



# The System Level Design Group

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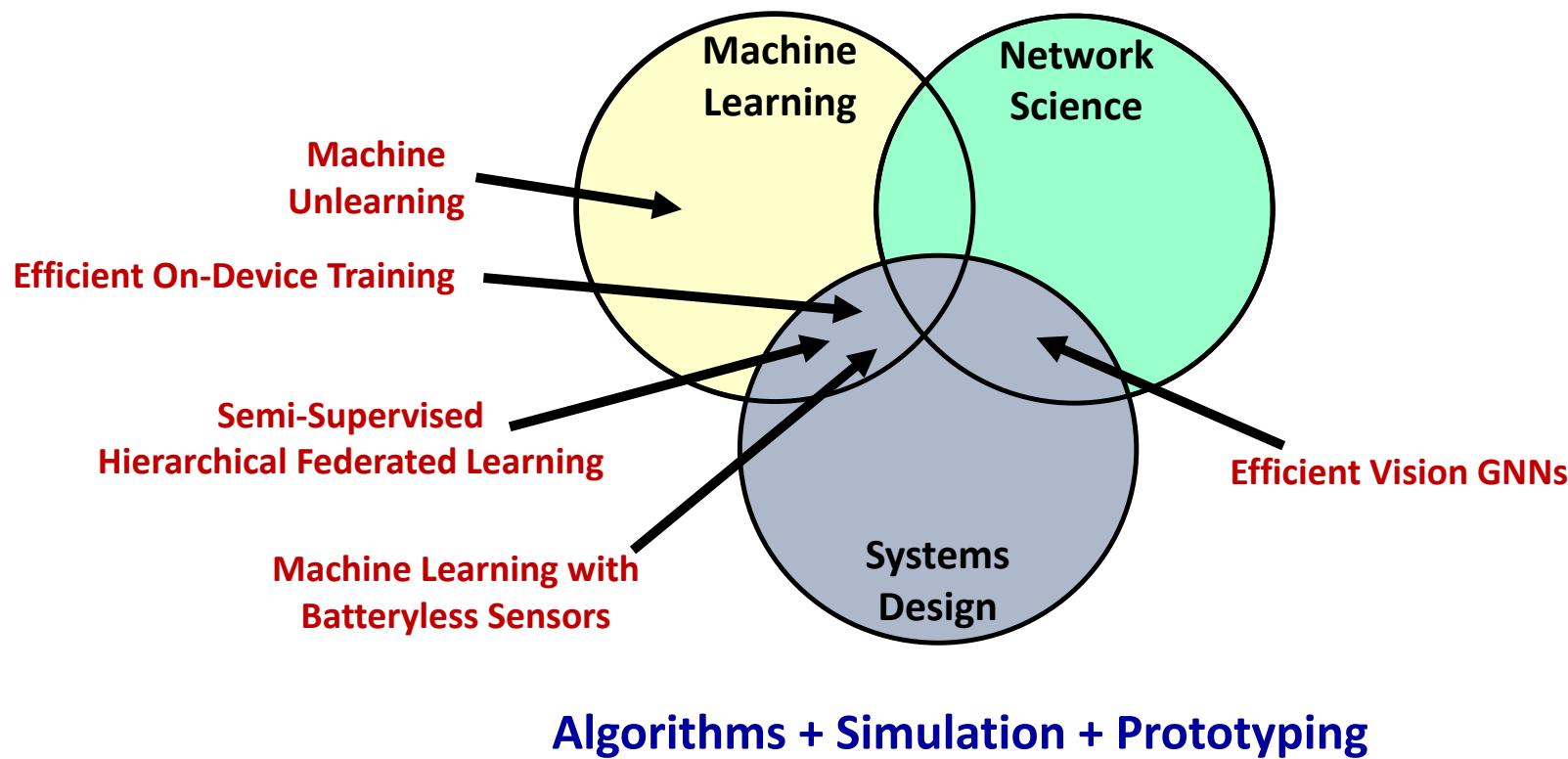
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The University of Texas at Austin  
Chandra Department of Electrical  
and Computer Engineering  
Cockrell School of Engineering

# SLD Group @UT



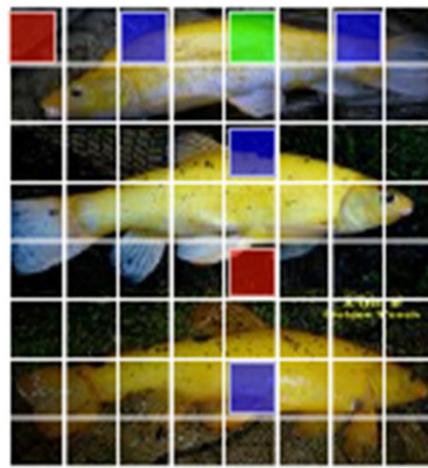
# **Vision Graph Neural Networks**

# Dynamic Axial Graph Construction (DAGC) and GreedyViG Architecture

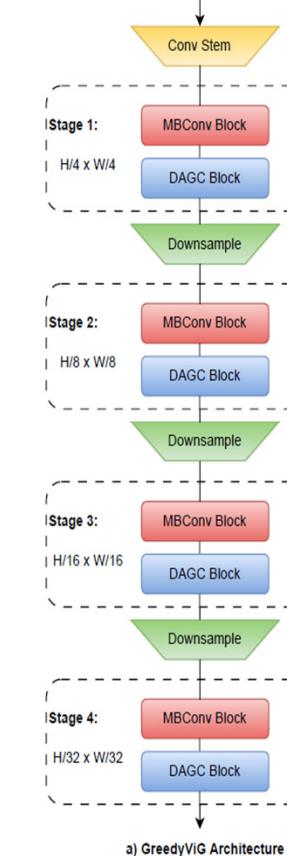
a) SVGA



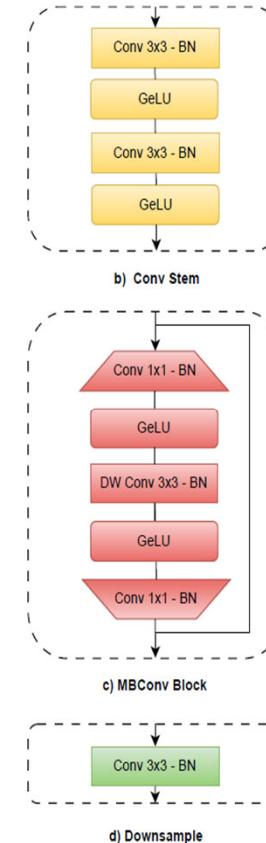
b) DAGC



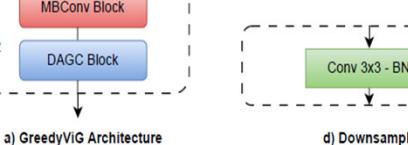
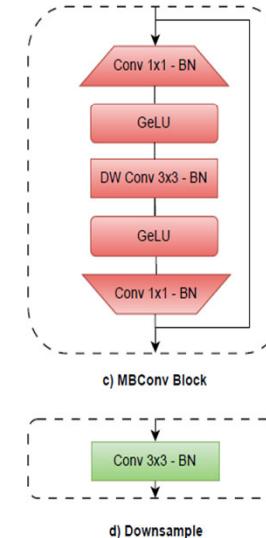
**DAGC dynamically constructs a graph** along the axes, through applying a mask (the blue patches) to only connect similar patches in terms of Euclidean distance.



a) GreedyViG Architecture

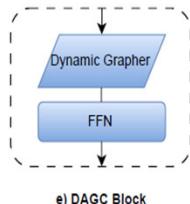


b) Conv Stem

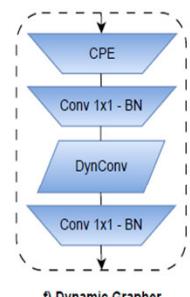


c) MBConv Block

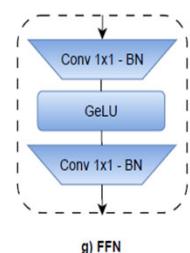
d) Downsample



e) DAGC Block



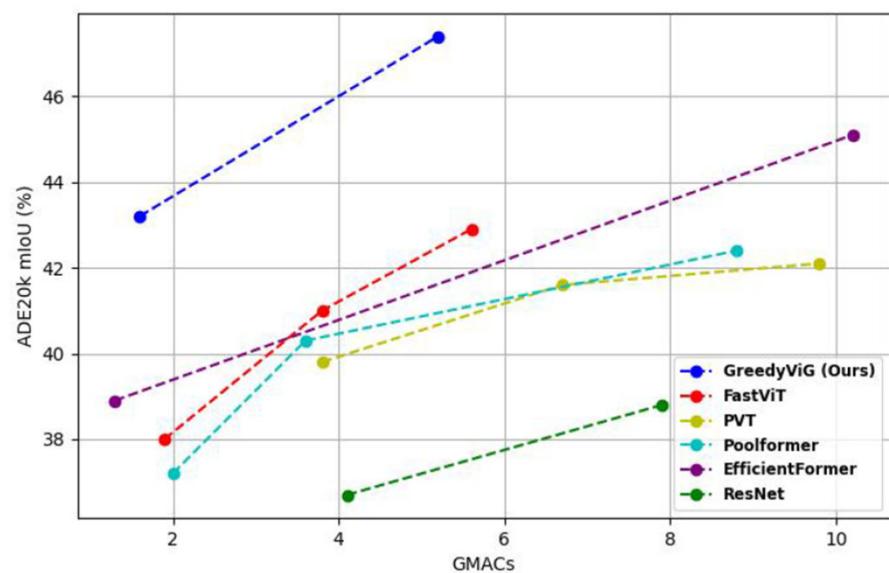
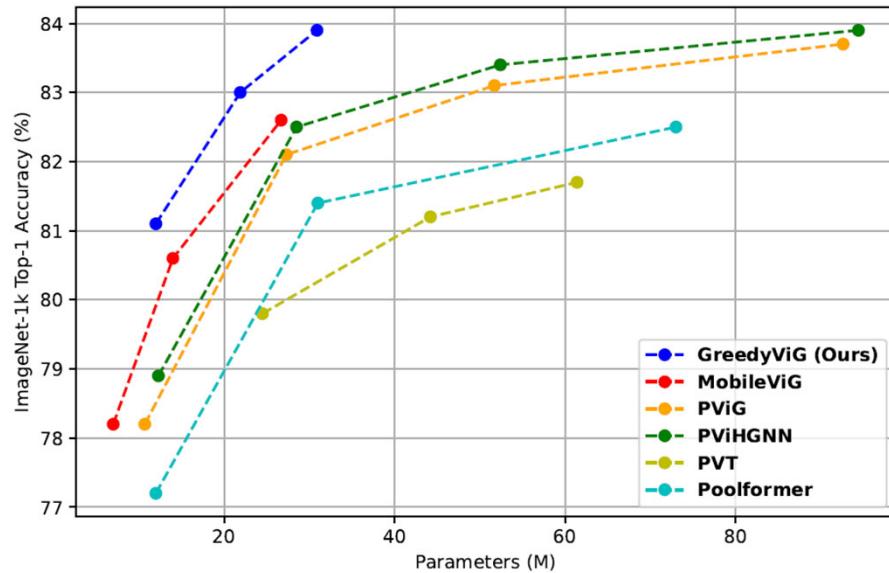
f) Dynamic Grapher



g) FFN

**Proposed architecture of GreedyViG using Dynamic Axial Graph Construction.**

# Experimental Results on Classification and Segmentation



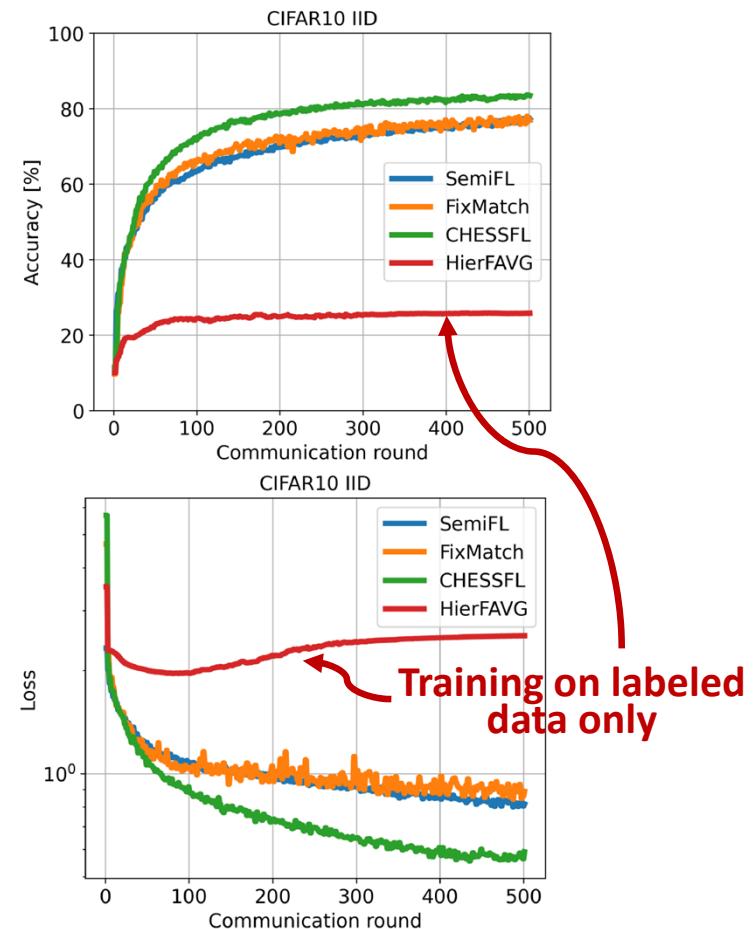
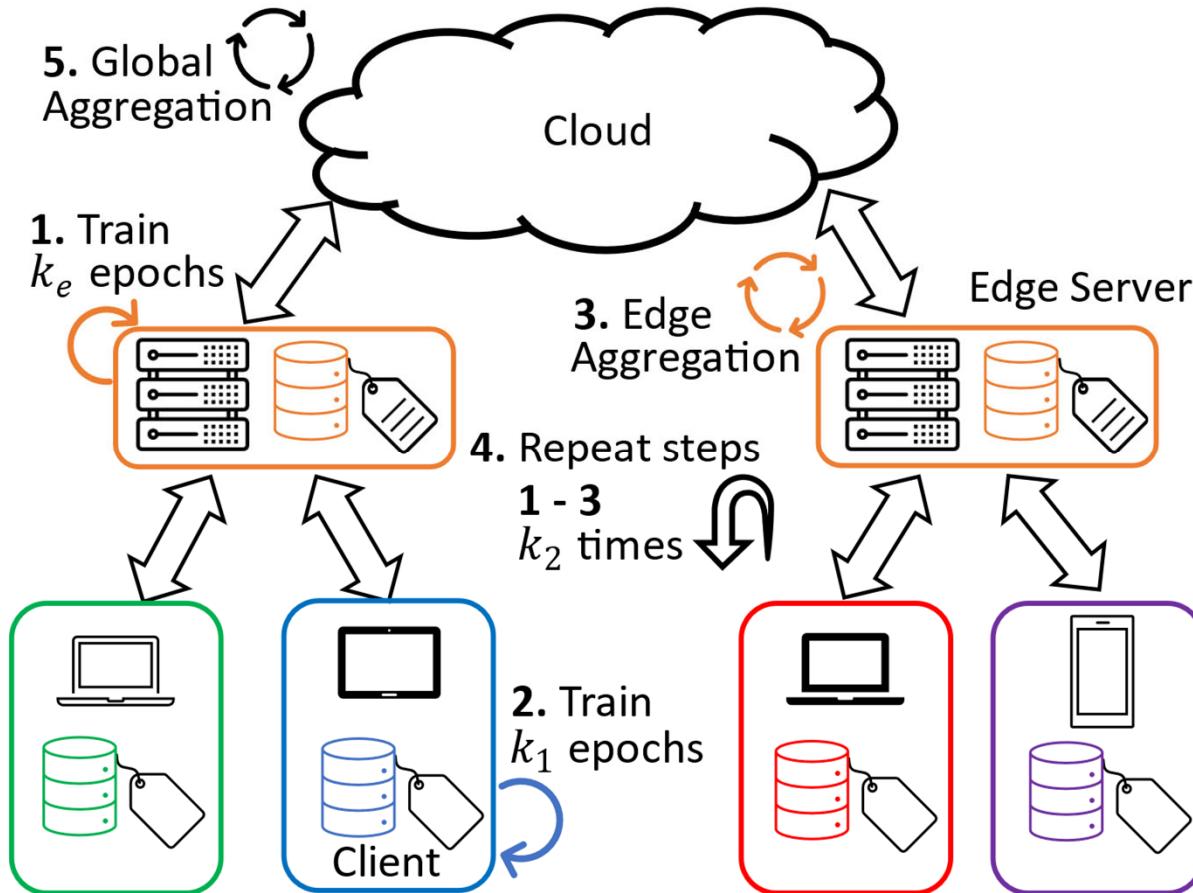
Backbone	Parameters (M)	$AP^{box}$	$AP_{50}^{box}$	$AP_{75}^{box}$	$AP^{mask}$	$AP_{50}^{mask}$	$AP_{75}^{mask}$	$mIoU$
ResNet18 [9]	11.7	34.0	54.0	36.7	31.2	51.0	32.7	32.9
EfficientFormer-L1 [23]	12.3	37.9	60.3	41.0	35.4	57.3	37.3	38.9
EfficientFormerV2-S2 [22]	12.6	43.4	65.4	47.5	39.5	62.4	42.2	42.4
PoolFormer-S12 [50]	12.0	37.3	59.0	40.1	34.6	55.8	36.9	37.2
FastViT-SA12 [41]	10.9	38.9	60.5	42.2	35.9	57.6	38.1	38.0
MobileViG-M [30]	14.0	41.3	62.8	45.1	38.1	60.1	40.8	-
GreedyViG-S (Ours)	12.0	43.2	65.2	47.3	39.8	62.2	43.2	43.2

Method is *efficient* and beats SOTA across multiple CV tasks.

# Efficient On-Device Training

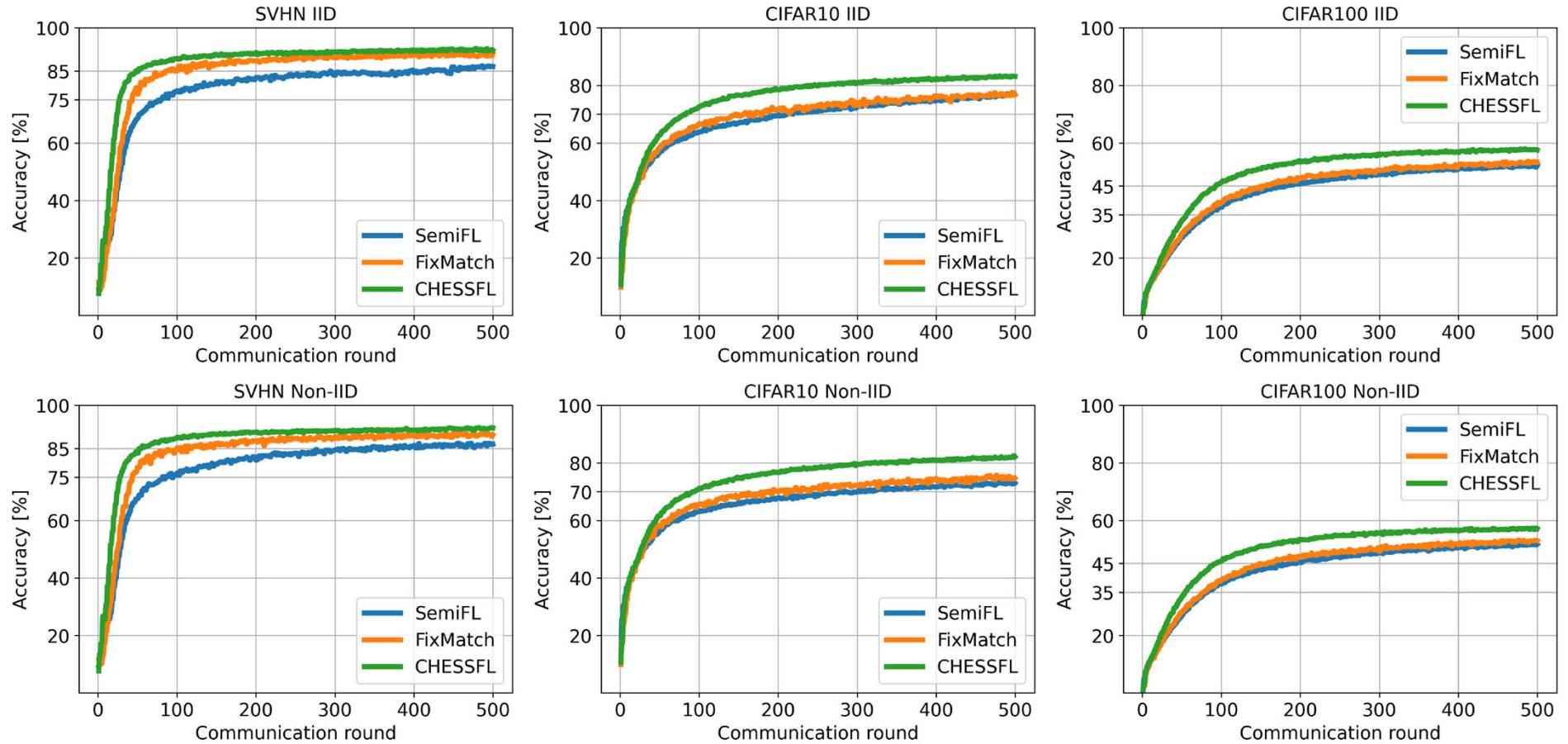
# **Semi-Supervised Hierarchical Federated Learning**

# Semi-Supervised Hierarchical Federated Learning Overview



The goal is to minimize the global loss function with *limited labeled data* available at the edge servers and *lots of unlabeled data* available at the clients.

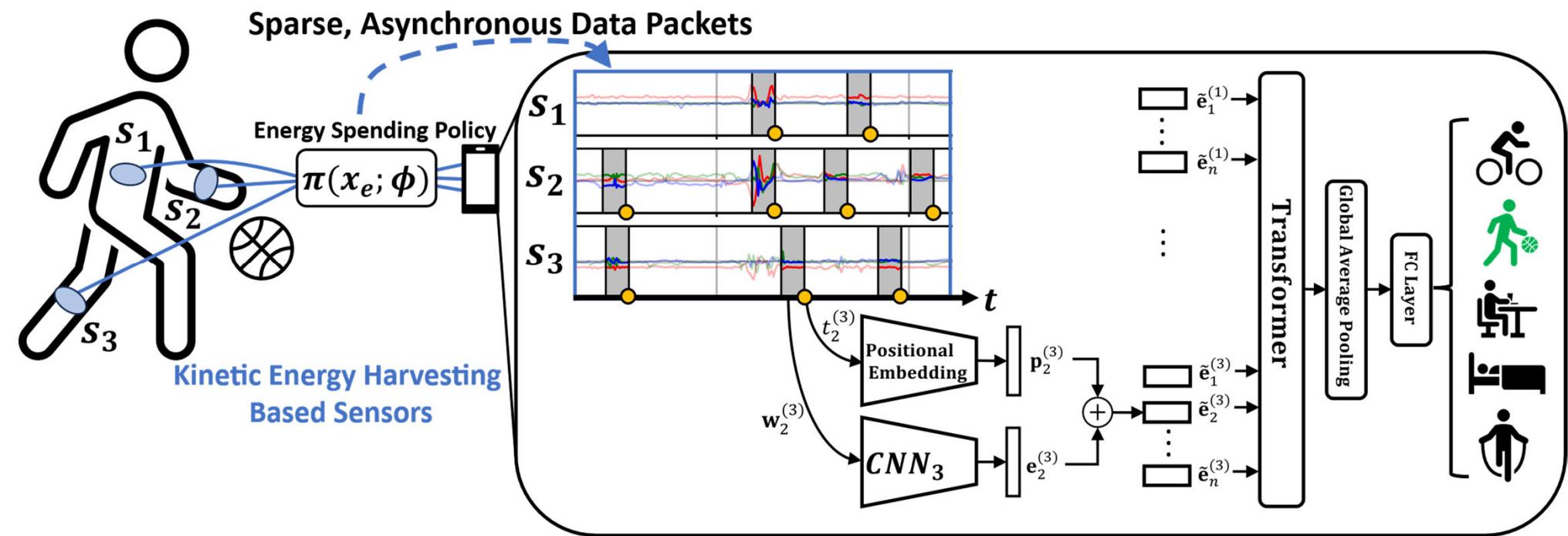
# CHESSFL: Clustering Hierarchical Embeddings for Semi-Supervised Federated Learning



**CHESSFL converges up to 5.11 $\times$  faster and achieves higher accuracy than state-of-the-art SSFL solutions on multiple datasets, with negligible communication overhead and enhanced robustness to non-IID data.**

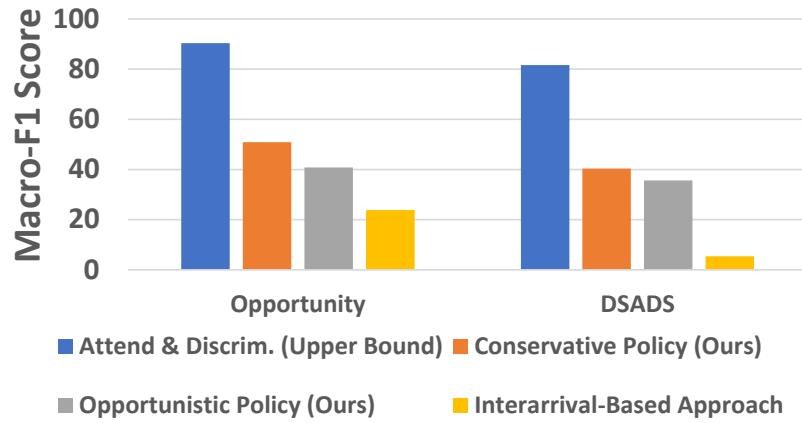
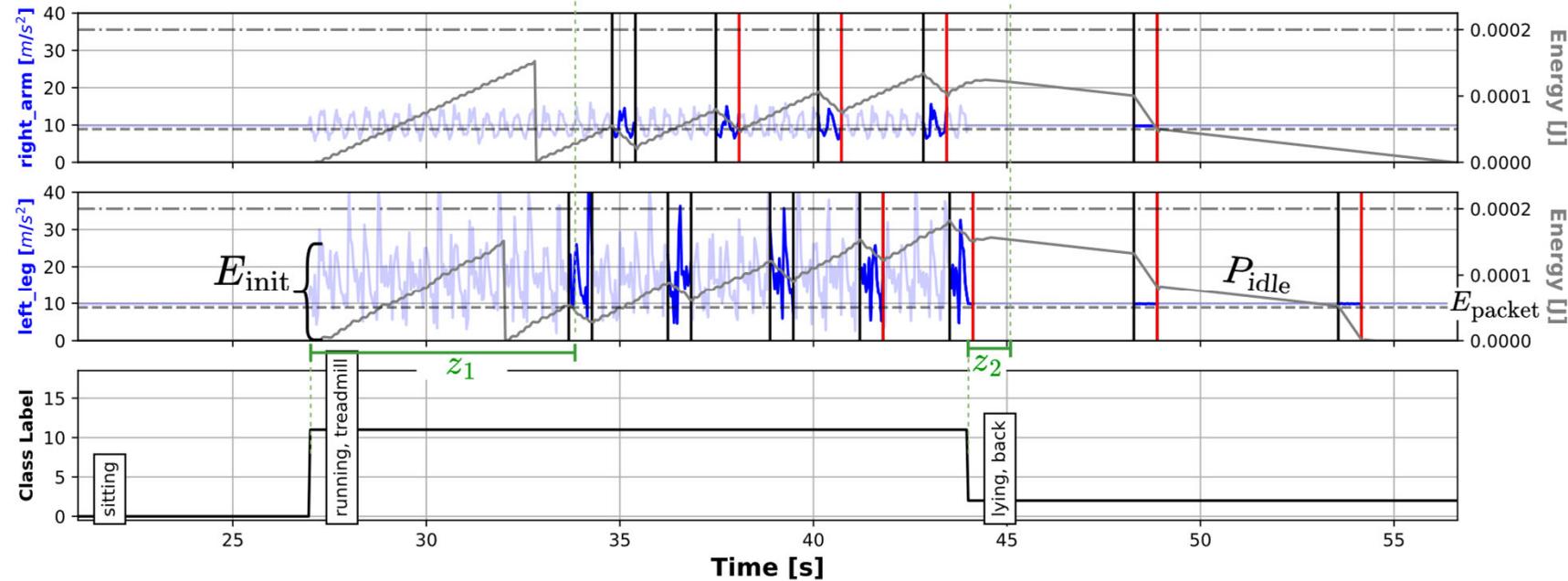
# Machine Learning with Batteryless Sensors

## Energy Harvesting Based Sensors Produce Sparse, Asynchronous Data



The goal is to *optimize an energy spending policy* to provide the most informative data, *while simultaneously training a deep learning model* to process the unstructured stream of packets.

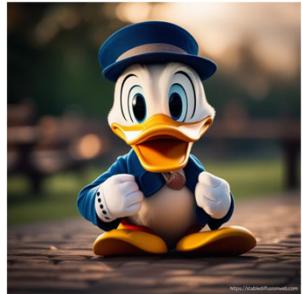
## We Synergize Energy Spending Policies with Deep Learning Models



Our transformer model significantly outperforms the interarrival time-based approach and improves when learning from a *conservative* energy spending policy.

# Unlearning for Image-to-Image Generative Models

# Risks of Generative Models and Potential Solutions



Copyright Infringement  
Training set



Porn/Violence



*Caption: Living in the light with Ann Graham Lotz*



*Prompt: Ann Graham Lotz*

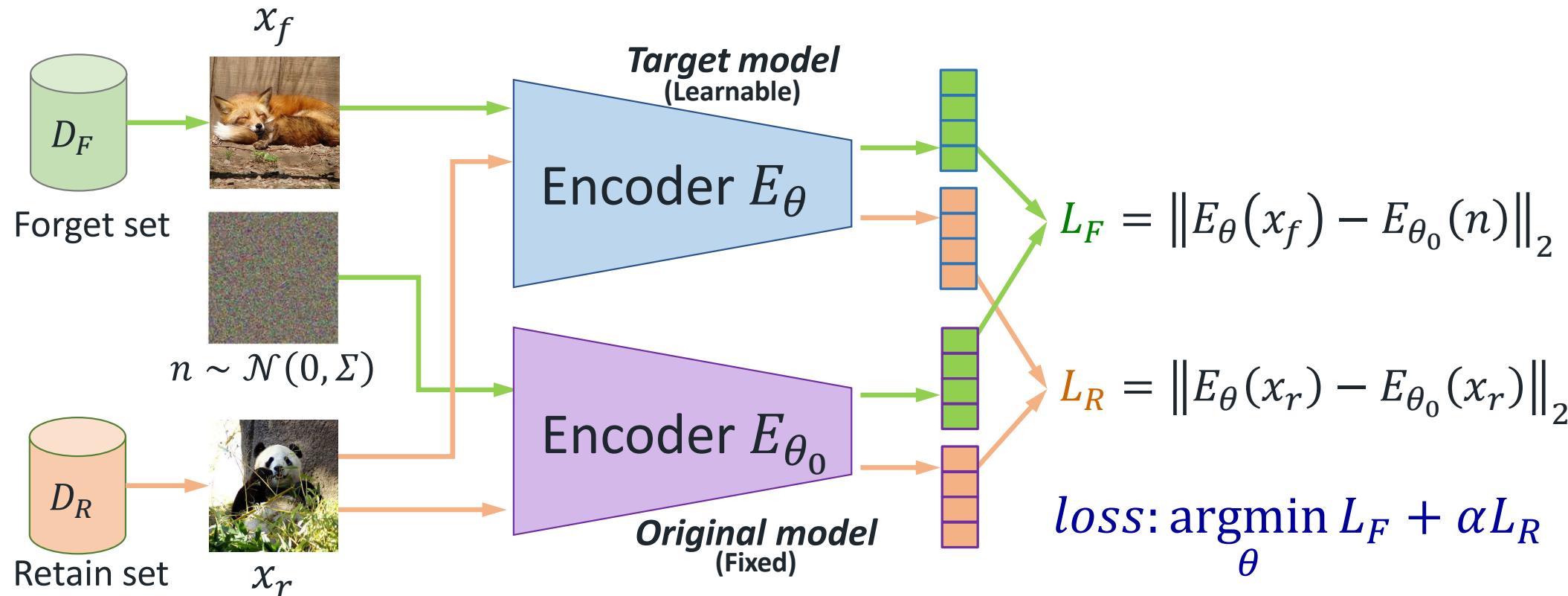
Privacy Leakage

Potential risks of image generative models



**Machine unlearning is a *promising* and *efficient technique* to resolve these issues yet relatively unexplored.**

## Our Proposed Solution for Efficient Unlearning on Generative Models



- Our method is applicable to *various* models, including GAN, diffusion model, and MAE
- Our method *reduce #tunable parameters by about half* and *speedup by up 4x*

## Acknowledgements

- Contributors



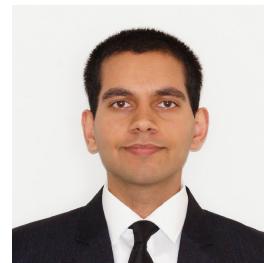
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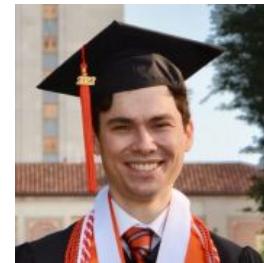
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- Sponsors & Collaborators



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Thank you!

