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Tracking and predicting growth areas in science

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We explore the possibility of using co-citation clusters over three time periods to track the emergence and growth of research areas, and predict their near term change. Data sets are from three overlapping six-year periods: 1996–2001, 1997–2002 and 1998–2003. The methodologies of co-citation clustering, mapping, and string formation are reviewed, and a measure of cluster currency is defined as the average age of highly cited papers relative to the year span of the data set. An association is found between the currency variable in a prior period and the percentage change in cluster size and citation frequency in the following period. The conflating factor of "single-issue clusters" is discussed and dealt with using a new metric called in-group citation.

Measuring the growth of research areas

The identification of research areas has been a perennial theme in scientometrics. By a research area I mean a set of documents or other bibliometric units that define a research topic and an associated group of researchers who share an interest in the topic. This definition of research area thus involves both content and social aspects. Earlier work in sociology of research areas emphasized the formal and informal communication ties among the practitioners (GRIFFITH & MULLINS, 1972), although these ties were not in and of themselves sufficient to define such areas. By the same token, a group of papers on the same topic may not constitute a research area if there is

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no communication among its practitioners. Thus, both cognitive and social forces work in tandem, and reinforce each other: the cognitive generating the social, and the social generating the cognitive.

Various types of data and techniques have been advocated for the purpose of delineating research areas including GARFIELD's historiographs (2004), document co-citation (SMALL, 1973) or author co-citation (WHITE & GRIFFITH, 1981), co-word analysis (CALLON et al., 1983), and journal mapping (LEYDESDORFF, 2004). Techniques focus on a wide range of clustering, ordination and multivariate methods. Desirable features of such methods are topic neutrality or the absence of topic bias, the ability to encompass multiple disciplines, the ability to follow time evolution, the ability to scale from the micro- to the macro-level, the ability to tune to different levels of detail or resolution, and the ability to reflect both cognitive and social aspects.

Having deployed such tools the question often arises whether there is any predictive value in them, that is, can they help predict the emergence or growth of scientific areas? Related questions are whether scientific discoveries can be predicted from the existing state of knowledge (SWANSON & SMALHEISER, 1997) or the more limited question of whether we can predict if an existing research area will advance or grow. Or is the best we can hope to achieve a retrospective monitoring and tracking of developments?

Types of leading bibliometric indicators, one might postulate, are temporal or structural. Examples of temporal or time based indicators are PRICE's index (1970), that can be framed in a general way as the percentage of papers or references in a specific time period, the mean or median age of papers such as so-called half-life measures, or immediacy indicators such as the immediacy index (GARFIELD, 1972). Structural indicators, which we will not deal with here, might also be considered, such as the linkage density, centrality, and interdisciplinarity.

The rationale for temporal indicators as predictors of growth is that a new discovery or development is likely to quickly attract the attention of researchers in the field, and the field will expand rapidly as scientists publish new papers building on and citing the original discovery papers. This would suggest that the more recent or current highly cited papers in a research area, the more likely the area will grow rapidly in the near future. We will propose a specific definition of currency based on the mean age of highly cited papers relative to a specific time frame.

Numerous earlier studies have focused in one way or another on this question, without however providing a definitive answer. The logistic curve proposed by PRICE (1961) and used by CRANE (1972) to describe the growth of research areas is in effect a model of how much an area will grow in the future. An early attempt to find a leading indicator of growth points in science is found in the work of MEADOWS (1971). GOFFMAN (1971) proposed an epidemic model of the growth and prediction of research areas in pulses which was later tested by WAGNER-DÖBLER (1999). TABAH (1992) attempted to use chaos theory to model the growth of literature in different areas.

Co-citation clusters of high currency have also been suggested as leading indicators of specialty growth. GRIFFITH & SMALL (1974) observed that co-discoveries in science are sometimes marked by the emergence of pairs of highly co-cited papers, such as the Temin and Baltimore co-discovery of reverse transcriptase. MERTON's observation (1963) that many discoveries are in fact multiples to varying degrees can be interpreted in a bibliometric context to mean that a group of related papers marks the emergence of a significant discovery, rather than an isolated paper.

Methodology for delineating research areas

Of course, to study the emergence and growth of research areas, we need a method for delineating them. It has been argued elsewhere (SMALL, 2004) that citation and co-citation patterns reflect a socialization process in science involving specialists coming to consensus on what documents are important and how they relate to one another. Cited works stand for or symbolize ideas or methods, and co-citation then defines a relation between these ideas. The method involves, in a nutshell, using highly cited papers, defined as the top one percent (1%) of papers in each of 22 broad disciplines, as the units of analysis (for the field definitions used see: http://www.in-cites.com/field-def.html). We assemble these units into co-citation networks through a series of clustering operations, yielding clusters at various levels of aggregation. We then track these objects over time by looking at successive time slices of data to determine the pattern of continuing highly cited papers from one set to the next. The threads of continuity are referred to as cluster strings (SMALL, 1977).

Three data sets of co-citation clusters were used representing three overlapping six year time frames: 1996–2001, 1997–2002 and 1998–2003. Both cited and citing items are restricted to these time spans. All co-citations among the selected highly cited papers are computed, each pair defining a link. To perform clustering, a threshold is set on the normalized co-citation coefficient (cosine similarity) which determines the selection of linked papers. The single-link cluster analysis gathers together the links that share common papers. To prevent chaining, a maximum cluster size is set with a provision for re-clustering at a higher threshold (SMALL & SWEENEY, 1985).

Table 1 gives statistics on the three data sets used: the number of clusters, highly cited papers, average citations per paper, and average publication year of papers.

Table 1. Statistics on clusters in three time periods

	1996–2001	1997–2002	1998–2003
# Clusters	5,005	5,221	5,269
# Papers	20,395	21,183	21,315
Cites per paper	70.6	74.9	76.9
Average year	1998.5	1999.5	2000.6

Once a cluster of co-cited documents is formed, a map or visualization can be created. Visualization provides a means of exploring the structure of the set of documents and for suggesting interpretations. All spatial solutions involving a reduction of dimensions are approximations, and thus maps are suggestive rather than definitive. On these maps the area of the circle is proportional to the citation frequency of the paper and the arrangement of circles reflects an attempt to minimize the net force on each node. Each co-citation link is modeled as an attractive force proportional to the normalized co-citation which varies linearly with distance between nodes (FRUCHTERMAN & REINGOLD, 1991). In addition there is a repulsive force among all nodes varying as the inverse square of the distance. Nodes are moved iteratively to minimize the forces acting on them, giving an average residual force per node after each iteration. For a front of 30 or so papers there might be a few hundred co-citation links that go into determining node positions. However, for clarity only the strongest links for each node are displayed, and dotted lines are used to represent a minimal spanning tree between any remaining separate components. Figure 1 shows a map for a cluster on webometrics from the period 1997–2002 containing 13 papers. Papers from the most recent year (2001) are darker in color.

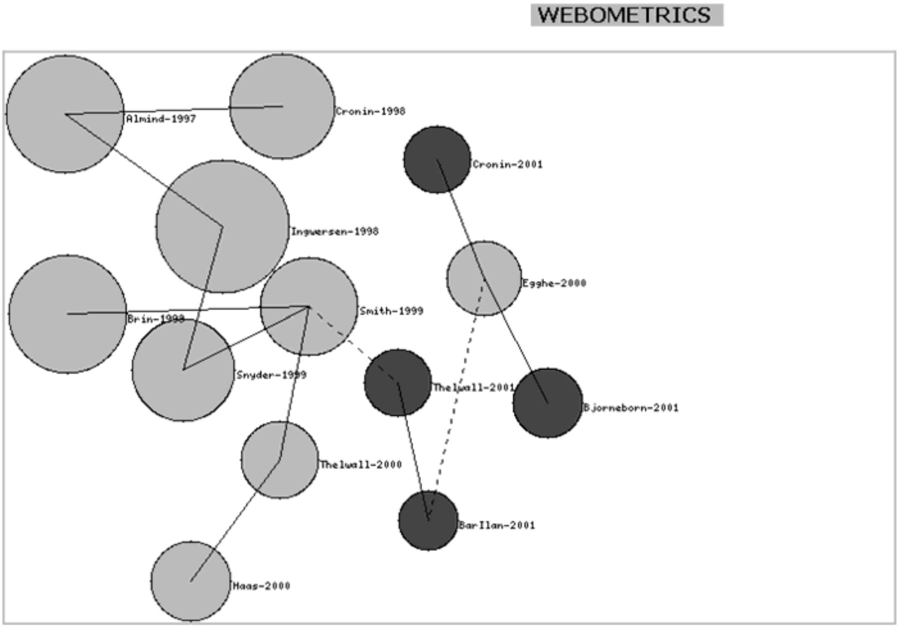


Figure 1. Map of webometrics 1997–2002 (force/node = 0.28)

After a mapping is carried out in one time period, change over time is studied by moving the time frame period by period, and tracking the highly cited papers from one period to the next. Cluster strings are formed when clusters in successive time periods share common papers.

The majority of strings are simple, linear continuations that extend over the three time periods. Two examples of simple strings (Figure 2) relevant to the field of scientometrics are small-world networks and webometrics. Both show substantial growth and have a high initial currency as defined below. The string diagram is chronological from left to right, and the size of the circle is proportional to the number of highly cited papers in the cluster (shown in the center of the circle).

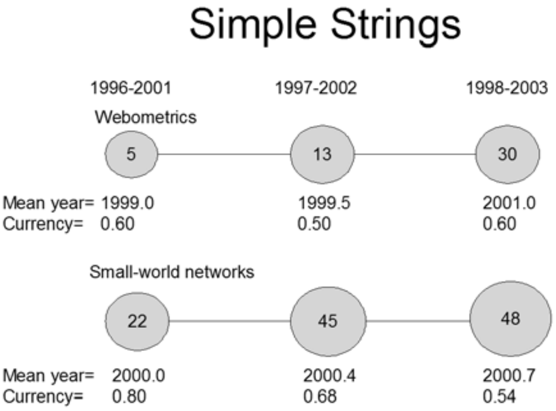


Figure 2. Two simple strings in scientometrics

Higher level clusters

The first level document clustering and mapping described above shows the structure of specialized scientific areas. To see the structure of larger fields or disciplines, we carry out another clustering and mapping process. Higher level structure is obtained by treating each initial level cluster as an object, re-computing the links between pairs of these objects, and re-clustering. This provides a telescoping of levels progressing from documents to specialties to disciplines, in a hierarchical schema. Not all first level objects have links to other objects at that level, reflecting differing degrees of isolation of research areas. It is possible to reintroduce isolates at each higher level to improve recall. To illustrate a hierarchy we start with a cluster on carbon nanotubes shown in Figure 3. Topics covered in the map are the solubilization of carbon nanotubes in the middle of the map, optical properties at the upper left, polymer wrapping at the upper right, fluorination at the lower right and sidewall functionalization at the lower left.

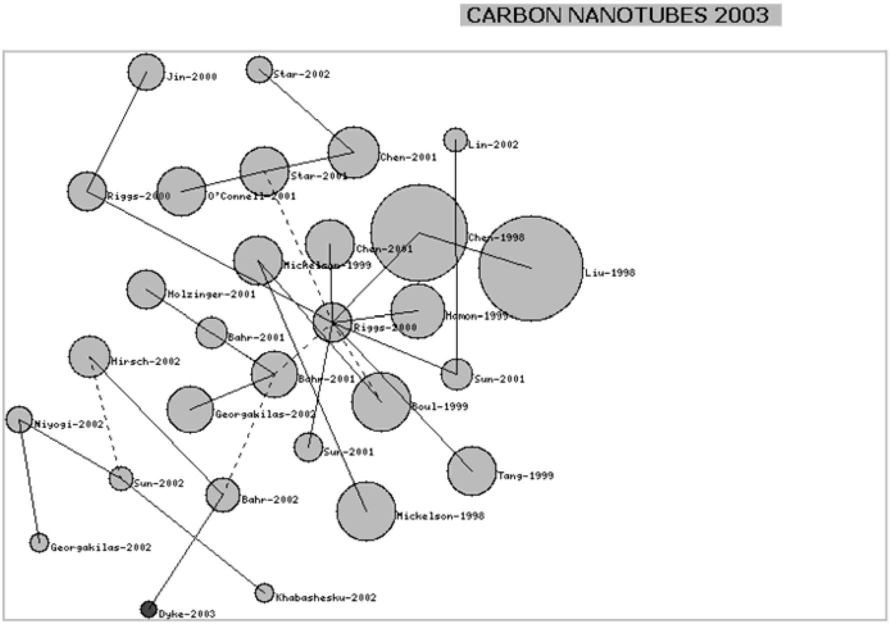


Figure 3. Carbon nanotube map 1998–2003 (force/node = 0.28)

Treating this group as a single object and collapsing its nodes, we compute its links to other objects at the same level. With another iteration of clustering the subject matter broadens, identifying a group of specialized areas in nanoscience generally (Figure 4), containing the above nanotube cluster as a single circle.

This second level map consisting of first level clusters shows areas dealing with a variety of nanostructures, including wires, rods, ribbons, and other nanostructures with electronic or chemical properties. Each level one cluster is treated analogously to a highly cited paper at the lower level. The first level carbon nanotube cluster is an object on this higher level map (#5940). Another iteration of clustering leads to a disciplinary view, in this case of materials science (Figure 5) containing the level 2 cluster as a single circle (#364).

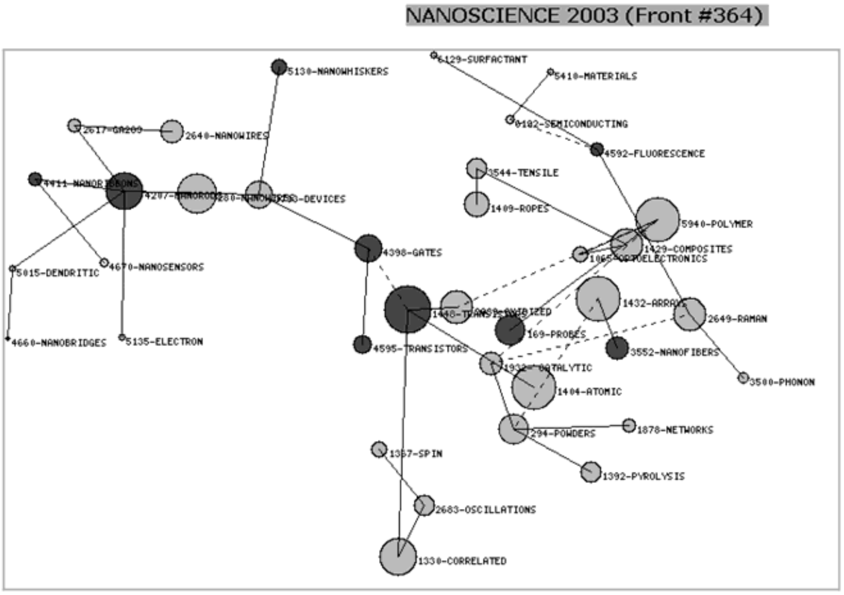


Figure 4. Level 2 map for nanoscience 1998–2003

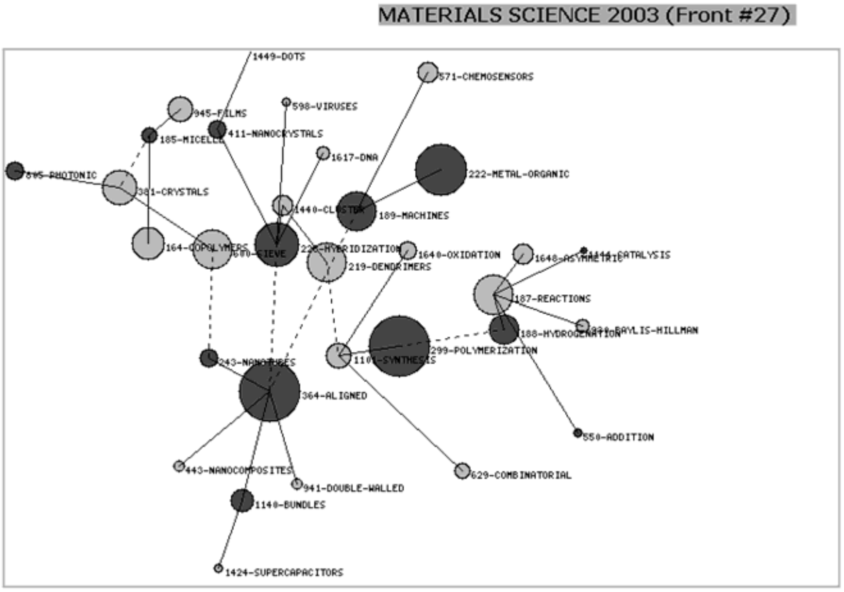


Figure 5. Level 3 map on materials science 1998–2003

On this third level map the network consists of second level objects and the spread of topics is closer to what might be called materials science. We find regions dealing with molecular machines, multilayer films, block copolymers, catalysis, crystals, synthetic chemistry, and DNA as an electronic device. Nanoscience from the previous figure is the large circle on the lower left connected above to molecular machines and DNA computing. At the next higher level we would reach a map of science, consisting of other higher level clusters in addition to materials science that have residual co-citation links.

Cluster strings can also be formed for higher level clusters in the same manner as first level strings. These higher level strings for nanoscience display a splitting or twigging pattern across the three time periods coincident with the emergence of the second level nanoscience maps. In an earlier study on AIDS (SMALL & GREENLEE, 1990) this twigging phenomenon was related to the progression of the research area from a single specialty within immunology to a separate biomedical discipline in its own right with its own higher level map.

New clusters

At the opposite extreme of continuity, we have new clusters which have no continuing papers from the prior period. Comparing the 1997–2002 dataset against 1998–2003 reveals 37% "new" clusters in the later period. Table 2 lists the five largest new clusters in 1998–2003 by number of highly cited papers, excluding "single issue" cases as explained below.

Table 2. New clusters 1998–2003

Cluster description	Papers
SEVERE ACUTE RESPIRATORY SYNDROME (SARS)	25
SONOGASHIRA COUPLING REACTION	23
ORAL DIRECT THROMBIN INHIBITORS	14
HEAT-SENSITIVE TRP CHANNELS (TEMPERATURE SENSING)	11
TWO-DIMENSIONAL GAS CHROMATOGRAPHY	11

The largest new area to emerge in 2003 was SARS consisting of 25 highly cited papers. All but two of its papers are published in 2003. Figure 6 is a map of this cluster with 2003 papers a darker color.

The map has a central region with papers describing the initial clinical outbreak, papers on SARS treatment on the lower left, and papers on the genome sequence of the coronavirus at the upper right. Moving up one level in the hierarchy we see SARS (near the top) in the context of other infectious diseases such as pneumonia, influenza, bird flu, streptococcal and pneumococcal infection (Figure 7).

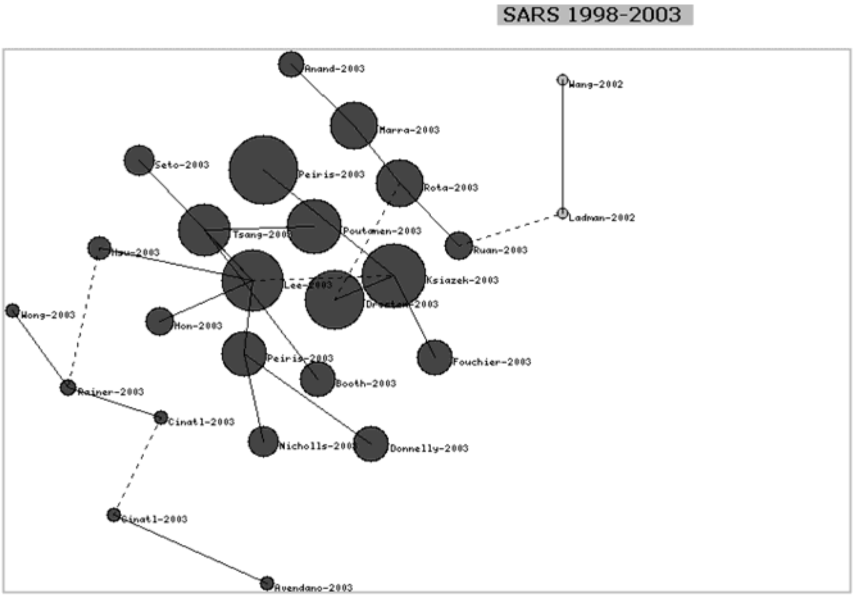


Figure 6. Map of emerging cluster on SARS 1998–2003

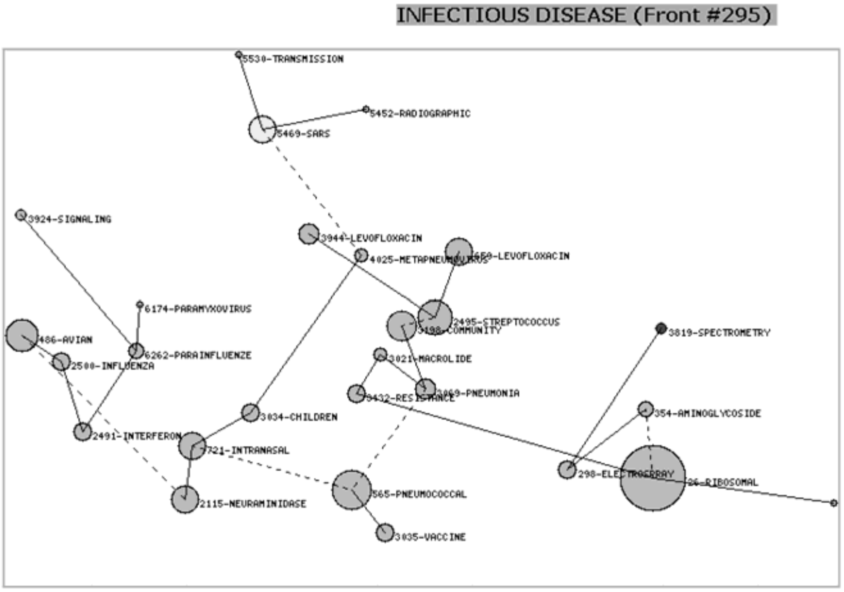


Figure 7. Level 2 map on infectious diseases containing SARS

Single issue clusters and in-group citation

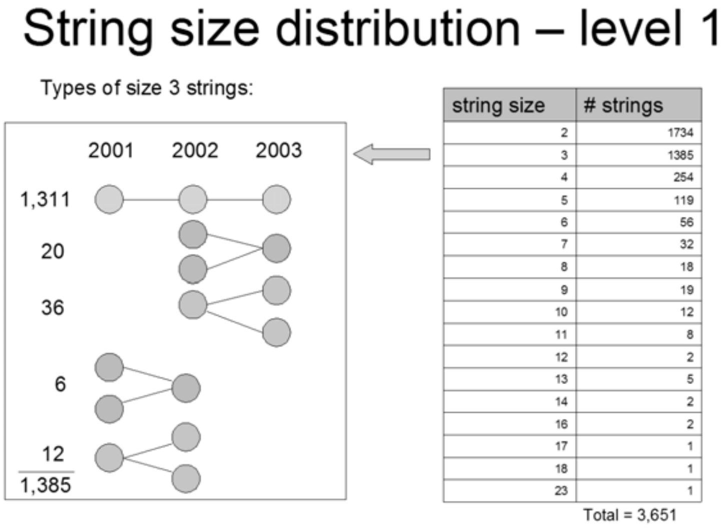
Before concluding that a new cluster represents a significant new area of research, it is necessary to examine whether it is the result of a publication artifact such as a special issue of a journal. This comes about, for example, when an editor arranges for each author of a paper in the special issue to cite the other papers in the issue. About 20 of the 90 largest new fronts in the 2003 file having 6 or more papers are to some degree "special issue" clusters, although this fraction declines rapidly as the cluster size diminishes. Such clusters are usually static and do not evolve over time.

To measure this phenomenon we created a metric called "in-group citation" which is the percentage of citing papers in the cluster that are also cited papers. Normally in co-citation clusters the cited and citing populations are distinct but in special issue clusters potentially all citing items are also cited items giving an in-group citation of 100%. The average in-group citation across the 1998–2003 cluster file is 2.3%, and only about 1.7% of clusters have an in-group value of 20% or higher. However, for the new clusters the average in-group citation is 3.7% and 4.3% of clusters have in-group values of 20% or higher. In fact, all but six of the 91 clusters in the high in-group set (≥20%) are new clusters. Thus, clusters with high in-group citation, including the "special issue" cases, are especially common in the set of new clusters.

Strings and the analysis of cluster change

As noted above, tracking fronts from one time period to the next is based on common or continuing highly cited papers. However, the evolution of fronts is often not a simple process of one area leading to another in a linear fashion. Patterns of development can be complex and involve a combination of branching and merging of clusters, and the death and birth of others.

A strategy to deal with this complexity is to create strings of clusters across time that share common cited papers including all the branching and merging lines (SMALL, 1977). Strings are created by a separate single-link cluster analysis based on inter-year cluster overlaps. Performing this analysis on the three time periods, and taking into consideration all year to year exchanges of highly cited papers at an inter-year coefficient of 0.1 (cosine coefficient), we obtain 3,651 strings involving first level clusters. The right side of Figure 8 shows the number of strings of different size, that is, the number of first level clusters in the string.



String size distribution – level 1

string size	# strings
2	1734
3	1385
4	254
5	119
6	56
7	32
8	18
9	19
10	12
11	8
12	2
13	5
14	2
16	2
17	1
18	1
23	1

Total = 3,651

Figure 8. Statistics on first level cluster strings (2001–2003)

Focusing on strings of size three, the left-hand side of Figure 8 shows the different developmental forms possible, with 95% continuing in a simple linear fashion across time. Linear sequences comprise 83% of all 3,651 strings in the three time periods, including strings of two clusters which are by definition linear.

Table 3 gives the topics of the seven largest strings and the number of fronts comprising them. We see a mix of pure and applied physical sciences as well as biomedical sciences. Five of the seven largest strings are from the physical sciences, and two are from biology. Three of the physical science areas are oriented to applied physics and engineering: molecular machines, vertical-cavity lasers, and plasma mass spectrometry.

Table 3. Largest level 1 strings: 2001–2003

String Description	# clusters
STRING THEORY OF D-BRANES	23
LINEAR MOLECULAR MACHINES AND MOLECULAR ELECTRONIC DEVICES	18
ALZHEIMER’S DISEASE-ASSOCIATED PRESENILIN-1 PROTEIN	17
QUANTUM WELL VERTICAL-CAVITY LASERS	16
PEROXISOMAL PROLIFERATOR-ACTIVATED RECEPTOR GAMMA (PPAR GAMMA)	16
LASER ABLATION INDUCTIVELY COUPLED PLASMA MASS SPECTROMETRY	14
POSITIVE MUON ANOMALOUS MAGNETIC MOMENT	14

As an example of a complex string, Alzheimer's disease (the third in the list of Table 3) shows the sudden emergence of a new area in 2002, consisting of 21 papers on the role of the presenilin-gamma-secretase complex (Figure 9).

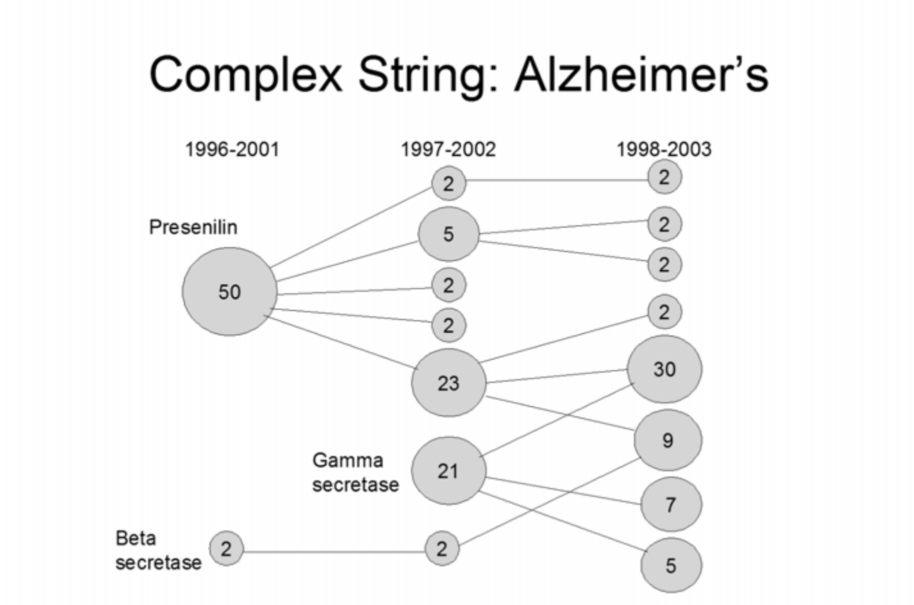


Figure 9. Complex string on Alzheimer's disease

The map for the gamma secretase cluster (Figure 10) shows a high influx of 2002 papers shown darker in color. Thirteen of the 21 papers are from 2002, the most current year of the middle period. Gamma secretase promised to provide insight into the molecular mechanism underlying Alzheimer's.

The Alzheimer's string also displays twigging, the splitting of clusters into various branches. The separation of lines of research corresponds to a proliferation of research topics.

It is often not easy to see whether strings are growing or declining when they contain multiple branching and merging patterns. We can overcome this by summing the sizes of each cluster connected in the string in each time period, and computing the aggregate rate of change of the connected areas. The most rapidly growing areas are shown in Table 4 among all strings in the three time periods. The fastest growing of these is a physics topic on "time-dependent string backgrounds" which emerged in the 2002 period and grew dramatically in 2003. The table shows the year the first front in the string appeared. The slope is defined as the change in size per year.

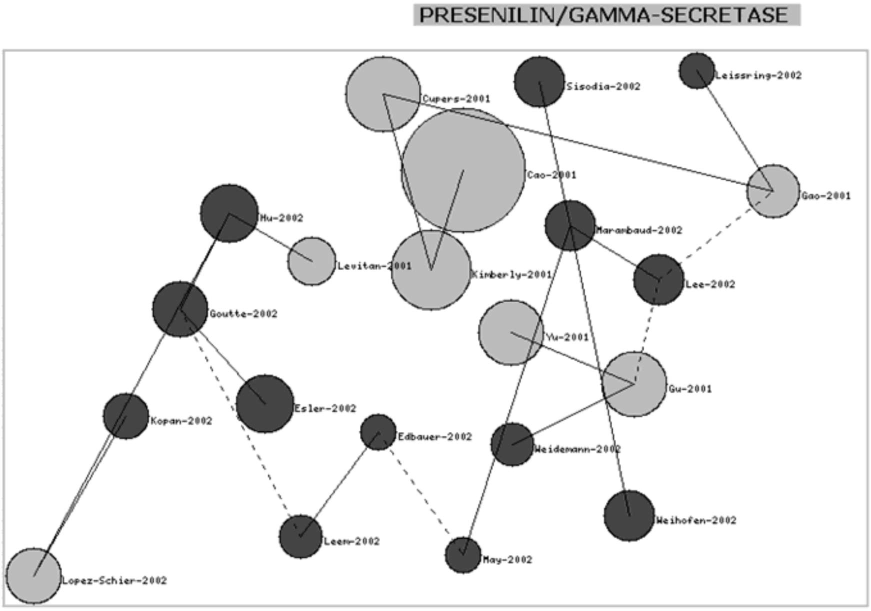


Figure 10. Map of gamma secretase in Alzheimer's 1997–2002

Table 4. Fast growing strings: 2001–2003

String description	Slope	1st Year
TIME-DEPENDENT STRING BACKGROUNDS	29.0	2002
BULK METALLIC GLASS	24.0	2002
SMALL INTERFERING RNAS	22.0	2002
COLLOIDAL SEMICONDUCTOR NANOCRYSTALLINE QUANTUM DOTS	21.0	2002
SUPERMASSIVE BLACK HOLES	20.5	2001
FAT-DERIVED HORMONE ADIPONECTIN AND INSULIN RESISTANCE	20.5	2001
SUPERSYMMETRIC EXTRA DIMENSIONS	20.0	2001

Predicting growth areas using strings

To test whether the number of recent papers in an area signals subsequent growth, we first define a measure of this "currency". Since a cluster consists of a set of papers from various earlier years within a defined period, a simple measure of currency is the mean year of publication. For comparisons over time or across different data sets this measure can be normalized to the year span of the data:

Currency of cluster = (([year span] - 1) – ([most recent year] – [mean year]))/([year span] - 1)

Currency is 1.0 if all the papers in the cluster are from the most recent year of the time window, and 0 if all the papers are from the first or earliest year of the window.

Table 5 relates the percentage change in cluster size to the currency of the *prior* year cluster, using all year-to-year transitions within strings of all degrees of complexity. To compile these data, the clusters were aggregated by year within each string, summing their sizes and total citations, and computing the average publication year for the pooled set of papers in the year. The first column in Table 5 is the currency range. The second column is the number of consecutive year-to-year transitions. The third column is the average percentage increase in string size (number of highly cited papers) from one period to the next. The fifth column is the mean currency of the later year. The last column is the percentage change in total citations. We see for example that strings with a currency between 0.8 and 1.0, of which there are 616 cases, have an average percentage increase in highly cited papers of 35.4% and an increase of 306.8% in total citations, while strings having a currency 0.2 or less decline in size by an average of 11% and have only a 5.3% increase in citations. The results suggest that strings with higher prior year currency have a larger percentage increase in size the next year than strings with lower prior year currency. Even more dramatic is the increase in citations for strings with high prior year currency. We also note that currencies in general diminish in the second year if the currency is higher the prior year.

Furthermore, strings at least doubling in size from one period to the next have an average prior year currency of 0.66, while strings declining in size by more than one-half have a prior year currency of 0.46. However, of those that double in size, 5% have a currency of 0.2 or less, and 8% of strings that decline by more than one-half have a currency greater than 0.8. Overall there is a rather low correlation (+0.20) between the prior year currency and percentage increase in size. The stronger tendency for clusters of high prior year currency to receive more citations the following year (correlation of +0.43) is somewhat expected due to the commonly observed peak in citations two to three years after publication.

If we correlate in-group citation with currency we get a positive correlation of 0.3 which means that high in-group behavior is more likely with clusters of high currency.

Table 5. All strings 2001–2002–2003

Currency range in Year-1	#string-year pairs	Mean % change in size	Mean currency in Year-2	% Change in citations
≤1.0 & >0.8	616	+35.4%	73.8%	306.8%
≤0.8 & >0.6	1,119	+18.8%	55.6%	89.1%
≤0.6 & >0.4	1,489	+9.4%	37.9%	45.9%
≤0.4 & >0.2	1,511	+0.33%	20.4%	23.3%
≤0.2 & >0	742	–11.0%	6.7%	5.3%

Furthermore, clusters of high currency are disproportionately represented in the set of clusters having an in-group citation of 20% or greater. One might also expect that since high in-group clusters do not generally grow in size, eliminating them would increase the correlation between currency and cluster size increase. However, eliminating the high in-group clusters did not materially increase this correlation, indicating that other factors besides currency are at work in determining the growth of research areas.

Conclusions

Co-citation clustering, mapping and cluster string formation allow us to study the emergence and growth of research areas from several perspectives. First level clusters and strings can show significant linear growth as in the case of webometrics and small-world networks. More complex and articulated growth is shown by nanoscience which, due to the splitting off of subspecialties, has formed a second level cluster, marking the transition from specialty to discipline. At the other extreme are cases of entirely new areas which appear quite suddenly. An example is SARS in the 1998-2003 period which resulted from a concerted global effort to halt the spread of the virus and elucidate its structure. This cluster showed a remarkable currency in its set of highly cited papers. Some "new" clusters proved to be artifacts due to special issues of journals, and a metric was proposed to detect such cases called in-group citation.

The study of change in large and complex strings is facilitated by a separate clustering process on the inter-period linkages. The large Alzheimer's string unexpectedly contained a significant new cluster which emerged suddenly and had a significant effect on the field the next year. A map of this area showed a high proportion of papers from the most recent year. Like nanoscience and AIDS, the Alzheimer's string displayed a high degree of twigging, suggesting the emergence of higher level structure. The growth rate of such complex strings is measured by aggregating the highly cited papers in each branch of the string by year, and looking at the time series of aggregate cluster sizes.

Since many cases of emerging and growing clusters have a high concentration of recent highly cited papers, this feature was explored as a leading indicator of research area growth. The relationship of the currency of highly cited papers to growth is expected if we consider that an area with new discoveries or findings will expand more rapidly from a smaller base than an older area whose rate of development may have slowed. The latter would be expected to grow only if it experienced rejuvenation through new findings or grew though a merger or combination with other older areas. A measure of currency is defined as the average publication year normalized with respect to the year span of the data set. The percentage increase in year-to-year cluster size was then compared with various ranges of the prior-year currency measure. The result was a slight tendency for clusters of high currency to grow more rapidly the following year than clusters of low currency, but the overall correlation was low. Thus, currency has some limited value as a short term predictor of year to year growth. Further work will be needed to identify other factors that might contribute to short term growth, and to understand the longer term dynamics of research areas.

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