks.
- **BigQuery**: Used for storing and analyzing large datasets.
- CloudSQL: Used for MLMD.
- VertexAI: For LLM(Gemini) capabilities.

## Contributing

We welcome contributions to improve the data pipeline. If you wish to contribute:

- Fork the repository.
- Make changes to the codebase.
- Submit a pull request detailing your modifications.

## License

Distributed under the MIT License. See LICENSE, txt for more information.

## Contact

For any inquiries or issues regarding the data pipeline, please reach out to one of the repository owners:

- Gibran Myageri myageri.g@northeastern.edu
- Goutham Yadavall yadavalli.s@northeastern.edu
- Kishore Sampath kishore.sampath@neu.edu
- Rushikesh Ghatage ghatage.r@northeastern.edu
- Mihir Athale athale.m@northeastern.edu