Decomposing Complementary and Substitutable Relations for Intercorporate Investment Recommendation

Le Dai[1], Yu Yin[1], Chuan Qin[2], Enhong Chen[1], Hui Xiong[3,4,*]
[1] School of Data Science & School of Computer Science and Technology, University of Science and Technology of China
[2] Talent Intelligence Center, Baidu Inc., [3] Hong Kong University of Science and Technology (Guangzhou)
[4] Guangzhou HKUST Fok Ying Tung Research Institute
{dl123, yxonic}@mail.ustc.edu.cn, chuanqin0426@gmail.com, cheneh@ustc.edu.cn, xionghui@ust.hk

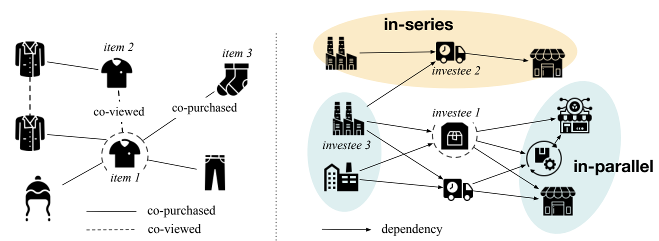
***Abstract*—Intercorporate investment has a large impact in financial performance and long-term development of a corporate. Among all the concerns for a company's investment strategy, complementary and substitutable investments are two fundamental factors. However, these two relations are implicit and entangled in the complex corporate network, requiring extra caution before investment. To this end, in this paper, we proposed a novel graph convolutional network called Series-Parallel decomposed Graph Convolutional Network (SPGCN). We first decompose the complementary and substitutable relations as two information propagating directions in company dependency graph, producing multifaceted node features. Then, with an Attentive Aggregation Module, we are able to further measure the impact of both features to the final investment decision making, producing an interpretable analysis for investment strategy. Finally, we conduct experiments on a real-world dataset, to show the effectiveness of decomposing two concerns on investment recommendation task. With visualization and case studies, our method also shows great potential to help understand and conduct complementary and substitutable investment decisions. We open source our code to support future research: https://github.com/lem0nle/SPGCN.**

***Index Terms*—complementary and substitutable investment, recommender system, graph neural network**

I. Introduction

Intercorporate investments, which occur when one company invests in the equity and debt securities of other companies, have significant impact on the investing company's financial performance [1]. For various business purposes from accessing into new market to obtaining competitive advantages, companies carefully adopt different investment strategies to build a more resilient business structure [2], [3]. Among all the concerns for a company's investment strategy, two of them are fundamentally important from a higher economic perspective, namely, *complementary* and *substitutable* investment [4], [5]. With one focusing on completeness, the other focusing on robustness of the business ecosystem, both of these concerns become key factors for companies to build a solid and resilient business investment moat.

In fact, selecting complementary and substitutable companies has an analogy with purchasing items. As shown in Figure 1(a), when a customer shows her interests in one T-shirt,



(a) Online item recommendation. (b) Intercorporate investment recommendation.

Fig. 1. Example of complementary and substitutable recommendations in online item recommendation and intercorporate investment recommendation.

it is rather reasonable for her to also want either a matching coat, or another similar T-shirts, i.e. complements and substitutes. In practice, customers tend to co-view the substitutes and co-purchase the complements on e-commerce businesses. Based on such paired co-viewing and co-purchasing behaviors, various studies are conducted to recommend complementary and substitutable items, achieving great enhancement in user experience. However, the situation in intercorporate investment recommendation is quite different and more complex. First, the corporates share more relations with each other, together forming a large, complex corporate network. Second, as shown in Figure 1(b), where a group of companies form a dependency graph consisting with supply chain relations, explicit edges in this corporate network fail to express complementary and substitutable relations. To infer complementary and substitutable relations, we should especially make use of the business, financial, or substantial dependencies, i.e. the various directed relations among corporates.

Luckily, we discover that complementary and substitutable relations can be seen as two directions on the corporate dependency network. Companies along the dependency chain, or in the *in-series* direction along the dependency graph, are likely to manufacture products of different stages, complementing each other in their business positions. On the other hand, corporates in the *in-parallel* direction across the dependency graph, are more likely to have a substitutable relation. Under this observation, we propose a novel architecture called Series-Parallel decomposed Graph Convolutional Network (SPGCN),

* Hui Xiong is the corresponding author.

and design a recommendation framework based on it for the investment recommendation problem. The contributions of this paper include:

- We introduce a novel design of GNN that decomposes the information propagation into in-series and in-parallel directions, in order to match the business concerns of complementary and substitutable relations.
- We propose a recommendation framework with an Attention Aggregation Module to measure the influence of both features generated from the decomposition, producing a more interpretable and reliable recommendation.
- We conduct exclusive experiments and empirical studies to further prove that features decomposed by SPGCN matches our business concerns, and is highly effective for company investment recommendation.

II. Related Work

A. Investment Analysis

Investment analysis is a broad topic that has been widely discussed by experts, which includes selecting the most suitable investment type for investors, predicting future performance based on the past returns or evaluating the risks and benefits of securities. Existing studies can be divided into the following three categories. Traditional studies focus on case studies [6], [7]. Relying on experts to conduct careful empirical studies over specific cases, those research can be rather labor intensive. More recently, machine learning and deep learning techniques have been applied to perform automatic analysis [8], [9]. There are also works utilizing company network on this topic [10]–[12]. As an example, Li et al. [11] investigate trade-offs between short-term and long-term resilience investments to enhance node risk capacity in supply chain network. Nonetheless, the analysis of economic investments between companies is rather limited, and none of existing research considers the complementary and substitutional investment strategies.

B. Recommender System

To conduct investment recommendation based on company relations, it is suitable to regard the company investment graph as a user-item graph, as in recommender system. The most common recommender system paradigm is collaborative filtering (CF), which learns the latent features of a user and an item, and then preforms rating prediction on them [13], [14]. More recent research tries to generate latent features or user-item interactions with neural network architecture [15], [16]. Especially, graph based embedding methods are incorporated with CF to make better use of the graph structural information [17]. Besides, there are also studies aiming at specific applications in recommender system [18], [19]. For example, Liu et al. [18] apply GCN for inferring substitutable and complementary items.

While substitutable and complementary item recommendation has been studied, all previous works rely on explicit ground truth labels. The implicit relations hidden in the corporate network are more difficult for their methods to capture. Moreover, they cannot explicitly measure the impact of both concerns on the final investment.

III. Preliminaries

A. Dataset Description

The dataset used in this paper is collected from Tianyancha[1], a public enterprise data service website in China. It consists of company basic financial information, investment records between companies, and multiple other relations among corporates. Through our analysis, we find that these relations often represent dependencies between companies. With these dependency relations, we define a Corporate Dependency Network (CDN) as a multi-relational dependency graph $G^{(D)} = (\mathcal{V}, \mathcal{E}^{(D)}, \mathcal{R})$, consists of a set of nodes $\mathcal{V}$ containing the full corporate set in the collected dataset, edge set $\mathcal{E}^{(D)}$ representing all the dependencies among corporates, allowing us to explore complementary and substitutable investment features from it.

In addition, aiming at the final investment recommendation task, we also represent all the investment records in the dataset as a bipartite Investment Graph $G^{(I)} = (\mathcal{U}, \mathcal{I}, \mathcal{E}^{(I)})$, which consists of a set of users (or investors in our setup) $\mathcal{U}$, a set of items (investees) $\mathcal{I}$, along with a set of edges (investments) $\mathcal{E}^{(I)}$ representing collected investment records.

B. Problem Definition

In this subsection, we formally introduce the investment recommendation problem. The main requirement of investment recommendation is to predict the probability $p_{u,i}$ of an investor u investing a company i. However, besides the prediction task, we also want to extract what structural factors are influencing the investment decision-making process, and distinguish between complementary and substitutable investment. Formally, we define our problem as:

Definition 3.1. **Investment recommendation problem**. Given the Corporate Dependency Network $G^{(D)} = (\mathcal{V}, \mathcal{E}^{(D)}, \mathcal{R})$, the Investment Graph $G^{(I)} = (\mathcal{U}, \mathcal{I}, \mathcal{E}^{(I)})$, a user u, and an item i, our goal is to predict the probability $p_{u,i}$ of user u investing on item i, based on the information given by two graphs. Along with the investment prediction, we should also obtain multifaceted node features S_i and P_i for each node i, explaining the impact of complementary and substitutable relations on the investment decision making.

IV. Methodology

In this section, we present the detailed construction of the SPGCN. Specifically, we first give a brief overview over how we decompose the propagation of information in graph convolution into two perpendicular directions. After that, we explain each way of propagation in our proposed SPGCN in detail, showing how they match the complementary and substitutable relations in a dependency graph.

[1]https://www.tianyancha.com

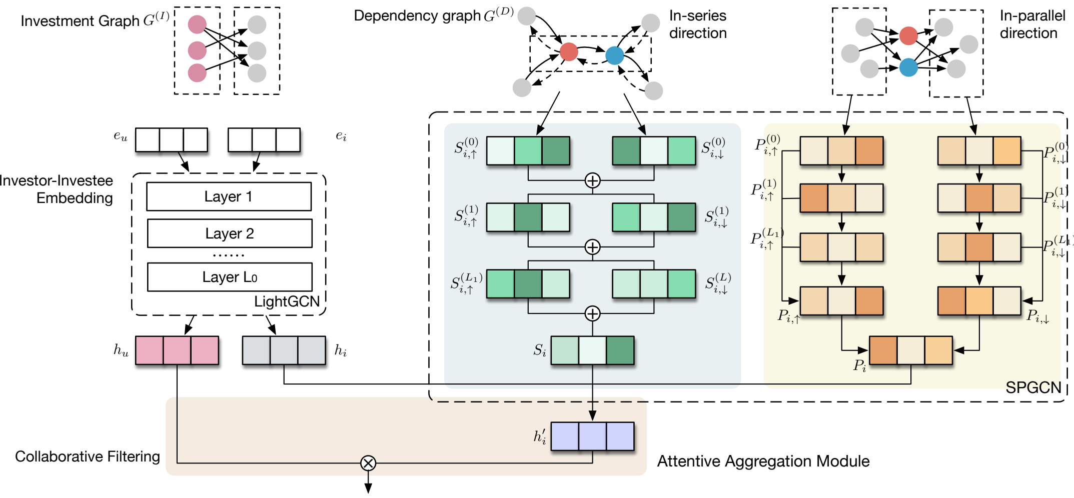


Fig. 2. The overall architecture of SPGCN, containing Investor-Investee Embedding, the SPGCN model, and the Attentive Aggregation Module. Specifically, SPGCN consists of a Series GCN on the left to capture in-series information for complementary feature extraction, and a Parallel GCN on the right aiming at substitutable feature with context proximity preserving.

A. Method Overview

Figure 2 shows the overall architecture of the investment recommendation framework and the Series-Parallel decomposed Graph Convolutional Network (SPGCN) that we propose. In general, the recommendation framework first generates the initial embedding of each corporate through Investor-Investee Embedding, based on the Investment Graph $G^{(I)}$. Then, the framework *decomposes* complementary and substitutable relations on the Corporate Dependency Network $G^{(D)}$ with SPGCN, generating multifaceted node features for each item. Finally, to recommend items while distinguishing complementary and substitutable concerns, an Attentive Aggregation Module is introduced to measure the impact of both relations on the final investment decision making.

In the following subsections, we will describe the details of each parts in the framework.

B. Investor-Investee Embedding

Decomposition of Corporate Dependency Network relies on the propagation of corporate initial embeddings. Layout initial embeddings coherently for all the corporates can help later decomposition. Thus, instead of applying SPGCN directly on CDN, we first incorporate the Investment Graph to help generate a better initial embedding. Following recent graph collaborate filtering methods [17], [20], we utilizing the state-of-the-art graph collaborative filtering model, LightGCN [17], as our investor-investee encoder:

$$\mathbf{h} = \text{LightGCN}(\mathbf{e}_u, \mathbf{e}_i, G^{(I)}). \tag{1}$$

C. SPGCN Model

In this subsection, we focus on the main challenge of extracting complementary and substitutable features from Corporate Dependency Network. As we mentioned before, complementary and substitutable concerns are related to in-series and in-parallel directions in CDN. We can use this observation to decompose them using graph neural networks.

We will start with SPGCN's decomposition with in-series direction, which relates to complementary relations.

1) Series graph convolutional network: For in-series direction, we consider two nodes (u, v) appears in-series in the dependency graph, i.e. co-occur in one dependency path. Intuitively, we want to emphasize the connection between them with a series SPGCN$^{(S)}$. The more u and v co-occur in dependency chains, the stronger the connection between them. To achieve this, we apply L_S layers of SPGCN$^{(S)}$ on the dependency graph. For each node i, the in-series node representation $S_i^{(l+1)}$ at layer $l+1$ comes from two directions:

$$S_{i,\uparrow}^{(l+1)} = \sum_r \sum_{j \in \mathcal{N}_{i,\uparrow}^r} \frac{1}{c_{i,r,\uparrow}} W_{r,\uparrow}^{(l)} S_j^{(l)} + W_{0,\uparrow}^{(l)} S_i^{(l)}, \tag{2}$$

$$S_{i,\downarrow}^{(l+1)} = \sum_r \sum_{j \in \mathcal{N}_{i,\downarrow}^r} \frac{1}{c_{i,r,\downarrow}} W_{r,\downarrow}^{(l)} S_j^{(l)} + W_{0,\downarrow}^{(l)} S_i^{(l)}, \tag{3}$$

$$S_i^{(l+1)} = \sigma\left(S_{i,\uparrow}^{(l+1)} + S_{i,\downarrow}^{(l+1)}\right), \tag{4}$$

where $\mathcal{N}_{i,\uparrow}^r$ and $\mathcal{N}_{i,\downarrow}^r$ denote the upstream and downstream neighbors of company i under relation r respectively, $c_{i,r,\uparrow}$ and $c_{i,r,\downarrow}$ are normalization constants of node i that are learnable parameters, and $W_{r,\uparrow}^{(l)}$, $W_{0,\uparrow}^{(l)}$, $W_{r,\downarrow}^{(l)}$ and $W_{0,\downarrow}^{(l)}$ are four weight matrices to be optimized. With the upstream spatial information obtained as $h_{i,\uparrow}^{(l+1)}$ and downstream spatial information obtained as $h_{i,\downarrow}^{(l+1)}$, we can calculate the complementary feature $S_i^{(l+1)}$ for node i through an activation function $\sigma(\cdot)$ (e.g. sigmoid or ReLU).

2) Parallel graph convolutional network: On the other perpendicular direction, we also revise the GCN structure for this specific propagation scheme. Considering a pair of nodes (u, v) that occurs in two dependency chains *in parallel*, the goal is equivalent to preserving their context proximity. Therefore, we design a parallel SPGCN$^{(P)}$, to preserve information across the dependency chains by maintaining the similarity of node features if they share a similar context. More specifically, for each node i, the in-parallel node representation $P_i^{(l+1)}$ at layer $l+1$ represents information from upstream and downstream neighbors l steps away:

$$P_{i,\uparrow}^{(l+1)} = \sigma\left(\sum_r \sum_{j\in\mathcal{N}_{i,\uparrow}^r} \frac{1}{c_{i,r,\uparrow}^{(l)}} W_{r,\uparrow}^{(l)} P_j^{(l)}\right), \tag{5}$$

$$P_{i,\downarrow}^{(l+1)} = \sigma\left(\sum_r \sum_{j\in\mathcal{N}_{i,\downarrow}^r} \frac{1}{c_{i,r,\downarrow}^{(l)}} W_{r,\downarrow}^{(l)} P_j^{(l)}\right), \tag{6}$$

For final representation $\mathbf{P}$, we join features representing both sides of the context, so that node information within the context with different distance can be accumulated:

$$P_{i,\uparrow} = \sum_{l=0}^{L_P} P_{i,\uparrow}^{(l)},\ P_{i,\downarrow} = \sum_{l=0}^{L_P} P_{i,\downarrow}^{(l)}. \tag{7}$$

Then, we concatenate these two features representing two side of the context into a single node representation:

$$P_i = P_{i,\uparrow} \oplus P_{i,\downarrow}. \tag{8}$$

D. Investment Recommendation

Finally, to explicitly model the impacts of complementary and substitutable features on investment recommendation, we leverage the attention mechanism to weigh the importance of both features, and conduct collaborative filtering with the final investor and investee features. Formally, the attentively weighted embedding of investee i is presented as:

$$h_i' = \alpha_i^{(S)} S_i + \alpha_i^{(P)} P_i + \alpha_i^{(R)} h_i, \tag{9}$$

where $\alpha_i^{(S)}$, $\alpha_i^{(P)}$ and $\alpha_i^{(R)}$ are attention weights according to the correlations between each investee feature and investor embedding. Then we predict the probability of investor u investing company i through standard collaborate filtering:

$$p_{(u,i)} = \text{sigmoid}(h_u \cdot h_i'). \tag{10}$$

With $p_{(u,i)}$ and proper negative sampling, we can then train the whole framework through standard gradient descent based optimization methods with cross entropy loss.

V. Experiment

A. Experimental Settings

1) Dataset: As mentioned in the preliminary section, our enterprise dataset was collected from a public website. Some statistics are listed in Table I to give an overview of the dataset. Our datasets were constructed as two main parts: the Corporate Dependency Network $G^{(D)}$ and the Investment Graph $G^{(I)}$. There are around 50k nodes in $G^{(I)}$, grouped as investors and investees. We also extracted all the directed relations and additional related nodes, and constructed the dependency graph. There are 20k+ additional nodes along with 4 additional relations in $G^{(D)}$, namely Shareholder, Subordinate, Supplier, and Client, with 130k+ edges in total.

TABLE I
Statistics of the enterprise dataset.

Data	Name	Value
Company Investment Graph ($G^{(I)}$)	# Investors	4,901
	# Investees	49,592
	# Investment records	88,334
	Sparsity	99.96%
	Avg. investment per investor	18.024
	Avg. investment per investee	1.781
Corporate Dependency Network ($G^{(D)}$)	# Total companies	75,139
	# Relation types	4
	# Edges	131,337
	# Shareholder	54,098
	# Subordinate	27,628
	# Supplier	25,354
	# Client	24,257
	Avg. edges per company	1.748
	Max edges of companies	40

2) Experimental setup: We implement our model using PyTorch[2] and DGL[3]. We set the number of SPGCN and LightGCN layers as 2, and all the embedding dimensions are set as 64. In the training process, we use Xavier [21] for parameter initialization and Adam optimizer [22] for optimization.

To demonstrate the effectiveness of our method, we compare our framework with some state-of-the-art approaches on the investment recommendation task. These baselines fall into two categories: a) recommender system based methods, and b) graph embedding models. All baselines are tuned to be optimal to ensure fair comparisons. We list the baselines below:

- **NCF** [15]: This is a collaborate filtering recommender system under the neural network framework.
- **LightGCN** [17]: This is a graph based recommender system. It uses a simplified architecture to achieve state-of-the-art results on many recommendation tasks.
- **GRU4Rec** [23]: This represents the category of sequential recommendation methods. We see investments as sequences according to investment date information, and evaluate the sequential predictions.
- **GraphSage** [24]: This is a simple but widely used method, which applies convolution neural network operating directly on graphs.
- **GAT** [25]: This is an alternative method that applies attention mechanism in graph embedding, measuring impacts of each neighbor on a node.
- **RGCN** [26]: This is the standard embedding method for multi-relational graphs. We combine all graphs together as the input and predict the investment with RGCN.

B. Overall Performance

We first show the performance of our framework and each baseline methods on investment prediction task, as well as an ablation study of our model. For all the experiments, we split our dataset chronologically, with training set containing only the investment events and other relations *before* 2020,

[2]http://pytorch.org
[3]https://github.com/dmlc/dgl

TABLE II
PERFORMANCE COMPARISONS ON INVESTMENT PREDICTION.

Method	AUC	Recall@5	Recall@10	Recall@20	MAP@5	MAP@10	MAP@20	NDCG@5	NDCG@10	NDCG@20
NCF	0.5991	0.2079	0.3046	0.4086	0.0983	0.1097	0.1207	0.1345	0.1643	0.2088
LightGCN	0.6079	0.2043	0.3146	0.4022	0.0999	0.1174	0.1263	0.1381	0.1797	0.2082
GRU4Rec	0.5785	0.1563	0.2921	0.3604	0.0696	0.0844	0.1094	0.1140	0.1457	0.1850
GraphSage	0.5872	0.1880	0.3088	0.3990	0.0666	0.0853	0.0949	0.1001	0.1462	0.1778
GAT	0.5877	0.2068	0.3207	0.4125	0.0763	0.0950	0.1047	0.1124	0.1572	0.1896
RGCN	0.6452	0.2714	**0.3750**	**0.4359**	0.1346	0.1531	0.1612	0.1855	0.2266	0.2497
SPGCN	**0.6964**	**0.2799**	0.3722	0.4296	**0.1525**	**0.1699**	**0.1774**	**0.2055**	**0.2415**	**0.2618**

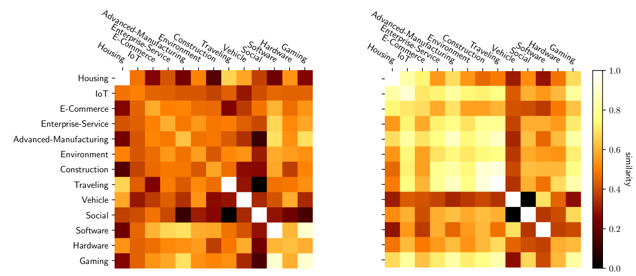
TABLE III
ABLATION STUDY DEMONSTRATING MODEL PERFORMANCE WITH DIFFERENT INPUT DATA AND MODULES COMBINATIONS.

Method	AUC	Recall@5	Recall@10	Recall@20	MAP@5	MAP@10	MAP@20	NDCG@5	NDCG@10	NDCG@20
-$G^{(I)}$	0.5812	0.1967	0.3098	0.4080	0.0834	0.0985	0.1072	0.1163	0.1589	0.1729
-$G^{(D)}$	0.6189	0.2758	0.3609	0.4197	0.1375	0.1533	0.1610	0.1940	0.2264	0.2476
-Attn	0.6402	0.2665	0.3502	**0.4479**	0.1417	0.1515	0.1686	0.1813	0.2243	0.2455
SPGCN$^{(S)}$	0.6474	0.2762	0.3662	0.4251	0.1432	0.1599	0.1676	0.1972	0.2324	0.2535
SPGCN$^{(P)}$	0.6594	0.2769	0.3616	0.4225	0.1447	0.1610	0.1686	0.1977	0.2320	0.2534
SPGCN	**0.6964**	**0.2799**	**0.3722**	0.4296	**0.1525**	**0.1699**	**0.1774**	**0.2055**	**0.2415**	**0.2618**

and test set containing information that was known later on. All the results are displayed in Table II and III in detail. We have the following observations: (1) We notice that our method have the best or second-best performance on all the metrics. This shows the effectiveness of our approach on the task of investment recommendation, as well as the usefulness of SPGCN decomposing propagation directions. (2) We can see the positive effect of using both Coporate Dependency Network and Investment Graph as input. For investment recommendation task, omitting investment graph completely largely harms the performance. Without the CDN, the performance also decreases considerably. (3) The performance declines without attention at the end of the model, close to the result of RGCN. This shows that without separate consideration of complementary and substitutable features, the entanglement of information harms the end performance.

C. Visualization of Complementary and Substitutable Features

To better understand how decomposing complementary and substitutable concerns affects an investment, in addition to performance experiments, we further explore these features from the industry's perspective, showing how different industries complement or substitute each other. In Figure 3, we show similarities of complementary and substitutable features as heat maps, from companies coming from 12 industries. In Figure 3(a), focusing on areas with higher values, we can draw the conclusion that, (1) Software, Hardware and Gaming industries are more likely to complement each other. The same holds for E-Commerce, Enterprise-Service, and Advanced Manufacturing. (2) Software industry, as well as Environment industry, may complement many other traditional industries in their functions. Meanwhile, from Figure 3(b), we have other conclusions: (1) Companies from the same industry are more likely to be substitutable for each other, from the observation that the diagonal have higher similarities. (2) Companies in



(a) Corporate industry similarities based on complementary features.

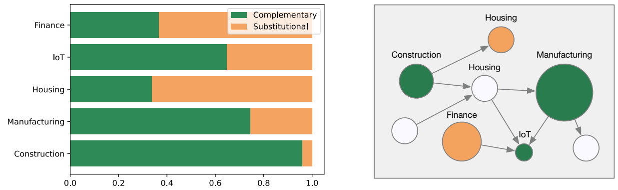
(b) Corporate industry similarities based on substitutable features.

Fig. 3. Visualization of complementary and substitutable feature similarities across different industries. Each square shows the average similarity between all company pairs from two industries.

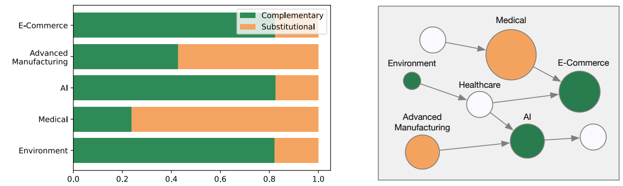
Vehicle industry seems to be not easily substitutable by any other industries, while it can be complemented by companies from Environment or Hardware.

D. Case Study

Another highlight of our work is that our method is able to measure the importance of complementary and substitutable relations in investment decision-making. In Figure 4, we have selected two investors, currently focusing on *Housing* and *Healthcare* investments, respectively, from our real-world dataset, and listed top 5 candidates our model recommended for them. From Figure 4(a), we can see how SPGCN model recommends corporates relating to Housing as substitutes, and companies from Construction, Manufacturing, and IoT, as complements. We can also observe their relationship on the CDN, and verify that complementary corporates co-occur on the same dependency chain, while substitutable corporates reside in parallel chains. Similarly, as shown in Figure 4(b), for an investor previously focusing on Health and Medical Care, SPGCN recommends Advanced-Manufacturing as slightly substitutable, and Environment, AI, E-Commerce as



(a) Suggested items for an investor currently focusing on *Housing*.



(b) Suggested items for an investor currently focusing on *Healthcare*.

Fig. 4. Case study of investment recommendation for two selected investors. Each figure shows top 5 candidates given by our recommender system, and weights of their complementary and substitutable concerns. We also include part of the dependency graph to further show the relationship between dependency network and complementary-substitutable decomposition. The size of the circles in the network is proportional to the amount of companies in each industry.

complementary, which are also reasonable choices. Both of the cases really demonstrate the accuracy of our model for separating the concerns of complementary and substitutable relations in investment analysis.

VI. Conclusion

In this paper, we propose SPGCN, a novel graph convolutional network with decomposed propagation directions, for exploring the complementary and substitutable relations on the investment recommendation problem, and further distinguish the impact of both features to the final investment decision making. In the future, we aim to further improve our work from two directions. We will incorporate more company side information to further enhance the performance on investment recommendation, and apply SPGCN to more general recommendation scenarios, leaving a chance to understand the underlying logic behind a user's preference and improve the recommendation interpretability.

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