

## Money Laundering Detection: Unsupervised Analysis on Banking Transaction Data

Faculty of Information Engineering, Informatics, and Statistics Master Degree in Data Science

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### **The Money Laundering Detection Problem**

Money laundering is the process of transforming the profits of crime and corruption into ostensibly "legitimate" assets.

• 3 steps:

- **Placement:** Initial entry of the "dirty" cash or proceeds of crime into the financial system.

- Layering: Separate the illicit money from its source.

- **Integration:** Money is returned to the criminal from what seem to be legitimate sources.

- **Placement**: Initial entry of the "dirty" cash or proceeds of crime into the financial system.

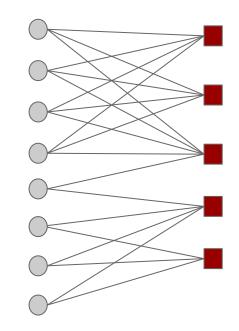
- Layering: Separate the illicit money from its source.
- Transactions of relevant amount, involving cash
- Transactions carried out at the same operative point (or neighboring operative points)
- Transactions carried out inside a narrow time frame (inside a temporal interval of 60 minutes, for instance)

- Integration: Money is returned to the criminal from what seem to be legitimate sources.

State of the Art: **GIANOS**  $\rightarrow$  find anomalies related to single cards behaviors, elaborated by hundreds of pre-established rules

#### Dataset

- Real Data (25 days of transactions)
- Each record is a financial operation (cash advance, purchase of goods, ...) [ID\_card, channel, ID\_operative\_point, timestamp, transaction\_amount, transaction\_type]
- Focus the attention just in cash advance operation
- Dataset Size: #transactions: 17.8M
   #cards: 5.1M
   #ATMs: 135K



#### <u>Transactions of relevant amount, involving cash</u>

Transactions carried out at the same operative point (or neighboring operative points)

Transactions carried out inside a narrow time frame (inside a temporal interval of 60 minutes, for instance)

#### **Transactions of Relevant Amount**

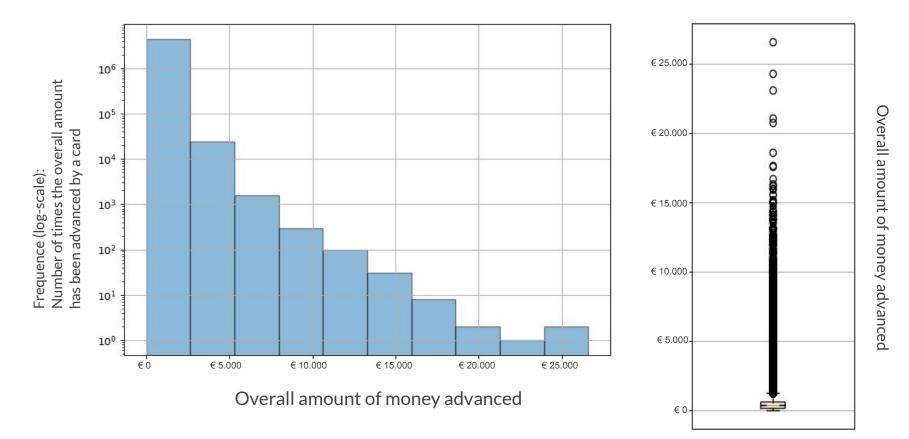
#### Transactions of interest:

- high amount of money
- made by the most active cards

#### Method:

- Detect the most active cards through a data driven threshold (?€)
- Exclude the single transactions of amount lower than a second data driven threshold (?€)

## Distribution of Overall Advanced Amount of Money



- First quartile  $\Rightarrow$  Data driven threshold  $\Rightarrow \in 150$
- FROM 17.8M transactions, 5.1M cards TO 10.4M transactions, 3.4M cards

#### **Distribution of Advanced Amount of Money**



- First quartile  $\Rightarrow$  Data driven threshold  $\Rightarrow \in 50$
- FROM 10.4M transactions, 3.4M cards TO 9M transactions, 3.4M cards

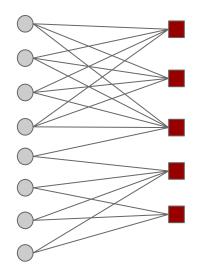
#### **Transactions of Relevant Amount**

#### Transactions of interest:

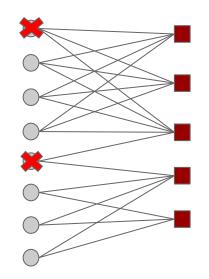
- high amount of money
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#### Method:

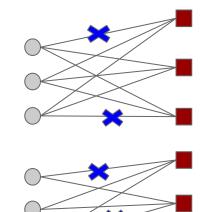
- Detect the most active cards through a data driven threshold (€ 150)
- Exclude the single transactions of amount lower than a second data driven threshold (€ 50)



17.8M transactions 5.1M cards



10.4M transactions 3.4M cards



9M transactions 3.4M cards

#### Transactions of relevant amount, involving cash

Transactions carried out at the same operative point (or neighboring operative points)

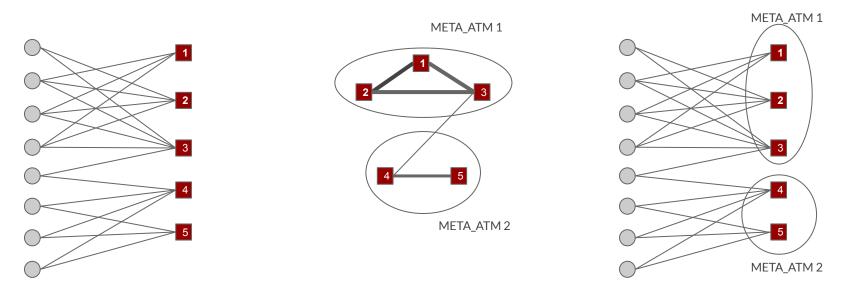
Transactions carried out inside a narrow time frame (inside a temporal interval of 60 minutes, for instance)

#### **Find Groups of Neighboring ATMs**

- **Goal**: Find geographically close groups of ATMs.
- **Problems/limitations**: No geospatial data on ATMs :(
- Idea/Assumption: the more cards two ATMs have in common, the closer they are ;)

#### How to Find Groups of Neighboring ATMs?

- 1. Model the dataset as a bipartite graph
  - Nodes: 5.183.308 cards and 135.503 ATMs.
  - Edges: 17.866.556 transactions.
- 2. Compress the graph on the ATMs nodes: 135.503 ATMs, 1.391.665 edges.
- Apply a community detection algorithm to find communities of neighboring ATMs ;)
   #META\_ATMs: <u>22.964</u>



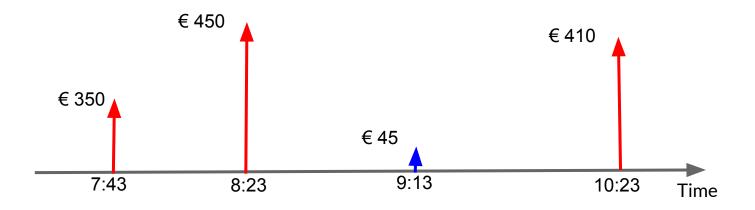
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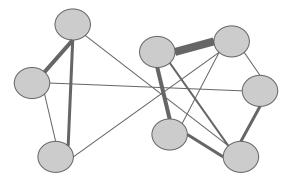
#### **Suspected Cards from a Temporal Point of View**

- **Definition:** two cards are suspected from a temporal point of view when they carry out at least two temporally close transactions.
- **Temporally close (assumption):** Two transactions are temporally close when they lie inside a temporal interval of 60 minutes.
- **Degree of Suspicion of a Couple of Cards:** the greater the number of times two cards make temporally close transactions, the greater their degree of suspicion is.
- **Goal:** detect the pairs of cards with the highest degree of suspicion.



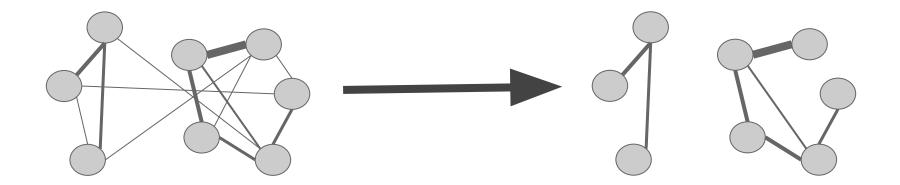
## **Temporal Locality Algorithm**

- For each Meta\_ATM
- Scan of all transactions in ascending order of time [ID\_card, ID\_Meta\_ATM, timestamp\_↑]
- Count the number of times a couple of cards make temporally close transactions
   ⇒ evaluating the degree of suspicion of a couple of cards
- OUTPUT: Mapping between pairs and their strength of interactions ⇒
   Weighted graph connecting cards with their degree of suspicion



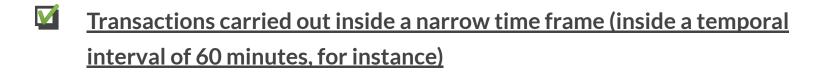
#### **Temporal Locality Algorithm: Relevant Data**

- 1. We are interested in groups of connected cards.
- 2. A lot of not relevant edges inside the weighted edgelist (low degree of suspicion).
- 3. Removing not relevant edges (low degree of suspicion).
- 4. Find the connected components of the resulting graph.



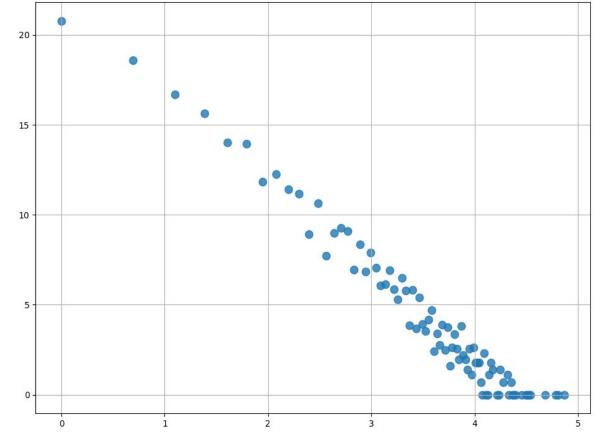
#### **<u>Transactions of relevant amount, involving cash</u>**

Transactions carried out at the same operative point (or neighboring operative points)



## Temporal Locality Algorithm: Results

Number of occurrences of each particular weight in the set of edges



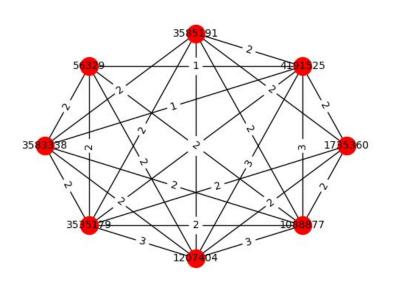
Weight of the edge

- Number of edges:

   1.193.539.139
   (1.049.755.424
   with weight=1, 88%)
- loglog scale
- trend similar to a power law

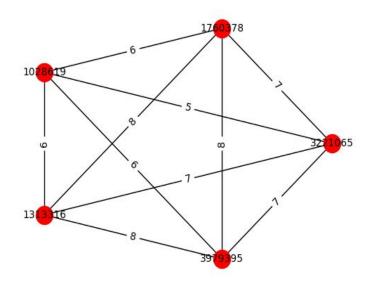
Applied to META\_ATM with the highest number of transactions (688k transactions, 312k cards)

#### **Temporal Locality Algorithm: Results**

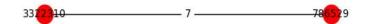


**COMMUNITY 1 - INTERACTIONS** 

**COMMUNITY 2 - INTERACTIONS** 

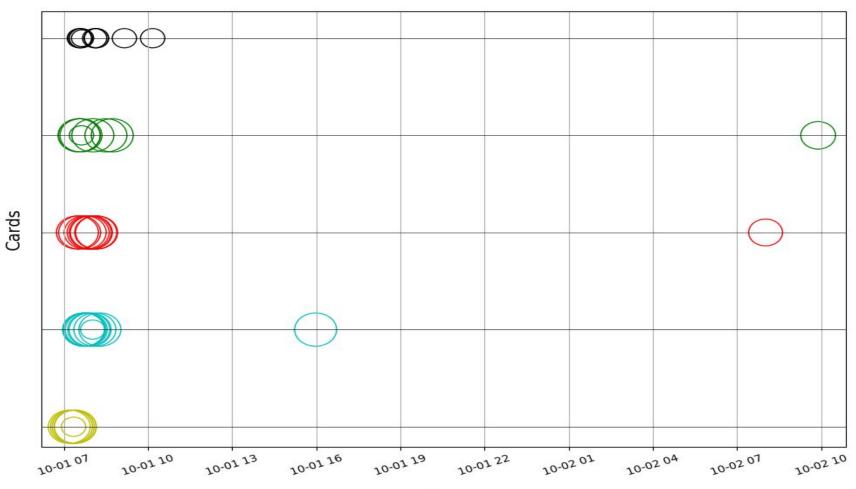


**COMMUNITY 3 - INTERACTIONS** 



#### **Temporal Locality Algorithm: Results**

#### **COMMUNITY 2 - TIME SERIES**



Time

20

## Temporal Locality Algorithm: Main Memory Constraint

- 1. Billions of spotted pairs  $\Rightarrow$  cannot be fitted in main memory :(
- 2. Flush on disk sub-mappings every time main memory is full;)
- 3. Sort the sub-mappings and merge them all
- 4. Obtain the overall mapping representing the strength of interaction of all the spotted pairs ⇒ Weighted graph connecting cards with their degree of suspicion

## **Temporal Locality: Probabilistic Approach**

- **Motivation**: We are interested in pairs of cards that appear many times during the scanning of the dataset: high degree of suspicion
- **First Step** (find good candidates): Every time we spot a pair of cards, add it into a set with probability p to guarantee that a relevant pair will be in the set with a certain input confidence
- Second Step (<u>compute the suspicious degree</u>): Scan a second time the dataset, adding to a map only pairs inside the set
- OUTPUT: A much smaller mapping w.r.t. the one obtained before
   ⇒ possible errors: ₩, FN

DETERMINISTIC RUNNING TIME:		RECALL:
0	<u>3h 25min 28secs</u>	0 0.93
PROBABILISTIC RUNNING TIME (conf=0.9 $\Rightarrow$ p=0.2056):		PRECISION:
0	<u>53min 48secs</u>	0 1.0

## Conclusions

- PROBLEM: Find groups of cards acting in anomalous way, by following the Bankitalia instructions
- APPROACH:

- Deterministic algorithm able to adapt to the available main memory (common laptop)

- Probabilistic approach that does not generate False Positives and 3.8 times faster

• GOAL: To help the money laundering experts by providing a smaller set of groups of cards classified as suspicious

# Thank You For the Attention

#### **Deterministic VS Probabilistic - Performance**

DETERMINISTIC

• TOTAL TIME: <u>3h 25min 28secs</u>

PROBABILISTIC (conf= $0.9 \Rightarrow p=0.2056$ )

• TOTAL TIME: <u>53min 48secs</u>

True Positives (TP):
 152.935 (on 164.344)

- False Positives (FP):
  273.619.520 (not a problem ;))
- True negatives (TN):
   1.193.363.386
- False negatives (FN): 11.409
- **Recall** = TP/(TP + FN) = 0.93
- **Precision** = TP/(TP + FP) = 1.0