The topology of the skill relatedness network of technologies.

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This paper uses the transition of inventors between technologies to estimate their proximity in terms of required skills. This proximity allows the construction of a skill relatedness network between technologies. The aim of the paper is to analyse which topological structures characterise this skill relatedness network.

In recent decades, academic research on the conditions that constrain or boost the generation of new technologies, as an expression of the combination of diverse knowledge and skills, has gained ground (Dosi & Nelson, 2010; Nelson & Winter, 1982). In this literature, a field of research has been developed that interpret the creation of knowledge, in the form of invention of new solutions or combinations, as the product of a complex adaptive system. This system is capable of leading to emergent phenomena (innovations) that transcend the sum of its parts (Fleming & Sorenson, 2001; Frenken, 2006; Martin & Sunley, 2007; Sorenson, Rivkin, & Fleming, 2006).

It is possible to operationalise these ideas by means of the methodological framework that arises from Hidalgo, Klinger, Barabasi, and Hausmann (2007) and Hidalgo and Hausmann (2009), where it is postulated that the economic development of a country is strongly related to the level of complexity of its productive structure. Of particular relevance within this framework of analysis is the “Principle of Relatedness” (Hidalgo et al., 2018), which uses information on the co-occurrence of activities to estimate their proximity.

For the purposes of this research, one particular type of relatedness is relevant, which is called skill relatedness. This approach stems from the work of Neffke and Henning (2013); Neffke, Otto, and Weyh (2017), where the movement of workers between industries is used as an input to estimate skill relatedness. This application of the relatedness principle is appropriate for inferring relatedness of skills between technologies, to the extent that we can observe inventors patenting in one and then in another technology. By this we will say that, if the number of inventors moving from technology X to technology Y is above what we would expect in a probability distribution conditional on the relative sizes of the production of both, then technology Y has a relatedness of skills to technology X. The works that have studied the relatedness between technologies do so by considering co-citation between technologies (Alstott, Triulzi, Yan, & Luo, 2017; Kogler, Rigby, & Tucker, 2013), but there are no works that study the relatedness of skills, between technologies, expressed by the movement of inventors.

This research make use of data from the United States Patent and Trademark Office (USPTO), obtained through the PatentsView project, which provides disambiguated information on the inventors and owners of patents, as well as the technologies in which each patent is classified, since 1976 to 2020. Also the database used allows us to know the order of the technological fields in which the patent is classified, for which the International Patent Classification (IPC) will be used.

With this information it will be possible to construct transition matrices (F) between technologies, based on the movements of inventors at the global level. To do this, if an individual patented in a technology j and then does so in a technology i, in our matrix we will have that $F_{j,i} = 1$. By aggregating all the moves, between each pair of technologies, we obtain an asymmetric matrix of $N \times N$, where N is the total number of technologies. From the F matrix, we can estimate a null model that allows us to measure the deviation of the observed transitions, with respect to the expected ones ($\hat{F}$). This is the basis for obtaining, following Neffke and Henning (2013) and Neffke et al. (2017), the skill relatedness indicator (sr) which is defined as:

$$\hat{F}_{i,j} = \frac{\sum_j F_{i,j} \sum_i F_{i,j}}{\sum_i \sum_j F_{i,j}}$$

$$sr^{**}_{i,j} = \frac{F_{i,j}}{\hat{F}_{i,j}}$$

This indicator compares the observed flows ($F_{i,j}$) with the estimated ($\hat{F}_{i,j}$). Therefore, if $0 \geq sr^{**}$, the observed flows going from technology i to j are below, or equal to, the estimated ones. Values of $sr** > 1$ indicate that the flow of individuals from i to j exceeds the expected, and can be interpreted as a relatedness of skills between the two technologies. The indicator defined in this way has the disadvantage of having a steep right tail, because it takes values between zero and infinity. Therefore, a normalisation of the indicator as presented in the following equation is proposed, where it is also imposed that each activity is perfectly related to itself.

$$sr^{*}_{i,j} = \begin{cases} \dfrac{sr^{**}_{i,j} - 1}{sr^{**}_{i,j} + 1} & \forall\, i \neq j \\ 1 & \forall\, i = j \end{cases}$$

Finally, the skill relatedness structure is symmetrized as follow:

$$sr_{i,j} = \frac{1}{2}\left(\frac{sr^{*}_{i,j} + sr^{*}_{j,i}}{2} + 1\right) \tag{1}$$

The equation 1 establishes that $sr \in [0,1]$, where pairs of technologies that show values close to 0 will be considered as markedly dissimilar in terms of skill requirements and those that are close to 1 will be those that are closer in this sense. The SR matrix, defined by the sr value between each pair of technologies, can be viewed as an undirected, weighted network. This network is the unimodal projection of the bipartite network of co-occurrence of inventors in technologies. In order to dichotomise this network, it is necessary to establish a threshold ($\theta \in (0,1]$) for the variable sr, from which we say that the skills relatedness is significant.

Based on the theoretical approach of this paper, if the SR describes the complex adaptive system that leads to the emergence of new technologies, then we can expect to observe a small-world structure in this network. Therefore the following hypotheses are proposed:

1. Links between knowledge communities allow to traverse the network in a reduced number of steps.
2. Relatedness links are more likely to be established between technologies that have relatedness links in common with other technologies.

The first implies that the diameter of the network is low and decreasing over time. The second hypothesis can be analysed through the evolution of the transitivity of the network, where it is expected to be high and increasing over time.

The formation of links in this network can be interpreted as the establishment of relatedness between two technologies. Understanding this process is a key input for the design of related and unrelated diversification policies, as it provides inputs for policy makers to define diversification strategies that are consistent with available capabilities.

The following figures show preliminary results for some relevant indicators.

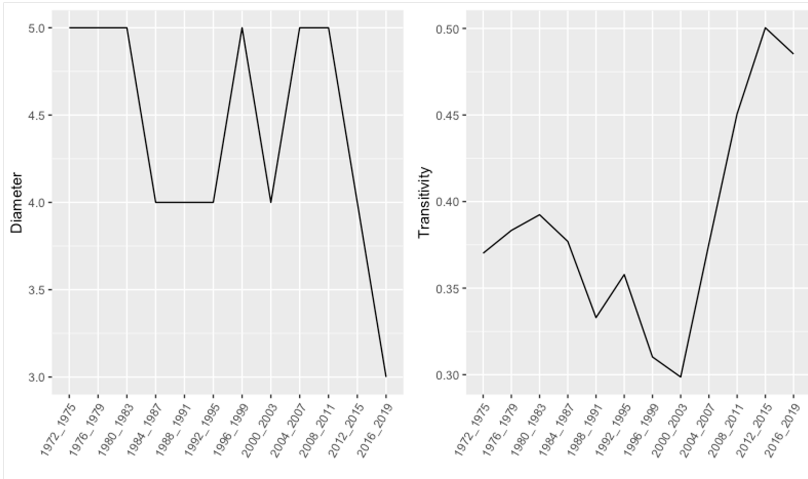

Figure 1: Left: Diameter evolution. Right: Transitivity evolution

References

Alstott, J., Triulzi, G., Yan, B., & Luo, J. (2017). Inventors' explorations across technology domains. *Design Science*, *3*, e20. doi: 10.1017/dsj.2017.21

Dosi, G., & Nelson, R. (2010). Technical Change and Industrial Dynamics as Evolutionary Processes. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the economics of innovation* (Vol. 1, pp. 51–127). Elsevier B.V. doi: 10.1016/S0169-7218(10)01003-8

Fleming, L., & Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research Policy*, *30*(7), 1019–1039. doi: 10.1016/S0048-7333(00)00135-9

Frenken, K. (2006). Technological innovation and complexity theory. *Economics of Innovation and New Technology*, *15*(2), 137–155. doi: 10.1080/10438590500141453

Hidalgo, C. A., Balland, P.-A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., … Zhu, S. (2018). The Principle of Relatedness. In *Springer proceedings in complexity* (pp. 451–457). doi: 10.1007/978-3-319-96661-8_46

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, *106*(26), 10570–10575. doi: 10.1073/pnas.0900943106

Hidalgo, C. A., Klinger, B., Barabasi, A.-L. A., & Hausmann, R. (2007). The Product Space Conditions the Development of Nations. *Science*, *317*(5837), 482–487. doi: 10.1126/science.1144581

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping Knowledge Space and Technological Relatedness in US Cities. *European Planning Studies*, *21*(9), 1374–1391. doi: 10.1080/09654313.2012.755832

Martin, R., & Sunley, P. (2007). Complexity thinking and evolutionary economic geography. *Journal of Economic Geography*, *7*(5), 573–601. doi: 10.1093/jeg/lbm019

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal*, *34*(3), 297–316. doi: 10.1002/smj.2014

Neffke, F., Otto, A., & Weyh, A. (2017). Inter-industry labor flows. *Journal of Economic Behavior and Organization*, *142*, 275–292. doi: 10.1016/j.jebo.2017.07.003

Nelson, R., & Winter, S. (1982). *An evolutionary theory of economic change*. Harvard Business School Press, Cambridge.

Sorenson, O., Rivkin, J. W., & Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, *35*(7), 994–1017. doi: 10.1016/j.respol.2006.05.002