Federated Learning

A collaboration on anti-money laundering

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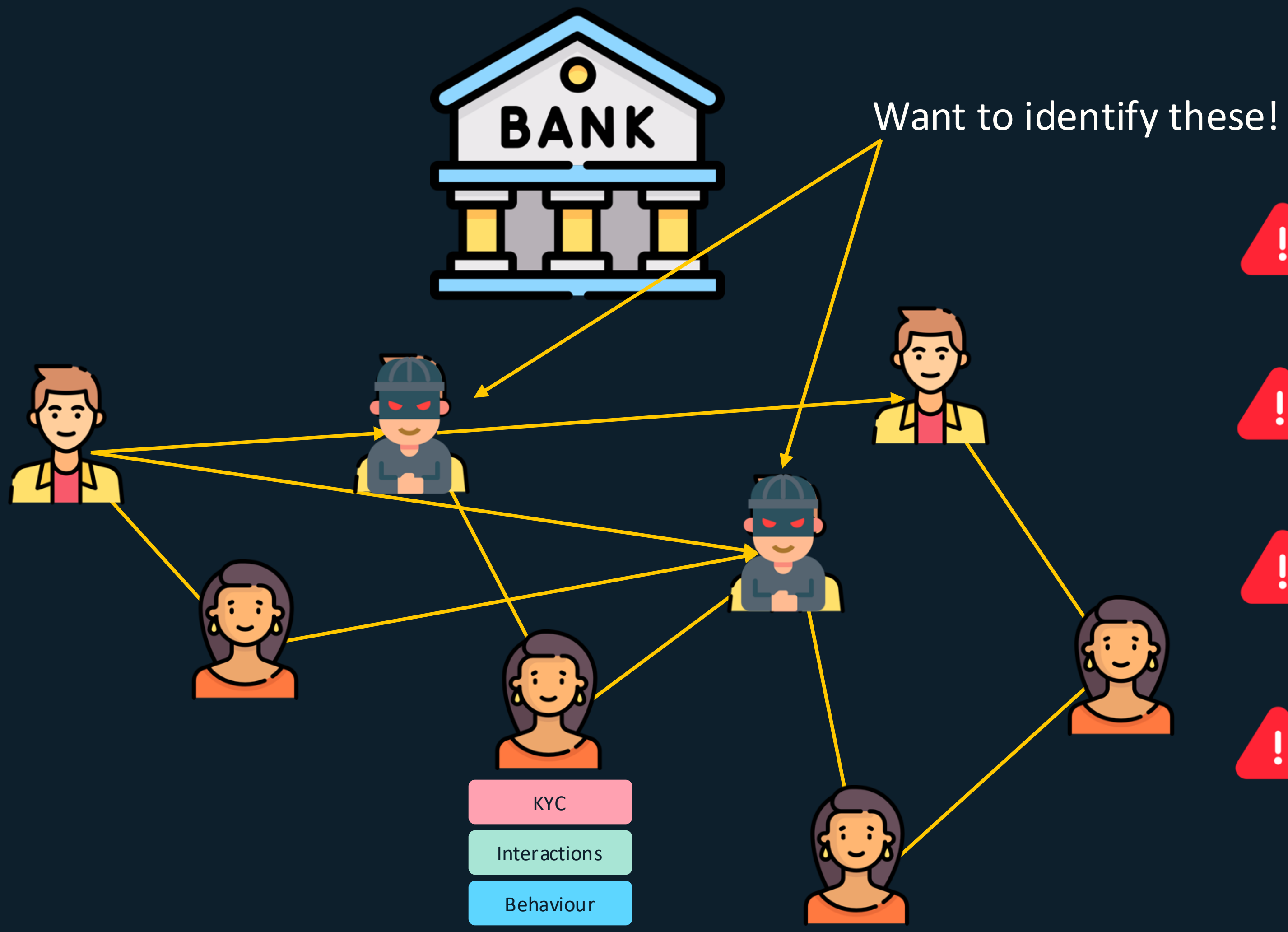
Agenda

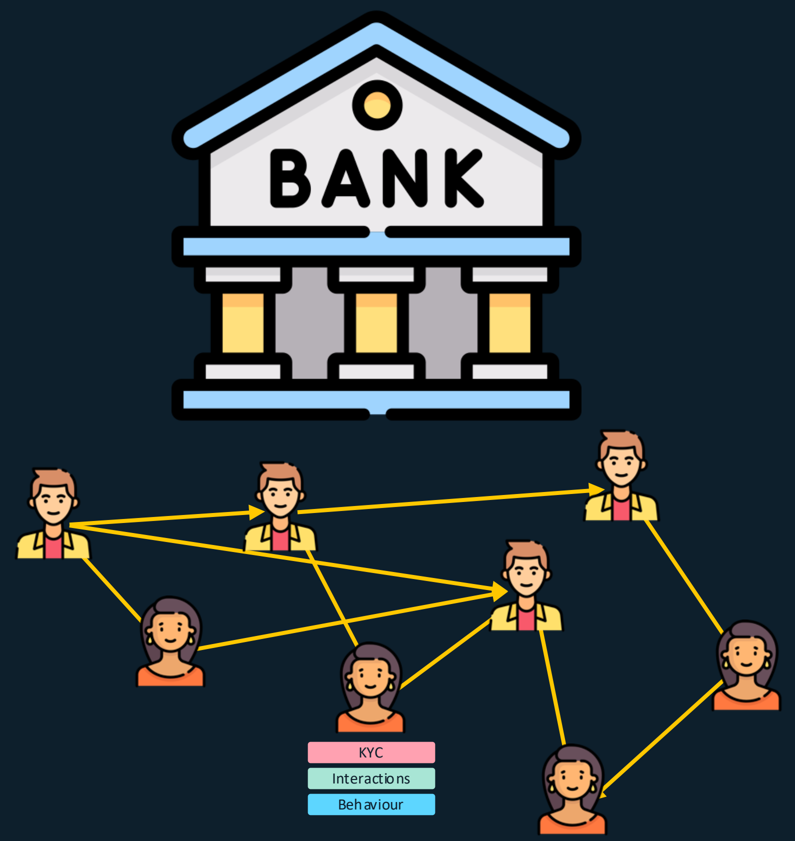
- The anti-money laundering (AML) problem
- Our holistic pipeline to attacking the AML problem
- Synthetic data
- Federated Learning
  - Requirements
  - Challenges
  - Opportunities
- Preliminary results

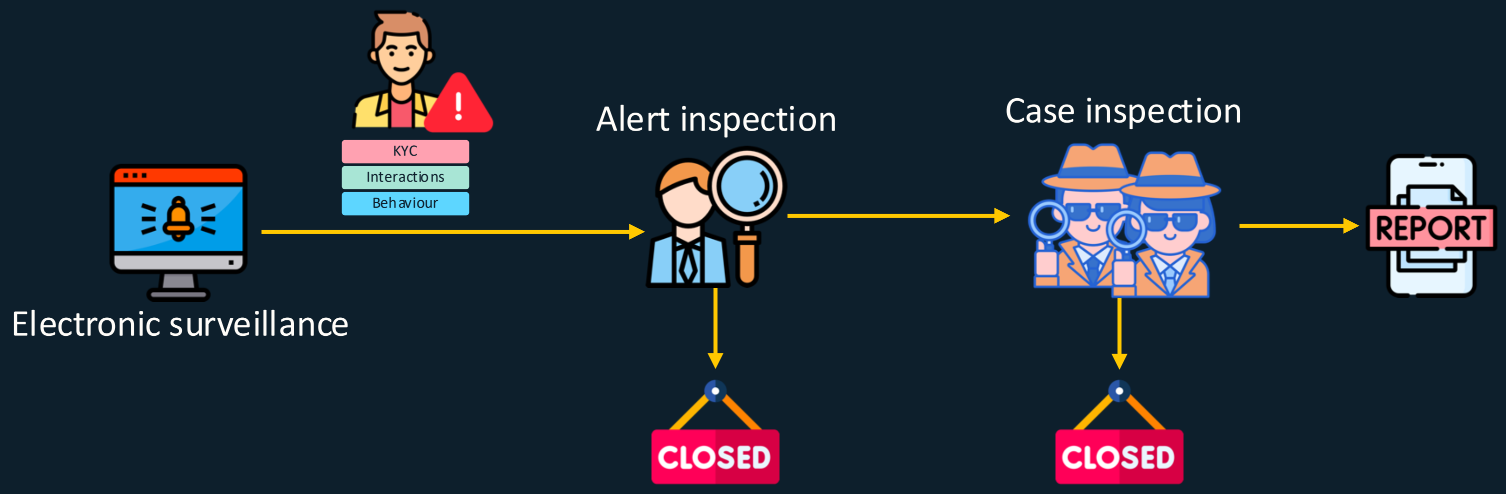
The Money Laundering Problem



- UN estimates €1.87 trillion laundered annually
- Significant resources are spent on AML
- High false-positive rate, estimated at ~98%
- In 2019, 58 cases of AML penalties total fines: $8.14 billion.

A typical AML pipeline[17]

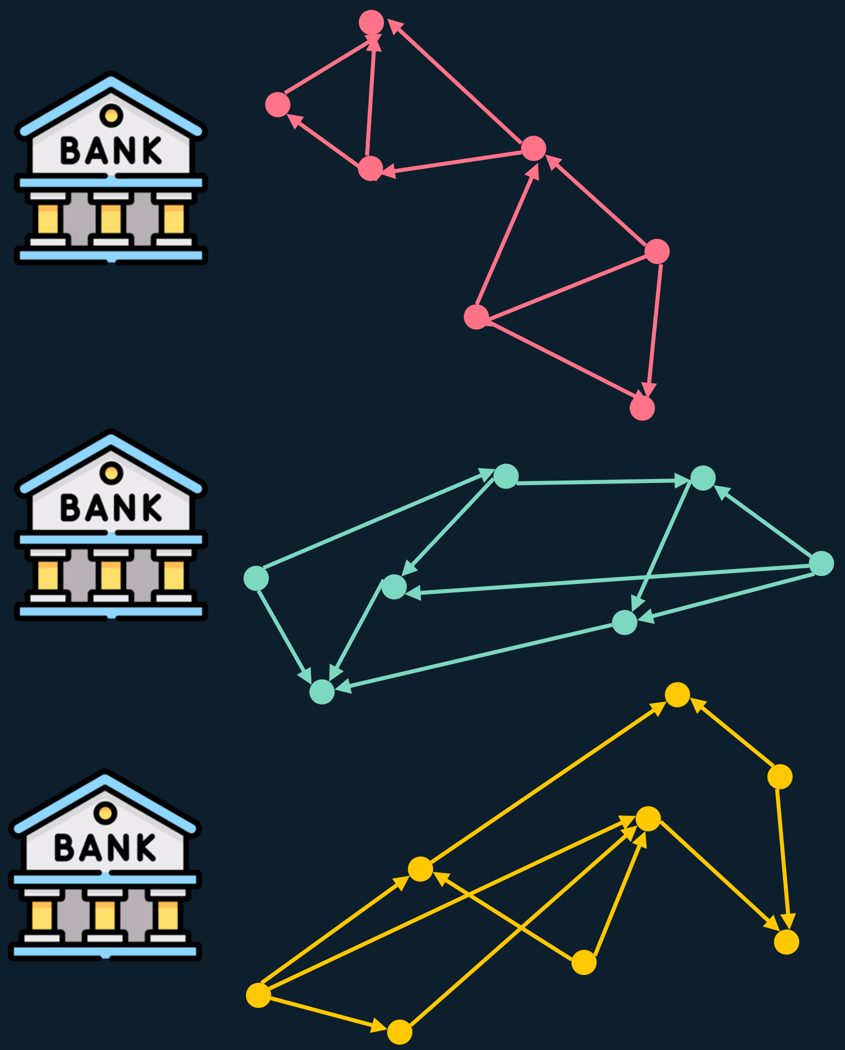


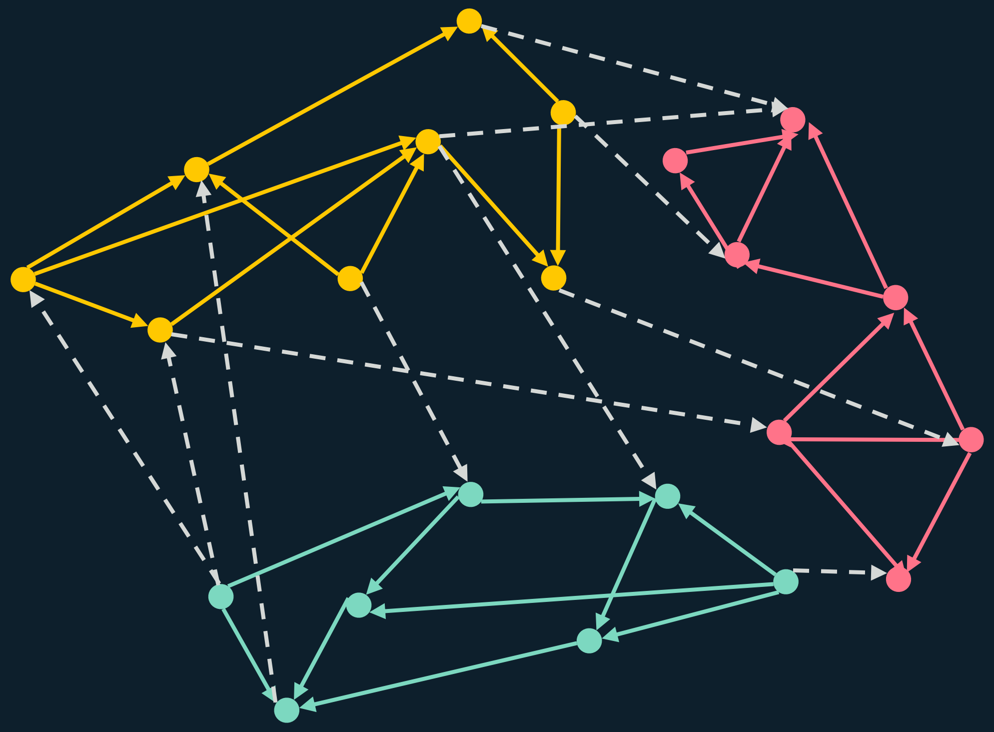


Large amount of false positives **ots of unnecessary resources spent**

[17] F. Johannesen and M. Jullum., "Finding Money Launderers Using Heterogeneous Graph Neural Networks", arXiv:2307.13499, 2023

The Global Transactional Network



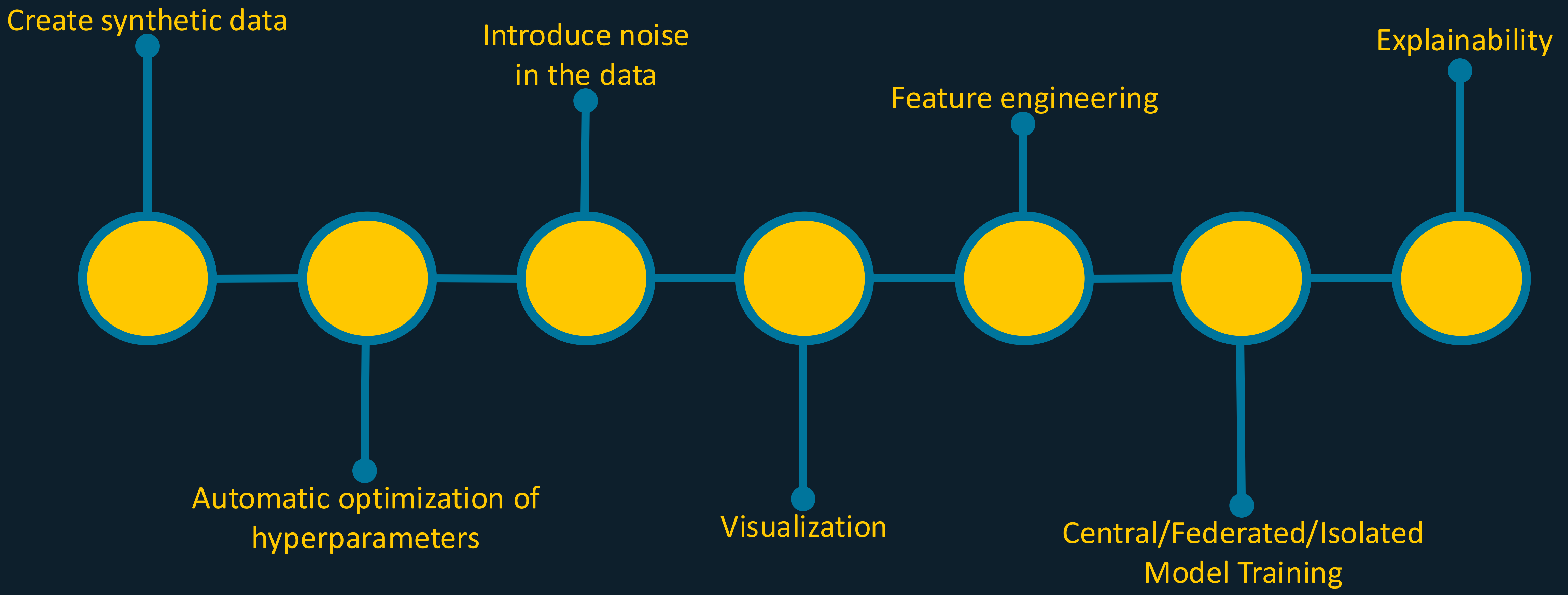


Banks are blind to what happens outside the local transaction network!

We ask ourselves:

- Can federated learning be used to collaborate between banks to detect money laundering?
- How can we collaborate without sharing sensitive data?
- How to federate the learning in practice?
- How to create realistic synthetic transaction data?
- What impact does unreliable data have?
- Does performance improve by exploiting the inherent graph-structure in the data?
- Can we use explainable AI to leverage deep learning?

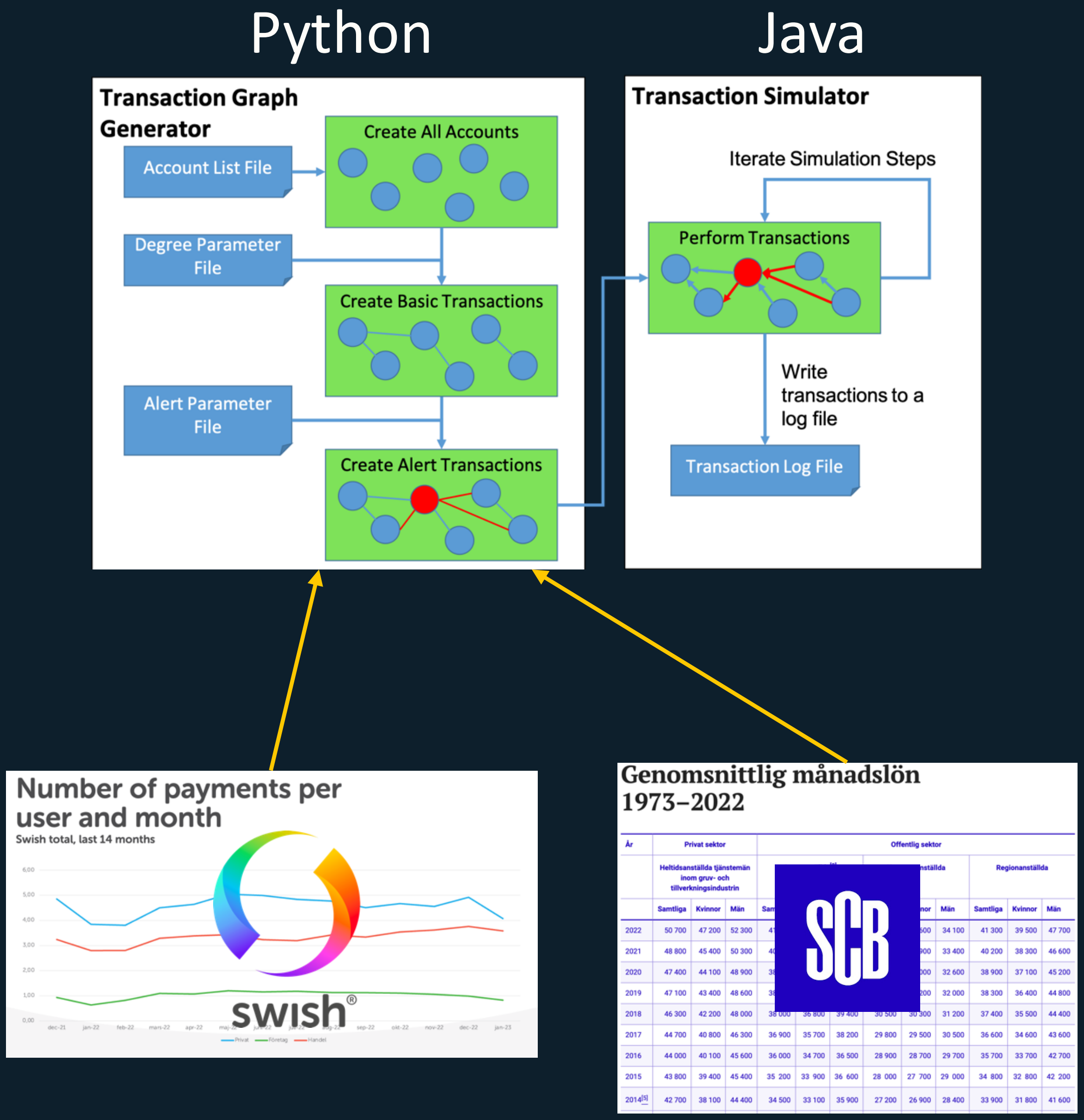
A Holistic Pipeline



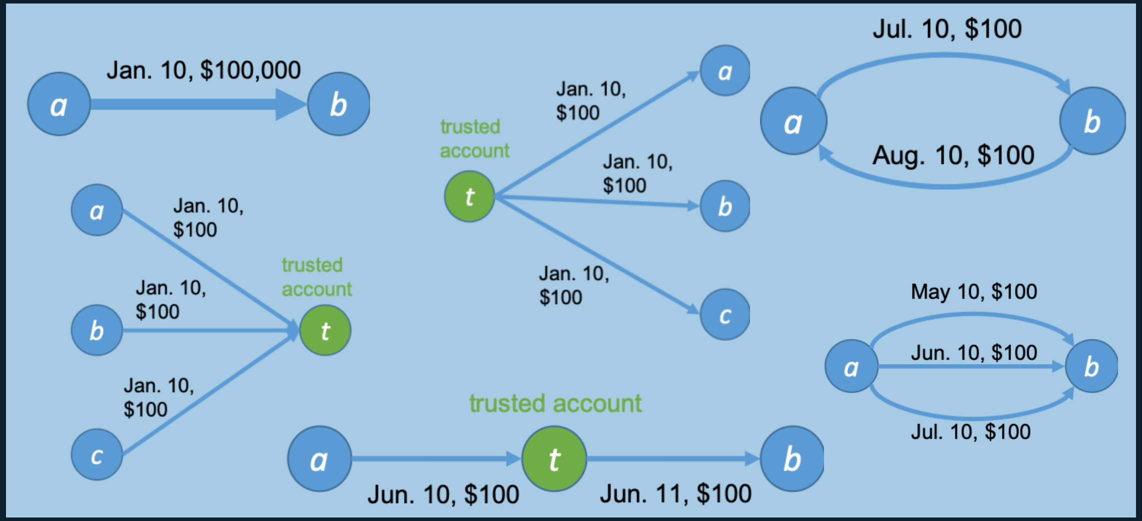
https://github.com/aidotse/flib

Synthetic Data

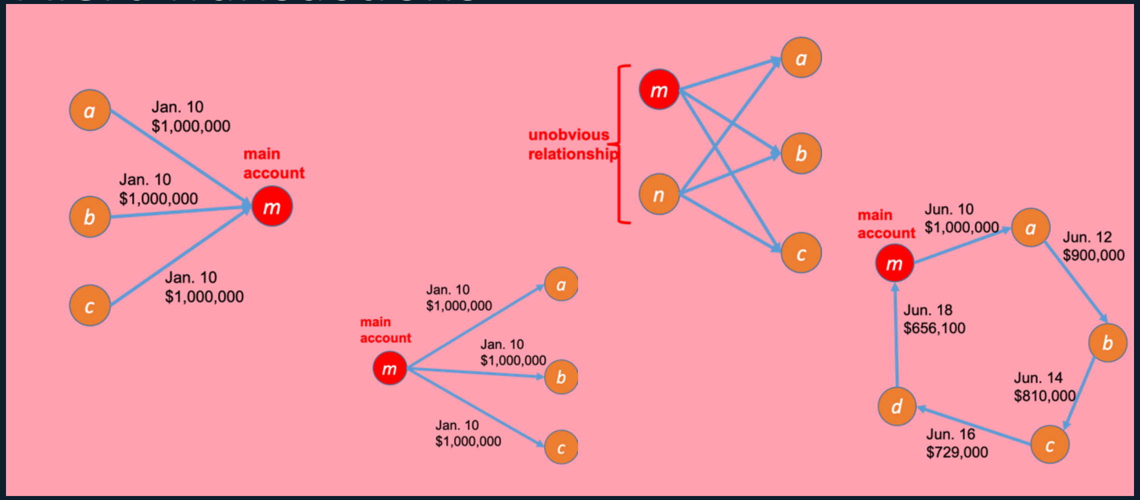
Synthetic Data: Engine[18]



Normal Transactions



Alert Transactions



[18] M. Weber, et al., "Scalable Graph Learning for Anti-Money Laundering: A First Look", arXiv1812:00076, 2018

Synthetic data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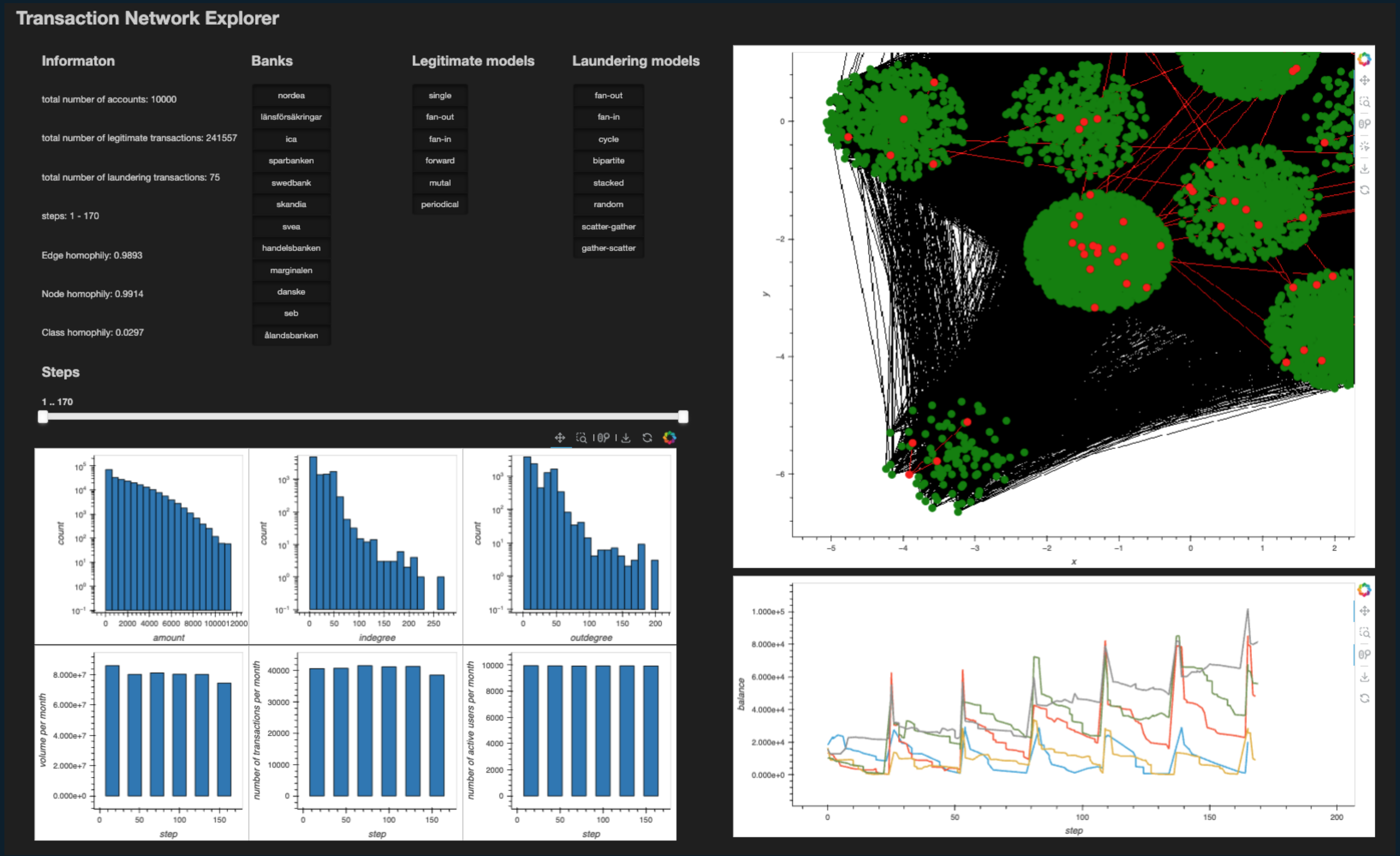
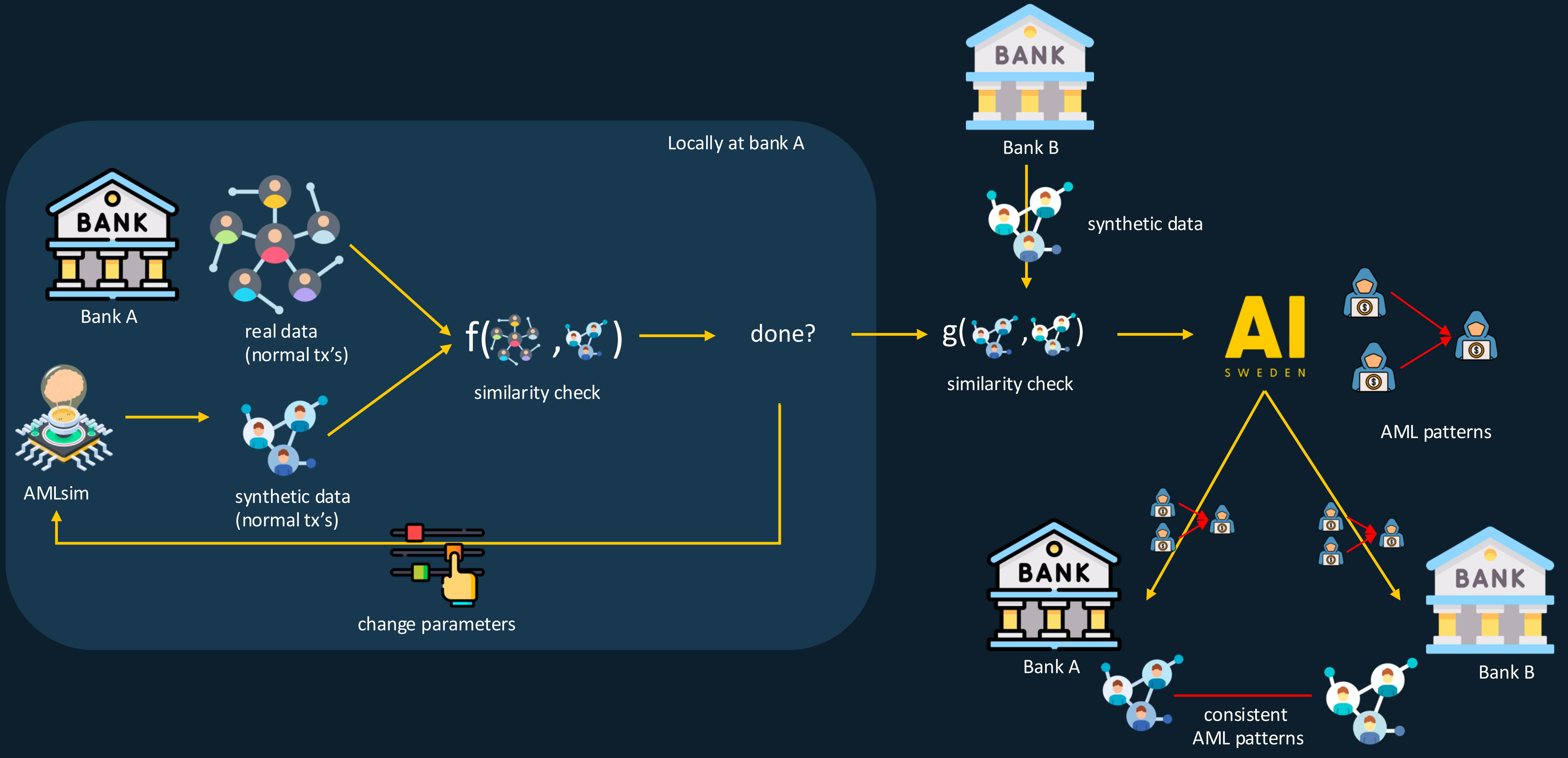


Synthetic Data: Boosting Fidelity



Federated Learning

Federated Learning

Local training

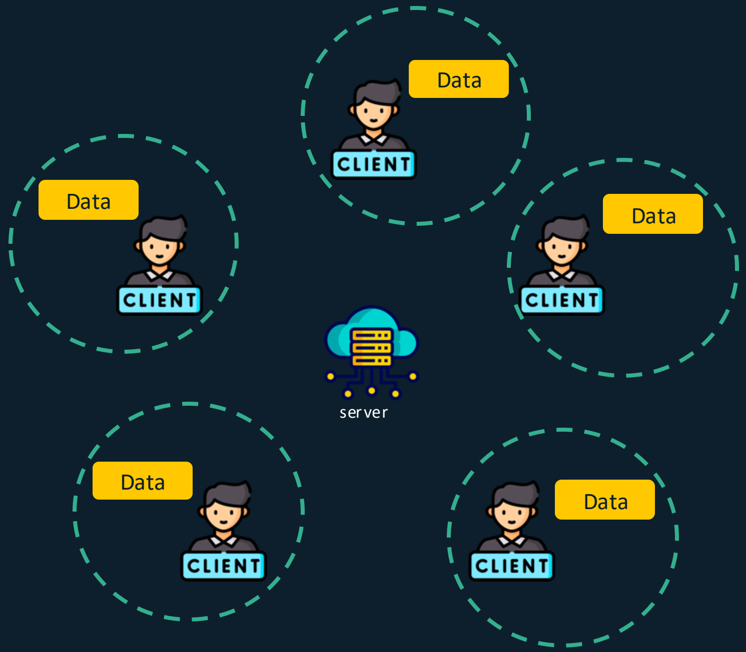
- ✗ dataset may be small
- ✓ dataset remain confidential

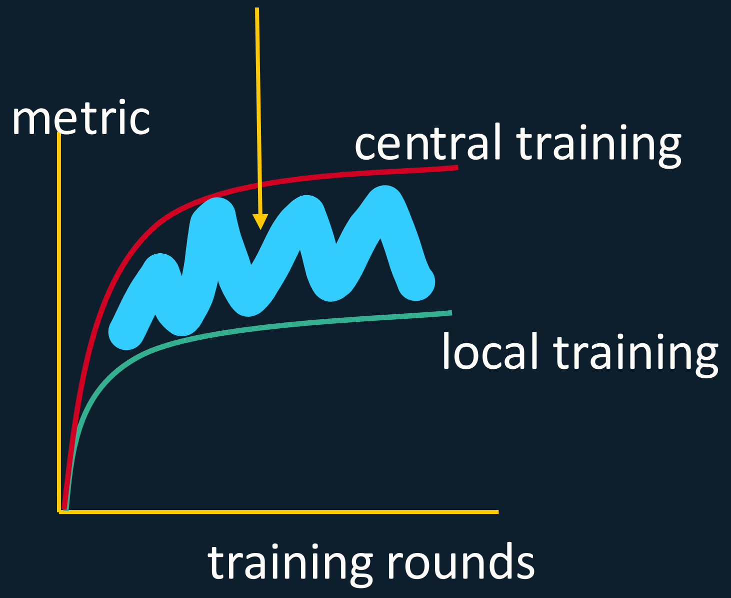
Federated training

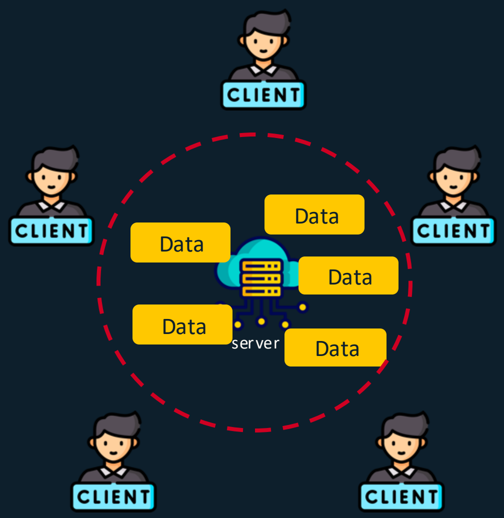
- ✓ Larger pool of data
- ✓ dataset remain confidential

Central training

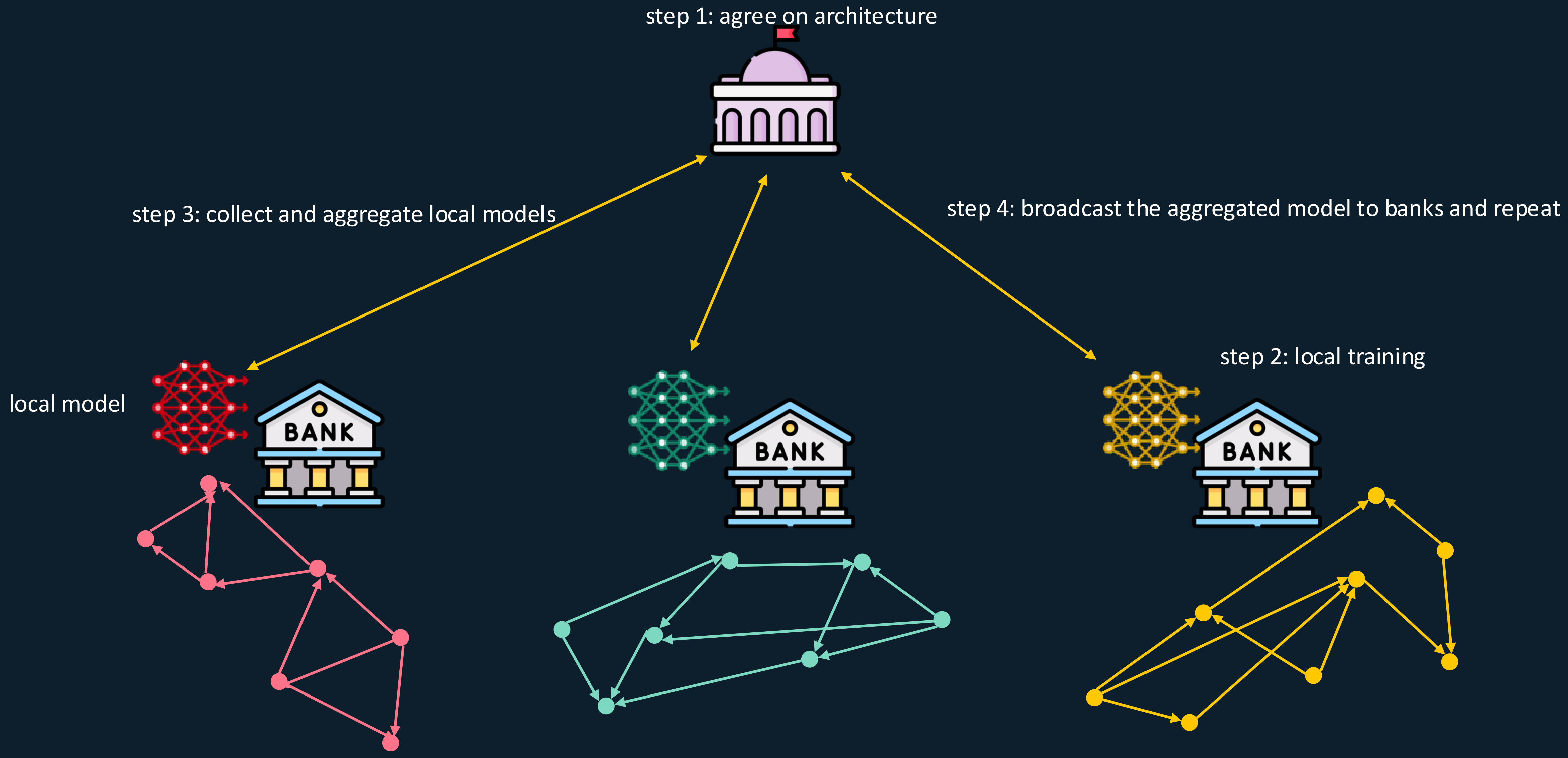
- ✓ Larger pool of data
- ✗ Data privacy violated





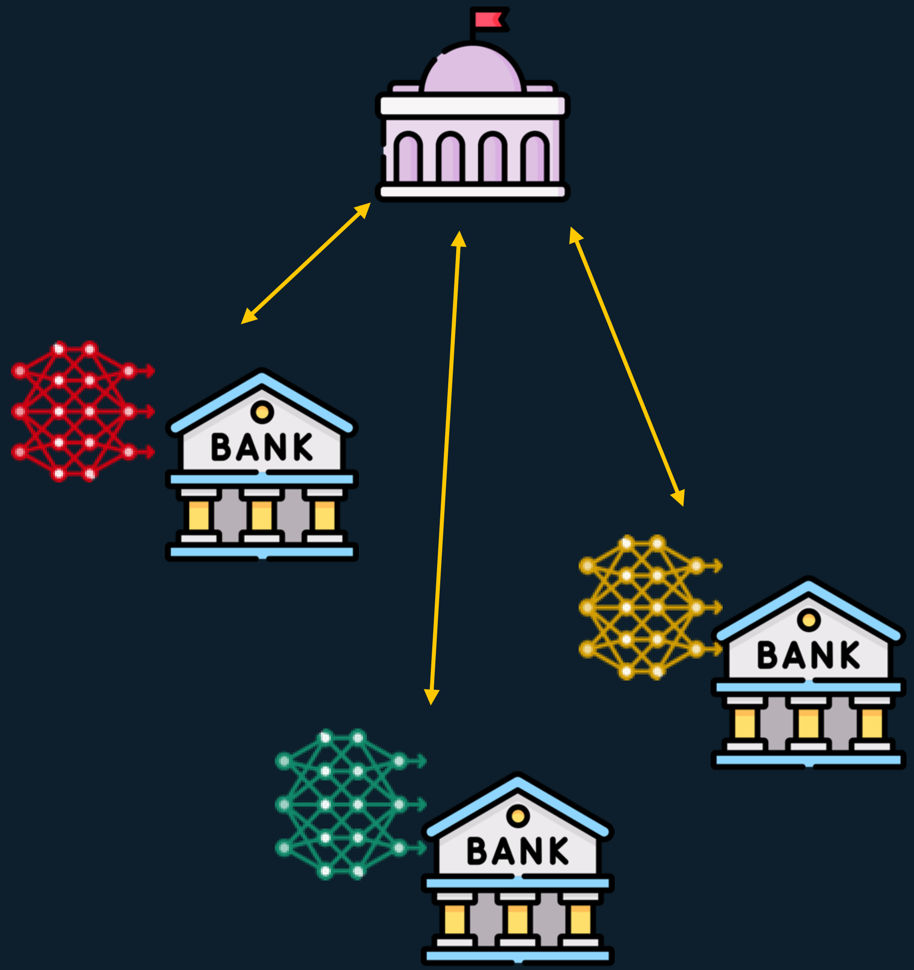


Federated Learning



Federated Learning in practice

Requirements



- Infrastructure
  - Central server
  - Clients with computational power

Flower

- Alignment on data structure
- People
  - Domain knowledge
  - Machine learning

Challenges

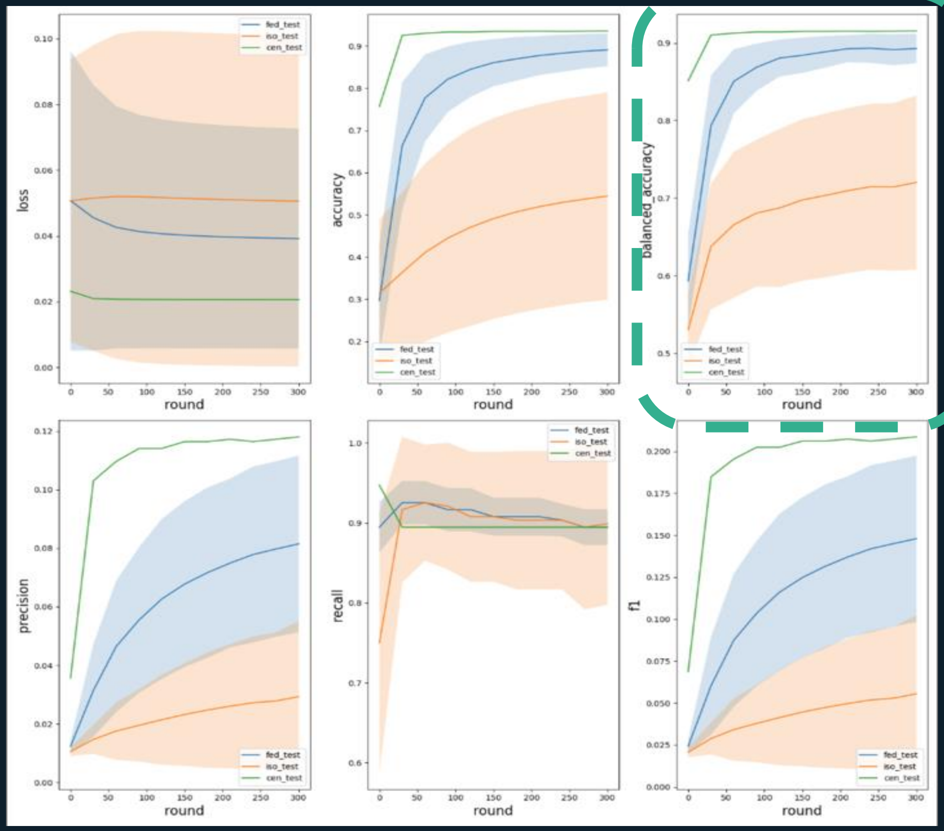
- Heterogenous data distributions
- Privacy concerns

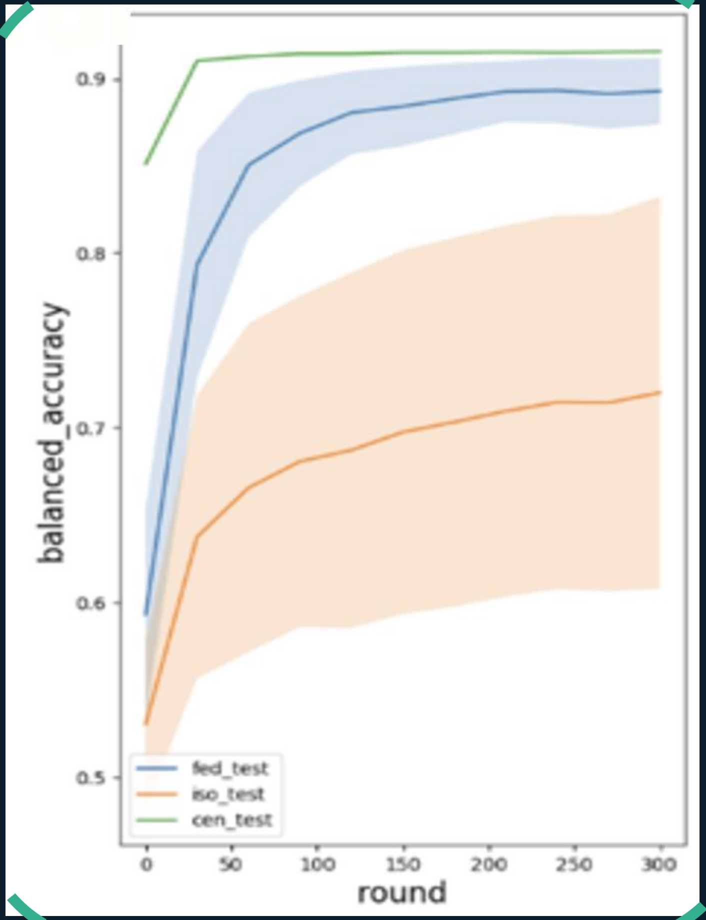
Opportunities

- Exposing the model to more data
  - Better performance
  - Better generalization

Results

Preliminary experiments





Centralized

Federated

Isolation

Thank you!

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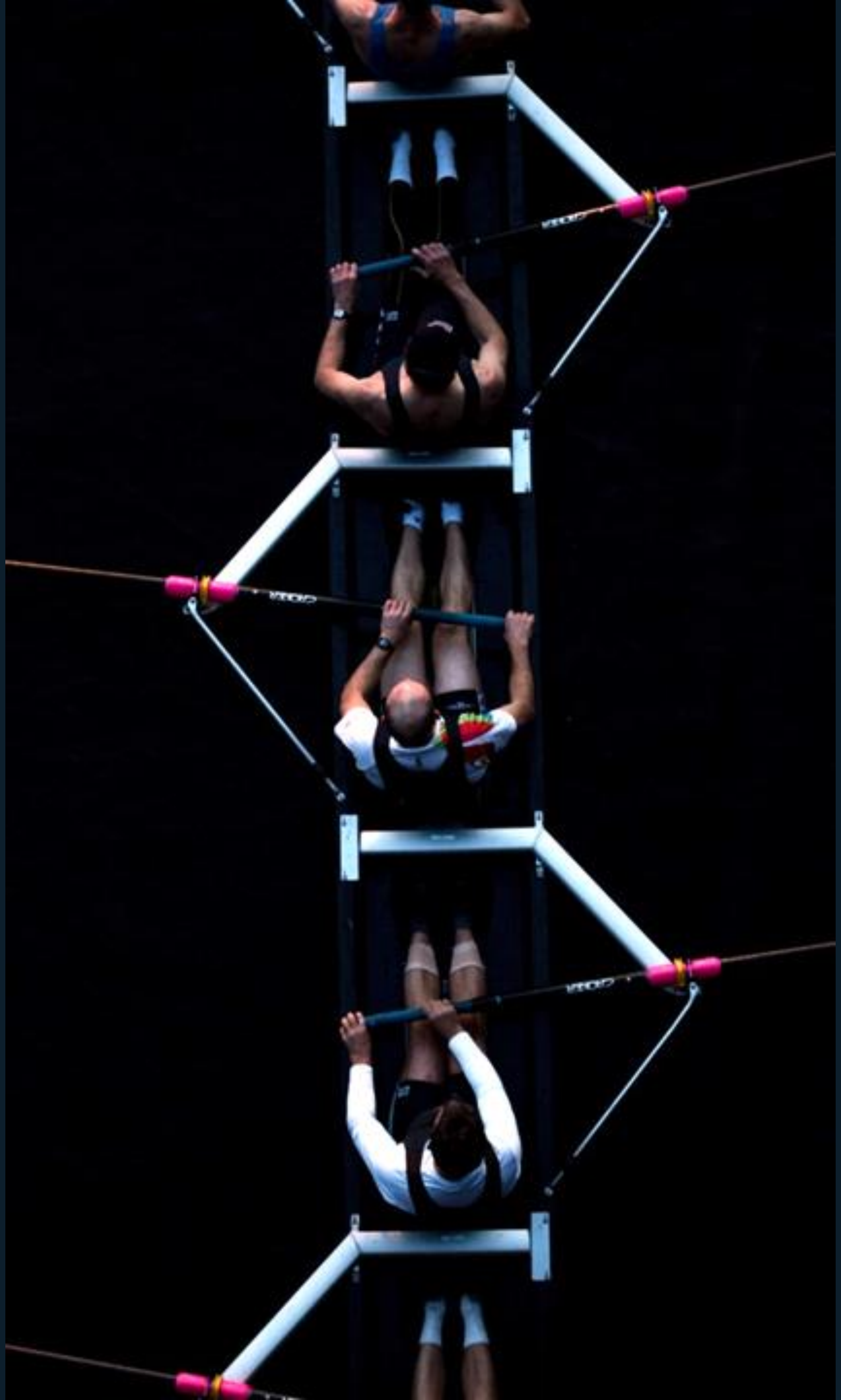

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