Federated Learning:

A Systems Engineering Approach to Smarter AI

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www.phronos.com
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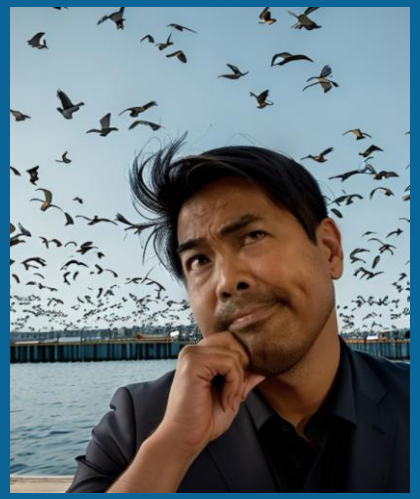

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Dr. Art Villanueva lives in the intersection of **artificial intelligence, emergence, and systems engineering**. His current research focuses on complex adaptive systems (CAS) – from brain mechanisms to autonomous unmanned aerial vehicles (UAVs). He is the founder of Phronos, an AI services company dedicated to leveraging AI and SE across domains. He also serves as a Senior Staff Engineer at General Atomics Aeronautical Systems, where he applies his expertise to the next-generation of aerospace programs.

Dr. Villanueva previously served as Chief AI Technologist for Dell Technologies' Federal Strategic Programs, guiding Dell's AI posture across government sectors. His multidisciplinary experience also spans large defense and public transportation projects as well as clean-tech entrepreneurship in renewable energy.

An inventor with multiple U.S. utility patents and several peer-reviewed publications, Dr. Villanueva holds a Doctor of Engineering in Systems Engineering from Colorado State University, where he specialized in meta-algorithmics for natural language processing. He also holds master's degrees in Systems Engineering and Computer Science from UC San Diego, and a B.S. in Applied Mathematics from UCLA. He is an INCOSE-certified Expert Systems Engineering Professional (ESEP).

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Agenda

I. Previously…
II. Intro and Motivation
III. Types of Machine Learning
IV. Federated Learning
V. Types of Federated Learning
VI. Examples of Federated Learning
VII. Swarm Intelligence
VIII. Technical Challenges
IX. Conclusion
X. Q-A-D: Question, Answer, Discussion

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Previously

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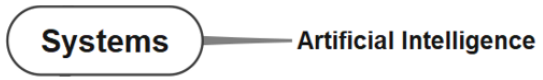
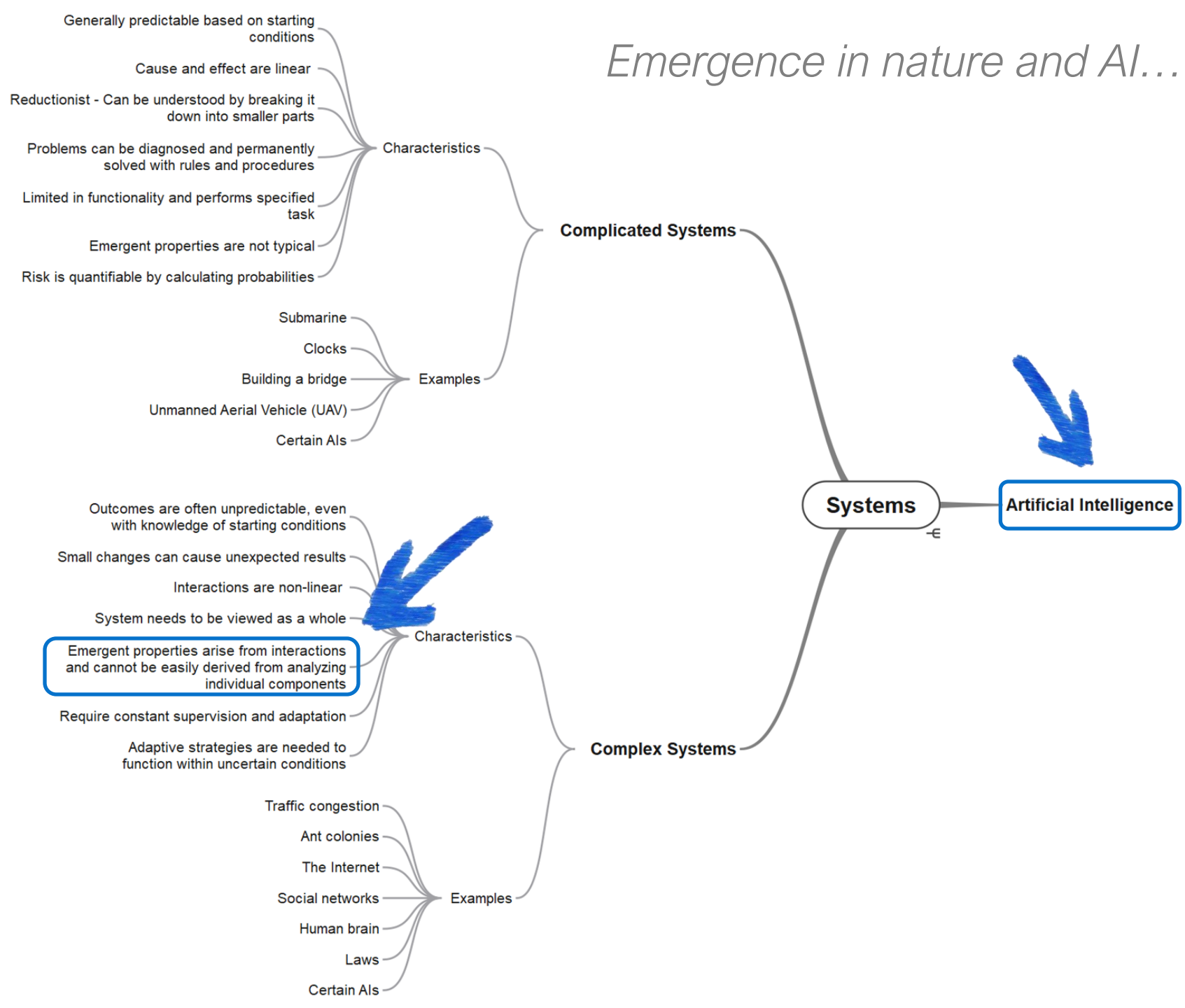
When ChatGPT 3.5 became a household name…



Emergence in nature and AI…



When security is of utmost importance…

- **Systems**
  - **Complicated Systems**
    - Characteristics
      - Generally predictable based on starting conditions
      - Cause and effect are linear
      - Reductionist - Can be understood by breaking it down into smaller parts
      - Problems can be diagnosed and permanently solved with rules and procedures
      - Limited in functionality and performs specified task
      - Emergent properties are not typical
      - Risk is quantifiable by calculating probabilities
    - Examples
      - Submarine
      - Clocks
      - Building a bridge
      - Unmanned Aerial Vehicle (UAV)
      - Certain AIs
  - **Complex Systems**
    - Characteristics
      - Outcomes are often unpredictable, even with knowledge of starting conditions
      - Small changes can cause unexpected results
      - Interactions are non-linear
      - System needs to be viewed as a whole
      - Emergent properties arise from interactions and cannot be easily derived from analyzing individual components
      - Require constant supervision and adaptation
      - Adaptive strategies are needed to function within uncertain conditions
    - Examples
      - Traffic congestion
      - Ant colonies
      - The Internet
      - Social networks
      - Human brain
      - Laws
      - Certain AIs
  - **Artificial Intelligence**
    - Types
      - Based on Capabilities
        - Narrow AI (or Weak AI)
        - Artificial General Intelligence (AGI)
        - Artificial Superintelligence (ASI)
      - Domains
        - Natural Language Understanding and Processing
        - Computer Vision
        - Robotics
      - Roles
        - Generative AI
        - Discriminative AI
      - Methods
        - GOFAI
        - Agentic AI
        - Quantum Machine Learning (QML)
        - Neuromorphic Processing
        - Expert systems (AI)
      - Based on Learning Methods
        - Supervised Learning
        - Unsupervised Learning
        - Semi-supervised Learning
        - Reinforcement Learning
        - Federated Learning

Intro and Motivation

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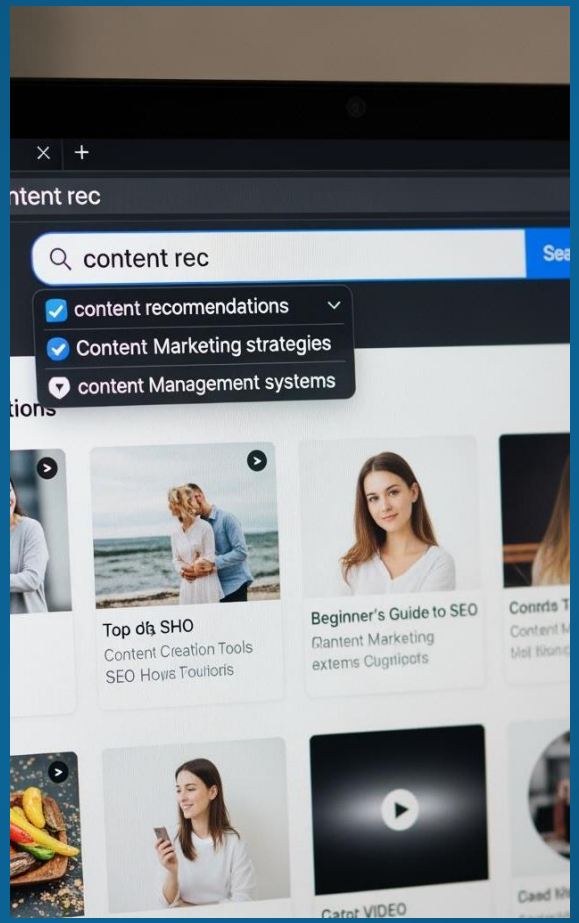
What do these scenarios have in common?

Wildfire Management

Personalized Recommendations



Disease Spread Mitigation

When data sharing is less than ideal…

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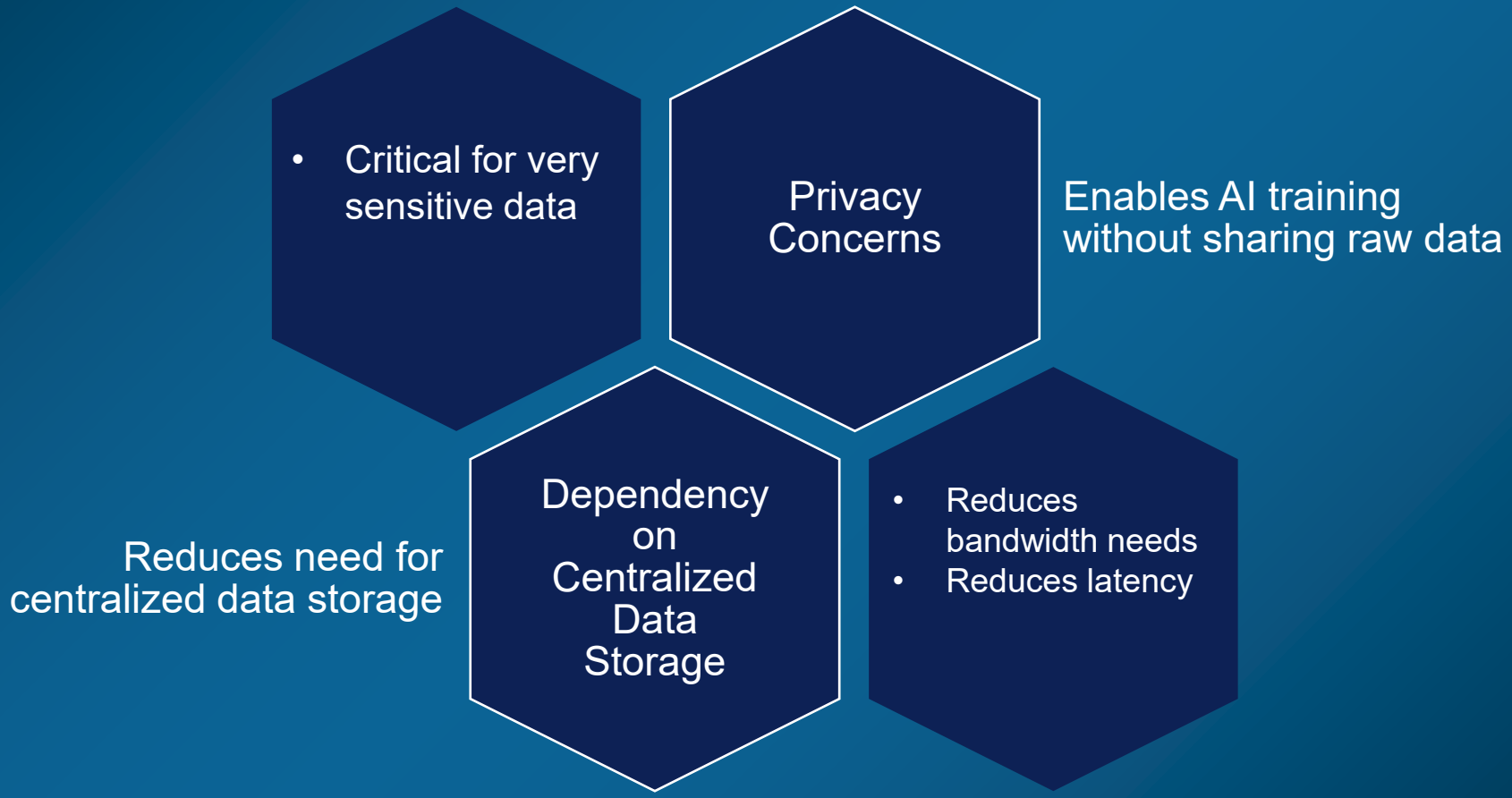
Why Federated Learning?



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Why Now?

- Rise of edge computing
  - phones, UAVs, sensors
  - data is coming from everywhere
- Data Breaches:
  - Data at rest: 60–80% of breaches
  - Data in motion: 10–25% of breaches
  - Data in use: 15–30% of breaches
- Privacy and regulatory drivers
  - e.g., GDPR, HIPAA
- Growing demand for on-device intelligence

Data Glut

Sensitive Data

Limited Connectivity

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What is Federated Learning?

Federated learning is a machine learning paradigm across decentralized devices while keeping data local.

Types of Machine Learning

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Discriminative vs Generative AI

Supervised ML

Predict outcomes from labeled data

Data Collection

Gather labeled data from sources (e.g., sensors, logs)

Preprocessing

Prepare and clean the data

Training

Use the labeled data to train the model on a central server

Validation

Evaluate the model's performance

Deployment

Deploy the trained model for real-world use

- Spam Detection
- House Price Prediction
- Medical Diagnosis

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Unsupervised ML

Discover hidden patterns in unlabeled data

Data Collection

Gather labeled data from sources (e.g., images, logs)

Preprocessing

Prepare and clean the data

Training

Train the model on a central server to find patterns or clusters

Insights

Analyze the results (e.g., clusters, associations)

Deployment

Deploy the trained model for real-world use

- Customer Segmentation
- Anomaly Detection
- Topic Modeling

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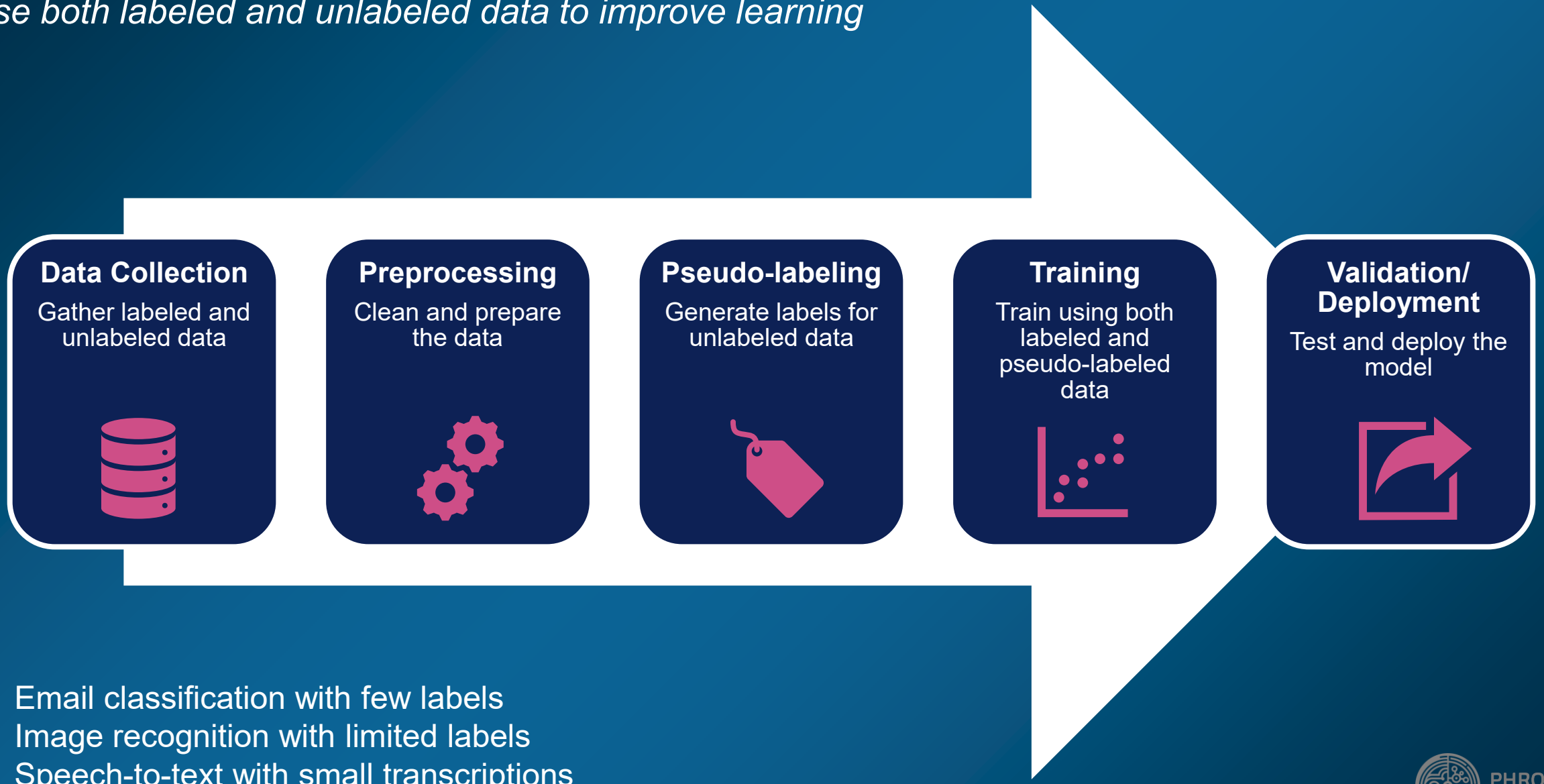
Semi-supervised ML

Use both labeled and unlabeled data to improve learning



- Email classification with few labels
- Image recognition with limited labels
- Speech-to-text with small transcriptions

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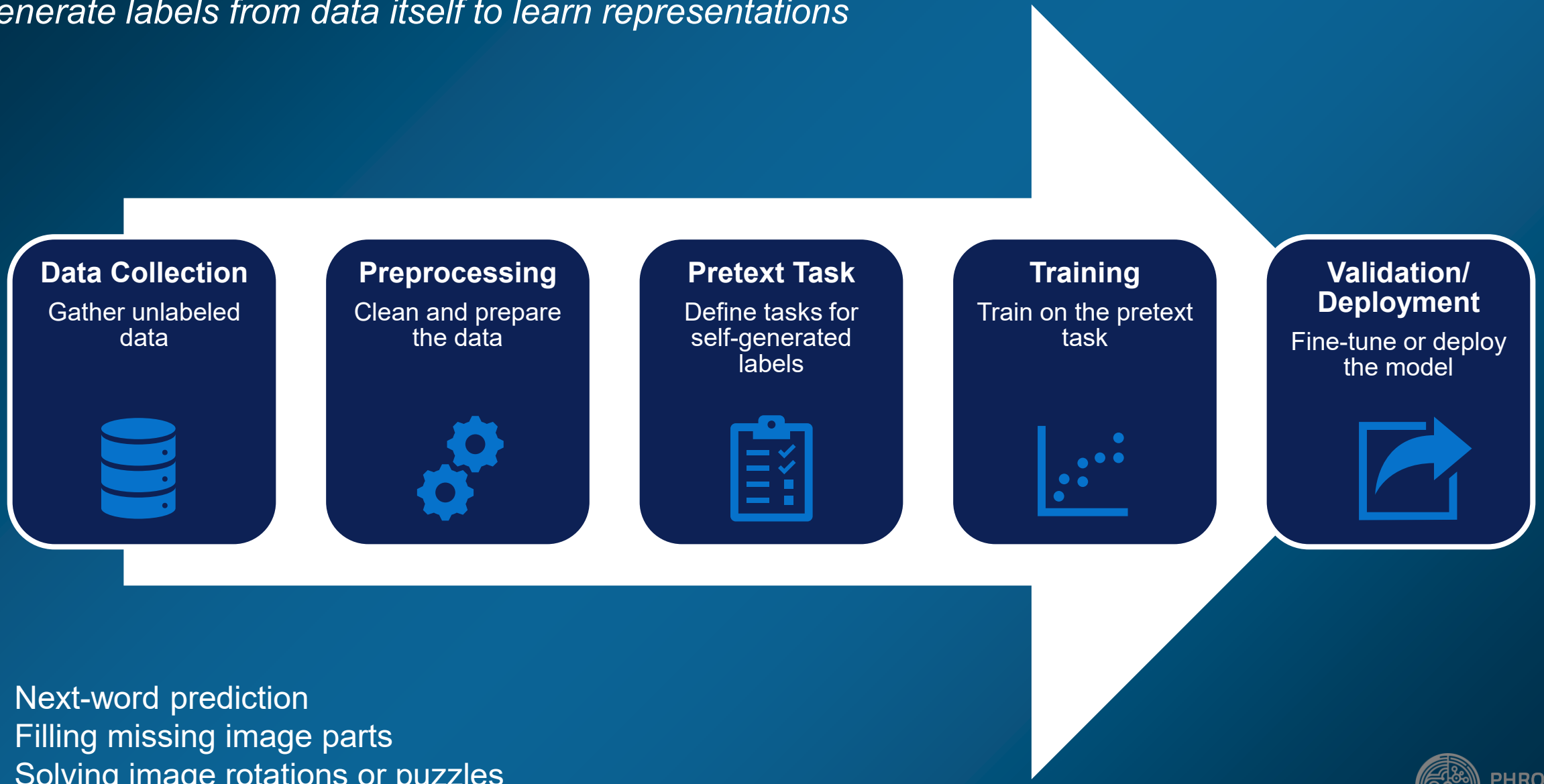
Self-supervised ML

Generate labels from data itself to learn representations



- Next-word prediction
- Filling missing image parts
- Solving image rotations or puzzles

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Reinforcement Learning

Train agents to make sequential decisions

Data Collection

Agent interacts with the environment to generate data

Action

Agent takes actions based on its current policy

Feedback

Environment provides rewards and new states

Training

Update the policy/model on a central server based on feedback

Deployment

Deploy the trained agent for real-world use

- Game AI
- Autonomous Driving
- Robotics

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Transfer Learning

Leverage pretrained models for new tasks

Pretraining

Use a large dataset to train a base model

Feature Extraction

Remove the final layers to extract useful features

Fine-tuning

Train the model on the new domain/task with a smaller dataset

Validation

Evaluate the fine-tuned model's performance

Deployment

Deploy the fine-tuned model for the specific application

- Image Classification
- Natural Language Processing
- Speech Recognition

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Federated Learning

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Federated Learning

Train models collaboratively without sharing raw data

Data Collection

Data is collected locally on edge devices (e.g., phones)

Local Training

Train models locally on each device

Model Updates

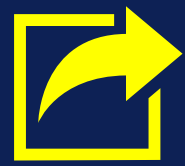
Send model updates (not raw data) to a central server

Aggregation

Combine updates into a global model on the central server

Deployment

Distribute the global model back to devices



- Predictive Text
- Healthcare Diagnostics
- Smart Home Devices

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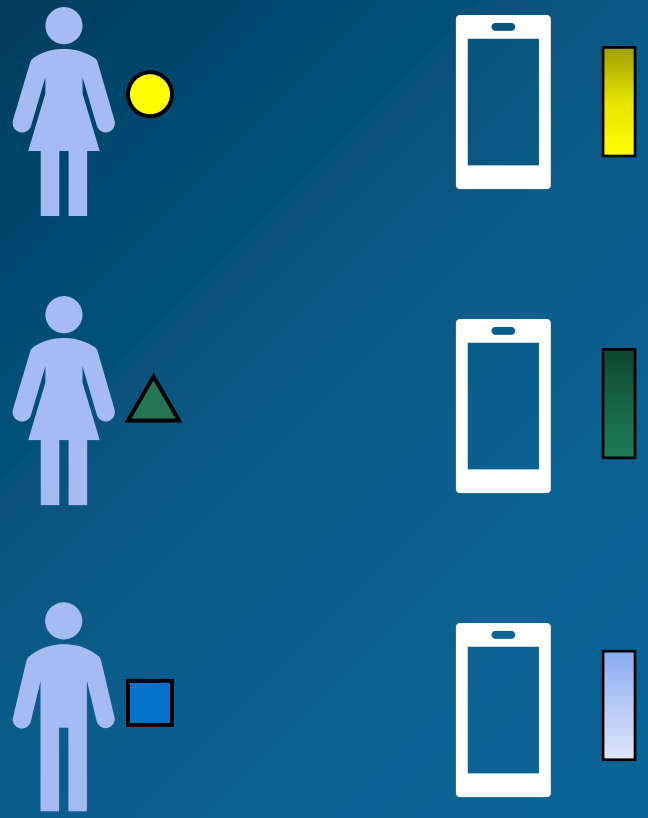
Federated Learning



1. Setup – We have a server and several edge devices
2. Server sends the model to the edge devices
3. Edge devices collect data from their environment
4. Edge devices generate gradients (deltas) comparing model prediction with reality
5. Edge devices send gradients to the server
6. Server collects all the gradients and updates the model
7. Repeat #2

$$w_{global} = \frac{\sum_{k=1}^{K} n_k \cdot w_k}{\sum_{k=1}^{K} n_k}$$

Federated Averaging
McMahan et al. (2017)

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Types of Federated Learning

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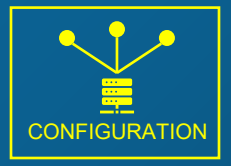
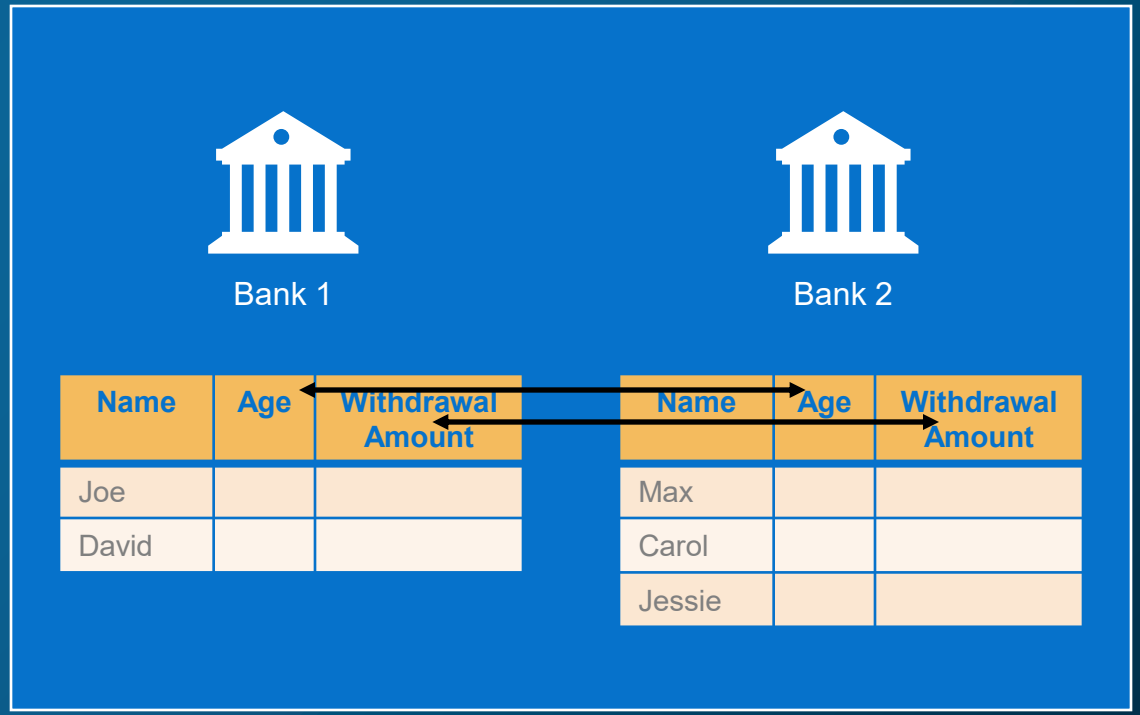
Horizontal Federated Learning (HFL)

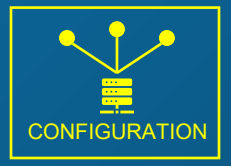


- Devices or organizations have similar feature spaces (e.g., same types of data) but different samples
  - Example: Banks in different regions collaborate on a fraud detection model using transaction data with the same features

Modality	Example	Key Feature
Text	Predictive text on smartphones	Same features, different samples
Audio	Speech recognition across smart speakers	Common audio features, unique users
Images	Facial recognition in security systems	Same features, different individuals
Sensor Data	Smart meters predicting energy usage	Similar features, household-specific data

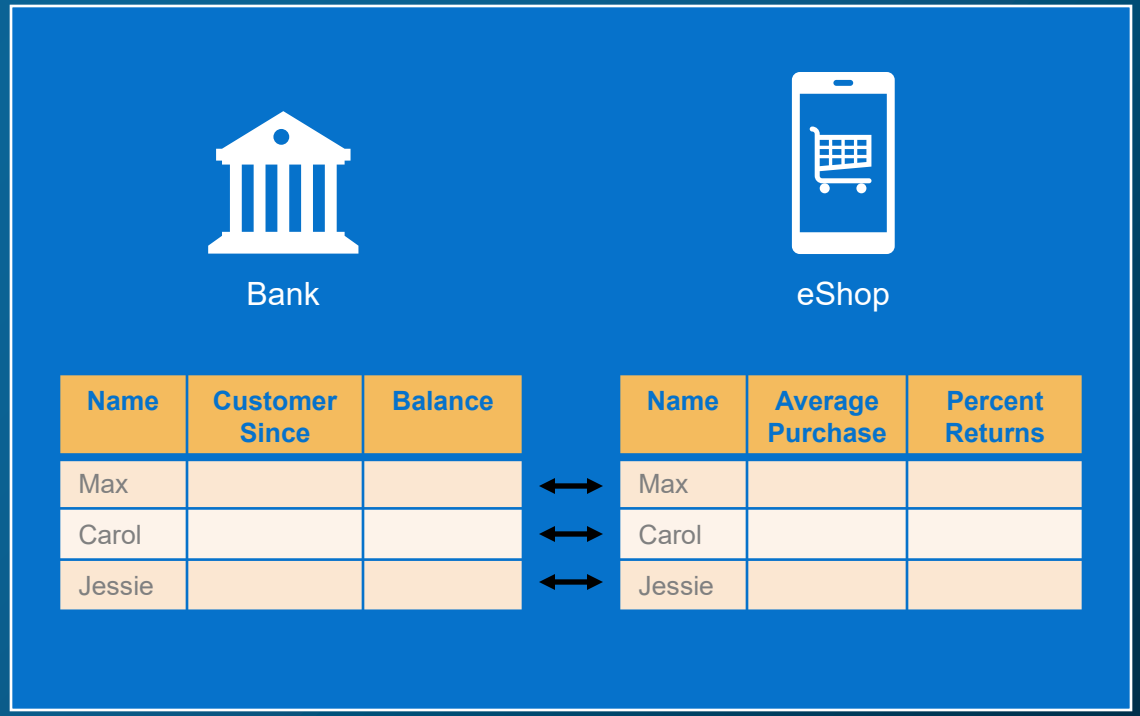


Vertical Federated Learning (VFL)



- Devices or organizations have different feature spaces but share overlapping samples (e.g., same users)
  - Example: A bank and an e-commerce platform collaborate to predict user creditworthiness using complementary data

Modality	Example	Key Feature
Text	Bank + e-commerce for loan prediction	Different features, same users
Audio	Mental health analysis using stress-level recordings and transcripts	Different features, overlapping samples
Images	Hospital + pharmacy collaboration (medical images + prescriptions)	Different data types, shared patients
Sensor Data	Traffic cameras + roadside sensors for congestion prediction	Different sensors, same vehicles



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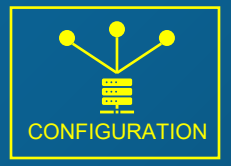
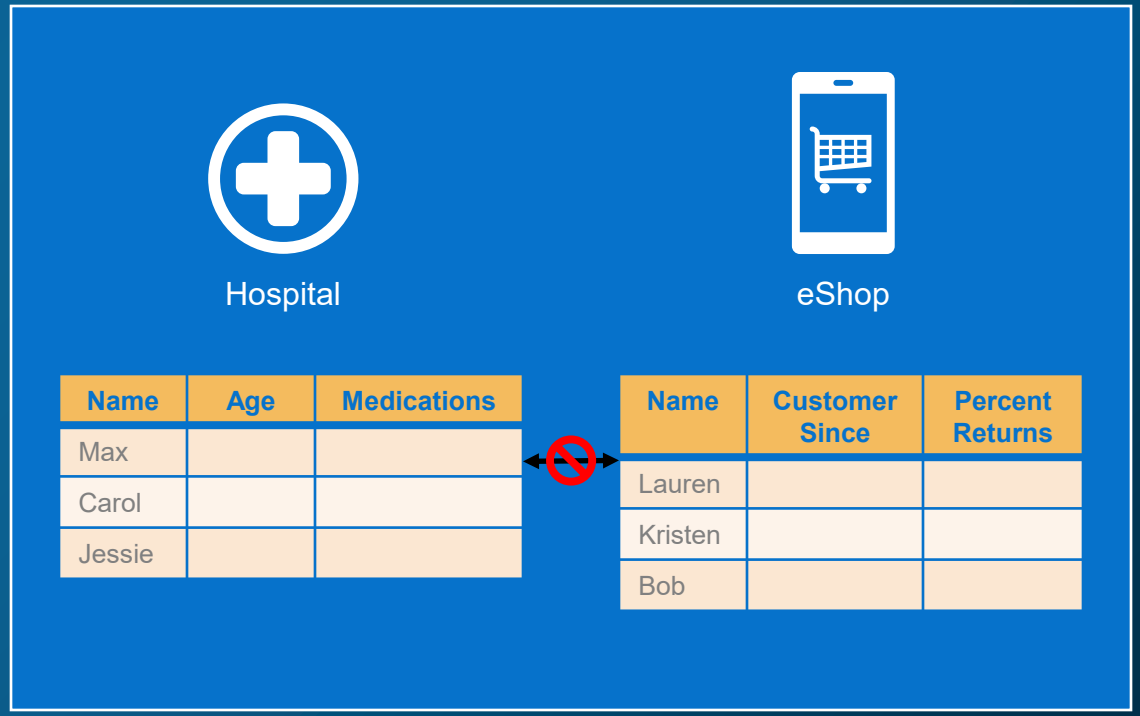
Federated Transfer Learning (FTL)

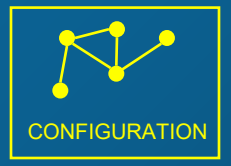


- Devices or organizations have different feature spaces and few (or no) overlapping samples, leveraging transfer learning to share knowledge
  - Example: A hospital and a retail store collaborate to improve prediction models by transferring learned patterns across domains

Modality	Example	Key Feature
Text	News agency + retail platform for cross-domain sentiment analysis	Knowledge transfer, no overlapping users
Audio	Cross-language speech recognition	Transfer learning for less-resourced data
Images	Medical X-rays + wildlife photos for injury detection	Transferable patterns, different domains
Sensor Data	Weather + soil moisture sensors for crop yield prediction	Different sensors, no direct overlap

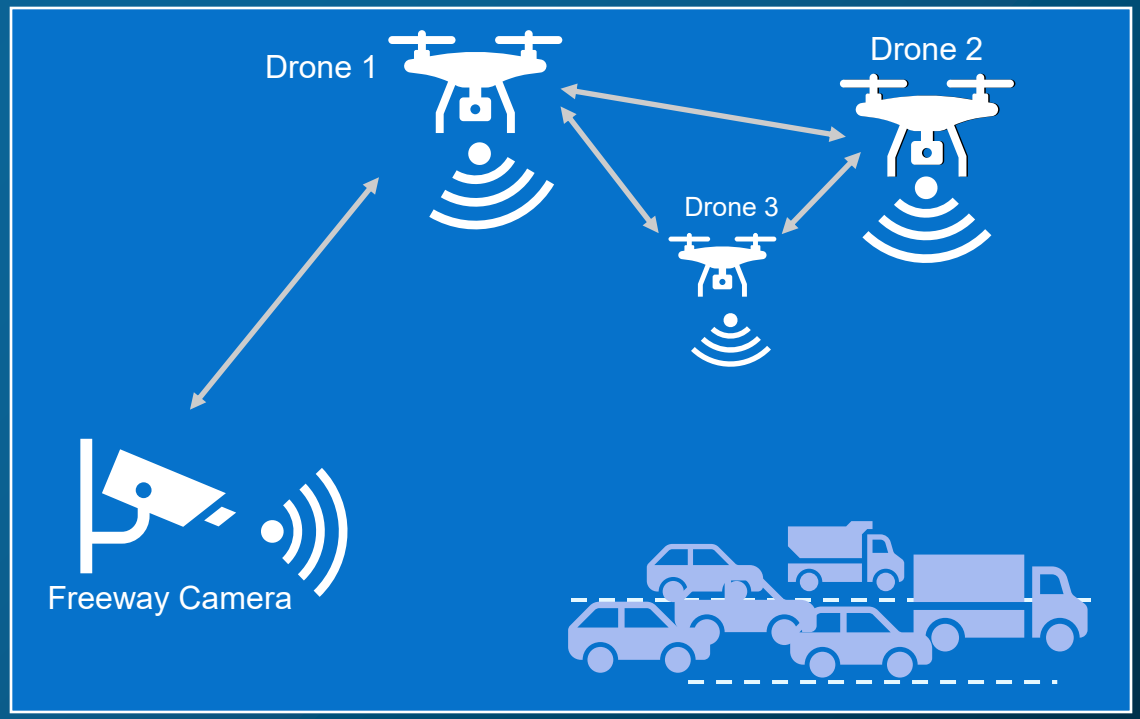


Peer-to-peer Federated Learning (P2P-FL)

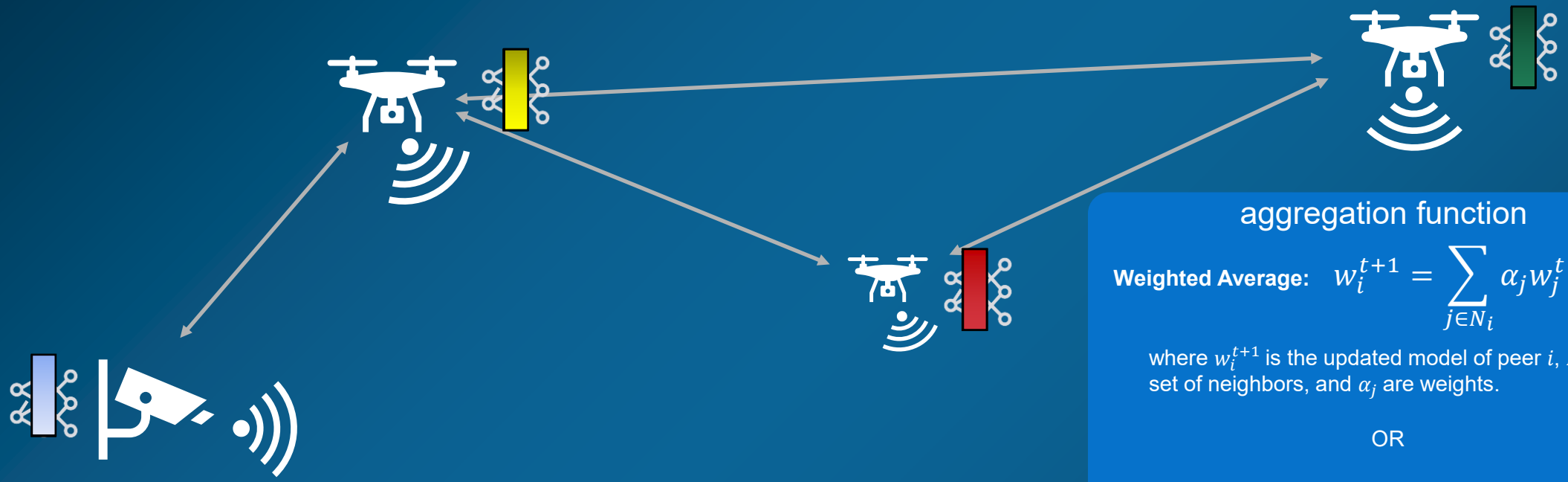


- Autonomous devices (or nodes) communicate directly with each other to collaboratively train a global model without a central server
  - Example: Drones and a freeway camera collaborate without the need for a central server

Modality	Example	Key Feature
Text	Decentralized spam detection using email clients	Peer-to-peer collaborative training
Audio	Wake-word detection training across voice assistants	Decentralized audio recognition
Images	Traffic monitoring with smart cameras	P2P collaboration for image analysis
Sensor Data	Air quality sensors collaboratively predicting pollution levels	Sensor-based peer-to-peer learning



Peer-to-peer Federated Learning



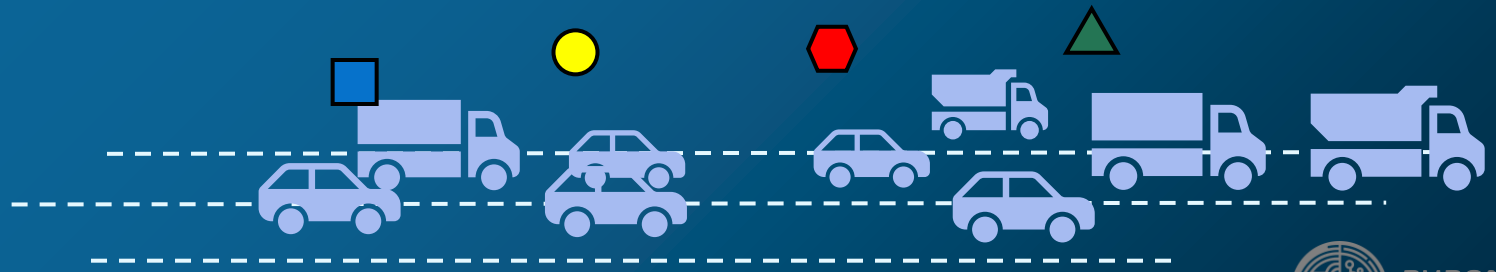
aggregation function

Weighted Average: $w_i^{t+1} = \sum_{j \in N_i} \alpha_j w_j^t$

where w_i^{t+1} is the updated model of peer i, N_i is the set of neighbors, and α_j are weights.

OR

Gossip Protocol: Peers randomly exchange and merge models to propagate updates gradually across the network.



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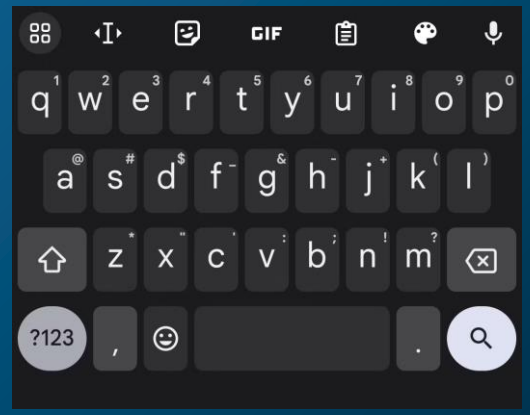
Real-Life Examples of Federated Learning

Application: Virtual Assistants

- Voice Assistants
  - e.g., Siri, Alexa, Google Assistant
- Smart Keyboards
  - AI-enhanced input tools designed to improve text input, offering features like predictive typing, autocorrect, and voice typing
  - e.g., Gboard
- Productivity Tools:
  - e.g., scheduling, note-taking, or quick searches



Application: Wildfire Detection with UAVs

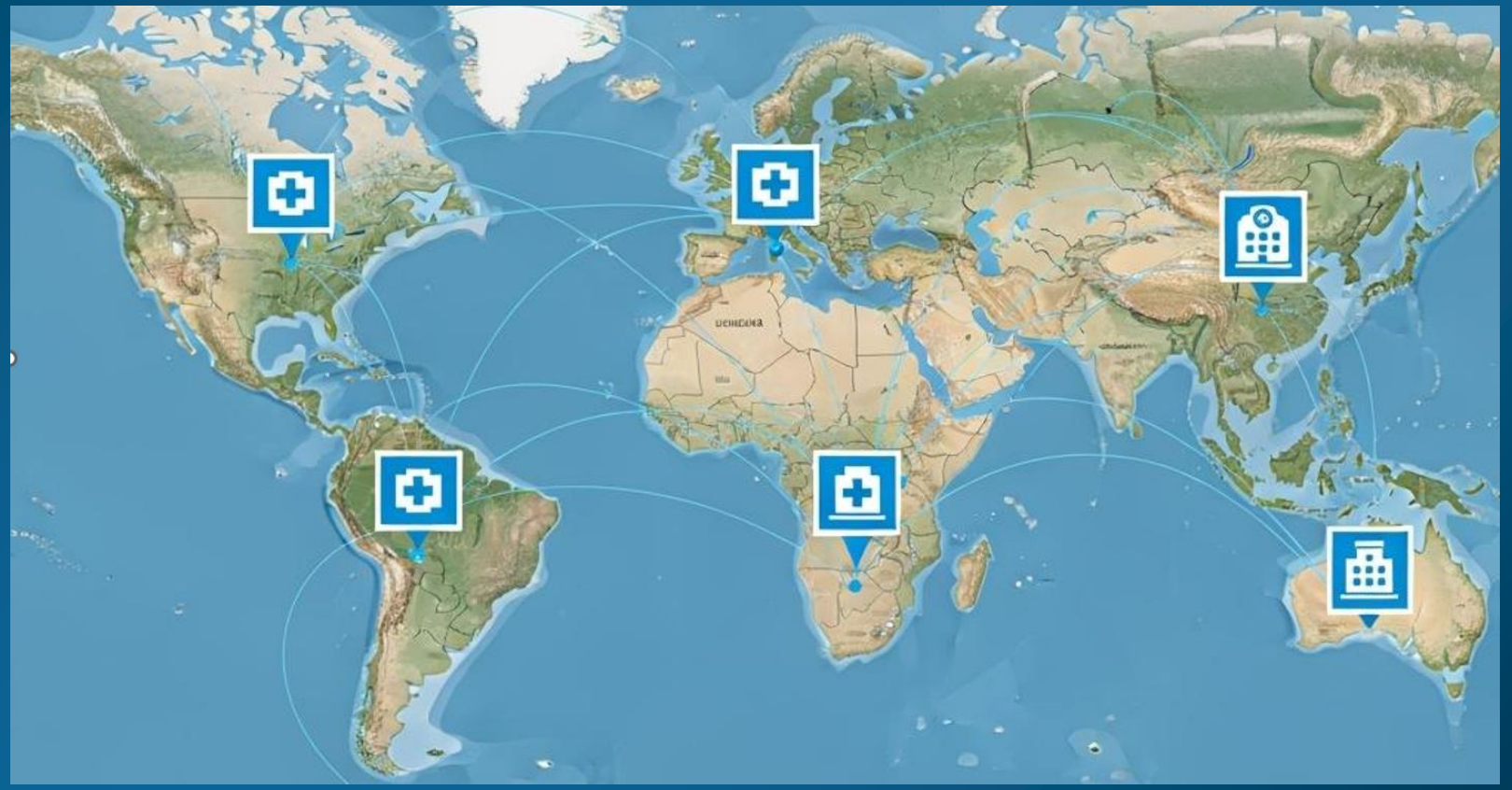
- Drones analyze local fire patterns
- Privacy: No raw images shared
- Collaboration: Improves detection across the fleet

Application: Environmental Monitoring

- Aggregate data from distributed sensors to identify patterns
- Applications include pollution mapping and climate-change monitoring

Application: Personalized Healthcare

- Hospitals collaboratively train models to detect cancer or rare diseases without sharing sensitive patient data



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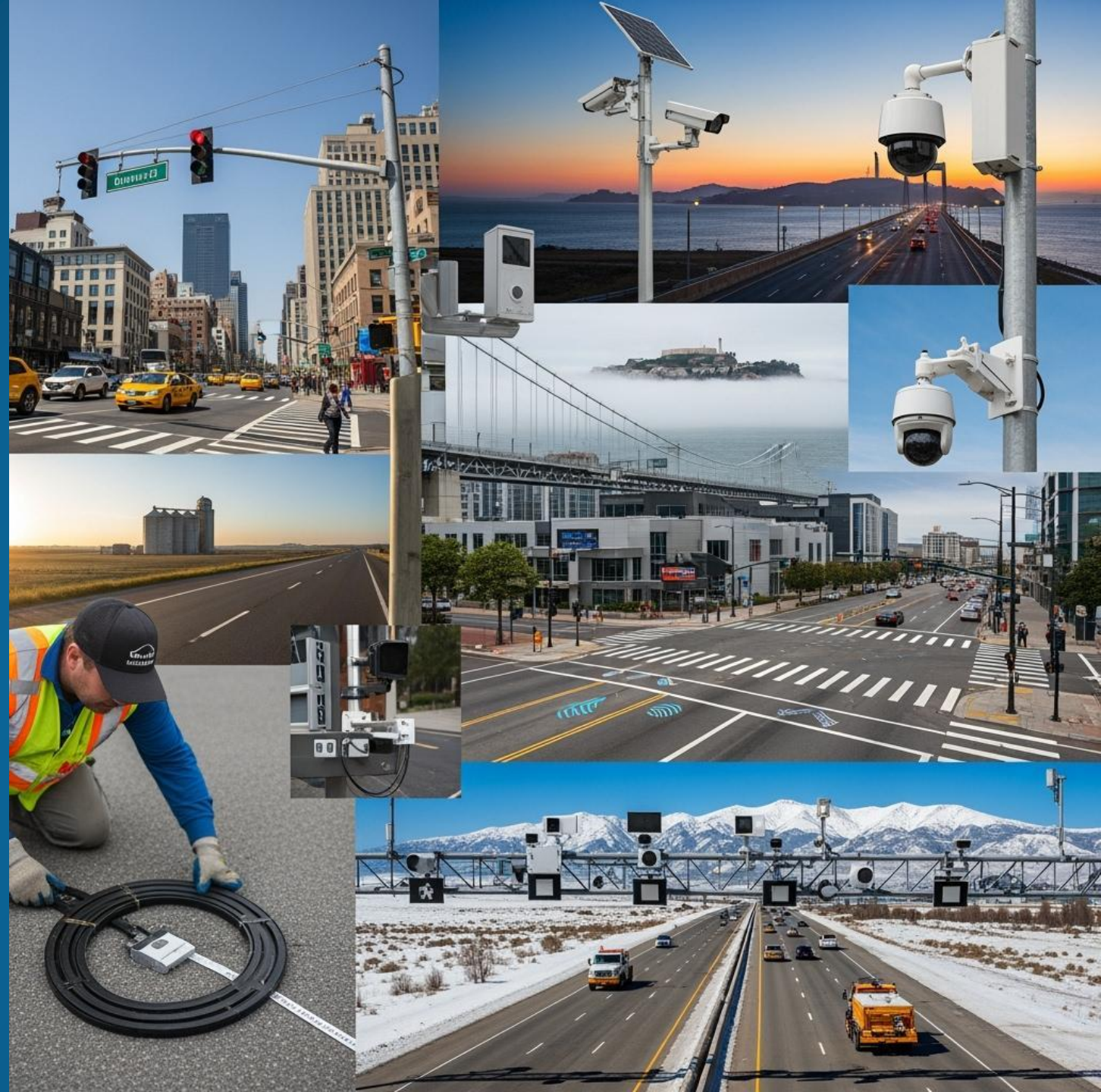
Application: Smart Cities

- Sensors collect local traffic data to optimize traffic signals
- FL enables cities to collaborate across regions for better models
- Privacy: Individual movements aren’t exposed



Application: Financial Services

- Banks train models collaboratively to detect fraudulent transactions
- Sensitive financial data stays within each institution

Swarm Intelligence

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Swarm Intelligence

- Definition
  - A collective behavior of decentralized, self-organized systems that solve problems through simple interactions
- Purpose
  - To achieve **complex problem-solving** or **optimization** by mimicking the behavior of natural swarms

Aspect	Federated Learning (FL)	Swarm Intelligence (SI)
Primary Goal	Train machine learning models collaboratively	Solve **optimization** problems (e.g., routing, resources)
Data Handling	Data remains local; only model updates are shared	Not focused on data privacy; agents share local information
Communication	Can be via server or fully decentralized	Local
Inspiration	Rooted in machine learning and privacy preservation.	Inspired by biological systems (e.g., ants, bees)
Emergent Behavior	Not a focus; behavior is pre-defined by algorithms	Emergent behavior arises from local interactions

Ant bridge from their live bodies
(e)Science News

- Minimizing travel time (path optimization)
- Resource allocation
- Dynamic adaptation
- Energy efficiency
- Emergent behavior

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Combining Swarm Intelligence and Federated Learning

- SI optimizes traffic
- FL learns patterns from local data.

Smart Cities

- SI coordinates drones
- FL trains models for victim detection
-

Disaster Response

- SI collects data
- FL improves predictions

Environmental Monitoring

- SI manages resources
- FL trains private predictive models

Healthcare

- SI optimizes tasks
- FL improves decisions from local conditions

Agriculture

- SI optimizes routes
- FL refines forecasts

Logistics

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Technical Challenges

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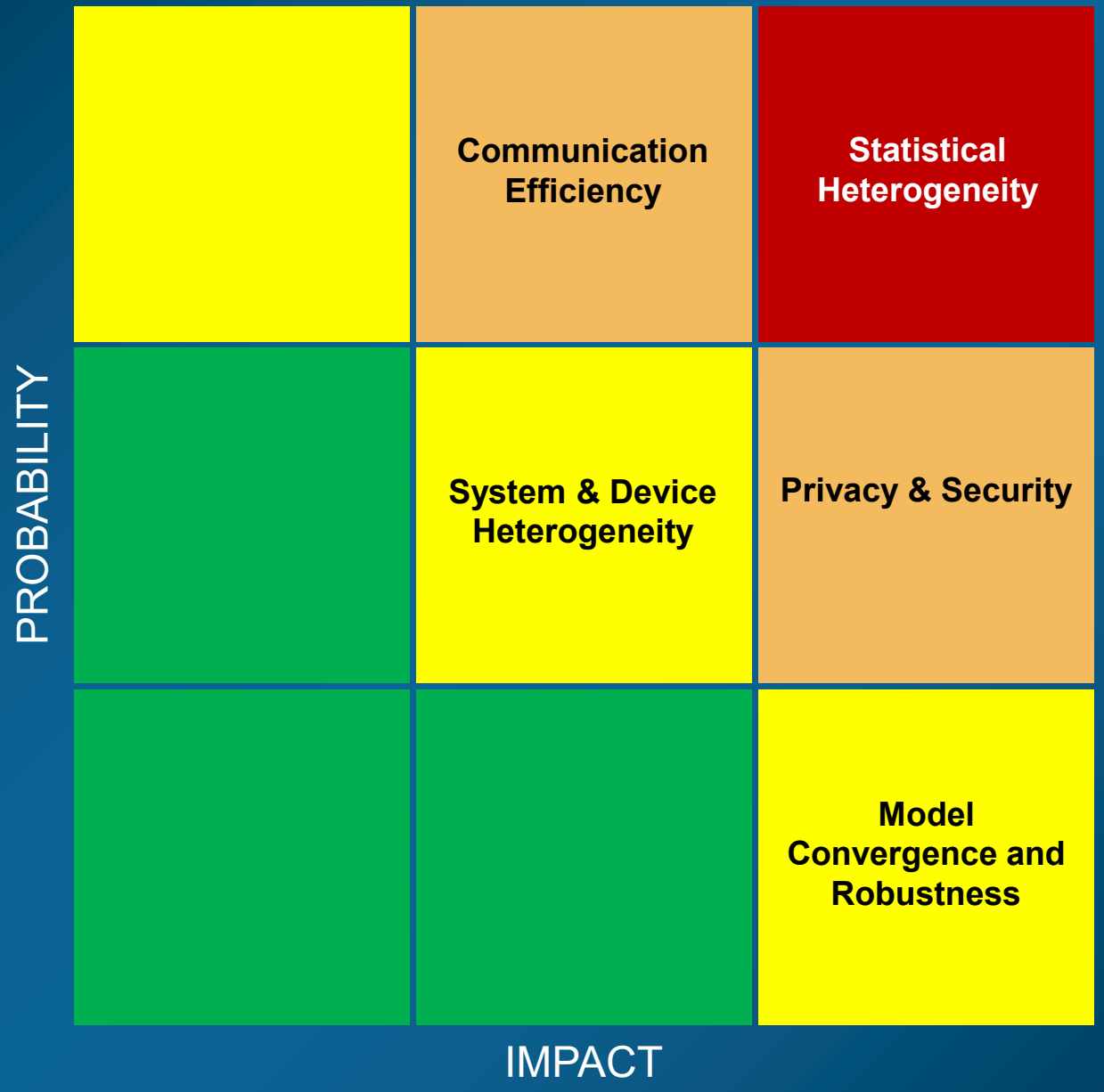
Technical Challenges

Challenge	Description	Mitigation
Communication Efficiency	Potentially high communication overhead on server or P2P participants	Optimize communication protocols and reduce the frequency or size updates: • Compress model updates • Increase local training epochs • Use partial client participation.
Privacy and Security	There is still a risk of leaking sensitive information through transmitted model updates or gradients	• Encrypt updates using secure aggregation • Detect and filter malicious updates
System and Device Heterogeneity	Variability in capabilities can affect training efficiency and model performance, especially when some devices may drop out or contribute unreliable updates	• Use lightweight or pruned models • Dynamically adjust workloads by device • Prioritize updates from reliable devices
Model Convergence and Robustness	Asynchronous updates, varying participation rates, and the impact of heterogeneous data may affect reliability in convergence of the global model. Risk of biased models that perform poorly on underrepresented data segments or in dynamic environments	• Use robust aggregators (e.g., Krum) • Adjust learning rates dynamically • Handle asynchronous updates with care

Risk Summary



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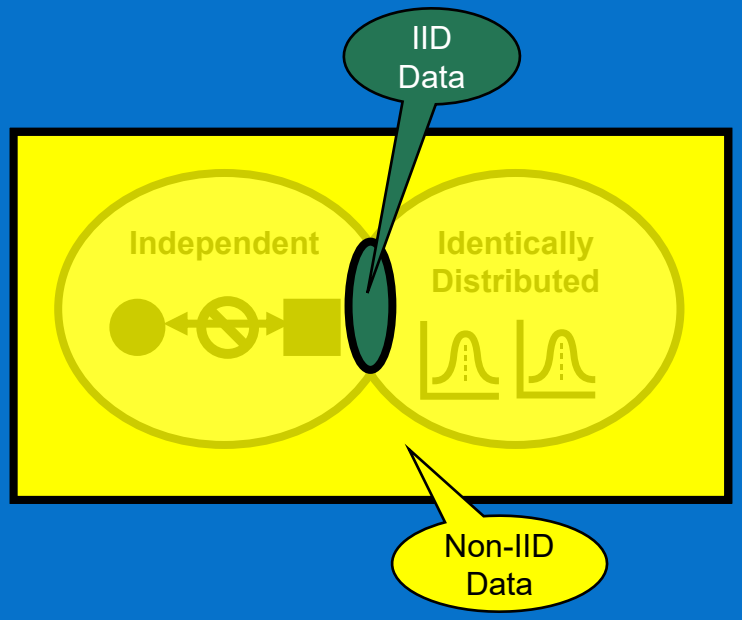
Statistical Heterogeneity (Non-IID Data)

- Scenario:
  - Devices typically hold non-IID data

What is non-IID



- **Independent:** data samples are not affected by one others
  - Ex: Each temperature sensor in a geographical area is not affected by other temperature sensors
- **Identically Distributed:** data samples are drawn from the same probability distribution
  - Ex: All sensors measure temperature under similar conditions, so their readings follow the same distribution

Statistical Heterogeneity (Non-IID Data)

- Widely recognized as the most critical challenge in federated learning
  - Causes biased updates
  - Slower convergence
  - Poor generalization
  - Makes it difficult to aggregate models effectively
- Currently a focus of research

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But, Art, dude, you said FEDERATED TRANSFER LEARNING deals with this stuff?
It can only help so much. *Stercus intrat, stercus exit*.

Image generated by Google Imagen.
I'm not violating copyright, am I?

Conclusion

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Summary

Paradigm	Data Dependency	Learning Objective	Key Applications
Supervised Learning	Requires fully labeled data	Predict outputs from labeled inputs	Image classification, spam detection, regression tasks
Unsupervised Learning	Works with unlabeled data	Discover hidden patterns or structures	Clustering, dimensionality reduction, anomaly detection
Semi-Supervised Learning	Combines labeled and unlabeled data	Improve performance using limited labeled data	Text classification with limited labels, medical image analysis
Self-Supervised Learning	Uses unlabeled data and generates labels from the data itself	Learn representations for downstream tasks	Pretraining models (e.g., GPT, BERT), masked autoencoders
Reinforcement Learning	Interacts with an environment	Optimize actions to maximize long-term rewards	Robotics, game-playing AI, autonomous vehicles
Federated Learning	Decentralized data across devices	Train models collaboratively without sharing raw data	Personalized recommendations, healthcare diagnostics, edge AI

Key Takeaways

- FL enables collaborative AI without data sharing
- From UAVs to hospitals, from phones to traffic sensors, FL is an invaluable systems architecture for AI
- Still many open challenges: privacy, robustness, optimization, and especially, statistical heterogeneity
- FL combined with SI is very powerful

Demonstration

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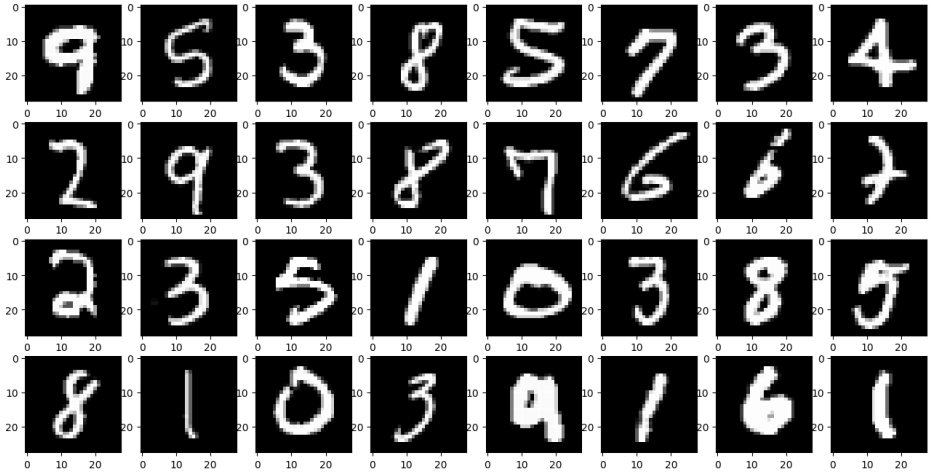
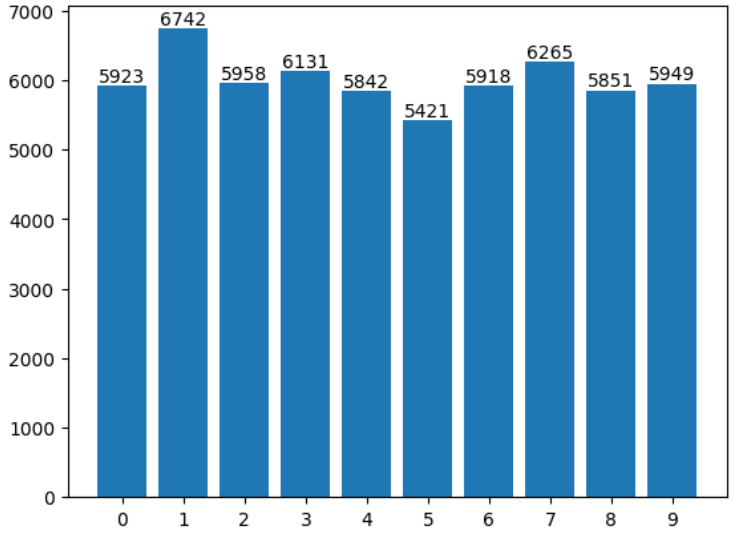
Demonstration: Flower

https://colab.research.google.com/github/adap/flower/blob/main/examples/flower-in-30-minutes/tutorial.ipynb

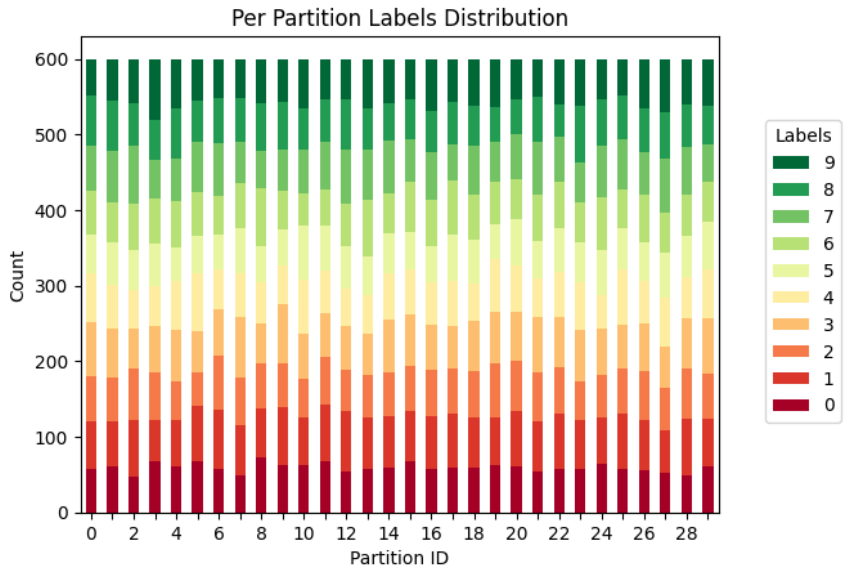
- Uses MNIST data set:
  - 70,000 28x28 handwritten digits
  - 60,000 for training
  - 10,000 for test



Centralized



Distributed
(first 30 of 100 clients shown)



Question-Answer-Discussion

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Federated Learning:

A Systems Engineering Approach to Smarter AI

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In the first presentation of this evolving series, Dr. Villanueva explored the convergence of Systems Engineering and Artificial Intelligence. In the second, he examined the phenomenon of emergence – how complex system-level behavior arises from simple, local interactions. This third installment delves into federated learning (FL), a distributed machine learning paradigm that applies principles of emergence at scale, enabling intelligent global behavior to arise from decentralized, local interactions.

Federated Learning enables edge devices to collaboratively train shared models without transferring raw data. Through decentralized computation and global aggregation, intelligent behavior emerges from the collective experience of autonomous participants – from smartphones and hospitals to fleets of unmanned aerial vehicles (UAVs). This talk will examine the algorithmic foundations of FL, its systemic challenges (non-IID data, intermittent connectivity, and adversarial threats), and its compelling applications in systems where privacy, resiliency, and autonomy converge.

From collaborative healthcare systems to adaptive environmental monitoring to smart infrastructure and UAV networks, federated learning provides a powerful framework for enabling distributed intelligence across diverse domains. Dr. Villanueva will examine how FL represents not just a technical tool, but a systems architecture for building complex, adaptive, and mission-aware AI at the edge, where privacy, resilience, and autonomy are paramount.