國立臺灣大學管理學院資訊管理學研究所

碩士論文

Department of Information Management

College of Management

National Taiwan University

Master Thesis

以時序圖神經網路進行半導體產業供應鏈短缺預測

Supply Chain Shortage Forecasting for Semiconductor Industry by Temporal Graph Neural Network

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中華民國 112 年 7 月

July 2023

doi:10.6342/NTU202301990

國立臺灣大學碩士學位論文
口試委員會審定書

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Supply Chain Shortage Forecasting for Semiconductor Industry by Temporal Graph Neural Network

本論文係簡辰安君（R10725021）在國立臺灣大學資訊管理研究所完成之碩士學位論文，於民國 112 年 07 月 07 日承下列考試委員審查通過及口試及格，特此證明

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doi:10.6342/NTU202301990

誌謝

感謝指導教授陳建錦教授對於題目設定、實驗設計及論文撰寫等多方面的指導，亦感謝台灣積體電路製造股份公司 AI4BI 及 MM 部門各位對於論文題目及產業知識的各種建議。能經由教授介紹參與台積電的實習機會並藉此合作研究實屬難得，不只在學術方面學到許多，也能有更好的機會接近實務，希望未來能不負所有人的提攜，在此基礎上能有更深入及廣泛的研究。

簡辰安 謹識

國立臺灣大學資訊管理研究所

中華民國一百一十二年七月

doi:10.6342/NTU202301990

摘要

半導體產業的高成本、垂直分工的供應鏈及短暫的產品生命週期使其非常仰賴穩定的供應鏈，供應鏈的延遲可能會導致生產停滯與伴隨而來的財務損失。爲了使半導體公司得以即使依照上游供應情況調整生產計劃，準確預測供應是否有短缺的風險至關重要。本論文提出了一種供應鏈短缺預測模型，爲了透過時序圖神經網路 (TGNN) 分析財務與文字資料，我們結合了存貨週期 (DOI) 和法說會逐字稿，並以實際案例證明其可以用於供應短缺預測。我們將供應鏈構建成一個網路，藉由考量上下游供應商之間的關係，試圖捕捉當上游供貨不穩定時，下游被波及的可能性與時間。爲了驗證模型，我們收集了2018年至2022年的五年間台灣積體電路製造股份有限公司 (TSMC) 的數據，其中包含供應商的供應鏈關係、財務數字及法說會逐字稿，並以實驗證明了機器學習模型在預測供應短缺方面的有效性，還有法説會逐字稿可以做爲輔助潛在短缺預測的指標。本研究開啓了將財務數字、文字及供應鏈關係整合到TGNN中以預測供應短缺的可能性，爲半導體供應商供應短缺提供了一種解決方法，並具有未來應用和研究的潛力。

關鍵字: 時序圖神經網路、供應鏈短缺、半導體產業、存貨天數、深度學習

doi:10.6342/NTU202301990

Abstract

The semiconductor industry heavily relies on a well-functioning and efficient supply chain due to its high cost, vertically divided supply chain, and short product life cycles. Delays in the supply chain can lead to production stagnation and associated financial losses. Accurately forecasting supply shortages is crucial for semiconductor companies to adjust their production plans based on upstream supply conditions. This master thesis proposes a supply chain shortage forecasting model that utilizes a Temporal Graph Neural Network (TGNN) to analyze financial and textual data. We incorporate Days of Inventory (DOI) and earnings call transcripts to predict potential supply shortages. By constructing a supply chain network that considers the relationships between upstream and downstream suppliers, we aim to capture the likelihood and timing of downstream disruptions when upstream supply is unstable. To validate the model, we collect the experimental data from Taiwan Semiconductor Manufacturing Company (TSMC) spanning a five-year period from 2018 to 2022, including suppliers' supply chain relations, financial numbers and earnings call transcripts. The experiments demonstrate the effectiveness of machine learning models in forecasting supply shortages, and earnings call transcripts serve as supplementary indicators for potential shortages. As a result, this research is the first

doi:10.6342/NTU202301990

work to integrate financial figures, textual data, and supply chain relationships into TGNN, providing a solution for predicting supplier shortages in the semiconductor industry and showing potential for future applications and research.

Keywords: temporal graph neural network, supply chain shortage, semiconductor industry, days of inventory, deep learning

doi:10.6342/NTU202301990

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Chapter 1

Introduction

The semiconductor industry is heavily reliant on a reliable and efficient supply chain. However, the vertically divided supply chain and short product life cycle make the manufacturing process have a lot of uncertainty (Guin et al., 2014); moreover, the long production line increases the difficulty of in time adjustment when unexpected delays occur in the process. Any delays or inadequacies in supply chains thus cause huge production stagnation and idling these expensive production lines will lead to huge losses (Mönch et al., 2018; Brown et al., 2000). One main reason for production inefficiency is the failure of manufacturers to obtain the required raw materials and equipment from upstream suppliers in a timely manner, which is also known as ”supply shortages”. Take the recent semiconductor shortage as an example, due to the Covid-19 pandemic and the trade war, chip makers were severely impacted by supply shortages of their upstream suppliers, leading to a significant semiconductor shortage. It affected over 169 sectors and consumer lines such as computers, automotive, and consumer electronics (Mohammad et al., 2022). The shortage posed a major obstacle for the semiconductor and its downstream industries in fully utilizing their production capacity (Krolikowski and Naggert, 2021; Leibovici and Dunn, 2021). Considering the growing significance of the upstream supply chain, there is an urgent

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need for forecasting potential shortages of upstream suppliers to help semiconductor companies adjust their production plans efficiently. Our study focuses on forecasting shortages by analyzing the financial and textual information of the supply chain using graph neural networks, which is widely adopted in various supply chain topics.

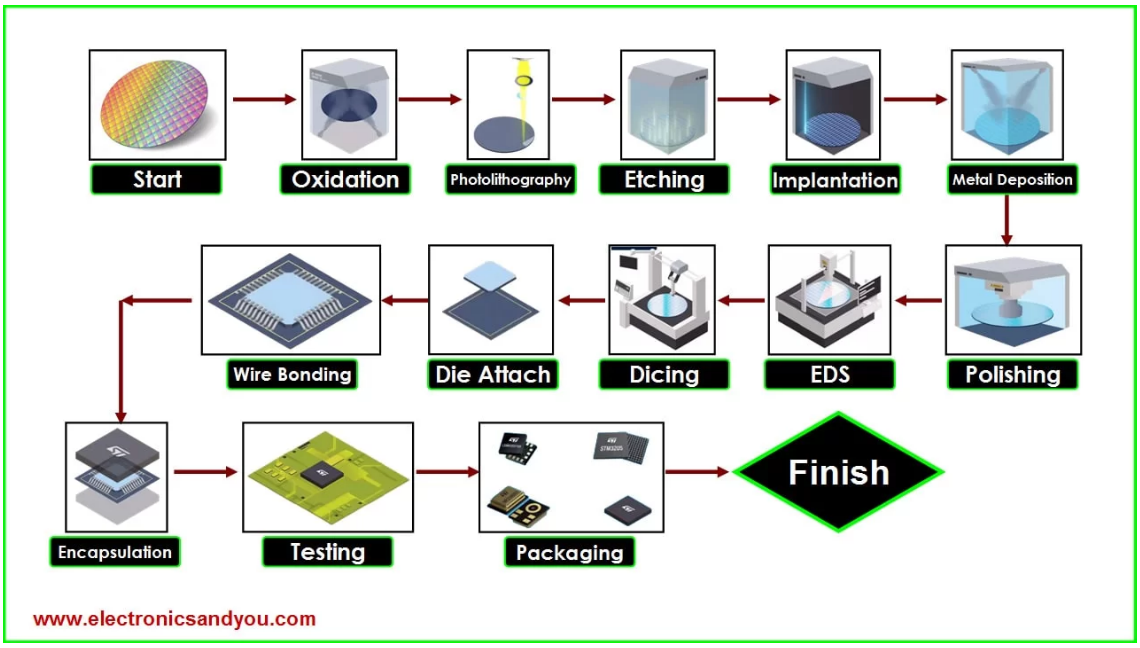

Figure 1.1: *Example of the long production line of the semiconductor industry*

To forecast supply shortages accurately, it is necessary to identify effective indicators that signal their occurrence. While increased backorder or prolonged lead-time are reliable indicators of a supply shortage, they are normally confidential and not readily available to the public. DOI, also referred to as day's sales of inventory, is a public metric that is closely tied to a supplier's supply shortages (Berk et al., 2013). It is calculated as inventory divided by cost of goods sold (COGS) multiplied by the relevant time period. DOI provides clues of an impending shortage before it significantly impacts downstream operations. For instance, a significant drop

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in DOI may be an indication of a forthcoming shortage. In addition to DOI, unstructured text information of companies are also helpful to forecast supply shortages. Several studies (Matsumoto et al., 2011; Pei, 2021) show that the earnings call transcripts released quarterly by companies frequently reveal shortage-related information. Although there is other text information (e.g., press releases) useful for supply shortage forecasting, many of them are not always available because semiconductor companies tend to have low exposure. Hence, in this study, we forecast supply shortages by exploring DOI and earnings call transcripts, both of which are readily available and reveal shortage-related information of companies. We explore these indicators and elaborate the relationship between them and supply shortages in Section 3.

The proposed supply shortage forecasting model is a temporal graph neural network model, which utilizes earnings call transcripts, DOI and DOI-related statistics of suppliers in the supply chain to forecast shortage situations of suppliers after one quarter. Specifically, for a semiconductor manufacturer, we consider two factors to conduct supply shortage forecasting, namely, 1) the inventory levels of its suppliers (called the tier-1 suppliers), and 2) the availability of goods from the suppliers of the tier-1 suppliers (called the tier-2 suppliers). We examine tier-2 suppliers because delays or shortages of tier-2 suppliers would affect tier-1 suppliers which subsequently incur supply shortages. The chain reaction can be seen as a kind of time shifting (Ye et al., 2022) indicating that before the inventory shortage of semiconductor equipment manufacturers, upstream suppliers already met shortage in the previous quarter. Hence, to have long-term planning and comprehensive shortage forecasting, potential supply delays from tier-2 suppliers need to be examined. To this end, we construct a supply chain network in which nodes stand for the tier-1 and tier-2 suppliers and edges represent their upstream and downstream

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relationships.

Based on the supply chain graph, the temporal graph neural network (TGNN) (Zhao et al., 2019; Zhu et al., 2021) is employed to predict supply shortages of the tier-1 suppliers. GNN is an advanced graph-based deep learning model that derives representative embeddings of nodes through graph connections. Studies show that GNN is capable of predicting the financial risks and financial numbers of companies in a supply chain (e.g., (Yang et al., 2021; Ye et al., 2022)). In addition, in the networks with upstream and downstream relationships, such as prediction of the number of vehicles in the traffic and the supply chain of e-commerce, GNN has also been proven to capture the timing relationship well with some adjustments (Zhao et al., 2019; Bai et al., 2021). In terms of supply shortage forecasting, while Wu (2022) and Ye et al. (2020) have utilized earnings call transcripts to predict supply chain risks and stock prices, they do not consider the complete network topology and temporal information. Our GNN leverages the features (e.g., inventory levels, earnings calls, and financial numbers) of the tier-2 suppliers to enrich the embeddings of the tier-1 suppliers that enhance our shortage forecasting. To the best of our knowledge, the previous works not only did not consider the supply chain relation and the earnings call transcript data at the same time, but also seldom took advantage of the phenomenon that the shortage of upstream suppliers may take a while to affect downstream. Our research thus is the first work that aims to integrate unstructured text information, supply chain connections, and temporal information into GNN for effective supply shortage forecasting. To validate the proposed model, we collect the supplier data of Taiwan Semiconductor Manufacturing Company (TSMC), a word-leading semiconductor company for a 5-year period (2018 to 2022). The evaluation dataset consists of the announced quarterly financial statements and earnings call transcripts of 96 tier-1

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and tier-2 companies. The results of experiments based on the real-world dataset demonstrate that the proposed TGNN-based model and several machine learning models are effective in forecasting supply shortages. Moreover, the unstructured text information, that is, the earnings call transcripts, are indicative of potential supply shortages. We summarize the contribution of this research as follows:

1. We first utilize a temporal graph neural network along with textual data to forecast potential supplier shortages in the upcoming quarter.
2. We investigate the relationship between Days of Inventory (DOI) and shortage situations and utilize DOI as an indicator to predict shortages.
3. We validate the accuracy of our model using real-world data from semiconductor companies, which demonstrates that examining the proposed features are crucial for accurate shortage forecasting. Our findings suggest that this approach has promising potential for future research in this field.

doi:10.6342/NTU202301990

doi:10.6342/NTU202301990

Chapter 2

Literature Review

2.1 Shortage Forecasting

Shortages can be detected through various approaches. One such approach is the prediction of backorders, where manufacturers are unable to meet delivery deadlines. In a study by Islam and Amin (2020a), Distributed Random Forest was employed to predict backorders using inventory, sales, forecast, and backorder decisions as features. The study revealed that transforming numerical data into ranges, as opposed to using raw numbers, improved performance. Another indicator of shortage is lead-time, as demonstrated in Alnahhal et al. (2021), where the lead-time for make-to-order supply chains was forecasted. Despite the challenge of accurately predicting lead-time due to longer production durations, traditional models such as weighted average, linear regression, and logistic regression achieved a precision of 0.93. However, both backorders and lead-time rely on internal company information, which is often difficult to obtain. To address this limitation, Khare et al. (2020) employed LDA and SVM as text models to predict shortage quantities based on social media data during natural disasters, allowing for more timely predictions without relying solely on internal data.

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In the field of shortage prediction, several machine learning models leveraging time series data have been applied. For inventory prediction, models such as ARIMA, exponential smoothing, and the Theta model have been utilized (Petropoulos et al., 2019). In the context of forecasting oil consumption, models such as LogR, decision trees, back propagation neural networks, and SVM were compared, with the inclusion of Google Trends data (Yu et al., 2019). Neural Network (NN) models, specifically designed for delivery forecasts in the semiconductor industry, were proposed (Lingitz et al., 2018). The backorder dataset on Kaggle was addressed using a combination of multiple machine learning models, with the imbalanced dataset problem tackled using SMOTE (Islam and Amin, 2020b). Considering the short product life cycle and long lead time of the semiconductor industry, deep reinforcement learning was employed for demand forecasting (Chien et al., 2020). However, in a demand forecasting experiment, it was found that modern deep learning models did not significantly outperform traditional machine learning models (Carbonneau et al., 2008). While recurrent neural networks (RNN) performed best, the margin over SVM was minimal. This suggests that for less complex problems, simple deep learning models may not fully leverage their advantages. Nonetheless, in a counterexample, a combination of convolutional neural networks (CNN) and long short-term memory (LSTM) was applied to simultaneously capture spatial and temporal information for inventory forecasting (Xue et al., 2019). Through algorithmic parameter optimization, this model achieved promising results, affirming the potential of deep learning in addressing shortage forecasting problems . Consequently, we aim to investigate the performance of Temporal Graph Neural Networks (TGNN) by incorporating text, time series, and supply chain networks, encompassing a wider range of data types than previous studies.

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2.2 Supply Chain

As highlighted in a comprehensive survey (Rahman et al., 2022), extensive research on the supply chain has been conducted. This research encompasses four key perspectives: preparedness, response, recovery, and integrated strategies, which are further categorized into seven domains: macro, supply, demand, manufacturing, information, and transportation. The information-level research emphasizes the significance of inventory within the supply chain (Soni et al., 2014; Pereira et al., 2014; Siva Kumar and Anbanandam, 2020; Namdar et al., 2021). Additionally, the exchange of information between supply chains is recognized as an effective strategy for managing disruptions (Rajesh, 2019). However, the collated papers reveal a limited number of studies that employ quantitative models to predict shortages in supply chain networks. Only one study used grey prediction to forecast five indicators of supply chain resilience: flexibility, responsiveness, quality, productivity, and accessibility (Rajesh, 2016).

In recent years, the application of deep learning in the supply chain has gained prominence. For instance, deep learning has been employed to predict stock prices (Xue et al., 2019; Rodriguez, 2021) and uncover hidden links within the supply chain (Gopal and Chang, 2021). The Graph Attention Network (GAT) with pairwise logistic loss was utilized to generate negative samples, enhancing the prediction of potential supply relationships (Islam and Amin, 2020a). Furthermore, research has emphasized the interpretability of predictions in addition to uncovering hidden links (Kosasih and Brintrup, 2022). Graph Neural Networks (GNNs) have also been leveraged to predict risks associated with companies in the supply chain, with a particular focus on small and medium-sized enterprises. This research highlights the ability to assess a company's risk by understanding its upstream and downstream connections, even in the absence of comprehensive

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company information (Yang et al., 2021). Moreover, studies have simultaneously predicted hidden links and risks between companies within the supply chain, incorporating knowledge graph reasoning for enhanced explainability (Kosasih et al., 2022). Industry classification of companies has proven helpful in comprehensively understanding the supply chain, including unlisted companies that do not provide public information (Wu et al., 2021). In the context of topics related to shortage forecasting, one study employed Artificial Neural Networks (ANN) with a Genetic Algorithm to predict lead time while considering path optimization issues (Dosdoğru et al., 2021). However, to the best of our knowledge, no research has yet explored the combination of supply chain analysis and GNNs for shortage prediction, presenting an unexplored area of investigation.

2.3 Graph Neural Network

The concept of Graph Neural Network (GNN) was initially introduced by Scarselli et al. (2008), and since then, several general-purpose models have been developed, including GCN (Bruna et al., 2013; Defferrard et al., 2016), GraphSage (Hamilton et al., 2017), and GAT (Veličković et al., 2017) which incorporates the concept of attention (Vaswani et al., 2017) into GNNs. GNNs have demonstrated exceptional performance across various domains, such as recommendation systems (Wu et al., 2019) and anomaly detection (Wang et al., 2021b).

While most GNN research has focused on static graphs, the dynamic nature of supply chain companies' interactions over time necessitates the consideration of temporal aspects. Although dynamic graphs have been explored in some studies (Wang et al., 2021a), this research primarily focuses on the semiconductor supply chain, which undergoes minimal changes over a few years.

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Therefore, our attention is directed towards Temporal GNNs, which integrate time-sequential features within a static network structure.

Before the emergence of GCN, RNNs and spatio-temporal graphs were combined to develop Structural-RNN for predicting character actions in films (Jain et al., 2016). Subsequently, Temporal GCN gained popularity in traffic prediction, exemplified by T-GCN (Zhao et al., 2019) and AST-GCN (Zhu et al., 2021). By representing the traffic road network as a graph and transforming junctions into graph embeddings using GCN, the model incorporates RNN-related components, such as GRU, to predict timing by considering the upstream traffic's influence on the downstream over time. Enhanced models, like A3T-GCN, further improved performance through the use of attention mechanisms (Bai et al., 2021). In the context of supply chain research with Temporal GNNs, one study focused on predicting the next day's stock prices based on the stock prices of the target company, as well as its upstream and downstream companies (Rodriguez, 2021). Another study leveraged link prediction to construct the supply chain network, considering spatial and temporal information to predict the risk of small and medium-sized enterprises (Yang et al., 2021). Additionally, a study forecasted the gross merchandise value of companies in the supply chain using three modules: Feature Fusion Layer, Temporal Embedding Layer, and ITA-GCN (Ye et al., 2022). The Temporal Embedding Layer employed convolutional units with different kernel sizes to capture various time periods' effects. Furthermore, ITA-GCN enhanced the attention mechanism through Convolution Attention Units, enabling better inter- and intra-attention between connected nodes. Experimental results demonstrated the model's ability to capture both local and global temporal shifts, incorporating information from the company itself and its neighboring nodes.

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2.4 Financial Number Prediction by Earnings Call Transcript

In our research, we investigated the use of earnings call transcripts from various companies as data to predict shortages. Earnings call transcripts contain valuable information that can be leveraged for analysis. Beyond textual content, these transcripts also provide potential indicators. For instance, during periods of poor company performance, there tends to be a shift in language usage, with fewer financial-related terms and a greater focus on future-oriented terms (Matsumoto et al., 2011; Pei, 2021). The application of earnings call transcripts for forecasting has been extensively studied in various financial domains, particularly in stock price prediction (Lingitz et al., 2018) and volatility forecasting (Qin and Yang, 2019a). Some studies have utilized BERT (Devlin et al., 2018) as a text model and specifically extracted numerical information from the text to predict stock price volatility following earnings calls (Chen et al., 2021). Corporate risk prediction is another common area of investigation. These studies have employed diverse text and vocal models such as LSTM with Attention, CNN-Text (Yoon, 2014), MDRM (Qin and Yang, 2019b) and HTML (Yang et al., 2020). Notably, they have found strong correlations between the sentiment of terms in earnings call transcripts and future indices, particularly negative correlations ranging from -0.45 to -0.5 (Li et al., 2020). Furthermore, a Multi-Round Q&A Attention Bi-LSTM model has been proposed to predict company risk (Ye et al., 2020). This model employs Bi-LSTM to convert text into embeddings for downstream tasks during the presentation part of earnings calls. For the Q&A section, Reinforcement Learning is used as a sentence selector to filter out less informative sentences (e.g., ”Thank you”). The model then generates attention between questions and answers, producing question and answer features.

doi:10.6342/NTU202301990

Chapter 3

Shortage Indicators

The goal of our shortage forecast is to predict potential supplier shortages that will occur in the upcoming quarters using financial data and earnings call transcripts. Intuitively, the forecast can be defined as a binary classification problem (i.e., to predict whether a supplier will create a shortage or not). However, due to the lack of reliable shortage labels for suppliers, we consider it as a regression problem and predict upcoming DOI's of suppliers. Below, we first explain supplier shortage and discuss how DOI's are related to shortage forecasting. Next, we show why text information are useful for DOI predictions.

3.1 Days of Inventory

There are two typical types of supply shortages, namely, (A) systematic shortages owing to surpassing demands over supply, and (B) sudden shortages due to the lack of critical components. To elucidate the shortage type A and its relation with DOI, we start with Schumpeter's market cycle (Kitchin, 1923) which indicates that the cycles of markets are normally short and their lengths are around 40 months. Although the cycle lengths observed by Schumpeter in 1923 would not be identical to those of modern markets, e.g., semiconductor industry where the production length

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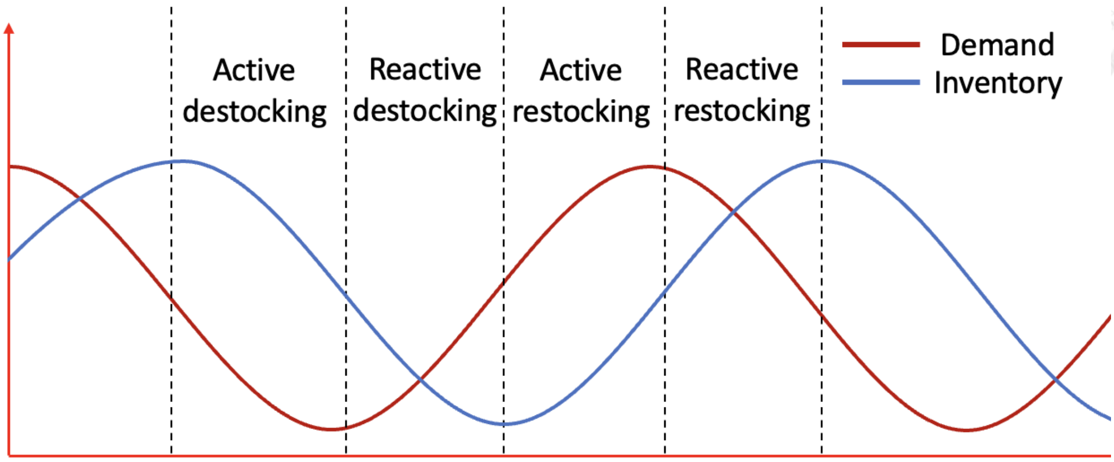

Figure 3.1: *Four stages of the inventory cycle*

can extend from six months to a year, the observed cycle is still useful to explain important market phenomena in the recent years. Four stages in the cycle was proposed to elucidate the Lehman wave observed in 2009, referring to an economy-wide fluctuation in production and economic activity occurring over a wavelength of 12 to 18 months (Steen, 2009; Peels et al., 2009). It is driven by a sudden and significant disruption within the economic system.

As illustrated in Figure 3.1 a market cycle consists of four stages, namely, active destocking, reactive destocking, active restocking, and reactive restocking. During reactive destocking, demands surpass inventory capacity. The upsurging demands results in inadequate production and serves as a primary catalyst for systematic shortages. Figure 3.2 shows a real-world example of the type A shortage (i.e., the systematic shortage). In this figure, the cost of goods sold (COGS) is deemed to be the demands and inventory still reflects inventory capacity. DOI (Days of Inventory) is a calculated metric that combines both values, providing a simpler measure of supply situation. From Q2 2020 to Q2 2021, Applied Materials (AMAT) was incapable of aligning inventory with the escalating COGS that led to a substantial decline in DOI. Consequently, the company suffered

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a systematic shortage during the period.

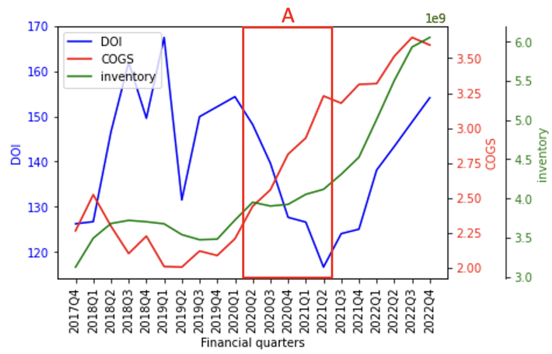

Figure 3.2: *AMAT's DOI and related financial numbers*

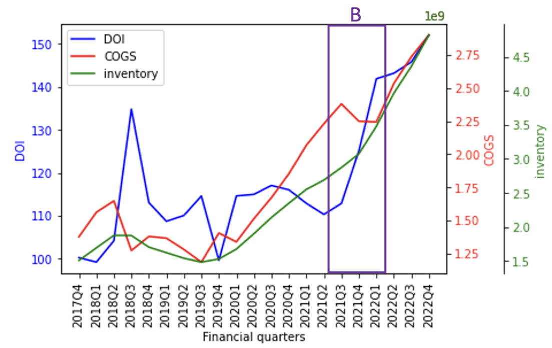

Figure 3.3: *LRCX's DOI and related financial numbers*

The shortage type B is caused by abnormal market conditions that cannot be accounted for by the market cycle. In the semiconductor industry, production often involves assembling diverse raw materials from various upstream suppliers. The absence of a particular raw material inevitably results in production failures and would produce partly manufactured products that stock inventory. However, because raw materials are often pre-ordered, the partly manufactured products keep accumulating that makes inventory levels rise. It is worth noting that the trends in DOI, inventory, and COGS for shortage type B are similar to those observed during reactive restocking in the market cycle. However, in this particular case, it does not indicate an actual shortage. The distinction lies in the fact that, in this case, the demand is typically weak, whereas

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in shortage type B, the demand is usually stable and strong. Figure 3.3 demonstrates an intriguing case of shortage type B involving Lam Research (LRCX) commencing from Q3 2021. During the period, Lam Research endured the unavailability of critical components that hindered their ability to meet the robust market demands. This accumulation occurs despite a robust market demand. As a result, its inventory increased while COGS remained relatively unchanged. This discrepancy leads to a significant rise in the DOI as shown in the figure.

In summary, when DOI abnormalities occur, they are often accompanied by one of the two supply shortage types. Moreover, based on domain experts' knowledge, for industries like semiconductors that have long lead times to produce and deliver their components or materials, there is usually a 1-to-2 quarter delay from the time when the upstream DOI problems impact their downstream. The above discussion and examples indicate DOI would be a useful leading indicator for supply shortage forecasting and an important criterion for judging whether a company is experiencing shortage. Therefore, in this research, we use DOI as a predictive feature to forecast the upcoming DOIs for effective supply shortage detections.

3.2 Text Information

As mentioned earlier, whether an abnormal DOI indicates an actual shortage situation depends on a comprehensive assessment of the market and the specific company's circumstances. For example, in Q2 2021, the earnings call transcripts of Applied Materials mentioned that "Current capacity shortfalls in some areas of the market show the highly efficient, 'just-in-time' supply chains that have served the semiconductor industry well for the past two decades, may not be the most effective strategy going forward." The company soon was struck by a significant

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drop in DOI that quarter, and then experienced backorders and was unable to fulfill downstream orders.” Subsequently, the company witnessed a substantial and consistent decline in DOI across consecutive quarters, unequivocally indicating a persistent and systematic shortage.

Regarding sudden shortages, in Lam Research’s Q4 2021 earnings call, it was stated, “In the December quarter, unexpected shipment delays, primarily for components from a critical supplier, surfaced in the last two weeks of the quarter, leaving us with insufficient time for full recovery despite the diligent efforts of our supplier and our global operations team. The resulting shipment delays caused revenues to come in below the midpoint of our guidance range.” This instance highlighted that the shortage was not solely due to production issues but also a lack of critical components and shipment delays, which were the primary reasons for the increased DOI. Through these examples, it becomes evident that there was a genuine shortage during those quarters, rather than the company’s financial adjustments. Thus, textual information plays a crucial role in supporting shortage forecasting data.

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Chapter 4

Research Design

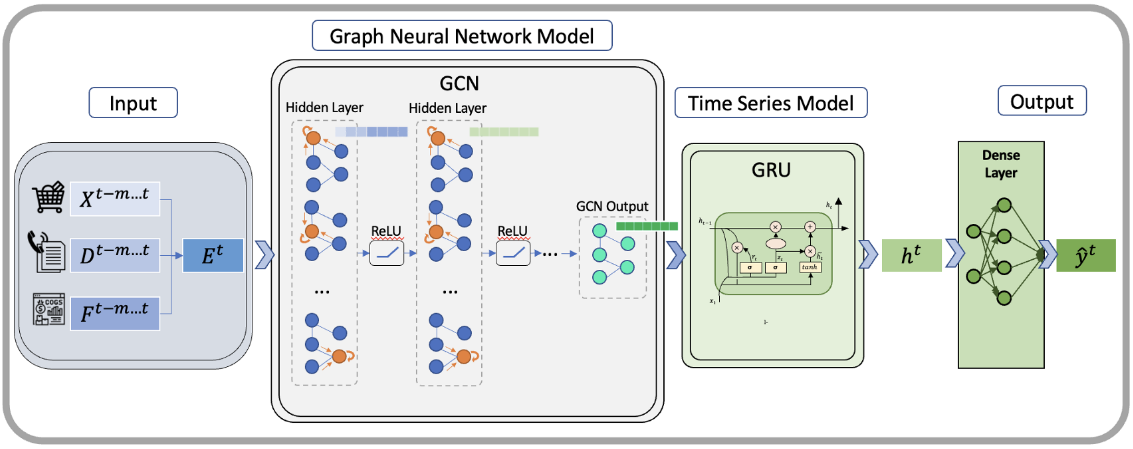

Figure 4.1: *The model structure for shortage forecast*

Figure 4.1 shows the structure of our shortage forecasting model extended from T-GCN (Yu et al., 2017) and AST-GCN Zhu et al. (2021). The model follows a process starting with problem definition and proceeds as follows: data processing to generate input embeddings, applying Graph Convolutional Networks (GCN) to generate graph embeddings, utilizing the graph embeddings as input to a Gated Recurrent Unit (GRU) to generate embeddings for each supplier at a given time point, and finally, making the final prediction through a dense layer.

doi:10.6342/NTU202301990

4.1 Problem Definition

Below, we formally define the DOI prediction task using supply chain networks. Let $G = (V, E)$ be a supply chain network, where $\{V = v_1, v_2, ..., v_n\}$ are nodes representing individual suppliers, and n is the total number of suppliers. $E = \{< v_i, v_j >\}$ is the set of edges that represent the supply relationships. An edge $< v_i, v_j >$ indicates that v_i is an upstream supplier of v_j. Note that the supply relationships are very sparse, therefore we categorize the product characteristics of V into ten types and establish edges between suppliers of the same type to enhance the information in G. Last, we use the adjacency matrix A to represent the network G, in which $A_{i,j}$ is 1 if suppliers v_i and v_j have a supply relationship or they are with the same product type

For each tier-1 supplier v_i, we examine its previous DOI's and features including the text information of its earnings call transcripts and financial numbers to predict the upcoming DOI's. Specifically, let vector x_i^t denote the DOI of supplier v_i at time t, and vector k_i^t comprises the features of v_i at time t. We train a GCN-based function f that leverages the historical data $(X =< x_i^1, x_i^2, \ldots, x_i^t >, K =< k_i^1, k_i^2, \ldots, k_i^t >)$ under the supply relationships in G to predict the upcoming DOI's of v_i as follows:

$$x_i^{t+1} = f(X, K|G) \tag{4.1}$$

Next, we detail our prediction model and the training process.

4.2 Feature Extraction

In this research, we examine two types of attributes: text attributes and financial attributes to predict the DOI's of suppliers.

doi:10.6342/NTU202301990

4.2.1 Text Embedding

To extract text information of suppliers, we count shortage-related keywords and the corresponding sentiment scores in each earnings call transcripts. We evaluate the text features because supply chain information only take limited space in earnings calls. Hence, fine tuning a pre-trained model to obtain text embeddings of whole earnings call transcripts may introduce bias. Moreover, the length of the text embeddings are normally long, and they will dominate the other features and cause our shortage forecasting model to overlook the financial numbers related to the DOI. Therefore, we adopt a more straightforward approach by counting the occurrence of 100 shortage-related keywords provided by domain experts (e.g. component, pandemic, congestion......) and their sentiment scores computed through an FinBERT (Araci, 2019) across all segments where the keywords occur. Considering the length of the features, we perform summation on the occurrence of 100 keywords and three types of sentiment scores to form $D \in R^{n\times(w*t)}$, a collection of w different text attributes $D_1, D_2, \ldots, D_w$ (in this case, $w = 4$).

4.2.2 Temporal Feature Generation

In addition to DOI, we select meaningful financial numbers for our shortage prediction task. Here, we choose inventory and COGS, which are highly associated with DOI, to form our financial attributes: $F \in R^{n\times(z*t)}$ - a collection of z different financial attributes $F_1, F_2, \ldots, F_z$. Then, we concatenate DOI, text attributes, and financial attributes to form:

$$E^t = [X^t, D_1^t, D_2^t, \ldots D_w^t, F_1^t, F_2^t, \ldots F_z^t] \tag{4.2}$$

, where $E^t \in R^{n\times(1+w+z)}$ as the features at time t.

doi:10.6342/NTU202301990

4.3 Temporal Graph Neural Network

To leverage the inherent graph structure of supply chains, we employ a graph-based approach. In addition, given the persistent nature of time shifting and shortages from tier-2 to tier-1, temporal information is critical as well. Therefore, we require a model that comprehensively integrates spatial and temporal information of data. We use the AST-GCN model (Zhu et al., 2021) as our model because its theoretical foundations align well with our scenario. Specifically, AST-GCN combines Graph Convolutional Networks (GCNs) graph embedding model with GRU to effectively capture temporal information and achieve accurate predictions. The mathematical foundation of GCN can be represented as follows: Let σ represents the activation function, $\tilde{A} = A + I$ denotes the adjacency matrix with self-loops, $\tilde{D}$ symbolizes the corresponding degree matrix, W_l represents the weight matrix of the l-th convolutional layer, y_l represents the output representation, and $y_0 = X$, in our case, $X = E^{1...t}$.

$$y_{l+1} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}y_l W_l) \tag{4.3}$$

The GRU model can be understood as a composition of update gates and reset gates. It takes into account the input node feature of at time $t-1 : x_{t-1}$, and the hidden states at time $t-k, ..., t-1, t$: $h_{t-k}, \ldots, h_{t-1}, h_t$ to determine the candidate hidden state c_t. The reset gate, r_t, combines the state of the previous stage h_{t-1} with current information x_t using the sigmoid activation function (σ) and $tanh$ to get the candidate hidden state c_t. The update gate, u_t, plays a pivotal role in determining the extent to which the previous state h_{t-1} should be disregarded and how much of the new information from c_t should be integrated, ultimately leading to the formation of the final hidden state h_t. In our case, the input x_{t-1} is the output of the GCN and the output h_t will used to predict the final y.

doi:10.6342/NTU202301990

4.3.1 Model Architecture

As shown in the Figure 4.1, various types of features are concatenated to form a comprehensive vector E, which serves as the input for forecasting the final result y.

$$\hat{y} = f(A, X, E) \tag{4.4}$$

The basic process is to feed the $feature$ into GCN to generate $node\ embedding$, then put the output into GRU to obtain the hidden state for that time, and finally, predict the result y.

$$\hat{y} = f(A, X, E) \tag{4.5}$$

$$u_t = \sigma(W_u \cdot [gc(E^t, A), h_{t-1}] + b_u) \tag{4.6}$$

$$r_t = \sigma(W_r \cdot [gc(E^t, A), h_{t-1}] + b_r) \tag{4.7}$$

$$c_t = tanh(W_c \cdot [gc(E^t, A), (r_t, h_{t-1})] + b_c) \tag{4.8}$$

$$h_t = u_t * h_{t-1} + (1 - u_t) * c_t \tag{4.9}$$

where $gc(\cdot)$ is the graph convolution operation.

4.3.2 Loss Function

Although we focus more on the prediction results of tier-1 suppliers, for model training, we predict for every tier-1 and tier-2 suppliers. We use y_t and $\hat{y}_t$ to denote the real DOI and the predicted DOI, respectively. The primary goal of the loss function is to minimize the prediction error associated with the DOI for all tier-1 and tier-2 suppliers.

$$Loss = \|y_t - \hat{y}_t\| + \lambda L_{reg} \tag{4.10}$$

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In this context, y_t represents the ground truth and $\hat{y}_t$ corresponds to the prediction. The equation incorporates the term L_{reg} as a regularization term to mitigate overfitting, with λ serving as a hyperparameter that governs the extent of its influence.

doi:10.6342/NTU202301990

Chapter 5

Experiments

5.1 Datasets

We collected real-world data from Q1 2018 to Q3 2022 for our performance evaluations. The dataset consists of 4 tier-1 semiconductor equipment suppliers listed in the United States and 92 tier-2 suppliers. To standardize the financial quarters across companies with varying definitions, we aligned the months specified in the financial reports by considering May to July as Q1, June to August as Q2, and so forth. The supply relationships were primarily based on the Bloomberg supply chain database, which gathers data from companies' financial reports and various public sources.

The collected data were split into training and testing sets. The training data includes the 2nd to 14th quarters, while the testing data comprises the 15th to 19th quarters. To reflect real-world scenarios, we set the time window at 2 in the experiment. Here, the time window specifies the (quarter) length of historical features used to predict the DOI of the next quarter. The predicted DOIs then are evaluated by the following evaluation metrics to show the shortage prediction performance.

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Table 5.1: *Basic statistics of the supply chain network*

Category	Metric	Value
Network	the number of nodes	96 (T1:4, T2:92)
	the number of edges	338
	Graph Density	0.037
Node	Max degree	24
	Min degree	1
	Average degree	3.52

Table 5.2: *Basic statistics of each features*

	DOI	COGS	Inventory	Positive	Negative	Neutral	Keyword counts
Mean	85.05	1,025M	731M	8.0	2.75	8.51	58.62
Max	3,925	19,128M	21,092M	58.98	33.0	64.53	228.0
Mean	-78.43	-167M	0	0	0	0	0

5.2 Evaluation Metrics

To assess the model's performance, we utilize the following widely recognized evaluation metrics:

(1) Root Mean Square Error (RMSE)

RMSE computes the root mean square difference between the predicted and the real DOIs. The smaller the value the better shortage forecasting performance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5.1}$$

(2) Mean Absolute Error (MAE)

MAE also measures the difference between the predicted and real DOIs. However, compared to RMSE, MAE is more sensitive to extreme values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5.2}$$

(3) R-Squared

doi:10.6342/NTU202301990

R-Squared, also known as the coefficient of determination, measures the proportion of the variance in the dependent variable that can be predicted from the independent variables.

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{5.3}$$

(4) Adjusted R-Squared (adj. R^2)

The adjusted R-Squared is a statistical measure that evaluates the goodness-of-fit of a regression model while considering the number of predictors (variables) used. It is an adjusted version of the regular R-squared that penalizes the inclusion of unnecessary predictors.

$$Adjusted\ R^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1} \tag{5.4}$$

5.3 Parameter Settings

The model's hyperparameters primarily consist of the learning rate, training epochs, and the number of hidden units for the graph embedding in GCN (equivalent to the length of GRU hidden units). These hyperparameters were manually set to 0.001, 200, and 64, respectively, as suggested by previous studies and experimental observations. As for the optimizer, we employed Adam, also based on previous research (Zhu et al., 2021).

5.4 Baseline Models

We conduct a comparative analysis of the proposed model (TGCN) against the following methods: (1) Linear regression (LR) (Weisberg, 2005), (2) Support vector regression (SVR) (Smola and Schölkopf, 2004), (3) Random Forest (RF) (Segal, 2004), (4) XGBoost (Brownlee, 2016), and (5) Graph Convolutional Network (GCN) (Defferrard et al., 2016). To ensure fair comparisons, all

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the methods were implemented using public code and packages. Their hyperparameters were set as suggested by the code developers.

5.5 Experiment Results

5.5.1 Comparison with Baseline Models

Table 5.3: *Performance comparison of different models for shortage forecast*

Model	RMSE	MAE	R^2	adj. R^2
Linear Regression	21.88	14.53	0.88	0.88
SVR	43.99	29.7	0.54	0.52
Random Forest	22.61	14.67	0.87	0.87
XGBoost	25.39	18.0	0.82	0.82
GCN	44.52	31.32	0.51	0.35
TGCN	43.51	31.47	0.54	0.38

In Table 5.1, we primarily investigate the compared models based on their RMSE results. Overall, Linear regression and Random Forest achieved RMSE values of 21.88 and 22.61, respectively, indicating good predictive performance. Surprisingly, graph models (i.e., GCN and TGCN) that utilized the supply chain network were not superior, suggesting that the dataset lacked sufficient information for the models to learn the network topology weights, and the inclusion of data from unrelated companies had a negative impact.

To further discuss the problem of the data insufficiency and the effects of textual and numerical supply chain information, we evaluate the models in terms of four perspectives: impact of supply chain topology, influence of textual information, effect of time window length, and prediction performance for tier-1 suppliers.

doi:10.6342/NTU202301990

Table 5.4: *Performance comparison of different graph-based models with or without network*

Model	RMSE	MAE	R^2	adj. R^2
GCN	44.52	31.32	0.51	0.35
TGCN	43.51	31.47	0.54	0.38
GCN w/ identity matrix	20.83	14.07	0.89	0.86
TGCN w/ identity matrix	27.09	18.16	0.83	0.74

5.5.2 Impact of Supply Chain

To examine the benefit of supply chain topology in shortage prediction, we compare the GCN-based models with and without using the supply chain network. When without using the network, we input the GCN model an identity matrix that implies no supply relationship between the companies, The RMSE value of GCN without the network is 20.83, and the value is comparable to several traditional models shown in Table 3.1, indicating that advanced neural networks still have potential. However, the current dataset was insufficient to train the GNN model, and TGCN, which is basically a neural network with an additional GRU layer, resulted in worse performance, indicating that the existing data and task were not suitable for overly complex models.

5.5.3 Ablation Study for Textual Information

Out of our expectation, the inclusion of textual data does not lead to significant improvement. It slightly reduces the RMSE and increases the adjusted R-squared for Linear regression, Random Forest, and XGBoost. The results show that domain-specific textual information does contribute to shortage forecasting. When using sentiment analysis or keyword count alone, there was a marginal improvement, but the combination of both yielded better results.

doi:10.6342/NTU202301990

Table 5.5: *Performance comparison of different models with different features*

Feature	Model	RMSE	MAE	R^2	adj. R^2
7 (all features)	Linear Regression	20.68	13.79	0.9	0.8
	SVR	43.41	43.41	0.58	0.58
	Random Forest	24.56	24.56	0.85	0.85
	XGBoost	27.31	27.31	0.82	0.81
	GCN w/ identity matrix	20.99	14.40	0.89	0.86
	TGCN w/ identity matrix	21.54	14.99	0.89	0.85
4 (w/ out text sentiments)	Linear Regression	20.61	13.81	0.9	0.89
	SVR	36.84	23.43	0.67	0.66
	Random Forest	26.21	16.89	0.83	0.83
	XGBoost	30.4	18.91	0.77	0.77
	GCN w/ identity matrix	20.85	14.10	0.89	0.86
	TGCN w/ identity matrix	21.33	14.61	0.89	0.85
3 (w/ out text sentiments and keyword counts)	Linear Regression	20.91	14.1	0.89	0.89
	SVR	32.48	19.2	0.74	0.74
	Random Forest	26.71	17.14	0.82	0.82
	XGBoost	28.55	17.83	0.8	0.8
	GCN w/ identity matrix	20.99	14.40	0.89	0.86
	TGCN w/ identity matrix	21.54	14.99	0.89	0.85

5.5.4 Impact of Time Window

The time window specifies the length of historical data (i.e., features) used to forecast DOIs for the next quarter. To avoid short training data due to lengthening the time window, we kept the training data consistent across all experiments except for the time window. The models performed better with shorter time windows, suggesting that, in theory, the temporal information does not contribute significantly to shortage forecasting. However, the insufficient training data may also be an affecting factor.

doi:10.6342/NTU202301990

Table 5.6: *Performance Comparison of Different Models with Different Time Windows*

Time window	Model	RMSE	MAE	R^2	adj. R^2
3	Linear Regression	22.86	14.59	0.87	0.86
	SVR	42.7	28.62	0.55	0.53
	Random Forest	22.21	14.49	0.88	0.87
	XGBoost	27.29	17.62	0.82	0.81
	GCN w/ identity matrix	22.92	14.61	0.88	0.81
	TGCN w/ identity matrix	36.58	22.47	0.68	0.53
2	Linear Regression	21.88	14.94	0.88	0.88
	SVR	43.99	30.35	0.53	0.51
	Random Forest	22.61	14.59	0.87	0.87
	XGBoost	25.39	16.92	0.84	0.84
	GCN w/ identity matrix	21.88	14.53	0.88	0.88
	TGCN w/ identity matrix	43.99	29.7	0.54	0.52
1	Linear Regression	20.76	13.97	0.89	0.89
	SVR	42.9	29.41	0.55	0.54
	Random Forest	24.26	15.86	0.86	0.85
	XGBoost	27.2	17.86	0.82	0.82
	GCN w/ identity matrix	20.78	14.0	0.89	0.86
	TGCN w/ identity matrix	21.31	14.55	0.89	0.85

5.5.5 Forecasting Result for Tier-1 Suppliers

Table 5.7: *Performance comparison of different models for tier-1 shortage forecast*

Model	RMSE	MAE	R^2	adj. R^2
Linear Regression	20.66	13.77	0.9	0.89
SVR	41.21	27.86	0.58	0.58
Random Forest	23.82	15.57	0.86	0.86
XGBoost	27.31	18.28	0.82	0.81
GCN w/ identity matrix	17.49	12.61	0.77	1.04
TGCN w/ identity matrix	22.48	17.73	0.57	1.06

Last, we study the prediction performance on the tier-1 suppliers. In our dataset, there are four tier-1 suppliers. The results showed in Table 5.5 indicate that the models are superior for the

doi:10.6342/NTU202301990

shortage prediction on the tier-1 suppliers. This is likely due to the fact that among other suppliers, there are companies such as energy companies that experience significant fluctuations in DOI due to seasonal variations or special financial operations, while tier-1 suppliers are comparatively more stable, while tier-1 suppliers are comparatively more stable.

5.6 Linear Regression Analysis

Table 5.8: *The result of linear regression analysis on each feature*

Feature	Coefficient	Standard Error	T value	P value
Constant	0.0406	0.005	7.896	0.000
DOI	0.858	0.015	57.190	0.000
Inventory	0.0451	0.025	1.777	0.076
COGS	-0.0582	0.026	-2.207	0.027
Positive	-0.0042	0.014	-0.301	0.763
Negative	0.0083	0.016	0.532	0.595
Neutral	0.0185	0.018	1.008	0.314
Keyword counts	0.0091	0.015	0.587	0.557

Due to the good overall performance and interpretability of the Linear Regression model, we investigate the influence of each feature on it. As shown in Table 5.6, DOI, COGS, and inventory demonstrated significant influence on the shortage prediction task, and their coefficients aligned with the expected direction based on the DOI formula. While the p-values for textual features were relatively high, the neutral and negative sentiment showed an increase in DOI, indicating that, for most companies' operations, a rise in DOI is generally associated with negative aspects. Overall, the coefficients aligned with expectations.

doi:10.6342/NTU202301990

Chapter 6

Conclusion

This study first attempted the use of modern machine learning models to predict semiconductor supply chain shortages. It proposed the utilization of Days of Inventory and textual data as shortage indicators, with the support of supply chain networks for prediction. The findings were validated and experimented with real supply chain scenarios. The results indicated that Days of Inventory was effective for prediction, and textual data also demonstrated certain utility. However, the performance of utilizing a temporal graph neural network with the supply chain network was inferior to traditional models such as linear regression. This could be attributed to the insufficient data available for the model to learn supply chain network-related information. We believe that with an extended time frame and a larger pool of suppliers, we would be able to further assess and validate the model's performance. In order to enhance this research, future developments can focus on the following aspects:

1. **Experimentation on larger and more comprehensive supply chains:** Currently, the duration and quantity of companies in the study were limited, and the supply chain itself only included US-based suppliers. However, as the semiconductor industry operates on a

doi:10.6342/NTU202301990

global supply chain, it is crucial to incorporate suppliers from other regions such as Japan, Taiwan, and South Korea.

2. **Exploration of advanced text data embedding methods:** The current methods were constrained by the small dataset, preventing the use of complex and lengthy models. It is believed that employing more advanced techniques like BERT or even incorporating features generated by large-scale language models (LLM) could enhance the analysis of textual data.

3. **In-depth research on graph-related models and methods:** Theoretically, supply chains are suitable for graph structures. While the current study did not yield successful results, there are still opportunities for further exploration by leveraging larger datasets or employing approaches that can adapt to smaller data sizes.

4. **Engaging in further discussions with domain experts is crucial:** Close collaboration with real business users is essential to ensure the practicality and usefulness of the results. For instance, the current evaluation metric we employed is based on a previous study that focuses on the precision of the model. However, from the perspective of business users, the accuracy of the predicted direction of the DOI holds greater significance, which should be given more consideration in future research endeavors.

doi:10.6342/NTU202301990

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