Sri Sivasubramaniya Nadar College of Engineering
Kalavakkam – 603 110

(An Autonomous Institution, Affiliated to Anna University, Chennai)

Department of Computer Science and Engineering

Batch : 2021-2025

UCS2612 - Machine Learning Laboratory
MINI PROJECT

ArXiv Dataset
Research Paper Recommendation System

NAME	REGISTER NUMBER
Ashwini Parvatha G S	3122215001016
A Bhavana	3122215001019
Charumathi P	3122215001020
Jaanus Sri K G	3122215001037

Introduction

In today's dynamic academic landscape, the sheer volume and diversity of research publications present considerable hurdles for scholars aiming to uncover pertinent literature and cultivate interdisciplinary partnerships.

This study aims to provide a solution by developing a system that utilizes advanced techniques to organize papers from the arXiv dataset. The goal is to simplify the process of discovering relevant literature and fostering interdisciplinary collaborations. Through the use of machine learning, the system will offer recommendations to researchers based on the domains of the given papers, assisting them in navigating the extensive landscape of scholarly literature and forming meaningful partnerships across different fields.

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 **recommendations** of relevant research categories and exemplary papers, empowering researchers to overcome obstacles in literature discovery and interdisciplinary partnership cultivation.

Domain: Education

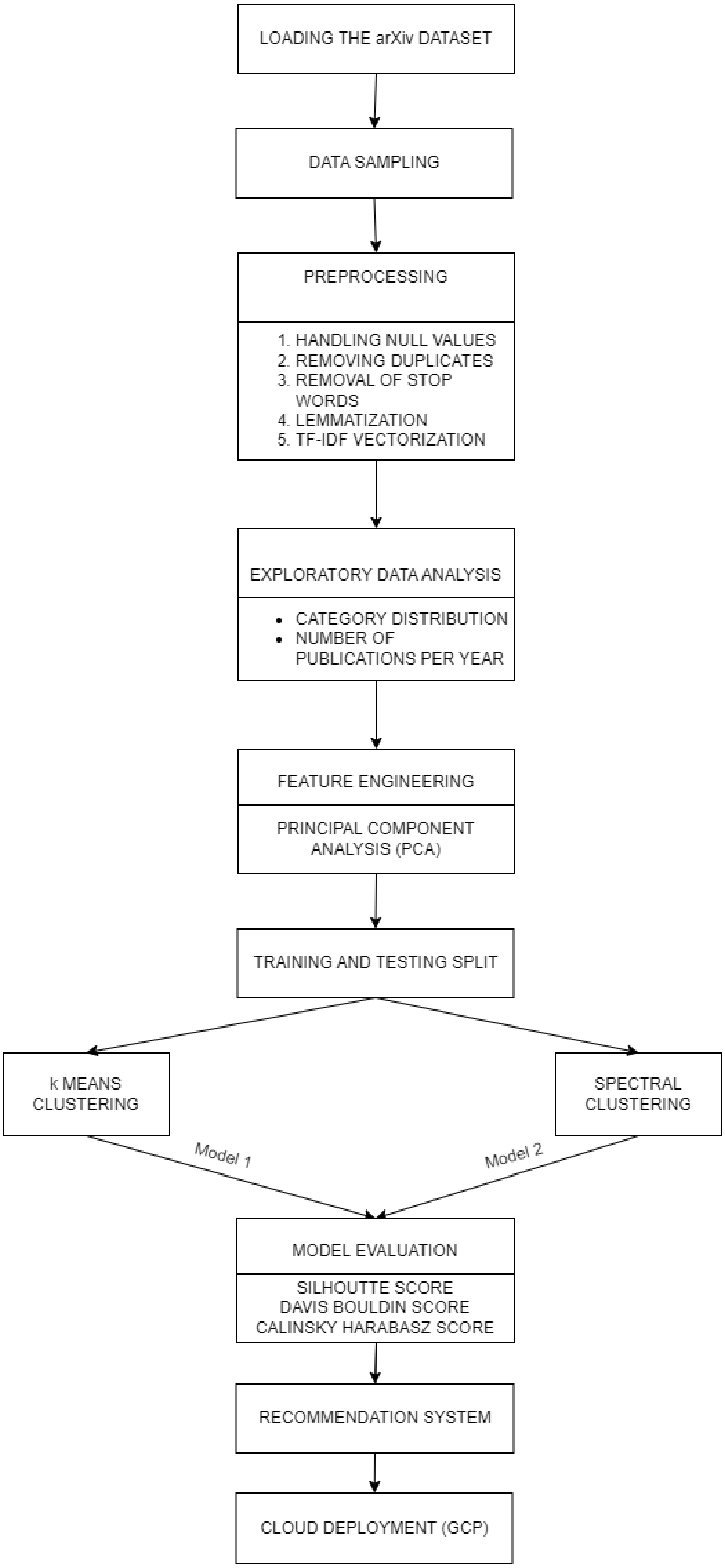
Type of Data : Text

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



Dataset Collection

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 like Authors, Title of Paper, Reference ID, Date of Publication, Categories/Domains, Abstract etc derived from 1.7M+ papers.

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

Sample Data :


```
"root":{14 items
"id":string"0704.0001"
"submitter":string"Pavel Nadolsky"
"authors":string"C. Bal\'azs, E. L. Berger, P. M. Nadolsky, C.-P. Yuan"
"title":string"Calculation of prompt diphoton production cross sections
at Tevatron and LHC energies"
"comments":string"37 pages, 15 figures; published version"
"journal-ref":string"Phys.Rev.D76:013009,2007"
"doi":string"10.1103/PhysRevD.76.013009"
"report-no":string"ANL-HEP-PR-07-12"
"categories":string"hep-ph"
"license":NULL
"abstract":string" A fully differential calculation in perturbative
quantum chromodynamics is presented for the production of massive
photon pairs at hadron colliders. All next-to-leading order
perturbative contributions from quark-antiquark, gluon-(anti)quark, and
gluon-gluon subprocesses are included, as well as all-orders
resummation of initial-state gluon radiation valid at next-to-next-to-
leading logarithmic accuracy. The region of phase space is specified in
which the calculation is most reliable. Good agreement is demonstrated
with data from the Fermilab Tevatron, and predictions are made for more
detailed tests with CDF and DO data. Predictions are shown for
distributions of diphoton pairs produced at the energy of the Large
Hadron Collider (LHC). Distributions of the diphoton pairs from the
decay of a Higgs boson are contrasted with those produced from QCD
processes at the LHC, showing that enhanced sensitivity to the signal
can be obtained with judicious selection of events. "
"versions":[2 items
```

```
0:{...}2 items
1:{...}2 items
]
"update_date":string"2008-11-26"
"authors_parsed":[4 items
0:[...]3 items
1:[...]3 items
2:[...]3 items
3:[...]3 items
]
}
```

	id	authors	title	doi	category	abstract
0	0704.0033	Maxim A. Yurkin, Valeri P. Maltsev, Alfons G. ...	Convergence of the discrete dipole approximati...	10.1364/JOSAA.23.002578 10.1364/JOSAA.32.002407	[physics.optics, physics.comp-ph]	We performed a rigorous theoretical converge...
1	0704.0038	Maxim A. Yurkin, Alfons G. Hoekstra	The discrete dipole approximation: an overview...	10.1016/j.jqsrt.2007.01.034 10.1016/j.jqsrt.20...	[physics.optics, physics.comp-ph]	We present a review of the discrete dipole a...
2	0704.0479	T.Geisser	The affine part of the Picard scheme	None	[math.AG, math.KT]	We describe the maximal torus and maximal un...
3	0704.1476	Chris Austin	TeV-scale gravity in Horava-Witten theory on a...	None	[hep-th]	The field equations and boundary conditions ...
4	0705.1155	Kerry M. Soileau	State Vector Determination By A Single Trackin...	None	[astro-ph]	Using only a single tracking satellite capab...

Implementation

1) Data Preprocessing:

- Filtered the documents based on the **latest version** created after 2020 to sample the data as well as to look into the recent trend in the research papers.
- Trimmed down the data to select specific columns like ID, category, and abstract.
- Removed **duplicate** abstracts.
- Handled the **missing values.**

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

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.

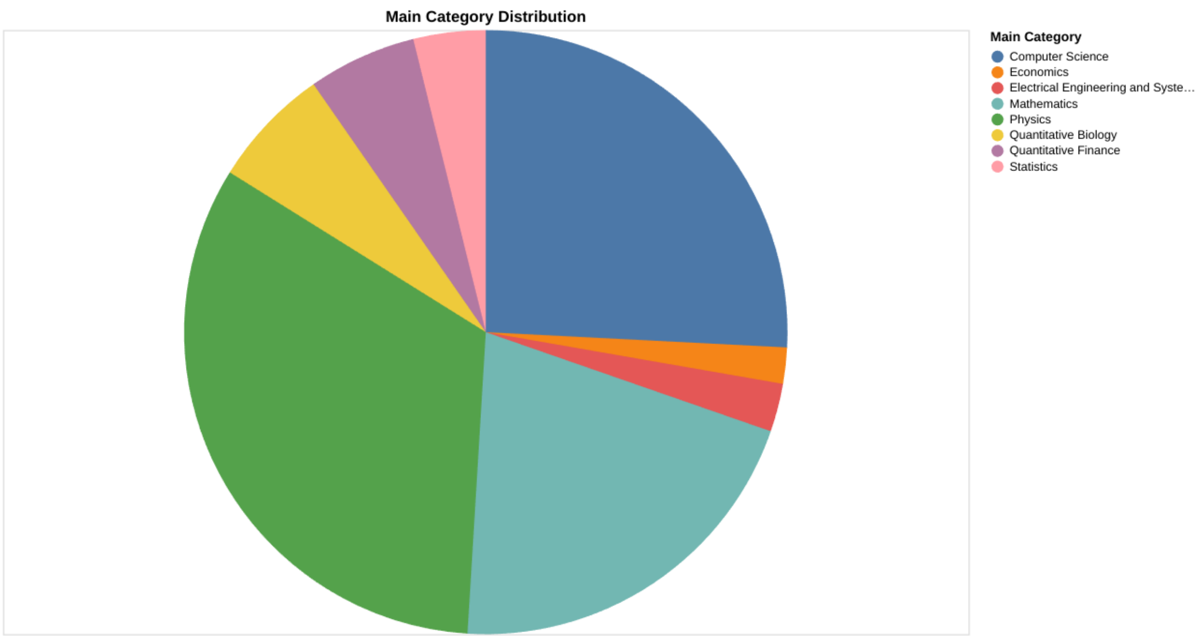
Text vectorization

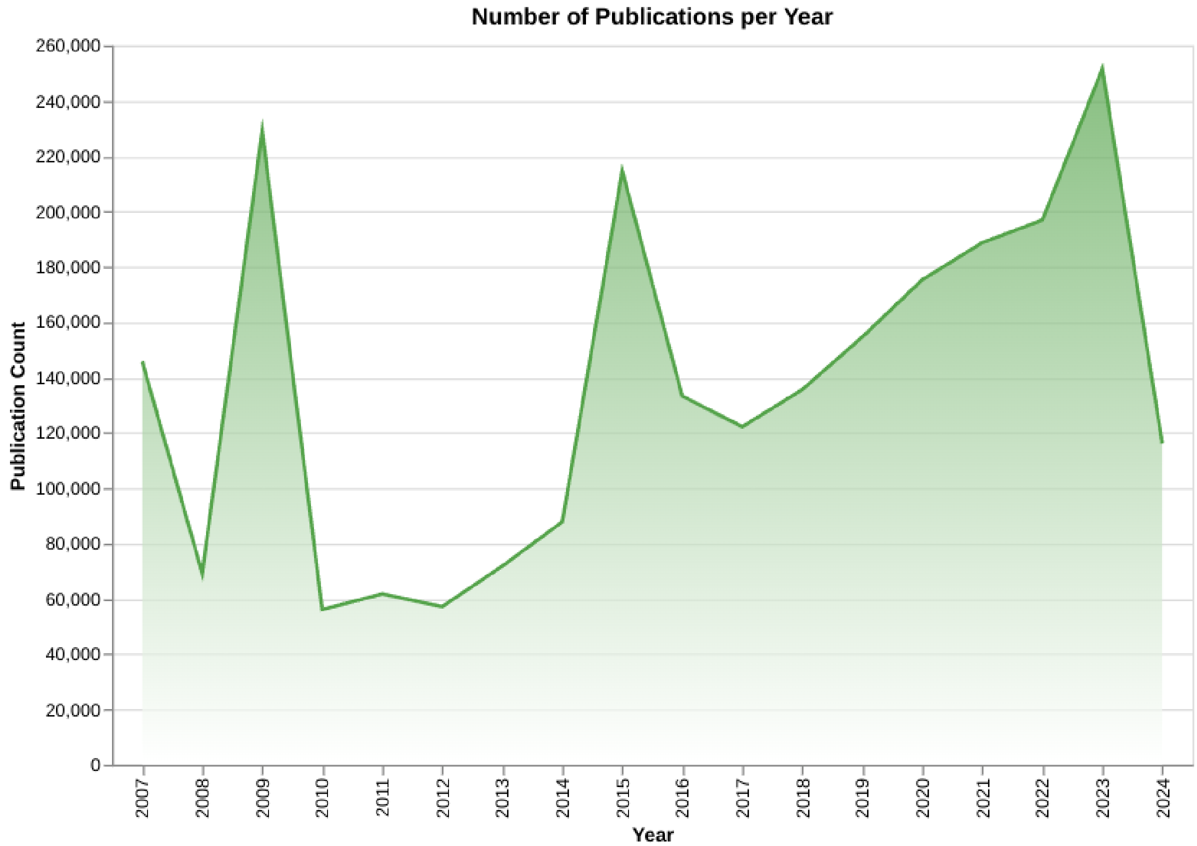
- Used TF-IDF vectorization to convert the preprocessed text into **numerical** form.
- Specified an arbitrary maximum number of features.
- Transformed the text data into a matrix representation (`X`).

2) Exploratory Data Analysis :

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.

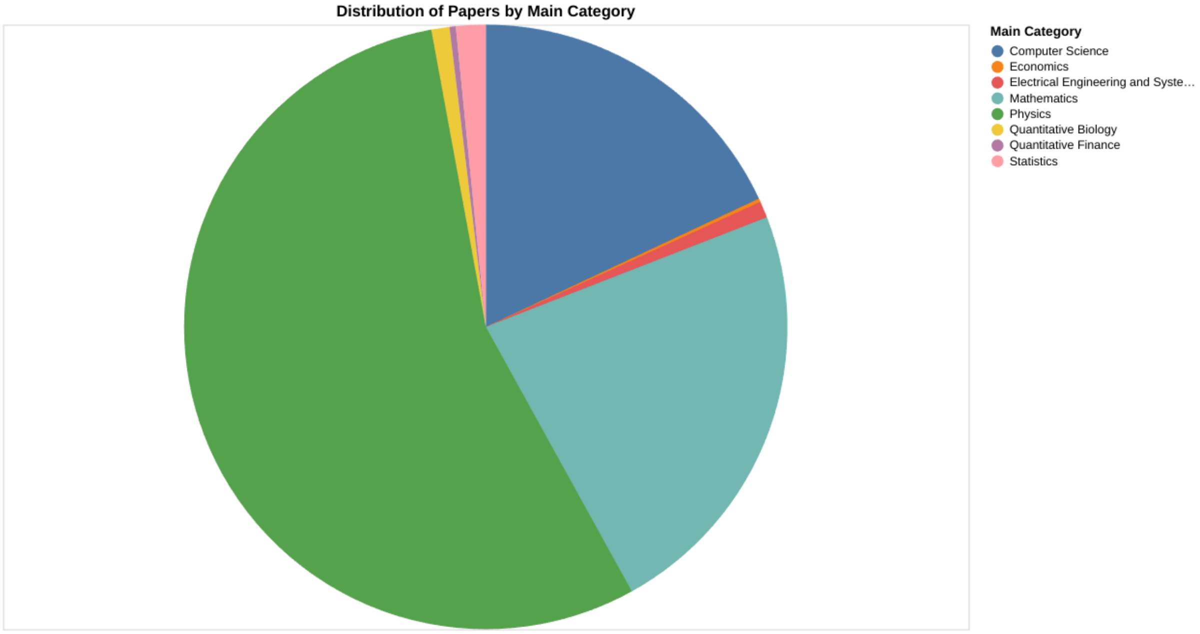
Based on the pie chart, the highest weightage is in the category "Computer Science" and the lowest weightage is in the category "Statistics".





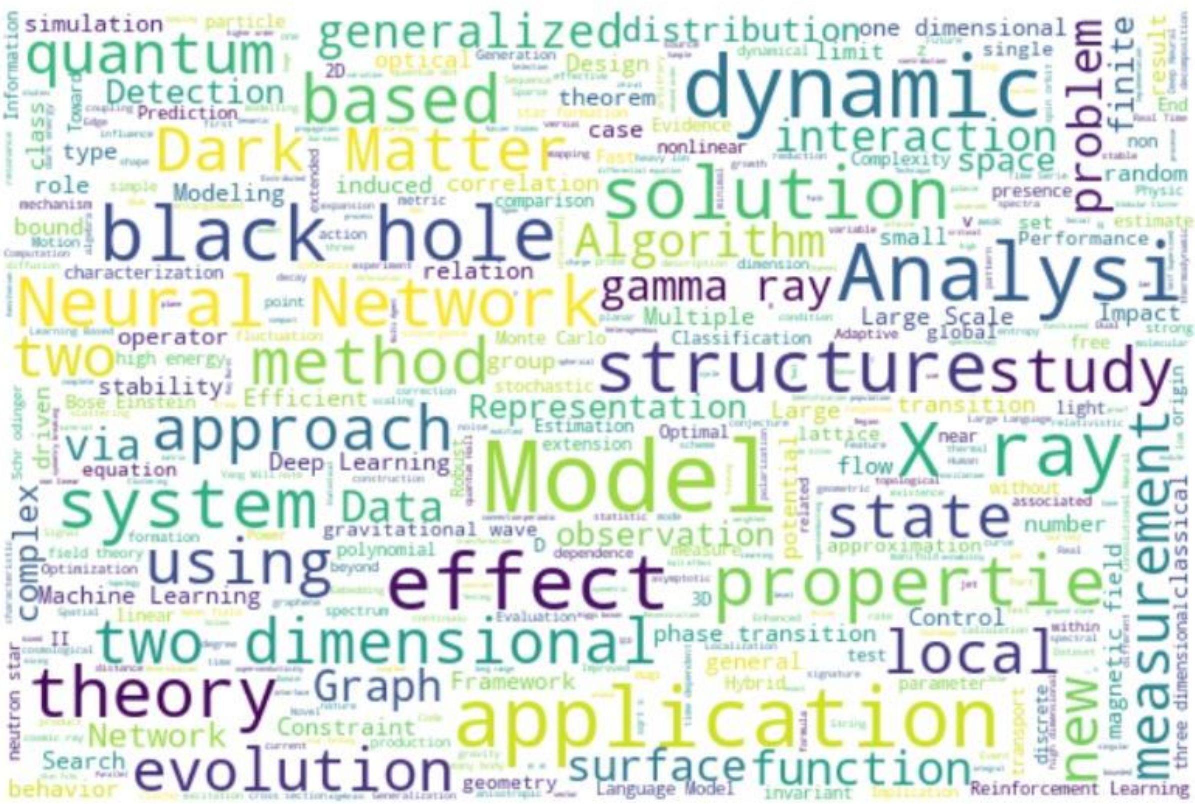
Year with Most Publications: 2023 appears to be the year with the most publications.

This plot shows that year by year the number of publications are gradually increasing except during few situations like COVID pandemic, disasters etc.

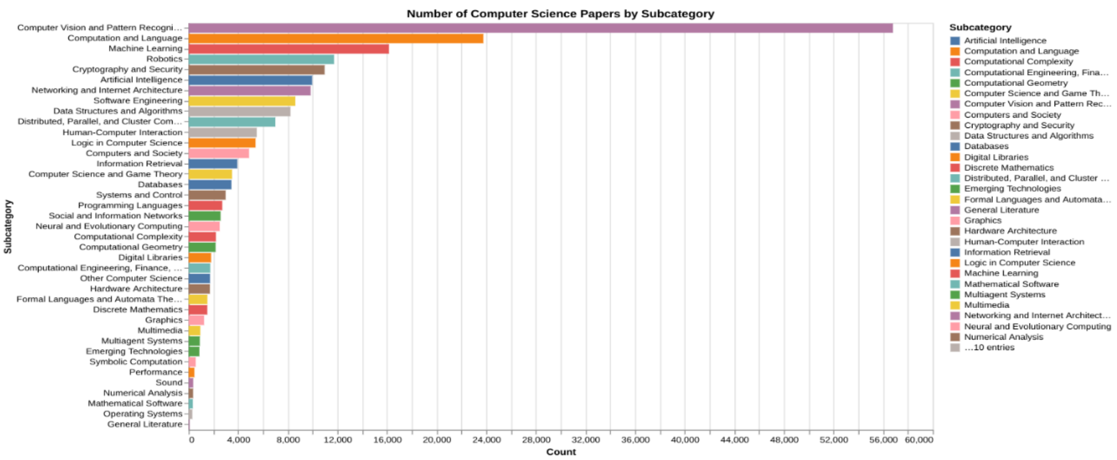


Based on the pie, the proportion of papers in "Quantitative Finance" is extremely lower and the proportion of papers in "Physics" is large compared to all other category of papers.

Word Cloud :



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.



3) Feature Engineering Techniques :

- Improves Model Performance: Well-engineered features enhance model accuracy and generalization.
- Handles Raw Data: Transforms messy or incomplete data into a format the model can understand.
- Reduces Overfitting: Removes noise and irrelevant information, preventing the model from fitting the training data too closely.
- Enables Interpretability: Makes models more understandable by representing data in a meaningful way.
- Addresses Non-Linearity: Captures complex relationships between features and the target variable.
- Enhances Robustness: Makes models more resilient to changes in data distribution or real-world variations.
- Incorporates Domain Knowledge: Allows domain expertise to influence model design and performance.

Dimensionality Reduction

- Applied **PCA** (Principal Component Analysis) to reduce the dimensionality of the TF-IDF matrix helps in mitigating the curse of dimensionality and improving computational efficiency.
- The number of components is chosen to retain 95% of the variance.

4) ML Model :

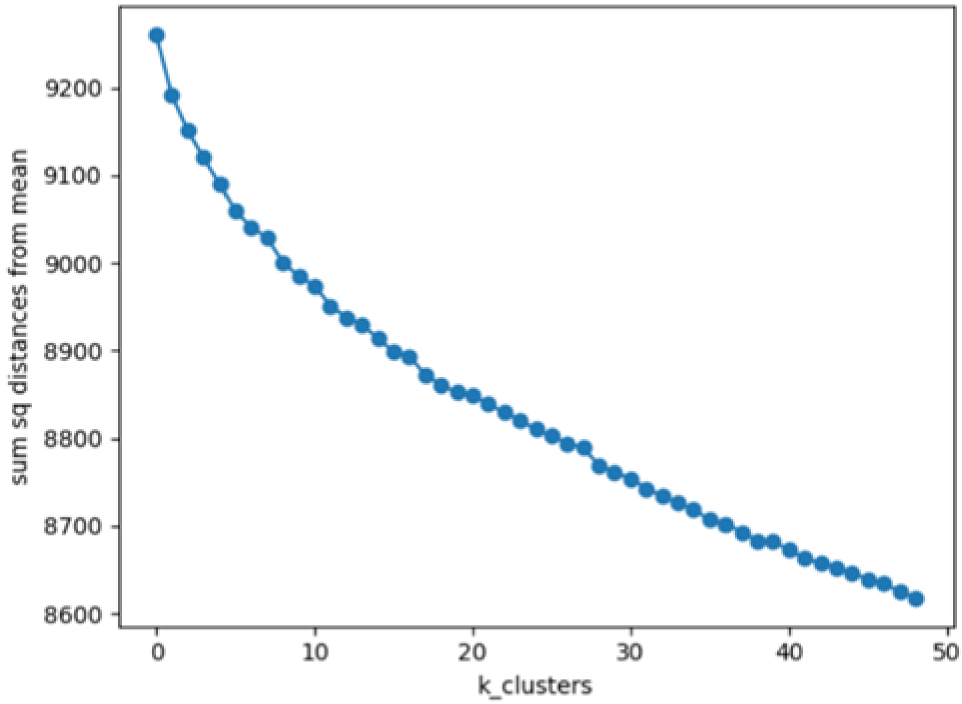
Type of Learning used – Unsupervised Learning.

Clustering techniques like KMeans Clustering and Spectral Clustering are performed on the arXiv dataset.

Clustering is chosen as it can reveal the patterns, trends, and relationships within the data, providing valuable insights into its characteristics. Once clusters are identified, they can be used to label class memberships, enabling classification based on similarity to existing data clusters.

In this work, the performance of KMeans and Spectral Clustering are compared and based on the best Clustering model, a simple Recommendation System is developed.

For this dataset, based on the below Elbow Curve, k = 28 is taken for Clustering for both the models.



KMeans Clustering :

Algorithm Steps :

1. The desired number of clusters is decided, denoted as k.
2. Next, a centroid is randomly assigned to each of these k clusters.
3. The distance between each observation and every centroid is calculated.
4. Each observation is assigned to the closest centroid based on its distance.
5. The new centroid location is computed by averaging the observations within each cluster.
6. Steps 3 to 5 are repeated iteratively until the centroids stabilize and no longer change position.

K-means operates by iteratively assigning each paper to the nearest centroid based on a chosen distance metric, such as Euclidean distance based on the abstract, category/domain of the paper.

Starting with random k cluster centers, the model iteratively refines to develop clusters where each cluster is a domain and each paper belongs to any one of the cluster based on the closely relatedness of the paper and the cluster's domain.

Spectral Clustering :

Algorithm Steps :

1) The data is projected to a lower dimensional space by using Graph Laplacian Matrix.
2) A similarity graph for the data is constructed by using metrics like epsilon neighbourhood, k nearest neighbours where each node represents a paper and the edges represent the similarity/pattern among them.
3) Eigen vectors of smaller eigen values are computed.
4) Clustering the data using KMeans Clustering method.

Textual content similarity or citation patterns are used for determining the similarity between the papers. Once the similarity graph is constructed, spectral clustering proceeds to extract the underlying structure of the data by analyzing the graph's eigenvalues and eigenvectors. Specifically, it employs spectral decomposition to transform the graph into a lower-dimensional space, where the data points can be more easily clustered. By retaining the top eigenvectors corresponding to the smallest eigenvalues, spectral clustering effectively captures the intrinsic structure of the dataset, emphasizing both local and global similarities among papers.

Next, the transformed data points are clustered using standard clustering algorithms, such as k-means, on the reduced-dimensional space. This step assigns each paper to a cluster based on its proximity to cluster centroids, effectively grouping together papers that exhibit similar characteristics or topics.

5) Comparison of ML models :

The models are compared by displaying the clusters as a plot and applying evaluation metrics for clustering like Silhoutte Score, Davis Bouldin Index, Calinsky Harabasz Score.

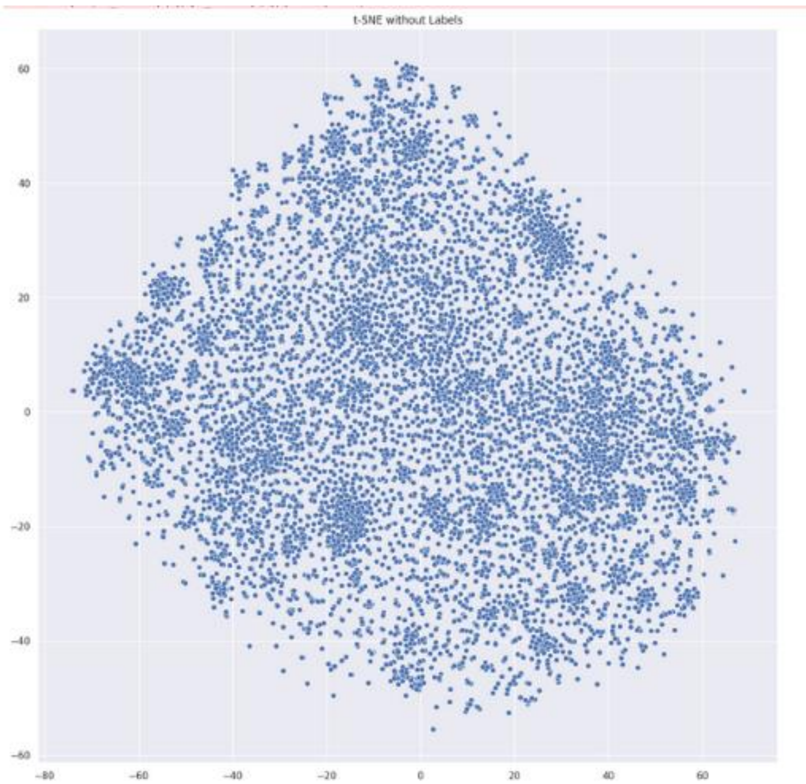
Silhoutte Score measures the compactness and separation of clusters in a dataset, with higher values indicating well-separated clusters and lower intra-cluster distances.

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.

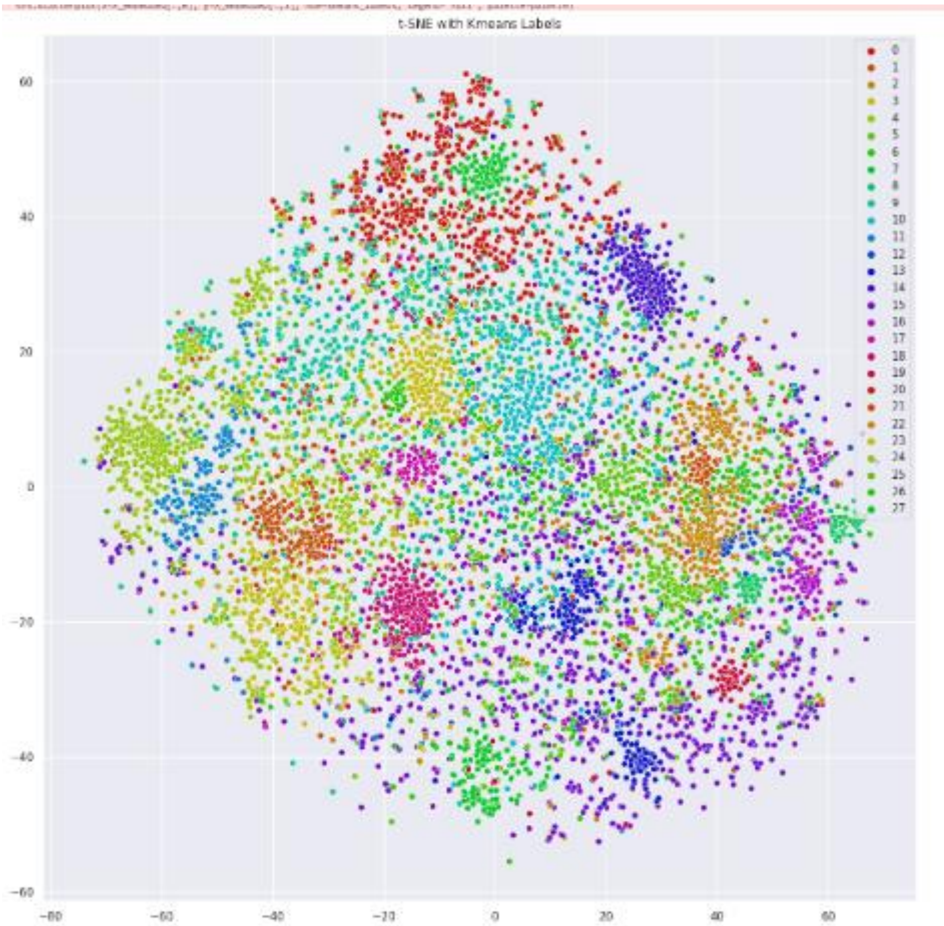
Calinsky Harabasz Score evaluates the quality of clustering in a dataset based on the ratio of between-cluster dispersion to within-cluster dispersion.

In order to display the clusters of such a huge data in 2D representation methods like t-SNE and UMAP are used to reduce the dimensionality of the data points and bring the points much closer for better visualization.

t-SNE (t-distributed Stochastic Neighbour Embedding) is a nonlinear dimensionality reduction technique renowned for its ability to visualize high-dimensional data in low-dimensional space while preserving local structures. It minimizes the divergence between pairwise similarities of the original data and those of the lower-dimensional embedding, effectively revealing complex patterns and relationships.



t-SNE for KMeans Clustering

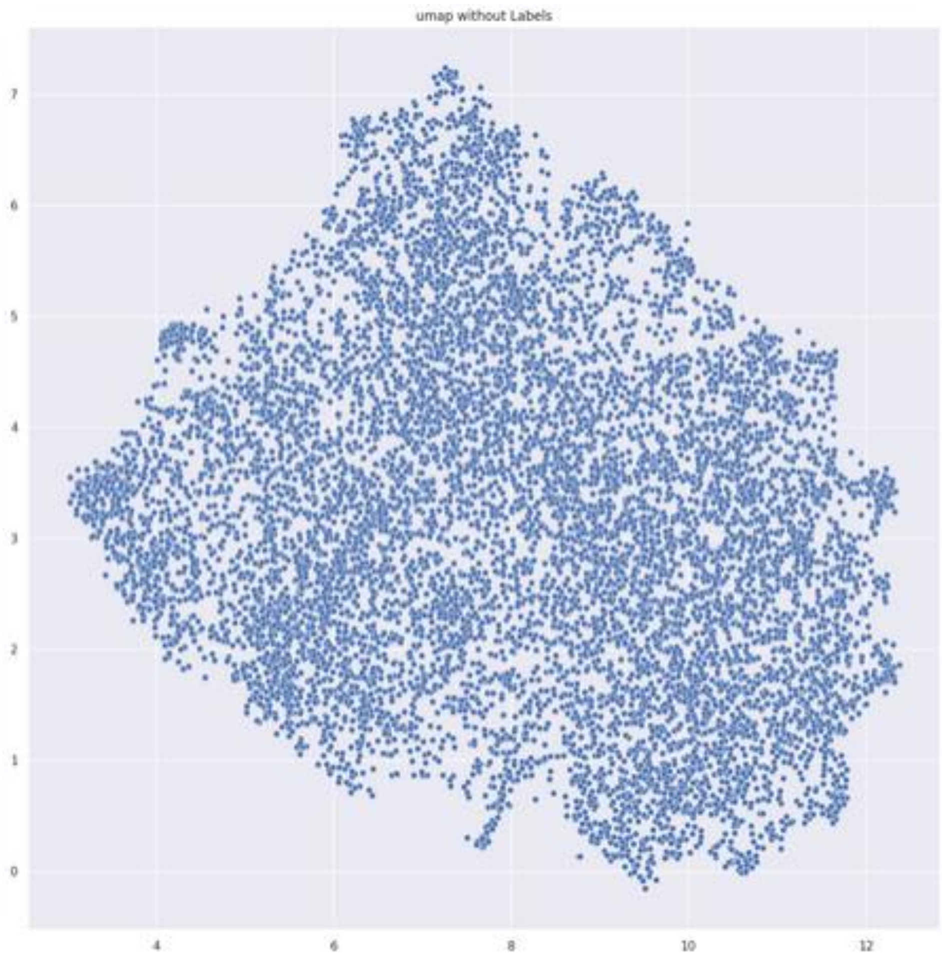


t-SNE for Spectral Clustering

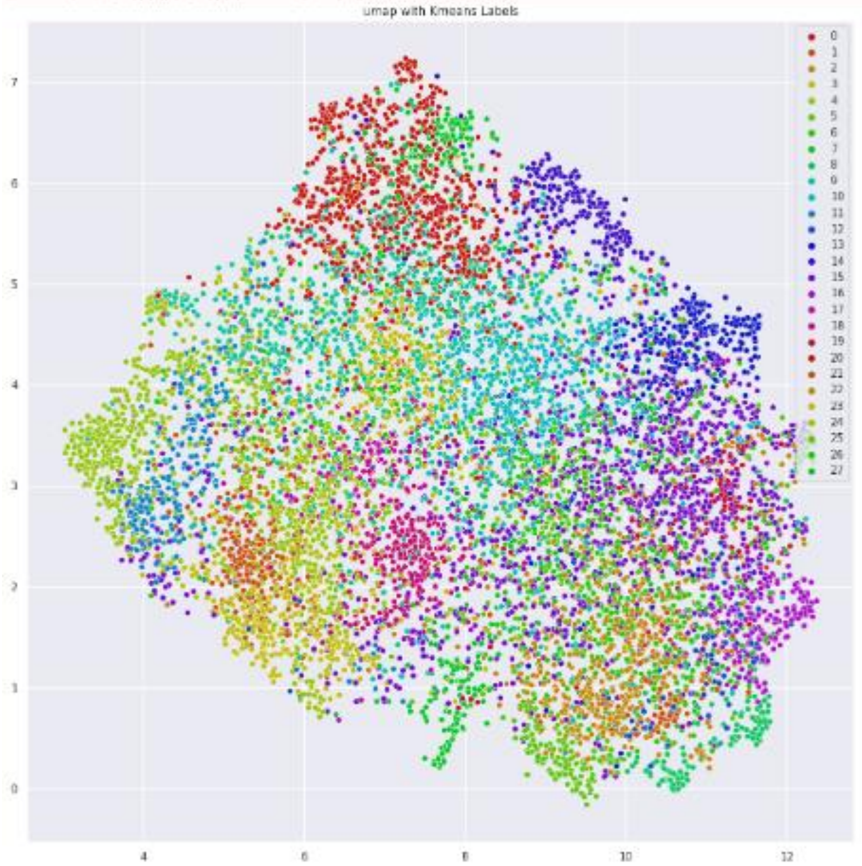
Kullback-Leibler (KL) divergence is utilized as the loss function to measure the dissimilarity between the distributions of pairwise similarities in the original high-dimensional space and the lower-dimensional embedding space. It ranges from 0 to infinity. Lesser the value, better is the performance of the model built.

Initially after 50 iterations the KL value was 83.328 but after 1000 iterations it highly reduced to 2.57 indicating the effectiveness of t-NSE.

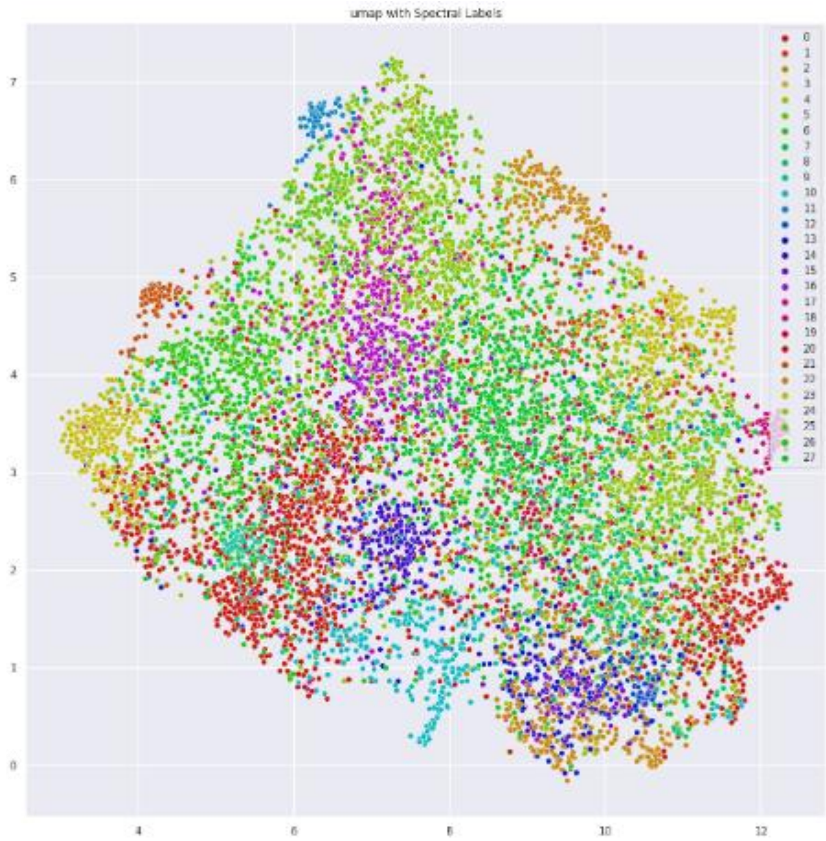
UMAP (Uniform Manifold Approximation and Projection) is another dimensionality reduction algorithm that excels in preserving both local and global structures of high-dimensional data. Unlike t-SNE, UMAP constructs a low-dimensional representation by approximating the manifold structure of the data, resulting in faster computation and better scalability. It is particularly adept at capturing complex geometric patterns and hierarchies within the data.



UMAP for KMeans Clustering

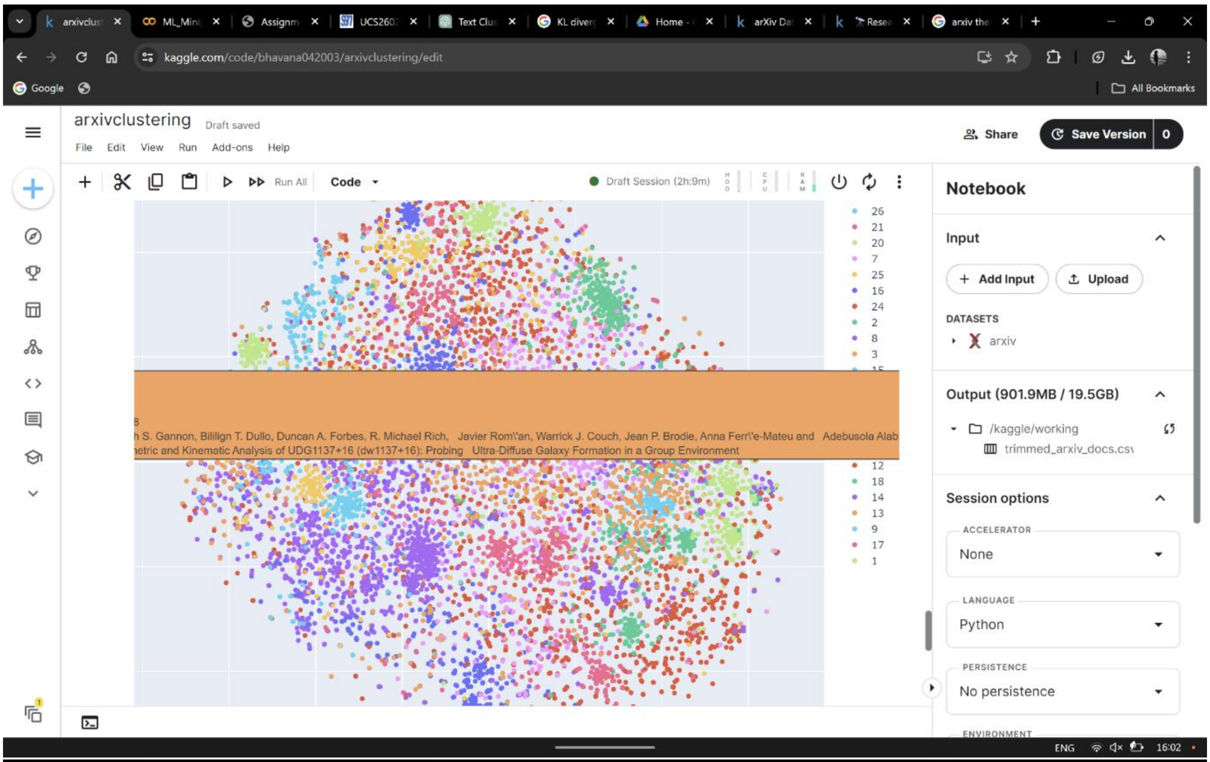


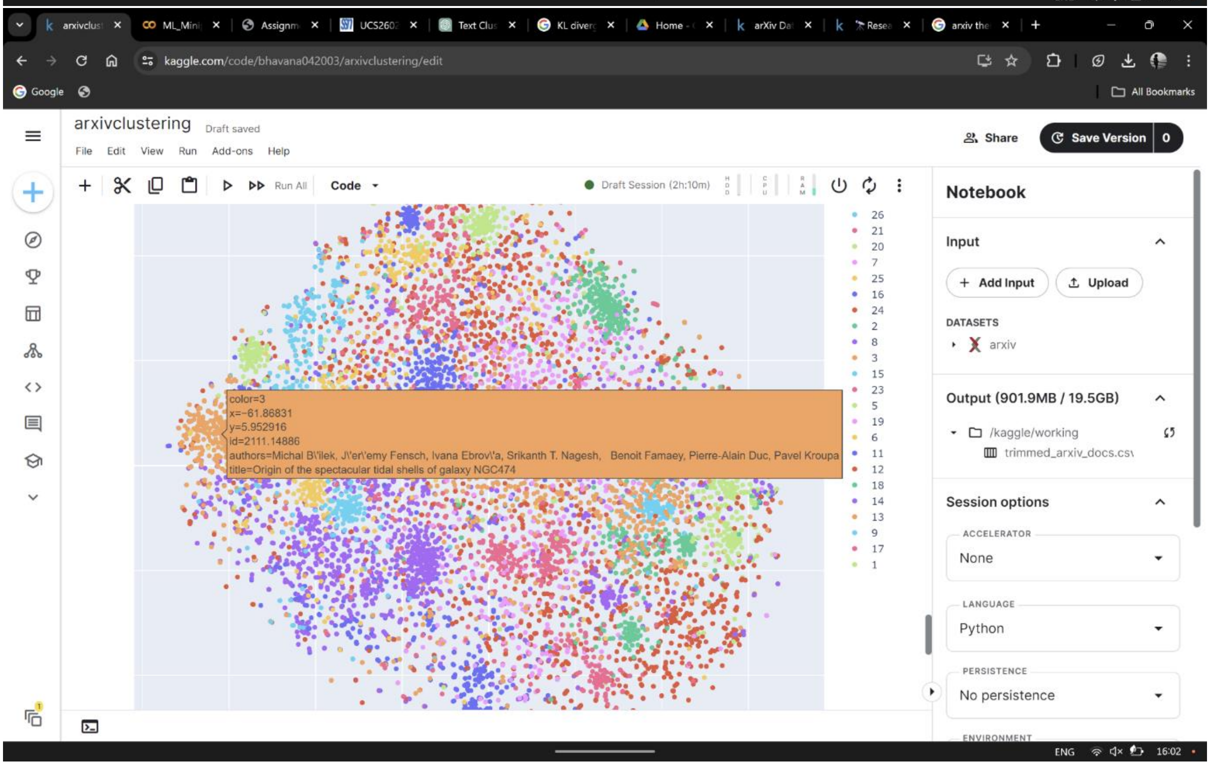
UMAP for Spectral Clustering

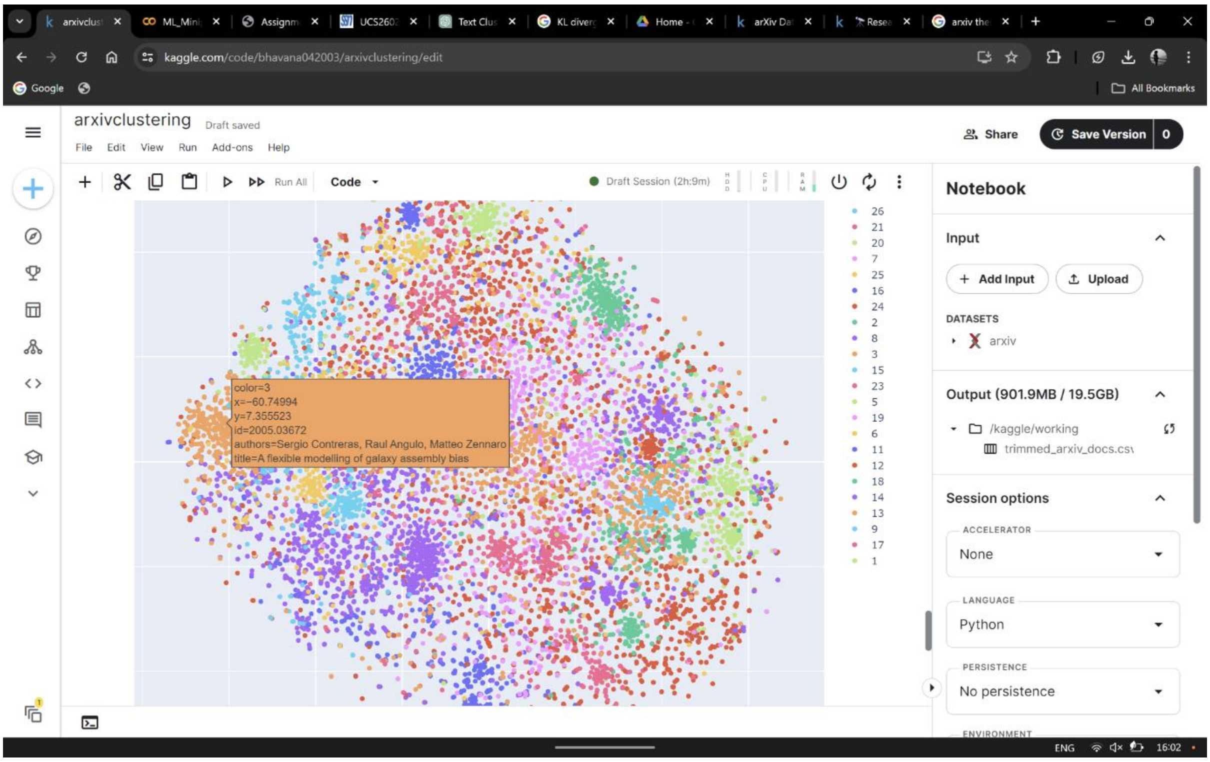


KMEANS CLUSTERING:

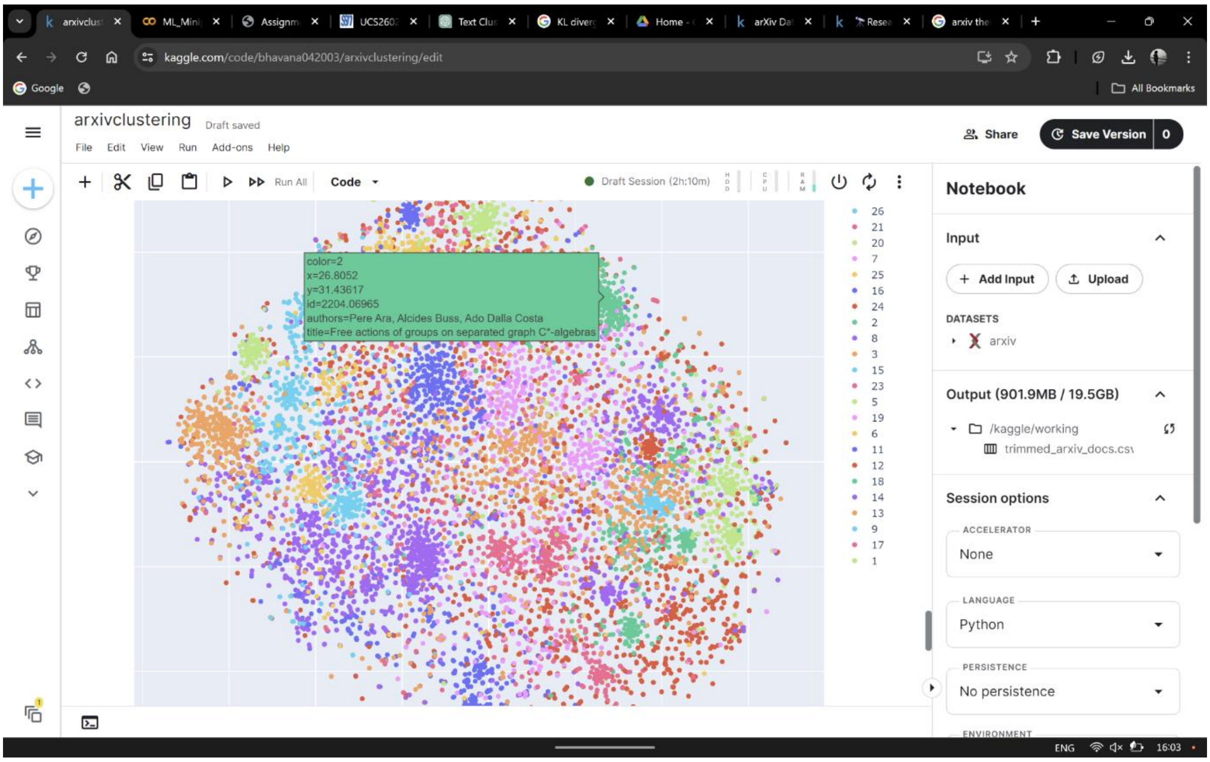
SPACE RESEARCH :

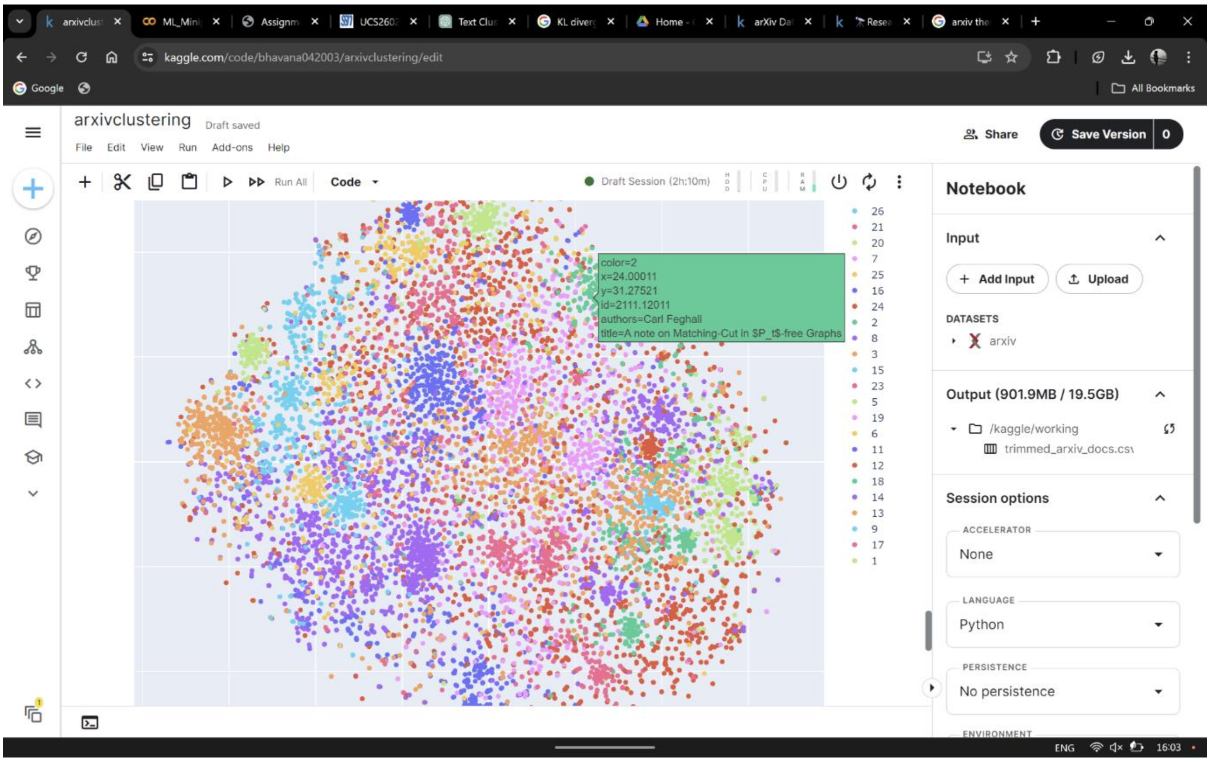




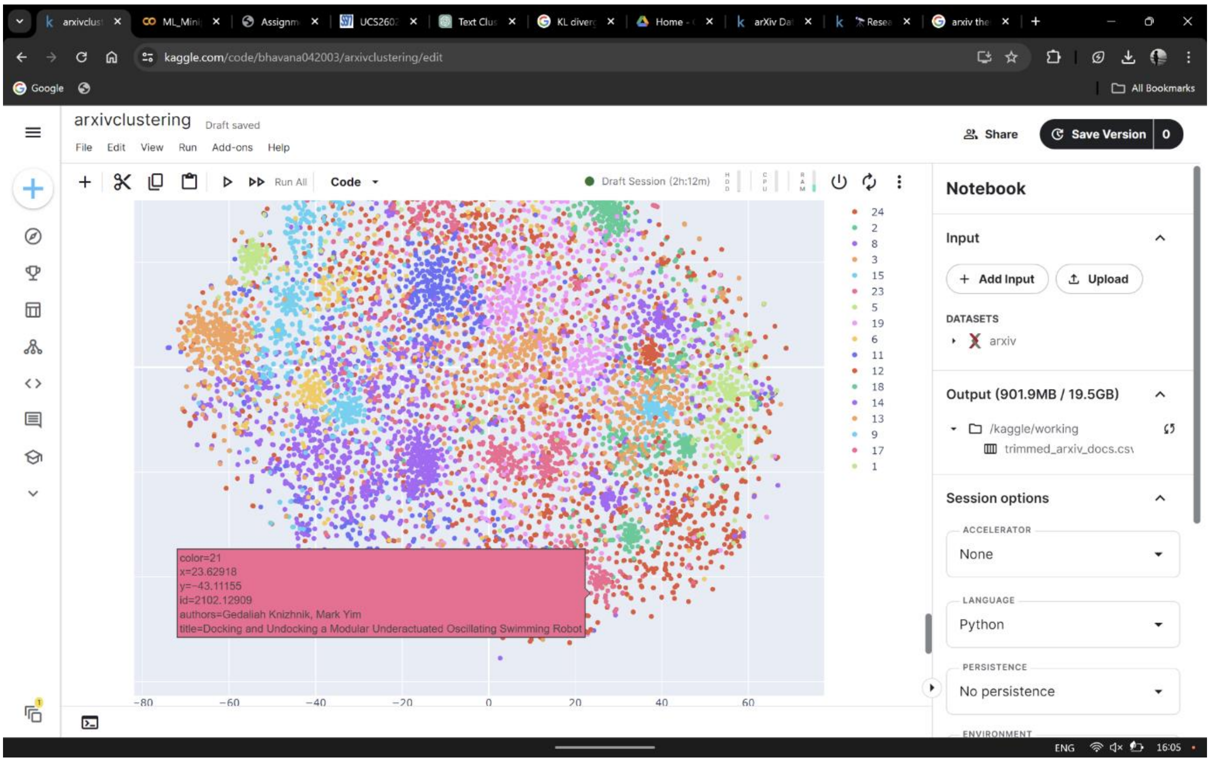

arxivclustering
Draft saved
color=3
x=-60.74994
y=7.355523
id=2005.03672
authors=Sergio Contreras, Raul Angulo, Matteo Zennaro
title=A flexible modelling of galaxy assembly bias
Notebook
Input
DATASETS
arxiv
Output (901.9MB / 19.5GB)
/kaggle/working
trimmed_arxiv_docs.csv
Session options
None
Python
No persistence

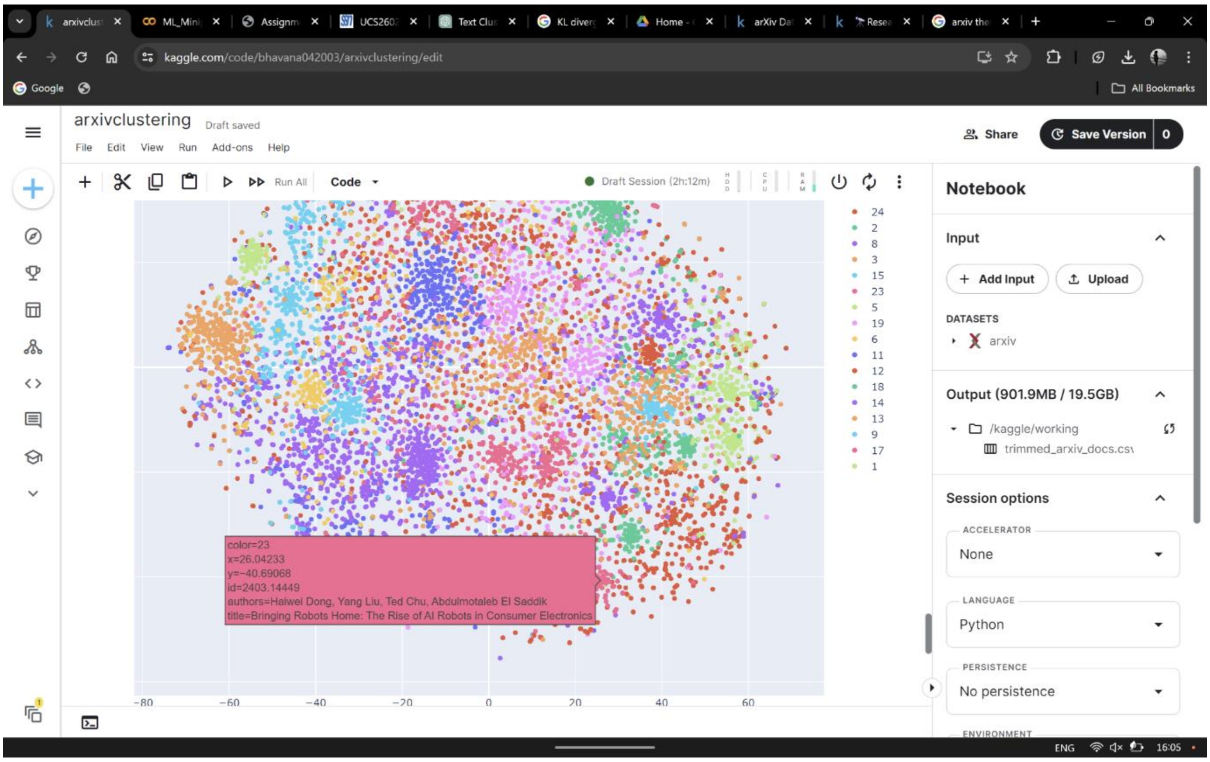
GRAPH :


arxivclustering
Draft saved
color=2
x=26.8052
y=31.43617
id=2204.06965
authors=Pere Ara, Alcides Buss, Ado Dalla Costa
title=Free actions of groups on separated graph C*-algebras
Notebook
Input
DATASETS
arxiv
Output (901.9MB / 19.5GB)
/kaggle/working
trimmed_arxiv_docs.csv
Session options
None
Python
No persistence


arxivclustering
Draft saved
color=2
x=24.00011
y=31.27521
id=2111.12011
authors=Carl Feghali
title=A note on Matching-Cut in P_t-free Graphs

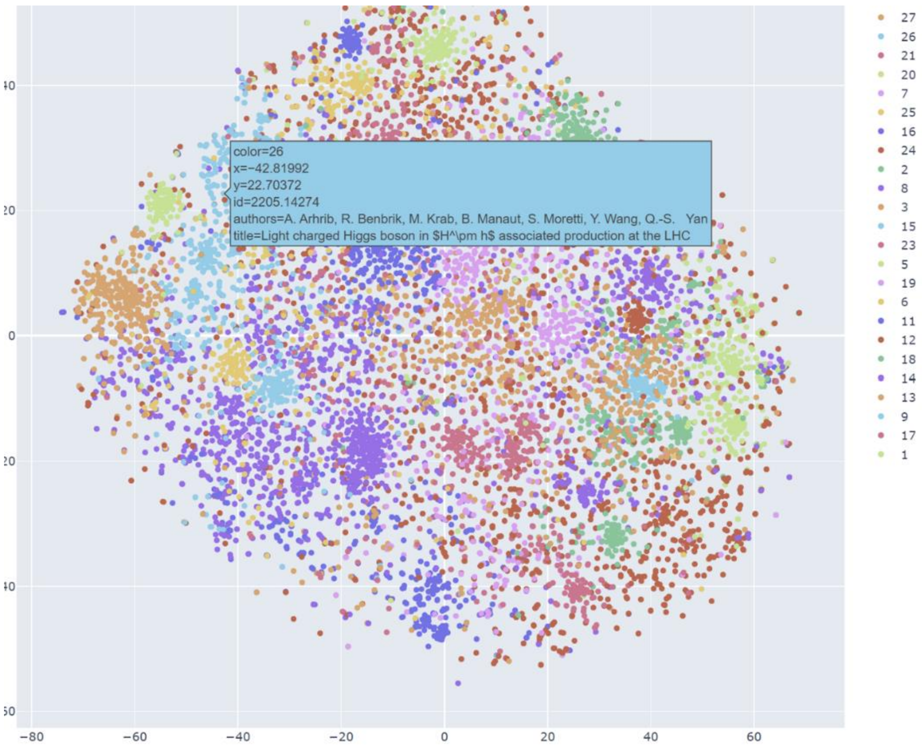
ROBOTICS :


arxivclustering
Draft saved
color=21
x=23.62918
y=−43.11155
id=2102.12909
authors=Gedaliah Knizhnik, Mark Yim
title=Docking and Undocking a Modular Underactuated Oscillating Swimming Robot

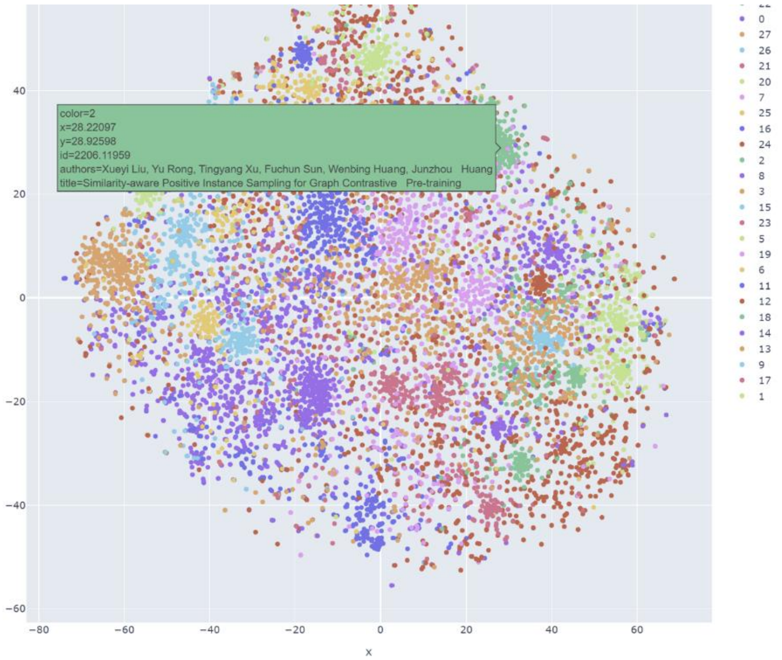


SPECTRAL CLUSTERING :

SPACE RESEARCH :



GRAPH :



Results

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

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

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 – RECOMMENDATION SYSTEM :

STEPS :

1) Extracting Research Papers data from Arxiv dataset
2) Using Universal Sentence Encoder to extract embeddings of Research Abstracts - using category with highest similarity score as label
3) 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.

```
===============

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

===============
```

```
===============

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

===============
```

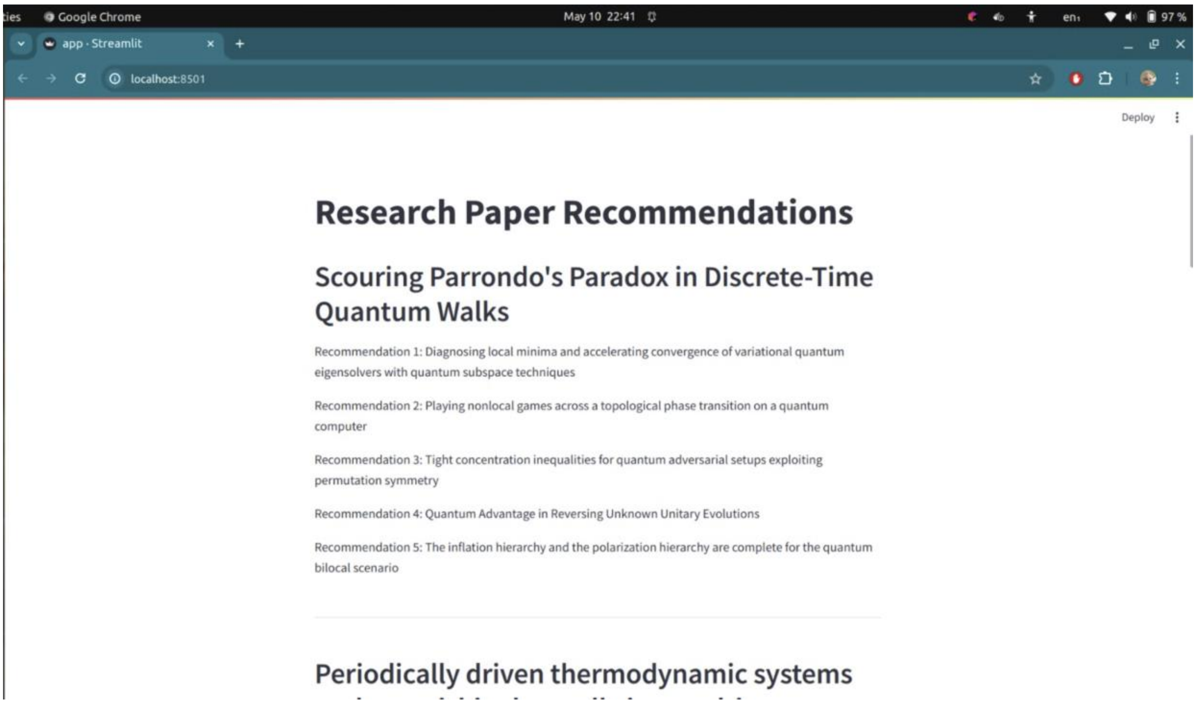
6) Deployment of ML model by hosting in Streamlit:

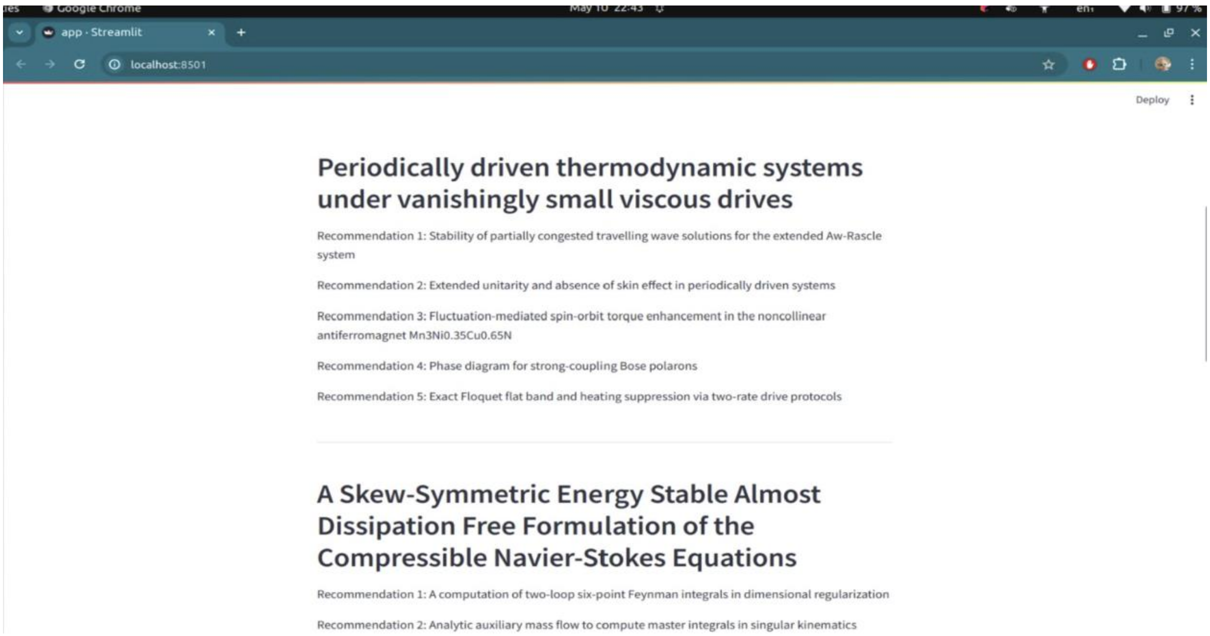
Steps to Deploy in Streamlit:

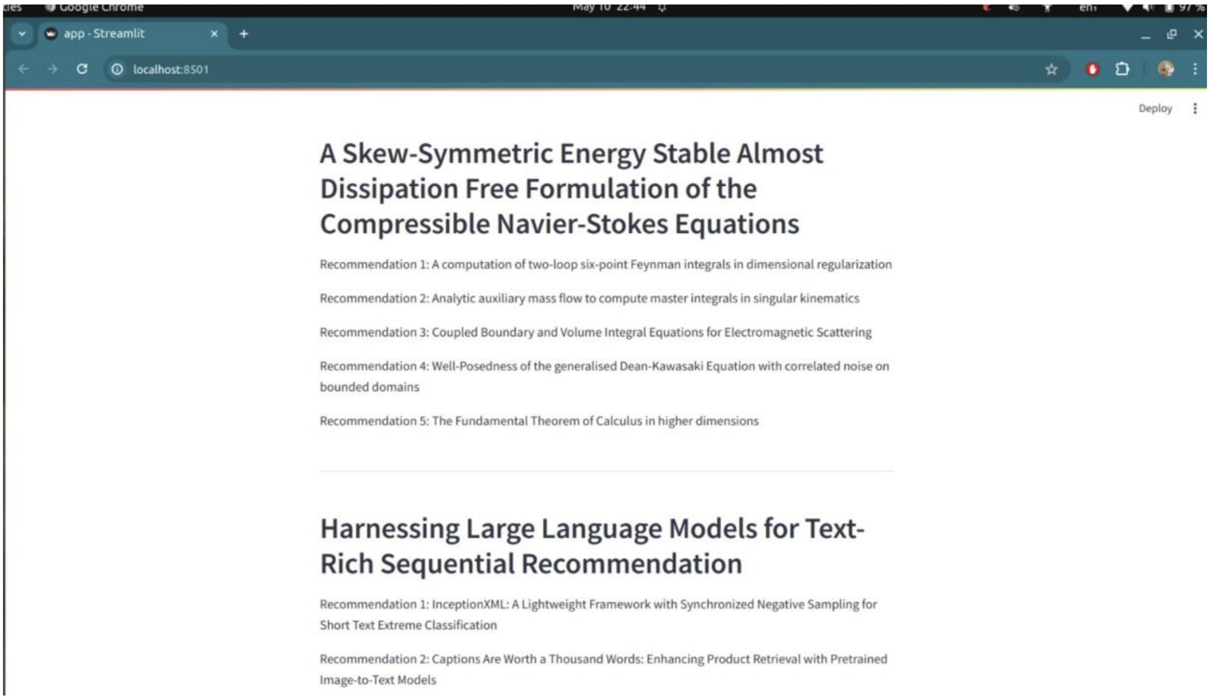
- Save trained model as joblib file
- Save model execution code as app.py
- Execute `streamlit run app.py`

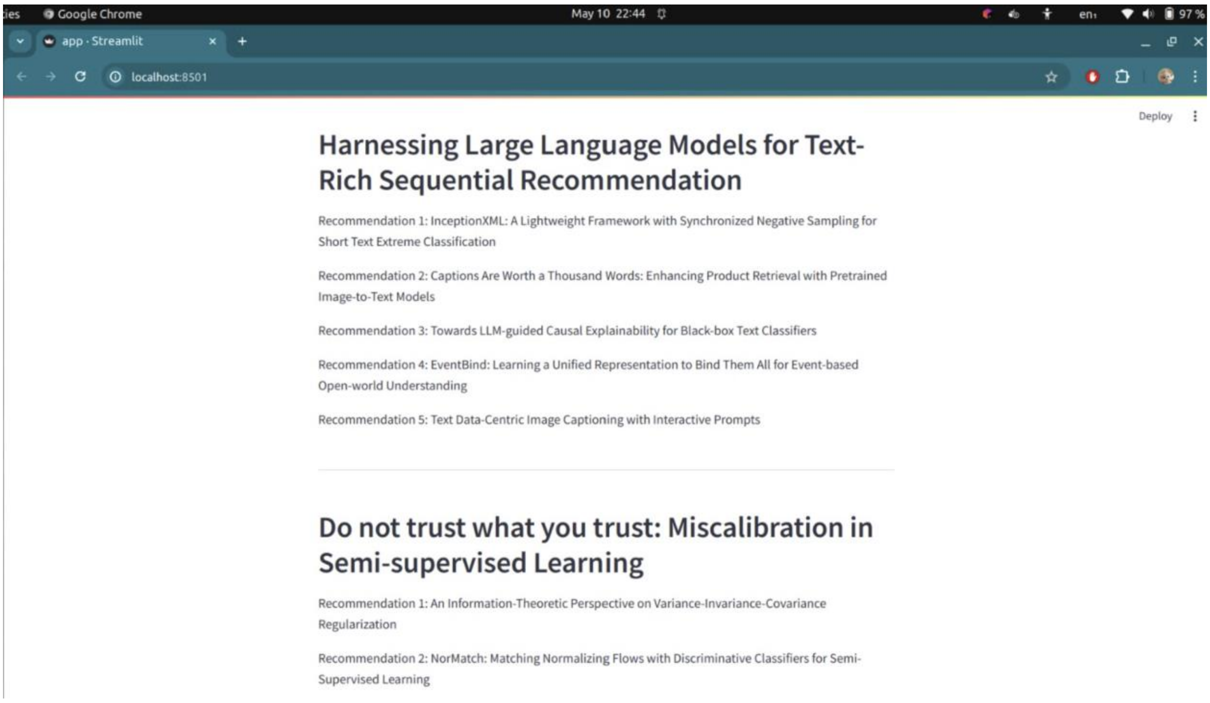
Link : http://localhost:8501

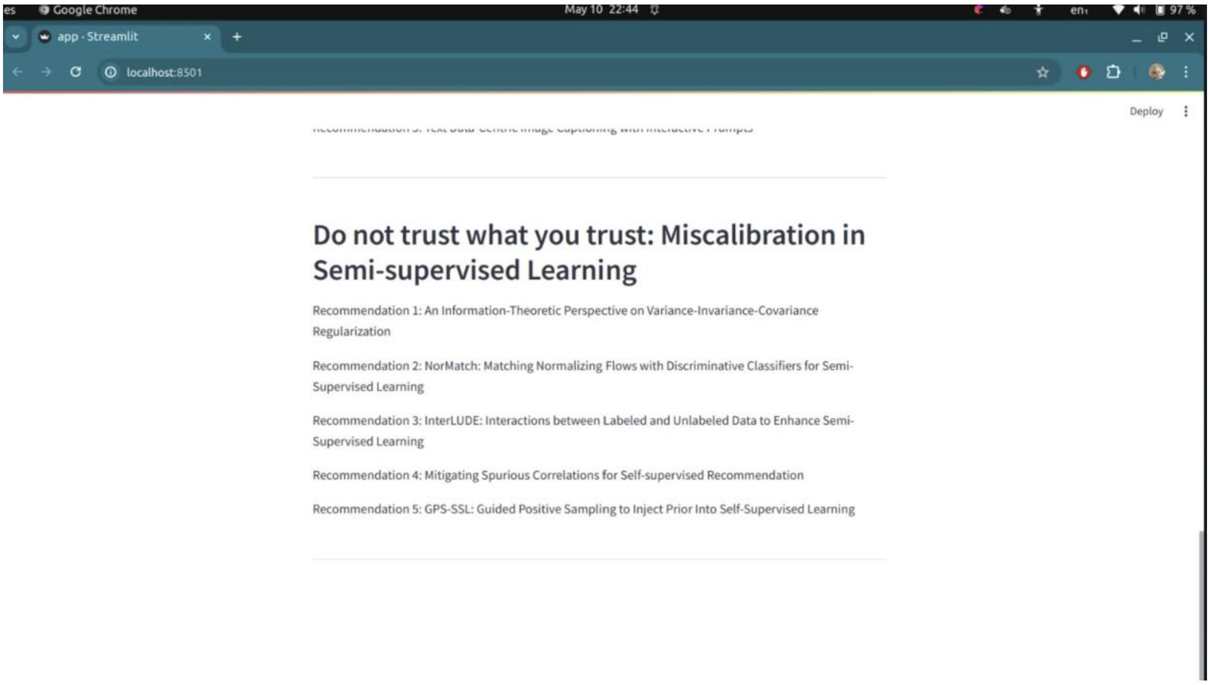
App Preview :

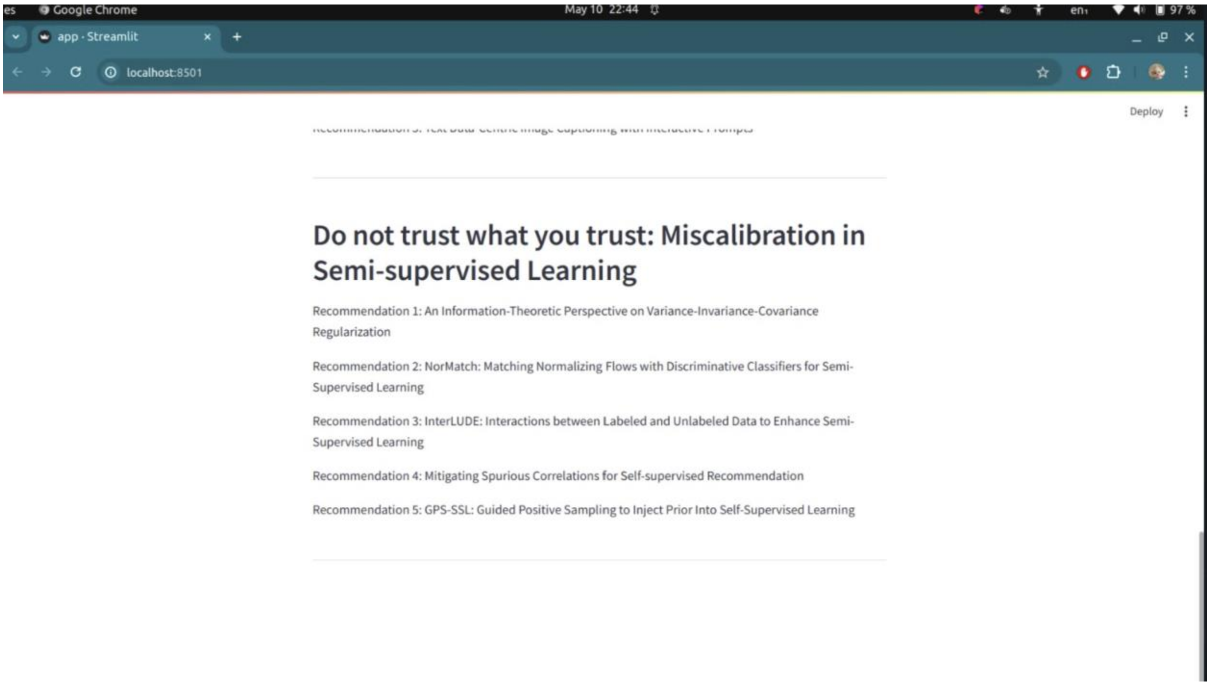





app · Streamlit
localhost:8501
Deploy
A Skew-Symmetric Energy Stable Almost Dissipation Free Formulation of the Compressible Navier-Stokes Equations
Recommendation 1: A computation of two-loop six-point Feynman integrals in dimensional regularization
Recommendation 2: Analytic auxiliary mass flow to compute master integrals in singular kinematics
Recommendation 3: Coupled Boundary and Volume Integral Equations for Electromagnetic Scattering
Recommendation 4: Well-Posedness of the generalised Dean-Kawasaki Equation with correlated noise on bounded domains
Recommendation 5: The Fundamental Theorem of Calculus in higher dimensions
Harnessing Large Language Models for Text-Rich Sequential Recommendation
Recommendation 1: InceptionXML: A Lightweight Framework with Synchronized Negative Sampling for Short Text Extreme Classification
Recommendation 2: Captions Are Worth a Thousand Words: Enhancing Product Retrieval with Pretrained Image-to-Text Models


Google Chrome
May 10 22:44
97 %
app · Streamlit
localhost:8501
Deploy
Harnessing Large Language Models for Text-Rich Sequential Recommendation
Recommendation 1: InceptionXML: A Lightweight Framework with Synchronized Negative Sampling for Short Text Extreme Classification
Recommendation 2: Captions Are Worth a Thousand Words: Enhancing Product Retrieval with Pretrained Image-to-Text Models
Recommendation 3: Towards LLM-guided Causal Explainability for Black-box Text Classifiers
Recommendation 4: EventBind: Learning a Unified Representation to Bind Them All for Event-based Open-world Understanding
Recommendation 5: Text Data-Centric Image Captioning with Interactive Prompts
Do not trust what you trust: Miscalibration in Semi-supervised Learning
Recommendation 1: An Information-Theoretic Perspective on Variance-Invariance-Covariance Regularization
Recommendation 2: NorMatch: Matching Normalizing Flows with Discriminative Classifiers for Semi-Supervised Learning





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 causes less usage of physical record maintenance)
- 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

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

2) 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.

3) Learnt various data and text Preprocessing techniques using spaCy.

4) Learnt Feature Engineering techniques like PCA, t-SNE, UMAP etc.

5) Learnt about the various evaluation metrics and methodologies such as Silhouette Score and Davies-Bouldin Index, Calinksy Harabasz Score.

6) Learnt about Universal Sentence Encoder to extract embeddings based on similarity scores.

7) Learnt to deploy a model in Streamlit platforms.

References

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

https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html

https://scikit-learn.org/stable/modules/generated/sklearn.cluster.SpectralClustering.html

https://www.analyticsvidhya.com/blog/2022/07/step-by-step-exploratory-data-analysis-eda-using-python/

https://umap-learn.readthedocs.io/en/latest/basic_usage.html

https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html

https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html

https://arxiv.org/pdf/2008.13538

https://journalofbigdata.springeropen.com/articles/10.1186/s40537-022-00592-5

https://towardsdatascience.com/7-evaluation-metrics-for-clustering-algorithms-bdc537ff54d2

https://discuss.streamlit.io/t/guide-how-to-build-and-deploy-streamlit-app-for-ml-model/37436