Federated Zero-Shot Learning: A Proposal

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Outline

- Introduction
  - Federated Learning
  - Zero-Shot Learning
- The Proposal
- Motivation
- Road Map

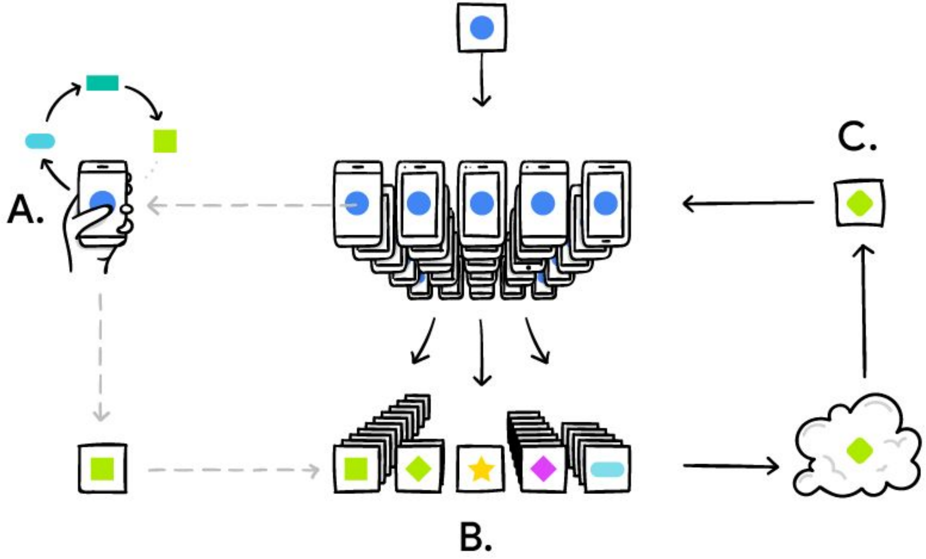
Federated Learning

Federated Learning (1)

Primary goal
Training a global shared model.

How?
Using data stored locally on remote devices.

Why?
Decentralization.
Privacy preserving.
Model adaptation.



Federated Learning (2)

Problem formulation

m total number of devices

$p_k \geq 0$ and $\sum_k p_k = 1$

F_k local objective function for the kth device

Goal

$$\min_w F(w)$$

$$F(w) := \sum_{k=1}^{m} p_k F_k(w)$$

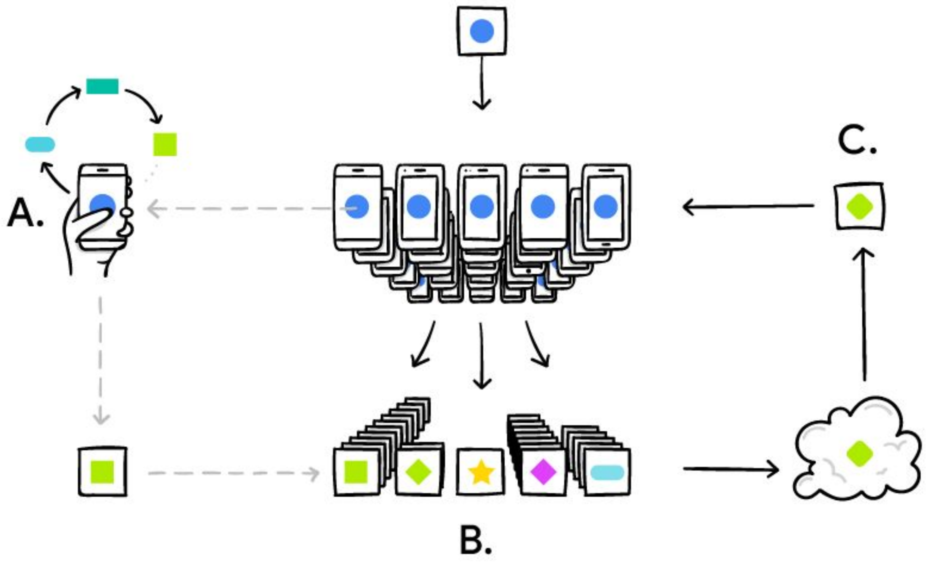
Federated Learning (3)

Steps

A. Local updates.

B. Models aggregation.

C. Global model distribution.



Federated Learning (4)

Key challenges

1. **Expensive communication**
   - Updates may become a bottleneck.
   - **Communication-efficient methods are necessary.**
2. **Systems heterogeneity**
   - High hardware variability.
   - Low amount of participation.
   - **Strategies to deal with HW heterogeneity.**
3. **Privacy**
   - Updates may reveal sensitive information.
   - **Trade-off between performance and privacy.**
4. **Statistical heterogeneity**
   - Each device generates its own data.
   - **Multi-task learning and meta-learning approaches.**

Zero-Shot Learning

Zero-Shot Learning (1)

Primary goal

Learn to classify unseen testing examples without training data.

How?

Using additional knowledge: a **semantic space**.

Why?

Learning with few data.
Adaptation to new unseen categories.
Deal with a variable number of categories.

Zero-Shot Learning (2)

Problem formulation

$\mathbf{S}$ seen classes, $\mathbf{U}$ unseen classes, $\mathbf{S} \cap \mathbf{U} = \emptyset$, $\mathbf{X}$ feature space

$$D^{tr} = \left\{ \left(x_i^{tr}, y_i^{tr} \right) \in \mathbf{X} \times \mathbf{S} \right\}_{i=1}^{N_{tr}}$$

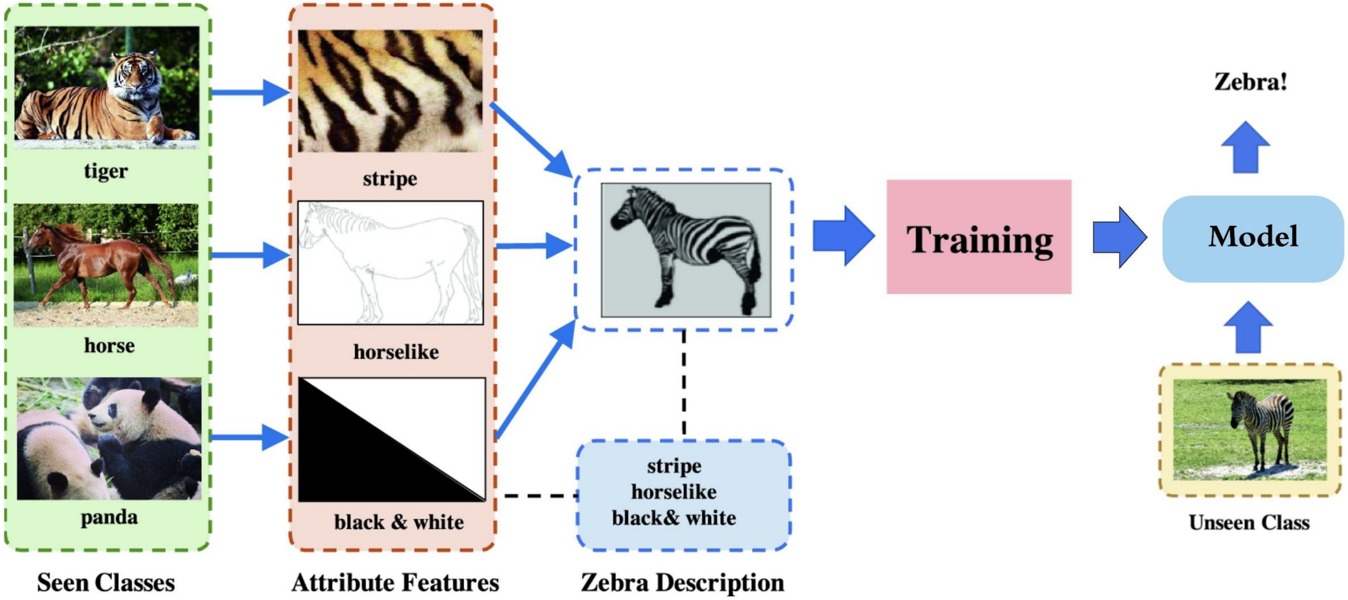
$$X^{te} = \left\{ x_i^{te} \in \mathbf{X} \right\}_{i=1}^{N_{te}} \text{ testing examples}$$

$$Y^{te} = \left\{ y_i^{te} \in \mathbf{U} \right\}_{i=1}^{N_{te}} \text{ labels to predict}$$

Goal

Given D^{tr}, learn a classifier $f^u(\cdot) : \mathbf{X} \to \mathbf{U}$

Zero-Shot Learning (3)



Zero-Shot Learning (4)

Key challenges

1. **Extend ZSL to different type of data.**
   - Most of the works focus on images.
2. **Exploit characteristics of input data.**
   - Time-series, for example.
3. **Combination with other learning paradigms.**
   - Why not Federated Learning?

Federated Zero-Shot Learning

Federated Zero-Shot Learning (1)

The proposal

Federate Learning + **Zero-Shot Learning**.

Motivation

Real world conditions ≠ Lab conditions.

- Few labeled data.
- Unseen classes.
- Data distributed across devices.
- GDPR regulation.

A novel paradigm is needed!

Federated Zero-Shot Learning (2)

Features

1. **Learning with few labeled data.**
    - Collaboration to enhance the global model.
    - ZSL to deal with unseen classes.
2. **Privacy.**
    - Training on remote devices.
3. **Human Centric AI.**
    - Local data.
    - Human feedback.
    - **User-based model → Services personalization.**

Road Map

Road Map

Goal

Federated Learning + Zero-Shot Learning → Services Personalization.

Models & Data

Recurrent models on sequential data e.g. time-series.

Challenges

1. Train recurrent models in FL scenarios.
    - Communication, privacy, new learning algorithms.
2. ZSL with time-series data.
    - Semantic space.
3. Incorporate human feedbacks during the training.
4. Put it all together!

References

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Questions?

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