Mapping the network of mathematics using ‘cognitive mobility’ or migration of authors between fields as an index

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Abstract

The structure of disciplines can be mapped using citation and co-citation analysis, viz. author, journal and document co-citation. Citation provides an underlying cognitive link between papers, journals, and authors that goes towards defining the interconnectedness of areas of research in these maps. In a less structured context, co-occurrence of names of terrorist organizations in reports of terrorist violence in India has been used to draw a map of terrorist groups and linkages. Words in editorials of Science and Nature have been analyzed for content analysis. In this paper we have looked at a new measure of connectedness between research areas, namely, the migration of authors between subfields. Migration may be considered as an embodied knowledge flow that bridges some part of the cognitive gap between fields. Our hypothesis is that the rate of author migration will reflect cognitive similarity or *affinity* between disciplines. This is graphically shown to be reasonable above certain levels of migration for our data from Mathematical Reviews spanning 17 years (1959-1975). The inter-related structure of Mathematics is then mapped using migration data in the appropriate range. We find the map to be a good reflection of the disciplinary variation in the field of Mathematics.

Introduction

The growth of scientific fields is frequently describable by S-shaped curves, with initial slow growth (as measured by research output in the form of publications) in the learning stages, followed by rapid growth and, subsequently, saturation as the potential of existing ideas to solve problems within that area is exhausted. A new idea introduced at this point can start another growth phase with similar characteristics. These ‘new’ ideas, methods or techniques are not necessarily those that have been created *ab initio*, but those that may already be in use in other areas and have been transplanted onto the new area.

Innovative ideas in science often have their roots in other disciplines. Major developments have been known to arise from trans-disciplinary migration, the case of Max Delbruck from physics to biology or John von Neumann from mathematics to economics being specific examples. Cognitive mobility brings about interdisciplinarity, which, according to modern theories, is at the heart of new forms of knowledge production. As knowledge transcends disciplinary boundaries, the boundaries themselves fade away and new synergetic combinations can be formed (Gibbons et al, 1994). Knowledge that is transferred to new fields is more likely to be method-centred rather than subject-centred. While historiographic accounts only highlight a tiny fraction of such migrations, a statistical analysis of the publication archives can bring out correlations and connections which may throw light on the evolution of fields, for example, it can identify emerging areas and which fields they draw upon.

Migration of authors between knowledge domains has been described by the term ‘cognitive mobility’, first introduced by Wagner Dobler (see, e.g., Wagner Dobler, 1999). As cited earlier, this can result in spectacular bursts of creativity in science and emergence of completely new directions in fields. Cognitive mobility can be measured by tracking the institutional or geographical movement of a scientist, say from one department to another with a different specialization, or through detailed surveys. However, a more reliable and complete indication can be obtained from the disciplinary orientation of papers authored at different points of time by the same scientist. In effect it is equivalent to analyzing the archives of science. The shortcoming is that it cannot incorporate all the informal aspects than can be brought out in surveys. To the best of our knowledge, a complete statistical analysis of disciplinary mobility has not been done so far, possibly due to the fact that it is a non-trivial task to extract such data from publication records.

An interesting question follows as to what are the deterrents to mobility? One deterrent is the barrier caused by the different forms of discourse, language or ontology, different communication fora such as journals and conferences, and forms of socialization and acculturation within each discipline. The divide is larger the more disparate the content and context of the disciplines. This should make it easier for an individual to migrate to a neighbouring field or subfield. In other words, it is possible that the ease of '*cognitive mobility*' between scientific fields can be used to define a structure of proximal relationships between the fields. This forms a novel way of mapping a network of scientific fields in addition to existing methods using co-authorship, co-citation or co-referencing. In the next section, we look briefly at the existing work related to mapping in bibliometrics.

Mapping and Visualization in Bibliometrics

The objectives of drawing bibliometric maps have varied together with the underlying method for their construction. In addition to co-citation of authors, journals, documents, other similarity measures have been used for connecting these entities such as bibliographic coupling and direct citation. The relative usefulness or accuracy of these measures has also been studied. The earliest reference to mapping in terms of co-word analysis was in Callon, Courtial and Rip (1986). Some illustrative examples of mapping are the early work of Small(1973, 1994, 1999) where co-citation clustering was defined and used in the software SCI-Map to create document clusters that reflected the topics in the AIDS literature and links to other topics. In a later work, (Small 2010) the interdisciplinarity of co-citation links was explored by looking at links between document clusters in disparate categories of journals. Author co-citation was used to map information science (White and McCain, 1997). Pathfinder networks were used in mapping (White, 2003) and animation (Chen et. al , 2002). Journal to journal citation networks were used in Chen (2008). At a macro scale, Boyack, Klavans and Borner (Boyack, et al. 2010) mapped over 7000 journals in the Science Citation and Social Science Citation Indices using several different similarity measures between the journals to provide a bird's eye view of the interconnectedness of today's science and social sciences. They found Biochemistry to be the most interdisciplinary subject. Leydesdorff, et al (2006, 2008a, 2010a, 2010b) have mapped journals, patents, Scopus journals and Arts and Humanities. One of the observations made by Leydesdorff is that co-classification is not as good a basis for mapping compared to co-citation for patent mapping. Dynamic animations of maps have also been developed by Leydesdorff (2008b). While not a comprehensive review, we have tried to illustrate different contexts and approaches to mapping in bibliometrics.

In a slightly different context, networks of terrorist organizations have been obtained using name co-occurrences (Basu, 2005). Maps have also been drawn in an interdisciplinary context to analyze the editorial content of Nature and Science using co-word analysis (Waijer, et al., 2010).

In almost all the cases cited here, the similarity measures used have been based on the reference lists in documents. Each similarity measure is ultimately derived from the citation process, except in the cases where word co-occurrence has been used.

Data & Methodology

In this paper, by looking at a large number of migrations over a long time span, and by examining the scatter of migrations against affinity, we have tried to see under what conditions migration frequency reflects the affinity between fields of mathematics, and when it can be used to map a scientific field. The basic data was collected from Mathematical Reviews for 17 years (1959-75) listing more than 300,000 journal papers. (The term 'field' is used in the same sense as subfield in the rest of the paper). The first author of each paper was noted as well as all the papers written by the same author. Every event where an author wrote two successive papers in fields with different classifications was taken as an instance of migration. If the paper has more than one classification category, then the first one is taken as the primary one. The data consists of bidirectional migrations between 39 subfields with more than 3000 papers each. Smaller areas that contributed less than 1% to the literature (total<10%) were dropped. The total number of transitions between fields numbered 66656, while the number of self migrations (two successive papers in the same field by an author) was 79333. Only the first author of a paper has been considered in counting migrations. The 39 fields of Mathematics in the data are shown in Table 1, which gives the number of in-migrations, out-migrations and self-migrations (where two successive papers by the same author are in the same field). The balance of migrations shows the net difference between in and out migrations, and is positive for fields that have gained author contributions from other fields through migration and negative for fields that have had a net loss of author contributions.

Table 1: Fields in Mathematics, with number of in-migrations and out-migrations of authors: Self-migrations indicate two successive papers in the same field.

Field	In Migrations	Out Migrations	Self Migrations	Balance of Migrations
1 History and Biography	1071	794	754	277
2 Logic and Foundations	764	692	949	72
5 Combinatorics	3878	4172	3658	-294
6 Order, Lattices, Ordered Algebraic Structures	1379	1204	1293	175
10 Number Theory	996	985	2734	11
14 Algebraic Geometry	2140	1790	1816	350
15 Linear and Multilinear Algebra; Matrix Theory	1052	1104	832	-52
16 Associative Rings and Algebra	2052	2033	3188	19
20 Group Theory	1498	1547	628	-49
22 Topological Groups, Lie Groups	867	839	1449	28
26 Real Functions	1915	2037	3913	-122
28 Measure and Integration	1301	1228	875	73
30 Functions of a Complex Variable	1503	1619	524	-116
32 Several Complex Variables and Analytic Spaces	1574	1621	935	-47
33 Special Functions	2050	2257	3267	-207
34 Ordinary Differential Equations	1016	850	1074	166
35 Partial Differential Equations	864	899	781	-35
41 Approximations and Expansions	3085	3298	4459	-213
42 Fourier, Abstract Harmonic Analysis	3485	3369	3900	116
46 Functional Analysis (from 1973)	1619	1567	997	52
47 Operator Theory	1558	1665	1400	-107
50 Geometry	3644	3405	2599	239
53 Differential Geometry	1023	1162	1117	-139
54 General Topology	1686	1881	3839	-195
55 Algebraic Topology	1828	1946	2541	-118
57 Topology, Geometry of Manifolds (1959-72)	1061	1214	1203	-153
60 Probability Theory and Stochastic Processes	3163	3186	4265	-23
62 Statistics	2208	2133	4406	75

65 Numerical Analysis	3401	3325	3736	76
68 Computing Machines, 1973: Computer Science	1137	814	721	323
73 Mechanics of Solids	837	947	1607	-110
76 Fluid Mechanics (from 1973: plus Acoustics)	1190	1277	1554	-87
78 Optics, Electromagnetic Theory	666	810	483	-144
81 Quantum Mechanics	1535	1657	3852	-122
82 Statistical Physics, Structure of Matter	1103	1001	875	102
83 Relativity	786	781	1174	5
90 Economics, Oper. Res., Programming, Games	2239	2002	2503	237
93 Systems, Control	1570	1504	1569	66
94 Information & Commun, Circuits, Automata	1912	2041	1863	-129
Total	66656	66656	79333	0

In the first instance we created a network map using UCINET (Borgatti, 2002) with a similarity measure taken as the migration data between fields. The map is clustered into components using the inbuilt program 'HiComp' (Figure 1). The hierarchical tree is shown in Figure 2. Results and analysis of the clusters are given in the results section. We found that the separation of fields into coherent groups was not entirely satisfactory. The cluster diagram indicated that the cluster structure emerges at higher values of migration (Figure 3). In an independent verification, it was found that migration grew with *affinity* between fields, but only beyond a certain threshold of *affinity*. Affinity is defined in terms of the co-occurrence frequency of field classification terms (Wagner Dobler, 1999). The graph of *affinity* vs. *migration* is showed in Figure 4, which shows that, at low levels of affinity, migration is not a good indicator of similarity. The second network map (Figure 5) is created by applying a suitable cut-off value for lower values of migration, to restrict it to the range where it adequately reflects affinity between the fields. We use centrality measures used in social network analysis to bring out the position of each field in the network of mathematics.

Results

Some general observations can be made with regard to migrations by authors between disciplines in mathematics. It was usually found that an author's productivity increased following migration. Transitions could be bi-directional; however it was rare for an individual author to be part of a reverse transition. The results of mapping using the full adjacency matrix of migrations are shown in Figure 1, where each field appears as a node in the network. The size of a node reflects the degree of connection to other nodes. Frequency of migration between areas is indicated by the thickness of the links between fields.

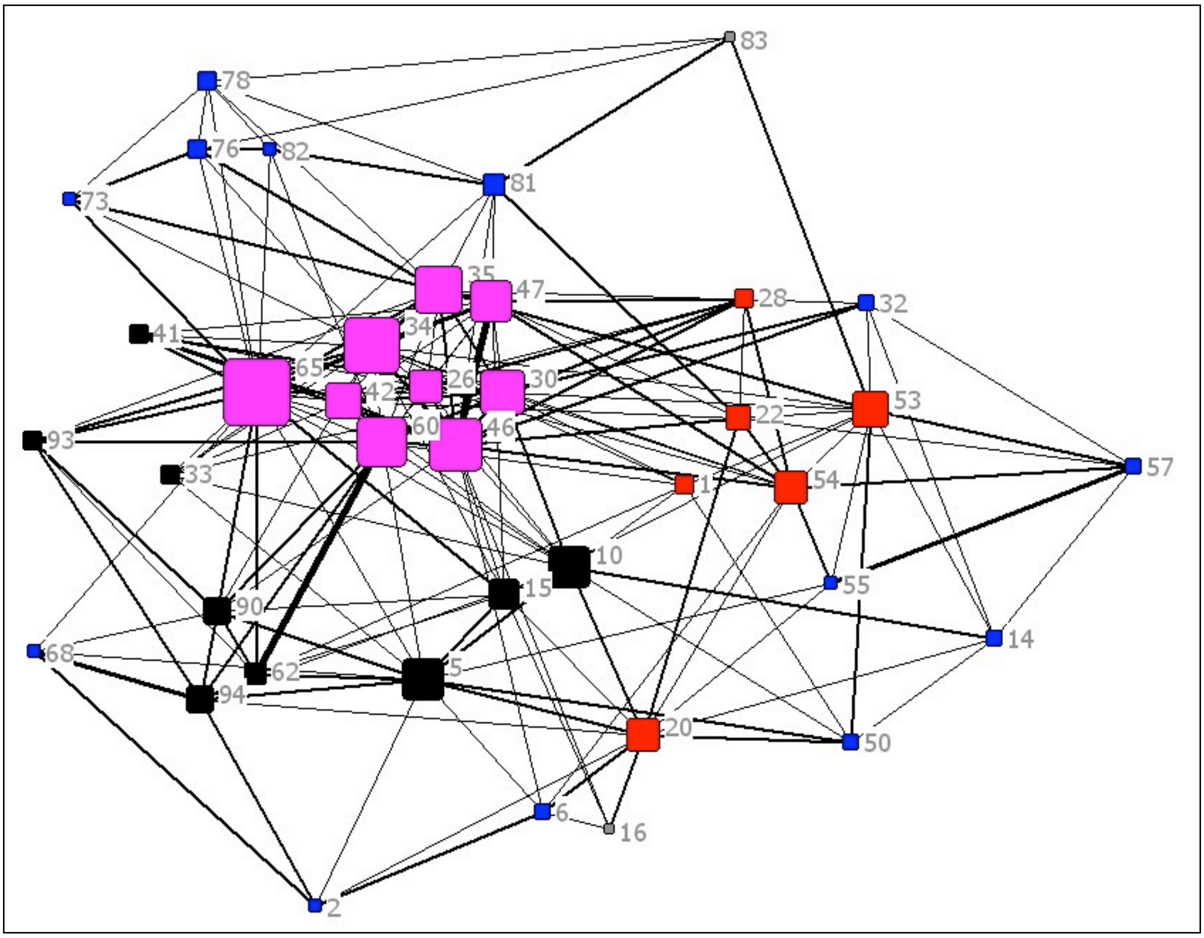

Figure 1. Initial network of fields using the full data on migrations (*see* Table 2 for Field names)

The Degree and Betweenness Centrality measures of the nodes have been computed and are shown in the Table 2. Degree Centrality tracks the number of transitions for a given field. Fields with high values of normalized degree centrality (>8) are Functional Analysis, Numerical Analysis, Operator Theory, Probability Theory, Ordinary and Partial Differential equations. Betweenness Centrality reflects how many paths between pairs of nodes pass through the given node. Normalized betweenness centrality is high (>10) for Partial Differential Equations, Operator Theory, Numerical Analysis, Economics, Systems and Control, Ordinary Differential Equations, Associative Rings and Algebras.
The corresponding cluster diagram is shown in Figure 3. It shows that clusters emerge only at higher values of migration (only migration levels higher than 180 transitions shown here).

Table 2: Degree and Betweeness Centrality based on the full data of migration

	OutDegree	InDegree	NrmOutDeg	NrmInDeg	FlowBet	nFlowBet
	------------	------------	------------	------------	------------	------------
1 History and Biography	794	1071	2.13	2.873	19.375	1.378
2 Logic and Foundations	985	996	2.642	2.672	7.828	0.557
5 Combinatorics	1790	2140	4.802	5.741	24.983	1.777
6 Order, Lattices, Ordered Algebraic Structures	1104	1052	2.962	2.822	10.808	0.769
10 Number Theory	2033	2052	5.454	5.505	115.862	8.241
14 Algebraic Geometry	692	764	1.856	2.049	4.687	0.333
15 Linear/ Multilinear Algebra; Matrix Theory	1547	1498	4.15	4.018	5.181	0.368
16 Associative Rings and Algebra	839	867	2.251	2.326	210.498	14.971

20 Group Theory	2037	1915	5.464	5.137	9.501	0.676
22 Topological Groups, Lie Groups	1228	1301	3.294	3.49	119.099	8.471
26 Real Functions	1619	1503	4.343	4.032	13.75	0.978
28 Measure and Integration	1621	1574	4.348	4.222	14.322	1.019
30 Functions of a Complex Variable	2257	2050	6.055	5.499	68.25	4.854
32 Several Complex Variables & Analytic Spaces	850	1016	2.28	2.725	11.31	0.804
33 Special Functions	899	864	2.412	2.318	30.171	2.146
34 Ordinary Differential Equations	3298	3085	8.847	8.276	145.525	10.35
35 Partial Differential Equations	3369	3485	9.038	9.349	665.954	47.365
41 Approximations and Expansions	1567	1619	4.204	4.343	104.577	7.438
42 Fourier, Abstract Harmonic Analysis	1665	1558	4.466	4.179	10.681	0.76
46 Functional Analysis (from 1973)	4172	3878	11.192	10.403	63.006	4.481
47 Operator Theory	3405	3644	9.134	9.775	348.338	24.775
50 Geometry	1162	1023	3.117	2.744	18.485	1.315
53 Differential Geometry	1881	1686	5.046	4.523	25.966	1.847
54 General Topology	1946	1828	5.22	4.904	19.992	1.422
55 Algebraic Topology	1214	1061	3.257	2.846	10.104	0.719
57 Topology, Geometry of Manifolds (1959-72)	1204	1379	3.23	3.699	109.293	7.773
60 Probability Theory and Stochastic Processes	3186	3163	8.547	8.485	3.914	0.278
62 Statistics	2133	2208	5.722	5.923	45.131	3.21
65 Numerical Analysis	3325	3401	8.919	9.123	215.195	15.305
68 Computing Machines, 1973: Computer Science	814	1137	2.184	3.05	15.612	1.11
73 Mechanics of Solids	947	837	2.54	2.245	14.277	1.015
76 Fluid Mechanics (from 1973: plus Acoustics)	1277	1190	3.426	3.192	10.932	0.778
78 Optics, Electromagnetic Theory	810	666	2.173	1.787	122.945	8.744
81 Quantum Mechanics	1657	1535	4.445	4.118	6.803	0.484
82 Statistical Physics, Structure of Matter	1001	1103	2.685	2.959	107.533	7.648
83 Relativity	781	786	2.095	2.108	4.986	0.355
90 Economics, Oper. Res., Programming, Games	2002	2239	5.37	6.006	178.255	12.678
93 Systems, Control	1504	1570	4.035	4.212	152.731	10.863
94 Information & Commun, Circuits, Automata	2041	1912	5.475	5.129	8.784	0.625

The nodes in Fig. 1 are clustered by degree of connectivity, the corresponding clusters and field names being given in Table 3. There are essentially 6 clusters, named as Pink, Red, Black, Blue1, Blue2, Blue3 and two isolated nodes, Grey. The central core of the network consists of several well connected Pink nodes, surrounded by less connected nodes.
We note from Table 3 that some expected associations between fields do not emerge in the clusters, a straightforward example being Probability (*Node 60*), which is not in the same cluster as Statistics (*Node 62*), even though there is a strong link between them (*see Fig.1)*. Information and Communication (*Node 94*) is not clustered with Computer Science (*Node 68*). There is no reason why History and Biography (*Node 1*) should be placed in the Red Cluster along with Groups (*Node 20*) Geometry (*Node 53*) and Topology (*Nodes 22, 54*), to mention just a few examples. The corresponding hierarchical tree and cluster diagrams are shown in Figures 2 and 3. Only the Blue3 cluster appears to be one related to the Physics disciplines, with the exception of Relativity (*Node 83*) which appears as a single node.

Table 3: Fields in Mathematics clustered by total migrations.

Pink
26 Real Functions
30 Functions of a Complex Variable
34 Ordinary Differential Equations
35 Partial Differential Equations
42 Fourier, Abstract Harmonic Analysis
46 Functional Analysis (from 1973)
47 Operator Theory
60 Probability Theory and Stochastic Processes
65 Numerical Analysis
Blue 1
2 Logic and Foundations
6 Order, Lattices, Ordered Algebraic Structures
68 Computing Machines, 1973: Computer Science
Grey1
16 Associative Rings and Algebra
Red
1 History and Biography
20 Group Theory
22 Topological Groups, Lie Groups
28 Measure and Integration
53 Differential Geometry
54 General Topology
Grey2
83 Relativity
Black
5 Combinatorics
10 Number Theory
15 Linear and Multilinear Algebra; Matrix Theory
33 Special Functions
41 Approximations and Expansions
62 Statistics
90 Economics, Operations Research, Programming, Games
93 Systems, Control
94 Information & Communication, Circuits, Automata
Blue2
14 Algebraic Geometry
32 Several Complex Variables and Analytic Spaces
50 Geometry
55 Algebraic Topology
57 Topology, Geometry of Manifolds (only 1959-72)
Blue 3
73 Mechanics of Solids
76 Fluid Mechanics (from 1973: plus Acoustics)
78 Optics, Electromagnetic Theory
81 Quantum Mechanics
82 Statistical Physics

The hierarchical tree obtained from our data using the inbuilt function in UCINET is shown in Fig.2. Field labels are on the left. Fig.2 indicates that a branched tree structure may reflect the structure of mathematics better than a cluster structure. One may conjecture that this could be due to the relatively higher degree of logical connectivity between sub-disciplines of mathematics, as compared to other fields of science. If a branched structure exists in the linkage pattern or association between fields, it may not be optimal to use clustering, which tries to assign a node uniquely to a cluster, when in fact it may act as a bridge between clusters.

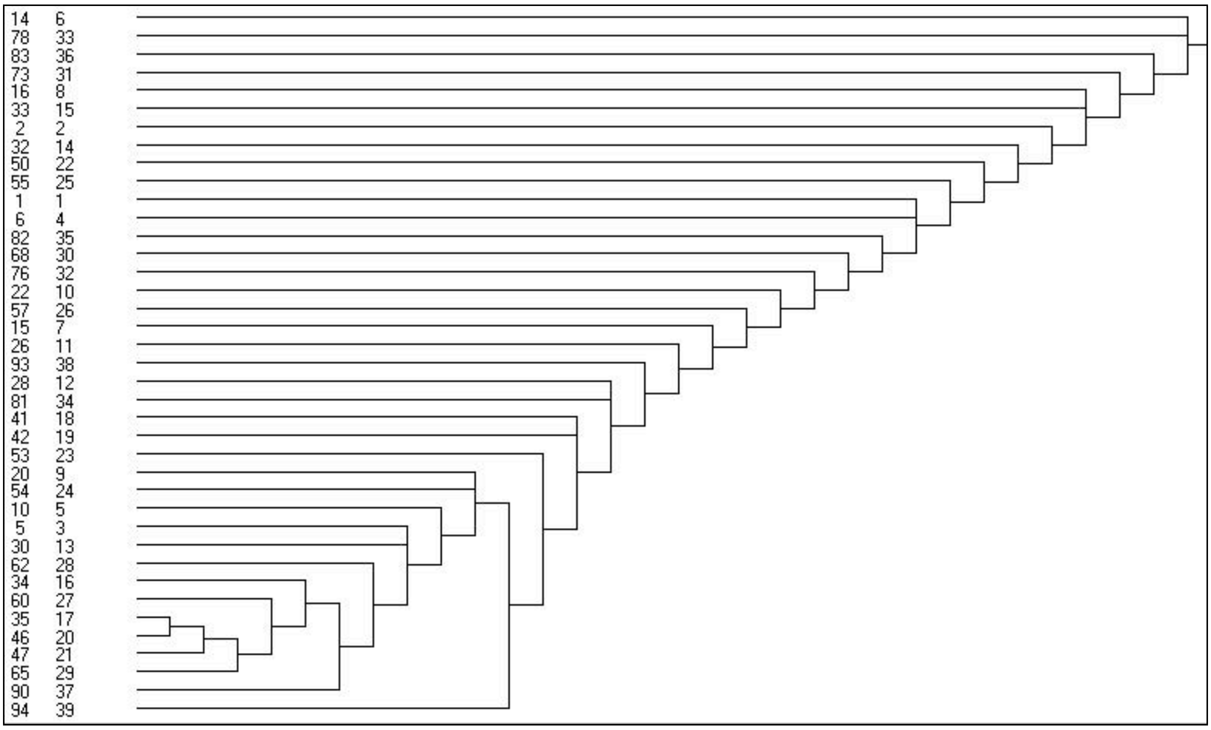

Figure 2. Hierarchical Tree Structure of fields in Mathematics (Field labels on left)

The corresponding cluster diagram is shown in Figure 3. It shows that well separated clusters emerge only at higher values of migration (only migration levels higher than 180 transitions shown here). The reason for this is obtained on examining the scatter of migrations with affinity between fields (Fig. 4) reproduced from Wagner Dobler ((1999). It is seen that when the affinity is low, migration is erratic. However at higher values of affinity there appears to be a good correlation between affinity and migration.

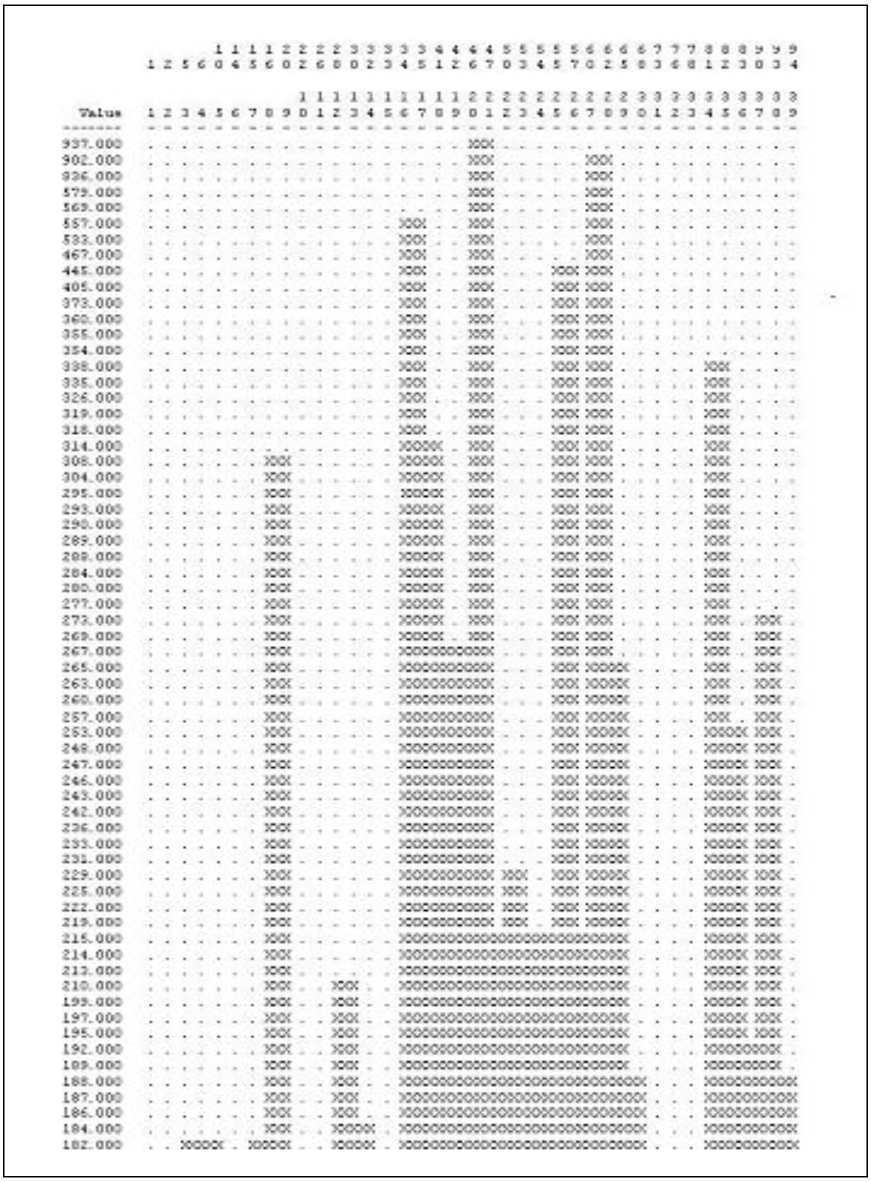

Figure 3: Emergence of structure in the association between fields at higher values of migration.

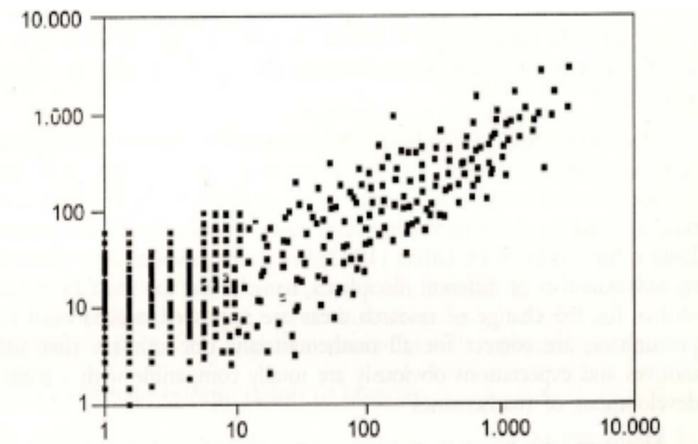

Figure 4: Scatter diagram of Affinity (X-axis) vs. Migration (Y-axis) showing poor correlation at lower levels but increasing migration with affinity at higher values.

Figure 4 shows clearly that the data on migration can be used as an index of field affinity or association only at higher values of migration. Values below some threshold add noise to the information content in the migration data. Keeping this in mind, the network is re-drawn after taking a threshold, eliminating links between areas with less than 165 migrations over a period of 17 years (Fig.5). The threshold was selected to include as many fields as possible, without vitiating the structure of the network. At higher levels of the threshold, areas start to get de-linked from the main network.

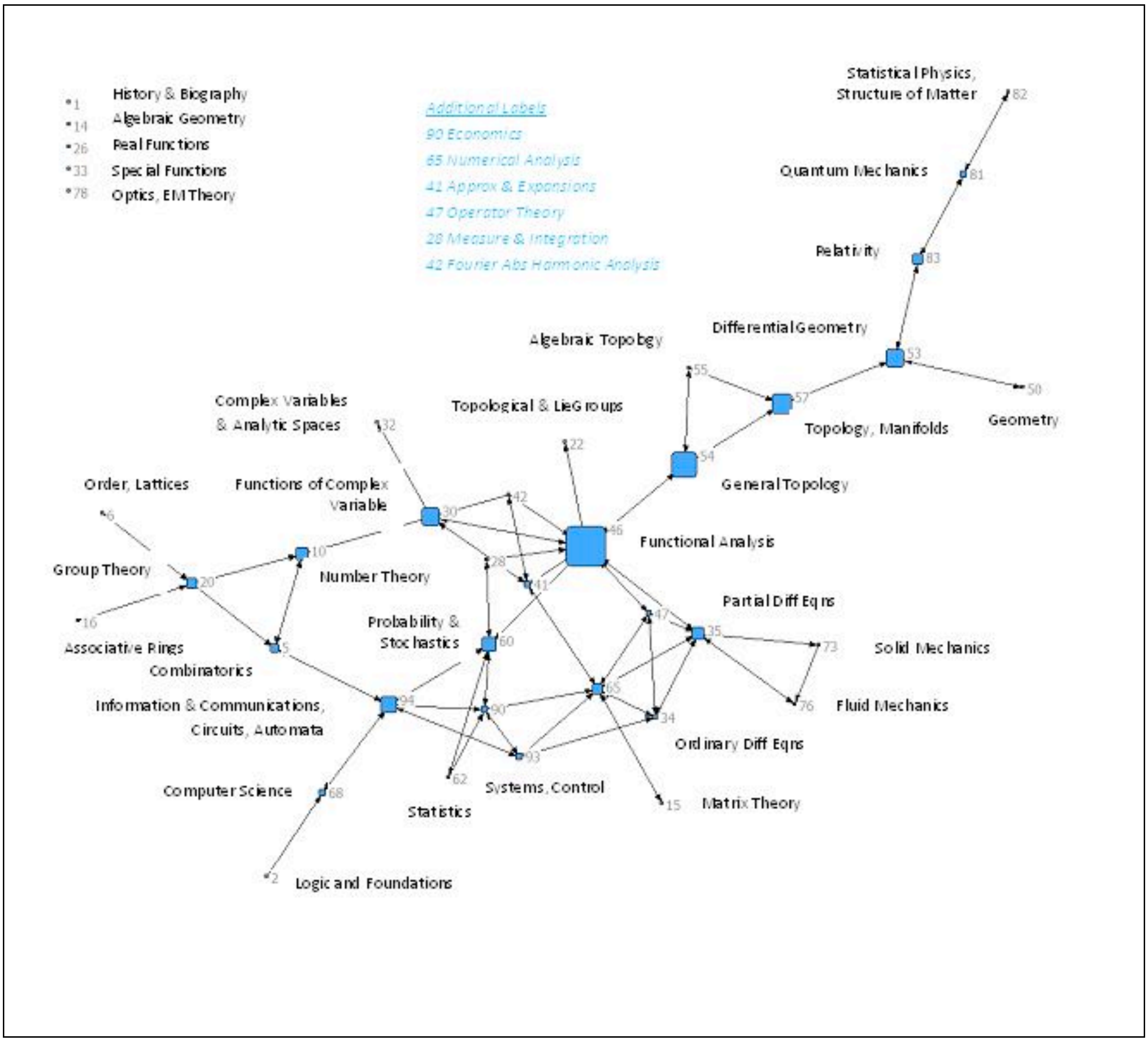

Figure 5. Labelled diagram of network of mathematics obtained from migration data(>165)

The labelled network structure of fields in mathematics at migration levels higher than 165 shows the disciplinary nuances within the field. Fields shown at the top left hand corner become disconnected from the network at this level. Wherever the labels could not be placed without obscuring details in the network, they are mentioned in the text at the top centre. The nodes in Fig. 5 are sized according to the betweenness values based on the modified data. It may be noted that there have been significant changes to the centrality values of different fields. Functional Analysis now has a central position with the highest betweenness centrality. Fig. 5 shows that Functional Analysis (46) holds the other areas of mathematics together as a fulcrum, even though it is not directly connected to all of them. The areas relating to Topology, General Topology (54), Topology and Manifolds (57), Algebraic Topology (55), are connected as a group. Topological and Lie Groups (22) is independently connected to Functional Analysis. The topology group is linked to Differential Geometry, which in turn is linked to Geometry along one branch and Relativity (83), Quantum Mechanics (81) and Statistical Physics (82) along the top right hand branch.

The lower left branch connects Logic and Foundations (2) to Computer Science (68), Information and Communication (94) and Probability and Stochastics (60).

Numerical Analysis is a hub that connects Operator Theory (47) and Ordinary and Partial Differential Equations (34 and 35). The last is connected to Solid and Fluid Mechanics (73 and 76). Economics (90) is another hub that connects to Numerical Analysis(65) Statistics(62), Systems and Control(93) and Information and Communication(94). Statistics also connects to Probability and Stochastics as expected. On the left of Figure 5, which has the more formal branches of mathematics, Information is connected to Combinatorics (5) which is connected to Number Theory (10) and Group Theory (20). The last is connected to Associative Rings (16) and Order Theory and Lattices (6). Close to Functional Analysis on the left are Complex Variables (30 and 32) and the areas Measure and Integration (28), Fourier Expansions (42) and Approximation and Expansions (41). History and Biography (1) which is likely to draw authors from all fields does not fall onto any branch, as do some other areas.

Discussion

We conclude that migration or cognitive mobility appears to give a fairly rational map for the discipline of mathematics, after the application of a suitable threshold. Areas which overlap with physics are on the upper branch while mechanics links to partial differential equations as expected. Similarly the connections to Economics and Probability are aligned to expectations as well as the links to Combinatorics. If a branched structure exists in the linkage pattern or association between fields, it may not be optimal to use clustering, which tries to assign a node uniquely to a cluster, when in fact it may act as a bridge between clusters. Some form of threshold may in general be required to bring out features of maps by excluding extraneous or random connections that may occur in the data (*see*, *e.g*., Basu, 2005). Our hypothesis that migration should reflect affinity between fields was based on the behavioural Zipf 'principle of least effort'. Since movement to another field of research involves a cost to the scientist, it is likely that more migrations will take place between neighbouring fields with lower transition costs. Low frequency migrations may reflect idiosyncratic transitions rather than statistically reliable trends, and need to be eliminated. Exceptions to the above may happen when migrations take place between unrelated areas, for example when a method or technique from one area is used in another. In such a case, migration may not reflect affinity between fields.

The correlation between migration and affinity, and the range where this holds has been independently validated in our study. It would be interesting to see if similar thresholds are required in drawing maps based on citations, and what is the rationale for their use. It has been observed by Small (2009) that beyond some critical threshold giant components emerge in the maps. It may therefore be necessary to consider applying thresholds in order to get meaningful groups in the mapping exercise.

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