Social Network Analysis
The evolution of the field

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1 Introduction

Social Network Analysis (SNA) has moved from a fragmented direction represented by the works of individual scientific groups unrelated to each other, to a discipline whose representatives by 1990 have formed an invisible college and achieved the status of what Kuhn had labeled a normal science (Freeman, 2004; Hummon and Carley, 1993).

Starting from that time, the field has grown significantly, which can be seen by the number of scientific publications (Otte and Rousseau, 2002) in different scientific fields, including Natural Sciences, which lead to the so called physicists‘ invasion into SNA (Batagelj et al., 2014) and resulted with the development of Network Science discipline.

This calls into a question whether the field remains unified and which scientific groups (by disciplines, thematic agenda, etc.) it is currently formed of. Thus, the aim of the current study is to trace the evolution of the field of Social Network Analysis using bibliographic approach.

2 Data

2.1 WoS

To the Web of Science (WoS), Clarivate Analyticss multidisciplinary databases of bibliographic information, we put the query

```
"social network*"
```

Additionally, all the articles from the following journals were collected:

```
Social Networks, Network Science,
Computational Social Networks, Applied Network Science,
Social Network Analysis and Mining,
Online Social Networks and Media, Journal of Complex
Networks, Journal of Social Structure, Connections
```

```
PT J
AU JOHNSTON, RD
   BARTON, GW
AF JOHNSTON, RD
   BARTON, GW
TI STRUCTURAL EQUIVALENCE AND MODEL-REDUCTION
SO INTERNATIONAL JOURNAL OF CONTROL
LA English
DT Article
RP JOHNSTON, RD (reprint author), UNIV SYDNEY,DEPT CHEM ENGN,SYDNEY,NSW 2006,AUSTRALIA.
CR JOHNSTON RD, 1984, INT J CONTROL, V40, P257, DOI 10.1080/00207178408933271
   JOHNSTON RD, 1984, UNPUB COMPUT CHEM EN
   MORARI M, 1980, AICHE J, V26, P232, DOI 10.1002/aic.690260206
   Morari M., 1977, THESIS U MINNESOTA
NR 4
TC 6
Z9 6
U1 0
U2 0
PU TAYLOR & FRANCIS LTD
PI LONDON
PA ONE GUNDPOWDER SQUARE, LONDON, ENGLAND EC4A 3DE
SN 0020-7179
J9 INT J CONTROL
JI Int. J. Control
PY 1985
VL 41
IS 6
BP 1477
EP 1491
DI 10.1080/0020718508961210
PG 15
WC Automation & Control Systems
SC Automation & Control Systems
GA AQJ42
UT WOS:A1985AQJ4200007
ER
```

Figure 1: WoS record

We limited the search to the Web of Science Core Collection because for other data bases from WoS the CR-fields (containing citation information) can not be exported.The first data set was collected in 2007, second - in June, 2018.

We call a *terminal* node a node without a description in the collected data set – it appears only in the WoS CR field as a reference.

We additionally collected on WoS and Google data for terminal nodes with large indegree in the citation network – highly cited works without description in the collected data set. If a description of a node was not available in WoS we manually constructed a corresponding description without CR data (using RIS biblographic format and converting it to WoS).

As the data set of 2007 was already completed, we made this additional search only for works 2008-* in July 2018.

3 Networks

3.1 Types of networks and partitions

We applied the WoS2Pajek 1.5 to the collected data.

The following networks were constructed:

1. the authorship network WA on works $\times$ authors (from the field AU),
2. the journalship network WJ on works $\times$ journals (from the field CR or J9),
3. the keywordship network WK on works $\times$ keywords (from the field ID or DE or TI),

4. the citation network $Cite$ on works (from the field CR).

We obtained also the following partitions:

1. partition $year$ of works by publication year,
2. the DC partition distinguishing between works with complete description (DC=1) and the cited only works (DC=0),
3. the vector of number of pages NP.

3.2 ISI names

The usual *ISI name* of a work (field CR)

`LEFKOVITCH LP, 1985, THEOR APPL GENET, V70, P585`

has the following structure

AU + `', '` + PY + `', '` + SO[:20] + `', V'` + VL + `', P'` + BP

All its elements are in upper case.

In WoS the same work can have different ISI names. To improve the precission the program **`WoS2Pajek`** supports also *short names* (similar to the names used in HISTCITE output). They have the format:

LastNm[:8] + `'_'` + FirstNm[0] + `'('` + PY + `')'` + VL + `':'` + BP

For example: `LEFKOVIT_L(1985)70:585`

From the last names with prefixes `VAN`, `DE`, ... the space is deleted. Unusual names start with character $\star$ or `$`.

3.3 Equivalent works

However, same works can be named by different names:

```
BOYD_D(2007)13:
BOYD_D(2008)13:210
```

There are two possibilities how to correct the data:

- to make corrections in the local copy of original data (WoS file);
- to make the equivalence partition of nodes and shrink the set of works accordingly in all obtained networks.

We used the second option. For the works with largest counts we prepared lists of possible equivalents and manually determined equivalence classes. With a program in R we produced a Pajek's partition $EQ.clu$ file used for shrinking the set of works.

Using the partition $p = worksEQ$, we shrink using Pajek the Citation network $cite$, WA, WJ, and WK.

We have to shrink also partitions $year$, DC and the vector NP.

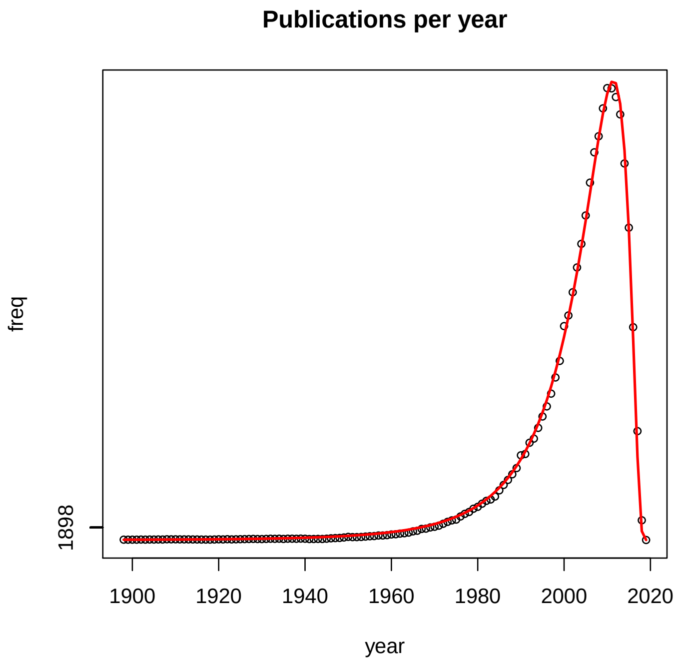

Figure 2: Citation network: Distribution of works by years

3.4 Networks construction

Works with complete description = 70795

1-mode network $Cite$:

	# nodes	# arcs
Cite	1297133	2753767

2-mode networks WA, WJ, WK:

	# nodes 1	# nodes 2	# nodes (sum)	# arcs
WA	1297133	395972	1693105	1442242
WJ	1297133	70425	1367558	1301276
WK	1297133	32409	1329542	1167670

An important property of all these networks is that they share as the first node set the same set the set of works (papers, reports, books, etc.) - they are *linked*.

4 Statistics

4.1 Citation network distributions

Figure 2. log normal distribution

$$c \cdot \text{dlnorm}(2019 - year, a, b)$$

$a = 2.543$, $b = 0.7206$, $c = 1.278 10^6$

Figure 3. The indegree distribution in citation network follows the *power law* $f = c \cdot n^{-\alpha}$.

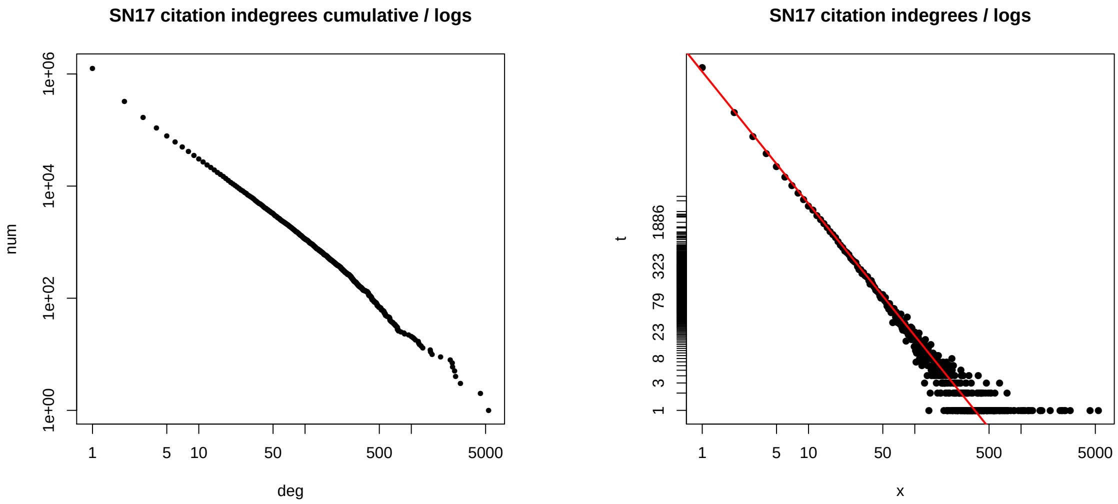

Figure 3: Citation network: Indegree distribution

Table 1: Citation net: The most cited works - indegree

i	freq	id	i	freq	id
1	5348	WASSERMA_S(1994):	31	734	NEWMAN_M(2001)98:404
2	4471	GRANOVET_M(1973)78:1360	32	719	NEWMAN_M(2010):
3	2906	WATTS_D(1998)393:440	33	701	PORTES_A(1998)24:1
4	2614	BARABASI_A(1999)286:509	34	687	BLEI_D(2003)3:993
5	2561	FREEMAN_L(1979)1:215	35	670	BURT_R(2004)110:349
6	2447	BOYD_D(2007)13:210	36	654	HANSEN_M(1999)44:82
7	2429	MCPHERSO_M(2001)27:415	37	639	PALLA_G(2005)435:814
8	2330	BURT_R(1992):	38	634	CLAUSET_A(2004)70:066111
9	1886	COLEMAN_J(1988)94:95	39	629	BONACICH_P(1987)92:1170
10	1572	NEWMAN_M(2003)45:167	40	628	ERDOS_P(1959)6:290
11	1520	GIRVAN_M(2002)99:7821	41	628	UZZI_B(1997)42:35
12	1510	PUTNAM_R(2000):	42	628	ROGERS_E(2003):
13	1285	ALBERT_R(2002)74:47	43	613	PUTNAM_R(1993):
14	1240	GRANOVET_M(1985)91:481	44	593	BERKMAN_L(1979)109:186
15	1192	SCOTT_J(2000):	45	583	ZACHARY_W(1977)33:452
16	1171	EVERETT_M(2002):	46	572	BORGATTI_S(2009)323:892
17	1166	NEWMAN_M(2004)69:026113	47	569	NEWMAN_M(2001)64:025102
18	1093	COLEMAN_J(1990):	48	565	BURT_R(2005):
19	1058	STEINFIE_C(2007)12:1143	49	561	ADLER_P(2002)27:17
20	1034	FORTUNAT_S(2010)486:75	50	559	CHRISTAK_N(2008)358:2249
21	999	BORGATTI_S(2002):	51	555	ROGERS_E(1995):
22	945	CHRISTAK_N(2007)357:370	52	554	MILGRAM_S(1967)1:61
23	867	FREEMAN_L(1977)40:35	53	553	BARON_R(1986)51:1173
24	854	HANNEMAN_R(2005):	54	550	GRANOVET_M(1978)83:1420
25	800	LIN_N(2001):	55	539	FISCHER_C(1982):
26	757	KAPLAN_A(2010)53:59	56	537	BRIN_S(1998)30:107
27	756	BLONDEL_V(2008):P10008	57	524	MARSDEN_P(1990)16:435
28	742	NAHAPIET_J(1998)23:242	58	523	KEMP_D(2003):137
29	740	FORNELL_C(1981)18:39	59	523	KLEINBER_J(1999)46:604
30	740	NEWMAN_M(2006)103:8577	60	517	BOCCALET_S(2006)424:175

Table 2: Citation net: The most citing work – outdegree

i	freq	id	i	freq	id
1	1572	CHAPMAN_C(2016):1	11	731	TSATSOU_P(2014):1
2	1406	HRUSCHKA_D(2010)5:1	12	654	GOODALE_E(2017):IX
3	1293	COWARD_F(2015):1	13	649	PEPPER_G(2017)40:S0140525X1700190X
4	1254	FITZGERA_P(2008):1	14	632	STROM_R(2012):1
5	1207	DAVIES_N(2015):V	15	613	SCHACHNE_G(2015)23:49
6	1055	MARSH_C(2009):1	16	597	COSTA_L(2011)60:329
7	942	YUS_F(2011)213:1	17	593	BRANDES_U(2005)3418:1
8	929	BOCCALET_S(2006)424:175	18	586	ROBERTS_J(2014):1
9	799	REEVES_M(2017):1	19	557	GUNTER_B(2016):1
10	768	GROSS_J(2007):1	20	547	CASTELLA_C(2009)81:591

Fitted $\alpha = 2.3007$, $c = 749338$.
Table 1.
Table 2.

- MUIJS, D., Reynolds, D., CHAPMAN, C. (2015). Educational effectiveness and improvement research and practice: The emergence of the discipline. In The Routledge International Handbook of Educational Effectiveness and Improvement (pp. 33-56). Routledge.
- Hruschka, D. J. (2010). Friendship: Development, ecology, and evolution of a relationship (Vol. 5). Univ of California Press.
- Coward, F., Hosfield, R., Pope, M., Wenban-Smith, F. (Eds.). (2015). Settlement, society and cognition in human evolution. Cambridge University Press.
- Fitzgerald, P., Lambkin, B. (2008). Migration in Irish history 1607-2007. Springer.
- Davies, N.B. Animal Social Networks Foreword. In: Krause, J., James, R., Franks, D. W., Croft, D. P. (Eds.). (2015). Animal social networks. Oxford University Press, USA.
- Marsh, C. J. (2009). Key concepts for understanding curriculum. Routledge.

4.2 Authors

Table 3.

The large number of Chinese authors in the list is a ”three Zhang, four Li” effect. It is out of our resources to drill into this. We can only make a warning.

Table 4.

Works with the largest number of authors:

Rank	Freq	Id
1	126	WANG_M(2016)34:828
2	53	VASHISHT_R(2012)7:0039808
3	48	SNIJDERS_T(2007)170:322
4	43	GUSTAVSS_A(2011)21:718
5	42	DOLL_L(1992)29:1
6	41	MAGLIANO_L(2006)15:219

WA net: Works with the largest number of authors – outdegree.

Sharing and community curation of mass spectrometry data with Global Natural Products Social Molecular Networking / Nature Biotechnology volume 34, pages 828837 (2016)

Table 3: WA net: Authors with the largest number of papers – indegree

Rank	Value	Id	Rank	Value	Id
1	1169	WANG_Y	21	552	KIM_H
2	883	ZHANG_Y	22	550	CHEN_J
3	868	CHEN_Y	23	536	LIU_X
4	847	LI_Y	24	533	WANG_L
5	838	WANG_X	25	509	LI_H
6	819	ZHANG_J	26	490	KIM_Y
7	788	WANG_J	27	485	ZHANG_Z
8	786	LIU_Y	28	474	WANG_Z
9	766	LEE_J	29	471	WANG_S
10	765	LEE_S	30	471	CHEN_X
11	749	LI_J	31	471	**NEWMAN_M**
12	708	LI_X	32	462	CHEN_L
13	696	CHEN_C	33	461	ZHANG_L
14	690	KIM_J	34	450	YANG_Y
15	620	WANG_H	35	450	ZHANG_H
16	611	ZHANG_X	36	432	WU_J
17	611	LIU_J	37	431	LEE_H
18	570	CHEN_H	38	420	LI_Z
19	557	KIM_S	39	420	WANG_W
20	554	WANG_C	40	417	LI_L

Table 4: WA net: Number of authors in works – outdegree

outdeg	Freq	Freq%	outdeg	Freq	Freq%
1	1239496	95.5566	21	4	0.0003
2	18637	1.4368	22	3	0.0002
3	16661	1.2844	23	4	0.0003
4	10617	0.8185	24	2	0.0002
5	5759	0.4440	25	1	0.0001
6	2802	0.2160	26	2	0.0002
7	1322	0.1019	27	5	0.0004
8	686	0.0529	28	2	0.0002
9	384	0.0296	29	1	0.0001
10	247	0.0190	31	3	0.0002
11	155	0.0119	36	1	0.0001
12	90	0.0069	41	1	0.0001
13	70	0.0054	42	1	0.0001
14	54	0.0042	43	1	0.0001
15	32	0.0025	48	1	0.0001
16	12	0.0009	53	1	0.0001
17	14	0.0011	126	1	0.0001
18	9	0.0007			
19	6	0.0005			
20	2	0.0002			
SUM				1297133	100

Mingxun Wang, Jeremy J Carver, Vanessa V Phelan, Laura M Sanchez, Neha Garg, Yao Peng, Don Duy Nguyen, Jeramie Watrous, Clifford A Kapono, Tal Luzzatto-Knaan, Carla Porto, Amina Bouslimani, Alexey V Melnik, Michael J Meehan, Wei-Ting Liu, Max Crsemann, Paul D Boudreau, Eduardo Esquenazi, Mario Sandoval-Caldern, Roland D Kersten, Laura A Pace, Robert A Quinn, Katherine R Duncan, Cheng-Chih Hsu, Dimitrios J Floros, Ronnie G Gavilan, Karin Kleigrewe, Trent Northen, Rachel J Dutton, Delphine Parrot, Erin E Carlson, Bertrand Aigle, Charlotte F Michelsen, Lars Jelsbak, Christian Sohlenkamp, Pavel Pevzner, Anna Edlund, Jeffrey McLean, Jrn Piel, Brian T Murphy, Lena Gerwick, Chih-Chuang Liaw, Yu-Liang Yang, Hans-Ulrich Humpf, Maria Maansson, Robert A Keyzers, Amy C Sims, Andrew R Johnson, Ashley M Sidebottom, Brian E Sedio, Andreas Klitgaard, Charles B Larson, Cristopher A Boya P, Daniel Torres-Mendoza, David J Gonzalez, Denise B Silva, Lucas M Marques, Daniel P Demarque, Egle Pociute, Ellis C O'Neill, Enora Briand, Eric J N Helfrich, Eve A Granatosky, Evgenia Glukhov, Florian Ryffel, Hailey Houson, Hosein Mohimani, Jenan J Kharbush, Yi Zeng, Julia A Vorholt, Kenji L Kurita, Pep Charusanti, Kerry L McPhail, Kristian Fog Nielsen, Lisa Vuong, Maryam Elfeki, Matthew F Traxler, Niclas Engene, Nobuhiro Koyama, Oliver B Vining, Ralph Baric, Ricardo R Silva, Samantha J Mascuch, Sophie Tomasi, Stefan Jenkins, Venkat Macherla, Thomas Hoffman, Vinayak Agarwal, Philip G Williams, Jingqui Dai, Ram Neupane, Joshua Gurr, Andrs M C Rodrguez, Anne Lamsa, Chen Zhang, Kathleen Dorrestein, Brendan M Duggan, Jehad Almaliti, Pierre-Marie Allard, Prasad Phapale, Louis-Felix Nothias, Theodore Alexandrov, Marc Litaudon, Jean-Luc Wolfender, Jennifer E Kyle, Thomas O Metz, Tyler Peryea, Dac-Trung Nguyen, Danielle VanLeer, Paul Shinn, Ajit Jadhav, Rolf Mller, Katrina M Waters, Wenyuan Shi, Xueting Liu, Lixin Zhang, Rob Knight, Paul R Jensen, Bernhard Palsson, Kit Pogliano, Roger G Linington, Marcelino Gutirrez, Norberto P Lopes, William H Gerwick, Bradley S Moore, Pieter C Dorrestein, Nuno Bandeira.

Table 5

Table 6

5 Citation network

5.1 Cite net: Boundary problem

The network Cite has 1297133 nodes and 2753767 arcs.

Most of nodes are terminal ($DCr = 0$) or nodes cited only once (indegree=1). We decided (boundary problem) to include in our networks nodes with $DCr > 0$ or indeg > 2 (partition boundary). They determine a subnetwork CiteB with 222 086 nodes and 1 521 434 arcs.

Table citeb

5.2 Making citation network acyclic

The citation network CiteB has 41 nontrivial strong components (see Figure 4).

To get an acyclic network we applied the *preprint transformation* to CiteB. The resulting network CiteT has 222 189 nodes and 1 521 658 arcs.

We computed the SPC weights on network arcs, and determined

- CPM path (Main path) = 59 nodes
- Key-routes = 127 nodes
- SPC link islands [Line weights] of sizes [20, 200] = 5 islands of 138, 65, 13, 12, and 11 nodes
- SPC node islands [Vertex weights] of sizs [20, 200] = 1 island of 200 nodes

Figure 4.

Table 5: WJ net: The most used journals – indegree

Rank	Value	Id	Rank	Value	Id
1	7080	LECT NOTES COMPUT SC	31	1258	AM J PSYCHIAT
2	3859	SOC SCI MED	32	1221	J BUS RES
3	3408	J PERS SOC PSYCHOL	33	1217	MANAGE SCI
4	2719	COMPUT HUM BEHAV	34	1185	ACAD MANAGE REV
5	2631	SCIENCE	35	1182	J CONSULT CLIN PSYCH
6	2602	AM J PUBLIC HEALTH	36	1151	ORGAN SCI
7	2599	P NATL ACAD SCI USA	37	1150	ADDICTION
8	2208	NATURE	38	1143	STRATEGIC MANAGE J
9	2058	AM SOCIOL REV	39	1087	J GERONTOL B-PSYCHOL
10	1945	PHYSICA A	40	1075	PEDIATRICS
11	1815	ANIM BEHAV	41	1055	AM J EPIDEMIOL
12	1778	JAMA-J AM MED ASSOC	42	1050	COMPUT EDUC
13	1763	LANCET	43	1022	DEV PSYCHOL
14	1759	SCIENTOMETRICS	44	1022	PSYCHOL BULL
15	1734	AM J SOCIOL	45	1007	J ADOLESCENT HEALTH
16	1703	ACAD MANAGE J	46	997	J MARKETING
17	1632	LECT NOTES ARTIF INT	47	996	ARCH GEN PSYCHIAT
18	1573	J APPL PSYCHOL	48	994	AIDS BEHAV
19	1551	SOC NETWORKS	49	972	PERS INDIV DIFFER
20	1509	AM ECON REV	50	949	PERS SOC PSYCHOL B
21	1433	J MARRIAGE FAM	51	947	J BUS ETHICS
22	1400	BRIT MED J	52	939	J MARKETING RES
23	1399	CHILD DEV	53	925	INFORM SCIENCES
24	1373	EXPERT SYST APPL	54	916	HARVARD BUS REV
25	1365	NEW ENGL J MED	55	915	IEEE T KNOWL DATA EN
26	1363	COMMUN ACM	56	901	DRUG ALCOHOL DEPEN
27	1355	RES POLICY	57	900	WORLD DEV
28	1279	GERONTOLOGIST	58	899	AM J PREV MED
29	1275	BRIT J PSYCHIAT	59	895	ADDICT BEHAV
30	1271	SOC FORCES	60	893	J CONSUM RES

Table 6: WK net: The most used keywords – indegree

Rank	Value	Id	Rank	Value	Id
1	51333	social	31	3485	structure
2	46191	network	32	3479	life
3	11751	analysis	33	3444	risk
4	10219	model	34	3358	research
5	8104	community	35	3143	learn
6	8090	use	36	3116	influence
7	7596	base	37	3054	student
8	7439	information	38	3054	impact
9	7061	health	39	3049	perspective
10	7023	behavior	40	3042	complex
11	6745	online	41	3024	theory
12	6087	networking	42	2859	organization
13	5833	media	43	2828	relationship
14	5404	support	44	2802	algorithm
15	5101	communication	45	2776	education
16	5013	study	46	2714	group
17	4759	datum	47	2704	mobile
18	4376	management	48	2698	tie
19	4372	internet	49	2695	adult
20	4164	knowledge	50	2633	approach
21	4126	user	51	2608	care
22	4023	facebook	52	2551	adolescent
23	3984	technology	53	2479	role
24	3907	site	54	2472	state
25	3888	web	55	2467	innovation
26	3855	self	56	2434	pattern
27	3784	graph	57	2385	effect
28	3676	performance	58	2339	people
29	3534	service	59	2333	trust
30	3512	dynamics	60	2332	family

Table 7: Citation network: Boundary problem

indeg	Freq	Freq%	CumFreq	CumFreq%
0	41954	3.2344	41954	3.2344
1	933315	71.9521	975269	75.1865
2	154895	11.9413	1130164	87.1278
3	58141	4.4823	1188305	91.6101
4	29885	2.3039	1218190	93.9140
5	17651	1.3608	1235841	95.2748

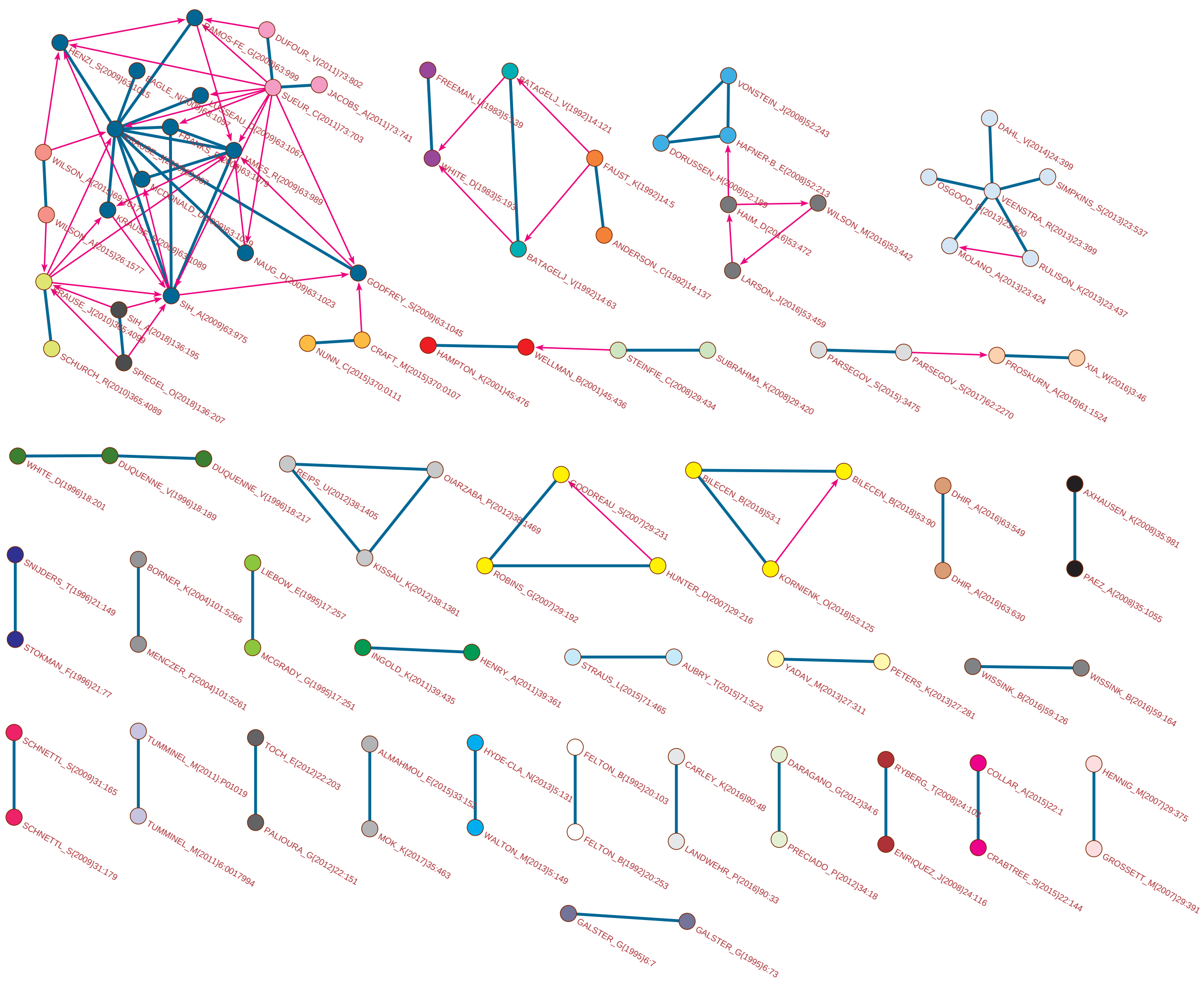

Figure 4: Strong components from SPC network

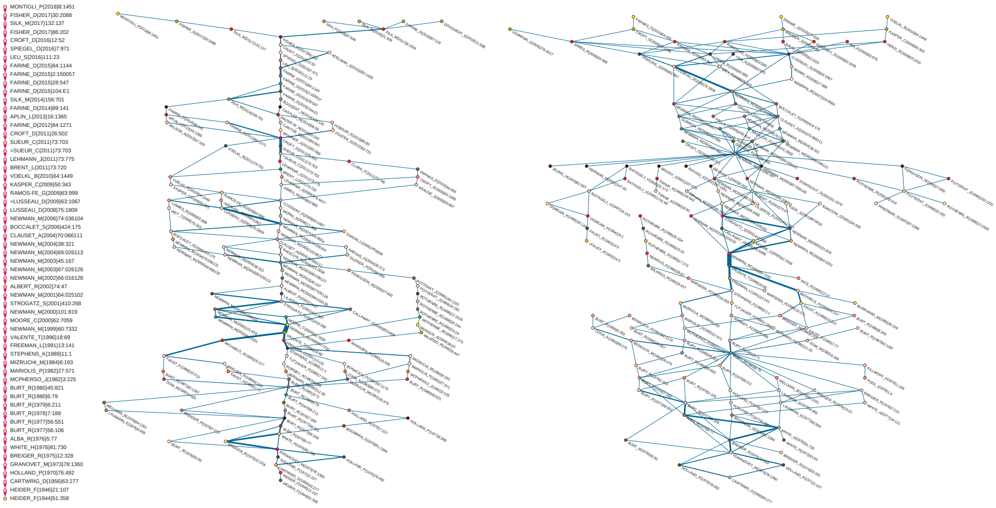

Figure 5: Main path, Key Routes, and Island 4 from SPC network

5.3 Main Path, Key-Routes, Main Link Island

Figure 5.

Figure 6.

Figure 7.

Figure 8.

5.4 Probabilistic flow

Table 8.

5.5 Comparisions

Table 9.

6 Conclusions

Basic statistics of derived networks allow us to get the most important works, authors, journals, keywords.

Citation network analysis reveals its main structure - gropus of works which are connected with each other. Obtained components are interlinked.

Deeper analysis of other derived networks, including those which can be constructed out of different initial ones (e.g., WA and KK), will show other patterns of Social Network Analysis field development.

Figure 6: Main path by fragments – sociology, physics, biology

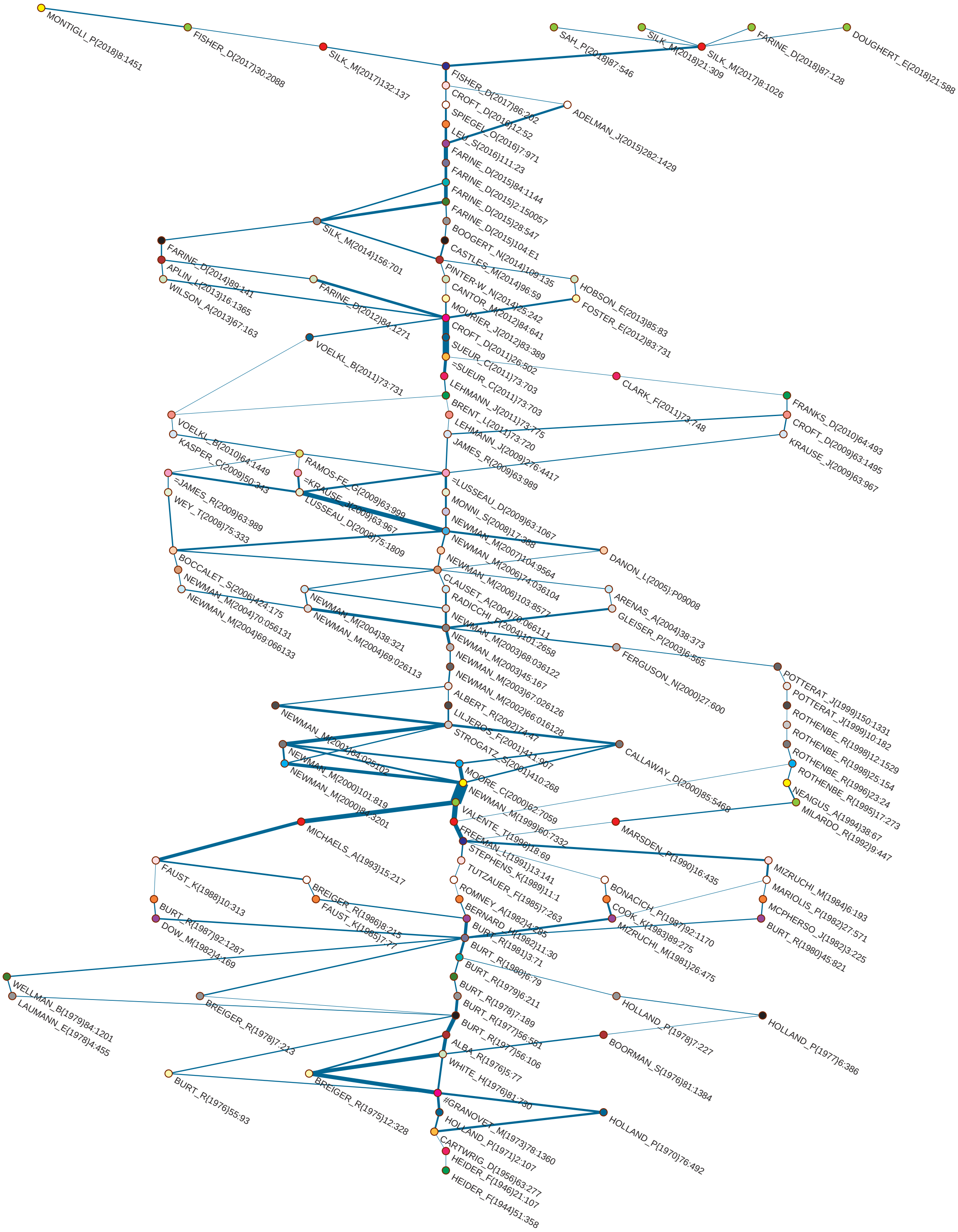

Figure 7: Key Routes

Table 8: Most important works from Probabilistic Flow network

Rank	Value	Id	Rank	Value	Id
1	4691	WASSERMA_S(1994):	31	545	BLONDEL_V(2008):P10008
2	2941	WATTS_D(1998)393:440	32	527	KATZ_L(1953)18:39
3	2676	GRANOVET_M(1973)78:1360	33	526	NEWMAN_M(2010):
4	2445	BOYD_D(2007)13:210	34	520	STROGATZ_S(2001)410:268
5	2241	BARABASI_A(1999)286:509	35	517	PALLA_G(2005)435:814
6	1926	FREEMAN_L(1979)1:215	36	499	CLAUSET_A(2004)70:066111
7	1396	GIRVAN_M(2002)99:7821	37	497	ERDOS_P(1960)5:17
8	1299	NEWMAN_M(2003)45:167	38	488	ROGERS_E(2003):
9	1227	MCPHERSO_M(2001)27:415	39	485	NEWMAN_M(2006)103:8577
10	1158	ALBERT_R(2002)74:47	40	481	COLEMAN_J(1990):
11	1105	SCOTT_J(2000):	41	478	BRIN_S(1998)30:107
12	1098	BURT_R(1992):	42	477	AMARAL_L(2000)97:11149
13	1045	MILGRAM_S(1967)1:61	43	475	ERDOS_P(1959)6:290
14	1013	NEWMAN_M(2004)69:026113	44	465	WATTS_D(1999):
15	928	KAPLAN_A(2010)53:59	45	462	LAVE_J(1991):
16	878	FREEMAN_L(1977)40:35	46	460	KLEINBER_J(1999)46:604
17	852	PUTNAM_R(2000):	47	449	SCOTT_J(1991):
18	847	COLEMAN_J(1988)94:95	48	446	BOLLOBAS_B(1985):
19	835	BLEI_D(2003)3:993	49	442	PAGE_L(1999):
20	742	GRANOVET_M(1985)91:481	50	440	NEWMAN_M(2001)64:025102
21	731	CHRISTAK_N(2007)357:370	51	436	NEWMAN_M(2004)69:066133
22	727	EVERETT_M(2002):	52	431	REDNER_S(1998)4:131
23	726	NEWMAN_M(2001)98:404	53	429	CHRISTAK_N(2008)358:2249
24	719	ALBERT_R(1999)401:130	54	424	ADOMAVIC_G(2005)17:734
25	701	O'REILLY_T(2005):	55	424	KEMP_D(2003):137
26	669	BORGATTI_S(2002):	56	423	DOMINGOS_P(2001):57
27	667	FORTUNAT_S(2010)486:75	57	423	MITCHELL_J(1969):
28	633	HANNEMAN_R(2005):	58	415	ALBERT_R(2000)406:378
29	569	STEINFIE_C(2007)12:1143	59	415	GLASER_B(1967):
30	549	ZACHARY_W(1977)33:452	60	410	ROGERS_E(1995):

Table 9: Cite net Overlapping of components

i	name	title	journal	comp
1	Granovet M	Strength of weak ties	amer j sociol	1, 2, 4, 5, 6
2	Newman M	The structure and function of complex networks	siam rev	1, 2, 4, 5, 6
3	Albert R	Statistical mechanics of complex networks	rev mod phys	1, 2, 4, 5, 6
4	Boccaletti S	Complex networks: structure and dynamics	phys rept	1, 2, 4, 5, 6
5	White H	Soc. str. from mult. nets. Blockmodels	amer j sociol	1, 2, 4, 5, 6
6	Newman M	Clustering and pref.l attach. in growing nets	phys rev e	1, 2, 4, 5, 6
7	Newman M	Finding and evaluating comm. struct. in nets	phys rev e	1, 2, 4, 5, 6
8	Newman M	Mixing patterns in networks	phys rev e	1, 2, 4, 5, 6
9	Strogatz S	Exploring complex networks	nature	1, 2, 4, 5, 6
10	Newman M	Detecting community structure in nets	eur phys j b	1, 2, 4, 5, 6
11	Newman M	Spread of epidemic disease on nets	phys rev e	1, 2, 4, 5, 6
12	Newman M	Finding community str. in nets using eigenvectors	phys rev e	1, 2, 4, 5, 6
13	Cartwright D	Structural balance - a generaliz. of heider theory	psychol rev	1, 2, 4, 5, 6
14	Clauset A	Finding community struct. in very large nets	phys rev e	1, 2, 4, 5, 6
15	Newman M	Models of the small world	j statist phys	1, 2, 4, 5
16	Newman M	Scaling and percolation in small-world net model	phys rev e	1, 2, 4, 5
17	Valente T	Social net thresholds in the diff. of innov.	soc networks	1, 2, 4, 5
18	Burt R	Cohesion versus structural equivalences as a basis for net subgroups	soc meth res	1, 2, 4, 5
19	Stephenson K	Rethinking centrality - methods and examples	soc networks	1, 2, 4, 5
20	Breiger R	Algorithm for clustering relational data	j math psychl	1, 2, 4, 5
21	Freeman L	Centrality in valued graphs - a measure of betweenness based on net flow	soc networks	1, 2, 4, 5
22	Burt R	Models of network structure	annu rev soc	1, 2, 4, 5
23	Holland P	Method for detecting structure in sociom. data	amer j sociol	1, 2, 4, 5
24	Alba R	Intersection of social circles	socl meth res	1, 2, 4, 5
25	Moore C	Exact solution of site and bond percolation on small-world net	phys rev e	1, 2, 4, 5
26	Mcpherson J	Hypernetwork sampling - duality and differentiation among voluntary organizations	soc networks	1, 2, 4, 5
27	Mariolis P	Centrality in corporate interlock networks	adm sci quart	1, 2, 4, 5
28	Burt R	Positions in multiple network systems 1. General conception of stratification and prestige	soc forces	1, 2, 4, 5
29	Burt R	Positions in multiple network systems 2. Stratification and prestige among elite	soc forces	1, 2, 4, 5
30	Mizruchi M	Interlock groups, cliques, or interest-groups	soc networks	1, 2, 4, 5

1- Key Routes, 2- Main Path (CPM), 3- Island5, 4 - Island 4, Node Island, 5 - Prob Flow Island

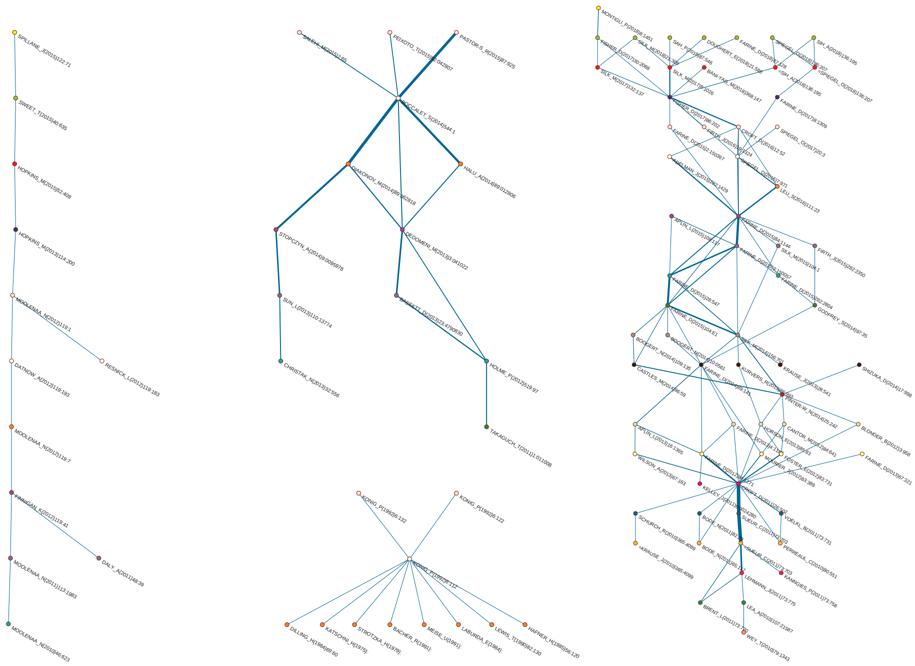

Figure 8: Islands 1-3, 5 e from SPC network

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