Analyzing and predicting user cross-chain behavior with temporal multilayer graphs

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onnets **LAB**

Queen Mary
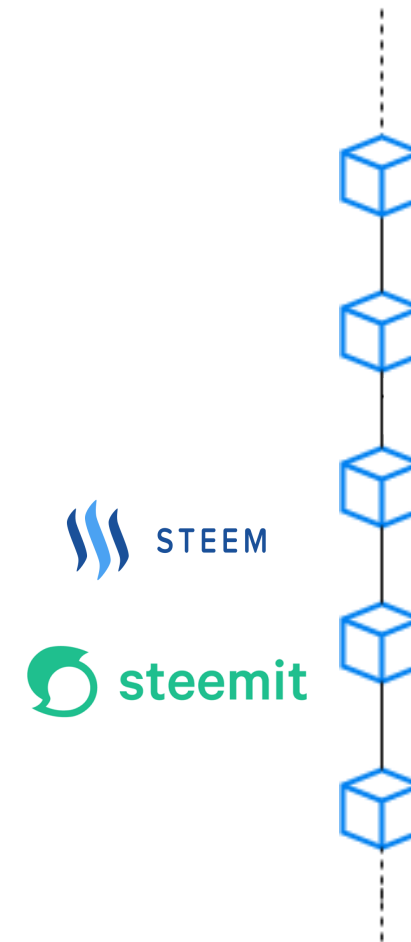University of London

Cross-chain behavior

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  - ‣ Interesting: human behavior, decision making
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  - ‣ Data validation and storage
  - ‣ Cryptocurrency for rewards and trades

STEEM

steemit

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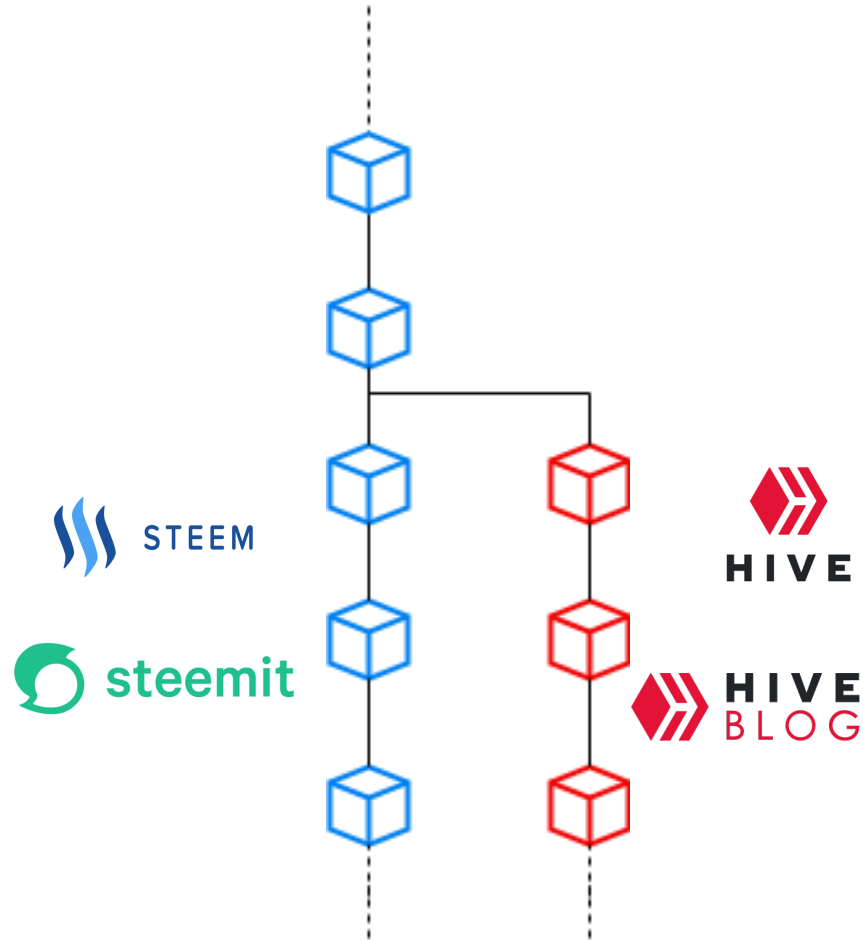 - ‣ Cryptocurrency for rewards and trades
- Fork events
  - ‣ Steemit and Hive
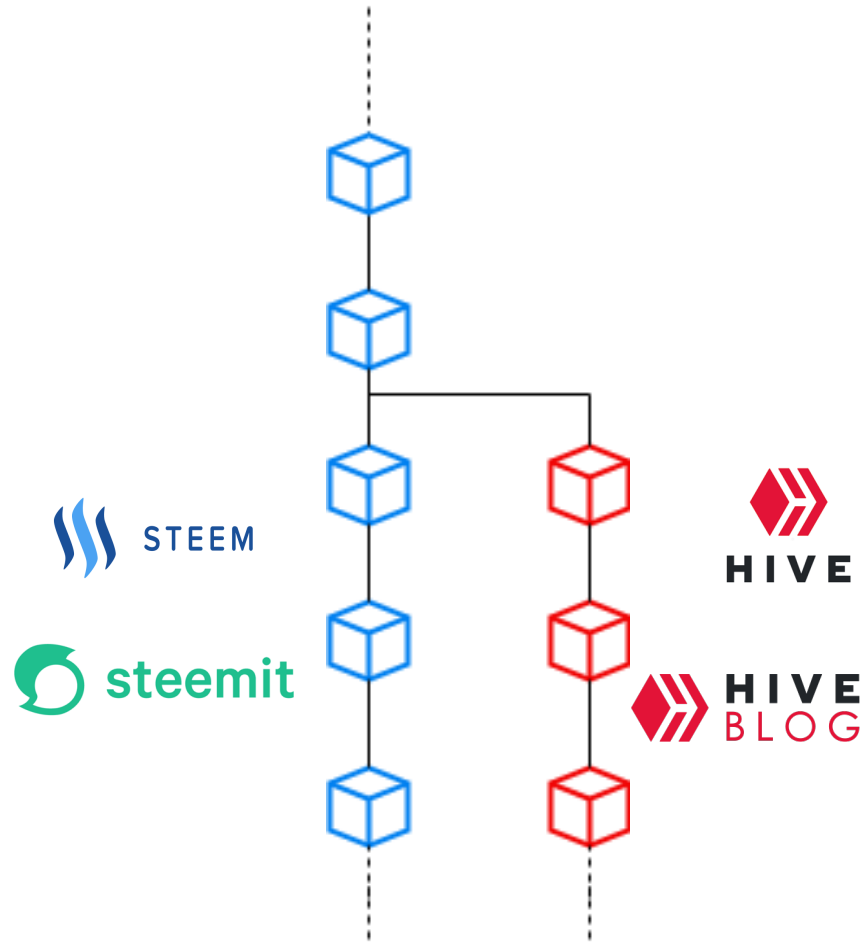 - ‣ Similar platforms, ***same accounts***
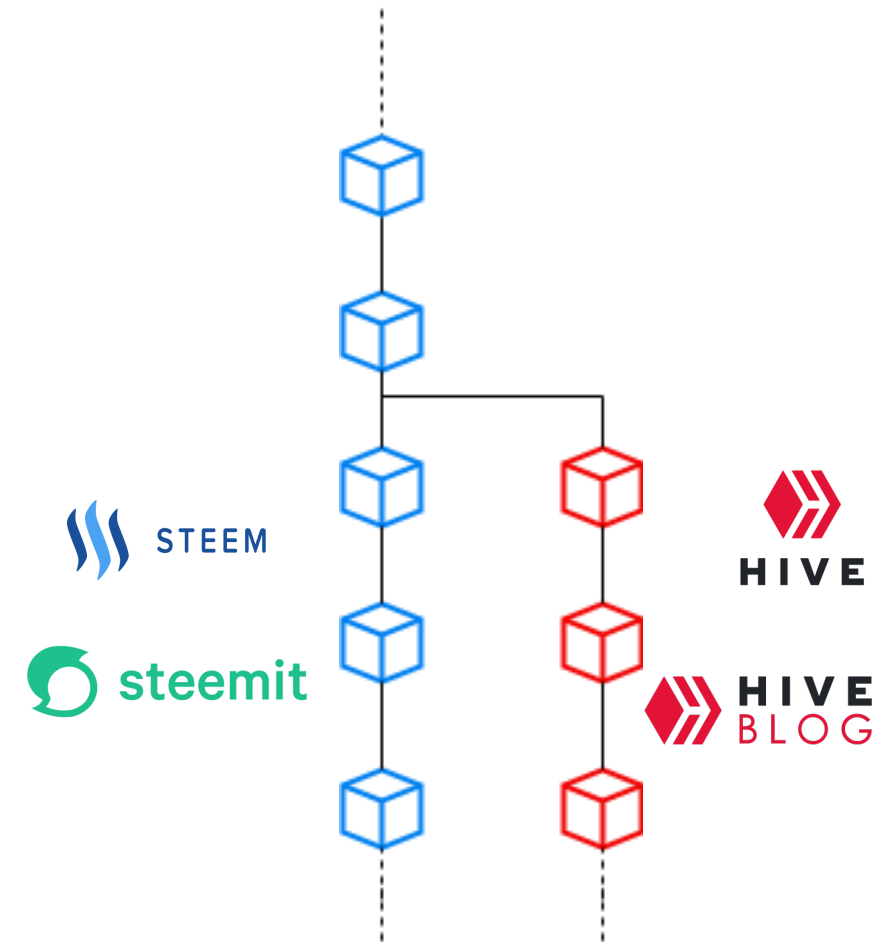
Case study

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- <u>*Social*</u> operations (Follow, Vote, Comment)
  - ‣ Steem (pre-fork) : 914,818,281
  - ‣ Steem (post-fork): 78,822,794
  - ‣ Hive (post-fork): 206,224,132
- <u>*Financial*</u> operations (Transfers, Savings, …)
  - ‣ Steem(pre-fork): 62,071,074
  - ‣ Steem (post-fork): 10,299,852
  - ‣ Hive (post-fork): 4,041,060

Objective

Research questions

What is the impact of user migration on the platforms?

Can we predict user migration?

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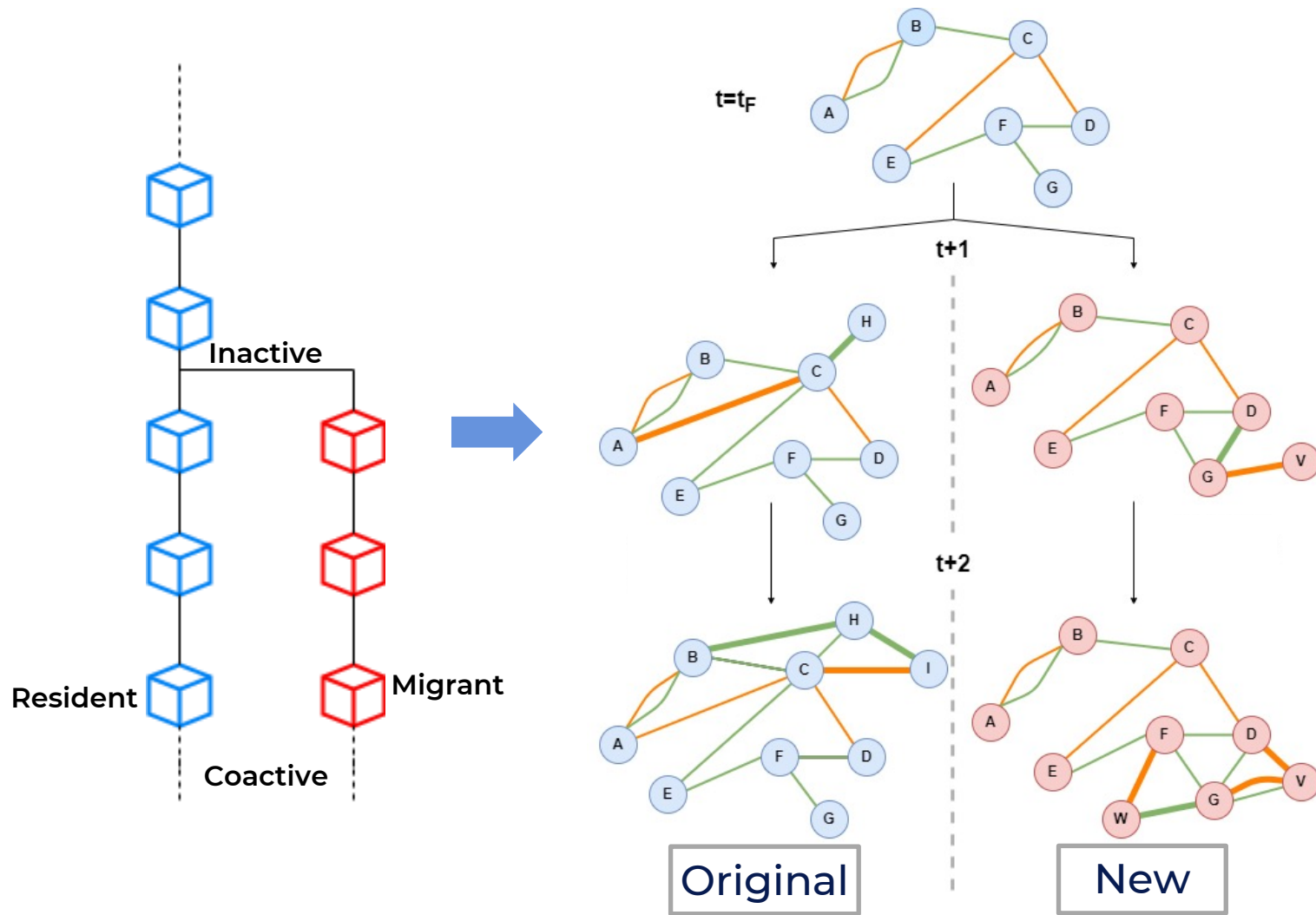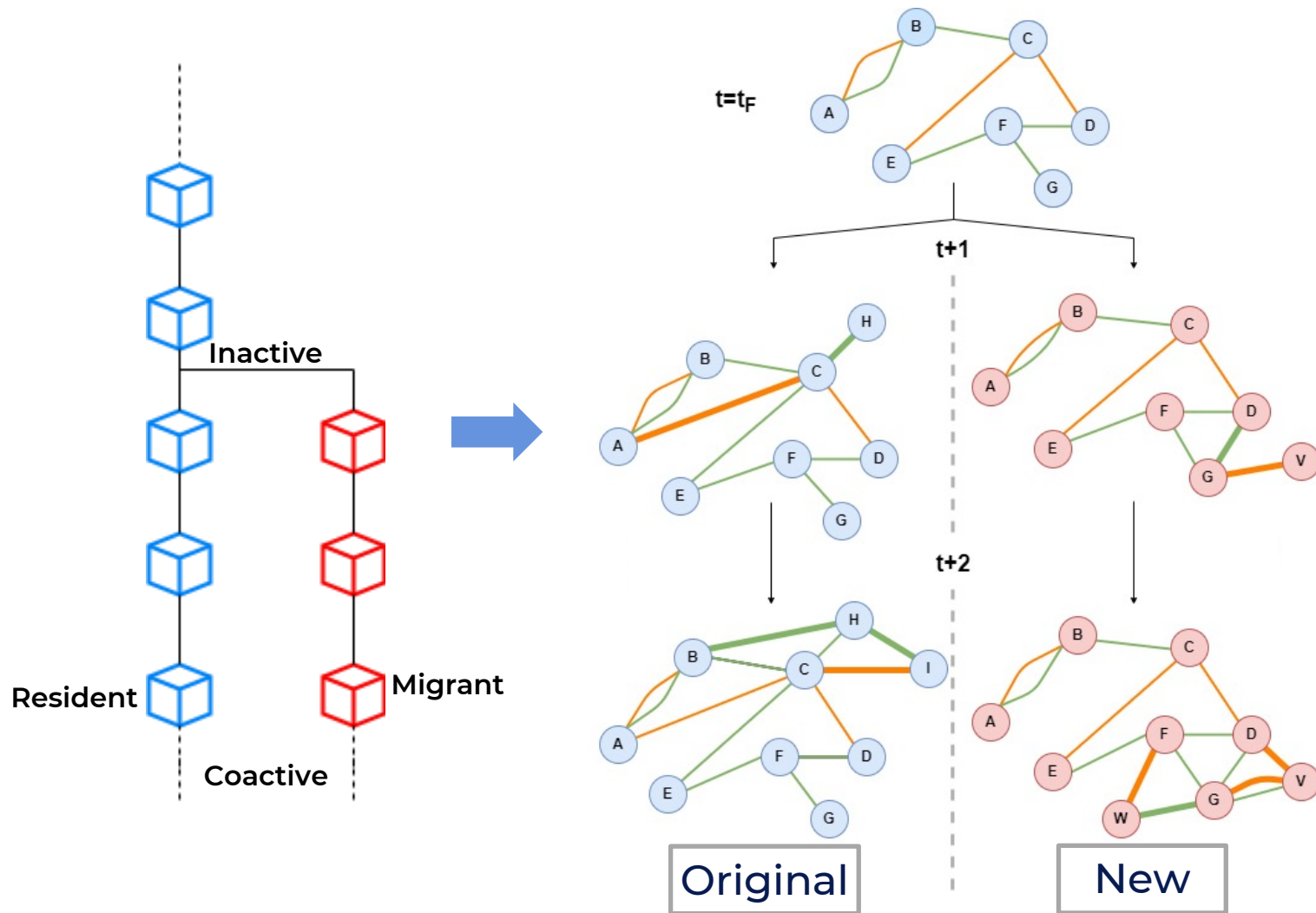
Can we predict user migration?

Our solution

General user migration model for the analysis of migration scenarios

Network based model for the description and forecast of user behavior

User migration model

User migration model

- Evolution multidigraphs
  ‣ Temporal multi-graph
  ‣ Weighted, Directed
  ‣ Multiple interactions type
- Describe network evolution and user characteristics

Network structure and user migration

NETWORK STATISTICS OVER TIME

- Many properties remain similar even after the split.

- Some properties change:
  - ‣ Density, Diameter
  - ‣ Both social and financial layers

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> User migration has an impact on global structure

User migration prediction

- Can user features, at the network structure level, be predictive a future user migration?

- Machine learning approach:
  - ‣ Supervised classification
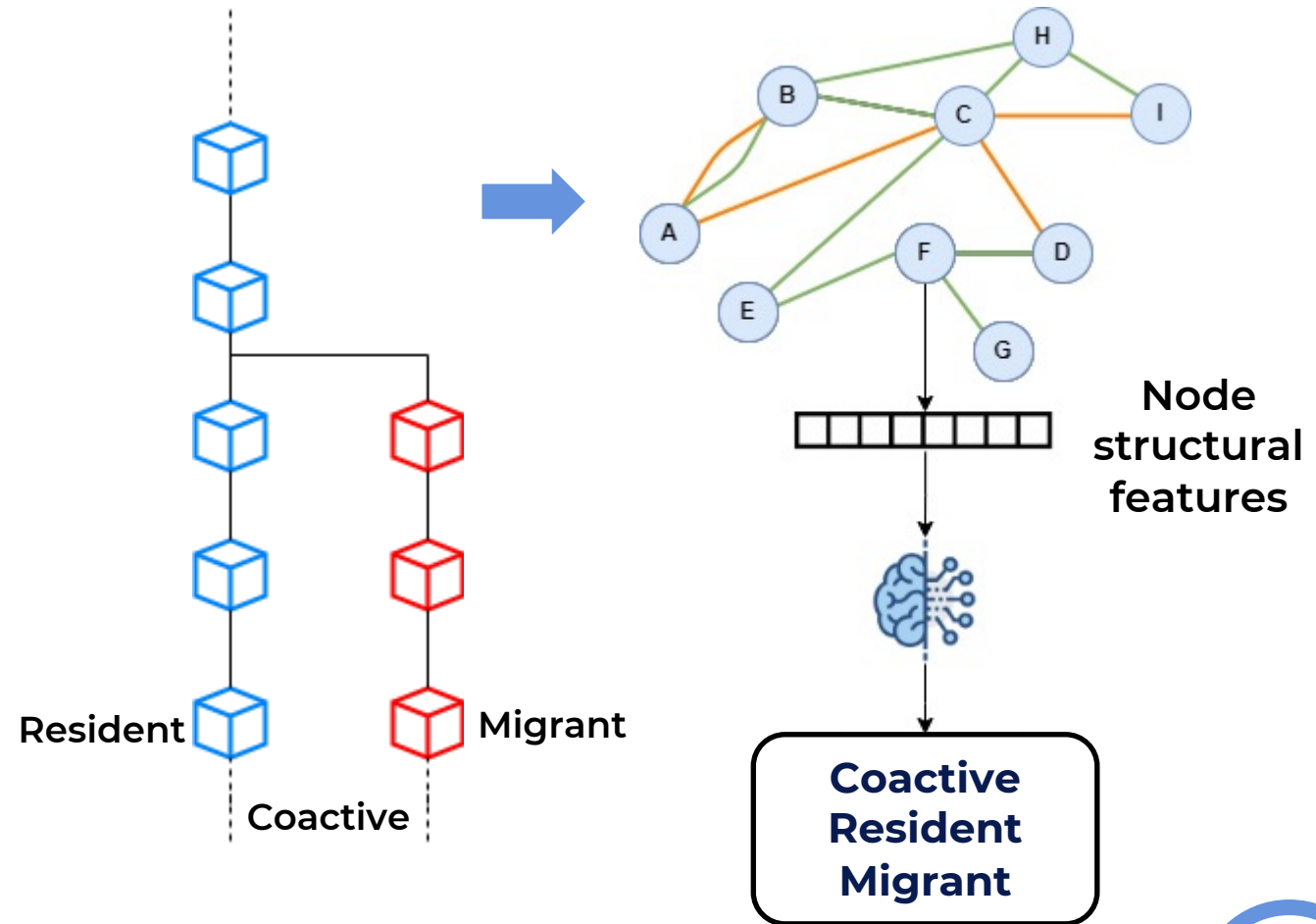 - ‣ Network level user features

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Resident

Migrant

Coactive

Node structural features
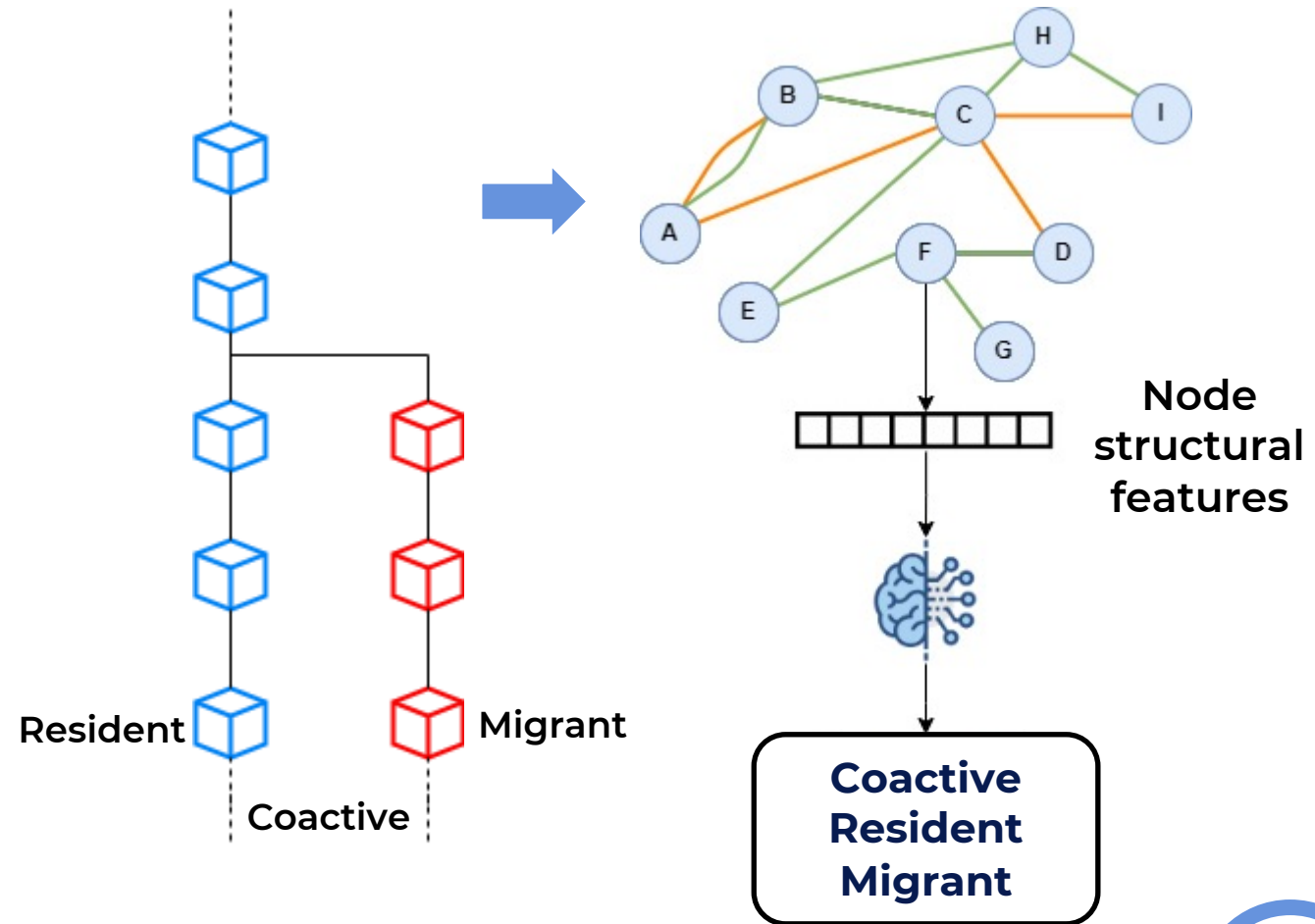
Coactive Resident Migrant

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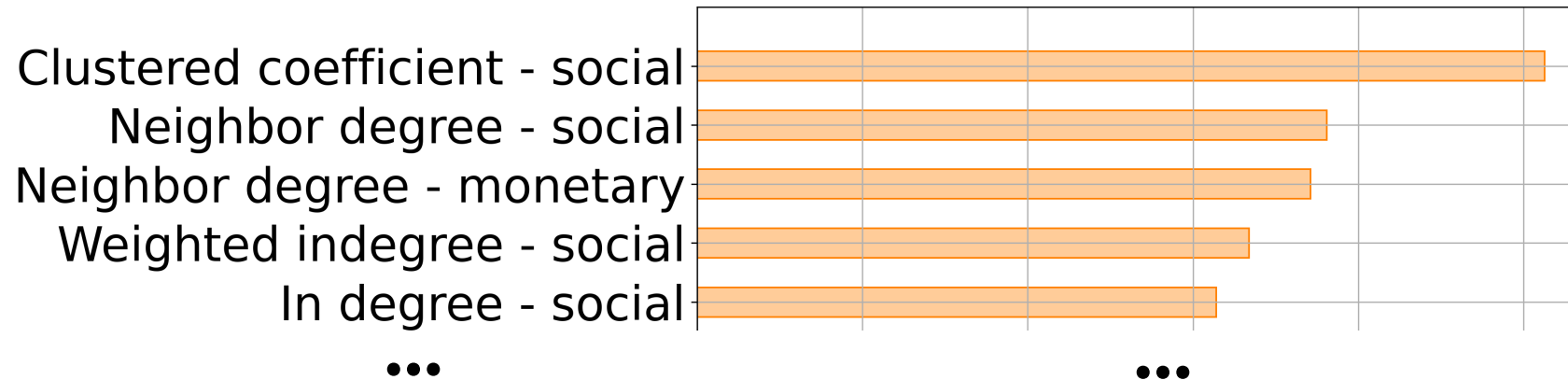Resident
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User migration prediction

PERFORMANCE AND FEATURES

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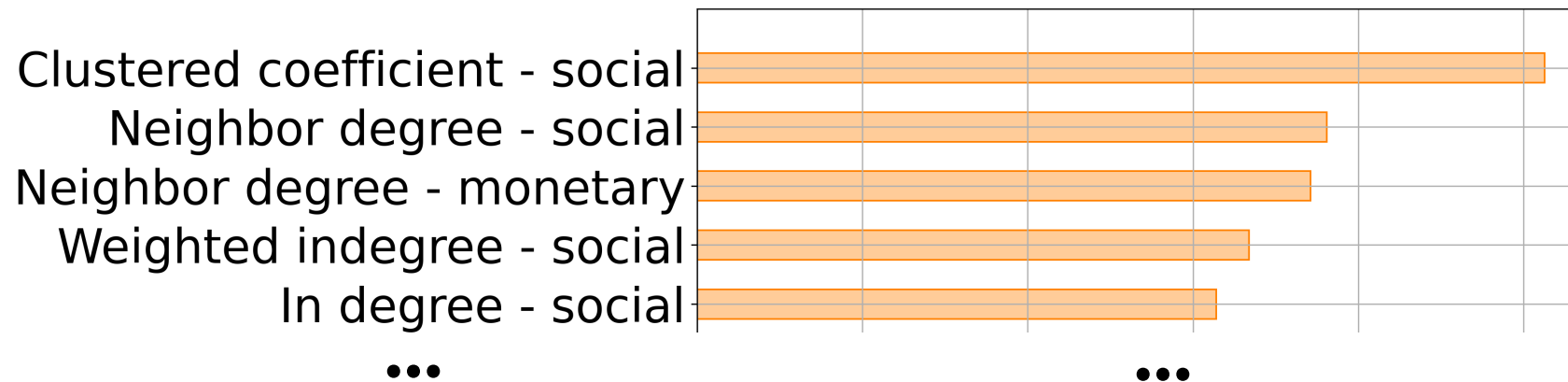
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Clustered coefficient - social	
Neighbor degree - social	
Neighbor degree - monetary	
Weighted indegree - social	
In degree - social	

⚠ Both social and economical dimensions are predictive and important

Conclusions

- **User migration influences (global) network structure**

- **Network structure can predict cross-chain user behavior**

- **Both social and economical dimensions are important**

- **Future works:**

  Application to other blockchain based systems

  Enhancement with external information sources