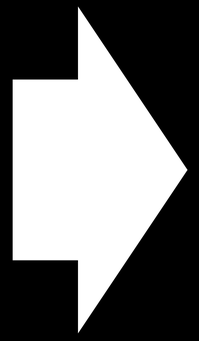

# Adventures in anti-money laundering and AI

1,400,000,000


Client on-boarding
Company structure
UBO
Legal representative
Identification
Verification
CDD / KYC
Sanctions screening
PEP screening
Expected transaction profile
Geography
Source of wealth
Adverse media
Source of funds
Business activity
Client risk assessment
Client exit
Client & transaction screening
Sanctions screening
Client screening
Transaction monitoring
Objective criteria
Subjective criteria
Alert handling
Research
UAR
UAR filing
FIU
Desk report
Periodic review
Event-driven review
Actual transaction profile
PEP Monitoring
News monitoring
Ownership monitoring

Deloitte.

# Shifting focus

**Detection**  **Investigation**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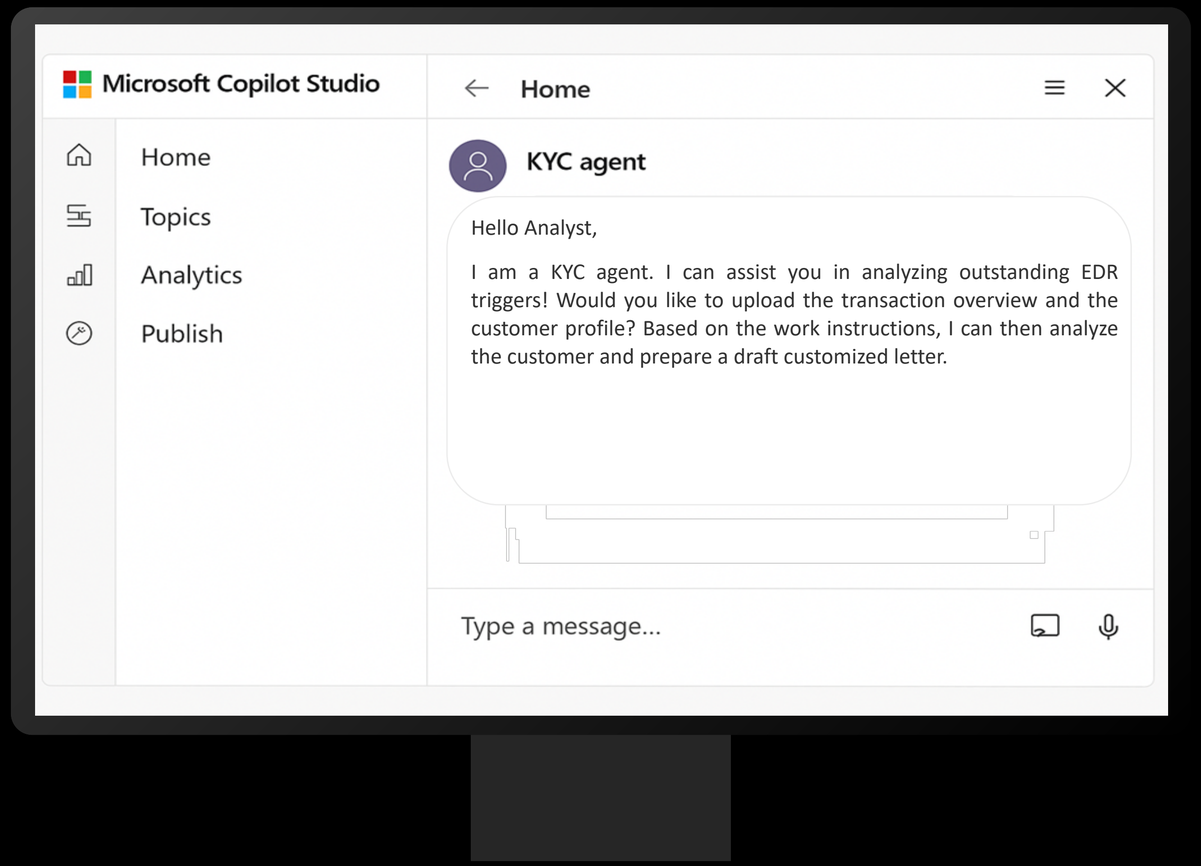
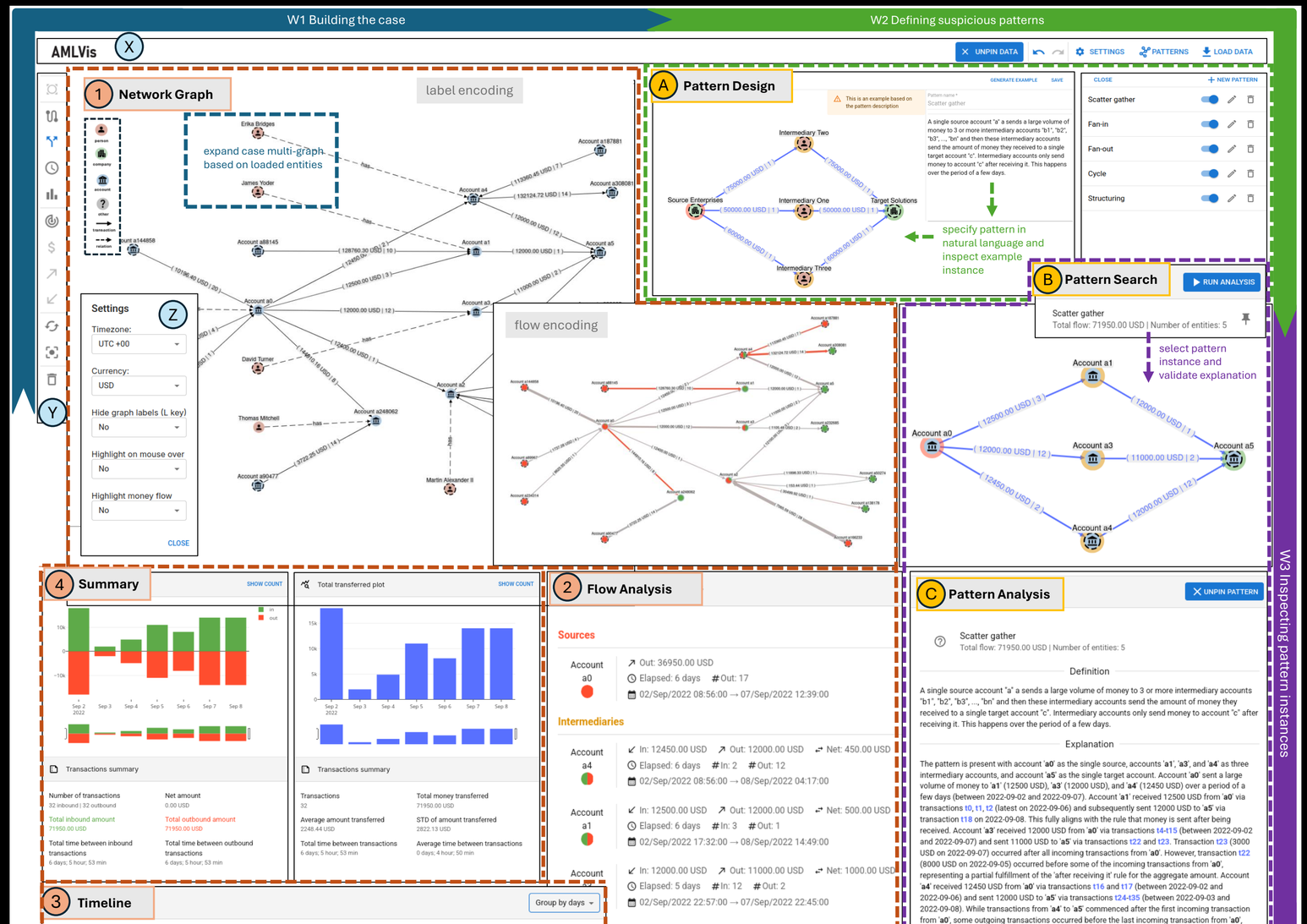
# Supporting Alert Investigations

## Productivity tools for alert handlers

- Reduce the cost of anti-money laundering operations
- RAG functionality for working instructions
- Comprehensive workflow support
- Summarising, drafting, etc.



# Supporting Network Analytics



W1 Building the case

W2 Defining suspicious patterns

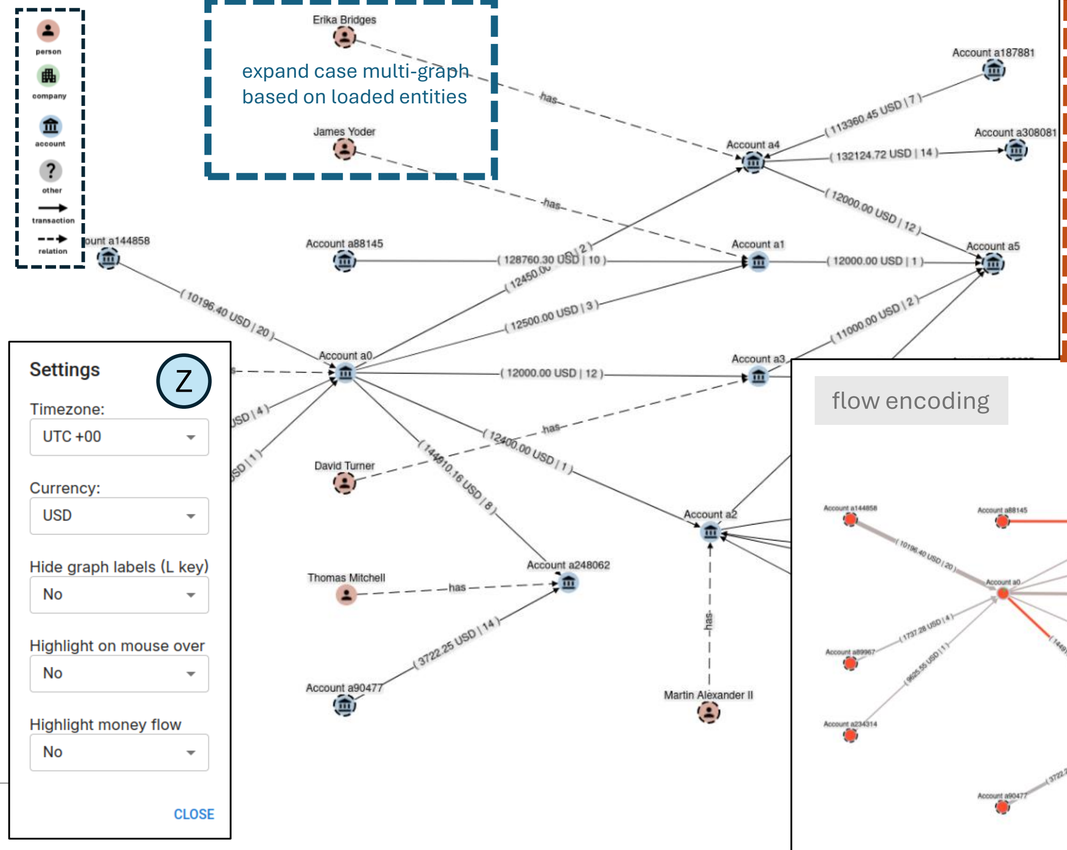
AMLVis (X)

UNPIN DATA | SETTINGS | PATTERNS | LOAD DATA

## 1 Network Graph

label encoding

expand case multi-graph based on loaded entities




### Settings (Z)

Timezone: UTC +00

Currency: USD

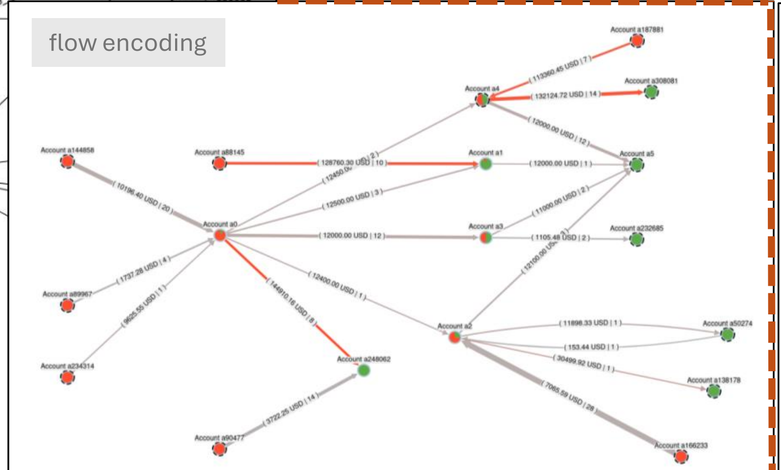
Hide graph labels (L key): No

Highlight on mouse over: No

Highlight money flow: No

CLOSE

flow encoding



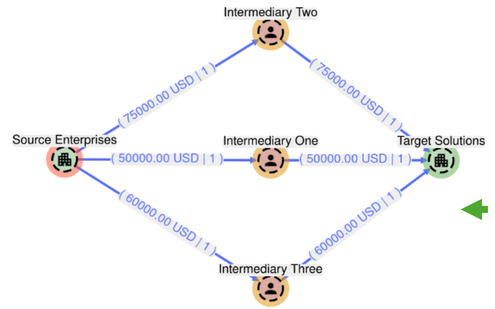
## A Pattern Design

GENERATE EXAMPLE | SAVE

This is an example based on the pattern description

Pattern name * Scatter gather

A single source account "a" a sends a large volume of money to 3 or more intermediary accounts "b1", "b2", "b3", ..., "bn" and then these intermediary accounts send the amount of money they received to a single target account "c". Intermediary accounts only send money to account "c" after receiving it. This happens over the period of a few days.




specify pattern in natural language and inspect example instance

CLOSE | + NEW PATTERN

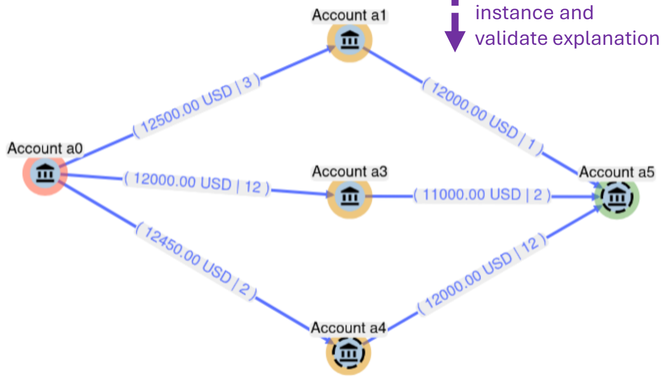
- Scatter gather
- Fan-in
- Fan-out
- Cycle
- Structuring

## B Pattern Search

RUN ANALYSIS

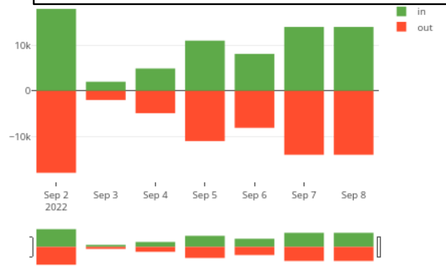
Scatter gather
Total flow: 71950.00 USD | Number of entities: 5

select pattern instance and validate explanation



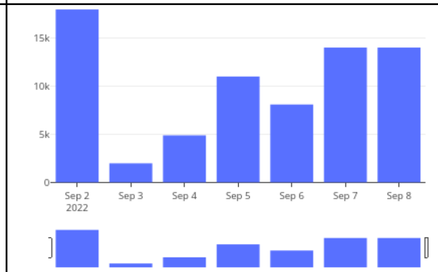

## 4 Summary

SHOW COUNT




Transactions summary

Total transferred plot SHOW COUNT




Transactions summary

## 2 Flow Analysis

### Sources

Account a0

Out: 36950.00 USD
Elapsed: 6 days  #Out: 17
02/Sep/2022 08:56:00 → 07/Sep/2022 12:39:00

### Intermediaries

Account a4

In: 12450.00 USD  Out: 12000.00 USD  Net: 450.00 USD
Elapsed: 6 days  #In: 2  #Out: 12

## C Pattern Analysis

UNPIN PATTERN

Scatter gather
Total flow: 71950.00 USD | Number of entities: 5

### Definition

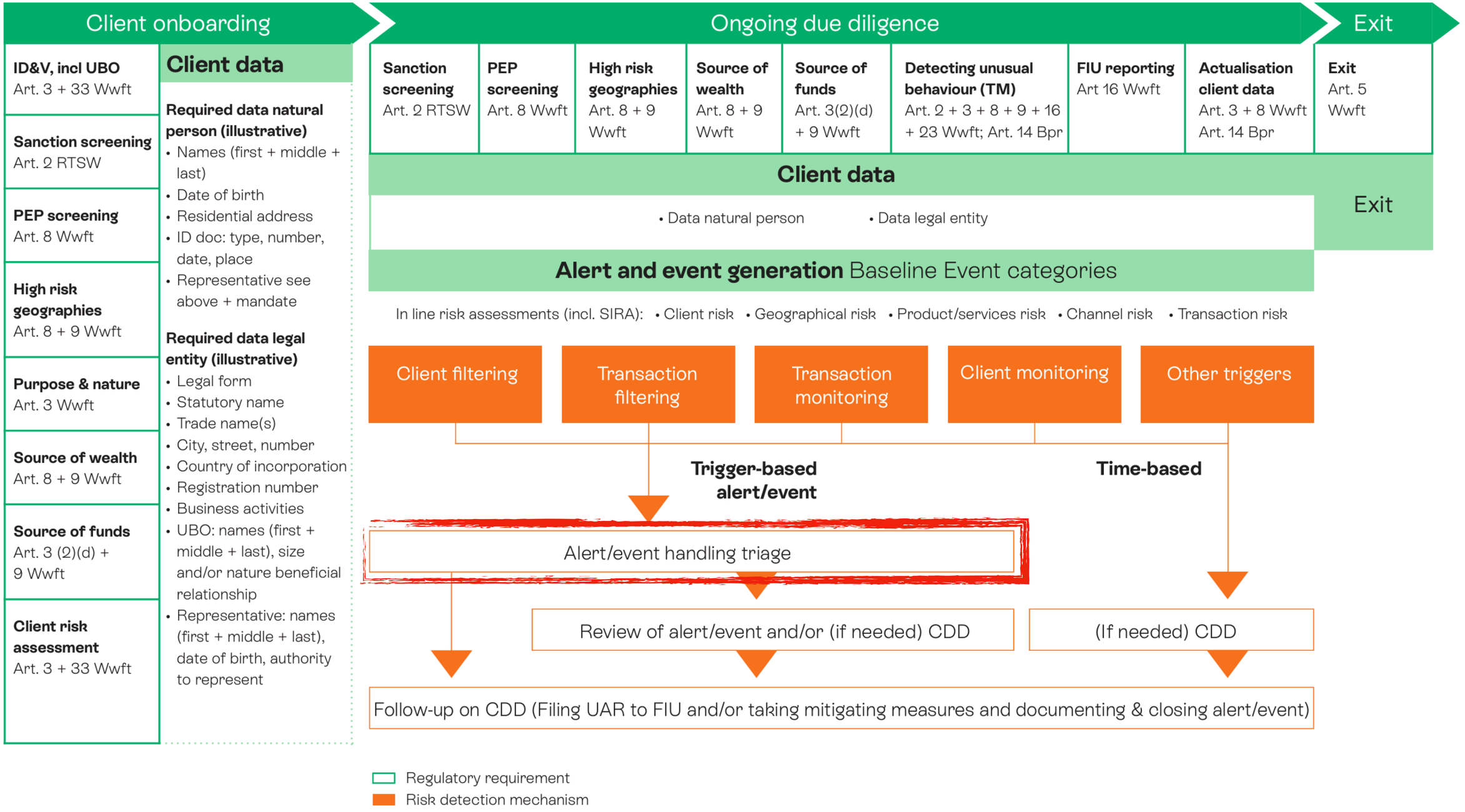
A single source account "a" a sends a large volume of money to 3 or more intermediary accounts "b1", "b2", "b3", ..., "bn" and then these intermediary accounts send the amount of money they received to a single target account "c". Intermediary accounts only send money to account "c" after receiving it. This happens over the period of a few days.

### Explanation

The pattern is present with account '**a0**' as the single source, accounts '**a1**', '**a3**', and '**a4**' as three

W3 Inspecting pattern instances

# Ehm, detection?


Client onboarding
Ongoing due diligence
Exit
ID&V, incl UBO
Art. 3 + 33 Wwft
Sanction screening
Art. 2 RTSW
PEP screening
Art. 8 Wwft
High risk geographies
Art. 8 + 9 Wwft
Purpose & nature
Art. 3 Wwft
Source of wealth
Art. 8 + 9 Wwft
Source of funds
Art. 3 (2)(d) + 9 Wwft
Client risk assessment
Art. 3 + 33 Wwft
Client data
Required data natural person (illustrative)
• Names (first + middle + last)
• Date of birth
• Residential address
• ID doc: type, number, date, place
• Representative see above + mandate
Required data legal entity (illustrative)
• Legal form
• Statutory name
• Trade name(s)
• City, street, number
• Country of incorporation
• Registration number
• Business activities
• UBO: names (first + middle + last), size and/or nature beneficial relationship
• Representative: names (first + middle + last), date of birth, authority to represent
Sanction screening
Art. 2 RTSW
PEP screening
Art. 8 Wwft
High risk geographies
Art. 8 + 9 Wwft
Source of wealth
Art. 8 + 9 Wwft
Source of funds
Art. 3(2)(d) + 9 Wwft
Detecting unusual behaviour (TM)
Art. 2 + 3 + 8 + 9 + 16 + 23 Wwft; Art. 14 Bpr
FIU reporting
Art 16 Wwft
Actualisation client data
Art. 3 + 8 Wwft
Art. 14 Bpr
Exit
Art. 5 Wwft
Client data
• Data natural person
• Data legal entity
Exit
Alert and event generation Baseline Event categories
In line risk assessments (incl. SIRA): • Client risk • Geographical risk • Product/services risk • Channel risk • Transaction risk
Client filtering
Transaction filtering
Transaction monitoring
Client monitoring
Other triggers
Trigger-based alert/event
Time-based
Alert/event handling triage
Review of alert/event and/or (if needed) CDD
(If needed) CDD
Follow-up on CDD (Filing UAR to FIU and/or taking mitigating measures and documenting & closing alert/event)
Regulatory requirement
Risk detection mechanism

# Anomaly detection

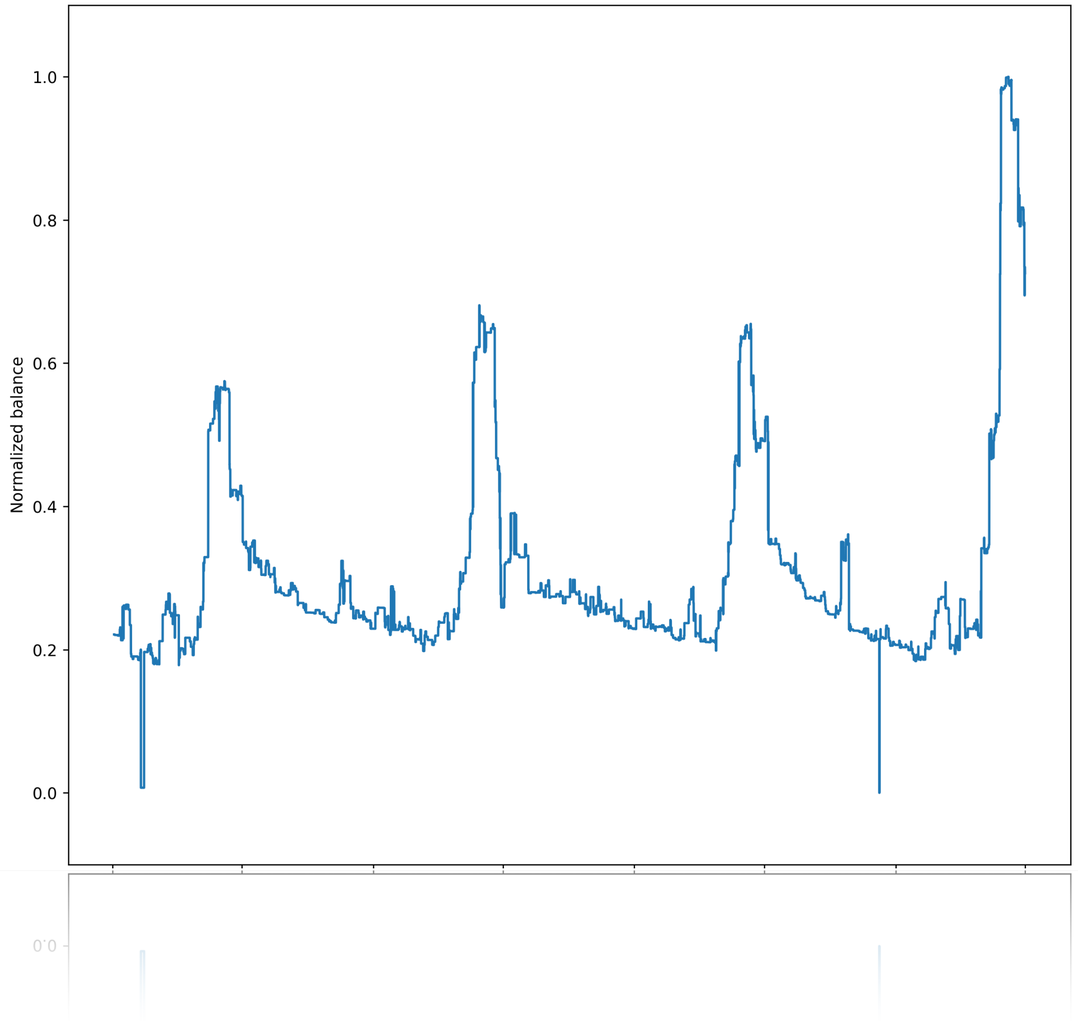
- Sparse labels? Anomaly detection to the rescue!
- Reduces preconceptions/biases business rules
- Can help identify ‘unknown unknowns’ and new risks

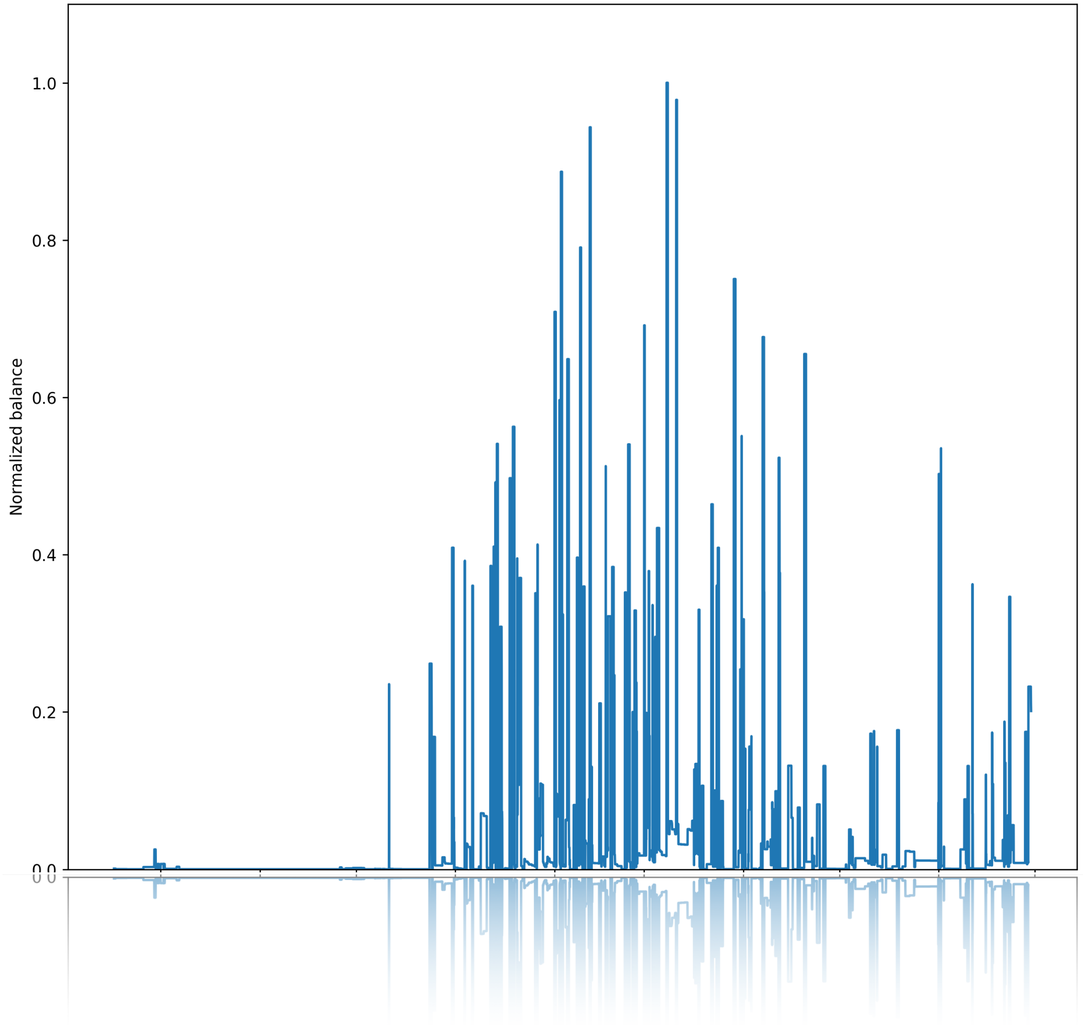
# Anomaly detection
## Practical considerations

- Extreme values rule
- Scaling, scaling
- One-hot encoding is evil
- Explanations matter
- Anomalies stand out better in peer groups
- Unknown unknowns…maybe not so much
- Refine features at every turn
- Excellent method to check data quality

# Detecting Rapid Movement Of Funds

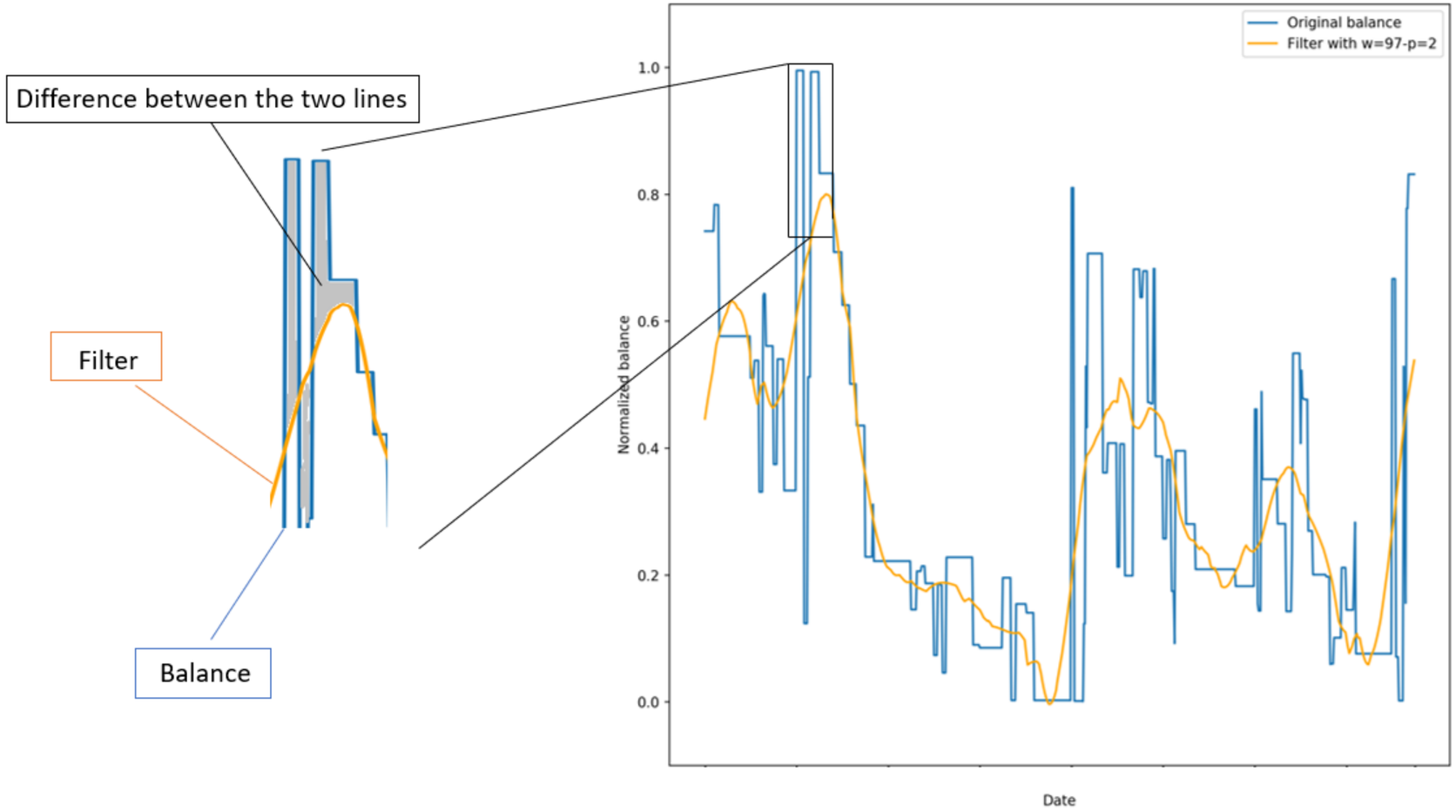
## RMOF is a well-known red flag for money laundering, fraud, and other financial misconduct



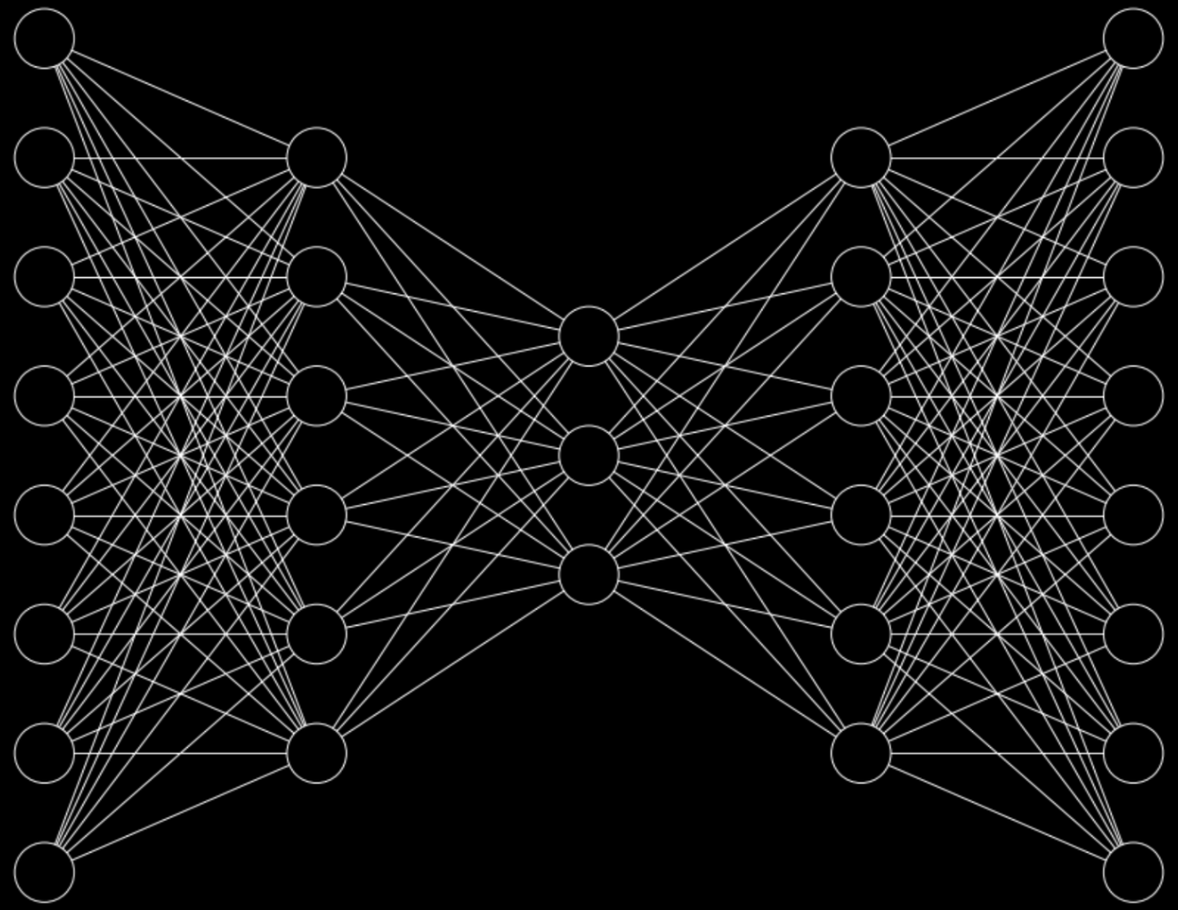
# Detecting Rapid Movement Of Funds

**RMOF is a well-known red flag for money laundering, fraud, and other financial misconduct**

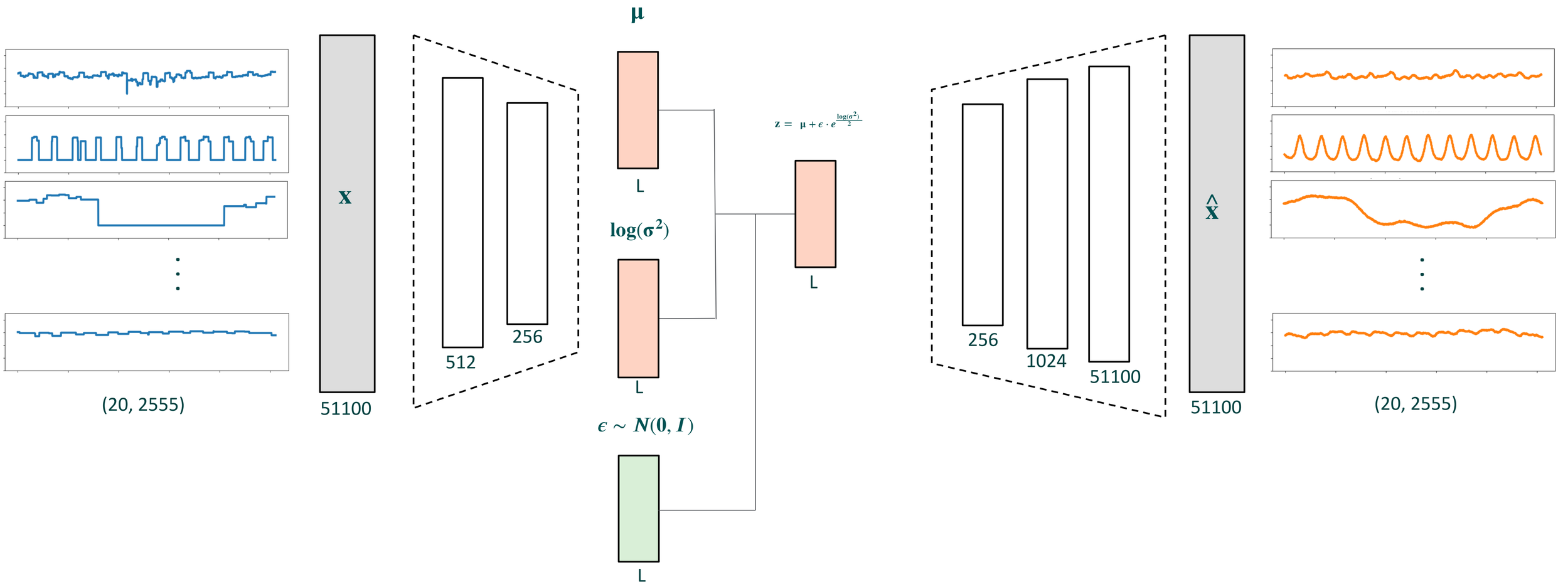


# Encoding Account Behaviour

- Need to describe transaction behaviour
- Historically: feature engineering; descriptive statistics of transaction sets
- An autoencoder provides a low-dimensional *latent* description of behaviour



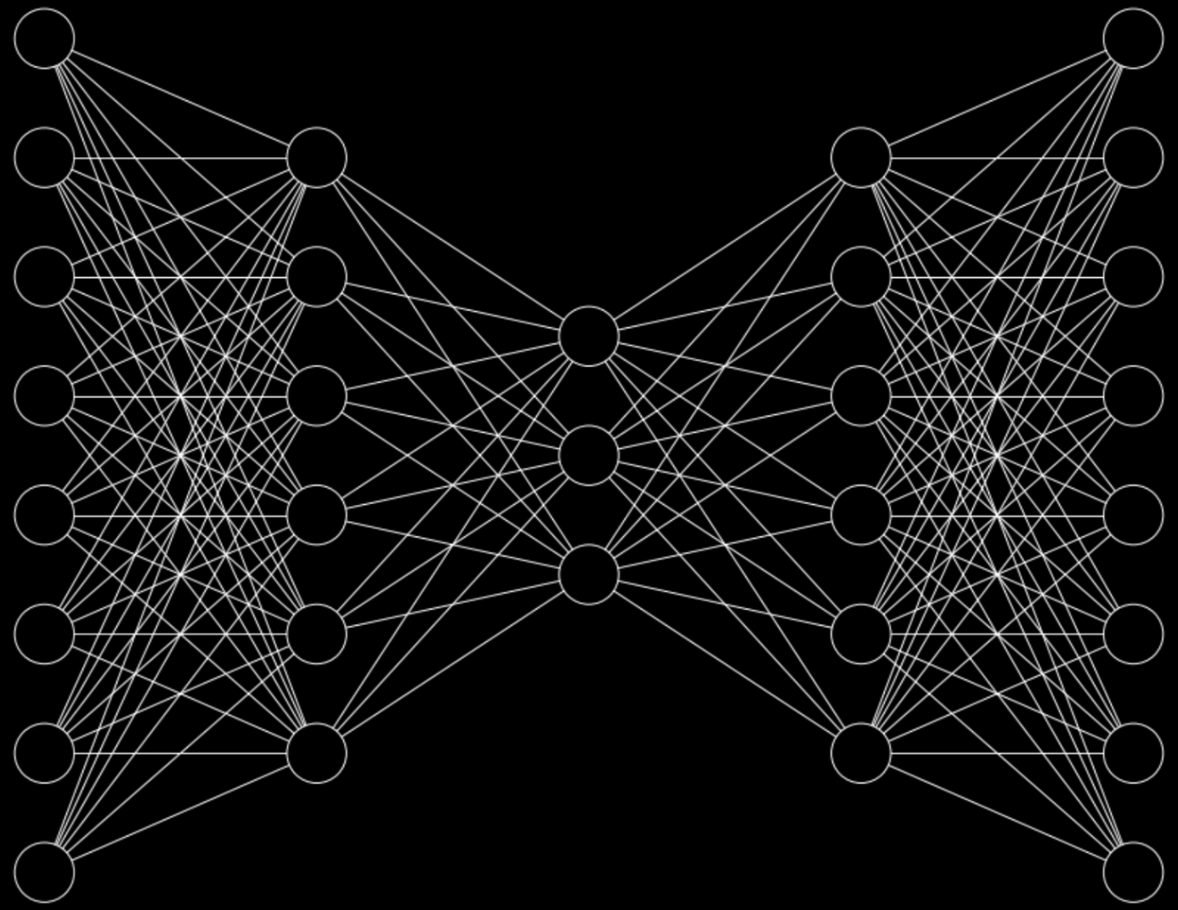
# Variational Autoencoder



# Encoding Account Behaviour

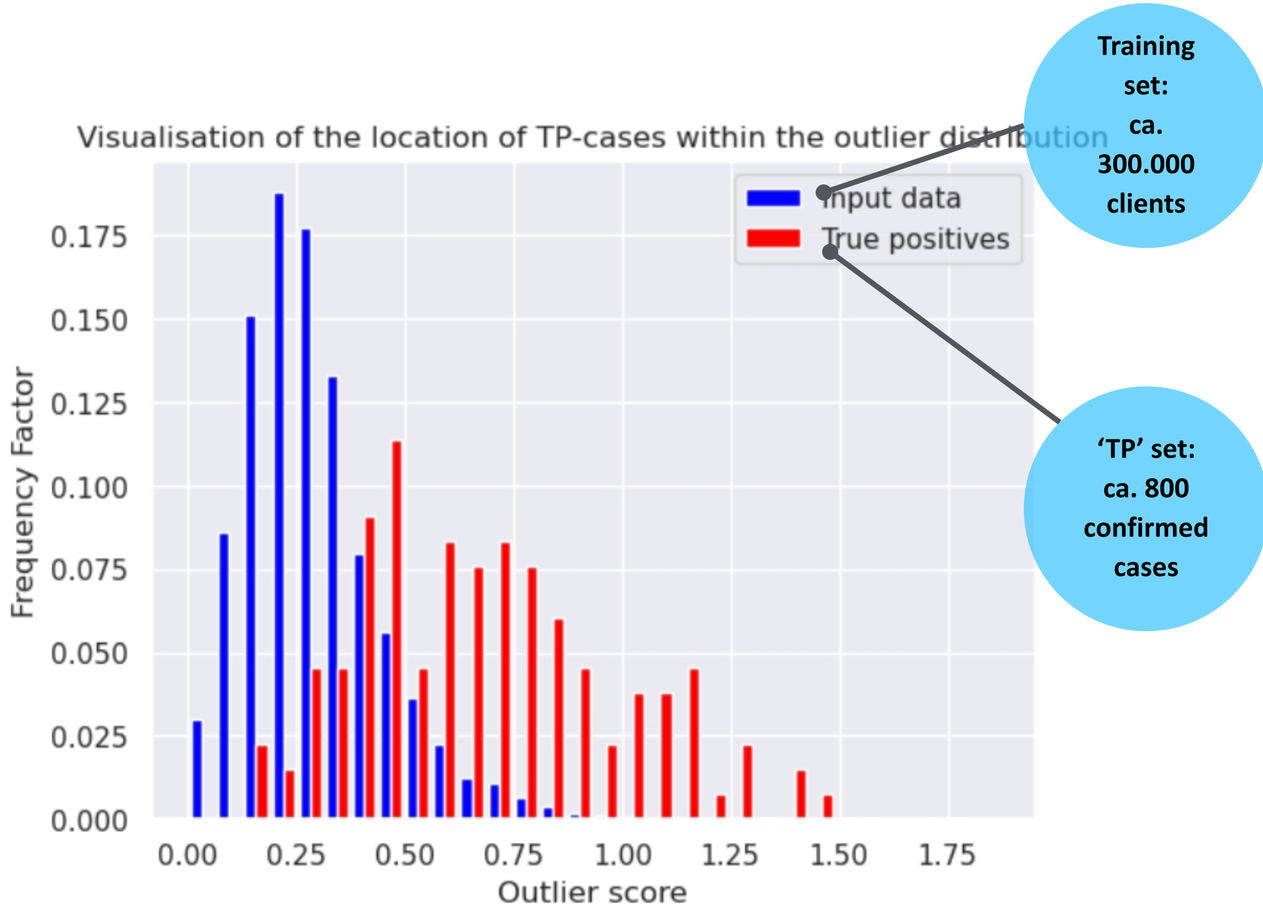
## Example ‘downstream’ use cases

- Anomaly detection
- Latent representation as feature for other models
  - Noise reduction
  - Client risk
- Compare behaviour of accounts
  - Clustering (peer grouping)
  - Support thematic investigations
- Typology analysis



# Autoencoder as Anomaly Detector

- Autoencoder learns to reconstruct typical patterns
- Samples that deviate yield high reconstruction error
- High reconstruction error implies atypical behaviour



# Foundational Models

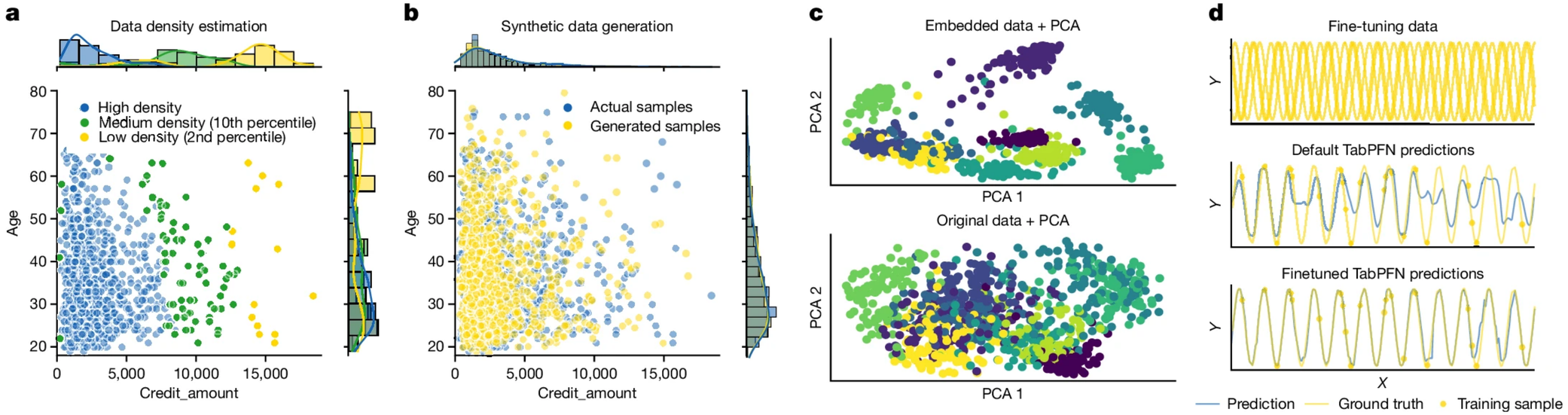
## For time series

Article | Open access | Published: 08 January 2025

### Accurate predictions on small data with a tabular foundation model

Noah Hollmann ✉, Samuel Müller ✉, Lennart Purucker, Arjun Krishnakumar, Max Körfer, Shi Bin Hoo, Robin Tibor Schirrmeister & Frank Hutter ✉

*Nature* **637**, 319–326 (2025) | Cite this article



# Foundational Models

## For behaviour / transactions

### PRAGMA: Revolut Foundation Model

**Maxim Ostroukhov**[1] **Ruslan Mikhailov**[1] **Vladimir Iashin**[1]
**Artem Sokolov**[1] **Andrei Akshonov**[1] **Vitaly Protasov**[1] **Dmitrii Beloborodov**[1]
**Vince Mullin**[2] **Roman Y. Enzmann**[2] **Georgios Kolovos**[2] **Jason Renders**[2]
**Pavel Nesterov**[1] **Anton Repushko**[1]

[1]*Revolut Research* [2]*NVIDIA*

| Task | Metric | Baseline (ref.) | PRAGMA |
|---|---|---|---|
| Credit scoring | PR-AUC | – | +130.2 % |
| | ROC-AUC | – | +12.4 % |
| Comm. engagement | PR-AUC | – | +79.4 % |
| | ROC-AUC | – | +20.4 % |
| External fraud | Precision | – | +16.7 % |
| | Recall | – | +64.7 % |
| Product rec. | mAP | – | +40.5 % |
| Recurrent txns | $F_1$ | – | +5.8 % |
| Lifetime value | PR-AUC | – | +1.8 % |
| | ROC-AUC | – | +2.6 % |

| Task | Metric | Baseline (ref.) | PRAGMA |
|---|---|---|---|
| Anti-money laundering | $F_{0.5}$ | – | −47.1 % |

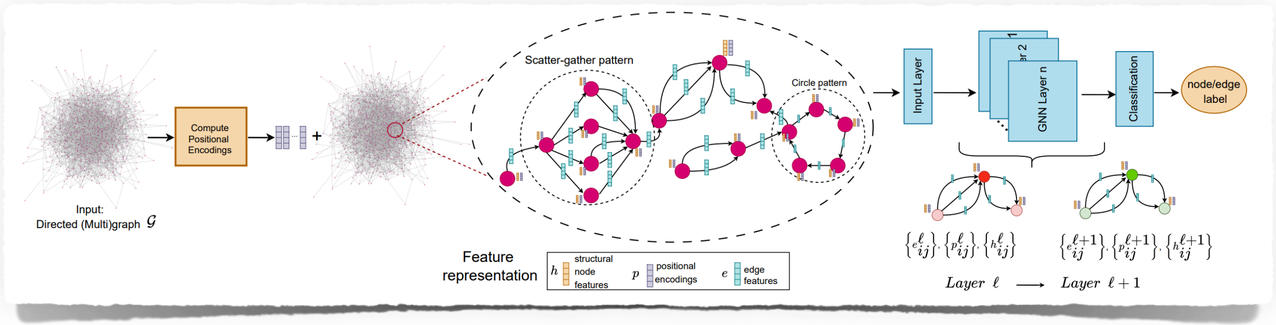
### Your Spending Needs Attention: Modeling Financial Habits with Transformers

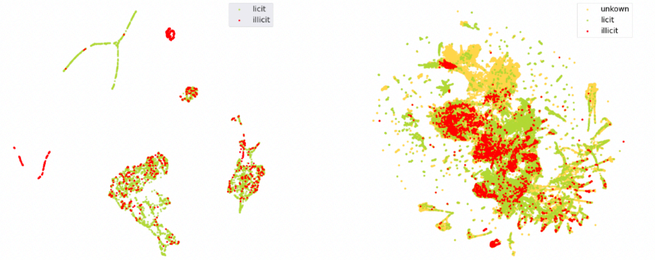
D. T. Braithwaite*, Misael Cavalcanti*, R. Austin McEver*, Hiroto Udagawa, Daniel Silva,
Rohan Ramanath, Felipe Meneses, Arissa Yoshida, Evan Wingert, Matheus Ramos, Brian Zanfelice,
Aman Gupta
Nubank
{daniel.braithwaite,misael.cavalcanti,austin.mcever}@nubank.com.br

### TransactionGPT

Visa Research

# Network Analytics




(a) Node Embeddings with DGI + GraphSAGE for the AMLSim data set.

(b) Node Embeddings with DGI + GraphSAGE for the Elliptic data set.

Fig. 11: Node Embeddings with DGI + GraphSAGE.

But…


"WANTS

# YOU"

# Thank you