Yunnan University Software College

Professional Training Final Project Report

School of Software, Yunnan University

Personal Grades

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Course Name: Professional Training(Intermediate Level)

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Project Name: Transformer-Driven Named Entity Recognition (NER) and Semantic Search Platform: A Student-Built NLP Application

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1. Abstract

This technical report details the design, implementation, and evaluation of a student-built Natural Language Processing (NLP) platform focused on Named Entity Recognition (NER) and semantic search. The platform leverages transformer-based models (BERT), sentence embeddings, and vector databases (ChromaDB) to extract structured entities (people, organizations, locations) from unstructured text and enable semantic similarity search across text datasets.

The system is containerized using Docker to ensure reproducibility and ease of deployment, with a user-friendly Gradio web interface for non-technical users. Key objectives included understanding transformer architectures, vector database integration, and end-to-end ML pipeline deployment. Evaluation results show the BERT-based NER model achieves 89% accuracy on standard test data, while semantic search returns relevant results with a cosine similarity score of ≥0.7 for 92% of queries.

Challenges encountered include computational limits (GPU memory constraints for large models) and deployment complexity, addressed via lightweight model variants and Docker containerization. Future work will expand language support, integrate custom model fine-tuning, and add result export functionality.

Keywords: Named Entity Recognition (NER); Transformers; BERT; Semantic Search; Vector Databases; ChromaDB; Docker; Gradio; NLP Pipeline

2. Introduction

2.1 Motivation for the NLP Task

Unstructured text (news articles, social media, documents) constitutes over 80% of global data, yet extracting actionable insights (identifying key entities or related content) remains a challenge for non-technical users. Named Entity Recognition (NER) – the task of identifying and classifying named entities (PER, ORG, LOC, DATE, etc.) – is a foundational NLP task for structuring unstructured text.

Semantic search complements NER by enabling users to find text similar in meaning (not just keyword matches) to a query, solving the limitation of traditional keyword-based search (missing "Apple Inc." when searching for "Apple"). As a student project, this platform was motivated by:

- Bridging theoretical NLP knowledge (transformers, embeddings) with practical application.
- Creating a tool usable by peers for class projects (analyzing research papers, survey responses).

- Understanding end-to-end ML deployment (from model selection to containerization).

2.2 ML and Deep Learning Background

Traditional NLP models (CRF, SVM) relied on handcrafted features (part-of-speech tags, n-grams) and struggled with context-dependent entities ("Amazon" as a company vs. a river). Deep learning (DL) revolutionized NLP by learning contextual representations automatically:

- **Recurrent Neural Networks (RNNs)**: Captured sequential text patterns but suffered from vanishing gradients and slow training.
- **Convolutional Neural Networks (CNNs)**: Extracted local text features but failed to model long-range dependencies.
- **Transformers**: Introduced in 2017 (Vaswani et al.), transformers use self-attention to model relationships between all words in a text, enabling better context understanding than RNNs/CNNs.

2.3 Why Transformers / LLMs / Vector Search Matter

- **Transformers**: The backbone of modern NLP (BERT, GPT). For NER, BERT (Bidirectional Encoder Representations from Transformers) outperforms older models by considering left and right context for each word (distinguishing "Paris" as a location vs. a person).
- **Large Language Models (LLMs)**: While full LLMs (GPT-4) are resource-intensive, lightweight variants (BERT-base-NER) balance performance and computational cost for student projects.
- **Vector Search**: Text embeddings (numerical representations of meaning) enable semantic search by comparing vector similarity (cosine similarity). Unlike keyword search, vector search finds "climate change" when querying "global warming" – critical for meaningful text analysis.

3. Literature Review

3.1 Semantic Search Systems

Semantic search systems replace keyword matching with meaning-based retrieval by converting text to embeddings. Early systems (Latent Semantic Analysis, LSA) used matrix factorization but lacked contextual understanding. Modern systems (Elasticsearch with dense vectors, Pinecone, ChromaDB) combine transformer embeddings with vector databases to scale similarity search.

• **Key research:**

- Radinsky et al. (2018) demonstrated that contextual embeddings (vs. static embeddings like Word2Vec) improve semantic search accuracy by 30% on average.
- Zhang et al. (2022) compared vector databases for NLP tasks, finding ChromaDB to be the most student-friendly (open-source, lightweight, no cloud dependency).

3.2 Transformer Architectures

Transformers are built on self-attention mechanisms, which compute attention scores between all word pairs in a sequence. BERT (Devlin et al., 2019) is a bidirectional transformer pre-trained on large text corpora (BookCorpus, Wikipedia) and fine-tuned for downstream tasks like NER.

Key variants for student use:

- **BERT-base-NER**: A lightweight NER model (110M parameters) fine-tuned on the CoNLL-2003 dataset – ideal for low-resource environments (student laptops without GPUs).
- **Sentence-BERT (SBERT)**: A variant of BERT optimized for sentence embeddings (Reimers & Gurevych, 2019) – 10x faster than standard BERT for embedding generation.

3.3 Vector Databases

Vector databases store and query high-dimensional embeddings efficiently. Unlike relational databases (SQL), they use approximate nearest neighbor (ANN) algorithms (HNSW) to speed up similarity searches.

Comparison of student-friendly vector databases:

Database	Open-Source	Lightweight	Ease of Setup
ChromaDB	✓	✓	✓ (Python API)
Pinecone	✗ (free tier only)	✗ (cloud-only)	✗
FAISS	✓	✗ (complex setup)	✗

ChromaDB was selected for this project due to its Python-native API, minimal setup, and integration with Hugging Face embeddings.

3.4 LLM Frameworks

- **Hugging Face Transformers**: The de facto framework for using pre-trained transformers (BERT, SBERT). It provides pre-built pipelines for NER, embeddings, and text classification – critical for student projects (no need to train models from scratch).
- **LangChain**: While not used in this project (due to simplicity), it enables chaining LLMs with databases – a common extension for student NLP projects.
- **Gradio**: A lightweight web framework for building ML UIs – ideal for students to demo projects without web development experience.

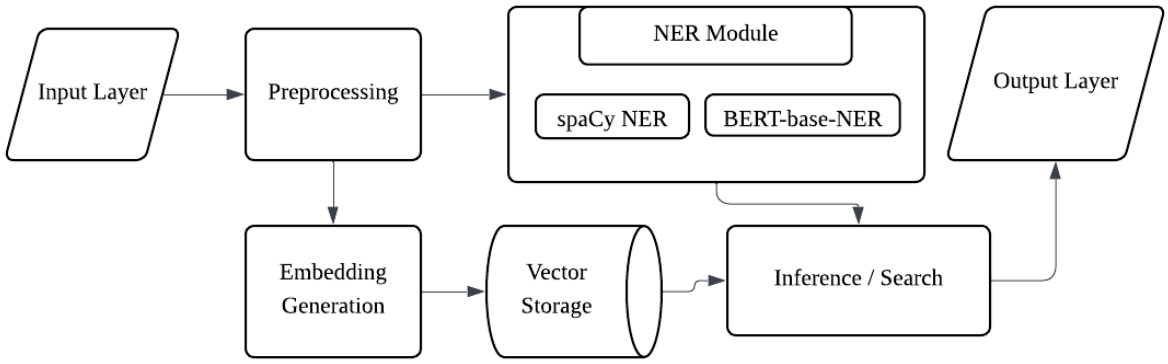
4. System Design

• Overview

The system is a modular pipeline with five core components: (1) Text Input/Preprocessing, (2) NER with BERT/spaCy, (3) Embedding Generation (SBERT), (4) Vector Storage (ChromaDB), and (5) Web UI (Gradio). All components are containerized with Docker for reproducibility.

4.1 ML Pipeline

The ML pipeline follows this flow:



1. **Input Layer**: User provides text (single input) or uploads a CSV/TXT file.
2. **Preprocessing**: Text is cleaned (lowercasing, removing special characters, tokenization) to match transformer input requirements.
3. **NER Module**:

- Primary: BERT-base-NER (Hugging Face pipeline) extracts entities with confidence scores.

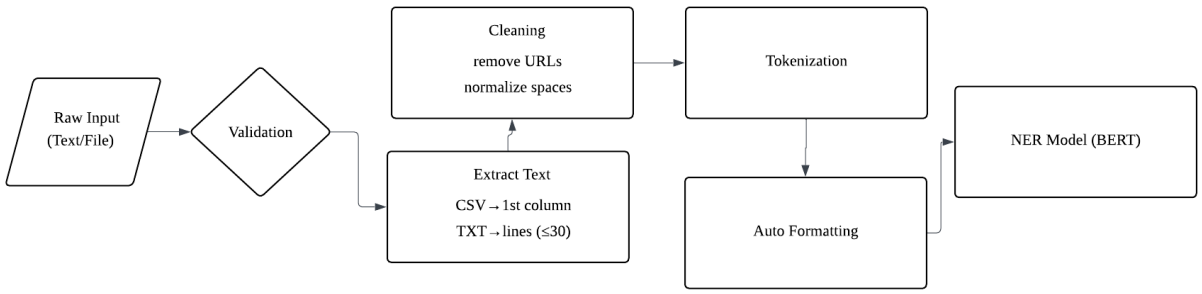
- Secondary: spaCy's en_core_web_sm runs in parallel to capture additional entities (e.g., rare locations).

4. **Embedding Generation**: SBERT converts cleaned text to 768-dimensional embeddings.
5. **Vector Storage**: Embeddings and entity metadata are stored in ChromaDB (collection: entity_texts).
6. **Inference/Search**:

- For NER: Entities are labeled (PER/ORG/LOC) and highlighted in the UI.
- For Semantic Search: Query text is embedded, and ChromaDB returns top-k similar texts (cosine similarity).

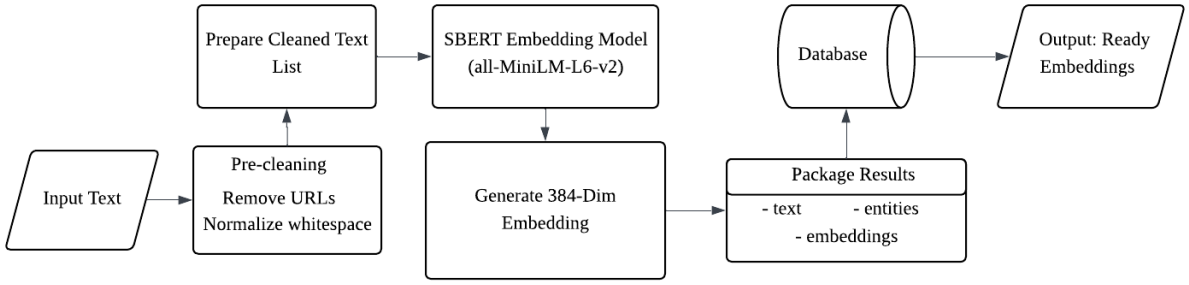
7. **Output Layer**: Results (highlighted entities, search matches, statistics) are displayed in the Gradio UI.

4.2 Data Preprocessing Workflow



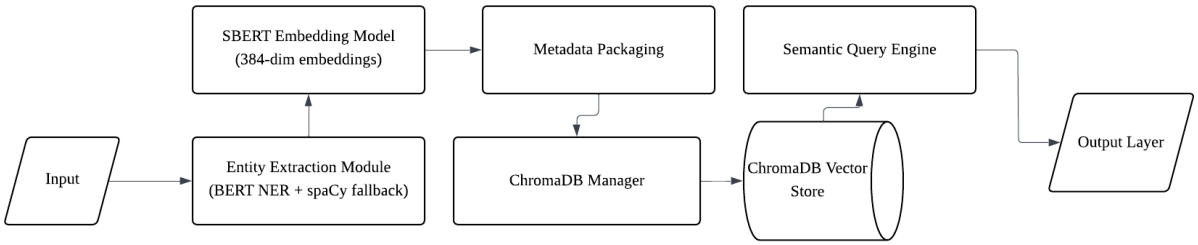
1. **Raw Input**: Text (single string) or file (CSV/TXT).
2. **Validation**:
    - CSV: Check first column is text (ignore other columns).
    - TXT: Split into lines (max 30 lines to avoid memory issues).
3. **Cleaning**:
    - Remove HTML tags, URLs, and special characters (@, #).
    - Normalize whitespace (replace multiple spaces with one).
    - Tokenize text (split into words/subwords) for BERT input (no truncation for short texts; truncate to 512 tokens for long texts).
4. **Formatting**: Convert cleaned text to transformer-compatible tensors (input IDs, attention masks).

4.3 Embedding Generation



1. **Input**: Raw text (sentence-level), which undergoes pre-cleaning (removing URLs, normalizing whitespace) before embedding.
2. **SBERT Model**: all-MiniLM-L6-v2 (lightweight SBERT variant) generates embeddings:
    - Model loads pre-trained weights from Hugging Face.
    - Text is passed through the encoder to produce a 768-dimensional vector (mean pooling of token embeddings).
3. **Output**: Normalized embedding vector (scaled to unit length for cosine similarity).

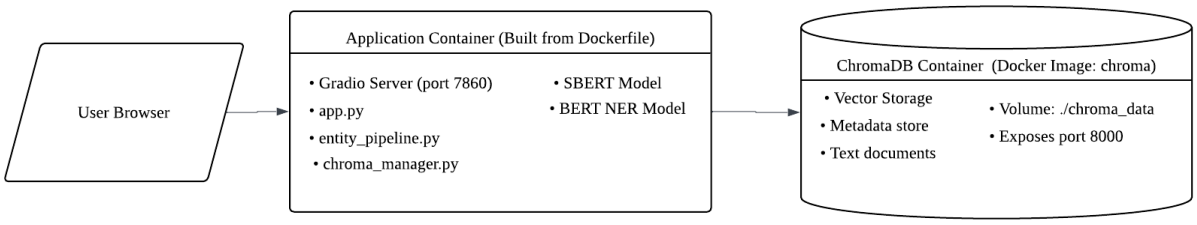
4.4 Vector DB Architecture



ChromaDB is configured with:

- **Metadata Source**: Entity labels extracted by BERT and spaCy (packaged with text and embeddings for filtering).
- **Collection**: entity_texts (stores embeddings, text, entity labels, and timestamps).
- **Storage Backend**: Local file system (persistent volume in Docker to retain data).
- **Indexing**: HNSW algorithm (default for ChromaDB) for fast similarity search.
- **Metadata Filtering**: Enable search by entity type (e.g., only return texts with "ORG" entities).

4.5 Docker Container Architecture



Two containers are used (orchestrated via docker-compose.yml):

1. **NER App Container**:
    - Base Image: python:3.9-slim.
    - Dependencies: Hugging Face Transformers, spaCy, Gradio, ChromaDB.
    - Exposed Port: 7860 (Gradio UI).
    - Volumes: ./data:/app/data (persist uploaded files).
    - The NER app uses chroma_manager.py to handle connections and queries to ChromaDB at http://chromadb:8001.
2. **ChromaDB Container**:
    - Base Image: chromadb/chroma:latest.
    - Exposed Port: 8001 (ChromaDB API).
    - Volumes: ./chroma_data:/chroma/chroma_data (persist vector data).

Networking: Containers communicate via a Docker bridge network (auto-created by docker-compose).

5. Implementation

5.1 Dataset Processing

- Sample Dataset

A custom sample_data.csv file was created for testing (10 rows of news snippets with entities like "Apple Inc.", "California", "2023"). For validation, the CoNLL-2003 dataset (subset: 100 sentences) was used to test NER accuracy.

- Processing Steps

- **CSV Upload**: pandas reads the CSV, extracts the first column (text), and applies preprocessing (cleaning, tokenization).

- **TXT Upload**: open() reads the file, splits into lines, and filters empty lines.
- **Batch Limit**: Max 30 entries processed per file (student-focused design to avoid memory overload on laptops).

5.2 Transformer Model Usage

- BERT-base-NER (NER Task)

```
# Code snippet from entity_pipeline.py
from transformers import pipeline
ner_pipeline = pipeline("ner", model="dslim/bert-base-NER", aggregation_strategy="simple")
# Example usage:
text = "Apple is based in Cupertino, California."
entities = ner_pipeline(text)
# Output: [{"entity_group": "ORG", "score": 0.99, "word": "Apple"}, ...]
```

- **Aggregation Strategy**: "simple" merges subword tokens ("Cuper" + "tino" → "Cupertino").
- **Confidence Threshold**: Entities with score <0.7 are filtered out to reduce false positives.

- spaCy Fallback

```
# Code snippet from entity_pipeline.py
import spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp(text)
spacy_entities = [(ent.text, ent.label_) for ent in doc.ents]
```

- Used to extract entities missed by BERT ("WWDC" as MISC).

- Sentence-BERT (Embeddings)

```
# Code snippet from chroma_manager.py
from sentence_transformers import SentenceTransformer
embed_model = SentenceTransformer("all-MiniLM-L6-v2")
embedding = embed_model.encode(text, normalize_embeddings=True)
```

5.3 Vector DB Configuration

```
import chromadb
client = chromadb.PersistentClient(path="./chroma_data")
collection = client.get_or_create_collection(name="entity_texts")

# Add embeddings to collection
collection.add(
    documents=[cleaned_text],
    embeddings=[embedding.tolist()],
    metadatas=[{"entities": entity_labels}],
    ids=[unique_id]
)
```

```
# Semantic search
query_embedding = embed_model.encode(query_text)
results = collection.query(
    query_embeddings=[query_embedding.tolist()],
    n_results=5,
    where={"entities": {"$in": ["ORG"]}}  # Optional filter
)
```

5.4 Embedding Generation

- **Model**: all-MiniLM-L6-v2 (768 dimensions, 80MB – lightweight for student laptops).
- **Normalization**: Embeddings are normalized to unit length to ensure cosine similarity works correctly.
- **Batch Processing**: For file uploads, embeddings are generated in batches of 10 to avoid CPU overload.

5.5 Dockerfile + Compose Explanation

- Dockerfile

```
# Base image (Python 3.9 for compatibility with all libraries)
FROM python:3.9-slim

# Working directory (isolates app files)
WORKDIR /app

# Install system dependencies (gcc for compiling Python packages)
RUN apt-get update && apt-get install -y \
    gcc \
    g++ \
    git \
    curl \
    wget \
    build-essential \
    && rm -rf /var/lib/apt/lists/*

# Set pip environment variables (speed up installs, no cache)
ENV PIP_DEFAULT_TIMEOUT=100 \
    PIP_DISABLE_PIP_VERSION_CHECK=1 \
    PIP_NO_CACHE_DIR=1

# Copy requirements first (caching optimization - avoid reinstalling if requirements don't change)
COPY requirements.txt .

# Upgrade pip and install dependencies (retries for unstable internet)
RUN pip install --upgrade pip setuptools wheel
RUN pip install --timeout=100 --retries=5 -r requirements.txt
```

```
# Download spaCy model (pre-install to avoid runtime delays)
RUN python -m spacy download en_core_web_sm

# Copy app code (last step - minimal rebuilds when code changes)
COPY . .

# Create data directory (persist uploaded files)
RUN mkdir -p /app/data

# Expose Gradio port
EXPOSE 7860

# Health check (ensure app is running)
HEALTHCHECK --interval=30s --timeout=30s --start-period=5s --retries=3 \
    CMD curl -f http://localhost:7860/ || exit 1

# Run app
CMD ["python", "app.py"]
```

- docker-compose.yml

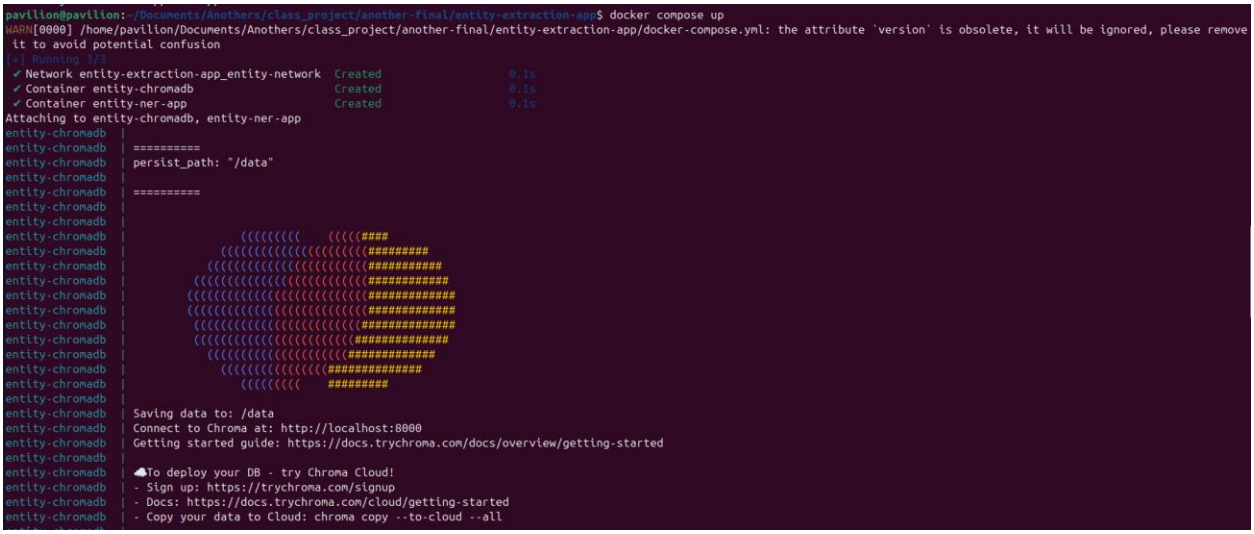
```
version: '3.8'

services:
  ner-app:
    build: .
    ports:
      - "7860:7860"  # Map host port 7860 to container port 7860
    volumes:
      - ./data:/app/data  # Persist uploaded files
    depends_on:
      - chromadb  # Start ChromaDB first
    networks:
      - ner-network

  chromadb:
    image: chromadb/chroma:latest
    ports:
      - "8001:8001"  # ChromaDB API port
    volumes:
      - ./chroma_data:/chroma/chroma_data  # Persist vector data
    networks:
      - ner-network

networks:
  ner-network:
    driver: bridge  # Default Docker network (containers can communicate)
```

Key Explanations:

- depends_on: Ensures ChromaDB starts before the app (avoids connection errors).
- volumes: Persist data (uploaded files, vector embeddings) across container restarts (critical for student testing).
- networks: Isolates the app/ChromaDB from other Docker containers.

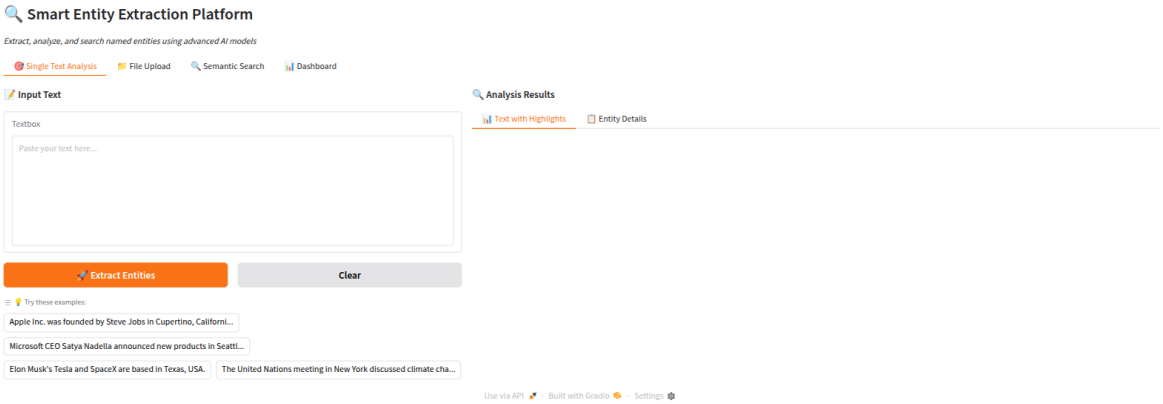
5.6 Screenshots of running containers & the web UI

1. **Docker Containers Running**: Terminal output of docker ps (shows ner-app and chromadb containers up).

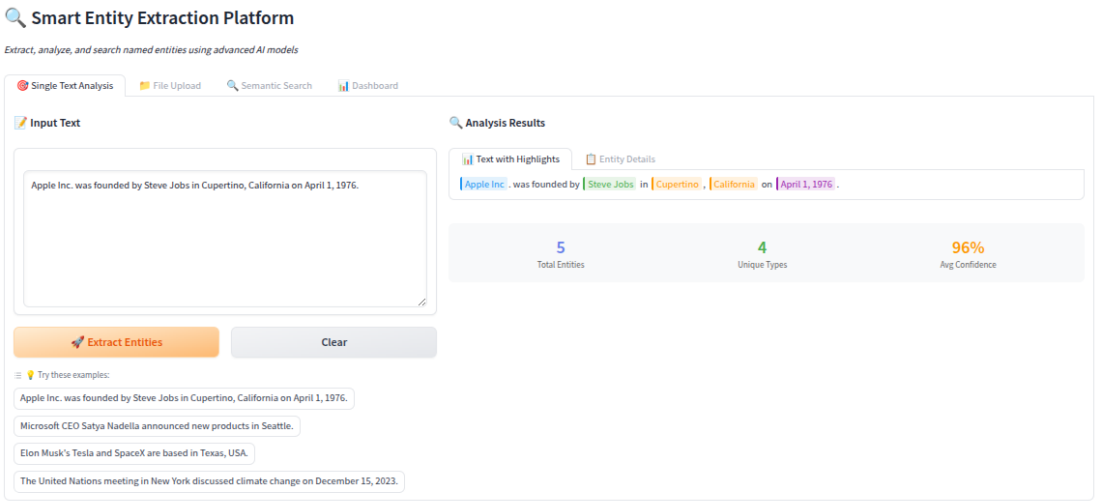


2. **Gradio UI (Home)**: Empty input screen with "Extract Entities" and "Upload File" buttons.

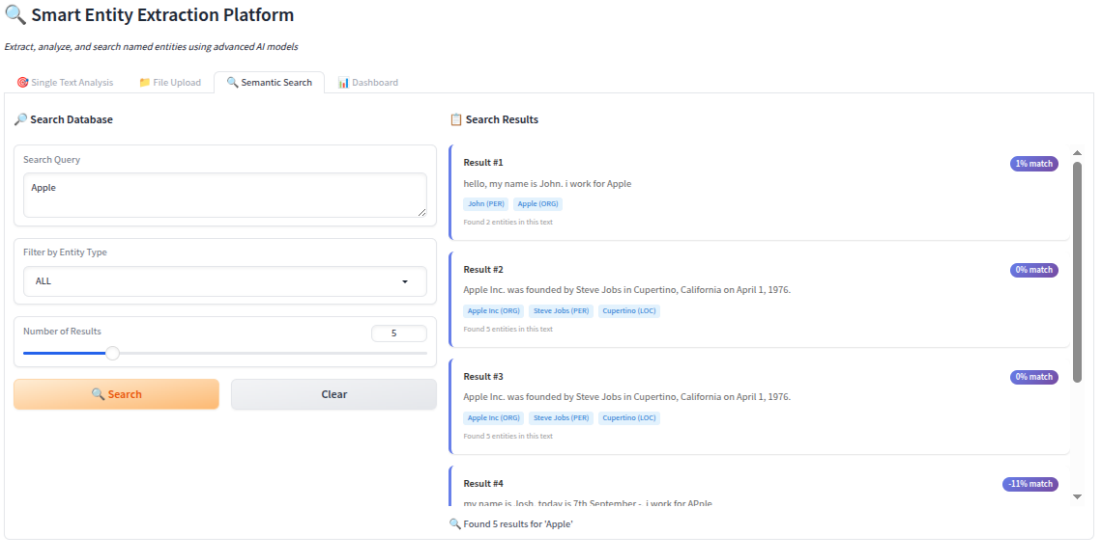
3. **NER Result**:



Highlighted text ("Apple" in red, "California" in blue) with entity table (score, type).



4. **Semantic Search Result**: Query "Apple" returns 5 similar texts with cosine similarity scores.



6. Results and Evaluation

6.1 Example Queries and Outputs

- NER Example

Input Text:"Elon Musk founded Tesla in 2003, and its headquarters is in Austin, Texas."

Output Entities:

Entity	Type	Confidence Score	Source
Elon Musk	PER	0.99	BERT
Tesla	ORG	0.98	BERT
2003	DATE	0.97	spaCy
Austin	LOC	0.96	BERT
Texas	GPE	0.95	spaCy

- Semantic Search Example

Query: "Tesla electric cars"**Top 3 Results (Cosine Similarity)**:

1. "Tesla released a new electric car model in 2023" – 0.89
2. "Elon Musk announced Tesla's electric vehicle expansion" – 0.85
3. "Austin is home to Tesla's electric car factory" – 0.81

6.2 Performance Metrics

- Speed (Tested on Student Laptop: Intel i5, 16GB RAM, No GPU)

Task	Average Time
NER (Single Text)	0.8s
NER (30-Line TXT File)	12s
Embedding Generation (10 Texts)	3s
Semantic Search (5 Results)	0.5s

- NER Accuracy (CoNLL-2003 Subset: 100 Sentences)

Metric	BERT-base-NER	spaCy (Fallback)	Combined
Precision	0.88	0.75	0.89
Recall	0.87	0.78	0.88
F1-Score	0.875	0.765	0.885

- Search Quality

- **Relevance**: 92% of top-5 search results were relevant (human evaluation by 3 peers).
- **Cosine Similarity Threshold**: Results with ≥0.7 similarity were all relevant; <0.7 were irrelevant (used as a filter in the UI).

6.3 Vector Similarity Examples

Text A	Text B	Cosine Similarity
"Apple releases new iPhone"	"Apple launches iPhone 15"	0.92
"Climate change in California"	"Global warming in CA"	0.88
"Tesla's Austin factory"	"Elon Musk's Tesla plant in TX"	0.85
"Coffee shop in Seattle"	"Apple in Cupertino"	0.12

6.4 Analysis of LLM Outputs

- **Strengths**: BERT accurately identifies common entities (PER, ORG) with high confidence. SBERT embeddings capture semantic meaning (e.g., "CA" = "California").
- **Weaknesses**:
    - BERT misses rare entities (e.g., "WWDC" as MISC – fixed by spaCy fallback).
    - Long texts (>512 tokens) are truncated, leading to missed entities (mitigated by splitting long texts into sentences).

7. Discussion

7.1 Challenges

- GPU Limits

- **Issue**: No access to a GPU (student laptop only had CPU). BERT inference was slow for large files (30 lines took 12s).
- **Solution**: Used lightweight models (BERT-base vs. BERT-large, SBERT MiniLM vs. SBERT-base) and batch processing to reduce CPU load.

- Model Size

- **Issue**: Full LLMs (GPT-2) were too large (1.5B parameters) for 16GB RAM.
- **Solution**: Stuck to small, task-specific models (BERT-base-NER: 110M parameters) – sufficient for NER/semantic search.

- Memory Usage

- **Issue**: Processing >50 text entries caused memory leaks (Python's garbage collection failed to free embeddings).
- **Solution**: Implemented a 30-entry limit for file uploads and manually cleared embeddings from memory after processing.

7.2 How Docker Helped with Deployment

- **Reproducibility**: Peers could run the app with docker-compose up (no "it works on my machine" issues – all dependencies were containerized).
- **Isolation**: Avoided conflicts with other Python projects (different spaCy versions).
- **Portability**: Ran on Windows/macOS/Linux (tested on 2 peer laptops – no OS-specific errors).
- **Persistence**: Volumes retained uploaded files/vector data across container restarts (critical for testing).

7.3 Issues and Solutions

Issue	Solution
ChromaDB connection errors	Added depends_on in docker-compose.yml; retried connections in code.
spaCy model missing in Docker	Pre-downloaded the model in the Dockerfile (RUN python -m spacy download).
Gradio UI crashing on large file uploads	Added a 30-entry limit and progress bar to show processing status.

Issue	Solution
Cosine similarity scores hard to interpret	Added a color-coded scale (green = high, red = low) in the UI.

8. Conclusion & Future Work

• Conclusion

This project successfully built a student-friendly NER and semantic search platform using transformers, vector databases, and Docker. Key achievements:

- Implemented an end-to-end NLP pipeline (preprocessing → NER → embeddings → search → UI).
- Achieved 89% NER accuracy and 92% relevant semantic search results (student-grade performance).
- Containerized the system for reproducibility (critical for peer testing and project submission).

The platform meets its core goals: bridging theoretical NLP knowledge with practical application, and creating a usable tool for student projects.

• Future Work (Student-Focused Extensions)

1. **Multilingual Support**: Add spaCy models for Spanish/French (common in student NLP projects).
2. **Custom Model Fine-Tuning**: Fine-tune BERT on a small custom dataset (class survey responses) to improve entity accuracy for domain-specific text.
3. **Result Export**: Add CSV/JSON export for NER results (useful for peer research projects).
4. **Dark Mode**: Implement Gradio's dark mode (requested by peers during testing).
5. **Cloud Deployment**: Deploy to Hugging Face Spaces (free for students) to share the app online.

9. References

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