USING ENHANCED PATENT DATA FOR FUTURE-ORIENTED TECHNOLOGY ANALYSIS

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Abstract

Patents represent one of the most complete sources of information related to technological change and they also contain much detailed information not available anywhere else. Thus, patents are the "big data" source most closely related to Future-oriented Technology Analysis (FTA). Not surprisingly, therefore, there is very significant practical and academic use of the patent database for understanding past technical change and attempting to forecast future change. This paper summarizes several new methods and demonstrates their combined effectiveness in establishing a cutting-edge capability for patent study not previously available. This capability can be stated as *a link between the information in patents and the dynamics of technological change*.

The demonstrated capability relies upon the use of a database containing the rates of improvement for various technologies. We also specify the term we use for the analyzed units of technology: a technological domain is *a set of artifacts that meets a specific generic function while utilizing a specific set of engineering and scientific knowledge*. This definition is unambiguous enough so technological domains can be linked with progress rates and is sufficiently flexible to accommodate the large scale and complexity of the patent database. The existence of an improvement rates database and its quality are a critical foundation for this paper.

Establishing the overall capability also involves relating the rate of improvement of a technological domain to the patents in *that* domain. We show that a recently developed method called the classification overlap method (COM) provides a reliable and largely automated way to break the patent database into understandable technological domains where progress can be measured. In this paper, we show how this method overcomes the third limitation of the patent database.

The major conclusion of the paper is that there is now an overall objective method named Patent Technology Rate Indicator (PTRI) for using *just* patent data to reliably estimate the rate of technological progress in a technological domain. Thus, the first link between the patent database information and the dynamics of technological change is now firmly established; robustness and back-casting tests have shown that the assertion of reliability is meaningful and that the estimate has predictive value.

We demonstrate the usefulness of this method by estimating technological improvement rates for a set of 15 technologies that may be important in the future including 3D-printing, neural networks, food engineering and water purification.

Keywords: Patent Analysis, Future-oriented technology analysis, Big Data, Nuclear, Water Purification

Introduction

This paper introduces the results of a new forecasting method called the Patent Technology Rate Indicator (PTRI) method that uses patent data to better predict time-based performance improvement rates of technologies whose performance trend is otherwise unknown. While the focus of the research is on quantitative performance trends, we do not want to suggest that such results will be all one desires for technological forecasting. Haegerman et al (2013) explain the various focuses of several different disciplines within the FTA community:

'It is acknowledged that, within the FTA community (which comprises Foresight, Forecasting and Technology Assessment),[1] foresight practitioners have traditionally concentrated on participatory methods based on qualitative data, on the grounds that quantitative extrapolation from past data is not sufficient to address the uncertainties of the future and that emerging changes in the socio-economic and technological landscapes need to be taken into account. Another part of the FTA community, constituted by Forecasting and Technology Assessment practitioners, holds an opposite standpoint, considering qualitative and participatory approaches as a second best option, to which we are somehow compelled to refer until adequate quantitative methods arise. ' (Haegerman et al, 2013)

Our viewpoint is that both qualitative and quantitative approaches are needed for this complex issue and improvement of both is needed. Rosenberg's analysis done more than 20 years ago (Rosenberg, 1982*)* categorized four areas of difficulty in any technological forecasting which includes the socio-economic aspect; these are:

1) At emergence, the focal (or new technology) is not very capable;

2) Vital complementary technologies are potentially underdeveloped;

3) System design/evolution that may be necessary for large impact has not occurred;

4) The human user ingenuity that will greatly impact the technology and its impact has great diversity and is unknown at the early stages.

While we believe that a focus on quantitative performance improvement prediction can contribute to items 1) and 2) in Rosenberg's analysis, we believe that qualitative approaches will also be valuable not only in items 3) and 4) but also in 1) and 2).

Gao et al (2013) introduced an important aspect of the quantitative approach by exploring technological performance over time using FTA techniques. In our analysis we predict time-based technological improvements rates similar to the type made famous by Moore's law, where a specific technical metric (transistors/die) is measured over a period of time and is found to improve at a relatively constant percentage per year. This is not the first attempt at using technological improvement rates as part of forecasting but most predecessors have done so by attempting to utilize learning rates, which compare the improvement of a technical metric with production (Nemet, 2006) rather than with time. In particular we are interested in estimating the yearly technical improvement rate of a technology, represented by the variable 'k' in equation 1.

$$q = q_0 \exp(k(t - t_0)) \quad \text{Equation 1}$$

While Sahal (1979) and Nagy et al (2013) showed that the actual practical implications of the time-based and production-based improvement rates are very similar, this paper will focus solely on the time-based rates due to the evidence that they are more fundamental (Magee et al, 2014). Additionally, in performing this analysis we are building off of the strongly established results that show long-term time-based technical improvement rate stability (Magee et al, 2014), that is, that the improvement rate of a technology does not change considerably over time or at the very least changes considerably less between times than the rates change between technologies. This same argument is appropriate for the different complete technical metrics that can be used to measure the performance of a technology (i.e. W_p/\$ or kWhr/\$ for measuring solar PV output) (Benson and Magee, 2014a). Thus, we will focus almost entirely on the rate differences between technologies and not the differences within a technological domain between metrics.

The PTRI can estimate nearly any time-based technological improvement rate using a set of patents that represents each technological domain. The use of patents in FTA is given precedence by (Gao et al, 2014) when they used patent indicators to estimate the level of technological maturity for a given domain. In a very similar way, the PTRI uses patent indicators as correlation factors for forecasting technological improvement rates of a domain and is based upon an extensive study reported in Benson and Magee (2014c). The results of the PTRI method can project relative improvement rates of technologies – which may be useful for investment decisions by private parties or governments. Additionally, the data can be used to aid in uncertainty analyses for future technological capabilities of a specific domain, which is often used in long term product planning by large companies and the military. Both of these uses can aid in influencing both private and public policies, which has been the outcome of several FTA techniques in the past (Schaper-Rinkel, 2013).

Methodology

The PTRI is based upon the finding by Benson and Magee (2014c) that the information contained in patents is sufficient for understanding differences in technical improvement rates between different domains. A number of patent metrics were studied by (Benson and Magee, 2014c) and were combined with multivariate regression tools to create a model for forecasting technological improvement rates. The resulting regression was found to be accurate for 12 years into the future. The PTRI method is summarized in figure 1 below:

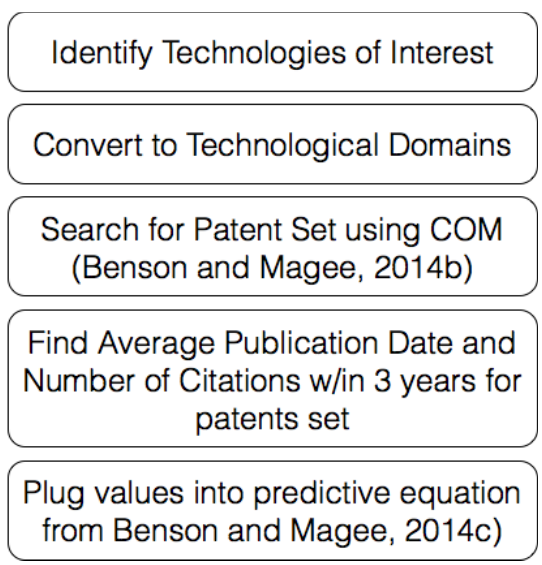

Figure 1: PTRI Method

The PTRI method begins with the identification of a technology of interest, then a technology needs to be converted to an appropriate technological domain. In order to convert from a technology to a technological domain, it is useful to think not just about the embodiment of an invention, but rather the use it fulfils and the underlying scientific principles that it makes use of.

The intention behind this is to specifically clarify the unit of analysis by using a standardized definition of technological domain:

A technological domain can be defined as: The set of artifacts that fulfill a specific generic function utilizing a particular, recognizable body of knowledge.

Once a technological domain has been defined, the next step is the selection of a set of patents that represent the domain, this step is very important because the set of patents that are selected will be the input data source for the method. The sets of patents can be selected by using a methodology called the classification overlap method (COM) that relies upon the different types of patent classification systems used by the US and International patent offices (UPC and IPC) (Benson and Magee, 2013, 2014b). The input to the COM is a set of keywords related to the technological domain as well as potentially some supporting information such as key companies or inventors in the domain. These inputs can then be used to select a set of patents contained within the overlap between the most appropriate UPC and IPC based upon the COM. All of the patent set searches for this paper were done using Patsnap (www.patsnap.com) and included only issues US patents from January 1st, 1976 to July 1st, 2013, these dates were chosen so they could be compared with prior results from Benson and Magee (2014c).

Due to the importance of the patent sets for the PTRI method, it is important to ensure that the patents in the data set accurately represent the technological domain of interest. This is done manually by reading representative sampling of the data sets and qualitatively assigning each read patent a value of '1' for 'relevant or '0' for 'not relevant' to the domain of interest. The average relevancy score can then be added by summing the total relevant determinations and dividing by the number of total patents in the data set. In general an acceptable value for relevance is greater than 0.65, however a good patent set will have relevancy above 0.8.

Once the data set has been verified for relevancy, the patent indicators can be calculated using the meta-data included in the patents. The PTRI uses two indicators for calculating the estimated technological improvement rate: average publication data and average number of forward citations within 3 years of publication as described in Benson and Magee (2014c).

The *Average number of Forward Citations within 3 years of publication* is the average number of forward citations that each patent received within 3 years of publication for patents in a technological domain. The metric is calculated using Equation 2 where SPC is the simple patent count, FC_i is the number of Forward citations for patent *i*, $t_{i_{pub}}$ is the publication year of patent *i*, $t_{ij_{pub}}$ is the publication date of forward citation *j* of patent *i*, and the function *IF(arg)* only counts the values if the argument is satisfied.

$$\sum_{i=1}^{SPC}\sum_{j=1}^{FC_i} IF(t_{ij_{pub}} - t_{i_{pub}} \leq 3) \quad \text{(Equation 2)}$$

The *Average Publication Year* for the patents in a domain includes patents that were published between January 1st, 1976 and July 1st, 2013. This measure is calculated using Equation 3 where SPC is the simple patent count and $t_{i_{pub}}$ is the publication year of patent *i*.

$$\frac{\sum_{i=1}^{SPC} t_{i_{pub}}}{SPC} \quad \text{(Equation 3)}$$

After these two values are calculated for the domain of interest, they can be plugged into the regression model developed in Benson and Magee (2014c):

$$k = -31.1285 + 0.0155 * AvePubYear + 0.1406 * Cite3 \quad \text{(Equation 4)}$$

The result is a simple number that represents the time-based technological improvement rate for the domain of interest.

Results, discussion and implications

The aim of this paper is to explore results of the PTRI methodology applied to a number of potentially important technologies in the future. To act as a basis of what technologies would be important in the future, we used a pre-made list of the '10 breakthrough technologies of 2014' as noted by the MIT Technology Review (2014) as a basis for a list of potential transformational technologies that would be of interest to know an estimated technological improvement rate.

Following the PTRI Methodology described in the previous section, this section will build upon the 10 technologies listed in the MIT technology review and add five others, all 15 technologies will be translated into technological domains, then representative patent sets will be selected, patent indicators calculated and technological improvement rates determined. The end result will be estimated technological improvement rates for 15 technological domains.

Defining the domains

The first step is to translate the list of ten technologies into a list of technological domains. Table 1 shows the list of 10 technologies from the MIT Technology Review along with the 10 domains and a short description of the domain. The final 4 rows are additional technologies that the authors decided to include based upon their subjective potential importance in the upcoming near future and the academic and media interest paid to the domains.

Technology Candidate (from MIT Technology Review)	**Derived Technological Domain**	**Description of Domain**
Agricultural Drones	Remote flight control technologies	Controlling flying vehicles from afar, including drones and advanced flight controls.
Ultraprivate smartphones	Information Security	Information security across all form factors.
Brain Mapping	Brain Scanning	Determining brain features and structure using a number of tools (CT, MRI…)

Neuromorphic chips	Artificial Neural Network Computing	Computing architectures that resemble that of the human brain.
Genome Editing	Genome Sequencing	Determining the genomes of specific strands of DNA.
Microscale 3D printing	SLA 3D Printing	Additive manufacturing using light to cure resins.
Mobile Collaboration	Online Learning	Education in digital classrooms.
Oculus Rift	Digital Representation	Digital modelling of reality (Includes virtual reality as well as less immersive forms of digital representation of the physical world.)
Agile Robots	Robotics	Performance of physical functions by Automatic mechanical devices
Smart Wind and Solar Power	Wind Turbines	Energy generation from moving air.
	Solar PV	Energy generation using the photoelectric effect.
-	Nuclear Fusion	Energy generation relying directly on atomic fusion.
-	Water Purification	Removing salt from water using reverse osmosis.
-	Food Engineering	Chemical and genetic modifications for enhanced food production
-	Gaseous Purification	More broad term for one enabling technology behind climate geo-engineering

Table 1: Technical Domains as Inputs into PTRI

As an example, the technology ‘Agricultural Drones’ from the MIT Technology Review list was determined to be slightly narrow in its scope as it was only focusing on one potential use for the automated air vehicles that they were intended to represent. Focusing first on the broad function, we arrive at remote flight control. Following this path further, while ‘drones’ themselves are a rather broad category, they do not represent a particularly specific technological domain in that the term drone could be interpreted in a number of ways (Wikipedia lists 11 possible interpretations for the term ‘drone’ not including the entertainment or music categories (Star Wars: Attack of the Drones). Thus we added further clarity to the definition by referring to the technological domain as remote flight control technologies. With the specific generic purpose being remote flight control, and the underlying set of knowledge being a unique overlap of aeronautics, control theory, and signal transmission methods. Note that this new domain does not necessarily preclude manned aircraft, as there are plenty of reasons to control a vehicle remotely even when a pilot is sitting in the cockpit.

Other domains of interest are the transformation from ultra-private smartphone to information security – as the smartphone form factor seems a wholly unnecessary constraint for the analysis of the improvement rate of information security technologies. Admittedly, the most liberty was taken in translating mobile collaboration to online learning – this was done partially due to the lack of clarity over what exactly constitutes mobile collaboration and the recent intense emphasis on online learning and MOOCs, therefore this 'translation' could be more appropriately termed a 'substitution' of near neighbour technologies.

Patent sets selected using the COM

The next step in the PTRI (figure 1) is to find relevant patent sets for each of the technological domains using the COM, as described at the top of page 4. Columns 2 of Table 3 show the patent classes that were used to define each domain, Column 3 the size of the overall patent set and column 4 the relevancy as determined by subjective reading of a sampling of 200 patents from each domain.

Domain	Patent sets	Number of Patents	Relevance Ratio	Average date of publication of patents	Cite 3	Predicted K
Artificial Neural Network Computing	706/15 AND G06F	361	0.71	2007.3	3.49	0.407
Brain Scanning	(600 AND 382) AND A61B AND "brain"	284	0.93	2009.3	3.14	0.390
Water Purification	C02F1/44 AND 210	1033	0.63	2003.6	3.80	0.393
Digital Representation	345/419 AND G06F3	486	0.655	2004.9	5.85	0.702
Food Engineering	426 AND C12N	1865	0.96	1992.2	1.50	-0.107
Genome Sequencing	(435/6.11 OR 435/6.12) AND C12Q	3990	0.74	2006.7	2.15	0.209
Gaseous Purification	(95 AND 423) AND B01D	1683	0.72	1993.1	2.40	0.034
Information Security	726 AND H04L	13607	0.985	2010.1	3.52	0.454
Nuclear Fusion	(G21B OR H05H) AND 376	508	0.95	1992.4	1.52	-0.102
Online Learning	G06Q50 AND 434	197	0.78	2001.8	6.62	0.76
Remote flight control technologies	(701/2 OR 701/3) AND B64C	328	0.855	2003.1	3.18	0.299
Robotics	B25J AND 901	4122	0.935	1994.6	3.74	0.245
SLA 3D Printing	264/401 AND B29C35/08	251	0.93	2001.4	3.98	0.385
Solar Photovoltaic Energy Generation	136 AND H01L	5203	0.85	1998.6	2.73	0.165
Wind Turbine Energy Generation	(416 OR 290) AND F03D	2498	0.94	2002.8	2.17	0.152

Table 2: PTRI Input and Output

As noted earlier, each technological domain is represented by a set of patents that are defined by a combination of overlapping US and international patent codes. As an example, the 'remote flight control technologies' domain is defined by the overlap of either of the US codes 701/2 or 701/3 (Data Processing: vehicles, navigation, and relative location /2 Remote Control system /3 Aeronautical Vehicle) and the international patent code B64C (Airplanes, Helicopters). This overlap results in 328 patents that were qualitatively determined to be ~85% relevant. This same process was repeated for all 15 technological domains and the results are in Table 2.

Calculating the Patent Indicators and Using the PTRI Regression Model to Estimate Technological Improvement Rates

The next step from figure 1 is digesting the patent information in order to calculate the patent indicators required by PTRI regression model: average year of publication and number of citations received within 3 years of publication (Cite 3). These values for each of the domains are shown in columns 5 and 6 of Table 3. It is interesting to note the extremes of each patent indicator. In this study, the oldest average date of publication is 1992 (food engineering and nuclear fusion) while the newest average publication date is 2010 for information security. The large size of the information security patent set (13,607) and the very high relevance ratio (0.985) give credibility to this very recent average publication date and indicate that this is likely a very dynamic domain and that the recency is unlikely an artefact of the data. These numbers are in line with the oldest and newest average publication date of the 29 technological sets used to construct the PTRI regression model with 1992 and 2006 respectively (Benson and Magee, 2014c).

The smallest Cite 3 technological domain had just 1.5 forward citations within the first 3 years of publication on average (food engineering), while the largest belongs to digital representation with 5.85 citations within 3 years, which is a higher value than any of the original 29 domains used to create the PTRI (4.62-MRI).

These patent indicators can now be plugged into equation 4 to calculate the estimated technological improvement rates for each of the 15 domains as shown in the final column of Table 3.

Discussion And Conclusions

One note to point out is that some of the values end up negative, which would seem to indicate that the particular technological domain is getting worse with time. Obviously this explanation is logically inconsistent, and the more correct interpretation is that the PTRI model does a poor job of distinguishing among very slowly improving technologies, and that any technology that is estimated as a negative improvement rate is simply a very slowly improving domain (< 5%). Additionally, the PTRI model as shown in Benson and Magee (2014c) tends to give estimates that fall within ±0.10 of the measured technological improvement rates. In the future, more accurate confidence intervals should be developed to accompany the estimated k. To demonstrate this further, some of the technologies that were predicted in this study have been measured before and the comparison between the empirically measured values and the estimated values is shown in Table 3.

Technical Domain	Technical Measure	Estimated	Empirically

		k	Measured k
Genome Sequencing	(basepairs/$)	0.209	0.29
SLA 3D Printing	(1/sec*$(including build volume/machine size)))	0.385	0.38
Solar Photovoltaic Energy Generation	(W_p/$)	0.165	0.09
Wind Turbine Energy Generation	(W_p/$)	0.152	0.09

Table 3: Estimated and Measured ks

The close results between the predicted values and the empirically measured values lend credibility to the predicted values shown above and are consistent with the relatively close correlation between the PTIR model and previously measured empirical values.

The highest technological improvement rate is digital representation with an estimated k of 0.7, which would indicate that its capabilities would more than double every year. The interesting part of the PTIR method is that it seems rather difficult to imagine a way to objectively measure the improvement rate of the how well the digital world represents the real world, however this high rate is not inconsistent with the subjective experiences of the rapidly changing digital world and the ever-increasing ways that people spend on a digital version of what used to be physical (i.e. social networking, talking, banking, watching entertainment, etc…). Thus the PTIR allows us to map technological improvement rates to technologies that may be improving but are hard to measure due to lack of metrics or data or other reasons.

These improvement rate estimates should be used, however, in conjunction with increased knowledge about the measures by which the technical domains improve. Table 3 shows a few examples of technical measures by which the domains improved, including more simple measures like W_p/$ for solar PV and wind turbines and more complex measures for 3D printing, which includes metrics for speed of printing (mm/sec), resolution(1/mm) of the machine, cost ($, machine size), and flexibility (build volume), which when combined result in the “highly complete” measure in Table 3 for 3d printing.

When evaluating technologies using the PTIR model, the measures can be estimated and can be somewhat more abstract, but must always include a benefit and a cost. For example, when considering water purification, the benefit of the process is clean water and the cost is energy or price. Thus an appropriate measure for the improvement rate of water purification could be gallons of clean water per kWhr or per dollar.

The second highest k-values are grouped into a clump around 0.4 with Information Security, Brain Mapping, Artificial Neural Networks, 3D-Printing and Purification all within 0.06 of one another. These rather disparate technologies are predicted to improve at relatively rapid rates similar to those of Moore’s law (k = 0.36). While some may not be surprised to see information security and neural networks improving at this rate due to their relation to information technology, the estimated rapid rate of growth for Brain Mapping, 3D-Printing and Purification have less to do with the rapid rate of improvement of information technology yet are still estimated to be improving at a high rate.

Remote Flight control, Robotics, Genome Sequencing, Solar PV and Wind Turbines make up the next grouping of technologies that have estimated improvement rates between 0.15 and 0.3, corresponding with a doubling of capability every 2.5-5 years. These technologies also seem to be rather disparate yet all seem to have less of a pure reliance on information technology than does the top group.

The bottom dwellers, with estimated rates ranging from -0.1 to 0.03 include gaseous engineering, nuclear fusion and food engineering. As was mentioned previously it is unlikely that these particular domains are decreasing in capability over time, and it is much more likely that all three of these domains have been improving at a very slow rate.

While the topic was touched upon briefly in the results section, the intent of this paper is not to look at commonalities between domains with high (or low) estimated technological improvement rates, as that topic is covered in depth in Benson and Magee (2014c); rather the goal of this paper is to introduce the PTRI methodology into the FTA world as a tool that can be used to combine qualitative and quantitative data to provide numeric estimates of technological potential for the future. This tool can be especially useful for technical domains which are hard to measure or have scarce data such as may become more common as technology improves accelerates.

While this paper is mainly focused on demonstrating the potential of the PTRI for estimating quantitative technological growth rates, it will be important in practical use to include qualitative analysis to complement the quantitative estimates. For example, information security is estimated to be a fast growing technological domain with a k-value of 0.45, likewise, purification is estimated to improve at a k-value of 0.39. These two values fall well within the rough confidence interval of +/- 0.1 and therefore it is reasonable to assume that they will improve at similar rates. Despite this fact, however, the results of the improvements could well be rather different.

Information security, while it may be improving quickly is constantly having to compete with other people who are looking to break through that security, which relies on similar principles and may improve at a similar rate, leading to an arms race in information protection, therefore while we would expect the capabilities of information security to increase drastically, we might not expect the number of information security breaches to decrease at the same rate due to the concurrent increasing capabilities of hackers and electronic thieves.

A different story can be told about water purification, as was mentioned earlier, increases in purification capabilities should rapidly increase the capability to create drinking water using fewer resources. Thus, the high k for purification could indicate that the problem of water scarcity should not be a high risk if the purification technologies continue to improve at their estimated rates, which is a relatively safe bet considering the long-term stability of k for most technological domains.

The PTRI method, when combined with appropriate qualitative analysis can be a powerful tool for policymakers, technological strategists and investors of many kinds. The development of more powerful patent analysis techniques to produce quantitative estimates of technological change can help decrease technological uncertainty for current and future technologies.

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