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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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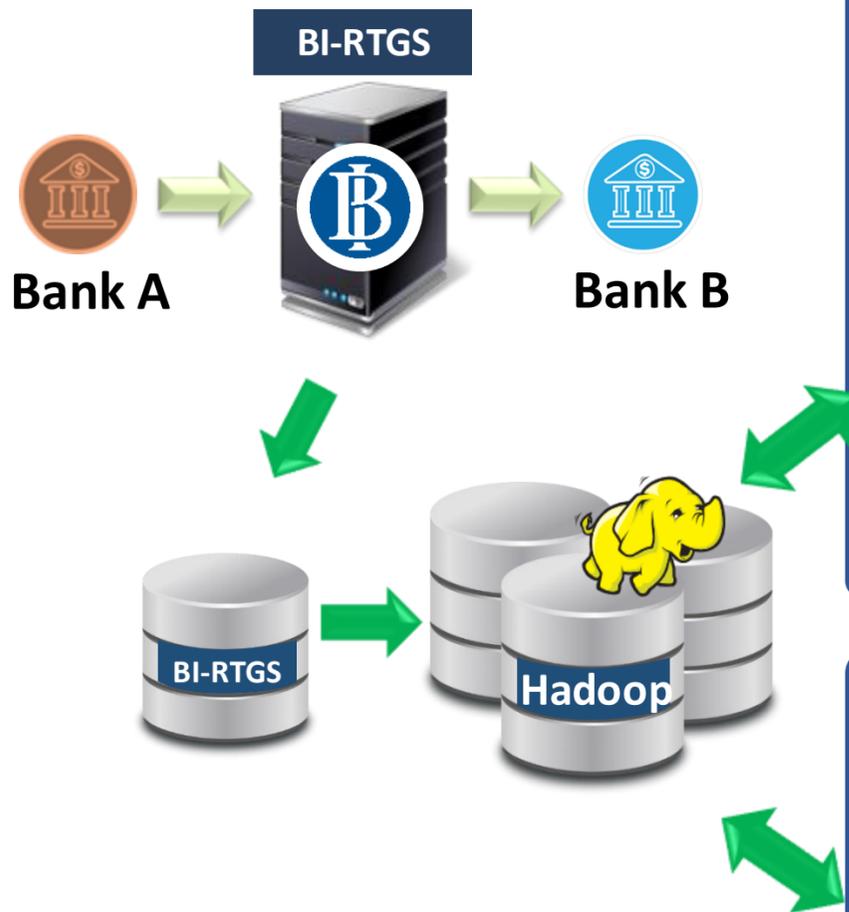
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## BACKGROUND

- 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.



- ✓ 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

### **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.

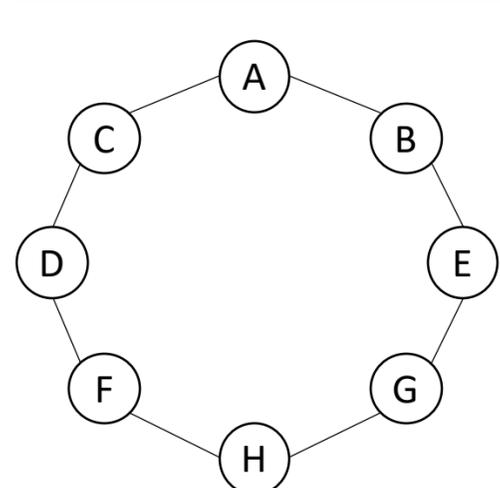
### **5. SVM Classification**

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

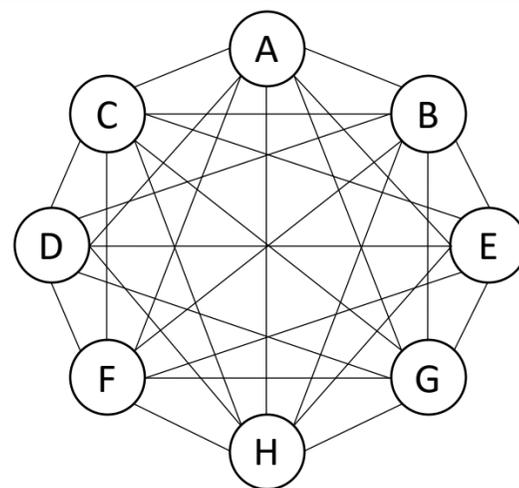
Numerous studies on interbank & payment system networks indicate that the observed structure exhibits a hierarchical pattern, often referred to as interbank tiering.

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

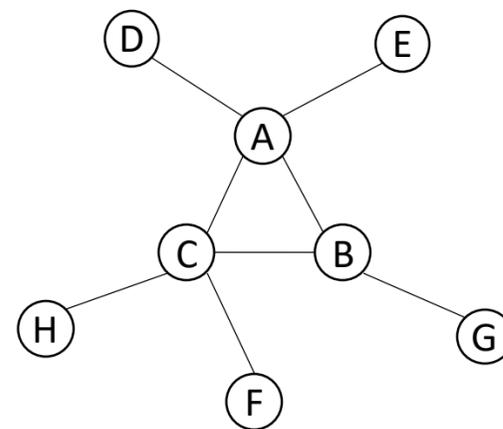
The model often used to identify such network structures is the core-periphery model (Craig & Peter, 2010).



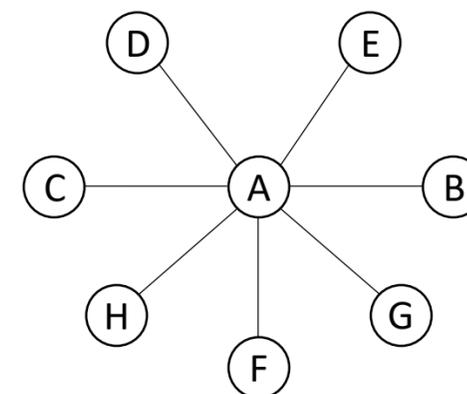
**Ring**



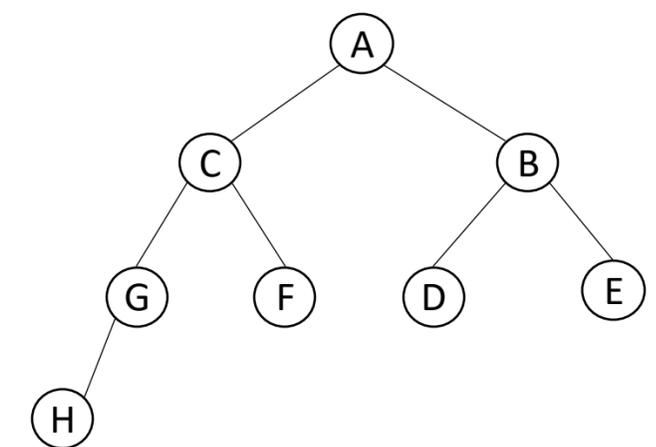
**Full Mesh**



**Core – Periphery**



**Star**



**Tree**

	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**

	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**

## Model *Symmetric Discrete* Borgatti dan Everett, 1999

**Objective:** To classify nodes in an undirected network into core and periphery nodes.

**Data:** Connectivity between nodes in a network (0: not connected, 1: connected).

## Model *Symmetric Continuous* Borgatti dan Everett, 1999

**Objectives:** To determine the coreness value of each node in an undirected network.

**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	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 *Asymmetric Discrete* Craig dan Peter, 2010

**Objective:** To classify nodes in a directed network into core and periphery nodes.

**Data :** Connectivity between banks in a network (0: not connected, 1: connected).

## Model *Asymmetric Continuous* Boyd et al., 2010

**Objectives:** To determine the coreness value of each node in a directed network

**Data :** Edge weights in the network with continuous values (e.g., based on transaction amount or frequency).

Model used to identify BI-RTGS *network*

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*)

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

- 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*

		Core			Periphery				
		A	B	C	D	E	F	G	H
Core	A	0	1	1	0	1	0	0	0
	B	1	0	1	0	0	0	1	0
	C	1	1	0	0	0	0	0	1
Periphery	D	1	0	0	0	0	0	0	0
	E	0	1	0	0	0	0	0	0
	F	0	0	1	0	0	0	0	0
	G	0	1	0	0	0	0	0	0
	H	0	0	0	0	0	0	0	0

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

**RR:** At least 1 connection in every row **CR:** At least 1 connection in every column.

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

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

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

for  $i = 1, 2, \dots, n$  and  $j = 1, 2, \dots, n$

- 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  $CC$

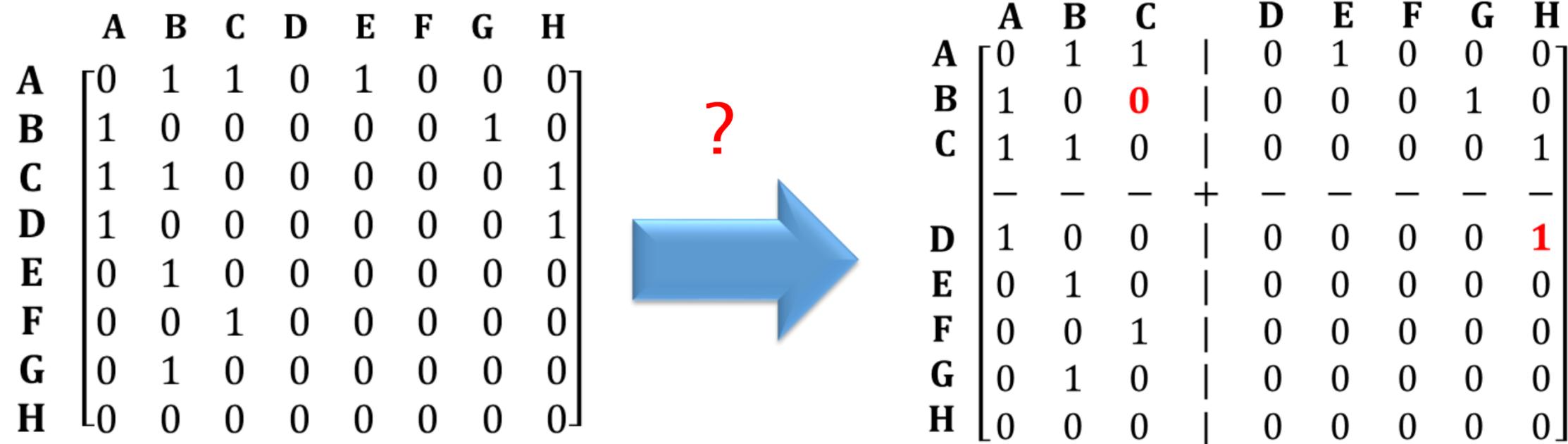
$e_{pp}$  = Error at block  $PP$

$e_{CP}$  = 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).**



- 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.

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



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

$N$  : **Matriks Adjacency**  
nominal transaction data



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

- $u_i$  : **coreness** bank  $i$  as sender
- $v_j$  : **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:

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

where  $\mathbf{u}$ : **out-coreness vector** &  $\mathbf{v}$ : **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:  $N_{ij} = \begin{cases} \text{transaction nominal or frequency,} & \text{if there is transaction from } i \text{ to } j \\ 0, & \text{if there is no transaction from } i \text{ to } j \end{cases}$   
for  $i = 1, 2, \dots, n$  dan  $j = 1, 2, \dots, n$
- Let  $u$  be defined as the out-coreness vector and  $v$  as the in-coreness vector.

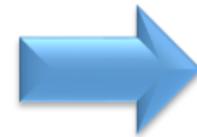
## Objective Function

$$\arg \min_{u,v} \sum_i \sum_{j \neq i} (N_{ij} - u_i v_j^T)^2$$

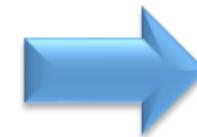
### Contoh\*

	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



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

$$u_A v_B = (0.85)(0.46) = 0.391$$

$$u_B v_A = (0.42)(0.68) = 0.285$$

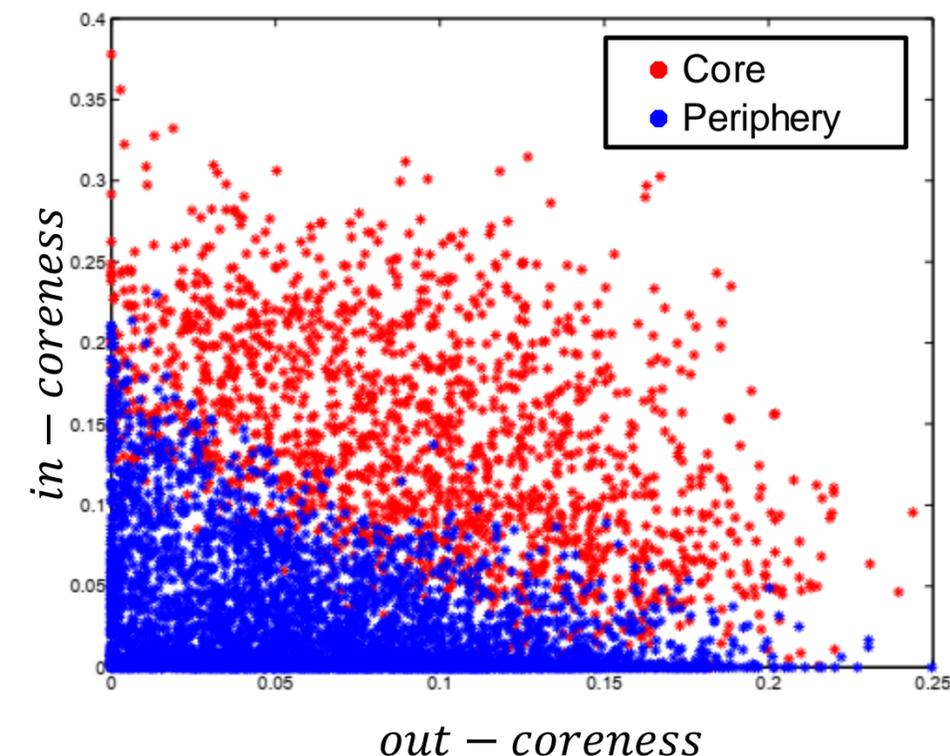
## Model Asymmetric Discrete

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

## Model Asymmetric Continuous

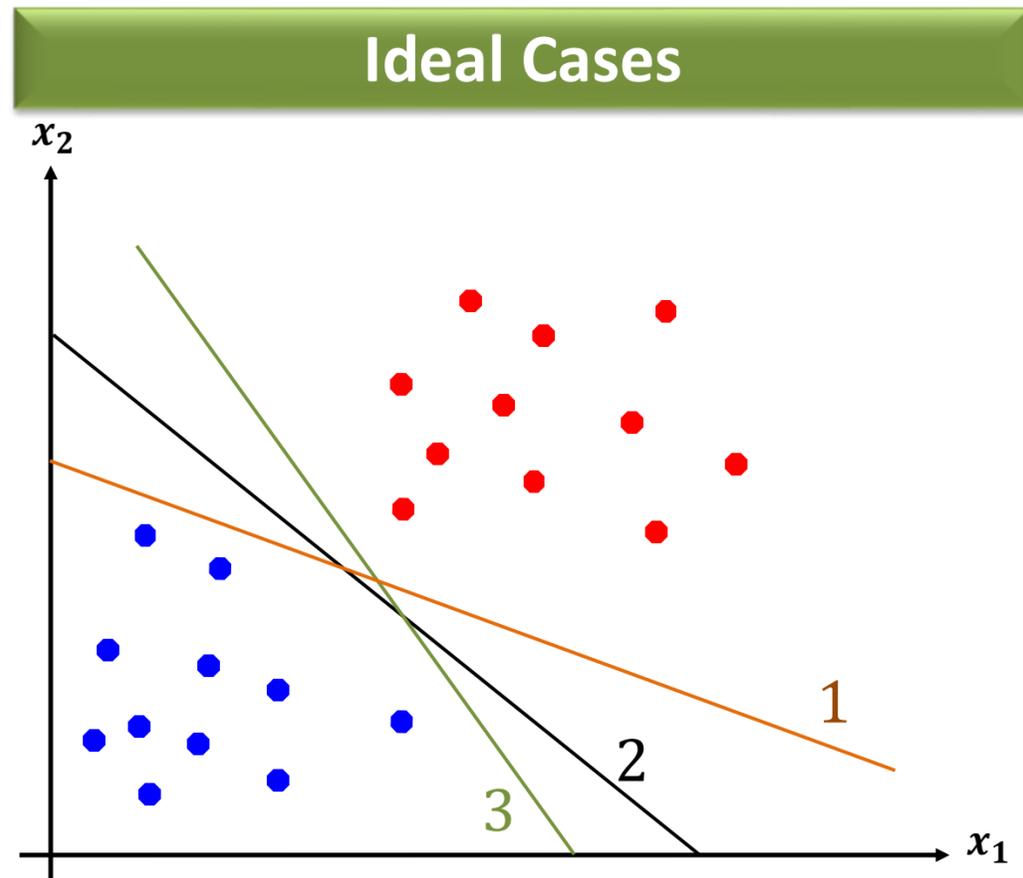
- **Objective:** Measure coreness, indicating the 'core' strength of each bank in a network.
- **Criteria:** Considers both transaction values and interbank connections when determining the coreness value of each bank.

Scatter plot of Coreness

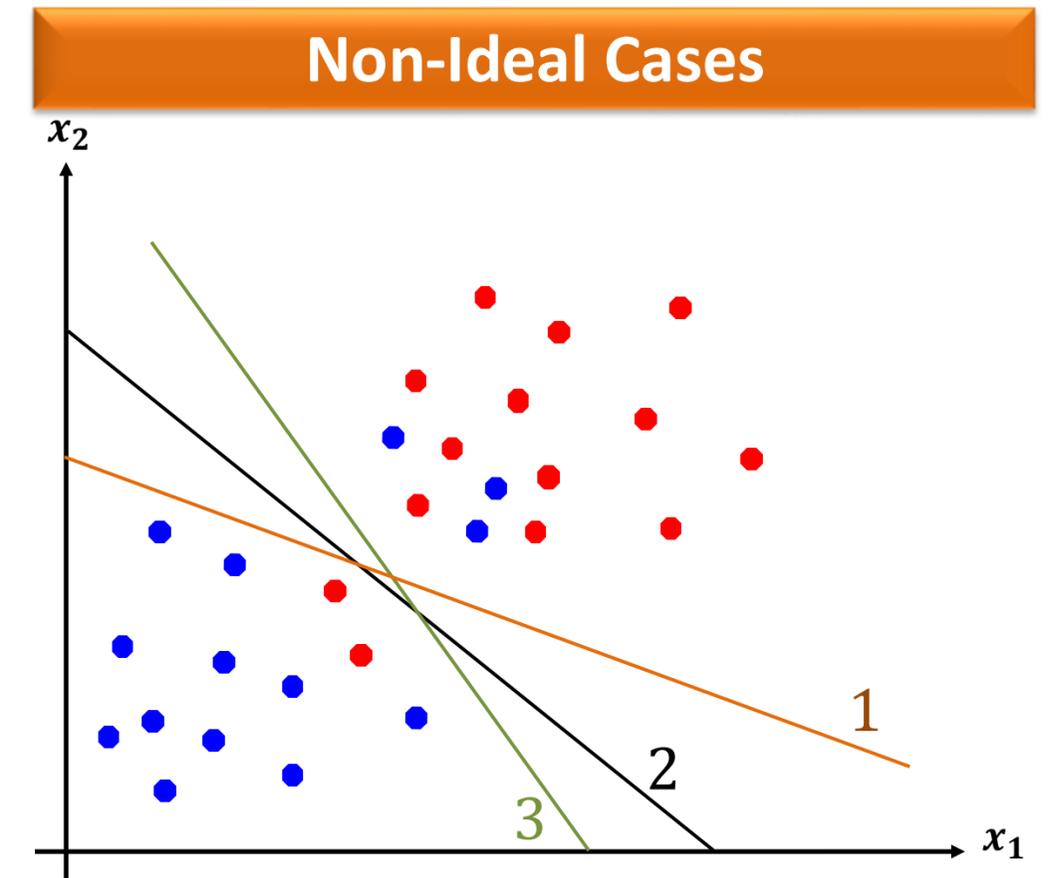


### Core and periphery bank characteristic based on coreness value

- **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.



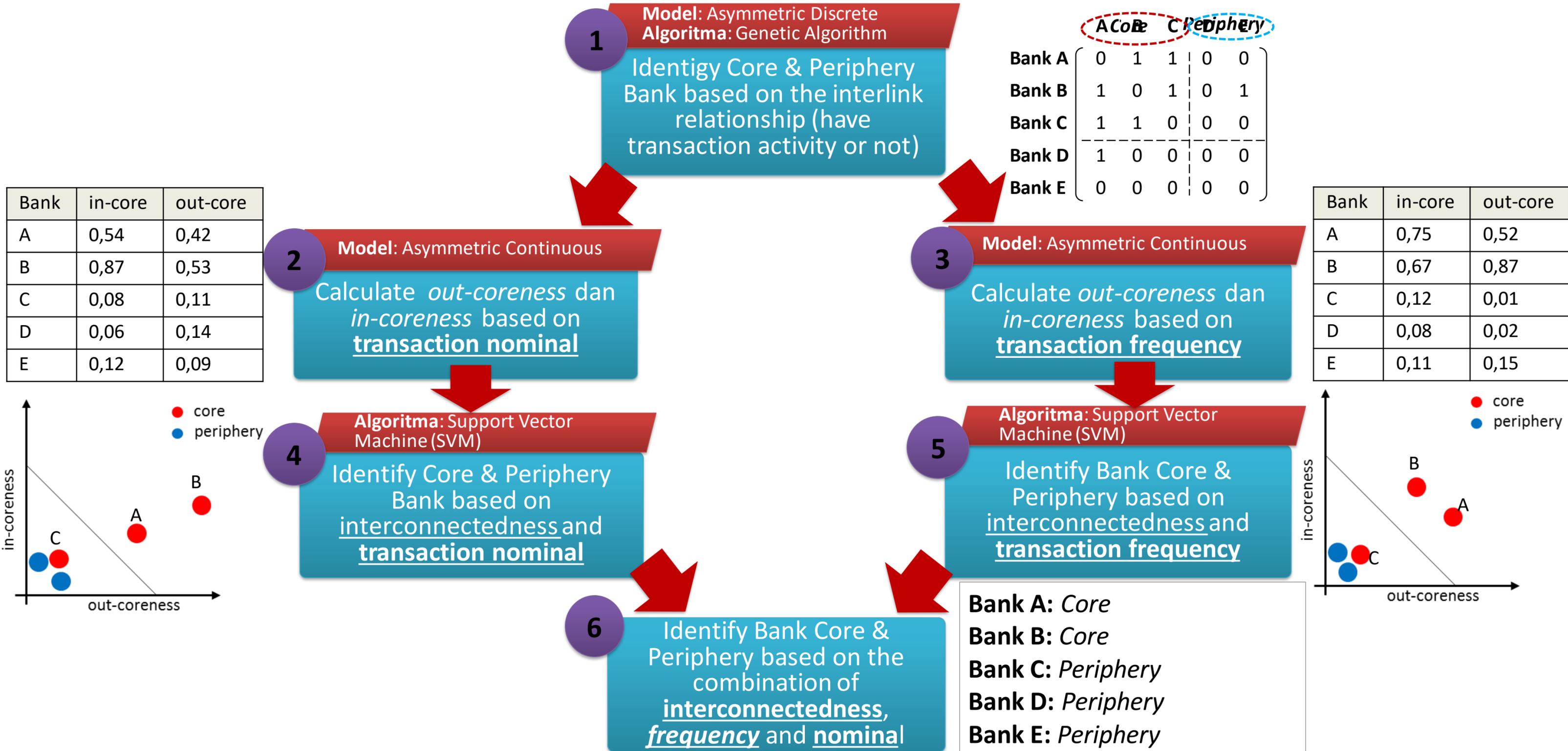
● Core  
● Periphery  
 $x_1$  : *out – coreness*  
 $x_2$  : *in – coreness*



- ❑ 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)*

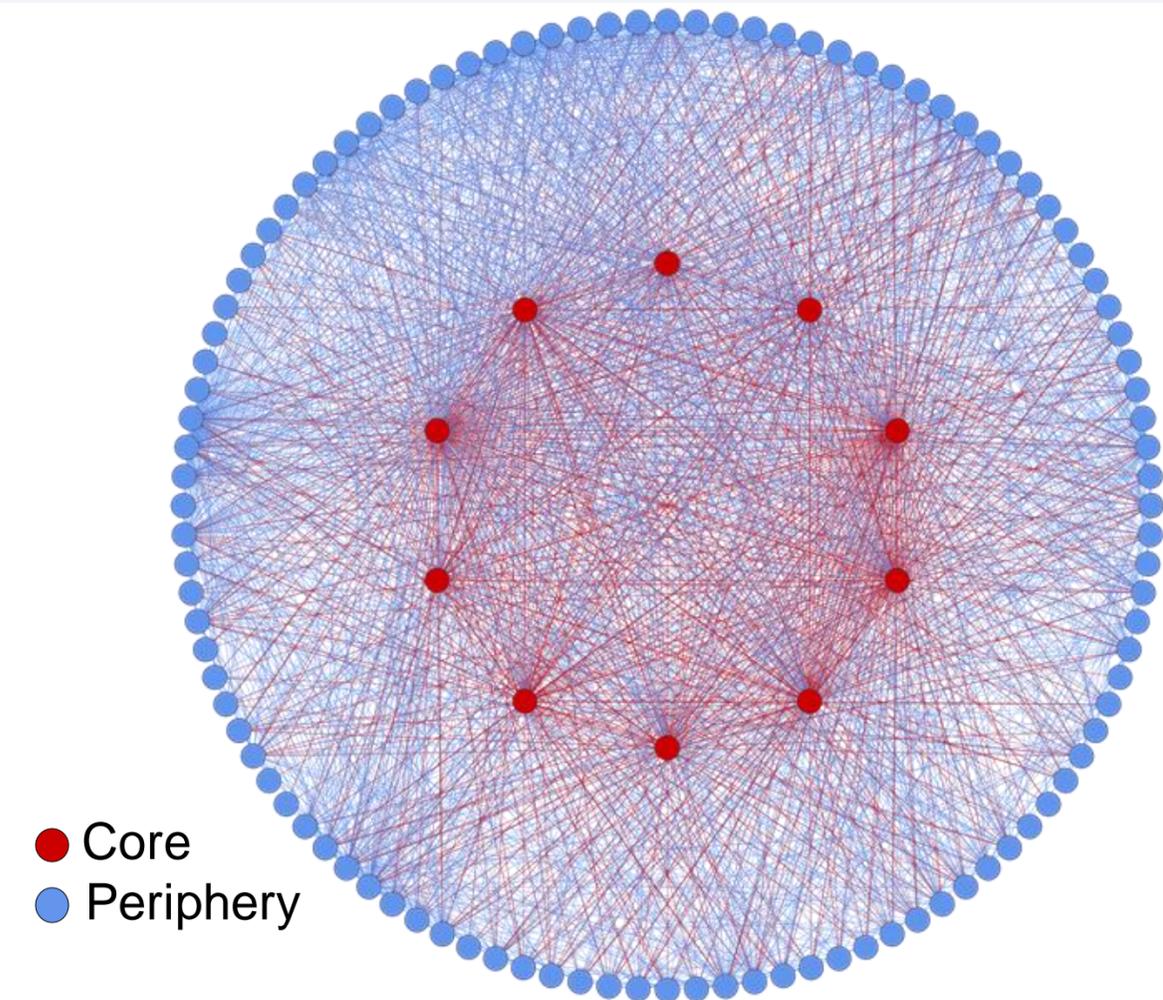
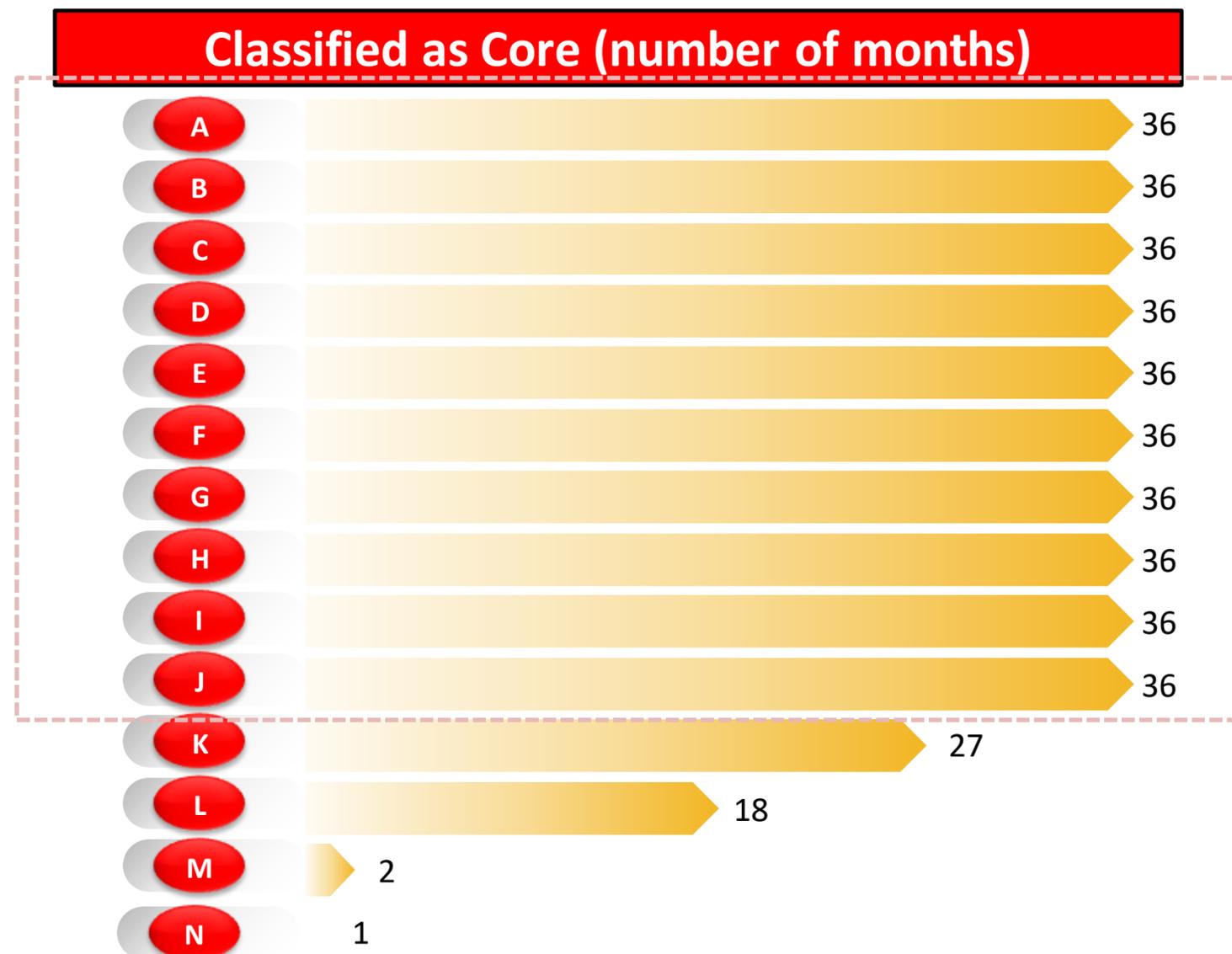
# Core-Periphery Classification Using SVM



# Core-Periphery Model Result

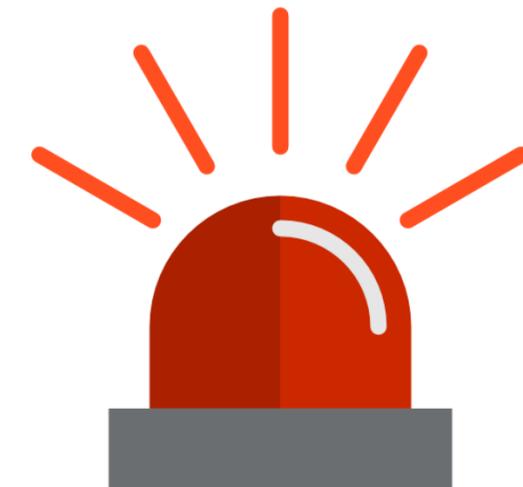
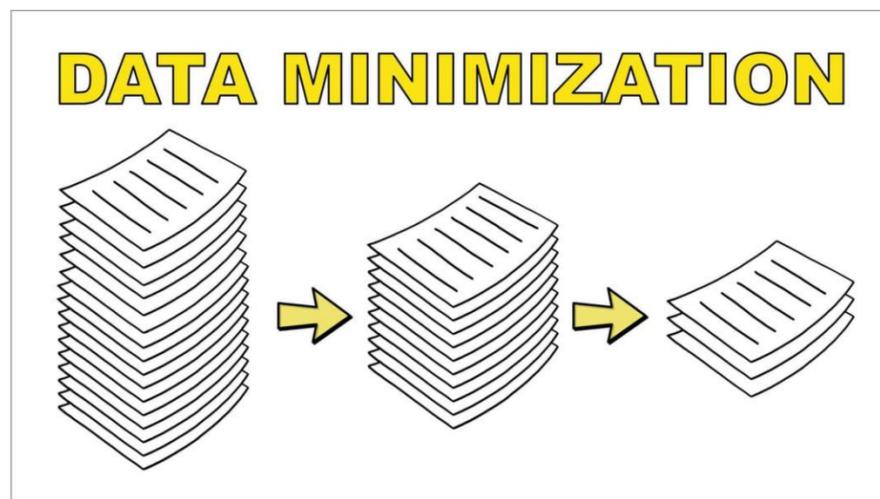


- The identification of the BI-RTGS network structure with the core-periphery model was conducted every month from January 2016 to December 2018 (36 months).
- Based on the results obtained, a core-periphery structure was identified within the BI-RTGS interbank transactions.
- This is evidenced by the 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 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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# Thank You