Change-Point Detection in Core-Periphery Networks: A Case Study on Interbank Lending Networks

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Content

- Personal background
- A previous Project (with Prof. Shawn Mankad at Cornell University)
  - Change point detection in networks
- Planned project at CBB
  - Emittance preservation of electron microscopes

Personal Background

- Desheng Ma
- PhD student in Applied Physics, Cornell
- B.S. Nankai University, China
- Research experience:
  - Ultracold Atoms (Will Lab, Columbia)
  - Ferroelectrics (China)
  - Cosmology (Bachelor thesis)
  - Networks (Cornell)
  - Microscopy…

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Motivation

Networks are everywhere.

Driven by technological advancements, data collection & IT systems have made it easy to collect entity-level data.

When you have interactions between entities, often a natural way to model these interactions and visualize the data is using networks (graphs).

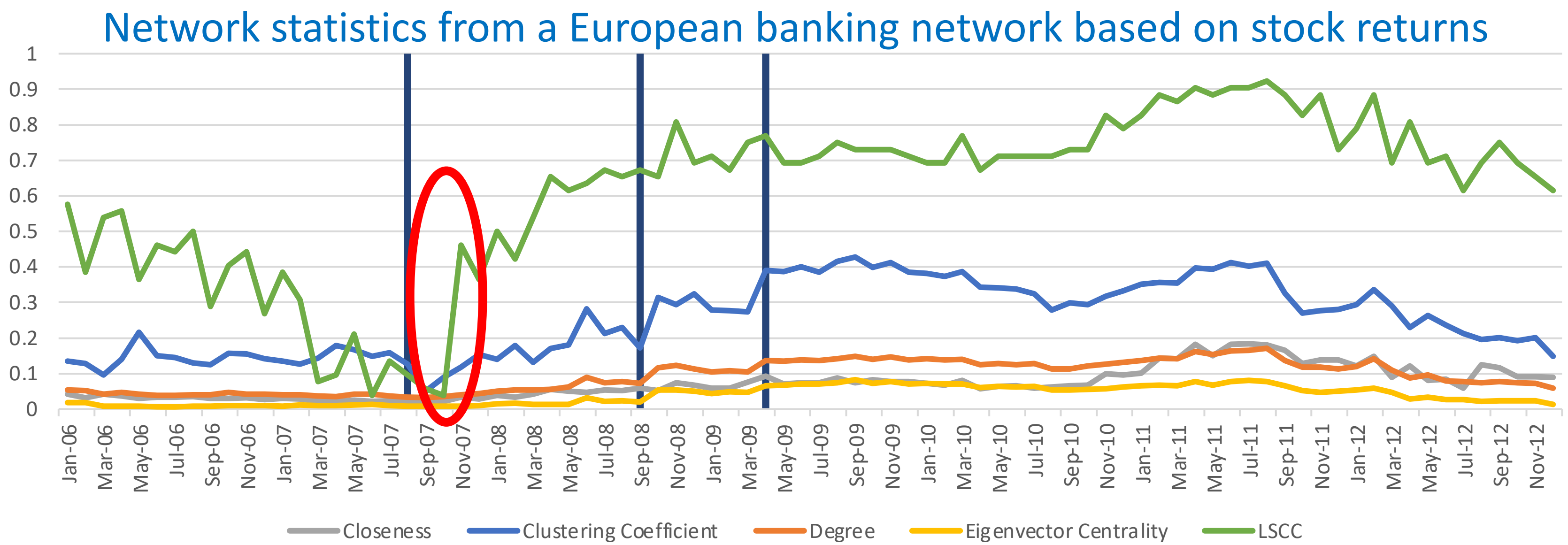
- Social networks: Facebook & Twitter interactions
- Biology networks: Gene co-expressions
- Communication networks: Emails, Internet traffic, cell phone records
- Information networks: WWW
- Financial Networks: Loans or contracts between financial institutions

Change Detection in Dynamic Networks

Typically, networks are analyzed using statistics developed from the social network or graph theory literatures:

- Degree, eigenvector centrality, diameter, shortest path, etc.

When faced with a time-series of networks, to detect changes in the underlying system, one can inspect the time-series of network statistics.



Objective and Challenges

Objective:

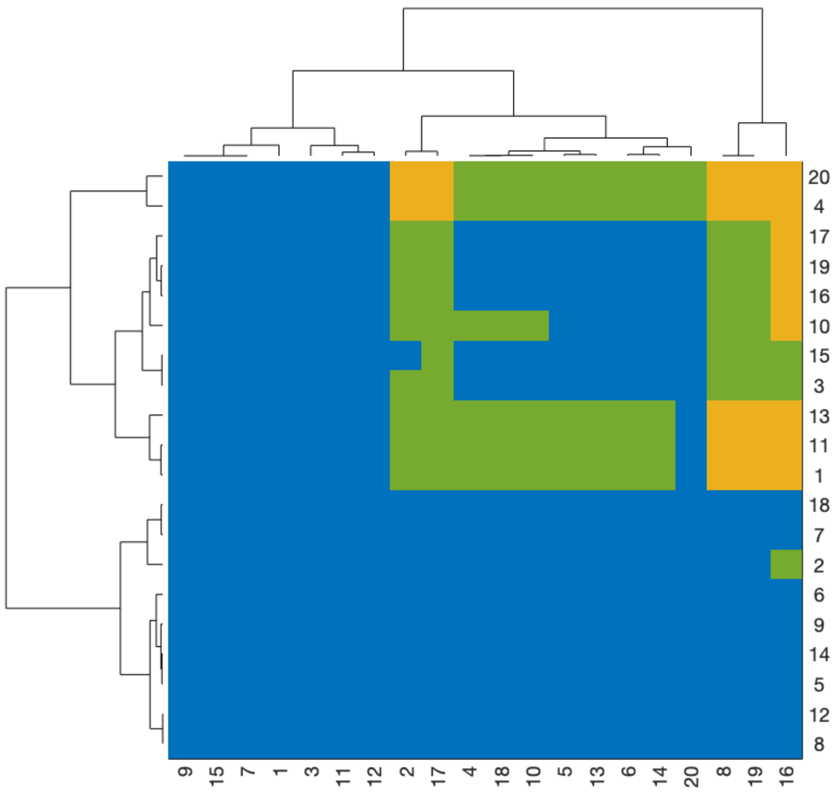
Detect key changes to the observed network series in real-time and faster than benchmarks.

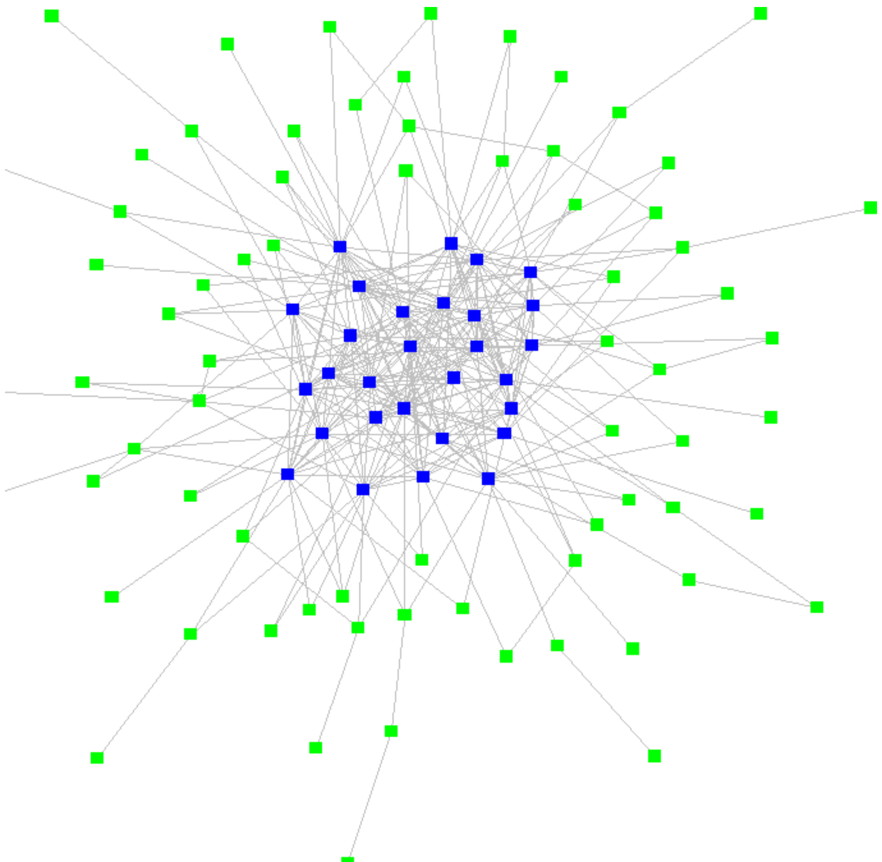
Challenges:

- Sparsity: Rarely see connections between nodes (banks), especially in crisis environments.
- Weighted: Edges in our application are weighted.
- Community Structure: Multiple core-periphery layers.
- Dynamic: Natural evolution to the system over time.
- Monitoring: Real-time change point detection.

Core-Periphery Topology

- Core-periphery structure are commonly found in networks.
  - Wide-spread usage in economics and finance.
  - Our data (interbank networks) have been observed to have CP structure (Fricke and Lux 2015).





Proposed Solution

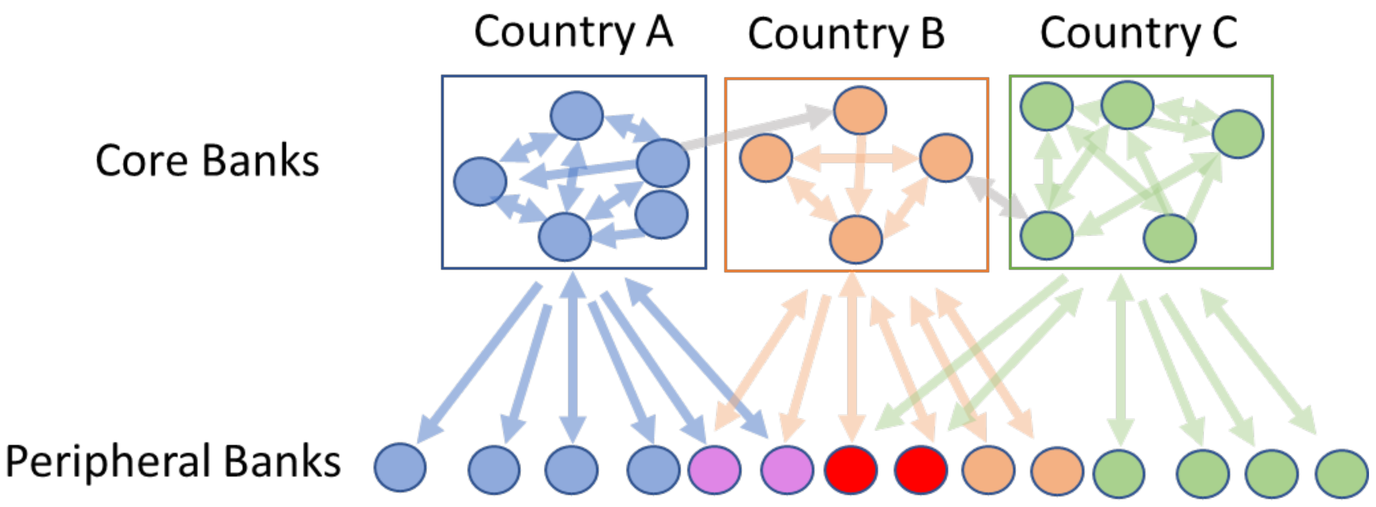
Solution: Penalized NMF + EWMA Monitoring

- Sparsity: Penalized Poisson likelihood.
  - Different penalty than the usual l_1 norm penalty.
- Weighted Edges & Community Structure: NMF Model.
- Dynamic: Estimation done with a rolling window.
- Monitoring: Inspecting local deviations with EWMA control chart.

Multiple Core-Periphery Layers

Suppose A_{ij} is composed of K multiple cores: $A_{ij} = \sum_k A_{ij}^{(k)}$

If each core has edge weights given by Poisson, $A_{ij}^{(k)} \sim \text{Poisson}(u_{ik} v_{kj})$, then the observed edges are also Poisson: $A_{ij} \sim \text{Poisson}(\sum_k U_{ik} V_{kj})$.



Proposed Model & Estimation

Log-likelihood given the observed network is:

$$l(U,V|A) \propto \sum_{i,j}\left(A_{ij}\log\left(\sum_k U_{ik}V_{kj}\right) - \sum_k U_{ik}V_{kj}\right) + \lambda \sum_{k,j} f\left(\frac{V_{kj}}{\sigma_k}\right),$$

$$\sigma_k = \sqrt{\frac{1}{n}\sum_j V_{kj}^2} \text{ and } f(x) = \log(x^2+1).$$

Following usual arguments, the update rules can be seen as a diagonally rescaled gradient descent:

$$U_{ik} \leftarrow U_{ik}\frac{\sum_j A_{ij}V_{kj}/(UV)_{ij}}{\sum_j V_{kj}}$$

$$V_{kj} \leftarrow V_{kj}\frac{\sum_j A_{ij}U_{ik}/(UV)_{ij} + \frac{V_{kj}\sqrt{n}\sum_j V_{kj}}{\left(\sum_j V_{kj}^2\right)^{3/2}}}{\sum_i U_{ik} + \frac{\sqrt{n}}{\left(\sum_j V_{kj}^2\right)^{1/2}}}.$$

Monitoring: EWMA

1. Fit the factorization on $A(t), A(t-1), \dots., A(t-W)$.

2. For each node, define the average difference between the estimate for the current time point and the average in the rolling window:

$$\mu_{dU_i} = \frac{1}{K}\sum_k |U_{ik}(t) - \bar{U}_{ik}|$$

$$\mu_{dV_j} = \frac{1}{K}\sum_k |V_{kj}(t) - \bar{V}_{kj}|.$$

3. Monitor κ, combined deviation of each factor, with EWMA:

$$\kappa = \frac{\sum_i \mu_{dU_i}\mu_{dV_i}}{n}.$$

Case Study:
The 2007-09 Financial Crisis in European Interbank Lending Data

e-MID dataset: loans between European banks from January 2006 through December 2012.
- 212 banks, 464772 edges over 84 months.

We construct monthly networks by connecting lender and borrowers.
- Edge is weighted by the transaction volume between two banks in that month.

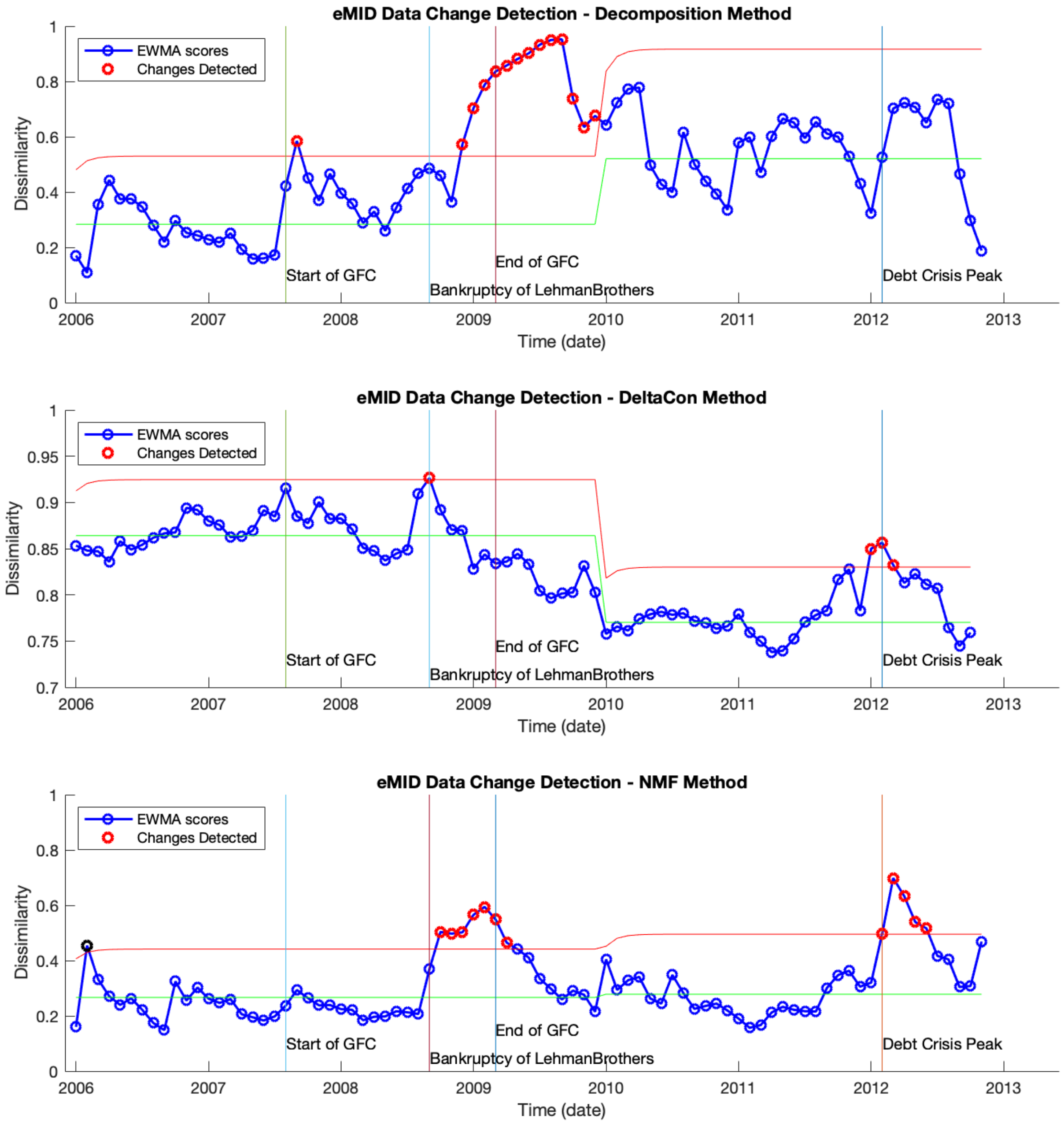
Important Dates

- **Pre-crisis**: 2-Jan-06 : 8-Aug-07
- **Crisis 1 (Bear Stearns)**: 9-Aug-07 : 12-Sep-08
- **Crisis 2 (Lehman)**: 16-Sep-08 : 1-Apr-09
- **Crisis 3 (Sovereign Debt)**: 15-Nov-11: 6-Sep-12

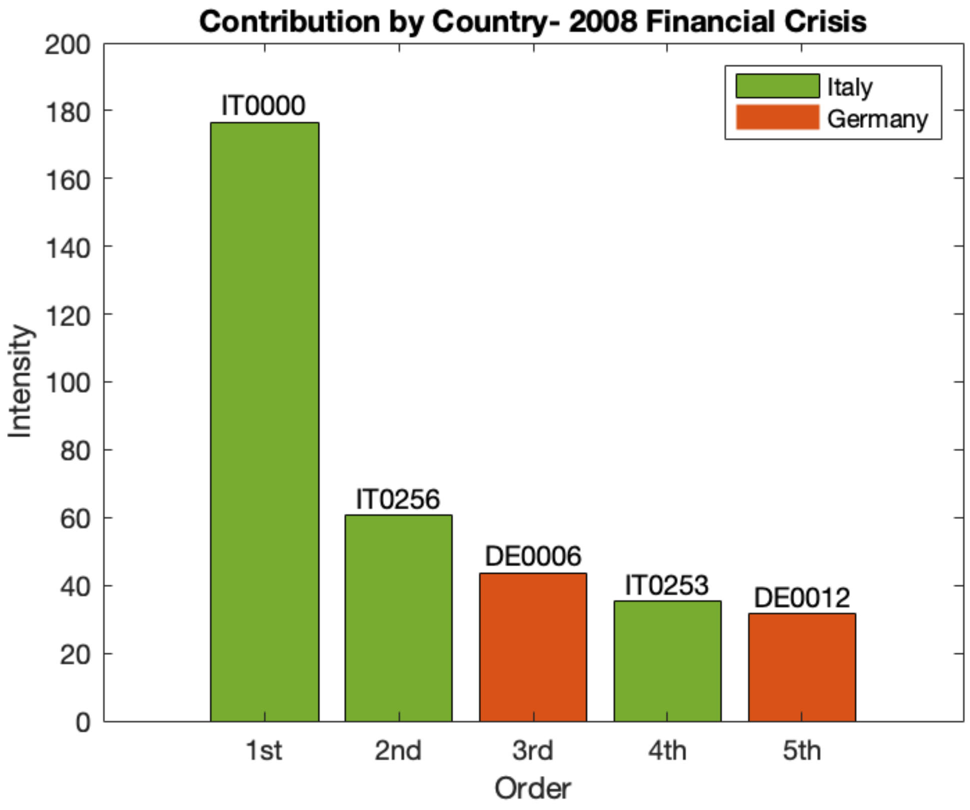
Results

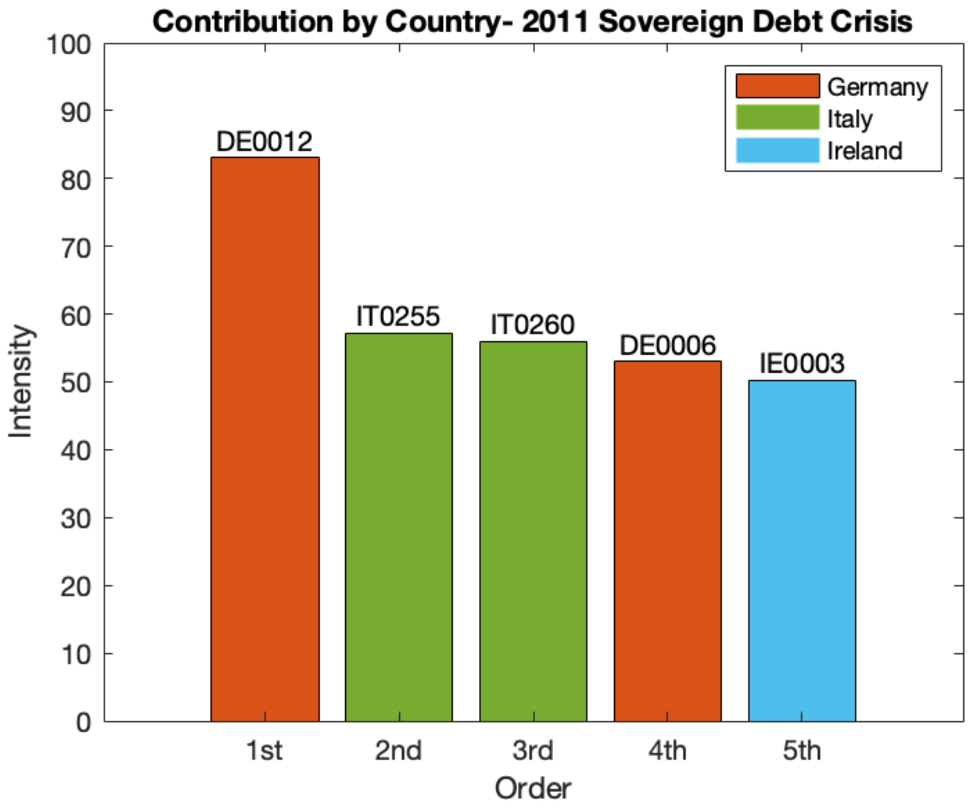
Comparison among change point detection methods using EWMA monitoring on the e-MID network data。

Our proposed NMF outperforms!



Decomposing: Who caused the change?

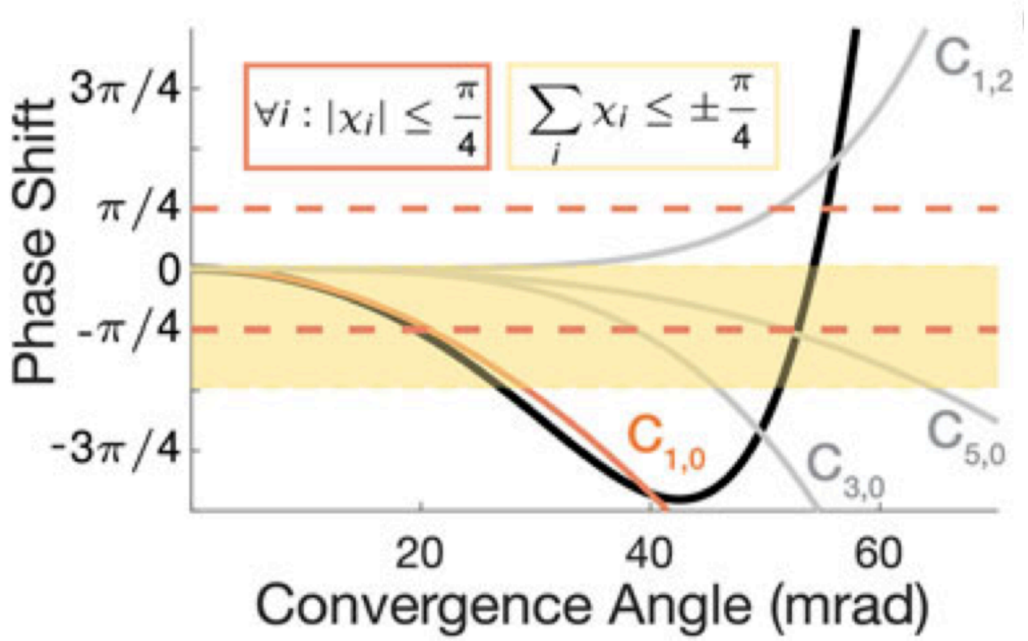


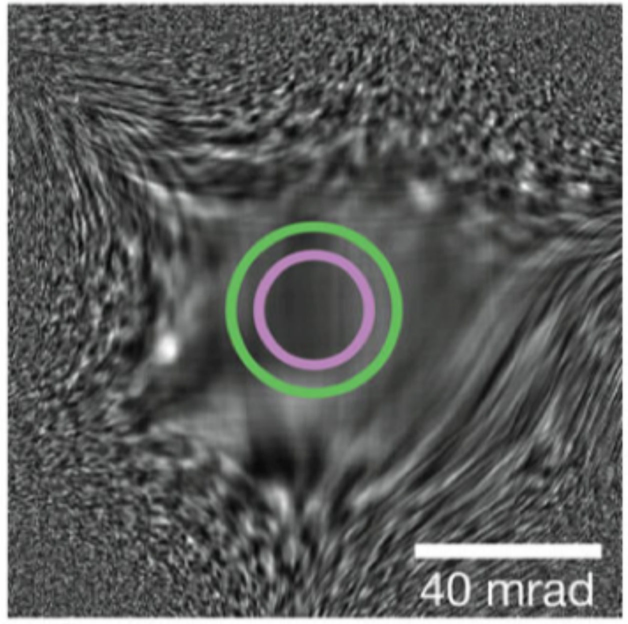


Emittance Preservation of Electron Microscopes

Aberration (Krivanek notation (Krivanek et al., 1999))

$$\chi(\alpha, \phi) = \frac{2\pi}{\lambda} \sum_{n,m} \frac{C_{n,m}\alpha^{n+1}\cos(m(\phi - \phi_{n,m}))}{n+1}$$





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doi:10.1017/S1431927620001841

Microscopy AND Microanalysis

Original Article

Optimal STEM Convergence Angle Selection Using a Convolutional Neural Network and the Strehl Ratio

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Potential Solution

- A mapping from Ronchigrams to emittance
  - Deep learning approaches, e.g. CNN
- A surrogate model to optimize for best emittance
  - Uncertainty quantified machine learning approaches, e.g. Gaussian Processes

Thank you!

References

[1] Ma, D., & Mankad, S. (2020). Change Detection in Core-Periphery Networks: A Case Study on Detecting Financial Crises in the Interbank Market. Available at SSRN 3742790.

[2] Schnitzer, N., Sung, S. H., & Hovden, R. (2020). Optimal STEM Convergence Angle Selection Using a Convolutional Neural Network and the Strehl Ratio. Microscopy and Microanalysis, 26(5), 921-928.