A Survey on Data Visualization Techniques for International Trade

Anthony Bias[1], Raga Mouni Batchu[1], Stefanie Amiruzzaman[1], Md Amiruzzaman[1], Rizal Mohd Nor[2]

[1]West Chester University, Pennsylvania, United States

[2]International Islamic University, Malaysia

Received: September 27, 2025; Revised: November 19, 2025; Accepted: December 11, 2025; Published: December 23, 2025

Abstract

In the globalized world we live in, international trade plays a massive role in providing people with products from bananas to computers. With this in mind, a good understanding of international trade is important for a firm understanding of the world and essential for any large private or state actors to plan policy. However, with the sheer number of different products to trade and countries to trade them, there is a lot of data to analyze. Data visualization can show this data in a much easier form for humans to understand and analyze. This paper explores various techniques and tools for visualizing international trade data after a brief look at some relevant concepts.

Keywords: data visualization, human, international trade, network analysis.

1 Introduction

International trade is used to meet the material needs of many people across the globe. Its importance in keeping so many people alive behooves anyone seeking to understand the modern world to have a better understanding of it.

Data visualization helps researchers analyze large amounts of data by showing it in a form that makes it easier for humans to understand. Considering that international trade involves the exchange of myriad types and quantities of goods between many different countries by different means of transportation (among other factors), there is a lot of data to be collected and analyzed about it; this makes data visualization useful for this domain.

This paper seeks to review the literature on the intersection of international trade and data visualization to discuss different approaches being used. The rest of the article is as follows. Section II covers some background information that is helpful to know when talking about international trade. Section III details numerous techniques for visualizing international trade data. Section IV describes two interactive tools for visualizing international trade. Section V concludes the paper.

2 Background Information

There are many aspects of international trade and numerous variables that researchers consider, along with several important concepts that help in interpreting global trade data. This section introduces several concepts that are relevant when trying to make sense of international trade data, explains why they are relevant, and briefly summarizes them.

2.1 Network Analysis

International trade can quite intuitively be modeled as a graph where each country is a vertex and trade between each individual country is an edge, and has been modeled as such by economists as far back as the 1940s (Hilgerdt 1943). Data in this category are concerned primarily with which country/region is trading with which other countries/regions; trade volume (for bilateral trade taken as a whole or imports and exports individually) between countries or types of products traded may be included, but are examined through the lens of how the network is structured.

One aspect of network topology that is often subject to study is the presence and composition of communities. A community is a group of vertices in a network that has many edges between members of the group but few edges between members and nonmembers (Newman 2018). Applying community detection to international trade networks helps reveal the structure of those networks; (Jiang et al. 2021), for example, showed that the global primary product trade network fell into 3 large communities with a few countries having significantly more connections (bilateral trade with other countries), as well as significantly more high weight (trade volume) connections, than most other countries in their community. Communities can also be analyzed for their consistency (Lee et al. 2021), which was used by Cho et al. (2023) to show that a country's membership inconsistency (see Figure. 1) impacts its instability in terms of external intervention.

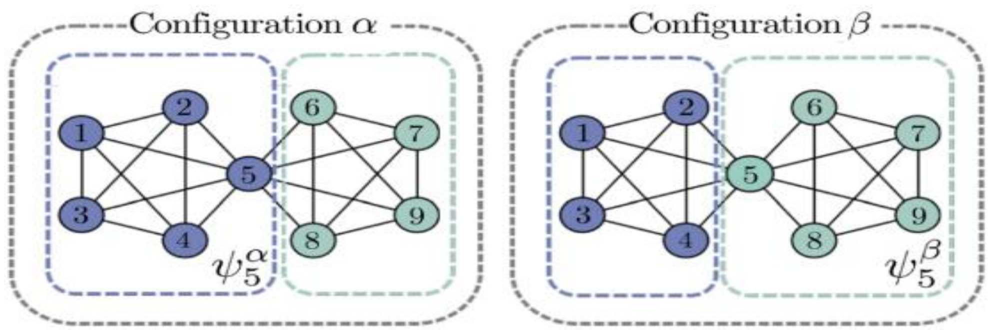

Figure 1: Two alternate conFigureurations for dividing a simple network into communities. Notice that there are 2 groups of 5 nodes and that node 5 is where they overlap. Because it has the same number of edges for each group, which community node 5 belongs to tends to vary between different conFigureurations of community detection algorithms, while the other nodes will consistently belong to the same community. This is a membership inconsistency. Image taken from (Cho et al. 2023, Figure. 2a) and reused under Creative Commons CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

Besides looking at which nodes are connected and how strong those connections are, network analysis often involves studying how nodes connect to their neighbors. To that end, researchers employ a useful concept: subgraphs. A graph G_s is a subgraph of the graph G if the set of G_s's nodes and lines are subsets of G's nodes and lines respectively (Wasserman and Faust 1994, 97). While there are many types of subgraphs that can be made, triads are of particular interest to researchers. "A triad is a subgraph consisting of three nodes and the possible lines among them" (Wasserman and Faust 1994, 99). Triads are the smallest possible graphs that truly have the character of a society (Robert A. Hanneman and Riddle 2005). In existing literature, triadic analysis has empowered researchers to gain deep insights into social systems such as discovering that the role a of a country in a given triad type correlates with its stage of economic development (Shutters and Muneepeerakul 2012) and discovering that the international energy trade network is topologically stable even after having 80% of its nodes removed, indicating that it is robust against disruptions (Shutters et al. 2022).

Another aspect of network topology useful to the study of international trade is its centrality statistics, which are used by researchers to compare the roles of nodes within a network (Gönçer-Demiral and İnce-Yenilmez 2022). There are four centrality statistics used by the literature reviewed in writing this paper: degree centrality, which is defined the degree of a node (i.e. the number of other nodes the node in question is connected to); closeness centrality, which is derived from the average distance between a node and any other node in the network; betweenness centrality, which is based on how often a given node appears in the shortest path between pairs of nodes in the network; and eigenvector centrality which, roughly speaking, is based on how central all of the neighbors of a given node are (Jackson 2010). Centrality statistics have been integral in some serious research, such as establishing localization (a feature of eigenvector centrality) as a sign of impending global crises (Alves et al. 2022) and examining the structure of China's Belt and Road Initiative (Liu et al. 2018).

2.2 Products

A necessary part of trade (international or otherwise) is a commodity to exchange, whether it be raw materials like ore and crude oil, more labor-intensive products like machinery, or even intangible goods like software or entertainment media. With all the types of products there are to exchange, researchers can use information related to products traded to gain insights into the global economy. Besides the previous truism about trade requiring something to trade, the kind of products a country produces strongly influences what and with whom that country trades, its development level, and inequality both within and outside its borders. To better understand this, and to illustrate the importance of product data in the study of international trade more broadly, it is helpful to take a moment to discuss the concept of comparative advantage.

A. Comparative Advantage

Comparative advantage concerns how a country that conducts foreign trade can efficiently allocate resources among its commodity producing sectors, specifically whether it should produce certain goods itself or rely on imports from other countries to meet demand; ideally, the country can meet its demand for a given product while minimizing the resources spent to acquire it, leaving more resources to acquire other goods and services (Warr 1994). Ricardo (one of the earliest and most noteworthy economists to expound the principle) expressed this principal in a thought experiment: suppose it takes England the work of 100 people to meet its supply of cloth and the work of 120 people to meet its yearly demand of wine; in addition, suppose it takes Portugal the work of 90 and 80 people respectively towards these ends. Intuition may lead one to think that, due to the lower cost of production for both commodities, both England and Portugal should source both commodities from Portugal. However, Ricardo argues that it would be most efficient from the perspective of both countries for England to source cloth locally and import wine from Portugal, and vice versa for Portugal. This is because neither country would need to divert capital away from industries in which it is most effectively mobilized. In Ricardo's own words, "[C]loth cannot be imported into Portugal, unless it sells there for more gold than it costs in the country from which it was imported; and wine cannot be imported into England, unless it will sell for more there than it costs in Portugal." (Ricardo 2010)

The model just espoused is, of course, quite simplistic. In the two centuries since Ricardo expounded the principle, there have been models that seek to account for the complex factors involved with international trade while still preserving the core idea of relative costs to produce goods predicting trade relationships and benefiting all involved (Jones 2008; Costinot 2009), as well as others who argue it is has so little use in policy or prediction making that it should be dismissed entirely in favor of another concept (Warr 1994; Schumacher 2013). A thorough exploration of critiques, defenses, and modifications of the principle of comparative advantage is beyond the scope of this paper; the brief explanation given is sufficient both to emphasize product data's importance in international trade research and to provide the background to understand an aspect of international trade that lends itself well to data visualization: the product space.

B. The Product Space

A country may have a set of endowments that make different commodities more or less costly to produce, but it can only grow its economy so much by juggling which commodities it sources locally and which it sources from foreign trade. As new commodities are introduced into the world market, the country will be repeatedly faced with the local vs import decision; regardless of the choice, the mobilization of existing capital into new industries will be necessary. How can one know which industry a country can branch into to actualize the benefits of its comparative advantage, and how can one predict which industries a country will branch into given its existing industries? While many models grouping similar products together based on various factors have been made over the years based on a priori notions of similarity, a widely used and relatively recent model, the product space, offers an explanation based on trade data for many different countries (Hidalgo et al. 2007).

Core to the concept of the product space is the idea that if two products require similar combinations of factors to produce (meaning they're related), then they should both tend to be produced at the same time by any given country and vice. versa (Hidalgo et al. 2007). Two products are considered similar based on the conditional probability of a country having a relative comparative advantage (i.e., whether a given country's share in exports for a given product is greater than its share of total (Balassa 1965)) for both products (Hidalgo et al. 2007).

3 Visualization Techniques

As the previous section has shown, researchers use a multitude of different models to make sense of international trade. For those models to be put into practice, data from the real world is required; the massive and complex datasets related to international trade mean the subject can benefit greatly from the use of information visualization, which enables quick and efficient interaction with large datasets to make discoveries (Gershon et al. 1998).

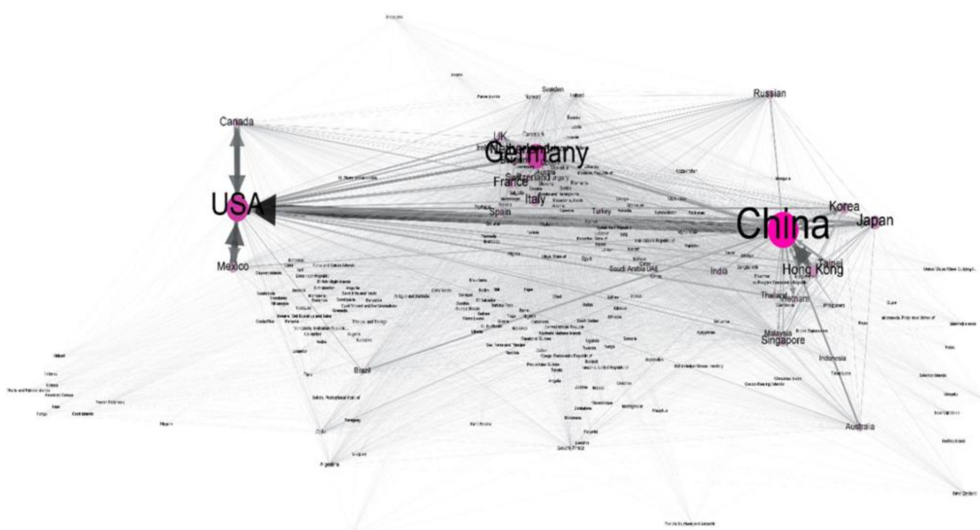

Figure 2: Directed node-link diagram of trade flow in the world trade network that uses a geo layout algorithm to space the nodes relative to each other, similar to a world map. Trade volume is represented as the thickness of each edge. Taken from (Gönçer-Demiral and İnce-Yenilmez 2022, Figure. 1) by Gönçer-Demiral and İnce-Yenilmez. Reuses following Springer's open access license (https://www.springeropen.com/about/policies/reprints-and-permissions).

3.1 Node-link Diagrams

Considering that international trade consists of many networks, node-link diagrams are a natural choice to show the relationship between data points. The aspect of international trade most intuitively visualized with the node-link diagram is trade flow. A basic node-link diagram of global trade flow might have each country as a node and trade flow between each country as an edge (directed or undirected, depending on what is more useful for a particular study). If a researcher wants to show the volume of the trade flow for edges, they often use thickness, with more thickness meaning a higher volume and vice versa. Figure. 2 shows some node-link diagrams that meet this description.

One downside of node-link diagrams is that, given a sufficiently large or dense network and a naive node layout algorithm, a node-link diagram can be visually cluttered and thus difficult to read (Didimo et al. 2024). While none of the link diagrams used in the literature reviewed reached the level of "hairball drawing" (Didimo et al. 2024, Figure. 1.3a), the diagrams are often complex to the point where it is hard to visually glean all but the most general information. This comports with the findings from (Huang et al. 2009), which show that even node link diagrams with as few as 25 nodes and 98 edges (trifling amounts compared to what are used in node link diagrams of the international trade network) are sufficiently large and dense to create enough cognitive load to cause errors in the performance of complex tasks. One potential technique to make node-link diagrams easier to understand is the topological attribute map (Preiner et al. 2020).

Often, researchers aren't interested in the flow of all products through all countries in the world trade network; they may also want to view the network at different periods of time. Handling this is usually as simple as putting the different divisions of data into different node-link diagrams. Figure. 3 shows a visualization applying all three constraints.

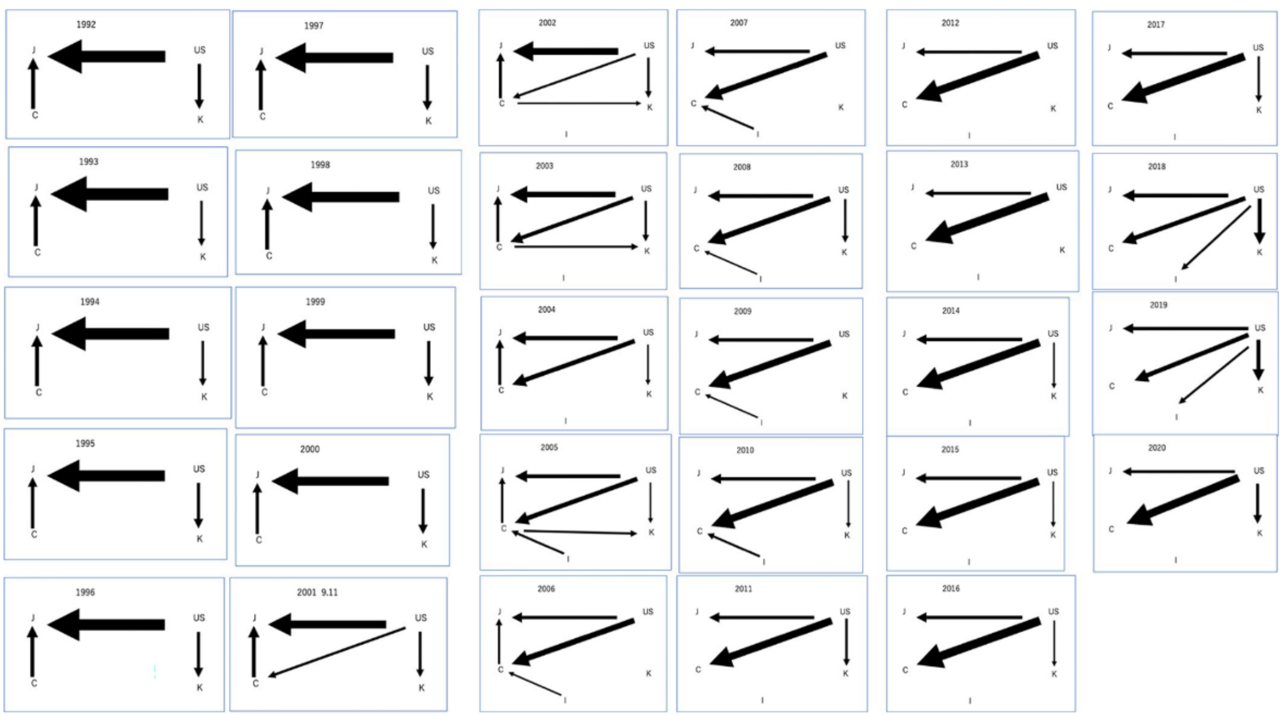

Figure 3: Yearly trade flow of raw materials between the US, China (C), Japan (J), South Korea (K), and India (I) from 1992-2020 (Yazawa 2023, Figure. 8). Yazawa's work is reused here under the Creative Commons CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

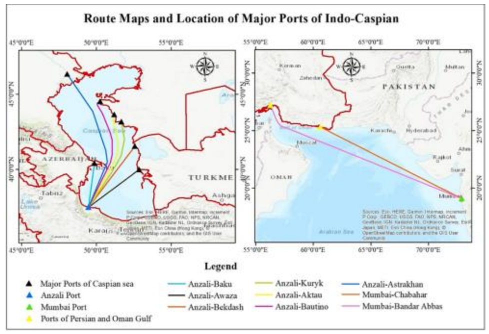

Figure 4: A map of routes and ports from a paper studying trade between India and countries in the Caspian Sea (Khan et al. 2023, Figure. 3). This Figure from Khan et al. reused under the Creative Commons CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

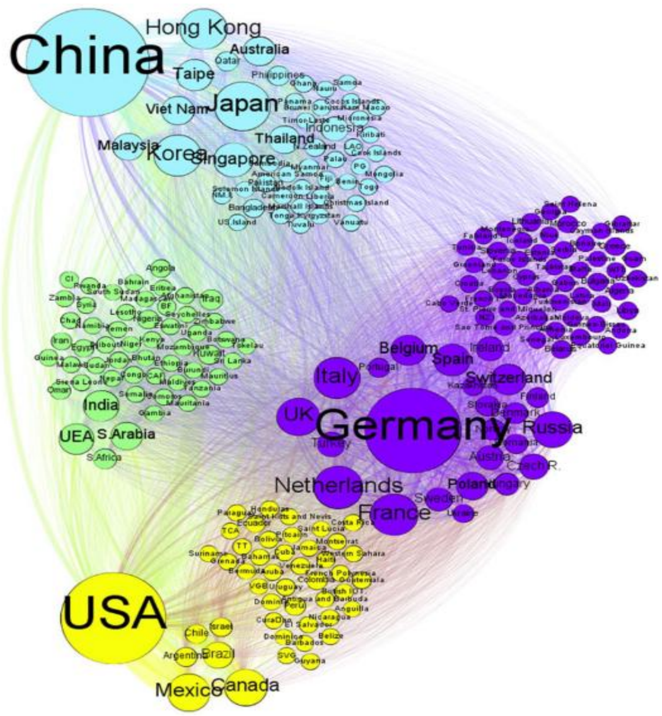

Figure 5: Visualization of a community analysis of the world trade network in 2019 (Gönçer-Demiral and İnce-Yenilmez 2022, Figure. 4a). This Figure by Gönçer-Demiral and İnce-Yenilmez is reused following Springer's open access license (https://www.springeropen.com/about/policies/reprints-and-permissions).

A node-link diagram can show more than just who is trading with whom and the magnitude of that trade. For instance, node-link diagrams are an effective way to show community structure. Color, positioning, or some combination of both can be used to display which countries are part of which community, as can be seen in Figure. 5. Using different colors for connections between clusters (communities in this case) and within clusters can enhance viewers' ability to perceive how connected nodes are to similar nodes (Reimann et al. 2023). Further, some orderable node-link layouts—like arc diagrams, symmetrical arc diagrams, and radial diagrams—show promise in aiding users to count clusters with more speed and accuracy (Al-Naami et al. 2025).

3.2 Maps

Since international trade deals with the spread of goods across the world, it is not surprising that maps are used for visualization of international trade data. Maps lend themselves particularly well to data that are spatial in nature, notably trade routes.

In its simplest form, a map can show the world (or a region of the world) with some relevant features marked, such as borders, trade routes, and ports (Figure. 4). This works well for information that is likely to remain stable over a long period of time. For scalar data that varies by region, choropleth maps are a popular choice (though care must be taken to account for biases arising from human perception, such as the dark-is-more bias and area-size bias) (Schiewe 2019). When looking at such data over time, banded choropleth and tile maps show promise effectively helping users understand regional (though not global) changes over time (Calvo et al. 2023).

Different kinds of maps used for tracking trade routes used by vessels. (a) shows vessel location trends from January 2012 to March 2016, with purple being an upwards trend, green being a downward trend, and the shade depending on confidence (Arco et al. 2021, Figure. 10). (b) uses linear kernel density based on real-time cargo ship locations to show trade routes (Shen et al. 2020, Figure. 11b). Both Figures are reused under the Creative Commons CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

There is one type of map that is different enough from other map visualizations that it warrants its own section to discuss.

A) **B)**

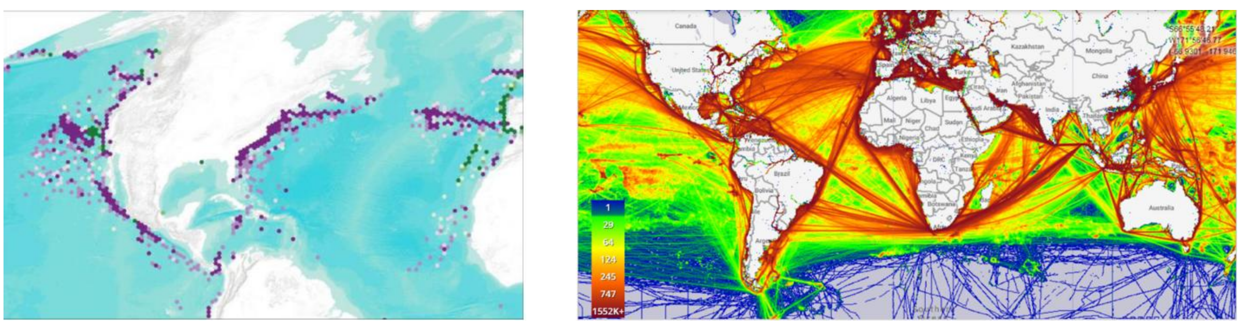

Figure. 6: Different kinds of maps used for tracking trade routes used by vessels. (a) shows vessel location trends from January 2012 to March 2016, with purple being an upwards trend, green being a downward trend, and the shade depending on confidence (Arco et al. 2021, Figure. 10). (b) uses linear kernel density based on real-time cargo ship locations to show trade routes (Shen et al. 2020, Figure. 11b). Both Figures are reused under the Creative Commons CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

3.3 Digital Trade Feature Map

The digital trade feature map (DTFM) was created to study trade features for product types at a small scale. Other methods, including the product space, were too complicated to be used for the researchers' focus of studying bilateral trade between the US and China (Ye et al. 2020). The digital trade feature map makes a uses a grid to show different areas corresponding to different product categories by HS (Harmonized Product Description and Coding System) 2-digit codes; each cell corresponds to a product type by HS 4-digit code (Ye et al. 2020). In the literature surveyed for this paper, there were only 2 that used the DTFM (Ye et al. 2020; Han et al. 2023). Figure. 7 shows a DTFM in action.

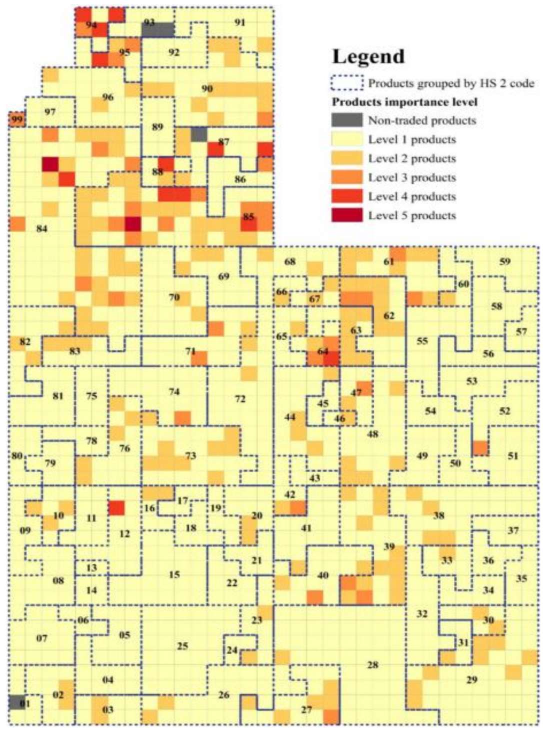

Figure 7: Digital trade feature map based on US-China bilateral trade from 1992 from 2018 (Ye et al. 2020, Figure. 5). Reused under Creative Commons CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

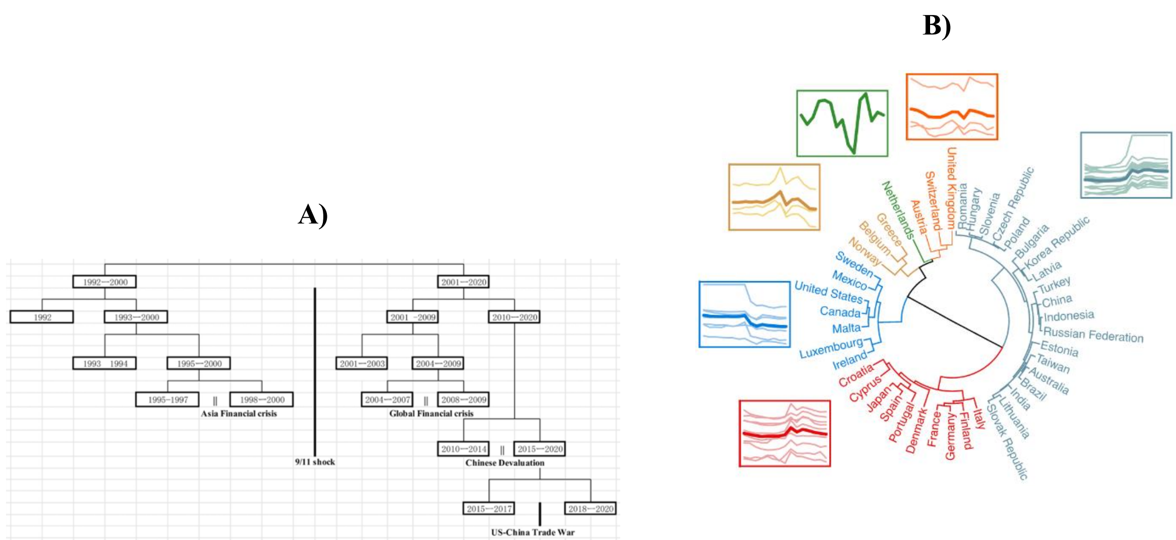

Figure. 8: Dendrograms. (a) is a dendrogram of hierarchical year span clusters [25, Figure. 9]. (b) is a dendrogram of economic dominance of buyers based on eigenvector centrality from 2000-2014 [12, Figure. 3]. Both Figures reused under Creative Commons CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

3.4 Sankey Diagrams

A Sankey diagram is a visualization technique that displays flows from one place to another. In the Sankey diagrams found in the literature reviewed for this paper, there is typically a group of buckets on the left and right sides of the diagram with flows going from one bucket to another. The buckets are arranged vertically on top of each other in descending order, and the thickness of the flow lines corresponds to the magnitude of the flow being represented. This combination of properties makes it easy to discern the relative size of flows compared to certain other flow diagrams (Gutwin et al. 2023). If more data than just flow needs to be tracked, there exist hybrid Sankey diagrams (Lupton and Allwood 2017).

3.5 Dendrograms

Sometimes a researcher needs to show a visualization for a hierarchical relationship. In the literature reviewed for this paper, dendrograms tend to be employed when some form of data clustering is used, such as clustering by similarity of trade data over spans of years (Yazawa 2023, Figure. 9), clustering by community along different co-occurrence thresholds (Cho et al. 2023, Figure. 3), and economic dominance of different trade blocs (Alves et al. 2022, Figure. 3). Researchers of international trade may find use in other cluster visualization techniques, such as stacked trees (Bisson and Blanch 2012) or the hybrid approach used in (Blanch et al. 2015). Some dendrograms can be seen in Figure. 8.

Dendrograms. (a) is a dendrogram of hierarchical year span clusters (Yazawa 2023, Figure. 9). (b) is a dendrogram of economic dominance of buyers based on eigenvector centrality from 2000-2014 (Alves et al. 2022, Figure. 3). Both Figures reused under Creative Commons CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

4 Visualization Tools

The visualization methods discussed previously are all static: They can be generated, put in a paper, and looked at, but that is the extent of their use. This is perfectly fine for publications like journals or conference papers where the visualization pertains to the research performed in the paper. However, sometimes researchers want to use visualizations to explore data in order to form new hypotheses, and sometimes the person exploring the data is a non-expert. To this end, some interactive tools were created to facilitate data exploration. This paper covers two of them.

4.1 A Visual Analytics Framework for Spatiotemporal Trade Network Analysis

Created to help researchers explore local trade structures and vulnerabilities while avoiding over-plotting, the model from (Wang et al. 2019) uses triadic analysis to detect anomalies, combines time series analysis with clustering to compare potential anomalies between countries, visualizes trade influences over countries with a diffusion graph, and integrates correlation analysis with anomaly detection to enable visual analysis of the impact of trade-related anomalies on social instability. The tool consists of various visualizations arranged into one interface.

The first view is a correlation-based country-product matrix. The shade of each cell corresponds to the number of correlations, with darker shades meaning a higher number and lighter shades meaning a lower number. The matrix is sorted so that darker shades tend towards being in the top left. Upon selecting one or multiple cells, the user is presented with a detailed view that displays individual correlations. These correlations give a hint of possible links between trade and stability and serve as a starting point for the user to identify a starting point for analysis. Once a country and product pair is selected, more visualizations become available.

One such visualization is the anomaly time series, which makes it easier for users to detect anomalies as they happen over time and possibly hypothesize what world event said anomalies correspond to. The authors define an anomaly as a sudden rise or drop from the previous year. Users can view the trade measures, triad counts, and social stability by year.

Prominently displayed in the interface is the main choropleth map, which allows users to see the relations between a selected country and the rest of the world with respect to trade measures, dependency and leverage, and triad distribution for a given product. There is also a view of several choropleth maps to show users which other countries are similar to the selected one in terms of anomalies.

In addition to all that was listed, there are also views for tracing how anomalies in one country impact other countries.

4.2 VIEA

VIEA, the visualization tool from (Wu et al. 2024), was created to empower novice users and experienced users who have advanced requirements to conduct economic research. Like the previously discussed tool, VIEA has many different visualizations combined into one interactive interface.

One of the most standout views is the Maptrix view, which looks like a matrix rotated 45° that has lines running from its various cells to different countries on two copies of a world map. It makes exact import and export values clear at the expense of not being able to see the structure of an industry.

Another view shows a graph similar to those discussed, with nodes being countries and trade flows being edges. To reduce clutter, only the biggest trade partner for each country is presented.

Other views included in the interface include: a country list with radar charts with features for each industry category; a comparison view with a world map that users can drag radar charts from the country list onto to see which countries import more from each country that is being compared; a stacked chart of total exports from each industry to help users locate a year they want to investigate; a timeline strip with which users can set the time they are interested in studying; and a tabular view of raw data.

5 Conclusion

This paper covers some concepts useful to understanding international trade, presents several techniques that are used to visualize world trade data, and introduces two tools that allow users to explore said data using various visualization techniques via an interactive graphical user interface. It discusses the advantages and disadvantages of each visualization and provides applications.

We systematically surveyed the fundamental concepts and key techniques employed for visualizing the complex, high-dimensional data generated by international trade. We established that due to the sheer volume and intricate nature of global trade statistics, effective visualization is critical for converting raw data into usable knowledge for policymakers and business leaders. Our review first grounded the discussion in core theoretical frameworks, detailing the utility of Network Analysis concepts, such as community detection, triadic structures, and centrality metrics for modeling trade relationships. Furthermore, we emphasized the importance of product-level data, showcasing the theoretical power of Comparative Advantage and the practical, data-driven mapping provided by the Product Space.

Acknowledgements

This research did not receive any specific grant from any funding agency in the public, commercial or not-for-profit sector.

References

[1] Abdelaal M, Li Y, Gove R & Lex A 2022 'Comparative Evaluation of Bipartite, Node-Link, and Matrix-Based Network Representations', IEEE Transactions on Visualization and Computer Graphics, 1–11. https://doi.org/10.1109/TVCG.2022.3209427.

[2] Al-Naami, Nora, Nicolas Médoc, Matteo Magnani, and Mohammad Ghoniem. 2025. “Improved Visual Saliency of Graph Clusters with Orderable Node-Link Layouts.” IEEE Transactions on Visualization and Computer Graphics 31 (1): 1028–38. https://doi.org/10.1109/TVCG.2024.3456167.
[3] Alves, Luiz G. A., Giuseppe Mangioni, Francisco A. Rodrigues, Pietro Panzarasa, and Yamir Moreno. 2022. “The Rise and Fall of Countries in the Global Value Chains.” Scientific Reports 12 (1): 9086. https://doi.org/10.1038/s41598-022-12067-x.
[4] Arco, E., A. Ajmar, F. Cremaschini, and C. Monaco. 2021. “SPATIO TEMPORAL DATA CUBE APPLIED TO AIS CONTAINERSHIPS TREND ANALYSIS IN THE EARLY YEARS OF THE BELT AND ROAD INITIATIVE – FROM GLOBAL TO LOCAL SCALE.” The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XLIII-B4-2021 (June): 71–78. https://doi.org/10.5194/isprs-archives-XLIII-B4-2021-71-2021.
[5] Balassa, Bela. 1965. “Trade Liberalisation and ‘Revealed’ Comparative Advantage.” The Manchester School 33 (2): 99–123. https://doi.org/10.1111/j.1467-9957.1965.tb00050.x.
[6] Bisson, Gilles, and Renaud Blanch. 2012. “Improving Visualization of Large Hierarchical Clustering.” 2012 16th International Conference on Information Visualisation (Montpellier, France), July, 220–28. https://doi.org/10.1109/IV.2012.45.
[7] Blanch, Renaud, Remy Dautriche, and Gilles Bisson. 2015. “Dendrogramix: A Hybrid Tree-Matrix Visualization Technique to Support Interactive Exploration of Dendrograms.” 2015 IEEE Pacific Visualization Symposium (PacificVis) (Hangzhou, China), April, 31–38. https://doi.org/10.1109/PACIFICVIS.2015.7156353.
[8] Calvo, Luz, Fernando Cucchietti, and Mario Pérez-Montoro. 2023. “Measuring the Effectiveness of Static Maps to Communicate Changes Over Time.” IEEE Transactions on Visualization and Computer Graphics 29 (10): 4243–55. https://doi.org/10.1109/TVCG.2022.3188940.
[9] Cho, Wonguk, Daekyung Lee, and Beom Jun Kim. 2023. “A Multiresolution Framework for the Analysis of Community Structure in International Trade Networks.” Scientific Reports 13 (1): 5721. https://doi.org/10.1038/s41598-023-32686-2.
[10] Costinot, Arnaud. 2009. “On the Origins of Comparative Advantage.” Journal of International Economics 77 (2): 255–64. https://doi.org/10.1016/j.jinteco.2009.01.007.
[11] Didimo, Walter, Giuseppe Liotta, and Fabrizio Montecchiani. 2024. “Network Data Visualization.” In Handbook of Social Computing, edited by Peter A. Gloor, Francesca Grippa, Andrea Fronzetti Colladon, and Aleksandra Przegalinska. Edward Elgar Publishing. https://doi.org/10.4337/9781803921259.00007.
[12] Gershon, Nahum, Stephen G. Eick, and Stuart Card. 1998. “Information Visualization.” Interactions 5 (2): 9–15. https://doi.org/10.1145/274430.274432.
[13] Gönçer-Demiral, Dilek, and Meltem İnce-Yenilmez. 2022. “Network Analysis of International Export Pattern.” Social Network Analysis and Mining 12 (1): 156. https://doi.org/10.1007/s13278-022-00984-8.
[14] Gutwin, Carl, Aristides Mairena, and Venkat Bandi. 2023. “Showing Flow: Comparing Usability of Chord and Sankey Diagrams.” Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (Hamburg Germany), April, 1–10. https://doi.org/10.1145/3544548.3581119.
[15] Han, Xiaoyang, Sijing Ye, Shuyi Ren, and Changqing Song. 2023. “Using the DTFM Method to Analyse the Degradation Process of Bilateral Trade Relations Between China and Australia.” Sustainability 15 (9): 7297. https://doi.org/10.3390/su15097297.
[16] Hidalgo, C. A., B. Klinger, A.-L. Barabási, and R. Hausmann. 2007. “The Product Space Conditions the Development of Nations.” Science 317 (5837): 482–87. https://doi.org/10.1126/science.1144581.
[17] Hilgerdt, Folke. 1943. “The Case for Multilateral Trade.” The American Economic Review 33 (1): 393–407. http://www.jstor.org/stable/1819026.
[18] Huang, Weidong, Peter Eades, and Seok-Hee Hong. 2009. “Measuring Effectiveness of Graph Visualizations: A Cognitive Load Perspective.” Information Visualization 8 (3): 139–52. https://doi.org/10.1057/ivs.2009.10.
[19] Jackson, Matthew O. 2010. Social and Economic Networks. Princeton University Press. https://doi.org/10.2307/j.ctvcm4gh1.
[20] Jiang, Haowen, Jiadong Shen, Qiujie Chou, Ziling Dong, and Shenghui Cheng. 2021. “Visual Analytics for the International Trade.” 2021 5th International Conference on Vision, Image and Signal Processing (ICVISP) (Kuala Lumpur, Malaysia), December, 296–301. https://doi.org/10.1109/ICVISP54630.2021.00059.
[21] Jones, Ronald W. 2008. “Heckscher-Ohlin Trade Theory.” In The New Palgrave Dictionary of Economics: Volume 1 – 8, edited by Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-58802-2_717.
[22] Khan, Zainab, Kashif Hasan Khan, and Halil Koch. 2023. “Aggregating an Economic Model and GIS to

Explore Trade Potentials of India-Caspian Countries and a Way Forward for INSTC." Research in Globalization 7 (December): 100154. https://doi.org/10.1016/j.resglo.2023.100154.
[23] Lee, Daekyung, Sang Hoon Lee, Beom Jun Kim, and Heetae Kim. 2021. "Consistency Landscape of Network Communities." Physical Review E 103 (5): 052306. https://doi.org/10.1103/PhysRevE.103.052306.
[24] Liu, Zhigao, Tao Wang, Jung Won Sonn, and Wei Chen. 2018. "The Structure and Evolution of Trade Relations Between Countries Along the Belt and Road." Journal of Geographical Sciences 28 (9): 1233–48. https://doi.org/10.1007/s11442-018-1522-9.
[25] Lupton, R. C., and J. M. Allwood. 2017. "Hybrid Sankey Diagrams: Visual Analysis of Multidimensional Data for Understanding Resource Use." Resources, Conservation and Recycling 124 (September): 141–51. https://doi.org/10.1016/j.resconrec.2017.05.002.
[26] Newman, Mark. 2018. Networks. 2nd ed. Oxford University Press. https://doi.org/10.1093/oso/9780198805090.001.0001.
[27] Preiner, R., J. Schmidt, K. Krösl, T. Schreck, and G. Mistelbauer. 2020. "Augmenting Node-Link Diagrams with Topographic Attribute Maps." Computer Graphics Forum 39 (3): 369–81. https://doi.org/10.1111/cgf.13987.
[28] Reimann, Daniel, André Schulz, Nilam Ram, and Robert Gaschler. 2023. "Color-Encoded Links Improve Homophily Perception in Node-Link Diagrams." IEEE Transactions on Visualization and Computer Graphics 29 (12): 5593–98. https://doi.org/10.1109/TVCG.2022.3221014.
[29] Ricardo, David. 2010. "Foreign Trade." In On The Principles of Political Economy, and Taxation. Project Gutenberg. https://www.gutenberg.org/ebooks/33310.
[30] Robert A. Hanneman, and Mark Riddle. 2005. Introduction to Social Network Methods. University of California, Riverside.
[31] Schiewe, Jochen. 2019. "Empirical Studies on the Visual Perception of Spatial Patterns in Choropleth Maps." KN - Journal of Cartography and Geographic Information 69 (3): 217–28. https://doi.org/10.1007/s42489-019-00026-y.
[32] Schumacher, Reinhard. 2013. "Deconstructing the Theory of Comparative Advantage." World Economic Review 2013 (2): 83–105.
[33] Shen, Guoqiang, Xiaoyi Yan, Long Zhou, and Zhangye Wang. 2020. "Visualizing the USA's Maritime Freight Flows Using DM, LP, and AON in GIS." ISPRS International Journal of Geo-Information 9 (5): 286. https://doi.org/10.3390/ijgi9050286.
[34] Shutters, Shade T., and Rachata Muneepeerakul. 2012. "Agricultural Trade Networks and Patterns of Economic Development." PLoS ONE 7 (7): e39756. https://doi.org/10.1371/journal.pone.0039756.
[35] Shutters, Shade T., Keith Waters, and Rachata Muneepeerakul. 2022. "Triad Analysis of Global Energy Trade Networks and Implications for Energy Trade Stability." Energies 15 (10): 3673. https://doi.org/10.3390/en15103673.
[36] Wang, H., Lu, Y., Shutters, S.T., Chapman, M., Fung, P., Mukhopadhyay, S., Kang, Y. and Tong, X. (2019) 'A visual analytics framework for spatiotemporal trade network analysis', IEEE Transactions on Visualization and Computer Graphics, 25(1), 331–341. https://doi:10.1109/TVCG.2018.2864844.
[37] Warr, Peter G. 1994. "Comparative and Competitive Advantage." Asian-Pacific Economic Literature 8 (2): 1–14. https://doi.org/10.1111/j.1467-8411.1994.tb00091.x.
[38] Wasserman, Stanley, and Katherine Faust. 1994. Social Network Analysis: Methods and Applications. 1st ed. Cambridge University Press. https://doi.org/10.1017/CBO9780511815478.
[39] Wu, Z., Liu, S., Zhou, Y., Liu, Y., Zhu, H. and Wang, J. (2024) 'VIEA: A visualization system for industrial economics analysis based on trade data', IEEE Transactions on Computational Social Systems, 11(2), 2807–2818. https://doi.org/10.1109/TCSS.2023.3288671.
[40] Yazawa, Nobuo. 2023. "Dynamics of International Trade: A 30-Year Analysis of Key Exporting Nations." PLOS ONE 18 (8): e0289040. https://doi.org/10.1371/journal.pone.0289040.
[41] Ye, S., Song, C., Cheng, C., Li, X., Wang, J. and Yang, H. (2020) 'Digital trade feature map: A new method for visualization and analysis of spatial patterns in bilateral trade', ISPRS International Journal of Geo-Information, 9(6), 363. https://doi.org/10.3390/ijgi9060363.