Research on the Identification of breakthrough technologies driven by science

Dan Wang[1], Xiao Zhou[1,*], Pengwei Zhao[1] , Juan Pang[1] and Qiaoyang Ren[1]

[1] *Xidian University, Xifeng 266 710126 Xi'an, Shaanxi Province, China*

Abstract

The identification of breakthrough technologies plays a crucial role in driving technological innovation forward. The science-driven technology innovation pattern has emerged as a significant approach for identifying breakthrough technologies. This paper presents a novel framework for identifying breakthrough technologies based on a science-driven technological breakthrough pattern. The effectiveness of this framework is validated using the field of artificial intelligence as an illustrative example. This method not only assists researchers in accurately identifying the sources and development paths of technological breakthroughs but also provides important information for the formulation of future research and development policies.

Keywords

Breakthrough technology, Knowledge networks, Link prediction, Structural entropy

1. Introduction

Breakthrough innovation, characterized by its highly revolutionary nature, plays a pivotal role in enabling enterprises to overhaul industry chains, enhance competitiveness, and seize prime opportunities in the increasingly competitive global landscape [1]. Recent research has highlighted the significance of the interplay between science (S) and technology (T) in fostering potential breakthrough technologies [2]. Scholars have started to explore the complex correlation between S and T by integrating scientific literature and patent information. This integration has led to the identification of three primary interaction patterns: science-driven (S-T), technology-pull (T-S), and science-technology synergy (S&T). Notably, the science-driven technology pattern signifies instances where technological advancements stem from scientific discoveries, serving as a key driver of technological innovation [3][4]. The incorporation of scientific insights into technological progress plays a pivotal role in enhancing national innovation capabilities and competitiveness [5][6][7].

This paper adopts a fine-grained representation approach, considering breakthrough technologies as composed of several closely related scientific and technological knowledge elements. To do so, this paper constructs a breakthrough technology identification framework based on the science-driven technology innovation pattern. The core idea of the study is to use new science as a signal of innovation, to deeply explore the mechanisms and evolutionary paths through which new science leads to technological breakthroughs, and on this basis, to identify breakthrough technologies.

2. Data and Method

The framework for identifying breakthrough technology is shown in Figure 1. Firstly, we use papers and patents as carriers of science and technology, respectively. We collect data from the Web of Science (WOS)

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* Corresponding author.
EMAIL: belinda1214@126.com (Xiao Zhou)

and Incopat patent databases, using search queries related to the research topics to download relevant scientific papers and patents. Secondly, we focus on the acquisition of new science, which is defined as scientific topics that are both novel and impactful, yet have not been integrated into existing technological systems. We adopted Sentence-BERT (SBERT) [8] and Local Outlier Factor (LOF) [9] to quantify the novelty of papers, while utilizing citation counts as a metric for assessing paper impact.

Subsequently, we integrate new science into the existing technological system through the construction of a science-technology network. This network acts as a channel for merging new scientific findings with established technological advancements. Link prediction is employed to uncover deep semantic links between new science and technology. This is followed by the application of community detection algorithms to filter subnetworks containing new science-technology links. These subnetworks serve as focal points for further analysis and evaluation. Finally, the impact of these subnetworks is evaluated using structural entropy to identify breakthrough technologies.

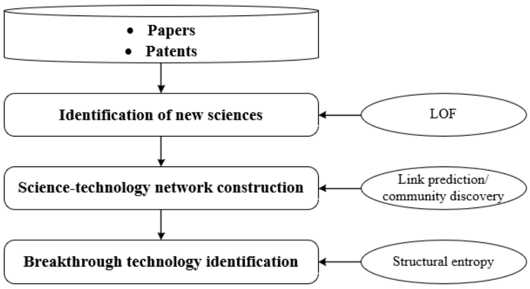

Figure 1: Research framework for identifying breakthrough technology

3. Empirical analysis

To assess the efficacy of the suggested approach, the domain of artificial intelligence (AI) is selected as a representative case study. Following a methodology similar to that outlined by Tsay et al. [10] and subsequent removal of duplicate records, a total of 236,333 publications and 29,468 patents related to AI, published between 2014 and 2018, were identified.

The science-technology network consists of 1,161 nodes and 62975 connecting edges, yielding a network density of 0. 0935. We adopt an attribute feature-based graph convolutional network (GCN) [11] for link prediction in the science-technology network to discover potential linkages between new science topics and technological topics. After link prediction, Liu et al.'s method [12] is used to partition the S-T revised network into 13 subnetworks. Two subnetworks that do not contain new science topics are excluded, leaving 11 subnetworks for further investigation.

We employ the structural entropy measure proposed by Xu et al. [13] to calculate the structural entropy influence of each subnetwork. We utilized the median as a threshold and identified five subnetworks above this median as potential breakthrough technologies. The final results were determined in conjunction with expert opinions. Ultimately, the study identified five breakthrough technologies. Among them, drug discovery stands out due to its particularly significant impact. We conducted a detailed analysis of this breakthrough technology. Deep learning can train models using large-scale biological data to predict the activity, toxicity, and other properties of compounds, thereby rapidly screening candidate drugs with potential therapeutic effects [14]. AI-discovered molecules were listed among the Massachusetts Institute of Technology (MIT)'s top ten breakthrough technologies in 2020. In recent years, drug discovery based on deep learning algorithms has gradually transitioned from research and development to practical technology development. The from-scratch drug design based on deep learning algorithms was recognized by MIT as a breakthrough in successfully applying artificial intelligence to the drug design process [15].

4. Discussion and Conclusion

This paper proposes a framework for identifying breakthrough technology, starting with new sciences as an innovation signal and tracking the evolution of technological breakthroughs stemming from them. The primary contributions of this study can be listed as follows. First, this study proposes a novel method for identifying breakthrough technologies based on the innovation pattern of science-driven technological breakthroughs. This approach enables dynamic tracking and measurement of the innovation process triggered by new science. Second, it provides an in-depth characterization of the essence and core features of new science. Furthermore, by employing a topic-based fine-grained approach, the study identifies breakthrough technologies, while also tracking the dynamic interaction trajectories between new science and technology at the semantic level.

Several limitations of our proposed method require further improvement. This paper primarily considers the driving effect of science on technological breakthroughs. Future research could explore the identification of breakthrough technologies under different patterns of science and technology interaction. Moreover, alongside scientific influence, the commercial aspect warrants attention.

5. Acknowledgements

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6. References

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