# ArXiv dataset research paper recommendation system

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# Problem statement

In the **dynamic academic environment**, scholars face significant hurdles in navigating the vast and diverse landscape of research publications and fostering interdisciplinary collaborations.

This study aims to address this challenge by developing a comprehensive recommendation system utilizing Spectral and KMeans clustering on the arXiv dataset.

The system's core objective is to enhance the accessibility of research papers and promote interdisciplinary collaboration among scholars. By leveraging machine learning techniques, the system will provide personalized **recommendations of relevant research categories** and exemplary papers, empowering researchers to overcome obstacles in literature discovery and **interdisciplinary partnership** cultivation.

**Domain:** Education

**Type of Data :** Text

# Objective

**Model Development:** Develop a system that can effectively enhance the accessibility of research papers and promote interdisciplinary collaboration among scholars.

**Model Comparison :** Compare the performance of KMeans and Spectral Clustering based on the category/domain of the papers.

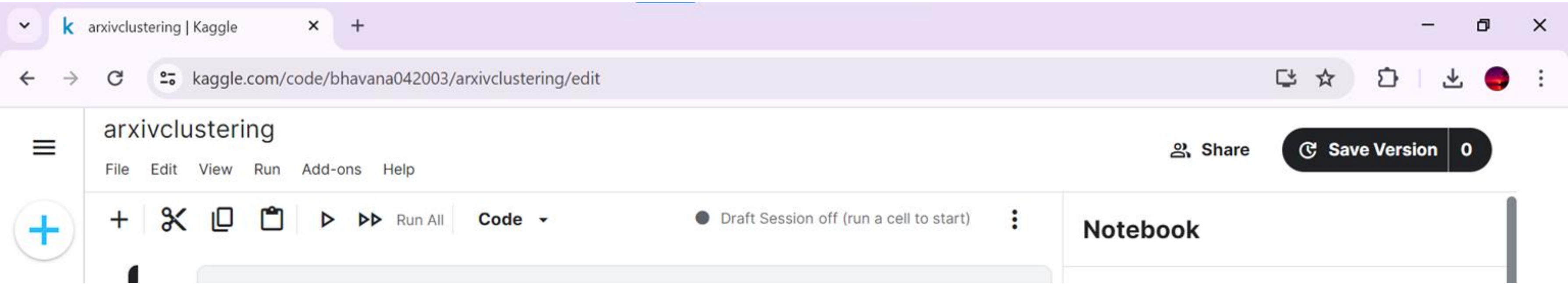
**Documentation:** Preparation of detailed documentation covering system architecture, algorithms employed, user guidelines, and technical specifications.

**Deployment:** Deployment of the recommendation system in academic environments like GCP Cloud Platform.

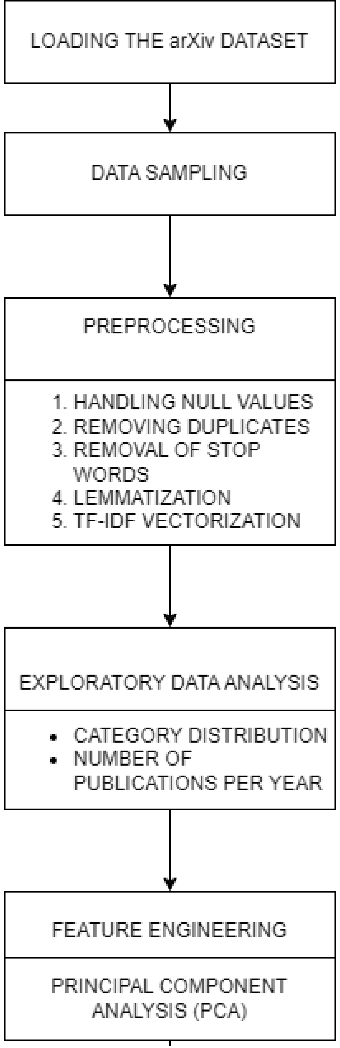
# Development Environment

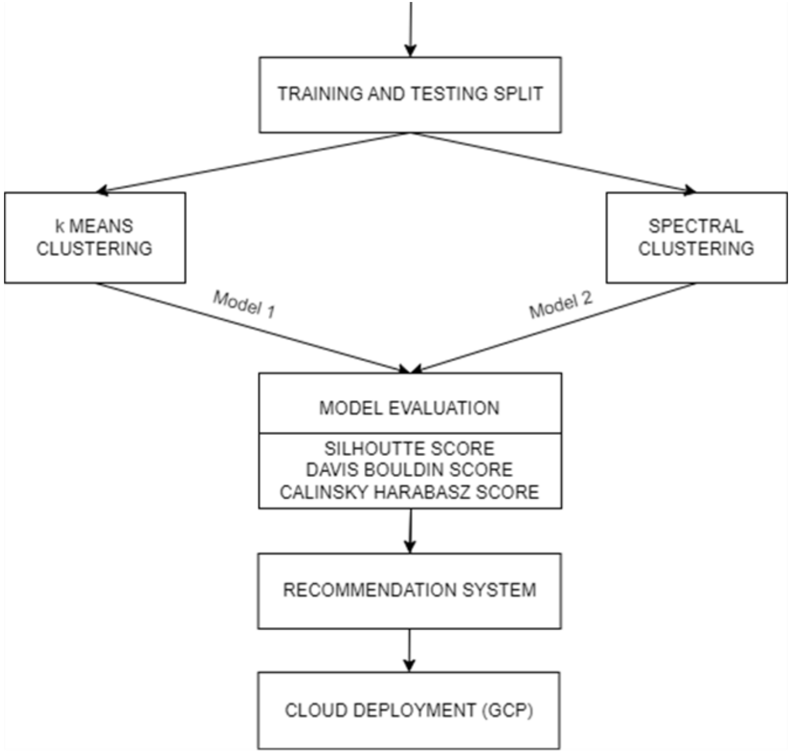
The development environment for the proposed application is **Kaggle Jupyter Notebook** which was suitable for the enormous arXiv dataset.

Other environments like VS Code, Google Colab, RapidMiner didn't support this huge dataset even after sampling.



# System Architecture



# About Dataset

ArXiv is a dataset containing scholarly articles, from the vast branches of physics to the many subdisciplines of computer science to everything in between, including math, statistics, electrical engineering, quantitative biology, and economics.

It has more than 20,00,000+ rows with 14 columns.

https://www.kaggle.com/datasets/Cornell-University/arxiv

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| **4** | 0705.1155 | Kerry M. Soileau | State Vector Determination By A Single Trackin... | None | [astro-ph] | Using only a single tracking satellite capab... |

# ML Models Used

**Type of learning:** Unsupervised Learning

arXiv Dataset of Research papers doesn’t have class label of category. Moreover, in order to find the inherent structures or patterns within the data and group similar papers for the recommendation of papers, Clustering techniques were applied instead of Classification techniques.

1) K - Means Clustering
2) Spectral Clustering

# Data preprocessing

Filtered the documents based on the **latest version** created after 2020.

Trimmed down the data to select **specific columns** like ID, category, and abstract.

Handled **missing values.**

Removed **duplicate** abstracts.

**Sampled 10,000** rows randomly from the dataset.

# Data preprocessing: Text processing

Loaded a **spaCy** model specifically designed for scientific text (en_core_sci_lg).

Defined a function spacy_tokenizer to preprocess the abstracts, which includes **lemmatization, lowercasing, and removing stopwords** and **punctuations**.

Applied this **tokenizer function** to the “abstract” column using Pandas' progress_apply method.

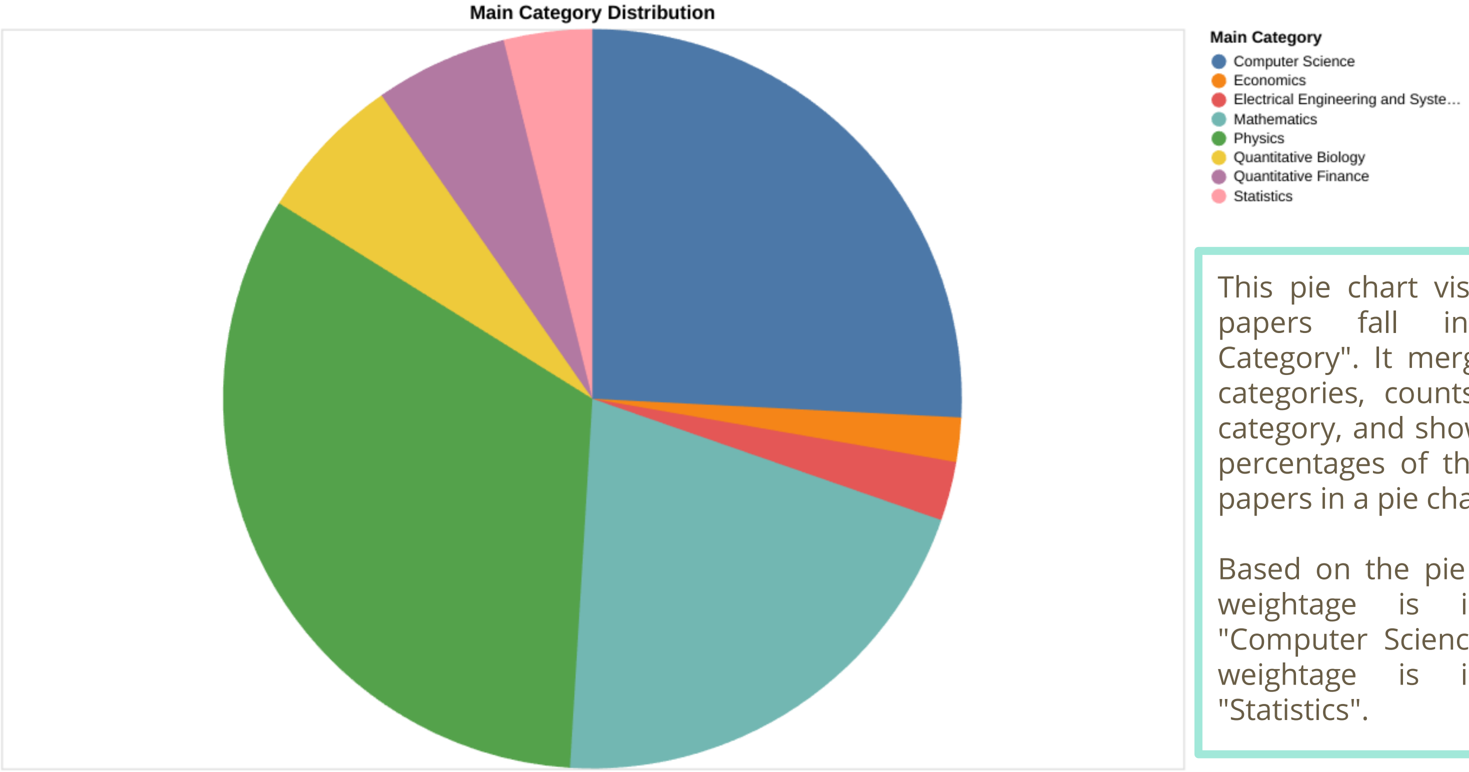
# Data preprocessing: Text vectorization

Used **TF-IDF vectorization** to convert the preprocessed text into numerical form.

Specified an **arbitrary maximum** number of features.

Transformed the **text data** into a **matrix representation (`X`)**.

# Exploratory Data Analysis: Category distribution

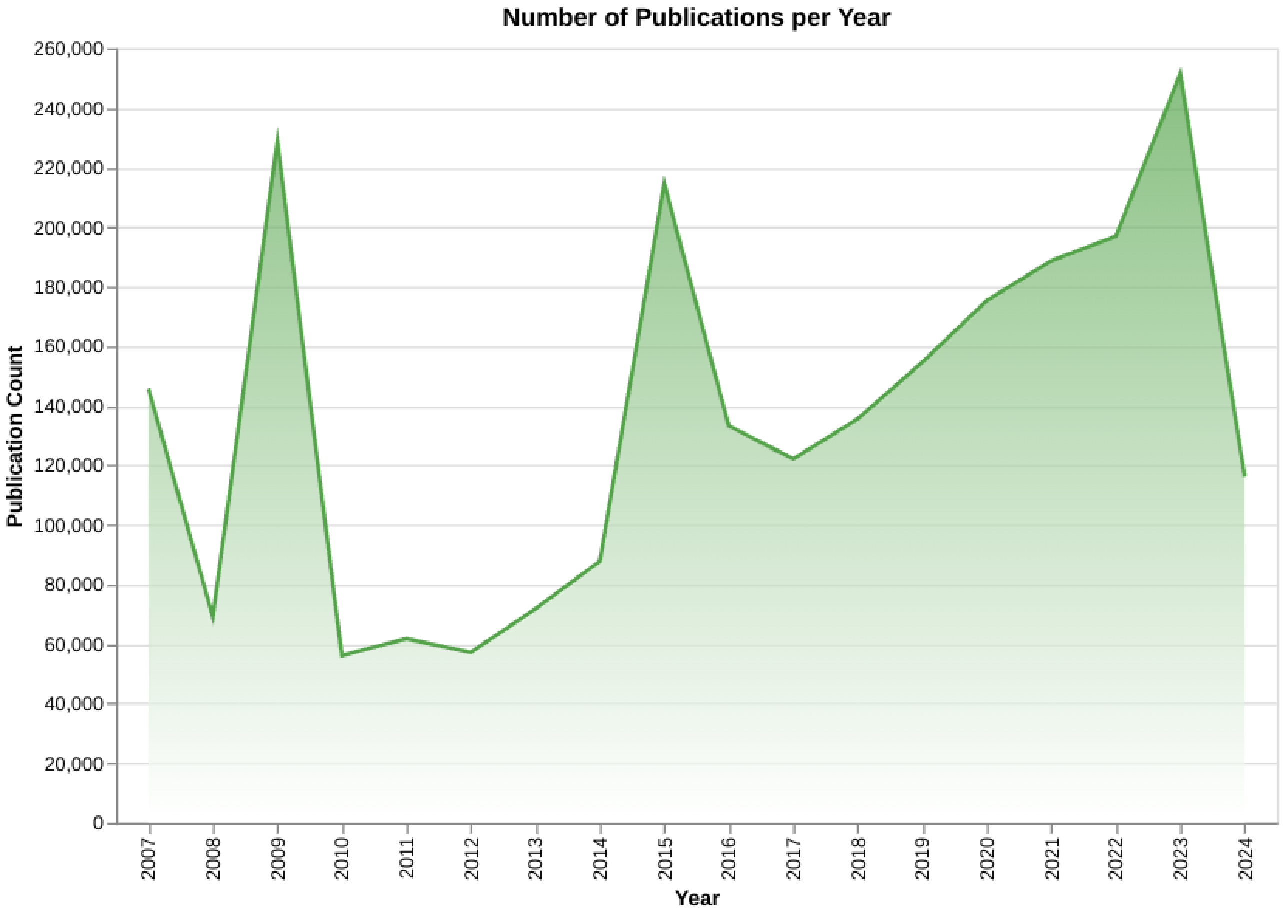



This pie chart visualizes how many papers fall into each "Main Category". It merges data on paper categories, counts entries for each category, and shows those counts as percentages of the total number of papers in a pie chart.

Based on the pie chart, the highest weightage is in the category "Computer Science" and the lowest weightage is in the category "Statistics".

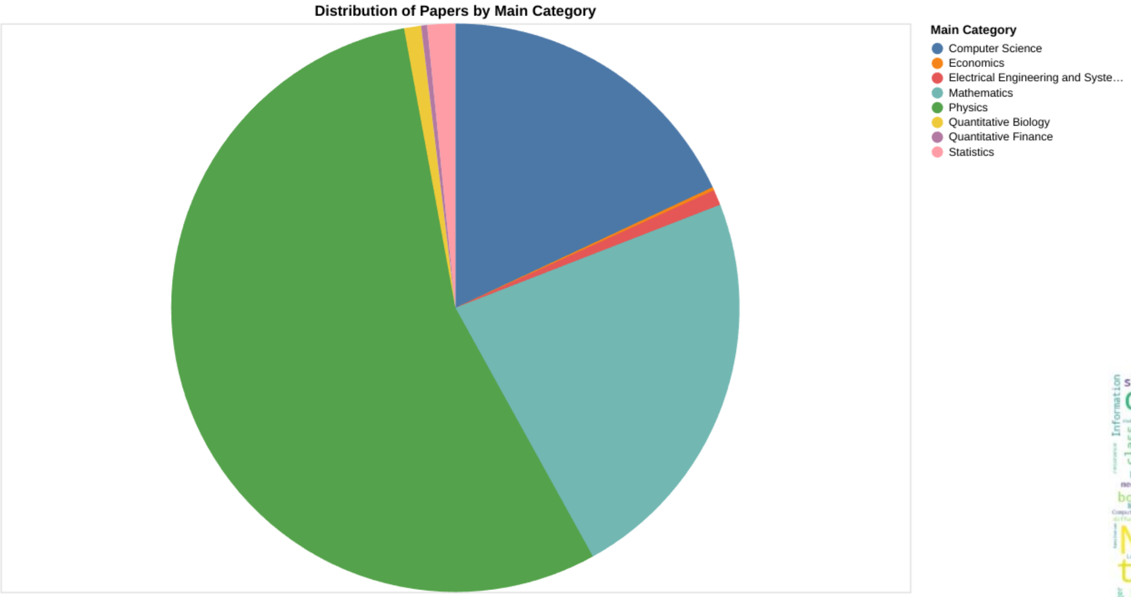
# Number of Publication per year

The slope of the area chart changes throughout the years shown



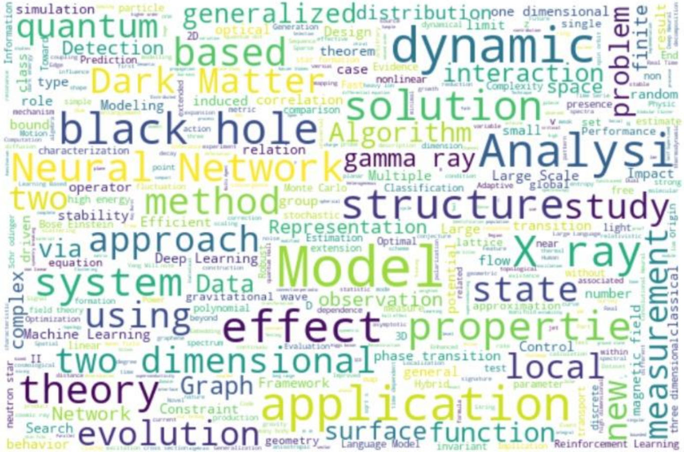

**Year with Most Publications**: 2023 appears to be the year with the most publications.

# Percentage of paper for each category



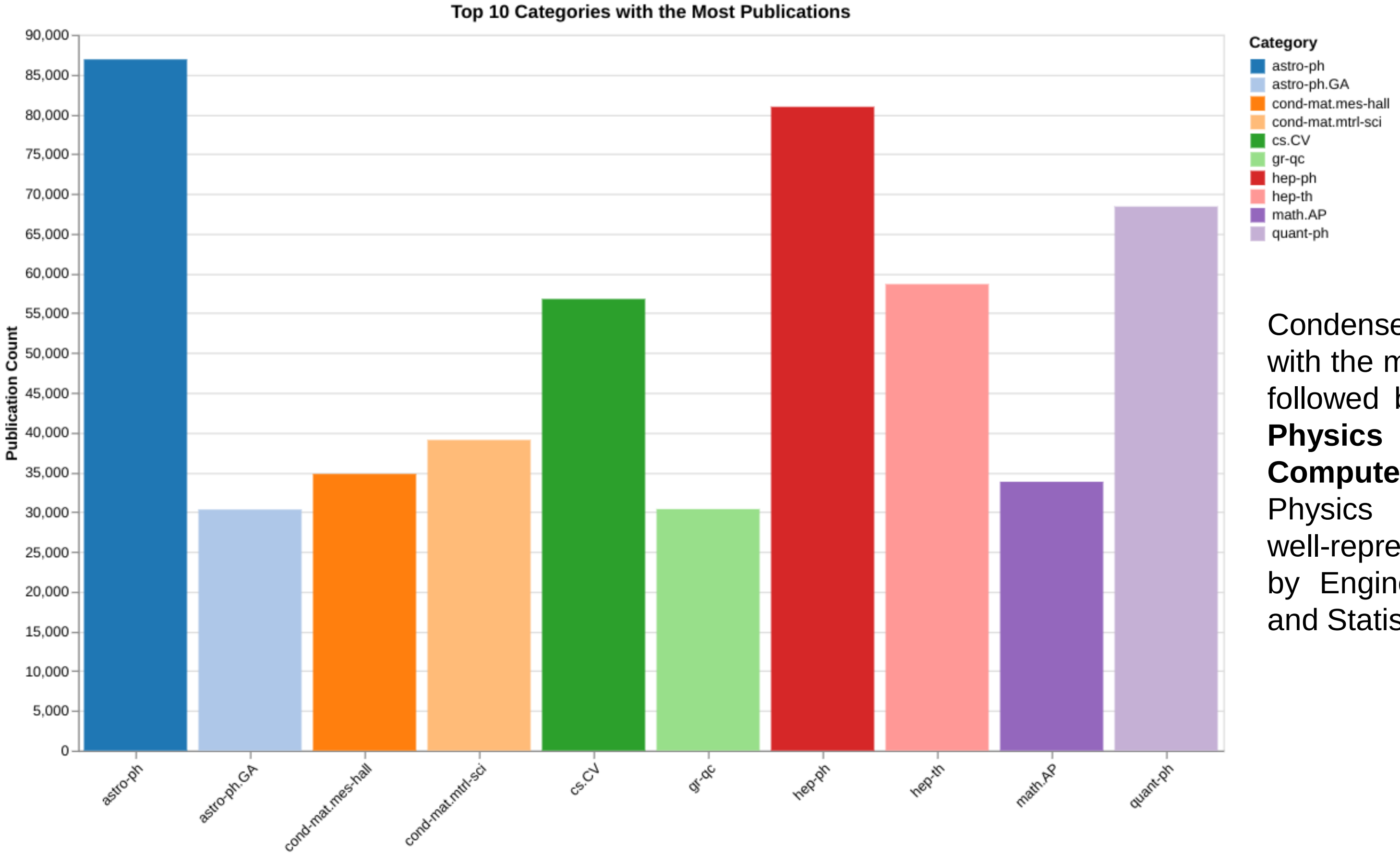

Visualization of the most frequent words appearing in the titles of **1,747,307 research papers**

Overall, the word cloud suggests a collection of research papers in various scientific disciplines, possibly with a focus on **physics and related fields.**



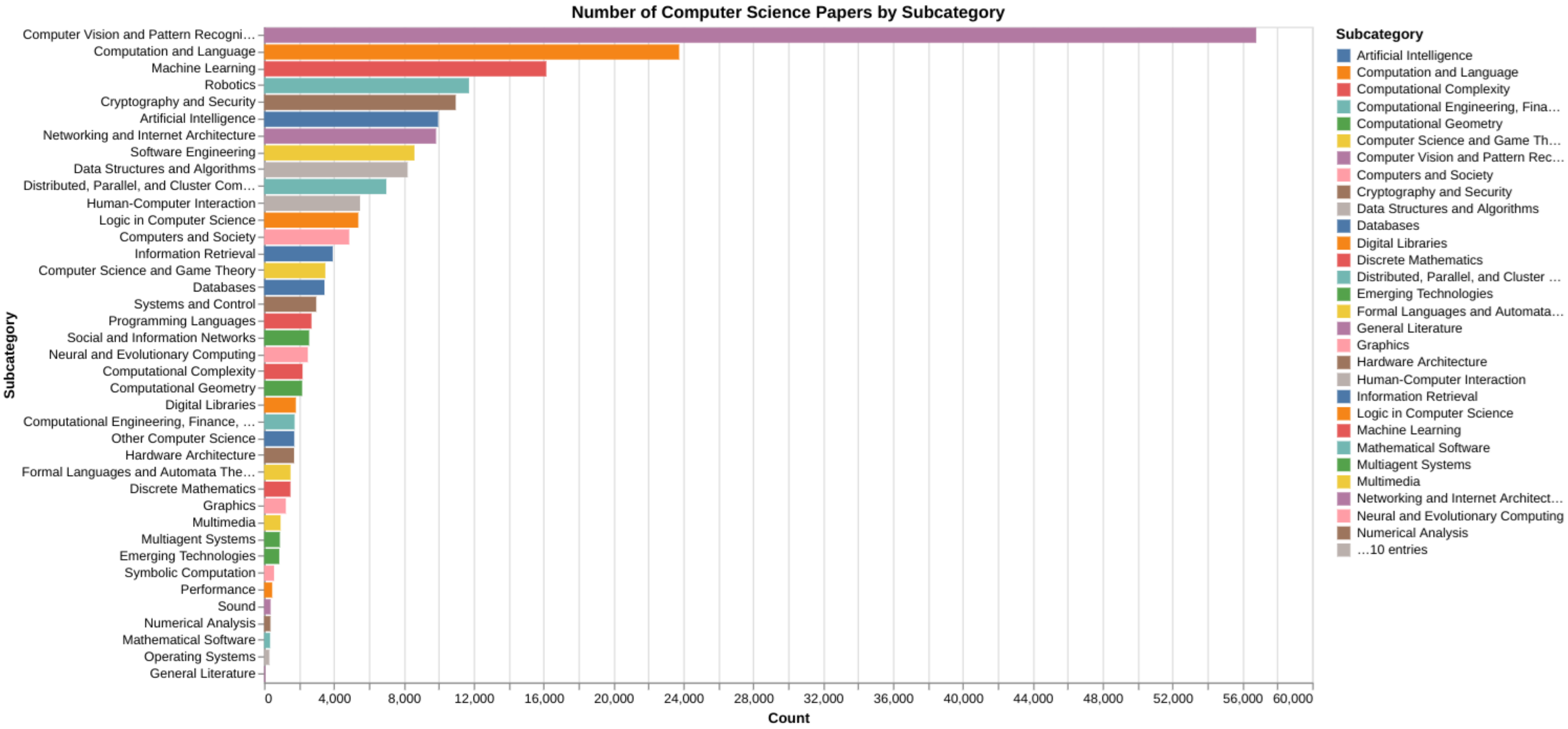

Based on the pie, the proportion of papers in **"Quantitative Finance"** is extremely lower and the proportion of papers in "**Physics**" is large compared to all other category of papers.

# Categories with most publications

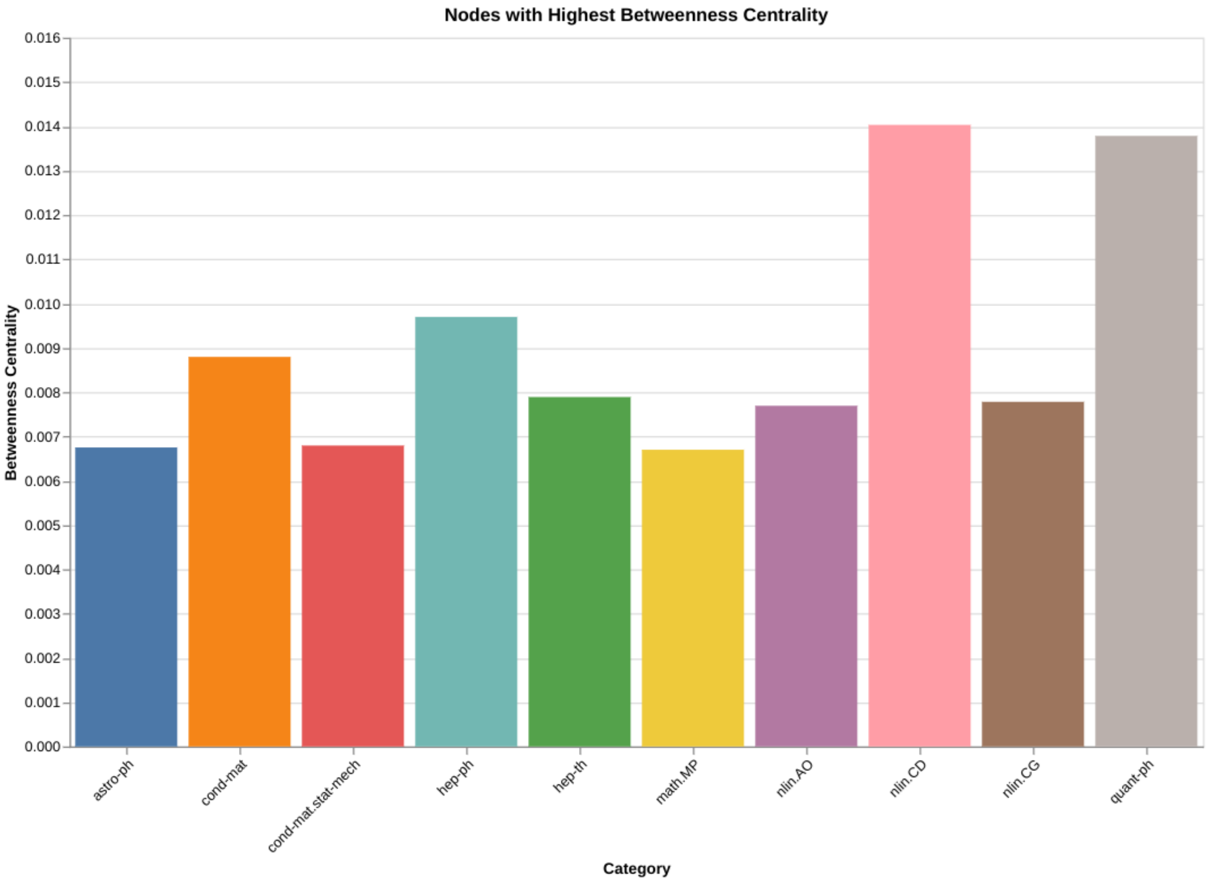



Condensed Matter leads with the most publications, followed by **High Energy Physics - Theory and Computer Science.** Physics and Math are well-represented, followed by Engineering, Finance, and Statistics.

# Computer Science papers for each subcategory



# Nodes with Highest Betweenness Centrality



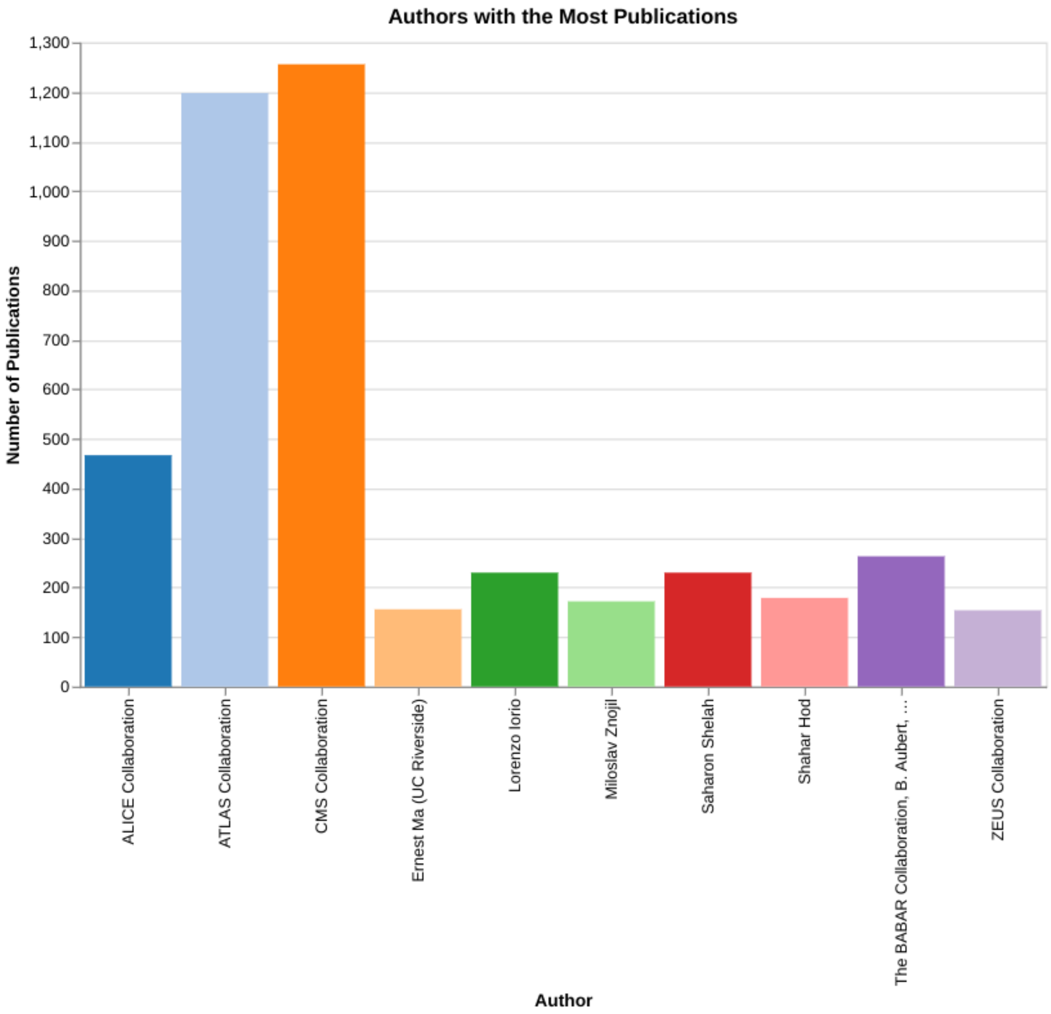

Betweenness centrality indicates a category's influence in information flow between other categories

"**Condensation Matter**" and "**High Energy Physics - Theory**" appear to be the most influential categories for information flow.

# Authors with the Most Publications

CMS Collaboration leads the list with over 1,000 publications, followed by several authors with publication counts around 1,000.

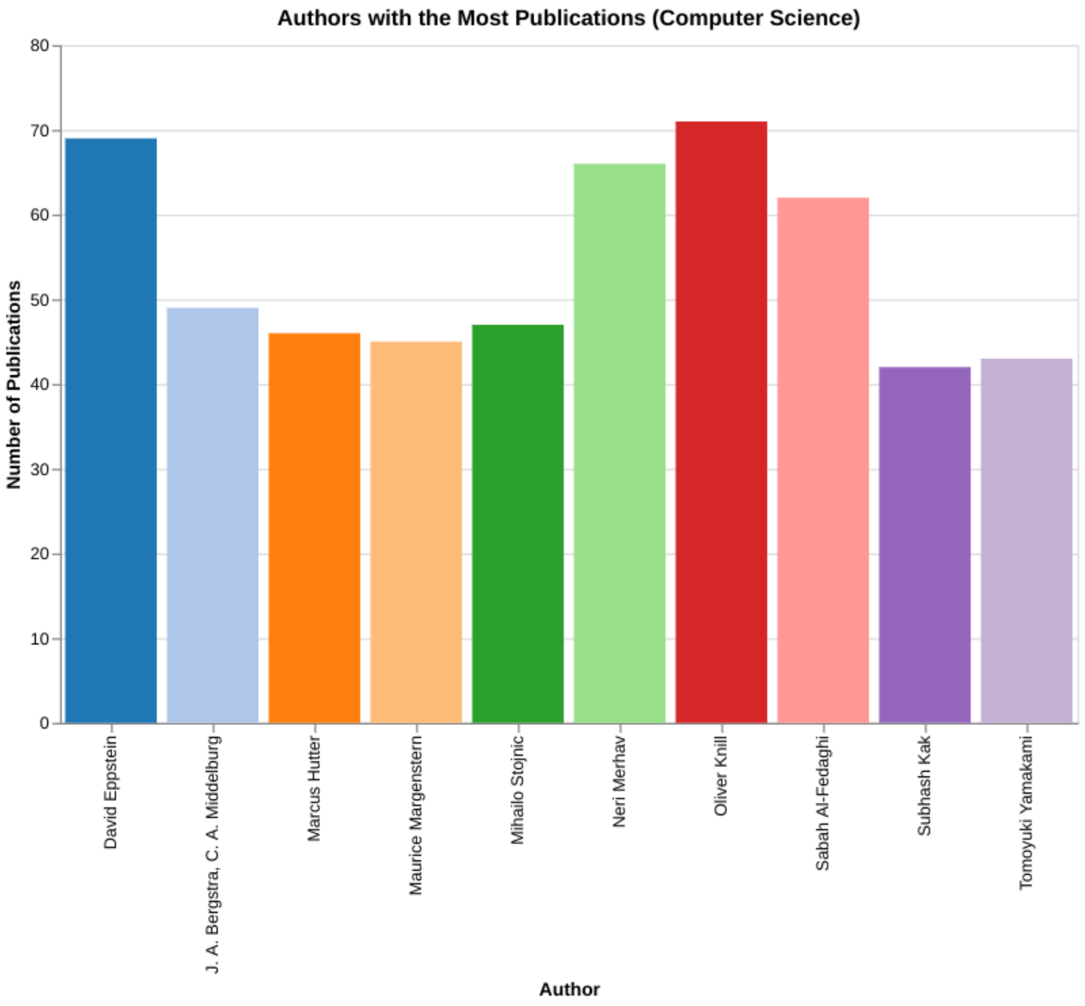
It's likely there are many authors with similar publication counts beyond the top 10 shown here.



# Authors with the Most Publications (Computer Science)

This chart focuses on **individual authors**, not collaboration groups.

**Oliver Knill** appears to be the most prolific author in computer science with the highest publication count



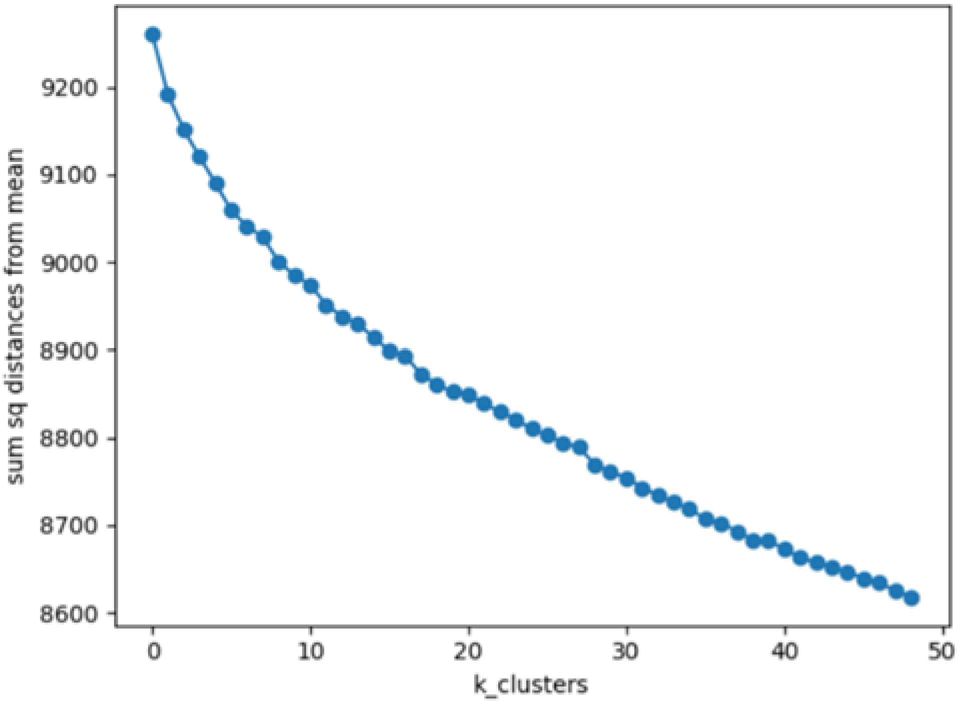
# Feature Engineering techniques: Dimensionality Reduction

Applied **PCA (Principal Component Analysis)** to reduce the dimensionality of the TF-IDF matrix.

The number of components is chosen to retain **95%** of the variance.

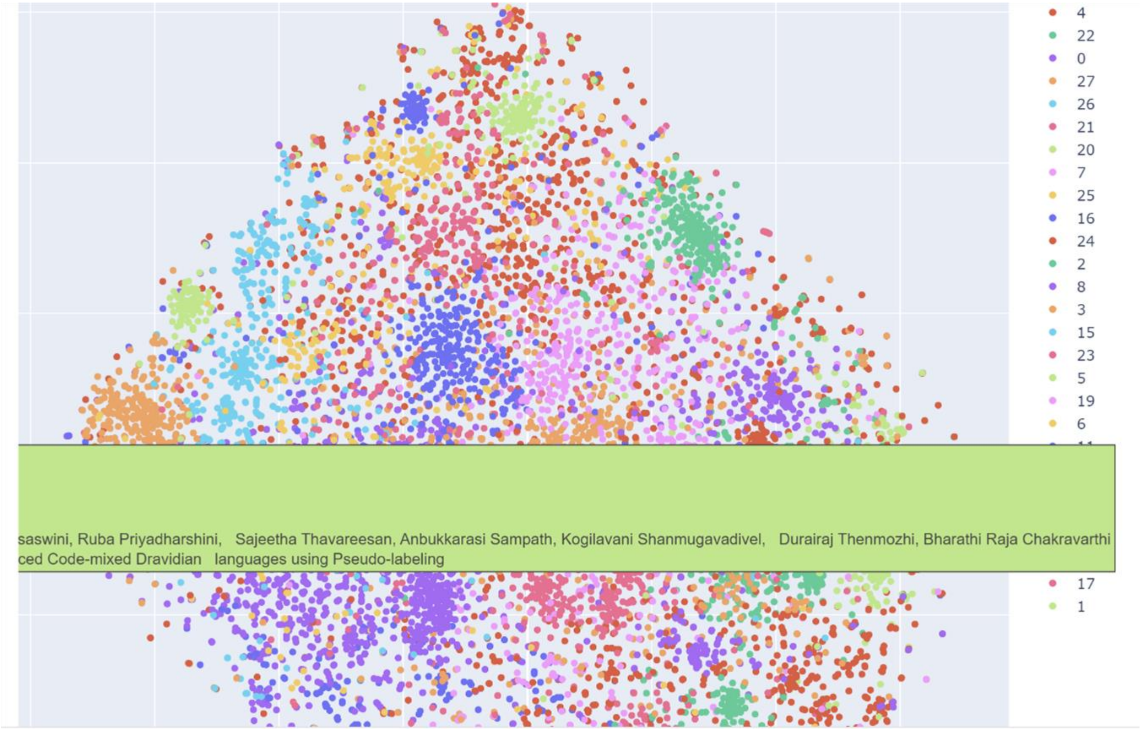
The clustered data is mapped to a lower dimension in order to have a better visualisation and represent the huge set of clusters in 2D using **t-SNE** (t-distributed Stochastic Neighbor Embedding) and **UMAP** (Uniform Manifold Approximation and Projection)

# Models Used: Elbow Method




Based on the Elbow Curve, the no of clusters chosen is **28**

# Models Used: K-means clustering




* NLP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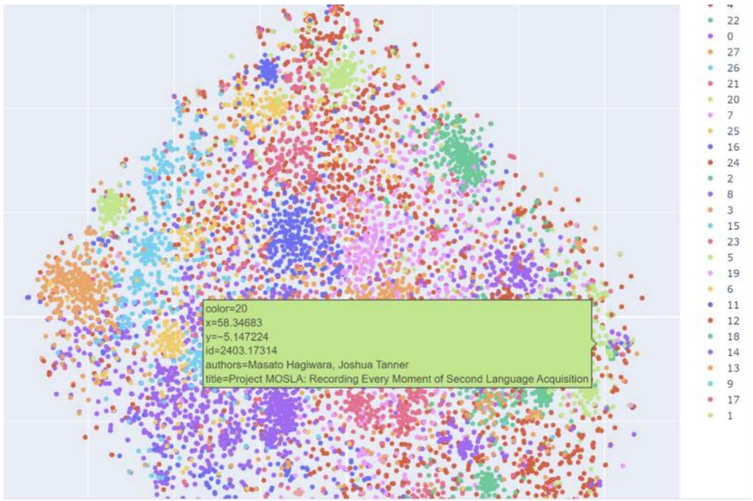
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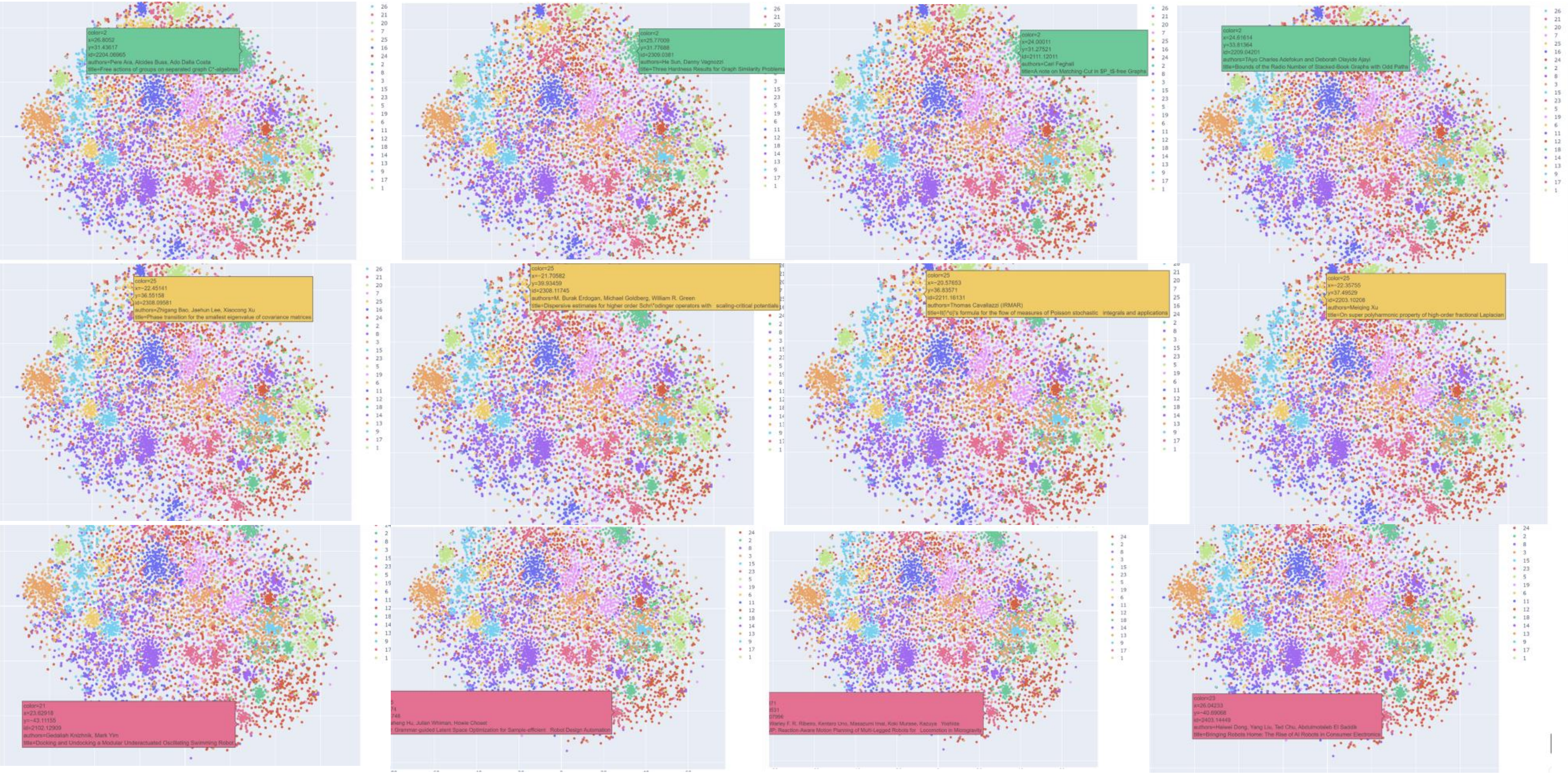
* NLP

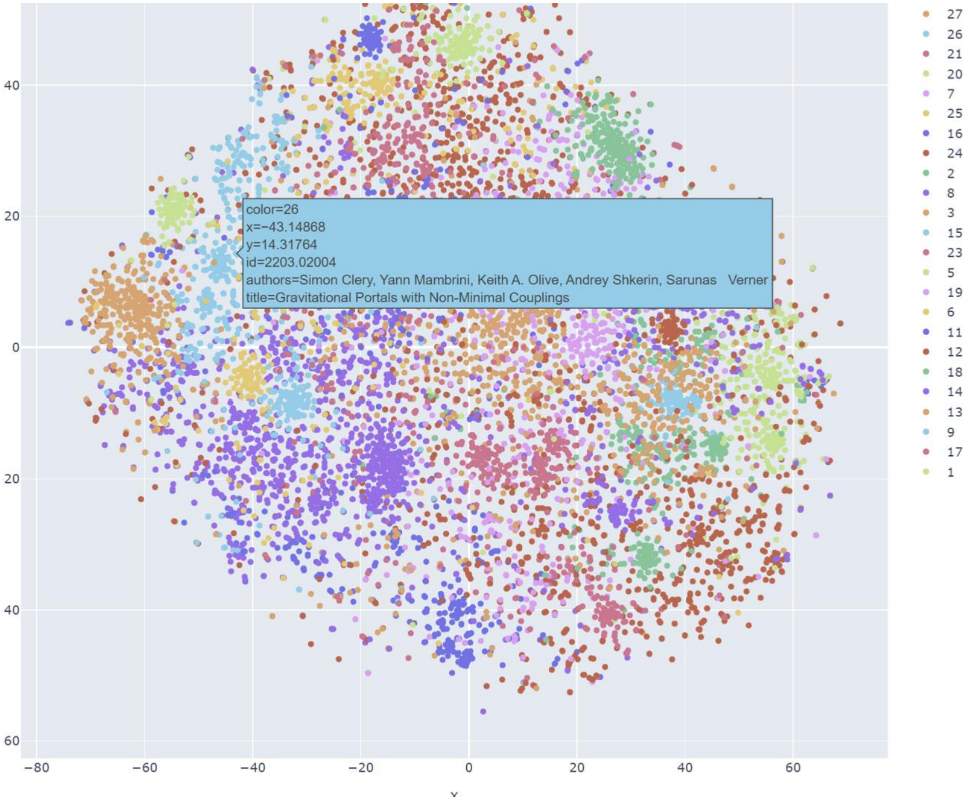


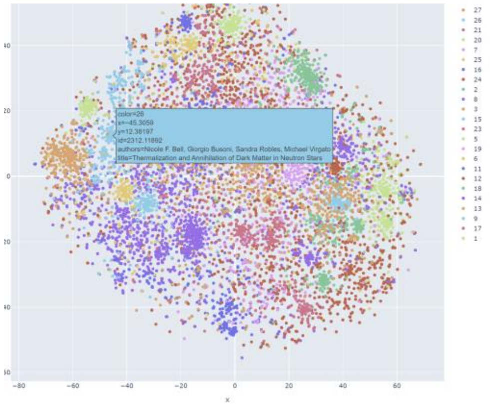

* space research

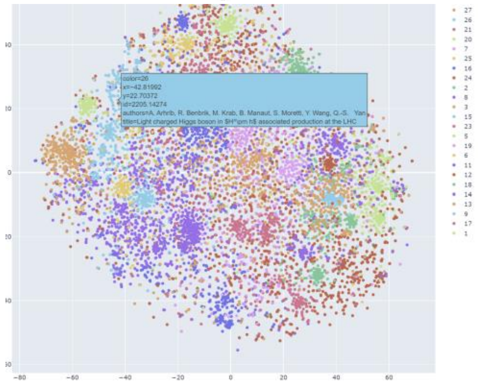



* robotics * graph * Yellow mathematics calculus

# Models Used: Spectral clustering

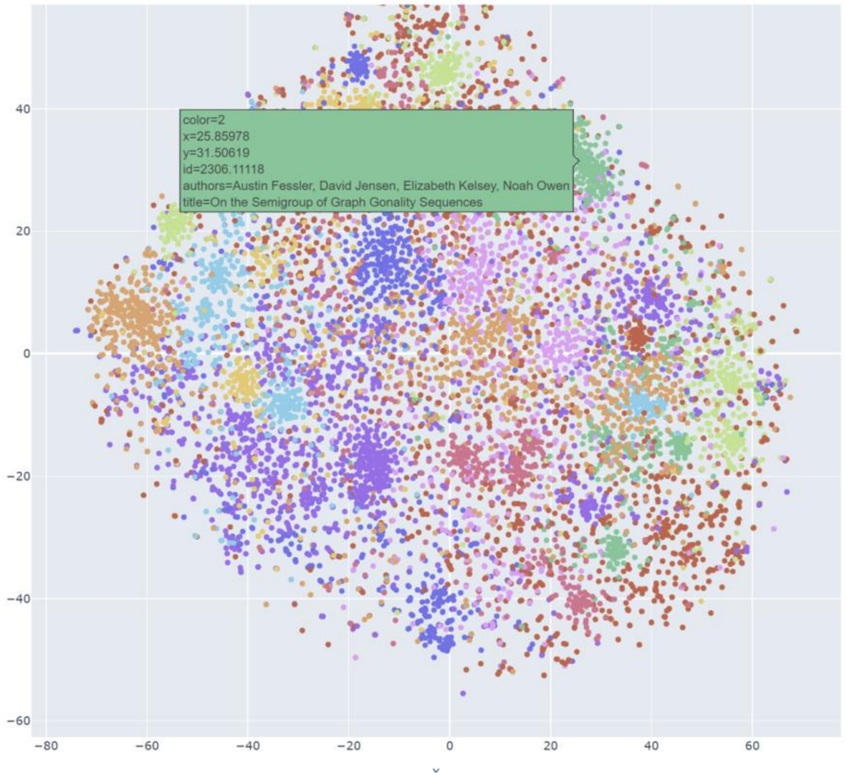


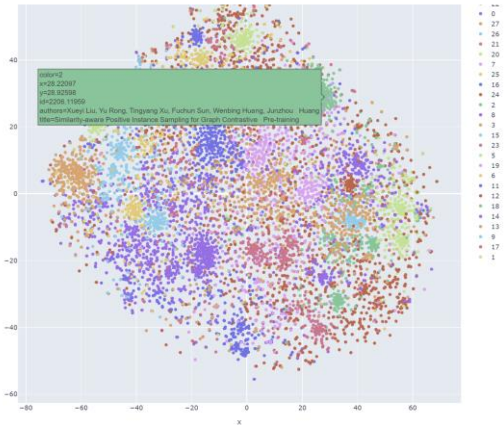



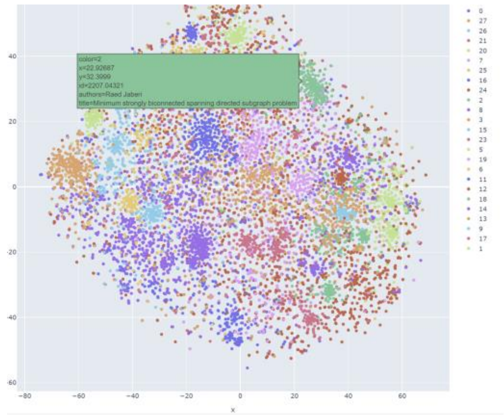


* Space Research

# Models Used: Spectral clustering




* Graph Theory

# Inference

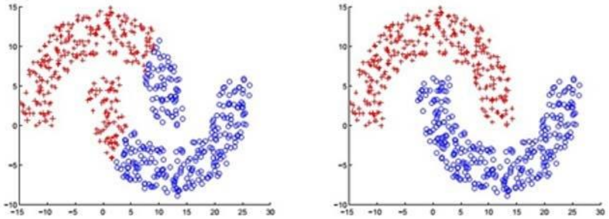
## Evaluation Metrics

- **Silhoutte Score** measures the compactness and separation of clusters in a dataset, with higher values indicating well-separated clusters and lower intra-cluster distances.
- **Davis-Bouldin index** evaluates clustering quality by considering both intra-cluster similarity and inter-cluster dissimilarity, where lower values indicate better clustering performance with more distinct and compact clusters.
- **Calinski-Harabasz Index (Variance Ratio Criterion)** is be used to evaluate the model when ground truth labels are not known where the validation of how well the clustering has been done is made using quantities and features inherent to the dataset.

# Inference

| Metric | KMeans with PCA | Spectral with PCA |
|---|---|---|
| **Silhoutte Score** | **0.0096** | 0.0087 |
| **Davis Bouldin Index** | 7.85 | **7.5** |
| **Calinski-Harabasz Index** | 19.83 | **20.34** |

# Inference



(a) K-means (b) Spectral Clustering

Due to the dynamic nature of the data and categories as well as new categories emerging due to interdisciplinary research, both the models do not yield ideal (Silhouette = 1, DB score = 0, CH index = greater the value better clustering) scores.

Based on the 3 metrics used in an ensemble method, comparatively, **Spectral Clustering** performs better than K-Means Clustering.

The possible reason for that is Spectral clustering uses **connectivity** metric whereas K-Means uses **compactness** metric. For this dataset, more than closeness of the papers, the connectivity among them based on the category/domain groups them together the best.

# Application: Research paper recommendation system

**Steps** :

- Extracting Research Papers data from Arxiv dataset
- Using Universal Sentence Encoder to extract embeddings of Research Abstracts - using category with highest similarity score as label
- Training a K Neighbors Classifier to find similar research papers

The Universal Sentence Encoder encodes text into high dimensional vectors that can be used for text classification, semantic similarity, clustering and other natural language tasks.

# Application: Research paper recommendation system

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Sample:
Counting Perfect Matchings in Dense Graphs Is Hard

Recommendation 1:
Oriented Bipartite Graphs and the Goldbach Graph

Recommendation 2:
Tuza's Conjecture for Threshold Graphs

Recommendation 3:
Graphs with at most two moplexes

Recommendation 4:
Extremal values of degree-based entropies of bipartite graphs

Recommendation 5:
Modularity of nearly complete graphs and bipartite graphs

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Sample:
TabR: Tabular Deep Learning Meets Nearest Neighbors in 2023

Recommendation 1:
Revisiting Pretraining Objectives for Tabular Deep Learning

Recommendation 2:
CELDA: Leveraging Black-box Language Model as Enhanced Classifier
  without Labels

Recommendation 3:
Generative Negative Text Replay for Continual Vision-Language
  Pretraining

Recommendation 4:
Tree-Regularized Tabular Embeddings

Recommendation 5:
Data Transformation to Construct a Dataset for Generating
  Entity-Relationship Model from Natural Language

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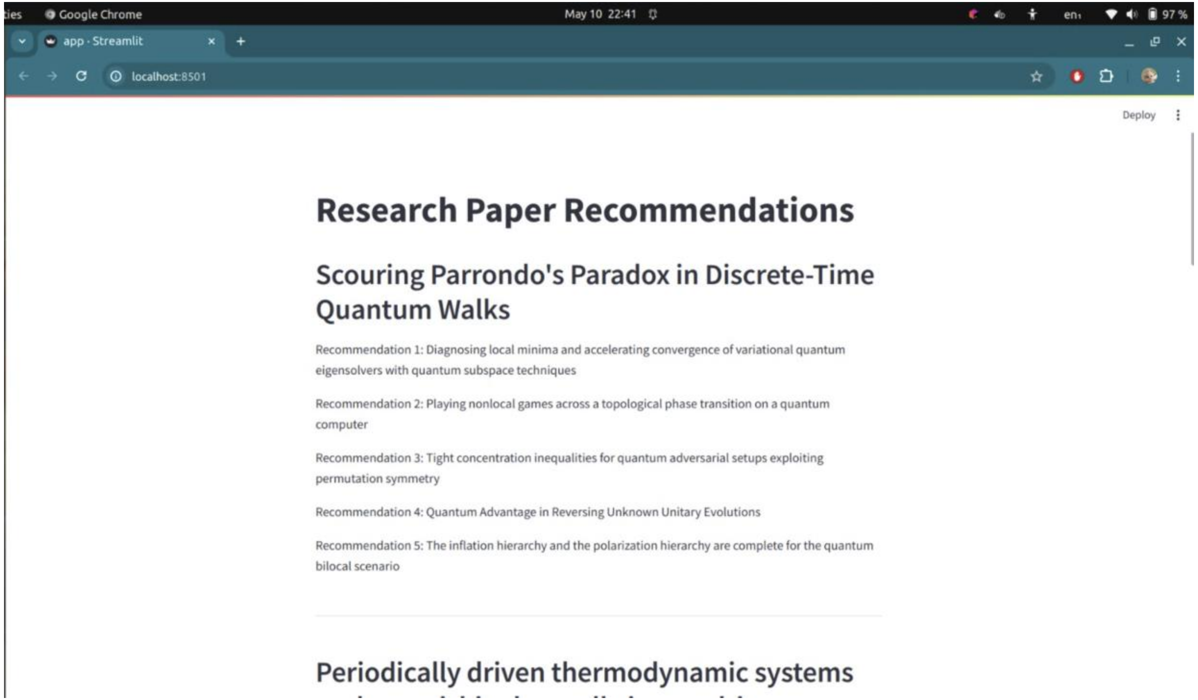
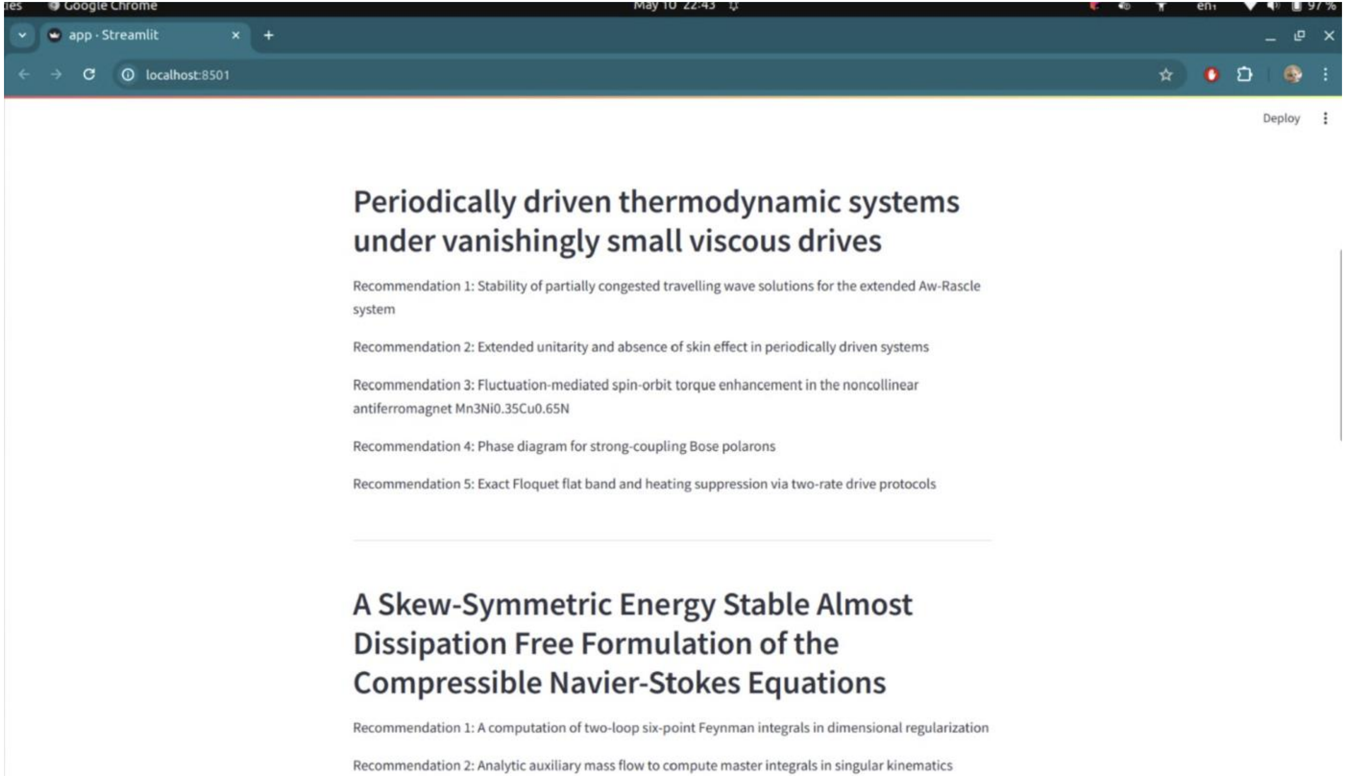
# Deployment: Hosting in Streamlit



# Deployment: Hosting in Streamlit



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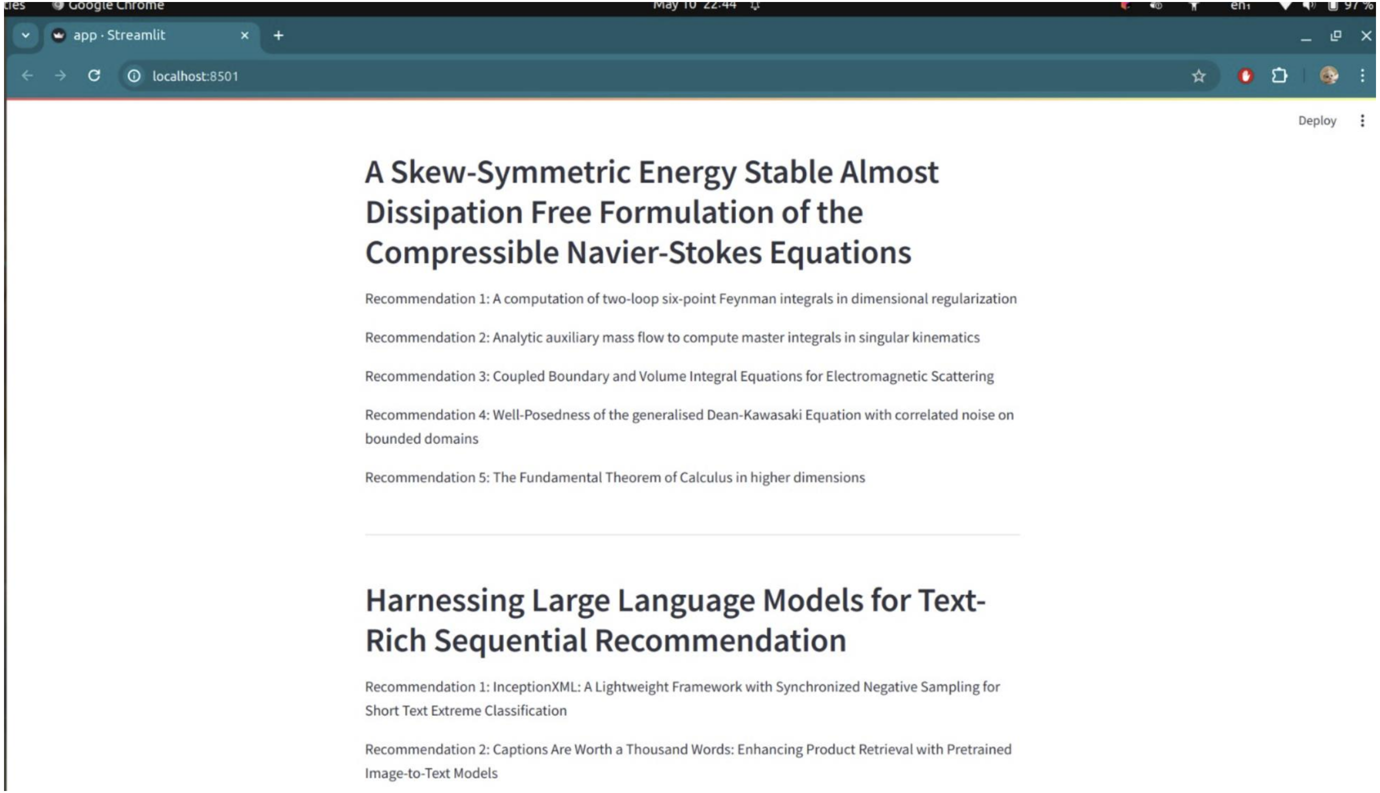

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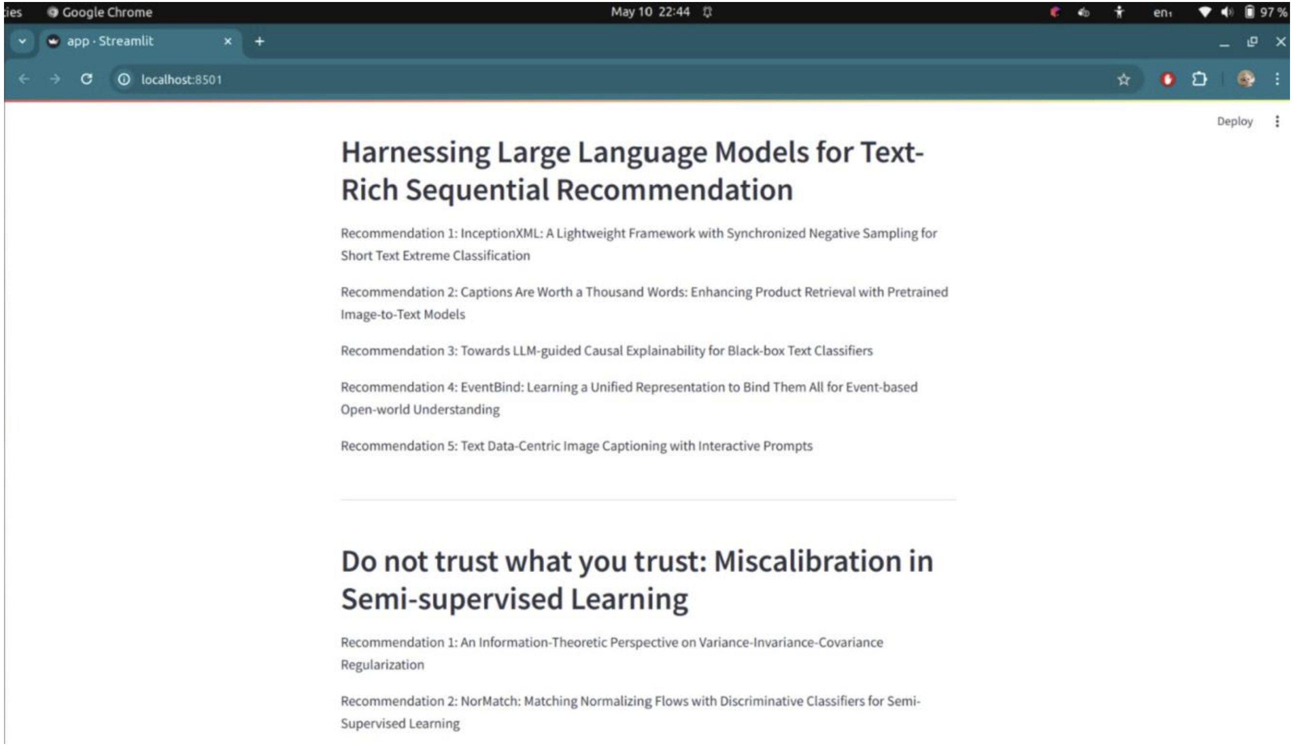

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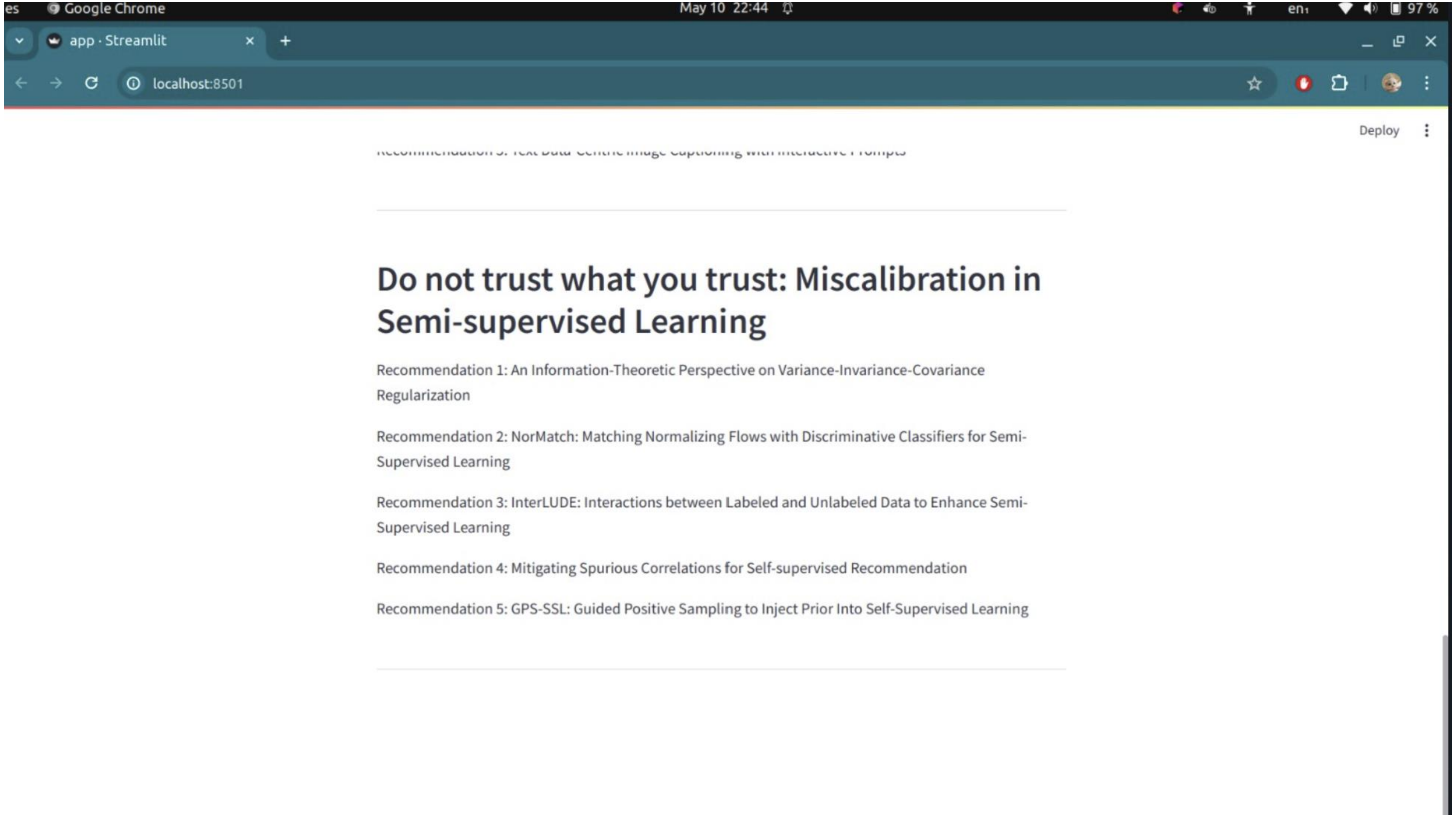

# Impact of the project on human, societal, ethical and sustainable development

- Enhanced Research Efficiency
- Knowledge Accessibility and Inclusivity
- Reduced Environmental Impact (The transition from physical to digital access to research papers)
- Empowerment of Early Career Researchers

# Conclusion and Future Work

By leveraging advanced machine learning techniques, including **K-means clustering** and **spectral clustering**, this system addresses the challenges of information overload, inefficiency in literature discovery, and barriers to access, thereby enhancing the research experience for scholars across diverse disciplines.

While the research paper recommendation system represents a significant step forward in enhancing scholarly communication, there are several avenues for future research and development to further improve its effectiveness and impact: **Enhanced Personalization** and **User Interaction and Feedback Mechanisms**

# Learning Outcomes

Gained a comprehensive understanding of recommendation systems and their role in enhancing **information retrieval** and **user experience** in various domains, particularly in scholarly communication.

Acquired proficiency in machine learning algorithms, including **K-means clustering** and **spectral clustering**, and their application in clustering and grouping research papers based on thematic similarity.

Implemented **data Preprocessing** and **Feature Engineering**.

Validated the model using various **evaluation metrics** and **methodologies** such as Silhouette Score, Davies-Bouldin Index and CH Index.

# References


1. https://www.kaggle.com/datasets/Cornell-University/arxiv
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6. https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html
7. https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html
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