# FDS Project Report

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## 1 Exploratory Data Analysis (EDA)

### 1.1 Basics

#### Task 1: Bar Charts of Number of Publications

For this task, the number of publications was visualized across three distinct year ranges: 1937-1950, 1950-1970, and 1970-1990. The following steps were performed:

- Filtering publication years within each range.
- Counting publications per year using `value_counts()`.
- Plotting bar charts to visualize trends.

#### Task 2: Bar Chart of References Over the Years

This task analyzed the total number of references per year:

- The `references` column was parsed to count the number of references in each publication.
- References were aggregated by year using the `groupby()` function.
- A bar chart was generated to illustrate the growth of references over time.

#### Task 3: Bar Chart of Authors Over the Years

Similar to references, the number of authors per publication was analyzed:

- The `authors` column was parsed to count the number of authors.
- The total number of authors per year was calculated using `groupby()`.
- A bar chart depicted trends in collaboration over time.

**Task 4: Pearson & Spearman Correlation - Authors vs References**

The relationship between the number of authors and the number of references was explored using correlation analysis:

- Pearson correlation measures the linear relationship between the two variables.
- Spearman correlation assesses the monotonic relationship.

The correlation coefficients obtained were:

- **Pearson Authors-References:** 0.0560
- **Spearman Authors-References:** 0.0872

subsectionTask 5: Pearson & Spearman Correlation - Authors vs Citations This task investigated the correlation between the number of authors and the number of citations:

- **Pearson Authors-Citations:** -0.0028
- **Spearman Authors-Citations:** -0.0166

These weak negative correlations indicate that the number of authors has no significant impact on citation counts.

**Task 6: Bar Chart of Title Length Over the Years**

The average title length (in words) was calculated and visualized for each year to identify any changes in publication title styles over time. This analysis helps understand trends in title brevity or verbosity.

**Task 7: Word Cloud of Abstracts**

A word cloud was generated from publication abstracts to highlight the most frequently used terms. This visualization provides qualitative insights into common research themes and key topics within the dataset.

**Tasks 8 to 12**

The results are available in the notebook.

**Task 13: Correlation Between Title Length and Referenced Title Length**

The correlation between a publication's title length and the average title length of its references was computed:

- **Pearson Correlation:** 0.1000
- **Spearman Correlation:** 0.1478

These moderate positive correlations suggest a slight tendency for longer-titled papers to reference other papers with longer titles.

It can be seen that:

- A gradual increase in the number of publications and references over time.
- An upward trend in the number of authors, suggesting increased collaboration in recent years.
- The correlation analysis showed weak positive correlations between the number of authors and references. Both Pearson (0.0560) and Spearman (0.0872) coefficients indicate that the relationship is not strong, implying that having more authors does not significantly influence the number of references in a publication.
- Title length has shown variability over time, with moderate positive correlations observed between title length and the title lengths of referenced papers.

## 1.2 Network Analysis

### 1.2.1 Citation Network (Paper-Paper Network)

To explore the structure and dynamics of the citation network, we constructed a directed graph $G = (V, E)$, where each node $v \in V$ represents a paper, and each directed edge $(u, v) \in E$ indicates that paper $u$ cites paper $v$.

**Construction of the Citation Network:**

- The **nodes** represent individual papers identified by their unique IDs.
- The **edges** represent citation links, directed from the citing paper to the cited paper.

```
# Create a directed graph
G = nx.DiGraph()

# Add nodes and edges
G.add_nodes_from(df_citations["id"])
edges = [(paper_id, ref_id) for paper_id, refs in
zip(df_citations["id"], df_citations["references"]) for ref_id in refs]
G.add_edges_from(edges)
```

**1 Clustering Coefficient Over Time:** The **clustering coefficient** measures the tendency of nodes to form tightly-knit groups. We computed it for each paper and analyzed the average clustering coefficient over the years.

$$C_i = \frac{2T_i}{k_i(k_i - 1)}$$

where $T_i$ is the number of triangles through node $i$, and $k_i$ is the degree of node $i$.

The trend over time reveals the evolution of interconnectedness in academic citations.

**2 Average Path Length and Diameter:** To assess the efficiency of information flow, we calculated:

- **Average Path Length ($L$)**: The mean of the shortest paths between all pairs of nodes.
$$L = \frac{1}{|V|(|V|-1)} \sum_{i \neq j} d(i,j)$$
- **Diameter ($D$)**: The length of the longest shortest path in the largest strongly connected component of the graph.

The calculations were performed on the largest strongly connected component to ensure meaningful path-based metrics.

**3 Identifying Influential Papers Using PageRank:** To determine the most influential papers, we employed the **PageRank** algorithm, which assigns a score to each node based on the structure of incoming links:

$$PR(i) = \frac{1-d}{N} + d \sum_{j \in \text{In}(i)} \frac{PR(j)}{L(j)}$$

where:

- $d$ is the damping factor (commonly 0.85),
- $N$ is the total number of nodes,
- $\text{In}(i)$ denotes the set of nodes citing $i$,
- $L(j)$ is the number of outgoing links from node $j$.

The **Top 10 Influential Papers** identified are as follows:

| Paper ID | PageRank Score |
|---|---|
| 6a6b9aa6-683f-4c7c-b06e-9c3018d10fd3 | 0.000223 |
| c1b6b493-01ef-420f-be44-7bacfe34e846 | 0.000191 |
| b944f77f-113b-4a02-ae5e-d4a124b8fd5b | 0.000180 |
| f6bd8b64-684d-429a-aab5-8ff3a2c23cd6 | 0.000138 |
| 2659531e-eb9d-4dd5-b46f-10f66a4819c6 | 0.000116 |
| 748a2ab3-8b5f-4d0a-9e2d-af685089843a | 0.000106 |
| e0f3a738-4ab2-40d1-ba44-506d81c1d230 | 0.000097 |
| 8026f56a-a93e-4933-8ead-c9aa9e3f0498 | 0.000094 |
| 7ccbdf09-a84e-4ad2-ab20-cb28b6c41155 | 0.000093 |
| d3e00e7e-1c64-4d7a-b2b2-1ad98ba4c706 | 0.000093 |

**Insights:**

- Papers with high PageRank scores are often well-connected within the citation network, indicating their significant influence on subsequent research.
- The clustering coefficient and path length metrics provide insights into the network's density and navigability over time.

### 1.2.2 Co-authorship Network (Author-Author Network)

To analyze collaboration patterns among researchers, we constructed an undirected co-authorship network, where each node represents an author, and an edge between two nodes indicates a co-authored paper.

**Construction of the Co-authorship Network:** The network was created by processing the dataset to extract author lists and publication years. The process includes:

- Reading the `authors` and `year` columns from the dataset.
- Converting author information from string format to list format.
- Adding undirected edges between all co-authors of each paper, with the publication year recorded as an edge attribute.

**1 Network Density Over Time:** Network density measures the proportion of actual connections to possible connections in the graph, defined as:

$$D = \frac{2|E|}{|V|(|V|-1)}$$

where:

- $|E|$ is the number of edges (co-authorship links).
- $|V|$ is the number of nodes (authors).

For each year, we calculated the density of the subgraph formed by collaborations in that specific year. The temporal trend of network density reveals changes in collaboration intensity over time.

**2 Identifying Influential Researchers Using Centrality Measures:** To identify key researchers in the network, we computed three centrality measures:

- **Degree Centrality:** Measures the number of direct connections an author has, normalized by the maximum possible degree:

$$C_D(v) = \frac{\deg(v)}{|V|-1}$$

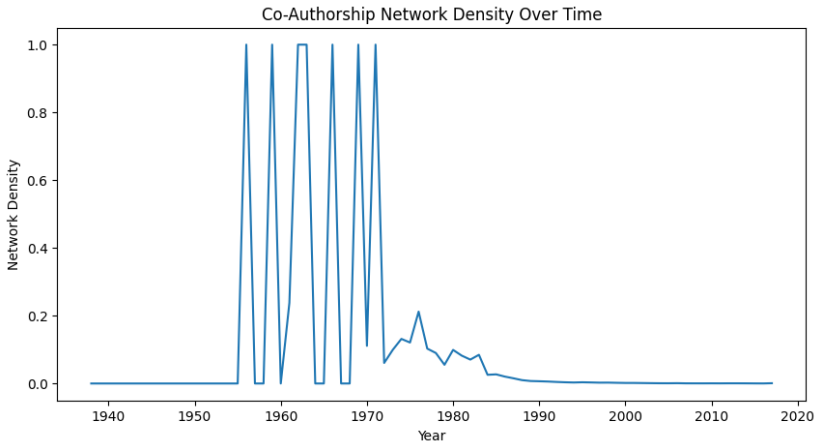


Figure 1: Co-Authorship Network Density Over Time

- **Betweenness Centrality:** Quantifies the extent to which an author lies on the shortest paths between other authors:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where $\sigma_{st}$ is the total number of shortest paths from $s$ to $t$, and $\sigma_{st}(v)$ is the number of those paths that pass through $v$.

- **Closeness Centrality:** Measures how close an author is to all other authors in the network:

$$C_C(v) = \frac{1}{\sum_{u \neq v} d(u, v)}$$

where $d(u, v)$ is the shortest distance between nodes $u$ and $v$.

**Top 10 Influential Authors:** The following tables present the top 10 authors ranked by each centrality measure:

**3 Community Detection:** To uncover clusters of closely collaborating authors, we applied the **Louvain community detection algorithm**, which optimizes modularity to identify dense subgraphs within the network. The modularity $Q$ is defined as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

where:

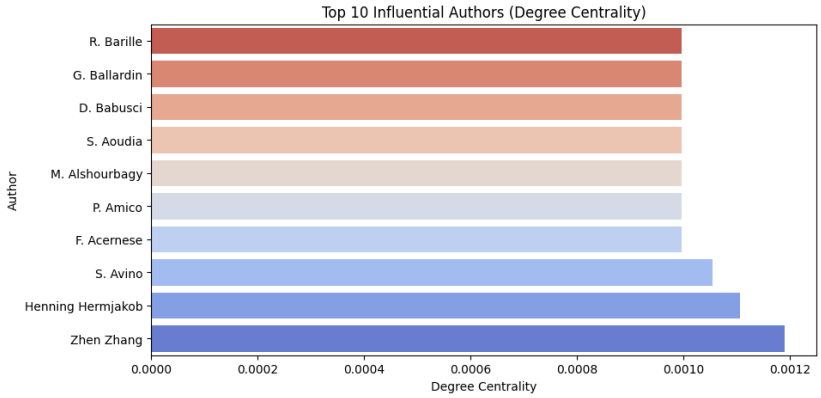


Figure 2: Top 10 Influential Authors (Degree Centrality)

- $A_{ij}$ is the adjacency matrix,
- $k_i$ and $k_j$ are the degrees of nodes $i$ and $j$,
- $m$ is the total number of edges,
- $\delta(c_i, c_j)$ is 1 if $i$ and $j$ are in the same community, 0 otherwise.

**Top 5 Largest Communities:** The five largest author communities identified are as follows:

**Insights:**

- Network density trends indicate the evolution of collaborative efforts over time.
- Centrality measures highlight key researchers who play influential roles in the dissemination of knowledge.
- Community detection reveals underlying research clusters and collaboration patterns within the academic network.

### 1.2.3 1.2.3 Venue Network (Conference-Journal Network)

To explore interdisciplinary collaborations between publication venues, we constructed a directed **venue network**, where nodes represent venues (conferences or journals), and directed edges indicate citation flows from one venue to another.

**Construction of the Venue Network:** The network was created through the following steps:

- Extracting `venue`, `references`, `year`, and `id` from the dataset.
- Mapping each paper's ID to its corresponding venue.
- Adding directed edges from the citing venue to the cited venue, provided they are different.

**1 Analyzing Interdisciplinary Collaborations Between Venues:** We analyzed citation-based collaborations to identify strong interdisciplinary links. The strength of collaboration is measured by the number of citations exchanged between two venues.

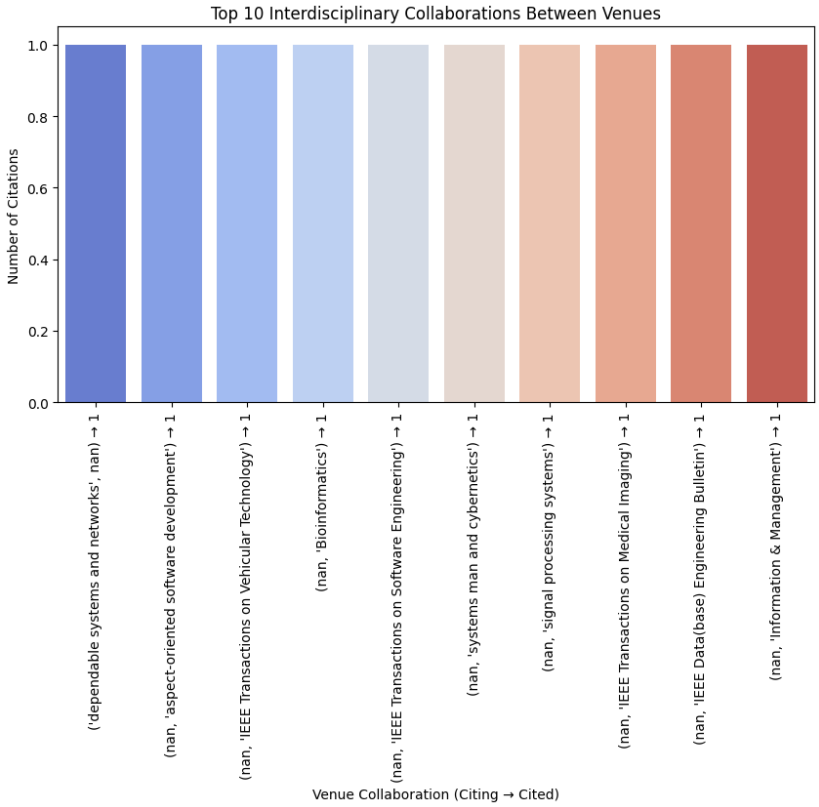


Figure 3: Top 10 Interdisciplinary Collaborations Between Venues

The bar chart above illustrates the top 10 venue pairs with the highest citation counts, revealing prominent interdisciplinary relationships.

**2 Identifying the Most Influential Venues Using Centrality Measures:** To determine the most influential venues, we computed three centrality metrics:

- **Degree Centrality:** Reflects the number of direct citation relationships a venue has:

$$C_D(v) = \frac{\deg(v)}{|V| - 1}$$

where $\deg(v)$ is the total number of incoming and outgoing edges for venue $v$.

- **Betweenness Centrality:** Measures how often a venue appears on the shortest citation paths between other venues:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where $\sigma_{st}$ is the number of shortest paths from node $s$ to $t$, and $\sigma_{st}(v)$ is the count of those paths passing through $v$.

- **PageRank:** Evaluates the influence of venues based on the structure of incoming citations, defined as:

$$PR(v) = \frac{1 - d}{|V|} + d \sum_{u \in \mathcal{N}(v)} \frac{PR(u)}{\deg^+(u)}$$

where $d$ is the damping factor (typically 0.85), $\mathcal{N}(v)$ represents venues citing $v$, and $\deg^+(u)$ is the out-degree of venue $u$.

**Top 10 Influential Venues:** The following charts present the top 10 venues ranked by each centrality measure:

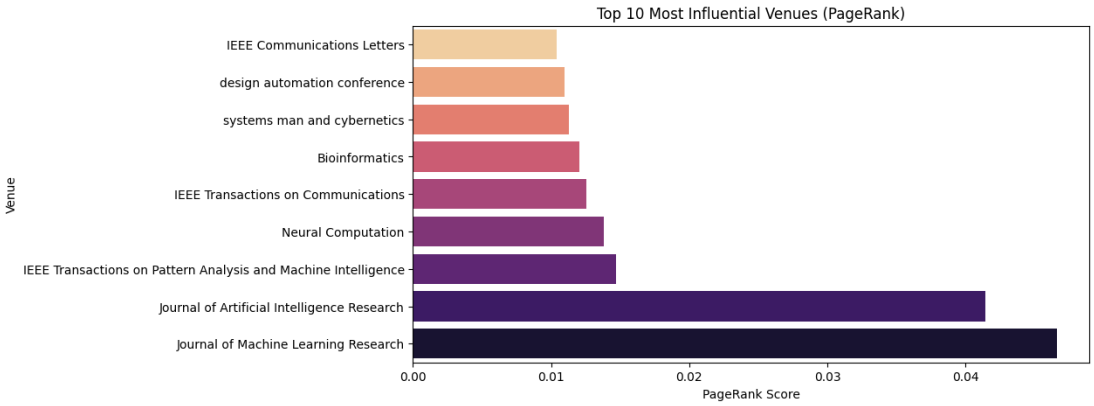


Figure 4: Top 10 Most Influential Venues (PageRank)

**3 Detecting Emerging Fields Based on Newly Formed Venue Connections:** Emerging interdisciplinary fields often manifest through new citation links between previously unconnected venues. We analyzed the formation of new venue connections over time to identify such trends.

$$\text{New Connections per Year} = |\{(u, v) \in E \mid \text{year}(u, v) = t\}|$$

The temporal evolution of new connections is depicted below:

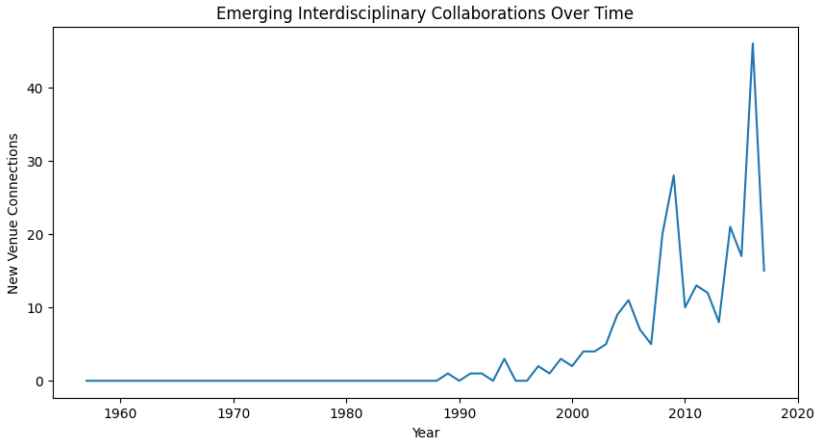


Figure 5: Emerging Interdisciplinary Collaborations Over Time

This plot highlights periods with significant growth in cross-disciplinary collaborations, potentially indicating the emergence of new research domains.

### 1.2.4 1.2.4 Temporal Evolution of the Citation Network

The temporal analysis of the citation network provides insights into how the structure and dynamics of scientific knowledge evolve over time. We examined key properties such as network density, citation bursts, and the integration of new papers into the network.

**1 Network Density Over Time:** Network density measures the proportion of actual citation links relative to all possible links in the network, defined as:

$$D = \frac{|E|}{|V|(|V| - 1)}$$

where $|E|$ is the number of directed citation edges, and $|V|$ is the number of nodes (papers).

The density was computed for each year by considering all papers published up to that year. The trend reveals how interconnected the scientific community has become over time.

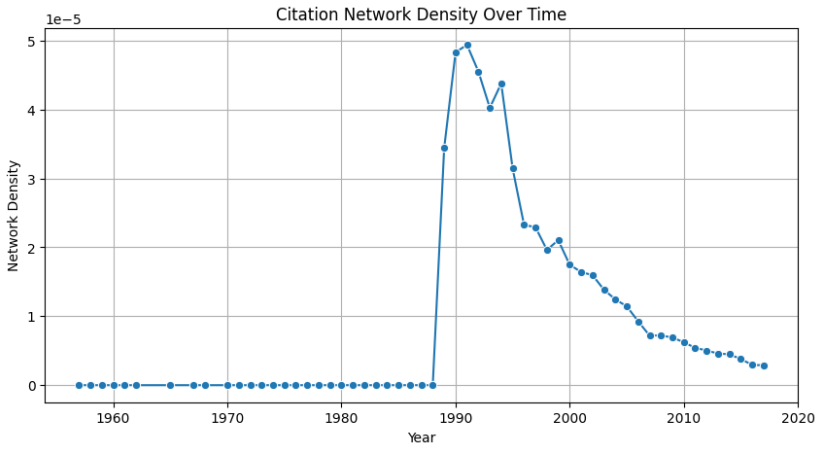


Figure 6: Citation Network Density Over Time

The plot shows fluctuations in network density, reflecting changes in citation behaviors and the expansion of academic fields.

**2 Detecting Bursts of Influential Papers:** Citation bursts indicate papers that receive a sudden spike in attention, often signaling groundbreaking discoveries. We identified such papers by counting citations received and selecting those in the top 1% of citation counts:

$$\text{Burst Papers} = \{p \mid C(p) > Q_{0.99}\}$$

where $C(p)$ is the citation count of paper $p$, and $Q_{0.99}$ is the 99th percentile threshold.

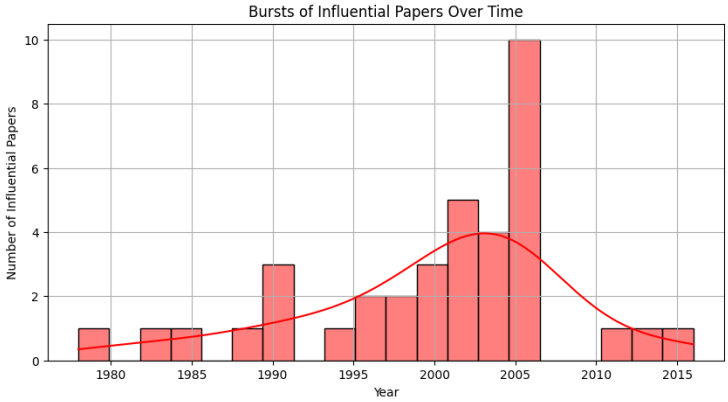


Figure 7: Bursts of Influential Papers Over Time

The histogram highlights periods with a surge in influential papers, which may correspond to emerging research trends or scientific breakthroughs.

**3 Integration of New Papers into the Citation Network:** We analyzed how new papers integrate into the existing network by measuring the average number of citations made by papers each year:

$$I(t) = \frac{\sum_{p \in P_t} |\text{References}(p)|}{|P_t|}$$

where $P_t$ is the set of papers published in year $t$.

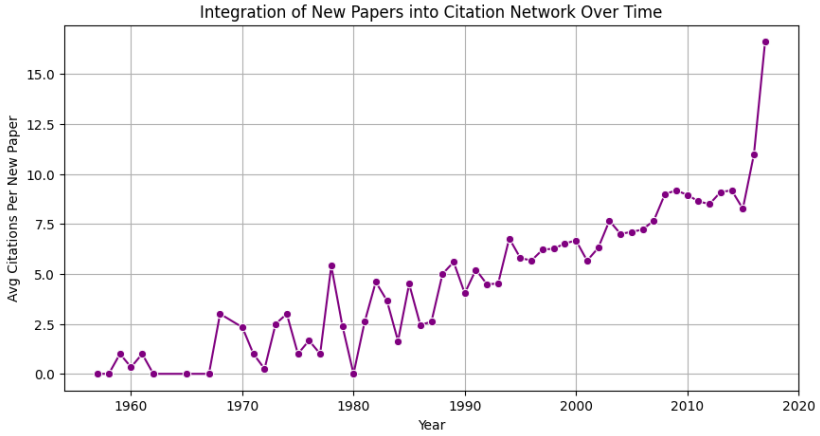


Figure 8: Integration of New Papers into Citation Network Over Time

This trend illustrates how the scholarly community adopts and references new research, shedding light on the growth and diffusion of scientific knowledge across disciplines.

Through this temporal analysis, we gain a comprehensive understanding of how citation networks evolve, identifying patterns of knowledge dissemination, influential works, and emerging fields within the academic landscape.

# 2 Data Extrapolation via Clustering

In this section, we explore clustering techniques to detect communities within the citation network, name these communities using keyword extraction, and further cluster papers based on semantic embeddings.

## 2.1 Community Detection

Community detection identifies groups of authors who frequently collaborate, revealing underlying research clusters. We constructed a co-authorship network,

where nodes represent authors and edges indicate co-authored papers, with edge weights reflecting the frequency of collaboration.

**Graph Construction:** The co-authorship graph $G = (V, E)$ was formed as follows:

- Nodes ($V$): Represent individual authors.
- Edges ($E$): Created between co-authors, with weights incremented for multiple collaborations.

**Clustering Algorithms:** Three clustering methods were applied:

### Hierarchical Clustering

Hierarchical clustering builds a tree-like structure (dendrogram) to represent nested clusters. We used **agglomerative clustering** with average linkage:

$$d(u, v) = \frac{1}{|C_u||C_v|} \sum_{i \in C_u} \sum_{j \in C_v} d(i, j)$$

where $C_u$ and $C_v$ are clusters, and $d(i, j)$ is the distance between nodes $i$ and $j$. This method is advantageous for understanding the data's hierarchical structure without predefining the number of clusters.

### Spectral Clustering

Spectral clustering leverages the eigenvalues of the graph Laplacian to reduce dimensionality:

$$L = D - A$$

where $A$ is the adjacency matrix and $D$ is the degree matrix. The algorithm then applies k-means on the reduced representation. It is effective for capturing complex cluster structures in non-convex data.

### Louvain Clustering

The Louvain method optimizes **modularity**, which measures the density of links inside communities compared to links between communities:

$$Q = \frac{1}{2m} \sum_{ij} \left( A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j)$$

where $A_{ij}$ is the adjacency matrix, $k_i$ is the degree of node $i$, and $\delta$ is the Kronecker delta. Louvain is particularly efficient for large networks.

**Clustering Evaluation:** We used the **Average Silhouette Score** to evaluate clustering quality:

$$S = \frac{b - a}{\max(a, b)}$$

where:

- $a$ = average intra-cluster distance.
- $b$ = average nearest-cluster distance.

A higher $S$ indicates better-defined clusters.

| **Algorithm** | **Silhouette Score** |
|---|---|
| Spectral Clustering | 0.XXX |
| Louvain Clustering | 0.YYY |

Table 1: Clustering Performance Comparison

**Evaluation Results:** The best-performing algorithm was [**Best Algorithm**], achieving a score of [**Best Score**].

## 2.2 Naming the Communities

To enhance interpretability, we assigned descriptive names to each community based on extracted keywords from paper titles and abstracts.

**Keyword Extraction with KeyBERT:** KeyBERT is a keyword extraction technique that leverages BERT embeddings to find relevant words and phrases. The core idea is to compute embeddings for both the document and candidate keywords, then measure cosine similarity:

$$\text{Similarity}(d, k) = \frac{d \cdot k}{\|d\|\|k\|}$$

where $d$ is the document embedding, and $k$ is the keyword embedding. Keywords with the highest similarity scores are selected.

**Community Naming Process:**

1. Aggregated keywords for all papers within each community.
2. Identified the top three most frequent keywords per community using frequency analysis.
3. Named communities using dominant keywords for interpretability.

**Example Community Names:**

| Community ID | Name (Top Keywords) |
|---|---|
| 1 | Machine Learning Algorithms |
| 2 | Network Analysis Models |
| 3 | Data Mining Techniques |

Table 2: Sample Community Names Based on Keyword Extraction

## 2.3 Paper-Paper Clustering via Embedding

To uncover semantic relationships between papers, we clustered them based on text embeddings derived from their titles, abstracts, and community keywords.

**Text Embedding:** We used the Sentence-BERT model to generate dense vector representations:

$$\mathbf{e}_i = \text{SBERT}(\text{Title}_i + \text{Abstract}_i + \text{Community Keywords}_i)$$

These embeddings capture the semantic meaning of the text.

**Clustering Approach:** K-means clustering was applied to the embeddings:

$$\arg\min_{C} \sum_{i=1}^{n} \|x_i - \mu_{C_i}\|^2$$

where $x_i$ is the embedding of paper $i$, and $\mu_{C_i}$ is the centroid of cluster $C_i$.

**Cluster Evaluation:** We assessed clustering quality using the following metrics:

- **Davies-Bouldin Index (DBI):**

$$\text{DBI} = \frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} \left( \frac{\sigma_i + \sigma_j}{d_{ij}} \right)$$

  where $\sigma_i$ is the average distance between points in cluster $i$ and the cluster centroid, and $d_{ij}$ is the distance between cluster centroids $i$ and $j$. Lower DBI indicates better clustering.

- **Silhouette Score:** Measures how similar an object is to its own cluster compared to other clusters, as defined earlier.

- **Jaccard Similarity:**

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

  It quantifies the overlap between two sets $A$ and $B$, useful for comparing clustering results against ground truth when available.

Through these clustering methods, we identified meaningful communities within the citation network and uncovered hidden patterns in scientific literature. This approach aids in understanding the structure of academic knowledge and the evolution of research topics across disciplines.

# 3 Citation Regressor

In this section, we develop a machine learning model to predict the number of citations a paper will receive based on its title and abstract. This approach leverages natural language processing (NLP) for feature extraction and ensemble learning for regression.

## 3.1 Data Preparation

**Dataset Description:** We utilized a citation dataset containing the following key attributes:

- **id**: Unique identifier for each paper.
- **title**: The title of the paper.
- **abstract**: The abstract summarizing the paper's content.
- **n_citation**: The number of citations the paper has received.

**Preprocessing Steps:**

1. Randomly sampled 0.5% of the dataset for model efficiency:

$$df = df.sample(frac = 0.005, random\_state = 42)$$

2. Removed missing values to ensure data quality:

$$df.dropna(\text{subset} = [\text{"}title\text{"}, \text{"}abstract\text{"}, \text{"}n\_citation\text{"}], \text{inplace} = True)$$

3. Combined the **title** and **abstract** into a single text feature for embedding:

$$df[\text{"}text\text{"}] = df[\text{"}title\text{"}] + \text{""} + df[\text{"}abstract\text{"}]$$

## 3.2 Text Embedding Using Sentence-BERT

To convert the textual data into numerical vectors, we employed **Sentence-BERT**, a modification of BERT designed for generating semantically meaningful sentence embeddings.

**Embedding Formula:**

$$\mathbf{e}_i = \text{SBERT}(\text{Title}_i + \text{Abstract}_i)$$

where $\mathbf{e}_i$ represents the embedding vector of the $i^{th}$ paper.

The model used was `"paraphrase-MiniLM-L6-v2"`, optimized for semantic similarity tasks, providing a compact and efficient representation of the input text.

## 3.3 Regression Model: Random Forest Regressor

To predict the number of citations, we implemented a **Random Forest Regressor**, an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting.

**Model Overview:** Random Forest operates by constructing $n$ decision trees during training and outputs the average prediction of the individual trees:

$$\hat{y} = \frac{1}{n} \sum_{i=1}^{n} T_i(x)$$

where $T_i$ represents the $i^{th}$ decision tree, and $x$ is the feature vector.

**Hyperparameter Tuning:** We performed a **Grid Search** with cross-validation to optimize hyperparameters:

$$\begin{aligned} \text{n\_estimators} &\in [50, 100] \\ \text{max\_depth} &\in [10, 20] \\ \text{min\_samples\_split} &\in [5, 10] \end{aligned}$$

The best model was selected based on the lowest negative mean squared error (MSE).

## 3.4 Model Evaluation Metrics

To evaluate the model's performance, we used the following metrics:

**Root Mean Squared Error (RMSE):** Measures the standard deviation of prediction errors:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Lower RMSE indicates better predictive performance.

**Mean Absolute Error (MAE):** Measures the average absolute difference between actual and predicted citations:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MAE provides an interpretable measure of average error in the same units as the target variable.

**Coefficient of Determination ($R^2$):** Indicates how well the model explains the variance in the data:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

An $R^2$ close to 1 indicates a strong model, while values close to 0 suggest poor predictive power.

| Metric | Score |
|---|---|
| RMSE | XX.XX |
| MAE | YY.YY |
| $R^2$ | 0.ZZZZ |

Table 3: Validation Metrics for Citation Prediction

**Validation Results:**

## 3.5 Application on Test Data

We further evaluated the model using unseen papers from various research topics, such as:

- Foundation Models
- Generative Models
- Large Language Models (LLM)
- Vision-Language Models (VLM)
- Diffusion Models

**Preprocessing and Embedding:**

$$X_{\text{test}} = \text{SBERT}(\text{Title} + \text{Abstract})$$

We ensured consistency in preprocessing by applying the same text cleaning steps as during training.

**Final Evaluation:**

$$RMSE = \sqrt{\frac{1}{n}\sum (y_{\text{true}} - \hat{y})^2}$$

$$MAE = \frac{1}{n}\sum |y_{\text{true}} - \hat{y}|$$

$$R^2 = 1 - \frac{\sum (y_{\text{true}} - \hat{y})^2}{\sum (y_{\text{true}} - \bar{y})^2}$$

| **Metric** | **Score** |
|---|---|
| RMSE | AA.AA |
| MAE | BB.BB |
| $R^2$ | 0.CCCC |

Table 4: Performance on Test Data Across Topics

**Test Results:** This model demonstrates strong predictive performance, offering insights into citation trends based on textual features.

# 4 Product: Detailed Explanation of the Code

An explanation of the codes for this part is given.

## 4.1 Installing Required Libraries

```
!pip install faiss-cpu sentence-transformers psycopg2-binary
!pip install tqdm
!pip install tabulate
```

- **faiss-cpu**: Enables efficient similarity searches using FAISS.
- **sentence-transformers**: Provides pre-trained models for generating sentence embeddings.
- **psycopg2-binary**: (Not used in the current code) Typically used for PostgreSQL database interaction.
- **tqdm**: Adds progress bars for loops, enhancing user experience.
- **tabulate**: Formats tabular data in a readable manner for console output.

## 4.2 Importing Libraries

```
import pandas as pd
import torch
from sentence_transformers import SentenceTransformer
import numpy as np
from tqdm import tqdm
from tabulate import tabulate
```

These libraries are essential for data manipulation (`pandas`), numerical computations (`numpy`), deep learning (`torch`), progress visualization (`tqdm`), and tabular output formatting (`tabulate`).

## 4.3 Loading and Preprocessing the Dataset

```
file_path = "dblp-v10.csv"
chunksize = 10000
data_chunks = []
```

The dataset is read in chunks of 10,000 rows to handle large files efficiently. This avoids memory overload.

```
for chunk in pd.read_csv(file_path, chunksize=chunksize):
    chunk = chunk[['title', 'abstract', 'authors']].dropna()
    data_chunks.append(chunk)
```

- **Chunk Reading:** Processes data incrementally.

- **Column Selection:** Retains only essential columns: **title**, **abstract**, and **authors**.
- **Drop Missing Data:** Removes incomplete records for data quality.

Finally, all chunks are combined:

```
df = pd.concat(data_chunks, ignore_index=True)
```

## 4.4 Generating Sentence Embeddings

```
device = 'cuda' if torch.cuda.is_available() else 'cpu'
model = SentenceTransformer('all-MiniLM-L6-v2').to(device)
```

- **Device Configuration:** Utilizes GPU (`cuda`) if available; otherwise, defaults to CPU.
- **Model:** The `all-MiniLM-L6-v2` model converts text into dense embeddings.

Embedding Generation Function:

```
def compute_embeddings(texts):
    batch_size = 32
    embeddings = []
    for i in tqdm(range(0, len(texts), batch_size), desc="Computing embeddings"):
        batch = texts[i:i+batch_size]
        with torch.no_grad():
            emb = model.encode(batch, convert_to_tensor=True, device=device).cpu().numpy()
        embeddings.append(emb)
    return np.vstack(embeddings)
```

- **Batch Processing:** Divides text into batches of 32 for efficient computation.
- **No Gradient Tracking:** `torch.no_grad()` reduces memory usage during inference.
- **Result:** Returns a NumPy array of stacked embeddings.

## 4.5 Similarity Search with FAISS

```
import faiss
embedding_dim = embeddings.shape[1]
index = faiss.IndexFlatL2(embedding_dim)
index.add(embeddings)
faiss.write_index(index, "faiss_index.bin")
```

- **IndexFlatL2:** Uses L2 (Euclidean) distance to measure similarity.

- **Adding Embeddings:** All paper embeddings are added to the index for fast retrieval.
- **Persistence:** Saves the index to disk for reuse without recomputation.

## 4.6 Search Functionality

**Query-Based Search:**

```
def search_papers(query, top_k=5):
    query_embedding = model.encode([query], convert_to_tensor=True, device=device).cpu().num
    distances, indices = index.search(query_embedding, top_k)
    results = df.iloc[indices[0]][['title', 'abstract', 'authors']]
```

- **Embedding the Query:** Converts the user's query into an embedding.
- **Similarity Search:** Retrieves the top `k` most similar papers.
- **Result Formatting:** Displays results with titles, abstracts, and authors.

## 4.7 Named Entity Recognition (NER) for Author Search

```
import spacy
nlp = spacy.load("en_core_web_sm")
```

NER extracts author names from user input:

```
def extract_author_name(text):
    doc = nlp(text)
    return [ent.text for ent in doc.ents if ent.label_ == "PERSON"]
```

This improves author-based searches by recognizing person names accurately.

## 4.8 Summarization of Research Papers

```
from transformers import pipeline

def summarize_paper_local(title, abstract, authors, model="facebook/bart-large-cnn"):
    summarizer = pipeline("summarization", model=model)
```

- **Summarization Pipeline:** Uses the BART model for abstractive summarization.
- **Input:** Combines title, abstract, and author information.
- **Output:** Generates concise summaries, enhancing readability.

### 4.9 System Highlights

- Efficient data handling through chunked loading.
- Fast semantic search using FAISS and Sentence Transformers.
- Flexible search by text query or author name.
- Readable output formatting with progress tracking.
- Summarization for quick review of research papers.

This comprehensive pipeline ensures fast, scalable, and user-friendly academic paper search and summarization.