

ACIL: ACTIVE CLASS INCREMENTAL LEARNING FOR IMAGE CLASSIFICATION



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PROBLEM MOTIVATION

Class Incremental Learning (CIL)

- In many real-world applications, training data arrives in episodes over time
- Deep Neural Networks (DNNs) should learn incrementally from these new classes from their episodic data
- They should also retain knowledge about the formerly learned classes (avoid *catastrophic forgetting*)

Active Learning (AL)

- Automatically identifies salient and exemplar samples from large amounts of unlabeled data
- Reduces human annotation effort
- Model gets trained on the informative samples
- Better generalization capability

Active Class Incremental Learning (ACIL)



- Data arrives sequentially over n episodes ($0, 1, \dots, N-1$)
- $X_n^L \rightarrow$ labeled data in episode n ; $X_n^U \rightarrow$ unlabeled data in episode n ; $E_{n-1} \rightarrow$ labeled exemplar set from episode $n-1$
- Goal is to select an exemplar set of size k from episode n , containing a subset of samples from X_n^L , X_n^U and E_{n-1}

PROPOSED FRAMEWORK

Budget Splitting Strategy

- Split the budget to select samples both from the labeled exemplar set and unlabeled set
- These samples will be propagated to the next episode as the exemplar set E_n
- Rationale is to split the budget k between X_n^U and E_{n-1} in the same proportion as the number of classes in the two sets:

$$k_{\text{unlabeled}} = \left(\frac{|C_{\text{episode}}|}{|C_{\text{episode}}| + |C_{\text{exemplar}}|} \right) \cdot k \quad k_{\text{exemplar}} = \left(\frac{|C_{\text{exemplar}}|}{|C_{\text{episode}}| + |C_{\text{exemplar}}|} \right) \cdot k$$

- We use the pseudo-labels furnished by the DNN to select samples from each class in X_n^U
- Exemplar set E_n thus contains a good representation of all the classes seen so far

Active Sampling Strategy

- Active sampling is applied class-wise, using a strategy based on uncertainty and diversity
- Partition the samples in X into B diverse sets using a partition function: $P: X \rightarrow \{X_1, X_2, \dots, X_B\}$
- Goal is to minimize the variance of each partition:

$$\sigma^2(X_b) = \frac{1}{2|X_b|^2} \sum_{x_i, x_j \in X_b} \|\mathcal{F}(x_i) - \mathcal{F}(x_j)\|^2$$

- Reformulate to minimize the *weighted variance* within each partition:

$$\arg \min_{\mathcal{P}} \sum_{b=1}^B \sum_{x \in X_b} \mathcal{I}(x) \|\mathcal{F}(x) - c_b\|^2$$

- Each sample is weighted by its prediction uncertainty $\mathcal{I}(x)$

Loss Function

- In each episode, DNN is trained on the labeled episodic data X_n^L , and labeled exemplar set E_{n-1}
- Class imbalance may exist in $X_n^L \cup E_{n-1}$ as $|X_n^L| \gg |E_{n-1}|$
- Use weighted CE loss to train the DNN:

$$\mathcal{L}_{\text{WCE}}(x_i) = - \sum_{j=1}^C \delta(y_i == j) w_j \log p_{ij}$$

- Total loss over all the samples is:

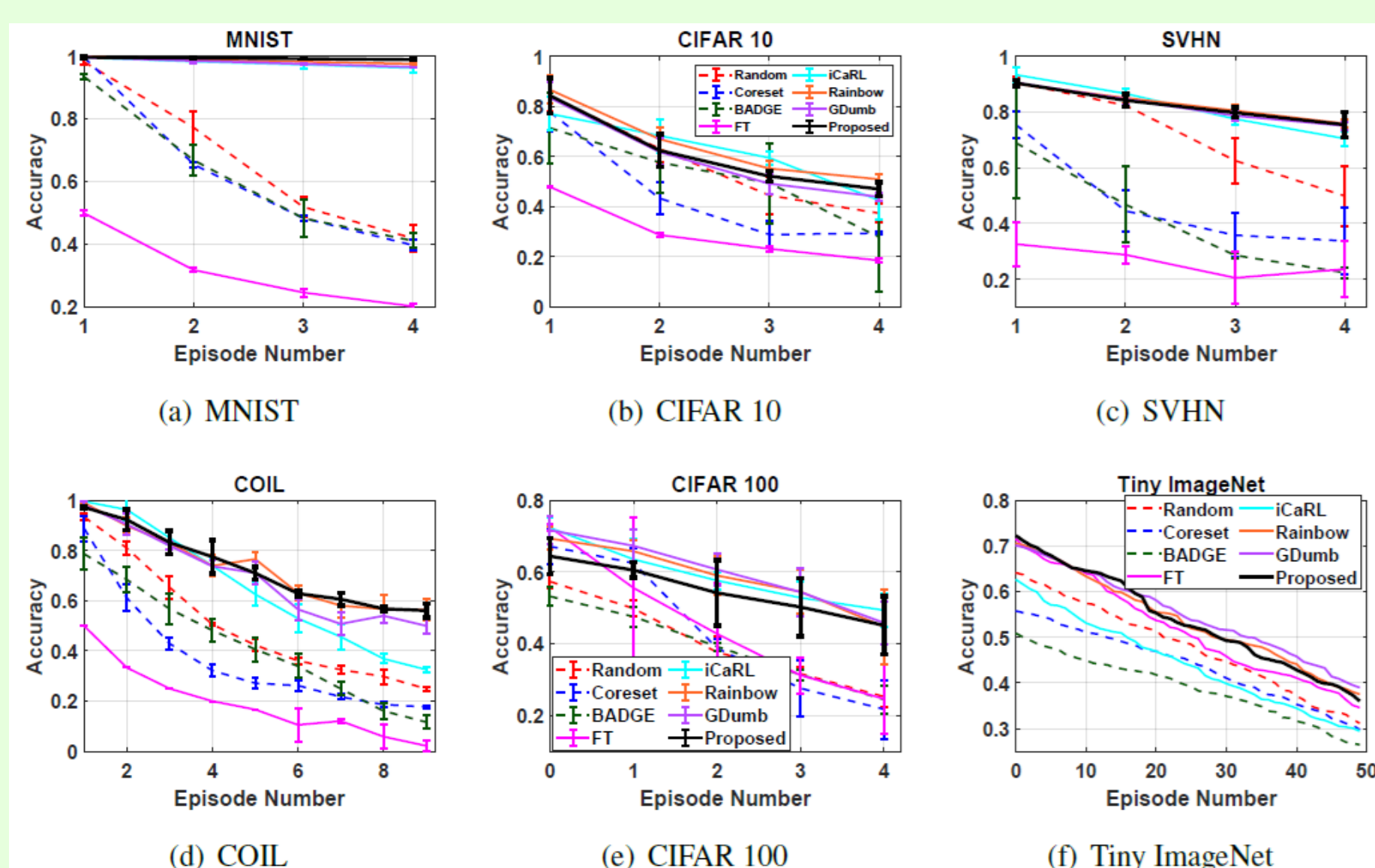
$$\mathcal{L}_{\text{WCE}} = \frac{1}{|L|} \sum_{i=1}^{|L|} \mathcal{L}_{\text{WCE}}(x_i)$$

- Include a distillation loss term between the model predictions in two successive episodes. Final loss function is given by:

$$\mathcal{L} = \mathcal{L}_{\text{WCE}} + \lambda \mathcal{L}_{\mathcal{D}}$$

SAMPLE RESULTS

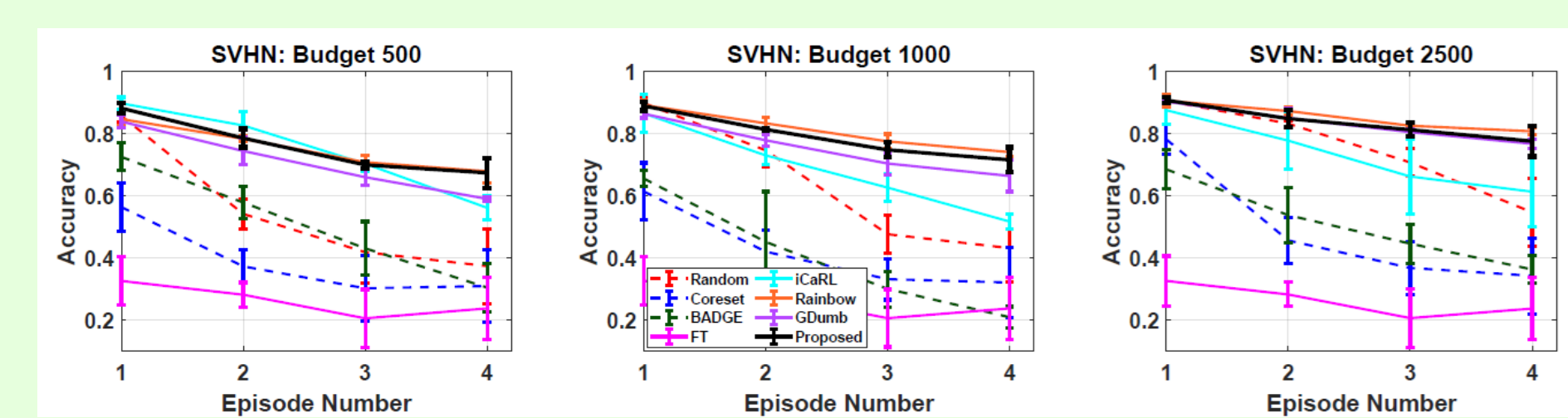
Accuracy Plots



Annotation Effort Analysis

	CIL Baselines	AL Baselines	Proposed
MNIST	12,000 ± 478.12	3,359.6 ± 483.43	2,899.6 ± 447.38
CIFAR 10	10,000 ± 0.00	2,800 ± 414.04	2,417.2 ± 344.90
SVHN	14,651.40 ± 5,542.22	4,530 ± 1,181.98	3,763.60 ± 1,455.34
COIL	570 ± 0.00	204 ± 30.51	153.33 ± 25.38
CIFAR 100	5,000 ± 0.00	1,450 ± 152.56	1,158 ± 131.53
Tiny ImageNet	1,000 ± 0.00	299 ± 9.97	232.07 ± 21.92

Study of Exemplar Set Size



	CIL Baselines	AL Baselines	Proposed
SVHN: Budget 500	14,651.40 ± 5,542.22	3,330 ± 1,068.78	3,139.20 ± 1,166.54
SVHN: Budget 1,000	14,651.40 ± 5,542.22	3,730 ± 1,068.41	3,347.20 ± 1,246.61
SVHN: Budget 2,500	14,651.40 ± 5,542.22	4,930 ± 1,285.86	3,972.80 ± 1,577.21

Accuracy after Last Episode

	Random	Coreset	BADGE	FT	iCaRL	Rainbow	GDumb	Proposed
MNIST	0.41 ± 0.03	0.39 ± 0.01	0.41 ± 0.02	0.20 ± 0.01	0.96 ± 0.01	0.97 ± 0.01	0.96 ± 0.01	0.98 ± 0.02
CIFAR 10	0.37 ± 0.03	0.29 ± 0.03	0.27 ± 0.17	0.18 ± 0.04	0.42 ± 0.06	0.5 ± 0.02	0.43 ± 0.01	0.42 ± 0.02
SVHN	0.49 ± 0.09	0.33 ± 0.1	0.22 ± 0.02	0.23 ± 0.08	0.70 ± 0.02	0.75 ± 0.03	0.75 ± 0.01	0.75 ± 0.04
COIL	0.24 ± 0.05	0.17 ± 0.02	0.11 ± 0.02	0.02 ± 0.02	0.32 ± 0.01	0.56 ± 0.04	0.5 ± 0.03	0.56 ± 0.02
CIFAR 100	0.25 ± 0.03	0.22 ± 0.08	0.24 ± 0.04	0.25 ± 0.10	0.49 ± 0.05	0.45 ± 0.10	0.46 ± 0.06	0.45 ± 0.08
Tiny ImageNet	0.31 ± 0.01	0.30 ± 0.03	0.26 ± 0.04	0.35 ± 0.02	0.29 ± 0.02	0.38 ± 0.05	0.39 ± 0.04	0.36 ± 0.04

* These authors contributed equally to this work