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Application and Technology Network of Standard Essential Patents in Machine Learning

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Abstract

The development of artificial intelligence has caused rapid growth in the industrial applications of machine learning. Studies on technology trends have mostly focused on patents applied to or approved by major patent offices and few studies have investigated standard essential patents (SEPs). Although recent studies have explored SEPs, most have only discussed legal regulations and intellectual property rights or current developments in SEPs and SEP declarations. Because SEPs are essential standard technologies in industrial development, their technological development can reveal valuable insights. This study employed SEPs as the research subject to observe the trends in the development of SEPs for machine learning technologies. The results revealed key technologies in machine learning SEPs, namely wireless communication networks, transmission of digital information (e.g., telegraphic communication), electric digital data processing, and conjoint control of vehicle sub-units of different type or different function. Operators and governments should closely follow and invest in these technologies. The technology network model constructed in the present study to explore the technological application fields of machine learning SEPs can serve as a reference for industry operators and governments when allocating research and development resources.

Keywords

Machine learning, Network analysis, Standard essential patent, Technological analysis

Introduction

Artificial intelligence (AI) has become ingrained in society. The aim of AI is to enable information systems to mimic human behavior, and this is approached by improving computer system efficiency through experience-based learning. A World Intellectual Property Organization (WIPO) report identified that one of the most notable characteristics of AI research is its recent growth of patent applications. However, the percentage of scientific papers written in the field has decreased, implying that AI technology has transcended from theoretical research to commercial products and services. This trend is also reflected in the types of patents applied for. AI applications have experienced significant growth in certain industrial fields [1], including communications [2,3], health care [4], industrial manufacturing [5], and commercial decision-making [6,7]. Among trends in AI techniques, machine learning predominates; it represents 89% of filings mentioning this AI technique and 40% of all AI-related patents [1]. The development of AI technology has increased the popularity of machine learning in industrial applications. Understanding the development trends of novel technologies and industry standard settings is crucial for determining the industrial foundation of AI technology applications. By analyzing standard essential patents (SEPs), the present study observed the application and development trends of machine learning technologies.

SEPs have received increasing attention in the industrial field, and the number of SEPs owned by an enterprise has become an indicator of competitiveness [8-10]. However, few studies on technology trends have employed SEPs, and most have analyzed the patents applied to or approved by major patent offices, such as the United States Patent and Trademark Office (USPTO) [11] and the European Patent Office (EPO) [12]. Because SEPs are valuable assets embodying essential standard technologies for industrial development [9], SEPs are suitable for observing technology development trends. Studies on SEPs have rarely focused on technology trends.

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Most related studies have concentrated on legal regulations and strategies for intellectual property rights [13,14], and others have explored currently declared and developing SEPs [15,16]. Therefore, the present study explored SEPs to determine the key technology fields of machine learning applications in industry standard settings.

Two research gaps are addressed in the present study: (1) to guide industrial development, we used SEPs to observe the practical actions taken in machine learning and (2) we conducted focused research on SEPs to clarify SEP technology development trends. Because SEPs represent essential technologies in industrial development, SEP technology networks can effectively reveal the key technologies of machine learning in industry standard settings.

In contrast to studies of the legal aspects and current development of SEPs, the aim of the present study was to explore the key technologies in machine learning SEPs and to establish an SEP technology network model, which can provide a reference for government and industry.

Literature Review

This literature review contains three parts discussing machine learning development, SEPs, and patent technology network analysis.

Machine learning development

Machine learning is a critical AI technology, accounting for more than one-third of invention patents in the AI field. Machine learning patent applications have an average annual growth rate of 28% [1]. These technologies automatically analyze data to detect specific patterns and then apply the identified patterns to make predictions regarding unseen data. With increased efficiency in big data collection and with advancements in computational efficiency, the industrial applications of machine learning have been extended to financial forecasts [17], communication [18], production scheduling [19,20], bio-inspired fields [1,21], and energy [22]. Accordingly, a significant growth has been observed in machine learning patents, with deep learning and neural network patents exhibiting the fastest growth. The Chinese Academy of Sciences has the largest portfolio of patents explicitly related to deep learning techniques. Baidu has the largest portfolio of patents related to the deep learning, followed by Alphabet, Siemens, Xiaomi, Microsoft, Samsung, IBM, and NEC [1]. The development of machine learning technology has transcended from an academic field and is now widely applied in industrial applications, including in visual and audio recognition, forecasting, classification, associative learning, statistics, extraction, and regression applications. Given the widespread and interdisciplinary applications of machine learning, the present study analyzed SEPs to identify the main fields of machine learning technologies in industry standard settings and to determine the industrial applications of machine learning technologies that meet market demands.

Standard essential patents

SEPs are a patent application mode used by standard-setting organizations (SSOs). The main purpose of an SEP is to balance the universality of standard shared technology with the profits of patentees. SEPs combine developing and crucial standard shared technologies with patent protection, and they require patentees to sign the Fair, Reasonable, and Non-discriminatory licensing terms to ensure that patentees can collect a reasonable fee when granting SSO members the right to use said patent. SEPs are considered an intersection between standards and patents. The technologies described in SEPs are essential to industry standards and are referenced by subsequent technologies, thus influencing industrial development [8]. Because of their status as practical universal principles in industrial applications, SEPs have commercial value in technology development [9]. Studies have used the number of SEPs owned by a corporation as an indicator of its market control [8], because technologies embodied in SEPs represent crucial industrial innovations.

Accordingly, by observing SEPs and discussing the industrial development purpose of the specific technologies, we can identify the proposed technological interoperability, including Universal Serial Bus, Long Term Evolution, Wireless Fidelity, HyperText Transfer Protocol, and MPEG Audio Layer 3 [9]. Such interoperability standards are designed to ensure compatibility between products, thereby enhancing product quality and efficiency. Currently, international organizations such as the European Telecommunication Standard Institute, International Organization for Standardization, Internet Engineering Task Force, ITU Telecommunication Standardization Sector, and Institute of Electrical and Electronics Engineers have established relevant standards for various technologies. Additionally, research and development corporations have combined various standard technologies with patient protection to collect reasonably priced patent right fees from SSO members for the right to use said patents [8].

The present study analyzed SEPs to identify key machine learning technologies. Additionally, a technology network was established to determine whether key technologies meet industry standards and market demands.

Network analysis for patent technologies

Recent studies have employed network analysis to explore the development and target of technological collaborations [23,24], the current condition of technology transfers [25,26], and the clustering of technological development [28,29]. Based on a network analysis, the present study used classification analysis to determine the relationship between technological fields. Studies have employed classification methods to analyze industry convergence [30] and to determine the technology fields driving it. Based on the technological field of each patent, the present study established a technology network to determine key machine learning technologies in SEP applications. Patents may belong to multiple technological fields according to their patent classification code, which is assigned by a patent office. This study employed classification to define the relationships between technological fields. After establishing the technology networks of machine learning SEPs, this study identified the key technological fields. Two policy implications are provided on the basis of the results. First, the application of machine learning to meet industrial demands has received increased attention in recent years [1,19]. The centrality of each technological field was used to determine the direction of technological applications in machine learning, thereby indicating a reliable direction for technology development. Second, because SEPs embody standard essential technologies [8], the key technologies of machine learning can be identified by analyzing the SEP technology networks. The present study explored the core technologies and development directions of machine learning SEPs to determine the development trends of commercialized technologies.

Research Design

Data collection and evaluation

The present study used the iPlytics platform to collect SEPs data. The platform includes 4 million standard documents and data on 280,000 SEPs and 4 million companies [31]. Key technologies were observed by collecting data on machine learning SEPs for 2016 to 2020. By using ((TTL/machine learning) or (ABST/machine learning) or (ACLM/machine learning)) as the search term, 47 SEPs were retrieved. Subsequently, we employed the cooperative patent classification (CPC) system, which is jointly implemented by the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO), to classify the retrieved technologies.

Centrality analysis

Centrality analysis was performed to determine the key technologies in the established technological networks. This assessment method is further detailed in the following sections.

Closeness centrality: Closeness centrality is the reciprocal of the distance between two nodes. Nodes with closer distances have higher closeness centrality or accessibility.

$$C_C(P_i)^{-1} = \sum_{j=1}^{n} d(P_i, P_j) with i \neq j$$

where (P_i, P_j) represents the distance from node i to j.

Bonacich power centrality: Bonacich power centrality relies not only on the direct connection between neighboring nodes but also on their relationships and connections with other nodes [32]. In other words, other nodes influence the calculated centrality based on their direct and indirect connection relationships. In addition to relationships at the first level, the relationships with nodes connected to the first level must also be considered. Furthermore, the relationships at the first level are also influenced by relationships with second-level nodes. Thus, the relationships of the current node with all connected nodes must be considered. Based on this indicator, if node i influences multiple other members, or influences a member who is capable of influencing multiple other members, then, node i demonstrates a high degree of influence.

$$C_b(P_i) = C_i(\alpha, \beta) = \sum_{j=1}^{n} (\alpha + \beta C_j) R_{ij}$$

where R_{ij} is the network matrix representing the relationships between nodes, α is the number of relationships of the current node with neighboring nodes, and β is the attenuation factor, which represents the weight of the relationship with node i.

Fragmentation centrality: Fragmentation centrality refers to the loss of network cohesion if the node is removed from the network. It is calculated as the percentage of nodes that are disconnected when a certain node is removed. A lower fragmentation centrality indicates that the network remains stable after the node is removed, implying that the node has lower importance. In this study, the distance-weighted fragmentation value proposed by referenced Borgatti [33] was adopted for evaluation.

$$C_j(P_i) = 1 - \frac{2\sum i > j \frac{1}{d(P_i, P_J)}}{n(n-1)}$$

where $d(P_i, P_j)$ represents the distance from node i to node j and n is the total number of nodes.

Empirical study

Patent search results

Because of the technology development of machine learning, the number of SEPs related to machine learning technologies has increased annually. The development trend is presented in Figure 1.

Figure 2 reveals a rapid growth in machine learning SEPs. Studies have indicated that a three-level network model is sufficient to represent the technological properties of patents [33,34]. Most SEPs were classified under H04W (28SEPs, 29.79%), H04L (19SEPs, 20.21%), and H04B (8SEPs, 8.51%). The CPC definitions of these codes are listed in Appendix 1. Further analysis on the distribution of patent office's these SEPs were applied to revealed that Most SEPs were applied to the USPTO (13 SEPs, 27.66%), followed by the WIPO (11 SEPs; 23.40%). In particular, WIPO patents included patent cooperation treaties (PCTs) applied to the WIPO International Bureau. Machine learning SEPs were mostly applied to the USPTO, signifying that the United States is a vital technology market. By contrast, applying for multinational patents through the WIPO PCTs is also a common patent portfolio strategy.

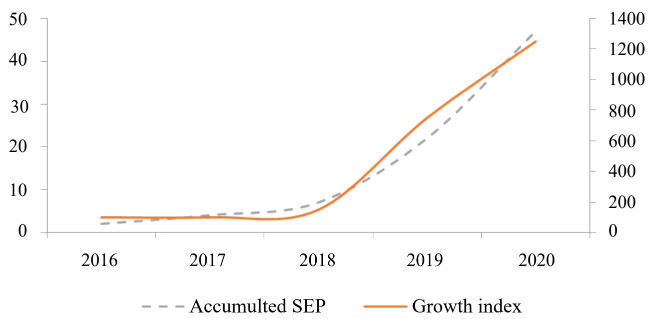

Figure 1: Growth trend in machine learning SEPs.

Note: The number of SEPs in the base year is 100. The growth index each year is calculated as (number of SEPs in each year/number of SEPs in the base year) ×100. The cumulative SEPs is the total number of SEPs accumulated from the start of the study period.

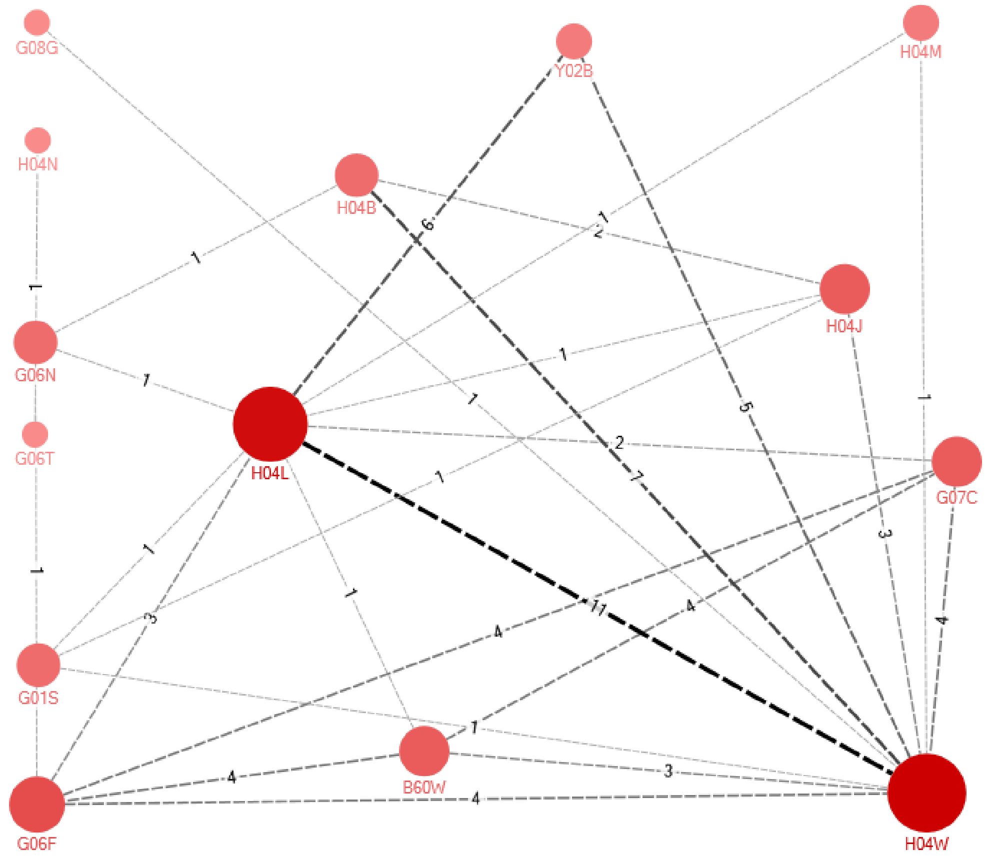

Figure 2: Presents the network model of the key technologies in machine learning SEPs. Three-level network model of machine learning SEPs (represented by CPC codes).

Note: Node size represents the number of connected nodes; vertex thickness represents the relationship intensity (i.e., the number of shared patents).

Table 1: Lists the centrality results for each technology. Centrality results (top five) of machine learning SEP technologies.

CPC	Closeness centrality	CPC	Bonacich power centrality	CPC	Fragmentation centrality
H04W	10.500	H04W	1913.045	H04W	0.667
H04L	10.500	H04L	1859.856	H04L	0.606
G06F	8.000	G06F	1317.078	G06F	0.579
B60W	7.500	B60W	1198.095	B60W	0.573
H04J	7.500	G07C	1198.095	H04J	0.573

Key technologies of machine learning SEPs

According to Table 1, H04W, H04L, G06F, and B60W were the technological fields with the five highest results for closeness centrality, Bonacich power centrality, and fragmentation centrality. Thus, the key technologies in machine learning SEPs are wireless communication networks (H04W), transmission of digital information (e.g., telegraphic communication; H04L), electric digital data processing (G06F), and conjoint control of vehicle sub-units of different type or different function (B60W).

Conclusion

Discussion

This study performed network analysis of machine learning SEPs to explore their key technologies. Research models derived from previous studies were used throughout the research process. The findings are detailed as follows.

Empirical results revealed that wireless communication networks (H04W), transmission of digital information (e.g., telegraphic communication; H04L), electric digital data processing (G06F), and conjoint control of vehicle sub-units of different type or different function (B60W) are the key technologies in the technological network of machine learning SEPs. Therefore, these four technological fields are as essential when setting industry standards and they may be the technologies that best represent industrial applications. These four fields were determined to have the highest connection frequency and the densest connections with other nodes; thus, these are the technologies used in industrial applications of machine learning.

The industry standards for machine learning technologies are applicable to telecoms, wireless communication networks, and conjoint control of vehicle sub-units. This suggests that the application of machine learning in the autonomous car industry is a development trend. Studies have indicated that coordination between the sensors, data processing, simultaneous localization and mapping functions, and path planning of autonomous cars can improve machine learning outcomes [35]. Recent developments in machine learning have enabled the prediction of spatial information, which is useful for smart mobility services including navigation, driving assistance, and self-driving [36]. Machine learning has a wide range of applications in vehicle autonomy, including vision and decision-making. Therefore, development of machine learning technologies for autonomous vehicles and related industry standards is a key development trend.

Most studies assessing technology development directions have employed patents applied to or approved by major patent office's [11-12]. Few studies have used SEPs to determine the direction of technology development. Additionally, the few recent studies that have examined SEPs have focused on legal regulations and property rights [14,15] or currently declared and developing SEPs [16,17]. Few studies have used SEPs to investigate key technologies and technology trends, particularly in the machine learning field. Accordingly, the present study established a technological network to comprehensively examine machine learning SEPs.

The present study established a technology network model for machine learning SEPs, which may be valuable for industry operators and governments. This technological network illustrates the focus of technological development; operators can use this information to allocate research and development resources, and governments can use it to promote information pertaining to novel technologies. This study revealed that the incorporation of machine learning in the development of autonomous cars is a key development trend for industry standards. Given that government subsidies can catalyze technology development [37], governments can provide long-term subsidies to support and cultivate talents in relevant technological fields to strengthen research.

Limitations and future research directions

The processes of setting standards and applying for SEPs requires time. The present study adopted SEPs to observe machine learning technologies. Although this approach reflects the industry standard applications of machine learning technologies, the newest technological developments were not included in the present findings. Moreover, this study was based on a technology network. The findings reveal the key technologies of machine learning; however, they do not provide a detailed technological analysis of the development processes and practical applications of these technologies. Future studies should conduct interviews, perform content analysis, and employ other research methods to expand on the academic value of this study. Because the characteristics and industrial environment of each technology differs, patentees from different technology fields have different motivations for SEP applications. For example, in the machine learning field, few SEPs are related to consumer goods. The present study analyzed the technological fields in which SSOs and SEPs are centralized. Therefore, future studies should verify the present results using other sources of patent data. For example, researchers may observe patents using USPTO and EPO data to expand the research scope.

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Appendix 1

CPC Categories	Meaning
B60W	Conjoint control of vehicle sub-units of different type or different function; control systems specially adapted for hybrid vehicles; road vehicle drive control systems for purposes not related to the control of a particular sub-unit
G06F	Electric digital data processing
G07C	Time or attendance registers; registering or indicating the working of machines; generating random numbers; voting or lottery apparatus; arrangements, systems or apparatus for checking not provided for elsewhere
H04J	Multiplex communication
H04L	Transmission of digital information, e.g. telegraphic communication
H04W	Wireless communication networks

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