BILATERAL TRADE MODELING WITH GRAPH NEURAL NETWORKS

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Our work

- Data-driven and graph representation learning approach to modeling bilateral trade between countries
- Predicting potential trade partners → link prediction problem
- Classifying countries into income levels → node classification problem
    - Income Levels
        - High
        - Upper-middle
        - Lower-middle
        - Lower

Motivation I

Gravity model

GDP of country i

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

GDP of country j

constant

Trade flow (i, j)

Geographical distance (i, j)

Motivation I

Gravity Model

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

$$\ln F_{ij} = c_0 + c_1 \ln \underline{GDP}_i + c_2 \ln \underline{GDP}_j + c_3 \ln \underline{D}_{ij} + \underline{c_4 d + c_5 P_{ij} + \epsilon_{ij}}$$

- c_k - hand-engineered constants
- P_{ij} - political influence term
- ϵ_{ij} - error correction term
- d - cultural influence

Motivation I

Gravity Model

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

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- c_k - hand-engineered constants **Difficult** ❗

Motivation I

Gravity Model

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

Not informed by previous trade information ❗

Motivation II

- Past trade information between countries may contribute to their income level prediction

Data and Representation

Data sources: The United Nations Comtrade Database (UNCD), Kaggle

UNCD: Reporter-partner trade statistics

- imports and exports
- trade value in USD

Kaggle: Countries profile

- financial
- geographical
- income level

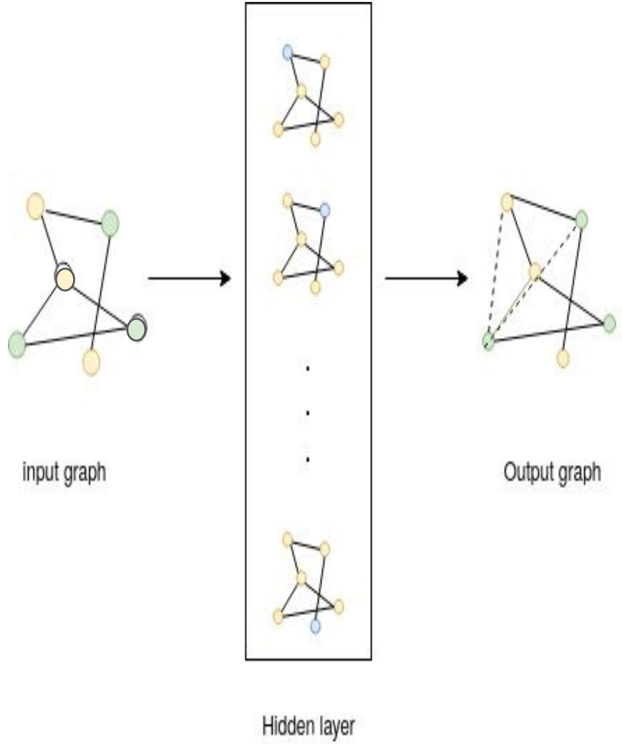
Data and Representation

Feature	**Notation**	**Size**	**Representation**
nodes	$\mathcal{V}$	111	countries
Node features	X	38	ie. population
Edges	A	476	trade indicator
Edge weights	$\mathcal{E}$	476	net trade value (USD)
Node labels	$\mathcal{Y}$	4	Income levels

Table 2: summary of data features and representation

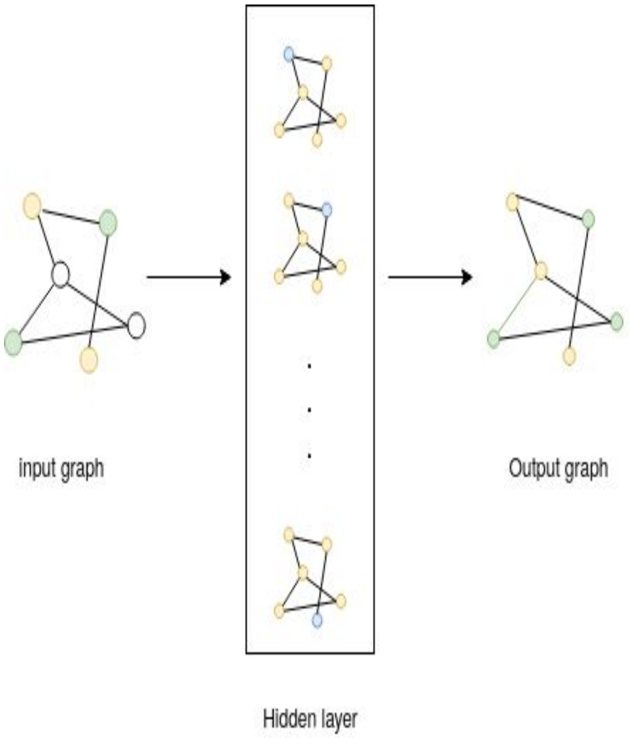
Tasks

- Trade partner prediction:



Tasks

- Income level prediction:



Tasks and Exp’tal setup

- **Country Classification**: Predicting the income levels of countries
  - Graph Convolutional Network (GCN)
  - Attention-based Graph Neural Networks (AGNN)
  - Graph Attention Network (GAT)
  - Chebyshev Convolution Networks (ChebNet)
- **Trade Partner prediction**: Predicting potential trade partners in trade graph
  - Graph Autoencoder (GAE)
  - Variational Graph Autoencoder (VGAE)

Tasks and Exp’tal setup

- Baselines -
  - Multilayer perceptron (MLP)
  - Logistic regression

Results

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

Table 3: Mean node classification results, 1200 epochs, 100 runs

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

Table 4: Results for link prediction task

Results - Node classification

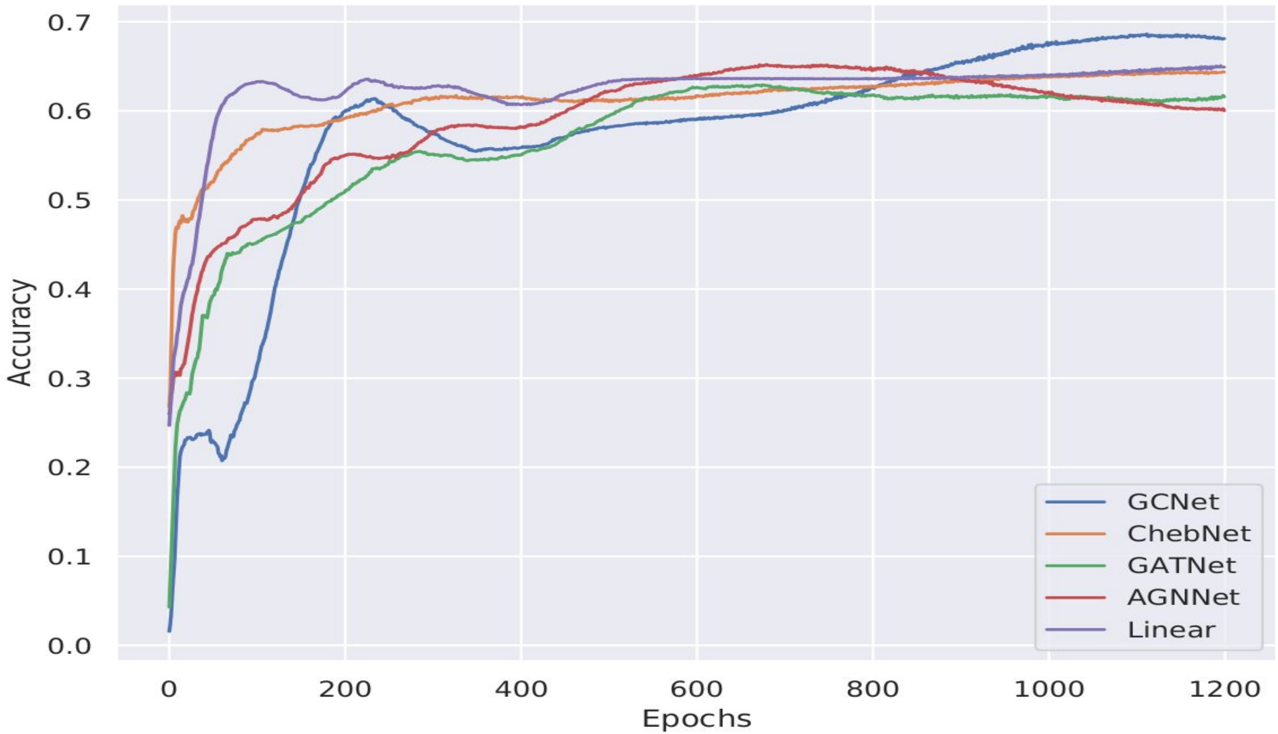


Fig 1: Model performance on node classification averaged over 100 runs

Results - Link Prediction

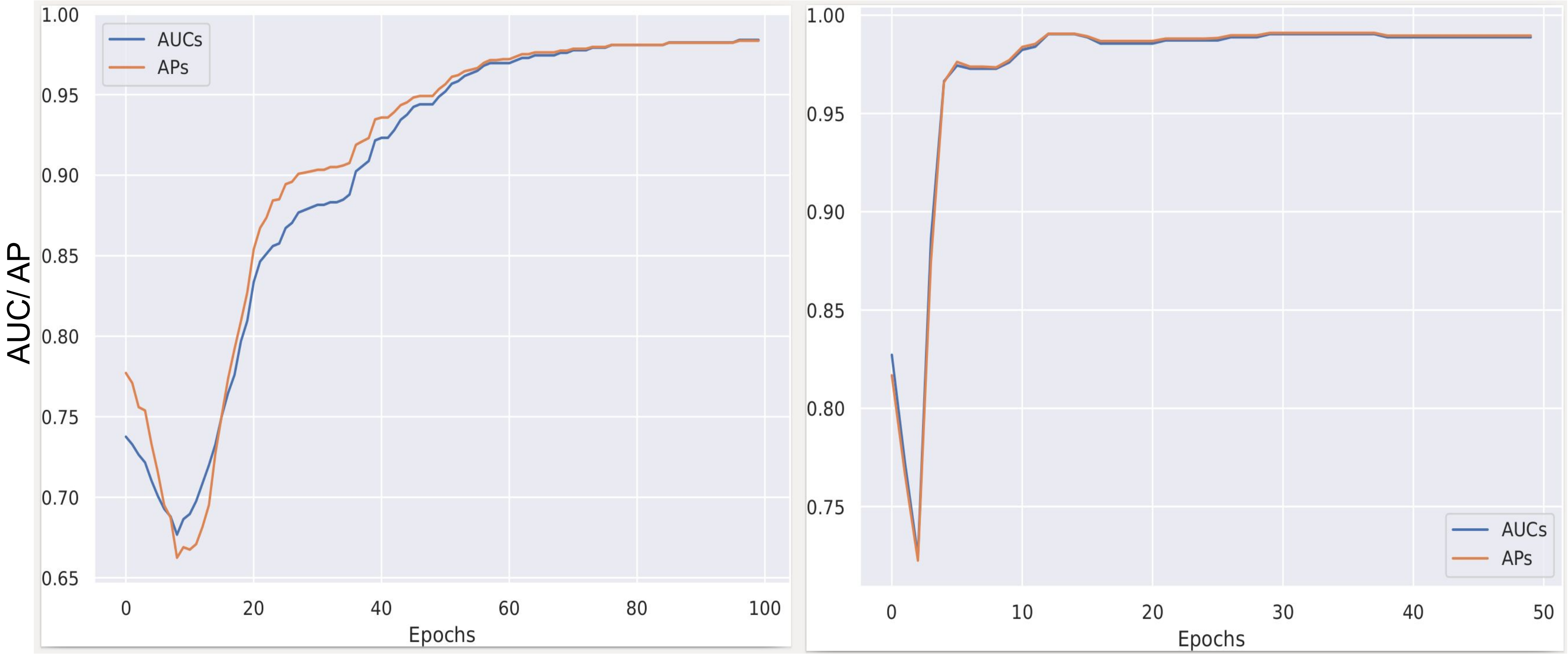


Fig 2: AUC and AP scores on reconstruction with (a) GAE (b) VGAE

Conclusion

- Here, we encourage a graph representation learning approach to trade partner prediction and income level classification of countries.
- We use historical trade data to construct a graph for active trade relationship between countries.
- Up to 98% accuracy on predicting trading partners and 68% on income level classification
- One future direction is to consider a dynamic graph instead of a static one
    - How *trade activities* evolve with time -- temporal prediction of *edges* between countries
    - How *income levels* of countries change with time

Thank You

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