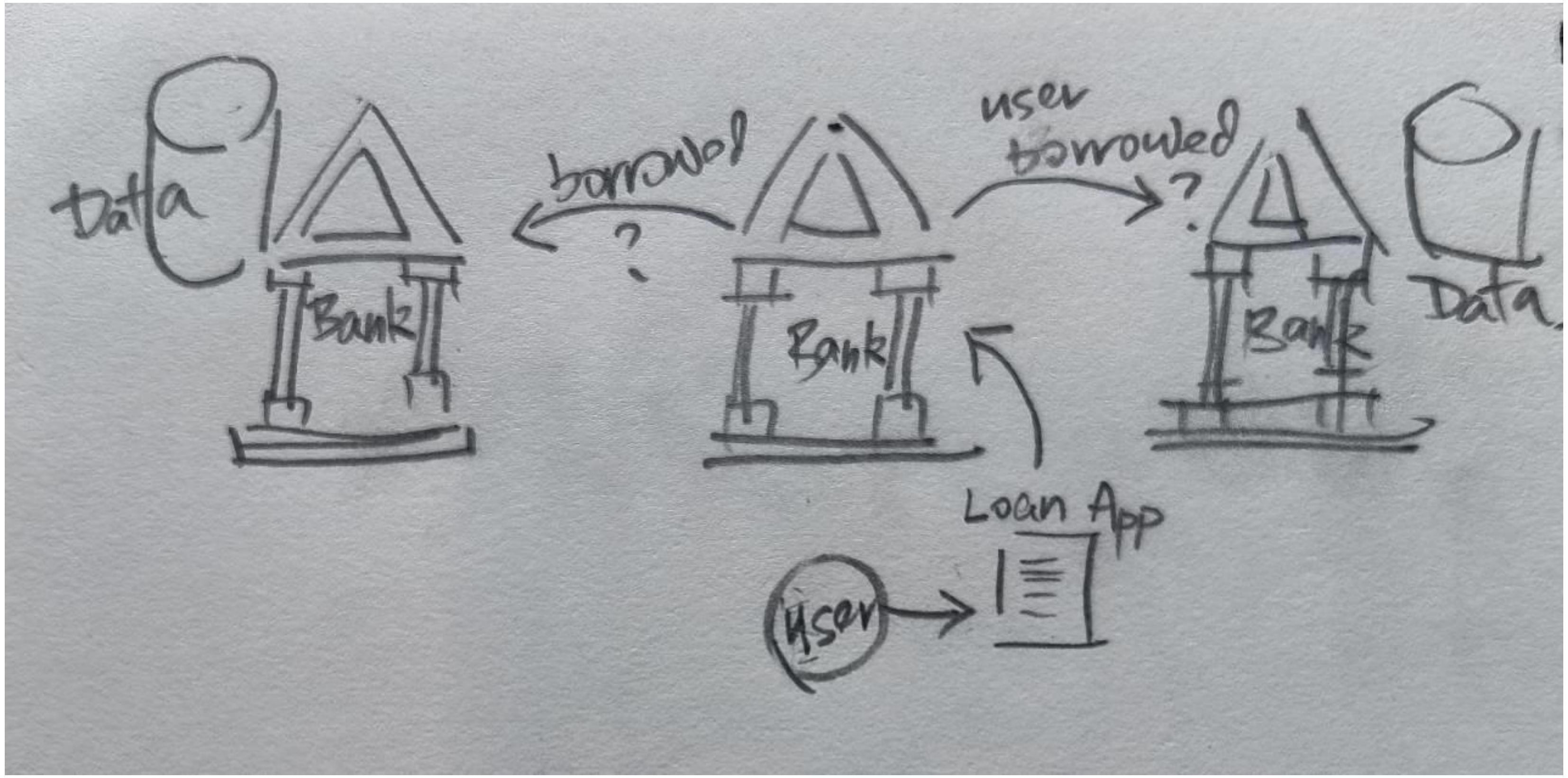
Trustworthy Federated Learning

QIANG YANG

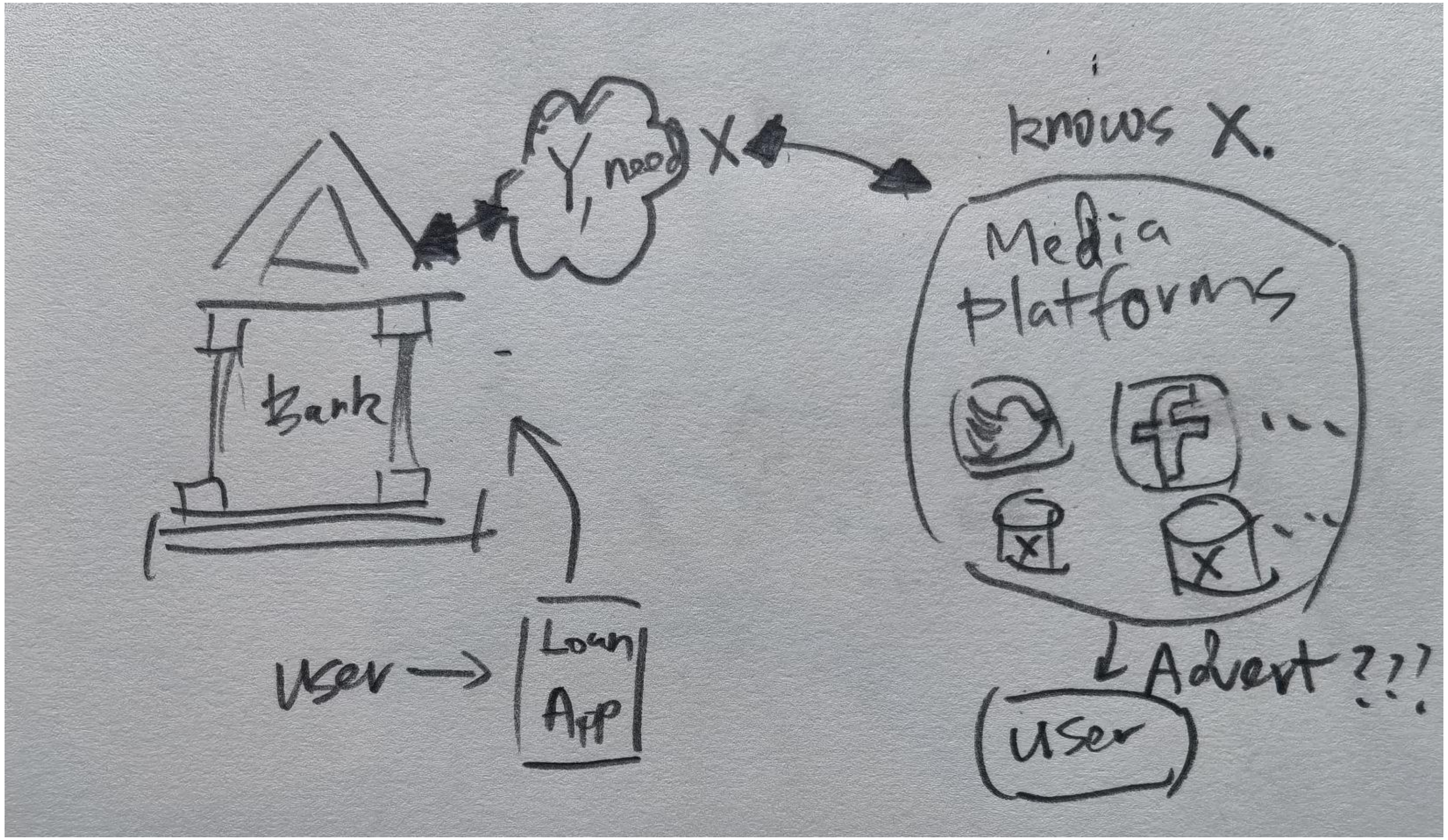
HKUST，WeBank

Case 1: Bank Loan, Anti-fraud Applications



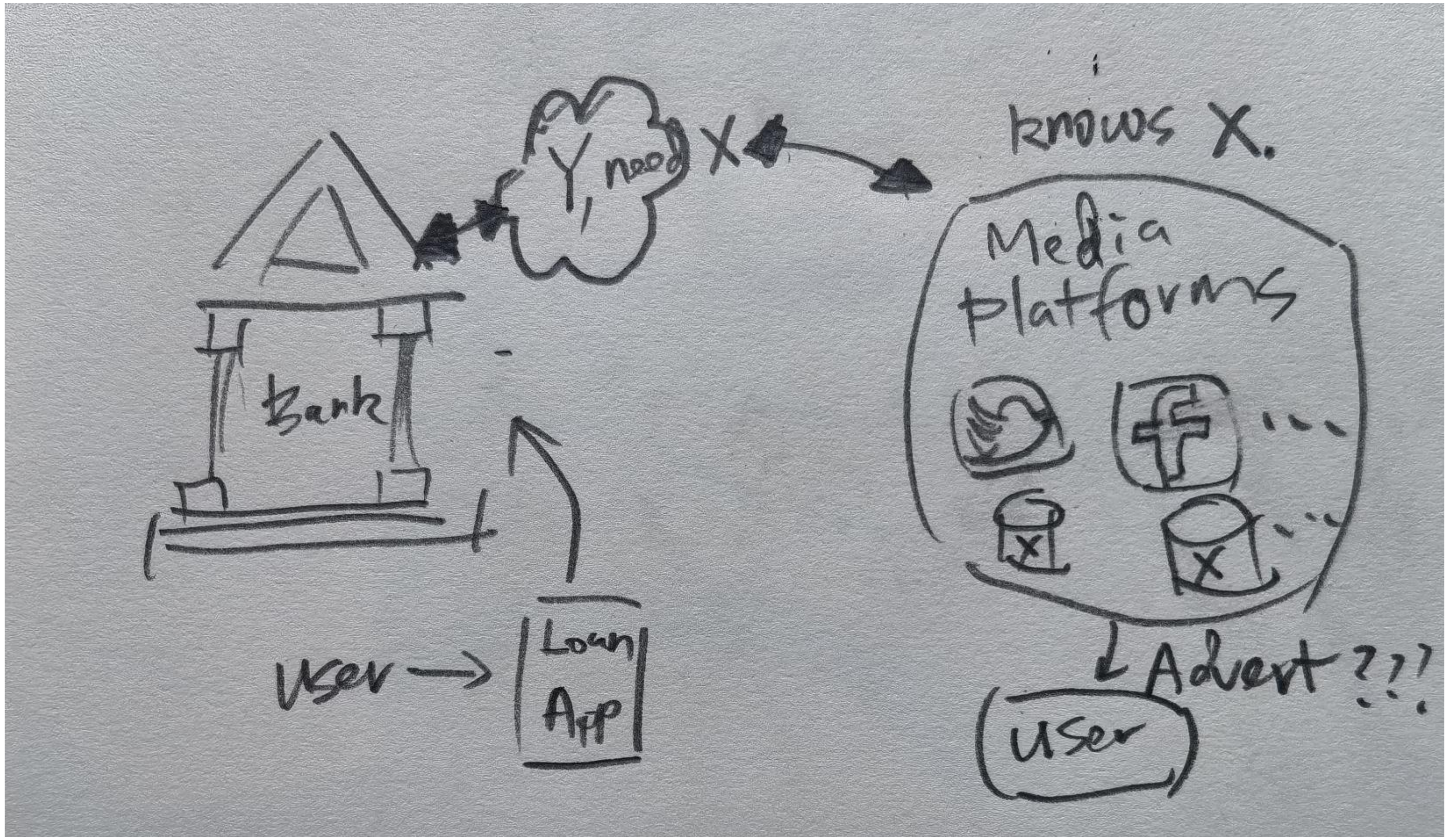
- User Applying Bank Loan
  - Has the user got loans from other banks?
  - Is this a case of fraud?

Case 2: Financial Credit Rating



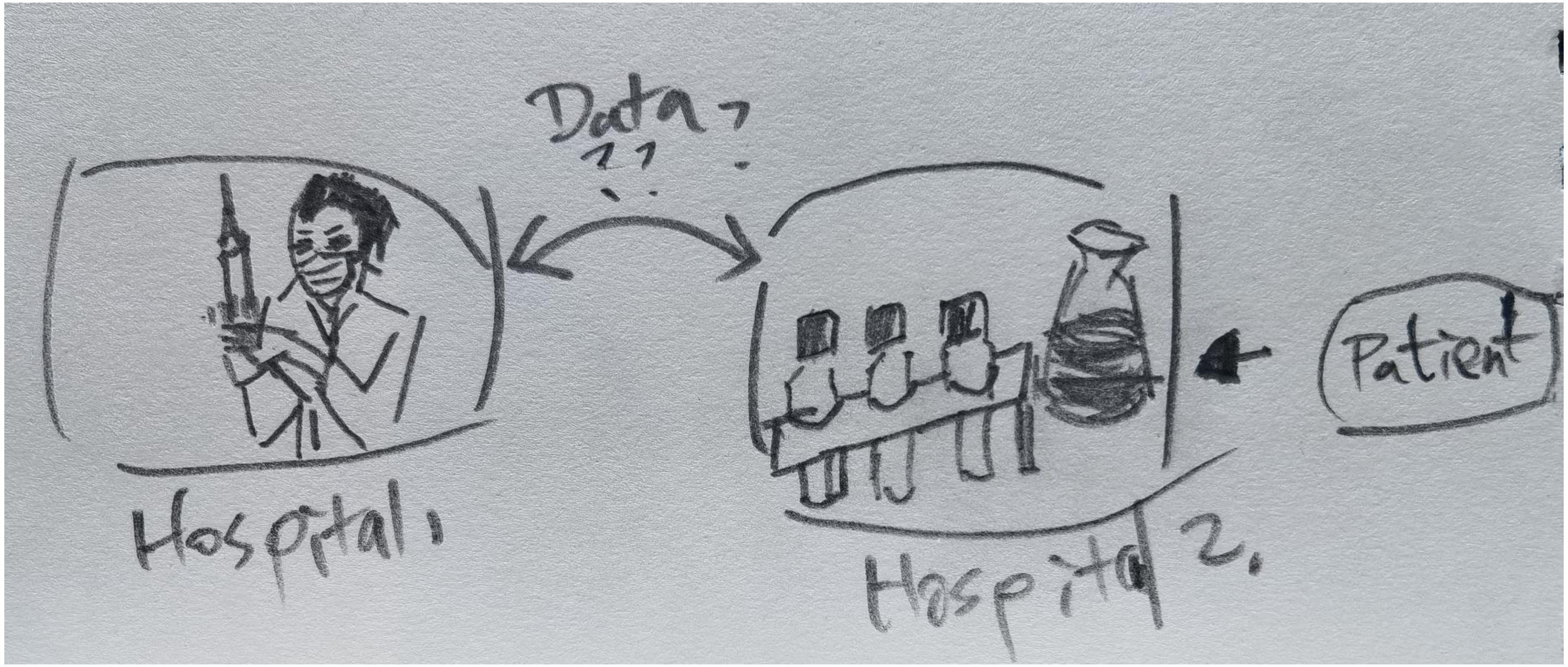
- User Applying Bank Loan
  - Is the user credible?
  - How is the user’s other behavior?
- Bank knows Y (credit history)
- Media knows X (Behavior)
- Can they build a collective model at the bank side?

Case 3: Advertising

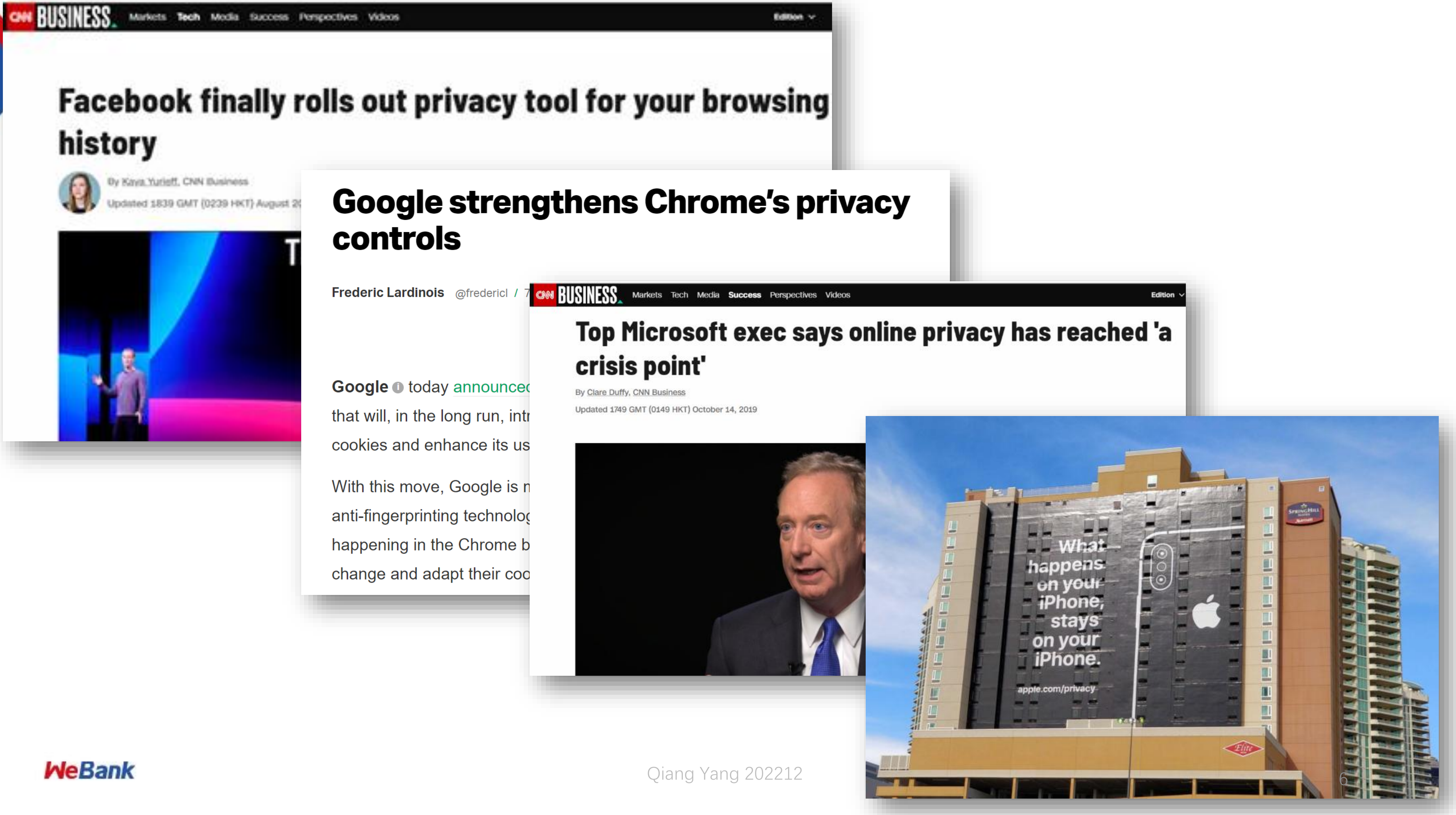


- Bank needs to advertise to users with good credit history
- But the data cannot be given to media companies
- Should a media company advertise to a user?

Case 4: Multiple hospitals build collective model



- Early detection of illness such as stroke
- Design new drugs
- …



Facebook finally rolls out privacy tool for your browsing history

By Kaya Yurieff, CNN Business

Updated 1839 GMT (0239 HKT) August 2

Google strengthens Chrome's privacy controls

Frederic Lardinois @fredericl / 7

Google today announce
that will, in the long run, intr
cookies and enhance its us

With this move, Google is n
anti-fingerprinting technolog
happening in the Chrome b
change and adapt their coo

Top Microsoft exec says online privacy has reached 'a crisis point'

By Clare Duffy, CNN Business

Updated 1749 GMT (0149 HKT) October 14, 2019

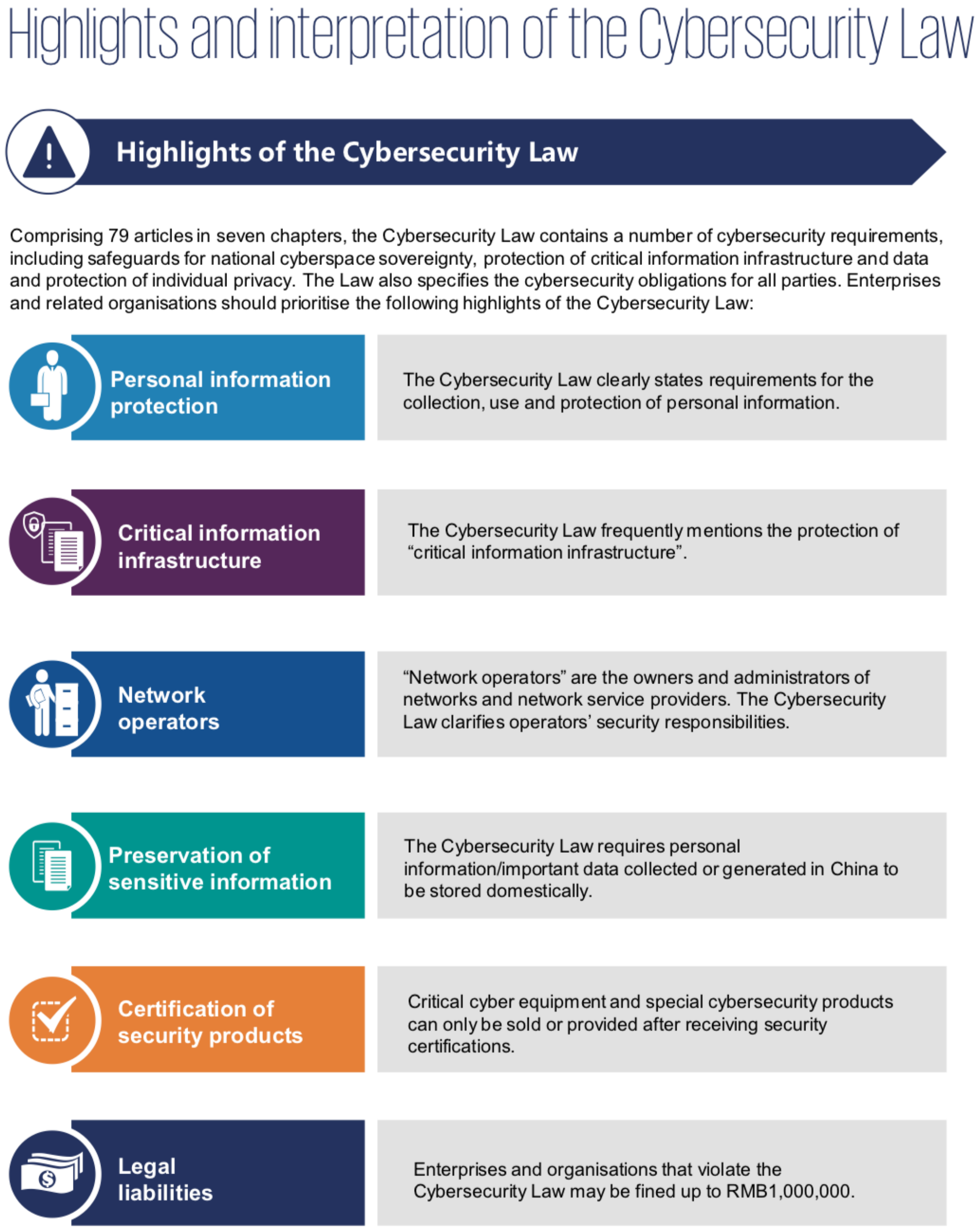
What happens on your iPhone, stays on your iPhone.
apple.com/privacy
SpringHill Suites Marriott
Elite

Data Sharing Among Parties: Difficult, Impossible, Illegal

- **Medical clinical trial data cannot be shared (by R. Stegeman 2018 on Genemetics)**
- **Our society demands more control on data privacy and security**
    - GDPR, Government Regulations
    - Corporate Security and Confidentiality Concerns
    - Data privacy concerns

China’ s Data Privacy Laws

- Three major data security laws in 2021:
  - Personal Data Privacy Protection Regulation
  - Data Security Law
  - Cybersecurity Law
- Require businesses to get user consent, not leak out or tamper with data
- When conducting data transactions with third parties, proposed contract should follow legal data protection regulations.



Highlights and interpretation of the Cybersecurity Law

Highlights of the Cybersecurity Law

Comprising 79 articles in seven chapters, the Cybersecurity Law contains a number of cybersecurity requirements, including safeguards for national cyberspace sovereignty, protection of critical information infrastructure and data and protection of individual privacy. The Law also specifies the cybersecurity obligations for all parties. Enterprises and related organisations should prioritise the following highlights of the Cybersecurity Law:

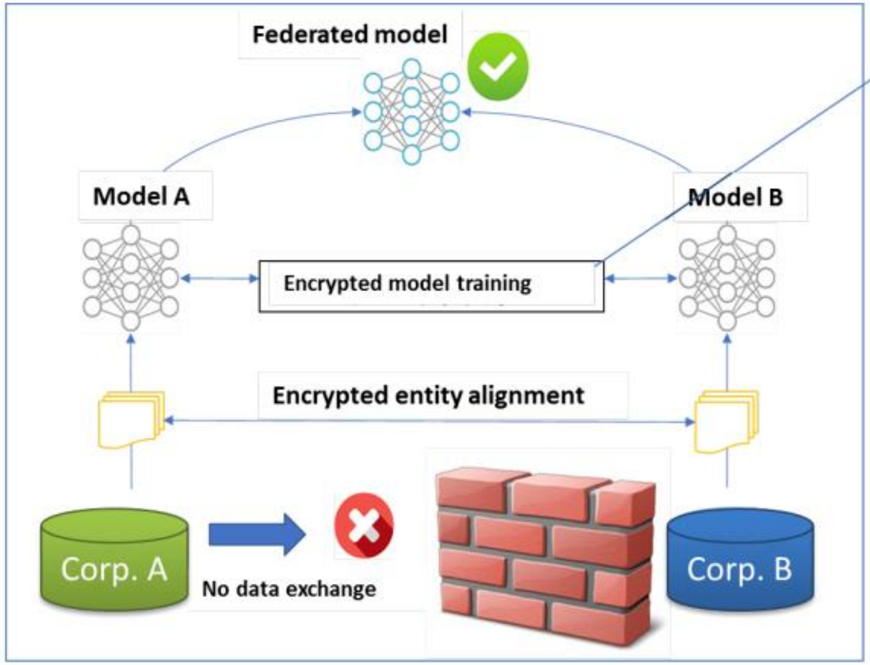
Personal information protection	The Cybersecurity Law clearly states requirements for the collection, use and protection of personal information.
Critical information infrastructure	The Cybersecurity Law frequently mentions the protection of “critical information infrastructure”.
Network operators	“Network operators” are the owners and administrators of networks and network service providers. The Cybersecurity Law clarifies operators’ security responsibilities.
Preservation of sensitive information	The Cybersecurity Law requires personal information/important data collected or generated in China to be stored domestically.
Certification of security products	Critical cyber equipment and special cybersecurity products can only be sold or provided after receiving security certifications.
Legal liabilities	Enterprises and organisations that violate the Cybersecurity Law may be fined up to RMB1,000,000.

From Report by KPMG 2017

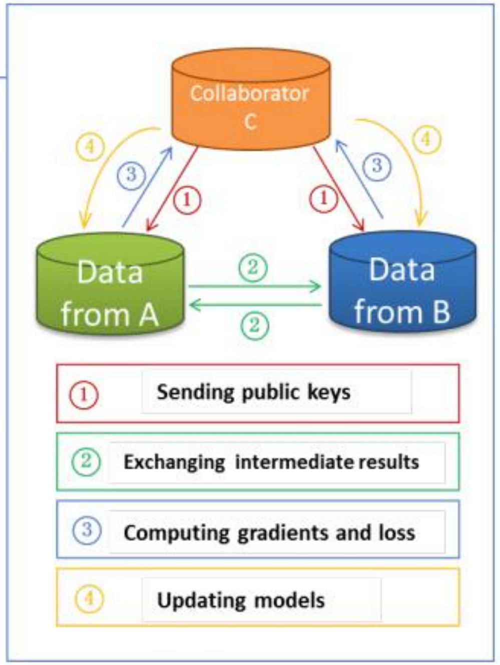
Qiang Yang et al, *Federated Learning*, Morgan & Claypool Publishers, 2019, section 1.2, page 3

Federated Learning

- Federated Machine Learning
  - Multiple parties compute a model
  - Each party contributes some local data, without sharing the data
- Horizontal and Vertical Federated Learning



a



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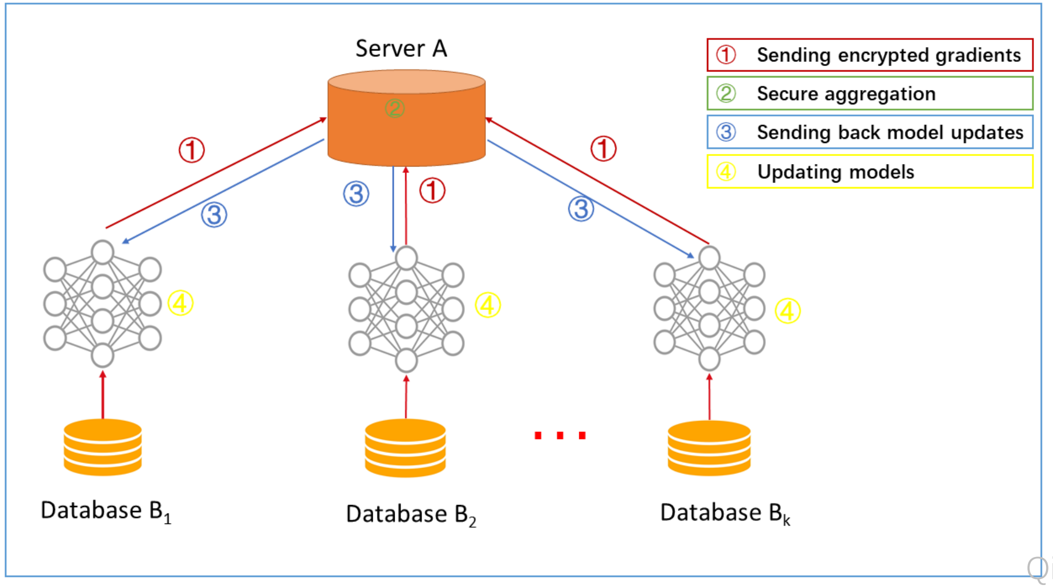
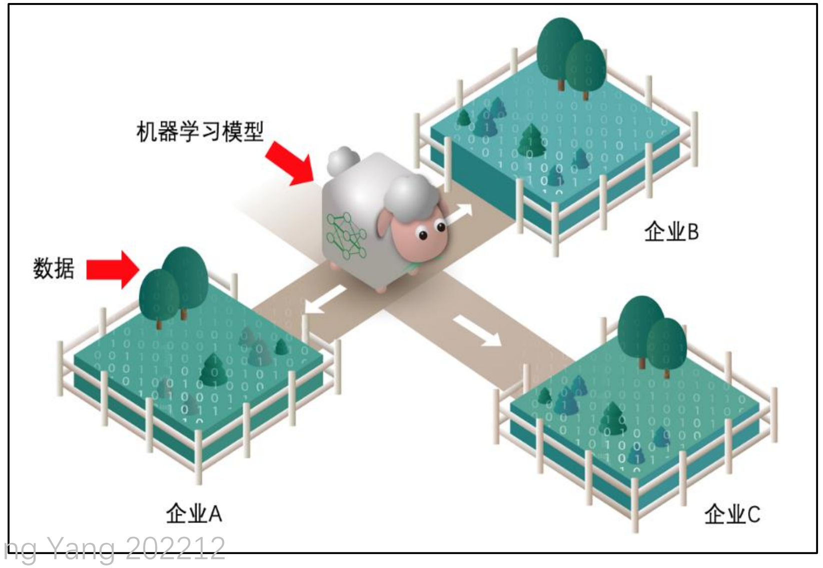
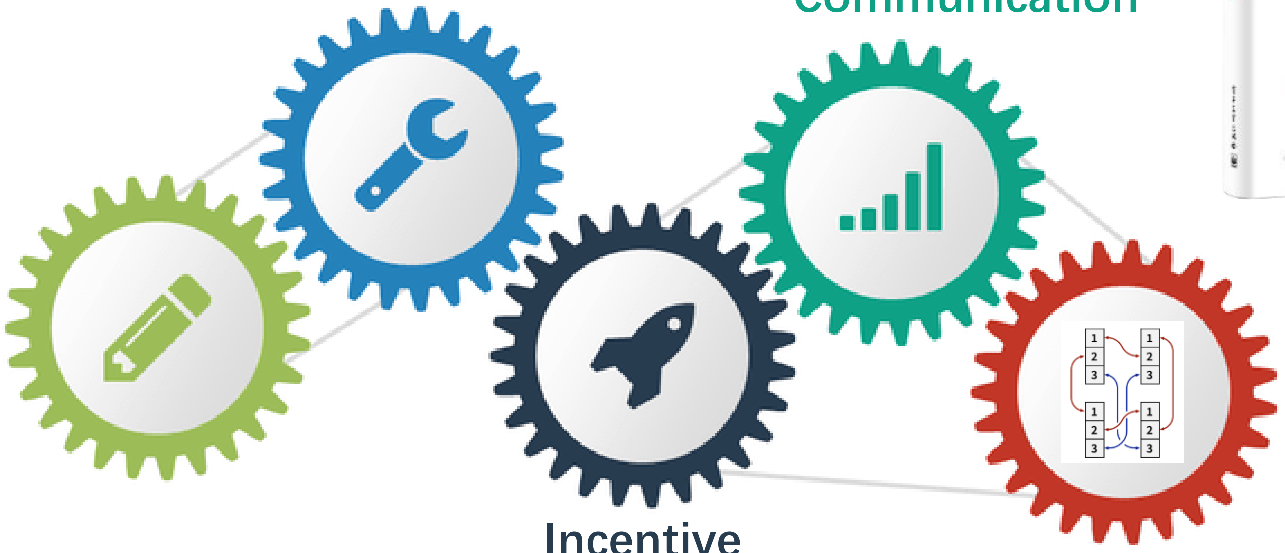




Key Components in Federated Learning



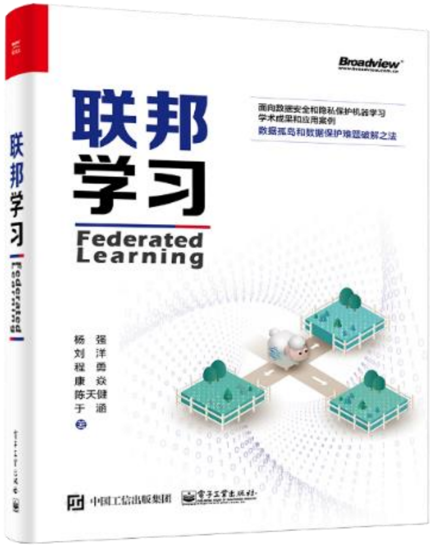
Model Design

Communication

Privacy & Security

Distributed ML

Incentive



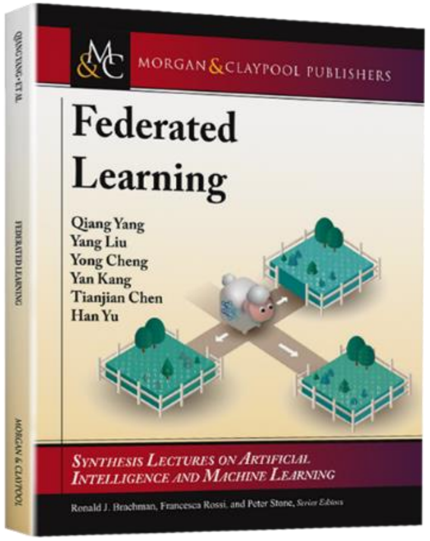
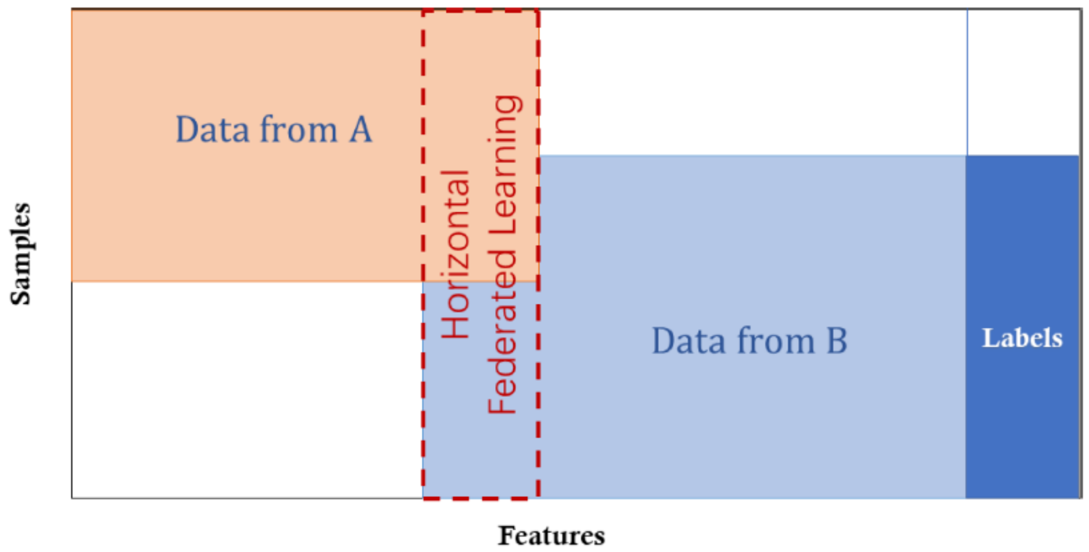

MORGAN & CLAYPOOL PUBLISHERS
Federated Learning
Qiang Yang
Yang Liu
Yong Cheng
Yan Kang
Tianjian Chen
Han Yu
Synthesis Lectures on Artificial Intelligence and Machine Learning
Ronald J. Brachman, Francesca Rossi, and Peter Stone, Series Editors

Image from Google

Horizontal Federated Learning: Divide by Users/Samples



(a) Horizontal Federated Learning

FEDERATED LEARNING FOR MOBILE KEYBOARD PREDICTION, Andrew Hard, et al., Google, 2018

Step 1: Participants compute training gradients locally

- mask gradients with encryption, differential privacy, or secret sharing techniques
- all participants send their masked results to server

Step 2: The server performs secure aggregation without learning information about any participant

Step 3: The server sends back the aggregated results to participants

Step 4: Participants update their respective model with the decrypted gradients

Vertical Federated Learning, VFL

- Parties hold data with identical data ID (i.e. training samples), but with different features.
  - A.k.a “Cross-feature federated learning”, “sample-aligned federated learning”. Suitable for federated learning across industries.
  - Before training, we take the intersection of data IDs held by different parties.
  - VFL increases data dimensionality at the cost of sample size (due to intersection of IDs).

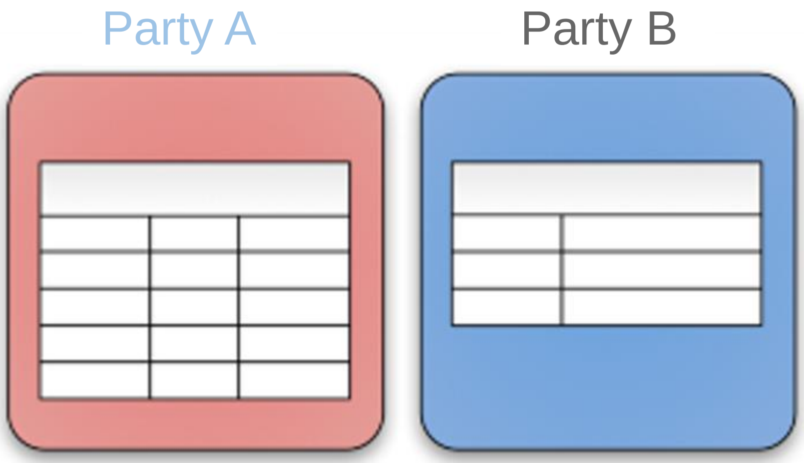
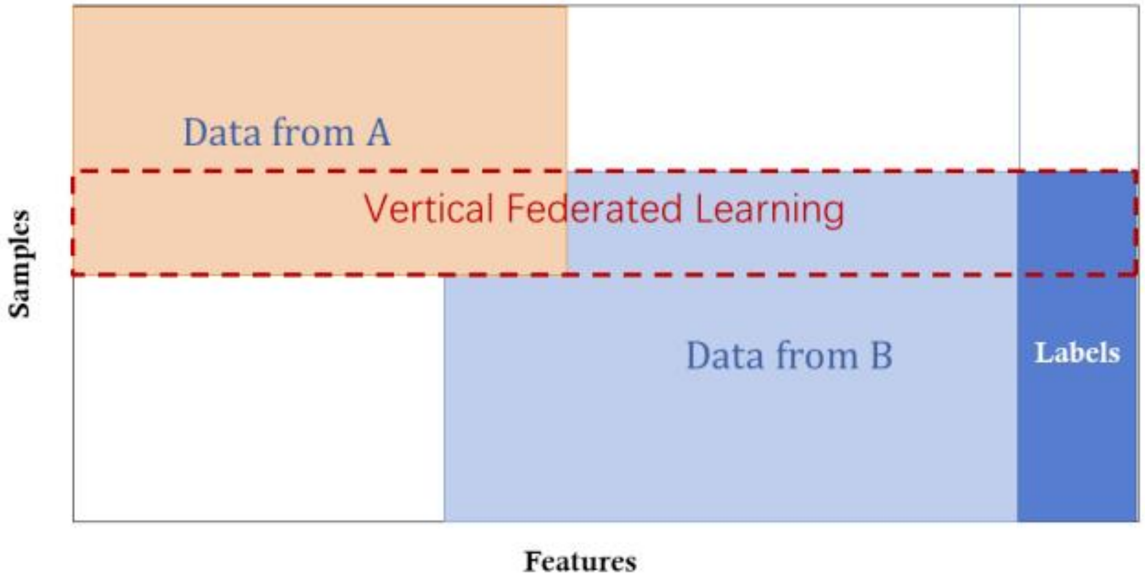


Image from Google

Vertically partitioned data: partition data frames into columns, with each column holding the same feature.



[Yang’19] Qiang Yang, et al., Federated machine learning: Concept and Applications, WeBank, 2019.

XGBoost in Federated Learning

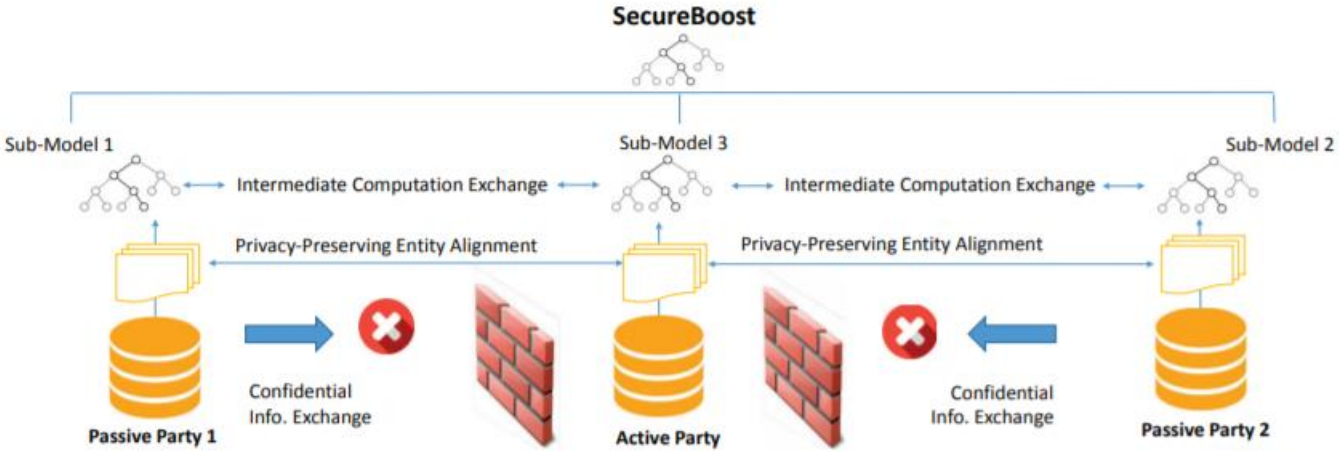
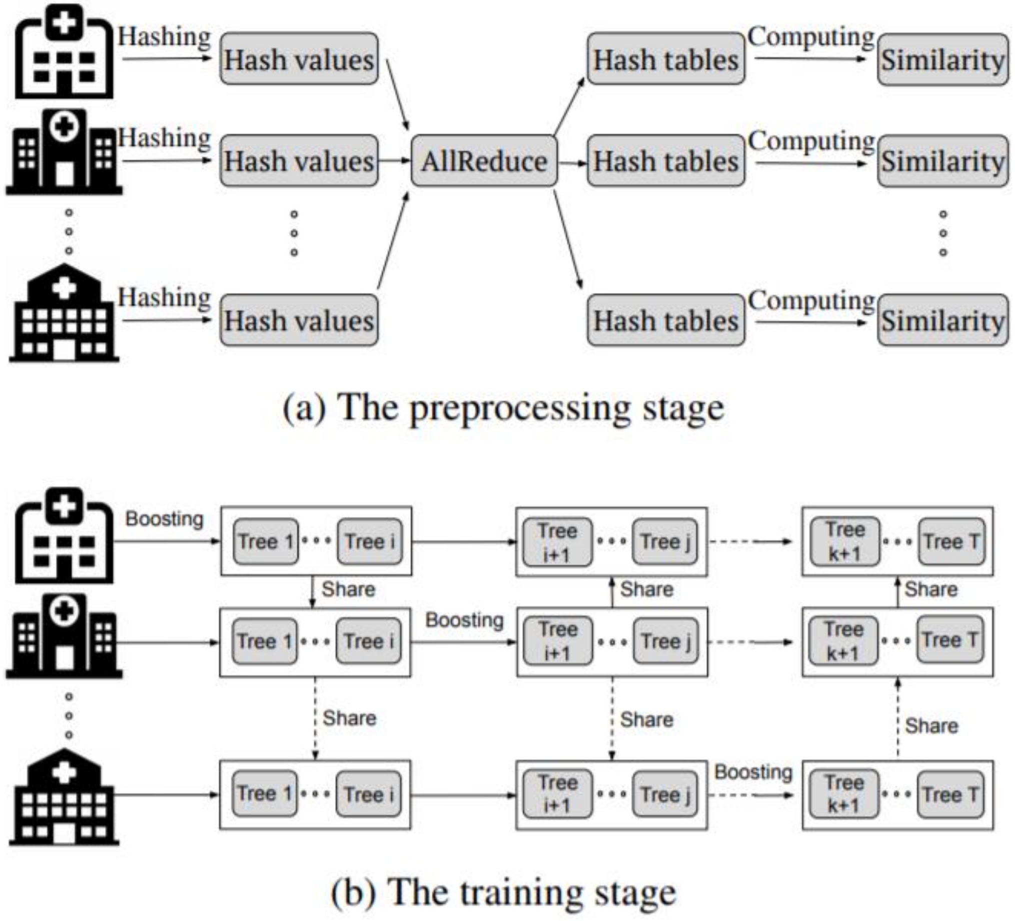

SecureBoost
Sub-Model 1
Sub-Model 3
Sub-Model 2
Intermediate Computation Exchange
Intermediate Computation Exchange
Privacy-Preserving Entity Alignment
Privacy-Preserving Entity Alignment
Confidential Info. Exchange
Confidential Info. Exchange
Passive Party 1
Active Party
Passive Party 2

Figure 1: Illustration of the proposed SecureBoost framework

Kewei Cheng, Tao Fan, Yilun Jin, Yang Liu, Tianjian Chen, Qiang Yang, SecureBoost: A Lossless Federated Learning Framework, IEEE Intelligent Systems 2020

GBDT in HFL



(a) The preprocessing stage

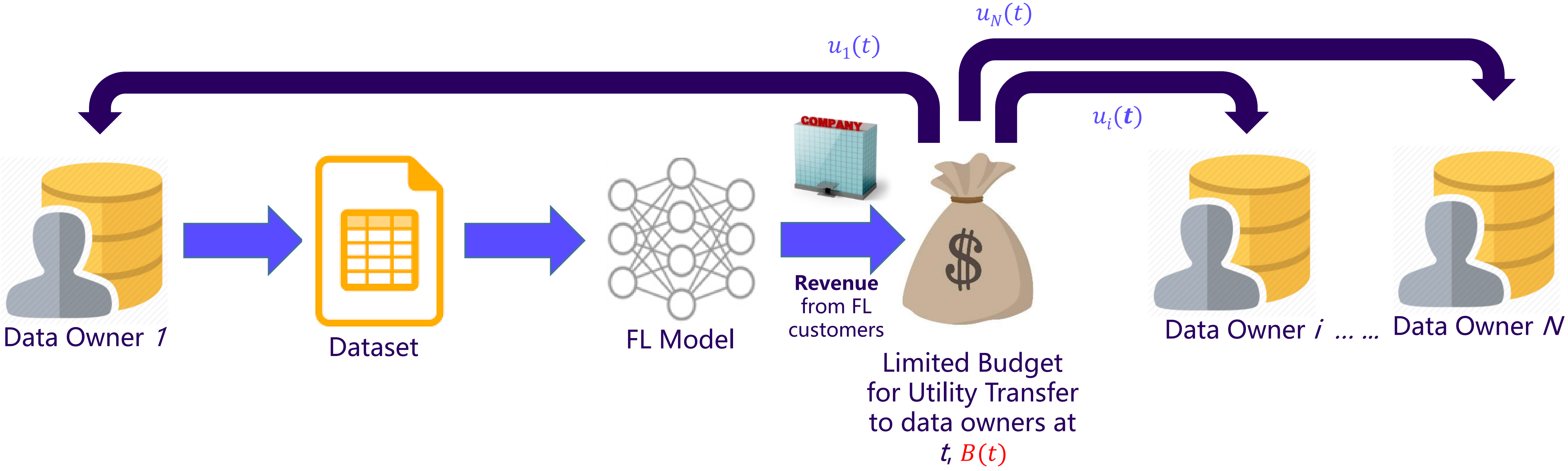
(b) The training stage

Qinbin Li, Zeyi Wen, Bingsheng He, Practical Federated Gradient Boosting Decision Trees, AAAI, 2019

Incentivize Parties to Join: Federated Learning Exchange

- **Observation:** The success of a federation depends on data owners to share data with the federation

- **Challenge:** How to motivate continued participation by data owners in a federation?



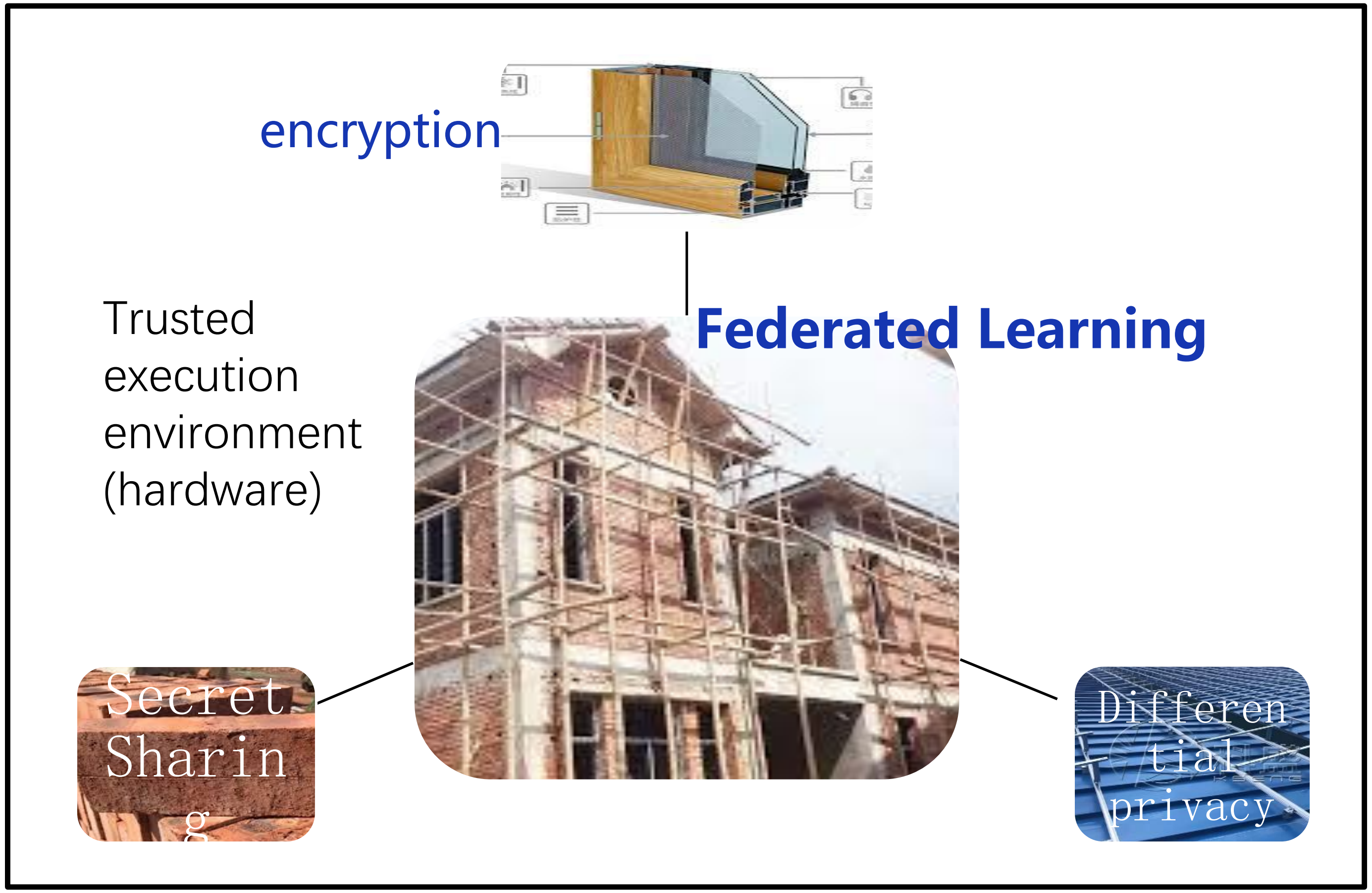
$u_N(t)$
$u_1(t)$
$u_i(t)$
COMPANY
Data Owner 1
Dataset
FL Model
Revenue from FL customers
Limited Budget for Utility Transfer to data owners at t, $B(t)$
Data Owner i … …
Data Owner N

•*Qiang Yang, Yang Liu, Tianjian Chen, Yongxin Tong:*
Federated Machine Learning: Concept and Applications. *ACM TIST 10(2): 12:1-12:19 (2019)*

Federated Learning: Best for AI Models

One-off MPC Projects

Standard Federated Learning



encryption

Trusted execution environment (hardware)

Federated Learning

Secret Sharing

Differential privacy

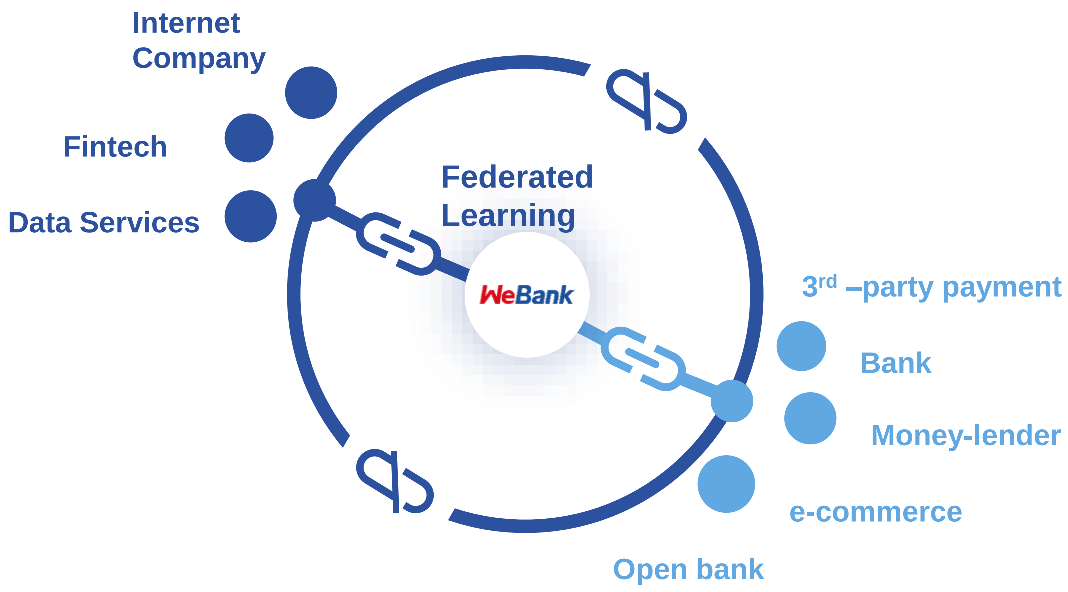
Advances and Open Problems in Federated Learning

Peter Kairouz[7,*] H. Brendan McMahan[7,*] Brendan Avent[21] Aurélien Bellet[9]
Mehdi Bennis[19] Arjun Nitin Bhagoji[13] Keith Bonawitz[7] Zachary Charles[7]
Graham Cormode[23] Rachel Cummings[6] Rafael G.L. D'Oliveira[14]
Salim El Rouayheb[14] David Evans[22] Josh Gardner[24] Zachary Garrett[7]
Adrià Gascón[7] Badih Ghazi[7] Phillip B. Gibbons[2] Marco Gruteser[7,14]
Zaid Harchaoui[24] Chaoyang He[21] Lie He [4] Zhouyuan Huo [20]
Ben Hutchinson[7] Justin Hsu[25] Martin Jaggi[4] Tara Javidi[17] Gauri Joshi[2]
Mikhail Khodak[2] Jakub Konečný[7] Aleksandra Korolova[21] Farinaz Koushanfar[17]
Sanmi Koyejo[7,18] Tancrède Lepoint[7] Yang Liu[12] Prateek Mittal[13]
Mehryar Mohri[7] Richard Nock[1] Ayfer Özgür[15] Rasmus Pagh[7,10]
Mariana Raykova[7] Hang Qi[7] Daniel Ramage[7] Ramesh Raskar[11]
Dawn Song[16] Weikang Song[7] Sebastian U. Stich[4] Ziteng Sun[3]
Ananda Theertha Suresh[7] Florian Tramèr[15] Praneeth Vepakomma[11] Jianyu Wang[2]
Li Xiong[5] Zheng Xu[7] Qiang Yang[8] Felix X. Yu[7] Han Yu[12] Sen Zhao[7]

[1]Australian National University, [2]Carnegie Mellon University, [3]Cornell University,
[4]École Polytechnique Fédérale de Lausanne, [5]Emory University, [6]Georgia Institute of Technology,
[7]Google Research, [8]Hong Kong University of Science and Technology, [9]INRIA, [10]IT University of Copenhagen,
[11]Massachusetts Institute of Technology, [12]Nanyang Technological University, [13]Princeton University,
[14]Rutgers University, [15]Stanford University, [16]University of California Berkeley,
[17] University of California San Diego, [18]University of Illinois Urbana-Champaign, [19]University of Oulu,
[20]University of Pittsburgh, [21]University of Southern California, [22]University of Virginia,
[23]University of Warwick, [24]University of Washington, [25]University of Wisconsin–Madison

Multiple Data Sources in Credit Rating

Build local models → Federated Modeling → Rating

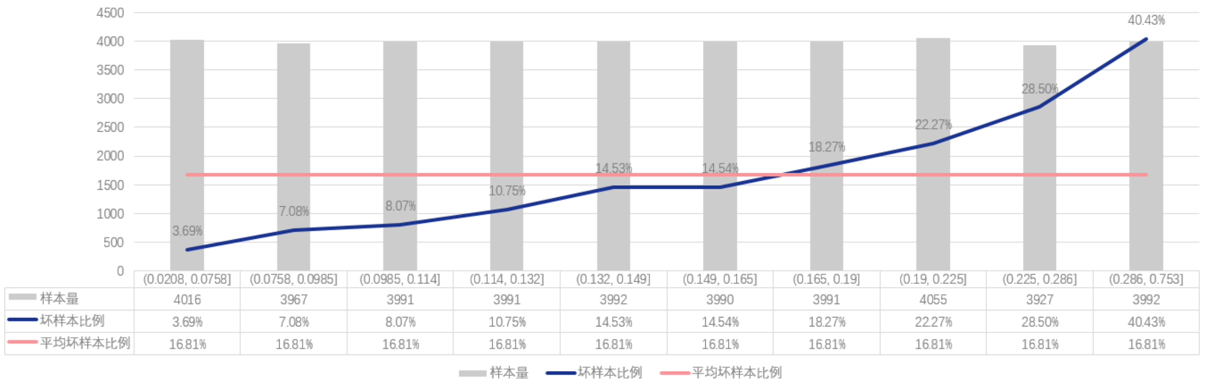


Increase the accuracy of models

Score to Indicate High/Medium/Low Risk Level

Model performance :

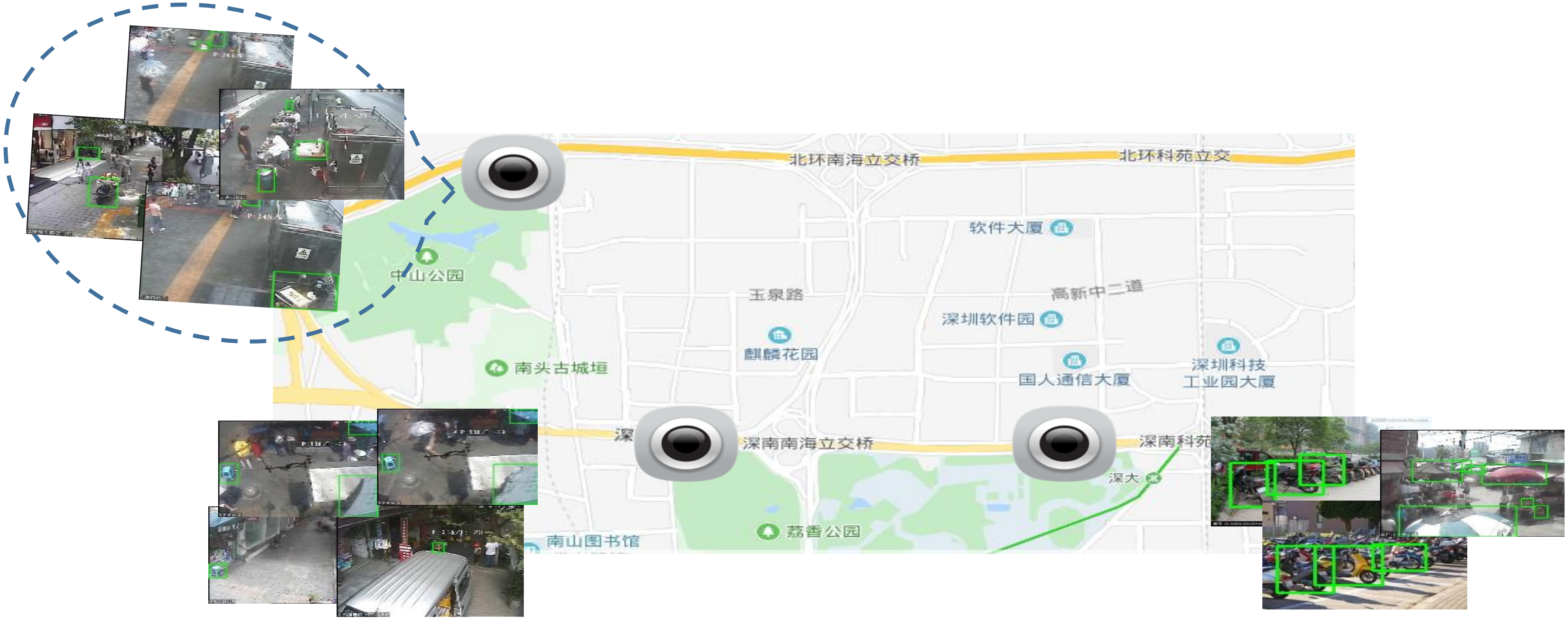
AUC=0.70
KS=30
x2.4 bad rate in the bottom decile



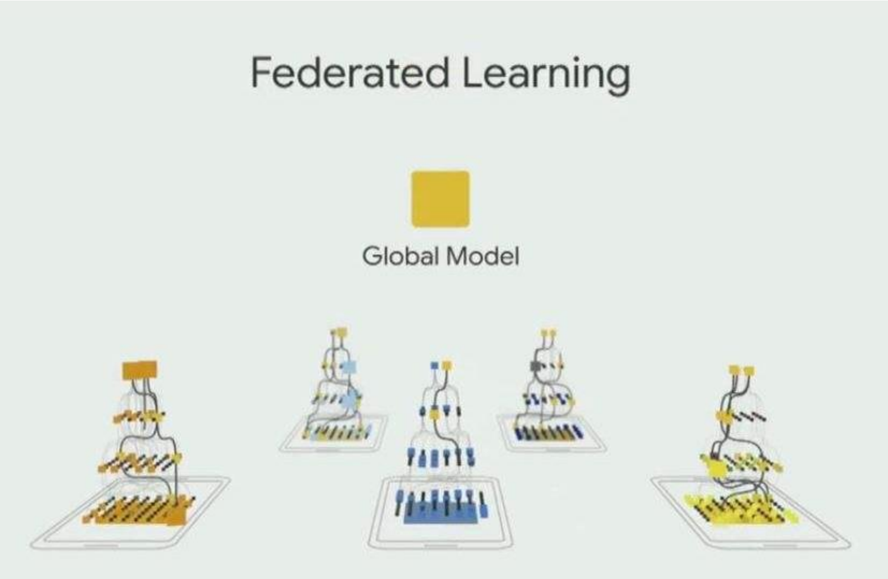
	(0.0208, 0.0758]	(0.0758, 0.0985]	(0.0985, 0.114]	(0.114, 0.132]	(0.132, 0.149]	(0.149, 0.165]	(0.165, 0.19]	(0.19, 0.225]	(0.225, 0.286]	(0.286, 0.753]
样本量	4016	3967	3991	3991	3992	3990	3991	4055	3927	3992
坏样本比例	3.69%	7.08%	8.07%	10.75%	14.53%	14.54%	18.27%	22.27%	28.50%	40.43%
平均坏样本比例	16.81%	16.81%	16.81%	16.81%	16.81%	16.81%	16.81%	16.81%	16.81%	16.81%

Construction-Site Safety w/ Federated Computer Vision

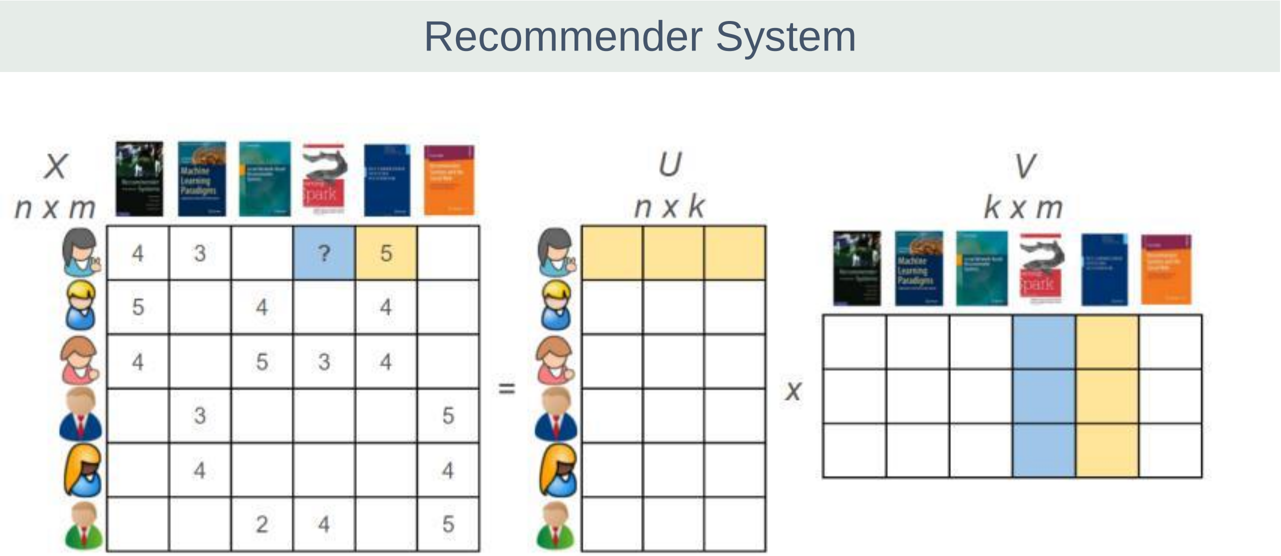
WeBank AI X Extreme Vision



Federated Recommendation Systems



+



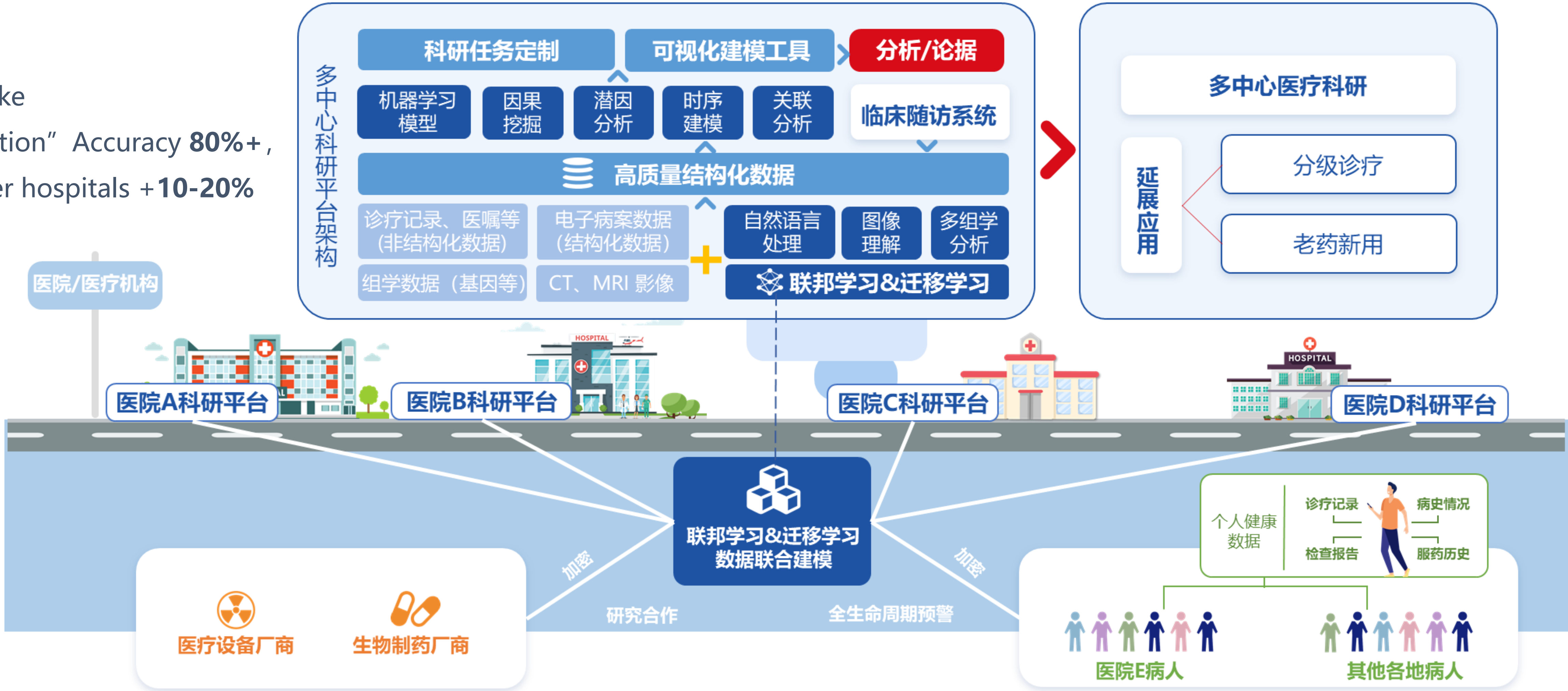
4	3		?	5	
5		4		4	
4		5	3	4	
	3				5
	4				4
		2	4		5

Assumption: a trustworthy 3rd-party as coordinator, which can be removed

Drug Discovery from Multiple Data Sources

Multiple hospitals, medical centers and drug companies

- “Stroke Prediction” Accuracy **80%+**, Smaller hospitals +**10-20%**



多中心科研平台架构

科研任务定制

可视化建模工具

分析/论据

机器学习模型

因果挖掘

潜因分析

时序建模

关联分析

临床随访系统

高质量结构化数据

诊疗记录、医嘱等（非结构化数据）

电子病案数据（结构化数据）

组学数据（基因等）

CT、MRI 影像

自然语言处理

图像理解

多组学分析

联邦学习&迁移学习

多中心医疗科研

延展应用

分级诊疗

老药新用

医院/医疗机构

医院A科研平台

医院B科研平台

医院C科研平台

医院D科研平台

联邦学习&迁移学习数据联合建模

加密

加密

研究合作

全生命周期预警

医疗设备厂商

生物制药厂商

个人健康数据

诊疗记录

病史情况

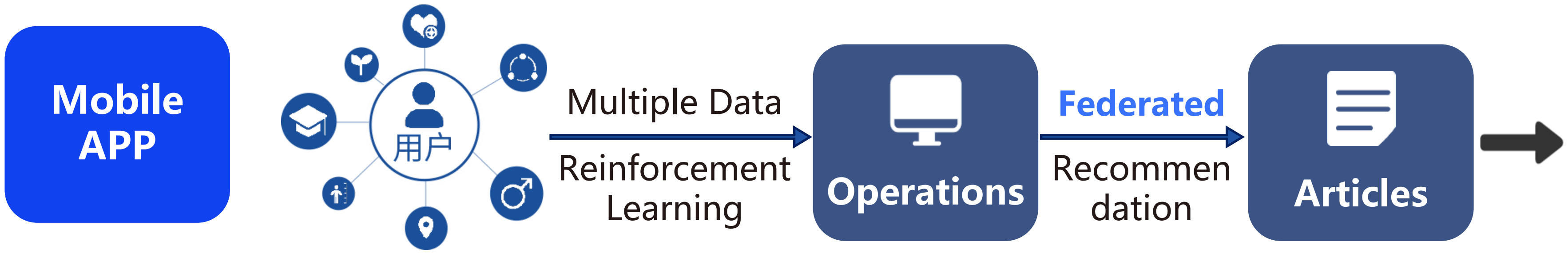
检查报告

服药历史

医院E病人

其他各地病人

News Recommendation on Mobile Phones

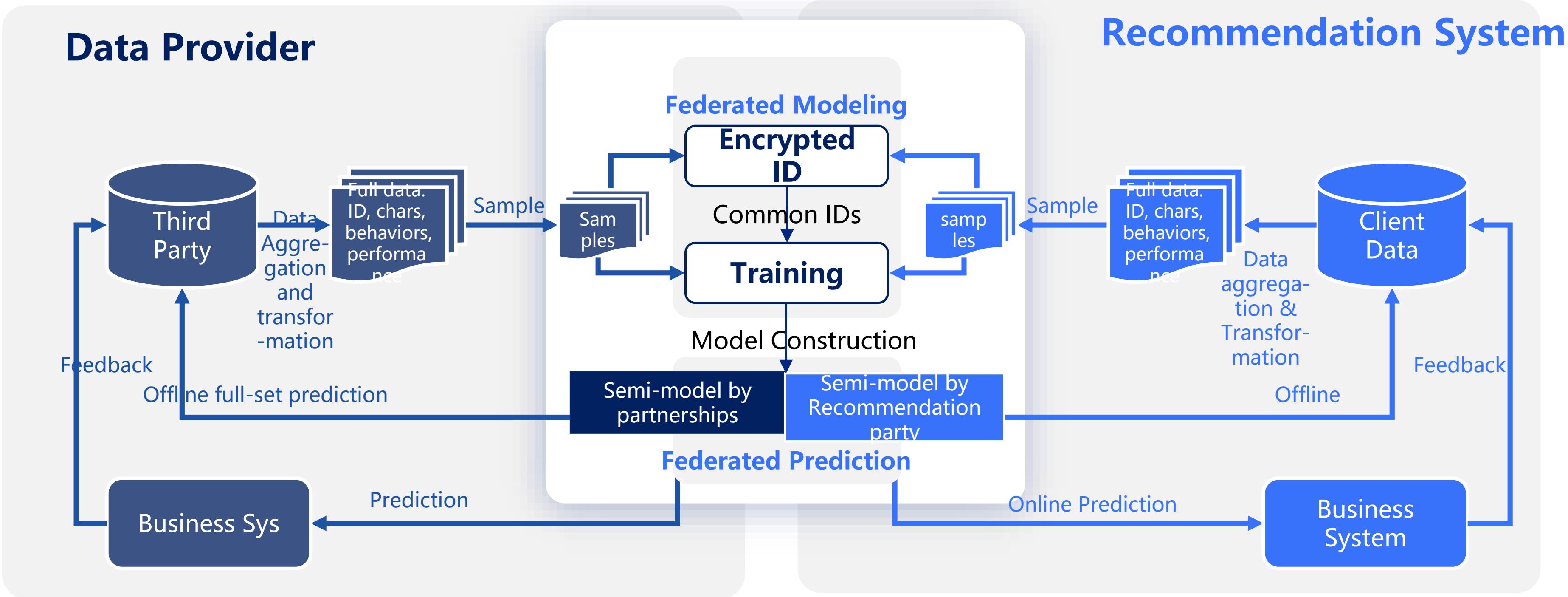


Page View + 21%

Reading Time + 22%

Click Through +11%

Process of FL



Note: Customer ID includes but not limited to government ID, mobile phone numbers, device ID, etc.;
Federated model training is initiated by the party who has y-feature

Qiang Yang 202212

Speech Recognition on Multiple Data Sources

1

Vendor仅可以根据Client提供的文本信息微调语言模型

Speech Models

2

Client需要给Vendor暴露明文数据来微调ASR

Client Privacy Protection

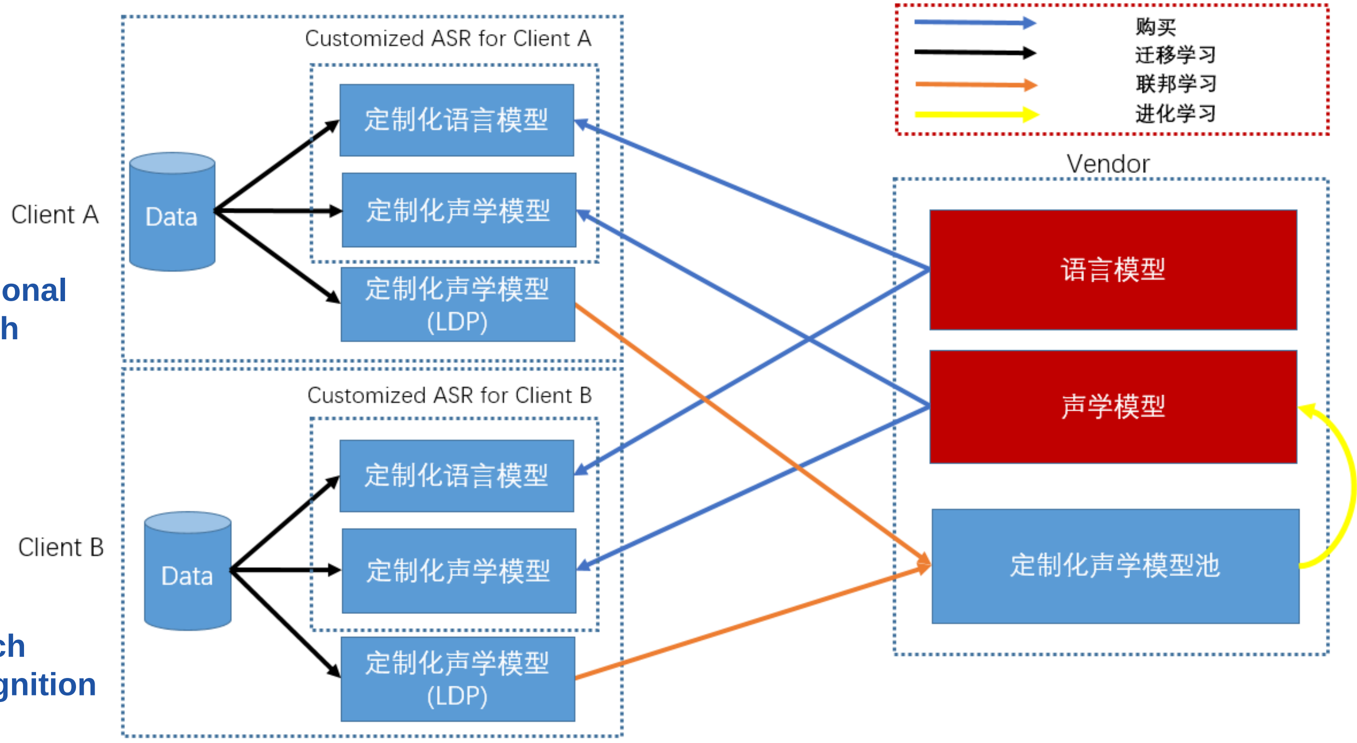
3

Vendor和Client之间只存在购买这一单向行为

Recurrent training

TFE= Transfer + Federated + Evolutionary

Traditional Speech Recognition



Reduced error by 10%~20%

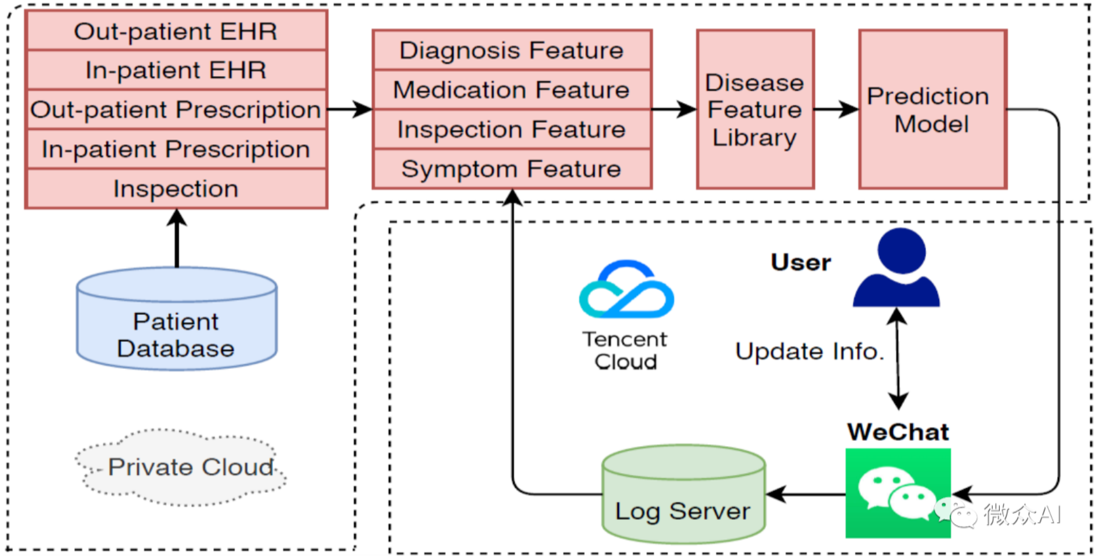
WeBank-AI and Tencent Joint Project

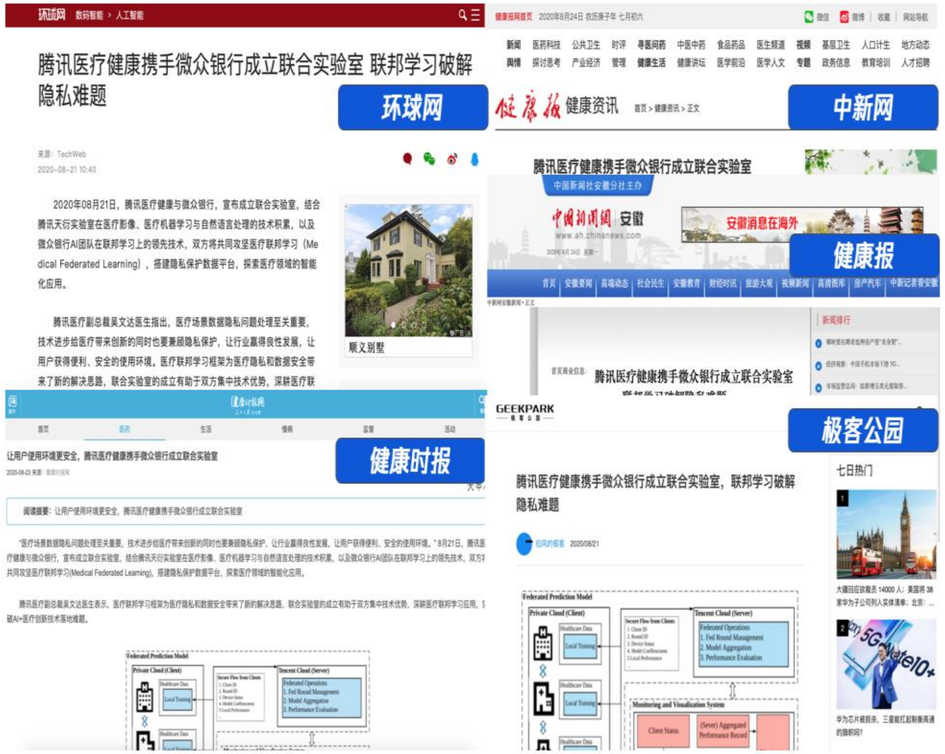
- Accuracy: Improvement over 80%
- Small hospitals: 10-20%

FL-IJCAI' 20 Paper

Privacy-Preserving Technology to Help Millions of People: Federated Prediction Model for Stroke Prevention

Ce Ju[1,*], Ruihui Zhao[2,*], Jichao Sun[2,*], Xiguang Wei[1,*], Bo Zhao[2], Yang Liu[1], Hongshan Li[3], Tianjian Chen[1], Xinwei Zhang[4], Dashan Gao[5,6], Ben Tan[1], Han Yu[7] and Yuan Jin[8]




环球网 数码智能 › 人工智能

腾讯医疗健康携手微众银行成立联合实验室 联邦学习破解隐私难题

环球网

来源：TechWeb
2020-08-21 10:40

2020年08月21日，腾讯医疗健康与微众银行，宣布成立联合实验室，结合腾讯天衍实验室在医疗影像、医疗机器学习与自然语言处理的技术积累，以及微众银行AI团队在联邦学习上的领先技术，双方将共同攻坚医疗联邦学习（Medical Federated Learning），搭建隐私保护数据平台，探索医疗领域的智能化应用。

腾讯医疗副总裁吴文达医生指出，医疗场景数据隐私问题处理至关重要，技术进步给医疗带来创新的同时也要兼顾隐私保护，让行业赢得良性发展，让用户获得便利、安全的使用环境。医疗联邦学习框架为医疗隐私和数据安全带来了新的解决思路，联合实验室的成立有助于双方集中技术优势，深耕医疗联

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让用户使用环境更安全，腾讯医疗健康携手微众银行成立联合实验室

健康时报

阅读提要：让用户使用环境更安全，腾讯医疗健康携手微众银行成立联合实验室

"医疗场景数据隐私问题处理至关重要，技术进步给医疗带来创新的同时也要兼顾隐私保护，让行业赢得良性发展，让用户获得便利、安全的使用环境。"8月21日，腾讯医疗健康与微众银行，宣布成立联合实验室，结合腾讯天衍实验室在医疗影像、医疗机器学习与自然语言处理的技术积累，以及微众银行AI团队在联邦学习上的领先技术，双方将共同攻坚医疗联邦学习(Medical Federated Learning)，搭建隐私保护数据平台，探索医疗领域的智能化应用。

腾讯医疗副总裁吴文达医生表示，医疗联邦学习框架为医疗隐私和数据安全带来了新的解决思路，联合实验室的成立有助于双方集中技术优势，深耕医疗联邦学习应用，突破AI+医疗创新技术落地难题。

GEEKPARK 极客公园

极客公园

腾讯医疗健康携手微众银行成立联合实验室，联邦学习破解隐私难题

拉风的极客 2020/08/21

七日热门

1 大疆回应裁员 14000 人；美国将 38 家华为子公司列入实体清单；北京：...

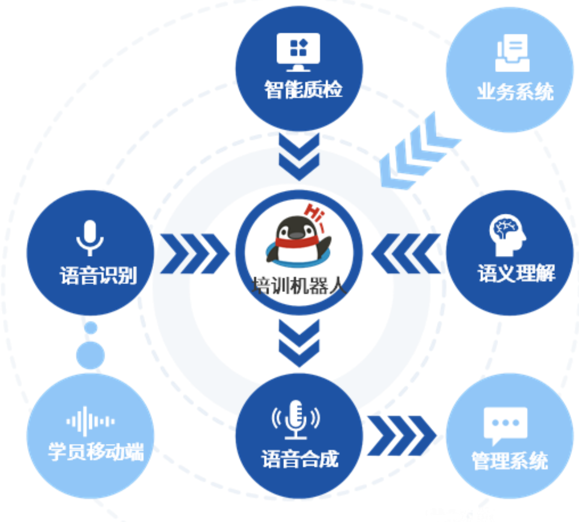
2 华为芯片被扼杀，三星能扛起制衡高通的旗帜吗？

Application： online service robots KYC, AI services @ WeBank)

AI soft robots training of service persons

智能培训

通过“语音识别+语义理解+语音合成+智能质检”方案，录入真实案例，**以场景互动方式传授说话技巧并与学员进行对话练习。**



功能优势

- 录入海量教学案例以语音对话方式进行教学
- 模拟真实销售、客服服务场景与学员情景对练
- 对学员的回复进行实时质检
- 建立学员画像，对学员成绩进行个性化分析
- 支持APP、小程序、PC端多渠道教学

应用场景&效果

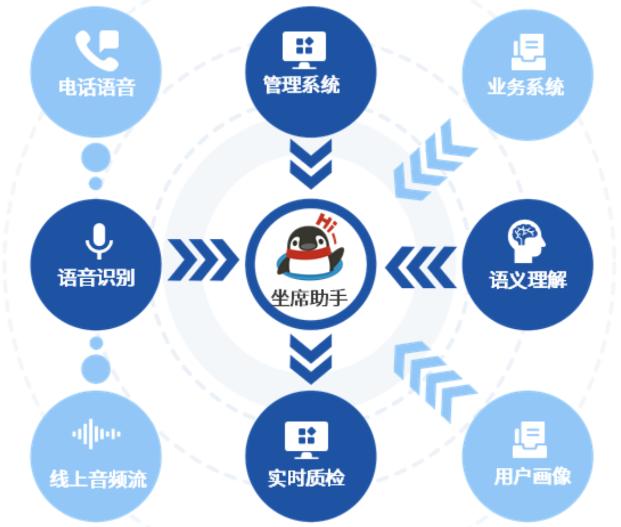
面对各业务销售及客服服务领域，提供高效、便捷的情景对练式培训，有效降低人力成本，提升培训效果，降低销售、客服人员流动性大带来的培训风险。

保险销售 汽车销售 房产销售 客服培训

AI soft robots answering questions online

电话坐席助手

通过语音识别、语义理解、用户画像等技术，**坐席助手可以提供用户画像辅助坐席决策，提供实时话术推荐辅助坐席对话，并对所有客服通话内容进行实时质检和管控。**



功能优势

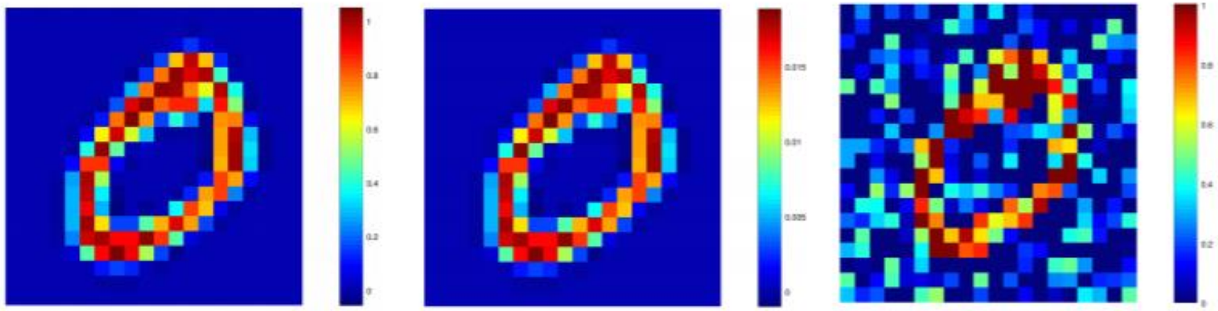
- 语音内容实时转译
- 实时知识点推荐搜索
- 业务流程提示，标准话术引导
- 对通话内容实时质检
- 用户画像信息展示

应用场景&效果

将纯人工电话坐席场景应用模式升级，深度人机协同，实时过程管控，端到端话术沉淀。

⬆ 业务效率 ⬇ 服务风险 ⬆ 营销转化

Is the Gradient Info Safe to Share?



(a) Original 20x20 image of handwritten number 0, seen as a vector over $\mathbb{R}^{400}$ fed to a neural network.

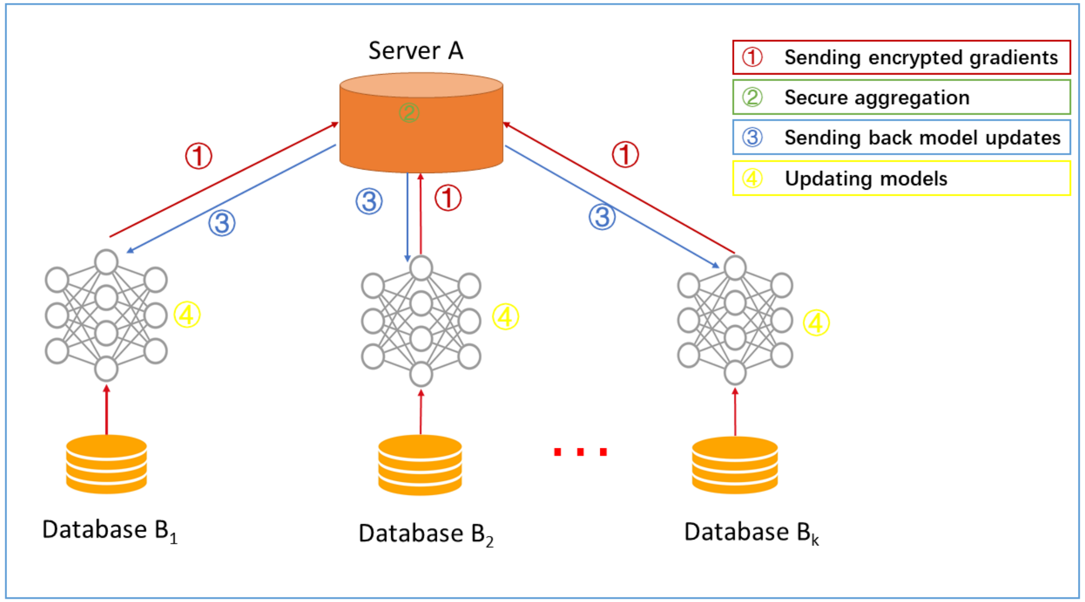
(b) Recovered image using 400/10285 (3.89%) gradients (see Sect.3, Example 2). The difference with the original (a) is only at the value bar.

(c) Recovered image using 400/10285 (3.89%) gradients (see Sect.3, Example 3). There are noises but the truth label 0 can still be seen.

Fig. 3. Original data (a) vs. leakage information (b), (c) from a small part of gradients in a neural network.

Le Trieu Phong, et al. 2018. Privacy-Preserving Deep Learning via Additively Homomorphic Encryption. IEEE Trans. Information Forensics and Security, 13, 5 (2018),1333–1345

Protect gradients with Homomorphic Encryption



Algorithm ensures that no information is leaked to the semi-honest server, provided that the underlying additively homomorphic encryption scheme is secure*.

* Q. Yang, Y. Liu, T. Chen, Y. Tong, Federated machine learning: concepts and applications, ACM TIST , 2018

Challenges for Federated Learning

Models [BVH+18]

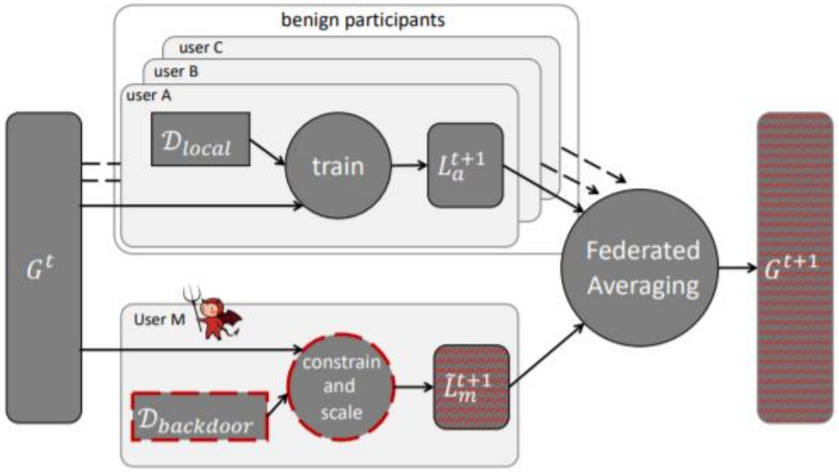
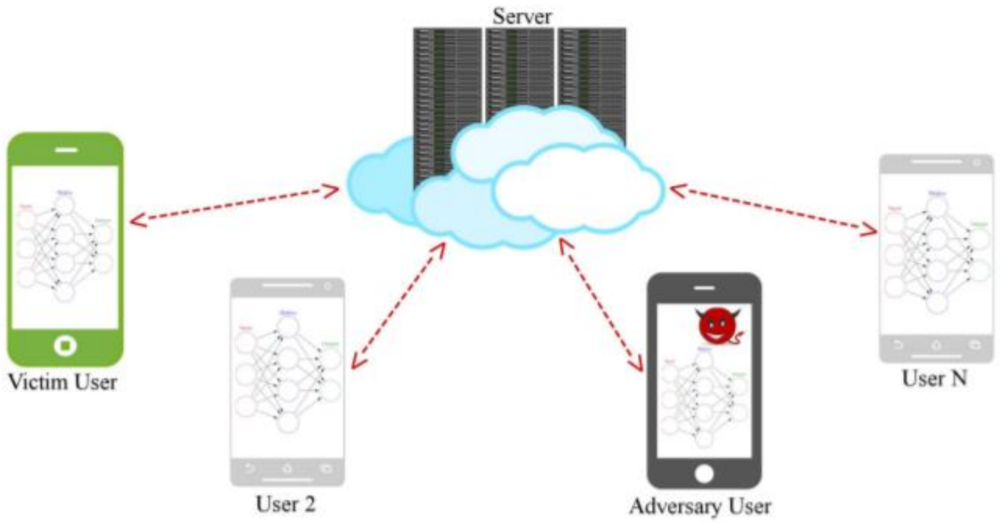


Fig. 1: **Overview of the attack.** The attacker compromises one or more of the participants, trains a model on the backdoor data using our new constrain-and-scale technique, and submits the resulting model. After federated averaging, the global model is replaced by the attacker's backdoored model.

Eugene B et al. 2018. ***How To Backdoor Federated Learning.*** arXiv:cs.CR/1807.00459

Data [HAP17]

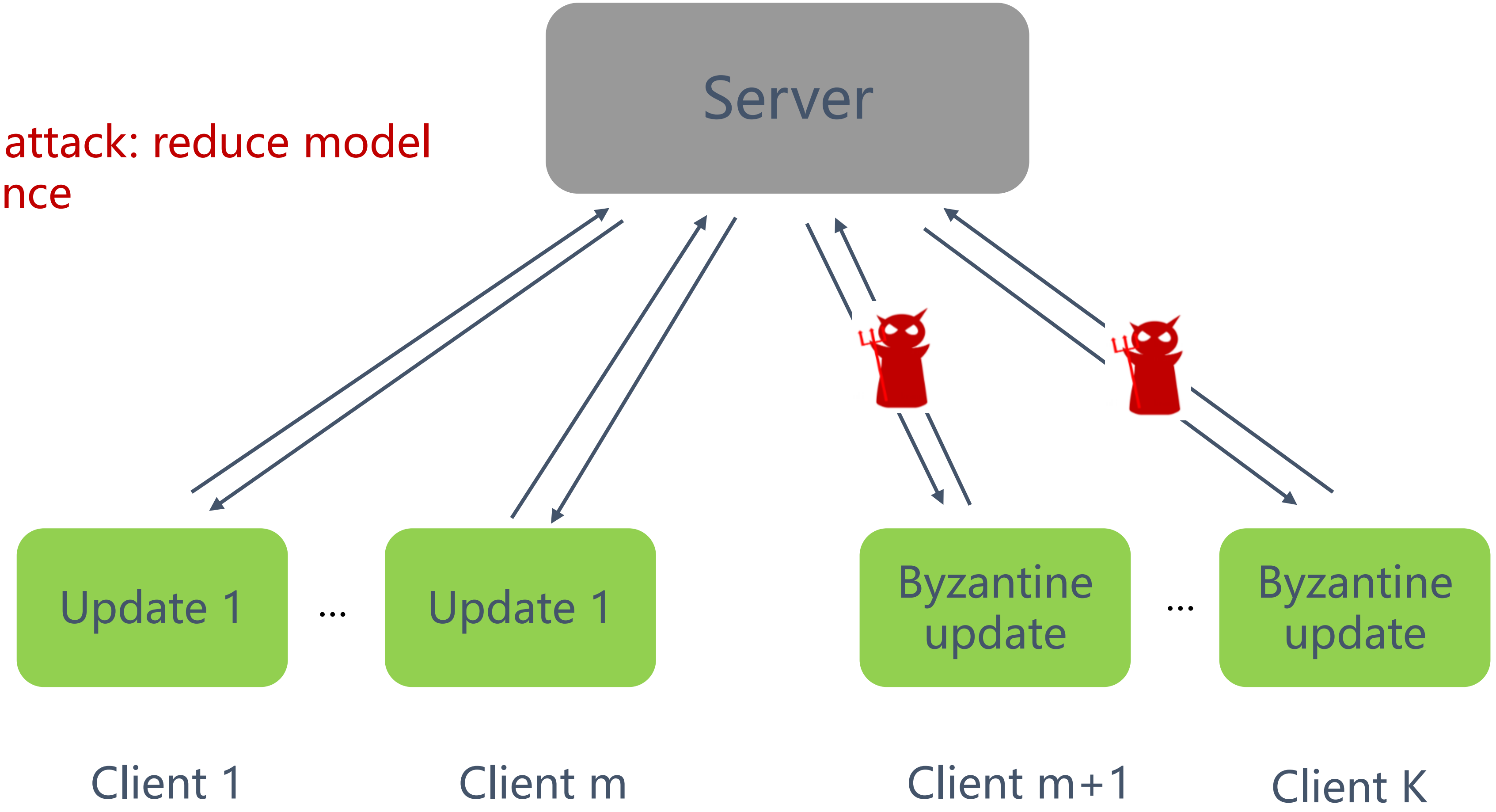


(b) Collaborative Learning

Briland H et al. 2017. ***Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning***

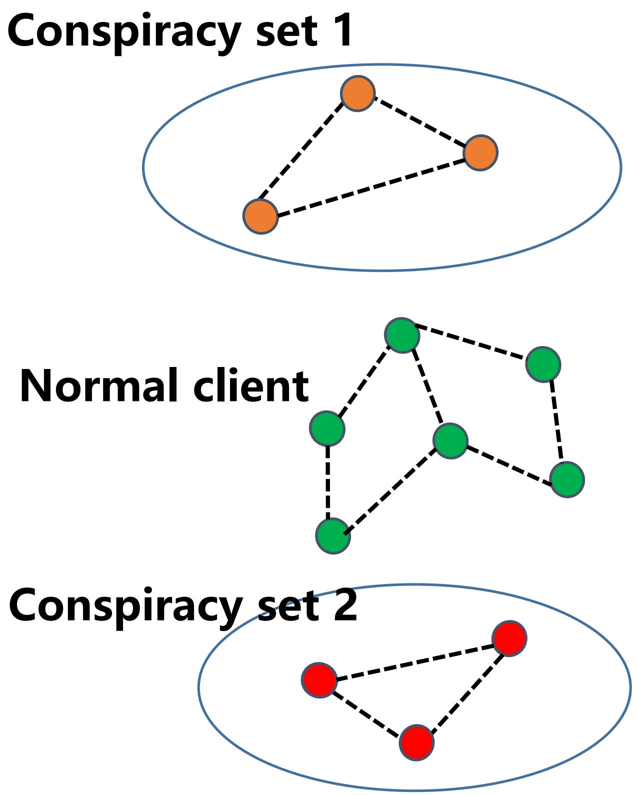
New in Federated Learning: Reliable Detection of Byzantine Colluders

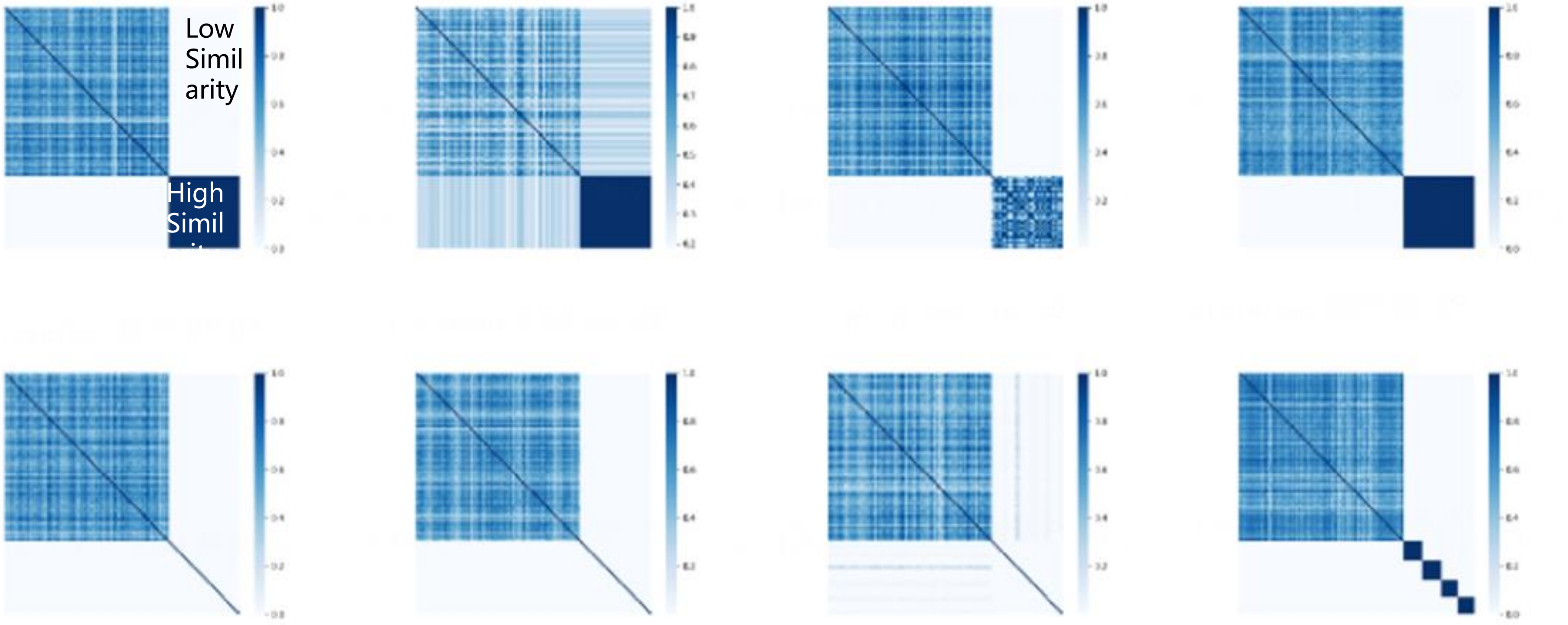
Target of attack: reduce model performance



FedSpectral: A Spectral Analysis Framework for Reliable Detection of Byzantine Colluders (submitted)

Reliable Detection of Byzantine Colluders

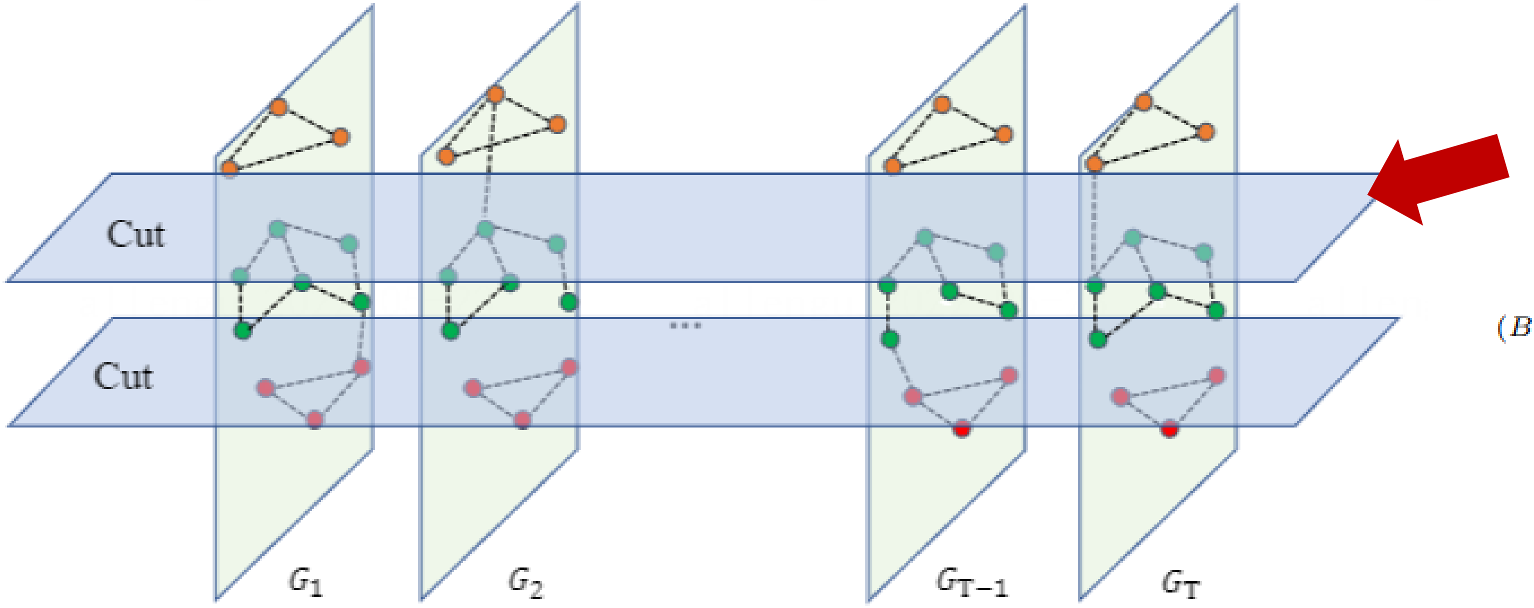




FedSpectral: A Spectral Analysis Framework for Reliable Detection of Byzantine Colluders (submitted)

Reliable Detection of Byzantine Colluders

- 对T轮的多个client模型更新向量， 构建一个G1至GT层的**spatial-temporal图**
- 把检测看成是一个经典的图**Ncut分割**问题, 使得分割后的两个子图, 相互间的连接最弱（最不相似）， 子图内部节点间的连接最强（最相似）
- 利用谱分析的eigengap heuristic来估计**共谋组的个数**，从而提升共谋检测的精确度**, 及联邦模型的性能**



Ncut Goal:

$$\min_{(B_1\cup\cdots\cup B_C)=V} \sum_{t=1}^{T}\sum_{i=1}^{k}\frac{W^t(B_i,\overline{B_i})}{Vol^t(B_i)},$$

FedSpectral: A Spectral Analysis Framework for Reliable Detection of Byzantine Colluders (submitted）

Reliable Detection of Byzantine Colluders

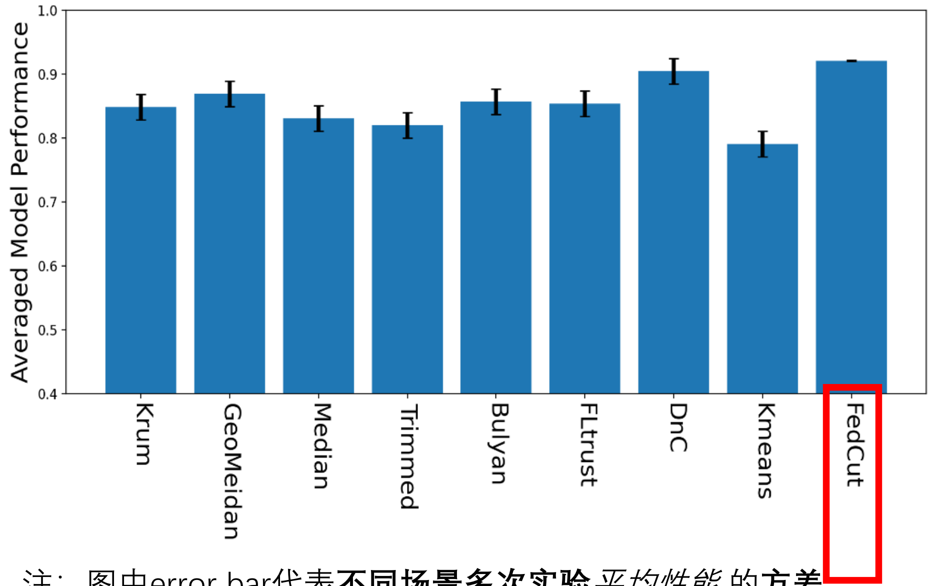
Federated Learning’s Mean Performance:

Best overall（>92%）

Worst Performance：

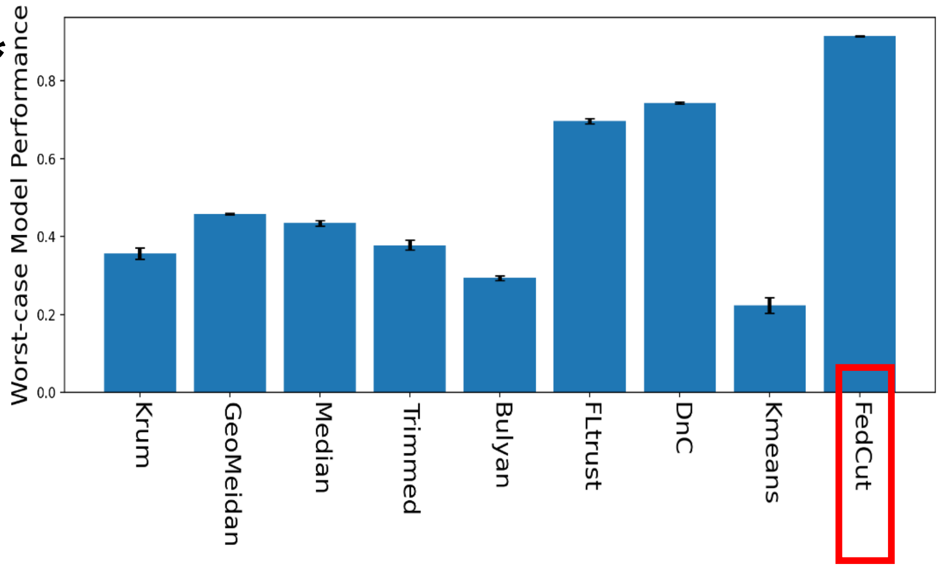
Federated Learning still best （>87%）
Variance small（≈5%）

性能



注：图中error bar代表**不同场景多次实验***平均性能* 的**方差**
（FedCut比它8种防御方法的方差更小，更鲁棒）

性能



注：图中error bar代表**不同场景多次实验***最差性能* 的**方差**
（FedCut比它8种防御方法的方差更小，更鲁棒）

FedSpectral: A Spectral Analysis Framework for Reliable Detection of Byzantine Colluders (submitted)

‘Federated Learning' Standards

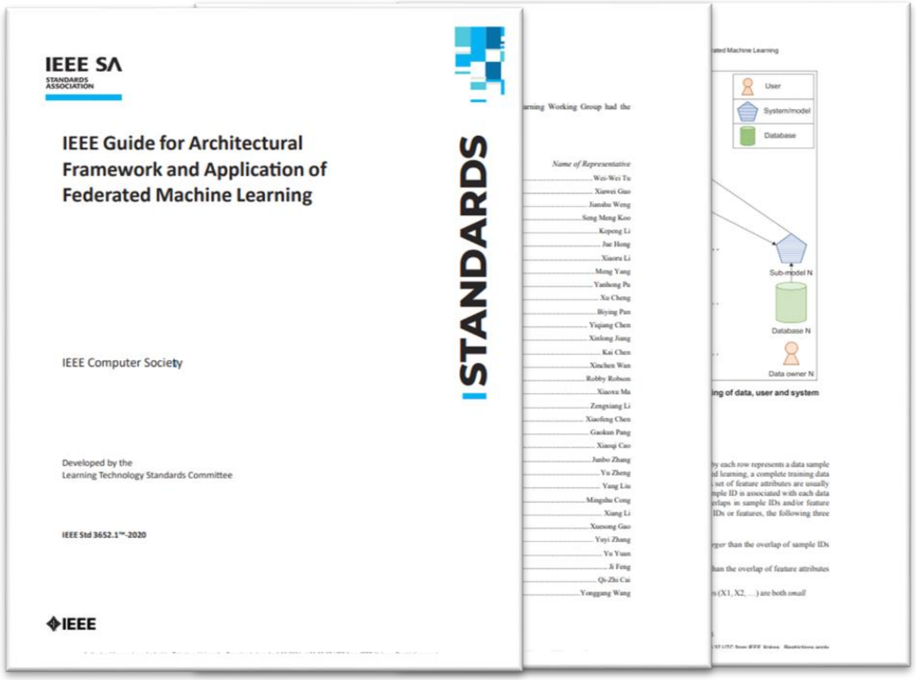
Published

IEEE P3652.1 《 **Guide for Architectural Framework and Application of Federated Machine Learning**》

- **March, 2021**， **first federated learning standards in the world**， **20 participants, 6 meetings, 10 scenarios**

China Communications Standards 《 **Technical Requirements and Test Methods for Federated-Learning-based Data Products** 》

- **July 2020**， **17** participants
- Scheduling management, testing etc.



IEEE SA
STANDARDS ASSOCIATION

IEEE Guide for Architectural Framework and Application of Federated Machine Learning

IEEE Computer Society

Developed by the
Learning Technology Standards Committee

IEEE Std 3652.1™-2020

IEEE

STANDARDS

Ongoing

- Financial Industry《 **The Financial Applications of Federated Learning and its Connectivity Specifications** 》
- Telecom Industry（CCSA-TC1/TF1）: 《**The Technical Requirements and Test Methods of Safety Assessment for Federated Learning**》《**The Interoperability Technical Requirements of the Cross-Framework in Federated Learning**》
- Intra-enterprise （CCSA-T601）： 《**The Interoperability Standards of the Cross-Platform in Federated Learning** 》

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腾讯云
京东城市

Federated Learning Open Source Platform: FATE

FATE

I. Industrial Scale
II. Government certified
III. Efficient, Safe, Easy to use

Design

I. Many algorithms in machine learning
II. Many privacy-preserving computation operators including MPC

Participants include

中国工商银行 INDUSTRIAL AND COMMERCIAL BANK OF CHINA
UnionPay 银联 中国银联 China UnionPay
WeBank
vmware
CLUSTAR 星云
Tencent
中国银行 BANK OF CHINA
中国电信 CHINA TELECOM
光大科技有限公司 EVERBRIGHT TECHNOLOGY CO. LTD
建信金融科技 CCB Fintech
中国农业银行 AGRICULTURAL BANK OF CHINA

FATE

LINUX FOUNDATION

Domestic Patent 427

International PCT 26

1000+ enterprises， **400+** Universities

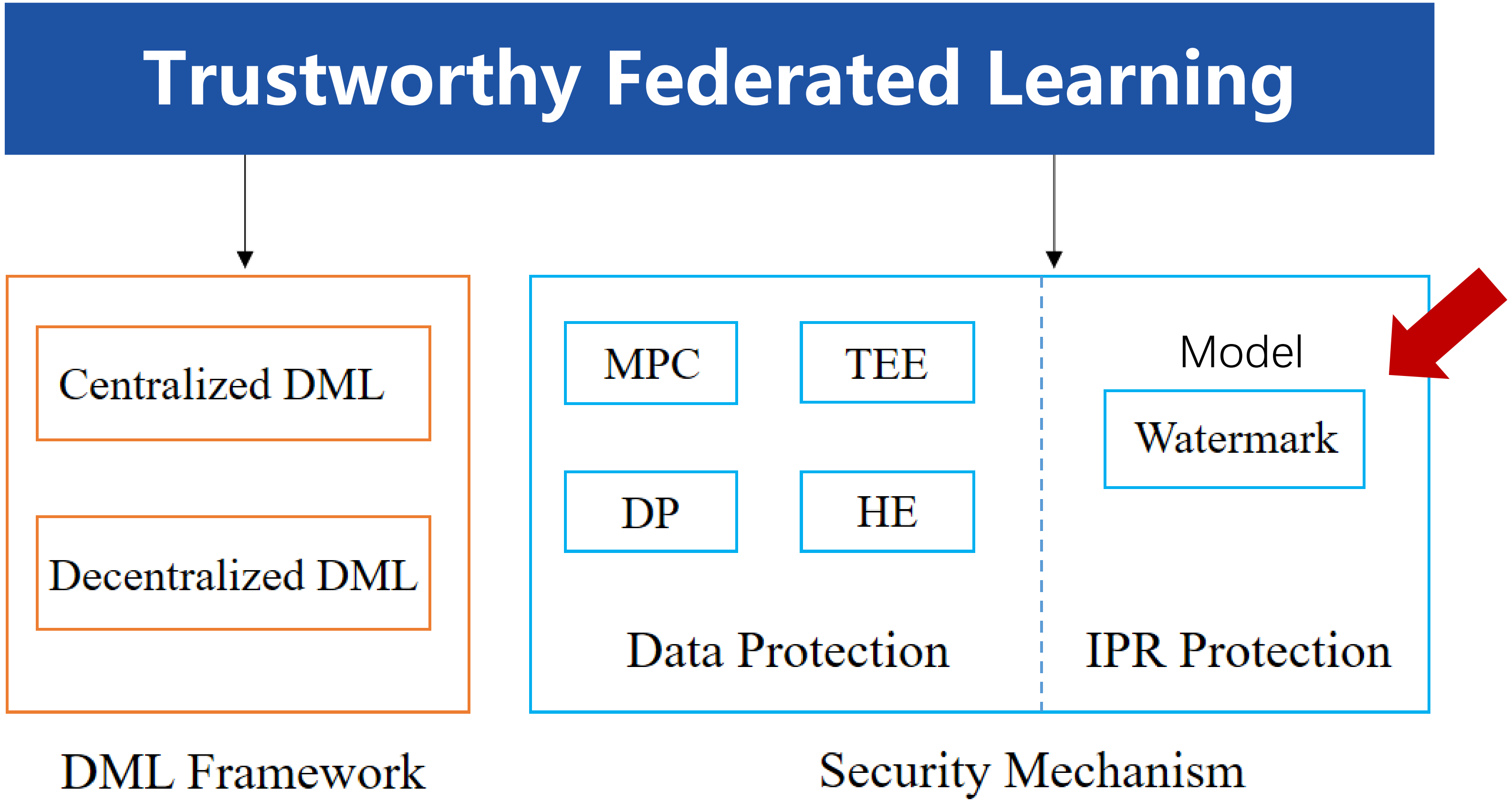
4600 GitHub Stars

19 organizations joined the FATE federated learning eco-system, including Tencent cloud, Union Pay, etc.

https://github.com/FederatedAI/

Copyright Protection for Models (FedIPR)

- Privacy Protection
- Model Protection
- **Model IP Right**
- Explainable
- Open Source



Trustworthy Federated Learning: Protection of Model IP Rights

model stealing attack [17]:

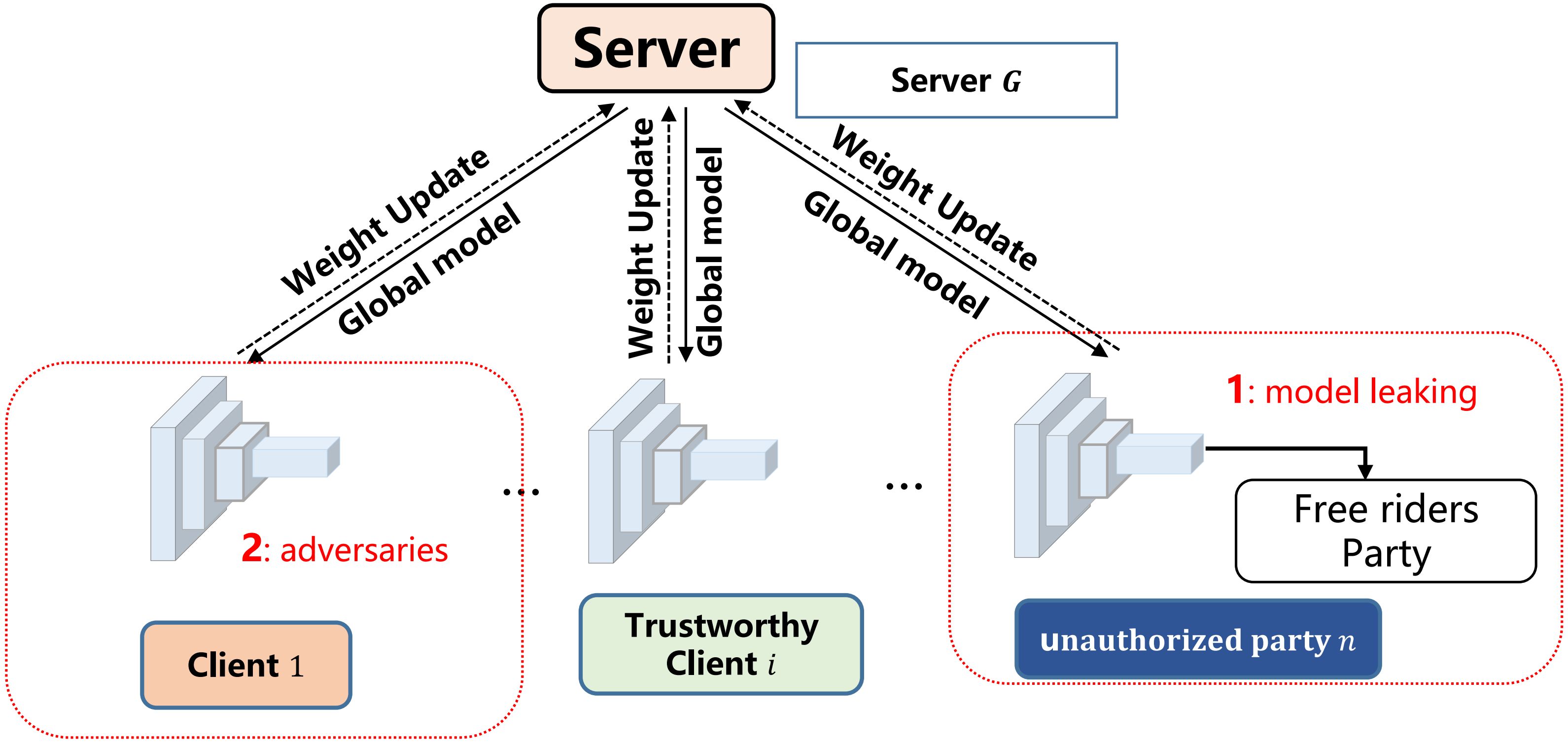
Tramer et al. proposed that adversaries can steal the (deployed) victim model with technical methods.

freerider attack [18]:

- Fraboni et al. demonstrated the possibility that freeriders join in federated learning only for plagiarizing the valuable trained models.

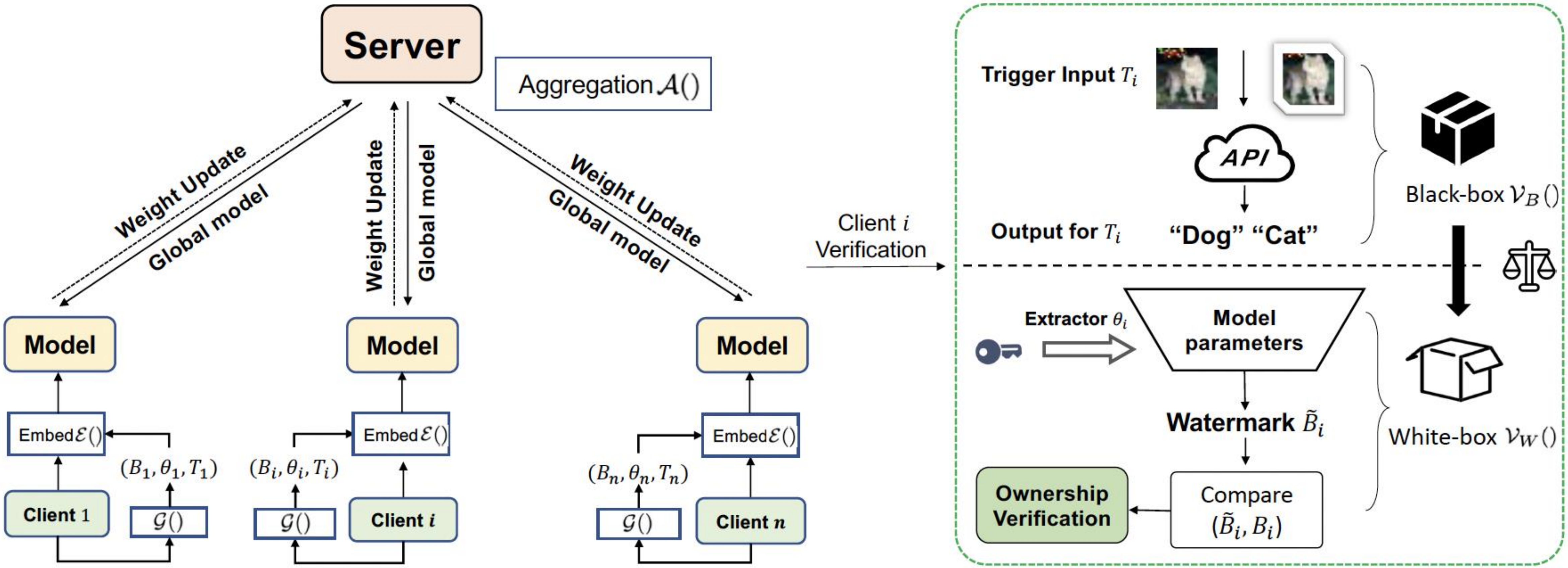
non-technical infringement:

- unauthorized parties may plagiarize the federated model with non-technical methods.



Trustworthy Federated Learning: Protection of Model IP Rights

Private watermarks



Trustworthy Federated Learning: Protection of Model IP Rights

Model tracing?

Watermarking

苏康码

苏康码

姓名：[redacted]

更新于: 2021-01-21 12:28:55

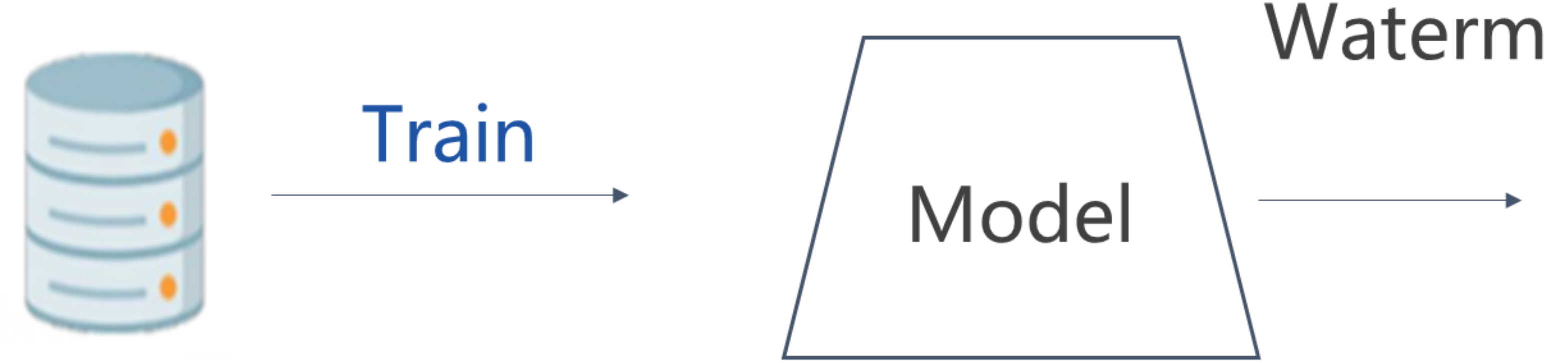
国家防疫健康信息码 增加家庭成员

★健康提示

核酸/抗体检测查询

新冠疫苗接种信息查询(江苏省)

绿色：勤洗手、常通风、戴口罩，出现发热咳嗽等症状请及时就医



Train

Model

trustworthy

昌吉州核酸检测码

昌吉州核酸检测码 切换检测码

姓名：周[redacted]

证件号：350******3524

有效期还剩 22:24:00

[redacted]

凭此码可在昌吉州范围内通行，请主动出示，配合检查

2021-01-08 13:24:34

2021-01-02, 昌吉分院, 阴性
2020-12-04, 昌吉分院, [illegible]
2020-10-04, 昌吉分院, [illegible]

我的核酸检测报告

昌吉州卫生健康委员会

Watermarks on data

Assessment functions

Explainability of AI Models

- A New Book

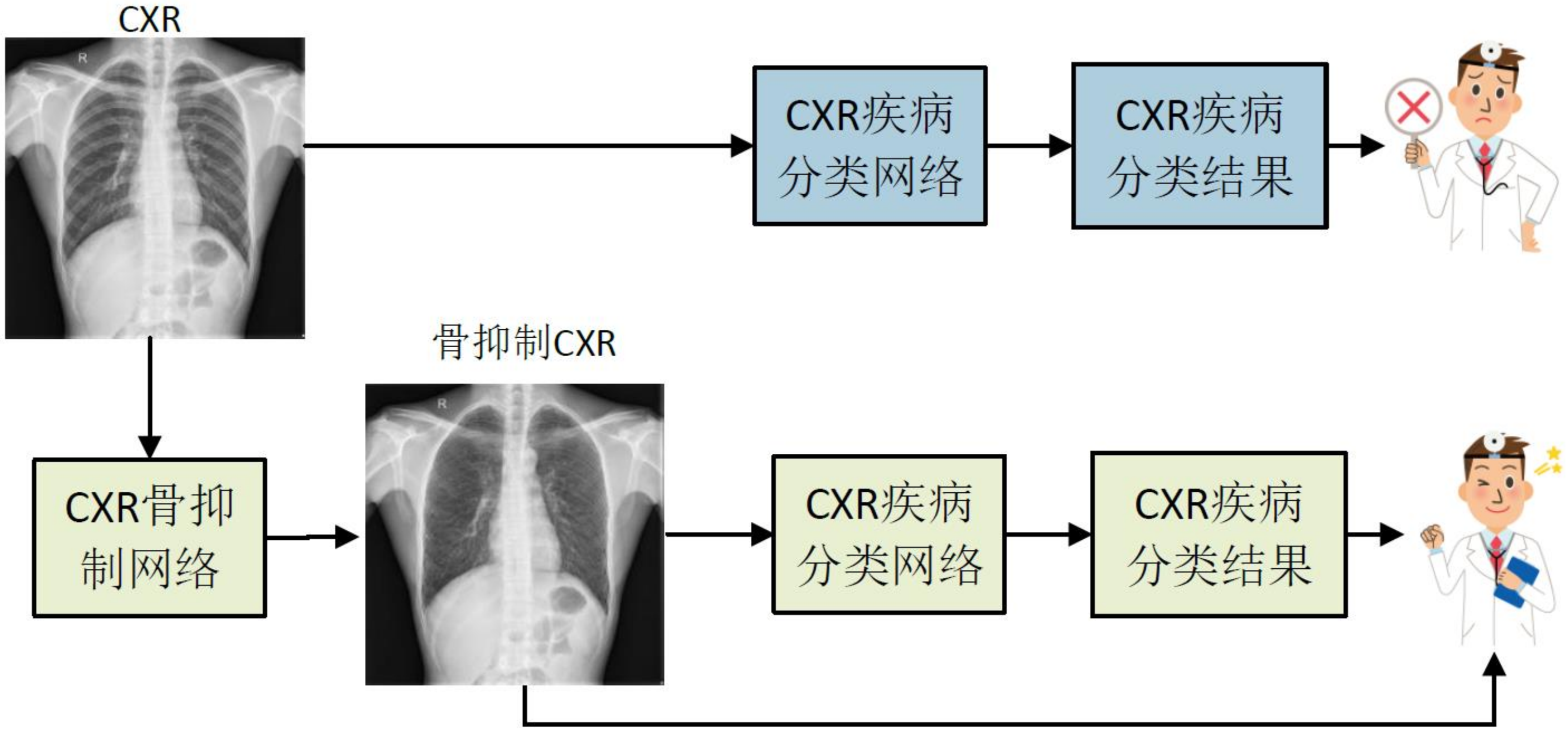


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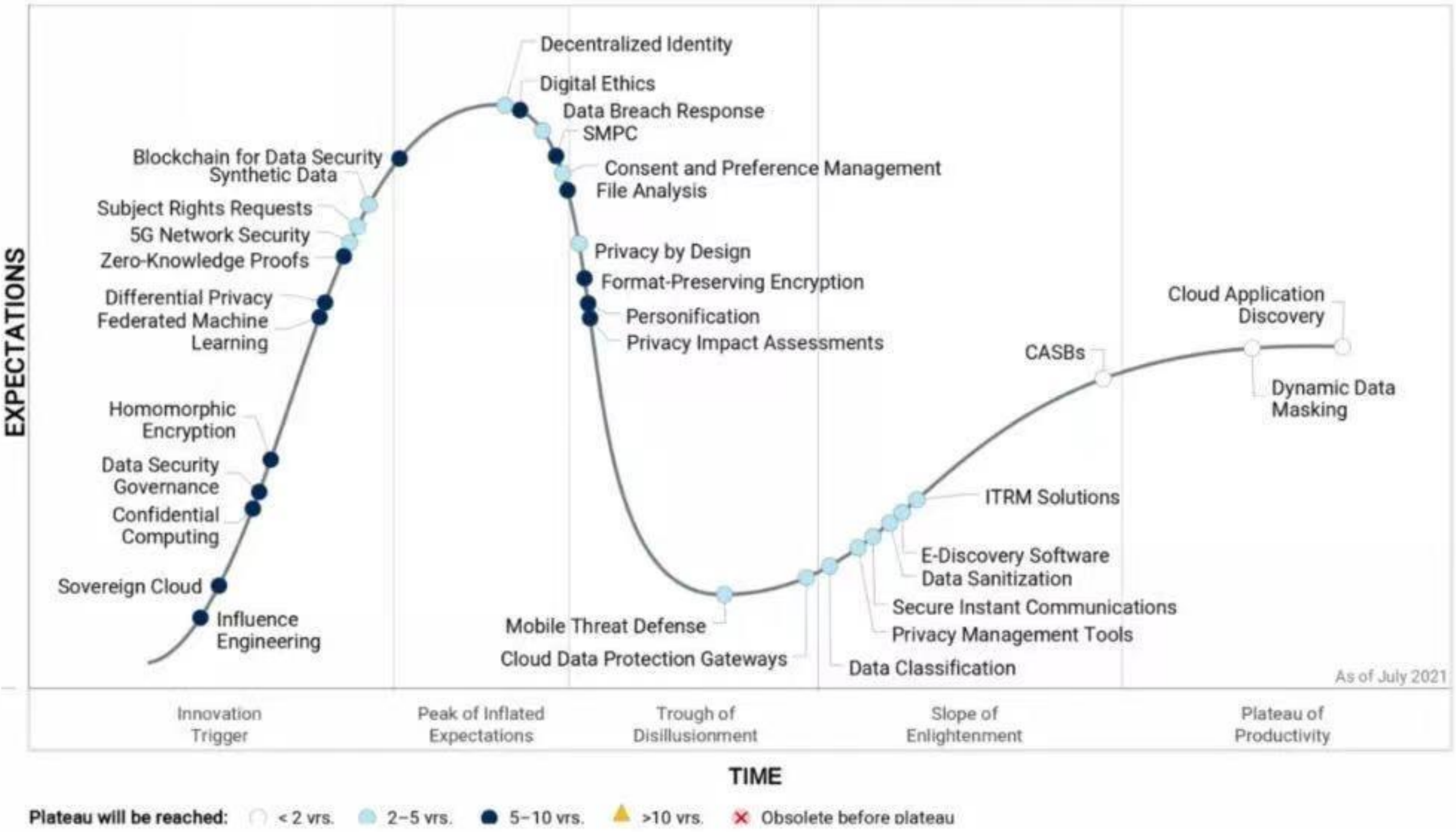
Figure 1: Hype Cycle for Privacy, 2021



Gartner

Source: Gartner (July 2021)

WeBank

Thank You