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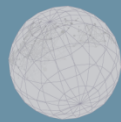
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Using take-off phase data for forecasting the evolution of emergent technologies¹

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Introduction

The simple logistic S-curve has been extensively used to predict the adoption and the development of technologies, but being intellectually appealing and intuitive, this tool is easy to be mismanaged and can lead to bizarre results (Kucharavy & De Guio, 2015). The abundance of data considerably improves the forecasting analysis using S-curves, but external "shocks" such as the heavy subsidization of a certain technology, a sudden hype followed by a letdown or restrictive regulation can quickly make any forecasting attempt perfectly useless (Rao & Kishore, 2010). The approach chosen in this study is just one among many in the utilization of S-curve diffusion patterns: the epidemic model and probit model are some popular alternatives, the former being the predominant paradigm in policy making. Epidemic models often point at the excessive slowness of technology diffusion and in doing so justify public intervention via subsidies or promotion of communication between the agents involved, while probit models focus on firm's behavior and considerably downplay the range and effectiveness of policy tools that could be deployed to foster technology diffusion (Geroski, 2000). In this paper we propose a method for forecasting emerging technologies in their take-off phase by identifying mature technologies with a similar behavior in that phase, and subsequently using S-curve models to predict both the time and the expected total patent number an emerging technology will achieve in its maturity.

Methodology

This study tries to forecast the evolution of five emerging technologies, namely 3d printing, unmanned aerial vehicles (drone), blockchain technology, natural language processing (NLP) and virtual reality (VR) by comparing the evolution in patent number of these technologies (they are all at take-off phase at year 2016) with the pattern shown by a set of mature technologies on that same phase. With this purpose on mind, the first step consists of modeling the initial growth phases of a set of mature technologies using the annual compound interest growth formula. We downloaded the patent data up to year 2016 corresponding to a sample of six mature technologies, namely magnetic tape, personal digital assistants (PDA), telefacsimile technology (FAX), cathode ray technology, photocopiers and photography film, and used Microsoft Excel ® Solver tool to fit an interest growth formula to the take-off phase of these technologies. The same fitting process was conducted with emerging technologies so we could compare growth rates during take-off phases for both emerging and mature

technologies. Table 1 shows the emergent-mature technology pairs that had the most similar growth factor during take-off phases.

Table 1. List of emerging technologies and the mature technology used for forecasting on each case.

Emerging technology	Mature technology	Growth factor (emerging vs mature, calculated for the same time interval)
3d Printing	PDA	1.66 vs 1.32
Drone	FAX	1.06 vs 0.84
Blockchain	PDA	2.19 vs 1.32
NPL	FAX	0.84 vs 0.84
VR	FAX	2.11 vs 1.50

Once the mature reference was set for each emergent technology, a logistic growth curve was fit to the mature technology by following the method described in Matheus (1992). Equation 1 shows the variables of this model:

$$p(t) = \frac{L}{1 + ce^{r(t-t_0)}} \quad (1)$$

Where L is the maximum of the maturity curve (we took the present number of patents for each technology, given the fact that they are well into their maturity) and c and r determine the length of the lower tail of the curve and the steepness of the curve, respectively. The final step consists of re-fitting each of these curves to the corresponding emergent technology, by taking the values of c and r of the mature technology and finding the value of L that makes the curve fit with the 2016 value of the emergent technology.

Results and conclusions

Table 1 presents the results of this study. The technology in brackets in the first column is the mature technology that has been used as a predictor for each case. The point where the yearly growth in patents gets lower than 1% has been determined to be the maturity year.

Table 2. Forecasting of maturity year and total patent number at maturity.

Emerging technology	Maturity Year	Total patent number at maturity
3d printing (PDA)	2030	166,888
Drone (FAX)	2046	86,090
Blockchain (PDA)	2032	36,628
NPL (FAX)	2046	37,106
VR (FAX)	2049	399,189

Our method forecasts a quick development and saturation (maturity stage) for 3d printing and blockchain technologies, in accordance with the high growth speed they show in the take-off phase, on the other side, drone, NLP and VR technologies are expected to achieve the maturity much later. It must be pointed out that the total patent number predicted for VR technology seems irrational to us. An abnormal spike in fax patent production on the first

three years of its take-off phase led us, according to our method, to use fax patent curve to predict VR, the emergent technology with the highest growth rate in our sample (2.11). This anomaly is something that we will take into account in our future works. We conclude that this method can be suitable for predicting the evolution of emerging technologies, particularly when the technology under analysis is well into the take-off phase and a mature technology with similar features in that phase is available.

Future research

This method would be further improved by increasing the size of the mature technology sample. A more ambitious goal would be that of building separate databases for a set of technology areas, in order to predict the evolution of emergent technologies using data from the same area, thus enhancing the comparability.

There are several options other than the compound interest growth to fit the take-off behavior of technologies. Custom exponential formulas may lead us to better results, and further research is needed in order to find the optimum model for this fitting.

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