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Book Recommender using NLP

Book Recommender using NLP

Carsten Lydeking

Zealand Business College

Oral Exam – AI and ML, 4th Semester

OPENING (30 seconds):

- Good morning, I'm Carsten
- Book recommender using NLP for oral exam
- 10 min presentation + questions
- Focus on concepts and implementation

Book Recommender using NLP

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- **Growing privacy and cost concerns** with cloud-based systems
- Traditional systems require **user profiles and data collection**
- **Goal:** Build a fully offline, content-based book recommender
- **Research Question:**

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

- **Key Requirements:** No external APIs, no user tracking, semantic understanding

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└ Motivation and Problem

1. Welcome to the talk!
2. As you can see, this slidedeck is a work in progress.

Motivation and Problem

- Growing privacy and cost concerns with cloud-based systems
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- **Goal:** Build a fully offline, content-based book recommender
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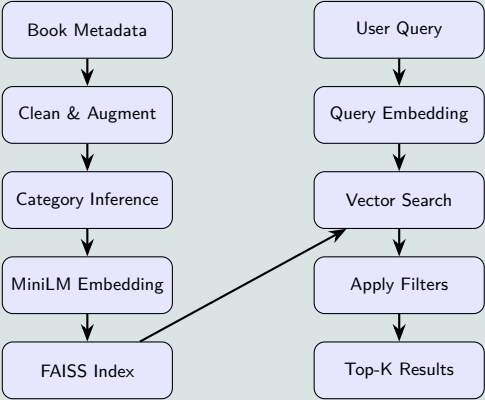
- **Key Requirements:** No external APIs, no user tracking, semantic understanding



Core Components:

- **Data Pipeline:** Clean & augment book metadata
- **Category Inference:** Zero-shot classification + fallback rules
- **Semantic Embedding:** MiniLM sentence transformers
- **Vector Search:** FAISS similarity matching
- **Local UI:** Streamlit interface

Key Innovation: Fully local semantic search without cloud dependencies



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Architecture Overview



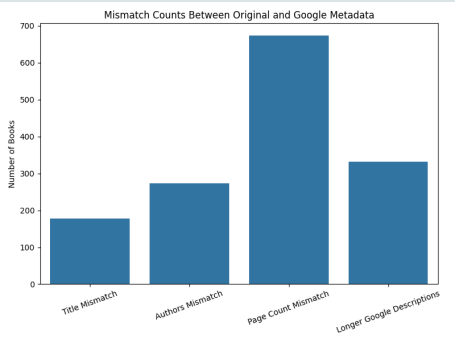


Data Quality Challenges:

- ▶ Started with **6,800 books** from multiple sources
- ▶ **Issues found:**
 - ▷ Missing author/category information
 - ▷ Very short descriptions (< 9 words)
 - ▷ Inconsistent categorization across sources

Data Engineering Solutions:

- ▶ **API enrichment:** OpenLibrary & Google Books
- ▶ **Quality filtering:** Remove inadequate descriptions
- ▶ **Final dataset:** 5,160 high-quality books



Data inconsistencies across sources required systematic cleaning and validation

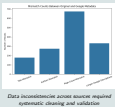
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Dataset Exploration & Processing

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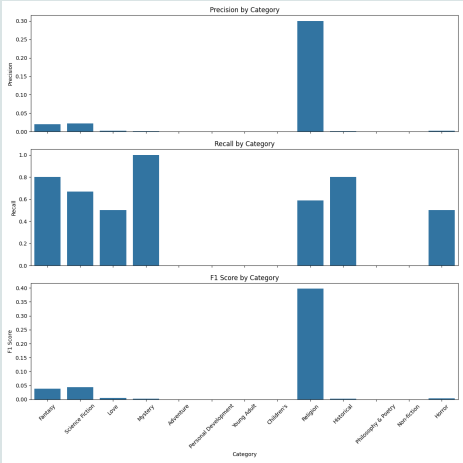


Two-Tier Classification Approach:

- **Primary:** Zero-shot classification with BART-MNLI
 - ▷ No training data required
 - ▷ 13 predefined book categories
 - ▷ Confidence scoring for predictions
- **Fallback:** Rule-based keyword matching
 - ▷ When confidence < threshold
 - ▷ Genre-specific keyword patterns

Quality Control:

- Description length \geq 200 chars
- Average confidence \geq 0.2
- Maximum confidence \geq 0.4



Results focus on high-confidence predictions rather than perfect recall across all categories

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Category Inference Strategy

Category Inference Strategy

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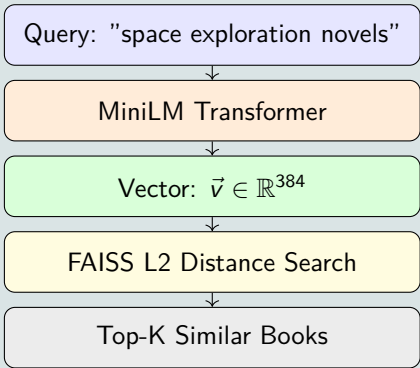


Sentence Embedding with MiniLM:

- **Model:** all-MiniLM-L6-v2
- **Input format:**
"Title: ... Author: ... Description: ..."
- **Output:** 384-dimensional vectors
- **Advantage:** Semantic similarity beyond keywords

Vector Search with FAISS:

- **Index:** 5,160 book embeddings
- **Search:** L2 distance (exact search)
- **Performance:** < 10ms query time
- **Local:** No external dependencies



End-to-end semantic search in < 200ms

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Semantic Embedding & Vector Search

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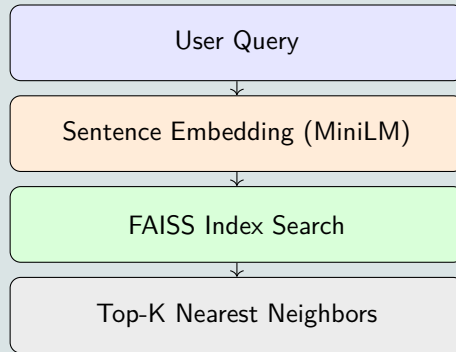
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```
graph TD; A[Query: "space exploration novels"] --> B[MiniLM Transformer]; B --> C["Vector:  $\vec{v} \in \mathbb{R}^{384}$ "]; C --> D[FAISS L2 Distance Search]; D --> E[Top-K Similar Books];
```

End-to-end semantic search in < 200ms



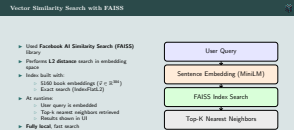
- Used **Facebook AI Similarity Search (FAISS)** library
- Performs **L2 distance** search in embedding space
- Index built with:
 - ▷ 5160 book embeddings ($\vec{v} \in \mathbb{R}^{384}$)
 - ▷ Exact search (IndexFlatL2)
- At runtime:
 - ▷ User query is embedded
 - ▷ Top-k nearest neighbors retrieved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



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Vector Similarity Search with FAISS





Implementation Strengths:

- **Privacy-preserving** by design
- **Semantic understanding** beyond keyword matching
- **Lightweight** - runs on consumer hardware
- **Modular architecture** for easy extension

Current Limitations:

- **No personalization** - stateless by design
- **Dataset scope** - 5,160 books vs. commercial scale
- **Cold start problem** for new books
- **No feedback learning** - static recommendations

Future Research Directions:

- **Hybrid approach:** Combine content-based with collaborative filtering
- **Better embeddings:** Experiment with domain-specific models
- **Privacy-preserving personalization:** Local user preference learning
- **Multi-modal features:** Include cover images, genre embeddings

"Demonstrates that local-first ML - or using a more popular term - edge AI, can provide meaningful semantic recommendations without compromising user privacy or requiring cloud infrastructure."

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└ Critical Analysis & Future Directions

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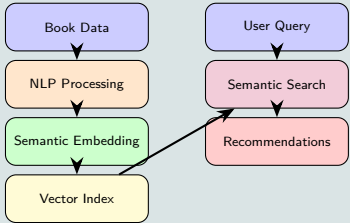
Research Question Answered:

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

Solution Implemented:

- **Semantic embeddings** with MiniLM transformers
- **Vector similarity search** using FAISS
- **Zero-shot classification** for categorization
- **Privacy-first design** - fully local processing
- **Key Contributions:** *Proof-of-concept that modern NLP enables practical, privacy-preserving recommendation systems*

System Architecture:



Impact & Applications:

- Educational tool for privacy-aware ML
- Foundation for local-first recommendation systems
- Demonstrates transformer accessibility on consumer hardware

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Conclusion

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Research Question Answered:

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System Architecture:

```
graph TD;
    A[Book Data] --> B[NLP Processing];
    B --> C[Semantic Embedding];
    C --> D[Vector Index];
    D --> E[Semantic Search];
    F[User Query] --> E;
    E --> G[Recommendations];
```

Impact & Applications:

- Educational tool for privacy-aware ML
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Thank you for your attention!



Questions?

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└ End of Presentation

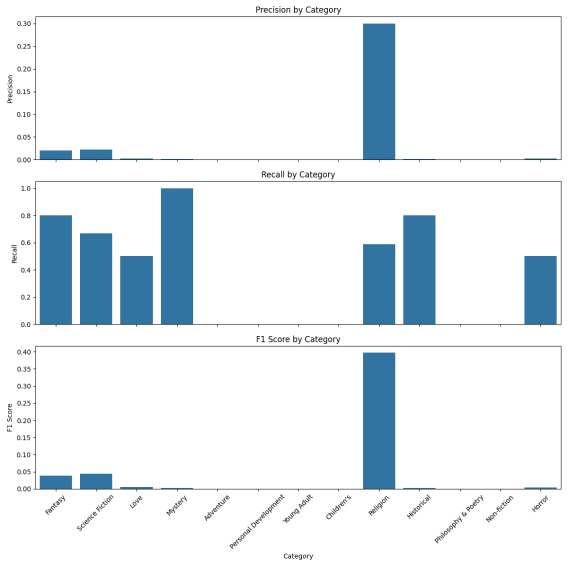


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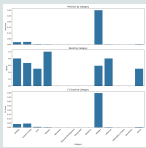
Backup: Per-Category Metrics



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Backup: Per-Category Metrics





- ▶ 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

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└ Backup: Fallback Keywords

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- 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

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Example Query 1:

"Books about artificial intelligence and ethics"

Top Results:

- ▶ "The Alignment Problem" - Brian Christian
- ▶ "Life 3.0" - Max Tegmark
- ▶ "Weapons of Math Destruction" - Cathy O’Neil

Example Query 2:

"mystery novels with unreliable narrators"

Top Results:

- ▶ "Gone Girl" - Gillian Flynn
- ▶ "The Girl on the Train" - Paula Hawkins
- ▶ "In the Woods" - Tana French

What This Demonstrates:

- ▶ **Semantic understanding** beyond keywords
- ▶ **Abstract concept matching** (ethics, unreliable narrators)
- ▶ **Cross-genre discovery** potential

Evaluation Challenges:

- ▶ No ground truth for "perfect" recommendations
- ▶ Subjective nature of book preferences
- ▶ **Solution:** Focus on semantic relevance rather than prediction accuracy

Discussion Starters:

- ▶ How could one evaluate recommendation quality
- ▶ Books with sparse descriptions
- ▶ Could this approach work for other domains?

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Backup: Concrete Examples

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