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 $k$th 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

S seen classes, U unseen classes, S ∩ U = ∅, X feature space

\[ D^{tr} = \{(x_i^{tr}, y_i^{tr}) \in X \times S\}_{i=1}^{N_{tr}} \]

\[ X^{te} = \{x_i^{te} \in X\}_{i=1}^{N_{te}} \text{ testing examples} \]

\[ Y^{te} = \{y_i^{te} \in U\}_{i=1}^{N_{te}} \text{ labels to predict} \]

Goal

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


Questions?

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