



Towards Context-aware Distributed Learning for CNN in Mobile Applications

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Introduction

Distributed Learning on Mobile Devices

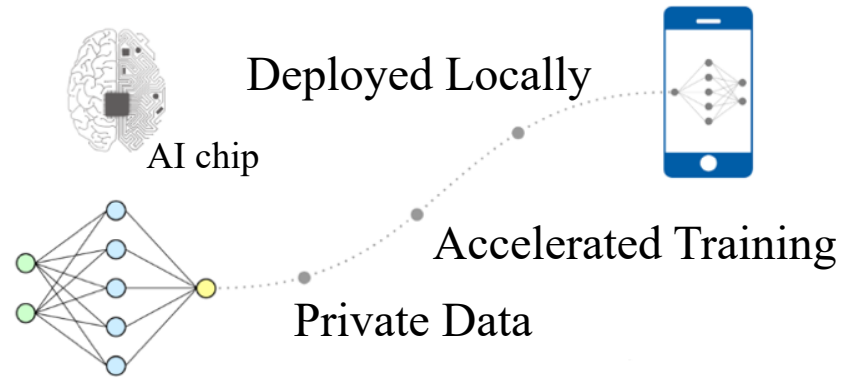
Traditional Distributed Learning Framework

Context-aware Distributed Mobile Learning

Conclusion

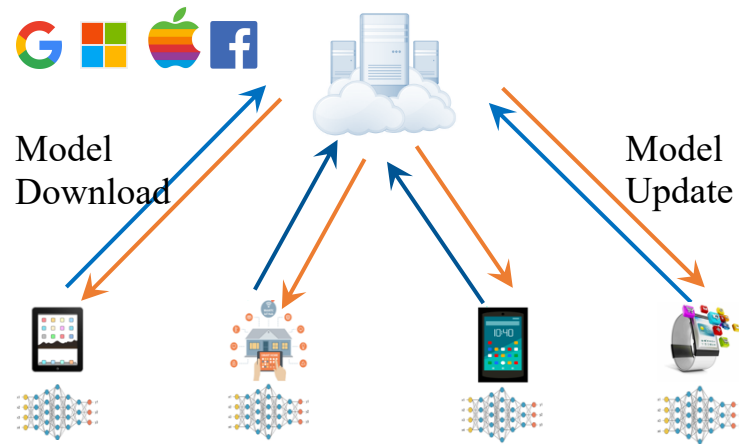
Distributed Learning on Mobile Devices

Massive Amount of Mobile Devices



- Featured with an AI chip
- Underutilized Processing Capacity

Large Scale System Deployment

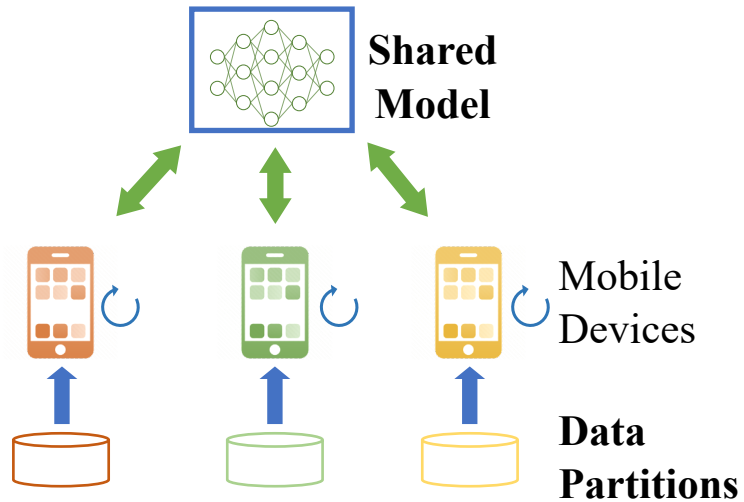


- Efficient Computation and Communication
- Scalable Number of Devices
- Accurate Distributed Aggregation

Traditional Distributed Learning Framework

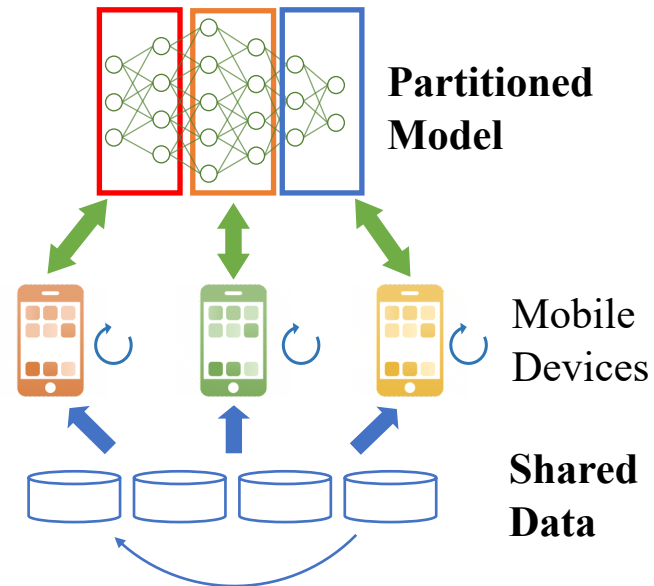
Parallelism in Distributed Neural Network Training

Data Parallelism



- High Data Throughput
- Heavy Computation Load

Model Parallelism

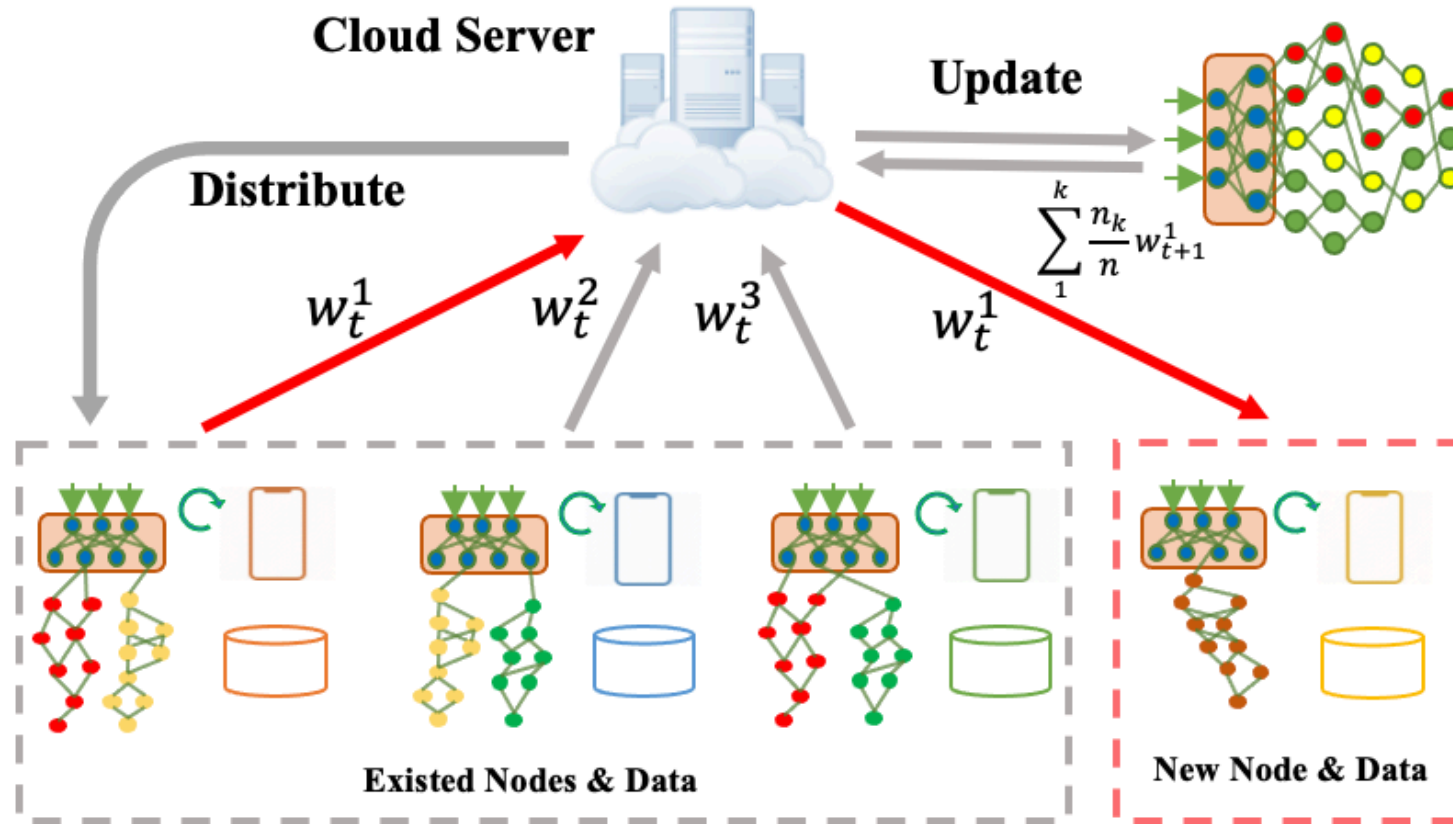


- Massive Node Communication
- Unscalable Collaboration Topology

Works	M	D	Works	M	D
Federated Learning	×	✓	DistBelief	✓	×
Parameter Server	×	✓	COTS	✓	×
1-bit SGD	×	✓	SpecTrain	✓	×
ParallelSGD	×	✓	Ours	✓	✓

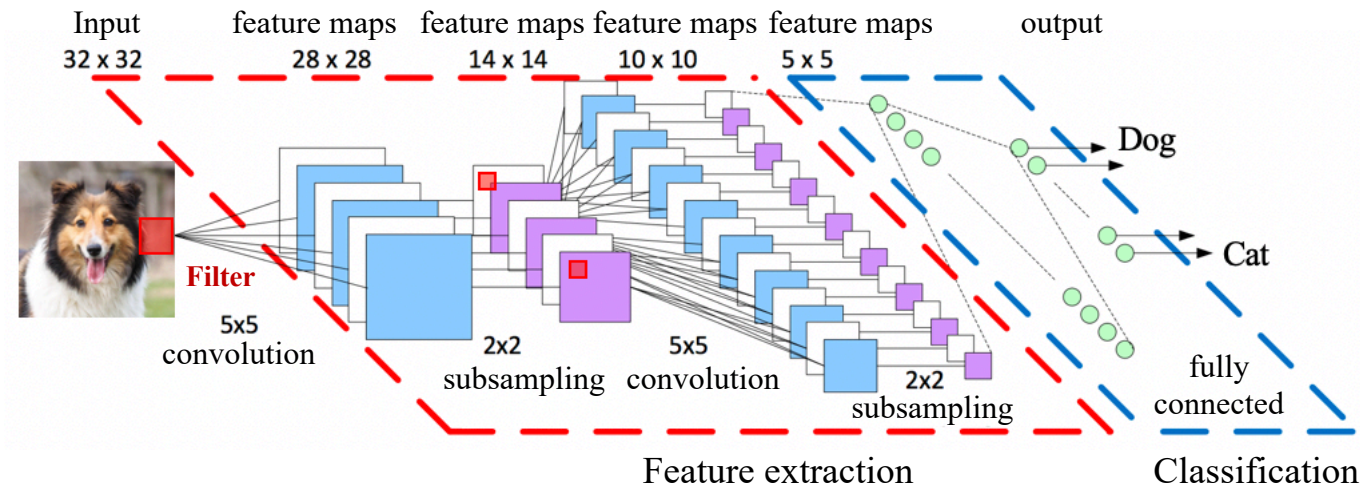
Ours: Context-aware Distributed Learning Framework

Framework Overview

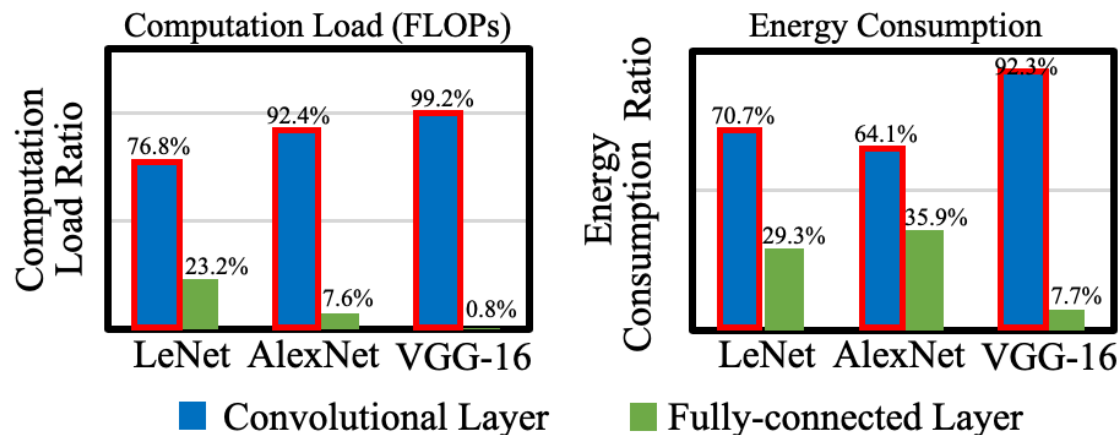


Neural Network Computation

Convolutional Neural Network (CNN) for Image Classification



Intensive Computation Load for Convolutional Operation



Optimization Target:
Convolutional Layers

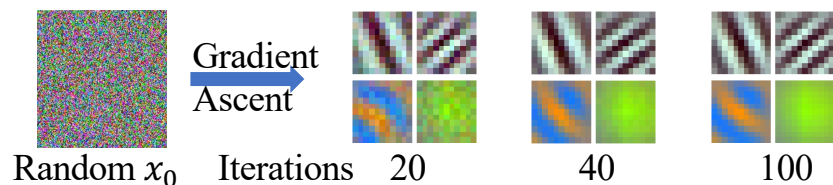
Convolutional Filter Visualization

Filter Visualization by Activation Maximization

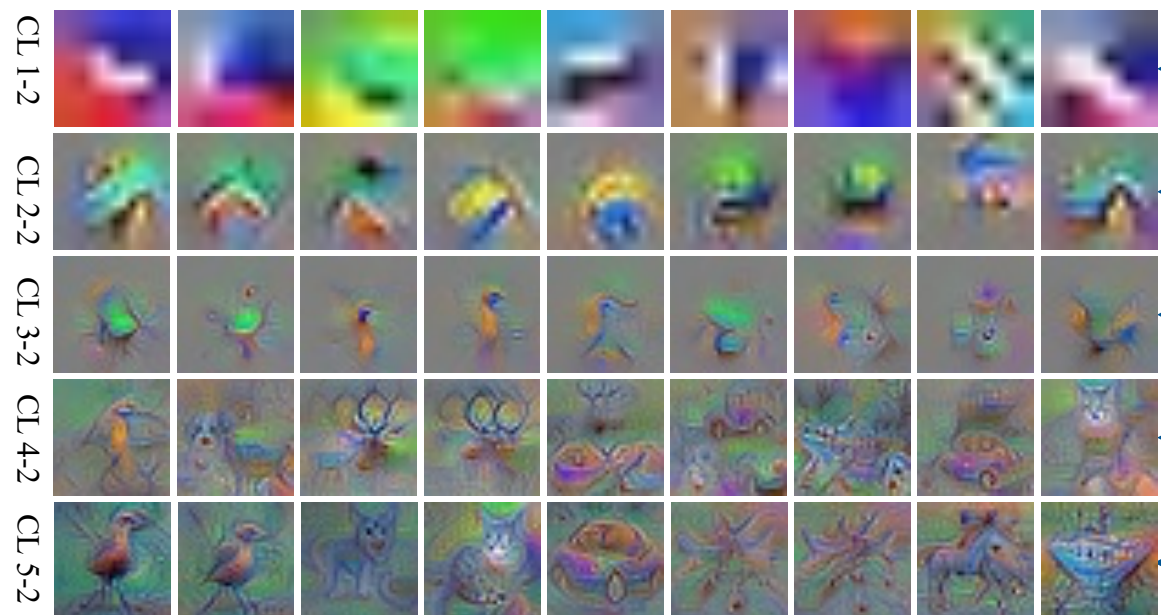
$$I^* = \underset{I}{\operatorname{argmax}} (A_i(x) - R_\theta(x))$$

$$x \leftarrow r_\theta \left(x + \eta \frac{\partial A_i(x)}{\partial x} \right)$$

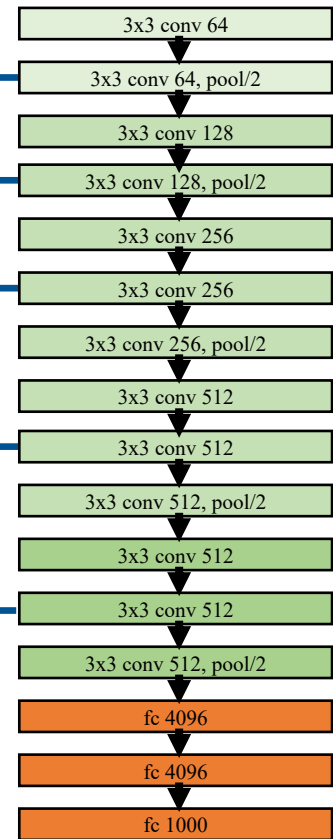
$A_i(x)$: Activation (feature map)
 $R_\theta(x)$: Parameterized Regularization



Interpret Filters in Arbitrary Layers



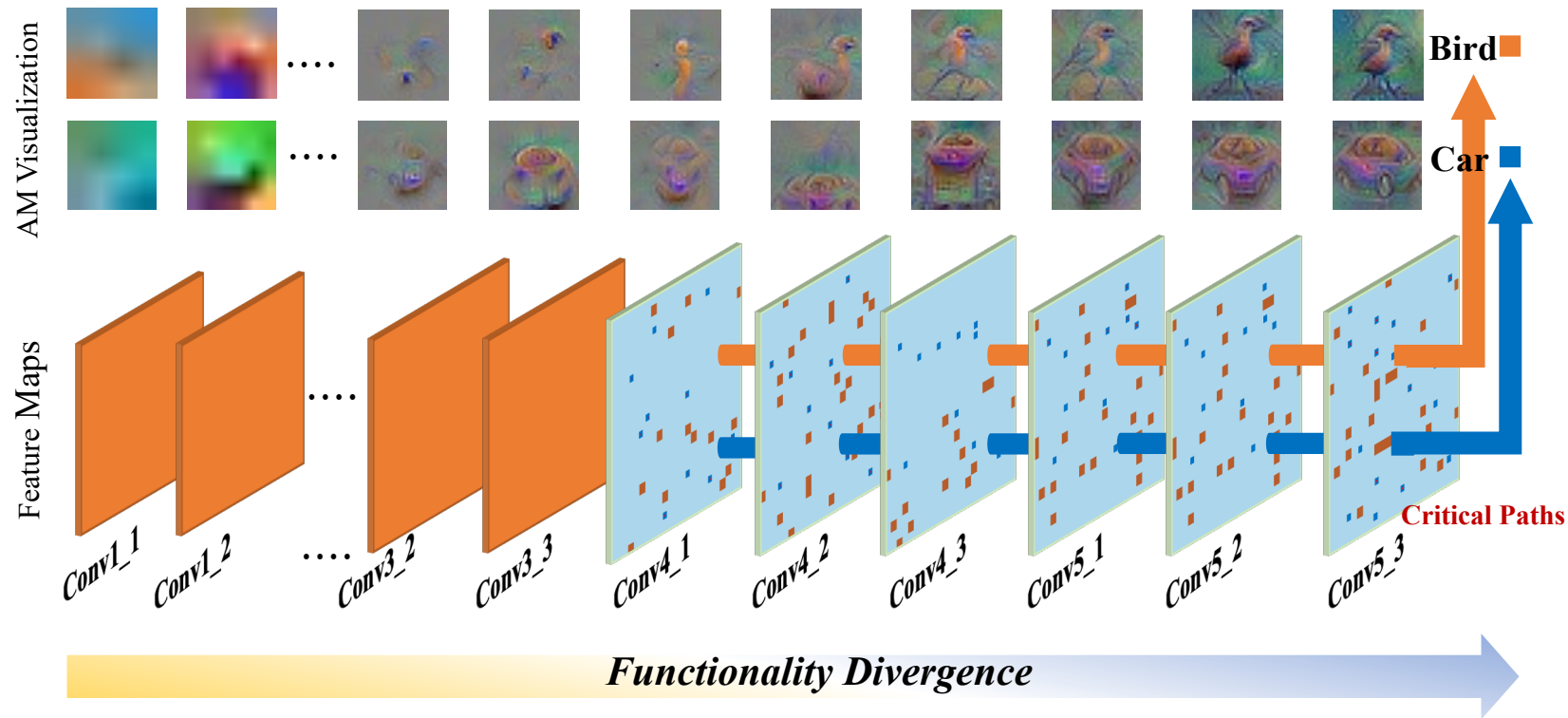
VGG-16



Visualized Patterns
Filters' Functionality

Class-specific “Critical Paths” of Filters

Filter Functionality Divergence

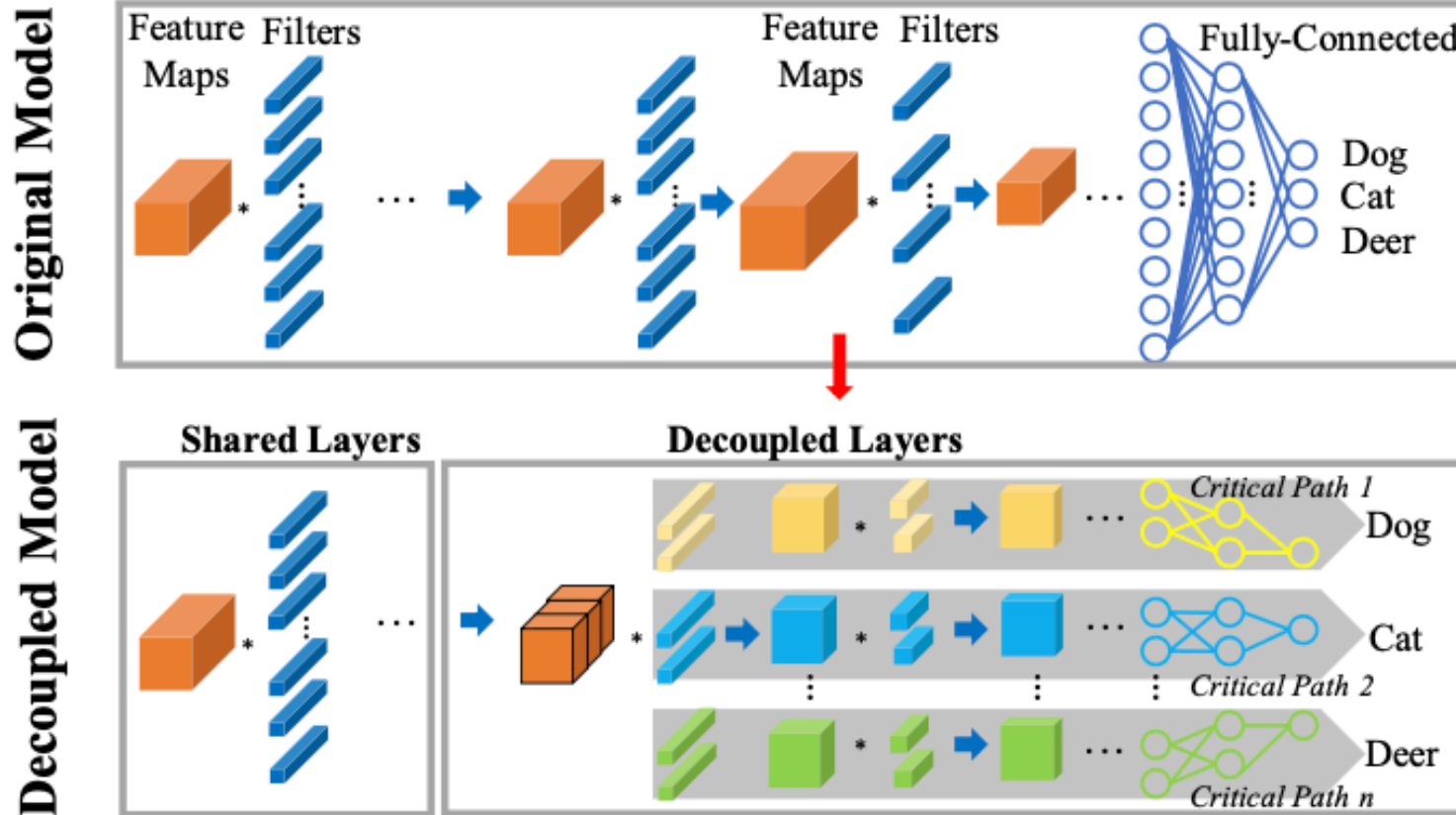


- Shallow layers extract basic features.
- Deeper layers extract class-specific features.
- **Class-specific “Critical Paths” exist in deep layers !**

Heterogenous Model Initialization by Model Decoupling

Neural Network Decoupling

$$C = \text{Arg max}_C \sum_i A_i^l(x_i^C) \cdot \bullet \quad \text{Per-class Activation Preference for Each Filter}$$

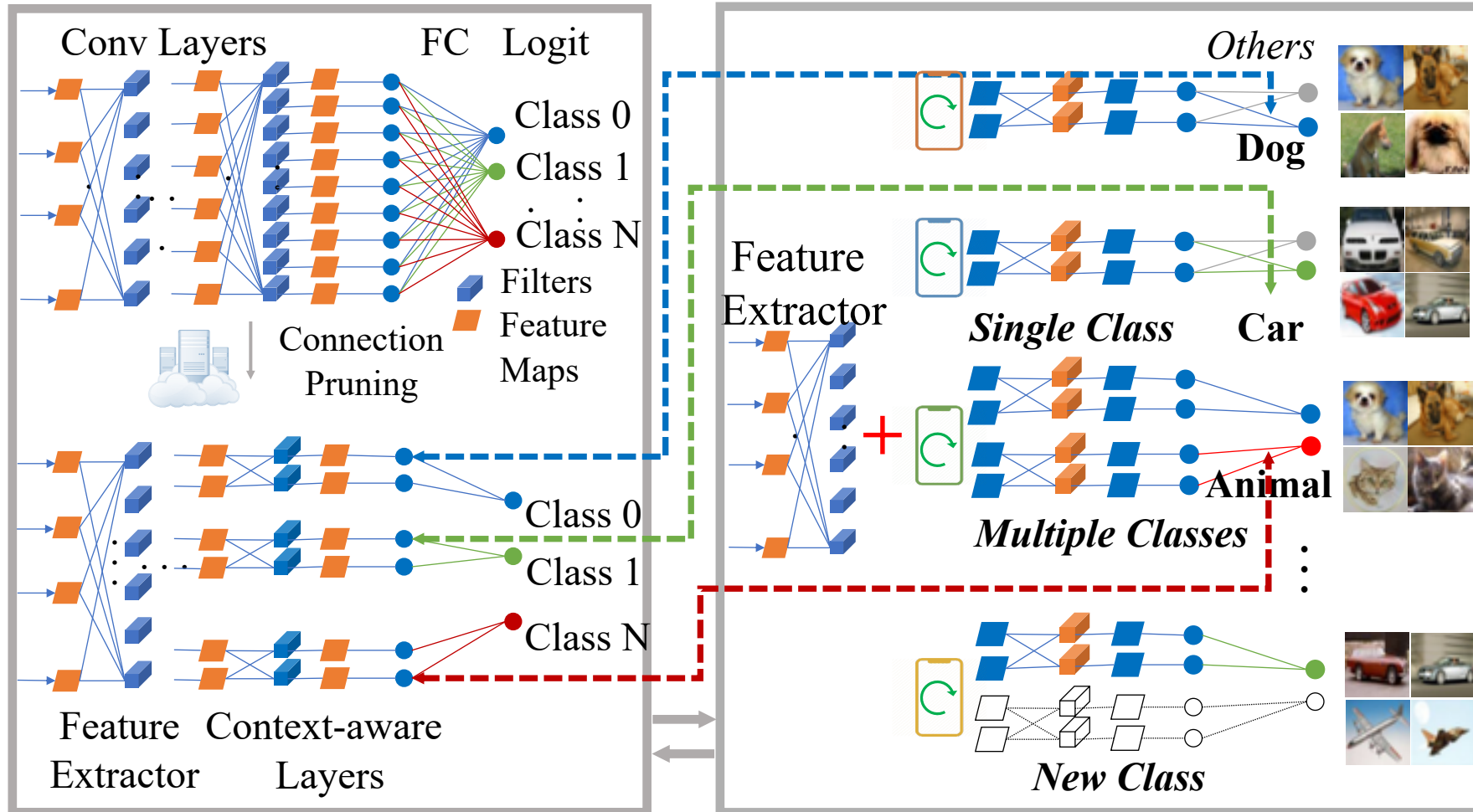


CAD: Context-aware Distributed Learning Framework

Distributed Learning

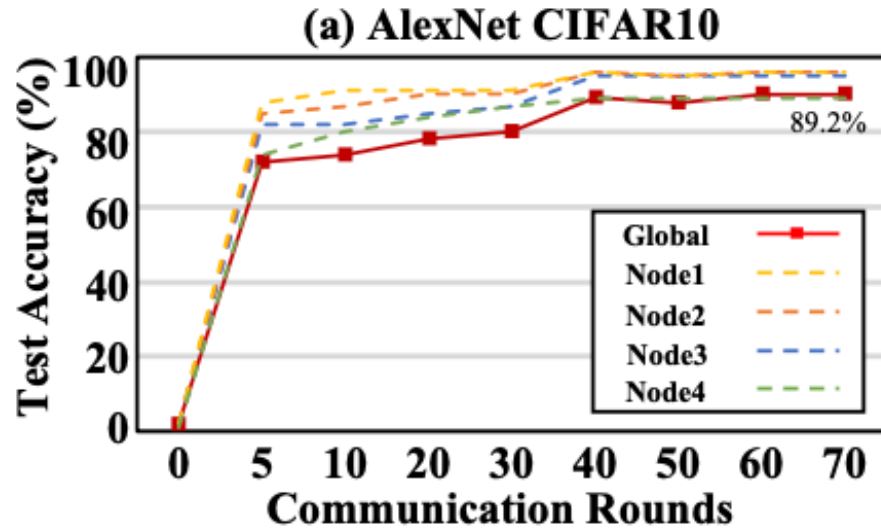
Could Aggregation

On Device Mobile Training

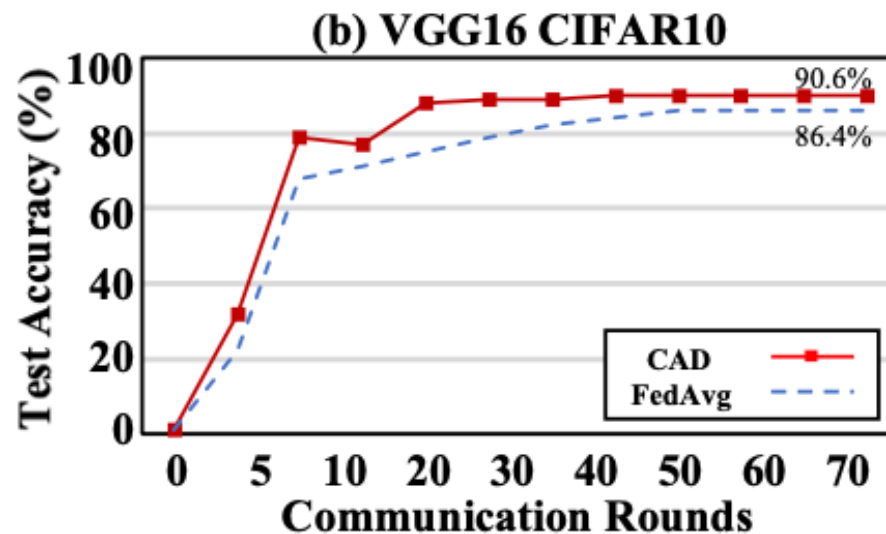


Preliminary Results

Convergence Evaluation



- Randomly select 5 classes from CIFAR10 dataset
- 1 Epoch Local Training



- High Convergence Speed
- High Convergence Accuracy

Conclusion

- We explored the context-aware distributed learning for CNN in mobile applications.
- We can re-configure the pre-defined CNN models into context-adaptive sub-models for on-device training.
- Experiment results show that our framework can achieve higher convergence speed as well as higher convergence accuracy.

Thank You!

