

Personalized Federated Learning:

The next major boost in ML Performance

Vaikkunth Mugunthan, Ph.D.

CEO and Cofounder of DynamoFL



About Me

- Ph.D. in privacy-preserving distributed machine learning at MIT
- Founder and CEO of DynamoFL (YC W22)
 - Personalized and Privacy-Preserving ML
 - Backed by Samsung Next, Nexus, YCombinator, GFC, Liquid2, etc.

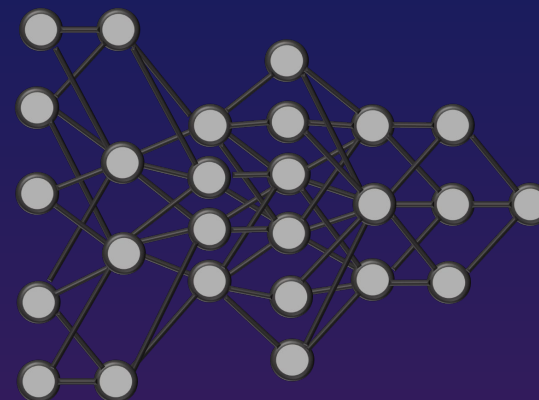
How can you train a model that captures diverse real-world data?



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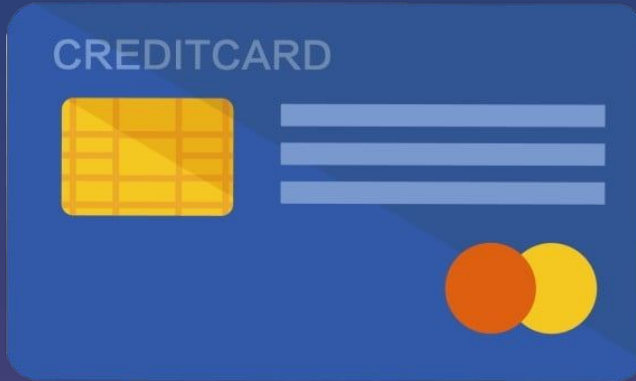


Today's Solution: One-size-fits-all Model



Challenge 1: Can't Access Diverse Privacy-Critical Data

Transactional Data



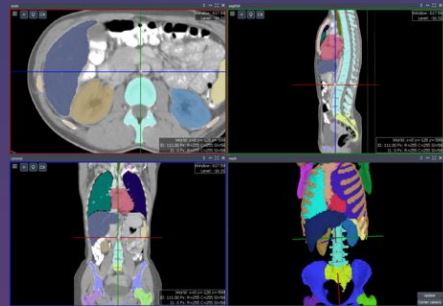
Clinical Trials / Life Sciences Data



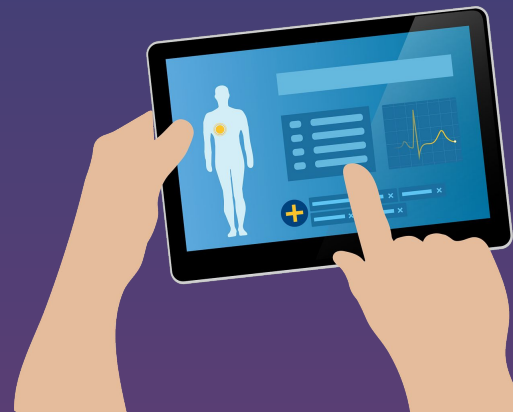
Risk Prediction



Medical Imaging Data



EHR/EMR/PHI



Regulations



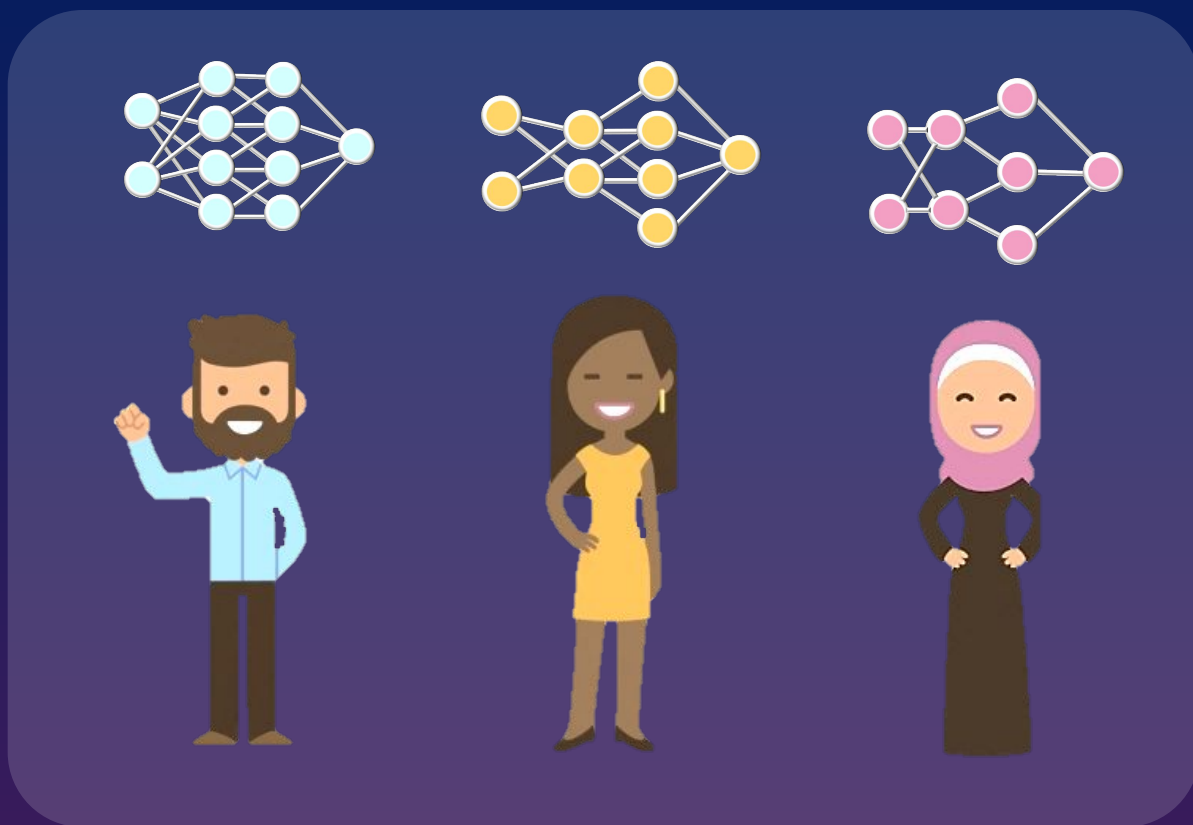
Challenge 2: Poor Performance across Diverse Cohorts

Cohorts



One-size-fits-all model struggles across under-represented cohorts

How can you train a model that captures diverse real-world data?



Our Solution:
Personalized
Federated Learning

Our Solution: Personalized Federated Learning

User Privacy

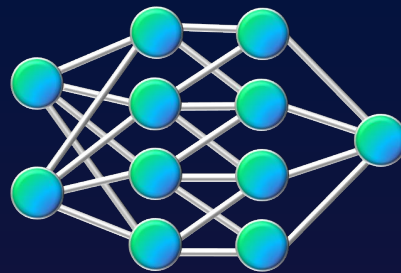


Never collect sensitive user data

Robust against privacy attacks

(Model Inversion, Membership inference, *etc.*)

Boost Performance



Boosted Top-1 Accuracy by **+14.2%** for CV Task
(work accepted for ECCV '22)

Reduced time-series prediction error by 28% for asset-forecasting case study

Slash Data Costs

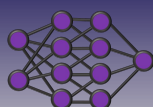


~10,000× lower data transfer costs compared to mass data upload

Never Collect Sensitive User Data

Federated Learning Workflow

Dataset 1



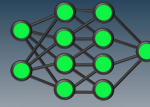
Model 1

Dataset 2



Model 2

Dataset 3



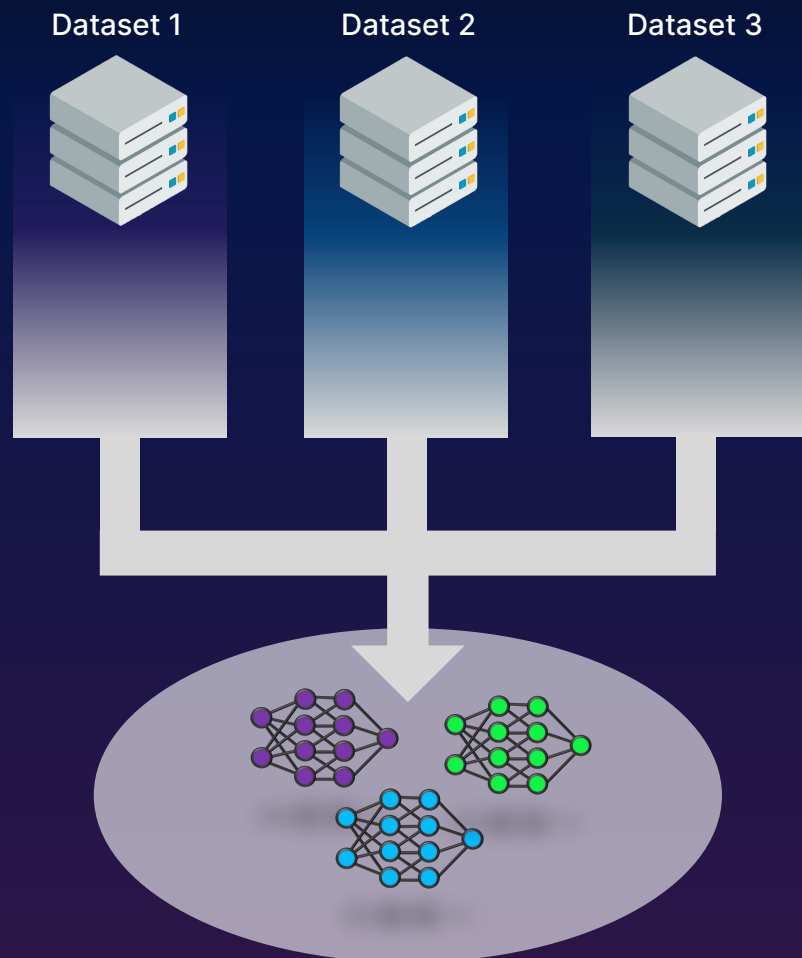
Model 3

1

Models independently trained on local datasets

Never Collect Sensitive User Data

Federated Learning Workflow



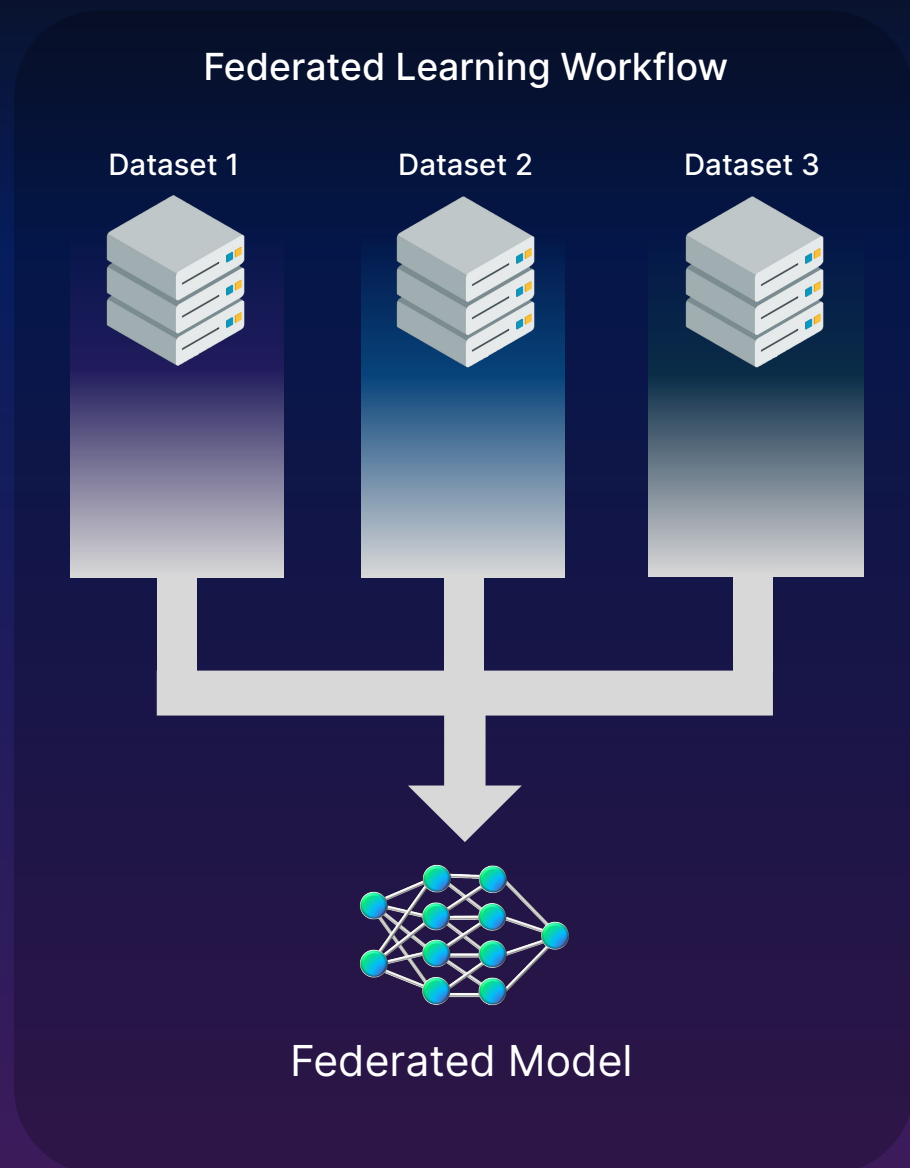
1

Models independently trained on local datasets

2

Models pushed to central federation server

Never Collect Sensitive User Data



1

Models independently trained on local datasets

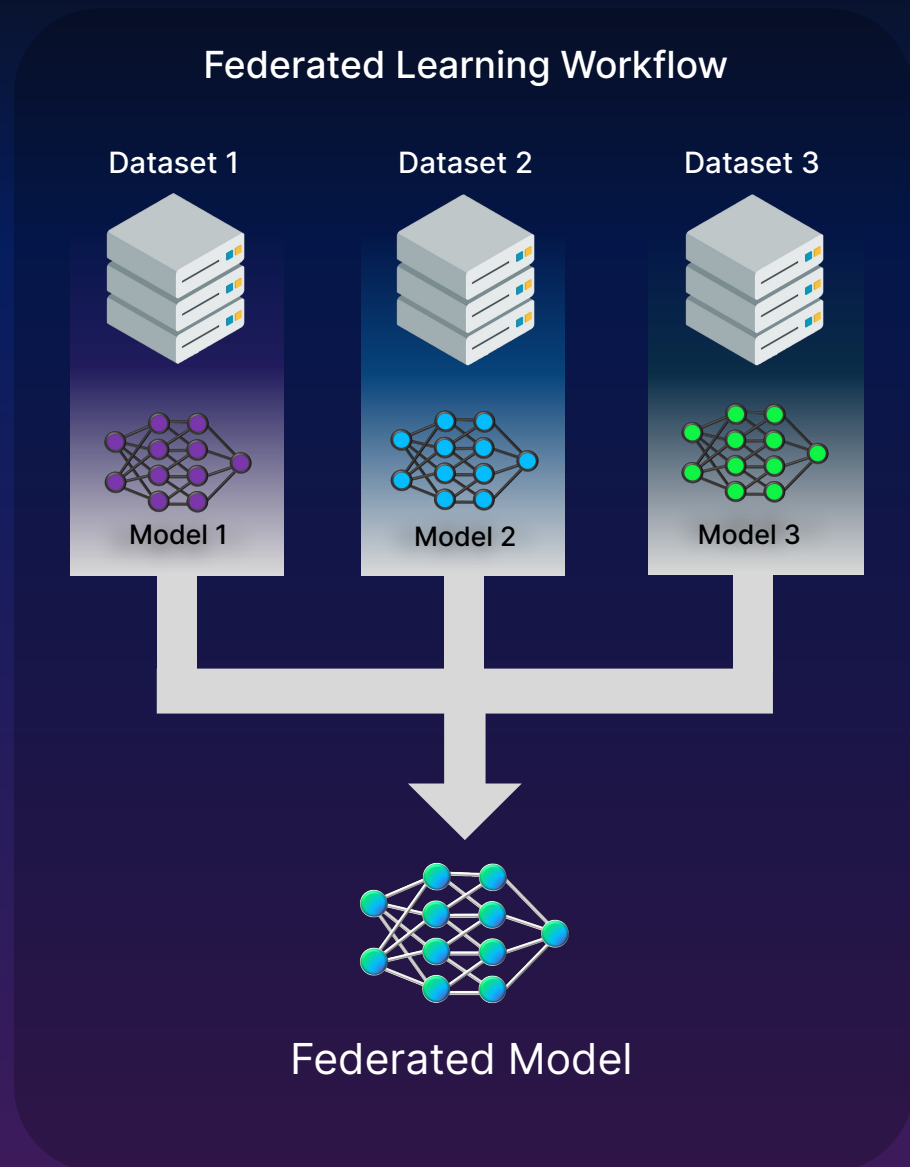
2

Models pushed to central federation server

3

Models combined on central federation server

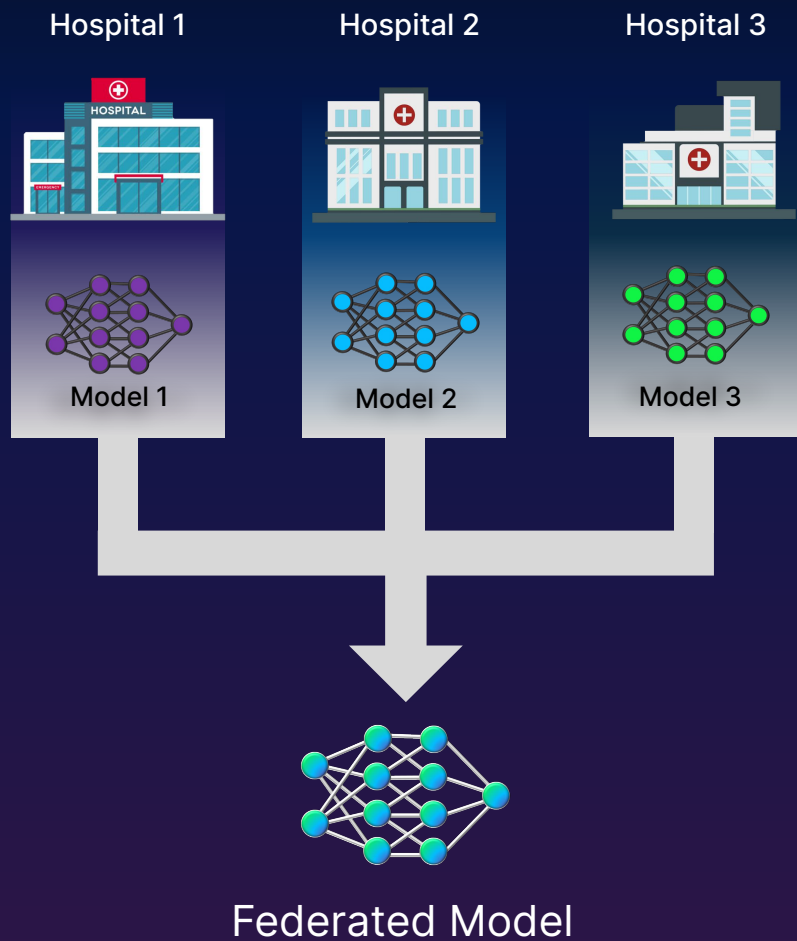
Never Collect Sensitive User Data



**Private data never leaves
its original source!**

Never Collect Sensitive Medical Data

Federated Learning Workflow



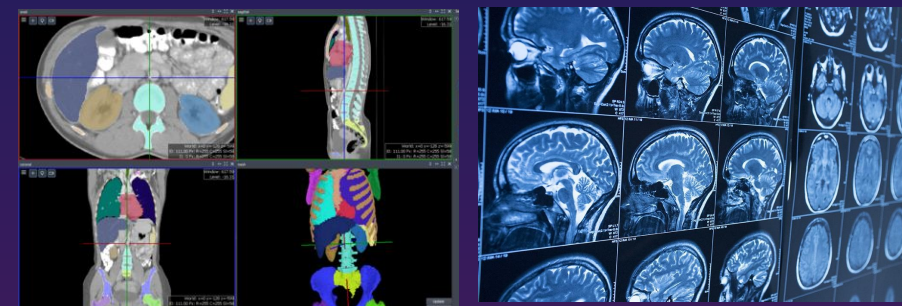
Clinical Trials / Life Sciences Data



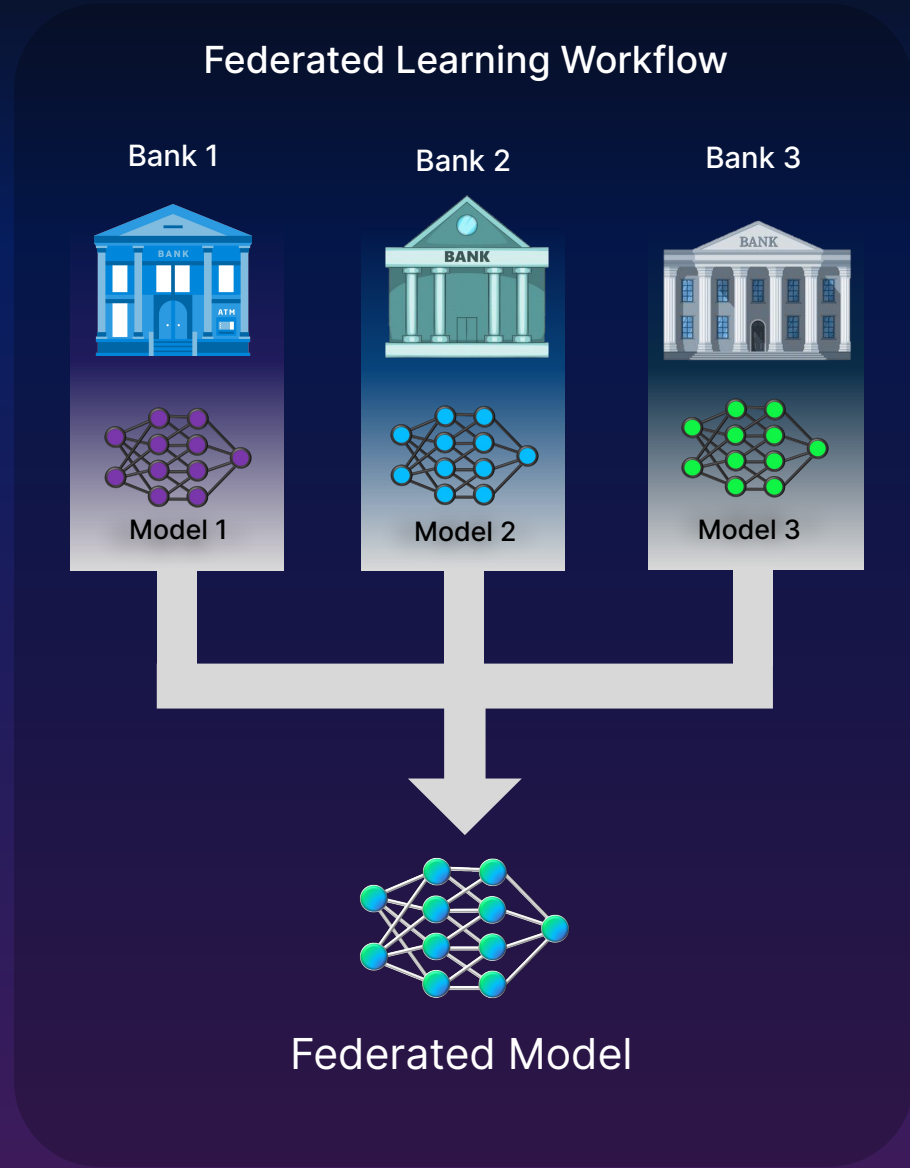
EHR/EMR/PHI



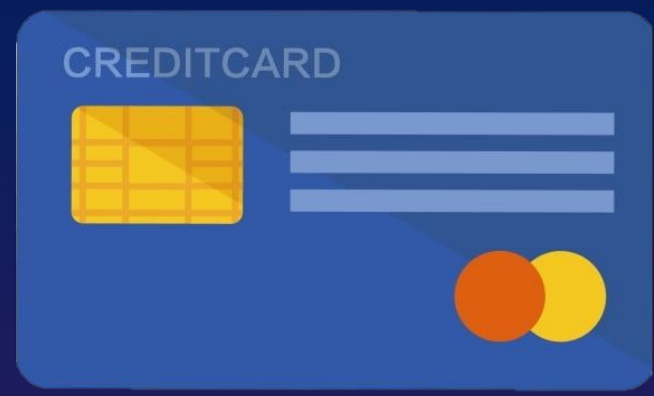
Medical Imaging Data



Never Collect Sensitive Financial Data



Fraud Detection Models



Risk Prediction



Financial Services & Product Recommendations




Our Solution: Personalized Federated Learning




“Hi!”
“ily!”
“How r u”



 “Ciao!”
“Hello”



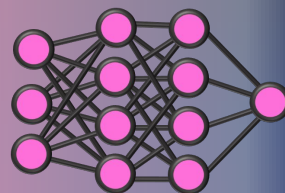
“What’s up?”
 “hbu?”


Users have diverse texting patterns

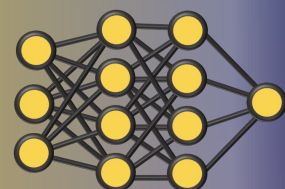
Our Solution: Personalized Federated Learning

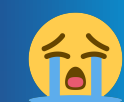


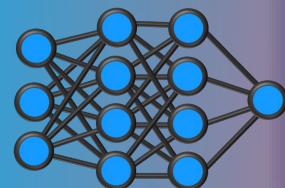
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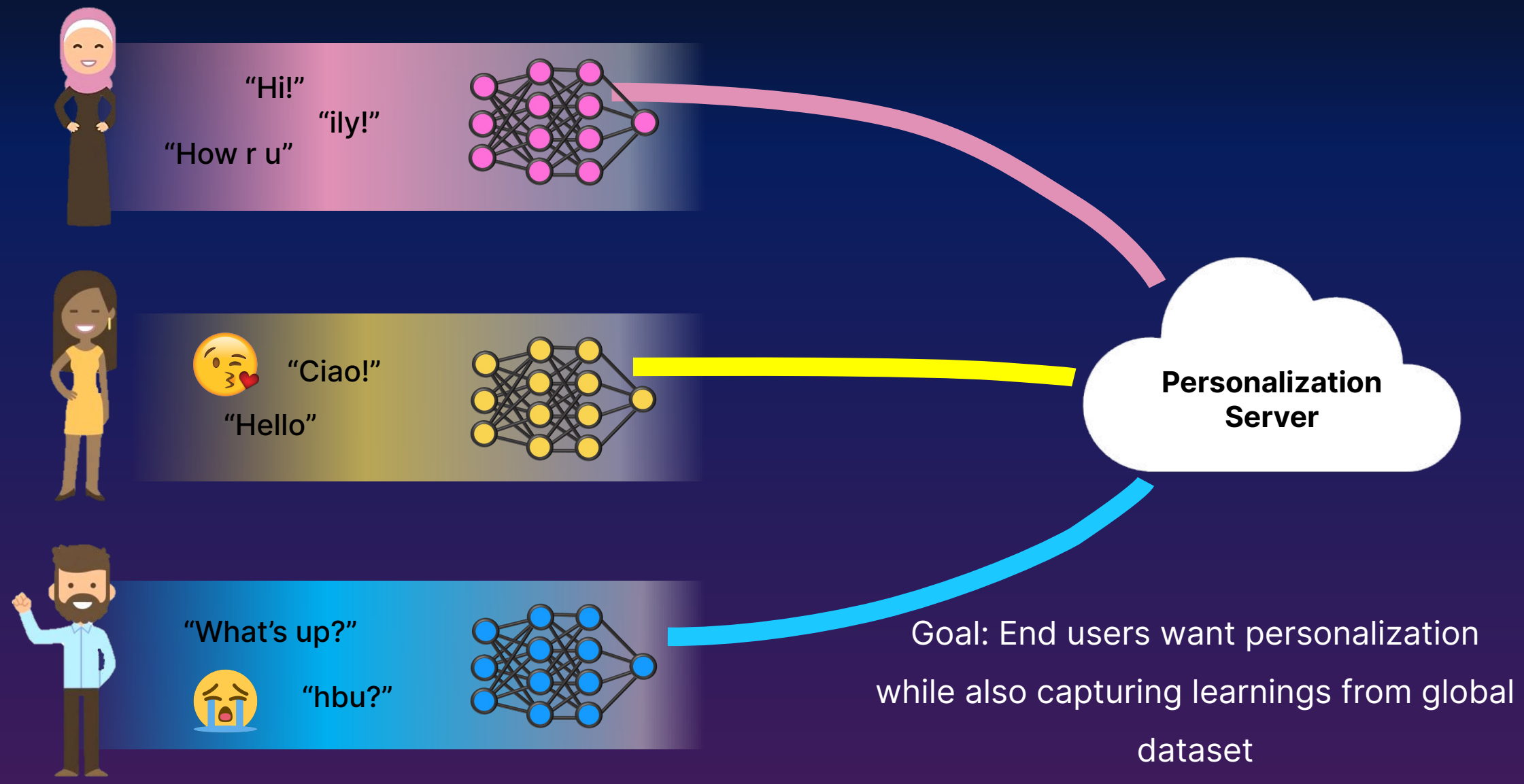


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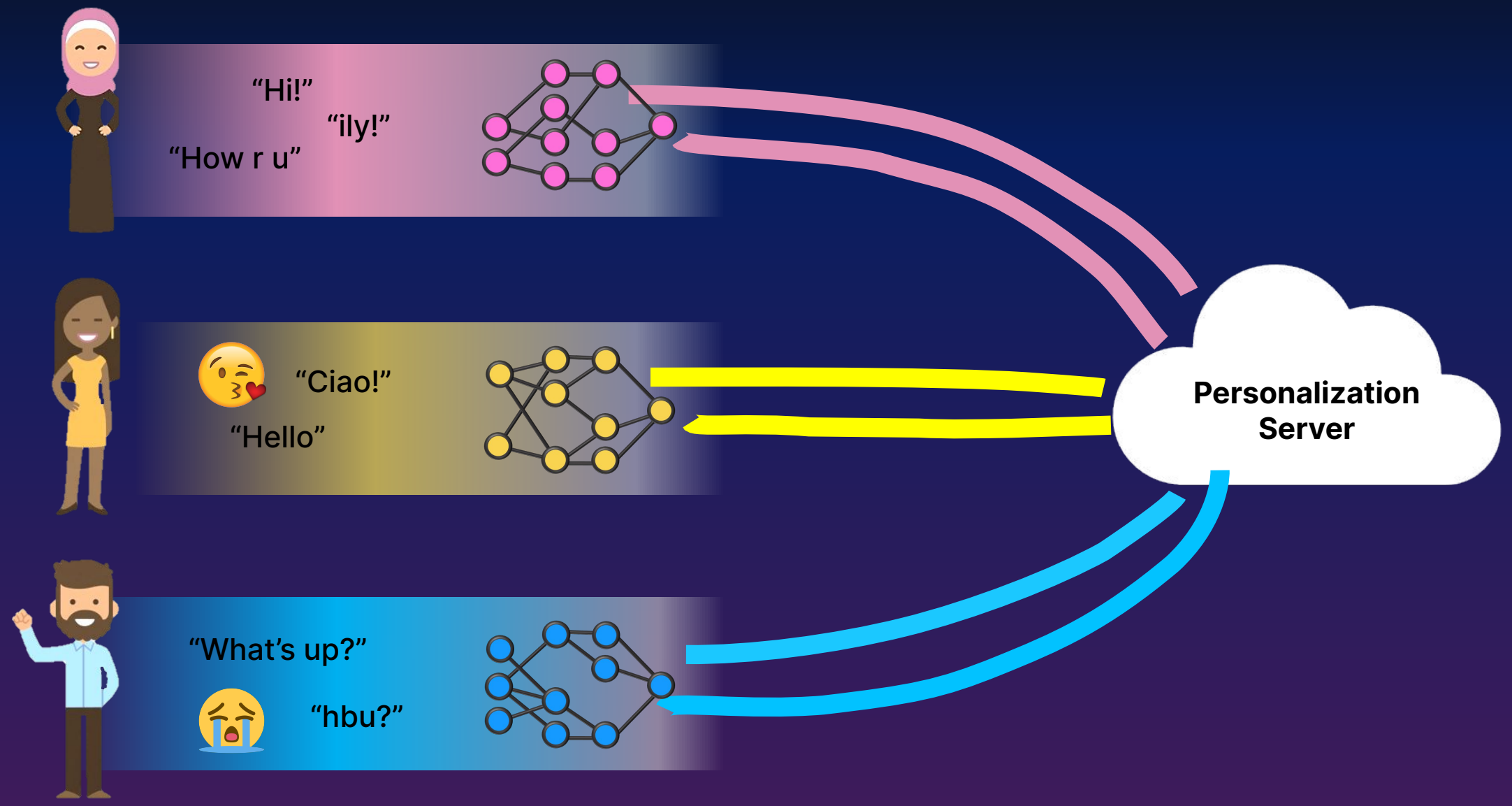


Train Next-Word-Prediction Models on User Text Data

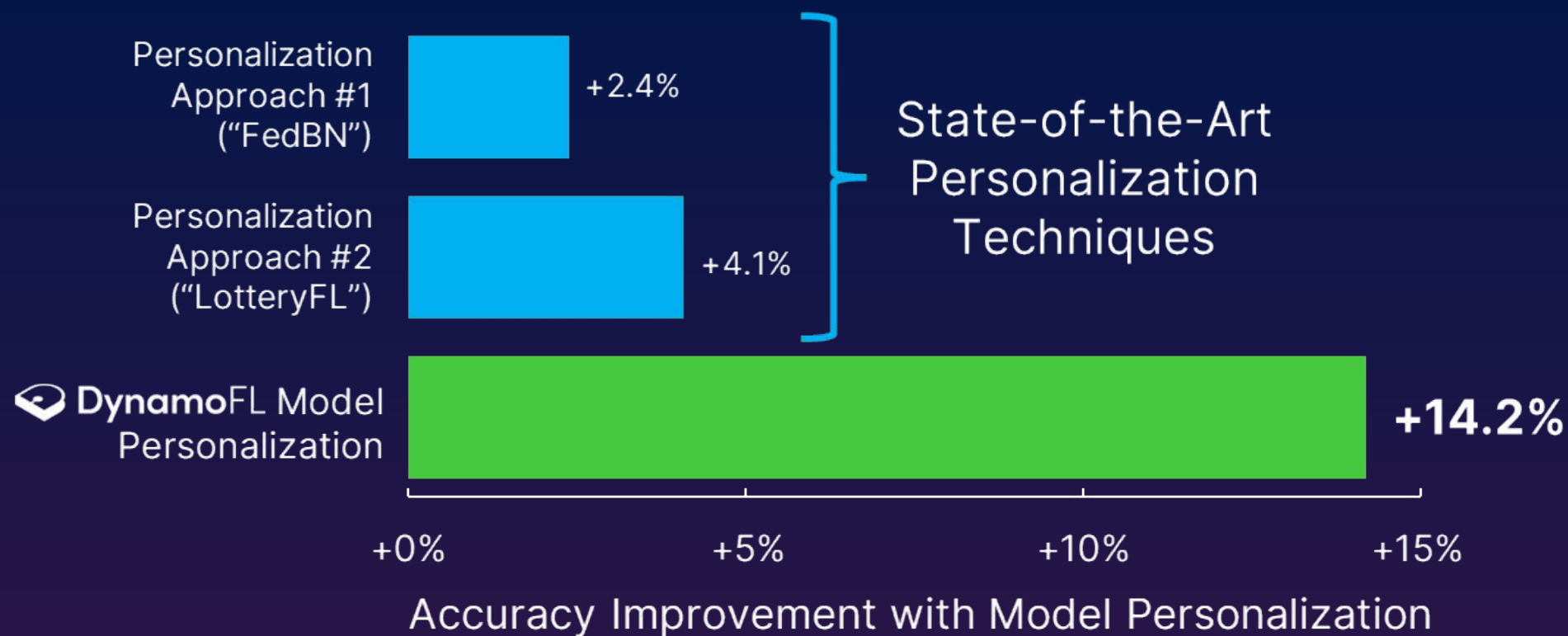
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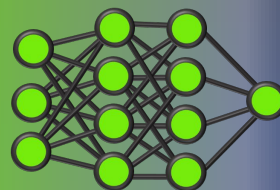
Boost Performance with Personalized Federated Learning



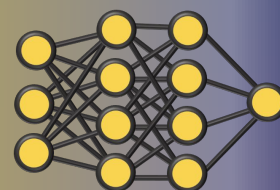
Performance Case Study: Quantitative Finance



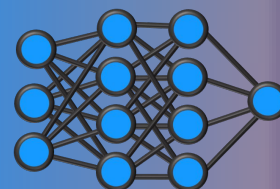
USD-Pair
Forecasting Model



Yen-Pair
Forecasting Model

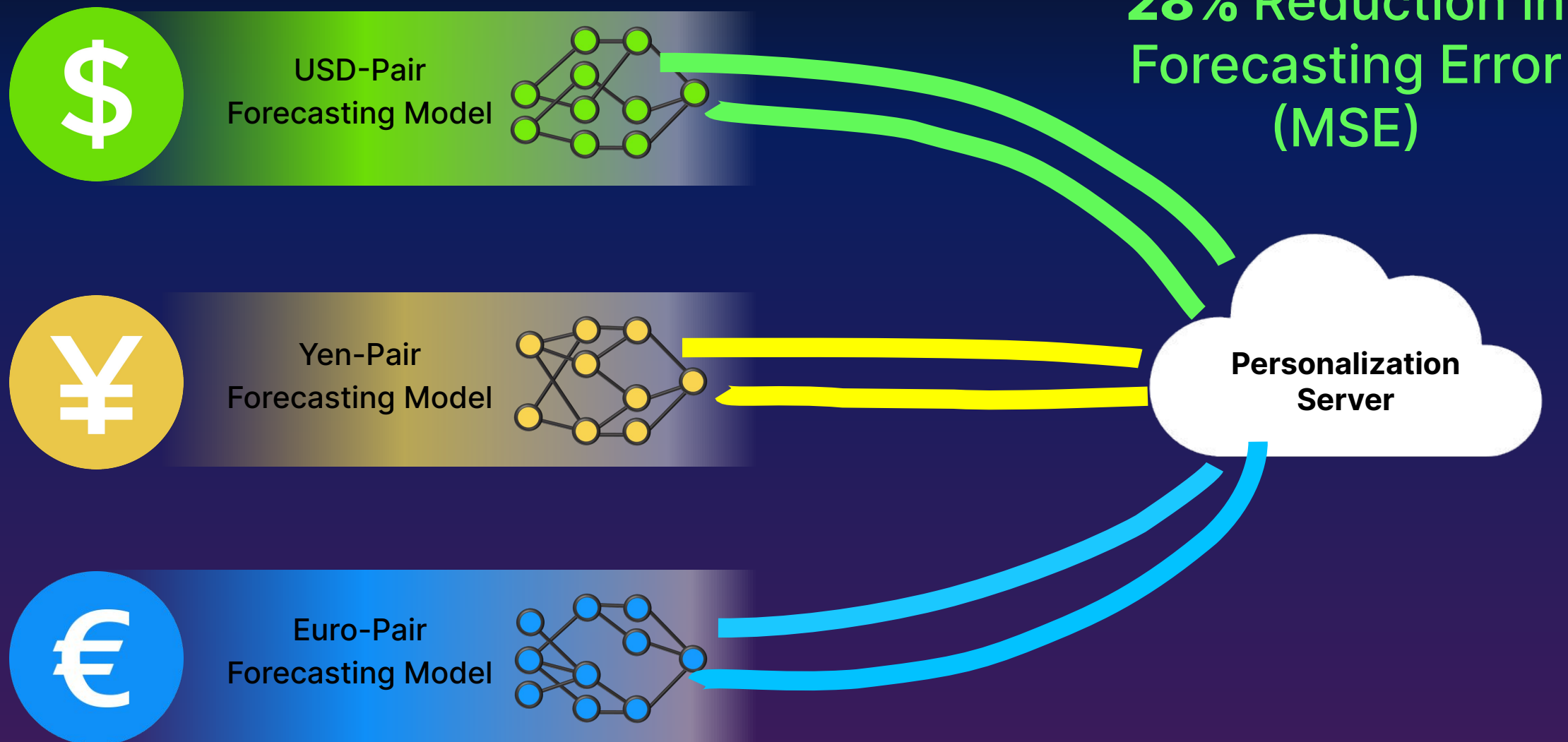


Euro-Pair
Forecasting Model

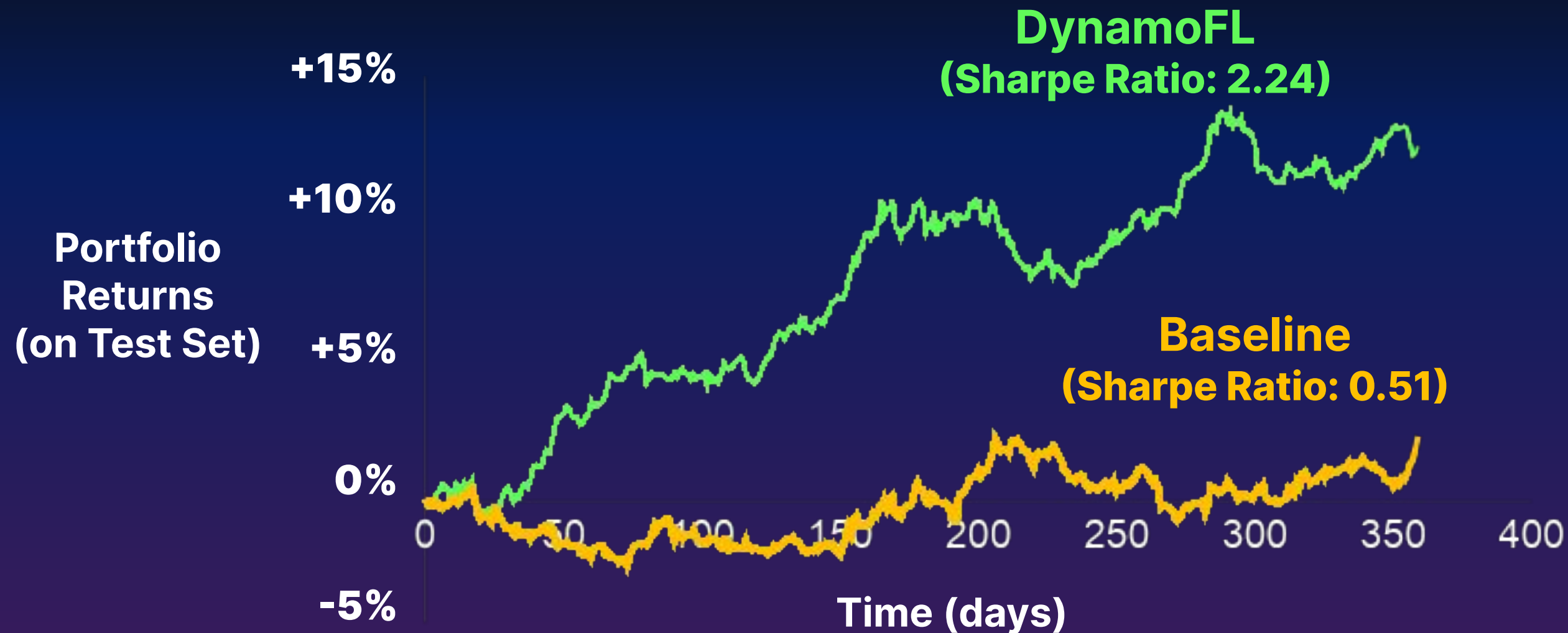


Train ForEx Models Locally
on Currency Data

Performance Case Study: Quantitative Finance



Performance Case Study: Quantitative Finance



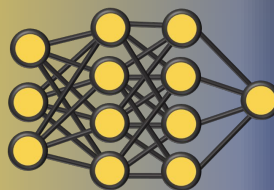
Portfolio created by trading 9 ETFs daily. Both DynamoFL and Baseline methods use the same autoformer model architecture for forecasting prices. Baseline uses models trained independently on ETFs. DynamoFL Method uses FL to personalize Baseline models.

Performance Case Study: Speech Recognition



Majority Class:

90% German



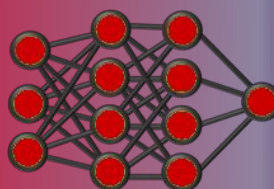
Minority Class:

5% South African



Minority Class:

5% Singaporean

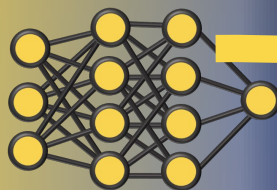


Accented Speech
Recognition with Minority
Classes

Performance Case Study: Speech Recognition



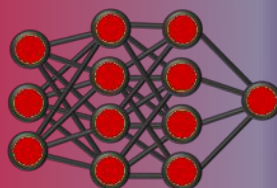
Majority Class:
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Minority Class:
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Minority Class:
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Performance Case Study: Speech Recognition

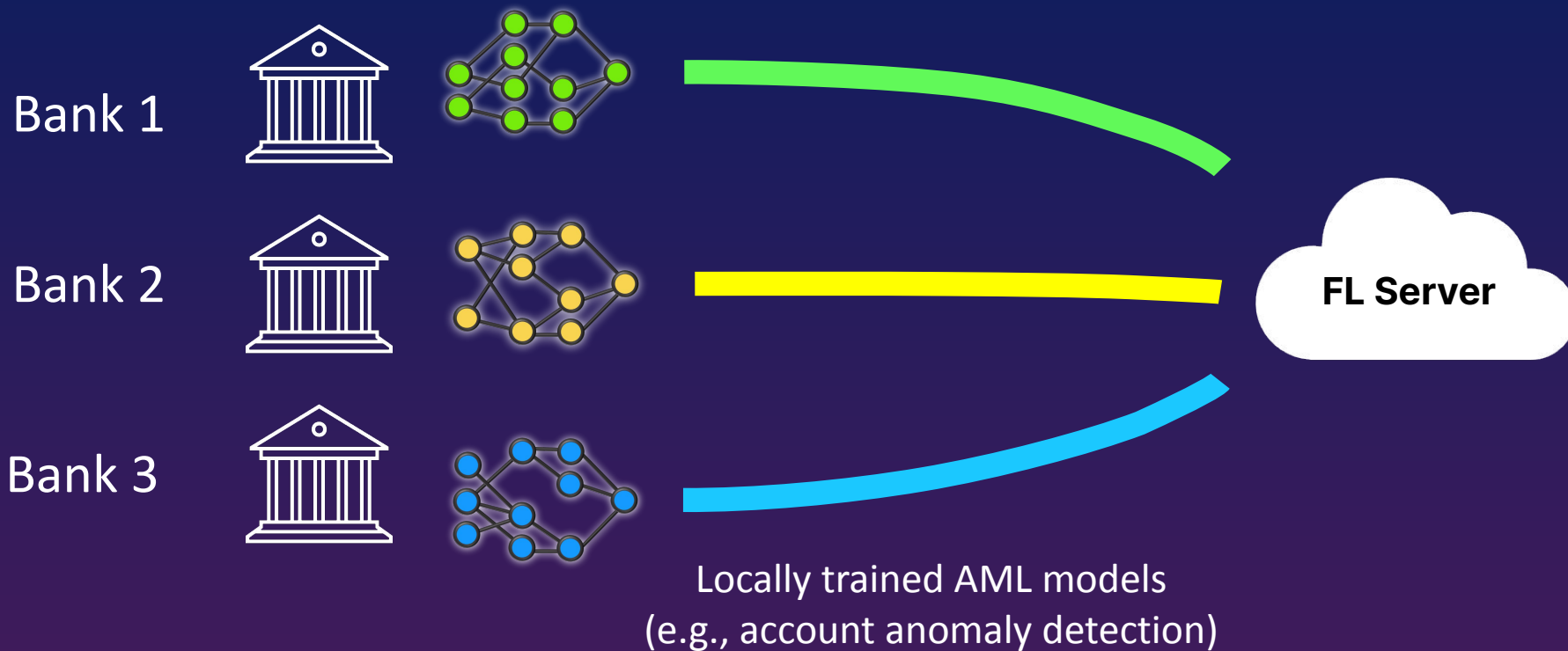
	Central Model	DynamoFL
WER German	36.0%	34.7%
WER South African	52.9%	48.8%
WER Singaporean	65.0%	45.9%
WER Average	51.3%	43.2%

Strong performance improvement for minority classes enables fairer models

Training and evaluation performed on CommonVoice dataset. Both DynamoFL and central experiments were performed using the same pretrained Wav2Vec 2.0 model architecture

Compliance Case Study: Anti-Money Laundering (AML)

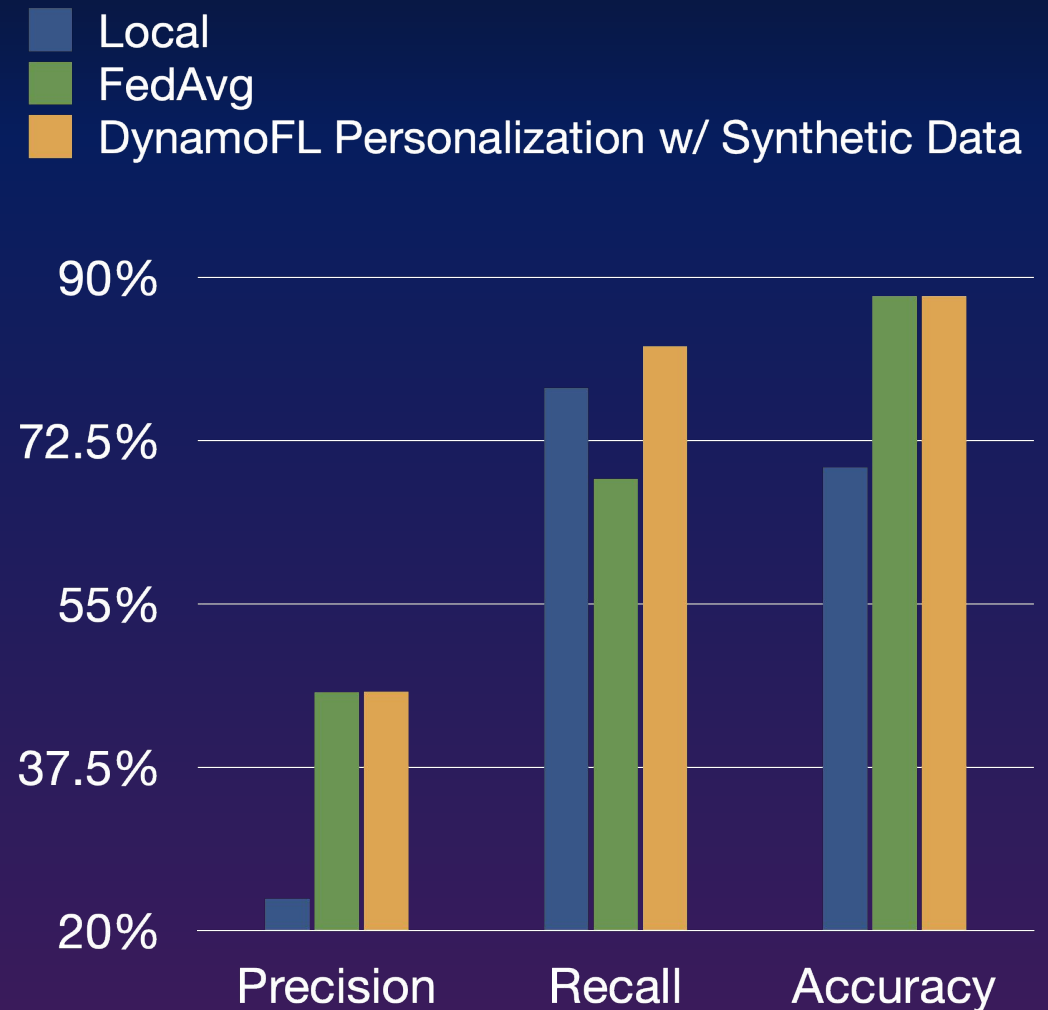
Banks across different regions can collaborate to train AML model



Compliance Case Study: Anti-Money Laundering (AML)

On a public AML dataset with accounts siloed across geographic regions (states):

- Local-only models achieves poor precision and accuracy
- FedAvg improves precision (for minority/anomaly class) at the expense of recall
- **DynamoFL model personalization boosts or matches baselines across all metrics**



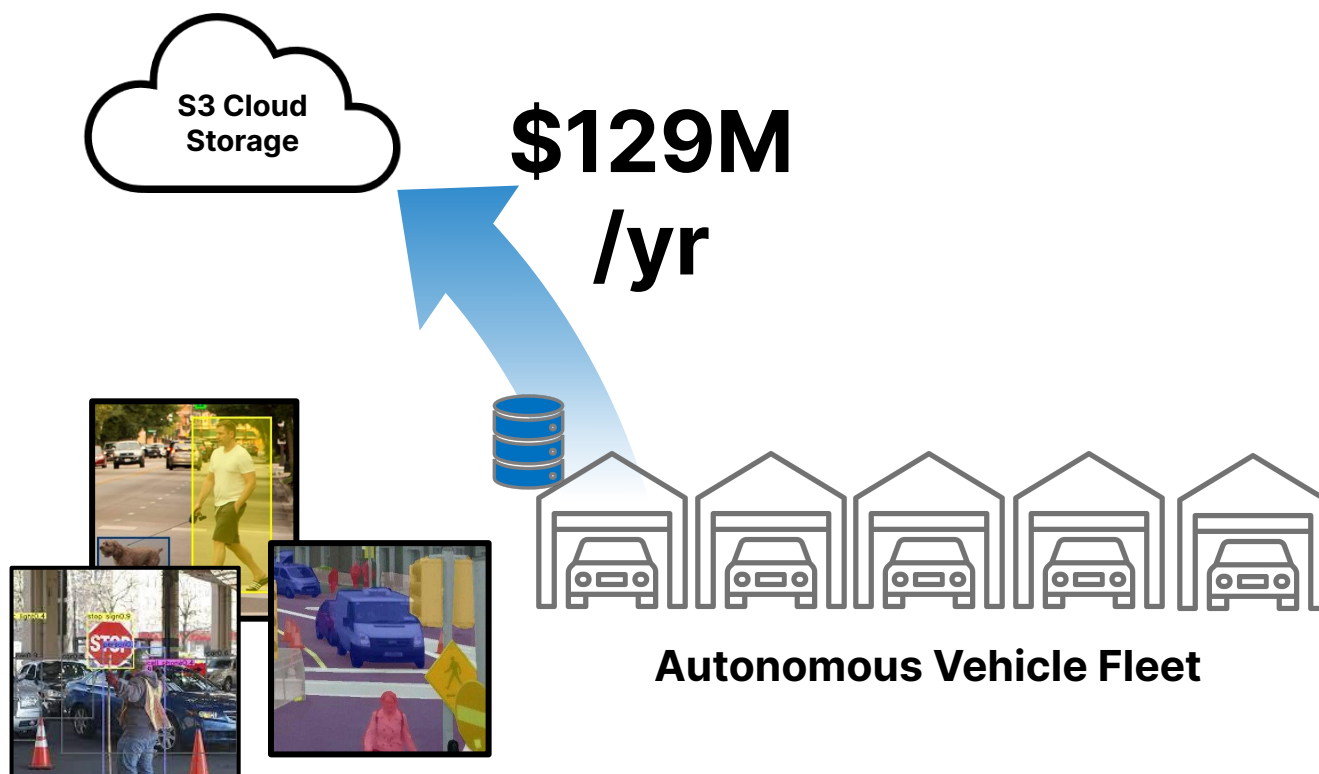
Analytics Case Study: Privacy Risk Score

- Often, we'd like to get an intuition for **how private** are the trained models
- DynamoFL systematically examines
 - potential attacks,
 - deployed defenses, and
 - a suite of empirical tests to arrive a normalized **privacy risk score** for non-technical users

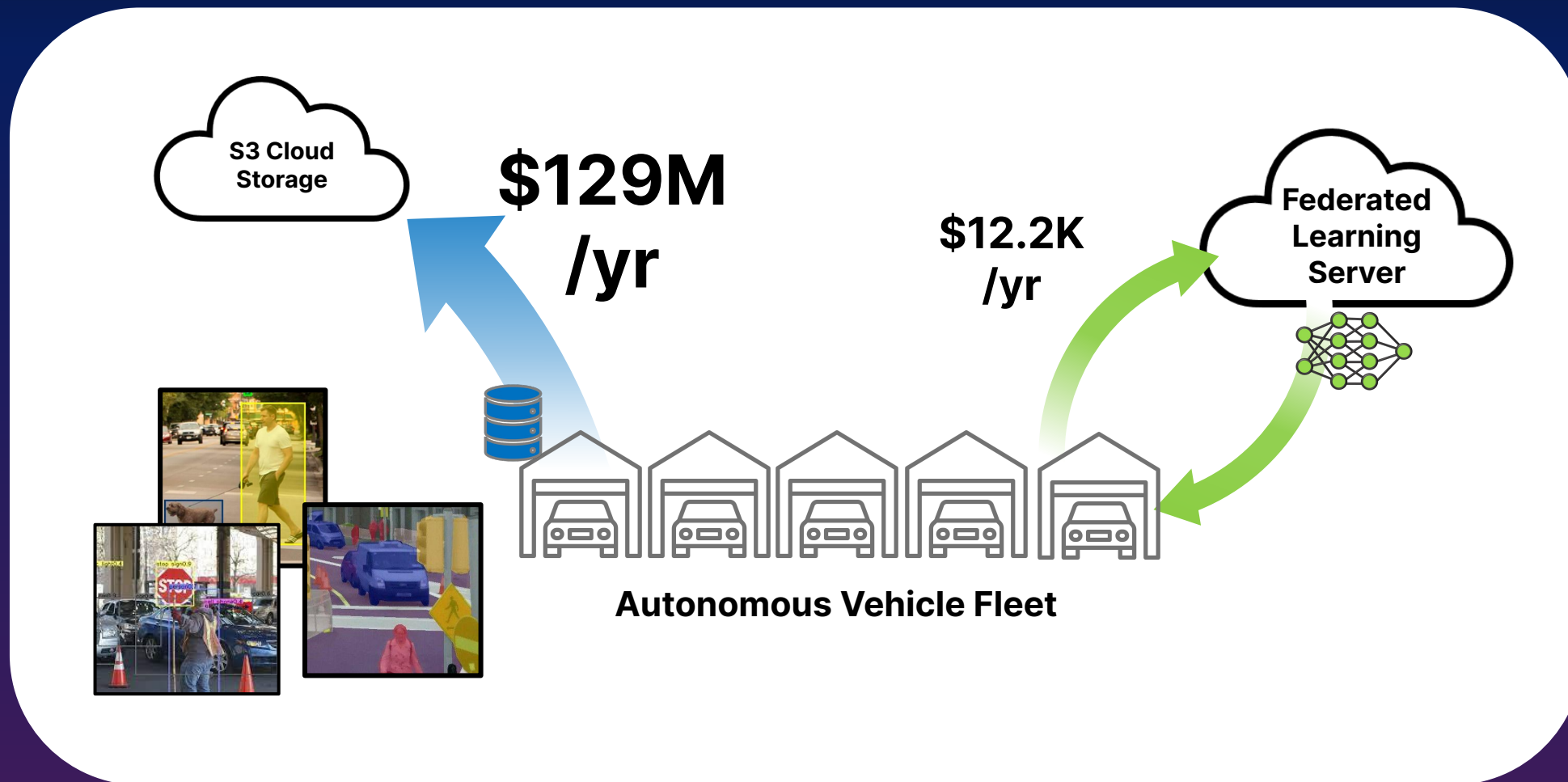
	De-identification (e.g., k-anonymity)	Robust Aggregation	SecAgg	Differential Privacy (DP)	...	Empirical Test Score
Membership Inference	Weak	Weak	Weak	Strong		...
Attribute Inference	Weak	Weak	Weak	Strong		...
Model Inversion	Weak	Weak	Weak	Strong		...
Unreliable Channels	Moderate	Strong	Weak	Moderate/ Strong		...
Semi-Honest Server	Weak	Weak	Strong	Moderate/ Strong		...
Poisoning	Weak	Moderate	Weak	Moderate		...
Model Backdoors	Weak	Weak	Weak	Moderate		...
...						...

Example attacks and how they may be mitigated

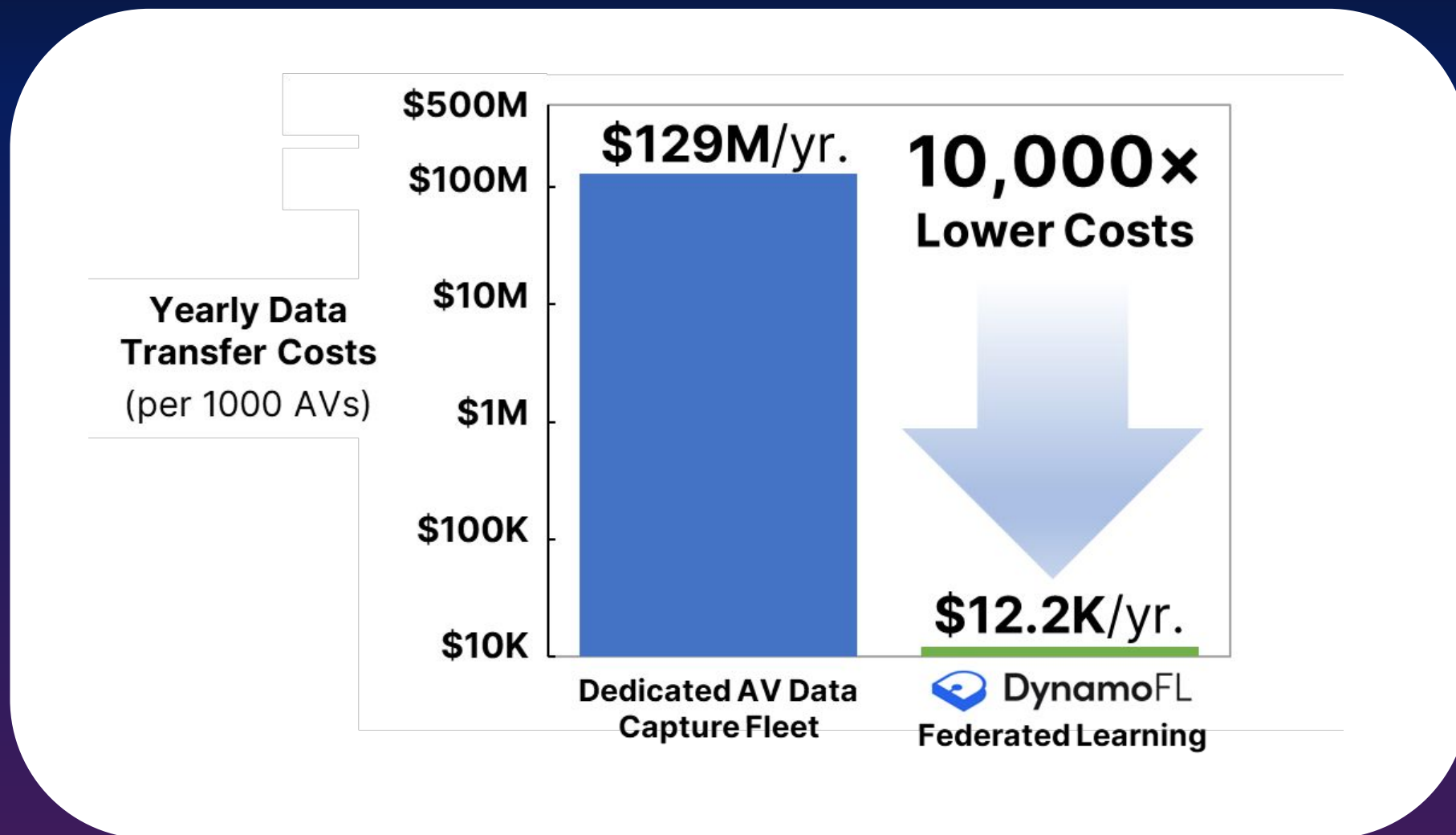
Cost Savings Case Study: Automotive



Cost Savings Case Study: Automotive

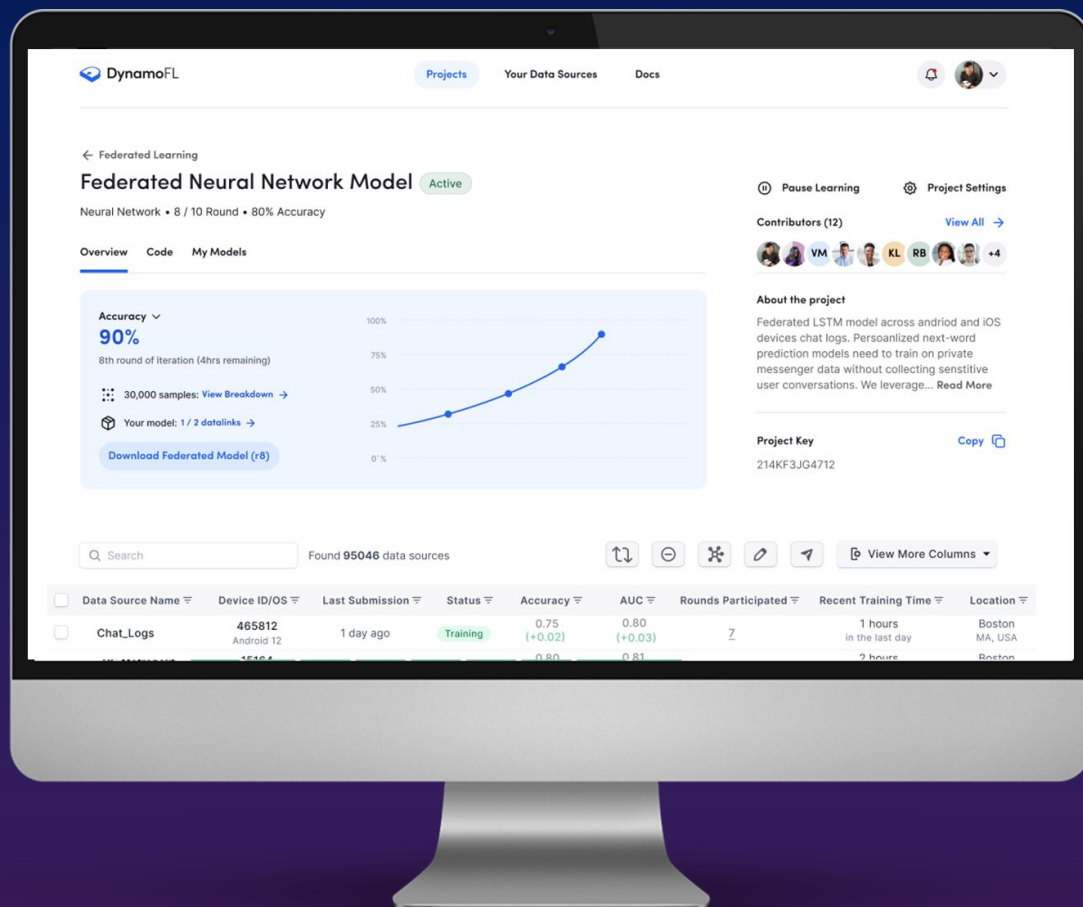


Cost Savings Case Study: Automotive



DynamoFL

The Platform for Personalized Federated Learning



- Integrated Personalized FL Technology
- End-to-end federated learning infrastructure
- Mobile and Python SDKs + Dockerized Solutions



Contact

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or visit <https://www.dynamofl.com/>



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