

Advanced Behavioral Analysis Using Inferred Social Networks - Vision

Irena Holubová, Martin Svoboda, Tomáš Skopal,
David Bernhauer, **Ladislav Peška**

Faculty of Mathematics and Physics, Charles University, Prague, CZ

TIR 2019, Linz, Austria

Context & Disclaimer

- Industry-based project

- Co-operation with a modest-sized bank & Profinit EU (data analytics)
- General motivation: „get to know“ our clients better
 - Increased revenues, detect potential problems, unwanted situations etc.
- Rather a fuzzy task without strict goals
- *Work-in-progress (more questions than answers 😊)*

- Traditional banking

- Relational data (clients, products, transactions)
- Standard analytics (SELECT/GROUP BY/FILTER), ML based on facts
- Some statistical task-specific analytics
 - Mostly predictions in risk management (loan/mortgage business), fraud detection/prevention
 - Common ML techniques, simple features (demographics, risk classes, income, etc.)

Motivation

- What can be done beyond traditional approaches?
 - Go beyond explicit fact checking
 - Model similarities of bank clients based on their behavior
 - Construct some latent „social network“ based on clients' similarities
 - Social relations, locality relations, financial behavior patterns, etc.
 - No explicitly given task -> focus on new business cases
 - Personalized marketing, insurance recommendation, investments, financial consultation, insolvency prevention, etc.

GOALS (bank's point of view):

- *Offer appropriate financial products to relevant clients **at the right time***
- ***Predict & prevent unwanted situations** (frauds, loan payment problems)*
- ***Find new business models***

Motivation

- Kate just added travel insurance to her card
 - William is similar to Kate w.r.t. expenses structure, withdrawn ATM's countries and location patterns.
 - *Human readable explanation: they both travel but don't like extreme sports => basic insurance will do. Also, maybe they're a family?*
 - *What about recommending travel insurance to William as well?*
 - *Further confirmation: in past, recommendations along these axes worked well.*
- Miloš did not received his salary last two months
 - His expenses remain similar & he keeps withdrawing from „booze ATMs“ cluster
 - *Human explanation: he lost his job, but he keeps drinking like hell*
 - *What about offering him a loan?*
 - **Maybe, not a good idea:**
 - **Miloš's expenses structure & withdrawn ATM's clusters are similar to how did Andrej behaved a year ago. Andrej received a loan, but failed to repay it.**

Data available

- Demographics

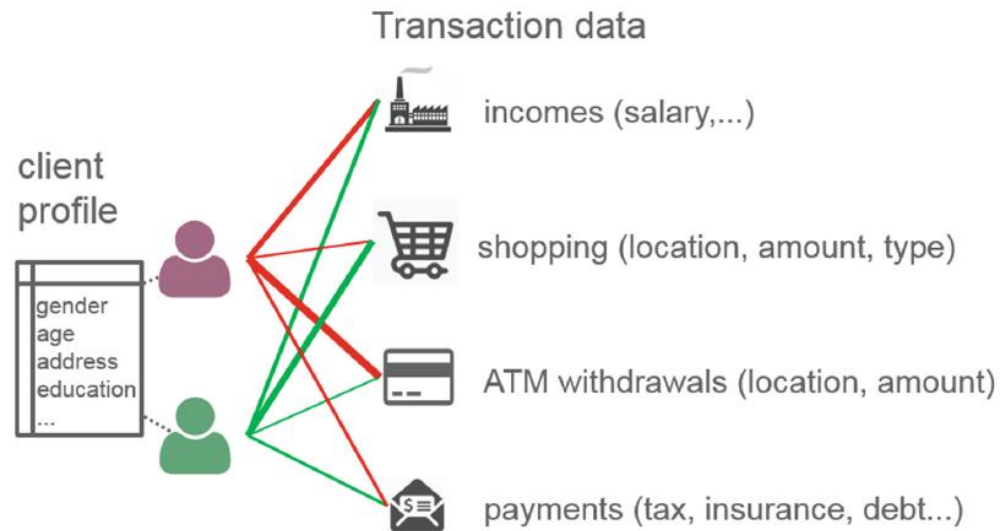
- Name, gender, age, address...
- Credit score, loan payment history, frauds...
- *Some data anonymized / hashed for us*

- Transactions

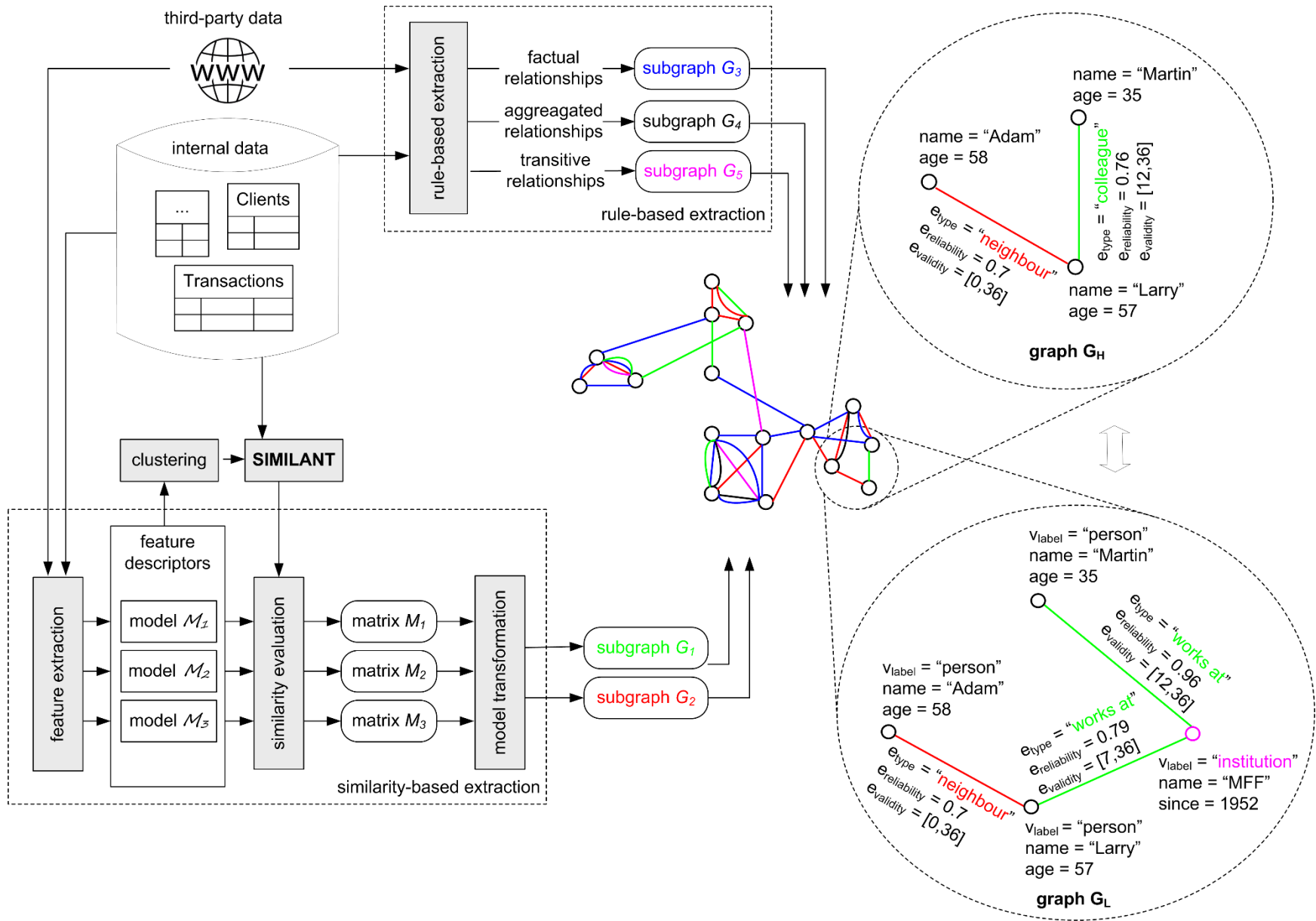
- Allow to model similarities of clients based on various financial behavior profiles
- Rich attribute structure
- Temporal context

- 3rd Party Data

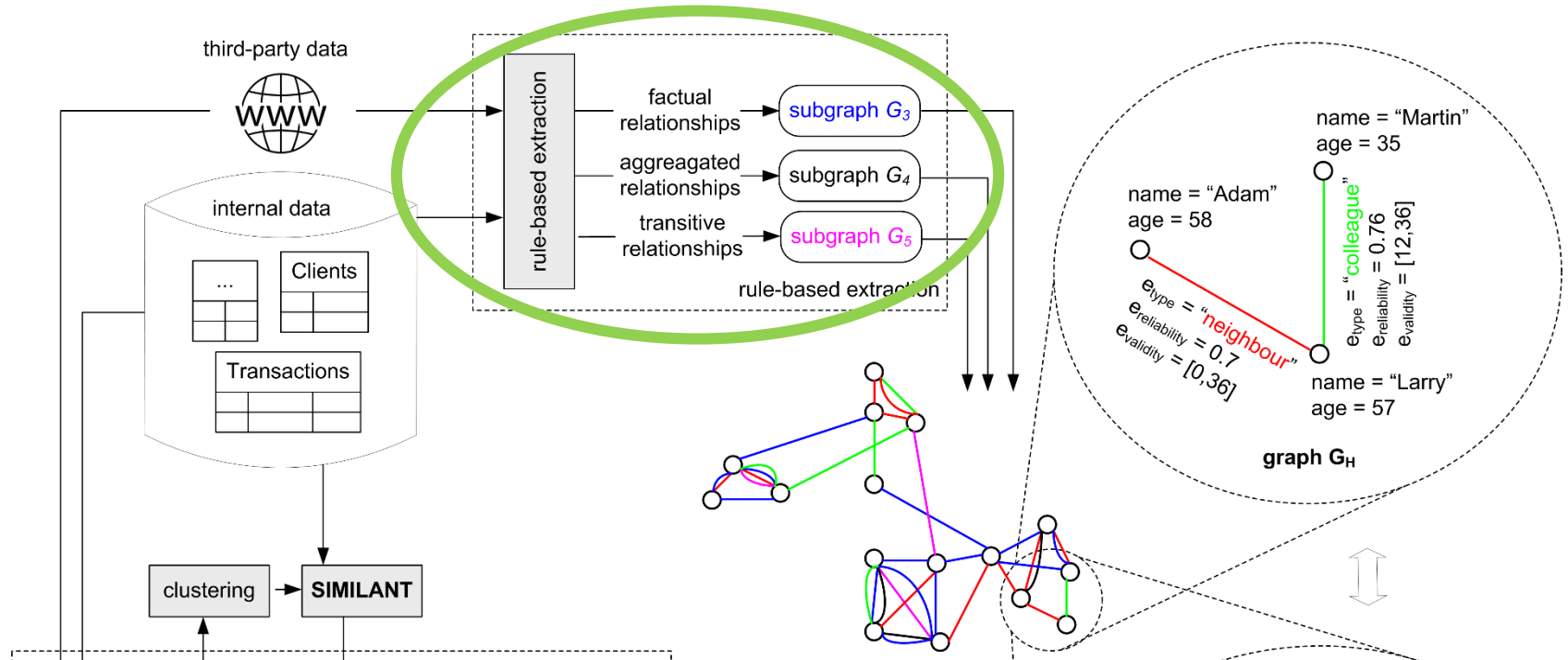
- E.g. Real estate, business or criminal registers
- Legal concerns (however useful for manual verification)



Latent social network model



Latent social network model

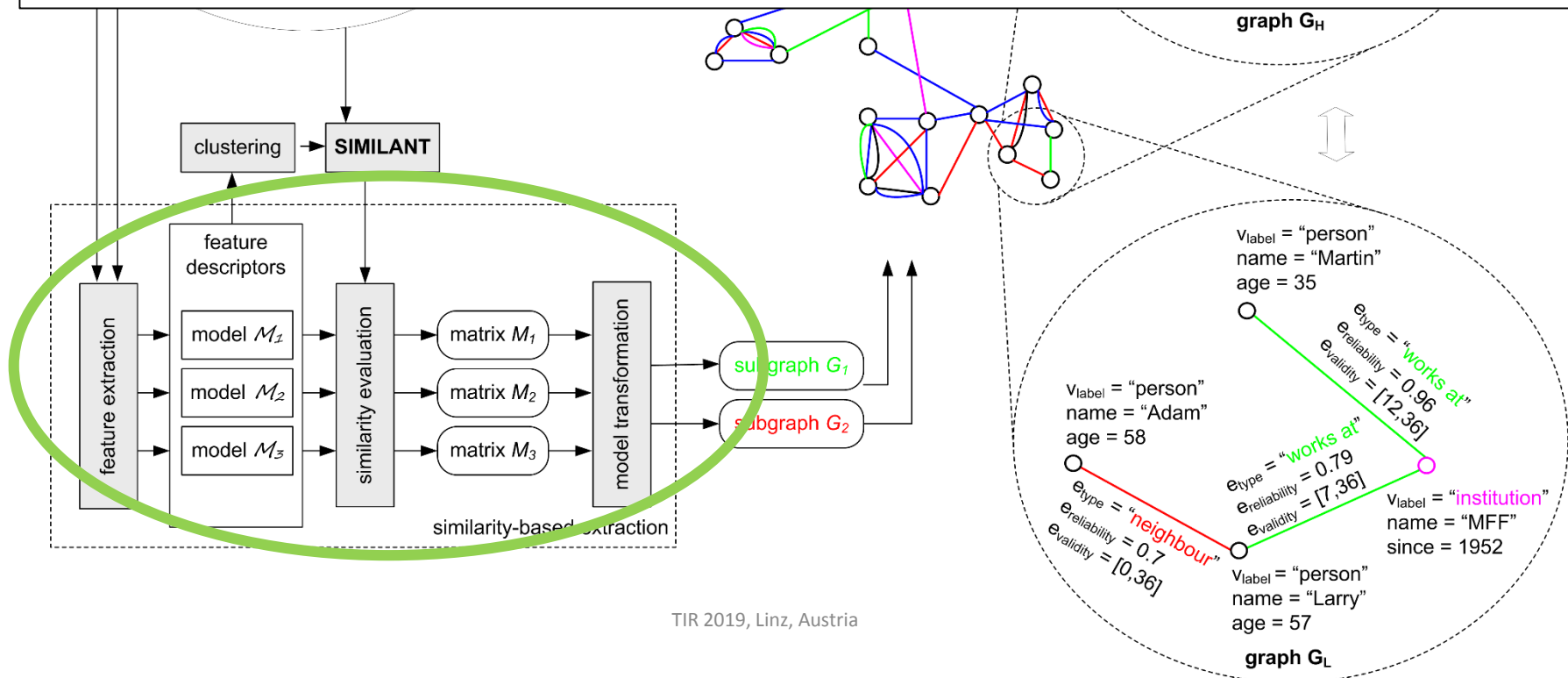


- Rule-based edge extractions

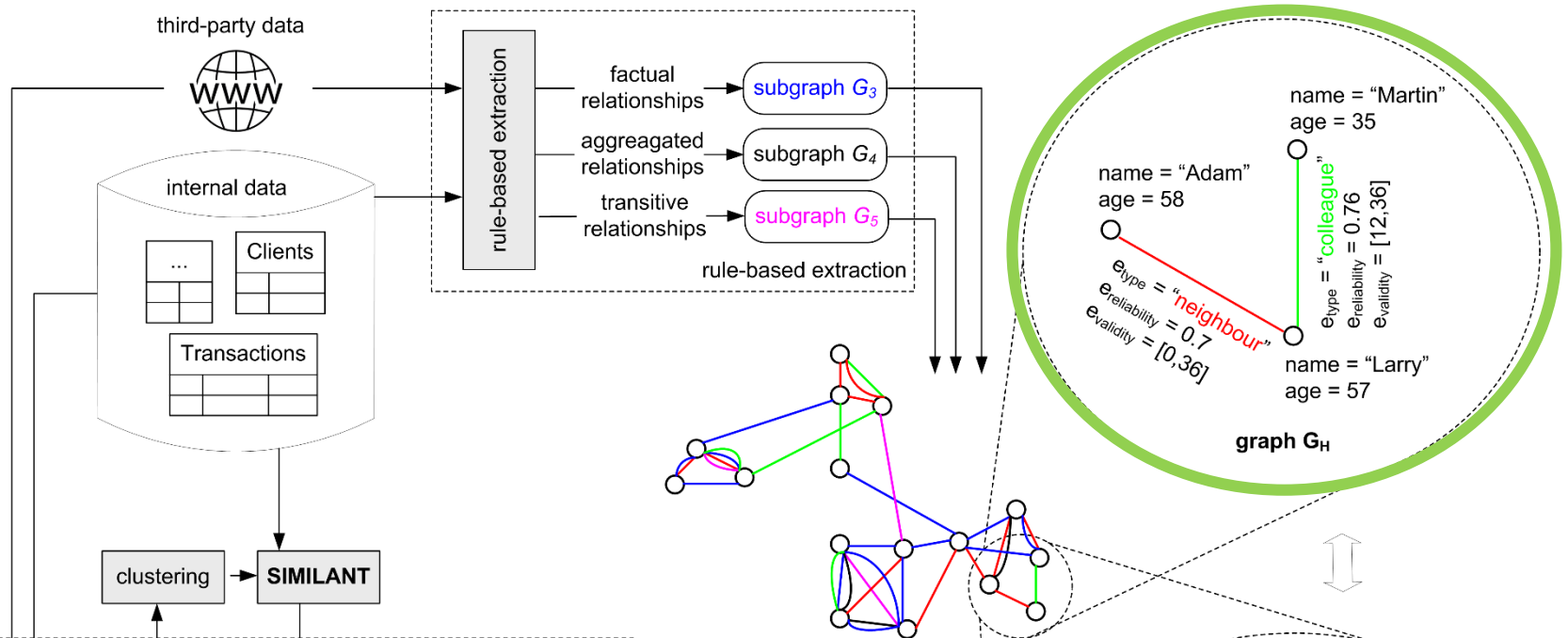
- Fact checking, e.g., family/relatives, co-workers
- Aggregated relations (e.g., mutual transactions -> business relations / employers)
- *Can be done with traditional approaches*

Latent social network model

- Similarity-based edge extractions
 - Focus on client's behavior
 - Stream of transactions (possibly window-based aggregations)
 - Amount, datetime, location, frequency, counterparty, transaction type, type of business (+ brand) etc.



Latent social network model



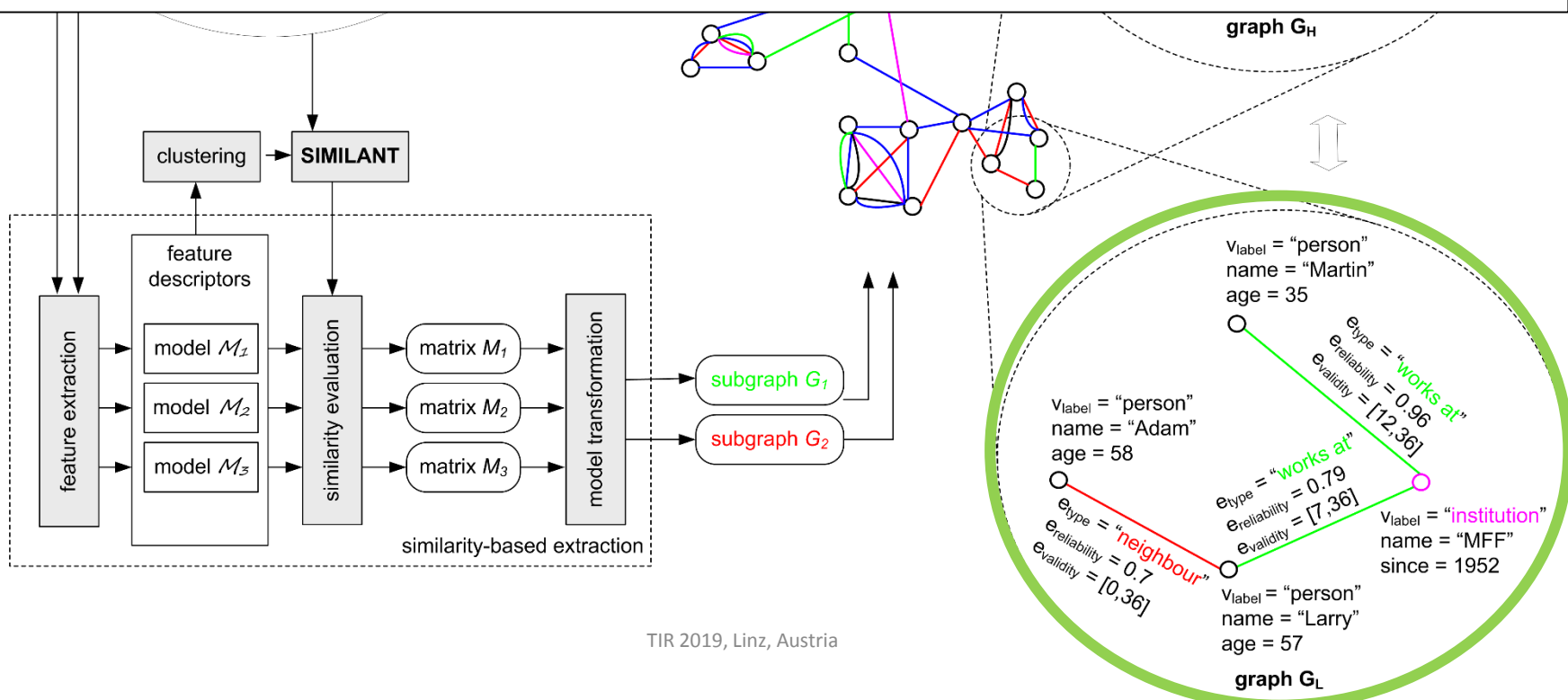
- High-level latent social multigraph

- Relations among clients (aggregated from low-level edges)
- Client's attributes (both factual and inferred)
- Time-aware edges, relation relevance score

Latent social network model

- Low-level latent social multigraph

- Decomposed relations over other node types (locations, institutions etc.)
 - E.g. **Person1-Colleague-Person2** ->
Person1 – works_at – Institution & Person2 – works_at - Institution
- Finer grained relationship mining



Latent social network model

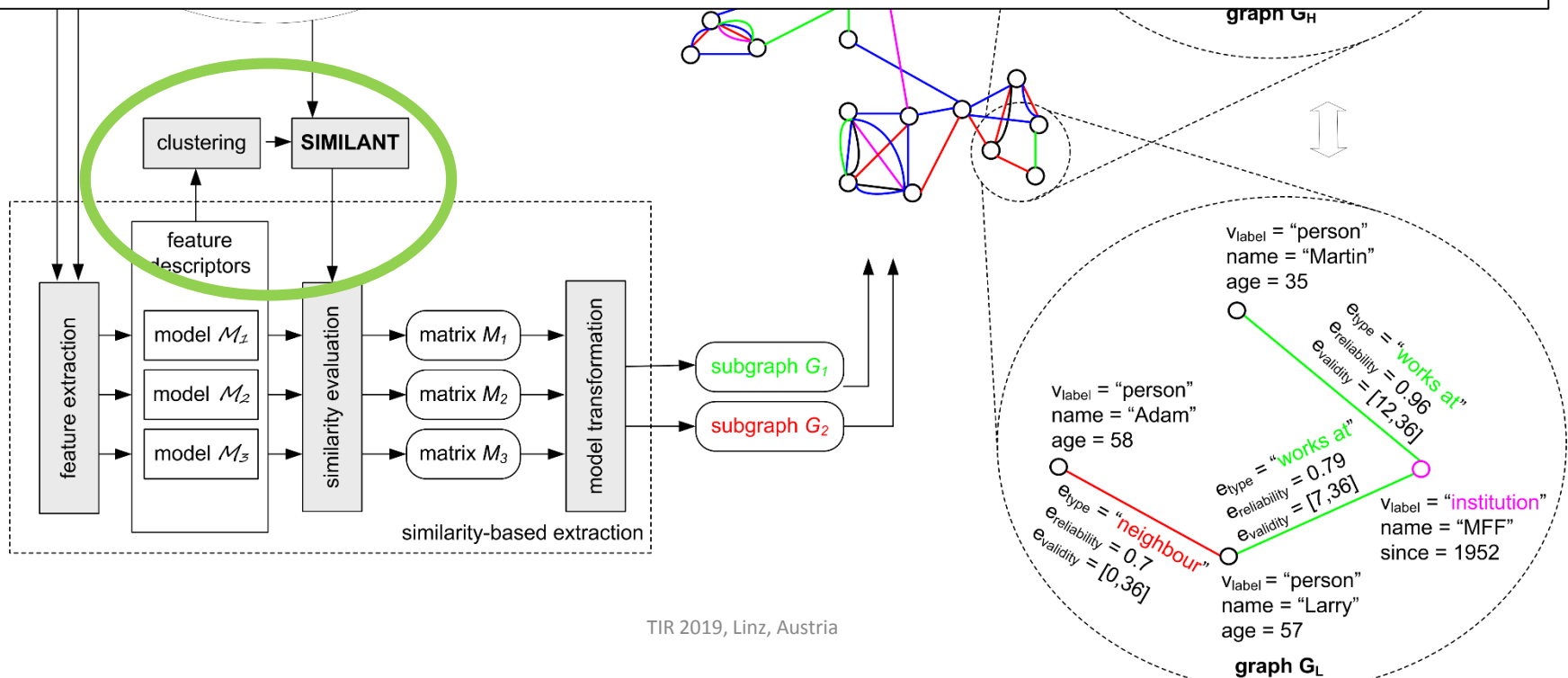
- SIMILANT

- Analytic tool to evaluate similarity descriptors

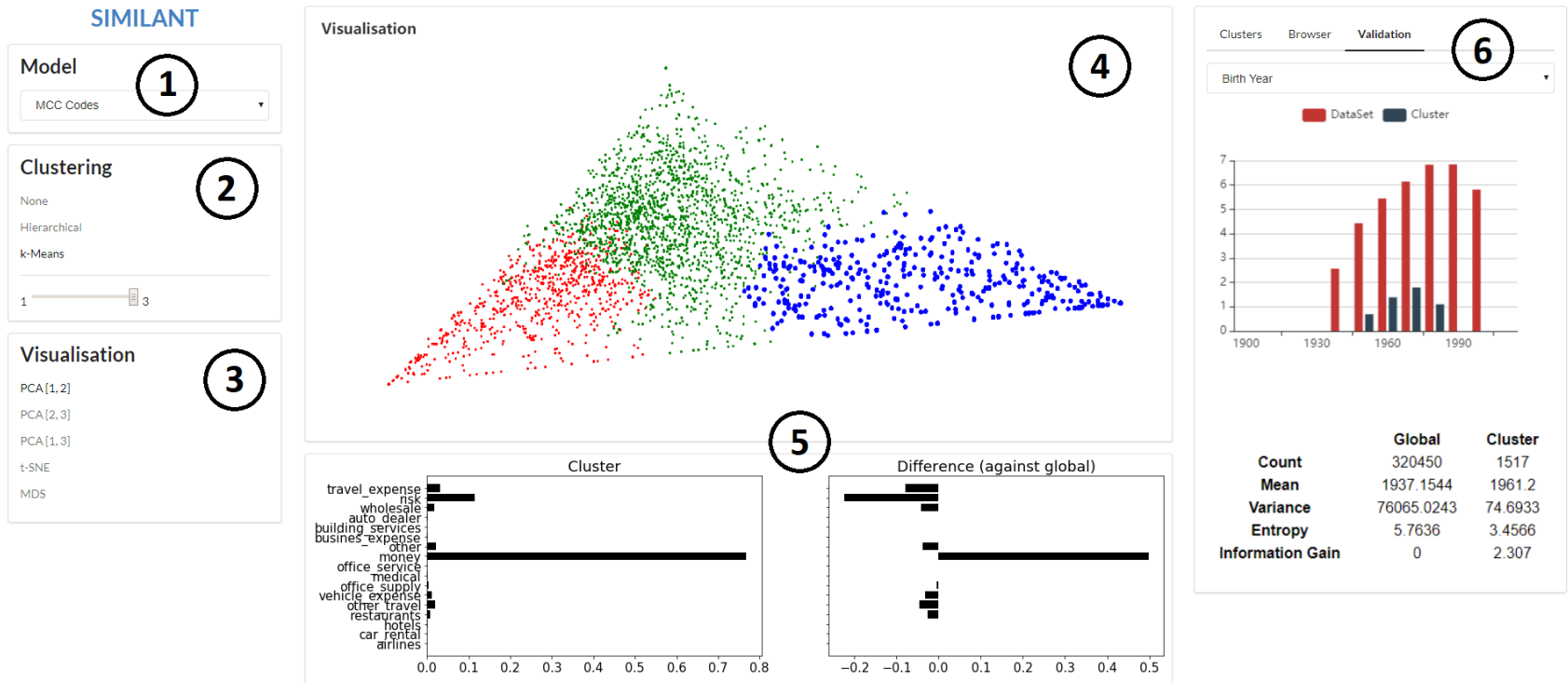
- *Which descriptors are meaningful? What pre/post-processing? What similarity metric?*

- Clustering & visual evaluation, inferred node's attributes

- Possible automated validation w.r.t. available targets & e.g. Information gain



SIMILANT



- 1-3) Select descriptor&similarity metric, clustering, visualization
- 4-5) Visualize clusters and features of the descriptor
- 6) Browse selected cluster, its instances & validate over known targets

SIMILANT

SIMILANT

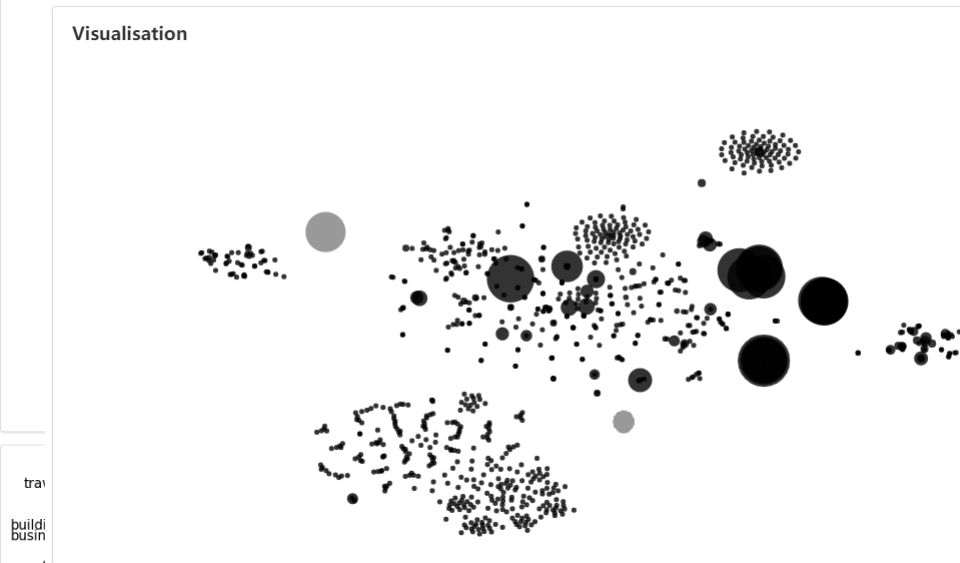
Model 1
MCC Codes

Clustering 2
None
Hierarchical
k-Means
1 ——— 3

Visualisation 3
PCA[1,2]
PCA[2,3]
PCA[1,3]
t-SNE
MDS

Validation 6

DataSet Cluster



Global Cluster

| Global | Cluster |
|------------|---------|
| 320450 | 1517 |
| 1937.1544 | 1961.2 |
| 76065.0243 | 74.6933 |
| 5.7636 | 3.4566 |
| 0 | 2.307 |

Katastrální mapa RÚIAN INSPIRE
SHP stav Geometrické plány Parcely DGN DXF
současnost VFK volební okrsky Adresní místa historie CSV Obce
adresy Adresy Budovy číselník CSÚ vazba volby výsledky voleb GIS

výsledky voleb volby okres Karviná
Poslanecká sněmovna

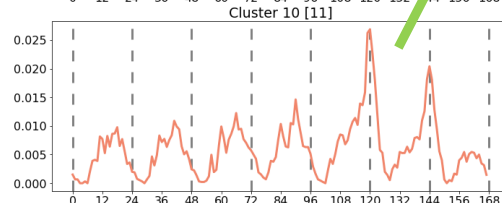
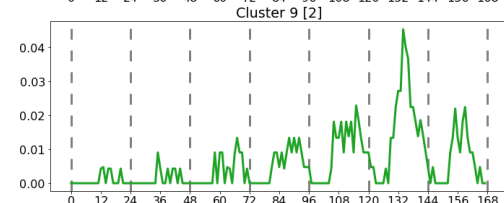
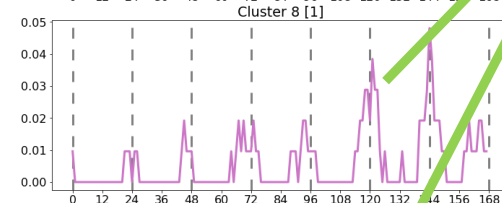
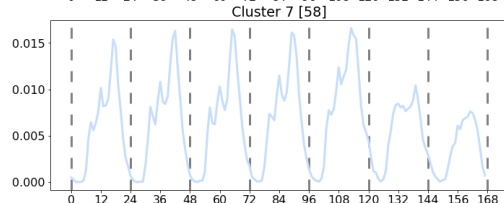
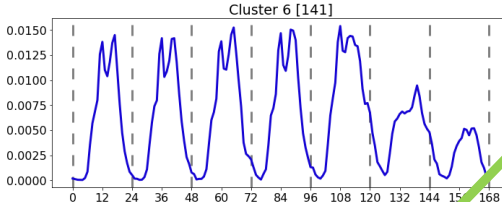
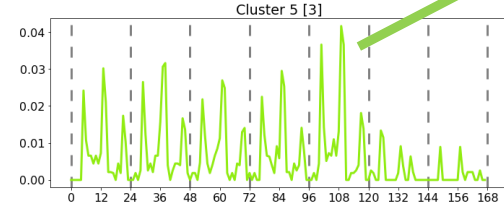
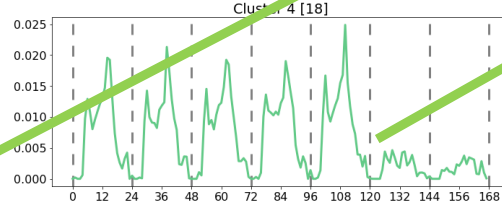
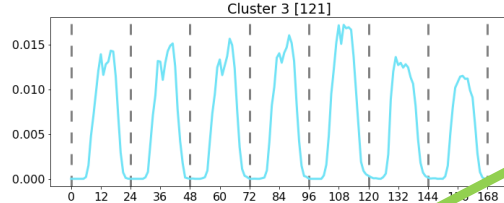
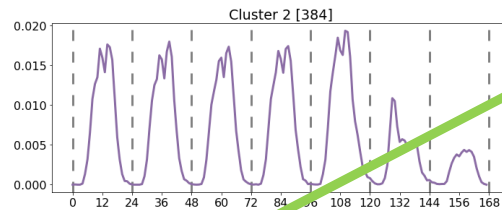
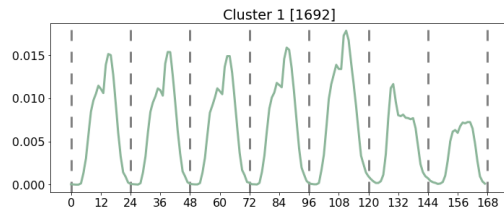
- Several visualization variants
 - Various per-cluster features can be mapped to cluster size and color
- Several options to display & compare cluster descriptors

Do we have relevant knowledge?

- Heavy anonymization caused several problems
 - Lack of proper targets (what to validate against?)
 - Final solution may differ from some current proposals
 - household detection might be just a hidden attribute
 - Dataset is quite noisy (e.g., outdated addresses)
- Nonetheless, still capable to disclose interesting features*

Some examples so far

ATM's withdrawn amount weekly per hour



3-shift factory workers

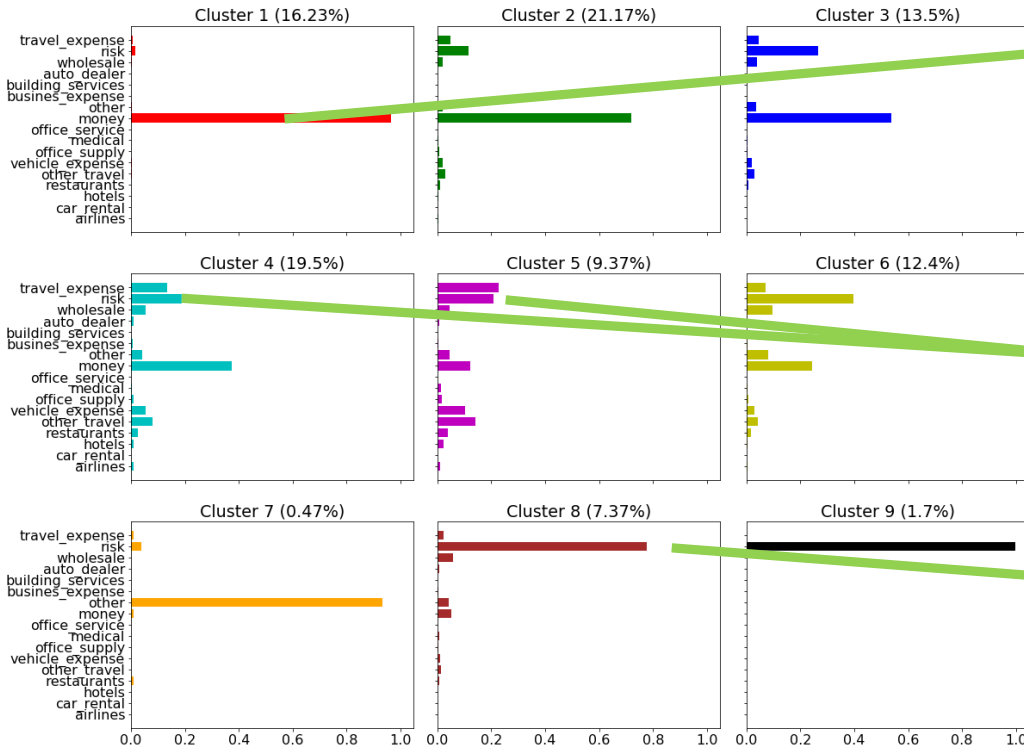
Business centres (drop on weekends)

„booze ATMs“ (close to bars)

Another example: high average night withdrawals for an ATM close to a night club

Some examples so far

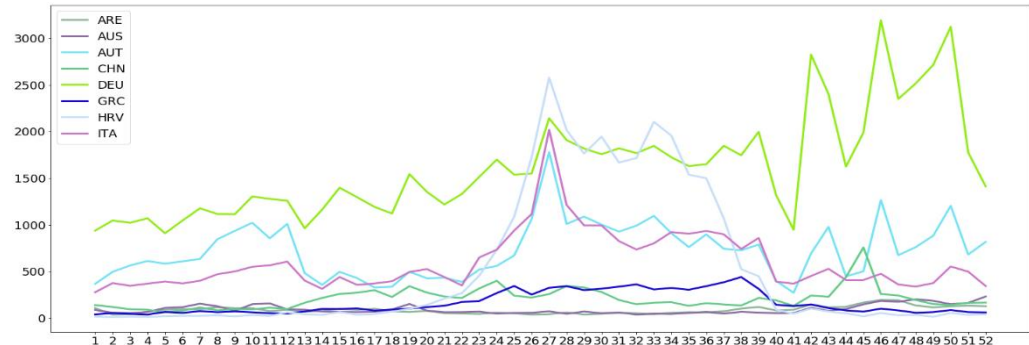
Card payment MCC codes



Mostly ATM withdrawals – do not like card payments / elderly persons?

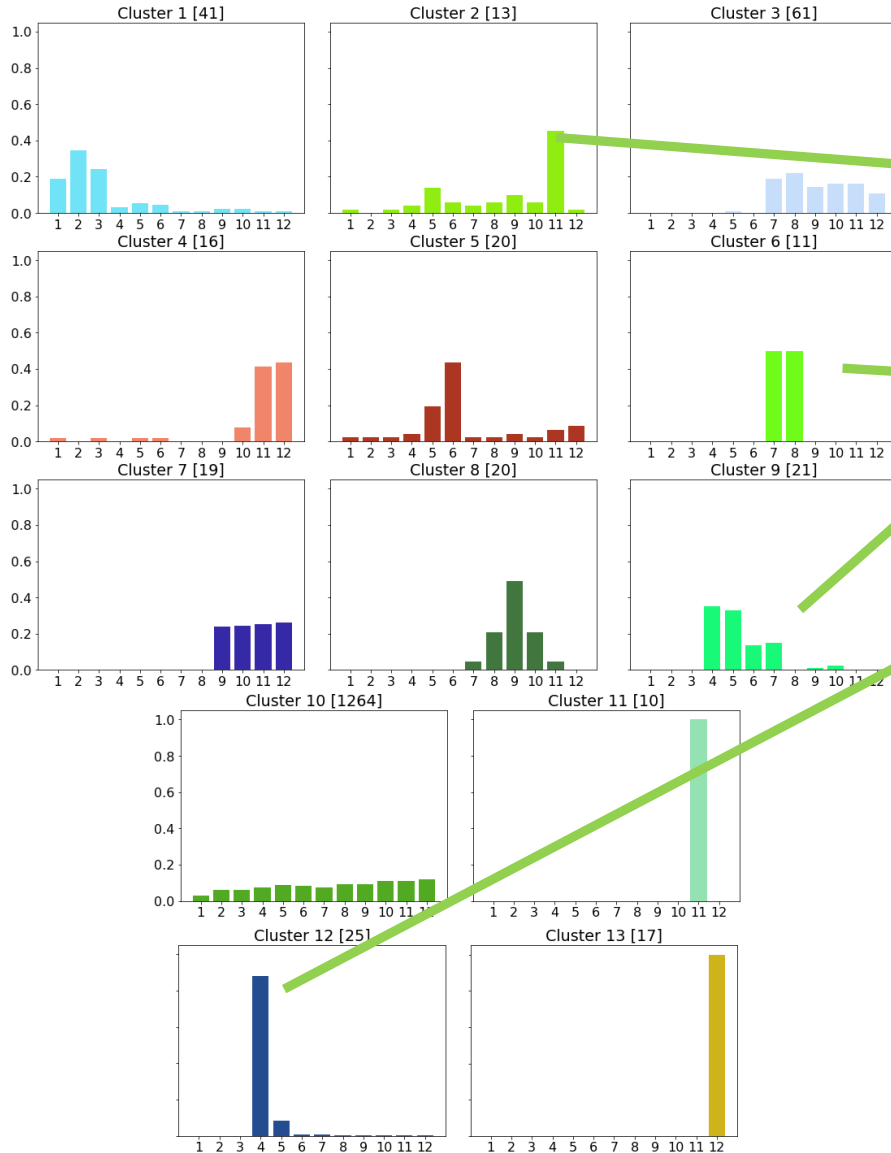
Frequent travellers

Paying by card for common things



Weekly payments in foreign countries (holiday peaks): distinguish between travels for work and leisure

Some examples so far



Counterparties: per month outcomes

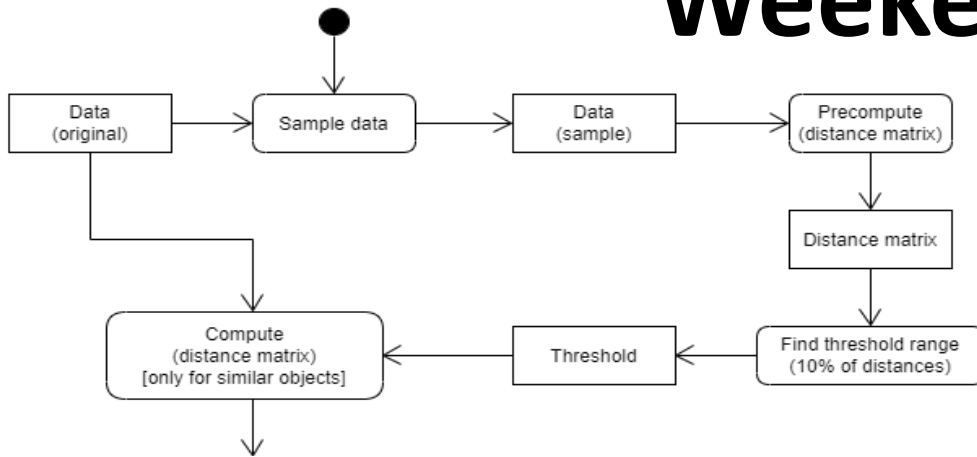
Christmas loans?

Seasonal labor?

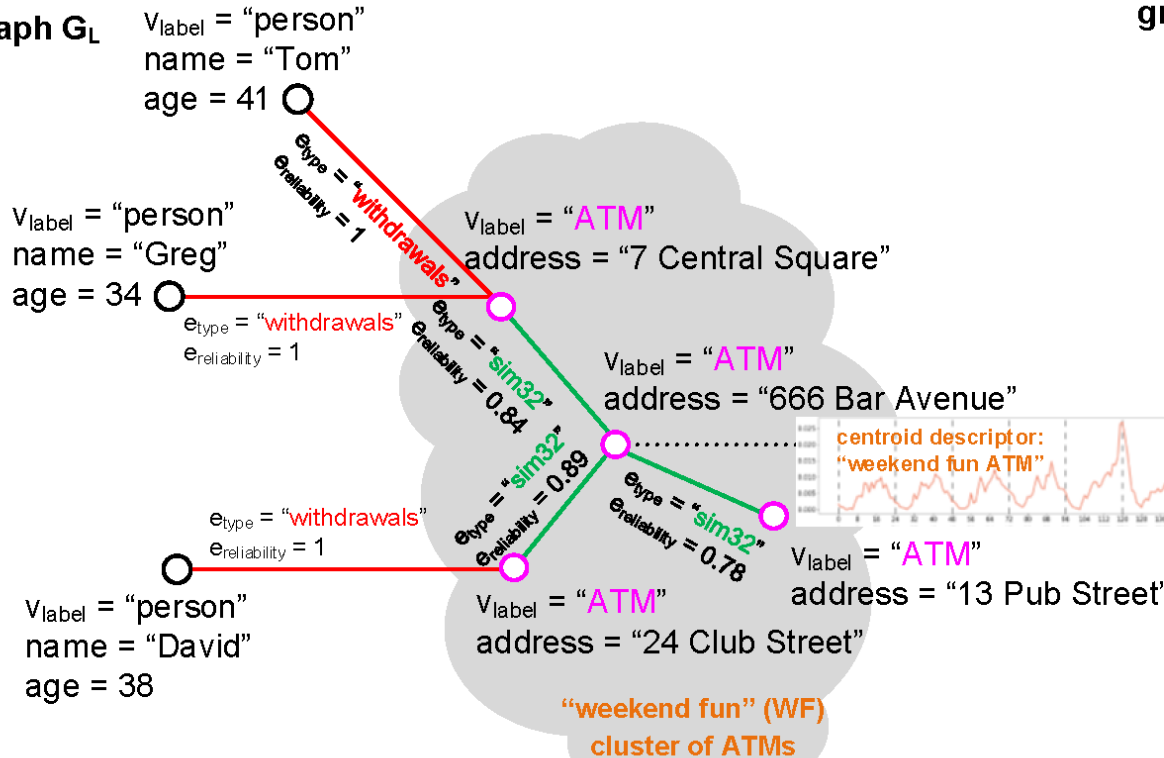
Financial office (tax refunds)

No need to explain everything, just to believe that similarity is meaningful

Weekend fun example

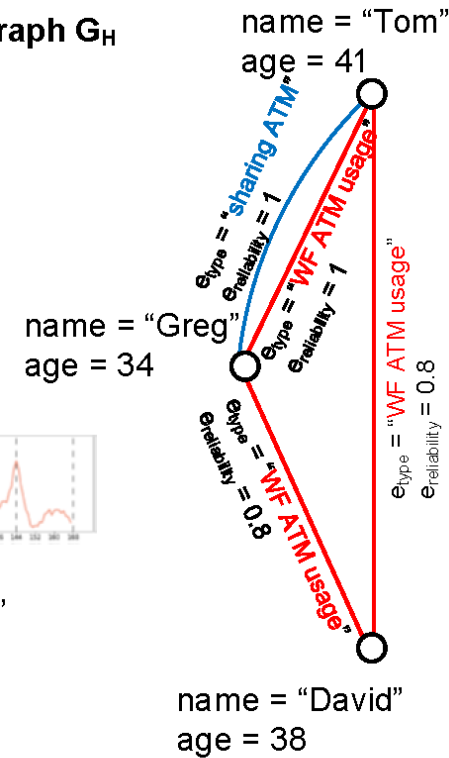


graph G_L



„sim32“ = DTW on hourly withdrawals

graph G_H



Current state & Future work

- Preliminary network construction process ready
- SIMILANT tool for evaluating individual similarity descriptors
- **Some early results seems promising**
 - Partially explored: client features, counterparties, countries, ATM withdrawals
 - TODO: merchant descriptions, payment patterns, locations etc.
- **Challenges**
 - A bit too broad domain (too many possible hypotheses, pre-processing, descriptors, similarity metrics, clustering & parameters)
 - Dynamic domain, detection of changes (life milestones, business closures), time-aware edges
 - **Ethical challenges** - reliability of latent edges, validity for important decisions
- **Future plans**
 - Compare with std. social network properties (communities, hubs?)
 - Time-aware models
 - Network visualization & exploration
 - **Explanations & action recommendations**
 - Expansion beyond banking domain (insurance, teleco etc.)

Thank you!
Questions?