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

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1 Analysing a large corpus of articles

In this section we will focus on the analysis of the study of the prisoner's dilemma using a large dataset of articles. In Section 1.1 the data will be described and analysed in Section 1.2. In Section 1.3 the author relationships will be analysed graph theoretically to ascertain the level of collaborative nature of the field and identify influencer. This will be done relative to:

- two other sub fields of game theory: auction games [50] and the price of anarchy [66].

1.1 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 what is wanted. Figure 1 presents an example of 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) format [61]. Similarly to the request message, the structure of the received data differs from journal to journal.

```
http://export.arxiv.org/api/query?search_query=abs:prisoner's dilemma&max_results=1
```

Figure 1: A request message for the arXiv API.

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 [55]. 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 [55] allow us to collect articles from a list of APIS by specifying just a single keyword. The following sources were used to collect data for this analysis:

1. PLOS [27];

2. Nature [31];
3. IEEE [37];
4. Springer [49].
5. arXiv [47];

These are four prominent journals in the field, as well as the pre print server arXiv [47]. In the case of an article being both in a journal and the arXiv, only the journal version was considered.

For each article [55] collects a list of the features, shown in Table 1. Note that the plain text of the article is not collected, just the metadata. The data is archived and available at. In this work only the features of Table 2 are used.

	Result name	Explanation
1	Abstract	The abstract of the article.
2	Author	A single entity of an author from the list of authors of the respective article. Thus there are multiple entries for each article.
3	Date	Year of publication.
4	Journal	Journal of publication.
5	Key	A generated key containing an authors name and publication year (ex. Glynatsi2017).
6	Keyword	A single entity of a keyword assigned to the article by the given journal.
7	Labels	A single entity of labels assigned to the article manual by us.
8	Pages	Pages of publication.
9	Provenance	Scholarly database for where the article was collected.
10	Score	Score given to article by the given journal.
11	Title	Title of article.
12	Unique key	A unique hash.

Table 1: Metadata for each entry.

	Result name	Explanation
1	Abstract	The abstract of the article.
2	Author	A single entity of an author from the list of authors of the respective article.
3	Date	Year of publication.
4	Journal	Journal of publication.
5	Provenance	Scholarly database for where the article was collected.
6	Title	Title of article.

Table 2: Structure of data set used for this work.

A series of keywords were used to identify relevant articles. Articles for which any of these keywords existed within the title or the abstract are included in the analysis. The keywords used to collect the main data set were,

- "prisoner's dilemma",
- "prisoners dilemma",
- "tit-for-tat",
- "tit for tat",
- "zero determinant strategies".

As will be described in Section 1.2, two other game theoretic subfields were also considered in this work, auction games and the price of anarchy. For collecting data on these subfields the following keywords were used:

- key: "auction game theory";

- key: "price of anarchy".

For both of these topics only a single keyword has been used. In comparison 5 different keywords were used to search of articles on the prisoner's dilemma. The amount of articles collected from the key such as 'tit for tat' and 'zero determinant' had a small contribution to the size of the data set.

1.2 Preliminary Analysis

A total of three data sets are explored in this work. A summary of each data 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.

1.2.1 The prisoner's dilemma data set

The main data set and the main focus of this analysis. This data set consists of 1150 articles, where 1145 have unique titles. This is because a total of 5 articles have been collected from both a journal and arXiv. All duplicates from arXiv are dropped, thus hereupon we consider 1145 unique article entries.

Of these 1150 41 articles that 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 **??**. A more detailed summary of the articles' provenance is given in Table 3. The larger number of articles were collected from arXiv, Springer and IEEE. Both Nature and PLOS have a small contribution to the size of the data set. The oldest article was published in 1944 and the most recent one in 2017. Note that the latest data collection was on December 2017.

	Provenance	Total articles
1	arXiv	470
2	Springer	312
3	IEEE	241
4	PLOS	63
5	Nature	23
6	Manual	41

Table 3: Articles' provenance for main data set.

Not all journal have existed for the same ammount og time, so thus calculate the average publication over time. This is done for the overall data set and for each journal individually. This 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 2017 and the first published article within the data.

Table 4 summarises these averages. Overall an average of 21 articles are published per year on the topic. The most significant contribution to this appears to be from arXiv with 8 articles per year, followed by Springer with 5 articles per year.

	Av. publication
Overall	21.167
IEEE	4.463
Nature	0.426
PLOS	1.167
Springer	5.741
arXiv	8.611

Table 4: Average publication for main data set.

Though the average publication offers insights about the publications of the fields, it is still a constant number. The data we are handling here is a time series which appears to have a trend. This is shown by calculating the rolling average which is plotted in Figure 2. The rolling average of each time point is calculated as the average of the points on either side of it.

The rolling average indicates that the time series has an increasing trend. Even so there seems to be a small decrease by the last time point. In order to offer some insights as to what expected of the field in the next years we conduct a forecast for the next time periods.

Initially we test for stationarity using an Augmented Dickey-Fuller test [35]. A time series data is said to be stationary if its statistical properties such as mean and variance remain constant over time. The results show that our data are not significantly stationary at the 0.005 level ($p > 0.005$).

For projecting the behaviour of the field of the new years we are using an ARIMA [20] model which is able to handel non stationary data. The parameters of the model have been fitted using the Akaike Information Criterion value. The model used was ARIMA $(1, 1, 1)$ at the forecast for the next 10 time periods are given by Table 5.

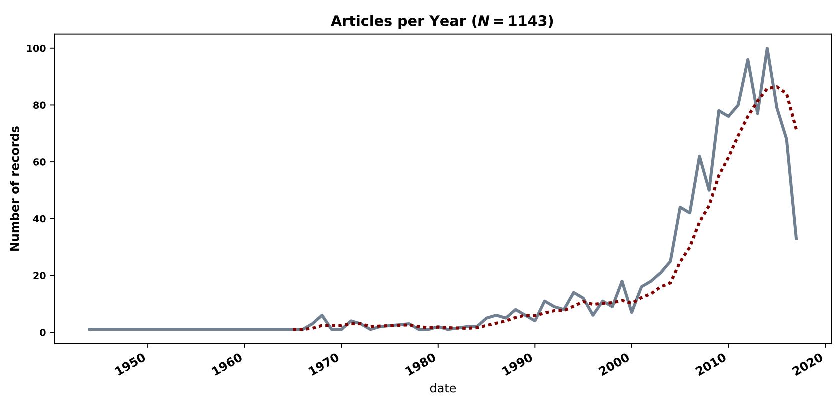


Figure 2: Time series of main data set and the rolling average.

Thought the time series has indicated a slight decrease we can see that the model forecasts an increase over the next years.

1.2.2 Auction games and the price of anarchy data sets

Two subfields of game theory are chosen for this work; auction game and the price of anarchy. A summary of both data sets collected on this two topics is given by Table 6.

A total of 2103 articles with 3860 unique authors are examined for auction games. Auction games is well studied topic with the earliest entry going back to 1974. In comparison, 296 unique articles have been collected on price of anarchy. The earliest entry being in 2003 and a total of 668 unique authors have written about the topic.

In Figure 3 a time plot for each topic is displayed and is exhibited that both topics have had an increasing trend over the years. Though price of anarchy is clearly a new topic compared to auction games.

	Forecast
2018	47.202770
2019	42.969775
2020	45.644469
2021	45.730924
2022	46.787166
2023	47.480038
2024	48.309061
2025	49.087070
2026	49.884193
2027	50.674154

Table 5: Forecasting the number of publications over the next 10 years.

The frequency of the prisoner's dilemma, for both articles and authors, lies between the frequencies of these two topics.

	Price of anarchy	Auction games
Unique articles	296	2103
Unique authors	668	3860
Min publication year	2003	1974
Max publication year	2017	2017

Table 6: Secondary data sets summaries.

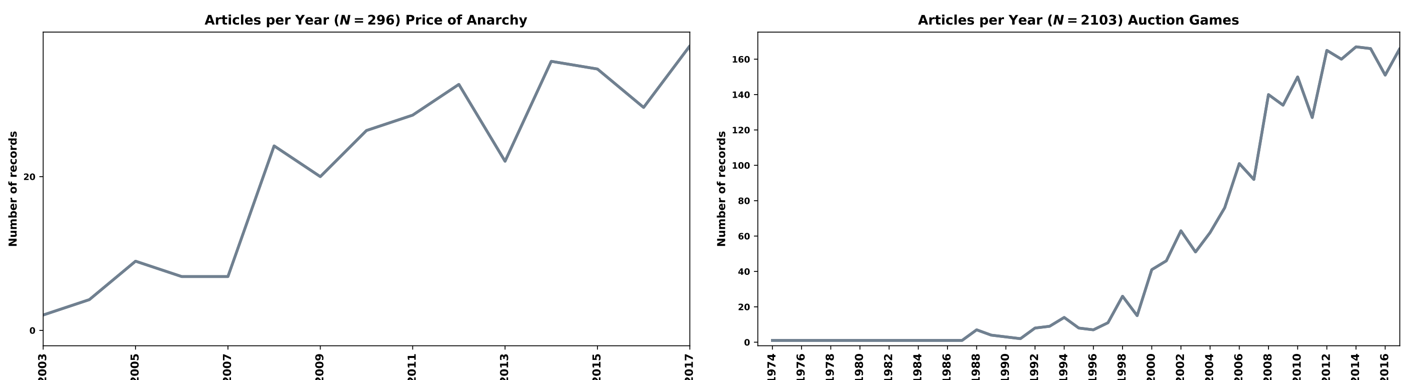


Figure 3: Time plots for secondary data sets.

The provenance of the articles is given by Table 7. Almost 1500 article for auction games have been collected from Springer, that is more than three times the articles that have been collected from other sources. PLOS and Nature have a minor contribution and PLOS and Nature had no articles on the price of anarchy.

The overall average publication for auction games and the price of anarchy are 59 and 20 articles respectively. It appears that auction games publication is largely different for both the prisoner's dilemma and the price of anarchy. These two topics have the same average publication. Note that the significance of each journal differs from topic to topic. Though this analysis will not focus on individual sources from hereupon.

In this section we have described the three data sets that we are going to use in the following sections in order to identify collaborative behaviour and influence. Two data sets of different topics are used for comparison reasons. The frequency of articles and authors differs within the three data sets which is ideal.

Provenance	Total articles (auction games)	Total articles (price of anarchy)
Springer	1429	78
arXiv	436	108
IEEE	301	131
PLOS	15	-
Nature	1	-

Table 7: Articles' provenance for secondary data sets.

Provenance	Av. publication (auction games)	Av. publication (price of anarchy)
Overall	58.973	19.812
Springer	38.622	4.875
arXiv	11.784	6.750
IEEE	8.135	8.188
PLOS	0.405	-
Nature	0.027	-

Table 8: Average publication for auction games and the price of anarchy.

1.3 Co authorship Analysis

Most academic research is undertaken in the form of collaborative effort. As discussed in [40], it is rationale that two or more people have the potential to do better as a group than individually. Academic collaborations have many different forms. Researchers might have immediately collaborated and written together. Others might have collaborated through a common co author.

Collaboration in groups has a long tradition in experimental sciences and it has be proven to be productive according to [23]. Even so, the number of collaborations can be very different between research fields and measuring collaboration is not always an easy task. Another aspect of collaborative behaviour is influence. For example academics can influence through workshops, talks or by collaborating with people in our environment.

Several studies tend to consider academic citations as a measure for these things. As discussed in [56], depending on citations can often be misleading. This is because:

- The true number of citations can not be known. Citations can be missed due to data entry errors.
- Academics are influenced by many more papers than they actually cite.
- Several citations are superficial.

We suggest an alternative measure of collaboration and influence by looking at the co authorship network. A co authorship network, is a network where academics that have written and published together are connected.

Using graph theoretic concepts this network will be analysed to undestand:

- Collaborativeness; for example the number of connections an author has as well as more sophisticated measures of closeness.
- Influence; how many connections are made possible because of an author.

We introduced several network measures that we will be using such as:

- Number of connected components.
- Clustering coefficient.
- Degree distributions.
- Centrality.

1.3.1 Constructing a co authorship network

To construct a co authorship network we need to consider all the unique authors. The issue with retrieving the unique authors is that authors names can be written in different ways in different sources. For example consider the author of this paper:

- Nikoleta Glynatsi
- Nikoleta E. Glynatsi
- Nikoleta Evdokia Glynatsi

Consequently, several different entries of the same author existed within the data set. Thus we wanted to figure out when two author names were the same in real life. Though identifying if two string correspond to the same author is human possible the data sets consited of more than 1000 authors, thus we wanted to automate the procedure.

This was done by using the Levenshtein Distance [52]. The Levenshtein Distance is a metric for measuring the difference between two sequences. It is based upon the number of actions one has to take to transform one string into the other. These actions include:

1. Insertion;
2. Deletion;
3. Substitution of a single character.

Let us consider an example where we are trying to calculate the distance between the two strings. These are 'Wang' and 'Yang'. To compute the distance in a non-recursive way, we use a matrix D containing the distances between all the prefixes of the two strings. The first row and column are indexed by empty strings. The rest of the rows and columns are index by the prefixes of the two strings.

The matrix is filled from left to right. The first row is filled as follows:

1. To go from an empty string to an empty string zero actions are needed. Thus the $D_{\text{e,e}}$ is 0.
2. To go from an empty string to 'W', or the other way around, 1 action is needed. Thus the $D_{\text{e,W}}$ is 1.
3. For every new letter we have to take another action (+1).

Similarly, this is done for the first columns. For rest of the elements we follow a similar approach, but this time the previous distances are also taken in account. For example, $D_{\text{Y,W}}$. For the letter 'Y' to go to 'W' a single action is required. Note that now 1 is added to the minimum distance between of $D_{\text{e,e}}, D_{\text{e,W}}$ and $D_{\text{e,Y}}$.

Similarly we fill the rest of matrix. The last value computed, bottom right, is the Levenshtein Distance of the two strings. In our example it is calculated to be 1.

$$
D = \begin{array}{c} \\ \text{e} \\ \text{Y} \\ \text{A} \\ \text{N} \\ \text{G} \end{array}
\begin{array}{c}
\begin{array}{ccccc} \text{e} & \text{W} & \text{A} & \text{N} & \text{G} \end{array} \\
\begin{bmatrix}
0 & 1 & 2 & 3 & 4 \\
1 & 1 & 2 & 3 & 4 \\
2 & 2 & 1 & 2 & 3 \\
3 & 3 & 2 & 1 & 2 \\
4 & 4 & 3 & 2 & 1
\end{bmatrix}
\end{array}
$$

In this work we calculate the ratio of two string matching for all possible pairs of authors in the data sets. The matching ratio is calculated as,

$$(1 - \frac{\text{lev}}{m}) \times 100,$$

where lev is the distance and m is the length of the longest of the two words. If the ratio of a pair was between 85 and 99 both entries were highlighted. The highlighted entries were manually checked to assure that there were indeed the same author and then one of them was replaced by the other.

For example all entries with author name written as example "Y. Moreno" were replaced by "Yamir Moreno".

The manual check is performed because not all highlighted entries are indeed the same. For example:

1. Zhen Yang and
2. Zhen Wang

are two different authors. Once the name entries have been cleaned the co authorship networks can be defined. The definition of a co authorship network is given by:

Definition 1.1. Co authorship network. A co authorship network is an undirected network G of vertices V and edges E where vertices representing each unique author and an edge connects two authors if and only if those authors have written together. No weight has been applied to the edges nor the nodes.

The three networks considered:

- G_1, the prisoner's dilemma network, where $V(G_1) = 2101$ and $E(G_1) = 3174$.
- G_2, the auction games network, where $V(G_2) = 3676$ and $E(G_2) = 5643$.
- G_3, the auction games network, where $V(G_3) = 637$ and $E(G_3) = 865$.

The respective illustrations of G_1, G_2 and G_3 are given by Figures 4 and 5.

1.3.2 Measures of collaboration

In this section we ascertain the level of collaborative nature of the field. This is measured as the connections authors can have within their groups. Moreover, how strongly connected these groups are. Several connectivity measures will be used to explain such behaviour which are introduced through various examples.

The first measure introduced is the **number of connected components**. A connected component of an undirected graph is a maximal set of nodes such that each pair of nodes is connected by a path. Two examples are illustrated in Figure 6. These are two different sub graphs of G_1 with a number of connected components of 1 and 5.

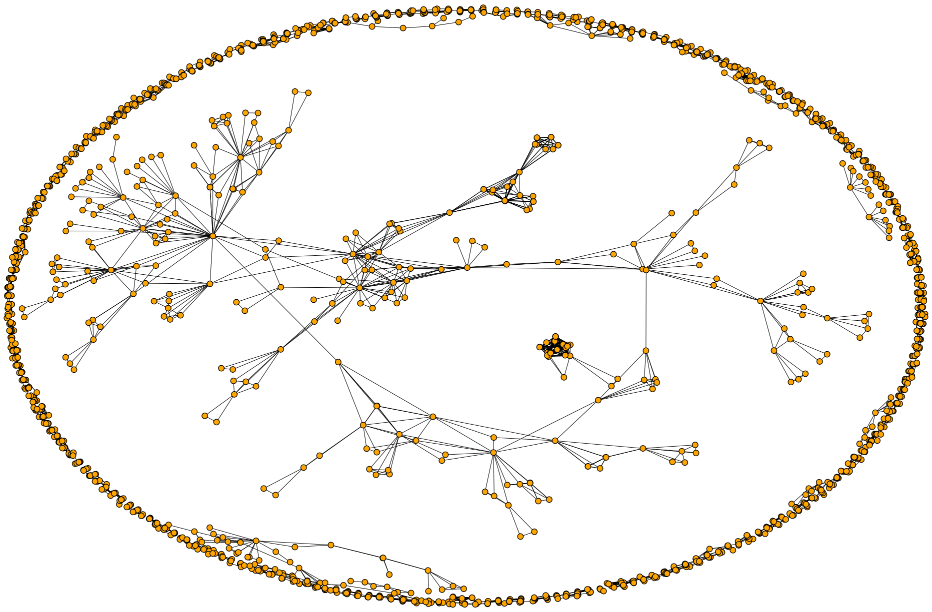
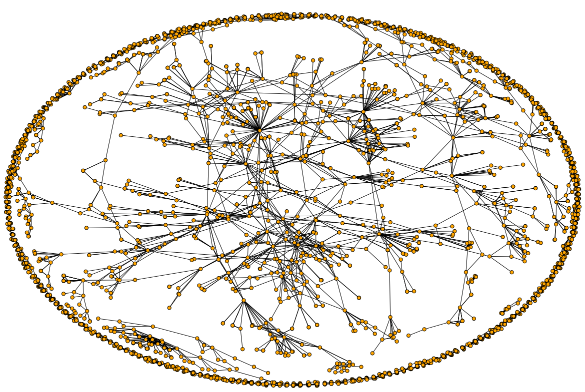
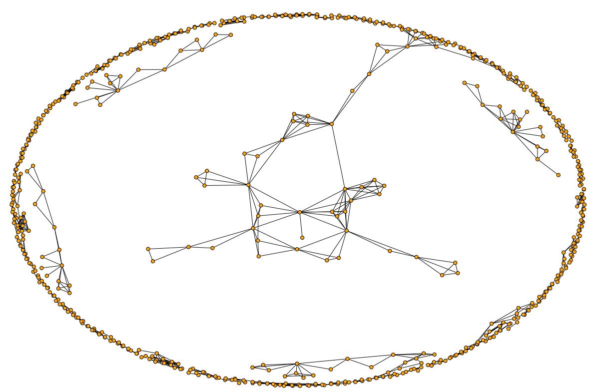


Figure 4: Co authorship network for the prisoner's dilemma.

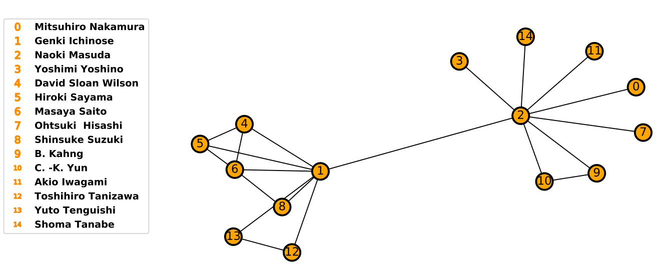


(a) Co authorship network for auction games.

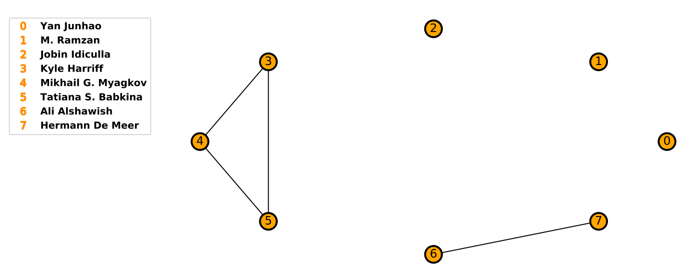


(b) Co authorship network for the price of anarchy.

Figure 5: Co authorship network for secondary data sets.



(a) A sub graph of G_1 with 1 connected component.



(b) A sub graph of G_1 with 5 connected component.

Figure 6: Connected components examples.

Note that a vertex with no incident edges is itself a connected component. The number of connected components gives a naive measure of how disjoint the network is. In essence the number of groups in the field.

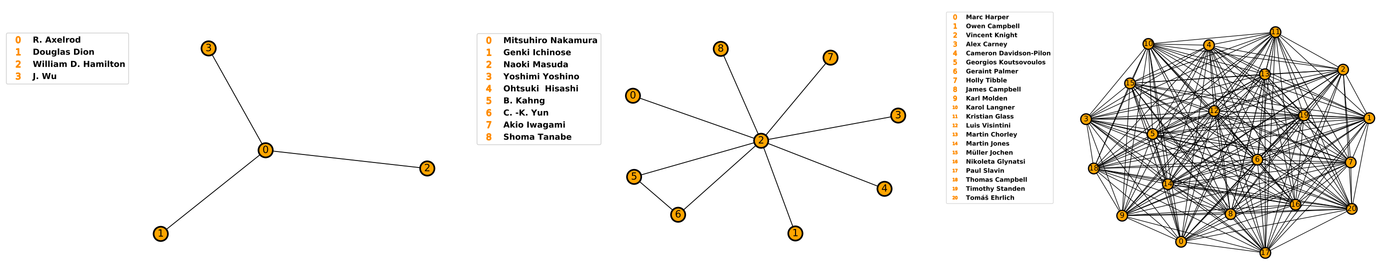
The second measure considered is the **degree**. The degree of a node express the number of connections a node has. We will consider the degree distribution of a network. It will allow us to understand the mean connection that authors have in the network's groups.

The final measure is the **clustering coefficient**. The clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. There are two types of this measure; the local and the global coefficients. The local coefficient is the clustering coefficient of a single vertex. It is calculated as,

$$C_u = \frac{2 \times L_u}{(k_u(k_u - 1)},$$

where k_u is the degree of vertex u and L_u is the number of edges between k_u neighbours of vertex u.

The global coefficient, $\bar{C}$, is calculated by averaging all the local coefficients of the graph. The values of the measure can range between 0 and 1. Figure 7 illustrates several sub graphs with different $\bar{C}$ values.



(a) A sub graph of G_1 with a global clustering coefficient of 0.

(b) A sub graph of G_1 with a global clustering coefficient of 0.23.

(c) A sub graph of G_1 with a global clustering coefficient of 1.

Figure 7: Clustering coefficients examples.

A clustering coefficient of 1 indicates that a graph is a complete graph. On the contrary, a coefficient of 0 indicates that authors write with just a single co author.

1.3.2.1 Analysis

All connectivity measures are calculated for G_1, G_2 and G_3. This is done using the open source package networkx [33].

We are aware that all three of the networks are disjoint. This is also verified by the number of connected components. More specifically there are 529 , 797 and 162 for graphs G_1, G_2 and G_3 respectively. A total of 51 , 63 , 4 authors have written by themselves, for graphs G_1, G_2 and G_3 respectively.

The normalised degree distributions of all three networks are shown in Figure 8. They have been normalised such that the frequencies sum to one. None of the distributions is normally distributed thus the non parametric test Kruskal-Wallis is used [48]. Kruskal-Wallis allow us to compare the medians of two or more distributions. The test returns a p-value of 0.29. Thus there is significant difference at the level of 0.005.

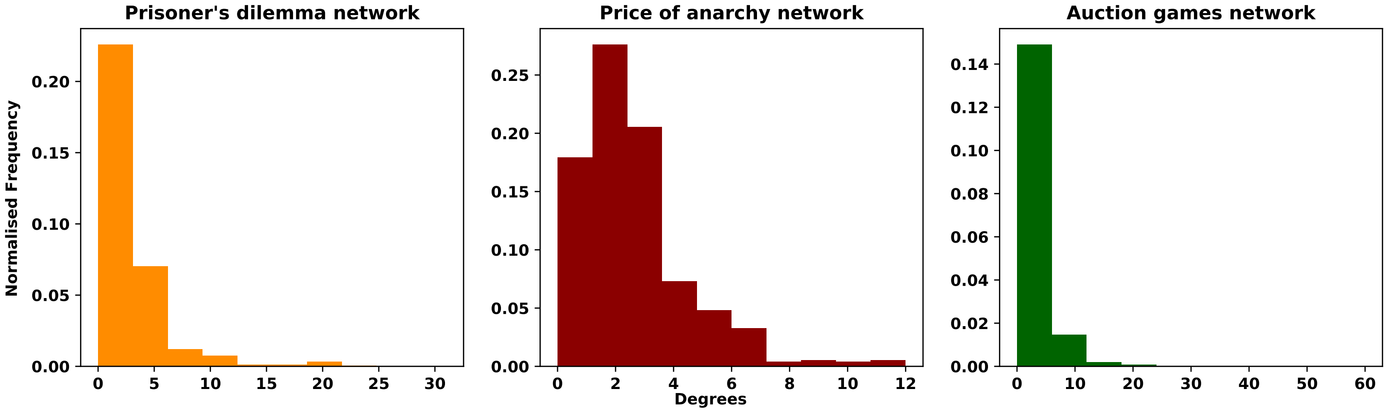


Figure 8: Degree distributions for all three networks.

The global clustering coefficients of all three networks are presented in Table 9. The price of anarchy has the largest clustering coefficient followed by G_1 and G_2.

	$\bar{C}$
G_1	0.68
G_2	0.677
G_3	0.712

Table 9: Global clustering coefficient for all three networks.

1.3.3 Measures of Influence

Network centrality is used in network theory to study which nodes of a graph are the most important. There are several centrality measures used to explain different behaviours of the nodes. Centrality will be used here to explain influence. The two centrality which are used are:

- Closeness centrality C_C.
- Betweenness centrality C_B.

Both network measures are explained with an example. The definitions for both centralities are given by Definition 1.2 and 1.3.

Definition 1.2. Closeness. Closenesse centrality of a node u is the reciprocal of the average shortest path distance to u over all $n-1$ reachable nodes. It is denoted as,

$$C_C(u) = \frac{n-1}{\Sigma_{v=1}^{n-1} d(v,u)}$$

where $d(v,u)$ is the shortest-path distance between v and u, and n is the number of nodes that can reach u. The mornalised centrality is C_C normalised by the number of nodes in the connected part of the graph.

Definition 1.3. Betweenness. Betweenness centrality of a node u is the sum of the fraction of all-pairs of shortest paths that pass through u. It is denoted as,

$$C_B(u) = \Sigma_{s,t \in V} \frac{\sigma(s,t|u)}{\sigma(s,t)}$$

where V is the set of nodes, $\sigma(s,t)$ is the number of shortest (s,t)-paths, and $\sigma(s,t|v)$ is the number of those paths passing through some node u other than s,t. If $s = t$, $\sigma(s,t) = 1$, and if $u \in s,t, \sigma(s,t|u) = 0$. Normalised C_B is normalized by $\frac{2}{((n-1)(n-2))}$

Closeness is a measure that shows how well a node connects other nodes. Equivalently, how well an author is connected to other authors and contributes to them collaborating. On the other hand betweenness is about how connected a node is, thus how much influence an author can gain from their environment.

As an example consider a sub graph of G_1 which is illustrated in Figure 9. Note that nodes 1, 2 and 3 are connected to three authors. Thus we expect their betweenness centrality to be the same. However, this is not true for closeness centrality. Node 3 is the connecting link between at least 4 people. Thus node 3 is the person in the sub graph that influences most authors. Node 3 also gains influence due ot its rule in the team, but node 2 achieves the same without connecting people as much as node 3.

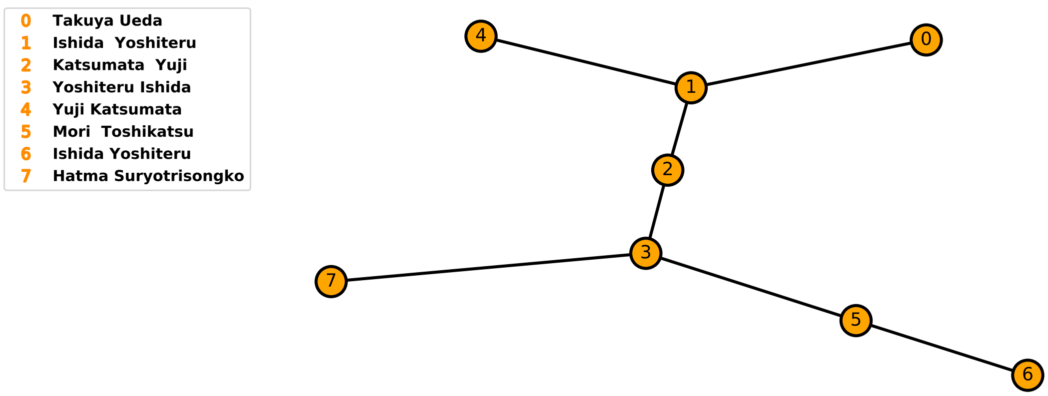


Figure 9: A sub graph of G_1.

The centrality for all three networks are calculated using [33]. Table 10 summarises the most important authors of network G_1 based on the two centralities. The people that influence the field the most are Matjaz Perc, Yamir Moreno, Luo-Luo Jiang, Arne Traulsen and Martin A. Nowak. Their work have been discussed in Section **??**. Though Matjaz Perc and Yamir Moreno appear to both influence and gain from the networks influence, it does not hold for the rest of the three authors.

	Author name	Betweeness		Author name	Closeness
1	Matjaz Perc	0.010584	1	Matjaz Perc	0.044428
2	Yamir Moreno	0.008786	2	Yamir Moreno	0.043561
3	Luo-Luo Jiang	0.004319	3	Cheng-Yi Xia	0.038910
4	Arne Traulsen	0.003920	4	Sandro Meloni	0.037959
5	Martin A. Nowak	0.003832	5	Alberto Aleta	0.037600

Table 10: Top 5 ranked authors of G_1 based on different centrality measures.

1.3.3.1 Analysis

Influence for a given network is calculated easily. However, we want to assert the power of the influence of G_1 by comparing the results to those of G_2 and G_3. Using the distribution of the centralities will we statistically tests whether a difference does exist between them.

For C_C all distributions are not normally distributed so we will use the non parametric test Kruskal Wallis. The test returns a p value of 0.0 thus it can be stated with 95% confidence of that the distributions are statistically different. These are plotted as violin plots in Figure 11.

Note that the centrality values range between 0 and 1. For all three graphs C_C have low values. Both G_1 and G_2 appear to have a similar distributions. Most authors have have a coefficient of zero and a few authors by the tails appear to have a larger coefficient. This means that for the two topics, the highest frequency of authors have a very small influence in their field. Though there are people with a high influence they are only a few.

The coefficients of G_3 are different from the other topics. Overall it can be seen that authors' centrality is more spread through the different values.

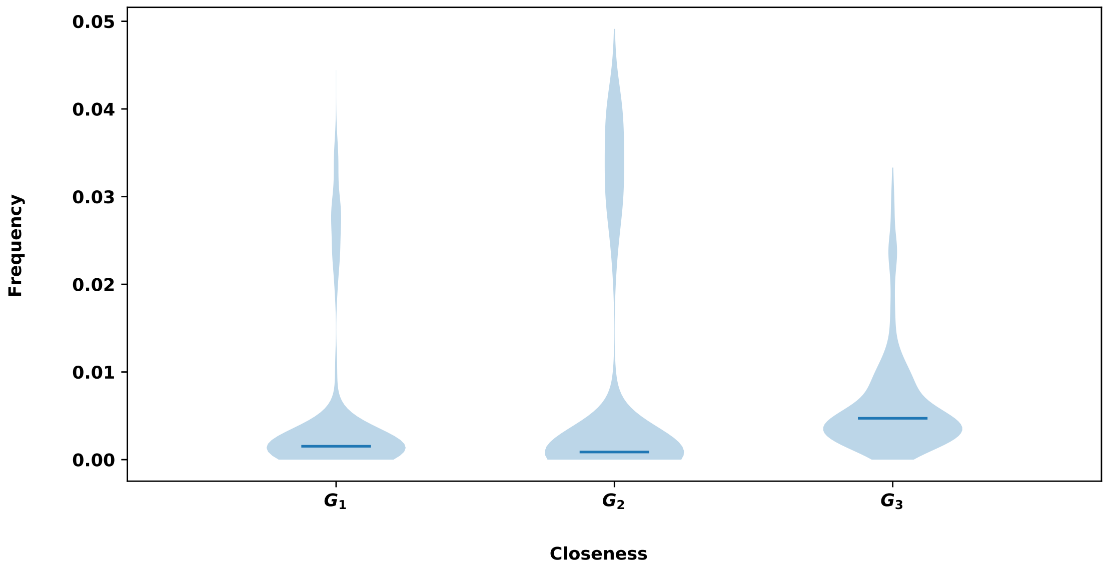


Figure 10: Closeness distributions for all three networks.

Figure 11 shows that all coefficients are clustered around the value of zero.

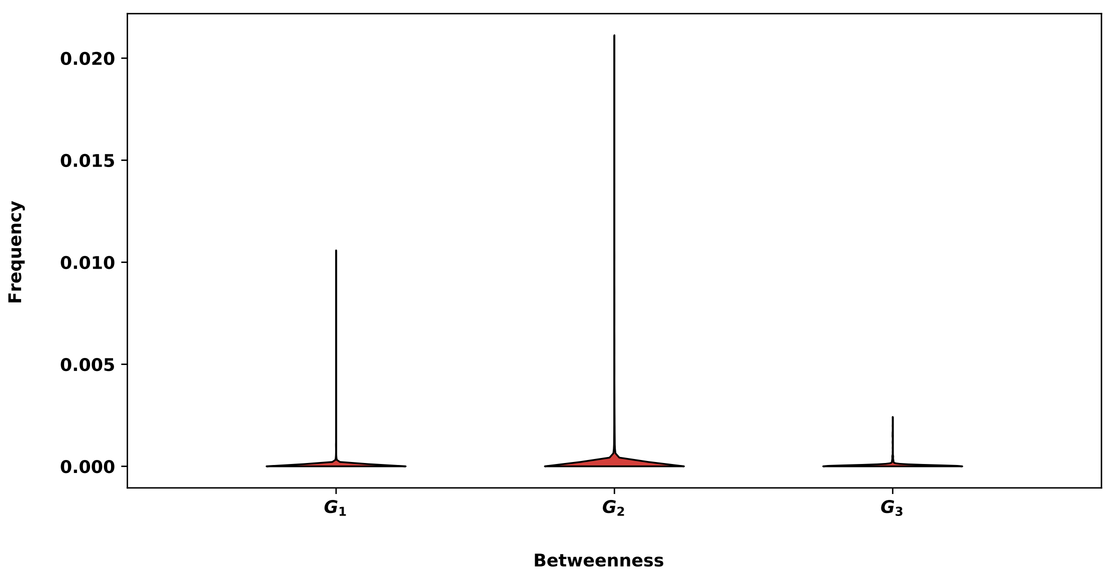


Figure 11: Betweenness distributions for all three networks.

1.3.4 Conclusion

In this section we have conducted an investigation of the literature based on a data analysis. More specifically, this was mainly done using network theory.

Initially, we gave a summary on the data collection. An open source project which was developed for the purpose of this work was used [55]. The project takes advantage of the API system several academic journals offer today. The procedure, the sources as well as the keywords used in the process of collection have been clearly specified making the process reproducible.

Three data sets have been composed for three different topics of game theory. These are:

- The prisoner's dilemma. The main focus of this paper.
- Auction games. A sub field of game theory used for comparison reasons.
- The price of anarchy. A sub field of game theory used for comparison reasons.

We conducted a brief preliminary analysis on these data sets. Mainly to understand the sizes, provenance and trends of each topic. The main data set was also partitioned into time periods such that an temporal comparison could be conducted.

The main focus of the analysis has been to explain collaborative behaviour and influence. Both terms have been defined and we have explained how network measures of the co authorship network were used to quantify them. The co authorship network is a network representing all the unique authors of a topic. An edge exists within two authors if they have written together. Co authorship was decided to be used as be believe other measures, such as citations, perform less well.

All three networks have been disjointed with a large number of connected components. The collaborative behaviour was based on the nature of these connected components. The median connection of an author has been the same for all three networks. However, the price of anarchy had a smaller number of authors that prefer to write on their own and based on the clustering coefficient the collaboration of the field authors appears to be stronger. The collaboration for both the prisoner's dilemma and auction games it's similar. Note though that the price of anarchy is a new topic with less authors. It makes more sense for a few people that work on the topic to be more collaborative which each other.

Similarly influence was studied using two centrality measures. For G_1 and G_2 we conclude that there are only a few authors that have power of influence on the network. For research this is not ideal. It could mean that the research is only driven from the work of specific people. It could also indicate a hostile environment for new authors. In comparison, G_3 has several authors that have different influence on their neighbours. A wider spread of influence could indicate a nice flow of knowledge across the field from different people. This could help the growth of a field and accelerate findings. The influence that authors gain from the respective networks was also explored. The results argued that the gain was very low for all three networks.

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