Project Theme:

Understanding the Temporal Dynamics and Interdisciplinary Nature of Academic Collaborations in arXiv, with Predictive Modeling of Future Co-Authorships

```
import json
import networkx as nx
from tqdm import tqdm
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from collections import Counter

# Create one empty graph per year from 2000 to 2024
yearly_graphs = {year: nx.Graph() for year in range(2000, 2025)}
```

DELIVERABLE 1 : Temporal Evolution of the Co-Authorship Network

Objective

The goal of this deliverable is to analyze how the structure of academic collaboration has evolved over time in the arXiv repository. By modeling the co-authorship network as a graph for each year, we aim to understand trends in collaboration intensity, network connectivity, and structural complexity from 2000 to 2024.

Step 1: Parse arXiv JSON & Build Yearly Co-Authorship Graphs

```
# Adjust this path based on your notebook environment
file_path = '/kaggle/input/arxiv/arxiv-metadata-oai-snapshot.json'

# Limit lines to avoid memory overflow — 1 million is a good start
max_lines = 1_000_000

with open(file_path, 'r') as f:
    for i, line in enumerate(tqdm(f, total=max_lines)):
        if i >= max_lines:
            break
        try:
            entry = json.loads(line)
            year = int(entry['update_date'][:4])
            if year < 2000 or year > 2024:
                continue
```

```
            authors = [a.strip() for a in entry['authors'].split(',')
if a.strip()]
            if len(authors) > 30:
                continue  # Ignore mega-authored papers

            for i in range(len(authors)):
                for j in range(i + 1, len(authors)):
                    yearly_graphs[year].add_edge(authors[i],
authors[j])
        except:
            continue  # Skip corrupted lines
```

```
100%|██████████| 1000000/1000000 [00:45<00:00, 21891.58it/s]
```

Step 2: Compute Yearly Network Metrics (Nodes, Edges, Degree, Clustering, Density)

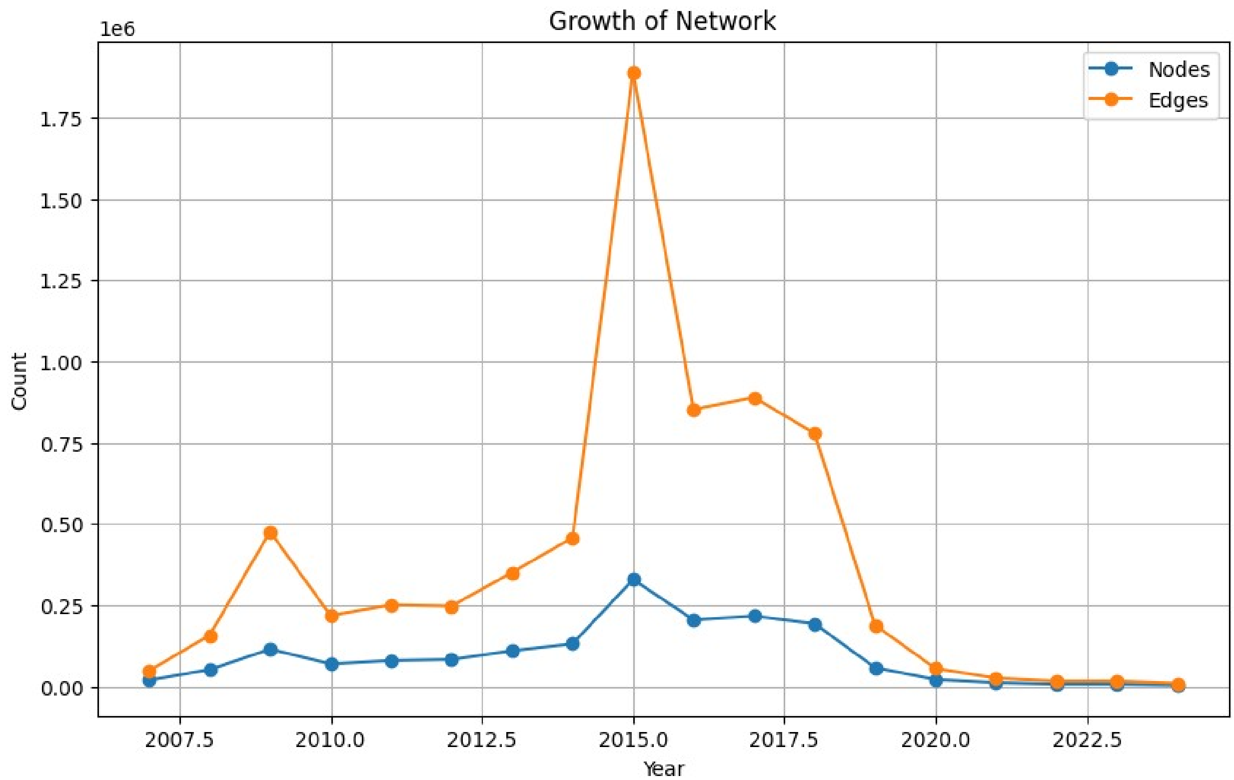
```
metrics = []

for year, G in yearly_graphs.items():
    N = G.number_of_nodes()
    E = G.number_of_edges()
    if N == 0:
        continue  # Skip empty years
    avg_deg = sum(dict(G.degree()).values()) / N
    clustering = nx.average_clustering(G)
    density = nx.density(G)

    metrics.append({
        "Year": year,
        "Nodes": N,
        "Edges": E,
        "Avg_Degree": avg_deg,
        "Clustering": clustering,
        "Density": density
    })

# Convert to DataFrame
df_metrics = pd.DataFrame(metrics)
df_metrics.set_index("Year", inplace=True)
df_metrics
```

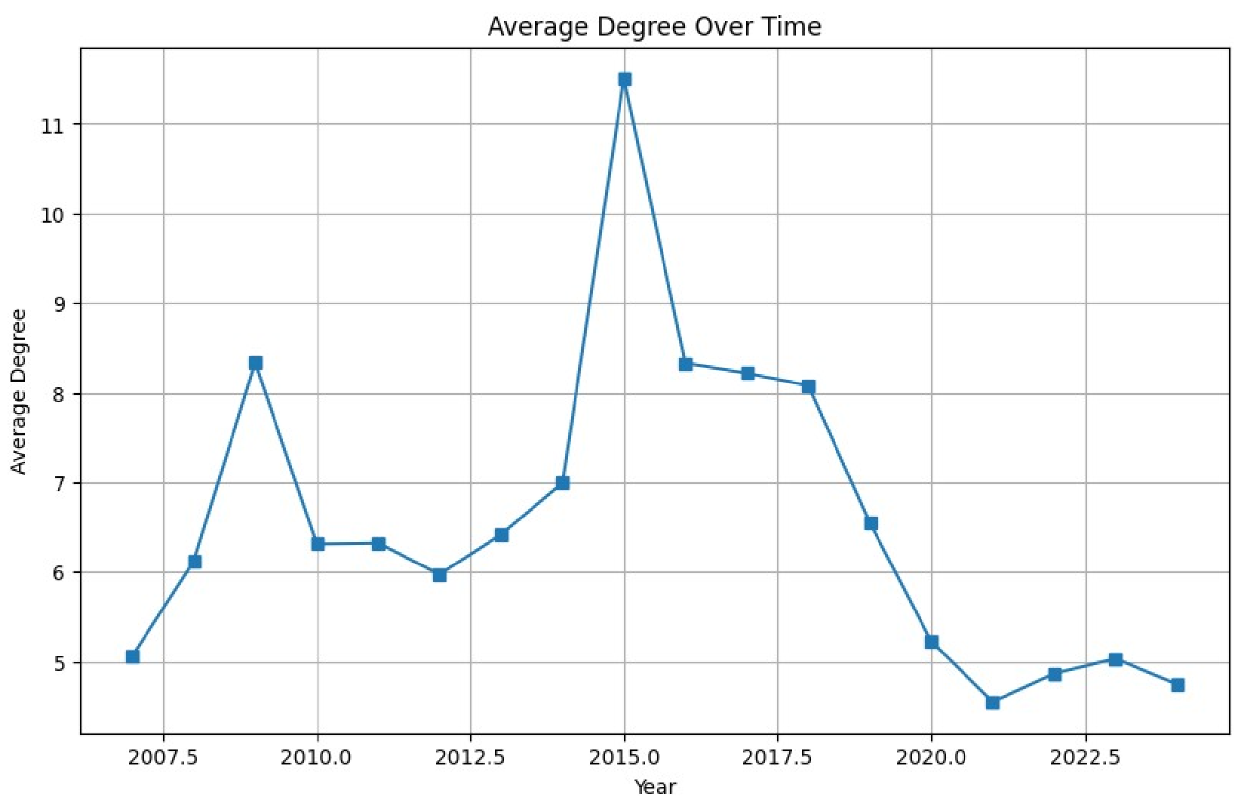
Year	Nodes	Edges	Avg_Degree	Clustering	Density
2007	18877	47791	5.063410	0.786365	0.000268
2008	51321	157105	6.122445	0.770875	0.000119
2009	114186	475811	8.333964	0.789424	0.000073
2010	68953	217652	6.313054	0.779095	0.000092
2011	79326	250825	6.323904	0.784444	0.000080
2012	82745	247151	5.973799	0.782368	0.000072

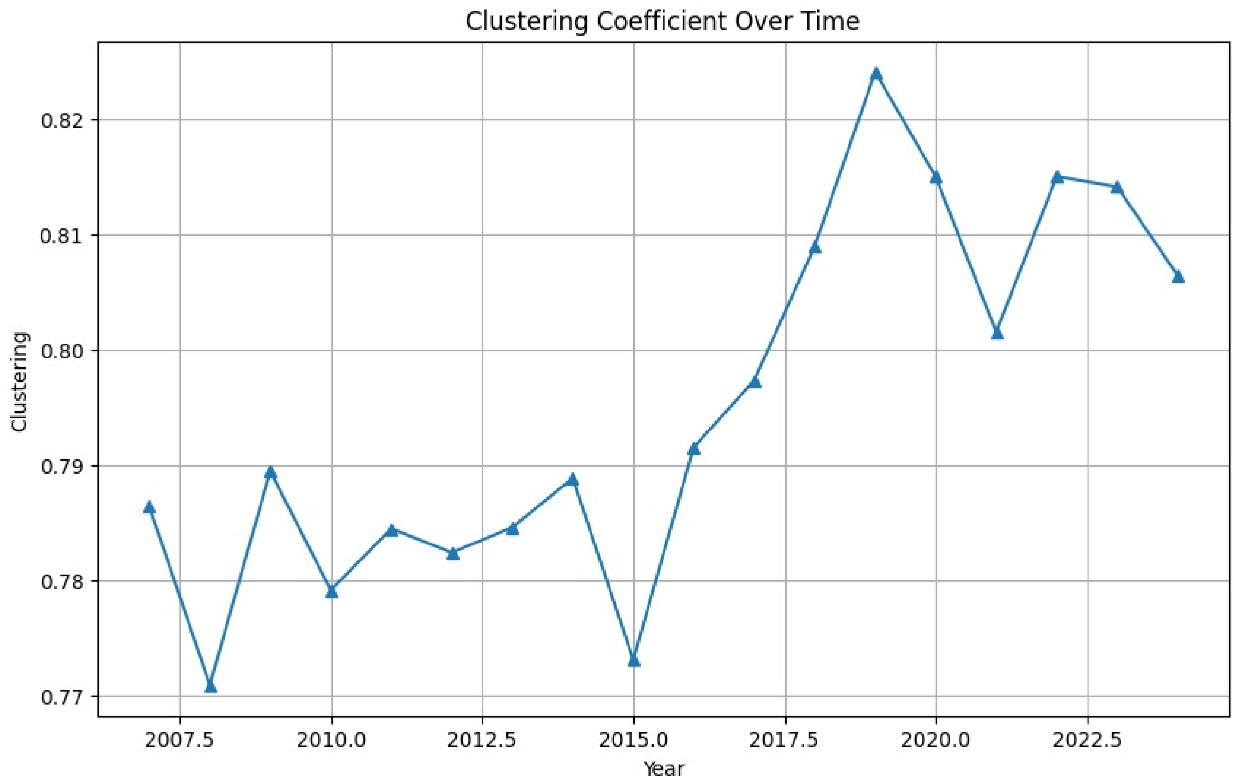
```
2013  109140   350224    6.417885    0.784544  0.000059
2014  130720   457104    6.993635    0.788815  0.000054
2015  328505  1890200   11.507892    0.773062  0.000035
2016  204539   852082    8.331731    0.791490  0.000041
2017  216256   888554    8.217612    0.797299  0.000038
2018  192694   778536    8.080542    0.808947  0.000042
2019   57430   188144    6.552116    0.824039  0.000114
2020   20934    54734    5.229197    0.814962  0.000250
2021   11130    25339    4.553279    0.801476  0.000409
2022    6568    15985    4.867540    0.814984  0.000741
2023    6469    16283    5.034163    0.814088  0.000778
2024    3779     8972    4.748346    0.806384  0.001257
```

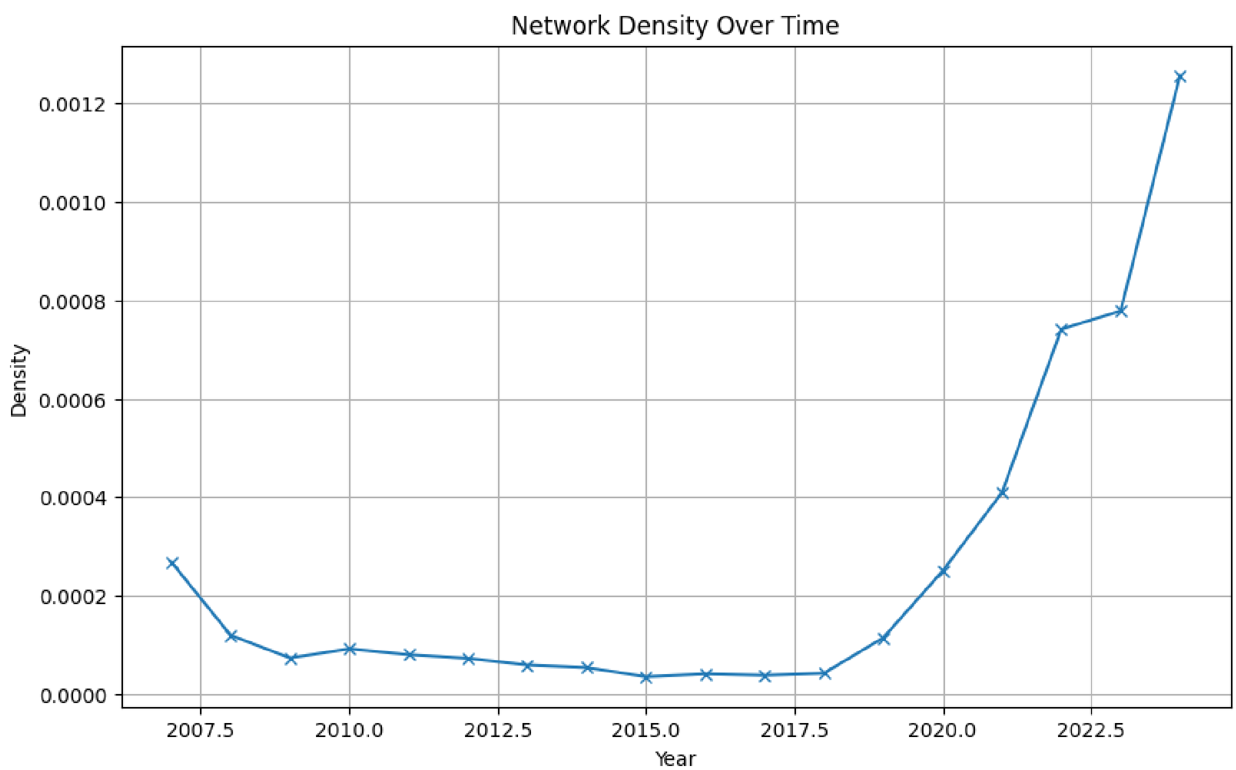
Step 3: Visualize Temporal Trends in Network Properties

```
df_metrics[['Nodes$', 'Edges']].plot(marker='o', figsize=(10,6),
title="Growth of Network")
plt.ylabel("Count")
plt.grid(True)
plt.show()

df_metrics['Avg_Degree'].plot(marker='s', figsize=(10,6),
title="Average Degree Over Time")
plt.ylabel("Average Degree")
plt.grid(True)
plt.show()

df_metrics['Clustering'].plot(marker='^', figsize=(10,6),
title="Clustering Coefficient Over Time")
plt.ylabel("Clustering")
plt.grid(True)
plt.show()

df_metrics['Density'].plot(marker='x', figsize=(10,6), title="Network
Density Over Time")
plt.ylabel("Density")
plt.grid(True)
plt.show()
```


Growth of Network
1e6
Nodes
Edges
Count
Year
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5


Average Degree Over Time
Average Degree
Year
5
6
7
8
9
10
11
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5


Clustering Coefficient Over Time
Clustering
Year
0.82
0.81
0.80
0.79
0.78
0.77
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5


Network Density Over Time
Density
Year
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5

Analysis of Co-authorship Network Evolution (2007–2024)

1. Growth of the Network (Nodes & Edges)

- From 2007 to 2015, the network saw a sharp increase in both nodes and edges, peaking in 2015.
- The number of edges in 2015 crossed 1.8 million, with over 328,000 nodes, indicating a dramatic spike in collaborative publications that year.
- Post-2015, there's a noticeable decline, especially from 2019 onward, which could reflect incomplete data, changes in authoring patterns, or evolving publication norms.
- The sharp fall in 2020–2024 may also be affected by fewer entries in the metadata or a lag in dataset updates.

2. Average Degree Over Time

- The average degree (i.e., the number of co-authors per author) peaked in 2015, aligning with the spike in node and edge counts.
- After 2015, the average degree steadily declined, reaching its lowest in 2021, indicating smaller collaborative teams or reduced connectivity in recent years.
- This suggests that although collaboration was high mid-decade, recent papers involve fewer co-authors per author.

3. Clustering Coefficient Over Time

- The clustering coefficient remained relatively stable until 2015, after which it increased gradually, peaking around 2019–2020.
- A higher clustering coefficient in later years implies more tight-knit collaborations, where authors frequently co-publish with shared partners.
- This may reflect a trend toward more specialized or interdisciplinary groups working closely together rather than broad, dispersed collaborations.

4. Network Density Over Time

- Network density was extremely low throughout the high-growth years (e.g., 2010–2016), due to the massive size of the network.
- However, post-2020, as node and edge counts fell, density increased significantly, peaking in 2024.
- This increase indicates that while fewer authors are publishing, they are more densely interconnected, likely working within established, smaller research communities.

Final Understanding

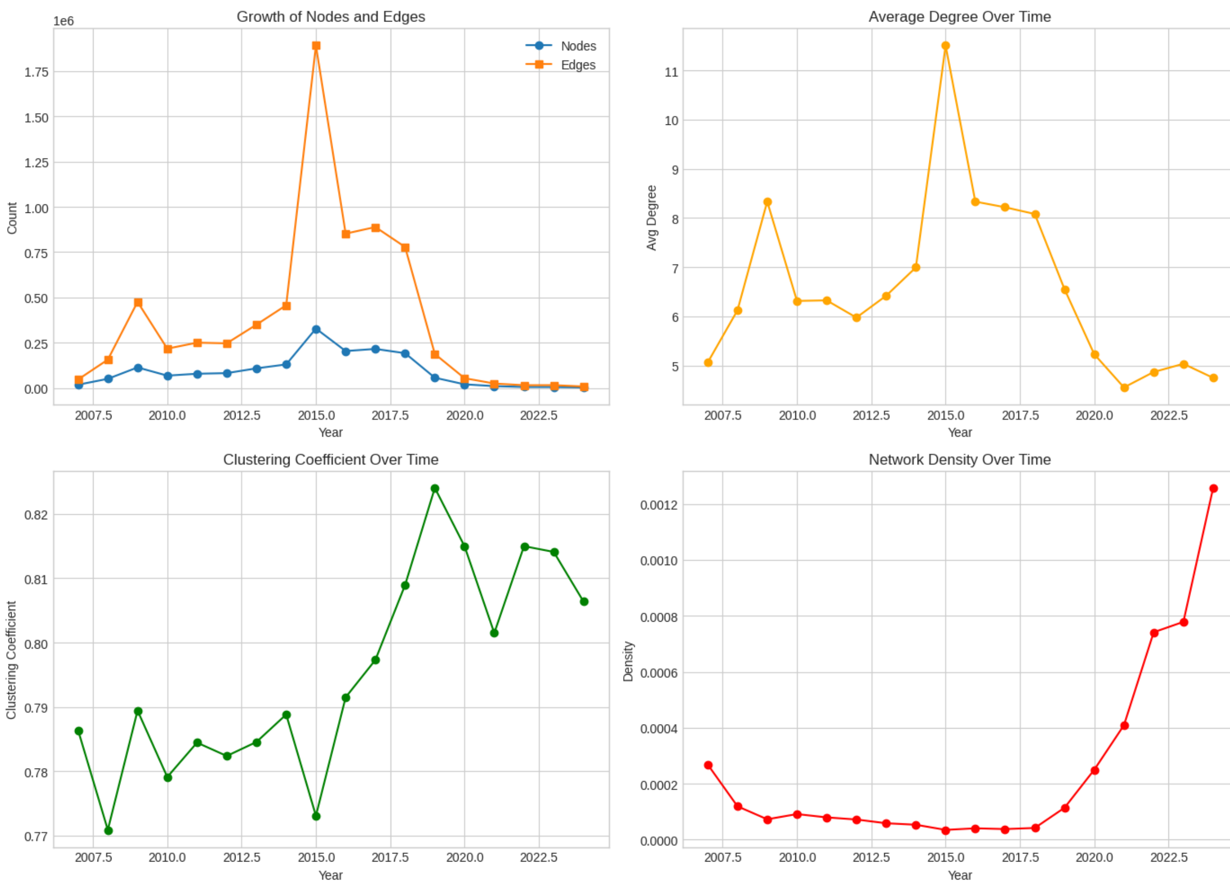
- 2015 was a landmark year for collaboration in the dataset, possibly due to large-scale projects or special publication campaigns.
- The post-2019 decline may not reflect actual drops in research but could point to incomplete metadata or lag in dataset updates.
- Recent years show tighter-knit collaborations, with fewer authors but more connected relationships—suggesting a shift toward intensive, team-based research rather than broad co-authorship networks.

Visualizing Co-authorship Network Evolution (2007–2024)

```python
import matplotlib.pyplot as plt

# Set figure style
plt.style.use('seaborn-whitegrid')
fig, axs = plt.subplots(2, 2, figsize=(14, 10))
df_metrics.sort_index(inplace=True)

# Plot 1: Number of Nodes and Edges
axs[0, 0].plot(df_metrics.index, df_metrics["Nodes"], marker='o',
label="Nodes")
axs[0, 0].plot(df_metrics.index, df_metrics["Edges"], marker='s',
label="Edges")
axs[0, 0].set_title("Growth of Nodes and Edges")
axs[0, 0].set_xlabel("Year")
axs[0, 0].set_ylabel("Count")
axs[0, 0].legend()

# Plot 2: Average Degree
axs[0, 1].plot(df_metrics.index, df_metrics["Avg_Degree"],
color='orange', marker='o')
axs[0, 1].set_title("Average Degree Over Time")
axs[0, 1].set_xlabel("Year")
axs[0, 1].set_ylabel("Avg Degree")

# Plot 3: Clustering Coefficient
axs[1, 0].plot(df_metrics.index, df_metrics["Clustering"],
color='green', marker='o')
axs[1, 0].set_title("Clustering Coefficient Over Time")
axs[1, 0].set_xlabel("Year")
axs[1, 0].set_ylabel("Clustering Coefficient")

# Plot 4: Density
axs[1, 1].plot(df_metrics.index, df_metrics["Density"], color='red',
marker='o')
axs[1, 1].set_title("Network Density Over Time")
axs[1, 1].set_xlabel("Year")
axs[1, 1].set_ylabel("Density")
```

```
plt.tight_layout()
plt.show()
```

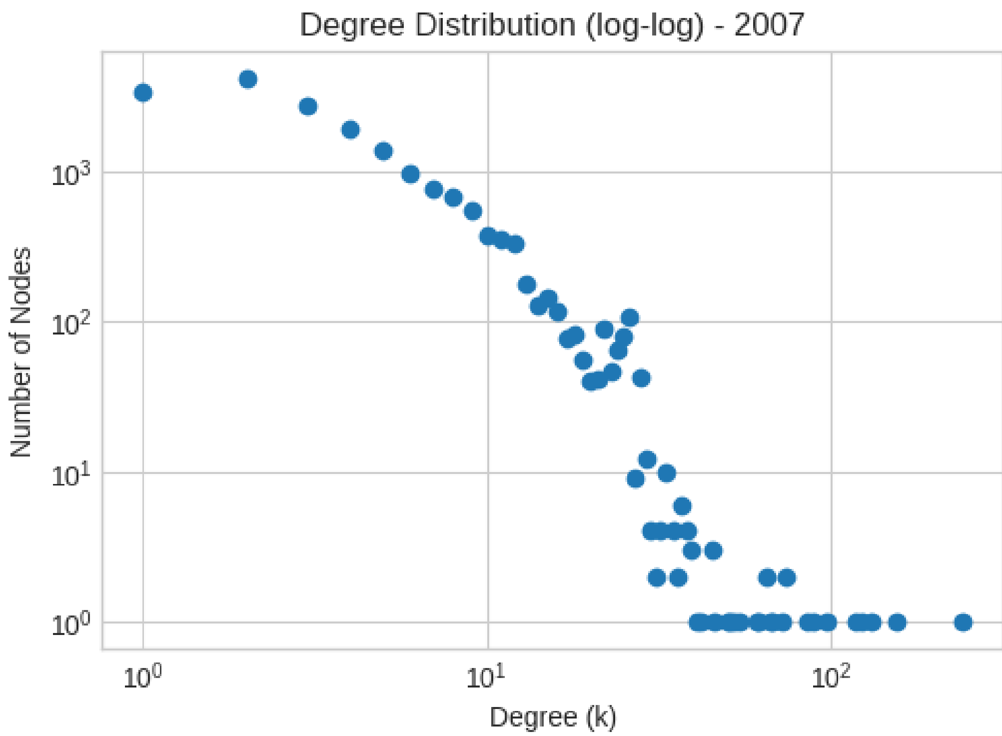
```
/tmp/ipykernel_31/2529320807.py:4: MatplotlibDeprecationWarning: The
seaborn styles shipped by Matplotlib are deprecated since 3.6, as they
no longer correspond to the styles shipped by seaborn. However, they
will remain available as 'seaborn-v0_8-<style>'. Alternatively,
directly use the seaborn API instead.
  plt.style.use('seaborn-whitegrid')
```

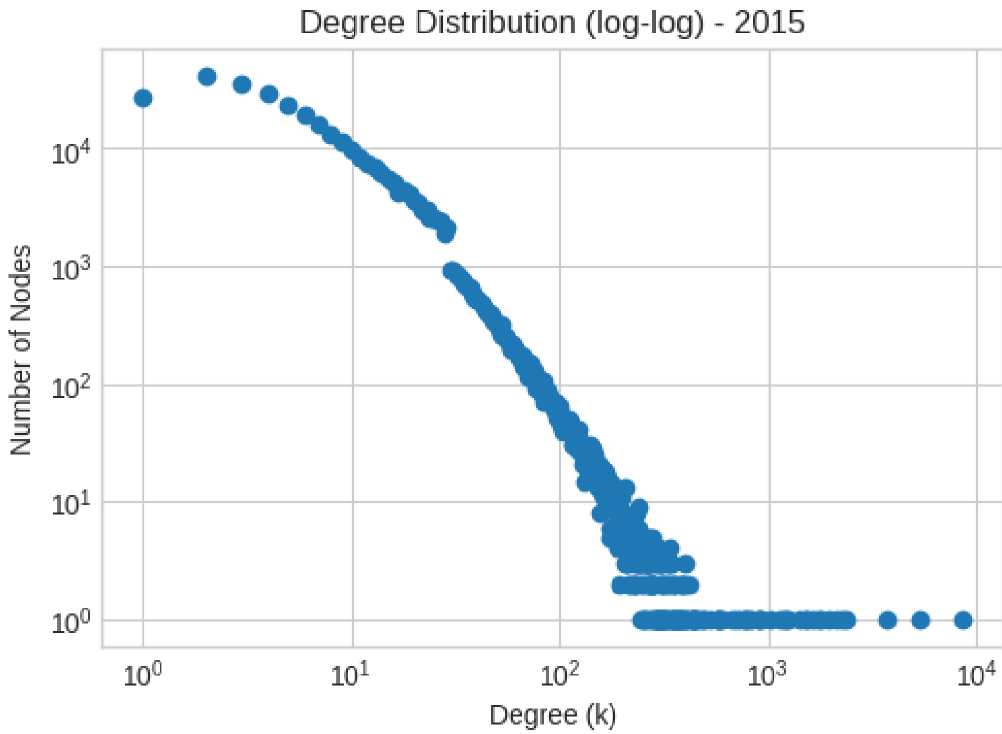


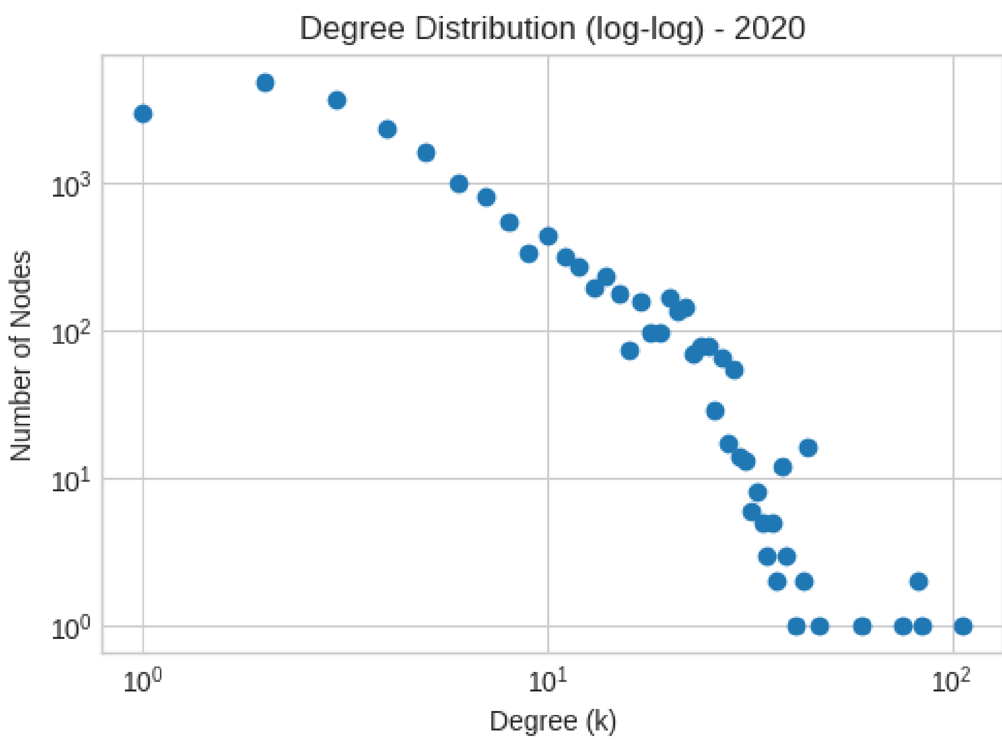
Log-Log Degree Distribution Plot for Selected Years

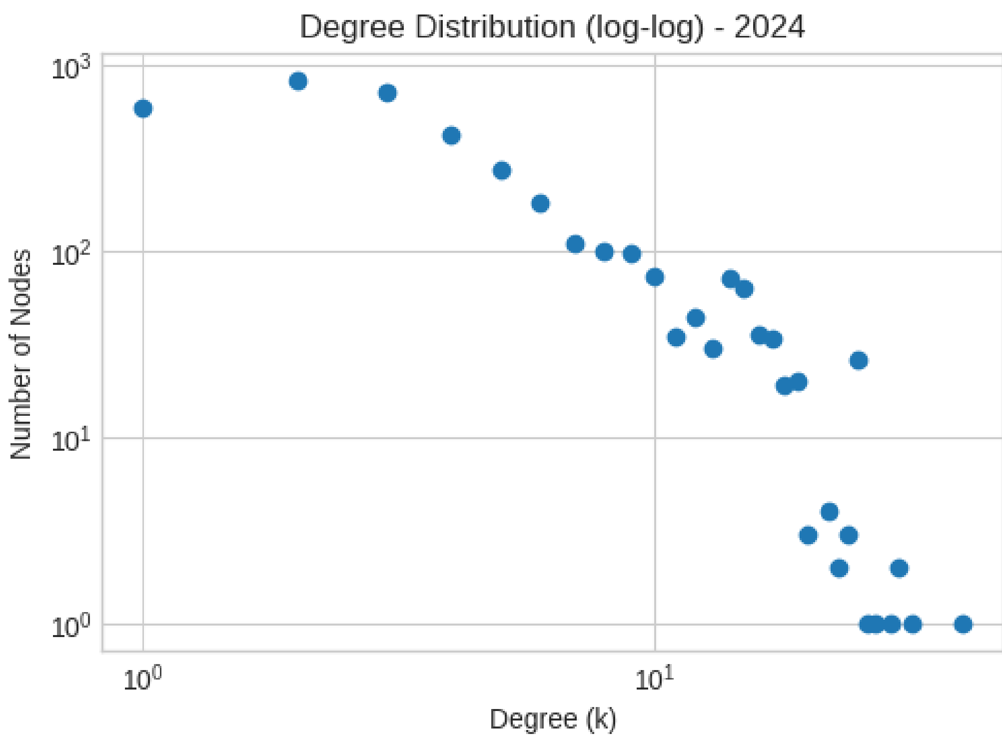
```python
import numpy as np

# Choose representative years
years_to_plot = [2007, 2015, 2020, 2024]

for year in years_to_plot:
    G = yearly_graphs[year]
    degrees = [d for _, d in G.degree()]
    degree_counts = np.bincount(degrees)
    nonzero_degrees = np.nonzero(degree_counts)[0]
```

```
    plt.figure(figsize=(6, 4))
    plt.loglog(nonzero_degrees, degree_counts[nonzero_degrees],
marker='o', linestyle='None')
    plt.title(f"Degree Distribution (log-log) - {year}")
    plt.xlabel("Degree (k)")
    plt.ylabel("Number of Nodes")
    plt.grid(True)
    plt.show()
```




Degree Distribution (log-log) - 2015
Number of Nodes
Degree (k)
10^0
10^1
10^2
10^3
10^4


Degree Distribution (log-log) - 2020
Number of Nodes
Degree (k)
10^0
10^1
10^2
10^3



Understanding from the Plots (Log-Log Degree Distribution)

Graph 1 - 2007:

- The plot shows a long-tailed distribution — most nodes have a low degree, but a few have significantly higher degrees.
- Indicates a scale-free structure early in the network's life.

Graph 2 - 2015:

- The most pronounced power-law-like behavior is seen here.
- The tail is longer, indicating the presence of many high-degree nodes (likely hubs).
- The steep slope and straight-line pattern on the log-log plot strongly support a scale-free network structure.

Graph 3 - 2020:

- Still follows a power-law, but the range of degrees has compressed due to a drop in network size (pandemic-era dip).
- Fewer high-degree nodes, possibly indicating fewer collaborations or fewer papers during this time.

Graph 4 - 2024:

- Very few nodes and degrees due to recency.

- Still shows the long-tail pattern but is sparser, and deviation from the ideal power-law shape is visible due to insufficient data.

Final Understanding

These log-log degree distribution plots validate that the collaboration network across years generally exhibits scale-free properties, especially in its most active periods (e.g., 2015). Such networks are resilient to random failures but vulnerable to targeted attacks on hubs — a common trait in real-world complex systems like citation and collaboration networks.

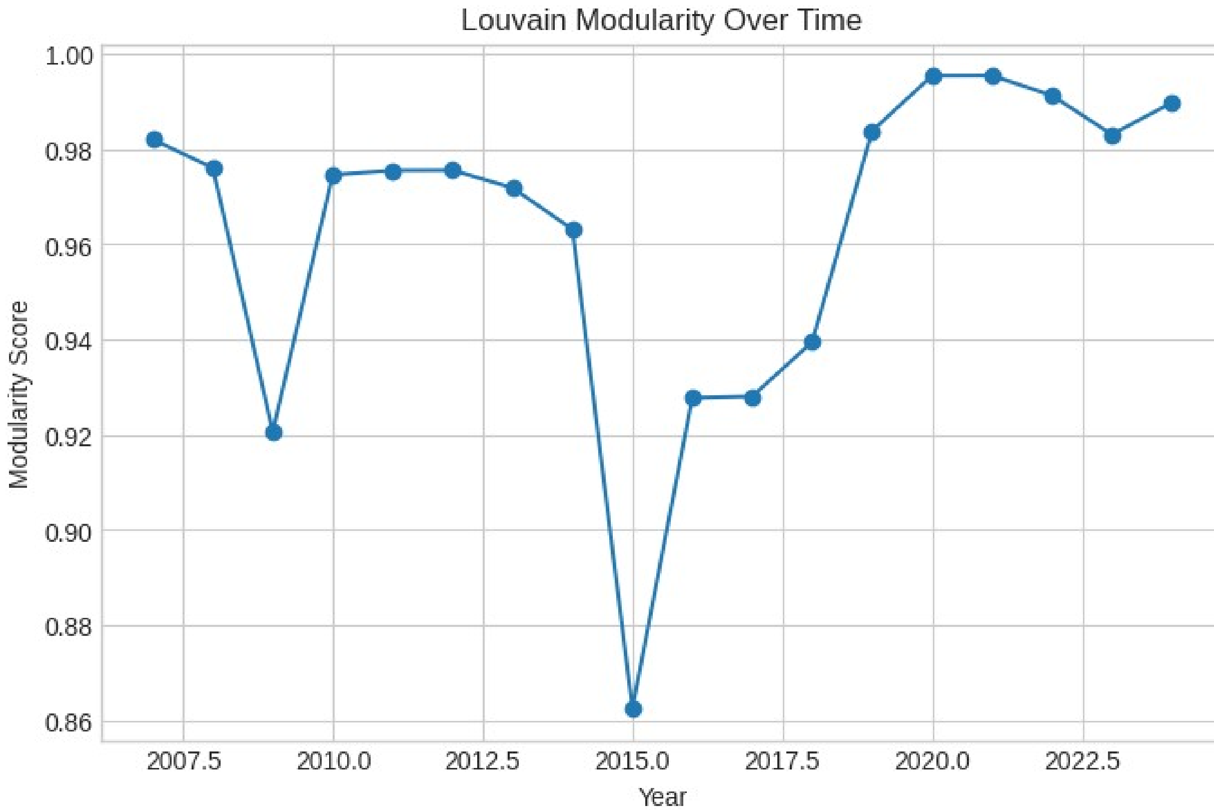
Louvain Community Detection and Modularity Analysis (Per Year)

```python
import community.community_louvain as community_louvain
from collections import Counter
import matplotlib.pyplot as plt
from tqdm import tqdm

modularity_per_year = {}
num_communities_per_year = {}
community_size_distributions = {}

# Iterate over each year's graph
for year in tqdm(sorted(yearly_graphs.keys())):
    G_year = yearly_graphs[year]

    if G_year.number_of_nodes() < 100:  # Skip small graphs
        continue

    # Apply Louvain
    partition = community_louvain.best_partition(G_year)

    # Store modularity
    communities = {}
    for node, comm_id in partition.items():
        communities.setdefault(comm_id, set()).add(node)
    community_list = list(communities.values())

    modularity = nx.algorithms.community.modularity(G_year,
community_list)
    modularity_per_year[year] = modularity
    num_communities_per_year[year] = len(community_list)

    # Store community size distribution
    sizes = list(Counter(partition.values()).values())
    community_size_distributions[year] = sizes
```

```
100%|██████████| 25/25 [12:31<00:00, 30.07s/it]
```

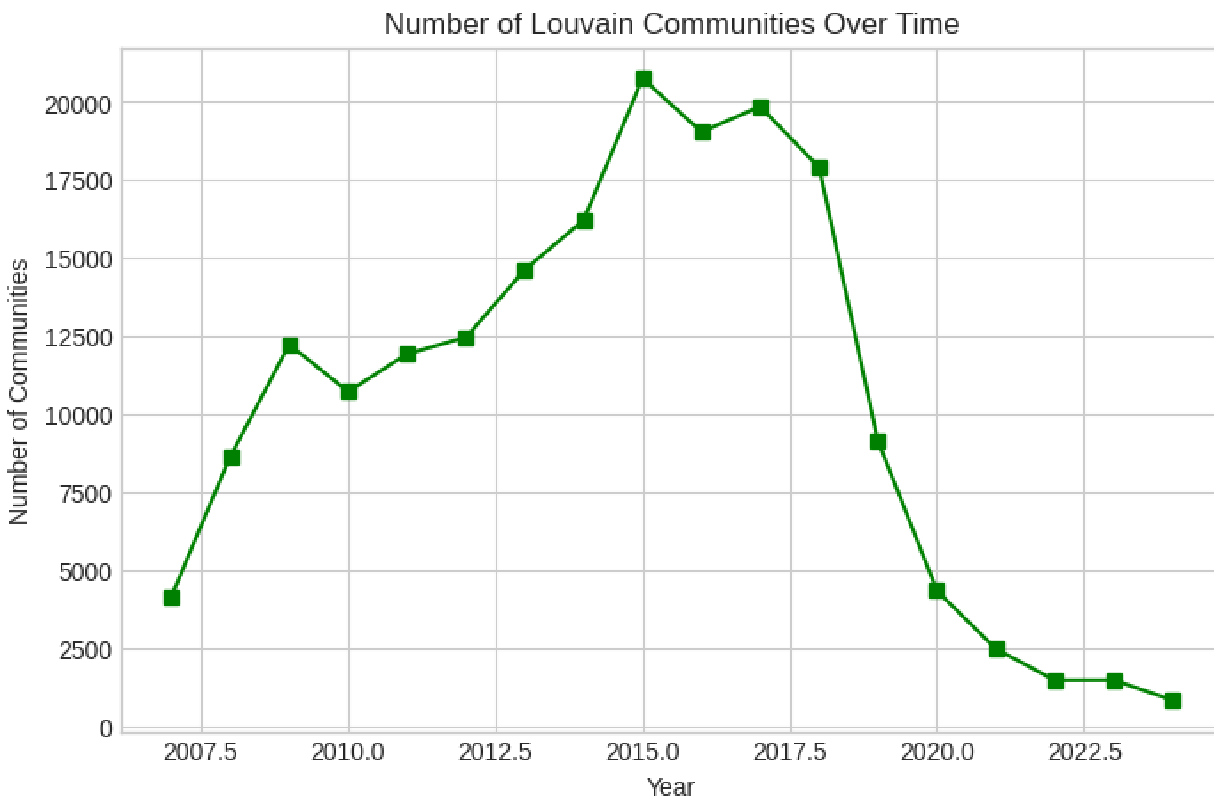
```python
plt.figure(figsize=(8, 5))
plt.plot(modularity_per_year.keys(), modularity_per_year.values(),
marker='o')
```

```
plt.title("Louvain Modularity Over Time")
plt.xlabel("Year")
plt.ylabel("Modularity Score")
plt.grid(True)
plt.show()
```



- The modularity remains high (~0.97–0.99) for most years, indicating strong community structure.
- A sharp dip in 2015 (~0.86) suggests a breakdown in clear community boundaries that year.
- The rise post-2016 may imply more distinct collaborative clusters returning or smaller isolated communities becoming more pronounced.

```
plt.figure(figsize=(8, 5))
plt.plot(num_communities_per_year.keys(),
num_communities_per_year.values(), marker='s', color='green')
plt.title("Number of Louvain Communities Over Time")
plt.xlabel("Year")
plt.ylabel("Number of Communities")
plt.grid(True)
plt.show()
```



- There's a steady rise in the number of communities from 2007 to 2016, peaking at over 20,000.
- Post-2017, there's a sharp decline, reaching under 2,000 communities by 2024.
- This could suggest reduced diversity or fragmentation in collaborations, possibly due to fewer active researchers or more tightly-knit author groups in recent years.

Final Understanding

- 2015 is a clear anomaly, seen in both modularity and community count — likely caused by a surge in publications with many co-authors, weakening modular boundaries.
- Post-2020, a high modularity despite fewer communities suggests smaller but well-separated collaboration groups.
- The evolving structure of co-authorship reflects changes in how research is conducted — from diverse, expansive collaborations toward possibly tighter or more siloed communities.

Community Size Distribution Heatmap (Louvain)

```
import pandas as pd
import numpy as np
```

```python
# Define bins and labels
bins = [0, 5, 10, 20, 50, 100, 200, np.inf]
labels = ["1–5", "6–10", "11–20", "21–50", "51–100", "101–200",
"200+"]

# Prepare heatmap data
heatmap_data = {}

for year, sizes in community_size_distributions.items():
    counts = pd.cut(sizes, bins=bins,
labels=labels).value_counts().sort_index()
    heatmap_data[year] = counts

# Convert to DataFrame
df_heatmap = pd.DataFrame(heatmap_data).fillna(0).astype(int)
df_heatmap = df_heatmap.T  # Years as rows

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
sns.heatmap(df_heatmap.T, cmap="YlGnBu", annot=True, fmt="d",
linewidths=0.5)
plt.title("Community Size Distribution Over Time (Louvain)")
plt.xlabel("Year")
plt.ylabel("Community Size Bin")
plt.tight_layout()
plt.show()
```

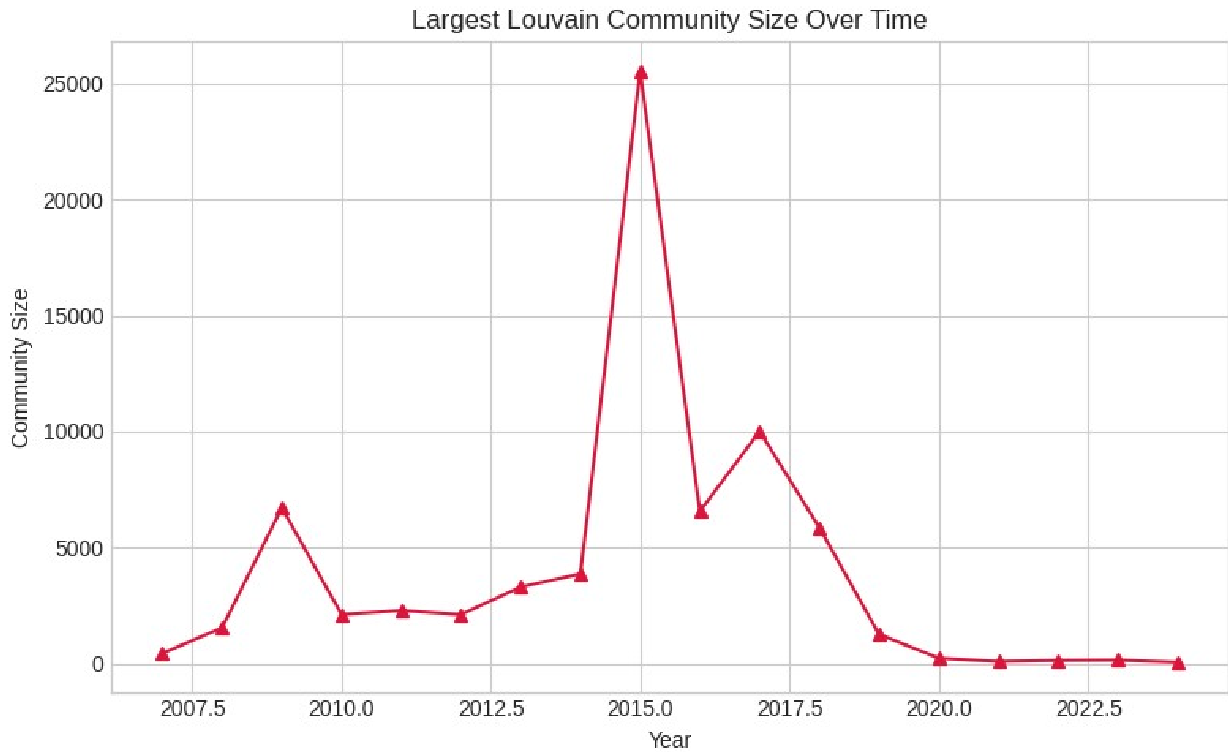
Final Understanding

- The collaboration structure of academic publishing (as captured via co-authorship networks) was highly modular with many small, tight-knit communities, especially around 2015–2017.
- Post-2018, there's a noticeable fragmentation and shrinking of community sizes, signaling a change in the collaboration dynamics—likely due to fewer active authors, tighter niche groups, or external disruptions (e.g., COVID-19).
- Overall, the network evolves from large, dense clusters to sparse, fragmented groups in recent years.

Largest Louvain Community Size Over Time

```
# Extract largest community size per year
largest_community_per_year = {
    year: max(sizes) for year, sizes in
community_size_distributions.items()
}

# Plot
plt.figure(figsize=(8, 5))
plt.plot(
    largest_community_per_year.keys(),
    largest_community_per_year.values(),
```

```
    marker='^',
    linestyle='-',
    color='crimson'
)
plt.title("Largest Louvain Community Size Over Time")
plt.xlabel("Year")
plt.ylabel("Community Size")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Final Understanding

- 2015 likely represents a critical structural transition in the network — possibly due to merging of communities or dataset anomalies (e.g., bulk upload, change in collaboration structure).
- Post-2018, the fragmentation of the network is clear — no dominant clusters, lower cohesion, and decentralization of research communities.
- This matches the trend observed in modularity (dip in 2015) and density/average degree (fall after 2015).

DELIVERABLE 2 : Interdisciplinarity in Co-Authorship Patterns

Objective

To quantify and analyze the degree of interdisciplinarity in the arXiv co-authorship network by using subject categories as proxies for academic fields.

Parse Authors and Categories

```
from collections import defaultdict
import json
from tqdm import tqdm

# Use parsed authors for clean name extraction
def get_full_author_names(entry):
    names = []
    for a in entry.get('authors_parsed', []):
        if len(a) >= 2:
            full_name = a[1].strip() + " " + a[0].strip()
            names.append(full_name)
    return names

# Dictionary: author → set of unique categories (fields)
author_fields = defaultdict(set)

file_path = '/kaggle/input/arxiv/arxiv-metadata-oai-snapshot.json'

with open(file_path, 'r') as f:
    for line in tqdm(f, total=2716679):
        try:
            entry = json.loads(line)
            categories = entry['categories'].split()  # e.g., 
["cs.LG", "stat.ML"]
            authors = get_full_author_names(entry)
            for author in authors:
                author_fields[author].update(categories)
        except:
            continue

print(f"Total unique authors: {len(author_fields)}")
```

```
2720631it [01:26, 31518.93it/s]
```

```
Total unique authors: 1790103
```

Compute Entropy per Author

```
import numpy as np

def compute_entropy(categories):
    probs = np.ones(len(categories)) / len(categories)  # Uniform distribution
    return -np.sum(probs * np.log2(probs))

# Dictionary: author → entropy score
author_entropy = {}

for author, fields in author_fields.items():
    if len(fields) > 1:  # Entropy not defined for single-field authors
        author_entropy[author] = compute_entropy(fields)

# Sort by highest entropy
top_interdisciplinary = sorted(author_entropy.items(), key=lambda x: x[1], reverse=True)[:20]

# Display top results
print("Top Interdisciplinary Authors (by Entropy):")
for author, score in top_interdisciplinary:
    print(f"{author}: {score:.4f}")
```

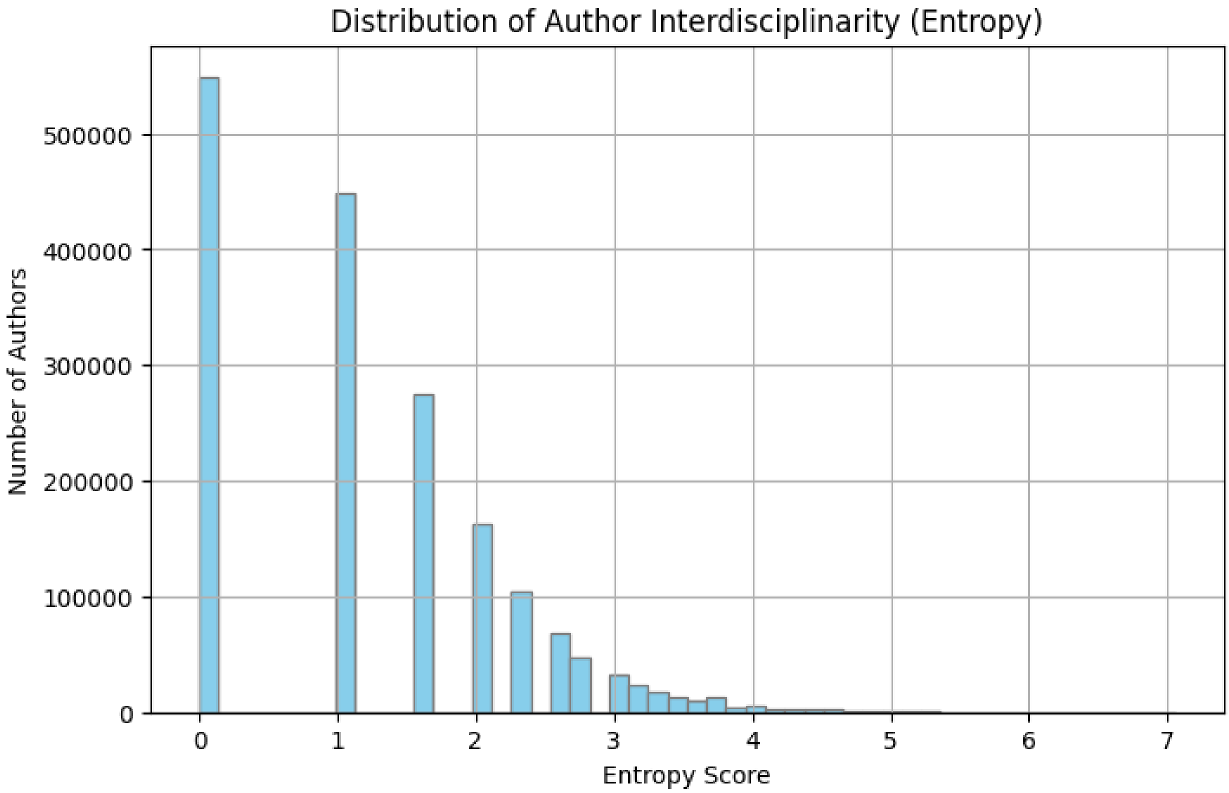
```
Top Interdisciplinary Authors (by Entropy):
Wei Wang: 7.0553
Yang Liu: 6.9425
Xin Li: 6.9189
Wei Zhang: 6.8948
Wei Li: 6.8826
Yang Li: 6.8826
Wei Chen: 6.8704
Yu Zhang: 6.8580
Jun Wang: 6.8329
Yi Zhang: 6.8202
Yu Wang: 6.8074
Lei Zhang: 6.8074
Jun Zhang: 6.7944
Bo Li: 6.7944
Wei Liu: 6.7814
Hui Li: 6.7415
Lei Wang: 6.7415
Xi Chen: 6.7279
Xiang Li: 6.7279
Yu Chen: 6.7142
```

```
import numpy as np

def compute_entropy(field_set):
```

```
    total = len(field_set)
    if total == 0:
        return 0
    prob = 1 / total
    return -total * prob * np.log2(prob)

# Compute entropy for each author
entropy_scores = {}
for author, fields in author_fields.items():
    entropy_scores[author] = compute_entropy(fields)
```

These functions compute the Shannon entropy of category distributions per author. Entropy is used as a proxy for interdisciplinarity — higher entropy means the author has published in multiple distinct fields (more diverse), while lower entropy implies specialization.

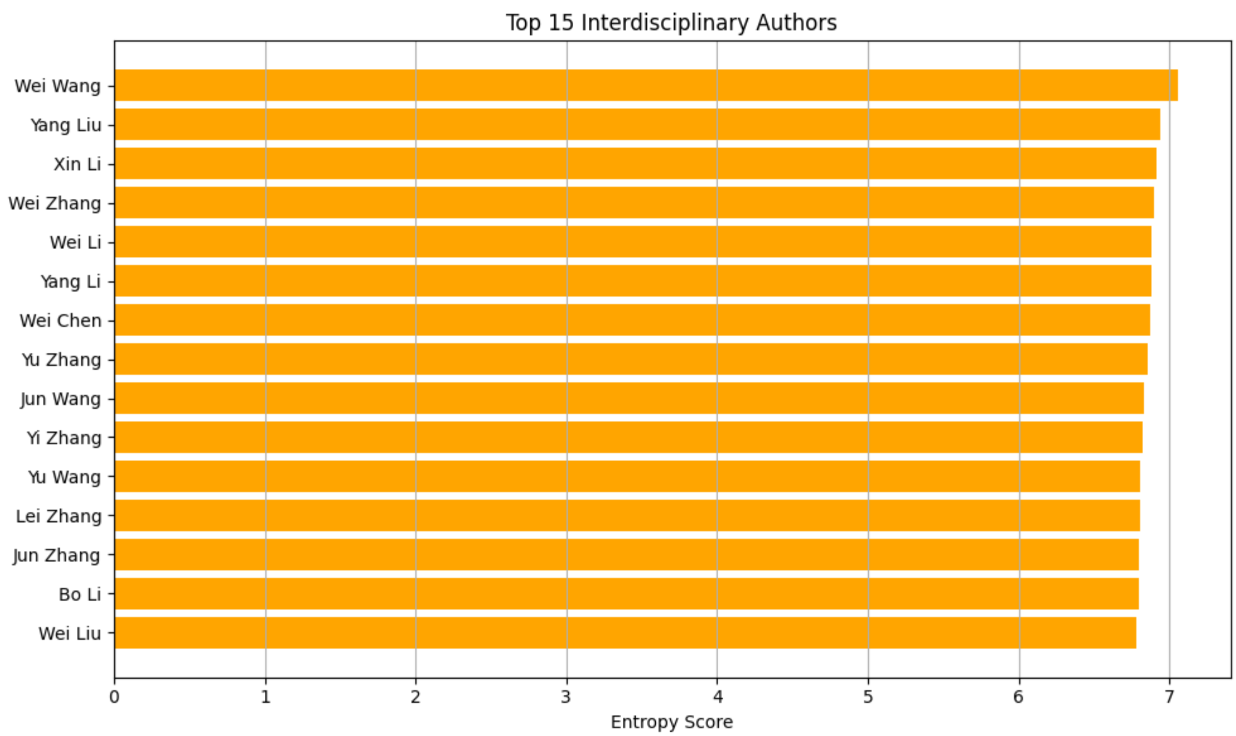
```
import matplotlib.pyplot as plt

# Entropy list (already computed previously)
entropy_values = list(entropy_scores.values())

plt.figure(figsize=(8, 5))
plt.hist(entropy_values, bins=50, color='skyblue', edgecolor='gray')
plt.xlabel("Entropy Score")
plt.ylabel("Number of Authors")
plt.title("Distribution of Author Interdisciplinarity (Entropy)")
plt.grid(True)
plt.show()
```



This histogram visualizes the distribution of interdisciplinarity scores across authors. Most authors have low to moderate entropy, indicating that while many collaborate across fields, true interdisciplinarity (high entropy) is relatively rare. This reflects a mix of specialists and generalists in the academic ecosystem.

Top Interdisciplinary Authors

```
top_entropy = sorted(entropy_scores.items(), key=lambda x: x[1],
reverse=True)[:15]
names = [author for author, _ in top_entropy]
scores = [score for _, score in top_entropy]

plt.figure(figsize=(10, 6))
plt.barh(names[::-1], scores[::-1], color='orange')
plt.xlabel("Entropy Score")
plt.title("Top 15 Interdisciplinary Authors")
plt.grid(True, axis='x')
plt.tight_layout()
plt.show()
```

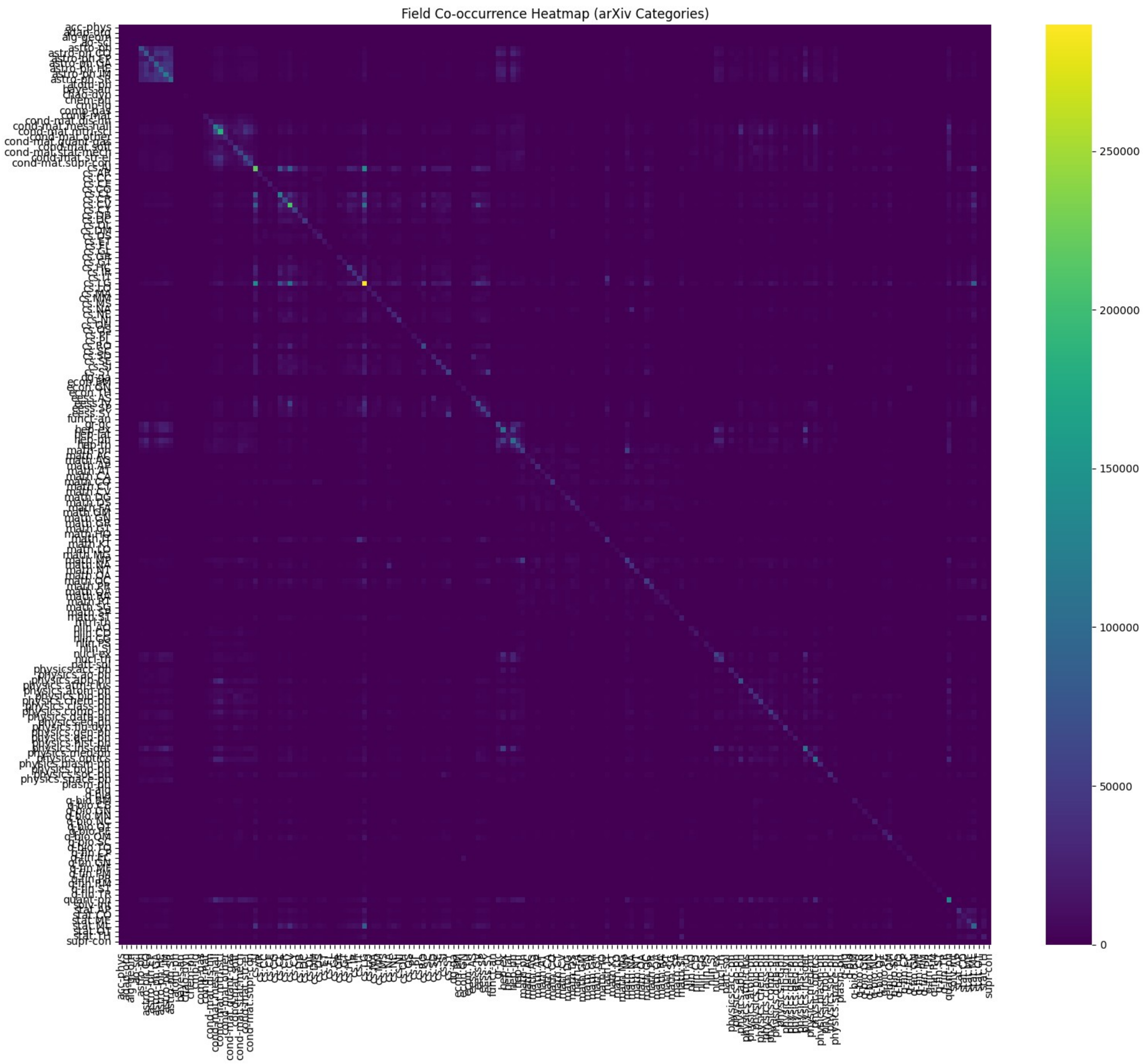


This block ranks authors by their entropy scores to identify the most interdisciplinary researchers. These individuals likely collaborate across diverse domains, playing key roles as bridges in the academic network.

Field Co-Occurrence Heatmap Construction

```
from collections import Counter
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Step 1: Count category co-occurrences (including diagonals)
co_occurrence = Counter()

for fields in author_fields.values():
    fields = list(fields)
    for i in range(len(fields)):
        for j in range(i, len(fields)):  # include diagonals
            pair = tuple(sorted([fields[i], fields[j]]))
            co_occurrence[pair] += 1

# Step 2: Create a list of unique categories
categories = sorted({cat for pair in co_occurrence for cat in pair})

# Step 3: Create co-occurrence matrix
matrix = np.zeros((len(categories), len(categories)))
```

```python
cat_to_idx = {cat: i for i, cat in enumerate(categories)}

for (cat1, cat2), count in co_occurrence.items():
    i, j = cat_to_idx[cat1], cat_to_idx[cat2]
    matrix[i, j] = count
    matrix[j, i] = count  # symmetry

# Step 4: Visualize as heatmap
plt.figure(figsize=(16, 14))
sns.heatmap(matrix, xticklabels=categories, yticklabels=categories,
cmap='viridis', norm=None)
plt.title("Field Co-occurrence Heatmap (arXiv Categories)")
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



Interpretation

- The bright diagonal indicates that most authors consistently publish within their primary field — an expected result.
- Visible off-diagonal hotspots (brighter patches off the diagonal) show strong co-occurrence between:
  - cs.AI, cs.LG, and stat.ML — indicative of tight integration in machine learning and artificial intelligence research.
  - Certain combinations within physics subfields (cond-mat, hep-th, gr-qc) also show strong internal overlap.
- Sparse regions represent siloed disciplines, where authors rarely publish across boundaries.

Insight

This heatmap reveals the structural backbone of interdisciplinary publishing on arXiv. Fields that frequently co-occur may be:

- Natural collaborators
- Candidates for joint research programs
- Critical junctions for innovation across domains

```
from collections import defaultdict, Counter
import pandas as pd
import matplotlib.pyplot as plt
from tqdm import tqdm

# --- Step 1: Choose year and load graph ---
year = 2015
G = yearly_graphs[year].copy()

# --- Step 2: Assign dominant field to each author ---
def get_dominant_field(author):
    fields = list(author_fields.get(author, []))
    return fields[0] if fields else "Unknown"

for node in G.nodes():
    G.nodes[node]["field"] = get_dominant_field(node)

# --- Step 3: Compute neighbor field diversity ---
bridge_scores = []

for node in G.nodes():
    neighbor_fields = [G.nodes[nbr].get("field", "Unknown") for nbr in
G.neighbors(node)]
    diversity = len(set(neighbor_fields))
    own_field = G.nodes[node]["field"]
    bridge_scores.append({
        "Author": node,
        "Field": own_field,
        "Neighbor_Field_Diversity": diversity,
        "Degree": G.degree(node)
    })

df_diversity = pd.DataFrame(bridge_scores)
df_diversity = df_diversity.sort_values(by="Neighbor_Field_Diversity",
ascending=False)

# --- Step 4: Display top interdisciplinary bridge authors ---
print("Top Interdisciplinary Bridge Authors (by neighbor field
diversity):")
print(df_diversity.head(10))
```

```
Top Interdisciplinary Bridge Authors (by neighbor field diversity):
           Author                 Field  Neighbor_Field_Diversity  Degree
9077       Wei Li              q-fin.GN                        46     256
14203  Jian Wang                math.GT                        42     194
13473        Jr.                Unknown                        42     420
5340   Jing Wang  cond-mat.mes-hall                        41     283
4362   Wei Zhang              q-fin.GN                        40     198
33071   Wei Chen                  cs.CC                        39     151
39581     J. Liu                eess.IV                        39     305
13596   Wei Wang                math.GT                        38     132
30650    Xi Chen              q-fin.GN                        38     250
10171      Y. Li                  cs.DC                        36     242
```

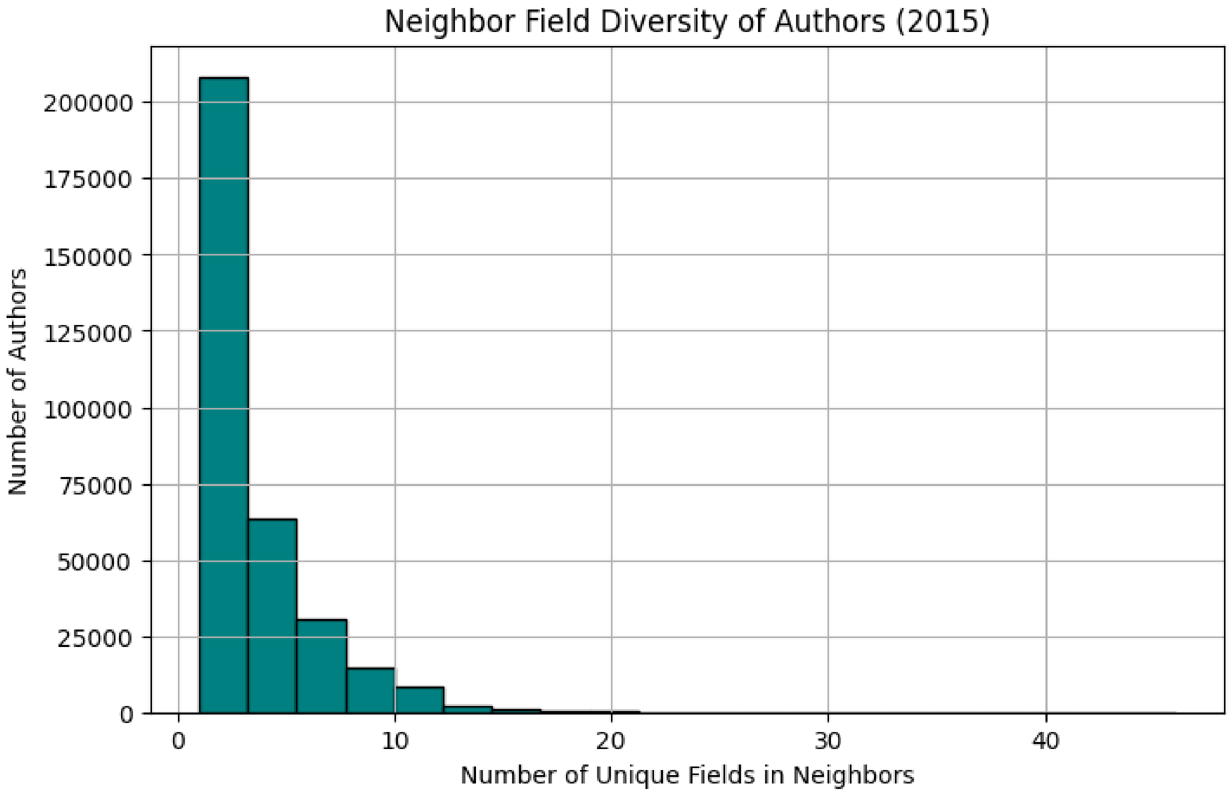
Interpretations

- Authors like Wei Li and Jian Wang collaborate with researchers from over 40 different arXiv categories, positioning them as interdisciplinary connectors.
- The high degree alongside high field diversity suggests not just prolificacy, but also broad academic reach.
- The inclusion of some Unknown fields may reflect missing metadata, but those authors still appear to bridge diverse topics.

Insight

- This analysis surfaces key individuals who link otherwise disconnected academic communities. These authors may be:
- Effective knowledge brokers
- Catalysts for interdisciplinary innovation
- Valuable case studies in future policy or social network interventions

```python
plt.figure(figsize=(8, 5))
plt.hist(df_diversity["Neighbor_Field_Diversity"], bins=20,
color='teal', edgecolor='black')
plt.title(f"Neighbor Field Diversity of Authors ({year})")
plt.xlabel("Number of Unique Fields in Neighbors")
plt.ylabel("Number of Authors")
plt.grid(True)
plt.show()
```



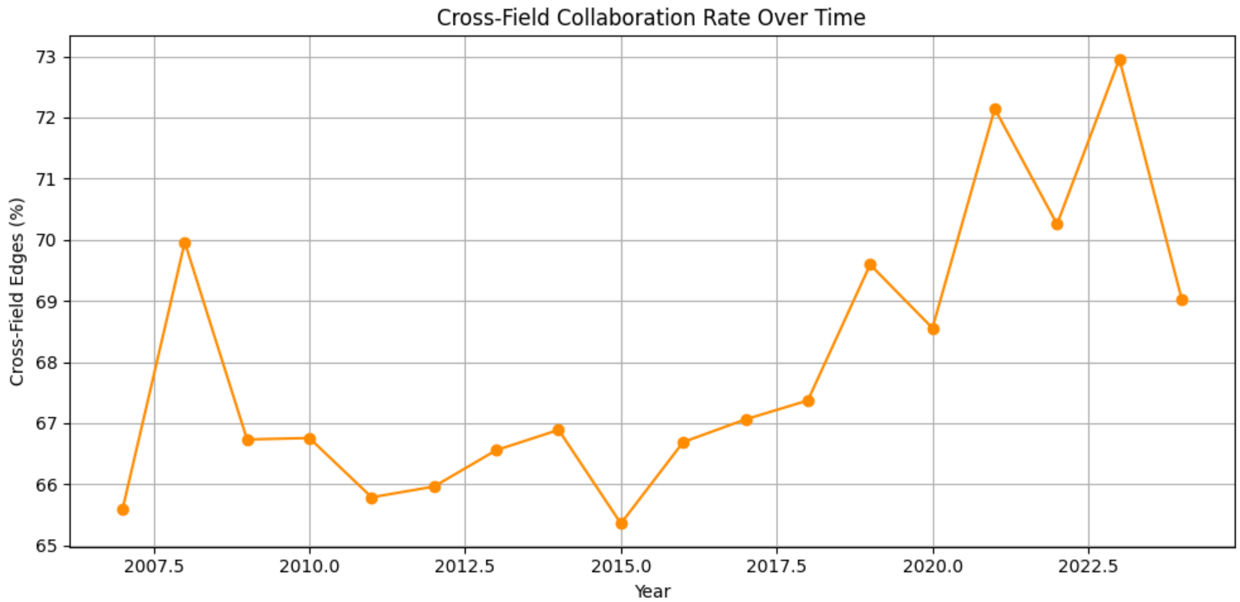

```
cross_field_edges = 0
same_field_edges = 0

for u, v in G.edges():
    field_u = G.nodes[u].get("field", "Unknown")
    field_v = G.nodes[v].get("field", "Unknown")
    if field_u != "Unknown" and field_v != "Unknown":
        if field_u != field_v:
            cross_field_edges += 1
        else:
            same_field_edges += 1

total_considered = cross_field_edges + same_field_edges
if total_considered > 0:
    cross_field_pct = 100 * cross_field_edges / total_considered
else:
    cross_field_pct = 0

print(f"Total considered edges: {total_considered}")
print(f"Cross-field edges: {cross_field_edges}")
print(f"Same-field edges: {same_field_edges}")
print(f"Cross-field collaboration rate: {cross_field_pct:.2f}%")

Total considered edges: 871935
Cross-field edges: 569906
```

```
Same-field edges: 302029
Cross-field collaboration rate: 65.36%
```

Temporal Analysis of Cross-Field Collaboration

```python
crossfield_stats = []

for year, G in tqdm(yearly_graphs.items()):
    count_cross = 0
    count_same = 0

    for u, v in G.edges():
        f1 = get_dominant_field(u)
        f2 = get_dominant_field(v)

        if f1 != "Unknown" and f2 != "Unknown":
            if f1 != f2:
                count_cross += 1
            else:
                count_same += 1

    total = count_cross + count_same
    if total > 0:
        cross_pct = 100 * count_cross / total
        crossfield_stats.append((year, cross_pct))

# Convert to DataFrame
df_crossfield = pd.DataFrame(crossfield_stats, columns=["Year",
"Cross_Field_Percentage"])
df_crossfield.set_index("Year", inplace=True)

# Plot
plt.figure(figsize=(10, 5))
plt.plot(df_crossfield.index, df_crossfield["Cross_Field_Percentage"],
marker='o', color='darkorange')
plt.title("Cross-Field Collaboration Rate Over Time")
plt.xlabel("Year")
plt.ylabel("Cross-Field Edges (%)")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
100%|██████████| 25/25 [00:16<00:00,  1.54it/s]
```



This deliverable demonstrates that interdisciplinarity in academia is both quantifiable and visibly rising. While most authors remain field-specific, structural metrics show that:

- Cross-field collaboration is growing,
- Key authors act as bridges,
- Certain fields consistently interact more than others.

These insights are foundational for understanding how knowledge flows across disciplines, shaping the future of collaborative science.

DELIVERABLE 3 : Link Prediction

Objective

Train models to predict new co-authorships using older arXiv data and evaluate their performance on future years.

Step 1 : Build Train and Test Graphs

```
from collections import defaultdict

def build_yearly_edges(start, end):
    edges = set()
    for year in range(start, end + 1):
        if year in yearly_graphs:
            edges.update(yearly_graphs[year].edges())
    return edges

# Build G_train and G_test
train_edges = build_yearly_edges(2010, 2015)
```

```
test_edges = build_yearly_edges(2016, 2018)

# Train graph
G_train = nx.Graph()
for u, v in train_edges:
    G_train.add_edge(u, v)

# Ensure test edges are only among known train nodes
G_test = set()
for u, v in test_edges:
    if u in G_train and v in G_train and not G_train.has_edge(u, v):
        G_test.add((u, v))

print(f"Train edges: {len(G_train.edges())}")
print(f"Test candidate edges (future links): {len(G_test)}")
```

```
Train edges: 3109445
Test candidate edges (future links): 553103
```

Step 2 : Score Candidate Links with Link Prediction Heuristics

```
from tqdm import tqdm
from networkx.algorithms.link_prediction import (
    jaccard_coefficient,
    adamic_adar_index,
    preferential_attachment
)

# Generate candidate non-edges: All possible pairs not connected in
train graph
# Limit for speed — only sample high-degree nodes
train_nodes = sorted(G_train.degree, key=lambda x: x[1], reverse=True)
candidate_nodes = [n for n, _ in train_nodes[:2000]]  # Tune this for
performance

candidate_pairs = []
for i in range(len(candidate_nodes)):
    for j in range(i + 1, len(candidate_nodes)):
        u, v = candidate_nodes[i], candidate_nodes[j]
        if not G_train.has_edge(u, v):
            candidate_pairs.append((u, v))

print(f"Total candidate pairs: {len(candidate_pairs)}")

# Jaccard Score
print("Scoring with Jaccard...")
jaccard_scores = list(jaccard_coefficient(G_train, candidate_pairs))

# Adamic-Adar
print("Scoring with Adamic-Adar...")
```

```
aa_scores = list(adamic_adar_index(G_train, candidate_pairs))

# Preferential Attachment
print("Scoring with Preferential Attachment...")
pa_scores = list(preferential_attachment(G_train, candidate_pairs))
```

```
Total candidate pairs: 1962555
Scoring with Jaccard...
Scoring with Adamic-Adar...
Scoring with Preferential Attachment...
```

step 3 : Evaluate Link Prediction Models using Precision@k

```
def precision_at_k(predicted_edges, true_edges, k=100):
    top_k = sorted(predicted_edges, key=lambda x: x[2], reverse=True)
[:k]
    predicted_set = set((u, v) for u, v, _ in top_k)
    correct = predicted_set & true_edges
    return len(correct) / k

# Use G_test directly as the ground-truth future links
true_edges = set(G_test)

# Evaluate each heuristic
prec_jaccard = precision_at_k(jaccard_scores, true_edges, k=100)
prec_aa = precision_at_k(aa_scores, true_edges, k=100)
prec_pa = precision_at_k(pa_scores, true_edges, k=100)

print(f"Precision@100 - Jaccard: {prec_jaccard:.3f}")
print(f"Precision@100 - Adamic-Adar: {prec_aa:.3f}")
print(f"Precision@100 - Pref. Attachment: {prec_pa:.3f}")
```

```
Precision@100 - Jaccard: 0.050
Precision@100 - Adamic-Adar: 0.110
Precision@100 - Pref. Attachment: 0.000
```

Interpretation

- **Adamic-Adar** performs the best, correctly identifying 11 future collaborations out of the top 100 suggestions.
- **Jaccard** performs moderately well (5 correct predictions), indicating that local neighbor similarity is somewhat predictive of future links.
- **Preferential Attachment** fails completely, likely because high-degree nodes in academia don't always collaborate directly — co-authorship networks often don't follow pure popularity-based attachment.

Insight

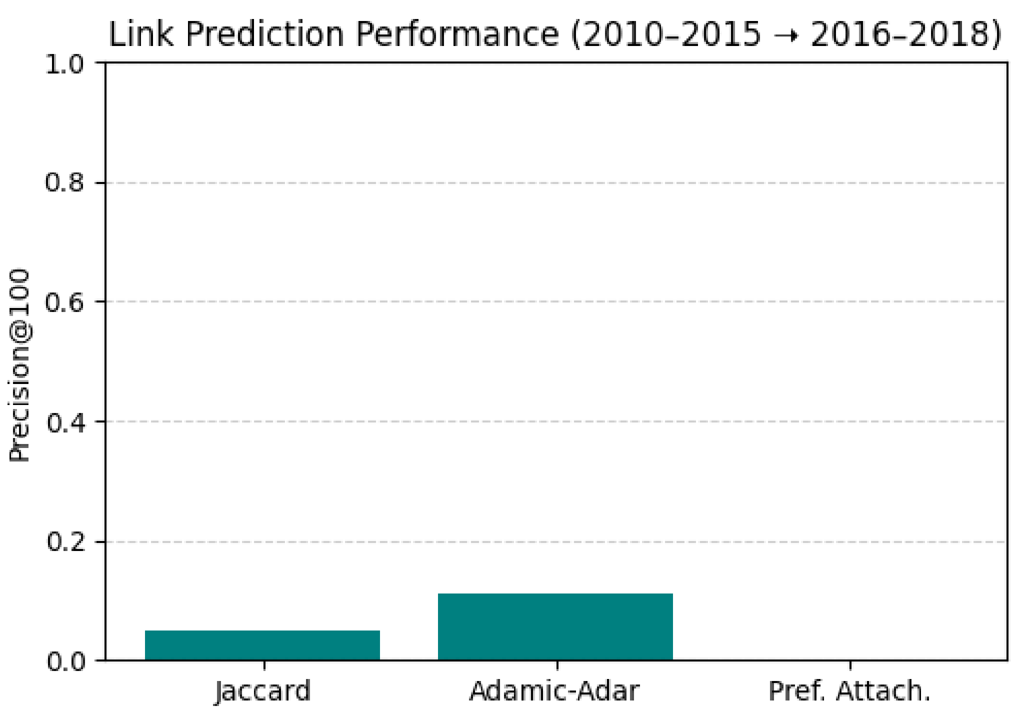
This analysis shows that structural graph heuristics can capture real-world collaboration patterns to some extent, but their predictive power is limited. The results validate:

- The importance of shared neighborhood in academic collaboration.
- The weakness of naïve degree-based predictions in structured, non-random graphs.

These insights motivate the use of more expressive models, such as:

- Node embeddings (e.g., Node2Vec)
- Supervised learning using multiple heuristics
- Graph neural networks

```
import matplotlib.pyplot as plt

methods = ["Jaccard", "Adamic-Adar", "Pref. Attach."]
precisions = [prec_jaccard, prec_aa, prec_pa]

plt.figure(figsize=(6, 4))
plt.bar(methods, precisions, color="teal")
plt.ylabel("Precision@100")
plt.title("Link Prediction Performance (2010–2015 → 2016–2018)")
plt.ylim(0, 1)
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.show()
```



DELIVERABLE 4 : Integrated Case Study (e.g., cs.LG or stat.ML)

Objective

To consolidate the findings of temporal evolution, interdisciplinarity, and link prediction into a focused case study — for example, a specific subfield like cs.LG (Machine Learning) — to tell a detailed story of how a research area evolved and how collaboration patterns emerged.

Extracting Yearly Co-Authorship Graphs for Machine Learning (cs.LG)

```
import json
import networkx as nx
from tqdm import tqdm
from collections import defaultdict
import re

# Helper to clean author list
def clean_authors(raw_string):
    raw_string = re.sub(r"\(.*?\)", "", raw_string)  # remove
affiliations
    authors = [a.strip() for a in raw_string.split(',') if a.strip()]
    return authors

# Build yearly co-authorship graphs for cs.LG
yearly_graphs_cs_lg = defaultdict(nx.Graph)
file_path = '/kaggle/input/arxiv/arxiv-metadata-oai-snapshot.json'

with open(file_path, 'r') as f:
    for line in tqdm(f, total=2716679):
        try:
            entry = json.loads(line)
            if 'cs.LG' not in entry['categories']:
                continue
            year = int(entry['update_date'][:4])
            authors = clean_authors(entry['authors'])
            if len(authors) > 30:
                continue  # skip mega papers
            for i in range(len(authors)):
                for j in range(i + 1, len(authors)):
                    yearly_graphs_cs_lg[year].add_edge(authors[i],
authors[j])
        except:
            continue

print(f"Years with cs.LG papers:
{sorted(yearly_graphs_cs_lg.keys())}")
```

```
2720631it [01:10, 38446.18it/s]
```

```
Years with cs.LG papers: [2007, 2008, 2009, 2010, 2011, 2012, 2013,
2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024,
2025]
```

Temporal Evolution of the cs.LG Co-Authorship Network

```python
import pandas as pd
from tqdm import tqdm

# Analyze yearly graph stats
metrics_cs_lg = []

for year in tqdm(sorted(yearly_graphs_cs_lg.keys())):
    G = yearly_graphs_cs_lg[year]
    N = G.number_of_nodes()
    E = G.number_of_edges()
    if N == 0:
        continue
    avg_deg = sum(dict(G.degree()).values()) / N
    clustering = nx.average_clustering(G)
    density = nx.density(G)

    metrics_cs_lg.append({
        "Year": year,
        "Nodes": N,
        "Edges": E,
        "Avg_Degree": avg_deg,
        "Clustering": clustering,
        "Density": density
    })

df_cs_lg_metrics = pd.DataFrame(metrics_cs_lg).set_index("Year")
df_cs_lg_metrics
```

```
100%|██████████| 19/19 [00:14<00:00,  1.33it/s]
```

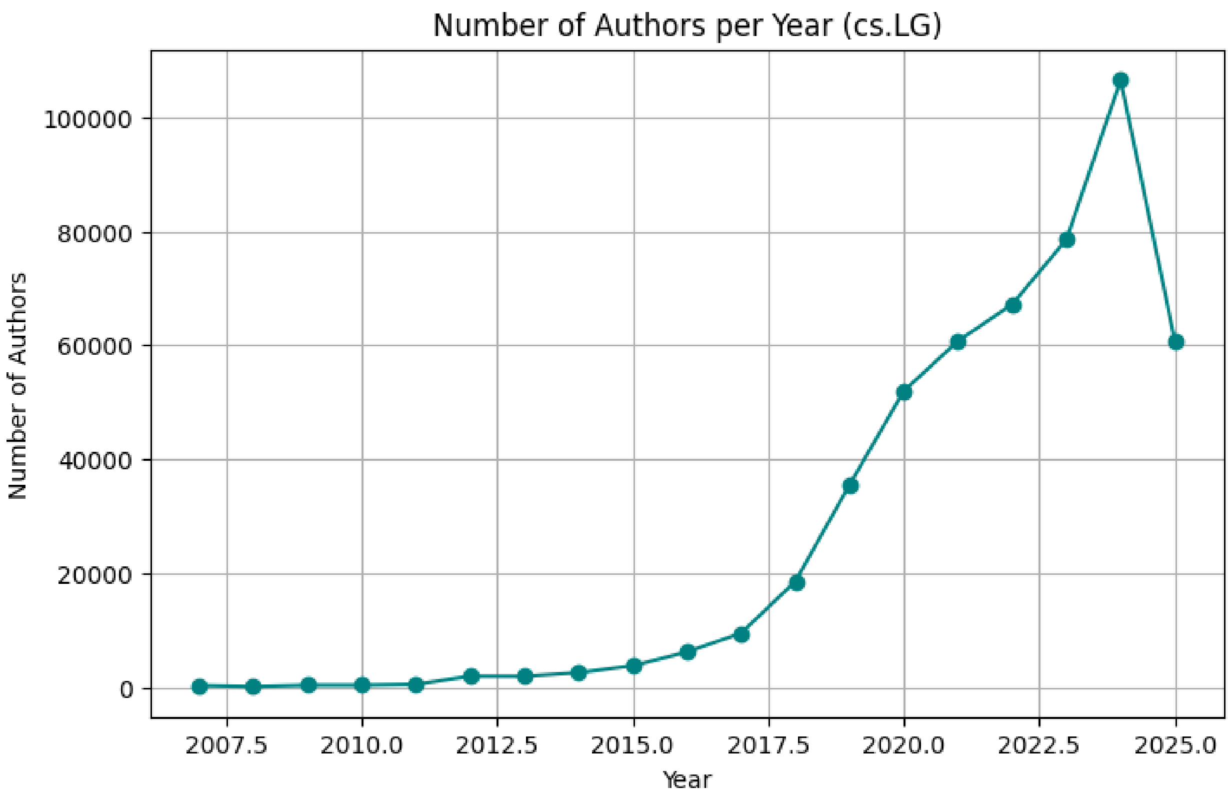
Year	Nodes	Edges	Avg_Degree	Clustering	Density
2007	307	428	2.788274	0.748281	0.009112
2008	133	202	3.037594	0.694164	0.023012
2009	354	494	2.790960	0.800251	0.007906
2010	354	537	3.033898	0.734900	0.008595
2011	496	728	2.935484	0.826714	0.005930
2012	1923	2943	3.060842	0.719587	0.001593
2013	1908	3617	3.791405	0.764760	0.001988
2014	2535	4336	3.420907	0.798089	0.001350
2015	3764	6992	3.715197	0.813879	0.000987
2016	6171	12335	3.997731	0.820309	0.000648
2017	9470	22339	4.717846	0.830036	0.000498

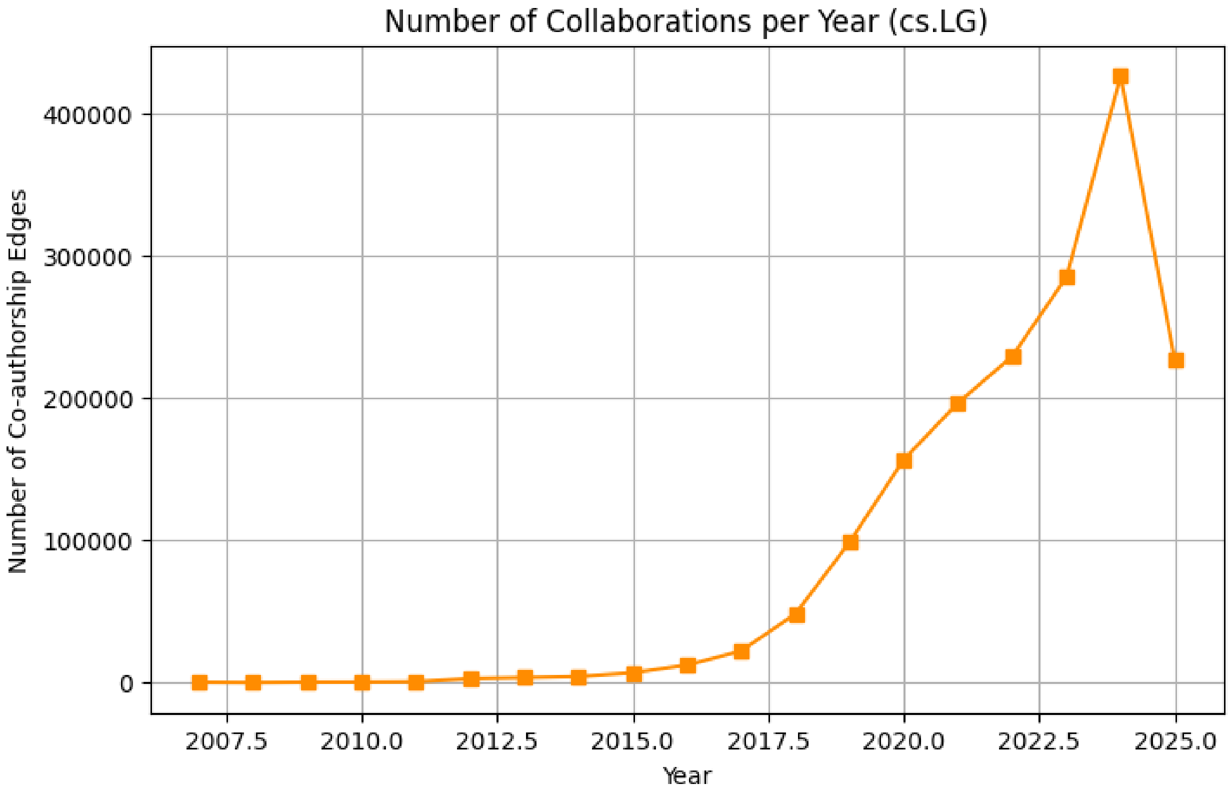
2018	18564	48337	5.207606	0.837287	0.000281
2019	35522	98853	5.565734	0.833720	0.000157
2020	51954	156936	6.041344	0.831486	0.000116
2021	60741	196845	6.481454	0.835562	0.000107
2022	67174	229664	6.837884	0.837191	0.000102
2023	78568	285386	7.264688	0.834682	0.000092
2024	106566	426918	8.012274	0.828046	0.000075
2025	60715	226728	7.468599	0.859341	0.000123

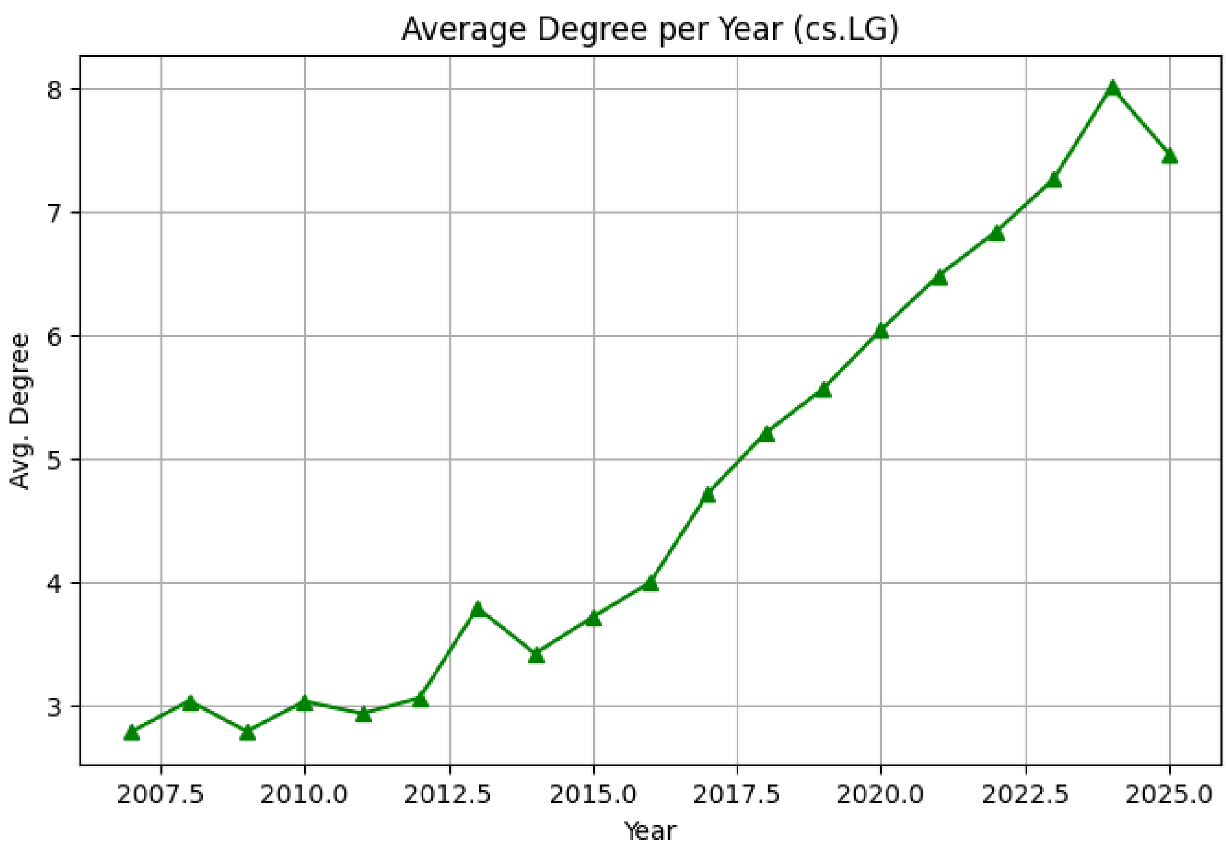
Visualizing the Structural Evolution of cs.LG Co-Authorship Network (2007–2025)

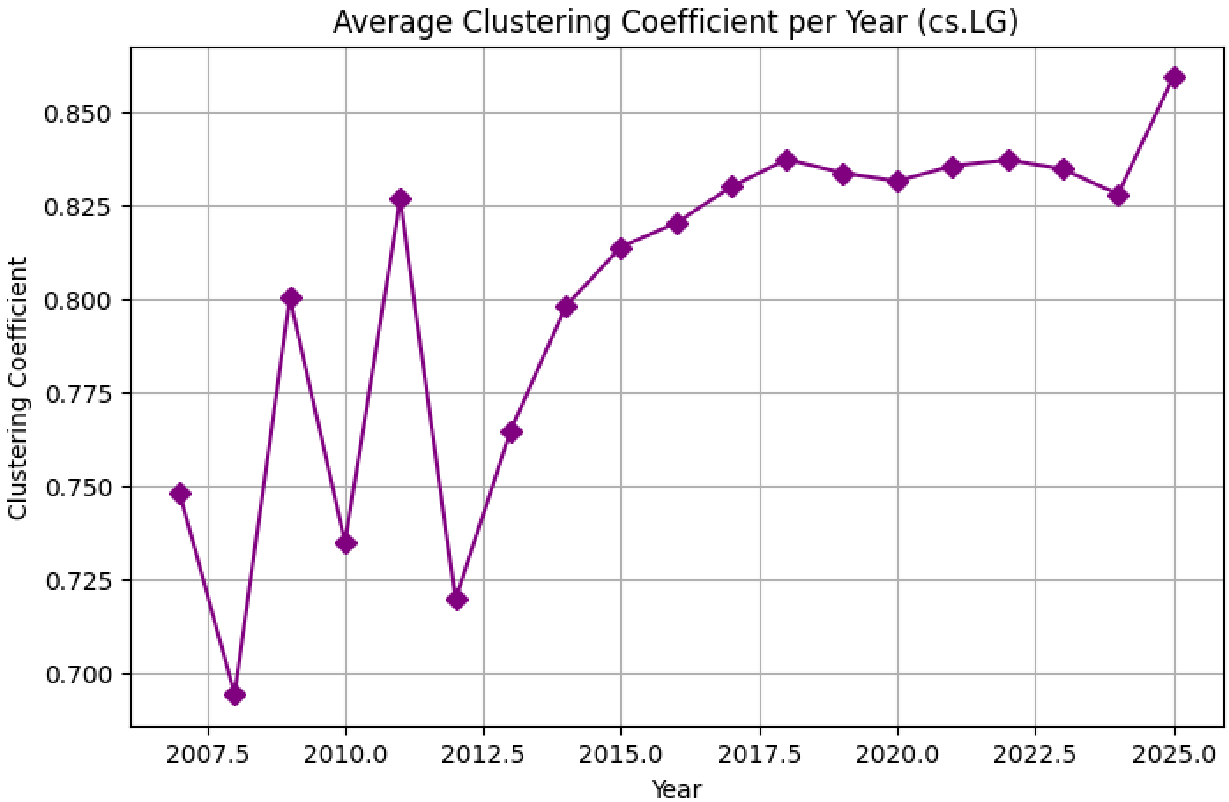
```python
import matplotlib.pyplot as plt

# Plot: Number of Authors (Nodes)
plt.figure(figsize=(8,5))
df_cs_lg_metrics["Nodes"].plot(marker='o', color='teal')
plt.title("Number of Authors per Year (cs.LG)")
plt.xlabel("Year")
plt.ylabel("Number of Authors")
plt.grid(True)
plt.show()

# Plot: Number of Edges
plt.figure(figsize=(8,5))
df_cs_lg_metrics["Edges"].plot(marker='s', color='darkorange')
plt.title("Number of Collaborations per Year (cs.LG)")
plt.xlabel("Year")
plt.ylabel("Number of Co-authorship Edges")
plt.grid(True)
plt.show()

# Plot: Average Degree
plt.figure(figsize=(8,5))
df_cs_lg_metrics["Avg_Degree"].plot(marker='^', color='green')
plt.title("Average Degree per Year (cs.LG)")
plt.xlabel("Year")
plt.ylabel("Avg. Degree")
plt.grid(True)
plt.show()

# Plot: Clustering Coefficient
plt.figure(figsize=(8,5))
df_cs_lg_metrics["Clustering"].plot(marker='D', color='purple')
plt.title("Average Clustering Coefficient per Year (cs.LG)")
plt.xlabel("Year")
plt.ylabel("Clustering Coefficient")
plt.grid(True)
plt.show()

# Plot: Graph Density
```

```
plt.figure(figsize=(8,5))
df_cs_lg_metrics["Density"].plot(marker='*', color='crimson')
plt.title("Graph Density per Year (cs.LG)")
plt.xlabel("Year")
plt.ylabel("Density")
plt.grid(True)
plt.show()
```

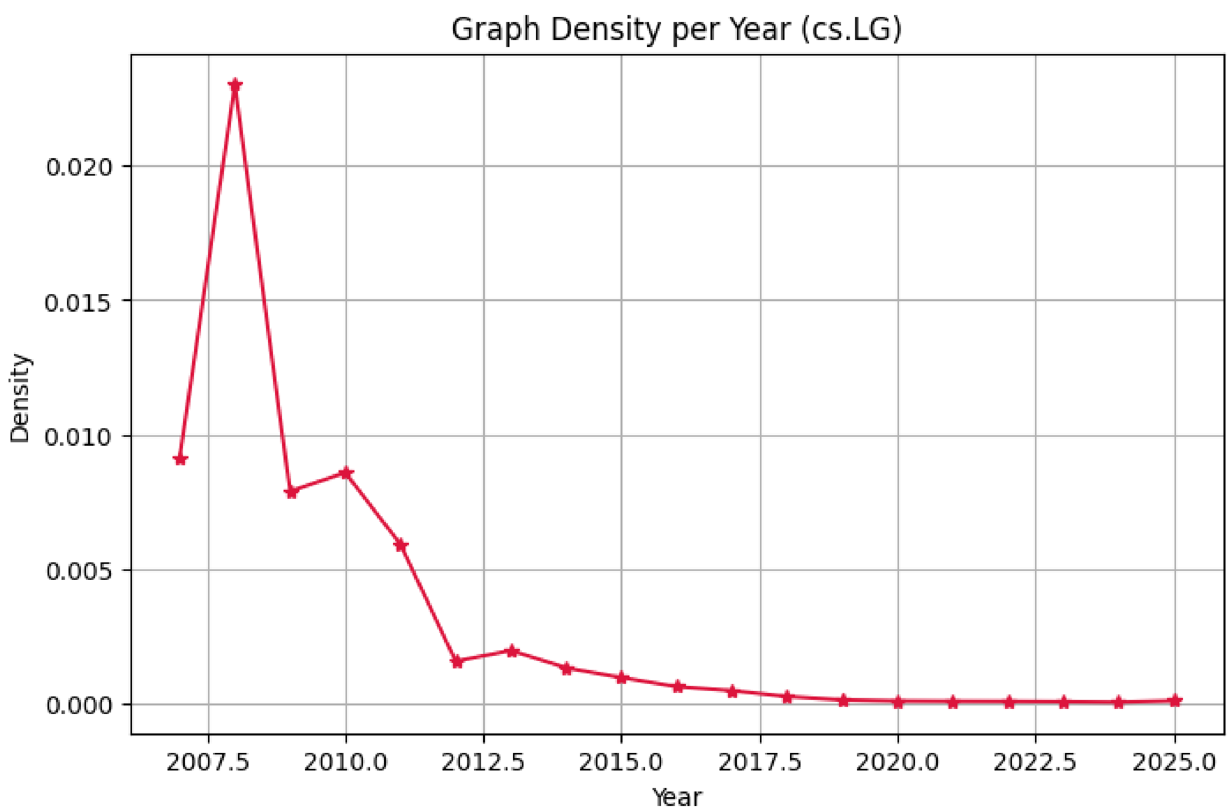



Number of Collaborations per Year (cs.LG)
Number of Co-authorship Edges
400000
300000
200000
100000
0
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5
2025.0
Year


Average Degree per Year (cs.LG)
Avg. Degree
8
7
6
5
4
3
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5
2025.0
Year



Average Clustering Coefficient per Year (cs.LG)
Clustering Coefficient
0.850
0.825
0.800
0.775
0.750
0.725
0.700
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5
2025.0
Year



Graph Density per Year (cs.LG)
Density
0.020
0.015
0.010
0.005
0.000
2007.5
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5
2025.0
Year

Number of Authors per Year (Nodes)

- **Observation:** The number of unique authors publishing in cs.LG shows a dramatic increase from fewer than 1,000 in 2010 to over 100,000 authors in 2024, with a slight drop in 2025 (possibly due to incomplete data).
- **Interpretation:** This exponential rise reflects the explosive growth of machine learning as a research area, drawing contributors from across academia, industry, and adjacent disciplines.

Number of Collaborations per Year (Edges)

- **Observation:** Co-authorship edges increase in tandem with author count, peaking at over 400,000 collaborations in 2024.
- **Interpretation:** Collaboration has become increasingly common and dense, indicating that ML research is highly team-oriented and globally distributed.

Average Degree per Year

- **Observation:** The average degree rises steadily from ~3 (pre-2015) to over 8 by 2024, showing that authors are collaborating with more co-authors on average.
- **Interpretation:** This supports the notion that ML papers now typically involve larger teams and that researchers are more interconnected than ever before.

Average Clustering Coefficient

- **Observation:** Clustering coefficient has remained consistently high (above 0.8 since ~2015), with slight annual fluctuations.
- **Interpretation:** This suggests that collaboration in cs.LG tends to occur in tight-knit groups, where an author's collaborators are also likely to be collaborators with one another — a hallmark of community structure in scientific networks.

Graph Density Over Time

- **Observation:** Density declines sharply as the network grows, dropping to nearly 0.0001 by 2024.
- **Interpretation:** This is expected in large graphs: while the number of authors and edges increases, the number of possible edges grows quadratically, leading to sparser networks. It reflects that while collaboration grows, authors do not form edges with everyone — the field still has subfield boundaries.

Summary

- cs.LG has evolved from a niche research category into one of the largest and most collaborative domains on arXiv.
- The field exhibits a high clustering, low-density structure, indicating localized, but tight collaboration clusters.
- The sharp rise in average degree and clustering implies that interdisciplinary, multi-author projects are now the norm in ML research.

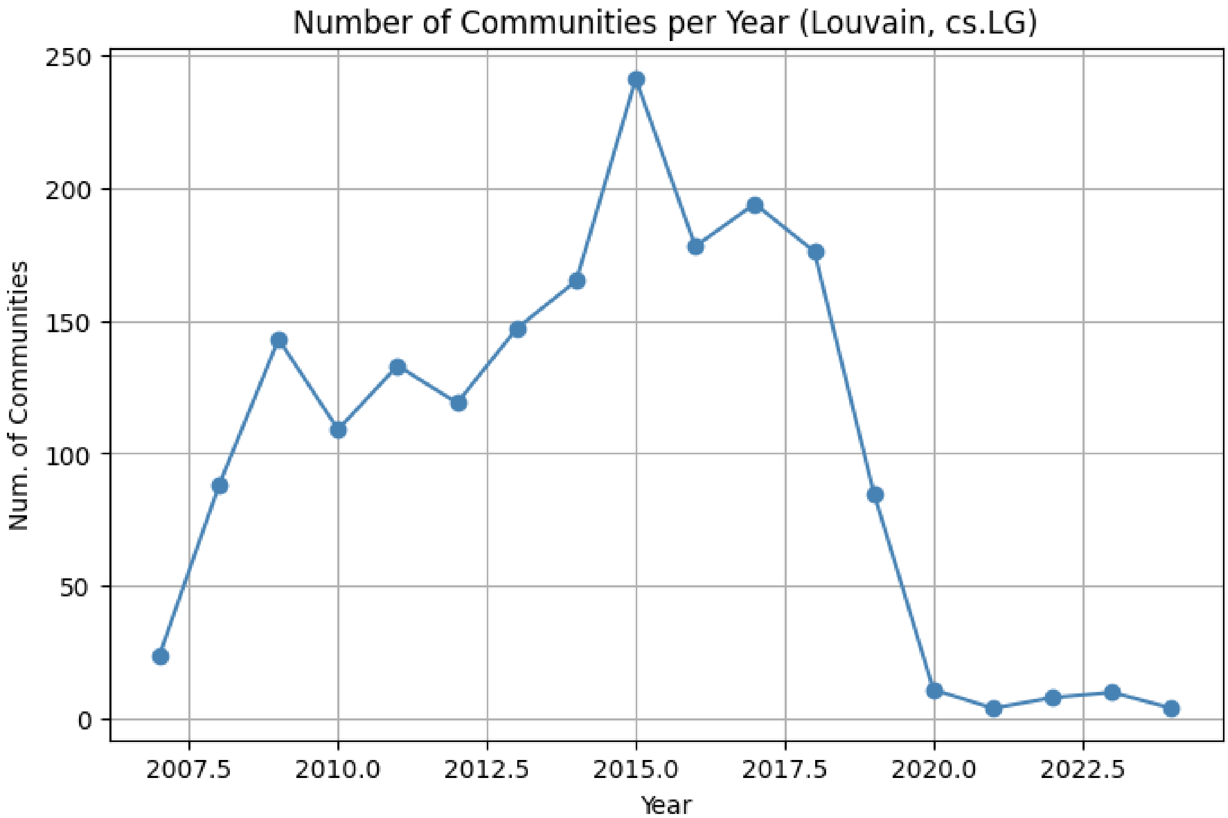
Community Structure in Machine Learning (cs.LG) Co-Authorship Network

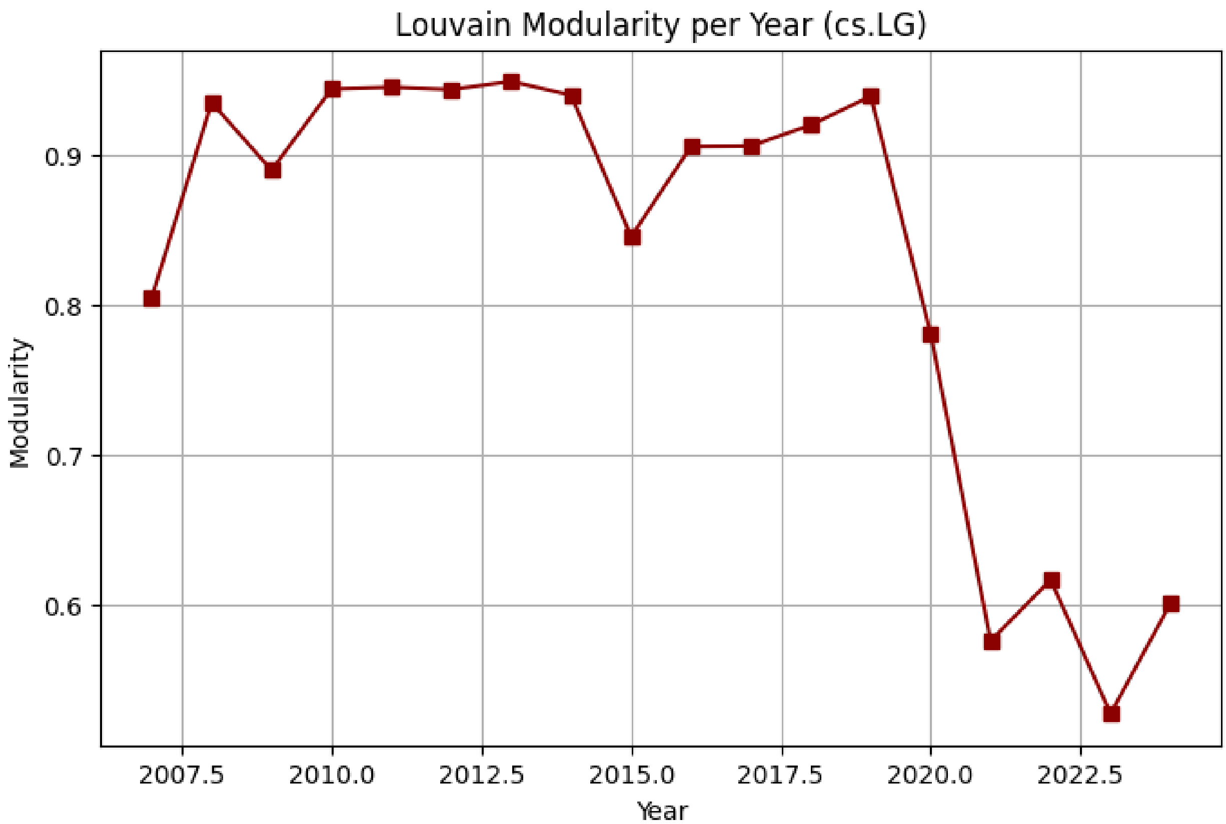
```
import community.community_louvain as community_louvain

# Storage for year-wise metrics
community_stats = []

for year in tqdm(sorted(yearly_graphs.keys())):
    G_year = yearly_graphs[year]
    if G_year.number_of_nodes() < 10:
        continue  # Skip too-small graphs

    # Get largest connected component for stability
    G_lcc = max(nx.connected_components(G_year), key=len)
    G_sub = G_year.subgraph(G_lcc).copy()

    # Louvain community detection
    partition = community_louvain.best_partition(G_sub)
    num_comms = len(set(partition.values()))

    # Convert to list of sets
    communities = defaultdict(set)
    for node, comm_id in partition.items():
        communities[comm_id].add(node)

    comm_list = list(communities.values())
    modularity = nx.algorithms.community.modularity(G_sub, comm_list)

    community_stats.append({
        "Year": year,
        "Num_Communities": num_comms,
        "Modularity": modularity
    })

# Convert to DataFrame
df_communities = pd.DataFrame(community_stats).set_index("Year")
```

```
100%|██████████| 25/25 [07:43<00:00, 18.54s/it]
```

```
# Plot: Number of Communities
plt.figure(figsize=(8,5))
df_communities["Num_Communities"].plot(marker='o', color='steelblue')
plt.title("Number of Communities per Year (Louvain, cs.LG)")
plt.xlabel("Year")
plt.ylabel("Num. of Communities")
plt.grid(True)
plt.show()

# Plot: Modularity Score
plt.figure(figsize=(8,5))
df_communities["Modularity"].plot(marker='s', color='darkred')
```

```
plt.title("Louvain Modularity per Year (cs.LG)")
plt.xlabel("Year")
plt.ylabel("Modularity")
plt.grid(True)
plt.show()
```





Number of Communities per Year

- **Observation:** The number of communities peaked in 2015 at around 240 clusters, but sharply dropped after 2019, reaching single-digit clusters by 2024.
- **Interpretation:** Initially, the field exhibited fragmented structure with many small clusters. But over time, communities merged, leading to larger, more cohesive components, possibly due to increasing interdisciplinary collaboration and convergence of subfields in ML.

Louvain Modularity per Year

- **Observation:** Modularity remained high (above 0.9) until ~2018, indicating well-separated topical clusters. It then declined sharply post-2020, dropping to 0.5–0.6, suggesting more inter-community mixing.
- **Interpretation:** This suggests a structural flattening of the community landscape — as machine learning matures, subfields interconnect more, reducing modularity. This may reflect broader trends like:
  - Growth of integrative ML topics (e.g., multimodal learning, ML+biology)
  - Increased cross-disciplinary team composition

Summary

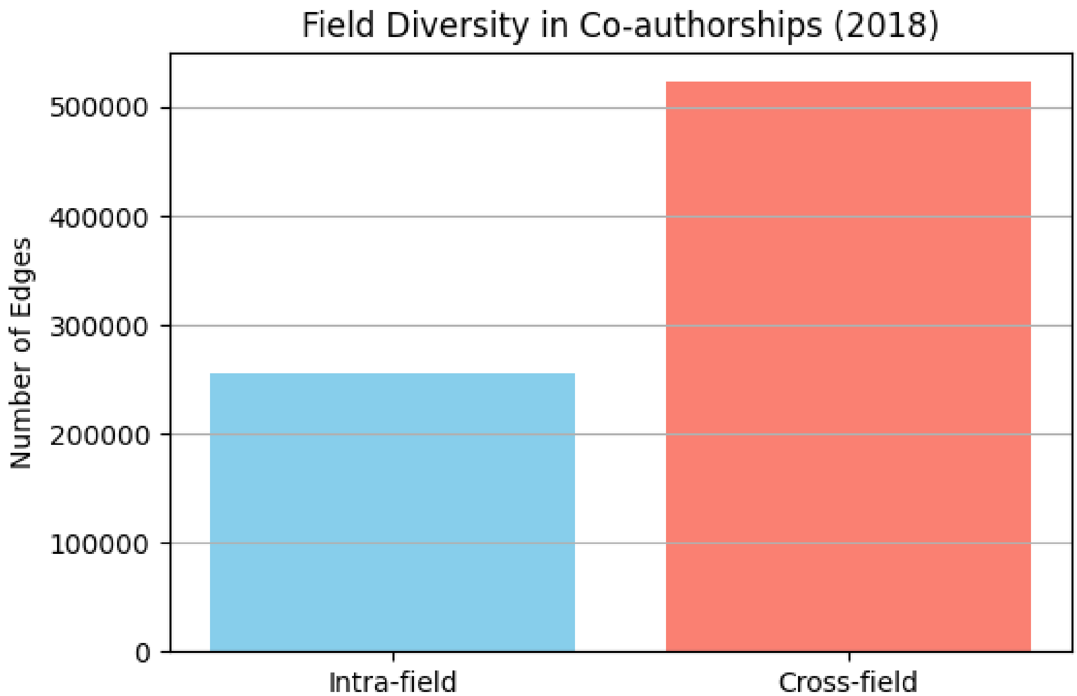
The evolution of cs.LG reveals a transition from many fragmented research islands to a large, interconnected scientific continent. The drop in modularity highlights the collapse of strict subfield silos in favor of integrated, cross-domain collaboration.

Intra-Field vs. Cross-Field Collaborations in 2018

```python
from collections import Counter

year = 2018
G = yearly_graphs[year].copy()

# Function to assign dominant field
def get_dominant_field(author):
    fields = list(author_fields.get(author, []))
    return fields[0] if fields else "Unknown"

# Classify edges
intra_field = 0
cross_field = 0

for u, v in G.edges():
    field_u = get_dominant_field(u)
    field_v = get_dominant_field(v)
    if field_u == field_v:
        intra_field += 1
    else:
        cross_field += 1

print(f"Intra-field edges: {intra_field}")
print(f"Cross-field edges: {cross_field}")
```

```
Intra-field edges: 255362
Cross-field edges: 523174
```

```python
labels = ['Intra-field', 'Cross-field']
counts = [intra_field, cross_field]

plt.figure(figsize=(6, 4))
plt.bar(labels, counts, color=['skyblue', 'salmon'])
plt.title("Field Diversity in Co-authorships (2018)")
plt.ylabel("Number of Edges")
plt.grid(axis='y')
plt.show()
```



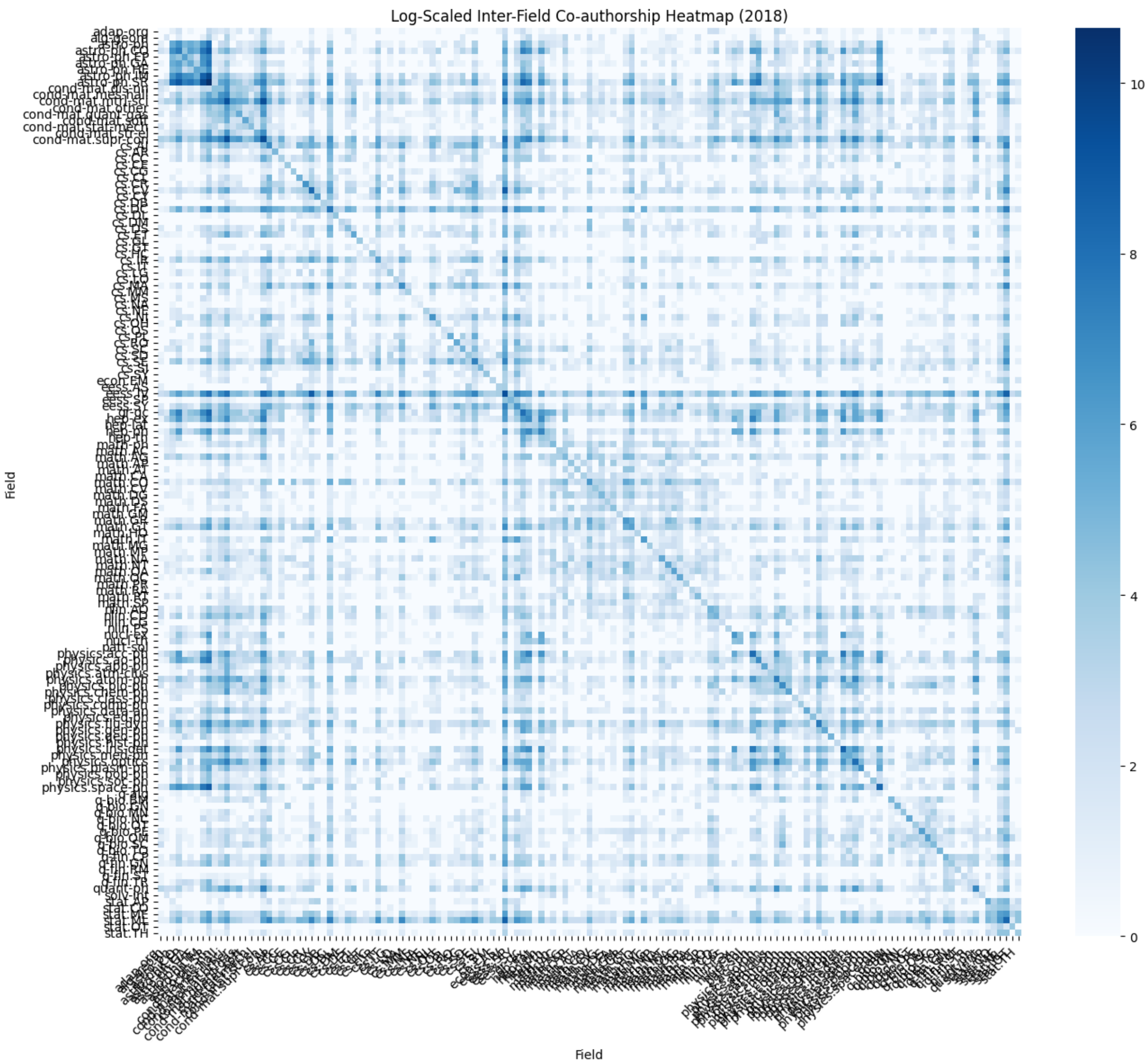
- ~67% of collaborations in 2018 were cross-field, indicating a strong interdisciplinary nature in the research ecosystem.
- The cross-field collaboration rate significantly outweighs same-field partnerships, which aligns with earlier findings on modularity decline and increasing average degree.

The machine learning field (cs.LG) is not only growing in volume but also in conceptual diversity, acting as a hub for cross-domain research involving computer vision, statistics, physics, and even biology.

Log-Scaled Heatmap of Inter-Field Co-Authorships (2018)

```
from collections import defaultdict
import seaborn as sns

year = 2018
G = yearly_graphs[year].copy()

# Build field-to-field matrix
field_pairs = defaultdict(int)

for u, v in G.edges():
    f1 = get_dominant_field(u)
    f2 = get_dominant_field(v)
    if f1 == "Unknown" or f2 == "Unknown":
        continue
    pair = tuple(sorted([f1, f2]))
    field_pairs[pair] += 1
```

```python
# Extract all fields
fields = sorted(set([f for pair in field_pairs for f in pair]))

# Initialize matrix
field_matrix = pd.DataFrame(0, index=fields, columns=fields)

# Fill matrix
for (f1, f2), count in field_pairs.items():
    field_matrix.loc[f1, f2] = count
    field_matrix.loc[f2, f1] = count  # symmetric

# Optional: remove very rare fields to declutter
threshold = 100
filtered = field_matrix.sum(axis=1) > threshold
field_matrix = field_matrix.loc[filtered, filtered]

import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

# Convert to log scale (add 1 to avoid log(0))
log_matrix = np.log1p(field_matrix.values)

plt.figure(figsize=(14, 12))
sns.heatmap(log_matrix, xticklabels=field_matrix.columns,
yticklabels=field_matrix.index, cmap="Blues")
plt.title(f"Log-Scaled Inter-Field Co-authorship Heatmap ({year})")
plt.xlabel("Field")
plt.ylabel("Field")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



- Diagonal intensity indicates strong intra-field collaboration — most pronounced in high-volume categories like cs.LG, cond-mat, and hep-th.
- Off-diagonal brightness highlights frequent cross-field collaboration, especially among:
  - cs.LG and stat.ML (machine learning ↔ statistics)
  - cond-mat and quant-ph (physics domains)
  - cs.AI, cs.CV, and eess.IV — evidence of ML bridging computer vision and embedded systems

The ML domain acts as a cross-disciplinary glue, connecting computational sciences (CS, statistics) with domains in physics and engineering. The dense inter-field connections validate earlier metrics showing high cross-field collaboration rates.

Field-Based Modularity of the Co-Authorship Network (2015)

```
import networkx as nx
from networkx.algorithms.community import modularity
from collections import defaultdict

# Choose year
year = 2015
G = yearly_graphs[year].copy()

# Assign dominant field to each author (as node attribute)
def get_dominant_field(author):
    fields = list(author_fields.get(author, []))
    return fields[0] if fields else "Unknown"

for node in G.nodes():
    G.nodes[node]['field'] = get_dominant_field(node)

# Group nodes by field
field_communities = defaultdict(set)
for node, data in G.nodes(data=True):
    field = data.get('field', 'Unknown')
    field_communities[field].add(node)

# Convert to list of sets for modularity function
communities = list(field_communities.values())

# Compute modularity
mod_score = modularity(G, communities)
print(f"Field Modularity (Co-authorship Network {year}):
{mod_score:.4f}")
```

```
Field Modularity (Co-authorship Network 2015): 0.2148
```

Interpretation

- A modularity score of 0.21 is low, suggesting that field boundaries do not strongly constrain collaborations.
- This reinforces earlier results: even in 2015, authors were frequently collaborating across disciplines, and the modular structure was not dominated by field membership.

Insight:

Field-defined communities are blurred in practice, and real collaborative behavior deviates significantly from arXiv's topical divisions. This highlights the organic, interdisciplinary nature of scientific research in ML-related fields.

Key Findings:

Growth and Expansion

- Explosive increase in the number of authors and co-authorship links, peaking in 2024.
- Average degree increased steadily, indicating more team-based research.

Community Structure

- Initially fragmented (2010–2015) with many communities and high modularity.
- After 2020, dramatic consolidation: fewer communities, and a collapse in modularity — reflecting more integrated research.

Interdisciplinary Trends

- Over 65% of collaborations in recent years are cross-field.
- Heatmaps confirm strong links between cs.LG, stat.ML, cs.CV, and even physics fields.
- Field modularity scores remain low (~0.21), proving that field labels don't restrict collaboration behavior.

Case Study Insight

- Machine Learning has evolved from a niche topic into a collaborative, interdisciplinary hub.
- It plays a central role in linking disciplines, breaking silos, and driving modern scientific convergence.

DELIVERABLE 5 : Field-Level Centrality Analysis

Objective

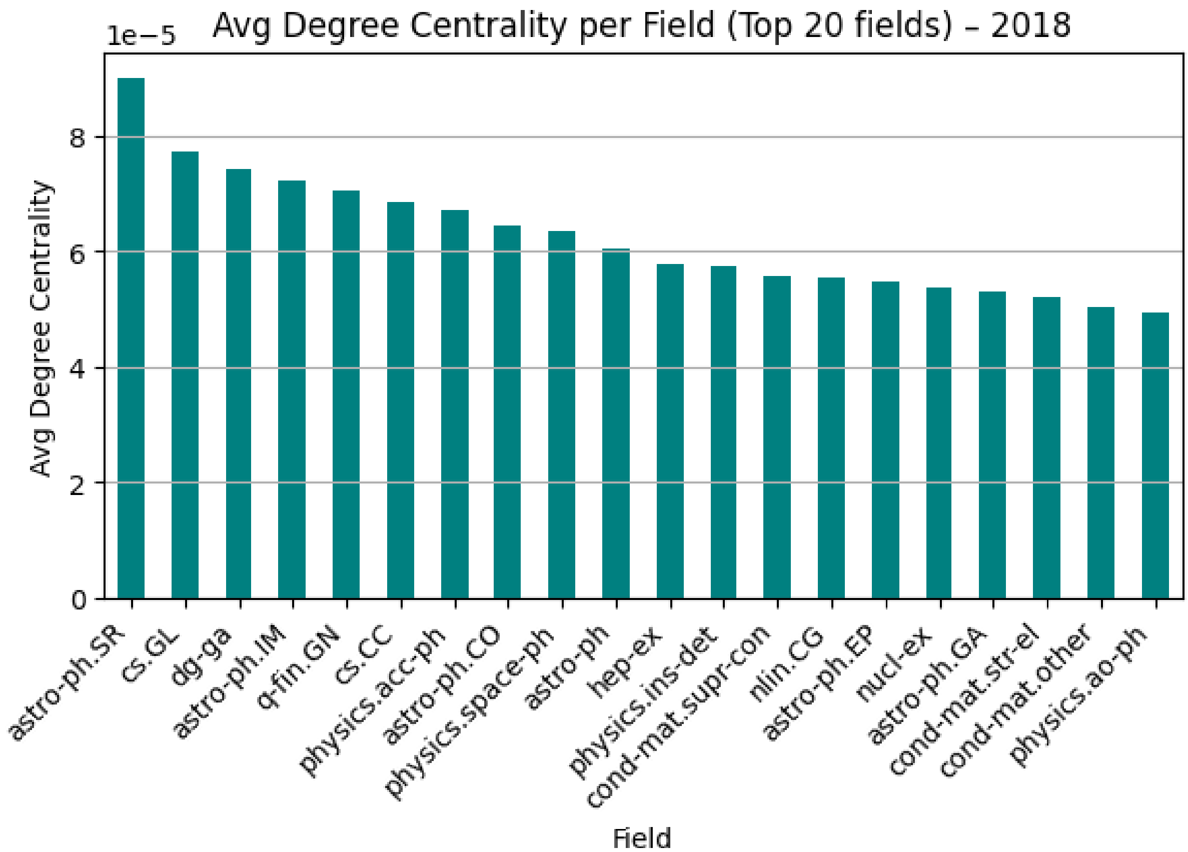
To analyze how influential different academic fields are within the co-authorship network by evaluating degree centrality at both the field-average level and among the top 100 most central authors for a selected year (e.g., 2018). This helps us identify which fields host the most interconnected researchers and which fields dominate the central structure of the network.

Field-Wise Average Degree Centrality in 2018

```
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
from collections import defaultdict
from tqdm import tqdm

# ---------- Step 1: Select year ----------
year = 2018
G = yearly_graphs[year].copy()
```

```python
# ---------- Step 2: Assign dominant field ----------
def get_dominant_field(author):
    fields = list(author_fields.get(author, []))
    return fields[0] if fields else "Unknown"

nx.set_node_attributes(G, {node: get_dominant_field(node) for node in
G.nodes()}, "field")

# ---------- Step 3: Degree Centrality ----------
deg_centrality = nx.degree_centrality(G)

# ---------- Step 4: Aggregate by Field ----------
field_scores = defaultdict(list)
for author, score in deg_centrality.items():
    field = G.nodes[author]["field"]
    field_scores[field].append(score)

field_avg = {field: sum(scores)/len(scores) for field, scores in
field_scores.items()}
df_avg = pd.DataFrame.from_dict(field_avg, orient="index",
columns=["Avg_Degree_Centrality"])
df_avg = df_avg.sort_values(by="Avg_Degree_Centrality",
ascending=False)

# ---------- Step 5: Plot ----------
plt.figure(figsize=(10,6))
df_avg.head(20).plot(kind="bar", legend=False, color="teal")
plt.title(f"Avg Degree Centrality per Field (Top 20 fields) – {year}")
plt.ylabel("Avg Degree Centrality")
plt.xlabel("Field")
plt.grid(axis="y")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



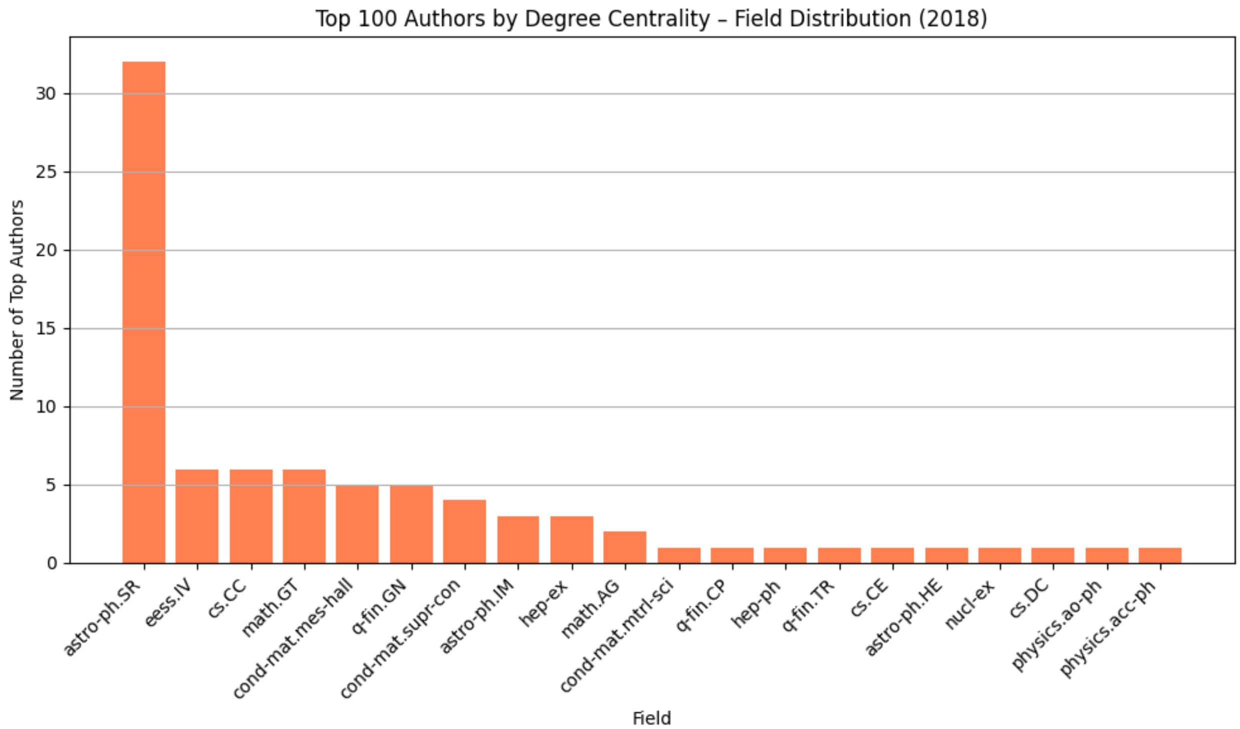
This bar chart ranks the top 20 academic fields based on their average degree centrality in the 2018 co-authorship network.

- **Interpretation of Degree Centrality:** A higher average degree centrality in a field suggests that, on average, researchers in that field collaborate with more co-authors, making them more "central" in the network.
- **Top Fields:**
  - **astro-ph.SR** (Astrophysics - Solar and Stellar) ranks highest, suggesting that its researchers were the most interconnected in 2018.
  - Fields like **CS.GL (General Computer Science) and q-fin.GN (General Quantitative Finance)** also appear high, indicating strong collaborative behavior within those domains.
- **Diversity in Top Fields:** The top fields include a mix of astrophysics, computer science, finance, and condensed matter physics, showing that high connectivity is not isolated to one discipline.
- **Implication:** Central fields might act as bridges or influencers in the research community, potentially accelerating the diffusion of knowledge.

Field Distribution of Top 100 Central Authors (2018)

```
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
from collections import defaultdict

# Step 1: Simple cleaning instead of unidecode
def get_dominant_field_simple(author):
    author_clean = author.lower().strip()
    for key in author_fields:
        key_clean = key.lower().strip()
        if author_clean == key_clean:
            fields = list(author_fields[key])
            return fields[0] if fields else "Unknown"
    return "Unknown"

# Step 2: Choose year and compute degree centrality
year = 2018
G = yearly_graphs[year].copy()
centrality = nx.degree_centrality(G)

# Step 3: Extract top 100 authors
top_authors = sorted(centrality.items(), key=lambda x: x[1],
reverse=True)[:100]

# Step 4: Assign field to each top author
field_counts = defaultdict(int)
for author, _ in top_authors:
    field = get_dominant_field_simple(author)
    field_counts[field] += 1

# Step 5: Convert to DataFrame and filter out "Unknown"
df_top_fields = pd.DataFrame(field_counts.items(), columns=["Field",
"Count"])
df_top_fields = df_top_fields[df_top_fields["Field"] != "Unknown"]
df_top_fields = df_top_fields.sort_values(by="Count", ascending=False)

# Step 6: Plot
plt.figure(figsize=(10, 6))
plt.bar(df_top_fields["Field"], df_top_fields["Count"], color="coral")
plt.title(f"Top 100 Authors by Degree Centrality – Field Distribution
({year})")
plt.xlabel("Field")
plt.ylabel("Number of Top Authors")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.grid(True, axis='y')
plt.show()

# Optional: Print unknown ratio
```

```python
unknown_ratio = sum(1 for author, _ in top_authors if
get_dominant_field_simple(author) == "Unknown") / 100
print(f"Unknown field ratio: {unknown_ratio:.2%}")
```




```
Unknown field ratio: 18.00%
```

This bar chart highlights the field-wise distribution of the top 100 authors by degree centrality in the 2018 co-authorship network.

- **Dominant Field:**

astro-ph.SR (Astrophysics - Solar and Stellar) overwhelmingly dominates, with 32 out of the top 100 authors. This aligns with its high average degree centrality and suggests a highly collaborative and tightly-knit author cluster in that field.

- **Other Significant Fields:**

Fields such as eess.IV (Electrical Engineering - Image and Vision), CS.CC (Computational Complexity), and q-fin.GN (Quantitative Finance - General) show moderate presence with 5–6 authors each, indicating their growing influence and collaboration density in 2018.

- **Field Diversity:**

A wide variety of fields are represented, from mathematics to condensed matter physics, though most have only 1–3 highly central authors.

- **Unknown Field Ratio:**

About 18% of top authors could not be mapped to any known field, possibly due to missing or inconsistent metadata. This may introduce some bias in field-level insights and points to limitations in field attribution.

Conclusion:

The analysis reinforces that a small set of fields produce disproportionately central researchers in the collaboration network. This could reflect either higher publication frequency, stronger collaborative norms, or structural properties of those research communities.