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Tracking innovation diffusion: AI analysis of large-scale patent data towards an agenda for further research

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Tracking innovation diffusion: AI analysis of large-scale patent data towards an agenda for further research

Abstract

The objective of this article is to add to the current understandings of how AI can be used in tracking technological trends by proposing that density-based spatial clustering of applications with noise (DBSCAN) is an AI method that can be used when it come to the specific purpose of tracking technological trends. In this research, we illustrate how AI can be used to research an area that has not been given much attention in previous research. In order to illustrate our message and provide guidance for further research in this area we have acquired data related to titles of all US patents for 42 years (1976-2017) and analyzed how technological trends occurs and develop. We apply the DBSCAN method to cluster the patents that are most similar in each year. Then we compare the clusters in each year to find the trends. We illustrate the findings in word clouds. That gives us new insights about the trends of the technologies.

Introduction

All industries undergo changes with the technological basis in how business models are defined and executed (Rothaermel and Hill, 2005; Sirmon et al., 2008; Teece, 2006). The logics or frameworks that generate profits by creating value to customers is often gradually, but fundamentally changed over time, which has implications for how products and services are distributed with technology and the long-term survival of organizations (Zott et al., 2011; Zott and Amit, 2008). While both start-ups and incumbent firms respond to the emergent changes by changing to the technological basis upon what they deliver the products and services (Rothaermel and Boeker, 2008; Sirmon et al., 2008), the current focus has merely been upon the business model itself (Chesbrough, 2010; Chesbrough and Rosenbloom, 2002) and far less attention has been given to the underlying changes upon how these technology trends are emerging and changing the fundaments upon how products and services are created. Many firms change and add to the business models and the technologies of which they execute and capture their value, but what are the early trends that both start-ups and incumbents react and create?

The above is a challenging research question. Tracking the technological trends capture any attempt to venture into new industries by providing knowledge about the market trends and new opportunities. While some industries are mature and even declining, others are just at the verge of appearance. Additionally, in the early stages, the exact industry is hard to define. Therefore, knowledge about early changes in technological trends that spot emerging— as well as mature—trends in technologies and industrial opportunities is challenging and has not much been researched. The lack of scientific attention to tracking technological trends and the use cases of modern AI and machine learning techniques lead to a shortcoming to our understanding of the past and current states of technologies (Lee et al., 2009b; Yoon, 2008), the fundamental basis for entrepreneurial opportunities (Anokhin et al., 2011), and less-informed knowledge of the underlying fundamentals for business models (Chesbrough, 2010).

The advent of data availability at large scale, data analysis techniques, and technologies, including Artificial Intelligence (AI) has provided opportunities to research this area of inquiry. The opportunity lies in utilizing large scale of data on patent texts to track the trends of technologies. Scholars have started utilizing available data on patents to track technological trends (Tseng et al., 2007). This approach, until recently, was limited because of restrictions in computing power and analysis techniques. These restrictions are now starting to become alleviated, which opens up an opportunity for utilizing AI for tracking technological trends and researching these underlying logics for the larger literatures about strategy, entrepreneurship, business models and innovation. So far, different techniques have been used to get insight from patent bibliographic data (e.g. Lee et al., 2011). They include conventional techniques, and unsupervised machine learning, which is an instance of AI-related technique. For example, K-means clustering has been implemented for the purpose of tracking technological trends (Suominen et al., 2017). This leaves overlooked analysis of how more sophisticated AI can be used to predicting and tracking the technology trends upon which start-ups and incumbents deliver value.

The objective of this article is to add to the current understandings of how AI can be used in tracking technological trends. We aim to propose that density-based spatial clustering of applications with noise (DBSCAN) is an AI method that can be used when it come to the specific purpose of tracking technological trends so to assist decision making regarding technological opportunities. In this research, we specifically review the use of AI and machine learning in the innovation literature and illustrate how AI can be used to research an area that has not been given much attention in previous research.

Literature Review

Tracking Technological Trends

It has been well established in the literature that technologies and industries have life cycles (Lee et al., 2016). New technologies emerge, and after early adoption, they go through a stage of growth until they get mature and saturated (Ernst, 1997). Part of the reason why the emerge is due to the knowledge diffused from other technologies or other geographical places (Chang et al., 2009). Especially, the theory of technology diffusion implies such diffusions and life cycles. It refers to the process through which certain technology is adopted and spread within and across economies (Rogers, 2010). The spread of technologies is due to the fact that they are not isolated, rather, they are part of an ecosystem with other sets of knowledge and technologies.

An economy therefore represents an ecosystem representing a mixture of numerous technologies each in different stages of their life cycles. This mixture has a dynamic nature and changes over time (Lafond and Kim, 2019). Knowledge transfers between the technologies leading to a constantly changing state of the economy in terms of the technologies it represents. In that sense, researchers have investigated maps that show the state of the trends in technologies over time (Lee et al., 2009b). Such maps, in addition to life cycle of one specific technology, could show the coexistence of all technologies, life cycles of each of them, and thus better illustrate the process of technology diffusion.

Technology maps could provide information that help identifying opportunities (Lee et al., 2009a) for new products and services (Sirmon et al., 2008). The maps would show the dynamic state of the economy in how it facilitates technology diffusion, what technologies are relevant, what technologies are emerging, and how and technologies are evolving over time. Scholars could use the measures provided by these maps in studying the state of the economy, policy makers could use them in making decisions, and entrepreneurs and established companies could use them in their decisions regarding definition and execution of new business model (Rothaermel and Boeker, 2008; Teece, 2006).

Informed Decisions regarding Technological Opportunities

Technologies provide new ways in which the resources can be bundled in order to introduce new products and services, in other words, new technologies are a source of entrepreneurial opportunities (Acemoglu, 2012; Anokhin et al., 2011; Eckhardt and Shane, 2011). Therefore, in addition to business models, an attention to technological trends assists entrepreneurs and companies to deliver value to the customers (Rothaermel and Hill, 2005; Zott and Amit, 2008). Technologies on the other hand are constantly changing and evolving. Therefore, an entrepreneur needs to make decisions regarding the technologies and the opportunities they provide (Sirmon et al., 2008).

Theories of decision making point to different processes through which we make decisions. They vary from using our "guts" to being rational and to using analytical tools (Buchanan and O Connell, 2006). When it comes to choosing the technology in which an organization wants to invest, for example, the decision makers could use their intuition (Miller and Ireland, 2005). Even so, analytical tools that reveal information about the actual state of the technology in the market, which otherwise would be unknown, could assist practitioners to make informed decisions. Such tools could especially assist decision making regarding policy making related to facilitating knowledge diffusion and the emerging technologies that are in need of support.

In recent years AI has shown its potential as an analytical tool that could reveal information in predicting different phenomena. It has already replaced human decision making—in most cases however with human supervision. For example, there are AI-based algorithms that automatically decide and act upon which stocks are the most promising for allocating an investment firm's capital. Additionally, as an analytical tool, AI has been utilized in predicting and illustrating technological maps and trends (Suominen et al., 2017). Application of AI in producing such maps could eventually provide roadmaps for decision makings regarding the opportunities that the evolving technologies provide.

Although there are several recent attempts in utilizing AI in this topic, they have been limited by the computing power and available AI algorithms. Recent advances both in increased computing power and in AI statistical algorithms is, however, opening new opportunities for higher range of applications (Webster and Ivanov, 2020). Applying the advanced AI algorithms using powerful computers makes it possible to created AI-based tools that map technological trends, which in turn could facilitate informed decision making (Nigam et al., 2000; Power, 2008).

AI, Unsupervised Learning, and DBSCAN

AI algorithms collect input data and utilize the data to find patterns that can be used for prediction, action, and decision making. Machine learning plays an essential role in that process. Machine learning is application of mathematical models on a set of data to uncover hidden patterns. In recent years, machine learning and AI have been applied to find patterns in a wide range of topics (Iqbal et al., 2018), including finding emerging technologies (Lee et al., 2018).

Of different types of machine learning, unsupervised learning is especially relevant for this study. That is because, the aim is to find existing and evolving technologies without knowing what technologies they are. In other words, there are no the target variables in the task we are seeking to accomplish. Without a target variable we are dealing with unsupervised learning while attempting to find patterns in the input data (Suominen et al., 2017). Previously, scholars have applied algorithms such as k-means for tracking technological trends (Yoon et al., 2013). After giving the algorithm a number for existing clusters (in the case of this study, clusters of words in patent titles), it assigns same number of points in the space and cluster all the observations to one of the points. It attempts to minimize the means of error in the clusters (Jain, 2010). DBSCAN is another algorithm for unsupervised clustering. In comparison to k-means, it takes a distance and decides the clusters depending on is the distance between the observations is less than the defined distance (Ester et al., 1996).

In this study, we apply DBSCAN algorithm for clustering of patents' titles. This is due to two reasons. We observe that there are many patents that represent isolated innovations, which are irrelevant in defining a technology. One of the characteristics of DBSCAN is that it identifies those observations as noise. The noise data could make the clusters that are found through alternative algorithms such as k-means to be biased. Another characteristic of DBSCAN is that it does not require the number of clusters beforehand. Instead, it clusters all the observations that are close to each other as Instead, it groups all the observations that are close to each other as clusters (Ester et al., 1996; Hahsler et al., 2019). Therefore, we argue that for the purpose of clustering patents to find clusters that define technologies, DBSCAN is a preferred machine learning algorithm, which could be used in AI tools that map the trends of technologies in order to find opportunities.

Data Source and Data Approach

We utilize textual data on patent titles for the purpose of unsupervised machine learning. USPTO provides freely available data on more than 7 million patents over 40 years in the US. Namely, we collect Patent Grant Bibliographic (Front Page) Text Data (1976 - 2017) (cf. Lafond and Kim, 2019). The data came in various formats including different formats of dat and xml files. We are interested in data on the patent title texts in order to find clusters of technology. As such, we took three steps to prepare the data for our analysis.

First, we downloaded the data from USPTO website[1]. Size of the downloaded data accounted for 71.5 GB of disc storage. For the second and the third steps, we needed to write Python algorithms to prepare the data for our analyses. The second step was to access different file formats of the data and specifically list all titles of patents in each year in simpler csv data files. This was not without challenge since size of some of the files was as large as 7 GB which makes it impossible to open considering the limits of Random-Access Memory (RAM). Therefore, our algorithm needed to break some of the files into pieces in order to collect the title texts.

The third step was to clean the title texts (Niemann et al., 2017). Cleaning the text has few purposes. We need to make the words standardized in order to cluster them. That means, for example, “power”, “Power”, “powered”, “Powering”, and “-powered” should all be considered as

[1] https://bulkdata.uspto.gov/

one word. We also need to exclude signs, numbers, and punctuations as they do not provide useful information when the purpose is clustering. Finally, we need to leave out words that occur very frequently, both in the English language and in the context of patents. In order to do these, our algorithm, first, made all characters in the patent titles as lower-case. Then it removed numbers and punctuations. Then it replaced the words with stems. Then it removed any word that is only one character long as they do not give useful information in clustering. Then, it took English stop words out. Finally, it removed all the words in our defined patent-related stop words. We defined a list of stop words that are common in patents. They included two types of words. One those that refers to the patented object, including "apparatus", "system", "machine", and "product". The second category include verbs in patents about the functionality or make of the patented object including "contain", "use", "comprise", and "make". We used the Python package nltk while cleaning the texts. After cleaning, we obtained 42 single column csv files comprising cleaned patent title texts for years 1976-2017.

AI Methods and Algorithm

One way to cluster the information to spot new categories is to follow unsupervised machine learning techniques. Titles of more than 7 million patents provide a big amount of data that can be used in the unsupervised learning. While processing the titles, we apply unsupervised text clustering techniques (Nigam et al., 2000) namely DBSCAN (Ester et al., 1996). DBSCAN algorithm clusters those points in space that are closely packed. It leaves out outliers that are not close to any cluster. It, furthermore, does not require predetermining the number of clusters. The required parameters are minimal and include minimum number of points to be considered as a cluster (minobs), and ε (eps) neighborhood of every point.

Before doing the analysis, a pipeline was required to feed the data in DBSCAN algorithm. As the number of observations and the number of different words in all patents were too large, we needed to limit them to a size that can be processed by a desktop computer. Since the number would still remain large, this sampling does not affect the results. We ran the algorithm several times with different observations in the sampling to make sure this was the case. We chose to cluster 16384 observations per year by analyzing 128 most common words. Then, we needed to quantify the words. We followed term frequency–inverse document frequency (tf-idf) algorithm for that purpose (Joung and Kim, 2017).

To choose the optimal values for the parameters (minobs and eps) we did a sensitivity analysis (cf. Hahsler et al., 2019). For the chosen values, we obtained, for example in 2017, that 49.86% of the observations to be noises. We found the rest of the observations to be clustered into 122 main clusters (not noise). Increasing or decreasing both eps and minobs would either further increase the number of observations that are noise, or make the number of main clusters to be too low or too large to be close to the correct number. Doing this type of sensitivity analysis for all the years, we observed that minobs of 16 and eps of 0.5 are optimal.

Table 1. Sensitivity Analysis for DBSCAN parameters (Year 2017)

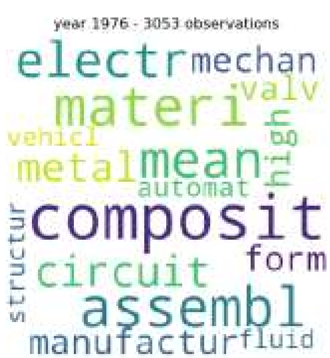
minobs	**eps**	**Number of main clusters**	**Ratio of Noise to Total Observations**
16	0.5	122	0.4986
16	0.3	117	0.5815
16	0.7	16	0.5814
9	0.5	140	0.4753
23	0.5	104	0.5177

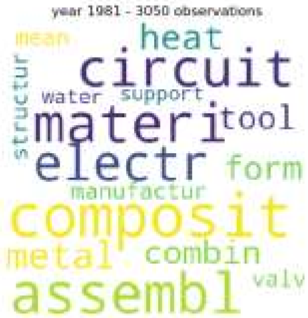
Results

We fed the DBSCAN algorithm with quantified words (using tf-idf) in titles of patents of each year. The algorithm grouped together the words into handful of clusters. The results therefore include 42 sets of clustered words related to the years included in the analysis. Each of the sets, that represent one year, involves one cluster for excluded noise and the main clusters. Each cluster illustrate words (cleaned versions) that are common in titles of patents in the respective cluster. We save these clusters as json files, but also drew word clouds for visualizing the most common words in each cluster together with frequency of appearance of the word in that cluster. Supplementary material includes an example of json file for the year 2000.

Illustrating all clusters of all years would risk overcrowding. Therefore, we only illustrate the word clouds of the most populated (primary) cluster of the years, starting from 1976 to 2016, with a four-year gap. This would show the primary trends in technology. Additionally, we illustrate the first four clusters of five year (2013-2017), to show how the clusters in each year are distinguished.

Figure 1. Word clouds of the primary technology trends in different years

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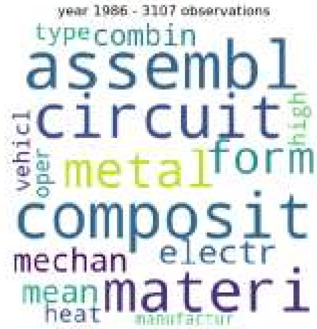
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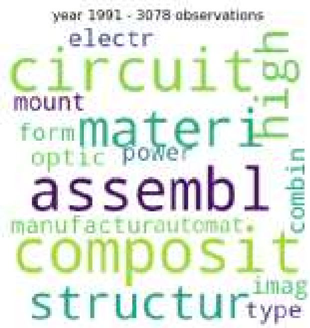
year 1991 - 3078 observations
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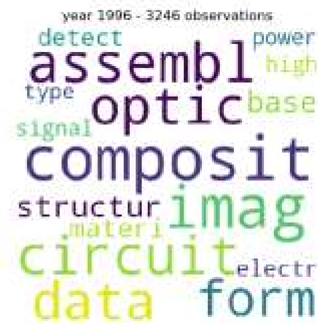
year 1996 - 3246 observations
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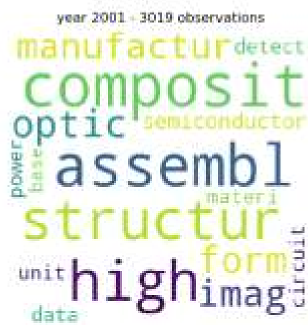
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year 2006 - 2501 observations
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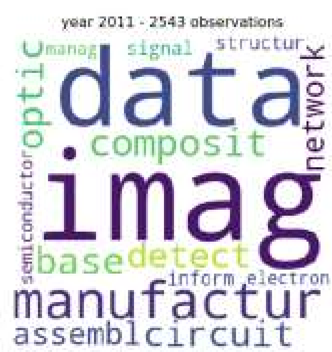
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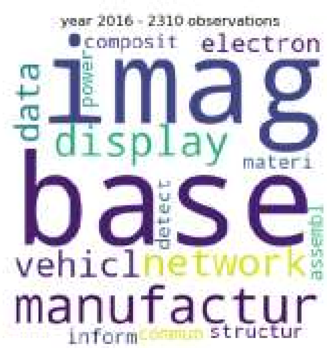
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The results above reveal trends in primary technology in different years. In addition to looking into the primary clusters, it is possible to investigate first few dominant clusters in each year. This way, the clusters could show how interdisciplinary technologies form, overlap, and evolve. For example, as Table 2 presents. in 2017, the primary cluster include words such as ‘data’, ‘base’ ‘network’, ‘imag’, ‘display’, ‘power’, ‘vehicl’, and ‘inform’. It can be argued that self-driving cars belong to this cluster of technology in 2017. In the same year, the forth dominant cluster presents words including ‘electron’, ‘display’, ‘imag’, ‘light’, ‘data’, ‘digit’, and ‘optic’. While words such as data and image are present in both the first and the forth clusters of 2017, the latter points to another trend that could be related to digital display and optics. Note that the table below does not illustrate the frequency of the words in each cluster.

Table 2: Most dominant clusters during years 2013-2017

	2013	**2014**	**2015**	**2016**	**2017**
CLUSTER 1	imag data base network semiconductor display composit power gener	data base network imag infrm display composit circuit gener	data base network composit comun inform imag display power	imag display data network vehicl electron inform composit	data base network imag display power vehicl inform composit
CLUSTER 2	display data network modul optic storag vehicle signal	imag display data electron commun drive signal network	imag data network inform display memori light optic	imag inform data base commun electron vehicl power game	display memori network optic vehicl detect data composit
CLUSTER 3	imag data composit electrol cell comput signal optic	data display power composit electron inform mobil memori	termin imag data power composit display commun memori	display power data base composit interface touch secur electron	termin imag data base display storag motor composit servic
CLUSTER 4	detect imag composit network circuit termin switch	imag display data base electron inform optic storag distribut	imag display inform memori database network materi layer	composit network commun storag display gener mobil circuit	electron display imag light liquid data digit optic

Discussions

Management literature has widely studied business models (Zott et al., 2011). Furthermore, it has been proposed that technological change provide opportunities in introducing new product, services, and business models (Rothaermel and Hill, 2005; Sirmon et al., 2008). The aim of this study is to continue the discussion in the literature by proposing that AI and specifically DBSCAN can be utilized to map technological trends in order to facilitate decision making regarding the opportunities that the changing technologies provide.

Studying the big data helps us to understand how the interests in different industries have been shifting. We can spot emerging and mature industries with more precision. Furthermore, we provide a tool to facilitate corporates and individuals' inquiry into potential entrepreneurial opportunities. The resulted map has academic and practical outcomes. Previous research has emphasized the role of evolving technologies in generating opportunities (Anokhin et al., 2011; Rothaermel and Hill, 2005) and in decision making regarding recognition of opportunities. This study proposes the application of AI in measuring and mapping ecosystem of clusters of technologies throughout time. The map could be used as a data source to study opportunities. These processes, moreover, can be seen in light of other issues such as institutional differences and knowledge spillovers. In practice, the map equips entrepreneurs, be it individuals or corporations, with a more precise tool to decide whether an opportunity is worth investing, and therefore, assist the practitioners in decision making.

Directions for future research include further attempts to find how the changing ecosystem of the clusters of technologies provide opportunities to provide value to the customers and how entrepreneurs and firms decide in acting upon such opportunities. In addition to the focus that has been primarily on business models, as the economic growth theories suggest, technologies are a major source for new opportunities and growth in an economy (Acemoglu, 2012) and further investigation are needed of the how practitioners could recognize the technological opportunities. In addition, future research could continue developing the measures provided by AI. This research was an initial attempt to find and apply suitable AI algorithms (namely DBSCAN) for the purpose of tracking technological trends. More research is therefore needed to develop the approach presented in this paper by, for example, investigating alternative parameters, sample sizes, word tokenization algorithms, etc. This research furthermore provides a way to generate data. For example, the json file in the supplementary material includes the clusters of words in patent titles (with their frequency) of year 2000. Such data could be utilized for studying the relationships between evolving ecosystem of technologies and other phenomena such as entrepreneurship and knowledge spillovers.

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