Large-Scale Deep Class-Incremental Learning

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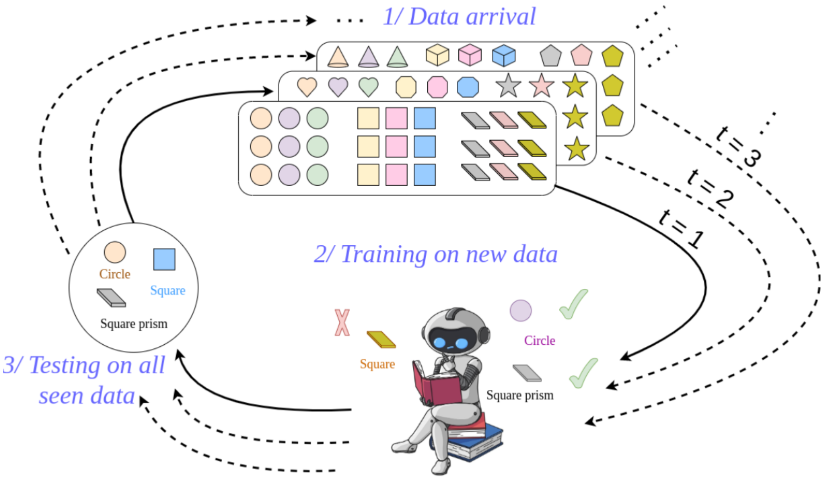
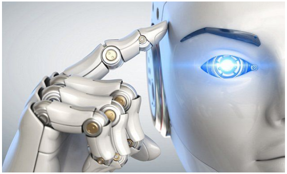


Continual Learning

Application examples of continual learning

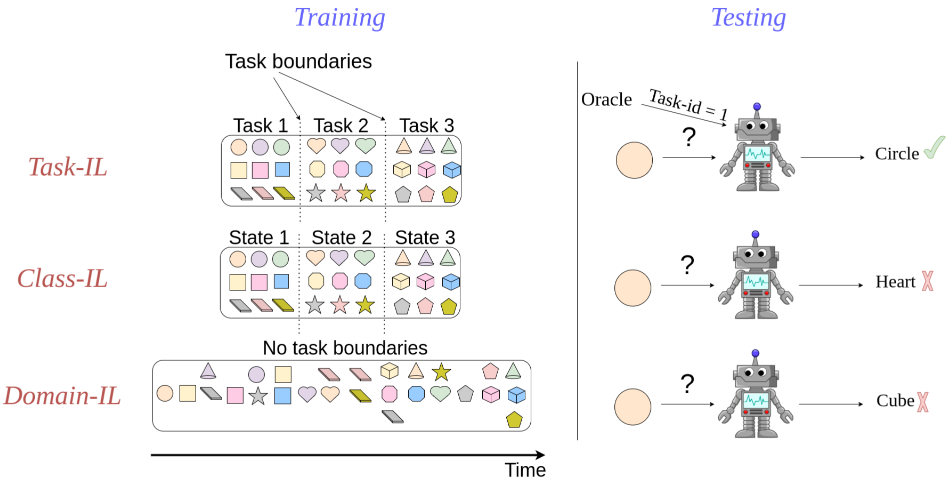
Face Recognition



Robotics

Health

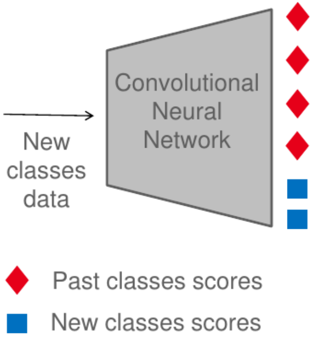
[Images taken from the web]

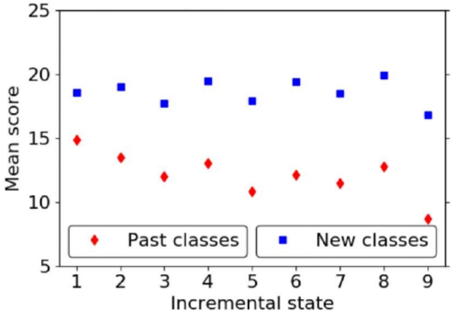


Three Scenarios of Continual Learning

Catastrophic forgetting

- Tendency of neural networks to underfit past data when new one is ingested



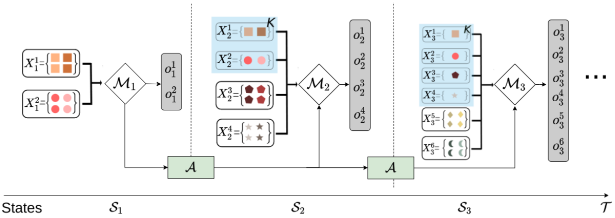


CIL process notations			**Model-related notations in state $\mathcal{S}_t$**		
$\mathcal{A}$	-	CIL algorithm	$\mathcal{M}_t$	-	Model in state $\mathcal{S}_t$
$\mathcal{T}$	-	Total number of states	$\mathcal{F}_t$	-	Feature extractor
$\mathcal{S}_t$	-	State	$\mathcal{C}_t$	-	Classification component
P_t	-	Number of new classes	$\boldsymbol{\mathcal{W}_t}$	-	Last layer weights matrix
N_t	-	Total number of classes until state $\mathcal{S}_t$	$\boldsymbol{W_t^j}$	-	weitgh vector of class j
$\mathcal{K}$	-	Exemplars memory	$\boldsymbol{o_t}$	-	Raw output scores vector
$\mathcal{I}$	-	Secondary memory	o_t^j	-	score of class j

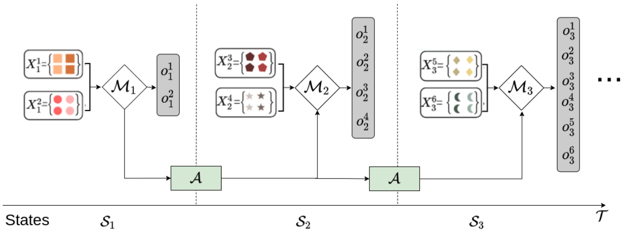
Introduction

Two scenarios of Class-Incremental Learning

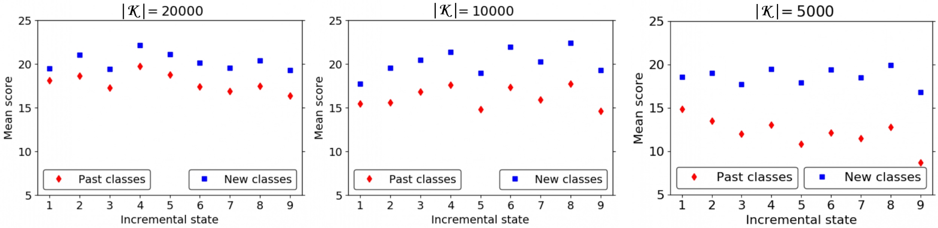
- Incremental Learning with memory



- Incremental Learning without memory



Reduce prediction bias towards new classes



Mean prediction scores of past and new classes with vanilla fine tuning

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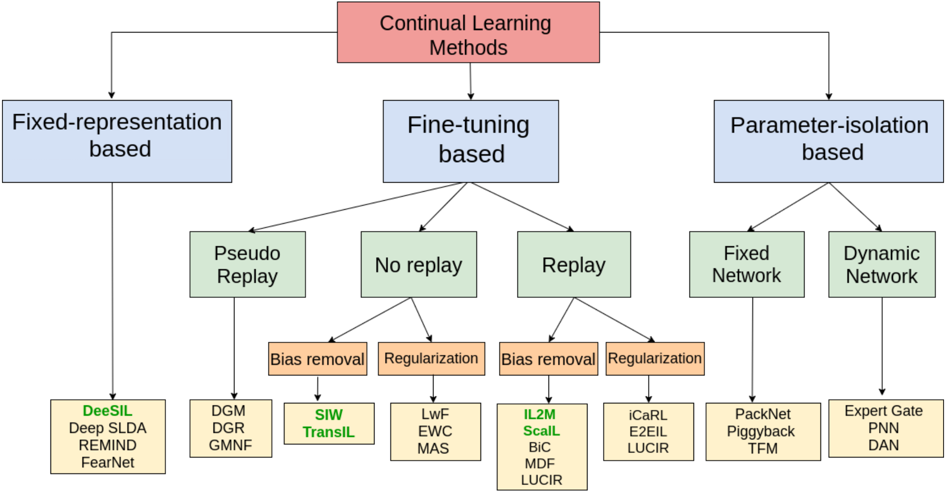
State of the art



[Schema inspired by Lange et al., 2019]

[References are in appendix slides]

- **Complexity*** - capacity to integrate new information with a minimal change in terms of the model structure
- **Memory*** - ability to work with or without a fixed-size memory of past classes
- **Accuracy*** - performance for past and new classes should approach that of a non-incremental learning process that has access to all data at all times.
- **Timeliness** - delay needed between the occurrence of new data and its integration in the incremental models
- **Plasticity-Stability** - capacity not only to deal with new classes that are significantly different from the ones learned in the past but also to keep as much knowledge as possible from the past.
- **Scalability** - the aptitude for learning a large number of classes

** [Inspired by Rebuffi et al., 2017]*

State of the art
Pros and Cons

	Complexity	Memory	Accuracy	Timeliness	Plasticity-Stability	Scalability
Fine tuning based	Increases slowly	The bigger the memory, the better the model	Best SoTA results with memory	Retraining is needed at each state	Depends on the availability of the memory	Depends on the size of the memory
Fixed representation based	Increases slowly	Low dependency	Good if the initial model is trained on large dataset	Fast	Bad if incremental classes are different from the initial ones	Heavily depends on the fixed representation
Parameter isolation based	Depends if fixed or dynamic network	Non compulsory	Depends on how much the model architecture can increase	Retraining is needed at each state	Good	Scale well if resources are available

LwF: Learning without Forgetting (Li and Hoiem, 2016)

- Fine Tuning with distillation loss

$$\mathcal{L}_t^d(x) = \sum_{(x,y)\ \in\ \mathcal{D}_t} \sum_{j=1}^{N_{t-1}} -\hat{\sigma}_{t-1}^j(x)\ log[\hat{\sigma}_t^j(x)] \tag{1}$$

where $\hat{\sigma}$ is the softened softmax

- (+) No memory of the past is needed
- (−) The gap with a *Joint* training is large

iCaRL: Incremental Classifier and Representation Learning (Rebuffi et al., 2017)

- *LwF* with memory
- Herding to select exemplars

$$e \leftarrow \underset{x \in X}{\arg\min} \|\mu - \frac{1}{k}[f(x) + \sum_{j=1}^{k-1} f(e_j)]\| \quad (2)$$

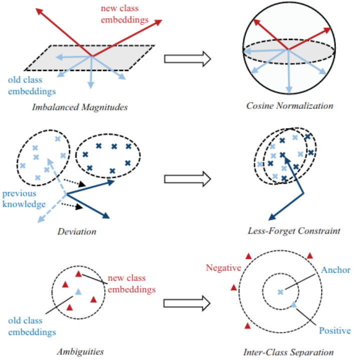
- Nearest Exemplars Mean (NEM)

$$y^* = \underset{y \in [1, N_t]}{\arg\min} \|f(x) - \mu_y\| \quad (3)$$

  - (+) Combination of powerful components
  - (−) Unfair comparison with baselines

LUCIR: Learning a Unified Classifier Incrementally via Rebalancing (Hou et al., 2019)

- Cosine normalization
- Less-forget constraint
- Inter-class separation



- (+) Powerful objective
- (−) Important execution time

BiC: Bias Correction (Wu et al., 2019)

- Distillation loss
- Bias-removal layer

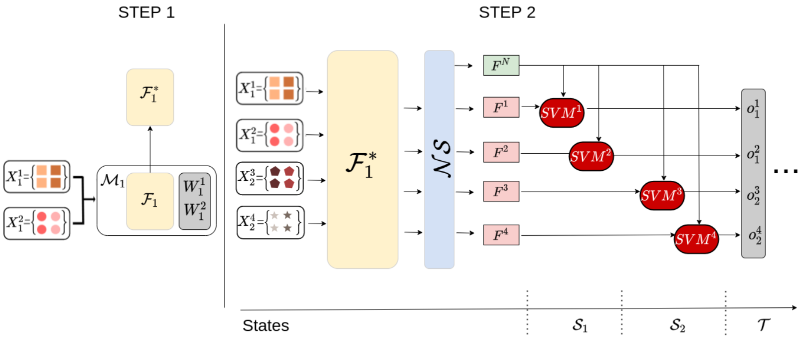
$$BiC(\boldsymbol{o}_t^k) = \begin{cases} \boldsymbol{o}_t^k & \text{if} \quad k \in [1,\ t-1] \\ \alpha_t \boldsymbol{o}_t^k + \beta_t \cdot 1 & \text{if} \quad k = t \end{cases} \tag{4}$$

  - (+) Simple, fast, and accurate
  - (−) Uses a validation set (memory required)

2. Class-incremental learning with memory

DeeSIL: Deep-Shallow Incremental Learning
(Belouadah and Popescu, 2018, W-ECCV)

- Fixed Representation based
- Inspired by transfer learning
- Works with and without memory

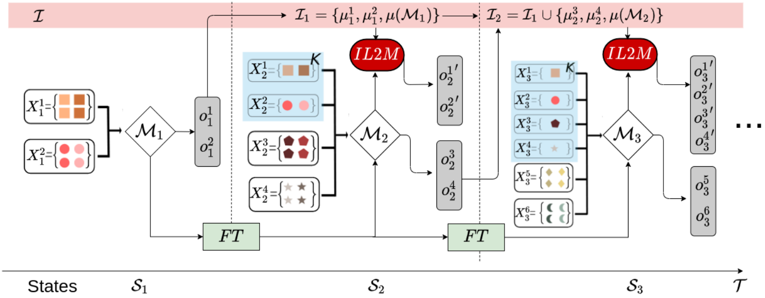


Overview of *DeeSIL*

IL2M: Incremental Learning with Dual memory

(Belouadah and Popescu, 2019, ICCV)

- Fine Tuning based
- Leverages past class statistics



Overview of *IL2M*

- Past class score rectification

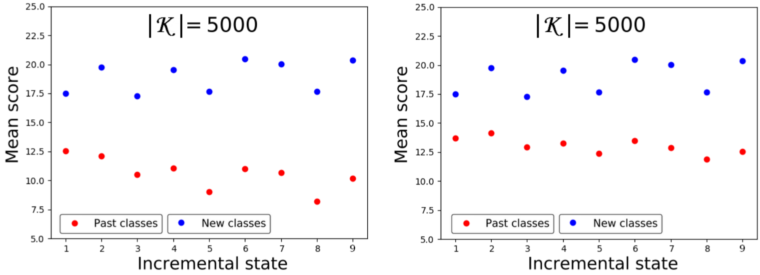
For all past classes ($j = 1, \ldots, N_{t-1}$):

$$o_t^{j\prime} = IL2M(o_t^j) = \begin{cases} o_t^j \times \frac{\mu_i^j}{\mu_t^j} \times \frac{\mu(\mathcal{M}_t)}{\mu(\mathcal{M}_i)}, & \text{if } pred = new \\ o_t^j, & \text{otherwise} \end{cases} \tag{5}$$

with:

- i - the initial state in which the j^{th} class was learned
- t - the current incremental state
- o_t^j - the raw prediction the j^{th} class in the current state t
- μ_i^j and μ_t^j - the mean classification scores of the j^{th} class in states i and t
- $\mu(\mathcal{M}_t)$ and $\mu(\mathcal{M}_i)$ - the model confidences in states t and i

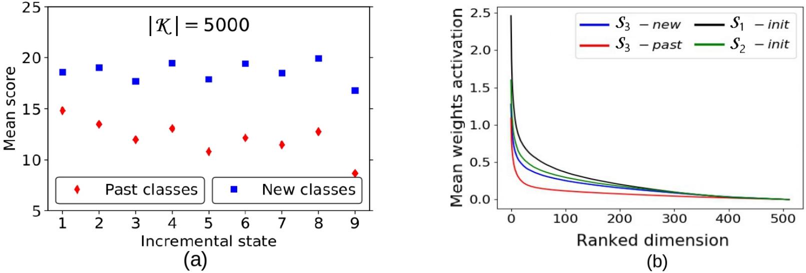
- Effect of *IL2M*



Before   After

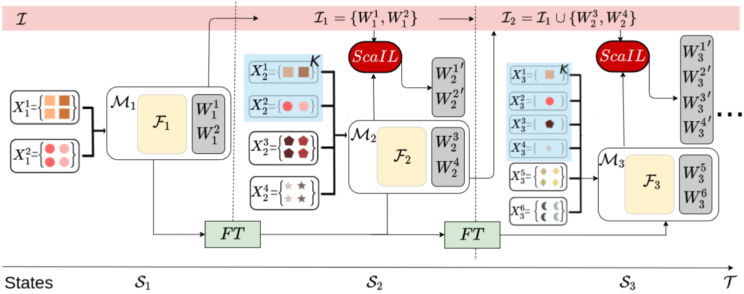
ScaIL: Classifier weights Scaling for Class IL
(Belouadah and Popescu, 2020, WACV)

- Fine Tuning based
- Forgetting happens mainly in the final layer
- Features are usable across incremental states



Mean prediction scores and weights magnitudes

- Past class weights replay



Overview of *ScaIL*

- Sort class weights

$$\widehat{\boldsymbol{W}_{\boldsymbol{t}}^{\boldsymbol{j}}} = sort(|w_j^1|, |w_j^2|, ..., |w_j^d|, ..., |w_j^D|) \ \ ; j \in [N_{t-1}, N_t] \, , d \in [1, D] \quad (6)$$

$\widehat{\boldsymbol{W}_{\boldsymbol{t}}^{\boldsymbol{j}}}$ is the sorted version of the initial weights vector of new class j.

- Compute state mean vector

$$\mu_t^d = \frac{1}{P_t} \times \sum_{j=N_{t-1}}^{N_t} \widehat{w}_j^d \qquad d \in [1, D] \quad (7)$$

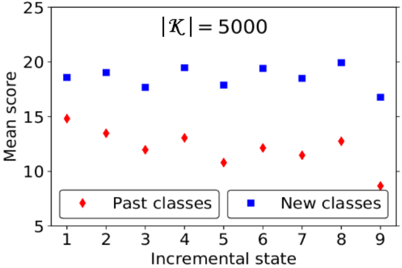
where μ_t (of dimension D) is the mean vector of the ranked new classes' weights in the state $\mathcal{S}_t$, and d is a dimension in the feature vector.

- Normalize past class weights

$$w_j^{d'} = \frac{\mu_t^{R(d)}}{\mu_i^{R(d)}} \times w_j^d \quad (8)$$

$w_j^{d'}$ is the scaled version of w_j^d, the d^{th} dimension of the initial classifier W_i^j of the j^{th} past class.

- Effect of *ScaIL*



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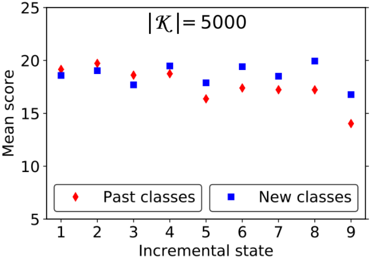


After

FT+th: Fine tuning with threshold calibration (Belouadah et al., 2020a, W-ECCV)

• Inspired by an imbalanced-learning approach proposed by Buda et al., 2018

• Increases the classification score of the least represented classes (past and new)

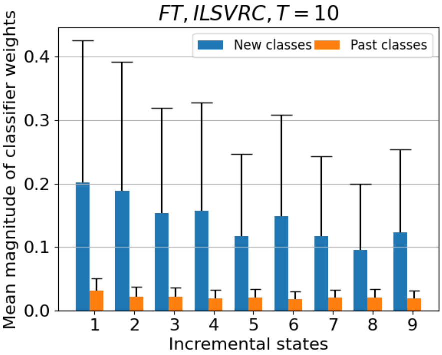
$$p_t^{j\prime} = p_t^j \times \frac{|\mathcal{X}_t \cup \mathcal{K}|}{|X_t^j|} \tag{9}$$

- $|X_t^j|$ is the number of training examples for the class j in state $\mathcal{S}_t$
- $|\mathcal{X}_t^l \cup \mathcal{K}|$ is the total number of training examples in state $\mathcal{S}_t$

2. Class-incremental learning without memory

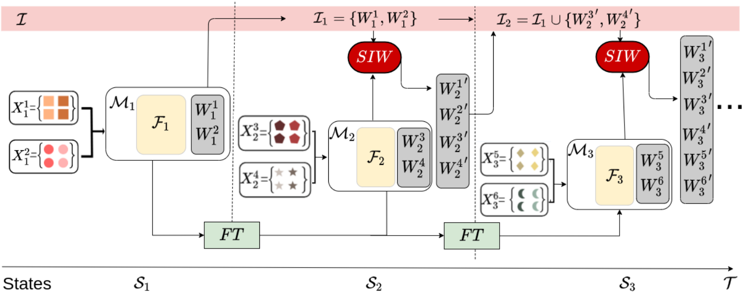
SIW: Standardization of Initial Weights for Class Incremental Learning (Belouadah et al., 2020b, BMVC)

- Fine Tuning based
- Bias in the mean weights magnitudes



Mean weights magnitudes without memory

- Past class weights replay

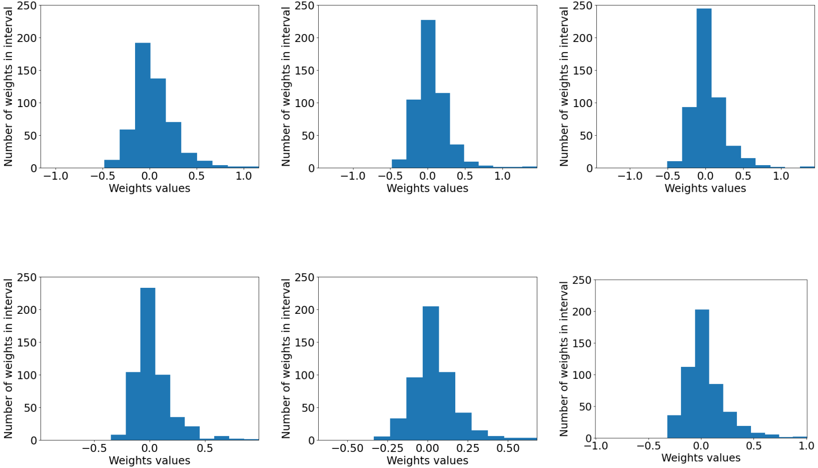


Overview of *SIW*

Class-Incremental Learning without memory

SIW: Standardization of Initial Weights for Class IL (BMVC 2020)

- Classifier weights distribution



- Standardization of Initial Weights

$$w'_d = \frac{w_d - \mu(\boldsymbol{W})}{\sigma(\boldsymbol{W})} \tag{10}$$

with:

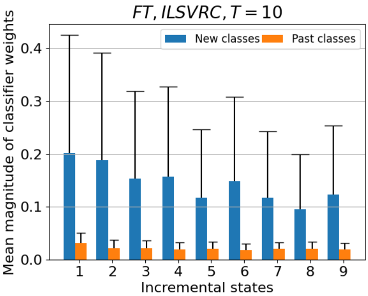
w_d is the d^{th} dimension of an initial classifier $\boldsymbol{W}$, $\mu(\boldsymbol{W})$ and $\sigma(\boldsymbol{W})$ are the mean and standard deviation of $\boldsymbol{W}$.

- State-level calibration

$$o_t^j(x) = (\boldsymbol{f_t}(\boldsymbol{x}) \cdot \boldsymbol{W_t^j}' + b_j^i) \times \frac{\mu(\mathcal{M}_t)}{\mu(\mathcal{M}_i)} \tag{11}$$

$\mu(\mathcal{M}_t)$ and $\mu(\mathcal{M}_i)$ are means of top-1 predictions of models learned in the t^{th} and i^{th} states

- Effect of *SIW* on weights magnitudes



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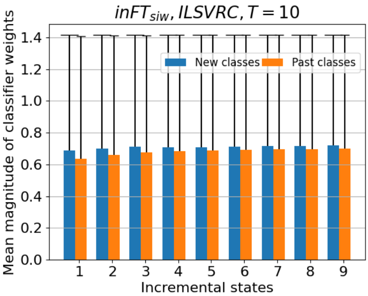
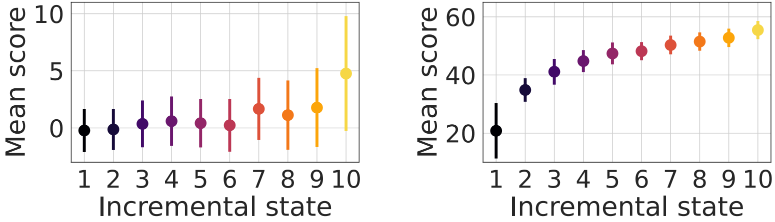


After

TransIL: Dataset Knowledge Transfer for Class IL
(Slim et al., 2022, WACV)

- Fine Tuning based
- Bias in the mean classification scores after *LwF* and *LUCIR*



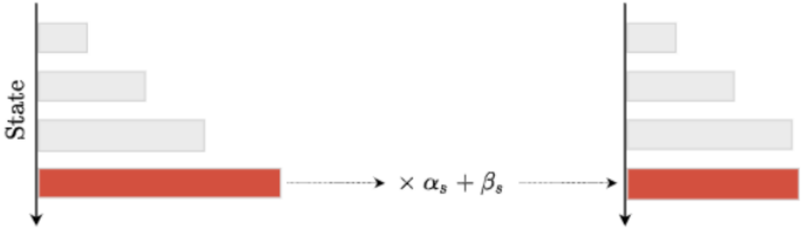
LwF (Li and Hoiem, 2016) LUCIR (Hou et al., 2019)

Mean prediction scores and standard deviation

Enable the use of Bias Correction layers in a memoryless scenario

- *BiC* : Bias Correction (Wu et al., 2019)

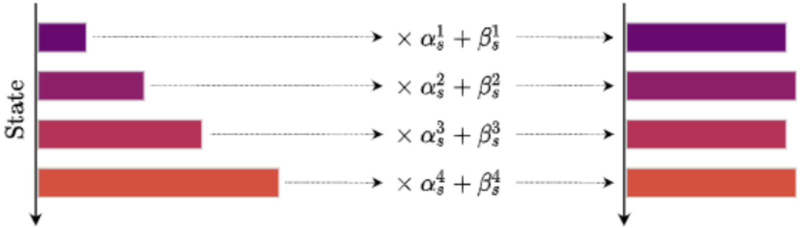
$$BiC(\boldsymbol{o}_t^k) = \begin{cases} \boldsymbol{o}_t^k & \text{if} \quad k \in [1, \ t-1] \\ \alpha_t \boldsymbol{o}_t^k + \beta_t \cdot 1 & \text{if} \quad k = t \end{cases} \tag{12}$$



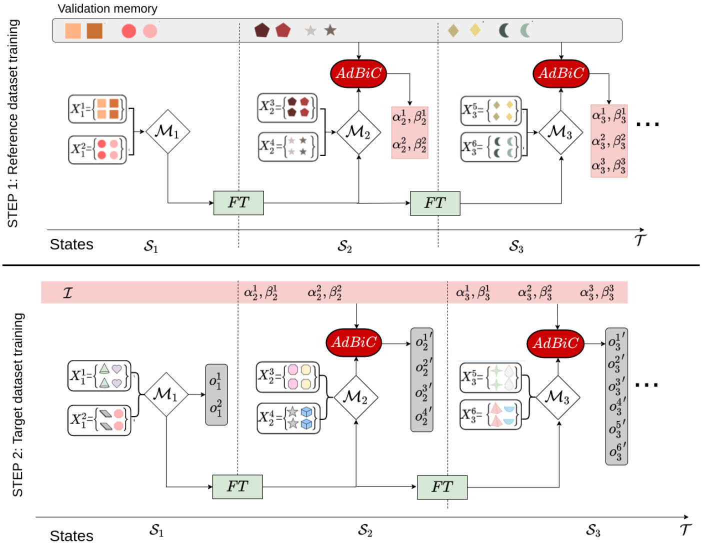
- *adBiC* : Adaptive Bias Correction (proposed)

$$adBiC(\boldsymbol{o_t^k}) = \alpha_t^k \boldsymbol{o_t^k} + \beta_t^k \cdot 1 \; ; \quad k \in [1, t] \qquad (13)$$

where α_t^k, β_t^k are the parameters applied in state $\mathcal{S}_t$ to classes first learned in state $\mathcal{S}_k$.



- Dataset knowledge transfer



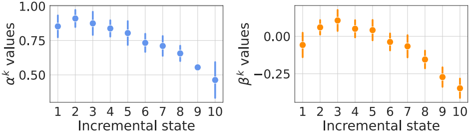
Overview of *TransIL*

Class-Incremental Learning without memory
TransIL: Dataset Knowledge Transfer for Class IL (WACV 2022)

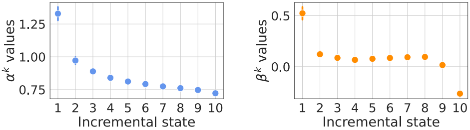
- Optimization of calibration parameters on reference datasets

$$\mathcal{L}(\boldsymbol{q_t}, y) = -\sum_{k=1}^{t}\sum_{j=1}^{|P_k|} \delta_{y=\widehat{y}} \log\left(q_{t,j}^k\right)$$

- y is the ground-truth label
- $\widehat{y}$ is the predicted label
- δ is the Kronecker delta
- $\boldsymbol{q_t}$ is the corrected softmax output of the sample



LwF (Li and Hoiem, 2016)



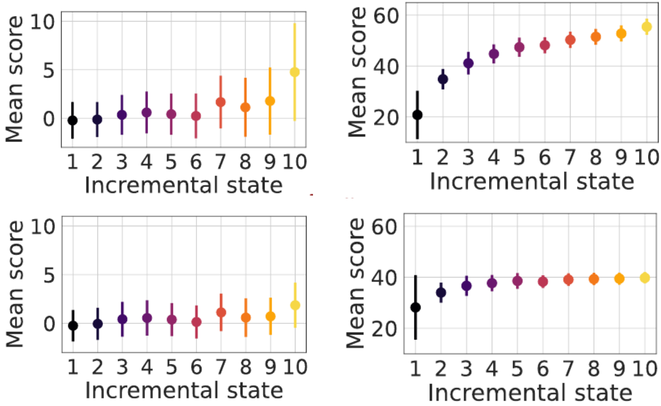
LUCIR (Hou et al., 2019)

Averaged calibration parameters values

- Effect on classification scores

Before

After

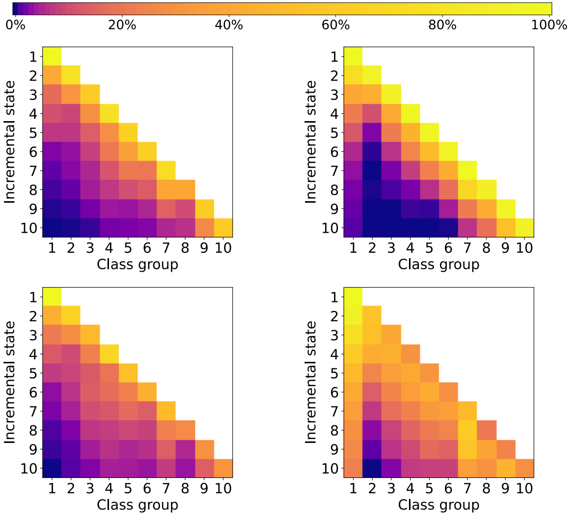


LwF (Li and Hoiem, 2016) *LUCIR* (Hou et al., 2019)

- Effect on the percentage of correct and wrong predictions

Before

After



LwF (Li and Hoiem, 2016)   *LUCIR* (Hou et al., 2019)

Experiments and Results

- Evaluation of *DeeSIL*, *IL2M*, *ScaIL*, FT^{th} and *SIW*

Dataset	#Train	#Test	#Classes	μ(train)	σ(train)
ILSVRC (Russakovsky et al., 2015)	1,231,167	50,000	1,000	1231.2	70.2
VGGFACE2 (Cao et al., 2018)	491,746	50,000	1,000	491.7	49.4
LANDMARKS (Noh et al., 2017)	374,367	20,000	1,000	374.4	103.8
CIFAR-100 (Krizhevsky, 2009)	50,000	10,000	100	500.00	0.00

Summary of the datasets used for evaluation

- Architecture: a ResNet-18 network
- Memory size : $|\mathcal{K}| = \{2\%, 1\%, 0.5\%\}$ of the training set, and no memory.
- Number of states: $\mathcal{T} = \{10, 20, 50\}$

- Evaluation of *TransIL*

10 Reference datasets

10 random 100 leaf classes from ImageNet (Deng et al., 2009)	
Train	500 images per class
Val	200 images per class

4 Test datasets

CIFAR-100 (Krizhevsky, 2009), IMN-100 (Deng et al., 2009), BIRDS-100 (Deng et al., 2009), FOOD-100 (Bossard et al., 2014)	
Train	500 images per class
Test	100 images per class

- Architecture: a ResNet-18 network
- No memory of the past
- Number of states: $\mathcal{T} = \{5, 10, 20\}$

Experiments and Results
Experimental protocol

- Baselines - with memory

Method	works without memory?
FT	✓
FR	✓
iCaRL (Rebuffi et al., 2017)	*LwF* (Li and Hoiem, 2016)
LUCIR (Hou et al., 2019)	✓
BiC (Wu et al., 2019)	×
REMIND (Hayes et al., 2019)	✓

- Baselines - without memory
  - *FT*, *FR*, *LwF* (Li and Hoiem, 2016), *LUCIR* (Hou et al., 2019), *REMIND* (Hayes et al., 2019)
  - *FT+* (Masana et al., 2021)
  - *Deep-SLDA* (Hayes and Kanan, 2019)

- Plugins applied on top of *FT*
  - **init** - use of initial classifiers of past classes (used in *ScaIL* and *SIW*)
  - **L2** - L2 normalization of the weights matrix
  - **mc** - mean state calibration (used in *IL2M* and *SIW*)
  - **th** - threshold calibration (Buda et al., 2018)
  - **BAL** - balanced fine tuning (Castro et al., 2018)
  - **NEM** - nearest exemplars mean (Rebuffi et al., 2017)
- Upper bound of Class IL
  - **Joint** - full training with all data

- Evaluation metrics
  - Average incremental accuracy (Castro et al., 2018)
  - G_{IL} aggregation measure

$$G_{IL} = \frac{1}{C} \times \sum_{c=1}^{C} \frac{A(c) - A(Joint)}{A_{max} - A(Joint)} \tag{14}$$

C - number of tested configurations; $A(c)$ - accuracy of each configuration ; $A(Joint)$ - accuracy of *Joint* ; $A_{max} = 100$

Top-5 results with herding ($\mathcal{T}$ fixed, $|\mathcal{K}|$ variable)

States	$\mathcal{T} = 10$											
Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100		
$\|\mathcal{K}\|$	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%
iCaRL	79.3	76.5	71.0	96.0	95.3	93.9	95.1	94.0	91.8	66.5	56.1	47.9
FT	79.4	74.4	65.9	96.4	94.5	91.3	96.6	94.7	91.4	82.4	77.9	70.7
FT+init	79.2	76.5	73.0	95.9	95.2	94.6	97.0	95.5	92.7	83.4	80.5	75.2
FT+NEM	81.4	79.0	75.0	96.4	95.4	94.0	96.1	94.6	92.6	85.1	81.7	76.0
FT+BAL	84.0	80.9	76.5	97.0	95.7	92.4	96.9	95.3	92.2	80.0	74.0	69.0
FT+th	84.3	82.1	78.3	97.2	96.3	94.8	97.2	95.8	94.0	86.4	83.9	79.1
LUCIR	79.9	76.4	72.6	97.2	**96.9**	**96.5**	97.2	96.6	96.1	79.8	75.4	69.9
BiC	**85.5**	**82.8**	**79.7**	**97.3**	96.6	95.7	**97.9**	**97.3**	**96.6**	**88.8**	**87.6**	**83.5**
ScaIL	82.0	79.8	76.6	96.5	95.8	95.2	97.3	96.0	94.0	85.6	83.2	79.1
IL2M	80.9	78.1	73.9	96.7	95.4	93.4	96.5	94.7	92.5	81.8	77.0	71.2
FR	76.7	76.6	76.4	91.7	91.5	89.7	93.8	93.5	93.5	79.5	79.4	78.7
DeeSIL	75.5	75.1	74.3	92.7	92.5	92.2	94.0	93.7	93.2	66.9	65.8	64.2
REMIND	80.9	80.7	78.2	94.7	93.2	93.0	96.3	95.8	94.7	60.7	60.7	60.7
Joint	92.3			99.2			99.1			91.2		

Top-5 results with herding ($\mathcal{T}$ fixed, $|\mathcal{K}|$ variable)

States	$\mathcal{T} = 10$											
Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100		
$\lvert\mathcal{K}\rvert$	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%
iCaRL	79.3	76.5	71.0	96.0	95.3	93.9	95.1	94.0	91.8	66.5	56.1	47.9
FT	79.4	74.4	65.9	96.4	94.5	91.3	96.6	94.7	91.4	82.4	77.9	70.7
FT+init	79.2	76.5	73.0	95.9	95.2	94.6	97.0	95.5	92.7	83.4	80.5	75.2
FT+NEM	81.4	79.0	75.0	96.4	95.4	94.0	96.1	94.6	92.6	85.1	81.7	76.0
FT+BAL	84.0	80.9	76.5	97.0	95.7	92.4	96.9	95.3	92.2	80.0	74.0	69.0
FT+th	84.3	82.1	78.3	97.2	96.3	94.8	97.2	95.8	94.0	86.4	83.9	79.1
LUCIR	79.9	76.4	72.6	97.2	**96.9**	**96.5**	97.2	96.6	96.1	79.8	75.4	69.9
BiC	**85.5**	**82.8**	**79.7**	**97.3**	96.6	95.7	**97.9**	**97.3**	**96.6**	**88.8**	**87.6**	**83.5**
ScaIL	82.0	79.8	76.6	96.5	95.8	95.2	97.3	96.0	94.0	85.6	83.2	79.1
IL2M	80.9	78.1	73.9	96.7	95.4	93.4	96.5	94.7	92.5	81.8	77.0	71.2
FR	76.7	76.6	76.4	91.7	91.5	89.7	93.8	93.5	93.5	79.5	79.4	78.7
DeeSIL	75.5	75.1	74.3	92.7	92.5	92.2	94.0	93.7	93.2	66.9	65.8	64.2
REMIND	80.9	80.7	78.2	94.7	93.2	93.0	96.3	95.8	94.7	60.7	60.7	60.7
Joint	92.3			99.2			99.1			91.2		

Top-5 results with herding ($\mathcal{T}$ fixed, $|\mathcal{K}|$ variable)

States	$\mathcal{T} = 10$											
Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100		
$\lvert\mathcal{K}\rvert$	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%
iCaRL	79.3	76.5	71.0	96.0	95.3	93.9	95.1	94.0	91.8	66.5	56.1	47.9
FT	79.4	74.4	65.9	96.4	94.5	91.3	96.6	94.7	91.4	82.4	77.9	70.7
FT+init	79.2	76.5	73.0	95.9	95.2	94.6	97.0	95.5	92.7	83.4	80.5	75.2
FT+NEM	81.4	79.0	75.0	96.4	95.4	94.0	96.1	94.6	92.6	85.1	81.7	76.0
FT+BAL	84.0	80.9	76.5	97.0	95.7	92.4	96.9	95.3	92.2	80.0	74.0	69.0
FT+th	84.3	82.1	78.3	97.2	96.3	94.8	97.2	95.8	94.0	86.4	83.9	79.1
LUCIR	79.9	76.4	72.6	97.2	**96.9**	**96.5**	97.2	96.6	96.1	79.8	75.4	69.9
BiC	**85.5**	**82.8**	**79.7**	**97.3**	96.6	95.7	**97.9**	**97.3**	**96.6**	**88.8**	**87.6**	**83.5**
ScaIL	82.0	79.8	76.6	96.5	95.8	95.2	97.3	96.0	94.0	85.6	83.2	79.1
IL2M	80.9	78.1	73.9	96.7	95.4	93.4	96.5	94.7	92.5	81.8	77.0	71.2
FR	76.7	76.6	76.4	91.7	91.5	89.7	93.8	93.5	93.5	79.5	79.4	78.7
DeeSIL	75.5	75.1	74.3	92.7	92.5	92.2	94.0	93.7	93.2	66.9	65.8	64.2
REMIND	80.9	80.7	78.2	94.7	93.2	93.0	96.3	95.8	94.7	60.7	60.7	60.7
Joint	92.3			99.2			99.1			91.2		

Top-5 results with herding ($\mathcal{T}$ fixed, $|\mathcal{K}|$ variable)

States	$\mathcal{T} = 10$											
Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100		
$\lvert\mathcal{K}\rvert$	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%
iCaRL	79.3	76.5	71.0	96.0	95.3	93.9	95.1	94.0	91.8	66.5	56.1	47.9
FT	79.4	74.4	65.9	96.4	94.5	91.3	96.6	94.7	91.4	82.4	77.9	70.7
FT+init	79.2	76.5	73.0	95.9	95.2	94.6	97.0	95.5	92.7	83.4	80.5	75.2
FT+NEM	81.4	79.0	75.0	96.4	95.4	94.0	96.1	94.6	92.6	85.1	81.7	76.0
FT+BAL	84.0	80.9	76.5	97.0	95.7	92.4	96.9	95.3	92.2	80.0	74.0	69.0
FT+th	84.3	82.1	78.3	97.2	96.3	94.8	97.2	95.8	94.0	86.4	83.9	79.1
LUCIR	79.9	76.4	72.6	97.2	**96.9**	**96.5**	97.2	96.6	96.1	79.8	75.4	69.9
BiC	**85.5**	**82.8**	**79.7**	**97.3**	96.6	95.7	**97.9**	**97.3**	**96.6**	**88.8**	**87.6**	**83.5**
ScaIL	82.0	79.8	76.6	96.5	95.8	95.2	97.3	96.0	94.0	85.6	83.2	79.1
IL2M	80.9	78.1	73.9	96.7	95.4	93.4	96.5	94.7	92.5	81.8	77.0	71.2
FR	76.7	76.6	76.4	91.7	91.5	89.7	93.8	93.5	93.5	79.5	79.4	78.7
DeeSIL	75.5	75.1	74.3	92.7	92.5	92.2	94.0	93.7	93.2	66.9	65.8	64.2
REMIND	80.9	80.7	78.2	94.7	93.2	93.0	96.3	95.8	94.7	60.7	60.7	60.7
Joint	92.3			99.2			99.1			91.2		

Top-5 results with herding ($\mathcal{T}$ fixed, $|\mathcal{K}|$ variable)

States	$\mathcal{T}=10$											
Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100		
$\|\mathcal{K}\|$	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%
iCaRL	79.3	76.5	71.0	96.0	95.3	93.9	95.1	94.0	91.8	66.5	56.1	47.9
FT	79.4	74.4	65.9	96.4	94.5	91.3	96.6	94.7	91.4	82.4	77.9	70.7
FT+init	79.2	76.5	73.0	95.9	95.2	94.6	97.0	95.5	92.7	83.4	80.5	75.2
FT+NEM	81.4	79.0	75.0	96.4	95.4	94.0	96.1	94.6	92.6	85.1	81.7	76.0
FT+BAL	84.0	80.9	76.5	97.0	95.7	92.4	96.9	95.3	92.2	80.0	74.0	69.0
FT+th	84.3	82.1	78.3	97.2	96.3	94.8	97.2	95.8	94.0	86.4	83.9	79.1
LUCIR	79.9	76.4	72.6	97.2	**96.9**	**96.5**	97.2	96.6	96.1	79.8	75.4	69.9
BiC	**85.5**	**82.8**	**79.7**	**97.3**	96.6	95.7	**97.9**	**97.3**	**96.6**	**88.8**	**87.6**	**83.5**
ScaIL	82.0	79.8	76.6	96.5	95.8	95.2	97.3	96.0	94.0	85.6	83.2	79.1
IL2M	80.9	78.1	73.9	96.7	95.4	93.4	96.5	94.7	92.5	81.8	77.0	71.2
FR	76.7	76.6	76.4	91.7	91.5	89.7	93.8	93.5	93.5	79.5	79.4	78.7
DeeSIL	75.5	75.1	74.3	92.7	92.5	92.2	94.0	93.7	93.2	66.9	65.8	64.2
REMIND	80.9	80.7	78.2	94.7	93.2	93.0	96.3	95.8	94.7	60.7	60.7	60.7
Joint	92.3			99.2			99.1			91.2		

Top-5 results with herding ($\mathcal{T}$ fixed, $|\mathcal{K}|$ variable)

States	$\mathcal{T} = 10$											
Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100		
$\lvert\mathcal{K}\rvert$	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%	2%	1%	0.5%
iCaRL	79.3	76.5	71.0	96.0	95.3	93.9	95.1	94.0	91.8	66.5	56.1	47.9
FT	79.4	74.4	65.9	96.4	94.5	91.3	96.6	94.7	91.4	82.4	77.9	70.7
FT+init	79.2	76.5	73.0	95.9	95.2	94.6	97.0	95.5	92.7	83.4	80.5	75.2
FT+NEM	81.4	79.0	75.0	96.4	95.4	94.0	96.1	94.6	92.6	85.1	81.7	76.0
FT+BAL	84.0	80.9	76.5	97.0	95.7	92.4	96.9	95.3	92.2	80.0	74.0	69.0
FT+th	84.3	82.1	78.3	97.2	96.3	94.8	97.2	95.8	94.0	86.4	83.9	79.1
LUCIR	79.9	76.4	72.6	97.2	**96.9**	**96.5**	97.2	96.6	96.1	79.8	75.4	69.9
BiC	**85.5**	**82.8**	**79.7**	**97.3**	96.6	95.7	**97.9**	**97.3**	**96.6**	**88.8**	**87.6**	**83.5**
ScaIL	82.0	79.8	76.6	96.5	95.8	95.2	97.3	96.0	94.0	85.6	83.2	79.1
IL2M	80.9	78.1	73.9	96.7	95.4	93.4	96.5	94.7	92.5	81.8	77.0	71.2
FR	76.7	76.6	76.4	91.7	91.5	89.7	93.8	93.5	93.5	79.5	79.4	78.7
DeeSIL	75.5	75.1	74.3	92.7	92.5	92.2	94.0	93.7	93.2	66.9	65.8	64.2
REMIND	80.9	80.7	78.2	94.7	93.2	93.0	96.3	95.8	94.7	60.7	60.7	60.7
Joint	92.3			99.2			99.1			91.2		

Top-5 results with herding ($|\mathcal{K}|$ fixed, $\mathcal{T}$ variable)

States	$\|\mathcal{K}\| = 0.5\%$								
Dataset	ILSVRC		VGGFACE2		LANDMARKS		CIFAR-100		G_{IL}
$\mathcal{T}$	20	50	20	50	20	50	20	50	
iCaRL	55.9	45.0	88.5	78.2	86.8	82.4	35.5	35.4	-7.36
FT	69.4	64.3	91.6	89.2	90.9	89.0	64.3	54.8	-5.19
FT+init	73.6	67.3	94.6	91.4	91.2	88.5	63.6	44.1	-4.43
FT+NEM	76.5	69.0	94.0	91.1	91.9	89.9	68.8	55.9	-4.28
FT+BAL	75.9	67.1	92.3	89.5	91.2	88.9	62.9	54.2	-4.70
FT+th	**78.6**	**71.2**	94.3	91.6	92.9	**90.7**	**71.4**	**57.9**	**-3.62**
LUCIR	63.9	55.3	93.5	88.3	93.7	90.5	53.5	47.9	-4.13
BiC	74.6	63.9	92.3	85.3	**94.7**	90.5	50.5	19.6	-4.03
ScaIL	76.6	70.9	**95.0**	**92.4**	92.6	90.4	69.8	51.0	-3.70
IL2M	70.9	60.6	92.5	88.4	90.8	88.1	61.5	51.0	-4.95
FR	69.2	58.2	85.8	75.2	89.3	82.8	62.3	33.5	-7.62
DeeSIL	73.0	58.1	87.2	80.0	90.5	85.1	63.9	44.0	-6.92
REMIND	73.9	65.0	87.4	80.1	92.8	88.6	52.8	46.4	-6.02
Joint	92.3		99.2		99.1		91.2		-

Top-5 results with herding ($|\mathcal{K}|$ fixed, $\mathcal{T}$ variable)

States	$\|\mathcal{K}\| = 0.5\%$								
Dataset	ILSVRC		VGGFACE2		LANDMARKS		CIFAR-100		G_{IL}
$\mathcal{T}$	20	50	20	50	20	50	20	50	
iCaRL	55.9	45.0	88.5	78.2	86.8	82.4	35.5	35.4	-7.36
FT	69.4	64.3	91.6	89.2	90.9	89.0	64.3	54.8	-5.19
FT+init	73.6	67.3	94.6	91.4	91.2	88.5	63.6	44.1	-4.43
FT+NEM	76.5	69.0	94.0	91.1	91.9	89.9	68.8	55.9	-4.28
FT+BAL	75.9	67.1	92.3	89.5	91.2	88.9	62.9	54.2	-4.70
FT+th	**78.6**	**71.2**	94.3	91.6	92.9	**90.7**	**71.4**	**57.9**	**-3.62**
LUCIR	63.9	55.3	93.5	88.3	93.7	90.5	53.5	47.9	-4.13
BiC	74.6	63.9	92.3	85.3	**94.7**	90.5	50.5	19.6	-4.03
ScaIL	76.6	70.9	**95.0**	**92.4**	92.6	90.4	69.8	51.0	-3.70
IL2M	70.9	60.6	92.5	88.4	90.8	88.1	61.5	51.0	-4.95
FR	69.2	58.2	85.8	75.2	89.3	82.8	62.3	33.5	-7.62
DeeSIL	73.0	58.1	87.2	80.0	90.5	85.1	63.9	44.0	-6.92
REMIND	73.9	65.0	87.4	80.1	92.8	88.6	52.8	46.4	-6.02
Joint	92.3		99.2		99.1		91.2		-

Top-5 results with herding ($|\mathcal{K}|$ fixed, $\mathcal{T}$ variable)

States	$\|\mathcal{K}\| = 0.5\%$								
Dataset	ILSVRC		VGGFACE2		LANDMARKS		CIFAR-100		G_{IL}
$\mathcal{T}$	20	50	20	50	20	50	20	50	
iCaRL	55.9	45.0	88.5	78.2	86.8	82.4	35.5	35.4	-7.36
FT	69.4	64.3	91.6	89.2	90.9	89.0	64.3	54.8	-5.19
FT+init	73.6	67.3	94.6	91.4	91.2	88.5	63.6	44.1	-4.43
FT+NEM	76.5	69.0	94.0	91.1	91.9	89.9	68.8	55.9	-4.28
FT+BAL	75.9	67.1	92.3	89.5	91.2	88.9	62.9	54.2	-4.70
FT+th	**78.6**	**71.2**	94.3	91.6	92.9	**90.7**	**71.4**	**57.9**	**-3.62**
LUCIR	63.9	55.3	93.5	88.3	93.7	90.5	53.5	47.9	-4.13
BiC	74.6	63.9	92.3	85.3	**94.7**	90.5	50.5	19.6	-4.03
ScaIL	76.6	70.9	**95.0**	**92.4**	92.6	90.4	69.8	51.0	-3.70
IL2M	70.9	60.6	92.5	88.4	90.8	88.1	61.5	51.0	-4.95
FR	69.2	58.2	85.8	75.2	89.3	82.8	62.3	33.5	-7.62
DeeSIL	73.0	58.1	87.2	80.0	90.5	85.1	63.9	44.0	-6.92
REMIND	73.9	65.0	87.4	80.1	92.8	88.6	52.8	46.4	-6.02
Joint	92.3		99.2		99.1		91.2		-

Top-5 results with herding ($|\mathcal{K}|$ fixed, $\mathcal{T}$ variable)

States	$\|\mathcal{K}\| = 0.5\%$								
Dataset	ILSVRC		VGGFACE2		LANDMARKS		CIFAR-100		G_{IL}
$\mathcal{T}$	20	50	20	50	20	50	20	50	
iCaRL	55.9	45.0	88.5	78.2	86.8	82.4	35.5	35.4	-7.36
FT	69.4	64.3	91.6	89.2	90.9	89.0	64.3	54.8	-5.19
FT+init	73.6	67.3	94.6	91.4	91.2	88.5	63.6	44.1	-4.43
FT+NEM	76.5	69.0	94.0	91.1	91.9	89.9	68.8	55.9	-4.28
FT+BAL	75.9	67.1	92.3	89.5	91.2	88.9	62.9	54.2	-4.70
FT+th	**78.6**	**71.2**	94.3	91.6	92.9	**90.7**	**71.4**	**57.9**	**-3.62**
LUCIR	63.9	55.3	93.5	88.3	93.7	90.5	53.5	47.9	-4.13
BiC	74.6	63.9	92.3	85.3	**94.7**	90.5	50.5	19.6	-4.03
ScaIL	76.6	70.9	**95.0**	**92.4**	92.6	90.4	69.8	51.0	-3.70
IL2M	70.9	60.6	92.5	88.4	90.8	88.1	61.5	51.0	-4.95
FR	69.2	58.2	85.8	75.2	89.3	82.8	62.3	33.5	-7.62
DeeSIL	73.0	58.1	87.2	80.0	90.5	85.1	63.9	44.0	-6.92
REMIND	73.9	65.0	87.4	80.1	92.8	88.6	52.8	46.4	-6.02
Joint	92.3		99.2		99.1		91.2		-

Top-5 results with herding ($|\mathcal{K}|$ fixed, $\mathcal{T}$ variable)

States	$\lvert\mathcal{K}\rvert = 0.5\%$								G_{IL}
Dataset	ILSVRC		VGGFACE2		LANDMARKS		CIFAR-100		
$\mathcal{T}$	20	50	20	50	20	50	20	50	
iCaRL	55.9	45.0	88.5	78.2	86.8	82.4	35.5	35.4	-7.36
FT	69.4	64.3	91.6	89.2	90.9	89.0	64.3	54.8	-5.19
FT+init	73.6	67.3	94.6	91.4	91.2	88.5	63.6	44.1	-4.43
FT+NEM	76.5	69.0	94.0	91.1	91.9	89.9	68.8	55.9	-4.28
FT+BAL	75.9	67.1	92.3	89.5	91.2	88.9	62.9	54.2	-4.70
FT+th	**78.6**	**71.2**	94.3	91.6	92.9	**90.7**	**71.4**	**57.9**	**-3.62**
LUCIR	63.9	55.3	93.5	88.3	93.7	90.5	53.5	47.9	-4.13
BiC	74.6	63.9	92.3	85.3	**94.7**	90.5	50.5	19.6	-4.03
ScaIL	76.6	70.9	**95.0**	**92.4**	92.6	90.4	69.8	51.0	-3.70
IL2M	70.9	60.6	92.5	88.4	90.8	88.1	61.5	51.0	-4.95
FR	69.2	58.2	85.8	75.2	89.3	82.8	62.3	33.5	-7.62
DeeSIL	73.0	58.1	87.2	80.0	90.5	85.1	63.9	44.0	-6.92
REMIND	73.9	65.0	87.4	80.1	92.8	88.6	52.8	46.4	-6.02
Joint	92.3		99.2		99.1		91.2		-

Top-5 results without memory

Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100			G_{IL}
States $\mathcal{T}$	10	20	50	10	20	50	10	20	50	10	20	50	
FT	20.6	13.4	7.1	21.3	13.6	7.1	21.3	13.6	7.1	21.3	13.7	17.4	-54.91
LwF	45.3	37.6	27.1	53.3	42.6	30.8	58.8	49.2	35.2	79.5	65.3	39.0	-34.72
FT+init	61.0	44.9	23.8	90.9	64.4	33.1	68.8	49.4	22.2	55.1	40.8	19.9	-28.99
FT+init+L2	51.6	43.3	34.5	76.8	66.8	55.1	61.4	52.5	39.2	47.5	39.3	22.5	-26.80
FT+init+L2+mc	53.6	42.7	35.6	86.9	71.4	53.6	66.2	52.6	37.9	52.6	43.1	18.2	**-25.02**
SIW(FT)	64.4	54.3	41.4	88.6	84.1	62.6	79.5	64.5	43.2	59.7	44.3	18.4	-19.38
SIW(LwF)	54.0	45.8	35.1	70.4	59.3	45.2	61.0	53.8	42.2	**80.0**	**68.8**	44.6	-28.06
LUCIR	57.6	39.4	21.9	91.4	68.2	32.2	87.8	63.7	32.3	57.5	35.3	21.0	-24.75
FR	74.0	66.9	49.2	88.7	83.0	54.4	**93.6**	88.1	71.2	73.1	54.8	27.4	-16.30
DeeSIL	**73.9**	**67.5**	53.9	**92.3**	**87.5**	75.1	**93.6**	**91.1**	**82.1**	65.2	63.4	32.3	**-9.22**
REMIND	62.2	56.3	44.4	86.8	81.4	69.2	84.5	79.6	69.0	52.7	40.5	25.7	-22.00
Deep-SLDA	70.3	64.5	**56.0**	90.2	85.4	**78.2**	89.3	86.4	81.3	68.9	64.4	**54.5**	-15.40
Joint	92.3			99.2			99.1			91.2			-

Top-5 results without memory

Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100			G_{IL}
States $\mathcal{T}$	10	20	50	10	20	50	10	20	50	10	20	50	
FT	20.6	13.4	7.1	21.3	13.6	7.1	21.3	13.6	7.1	21.3	13.7	17.4	-54.91
LwF	45.3	37.6	27.1	53.3	42.6	30.8	58.8	49.2	35.2	79.5	65.3	39.0	-34.72
FT+init	61.0	44.9	23.8	90.9	64.4	33.1	68.8	49.4	22.2	55.1	40.8	19.9	-28.99
FT+init+L2	51.6	43.3	34.5	76.8	66.8	55.1	61.4	52.5	39.2	47.5	39.3	22.5	-26.80
FT+init+L2+mc	53.6	42.7	35.6	86.9	71.4	53.6	66.2	52.6	37.9	52.6	43.1	18.2	**-25.02**
SIW(FT)	64.4	54.3	41.4	88.6	84.1	62.6	79.5	64.5	43.2	59.7	44.3	18.4	-19.38
SIW(LwF)	54.0	45.8	35.1	70.4	59.3	45.2	61.0	53.8	42.2	**80.0**	**68.8**	44.6	-28.06
LUCIR	57.6	39.4	21.9	91.4	68.2	32.2	87.8	63.7	32.3	57.5	35.3	21.0	-24.75
FR	74.0	66.9	49.2	88.7	83.0	54.4	**93.6**	88.1	71.2	73.1	54.8	27.4	-16.30
DeeSIL	**73.9**	**67.5**	53.9	**92.3**	**87.5**	75.1	**93.6**	**91.1**	**82.1**	65.2	63.4	32.3	**-9.22**
REMIND	62.2	56.3	44.4	86.8	81.4	69.2	84.5	79.6	69.0	52.7	40.5	25.7	-22.00
Deep-SLDA	70.3	64.5	**56.0**	90.2	85.4	**78.2**	89.3	86.4	81.3	68.9	64.4	**54.5**	-15.40
Joint	92.3			99.2			99.1			91.2			-

Top-5 results without memory

Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100			G_{IL}
States $\mathcal{T}$	10	20	50	10	20	50	10	20	50	10	20	50	
FT	20.6	13.4	7.1	21.3	13.6	7.1	21.3	13.6	7.1	21.3	13.7	17.4	-54.91
LwF	45.3	37.6	27.1	53.3	42.6	30.8	58.8	49.2	35.2	79.5	65.3	39.0	-34.72
FT+init	61.0	44.9	23.8	90.9	64.4	33.1	68.8	49.4	22.2	55.1	40.8	19.9	-28.99
FT+init+L2	51.6	43.3	34.5	76.8	66.8	55.1	61.4	52.5	39.2	47.5	39.3	22.5	-26.80
FT+init+L2+mc	53.6	42.7	35.6	86.9	71.4	53.6	66.2	52.6	37.9	52.6	43.1	18.2	**-25.02**
SIW(FT)	64.4	54.3	41.4	88.6	84.1	62.6	79.5	64.5	43.2	59.7	44.3	18.4	-19.38
SIW(LwF)	54.0	45.8	35.1	70.4	59.3	45.2	61.0	53.8	42.2	**80.0**	**68.8**	44.6	-28.06
LUCIR	57.6	39.4	21.9	91.4	68.2	32.2	87.8	63.7	32.3	57.5	35.3	21.0	-24.75
FR	74.0	66.9	49.2	88.7	83.0	54.4	**93.6**	88.1	71.2	73.1	54.8	27.4	-16.30
DeeSIL	**73.9**	**67.5**	53.9	**92.3**	**87.5**	75.1	**93.6**	**91.1**	**82.1**	65.2	63.4	32.3	**-9.22**
REMIND	62.2	56.3	44.4	86.8	81.4	69.2	84.5	79.6	69.0	52.7	40.5	25.7	-22.00
Deep-SLDA	70.3	64.5	**56.0**	90.2	85.4	**78.2**	89.3	86.4	81.3	68.9	64.4	**54.5**	-15.40
Joint	92.3			99.2			99.1			91.2			-

Top-5 results without memory

Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100			G_{IL}
States $\mathcal{T}$	10	20	50	10	20	50	10	20	50	10	20	50	
FT	20.6	13.4	7.1	21.3	13.6	7.1	21.3	13.6	7.1	21.3	13.7	17.4	-54.91
LwF	45.3	37.6	27.1	53.3	42.6	30.8	58.8	49.2	35.2	79.5	65.3	39.0	-34.72
FT+init	61.0	44.9	23.8	90.9	64.4	33.1	68.8	49.4	22.2	55.1	40.8	19.9	-28.99
FT+init+L2	51.6	43.3	34.5	76.8	66.8	55.1	61.4	52.5	39.2	47.5	39.3	22.5	-26.80
FT+init+L2+mc	53.6	42.7	35.6	86.9	71.4	53.6	66.2	52.6	37.9	52.6	43.1	18.2	**-25.02**
SIW(FT)	64.4	54.3	41.4	88.6	84.1	62.6	79.5	64.5	43.2	59.7	44.3	18.4	-19.38
SIW(LwF)	54.0	45.8	35.1	70.4	59.3	45.2	61.0	53.8	42.2	**80.0**	**68.8**	44.6	-28.06
LUCIR	57.6	39.4	21.9	91.4	68.2	32.2	87.8	63.7	32.3	57.5	35.3	21.0	-24.75
FR	74.0	66.9	49.2	88.7	83.0	54.4	**93.6**	88.1	71.2	73.1	54.8	27.4	-16.30
DeeSIL	**73.9**	**67.5**	53.9	**92.3**	**87.5**	75.1	**93.6**	**91.1**	**82.1**	65.2	63.4	32.3	**-9.22**
REMIND	62.2	56.3	44.4	86.8	81.4	69.2	84.5	79.6	69.0	52.7	40.5	25.7	-22.00
Deep-SLDA	70.3	64.5	**56.0**	90.2	85.4	**78.2**	89.3	86.4	81.3	68.9	64.4	**54.5**	-15.40
Joint	92.3			99.2			99.1			91.2			-

Top-5 results without memory

Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100			G_{IL}
States $\mathcal{T}$	10	20	50	10	20	50	10	20	50	10	20	50	
FT	20.6	13.4	7.1	21.3	13.6	7.1	21.3	13.6	7.1	21.3	13.7	17.4	-54.91
LwF	45.3	37.6	27.1	53.3	42.6	30.8	58.8	49.2	35.2	79.5	65.3	39.0	-34.72
FT+init	61.0	44.9	23.8	90.9	64.4	33.1	68.8	49.4	22.2	55.1	40.8	19.9	-28.99
FT+init+L2	51.6	43.3	34.5	76.8	66.8	55.1	61.4	52.5	39.2	47.5	39.3	22.5	-26.80
FT+init+L2+mc	53.6	42.7	35.6	86.9	71.4	53.6	66.2	52.6	37.9	52.6	43.1	18.2	**-25.02**
SIW(FT)	64.4	54.3	41.4	88.6	84.1	62.6	79.5	64.5	43.2	59.7	44.3	18.4	-19.38
SIW(LwF)	54.0	45.8	35.1	70.4	59.3	45.2	61.0	53.8	42.2	**80.0**	**68.8**	44.6	-28.06
LUCIR	57.6	39.4	21.9	91.4	68.2	32.2	87.8	63.7	32.3	57.5	35.3	21.0	-24.75
FR	74.0	66.9	49.2	88.7	83.0	54.4	**93.6**	88.1	71.2	73.1	54.8	27.4	-16.30
DeeSIL	**73.9**	**67.5**	53.9	**92.3**	**87.5**	75.1	**93.6**	**91.1**	**82.1**	65.2	63.4	32.3	**-9.22**
REMIND	62.2	56.3	44.4	86.8	81.4	69.2	84.5	79.6	69.0	52.7	40.5	25.7	-22.00
Deep-SLDA	70.3	64.5	**56.0**	90.2	85.4	**78.2**	89.3	86.4	81.3	68.9	64.4	**54.5**	-15.40
Joint	92.3			99.2			99.1			91.2			-

Top-5 results without memory

Dataset	ILSVRC			VGGFACE2			LANDMARKS			CIFAR-100			G_{IL}
States $\mathcal{T}$	10	20	50	10	20	50	10	20	50	10	20	50	
FT	20.6	13.4	7.1	21.3	13.6	7.1	21.3	13.6	7.1	21.3	13.7	17.4	-54.91
LwF	45.3	37.6	27.1	53.3	42.6	30.8	58.8	49.2	35.2	79.5	65.3	39.0	-34.72
FT+init	61.0	44.9	23.8	90.9	64.4	33.1	68.8	49.4	22.2	55.1	40.8	19.9	-28.99
FT+init+L2	51.6	43.3	34.5	76.8	66.8	55.1	61.4	52.5	39.2	47.5	39.3	22.5	-26.80
FT+init+L2+mc	53.6	42.7	35.6	86.9	71.4	53.6	66.2	52.6	37.9	52.6	43.1	18.2	**-25.02**
SIW(FT)	64.4	54.3	41.4	88.6	84.1	62.6	79.5	64.5	43.2	59.7	44.3	18.4	-19.38
SIW(LwF)	54.0	45.8	35.1	70.4	59.3	45.2	61.0	53.8	42.2	**80.0**	**68.8**	44.6	-28.06
LUCIR	57.6	39.4	21.9	91.4	68.2	32.2	87.8	63.7	32.3	57.5	35.3	21.0	-24.75
FR	74.0	66.9	49.2	88.7	83.0	54.4	**93.6**	88.1	71.2	73.1	54.8	27.4	-16.30
DeeSIL	**73.9**	**67.5**	53.9	**92.3**	**87.5**	75.1	**93.6**	**91.1**	**82.1**	65.2	63.4	32.3	**-9.22**
REMIND	62.2	56.3	44.4	86.8	81.4	69.2	84.5	79.6	69.0	52.7	40.5	25.7	-22.00
Deep-SLDA	70.3	64.5	**56.0**	90.2	85.4	**78.2**	89.3	86.4	81.3	68.9	64.4	**54.5**	-15.40
Joint	92.3			99.2			99.1			91.2			-

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Results and discussion

Class-Incremental Learning without memory

Top-1 results without memory

Method / States	CIFAR-100 $\mathcal{T}=5$	CIFAR-100 $\mathcal{T}=10$	CIFAR-100 $\mathcal{T}=20$	BIRDS-100 $\mathcal{T}=5$	BIRDS-100 $\mathcal{T}=10$	BIRDS-100 $\mathcal{T}=20$	FOOD-100 $\mathcal{T}=5$	FOOD-100 $\mathcal{T}=10$	FOOD-100 $\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC + $\mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC $+ \mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
w/ AdBiC $+ \mathbb{O}$	55.5 + 5.4	43.6 + 9.9	31.2 + 11.7	59.0 + 8.2	46.0 + 14.6	28.8 + 10.9	52.6 + 8.4	38.2 + 11.8	21.0 + 5.5
SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC $+ \mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC $+ \mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Top-1 results without memory

Method	CIFAR-100			BIRDS-100			FOOD-100		
States	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$	$\mathcal{T}=5$	$\mathcal{T}=10$	$\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
w/ BiC	54.0 + 1.0	45.5 + 1.5	30.8 + 1.7	54.6 + 0.9	43.1 + 1.3	31.8 + 1.7	43.4 + 0.5	32.6 + 0.8	23.8 + 1.6
w/ AdBiC	54.3 + 1.3	**46.4** + 2.4	**32.3** + 3.2	55.0 + 1.3	44.0 + 2.2	**32.8** + 2.7	43.5 + 0.6	33.3 + 1.5	**24.7** + 2.5
w/ AdBiC + $\mathbb{O}$	54.9 + 1.9	47.3 + 3.3	32.6 + 3.5	55.8 + 2.1	44.8 + 3.0	33.3 + 3.2	44.0 + 1.1	34.2 + 2.4	25.3 + 3.1
LUCIR	50.1	33.7	19.5	50.8	31.4	17.9	44.2	26.4	15.5
w/ BiC	52.5 + 2.4	37.1 + 3.4	22.4 + 2.9	56.0 + 5.2	37.7 + 6.3	20.6 + 2.7	49.9 + 5.7	31.5 + 5.1	17.2 + 1.7
w/ AdBiC	**54.8** + 4.7	42.2 + 8.5	28.4 + 8.9	**58.5** + 7.7	**45.4** + 14.0	27.3 + 9.4	**52.0** + 7.8	**37.1** + 10.7	17.7 + 2.2
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SIW	29.9	22.7	14.8	30.6	23.2	14.9	29.4	21.6	14.1
w/ BiC	31.4 + 1.5	22.8 + 0.1	14.7 - 0.1	32.8 + 2.2	22.7 - 0.5	12.8 - 2.1	29.1 - 0.3	20.3 - 1.3	12.1 - 2.0
w/ AdBiC	31.7 + 1.8	24.1 + 1.4	15.8 + 1.0	33.0 + 2.4	25.2 + 2.0	15.3 + 0.4	30.9 + 1.5	21.3 - 0.3	14.5 + 0.4
w/ AdBiC + $\mathbb{O}$	32.8 + 2.9	25.0 + 2.3	16.5 + 1.7	34.4 + 3.8	26.2 + 3.0	16.3 + 1.4	31.5 + 2.1	22.6 + 1.0	15.1 + 1.0
FT+	28.9	22.6	14.5	29.7	23.3	13.5	28.7	21.1	13.3
w/ BiC	30.7 + 1.8	22.5 - 0.1	14.8 + 0.3	32.3 + 2.6	22.5 - 0.8	12.4 - 1.1	28.6 - 0.1	20.6 - 0.5	11.8 - 1.5
w/ AdBiC	31.9 + 3.0	23.6 + 1.0	15.0 + 0.5	34.0 + 4.3	25.0 + 1.7	14.2 + 0.7	30.8 + 2.1	22.2 + 1.1	14.2 + 0.9
w/ AdBiC + $\mathbb{O}$	32.5 + 3.6	24.6 + 2.0	15.9 + 1.4	34.5 + 4.8	25.7 + 2.4	15.4 + 1.9	31.3 + 2.6	22.7 + 1.6	14.5 + 1.2
Joint	72.7			80.9			71.03		

gains, losses

Conclusions and future work

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Conclusions

- In fine tuning, the classification layer is the most affected by catastrophic forgetting
- Fine-tuning-based methods are the best option when a memory is allowed
- Fixed representations are an appropriate choice without memory
- Usefulness of distillation is reduced at large scale
- We reduce the model's footprint by half compared to distillation-based methods

Future work

- Propose an alternative of the distillation loss

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Future work

- Propose an alternative of the distillation loss
- Focus more on class-incremental learning without memory
- Explore methods that make a better compromise between stability and plasticity of the network
- Work on feature transferability between states

Publications

Journal papers

- Belouadah, E., Popescu, A., Kanellos, I. **A Comprehensive Study of Class Incremental Learning Algorithms for Visual Tasks**. Neural Networks, t. 135, pp. 38-54
- Aggarwal, U., Popescu, A., Belouadah, E. and Hudelot, C., 2020. **A Comparative Study of Calibration Methods for Imbalanced Class Incremental Learning**. Multimedia Tools and Applications.

Conference papers (1/2)

- Belouadah, E., Popescu, A. **IL2M: Class Incremental Learning with Dual Memory**. Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2019, p583-592.
- Belouadah, E., Popescu, A. **ScaIL: Classifier Weights Scaling for Class Incremental Learning**. The IEEE Winter Conference on Applications of Computer Vision (WACV), 2020, p1266-1275.
- Belouadah, E., Popescu, A., Kanellos, I. **Initial Classifier Weights Replay for Memoryless Class Incremental Learning**. British Machine Vision Conference (BMVC) 2020.

Conference papers (2/2)

- Slim, H.†, Belouadah, E.†, Popescu, A., Onchis, D. **Dataset Knowledge Transfer for Class-Incremental Learning without Memory**. The IEEE Winter Conference on Applications of Computer Vision (WACV), 2022.

†: equal contribution

Workshop papers

- Belouadah, E., Popescu, A. **DeeSIL: Deep-Shallow Incremental Learning**. Proceeding of the European Conference on Computer Vision workshops (W-ECCV 2018)
- Belouadah, E., Popescu, A., Aggarwal, U., Saci L. **Active Class Incremental Learning for Imbalanced Datasets**. IPCV workshop of the European Conference on Computer Vision (ECCV) 2020.

Codes and dataset details:

https://github.com/EdenBelouadah/class-incremental-learning

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Appendix

Fixed-Representation-based methods:

DeeSIL (Belouadah and Popescu, 2018), *Deep-SLDA* (Hayes and Kanan, 2019), *REMIND* (Hayes et al., 2019), *FearNet* Kemker and Kanan, 2018.

Fine-Tuning-based methods:

DGM (Ostapenko et al., 2019), *DGR* (Shin et al., 2017), *GMNF* (Cong et al., 2020), *LwF* (Li and Hoiem, 2016), *EWC* (Kirkpatrick et al., 2016), *MAS* (Aljundi et al., 2018), *BiC* (Wu et al., 2019), *MDF* (Zhao et al., 2020), *LUCIR* (Hou et al., 2019), *iCaRL* (Rebuffi et al., 2017), *E2EIL* (Castro et al., 2018).

Parameter-isolation-based methods:

PackNet (Mallya and Lazebnik, 2018), *PiggyBack* (Mallya et al., 2018), *TFM* (Masana et al., 2020), $Expert - Gate$ (Aljundi et al., 2017), *PNN* (Rusu et al., 2016), *DAN* (Rosenfeld and Tsotsos, 2017).

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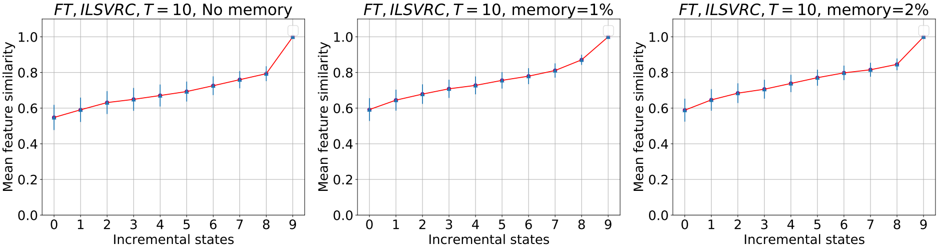
Backup Slides

Mean Features Similarity



(a) (b) (c)

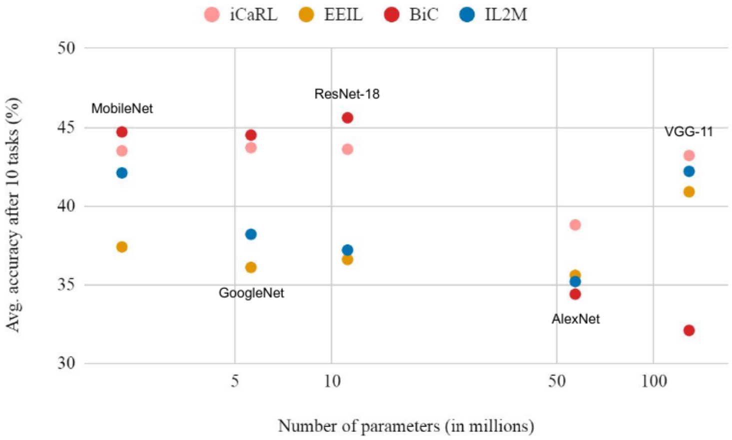
Mean feature similarities between incremental states for test images of the first state.

Additional Storage of our methods

Method	Additional Storage (AS) in float	AS for $N_{\mathcal{T}} = 1000$				
		$\mathcal{T} = 5$	$\mathcal{T} = 10$	$\mathcal{T} = 20$	$\mathcal{T} = 50$	$\mathcal{T} = 100$
DeeSIL	0	0	0	0	0	0
IL2M	$\mathcal{T} + N_{\mathcal{T}}$	4.02 KB	4.04 KB	4.08 KB	4.2 KB	4.4 KB
ScaIL	$N_{\mathcal{T}} \times D$	2.05 MB	2.05 MB	2.05 MB	2.05 MB	2.05 MB
SIW	$\mathcal{T} + N_{\mathcal{T}} \times D$	2.05 MB	2.05 MB	2.05 MB	2.05 MB	2.05 MB
TransIL (*AdBiC*)	$R \times (\mathcal{T} + 2) \times (\mathcal{T} - 1)$	1.12 KB	4.32 KB	16.72 KB	101.92 KB	403.92 KB
TransIL (*BiC*)	$2 \times R \times (\mathcal{T} - 1)$	320 B	720 B	1.52 KB	3.92 KB	7.92 KB

Additional Storage (AS) of our proposed IL approaches

Results with other deep architectures



Results with other architectures (Masana et al., 2021)