Discovering Supply Chain Links with Augmented Intelligence

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One of the key components in analyzing the risk of a company is understanding a company’s supply chain. Supply chains are constantly disrupted, whether by tariffs, pandemics, severe weather, etc. In this paper, we tackle the problem of predicting previously unknown suppliers and customers of companies using graph neural networks (GNNs) and show strong performance in finding previously unknown connections by combining the predictions of our model and the domain expertise of supply chain analysts.

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1 INTRODUCTION
A key component in analyzing the risk of a company is understanding a company’s supply chain. Supply chains are constantly disrupted, whether by tariffs [25], pandemics [80], climate change [23], etc. Understanding the risk attributed to such supply chain disruptions is crucial in ensuring safe investments. Though there are regulations in some countries requiring reporting of supply chain relationships [20], these regulations do not require all to be reported and many go unannounced. Hence, we need methods to help shed light on likely connections; in this paper, we use machine learning to help with this task.

Though often the goal of artificial intelligence (AI) is posed as replacing humans, in the majority of problems, this goal is still far out of reach. Due to this, a more realistic goal is augmented intelligence, “increasing the capability of a man to approach a complex problem situation, to gain comprehension to suit his particular needs, and to derive solutions to problems.” [19]. In other words, the goal is a partnership between people and artificial intelligence, working together to combine the strengths of both in order to improve decision making.

Though machines are well-suited to processing large amounts of data and learning statistical relationships from data, there can be (and more often are) nuances and causal relationships that a human is much better at sifting through. It is these two strengths that we aim to combine in this paper to find previously unknown customers. We achieve this goal by:

(1) First, training a Graph Neural Network (GNN) (Section 5) on our Supply Chain dataset (Section 3) as well as many other company-level datasets (Section 4) to learn to recognize situations where there is a high chance that a company is trading with another, though we have not found evidence yet.

∗ Work done while at Bloomberg
1 In this paper, we focus our analysis on predicting customers though the model can trivially be extended to suppliers.

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(2) Second, taking the predictions from our GNN, we search for evidence in primary sources for the existence of these new edges (Section 7).

2 TERMINOLOGY

- **Positive/negative edge** An edge in the supply chain dataset refers to a supplier-customer connection between two companies. We refer to this as a positive edge since, in the binary classification context, we can view the existence of an edge as the positive class; a negative edge in the supply chain dataset refers to a supplier-customer connection that does not exist between two companies.

- **Number of hops** We use the word *hops* to denote the distance between two nodes where distance is defined by the minimum number of edges needed to connect the nodes. For example, nodes that are one-hop away are the neighbors of a node, i.e. the suppliers and customers of a company; nodes that are two-hops away are the neighbors of the neighbors, i.e. suppliers and customers of the suppliers and customers of a company.

3 SUPPLY CHAIN DATA

Our Supply Chain dataset covers a global set of over 23,000 companies and provides information on the supplier-customer relationships between those companies and others. Since each company can have multiple relationships, there are over 250,000 companies in the dataset in total. These connections were found from primary sources such as company presentations.

In Table 1, we can see that the average number of edges per company per country is much larger than the median number of edges; this implies a highly skewed distribution where the majority of companies have very few observed edges. For example, 63% of US companies only have one reported edge; however, there is one US company where 1077 customers are covered. This is seen in Figure 1 where the y-axis is log scale, showing that majority of companies have very few reported customers. The impact of the skew in terms of evaluation will be revisited in the construction of the validation set (Section 6.1).

Important, the fact that we have very few edges for the majority of companies motivates the importance of the problem; without broader insight into the supply chains of these companies, the risk will be unclear.

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Table 1. Supply chain coverage statistics for 2020. The five countries with the highest number of companies are shown. We also present the average/median/max number of edges (customers) per company in the country.

| Country | Average | Median | Max |
|---------|---------|--------|-----|
| China   | 5.33    | 1      | 617 |
| United States | 7.98 | 1  | 1077 |
| Japan   | 7.60    | 1      | 1137|
| Korea   | 7.65    | 2      | 358 |
| India   | 5.44    | 1      | 285 |

Fig. 1. Number of edges per US company for 2020 supply chain data.
4 COMPANY-LEVEL DATA

Though many methods in the literature approach link prediction using a transductive method (e.g. [7, 35]), we use an inductive approach. In other words, we use features (external information) for each company instead of using only an embedding given the company ID. One reason for this is that it allows our model to generalize to companies it has never seen before. Further, the intuition behind adding features to the model is that it gives the model hints on notions of similarity.

In order to help our model be able to make strong specific predictions, in addition to the Supply Chain dataset (Section 3), we included datasets domain experts currently use in their analysis of edge predictions as well as datasets they believe would be useful. An important method in deciding datasets is to not only include the information that domain experts currently use, but to include finer grained information of that data that humans might have a harder time learning relationships from. For example, one methodology used by domain experts is to analyze the industry, location, and size of companies. When this information is insufficient or missing, domain experts might further use company description and competitors.

Using this, we included industry classification, revenue segmentation (percentage of revenue from each industry sector), locations (where the company is located as well as location of facilities), company financials (balance sheet, income statement, and statement of cash flows), raw materials the company makes, company description (textual data), and competitors.

5 MODEL METHODOLOGY

In this section, we break down our model methodology into two parts: the model architecture (Section 5.1) and the model training (Section 5.2). At a high level, we use graph attention networks as our model architecture and used a two-step training procedure where the first step focuses on recall and the second focuses on precision.

5.1 Model Architecture

A common theme in the success of deep learning has been in the finding and usage of models that are well-catered to the structure of the data, e.g. recurrent neural networks for time series [13, 32, 59], attention for language [17, 54, 66], and convolutional networks for images [1, 30]. Supply chain and competitors data is easiest to represent in the form of a graph. Among the methods that exist to process graphs, Graph Attention Networks [67] best fit our needs.

Our model can be decomposed into four components:

1. **Feature MLP**: We first apply a multilayer perceptron (MLP) on the features of each node in the graph, aggregating the many different datasets we are using (Section 4). Though most of the data we utilized is numerical, company description is not; we processed (embedded) company description using BERT [17]. A more thorough analysis of BERT and its variants can be found in Appendix C.

2. **Neighbor aggregation**: The specific formulation of the graph attentional layer (GAT) can be found in Appendix B.2. At a high level, the layer takes a graph and representations \( \tilde{h}_i \) for each node \( i \) as input and outputs a new representation \( \tilde{h}'_{i,e} \) (\( e \) denoting the edge type) for each node where the new representation is formed by using an attention-based function whose inputs are the previous representation of the node and the previous representations of the neighbors of the node. To handle multiple edge types, we apply the graph attention layer (Equation 2) per edge type (i.e. once for suppliers \( \tilde{h}'_{i,s} \), once for customers \( \tilde{h}'_{i,c} \), and once for competitors \( \tilde{h}'_{i,t} \)). To aggregate this information, we concatenate the outputs for each edge type along with the node features and
apply an MLP to aggregate the information:

$$h'_i = f_\theta(h'_{i,s} || h'_{i,c} || h'_{i,t} || h_i)$$

where $\|$ denotes concatenation and $f_\theta$ is an MLP.

3) **Aggregating multiple hops**: To handle multiple hops, we apply a GAT layer for each hop away. For example, for a two-hop model, we first apply a GAT layer for nodes two-hops away; using the outputs from that layer, we apply another GAT layer one-hop away; finally, we aggregate that information using a GAT layer at the node in question.

4) **Scoring a pair of companies**: Using the architecture above, we apply it to the supplier side (company A) and customer side (company B) to get representations $e_a$ and $e_b$, respectively. Given the two embeddings, we generate a score for how likely there is a supplier-customer edge between the two by taking the dot product of the two:

$$s_{a,b} = e_a \cdot e_b$$

By using a different network for suppliers and a different network for customers, we allow for asymmetry in prediction (company B being company A’s supplier does not imply company A is company B’s supplier).

### 5.2 Model Training

The main difficulties in link prediction come down to two things: there are no negative edges (we do not know with certainty which edges do not exist) and highly imbalanced classes (there is a significantly larger number of negative edges than positive edges).

Though there is no rigorous solution to the first problem, we simply sample random company pairs from unconnected companies and denote them as a negative edge. We argue this works since most company pairs are not valid relationships (the second issue), meaning if we randomly sample a pair of companies, there is a very low probability that the random pair is a valid supply chain relationship.

Taken from the link prediction literature, we use “pairwise logistic loss” [47]. Given a positive pair (A, B), we randomly sample a new company C to create a negative pair (A, C). We then score the pairs using the architecture described in the previous section (Section 5.1) to get scores $s_{a,b}$ and $s_{a,c}$. Given these scores, the loss function is:

$$\log \left( 1 + e^{s_{a,b} - s_{a,c}} \right)$$

One interpretation of the sampling method used for this loss function is that, though there are significantly more negative examples than positive ones, we resample such that the two classes are balanced.

Though there is a large body of literature on different loss functions for knowledge graph models [7, 16, 37, 49, 50, 65, 75], we leave it to future work to explore more variants; however, preliminary experiments showed that RankNet [12] and LambdaRANK [11] hurt performance.

One issue with the training procedure described above is the imbalanced classes. The main issue with imbalanced classes is that neural networks might struggle to learn both obvious relationships (the relationships that can easily be noticed to be a negative edge) and specific relationships (the nuances that are required to reject certain relationships).

To fix this problem, we use a two-step model: first, we train a model where the negative pairs are created by sampling randomly; second, we train another model from scratch where the negative pairs used are pairs that the first model gives a large score to. “Large score” here means the score is larger than some predefined threshold. This method can be viewed as boosting where the second model boosts performance by fixing the mistakes of the first model.
|                | Mean Rank (↓) | Recall@100 (↑) | Hit@20 (↑) |
|----------------|---------------|----------------|------------|
| Baseline       | 2246          | 25%            | 16%        |
| + Facilities   | 2058          | 27%            | 18%        |
| + Fundamentals + Raw | 1854  | 32%            | 22%        |
| + BERT         | 1832          | 31%            | 22%        |
| - BERT + Graph | 947           | 53%            | 40%        |
| + Two step (Final) | 938    | 56%            | 45%        |

Table 2. Evaluation of our model given different amounts of data. The baseline model contains industry classification, segmentation, and country data. The models with graph information contains all the features before it (except BERT).

6 MODEL VALIDATION

6.1 Validation Set

In order to validate our model, we split the observed edges (supplier-customer relationships) into a training and validation set. However, we do not randomly split the edges as this would lead our validation set to contain more edges from companies that already have a lot of edges. As mentioned in Section 3, there are some companies with hundreds of known customers. In terms of evaluation, we care more about our model’s performance on companies with only a few observed edges; due to this, we create our validation set by sampling two edges per company for companies that we have no more than twenty known customers. Further, since we trained our model on historical supply chain data, to ensure no data leakage, for every edge in the validation set, we removed it from the training set across all years.

6.2 Evaluation Metrics

To evaluate our model, for each company in our validation set, we score every other company with respect to it. Using these scores, we get the rank for each company; importantly, we filter out pairs that were in the training set before computing the ranks since the ranks for training edges are generally higher than for other edges.

To evaluate, we used the mean rank, recall@N (percentage of edges in the validation set whose rank is less than N), and hit@N (percentage of companies that have at least one positive edge in the top N). Note in the last two metrics, the percentages get larger as N grows. Further, since there are many edges we do not know of, the recall@N and hit@N are lower bounds on the true value. For example, if the hit@20 is 40% (meaning that 40% of the companies have at least one true edge in the top 20), for the other 60% companies, there might be true edges in the top 20 that we currently do not know of.

Though there can sometimes be tradeoffs with respect to the three metrics, the metric we gave priority to was hit@20 because the goal (Section 7) is to find previously unknown edges.

6.3 Evaluation

In Figure 2, we show the performance on our validation set given different amounts of data. Our baseline model contains industry classification, segmentation, and country information. As can be seen, facilities gives a reasonable boost over the information contained in country data; further, adding fundamentals and raw materials (more information about the business of the company) also gives a reasonable boost in performance. However, BERT hurts performance suggesting
that the information in the company description is encompassed by the features already contained in the model and that adding BERT has simply lead to overfitting; though BERT hurts performance, Appendix C shows that, for companies with limited data, BERT (company description) can lend valuable information. The biggest boost in performance comes from adding supply chain and competitors data where, to incorporate this information, we tuned the number of hops. Further, training a second step model, though not a big improvement, gives a measurable performance boost.

7 FINDING PREVIOUSLY UNKNOWN LINKS

As noted previously, since there are many edges that we do not know of, the hit@20 is a lower bound on the true value. To get a better understanding of the true hit@20, we gave the top twenty predictions of all companies from our final model to supply chain analysts (domain experts) to see if they can find evidence for the predictions. For our analysis, supply chain experts selected ten industries where the current coverage has enough observations for the model to have learned something meaningful while not so many where most of the publicly available relations are previously found. From these industries, twenty predictions were sampled randomly and assigned to experts in those industries. In total, 180 predictions were analyzed by nine experts. In addition to these predictions, we gave two Google search URLs: customer name from supplier’s website and vice versa.

In Table 3, we see that evidence was found for approximately 21% of the edges evaluated; in other words, the hit@10 is approximately 91%\(^2\). Thus, whereas our hit@10 for our model is 36%, directly measuring this statistic using predictions and external sources shows our model is much better than the statistics show (as is expected from the fact that we knew our metrics would be lower bounds of the real value).

Further, if we focus on results where the supplier is a US company, nearly 39% of the relationships were found. This percentage is expected to be higher as the ability to find evidence for edges can sometimes be predicated upon knowing the language of the country in which the companies are in. In terms of the usefulness of the Google links given, 60% of the edges found were found from one of the two Google links given and nearly 70% of the US edges found were found from one of the Google links.

In conclusion, combining these observations together, a simple method to find new edges with primary evidence is taking the top twenty predictions of our model for US companies and searching only two Google links. Further, these results also validate the overall quality of our model, and that, even if primary evidence cannot be found, the predictions can be trusted.

\(^2\)0.91 = 1 - (1 - 0.21) \(^{10}\), assuming the ability to find an edge is independent of the supplier and customer

Table 3. Results of analysis by domain experts. The results shown are grouped by supplier-side country and the five countries with the most edges analyzed are shown.

| Country   | Total | Found | % Found | Found by Google |
|-----------|-------|-------|---------|-----------------|
| United States | 33    | 13    | 39%     | 9               |
| China     | 29    | 4     | 14%     | 0               |
| Japan     | 17    | 2     | 12%     | 1               |
| India     | 13    | 2     | 15%     | 2               |
| Taiwan    | 11    | 1     | 9%      | 1               |
| Total     | 180   | 37    | 21%     | 22              |
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A RELATED WORK

A literature survey of knowledge graph embedding methods has been conducted by Wang et al. [69]. The methods can be categorized into two types of models. Say, we are given two entities $e_1$ and $e_2$ connected by a relationship $r$. The methods used in knowledge graph embeddings use a function to embed the entities ($h_{e_1}$ and $h_{e_2}$) and use some representation of $r$. Translational distance methods aim to minimize the distance between $h_{e_1} + g(r)$ and $h_{e_2}$, where $g(r)$ is some vector representation of the relationship $r$ [7, 72]. Semantic matching models, on the other hand, employ similarity-based scoring functions [50, 75]. DistMult [75] used a bilinear function $h_{e_1}^T A_r h_{e_2}$ to score the relationship where $A_r$ is a matrix representation of the relationship $r$. Our model architecture (Section 5.1) uses a similar method to score supplier-customer relationships.

The above methods, however, only use structural information observed in triples while different kinds of external information has been used to improve performance. For textual descriptions, methods vary from using word embeddings [61, 70, 71] to convolutions [73] to attention [2, 74]. Similar to our method of handling company description, Yao et al. [76] used BERT to handle encoding of textual information.

Another type of additional information that has been added is the graph structure (akin to the GNN we use in our architecture). In addition to the triples observed in a knowledge graph, path context (other paths connecting the two entities) have been used [21, 27, 42] as well as neighboring triplets [21, 34]. Temporal information and information about when the relationship previously existed has also been incorporated [64], similar to our model using historical supply chain data.

One main difference between our link prediction task and those of knowledge graph embeddings is we have only one type of link we are trying to predict.

In Appendix B.1, we discuss the relevant literature behind graph neural networks. Many of these methods can and have been used in link prediction. Some baselines include matrix factorization and node2vec [26], though both are transductive methods. Another method for link prediction is SEAL [40, 77] where a local enclosing subgraph is extracted around each target link and the nodes in each enclosing subgraph are labeled differently according to their distances to the source and target nodes [78].

B GRAPH NEURAL NETWORKS

B.1 Background on Graph Neural Networks

There has been many networks introduced to deal with arbitrarily structured graphs. Early work approached the problem using recurrent neural networks (RNNs). Frasconi et al. [22] and Sperduti and Starita [62] used RNNs to process directed acyclic graphs; Gori et al. [24] and Scarselli et al. [60] developed a generalization of RNNs that can handle a large class of graphs. The method was further improved upon by Li et al. [41] which used gated recurrent units (GRUs, [13]) in the propagation step.

In addition to the RNN approach, there has been research in generalizing convolutions to handle graphs. One method used convolutions in conjunction with a spectral representation of the graph such as the work in [10, 15, 31, 35]. Another method used convolutions directly on the graph [4, 18, 29, 48]; however, one challenge of these approaches is handling different sized neighborhoods and retaining the weight sharing property of convolutional networks. Though, most of these methods are transductive (learn a representation per node), GraphSAGE [29] used an inductive method to create node representations.
As attention-based mechanisms become the de facto method for many tasks with variable sized inputs [5, 17, 66], Veličković et al. [67] introduced Graph Attention Networks allowing for easier handling different size neighborhoods. A thorough literature survey of graph neural networks has been conducted by Zhou et al. [79].

B.2 Graph Attentional Layer

Among the methods that exist to process graphs, Graph Attention Networks [67] best fit our needs as we need a method that:

1. Can be applied to graphs with differing structures since we would not want to have to retrain our models anytime the data is updated; ideally, our model could continue to use new information as it arrives
2. Is inductive (as opposed to transductive), or in other words, can make predictions on nodes (companies) that the model has never seen before by using feature information to generate node embeddings
3. Allows for flexibility in the face of different sized neighborhoods (variable number of neighbors)

The first requirement precludes the usage of spectral convolutional methods [10, 15, 31] since these methods require filters trained on specific spectral representations (Laplacian eigenbasis) which depends on the graph structure. The second requirement does not necessarily preclude us from using many methods such as graph convolutional networks (GCNs, [35]) as these often are extendable to the inductive case [28]. The third requirement leads us to use attention when aggregating neighborhoods instead of using other aggregators such as the mean over the feature vectors of the neighbors or using an RNN over the feature vectors. An important consideration when choosing an aggregator is to choose a function that is permutation-invariant since there is no inherent ordering of neighbors.

At a high level, the layer takes representations $\tilde{h}_i$ for each node $i$ and a graph (the neighbors of each node) as input and outputs a new representation $\tilde{h}'_i$ for each node. The new representation is formed by using an attention-based function whose inputs are the previous representation of the node and the previous representations of the neighbors of the node.

More specifically, for some node $i$, we denote $N(i)$ as the neighbors of $i$. Using attention means that, for each node $i$, we compute a weight $w_{ij}$ by using its query $\tilde{q}_i$ and the keys $\tilde{k}_j$ for each of its neighbors $j$ and then output a weighted sum of the values $\sum_j w_{ij} \tilde{v}_j$. For the graph attentional layer, this is achieved by:

\[
\begin{align*}
\tilde{q}_i &= W_q h_i \\
\tilde{k}_j &= W_k h_j \\
\tilde{v}_k &= W_v h_k \\
\tilde{a}_{ij} &= \tilde{q}_i \cdot \tilde{k}_j \\
w_{ij} &= \frac{\tilde{a}_{ij}}{\sum_{k \in N(i)} \tilde{a}_{ik}} \\
\tilde{h}'_i &= \sum_{j \in N(i)} w_{ij} \tilde{v}_j
\end{align*}
\]

The choice in definition for $N(i)$ is arguably an arbitrary choice made by the modeler, but often the choice comes down to whether or not to include a self-connection (is $i$ in $N(i)$)? In Veličković et al. [67], the self-connection is included; in our model, we do not include the self-connection (more details in Section 5.1).
C COMPARING BERTS

C.1 Background on Pretrained Language Models

Learning representations of words and documents that are applicable to many tasks has been an active area of research for decades, including non-neural [3, 6, 8] and neural methods [46, 51]. In early methods such as word2vec [46] and GloVe [51], the representations of the words lacked contextual information, e.g., though Apple is both a company and fruit, these methods would give the same embedding for apple, no matter the context. These approaches were generalized to sentence embeddings [36, 45] and paragraph embeddings [39].

ELMo [53] and its predecessor [52] generalized word embeddings by extracting context-sensitive information from a left-to-right and a right-to-left language model and concatenating the representations from the two models.

Whereas ELMo used LSTMs, later work utilized Transformers [66] much more. GPT and its variants [9, 54, 55] use left-to-right language models. The method often used today to improve performance on NLP tasks has been BERT [17] and its variants [38, 44, 58]. BERT was trained using a loss to reconstruct masked tokens and a loss based on predicting whether, given a pair of sentences, does the second sentence follow the first in the original document.

C.2 BERT Experiments

Though BERT has been shown to achieve strong performance in many NLP tasks [14, 17], there has been variations in performance in downstream tasks depending on the BERT model used. For example, RoBERTa was shown to outperform BERT on GLUE (a collection of nine datasets for evaluating natural language understanding, [68]) and SQuAD (a question-answering dataset, [56, 57]); however, on sentence-level tasks such as Textual Similarity tasks, Sentence-BERTs outperform BERT [58]. Thus, in this section, we show the performance for supply chain link prediction across many different BERTs.

To simplify the task, we compare the performance between a model with only industry and country information versus a model with both as well as company description (processed using BERT). Due to the computational cost of fine-tuning BERT in concurrence with supply chain dataset, we focused on the case of static embeddings (no fine-tuning of BERT). However, there are many methods to create static embeddings from BERT; we experimented with:

1. Mean along sequence dimension of token embeddings (mean pooling)
2. CLS vector
   In BERT models, sentences are padded with a start token, also know as CLS token. Using the CLS vector is the same as using the embedding for the first token. The justification for this is that when pretraining BERT, the CLS vector is used for the sentence level task (next sentence prediction).
3. Bidirectional-LSTM and aggregation
   Instead of fine-tuning, to add more expressivity, we used the token-level embeddings and passed those through a learnable bidirectional-LSTM. Then, we aggregate the processed token embeddings using one of the two aggregators above (mean pooling and CLS) or the maximum along sequence dimension of token embeddings (max pooling).

   We did not use the maximum along sequence dimension on the token embeddings from BERT as preliminary results showed this did not work well.

   For the sentence BERTs, we only used the method that the model was intended to use; specifically, we focused on the sentence BERTs where the mean was used as the intended sentence embedding. This was only considered when not using a bidirectional LSTM; for the bidirectional LSTM, we tested all three aggregation methods.
Further, there have been studies on which layer to use when using BERT \cite{33, 43, 63}; thus, we compare using the last layer versus the second to last layer.

The models we compared were: BERT-base, BERT-large, RoBERTa, and three variants of sentence BERT (denoted sentence BERT, paraphrase and mini-paraphrase). Further, to ensure the difference in performance is coming from an understanding of company description, the suppliers in our validation set only included companies that were never seen in the training set. We ran each experiments three times.
In Figure 2a, we compare the performance on the validation set across the many different BERT models and aggregate methods, without LSTMs. We can see that the Sentence-BERTs significantly underperform the other BERTs. Further, though using the CLS token from the second to last layer in RoBERTa and BERT-base hurt performance, the performance for BERT-large is not significantly different from using the mean of the token embeddings. Further, for BERT-base and RoBERTa, the mean of the last layer performed the best whereas for BERT-large the mean of the second to last layer performed the best.

In Figure 2b, we compare the performance using a bidirectional LSTM over the token embeddings. We can see that the best trainings of BERT and RoBERTA outperform sentence-BERT and its variants (Figure 2c). From Figure 2d, we can see the LSTM gives a significant performance boost for BERT. Further, though max pooling allows for faster learning in the BERT models, the performance gap between it and mean pooling is reduced with further training; in the sentence BERT models, max pooling gave the best performance when combined with bidirectional LSTMs.

In conclusion, due to the size of our supply chain model, we use the mean embeddings of the second to last layer of BERT-large instead of using a bidirectional LSTM with the token embeddings. Though, since our experiments showed an improvement with bidirectional LSTM, we leave it to future work to utilize this observation to its fully extent.

D ADDITIONAL EVALUATION

D.1 Stratified Performance

Though we show strong performance in aggregate (Section 6.3), we believe it to be a useful endeavor (especially when using a model in practice) to get a deeper understanding of performance across different subsets of the data. Specifically, we focus on the performance across different industries (Figure 3, Table 4, Table 5) as well as countries (Figure 4, Table 6, Table 7).

In Table 6 and Table 7, we can see qualitatively that the performance is reasonably uniform; however, there is a bit of dip in performance for a few countries on the customer side. However, in Table 4 and Table 5, we can see that there are industries the model struggles with more. Specifically, the largest hit in performance comes from Financials and Real

| Supplier Industry   | Recall@100 | Hit@20 |
|---------------------|------------|--------|
| Communications      | 0.64       | 0.50   |
| Consumer Discretionary | 0.56   | 0.45   |
| Consumer Staples    | 0.62       | 0.51   |
| Energy              | 0.65       | 0.53   |
| Financials          | 0.37       | 0.23   |
| Health Care         | 0.56       | 0.44   |
| Industrials         | 0.53       | 0.45   |
| Materials           | 0.54       | 0.42   |
| Real Estate         | 0.43       | 0.29   |
| Technology          | 0.59       | 0.50   |
| Utilities           | 0.54       | 0.42   |

| Customer Industry   | Recall@100 | Hit@20 |
|---------------------|------------|--------|
| Communications      | 0.68       | 0.49   |
| Consumer Discretionary | 0.55   | 0.37   |
| Consumer Staples    | 0.61       | 0.40   |
| Energy              | 0.72       | 0.50   |
| Financials          | 0.39       | 0.20   |
| Health Care         | 0.55       | 0.36   |
| Industrials         | 0.49       | 0.31   |
| Materials           | 0.49       | 0.28   |
| Real Estate         | 0.36       | 0.17   |
| Technology          | 0.59       | 0.39   |
| Utilities           | 0.62       | 0.39   |

Table 4. Performance of our model on validation set across different industries on supplier side.

Table 5. Performance of our model on validation set across different industries on customer side.
Estate companies. This is to be expected as the amount of data in these industries is lower; further, many relationships in the real estate space can be from leasing to anyone, making it difficult to predict.
Fig. 3. Performance of our model on validation set across different industries. We further give the counts in the corresponding to buckets to give a better sense if the performance metrics were computed with a sufficient number of observations.
Fig. 4. Performance of our model on validation set across different countries. We show performance on only nine countries. We further give the counts in the corresponding to buckets to give a better sense if the performance metrics were computed with a sufficient number of observations. For example, though there is a 100% recall from Italian to Indian companies, there is only one observation in that bucket; similarly, for Russian to Denmark companies, the recall is 0% but also only has one observation.