A
Project Report
on

Big Data Analytics

UNCOVERING RESEARCH TRENDS AND RECOMMENDING PAPERS: A LOOK AT ARXIV DATA

Submitted by-

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Finally, a heartfelt thankful to my friends who helped me during the times where I struck with troubles and challenges with this project

Thanking You
Sumanth

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Abstract

The analysis and development of research papers databases have proven valuable and essential with the growth of the volume of papers making it challenging to find the relevant one from the vast volumes of publications in the recent years.In this paper we explore the world of research papers, the growth, trends, relationships between categories, changes during the years and how to find proper relevant papers.

Understanding the research landscape by analyzing the large database of research papers from the official source Arxiv could be insightful.With the data analysis, feature engineering makes it into a dataframe to built the recommendation engine based on the given title by the user. Using the advanced techniques like Multi Layer Perceptron(MLP) and sentence transformers which we used for embedding the titles in the dataframe can make the approach of this paper pretty unique.

This Report is totally based on the analysis of the research paper's metadata and trends along with unique advanced techniques to improve recommendation efficiency which we achieved with good accuracy and good recommendations for valuable usage.

Motivation

Discovering the relevant studies and the interest to work on the factors which can affect the growth and changes in a field is one of the motivations in choosing this concept to work. The availability of the data on this is few and choosing the Arxiv is helpful in understanding the research landscape, extracting meaningful insights like publication trends, authorship analysis, Topic analysis.

The difficulty of research paper discovery in the age of Information overload can be said as one of the motivations because for finding the relevant papers process can be exhaustive to go through multiple sources without having much context can be more difficult for a user.

When a user with low contextual awareness cannot have much help by surfing the internet to find the relevant one with one title as a source because there can be many papers which look like it is similar but the concept, the category can be different. This is where this can be a solution as the system is built with the concept of suggesting paper based on the title when the user recommends a few papers after embedding it using category and abstract stored vocabularies give related papers with pretty much better relevance.

1. **INTRODUCTION**

The latest advancements in various fields lies in the tireless efforts of various researchers who share their research through the research papers. We can say these research papers are the building blocks for the progress in various fields which contain in detailed way; Title, Authors, Abstract, Introduction, Methodology and many more.

The growth in the number of publications of research papers which can be pretty helpful in terms of scientific progress but also can be a bigger challenging task for finding relevant papers. To tackle this there are numerous approaches and numerous universities and companies building a database collecting the publications and updating and meta information of papers.

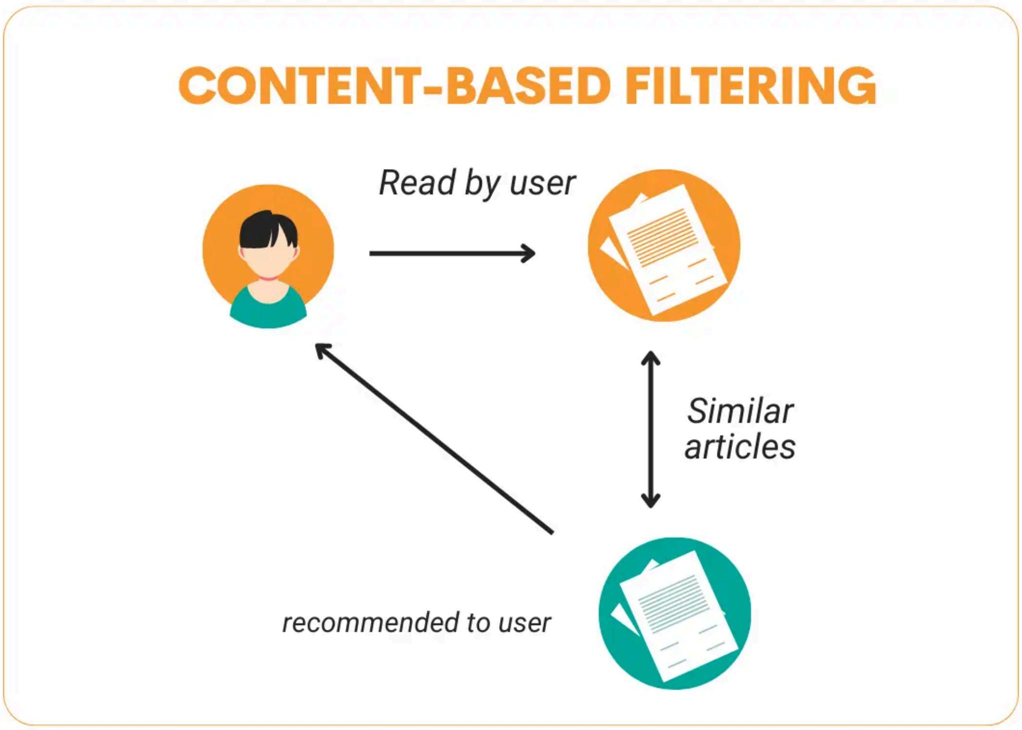
Traditionally, the searching of research papers across vast amounts is keyword-based and browsing through journals.While these can be helpful for users to find the relevant papers it can be exhaustive.The Recommendation are based on various types which can be categorized into two main namely, Collaborative Filtering and Content based Filtering.

Collaborative filtering Recommendation system uses the user behavior pattern to recommend papers. It analyzes the searches, categorizes which the user is more inclined to using the data of the past visits like the read, cited and downloaded ounces. This is a pretty complex structure to build but for research paper recommendation the content based has more advantages as it is the type where the system focuses on content and characteristics of the available data and analyzes its features.

While watching millions of paper's meta data is available open, it can be useful to find the exponential growth of papers, changes over the years, publication trends, authorship analysis can reveal and discover some patterns, trends.The ArXiv which has served as an open source of various scholarly articles over more than two decades which has been maintained by Cornell University is used in this process. Understanding the rich corpus information can help significantly to all, through kaggle, using an open pipeline they converted it into a dataset in JSON format.

2. PROBLEM STATEMENT

The exponential growth of research papers presents the big challenges to researchers and to all is to discover relevant studies within their field. To understand and build a recommendation engine a thorough analysis and thorough experience in understanding the landscape of this database. This can help to unreveal the hidden patterns and growth in fields in recent years, collaboration of various fields and many publications and authorship analysis with the topic analysis.



This can insignificantly help in understanding the data and help in developing a useful approach which is less time consuming and more relative recommendation. Content-based Filtering which is the major usage in this field can be developed using the information gained with exploration analysis is our objective and aim to try through this report.

3. **LITERATURE REVIEW**

3.1. Existing State-of-the-Art in Personalized Research Paper Recommendation

The field of research paper recommendations have seen major advancements in recent years as it can be used for many purposes, one such is mainly for citations. While exploring there are some key papers with various approaches for this recommendation purposes, they are:

A) Content-Based Filtering:

a) Pan et al. (2018) [1] proposed a personalized recommendation system which uses the features like keywords, abstracts and citations data which achieved good results but faced some limitations while handling complex relationships between content elements.

b) Wei Fan et al. (2013) [2] proposed a unique research paper recommendation which focused more on systematic reviews to achieve high precision using content analysis features like keywords and MeSH terms. However he faced limitations as their system struggled with broader data to work on.

c) Wu et al. (2011) [3] proposed a system which uses user-assigned tags for collaborative filtering. While it is effective for actively tagged papers, their approach didn't work well for untagged content.

d) Xu et al. (2010) [4] proposed a system which employed hierarchical topic models to capture both broad and specific research areas for advance level recommendations but the only limitation they faced is for this advance level system the model which used requires high training data and optimal performance.

B) Collaborative Filtering:

Fawzy et al. (2017) [5] and Wei et al. (2016) [6] explored many approaches and decided to work on a hybrid approach which is to combine content-based filtering with collaborative filtering techniques. This gave them better performance compared to systems which work only based on content-based methods, but the issue is that it could be computationally expensive for large datasets.

C) Other Techniques:

a) Chen et al. (2015) [7] introduced a unique method called context-aware system which considers taking the research goals and publication time from the user to recommend the research paper. While it looks promising, the issue they faced is their rule-based approach might require further refinement for complex recommendation scenarios for better recommendation.

b) Li et al. (2014) [8] built a recommendation engine that offers a unique way which focuses on author expertise and co-authorship analysis. Their system can get better if they combine the author information with content analysis for even more targeted recommendations as their unique method works independently.

c) Sun et al. (2012) [9] explored the user reviews and ratings of research articles to improve recommendations with user feedback. However, their method might be limited by the availability and quality of user-generated content. As the reviews and ratings need to have for big data and need to be thoroughly analyzed.

d) Ekstrand et al. (2009) [10] addressed a unique method called "silo effect" which recommends papers across disciplines.This approach is useful for developing collaborative study on the research papers but might require extra methods to ensure recommendations are related to the user's specific research area.

3.2. Advancements

Overall, the existing research shows the potential of various approaches for personalized research paper recommendation.Content-based filtering offers a foundation, while collaborative filtering and other techniques can enhance recommendation accuracy and address limitations. Using NLP techniques for the content based filtering and analyzing the hidden patterns can help to gain further insights and better recommendations of research format.

Table. 1:Table of Analysis of Literature Study

S.No.	Existing State-of-the-Art (Citation)	Drawbacks	Overcome
1	Personalized Academic Research Paper Recommendation System (Pan et al., 2018)	Limited ability to capture complex relationships between content elements.	Explores advanced natural language processing (NLP) techniques for deeper content analysis in future work.
2	A Hybrid Recommendation Model for Research Papers using Content-Based and Collaborative	Can be computationally expensive for large datasets.	Explores distributed computing approaches to handle scalability in future work.
3	A Topic-Aware Collaborative Filtering Recommendation Model for Research Papers (Wei et al., 2016)	Relies on sufficient data for topic modeling to be effective.	Investigates incorporating dynamic topic modeling techniques to adapt to evolving research areas.
4	A Context-Aware Personalized Recommendation System for Research	Rule-based approach might require further refinement for complex scenarios.	Explores integrating user feedback and machine learning techniques to enhance context awareness.

	Papers (Chen et al., 2015)		
5	Personalized Recommendation of Research Papers Using Author Expertise and Co-authorship Analysis (Li et al., 2014)	Lacks comprehensive content analysis of the papers themselves.	Aims to combine author information with content analysis for a more holistic recommendation approach.
6	A Content-Based Paper Recommendation System for Supporting Systematic Reviews (Fan et al., 2013)	May not generalize well to broader research paper recommendation.	Explores extending the system to incorporate a wider range of content features beyond those specific to systematic reviews.
7	Improving Research Paper Recommendation with User Reviews and Ratings (Sun et al., 2012)	Limited by the availability and quality of user-generated content.	Investigates alternative methods for incorporating user feedback, such as implicit feedback through user interactions.
8	Tag-based Collaborative Filtering for Research Paper Recommendation (Wu et al., 2011)	Less effective for untagged or sparsely tagged content.	Explores integrating with automatic tagging techniques and leveraging other user-generated content besides tags.
9	Personalized Recommendation of Research Papers using Hierarchical Topic Models (Xu et al., 2010)	Requires significant training data for optimal performance.	Aims to develop more efficient training methods and explore transfer learning approaches for topic models.
10	Personalized Recommendation of Scientific Publications: Breaking the Silo Effect (Ekstrand et al., 2009)	Balancing interdisciplinary recommendations with the user's specific research area.	Aims to develop user-centric filtering mechanisms to ensure recommendations are relevant within the user's domain.

4. METHODOLOGY

4.1 Analysis of the Research Papers Data

We followed a set of steps to achieve the research objectives and implementation led to the proper structural dataframe and effective visualization of the dataframe helped to understand the patterns, trends and many elements contained in the data. The flowchart below shows the order of processes we implemented and each step are described further.

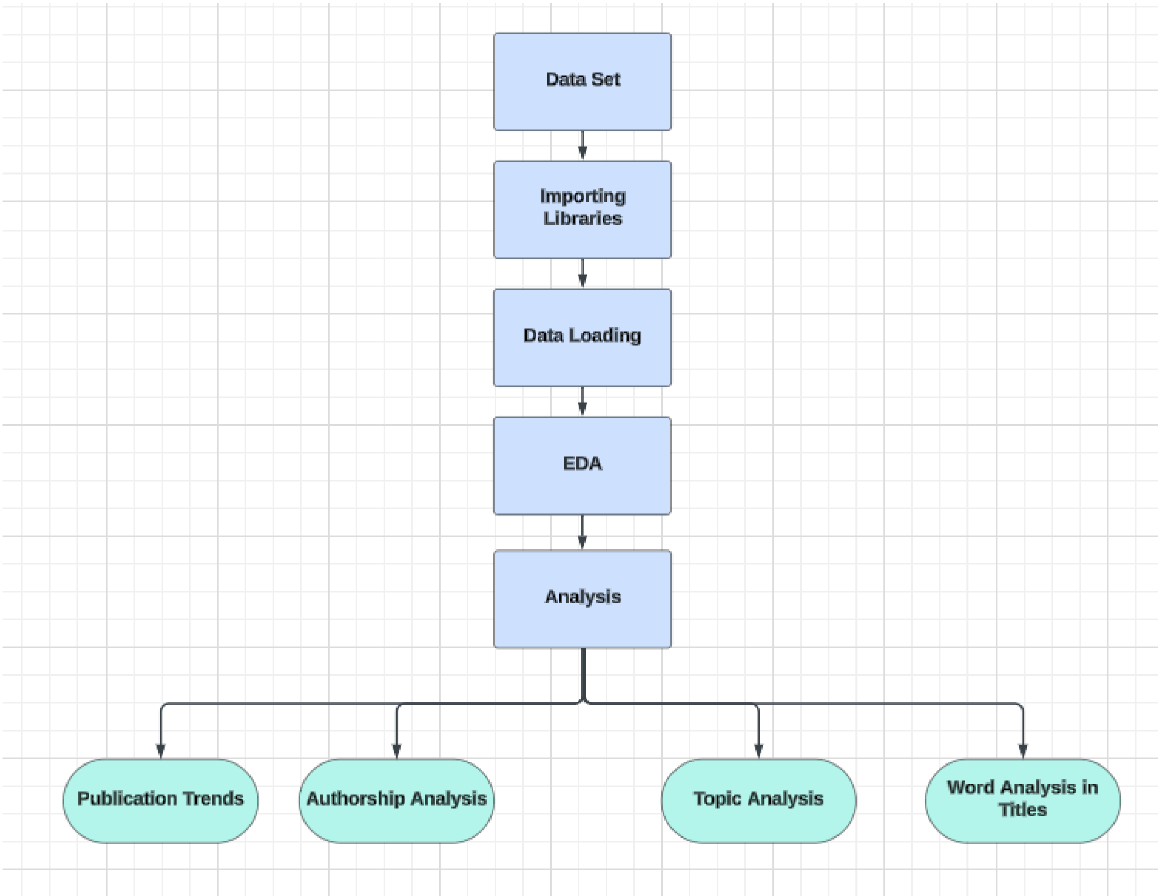


Fig. 1: Flowchart of the analyzing process

4.1.1. Dataset Description

The dataset used is taken from Kaggle which contains the ArXiv website's total research papers. As we know, Arxiv is a collaboratively funded, community-supported resource founded by Paul Ginsparg in 1991 and maintained and operated by Cornell University.

The dataset contains 24 lakh entries of research papers specified in it which is in JSON format which requires some libraries to read, some functions to analyze , some conversions to make it into a dataframe.

4.1.2. Importing Libraries

A) Data Handling and Processing:

a) **JSON**: As we know that the dataset is in JSON format JSON library is used as it is used to load, parse, dump and manipulate the dataset.

b) **Dask bag:** It is the one most required to process the data because to load the dataset of 24 lakh entries with multiple columns and to manipulate and process can be a challenging task in Google Colaboratory to perform various tasks without converting to dataframe, it is used.

c) **Pandas and Numpy:** To organize, clean, make it into data structure pandas are imported and to perform various numerical operations and computing numpy are imported.

B) Data Visualization:

a) **Altair**: It is imported to make interactive charts of data using high level grammar, making the ordinal, nominal type of data in declarative form easier to understand.

b) **Plotly.express and Networkx**: It is used to make plots of high level APIs and manipulate data to convert into nodes for forming networks. It simplifies the process of plotting complex types of data frames.

c) **Seaborn and matplotlib**: For statistical data visualizations these are used. To create informative graphs related to statistics these are best to use.

C) Web Scraping:

a) **Beautiful Soap and requests:** For gaining the information and data from the website, web scraping is required, which can be achieved in python by using these two libraries their main function is to parse data from the HTML and XML documents. This parsed data is furtherly processed by converting to dataframe and visualized.

4.1.3. Data Loading

The data is loaded into Colab using Dask and JSON and to understand the data structure one entry is printed which is given below.


```
Data Structure:
({'id': '0704.0001',
  'submitter': 'Pavel Nadolsky',
  'authors': "C. Bal\\'azs, E. L. Berger, P. M. Nadolsky, C.-P. Yuan",
  'title': 'Calculation of prompt diphoton production cross sections at Tevatron and\n  LHC energies',
  'comments': '37 pages, 15 figures; published version',
  'journal-ref': 'Phys.Rev.D76:013009,2007',
  'doi': '10.1103/PhysRevD.76.013009',
  'report-no': 'ANL-HEP-PR-07-12',
  'categories': 'hep-ph',
  'license': None,
  'abstract': '  A fully differential calculation in perturbative quantum chromodynamics is\npresented for the production of
massive photon pairs at hadron colliders. All\nnext-to-leading order perturbative contributions from quark-antiquark,\ngluon-
(anti)quark, and gluon-gluon subprocesses are included, as well as\nall-orders resummation of initial-state gluon radiation valid
at\nnext-to-next-to-leading logarithmic accuracy. The region of phase space is\nspecified in which the calculation is most
reliable. Good agreement is\ndemonstrated with data from the Fermilab Tevatron, and predictions are made for\nmore detailed tests
with CDF and DO data. Predictions are shown for\ndistributions of diphoton pairs produced at the energy of the Large
Hadron\nCollider (LHC). Distributions of the diphoton pairs from the decay of a Higgs\nboson are contrasted with those produced
from QCD processes at the LHC, showing\nthat enhanced sensitivity to the signal can be obtained with judicious\nselection of
events.\n',
  'versions': [{'version': 'v1', 'created': 'Mon, 2 Apr 2007 19:18:42 GMT'},
   {'version': 'v2', 'created': 'Tue, 24 Jul 2007 20:10:27 GMT'}],
  'update_date': '2008-11-26',
  'authors_parsed': [['Balázs', 'C.', ''],
   ['Berger', 'E. L.', ''],
   ['Nadolsky', 'P. M.', ''],
   ['Yuan', 'C. -P.', '']]},)
```


Fig. 2: Data Structure of the dataset

Observing the data we can understand that it requires conversion to dataframe and also some feature engineering is required as we can see the text in abstract containing **"/n",** some symbols are in between text of authors and the categories are in the form of a unique short form difficult to understand.

In the ArXiv website there is a special web page to explain the category taxonomy. It was scraped using Beautiful Soap and requests and converted into a data frame containing columns Category as ID, Main Category and the full form as Name with description is shown below.

	ID	Main Category	Name	Description
0	cs.AI	Computer Science	Artificial Intelligence	Covers all areas of AI except Vision, Robotics...
1	cs.AR	Computer Science	Hardware Architecture	Covers systems organization and hardware archi...
2	cs.CC	Computer Science	Computational Complexity	Covers models of computation, complexity class...
3	cs.CE	Computer Science	Computational Engineering, Finance, and Science	Covers applications of computer science to the...
4	cs.CG	Computer Science	Computational Geometry	Roughly includes material in ACM Subject Class...
...	...	...	...	...
150	stat.CO	Statistics	Computation	Algorithms, Simulation, Visualization
151	stat.ME	Statistics	Methodology	Design, Surveys, Model Selection, Multiple Tes...
152	stat.ML	Statistics	Machine Learning	Covers machine learning papers (supervised, un...
153	stat.OT	Statistics	Other Statistics	Work in statistics that does not fit into the ...
154	stat.TH	Statistics	Statistics Theory	stat.TH is an alias for math.ST. Asymptotics, ...

155 rows × 4 columns

Fig. 3: Data frame containing Categories

The entries in the JSON file are of total 2477303 entries which is quite complex for Colab Ram and system Ram to handle. For detailed Analysis, we created a JSON file of CS-Computer Science categories and the reason why will be explained in detail during visualizations, The resulting data frame contains a total of 621547 entries.

4.1.3. Exploratory Data Analysis (EDA):

Before exploring the dataset and visualizing the patterns all the dataset needs to be processed, manipulated, and many steps need to be done which is shown in flowchart

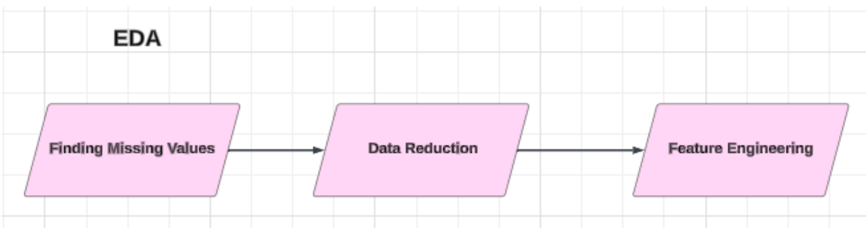


Fig. 4: Flow chart of showing process of EDA

A) Handling Missing Values:

The data frame information is given below showing the change in number of entries in each column and type of column.

```
Data columns (total 14 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   id              621547 non-null  object
 1   submitter       621320 non-null  object
 2   authors         621547 non-null  object
 3   title           621547 non-null  object
 4   comments        374033 non-null  object
 5   journal-ref     82675 non-null   object
 6   doi             110740 non-null  object
 7   report-no       9838 non-null    object
 8   categories      621547 non-null  object
 9   license         610164 non-null  object
 10  abstract        621547 non-null  object
 11  versions        621547 non-null  object
 12  update_date     621547 non-null  object
 13  authors_parsed  621547 non-null  object
dtypes: object(14)
memory usage: 66.4+ MB
```

Fig. 5: Dataset information

The number of null values calculated and shown in the graph below indicates the huge difference in percentage of null values in columns, which is achieved by converting them into tuples and calculating using numpy.

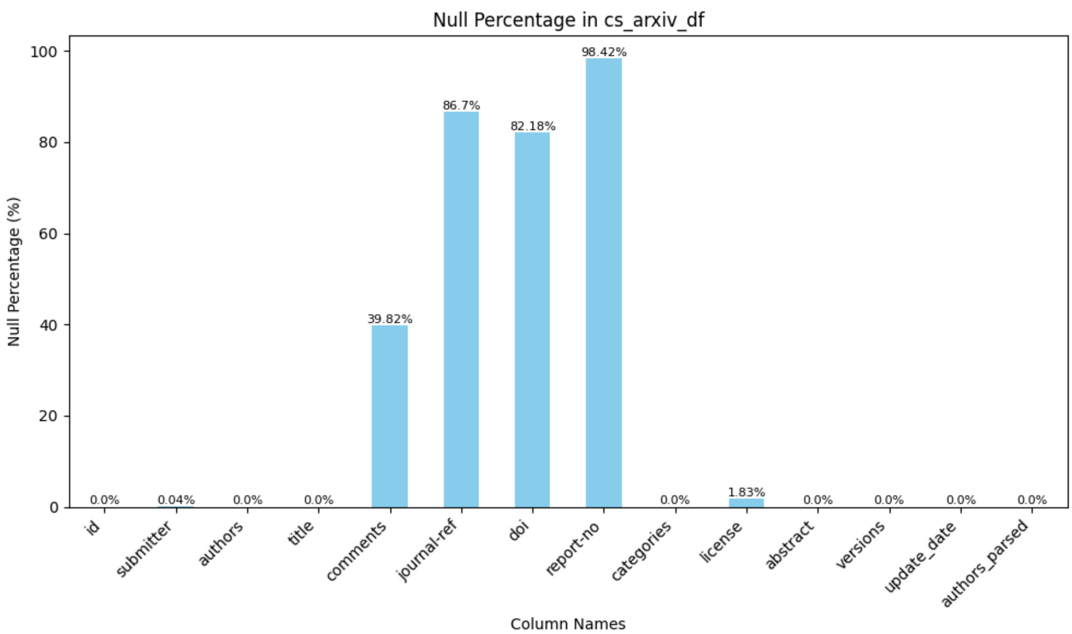


Fig. 6: Representation of null value percentage in each column in form of bar plot

B) Data Reduction:

The columns with more then 30 percent null values are dropped from the dataset as we cannot handle or make much use from that relatively low available data and the license column which wouldn't be much helpful was dropped. As for the submitter column the rows with null values are dropped making it helpful for analysis.

C) Feature Engineering:

As observed there need to be some changes to the authors column and abstract column as it contains many unnecessary letters and symbols which doesn't make any sense. Even in the category column and author column the format of multiple authors and multiple categories are placed with space which is difficult to analyze, so feature engineering is done to authors column by firstly adding a delimiter (comma) after splitting and replacing with words like “and”, “/n” type of text with space; multiple categories are splitted and a delimiter (comma) is introduced between them and the resultant dataset is in this format. Even the texts like “/n”, “n”, “(k,ℓ)-” are observed in title and abstract which are removed by replacing them with space.

	id	submitter	authors	title	categories	license	abstract	versions	update_date	authors_parsed
0	0704.0002	Louis Theran	Ileana Streinu,Louis Theran	Sparsity-certifying Graph Decompositions	[math.CO, cs.CG]	http://arxiv.org/licenses/nonexclusive-distrib/1.0/	We describe a new algorithm, the pebble game with colors, and use it obtain a characterization of the family of sparse graphs and algorithmic solutions to a family of problems concerning tree decompositions of graphs. Special instances of sparse graphs appear in rigidity theory and have received increased attention in recent years. In particular, our colored pebbles generalize and strengthen the previous results of Lee and Streinu and give a new proof of the Tutte-Nash-Williams characterization of arboricity. We also present a new decomposition that certifies sparsity based on the pebble game with colors. Our work also exposes connections between pebble game algorithms and previous sparse graph algorithms by Gabow, Gabow and Westermann and Hendrickson.	[{'version': 'v1', 'created': 'Sat, 31 Mar 2007 02:26:18 GMT'}, {'version': 'v2', 'created': 'Sat, 13 Dec 2008 17:26:00 GMT'}]	2008-12-13	[[Streinu, Ileana,], [Theran, Louis,]]

4.1.4. Publication Trends:

The time-stamp given in versions was taken from versions; only the first version's time stamp is taken from the JSON dataset and based on year and number of submissions a line graph is plotted showing the number of submissions in each year; the growth of number of submissions from 1995 to 2024 (till now) in ArXiv.

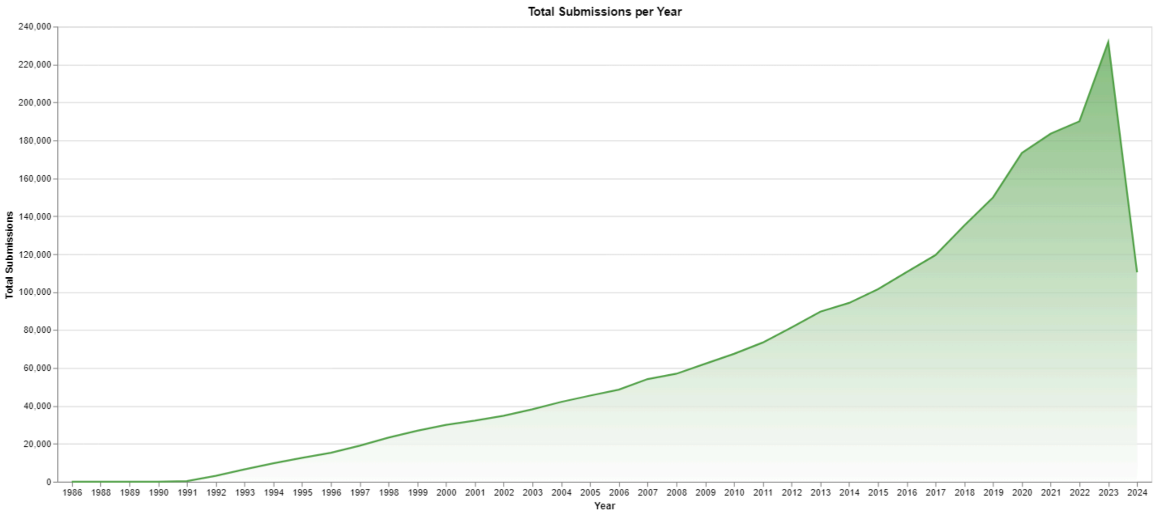


Fig. 7:Line plot representing no.of submissions in each year

From the formatted dataset of CS-publications, the same process is done and the timeline of its growth across the years is shown as it is from 2007 the era of CS publications started and at present more than 1.1 lakh publications happened from CS publications out of 2.3 lakh submissions.

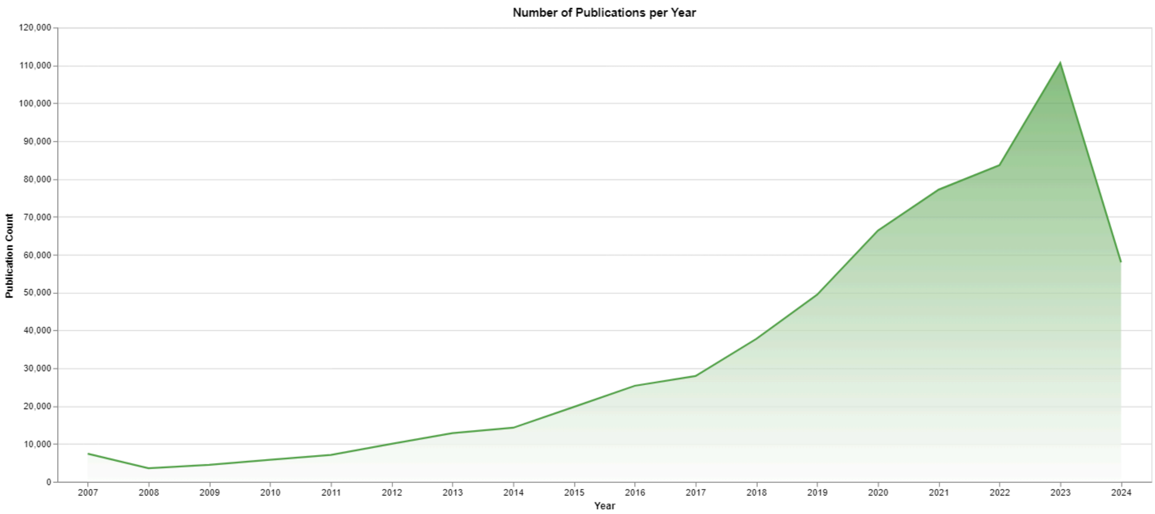


Fig. 8: Line plot representing CS-publications in each year

4.1.5. Authorship Analysis:

With making the data seamlessly easier to analyze, using the Dask bag and plotly.express plotting the top 20 authors with most number of publications is done through making the dataframe containing the authors and frequencies which is gained from author's parsed column after splitting them and taking each author as one entry.

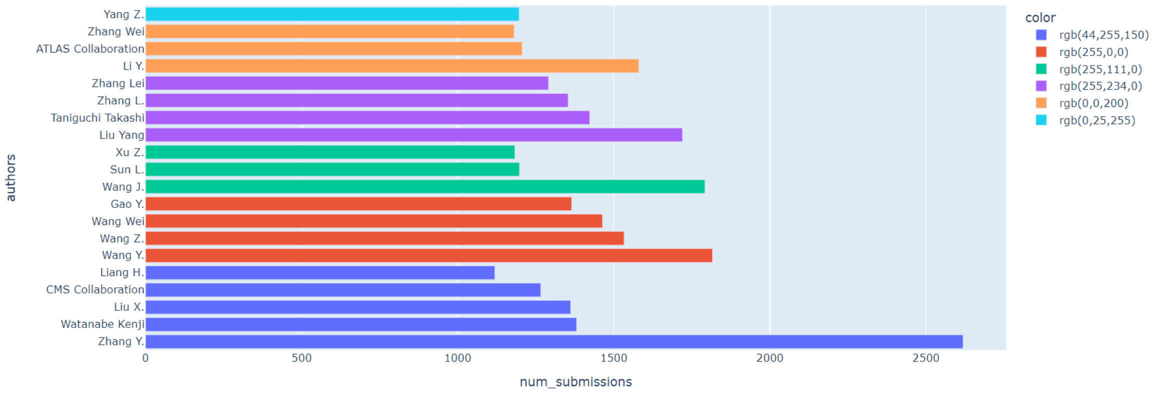


Fig .9: Representation of top 20 authors with most number of publications

The same process can be done to CS-publications data set which gives the below plot, we can observe that the number of publications from each author is quite low compared to total number of publications happening in each year, which gives the doubt of checking

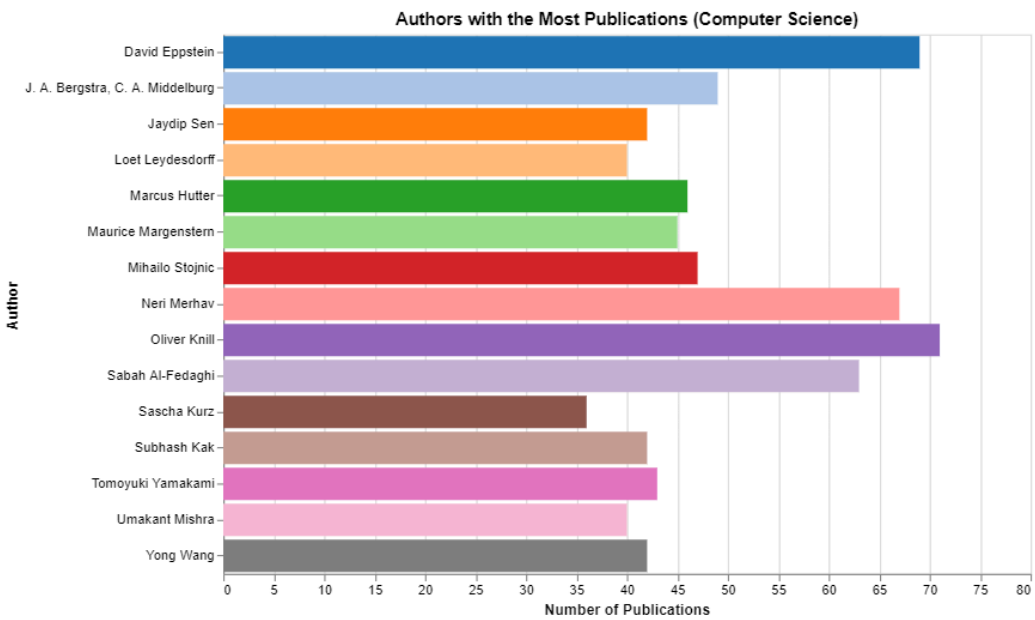


Fig. 9: Representation of top 20 authors having most number of publications

the top submitter has the most number of publications as there can be many companies investing in the research field and publishing them officially under their name which is true with what the below plot shows.

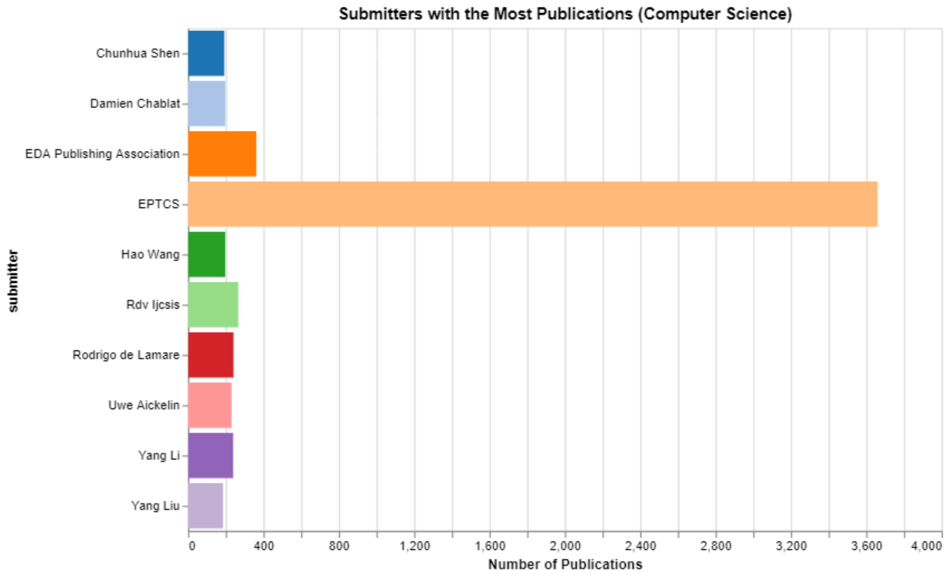


Fig. 10: representation of top submitters with most number of publications

We can see that the authors work in groups with what we observed from the dataset and what we observed with each individual author having very few papers which gives the doubt of checking that how many authors are collaborating on average for a paper across the years? ; this is plotted by making statistical data from authors from CS-Publications.

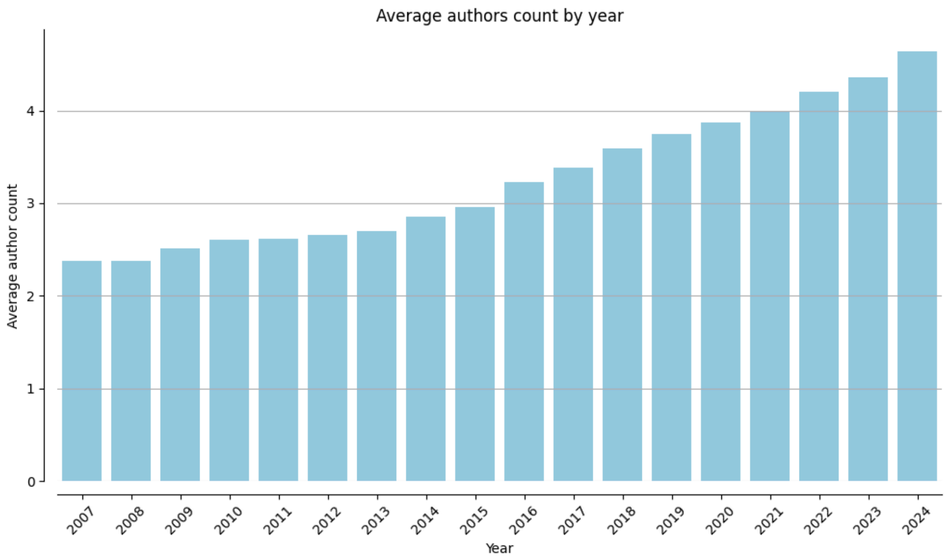


Fig. 11: Representation of average no. of Authors collaborating for paper across years

4.1.6. Topic Analysis :

To understand the distribution of number of sub categories and number of categories across the whole dataset , using the dataset which made from scraping from ArXiv taxonomy is used and plotted a pie chart to show the share of each category occupying the dataset given below.

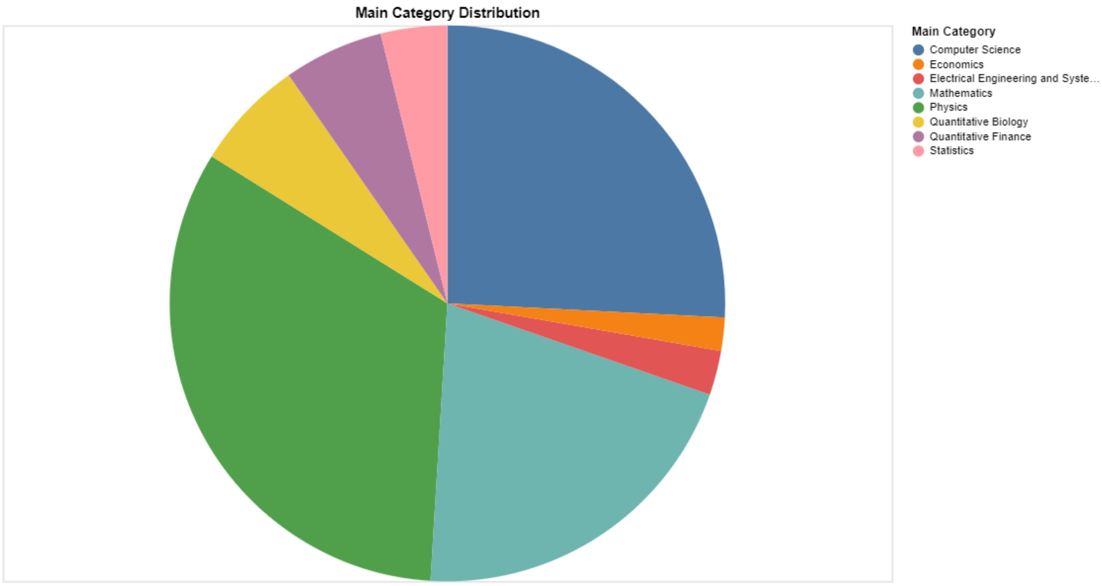


Fig. 12: Representation of Main Categories distribution

As we observe the data we can understand that the paper belongs to multiple categories so to know and understand the publication types, make a plot if it contains more than one category it is made into one count for multiple categories and a bar graph is plotted.

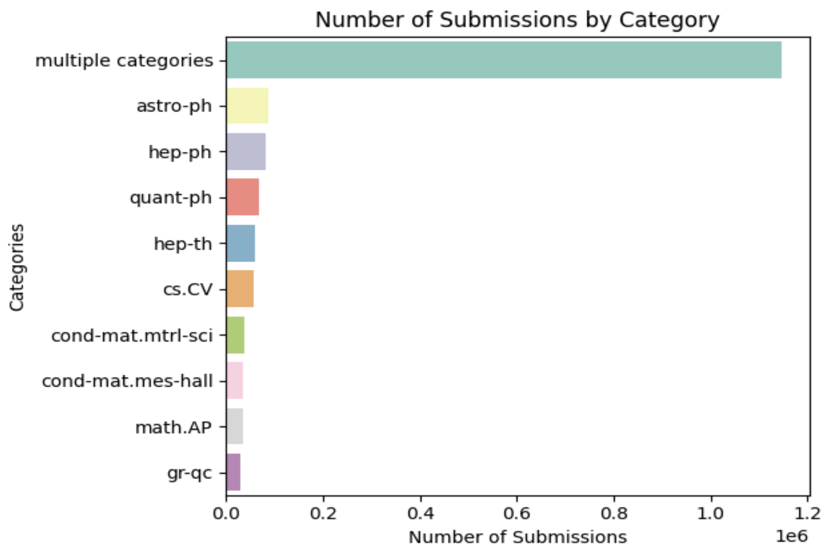


Fig. 13: Representation of of number of submissions across categories

The distribution of papers across top 20 sub categories are plotted by making a dataframe and checking the frequency making another column named number of papers to understand the dominance of categories across dataset and we got to know the CS-category dominates the dataset which is the reason to make dataset of CS-Publications and analyze the growth from the start.

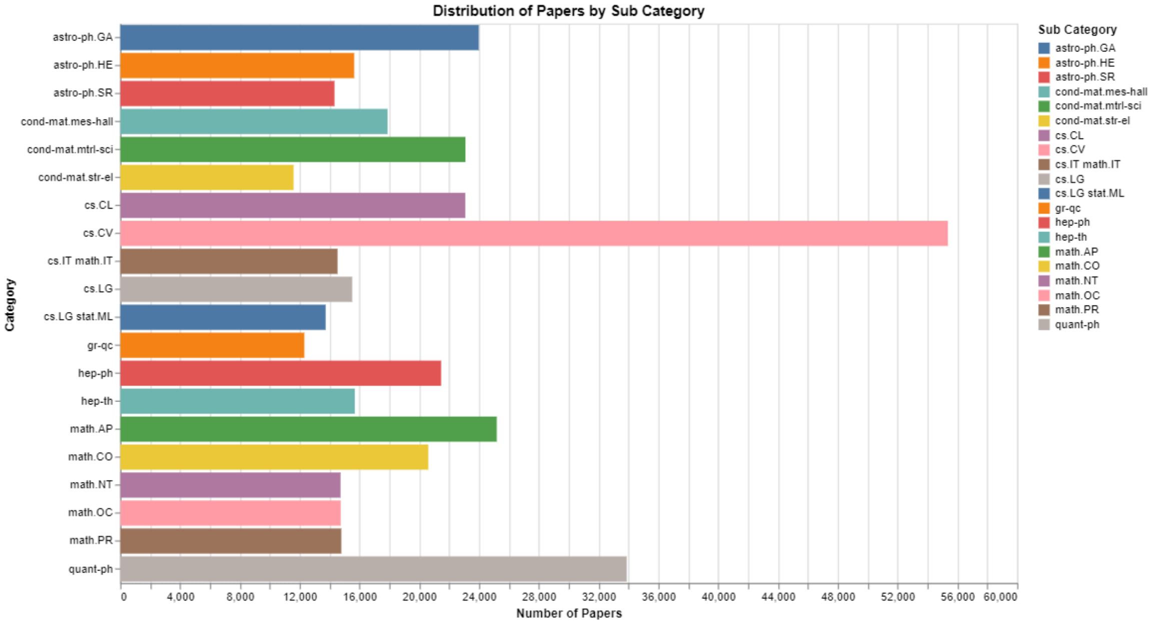


Fig. 14: Representation of distribution of papers by sub category

The distribution of papers by sub category wise in CS-publications is plotted using bar graph to know the rise in some major fields and which fields we can predict can have more publications in the future.

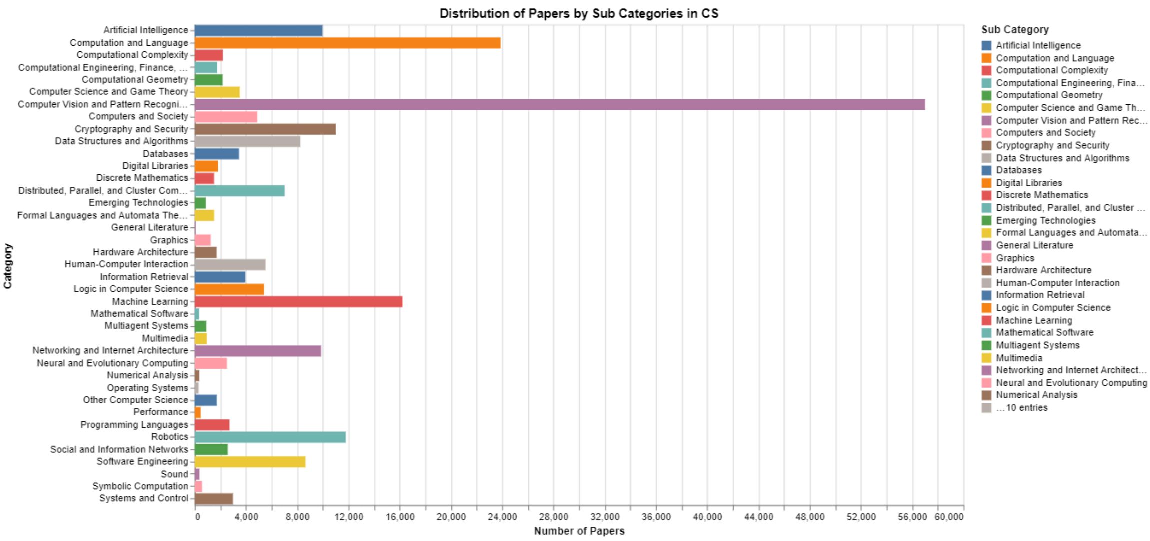


Fig. 15:Representation of distribution of papers by sub category in CS

The interconnections between the categories is the most crucial thing we need to find from this type of dataset on with which and which categories it is collaborating with and how many times to represent this graphically a network is build such a way the nodes represent the sub categories and the edges represents number of interactions between them, the larger the node the bigger is it's impact in this research field.

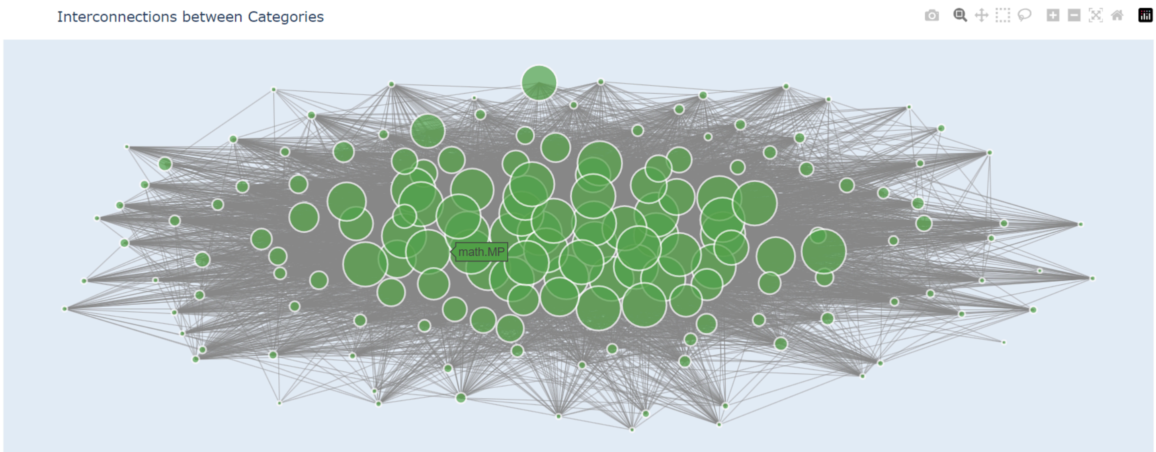


Fig. 16: Representation of interactions between Categories

On zooming the network, we can see the clear edges and how many they are between each sub category and the distance between the nodes depends on the number of interactions it makes with other nodes. The network plot is a 3D structure and no measurement is used to understand it as the type on how much the size of node and length of edge is purely based on data.

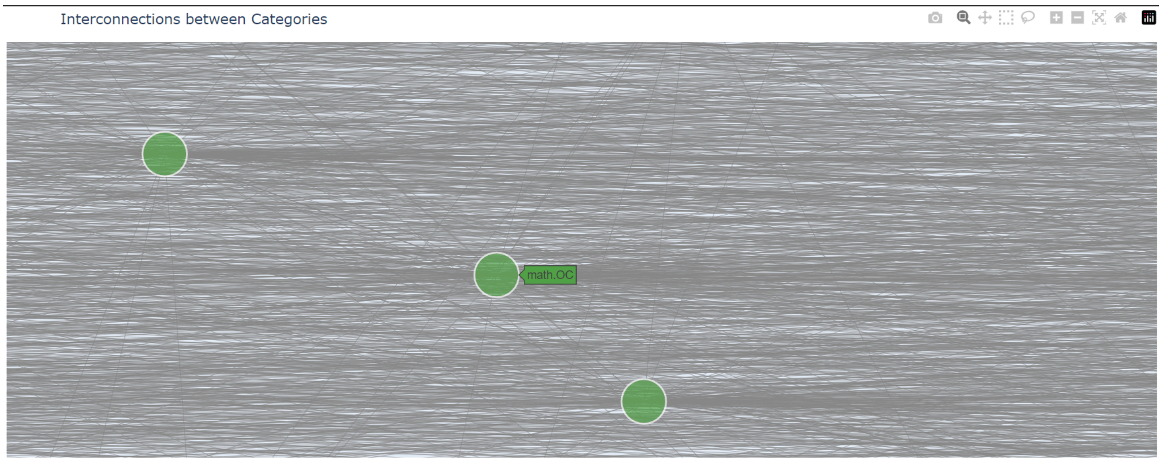


Fig. 17:Relationship between the subcategories in form of nodes

The number of collaborations between categories in each paper on average is calculated and plotted across the years to understand the behavior, collaborations in CS-publications shows the collaboration between fields is happening more in recent years.

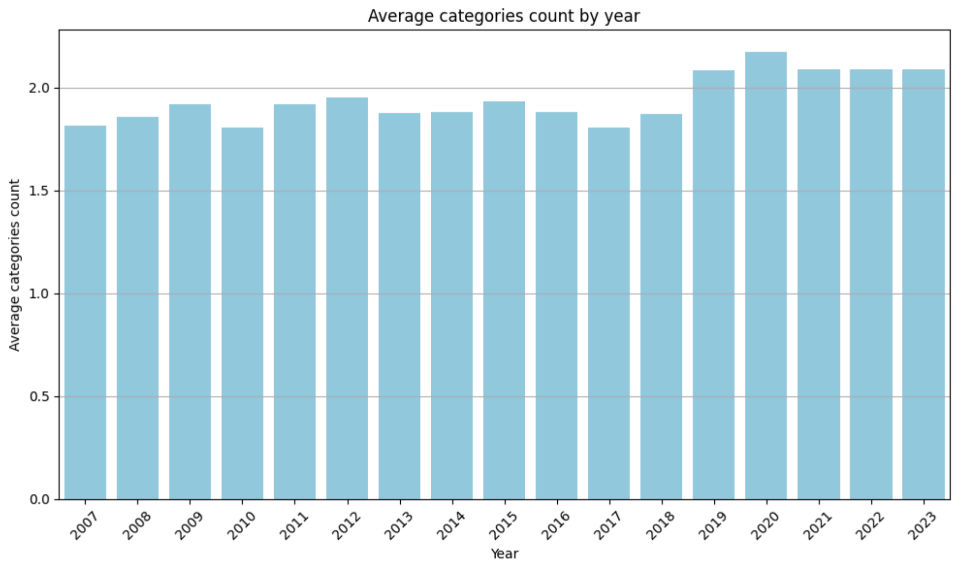


Fig. 18: Representation of of average number of categories count by year

The line plot is plotted between categories, the CS line shows the total number of publications happening in CS-field in each year and the remaining fields show the number of collaborations it happened with CS-field,

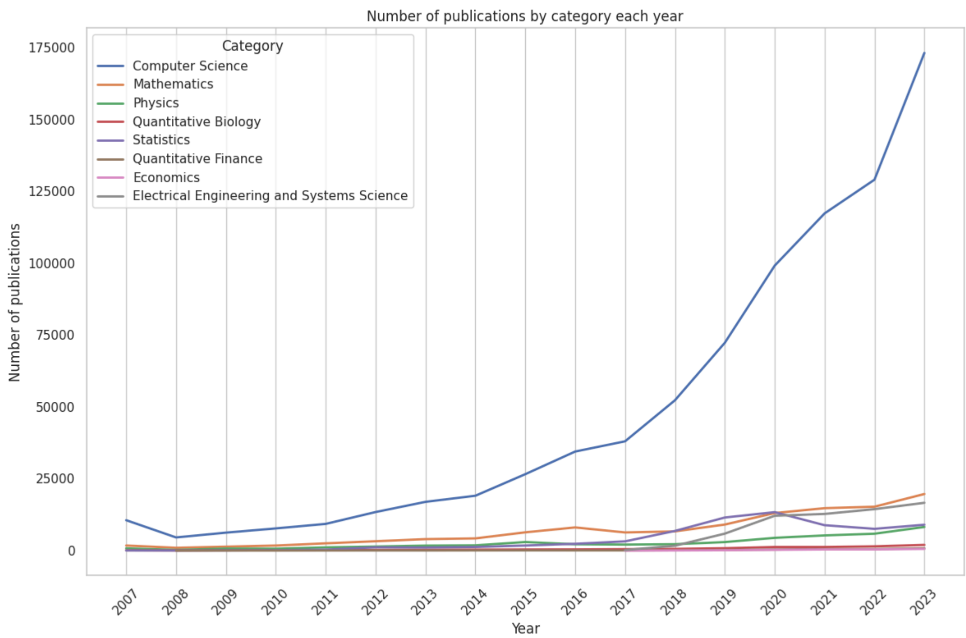


Fig. 19: Representation of line plot across various field collaborating with CS

4.1.6. Title Analysis :

During the Topic analysis we got to know the top categories having high number of publications in recent years so below we tried to plot some bar graphs showing the top words with more number of repetitions in titles in top 5 categories and given below are two of them to show the type of words the title is made of most in each specific category and it helps in building the recommendation based on content based filtering.

In title there are occurrences of prepositions, conjunctions and many words which wouldn't be much helpful to understand based on them so stopwords are imported from nltk.corpus for better understanding of the behavior of pattern.

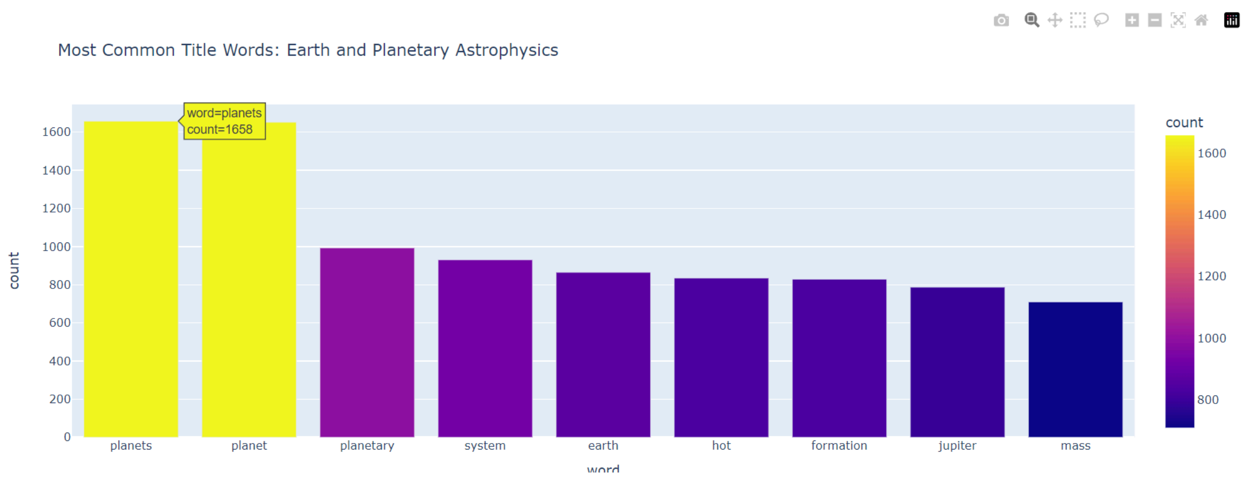


Fig. 20: Representation of most common words in Title in Astrophysics

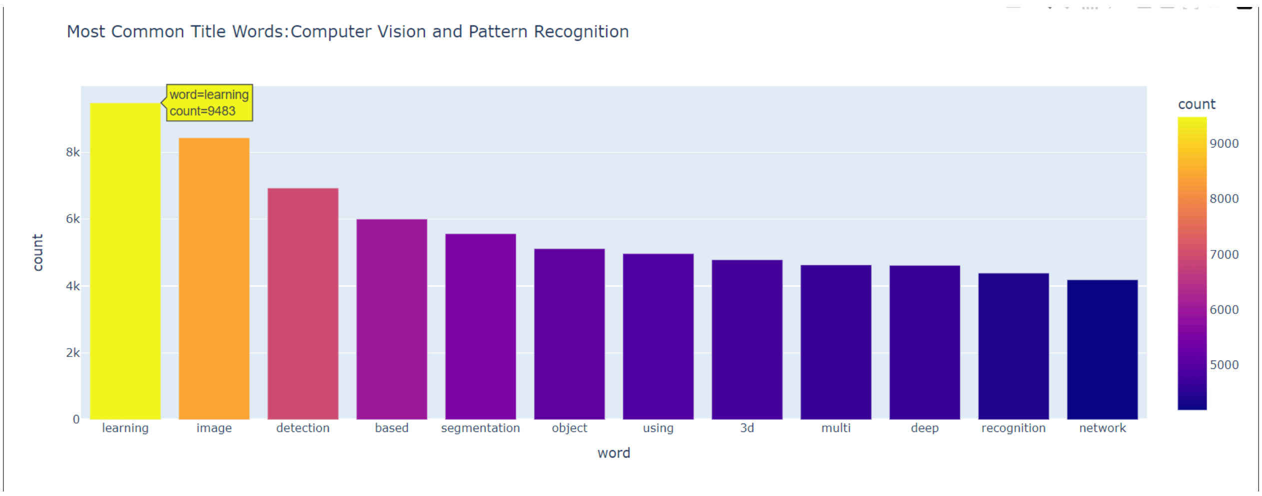


Fig. 21: Representation of most common words in Title in CS-CV

4.2 Recommendation Model:

The recommendation model is built on following various steps ensuring a proper strategy to do content based filtering in a personalized way. The steps are given in the flow chart. The recommendation is based on what title the user gives. The system works on the category, abstract and title in the back-end process to recommend the titles of papers.

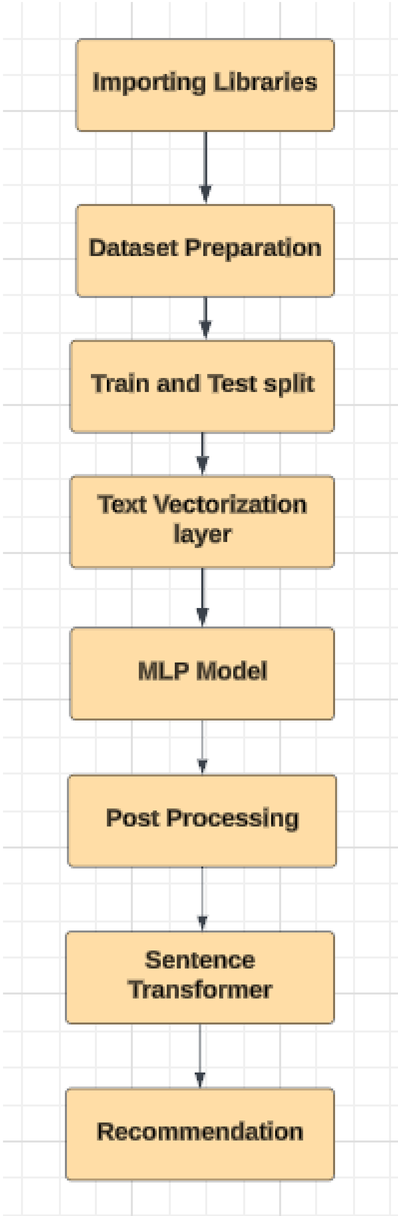


Fig. 22: Flowchart Representation of Model Building process

4.2.1. Importing Libraries:

a) **Tensorflow(tf):** It is a powerful open source framework which is generally used for deep learning and machine learning tasks.keras and layers which are submodules are imported which are generally used for building and training the models.

b) **Scikit-learn Library:** Generally it is used for splitting the datasets for training and testing. That is the same purpose for importing them.

c) **ast:** For safely evaluation of python literal or string as a python object it is used. ast.literal_eval is used after importing for data preparation.

d) **Pickle:** To store the embeddings, text vectors, models, vocabs and all pickles are imported which helps to decrease the workload for everytime, one requires to work using the model.

4.2.2. Data Preparation:

The dataset is a collection of research papers of multiple categories made from arxiv dataset. This dataset is made in such a way to work for multi label text classification so which would be helpful for training and building the prototype for recommendation engine for research papers

Fig. 23: Flowchart representation of data pre processing

After loading the dataset as per flowchart null values are checked and found the duplicated values. The unique labels in the term column is calculation which is filtered and stored as an array for future use. After removing the duplicate entries based on the term's the data split occurs.

	terms	titles	abstracts
0	['cs.LG']	Multi-Level Attention Pooling for Graph Neural...	Graph neural networks (GNNs) have been widely ...
1	['cs.LG', 'cs.AI']	Decision Forests vs. Deep Networks: Conceptual...	Deep networks and decision forests (such as ra...
2	['cs.LG', 'cs.CR', 'stat.ML']	Power up! Robust Graph Convolutional Network v...	Graph convolutional networks (GCNs) are powerf...
3	['cs.LG', 'cs.CR']	Releasing Graph Neural Networks with Different...	With the increasing popularity of Graph Neural...
4	['cs.LG']	Recurrence-Aware Long-Term Cognitive Network f...	Machine learning solutions for pattern classif...

Fig. 24: Representation of Dataset

4.2.3. Data Split :

We have used the stratify parameter to ensure that the splitting is done in a way that preserves the same distribution of labels (terms) in both the training and test sets. After the train and test splitting, the test set further into validation and new test sets.

The test split happened to be 0.1 and half of it was splitted further for making a validation set. Below shows the entries in each set.

```
Number of rows in training set: 34741
Number of rows in validation set: 1930
Number of rows in test set: 1931
```

Fig. 24: Representation of data split

4.2.4. Data preparation and Text Vectorization Layer:

In the beginning we follow the below steps to ensure the data be stored, converted, retrieved when needed to load to the model.

1. Here we created a TensorFlow RaggedTensor (terms) from the values in the "terms" column of the train_df DataFrame. A RaggedTensor is a tensor with non-uniform shapes
2. After step 1 we implemented the StringLookup layer using TensorFlow. The purpose of this layer is to map strings to integer indices and vice versa. The output_mode="multi_hot" indicates that the layer will output a multi-hot encoded representation of the input strings.
3. The lookup adapts the StringLookup layer to the unique values in the "terms" column, building the vocabulary.
4. In the end we retrieve the vocabulary

```
Vocabulary:

['[UNK]', 'cs.CV', 'cs.LG', 'stat.ML', 'cs.AI', 'eess.IV', 'cs.RO', 'cs.CL',
```

Fig. 25: Vocabulary made of terms

After making it into vocabulary we designed a make_dataset function to create a dataset suitable for training a model. It takes a dataframe as input, assumes it has "abstracts" and "terms" columns, and creates a dataset of batches where each batch consists of abstract sequences and their corresponding binarized label sequences.

```
Original label: ['cs.CV']
Label-binarized representation: [[0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
  0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

Fig. 26: Binarized representation of each label in vocabulary

1. max_seqlen: Maximum sequence length. It indicates the maximum length allowed for sequences.
2. batch_size: Batch size. It specifies the number of samples to use in each iteration.
3. padding_token: A token used for padding sequences.
4. auto = tf.data.AUTOTUNE: auto is assigned the value tf.data.AUTOTUNE.

```
Abstract: b'One of the main challenges in the vision-based grasping is the selection of\nfeasible grasp regions while interacting with novel objects.
Label(s): ['cs.CV', 'eess.IV', 'cs.RO']

Abstract: b'With the rise of deep learning models in the field of computer vision, new\npossibilities for their application in industrial processes pr
Label(s): ['cs.CV', 'cs.AI']

Abstract: b'In this work, we propose a novel procedure for video super-resolution, that\nis the recovery of a sequence of high-resolution images from
Label(s): ['cs.CV']

Abstract: b'Automatic image aesthetics assessment is a computer vision problem that deals\nwith the categorization of images into different aesthetic
Label(s): ['cs.CV']

Abstract: b'Public transport has become an essential part of urban existence with\nincreased population densities and environmental awareness. Large q
Label(s): ['cs.LG', 'stat.ML']
```

Fig. 27: Representation of Abstract and Label

Here after all the above processes we map the text vectorization operation to each element of the training, validation, and test datasets. This ensures that the text data in each dataset is transformed into numerical vectors using the adapted TextVectorization layer. The num_parallel_calls parameter is used to parallelize the mapping process, and prefetch is applied to prefetch data batches for better performance.

4.2.5. MLP Model:

Fig. 28:Flow chart Representation of Model process

Creating shallow_mlp_model (MLP) with dropout layers

1. First hidden layer: 512 neurons, ReLU activation function, with dropout.
2. Second hidden layer: 256 neurons, ReLU activation function, with dropout.
3. Output layer: The number of neurons equals the vocabulary size (output vocabulary of the StringLookup layer), with a sigmoid activation function. The model's train and validation loss and binary accuracy are plotted to understand the model's behavior across each epoch. Further, the categorical accuracy of test and validation set's values are given below. this explains the model is working good for this data.

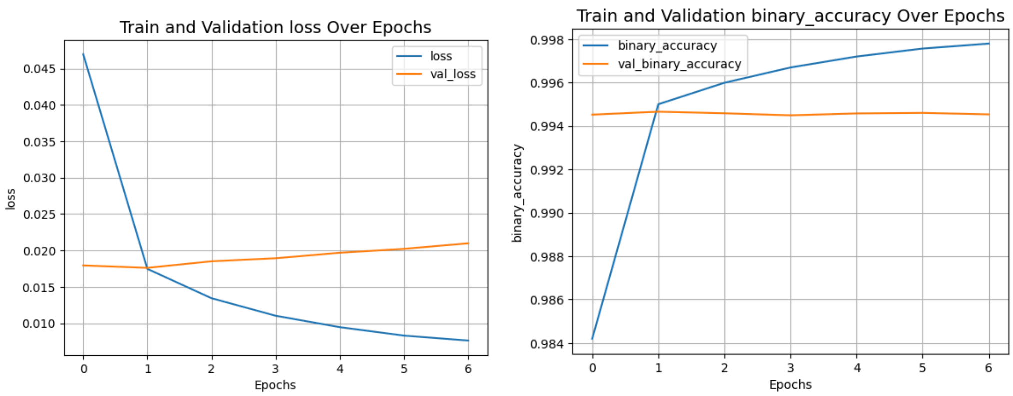


Fig. 29: Representation of loss and accuracy of train and validation using line graph

```
16/16 [==============================] - 1s 63ms/step - loss: 0.0177 - binary_accuracy: 0.9946
16/16 [==============================] - 1s 62ms/step - loss: 0.0182 - binary_accuracy: 0.9946
Categorical accuracy on the test set: 99.46%.
Categorical accuracy on the validation set: 99.46%.
```

Fig. 30: Categorical Accuracies of Test and Validation Set

The model, vocabulary which contains terms and text vectorizations are stored, saved using pickle library so that in future for the recommendation system there would be no need to run the model and vectorization process every time.

4.2.6. Post Processing:

After all the model work is done, the processing work remains which is needed before going to the sentence transformation which can be useful for the recommendation function.

1. Here we reverse single multi-hot encoded labels to a tuple of vocab terms.
2. After the above step we defined a function to predict categories for titles.

4.2.7. Sentence Transformation:

The Sentence transformer is used to do the embedding work on the titles for that we make a dataframe removing terms and abstract from the existing dataframe.

We load **all-MiniLM-L6-v2**, which is a MiniLM model fine tuned on a large dataset of over 1 billion training pairs. We initialize it from Sentence Transformers because it is capable of encoding sentences into fixed-size vectors (embeddings). The embedding length needs to be the same for all so that it would be easier for the recommendation function to process it.

After this we store the sentences, rec_model and embeddings using pickle so these all won't be needed to run every time we need to use the recommendation engine.

4.2.8. Recommendation:

In recommendation function:

1. We Calculate cosine similarity scores between the embeddings of input_paper and all papers in the dataset.
2. It gets the indices of the top-k most similar papers based on cosine similarity.(We gave K as 6)
3. It retrieves the titles of the top similar papers.

5. RESULTS AND DISCUSSION

When the function is run after loading the saved files, the user can give the title of the paper for which he needs similar papers. It gives the recommendation of papers which are top five based on the cosine similarity. Given below shows the output for it.

```
Enter the title of any paper you likeMulti-Level Attention Pooling for Graph Neural Networks: Unifying Graph Representations with
We recommend to read this paper...........
=============================================
Multi-Level Attention Pooling for Graph Neural Networks: Unifying Graph Representations with Multiple Localities
PiNet: Attention Pooling for Graph Classification
Context-Aware Graph Attention Networks
Attention-driven Graph Clustering Network
Graph Attention Multi-Layer Perceptron
Graph Attention Networks
```

```
Enter the title of any paper you likeDecision Forests vs. Deep Networks: Conceptual Similarities and Empirical Differences at Smal
We recommend to read this paper...........
=============================================
Decision Forests vs. Deep Networks: Conceptual Similarities and Empirical Differences at Small Sample Sizes
Decision Forests, Convolutional Networks and the Models in-Between
Dive into Decision Trees and Forests: A Theoretical Demonstration
Deep Neural Decision Trees
Training Decision Trees as Replacement for Convolution Layers
Towards the effectiveness of Deep Convolutional Neural Network based Fast Random Forest Classifier
```

```
Enter the title of any paper you likePower up! Robust Graph Convolutional Network via Graph Powering
We recommend to read this paper...........
=============================================
Power up! Robust Graph Convolutional Network via Graph Powering
An Introduction to Robust Graph Convolutional Networks
Node Feature Kernels Increase Graph Convolutional Network Robustness
I-GCN: Robust Graph Convolutional Network via Influence Mechanism
Spatio-Temporal Sparsification for General Robust Graph Convolution Networks
Simplifying Graph Convolutional Networks
```

```
Enter the title of any paper you like Releasing Graph Neural Networks with Differential Privacy Guarantees
We recommend to read this paper...........
=============================================
Releasing Graph Neural Networks with Differential Privacy Guarantees
Locally Private Graph Neural Networks
NetFense: Adversarial Defenses against Privacy Attacks on Neural Networks for Graph Data
Vertically Federated Graph Neural Network for Privacy-Preserving Node Classification
Towards Representation Identical Privacy-Preserving Graph Neural Network via Split Learning
GraphMI: Extracting Private Graph Data from Graph Neural Networks
```

```
Enter the title of any paper you like Lifelong Graph Learning
We recommend to read this paper............
=============================================
Lifelong Graph Learning
Lifelong Learning of Graph Neural Networks for Open-World Node Classification
Graph-Based Continual Learning
Graph Learning with Loss-Guided Training
An Uncoupled Training Architecture for Large Graph Learning
Fast Graph Learning with Unique Optimal Solutions
```

6. CONCLUSIONS AND FUTURE WORK

With the analysis we observed the patterns and growth in research papers over the years, observed the growth of CS in research papers which can become a major domain in future.Through the understanding of the analysis and understanding the works done in this field for recommendation of research papers we built a prototype which works using NLP tokenization and embedding techniques over the title, categories and abstract, used vocabulary which store the keywords. Existing models work on keywords and title and abstract mostly. While understanding the importance of categorization of the research papers and analyzing based on that would truly make the recommendation better.

This can be developed further by working on bigger data size and more on citation data and collaboration of both categorical, citation's data and based on author's peak value can be assigned to give better recommendation.

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