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

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

- GDP of country i
- GDP of country j
- Trade flow (i, j)
- Geographical distance (i, j)
- Constant
Motivation I

Gravity Model

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

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

- \( c_k \) - hand-engineered constants
- \( P_{ij} \) - political influence term
- \( \epsilon_{ij} \) - error correction term
- \( d \) - cultural influence
Motivation I

Gravity Model

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

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

- \(c_k\) - hand-engineered constants

Difficult ⚠️
Motivation I

Gravity Model

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

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

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

<table>
<thead>
<tr>
<th>Feature</th>
<th>Notation</th>
<th>Size</th>
<th>Representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>nodes</td>
<td>$\mathcal{Y}$</td>
<td>111</td>
<td>countries</td>
</tr>
<tr>
<td>Node features</td>
<td>$X$</td>
<td>38</td>
<td>ie. population</td>
</tr>
<tr>
<td>Edges</td>
<td>$A$</td>
<td>476</td>
<td>trade indicator</td>
</tr>
<tr>
<td>Edge weights</td>
<td>$\mathcal{E}$</td>
<td>476</td>
<td>net trade value (USD)</td>
</tr>
<tr>
<td>Node labels</td>
<td>$\mathcal{Y}$</td>
<td>4</td>
<td>Income levels</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>GCN</th>
<th>ChebNet</th>
<th>GAT</th>
<th>AGNN</th>
<th>Linear</th>
<th>Logistic Reg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test Accuracy</td>
<td>0.6812</td>
<td>0.6436</td>
<td>0.6158</td>
<td>0.6003</td>
<td>0.6491</td>
<td>0.5758</td>
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</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>GAE</th>
<th>VGAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUC</td>
<td>0.9840</td>
<td>0.9888</td>
</tr>
<tr>
<td>Average Precision</td>
<td>0.9835</td>
<td>0.9896</td>
</tr>
</tbody>
</table>

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
References

James E Anderson. The gravity model: Annual review of economics. 2011


Matthias Fey and Jan E. Lenssen. Fast graph representation learning with PyTorch Geometric. In ICLR Workshop on Representation Learning on Graphs and Manifolds, 2019


Patrick Steiner. Determinants of bilateral trade flows, 2015