Neural Network ODL (On-Device Rearning) for Wireless Sensor Nodes

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@tinyML On Device Learning Forum (Aug 31, 2022)

IoT: Applications

• ML application in real fields (e.g., anomaly detection) Factory, monitoring, robot, safety, security, surveillance, ...



Edge AI: Equipment monitoring

Monitoring of air-conditioning systems (e.g., fans)
Using wireless sensor nodes that can train and predict











Edge AI: Equipment monitoring

• Wireless sensor nodes that can train and predict [1] Raspberry Pi Pico, sensors, magnet, battery, LoRa module On-device learning of neural networks



[1] Hiroki Matsutani et al., "On-Device Learning: A Neural Network Based Field-Trainable Edge AI", arXiv:2203.01077 (2022)

Edge AI: Classification



On-device learning: Motivation

 Challenges of edge AI: Addressing the gap between training data and deployed environment

Training Function

Flat Minimum

<u>Typical solution</u>
✓ Generalization capability to absorb the gap

Testing Function

Typical edge AI use case

- **1. Collect train data**
- 2. Train at server
- 3. Predict at edge

At <u>different</u> environments

On-device learning: Motivation

 Challenges of edge AI: Addressing the gap between training data and deployed environment at low-cost



[1] Mineto Tsukada et al., "A Neural Network-Based On-device Learning Anomaly Detector for Edge Devices", IEEE Trans. on Computers (2020).

<u>On-device learning: Two modes</u>

1. Train mode

2. Predict-only mode

Question: How and when is the mode changed?



On-device learning: Two approaches

1. Field-tunable AI

2. Field-adaptive AI

Field-engineers can train edge AI whenever they want Automatically trained when concept drift is detected



[1] Hiroki Matsutani et al., "On-Device Learning: A Neural Network Based Field-Trainable Edge AI", arXiv:2203.01077 (2022

On-device learning: Demonstration





On-Device Learning Modules (Left: Accelerometer, Right: Thermal Camera)



<u>On-device learning: Other demos</u>

On-Device Learning

A New Edge Al for On-Site Learning

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SE Mobile robot (UAV)

Normal propeller (white) and damaged propeller (red) \rightarrow Detect anomaly pattern





loss value that indicates difference from the normal pattern also increases.

ASE Surveillance camera

Normal behaviors differ depending on position/angle of camera \rightarrow Normal should be learned autonomously





Object tracking



Object tracking + Abnormal behavior detection

On-device learning: Algorithm

 K-class anomaly detection with K autoencoder neural networks (i.e., instances)
Each autoencoder is trained to be specialized to each class



Example: 4-class anomaly detection on cooling fan dataset (mentioned later) 15

On-device learning: Prediction

 Prediction is done by K instances, each of which is specialized to each class
Input: n-dimensional data, Output: Loss I and class k



Instance with the smallest loss value is "the closest" instance or class

On-device learning: Sequential training

 "The closest instance" is updated with the input data OS-ELM [1] is used as sequential training algorithm Batch size is fixed to 1 to eliminate pseudo inverse operation



[1] N. Y. Liang, G. B. Huang, P. Saratchandran, N. Sundararajan, "A Fast and Accurate Online Sequential Learning Algorithm for Feedforward Networks", IEEE Trans. on Neural Networks, vol. 17, no. 6, pp. 1411-1423, Nov. 2006.

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Evaluations: Execution time

Raspberry Pi Pico @133MHz + LoRa module



On-device learning Sensing, Prediction, Training

Monitor & control 20

Magnet

Evaluations: Execution time

Four 3-layer neural networks (256-32-256 nodes)





On-device learning Sensing, Prediction, Training

Evaluations: Communication size

Communication size reduction not sending train data



Monitor & control

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On-device learning Sensing, Prediction, Training

Evaluations: Cooling fan dataset

Trained at normal but predict at noisy environment
Predict only: Cannot adapt to the noisy environment ®
On-device learning: Can adapt to the noisy environment ©

Big difference between training function and testing function



(Normal environment: office room, Noisy environment: near a ventilation fan)

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Evaluations: Cooling fan dataset

Trained at normal but predict at noisy environment
Predict only: Cannot adapt to the noisy environment ®
On-device learning: Can adapt to the noisy environment ©



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(Normal environment: office room, Noisy environment: near a ventilation fan)

Evaluations: ROC-AUC / Accuracy

Trained at normal but predict at noisy environment
Predict only: Cannot adapt to the noisy environment 8
On-device learning: Can adapt to the noisy environment 9





(a) Summary of seven tasks

(c) Result of Damage1 task

Evaluations: ROC-AUC / Accuracy

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(a) Summary of seven tasks

c) Result of Damage1 task

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(a) Summary of seven tasks

(c) Result of Damage1 task

On-device learning: Summary

