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Unveiling the interconnectedness of banks in payment system: methodology, utilization, and data governance considerations[1]

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[1] This contribution was prepared for the workshop. The views expressed are those of the authors and do not necessarily reflect the views of the Bank of Italy, the BIS, the IFC or the other central banks and institutions represented at the event.

Unveiling the interconnectedness of banks in Payment System - Methodology, Utilization, and Data Governance Considerations

Renardi Ardiya Bimantoro[1], Irfan Sampe[2], Mohammad Khoyrul Hidayat [3],

Abstract

The global financial crisis was a reminder of the importance of understanding the interconnectedness of financial systems. Financial networks often have a small number of main players that are highly connected to each other. Nevertheless, disruptions to one of these players could expose a risk to the rest of the network. Understanding how liquidity shocks propagate throughout the interbank market relies on a network topology that can be constructed using payment system data. Several studies have shown that interbank payment systems and interbank markets tend to have a core-periphery structure, with banks operating in a hierarchy. The network can be exploited to prioritize liquidity monitoring on banks that are identified as core and to analyse contagion effect. On the other hand, while understanding the structure of financial networks is critical in systemic risk assessment, the network structure utilizes the bank's individual data that could pose a data privacy or security risk during its generation or dissemination to users. Therefore, various protection measures need to be taken to ensure the confidentiality of the bank's data. This paper aims to capture the network topology in Bank Indonesia's Real Time Gross Settlement (BI-RTGS) and examine if Indonesia's interbank payment system has a core-periphery structure while ensuring its usage adheres to governance principles.

Keywords: interconnectedness, systemic risk, payment system, core-periphery, support vector machine (SVM), big data analytics, data governance, data privacy

JEL classification: D85, G21, K20

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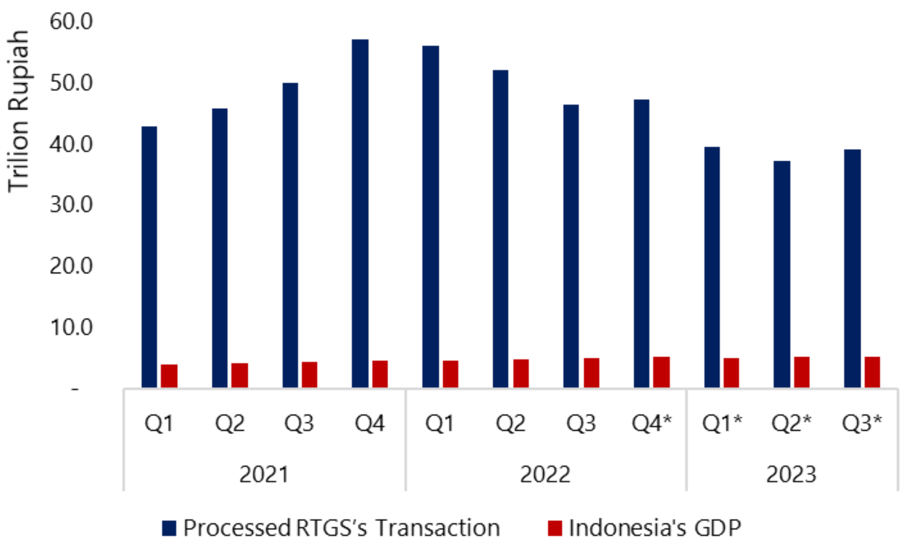
1. Background

Currently, the majority of economic transactions are carried out through the fund transfer payment method. This comprises a wide range of transaction methods, ranging from retail payments such as card-based transactions, QR-based transactions, and internet-based transactions to large-scale gross settlements. Contrary to retail payments, which are usually of smaller value with high frequency, large-scale gross settlements are commonly employed for high-value transactions, albeit with a lower frequency. These settlements play a vital role in facilitating the flow of funds across the economy.

Bank Indonesia, in collaboration with the government, consistently endeavors to develop suitable policies to achieve its three primary objectives: monetary stability, financial system stability, and payment system stability. Bank Indonesia has implemented and operated the BI-RTGS payment system since November 17, 2000. Due to its coverage of about 90% of total payment transactions in Indonesia, BI-RTGS has been designated as a systemically important payment system.

Processed RTGS's Transaction Compared to Indonesia GDP in 2021-2023

Figure 1



Source: Bank Indonesia & BPS

*) Temporary Number

The significant role of the large value payment system (BI-RTGS) in maintaining financial system stability and mitigating systemic risk, makes it crucial for the central bank to thoroughly analyse the structure of the interconnections among participants in the payment system. Furthermore, the global financial crisis served as a reminder of the significance of comprehending the interdependence of financial institutions. Hence, it is imperative to ascertain the configuration of connections among actors (banks) in the BI-RTGS payment system through network analysis.

The network structure in the interbank market can be described as tiered, with a cluster of highly interconnected institutions that also serve as intermediates for other banks with fewer connections. Multiple studies have demonstrated that interbank markets typically exhibit a core-periphery structure, wherein banks function within a hierarchical system. Any disruption to one of these players could potentially pose a risk to the entire network. The comprehension of how liquidity shocks spread across the interbank market depends on the construction of a network topology utilizing payment system data. Utilizing the network can be advantageous in prioritizing liquidity monitoring at institutions that are recognized as core and in analysing the contagion effect.

However, the utilization of the bank's private data in the network structure could potentially create data privacy or security concerns when it is generated or shared with users. Hence, it is necessary to implement security measures to guarantee the confidentiality of the bank's data. The objective of this article is to analyse the network structure of Bank Indonesia's Real Time Gross Settlement (BI-RTGS) system and determine if the interbank market in Indonesia exhibits a core-periphery structure, while also ensuring compliance with governance standards.

2. Literature Review

2.1 Empirical Evidence of Contagion Effect in Financial Market

The global financial crisis served as a reminder of the significance of comprehending the danger of contagion when major institutions are unable to meet their payment obligations. Kaufman (1992) defines contagion as the transmission of shock effects from one or more firms to others. This issue is more prevalent in the banking business than in other industries. Financial instability and contagion in the financial system can arise from a bankruptcy or other force majeure event (Heijmans & Wendt, 2023).

In their study, Zhang (2021) analyse the influence of bank liquidity production on systemic risk and its varying effect on network interconnectedness. The authors of this study put up three hypotheses: (1) The generation of excessive bank liquidity raises the level of systemic risk. (2) Internal and external liquidity creation have distinct impacts on systemic risk. (3) The influence of liquidity creation on systemic risk intensifies as the interconnectivity of the bank network rises. The study found that the interconnection between banks is crucial in determining the risk of spill over and contagion. This highlights the need for monitoring the financial network within the regulatory framework.

Another supporting evidence of contagion found in banking markets (Ballester, 2016). It is identified through an initial indication of increased co-movement in Credit Default Swap (CDS) returns. The significant rise in prevalence should be seen as a preliminary indication, prompting authorities to act. The contagion occurred in multiple waves, starting in July 2007, and the financial and eurozone crises were separate occurrences. During the financial crisis, contagion was characterized by a systematic aspect. However, with the eurozone crisis, the idiosyncratic component became more prominent.

By using net directional return spillover metrics, the study was able to identify a set of banks in certain countries that act as both sources and recipients of contagion. US banks seem to have been net transmitters throughout the period from 2007 to 2009. Amidst the eurozone crisis, banks in euro-peripheral nations played a significant role in transmitting idiosyncratic spillovers, while the issues in the eurozone had less impact on US banks. The variations in susceptibility to contagion within Europe, and even within the eurozone, are striking, with the eurozone periphery being more susceptible to systematic transmission.

The examination of the spread of contagion inside the euro-periphery portfolio verifies the presence of elevated levels of the systematic contagion index. Spanish banks transmit both systematic and idiosyncratic risk spillovers to Greek banks, which act as net recipients of these risks.

Collectively, these results suggest that the interconnections between financial markets across countries play a crucial role in the propagation of shocks. This is evident from the fact that the overall spillover index consistently shows a higher contribution from systematic factors compared to idiosyncratic factors. Nevertheless, there have been certain cases during the recent eurozone crisis where unique and unpredictable events have resulted in the transmission of negative effects to other banking markets. This appears to be associated with instances of bank failure, such as the Lehman Brothers' collapse in September 2008, or heightened vulnerability to bank failure, as seen in Spanish banks during the latter two quarters of 2011.

2.2 Core-Periphery Structure in Financial Network

Central bank research conducted in several countries, including Germany, the Netherlands, Italy, the UK, and Korea, has found networks inside the interbank market and interbank payment system. The objective of this research is to comprehend the network structure that exists in these systems. These findings demonstrate that the observed network structure exhibits a hierarchical organization. The majority of the research focuses on the interbank tiering concept that Craig and Von Peter (2010) introduced. In their study, Craig and Peter (2010) suggest that the interbank payment system functions in a hierarchical manner, with banks at lower levels being connected solely through transaction centers known as core. This network configuration is an expansion of the core-periphery structure that Borgatti & Everett (1999) first proposed and which later served as a benchmark for other central banks in determining the layout of the interbank network.

In 2010, Craig and Peter utilized Borgatti and Everett's core-periphery structure approach to examine the network topology within an interbank market. Craig and Peter suggest that the network structure of the interbank market exhibits a hierarchical arrangement, sometimes known as tiering. The interbank tiering notion refers to the formation of a network structure that arises when a set of interconnected banks also serve as intermediates for other non-interconnected banks. The attributes of an ideal core-periphery model in an interbank market are defined as follows:

i. Top-tier banks (core) are interconnected with each other.
ii. Lower-tier banks (periphery) are not interconnected with each other.
iii. Top-tier banks (core) are connected with (some) lower-tier banks (periphery)

Typically, interbank transactions in a payment system are one-way, meaning that bank A can send a transaction to bank B, but the opposite may not be true. The payment system network is seen to be a directed network. Hence, the models suitable for discerning the network structure in the payment system are the asymmetric discrete model (Craig & Peter, 2010) and the asymmetric continuous model (Boyd et al., 2010).

Bank Indonesia is conducting research to build a network analytics approach that utilizes the core-periphery model and machine learning algorithms. The objective is to discover the connectivity structure of participants (banks) in the BI-RTGS payment system. This can be utilized to enhance the efficacy of systemic impact assessments in the financial system. This methodology is anticipated to be beneficial in identifying banks classified as core banks, which are institutions that could have a substantial impact on the payment system. Additionally, there is a concern for data protection, emphasizing the need for secure handling and confidentiality of banking data in this analysis to prevent unauthorized access or data breaches.

Thus, this study is expected to answer the following research questions:

1. Does Indonesia's RTGS interbank payment system exhibit a core-periphery structure in its network topology?
2. What steps can be taken to keep individual bank data safe and private while studying Indonesia's bank network in the BI-RTGS system?

3. Methodology

3.1 Data

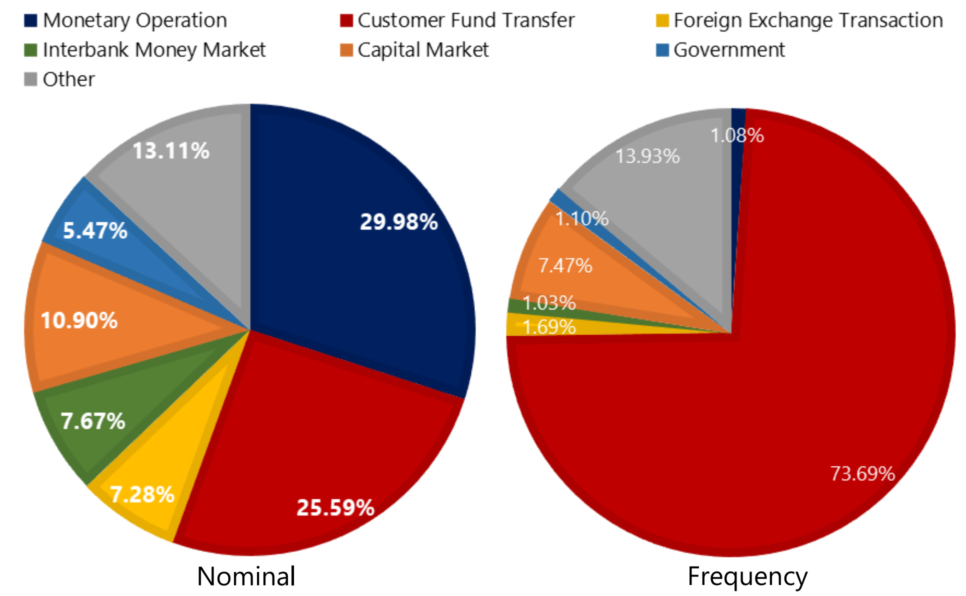
The study utilized data sourced from the Bank Indonesia Real Time Gross Settlement (BI-RTGS). BI-RTGS is a financial infrastructure managed by Bank Indonesia that facilitates high-value fund transfers, debit clearing, regular payments, and regular billing services (as stated in Regulation of Member of Board of Governors Number 24/5/PADG/2022). Since November 2000, the Real Time Gross Settlement (RTGS) system has had the capability to handle payment transactions exceeding Rp. 100,000,000.00 (one hundred million rupiah) in value.

The data included in this study encompasses RTGS transaction data spanning from January 2018 to December 2023. On average, the value of transactions through this service amounts to approximately 13,000 Trillion Rupiah per month. The Real Time Gross Settlement (RTGS) system encompasses various transaction types:

1. Monetary operations, which encompasses expenses and the duration of financial instruments.
2. Interbank Money Market, which encompasses the maturity of transactions inside this market.
3. Government transactions encompassing the issuance of SBN (Sovereign Bonds), redemption of SBN, SBN coupons, and other related activities.
4. Customer Fund Transfer
5. The capital market, which encompasses securities transactions.
6. Foreign exchange transactions

The share for each transaction type is shown in Figure 2, which shows that the largest share of transaction (±29%) is monetary operation, followed by customer fund transfer (±25). The data structure obtained from the RTGS system is as shown in Table 1.

Nominal and Frequency Share of RTGS Transactions Based on Transaction Type in November 2023 Figure 2



Source: BI-RTGS (processed)

RTGS Data Structure Table 1

No.	Data Field
1	SETTLEMENT TIME
2	SENDING PARTICIPANT
3	RECEIVING PARTICIPNAT
4	STATUS
5	TRANSACTION CODE
6	MESSAGE TYPE
7	CURRENCY CODE
8	AMOUNT (NOMINAL)
9	BLOCK4*

*) Block 4 information contains transaction detail related to costumer information.

Despite the BI-RTGS structure data containing quite information, particularly related to the individual details of financial institutions and their customers, our focus on data governance necessitates a prudent approach during data processing and analysis. We adhere to data minimization principle, only collecting and processing the minimum amount of data necessary to identify the core-periphery structure. In this study, we only use settlement time, sending/receiving bank, transaction code, status, and amount to reduce the risk of data breaches and ensures compliance with data protection regulations.

3.2 Workflow

To obtain the classification of core and periphery banks within a payment system network that consider not only the links between banks but also take into account the weight of those links, which is characterized by their transaction nominal and frequency, We propose a novel methodology that examines machine learning and core periphery model. In general, the workflow consists of data preprocessing and extraction.

3.2.1 Data Preprocessing

The data preprocessing stage is carried out to prepare the raw RTGS fund transfer transaction data so that they can be further processed at the next stage. The process is as follows:

1. Filter out non-bank BI-RTGS participants.

To filter out non-bank BI-RTGS participants names, we cross-referencing the participant list with the official records of authorized bank participants. We then identify and eliminate any names that do not belong to banks. For example, switching company and bank indonesia account are excluded.

2. Map branch unit bank to their parent bank

In order to establish the relationship between branch unit banks and their parent banks, we examine the hierarchical arrangement of the banking system and align each branch unit bank with its parent bank using official records and organizational connections. We perceive the parent and child corporations as a single entity of a network structure.

3. Codify the Bank Name using Bank Code

Before processing and analyzing the data, we ensure that all bank identifiers are anonymized. We replace bank names or any other identifiable information with generic IDs or pseudonyms (e.g. Bank A, B, C). This approach prevents that individual banks cannot be directly identified from the data, protecting their privacy and ensuring compliance with data protection standards.

4. Data Aggregation & Matrix Representation

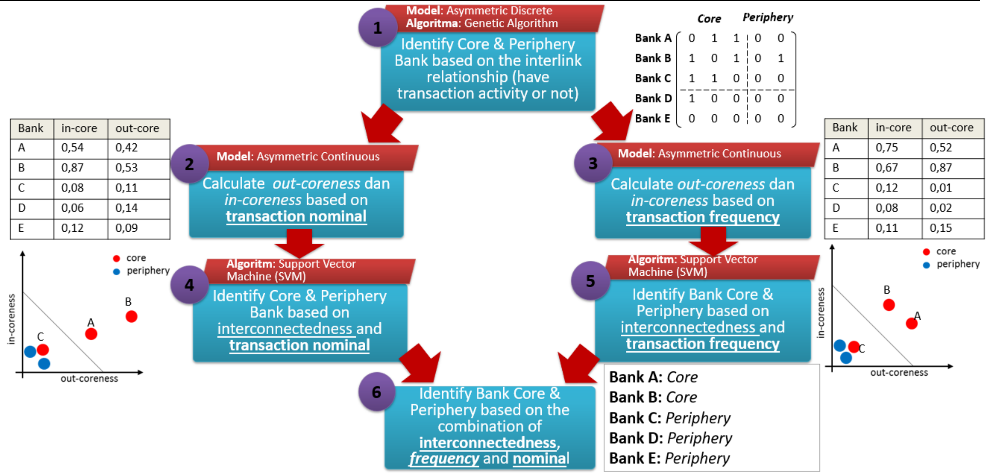
We consolidate the data monthly basis and represent the data in both discrete (binary, 1: connected and 0: not connected) and continuous matrices. This stage is essential for the subsequent data processing technique, in which we will employ the block modeling method on discrete matrices and the matrix decomposition method on continuous matrices.

3.2.2 Data Extraction

In order to incorporate both the quantity and intensity of connections between banks (as indicated by the transaction amount or frequency of transactions), this study aims to merge the concepts of the asymmetric discrete model and the asymmetric continuous model to establish a core-periphery classification. We employ a machine learning technique, specifically Support Vector Machine (SVM), to categorize banks into core and periphery based on the outcomes of both models. Figure 3 presents the structure for the core-periphery bank classification.

The Methodoloy of Core-Periphery Bank Classification

Figure 3



1. Assymmetric Discrete Model

During the initial stage, we employ the Asymmetric Discrete Model to determine the most favorable division of core-periphery banks in the BI-RTGS network. This division is based on the connection data, where 1 represents a link and 0 represents no connection. The model in this study is implemented using a Genetic Algorithm. The nominal transaction data is encoded as a binary transition matrix for each period and kind of transaction. By utilizing a Genetic Algorithm software, we can derive the best core-periphery partition. Borgatti (1999) states that the Genetic Algorithm outperforms other algorithms in identifying core-periphery partitions due to its ability to generate more resilient outcomes.

2. Assymmetric Continous Model

During phases 2 and 3, we employ the asymmetric continuous model to determine the out-coreness and in-coreness values for each bank in the BI-RTGS network. The input consists of a continuous transition matrix that represents the nominal data and frequency of transactions for each time and kind of transaction. Next, we ascertain the values of out-coreness and in-coreness that may generate a transition matrix resembling the original one with the least disparity, hence minimizing the loss in matrix reconstruction.

3. Machine Learning Model (SVM)

Subsequently, during phases 4 and 5, we employ a machine learning technique to categorize banks into core and periphery categories, utilizing the outcomes obtained from the discrete and continuous models. The SVM method is employed to implement this classification, utilizing the discrete model's outcomes as labels. The classification is based on the similarity between the out-coreness and in-coreness values of each core and periphery bank, taking into account nominal and transaction frequency.

4. Result and Analysis

In the context of the core-periphery structure, a bank is considered "core" if it is consistently designated as such every month throughout the observation period. According to the classification results, we have successfully identified a core-periphery structure in the BI-RTGS interbank payment system. This structure consists of a number of banks that have been consistently identified as the core over the whole observation period. Below are the findings from the identification process in BI-RTGS transactions.

Comparison of Core Periphery Classification Model

Table 2

		SVM	
	Classification	**Core**	**Periphery**
DISCRETE	**Core**	**10**	**41**
	Periphery	**0**	**54**

Among the many banks that participate in BI RTGS, there are 10 banks that are consistently categorized as core banks by SVM for a period of 24 months. According to Craig & Peter's (2010) core-periphery model, these 10 banks are considered the core banks in the BI-RTGS network. They are interconnected with each other and serve as intermediaries for other lower-tier banks, making them top-tier banks in the core-periphery structure. While the research did not discover a structure that precisely matches the ideal model proposed by Craig & Peter (such as the presence of periphery banks connected exclusively to other periphery banks), it did effectively identify a stable core-periphery structure throughout the observation period.

The Department of Financial System Surveillance (DSSK) at Bank Indonesia employs these identification results, which are displayed on our network analytics dashboard for supervisory purposes as a part of the Supervisory Technology Framework. They further analyse the results by conducting an assessment of intraday liquidity risk to evaluate how well the identified core banks manage their intraday liquidity. In addition, the application of core-periphery analysis in network mapping can be utilized to examine the spread of contagion.

Moreover, access to the dashboard, where the results are displayed, is strictly available only to users who have agreed to a non-disclosure agreement. We implement access controls to ensure that only authorized user can view and interpret the classification results. This not only safeguards data privacy but also prevents the potential for data misuse. Nevertheless, despite the benefits of this finding as an early warning tool to identify risks within the banking network, it is crucial to recognize that these classifications have significant financial or reputational implications for the banks involved. Consequently, reliance on this finding as the sole basis for decision-making is inadvisable. It is essential to consider the ethical implications of this result of classifying banks while conducting financial stability surveillance.

To strengthen surveillance in the financial sector, we also have develop a system for identifying the primary players (banks) in foreign exchange transactions. Bank Indonesia can systematically monitor the conduct and composition of foreign exchange market players under its supervision by utilizing the technique previously outlined, which focuses on analyzing interbank transaction data in the BI-RTGS system. This evaluation is of utmost importance due to the potential occurrence of exchange rate risk and liquidity risk resulting from the actions of market participants.

5. Conclusion and Future Work

5.1 Conclusion

In this study, we have proposed a novel approach to identifiying core-periphery structure. We examine machine learning to categorize banks into core and periphery banks, using discrete and continuous models and the SVM method based on the similarity between out-coreness and in-coreness values.

The BI-RTGS interbank payment system has identified a core-periphery structure consisting of 10 banks consistently categorized as core banks for 24 months. These banks are interconnected and serve as intermediaries for lower-tier banks, making them top-tier in the core-periphery structure. The Department of Financial System Surveillance (DSSK) at Bank Indonesia uses these identification results for supervisory purposes, assessing intraday liquidity risk and examining contagion spread. To enhance financial sector surveillance, DSSK used the result for identifying primary players in foreign exchange transactions, analyzing interbank transaction data in the BI-RTGS system.

We have implemented various protective measures to ensure the confidentiality of the banks' data. These include data minimization, bank anonymization, implementing stringent access controls to our network analytics dashboard, and utilizing the results by always consider the ethical implications of classifying banks and ensuring these are used responsibly in the context of financial stability oversight.

5.2 Future Work

There are several improvements in the methodology that can be applied for future works.

1. Strengthen the monitoring and analysis (e.g. liquidity risk and contagion) of core and periphery banks at a more frequently level, such as weekly or daily intervals, to detect any occurrences that could influence the network.
2. Enhance the data source to encompass the whole interbank payment system in Indonesia, including but not limited to retail payment system like fast payment and card-based transaction.
3. Incorporate additional economic indicators into the BI-RTGS transactions to enrich understanding of the overall economic ecosystem and its influence on the core-periphery structure e.g. macroeconomic and sectoral indicators.

References

Baek, S., Soramaki, K., & Yoon, J. 2014. "Network indicators for monitoring intraday liquidity in BOK-Wire+". Journal of Financial Market Infrastructures 2(3), 37-66

Boyd, J. P., Fitzgerald, W. J., Mahutga, M. C., &Smith, D. A. 2010. "Computing continuous core/periphery structures for social relations data with MINRES/SVD". Social Networks, 32(2), 125–137 3.

Craig, Ben R. & von Peter, Goetz, 2010. "Interbank tiering and money center banks". BIS Working Papers 322, Bank for International Settlements.

Fricke, D., Lux, T., 2014, "Core-periphery structure in the overnight money market: Evidence from the e-MID trading platform". Computational Economics 45:359–395

Goldberg, David E. 1989. Genetic Algorithms in Search, Optimization and Machine Learning, Kluwer Academic Publishers, Boston, MA.

Untoro, Widodo P.R., dan Yuwana W. 2014. "Kajian Penggunaan Instrumen Sistem Pembayaran sebagai Leading Indicator Stabilitas Sistem Keuangan. Working Paper, Bank Indonesia.

Van Lelyveld, I., in 't Veld, D., 2012, "Finding the core: Network structure in interbank markets". DNB Working Paper 348, DNB.

Abduraimova, K. (2022). Contagion and tail risk in complex financial networks. Durham University Business School, United Kingdom. Available online 29 May 2022. Article history: Received 31 October 2020; Accepted 28 May 2022.

Ballester, L., Casu, B., & González-Urteaga, A. (2016). Bank fragility and contagion: Evidence from the bank CDS market.

Zhang, X., Fu, Q., Lu, L., Wang, Q., & Zhang, S. (2021). Bank liquidity creation, network contagion and systemic risk: Evidence from Chinese listed banks.

Heijmans, R., & Wendt, F. (2023.). Measuring the impact of a failing participant in payment systems. De Nederlandsche Bank, Netherlands; International Monetary Fund, United States of America.

Fricke, D., & Lux, T. (2012). Core-periphery structure in the overnight money market: Evidence from the e-MID trading platform. Kiel Working Papers, No. 1759.

In 't Veld, D., Van der Leij, M., & Hommes, C. (2020). The formation of a core-periphery structure in heterogeneous financial networks.

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Unveiling the Interconnectedness of Banks in Payment Systems: Methodology, Utilization, and Data Governance Considerations

17 October 2023

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Background

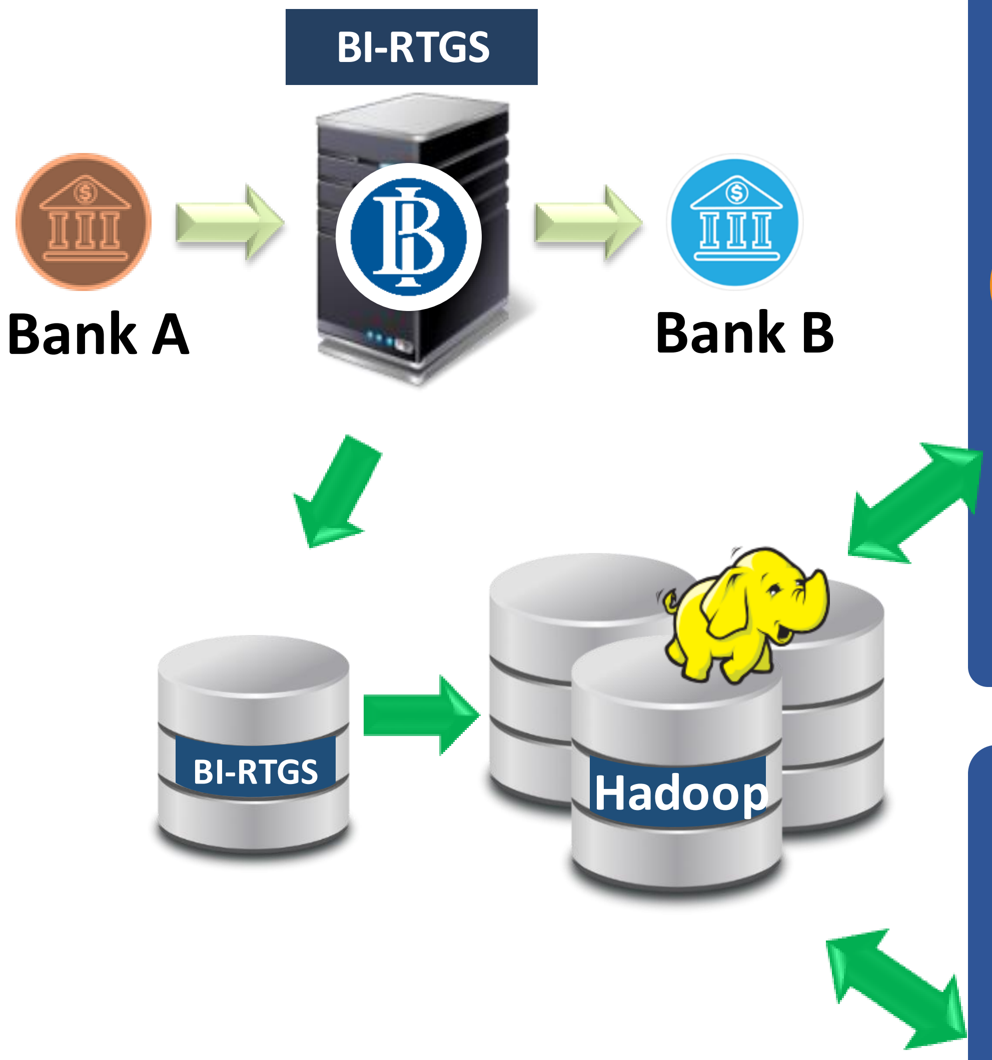
BACKGROUND

- In the payment system, every bank is interconnected with each other. When problems occurs in one bank, they can potentially have ripple effects on other linked institutions. Therefore, it's crucial to identify the interconnected structure of participants in the payment system.
- Leveraging Big Data Analytics through the core-periphery model to visualize the systemic structure (interbank tiering) comprehensively serves to complement the interconnectedness analysis that has been conducted so far.

OBJECTIVE

Discover the interlinked structure of participants in the payment system by applying network analysis method.

DATA SOURCES & METHODOLOGY



- ✓ Total transaction rows: ± 1 million rows per month
- ✓ Number of banks transacting: 117 banks
- ✓ Transaction amount ≥ Rp.100 million or ≥ USD 6,390

Data Preparation

1. Filtering & Mapping

- Filter out non-bank BI-RTGS participants names.
- Map branch unit bank to their parents bank
- Codify the Bank Name using Bank Code

2. Data Aggregation & Matrix Representation

- Aggregate transaction data on a monthly basis.
- Represent transaction data in discrete matrices (connectivity) & continuous matrices (transaction amount/frequency).

Data Extraction

Model Core - Periphery

3. Model Asymmetric Discrete

Identify Core & Periphery banks based on connectivity (presence or absence of transactions).

4. Model Asymmetric Continuous

Calculate out-coreness and in-coreness based on transaction amount & frequency.

5. SVM Classification

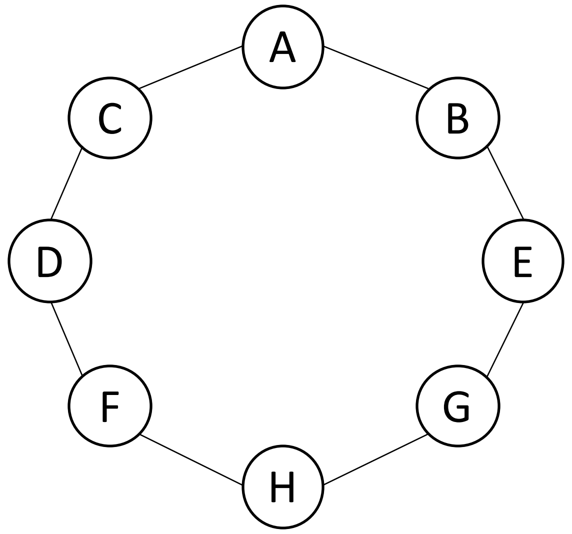
Classification using Support Vector Machine (SVM) based on the results of discrete and continuous models.

Interbank & Payment System Network

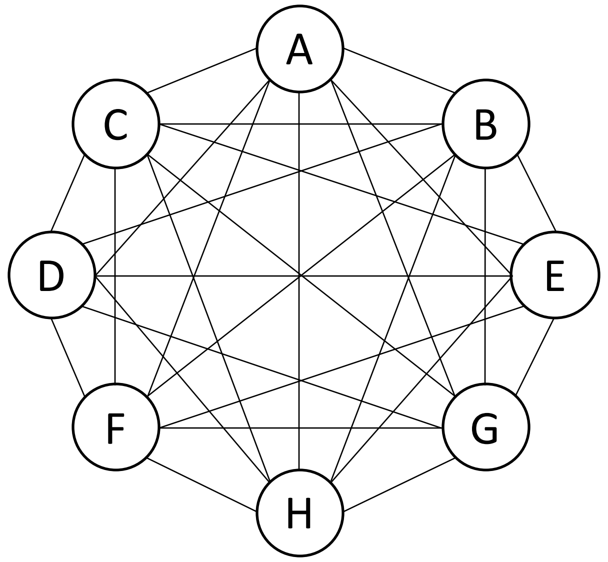
Numerous studies on interbank & payment system networks indicate that the observed structure exhibits a hierarchical pattern, often referred to as interbank tiering.

Interbank tiering describes the interbank structure that emerges when there are interconnected banks also function as intermediaries between non-interconnected banks (Craig & Peter, 2010).

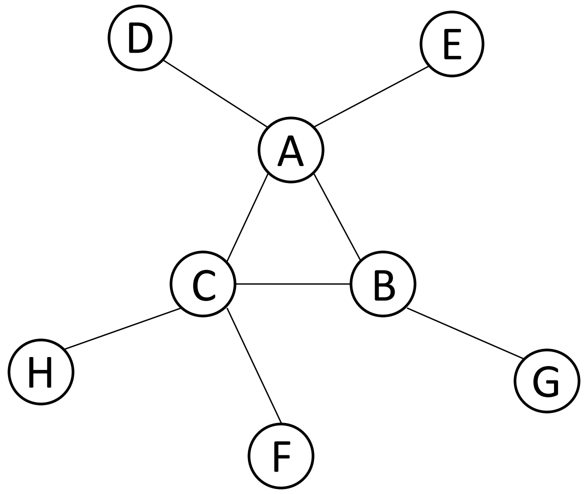
The model often used to identify such network structures is the core-periphery model (Craig & Peter, 2010).



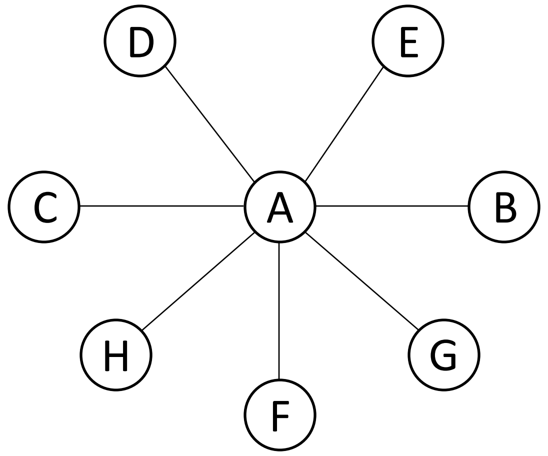
Ring



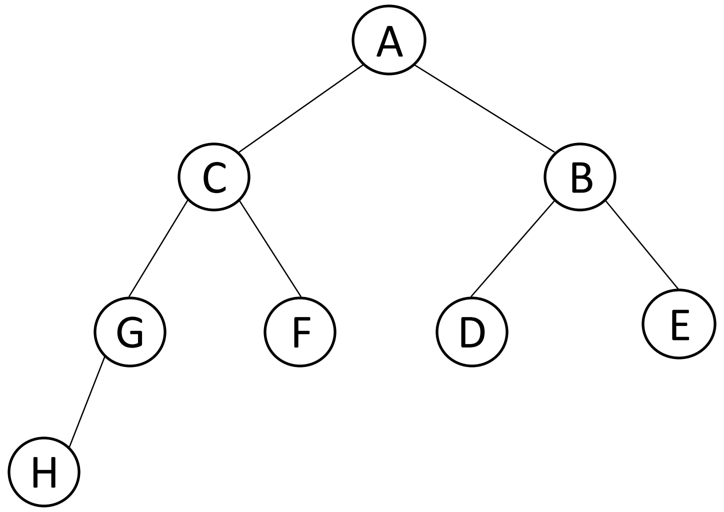
Full Mesh



Core – Periphery



Star



Tree

Core-Periphery Model Type

	A	B	C	D	E
A	0	1	1	0	0
B	1	0	0	1	1
C	1	0	0	1	0
D	0	1	1	0	1
E	0	1	0	1	0

Matriks Biner Simetris

Model *Symmetric Discrete* Borgatti dan Everett, 1999	**Model *Symmetric Continuous*** Borgatti dan Everett, 1999
Objective: To classify nodes in an undirected network into core and periphery nodes.	**Objectives:** To determine the coreness value of each node in an undirected network.
Data: Connectivity between nodes in a network (0: not connected, 1: connected).	**Data :** Edge weights in the network with continuous values (e.g., based on transaction amount or frequency).
Model *Asymmetric Discrete* Craig dan Peter, 2010	**Model *Asymmetric Continuous*** Boyd et al., 2010
Objective: To classify nodes in a directed network into core and periphery nodes.	**Objectives:** To determine the coreness value of each node in a directed network
Data : Connectivity between banks in a network (0: not connected, 1: connected).	**Data :** Edge weights in the network with continuous values (e.g., based on transaction amount or frequency).

	A	B	C	D	E
A	0	10	5	0	0
B	10	0	0	15	25
C	5	0	0	3	0
D	0	15	3	0	30
E	0	25	0	30	0

Matriks Kontinu Simetris

	A	B	C	D	E
A	0	1	1	0	0
B	0	0	0	1	1
C	1	1	0	1	0
D	1	0	0	0	1
E	1	0	1	0	0

Matriks Biner Asimetris

	A	B	C	D	E
A	0	10	18	0	0
B	0	0	0	20	1
C	15	10	0	2	18
D	30	0	0	0	10
E	25	0	3	0	0

Matriks Kontinu Asimetris

Model used to identify BI-RTGS *network*

Model Asymmetric Discrete

Using blockmodelling techniques to identify core and periphery banks based on interbank connectivity patterns. (Craig & Peter, 2010)

Blockmodelling is a network analysis method that partitions a network into several groups (also called blocks), where each group consists of nodes that have similar connectivity patterns with other members.

The ideal blockmodel is achieved when the three properties of the model are met, namely:

- ✓ ***Top-tier banks*** (***core***) are interconnected with each other. (CC)
- ✓ ***Lower-tier banks*** (***periphery***) are not interconnected with each other. (PP)
- ✓ ***Top-tier banks (core)*** are connected to (some) ***lower-tier banks (periphery)***. $(CP\ \&\ PC)$

$$\begin{bmatrix} CC & CP \\ PC & PP \end{bmatrix} = \begin{bmatrix} \mathbf{1} & \boldsymbol{RR} \\ \boldsymbol{CR} & \mathbf{0} \end{bmatrix}$$

Blok *CC* (*Core to Core*) : Connectivity between core banks
Blok *PP* (*Periphery to Periphery*) : Connectivity between *periphery* banks
Blok *CP* (*Core to Periphery*) : Connectivity from *core bank* → *periphery bank*
Blok *PC* (*Periphery to Core*) : Connectivity from *periphery bank* → *core bank*

$\boldsymbol{RR}$: *At least* 1 *connection in every row* $\boldsymbol{CR}$: *At least* 1 *connection in every column.*

$$\begin{array}{cc} & \begin{array}{ccc} \text{Core} & & \text{Periphery} \end{array} \\ & \begin{array}{cccccccc} \boldsymbol{A} & \boldsymbol{B} & \boldsymbol{C} & \boldsymbol{D} & \boldsymbol{E} & \boldsymbol{F} & \boldsymbol{G} & \boldsymbol{H} \end{array} \\ \begin{array}{c} \text{Core} \\ \\ \\ \text{Periphery} \end{array} \begin{array}{c} \boldsymbol{A} \\ \boldsymbol{B} \\ \boldsymbol{C} \\ \boldsymbol{D} \\ \boldsymbol{E} \\ \boldsymbol{F} \\ \boldsymbol{G} \\ \boldsymbol{H} \end{array} & \left[\begin{array}{ccc|ccccc} 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ \hline 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}\right] \end{array}$$

Example of block model with 3 Cores (A, B, C)

Model Asymmetric Discrete

Let's suppose there are n banks labeled 1,2,..., n.

- The interbank connectivity data (transactions) is stored in matrix N where:

$$N_{ij} = \begin{cases} 1, & \text{if there is a transaction from } i \text{ to } j \\ 0, & \text{if there is a transaction rom } j \text{ to } i \end{cases}$$

for $i = 1,2,\ldots n$ $\quad and \quad j = 1,2,\ldots n$

- Define C^* as a set of banks designated as core, and N_{C^*} is the blockmodel of matrix N

Objective Function

$$\arg\min_{C^*}\left[e(N_{C^*}) = \frac{e_{cc} + e_{pp} + (e_{cp} + e_{pc})}{\sum_i \sum_j N_{ij}}\right]$$

Where

$$E = \begin{bmatrix} e_{cc} & e_{cp} \\ e_{pc} & e_{pp} \end{bmatrix} = \begin{bmatrix} c(c-1) - \sum_{i\in C^*}\sum_{j\in C^*} N_{ij} & (n-c)\sum_{i\in C^*} \max\left\{0,1-\sum_{j\notin C^*} N_{ij}\right\} \\ (n-c)\sum_{j\in C^*} \max\left\{0,1-\sum_{i\notin C^*} N_{ij}\right\} & \sum_{i\notin C^*}\sum_{j\notin C^*} N_{ij} \end{bmatrix}$$

$e(N_{C^*})$ = Total *error* (*blockmodel* N_{C^*})
e_{CC} = *Error* at block *CC*
e_{PP} = *Error* at block *PP*
e_{CP} = *Error* at block *CP*
e_{PC} = *Error* at block *PC*
N_{ij} = Transaction Matrix Element *at* row i and column j

The optimal partition is a set of core banks (C^*) that produces the smallest error value ($e(N_{C^*})$) (closest to the ideal blockmodel).

Model Asymmetric Discrete

$$
\begin{array}{cc}
 & \begin{array}{cccccccc} A & B & C & D & E & F & G & H \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \\ E \\ F \\ G \\ H \end{array} &
\begin{bmatrix}
0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{array}
$$

?

$$
\begin{array}{cc}
 & \begin{array}{ccccccccc} A & B & C & & D & E & F & G & H \end{array} \\
\begin{array}{c} A \\ B \\ C \\ \\ D \\ E \\ F \\ G \\ H \end{array} &
\left[\begin{array}{ccc|ccccc}
0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & \color{red}{0} & 0 & 0 & 0 & 1 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 & 0 & 0 & 0 & \color{red}{1} \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{array}\right]
\end{array}
$$

- ❑ If the number of nodes in a network is n, then there are $2^n - n - 1$ choices in determining which nodes become the core in order to produce an optimal blockmodel (closest to the ideal blockmodel).
- ❑ How to obtain the optimal blockmodel?

- ✓ **Heuristic algorithms can be used to obtain the optimal blockmodel.**
- ✓ **According to Borgatti (1999), the Genetic Algorithm is better for finding the optimal blockmodel as it provides more stable results compared to other algorithms.**

Model Asymmetric Continues

The matrix decomposition method is utilized to measure the 'core' strength of each bank. (Fricke & Lux, 2012)

Pengirim	Penerima	Nominal Transaksi
A	B	143
A	C	95
A	E	61
B	A	61
B	C	70
B	D	72
C	A	66
C	B	86
C	E	50
D	A	20
E	B	29

$$\begin{array}{c} \\ \mathbf{A} \\ \mathbf{B} \\ \mathbf{C} \\ \mathbf{D} \\ \mathbf{E} \end{array} \begin{array}{c} \begin{array}{ccccc} \mathbf{A} & \mathbf{B} & \mathbf{C} & \mathbf{D} & \mathbf{E} \end{array} \\ \underbrace{\begin{bmatrix} 0 & 143 & 95 & 0 & 61 \\ 61 & 0 & 70 & 72 & 0 \\ 66 & 86 & 0 & 0 & 50 \\ 20 & 0 & 0 & 0 & 0 \\ 0 & 29 & 0 & 0 & 0 \end{bmatrix}} \end{array}$$

$\boldsymbol{N}$: **Matriks *Adjacency***
nominal transaction data

$$\boldsymbol{u} = \begin{bmatrix} 0.355 \\ 0.340 \\ 0.232 \\ 0.016 \\ 0.042 \end{bmatrix} \begin{array}{c} \mathbf{A} \\ \mathbf{B} \\ \mathbf{C} \\ \mathbf{D} \\ \mathbf{E} \end{array}, \boldsymbol{v} = \begin{bmatrix} 0.212 \\ 0.396 \\ 0.236 \\ 0.130 \\ 0.113 \end{bmatrix} \begin{array}{c} \mathbf{A} \\ \mathbf{B} \\ \mathbf{C} \\ \mathbf{D} \\ \mathbf{E} \end{array}$$

- $\boldsymbol{u_i}$: ***coreness*** bank i as sender
- $\boldsymbol{v_j}$: ***coreness*** bank j as receiver

The fundamental concept of the **Asymmetric Continuous Model** is to decompose the adjacency matrix into '**out-coreness**' and '**in-coreness**' as follows:

$$\boldsymbol{N} = \begin{cases} \boldsymbol{u}\boldsymbol{v}^T, & off-diagonal \\ 0, & diagonal \end{cases}$$

where $\boldsymbol{u}$: **out-coreness vector** & $\boldsymbol{v}$: **in-coreness vector**.

Model Asymmetric Continues

Suppose there are n banks labeled as $1,2,\dots,n$

- The nominal or frequency of interbank transactions is stored in the matrix N
- where: $N_{ij} = \begin{cases} transaction\ nominal\ or\ frequency, & if\ there\ is\ transaction\ from\ i\ to\ j \\ 0, & if\ there\ is\ no\ transaction\ from\ i\ to\ j \end{cases}$

  for $i = 1,2,\dots n \quad dan \quad j = 1,2,\dots n$
- Let u be defined as the out-coreness vector and v as the in-coreness vector.

Objective Function

$$\arg\min_{\boldsymbol{u},\boldsymbol{v}} \sum_{i} \sum_{j \neq i} \left(N_{ij} - \boldsymbol{u}_i \boldsymbol{v}_j^T\right)^2$$

Contoh*

	B	C	H	A	F	D	E	G
B	0	144	59	281	78	114	93	67
C	110	0	34	161	45	65	53	39
H	20	15	0	28	8	12	9	7
A	396	296	120	0	161	234	191	138
F	34	26	10	50	0	20	16	12
D	70	52	21	102	28	0	34	24
E	48	36	14	69	19	28	0	17
G	25	19	8	37	10	15	12	0

Normalisasi

	B	C	H	A	F	D	E	G
B	0	0.144	0.059	0.281	0.078	0.114	0.093	0.067
C	0.11	0	0.034	0.161	0.045	0.065	0.053	0.039
H	0.02	0.015	0	0.028	0.008	0.012	0.009	0.007
A	0.396	0.296	0.12	0	0.161	0.234	0.191	0.138
F	0.034	0.026	0.01	0.05	0	0.02	0.016	0.012
D	0.07	0.052	0.021	0.102	0.028	0	0.034	0.024
E	0.048	0.036	0.014	0.069	0.019	0.028	0	0.017
G	0.025	0.019	0.008	0.037	0.01	0.015	0.012	0

$$\boldsymbol{u} = \begin{array}{c} \begin{bmatrix} 0.85 \\ 0.42 \\ 0.24 \\ 0.24 \\ 0.15 \\ 0.10 \\ 0.07 \\ 0.05 \end{bmatrix} \end{array} \begin{array}{c} \mathbf{A} \\ \mathbf{B} \\ \mathbf{C} \\ \mathbf{D} \\ \mathbf{E} \\ \mathbf{F} \\ \mathbf{G} \\ \mathbf{H} \end{array}, \boldsymbol{v} = \begin{array}{c} \begin{bmatrix} 0.68 \\ 0.46 \\ 0.35 \\ 0.27 \\ 0.22 \\ 0.19 \\ 0.16 \\ 0.14 \end{bmatrix} \end{array} \begin{array}{c} \mathbf{A} \\ \mathbf{B} \\ \mathbf{C} \\ \mathbf{D} \\ \mathbf{E} \\ \mathbf{F} \\ \mathbf{G} \\ \mathbf{H} \end{array}$$

$u_A v_B = (0.85)(0.46) = \boxed{0.391}$

$u_B v_A = (0.42)(0.68) = \boxed{0.285}$

Model Asymmetric Continues

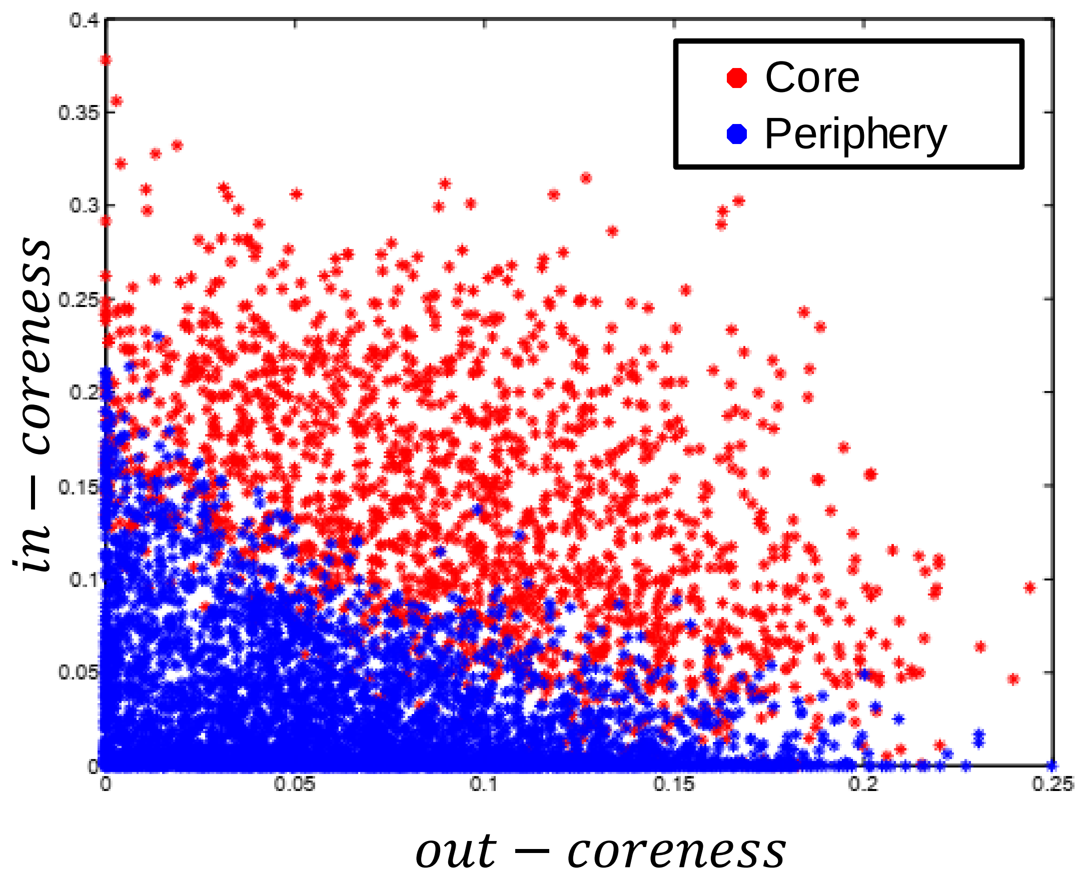
Model *Asymmetric Discrete*

- **Objective:** Classify banks into core and periphery.
- **Criteria:** Only considers the interbank connections in a network. **(0: not connected, 1: connected).**

Model *Asymmetric Continuous*

- **Objective:** Measure coreness, indicating the 'core' strength of each bank in a network.
- **Criteria:** Considers both transaction values and interbank connections when determining the coreness value of each bank.

Scatter plot of Coreness

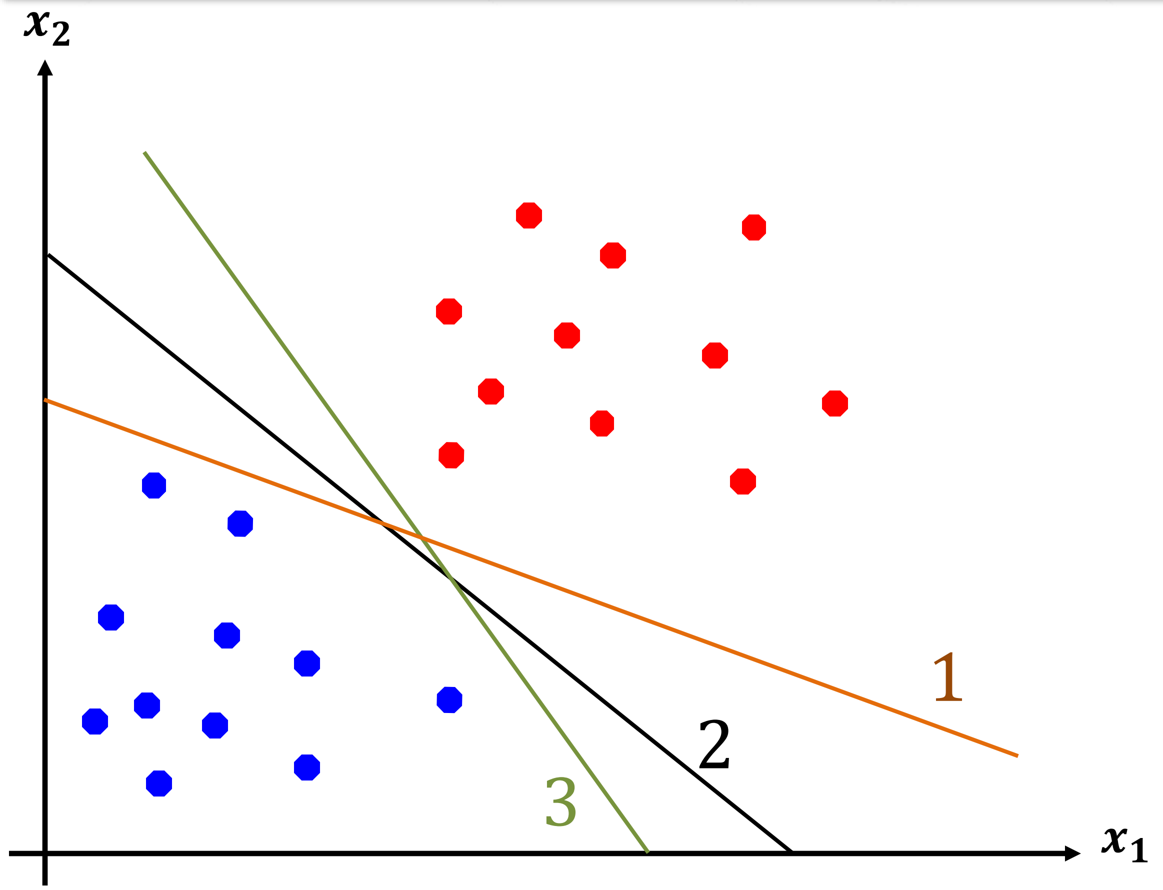


Core and periphery bank characteristic based on coreness value

- **Visualization:** A scatter plot of coreness values can be used to analyze the relationship between the results of the discrete model and the continuous model.
- **Plot Details:** The scatter plot is formed based on out-coreness values (x-axis), in-coreness values (y-axis), and the classification results of the discrete model (color of the dots).
- **Observation:** The out-coreness and in-coreness values of core banks should be significantly higher compared to periphery banks.

Model Asymmetric Continues

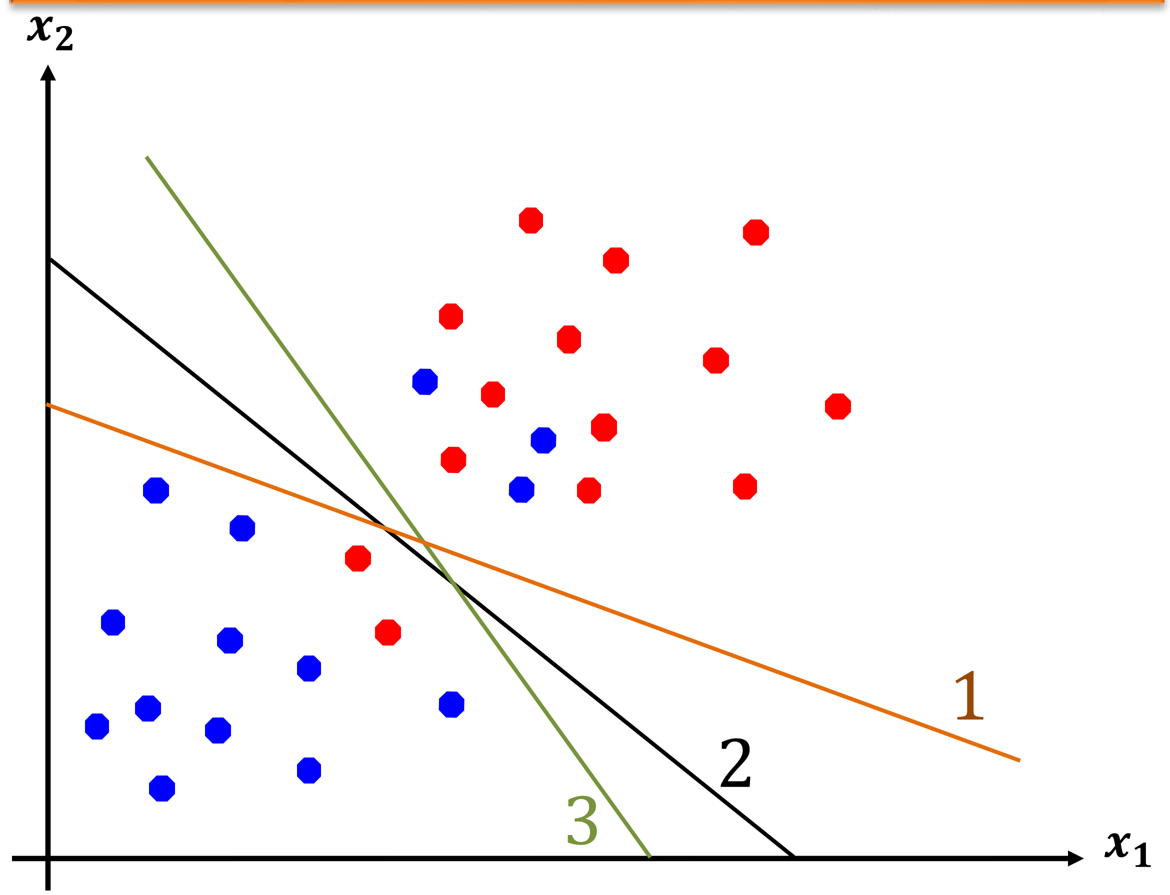
Ideal Cases



- Core
- Periphery

x_1 : *out – coreness*
x_2 : *in – coreness*

Non-Ideal Cases



- ❑ A **line equation** can be used as a **boundary that separates the core and periphery regions**.
- ❑ There **are several possible line equations**; which equation will be chosen or is the most optimal? **1, 2, or 3?**

Using machine learning algorithm to determine the core and periphery threshold area
Example: *Support Vector Machine* (SVM)

Core-Periphery Classification Using SVM

1

Model: Asymmetric Discrete
Algoritma: Genetic Algorithm

Identigy Core & Periphery Bank based on the interlink relationship (have transaction activity or not)

Core: A, B, C — Periphery: D, E

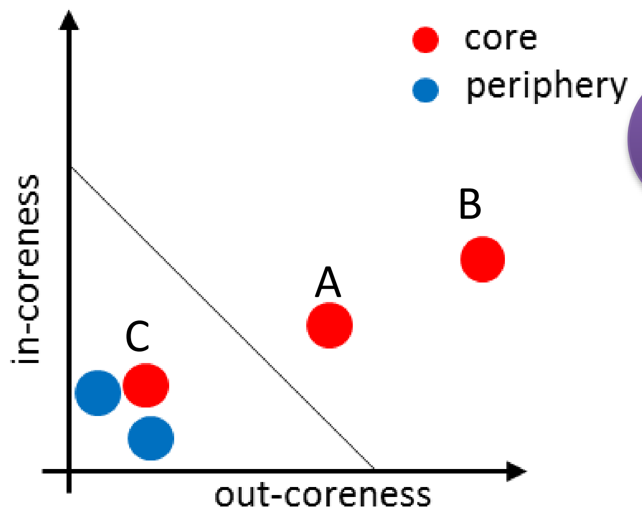
	A	B	C	D	E
Bank A	0	1	1	0	0
Bank B	1	0	1	0	1
Bank C	1	1	0	0	0
Bank D	1	0	0	0	0
Bank E	0	0	0	0	0

2

Model: Asymmetric Continuous

Calculate *out-coreness* dan *in-coreness* based on **transaction nominal**

Bank	in-core	out-core
A	0,54	0,42
B	0,87	0,53
C	0,08	0,11
D	0,06	0,14
E	0,12	0,09

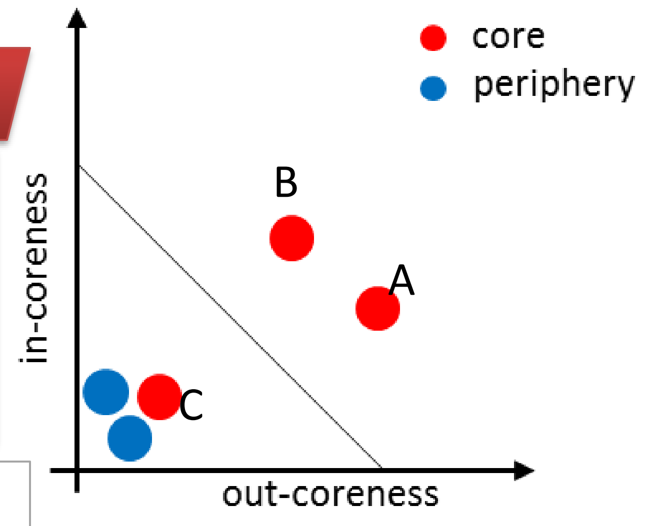


3

Model: Asymmetric Continuous

Calculate *out-coreness* dan *in-coreness* based on **transaction frequency**

Bank	in-core	out-core
A	0,75	0,52
B	0,67	0,87
C	0,12	0,01
D	0,08	0,02
E	0,11	0,15



4

Algoritma: Support Vector Machine (SVM)

Identify Core & Periphery Bank based on interconnectedness and **transaction nominal**

5

Algoritma: Support Vector Machine (SVM)

Identify Bank Core & Periphery based on interconnectedness and **transaction frequency**

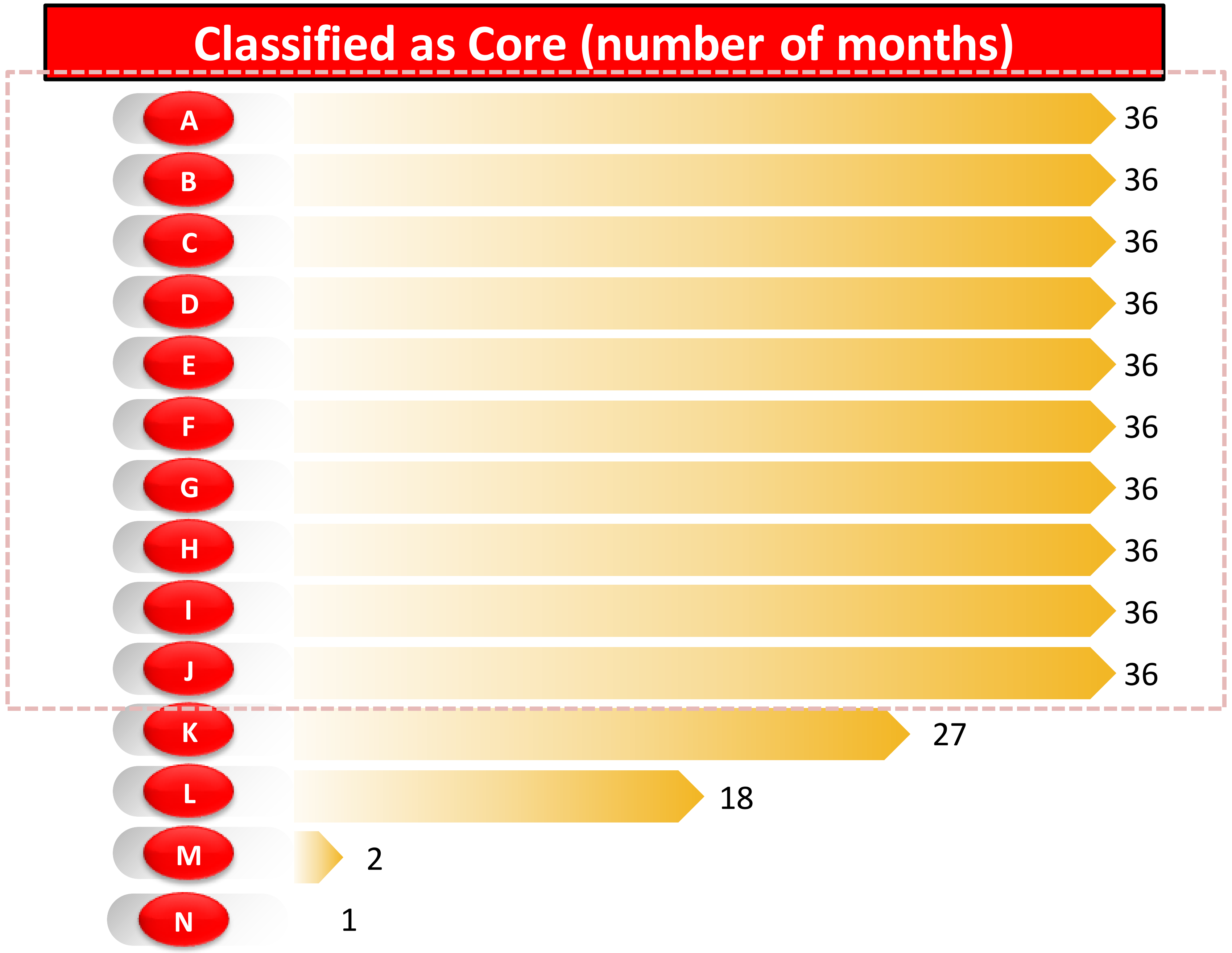
6

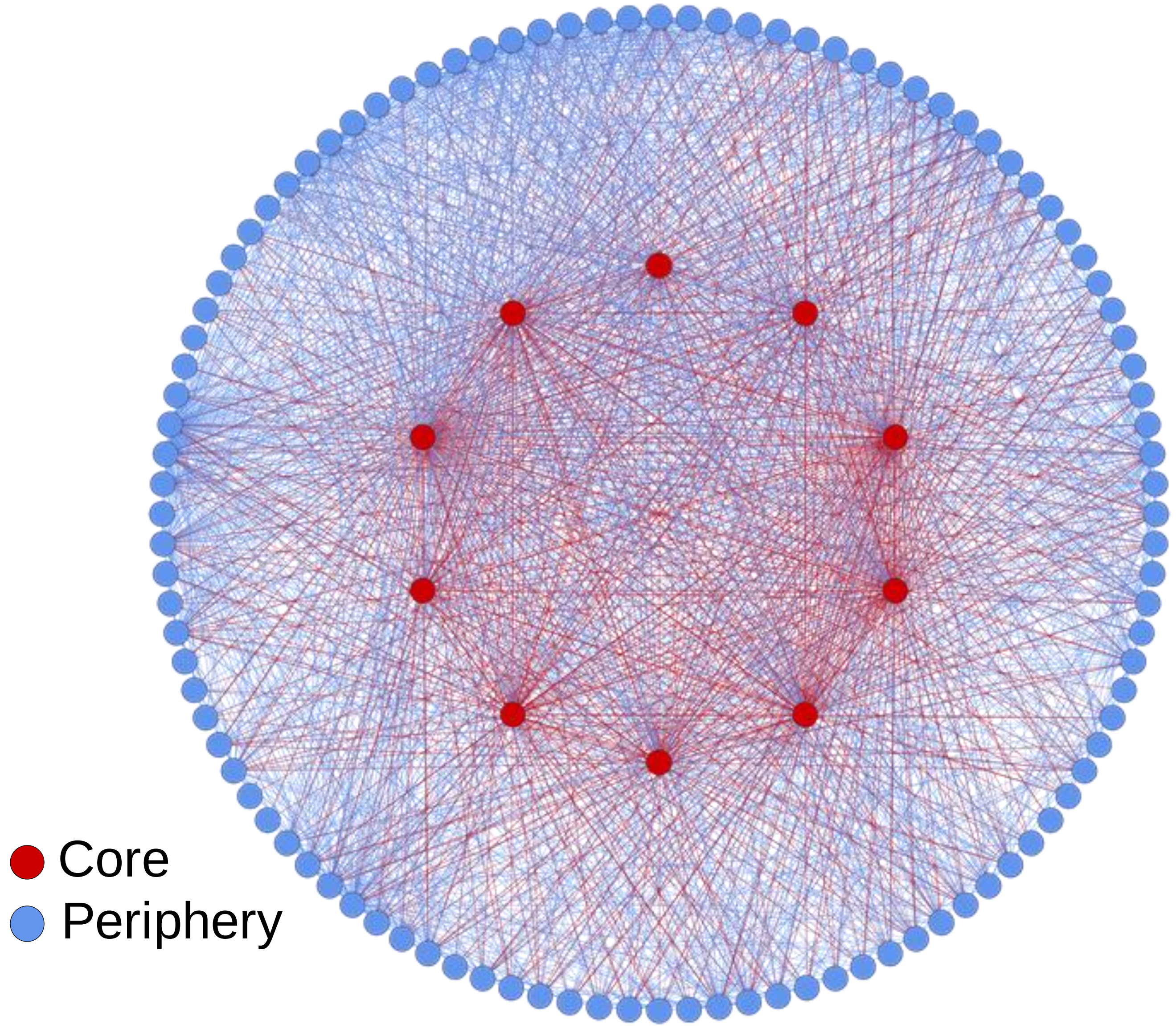
Identify Bank Core & Periphery based on the combination of **interconnectedness**, ***frequency*** and **nominal**

Bank A: *Core*
Bank B: *Core*
Bank C: *Periphery*
Bank D: *Periphery*
Bank E: *Periphery*

Core-Periphery Model Result

- The identification of the BI-RTGS network structure with the core-periphery model was conducted every month from January 2016 to December 2018 (36 months).
- Based on the results obtained, a core-periphery structure was identified within the BI-RTGS interbank transactions.
- This is evidenced by the presence of 10 banks that were identified as core banks (out of 117 banks that transacted with each other) throughout the observation period (36 months).

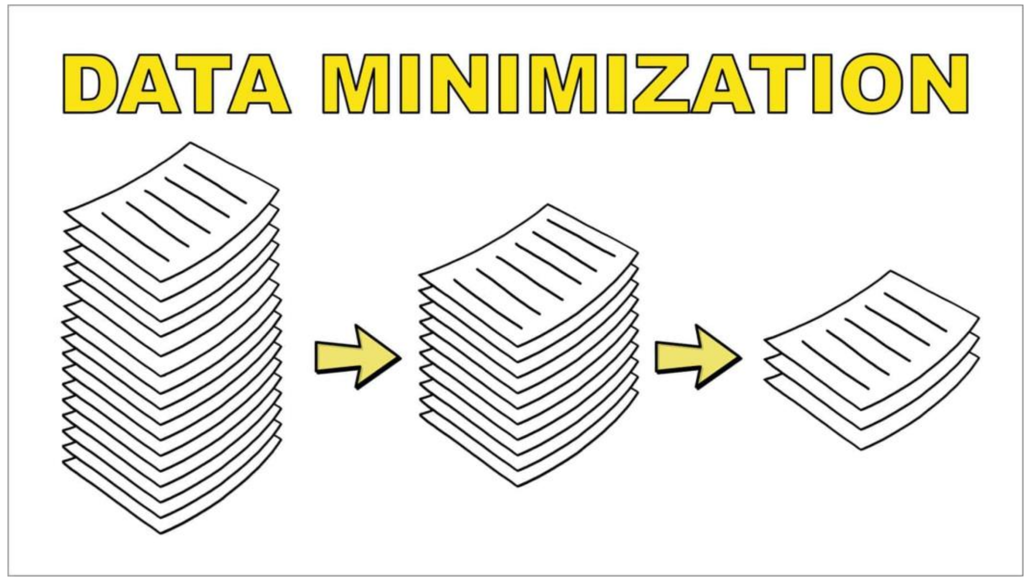


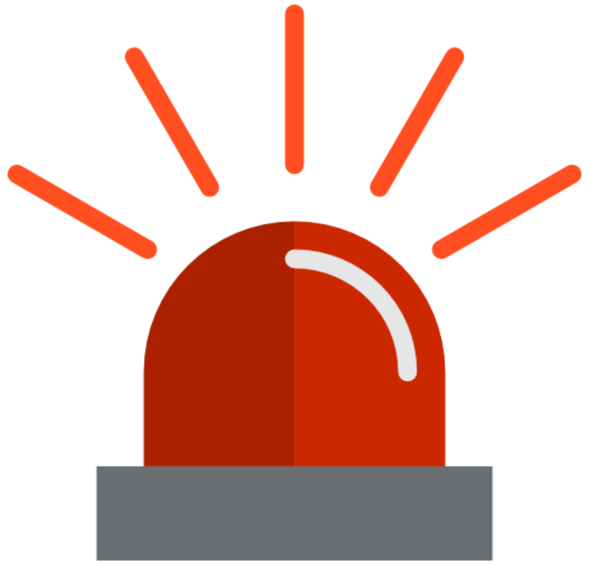


Struktur *Core-Periphery* in BI-RTGS Transaction

Data Governance Considerations

- **Data Minimization:** Only collect and process the minimum amount of data necessary to identify the core-periphery structure. In this case, we only use settlement time, sending/receiving bank, trx status, and amount. This reduces the risk of data breaches and ensures compliance with data protection regulations.
- **Bank Anonymization:** Before processing and analyzing the data, we ensure that all bank identifiers are anonymized. We replace bank names or any other identifiable information with generic IDs or pseudonyms. This ensures that individual banks cannot be directly identified from the data, protecting their privacy and ensuring compliance with data protection standards.
- **User Access Control:** Implement access controls to ensure that only authorized personnel can view and interpret the classification results. This not only ensures data privacy but also prevents potential misuse of the data.
- **Model Usage:** The core-periphery classification model should be used cautiously. For instance, it can be employed as an early warning system to highlight potential risks in the banking network. However, it should not be the sole source for making critical decisions. Always consider the ethical implications of classifying banks, especially if these classifications have significant financial or reputational implications for the banks involved.





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