Project Progress Report

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Spring Semester 2025

1. Study Overview

This study focuses on:

- Training Merjek Al models on a GPU cluster.

2. Early Steps & Prompt Generation

The initial phase involved testing different LLM models for prompt generation and analyzing their outputs after database insertion.

3. Models Tested

Several models were tested for effectiveness and performance:

- Open-source models (e.g., LLama 3.1 8B, DeepSeek R1 1.5B, Mistral 7B v0.3)

4. GPU Cluster Specifications

Cluster Quota specifications:

- Max Jobs: 6

- Max Nodes: 3

- Max GPUs per Job: 4

- Max Runtime per Job: 48 hours

Training Progress:(1/24)

- Initial meeting

Training Progress: (2/7)

- Installation of Ollama and different open-source LLM models.
- Prompt generation and insertion into MySQL Workbench.

Training Progress: (2/14-2/28)

- Initial training/test practice, locally and in GPU Cluster, with Human Trafficking and Campus csv files.
- Migration to MongoDB Atlas/Compass

Training Progress: (3/7/25)

- Dataset: 2,000 documents (subset of 10K)
- Split: 80% train, 20% test
- Tested on 2 GPUs (1 node)
- Estimated training time: ~52 minutes for 1 epoch

Training Progress: (3/14/25)

- Created Merjek Github
- Prompt generation 5 hours per 1000 documents
- Meeting at library helping Md with MongoDB setup and prompt generation
- Continue generating ~8K prompts for the entire dataset of ~10K documents.
- Mistral 7B v0.3 is the model used for prompt generation. (LM Studio on my Windows setup)
- After generation, iterated through MongoDB collection to add prompts into arrays.
- Edit Slurm training script before executing within GPU cluster.
- Scaled training from 2,000 docs at 1 epoch to 10,000 docs at 3 epochs.
 - ✓ Loaded 305835 valid prompts from the first 10,000 documents.

Training samples: 244668

Validation samples: 61167

Using device: cuda, Batch size: 16

GPU #: 4

Estimated train time for 1 epoch: 4 hours 41 minutes

Estimated train time for 3 epochs: 14 hours 4 minutes

View inside cluster after 1 epoch for 10K docs:

```
PS C:\MINDOMS\system32> ssh jmflagg@itiger.memphis.edu
jmflagg@itiger.memphis.edu's password:
Last login: Tue Mar II 20:17:26 2025 from 10.228.110.243
[jmflagg@itiger.msrpis.edu's password:
Last login: Tue Mar II 20:17:26 2025 from 10.228.110.243
[jmflagg@itiger.msrpiek-study]$ squeur -u SUSER
JDGIDPARHITION
NAME USERS TIME NODES NODELIST(REASON)

5421 bigfiger msrpiek-study]$ tail merjekai -finaing-output.txt
('eval_loss': 8.80588817596455; 'eval_runtime': 43.2028, 'eval_samples_per_second': 1412.866, 'eval_steps_per_second': 22.082, 'epoch': 0.62)
('loss': 8.81016, grad_norm': 209776.69375, 'learning_rate': 7.409739315965362-06, 'epoch': 0.63)
('eval_loss': 8.804989409769598, 'eval_runtime': 42.7269, 'eval_samples_per_second': 1413.682, 'eval_steps_per_second': 22.375, 'epoch': 0.63)
('eval_loss': 8.804989699888867, 'eval_runtime': 42.5937, 'eval_samples_per_second': 1413.682, 'eval_steps_per_second': 22.445, 'epoch': 0.63)
('eval_loss': 8.80498969988867, 'eval_runtime': 42.5937, 'eval_samples_per_second': 1416.097, 'eval_steps_per_second': 22.445, 'epoch': 0.63)
('eval_loss': 8.80491409768680, 'eval_runtime': 43.2752, 'eval_samples_per_second': 1413.482, 'eval_steps_per_second': 22.091, 'epoch': 0.63)
('eval_loss': 8.80491409768680, 'eval_runtime': 43.2752, 'eval_samples_per_second': 1413.482, 'eval_steps_per_second': 22.091, 'epoch': 0.63)
('eval_loss': 8.804917996208496, 'eval_runtime': 43.2485, 'eval_samples_per_second': 1411.825, 'eval_steps_per_second': 22.066, 'epoch': 0.63)
('eval_loss': 8.004917996208496, 'eval_runtime': 43.2485, 'eval_samples_per_second': 1411.825, 'eval_steps_per_second': 22.066, 'epoch': 0.63)
('eval_loss': 8.004917996208496, 'eval_runtime': 43.2485, 'eval_samples_per_second': 1411.825, 'eval_steps_per_second': 22.066, 'epoch': 0.63)
('eval_loss': 8.004917996208496, 'eval_runtime': 43.2485, 'eval_samples_per_second': 1411.825, 'eval_steps_per_second': 22.066, 'epoch': 0.63)

('eval_loss': 8.004917996208496, 'eval_runtime': 43.2485, 'eval_samples_per_second': 1411.825, 'eval_steps_
```

View inside cluster after 3 epochs for 10K:

```
[jmflagg@itiger merjek-study]$ head merjekai-training-output.txt

$\footnotest \text{Starting merjekai.py...}

$\footnotest \text{ to Mongood Atlas successfully.}

\[
\text{Oconnected to Mongood Atlas successfully.}

\text{Connected to Mongood Atlas successfully.}

\text{Connected to Mongood Atlas successfully.}

\text{Loaded 305835 valid prompts from the first 10,000 documents.}

\text{Training samples: 244668}

\text{Validation samples: 244668}

\text{Validation samples: 61167}

\text{Using device: cuda, Batch size: 16}

\text{Starting training...}

\text{Closs': 9.2462, 'grad_norm': 176753.75, 'learning_rate': 1.99825616880286e-05, 'epoch': 0.0}

\text{{'eval_loss': 9.227972259521484, 'eval_runtime': 43.31, 'eval_samples_per_second': 1412.307, 'eval_steps_per_second': 22.073, 'epoch': 0.0}

\text{[jmflagg@itiger merjek-study]$ tail merjekai-training-output.txt}

\text{{'loss': 8.2178, 'grad_norm': 242138.140625, 'learning_rate': 3.132792745662224e-08, 'epoch': 3.0}

\text{{'eval_loss': 8.314220428466797, 'eval_runtime': 43.37, 'eval_samples_per_second': 1410.351, 'eval_steps_per_second': 22.043, 'epoch': 3.0}

\text{{'eval_loss': 8.314230428466797, 'eval_runtime': 43.37, 'eval_samples_per_second': 1418.914, 'eval_steps_per_second': 22.177, 'epoch': 3.0}

\text{{'train_runtime': 50719.8742, 'train_samples_per_second': 14.472, 'train_steps_per_second': 0.226, 'train_loss': 8.52074397049928, 'epoch': 3.0}

\text{{\text{Valuating model...}}

\text{{\text{Valuating model to ./fine-tuned-model-merjekai3}}

\text{\text{Model and tokenizer saved successfully.}}

\text{\text{\text{Train_loss}}

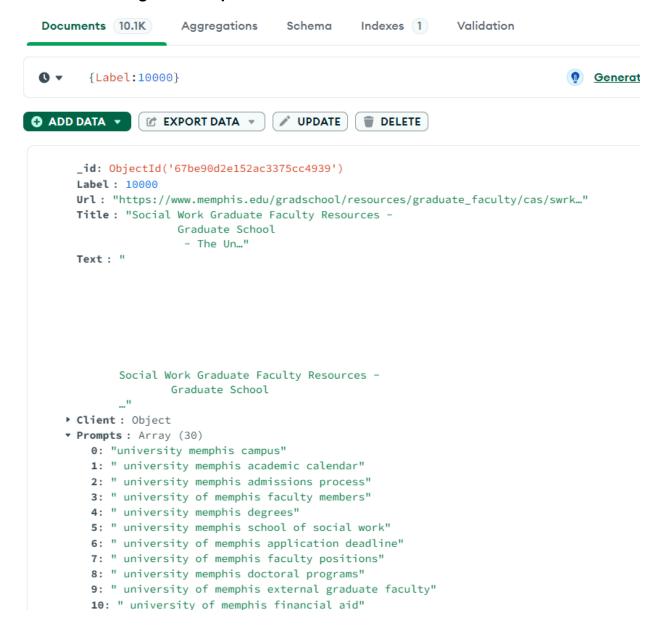
\text{\text{\text{Proining job completed.}}

\text{[jmflagg@itiger merjek-study]$}

\end{\text{\text{\text{Train_loss}}}

\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\t
```

View inside MongoDB Compass:



Training Progress: (3/21/25 - 3/28/25)

Goal: Find a way to utilize the GPU cluster for prompt generation

- 1. Initial Attempt with vLLM
 - Tried using vLLM for running LLaMA 3.1 8B.
 - Faced challenges and decided to move on to other methods.

2. Transformers Library Approach

- Attempted to use the Transformers library and download LLaMA 3.1 8B from HuggingFace.
- Performance was poor, comparable to 1B models.
- Assumed Ollama optimizes models behind the scenes for better performance.

3. Dockerized Ollama Installation

- Installed a Dockerized version of Ollama on the cluster using Podman (compatible with Docker).
- Downloaded and tested the LLaMA 3.2B model.
- The model worked but encountered two major issues:
 - No External Access: Unable to access Ollama from outside the container, even though ports were open and listening.
 - CPU-Only Inference: Without external access, couldn't create a Slurm script for GPU usage, resulting in CPU-only inference.

4. Native Ollama Installation

 Installed Ollama natively by downloading and extracting the binary to a directory. • Still faced CPU-only inference since GPUs on the cluster are only accessible through Slurm.

5. Understanding Cluster Architecture

- Gained better insight into the cluster's architecture:
 - Head Node: Where users log in, but no GPUs are available.
 - Worker Nodes: GPUs are only available on these nodes through Slurm jobs.
- Confirmed that Ollama needs to run on worker nodes for GPU access.

6. Issues with Docker GPU Pass-Through

- Directly using Docker containers for Ollama with GPU pass-through was unsuccessful.
- The cluster's GPU access is restricted, and Docker doesn't support direct GPU usage in this environment.

7. Solution: Using Apptainer

- Identified Apptainer (formerly Singularity) as the only functional solution for GPU access on the cluster.
- Apptainer is installed on the cluster and supports GPU pass-through.
- This method allows Ollama to run with GPU acceleration via Slurm jobs.

Prompt Generation Analysis

Database: crawled_cs_pages2

■ Total Documents: ~548 docs

【 Total Time: 410 seconds | 6m 50s

Model Tested: Llama 3.2:3b

```
grants; University of Memphis cybersecurity degree; University of
                 'Memphis online courses; University of Memphis academic misconduct
                 'policy; University of Memphis student conduct code; University of ''Memphis data science program; University of Memphis computer ''engineering; University of Memphis artificial intelligence; '
                 'University of Memphis IT department contact; University of '
'Memphis student organization; University of Memphis club sports; '
                 'University of Memphis campus map; University of Memphis parking
 'rules; University of Memphis library hours;',
'Url': 'https://www.memphis.edu/cs/courses/syllabi/7900.pdf',
 '_id': ObjectId('677ff6dccae52426f563c996')}
Processing document with _id: 677ff6decae52426f563c998...
Generated LLama Prompts:
'website; COMP 7/8998 university; University of Memphis cloud '
'security course; MEMPHIS CS department; COMP 7998 grading policy; '
                 'University of Memphis plagiarism policy; University of Memphis
                 'disability services; Cloud computing security; Internet of Things 'security; Attribute-based access control; Efficient search over 'encrypted data; Fog computing; Crowdsourcing authentication; '
                 'Blockchain introduction; University of Memphis computer science '
                 'courses; MEMPHIS graduate programs; University of Memphis online 'courses; COMP 7/8998 course description; University of Memphis '
                 'research centers; Computer science department at Memphis.',
 'Url': 'https://www.memphis.edu/cs/courses/syllabi/7998.pdf',
'_id': ObjectId('677ff6decae52426f563c998')}
Document processing job completed.
  Job completed in 410 seconds.
[jmflagg@itiger ollama]$
```

Ollama Setup and GPU Usage on Cluster

Check for Apptainer Installation

which apptainer

/usr/bin/apptainer

▲ Download and Convert Ollama Docker Image to SIF apptainer pull docker://ollama/ollama:latest

• Converts Docker image to SIF format for Apptainer compatibility.

Verify SIF File

Is -Ih *.sif

Example Output:

-rwxr-xr-x 1 jmflagg users 1.7G Mar 26 18:44 ollama latest.sif

📊 Cluster Management

Check Node Status

sinfo

- Provides general info about available nodes.
- **Detailed Node Information**

sinfo -N -o "%N %P %C %G %T %M %E"

• Displays node-specific details like CPU, GPU availability, state, and errors.

Running Jobs on Specific Nodes

SSH into Cluster

ssh jmflagg@itiger.memphis.edu

Navigate to Project Directory

cd /project/jmflagg/ollama

Submit a Job to Specific Node

srun --partition=bigTiger --nodelist=itiger03 --gres=gpu:1 --mem=64G --time=1:00:00 --pty bash

- Requests a GPU node for one hour with 64GB memory.
- Check Running Jobs

squeue -u \$USER

Monitor GPU Status

nvidia-smi

- Displays real-time GPU usage and memory allocation.
- ▲ Submit Job with SBATCH to specific node

sbatch --nodelist=itiger03 app-job.sh

X Install Ollama Natively



Download Ollama Binary

curl -L https://ollama.com/download/ollama-linux-amd64.tgz -o ollama-linux-amd64.tgz

Extract and Install

mkdir -p ~/ollama

tar -xzf ollama-linux-amd64.tgz -C ~/ollama

Add Ollama to Path

export PATH=\$HOME/ollama/bin:\$PATH

Confirm installation

ollama --version

Python file for Prompt Generation

```
import os
import ollama
import pprint
import time
from pymongo import MongoClient
# MongoDB connection details
MONGO_URI =
"mongodb+srv://jeremy-flagg:eWK4Bo7sR8bhDMn5@merjekcluster1.mwxms.mongodb.net/?re
tryWrites=true&w=majority&appName=MerjekCluster1"
DATABASE_NAME = "merjekaidb"
COLLECTION_NAME = "crawled_cs_pages2"
OLLAMA_HOST = "http://127.0.0.1:11434" # Use localhost for Ollama
OLLAMA MODEL NAME = "llama3.2:3b"
# Set the OLLAMA_HOST environment variable before calling Ollama
os.environ["OLLAMA_HOST"] = OLLAMA_HOST
def generate_prompts_with_ollama(text):
   try:
        # Construct the prompt for Ollama API
        prompt = f"""
        You are extracting **up to 40 highly relevant search queries** from the
```

```
given text. **Do not summarize, analyze, or paraphrase.**
### **Instructions:**
 Each query must be **1-8 words long** and relate to the **"University of
Memphis."**
 Queries should be **keywords, short questions, or phrases** (not full
sentences).
 **Strictly separate each query with a semicolon (;)** on a single line.
 **Do not add newlines, explanations, numbers, or extra formatting.**
### **Text to Process:**
{text}
### **Output Format (Example):**
University of Memphis computer science; University of Memphis AI research;
University of Memphis admission requirements; University of Memphis data science
program
### **Your Output:**
(Ensure queries are in one single line, semicolon-separated, no newlines)
        # Now call Ollama without specifying the host directly
        output = ollama.generate(model=OLLAMA_MODEL_NAME, prompt=prompt)
```

```
response = output.get('response', "").strip()
        if not response:
            raise ValueError("No response received from Ollama API.")
        # Ensure response is formatted correctly
        formatted_response = response.replace("\n", " ").strip()
       # Validate format: Must contain semicolon-separated queries
       if ";" not in formatted_response:
            raise ValueError(f"Unexpected response format from LLM:
{formatted_response}")
        return formatted_response
   except Exception as e:
        print(f"Error generating prompts: {e}")
        return ""
def connect_to_mongodb():
   try:
        # Connect to MongoDB
        db_client = MongoClient(MONGO_URI)
```

```
print("Connected to MongoDB.")
        return db_client[DATABASE_NAME]
   except Exception as e:
       print(f"Error connecting to MongoDB: {e}")
        return None
def process_documents(collection, start_label=1):
   for document in collection.find({"Label": {"$gte": start_label}}).limit(10):
       text = document.get("Text", "")
       if not text or len(text) < 15:</pre>
            print(f"Skipping document with _id: {document['_id']} due to missing
or short 'Text' field.")
            continue
        print(f"\nProcessing document with _id: {document['_id']}...")
        start_time = time.time()
        prompts = generate_prompts_with_ollama(text)
        end_time = time.time()
        processing_time = round(end_time - start_time, 2)
        # Pretty-print the result
        print("\nGenerated LLama Prompts:")
        pprint.pprint({
```

```
"_id": document["_id"],
            "Label": document["Label"],
            "Url": document.get("Url", "N/A"), # Print URL or "N/A" if it
doesn't exist
            "Prompts": prompts,
            "Processing Time (s)": processing_time
       })
       print("-" * 80)
if __name__ == "__main__":
   db = connect_to_mongodb()
   if db is not None:
       collection = db[COLLECTION_NAME]
       process_documents(collection)
    else:
        print("Unable to connect to database. Exiting.")
```

Slurm Script

```
#!/bin/bash
#SBATCH --job-name=olam-gen
#SBATCH --output=olam-output.txt
#SBATCH --error=olam-error.txt
#SBATCH --partition=bigTiger
#SBATCH --nodes=1
#SBATCH --ntasks=1
#SBATCH --gres=gpu:2
#SBATCH --mem=64G
#SBATCH --time=48:00:00
export OLLAMA_HOST=http://0.0.0.0:11434  # All connections
apptainer run --nv --bind /project/jmflagg/ollama/data:/data --bind
/project/jmflagg/ollama:/ollama ollama_latest.sif serve &
# Give the container a few seconds to start up
sleep 5
# Confirm Ollama is accessible
echo "  Checking Ollama connection..."
curl -s $OLLAMA_HOST || { echo " | Failed to connect to Ollama. Ensure it is
running on the node. Exiting."; exit 1; }
```

```
# Activate virtual environment

source /project/jmflagg/ollama/ollama_env/bin/activate # Install ollama and pymongo libraries with pip in your venv

# Run the Python script

echo "* Starting document processing with Ollama..."

python /project/jmflagg/ollama/cluster_gen2.py # Whatever your python file name is

# Deactivate virtual environment after the job is done deactivate

echo "* Document processing job completed."
```

Training Progress: (4/4/25)

Goal: Find a way to use multi-gpus for generation

Success/failure: Failure. The 4 GPUs(RTX 6000 on node 06) are recognized, but Ollama fails to generate prompts using all 4.

Learned: Ollama does not natively support multi-GPU inference and needs external tools like PyTorch, TensorFlow, or HuggingF Transformers to enable it. Still need to test these.

10K Prompt Generation Analysis

Database: merjekaidb.uofm_pages_crawled

Total Documents: ~10,048 docs

Total Time: ~ 4 hours, 30 mins

Model Tested: Llama 3.2:3b

Python Code Implementation:

```
import os
import ollama
import pprint
import time
from pymongo import MongoClient

# MongoDB Atlas connection details

MONGO_URI =
"mongodb+srv://jeremyflagg12:QGTrn5lbWa2qrXFL@cluster0.t4orq.mongodb.net/?retryWrites=true&w=majority&appName=Cluster0"

DATABASE_NAME = "Prompts"

COLLECTION_NAME = "merjekai4"
```

```
OLLAMA_HOST = "http://127.0.0.1:11434" # Use localhost for Ollama
OLLAMA MODEL NAME = "llama3.2:3b"
# Set the OLLAMA_HOST environment variable before calling Ollama
os.environ["OLLAMA_HOST"] = OLLAMA_HOST
BATCH_SIZE = 100 # Process in small batches to avoid cursor timeouts
def generate prompts with ollama(text):
   try:
       prompt = f"""
        You are extracting **up to 40 highly relevant search queries** from the
given text...
        output = ollama.generate(model=OLLAMA MODEL NAME, prompt=prompt)
        response = output.get('response', "").strip()
        return response.replace("\n", " ").strip() if response else ""
    except Exception as e:
        print(f"Error generating prompts: {e}")
        return ""
def connect_to_mongodb():
   try:
        db_client = MongoClient(MONGO_URI)
        print("Connected to MongoDB Atlas.")
        return db_client[DATABASE_NAME]
```

```
except Exception as e:
        print(f"Error connecting to MongoDB Atlas: {e}")
        return None
def process_documents(collection):
   last_id = None # Track last processed document
   while True:
        query = {"$or": [{"Prompts": {"$size": 0}}, {"Prompts": {"$exists":
False}}]}
        if last id:
            query["_id"] = {"$gt": last_id} # Pagination using _id
        documents = list(collection.find(query).sort("_id").limit(BATCH_SIZE))
        if not documents:
            break # No more documents left
        for document in documents:
            try:
                label = document.get("Label", "UNKNOWN")
                text = document.get("Text", "")
                if not text or len(text) < 15:</pre>
                    collection.update_one({"_id": document["_id"]}, {"$set":
{"Prompts": ["INSUFFICIENT_TEXT"]}})
                    continue
                start_time = time.time()
```

```
prompts = generate_prompts_with_ollama(text)
                processing_time = round(time.time() - start_time, 2)
                collection.update_one(
                   {"_id": document["_id"]},
                    {"$set": {"Processing Time (s)": processing_time, "Prompts":
prompts.split("; ")}}
                )
                last_id = document["_id"] # Update last processed ID
                time.sleep(2) # Prevent rate limits
            except Exception as e:
                print(f"Error processing document {document.get('Label',
'UNKNOWN')}: {e}")
                collection.update_one({"_id": document["_id"]}, {"$set":
{"Prompts": ["PROCESSING_ERROR"]}})
                time.sleep(5)
if __name__ == "__main__":
   db = connect_to_mongodb()
   if db:
        collection = db[COLLECTION_NAME]
        process_documents(collection)
    else:
        print("Unable to connect to database. Exiting.")
```

Slurm Script

```
#!/bin/bash
#SBATCH --job-name=ten-gen
#SBATCH --output=ten-output.txt
#SBATCH --error=ten-error.txt
#SBATCH --partition=bigTiger
#SBATCH --nodes=1
#SBATCH --ntasks=1
#SBATCH --gres=gpu:4
#SBATCH --time=48:00:00
#SBATCH --nodelist=itiger07
export OLLAMA_HOST=http://0.0.0.0:11434
apptainer run --nv --bind /project/jmflagg/ollama/data:/data --bind /project/jmflagg/ollama:/ollama ollama_latest.sif serve &
# Give the container a few seconds to start up
sleep 5
 # Confirm Ollama is accessible
echo "📝 Checking Ollama connection..."
curl -s 0 = 0 (echo " ! Failed to connect to 0 = 0 curl -s 0 = 0 curl -
# Activate virtual environment
source /project/jmflagg/ollama/ollama_env/bin/activate
 # Run the Python script
echo "🚀 Starting document processing with Ollama..."
python /project/jmflagg/ollama/prompt_gen.py
```

Deactivate virtual environment after the job is done
deactivate

This command is important for checking which node has enough resources to allocate to your specific needs.

Detailed Node Information

sinfo -N -o "%N %P %C %G %T %M %E"

```
[jmflagg@itiger ollama]$ sinfo -N -o "%N %P %C %G %T %M %E"

NODELIST PARTITION CPUS(A/I/O/T) GRES STATE PREEMPT_MODE REASON

itiger01 bigTiger* 36/28/0/64 gpu:h100_80gb:8(S:0-1) mixed OFF none

itiger02 bigTiger* 16/48/0/64 gpu:rtx_6000:8(S:0-1) mixed OFF none

itiger03 bigTiger* 4/60/0/64 gpu:rtx_6000:8(S:0-1) mixed OFF none

itiger04 bigTiger* 64/0/0/64 gpu:rtx_6000:8(S:0-1) allocated OFF none

itiger05 bigTiger* 64/0/0/64 gpu:rtx_6000:8(S:0-1) allocated OFF none

itiger06 bigTiger* 40/24/0/64 gpu:rtx_6000:8(S:0-1) mixed OFF none

itiger07 bigTiger* 0/64/0/64 gpu:rtx_5000:8(S:0-1) idle OFF none

itiger08 bigTiger* 0/64/0/64 gpu:rtx_5000:8(S:0-1) idle OFF none

itiger09 bigTiger* 0/64/0/64 gpu:rtx_5000:8(S:0-1) idle OFF none

itiger10 bigTiger* 0/64/0/64 gpu:rtx_5000:8(S:0-1) idle OFF none

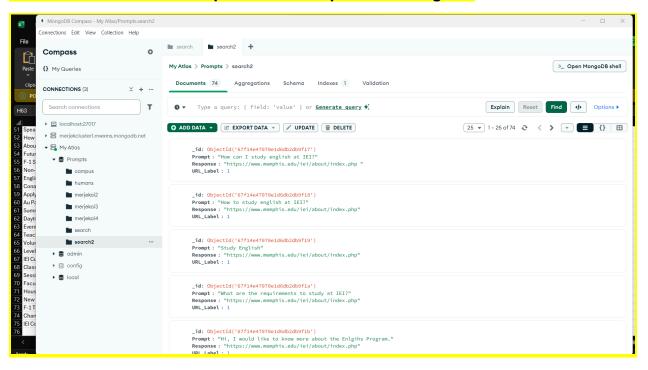
itiger11 bigTiger* 0/64/0/64 gpu:rtx_5000:8(S:0-1) idle OFF none
```

Progress 4/11

Goal: Train model on IEI CSV and build search engine

Step 1:

Create labels for each unique URL and import into MongoDB



Step 2: BERT Model

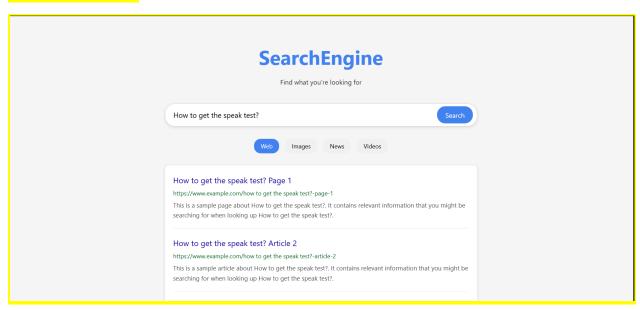
Initial results after training on 3 epochs (Realized some labels were wrong, so I had to remake dataset. Still inaccurate after 10 epochs)

```
train_model_local.py
   1 from datasets import Dataset
         import pandas as pd
         from sklearn.model_selection import train_test_split
          BertTokenizer,
DataCollatorWithPadding,
BertForSequenceClassification,
            TrainingArguments
  import torch
from pymongo import MongoClient
 import numpy as np
import evaluate
 PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
 Evaluation Results: {'accuracy': 0.26397800183318054, 'f1': 0.11026202252060334}
                                                                                                                                                    273/273 [15:09<00:00, 3.33s/it]
Featuration Results: {'accuracy': 0.26397800183318054, 'f1': 0.11026202252060334} 
Evaluation Results: {'accuracy': 0.26397800183318054, 'f1': 0.11026202252060334} 
Test predictions saved to test_predictions_output.csv
 (venv) PS C:\Users\jerem\Desktop\merjek-study> python '.\test_model_local.py'
 Device set to use cpu
 User input: How can I study english at IEI?
Predicted label: 2
 Confidence: 0.2256
Associated URL: https://www.memphis.edu/iei/about/index.php
(venv) PS C:\Users\jerem\Desktop\merjek-study> python '.\test_model_local.py'
Device set to use cpu
User input: How much?
Predicted label: 2
 True label: 4
Associated URL: https://www.memphis.edu/iei/about/fees.php
(venv) PS C:\Users\jerem\Desktop\merjek-study> nvcc --version
```

Step 3: DistilBERT Model: 15 epoch

DistilBERT is smaller and offers faster training when it comes to small datasets, but it is still struggling with accuracy. Virtually no improvement compared to the bigger BERT model.

Front End Debut:



U of M pages crawled prompt generation sample:

Duration: ??? Ended early when bug was revealed

Model Tested: Llama 3.2: 3b

Bug: Ollama makes generate() API call successfully, but refuses to generate prompt inside DB starting near prompt 4800 and onwards.

```
100 v 1 – 100 of 9000
      ▼ Prompts : Array (4)
         0: "What is the University of Memphis computer science department's curric..."
         1: "what types of projects does the University of Memphis AI research grou..."
         2: "what are the admission requirements for University of Memphis graduate..."
         3: "what kind of specializations or concentrations does the University of ..."
        _id: ObjectId('67f1694cd8570f5e9d2591c2')
       LabelNo: 45
       Url: "https://www.memphis.edu/student-affairs/index.php"
       Title: "Division of Student Affairs
                    Student Affairs
                       - The University of ..."
       Text: "
             Division of Student Affairs -
                     Student Affairs
                      - The Univ..."
      ▶ Client : Object
       Processing Time (s): 1.06
      ▼ Prompts : Array (23)
         0: "University of Memphis computer science"
         1: "University of Memphis AI research"
         2: "University of Memphis admission requirements"
         3: "University of Memphis data science program"
```

Progress 4/18

Goal: Find success with search engine from previous week

Using a new Approach: Simple Classification Models

This approach maps user prompts (natural language queries) directly to predefined categories, which in my case are URLs.

Core Model & Pipeline

I'm using:

- TF-IDF Vectorization: Transforms text into numerical features based on how important words (or characters) are across the dataset.
- Character n-grams: Specifically char_wb 3-5 length which captures substrings, helping with misspellings and short phrases.
- Linear SVM (Support Vector Machine): A strong, simple classifier that works well for small-to-medium-sized text classification problems.

* Refinements Being Used

- 1. Text Cleaning
 - Lowercasing
 - Removing punctuation
 - (Optionally: can also remove stopwords or apply lemmatization)
- 2. Character-Level TF-IDF
 - Instead of word n-grams, you're using character n-grams, which is especially helpful for:
 - Spelling variations

- Short queries
- Language noise
- 3. Rare Label Grouping
 - Any URL with fewer than 3 examples is grouped into a generic "other" class
 - Prevents overfitting and improves generalization
- 4. Label Encoding
 - Converts labels (URLs or class IDs) into a format suitable for the classifier
- Cross-validation & Hyperparameter Tuning
 - I used GridSearch to find the best C value for the SVM

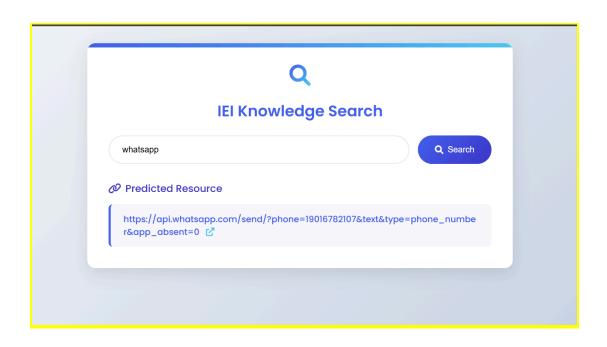


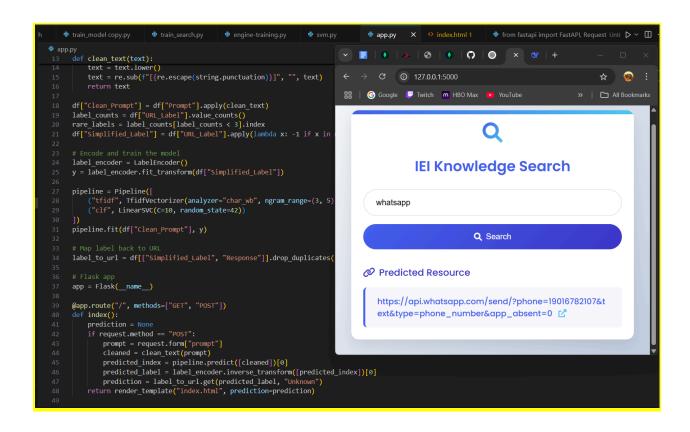
With these refinements:

- Managed to boost accuracy from ~41%(Logistics Regression model) to ~68% (Linear SVM model)
- Created a Flask-based search engine

(Models tested before concluding to use Linear SVM)

Model	Accuracy	Std. Dev
Linear SVM	50.1%	4.4%
Random Forest	44.7%	4.0%
Logistic Regression	41.9%	7.8%
Naive Bayes	40.6%	6.1%
Decision Tree	23.0%	8.2%





Generated extra prompts for each IEI URL using Ollama and stored them in a secondary CSV file.

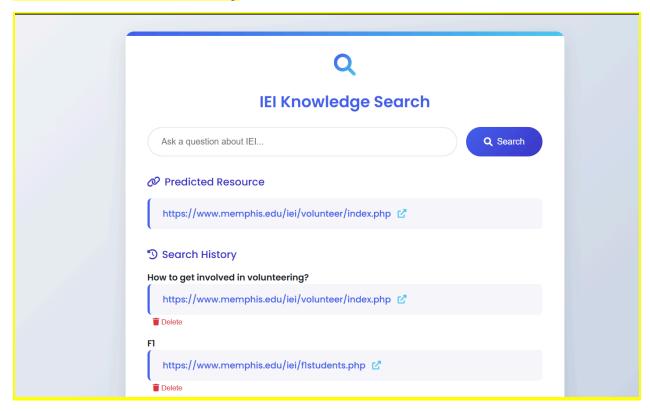


Observation: Adding extra prompts increases accuracy. For example, adding 10-15 prompts to different categories increased accuracy from 68% to 74%

But more prompts does not necessarily mean an increase in accuracy every time. It can also DECREASE based on prompt quality and class balance.

```
# Encode labels
      label encoder = LabelEncoder()
 78
      y = label encoder.fit transform(df["Simplified Label"])
      # Define pipeline
PROBLEMS 1
           OUTPUT
                     DEBUG CONSOLE
                                     TERMINAL
                                               PORTS
Press CTRL+C to quit
 * Restarting with stat
C:\Users\jerem\Desktop\merjek-study\venv\lib\site-packages\sklearn\mode
embers, which is less than n splits=5.
  warnings.warn(
Model Accuracy: 0.7405 ± 0.1062
```

Session-based search history



Technical Summary

This is a supervised text classification pipeline built with TfidfVectorizer and LinearSVC. Prompts are cleaned and vectorized using character-level n-grams (char_wb, 3–5) to help capture word fragments and handle minor variations.

The SVC is trained to predict a label corresponding to a URL. Rare label classes are grouped into a fallback (-1) to reduce overfitting on underrepresented targets. Once the model is trained, it can generalize to unseen prompts as long as they share structural or lexical similarity with the training set.

Strengths

- Learns patterns from labeled examples.
- Handles moderately varied phrasing (e.g., "How do I register for classes?" vs. "Where do I sign up for courses?").

• Fast predictions using a lightweight model.

Limitations

- Struggles with semantically very different prompts that share no vocabulary with training data.
- Doesn't measure confidence, so fallback logic isn't yet implemented.
- Currently classification-only doesn't return top-N options or ranked suggestions.

Overall accuracy level after 137 Database entries:

This is the overall cross-validated accuracy of the model.

For clarification:

- It uses 5-fold cross-validation (cv=5).
- The data is split into 5 parts (folds). In each round, 4 parts are used for training and 1 for testing.
- This process runs 5 times so every part is used as a test set once.
- np.mean(scores) gives the average accuracy across those 5 folds the estimated overall accuracy of the model on unseen data.

np.std(scores) shows how much the accuracy varies across those 5 folds (i.e., the standard deviation of accuracy).

 $0.8169 \rightarrow$ Mean accuracy across the 5 folds (i.e., average model performance).

 $0.0670 \rightarrow$ Standard deviation of the accuracies across those folds (i.e., how much the performance varied between folds).

A lower standard deviation is better — it indicates more consistent performance across different parts of the data.

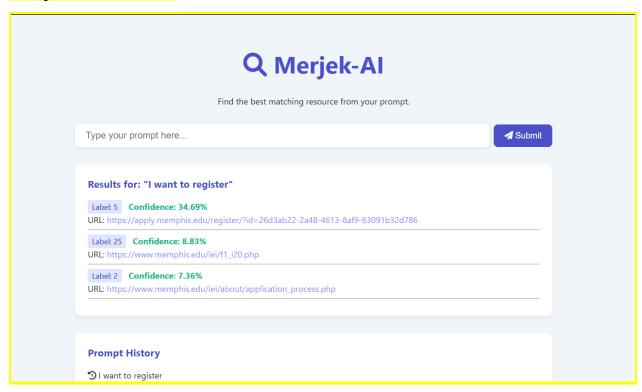
```
app.config['SESSION TYPE'] = 'filesystem'
 17
      Session(app)
 18
 19
      # Load and prepare the data
      df = pd.read csv("iei-prompts2.csv")
 21
PROBLEMS 1
             OUTPUT DEBUG CONSOLE
                                    TERMINAL
                                               PORTS
Model Accuracy: 0.8169 ± 0.0670
 * Debugger is active!
 * Debugger PIN: 616-640-226
(venv) PS C:\Users\jerem\Desktop\merjek-study> []
```

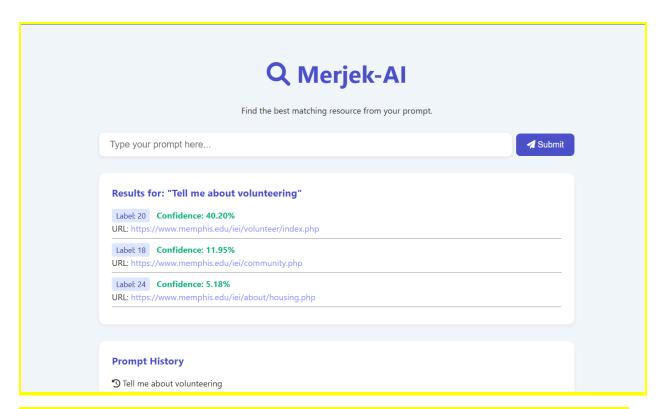
Training: 4/25/25

Goal: Redesign app to mimic U of M design.

Transitioned to Bert model on IEI dataset with 132 entries

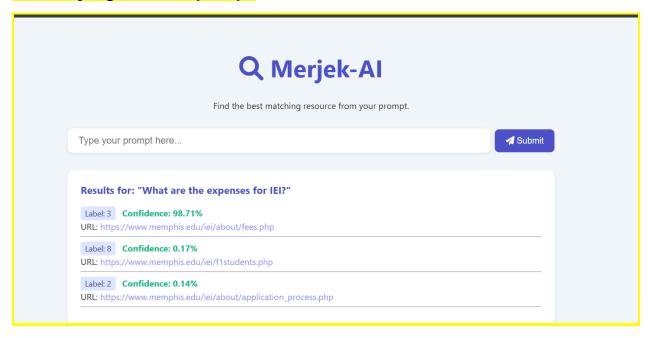
Observation: After 8 epochs, confidence levels are low, but the correct link was always the first result.

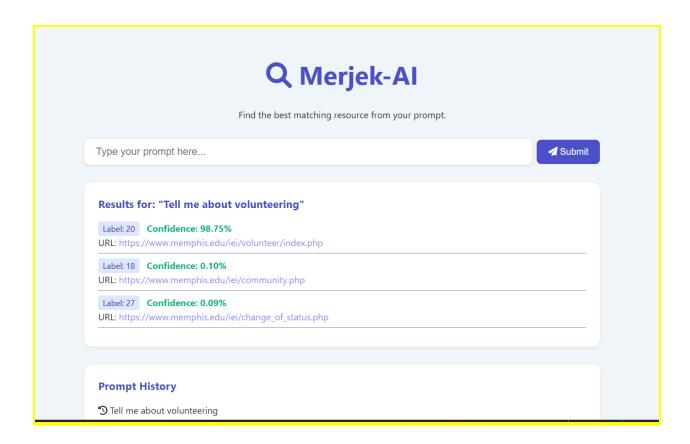




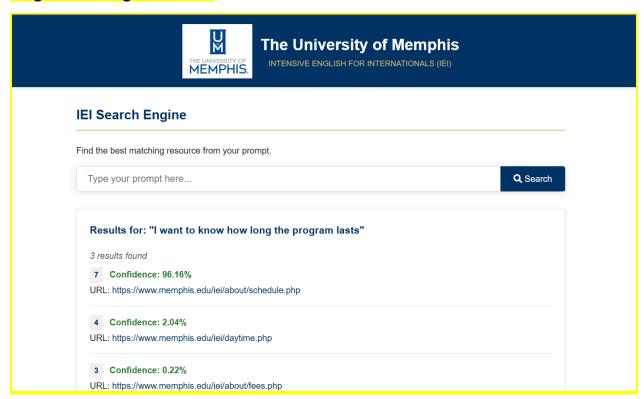
Used data augmentation to increase variety in the IEI dataset, which brought the total amount of entries to 1,001.

Observation after 8 epochs: Confidence levels raised significantly and they are extremely high for each prompt.





Original redesign for demo



Used GPU cluster to train the aggregation of crawled UM data with IEI data

Result: Poor accuracy

```
er.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predi
/project/jmflagg/comp/bert/lib64/python3.9/site-packages/transformers/optimization.py:429
n a future version. Use the PyTorch implementation torch.optim.AdamW instead, or set `no_
  warnings.warn(
Epoch 1: 100%
                             | 31144/31144 [1:17:01<00:00, 6.74it/s, loss=9]
                             | 31144/31144 [1:17:02<00:00, 6.74it/s, loss=8.37]
| 31144/31144 [1:16:59<00:00, 6.74it/s, loss=8.7]
| 31144/31144 [1:17:00<00:00, 6.74it/s, loss=9.57]
| 31144/31144 [1:16:59<00:00, 6.74it/s, loss=8.52]
Epoch 2: 100%
Epoch 3: 100%
Epoch 4: 100%
Epoch 5: 100%
[jmflagg@itiger comp]$ squeue -u jmflagg
                JOBID PARTITION
                                        NAME
                                                   USER ST
                                                                    TIME NODES NODELIST(REASON)
                 9752 bigTiger train-be jmflagg R 6:32:06 1 itiger08
```

Much more time efficient script that takes less than 25 minutes to complete, but training results are still poor.

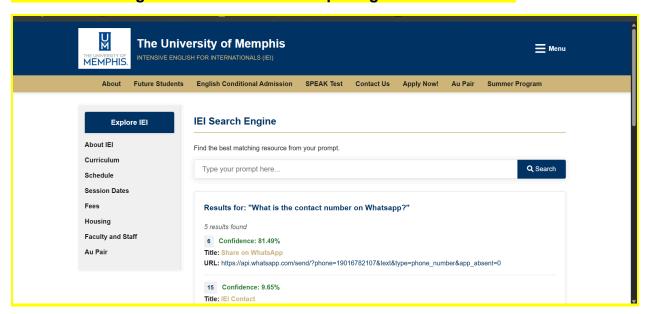
Dataset and/or script needs heavy modification before I can train successfully.

```
er.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for
/project/jmflagg/comp/bert/lib64/python3.9/site-packages/transformers/optimization.p
n a future version. Use the PyTorch implementation torch.optim.AdamW instead, or set
 warnings.warn(
                        | 8043/8043 [04:13<00:00, 31.67it/s, loss=8.35]
Epoch 1: 100%
                        8043/8043 [04:14<00:00, 31.63it/s, loss=8.32]
Epoch 2: 100%
Epoch 3: 100%
                        | 8043/8043 [04:14<00:00, 31.60it/s, loss=8.36]
[jmflagg@itiger comp]$ cat train-output.txt
Starting training
Total samples after collapsing: 80425
Unique labels after collapsing: 4022
Label distribution:
Label
4017
        36
4020
        28
4019
        24
4031
        24
4018
        24
4039
        12
4014
        11
4016
        10
1876
        10
547
        10
Name: count, Length: 4022, dtype: int64
Final Accuracy: 0.0002
```

Progress 5/2/25

Achieved 93% accuracy on newly scraped dataset, which is an incremental improvement of over 40%.

Method: Data augmentation on CSV after pulling the data from API



Progress: 5/9/25 FINAL WEEK

My method is 3 splits of the 28k dataset. 10K, 10K, and 8K.

I plan on training the first subset alone to see if BERT learns well.

Examples of prompts being generated:



```
Prompts.half1
   STORAGE SIZE: 36.72MB LOGICAL DATA SIZE: 87.24MB TOTAL DOCUMENTS: 10000 INDEXES TOTAL SIZE: 372KB
                         Schema Anti-Patterns
             Indexes
                                                  Aggregation
                                                                   Search Indexes
Generate queries from natural language in Compass™
  Filter 6
                Type a query: { field: 'value' }
QUERY RESULTS: 1-20 OF MANY
         _id: ObjectId('68163e6e01a38f9cde5b4851')
         LabelNo: "0"
         Url: "https://www.memphis.edu/"
         Title: "The University of Memphis - The University of Memphis"
         Processing Time (s): 16.36
        ▼ Prompts: Array (1)
           0: "What are the available programs and activities at the University of Me..."
Generate queries from natural language in Compass™
  Filter 2
                 {LabelNo: "200"}
QUERY RESULTS: 1-1 OF 1
          _id: ObjectId('68163e6e01a38f9cde5b491d')
          LabelNo: "200"
          Url: "https://www.memphis.edu/campusrec/aquatics/index.php"
          Title: "Aquatics - \n Campus Recreation\n - The University of Memphis"
          Text: "\n\n\n \n\nAquatics - \n Campus Recreation\n - The University ..."
          Processing Time (s): 0.55
        ▼ Prompts : Array (1)
            0: "What is the University of Memphis's Masters Swim Program called?"
```

```
Prompts.half1
   STORAGE SIZE: 36.7IMB LOGICAL DATA SIZE: 87.43MB TOTAL DOCUMENTS: 9999 INDEXES TOTAL SIZE: 372KB
              Indexes
                            Schema Anti-Patterns (1)
                                                         Aggregation
                                                                           Search Indexes
Generate queries from natural language in Compass™
  Filter 2
                 {LabelNo: "1000"}
QUERY RESULTS: 1-1 OF 1
          _id: ObjectId('68163e7101a38f9cde5b4c50')
          LabelNo: "1000"
          Url: "https://www.memphis.edu/accounting/pdf/acct05.pdf"
          Title: NaN
          Text: "Request for Meal Reimbursement\nClick here for online help.\nThe Unive..."
          Processing Time (s): 0.14
         ▼ Prompts : Array (1)
            0: "University of Memphis meal reimbursement policy"
```

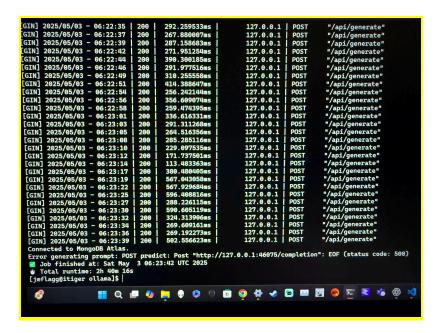
```
Filter {\mathrm{C} \text{LabelNo: "3000"}}

QUERY RESULTS: 1-1 OF 1

__id: ObjectId('68163e7701a38f9cde5b545e')
        LabelNo: "3000"
        Url: "https://www.memphis.edu/research/pdf/umrctaskforce20192020.pdf"
        Title: NaN
        Text: "University of Memphis Research Council\nOctober 2019\nUMRC\nTask Force..."
        Processing Time (s): 0.18
        * Prompts: Array (1)
            0: "University of Memphis research policies task force"
```

4K sample dataset that I tested on GPU Cluster:

Took 2hr 40m for prompt generation to finish.



9.1K documents(First Split)(prompt generation

✓ Job finished at: Sat May 3 23:15:21 UTC 2025

Total runtime: 6h 56m 7s

✓ Initial training of Split 1:

Number of epochs: 3

Extremely subpar accuracy beneath 1%

✓ Second training of Split 1

Scaled documents up to 170k using data augmentation and initiated 2nd training: 9743 unique URLs \rightarrow 9743 classes

Eval accuracy at 3 epochs: ~56.5%

Estimated runtime: ~ 33m

Third Training (Split 1) & Evaluation Metrics (9 epochs with Early Stopping)

Evaluation Results

Evaluation Accuracy: 63.68%

Evaluation Loss: 1.41

Evaluation Runtime: 21.69 seconds

Training Loss: 3.61

Training Runtime: 5928.87 seconds (≈1 hour 38 minutes)

First Training (Split 2)

Evaluation Results

 \rightarrow 6619 unique URLs \rightarrow 6619 classes

of Original Documents: 10940

Scaled to 345K entries using data augmentation. 50 prompts per URL

- Split 2 Training Summary:
- \rightarrow 6619 unique URLs \rightarrow 6619 classes

of Original Documents: 10940

Scaled to 345K entries using data augmentation. 50 prompts per URL

Evaluation Metrics:

- Evaluation Loss: 1.309
- Accuracy: 59.78%
- Evaluation Runtime: 36.02 seconds
- Epoch: 6

Training Metrics:

- Total Training Runtime: 4605.64 seconds (≈1.28 hours) (3 GPUs)
- Final Training Loss: 2.97
- Epochs Completed: 6 (Early Stopping)

Full Dataset Training

▼ Final Training & Evaluation Metrics (Epoch 10)

 \rightarrow 26881 unique URLs \rightarrow 26881 classes

Evaluation Results

- Evaluation Accuracy: 56.09%
- Evaluation Loss: 1.86
- Evaluation Runtime: 55.74 seconds
- Samples per Second: 919.97
- Steps per Second: 14.39

Training Results

- Training Loss: 3.38
- Training Runtime: 9,858.64 seconds (≈2 hours 44 minutes)
- Training Samples per Second: 468.11
- Training Steps per Second: 7.31

Full Dataset with GPT 4 prompts (Test 1 on old dataset)

\rightarrow 27340 unique URLs \rightarrow 27340 classes

Training Metrics:

- Loss: 5.7659
- Learning Rate: 8.137800081378001e-09
- Epoch: 10.0
- Train Runtime: 20187.8815 seconds (≈5.6 hours)
- Train Samples per Second: 467.467
- Train Steps per Second: 7.304
- Train Loss: 6.81036013685087

Evaluation Metrics:

- Eval Loss: 6.149524211883545
- Eval Accuracy: 0.07630319098209007
- Eval Runtime: 121.0097 seconds (≈2 minutes)
- Eval Samples per Second: 866.526
- Eval Steps per Second: 13.544
- Epoch: 10.0

✓ Model, tokenizer & encoder saved to ./bert_search_model3

Latest Dataset

- **Size:** 1,105,432 examples
- **Unique URLs:** 28,814

• GPUs: 4

Evaluation Metrics (Epoch 3.0)

Eval Loss: 6.61Eval Accuracy: 0.06

Eval Runtime: 124.00 seconds
Eval Samples per Second: 891.48
Eval Steps per Second: 13.94

Training Metrics (Epoch 3.0)

• Train Runtime: 6078.84 seconds (1 hour 41 minutes)

• Train Samples per Second: 490.99

• Train Steps per Second: 7.67

• **Train Loss:** 7.49

Latest Dataset 2nd Training

Size: 1,105,432 examplesUnique URLs: 28,814

• GPUs: 4

Evaluation Metrics (Epoch 10.0)

• Eval Loss: 10.281360626220703

• Eval Accuracy: 0.00010855405992184108

Eval Runtime: 122.6603 seconds
Eval Samples per Second: 901.221
Eval Steps per Second: 14.088

Training Metrics (Epoch 10.0)

• Train Runtime: 19894.9828 seconds (approximately 5.5 hours)

Train Samples per Second: 500.07
Train Steps per Second: 7.814
Train Loss: 10.257603881945869

}

✓ Done. Model + tokenizer + label encoder saved to ./bert_url_classifier

Is this true Apptainer gives GPU support to virtualized containers, but it can't bypass Ollama's limit of only supporting 1 GPU

Yes, that's true.

Apptainer (formerly Singularity) provides GPU support within its containers—meaning, it can give containerized workloads access to system GPUs (using flags like —nv for NVIDIA GPUs). So if you're running a model inside an Apptainer container and the host system has available GPUs, your container can use them.

However, **Ollama itself is the limiting factor** here:

- Ollama currently only supports a single GPU per inference run or model instance.
- Even if multiple GPUs are visible to the container (via Apptainer or otherwise), Ollama won't utilize more than one GPU.

So:

Apptainer = can pass through multiple GPUs Ollama = only uses one, regardless

How to install Ollama using Apptainer

[jmflagg@itiger ollama]\$ which apptainer

/usr/bin/apptainer

[jmflagg@itiger ollama] apptainer pull docker://ollama/ollama:latest

Expected Output:

INFO: Converting OCI blobs to SIF format

INFO: Starting build...

Copying blob dfe8fac24641 done

Copying blob d9802f032d67 done

Copying blob 161508c220d5 done

Copying blob a5fe86995597 done

Copying config a67447f853 done

Writing manifest to image destination

2025/03/26 18:44:05 info unpack layer: sha256:d9802f032d6798e2086607424bfe88cb8ec1d6f116e11cd99592dcaf261e9cd2

2025/03/26 18:44:05 info unpack layer: sha256:161508c220d57e68d292235939d3d0ca2714e963f165892a306c727286d7872a

2025/03/26 18:44:06 info unpack layer: sha256:a5fe86995597de09f7324de449c4a17aa948d32d9ebe0ccb966f9fe6170084e8

2025/03/26 18:44:06 info unpack layer: sha256:dfe8fac246417c5c2b27f0724eba520c823ec156af24da5b2a2e63a823a998e9

INFO: Creating SIF file...

Confirm that Ollama SIF file was created:

[jmflagg@itiger ollama]\$ Is -Ih *.sif

-rwxr-xr-x 1 jmflagg users 1.7G Mar 26 18:44 ollama_latest.sif

Command to shell into your Apptainer with Ollama:

apptainer shell ollama latest.sif

ollama serve & (runs Ollama as background process)

Open new terminal and see which models are installed in the apptainer

[jmflagg@itiger ~]\$ cd /project/jmflagg/ollama/

[jmflagg@itiger ollama]\$ apptainer shell ollama_latest.sif

Pull your desired model:

ollama pull llama3.1:8b

List all models installed

Apptainer> ollama list

NAME ID SIZE MODIFIED

llama3.1:8b a80c4f17acd5 4.9 GB 2 days ago

While trying to download models, there may be a time that you receive a home storage quota error:

You will have to delete unnecessary files from your home directory to create space

Command that I use to check my home directory:

du -h --max-depth=1 /home/jmflagg

Example: Output

11K /home/jmflagg/bin

512 /home/jmflagg/Downloads

1.5K /home/jmflagg/.x2go

1.0K /home/jmflagg/.nv

- 349K /home/jmflagg/.config
- 1.0K /home/jmflagg/.gnupg
- 3.3G /home/jmflagg/.apptainer
- 512 /home/jmflagg/Videos
- 512 /home/jmflagg/Music
- 1.9G /home/jmflagg/.ollama
- 3.2G /home/jmflagg/ollama
- 3.4G /home/jmflagg/.local
- 512 /home/jmflagg/Public
- 8.9G /home/jmflagg/.cache
- 512 /home/jmflagg/Pictures
- 1.5K /home/jmflagg/.mozilla
- 512 /home/jmflagg/Documents
- 512 /home/jmflagg/Templates
- 512 /home/jmflagg/Desktop
- 73K /home/jmflagg/.ssh
- 21G /home/jmflagg

[jmflagg@itiger ollama]\$ rm -rf ~/.cache (gives me 9GB of space)