BILATERAL TRADE MODELING WITH GRAPH NEURAL NETWORKS

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ABSTRACT

Bilateral trade agreements confer preferred trading status between participating countries, enabling increased trade and potential economic growth. Predicting such trade flows often serve as critical economic indicators used by economists and policymakers with impactful ramifications in economic policies adopted by respective countries. However, traditional approaches to predicting potential trade partners are through the use of gravity methods, which are cumbersome to define due to the exponentially growing number of constants that need to be considered. In this work, we present a framework for directly predicting bilateral trade partners from observed trade records using *graph representation learning*. Furthermore, we show as a downstream task that modeling bilateral trade as a graph allows for the classification of countries into various income levels. Empirically, we observe accuracies of up to 98% for predicting trading partners and 68% on income level classification.

1 INTRODUCTION

International trade involves the exchange of goods, capital, and services between countries, and where two countries are concerned, it is referred to as *bilateral trade*. Often, the deficit and surpluses created via bilateral trade represent important economic development indicators, which drive the adoption of specific domestic economic policies –i.e., relaxation of restrictions and trade barriers, in either country. Consequently, various models have been employed by economists to understand trade patterns and factors that account for the observed trade activities between countries. For instance, the Ricardian model introduced the idea of comparative advantage of nations, whereby a country exports more of the goods they can produce at a lower cost (Ricardo, 1817). In a similar vein, the "factor of abundance" argues that the trading behavior of a country is influenced by what they confidently produce in abundance (Steiner, 2015).

The most popular method with practical benefits is known as the Gravity Model of trade, which is motivated by Newton's law of gravitation. The gravity model relates the bilateral trade flows between two countries using the respective gross domestic product (GDP) of each country while taking into account the geographical distance. Intuitively, trade flow is high when participating countries have high GDPs and are geographically close to each other (Deardorff, 1998). While the gravity model is an effective empirical measure for bilateral trade flow, it lacks both a theoretical justification (Anderson, 2011), as well as suffers from practical limitations. In particular, model performance is dictated by defining handcrafted features such as cultural differences and political terms that require significant domain knowledge.

[*]Code can be found at https://github.com/panford/BiTrade-Graphs.

Present work. In this paper, we take a data-driven approach to modeling bilateral trade. We first observe that trade flows can naturally be interpreted as a graph wherein countries are nodes and edges represent countries undertaking bilateral trade. We leverage recent advances in graph representation learning and predict trade links between countries, crucially without first estimating trade flow heuristics. We further analyze the graphical structure of trade relationships between countries and use it to power a supervised learning approach to predict the income levels of countries using graph neural networks (GNNs). Empirically we observe 98% and 68% accuracies in predicting bilateral trade links and income levels, respectively.

2 Background

2.1 Gravity Model of Trade

Inspired by Newton's law of universal gravitation, the gravity model provides a theoretical approach to representing the numerical trade strength between any two countries. The gravity model is used to compute the magnitude of trade strength, —i.e., trade flow, between any two countries. The magnitude of this trade value increases with increasing respective net income or GDP and decreases with increasing distance (Deardorff, 1998; Chaney, 2013). It is expressed as

$$F_{ij} = M\frac{GDP_i \cdot GDP_j}{D_{ij}}, \tag{1}$$

where F_{ij} is the trade flow between countries i and j, GDP_i is the GDP of country i, M is a proportionality constant, and D_{ij} is the geographical distance between countries i and j. A more convenient way to deal with this equation is to express it in $\log$ and introduce coefficients and placeholder variables to account for other unanticipated factors such as cultural influences and political terms. Equation 1 can then be expressed as follows:

$$\ln F_{ij} = c_0 + c_1 \ln GDP_i + c_2 \ln GDP_j + c_3 \ln D_{ij} + c_4 d + c_5 P_{ij} + \epsilon_{ij},$$

Where c_k are hand-engineered constants, P_{ij} is a political influence term, d is a cultural influence term, and ϵ_{ij} is an error correction term. (Helpman et al., 2008)

2.2 Country Classification

The World Bank defines four income groups for all countries in the world, namely: high-, upper-middle, lower-middle, and low-income. The division into these income groups is based on the total annual income called the gross national income (GNI) per capita. The GNI of a country gives an idea of its economic strength and weaknesses and in general, the standard of living of the average citizen. Countries are classified into various income groups if their GNI falls within a certain threshold, as shown in table 1 (Team, 2017). This classification by income levels can be used to measure progress over time or analyze data for countries falling into the same income groups.

Table 1: Country GNI and income group - World Bank, 2017.

Income Group	GNI threshold
lower	1,005 and below
lower-middle	1,006 - 3,955
upper-middle	3,956 - 12,236
high	12,235 and above

Table 2: Summary of data features and representation.

Feature	Notation	Size	Representation
nodes	$\mathcal{V}$	111	countries
node features	X	38	population etc.[1]
edges	$\mathbf{A}$	476	trade indicator
edge weights	$\mathcal{E}$	476	net trade val (USD)
node labels	$\mathcal{Y}$	4	income group

2.3 Graph Neural Networks

Given a simple graph $\mathcal{G} = (\mathcal{V}, X, \mathbf{A}, \mathcal{E})$ that contains a single type of relationship and no self-loops with individual entities —i.e., countries, referred to as nodes $\mathcal{V}$ with real-valued features

$\mathbf{X} \in \mathbb{R}^{|\mathcal{V}| \times D}$. Here, $|\mathcal{V}|$ and D are the numbers of nodes and the dimensionality of node features, respectively. The dense square matrix $\mathbf{A} \in \mathbb{R}^{|\mathcal{V}| \times |\mathcal{V}|}$ is known as the adjacency matrix and $\mathbf{a}_{ij} = 1$ if there exists an edge between nodes i and j and zero otherwise. $\mathcal{E}$ is the edge weights matrix whose entries are the weights. $\mathbf{a}_{ij}$.

Graph Neural Networks (GNNs) are a family of approaches that aim to generalize neural networks, developed for Euclidean data, to graphs (Scarselli et al., 2009). Typical tasks on graph-structured data involve link prediction, where the goal is to predict potential edges between nodes, and node classification where the classifier has to predict a label $y \in \mathcal{Y}$ (Kipf & Welling, 2016a; Bhagat et al., 2011; Zhang & Chen, 2018). While there are many other interesting problems with graph-structured data, we focus on the problem of link prediction and node classification and direct the interested reader to the following surveys for more information (Hamilton et al., 2017).

3 Data and Tasks

We now outline our proposed approach to modeling bilateral trade using graph representation learning. We first describe the basic components of a typical graph and relate each to a component in our data. Our primary goals are to (1) predict potential trade partners, and (2) classify countries into their respective income groups. These are essentially multi-class node classification and link prediction tasks. We trained Graph Neural Network models and baseline models to perform the tasks mentioned above. In the next subsection, we talk about how we collected the data, the representation approach we took, and the GNN models adopted for the downstream tasks.

3.1 Data Collection and Representation

The data used for this study are taken from two different sources: the United Nations Comtrade Database and Kaggle. The United Nations Comtrade Database[2] is an international trade database containing the reporter-partner trade statistics collated for about 170 countries over a certain period of time. These trade statistics include (1) imports, exports, re-exports, and re-imports, (2) commodities exchanges between the trade partner and reporter, (3) trade value in US dollars.

The data retrieved from Kaggle, on the other hand, contains the profile of specific countries, which included geographical, financial, geological, and other information. To ensure consistency, we used data for a particular year and accumulated the trade and profile information for a total of 111 countries together, along with their income groups, which are used as target labels.

Each country considered is a node in our graph and contains 38 node features, which are simply the collected profile information. We then used the net trade balance between the countries to construct an adjacency matrix such that there is an edge between the countries if the trade balance was not zero and vice versa. An entry of 1 is assigned if there is an edge and 0 otherwise. The trade values are in US dollars and constitute the edge weight matrix. A summary of features and the representation is provided in Table 2.

4 Experiments

We evaluate our approach to modeling bilateral trade using GNNs in two settings: link prediction of withheld edges between trading countries and income classification of countries (node classification) as a separate downstream task. We train all GNN based models using PyTorch Geometric (Fey & Lenssen, 2019) using 80% and 20% for training and test sets. For optimization of model parameters, we use the Adam optimizer (Kingma & Ba, 2014), while hyperparameters are tuned using Bayesian optimization (Snoek et al., 2012; Brochu et al., 2010).

Setup and Baselines. In addition to GNNs, we test a multi-layer perceptron (MLP) and a logistic regression model as baseline models for node classification. Both MLP and the logistic regression model consume node features as input, but critically do not have access to any underlying graph structure in the form of an adjacency matrix. We hypothesize that effective learning requires the

[2]https://comtrade.un.org/data/

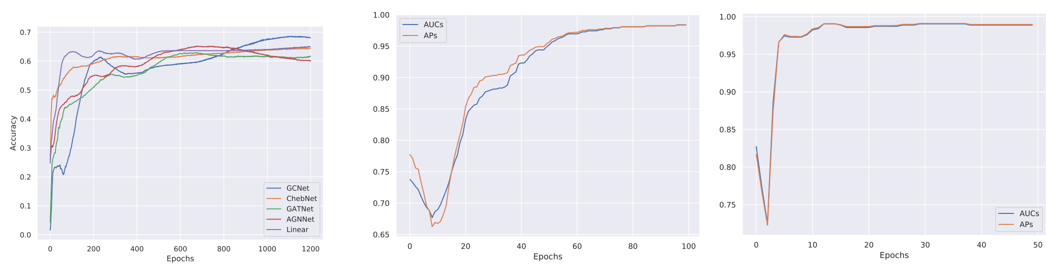
utilization of local neighborhood information available via the adjacency matrix —i.e., adoption of specific domestic trade policies in one country can influence similar policies to its neighbors.

4.1 Link Prediction

In the link prediction task, we used the graph autoencoder (GAE) and variational graph autoencoder (VGAE) (Kipf & Welling, 2016b) to learn a latent representation of the input graph. The input graph is having few observed edges and hence a sparse adjacency matrix.This input graph is fed into the link prediction model, which then reconstructs a new adjacency matrix representing a new neighborhood structure for each node in the graph. We evaluate the reconstruction accuracy using the area under the curve (AUC) and average precision (AP) metrics. In Table 4, we report high AUC and AP scores for both GAE and VGAE. This is indicative of how well these models are reliably able to reconstruct the adjacency matrix from the learned latent representation.

4.2 Node Classification

We used the graph convolution network (GCN) (Kipf & Welling, 2016a), ChebNet (Defferrard et al., 2016), graph attention network (GAT) (Veličković et al., 2018) and attention-based graph neural network (AGNN) (Thekumparampil et al., 2018) models described in Section 2 to perform a multi-class node classification with the input graph. We split the data into train and test sets. We do this by randomly masking out 20% of the total nodes and edge indices from the adjacency matrix and using the 80% for training. The learned model is then used to predict labels for the masked out set of nodes. We then report the classification accuracy on the test accuracy as a measure of model performance. We summarize results denoting mean results after 100 runs in Table 3. We report that the GCN has the best accuracy score after 1200 epochs where we do an early stopping to avoid deterioration of model performance, as was observed. ChebNet also compares competitively with the linear baseline model.



a b c

Figure 1: (a) Model performance on node classification over 100 runs (b) AUC and AP scores on reconstruction with GAE (c) AUC and AP scores on reconstruction with VGAE

Table 3: Results for the multi-class node classification task

	GCN	ChebNet	GAT	AGNN	Linear	Logistic Reg
Test Accuracy	**0.6812**	0.6436	0.6158	0.6003	0.6491	0.5758

Table 4: Results for the link prediction task

	GAE	VGAE
AUC	0.9840	**0.9888**
Average Precision	0.9835	**0.9896**

5 Discussion and Conclusion

In this paper, we approach modeling bilateral trade and related downstream tasks — potential trade partners prediction among countries and income level classification — as a problem in graph representation learning. We leverage historical mutual trade relationships first to construct a graph and where nodes are countries and edges represent active trade between any two given countries before utilizing graph neural networks. Our approach naturally points to a new direction machine learning, particularly graph representation learning and application in the field of Economics. Empirically, we confirm that our approach does well for the intended tasks and can potentially aid future trade analysis. While we considered modeling trade as a static graph an exciting future direction is to model the time evolution of bilateral trade as a dynamic graph. This will encourage analyses of (1) how countries evolve from one income class to the other with time and (2) how trade activities between countries change over time . In the latter case, a temporal prediction of an edge between any two countries will be an indication of how likely they will partner in trade in the future.

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