Application of Subset Selection in Efficient Machine Learning

Maitreyee Research Showcase

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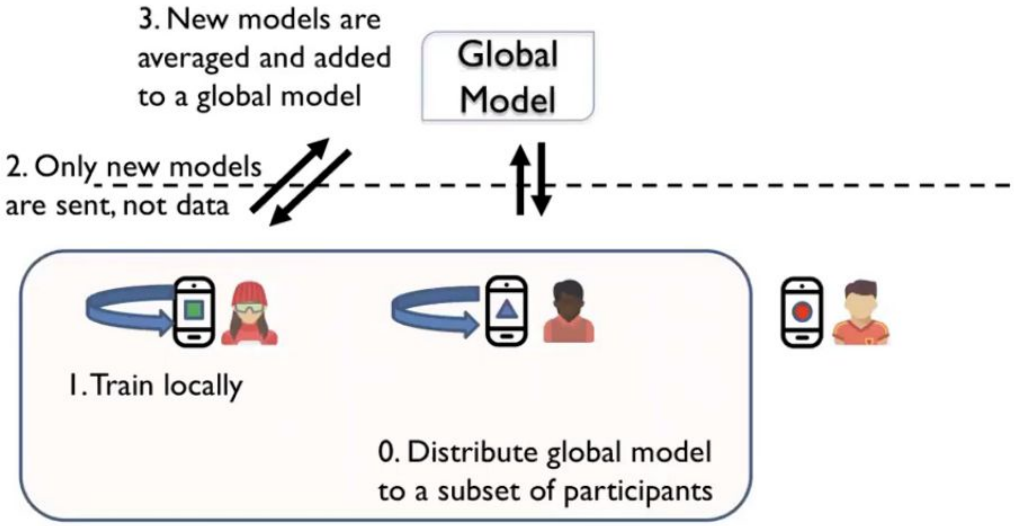
Outline

1. A Greedy Hierarchical Approach to Whole-Network Filter-Pruning in CNNs *(TMLR 2024)*

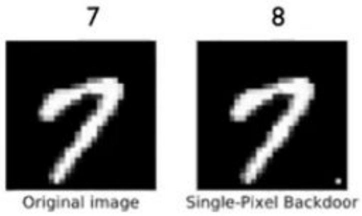
2. Efficient Exemplar Subset Selection for Complex Reasoning *(submitted)*

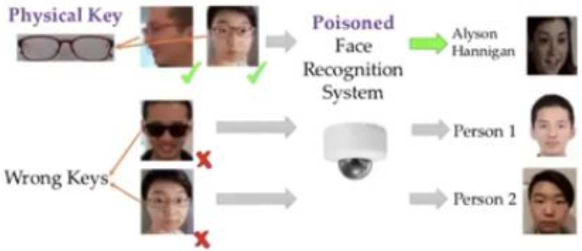
Federated Learning



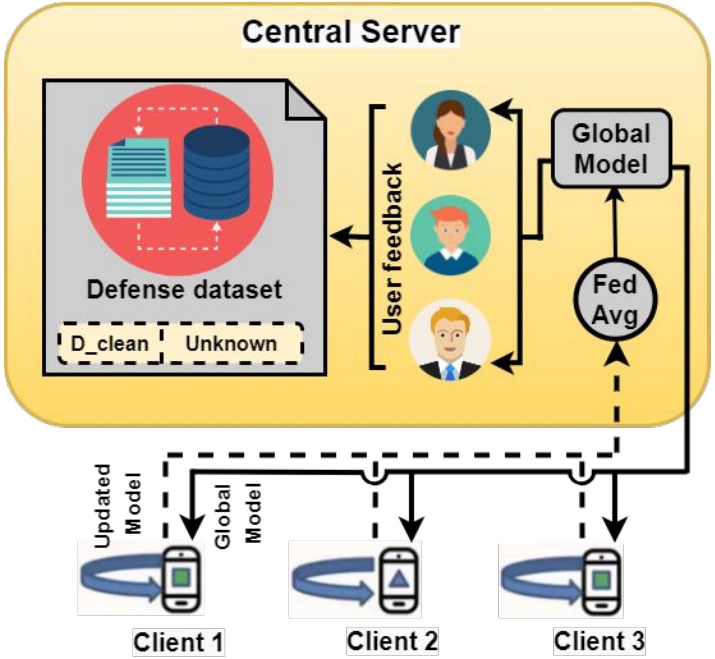
Backdoor Attacks

- Subtype of data poisoning
- Images with certain features are labeled differently
- Backdoor features can be artificial or natural
- Overall classification accuracy remains the same



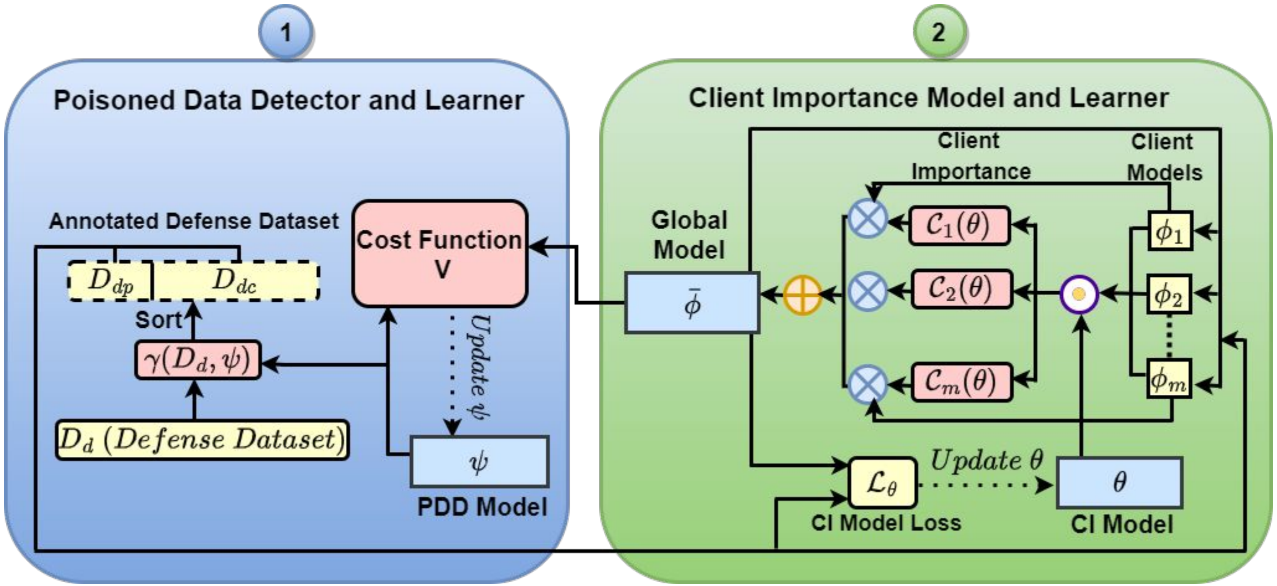


DataDefense



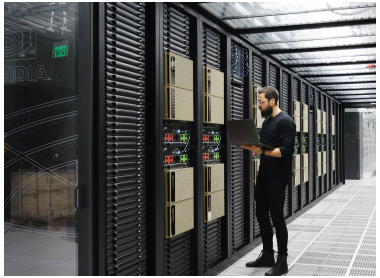
* accepted at **ECAI 2024** (*A Data-Driven Defense against Edge-case Model Poisoning Attacks on Federated Learning*)

Architecture of DataDefense



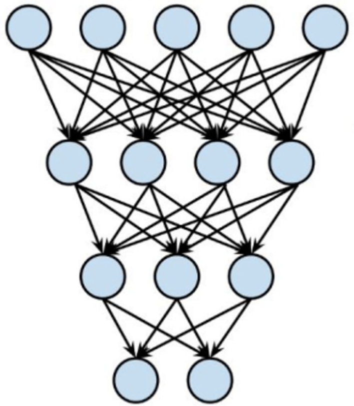
Filter Pruning

Burden of CNNs ——ResNet-152	Filter Pruning ——Benefits
60.2 million parameters and 231MB storage spaces;	reduces the storage usage
380MB memory footprint	decreases the memory footprint
11.3 billion float point operations (FLOPs).	accelerates the inference

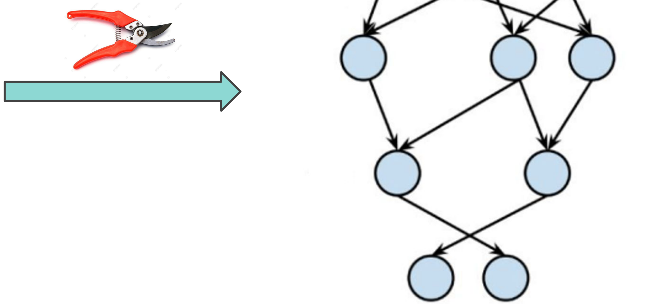


Network Pruning

Given a pre-trained network Φ(.), the goal is to compress the network while maintaining the high performance as much as possible by removing the unnecessary parameters.

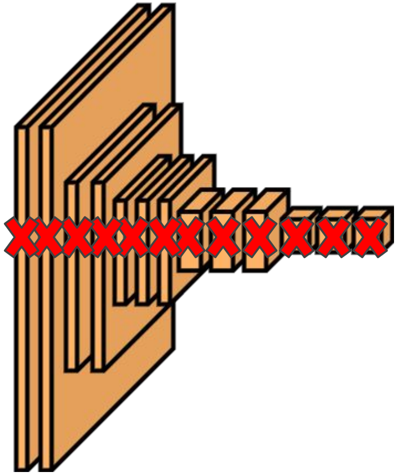


Pre-trained original network Φ(.)



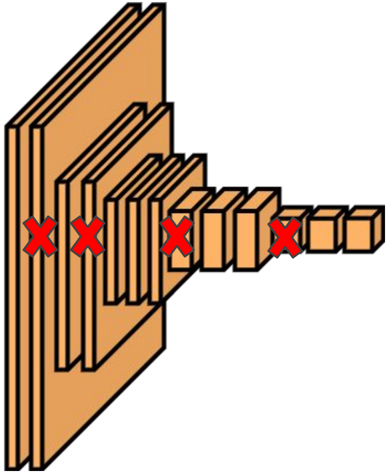
Final pruned network Φ'(.)

Filter Pruning



Uniform Pruning

- Prune filters uniformly from each layer
- Process each layer independently and sequentially.



Non-Uniform Pruning

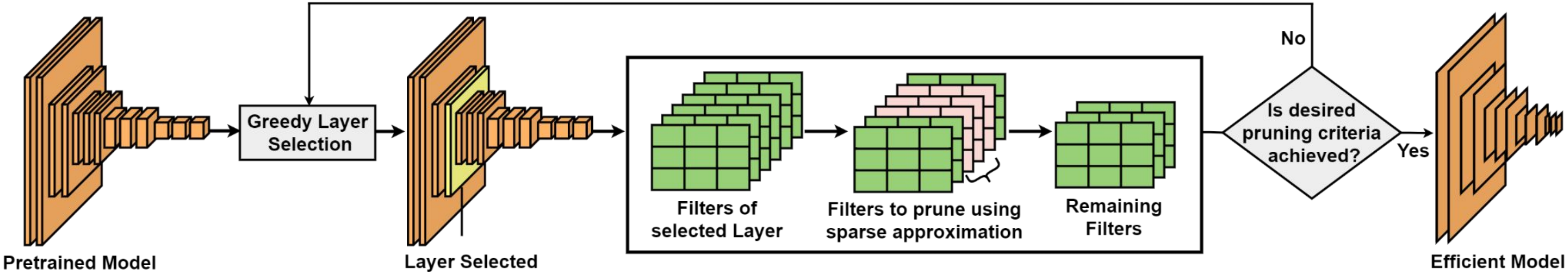
- Prune different fractions of filters from each layer
- All the layers in the network collectively make the final prediction

* accepted at **AIMLSystems 2022** (*Accurate and Efficient Channel pruning via Orthogonal Matching Pursuit*)

A Greedy Hierarchical Approach

- We developed faster **non-uniform pruning** methods.
- We used a hierarchical scheme with two-levels:
  - **filter pruning** - this step identifies the most appropriate filters to be pruned from each layer.
  - **layer selection** - this step selects the best layer to currently prune from.

We apply these two steps iteratively to achieve a non-uniform pruning.



* accepted at **TMLR 2024** (*A Greedy Hierarchical Approach to Whole-Network Filter-Pruning in CNNs*)

Results and Analysis

Method	Test Acc (%)	Acc ↓ (%)	Param ↓ (%)	FLOPs ↓ (%)	VRAM (GB)
Dense RN16	92.1	0	-	-	7.62
Dense RN8	91.8	0	-	-	3.91
FP-Backward	92.9	-0.8	98.5	89.9	1.59
HBGS-B	**93.0**	-0.9	98.7	92.1	1.55
HBGTS-B	**93.2**	-1.1	98.8	94.3	1.51

Table: Comparison of pruning methods for ResNext101 32x16d (RN16) and a similar sized dense ResNext101 32x8d (RN8) on CIFAR10 at 98% parameter reduction.

- Our greedy hierarchical methods can be used for effectively pruning large models that exceed the capacity of commodity GPUs.
- ResNext101 32x16d has 193 M parameters and requires 7.62 GB of GPU memory for loading.
- We can efficiently deploy the pruned model on edge devices with GPU memory less than 2GB.

In-Context Learning (ICL)

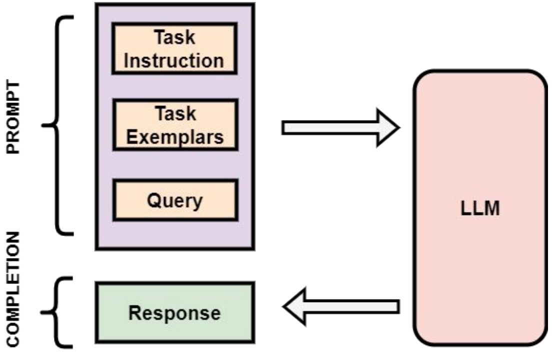


Fig: Block Diagram of ICL

Exemplars / In-context examples / demonstration samples

<Question, Explanation, Answer>

Prompt

Instruction:`You are a helpful, respectful and honest assistant helping to solve math word problems or tasks requiring reasoning or math. Follow given examples and solve the problems in step by step manner.`

Exemplars :

[Question]: *The average age of three boys is 45 years and their ages are in proportion 3:5:7. What is the age in years of the youngest boy?*

[Explanation]: $3x + 5x + 7x = 45$,

$x = 3$,

$3x = 9$

[Answer]: The answer is 9

...

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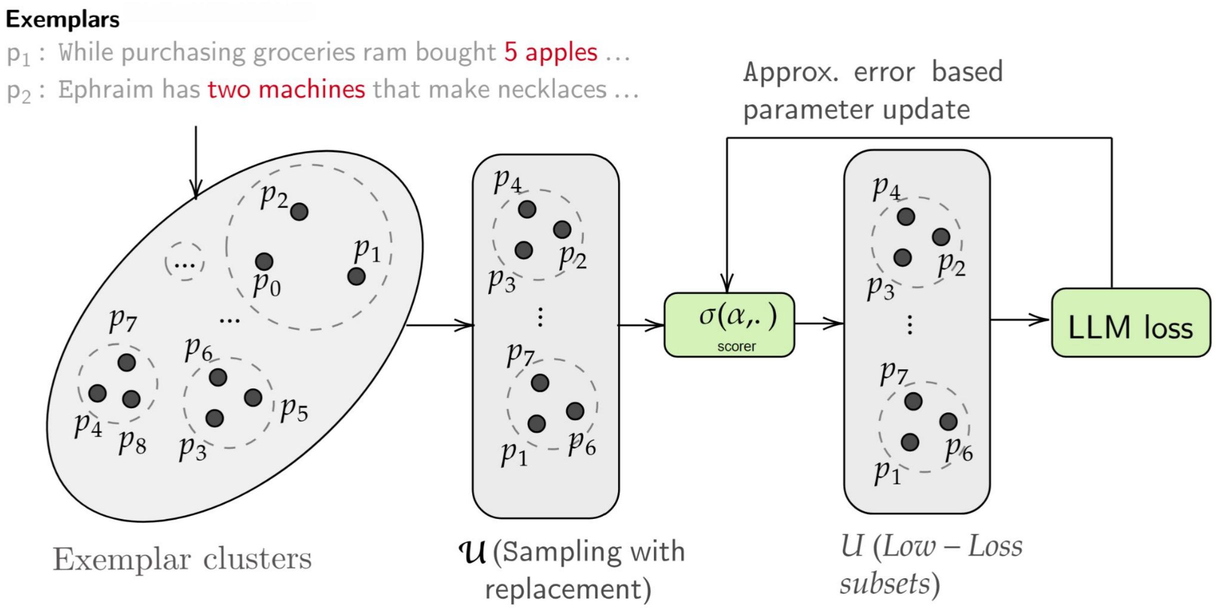
Test Input : Question:

Explanation: [INS] Answer: [INS]

Explore-Exploit Paradigm



* under review

Results and Analysis

Method	GSM8K	AquaRat	TabMWP	FinQA	StrategyQA
		GPT-3.5-turbo			
dynamic					
KNN (Rubin et al., 2022)	53.45	51.96	77.07	51.52	81.83
KNN (S-BERT) (Rubin et al., 2022)	53.07	52.75	77.95	52.65	81.83
MMR (Ye et al., 2023b)	54.36	51.18	77.32	49.87	82.86
KNN+SC (Wang et al., 2023c)	80.21	62.59	83.08	54.49	83.88
MMR+SC (Wang et al., 2023c)	78.01	59.45	81.36	50.74	83.88
PromptPG (Lu et al., 2023b)	-	-	68.23	53.56	-
static					
Zero-Shot COT (Kojima et al., 2023)	67.02	49.60	57.10	47.51	59.75
Manual Few-Shot COT (Wei et al., 2023)	73.46	44.88	71.22	52.22	73.06
Random	67.79	49.80	55.89	53.70	81.02
PS+ (Wang et al., 2023b)	59.30	46.00	-	-	-
Auto-COT (Zhang et al., 2023b)	57.10	41.70	-	-	71.20
GraphCut (Iyer and Bilmes, 2013)	66.19	47.24	60.45	52.31	80.00
FacilityLocation (Iyer and Bilmes, 2013)	68.61	48.43	67.66	36.79	81.63
LENS (Li and Qiu, 2023)	69.37	48.82	77.27	54.75	79.79
LENS+SC (Li and Qiu, 2023)	79.37	57.87	80.68	60.06	82.24
Our Approach					
EXPLORA	77.86(▲12.24%) †	53.54(▲9.67%)†	83.07(▲7.51%) †	59.46(▲8.60%) †	85.71(▲5.63%) †
EXPLORA+SC	**86.35**(▲24.48%) ‡	63.39(▲29.84%) ‡	85.52(▲10.68%) ‡	64.52(▲17.84%) ‡	87.14 (▲9.21%)†
EXPLORA+KNN+SC	85.14 (▲22.73%)‡	62.20(▲27.41%)‡	86.29(▲12.39%) ‡	**65.12**(▲18.94%) ‡	**88.37**(▲10.75%)†
EXPLORA+MMR+SC	86.13(▲24.16%) ‡	**63.78**(▲30.64%) ‡	**86.96**(▲12.54%)‡	64.60(▲17.99%) ‡	87.55(▲9.73%)†
		GPT-4o			
LENS (Li and Qiu, 2023)	76.19	64.56	86.34	69.31	92.85
EXPLORA	93.63	69.29	90.12	72.71	95.10

THANK YOU
FOR
YOUR ATTENTION!!!

https://github.com/kiranpurohit/

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