

Seagull: A Bird’s-Eye View of the Evolution of Technical Games Research

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Abstract

Within Entertainment Computing, games research has grown to be its own area, with numerous publication venues dedicated to it. As this area evolves, it is fruitful to examine its overall development—which subcommunities and research interests were present from the start, which have come and gone, and which are currently active—to better understand the research community as a whole and where it may proceed. In this paper, we present a data-driven analysis and interactive visualization tool to shed light on how technical domains within the games research field have evolved from 2000 - 2013, based on publication data from over 8,000 articles collected from 48 games research venues, including Entertainment Computing, FDG, AIIDE, and DiGRA. The approach we present is descriptive. We first used data mining algorithms to group related papers into clusters of similar research topics and evolve these clusters over time. We then designed an interactive visualization system, named Seagull, comprised of Sankey diagrams that allow us to interactively visualize and examine the transition and coalescing of different clusters across time. We present our descriptive analysis in this paper and also contribute the visualization interface, at <https://truonghuy.github.io/seagull/>, to allow other researchers to examine the data and develop their own analysis.

Keywords: games research; games field mapping; data-driven meta-analysis; research community co-evolution; game field visualization

1. Introduction

Entertainment computing is a rapidly growing sector of the economy and research, justifying the development of a journal to address its contributions and expand its community. In particular, games and interactive media have become an important part of our lives, industry and research. The Entertainment Software Association reports that more than 150 million U.S. Americans of different gender and age groups (occupying 65% of US households) now regularly play digital games, spending more than 30 billion USD on video games in 2016 [1]. In terms of economic contribution, the video game industry directly employs more than 65,000 workers, resulting in a 2.9% compound annual increase over that in 2013, which is higher than the 1.99% average growth in all US industries [2]. As the result, the US video game industry has increased its contribution to the nation’s GDP by 3.7% in 2015, reaching 11.8 billion USD. In addition to industry growth, ‘Games Research’ as an area of academic study is rapidly establishing itself, emerging from multiple disciplines rooted in human computer interaction, computer science, humanities, media studies, social sciences, and the arts. Based on a recent analysis, the academic field of games research includes at least 48 major venues and over seven distinct communities [3]. These communities include research topics that range from developing serious games, to studying the effects of gaming in social interactions, to creating computational algorithms that advance technical aspects of games, to name a few.

As this field has constantly developed over the years, it is important as an academic community to understand its growth, its current state, open problems, and directions for future research. This not only has implications for new researchers in the field but also for researchers outside the field to understand its evolution over time, in order to aid discussion of what the future might hold for this field. As such, in this article we address the following overarching question: *how has this field evolved?*

In the early 2000’s, there were few distinct existing games research venues and many core games research subcommunities were still attempting to differentiate digital games research as a viable, international field of study [4].

Changes in the field from that time—when games research groups were a minority in many communities and conferences—to now—where there are a variety of major technical conferences and journals dedicated to studying aspects of digital games—raise some important questions regarding the evolution of games research and its future research directions. Some questions of interest include: *How one would describe the diverse technical research of this field and its methodological underpinnings? What communities, trends, and areas of study have emerged over time and will continue to influence the field moving forward?* By better understanding the history and evolution of technical games research, we can obtain a more nuanced understanding of the present field and future research directions it could explore. Furthermore, a more detailed, visual, and interactive presentation of technical games research as it has changed over time could greatly benefit young scholars just entering the field and researchers outside of it in better understanding the core topics of interest and what has or hasn't been explored thus far.

To answer these questions, we present results from a data-driven study on the evolution of games research since 2000. This work is descriptive, i.e., we present results from an evolutionary algorithm and visualization tool that sheds some light on seven core communities that evolved and persisted over time in technical games research. It is, therefore, not meant to be definitive or conclusive, but rather corroborate existing work detailing the evolution of individual communities and framing those changes simultaneously within the larger picture of games research from 2000 to 2013. In addition to presenting a descriptive analysis of the field, we also hope this article will serve as an entry point for community discussion around addressing questions of open problems and future directions of the field.

For our analysis of the games research field, we used a data-driven approach. In particular, we collected data in the form of publication meta-data from 48 conferences and journals, totaling 8,207 papers from 2000 to 2013. Venues selected for collection were identified as core games research focused venues by leading researchers among major games research groups in the United States, such as University of California-Santa Cruz (UCSC), North Carolina State University (NCSU), New York University (NYU), and Northeastern University (NEU). These venues include Advances in Computer Entertainment Technology (ACE), Computers in Entertainment (CIE), and Entertainment Computing, to name a few. Notably, we treat many of the entertainment computing related venues as central to due to their historical connections with and influences on games research. Non-core game venues that have published games research papers—such as International Communication Association (ICA), AAAI, SIGCHI and SIGGRAPH—were excluded since their primary focus is not games research and correctly collecting/identifying only game focused publications in these large interdisciplinary venues would pose significant difficulty. We argue that much of the research trends and themes in larger non-core game venues such as AAAI could be encapsulated by papers published in smaller core games venues focusing on artificial intelligence in games, such as Artificial Intelligence and Interactive Digital Entertainment (AIIDE) or IEEE Computational Intelligence in Games (CIG). Besides, attempting to exhaustively collect all games-related papers in every venue possible will add venues and articles at an exponential rate [5], potentially diluting the main technical research trends to be discovered.

It is also important to note that, due to the data-collection strategy for this study, the sub-groups that arose tended to be more technically focused. We believe the cause of this is twofold. First, publications in conferences and journals have greater weight for technical researchers [6], whereas other games research communities view books, monographs, anthologies etc. as equally or more important [7,8]; and books were not included in the dataset. Second, by excluding interdisciplinary and adjacent venues (such as SIGCHI and AAAI), we are likely favoring more specialist disciplines over generalist ones. For instance, computer scientists in games research commonly have very specific goals to work towards and areas of study to cluster around as they build on each other's work; resulting in more focused venues/lexicons which make clustering easier. Specifically, a notable number of the venues in our dataset are centered on specific technical topics such as intelligent narrative and storytelling or AI in games, which in turn use very specific terminology and techniques such as tree searching, neural networks, and Monte Carlo methods. On the other hand, social science, humanities, and game design scholars may be more inclined to seek and utilize perspectives outside of games research, as a result searching for more broad and general venues in order to attract many different viewpoints on a problem. Consequently, due to the selection criteria for our dataset, our analysis focuses heavily on technical papers and research.

We used Evo-NetClus [9], a network mining algorithm, to iteratively group related papers into clusters of similar research topics (based on authors, keywords, venues, and references) and examine how these clusters changed from one timeframe to another. This in effect informs us of different sub-groups within games research and how these groups have changed over time, particularly showing how areas grew, diminished, or transformed. We chose Evo-NetClus algorithm due to its proven capability to deal with and discover temporally evolving communities within

other research fields such as Data Mining, Information Retrieval, Database, and Machine Learning [9]. We then developed a visualization system, named *Seagull*, to allow us to interactively investigate these areas and understand how the field evolved over time.

The contribution of this paper is threefold. First, we present results that provide insights to fellow games researchers about their field. Specifically, we outline how communities, trends, and areas of study/interest within technical games research have emerged, grown, interacted, and declined over time in order for the field to become what it is today. This can greatly aid scholars that are new to the field by providing them with an overview of major trends, highlighting what has already been explored and what may be an emerging topic of interest. This in turn helps to avoid reinvention of the wheel and identifies what new work may be particularly relevant or substantial to the field of games research. Second, we present the dataset and visualization system as a general, freely available tool to enable other researchers to interpret the results and publish different perspectives on the evolution of the games research field. Third, beyond this field, we present a novel data-driven method and analysis technique for performing meta-analysis on a field's evolution. In existing scientometrics literature, the general approach to modeling and detecting the evolution of research fields is to conduct co-word or co-citation analysis on predefined time slices for the data collected—each slice usually consisting of 4 years of papers or more (see [10–17] for examples). These approaches only consider one type of paper attributes (e.g., co-citations or keywords) to detect research commonalities such as themes or communities. In contrast, our approach utilizes multiple attributes (i.e., combination of keywords, venues, authors, references, and citations) to identify communities and visualizes their transformations annually through the use of a Sankey diagram [18]. The methodology described here contributes a general method that can be used as an analytic lens to study fields that are evolving over time.

The rest of the paper is organized as follows. First, we discuss related work analyzing games research and providing background on co-evolution techniques and their usage. We then review the data collection process and discuss our analysis algorithm in detail. Next, we discuss our visualization system *Seagull*, the implementation of which can be found at <https://truonghuy.github.io/seagull/>. Results of the algorithm and analysis interpreted by several researchers using the visualization system are then discussed. Finally, we conclude with a discussion of limitations and future directions for this work.

2. Related Work

2.1. Scientometric Studies of Games Research

While our work is among the first of its kind to perform a data-driven analysis on the evolution of technical games research, there have been other endeavors to examine specific aspects or areas within technical games research domains. Yannakakis and Togelius [19] identified 10 primary research areas for the field of artificial and computational intelligence (AI/CI) in Games based on expert discussion from a seminar on the topic. In a related vein, Lara-Cabrera et al. [20] analyzed the collaboration network of AI/CI in games to examine growth, evolution, interactions, and key researchers that are impacting development within the field. For the intersection of HCI and games research (i.e., 'Player-Computer Interaction'), Carter et al. [21] applied an open and axial coding process to 178 game papers between the years of 2003 and 2013 from the SIGCHI Conference on Human Factors in Computing Systems (CHI). They identified several discrete research domains that were later conceptualized into 4 research paradigms. While this work helps to understand themes, collaboration networks, and evolution within these technical research communities, it only provides a limited understanding of their relations to each other or games research as a whole.

In more social science and humanities oriented games research disciplines such as game studies, there has also been notable work to understand the field and scholars within it. Coavoux et al. [22] utilized scientometric and lexicometric tools to analyze core game studies venues and take an emic view of the game studies community (i.e., concerned with the manner in which the community defines itself rather than with research about games in general). Additionally, Mäyrä et al. [23] and Quandt et al. [24] surveyed game scholars on background education, orientation and academic practices to better understand collective viewpoints on aspects of digital games and if contemporary academics share a common disciplinary identity. Their findings highlight that despite a diversity of educational backgrounds, games researchers share relatively homogeneous viewpoints about games and have a strongly shared identity as “digital games researcher”.

For the games research field as a whole, Melcer et al. previously performed a static co-word and co-venue analysis to identify key communities and themes [3]. Their analyses resulted in the classification of 20 major research themes and 7 distinct communities. One important limitation noted for the study was the static nature of a single co-word analysis over more than ten years of games research. Such analysis can only provide a general picture of themes and communities that were substantial, but has difficulty uncovering the subtle nuances of how and when communities have evolved over time (i.e., emerged, grown, interacted, and declined). This is the fundamental motivation for this paper as we seek to analyze and present the details of the field's evolution in a more descriptive way through co-evolution analysis on a dataset.

2.2. Detecting the Evolution of Research Fields

In the literature of scientometrics, modeling and detecting the evolution of research fields is a common research task. The general approach is to conduct co-word or co-citation analysis on predefined time slices for the data collected—each slice usually consisting of 4 years of papers or more [10–17]. One common characteristic of these analyses is that they only consider one type of paper attribute at a time (e.g., co-citations or keywords) to detect research commonalities such as themes or communities. For instance, Small [25] analyzed the growth of a research field using cluster analysis on co-citation networks comprising of highly cited papers. The clusters are then connected from one time slice to another, with links representing shared common papers, to depict the dynamics of the field over time. Garfield [26] utilized citation linkage software called HistCite to visualize the evolution of the Scientometrics field. The growth of the field was examined by considering citations to the work by Price, a researcher who arguably founded the field. To illustrate the growth of the field, Garfield used a line chart (x-axis is years, y-axis is number of papers citing Price), node-link graph (nodes represent papers, and links represent citation, laid out in a 2D plane with y-axis being the year, and node size represents the number of citations), and tables containing chronological references to show the timeline of the field's history.

The idea of examining the history of a field using citation networks is prevalent, having been implemented in some widely popular software systems including VOSviewer [27], CitNetExplorer [28], and CiteSpace [29]. In these software systems, the papers representing a field are visualized using a node-link graph, with nodes representing papers. Unlike those of nodes, which tend to be fixed, the meaning of links depends on the network type. Links in a *co-citation* network are undirected, signifying the number of times the two papers are cited in the same documents, while those in the *direct citation* network are directed with the citing paper as the source and the cited as the target.

A survey of bibliometric mapping software systems, most of which aim to visualize bibliometrics for better understanding of research communities, were presented in a recent publication [30]. Bibliometric mapping refers to the task of collecting data related to a certain scientific field and visualizing it so as to exposes the structure of the targeted field [31]. While many of the discussed techniques focus on revealing the structure of the field as a whole, those that facilitate temporal analysis to reveal the development and progress of the research fields utilize mainly co-occurrence information of a single attribute such as citations.

In this work, we present a different approach, examining the evolution of the game research field using a Sankey-based interactive visualization that shows the relationships among clusters of papers, as grouped using a co-evolution detection algorithm that relate papers using multiple attributes, e.g., authors, keywords, citations, etc., instead of just single ones.

3. Publication Data Identification and Collection

3.1. Venue identification

The first step in the data collection process was to identify appropriate core games research venues. For this purpose, we consulted leading researchers among major games research groups in the US, including UCSC, NCSU, NYU, and NEU. There were a total of 16 experts responding to our solicitation, with an average h-index of 19.44 (as retrieved from Google Scholar, SD = 9.67), and average number of years as a researcher of 15.8 (SD = 6.92). Figure 1 plots the histograms of the experts' h-index and years of experience as a researcher. The research areas of these experts range from game studies, design, interactive media, edutainment, and serious games, to game AI, analytics, procedural content generation, affective computing, and computer graphics. Importantly, although researchers solicited were predominantly from the North American region, several experts were long time scholars in the European community before moving to North American universities. This helped to provide a broader coverage of venues in both North America and Europe.

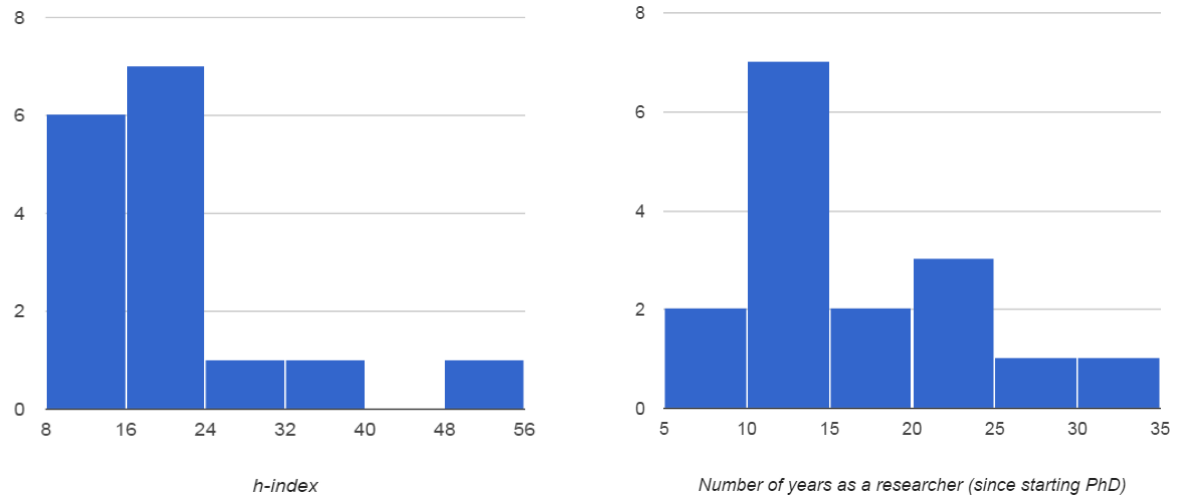


Fig. 1. Histograms of experts' h-index (left) and research years (right).

Based on the expert recommendations, we identified 22 core games research journals and 26 core games research conferences (see Table 1). We excluded non-core game venues that have published games research papers—such as AAAI, SIGCHI and SIGGRAPH—since their primary focus is not games research and correctly collecting/identifying only game focused publications in these large interdisciplinary venues would pose significant difficulty. For instance, prior work identifying games research in interdisciplinary venues such as SIGCHI found that using an automated search on core keywords such as “*game*” and “*play*” resulted in more than 1/3 of the collected papers being irrelevant to games research; having to be hand identified and removed as a result [21]. Given the quantity and size of these interdisciplinary venues, such a laborious approach would not be as feasible for our dataset. Moreover, attempting to gather all games papers possible will add venues and articles at an exponential rate [5], which would also hinder the progress of this project due to the time consuming nature of data collection. Additionally, we believe that for works which address significant topics to games research published in interdisciplinary venues, there is also a high probability that related work will similarly be published in core game venues. As such, we feel this exclusion is acceptable since we do not aim to discover all possible technical games research topics, but only those that make up significant trends and communities in the past years. Overall, a total of 8,207 papers were collected for analysis.

Table 1. Expert generated list of core research conferences and journals in alphabetical order.

Conferences	Journals
1. AAAI Spring Symposium on AI and Interactive Entertainment (AAAI&IIE)	1. Computers in Entertainment (CIE)
2. ACM SIGGRAPH Sandbox Symposium (Sandbox)	2. Eludamos. Journal for Computer Game Culture (Eludamos)
3. Advances in Computer Entertainment Technology (ACE)	3. Entertainment Computing
4. Artificial Intelligence and Interactive Digital Entertainment (AIIDE)	4. Game Studies
5. Computational Intelligence and Games (CIG)	5. GAME The Italian Journal of Game Studies (G A M E)
6. Digital Games Research Association Conference (DIGRA)	6. Games and Culture (G & C)
7. European Conference on Games Based Learning (ECGBL)	7. IEEE Transactions on Computational Intelligence and AI in Games (TCIAIG)
8. Foundations of Digital Games (FDG)	8. International Computer Games Association Journal (ICGA)
9. Future Play	9. International Digital Media and Arts Association (IDMAa)
10. Games Learning Society (GLS)	10. International Journal of Arts and Technology (IJART)
11. Gamification	11. International Journal of Computer Games Technology (IJCGT)
12. Intelligent Narrative Technologies Workshop (INT)	12. International Journal of Game-Based Learning (IJGBL)
13. Intelligent Technologies for Interactive Entertainment (INTETAIN)	13. International Journal of Gaming and Computer-Mediated Simulations (IJGCMS)

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| 14. International Computer Games Conference (CGAMES) | 14. International Journal of Role-Playing (IJRP) |
| 15. International Conference on E-Learning and Games (Edutainment) | 15. International Journal of Serious Games (IJSG) |
| 16. International Conference on Entertainment Computing (ICEC) | 16. Journal of Game Design and Development Education (JGDDE) |
| 17. International Conference on Interactive Digital Storytelling (ICIDS) | 17. Journal of Game Development (JOGD) |
| 18. International Conference on Virtual Storytelling (ICVS) | 18. Journal of Gaming & Virtual Worlds (JGVW) |
| 19. International Games Innovation Conference (IGIC) | 19. Journal of Virtual Worlds Research (JVWR) |
| 20. International Simulation and Gaming Association Conference (ISAGA) | 20. Simulation & Gaming (S&G) |
| 21. Meaningful Play | 21. The Computer Games Journal (TCGJ) |
| 22. Serious Games Development and Applications (SGDA) | 22. Well Played |
| 23. Technologies for Interactive Digital Storytelling and Entertainment (TIDSE) | |
| 24. The Philosophy of Computer Games | |
| 25. Under the Mask | |
| 26. Workshop on Network and Systems Support for Games (NetGames) | |
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3.2. Collection and Verification

We contacted publishers of each venue for approval to batch download articles from their repositories, and used a data crawler to automate the collection process. In cases where publications are not stored in PDF format, we manually collected the articles, and used scripts to convert them into text, before running an additional script to extract meta-data from the resulting text. This step is single-handedly the most time-consuming phase of our project, as approvals take time to go through, due to legal and other service issues.

Notably, the initial data set collected originally suffered from entry duplication and articles that were prematurely reported or not peer-reviewed, such as extended abstracts, book reviews, panels, and editorial introductions. These articles were automatically and manually detected on a per venue basis and removed. Specifically, entry duplication was detected and filtered automatically using database queries that search for articles with similar titles, similar author lists, as well as year of publication and venue. Non peer-reviewed articles are detected through a trace-and-span manual process: First, we did a cursory check on the titles and venue information. If we encounter an entry that is possibly not peer-reviewed, such as when its title or venue includes “Extended Abstracts”, or “Panel”, or “Editorial Introduction”, we would check all papers in that conference or journal for papers with similar patterns and remove them.

Another issue with the collected data was the appearance of editors’ names in the co-author list of papers. In particular, some online repositories show editors’ names alongside the authors, which caused inconsistencies. Potential editors in the data were identified, manually verified, and then deleted. More specifically, potential candidates for editors were initially identified as authors with at least 5 papers in the same publishing venue in any particular year. The number 5 was selected since it is an unrealistically large number of similarly authored papers, which rarely happens in any conference. Next, for each editor candidate, we visited the conference website or proceeding repository to manually verify whether the candidate’s name was listed as an editor and whether the pertinent papers have his/her name listed as a co-author. If the candidate is found to be an editor, his/her name is removed from the associated papers’ author lists.

After the data was cleaned, we had a total of 8,207 game papers in the period from 2000 to 2013. In order to confirm the completeness of our collection process, we conducted a verification step that randomly selects two papers from each venue and checks for their existence in our database. The verification process shows that we collected a reasonably large percentage (86.17%) of the articles from our core games research venues over the 2000 - 2013 time period.

4. Publication Data Processing and Analysis

The set of collected papers are spread over 14 years, with an average of approximately 500 papers published per year. To address questions around growth of the games research field, we are interested in understanding the temporal co-evolution of research communities and themes embedded in this corpus. As a result, our goal is to algorithmically identify research communities in each year and the relationships among them using a co-evolution technique.

The term "research communities" here is characterized as groups of papers that are closely related to one another. "Relatedness" can be established by the following attributes of a paper: (1) authors, (2) keywords, (3) venues, (4) references, and (5) citations. The rationale to define relatedness this way is due to the intuition that commonalities in these aspects of papers signify the possibility that the papers discuss similar research topics. For example, papers published in ICEC and Entertainment Computing mainly discuss topics related to the technologies and algorithms in creating games and simulations that enhance user and player experience, while those in Games and Culture touch more on the social aspects of games. Admittedly, being published by the same author or being cited by the same paper alone does not guarantee thematic commonality, as authors could be active in different communities, or papers can be cited for motivation purposes. However, we argue that the combination of all aforementioned attributes is a reasonable way to capture the thematic relatedness of papers, i.e., the more attributes that are shared among papers, the more probable that they belong to the same research community.

As presented in the Related Work section, previous works in Scientometrics mainly examined co-occurrence models of homogeneous items, e.g., co-citation networks, for analysis [25]. While such approach is suitable for mature fields in which ideas often share similar origins, which can be traced from co-cited papers, it is not adequate for analyzing the game research field, which is a young field comprising of specialized communities that may have very little interaction. For example, communities that work exclusively on technical challenges in creating networked games or Virtual Reality (VR) games seldom cite works in understanding player strategies in a puzzle game, although they may share a similar keyword, e.g., "video games". To make sure that we can account for such relationships in analyzing the game field, we therefore need to rely on recent advancements in the data mining community that investigate multi-attributed relationships.

In the literature of temporal cluster analysis, there has been some work on multi-faceted temporal clustering, in which multiple attributes are taken into consideration [9,32]. Specifically, Sun et al. [9] presented a method for algorithmically deriving the evolution of a field that provides more granularity (i.e., smaller time periods for analysis) and reliability due to its use of multiple attributes from a paper (i.e., combination of keywords, venues, authors, references, and citations). In their work, a field is numerically represented as a graph comprised of heterogeneous nodes such as papers, keywords, venues, and authors over time. Network analysis is then conducted on this graph to discover highly related nodes based on all properties and cluster them as communities. In this paper, we apply this method to discover temporal relationships within the games research field.

While examining the collected paper corpus, we quickly identified two main issues with the data that need to be addressed before applying the analysis. First, missing keywords: while most papers have associated keywords, about a third of our dataset lacked keyword information. Second, missing citations: with the exception of those published in Springer, SAGE, ACM, and IEEE, citation information is not available for most papers. Even some of the above publishers only account for citations from within their database.

To overcome these stumbling blocks, we first enriched the data set by filling in missing keywords and then extracting citation information from Google Scholar. Finally, we applied a social network algorithm, namely Evo-NetClus [9] to obtain the co-evolution patterns that will be used in our visualization tool and descriptive analysis.

4.1. Keyword Generation

Keywords are essential pieces of information to connect papers in the same research community, and therefore critical for our analysis. About one third of the papers in the dataset did not originally contain keyword information. This was due to incomplete data sources or lack of keywords in the original publication. For papers missing keywords, we automatically generated some based on the title and abstract. The algorithm to generate keywords for these papers is shown in Table 2.

Table 2. The algorithm for generating missing keywords based on titles and abstracts

Algorithm 1

1. Initialize the set of keywords K with existing keywords from the papers in the database.
 2. Enhance K with 2-gram candidates (k_{2g}) by:
 - Extracting k_{2g} from titles and abstracts of all papers in the database using Fox's stop words [33].
 - Manually filtering out k_{2g} which are (1) either meaningless, (2) too general, or (3) not frequent enough (i.e., appearing less than $F_{thres} = 5$), such as "recent years" or "considerable amount".
 3. For each paper, P , without keywords:
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- Split titles and abstracts into phrases, ph , using Fox’s stop words.
 - For each ph :
 - if ph is in K : Add ph to the keyword list of P .
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Our idea is to enhance the current pool of keywords with frequently occurring 2-grams, i.e., phrases comprising of two words [34], as extracted from titles and abstracts of papers. In Step 2 of the keyword generation algorithm in Table 2, we manually excluded 2-grams deemed not suitable for a keyword, i.e., too general or infrequent. Step 3 populates papers that previously had no keyword with candidate keywords from the newly enhanced pool.

We decided to enhance the pool with 2-gram keyword candidates, instead of unigrams or 3-grams and above, due to the observations that (1) 1-grams, if not already covered by existing keywords, are mostly irrelevant common words, and (2) in the original set of keywords, n -gram keywords with $n \geq 3$ are rare. This is illustrated in Figure 2, which plots the distribution of existing keyword lengths in our dataset. We can see that keyword length follows the power law, i.e., longer keywords appear exponentially less frequently than shorter ones.

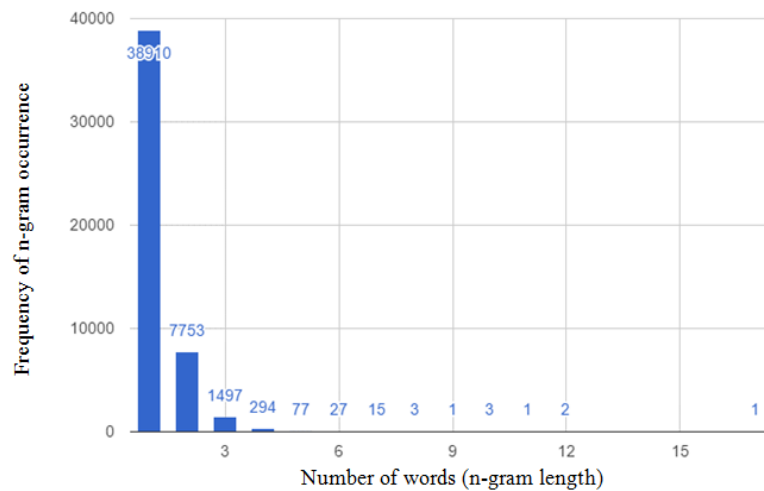


Fig. 2. The distribution of keyword length in our dataset, which follows the power law. I.e., longer keywords appear exponentially less frequently than shorter keywords.

Note that while the algorithm itself automatically generates keywords for most keyword-less papers successfully, it still leaves 48 papers without any appropriate keywords. This limitation is because these papers have titles and/or abstracts that contain words too generic and not frequently encountered in the data set. For instance, some of such papers are “Paintrix: color up your life!” from ACE conference [35] or “A day in the life” in CIE journal [36]. We chose to leave these papers as is since they comprise a very small percentage of all papers (about 0.6% of the 8,207 papers), and other attributes such as venue and author information can be used in our co-evolution algorithm to establish a connection to research communities.

It should be noted that we did not use mainstream algorithms like RAKE [37]—a widely used algorithm for keyword generation. This is because RAKE has the issue of bias towards long phrases even though the frequency of such phrases is low, see Figure 2. For example, the phrase “active perception systems continuously analyze photorealistic retinal image streams” is selected by RAKE not because the whole phrase appears frequently, but due to the popularity of sub-phrases “active perception systems” and “photorealistic retinal image streams”. The modified algorithm above ensures that only words that often appear together in single phrases are counted as keywords.

4.2. Citation Retrieval

Since our goal is to analyze not only the research community landscape but also its evolution over time, we need to connect papers in terms of temporality and relatedness beyond just author or keyword information. Citation is therefore an important source of information for this purpose. Specifically, when paper A is cited by paper B, it is

likely that the former discusses subjects that are related to the latter. In many cases, they could be in the same research sub-community investigating the same research topic. While there are some repositories that update citation records of their articles (e.g., Springer, SAGE, ACM, and IEEE), most source meta-data for game literature does not contain citation information. To fill in missing citations for a paper, we made use of Google Scholar—a prominent source of bibliographic data that keeps track of papers’ citation information regardless of where they are published. Google Scholar (GS) was found to be quite exhaustive, containing about 90% of all scholarly articles published online [38].

We developed a script that searched for each paper and extracted citation information from GS using the title and year as the search terms (see Table 3 for the algorithm). We only include title and year as our search terms because other pieces of information such as author names and venues might be arbitrarily abbreviated by Google.

Note that the resultant citation set for a specific paper could contain (1) nothing, or (2) papers in a non-English, foreign language such as Chinese or Finnish. In the first situation, we denote that the paper does not yet have any citation. As GS is exhaustive, if a paper is not found to have any citation in GS database, it is highly likely that that is the case. In the second case, we decided not to count such citations, since these articles are often non-peer reviewed works that have unsubstantiated scholarly value such as a student term paper.

Table 3. The algorithm for collecting citation data from Google Scholar

Algorithm 2

Input: P is the paper to collect citation information

1. Search for P on Google Scholar
 - Search terms include the title and year.
 2. Select the best search result that matches P
 - Fuzzy string matching is used to select the right output entry, since Google Scholar could return a long list of results.
 3. Return the list of papers citing P
 - Each paper entry in Google Scholar has a list of papers citing it. In case Step 2 fails, i.e., the paper cannot be found in Google Scholar database, an empty list is returned.
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4.3. Co-Evolution Generation

To model the evolution of games research sub-communities, we leverage a data mining algorithm called *Evo-NetClus* by Sun et al. [9]. In this section, we will briefly present the gist of the algorithm and its process, including input and output descriptions. Interested readers could refer to the original paper for exact details of the algorithm.

Evo-NetClus belongs to a family of social network analysis algorithms that uncover latent relationships in networks of heterogeneous objects. Unlike a homogeneous network, which consists of objects (nodes and links) of the same type, a heterogeneous network contains objects of various types. For example, a co-author network, which has authors as nodes and co-authorships as links, is a homogeneous network. In contrast, a heterogeneous bibliography network can be constructed with nodes being any of the types: papers, authors, venues, keywords, and links representing corresponding relationships, e.g., authorship links between papers and authors, or publishing links between papers and venues. One particular type of heterogeneous network is the star network, whose links connect objects of a *center type* and objects of multiple *attributes*. The above mentioned heterogeneous bibliography network falls into the category of star network, in which paper nodes, as the center type, are linked to other attributes such as authors, keywords, venues, and references, but not to one another. Figure 3 depicts a sample component of such networks, in which paper p_1 shares with p_2 the author node a_1 and venue v_1 . This component captures the fact that the mentioned papers are authored by a common author a_1 and published in the same venue v_1 . Similarly, p_1 shares one common keyword (k_2) with p_4 , and two references (r_1 and r_2) with p_3 .

To uncover both clusters of highly related objects in a single time frame (also referred to as time slice or time window), and how these clusters change from one time frame to another, Evo-NetClus takes as input a sequence of star networks, each of which contains data (or papers and their attributes in our case) collected in one time frame, e.g., 2000-2001, 2001-2002, and so on. Next, for each time frame t , a three-step operation is executed to retrieve the communities in this time frame, as well as its relationship with time frame $t-1$ in the form of clustering commonalities.

First, papers in time window t are pre-grouped to the clusters from time window $t-1$, or to a new cluster that contains all the papers that do not fit into any existing clusters. This step discovers how papers from time window t can be fitted into previous clusters. This establishes the basis on which the algorithm determines commonalities among clusters in adjacent time frames, i.e., based on how papers in the current time frame's clusters would have belonged to should they appear in the previous time frame.

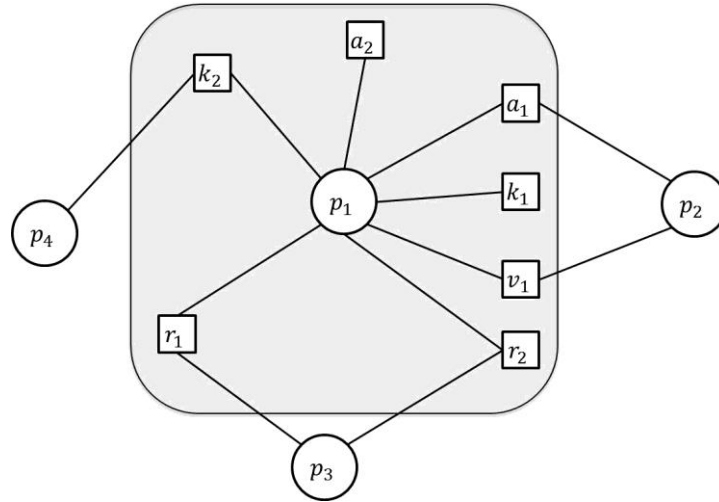


Fig. 3. A sample component of the star networks; circular nodes are of a center type (such as papers), and rectangular attributes. Note that there is no direct links between any two center-typed nodes; they are indirectly connected through the attribute nodes.

Second, papers within time window t are clustered based on a Dirichlet process-based mixture model called DP-NetClus [9]. Unlike traditional clustering algorithms, DP-NetClus does not require specifying the number of clusters beforehand. When a new paper comes as input, it always has a probability to be grouped to a new cluster, or some probabilities belonging to existing clusters from time window $t-1$, which depends on cluster sizes as well as similarities between the new paper and all papers in the corresponding clusters. Namely, the larger size a cluster has, or more similar papers a cluster has already possessed, the more likely the new paper will be grouped to the cluster. Evo-NetClus also introduces a damping factor λ to subside the impacts of the size of existing clusters from time window $t-1$. The similarity between two papers is determined by all attributes of the papers together, namely, venue, author and keyword. Following the idea of Collapsed Gibbs Sampling [39], Evo-NetClus ran multiple iterations of cluster assignment until a desired stability condition is met. In this step, the paper assignments form clusters (communities) by only looking at papers in time window t .

Third, combining pre-group assignments from Step 1 as well as cluster labels from Step 2, the algorithm depicts transformations of the clusters from the previous time window to the current time window. For example, consider a cluster of papers C obtained from Step 2. If about half of the papers in C belong to pre-group A in the first step, while the other half of cluster C papers were assigned to pre-group B , it could be obtained that community A and community B form a new community C in the new time window.

Through the above process, by iteratively constructing clustering models from one time frame to another while keeping track of how the models change over time, the algorithm detects the co-evolution patterns and outputs the following pieces of information:

1. The cluster formations in each time frame, i.e., the number of clusters and the papers in each cluster;
2. The top K most popular values of each features in each cluster with K being an input parameter specified a priori. In our case, we set $K = 10$ to obtain the top 10 most popular keywords, authors, venues, citations, and references in each cluster; and
3. The number of papers shared between any two temporally adjacent clusters; for instance, how many papers are shared between cluster 1 in 2000 and cluster 2 in 2001.

While the first and second parts of the output describe the communities detected, the last part captures the relatedness of communities across time frames.

5. Seagull: Interactive Visualization System

Given the co-evolution output, we developed an interactive visualization system called Seagull that allows us to interpret and analyze the data and results of the algorithm. The system uses a Sankey diagram [18] to visualize the transformations of paper clusters, augmented with query-based highlighting capability. Sankey diagrams are a specific type of flow diagrams that use link thickness to encode the significance of transitions, which we find especially suitable for visualizing evolution dynamics (growth, split, merge, etc.). In our visualization, different bodies of research are represented as groups of related papers in the same time frames (i.e., paper clusters), denoted by **nodes**, the sizes of which are proportionally scaled to the number of papers in the respective cluster, while temporal transformations among them as **links**, whose weights represent the number of papers shared between them.

Seagull was implemented as a web-based application using JavaScript and HTML, with the help of the D3.js library [40] to render visualizations. For more information, readers can interact with the visualization and the data collected by our group at <https://truonghuy.github.io/seagull/>.

5.1. Input Data

With a design intended to visualize communities and their evolutions, Seagull takes as input two pieces of information: (1) co-evolution data, and (2) thematic data. The former (co-evolution data) is readily available by applying a suitable evolution detection algorithm, such as Evo-NetClus. The latter, i.e., thematic data, captures the research themes in the paper corpus and will be used to color clusters when visualizing co-evolution data. One way to obtain the themes is to apply co-word analysis on a specific paper attribute, such as keyword or venue [3,41]. Each detected theme is represented as a frequency-weighted distribution of attribute values (e.g., keywords). Table 4 depicts the research themes that result from applying co-word analysis on our games research paper corpus.

5.2. Visual Representation

Seagull uses thematic data to color-code paper clusters and their transitions to facilitate comparison of different clusters' themes.

Coloring Paper Clusters. Each paper cluster can be associated with the research theme closest to it, with distance computed using cosine similarity on attributes of interest:

$$\text{sim}(X, C) = \cos(\vec{K}_X, \vec{K}_C) = \frac{\vec{K}_X \cdot \vec{K}_C}{\|\vec{K}_X\| * \|\vec{K}_C\|}$$

whereby:

- X is a paper cluster, C is a research theme
- \vec{K}_X, \vec{K}_C are attribute value distributions of X and C in the form of numeric vectors; for instance, if we use keyword as the attribute of comparison, the distributions here are keyword distributions as found in the paper clusters and the research themes, respectively.

With each theme C depicted as a different color (Table 4), paper clusters take the color of the theme closest to it, i.e.,

$$\text{color}(X) = \text{color}\left(\underset{C}{\operatorname{argmax}} \text{sim}(X, C)\right)$$

Additionally, transparent nodes indicate no theme could be associated, white nodes indicate emergence of a new community in the next time slice, and black nodes indicate closure of communities. We use our co-evolution output and research themes (represented by keywords) from Table 4 as input into the distance and coloring calculations.

Table 4. The color-coded major themes in games research identified using co-word analysis. Table shows the Theme ID and 5 most frequent keywords representing the core topics of each theme.

ID	5 Most Frequent Keywords
----	--------------------------

T1	Game Design, Serious Games, Game Based Learning, Educational Games, Gamification
T2	Interactive Storytelling, Interactive Narrative, Role Playing, Real World, Multiplayer Online
T3	Real Time, Virtual Reality, Virtual Environments, Virtual Characters, Game Engine
T4	Virtual Worlds, Massively Multiplayer Online Games, Second Life, Online Games, Avatars
T5	Gameplay, User Experience, Entertainment, Player Experience, Immersion
T6	Narrative, Art, Interactivity, Emotion, Aesthetics
T7	Game Theory, Evolutionary Computation, Computational Intelligence, Genetic Algorithms, Search Problems
T8	Augmented Reality, Mixed Reality, User Interface, Pervasive Games, Mobile Games
T9	Artificial Intelligence, Decision Making, Planning, Context, Cognition
T10	Human Computer Interaction, Digital Media, Interaction Design, New Media, Psychology
T11	Simulation, Role Play, History, Experiential Learning, Cooperation
T12	Learning Artificial Intelligence, Training, Machine Learning, Reinforcement Learning, Learning Systems
T13	Servers, Internet, Computer Architecture, Mobile Computing, Delay
T14	Learning, Education, Children, Storytelling, Creativity
T15	Humans, Neural Networks, Software Agents, Testing, Navigation, Computer Simulation
T16	Interaction, Communication, Role Playing Games, Player Behavior, Content Creation
T17	Educational Institutions, Computer Aided Instruction, Software Engineering, Software, Computer Science Education
T18	Collaboration, Board Games, Social Networks, Multiplayer Games, Social Media
T19	Monte Carlo Methods, Tree Searching, Algorithm Design and Analysis, Monte Carlo Tree Search
T20	Computational Modeling, Visualization, Engines, Databases

Coloring Cluster Links. A link connecting two clusters takes the color of its target cluster to reflect the theme the cluster is transforming into, while its weight (thickness) is proportional to the number of papers. For instance, if a cluster associated with Theme 3 (i.e., discussing mainly Virtual Characters, Reality, and Environments) at a previous time slice is connected with a cluster of Theme 8 (i.e., Augmented/Mixed Reality) in the current time slice, the link between them takes the color of Theme 8, to convey the message that some previous research works in VR (source cluster) have found successors in AR (target cluster) in this time slice. In cases when the target cluster is black, i.e., the part of research in previous time slice that disappears in the current time slice, the link will retain the color of its source cluster instead. This expresses the information on which clusters (thus research themes) have lost their mass when transitioning to the new time slice.

Note that the colors of the twenty different research themes are selected from 10 different contrasting colors (Table 4). This limit ensures the colors selected be visually different enough (especially effective when only a few research themes are highlighted), while minimizing the number of themes sharing the same color (i.e., any color is used to code at most only two themes). The decision came from multiple experiments with different number of colors, ranging from 10 to 20. As shown in Table 4, the colors are rotated among the themes and repeat themselves from Theme 11 onwards.

5.3. Interactivity Options

The main visual representation of Seagull is a color-coded Sankey diagram depicting the evolution of research themes found in the games research field paper corpus. Seagull also augments this visual representation with two interactive options: thematic highlighting, and attribute query highlighting (see Figure 4).

5.3.1. Thematic Highlighting

Users can select a theme from Table 4 to highlight, in which case all clusters and connecting links associated with the specified theme will be highlighted. Clusters associated with unrelated themes are faded from view. This allows quick inspection of the transformations of specific themes.

5.3.2. Attribute Query Highlighting

Users can also specify attribute queries (i.e., author, cited author, keyword, and venue) to filter certain clusters for examination in the Sankey diagram. Seagull's strength lies in the fact that it can handle attribute queries in disjunctive normal form, while the terms are partially-matched. For example, a highlighting query on venues "(aiide AND NOT fdg) OR digr" corresponds to all paper clusters that contain some paper published in AIIDE, but none in

FDG, or contain some paper published in DIGRA (note that “digr” is partially matched to DIGRA). This highlighting capability provides a powerful way to address questions related to tracking of specific paper property values. For example, *how has a specific author, A1, published over the past 15 years?* (Query: “A1”); or *how has the collaboration of two authors A1 and A2 evolved?* (Combination of queries: “A1”, “A2”, “A1 AND A2”, “A1 AND NOT A2”, “A2 AND NOT A1”).

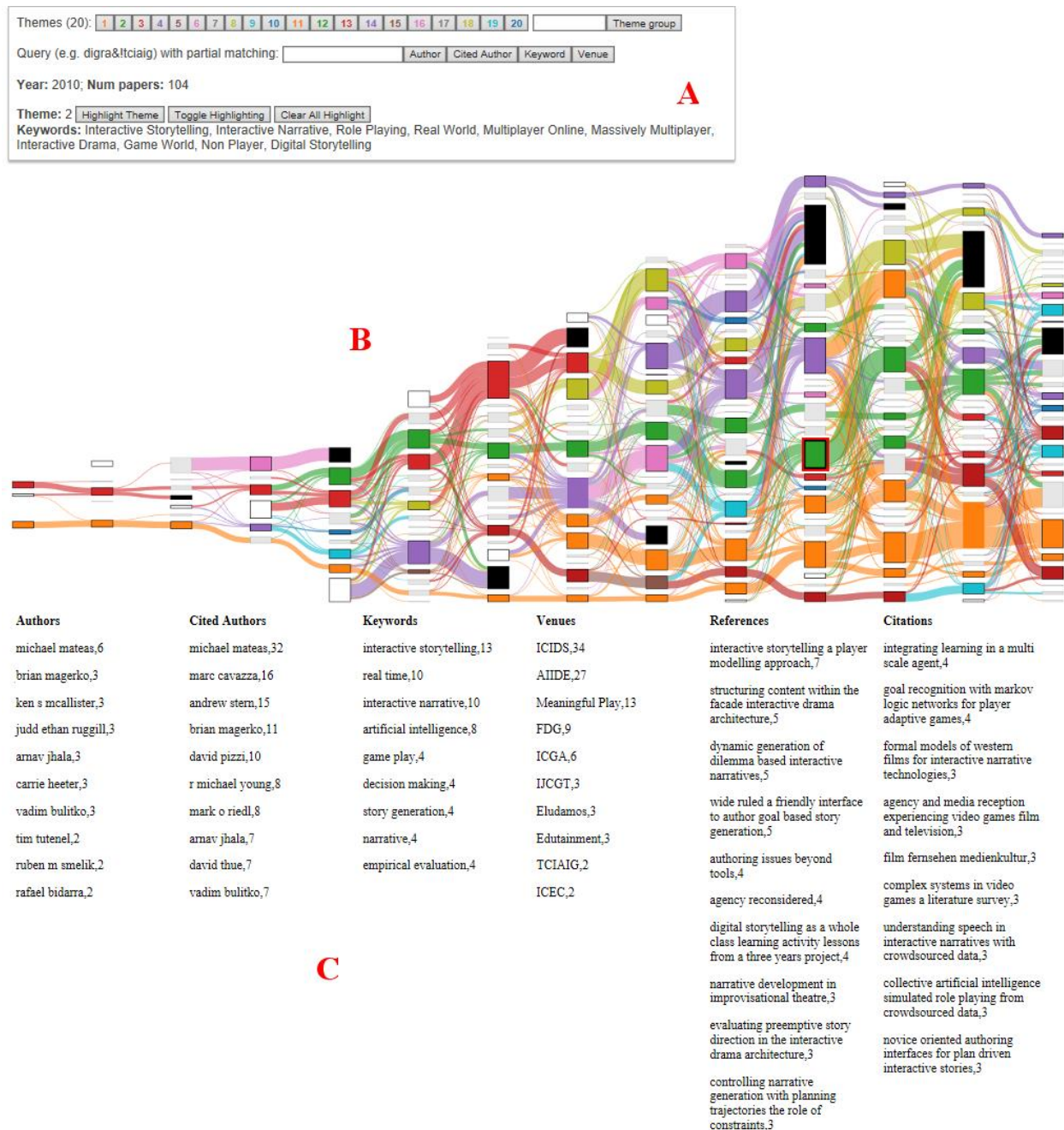


Fig. 4. Seagull’s main interface. (A) shows the interactivity options, with results visually displayed as highlights in (B) the Sankey diagram; (C) shows the attributes of a selected cluster. Each color in the Sankey diagram signifies a different research theme

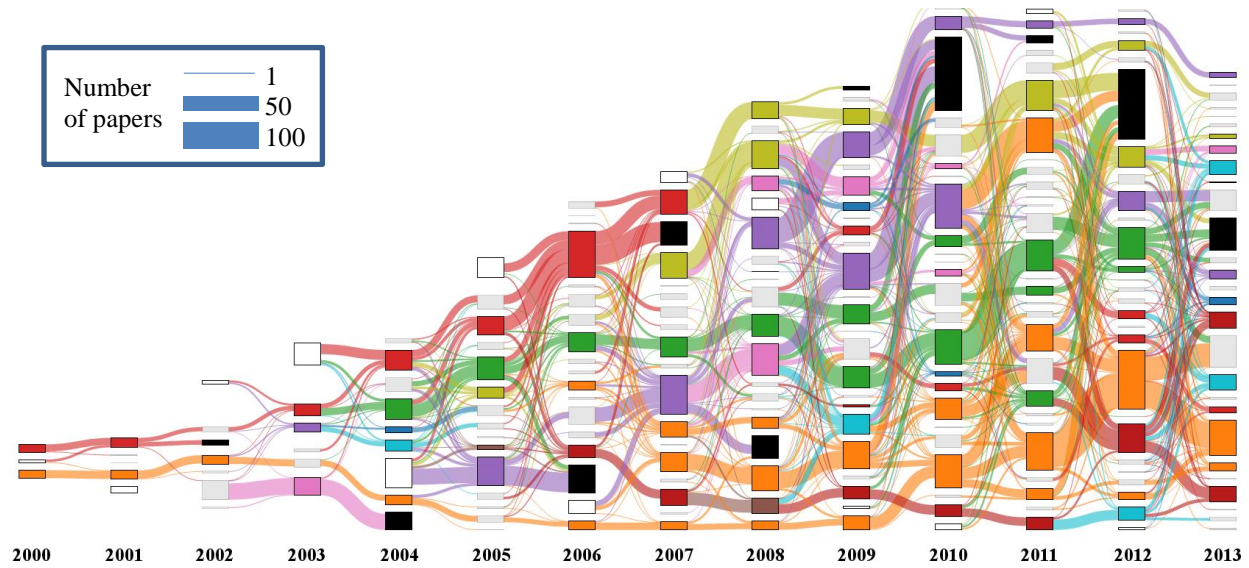


Fig. 5. Evolution of Games Research in the Seagull visualization (*Evo-NetClus* applied to game publication data); the x-axis shows time while the scale on the y-axis signifies the number of papers. The node size is scaled proportionally to the number of papers, while the thickness of links between nodes represents the amount of research (i.e., number of papers) persisting from the source cluster (in the previous timeframe) to the target cluster (in the current timeframe). The legend shows the correspondence between line thickness and node size to the number of papers.

6. Results and Discussion

Overall, the evolution of games research shown in Figure 5 is quite interesting. White nodes are present in almost every year from 2000 through 2012. This signifies that the field has been actively growing and evolving over time with many new research areas popping up. In addition, the emergence of black nodes over time demonstrates a similar pattern. Multiple sub-areas seem to close down in years 2002, 2004, 2006, 2007, 2008, 2010, 2012, and 2013. In such instances, research interest may have simply died out or research ideas and themes may have transferred to different nodes, clusters, or communities outside of core game venues (e.g., AAAI, SIGCHI, or SIGGRAPH). In the following subsections, we follow and analyze these trends to get a snapshot of which communities have evolved over time.

6.1. Prevalent Communities in Games Research

Using the theme tagging and coloring process of Seagull, we were able to further explore the data and identify 7 notable communities prevalent during the evolution of games research from 2000 - 2013. These are: Serious Games, Simulation and Role Play for Learning, AI, Interactive Narrative, Virtual Worlds, Virtual Reality and Environments, and Augmented/Mixed Reality.

6.1.1. Serious Games

This area of research is comprised primarily of clusters from Theme 1 in Table 4. Inspecting Figure 6, we see that after the Serious Games Initiative in 2002 [42] and formation of more focused sub-groups in 2004 (e.g., Games for Change and Games for Health [43]), serious games solidified into an area of study large enough to be detected by our analysis in 2006. Additionally, the time periods for appearance and explosive growth of serious games as seen in Figure 6 match survey results from a recent overview of serious games conducted by Laamarti et al. [44] that tracked the number of serious games in industry and papers in academia through the years. Over time, Serious

Games research has continued to expand and evolve, becoming more ingrained not only within academia and industry, but also within different communities of games research. Figures 5 & 6 and related work [3] illustrate how serious games and education are highly central topics to the games research community, connecting a variety of otherwise unrelated topics and communities.

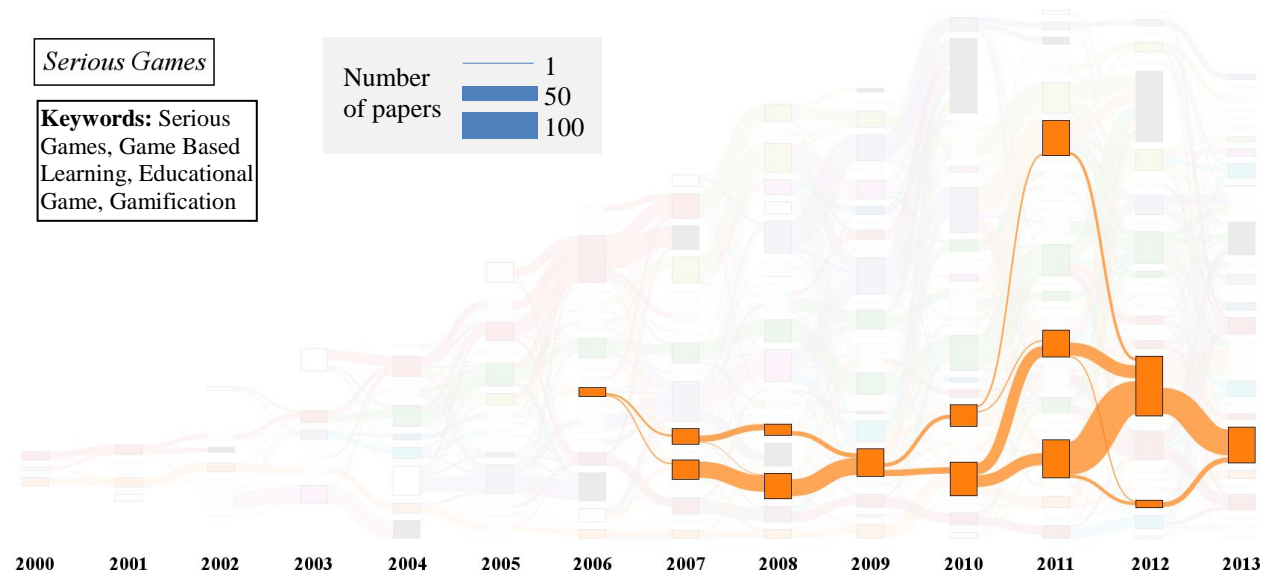


Fig. 6. Evolution of the Serious Games community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. As the Sankey diagram shows, research in this community has grown significantly over the year, with the first notable appearance between 2006-2008 and still going strong as of 2013.

6.1.2. Simulations and Role Play for Learning

This area of research consists primarily of clusters from Theme 11 in Table 4. Investigating Figure 7 and its position within Figure 5, we see the body of work has remained relatively small and stable in development. Moreover, the area stays largely isolated from the overall research community, as there is little connectivity observed between clusters in this theme and those from others. Considering the longevity of many simulation research venues (such as the journal *Simulation & Gaming* which has been active since 1970), it seems reasonable that the community would continue to be stable throughout 2013. Moreover, apparent isolation from the larger community is also understandable considering Crookall's retrospective on 30 years of simulation and games research [45] where he notes that the focus of such research is interdisciplinary in the sense that it is "taking on aspects and features of the area to which it is applied" (e.g., economics, business, military, etc.), rather than actively exploring broad community centered questions around games. Consequently, it is likely that much of simulations and games research can be found in interdisciplinary venues on economics, business, etc. outside of games research.

One interesting aspect relating to role play and related terms in our analysis is that they appear in multiple themes besides 11 (e.g., Themes 2 and 16 as well). This highlights a notable instance where one term has different meanings or applications depending on the context and communities in which it is used. For instance, with respect to education, role playing is often referred to in the same context as educational games and simulations; deepening learners' conceptual understandings by working within, reflecting upon, and acting as appropriate for a given role within a representation of a real environment [46]. On the other hand, in communities such as interactive storytelling, the focus may be more on the stories within games that support the playing of roles [47].

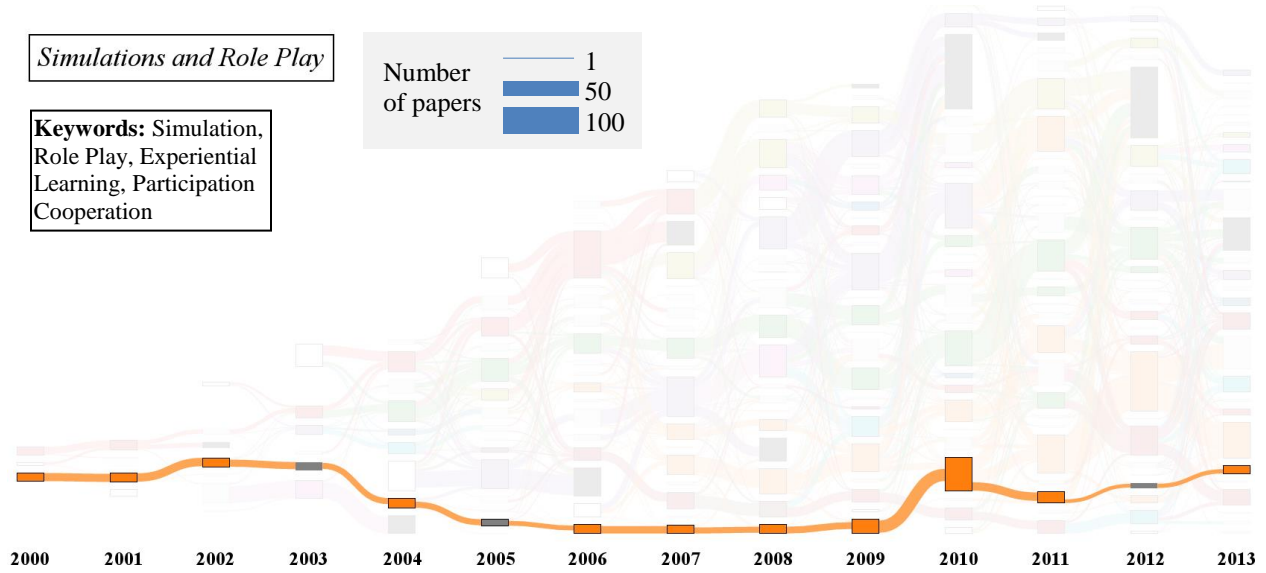


Fig. 7. Evolution of the Simulations and Role Play community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. Nodes of different colors highlighted here comprise of research papers with slightly different keyword distributions but still considered related to the theme. Overall, this community has consistent appearance in our data set, since the first timeframe (i.e., 2000) till the last (2013).

6.1.3. Artificial Intelligence (AI)

This area of research is spread over several themes in Table 4, including 7, 9, 12, 15 and 19, mostly focusing on using AI-related algorithms such as search algorithms, computational modeling, machine learning, and data mining to enhance games. These themes fall in line with several of the research areas for AI/CI in games identified by Yannakakis and Togelius [19] including “search and planning”, “player modeling”, and “general game AI” to name a few. Figure 8 shows how the community reached enough critical mass to be detected by our analysis in 2004 and evolved over time. This timeframe for emergence seems realistic considering the community did not fully solidify until the formation of IEEE Computational Intelligence and Games conference in 2005, and the transformation of the AAAI Spring Symposium on Artificial Intelligence and Interactive Entertainment (AAAIISAIIE) to the AAAI conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE) in 2004. Furthermore, the appearance and growth of the AI community in our analysis matches the findings of Lara-Cabrera et al. [20] which identified a marked increase in the number of papers and authors from 2005 onwards, sustaining the steady growth of the field. Thereafter, the community continues to develop and interact with others, especially interactive narrative.

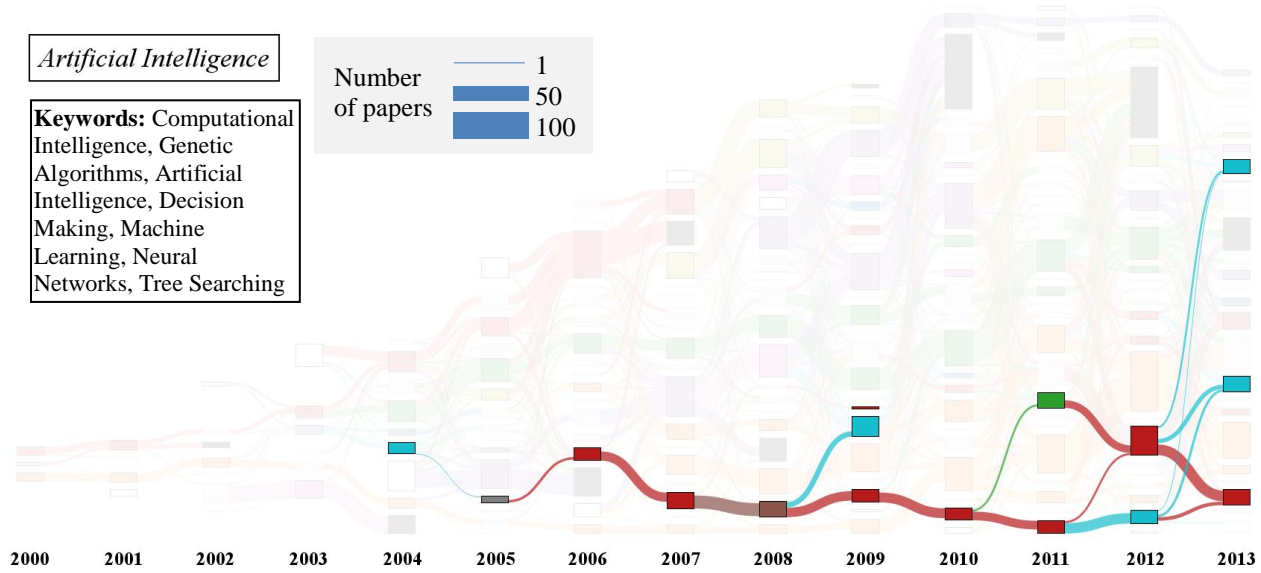


Fig. 8. Evolution of the Artificial Intelligence (AI) community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. Nodes of different colors highlighted here comprise of research papers with slightly different keyword distributions but still considered related to the theme. Overall, this graph indicates a growing body of research on AI in Games since 2004.

6.1.4. Interactive Narrative

Interactive narrative has its roots in an AAAI Symposia where researchers, particularly in the area of AI, were interested in modeling the process of storytelling through artificial intelligence algorithms. The area of research consists of clusters from Theme 2 in Table 4. Examining Figure 9, the community initially emerged in our analysis around 2004 and has shown steady growth from there. This time period for emergence in our analysis appears reasonable considering the recent establishment of major disciplinary venues—such as the International Conference on Technologies for Interactive Digital Storytelling and Entertainment in 2003 and International Conference on Virtual Storytelling in 2001—as well as the publication of notable books discussing the field at the time [48]. Moreover, the increase in growth of the community from 2008 onwards also makes sense considering the creation of additional interactive narrative venues at the time, such as the International Conference on Interactive Digital Storytelling in 2007. Work in this area continues to broaden in focus to address topics such as evaluation of storytelling systems, modeling emotions, virtual characters, and game narrative mechanics.

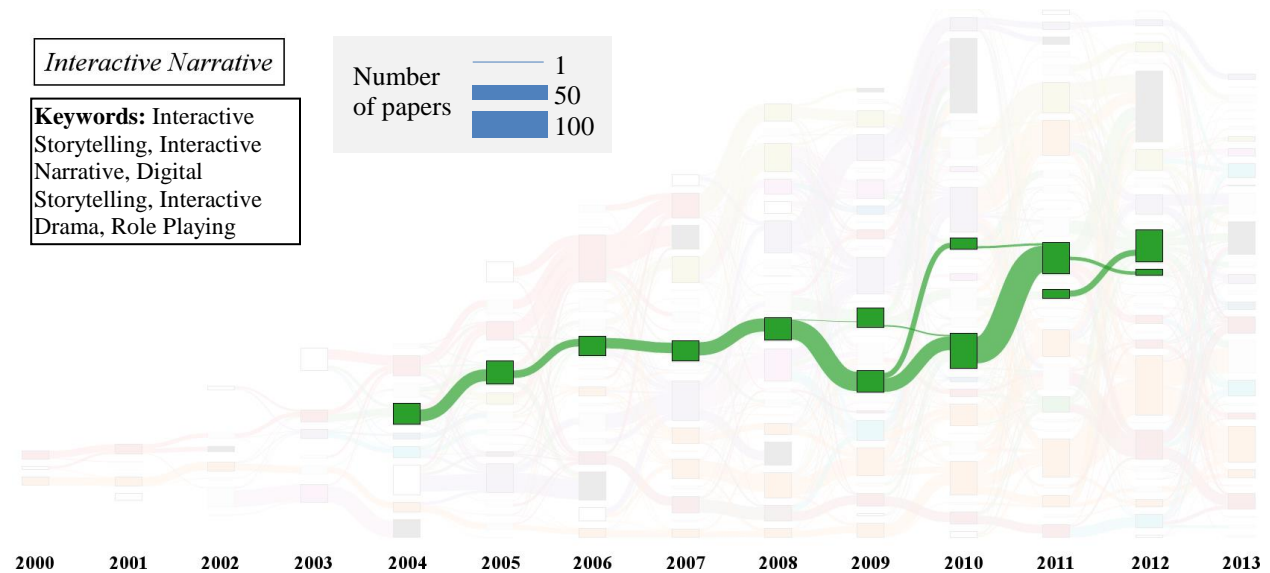


Fig. 9. Evolution of the Interactive Narrative community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. This community is one of the most prominent trends observed in our data set, with at least 50-100 papers published each year since 2004.

6.1.5. Virtual Worlds

This area of research primarily encompasses clusters from Theme 4 in Table 4. Examining Figure 10, we see the consolidation of enough focused research around virtual worlds to create the first detectable cluster in 2005. The Virtual Worlds research community also appears to have undergone a notable amount of growth from 2007 - 2010 where it has remained relatively stable since. The 2005 time period for emergence of virtual worlds research in our analysis seems reasonable when compared to a historical retrospective by Damer [49], noting the substantial decline of virtual worlds right before the “dotcom crash” in 2000 up until the massively successful releases of *Second Life* in 2003 and *World of Warcraft* in 2004. Furthermore, the apparent time period for growth of virtual worlds research aligns with a historical analysis by Messinger et al. [50], which comments on the exponential increase in adoption and use of virtual worlds such as *Second Life* during the mid to late 2000’s. This growth has aided virtual worlds research in the exploration of topics such as education, economics, sexuality, and norms of social behavior [50].

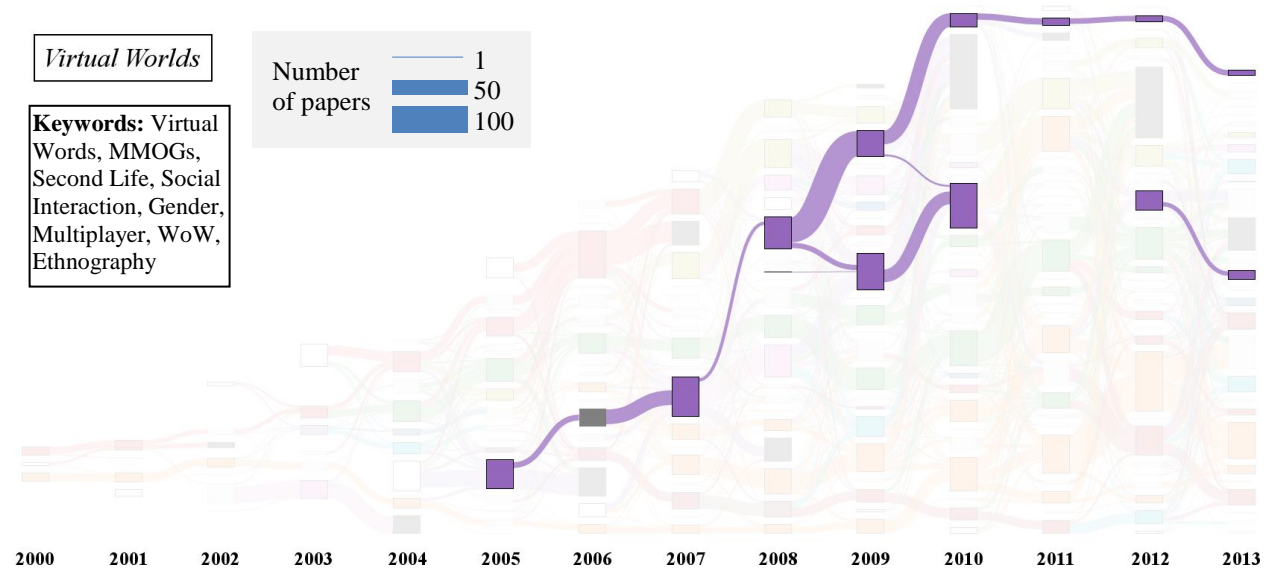


Fig. 10. Evolution of the Virtual Worlds community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. This research community has grown strong since 2005.

6.1.6. Virtual Reality and Virtual Environments

This area of research consists primarily of clusters from Theme 3 in Table 4. In Figure 11, we see the VR community was prevalent at the beginning of our analysis in 2000 and continued until around 2007 where it seemingly disappears until 2012 - 2013 where there is a small reemergence. The early presence of VR in games research is understandable considering the long history of the field before recounted by surveys [51], reviews [52], and reports [53]. Additionally, although the reason for disappearance is unclear, VR's return in 2012 - 2013 seems reasonable considering the appearance of many new VR technologies during that time period (e.g., Oculus Rift [54], Omni [55], and STEM [56]).

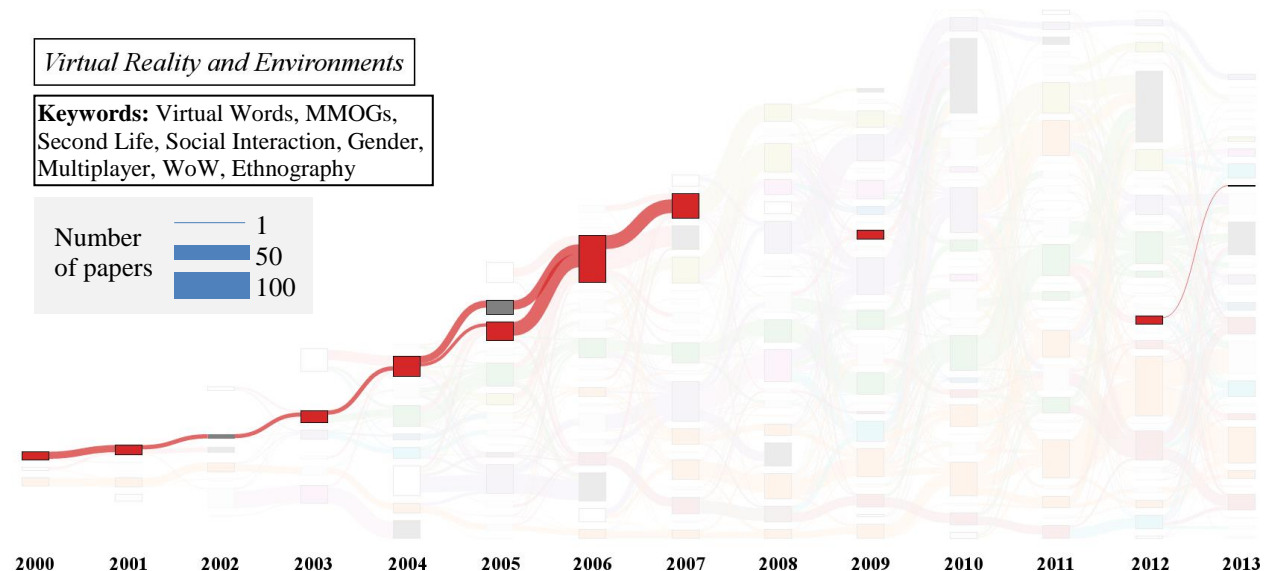


Fig. 11. Evolution of the Virtual Reality community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. Nodes of different colors highlighted here comprise of research papers with slightly different keyword distributions but still considered related to the theme. Overall, this community attracts a lot of papers in the first half of our data set (2000-2007), but its presence seems to significantly diminish in the second half (after 2007).

6.1.7. Augmented and Mixed Reality

This research area is composed mainly of clusters from Theme 8 in Table 4. Inspecting Figure 12, we see the emergence of the AR/MR community in 2005 followed by a considerable amount of growth in 2007 - 2008, and remaining fairly stable afterwards. The appearance and evolution of the AR/MR community in Figure 12 seems reasonably consistent with a review of existing AR games by Tan & Soh [57], which found very few games until 2005 when there was a substantial increase in the number of games, game genres, and types of technology used to implement them (e.g., GPS, camera, motion sensor, VR gloves, HMD). There is also a large number of formative early works from 2005 - 2007 attempting to define [58,59], classify [60], and address technical issues [61,62] around game focused applications of AR such as Pervasive Games.

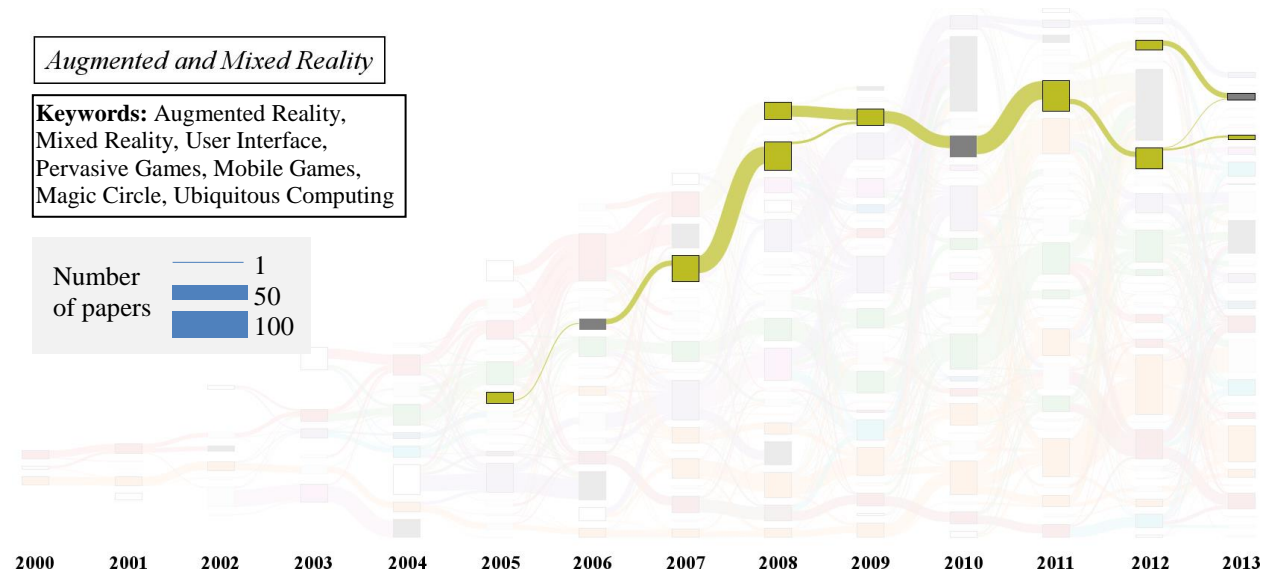


Fig. 12. Evolution of the Augmented and Mixed Reality community in games research over time, with representative keywords of the community shown in box labeled “Keywords”; the x-axis shows time while the scale on the y-axis signifies the number of papers. Nodes of different colors highlighted here comprise of research papers with slightly different keyword distributions but still considered related to the theme. Overall, the graph shows that this community emerges in 2005 with significant growth in 2007-2008 and remains fairly prominent thereafter.

6.2. Community Evolutions and Transitions

Through inspection of links between prevalent communities and other smaller clusters, we also find examples of how communities within games research have evolved (or were influenced by popular trends) and transitioned from one primary topic to another. Some of the more interesting examples found are shown in Figures 13 & 14 and discussed below.

6.2.1. The Evolution and Trends of Educational Games Research

One prominent example on the evolution and trends of a research community is the study of educational games. As noted earlier, Serious Games (Theme 1) is a prevalent community within games research, however it is not the only education-focused community. Looking at other education related themes from Table 4 (i.e., Themes 14 & 17), we see additional smaller communities that arise around education and impact the overall course of the educational games research field (see Figure 13).

Theme 14 is notable because it utilizes general and unfocused education terms such as “education” or “learning”, and appears the earliest chronologically but closes down shortly after the emergence of Serious Games. This seems to indicate that Theme 14 represents much of the early educational games research, and shows how the field transitioned from a relatively basic approach to a larger, more complex umbrella focus.

Theme 17 is also noteworthy because the clusters matched by Seagull tend to focus on gamification, illustrating how a popular term/trend from industry can impact academia. Examining Figure 13, we see the gamification trend became substantial enough to permeate the educational games research community in 2012 and 2013. After the initial popularity and usage of gamification within industry during 2010, its later appearance in games research matches the time period of many academic publications and books defining and applying the term (see [63–66]). Highlighting related clusters using the keyword ‘gamification’ allows investigation of how this sub-community emerges and evolves into a new independent community, starting with roots in Serious Games in 2012 and already beginning to define a new community in 2013.

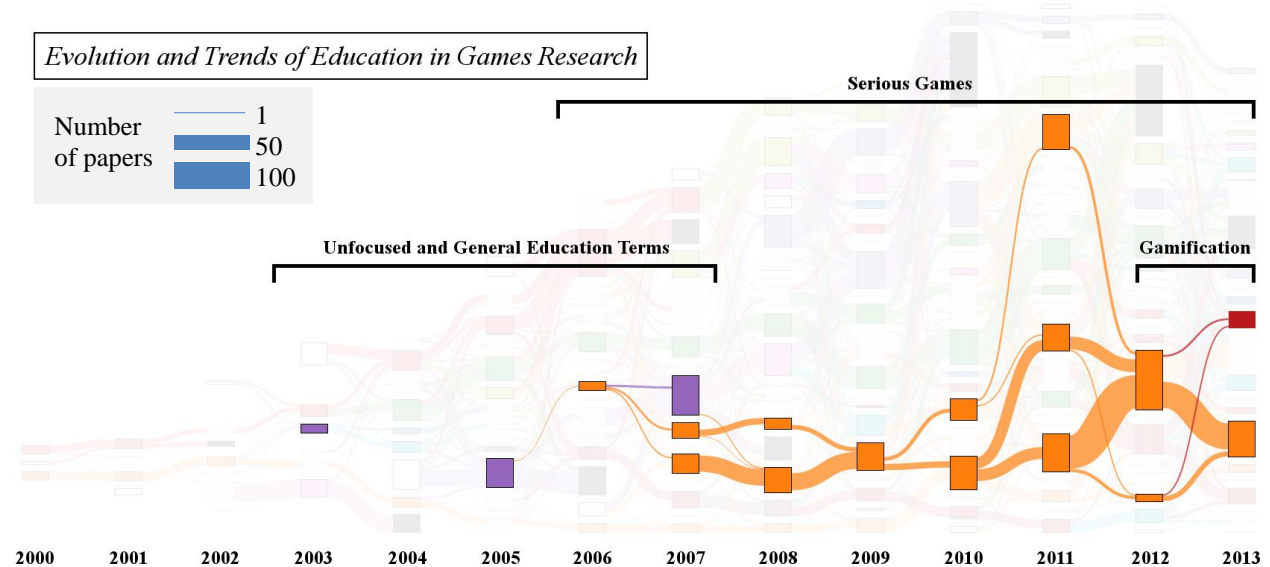


Fig. 13. Evolution and trends of education in games research over time; the x-axis shows time while the scale on the y-axis signifies the number of papers. Nodes of different colors highlighted here comprise of research papers with slightly different keyword distributions but still considered related to the overall theme. Over the years, we observed a growth from unfocused and generally labeled research (2003-2007) into solid communities in Serious Games and Gamification.

6.2.2. The Evolution and Trends of Virtual, Augmented and Mixed Reality Research

Another important event during the evolution of games research is the transition from one research community into another. A notable example of this occurrence is the switch from Virtual Reality research (Theme 3) to Augmented and Mixed Reality research (Theme 8) in 2007. In Figure 14, we see a predominance of VR research with limited amounts of AR/MR work from 2006 - 2007. However, from 2007 - 2008 there is a sudden shift in focus to exclusively working on AR/MR applications while the VR community almost entirely disappears until 2012. Many historical accounts of VR [67,68] note the technical difficulties and commercial failure of VR for games in the 1990's and early 2000's, leading to a "death of VR" until the emergence of new systems powerful enough for gaming in 2012. Although it is not completely clear why there is such a dramatic transition to AR during the 2006 - 2008 time period, it is possibly related to the creation and widespread commercial adoption of many Smartphone devices at the time (such as the first iPhone) [69,70].

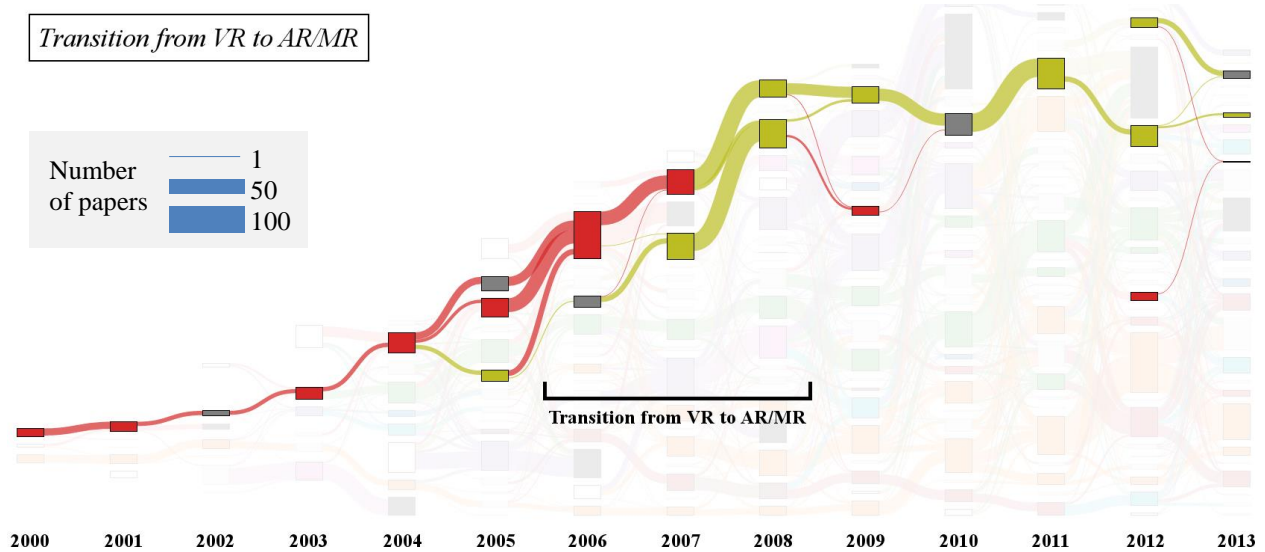


Fig. 14. Interactions and transitions over time for VR and AR/MR communities; the x-axis shows time while the scale on the y-axis signifies the number of papers. Red nodes contain papers belonging to VR research, while yellow nodes those of AR/MR research. Nodes of other colors highlighted here comprise of research papers with slightly different keyword distributions but still considered related to the overall theme. Overall, this diagram indicates a notable shift in research topics from VR to AR/MR during the 2006-2008 period

7. Limitations and Future Work

As noted earlier, the results and data presented here are descriptive and not meant to be definitive or conclusive. The best way to further our findings with more definitive analyses is to supplement it with qualitative data from experts in identified research communities. Their knowledge and insight would help to shed far more light on why a particular theme or community appears to emerge, merge with another community, or diminish altogether. We also provide access to the Seagull system so that fellow researchers may interact with the data further to identify trends and discuss their own conclusions about the field.

We would also like to acknowledge that our dataset contains papers in the period from 2000 to 2013, but not papers from 2014 onwards. The reason is due to the labor-intensive nature of the data collection step, which requires us to seek approvals from publishers for batch downloading of paper metadata, as well as putting together scripts to collect and clean data. The task becomes extremely demanding, as each paper repository has very different storage structure and download requirements. As such, we would like to keep a more up-to-date meta-analysis of the game field as part of our future work. Additionally, after our initial data collection, it has come to our attention that we missed several core European games research venues—i.e., the *Games and Learning Alliance (GALA)* conference, *International Conference on Virtual Worlds and Games for Serious Applications (VS-Games)*, *Joint Conference on Serious Games (JCSG)*, and *International Conference on Game Entertainment Technologies (GET)*. We plan to add these venues to our dataset for future meta-analysis.

7.1. Limitations of the Data-Driven Approach

One major limitation of the described data-driven approach is that while it is efficient in objectively identifying trends and communities, it is prone to the drawbacks of algorithmic automation: (1) the data collected is not exhaustive, missing non-digital and interdisciplinary venues which publish games research, and (2) it does not perform well with subtle changes that are not yet significant, such as merges and transformations that are still early in their development.

As discussed earlier, the data-collection strategy of only conference and journal papers resulted in more technically oriented, specialist themes and communities. This is likely a result of conference and journal publications having a greater weight for technical researchers [6], while other games research communities often view books, monographs, anthologies, and so forth as equally or more important [7,8]. Additionally, the more focused lexicon

and venues of specialist technical disciplines would make them more likely to cluster in our algorithm and appear in the results. In order to address this limited technical focus, future meta-analysis work should be geared towards examining significant generalist venues for games research (such as SIGCHI, SIGGRAPH, AAAI, and ICA). In these endeavors, one of the primary challenges will be vetting a list of keywords that cover as many games-related papers as possible while excluding tangential publications—which would dilute discovery of trends and communities. Furthermore, in order to address the second limitation and considering how constantly changing this young field is at the moment, we plan to conduct a qualitative study in which we will invite senior researchers of the field to comment on the trends observable from our Seagull visualization software. Such a study will hopefully help separate minor patterns that emerge our data-driven algorithmic approach from those that are signs of important new trends and developments.

7.2. Where has the Non-Technical Research Gone?

Perhaps the greatest surprise was to find out how little representation is given to certain less technically focused communities that have profound impact on games research such as Game Studies. Game studies, intended as a critical academic study of games, is an interdisciplinary field with practices that draw heavily from social sciences and the humanities. While social sciences are concerned with the effect that games have on people, the humanities focus on the meaning that can be created through games. Historically, this field has been one of the first to acknowledge the societal and cultural impact of games, and authors from this field have been deeply influential—e.g., Sherry Turkle, T. L. Taylor, and Edward Castronova in the social sciences and Espen Aarseth, Brenda Laurel, and Janet Murray in the humanities, to name a few. This community, albeit recognized and influential, is not clearly seen emerging as a cluster or clusters. This could be due to the large scope of the domain, where keywords are varied and covering many subjects such as immersion, procedural rhetoric, avatars, and online economies; and these are overarching themes used by many communities simultaneously. However, even searching for individual scholars as “author” and “cited author”, the analysis returns few clusters and it becomes very difficult to account for these absences. Only by examining the disciplinary differences did it become clear why this subdomain appears to be underrepresented. First, the selection of core venues for game research publication includes only conferences and journals, while the main publication outlets for this community seem to be books and book chapters, which are hard to retrieve due to their proprietary nature. As such, the exclusion of books and book chapters is problematic but also hardly trivial to address. Second, there are fundamental differences in citation practices: game studies scholars do not tend to map out a domain of inquiry by citing all work that has been done in a certain area, but only cite publications that directly deal with the issue discussed in the article at hand, thus reducing the connectivity within the same community. Third, computer science scholars tend to parcel publications in terms of minimum publishable content, but it is impossible to do so with a book for example, where chapters are not self-standing units but build on each other to create complex conceptual constructs. As such, chapters taken out of a book’s context tend to have less rigorous reference lists, making their connectivity to a community hard to uncover, especially when using automated means. Fourth, scholars from technical disciplines can count on larger and more numerous grants to fund their research, meaning that they can support a much larger number of post-doctoral fellows, PhD students, and graduate students. These students in turn publish papers that cite the work of their supervisors, making research continuity within the same community easier to maintain. These are only a few of the reasons that can begin to account for the relative invisibility of game studies and other less technical communities within games research in the current dataset. Unfortunately, even being aware of such limitations, it is impossible to control for such variables or expand the original dataset without incurring tremendous costs in terms of resources.

8. Conclusion

In this paper, we presented a descriptive data-driven analysis on how the games research field has evolved over time from 2000 – 2013, with a particular focus on technical games research. Conducting a co-evolution network analysis on a total of 8,207 papers collected from major Games Research conferences and journals, we identified 7 prominent communities prevalent during this time period (Serious Games, Simulation and Role Play for Learning, AI, Interactive Narrative, Virtual Worlds, Virtual Reality and Environments, and Augmented/Mixed Reality). Moreover, using a new Sankey-based interactive visualization platform (named Seagull), we discovered some notable evolutions, trends, and transitions that have impacted these communities within the field during the mentioned period, including the proliferation of research looking at Serious Games and their use in education, as well as the transition of research from Virtual Reality to Augmented/Mixed Reality.

As a byproduct of this study, we contributed a new scientometrics methodology towards understanding the evolution of research fields, which uncovers multi-attribute relationships among scholarly articles that make up different communities. Our descriptive presentation of results from this method highlight that such an approach can coherently analyze a field, producing meaningful clusters of research themes for analysis. We also provide Seagull, an interactive visualization system to help understand and analyze our co-evolution results, and allow readers/experts to explore the evolution of games research for themselves to find additional results and offer further insight. Our hope is that given the platform we have built, answers to questions that touch on more nuanced details of the game field, such as “*How to describe the diversity of this research field and its methodological underpinnings?*” and “*What communities, trends, and areas of study will emerge and continue to influence the field moving forward?*” will be found in the near future.

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