Book Recommender using NLP

Carsten Lydeking

Zealand Business College

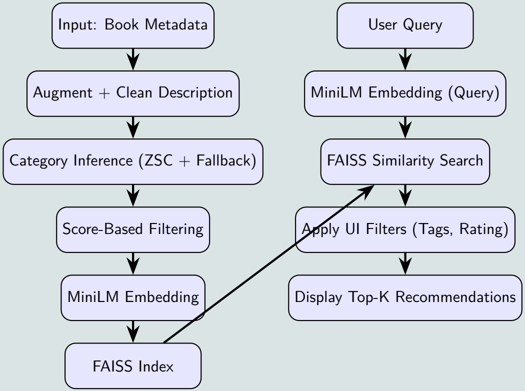
Oral Exam – AI and ML, 4th Semester

- Increasing demand for privacy-preserving, local-first ML applications.
- Typical recommender systems rely on cloud APIs and user profiles.
- Goal: explore feasibility of a fully offline, content-based book recommender system.
- Research question:

  How can a local ML model be used to recommend books based on natural language descriptions?

Modular, fully local processing pipeline:

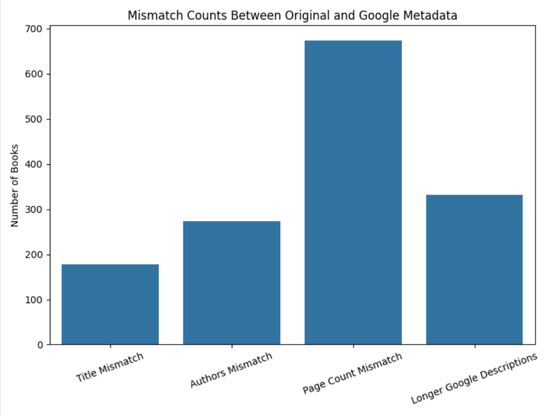
- Data cleaning and augmentation
- Category inference via zero-shot classification + fallback
- Sentence embedding with MiniLM
- Fast vector similarity search with FAISS
- Offline UI built with Streamlit



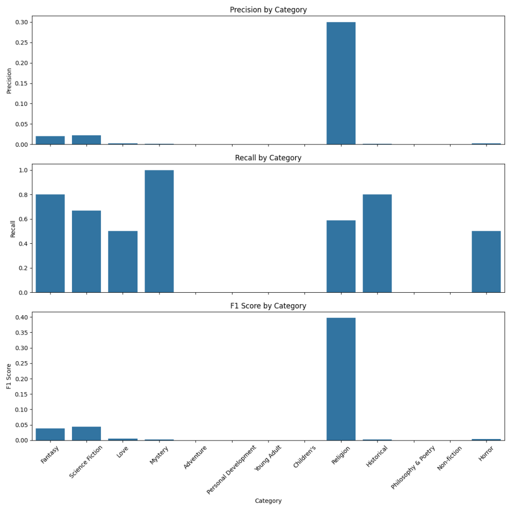
Dataset Exploration

Original dataset $\sim$ 6800 books

- Missing or inconsistent fields (authors, categories, descriptions)
- Very short or low-quality descriptions
- Category noise across sources
- OpenLibrary and Google Books API used to enrich metadata
- Rows with < 9 words in description removed
- Final dataset: 5160 high-confidence books

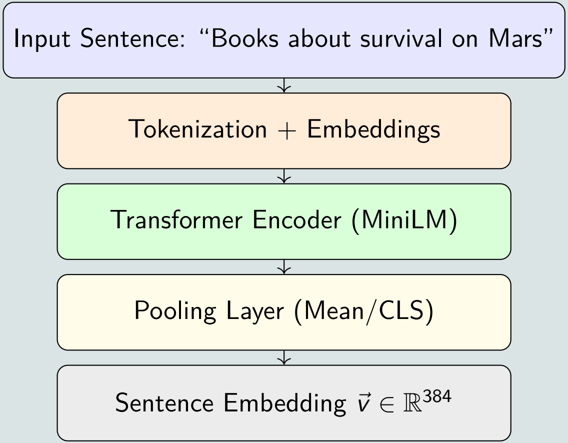


- Zero-shot classification with BART-MNLI
- 13 candidate categories defined
- Fallback keyword rules added for weak predictions
- Per-category metrics calculated:
  - Precision
  - Recall
  - F1-score
- Final filtering based on confidence thresholds:
  - description_length $\geq$ 200 chars
  - avg_score $\geq$ 0.2
  - max_score $\geq$ 0.4



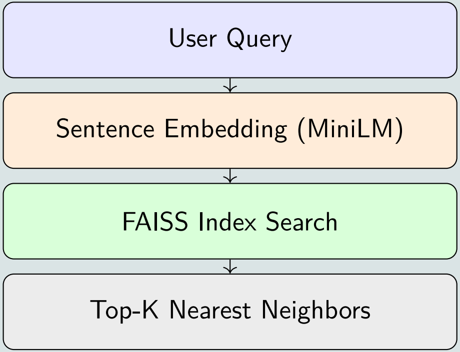
Sentence Embedding

- Used **all-MiniLM-L6-v2** sentence transformer
- Embedding captures semantic meaning of:
  - Title
  - Authors
  - Description
- Input format for embedding:
  Title: ... Author: ... Description: ...
- 384 dimension embedding vector
- Same embedding model used for:
  - Book metadata
  - User query
- Enables **semantic similarity search**, beyond keywords.

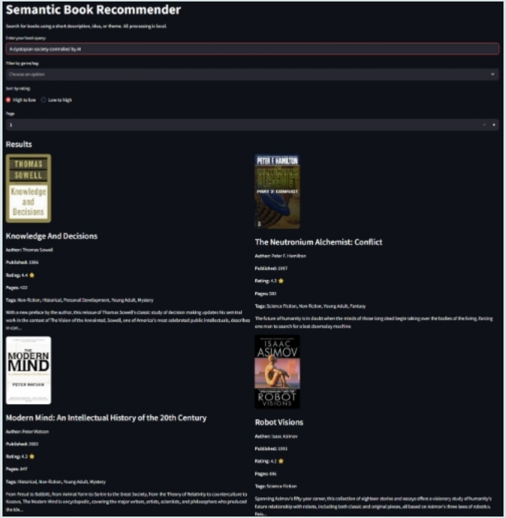


Vector Similarity Search with FAISS

- Used **Facebook AI Similarity Search (FAISS)** library
- Performs **L2 distance** search in embedding space
- Index built with:
  - 5160 book embeddings ($\vec{v} \in \mathbb{R}^{384}$)
  - Exact search (IndexFlatL2)
- At runtime:
  - User query is embedded
  - Top-k nearest neighbors retrieved
  - Results shown in UI
- **Fully local**, fast search



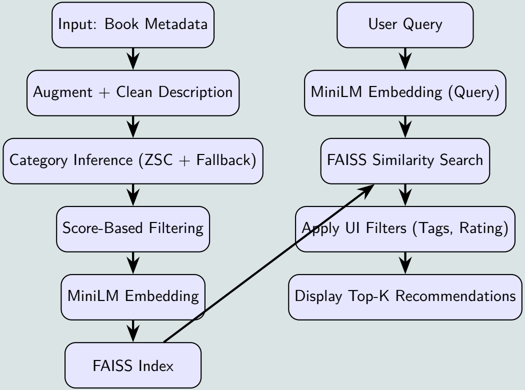
- Built with **Streamlit**
- **Fully offline** application:
  - No cloud calls
  - No tracking
  - No user profiles required
- Supports:
  - Natural language search
  - Filtering by category
  - Sorting by rating
  - Pagination of results
- Responsive UI:
  - Query time $\approx$ 200 ms
  - UI refresh $\approx$ 1-2 sec (including images)



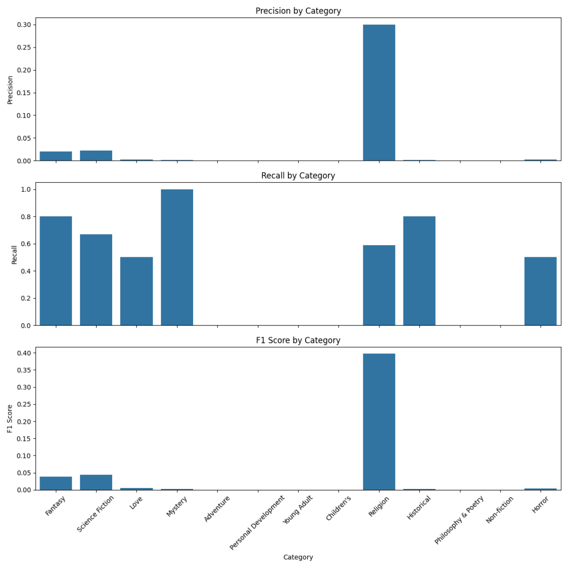
- **Strengths:**
  - Fully local, privacy-preserving recommendation system
  - Lightweight architecture
  - Semantic search works well even for abstract queries
- **Limitations:**
  - No personalization (no user profile or history)
  - Dependent on description quality
  - Dataset relatively small ($\sim$ 5160 books)
  - No learning from user feedback
- **Possible improvements:**
  - Larger, more diverse dataset
  - Explore better embedding models (MPNet, SBERT)
  - Implement re-ranking layer

"Even compact transformer models provide robust performance on consumer hardware."

- **Research question:**
  How can a local ML model be used to recommend books based on natural language descriptions?
- **Summary:**
  - Developed a fully local recommendation system
  - Used semantic embeddings and vector similarity search
  - No cloud, no tracking — privacy-first
  - User interface for natural language queries
- **Key takeaway:**
  - *"Local-first ML applications are practical and effective for semantic recommendation tasks."*



Backup: Per-Category Metrics



Backup: Fallback Keywords

- Fallback used when zero-shot model confidence was low
- Example keywords:
  - **Fantasy**: magic, wizard, dragon
  - **Science Fiction**: space, AI, dystopia
  - **Love**: romance, passion, relationship
  - **Mystery**: detective, clue, crime

Backup: Performance

- Embedding time per book: ≈ 2 ms (batch embedding)
- Query embedding: ≈ 50-200 ms
- FAISS search: < 10 ms
- UI render time: ≈ 1-2 seconds (including image loading)
- All processing fully local on consumer-grade laptop