Continual Learning for Image Classification and Object Detection

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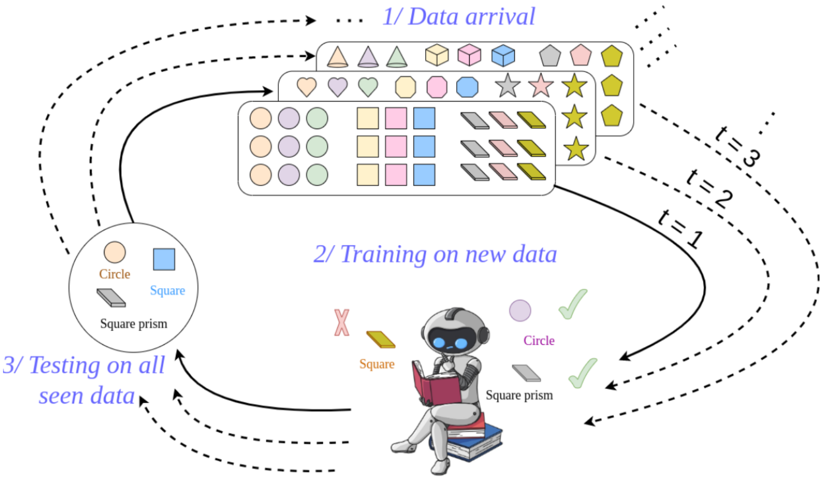
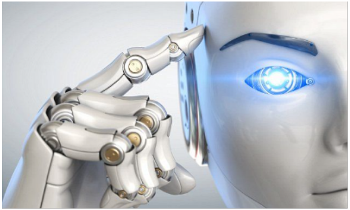


Continual Learning

Application examples of continual learning



Robotics

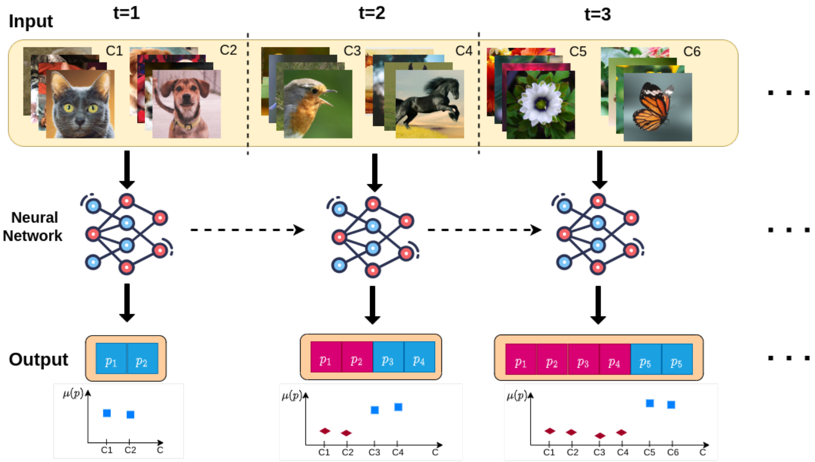
Autonomous cars

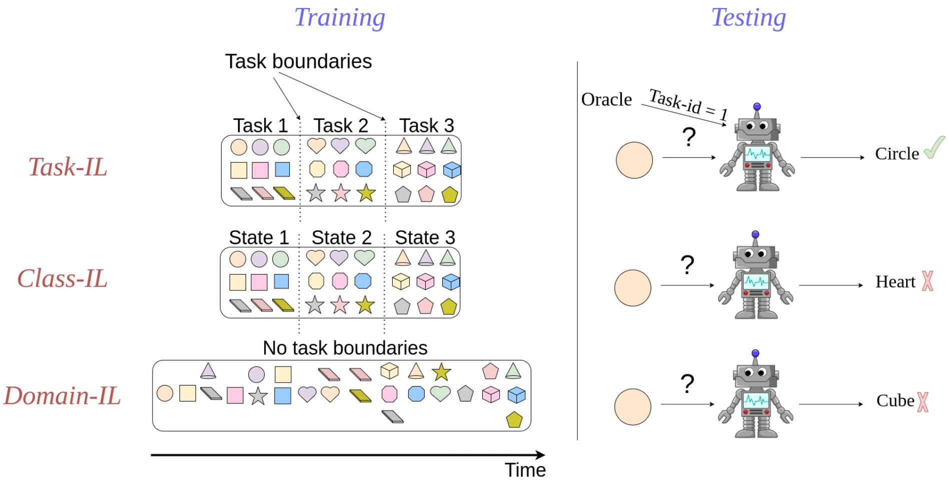
Face Recognition

Health

Catastrophic forgetting

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

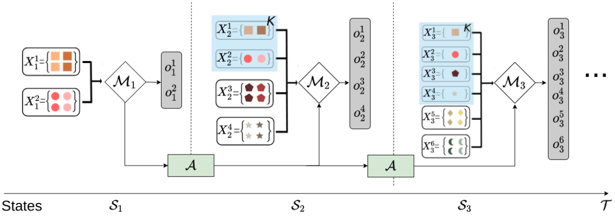




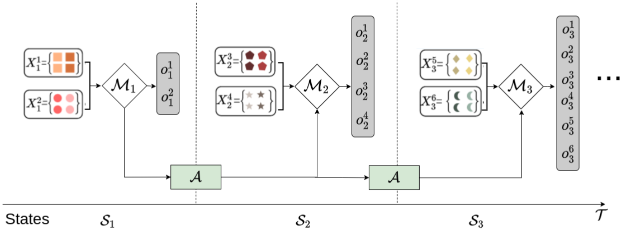
Three Scenarios of Continual Learning

Introduction
Two scenarios of Class-Incremental Learning

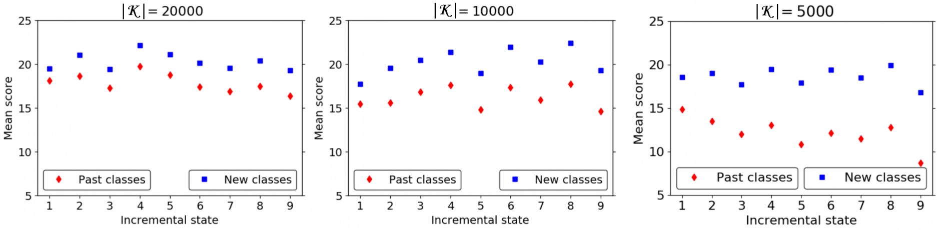
- Incremental Learning with memory



- Incremental Learning without memory

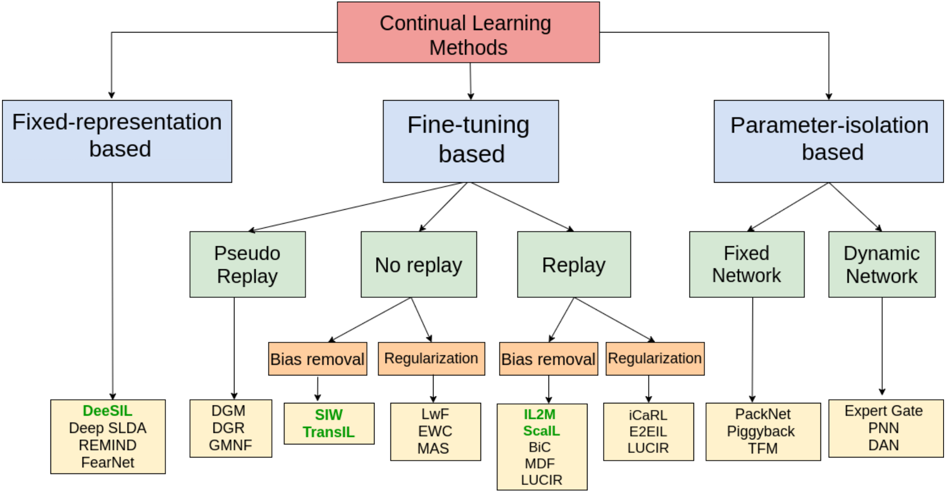


Memory reduces prediction bias towards new classes



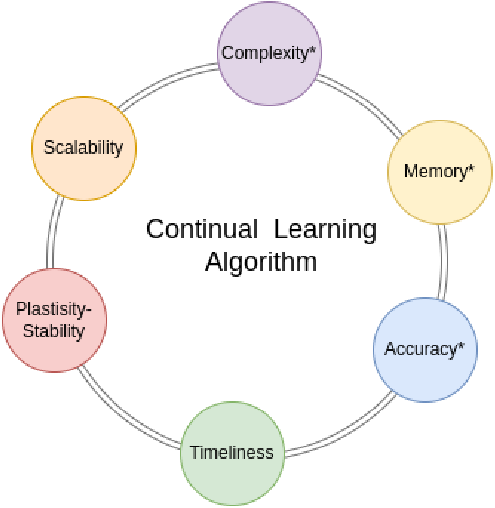
Mean prediction scores of past and new classes with vanilla fine tuning

1. State of the art



[Schema inspired by Lange et al., 2019]

[References are in appendix slides]



** [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

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

- Nearest Exemplars Mean (NEM)

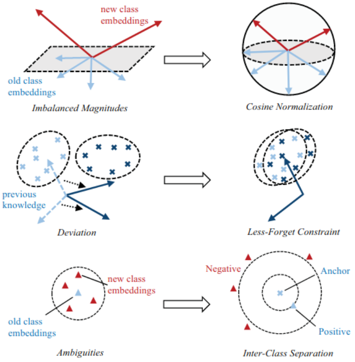
$$y^* = \underset{y \in [1, N_t]}{\arg\min} \left\| f(x) - \mu_y \right\| \tag{3}$$

  - (+) 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

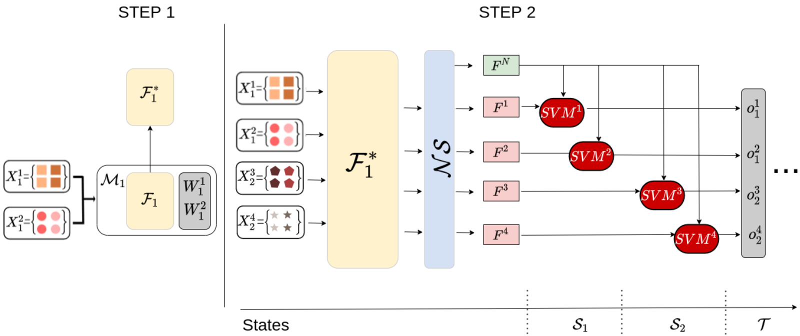
$$BiC(\boldsymbol{o}_t^k) = \begin{cases} \boldsymbol{o}_t^k & \text{if} \quad k \in [1,\ t-1] \\ \alpha_t \boldsymbol{o}_t^k + \beta_t \cdot \mathbf{1} & \text{if} \quad k = t \end{cases} \tag{4}$$

- (+) 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)

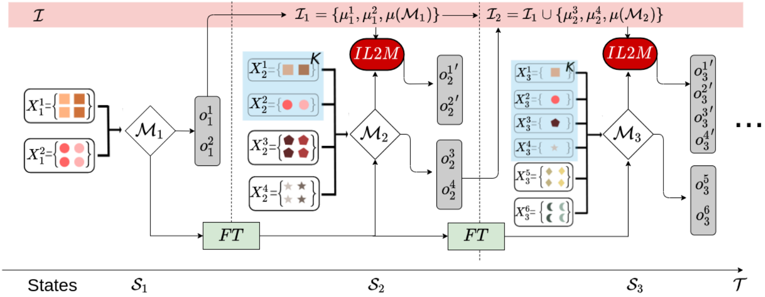
- Fixed Representation based
- Inspired by transfer learning
- Works with and without memory



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

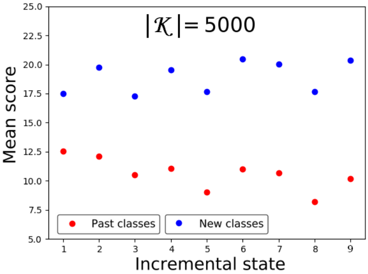
For all past classes ($j = 1, \ldots, N_{t-1}$):

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

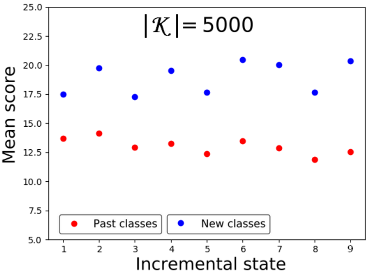
with:

- 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 mean score in states t and i

- Effect of *IL2M*



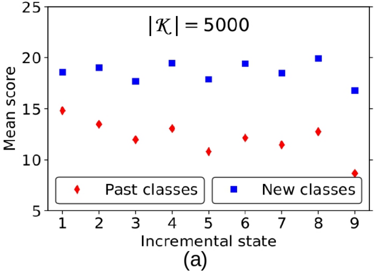
Before

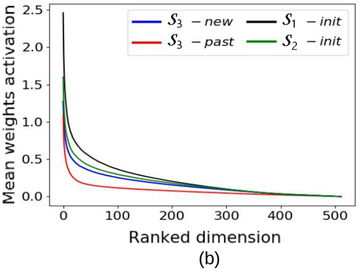


After

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

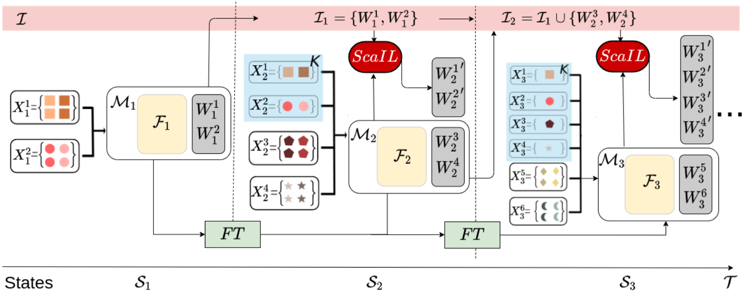
- Fine Tuning based
- Forgetting happens mainly in the final layer
- Features are usable across incremental states





Mean prediction scores and weights magnitudes

- Past class weights replay



Overview of *ScaIL*

- Sort class weights

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

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

- Compute state mean vector

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

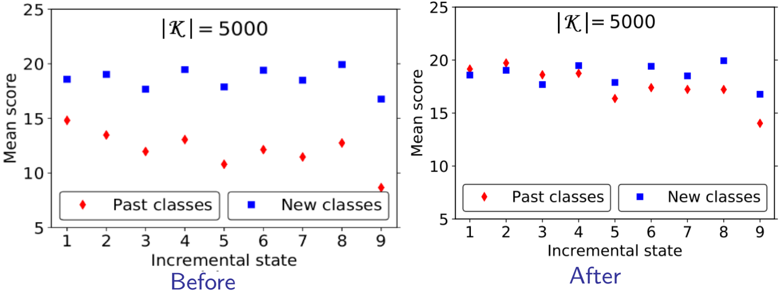
where μ_t (of dimension D) is the mean vector of the ranked new classes' weights in the state $\mathcal{S}_t$, and d is a dimension in the feature vector.

- 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.

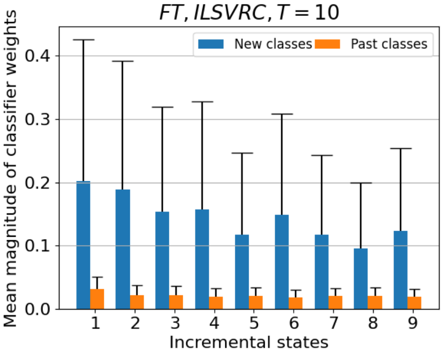
- Effect of *ScaIL*



2. Class-incremental learning without memory

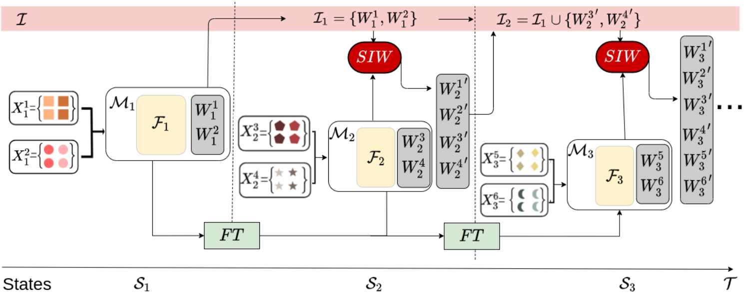
SIW: Standardization of Initial Weights for Class Incremental Learning (Belouadah et al., 2020, BMVC)

- Fine Tuning based
- Bias in the mean weights magnitudes



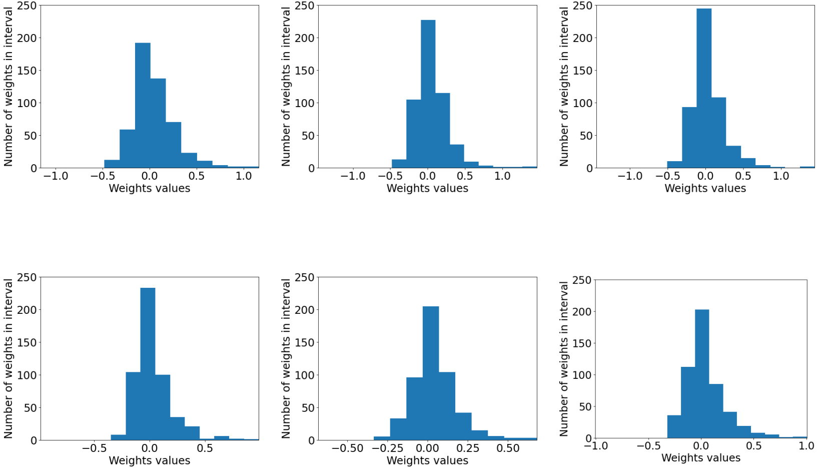
Mean weights magnitudes without memory

- Past class weights replay



Overview of *SIW*

- Classifier weights distribution



- Standardization of Initial Weights

$$w'_d = \frac{w_d - \mu(\boldsymbol{W})}{\sigma(\boldsymbol{W})} \tag{9}$$

with:

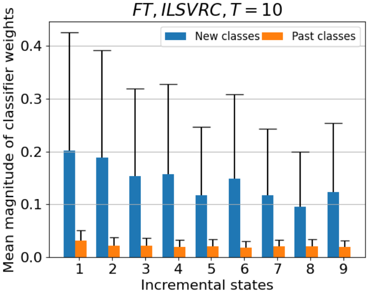
w_d is the d^{th} dimension of an initial classifier $\boldsymbol{W}$, $\mu(\boldsymbol{W})$ and $\sigma(\boldsymbol{W})$ are the mean and standard deviation of $\boldsymbol{W}$.

- State-level calibration

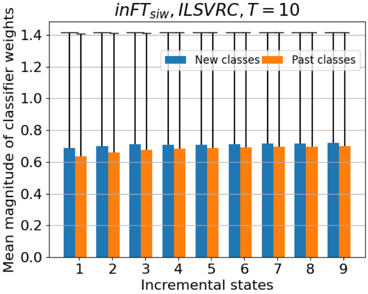
$$o_t^j(x) = (\boldsymbol{f_t}(\boldsymbol{x}) \cdot \boldsymbol{W_t^j}' + b_j^i) \times \frac{\mu(\mathcal{M}_t)}{\mu(\mathcal{M}_i)} \tag{10}$$

$\mu(\mathcal{M}_t)$ 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



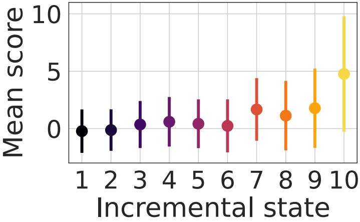
Before



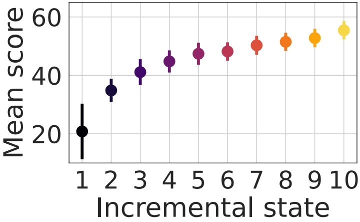
After

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)



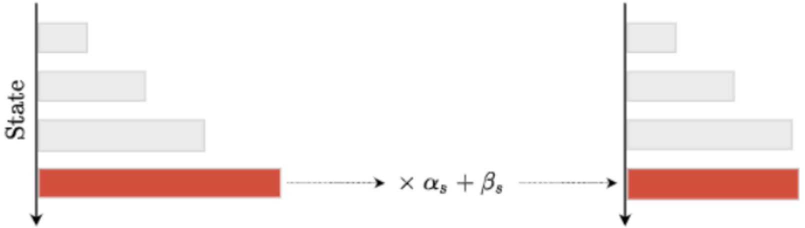
LUCIR (Hou et al., 2019)

Mean prediction scores and standard deviation

Enable the use of Bias Correction layers in a memoryless scenario

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

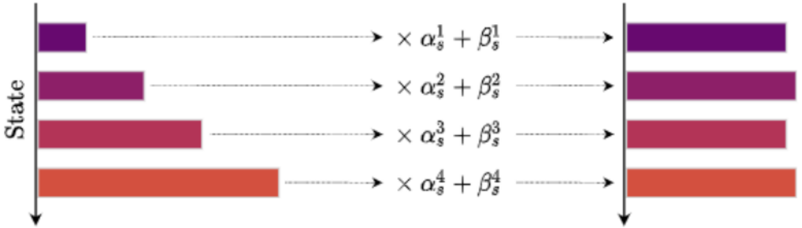
$$BiC(\boldsymbol{o}_t^k) = \begin{cases} \boldsymbol{o}_t^k & \text{if} \quad k \in [1,\ t-1] \\ \alpha_t \boldsymbol{o}_t^k + \beta_t \cdot \mathbf{1} & \text{if} \quad k = t \end{cases} \tag{11}$$



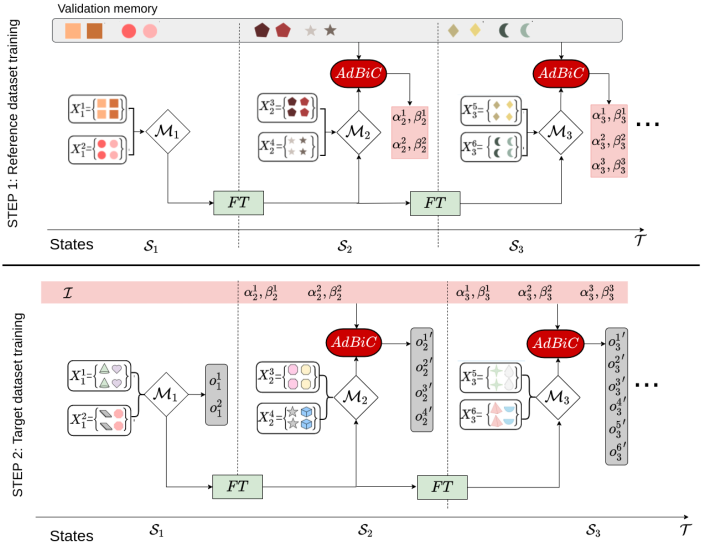
- *adBiC* : Adaptive Bias Correction (proposed)

$$adBiC(\boldsymbol{o_t^k}) = \alpha_t^k \boldsymbol{o_t^k} + \beta_t^k \cdot \mathbf{1} \; ; \quad k \in [1, t] \qquad (12)$$

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

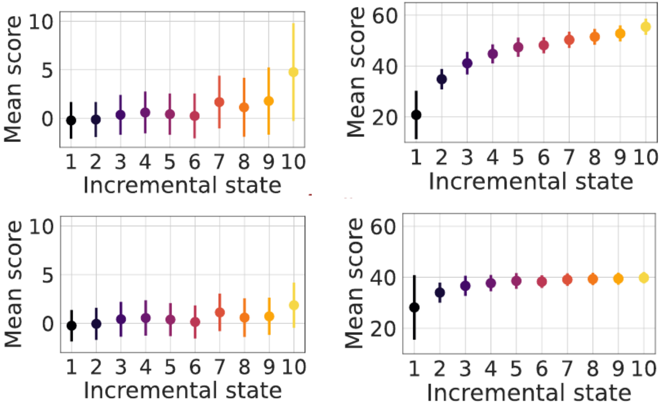


Overview of *TransIL*

- Effect on classification scores

Before

After



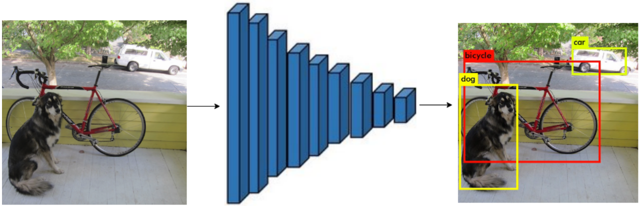
LwF (Li and Hoiem, 2016) *LUCIR* (Hou et al., 2019)

4. Continual Learning for Object Detection on the Edge

Object Detection: From generic to specific

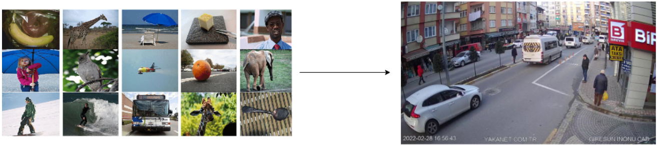
- Adapt pretrained models to specialized domains (fixed camera, few set of classes, fixed context...)

Object Detector



Input Image

Prediction



Source dataset

Target dataset

Challenges

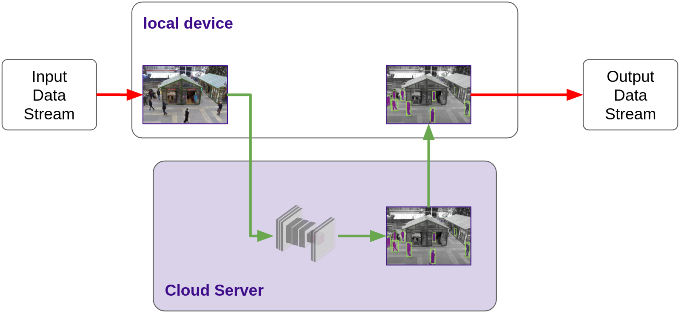
- Data is not annotated
- Limited resources in memory and computational power
- Overfitting
- Catastrophic Forgetting (Mccloskey and Cohen, 1989)
- Domain shift, low image resolution ...etc

Source
dataset

Target
dataset

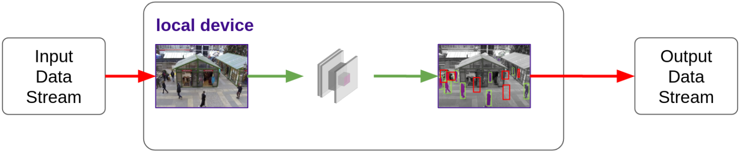
Classical solution: infer a large model on the cloud

- (+) Excellent performance
- (+) Straight forward deployment
- (−) Data sent to the cloud → not GDPR compliant
- (−) Frequent internet access
- (−) High cost



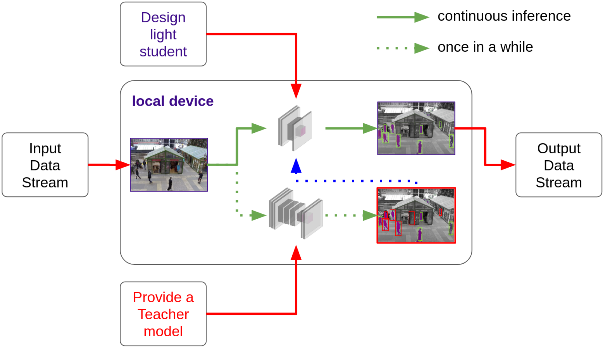
Wanted solution: infer tiny model on the edge

- (+) Straight forward deployment
- (+) GDPR compliant
- (+) No internet access
- (+) Low cost
- (−) Very poor performance



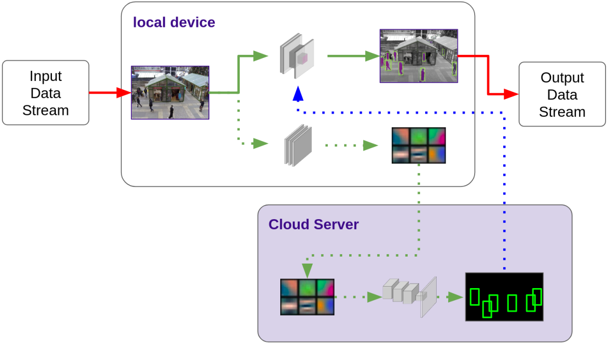
Solution 1: run both large and tiny model on the edge

- (+) Good performance
- (+) GDPR compliant
- (+) No internet access
- (+) Low cost
- (−) Assumes that the large model can fit the edge device



Solution 2: run only part of large model on the edge

- (+) Good performance
- (+) GDPR compliant
- (+) Energy consumption
- (−) Frequent internet access
- (−) Cloud cost



Experiments and Results

- Evaluation of *DeeSIL*, *IL2M*, *ScaIL*, 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: $\mathcal{T} = \{5, 10, 20\}$

Evaluation of Object Detection Model

Dataset	Total hours	# splits	# train (mn)	# val (mn)	classes
	10	10	40	20	car

Set	Total frames	1 frame per second	1 frame per two seconds
Train	72000	1200	600
Val	36000	×	300


Morning view


Night view

- Large model: YOLO-V4
- Small model: MobileNet-V1 + SSD with FPN

- Class-IL 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)	✓

- Class-IL 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 Class-IL *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

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

$$G_{IL} = \frac{1}{C} \times \sum_{c=1}^{C} \frac{A(c) - A(Joint)}{A_{max} - A(Joint)} \quad (13)$$

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

- Object Detection metric
  - Mean Average Precision at [0.5:0.05:0.95] IoU thresholds

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		
$\|\mathcal{K}\|$	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		
$\|\mathcal{K}\|$	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 ($|\mathcal{K}|$ 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	$\lvert\mathcal{K}\rvert = 0.5\%$								
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	$\lvert\mathcal{K}\rvert = 0.5\%$								
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 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			-

Results and discussion

Class-Incremental Learning without memory

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			-

Results and discussion

Class-Incremental Learning without memory

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

Results and discussion

Class-Incremental Learning without memory

Top-1 results without memory

Method States	CIFAR-100 $\mathcal{T}=5$	 $\mathcal{T}=10$	 $\mathcal{T}=20$	BIRDS-100 $\mathcal{T}=5$	 $\mathcal{T}=10$	 $\mathcal{T}=20$	FOOD-100 $\mathcal{T}=5$	 $\mathcal{T}=10$	 $\mathcal{T}=20$
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 / 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

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

Results and discussion

Class-Incremental Learning without memory

Top-1 results without memory

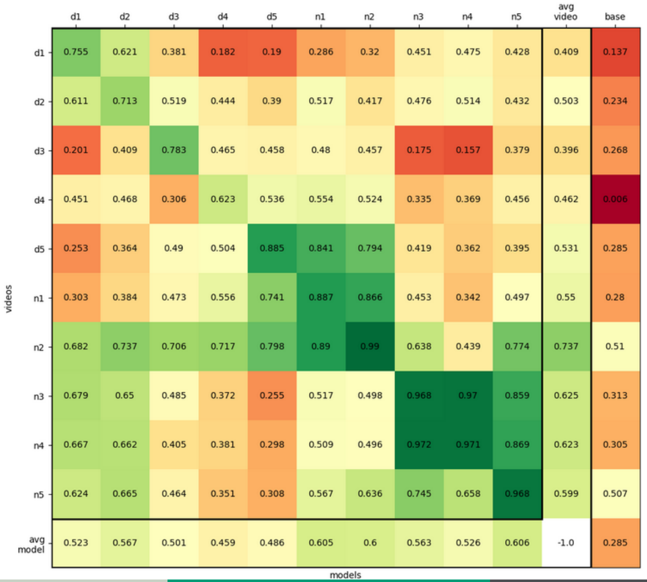
Method / States	CIFAR-100 $\mathcal{T}=5$	CIFAR-100 $\mathcal{T}=10$	CIFAR-100 $\mathcal{T}=20$	BIRDS-100 $\mathcal{T}=5$	BIRDS-100 $\mathcal{T}=10$	BIRDS-100 $\mathcal{T}=20$	FOOD-100 $\mathcal{T}=5$	FOOD-100 $\mathcal{T}=10$	FOOD-100 $\mathcal{T}=20$
LwF	53.0	44.0	29.1	53.7	41.8	30.1	42.9	31.8	22.2
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

- Results without Continual Learning

videos \ models	d1	d2	d3	d4	d5	n1	n2	n3	n4	n5	avg video	base
d1	0.714	0.53	0.013	0.031	0.113	0.076	0.009	0.169	0.156	0.174	0.198	0.137
d2	0.258	0.676	0.021	0.052	0.1	0.072	0.134	0.033	0.031	0.168	0.154	0.234
d3	0.005	0.257	0.727	0.229	0.262	0.07	0.078	0.004	0.005	0.018	0.166	0.268
d4	0.064	0.124	0.174	0.519	0.168	0.157	0.194	0.131	0.108	0.119	0.176	0.006
d5	0.0	0.179	0.081	0.021	0.801	0.577	0.3	0.005	0.014	0.157	0.213	0.285
n1	0.004	0.174	0.048	0.0	0.551	0.863	0.637	0.03	0.034	0.093	0.243	0.28
n2	0.263	0.299	0.002	0.0	0.432	0.687	0.978	0.174	0.155	0.275	0.326	0.51
n3	0.296	0.4	0.0	0.0	0.003	0.0	0.03	0.903	0.959	0.666	0.326	0.313
n4	0.481	0.315	0.0	0.0	0.002	0.017	0.041	0.88	0.96	0.696	0.339	0.305
n5	0.507	0.587	0.039	0.197	0.006	0.161	0.029	0.481	0.435	0.932	0.337	0.507
avg model	0.259	0.354	0.11	0.105	0.244	0.268	0.243	0.281	0.286	0.33	-1.0	0.285

- Results with Continual Learning



Conclusions and future work

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
- In object detection, transfer learning is useful to tackle both overfitting and forgetting

Future work

- Focus more on continual learning without memory
- Find or create challenging datasets for continual learning
- Propose a class-incremental method for object detection

Thank you!

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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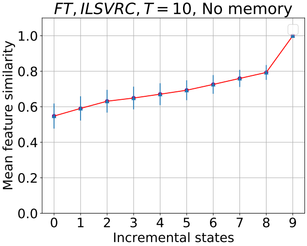
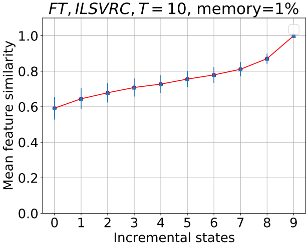
Backup Slides

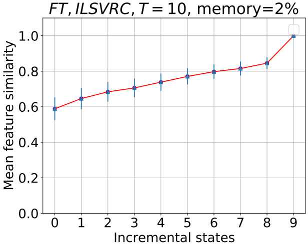
Mean Features Similarity



(a)



(b)



(c)

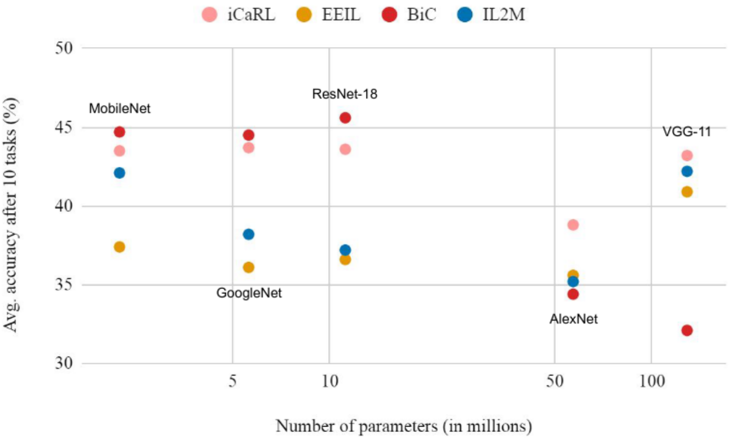
Mean feature similarities between incremental states for test images of the first state.

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)