Patent Overlay Mapping: Visualizing Technological Distance

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Abstract

The purpose of this paper is to present a new global patent map that represents all technological categories, and a method to locate patent data of individual organizations and technological fields on the global map. This second patent overlay map technique is shown to be of potential interest to support competitive intelligence and policy decision-making. The global patent map is based on similarities in citing-to-cited relationships between categories of the International Patent Classification (IPC) of European Patent Office (EPO) patents from 2000 to 2006. This patent dataset, extracted from PatStat database, represents more than 760,000 patent records in more than 400 IPC categories. To illustrate the kind of analytical support offered by this approach, the paper shows the overlay of nanotechnology-related patenting activities of two companies and two different nanotechnology subfields on to the global patent map. The exercise shows the potential of patent overlay maps to visualize technological areas and support decision-making. Furthermore, this study shows that IPC categories that are similar to one another based on co-citation (and thus close in the global patent map) are not necessarily in the same hierarchical IPC branch, thus revealing new relationships between technologies that are classified as pertaining to different (and sometimes distant) subject areas in the IPC.

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1. Introduction

The visualization of knowledge or technological landscapes has been a prominent part of publication and patent analyses since their origins (Small, 1973; Hinze et al., 1997). However, only in the last decades, improvements in computational power and algorithm have allowed the creation of large maps covering a full database, the so-called global maps of science (see reviews by Klavans & Boyack, 2009; Rafols et al., 2010).[1] These science maps or scientograms are the visualization of the relations between areas of science using network analysis algorithms.

Visualization procedures for science maps have generally been used to explore and visually identify scientific frontiers, grasp the extent and evolution of scientific domains, and analyze the frontiers of scientific research change (Van den Besselaar & Leydesdorff, 1996). Science mapping efforts have been also used to inspire cross-disciplinary discussion to find ways to communicate scientific progress (see, for example, Mapping Science at http://www.scimaps.org/). Although science maps cannot replace other methodological approaches to data analysis, "visual thinking" can help to interpret and find meaning in complex data by transforming abstract and intangible datasets into something visible and concrete (Chen, 2003). Diverse approaches can be used to create visualizations.

The purpose of this paper is twofold: first, to present the results of a global patent map and, second, to introduce the 'overlay map' technique to locate the relative technological position of an organization's patent activity to support competitive intelligence and policy decision-making. This research draws on the concept of technological distance to interpret linkages between the technologies and elaborate a method for a meaningful visualization of technological landscapes.

[1] Lately, there has been a proliferation of global maps (see, for example, Moya-Anegon et al., 2004; Boyack et al., 2005; Moya-Anegón et al., 2007; Bollen et al., 2009; Boyack et al., 2009; Janssens et al., 2009; Leydesdorff & Rafols, 2009; Rosvall & Bergstrom, 2010).

This visualization approach is a logical extension of the experience with overlay science maps. It draws closely on our previous work on this issue (Rafols et al., 2010) and opens up new avenues for patent research. The need for development of tools to benchmark and capture temporal change of organizational innovation activities or patterns of technological change also motivates this work. More generally, this new approach also accompanies the broader change from hierarchical, structured knowledge in science and technology (i.e. with subdisciplines and specialties that match departmental structures) to a web of "ways of knowing" resulting from changing social contract (Gibbons et al., 1994), increasing institutional hybridity (Etzkowitz & Leydesdorff, 2000), and dissonance between epistemic and social structures.

To illustrate the kind of analytical support offered by this approach, this paper illustrates the application of patent overlay maps to benchmark the nanotechnology-related patenting activities of two companies and reveal the core structure of patenting activities in two different nanotechnology subfields. Nanotechnology is an umbrella term referring to a diverse set of emerging technologies that improve or enable materials, devices and systems using novel properties resulting from the engineering and assembly of matter at extremely small scales. At the nanoscale, scientific discoveries have unveiled novel properties that offer the potential for applications in a wide array of market segments such as energy, pharmaceuticals, and semiconductors. With a wide range of potential applications, nanotechnology is anticipated to have significant business and economic impacts in future years. Our previous work illustrated how overlay science maps helped to provide a better understanding of the characteristics and evolution of the nanotechnology field or its subfields (see, for example, Porter & Youtie, 2009; Rafols & Meyer, 2010).

This paper is organized as follows. Section 2 discusses the concept of technological distance and the analysis of patent literature. Section 3 presents the methodological approach. Section 4 presents preliminary outputs based on the application of patent overlay maps to general patent datasets and the analysis of company patent portfolios and technological fields. Section 5 discusses the advantages and drawbacks of the method and elaborates on next steps and future of patent mapping. The paper also includes an Appendix with supplementary tables.

2. Technological distance and its operationalization

Technological distance, or the extent to which a set of patents reflects different types of technologies, is a key characteristic in being able to visualize innovative opportunities (Breschi et al., 2003). Patent documents that reference other patents in similar technology areas have been suggested to offer incremental opportunities to advance an area whereas patent documents that refer across diverse categories may offer the potential for radical innovation (Olsson, 2004). Technological distance is often proxied by patent categories, with patents in a given patent category being considered more similar to one another than to those in other patent categories (Jaffe, 1986; Kauffman et al., 2000). For example, Franz (2009) uses patent citations between U.S. patent categories and assigns weights to a patent citing another patent in a different category to reflect a larger technological distance. Hinze et al. (1997) look at co-assignment of multiple IPC categories as a measure of the distance between 30 technological fields. A challenge in relying on patent classifications is that, as technology changes, technology-oriented applications may draw from patents in different hierarchical categories, and subsequently lead to further diversity in the categories of patents that cite patents in these categories.

This investigation draws on the concept of technological distance and proposes an alternative approach to relying on administrative patent categories, using patent mapping

techniques to visualize technological landscapes. A patent map is a symbolic representation of technological fields which are associated with relevant themes. Technological fields are positioned in the map so that similar fields are situated nearby and dissimilar components are situated at a distance. The map is constructed from a similarity matrix based on co-citation of patents. The similarity measures are calculated from correlation functions between fields according to citations between patent categories. This multidimensional matrix is projected onto a two-dimensional space. This visual output provides for flexibility in interpreting the multidimensional relationships among the patent categories. In addition, this approach allows the user to "overlay" subsets of patent data–representing different types of technologies, institutions, or geographical regions–to understand the particular technological thrusts and areas of concentration of these actors (Rafols et al., 2010).

Other scholars have pursued a similar patent record-level approach to create global maps of technology that characterizes the proximity and dependency of technological areas (see, for example, Boyack and Klavans (2008, p. 181) or Villard (2012)). Those efforts have also sought to use the maps to benchmark industrial corporations to inform corporate and policy decision-making. The differences with the approach presented in this paper are primarily related to the definition of categories (which yields different number and composition of technology groups) and the relationships between them (generally based on citation-based co-occurrence of IPC categories, which yields maps with different structures.)

The approach used in this paper draws on learnings from the authors' prior work on science mapping, particularly the trade-off between sufficient detail and not too much detail that it cannot be easily visualized by the user. The challenges faced when developing this kind of patent map includes gathering patent data in appropriate quantity to create meaningful maps and

the choice of an equivalent to citation patterns (because citations may not be functionally equivalent to journal citations) and an equivalent to Web of Science Categories (previous known as ISI subject categories,) for which IPC categories may not be suitable analogs. Using IPC categories from patent documents also involves specific challenges, such as deciding on the appropriate level of analysis to obtain satisfactory results. This latter point is related to the IPC classification scheme which offers Sections, Classes, Sub Classes and Groups to choose from. While the Sub Class (i.e., four-digit IPC) level seems appropriate because of the degree of detail in subject matter definitions, it suffers a "population" problem related with the significant variation of the number of patents classified in each IPC Sub Class, which is likely to lead to underrepresented technologies in maps. Some Sub Classes have several hundred thousand patents, whereas others have only a few hundred. Thus, a more appropriate grouping of IPC categories is needed to more evenly represent the number of patents in the patent system.

3. Implementation

This paper presents a global patent map and a set of overlay maps to test and illustrate its application. The global map is based on citing to cited relationships between IPCs of European Patent Office (EPO) patents from 2000-2006. The dataset containing IPCs relationships, extracted from the Fall 2010 PatStat database version, represents more than 760,000 patent records in more than 400 IPC categories. This data range begins with patent EP0968708 (which was published in January 2000) and ends with patent EP1737233 (published in December 2006.) An analysis with this kind of coverage benefits from a relative stability of the patent classification system version 7 maintained during the 2000-to-2006 time period.

In this approach, the process of data gathering and pre-processing involves, first, going through each patent record to collect all the instances of IPC categories in the dataset and,

second, solving the aforementioned "population" problem. The proposed solution for patent categories with relatively few patents is to fold the IPC category up into the next highest level of aggregation to create relatively similar sized categories. This solution comprises three rules: 1) for IPC categories with large population, use the smallest Sub Group level; 2) for small population IPC categories, aggregate up to General Group level, Sub Class or Class; and, 3) establish a floor cut-off and drop very small aggregated populations. As a result, IPC categories with instance counts greater than 1,000 in the dataset were kept in their original state. Those categories with instance counts less than 1,000 were folded up to the next highest level until the count exceeded 1,000 or the Class level was reached. During the folding, any other IPC categories with counts exceeding 1,000 in the same branch were left out of the folding count. If at the Class level (i.e. 3-digit), the population was less than 1,000, the IPC code was dropped for being too small to map (Table 1).

[INSERT TABLE 1 ABOUT HERE]

This pre-processing yields IPC categories at the three digit, four digit, and seven digit levels, with levels that ensure broadly similar numbers (i.e. within two orders of magnitude) of patents across categories. Although we keep referring to these categories as 'IPC categories', they are not the standard IPC categories since they have a mixed hierarchical composition. The smallest categories in the dataset have 1,000 patents, with this bottom threshold chosen to yield a sufficient count for statistical analyses. The largest category, which is A61K (defined as "Preparations for Medical, Dental, or Toilet Purposes")—minus 16 seven-digit IPCs with more than 1,000 patents each—has more than 85,000 patents. The initial implementation actually involved testing several cut-off values (e.g. 700, 1,000 and 1,500 records,) which yielded different numbers of IPC categories. The cut-off at 1,000 was deemed suitable for this analysis,

as it seems to provide a sensible compromise between accuracy of the fields, and readability in the map. This choice produces 466 IPC categories that are mapped to a thesaurus for data pre-processing.

The next step involves extracting from Patstat the patents cited by the target records. The IPCs of those patents (if available) are mapped to the 466 IPC categories but in this case no cut-off is applied. The result of this data collection allows the creation of a table containing in each row sets of Patent Number, IPC Number, Cited Patent Number, and Cited IPC Number. The software *Pajek* was used to further process this data table, and save in an appropriate file format for the next step. This software also helped to create the global map and individual overlay maps for examples of companies and technological fields.

The final data processing steps involve generating a cosine similarity matrix between IPC categories, and then factor analysis of the IPC categories (following the method used in global science maps by (Leydesdorff and Rafols 2009)). A factor analysis of the citing to cited matrix between IPC categories is then used to reduce the 466 categories into 35 "macro patent categories" (see Table 1 in Appendix). We tested different factor solutions from 10 to 40. The 35-factor solution appears to provide a sensible and convenient classification of the IPC categories. These 35 factors form the basis for color coding the 466 categories that are represented in visualizations. The list of 35 factors is available in Supplementary File 1.[2] The visualizations also require converting IPC codes to succinct text labels, which we did manually on the basis of the lengthy IPC definitions. Therefore, labels may not fully capture all the technologies within a category. These IPC category labels were then used as a basis for creating descriptors for each factor as shown in the maps (see Figure 1.)

[2] See: http://www.sussex.ac.uk/Users/ir28/patmap/KaySupplementary1.xls

The creation of patent overlay maps raised some issues around the actual coverage of the thesaurus developed to match 466 categories of the global patent maps. While this dataset covers a wide range of IPC categories, the resulting thesaurus still does not match a number of IPC categories of company patent applications. The IPC categories not matched by the initial version of the thesaurus in datasets included, for instance, B82B-3/00, B82B-1/00, C09G-1/00, C09G-1/02, G06N-99/00, and G12B-21/00—categories that are relevant to the nanotechnology domain. This issue is solved temporarily by manually modifying the thesaurus to include key IPC categories of the companies (or technological fields) under analysis.

[INSERT TABLE 2 ABOUT HERE]

4. Test and preliminary results

4.1. The global patent map

The full map of patents shows all 466 categories in a layout that represents technological distances and groups of technologies in each of the 35 factors or technological areas (Figure 1). Label and color related settings were adjusted to produce a clearer map and facilitate its examination. The map suggests three broad dimensions of patenting interrelationships based on the overall position of technological areas. The left side of the map represents bioscience patents. The lower right part of the map includes semiconductor, electronics, and information and communications technologies. The upper right of the map is primarily comprised of automotive and metal-mechanic related technology groups. This structure is consistent with previous technological maps based on patents that used different algorithms for aggregating IPC categories (Boyack & Klavans, 2008, p. 181; Villard, 2012).

[INSERT FIGURE 1 ABOUT HERE]

A closer look shows that the structure of the map reflects technological relationships across the hierarchical administrative boundaries of the subject matter specifications in the IPC scheme. While counts of IPC sections (i.e., the first letter of IPC codes, A, B, C, D, E, F, G, H) are commonly used as a measure of technological distance in patents, the 35 technological areas that are derived from cross-citations in our patent map often span multiple sections (this can be better appreciated in Table 1 of the Appendix.) For instance, the Vehicles area includes six different sections, and the Heating and Cooling, Construction, and Metals areas include five different sections. Only Medical Devices, Food, Recording, Computing, and Radio Communication areas encompass a single section.

Another interesting feature of the global patent map is the high level of interconnectedness of most of the 35 technological areas. This can be observed not only in many connections between technology groups within each technological area, as shown by the densest areas of the map, but also across them. Some exceptions are areas such as Food, Drugs & Med Chem, Biologics, TV Imaging & Comm, Cosm & Med Chem, and Radio & Comm that form more uniform clusters of technology groups (i.e. they appear as clusters of nodes of same color) (Figure 1). Another notable feature is the short distance between technologies in a handful of groups such as Drugs & Med Chem and Biologics, as shown by denser areas and darker lines in the left hand side of the maps. The sparse areas of the map are those associated with technological areas that comprise fewer technology categories include, for example, Electric Power, Lighting, and Recording.

4.2. Patent overlay maps

Based on the global patent map, patent overlay maps allow, for example, benchmarking of companies and specific technological fields. To illustrate and test the application of patent map overlays, two corporate datasets of nanotechnology patent applications have been created for Samsung and DuPont and two nanotechnology subfield datasets have been created for Nano-Biosensors and Graphene nanotechnology applications, using data from the Georgia Tech Global Nanotechnology databases in the same time period (2000-2006).

The visual examination of maps shows nanotechnology development foci that vary across companies (even for those in similar industry sectors) and different patenting activity levels for the studied period. The two overlays presented herein appear diversified and encompass a number of technological areas. The patent overlay created for Samsung, for example, shows activity concentrated on semiconductors and optics, with a notable level of patenting activity across other areas as well (Figure 2a). The company has also some prominent activity on technological areas broadly defined as Catalysis & Separation, Photolithography, and Chemistry & Polymers. The focus of DuPont (Figure 2b), on the other hand, is more on Drugs, Medicine & Chemistry, Chemistry & Polymers, and Biologics. This company seems to have a portfolio of patent applications that is even more diversified but it also is less active in terms of patenting activity than Samsung.

[INSERT FIGURE 2 ABOUT HERE]

The application of patent overlays to the analysis of technological subfields can also help provide a better understanding of technologies involved in the development of these subfields and relationships between them and with the patent portfolio of companies. Yet, while the patent maps applied to companies reflect the result of a corporate strategy implemented by a single organization, patent maps applied to technological fields reflect the aggregation of activities of

multiple (and usually numerous) categories in the same or different sectors. In the application of patent overlay maps to nanotechnology, technological developments in nano-biosensors are focused on categories such as Laboratory Equipment, Semiconductors and Biologics (Figure 3a). The subfield of Graphene, a more recent development which was recognized with the 2010 Nobel Prize in Physics, presents lower activity levels with a diversified focus on Catalysis & Separation, Chemistry & Polymers, Semiconductors and Optics among others (Figure 3b).

[INSERT FIGURE 3 ABOUT HERE]

5. Discussion

This paper presented the preliminary results of a new patent visualization tool with potential to support competitive intelligence and policy decision-making following a methodology successfully used in science mapping (Rafols, Porter, and Leydesdorff 2010). The approach involves a two-step visualization process. First, we build a global map that shows the technological distance between patent categories using co-citation. Second, we overlay the patenting activity of specific organisations or in specific technological fields over the fixed "backbone" of the patent map. The aim of this superposition or overlay is to help understand the patent portfolio of an organisation in the context of the overall technological landscape.

The approach offers valuable information with parsimony. The definition of categories and its implementation using a thesaurus to match IPC categories helps to trace back individual categories to verify results and make improvements. These maps are only reliable to the extent that assignation of patents to IPC categories is accurate. Since patent assignation to IPCs is not always accurate, a large set of patents may be required to ensure that the portfolio of patents shown in an overlay map can be trusted to convey the patenting activities of an organisation represented (in the case of science maps, this was estimated to be above 1,500 publications for

high resolution accuracy, and above 100 publications for lower resolution) (see Appendix 1 in Rafols et al. (2010)).

One of the most interesting findings is that IPC categories that are close to one another in the patent map are not necessarily in the same hierarchical IPC branch. This finding reveals new patterns of relationships between technologies that pertain to different (and sometimes distant) subject areas. The finding suggests that technological distance is not always well proxied by relying on the IPC administrative structure, for example, by assuming that a set of patents represents substantial technological distance because the set references different IPC sections. This paper shows that patents in certain technology areas tend to cite multiple and diverse IPC sections. For example, the Drugs & Medicine and Biologics dimensions include various drug-related Sub Classes in IPC Class A61, but they also include several chemistry compound Sub Classes in IPC Class C07; traditional measures would assume that technologies in these dimensions are distant because they include two different sections (sections A and C), but our network map shows that technologies in these two sections are closely interrelated inasmuch as the patents in these Sub Classes tend to cite one-another. An improved measure of technological distance would take into consideration patent citation characteristics.

Potential applications of patent maps and overlays include organizational and regional/country benchmarking (e.g. for the examination of competitive positions,) exploration of potential collaborations, and general analysis of technological changes over time. For example, the comparison of maps over time can reveal new patterns of relationship between categories that might help to understand the emergence of new fields and the extent of their impact. Patent maps may also reveal relatively unexplored technological areas that are more central to other technologies or highlight denser areas with more technological interdependency

that might form platforms for the emergence of future technology applications (like the Drugs & Medicine and Biologics categories in the maps shown in this paper.)

Ongoing work has sought to overcome some issues found in the development of the original patent overlay maps. Among the most important issues is the coverage of the thesaurus developed to match 466 IPC categories based on the main patent dataset. While this dataset covers a wide range of IPC categories, the resulting thesaurus still does not match a number of IPC categories in the datasets created for patent overlay maps. This kind of issue varies across patent overlay datasets and may represent a significant proportion of the patent records in certain cases. This is, however, a problem that can be solved in future implementations by creating a new thesaurus based on a larger dataset that covers more than four years of patent activity.

Next steps in this research thrust include updates of the basemap based on the current version of the PatStat database and use of the most recent IPC classification, version 8. Refining the patent database to focus only on patent grants (it currently includes applications as well as grants) is one path for future work, while another is to develop a patent map for patents from other patent authorities besides the European Patent Office. In addition, the stability of the patent maps could be tested with the segmentation of maps by year or year ranges. The backbone patent map in this paper can be compared with results from other global patent mapping efforts to determine the extent of consistency between these maps. Potential future research includes the analysis of connections between patent maps and science maps, with particular focus on technological fields with strong science links.

Supplementary files

Supplementary file 1: Excel file containing the labels of IPC categories, citation and similarity matrices, factor analysis of IPC categories.

See: http://www.sussex.ac.uk/Users/ir28/patmap/KaySupplementary1.xls

Supplementary file 2: Examples of overlay maps of firms and research topics.

See: http://www.sussex.ac.uk/Users/ir28/patmap/KaySupplementary2.xls

Table 1. Data pre-processing to group IPC categories, selected examples

IPC categories (original groups)[1]	Number of patents (original groups)[2]	IPC categories (re-grouped)[3]	Number of patents (patent map)[4]
A61K	85,709	A61K	85,709
A61K 8/00	1,982	A61K 8/00	2,706
A61K 8/02	724	Folded up to A61K 8/00	
A61K 8/04	1,082	A61K 8/04	1,082

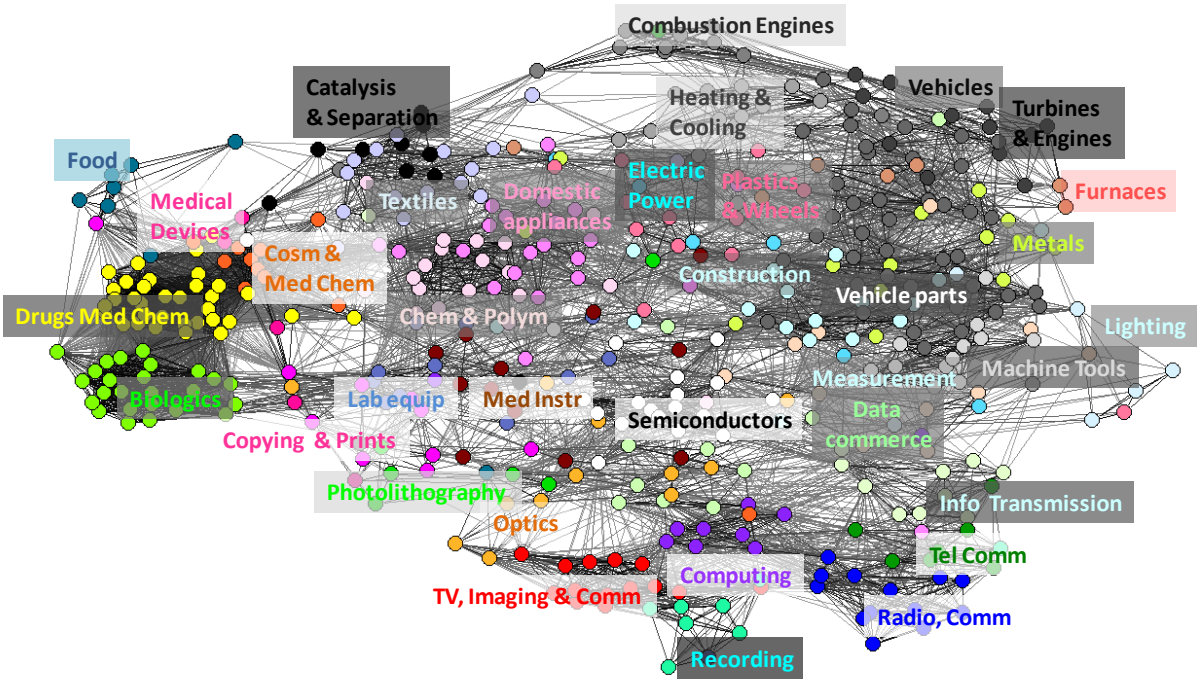
Note: 1. IPC categories as they appear in original PatStat database. 2. Number of patent applications by IPC category. 3. IPC categories that result from the application of the thesaurus created with 466 categories. 4. Number of patents in re-grouped IPC categories and visualized in patent maps.

Table 2. Application of thesaurus for 466 groups to company patent application portfolios

	Total Records[1]	Missing Records[2]	% not shown in overlay
Samsung	979	204	21%
Dupont	172	45	26%

Note: 1. Total records column shows the number of patent applications identified in the Georgia Tech Global Nanotechnology databases for each company. 2. Missing records column shows the number of total patent application records not matched by the thesaurus developed for the implementation of the patent maps as described in this paper.

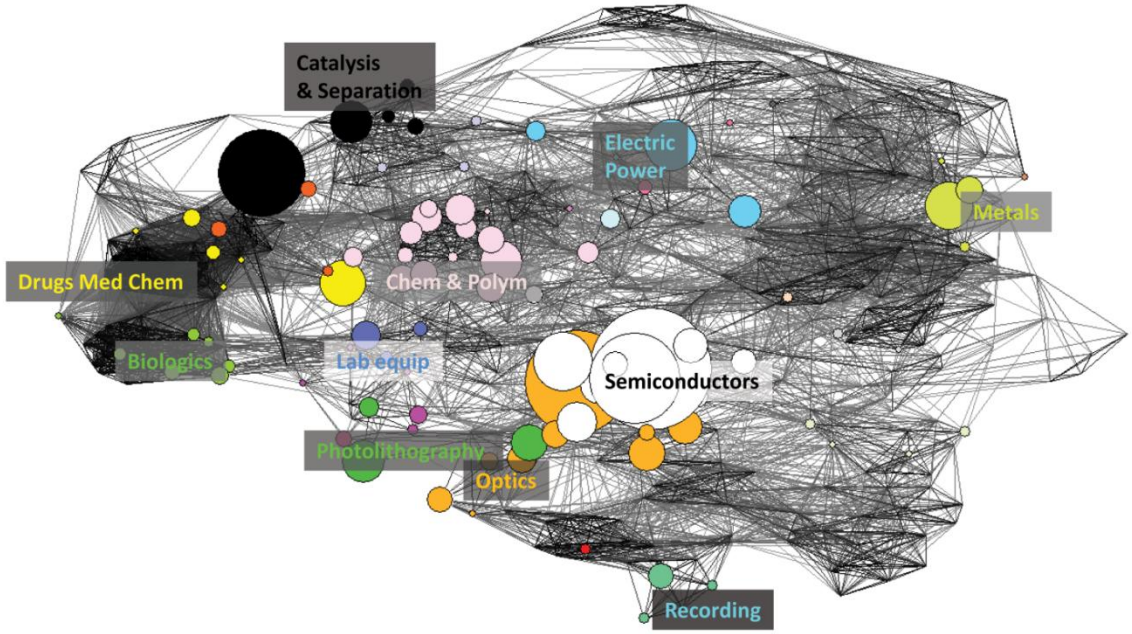
Figure 1. Full patent map of 466 technology categories and 35 technological areas



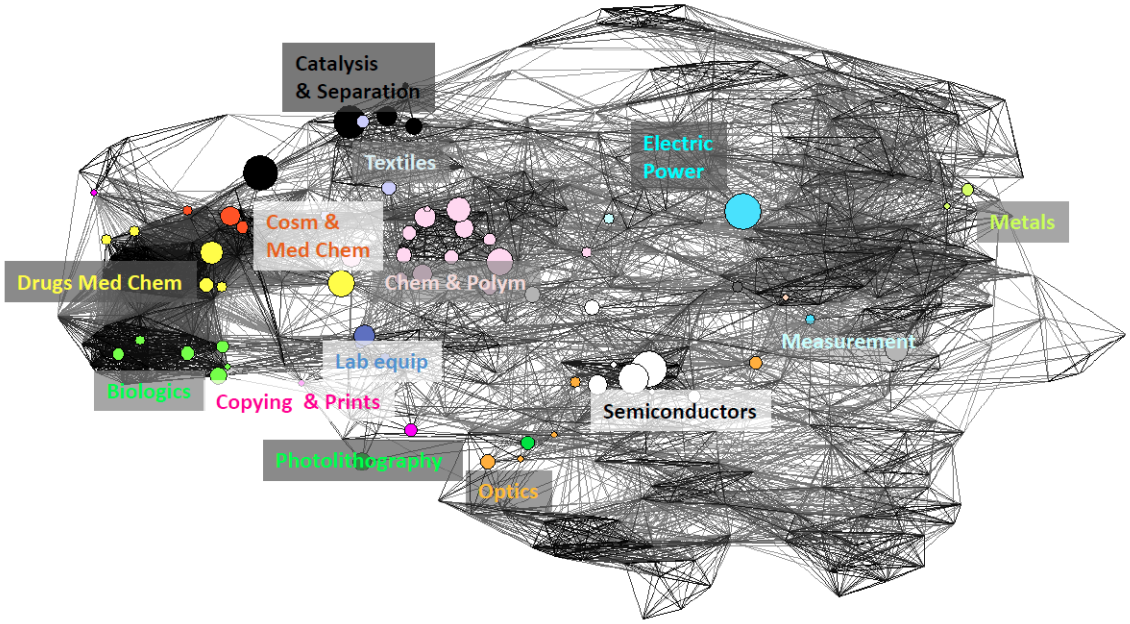
Note: each node color represents a technological area; lines represent relationships between technology categories (the darker the line the shorter the technological distance between categories;) labels for technological areas are placed close to the categories with largest number of patent applications in each area.

Figure 2. Patent overlays applied to company benchmarking

a) Samsung



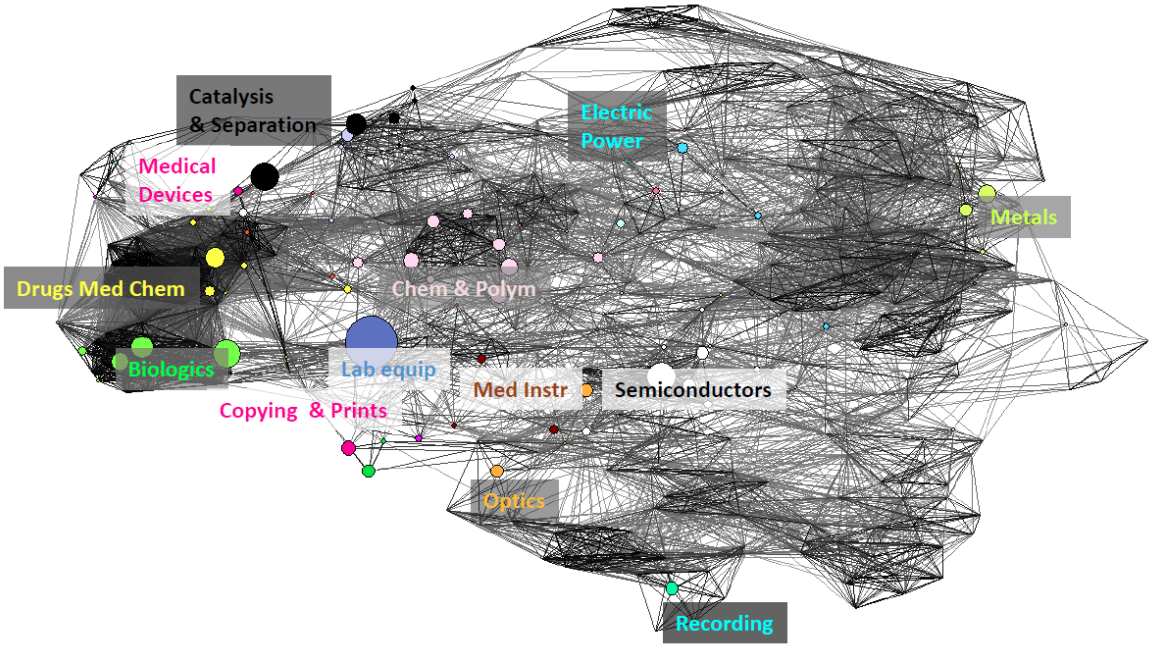
b) DuPont



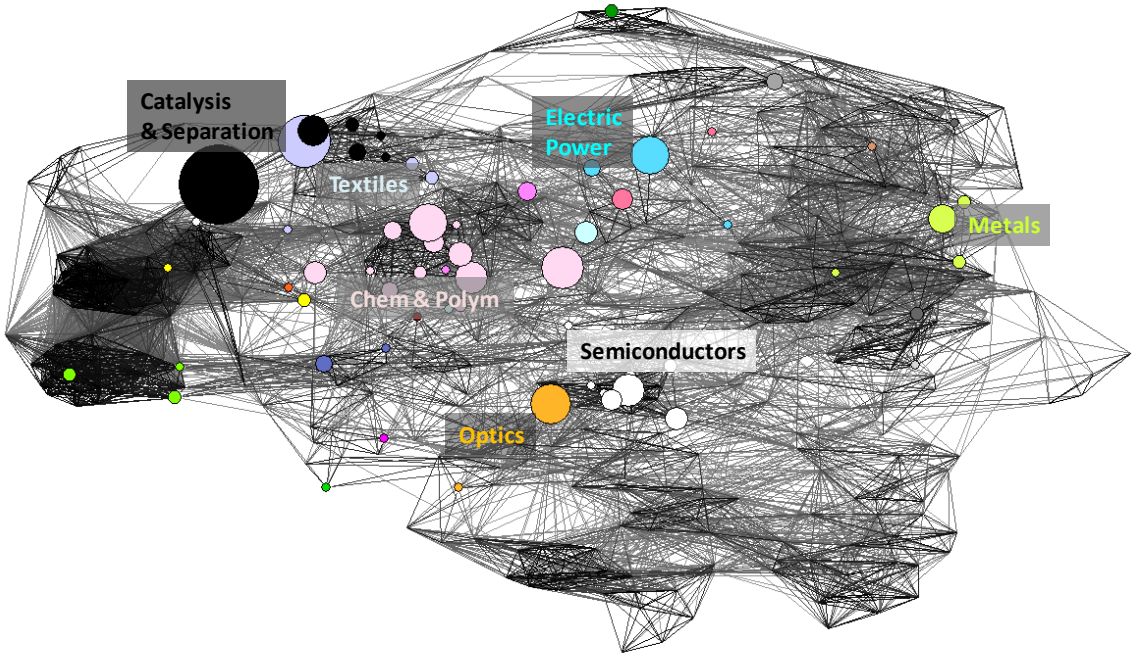
Note: labels shown only for top technological areas of the company patent portfolio; the size of nodes is proportional to the number of patent applications in the corresponding technology group. See Supplementary file 2 for higher resolution.

Figure 3. Patent overlays applied to field mapping (2000-2006)

a) Nano-biosensors



b) Graphene



Note: labels shown only for top technological areas in the subfield; the size of nodes is proportional to the number of patent applications in the corresponding technology group. See Supplementary file 2 for higher resolution.

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