Identifying and Improving AGU Collaborations Using Network Analysis and Scientometrics

Tom Narock[1], Sarah Hasnain[1], and Ronie Stephan[1]

[1]Notre Dame of Maryland University, Baltimore, MD, 21210, USA

Correspondence to: Tom Narock (tnarock@ndm.edu)

Abstract. The American Geophysical Union (AGU) is an Earth and space science professional society based in the United States. Research conducted by AGU members ranges from the Earth's deep interior to the outer planets of our solar system. Yet, little research exists on the AGU meeting itself. In this work, we apply network analysis and scientometrics to seventeen years of AGU Fall Meetings. We are interested in the AGU network structure and what its properties can tell us about how the procedures of the AGU Fall meeting can be enhanced to facilitate better scientific communication and collaboration. We quantify several network properties and illustrate how this type of analysis can enhance meeting planning and layout. We conclude with practical strategies for the AGU Program Committee.

1 Introduction

The American Geophysical Union (AGU) is an Earth and space science professional society based in the United States. AGU publishes scientific journals, sponsors meetings, and supports education and outreach efforts to promote public understanding of science. Research conducted by AGU members ranges from the Earth's deep interior to the outer planets of our solar system. Despite the *American* in its name, roughly 40% of the AGU's membership comes from outside of the U.S.[1]

Each year, the AGU hosts a Fall Meeting that draws tens of thousands of participants. The research presented at these meetings has been discussed and debated extensively. However, little research exists on the AGU meeting itself. In this work, we apply network analysis and scientometrics to seventeen years of AGU Fall Meetings. We model the AGU Fall Meetings as graphs in which presentation co-authors are connected nodes and analyze these graphs to ascertain their structure and properties. We are interested in what the structure and network properties can tell us about the scientometrics of the AGU.

Scientometrics is the science of measuring and analyzing science itself, such as a discipline's structure, growth, change, and interrelations (Hood and Wilson, 2001). Vassily Nalimov first coined the term in the 1960s and subsequent work has focused on a discipline's methodologies and principles as well as individual researchers' scientific output (Braun, Glänzel, and Schubert, 2006; Hirsh, 2005). Here, we are using "scientometrics" in the general sense of "the science of science" to understand how science operates and can be improved. Our work is an exploration of possible approaches to developing scientometrics within the Earth and space sciences. We are

[1] Based on data from the AGU's membership page: https://membership.agu.org/

interested in how science collaboration and networking are taking place and how the procedures of the AGU Fall Meeting could be enhanced to facilitate better scientific communication and collaboration. We provide suggestions on how our work can be operationalized; yet, are currently not at an operational stage.

2 Dataset, Assumptions, and Limitations

2.1 Dataset

The data in this study came from the AGU Abstract Browser[2]. The Abstract Browser is a publicly available database of historical abstracts presented at AGU meetings. This database contains abstracts from meetings other than the Fall Meeting, such as the Ocean Sciences Meetings; however, we limited our study to Fall Meetings only. The Fall Meetings are multi-disciplinary and provide the largest most comprehensive subset of data available. Restricting our study to Fall Meetings provides the most data and also ensures equal coverage of the sub-domains covered by AGU. Our study includes 17 years of data and covers the Fall Meetings from 2000 to 2017.

The AGU is divided into sections representing the subdisciplines of Earth and space science. As science evolves over the years, new sections are formed, and older ones can be merged or dissolved. The sections on which we had data to perform our analysis are listed in Table 1.

Table 1. The AGU sections covered in this study.

Abbreviation	Full Name
A	Atmospheric Sciences
AE	Atmospheric and Space Electricity
B	Biogeosciences
C	Cryosphere
DI	Study of the Earth's Deep Interior
ED	Education and Human Resources
EP	Earth and Planetary Surface Processes
G	Geodesy
GC	Global Environment Change
GP	Geomagnetism and Paleomagnetism
H	Hydrology
IN	Earth and Space Science Informatics
MR	Mineral and Rock Physics
NG	Nonlinear Geophysics
NH	Natural Hazards
NS	Near Surface Geophysics
OS	Ocean Sciences
P	Planetary Sciences
PA	Public Affairs
PP	Paleoceanography and Paleoclimatology
S	Seismology
SA	SPA-Aeronomy
SH	SPA-Solar and Heliospheric Physics
SM	SPA-Magnetospheric Physics
T	Tectonophysics
U	Union

[2] http://abstractsearch.agu.org/about/

V	Volcanology, Geochemistry, Petrology

Data were retrieved by programmatically querying the AGU Abstract Browser's Linked Open Data interface[3,4]. Linked Open Data (LOD, Berners Lee, 2006; Bizer et al., 2009) is part of the methods and tools collectively known as the *Semantic Web* (Hitzler et al., 2010), which aim to bring machine-readable meaning to the Web through common data formats, exchange protocols, and computational reasoning. The LOD methodology has become a widely adopted data sharing format and at last count (Hogan et al., 2011), roughly thirty billion semantic statements were available on the emerging "Web of Data". In 2012 the AGU's historical abstracts were converted to LOD (Narock, Rozell, and Robinson, 2012; Rozell, Narock, and Robinson, 2012) with new meeting data being added each year.

2.2 Limitations and Assumptions

The Abstract Browser contains Fall Meeting data such as sessions held, presentations given in each session (including title, authors, affiliations, and an abstract), and the AGU section in which the session was held. However, the author data contains only email address, last name, and initials. Moreover, the same author sometimes has only a first initial while other times having a first and middle initial. The first author of this study is a prime example. He appears in the abstract database as both: T. W. Narock and T. Narock. This raises significant challenges for autonomously disambiguating people. Further complicating this issue is the case where authors change institutions. For example, T. Narock appears with his graduate school email address and later with the email address of his affiliation post-graduation. Each author does have an organizational affiliation provided; however, this data is also messy and difficult to use for disambiguation. There is no standard naming convention and the same institution often appears with multiple names. For example, the NASA Goddard Space Flight Center is listed as NASA/Goddard, NASA/GSFC, and NASA/Goddard Space Flight Center. Ideally, authors would be listed with their ORCID (Haak et al., 2012); however, at present, such data is not available via any public AGU interface that we are aware of. Lacking the means to perform a large-scale crowdsourced disambiguation project, we sought other means to disambiguate authors.

We considered email address to be a unique and distinguishing feature. Our disambiguation efforts consisted of finding all cases where email address and last name were the same, but initials only partially matched. For example, [T. Narock, tom.narock@gsfc.nasa.gov] was considered the same person as [T. W. Narock, tom.narock@gsfc.nasa.gov]. This approach identified 56,155 matches, which we corrected in our dataset. Yet, there are likely many other authors who were not disambiguated. We identified an additional 19,896 cases where last names matched, initials were a partial match, and email addresses differed (e.g. [T. W. Narock, tom.narock@gsfc.nasa.gov] and [T. Narock, tnarock@ndm.edu]. Many of these people are likely the same (the example given here is known to be the same); yet, in the vast majority of cases we have no means of knowing for sure and have chosen not to claim these authors as identical. Thus, our results have an inherent uncertainty to them.

[3] http://abstractsearch.agu.org/about/lod
[4] http://abstractsearch.agu.org:8890/sparql

Specifically, the network graphs we construct from the AGU data likely have multiple nodes representing the same person. As such, we consider the network analysis portion of our study a lower limit. We know that the actual values for network density and connected components are not lower than the values reported here, and they would likely be a bit higher had we been able to uniquely identify all authors in our dataset. Despite this limitation, we feel our analysis can still provide useful insights into the AGU meetings.

All networks are comprised of nodes (also called vertices) and edges (connections between the nodes). Networks also come in multiple types ranging from directed to undirected. Twitter is an example of a directed network. Edges have directionality in a directed network. For example, Twitter user A can follow user B; however, user B is not obligated to follower user A back. The edge between users A and B would have directionality. In an undirected network all edges are bidirectional by default. This is how "friending" works in Facebook. Both users (nodes) must agree to the "friendship" and a link (edge) is created. There are no directed edges allowed in an undirected network.

We model each AGU section as an undirected network based on co-authorship. If A co-authored a presentation with B and C, then A, B, and C become nodes in the network with bidirectional links between each (e.g. A-B, A-C, B-C). We do not apply any weighting to the edges. If authors A and B co-authored a presentation at the 2000 Fall Meeting and then again at the 2010 Fall Meeting this adds no new information to the graph. We also consider edges to be eternal when studying the temporal evolution of the network. For example, if authors A and B co-authored a presentation at the 2000 Fall Meeting these nodes and edges persist in 2017 even if those authors never co-authored another presentation. We also note that we are measuring co-authorship and not necessarily collaboration. Our dataset does not contain references and acknowledgements used in presentations. These secondary connections (e.g. citing a paper or acknowledging a discussion) do not show up as edges in our graphs.

2.3 Open Source Software

The analysis software used in this study is freely and publicly available from Narock et al. (2019). The graph data generated from our software is available in Narock et al. (2018a)

3. Network Analysis

3.1 Network Density

Network density is defined as the ratio of actual connections to possible connections. Possible values for network density range from 0 (no connections at all) to 1 (everyone is connected to everyone else). Figure 1 illustrates the concept of network density on sample networks. In 1.) of Figure 1 there are three nodes and three potential connections. These three potential connections are realized as all nodes are connected to each other. This is representative of the AGU case in which A, B, and C have co-authored presentations with each other; although, not necessarily the same presentation. The network in 1.) has a density of 3/3 = 1.

The network shown in 2.) has the same three potential connections. However, only two of the nodes are directly connected. In this example, A has co-authored a presentation with B and B has co-authored a presentation with C; yet, A has not co-authored a presentation with C. The network in 2.) has a density of 2/3 = .67.

It's unlikely that a real-world network such as the AGU would have network density of 1. Given the diversity of research topics it's unlikely that the network would be completely connected. But, what are the actual density values and how do they change over time?

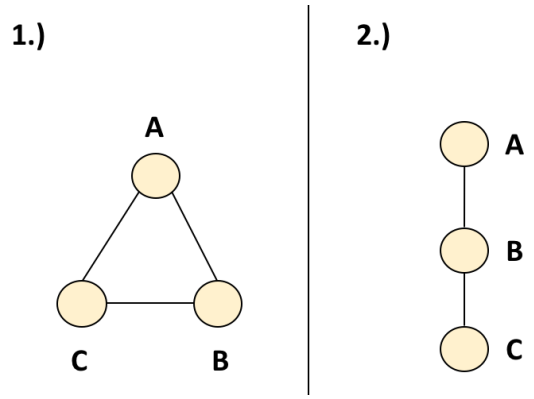

Figure 1. Example networks and network density.

To answer these questions, we first considered each AGU section to be its own network. Yearly network graphs were then created for each section using the Abstract Browser data. Next, we computed the percentage change in network density for each section. We note that percentage change values do not always encompass the whole 17 years of the data. For example, the Earth and Space Science Informatics (IN) section did not come into existence until 2005. Percentage change was computed using the first year in which we had data and 2017. Results are shown in Figure 2.

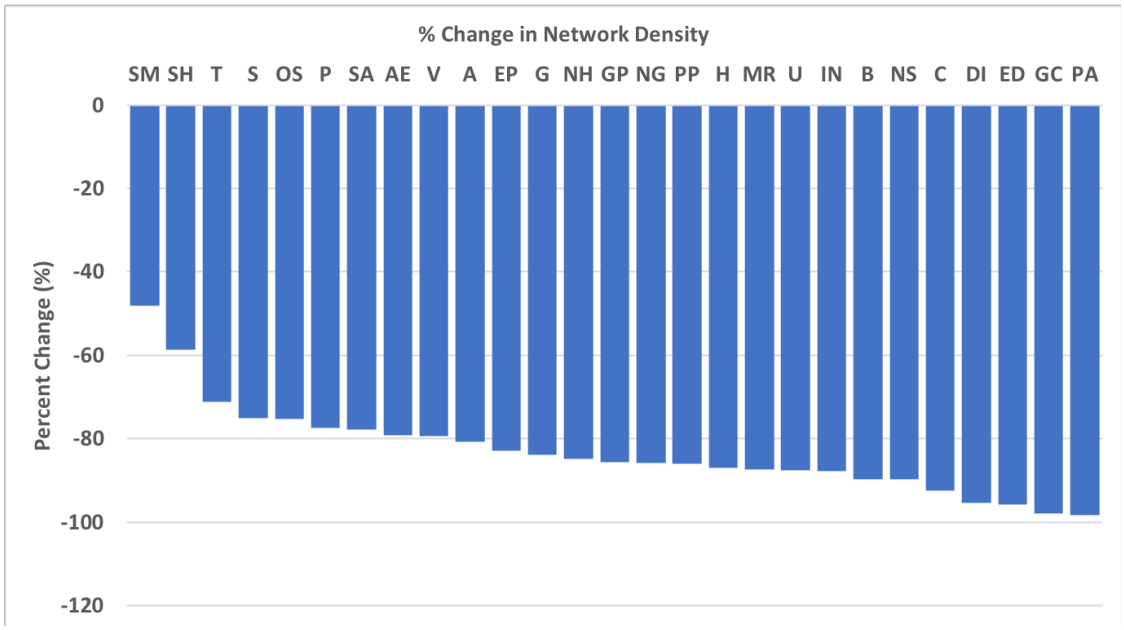

Figure 2. Percentage change in network density.

Network density decreases for all sections. This is telling us that nodes are being added faster than edges. In practical terms, the rate at which new people (nodes) are attending AGU sessions is greater than the rate at which continuing attendees (nodes) are making new connections. Again, these percentage change values should be considered a lower limit given our inability to completely disambiguate the authors in our data.

We expect network density to decrease over time. For density to remain constant, each new node must also be accompanied by an even larger number of new edges. However, we are surprised by the extent to which density is decreasing. If a large number of new collaborations were being found at AGU, then existing nodes would have new edges at a rate comparable to new nodes being added. This appears to not be the case.

3.2 Connected Components

In graph theory, a connected component of an undirected graph (also referred to as a component) is a subgraph within the whole graph. Figure 3 shows an example. The network in the figure is comprised of three connected components. Although not shown here, an isolated node not connected to any other nodes in the network is also considered a connected component. Analysis of connected components within the AGU networks gives us an indication of how fragmented the networks are.

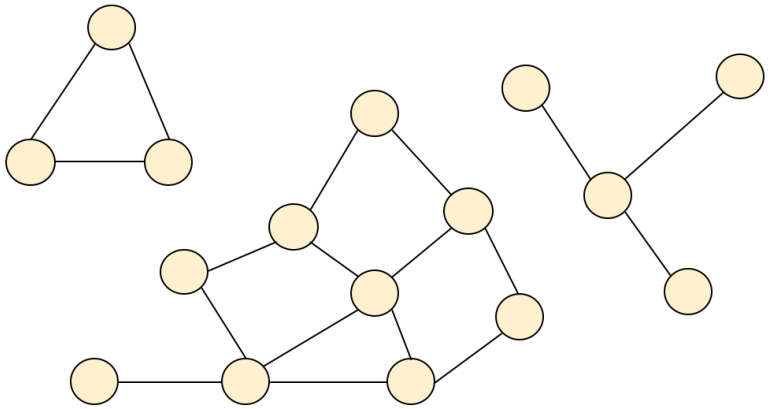

Figure 3. An illustration of connected components. This graph has three connected components.

Table 2 lists the connected components of the AGU section graphs. Specifically, we combined all 17 years of data for each section and computed the number of connected components for the section, the percentage of the total nodes that make up the largest component, and the percentage of components comprised of a single node. Sections in Table 2 are ordered by decreasing size (number of nodes).

Table 2. Connected Components of AGU Section Graphs (sorted by network size).

Section	Total Number of Nodes	Number of Connected Components	% of Total Nodes in Largest Component	% of Connected Components Having a Single Node
Hydrology (H)	40,311	2,060	88%	2.0%
Biogeosciences (B)	32,704	1,407	88%	1.4%
Atmospheric Sciences (A)	32,224	1,139	91%	1.4%
Tectonophysics (T)	20,955	814	92%	1.7%
Global Environment Change (GC)	20,852	1,770	76%	2.8%
Volcanology, Geochemistry, Petrology (V)	19,638	889	89%	1.8%
Ocean Sciences (OS)	19,202	1,235	84%	2.6%
Paleoceanography and Paleoclimatology (PP)	15,279	530	91%	1.1%
Seismology (S)	14,535	607	91%	1.9%
Education and Human Resources (ED)	12,867	1,970	60%	6.5%
Cryosphere (C)	12,508	508	89%	1.3%
Planetary Sciences (P)	12,476	495	90%	1.6%
Earth and Space Science Informatics (IN)	10,778	884	75%	2.6%
Earth and Planetary Surface Processes (EP)	10,681	883	73%	1.7%
Union (U)	10,489	1,426	63%	6.0%
Natural Hazards (NH)	9,611	1,125	60%	2.9%
Geodesy (G)	8,479	393	88%	1.6%
SPA-Magnetospheric Physics (SM)	7,415	169	95%	1.3%
SPA-Solar and Heliospheric Physics (SH)	6,584	262	92%	2.1%

Geomagnetism and Paleomagnetism (GP)	6,009	297	86%	1.6%
SPA-Aeronomy (SA)	6,003	202	92%	1.5%
Mineral and Rock Physics (MR)	5,649	481	74%	1.9%
Nonlinear Geophysics (NG)	4,943	884	43%	5.0%
Public Affairs (PA)	4,708	1,154	12%	9.4%
Study of the Earth's Deep Interior (DI)	4,286	267	82%	1.3%
Near Surface Geophysics (NS)	4,105	501	53%	1.9%
Atmospheric and Space Electricity (AE)	2,143	108	85%	1.4%

The diversity of research topics likely guarantees that we are going to have some fragmentation of the network. Not everyone is working on the same topic and we would expect to see the number of connected components greater than 1. Moreover, there's nothing wrong with working by oneself and single node components are to be expected. Yet, quantifying these network features helps in the development of geoscience communication strategies. From Table 2 we see that the majority of available nodes are part of the largest connected component. This is true regardless of section size. The only notable exceptions are Public Affairs and Nonlinear Geophysics. Similarly, we see a very small percentage of single node components. Notable exceptions here are Public Affairs, Education, and Union. Public Affairs, Education, and Union often have contributions from other sections, which likely accounts for the increased fragmentation and single node components. Although, Nonlinear Geophysics result is surprising and in need of further research.

3.3 Multi-Disciplinary Authors

We define a multi-disciplinary author as anyone who appears in the network graph of more than one AGU section. We looked at all pair-wise comparisons of sections and obtained the results in Figure 4, which shows the number of unique authors who have appeared in both sections over the 17 years of data. We account for differences in section size by normalizing the data. The fractional values shown in Figure 4 are the number of authors presenting in both sections divided by the combined sizes of both sections. For instance, there nearly 8,000 individuals who presented in both Biogeosciences (B) and Hydrology (H) during the time period 2000 to 2017. The B-H entry in Figure 4 is this 8,000-value divided by the total number of nodes in B and H.

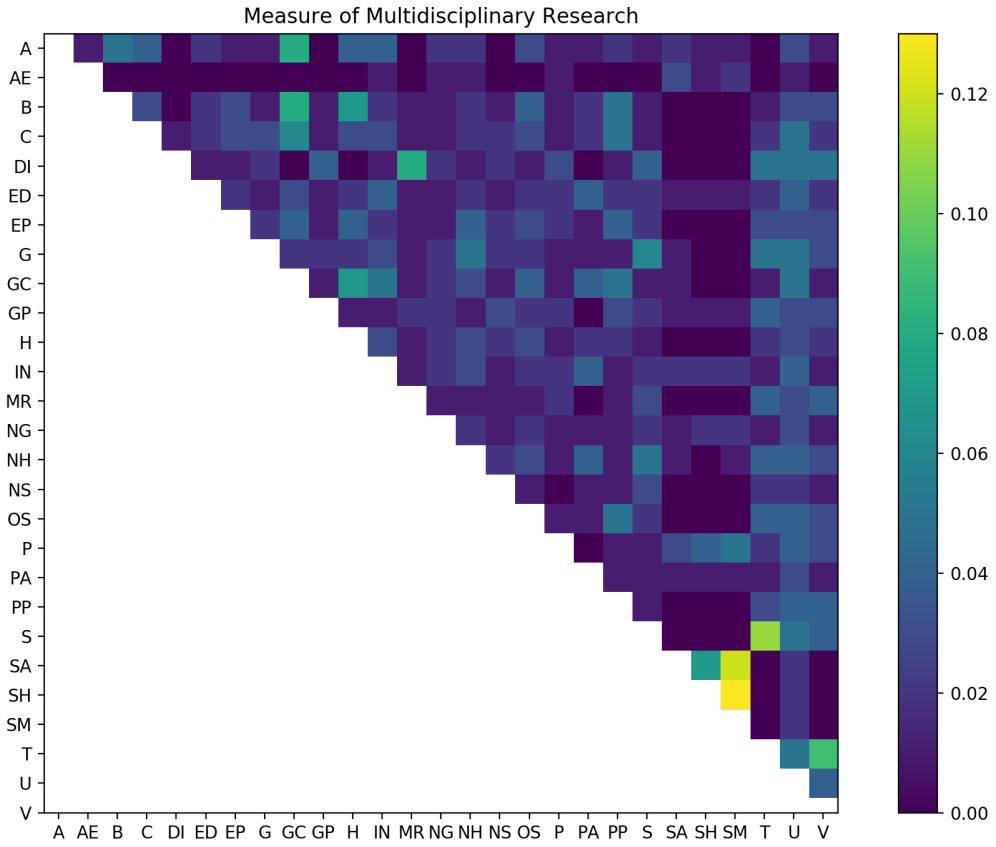

Figure 4. Normalized number of occurrences of authors presenting in more than one section over the years 2000-2017. The fractional values in each pair-wise comparison are the number of authors presenting in those sections over the time period 2000-2017 divided by the size of both sections.

Aside from the related space physics sections of SH and SM, we do not see a significant amount of presentations across sections. Authors tend to stay within their primary domains.

3.4 Keyword Usage Across Sections

Authors submitting to the Fall Meeting are asked to tag their abstracts with keywords from the AGU's keyword hierarchy[5]. We computed counts of each keyword category for each year of our dataset across all sections. For instance, *Post-secondary Education* and *Teaching Methods* are sub-topics within the higher-level *Education* section of the keyword hierarchy. If the Hydrology section had an abstract tagged with *Post-secondary Education* in 2005 and an abstract tagged with *Teaching Methods* in 2005 then this would be counted as two *Education* abstracts for the year 2005. We note that abstracts are not exclusive to one keyword group. Authors are free to self-tag their abstracts with multiple keywords that may span multiple parts of the keyword hierarchy. This is reflected in our analysis where the same abstract may contribute to keyword usage counts in multiple parts of the keyword hierarchy.

[5] https://publications.agu.org/author-resource-center/index-terms/

For clarity of display, we filtered out keyword groups that did not reach 100 occurrences during the 17 years in which we had data. Figures 5 through 8 highlight specific trends in keyword usage that were observed in our data. The full set of images showing keyword usage from all keyword categories is included in the Appendix.

Scenario 1 - Two (or more) seemingly unrelated groups use the same topics

The Earth and Space Science Informatics (IN) section self-describes[6] itself as being "concerned with evolving issues of data management and analysis, technologies and methodologies, large-scale computational experimentation and modeling, and hardware and software infrastructure needs". These concerns span many areas of geoscience and one might expect IN related keywords to appear in several computationally intensive domains. This does in fact occur as evidenced in Figure 5. Yet, we also see a sharp rise in the Natural Hazards section's usage of IN keywords from 2016 to 2017.

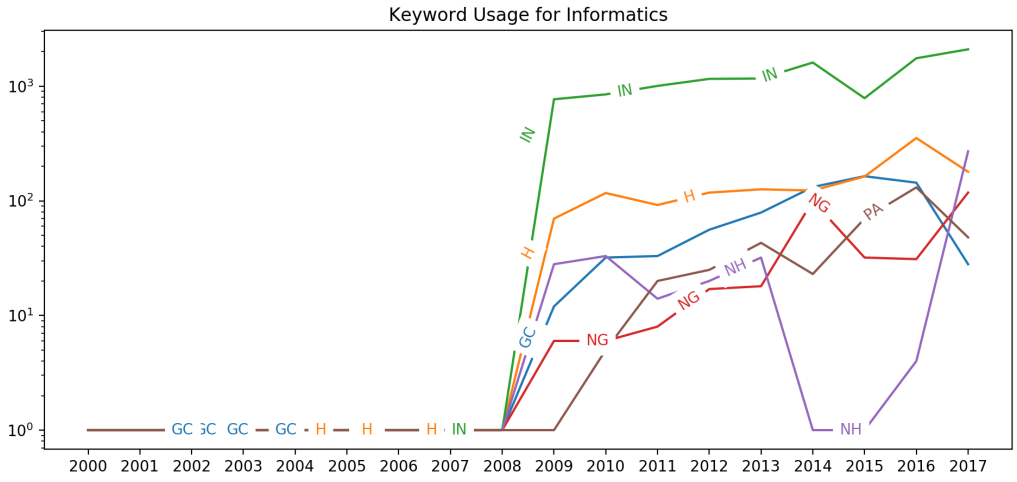

Figure 5. Informatics themed keyword usage

Prior to 2016, the Natural Hazard section never had a year in which they received more than 33 abstracts tagged with IN keywords (see 2010 through 2013 in Figure 5). Suddenly, in 2017 they received 270 abstracts tagged with IN keywords. This is up from 4 such abstracts in 2016. The bulk of these 270 abstracts in 2017 can be attributed to the *Data Assimilation, Integration, and Fusion* and *Forcasting* topics. These two keyword categories accounted for 87% of the Natural Hazard IN-related abstracts in 2017. In this particular case, it appears to be specific sessions soliciting topics as opposed to organic emergence of collaborations. The vast majority of these submissions are to one session, NH23E.

To us, this is indicative of the power of simple scientometric visualizations. By simply counting keywords we can begin to identify emerging trends, which, as we discuss further in the next section, can be exploited by meeting and section leadership to better structure future Fall Meetings. Further, more detailed analysis, such as the example

[6] https://essi.agu.org/

above, identify very effective session planning and emerging science, which can further be exploited by section leadership and the AGU Program Committee.

Scenario 2 – Increase in Volume

The Planetary Science section is the primary user of Astrobiology keywords as shown in Figure 6. Usage from 2005 to 2010 was more or less consistent. However, beginning in 2011 a sudden increase in usage is seen that continues to today. A similar trend is seen with Education keywords in Figure 7. In 2015, Public Affairs and Union sessions saw an increase in abstracts tagged with Education keywords. Yet, while Public Affairs usage of Education keywords increased gradually, Union's usage of the same keywords had a sudden uptick in 2017.

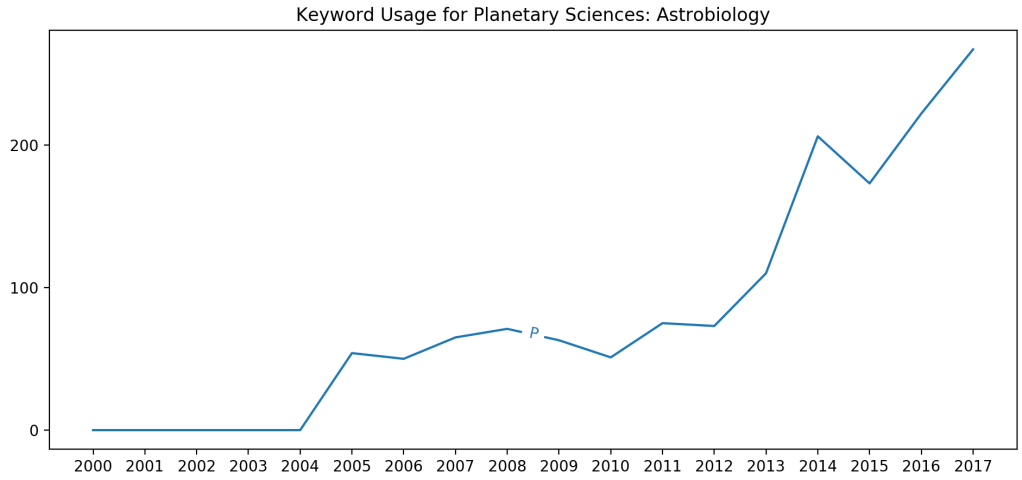

Figure 6. Astrobiology keyword usage.

It may not be surprising that planetary scientists are using astrobiology terms to tag their abstracts. Meeting attendees may even have anecdotal evidence of observing this themselves. Yet, had someone been tracking this data in 2012 and 2013 we could have seen this trend emerging. This information could have gone into meeting planning and potentially led to more physical space at the meeting venue, joint sessions, increased public outreach, and other initiatives that could have maximized the dissemination of astrobiology science.

The related trend, Figure 7, shows Union sessions having a sudden uptick in Education-related. A scientometrics and data driven AGU could leverage this information in being proactive with joint sessions and when/where presentations are given at the Fall Meeting. We explore this in more detail in the next section.

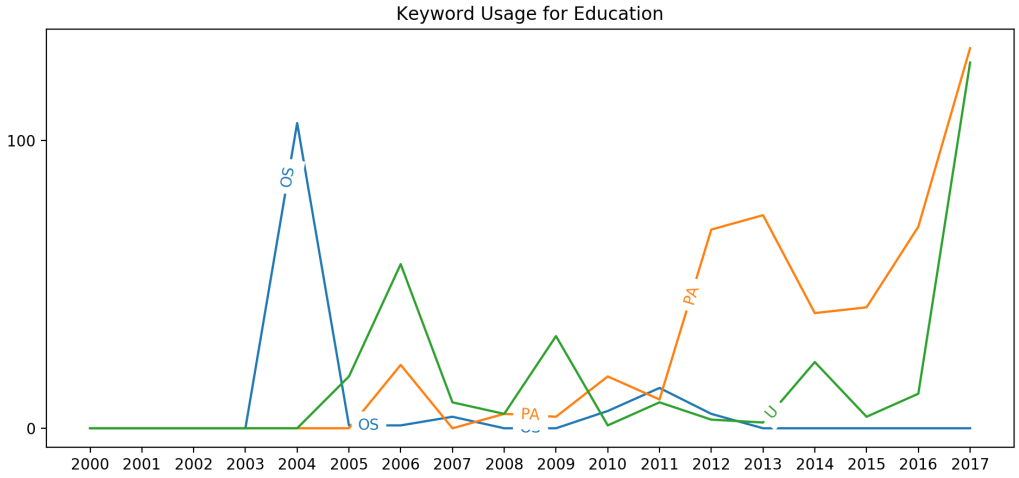

Figure 7. Education keyword usage.

Scenario 3 - Keyword Usage May Indicate New Science

The Earth and Space Science Informatics section was formed in 2005. From 2005 until 2008 this section did not have any section-specific keywords in the aforementioned AGU keyword hierarchy. In 2009 IN-specific keywords were introduced. We see this clearly in Figure 8 where IN's usage of *General or Miscellaneous* keywords decreased significantly between 2008 and 2011 as IN-specific keywords began to be used. Yet, we also see a steady increase in *General or Miscellaneous* from 2011 to 2015. Further analysis of this keyword group reveals steady usage of *General or Miscellaneous: Instruments useful in three or more fields* and *General or Miscellaneous: Techniques applicable in three or more fields* during the time period 2011 to 2015. This is suggestive to us that emerging computational approaches and collaborations are not adequately reflected in the AGU keyword hierarchy. This may be more than just the frustration of not finding an appropriate keyword to tag one's abstract. New science may be emerging that could be capitalized on in subsequent Fall Meetings if we are watching the evolution of the AGU network. Further exploration of this particular trend would involve more data than we currently have available and is outside of our current scope.

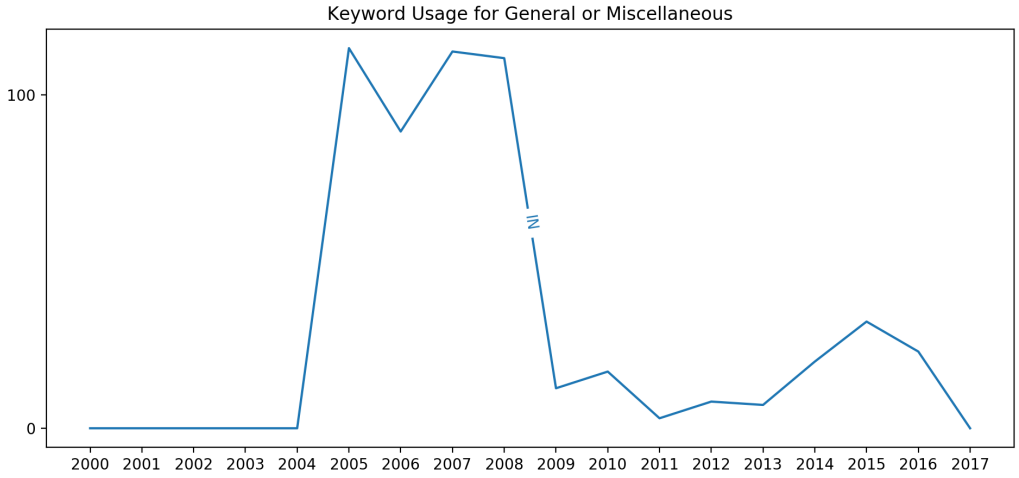

Figure 8. General or Miscellaneous keyword usage.

4 Scientometrics

AGU Fall Meetings are already very busy. Figure 9 shows the number of presentations given each year from 2000 to 2017. We see a steady increase in presentations with the 2017 Fall Meeting having over 20,000 accepted presentations. Fall Meeting attendees are already hard-pressed to see everything of interest. Using network analysis and having section leaders be proactive prior to a meeting can improve efficiency of science communication and collaboration.

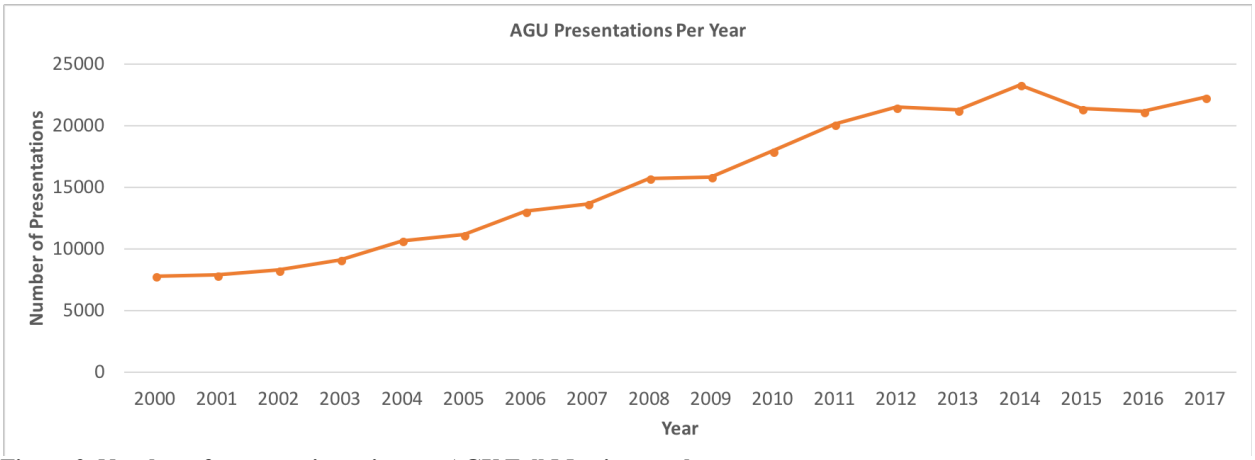

Figure 9. Number of presentations given at AGU Fall Meetings each year.

In regard to network density and connected components, there is no optimal network clustering value. However, lower density networks comprised of many loosely connected clusters have been shown to be beneficial (Burt, 2004). In these networks, everyone doesn't already know each other, and multiple clusters lead to new and unique perspectives. On the contrary, when everyone knows everyone else (density=1) you're more likely to repeatedly hear the same ideas (Burt, 2004).

In order for information to spread across a network there needs to be connections between the clusters. We want to avoid the scenario depicted in Figure 3 and have at least one connection between each connected component in an AGU section. By knowing how many connected components there are, what is the primary research topic of each (most used keyword), and whom the components are comprised of, can be beneficial for meeting planners and section leadership. For the AGU Fall Meeting, session proposal is open to any self-organized group of up to four AGU members. Authors then opt to have their submission assigned to a particular session. We could make this process more proactive by providing section leadership with connected component data and encouraging connections between specific AGU members. This could range from informal networking events to suggesting session co-conveners.

4.1 Steps Towards Optimizing Meeting Space

One potential means of enhancing the AGU Fall Meeting is to optimize the physical layout of the event. Historically, oral presentations are arranged by section with a section having all of its talks grouped in the same part of the building. The poster hall is organized alphabetically by section. What if we leveraged what we're seeing in Figures 5 and 7 to physically place related sections next to each other? For example, the Fall Meeting could place Natural Hazards posters next to Informatics posters to stimulate more discussion. Similarly, Public Affairs and Union sessions could be physically located near Education sessions and, having identified the trend in Figure 7, attendees could be encouraged to visit related presentations they may not otherwise be aware of. The AGU has been exploring a related idea via their Scientific Neighborhoods[7]. Although, to the best of our knowledge, Scientific Neighborhoods are not based on any network analysis.

Another option is to facilitate navigation of the meeting via analytics tools built on top of the AGU's historic meeting data. A simple example is shown in Figure 10. This so-called force directed graph adds additional information to a standard network graph. In a force directed graph the distance between two nodes is indicative of the strength of the connection. For instance, in Figure 10 we are showing the 10 AGU members who most used the oceanographic *Aerosols* keyword. R. Weber has used this keyword the most over the 17-year period 2000 to 2017. This is indicated in the figure where the R. Weber node is closest to the central *Aerosols* node.

[7] https://fallmeeting.agu.org/2018/scientific-neighborhoods/

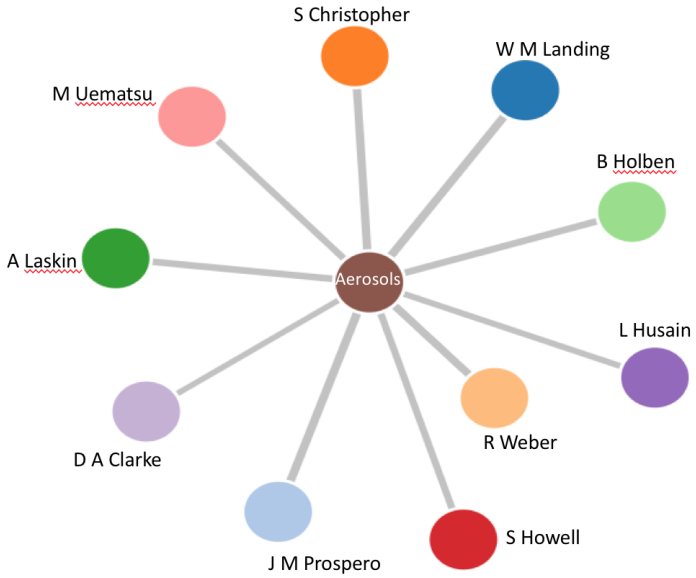

Figure 10. Force directed graph of oceanographic aerosols keyword usage.

We want to be clear that we are ***not*** advocating for any sort of new metric. We do not need to rank researchers nor do we need to rank the value of their work based on where it's presented. The journal impact factor does a poor enough job of this already (Shanahan, 2016). Rather, we are advocating for tools that would help attendees, especially early-career and new attendees, identify whom they might want to seek out based on their research interests. Figures 11 through 13 show an example tool we built for the AGU Open API Challenge[8,9]. After identifying a researcher, possibly through a visualization like Figure 10, the user is guided through finding that researcher in the historical abstract database (Figures 11 and 12). The co-authorship network is then leveraged to identify all AGU presenters who have co-authored a presentation with the researcher of interest. Figure 13 shows an example for our colleague Peter Wiebe. For brevity, only the 2018 co-authors are shown in the figure. The Abstract column in Figure 13 lists the year of presentation, the section of the presentation, and the presentation ID. Each row in the Abstract column is a clickable link that will take the user to a web page displaying the presentation title, keywords, and abstract. In this manner, AGU attendees can *follow the network* to explore existing connections amongst nodes and topics. At present, Fall Meeting data is not available in the Abstract Browser until after the Fall Meeting concludes. Making this data available prior to the meeting could lead to new tools and apps. AGU does appear headed in this direction with its recent Open API Challenge.

[8] https://developer.agu.org/projects/
[9] http://apiprojects.agu.org/project1/

Figure 11. Step one of the author search tool.

Name	Affiliation
Wiebe, B	University of the Fraser Valley, Abbotsford, BC, Canada
Wiebe, P H	Woods Hole Oceanographic Inst, Woods Hole, MA, United States
Wiebe, K	International Food Policy Research Institute, Washington, DC, United States

Figure 12. Step two of the author search tool. The system returns all matching authors.

Person	Abstract
Ake, H	2018, OS, OD34B-2759
Copley, N J	2018, OS, OD34B-2759
Saito, M A	2018, OS, OD34B-2759
Switzer, M	2018, OS, OD34B-2759
Biddle, M	2018, OS, OD34B-2759
Kinkade, D	2018, OS, OD34B-2759
Rauch, S	2018, OS, OD34B-2759
York, A	2018, OS, OD34B-2759
Shepherd, A	2018, OS, OD34B-2759
Gjster, H	2018, OS, ME34A-0957
Ingvaldsen, R B	2018, OS, ME34A-0957
Knutsen, T	2018, OS, ME34A-0957
Hobson, B	2018, OS, IS43B-02
Risi, M	2018, OS, IS43B-02
Yoerger, D R	2018, OS, IS43B-02
Breier, J A Jr	2018, OS, IS43B-02
Fujii, J	2018, OS, IS43B-02

Figure 13. The result of our author search tool is a web table with links to everyone who has ever co-authored a presentation with the author of interest. Users can explore the abstracts and network connections of those co-authors – and their co-authors.

4.2 Steps Toward Gender Equality

Ford and colleagues (Ford et al., 2018) have identified a gender imbalance in AGU presentations. Women are invited and assigned oral presentations less often than men. It was found that male primary conveners allocate invited abstracts and oral presentations to women less often and below the proportion of women authors. This trend was apparent regardless of the male primary conveners being students or at more senior career stages. Ford et al. (2018) also identified that women elect for poster only presentations more so than men.

The dataset used in this study has a longer timespan than the one used by Ford et al. (2018). However, our dataset does not include gender or career stage information. We cannot add any new information on the gender imbalance discussion. Scientometrics and network analysis may provide tools to counter this imbalance. Yet, we are cognizant that more open data may exacerbate the problem by exposing presenters to more opportunities for bias. We highlight these issues here as it is a discussion very much worth having. However, at this time, we are unable to offer any additional data, insights, or strategies.

4.3 Steps Toward Connections to Other Networks

GeoLink (Narock et al., 2014; Krisnadhi et al., 2015; Cheatham et al., 2018) is a collection of Linked Open Data that addresses scholarly discovery and collaboration in the geosciences. GeoLink leverages the Semantic Web to publish open data regarding data centers, digital repositories, libraries, and professional societies. One component of the GeoLink knowledge graph (Cheatham et al., 2018) is a collection of all National Science Foundation (NSF) funded projects. Figure 14 (reproduced from Narock and Wimmer, 2017) illustrates what can be done when one network is connected to another. This figure is produced by subsetting the GeoLink NSF funded projects by people who have presented at AGU. In particular, we are looking at *Semantic web and semantic integration* - a keyword in the Informatics portion of the AGU keyword hierarchy. Combining these two open datasets allowed us to identify which AGU authors had active funded grants at the time of their AGU presentation. We define “active funded grant” as the AGU presentation date falling between the NSF grant’s start and end date. We then looked at the distribution of funding sources. Figure 14 shows the NSF divisions and offices that have funded an AGU author’s semantic project. This is only one example and specific to one topic area. Yet, it illustrates the potential of open science and cross-organizational network analysis. We can begin to see how this research topic is funded by the NSF. In addition, we can start to see the scientific results (AGU presentations) attributable to each NSF division. In this regard, AGU scientometrics can go beyond optimizing Fall Meetings to more general enhancements of open science and science communication. Exponential growth is being observed with the amount of available Linked Open Data roughly doubling each year. Corporations (e.g., the BBC and BestBuy), governments (e.g., the U.S. and U.K. governments), Wikipedia, social networking sites (e.g.. Flicker, Facebook and Twitter), and various academic communities are all contributing to the movement (Hogan et al., 2011). We encourage AGU to do the same.

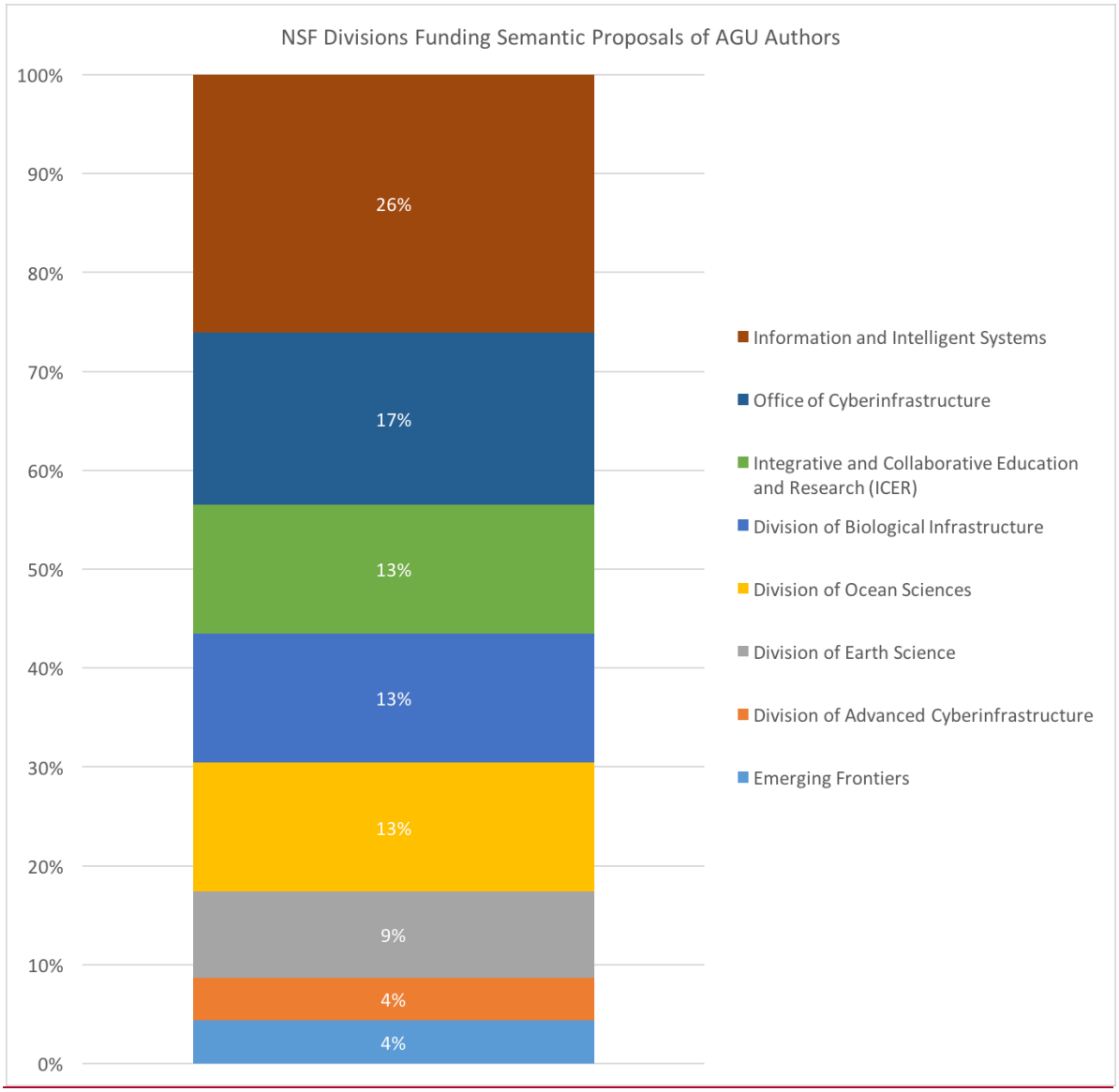

Figure 14. An example of combining network data. Here, AGU and NSF networks are merged to identify where AGU presenters are receiving their funding.

5 Conclusion

AGU is on the cusp of an incredible milestone. Founded in 1919, the AGU will celebrate its centennial in 2019. There is a lot we can learn from the past 100 years. Network analysis, scientometrics, and data science can help us quantify what we're doing right and identify paths toward improvement. Let's leverage open data and open science to improve how we present our science over the next 100 years. We conclude with a summary of recommendations.

- Further explore the percentage change in network density. AGU is highly invested in collaboration, as evidenced by Science Neighborhoods, Town Halls, and related events. If edges are being added at a rate far below the rate of new nodes, are these collaboration events truly effective?
- Explore connected components to identify clusters of research topics and who comprises each cluster. Combination with other datasets to identify career status (e.g. student, early career, senior researcher) can be helpful for the Program Committee in balancing session chairs. Connected component analysis may also be helpful in recommending collaboration amongst components.
- AGU covers a wide cross-section of the geosciences. Yet, the number of researchers presenting across sections appears minimal. The analysis of keywords reveals there are numerous sections interested in the same topics. AGU should take steps to enhance presentations across sections.
- Scientometric analysis can reveal emerging trends and hidden patterns. We advocate for the release of program data prior to the Fall Meeting and the development of open tools that leverage this data. Narock (2018b) presented techniques that can help operational this into predictive analytics.
- Unique identifiers, such as ORCID and the Global Research Identifier Database, can be used to clearly identify researchers and organizations.
- Technology and open data may help in efforts to battle gender and minority biases in science presentations. Yet, more data and easier access to a researcher's history may lead to unintended consequences and additional biases. Our community needs to continue having discussions in this area and actively evaluate the role scientometrics might play.
- There is currently a strong push for scientific data to adhere to the FAIR principles (Wilkinson et al., 2016). We believe our science communication efforts should adhere to these principles as well.

Acknowledgements

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The first author would also like to acknowledge the contributions of Eric Rozell and the Earth Science Information Partners (ESIP). Eric helped create the Linked Data version of the AGU Abstract Database used in this study while he was a student at Rensselaer Polytechnic Institute, Troy, NY. Eric's work was made possible through an ESIP mini-grant. The work ESIP enabled, and Eric's early discussions with the first author, helped lay the groundwork for the research presented here.

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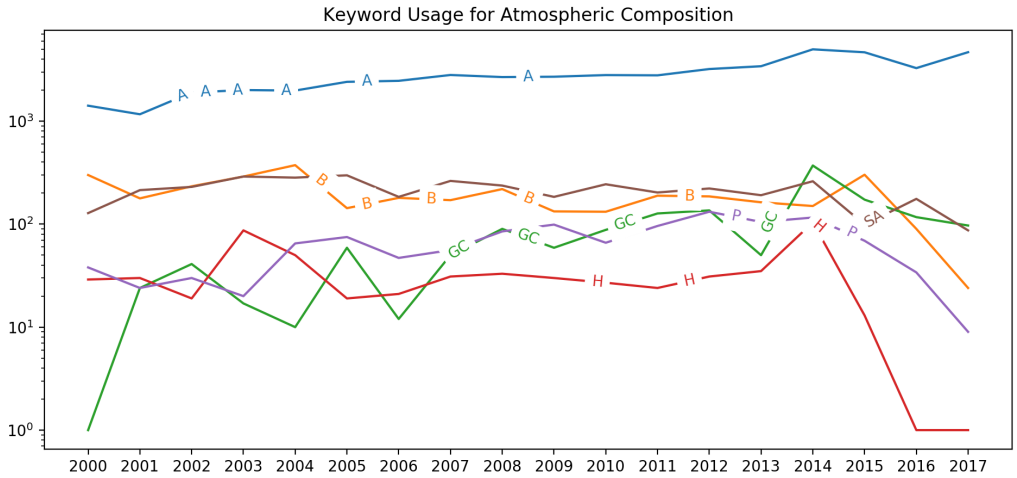
Appendix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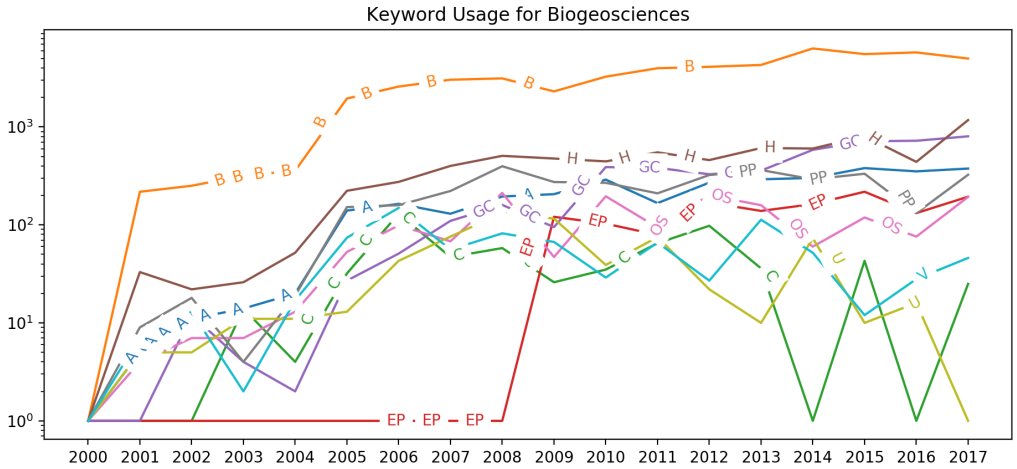
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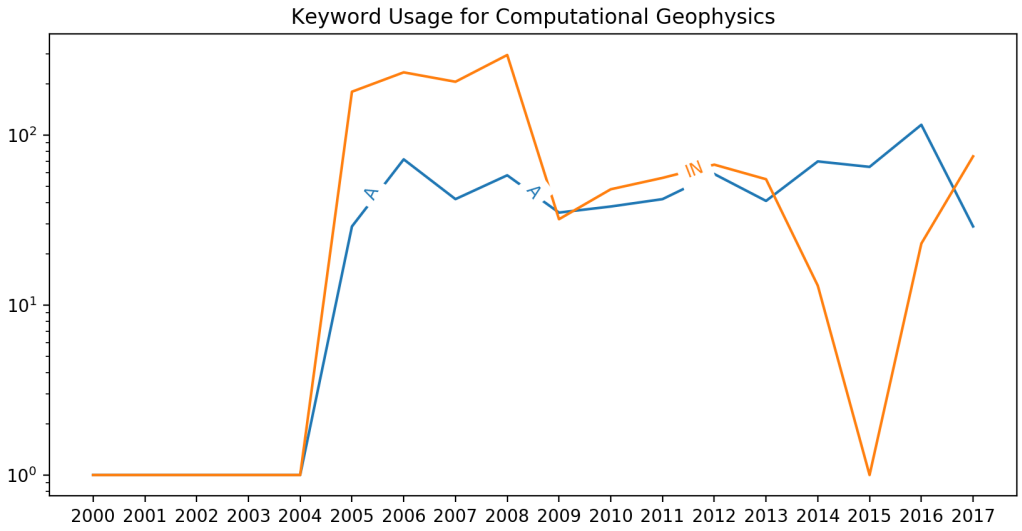
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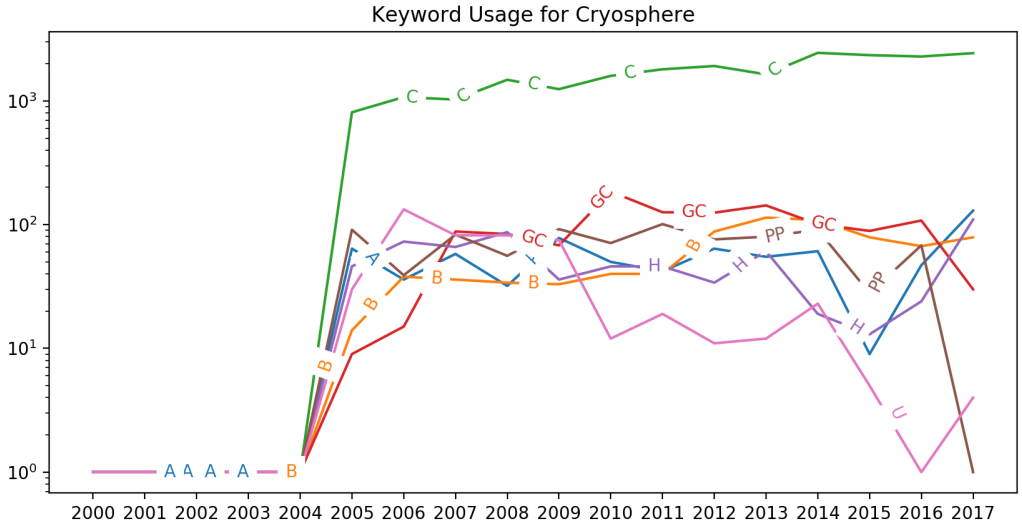
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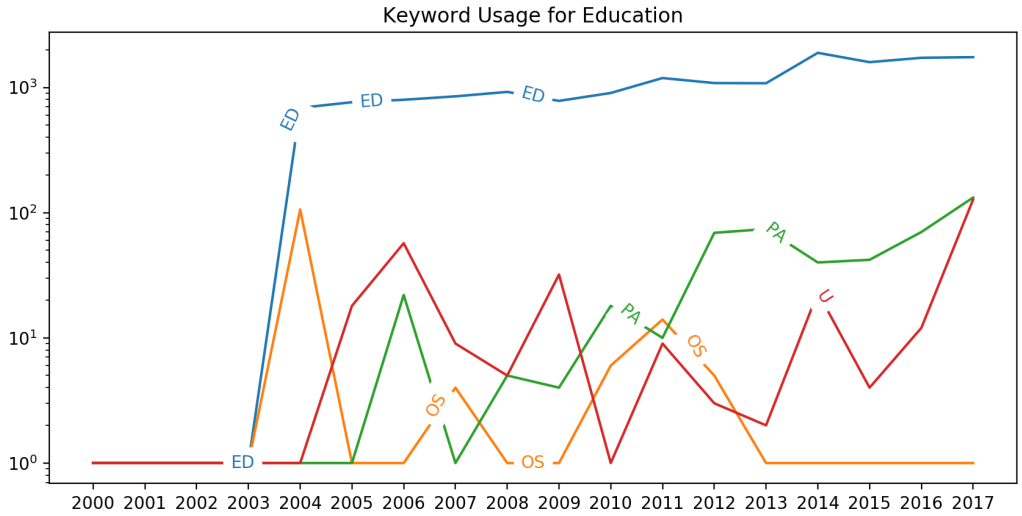
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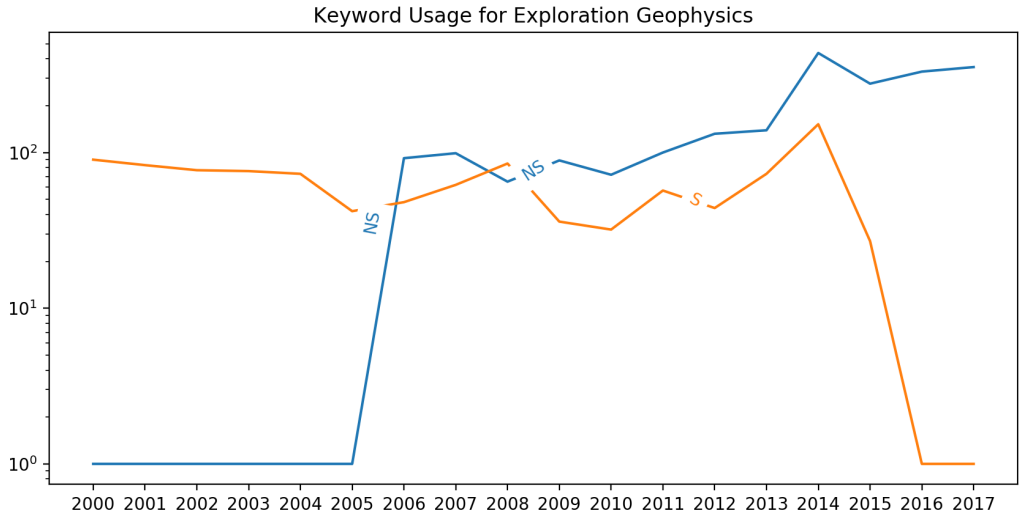
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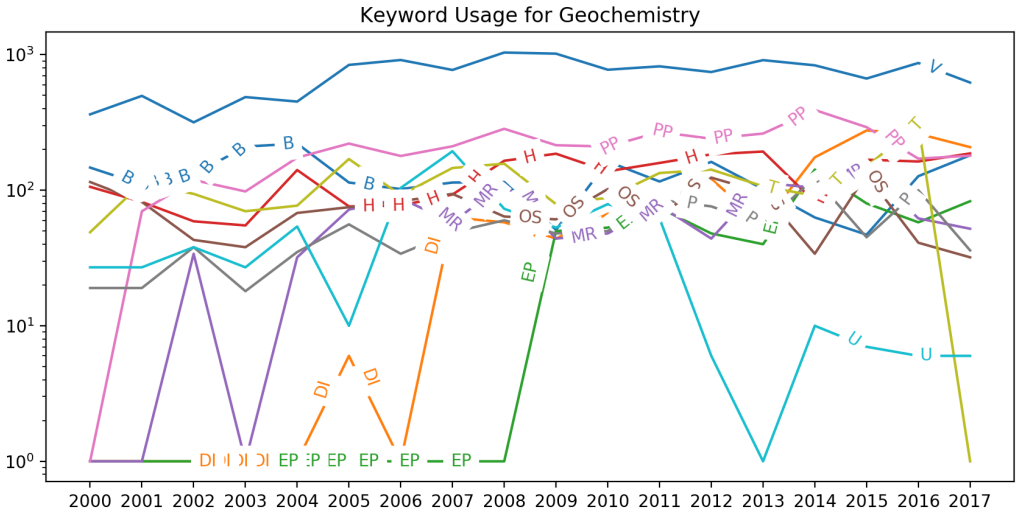
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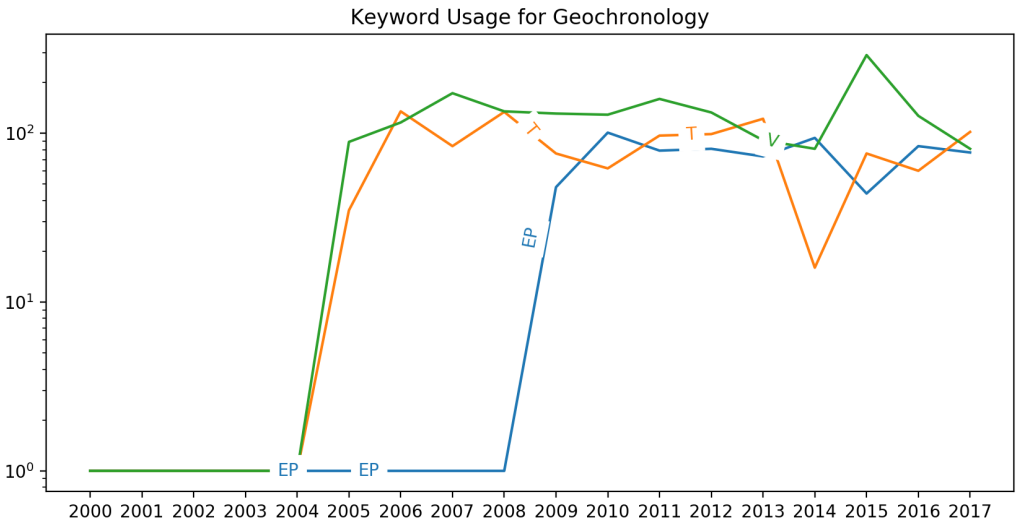
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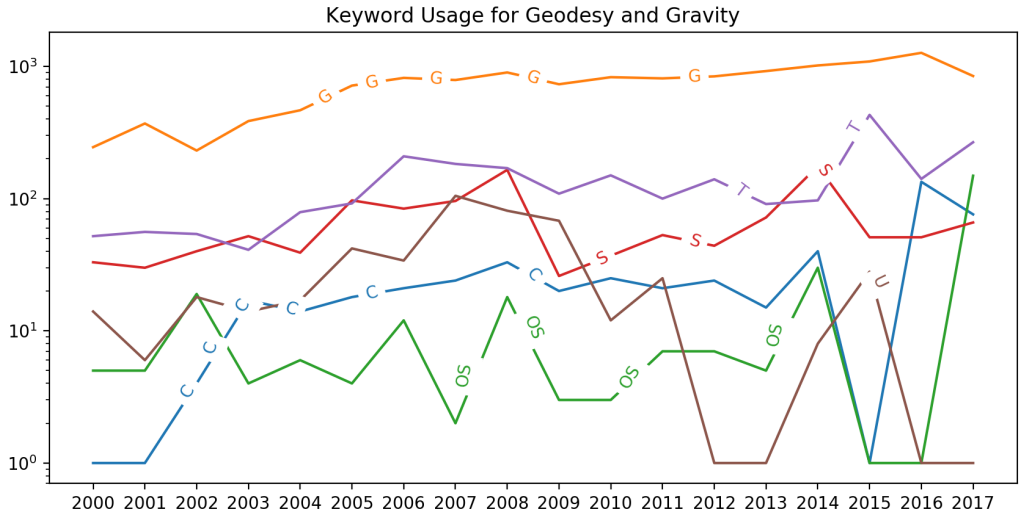
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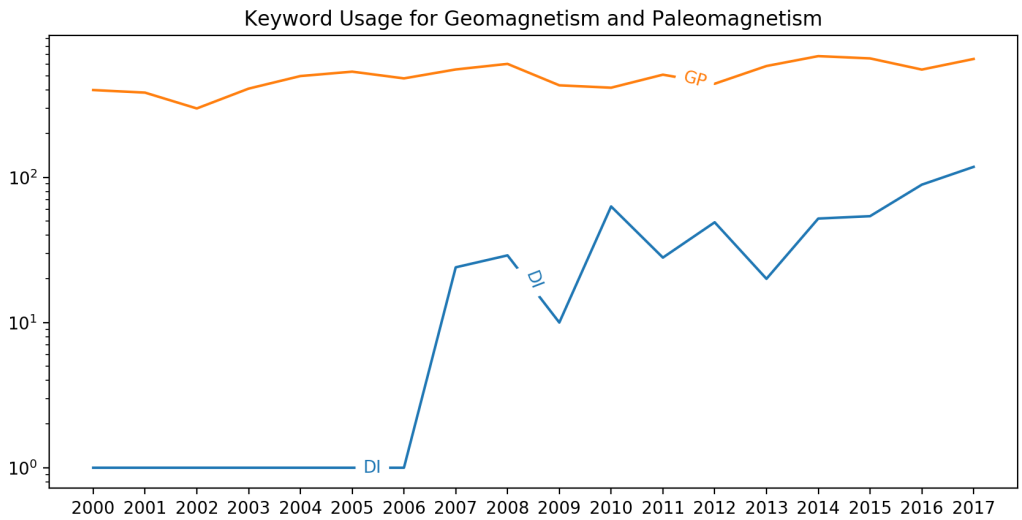
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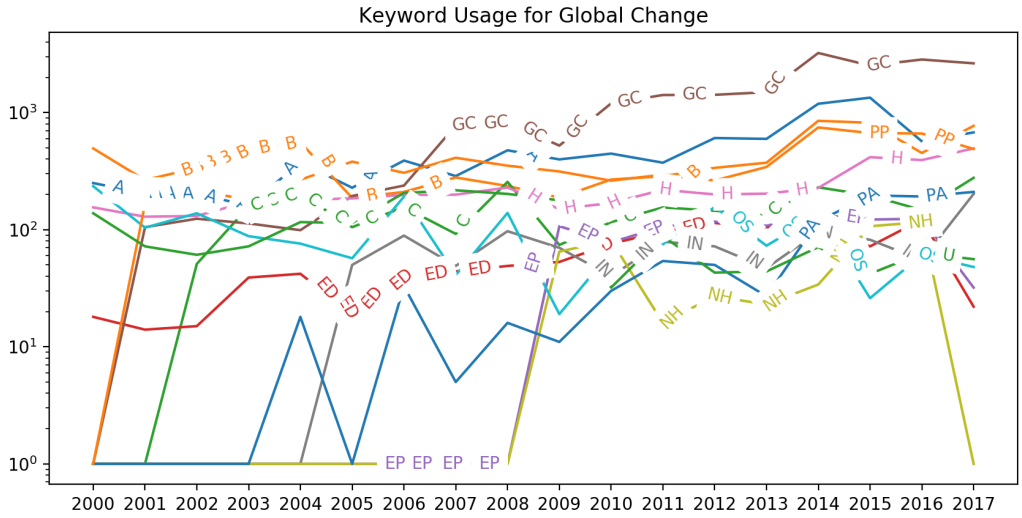
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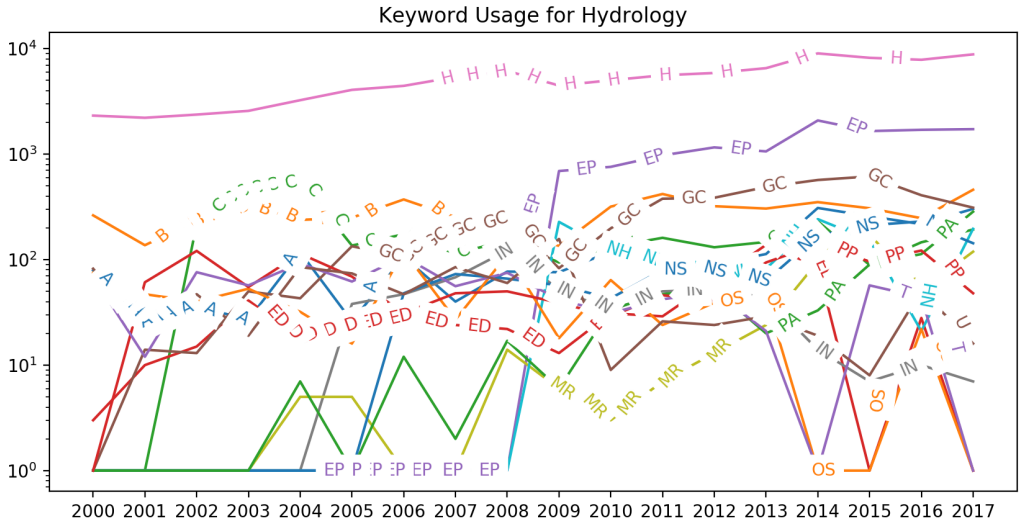
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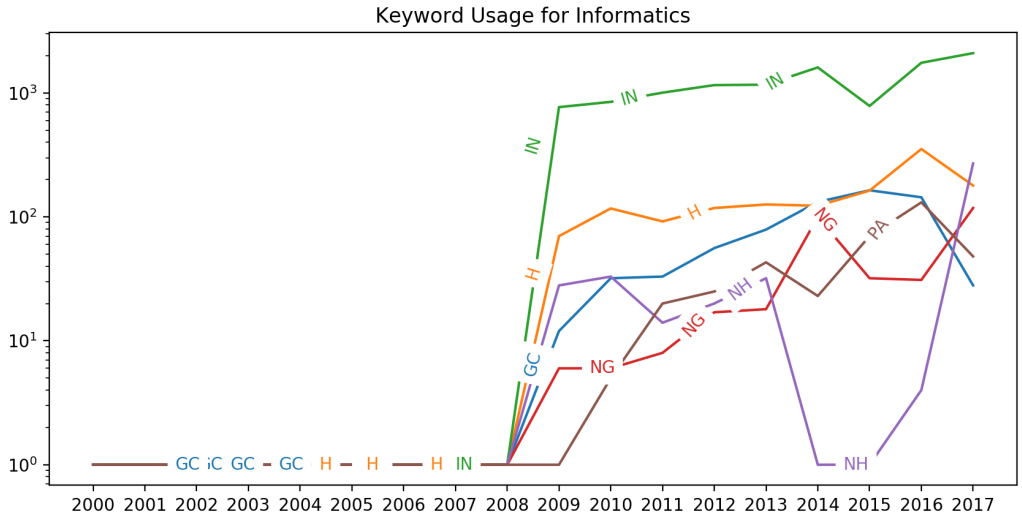
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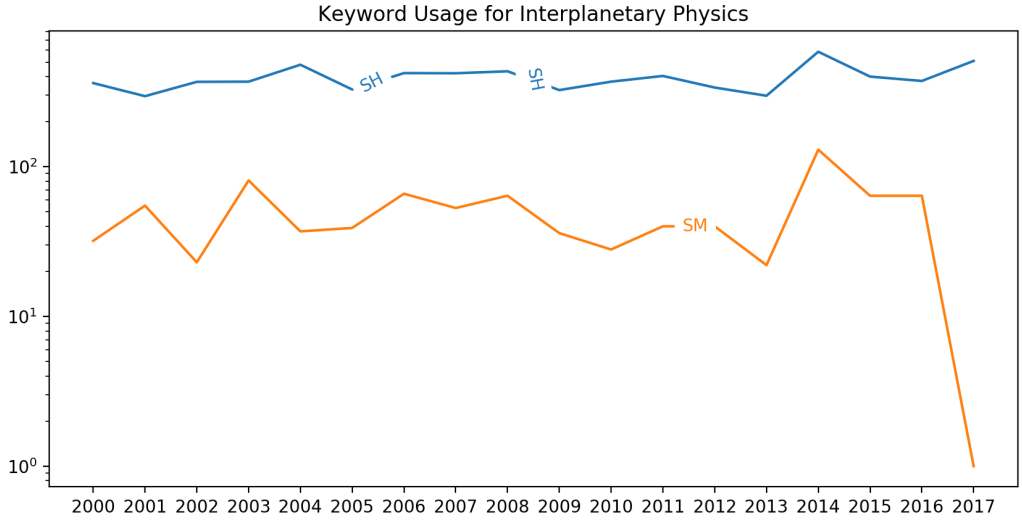
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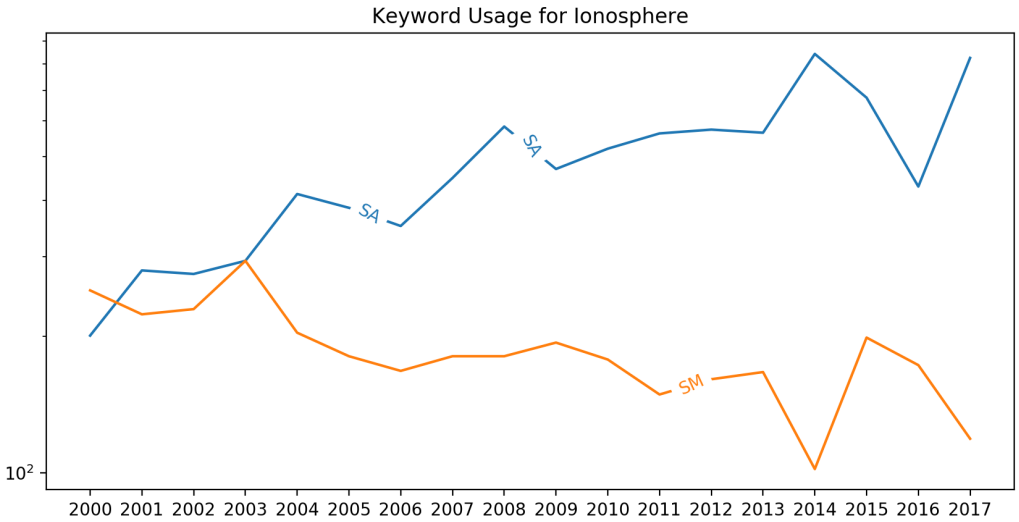
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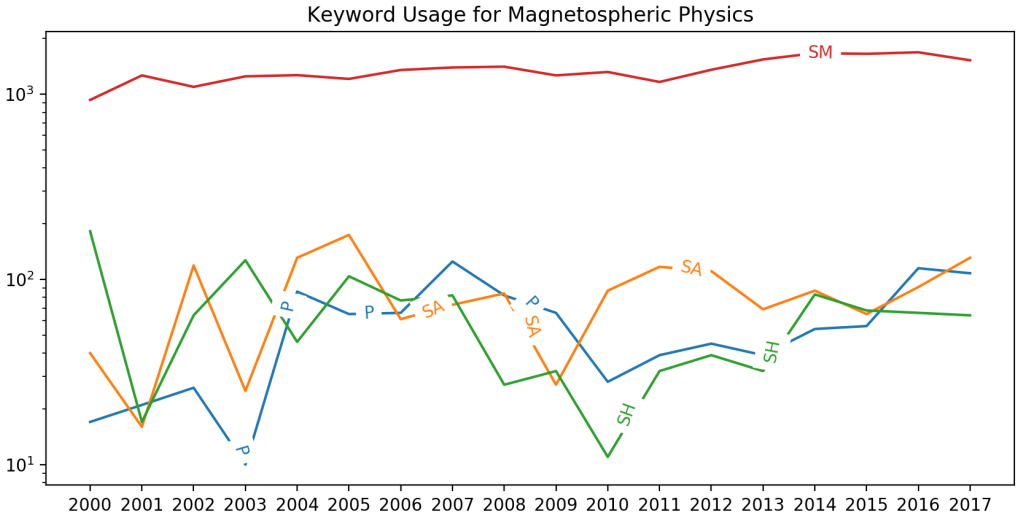
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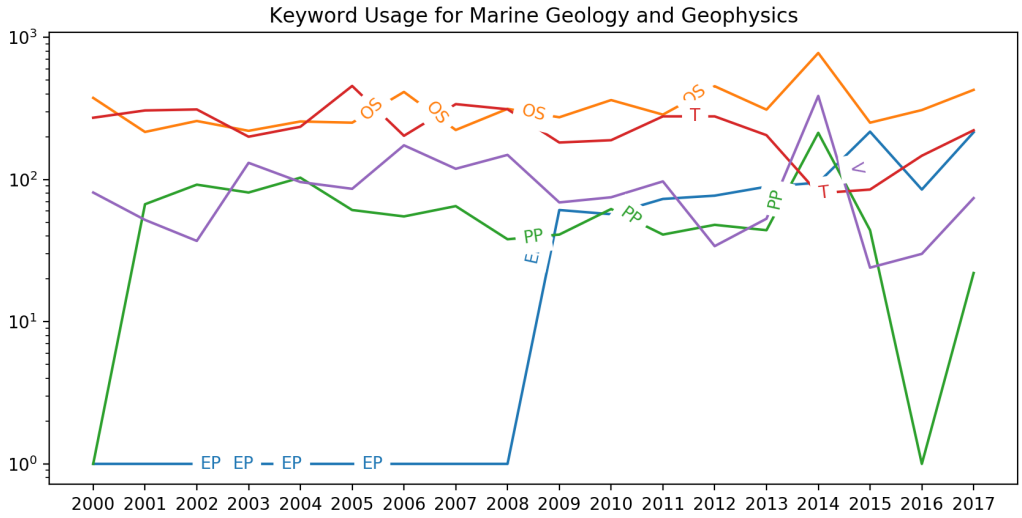
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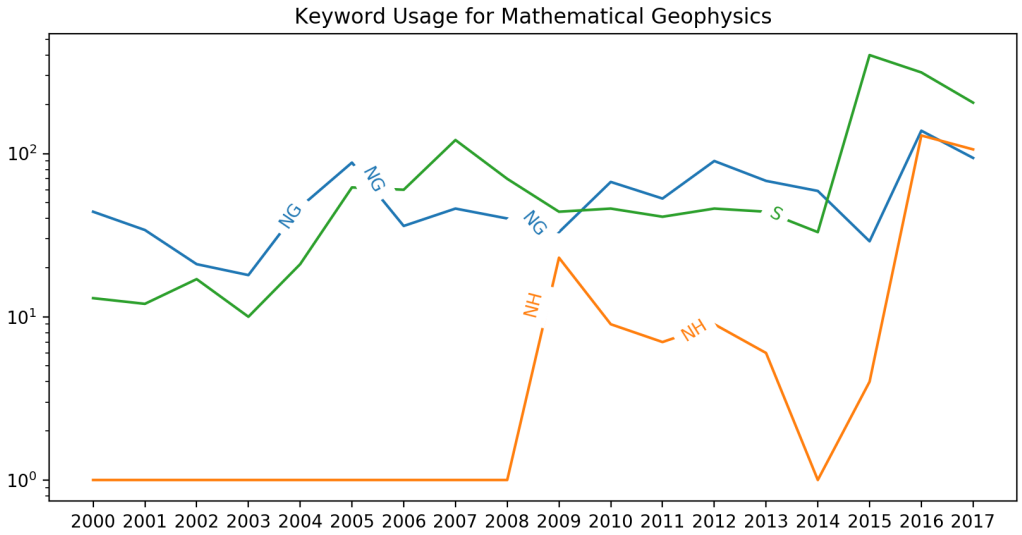
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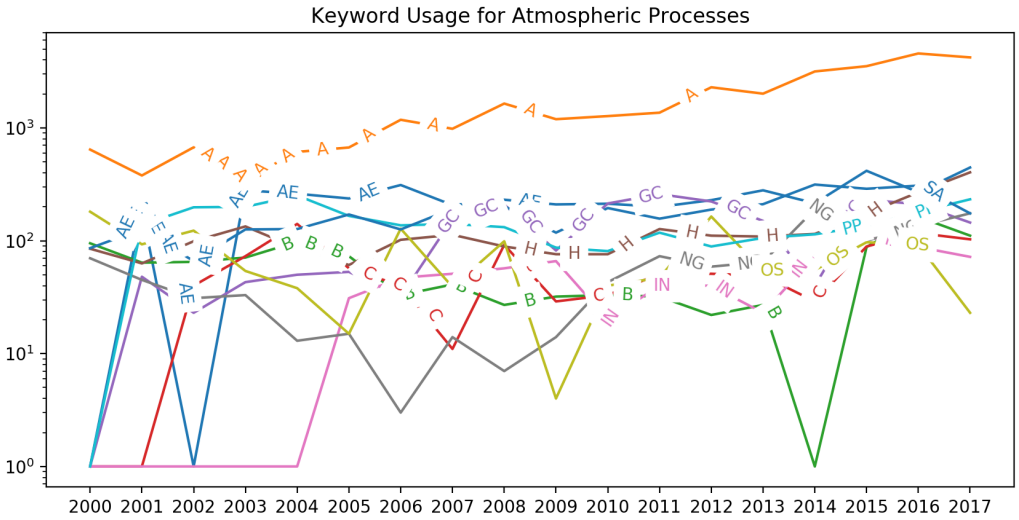
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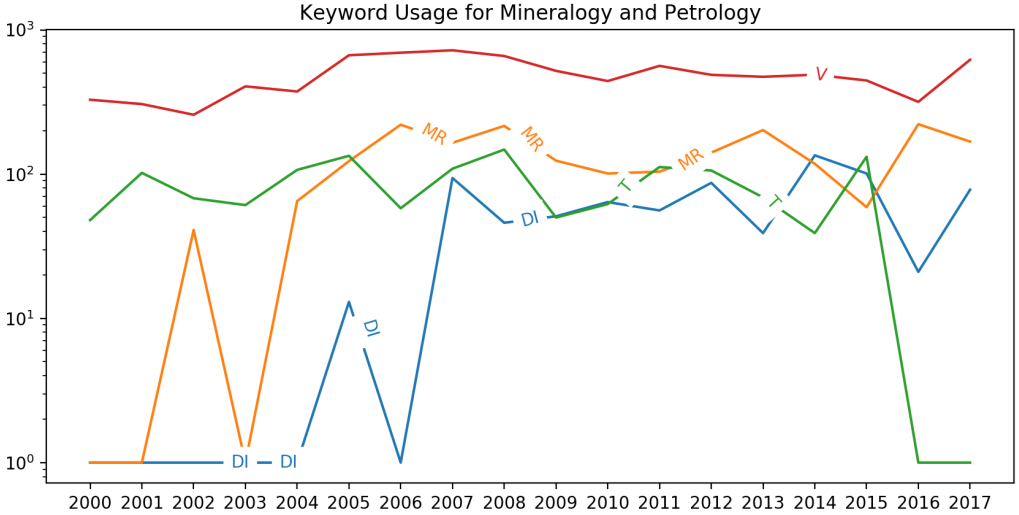
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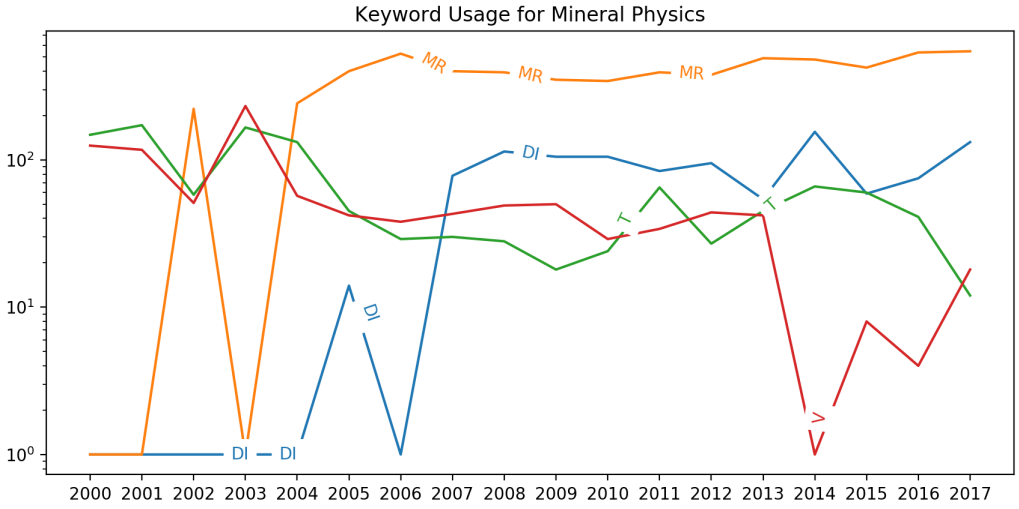
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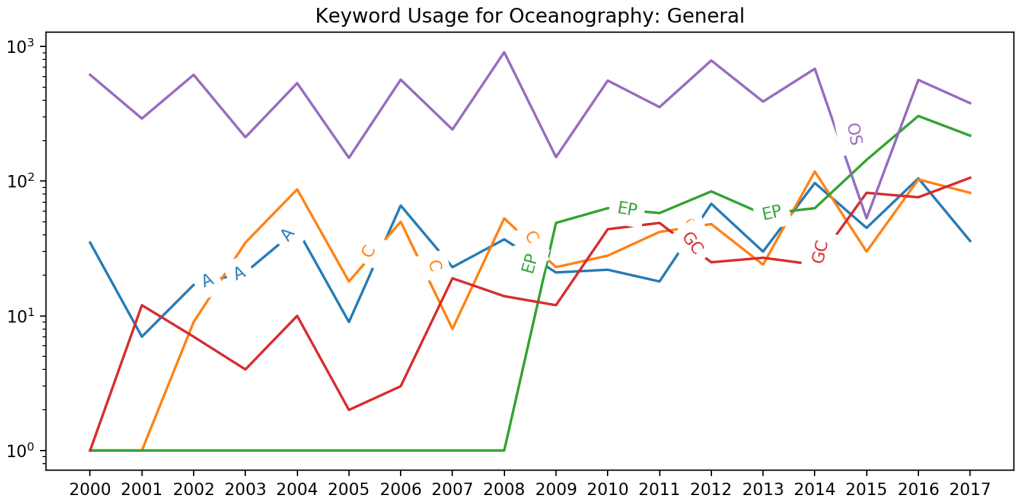
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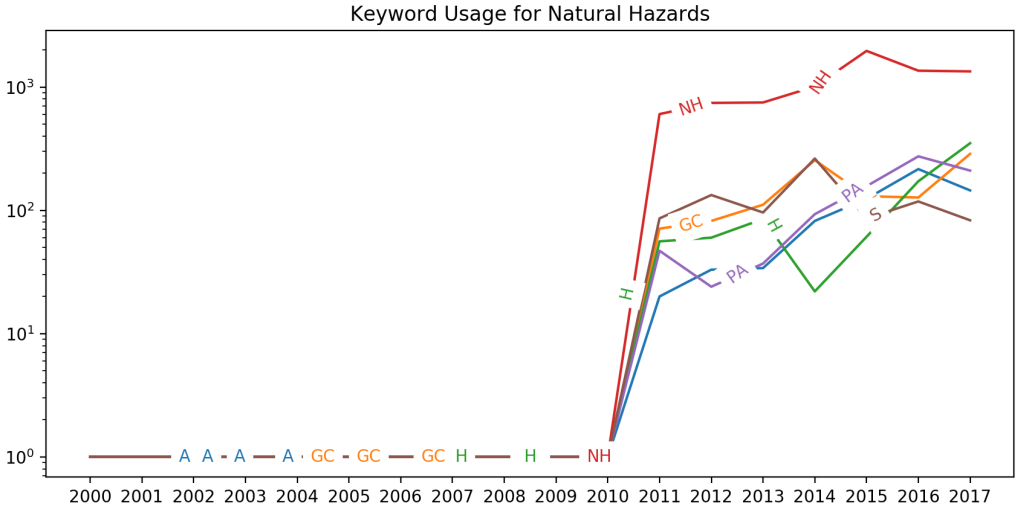
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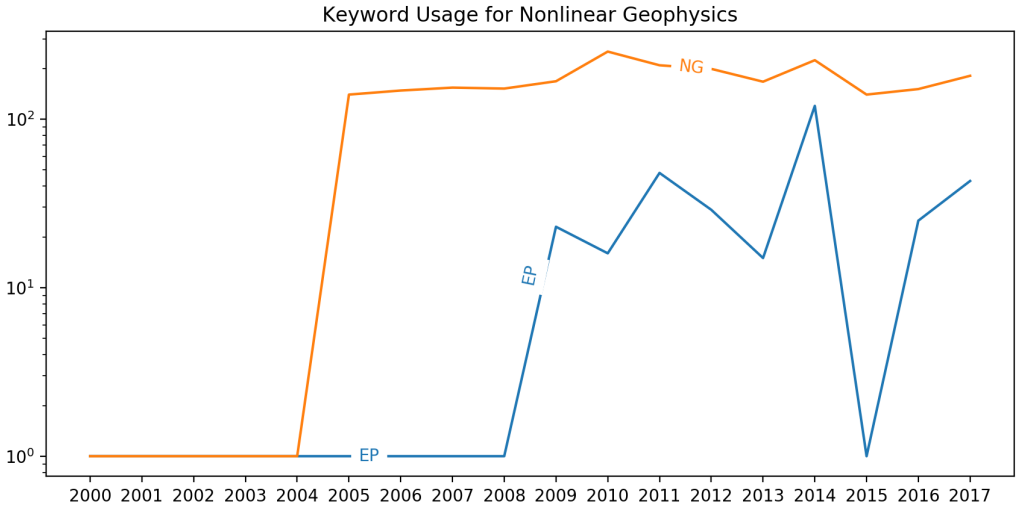
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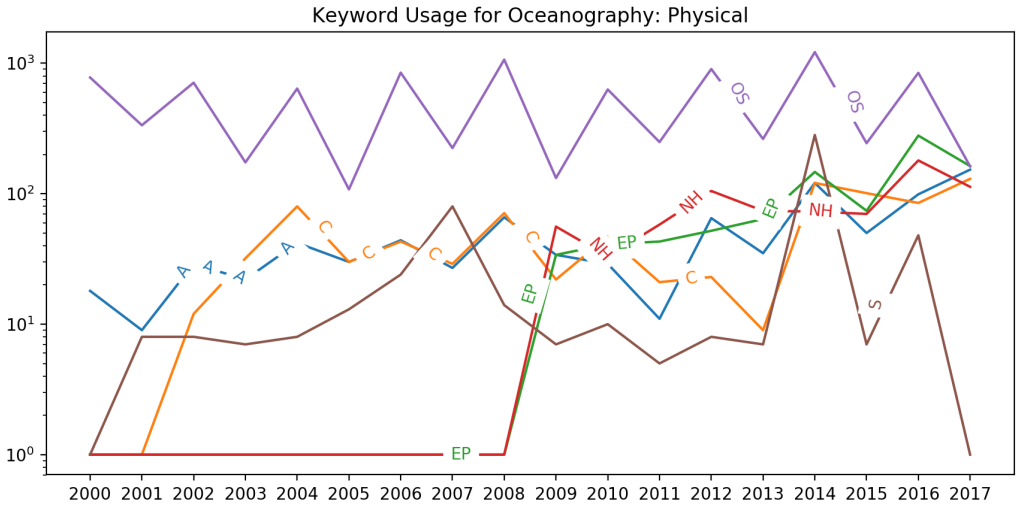
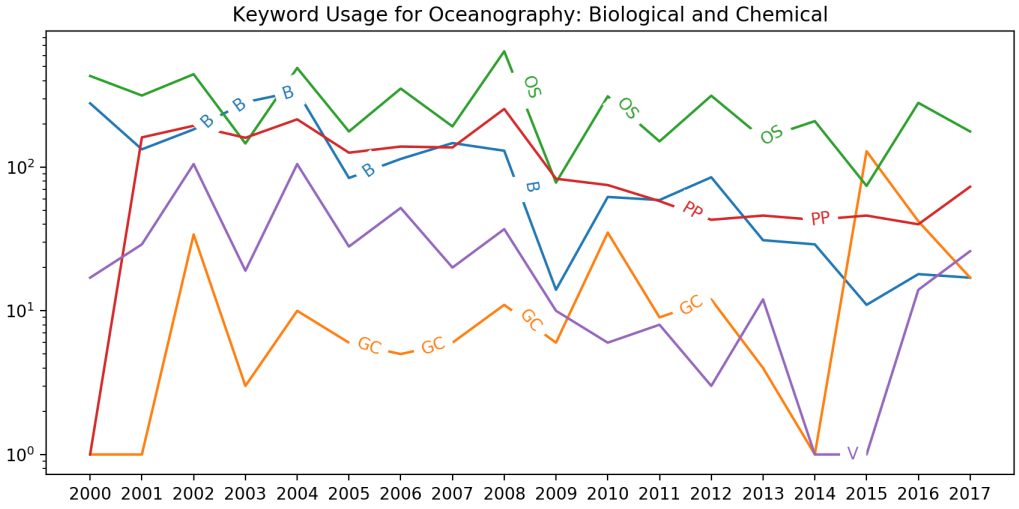
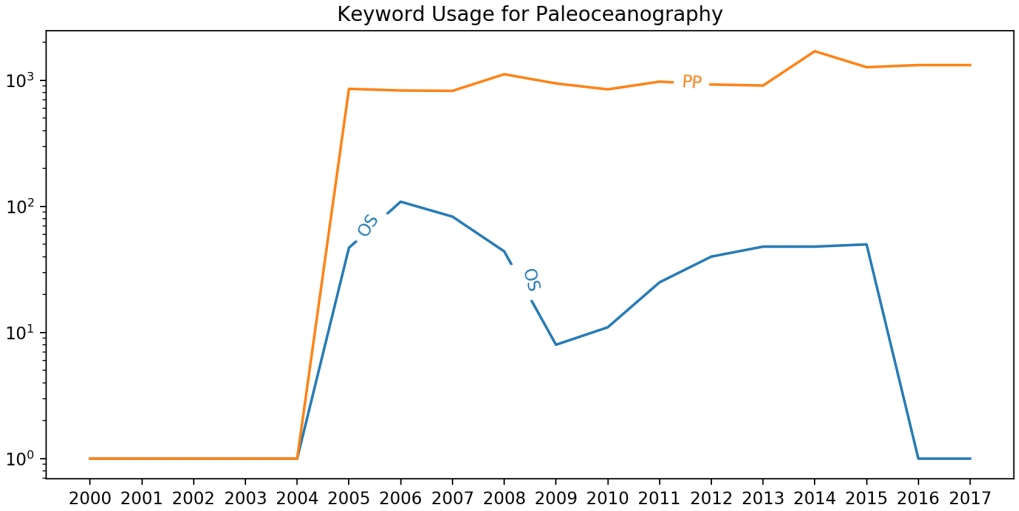

Keyword Usage for Oceanography: Physical
OS
OS
A
A
A
A
C
C
C
C
C
EP
NH
EP
NH
EP
NH
EP
C
S
10^3
10^2
10^1
10^0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

555


Keyword Usage for Oceanography: Biological and Chemical
10^2
10^1
10^0
B
OS
PP
GC
V
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Paleoceanography
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10^2
10^1
10^0
PP
OS
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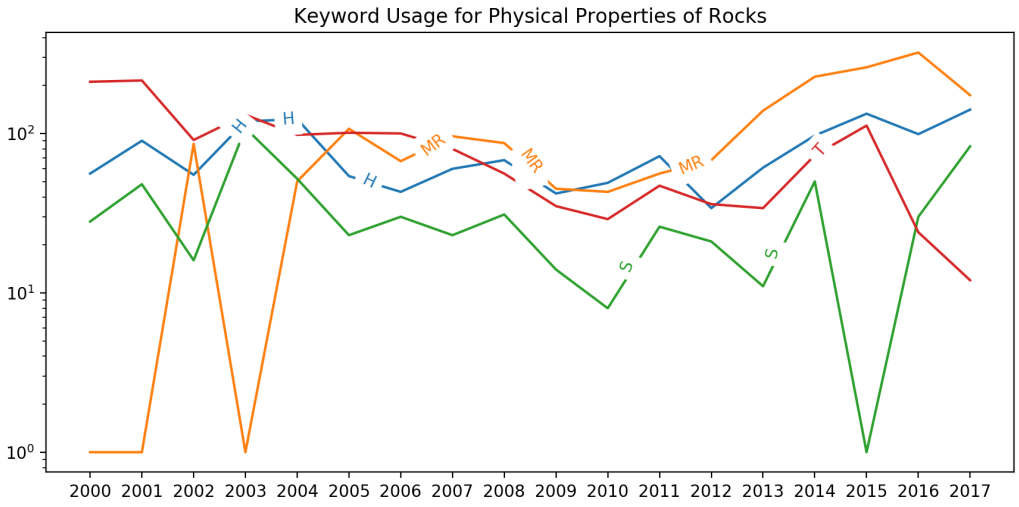
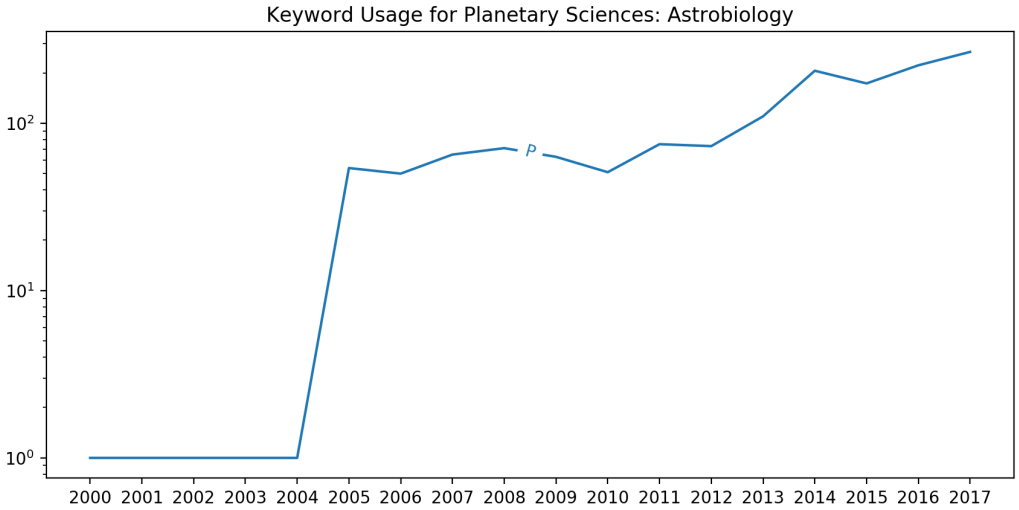

Keyword Usage for Physical Properties of Rocks
10^2
10^1
10^0
H
H
H
MR
MR
MR
S
S
T
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Planetary Sciences: Astrobiology
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10^1
10^0
P
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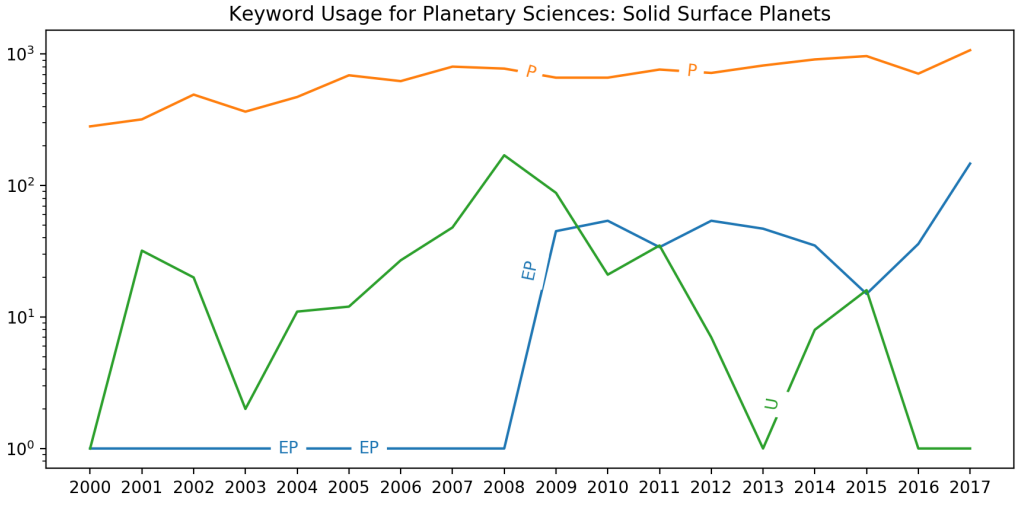
Keyword Usage for Planetary Sciences: Solid Surface Planets
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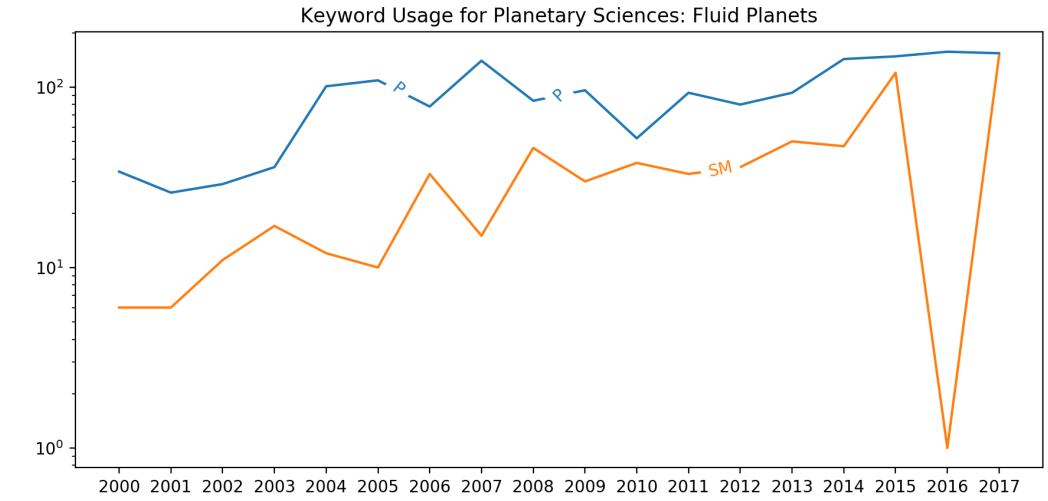
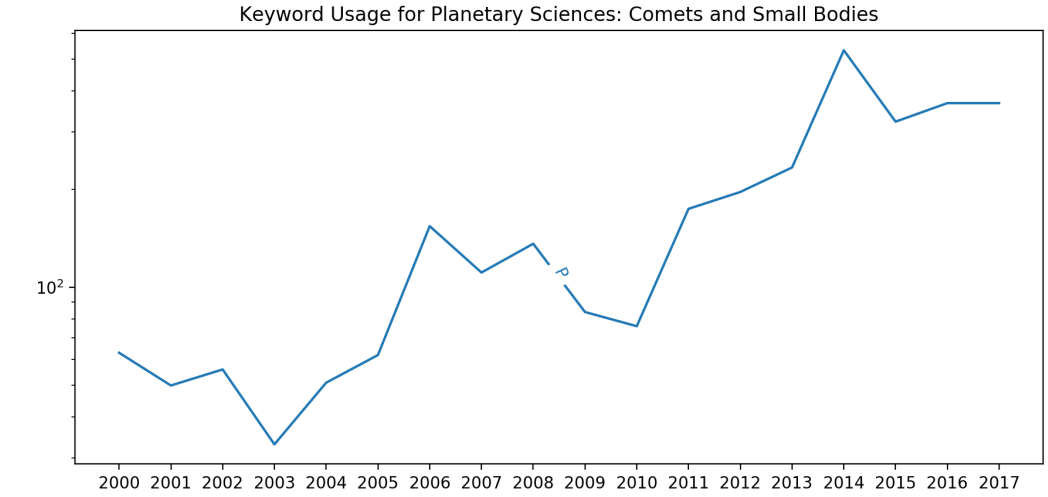
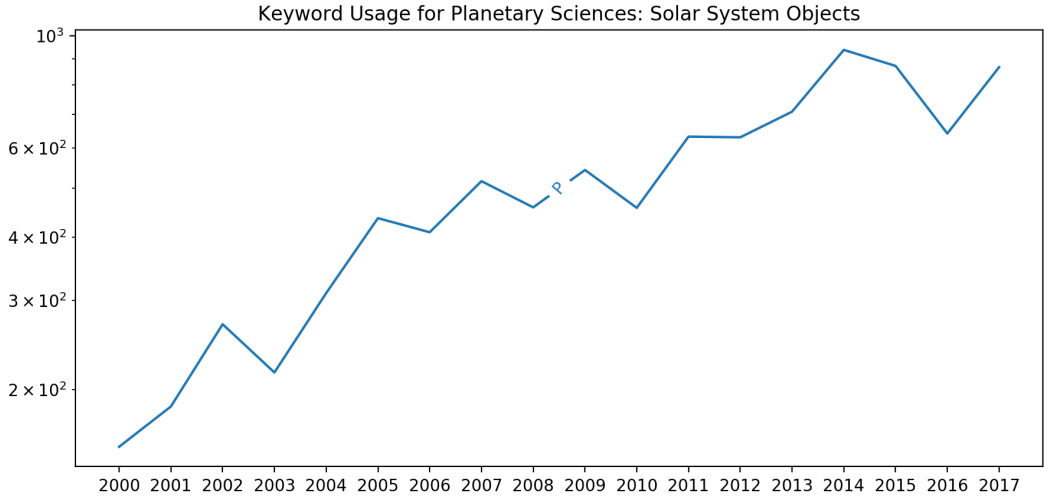
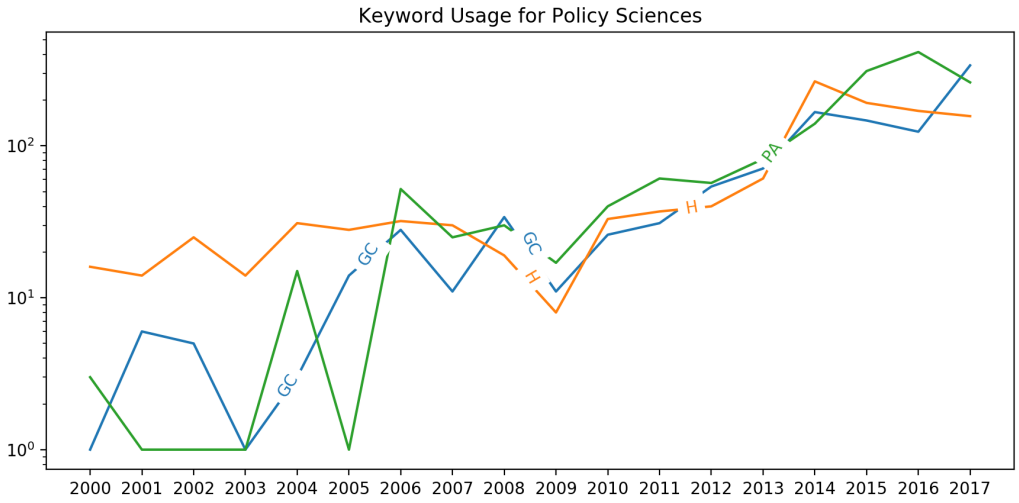
10^2
10^1
10^0
P
P
EP
EP
EP
U
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

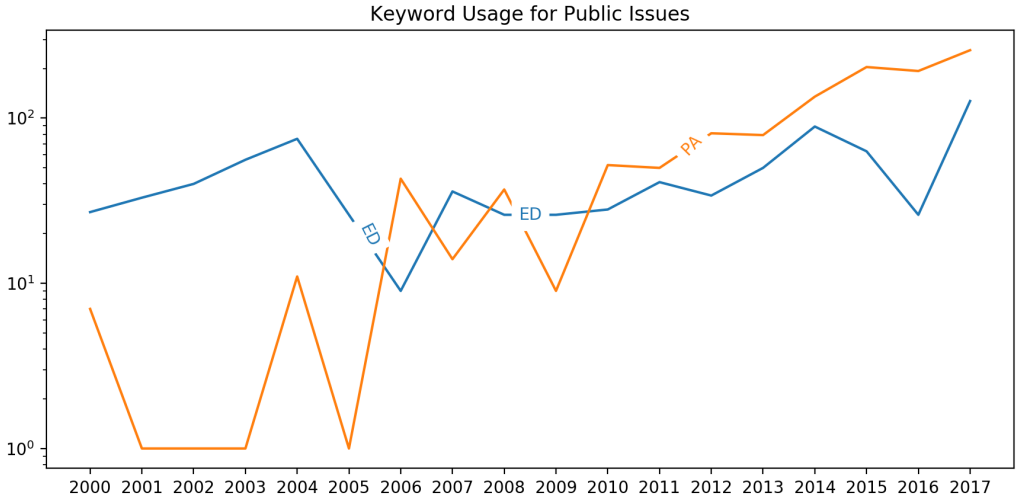
560


Keyword Usage for Planetary Sciences: Fluid Planets
P
P
SM
10^2
10^1
10^0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

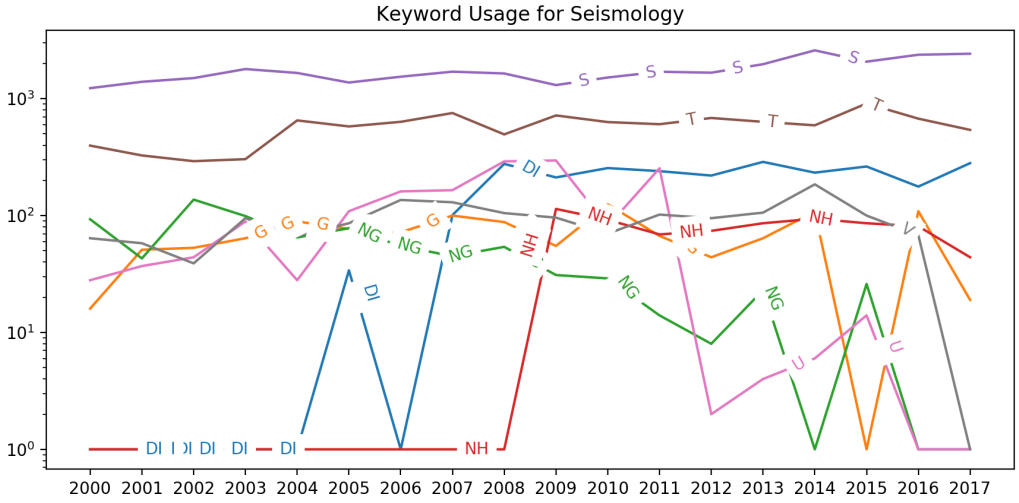

Keyword Usage for Planetary Sciences: Comets and Small Bodies
P
10^2
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

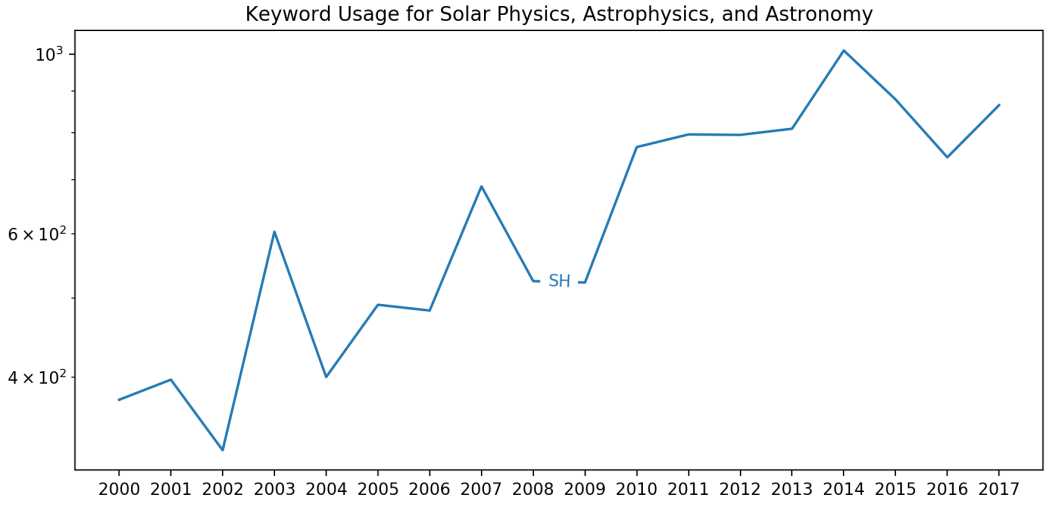

Keyword Usage for Planetary Sciences: Solar System Objects
P
10^3
6×10^2
4×10^2
3×10^2
2×10^2
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Policy Sciences
GC
H
PA
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Public Issues
ED
PA
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

565


Keyword Usage for Seismology
S
T
DI
NH
NG
U
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Solar Physics, Astrophysics, and Astronomy
10^3
6×10^2
4×10^2
SH
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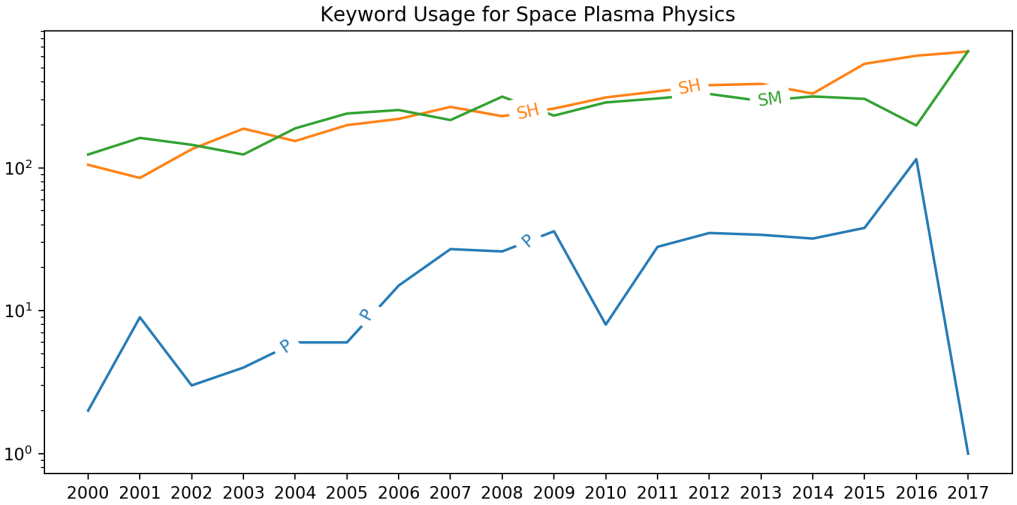
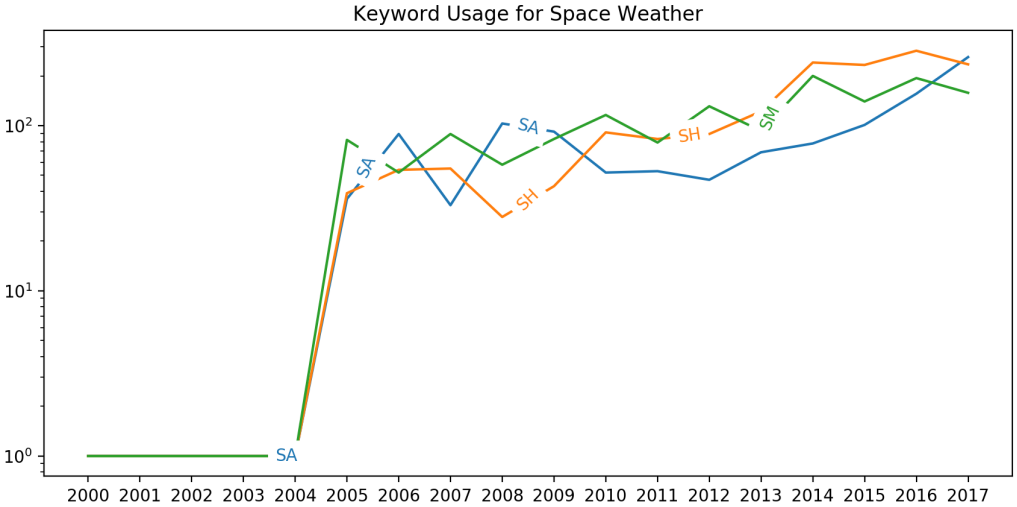
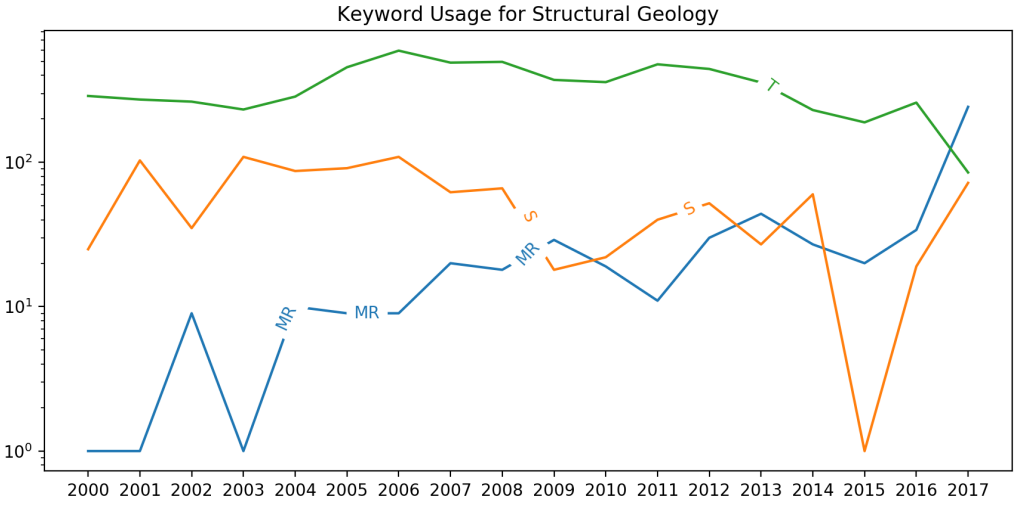

Keyword Usage for Space Plasma Physics
10^2
10^1
10^0
SH
SH
SM
P
P
P
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Space Weather
10^2
10^1
10^0
SA
SA
SA
SH
SH
SM
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Structural Geology
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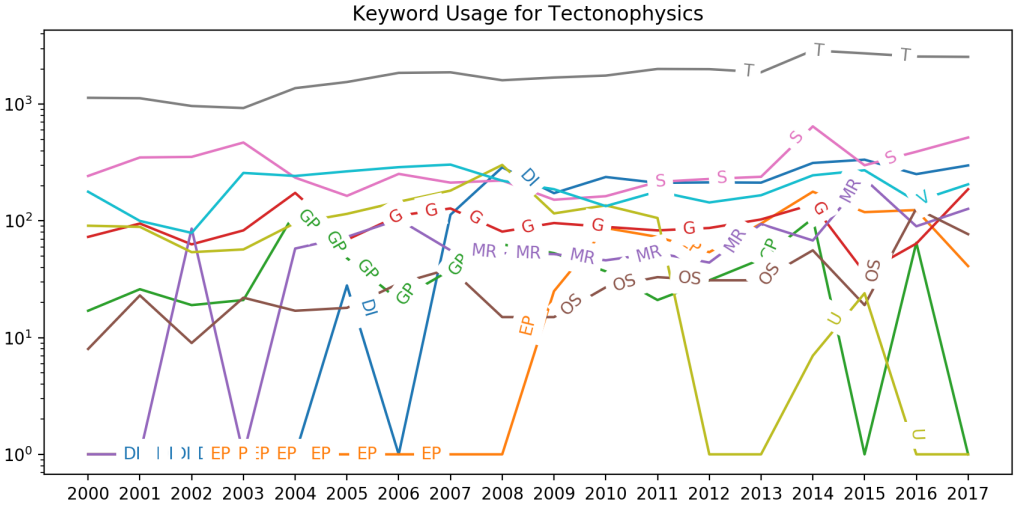
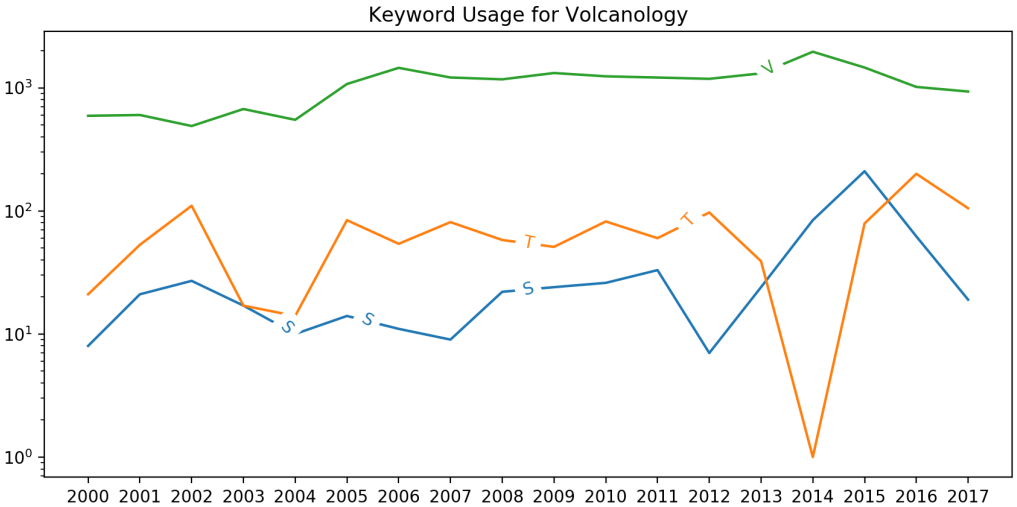

Keyword Usage for Tectonophysics
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017


Keyword Usage for Volcanology
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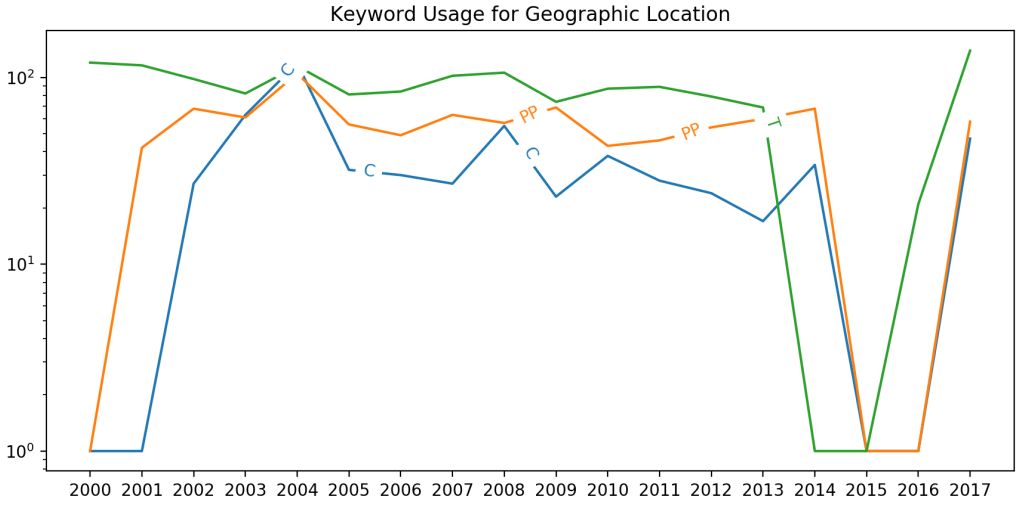
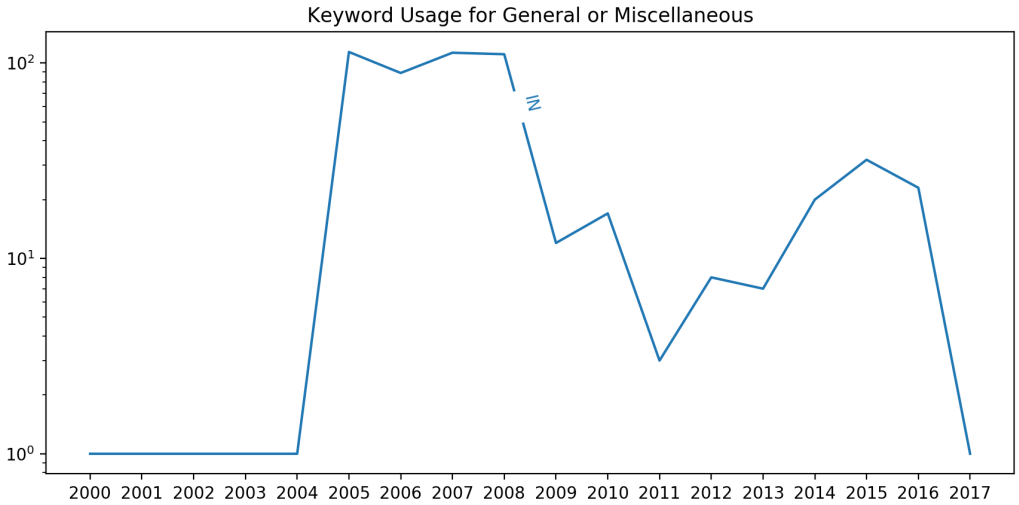

Keyword Usage for Geographic Location
10^2
10^1
10^0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
C
C
C
PP
PP
T


Keyword Usage for General or Miscellaneous
10^2
10^1
10^0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
IN