

A bibliometric study of collaboration and influence in the field of the Iterated Prisoner’s Dilemma

Nikoleta E. Glynatsi¹ and Vincent A. Knight¹

¹*Cardiff University, School of Mathematics, Cardiff, United Kingdom*

Abstract

This manuscript explores the collaborative behaviour of authors in the field of the Prisoner’s Dilemma using bibliometric analysis, topic modeling, and a graph theoretic analysis of the co-authorship network. The results demonstrate that the Prisoner’s Dilemma is a field of continued interest and a collaborative field. Authors are very like to cooperate with a collaborator’s co-author and single author publications are rare. The co-authorship network however suggests that authors are collaborative with authors from their communities, and now many connections across the communities exist, moreover, authors do not influence or gain much information by their connections, unless they are connected to a “main” group of authors. The topic modeling approach identified five different research topics within the field, these were human subject research, biological studies, strategies, evolutionary dynamics on networks and modeling problems as a Prisoner’s Dilemma game. The articles collected for this work are classified based on the language of their abstracts in five different topics, and the results are additionally verified by the topics’ networks.

1 Introduction

The Prisoner’s Dilemma (PD) is a well known game used since its introduction in the 1950’s [25] as a framework for studying the emergence of cooperation; a topic of continued interest for mathematical, social [55], biological [69] and ecological [74] sciences. This manuscript presents a bibliometric analysis of 2,420 published articles on the Prisoner’s Dilemma between 1951 and 2018. It presents the dominant topics in the PD publications, which have been identified using Latent Dirichlet Allocation, and it explores the changes in the dominant topics over time. The collaborative behaviour of the field is explored using the co-authorship network, and furthermore, the Latent Dirichlet Allocation topics are combined with the co-authorship network analysis to assess the relative influence of authors in these topics. Assessing the collaborative behaviour of the field of collaboration itself is the main aim of this work.

As discussed in [76], bibliometrics (the statistical analysis of published works originally described by [56]) has been used to support historical assumptions about the development of fields [57], identify connections between scientific growth and policy changes [21], develop a quantitative understanding of author order [63], and investigate the collaborative structure of an interdisciplinary field [44]. Most academic research is undertaken in the form of collaborative effort and as [40] points out, it is rational that two or more people have the potential to do better as a group than individually. Collaboration in groups has a long tradition in experimental sciences and it has been proven to be productive according to [23]. The number of collaborations can be very 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 [51] 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. In [44], the approach was applied to analyse the development of the field “evolution of cooperation”, and in [76] 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 [76], and extends their methodology. Though in [44, 76], they considered a data set from a single source, Web of Science, the data set described here, archived at [27], has been collected from five sources.

Latent Dirichlet Allocation (LDA) is a topic modeling technique proposed in [15] as a generative probabilistic model for discovering underlying topics in collections of data. Applications of the technique include detection in image data [3, 20] and detection in video [50, 73]. 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 [68], and LDA was expanded in [14] to include the correlation between topics. Another extension to the approach is to combine LDA with a co-authorship network analysis [13]. In [13] the scientific content presented at EvoLang conferences were initially quantified using LDA and the clustered, using a clustering algorithm, to reveal different domains. The work of [13] only considered the main network and no analysis was done in the individual sub graphs which corresponded to the clusters. Compared to that this manuscript applies LDA to identify topics and analysis the networks corresponding to each topic as well.

The methodology used in this manuscript, which includes the data collection, is covered in Section 2. The results regarding the amount of publications and the topics of the field are described in Section 3. In Section 4, graph theoretical methods are used to ascertain the level of collaborative nature of the field and identify influence. Finally, the results are summarised in Section 5.

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’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 [52]. Similarly to the request message, the structure of the received data differs from journal to journal.

The data collection is crucial to this study. To ensure that this study can be reproduced all code used to query the different APIs has been packaged as a Python library and is available online [28]. 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 [28] 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 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 British 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 available at [27]. Note that the latest data collection was performed on the 30th November 2018.

The relationship between the authors within a field will 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. The co-authorship network is constructed using the main data set [27] 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 7642. All authors’ names were formatted as their last name and first 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.

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 [22]. 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 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 [22]. It is precisely the probability that the collaborators of an author also write together. In comparison, modularity is a global measure designed to measure the strength of division of a network into communities. The number of communities will be reported using the Clauset-Newman-Moore method [19]. Also the modularity index is calculated using the Louvain method described in [16]. 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 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 [41]. Two centrality measures have been chosen for this paper and these are closeness and betweenness centrality.

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. Here, this is interpreted as a 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 [27] 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 [15, 29]. The documents are the articles’ abstracts and LDA was carried out using [58]. In LDA, each document/abstract is represented by a distribution over topics, and the topics themselves are represented by a distribution over words. A document’s dominant topic is based on which topic has the highest percentage contribution. For example let the words that contribute to a topic be:

- Topic A: $0.039 \times$ “cooperation”, $0.028 \times$ “study” and $0.026 \times$ “human”.
- Topic B: $0.020 \times$ “cooperation”, $0.028 \times$ “agents” and $0.026 \times$ “strategies”.

A document with abstract “The study of cooperation in humans” has a percentage contribution $0.039 + 0.028 + 0.026 = 0.093$ for Topic A and $0.020 + 0.0 + 0.0 = 0.020$ for Topic B. For the given document the dominant topic is Topic A. LAD requires that the number of topics is specified in advance before running the algorithm. The number of topics can be chosen using the coherence value [60] or through subjective minimisation of the overlapping keywords between two topics. Both these approaches will be used in this work.

Though several of the approaches described in this section have previously been carried out [13], [44], [68] and [76], the novelty here is combining the approaches and applying them to a new data set. The manuscript presents the identified topics in the field of the PD, and studies them over time. Moreover, the collaborativeness of the authors is explored using the co-authorship network, for the network as a whole and individually for each topic. Similarly, the influence of the authors is explored for the field as a whole and for individual topics. The results are presented in the following sections.

3 Preliminary Analysis

The data set [27] 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 because they are of interest to the authors. Examples of such papers include [25] the first publication on the PD, [53, 66] two well cited articles in the field, and a series of works from Robert Axelrod [6, 7, 8, 9, 59] a leading author of the field. 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.

The data handled here is in fact a time series starting from the 1950s and the formulation of the game, until 2018 (Figure 1). Two observations can be made from Figure 1.

	Number of Articles	Percentage %	Year of fist publication	Average number of publications
IEEE	294.0%	12.14	1973.0	5.0
Manual	76.0%	3.14	1951.0	1.0
Nature	436.0%	18.00	1959.0	8.0
PLOS	477.0%	19.69	2005.0	8.0
Springer	533.0%	22.01	1966.0	9.0
arXiv	654.0%	27.00	1993.0	11.0
Overall	-	-	-	43.0

Table 1: Articles' provenance for the main data set [27].

1. There is a steady increase to the number of publications since the 1980s and the introduction of computer tournaments [9] (a 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 (Figure 2). The fitted model can be used to forecast the behaviour of the field for the next 5 years (Figure 3). 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.

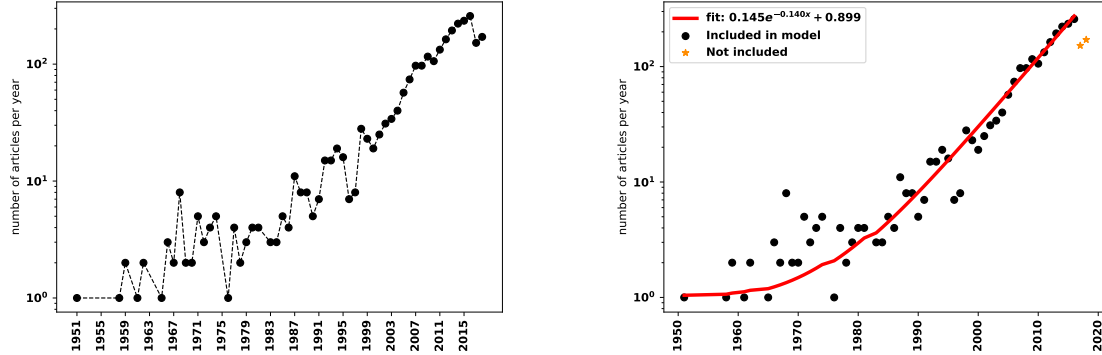


Figure 1: Line plot; number of articles published on the PD 1951-2019 (on a log scale). Figure 2: Scatter plot; number of articles published on the PD 1951-2019 (on a log scale).

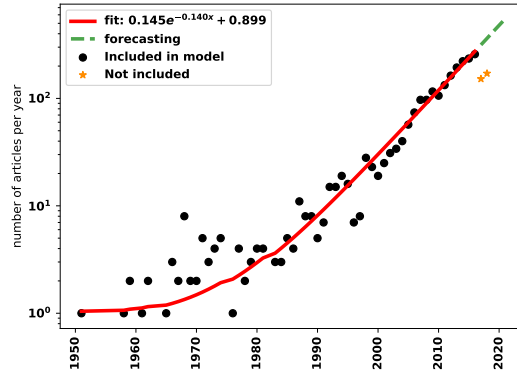


Figure 3: Forecast for 2017-2022 (on a log scale).

Is the PD a collaborative field?

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 quite standard compared to other fields such as cultural evolution [76], Astronomy and Astrophysics, Genetics and Heredity, Nuclear and Particle Physics as reported by [45]. This indicates the PD a collaborative field, but perhaps not more collaborative than other fields are.

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 [40]. From Figure 4 the trend of CI over the years is given. There are some peaks in the early years 1969 and 1980, however, a steady increase appears to happen after 2004. This could be an effect of better communication tools being introduced around that time which enabled more collaborations between researchers. The collaborative behaviour will be explored again in the following section using the co-authorship network.

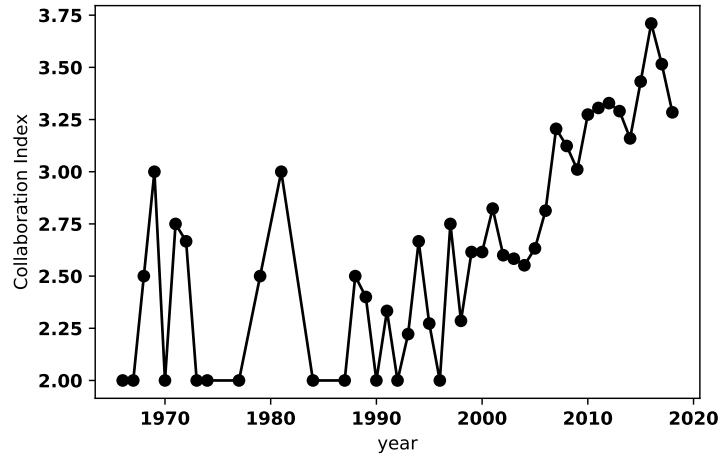


Figure 4: Collaboration index over time.

The authors in [27] 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. The distribution of the number of papers per author is given by Figure 5, and it can be seen that Matjaz Perc is an outlier. More specifically, most authors have 1 to 6 publications in the data set.

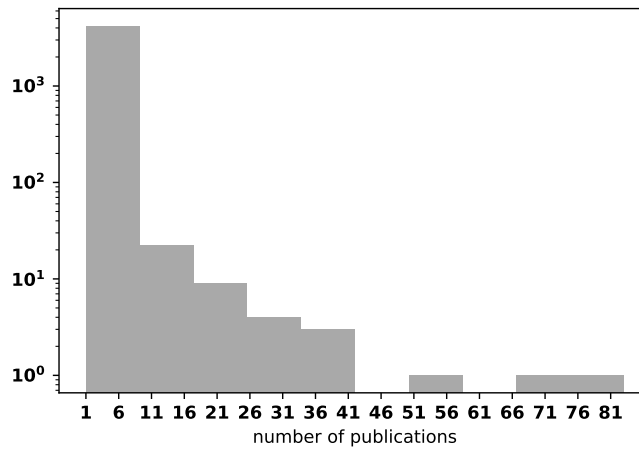


Figure 5: Distribution of number of papers per author (on a log scale).

What are the topics of the PD?

In order to identify the topics which are being discussed in the field of the PD, a LDA algorithm implemented in [58] is applied to the abstract's of the data set. As mentioned before, the number of topics needs to be specified before running the algorithm. To chose the appropriate number of topics the coherence value is used. Figure 6 gives the coherence values over 18 different models, and it can be seen than the most appropriate number of topics is 6 with a coherence value of 0.418.

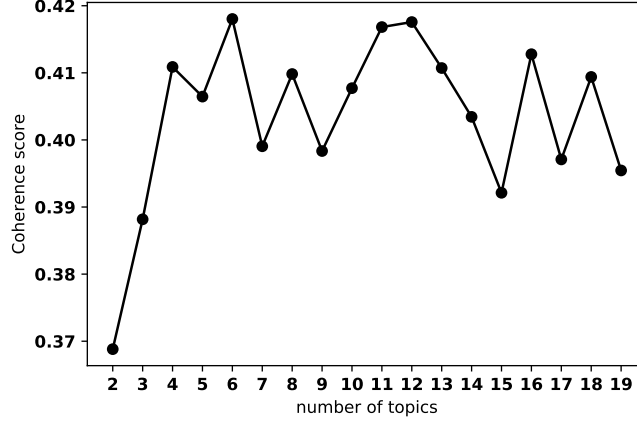


Figure 6: Coherence for LDA models over the number of topics.

A visualisation of the LDA model with 6 number of topics is given in Figure 7, this has been generated using [64] an open source designed for visualising LDA models. Each bubble of Figure 7 represents a topic. The bubbles are labelled 1 to 6 and the size of a bubble corresponds to the prevalence of the topic. From the visualisation it can be seen that two topics overlap (the keywords of these topics overlap). Even though several number of topics with higher values of coherence exist (apart from 6), a number of 5 topics is chosen to carry out the analysis of this work. That is because 5 minimises the number of overlapping topics. Five has a coherence value 0.406 which is close to 0.418.

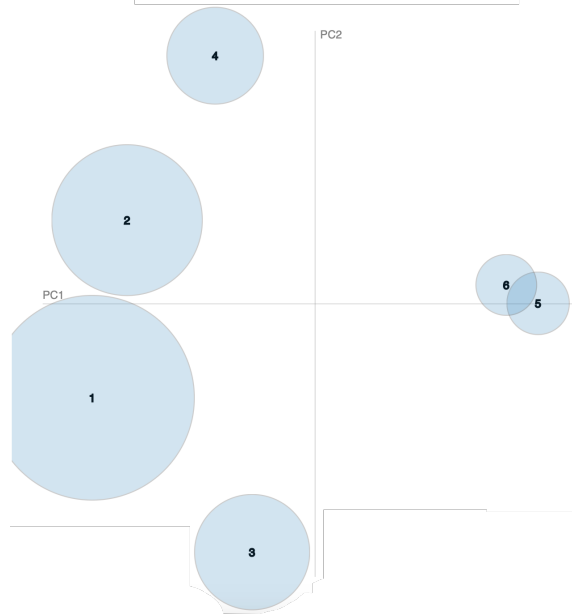


Figure 7: Visualisation of LDA model with 6 number of topics.

Based on 5 number of topics the articles have been clustered and assigned to the topic with the highest percentage contribution. The keywords associated with a topic, the most representative article of the given 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 simulated 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 [12] 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, 65], to the study of tumours [4, 62] and viruses [70]. Other works include how phenotype affinity can affect the emergence of cooperation [75] 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 [67], the search of optimality in strategies [10] and the training of strategies [38] with different representation methods. Moreover, publications which studied the evolutionary stability of strategies [2] and introduced methods of differentiating between them [5] are also assigned to the topic.
- 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, [72] which studied the effect of a strategy’s neighbourhood on the emergence of cooperation and [18] which explored the fixation probabilities of any two strategies in spatial structures.
- The publication assigned to Topic E are on **modeling problems as a PD game**. The problems formulated as a PD include decision making in operational research [54], information sharing among members in a virtual team [24], the measurement of influence in articles based on citations [34] and the price spikes in electric power markets [31].

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	[26]	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 <i>Pseudomonas syringae</i> pathovar phaseolicola	[65]	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	[65]	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	[17]	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 is.

The five topics in the PD publications 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 worth to start investigating?

Figure 8 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 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, any of the topics is worth to start investigating.

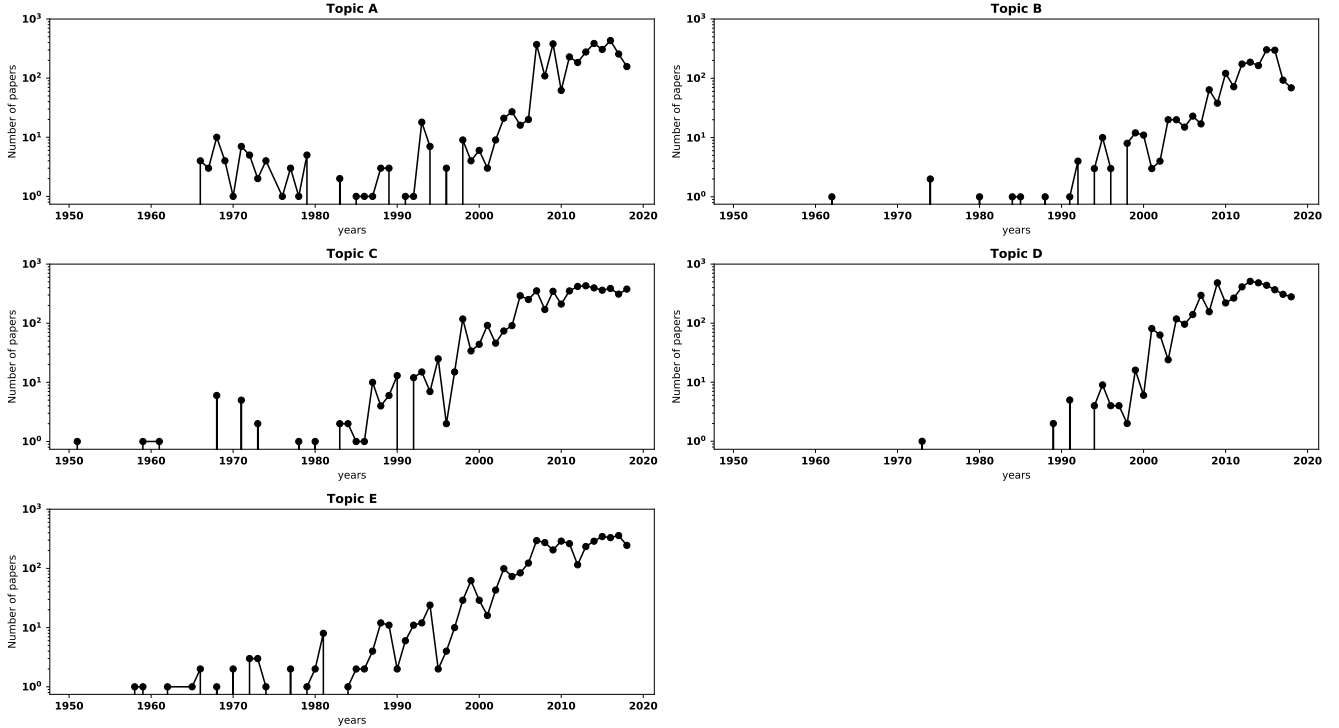


Figure 8: Number of articles per topic over the years (on a logged scale).

How do the topics of the PD change over time?

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. As a result, the period 1951-2018 has been assigned 6 number of topics 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 by Table 3.

But how do the five topics discussed earlier changed over time? The LDA models with a number of 5, 6 and optimal number of topics per period are used to calculate the contribution percentages for each document in the data of a given period. The highest contribution percentage is chosen for each document and the median of the highest contribution percentages for each model are given by Figure 9.

The model with 5 number of topics has always had a better median contribution than the model with 6 number of topics. Compared to the optimal models (Table 3) for periods 1951-1973 to 1951-1995 has a higher median. For periods 1951-2003 to 1951-2010 has a lower median, and both models contribute that same at the period 1951-1965. Overall the 5 topics appear to have fitted the publications over time well. The median highest contribution has been increasing over time. This result suggests that the topics have always been relevant in the PD publications.

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.

Period	Topic	Topic Keywords	Num of Documents	Percentage of Documents
1951-1965	0	problem, technology, divert, euler, subsystem, requirement, trace, technique, system, untried	3	0.375
1951-1965	1	interpret, requirement, programme, evolution, article, increase, policy, system, trace, technology	2	0.25
1951-1965	2	equipment, agency, conjecture, development, untried, programme, trend, technology, weapon, technique	1	0.125
1951-1965	3	variation, celebrated, trend, untried, change, involve, month, technique, subsystem, research	1	0.125
1951-1965	4	give, good, modern, trace, technique, ambiguity, problem, trend, technology, system	1	0.125
1951-1973	0	study, shock, cooperative, money, part, vary, investigate, good, receive, equipment	12	0.3243
1951-1973	1	cooperation, level, significantly, sequence, reward, provoke, descriptive, principal, display, argue	4	0.1081
1951-1973	2	player, make, effect, triad, experimental, motivation, dominate, hypothesis, instruction, trend	3	0.0811
1951-1973	3	ss, sex, male, female, dyad, design, suggest, college, factor, tend	3	0.0811
1951-1973	4	result, research, format, change, operational, analysis, relate, understanding, decision, money	2	0.0541
1951-1973	5	condition, give, high, treatment, conflict, cc, real, original, replication, promote	2	0.0541
1951-1973	6	group, competitive, show, interpret, scale, compete, escalation, free, variable, individualistic	2	0.0541
1951-1973	7	outcome, strategy, choice, type, pdg, difference, dummy, conclude, compare, consistent	2	0.0541
1951-1973	8	game, difference, pair, approach, behavior, person, weapon, occur, advantaged, differential	2	0.0541
1951-1973	9	response, present, dilemma, influence, cooperate, bias, point, amount, participate, factor	2	0.0541
1951-1973	10	trial, problem, previous, involve, prisoner, experiment, follow, tit, increase, initial	1	0.027
1951-1973	11	matrix, behavior, rational, black, model, research, broad, distance, complex, trace	1	0.027
1951-1973	12	play, finding, individual, noncooperative, white, nature, race, ratio, represent, prisoner	1	0.027
1951-1980	0	play, trial, group, follow, white, interpret, scale, black, trend, small	14	0.25
1951-1980	1	outcome, level, effect, type, dyad, vary, pdg, participate, understanding, arise	9	0.1607
1951-1980	2	game, strategy, cooperation, significant, difference, sentence, text, occur, differential, hypothesis	4	0.0714
1951-1980	3	male, female, find, result, sex, subject, experimental, situation, treatment, computer	4	0.0714
1951-1980	4	research, problem, influence, matrix, format, model, analysis, year, crime, equipment	4	0.0714
1951-1980	5	condition, dilemma, bias, free, attempt, book, year, dummy, prison, design	4	0.0714
1951-1980	6	variable, result, factor, individual, ability, triad, half, migration, change, investigate	3	0.0536
1951-1980	7	show, present, suggest, rational, compete, approach, characteristic, examine, person, conduct	3	0.0536
1951-1980	8	behavior, high, finding, relate, obtain, assistance, ratio, good, weapon, competition	3	0.0536
1951-1980	9	ss, shock, money, competitive, part, difference, pair, amount, man, information	3	0.0536
1951-1980	10	player, conflict, theory, decision, determine, produce, maker, cooperate, specialist, programming	2	0.0357
1951-1980	11	study, prisoner, make, response, experiment, noncooperative, standard, separate, conclude, initial	2	0.0357
1951-1980	12	give, cooperative, choice, cognitive, real, operational, set, subject, ascribe, concern	1	0.0179
1951-1988	0	trial, difference, find, choice, significant, competitive, effect, triad, interact, occur	24	0.2553
1951-1988	1	ss, shock, money, pair, response, part, high, tit, receive, amount	13	0.1383
1951-1988	2	suggest, paper, case, debate, view, achieve, framework, natural, assumption, finitely	10	0.1064
1951-1988	3	prisoner, dilemma, behavior, model, present, involve, person, increase, trust, experiment	8	0.0851
1951-1988	4	game, player, show, approach, repeat, previous, move, tat, related, include	8	0.0851
1951-1988	5	cooperation, level, mutual, equilibrium, standard, provide, information, human, real, question	6	0.0638
1951-1988	6	play, result, male, subject, female, cooperative, sex, experimental, treatment, computer	5	0.0532
1951-1988	7	research, study, variable, ability, factor, conflict, matrix, year, student, interpret	4	0.0426
1951-1988	8	problem, group, small, scale, social, issue, large, base, bias, party	4	0.0426
1951-1988	9	game, strategy, outcome, type, cooperate, ethical, pdg, explain, dependent, separate	4	0.0426
1951-1988	10	give, condition, individual, major, dyad, behaviour, produce, conflict, assistance, collectively	3	0.0319
1951-1988	11	situation, iterate, statement, rational, card, side, paradox, true, consequence, front	2	0.0213
1951-1988	12	inflation, hypothesis, rate, run, change, demand, nominal, cost, output, growth	2	0.0213
1951-1988	13	theory, make, analysis, decision, system, examine, work, soft, lead, hard	1	0.0106
1951-1995	0	strategy, population, evolution, iterate, tit, opponent, evolve, dynamic, set, tat	31	0.1732
1951-1995	1	game, repeat, assumption, rule, person, equilibrium, general, finitely, indefinitely, analyze	24	0.1341
1951-1995	2	inflation, long, rate, hypothesis, run, policy, cost, nominal, demand, programming	20	0.1117
1951-1995	3	condition, outcome, trial, find, difference, cooperation, experiment, level, significant, response	15	0.0838
1951-1995	4	rational, result, receive, statement, money, paradox, shock, iterate, consequence, common	14	0.0782
1951-1995	5	cooperation, show, competitive, high, probability, conflict, simulation, altruism, yield, natural	14	0.0782
1951-1995	6	prisoner, dilemma, give, point, defect, form, cooperator, increase, relate, ethical	10	0.0559
1951-1995	7	player, give, decision, provide, cooperative, game, previous, pair, determine, interact	9	0.0503
1951-1995	8	play, cooperate, result, male, subject, female, time, relationship, suggest, student	8	0.0447
1951-1995	9	problem, group, theory, good, approach, society, large, scale, issue, level	8	0.0447
1951-1995	10	study, situation, behaviour, computer, argue, change, implication, characteristic, real, associate	8	0.0447
1951-1995	11	model, paper, behavior, examine, present, mutual, expectation, develop, type, variable	7	0.0391
1951-1995	12	make, research, system, analysis, choice, work, base, relation, world, wide	6	0.0335
1951-1995	13	individual, social, behavior, standard, choose, evolutionary, partner, payoff, defection, small	5	0.0279
1951-2003	0	game, player, dilemma, prisoner, theory, give, paper, make, group, problem	151	0.4266
1951-2003	1	cooperation, result, play, show, cooperate, condition, cooperative, high, level, time	106	0.2994
1951-2003	2	strategy, model, agent, study, behavior, individual, population, evolutionary, state, player	97	0.274
1951-2010	0	model, theory, paper, base, make, present, problem, provide, human, decision	325	0.3454
1951-2010	1	game, strategy, player, agent, play, dilemma, system, behavior, show, state	322	0.3422
1951-2010	2	cooperation, network, study, population, individual, evolutionary, social, evolution, interaction, structure	294	0.3124
1951-2018	0	model, theory, system, base, paper, problem, propose, present, approach, provide	556	0.2251
1951-2018	1	behavior, social, human, decision, study, experiment, make, suggest, result, behaviour	482	0.1951
1951-2018	2	individual, group, good, social, punishment, level, cost, mechanism, dilemma, cooperative	428	0.1733
1951-2018	3	game, strategy, player, agent, play, dilemma, state, prisoner, payoff, equilibrium	380	0.1538
1951-2018	4	population, evolutionary, dynamic, model, selection, result, evolution, evolve, show, process	351	0.1421
1951-2018	5	cooperation, network, interaction, structure, study, evolution, find, behavior, cooperative, simulation	273	0.1105

Table 3: Topic modeling result for the cumulative data set over the periods

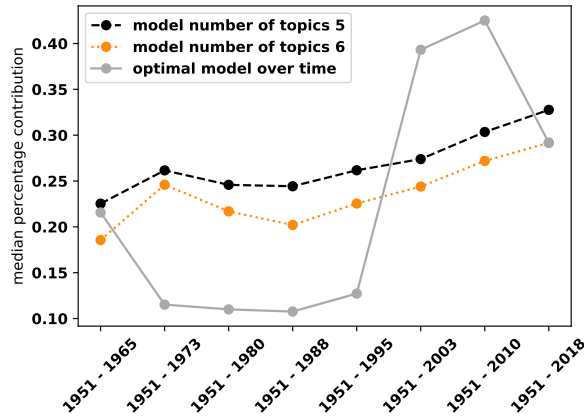


Figure 9: Medians of maximum percentage contributions over the time periods.

4 Analysis of co-authorship network

In this section the collaborative behaviour of authors in the field of the IPD is assessed using the co-authorship network, which as mentioned in Section 2 is denoted as G . There are a total of 947 connected components in G and the largest component has a size of 796 nodes. The largest connected component is going to be referred to as the main cluster of the network and is denoted as \bar{G} . A graphical representation of both networks is shown in Figure 10 and a metrics summary is given by Table 4.

Is the PD a collaborative field based on the co-authorship network?

Based on Table 4 an author in G has on average 4 collaborators and a 70% probability of collaborating with a collaborator's co-author. An author of \bar{G} on average is 7% more likely to write with a collaborator's co-author and on average has 2 more collaborators. Moreover, there are only 3.2 % of authors in the PD that has not connections to any other author. However, both networks have a high modularity and a large number of communities. 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 results confirm the results of Section 3, that the PD is indeed a collaborative field but perhaps it is not no more collaborative than other fields because there is not effort from the authors to write with people outside their community.

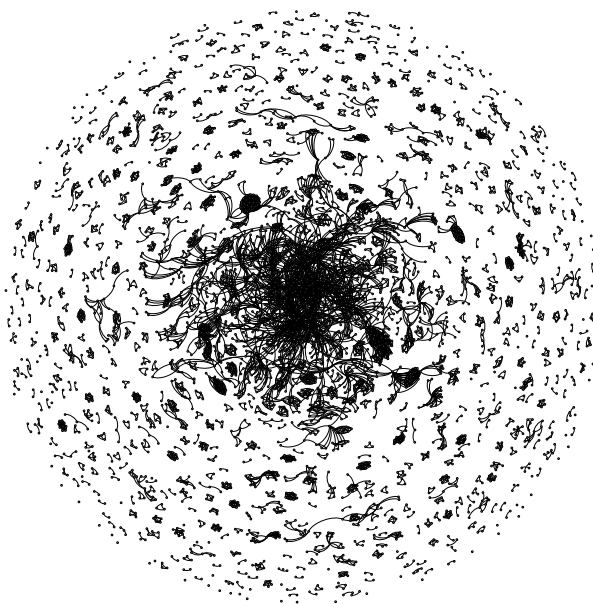
	# Nodes	# Edges	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
G	4011	7642	3.2	947	796	3.811	967	0.96491	0.701
\bar{G}	796	2214	0.0	1	796	5.563	25	0.84406	0.773

Table 4: Network metrics for G and \bar{G} respectively.

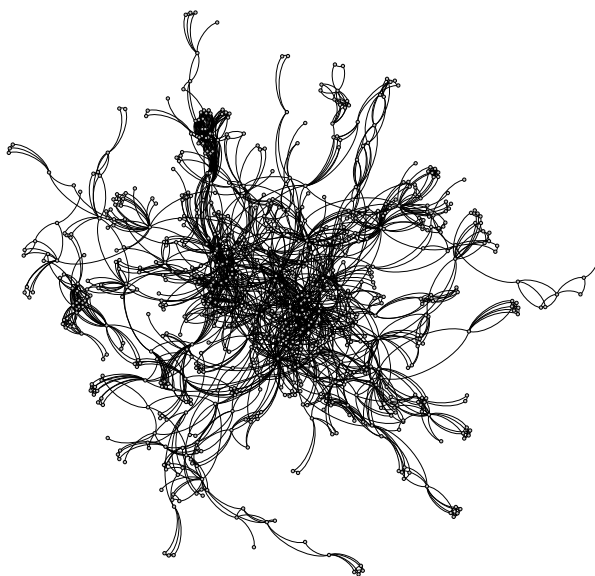
The evolution of the networks was also explored over time by constructing the network cumulatively over 51 periods. Except from the first period 1951-1966 the rest of the periods have a yearly interval (data for the years 1975 and 1982 were not collected by the collection data process). The metrics of each sub network are given in the Appendix A. The results, similarly to the results of [44], confirm that the networks grow over time and that the networks always had a high modularity. Thus, the trend of authors writing with people from their communities was not an effect of a specific period.

Are some topics more collaborative than other?

The networks corresponding to the topics of Section 3 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) G the co-authorship network for the IPD.



(b) \bar{G} the largest connected component of G .

Figure 10: A graphical representation of G and \bar{G}

A metrics’ summary for all five topic networks is given by Table 5.

Topic B is the smallest network with the highest average degree, followed by Topic A which has the second highest degree and is the largest network of all five. In both B and A the number of isolated nodes is very small (< 0.2). In comparison, in topics C and E authors are more likely to have no collaborators. Thus, in topics such as “human subject research” and “biological studies” author tend to be more collaborative than topics such as strategies (average degree 2.5) and authors in A and B are less likely to have written single author publications compared to modeling problems as a PD topic. Topic D is the topic associated with evolutionary dynamics on networks and in fact the network of D is a sub graph of \bar{G} . In the main cluster it was shown that the authors have on average 2 more collaborations and a higher likelihood of collaborating with a collaborator’s co-author and as it will be demonstrated in the following section gain more from the influence of the network.

	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
Topic A	1124	2137	15	1.3	264	56	3.802	265	0.983	0.759
Topic B	695	1382	13	1.9	157	80	3.977	158	0.950	0.773
Topic C	900	1141	41	4.6	281	29	2.536	281	0.981	0.636
Topic D	880	1509	17	1.9	174	312	3.430	183	0.918	0.701
Topic E	1045	1964	59	5.6	354	31	3.759	354	0.926	0.664

Table 5: Network metrics for topic networks.

Are there authors in a more favourable position on the network? and how does this corresponds to the networks

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 others, and consequently affect them; influence them. Thus closeness centrality here 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 have values ranging from 0 to 1. The influence and the amount of information an author has access to will be explored to assess whether there are authors that benefit from the position.

For G and \bar{G} the most central authors based on closeness and betweenness centralities are given by Table 6. The most central authors in \bar{G} are the same people as in G . This implies that the results on centrality heavily rely of the main cluster. Matjaz Perc is an author with 58 publications in the data set and the most central authors in G . 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 are authors that have access to information due to their positioning but do not influence the network as much and the opposite is true for the authors Attila Szolnoki, Luo-Luo Jiang Sandro Meloni, Cheng-Yi Xia and Xiaojie Chen.

The distributions of both centrality measures for both networks are given in the Appendix B.2.

From the distributions for G it is obvious that the values of centralities are overall low, and thus in the PD an author does not gain as much information or influence the field. This is not true for the authors in G . The centrality values are larger.

5 Conclusion

This manuscript has explored the number of publications, the authors’ collaborative behaviour and their influence in the research topic of the Iterated Prisoner’s Dilemma. This was achieved by applying network theoretic approaches and a bibliometric analysis in a data containing more than 2000 publications. The data set was automatically collected from five different sources using a bespoke piece of software written for this purpose [28].

G					\bar{G}			
	Name	Betweenness	Name	Closeness	Name	Betweenness	Name	Closeness
1	Matjaz Perc	0.015	Matjaz Perc	0.066	Matjaz Perc	0.373	Matjaz Perc	0.330
2	Zhen Wang	0.011	Long Wang	0.060	Zhen Wang	0.279	Long Wang	0.301
3	Long Wang	0.007	Yamir Moreno	0.059	Long Wang	0.170	Yamir Moreno	0.299
4	Martin Nowak	0.006	Attila Szolnoki	0.059	Martin Nowak	0.159	Attila Szolnoki	0.297
5	Angel Sanchez	0.004	Zhen Wang	0.059	Angel Sanchez	0.114	Zhen Wang	0.296
6	Yamir Moreno	0.004	Arne Traulsen	0.056	Yamir Moreno	0.110	Arne Traulsen	0.281
7	Arne Traulsen	0.004	Luo-Luo Jiang	0.055	Arne Traulsen	0.107	Luo-Luo Jiang	0.280
8	Franz Weissing	0.004	Sandro Meloni	0.055	Franz Weissing	0.101	Sandro Meloni	0.278
9	Jianye Hao	0.004	Cheng-Yi Xia	0.055	Jianye Hao	0.094	Cheng-Yi Xia	0.276
10	Valerio Capraro	0.004	Xiaojie Chen	0.055	Valerio Capraro	0.093	Xiaojie Chen	0.276

Table 6: 10 most central authors based on betweenness and closeness centralities for G and \bar{G} .

Topic A		Topic B		Topic C		Topic D		Topic E		
	Name	Betweenness	Name	Betweenness	Name	Betweenness	Name	Betweenness	Name	Betweenness
1	David Rand	0.002	Long Wang	0.006	Daniel Ashlock	0.001	Matjaz Perc	0.064	Zengru Di	0.0
2	Valerio Capraro	0.001	Luo-Luo Jiang	0.005	Matjaz Perc	0.000	Luo-Luo Jiang	0.037	Jian Yang	0.0
3	Angel Sanchez	0.001	Martin Nowak	0.004	Karl Tuyls	0.000	Yamir Moreno	0.031	Yevgeniy Vorobeychik	0.0
4	Feng Fu	0.001	Matjaz Perc	0.003	Philip Hingston	0.000	Christoph Hauert	0.027	Otavio Teixeira	0.0
5	Martin Nowak	0.000	Attila Szolnoki	0.003	Eun-Youn Kim	0.000	Long Wang	0.024	Roberto Oliveira	0.0
6	Nicholas Christakis	0.000	Christian Hilbe	0.002	Wendy Ashlock	0.000	Zhen Wang	0.024	M. Nowak	0.0
7	Pablo Branas-Garza	0.000	Yamir Moreno	0.002	Attila Szolnoki	0.000	Han-Xin Yang	0.023	M. Harper	0.0
8	Toshio Yamagishi	0.000	Xiaojie Chen	0.002	Seung Baek	0.000	Martin Nowak	0.020	Xiao Han	0.0
9	James Fowler	0.000	Arne Traulsen	0.002	Martin Nowak	0.000	Angel Sanchez	0.017	Zhesi Shen	0.0
10	Long Wang	0.000	Zhen Wang	0.002	Thore Graepel	0.000	Zhihai Rong	0.016	Wen-Xu Wang	0.0

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

Topic A			Topic B		Topic C		Topic D		Topic E	
Name	Closeness		Name	Closeness	Name	Closeness	Name	Closeness	Name	Closeness
1	David Rand	0.027	Long Wang	0.043	Karl Tuyls	0.022	Matjaz Perc	0.123	Stefanie Widder	0.029
2	Valerio Capraro	0.023	Matjaz Perc	0.041	Thore Graepel	0.019	Zhen Wang	0.109	Rosalind Allen	0.029
3	Jillian Jordan	0.022	Attila Szolnoki	0.040	Joel Leibo	0.018	Long Wang	0.107	Thomas Pfeiffer	0.029
4	Nicholas Christakis	0.021	Martin Nowak	0.040	Edward Hughes	0.017	Yamir Moreno	0.105	Thomas Curtis	0.029
5	James Fowler	0.020	Olivier Tenaillon	0.038	Matthew Phillips	0.017	Luo-Luo Jiang	0.104	Carsten Wiuf	0.029
6	Martin Nowak	0.020	Xiaojie Chen	0.038	Edgar Duenez-Guzman	0.017	Attila Szolnoki	0.103	William Sloan	0.029
7	Angel Sanchez	0.019	Bin Wu	0.038	Antonio Castaneda	0.017	Gyorgy Szabo	0.102	Otto Cordero	0.029
8	Gordon Kraft-Todd	0.019	Yanling Zhang	0.037	Iain Dunning	0.017	Xiaojie Chen	0.102	Sam Brown	0.029
9	Akihiro Nishi	0.019	Feng Fu	0.037	Tina Zhu	0.017	Guangming Xie	0.101	Babak Momeni	0.029
10	Anthony Evans	0.019	David Rand	0.037	Kevin Mckee	0.017	Lucas Wardil	0.101	Wenying Shou	0.029

Table 8: 10 most central authors based on closeness centrality for topics' networks.

The data collection and an introduction to the methodology used in this work were covered in Section 2. The data set contains a total of 2422 articles, it has been archived and is available in [27] for further analysis. Section 3 covered an initial analysis of the data set, and applied a topic modeling algorithm which classified the articles into topics. The initial analysis demonstrated that the field of the Prisoner’s Dilemma remains a prominent field with several papers being published in journals. The topic modeling analysis identified five different topics which appeared to be human subject research, biological studies, strategies and agent based simulations, evolutionary dynamics on networks and modeling problems as a PD. A temporal topic modeling analysis showed that over time not only the number of topics changed, but also the scientific language and the most important topics authors were publishing on.

Following Section 3, the collaborative behaviour of the field was explored in Section 4. It was concluded that the field of the Iterated Prisoner’s Dilemma 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. The results on collaborativeness were verified when studying the co-authorship network for each of the five topics defined in Section 3 as well. Exploring the influence of authors and their gain from being in the network of the field demonstrated that authors do not gain much, and the authors with influence are the ones connected to the main cluster, to a ”main” group of authors.

The study of the Prisoner’s Dilemma 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.

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A variety of software have been used in this work:

- The Matplotlib library for visualisation [33].
- The Numpy library for data manipulation [71].
- The Networkx [32] package for analysing networks.
- Gephi [11] open source package for visualising networks.
- The Gensim library for the topic modeling [58].
- The louvain library for calculating the networks modularity <https://github.com/taynaud/python-louvain>.

References

- [1] PLOS public library of science. <https://www.plos.org/>.
- [2] Christoph Adami and Arend Hintze. Evolutionary instability of zero-determinant strategies demonstrates that winning is not everything. *Nature communications*, 4:2193, 2013.
- [3] Ankur Agarwal and Bill Triggs. Multilevel image coding with hyperfeatures. *International Journal of Computer Vision*, 78(1):15–27, 2008.
- [4] Marco Archetti. Evolutionary game theory of growth factor production: implications for tumour heterogeneity and resistance to therapies. *British journal of cancer*, 109(4):1056, 2013.
- [5] Daniel Ashlock and Eun-Youn Kim. Fingerprinting: Visualization and automatic analysis of prisoner’s dilemma strategies. *IEEE Transactions on Evolutionary Computation*, 12(5):647–659, 2008.
- [6] Robert Axelrod. Effective choice in the prisoner’s dilemma. *Journal of conflict resolution*, 24(1):3–25, 1980.

- [7] Robert Axelrod. More effective choice in the prisoner’s dilemma. *Journal of Conflict Resolution*, 24(3):379–403, 1980.
- [8] Robert Axelrod et al. The evolution of strategies in the iterated prisoner’s dilemma. *The dynamics of norms*, pages 1–16, 1987.
- [9] Robert Axelrod and William D Hamilton. The evolution of cooperation. *science*, 211(4489):1390–1396, 1981.
- [10] Dipyaman Banerjee and Sandip Sen. Reaching pareto-optimality in prisoner’s dilemma using conditional joint action learning. *Autonomous Agents and Multi-Agent Systems*, 15(1):91–108, 2007.
- [11] M. Bastian, S. Heymann, and M. Jacomy. Gephi: An open source software for exploring and manipulating networks, 2009.
- [12] Raoul Bell, Laura Mieth, and Axel Buchner. Separating conditional and unconditional cooperation in a sequential prisoner’s dilemma game. *PloS one*, 12(11):e0187952, 2017.
- [13] TILL Bergmann and RICK Dale. A scientometric analysis of evolang: Intersections and authorships. In *The evolution of language: Proceedings of the 11th international conference (EVOLANGX11)*. <http://evolang.org/neworleans/papers/182.html>. Retrieved, volume 22, 2018.
- [14] David M Blei, John D Lafferty, et al. A correlated topic model of science. *The Annals of Applied Statistics*, 1(1):17–35, 2007.
- [15] David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. *Journal of machine Learning research*, 3(Jan):993–1022, 2003.
- [16] V. D. Blondel, J.L. Guillaume, R. Lambiotte, and E. Lefebvre. Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008(10):P10008, 2008.
- [17] Xiaojie Chen, Feng Fu, and Long Wang. Influence of initial distributions on robust cooperation in evolutionary prisoner’s dilemma. *arXiv preprint physics/0701318*, 2007.
- [18] Yu-Ting Chen, Alex McAvoy, and Martin A Nowak. Fixation probabilities for any configuration of two strategies on regular graphs. *Scientific reports*, 6:39181, 2016.
- [19] A. Clauset, M. E.J. Newman, and C. Moore. Finding community structure in very large networks. *Physical review E*, 70(6):066111, 2004.
- [20] Luis Pedro Coelho, Tao Peng, and Robert F Murphy. Quantifying the distribution of probes between subcellular locations using unsupervised pattern unmixing. *Bioinformatics*, 26(12):i7–i12, 2010.
- [21] R. das Neves Machado, B. Vargas-Quesada, and J. Leta. Intellectual structure in stem cell research: exploring brazilian scientific articles from 2001 to 2010. *Scientometrics*, 106(2):525–537, 2016.
- [22] D. Easley, J. Kleinberg, et al. *Networks, crowds, and markets*, volume 8. Cambridge university press Cambridge, 2010.
- [23] H. Etzkowitz. Individual investigators and their research groups. *Minerva*, 30(1):28–50, 1992.
- [24] Xiuzhen Feng and Yijian Liu. Trilateral game analysis on information sharing among members in a virtual team. In *2008 IEEE Symposium on Advanced Management of Information for Globalized Enterprises (AMIGE)*, pages 1–5. IEEE, 2008.
- [25] M. M. Flood. Some experimental games. *Management Science*, 5(1):5–26, 1958.
- [26] Shawn N Geniole, Amanda E Keyes, Catherine J Mondloch, Justin M Carré, and Cheryl M McCormick. Facing aggression: Cues differ for female versus male faces. *PLOS one*, 7(1):e30366, 2012.
- [27] N. E. Glynatsi. Articles’ meta data on the prisoner’s dilemma. <https://doi.org/10.5281/zenodo.3406536>, September 2019.

- [28] N. E. Glynnatsi and V. Knight. Nikoleta-v3/arcas: Arcas v 0.0.4, December 2017.
- [29] Justin Grimmer and Brandon M Stewart. Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political analysis*, 21(3):267–297, 2013.
- [30] Nature Publishing Group. Nature. <https://www.nature.com/>, 1869.
- [31] Xiaohong Guan. Gaming and price spikes in electric power markets and possible remedies. In *Proceedings. International Conference on Power System Technology*, volume 1, pages 188–vol. IEEE, 2002.
- [32] A. A. Hagberg, D. A. Schult, and P. J. Swart. Exploring network structure, dynamics, and function using NetworkX. In *Proceedings of the 7th Python in Science Conference (SciPy2008)*, pages 11–15, Pasadena, CA USA, August 2008.
- [33] J. D. Hunter. Matplotlib: A 2D graphics environment. *Computing In Science & Engineering*, 9(3):90–95, 2007.
- [34] B Ian Hutchins, Xin Yuan, James M Anderson, and George M Santangelo. Relative citation ratio (rcr): A new metric that uses citation rates to measure influence at the article level. *PLoS biology*, 14(9):e1002541, 2016.
- [35] Genki Ichinose, Yuto Tenguishi, and Toshihiro Tanizawa. Robustness of cooperation on scale-free networks under continuous topological change. *Physical Review E*, 88(5):052808, 2013.
- [36] IEEE. Ieee xplora digital library. <http://ieeexplore.ieee.org/Xplore/home.jsp>.
- [37] Matthew Inglis and Colin Foster. Five decades of mathematics education research. *Journal for Research in Mathematics Education*, 49(4):462–500, 2018.
- [38] Hisao Ishibuchi, Hiroyuki Ohyanagi, and Yusuke Nojima. Evolution of strategies with different representation schemes in a spatial iterated prisoner’s dilemma game. *IEEE Transactions on Computational Intelligence and AI in Games*, 3(1):67–82, 2011.
- [39] E. Jones, T. Oliphant, P. Peterson, et al. SciPy: Open source scientific tools for Python, 2001–. [Online; accessed jtoday].
- [40] S. Kyvik and I. Reymert. Research collaboration in groups and networks: differences across academic fields. *Scientometrics*, 113(2):951–967, 2017.
- [41] A. Landherr, B. Friedl, and J. Heidemann. A critical review of centrality measures in social networks. *Business & Information Systems Engineering*, 2(6):371–385, Dec 2010.
- [42] Jing Li, Liqi Zhu, and Michaela Gummerum. The relationship between moral judgment and cooperation in children with high-functioning autism. *Scientific Reports*, 4:4314, 2014.
- [43] Weihua Li, Tomaso Aste, Fabio Caccioli, and Giacomo Livan. Early coauthorship with top scientists predicts success in academic careers. *Nature Communications*, 10(1):2041–1723, 2019.
- [44] P. Liu and H. Xia. Structure and evolution of co-authorship network in an interdisciplinary research field. *Scientometrics*, 103(1):101–134, Apr 2015.
- [45] Smriti Mallapaty. Paper authorship goes hyper. <https://www.natureindex.com/news-blog/paper-authorship-goes-hyper>, 2018.
- [46] Yoshie Matsumoto, Toshio Yamagishi, Yang Li, and Toko Kiyonari. Prosocial behavior increases with age across five economic games. *PloS one*, 11(7):e0158671, 2016.
- [47] G. McKiernan. arxiv.org: the los alamos national laboratory e-print server. *International Journal on Grey Literature*, 1(3):127–138, 2000.
- [48] Mannheim Media. Springer publishing. <http://www.springer.com/>, 1950.

- [49] J Alberto Molina, J Ignacio Giménez-Nadal, José A Cuesta, Carlos Gracia-Lazaro, Yamir Moreno, and Angel Sanchez. Gender differences in cooperation: experimental evidence on high school students. *PloS one*, 8(12):e83700, 2013.
- [50] Juan Carlos Nibbles, Hongcheng Wang, and Li Fei-Fei. Unsupervised learning of human action categories using spatial-temporal words. *International journal of computer vision*, 79(3):299–318, 2008.
- [51] R. Van Noorden. The science that’s never been cited. <https://www.nature.com/articles/d41586-017-08404-0>, 2017.
- [52] N. Nurseitov, M. Paulson, R. Reynolds, and C. Izurieta. Comparison of json and xml data interchange formats: a case study. *Caine*, 2009:157–162, 2009.
- [53] Hisashi Ohtsuki, Christoph Hauert, Erez Lieberman, and Martin A Nowak. A simple rule for the evolution of cooperation on graphs and social networks. *Nature*, 441(7092):502, 2006.
- [54] Richard J Ormerod. Or as rational choice: A decision and game theory perspective. *Journal of the Operational Research Society*, 61(12):1761–1776, 2010.
- [55] Matjaž Perc and Attila Szolnoki. Social diversity and promotion of cooperation in the spatial prisoner’s dilemma game. *Physical Review E*, 77(1):011904, 2008.
- [56] A. Pritchard et al. Statistical bibliography or bibliometrics. *Journal of documentation*, 25(4):348–349, 1969.
- [57] D. Raina and B. M. Gupta. Four aspects of the institutionalization of physics research in india (1990–1950): Substantiating the claims of histortical sociology through bibliometrics. *Scientometrics*, 42(1):17–40, 1998.
- [58] Radim Řehůřek and Petr Sojka. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, pages 45–50, Valletta, Malta, May 2010. ELRA. <http://is.muni.cz/publication/884893/en>.
- [59] Rick L Riolo, Michael D Cohen, and Robert Axelrod. Evolution of cooperation without reciprocity. *Nature*, 414(6862):441, 2001.
- [60] Michael Röder, Andreas Both, and Alexander Hinneburg. Exploring the space of topic coherence measures. In *Proceedings of the eighth ACM international conference on Web search and data mining*, pages 399–408. ACM, 2015.
- [61] Lorenzo A Santorelli, Christopher RL Thompson, Elizabeth Villegas, Jessica Svetz, Christopher Dinh, Anup Parikh, Richard Sugang, Adam Kuspa, Joan E Strassmann, David C Queller, et al. Facultative cheater mutants reveal the genetic complexity of cooperation in social amoebae. *Nature*, 451(7182):1107, 2008.
- [62] Javad Salimi Sartakhti, Mohammad Hossein Manshaei, David Basanta, and Mehdi Sadeghi. Evolutionary emergence of angiogenesis in avascular tumors using a spatial public goods game. *PloS one*, 12(4):e0175063, 2017.
- [63] V. Sekara, P. Deville, S. E. Ahnert, A. Barabási, R. Sinatra, and S. Lehmann. The chaperone effect in scientific publishing. *Proceedings of the National Academy of Sciences*, 115(50):12603–12607, 2018.
- [64] Carson Sievert and Kenneth Shirley. Ldavis: A method for visualizing and interpreting topics. In *Proceedings of the workshop on interactive language learning, visualization, and interfaces*, pages 63–70, 2014.
- [65] Mark Sistrom, Derek Park, Heath E O’Brien, Zheng Wang, David S Guttman, Jeffrey P Townsend, and Paul E Turner. Genomic and gene-expression comparisons among phage-resistant type-iv pilus mutants of pseudomonas syringae pathovar phaseolicola. *PloS one*, 10(12):e0144514, 2015.
- [66] Alexander J Stewart and Joshua B Plotkin. Extortion and cooperation in the prisoner’s dilemma. *Proceedings of the National Academy of Sciences*, 109(26):10134–10135, 2012.
- [67] Alexander J Stewart and Joshua B Plotkin. From extortion to generosity, evolution in the iterated prisoner’s dilemma. *Proceedings of the National Academy of Sciences*, 110(38):15348–15353, 2013.

- [68] Cassidy R Sugimoto, Daifeng Li, Terrell G Russell, S Craig Finlay, and Ying Ding. The shifting sands of disciplinary development: Analyzing north american library and information science dissertations using latent dirichlet allocation. *Journal of the American Society for Information Science and Technology*, 62(1):185–204, 2011.
- [69] Paul E Turner and Lin Chao. Prisoner’s dilemma in an rna virus. *Nature*, 398(6726):441, 1999.
- [70] Paul E Turner and Lin Chao. Prisoner’s dilemma in an rna virus. *Nature*, 398(6726):441, 1999.
- [71] S. Walt, S. C. Colbert, and G. Varoquaux. The NumPy array: a structure for efficient numerical computation. *Computing in Science & Engineering*, 13(2):22–30, 2011.
- [72] Juan Wang, ChengYi Xia, YiLing Wang, Shuai Ding, and JunQing Sun. Spatial prisoner’s dilemma games with increasing size of the interaction neighborhood on regular lattices. *Chinese science bulletin*, 57(7):724–728, 2012.
- [73] Xiaogang Wang, Xiaoxu Ma, and W Eric L Grimson. Unsupervised activity perception in crowded and complicated scenes using hierarchical bayesian models. *IEEE Transactions on pattern analysis and machine intelligence*, 31(3):539–555, 2008.
- [74] Te Wu, Feng Fu, and Long Wang. Moving away from nasty encounters enhances cooperation in ecological prisoner’s dilemma game. *PLoS One*, 6(11):e27669, 2011.
- [75] Te Wu, Feng Fu, and Long Wang. Phenotype affinity mediated interactions can facilitate the evolution of cooperation. *Journal of theoretical biology*, 462:361–369, 2019.
- [76] M. Youngblood and D. Lahti. A bibliometric analysis of the interdisciplinary field of cultural evolution. *Palgrave Communications*, 4(1):120, 2018.

A Cumulative Networks Metrics

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

Period	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
1951 - 1966	6	3	0	0.0	3	2	1.000	3	0.667	0.000
1951 - 1967	8	4	0	0.0	4	2	1.000	4	0.750	0.000
1951 - 1968	19	15	0	0.0	8	5	1.579	8	0.684	0.228
1951 - 1969	20	17	0	0.0	8	6	1.700	8	0.630	0.250
1951 - 1970	22	18	0	0.0	9	6	1.636	9	0.667	0.227
1951 - 1971	33	28	0	0.0	13	6	1.697	13	0.827	0.424
1951 - 1972	39	34	0	0.0	15	6	1.744	15	0.867	0.513
1951 - 1973	42	35	1	2.4	17	6	1.667	17	0.873	0.476
1951 - 1974	42	35	1	2.4	17	6	1.667	17	0.873	0.476
1951 - 1976	42	35	1	2.4	17	6	1.667	17	0.873	0.476
1951 - 1977	44	36	1	2.3	18	6	1.636	18	0.880	0.455
1951 - 1978	44	36	1	2.3	18	6	1.636	18	0.880	0.455
1951 - 1979	47	40	1	2.1	18	6	1.702	18	0.884	0.454
1951 - 1980	47	40	1	2.1	18	6	1.702	18	0.884	0.454
1951 - 1981	50	46	1	2.0	18	6	1.840	18	0.889	0.497
1951 - 1983	51	46	2	3.9	19	6	1.804	19	0.889	0.487
1951 - 1984	53	47	2	3.8	20	6	1.774	20	0.894	0.469
1951 - 1985	53	47	2	3.8	20	6	1.774	20	0.894	0.469
1951 - 1986	53	47	2	3.8	20	6	1.774	20	0.894	0.469
1951 - 1987	56	48	3	5.4	22	6	1.714	22	0.898	0.443
1951 - 1988	62	52	4	6.5	25	6	1.677	25	0.909	0.449
1951 - 1989	75	62	5	6.7	31	6	1.653	31	0.926	0.424
1951 - 1990	79	64	5	6.3	33	6	1.620	33	0.930	0.403
1951 - 1991	87	69	6	6.9	37	6	1.586	37	0.937	0.400
1951 - 1992	95	72	10	10.5	42	6	1.516	42	0.941	0.367
1951 - 1993	106	81	12	11.3	47	6	1.528	47	0.947	0.366
1951 - 1994	124	95	16	12.9	56	6	1.532	56	0.955	0.394
1951 - 1995	135	102	17	12.6	61	6	1.511	61	0.960	0.384
1951 - 1996	142	105	18	12.7	65	6	1.479	65	0.962	0.365
1951 - 1997	155	115	20	12.9	71	6	1.484	71	0.966	0.392
1951 - 1998	191	140	21	11.0	87	6	1.466	87	0.973	0.367
1951 - 1999	221	169	25	11.3	99	6	1.529	99	0.977	0.397
1951 - 2000	250	195	27	10.8	110	6	1.560	110	0.979	0.418
1951 - 2001	287	235	30	10.5	125	7	1.638	125	0.977	0.419
1951 - 2002	335	278	36	10.7	146	7	1.660	146	0.979	0.428
1951 - 2003	381	310	40	10.5	168	7	1.627	168	0.982	0.413
1951 - 2004	437	370	40	9.2	185	10	1.693	185	0.983	0.424
1951 - 2005	532	476	41	7.7	214	19	1.789	214	0.985	0.458
1951 - 2006	640	603	43	6.7	246	22	1.884	246	0.987	0.486
1951 - 2007	793	877	46	5.8	283	25	2.212	283	0.985	0.532
1951 - 2008	948	1170	50	5.3	318	33	2.468	319	0.985	0.558
1951 - 2009	1108	1442	54	4.9	356	71	2.603	358	0.982	0.573
1951 - 2010	1300	1936	66	5.1	402	133	2.978	405	0.965	0.592
1951 - 2011	1560	2375	79	5.1	472	157	3.045	475	0.970	0.613
1951 - 2012	1837	2865	80	4.4	534	209	3.119	537	0.969	0.634
1951 - 2013	2149	3420	93	4.3	603	322	3.183	609	0.965	0.644
1951 - 2014	2481	3971	103	4.2	683	399	3.201	694	0.962	0.658
1951 - 2015	2938	4877	110	3.7	765	504	3.320	779	0.965	0.675
1951 - 2016	3469	6532	114	3.3	850	613	3.766	863	0.964	0.696
1951 - 2017	3735	7072	119	3.2	895	706	3.787	912	0.964	0.700
1951 - 2018	4011	7642	128	3.2	947	796	3.811	967	0.966	0.701

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

Periods	# Nodes	# Edges	# Isolated nodes	% Isolated nodes	# Connected components	Size of largest component	Av. degree	# Communities	Modularity	Clustering coeff
1951 - 1966	2	1	0	0.0	1	2	1.000	1	0.000	0.000
1951 - 1967	2	1	0	0.0	1	2	1.000	1	0.000	0.000
1951 - 1968	5	8	0	0.0	1	5	3.200	1	0.000	0.867
1951 - 1969	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1970	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1971	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1972	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1973	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1974	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1976	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1977	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1978	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1979	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1980	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1981	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1983	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1984	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1985	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1986	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1987	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1988	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1989	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1990	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1991	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1992	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1993	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1994	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1995	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1996	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1997	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1998	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 1999	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 2000	6	10	0	0.0	1	6	3.333	2	0.020	0.833
1951 - 2001	7	21	0	0.0	1	7	6.000	1	0.000	1.000
1951 - 2002	7	21	0	0.0	1	7	6.000	1	0.000	1.000
1951 - 2003	7	21	0	0.0	1	7	6.000	1	0.000	1.000
1951 - 2004	10	13	0	0.0	1	10	2.600	2	0.376	0.553
1951 - 2005	19	28	0	0.0	1	19	2.947	3	0.544	0.730
1951 - 2006	22	35	0	0.0	1	22	3.182	4	0.527	0.720
1951 - 2007	25	39	0	0.0	1	25	3.120	5	0.558	0.686
1951 - 2008	33	62	0	0.0	1	33	3.758	4	0.623	0.736
1951 - 2009	71	148	0	0.0	1	71	4.169	6	0.697	0.698
1951 - 2010	133	387	0	0.0	1	133	5.820	7	0.726	0.749
1951 - 2011	157	465	0	0.0	1	157	5.924	8	0.727	0.725
1951 - 2012	209	611	0	0.0	1	209	5.847	11	0.733	0.737
1951 - 2013	322	892	0	0.0	1	322	5.540	12	0.780	0.743
1951 - 2014	399	1109	0	0.0	1	399	5.559	15	0.794	0.742
1951 - 2015	504	1368	0	0.0	1	504	5.429	24	0.811	0.751
1951 - 2016	613	1677	0	0.0	1	613	5.471	21	0.819	0.761
1951 - 2017	706	1935	0	0.0	1	706	5.482	29	0.830	0.772
1951 - 2018	796	2214	0	0.0	1	796	5.563	25	0.845	0.773

B Centrality Measures Distributions

B.1 Distrubutions for G and \bar{G}

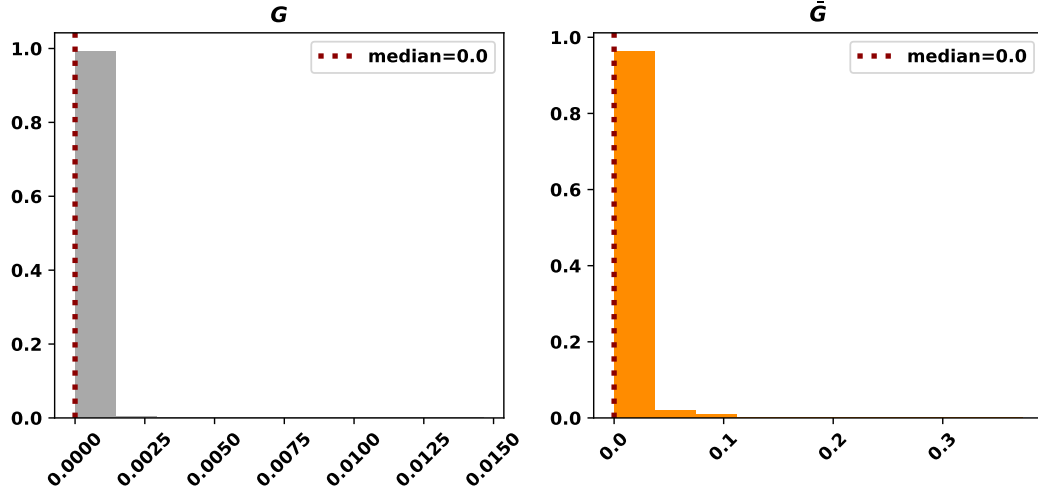


Figure 11: Distributions of betweenness centrality in G and \bar{G}

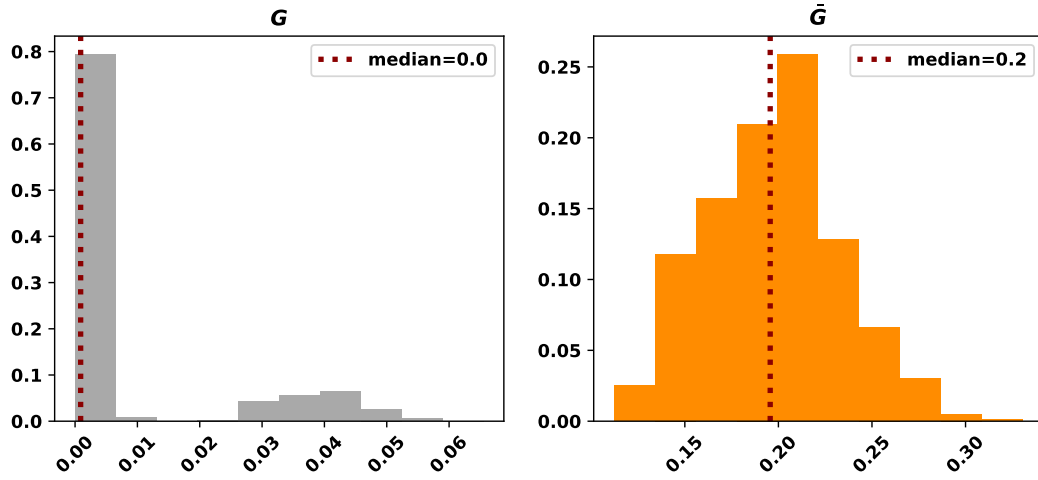


Figure 12: Distributions of closeness centrality in G and \bar{G}

B.2 Distrubutions for Topic Networks

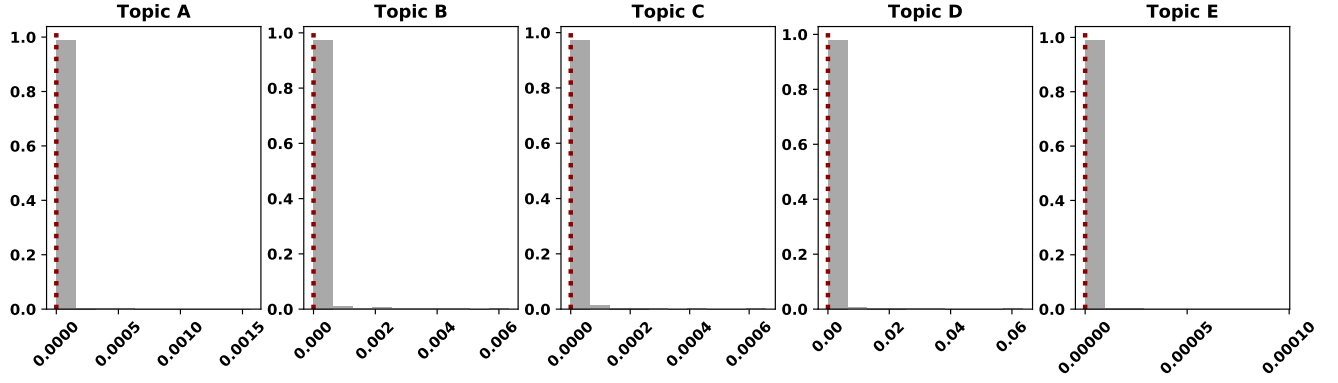


Figure 13: Distributions of betweenness centrality in topics' networks.

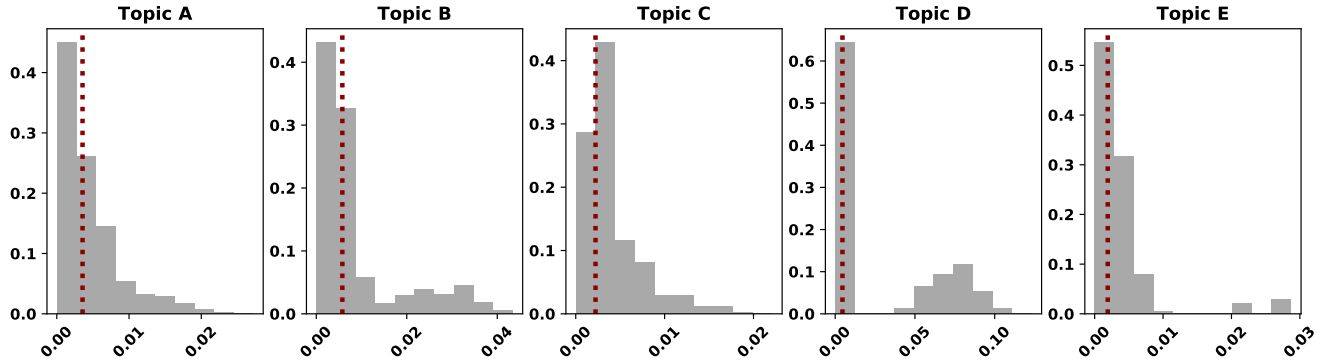


Figure 14: Distributions of closeness centrality in topics' networks.