

EVA: Visual Analytics to Identify Fraudulent Events

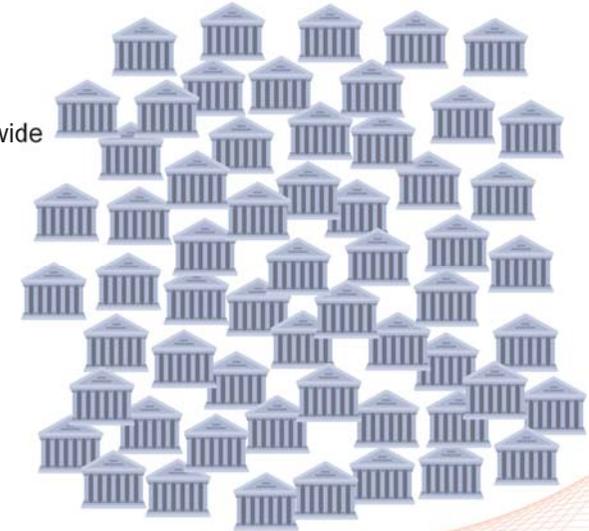


Roger A. Leite
Theresia Gschwandtner
Silvia Miksch
Margit Pohl
Erich Gstrein
Johannes Kuntner
Simone Kriglstein

Vienna University of Technology
Vienna University of Technology
Vienna University of Technology
Vienna University of Technology
Erste Group IT International
Erste Group IT International
University of Vienna

Motivation

Around 30.000 different banks world wide
Top 10 banks alone hold around \$25 tri
Banks succeed!

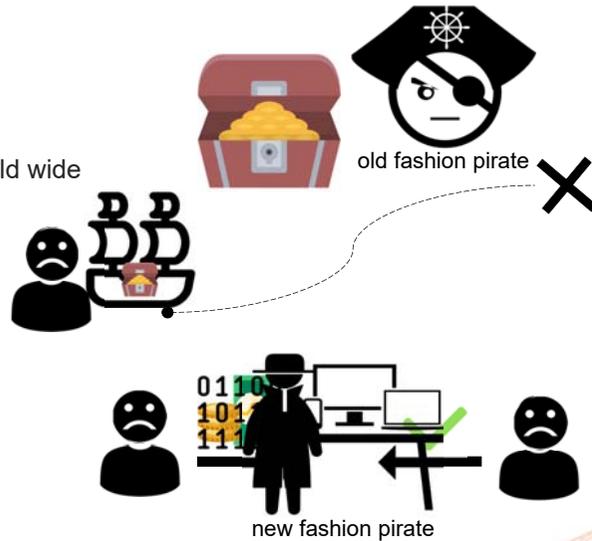


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Transaction security

Financial crime fashion changes



Motivation

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Transaction security

Financial crime fashion changes

Types of frauds

- Unauthorized Transaction
- Straw Person
- Internal Fraud
- Money Laundering
- ...



Roadmap

- Motivation
- Automatic Method
- Requirements
- EVA
- Evaluation
- Future Work
- Conclusion



Collaboration – The Beginning

A bank approached us with a problem concerning financial fraud detection.

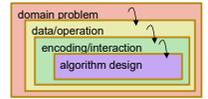


They had developed an **Automatic Method** for detecting financial frauds that had great results but could still be improved.



We decided for a **User Centered** design of a VA approach.

...let's take a look at this **Automatic Method**



[S. Miksch and W. Aigner, 2014] Nested Model [Tamara Munzner, 2009]

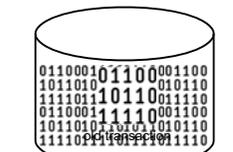
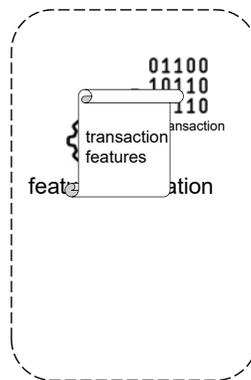


Automatic Method

Creates a **profile** for each customer



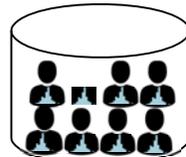
01100
10110
11110
new transaction



transactions database



profiles generation



profiles



Automatic Method

Creates a **profile** for each customer



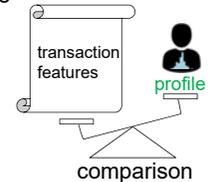
Scores are generated for each new transaction

01100
10110
11110

Scores represent suspiciousness

scores:

- operation time score
- location score
- amount of money score
- location and amount score
- location and time
- ...
- ...



Automatic Method



Creates a **profile** for each customer

01100
10110
11110

Scores are generated for each new transaction

Scores represent suspiciousness



Alarms are triggered by the **overall score**

scores:

operation time score
location score
amount of money score
location and amount score
location and time
...

subscores

transaction features



profile

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if overall score > threshold
alarm comparison



Requirements



System should be constantly updated
R1 - Visual support for scoring system

Hard to compare accounts
R2 - Account comparison

Hard to identify false-positives
R3 - Reasoning about potential frauds

Hard to identify false-negatives
R4 - Identification of hidden frauds

financial fraud
investigators
users

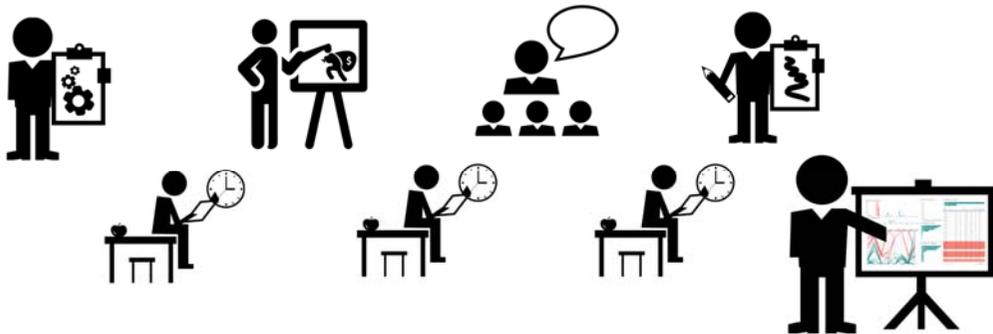
Visual Analytics
Methods

?
tasks

User Centered Design [Silvia Miksch and Wolfgang Aigner, 2014]



Collaboration – User Center Design



... 18 months project

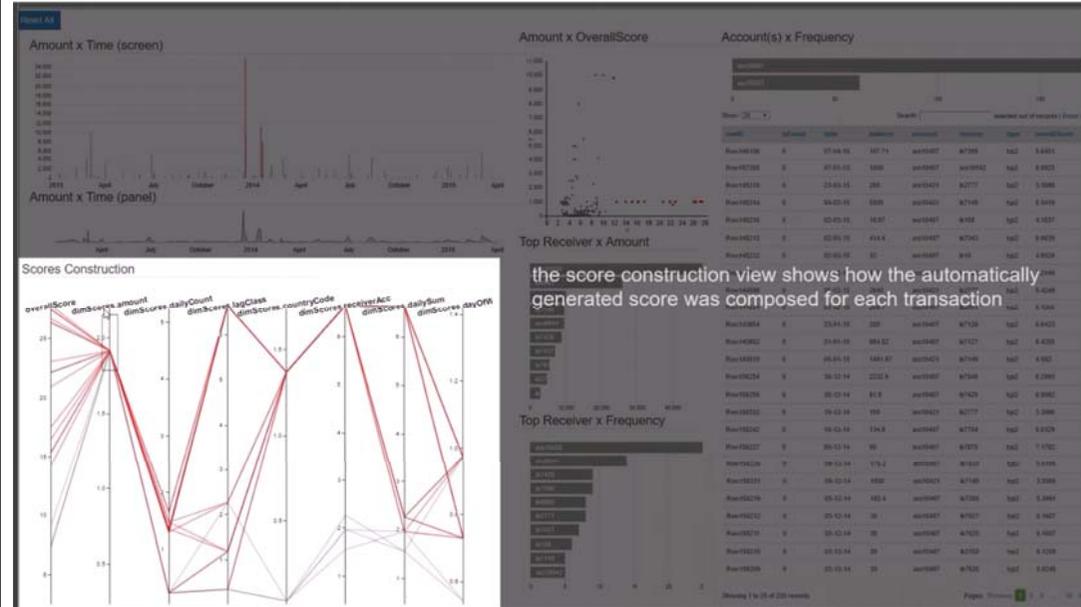
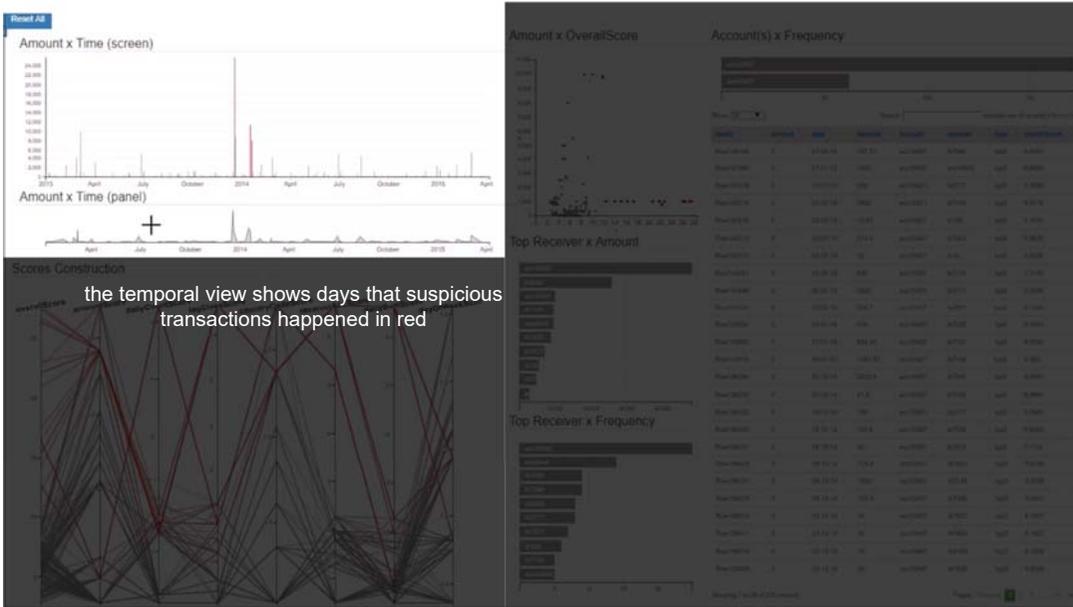
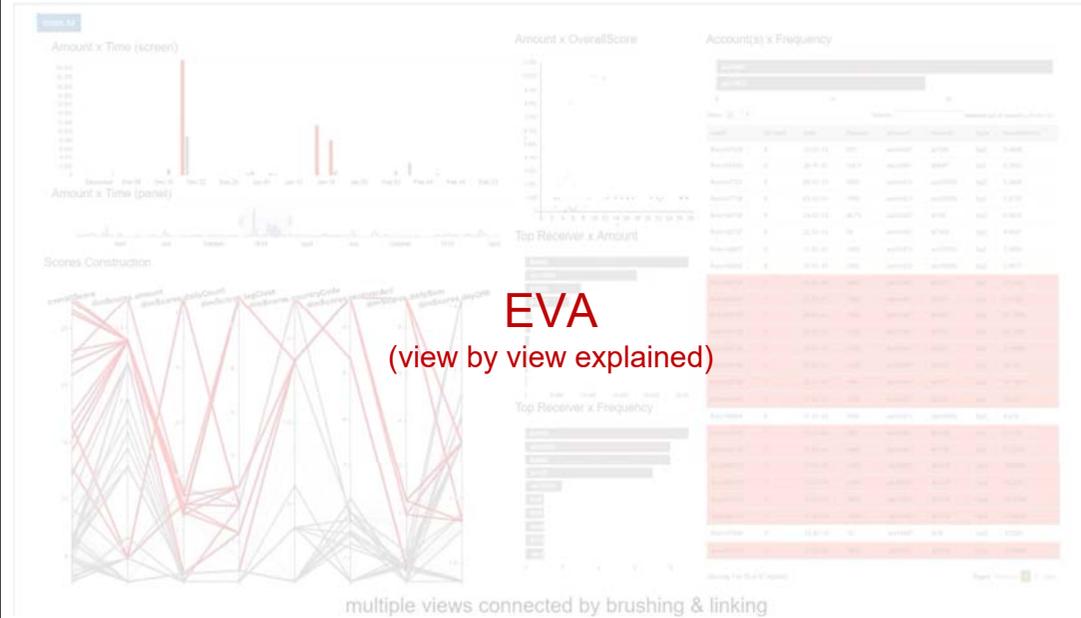
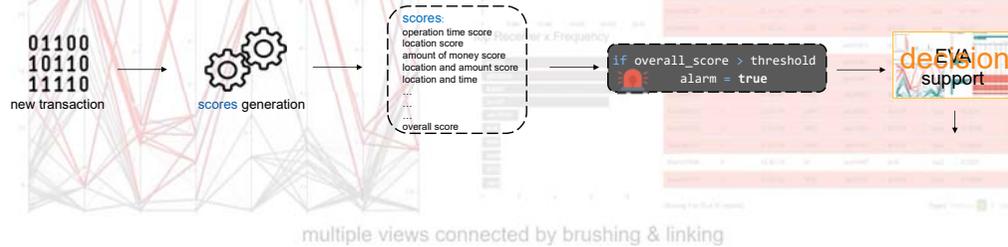


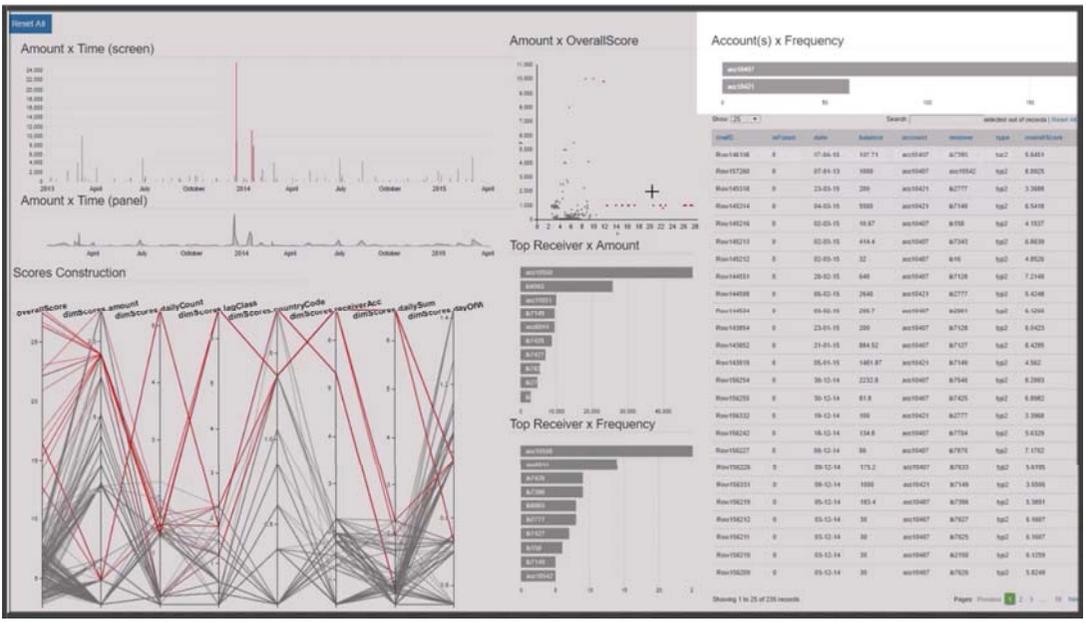
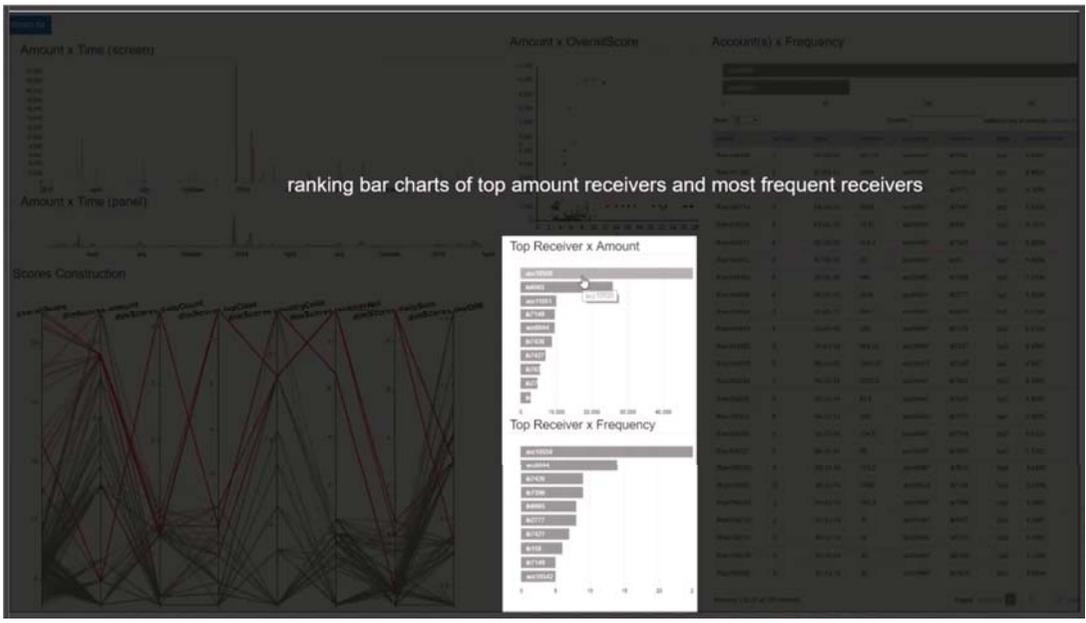
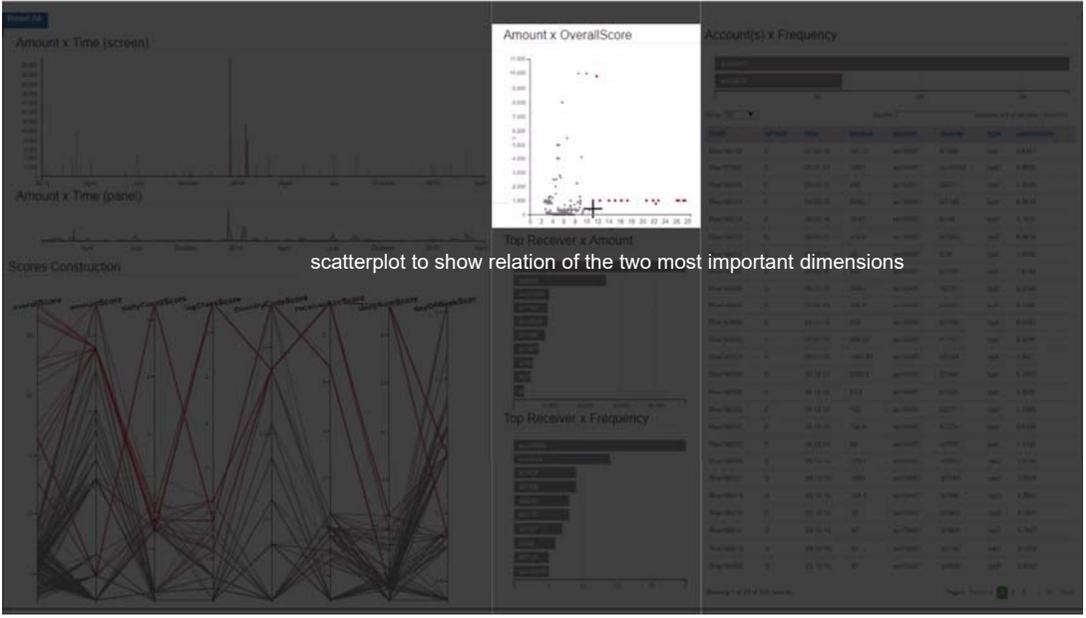
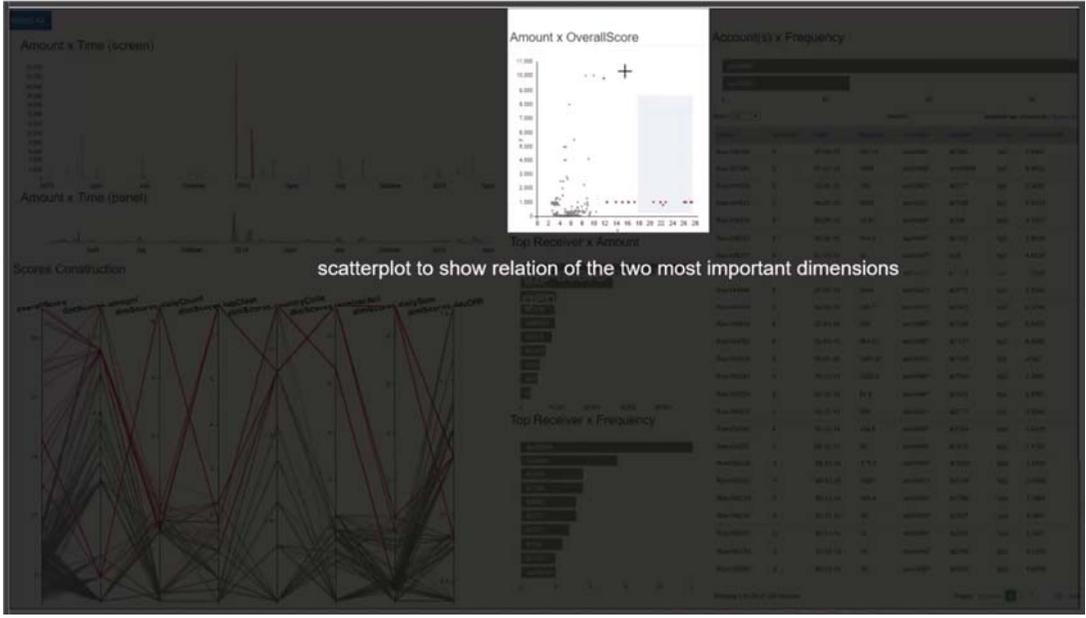
EVA

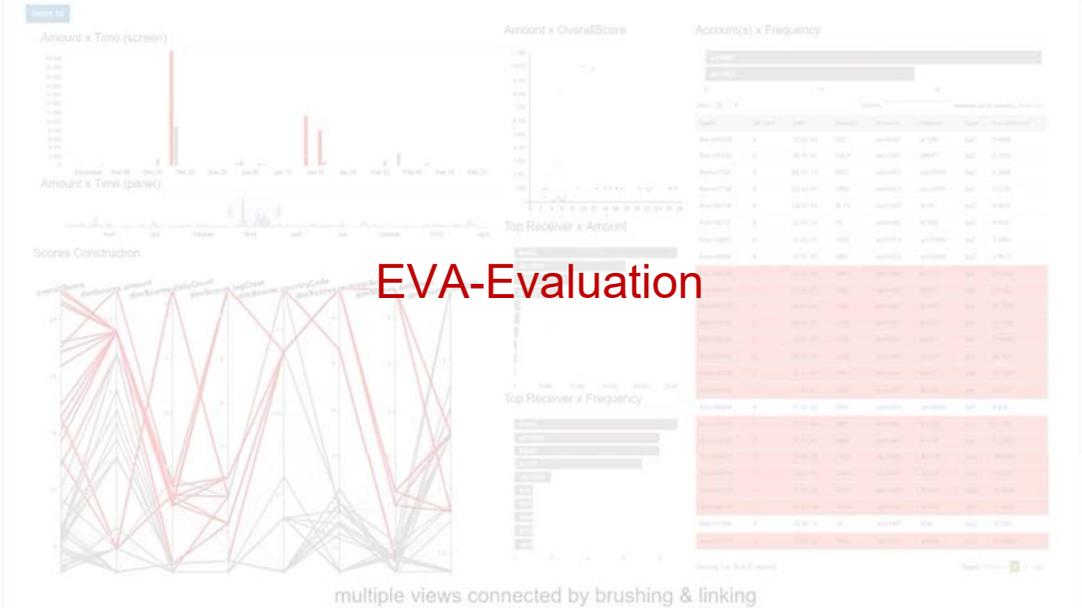
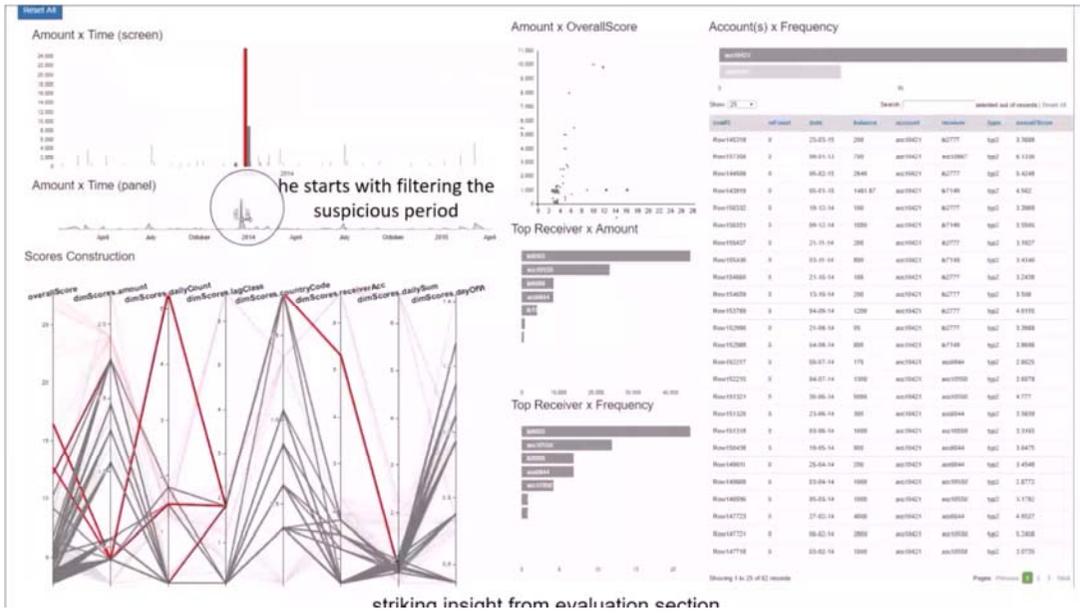
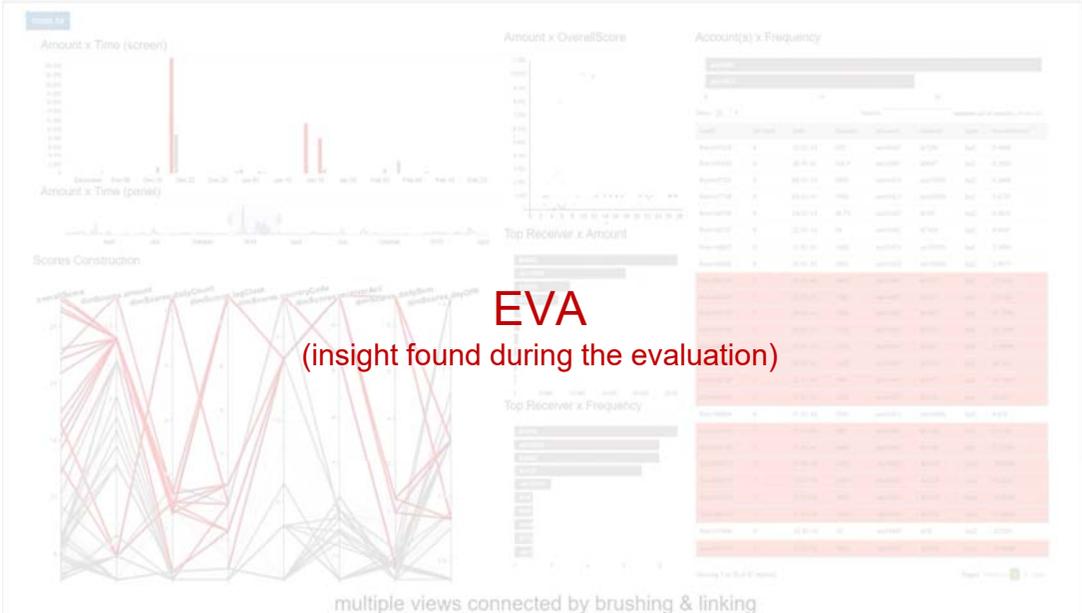
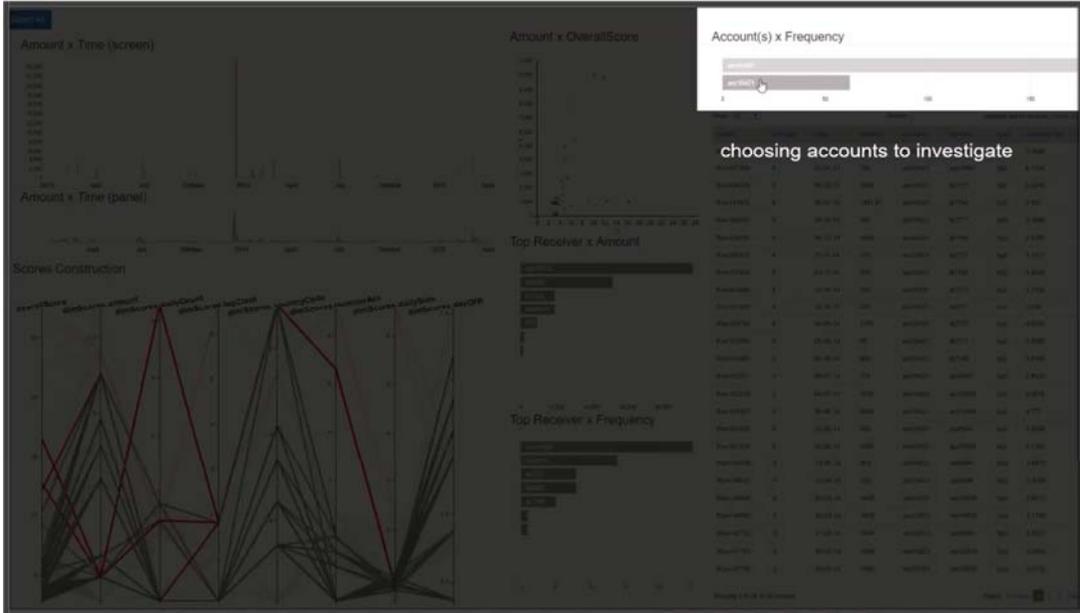
EVA combines **well-known visualization** techniques, which our domain experts are mostly familiar with, and automatic methods

6 views: bar chart, line chart, parallel coordinates, scatter plot, row charts, and a table

EVA proposes the integration of a VA step to the current detection and decision workflow







Evaluation - Sample

Anonymized real world 2 years dataset 

3 target users  \neq  domain experts

EVA introduction

Interviews

Designed 3 tasks based on the requirements

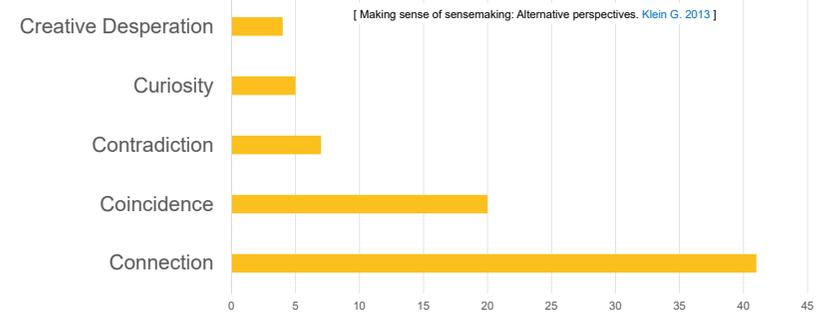
Requirements:

- R1 - visual support for scoring system
- R2 - account comparison
- R3 - reasoning about potential frauds
- R4 - identification of hidden frauds

	R1	R2	R3	R4
Task 1		•	•	
Task 2	•		•	•
Task 3		•	•	•

Evaluation - Results

Klein's sensemaking model:

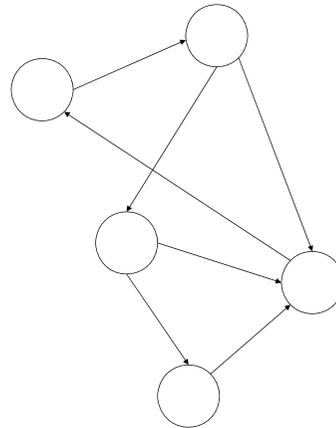


"I liked it because it is very interactive and you can browse the data, even if you don't know what you are looking for, and find new insights"

"Here we could see what is possible and what is available [...] So we can rethink what we can offer to the bank."

Future Work

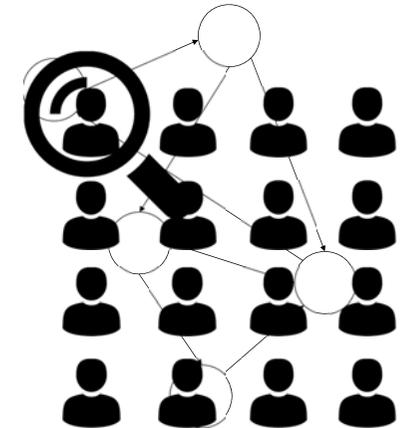
Network analysis



Future Work

Network analysis

Monitoring multiple customers

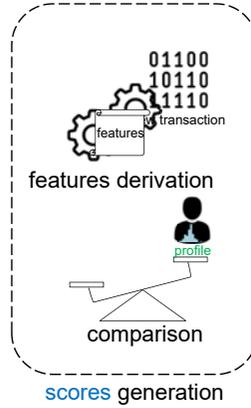


Future Work

- Network analysis
- Monitoring multiple customers
- Fine tuning fraud detection algorithm

Automatic Method:

01100
10110
11110
new transaction



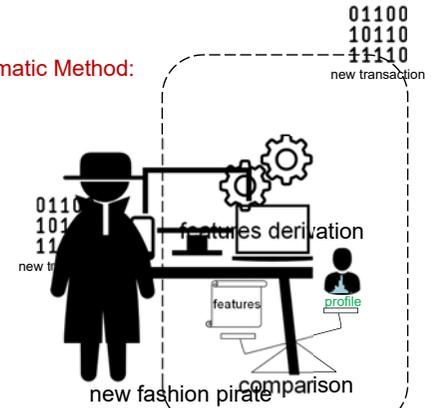
SCORES:
operation time
score
location score
amount of money
score...
overall score



Future Work

- Network analysis
- Monitoring multiple customers
- Fine tuning fraud detection algorithm
- Different types of fraud

Automatic Method:



SCORES:
operation time
score
location score
amount of money
score...
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Conclusion

Score system based VA approach for financial fraud detection

Tight collaboration with domain experts

Evaluation with three target users

Positive feedback

