Temporal analysis of multilateral spatial interactions

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Abstract

Conventional gravity-model estimates of spatial interactions assume that spatial interactions or flows from all locations to all other locations are independent of other flows and, therefore, overlook the latent multilateral influences in play. This research developed a novel application of Self-Organizing Map (SOM) to retrospectively examine historical spatial interactions among multiple locations for new insights into the spatial and temporal dependence of flows across locations. We built a SOM with units of spatial interaction patterns and traced changes in spatial interactions patterns for each location over time. By tracing the changes, we created new trajectories of spatial interactions on the SOM to contextualize spatial interactions at individual locations and among all locations over time. We used international trade data among 207 countries from 1900 to 2014 to demonstrate the proposed data-driven approach for retrospective analysis of spatial interactions. We created a SOM of international trade patterns, mapped each country's trading trajectory, and compared the trajectories among all 207 countries. We showed that the SOM application could answer questions about multilateral spatial interactions over time. Our findings extended earlier network analyses of the global system with an integrated space-time view of spatial interactions. The SOM approach is adaptable to other domains of spatial interactions (e.g., urban transportation, immigrations) to characterize spatial interactions among locations change over time individually or contextually among all locations.

Keywords: Spatial Interaction, trajectories, self-organizing map, international trade

Word count: 1473 (exclusive of references)

1. Introduction

Spatial interactions are flows of people, goods, and ideas between two locations. As early as the 1920s, the gravity model has been the traditional approach to predict spatial interactions between two locations (Reiley 1929). A key assumption to subserve such gravity relation is that the interaction between two locations is independent of interactions among all other locations. The simple view can lead to biases in gravity-based estimates of spatial interactions due to the omission of potential multilateral effects on spatial interactions. For example, the traffic between two locations may be influenced by traffic in the surrounding. As such, a non-linear system approach to assess spatial interactions across multiple locations can help draw new insights into the characteristics and evolution of spatial interaction patterns among multiple locations. Taking a data-driven approach, we applied the Self-Organizing Map (SOM) to categorize spatial interaction patterns and built trajectories on the SOM to trace changes in spatial interaction patterns at individual locations over time. We seek to answer the following new questions about spatial interactions:

1. How might the spatial interactions of one location to all other locations change over time in the context of spatial interactions among all other locations?
2. Did closer locations exhibit more similar spatial interactions with all other locations over time, reflecting geographic hierarchies of spatial interactions?
3. Alternatively, were there locations, while geographically distant, with similar changes in spatial interactions with other locations over time?

The extended abstract highlights our SOM approach. Our presentation and subsequent full paper will elaborate on the advantages of the approach over the conventional gravity model in analysing spatial interactions.

2. Use Self-Organizing Map for Multilateral Spatial Interactions

SOM is an effective information visualization tool for both spatial and non-spatial data (Agarwal and Skupin 2008). With geographic data, SOM applications allow mapping geographic data in a semantic space to illustrate the similarity of attributes among geographical locations and identify clusters of geographic entities sharing similar attributes. Skupin (2002, 2004) and Skupin and Fabrikant (2003) applied SOM to visualize reports from Reuters news archives. Skupin and Hagelman (2005) used SOM to interpolate and visualize how each of 254 counties in Texas changed its 32 demographic variables from 1980, 1985, 1990, 1995, ad 2000. Yan and Thill (2009), Guo (2009), and Zhang and Van de Weghe (2018) used SOM to elicit clusters of spatial events. Augustijn and Zurita-Milla (2013) classified areas of similar disease spread over time, and summarized disease spread patterns in sequential maps of synoptic states. All these existing SOM applications with geographic data use geographic entities (e.g., counties, events, or time-periods) as the unit of analysis with no consideration how these geographic entities relate spatially. The novelty of this study is the use of spatial interactions at one location to all other locations as the unit of analysis. Our approach embeds relationships among geographic entities and their temporal dependence to create a SOM of categorical spatial interaction patterns and contextualize a location's changes of spatial interactions over time in all the spatial interaction patterns as well as changes at other locations. We use Correlates of War International Trade Data to demonstrate our temporal analysis of multilateral spatial interactions.

Our unit of analysis is a vector of spatial interactions between a location i to all other locations j's, $[F_{ij}]_t$, at a given time stamp (t), where $j = 1 \dots n$; n represents the number of locations; F_{ij} represents flow (i.e. spatial interaction) between a location i to all other locations j's. When $j = i$, $F_{ij} = na$. As such, each location has a vector of spatial interactions, and there are $n \times t$ number of spatial interaction vectors input to create a SOM. Each vector $[F_{ij}]_t$ is then mapped to the Best Match Unit (BMU) on the SOM. For each location (i), connecting the correspondent BMU in the order of time (t) forms the trajectory of spatial interactions between the location and all other locations over time; that is, the development of multilateral spatial interactions. Clusters of these trajectories imply groups of locations with similar temporal development in spatial interactions with other locations. Locations in a group may or may not be geographically closer than locations in another group.

We use a case study on international trade to illustrate the approach, using imports and exports data from the Correlates of War (COW) project from 1900 to 2014. The COW team converted all trade values among 207 countries in local currencies to US millions of dollars (Barbieri, Keshk and Pollinus 2009). Figure 1 gives an example of an input vector to build a SOM. The country order on the x-axis follows geographic regions (e.g., North America, South America, West Europe, etc.) is fixed for all input vectors. Missing or *na* data may lead to overfitting BMU if a vector with high values with only a few countries. We set the minimum vector length of 68 (about 33% of the total countries) for input vectors to SOM building.

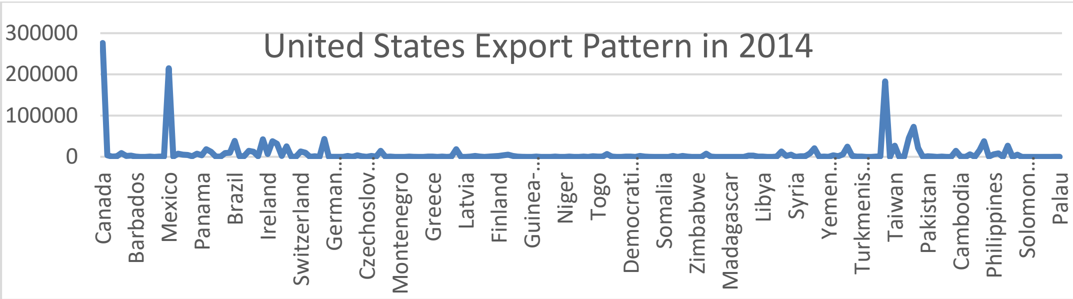


Figure 1: A unit of analysis in the export SOM analysis

In the retrospective analysis of exports, each input vector represents export values of a country to all other countries in a given year (same for the imports). Figure 2 shows BMUs (circles) of trading patterns and trajectories connecting BMUs in temporal orders. The red line in a circle represents a multilateral spatial interaction like the example in Figure 1. Each trajectory tells a story of how a country changed its imports or export patterns over time. The trajectories show that the US and China reached the most active patterns of imports in 1997 and 2010, respectively. The two countries experienced distinct developmental pathways to get there with pronounced differences with Europe. On exports, the US also higher exports to the Americas and Europe than Asia compared to China, but the US reached the most active pattern one year behind China (2007 vs. 2006). Our presentation and full-paper will interpret the patterns in individual nodes and the overall SOM.

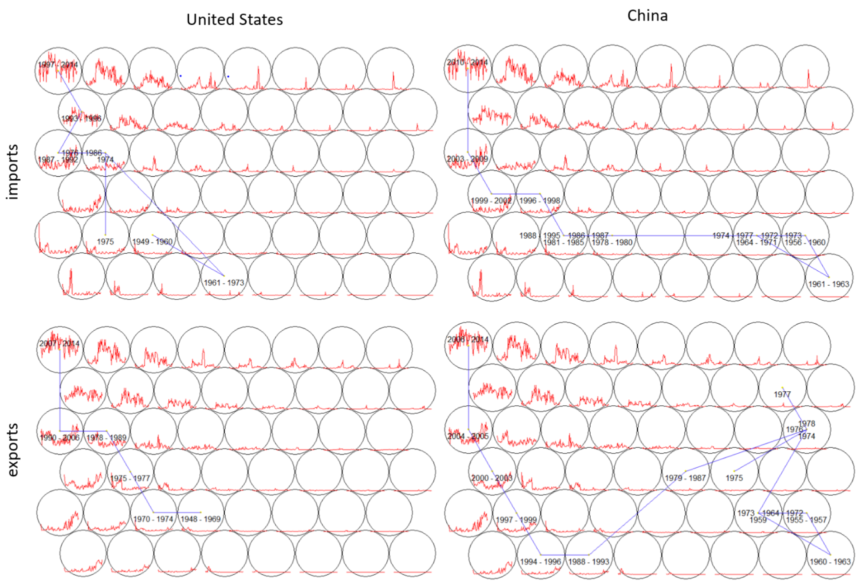
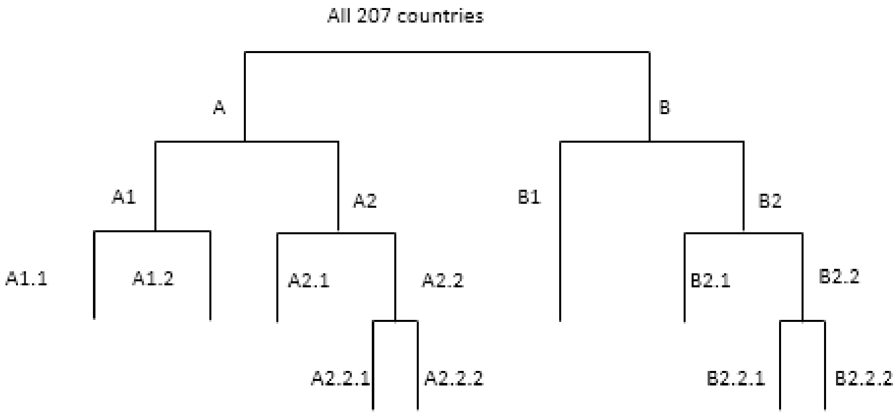


Figure 2: Examples of trajectories of imports and exports for the US and Chia

Hierarchical clustering of the trajectories for all countries shows a strong geographic coherence of imports/exports development among these countries (Figures 3 and 4). Outliers, such as North Korea in import group B2.2.2 (Figure 3) dominated by African countries, would account for political, historical, or other forces in play.



A1.1: Cyprus, Morocco, Tunisia, Sudan, Algeria, Romania, Iran, Libya, Lebanon, Bulgaria, Israel

A1.2: United Arab Emirates, India, Switzerland, Turkey, Greece, Egypt, Saudi Arabia, Kuwait, Syria, Iraq, Jordan

A 2.1: Germany, United States of America, United Kingdom, Spain, Netherlands, Belgium, France, Italy

A2.2.1: Mexico, Brazil, Argentina, Japan, Canada, Australia, Singapore, China, South Korea, Taiwan, Thailand, Malaysia, South Africa, Indonesia, Ireland, Portugal, Sweden, Finland, Norway, Denmark, Russia, Poland, Austria, Hungary

A 2.2.2: Yemen People's Republic, Yemen Arab Republic, German Democratic Republic, Czechoslovakia, Yugoslavia

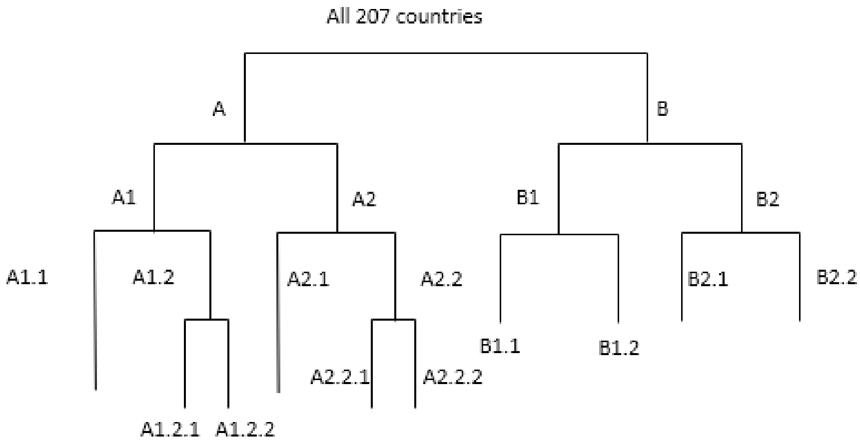
B1. Macedonia, Croatia, Slovenia, Czech Republic, Slovakia, Ukraine, Belarus, Estonia, Lithuania, Kazakhstan, Equatorial Guinea, Latvia, Yemen, Bosnia and Herzegovina, Georgia, Moldova, Azerbaijan, Armenia, Turkmenistan, Uzbekistan, Maldives, Nepal, Lesotho, Swaziland, Solomon Islands, St. Kitts and Nevis, Sao Tome and Principe, Antigua & Barbuda, Samoa, Namibia, Kyrgyzstan, Tajikistan, St. Lucia, Mongolia, German Federal Republic, Montenegro, Nauru, Kiribati, Tonga, Eritrea, Bhutan, Tuvalu

B2.1: Botswana, Comoros, Seychelles, Grenada, Suriname, Dominica, St. Vincent and the Grenadines, Brunei, Vanuatu, Bahrain, Qatar, Oman, Bangladesh, Bahamas, Mauritius, Fiji, Mozambique, Papua New Guinea, Guinea-Bissau, Angola, Djibouti, Belize, Albania

B2.2.1: Philippines, Sri Lanka, Pakistan, New Zealand, Cuba, Uruguay, Luxembourg, Chile, Venezuela, Colombia, Peru, El Salvador, Panama, Dominican Republic, Ecuador, Costa Rica, Guatemala, Honduras

B2.2.2: Nigeria, Mali, Ivory Coast, Senegal, Benin, Ghana, Mauritania, Congo, Cameroon, Gabon, Gambia, Guinea, Burkina Faso, Guyana, Zimbabwe, Malta, Kenya, Zambia, Malawi, Afghanistan, Paraguay, Vietnam, Cambodia, Laos, Nicaragua, Haiti, Ethiopia, Myanmar, Bolivia, Iceland, Democratic Republic of the Congo, Niger, Sierra Leone, Liberia, Togo, Trinidad and Tobago, Central African Republic, Chad, Barbados, Jamaica, Tanzania, North Korea, Burundi, Rwanda, Uganda, Somalia, Madagascar

Figure 3: Hierarchical clusters of import trajectories



A1.1: Ecuador, Peru, Colombia, Chile, Philippines, New Zealand, Guatemala, Costa Rica, El Salvador, Panama, Honduras, Nicaragua, Trinidad and Tobago, Paraguay, Bolivia, Uruguay

A1.2.1: United States of America, Japan, Brazil, Argentina, Mexico, Venezuela, Saudi Arabia, Canada, Australia

A 1.2.2: Iran, Kuwait, Nigeria, Algeria, United Arab Emirates, Singapore, Taiwan, Malaysia, India, Thailand, Indonesia, China, South Korea

A 2.1: Spain, Switzerland, Netherlands, Belgium, France, Italy, United Kingdom, Sweden, Russia, Finland, Norway, Denmark

A2.2.1: Syria, Cyprus, Morocco, Tunisia, Bulgaria, Israel, Poland, Austria, Hungary, Romania, Greece, Turkey, Egypt, Ireland, Portugal, Iraq, South Africa, Libya

A2.2.2: German Democratic Republic, Czechoslovakia, Yugoslavia, Yemen Arab Republic, Yemen People's Republic

B1.1 Ukraine, Belarus, Kazakhstan, Estonia, Latvia, Lithuania, Czech Republic, Slovakia, Slovenia, Germany, German Federal Republic

B1.2: Montenegro, Nauru, Kiribati, Tonga, Eritrea, Tuvalu, Namibia, Lesotho, Vanuatu, St. Lucia, Solomon Islands, Armenia, Antigua & Barbuda, St. Kitts and Nevis, Bhutan, Bosnia and Herzegovina, Tajikistan, Sao Tome and Principe, Kyrgyzstan, Yemen, Equatorial Guinea, Brunei, Azerbaijan, Macedonia, Croatia, Moldova, Uzbekistan, Georgia, Turkmenistan

B2.1: Congo, Mauritania, Cameroon, Zambia, Jamaica, North Korea, Benin, Togo, Chad, Cambodia, Democratic Republic of the Congo, Afghanistan, Liberia, Central African Republic, Madagascar, Somalia, Haiti, Niger, Burundi, Uganda, Rwanda, Mali, Sierra Leone, Tanzania, Laos, Barbados, Guyana, Burkina Faso, Gambia, Malawi, Fiji, Albania, Mauritius, Lebanon, Jordan, Iceland, Sri Lanka, Luxembourg, Pakistan, Cuba, Dominican Republic, Ethiopia, Myanmar, Ghana, Sudan, Malta, Kenya, Zimbabwe, Guinea, Ivory Coast, Senegal, Gabon

B2.2: Oman, Qatar, Vietnam, Angola, Bahrain, Bangladesh, Suriname, Bahamas, Papua New Guinea, St. Vincent and the Grenadines, Maldives, Samoa, Comoros, Mongolia, Dominica, Mozambique, Seychelles, Grenada, Guinea-Bissau, Djibouti, Botswana, Belize, Swaziland, Nepal

Figure 4: Hierarchical clusters of export trajectories

3. Concluding remarks

Figures 2, 3, and 4 give examples to answer the three questions listed in the introduction section. Figure 2 illustrates the use of trajectories to show how the spatial interactions of one location (the US or China) to all other locations (all other countries) might change over time. Figures 3 and 4 suggest countries within a geographic region are more likely to experience more similar import or export trajectories and hence more similar development of spatial interaction patterns in terms of international trading. Furthermore, Figures 3 and 4 also show that a group could include countries from multiple geographic regions, and hence geographically distant locations could experience similar development of spatial interactions with other locations over time.

The extended abstract highlights the novel application of SOM to explore spatial interaction patterns across multiple locations and over time simultaneously. While our application is a retrospective study, extending to predictive SOM is possible to interpolate or estimate spatial interactions between two locations and from a location to all other locations at a given time or future trajectories. Building interactive multimodal visualization tools will open opportunities to filter efficiently, detail, and compare spatial interactions from a location, among locations, and over time to discover how spatial interaction patterns relate. For example, when country A increased imports from country B and C, country C decreased exports to country D.

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