Deciphering Economic Clusters in Real-Time: Applying Machine Learning to Registre des Entreprises du Québec Data

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Introduction

Motivation

- Economic cluster is a way to investigate industry dynamics: their interdependencies and impacts on the economic landscape
- New data science techniques are now available to collect and analyze data

Question

Can data science techniques help revisit economic cluster analysis?

Goal

 Define clusters and analyze their changing dynamics in near real-time

Literature review

- Agglomeration economies (Marshall (1890), Robinson (1956), etc.)
 - This work: Internal economies and external economies of agglomeration economies
- Economic cluster
 - Comparable cluster definitions using multi-regions and many industries (Porter (2003), Delgado et al. (2016), etc.)
 - Region-specific cluster definitions: qualitative, case-studies (Feser et al.(2009), (Porter and Ramirez-Vallejo (2013), etc.)
 - This work: New measure of inter-industry linkages applicable in both approaches

Contributions

- We propose a new quantitative cluster definition: measuring inter-industry linkages using Growth Trajectory
 - Applicable both for region-specific and multi-region cluster definitions
 - Data-driven cluster definition
- Near real-time insight into changing inter-industry dynamics within a cluster

Findings

- Clustering using growth trajectory groups diverse industries within the same cluster
 - Hidden inter-industry linkages are captured
 - Beyond labor market pooling, specialized suppliers, knowledge spillovers
- Identifies the direction of effects on industries within specific clusters
 - Business cycles
 - Economic policies

 Step 1: Application of unsupervised machine learning algorithms (Hierarchical, K-means, K-medoids)

▶ Inputs: *S* data points with *p* features ($S \in \mathbb{R}^p$); Goal: $S = \bigcup_{k=1}^{K} C_k$ where ($K \in \mathbb{R}$)

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 - After all $\sum_{k=1}^{K} W(C_k)$ is the minimum, where $W(C_k) = \frac{1}{card(C_k)} \sum_{i,i' \in C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2$, using squared *Euclidean distance*, is the within-cluster variation

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 - K-medoids: Choose K, start by random assignment of observations, then iterate assignation to the closest centroid (median point of *C_j*) till convergence
 - Hierarchical: Start with S groups and merge groups till one group.

Step 2: Identification of sub-clusters

Use the same cluster algorithms or network analysis clustering on the clusters identified in Step 1

Step 3: Geo-spatial mapping of clusters

- Set a threshold of employment distribution across MRCs
- Identify clusters distribution
- Step 4: Analysis of temporal dynamics of clusters
 - Insights into cluster life cycles
 - Insights into cluster composition

Data and Summary Statistics I

- REQ data: (Warin, T. (2021). "Req: Client for accessing Quebec company registrar. v0.1.0")
 - The dataset is updated every two weeks
 - Dataset description

| Number of observations | Number of variables | Number of industries |
|------------------------|---------------------|----------------------|
| 2.36 millions | 61 | 1045 |

- Variables selected: Registration date, cessation date, industry code (4 digits CAE), number of employees (range), Latitude, Longitude
- Dataset transformation into time series
- Population over sample

Data and Summary Statistics II

Evolution of the number of firms in selected industries from 1990 to 2022

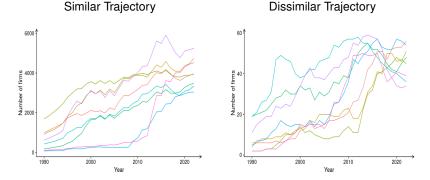


Figure 1: Evolution of Industry Size in Quebec

Data and Summary Statistics III

Correlation between industries' growth rate

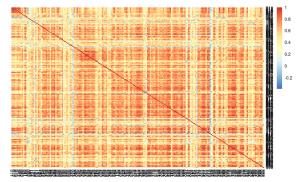


Figure 2: Heatmap of the correlation between industries

Selection of industries with correlation coefficient ≥ 0.95

- Selection of industries with correlation coefficient ≥ 0.95
- Network graph

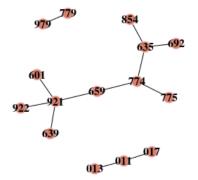


Figure 3: Network graph of highly correlated industries

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- Network graph

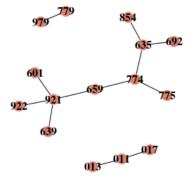
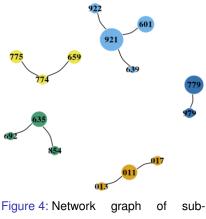


Figure 3: Network graph of highly correlated industries

- Minimum spanning tree representation
- Industry Description:

| CAE | Description |
|-----|---|
| 011 | Livestock and livestock farming poultry |
| 013 | Field crops |
| 017 | Farms Field crops and horticultural production |
| 601 | Food Stores |
| 639 | Other Types of Motor Vehicle Retail |
| 921 | Restoration |
| 922 | Taverns, bars and nightclubs |
| 635 | Workshops Motor Vehicle Repair |
| 692 | Direct Selling Companies |
| 854 | Teaching Personal & Popular Training |
| 659 | Other types of trade detail |
| 774 | Advertising Services |
| 775 | Offices architects and engineers and other services |
| 779 | Other business services |
| 979 | Other Personal Services & Domestic |



clusters of highly correlated industries

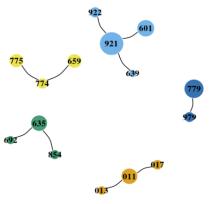
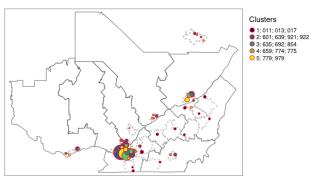


Figure 4: Network graph of subclusters of highly correlated industries

- Minimum spanning tree representation
- Clustering using hierarchical approach and modularity measure
 - Each node size is proportional to the average of the industry's size

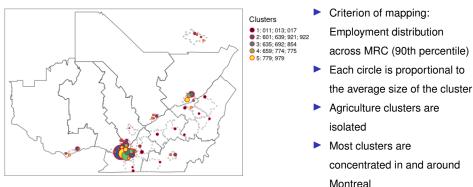
Preliminary Results: Geo-spatial mapping



Geographic distribution of the clusters

Figure 5: Geographic mapping of the clusters

Preliminary Results: Geo-spatial mapping



Geographic distribution of the clusters

Figure 5: Geographic mapping of the clusters

Preliminary Results: Clusters summary statistics

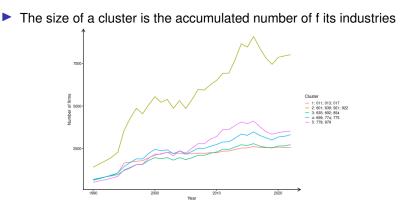


Figure 6: Evolution of the size of clusters

The evolution of the cluster of related industries shows their perimeter needs to be redefined

Take away

- Inductive approach that considers the changing dynamics of industries
- New inter-industry linkages measure that captures wider agglomeration economies and extends the perimeter of the cluster definition
- Economic cluster definitions based on our measure of inter-industry linkages are applicable in region-specific and multi-region contexts

THANK YOU !

Learn more about our work at CIRANO's Pole on Data Science for Trade and Intermodal Transportation

