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ANALYZING AND PREDICTING R&D COLLABORATION NETWORKS IN THE METAVERSE INDUSTRY

Abstract:

Innovation ecosystems have become an indispensable element in the growth strategy of firms in various industries. In the birth stage of innovation ecosystem, it is important for firms to assess technological positions of various actors in the innovation ecosystem to support decisions on external R&D collaboration. This research integrates semantic analysis and bibliometric analysis for predicting evolving collaboration patterns and predict collaboration potential. Semantic analysis applies the context-aware deep learning framework based on BERT [14] to analyze unstructured patent data and evaluate technological similarity between individual firms. In addition, biblio-metric analysis uses patent indicators related to technological capabilities and potential technology synergy of individual firms. Then, the deep neural network (DNN) approach is used to learn the relationships between descriptive features and collaboration potentials as target feature. Our findings suggest that the metaverse innovation ecosystem remains in its nascent stages, with the collaborative network still being sparse. The illustrative example reveals that recommended candidate partners often align with or resemble past partners from prior periods. This suggests that the pro-posed deep learning approach is capable of predicting collaborative relationships between various firms.

Keywords:

Innovation ecosystems, deep learning, collaboration network, natural language processing.

1 Introduction

Due to the increasingly complex technological solutions and industrial value networks (Wang, Lai et al. 2015), transforming emerging technologies into successful and superior products or services often requires various actors (e.g., universities, research institutes, and firms) with distinct capabilities collaborating together for creating and delivering values to customers. The concept of the innovation ecosystem has received increasing attention in recent years. It is a type of collaborative arrangement that allows various innovative actors to combine their individual offerings into a cohesive and innovative solution that enhances customer values (Granstrand and Holgersson 2020). Innovation ecosystems have become an indispensable element in the growth strategy of firms in various industries, such as smart manufacturing, smart health, and electrical vehicles. In the birth stage of innovation ecosystem, it is important for firms to understand technology landscape, identify promising emerging technologies, and assess technological positions of various actors in the innovation ecosystem to support decisions on internal R&D investment, external R&D collaboration, and potential merge/acquisition.

The literature of patent analytics have developed various approaches for analyzing innovation ecosystems and can be roughly categorized into three areas: bibliometrics approaches, citation-based approaches, and semantic analysis approaches. One of the major drawbacks of bibliometrics approaches and citation-based approaches is that they ignore texture data such as abstracts and claims that contain rich and valuable information (Milanez, Faria et al. 2017). Therefore, several semantic analysis approaches based on text mining (Tseng, Lin et al. 2007) were developed that retrieve keywords from texture patent data for measuring technology similarities or distances between different firms. However, previous text mining approaches require great human efforts for data cleaning and did not handle polysemy and homonymy properly.

Due to recent advances of deep learning in natural language processing (NLP) that can alleviate the aforementioned limitations (Krestel, Chikkamath et al. 2021), several studies have applied word-embedding techniques (e.g., word2vec, a kind of shallow neural networks) for topic extraction (Hu, Li et al. 2018) and technology convergence discovery (Kim and Sohn 2020), while deep learning techniques for information extraction (Chen, Xu et al. 2020), patent quality evaluation (Chung and Sohn 2020), patent document clustering (Lei, Qi et al. 2019), and patent classification (Li, Hu et al. 2018, Lee and Hsiang 2020). To the best of our knowledge, there is no studies using the state-of-the-art context-aware deep learning technique, such as Bidirectional Encoder Representations from Transformers (BERT) (Devlin, Chang et al. 2018), for analyzing innovation ecosystem, especially for the metaverse industry.

Since Facebook announced it new name as Meta and refocusing its future development, several other major players, such as Microsoft, Apple, and Google, and many other companies also entered the market to build metaverse or components of metaverse for the future. Apparently, metaverse is the next big thing in the following 10 to 15 years (News 2021). Especially after pandemics, industries seriously consider digitally transforming their business operations and processes that allowing employees to work remotely and businesses to function properly. Metaverse may provide an advanced and superior technological solution to achieve this goal.

This research integrates semantic analysis and bibliometric analysis to predict evolving collaboration patterns and assess collaboration potential. Utilizing patent documents obtained from the USPTO database, we construct the metaverse collaboration network based on co-applicant information extracted from patent data, thereby characterizing the metaverse innovation ecosystem. Subsequently, several network metrics based on the small-world network (Strogatz 2001) are employed to analyze the network properties of the metaverse collaboration network. Then, semantic analysis employs a context-aware deep learning framework based on BERT (Devlin, Chang et al. 2018), a state-of-the-art deep learning architecture in NLP, to analyze unstructured patent data and evaluate technological similarity among individual firms. Additionally, bibliometric analysis utilizes patent indicators associated with technological capabilities and the potential technology synergy of individual firms. Finally, the deep neural network (DNN) approach is employed to model the relationships between descriptive features and collaboration potentials as the target feature.

The structure of the paper is as follows. In Section 2, the literature on innovation ecosystems is introduced. In Section 3, the patent search strategy for SDV is presented in Section 3.1, and the proposed deep learning methodology is presented in Section 3.2. Then, Section 4 provides a detailed analysis and discussion of the results. Finally, Section 5 concludes the paper by summarizing the contributions and research findings.

2 Literature Review

The concept of innovation ecosystem has increasingly become an important issue in the literature of technological innovation. However, the literature did not provide a rigorous and consensus definition of innovation ecosystem, leading to fragmental research areas across strategy, innovation, and entrepreneurship (Oh, Phillips et al. 2016, Gomes, Facin et al. 2018). The earliest and the most popular definition was by Adner (2006): "the collaborative arrangements through which firms combine their individual offerings into a coherent, customer-facing solution". However, this definition lacks of new concepts in innovation management emerging in the last decade. For example, the difference between business ecosystem and innovation ecosystem was not clearly distinguished, leading to fragmented research areas. Granstrand and Holgersson (2020) provided a more robust definition that highlights three entities actors, activities, and artifacts and their competing and collaborative relationships: "An innovation ecosystem is the evolving set of actors, activities, and artifacts, and the institutions and relations, including complementary and substitute relations, that are important for the innovative performance of an actor or a population of actors". From the above definition, innovation ecosystem is more focused on value creation, while business ecosystem is on value capture.

Due to recent advances in data science and machine learning, patent analytics based on patent databases have been used to explore and analyze innovation ecosystems. Since patents can be considered as objective measures of the R&D activities of companies and industries, they can be used for monitoring and analyzing technology trends (Porter and Cunningham 2004). This research categories the literature of innovation ecosystems using patent data into two types: the patent citation approach and the co-assignee approach. The patent citation approach utilizes patent citation information to analyze network structure of technological knowledge flows in the innovation ecosystems. For example, Lee, Kim et al. (2015) analyzed the knowledge flow network of mobile ecosystem using centrality analysis and brokerage analysis to identify the roles of various firms in the ecosystem. In addition, Lee and Kim (2017) also analyzed changing patterns of mobile firms' position in the knowledge network and identified rapid emerging players in the mobile ecosystem.

The co-assignee approach uses the patent assignee information in patent data to construct the collaboration network that depicts the collaboration relationship between individual firms for developing certain technologies in the innovation ecosystem. For example, Xu, Wu et al. (2018) investigated the innovation capacities of a multi-layered innovation ecosystem that involves science, technology, and business sub-ecosystems for 3D printing in China. Science, technology, and business ecosystems were analyzed based on co-authorships in research publications, co-assignees in patents, and co-development from secondary sources. Degree centrality and betweenness centrality were used to identify key players, while cross-layer analysis was used to assess innovation capacities of different value functions in the ecosystem. Xu, Hu et al. (2020) also explore both knowledge and business ecosystems for China's machine tool industry using patent database and business transaction database, respectively. The fast-Newman topological clustering algorithm was used to identified communities on each layer and strategic roles of various firms were identified based on centrality of network position and diversity along value chain.

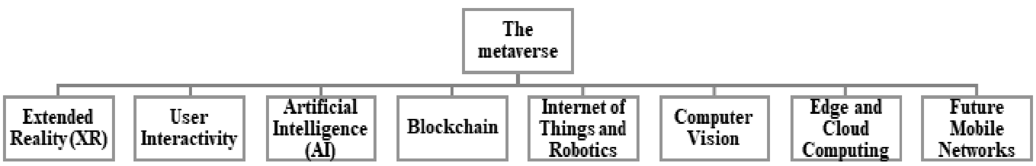
Although several studies have applied patent analytics for analyzing and understanding innovation ecosystem, most studies only construct knowledge flow networks or collaboration networks and conduct centrality analyses for analyzing ecosystems. There is no studies that applied a context-aware deep learning technique for analyzing technological capabilities of individual firms for exploring collaboration potentials. Kim, San Kim et al. (2020) applied doc2vec, a shallow neural network based on word2vec, to determine technological similarity between an acquiring company and a startup for technological collaboration. However, strictly speaking, doc2vec is not a deep learning approach (their paper title is misleading) and machine learning was not used in their work.

3 Data and Methodology

3.1 Data

The first step collects patent documents from the USPTO patent database for subsequent analyses. Since constructing the metaverse contains various technological categories (Figure 1), the broad query strategy is used to retrieve a wide coverage of patent data in this research.

Figure 1. Enabling technologies for the metaverse (Lee, Braud et al. 2021)



The query strategy is based on the use of Cooperative Patent Classification (CPC) codes and keywords related to the metaverse enabling technologies. It has the advantage of overcoming the limits of keywords-based queries when the technological field is intrinsically very large and the relation of the relevant inventions to the metaverse not always clearly explicit. Thus, the chosen query structure is as follows:

Block 1: List of CPC codes specific to the metaverse. For example, "G06T19/006" encompasses patents detailing methods for generating 3D mixed reality, highlighting advancements in seamlessly blending virtual and real-world elements.

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Block 2: List of specific keywords for the metaverse, such as "metaverse," "virtual reality," "augmented reality," "mixed reality," "extended reality," "head-up display," and "head-mounted display."

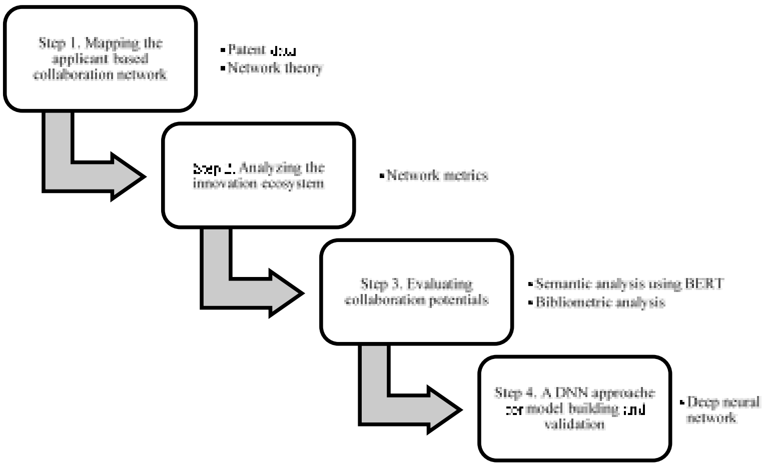
Since applicants may not have a unique name, we will examine patent data and change the different names of an applicant into a consistent name for subsequent analysis. In addition, we will remove individuals from the applicant field of a patent, because we are only interested in collaboration relationships between different firms.

The numbers of patent documents for the two blocks are 8,854 and 16,715, respectively. Following the elimination of duplicated patent documents, a total of 21,679 unique patent documents spanning from 2001 to 2021 were compiled.

3.2 Methodology

This research develops a DNN approach for predicting evolving collaboration patterns and recommending collaboration potential. The developed methodology consists of four steps as shown in Figure 2.

Figure 2. The research methodology



Step 1. Mapping the applicant-based collaboration network

To analyze the interaction between various firms in the innovation ecosystem, the co-applicant relationship that can be found from the patent data is used to construct the collaboration network. N = (V, E, W) is used to denote a collaboration network, where V is the set of nodes representing an applicant, E is the set of edges representing the collaboration relationship between two applicants, and W is the weight on each edge representing the number of patents owned by both applicants. If two applicants co-occur in the applicant field of a patent in the collected patent documents, then there is an edge between two nodes representing those two applicants.

Step 2. Analyzing the innovation ecosystem

This step analyzes the characteristics of the innovation ecosystem based on the network theory. The following network measures (Watts and Strogatz 1998) will be used to analyze the evolving patterns of the innovation ecosystem in different periods and can help policy makers understand the network properties of innovation ecosystem and improve innovation diffusion of the system:

Average degree: The average number of edges per node in the network, measuring the intensity of collaboration relationships in the innovation network.

Characteristic path length: The average shortest path length in a network. The shorter the length, the more likely it is easier to form collaboration relationship in the network. It is also used to measure the efficiency of information flow on a network

Clustering coefficient: The extent to which vertices linked to any other given vertex are also linked to each other. A large value for the clustering coefficient, the more likely each vertex of G is linked to a relatively well-connected set of neighboring vertices. It is used to measure the degree of herding effect in a network.

Network density: Network density is usually defined as the ratio between the actual number of edges and the maximum possible number of edges in the network

Step 3. Evaluating collaboration potentials

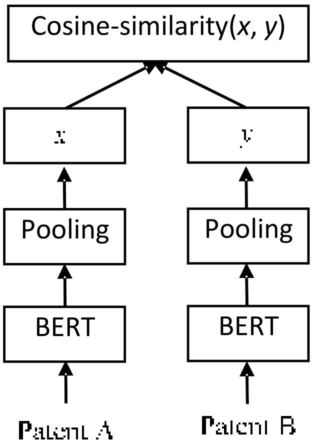
Most previous studies assessed potential collaboration relationship using bibliometric information (Chen and Fang 2014, Park, Jeong et al. 2015), network structure (Bian, Xie et al. 2014), or text information (Park, Jeong et al. 2015, Kim, San Kim et al. 2020). However, each method has their limitations. For example, in bibliometric analysis, patent citation suffers from the sequential interdependence problem. In other words, one can only cite studies that have been published before, though it has the same topic as the papers that will be published later. In addition, patent classification codes may not be updated in time as a new technological topic emerges. Therefore, it may not have enough bibliometric information for making reliable R&D decisions, especially for emerging technologies (Kim, San Kim et al. 2020). Network analysis has the similar limitation if the network construction is based on the patent citation information. Another limitation is that it only relies on the network metrics for evaluating the collaboration potential. Finally, previous text-based approaches that applied keywords or word2vec do not consider contextual relationships across long text inputs.

This research integrate semantic analysis and bibliometric analysis and applies machine learning for analyzing the relationship between two firms that may have collaboration potentials in the future. Two assessment approaches are presented as follows:

(1) Semantic analysis based on BERT

After collecting patent documents, individual patents are mapped into a multi-dimensional vector space using BERT, where each patent is represented as an embedded vector termed as technological position (Aharonson and Schilling 2016). Unlike traditional NLP models, BERT is a language model based on the Transformer architecture (Vaswani, Shazeer et al. 2017), which incorporates an attention mechanism to capture contextual relationships among words in text data. In this study, Sentence-BERT (SBERT) (Devlin, Chang et al. 2018, Reimers and Gurevych 2019), an extension of the BERT model, is employed to compute technological distances between individual patents characterized by their embedding vectors due to its computational efficiency in calculating semantic texture similarity (STS) scores between patents compared to BERT (refer to Figure 3). Cosine similarity is utilized to determine technological similarity or the STS score between the technological positions of two patents. This study defines the technological distance between individual patents as one minus the technological similarity between their technology positions.

Figure 3. SBERT model



According to the study of Aharonson and Schilling (2016), the technological capability of a firm can be delineated in terms of its technological footprint, defined as the technological position of the firm. Therefore, the technological breadth of a firm is defined as the average technological distance among every pair of technology positions within the firm. Similarly, technological similarity between two firms is defined as the average technological distance between their technology positions. Both technological breadth and technological similarity can be employed to assess potential collaborators for a firm [30].

(2) Bibliometric analysis

Patent documents contain bibliometric information that is useful for analyzing collaboration potential (Chen and Fang 2014). This research analyzes collaboration potential based on the following three standpoints and explained below: technological level, technological innovation capability, and potential technology synergy (Hung and Tang 2008).

The measure of technology level is used to evaluate current technological capabilities of a potential collaborator and can be measured by two criteria: technology quality and technology quantity. Technology quality can be measured by the number of forward citations for patents owned by a potential collaborator, while technology quantity can be evaluated by the number of granted patents received.

The measure of technological innovation capability is used to assess a firm's ability to create new ideas and convert them into new or improved technologies, products, or services that create customer values. Innovation capability can be assessed by two criteria: R&D achievement and R&D human resource. R&D achievement is measured by the percentage of patent application that have been granted for a company, while R&D human resource can be assessed by the number of individual inventors of all patents.

Potential technology synergy is to assess whether both firms have a lower cultural difference, because a higher cultural difference often has a higher failure rate. Compatibility of national culture is used to assess the cultural difference. If two applicants have the same nationality, then the variable is set to 1; otherwise set to 0.5. Global corporate culture is used to measure the nationality diversity of inventors; for example, the number of nationalities of patent inventors.

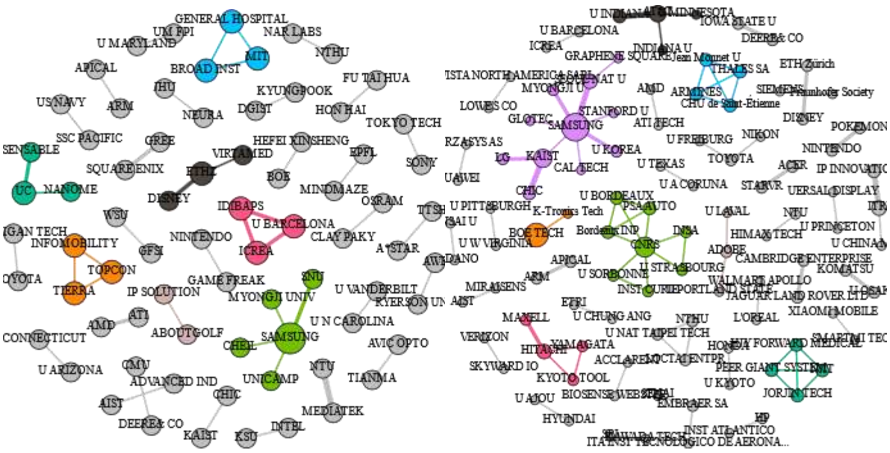
Step 4. DNN approach for model building and validation

DNN is a class of deep learning neural network models inspired by biological neural networks. It is a multilayer feed-forward neural network including an input layer, multiple hidden layers, and an output layer, where each unit in a layer provides input to each unit in the next forward layer. The major advantage of DNN is the ability to learn highly complicated relationships between the descriptive features and a target feature. However, it is not easy to determine the appropriate hyperparameters for a given problem, such as learning rate, number of hidden layers and number of nodes in each hidden layer. Furthermore, another weakness is the produced model is incomprehensible in providing insight for improving decision making. This research applies OPTUNA (Aceros, Pols et al.), a hyperparameter optimization framework, to automate the hyperparameter search. The exclusive computational experiments is conducted to validate the models built by the supervised machine learning methods. The best model will be chosen for predicting evolving collaboration patterns and recommending collaboration potential of a firm.

4 Results and Discussion

This study applies the DNN technique to build a binary classification deep learning model for partner recommendation. Based on the gathered patent data, 74 firms established 44 collaborative relationships between 2016 and 2018 (refer to Figure 4(a)), while 106 firms formed 80 collaborative relationships between 2019 and 2021 (see Figure 4(b)). A dataset was constructed for predicting potential collaboration relationships, where the 14 descriptive features were calculated using the semantic similarity analysis, bibliographic analysis, and link prediction analysis based on the data in the first period (2016-2018) and the target feature was whether there existed a collaboration relationship in the second period (2019-2021). Principal component analysis (PCA) is used to extract 7 representative features from the original dataset for reduction of dimensionality and noises. After PCA, the set of component values for a pair of organizations can form a feature vector for model building.

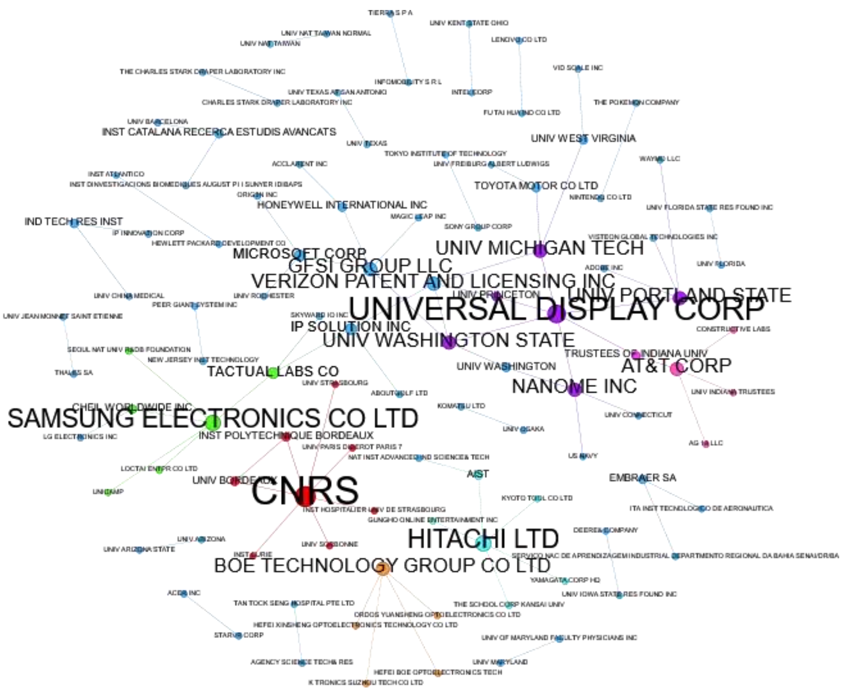
Figure 4. Exiting collaboration network: (a) 2016-2018 and (b) 2019-2021



The optimal hyperparameters identified through this process were as follows: learning rate: 0.0078, optimizer: Adam, number of hidden layers: 2, with the first hidden layer containing 36 neurons with dropout ratio 0.1427, the second hidden layer with 25 neurons with dropout ratio 0.3868, activation function: Relu, and learning rate decay: multistepLR (Milestones: [75, 148, 197], Gamma: 0.7385). The specified parameters were utilized to train the prediction model and then the prediction model was evaluated using the test dataset. For train-test data approach, the process is to split a given data set into 70% train data set and 30% test data set, yielding the following performance measures: accuracy of 99.96%, precision of 58.33%, recall of 35.00%, F1 score of 43.75%, and AUC of 92%.

The generated predictive model was utilized to forecast collaborative networks and recommend potential candidate partners for the subsequent time period, specifically employing the patent data from the second period (2021-2022). Figure 5 illustrates the predicted collaboration network, resulting in the identification of 83 pairs of potential partnerships. The predicted collaborative network's properties, including average degree, average path length, clustering coefficient, and network density, were measured at 1.596, 4.368, 0.681, and 0.015, respectively. Comparison with the collaborative network in the second period (1.509, 1.613, 0.686, 0.014) reveals a 5.7% increase in average degree and a 7.1% increase in network density. However, the average path length surged by 170.8%, and the clustering coefficient decreased by 0.73%. These findings suggest that collaboration within the metaverse industry remains sparse, with only smaller collaboration clusters forming.

Figure 5. Predicted metaverse collaborative network



Furthermore, for in-depth analysis, we illustrate a prominent participant within the projected collaborative network: Samsung. As illustrated in Figure 6, a total of 5 organizations are recommended as potential partners for Samsung. Except for Loctai and Tactual Labs, all other recommended partners have cooperated with Samsung from 2016 to 2018. According to the collected patents in the metaverse field, the top-5 technological field in terms of cooperative classification codes in a descending order were: G06T (image data processing), G06F (electric digital data processing), G02B (optical elements, systems or apparatus), H04N (pictorial communication), and G06K (graphical data reading).

For the newly recommended companies, Loctai enterprise Co. is the provider of industrial adhesives, automatic dispensing equipment, and industrial lubricants. The company possesses

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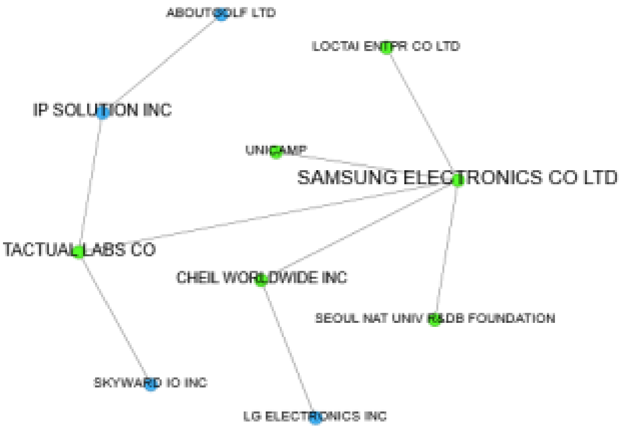
an invention that introduces a process planning apparatus utilizing augmented reality (AR) to streamline the programming by demonstration task for path planning in an automatic adhesive dispenser. This innovation effectively simulates dispenser tip motion within the AR environment. Through real-time augmented reality, instructional information is generated to aid human users in maneuvering the dispenser within the work environment, minimizing collision risks. Samsung may consider collaborating with Loctai to enhance the processing planning apparatus using AR or acquire the company's technological expertise in processing planning utilizing AR.

Figure 6. Samsung's predicted collaboration network



Furthermore, Tactual Labs specializes in human interface research and development, focusing on near-range radio-frequency sensing to monitor in-air, surface, and internal changes in humans, machinery, displays, and other objects. The company holds patents related to the design and production of touch-sensitive devices capable of detecting hover, contact, grip, and pressure information, enabling a comprehensive understanding of a user's touch, gestures, and interactions with handheld objects. Samsung might explore collaboration with Tactual Labs to enhance human-computer interaction in their AR/VR/MR devices.

5 Conclusions

The contributions of this study are as follows. Firstly, while existing literature has explored various studies on recommending potential partners using patent data, none have offered a Deep Neural Network (DNN) framework integrating bibliometric analysis and semantic analysis for partner recommendation. As each analytical approach has its merits, no concrete evidence suggests one approach surpasses the others. Hence, this research presents a integrated analytical framework utilizing the DNN approach to construct a prediction model capable of unveiling complex nonlinear relationships hidden within structured and unstructured data.

Moreover, beyond its role in suggesting potential partners for the focal firm, the predicted R&D collaborative network can serve as a valuable tool for gaining insights into the competitive landscape of industrial alliances. Our findings suggest that the metaverse innovation ecosystem remains in its nascent stages, with the collaborative network still being sparse. The illustrative example reveals that recommended candidate partners often align with or resemble past partners from prior periods. This suggests that the proposed deep learning approach is capable of predicting collaborative relationships between the focal firm and various potential candidate partners.

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