A bibliometric study of research topics, collaboration and ~~influence~~ centrality in the Iterated Prisoner's Dilemma

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Abstract

This manuscript explores the research topics and collaborative behaviour of authors in the field of the Prisoner's Dilemma using topic modeling and a graph theoretic analysis of the co-authorship network. The analysis identified five research topics in the Prisoner's Dilemma which have been relevant over the course of time. These are human subject research, biological studies, strategies, evolutionary dynamics on networks and modeling problems as a Prisoner's Dilemma game. Moreover, the results demonstrated the Prisoner's Dilemma is a field of continued interest, and ~~although~~ that it is a collaborative field ~~, it is not necessarily more collaborative than other scientific~~ compared to other game theoretic fields. The co-authorship network suggests that authors are focused on their communities and that not many connections across the communities are made. The ~~Prisoner Dilemma authors also do not influence or gain much information by their connections, unless they are connected to a "main " group of authors~~most central authors of the network are the authors connected to the main cluster, and through examining the networks of topics, it was uncovered that the main cluster is characterised by the collaboration of authors in a single topic.

1 Introduction

The Prisoner's Dilemma (PD) is a well known game used since its introduction in the 1950's [27] as a framework for studying the emergence of cooperation; a topic of continued interest for mathematical, social, biological and ecological sciences. This manuscript presents a bibliometric analysis of ~~2,420~~ 2420 published articles on the Prisoner's Dilemma between 1951 and 2018. It presents ~~the dominant~~ a number of research topics in the PD publications, which have been identified using Latent Dirichlet Allocation (LDA) [17], and it explores the changes in the ~~dominant~~ research topics over time. The collaborative behaviour of the field is explored using the co-authorship network, and furthermore, the ~~Latent Dirichlet Allocation~~ LDA topic analysis is combined with the co-authorship network analysis to assess the ~~relative influence of~~ most central authors in these topics. Assessing the collaborative behaviour of the field of collaboration itself is the main aim of this work.

As discussed in [70], bibliometrics (the statistical analysis of published works originally described by [54]) has been used to support historical assumptions about the development of fields [55], identify connections between scientific growth and policy changes [23], develop a quantitative understanding of author order [60], and investigate the collaborative structure of an interdisciplinary field [44]. Most academic research is undertaken in the form of collaborative effort and as [41] points out, it is rational that two or more people have the potential to do better as a group than individually. Indeed this is the very premise of the ~~Prisoner's Dilemma~~ PD itself. Collaboration in groups has a long tradition in experimental sciences and it has be proven to be productive according to [25]. The number of collaborations can be different between research fields and understanding how collaborative a field is not always an easy task. Several studies tend to consider academic citations as a measure for these things. A blog post published by Nature [50] 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 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 measuring collaborative behaviour, and to studying the development of a field is to use the co-authorship network, as described in [44]. The co-authorship network has many advantages as several graph theoretic measures can be used as proxies to explain author relationships. For example the average degree of a node corresponds to the average number of an authors' collaborators, and clustering coefficient corresponds to the extent that two collaborators of an author also collaborate with each other. In [44], the approach was applied to analyse the development of the field "evolution of cooperation", and in [70] to identify the subdisciplines of the interdisciplinary field of "cultural evolution" and investigate trends in collaboration and productivity between these subdisciplines. Moreover, [43] examined the long-term impact of co-authorship with established, highly-cited scientists on the careers of junior researchers. ~~This paper builds upon the work done by [44] and [70], and extends their methodology. In [44, 70], a data set from a single source, Web of Science, is considered whereas the data set described here, archived at [7], has been collected from five sources.~~

~~Latent Dirichlet Allocation (LDA)~~ LDA is a topic modeling technique proposed in [17] as a generative probabilistic model for discovering underlying topics in collections of data. Applications of the technique include detection in image data [22] and detection in video [68]. Nevertheless, LDA has been applied by several works on publication data for identifying the topic structure of a subject area. In [37], it was applied to the publications on mathematical education of the journals "Educational Studies in Mathematics" and "Journal for Research in Mathematics Education" to identify the dominant topics that each journal was publishing on. The topics of the North American library and Information Science dissertations were studied chronologically in [64], and the main topic of the scientific content presented at EvoLang conferences was identified in [16]. In [16] the LDA approach is combined with clustering and a co-authorship network analysis. A clustering analysis is applied to the LDA topics, and the co-authorship network is analysed as a whole where the clusters are only used to differentiate between the authors' topics. ~~In comparison, this works applies LDA to identify dominant topics in the Prisoner's Dilemma fields and analyses the networks corresponding to these topics individually.~~

This paper builds upon the previous works of [16, 44, 70]. It extends their methodology, it combines identified topics by an LDA model with the co-authorship network analysis, and applies all these techniques to a new data set. This data set was collected not from a single source but from five different sources. The four publishers were chosen because they are well known publishers in the field, and the arXiv preprint server. The search terms used to collect data appear on relevant articles and the search fields that were used were the title, abstract and text. However, papers can refer to the PD in the text but not analyze the topic. For this reason such articles were manually checked, so that only relevant papers are included in the analysis. Moreover, an amount of well known articles, which are not published in any of the selected publishers, were manually included in the data set.

The methodology used in this manuscript~~(including~~ , which includes the data collection ~~) is covered in Section 2~~ and a preliminary analysis of the data set~~is presented~~ , is covered in Section ~~??. This manuscript makes usage of the methodology and data to address the following questions:~~

~~What are the~~ 2. The results on the research topics of the ~~Prisoner's Dilemma? Is one topic currently more in fashion? How have the research topics changed over the years? Is the Prisoner's Dilemma a collaborative field? Are some topics more collaborative than others? Are there authors which benefit more from their position in the network?~~

~~Results regarding questions 1-3~~ PD are presented in Section ~~?? and questions 4-6 are addressed~~ 3.1, and the results on the co-authorship network are presented in Section ~~??. The results~~ 3.1. Finally, the conclusions are summarised in Section 4.

2 Methodology

Academic articles are accessible through scholarly databases. Several databases and collections today offer access through an open application protocol interface (API). An API allows users to query directly a ~~journal~~publisher's database and bypass the graphical user interface. 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. In this example the address corresponds to the API of arXiv. The second part of the request contains the search arguments. In this example it is requested that the word 'prisoners dilemma' exists within the article'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 satisfies the request message. The raw metadata are commonly received in extensive markup language (xml) or Javascript object notation (json) formats [51]. Similarly to the request message, the structure of the received data differs from ~~journal to journal~~publisher to publisher.

The data collection is crucial to this study. To ensure that this study can be reproduced all code used to query the different publishers' APIs has been packaged as a Python library and is available online [8]. 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 [8] ~~allow users to collect articles from a list of APIs by specifying just a single keyword. Articles for which any of the terms "prisoner's dilemma", "prisoners dilemma", "prisoner dilemma", "prisoners evolution", "prisoner game theory" existed within the title, the abstract or the text are included in the analysis. Four prominent journals in the field~~ can collect data from five different sources. These correspond to four publishers and a preprint server~~were used as sources to collect data for this analysis~~:

- arXiv [47]; a repository of electronic preprints. It consists of scientific papers in the fields of mathematics, physics, astronomy, electrical engineering, computer science, quantitative biology, statistics, and quantitative finance, which all can be accessed online.
- PLOS [1]; a library of open access journals and other scientific literature under an open content license. It launched its first journal, PLOS Biology, in October 2003 and publishes seven journals, as of October 2015.
- IEEE Xplore Digital Library (IEEE) [36]; a research database for discovery and access to journal articles, conference proceedings, technical standards, and related materials on computer science, electrical engineering and electronics, and allied fields. It contains material published mainly by the Institute of Electrical and Electronics Engineers and other partner publishers.
- Nature [30]; a multidisciplinary scientific journal, first published on 4 November 1869. It was ranked the world's most cited scientific journal by the Science Edition of the 2010 Journal Citation Reports and is ascribed an impact factor of 40.137, making it one of the world's top academic journals.
- Springer [48]; a leading global scientific publisher of books and journals. It publishes close to 500 academic and professional society journals.

~~The data set has been archived and is available at [7]. Note that the latest data collection was performed on the 30th November 2018.~~ These publishers were chosen because they are prominent publishers in the field. For each source, data can be collected by specifying a search term and a search field. Articles for which any of the terms:

~~The relationship between the authors within a fieldwill be modeled as a graph $G = (V_G, E_G)$ where V_G is the set of nodes and E_G is the set of edges. The set V_G represents the authors and an edge connects two authors if and only if those authors have written together. This co-authorship network is constructed using the main data set [7] and the open source package [32]. The PD network is denoted as G where the number of unique authors $|V(G)|$ is 4226 and $|E(G)|$ is . All authors' names were formatted as their first name and last name (i.e. Martin A. Nowak to Martin Nowak). This was done to avoid errors such as Martin A. Nowak and Martin Nowak being treated as a different person. There are some authors for which only their first initial was found. These entries are left as such.~~

- prisoner's dilemma
- prisoners dilemma
- prisoner dilemma
- prisoners evolution
- prisoner game theory

~~The collaborativeness of the authors will be analysed using measures such as, isolated nodes, connected components, clustering coefficient, communities, modularity and average degree. These measures show 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 [24]. The number of connected components as well as the size of the largest connected component in the network are reported. The size of the largest connected component represents the scale of the central cluster of the entire network, as will be discussed~~ existed within the title, the abstract or the text are included in the analysis~~section. Clustering coefficient and modularity are also calculated. The clustering coefficient, defined as 3 times the number of triangles on the graph divided by the 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 [24]. It shows to which extent 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 communities. The number of communities will be reported using the Clauset-Newman-Moore method [21]. Also the modularity index is calculated using the Louvain method described in [18]. The value of the modularity index can vary between~~ ~~$[-1,1]$~~~~, a high value of modularity corresponds to a structure where there are dense connections between the nodes within communities but sparse connections between nodes in different communities. That means~~. These terms we selected because they are occurring terms in paper known to be relevant in the field. However, the authors acknowledge that there are ~~many sub communities of authors that write together but not across communities. Two further points are aimed to be explored in this work, (1) which people control the flow of information; 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 centrality measures are going to be used. Centrality measures are often used to understand different aspects of social networks [?]. Two centrality measures have been chosen for this paper and these are closeness and betweenness centrality~~other terms that could have been used, for example “donation game”. The authors believe that the results of the manuscript do generalise to the overall stated goals (Section 1), but they are inferred only from the data collected on the specific search terms and search fields.

1. ~~In networks some nodes have a short distance to a lot of nodes and consequently are able to spread information on the network very effectively. A representative of this idea is **closeness centrality**, where a node is seen as centrally involved in the network if it requires only few intermediaries to contact others and thus is structurally relatively independent. Closeness centrality is interpreted as influence. Authors with a high value of closeness centrality, are the authors that spread scientific knowledge easier on the network and 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 node in question 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, this is interpreted as the gain from the influence, thus these authors gain the most from their networks.~~

~~The articles contained in the data set ([7]) will be classified into research topics using LDA an unsupervised machine learning technique designed to summarize large collections of documents by a small number of conceptually connected topics or themes [17, 29]. The documents are the articles' abstracts and LDA was carried out using [56] . In LDA, each document/abstract is represented by a distribution over topics, and the topics themselves are represented by a distribution over words. More specifically, each topics is described by weights associated with words and each document by the probabilities of belonging to a specific topic. The probability of a document belonging to a topic is referred to as the percentage contribution denoted as~~ ~~c~~~~. For example the words and their associated weights for two topics A and B could be:~~

- ~~Topic A: 0.039×“cooperation”, 0.028×“study” and 0.026×“human”.~~
- ~~Topic B: 0.020×“cooperation”, 0.028×“agents” and 0.026×“strategies”.~~

~~The percentage contribution for a document with abstract “The study of cooperation in humans” has a $c_A = 0.039 + 0.028 + 0.026$ and $c_B = .020 + 0.0 + 0.0 = 0.020$. The topic to which a document is assigned to is based on the highest percentage contribution denoted as c^*. For the given example the dominant topic is Topic A $c^* = c_A$. LAD requires that~~ The latest data collection was performed on the 30$^{\text{th}}$ November 2018. Following the automatic collection of articles from the sources, a cleaning process was applied to the ~~number of topics is specified in advance before running the algorithm. The number of topics can be chosen using the coherence value [58] or through subjective minimisation of the overlapping keywords between two topics. Both these approaches will be used in this work~~data. More specifically, all the titles of the collected articles were compared for semantic similarity. There were a total of 34 duplicate articles. That was because both the preprint and the published versions of a paper were collected. The preprint versions (collected from arXiv) were dropped at this stage. A semantic similarity check was also applied in the names of the collected authors. The names that were highlighted as similar were manually checked. In case of a duplicate, for example “Martin Nowak” and “Martin A. Nowak” are considered duplicates, all entries of that author were fixed to a single style. Most commonly the middle name was dropped. Finally, articles that were collected because the search terms existed within the text were checked to reassure their relevance to the PD topic. Non relevant articles were dropped at this stage.

~~Several of the approaches described in this section have previously been carried out in [16, 44, 64, 70], the novelty here is combining the approaches as well as applying them to a new data set. A preliminary analysis of the data set is presented in the following section.~~

3 ~~Preliminary Analysis~~

~~The data set [7] consists of 2422 articles with unique titles. In case of duplicates the preprint version of an article (collected from arXiv) was dropped. Similarly to [44], 76 articles have not been collected from the aforementioned APIs but have been manually added~~ Following the cleaning process, a total of 76 articles were manually added to the data set because they are of interest ~~.~~ to the field. This was also done in [44]. Examples of such papers include [27] the first publication on the PD, [52, 62] two well cited articles in the field, and a series of works from Robert Axelrod ~~[12, 57]~~ [9, 10, 11, 12, 57] a leading author of the field. The process of obtaining the data set used in analysis presented in the manuscript is illustrated in Figure 1. This data set has been archived and is available at [7].

The data set consists of 2422 articles with unique titles. A more detailed summary of the articles' provenance is given by Table 1. Only 3% of the data set consists of articles that were manually added and 27% of the articles were collected from arXiv. The average number of publications is also included in Table 1. Overall an average of 43 articles are published per year on the topic. The most significant contribution to this appears to be from arXiv with 11 articles per year, followed by Springer with 9 and PLOS with 8.

	Number of Articles	Percentage %	Year of first publication	Average number of publications per year
IEEE	294	12.14%	1973	5
Manual	76	3.14%	1951	1
Nature	436	18.00%	1959	8
PLOS	477	19.69%	2005	8
Springer	533	22.01%	1966	9
arXiv	654	27.00%	1993	11
Overall	2470	100.00%	1951	43

Table 1: Summary of [7] per provenance.

All the visualisations presented in the manuscript were generated using [33], and project [66] was used for manipulating the data.

The data handled here is in fact a time series from the 1950s, the formulation of the game, until 2018 (Figure 2).

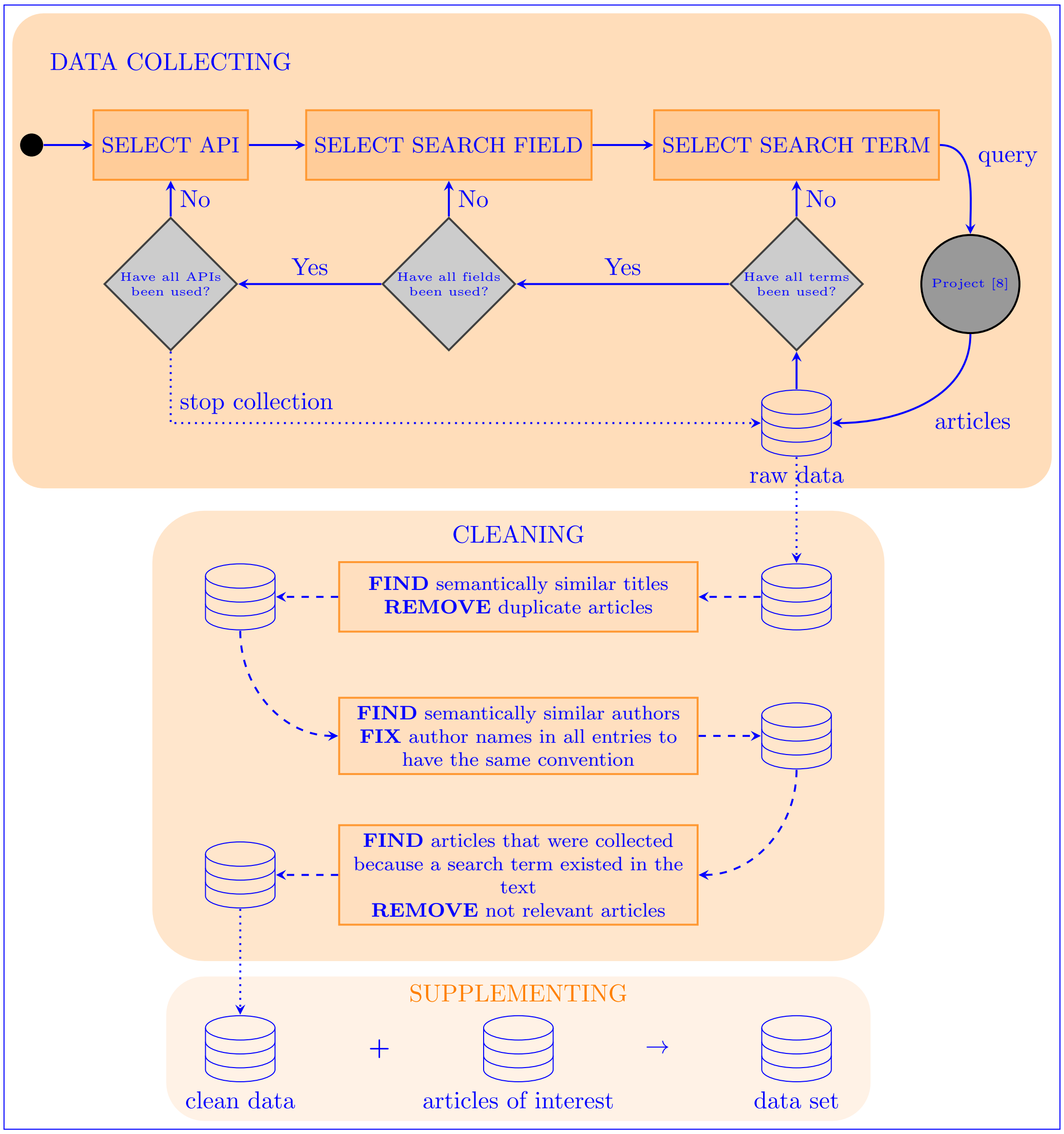


Figure 1: The generating process of the data set [7].

Two observations can be made from Figure 2.

1. There is a steady increase of the number of publications since the 1980s and the introduction of computer tournaments [12] (work by Robert Axelrod).
2. There is a decrease in 2017-2018. This is due to our data set being incomplete. Articles that have been written in 2017-2018 have either not being published or were not retrievable by the APIs at the time of the last data collection.

These observations can be confirmed by studying the time series. Using [39], an exponential distribution is fitted to the data. The fitted model can be used to forecast the behaviour of the field for the next 5 years. Even though the time series has indicated a slight decrease, the model forecasts that the number of publications will keep increasing, thus demonstrating that the field of the PD continues to attract academic attention.

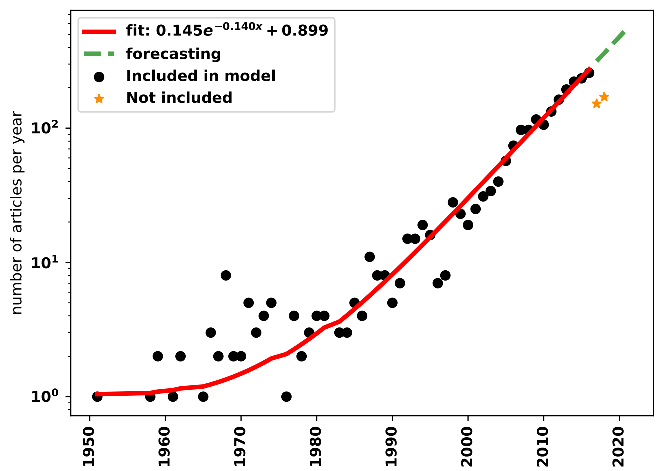


Figure 2: Number of articles published on the PD 1951-2018 (on a log scale), with a fitted exponential line, and a forecast for 2017-2022.

There are a total of 4226 authors in the data set ([7]) and several of these authors have had multiple publications collected from the data collection process. The highest number of articles collected for an author is 83 publications for Matjaz Perc. ~~Howver~~However, Matjaz Perc is an outlier most authors have 1 to 6 publications in the data set.

The overall Collaboration Index (CI) or the average number of authors on multi-authored papers is 3.2, thus on average a non single author publication in the PD has 3 authors. This appears to be quite standard compared to other fields such as cultural evolution [70], Astronomy and Astrophysics, Genetics and Heredity, Nuclear and Particle Physics as reported by [45]. There are only a total of 545 publications with a single author, which corresponds to the 22% of the papers. It appears that academic publications tend to be undertaken in the form of collaborative effort, which is in line with the claim of [41].

The collaborativeness of the authors is explored in more detail in Section ~~??~~ 3.1 using the co-authorship network. The collaborative behaviour ~~and relative influence~~ of authors will also be explored ~~in co-authorship networks which correspond to their publications research topics~~ at the research topics level. These topics and their relevance over time are presented in ~~the next section~~Section 3.1.

3 ~~Research topics in the Prisoner's Dilemma research~~Results

~~In order to identify the topics which are being discussed in the field of the PD, the LDA algorithm implemented in [56]is applied to the abstracts of the data set. As mentioned before,~~

3.1 Research topics in the Prisoner's Dilemma research

The articles contained in the data set ([7]) are classified into research topics using LDA, an unsupervised machine learning technique designed to summarize large collections of documents by a small number of conceptually connected topics or themes [17, 29]. The documents are the ~~number of topics, which will be denoted as n, needs to be specified~~ articles' abstracts and LDA was carried out using [56]. In LDA, each document/abstract is represented by a distribution over topics, and the topics themselves are represented by a distribution over words. More specifically, each topic is described by weights associated with words and each document by the probabilities of belonging to a specific topic. The probability of a document belonging to topic T is referred to as the percentage contribution denoted as c_T. For example the words and their associated weights for two topics A and B could be:

- Topic A: 0.039×"cooperation", 0.028×"study" and 0.026×"human".
- Topic B: 0.020×"cooperation", 0.028×"agents" and 0.026×"strategies".

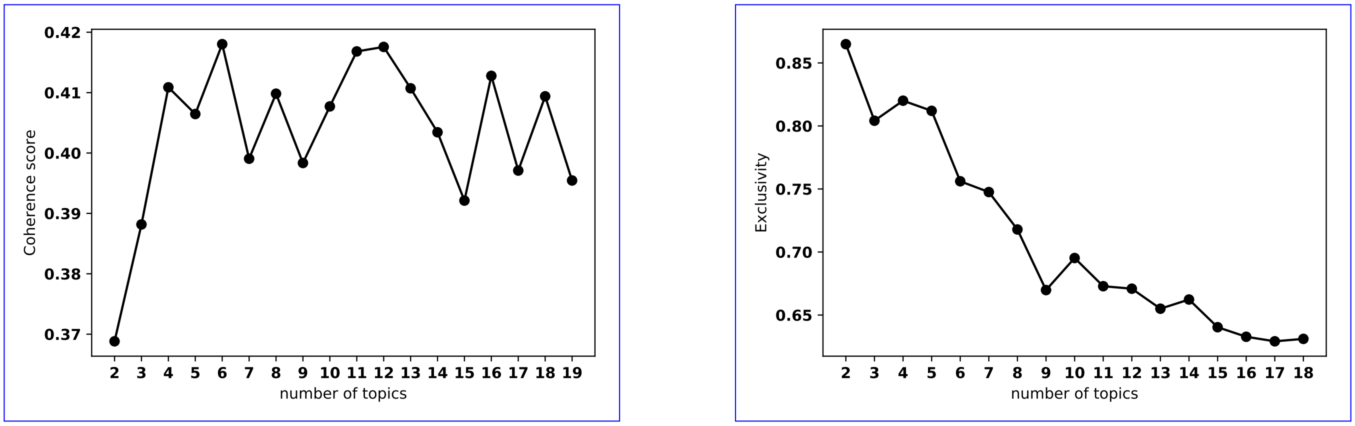
The percentage contribution for a document with abstract "The study of cooperation in humans" has a $c_A = 0.039 + 0.028 + 0.026$ and $c_B = .020 + 0.0 + 0.0 = 0.020$. The topic to which a document is assigned to is based on the highest percentage contribution denoted as c^*. For the given example the dominant topic is Topic A $c^* = c_A$.

LAD requires that the number of topics is specified in advance before running the algorithm. The appropriate number of topics ~~is~~ can be chosen based on the coherence ~~value [58]~~ score [58] or the exclusivity score [3]. The coherence ~~value was calculated for~~ score measures the degree of semantic similarity between highly weighted words of a topic. There are cases for which a few topics can be dominated by very common words, and for that reason the exclusivity of words to topics has also been calculated. Figure 3a gives the topic coherence and Figure 3b gives the exclusivity of 18 ~~models where $n \in \{2, 3, \dots, 19\}$, and the model with the highest coherence value was that of $n = 6$ with a coherence value of 0.418.~~

~~An LDA model outputs an $N \times n$ matrix - N rows for N abstracts and n columns for n topics . The cells contain the percentage contributions for each topic for each abstract, c_i^j for $i \in \{1, 2, \dots, n\}$ for $j \in \{1, 2, \dots, N\}$. In essence, LDA maps every paper to a vector space of dimension the number of topics. In the case of 6 topics it is difficult to visualise the clustering of topics~~ models where the number of topics $n \in \{2, 3, \dots, 18\}$. The topic coherence for each model was calculated using the open source project [56]. The exclusivity measure was calculated with an altered version of [56] which has been archived at [71]. ~~To overcome this a dimensionality reduction approach called t-Distributed Stochastic Neighbor Embedding (t-SNE) [?] is applied to the LDA model outputs. More specifically, t-SNE is used to reduce the dimensions of each c^j from n to 2. Figure ??, gives the visualisation of LDA for $n = 6$. Each point represents a single document and its color corresponds to the topic with the highest percentage contribution. The documents which are clustered together have a similar percentage contribution distribution over the topics.~~

~~Even though the LDA model with $n = 6$ has~~ From Figure 3a it can be seen that the number of topics with the highest coherence ~~value, Figure ?? shows that documents of the same topic are closer to documents from other topics than each other. For example the documents of topic 2 are divided into two clusters. The one cluster is closer to documents from topic 4 and the other has a few documents closer to topic 1. In the case of $n = 6$ topic 4 appears to be on "evolution of cooperation on networks", and the papers from topic 2 surrounded from topic 4 include the articles "Evolutionary prisoner's dilemma game on hierarchical lattices" [?] and "Social evolution in structured populations" [?]. Publications that clearly also fit topic 4.~~

~~In comparison, ?? gives the visualisation of LDA $n = 5$ where the separation of the documents is more clear. Though several models, Figure ??, have a higher coherence~~ score are $n = 6$ (coherence score of 0.418) and $n = 12$ (coherence score of 0.417). Figure 3a shows that the exclusivity of the highly weighted words of the topics is decreasing as the number of topics increases. A number of topics $n = 5$ has a better exclusivity value than the ~~LDA model with $n = 5$, the separation of topics is not as clear for any model as it is for $n = 5$. Thus, $n = 5$~~ model of $n = 6$, and its coherence score is 0.406 (which is closed to 0.418). For that reason $n = 5$ is chosen to carry out the analysis of this work~~, and moreover the LDA model for $n = 5$ has a coherence value 0.406 which is close to 0.418~~.



(a) ~~With $n=6$~~Coherence for LDA models over the number of topics.

(b) ~~With $n=5$~~Exclusivity for LDA models over the number of topics.

~~Visualisation of LDA on 2 dimensions.~~

~~What are the research topics of the Prisoner's Dilemma?~~

For $n = 5$ the articles are clustered and assigned to their dominant topic, based on the highest percentage contribution. The keywords associated with a topic, the most representative article of the topic (based on the percentage contribution) and its academic reference are given by Table 2. The topics are labelled as A, B, C, D and E, and more specifically:

- Based on the keywords associated with Topic A, and the most representative article, Topic A appears to be about **human subject research**. Several publications assigned to the topic study the PD by setting experiments and having human participants simulate the game instead of computer simulations. These articles include [46] which showed that prosocial behavior increased with the age of the participants, [42] which studied the difference in cooperation between high-functioning autistic and typically developing children, [49] explored the gender effect in highschool students and [15] explored the effect of facial expressions of individuals.
- Though it is not immediate from the keywords associated with Topic B, investigating the papers assigned to the topic indicate that it is focused on **biological studies**. Papers assigned to the topic include papers which apply the PD to genetics [61], to the study of tumours [59] and viruses [65]. Other works include how phenotype affinity can affect the emergence of cooperation [69] and modeling bacterial communities as a spatial structured social dilemma.
- Based on the keywords and the most representative article Topic C appears to include publications on PD **strategies**. Publications in the topic include the introduction of new strategies [63], the search of optimality in strategies [14] and the training of strategies [38] with different representation methods. Moreover, publications that study the evolutionary stability of strategies [2] and introduced methods of differentiating between them [4] are also assigned to C.
- The keywords associated with Topic D clearly show that the topic is focused on **evolutionary dynamics on networks**. Publications include [35] which explored the robustness of cooperation on networks, [67] which studied the effect of a strategy's neighbourhood on the emergence of cooperation and [20] which explored the fixation probabilities of any two strategies is spatial structures.
- The publication assigned to Topic E are on **modeling problems as a PD game**. Though Topic B is also concerned with problems being formulated as a PD, it includes only biological problems. In comparison, the problems in Topic E include decision making in operational research [53], information sharing among members in a virtual team [26], the measurement of influence in articles based on citations [34] and the price spikes in electric power markets [31], and not on biological studies.

Dominant Topic	Topic Keywords	Most Representative Article Title	Reference	# Documents	% Documents
A	social, behavior, human, study, experiment, cooperative, cooperation, suggest, find, behaviour	Facing Aggression: Cues Differ for Female versus Male Faces	[28]	496.0	0.2008
B	individual, group, good, show, high, increase, punishment, cost, result, benefit	Genomic and Gene-Expression Comparisons among Phage-Resistant Type-IV Pilus Mutants of Pseudomonas syringae pathovar phaseolicola	[61]	309.0	0.1251
C	game, strategy, player, agent, dilemma, play, payoff, state, prisoner, equilibrium	Fingerprinting: Visualization and Automatic Analysis of Prisoner's Dilemma Strategies	[4]	561.0	0.2271
D	cooperation, network, population, evolutionary, evolution, interaction, dynamic, structure, cooperator, study	Influence of initial distributions on robust cooperation in evolutionary Prisoner's Dilemma	[19]	556.0	0.2251
E	model, theory, base, system, problem, paper, propose, information, provide, approach	Gaming and price spikes in electric power markets and possible remedies	[31]	548.0	0.2219

Table 2: Keywords for each topic and the document with the most representative article for each topic.

Note that the whilst for the choice of 5 topics the actual clustering is not subjective (the algorithm is determining the output) the interpretation above is.

~~**Five topics in the PD publications identified by the data set of this work are human subject research, biological studies, strategies, evolutionary dynamics on networks and modeling problems as a PD**.~~

~~These 5 topics nicely summarise the PD research. They highlight the interdisciplinarity of the field; how it brings together applied modeling of real world situations (Topic B and E) and more theoretical notions such as evolutionary dynamics and optimality of strategies.~~

~~**Is one topic currently more in fashion?**~~

Figure 4 gives the number of articles per topic over time. The topics appear to have had a similar trend over the years, with topics B and D having a later start. Following the introduction of a topic the publications in that topic have been increasing~~. There~~, and there is no decreasing trend in any of the topics. All the topics have been publishing for years and they still attract the interest of academics. Thus, ~~**there does not seem to be any given topic more or less in fashion**~~there does not seem to be any given topic more or less in fashion.

~~**How do the research topics change over the years?**~~

To gain a better understanding regarding the change in the topics over the years, LDA is applied to the cumulative data set over 8 time periods. These periods are 1951-1965, 1951-1973, 1951-1980, 1951-1988, 1951-1995, 1951-2003, 1951-2010, 1951-2018. The number of topics for each cumulative subset is chosen based ~~on the coherence value and no objective approach is used~~only on the topic coherence, and the exclusivity is not taken into account. As a result, the period 1951-2018 has been assigned $n = 6$ which had the highest coherence value instead of 5. The chosen models for each period including the number of topics, their keywords and number of articles assigned to them are given in the Appendix A.

But how well do the five topics which were presented earlier fit the publications over time? This is answered by comparing the performance of three LDA models over the cumulative periods' publications. The three models are LDA models for the entire data set for n equal to 5, 6 and the ~~optimal number of topics over time .~~ models of Table 8 for each time period. Thus, for the period 1951-1980 the three model that are being compared are for n equal to 5, 6, and 13.

For each model the c^* is estimated for each document in the cumulative data sets. The performance of the models are then compared based on:

$$\bar{c^*} \times n \tag{1}$$

where $\bar{c^*}$ is the median highest percentage contribution and n is the number of topics of a given period. A model with more topics will have more difficulty to assign papers. Thus, equation (refeq:ratio) is a measure of confidence

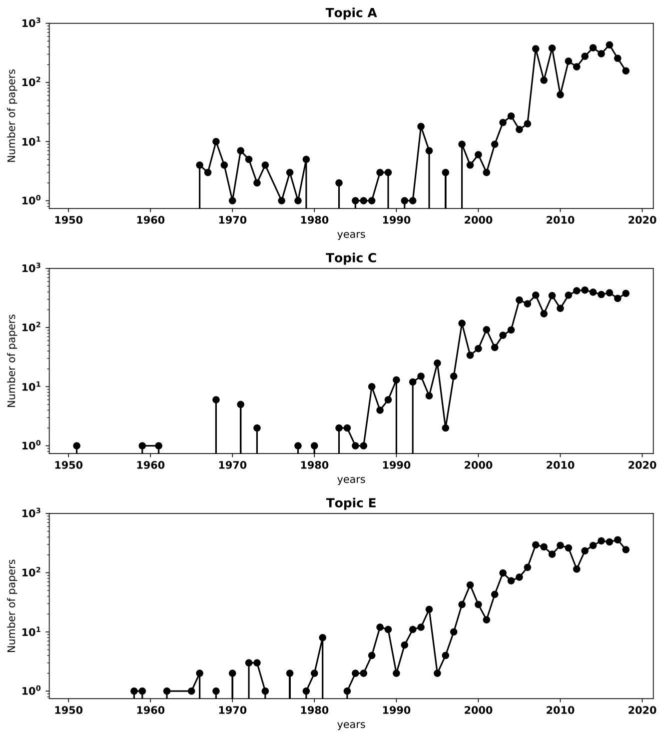


Figure 4: Number of articles per topic over the years (on a logged scale).

in assigning a given paper to its topic weighted by the number of topics. The performances are given by Figure 5.

The five topics of the PD presented in this manuscript appear to always be less good at fitting the publications compared to the six topics of LDA $n = 6$. Moreover, ~~there~~ these are less good than the ~~topics of the optimal number of topics from 1951 to 1995.~~ models of periods 1951-1965 to 1951-1995. The difference in the performance values, equation (1), however ~~are small.~~ ~~**The relevances of the five topics has been increasing over time, and though, the topics did not always fit the majority of published work over time, there were still papers being published on those topics**~~is small. The relevances of the five topics has been increasing over time, and though, the topics did not always fit the majority of published work, there were still papers being published on those topics.

In the following section the collaborative behaviour of authors in the field, and within the field's topics as were presented in this section, are explored using a network theoretic approach.

4 ~~Analysis of co-authorship network~~

3.1 Analysis of co-authorship network

The ~~collaborative behaviour of authors in the field of the PD is assessed using the co-authorship network , which as mentioned in Section 2 is~~ relationship between the authors within a field is modeled as a graph $G = (V_G, E_G)$ where V_G is the set of nodes and E_G is the set of edges. The set V_G represents the authors and an edge connects two authors if and only if those authors have written together. This co-authorship network is constructed using the main data set [7] and the open source package [32]. The PD network is denoted as ~~G.~~ G where the number of unique authors $|V(G)|$ is 4226 and $|E(G)|$ is 7642.

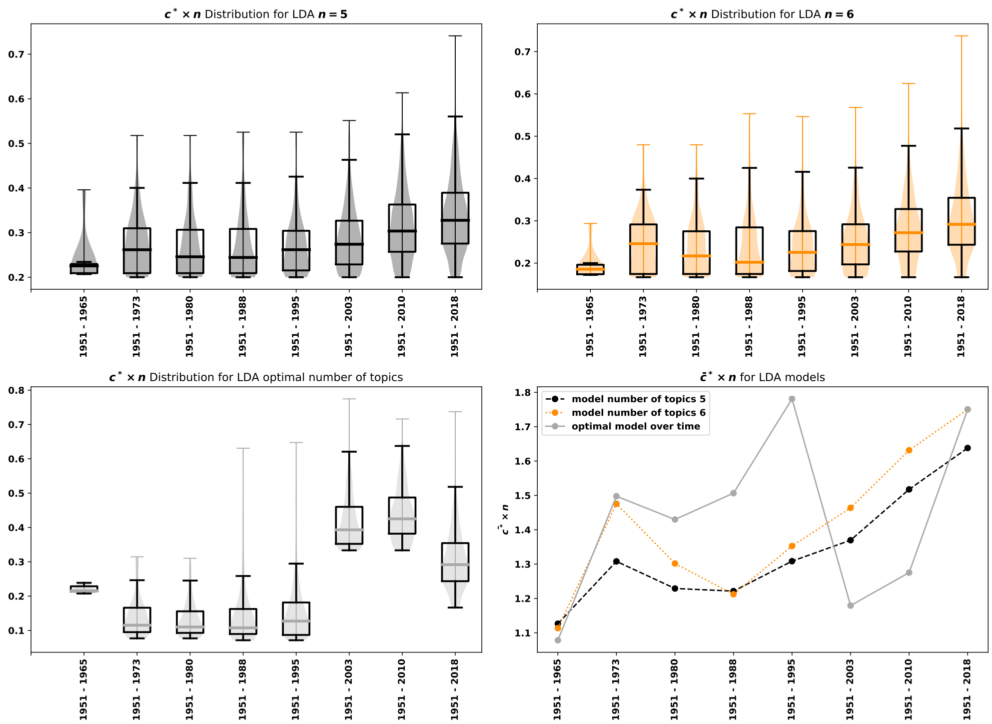


Figure 5: Maximum percentage contributions (c^*) over the time periods, for the LDA models for the entire data set for n equal to 5, 6 and for the ~~optimal number~~ models of ~~topics over time~~Table 8.

The collaborativeness of the authors is analysed using measures such as, number of isolated nodes, number of connected components, clustering coefficient, number of communities, modularity and average degree. These measures show 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 [24]. The number of connected components as well as the size of the largest connected component in the network are reported. The size of the largest connected component represents the scale of the central cluster of the entire network. Clustering coefficient and modularity are also calculated. The clustering coefficient, defined as 3 times the number of triangles on the graph divided by the 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 [24]. It shows to which extent 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 communities. The number of communities is reported using the Clauset-Newman-Moore method [21]. Also the modularity index based on the Louvain method [18] is calculated using [13]. The value of the modularity index can vary between $[-1, 1]$, a high value of modularity corresponds to a structure where there are dense connections between the nodes within communities but sparse connections between nodes in different communities. That means that there are many sub communities of authors that write together but not across communities. Two centrality measures are also reported. These are:

1. **Closeness centrality**, where a node is seen as centrally involved in the network if it requires only few intermediaries to contact others and thus is structurally relatively independent.
2. **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 node in question and the number of all shortest paths in the network. In betweenness centrality the position of the node matters.

There are a total of 1157 connected components in G and the largest component has a size of 796 nodes. The largest connected component is going to be refereed to as the main cluster of the network and is denoted as $\bar{G}$. A metrics summary of both networks is given by Table 3.

~~Is the Prisoner's Dilemma a collaborative field?~~

Based on Table 3 an author in G has on average 4 collaborators and a ~~70~~67% probability of collaborating with a collaborator's co-author. An author of $\bar{G}$ on average is ~~7~~10% more likely to write with a collaborator's co-author and on average has 2 more collaborators. Moreover, there are only 8.0 % of authors in the PD that ~~has~~ have no connection to any other author.

How does this compare to other fields? Two more data sets for the topics "Price of Anarchy" and "Auction Games" have been collected in order to compare the collaborative behaviour of the PD to other game theoretic fields. A total of 3444 publications have been collected for Auction games and 748 for Price of Anarchy. Price of Anarchy is relatively a new field, with the first publication on the topic being [40] in 1999. This explains the small number of articles that have been retrieved. Both data sets have been archived and are available in [5, 6]. The networks for both data sets have been generated in the same way as G~~. A~~ , and a summary of the networks' metrics ~~are~~ is also given by Table 3.

The average degrees for the Price of Anarchy and for Auction games are lower than the PD's~~. In Auction games an author is more likely to have no collaborators, and in the Price of Anarchy there are almost no authors that are not connected to someone. This could be an effect of the field being introduced in more modern days. Overall, an author in the PD has on average more collaborators and there are less isolated authorscompared to another well established game theoretic field~~, and so are their respective clustering coefficients. Moreover, both the Price of Anarchy and Auction games have a larger number of isolated authors. These results seem to indicate that the PD is a ~~*relatively* collaborative field.~~

relatively collaborative field, compared to other game theoretic fields. However, both G and $\bar{G}$ have a high modularity (larger than 0.84) and a large number of communities (967 and 25 respectively). A high modularity implies that authors create their own publishing communities but not many publications from authors from different communities occur. Thus, author tends to collaborate with authors in their communities but not many efforts are made to create new connections to other communities and spread the knowledge of the field across academic teams. The fields of both Price of Anarchy and Auction games also have high modularity, and that could indicate that is in fact how academic publications are.

~~Thus, **the PD is indeed a collaborative field but perhaps it is not more collaborative than other fields,** as there is no effort from the authors to write with people outside their community.~~

	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
G	4221	7642	338	8.0	1157	796	3.621	1177	0.965264	0.666
$\bar{G}$	796	2214	0	0.0	1	796	5.563	29	0.840138	0.773
Auction Games	5362	7861	453	8.4	1469	1348	2.932	1493	0.957238	0.599
Price of Anarchy	1315	1952	165	12.5	406	221	2.969	414	0.964498	0.626

Table 3: Network metrics for G and $\bar{G}$ respectively.

The evolution of the networks was also explored over time by constructing the network cumulatively over 51 periods. Except from the first period 1951-1966 the rest of the periods have a yearly interval (data for the years 1975 and 1982 were not retrieved by the collection data process). The metrics of each sub network are given in the Appendix B.

The results, similarly to the results of [44], confirm that the networks grow over time and that the networks always had a high modularity. Since the first publications authors tend to write with people from their communities, and that is not an effect of a specific time period.

~~Are some topics more collaborative than other?~~

The networks corresponding to the topics of Section ~~??~~ 3.1 have also been generated similarly to G. Note that authors with publications in more than one topic exist, and these authors are included in all the corresponding networks. A metrics' summary for all five topic networks is given by Table 4.

~~Topic B is the network with the~~ Topics A and B have the highest average degree ~~followed by Topic A. The topic with the smallest average degree, 2.5, is Topic C. In topics A and B the~~ and clustering coefficient. Moreover, both topics have a small number of isolated nodes~~is very small (less than 0.2) compared to Topic E where the percentage of isolated nodes is approximately 6%. Moreover, in topics C and E an author is 10% more likely to collaborate with a collaborator 's co-author. Thus,~~ ~~**topics "human subject research" and "biological studies" tend to be more collaborative than the topic of "strategies", and an authors in these are less likely to have at least one collaborator compared to the topic of "modeling problems as a PD"**.~~ . Compared to that Topic C has a smallest average degree and Topic E has the highest number of isolated authors. These indicate that the topics "human subject research" and "biological studies" tend to be more collaborative than the topic of "strategies", and authors in these are more likely to have at least one collaborator compared to the topic of "modeling problems as a PD".

~~**"Evolutionary dynamics on networks" also appear to be a collaborative topic**.~~ Topic "Evolutionary dynamics on networks" also appears to be a collaborative topic. It is the topic with smallest number of isolated authors, and has an average degree of 3.4. In fact the network of the topic is a sub graph of $\bar{G}$, the main cluster of ~~G and it will be demonstrated in the following section that authors in this network are more like to gain from the influence of the network compared to any other topic network~~G. This is discussed in the next part of this analysis.

	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
Topic A	1193	2137	84	7.0	333	56	3.583	334	0.983	0.715
Topic B	727	1382	45	6.2	189	80	3.802	190	0.950	0.739
Topic C	931	1141	72	7.7	312	29	2.451	312	0.981	0.615
Topic D	891	1509	28	3.1	185	312	3.387	193	0.917	0.692
Topic E	1152	1964	166	14.4	461	31	3.410	461	0.926	0.602

Table 4: Network metrics for topic networks.

~~**Are there authors which benefit more from their position in the network?**~~

There are two centrality measures reported in this work, closeness and betweenness centrality. Closeness centrality is a measure of how easy it is for an author to ~~contact~~ reach others, and ~~consequently affect them; influence them. Thus closeness centrality here~~ betweenness centrality is a measure of ~~influence. Betweenness centrality is a measure of~~ how many paths pass through a specific node~~, thus the amount of information this person has access to. Betweenness centrality is used here as a measure of how much an author gains from the field. All centrality measure can~~ . All centrality measures have values ranging from 0 to 1. ~~The influence and the amount of information an author has access to are used to explore which authors benefit more from their position.~~

For G and $\bar{G}$ the most central authors based on closeness and betweenness centralities are given by Table 5. The most central authors in G and $\bar{G}$ are the same. This implies that the results on centrality heavily rely on the main cluster (as expected). Matjaz Perc is an author with 83 publications in the data set and the most central authors based on both centrality measures. The most central authors are fairly similar between the two measures. The author that appear to be central based on one measure and not the other are Martin Nowak, Franz Weissing, Jianye Hao, Angel Sanchez and Valerio Capraro which ~~have access to information due to their positioning but do not influence the network as much~~are central based on betweeness centrality, and the opposite is true for Attila Szolnoki, Luo-Luo Jiang Sandro Meloni, Cheng-Yi Xia and Xiaojie Chen.

~~It is obvious that in G the centralities values are low which suggests that in the PD authors do not benefit from their positions. This could be an effect of information not flowing from one community to another as authors tend to write with people from their communities. Nevertheless,~~ ~~**there are authors that do benefit from their position, but these are only the authors connected to the main cluster**.~~

The centrality measures for the topic networks have also been estimated and are given in ~~Table ??. If information was flowing between the communities of the research topics then there would be an increase to the values of centralities for the sub networks . However, the only topic where authors gain from their positions are the authors~~

	G				$\bar{G}$			
	Name	Betweenness	Name	Closeness	Name	Betweenness	Name	Closeness
1	Matjaz Perc	0.013	Matjaz Perc	0.062	Matjaz Perc	0.373	Matjaz Perc	0.330
2	Zhen Wang	0.010	Long Wang	0.057	Zhen Wang	0.279	Long Wang	0.301
3	Long Wang	0.006	Yamir Moreno	0.056	Long Wang	0.170	Yamir Moreno	0.299
4	Martin Nowak	0.006	Attila Szolnoki	0.056	Martin Nowak	0.159	Attila Szolnoki	0.297
5	Angel Sanchez	0.004	Zhen Wang	0.056	Angel Sanchez	0.114	Zhen Wang	0.296
6	Yamir Moreno	0.004	Arne Traulsen	0.053	Yamir Moreno	0.110	Arne Traulsen	0.281
7	Arne Traulsen	0.004	Luo-Luo Jiang	0.053	Arne Traulsen	0.107	Luo-Luo Jiang	0.280
8	Franz Weissing	0.004	Sandro Meloni	0.052	Franz Weissing	0.101	Sandro Meloni	0.278
9	Jianye Hao	0.003	Cheng-Yi Xia	0.052	Jianye Hao	0.094	Cheng-Yi Xia	0.276
10	Valerio Capraro	0.003	Xiaojie Chen	0.052	Valerio Capraro	0.093	Xiaojie Chen	0.276

Table 5: 10 most central authors based on betweenness and closeness centralities for G and $\bar{G}$.

Tables 6 and 7. The centrality measure for the topics' networks are low except from the case of Topic D~~(topic on evolutionary dynamics on network)~~. From the list of names it is obvious that ~~these authors~~ the most central authors of Topic D are part of $\bar{G}$, and that the network of ~~Topic D~~ evolutionary dynamics on networks is a sub network of $\bar{G}$.

This confirms the ~~results. The people benefiting from their position in the~~ result that the most central authors of the co-authorship ~~networks corresponding to research topics of the PD are only the people from~~ network are the authors of the main cluster of G.

The fact that most authors of the main cluster are primarily publishing in evolutionary dynamics on networks indicates that publishing in this specific topic differs from the other topics covered in this manuscript. ~~There appears to be more collaboration and influence in the publications on evolutionary dynamics and authors are more likely to gain from their position, though it is not clear as to why~~It could also indicate that authors publishing in evolutionary dynamics are more similar to other disciplines as they can collaborate with them more.

	Topic A		Topic B		Topic C		Topic D			
	Name	Betweeness	Name	Betweeness	Name	Betweeness	Name	Betweeness	Name	Betweeness
1	David Rand	0.001	Long Wang	0.006	Daniel Ashlock	0.001	Matjaz Perc	0.062	Zengru Di	0.0
2	Valerio Capraro	0.001	Luo-Luo Jiang	0.004	Matjaz Perc	0.000	Luo-Luo Jiang	0.036	Jian Yang	0.0
3	Angel Sanchez	0.000	Martin Nowak	0.004	Karl Tuyls	0.000	Yamir Moreno	0.031	Yevgeniy Vorobeychik	0.0
4	Feng Fu	0.000	Matjaz Perc	0.003	Philip Hingston	0.000	Christoph Hauert	0.027	Otavio Teixeira	0.0
5	Martin Nowak	0.000	Attila Szolnoki	0.002	Eun-Youn Kim	0.000	Long Wang	0.023	Roberto Oliveira	0.0
6	Nicholas Christakis	0.000	Christian Hilbe	0.002	Wendy Ashlock	0.000	Zhen Wang	0.023	M. Nowak	0.0
7	Pablo Branas-Garza	0.000	Yamir Moreno	0.002	Attila Szolnoki	0.000	Han-Xin Yang	0.022	M. Harper	0.0
8	Toshio Yamagishi	0.000	Xiaojie Chen	0.002	Seung Baek	0.000	Martin Nowak	0.019	Xiao Han	0.0
9	James Fowler	0.000	Arne Traulsen	0.002	Martin Nowak	0.000	Angel Sanchez	0.016	Zhesi Shen	0.0
10	Long Wang	0.000	Zhen Wang	0.002	Thore Graepel	0.000	Zhihai Rong	0.015	Wen-Xu Wang	0.0

Table 6: 10 most central authors based on ~~two centralities~~ betweeness centrality for topics' networks.

	Topic A		Topic B		Topic C		Topic D			
	Name	Closeness	Name	Closeness	Name	Closeness	Name	Closeness	Name	Closeness
1	David Rand	0.026	Long Wang	0.042	Karl Tuyls	0.021	Matjaz Perc	0.122	Stefanie Widder	0.026
2	Valerio Capraro	0.022	Matjaz Perc	0.039	Thore Graepel	0.019	Zhen Wang	0.107	Rosalind Allen	0.026
3	Jillian Jordan	0.021	Attila Szolnoki	0.039	Joel Leibo	0.018	Long Wang	0.105	Thomas Pfeiffer	0.026
4	Nicholas Christakis	0.020	Martin Nowak	0.038	Edward Hughes	0.017	Yamir Moreno	0.103	Thomas Curtis	0.026
5	James Fowler	0.019	Olivier Tenaillon	0.037	Matthew Phillips	0.017	Luo-Luo Jiang	0.102	Carsten Wiuf	0.026
6	Martin Nowak	0.019	Xiaojie Chen	0.036	Edgar Duenez-Guzman	0.017	Attila Szolnoki	0.102	William Sloan	0.026
7	Angel Sanchez	0.018	Bin Wu	0.036	Antonio Castaneda	0.017	Gyorgy Szabo	0.101	Otto Cordero	0.026
8	Samuel Arbesman	0.018	Yanling Zhang	0.035	Iain Dunning	0.017	Xiaojie Chen	0.100	Sam Brown	0.026
9	Gordon Kraft-Todd	0.018	Feng Fu	0.035	Tina Zhu	0.017	Guangming Xie	0.100	Babak Momeni	0.026
10	Akihiro Nishi	0.018	David Rand	0.035	Kevin Mckee	0.017	Lucas Wardil	0.100	Wenying Shou	0.026

Table 7: 10 most central authors based on closeness centrality for topics' networks.

The distributions of both centrality measures for all the networks of this work are given in the Appendix C.2.

4 Conclusion

This manuscript has explored the research topics in the publications of the Iterated Prisoner's Dilemma, and moreover, the authors' collaborative behaviour and their ~~influence in the research field~~centrality. This was achieved by applying network theoretic approaches and a LDA algorithm to a total of 2422 publications. ~~Both the software [8] and the data [7] have been archived and are available to be used by other researchers.~~

The data collection and an ~~introduction to the methodology used in this work~~ initial analysis of the data set were covered in Section 2. ~~Section ?? covered an initial analysis of the data set which~~ The analysis demonstrated that the PD is a field that continues to attract academic attention and publications.

In Section ~~??~~ 3.1 LDA was applied to the data set to identify topics on which researchers have been publishing. The ~~LDA analysis showed that the data could be classified into 5 topics associated with~~ five topics in the PD publications identified by the data set of this work are human subject research, biological studies, strategies, evolutionary dynamics on networks and modeling problems as a PD. These ~~topics summarize the field of the PD well, as they demonstrate its interdisciplinarity and applications to a variety of problems~~5 topics nicely summarise PD research. They highlight the interdisciplinarity of the field; how it brings together applied modeling of real world situations (biological studies and modeling problems as a PD) and more theoretical notions such as evolutionary dynamics and optimality of strategies. A temporal analysis explored how relevant these topics have been over the course of time, and it revealed that even though ~~there were not the~~ they were not necessarily always the most discussed topics ~~they~~ there were still being explored by researchers.

The collaborative behaviour of the field was explored in Section ~~?? by constructing the co authorship~~ 3.1 investigated the co-authorship network. It was concluded that the field is a collaborative field, where authors are likely to write with a collaborator's co-authors and on average an author has 4 co-authors~~, however it not necessarily more collaborativethan other fields~~. The results were compared to the networks of two other game theoretic fields, and it was shown that the PD network is relatively more collaborative. The authors however, tend to collaborate with authors from one community, but not many authors are involved in multiple communities. This ~~however~~ might be an effect of academic research, and it might not be true just for the field of the PD. ~~Exploring the influence of authors and their gain from being in the network of the field demonstrated that~~

Exploring the centrality of authors showed that the most central author of this manuscript is Matjaz Perc. More importantly, it was shown that most central authors of the network were the authors ~~do not gain much, and the authors with influence are only the ones~~ connected to the main cluster~~, to a "main" group of authors. This 'main" group of authors consists of authors publishing in~~. Interestingly, it was uncovered that these authors were the most central due to their publication on a single topic alone. That was the topic of "evolutionary dynamics on networks~~. Thus, an author would be aiming to publish on this topic if they were interested in gaining~~". There appears to be more collaboration and more influence in the publications on evolutionary dynamics. The authors are most likely to gain from their position~~in the publications of the PD~~, and come across as the more important authors in the field. Though it is not clear as to why, attention should be paid to the collaborative behaviour of authors of "evolutionary dynamics on networks".

The study of the PD is the study of cooperation and investigating the cooperative behaviours of authors is what this work has aimed to achieve. Interesting areas of future work would include extending this analysis to more game theoretic sub fields, to evaluate whether the results remain the same. Moreover, the networks of this work were created by not taking into account the strength of ties. The strength of ties could be analysed to map multiple collaborations between two nodes. However, a preliminary assessment showed that the presented results do not change.

5 ~~Acknowledgements~~

Both the software [8] and the data [7] used in the manuscript have been archived and are available to be used by other researchers.

~~A variety of software have been used in this work :~~

- ~~The Matplotlib library for visualisation [33].~~
- ~~The Numpy library for data manipulation [66].~~
- ~~The Networkx [32] package for analysing networks.~~
- ~~Gephi [?] open source package for visualising networks.~~
- ~~The Gensim library for the topic modeling [56].~~
- ~~The louvain library for calculating the networks modularity .~~

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A Topic modeling ~~result for the cumulative data set~~ results over ~~the~~ time periods

B Cumulative Networks Metrics

B.1 Collaborativeness metrics for cumulative graphs, $\tilde{G} \subseteq G$

Period	Topic	Topic Keywords	Num of Documents	Percentage of Documents
1951-1965	1	problem, technology, divert, euler, subsystem, requirement, trace, technique, system, untried	3	0.375
1951-1965	2	interpret, requirement, programme, evolution, article, increase, policy, system, trace, technology	2	0.25
1951-1965	3	equipment, agency, conjecture, development, untried, programme, trend, technology, weapon, technique	1	0.125
1951-1965	4	variation, celebrated, trend, untried, change, involve, month, technique, subsystem, research	1	0.125
1951-1965	5	give, good, modern, trace, technique, ambiguity, problem, trend, technology, system	1	0.125
1951-1973	1	study, shock, cooperative, money, part, vary, investigate, good, receive, equipment	12	0.3243
1951-1973	2	cooperation, level, significantly, sequence, reward, provoke, descriptive, principal, display, argue	4	0.1081
1951-1973	3	player, make, effect, triad, experimental, motivation, dominate, hypothesis, instruction, trend	3	0.0811
1951-1973	4	ss, sex, male, female, dyad, design, suggest, college, factor, tend	3	0.0811
1951-1973	5	result, research, format, change, operational, analysis, relate, understanding, decision, money	2	0.0541
1951-1973	6	condition, give, high, treatment, conflict, cc, real, original, replication, promote	2	0.0541
1951-1973	7	group, competitive, show, interpret, scale, compete, escalation, free, variable, individualistic	2	0.0541
1951-1973	8	outcome, strategy, choice, type, pdg, difference, dummy, conclude, compare, consistent	2	0.0541
1951-1973	9	game, difference, pair, approach, behavior, person, weapon, occur, advantaged, differential	2	0.0541
1951-1973	10	response, present, dilemma, influence, cooperate, bias, point, amount, participate, factor	2	0.0541
1951-1973	11	trial, problem, previous, involve, prisoner, experiment, follow, tit, increase, initial	1	0.027
1951-1973	12	matrix, behavior, rational, black, model, research, broad, distance, complex, trace	1	0.027
1951-1973	13	play, finding, individual, noncooperative, white, nature, race, ratio, represent, prisoner	1	0.027
1951-1980	1	play, trial, group, follow, white, interpret, scale, black, trend, small	14	0.25
1951-1980	2	outcome, level, effect, type, dyad, vary, pdg, participate, understanding, arise	9	0.1607
1951-1980	3	game, strategy, cooperation, significant, difference, sentence, text, occur, differential, hypothesis	4	0.0714
1951-1980	4	male, female, find, result, sex, subject, experimental, situation, treatment, computer	4	0.0714
1951-1980	5	research, problem, influence, matrix, format, model, analysis, year, crime, equipment	4	0.0714
1951-1980	6	condition, dilemma, bias, free, attempt, book, year, dummy, prison, design	4	0.0714
1951-1980	7	variable, result, factor, individual, ability, triad, half, migration, change, investigate	3	0.0536
1951-1980	8	show, present, suggest, rational, compete, approach, characteristic, examine, person, conduct	3	0.0536
1951-1980	9	behavior, high, finding, relate, obtain, assistance, ratio, good, weapon, competition	3	0.0536
1951-1980	10	ss, shock, money, competitive, part, difference, pair, amount, man, information	3	0.0536
1951-1980	11	player, conflict, theory, decision, determine, produce, maker, cooperate, specialist, programming	2	0.0357
1951-1980	12	study, prisoner, make, response, experiment, noncooperative, standard, separate, conclude, initial	2	0.0357
1951-1980	13	give, cooperative, choice, cognitive, real, operational, set, subject, ascribe, concern	1	0.0179
1951-1988	1	trial, difference, find, choice, significant, competitive, effect, triad, interact, occur	24	0.2553
1951-1988	2	ss, shock, money, pair, response, part, high, tit, receive, amount	13	0.1383
1951-1988	3	suggest, paper, case, debate, view, achieve, framework, natural, assumption, finitely	10	0.1064
1951-1988	4	prisoner, dilemma, behavior, model, present, involve, person, increase, trust, experiment	8	0.0851
1951-1988	5	game, player, show, approach, repeat, previous, move, tat, related, include	8	0.0851
1951-1988	6	cooperation, level, mutual, equilibrium, standard, provide, information, human, real, question	6	0.0638
1951-1988	7	play, result, male, subject, female, cooperative, sex, experimental, treatment, computer	5	0.0532
1951-1988	8	research, study, variable, ability, factor, conflict, matrix, year, student, interpret	4	0.0426
1951-1988	9	problem, group, small, scale, social, issue, large, base, bias, party	4	0.0426
1951-1988	10	game, strategy, outcome, type, cooperate, ethical, pdg, explain, dependent, separate	4	0.0426
1951-1988	11	give, condition, individual, major, dyad, behaviour, produce, conflict, assistance, collectively	3	0.0319
1951-1988	12	situation, iterate, statement, rational, card, side, paradox, true, consequence, front	2	0.0213
1951-1988	13	inflation, hypothesis, rate, run, change, demand, nominal, cost, output, growth	2	0.0213
1951-1988	14	theory, make, analysis, decision, system, examine, work, soft, lead, hard	1	0.0106
1951-1995	1	strategy, population, evolution, iterate, tit, opponent, evolve, dynamic, set, tat	31	0.1732
1951-1995	2	game, repeat, assumption, rule, person, equilibrium, general, finitely, indefinitely, analyze	24	0.1341
1951-1995	3	inflation, long, rate, hypothesis, run, policy, cost, nominal, demand, programming	20	0.1117
1951-1995	4	condition, outcome, trial, find, difference, cooperation, experiment, level, significant, response	15	0.0838
1951-1995	5	rational, result, receive, statement, money, paradox, shock, iterate, consequence, common	14	0.0782
1951-1995	6	cooperation, show, competitive, high, probability, conflict, simulation, altruism, yield, natural	14	0.0782
1951-1995	7	prisoner, dilemma, give, point, defect, form, cooperator, increase, relate, ethical	10	0.0559
1951-1995	8	player, give, decision, provide, cooperative, game, previous, pair, determine, interact	9	0.0503
1951-1995	9	play, cooperate, result, male, subject, female, time, relationship, suggest, student	8	0.0447
1951-1995	10	problem, group, theory, good, approach, society, large, scale, issue, level	8	0.0447
1951-1995	11	study, situation, behaviour, computer, argue, change, implication, characteristic, real, associate	8	0.0447
1951-1995	12	model, paper, behavior, examine, present, mutual, expectation, develop, type, variable	7	0.0391
1951-1995	13	make, research, system, analysis, choice, work, base, relation, world, wide	6	0.0335
1951-1995	14	individual, social, behavior, standard, choose, evolutionary, partner, payoff, defection, small	5	0.0279
1951-2003	1	game, player, dilemma, prisoner, theory, give, paper, make, group, problem	151	0.4266
1951-2003	2	cooperation, result, play, show, cooperate, condition, cooperative, high, level, time	106	0.2994
1951-2003	3	strategy, model, agent, study, behavior, individual, population, evolutionary, state, player	97	0.274
1951-2010	1	model, theory, paper, base, make, present, problem, provide, human, decision	325	0.3454
1951-2010	2	game, strategy, player, agent, play, dilemma, system, behavior, show, state	322	0.3422
1951-2010	3	cooperation, network, study, population, individual, evolutionary, social, evolution, interaction, structure	294	0.3124
1951-2018	1	model, theory, system, base, paper, problem, propose, present, approach, provide	556	0.2251
1951-2018	2	behavior, social, human, decision, study, experiment, make, suggest, result, behaviour	482	0.1951
1951-2018	3	individual, group, good, social, punishment, level, cost, mechanism, dilemma, cooperative	428	0.1733
1951-2018	4	game, strategy, player, agent, play, dilemma, state, prisoner, payoff, equilibrium	380	0.1538
1951-2018	5	population, evolutionary, dynamic, model, selection, result, evolution, evolve, show, process	351	0.1421
1951-2018	6	cooperation, network, interaction, structure, study, evolution, find, behavior, cooperative, simulation	273	0.1105

Table 8: Topic modeling results for the cumulative data sets over the periods: 1951-1965, 1951-1973, 1951-1980, 1951-1988, 1951-1995, 1951-2003, 1951-2010, 1951-2018. The number of topics n for each period is given in the column "Topic". For example in the period 1951-1980 the selected n was 13. The number of topics here were chosen only based on the coherence score. The number of documents and the percentage of documents assigned to each topic, for each period is also given.

	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
Period 0	11	3	5	45.5	8	2	0.545	8	0.667	0.000
Period 1	14	4	6	42.9	10	2	0.571	10	0.750	0.000
Period 2	27	15	8	29.6	16	5	1.111	16	0.684	0.160
Period 3	29	17	9	31.0	17	6	1.172	17	0.630	0.172
Period 4	32	18	10	31.2	19	6	1.125	19	0.667	0.156
Period 5	43	28	10	23.3	23	6	1.302	23	0.827	0.326
Period 6	49	34	10	20.4	25	6	1.388	25	0.867	0.408
Period 7	52	35	11	21.2	27	6	1.346	27	0.873	0.385
Period 8	54	35	13	24.1	29	6	1.296	29	0.873	0.370
Period 9	54	35	13	24.1	29	6	1.296	29	0.873	0.370
Period 10	59	36	16	27.1	33	6	1.220	33	0.880	0.339
Period 11	60	36	17	28.3	34	6	1.200	34	0.880	0.333
Period 12	63	40	17	27.0	34	6	1.270	34	0.884	0.339
Period 13	65	40	19	29.2	36	6	1.231	36	0.884	0.328
Period 14	69	46	20	29.0	37	6	1.333	37	0.889	0.360
Period 15	71	46	22	31.0	39	6	1.296	39	0.889	0.350
Period 16	75	47	24	32.0	42	6	1.253	42	0.894	0.331
Period 17	80	47	29	36.2	47	6	1.175	47	0.894	0.310
Period 18	84	47	33	39.3	51	6	1.119	51	0.894	0.296
Period 19	92	48	39	42.4	58	6	1.043	58	0.898	0.270
Period 20	101	52	43	42.6	64	6	1.030	64	0.909	0.276
Period 21	114	62	44	38.6	70	6	1.088	70	0.926	0.279
Period 22	119	64	45	37.8	73	6	1.076	73	0.930	0.268
Period 23	129	69	48	37.2	79	6	1.070	79	0.937	0.270
Period 24	140	72	55	39.3	87	6	1.029	87	0.941	0.249
Period 25	154	81	60	39.0	95	6	1.052	95	0.947	0.252
Period 26	179	95	71	39.7	111	6	1.061	111	0.955	0.273
Period 27	192	102	74	38.5	118	6	1.062	118	0.960	0.270
Period 28	199	105	75	37.7	122	6	1.055	122	0.962	0.260
Period 29	214	115	79	36.9	130	6	1.075	130	0.966	0.284
Period 30	255	140	85	33.3	151	6	1.098	151	0.973	0.275
Period 31	288	169	92	31.9	166	6	1.174	166	0.977	0.304
Period 32	319	195	96	30.1	179	6	1.223	179	0.979	0.327
Period 33	360	235	103	28.6	198	7	1.306	198	0.977	0.334
Period 34	411	278	112	27.3	222	7	1.353	222	0.979	0.349
Period 35	459	310	118	25.7	246	7	1.351	246	0.982	0.343
Period 36	521	370	124	23.8	269	10	1.420	269	0.983	0.355
Period 37	621	476	130	20.9	303	19	1.533	303	0.985	0.393
Period 38	738	603	141	19.1	344	22	1.634	344	0.987	0.422
Period 39	904	877	157	17.4	394	25	1.940	394	0.985	0.467
Period 40	1062	1170	164	15.4	432	33	2.203	433	0.985	0.498
Period 41	1232	1442	178	14.4	480	71	2.341	482	0.982	0.515
Period 42	1429	1936	195	13.6	531	133	2.710	535	0.965	0.538
Period 43	1695	2375	214	12.6	607	157	2.802	610	0.970	0.564
Period 44	1980	2865	223	11.3	677	209	2.894	680	0.968	0.589
Period 45	2300	3420	244	10.6	754	322	2.974	760	0.965	0.602
Period 46	2643	3971	265	10.0	845	399	3.005	856	0.962	0.618
Period 47	3106	4877	278	9.0	933	504	3.140	947	0.965	0.639
Period 48	3664	6532	309	8.4	1045	613	3.566	1058	0.964	0.659
Period 49	3938	7072	322	8.2	1098	706	3.592	1115	0.965	0.664
Period 50	4221	7642	338	8.0	1157	796	3.621	1177	0.965	0.666

B.2 Collaborativeness metrics for cumulative graphs' main clusters, $\tilde{G} \subseteq \bar{G}$

C Centrality Measures Distributions

C.1 Distrubutions for G and $\bar{G}$

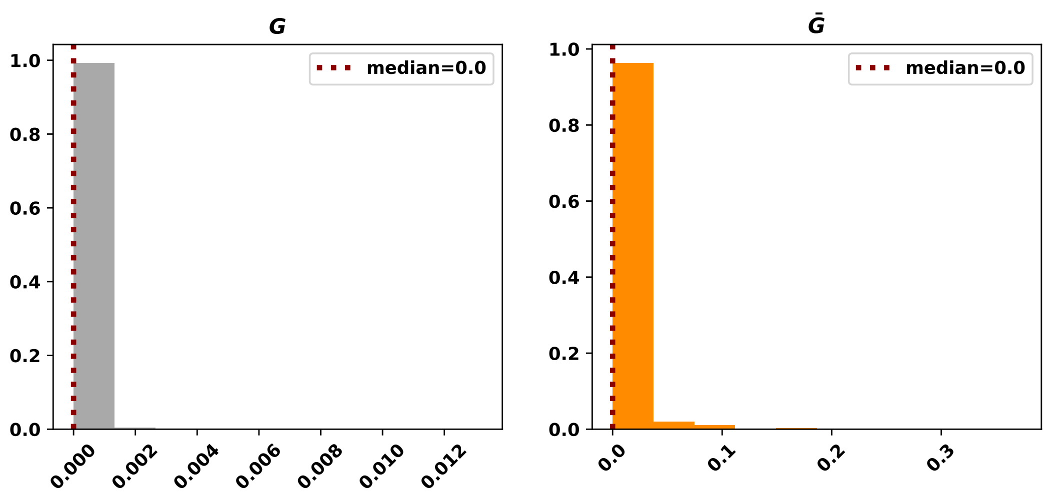

Figure 6: Distributions of betweenness centrality in G and $\bar{G}$

	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
0	2	1	0	0.0	1	2	1.000	1	0.000	0.000
1	2	1	0	0.0	1	2	1.000	1	0.000	0.000
2	5	8	0	0.0	1	5	3.200	1	0.000	0.867
3	6	10	0	0.0	1	6	3.333	2	0.020	0.833
4	6	10	0	0.0	1	6	3.333	2	0.020	0.833
5	6	10	0	0.0	1	6	3.333	2	0.020	0.833
6	6	10	0	0.0	1	6	3.333	2	0.020	0.833
7	6	10	0	0.0	1	6	3.333	2	0.020	0.833
8	6	10	0	0.0	1	6	3.333	2	0.020	0.833
9	6	10	0	0.0	1	6	3.333	2	0.020	0.833
10	6	10	0	0.0	1	6	3.333	2	0.020	0.833
11	6	10	0	0.0	1	6	3.333	2	0.020	0.833
12	6	10	0	0.0	1	6	3.333	2	0.020	0.833
13	6	10	0	0.0	1	6	3.333	2	0.020	0.833
14	6	10	0	0.0	1	6	3.333	2	0.020	0.833
15	6	10	0	0.0	1	6	3.333	2	0.020	0.833
16	6	10	0	0.0	1	6	3.333	2	0.020	0.833
17	6	10	0	0.0	1	6	3.333	2	0.020	0.833
18	6	10	0	0.0	1	6	3.333	2	0.020	0.833
19	6	10	0	0.0	1	6	3.333	2	0.020	0.833
20	6	10	0	0.0	1	6	3.333	2	0.020	0.833
21	6	10	0	0.0	1	6	3.333	2	0.020	0.833
22	6	10	0	0.0	1	6	3.333	2	0.020	0.833
23	6	10	0	0.0	1	6	3.333	2	0.020	0.833
24	6	10	0	0.0	1	6	3.333	2	0.020	0.833
25	6	10	0	0.0	1	6	3.333	2	0.020	0.833
26	6	10	0	0.0	1	6	3.333	2	0.020	0.833
27	6	10	0	0.0	1	6	3.333	2	0.020	0.833
28	6	10	0	0.0	1	6	3.333	2	0.020	0.833
29	6	10	0	0.0	1	6	3.333	2	0.020	0.833
30	6	10	0	0.0	1	6	3.333	2	0.020	0.833
31	6	10	0	0.0	1	6	3.333	2	0.020	0.833
32	6	10	0	0.0	1	6	3.333	2	0.020	0.833
33	7	21	0	0.0	1	7	6.000	1	0.000	1.000
34	7	21	0	0.0	1	7	6.000	1	0.000	1.000
35	7	21	0	0.0	1	7	6.000	1	0.000	1.000
36	10	13	0	0.0	1	10	2.600	2	0.376	0.553
37	19	28	0	0.0	1	19	2.947	3	0.544	0.730
38	22	35	0	0.0	1	22	3.182	4	0.541	0.720
39	25	39	0	0.0	1	25	3.120	5	0.558	0.686
40	33	62	0	0.0	1	33	3.758	4	0.623	0.736
41	71	148	0	0.0	1	71	4.169	6	0.726	0.698
42	133	387	0	0.0	1	133	5.820	7	0.726	0.749
43	157	465	0	0.0	1	157	5.924	8	0.721	0.725
44	209	611	0	0.0	1	209	5.847	13	0.738	0.737
45	322	892	0	0.0	1	322	5.540	16	0.780	0.743
46	399	1109	0	0.0	1	399	5.559	15	0.792	0.742
47	504	1368	0	0.0	1	504	5.429	21	0.809	0.751
48	613	1677	0	0.0	1	613	5.471	24	0.820	0.761
49	706	1935	0	0.0	1	706	5.482	28	0.832	0.772
50	796	2214	0	0.0	1	796	5.563	29	0.843	0.773

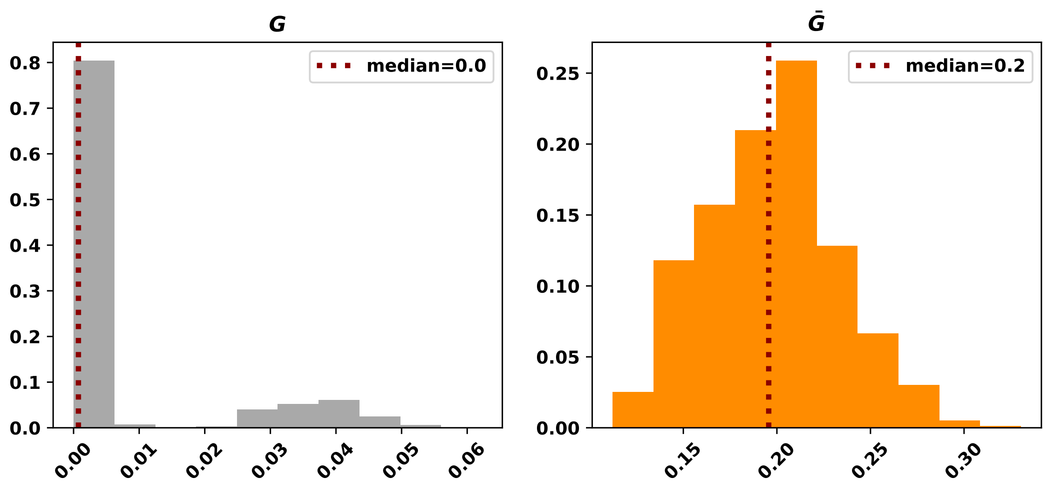

Figure 7: Distributions of closeness centrality in G and $\bar{G}$

C.2 Distrubutions for Topic Networks

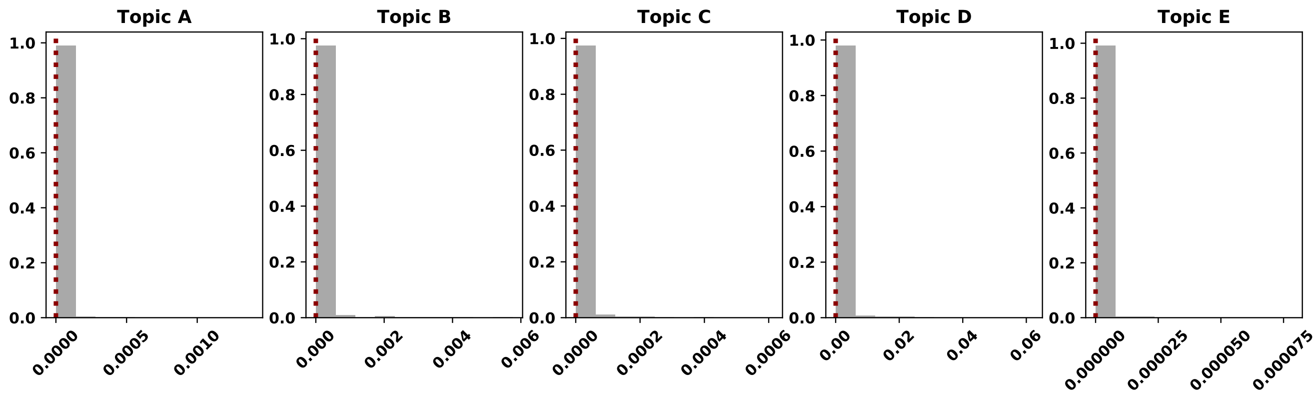

Figure 8: Distributions of betweenness centrality in topics' networks.

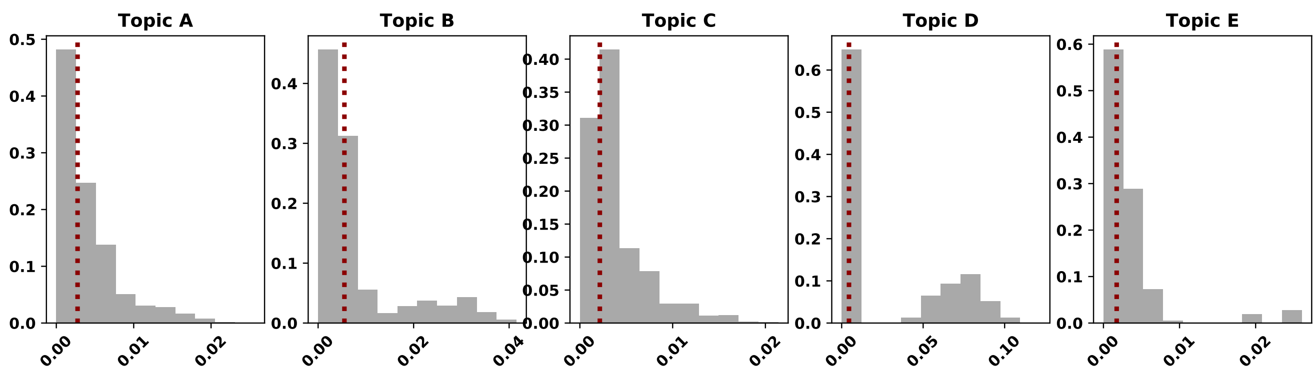

Figure 9: Distributions of closeness centrality in topics' networks.