Graph Network Application in Financial Risk Management

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FinTell AI Lab

Major achievements during American Express:

1. Served as the head of risk control model verification department of American Express, supervising 1000 models in 24 markets around the world;
2. The models cover the payment, credit, marketing and other scenarios, covering marketing, anti-fraud, credit, quota, consumption, collection and other links;
3. Led a team to participate in the company modeling competition 3 times, and won the top 3 of 100+ teams (the marketing model top 1, the anti-fraud model & the line model top 2)

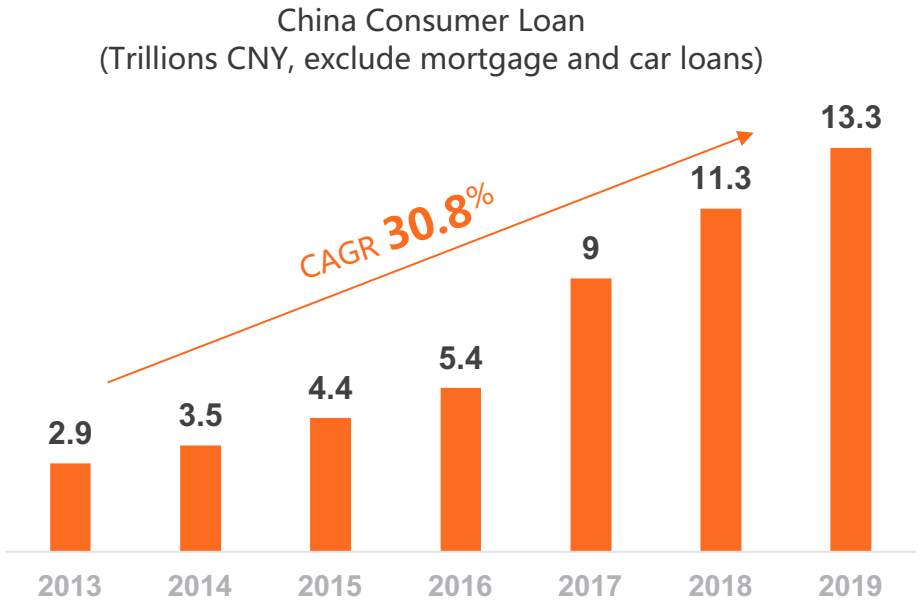
Major achievement during Baidu Finance:

1. Served as the head of the anti-fraud model of Baidu Finance
2. Delivered 30+ models, 90% reduction in risk loss, 60% reduction in business interruption
3. Having an in-depth systematic understanding of financial risk models, including scorecard model, LR, XGB, KNN, DNN, and graph neural network models based on graph data, such as GAT, GCN, etc.

Part 1:

Background

High Demand for Financial Technology in China



Drivers of FinTech Demand

- Upgrade to Consumption Driven Economy
- Lack of Credit Bureau Data
- Consumer Lack of Experience with Credit
- Organized Fraud Attacks
- Financial Institutions Weak in Online Business and Risk Management
- Lack of Modern Risk Managers

FinTech Development in China

- Online customer acquisitions cost increases requires better targeting
- New regulations on rate and collections require better risk managements to lower credit losses

Continuous Evolution of Graph Algorithms based on Graph Databases

2020 Key Words in KDD 2020

—Data Mining and Knowledge Discovery (KDD)

Part 2:

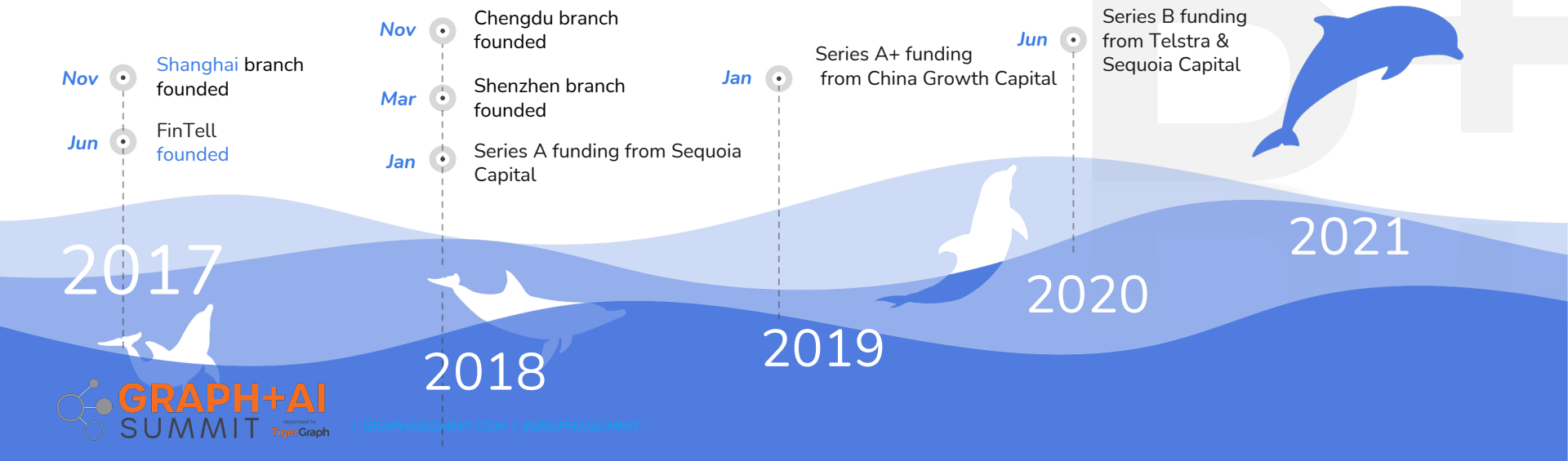
About FinTell

About FinTell

Become a high-end brand in the Fintech Industry-Powered by FinTell

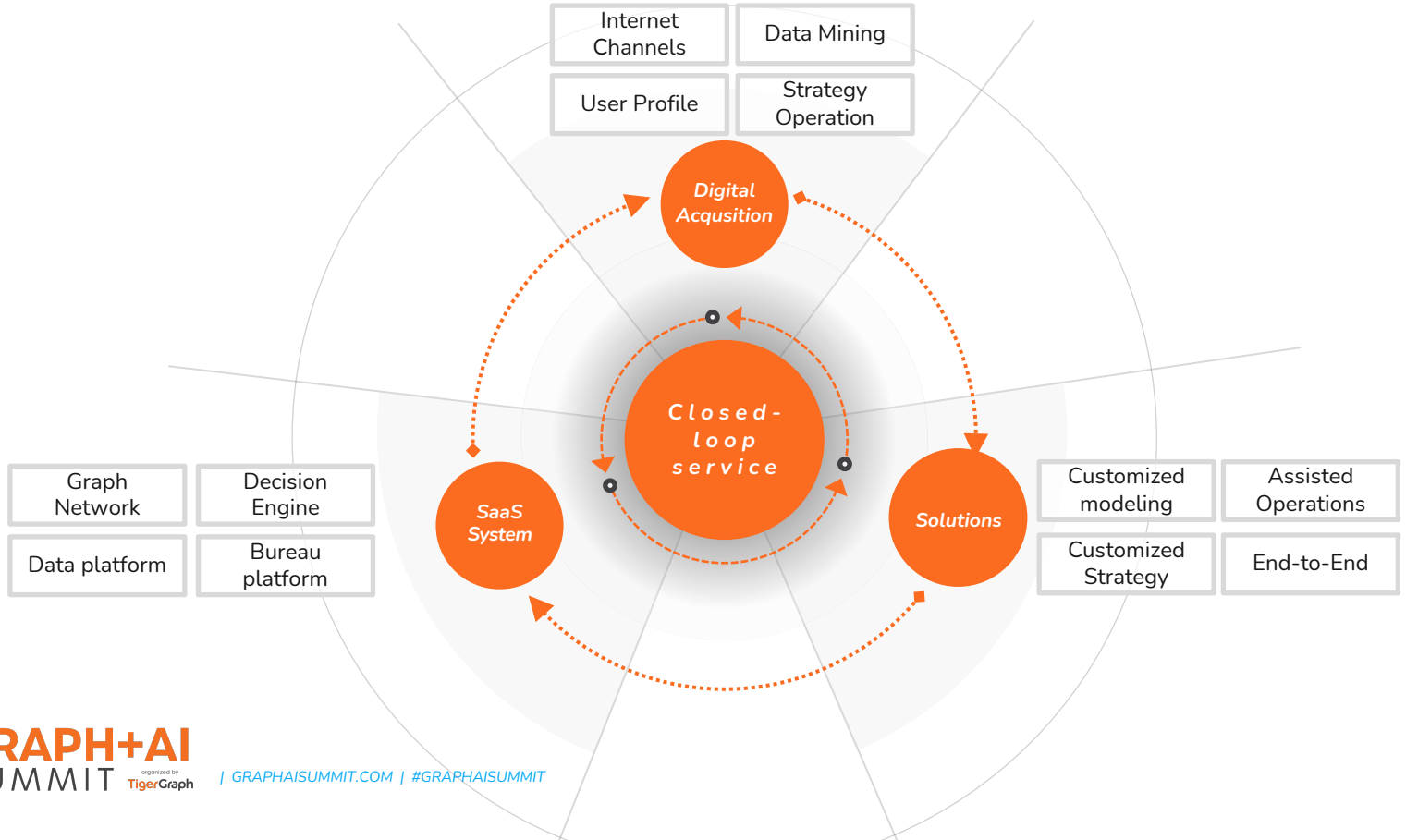
FinTell is a one-stop high-end fintech service company that provides intelligent ***risk management decisions*** and systematic solutions for banks and other licensed financial institutions by applying new technologies such as artificial intelligence and combining professional risk management experience.

Based on products and services, holding the concept of win-win sharing, FinTell help banks and other licensed financial institutions to realize inclusive finance and broaden service boundary, so as to realize the corporate vision of ***"empower finance with intelligence"***



The Product & Solution of FinTell

Closed-loop services including risk management, customer acquisition, operation, and systems



What Data do We Use

- Smart phone coverage ***90%+***
- Device usage, location, interaction, APP behavior

- E-commerce usage info, E-commerce active level, Account No., Consumption behavior

- Telecom consumption, Channel preference, Subsidy info, Social network, Internet preference

- Daily location needs, with high accuracy

- Online payment transactions

- ***100 million+*** ***business and financial data,***
- accurate business linking info

FinTell DATA INTEGRATION CAPABILITY

Who are FinTell's Clients: Over 100 Financial Institutions

Bank

招商銀行 CHINA MERCHANTS BANK
南京銀行 BANK OF NANJING
苏宁银行 SUNING BANK
广东华兴银行 GUANGDONG HUAXING BANK
中原银行 ZHONGYUAN BANK
北京中关村银行 ZHONGGUANCUN BANK
蓝海银行 BLUE OCEAN BANK
百信银行 aiBank
Chongqing Fumin Bank 重庆富民银行
江西裕民银行 JIANGXI YUMIN BANK CO.,LTD.

CONSUMER FINANCE

捷信 HOME CREDIT
锦程消费金融 JINCHENG CONSUMER FINANCE
幸福消费金融 HAPPY CONSUMER FINANCE
小米消费金融 XIAOMI CONSUMER FINANCE
中邮消费金融 PSBC CONSUMER FINANCE
杭银消费金融 www.51xf.cn
盛银消费金融 SHENGJING BANK CONSUMER FINANCE
中原消费金融 ZHONGYUAN CONSUMER FINANCE
哈银消费金融公司 Harbin Bank Consumer Finance Co., Ltd.
SUNING 苏宁消费金融
金美信消费金融 JMX Consumer Finance
长银消费金融 CHANGYIN CONSUMER FINANCE
中信消费金融有限公司 CITIC Consumer Finance Co.,Ltd.

INTERNET PLATFORM

ByteDance
ANT FINANCIAL
JD.COM
度小满金融 Du Xiaoman Financial
小米金融
WeBank
Ctrip 携程
360金融
滴滴
LEXIN 乐信

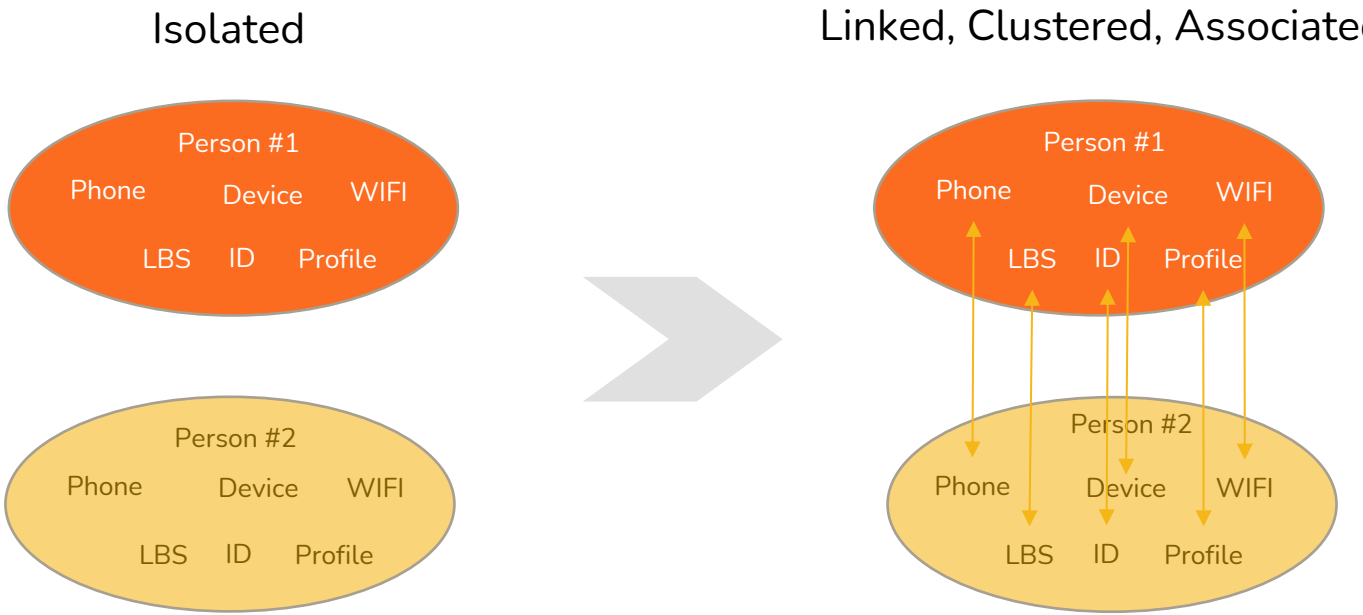
TRUSTS & INSURANCE

西藏信托有限公司 TTCO TRUST CORPORATION LIMITED
云南信托 YNTRUST
天津信托 TIANJIN TRUST
FOTIC 中国外贸信托
阳光保险集团 Sunshine Insurance Group
中国太平 CHINA TAIPING | 太平金服

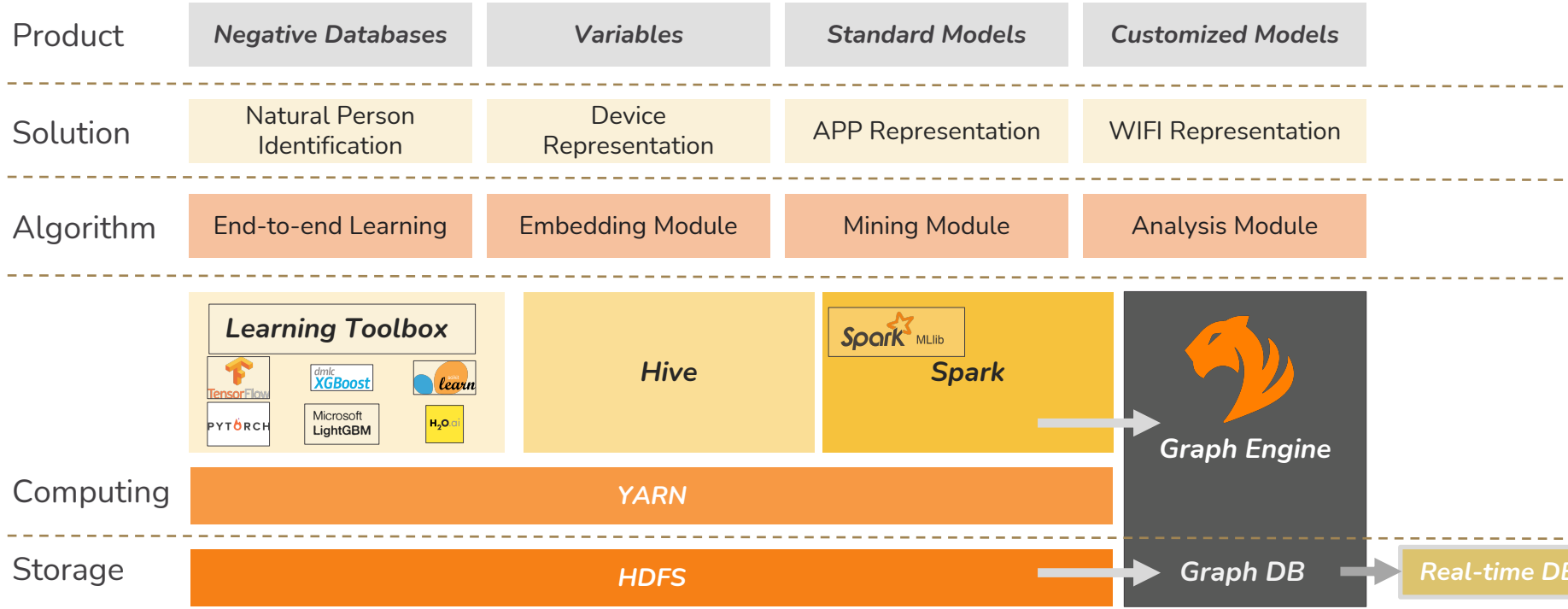
Part 3:

Graph Network Application in Financial Risk Management

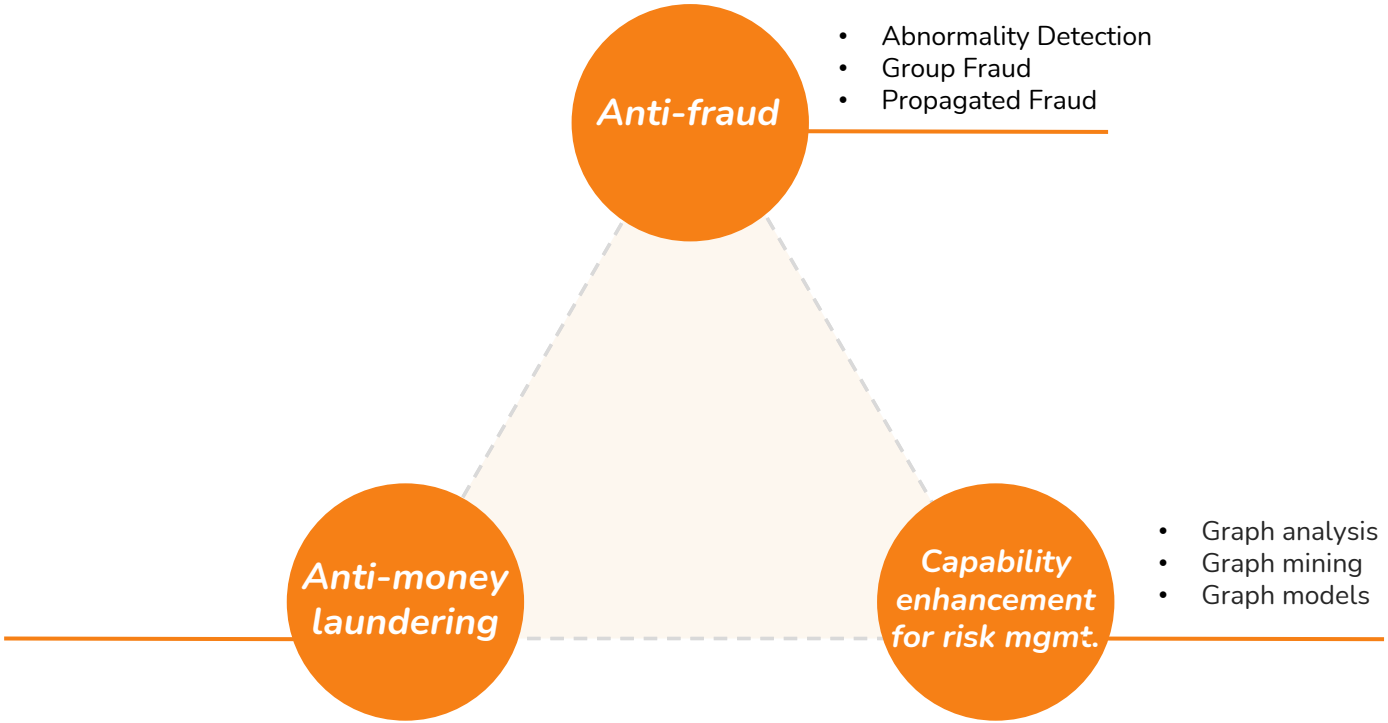
Fundamental Value of Graph Network



Architecture of Graph Network at FinTell



Wide Use of Graph Network in Fintech



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Part 3:

Use Case of Graph Network in Financial Risk Mgmt.

- CASE 1: Anti-fraud - Group Fraud
- CASE 2: Anti-fraud - Propagated Fraud
- CASE 3: App Classification
- CASE 4: ID Mapping – Natural Person ID

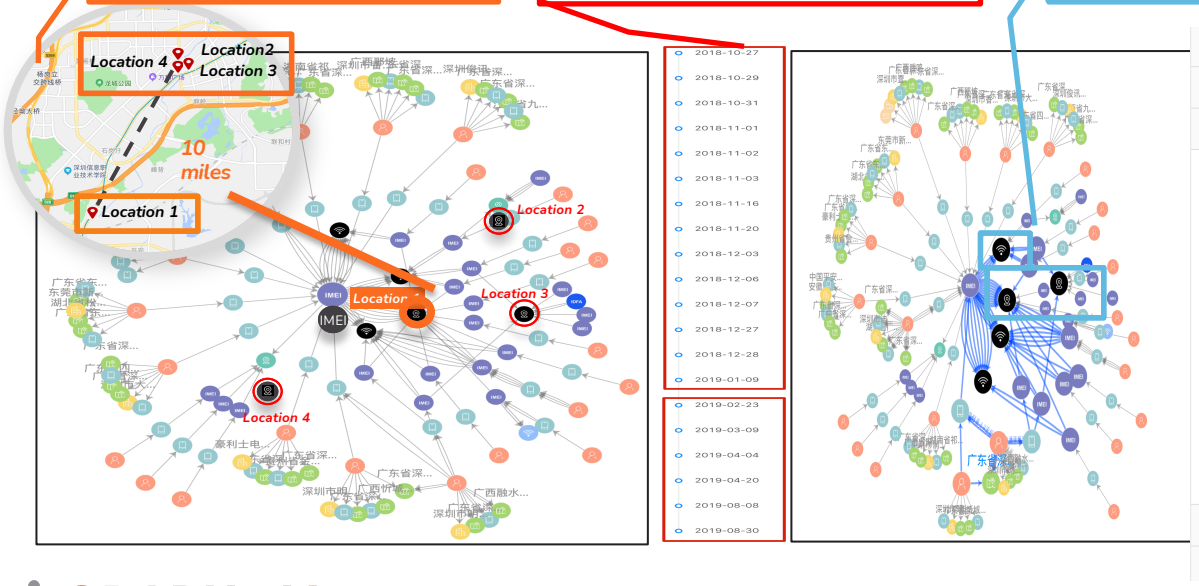
Case 1: Group Fraud Identification

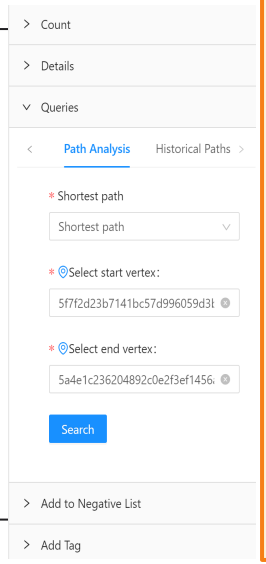
Fraud agent location changed ,but was using the WiFi device

Evidence 1:
4 geo-grid (location) vertexes were found, and 3 were connected.

Evidence 2:
Application time gap was found within locations.
Applications from location 1 were submitted before Jan. 2018, and what from location 2-4 were submitted after then.

Evidence 3:
All 4 locations were use the same WIFI





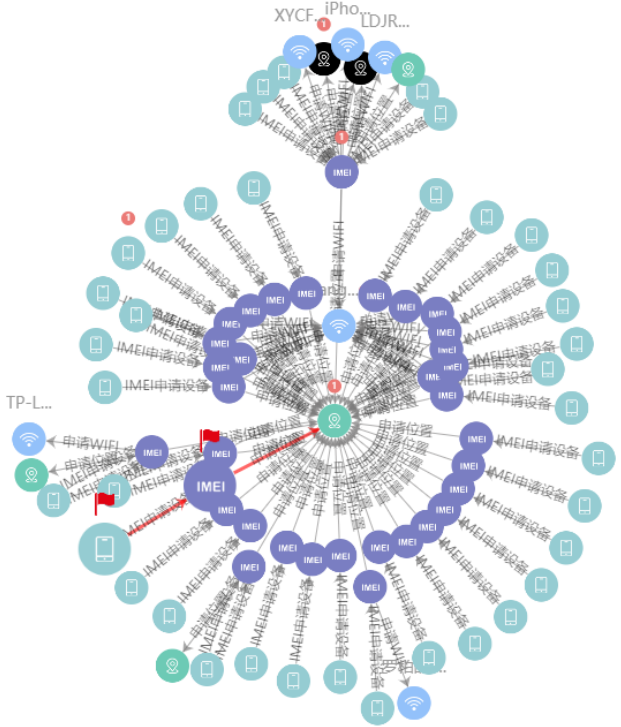
Investigation

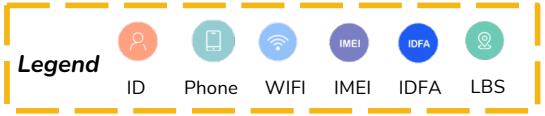
① A fraud agent was caught by monitoring from graph network platform.

② After the application was continuously declined, the fraud agent moved to a new location.

③ However, since the fraud agent was using the same WiFi, dozens of subsequent applications submitted form the agent were still being declined.

Case 2：Propagated Fraud - Cluster Grows by Time Series





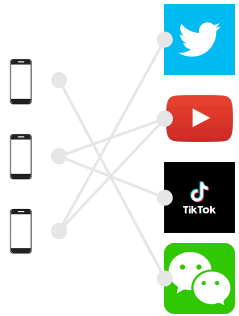
- **2019.11**
- **2019.12**
- **2020.04**
- **2020.07**

Case 3: App Classification using Graph Network

- APP installation is the core of describing mobile devices (users), which reflects the user's identity, class, interests, preferences, etc.
- Most of the existing and new APPs do not have the accurate classification, while the cost of manual labeling is very high

Case 3: App Classification using Graph Network

Analysis Process

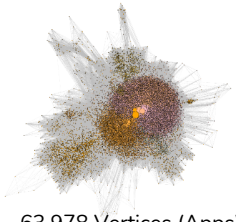


Relate 2 apps based on their shared installed devices

Tricks

Remove low-frequency apps

Control Killer apps' influence



63,978 Vertices (Apps)

32,782,561 edges (Relationships)

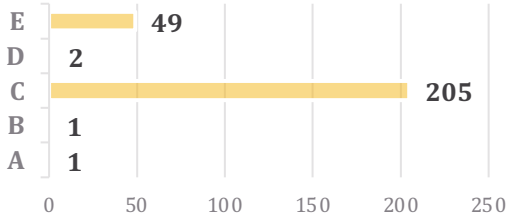
Detect 152 communities using Louvain Algorithm

258 manually labeled loan apps

grouped into 5 communities out of 152

Effect Verification

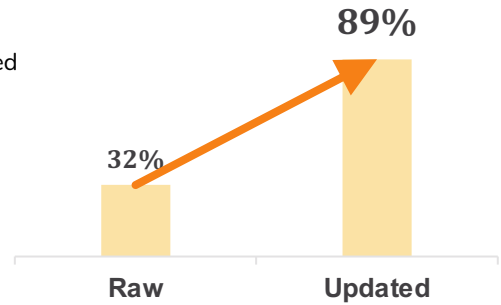
Community distribution of 258 labeled loan apps



About *80%* labeled apps reside in community C (approximate ***recall***)

check unlabeled apps in C

Loan APP accuracy in community C



After updating unlabeled apps' labels, the accuracy is increased to *89%*

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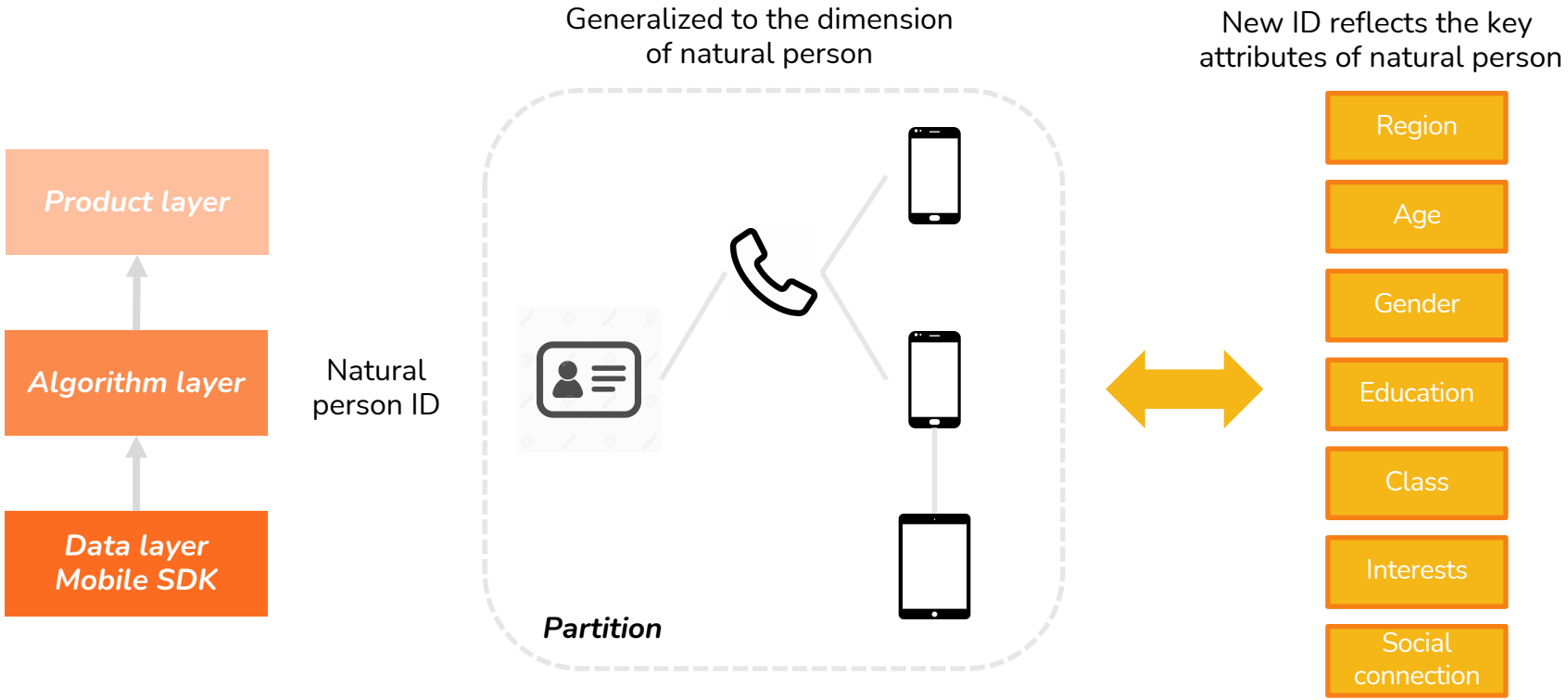
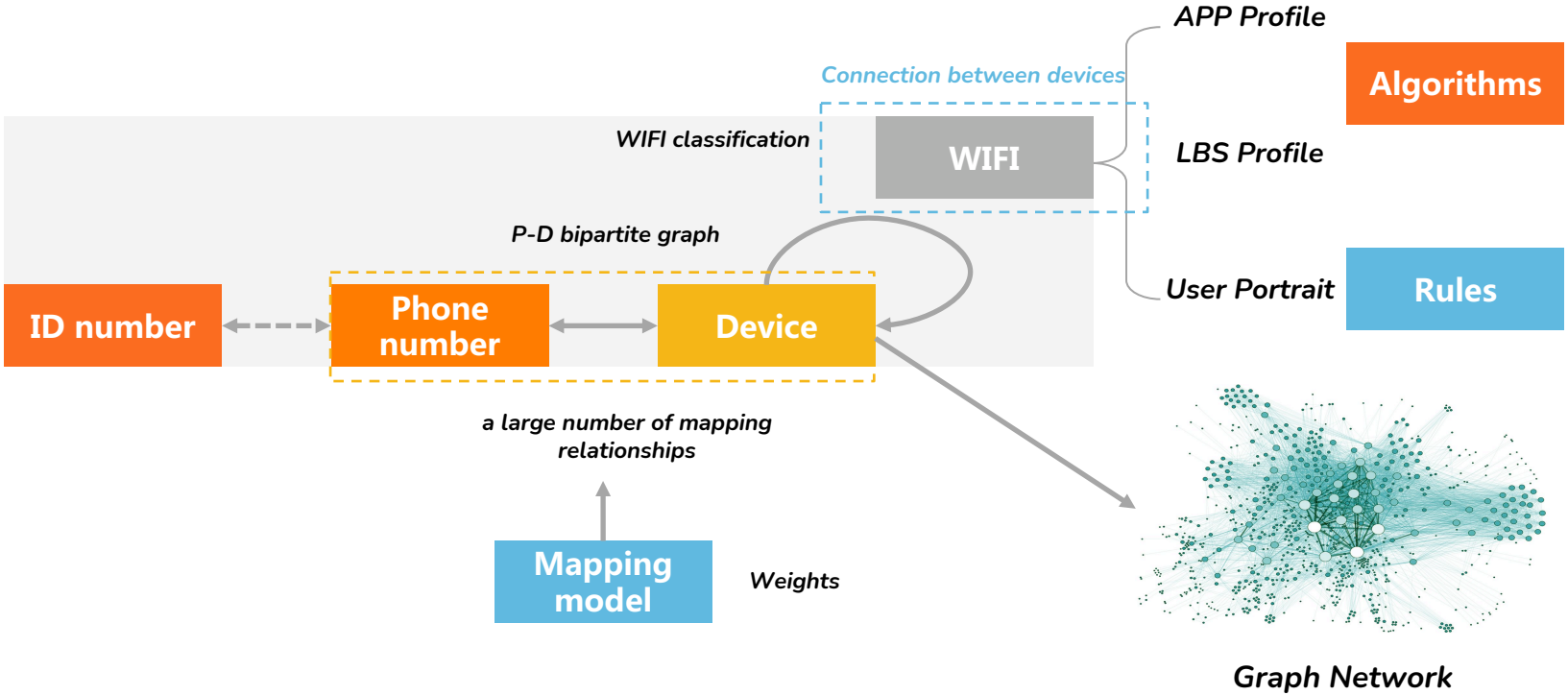
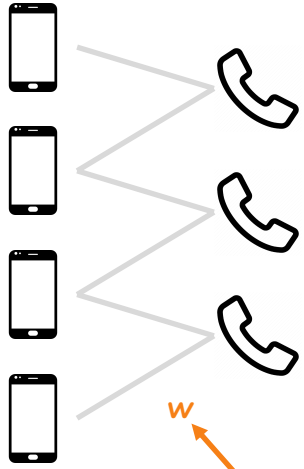


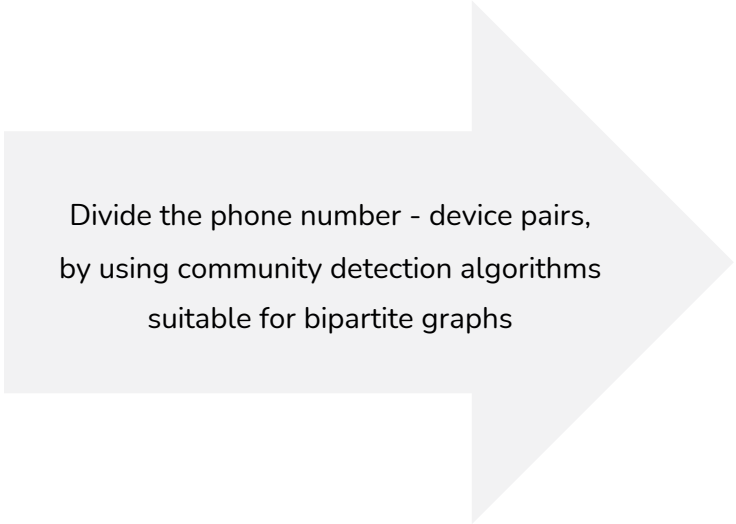
Case 4: ID Mapping – Natural Person ID Architecture

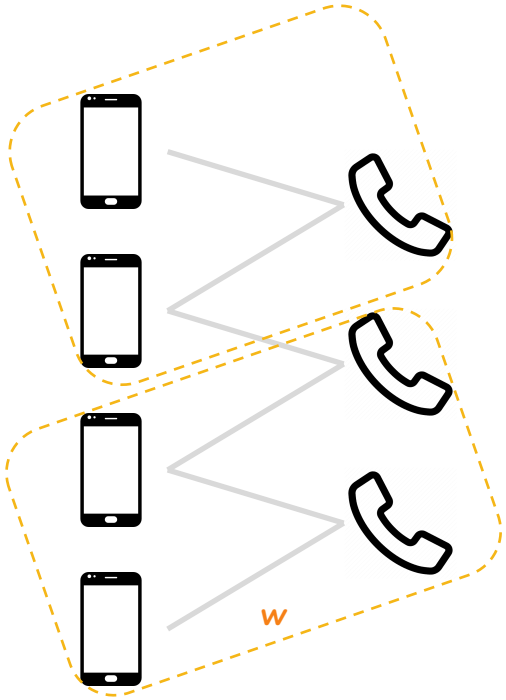


Case 4: Phone-Device Bipartite

Construct the weights of bipartite graph based on the reported confidence



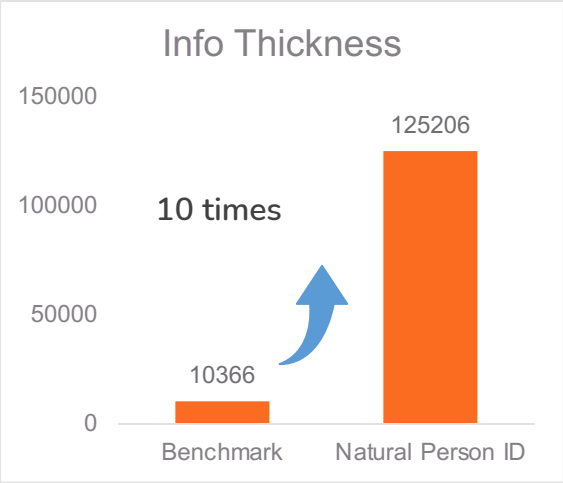


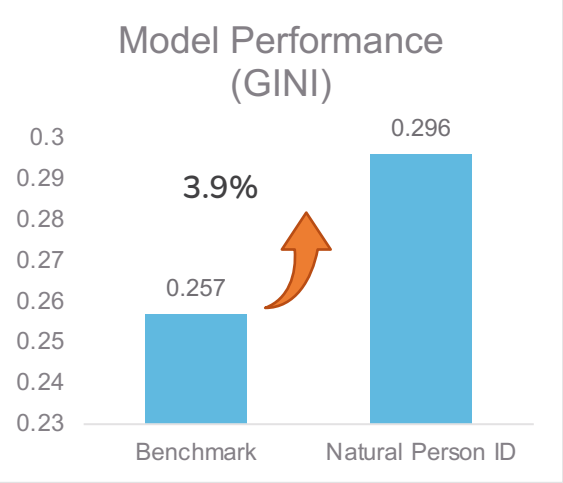


$$w_{p,d} = \sum_{upload} (\beta_{source} f_{source} + \beta_{bias} f_{bias} + b)^{duration}$$

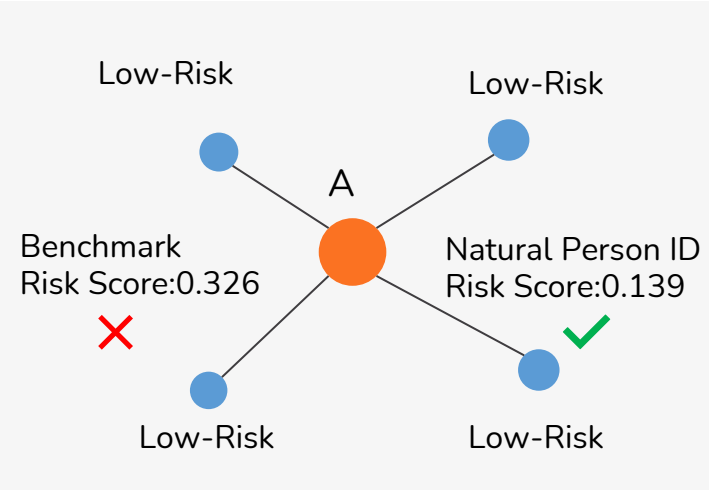
Case 4: Increment Value of Natural Person ID

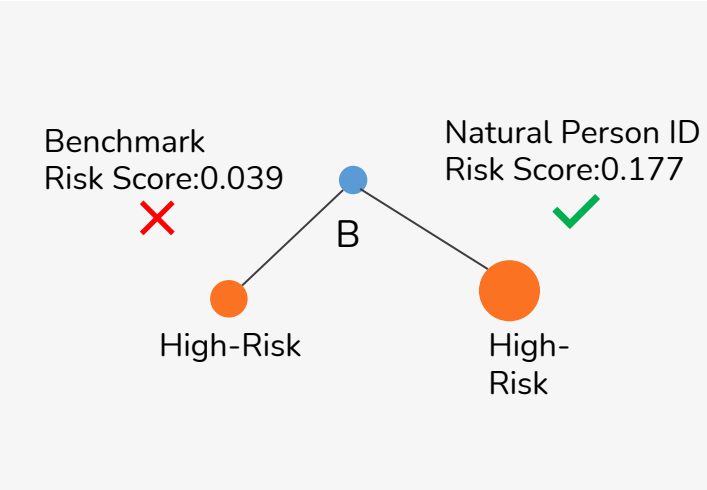
Compare the performance of credit scores based on devices vs. natural person ID





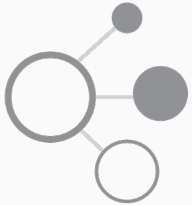
Case 4: Natural Person ID, Case Review





Vertex A is a labeled low-risk sample. However, it has a higher risk score in the model, which can be corrected by its low-risk neighbors.

Vertex B is a labeled high-risk sample. However, due to its insufficient information thickness, it has a low-risk score, which can be corrected by its high-risk neighbors.



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