A systematic literature review of the Prisoner's Dilemma; collaboration and influence.

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1 Timeline

2 Analysing a large corpus of articles

The focus of the paper has been the academic publications on the topic the iterated prisoner's dilemma. Whilst in Section 1 we covered several publications of specific interest and manually partitioned the literature in different sections, in the second part of this paper we analyse the publications using a large dataset of articles. The data collection process is covered in Section 2.1 and a preliminary analysis of the data is conducted in Section 2.2. In Section 2.3, we present the methodology which will be used to analyse the authors relationships. In summary, we will be using graph theoretical methods to ascertain the level of collaborative nature of the field and identify influence, relative to:

- Two other sub fields of game theory: auction games [11] and the price of anarchy [17].
- A temporal analysis.

Finally in Section 2.4, the results of the analysis are presented.

2.1 Data Collection

Academic articles are accessible through scholarly databases and collections of academic journals. Several databases and collections today offer access through an open application protocol interface (API). An API allows users to query directly a journal's database and bypass the user interface side of the journal. Interacting with an API has two phases: requesting and receiving. The request phase includes composing a url with the details of the request. For example, `http://export.arxiv.org/api/query?search_query=abs:prisoner'sdilemma&max_results=1` represents a request message. The first part of the request is the address of the API we are querying. In this example the address corresponds to the API of arXiv. The second part of the request contains the search arguments. In our example we are requesting for a single article that the word 'prisoners dilemma' exists within it's title. The format of the request message is different from API to API. The receive phase includes receiving a number of raw metadata of articles that satisfied the request message. The raw metadata are commonly received in extensive markup language (xml) or Javascript object notation (json) formats [14]. Similarly to the request message, the structure of the received data differs from journal to journal.

The data collection is crucial to this study. To ensure that this study can be reproduced all code used to query the different APIs has been packaged as a Python library and is available online [12]. The software could be used for any type of projects similar to the one described here, documentation for it is available at: `http://arcas.readthedocs.io/en/latest/`. Project [12] allow us to collect articles from a list of APIs by specifying just a single keyword. Four prominent journals in the field and a pre print server were used as sources to collect data for this analysis. Those were PLOS, Nature, IEEE, Springer and arXiv.

A series of search terms were used to identify relevant articles. The terms used to collect the main data set were,

- “prisoner’s dilemma”,
- “prisoners dilemma”,
- “prisoners evolution”,
- “prisoner dilemma”,
- “prisoner game theory”

and articles for which any of these terms existed within the title, the abstract or the text are included in the analysis. More specifically, 23% of article considered here were included because any of the above terms existed within the abstract, 50% within the main text and 27% within the title. As will be described in Section 2.2, two other game theoretic sub fields were also considered in this work, auction games and the price of anarchy. For collecting data on these sub fields the search terms used were “auction game theory” and “price of anarchy”. The three data sets are archived and available at. Note that the latest data collection was perform on November 2018.

2.2 Preliminary Analysis

A summary of each of the three data sets used is presented in this section. The three data sets are:

- The main data set which contains articles on the prisoner’s dilemma.
- A secondary data set which contains article on auction games.
- A secondary data set which contains articles on the price of anarchy.

The main data set and the main focus of this analysis is [ref]. It consists of 3089 articles with unique titles. In case of duplicates the preprint version of an article (collected from arXiv) was dropped. Of these 3089 article, 89 have not been collected from the aforementioned APIs. These articles were of specific interest and manually added to the dataset throughout the writing of Section 1. A more detailed summary of the articles’ provenance is given by Table 1. Only 3% of the data set consists by articles that were manually added and 33% of the articles were collected from arXiv. The rest four journals have contributed 9%-21% percent of the articles.

provenance	# of Articles	Percentage
Manual	89	2.81
IEEE	295	9.31
PLOS	482	15.22
Springer	572	18.06
Nature	673	21.25
arXiv	1056	33.34

Table 1: Articles’ provenance for main data set.

The average number of publications was calculated for the entire dataset and for each provenance. The average number of publications is denoted as, $\mu_P = \frac{N_A}{N_Y}$, where N_A is the total number of articles and N_Y is the years of publication. The years of publication is calculated as the range between 2018 and the first published article, for each provenance, within the data. These averages are summarised in Table 2. Overall an average of 49 articles are published per year on the topic. The most significant contribution to this appears to be from arXiv with 16 articles per year, followed by Nature with 10 and Springer with 9.

Though the average publication offers insights about the publications of the fields, it remains a constant number. The data we are handling here is a time series between 1950, when the game was introduced, and 2018 (Figure 1). Two observations can be made from Figure 1.

	Av. publication
IEEE	5.0
PLOS	8.0
Springer	9.0
Nature	11.0
arXiv	16.0
Overall	49.0

Table 2: Average publication for main data set.

1. A steady increase to the number of publications since the 1980s and the introduction of computer tournaments.
2. A decrease in 2017-2018. This is due our data set being incomplete. Articles that have been written in 2017-2018 have either not being published or have are not retrievable by the APIs yet.

These observations can be confirmed by studying the time series. Using [6], an exponential distribution is fitted to the data from 1980-2016. The perfect fitting proves that since 1980 there has been an exponential increase to the number of publications till 2016 (Figure 2). The fitted model can also be used to project the behaviour of the field for the next 5 years. The forecasted periods are plotted in Figure 3 and their exact values are given by Table 3. Thought the time series has indicated a slight decrease we can see that the model forecasts that the number of publications will keep increasing, thus indicating that the field of the iterated prisoner's dilemma still attracts academic attention.

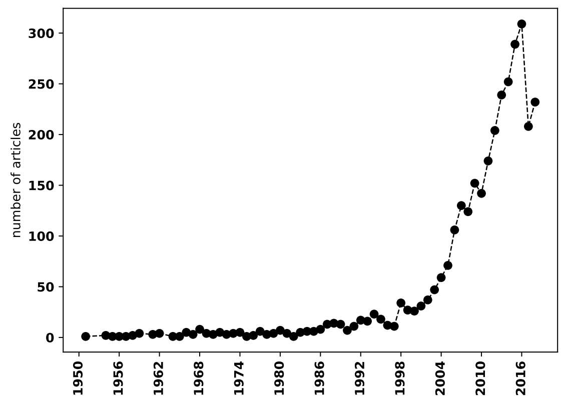


Figure 1: Line plot; # of articles published on the PD 1950-2019.

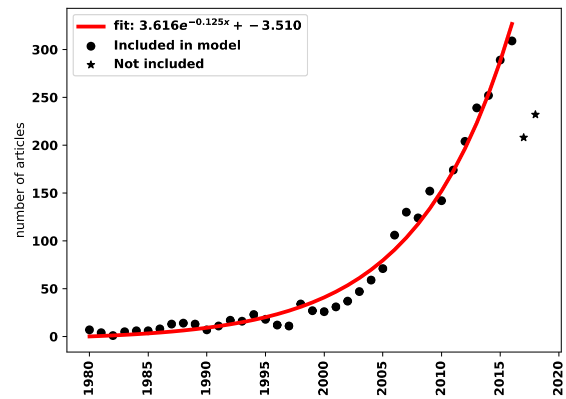


Figure 2: Scatter plot; # of articles published on the PD 1980-2019.

	Forecast
2017	371.0
2018	421.0
2019	478.0
2020	542.0
2021	615.0

Table 3: Forecasting the number of publications over the next 10 years.

Moreover, two sub fields of game theory have been chosen for this work; auction game and the price of anarchy.

- Auction theory is a branch of economics which deals with how people act in auction markets and researches the properties of auction markets. Game theory is being used for years to study auctions and the behaviour of the bidders [18]. The earlies entry in our data set [ref] goes back to 1974 (Figure 4).

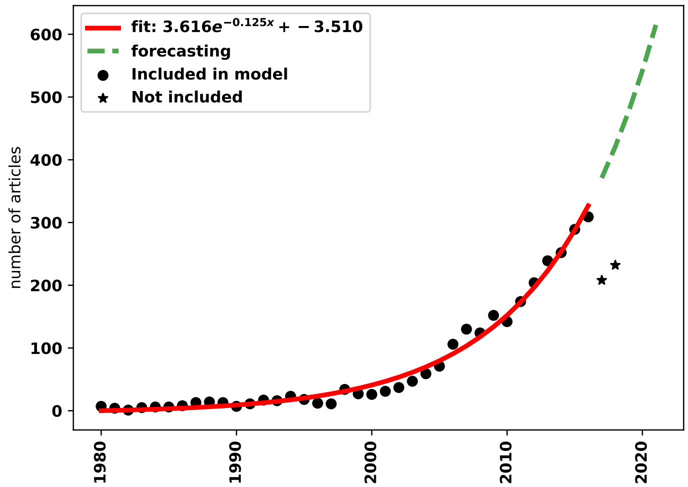


Figure 3: Forecast for 2017-2022

- Price of Anarchy is a concept in economics and game theory which measures how the efficiency of a system degrades due to selfish behaviour of it's agents. There is a variety of such measures however the price of anarchy has attracted a lot of attention since it's informal introduction in 1999 by [7]. The first entry in the data set [ref] is a year later in 2000 (Figure 5).

A summary of both data sets collected on both topics, in comparison to that of [ref], is given by Table 4.

The iterated prisoner's dilemma and auction theory are very well studied topics that have been publicising for decades. A large number of articles have been collected for both topics, 3089 and 34444 respectively. Though, auction games have a larger number of articles, the iterated prisoner's dilemma has almost 300 more authors. Auction games have an overall average publication of 93 articles compared to the prisoner's dilemma with 49. The 50% of articles for [ref] have been collected from the pre print server arXiv and no articles have been published in PLOS.

Compared to these two topics the price of anarchy is a fairly recent one. Only a total of 747 articles have been collected, however it has a large number of 1229 authors. Meaning that on average each paper had had at least two authors. It has an overall average publication of 39 articles and the biggest contribution has been made from Springer. Note that no article have been added manually for the data sets for the two extra sub fields.

	Num. Articles	Num. Authors	Manual (%)	PLOS (%)	Nature (%)	Springer (%)	IEEE (%)	arXiv (%)	Av. Publication
Prisoner's Dilemma	3089	5092	2.88	15.6	21.79	18.52	9.55	34.19	49.0
Auction Games	3444	4770	-	-	5.89	37.63	7.46	51.36	93.0
Price of Anarchy	746	1227	-	1.74	24.66	38.07	30.70	8.85	41.0

Table 4: Measures of all three data sets.

2.3 Methodology

As discussed in [19], bibliometrics or the statistical analysis of published works (originally described by [15]) have been used to support historical assumptions about the development of fields [16], identify connections between scientific growth and policy changes [3], and investigate the collaborative structure of an interdisciplinary field [10]. Most academic research is undertaken in the form of collaborative effort and as [8] points out, it is rationale that two or more people have the potential to do better as a group than individually. Collaboration in groups has a long tradition in experimental sciences and it has be proven to be productive according to [4]. The number of collaborations can be very different between research fields and understanding how collaborative a field is, it is not always an easy task. Several studies tend to consider academic citations as a measure for these things. A blog post published in Nature [13] argues that depending on citations can often be misleading because the true number of citations can not be known. Citations can be missed due to

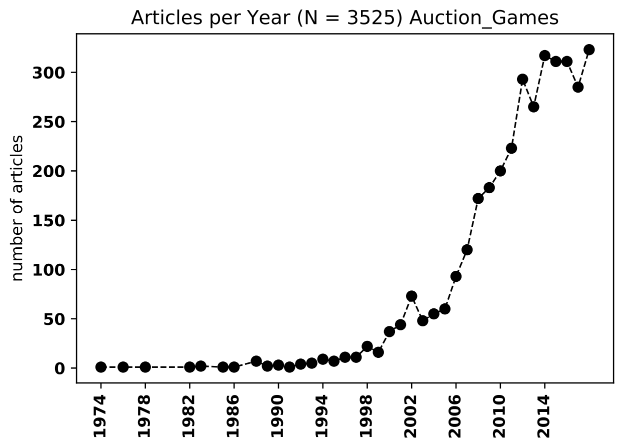


Figure 4: Line plot; # articles published on auction games 1974-2018.

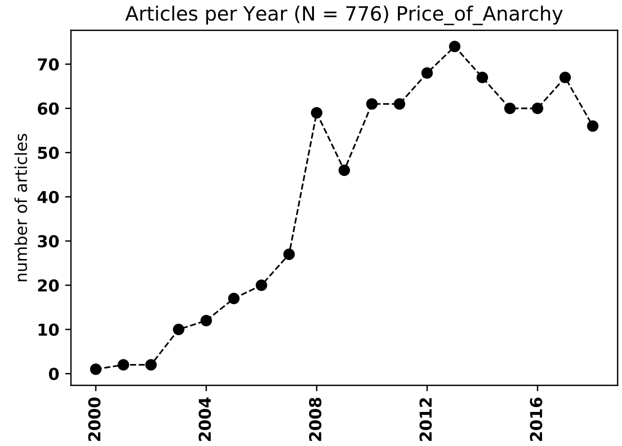


Figure 5: Line plot; # articles published on the price of anarchy.

data entry errors, academics are influenced by many more papers than they actually cite and several of the citations are superficial.

A more recent approach to measure collaborative behaviour is to use the co authorship network, as described in [10]. Using this approach has many advantages as several graph theoretic measures can be used as proxies to explain authors relationship. In [10], they analyse the development of the field “evolution of cooperation” using this approach. The topic “evolution of cooperation” is a multidisciplinary field which also includes a large number of publications on the prisoner’s dilemma. In this paper we build upon the work done by [10] and extend their methodology. Though in [10], they considered a data set from a single source, Web of Science, our data have been collected from five different sources. Moreover, the collaborative results of our analysis are compared to those of two different sub fields. Co authorship networks have also been used in [19] for classifying topics of an interdisciplinary field. This was done using centrality measures, which will be covered below, here we use centrality measures in order to understand the influence an author can have and can receive by being part of an academic group.

The relationship between the authors within a field will be modelled as a graph G with a set V_G of nodes and E_G of edges. The set V_G represents the authors and an edge connects two authors if and only if those authors have written together. The co authorship network is constructed using the main data set described in Section 2.2 and the open source package Networkx [5]. The prisoner’s dilemma network is denoted as G_1 where the number of unique authors $|V(G_1)|$ is 5092 and $|E(G_1)| = 9883$. Note that the names of all authors names were formatted as their last name and first initial (i.e. Martin A. Nowak to M.Nowak). This was done to avoid errors such as Martin A. Nowak and Martin Nowak, being treated as a different person. Networkx will also be used the following section to conduct our analysis.

Collaborativeness, will be analysed using measures such as, isolated nodes, connected components, clustering coefficient, modularity and average degree. These measures allow us to understand the number of connections authors can have and how strongly connected these people are. The number of isolated nodes is the number of nodes that are not connected to another node, thus the number of authors that have published alone. The average degree denotes the average number of neighbours for each nodes, i.e. the average number of collaborations between the authors.

A connected component is a maximal set of nodes such that each pair of nodes is connected by a path. We are interested in the number of connected components but also the size of the largest connected component in the network. The size of largest connected component represents the scale of the central cluster of the entire network, as it will discussed in the analysis section. Clustering coefficient and modularity and are also calculated. Clustering coefficient defined by,

$$\text{clustering coeff.} = \frac{3 \times (\text{number of triangle on the graph})}{\text{number of connected triples of nodes}}$$

is a local measure of the degree to which nodes in a graph tend to cluster together in a clique. It is precisely the probability that the collaborators of an author also write together. In comparison, modularity is a global measure designed to measure the strength of division of a network into modules. A high value of modularity corresponds to a structure where authors mainly write in groups and interact less with the rest of the network. We will be using the Louvain method described in [2] to calculate modularity.

Furthermore, the second part of the analysis focuses on the study of influence. Networks are commonly dominated by one person who controls information flow and people that receive a great amount of information due to their position. In this paper we aim to understand two things, (1) which people control the flow; as in which people influence the field the most and (2) which are the authors that gain the most from the influence of the field. To measure these concepts we will be using graph theoretic metrics, more specifically centrality measures. Centrality measures are often used to understand different aspects fo social networks [9]. In order to achieve that two centrality measures that have been chosen were closeness and betweenness centrality.

1. In networks some nodes have a short distance to other nodes and consequently are able to spread information on the network very effectively. A representative of this idea is **closeness centrality**, where a person is seen as centrally involved in the network if it requires only few intermediaries for contacting others and thus is structurally relatively independent. Here, we define this as influence. Authors with a high value of closeness centrality, are the authors that spread scientific knowledge easier on the network and we say that they have high influence.
2. Another centrality measure is the **betweenness centrality**, where the determination of an author's centrality is based on the quotient of the number of all shortest paths between nodes in the network that include the regarded node and the number of all shortest paths in the network. In betweenness centrality the position of the node matters. Nodes with a higher value of betweenness centrality are located in positions that a lot of information pass through them, we define this as the gain from the influence, thus these authors gain the most from their networks.

In the next section we will be using all the metrics discussed here to provide insights on the field.

2.4 Analysis of co authorship network

As mentioned previously, G_1 denotes the co authorship network of iterated prisoner's dilemma. The open source software Gephi [1] has been used to plot the networks of this work, more specifically G_1 is given by Figure. It is evident that our network is disjoint, which is only natural as many authors write academic articles on their own. More specifically, a total of 157 authors, have had single author publications, which corresponds to the 0.033 (%) of authors in G_1. There are a total of 1027 connected components and the largest one has a size of 1457 . The largest connected component is shown in Figure. The network as a clustering coefficient of 0.685 , thus you are 68% likely to write with a collaborators co author. Overall the networks have an average degree of 4.194 , meaning that the average publication on the field has 4 authors. The distribution of the degrees, Figure 6, indicates that thought the average is 4 there are authors with far more connections, the largest one being around 30.

How does these compare to other fields and more specifically to other fields of game theory? A summary of the two graphs, which be denoted as G_2 for auction games and G_3 for the price of anarchy, are given by Figure. A summary of metrics and for all three co authorship networks is given by Table 5. The following remarks can be made from Table 5.

- Comparing to another well studied topic (G_2), the co authorship network G_1 appears to be more modular. This is due the high values of modularity, connected components and clustering coefficient. Authors in G_1 tend to write in teams, separated from the main cluster and it's very likely to create smaller clusters of 3. Compared that G_2 has a smaller number of connected component but the the main cluster has a bigger size.
- In the more recent topic price of anarchy (G_3) there are hardly any people that have published a paper alone. There is already a small community that is connected with a main cluster of 421 authors. The network is also very modular. Indicating that people that are not connected to the main cluster are in smaller connected components. There is even higher clustering coefficient compared to the rest of networks so these connected components are very likely of size 3, which is also indicated by the degree distribution of G_3 (Figure 7).

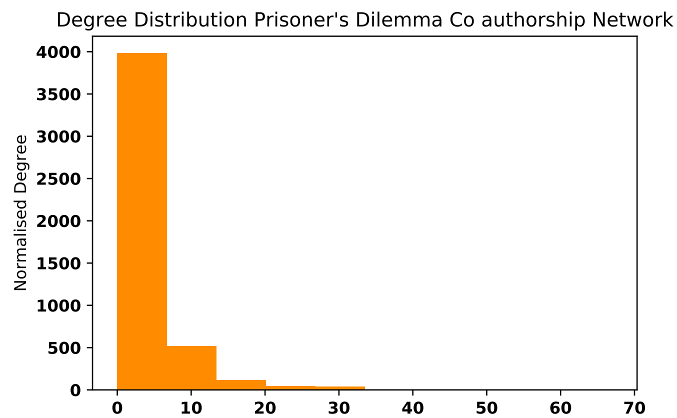


Figure 6: Degree distribution for network G_1.

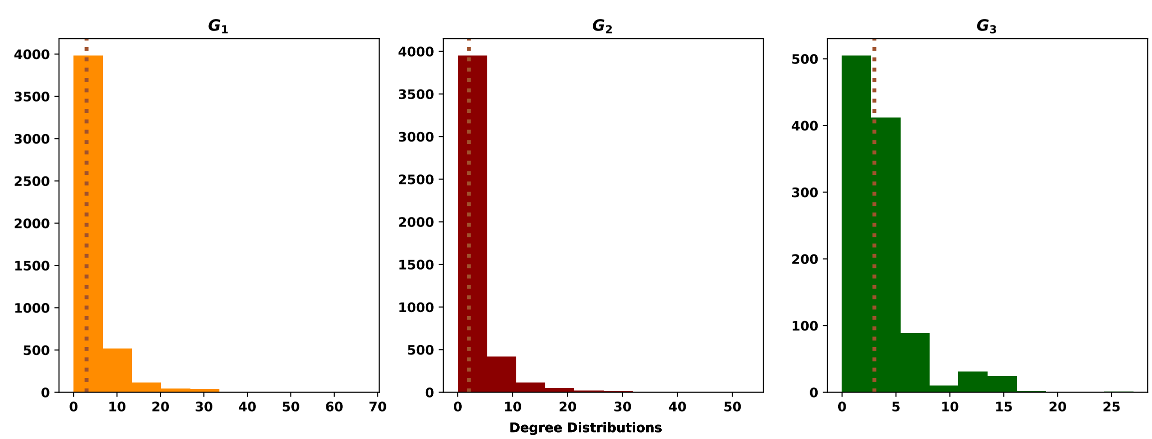


Figure 7: Degree distribution for networks $G_1 G_3$.

- Shown in Figure 7 the degree distributions of G_1 and G_2 are more skewed to the left, though there are some cases of high degree (> 20) this could be due the size of the networks and respectively the size of the main clusters.

	# Connected Components	# Edges	# Isolated	# Nodes	% Isolated	Av. Degree	Clustering	Largest cc	Modularity
Prisoner's Dilemma	1027	9883	157	4713	0.033	4.194	0.685	1457	0.931
Auction Games	949	7753	210	4576	0.046	3.389	0.595	2079	0.892
Price of Anarchy	194	1911	4	1074	0.004	3.559	0.703	421	0.948

Table 5: Network metrics for G_1, G_2, G_3.

The growth of collaborativeness behaviour can also be studied. To achieve that we construct the network cumulative with one year of publication interval There are a total of 64 graphs, for 64 periods starting from 1954. All the collaborative metrics have been calculated for each period and they are given in Table 6. Similar to the results of [10], we can observe that the network grows over time and that there is a rapid expansion to of its largest connected component. The size of it its rapidly ncressing seing that links are created over the authors of the field over time. However, since the beginining there has been a high value of modularity. People in G_1 tend to create smaller communities or clusters.

One might notice a sundent incrase to the network after 2000. This was briefly comment upon in [10]. In Figure 8, the number of nodes over time have been plotted. More specifically, we plot the normalised number of nodes which is calculated by dividing with the total number of nodes, in G_1 case that is 5092 . A steep increase, appears to be happening after 2000, though this could indicate a specific thing that happened only in G_1, Figure 9 argues with that. Compared to both G_2 and G_3 there is an increase in the number of authors since 2000.

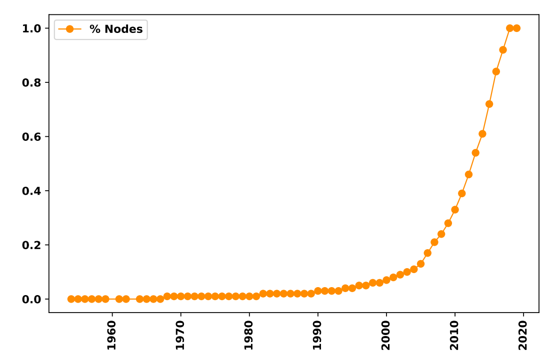


Figure 8: Normalized # Nodes over time for G_1.

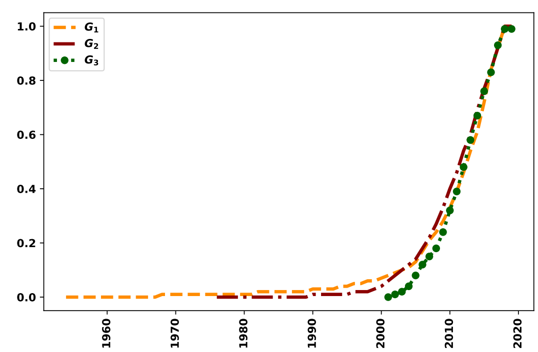


Figure 9: Normalized # Nodes over time for all networks.

The average degree over time for all three networks is given Figure 10. Thought auction game theory and the prisoners' dilemma have been for different time periods we can see that the follow a similar trend. A small peek after the first years of publications followed by a steady increase ever since with a highest value of an average degree of 4. Price of anarchy as a similar trend but suffered of a small decrease around 2003.

Morover, The influence of the networks were explored using centrality measures. For G_1 the most central author based on closeness and betweenness are given by Tables respectively.

The distrubtion of both centrality measures for $G_1 - G_3$ are given by Figures. These are used to explore the how strong influence is compared to other fields. The main coclusions that can be made are:

- For all three networks betweenness centrality is very skewed to the left size, around 0. This could indicate that in academia there is not as much gain as we would have thought from the network we belong to.
- On the other hand closeness appears to have more variation. From the authors of a cc ¿ 0.02 not attern was found. the provenance of their work, the year of publication have all been very different.
- closeness centrality the people with a higher calue are the people on the main clusters of their respective networks. The only way to have influence to the larger picture if to be in that main cluster.

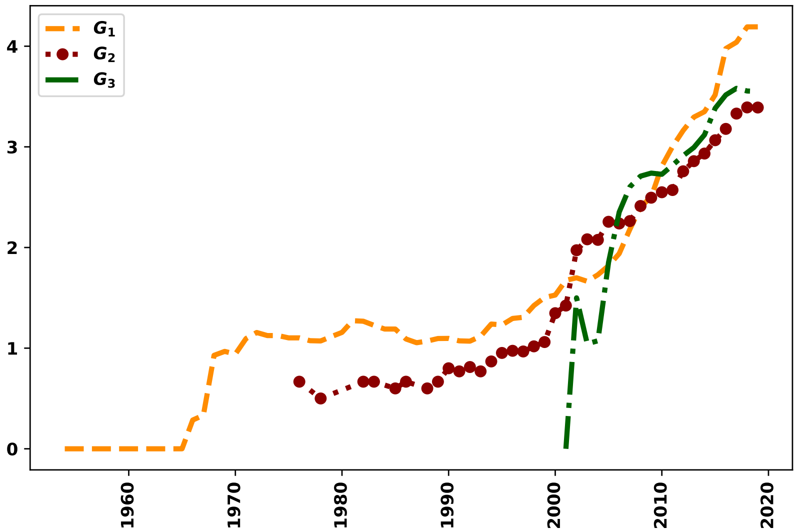


Figure 10: Degree distribution for network G_1.

	Name	Betweeness
1	M. Perc	0.018699
2	Z. Wang	0.015825
3	L. Wang	0.014812
4	Y. Zhang	0.012886
5	M. Nowak	0.011581
6	H. Wang	0.008221
7	Y. Chen	0.008008
8	Y. Li	0.007982
9	Y. Moreno	0.007335
10	N. Masuda	0.006087

Figure 11: Ten most influenced authors in G_1.

	Name	Closeness
1	L. Wang	0.096421
2	M. Perc	0.095338
3	Y. Zhang	0.094736
4	Z. Wang	0.094260
5	Y. Chen	0.090542
6	J. Wang	0.089248
7	X. Wang	0.088720
8	Y. Liu	0.088546
9	J. Zhang	0.088181
10	L. Zhang	0.087923

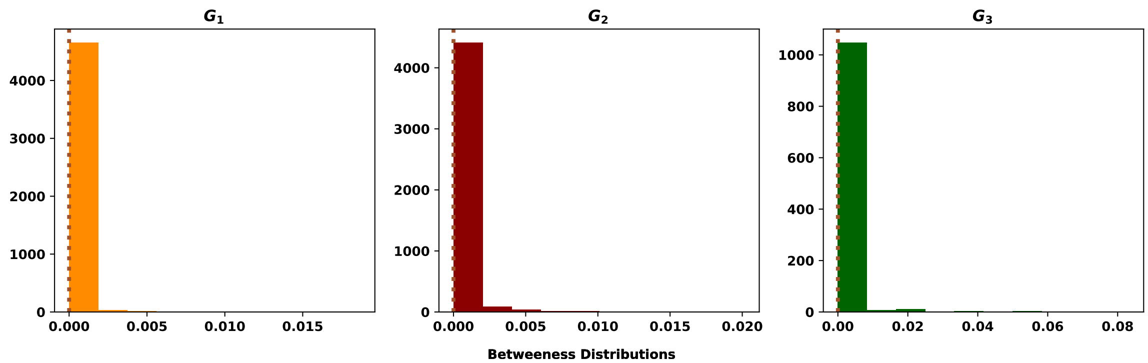
Figure 12: Authors that gain the most influence in G_1.

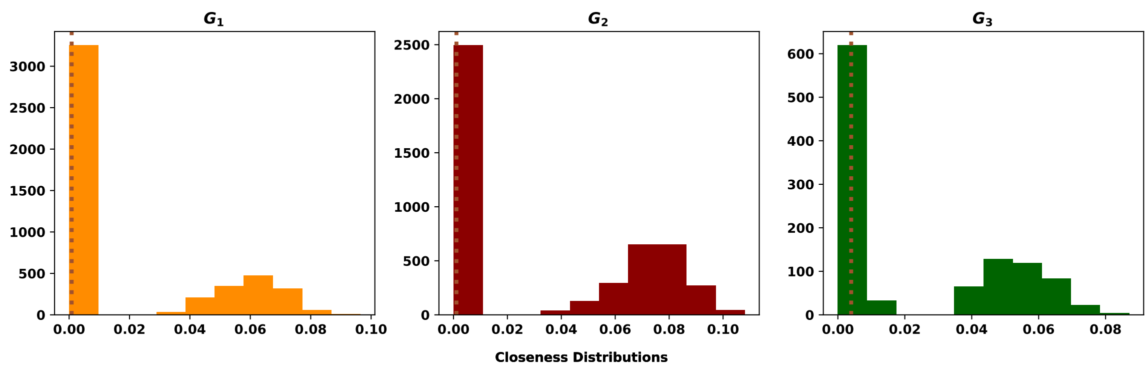
	# Connected Components	# Isolated	% Isolated	Av. Degree	Clustering	Largest cc	Modularity
Period 0	3	3	1.00	0.00	0.00	1	-
Period 1	2	2	1.00	0.00	0.00	1	-
Period 2	3	3	1.00	0.00	0.00	1	-
Period 3	4	4	1.00	0.00	0.00	1	-
Period 4	6	6	1.00	0.00	0.00	1	-
Period 5	7	7	1.00	0.00	0.00	1	-
Period 6	7	7	1.00	0.00	0.00	1	-
Period 7	8	8	1.00	0.00	0.00	1	-
Period 8	9	9	1.00	0.00	0.00	1	-
Period 9	10	10	1.00	0.00	0.00	1	-
Period 10	12	10	0.71	0.29	0.00	2	0.5
Period 11	15	12	0.67	0.33	0.00	2	0.666667
Period 12	19	13	0.46	0.93	0.16	5	0.591716
Period 13	21	15	0.48	0.97	0.16	6	0.533333
Period 14	23	16	0.47	0.94	0.15	6	0.585938
Period 15	26	16	0.38	1.10	0.26	6	0.763705
Period 16	27	16	0.36	1.16	0.31	6	0.801775
Period 17	29	17	0.35	1.12	0.29	6	0.814815
Period 18	29	17	0.35	1.12	0.29	6	0.814815
Period 19	30	18	0.37	1.10	0.29	6	0.814815
Period 20	30	18	0.37	1.10	0.29	6	0.814815
Period 21	33	19	0.35	1.07	0.26	6	0.837099
Period 22	34	19	0.34	1.07	0.25	6	0.846667
Period 23	36	21	0.34	1.11	0.25	6	0.854671
Period 24	37	22	0.34	1.16	0.28	6	0.866326
Period 25	37	22	0.33	1.27	0.29	6	0.85941
Period 26	40	24	0.34	1.27	0.32	6	0.873086
Period 27	43	26	0.35	1.23	0.30	6	0.878072
Period 28	46	28	0.35	1.19	0.28	6	0.882752
Period 29	46	28	0.35	1.19	0.28	6	0.882752
Period 30	54	35	0.40	1.09	0.26	6	0.887153
Period 31	58	38	0.41	1.05	0.24	6	0.891295
Period 32	61	39	0.39	1.07	0.26	6	0.903524
Period 33	70	43	0.37	1.10	0.26	6	0.921643
Period 34	75	45	0.36	1.10	0.26	6	0.930363
Period 35	84	50	0.36	1.07	0.26	6	0.939007
Period 36	87	52	0.36	1.07	0.25	6	0.942486
Period 37	95	54	0.34	1.12	0.26	6	0.951852
Period 38	110	62	0.32	1.24	0.33	6	0.95996
Period 39	118	64	0.31	1.23	0.31	6	0.964111
Period 40	127	68	0.30	1.30	0.32	6	0.966357
Period 41	137	71	0.29	1.31	0.34	6	0.970812
Period 42	138	55	0.20	1.42	0.36	6	0.976778
Period 43	139	49	0.17	1.50	0.38	6	0.979126
Period 44	156	54	0.16	1.53	0.40	6	0.981765
Period 45	157	42	0.12	1.67	0.42	9	0.980204
Period 46	178	48	0.12	1.70	0.43	9	0.982271
Period 47	208	54	0.11	1.66	0.43	9	0.985315
Period 48	230	54	0.10	1.73	0.44	10	0.986425
Period 49	256	54	0.09	1.82	0.47	20	0.985488
Period 50	309	62	0.08	1.94	0.50	22	0.988459
Period 51	361	72	0.07	2.18	0.53	26	0.986283
Period 52	404	82	0.07	2.40	0.55	40	0.984604
Period 53	451	94	0.07	2.50	0.55	70	0.979801
Period 54	503	106	0.07	2.81	0.56	195	0.965463
Period 55	570	116	0.06	3.00	0.59	259	0.965816
Period 56	637	120	0.05	3.16	0.62	377	0.961061
Period 57	700	131	0.05	3.30	0.63	498	0.954499
Period 58	769	139	0.05	3.35	0.64	651	0.9478
Period 59	857	148	0.04	3.52	0.65	845	0.943528
Period 60	935	155	0.04	3.98	0.67	1116	0.939878
Period 61	978	157	0.04	4.04	0.68	1253	0.938316
Period 62	1029	157	0.03	4.19	0.68	1456	0.930319
Period 63	1029	157	0.03	4.19	0.68	1456	0.928797

Table 6: Collaborativeness metrics for cumulative graphs.

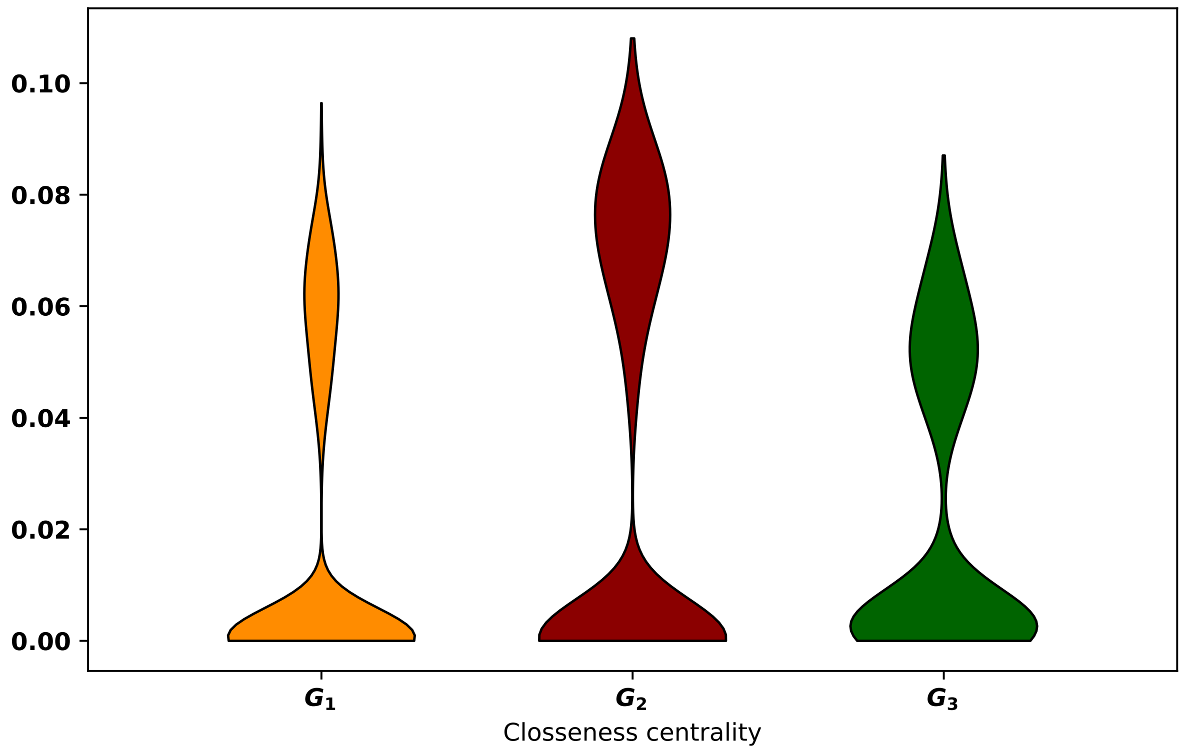
- We can explore the distribution of closeness even beter from Figure. There is a large amount of people near 0 and 0.0.3 G_3 has more people with higher values.

- the network with the highest value of cc is the network with the biger cluster.





2.5 Conclusion



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