



# Scholarly Topic Navigator

Explainable Research Digest Pipeline

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# The Information Overload Crisis

## The Problem

Thousands of NLP/ML papers flood platforms like ArXiv and ACL monthly. Researchers struggle to keep up, often spending 20+ hours weekly just tracking new publications.

### Manual Discovery

Time-consuming and incomplete, leading to missed critical research.

### Black Box Systems

Current recommendation engines lack transparency on *why* a paper is suggested.

# Our Solution: Explainable Pipeline

We introduce an automated pipeline that not only aggregates and processes research but explains its recommendations.



## Aggregate & Preprocess

Collects papers from ArXiv, ACL, and S2ORC, applying rigorous NLP cleaning.



## Embed & Retrieve

Uses Word2Vec, SBERT, and SciBERT for deep semantic understanding and hybrid search.



## Explainability

The key differentiator: LIME-based interpretable classification tells users *why* papers matter.

# End-to-End System Architecture

A modular pipeline designed for scalability and transparency.



## Data Ingestion

APIs fetch data from ArXiv, ACL Bibtex, and S2ORC, followed by normalization.

## Preprocessing

Language detection, tokenization, lemmatization, and stopword removal.

## Embeddings

Vectorization using Word2Vec (100d), SBERT (384d), and SciBERT (768d).

## Applications

Hybrid retrieval, Zero-Shot classification, and LIME explainability.

## Dashboard

Streamlit interface for search, analytics, and visual explanations.

# Primary Data Sources



## ArXiv (arxiv.org)

**Preprint server providing 20,983 papers across CS, AI, and ML categories. 100% abstract availability.**



## ACL Anthology

**Official conference repository. Parsed 118,461 entries, though limited by lack of abstracts in Bibtex format.**



## Semantic Scholar

**Academic search engine. Collected 1,553 papers with abstracts via Graph API, despite rate-limiting challenges.**

# Data Collection Statistics

From over 140k raw entries to a clean, usable dataset.

141K

Raw Collected

Total entries from all three sources.

22.5K

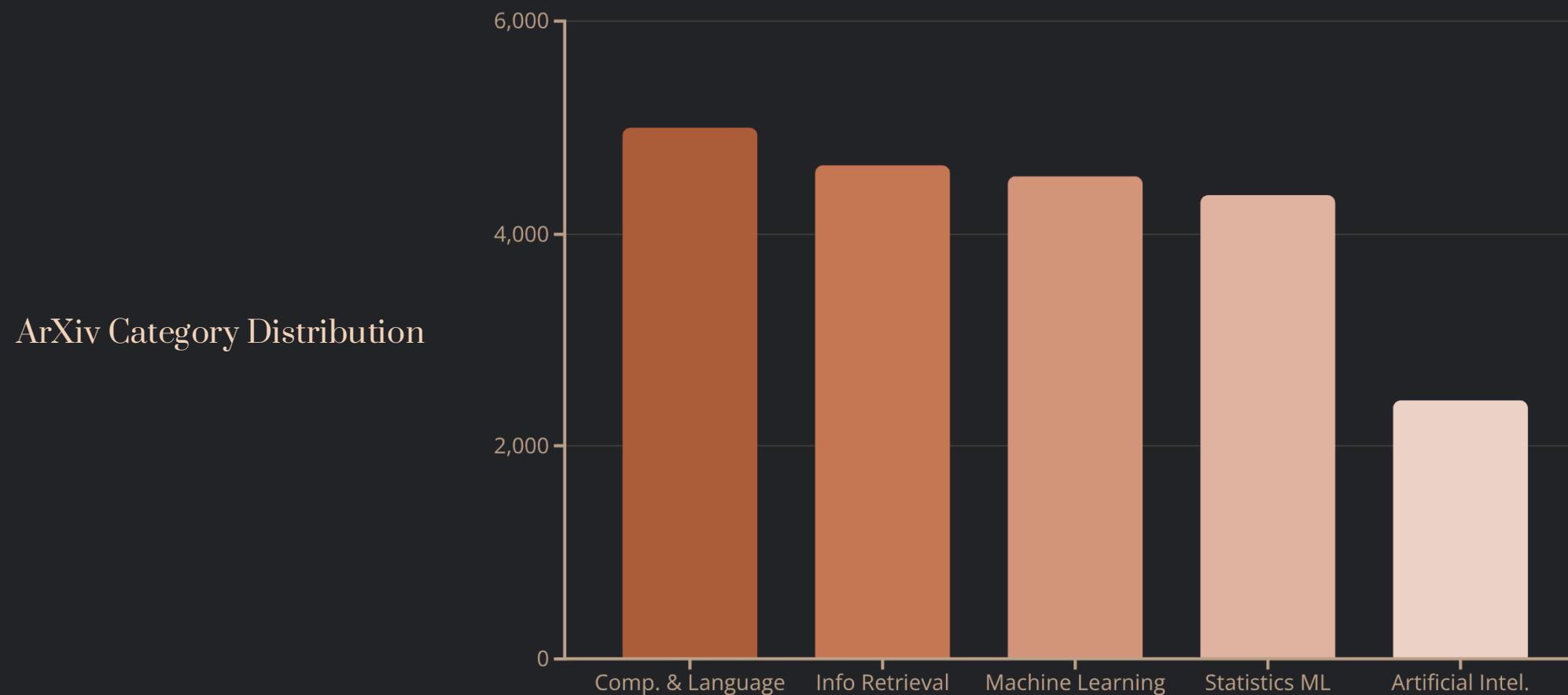
Final Clean Dataset

Papers with valid abstracts retained.

4K

Duplicates Removed

Cross-category overlap eliminated.



# Data Validation & Cleaning

Ensuring high-quality input for the NLP models required a rigorous filtration process.

## Validation Checks

1

Identified 82.9% missing abstracts (mostly ACL) and 2,832 missing authors. Validated year range (1995-2025).

## Filtering Criteria

2

Retained only English papers with titles >10 chars and abstracts >50 chars. Must have at least one author.

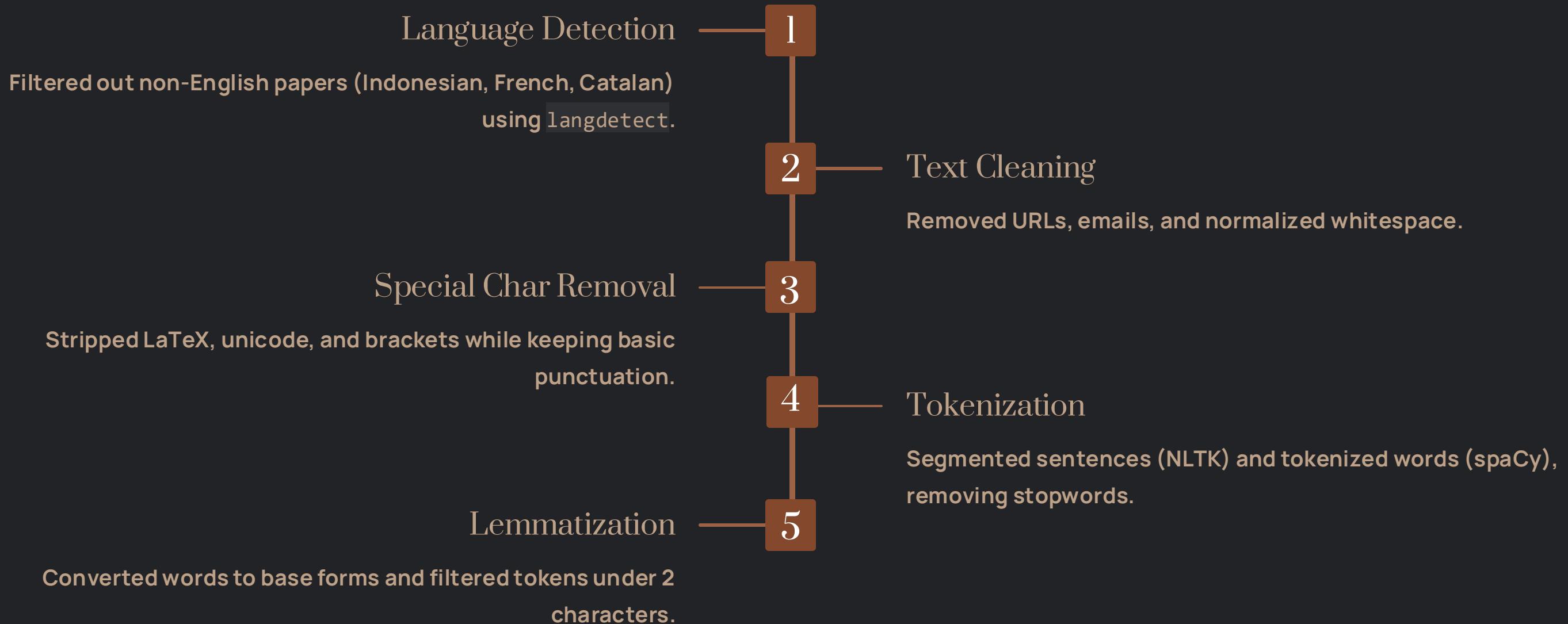
## Deduplication Strategy

3

Prioritized peer-reviewed sources: ACL > S2ORC > ArXiv. Kept the first occurrence based on this hierarchy.

# Text Preprocessing Pipeline

Transforming raw text into structured data took approximately 14 minutes for 22,522 papers.



# Preprocessing Statistics

## Token Metrics

2.7M

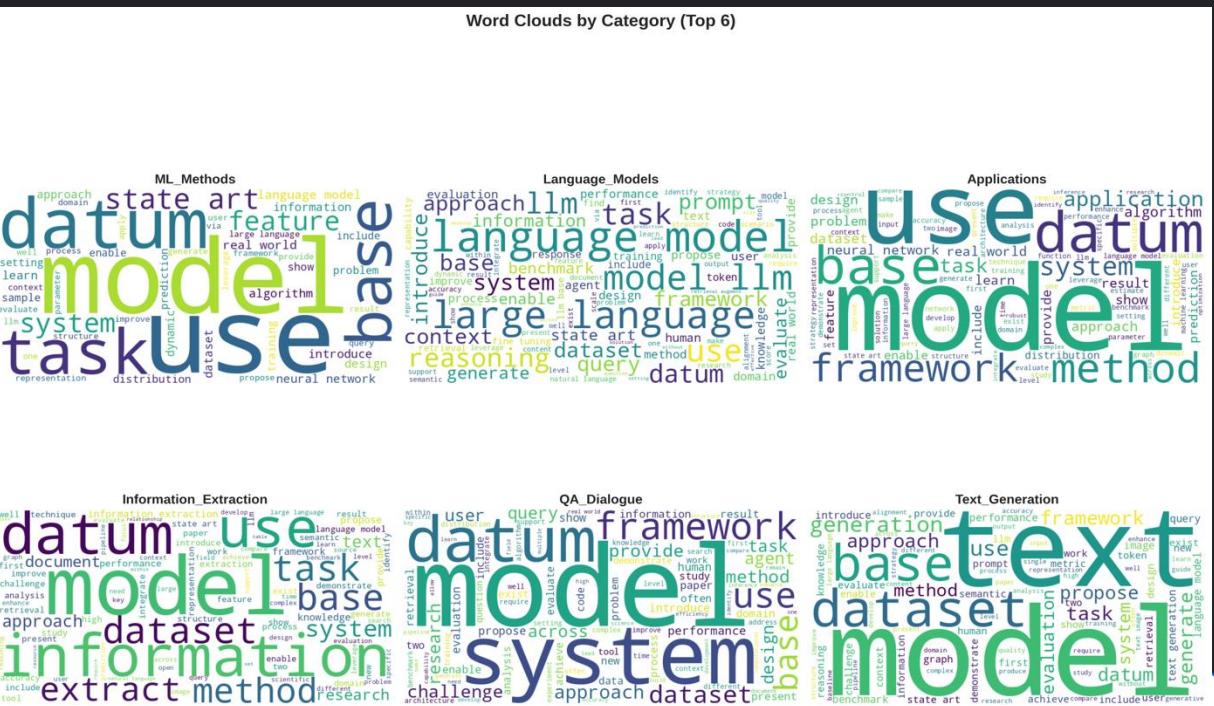
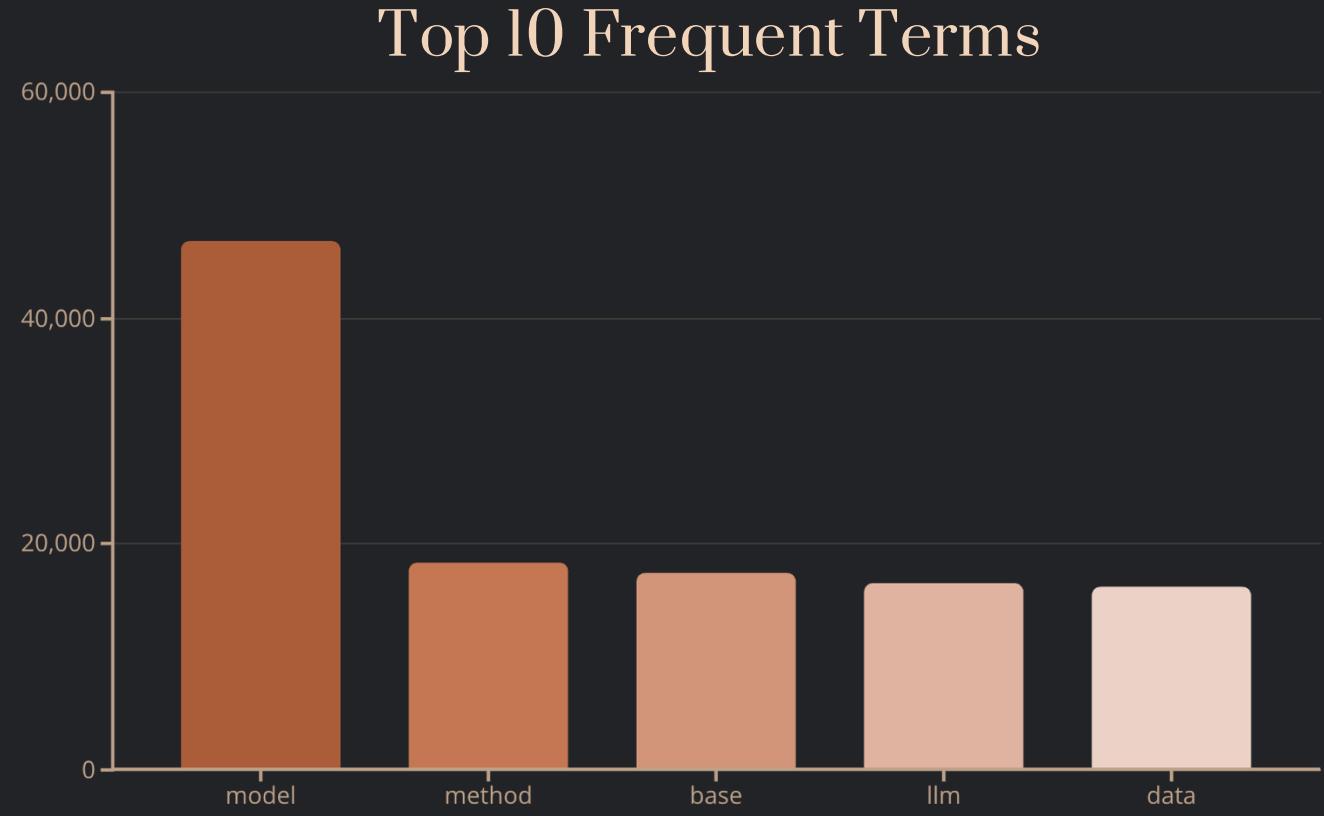
# Total Tokens

**48K**

# 121

## Avg Tokens/Paper

The high frequency of "LLM" (Rank 4) reflects the dominant research trend of 2024-2025.



# Embeddings, Retrieval & Classification

A technical deep dive into modern embedding representations, hybrid retrieval engines, and zero-shot classification pipelines for scientific literature analysis.

# Embedding Model Architectures

We evaluated three distinct approaches to representing text as vectors, ranging from traditional baselines to domain-specific transformers.

## Word2Vec (Baseline)

A traditional Gensim implementation using Skip-gram/CBOW architecture.

- Dimensions: 100
- Vocab: 28,727 words
- Method: Average of word vectors

## SBERT (General Purpose)

Modern `all-MiniLM-L6-v2` model trained on 1B+ sentence pairs.

- Dimensions: 384
- Speed: 5x faster than BERT-base
- Output: Abstract & Title embeddings

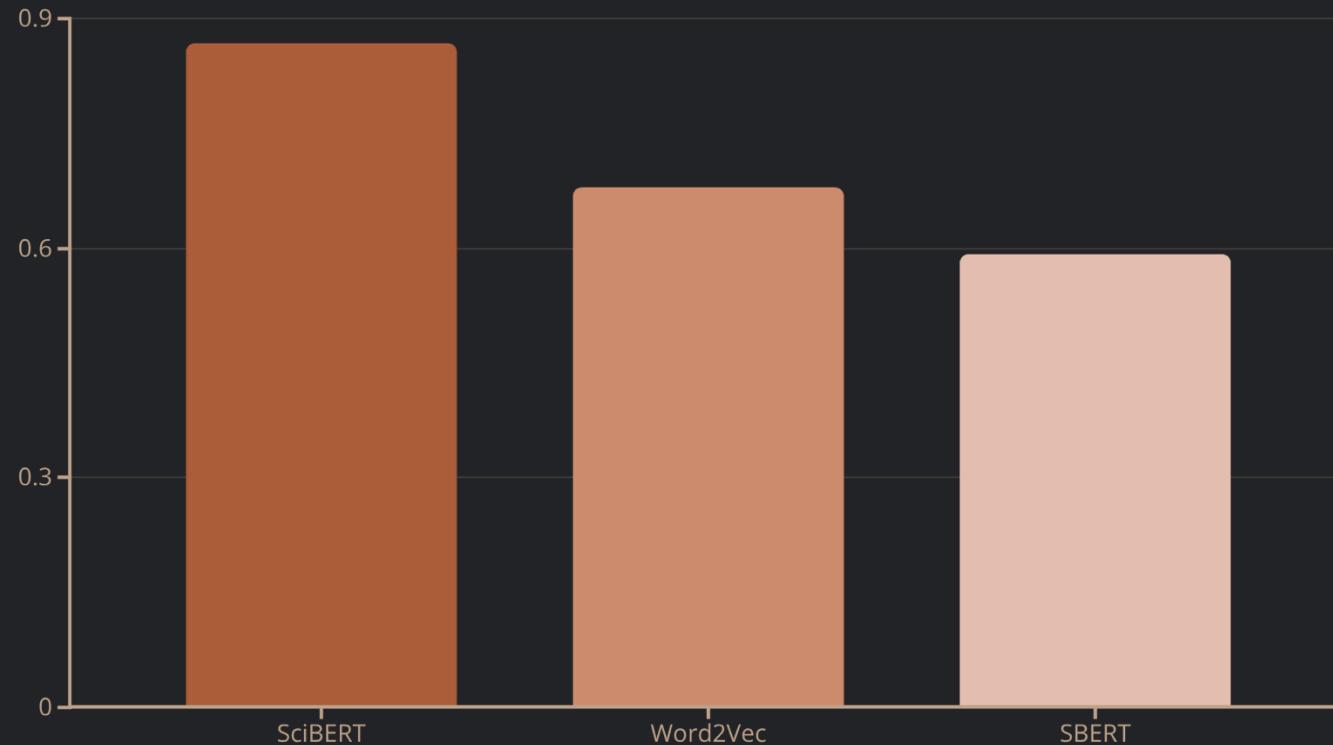
## SciBERT (Domain Specific)

The `allenai-specter` model optimized for citation prediction.

- Dimensions: 768
- Params: 110 million
- Training: Scientific papers

# Embedding Quality Analysis

We analyzed the Average Pairwise Cosine Similarity across a sample of 10 papers. Lower similarity indicates better separation for clustering tasks.



## Assessment Results

- **SBERT (Winner)**  
Achieved the best separation (0.593), making it ideal for topic modeling.
- **SciBERT Issues**  
High similarity (0.867) indicates "semantic collapse," where all papers appear too similar, risking clustering failure.
- **Recommendation**  
Use SBERT for topic modeling; reserve SciBERT for specific scientific similarity searches.

# Retrieval Engines: Keyword vs. Semantic

## BM25 (Keyword Retrieval)

Traditional probabilistic retrieval based on term frequency and inverse document frequency.

- Algorithm: Okapi BM25 with saturation.
- Pipeline: Tokenization, Stopword removal, Porter stemming.
- Strength: Exact keyword matching.

## FAISS (Vector Search)

Facebook AI Similarity Search for efficient dense vector retrieval.

- Index: IndexFlatIP (Exact search via Inner Product).
- Process: L2 Normalization of SBERT embeddings.
- Strength: Captures semantic meaning beyond keywords.

- ❑ Key Difference: BM25 finds exact text matches (e.g., "transformer"), while FAISS finds conceptual matches (e.g., "attention mechanism" results for "transformer" queries).

# Hybrid Retrieval System

To achieve the best of both worlds, we implemented a fusion algorithm using Weighted Reciprocal Rank.

## 1. Dual Retrieval

Execute parallel queries: get exact matches via BM25 and semantic matches via FAISS.

## 2. Normalization

Normalize scores from both engines to a [0, 1] scale to ensure comparability.

## 3. Weighted Fusion

Combine scores:  $\text{lambda} \cdot \text{BM25} + (1-\text{lambda}) \cdot \text{Semantic}$ .

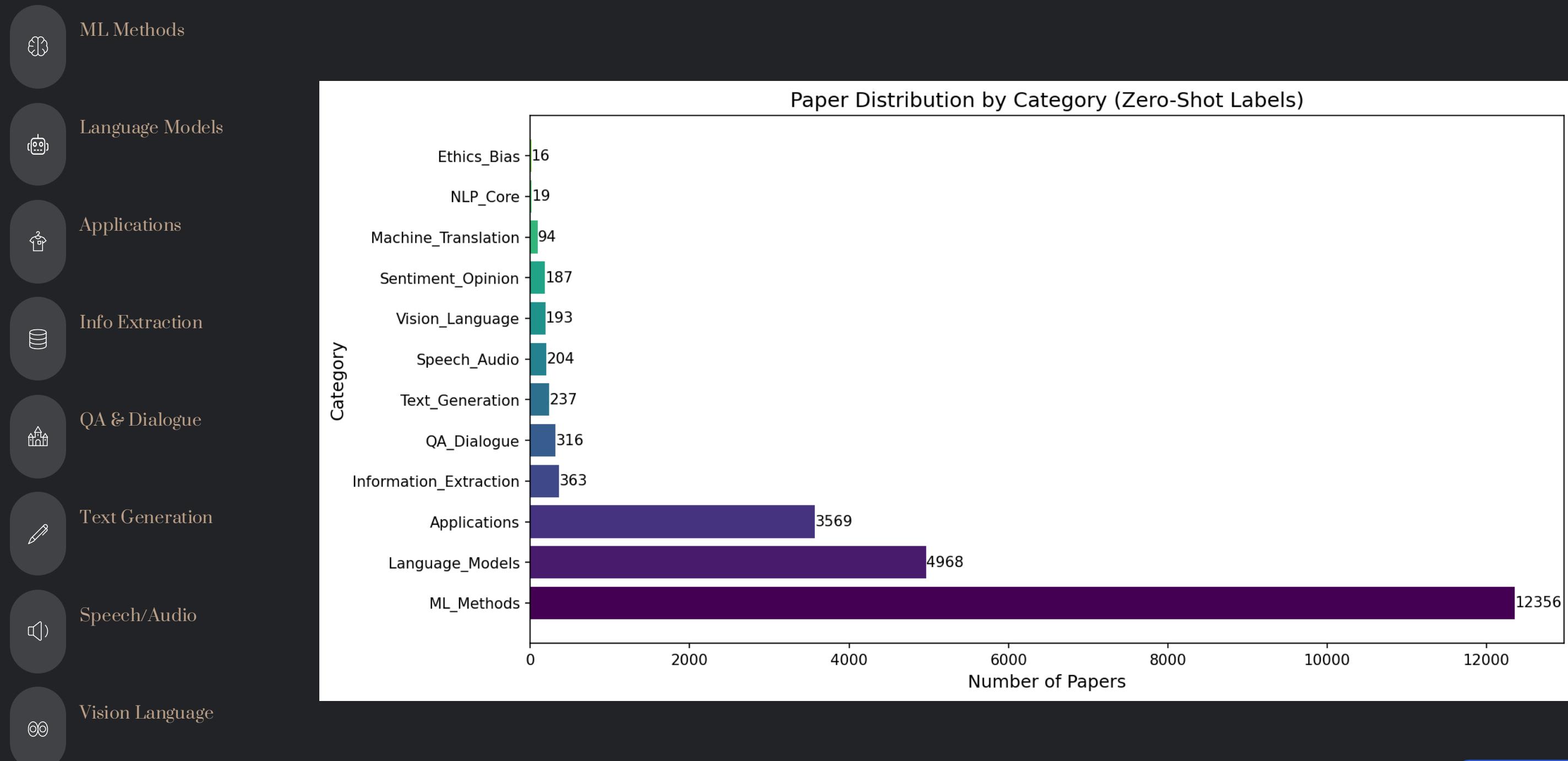
## 4. Re-Ranking

Final results are re-ranked based on the combined score.

Configuration: We utilize a semantic weight of 0.7 and a keyword weight of 0.3. This prioritizes semantic understanding to handle synonyms and varied scientific terminology.

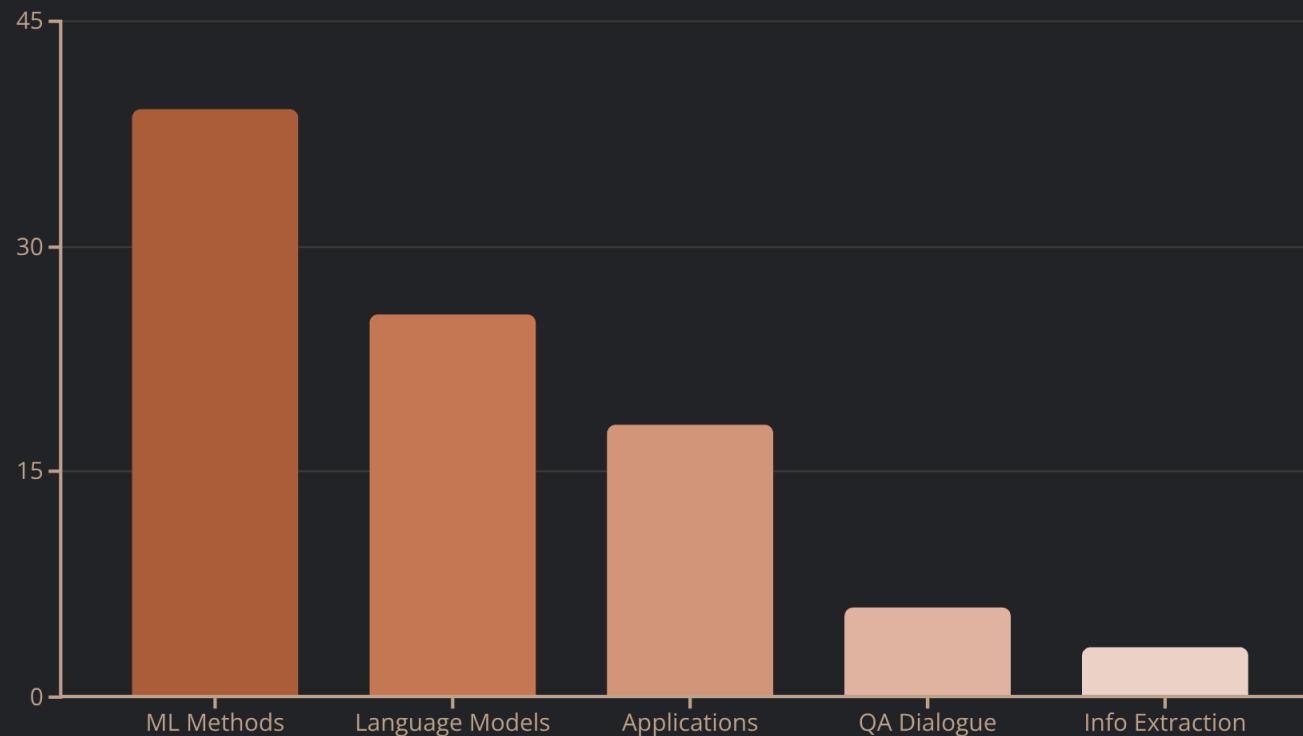
# Zero-Shot Classification

We utilized the `facebook/bart-large-mnli` model (400M parameters) to label 5,000 papers without training data. The model classifies content into 12 defined NLP research areas.



# Classification Distribution Results

Analysis of 5,000 sampled papers reveals the current landscape of NLP research.



## Key Insights

- **ML Methods Dominance (39%):** Reflects the heavy volume of algorithmic research in ArXiv's cs.LG category.
- **LLM Boom (26%):** Language Models represent the second largest category, driven by the 2024-2025 research surge.
- **Practical Focus (18%):** Significant portion of research is dedicated to real-world applications.

# Production Pipeline: Classification & Summarization

## Supervised Classifier

For production speed, we trained a lightweight classifier on the zero-shot pseudo-labels.

01

### Input

Paper abstract text.

02

### Encoder

Facebook's BART-large-MNLI model

03

### Model

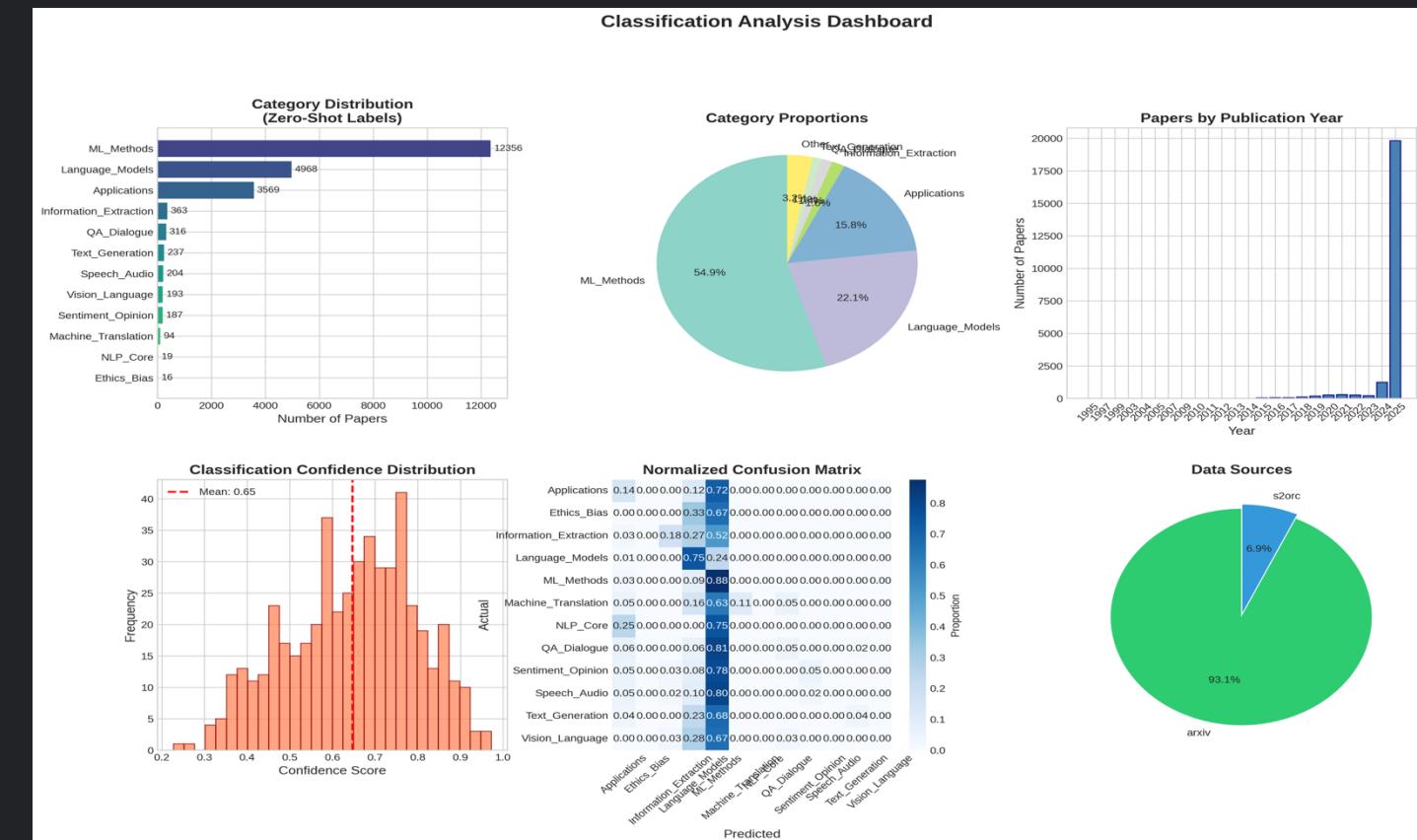
Logistic Regression.

Advantage: Fast inference and interpretable weights.

## Summarization Engine

We employ a dual approach depending on the user need.

- Extractive (TextRank): Logistic regression algorithm that selects top sentences. Very fast; used for quick previews.
- Abstractive (Facebook's BART-large-MNLI model): 400M parameter model that generates novel paraphrased text. Slower; used for detailed digests.



# Unsupervised Topic Discovery

Beyond zero-shot classification, we employed unsupervised topic modeling to uncover latent thematic patterns within the research corpus. This approach reveals natural topic clusters without predefined categories.



## LDA (Latent Dirichlet Allocation)

**Configuration:** 10 topics using Variational Bayes

**Approach:** Assumes documents are mixtures of topics, where each topic represents a distribution over words. Iteratively refines assignments through probabilistic inference.

**Tradeoffs:** Fast and interpretable, but bag-of-words representation loses contextual information and word order.



## BERTopic (Neural Topic Modeling)

**Pipeline:** SBERT embeddings → UMAP dimensionality reduction → HDBSCAN clustering → c-TF-IDF representation

**Model:** all-MiniLM-L6-v2 (384-dimensional semantic vectors)

**Approach:** Embeds documents in semantic space, reduces dimensions while preserving structure, applies density-based clustering, then extracts representative words using class-based TF-IDF.

**Tradeoffs:** Captures semantic relationships and synonyms effectively but requires more computational resources and careful hyperparameter tuning.

# Topic Discovery: Results & Evaluation

The BERTopic processing pipeline leverages advanced techniques to extract meaningful topics from unstructured text data.



## Text Corpus

Raw documents are preprocessed.

## SBERT Encoding

Semantic embeddings are generated.

## UMAP Reduction

High-dimensional data is compressed.

## HDBSCAN

Density-based clustering identifies topics.

## Topic Words

Representative keywords are extracted.

## Coherence Evaluation

Evaluating the quality of discovered topics using coherence scores:

- LDA Coherence Score: 0.42
- BERTopic Coherence Score: 0.58

Key insight: Contextual embeddings in BERTopic capture semantic nuances more effectively, leading to higher coherence scores compared to traditional methods like LDA.

## Discovered Topics: Sample Results

#	Topic Terms	Topic Category
0	machine, learning, models, data	Core ML concepts & techniques
1	neural, networks, deep, computer, vision	Advanced deep learning architectures
2	natural, language, processing, text, generation	NLP and text-based applications
3	reinforcement, agent, environment, reward	Reinforcement learning theory & practice
4	robotics, control, motion, autonomous	Robotics and autonomous systems
5	big, data, cloud, distributed, computing	Scalable data processing & cloud
6	ethics, bias, fairness, responsible, AI	Ethical considerations in AI development
7	healthcare, medical, diagnosis, imaging	AI applications in medicine & health
8	finance, trading, risk, market	AI in financial modeling & markets
9	education, learning, student, personalized	AI's role in educational technology

# Explainable NLP: Paper Discovery & Analysis

An end-to-end pipeline for scholarly paper discovery, featuring hybrid retrieval, zero-shot classification, and LIME-based explainability.

# Explainability with LIME

We utilize Local Interpretable Model-agnostic Explanations (LIME) to bring transparency to black-box models, ensuring users can trust recommendations in academic settings.

01

## Perturb Data

Generate samples by removing or masking words from the input text.

02

## Predict

Get model predictions for all perturbed variations.

03

## Fit Linear Model

Fit an interpretable linear model locally to the data.

04

## Extract Weights

Identify specific words that contributed positively or negatively to the prediction.

# LIME in Action: Analyzing Predictions

How the model interprets specific text inputs for classification.

## Input Text

"Recent coreference resolution models rely heavily on span representations to find coreference links between word spans..."

Prediction: ML\_Methods  
(Confidence: 89.72%)

## Word Importance Analysis



Supports Prediction  
**coreference (+0.0001)**



Opposes Prediction  
**links (-0.0001)**

# Streamlit Dashboard Features

A comprehensive interactive web application designed for researchers.



## Paper Search

Natural language queries using BM25, Semantic, or Hybrid retrieval methods.



## Analytics

Dataset statistics, category distributions, and embedding comparison metrics.



## Explainability

LIME explanations for predictions with word importance visualization.

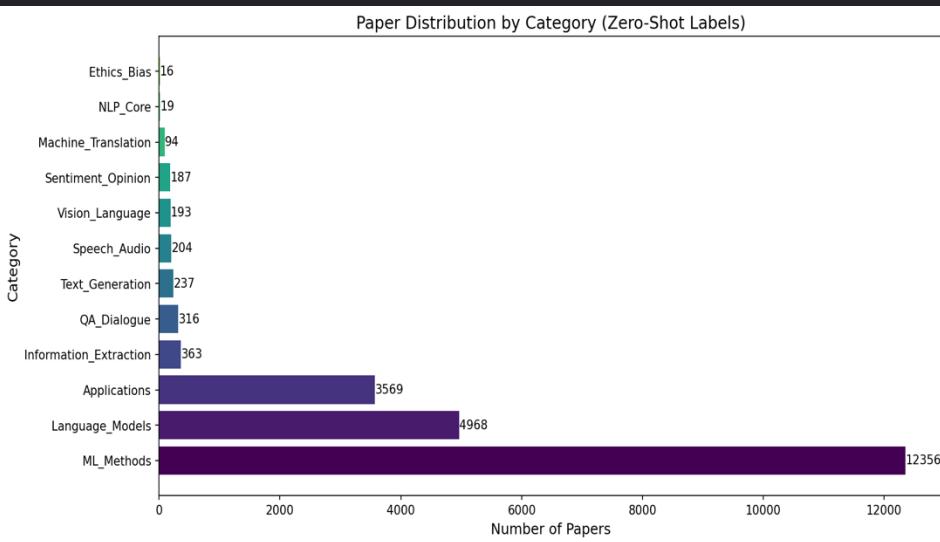


## Summarization

Dual approach using Extractive (TextRank) and Abstractive (BART) methods.

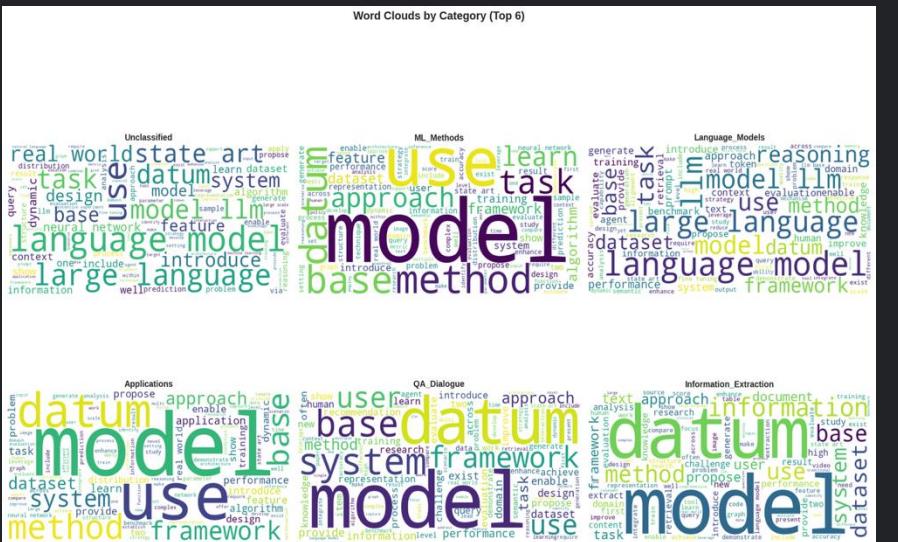
# Visualization Gallery

Visual insights generated to analyze the dataset and model performance.



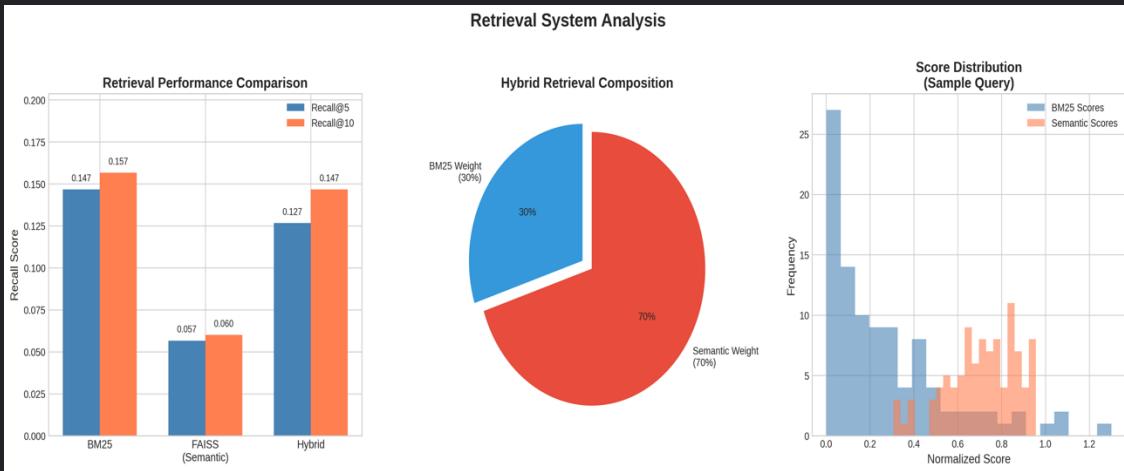
## Category Distribution

Horizontal bar charts color-coded by frequency showing papers per category.



## Word Clouds

2x3 grid visualizing top terms for each classification category.



## Retrieval Dashboard

Analysis of BM25 vs FAISS performance, score distributions, and overlap.

# Evaluation Metrics

Rigorous testing across the entire data and modeling pipeline.

1

## Data Quality

Achieved 99.98% English language accuracy and removed 3.0% duplicates.

2

## Embeddings

Evaluated embedding quality via mean intra class cosine similarity. SBERT achieved reasonable similarity score of 0.593 across papers within same category

3

## Retrieval

Measured via Recall@k, Precision@k, and Mean Reciprocal Rank (MRR).

4

## Classification

Zero-shot baseline accuracy assessed via per-category precision, recall, and F1 scores.

# Key Results & Achievements

Summary of the data pipeline, retrieval system, and user interface performance.

22k

Papers Processed

Aggregated from 3 sources  
with 48k vocabulary tokens  
extracted.

100ms

Query Latency

Fast hybrid search  
combining BM25 and  
Semantic retrieval.

12

Categories

Defined and labeled using  
zero-shot classification on  
5,000 papers.

# Challenges & Solutions

Overcoming technical hurdles during development.

## Missing Abstracts

**Problem:** ACL Anthology Bibtex lacked abstracts. **Solution:** Filtered during cleaning; future scraping planned.

## SciBERT Collapse

**Problem:** High similarity (0.867) caused poor clustering. **Solution:** Switched to SBERT for topic modeling tasks.

## API Rate Limiting

**Problem:** Semantic Scholar returned 429 errors. **Solution:** Implemented exponential backoff with jitter.

## Library Conflicts

**Problem:** Numpy 2.0 broke NLP libraries. **Solution:** Pinned specific versions (numpy<2.0.0).

# Conclusions & Future Work

A comprehensive academic search system combining explainability, hybrid retrieval, and zero-shot categorization to transform research discovery.

22K

Research Papers

Processed from three authoritative sources

48K

Unique Tokens

Complete vocabulary coverage

3

Embedding Models

W2V, SBERT, SciBERT compared

12

Research Categories

Automated via zero-shot classification



Explainability-First Design

LIME integration reveals exactly why papers are recommended, building trust and transparency in academic research settings.



Hybrid Retrieval Architecture

Combines BM25 keyword precision (30%) with FAISS semantic understanding (70%) for optimal search results.



Zero-Shot Taxonomy

Eliminates manual labeling requirements, enabling scalable classification across new research domains automatically.

## Future Roadmap

### Short-Term Enhancements

- ACL abstract scraping expansion
- Fine-tuning with human-labeled data
- User feedback integration loop
- Enhanced SciBERT clustering accuracy

### Long-Term Vision

- Citation network graph analysis
- Personalized recommendation engine
- Real-time daily paper ingestion
- Multi-language support
- Zotero and Mendeley integration

# Thank You