Modeling the Background for Incremental Learning in Semantic Segmentation

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Mapillary Research
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Outline

- Incremental Learning in Semantic Segmentation
- Modeling The Background
- Experimental Setting and Results
- Conclusion and Future Works

Introduction

- ➡ Semantic Segmentation
- ➡ Incremental Learning in Semantic Segmentation
- ➡ The Background Shift

Semantic Segmentation

PROBLEM

To goal of semantic segmentation is to assign to every pixel a class label. Pixels that do not belong to any class are assigned to a special class, i.e. the background.

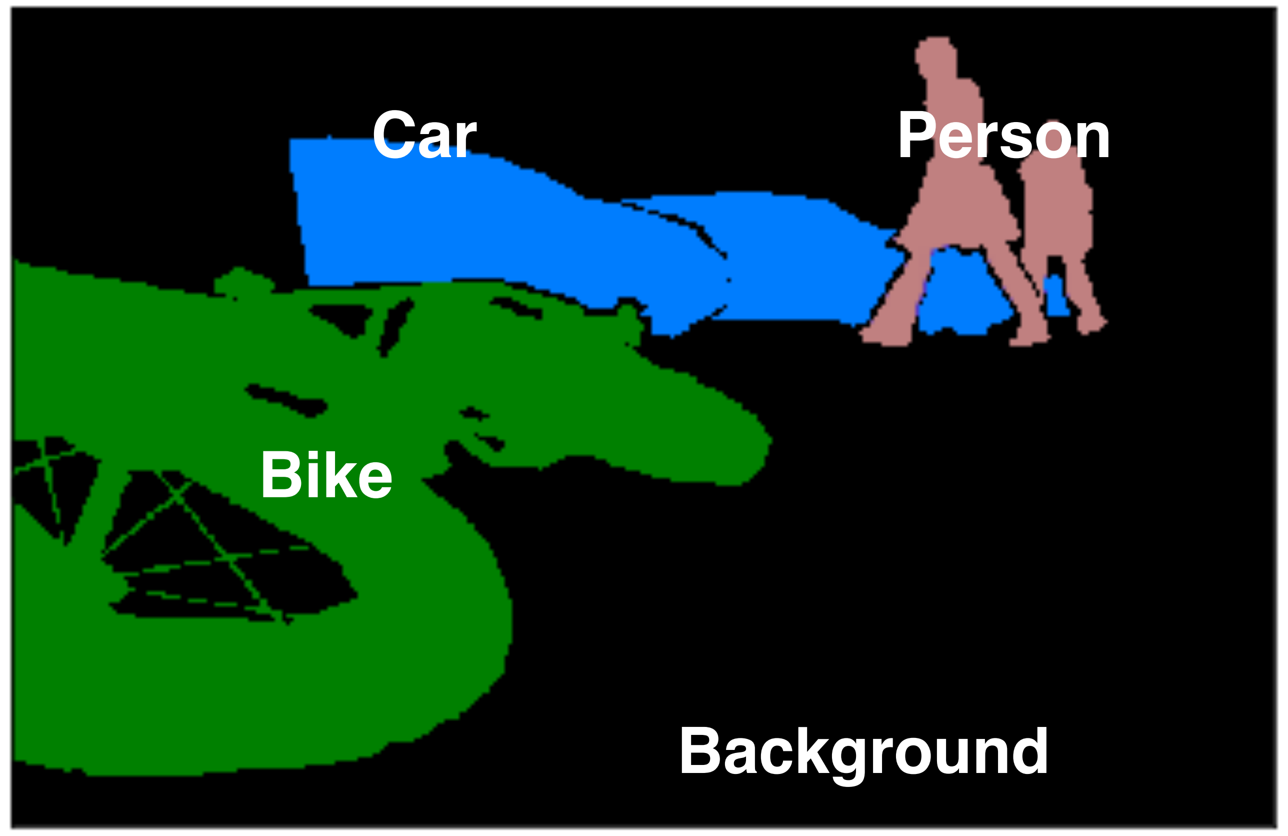


Image Credit: Pascal VOC dataset

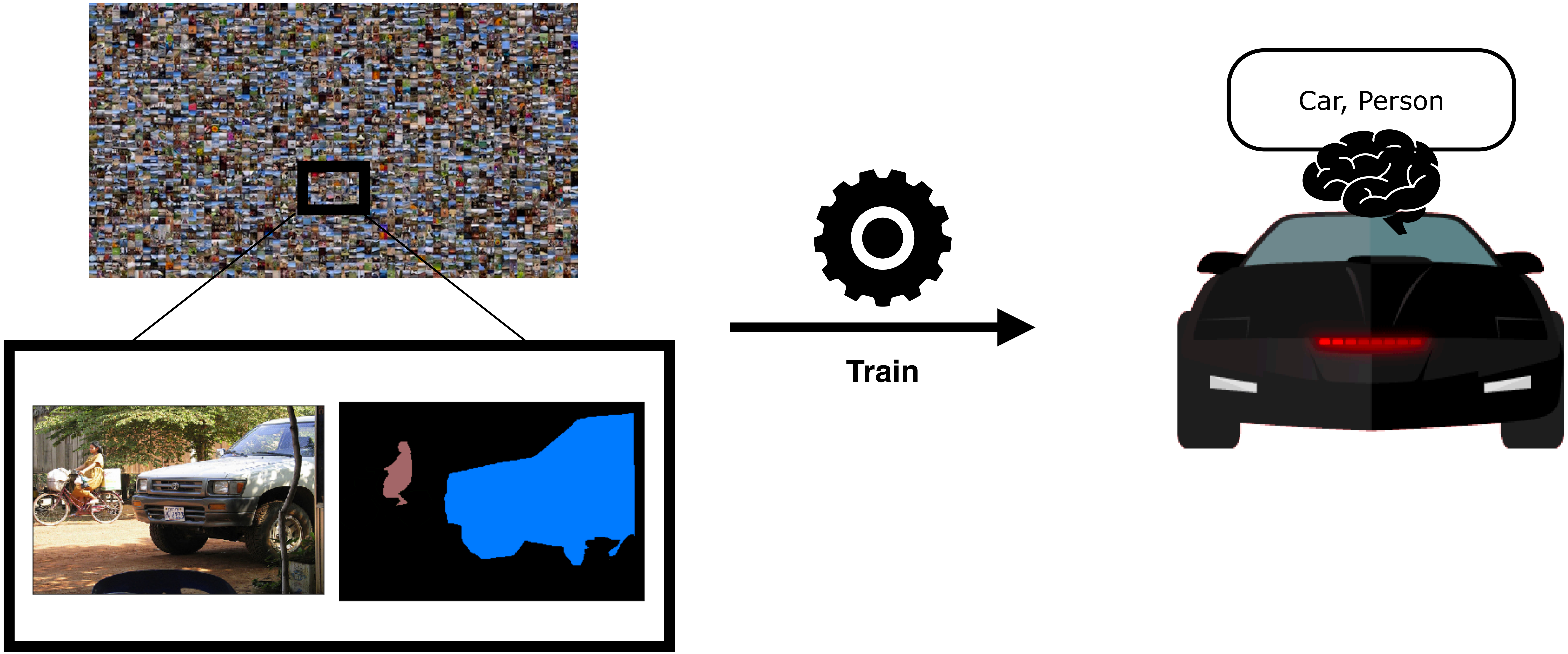
Incremental Learning in Semantic Segmentation

EXAMPLE

We want to train an intelligent car to segment Cars and Persons

Incremental Learning in Semantic Segmentation

EXAMPLE



Incremental Learning in Semantic Segmentation

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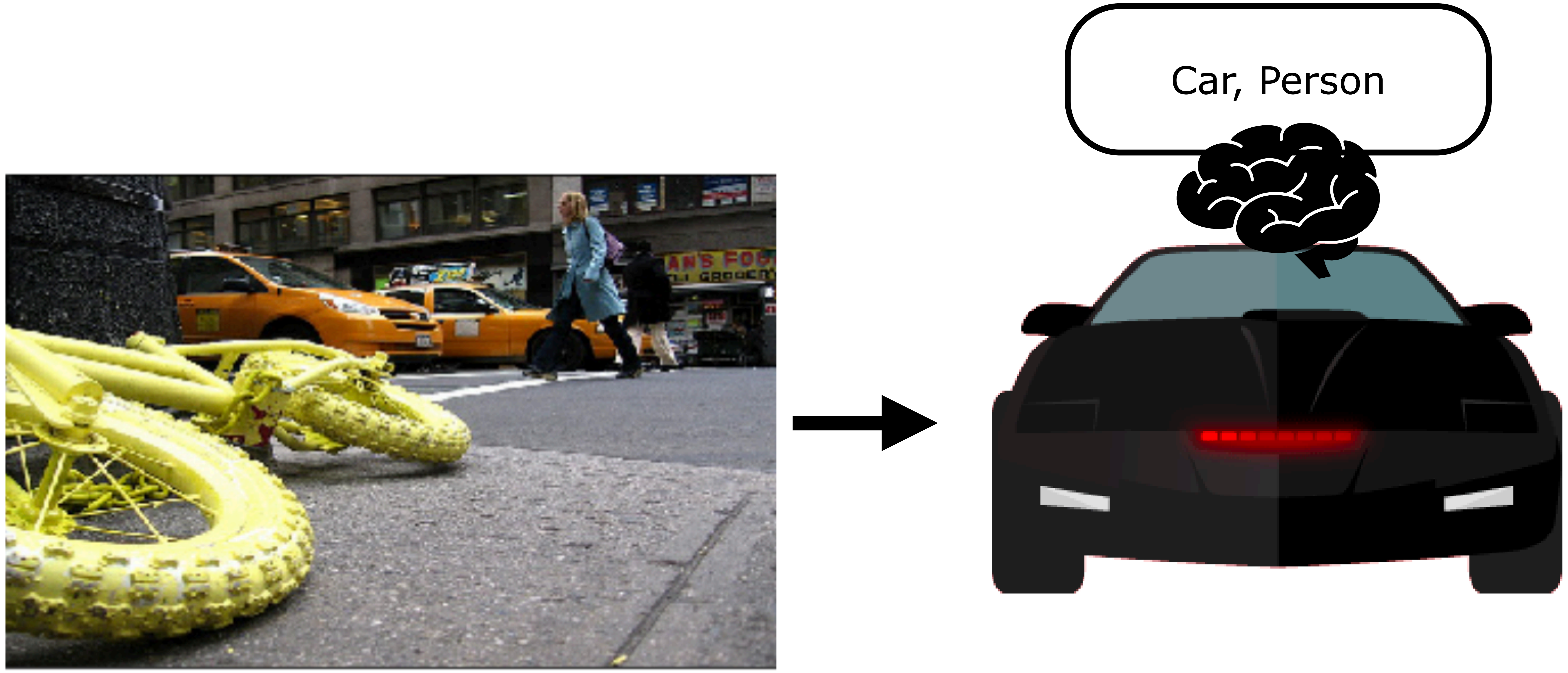
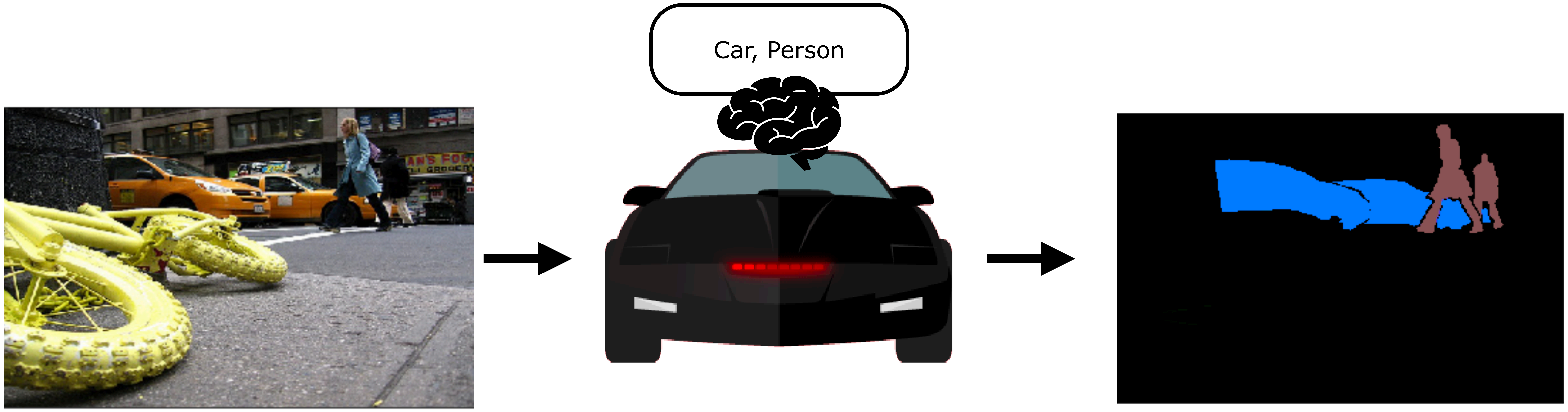


Incremental Learning in Semantic Segmentation

EXAMPLE

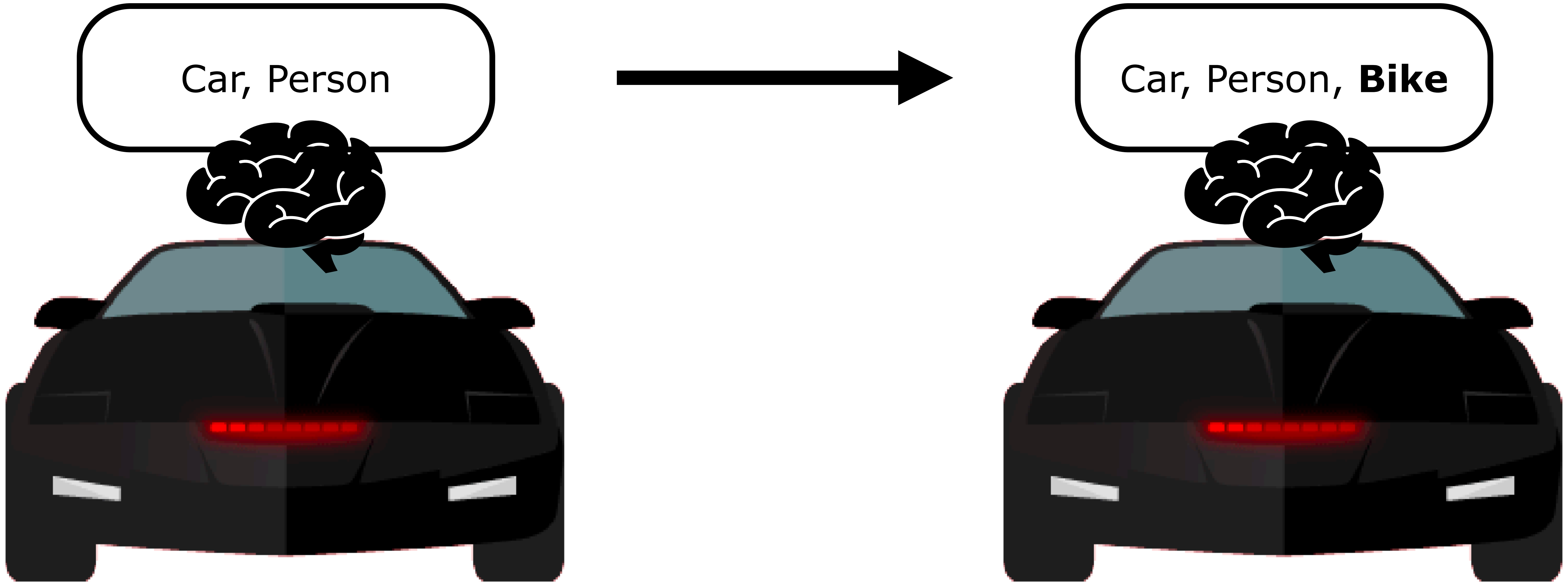


And the bike?

Incremental Learning in Semantic Segmentation

EXAMPLE

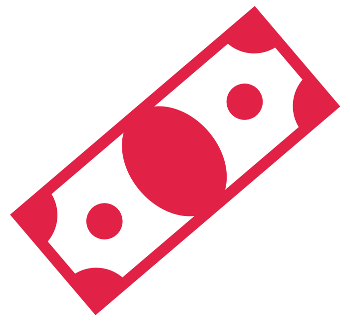
We want to extend the knowledge of the car to include the **bike** class



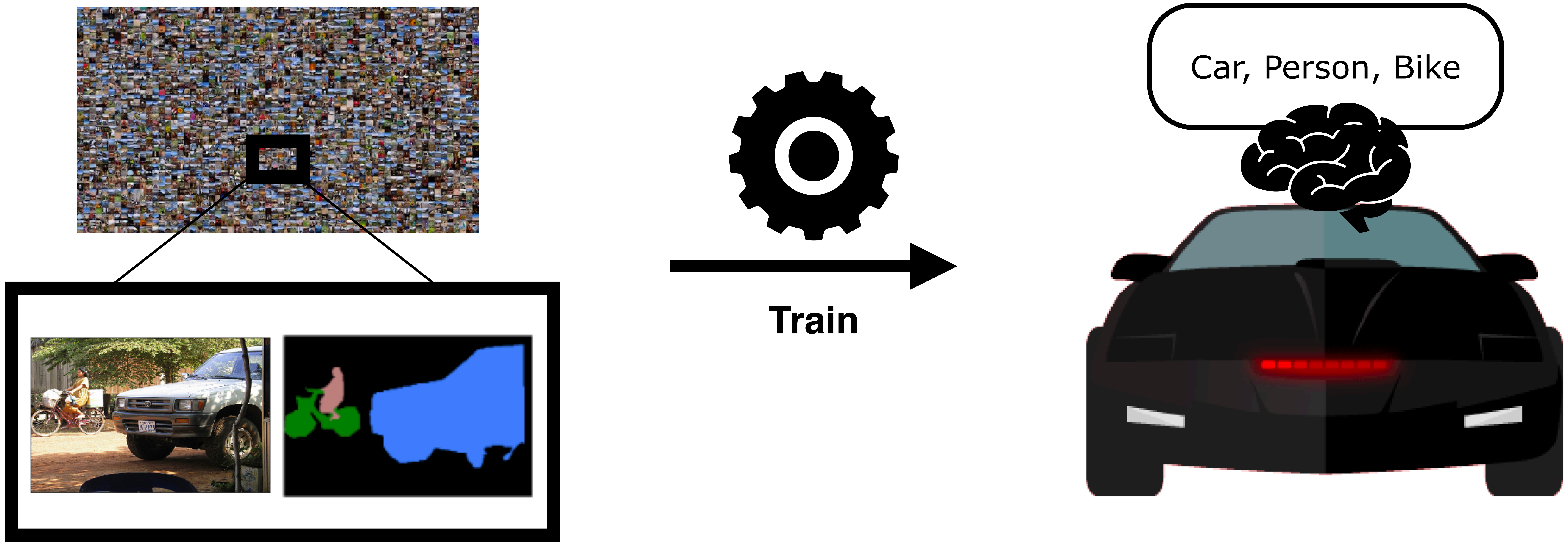
Incremental Learning in Semantic Segmentation

EXAMPLE

Solution 1: Discard old model, Relabel all the images with all the classes and train the model from scratch.



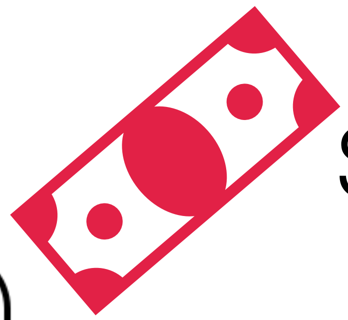
Expensive, time inefficient and original dataset may be unavailable!!



Incremental Learning in Semantic Segmentation

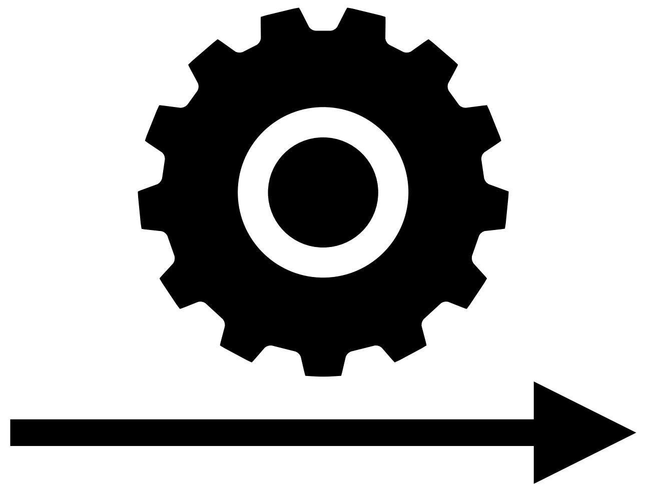
EXAMPLE

Solution 2: Collect a small dataset and label all the classes.



Still expensive and time consuming!

New dataset



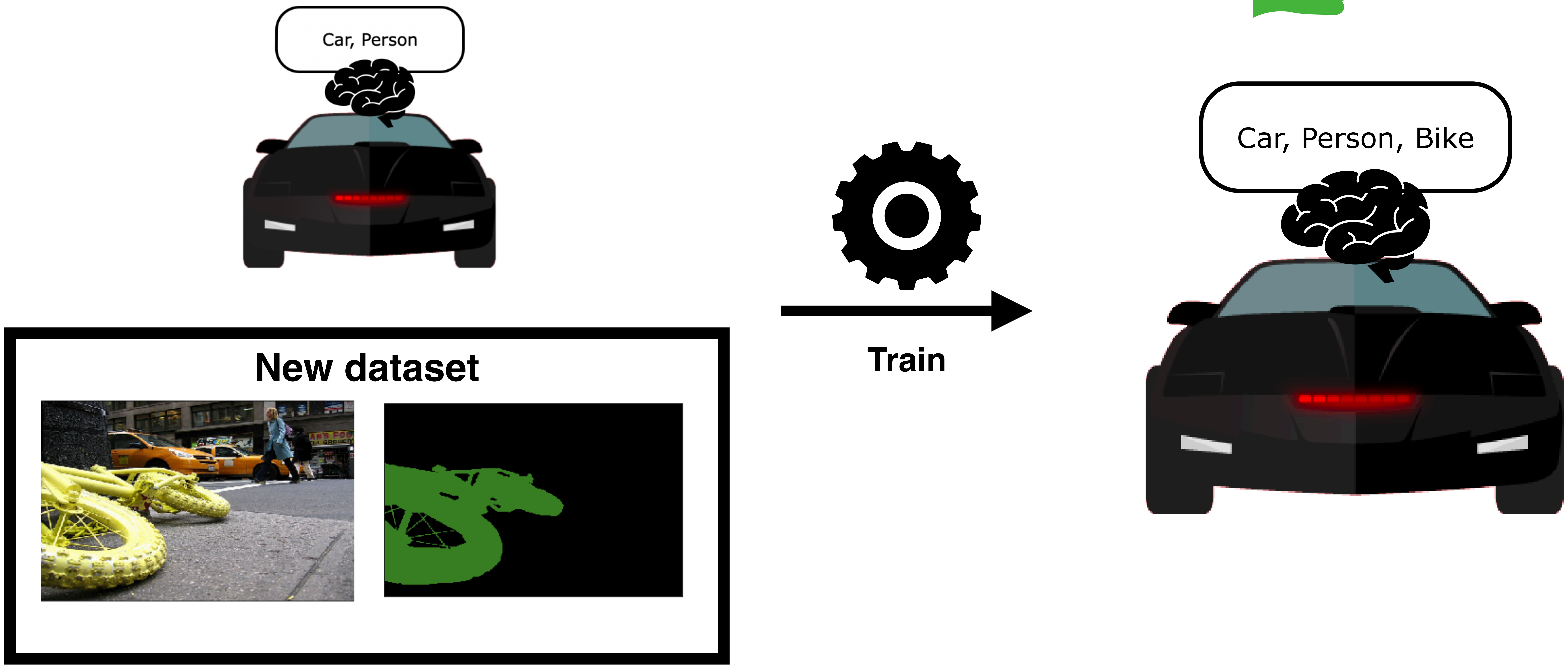
Train

Incremental Learning in Semantic Segmentation

EXAMPLE

Solution 3: Collect a small dataset and label only new classes.

Cheap, fast and re-use old knowledge!



Incremental Learning in Semantic Segmentation

PROBLEM

Knowledge: {Person}

Step t -1

{*person*, *background*}

{*bike*, *car*}

Incremental Learning:

Update the knowledge of the model when new classes are discovered.

Every learning step focuses on a specific set of classes, providing annotations only for them. All the other pixels are considered background.

Ground truth

Objects in background

Incremental Learning in Semantic Segmentation

PROBLEM

Knowledge: {Person, Car}

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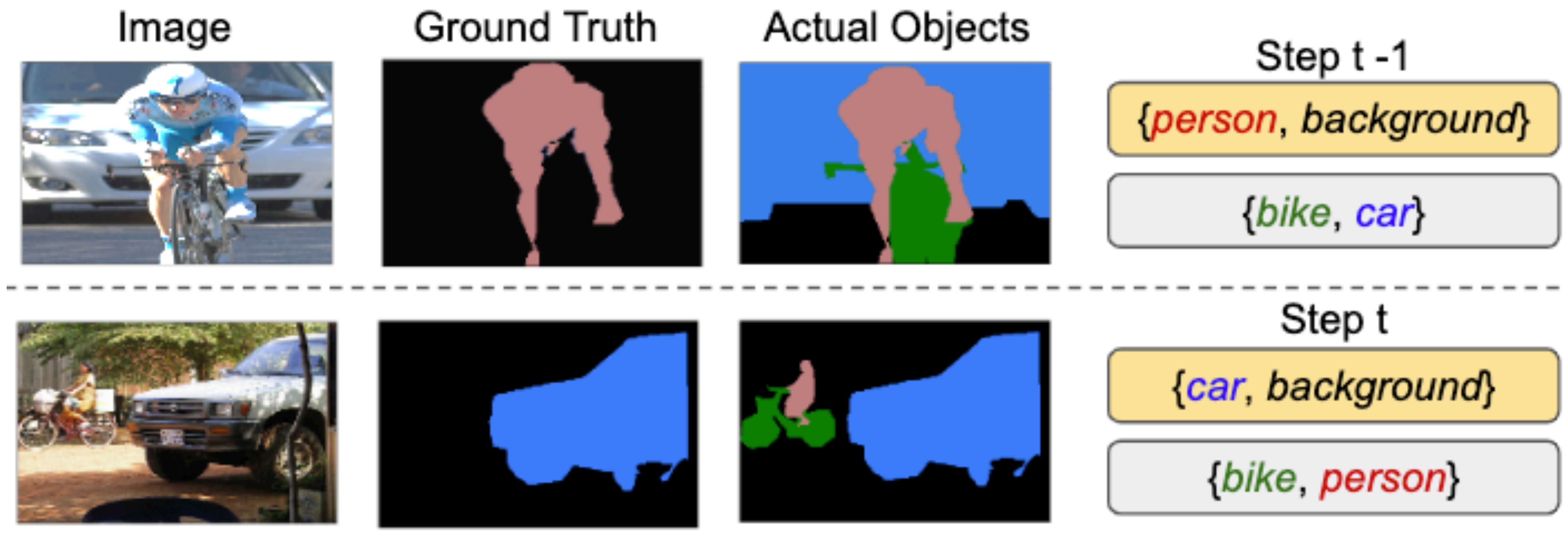

Ground truth

Objects in background

Incremental Learning in Semantic Segmentation

PROBLEM

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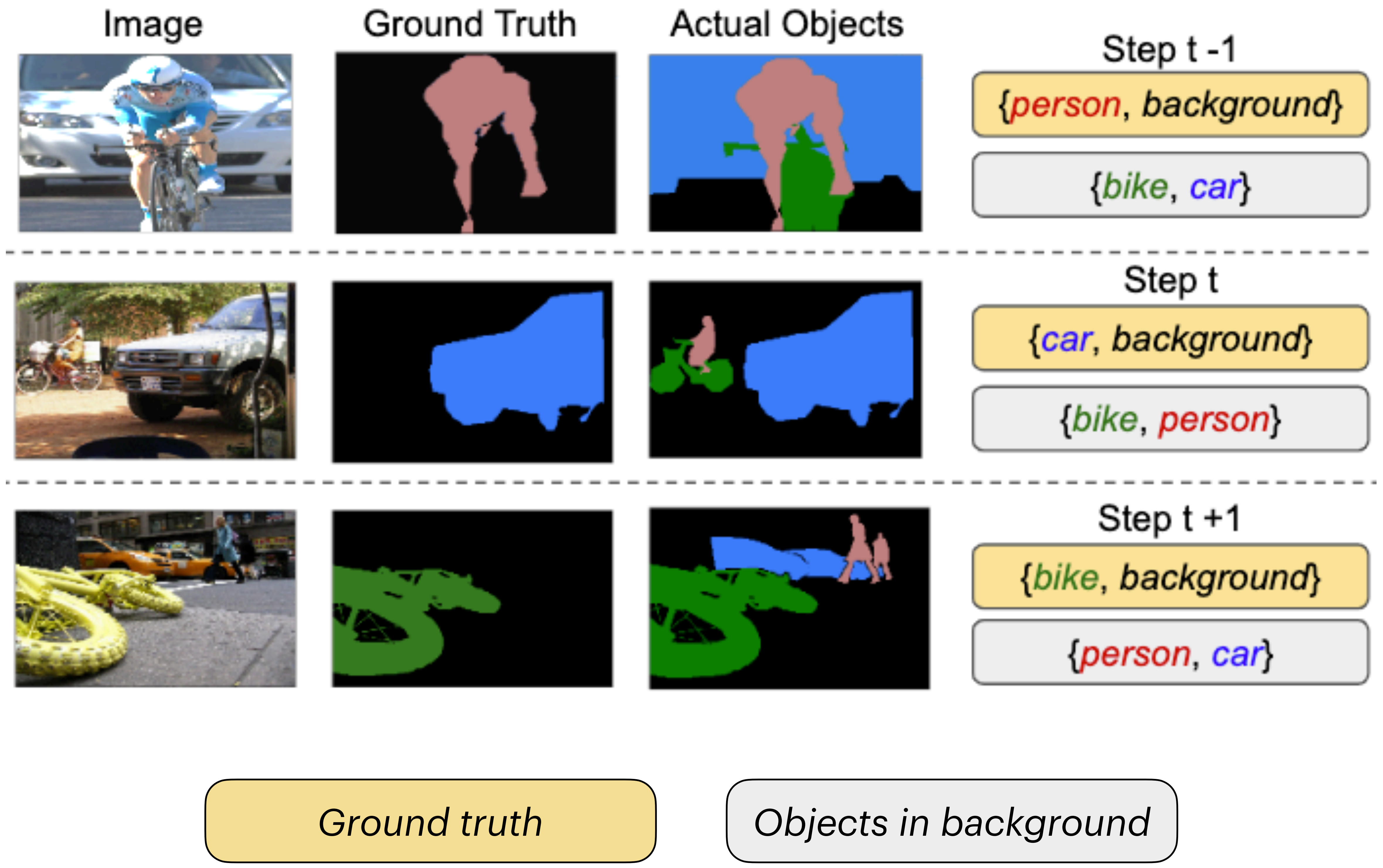


The Background Shift

MOTIVATION

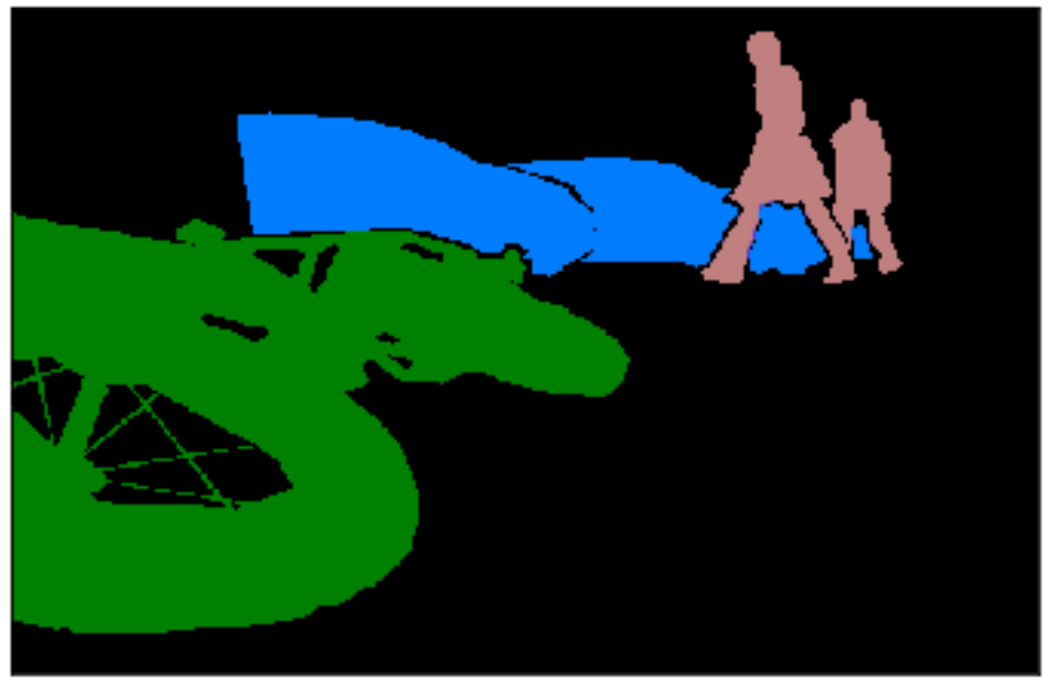
The background semantic changes at every step, including all the classes which are not learned in the current step.

Note that it might contain: (i) classes seen in previous learning steps or (ii) classes that will appear in future learning steps.

Image

Ground Truth

Objects in background



Actual objects

Step 0

We use the same image in different time steps only for illustration purposes.

The Background Shift

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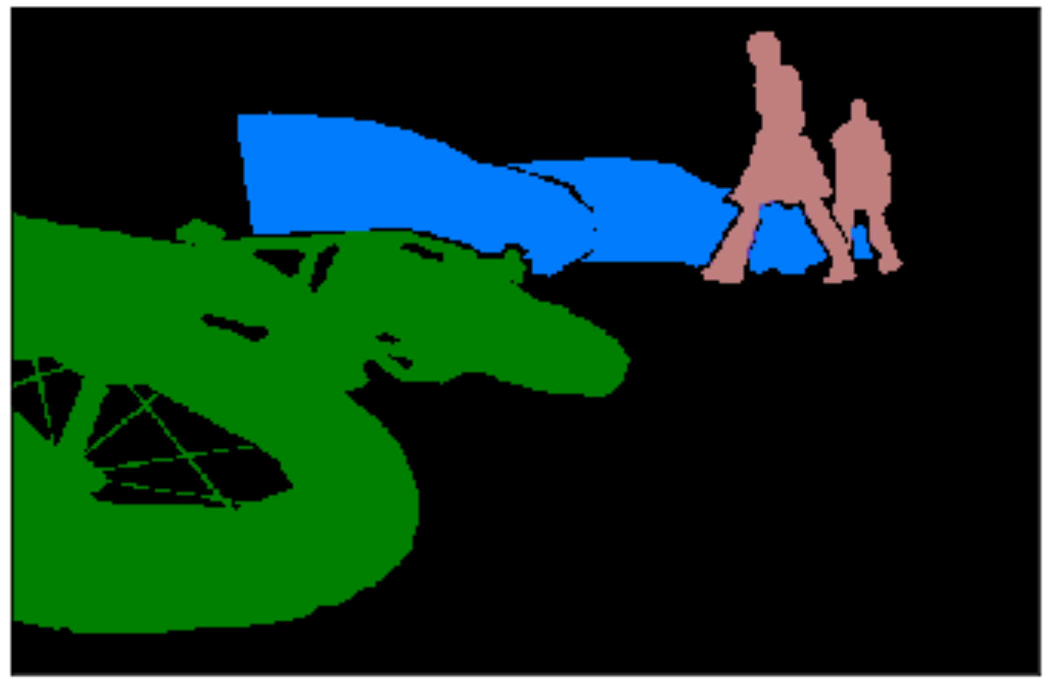
Image

Ground Truth

Objects in background



Actual objects

Step 1

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The Background Shift

MOTIVATION

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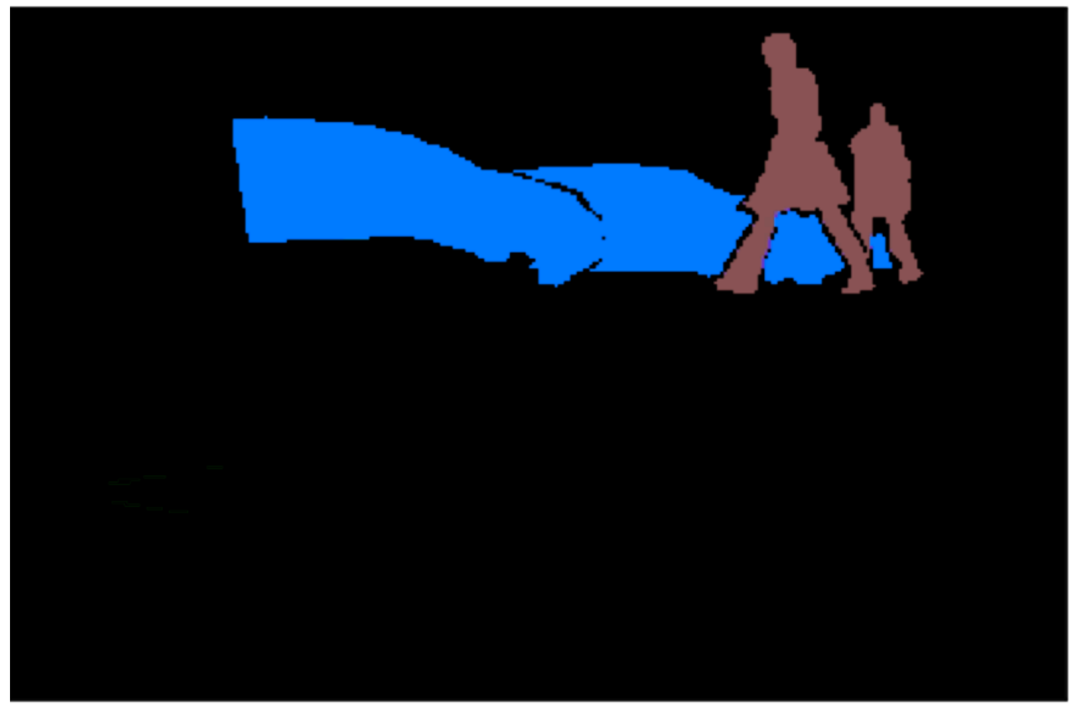
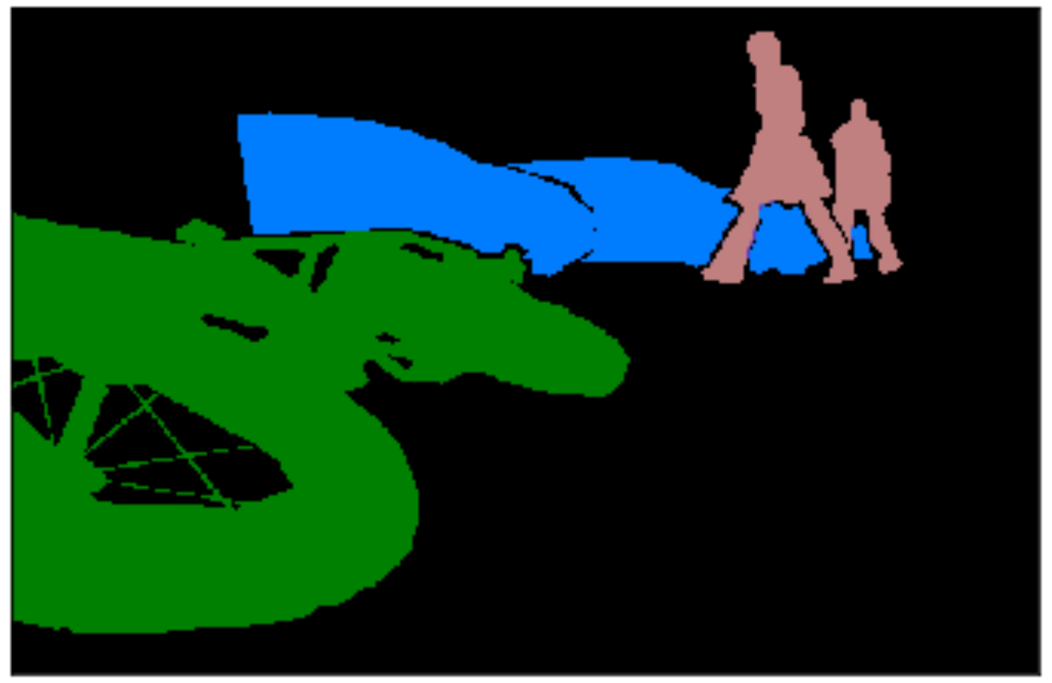
Image

Ground Truth



Objects in background



Actual objects

Step 2

We use the same image in different time steps only for illustration purposes.

Modeling The Background

- ➡ Starting Point
- ➡ Revisiting Cross Entropy Loss
- ➡ Revisiting Distillation Loss
- ➡ A new initialization scheme

Starting Point

A distillation approach

To prevent forgetting Li and Hoiem introduced a regularization term that distill the knowledge of the model at the previous step to the new one.

$$\mathcal{L}(\theta^t) = \frac{1}{|\mathcal{T}^t|} \sum_{(x,y)\in\mathcal{T}^t} \left(\ell_{ce}^{\theta^t}(x, y) + \lambda \ell_{kd}^{\theta^t}(x) \right)$$

Cross entropy loss

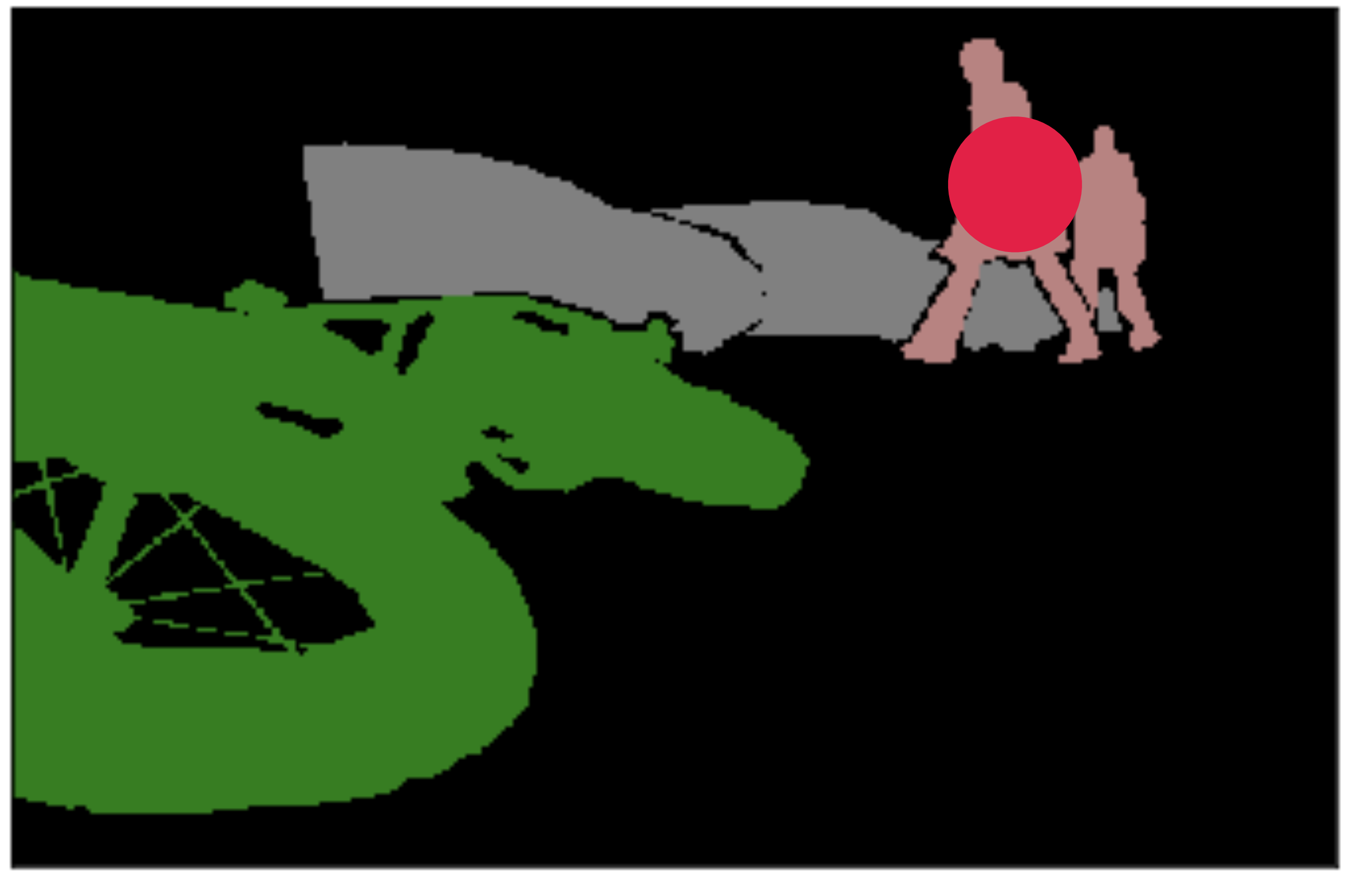
Distillation term

Z. Li and D. Hoiem. Learning without forgetting. In IEEE T-PAMI, 40(12):2935–2947, 2017

Modeling The Background (MiB)

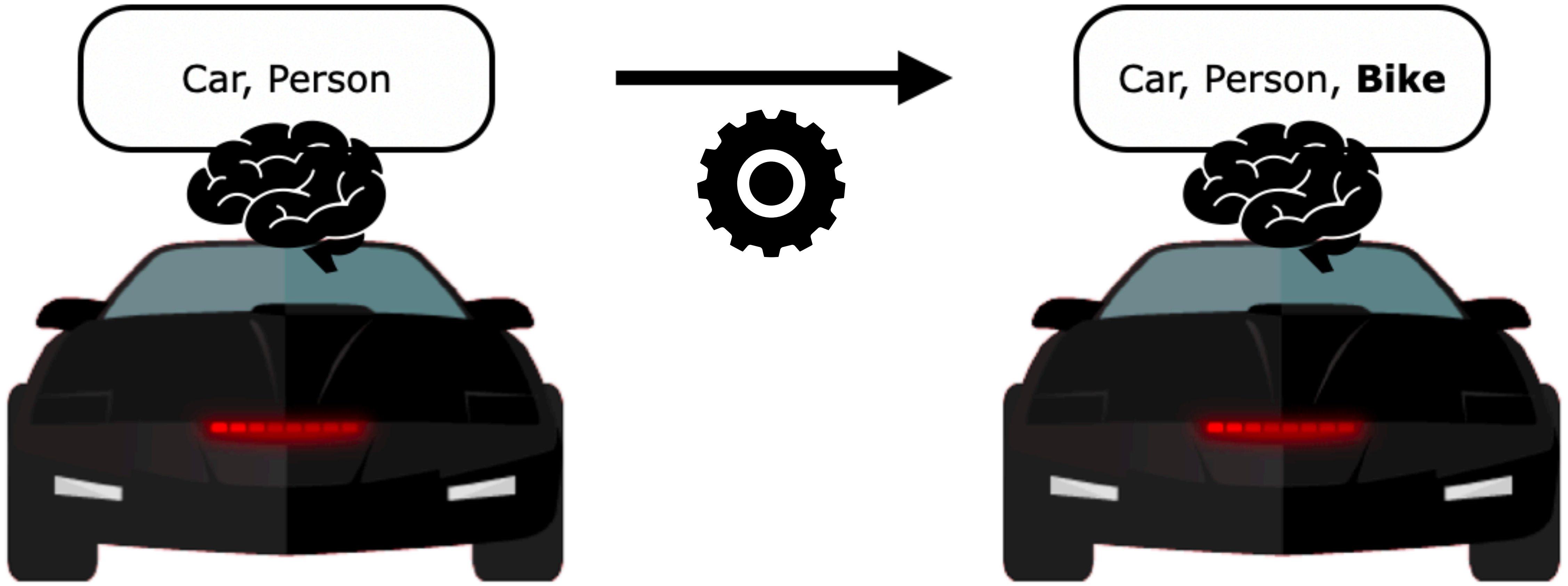
Revisiting Cross Entropy Loss

Image



Actual Objects

Ground truth



Modeling The Background (MiB)

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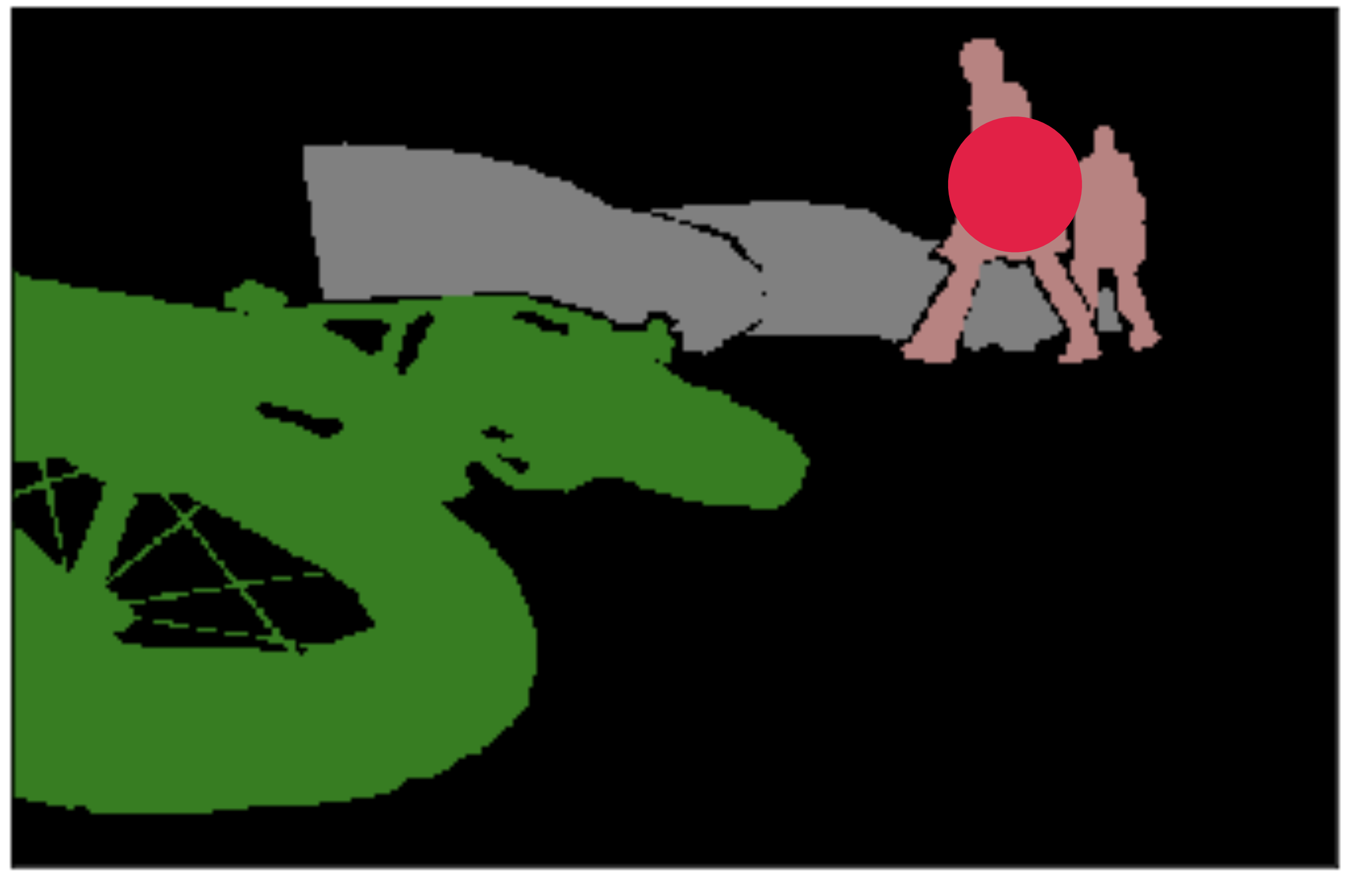
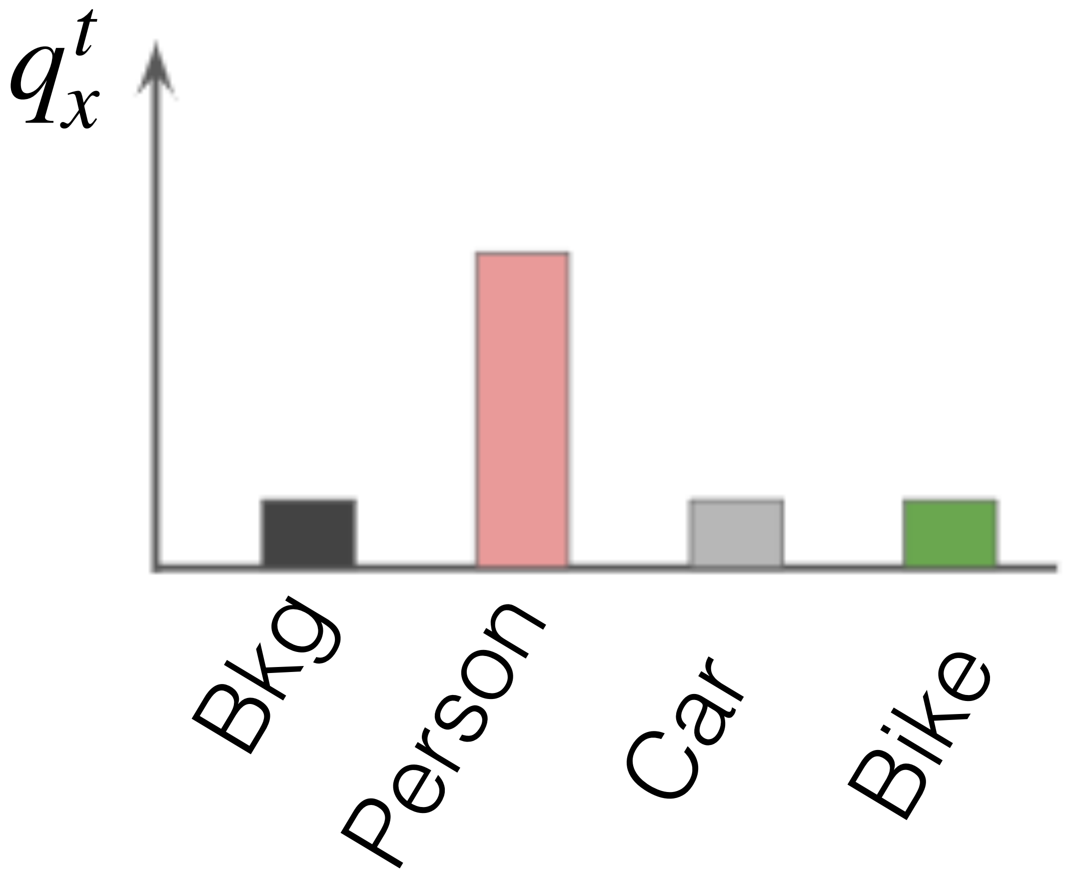


Actual Objects

Ground truth

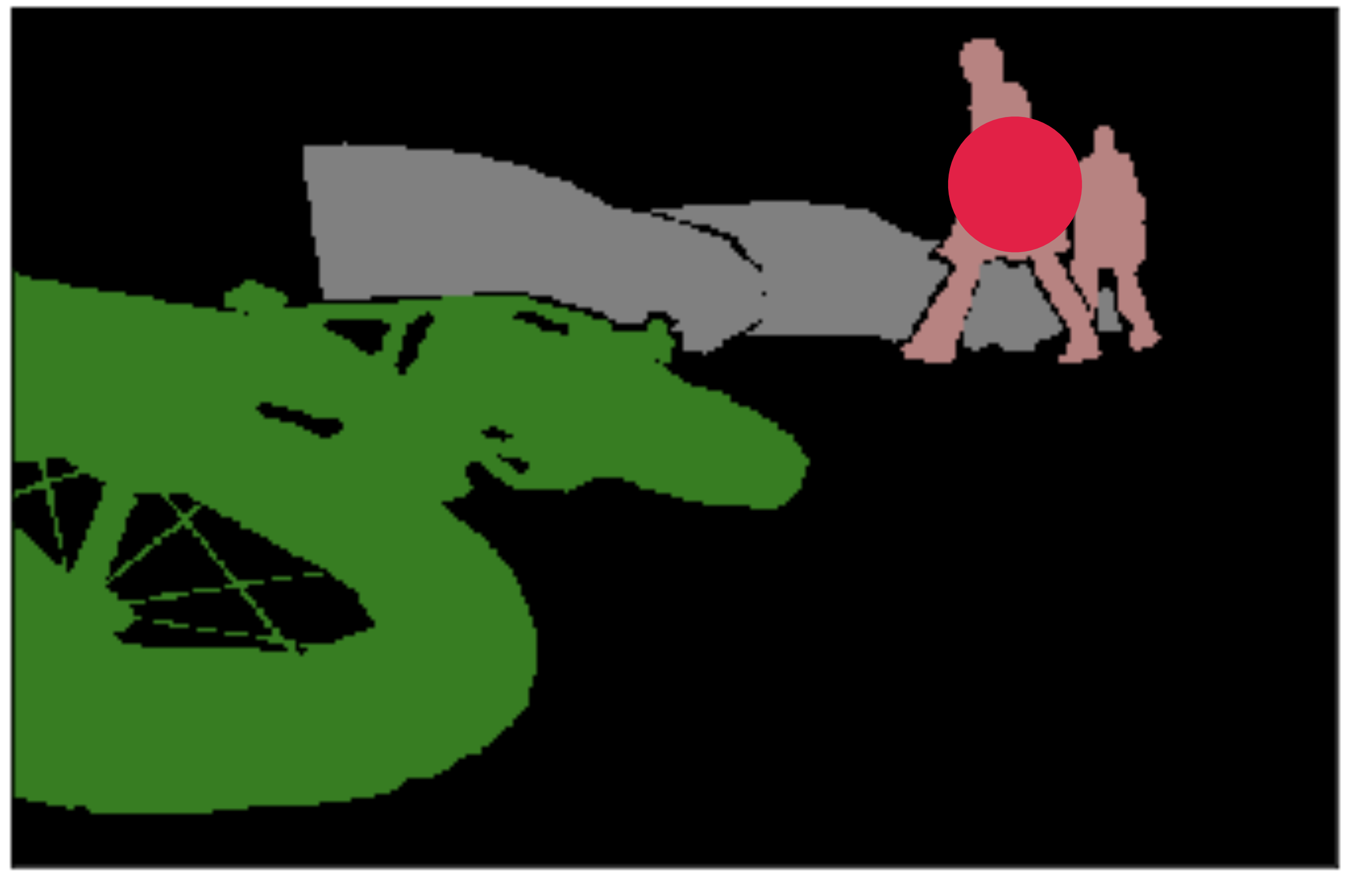
Model Prediction at



Modeling The Background (MiB)

Revisiting Cross Entropy Loss

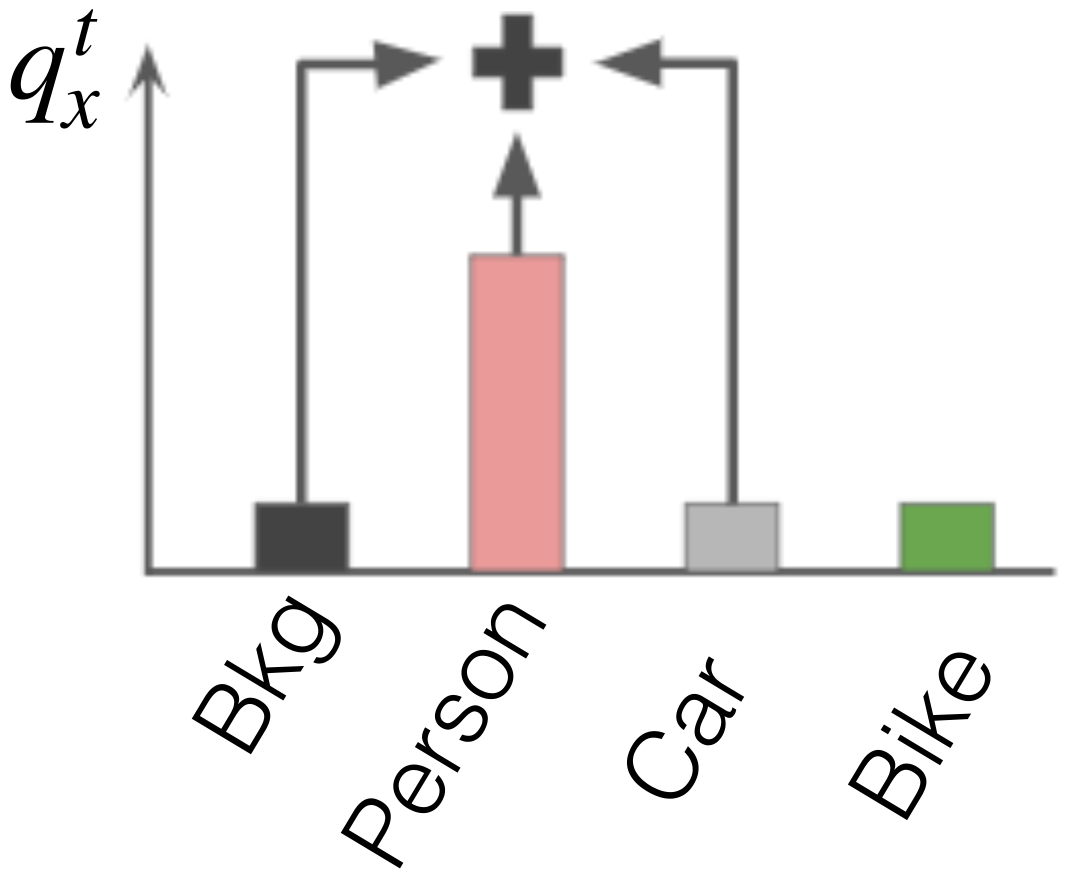
Image



Actual Objects

Ground truth

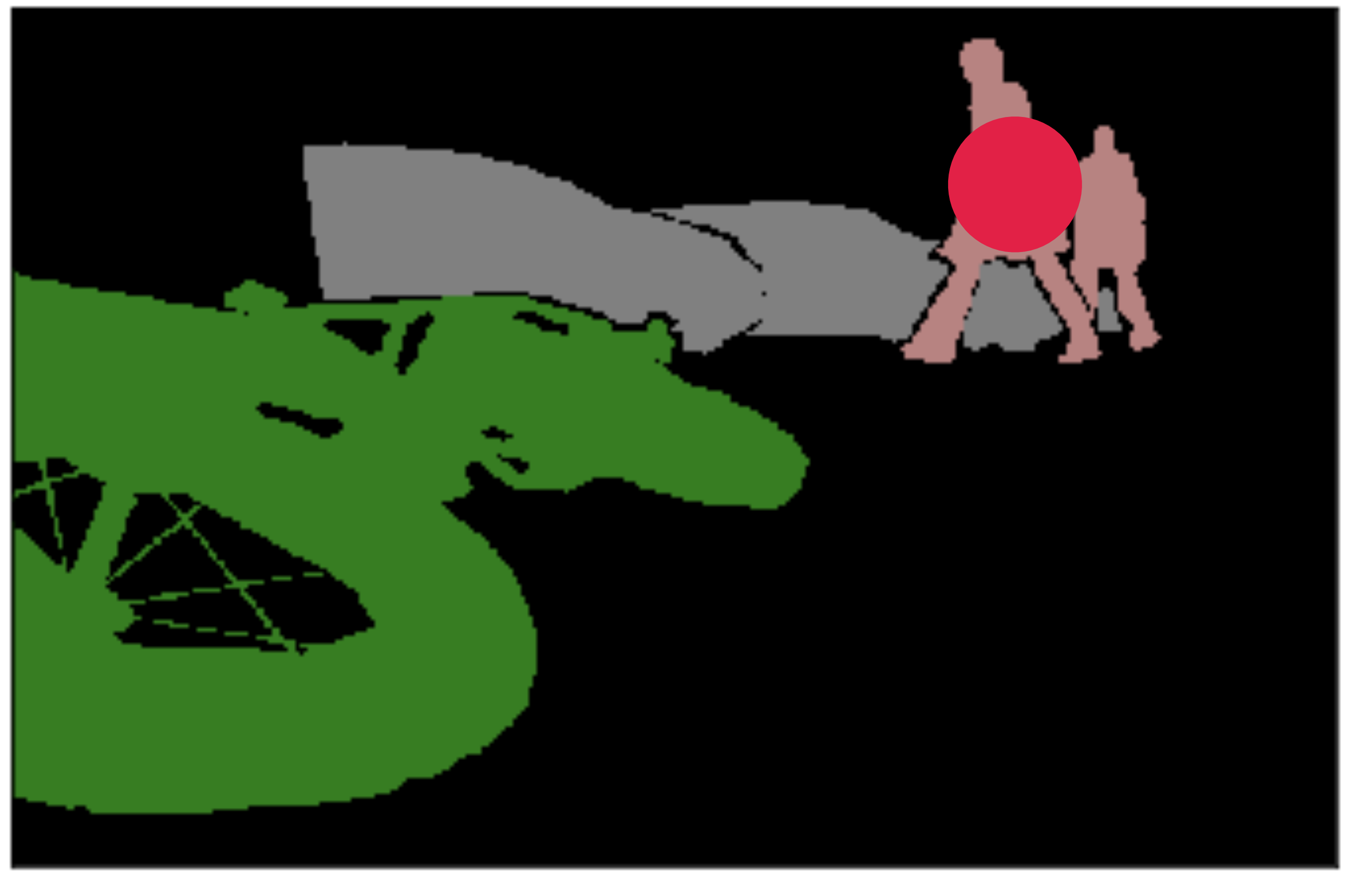
Model Prediction at



Modeling The Background (MiB)

Revisiting Cross Entropy Loss

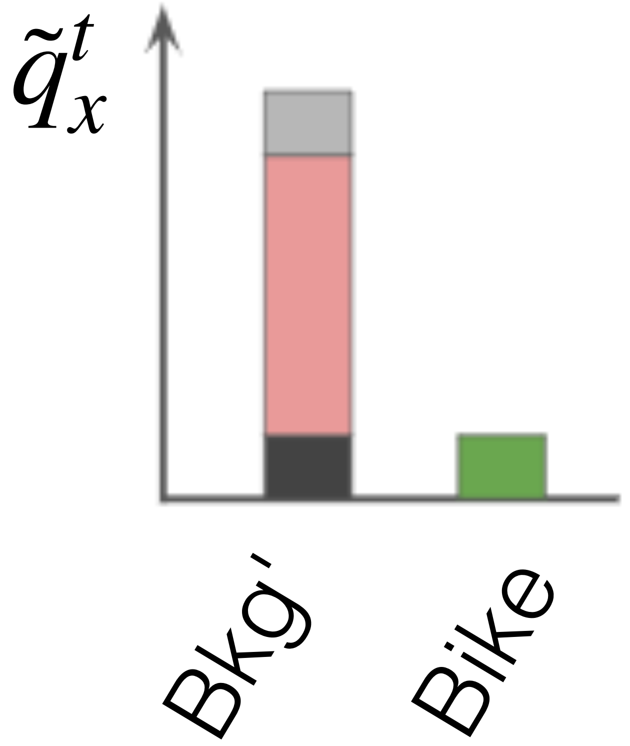
Image



Actual Objects

Ground truth

$$\tilde{q}^t_x(i,c) = \begin{cases} q^t_x(i,c) & \text{if } c \neq \mathtt{b} \\ \sum_{k\in\mathcal{Y}^{t-1}} q^t_x(i,k) & \text{if } c = \mathtt{b} \end{cases}$$

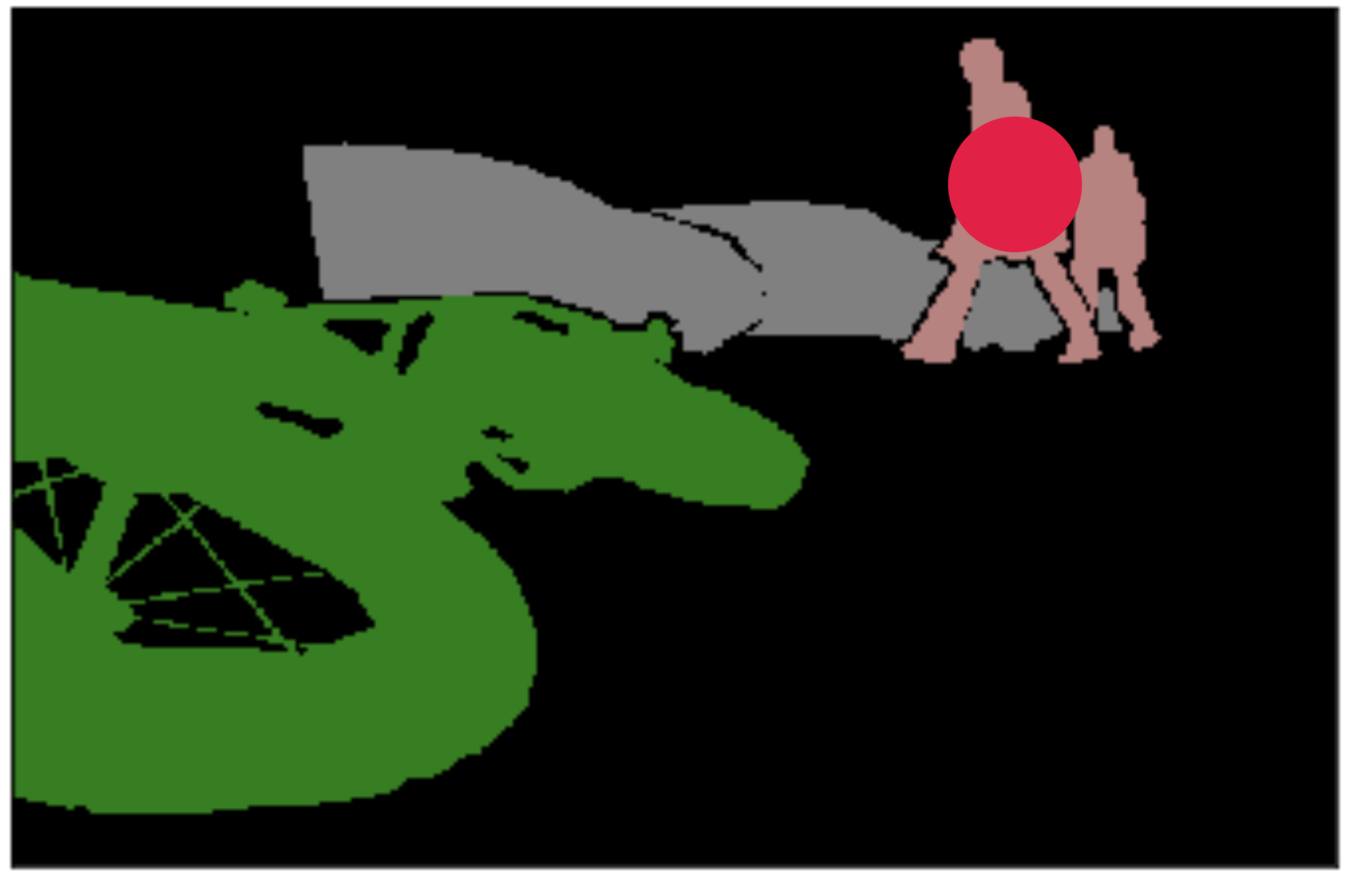


Bkg'= Person+ Car + Bkg

Modeling The Background (MiB)

Revisiting Cross Entropy Loss

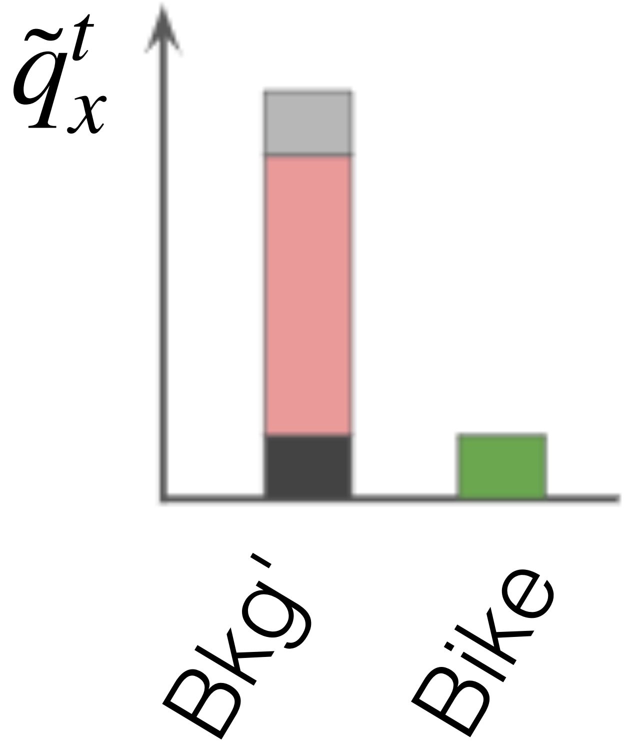
Image



Actual Objects

Ground truth

$$\tilde{q}_x^t(i,c) = \begin{cases} q_x^t(i,c) & \text{if } c \neq \mathtt{b} \\ \sum_{k \in \mathcal{Y}^{t-1}} q_x^t(i,k) & \text{if } c = \mathtt{b} \end{cases}$$



Bkg'= Person+ Car + Bkg

$$\rightarrow \quad \ell_{ce}^{\theta^t}(x,y) = -\frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log \tilde{q}_x^t(i, y_i)$$

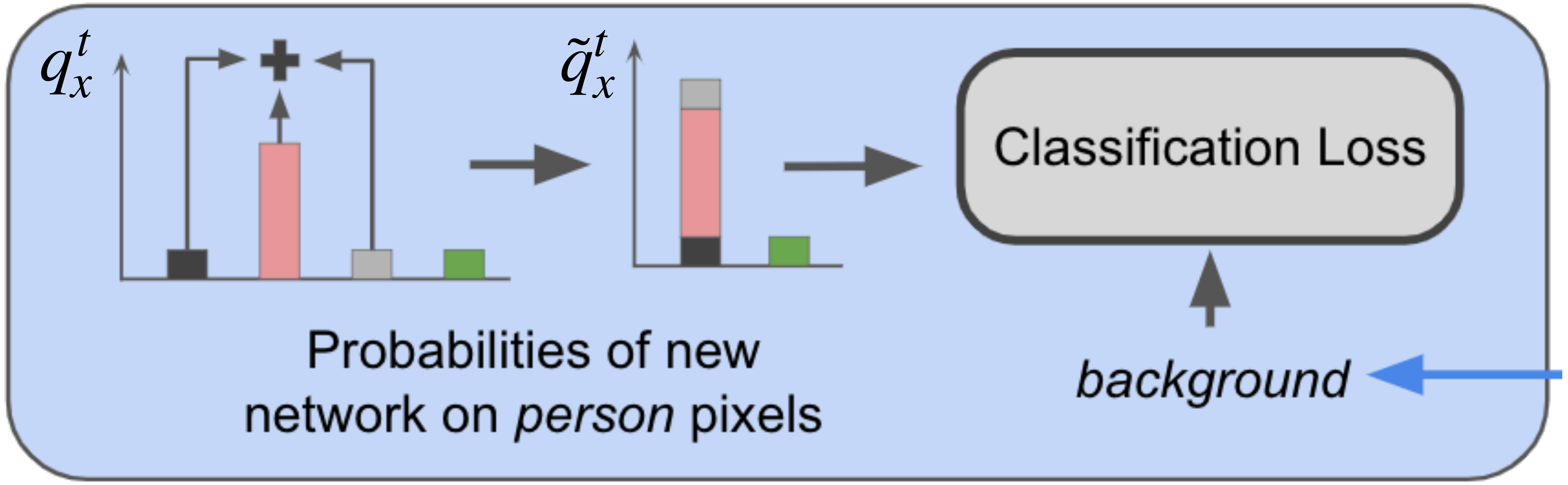
Modeling The Background (MiB)

Revisiting Cross Entropy Loss

We revisit the cross entropy loss aggregating, for pixels of the background class *b*, the probability q_x^t for old classes and the background.

This formulation allows to model the presence of classes seen in previous learning step in the background.

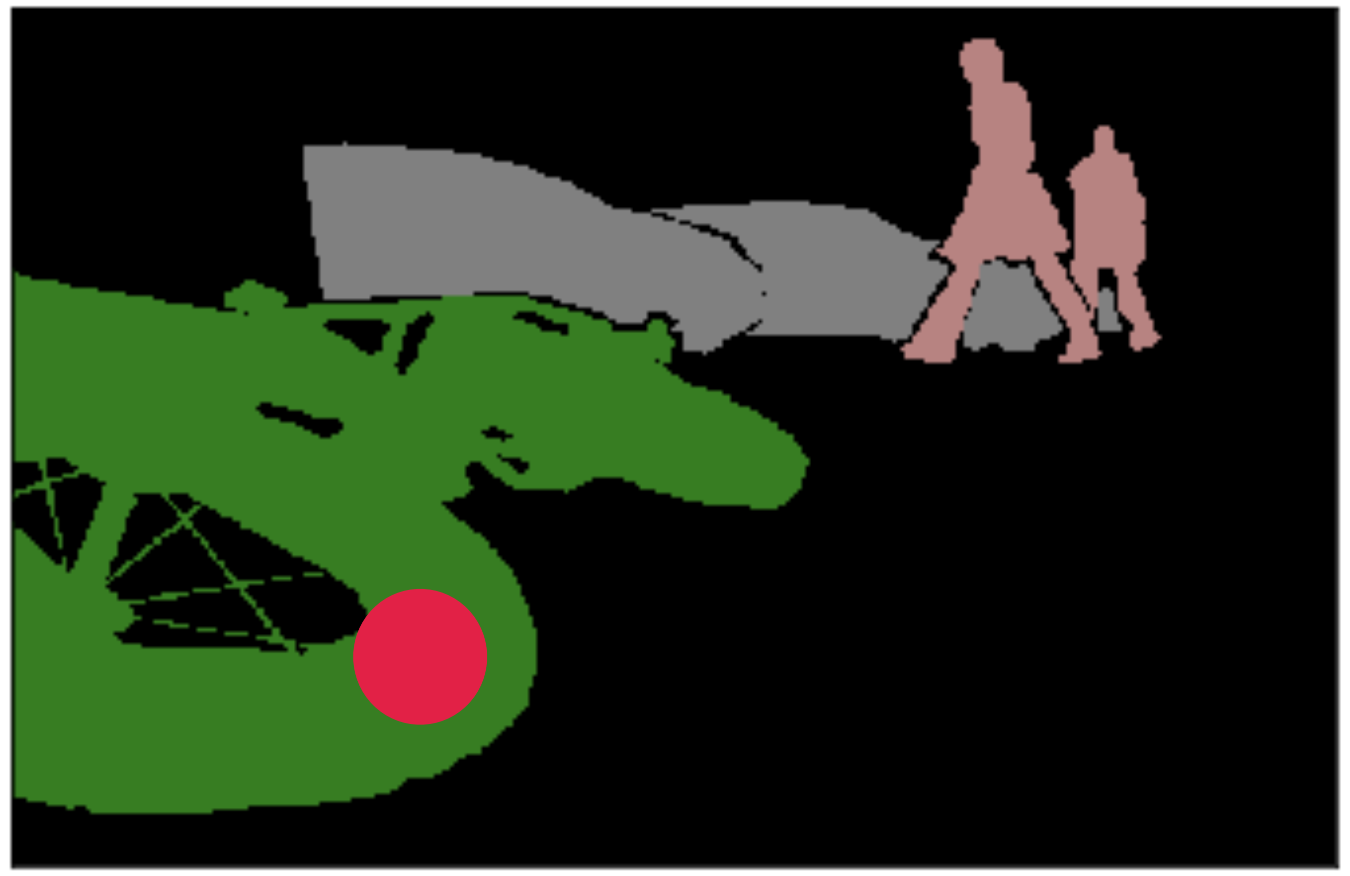
$$\ell_{ce}^{\theta^t}(x, y) = -\frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \log \tilde{q}_x^t(i, y_i) \qquad \tilde{q}_x^t(i, c) = \begin{cases} q_x^t(i, c) & \text{if } c \neq \mathtt{b} \\ \sum_{k \in \mathcal{Y}^{t-1}} q_x^t(i, k) & \text{if } c = \mathtt{b} \end{cases}$$



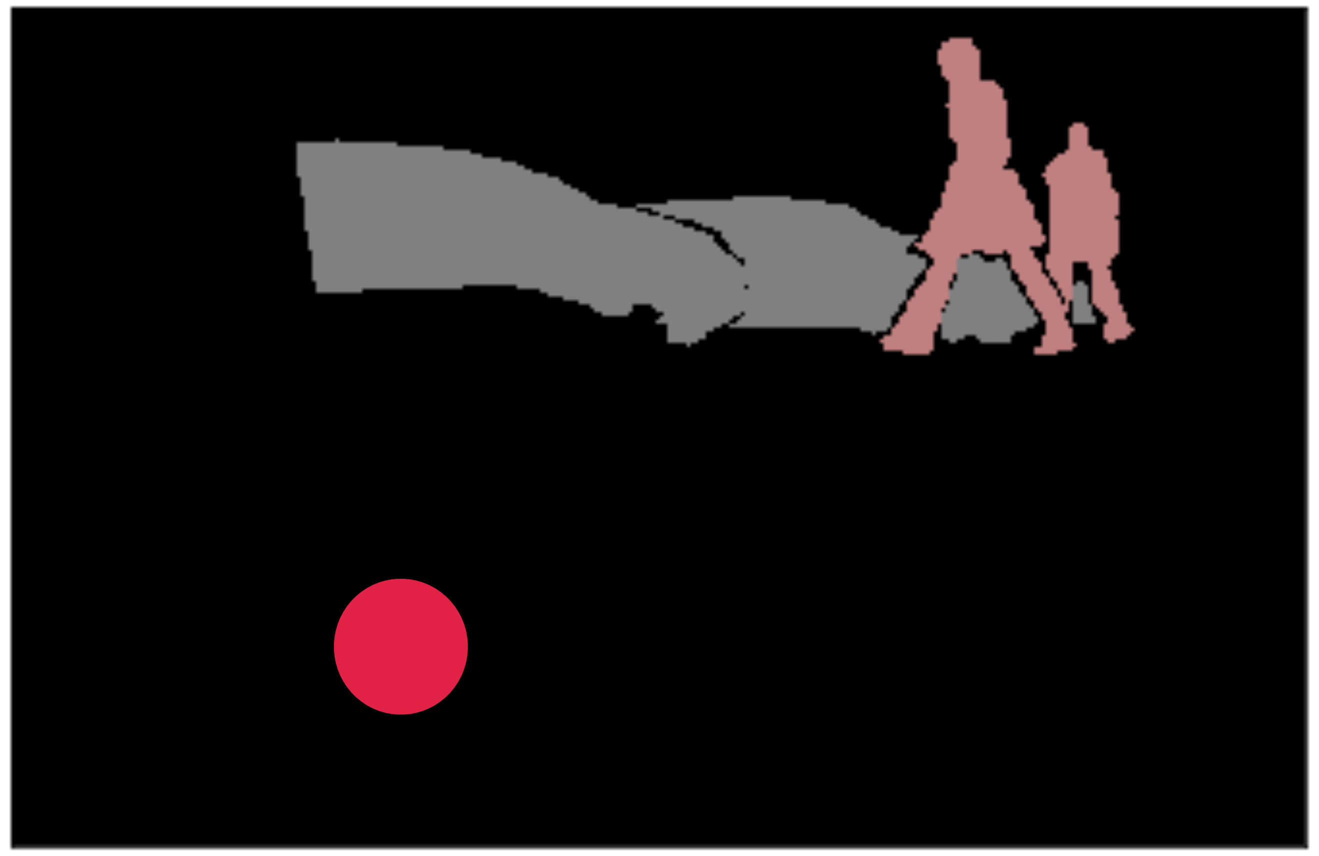
Modeling The Background (MiB)

Revisiting Distillation Loss

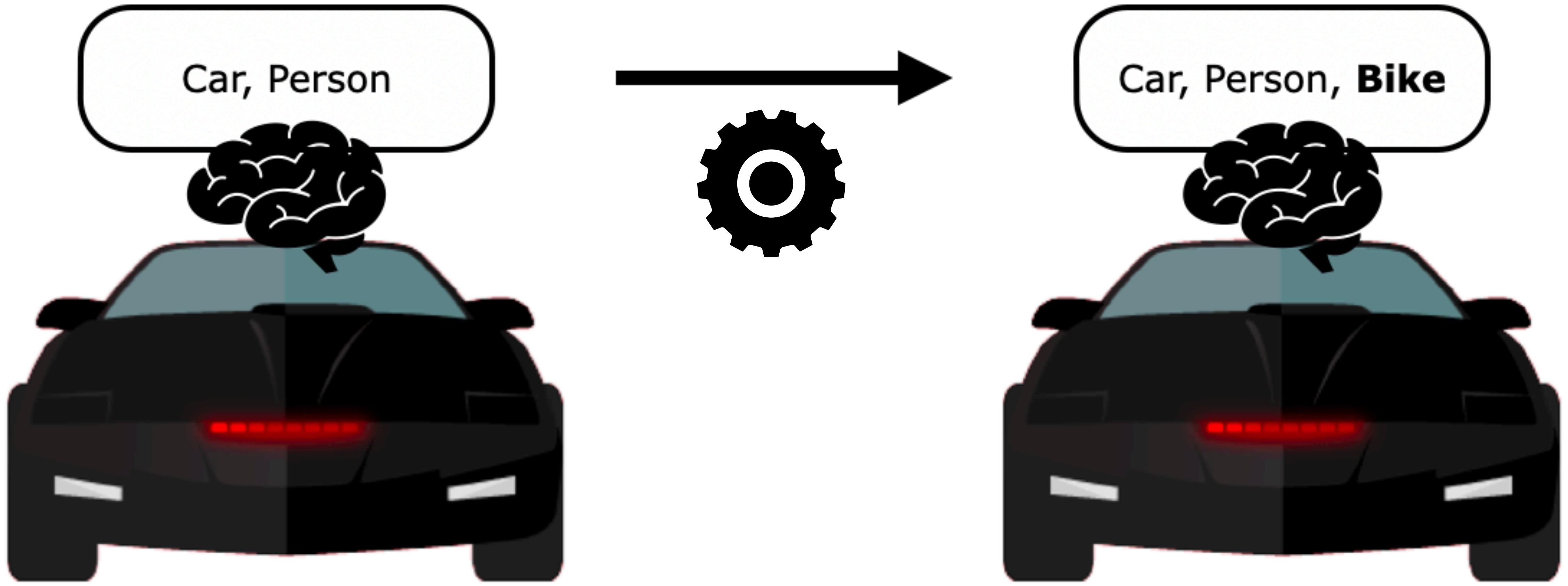
Image



Classes at step t



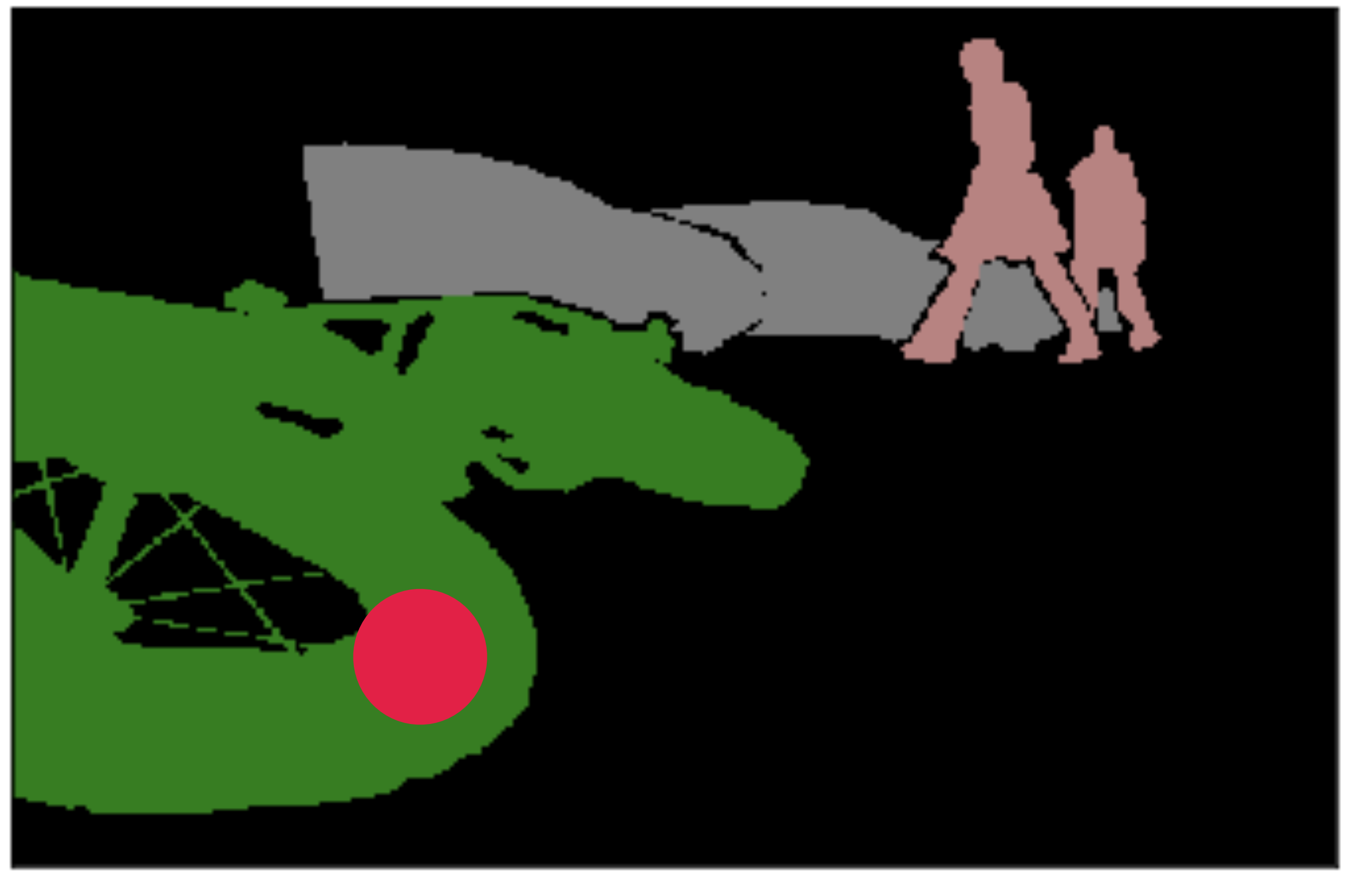
Classes at step t-1



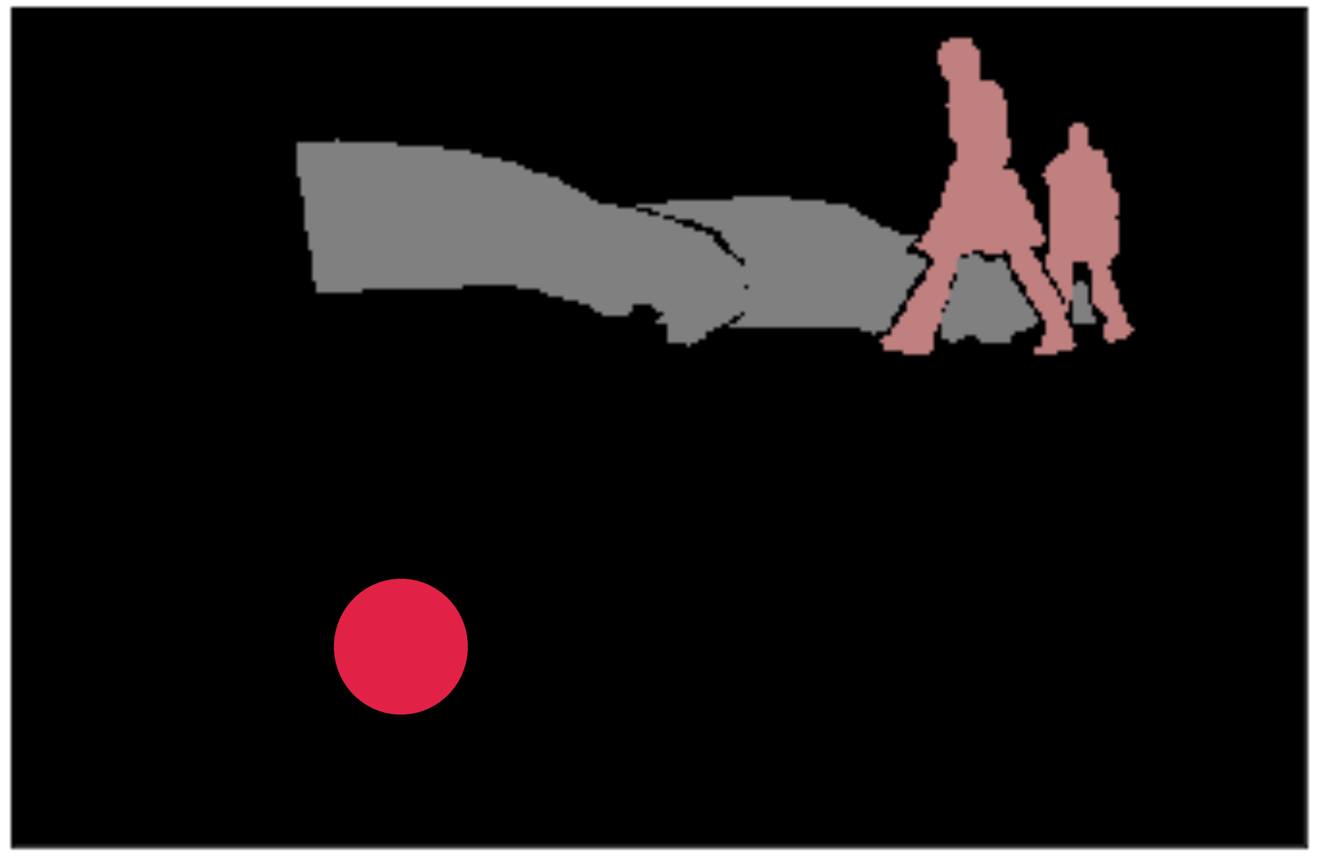
Modeling The Background (MiB)

Revisiting Distillation Loss

Image

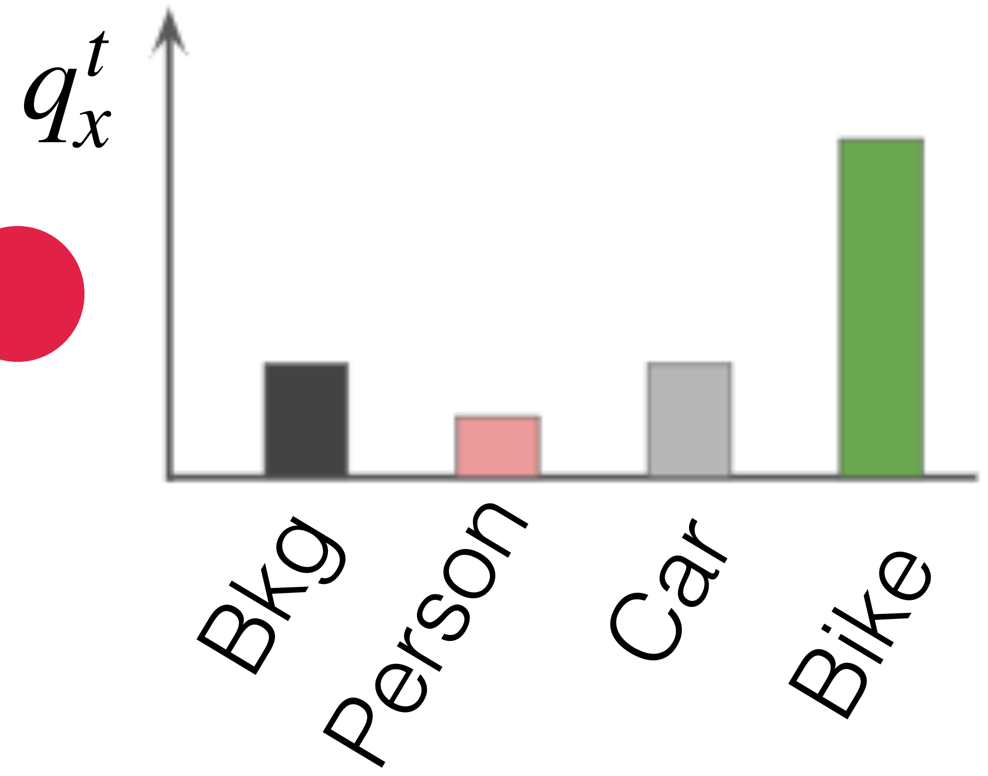


Classes at step t



Classes at step t-1

New Model Prediction at



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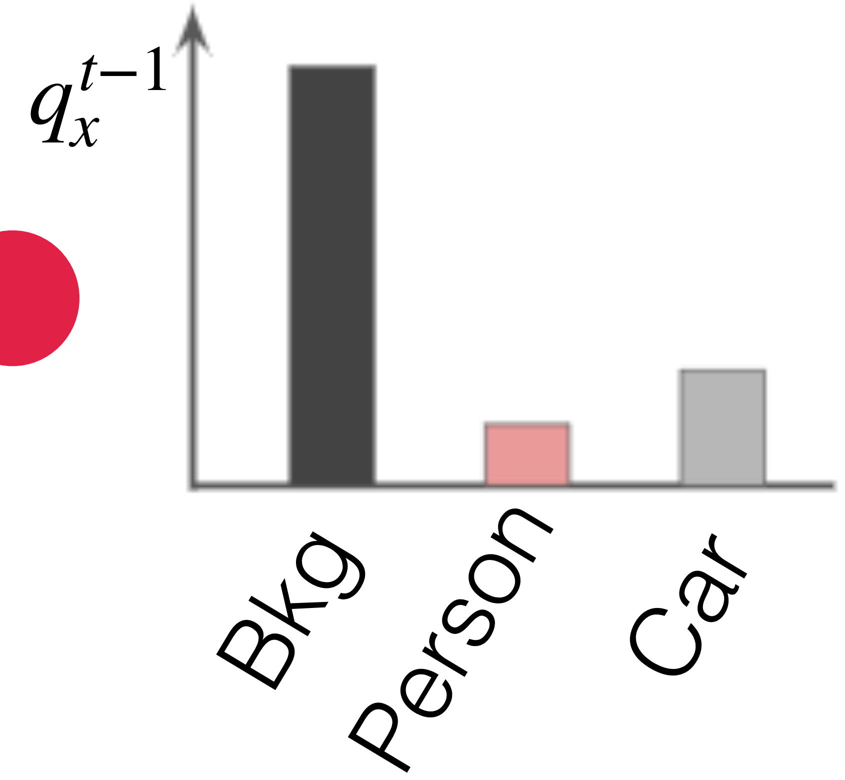
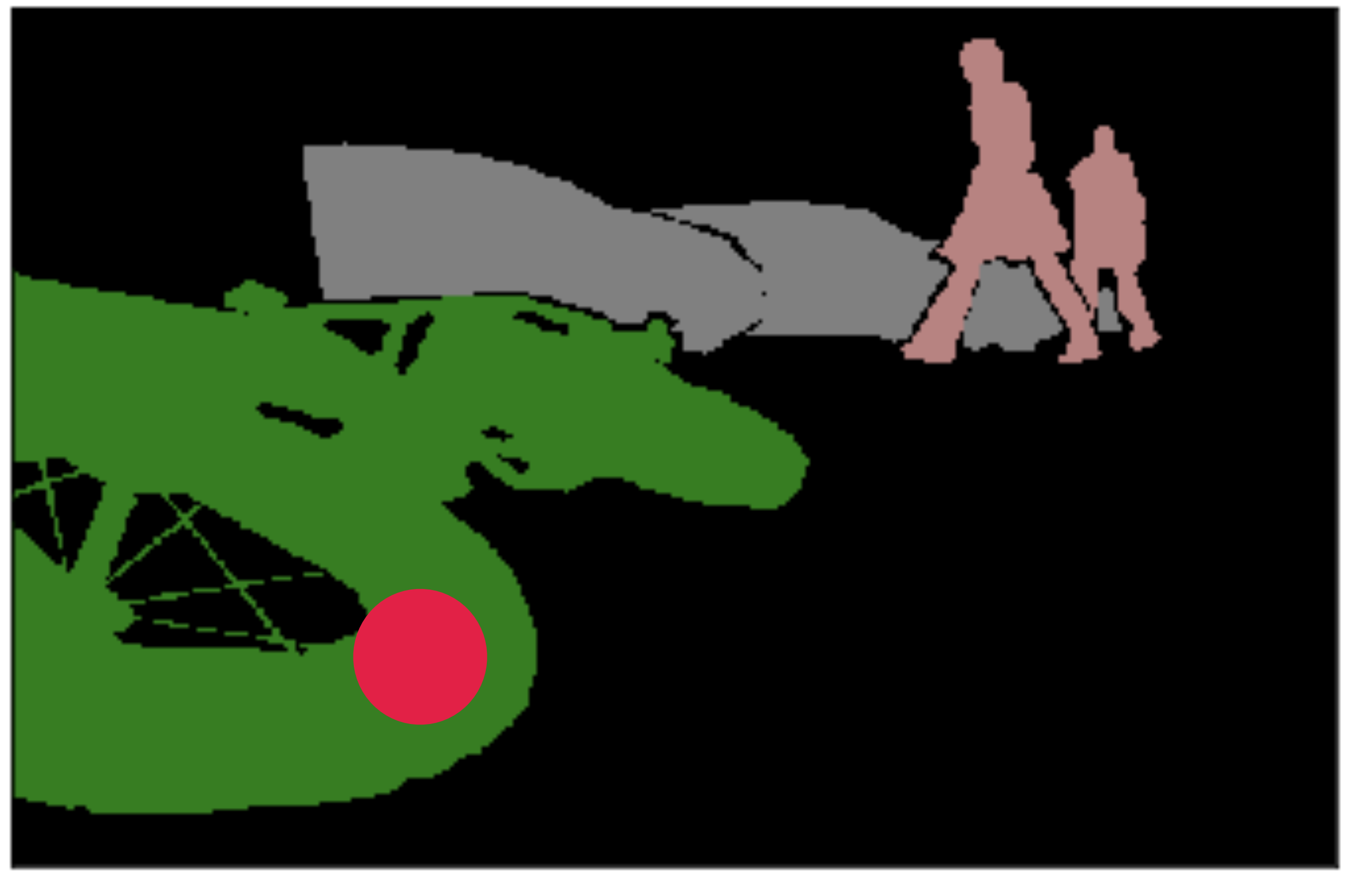


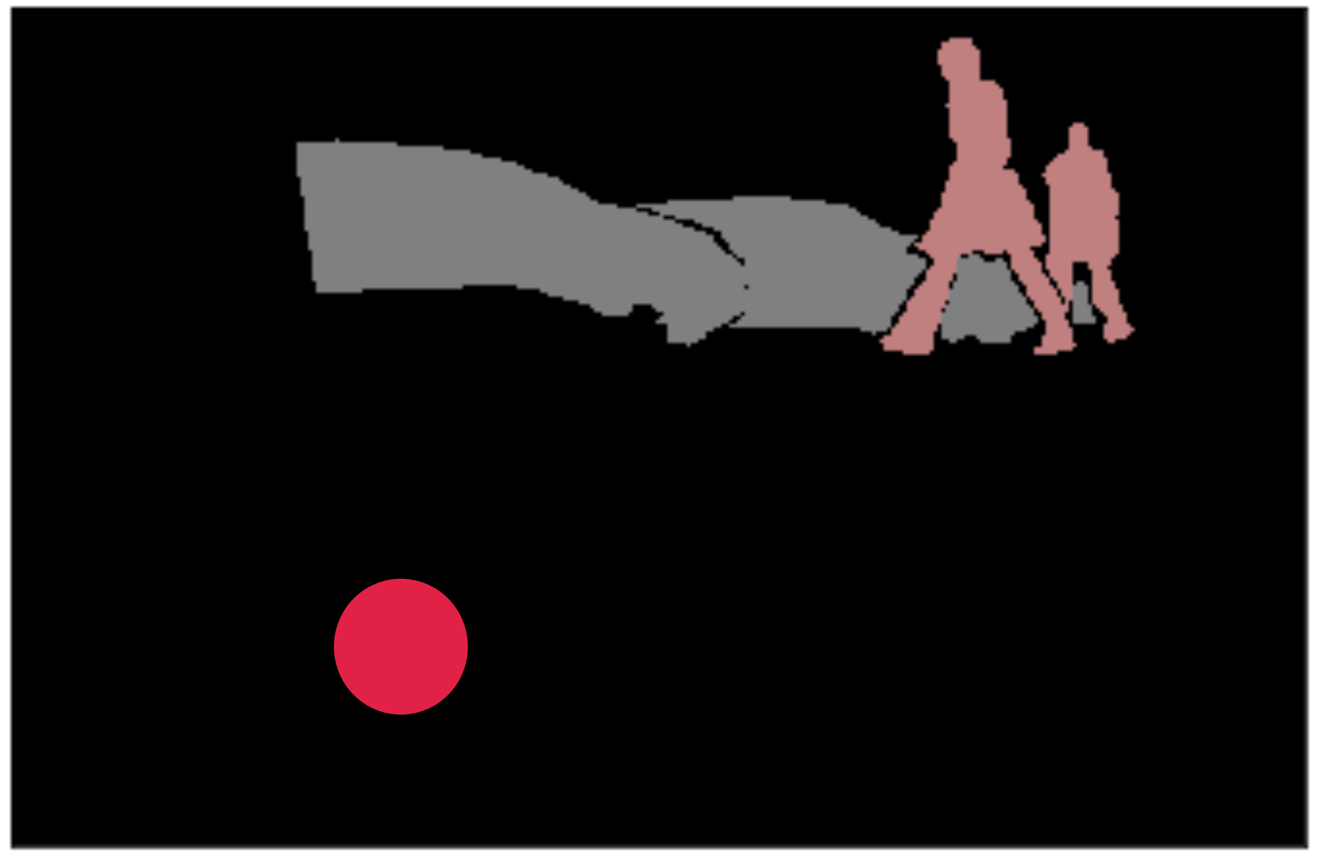
Modeling The Background (MiB)

Revisiting Distillation Loss

Image

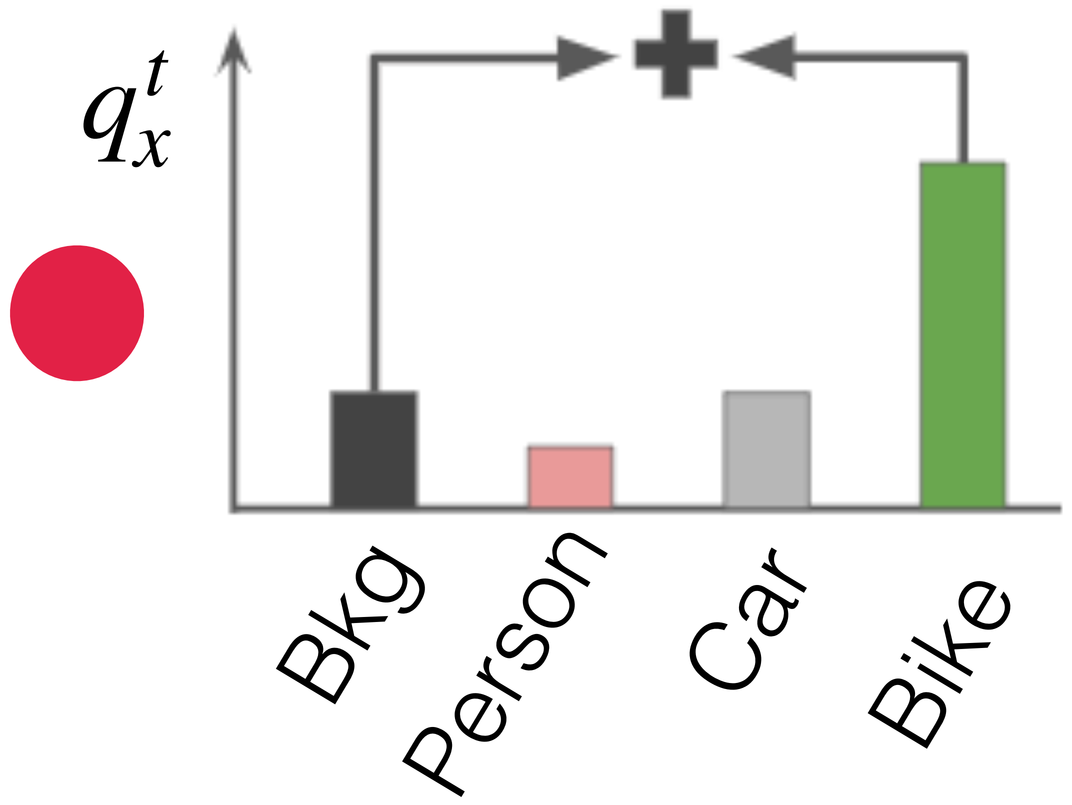


Classes at step t

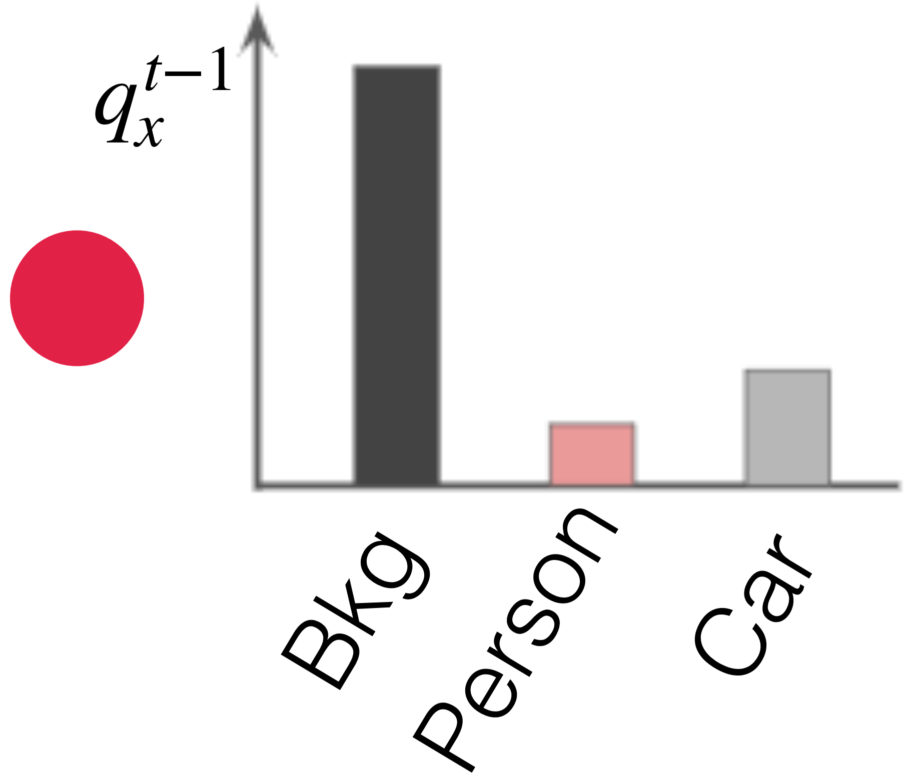


Classes at step t-1

New Model Prediction at



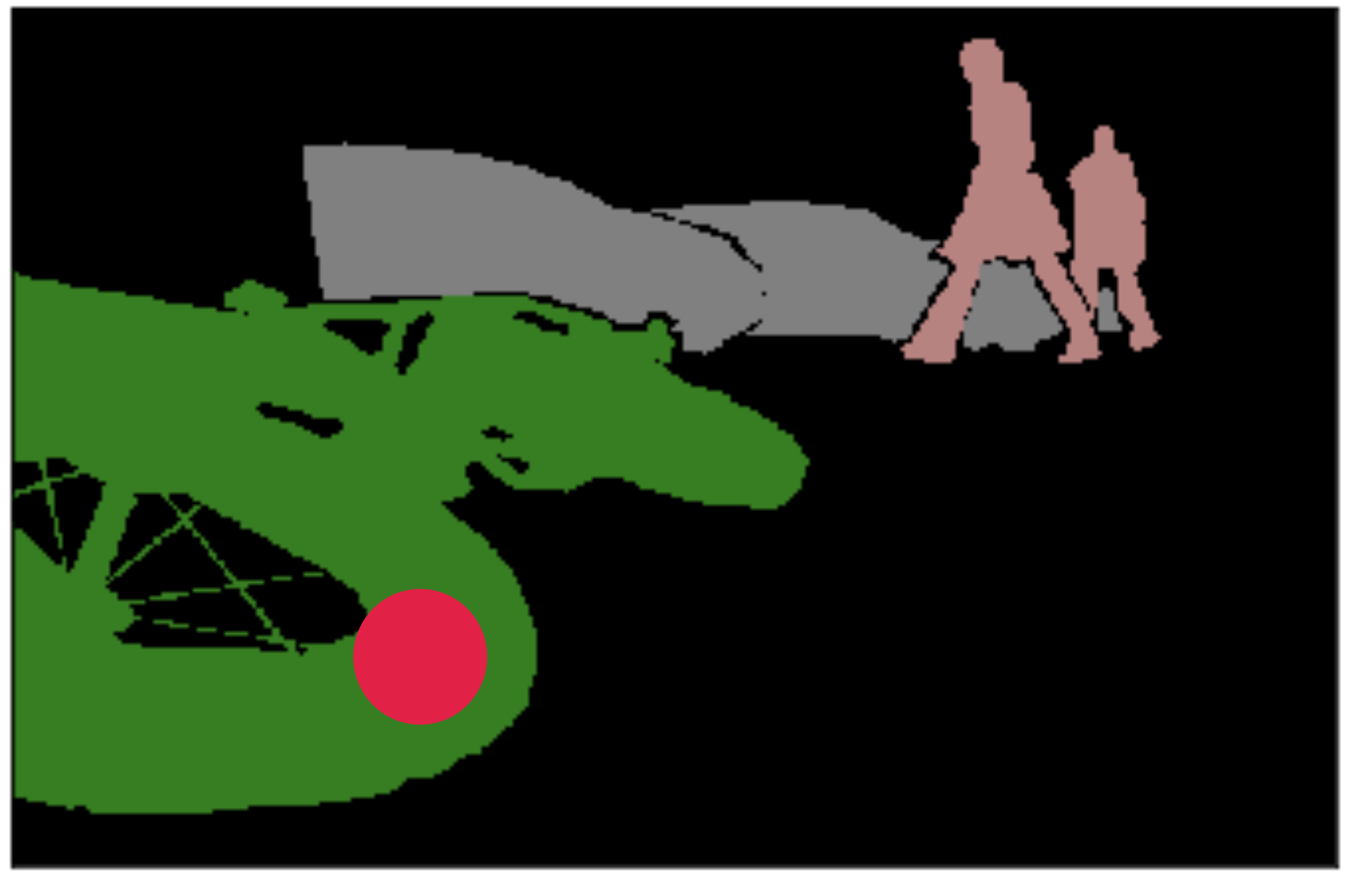
Old Model Prediction at



Modeling The Background (MiB)

Revisiting Distillation Loss

Image



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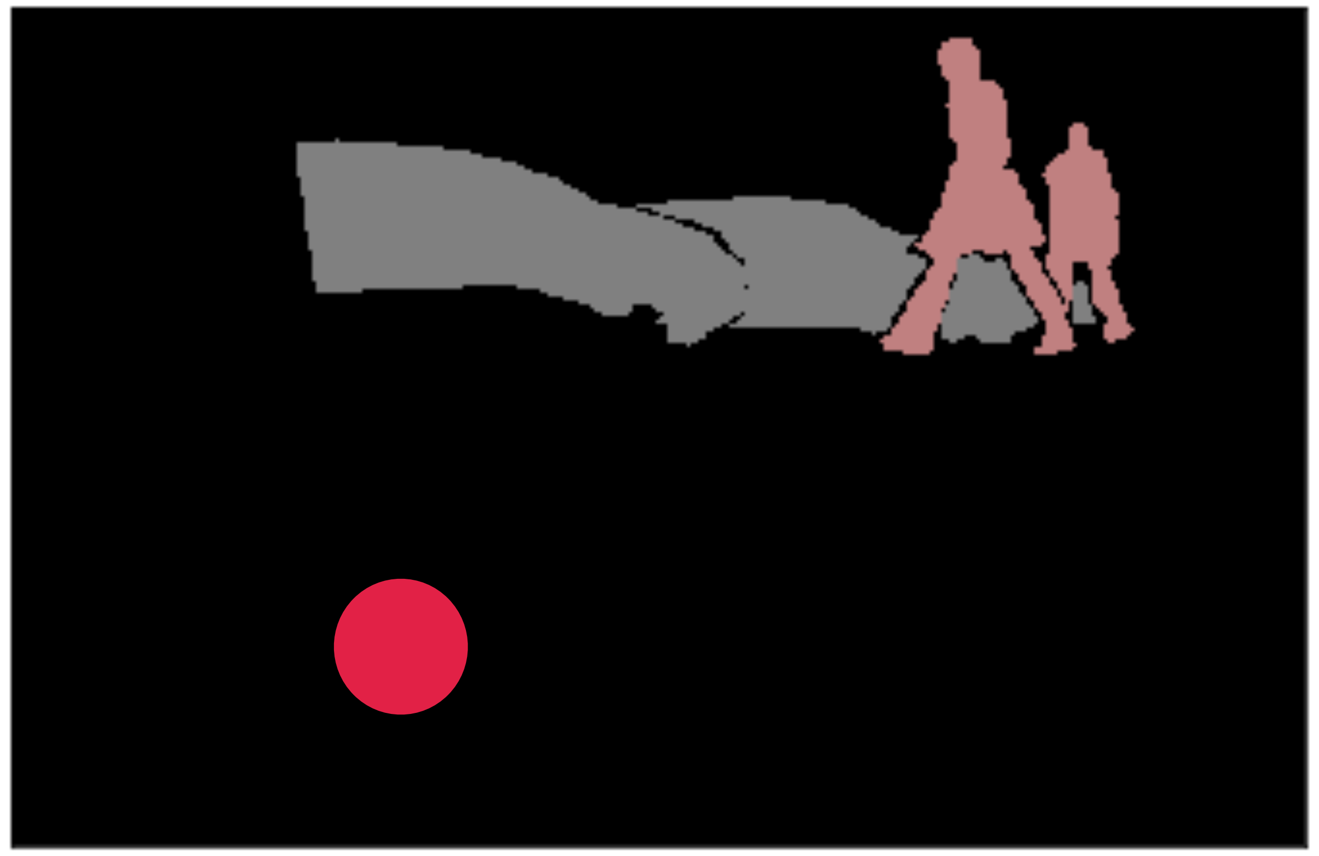
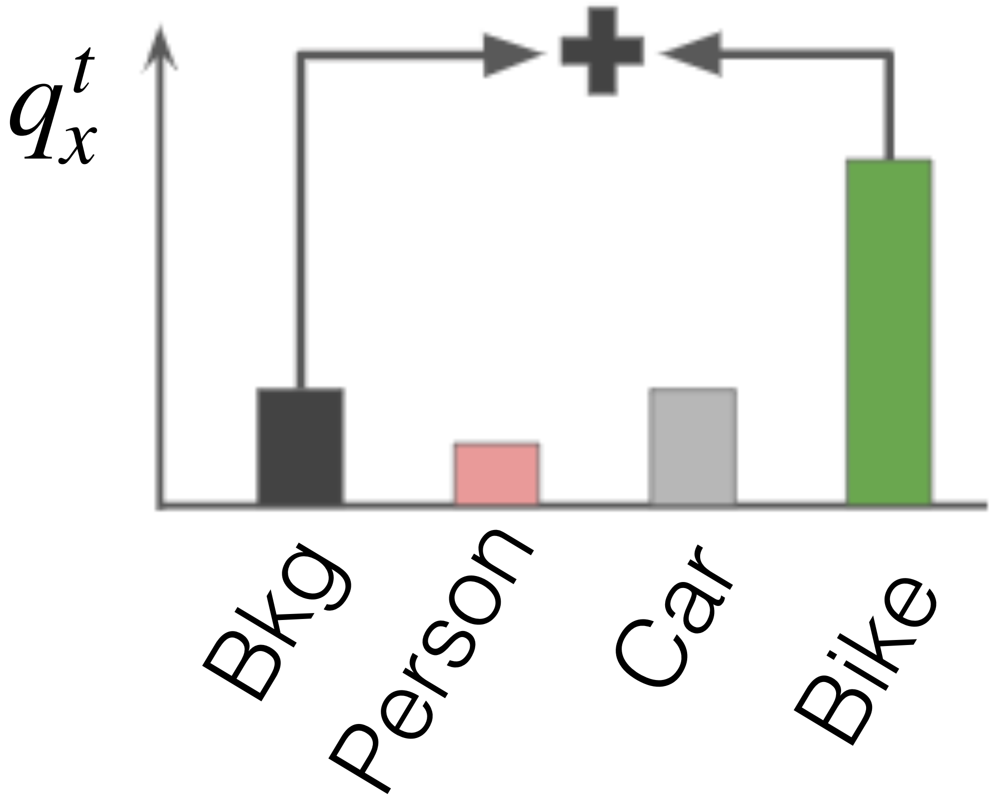
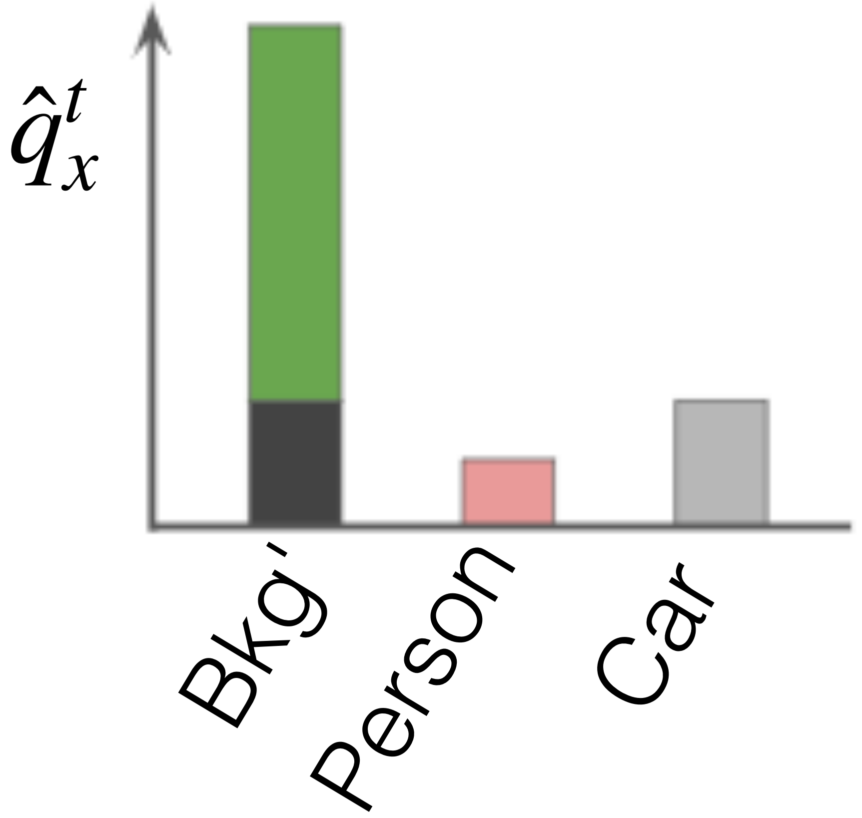


Classes at step t-1



$$\hat{q}_x^t(i,c) = \begin{cases} q_x^t(i,c) & \text{if } c \neq \mathtt{b} \\ \sum_{k \in \mathcal{C}^t} q_x^t(i,k) & \text{if } c = \mathtt{b} \end{cases}$$

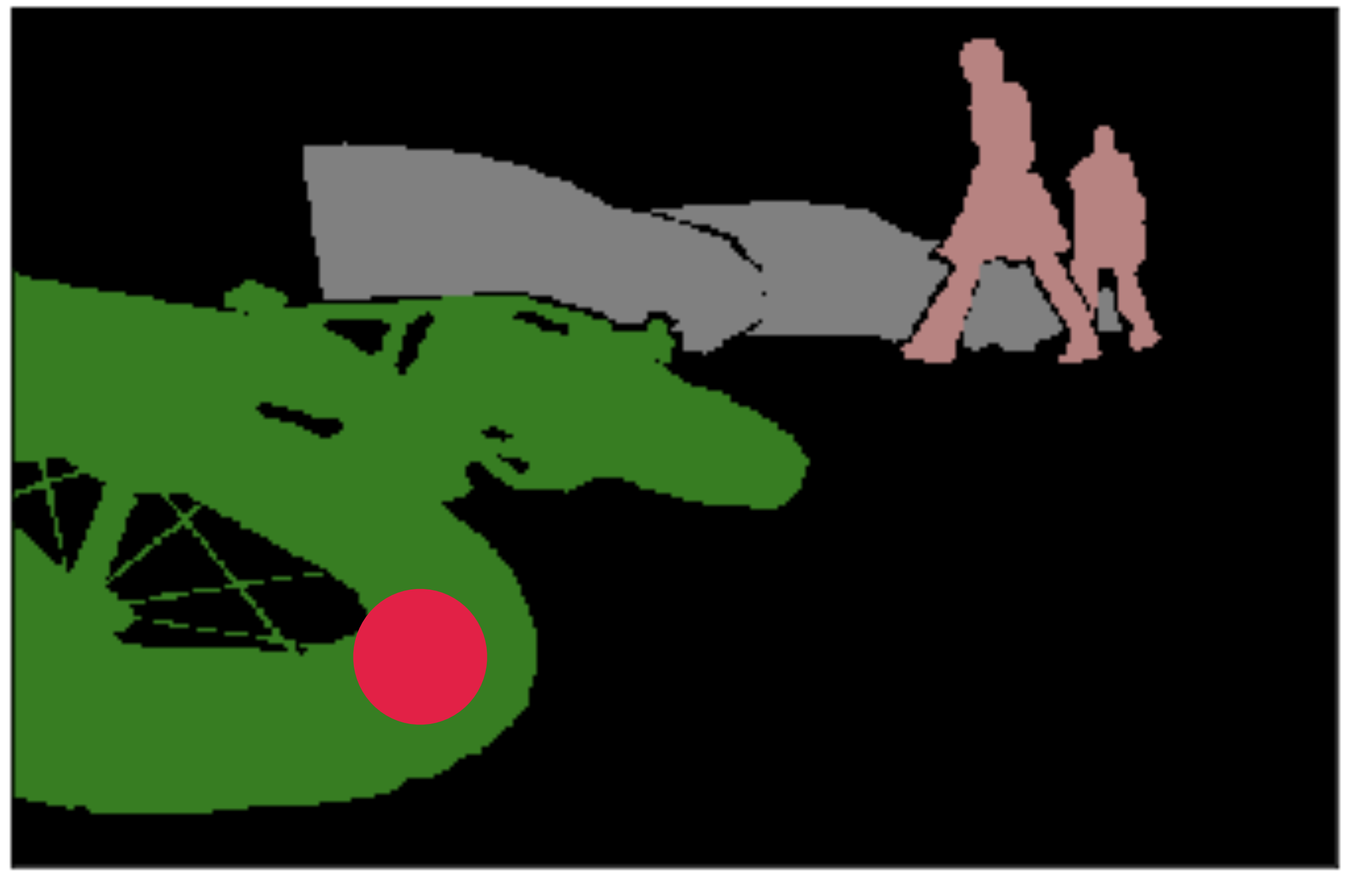
Bkg'= Bkg + Bike



Modeling The Background (MiB)

Revisiting Distillation Loss

Image



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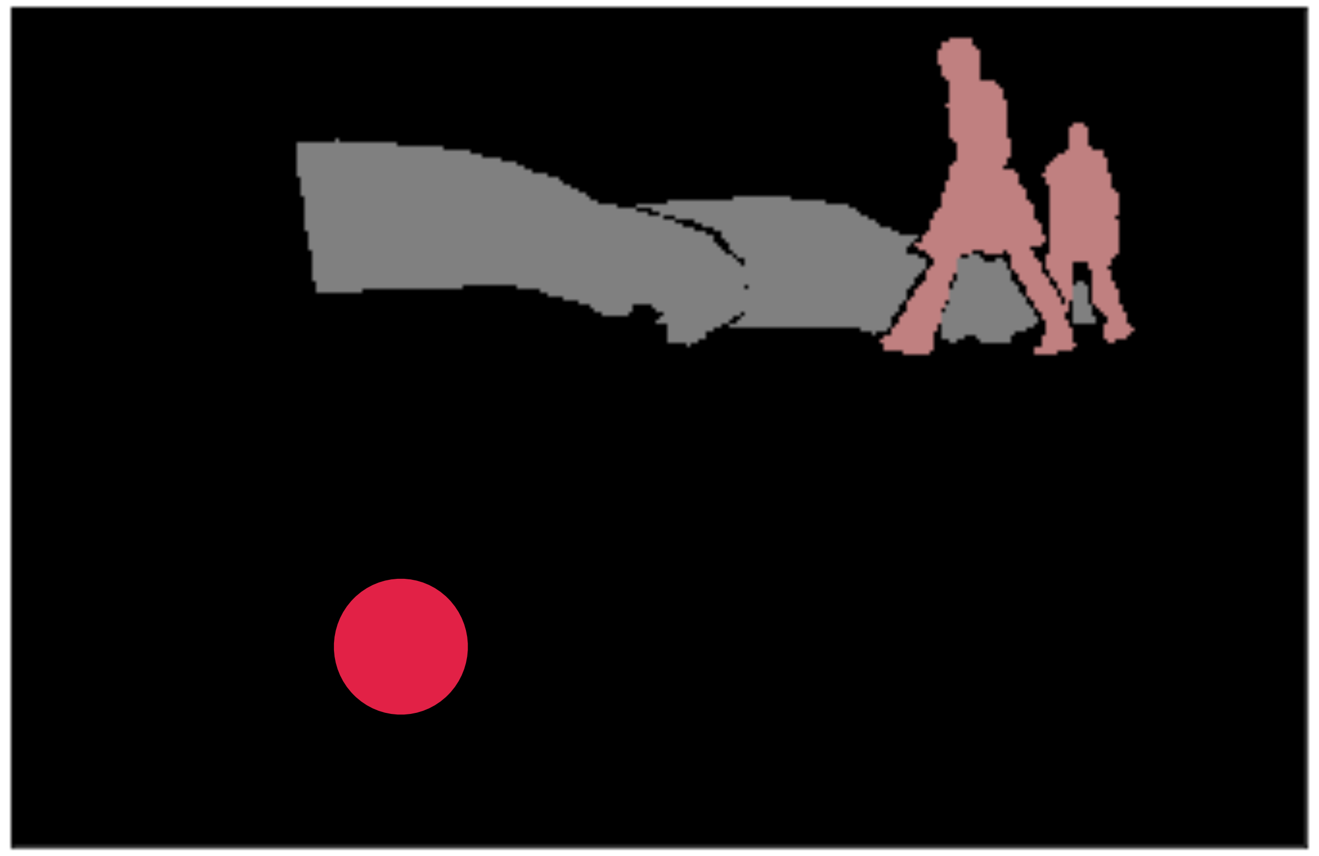

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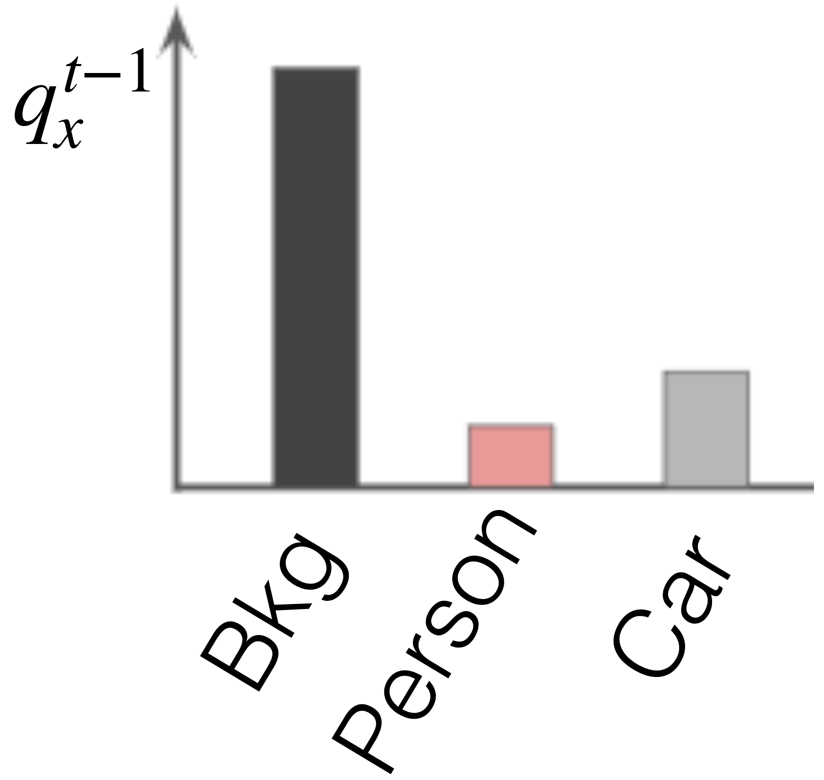
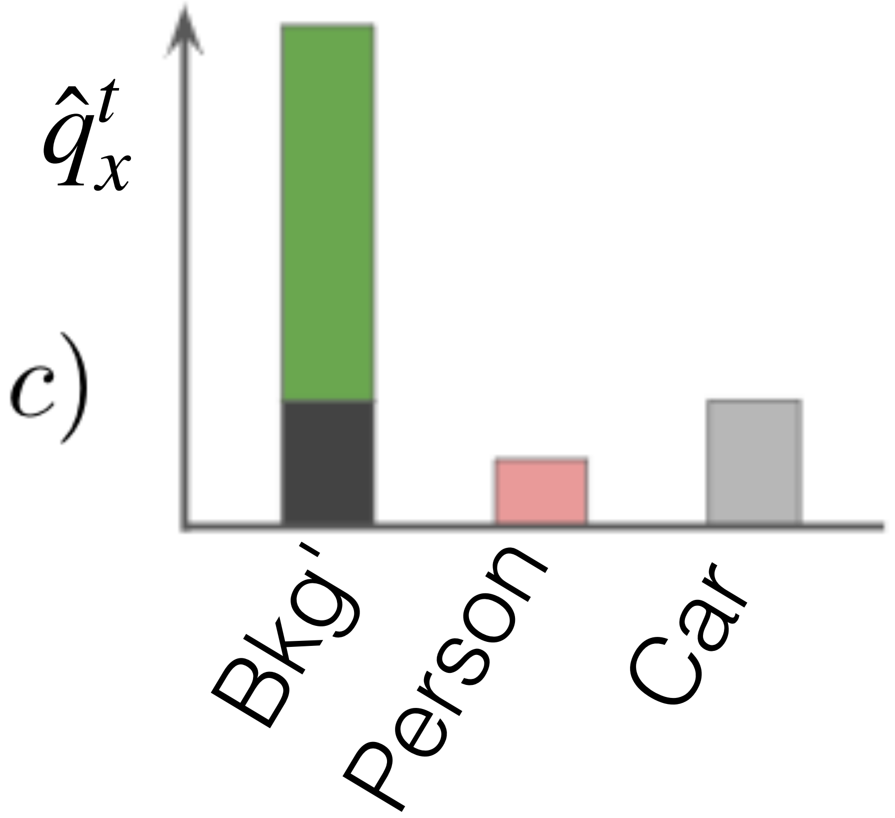


$$\ell_{kd}^{\theta^t}(x, y) = -\frac{1}{|\mathcal{I}|}\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{Y}^{t-1}} q_x^{t-1}(i,c)\log \hat{q}_x^t(i,c)$$



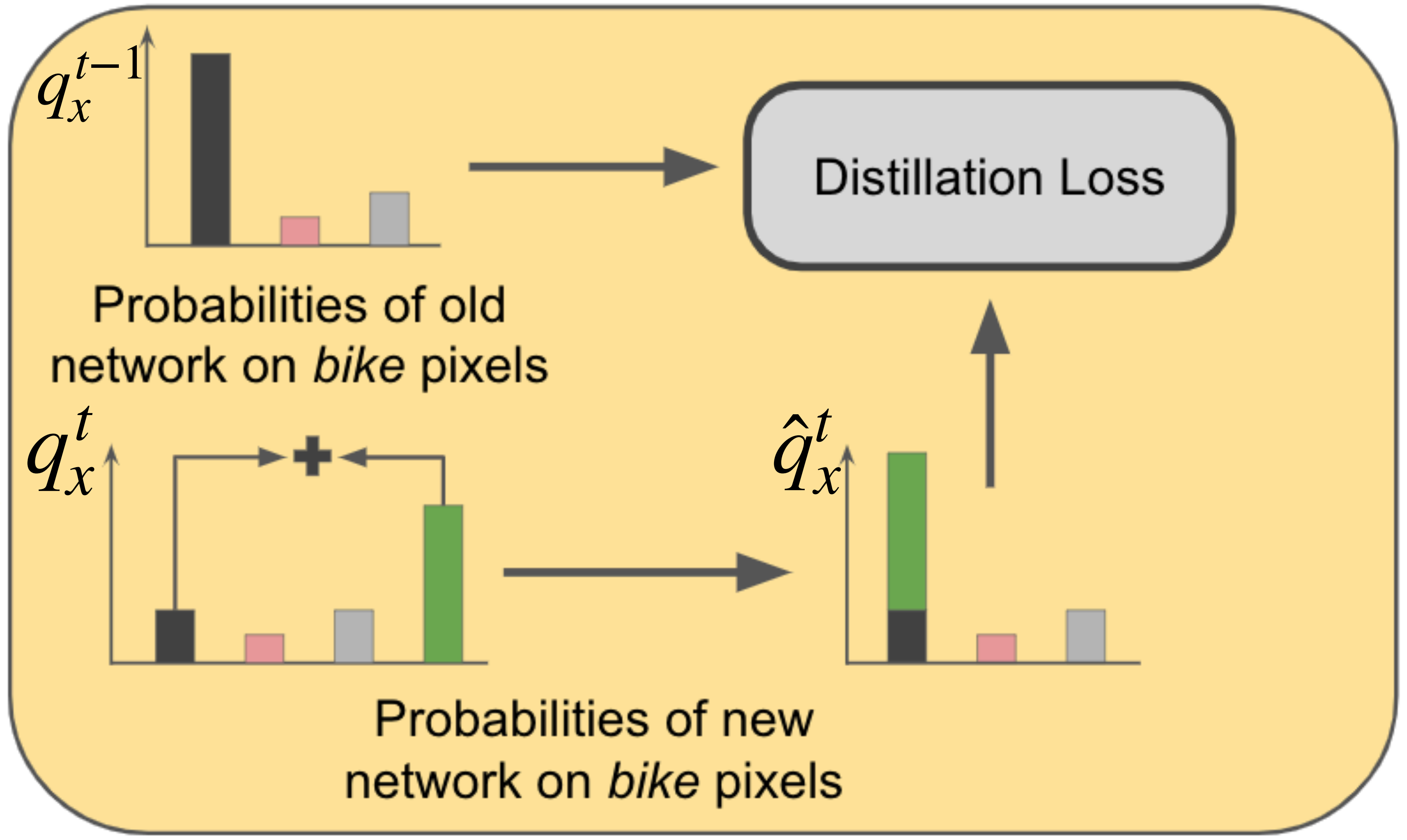
Modeling The Background (MiB)

Revisiting Distillation Loss

The background might have contained in previous steps the classes which are currently learned.

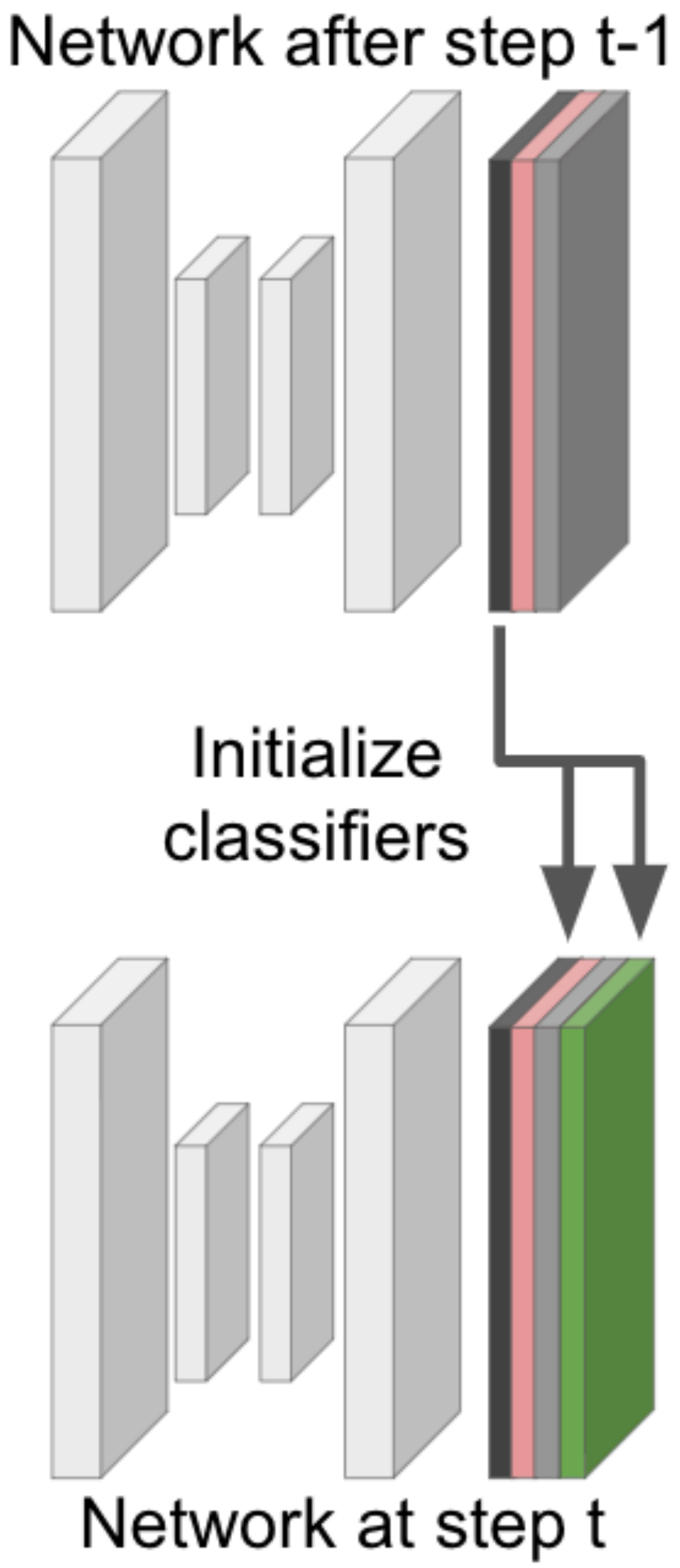
For this reason, we revisit the standard distillation term to match the old background probability $q_x^{t-1}(x, b)$ with the probability of having either a new class or the background $\hat{q}_x^t(x, b)$.

$$\ell_{kd}^{\theta^t}(x, y) = -\frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \sum_{c \in \mathcal{Y}^{t-1}} q_x^{t-1}(i, c) \log \hat{q}_x^t(i, c) \qquad \hat{q}_x^t(i, c) = \begin{cases} q_x^t(i, c) & \text{if } c \neq \mathrm{b} \\ \sum_{k \in \mathcal{C}^t} q_x^t(i, k) & \text{if } c = \mathrm{b} \end{cases}$$



Modeling The Background (MiB)

Initialize the new classifiers



Novel classes $c \in C^t$ very likely would be classified as background.
We model it spreading the background probability:

$$q_x^t(i,c) = \frac{q_x^{t-1}(i,b)}{|C^t|} \; \forall c \in C^t, \text{ with } b \in C^t.$$

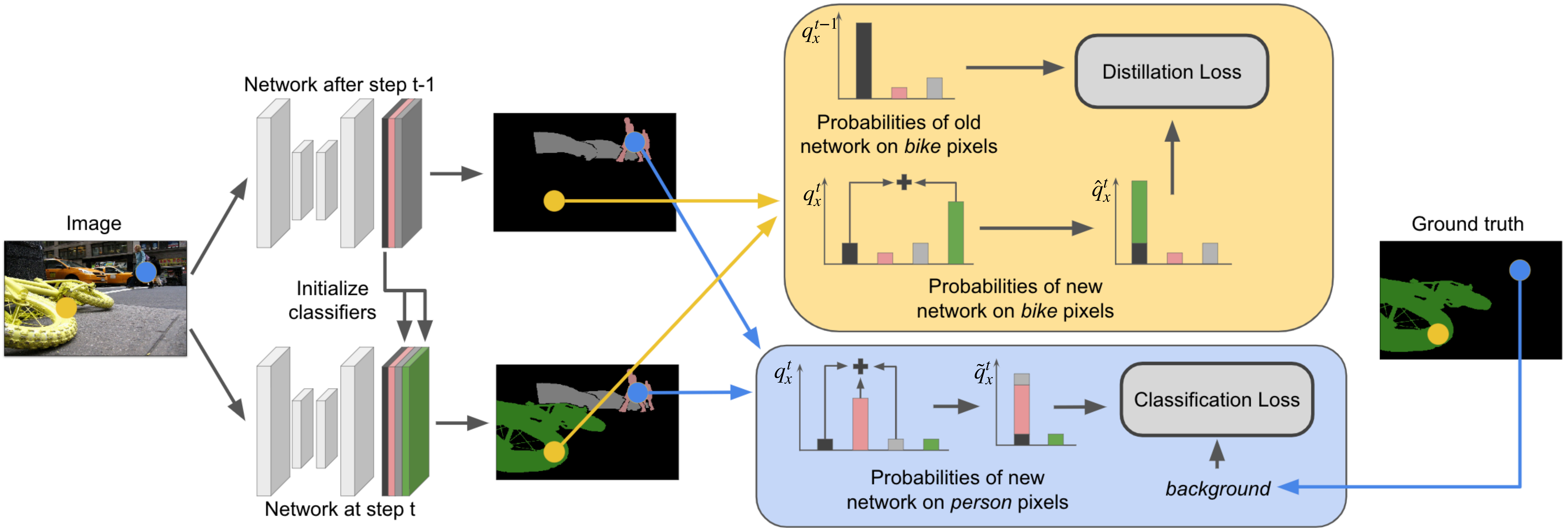
Can be obtained initializing weights ω_c^t and bias β_c^t
from the weights ω_b^{t-1} and bias β_b^{t-1} of the background class.

$$\omega_c^t = \begin{cases} \omega_{\mathtt{b}}^{t-1} & \text{if } c \in \mathcal{C}^t \\ \omega_c^{t-1} & \text{otherwise} \end{cases} \qquad \beta_c^t = \begin{cases} \beta_{\mathtt{b}}^{t-1} - \log(|\mathcal{C}^t|) & \text{if } c \in \mathcal{C}^t \\ \beta_c^{t-1} & \text{otherwise} \end{cases}$$

Modeling The Background (MiB)

Summary

We propose (i) to revisit the cross entropy loss and (ii) the distillation loss and (iii) a novel initialization scheme for new classifiers to model the background shift.



Experimental Setting

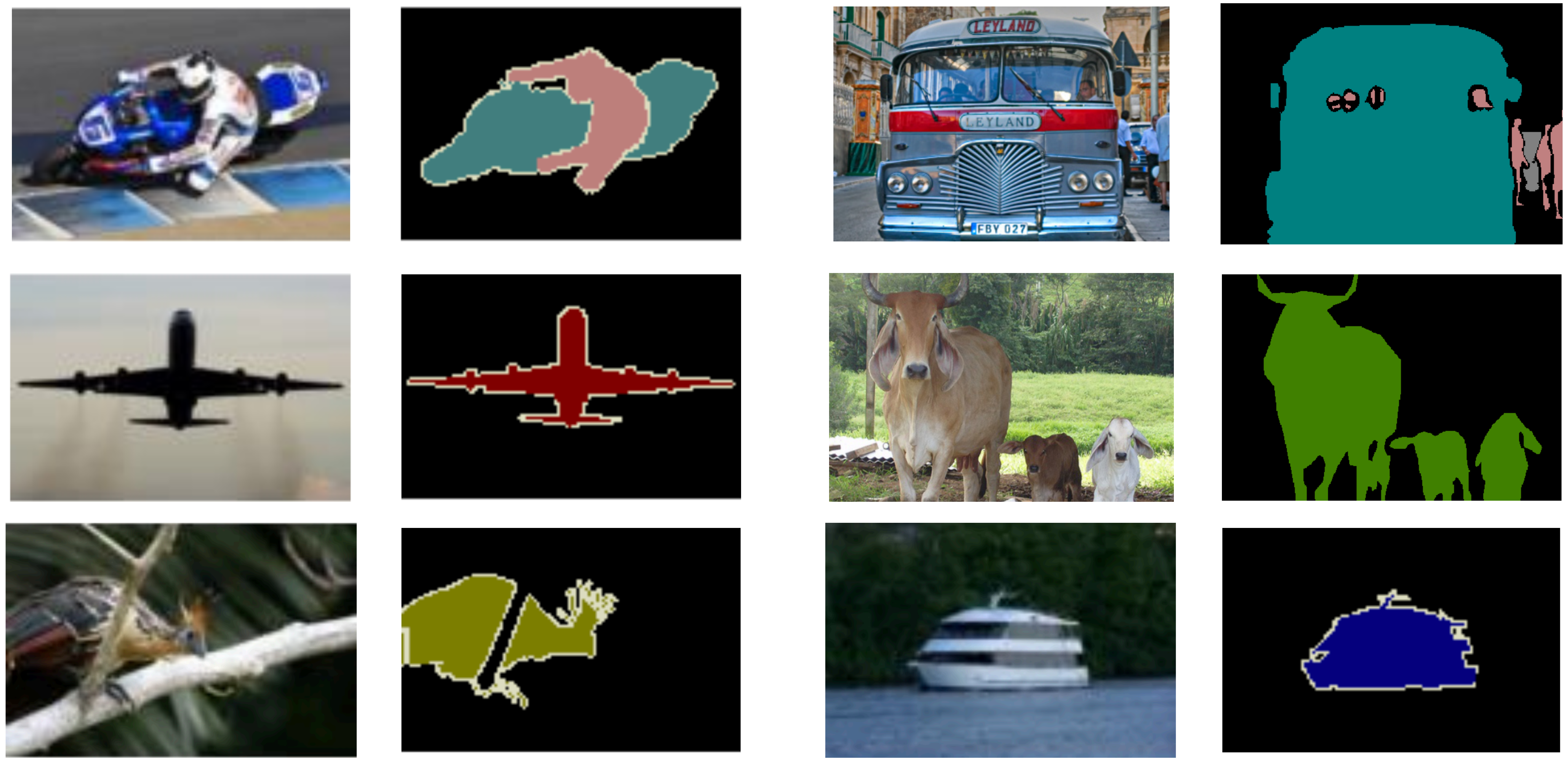
- ➡ Datasets
- ➡ Implementation Details
- ➡ Baselines
- ➡ Results

Datasets

Pascal-VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

20 object classes from different contexts. No stuffs (sky, grass, road, etc).



We propose three settings:

- 19 classes then 1
- 15 classes then 5
- 15 classes then 5 sequentially 1 by 1

And two data setups:

- Disjoint (images appear only once)
- Overlapped (images can appear multiple times but with different labels)

Datasets

ADE20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

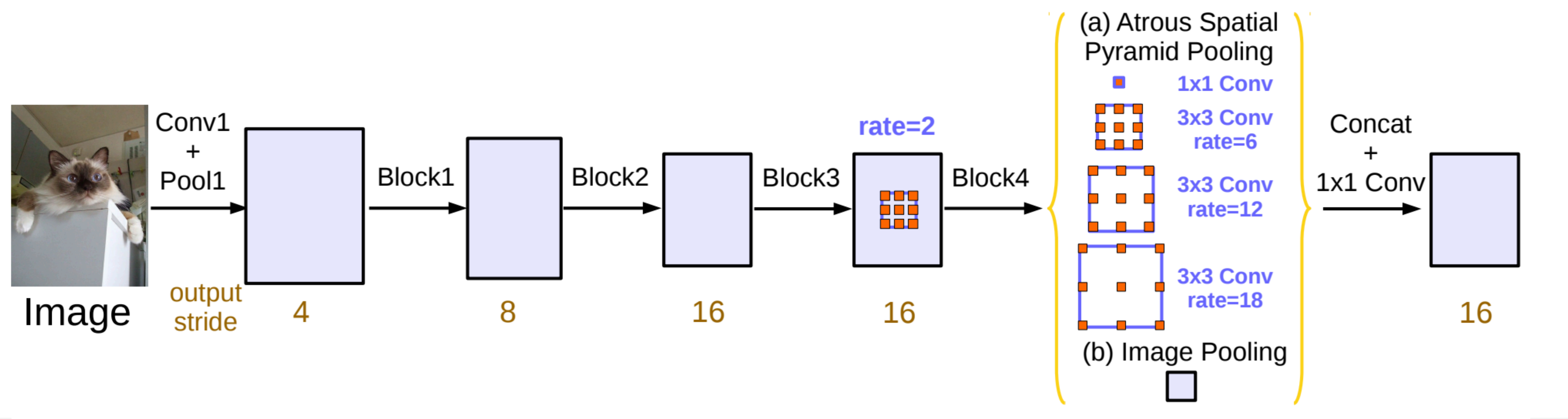
150 classes from different contexts. Both objects and stuffs.

We propose three settings:

- 100 classes then 50
- 100 classes then 50 sequentially 10 by 10
- 50 classes, then 50, then 50

We perform experiments on two orders of the classes and we report averaged results.

Implementation Details



We used a Deeplab-v3 architecture with a ResNet-101 backbone and output stride of 16.
We follow the same training protocol of Chen et al.

Liang-Chieh Chen et al. *Rethinking atrous convolution for semantic image segmentation*. 2017.

Baselines

Distillation Approaches

- Learning without forgetting [1]
- Learning without forgetting Multi-Class [5]
- Incremental learning techniques for semantic segmentation (ILT) [6]

Parameter Regularization Approaches

- Path Integral (PI) [2]
- Elastic Weight Consolidation (EWC) [3]
- Riemannian Walks (RW) [4]

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[2] F. Zenke, et al. *Continual learning through synaptic intelligence*. In ICML, 2017

[3] J. Kirkpatrick, et al. *Overcoming catastrophic forgetting in neural networks*. In P-NAS, 114(13):3521–3526, 2017

[4] A. Chaudhry et al. *Riemannian walk for incremental learning: Understanding forgetting and intransigence*. In ECCV, 2018

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV-W, 2019

Baselines

Distillation Approaches

- Learning
- Learning
- Incremen
  semantic

Parameter Regularization Approaches

EWC) [3]

We searched the best hyper-parameters (regularization strength) following the validation protocol proposed by De Lange et al. [7]

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[2] F. Zenke, et al. *Continual learning through synaptic intelligence*. In ICML, 2017

[3] J. Kirkpatrick, et al. *Overcoming catastrophic forgetting in neural networks*. In P-NAS, 114(13):3521–3526, 2017

[4] A. Chaudhry et al. *Riemannian walk for incremental learning: Understanding forgetting and intransigence*. In ECCV, 2018

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

[7] M. De Lange et al. *Continual learning: A comparative study on how to defy forgetting in classification tasks. 2019.*

Results

Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

	19-1						**15-5**						**15-1**					
	Disjoint			**Overlapped**			**Disjoint**			**Overlapped**			**Disjoint**			**Overlapped**		
Method	*1-19*	*20*	*all*	*1-19*	*20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*
FT	5.8	12.3	6.2	6.8	12.9	7.1	1.1	33.6	9.2	2.1	33.1	9.8	0.2	1.8	0.6	0.2	1.8	0.6
PI [2]	5.4	14.1	5.9	7.5	14.0	7.8	1.3	34.1	9.5	1.6	33.3	9.5	0.0	1.8	0.4	0.0	1.8	0.5
EWC [3]	23.2	16.0	22.9	26.9	14.0	26.3	26.7	37.7	29.4	24.3	35.5	27.1	0.3	4.3	1.3	0.3	4.3	1.3
RW [4]	19.4	15.7	19.2	23.3	14.2	22.9	17.9	36.9	22.7	16.6	34.9	21.2	0.2	5.4	1.5	0.0	5.2	1.3
LwF [1]	53.0	9.1	50.8	51.2	8.5	49.1	58.4	37.4	53.1	58.9	36.6	53.3	0.8	3.6	1.5	1.0	3.9	1.8
LwF-MC [5]	63.0	13.2	60.5	64.4	13.3	61.9	67.2	41.2	60.7	58.1	35.0	52.3	4.5	7.0	5.2	6.4	8.4	6.9
ILT [6]	69.1	16.4	66.4	67.1	12.3	64.4	63.2	39.5	57.3	66.3	40.6	59.9	3.7	5.7	4.2	4.9	7.8	5.7
MiB	**69.6**	**25.6**	**67.4**	**70.2**	**22.1**	**67.8**	**71.8**	**43.3**	**64.7**	**75.5**	**49.4**	**69.0**	**46.2**	**12.9**	**37.9**	**35.1**	**13.5**	**29.7**
Joint	77.4	78.0	77.4	77.4	78.0	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[2] F. Zenke, et al. *Continual learning through synaptic intelligence*. In ICML, 2017

[3] J. Kirkpatrick, et al. *Overcoming catastrophic forgetting in neural networks*. In P-NAS, 114(13):3521–3526, 2017

[4] A. Chaudhry et al. *Riemannian walk for incremental learning: Understanding forgetting and intransigence*. In ECCV, 2018

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

	19-1						15-5						15-1					
	Disjoint			**Overlapped**			**Disjoint**			**Overlapped**			**Disjoint**			**Overlapped**		
Method	*1-19*	*20*	*all*	*1-19*	*20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*
FT	5.8	12.3	6.2	6.8	12.9	7.1	1.1	33.6	9.2	2.1	33.1	9.8	0.2	1.8	0.6	0.2	1.8	0.6
PI [2]	5.4	14.1	5.9	7.5	14.0	7.8	1.3	34.1	9.5	1.6	33.3	9.5	0.0	1.8	0.4	0.0	1.8	0.5
EWC [3]	23.2	16.0	22.9	26.9	14.0	26.3	26.7	37.7	29.4	24.3	35.5	27.1	0.3	4.3	1.3	0.3	4.3	1.3
RW [4]	19.4	15.7	19.2	23.3	14.2	22.9	17.9	36.9	22.7	16.6	34.9	21.2	0.2	5.4	1.5	0.0	5.2	1.3
LwF [1]	53.0	9.1	50.8	51.2	8.5	49.1	58.4	37.4	53.1	58.9	36.6	53.3	0.8	3.6	1.5	1.0	3.9	1.8
LwF-MC [5]	63.0	13.2	60.5	64.4	13.3	61.9	67.2	41.2	60.7	58.1	35.0	52.3	4.5	7.0	5.2	6.4	8.4	6.9
ILT [6]	69.1	16.4	66.4	67.1	12.3	64.4	63.2	39.5	57.3	66.3	40.6	59.9	3.7	5.7	4.2	4.9	7.8	5.7
MiB	**69.6**	**25.6**	**67.4**	**70.2**	**22.1**	**67.8**	**71.8**	**43.3**	**64.7**	**75.5**	**49.4**	**69.0**	**46.2**	**12.9**	**37.9**	**35.1**	**13.5**	**29.7**
Joint	77.4	78.0	77.4	77.4	78.0	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[2] F. Zenke, et al. *Continual learning through synaptic intelligence*. In ICML, 2017

[3] J. Kirkpatrick, et al. *Overcoming catastrophic forgetting in neural networks*. In P-NAS, 114(13):3521–3526, 2017

[4] A. Chaudhry et al. *Riemannian walk for incremental learning: Understanding forgetting and intransigence*. In ECCV, 2018

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

	19-1						15-5						15-1					
	Disjoint			**Overlapped**			**Disjoint**			**Overlapped**			**Disjoint**			**Overlapped**		
Method	*1-19*	*20*	*all*	*1-19*	*20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*
FT	5.8	12.3	6.2	6.8	12.9	7.1	1.1	33.6	9.2	2.1	33.1	9.8	0.2	1.8	0.6	0.2	1.8	0.6
PI [2]	5.4	14.1	5.9	7.5	14.0	7.8	1.3	34.1	9.5	1.6	33.3	9.5	0.0	1.8	0.4	0.0	1.8	0.5
EWC [3]	23.2	16.0	22.9	26.9	14.0	26.3	26.7	37.7	29.4	24.3	35.5	27.1	0.3	4.3	1.3	0.3	4.3	1.3
RW [4]	19.4	15.7	19.2	23.3	14.2	22.9	17.9	36.9	22.7	16.6	34.9	21.2	0.2	5.4	1.5	0.0	5.2	1.3
LwF [1]	53.0	9.1	50.8	51.2	8.5	49.1	58.4	37.4	53.1	58.9	36.6	53.3	0.8	3.6	1.5	1.0	3.9	1.8
LwF-MC [5]	63.0	13.2	60.5	64.4	13.3	61.9	67.2	41.2	60.7	58.1	35.0	52.3	4.5	7.0	5.2	6.4	8.4	6.9
ILT [6]	69.1	16.4	66.4	67.1	12.3	64.4	63.2	39.5	57.3	66.3	40.6	59.9	3.7	5.7	4.2	4.9	7.8	5.7
MiB	**69.6**	**25.6**	**67.4**	**70.2**	**22.1**	**67.8**	**71.8**	**43.3**	**64.7**	**75.5**	**49.4**	**69.0**	**46.2**	**12.9**	**37.9**	**35.1**	**13.5**	**29.7**
Joint	77.4	78.0	77.4	77.4	78.0	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017
[2] F. Zenke, et al. *Continual learning through synaptic intelligence*. In ICML, 2017
[3] J. Kirkpatrick, et al. *Overcoming catastrophic forgetting in neural networks*. In P-NAS, 114(13):3521–3526, 2017
[4] A. Chaudhry et al. *Riemannian walk for incremental learning: Understanding forgetting and intransigence*. In ECCV, 2018
[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

	19-1						15-5						15-1					
	Disjoint			Overlapped			Disjoint			Overlapped			Disjoint			Overlapped		
Method	*1-19*	*20*	*all*	*1-19*	*20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*
FT	5.8	12.3	6.2	6.8	12.9	7.1	1.1	33.6	9.2	2.1	33.1	9.8	0.2	1.8	0.6	0.2	1.8	0.6
PI [2]	5.4	14.1	5.9	7.5	14.0	7.8	1.3	34.1	9.5	1.6	33.3	9.5	0.0	1.8	0.4	0.0	1.8	0.5
EWC [3]	23.2	16.0	22.9	26.9	14.0	26.3	26.7	37.7	29.4	24.3	35.5	27.1	0.3	4.3	1.3	0.3	4.3	1.3
RW [4]	19.4	15.7	19.2	23.3	14.2	22.9	17.9	36.9	22.7	16.6	34.9	21.2	0.2	5.4	1.5	0.0	5.2	1.3
LwF [1]	53.0	9.1	50.8	51.2	8.5	49.1	58.4	37.4	53.1	58.9	36.6	53.3	0.8	3.6	1.5	1.0	3.9	1.8
LwF-MC [5]	63.0	13.2	60.5	64.4	13.3	61.9	67.2	41.2	60.7	58.1	35.0	52.3	4.5	7.0	5.2	6.4	8.4	6.9
ILT [6]	69.1	16.4	66.4	67.1	12.3	64.4	63.2	39.5	57.3	66.3	40.6	59.9	3.7	5.7	4.2	4.9	7.8	5.7
MiB	**69.6**	**25.6**	**67.4**	**70.2**	**22.1**	**67.8**	**71.8**	**43.3**	**64.7**	**75.5**	**49.4**	**69.0**	**46.2**	**12.9**	**37.9**	**35.1**	**13.5**	**29.7**
Joint	77.4	78.0	77.4	77.4	78.0	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4	79.1	72.6	77.4

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[2] F. Zenke, et al. *Continual learning through synaptic intelligence*. In ICML, 2017

[3] J. Kirkpatrick, et al. *Overcoming catastrophic forgetting in neural networks*. In P-NAS, 114(13):3521–3526, 2017

[4] A. Chaudhry et al. *Riemannian walk for incremental learning: Understanding forgetting and intransigence*. In ECCV, 2018

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

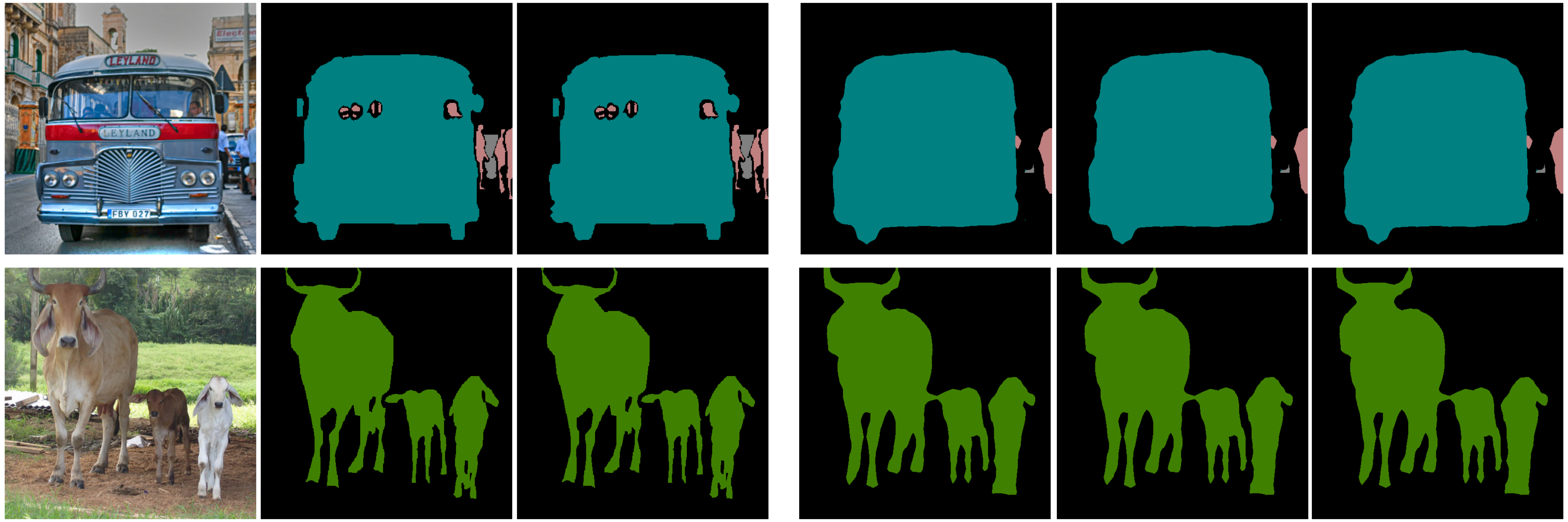
Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

On Pascal-VOC 2012 there are cases where new classes are either similar in appearance (e.g. Bus and Train) or appear in similar contexts (e.g. Sheep and Cow).

Step 0

Training Bus and Cow



Input | Labels | Knowledge | FT | ILT [6] | **MiB (ours)**

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

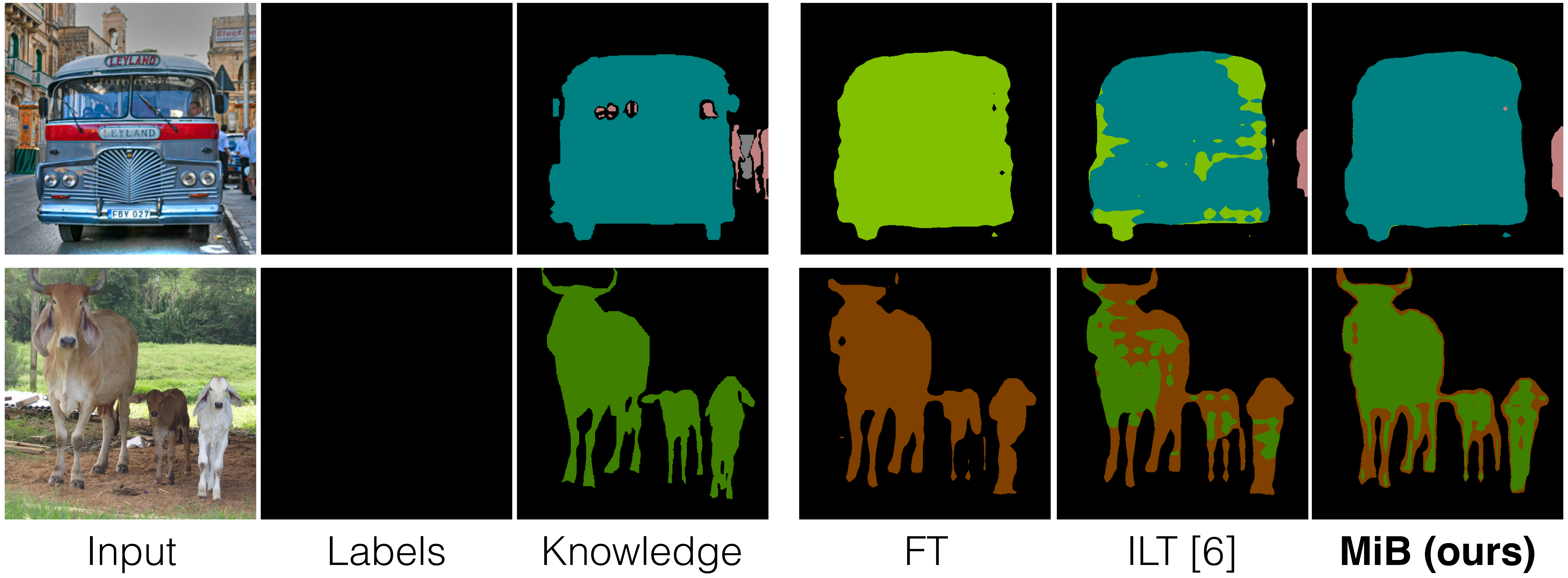
Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

On Pascal-VOC 2012 there are cases where new classes are either similar in appearance (e.g. Bus and Train) or appear in similar contexts (e.g. Sheep and Cow).

Step 1

Training Train and Sheep



[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Ablation Study

Pascal VOC 2012

M. Everingham, et al. *The PASCAL Visual Object Classes Challenge 2012 (VOC2012)*

We started from the LwF baseline and we introduced our three components: the revised cross entropy (CE), the revised distillation (KD) and the initialization strategy (init).

	19-1			15-5			15-1		
	1-19	*20*	*all*	*1-15*	*16-20*	*all*	*1-15*	*16-20*	*all*
LwF	51.2	8.5	49.1	58.9	36.6	53.3	1.0	3.9	1.8
+ *CE*	57.6	9.9	55.2	63.2	38.1	57.0	12.0	3.7	9.9
+ *KD*	66.0	11.9	63.3	72.9	46.3	66.3	34.8	4.5	27.2
+ *init*	**70.2**	**22.1**	**67.8**	**75.5**	**49.4**	**69.0**	**35.1**	**13.5**	**29.7**

Z. Li and D. Hoiem. Learning without forgetting. In IEEE T-PAMI, 40(12):2935–2947, 2017

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

	100-50			100-10							50-50			
Method	*1-100*	*101-150*	*all*	*1-100*	*100-110*	*110-120*	*120-130*	*130-140*	*140-150*	*all*	*1-50*	*51-100*	*101-150*	*all*
FT	0.0	24.9	8.3	0.0	0.0	0.0	0.0	0.0	16.6	1.1	0.0	0.0	22.0	7.3
LwF [1]	21.1	25.6	22.6	0.1	0.0	0.4	2.6	4.6	16.9	1.7	5.7	12.9	22.8	13.9
LwF-MC [5]	34.2	10.5	26.3	18.7	2.5	8.7	4.1	6.5	5.1	14.3	27.8	7.0	10.4	15.1
ILT [6]	22.9	18.9	21.6	0.3	0.0	1.0	2.1	4.6	10.7	1.4	8.4	9.7	14.3	10.8
MiB	**37.9**	**27.9**	**34.6**	**31.8**	**10.4**	**14.8**	**12.8**	**13.6**	**18.7**	**25.9**	**35.5**	**22.2**	**23.6**	**27.0**
Joint	44.3	28.2	38.9	44.3	26.1	42.8	26.7	28.1	17.3	38.9	51.1	38.3	28.2	38.9

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset.* In CVPR, 2017.

	100-50			100-10							50-50			
Method	*1-100*	*101-150*	*all*	*1-100*	*100-110*	*110-120*	*120-130*	*130-140*	*140-150*	*all*	*1-50*	*51-100*	*101-150*	*all*
FT	0.0	24.9	8.3	0.0	0.0	0.0	0.0	0.0	16.6	1.1	0.0	0.0	22.0	7.3
LwF [1]	21.1	25.6	22.6	0.1	0.0	0.4	2.6	4.6	16.9	1.7	5.7	12.9	22.8	13.9
LwF-MC [5]	34.2	10.5	26.3	18.7	2.5	8.7	4.1	6.5	5.1	14.3	27.8	7.0	10.4	15.1
ILT [6]	22.9	18.9	21.6	0.3	0.0	1.0	2.1	4.6	10.7	1.4	8.4	9.7	14.3	10.8
MiB	**37.9**	**27.9**	**34.6**	**31.8**	**10.4**	**14.8**	**12.8**	**13.6**	**18.7**	**25.9**	**35.5**	**22.2**	**23.6**	**27.0**
Joint	44.3	28.2	38.9	44.3	26.1	42.8	26.7	28.1	17.3	38.9	51.1	38.3	28.2	38.9

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Method	100-50			100-10							50-50			
	1-100	*101-150*	*all*	*1-100*	*100-110*	*110-120*	*120-130*	*130-140*	*140-150*	*all*	*1-50*	*51-100*	*101-150*	*all*
FT	0.0	24.9	8.3	0.0	0.0	0.0	0.0	0.0	16.6	1.1	0.0	0.0	22.0	7.3
LwF [1]	21.1	25.6	22.6	0.1	0.0	0.4	2.6	4.6	16.9	1.7	5.7	12.9	22.8	13.9
LwF-MC [5]	34.2	10.5	26.3	18.7	2.5	8.7	4.1	6.5	5.1	14.3	27.8	7.0	10.4	15.1
ILT [6]	22.9	18.9	21.6	0.3	0.0	1.0	2.1	4.6	10.7	1.4	8.4	9.7	14.3	10.8
MiB	**37.9**	**27.9**	**34.6**	**31.8**	**10.4**	**14.8**	**12.8**	**13.6**	**18.7**	**25.9**	**35.5**	**22.2**	**23.6**	**27.0**
Joint	44.3	28.2	38.9	44.3	26.1	42.8	26.7	28.1	17.3	38.9	51.1	38.3	28.2	38.9

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

	100-50			100-10							50-50			
Method	*1-100*	*101-150*	*all*	*1-100*	*100-110*	*110-120*	*120-130*	*130-140*	*140-150*	*all*	*1-50*	*51-100*	*101-150*	*all*
FT	0.0	24.9	8.3	0.0	0.0	0.0	0.0	0.0	16.6	1.1	0.0	0.0	22.0	7.3
LwF [1]	21.1	25.6	22.6	0.1	0.0	0.4	2.6	4.6	16.9	1.7	5.7	12.9	22.8	13.9
LwF-MC [5]	34.2	10.5	26.3	18.7	2.5	8.7	4.1	6.5	5.1	14.3	27.8	7.0	10.4	15.1
ILT [6]	22.9	18.9	21.6	0.3	0.0	1.0	2.1	4.6	10.7	1.4	8.4	9.7	14.3	10.8
MiB	**37.9**	**27.9**	**34.6**	**31.8**	**10.4**	**14.8**	**12.8**	**13.6**	**18.7**	**25.9**	**35.5**	**22.2**	**23.6**	**27.0**
Joint	44.3	28.2	38.9	44.3	26.1	42.8	26.7	28.1	17.3	38.9	51.1	38.3	28.2	38.9

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

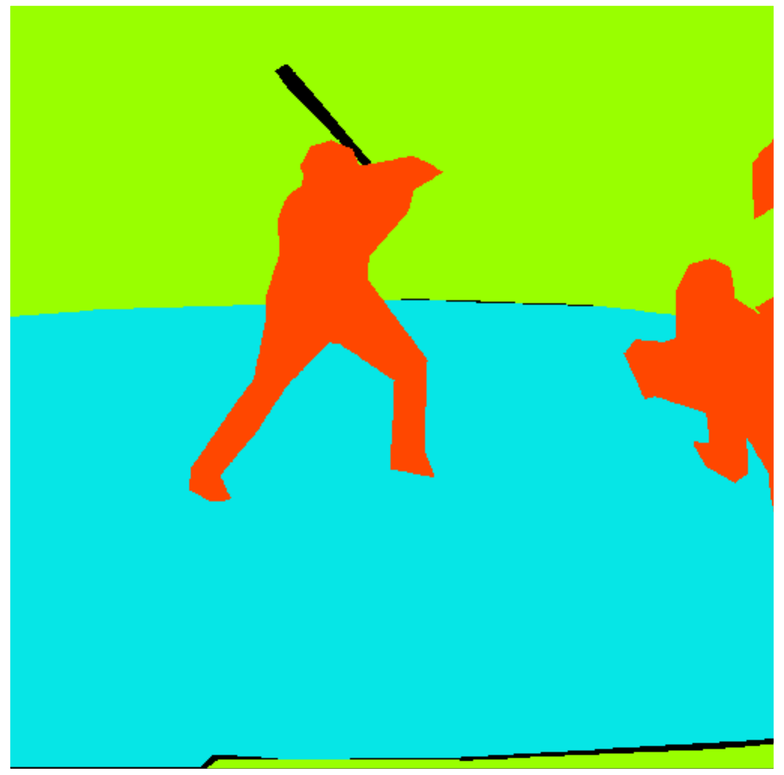
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

3 Steps of 50 Classes
Example 1

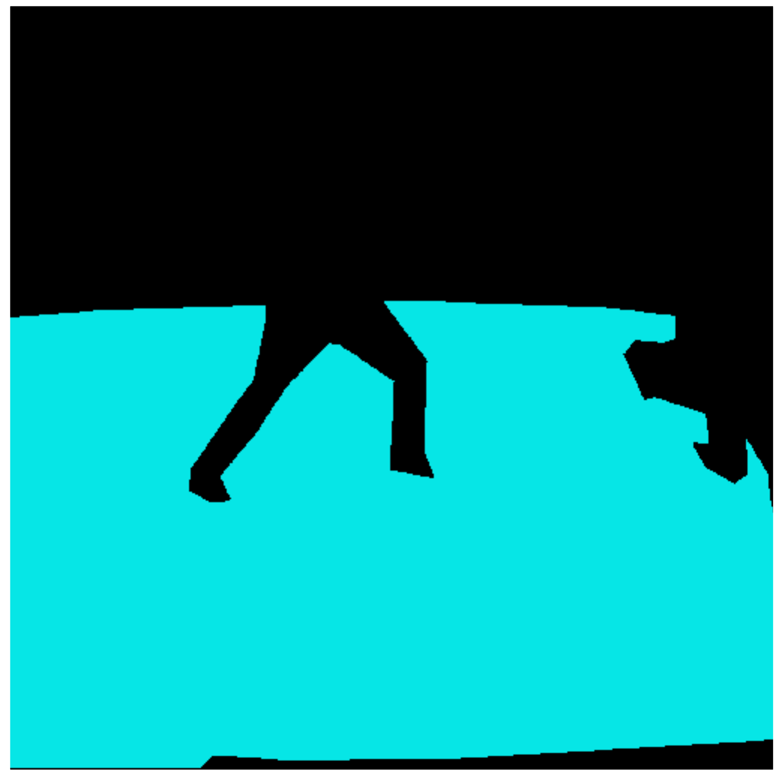


Results

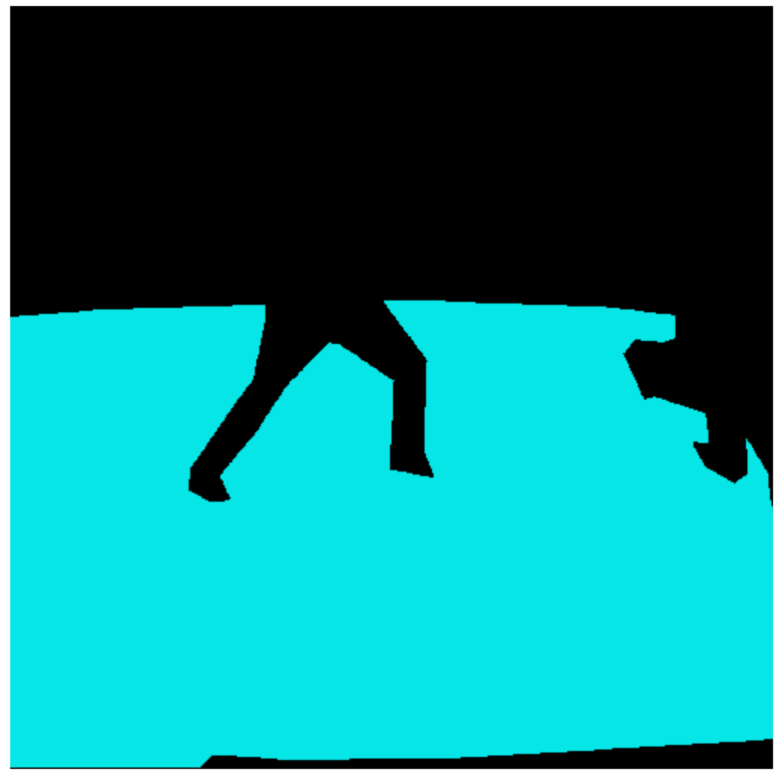
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image



Step ground truth



Known classes

50 classes - Step 0

FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

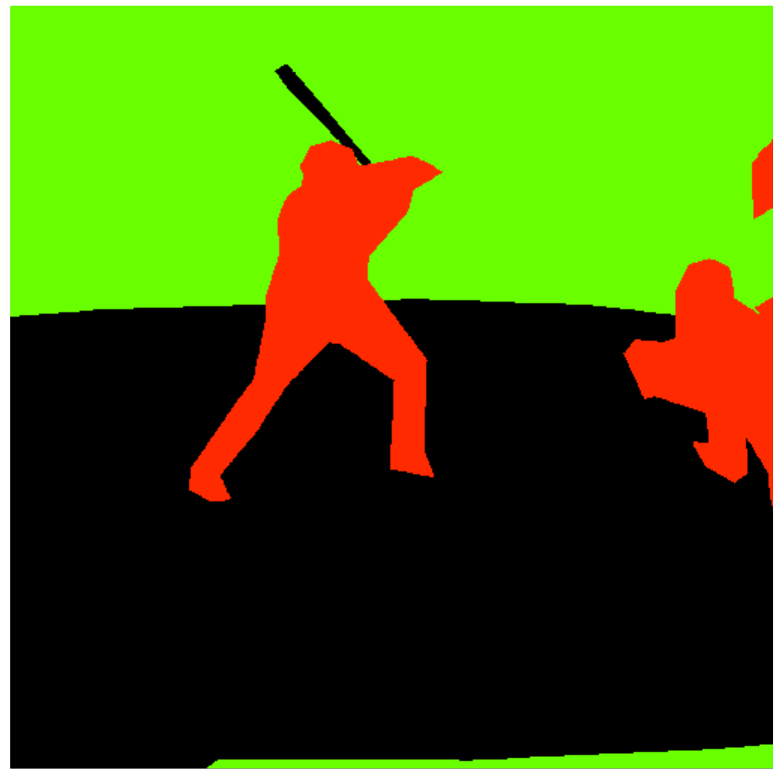
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

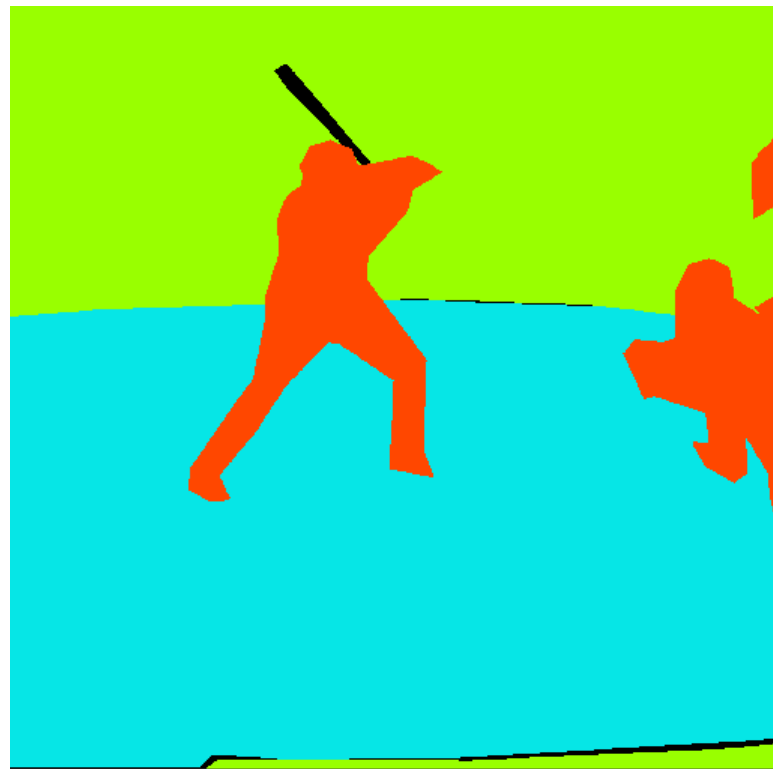
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image



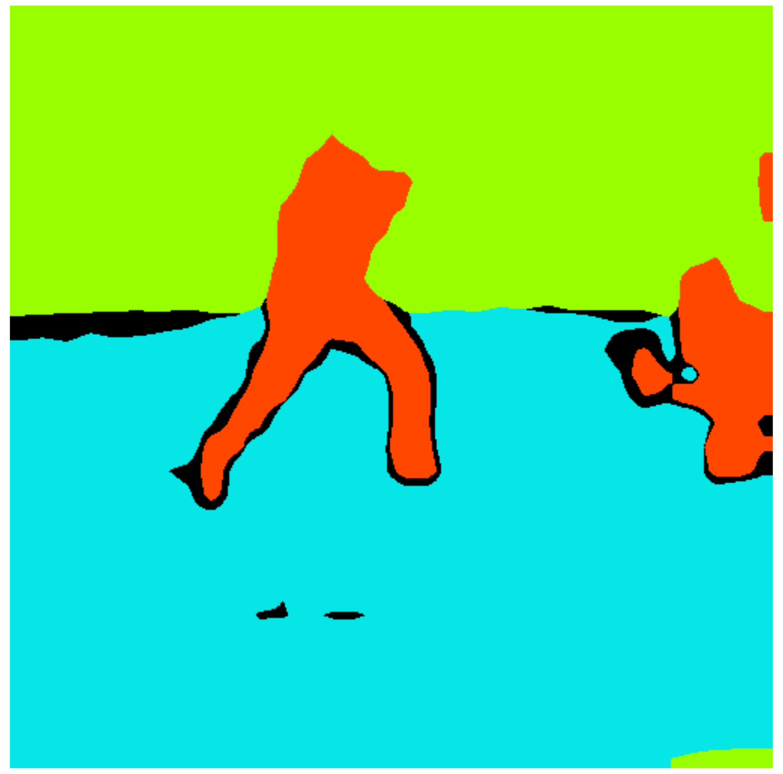
Step ground truth



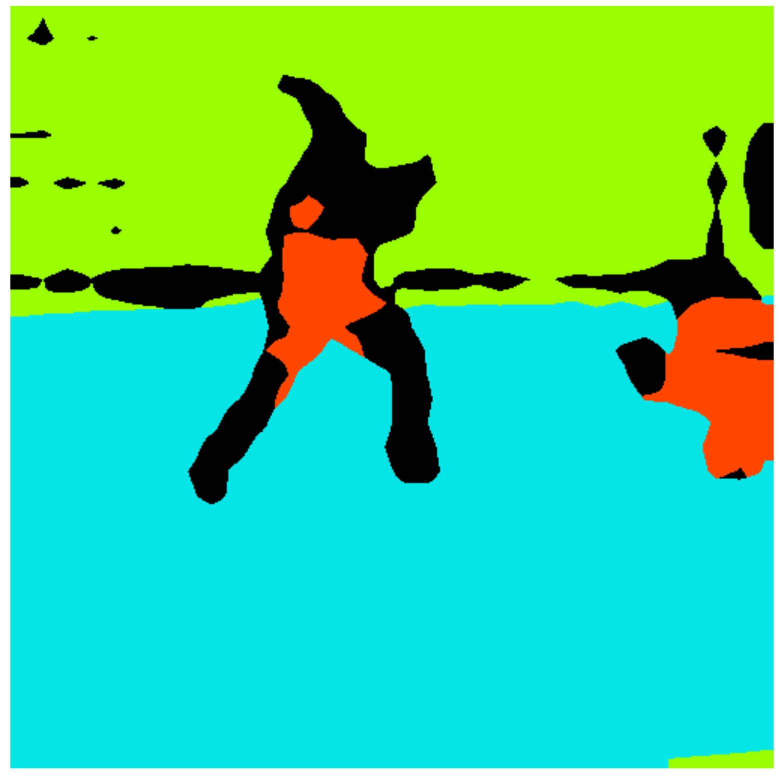
Known classes

50 classes - Step 1

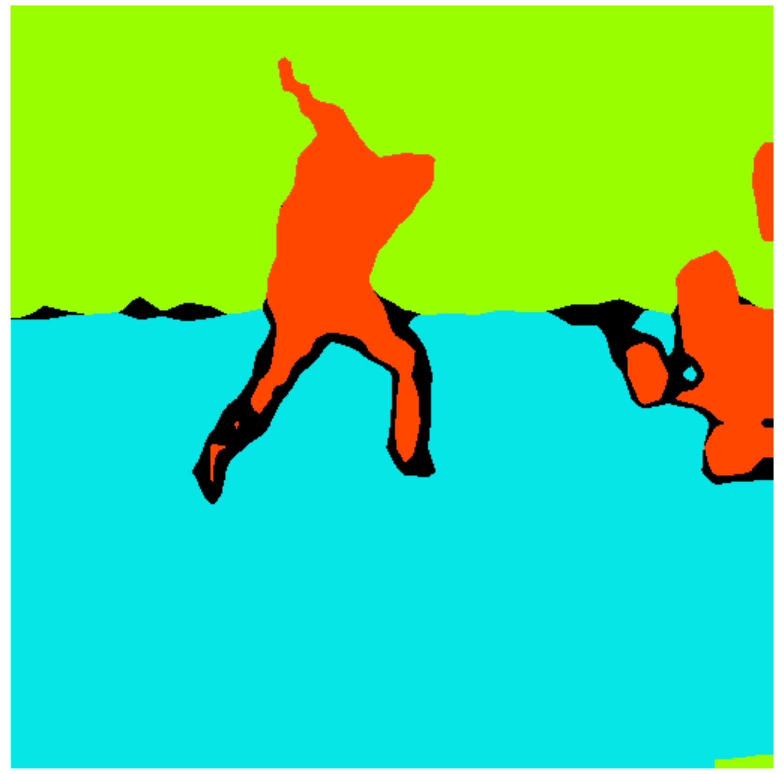
FT



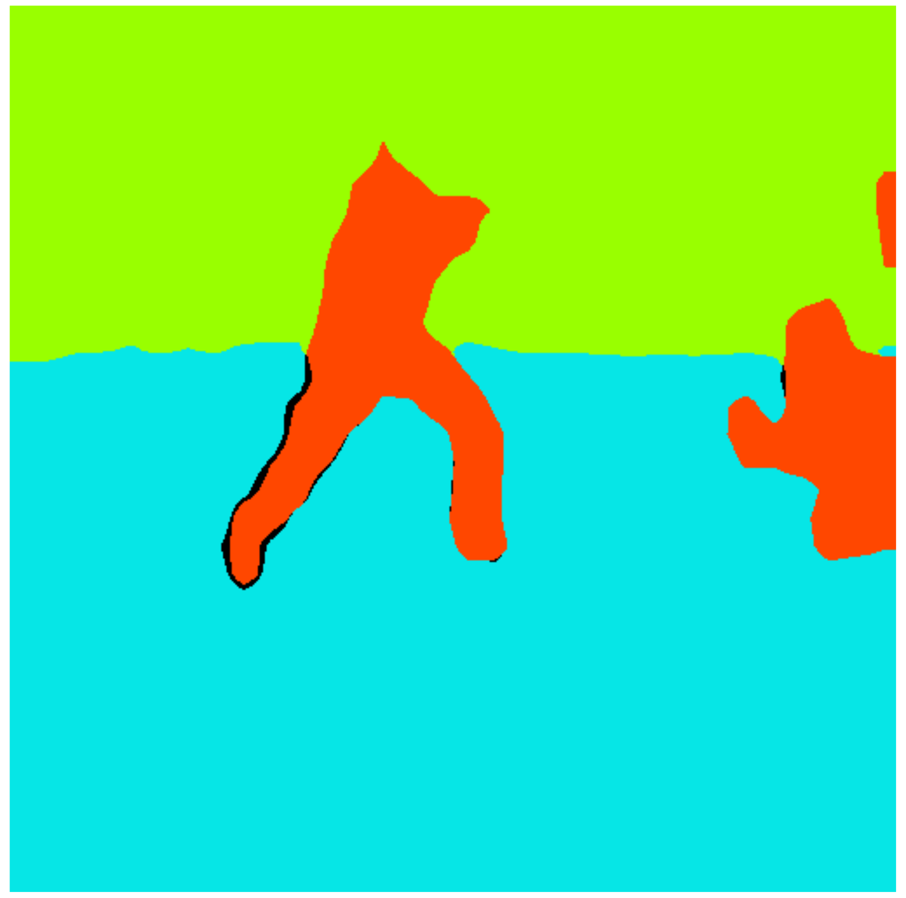
LwF [1]



LwF-MC [5]



ILT [6]



MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

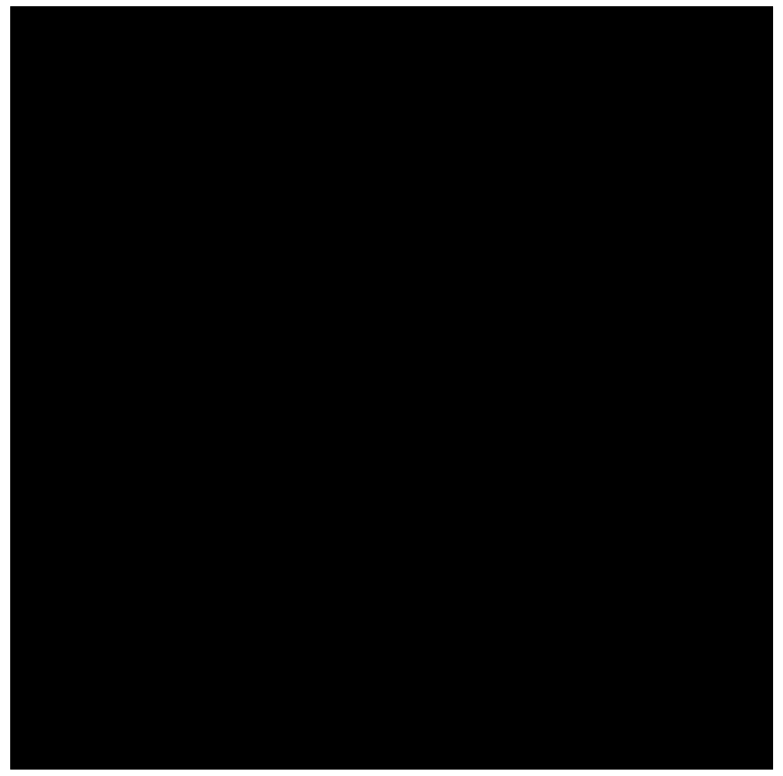
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

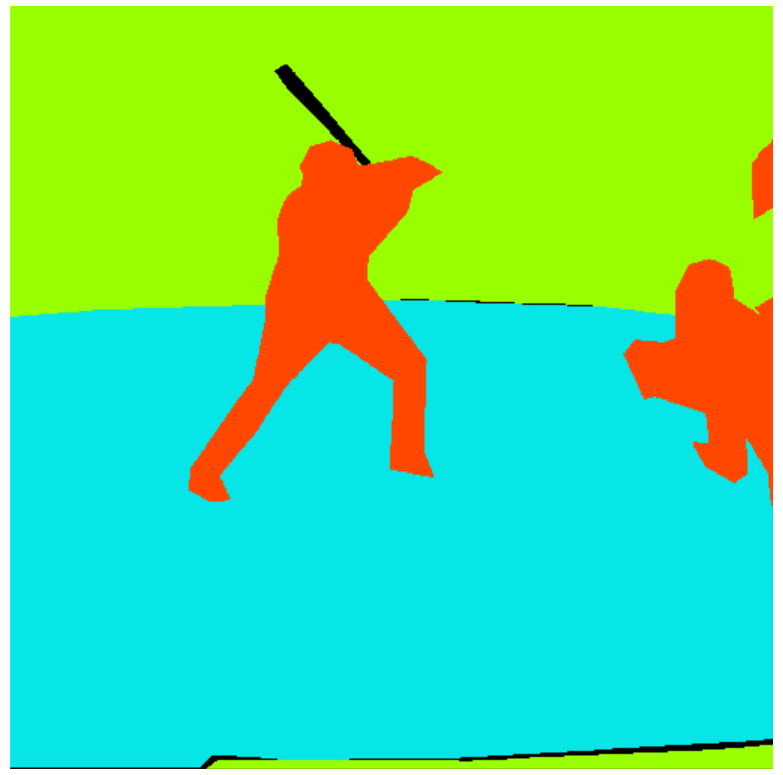
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

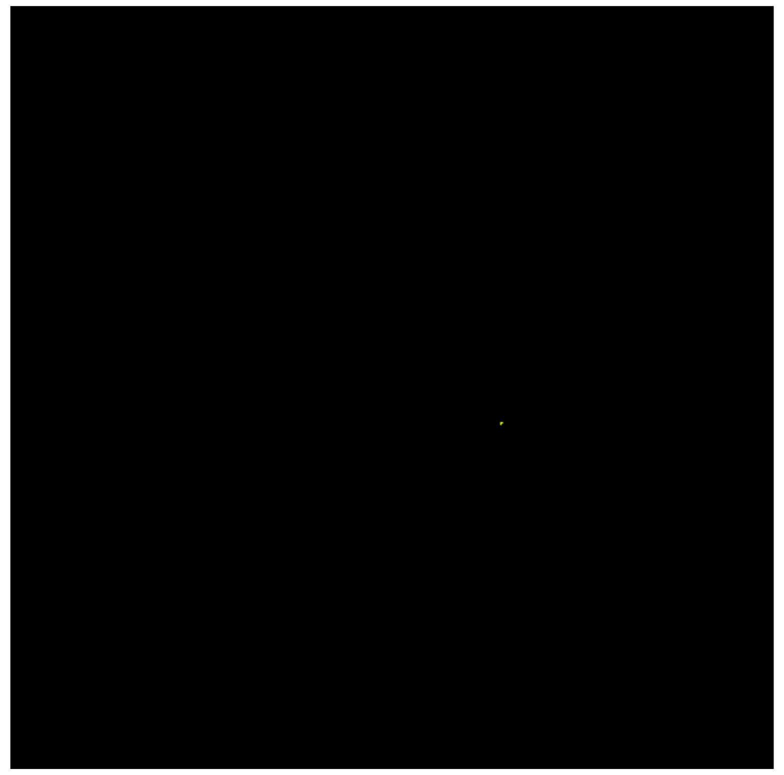


Step ground truth



Known classes

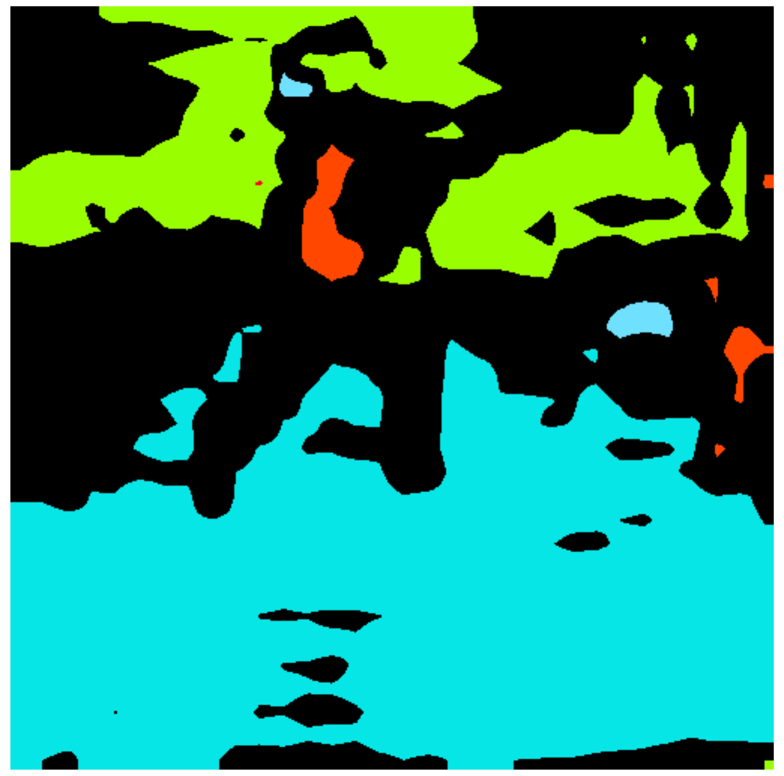
50 classes - Step 2



FT

LwF [1]

LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

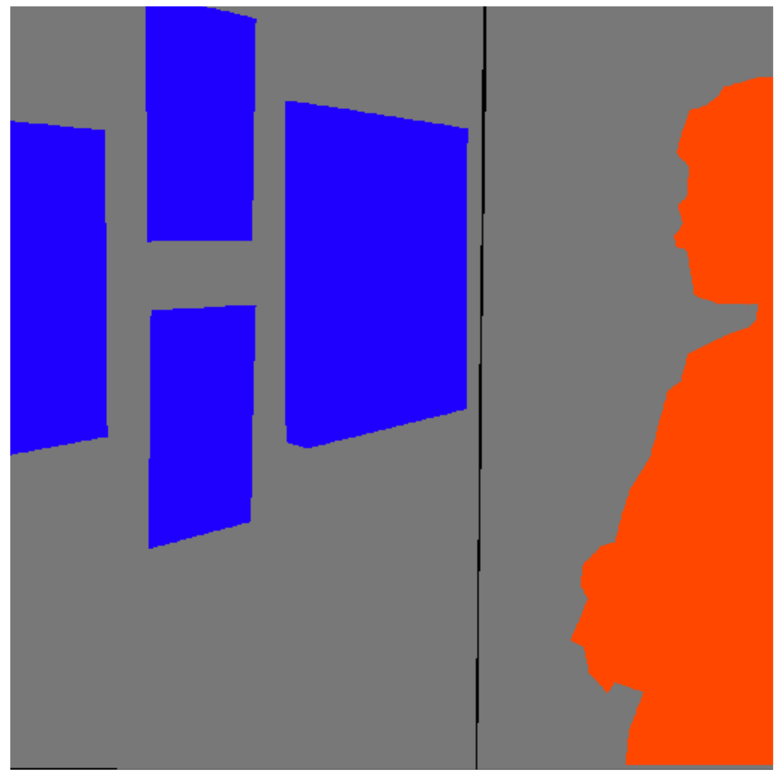
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

3 Steps of 50 Classes
Example 2



Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

Step ground truth

Known classes

50 classes - Step 0

FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

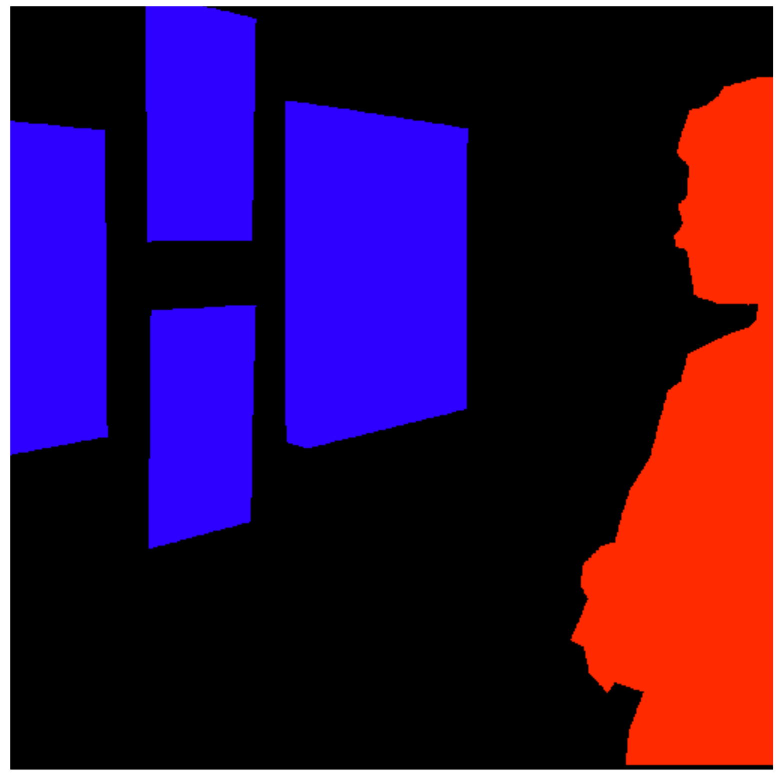
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

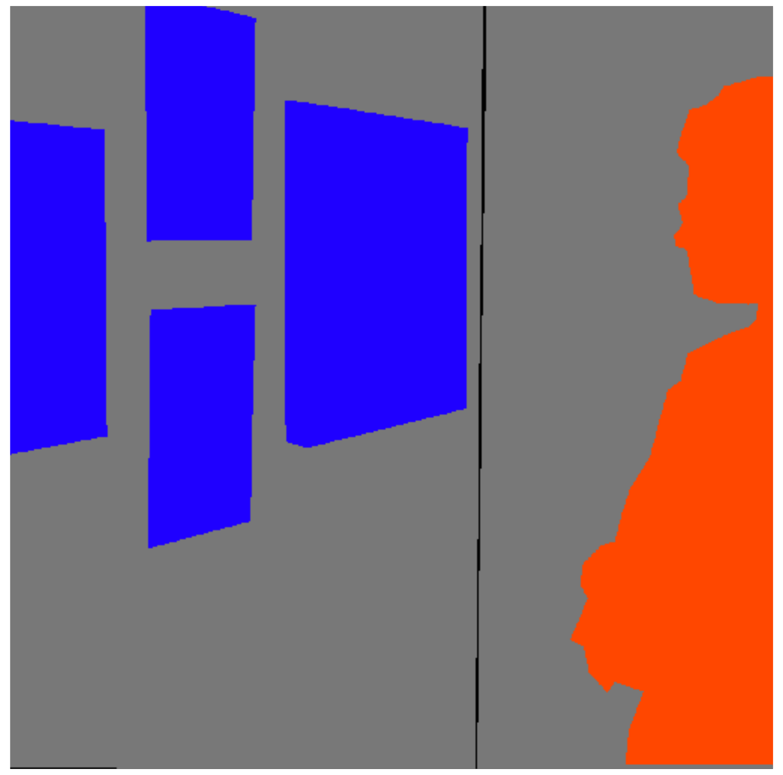
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image



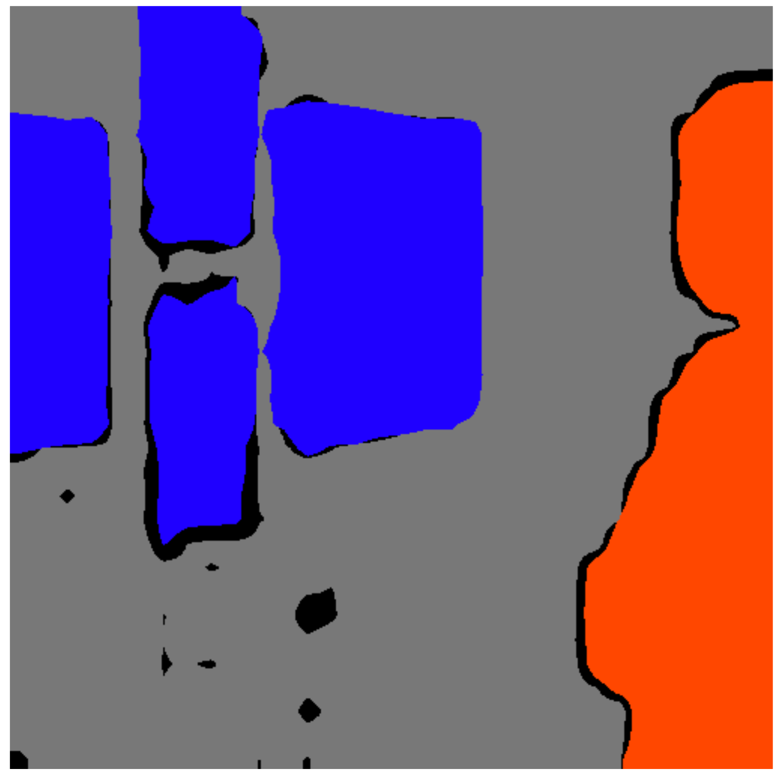
Step ground truth



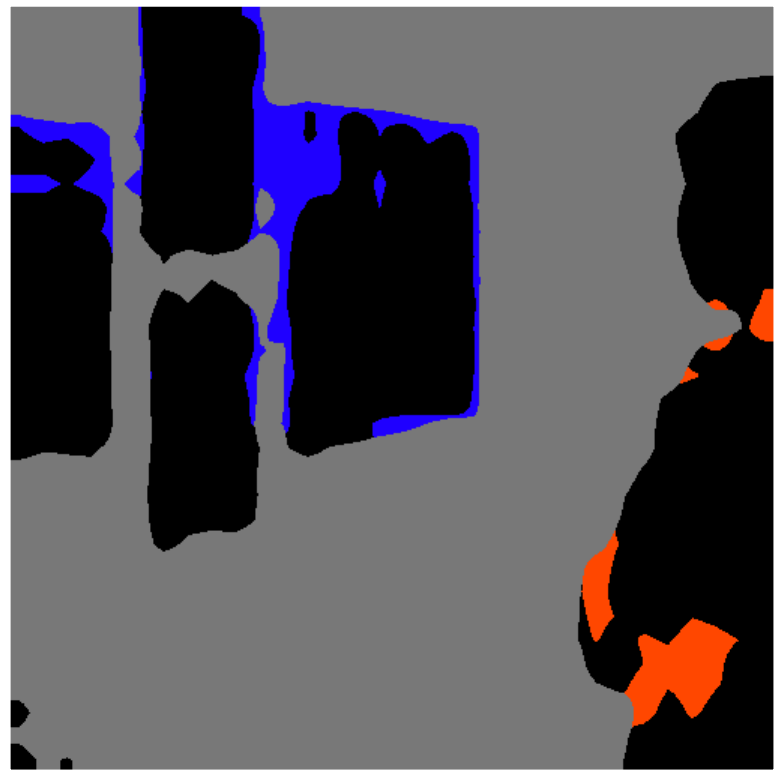
Known classes

50 classes - Step 1

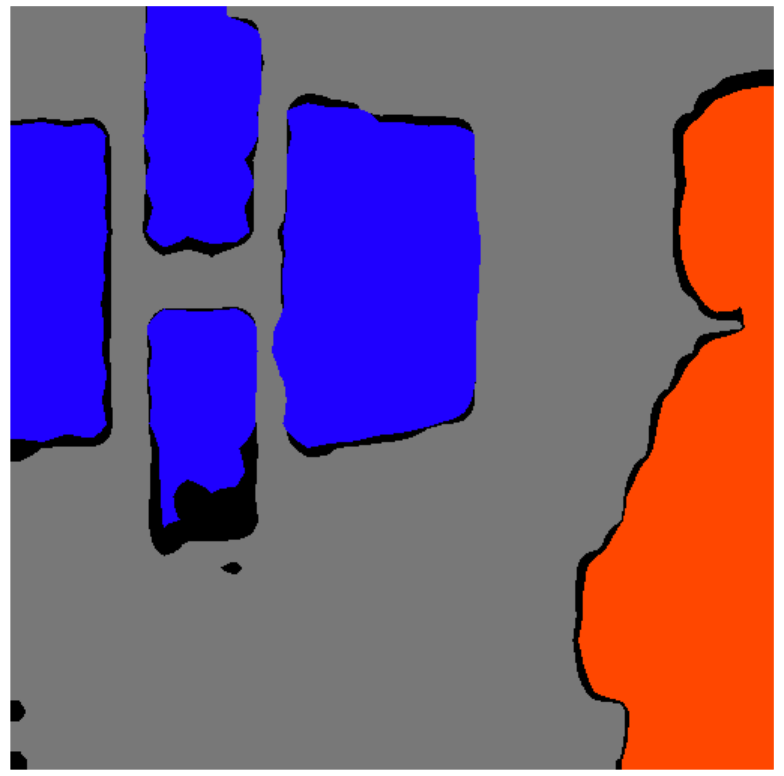
FT



LwF [1]



LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

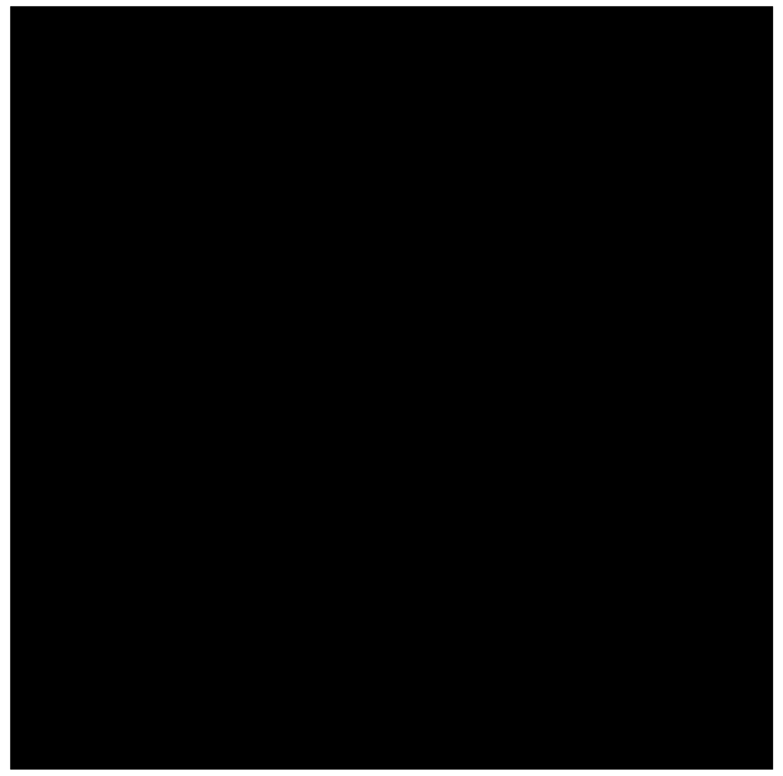
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

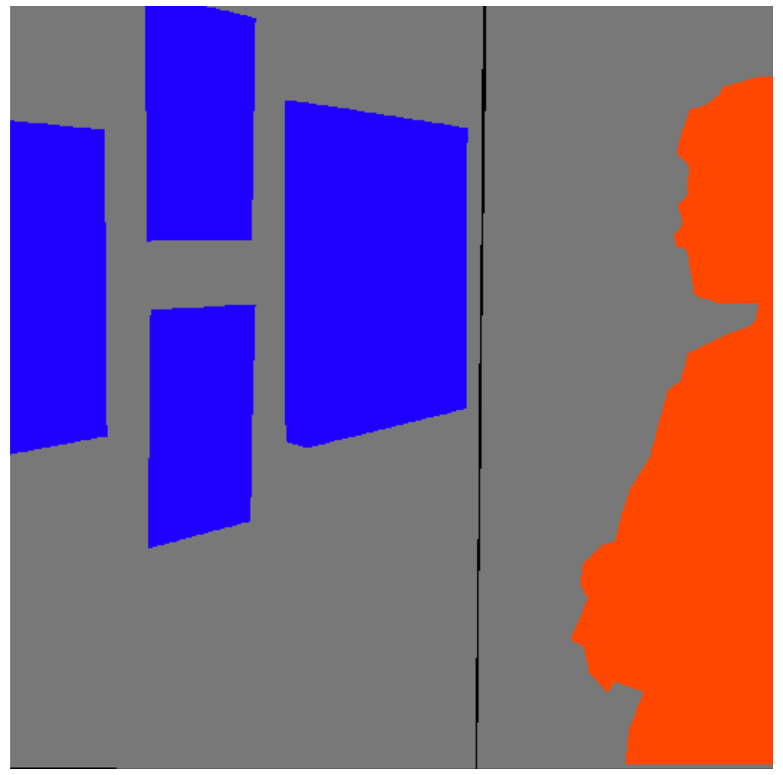
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image



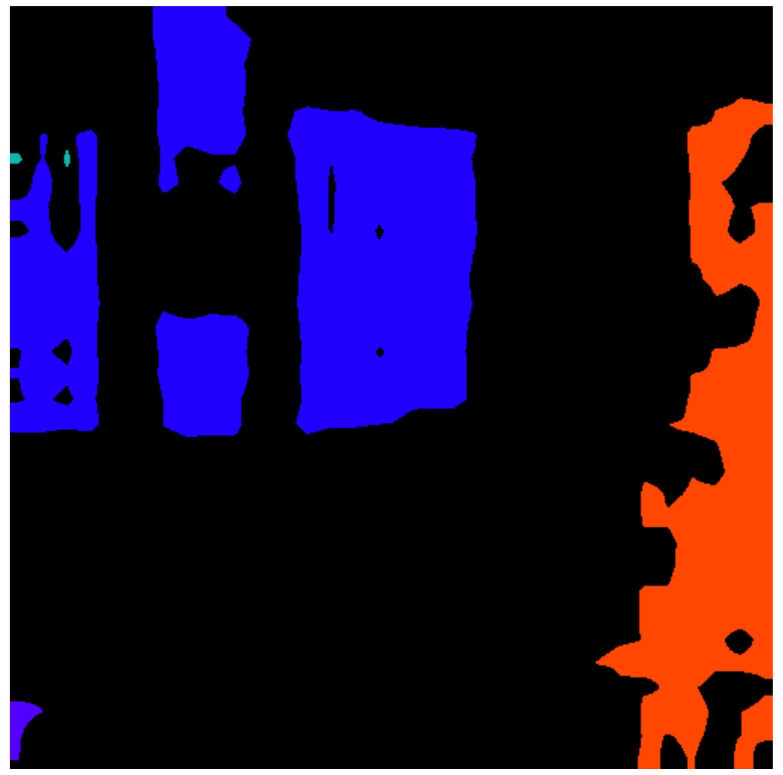
Step ground truth



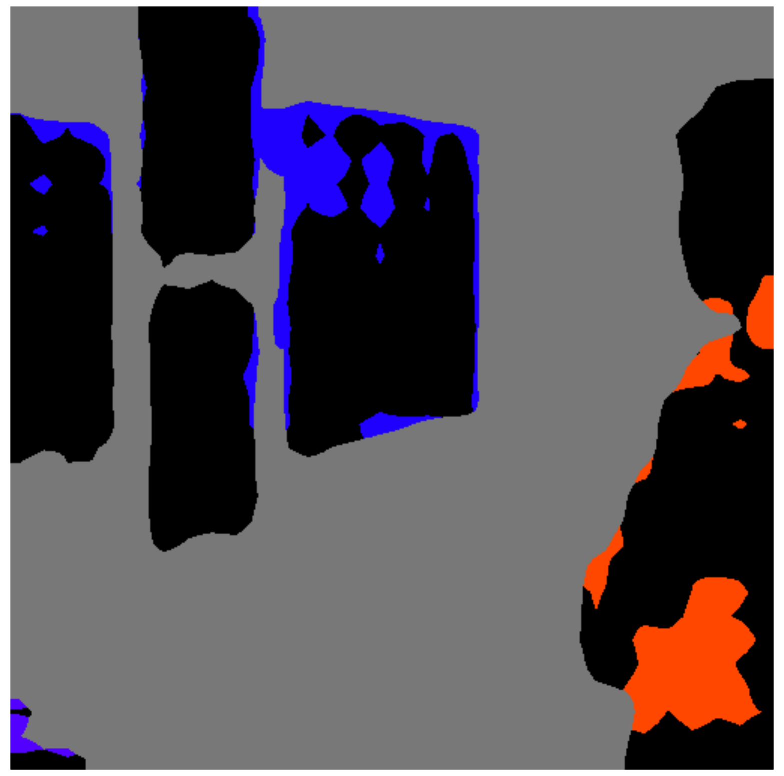
Known classes

50 classes - Step 2

FT



LwF [1]



LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

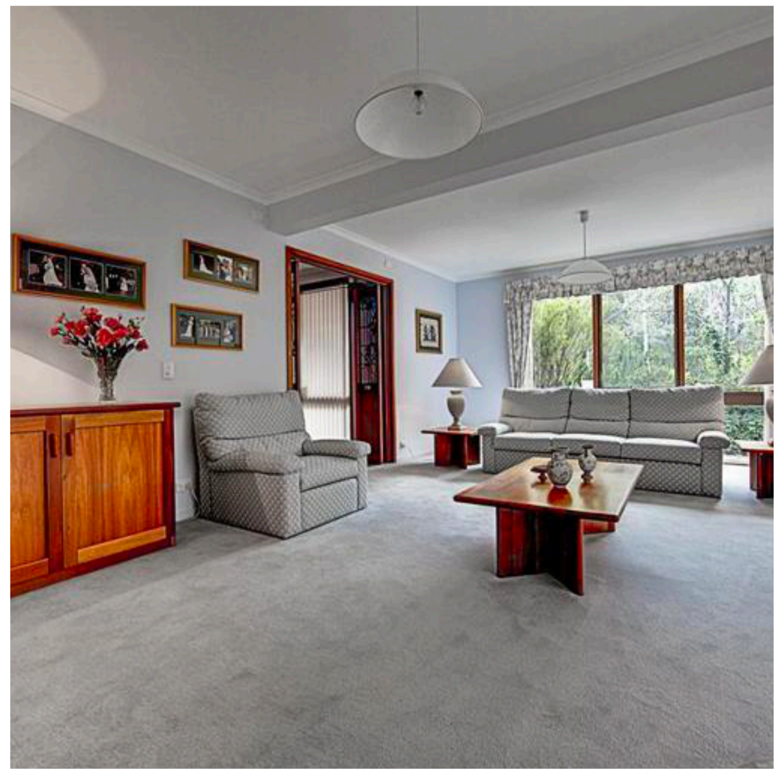
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

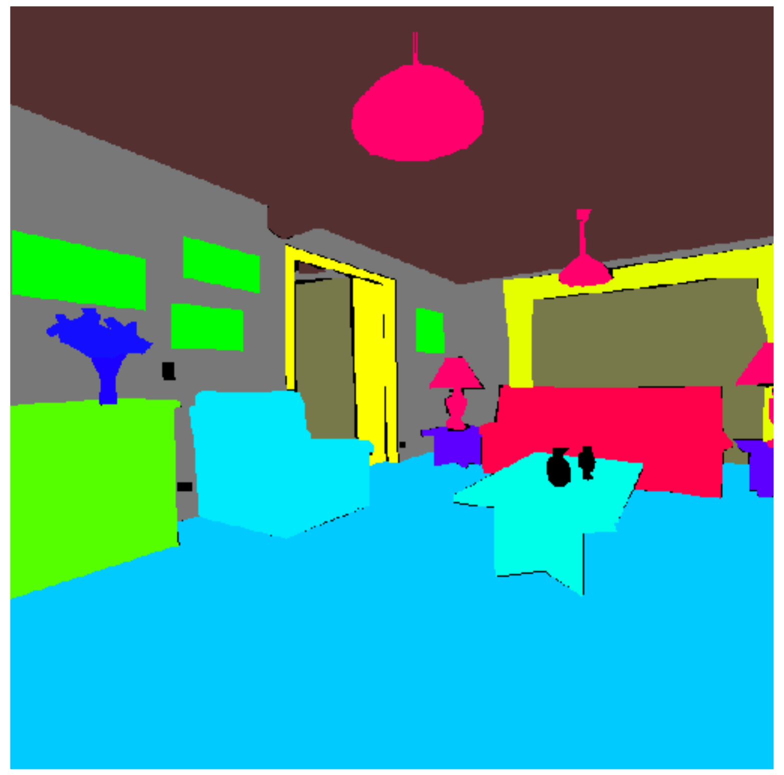
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

1 Step of 100 classes and 5 Steps of 10 Classes
Example 1

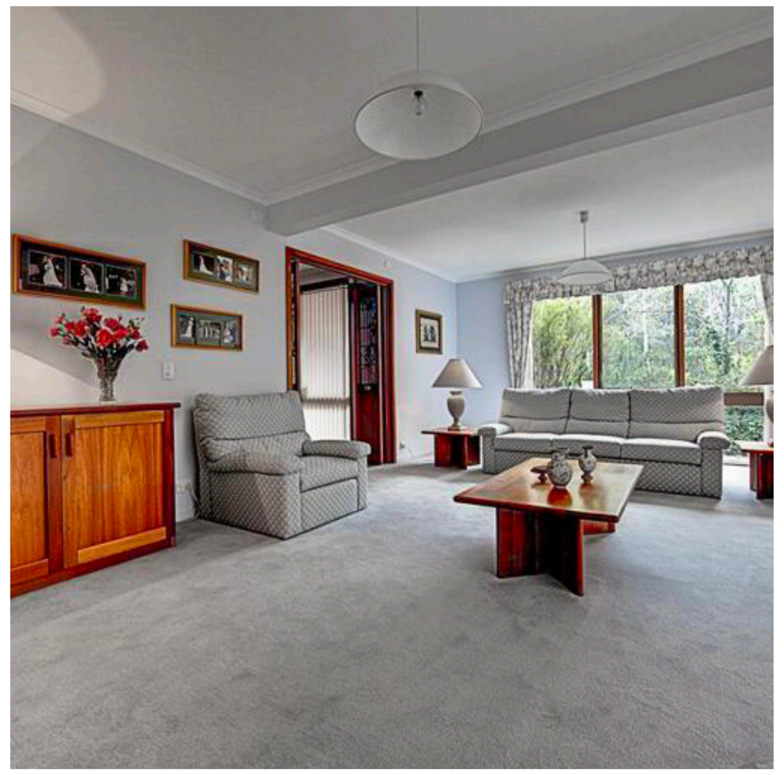




Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.



Image

Step ground truth

Known classes

100-10 classes - Step 0

FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

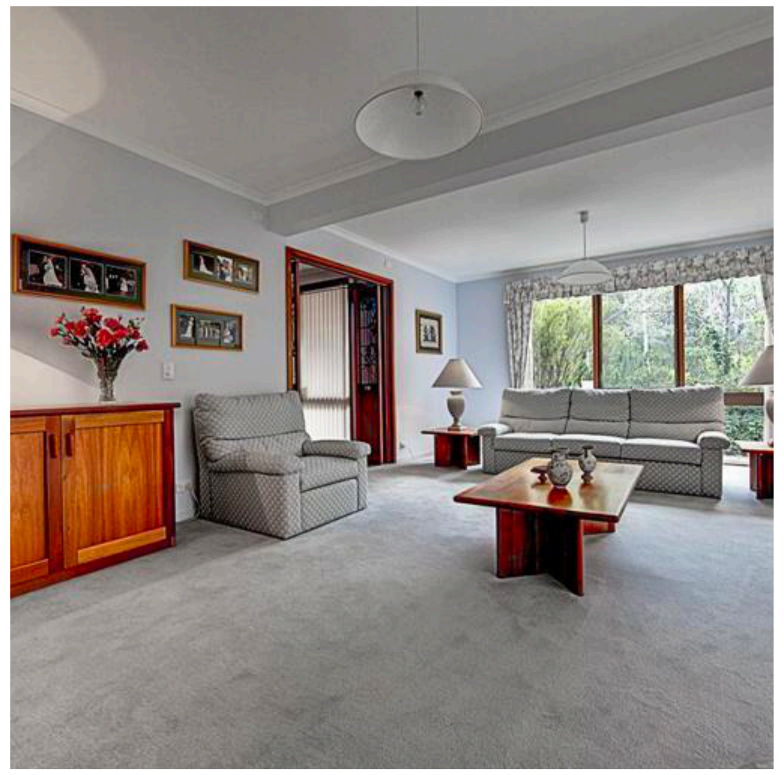
[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

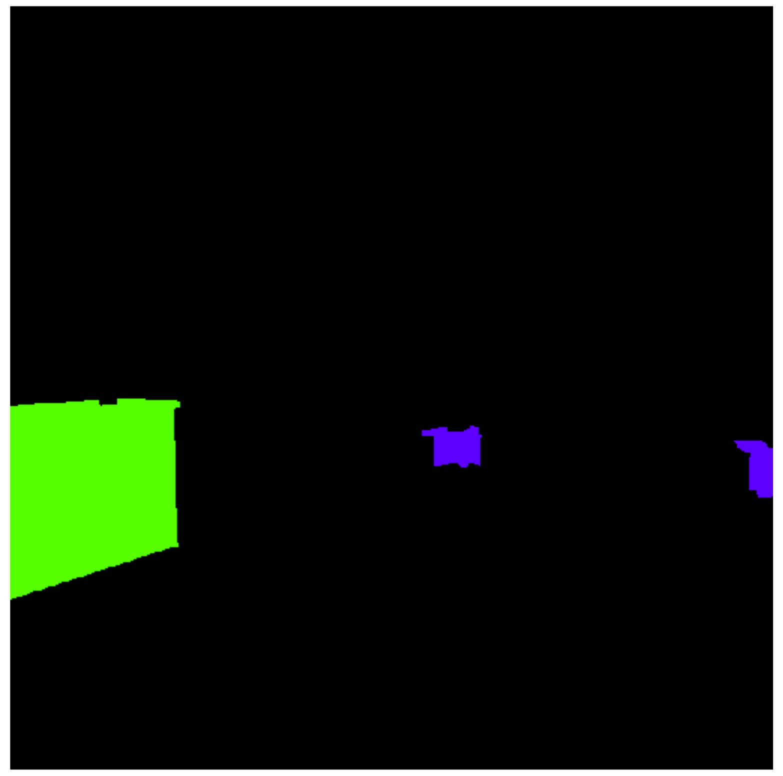
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.



Image

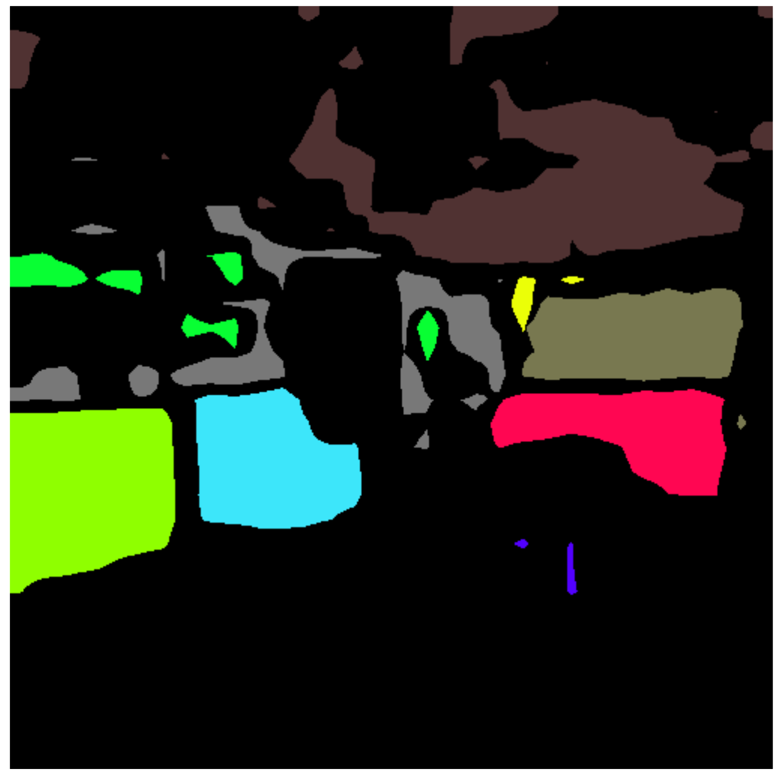


Step ground truth

Known classes

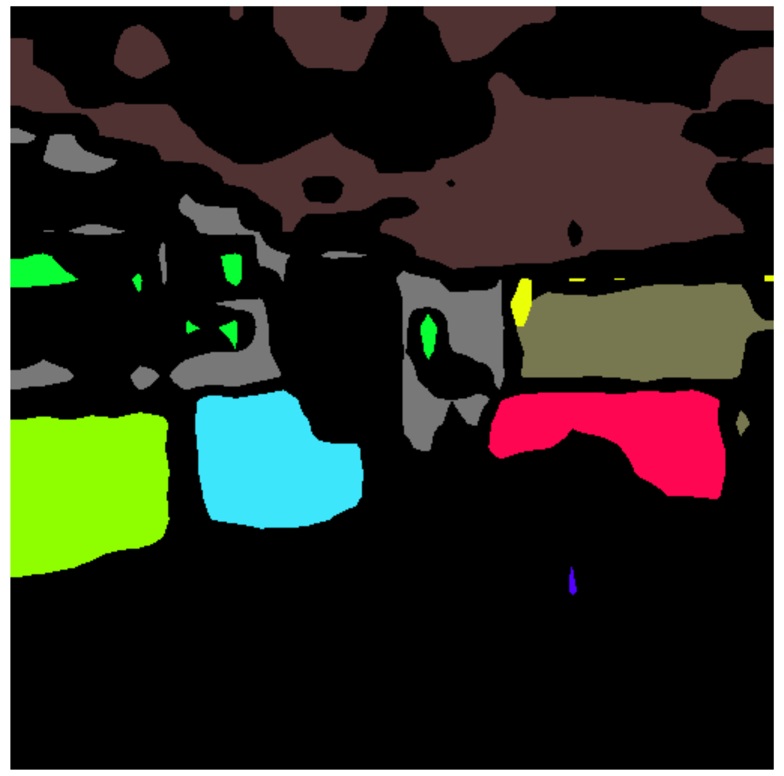
***100-10 classes* - Step 1**

FT



LwF [1]

LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

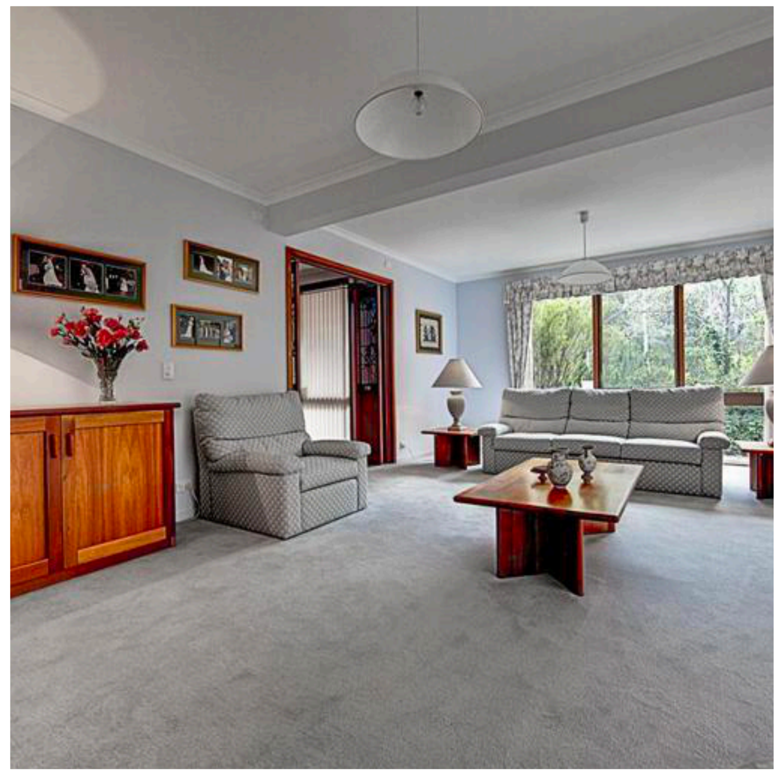
[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

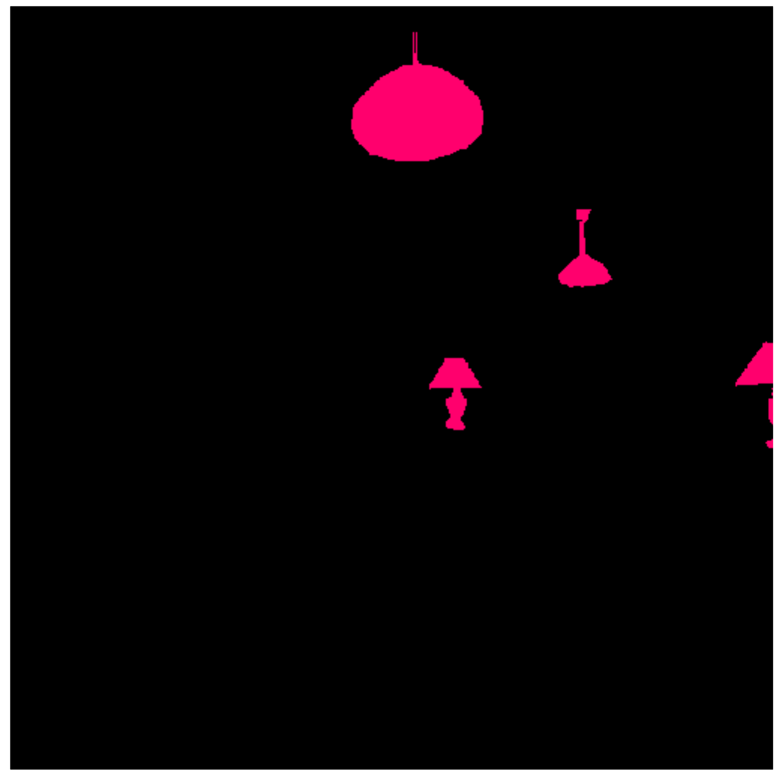
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.



Image

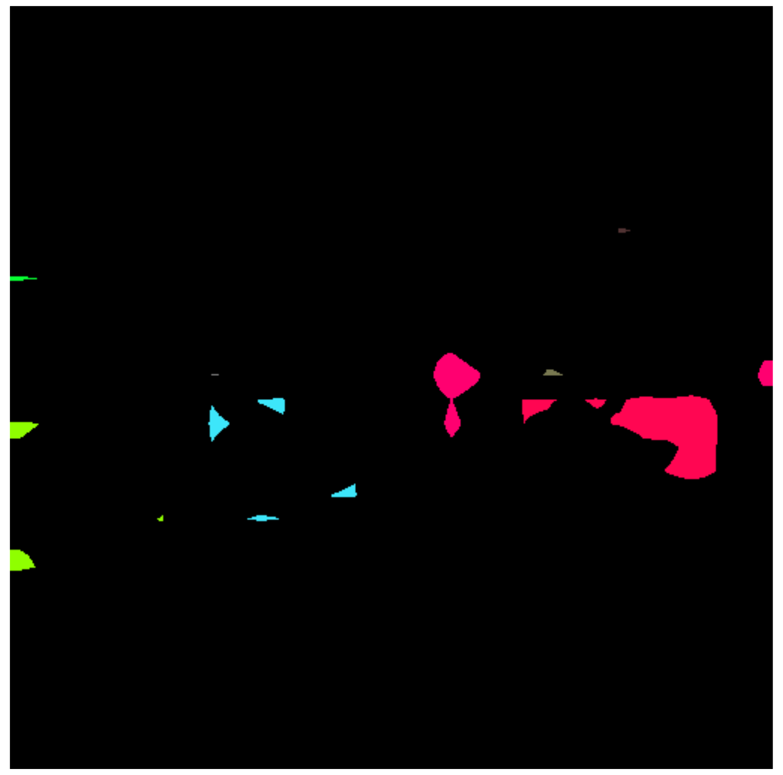


Step ground truth

Known classes

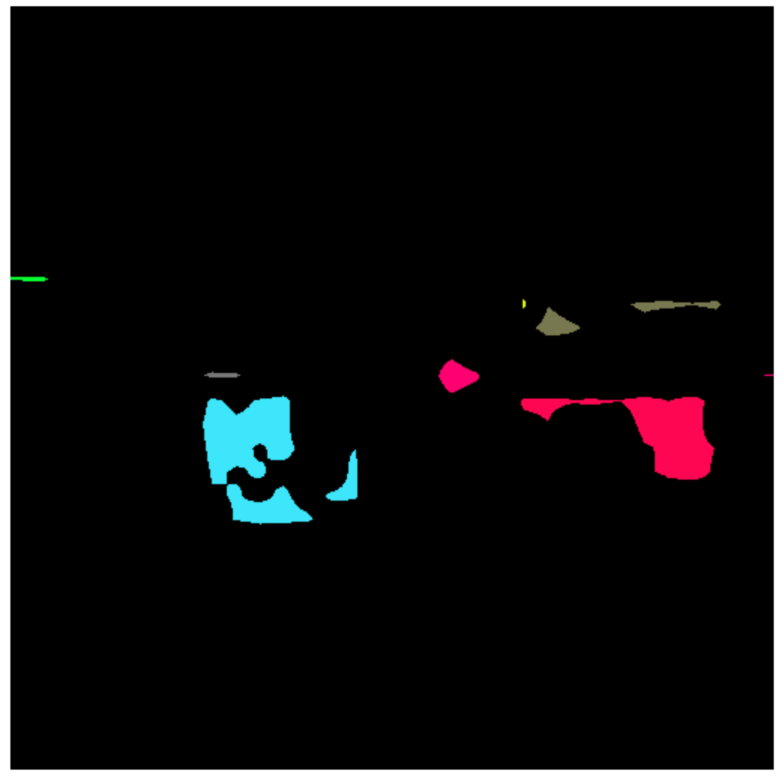
100-10 classes - Step 2

FT



LwF [1]

LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

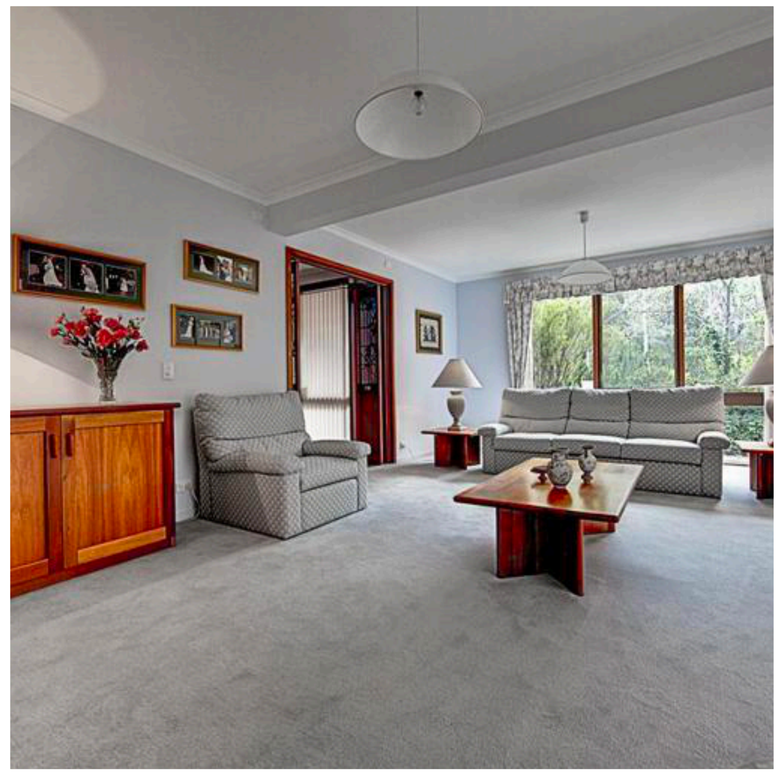
[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

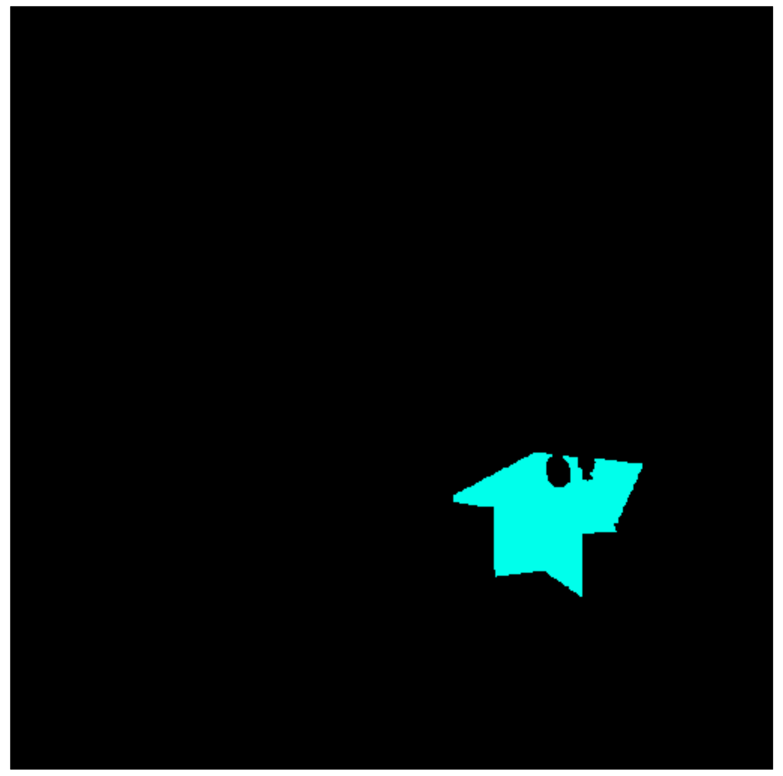
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.



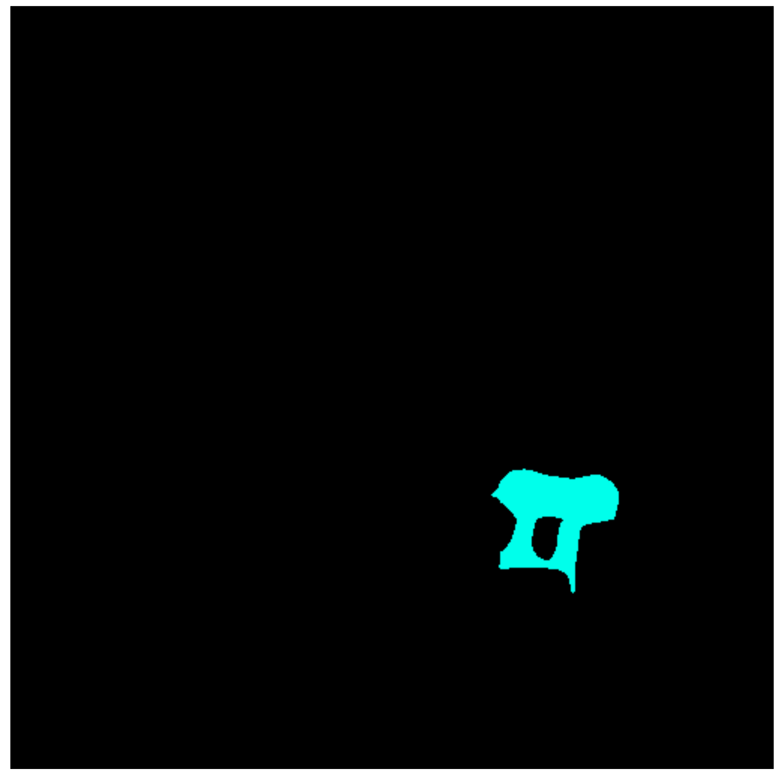
Image



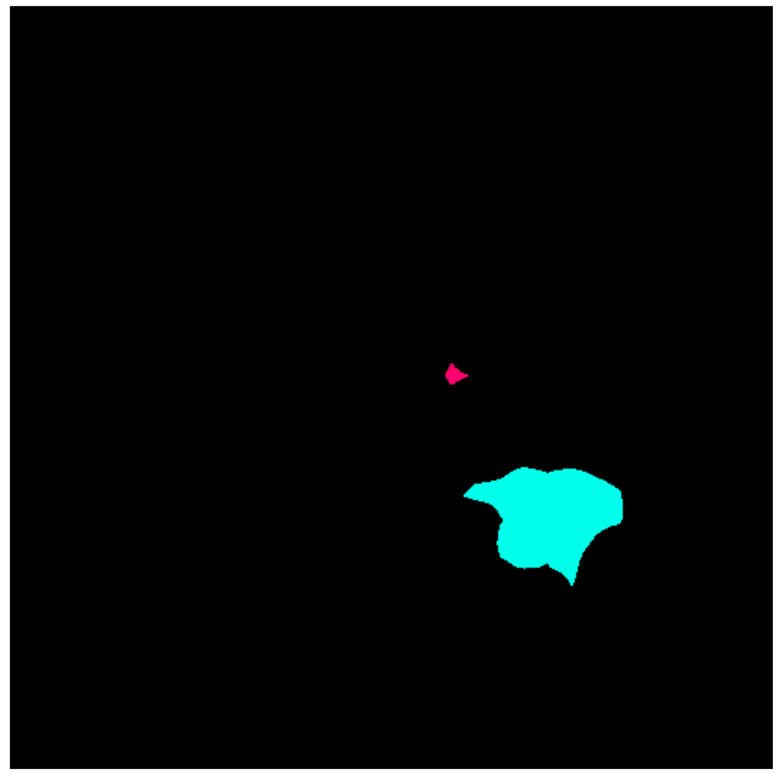
Step ground truth

Known classes

100-10 classes - Step 3



FT



LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

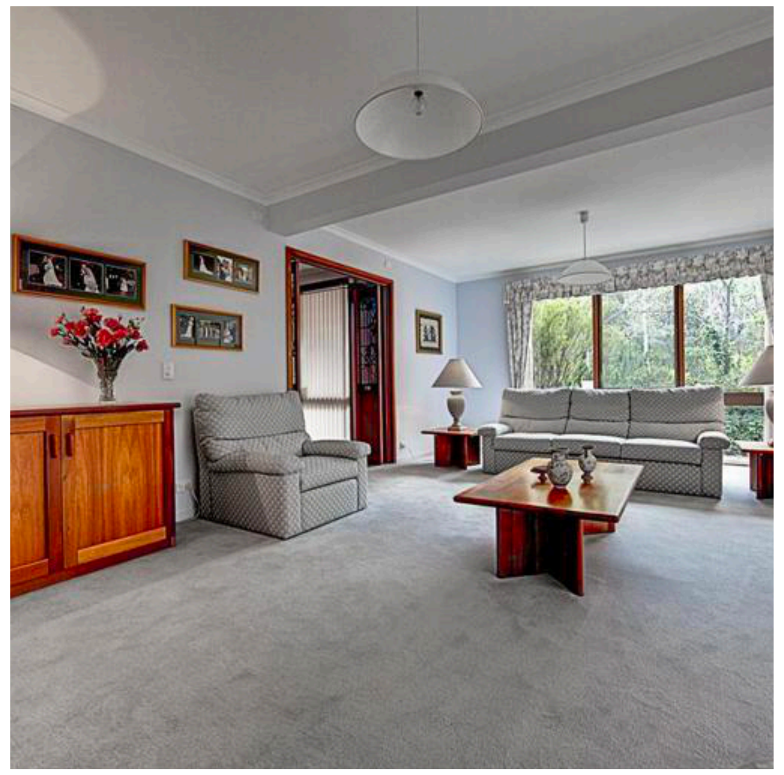
[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

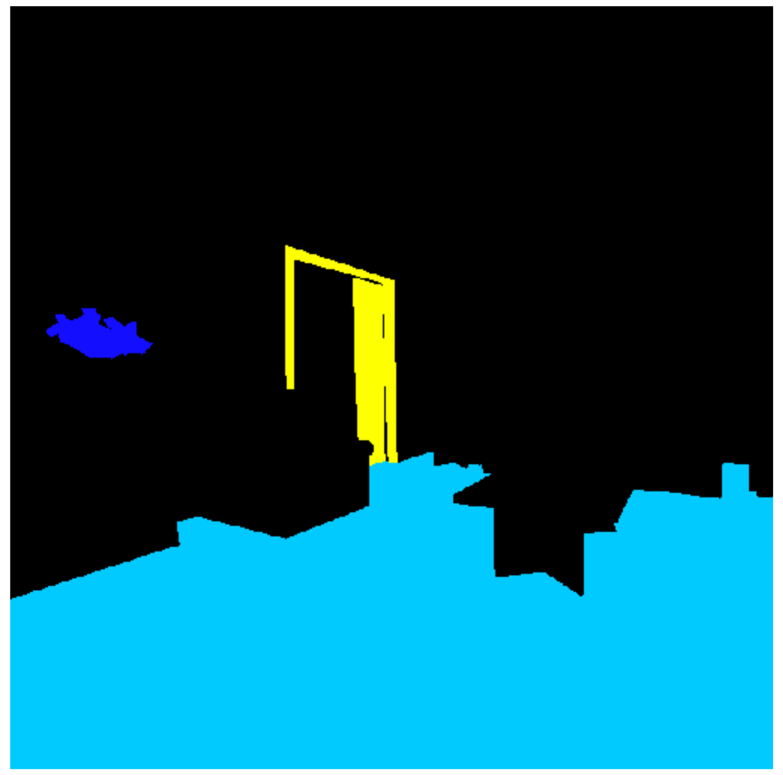
Results

ADE 20K

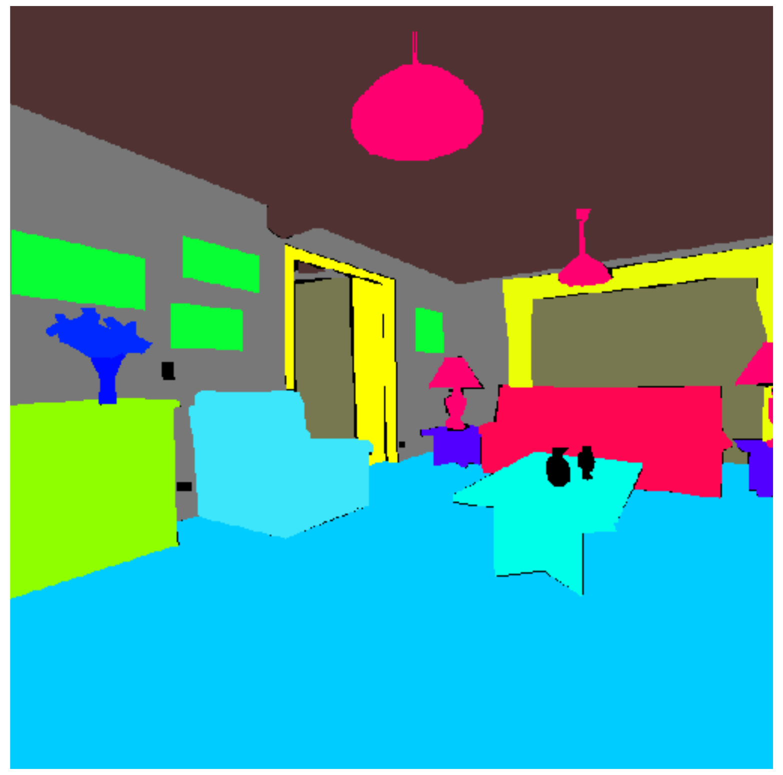
B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.



Image



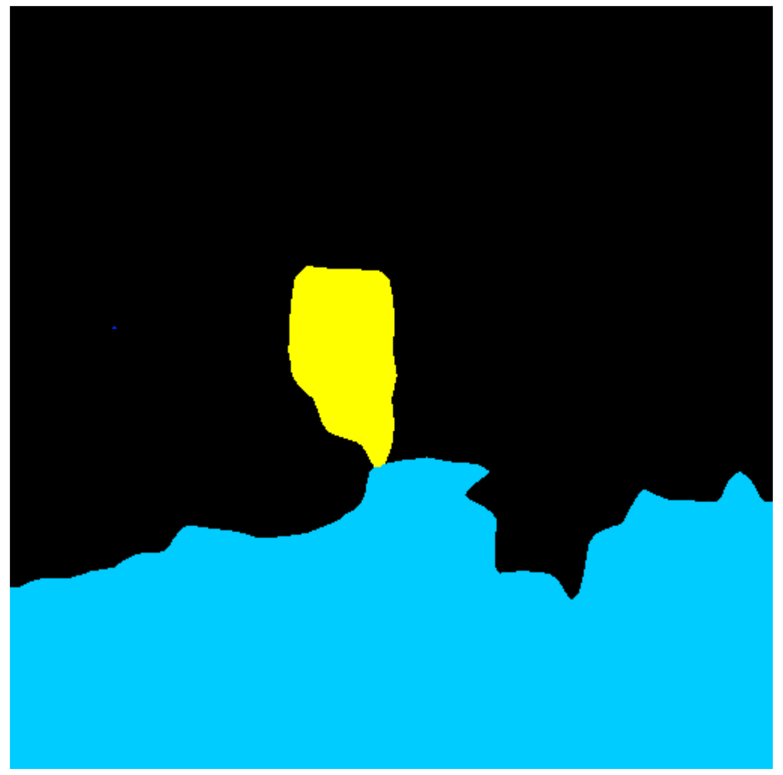
Step ground truth



Known classes

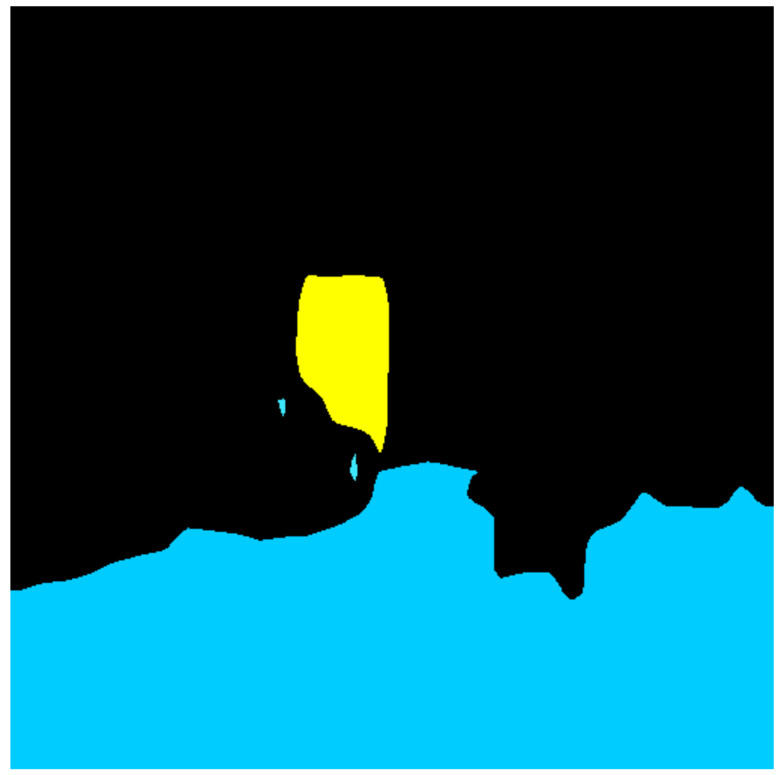
100-10 classes **- Step 4**

FT



LwF [1]

LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

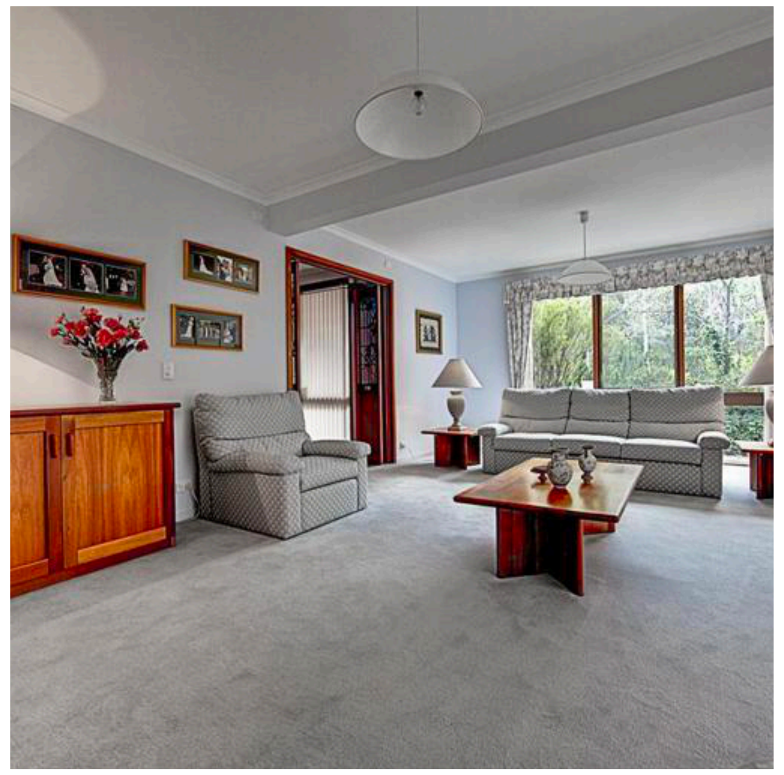
[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

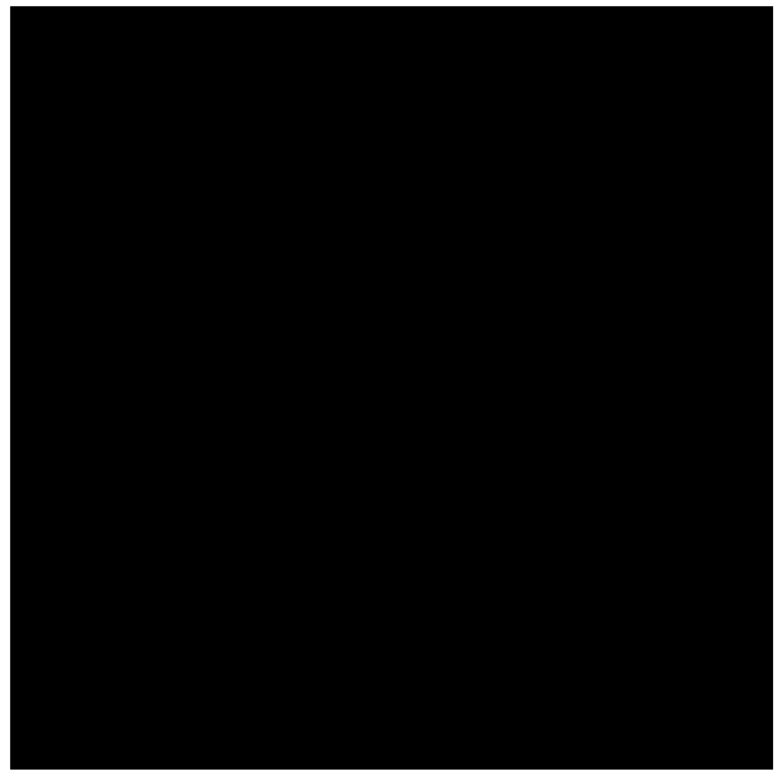
Results

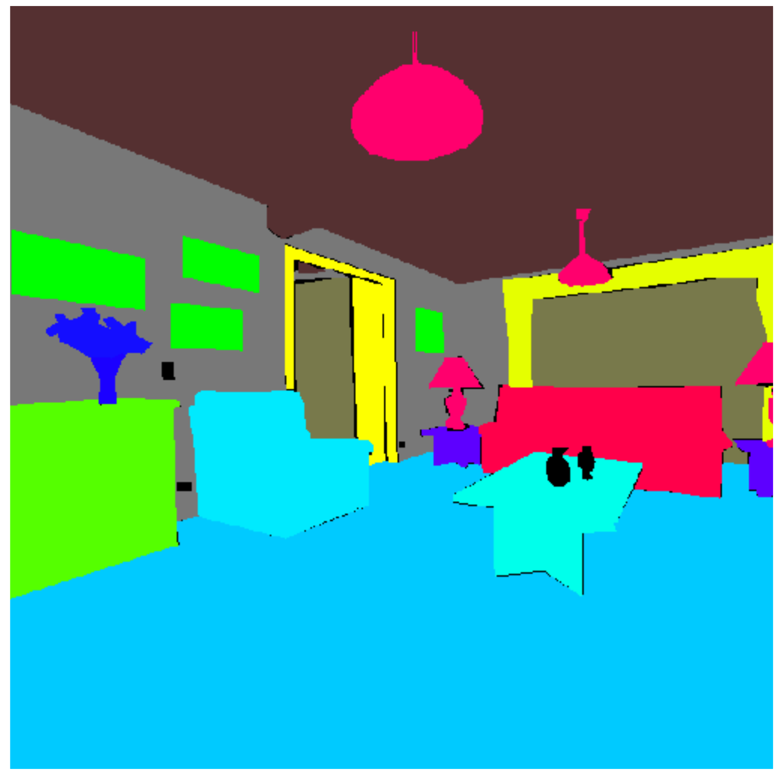
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

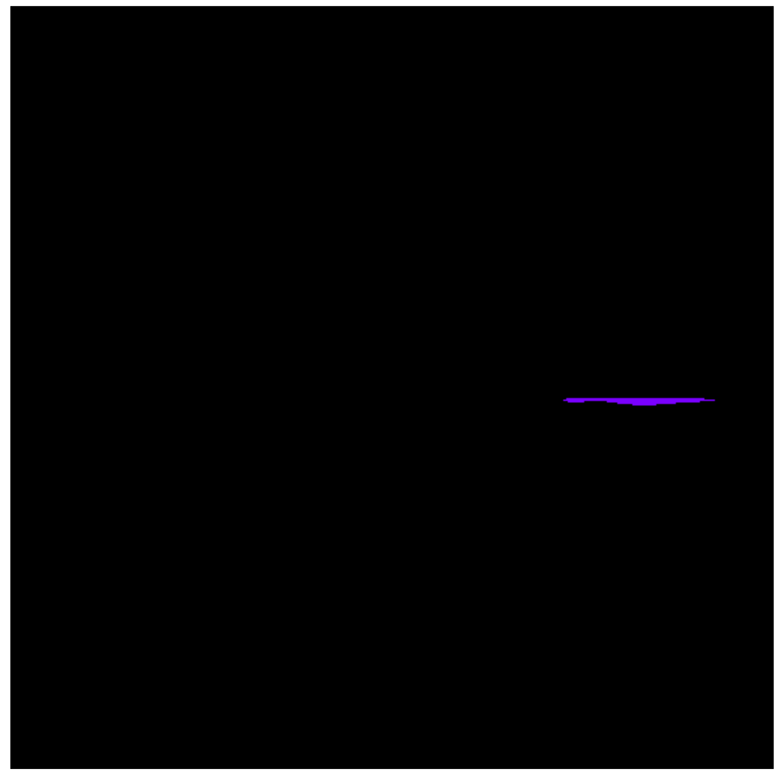


Image

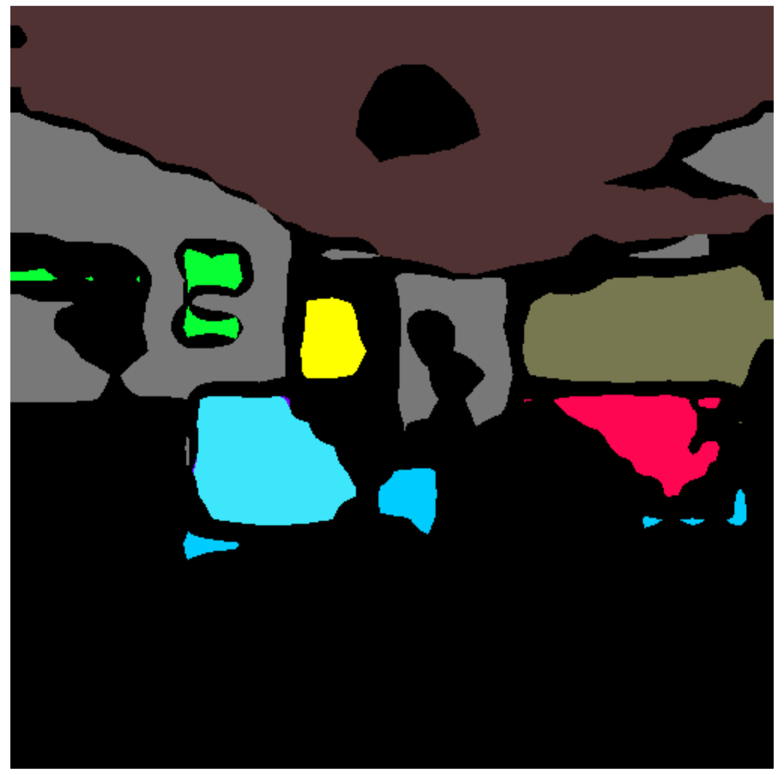

Step ground truth

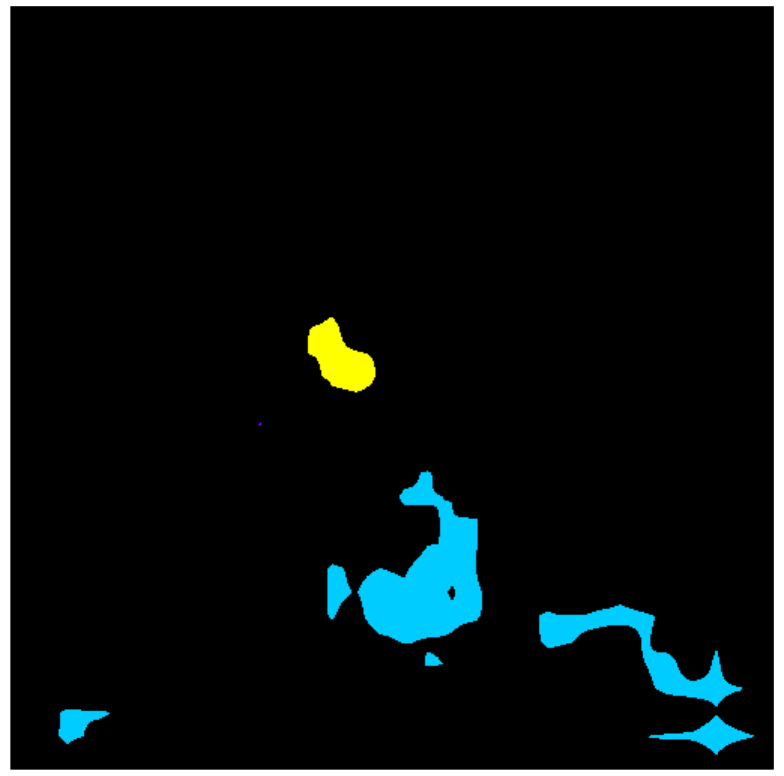

Known classes

100-10 classes - Step 5


FT


LwF [1]


LwF-MC [5]


ILT [6]


MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

1 Step of 100 classes and 5 Steps of 10 Classes
Example 2

Results

ADE 20K

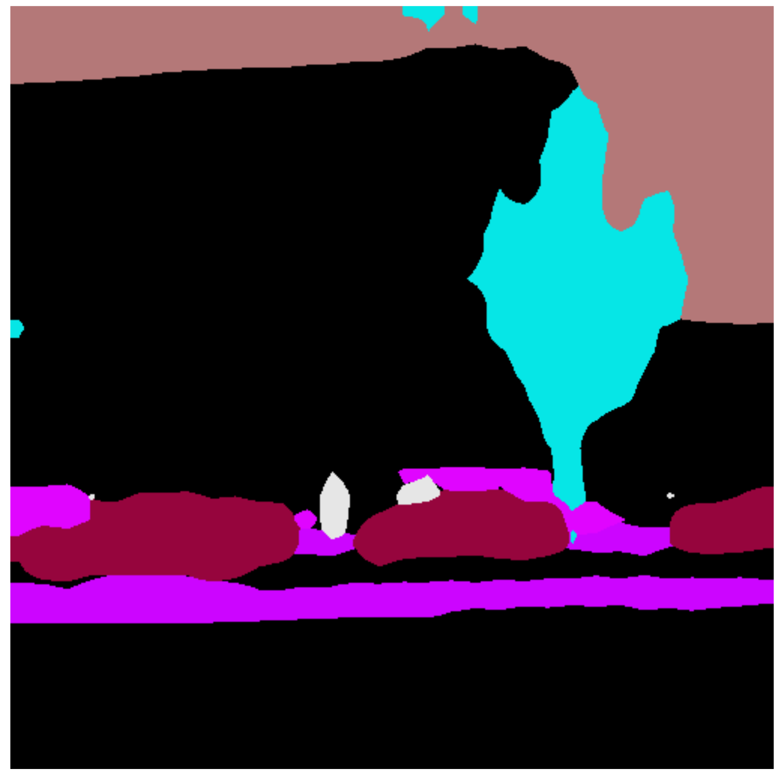
B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

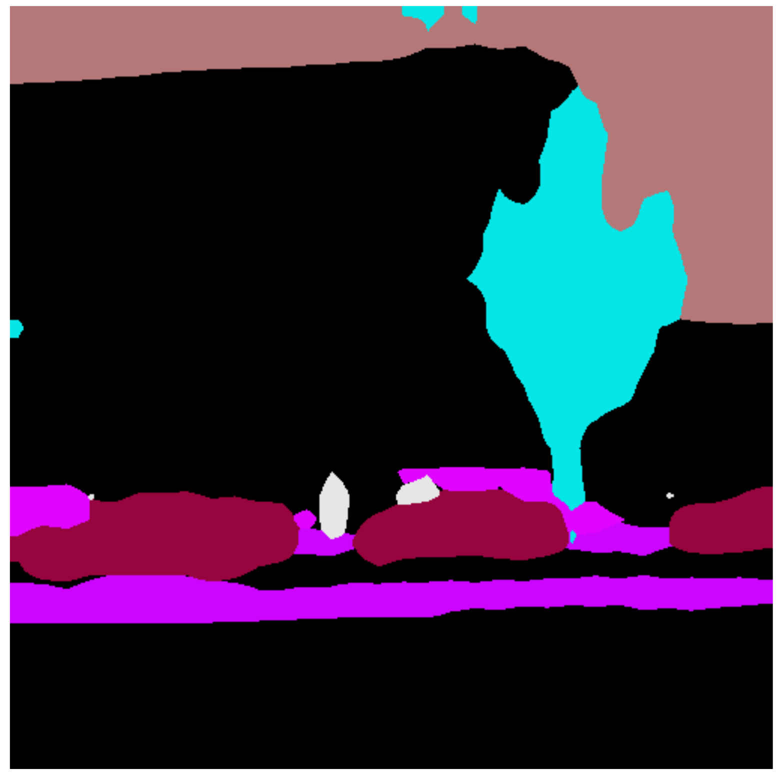
Step ground truth

Known classes

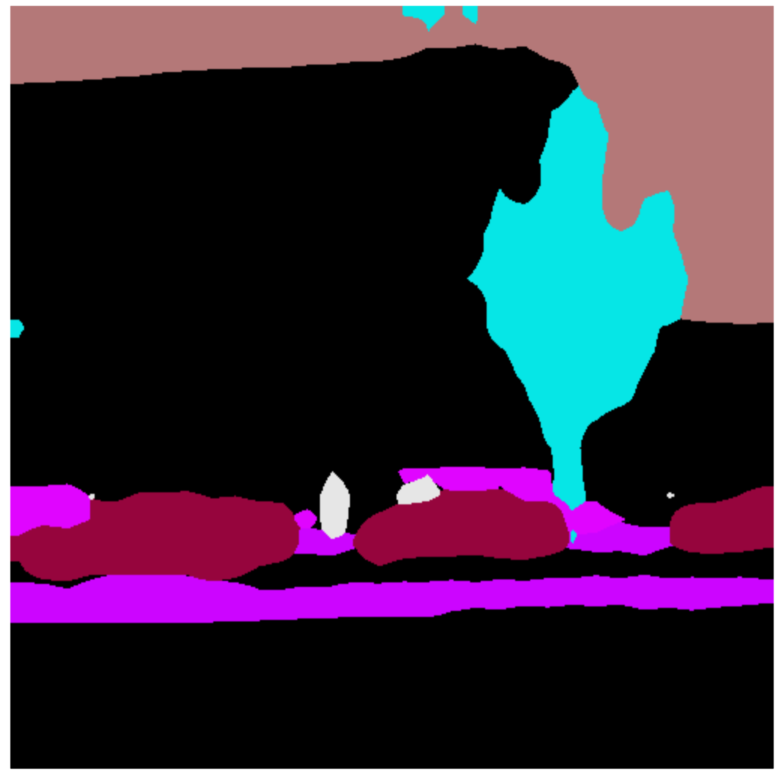
100-10 classes - Step 0



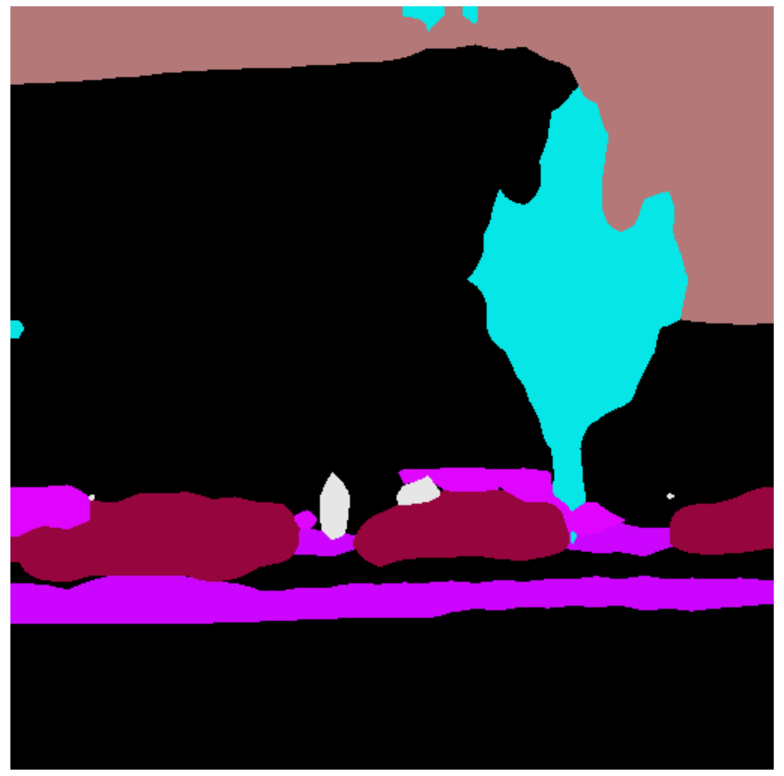
FT



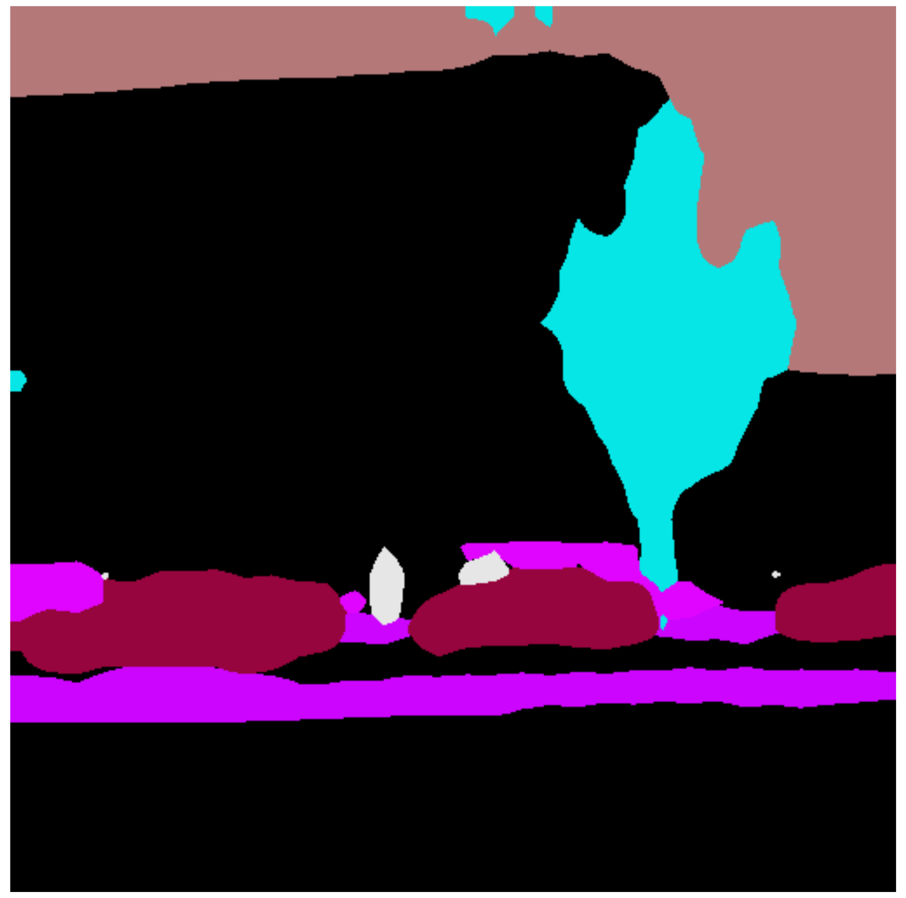
LwF [1]



LwF-MC [5]



ILT [6]



MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

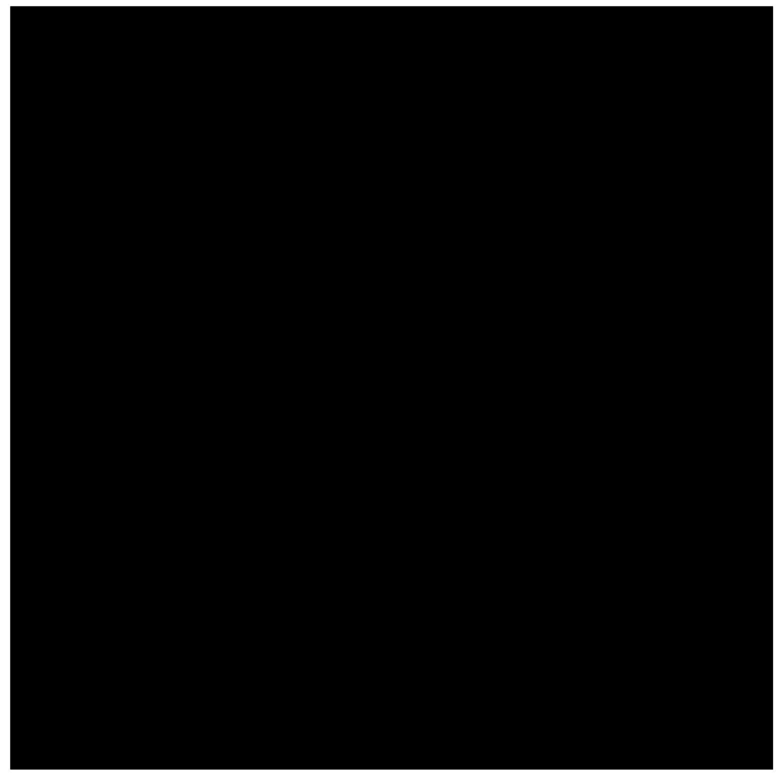
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

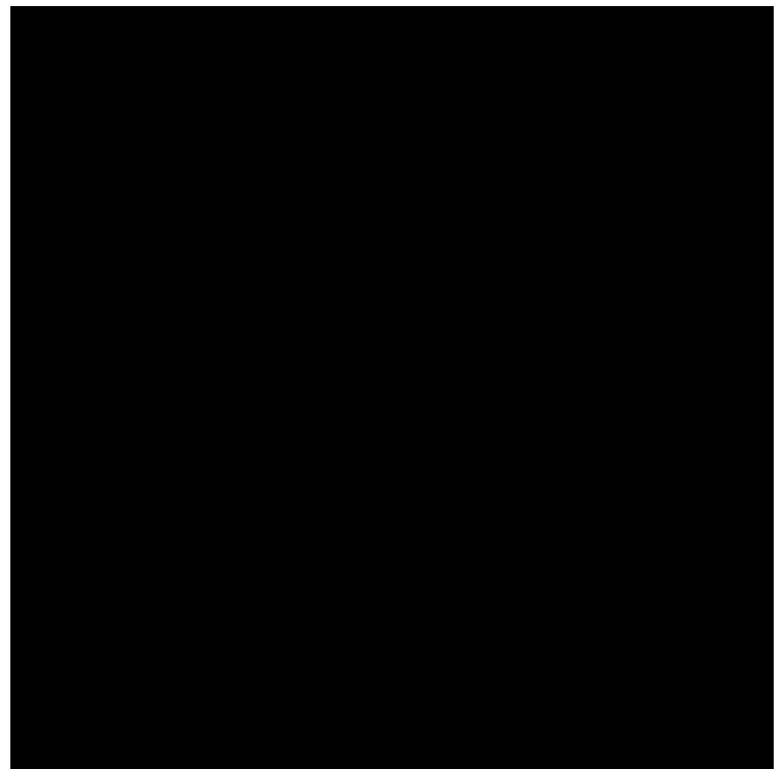
B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

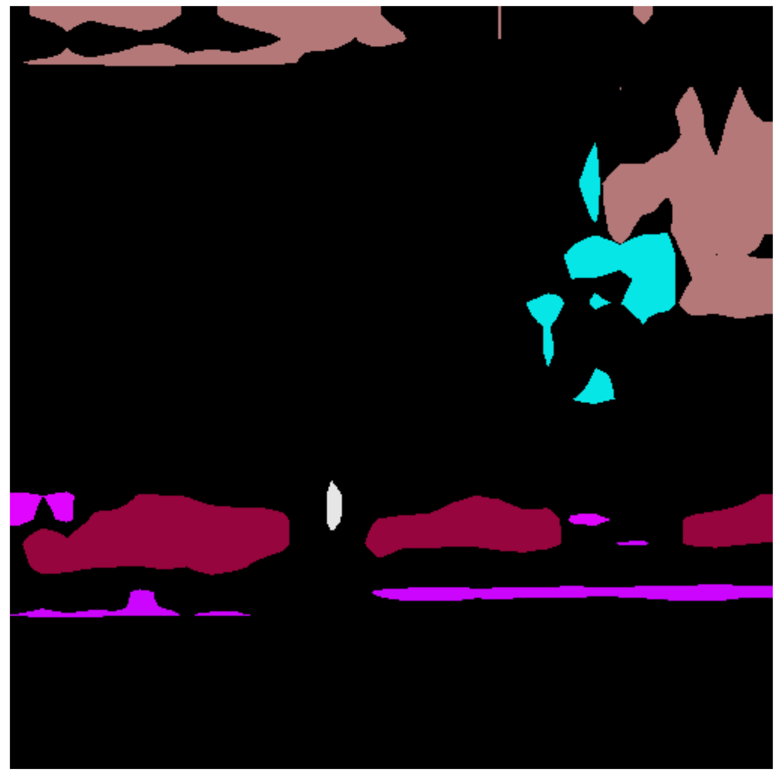

Image

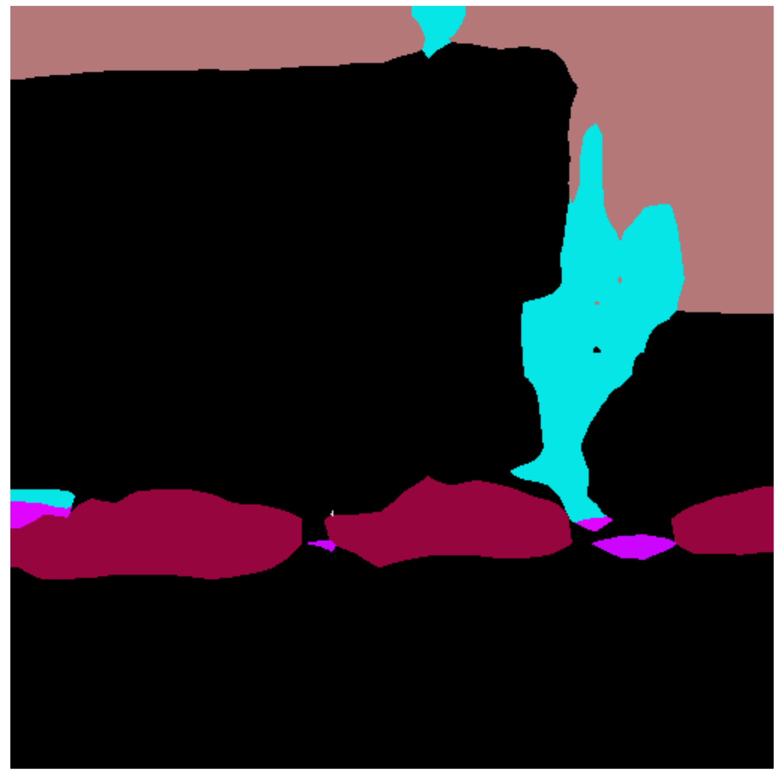

Step ground truth


Known classes

100-10 classes - Step 1


FT


LwF [1]


LwF-MC [5]


ILT [6]


MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

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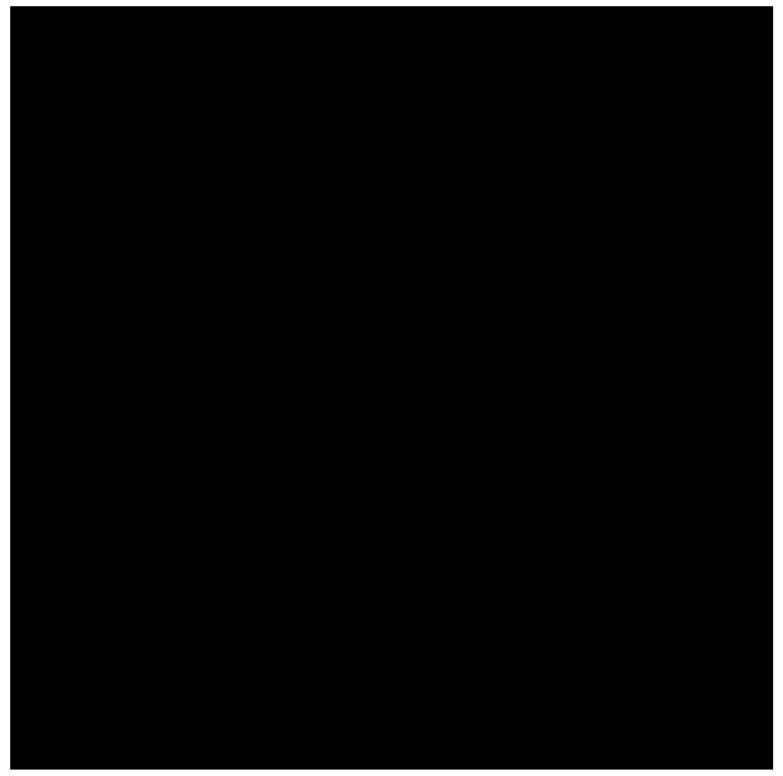
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

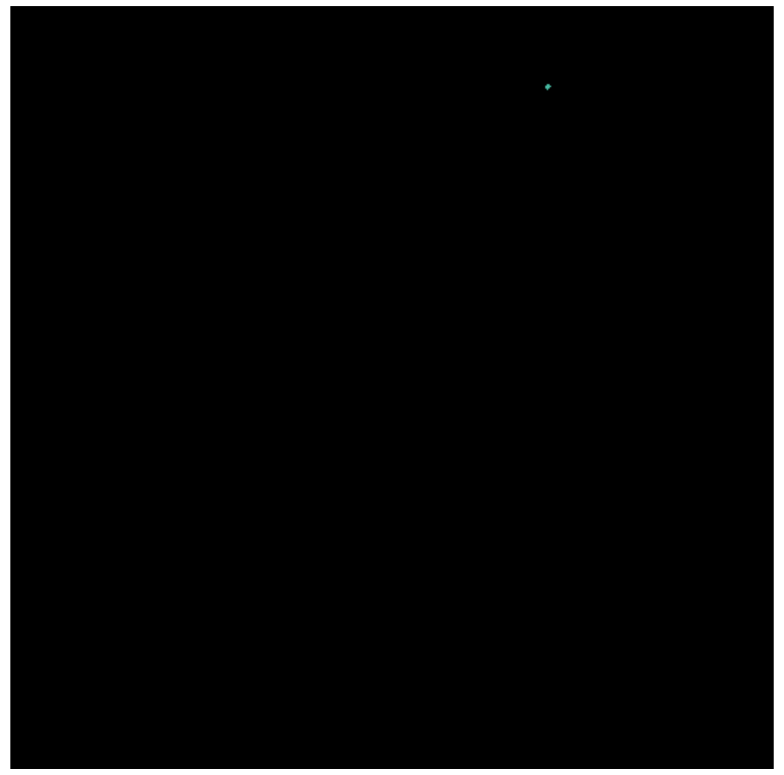
Image



Step ground truth

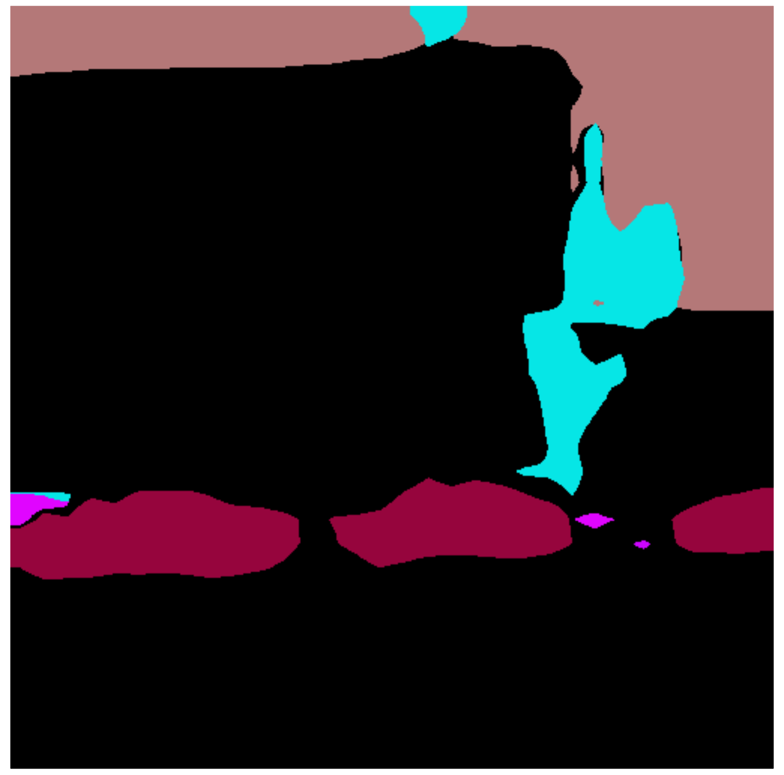
Known classes

100-10 classes - Step 2



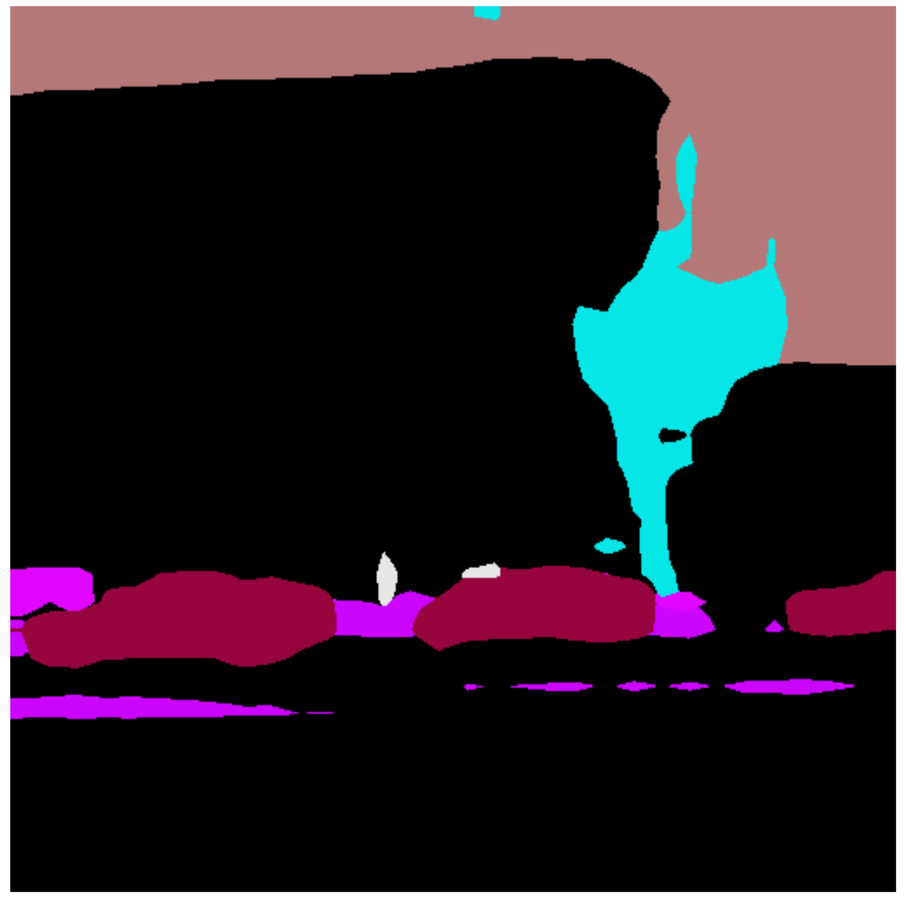
FT

LwF [1]



LwF-MC [5]

ILT [6]



MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

Step ground truth

Known classes

100-10 classes - Step 3

FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

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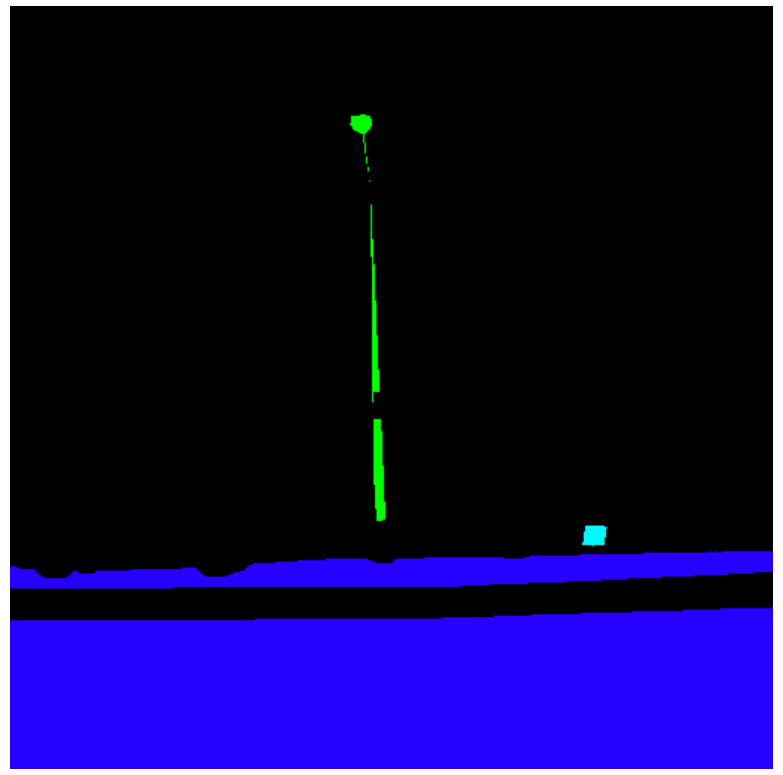
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

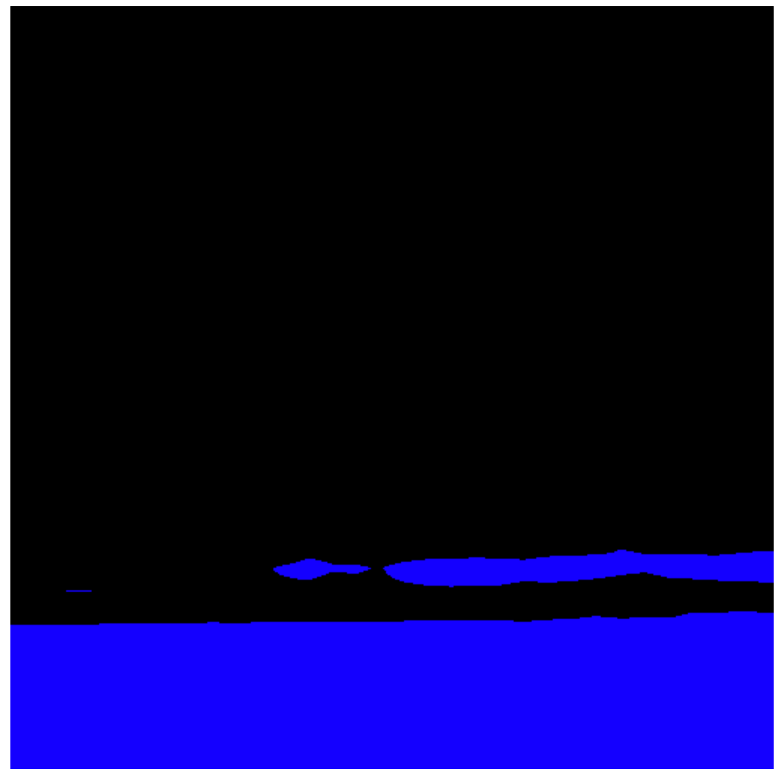
Image



Step ground truth

Known classes

100-10 classes - Step 4



FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

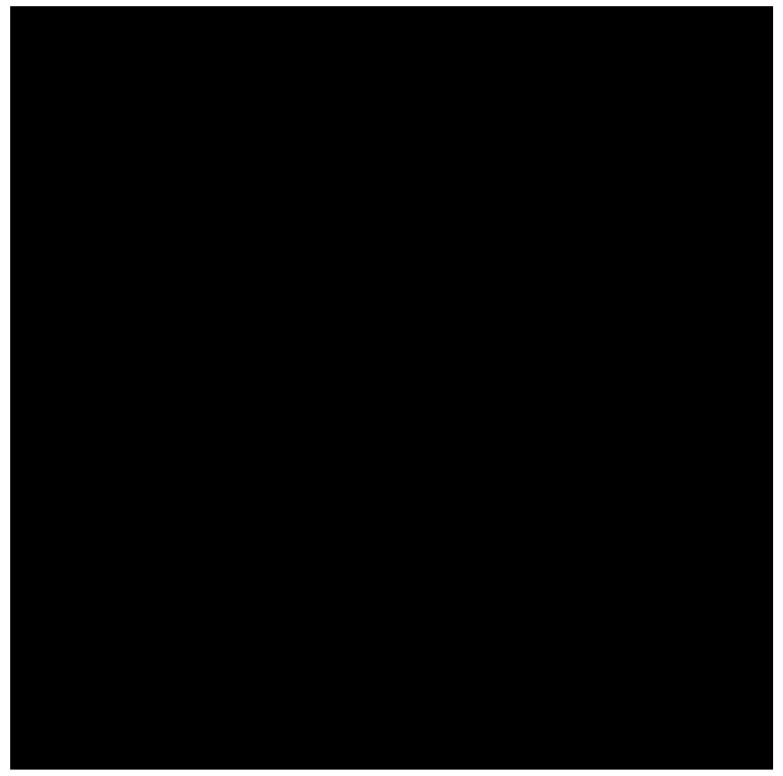
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

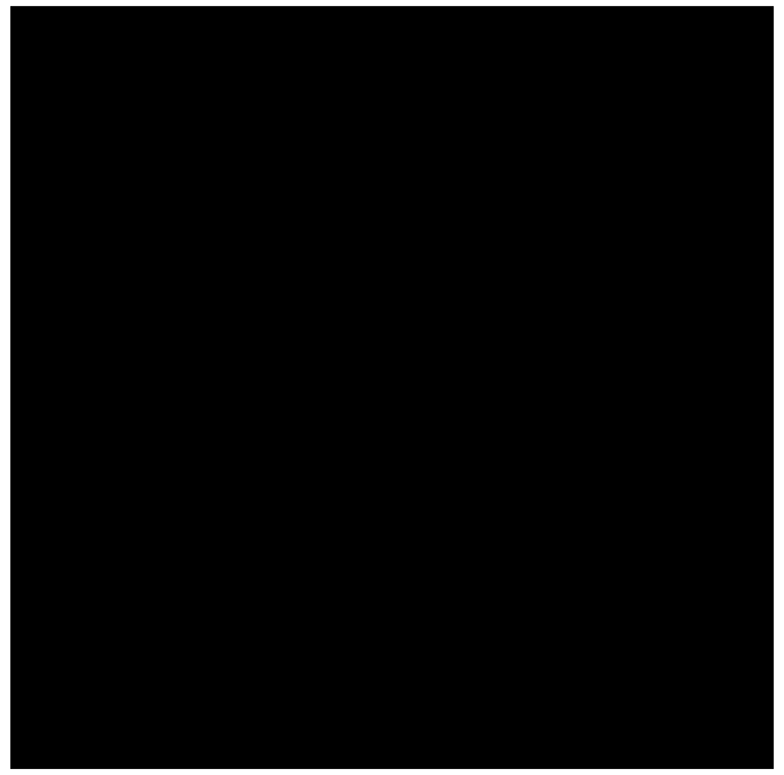
B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

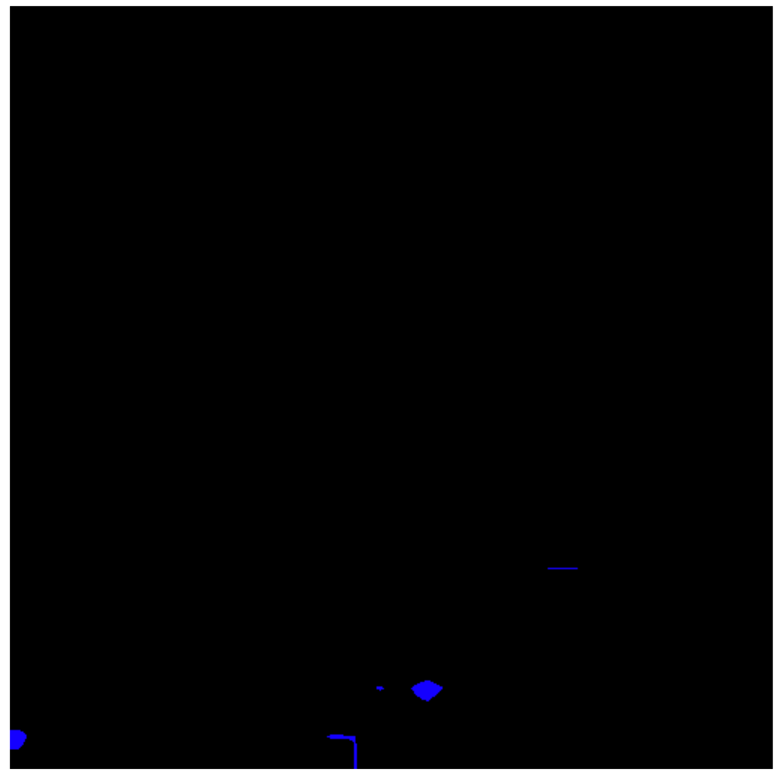

Image


Step ground truth

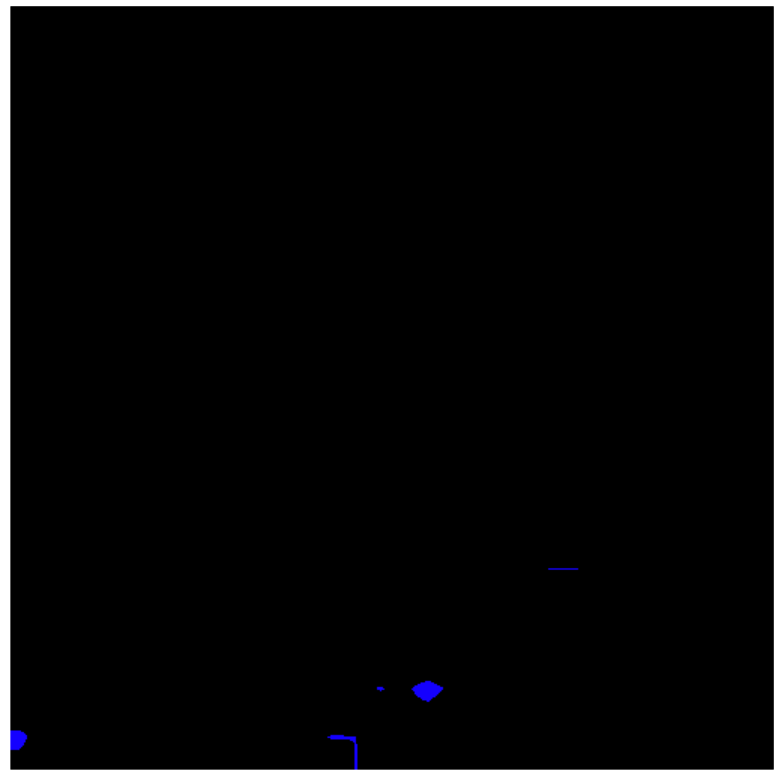

Known classes

100-10 classes - Step 5


FT


LwF [1]


LwF-MC [5]


ILT [6]


MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Future Works

While we reduced the background shift issue, we still struggle in avoiding forgetting when we learn new classes which appear in similar context of the previous ones (e.g. learning sheep after cow).

To solve this issue we may:

- Extend the benchmark to include rehearsal approaches (using exemplars or introducing a generative approach).
- Extend the method to effectively re-use old knowledge, introducing different pseudo-labeling techniques.

Conclusion

- We studied the incremental learning problem in semantic segmentation, identifying the background shift issue for the first time.
- We proposed a simple, yet effective, modification to the distillation approaches to tackle this scenario.
- We benchmarked our approach and other several previous methods on two popular segmentation datasets.

If you are interested, we released our code! https://github.com/fcdl94/MiB

Thank You!

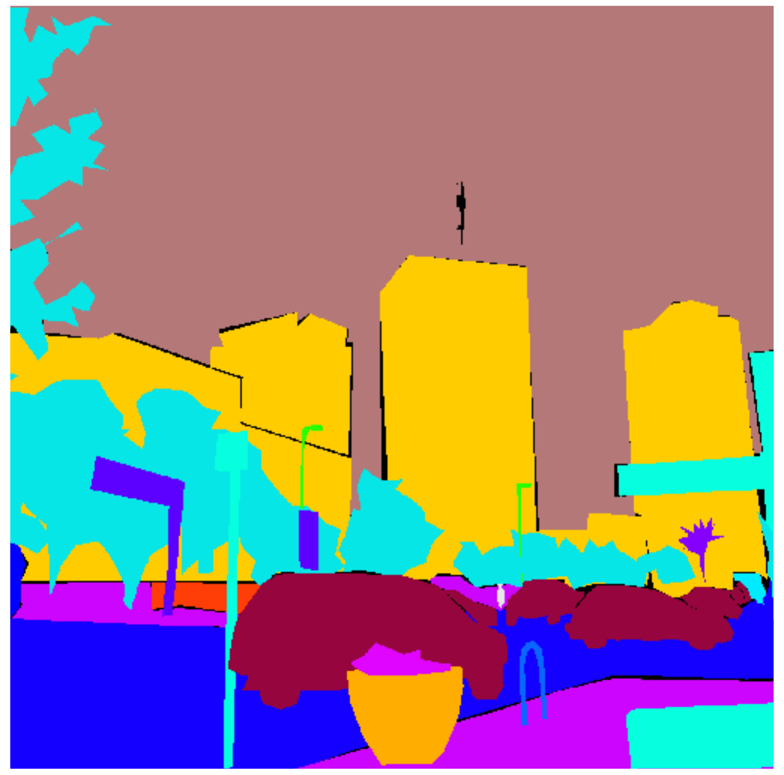
https://github.com/fcdl94/MiB

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

1 Step of 100 classes and 5 Steps of 10 Classes
Example 3

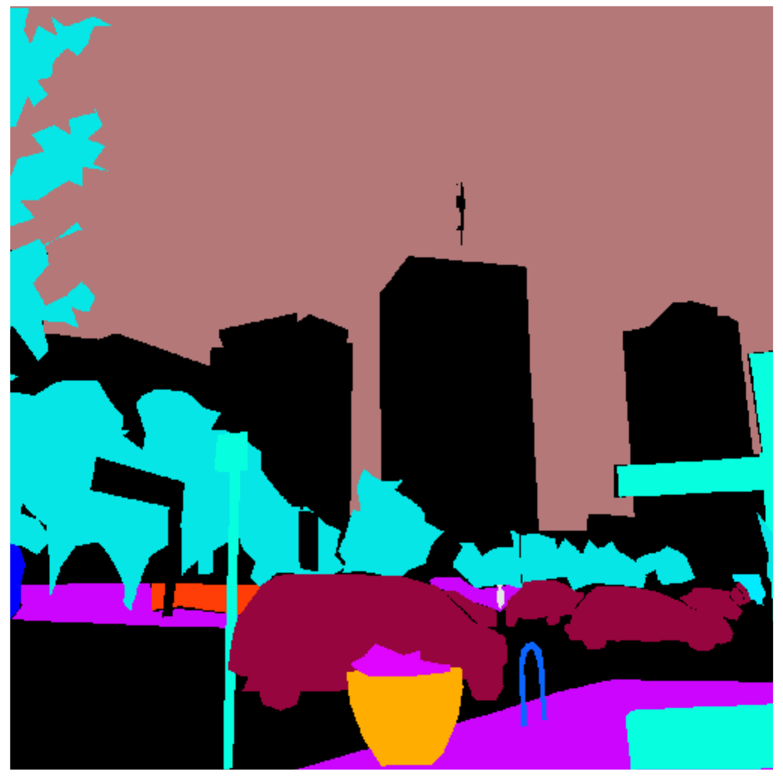


Results

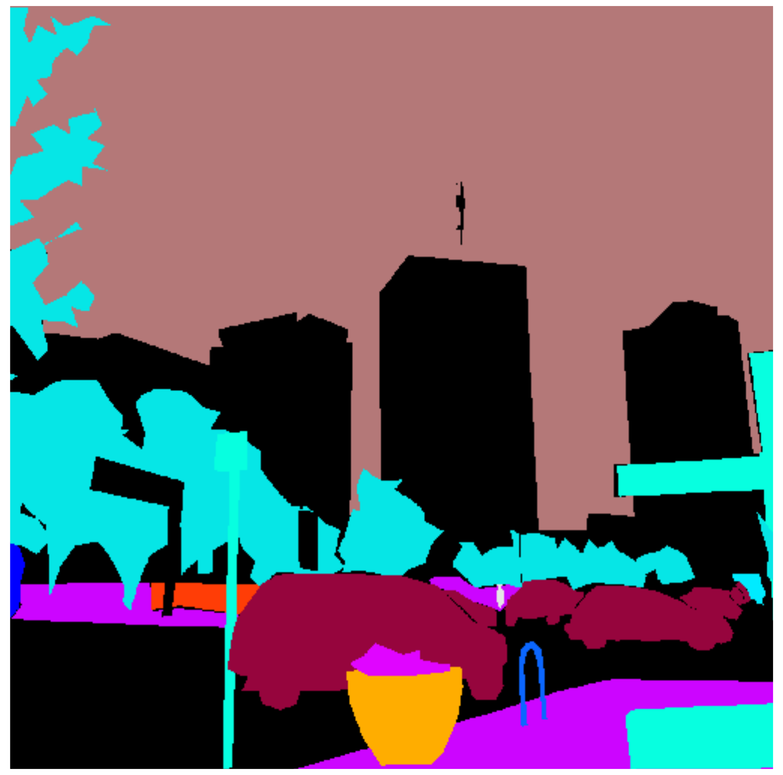
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image



Step ground truth



Known classes

100-10 classes - Step 0

FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

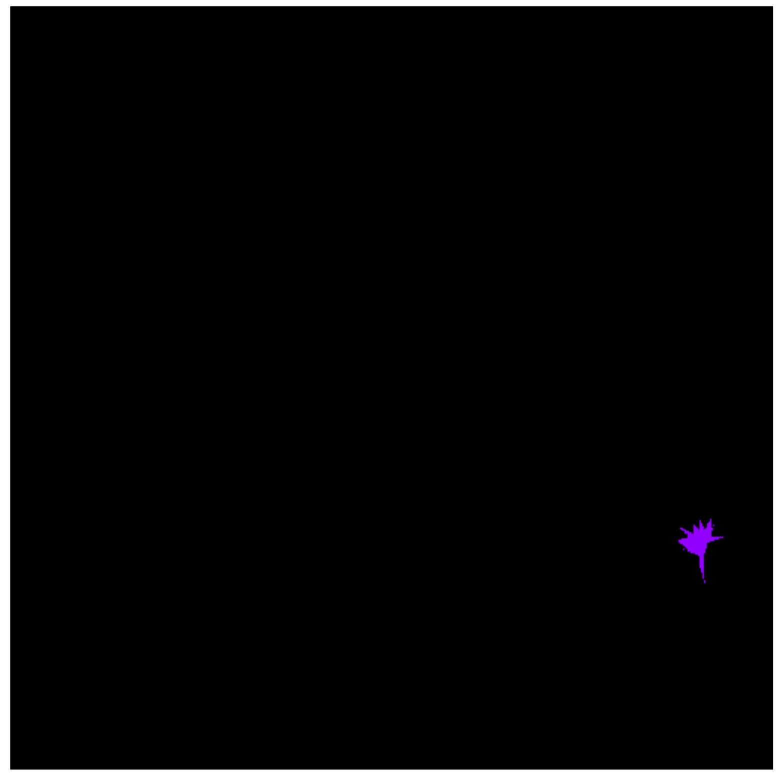
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

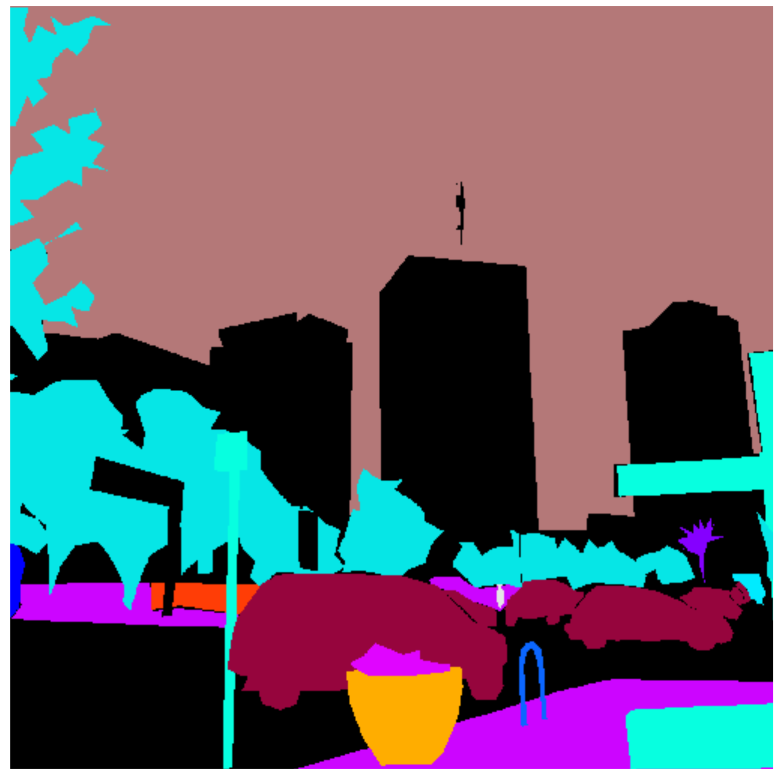
Results

ADE 20K

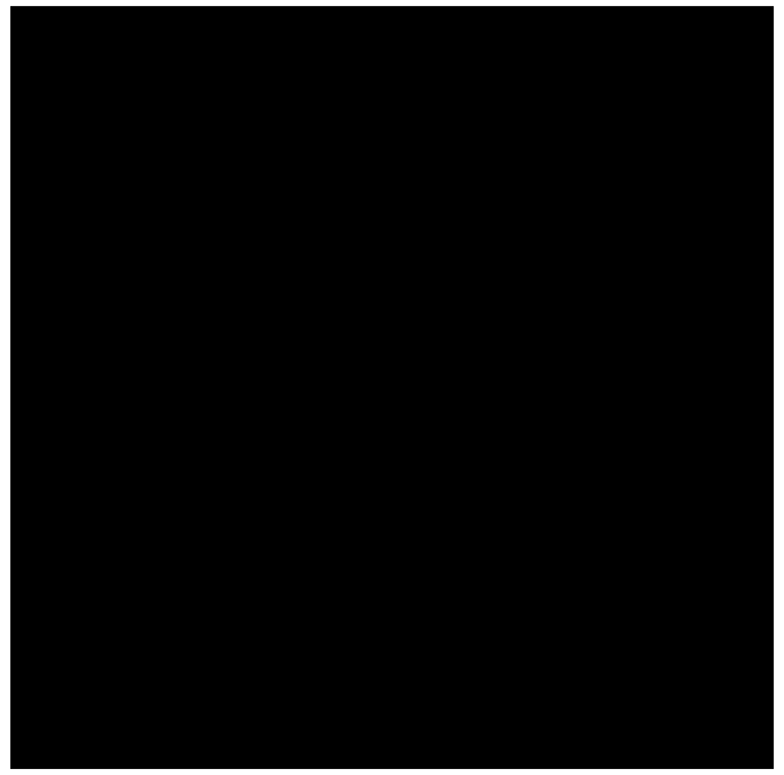
B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.


Image


Step ground truth

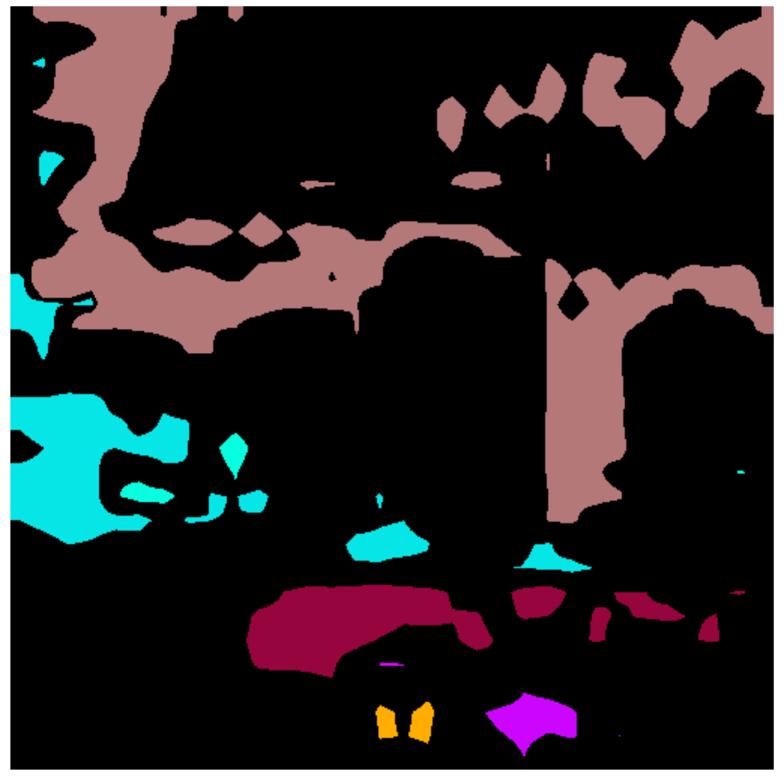

Known classes

100-10 classes - Step 1


FT


LwF [1]


LwF-MC [5]


ILT [6]


MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

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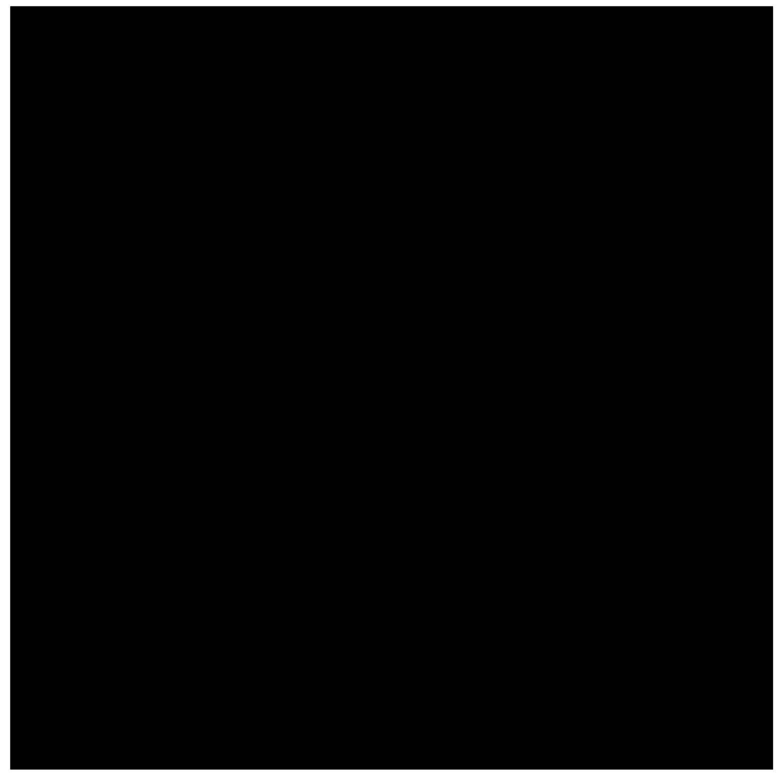
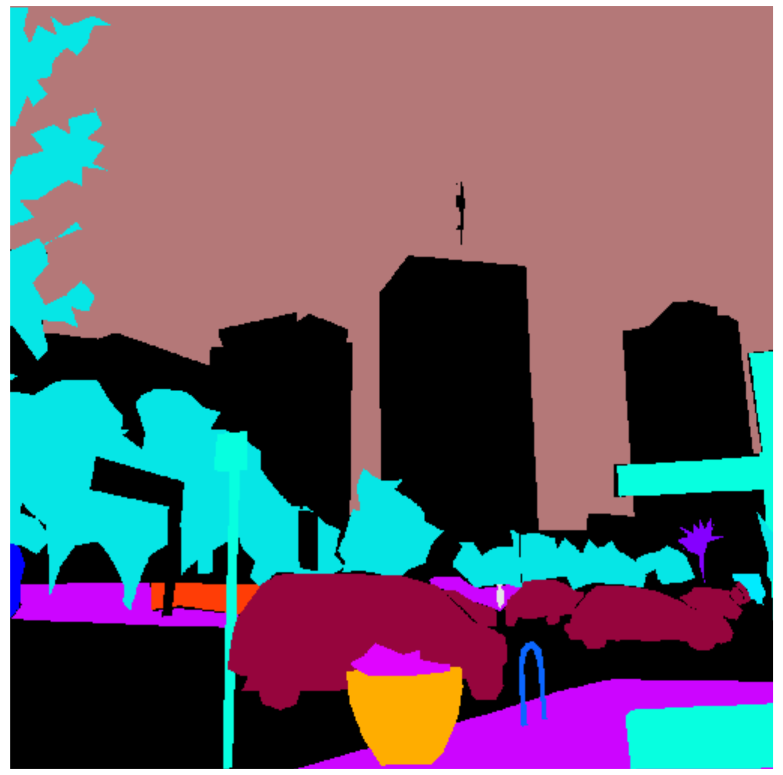
Image

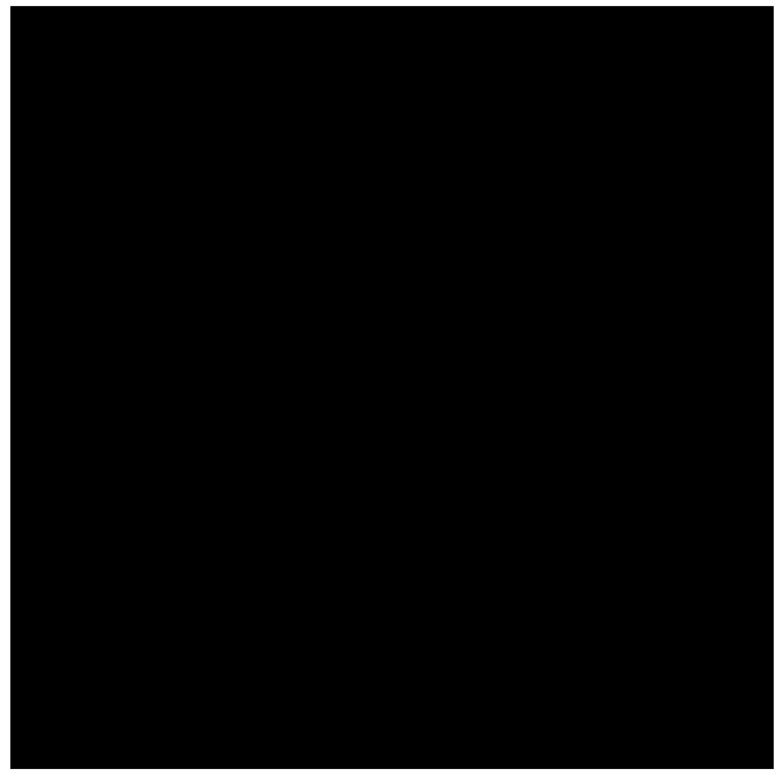


Step ground truth



Known classes

100-10 classes - Step 2



FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

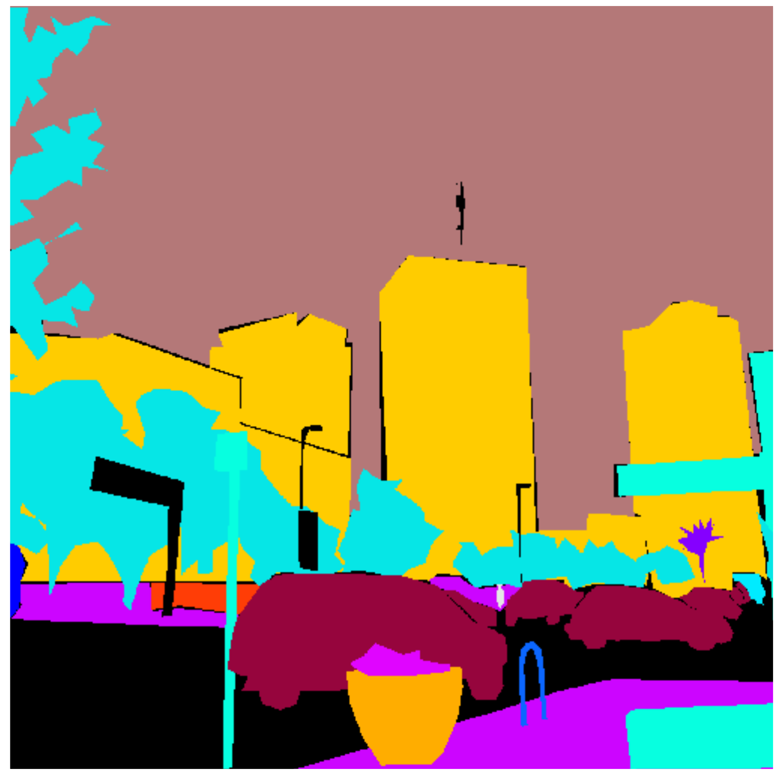
Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

Step ground truth



Known classes

100-10 classes - Step 3

FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

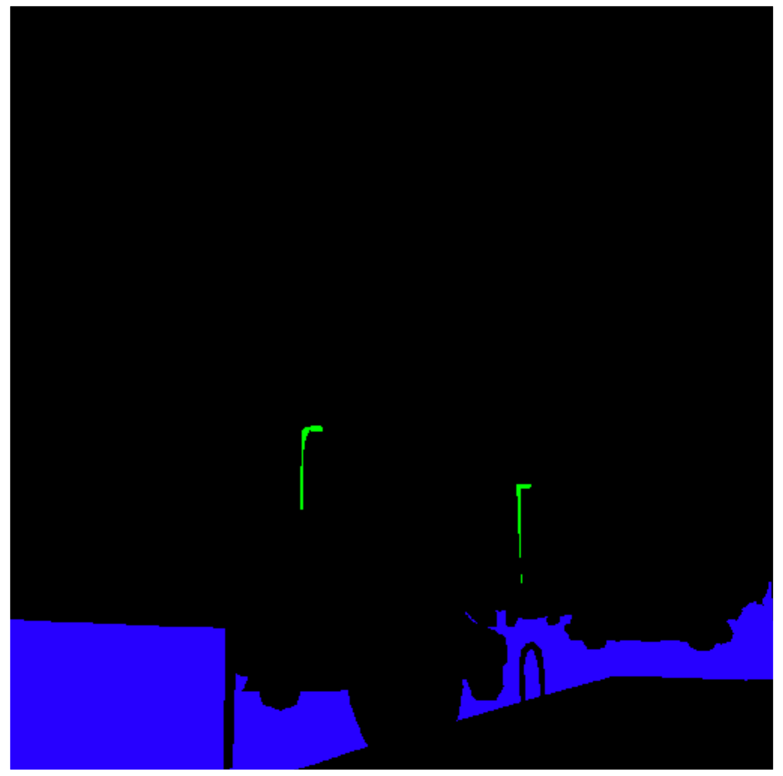
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

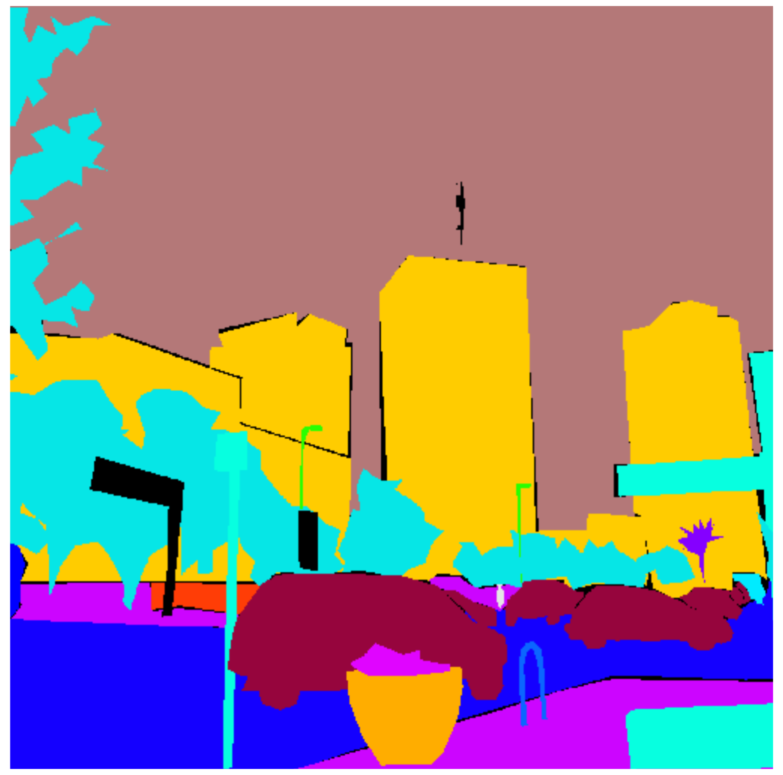
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image



Step ground truth

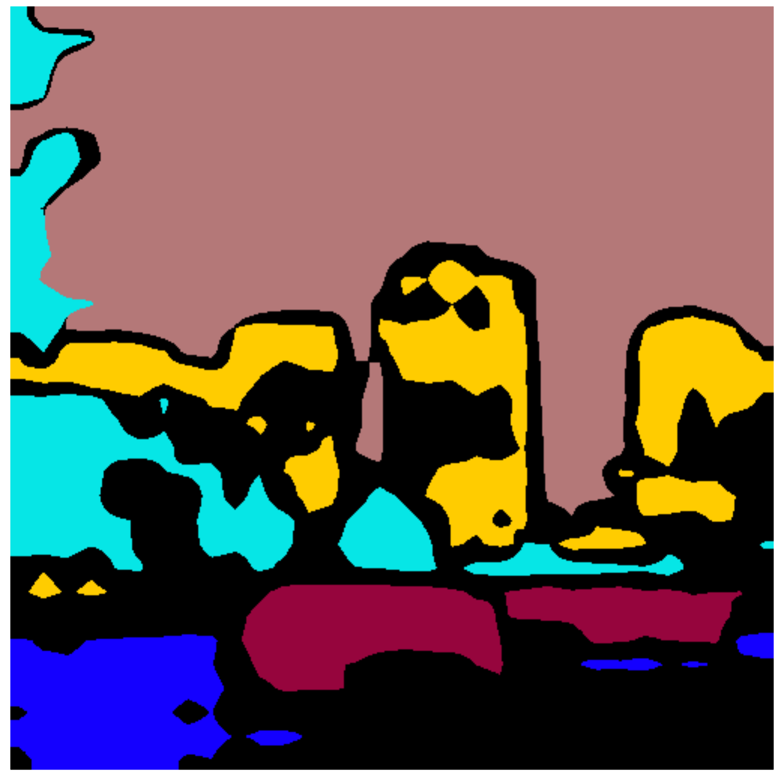


Known classes

100-10 classes - Step 4

FT

LwF [1]



LwF-MC [5]

ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

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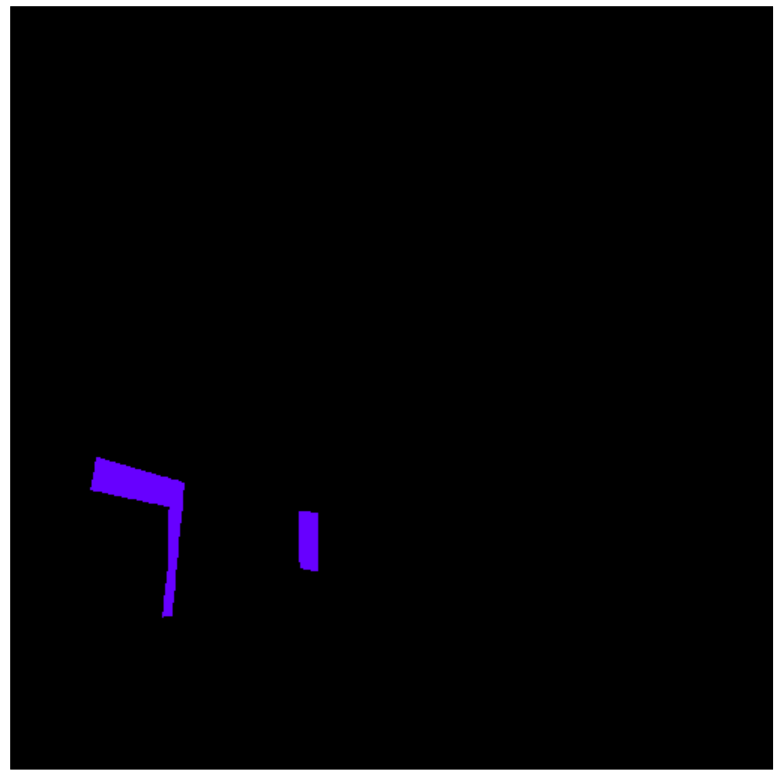
Results

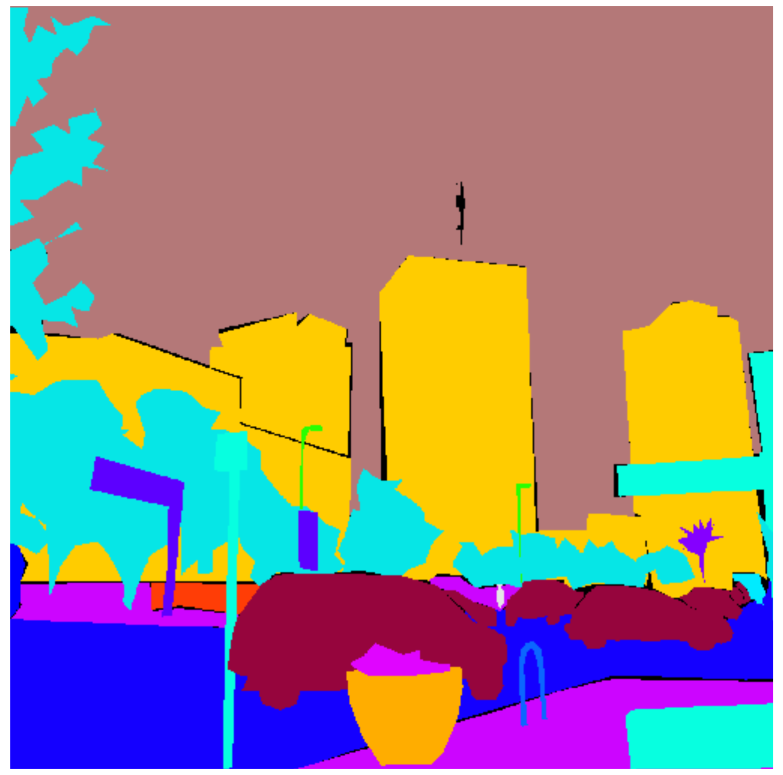
ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

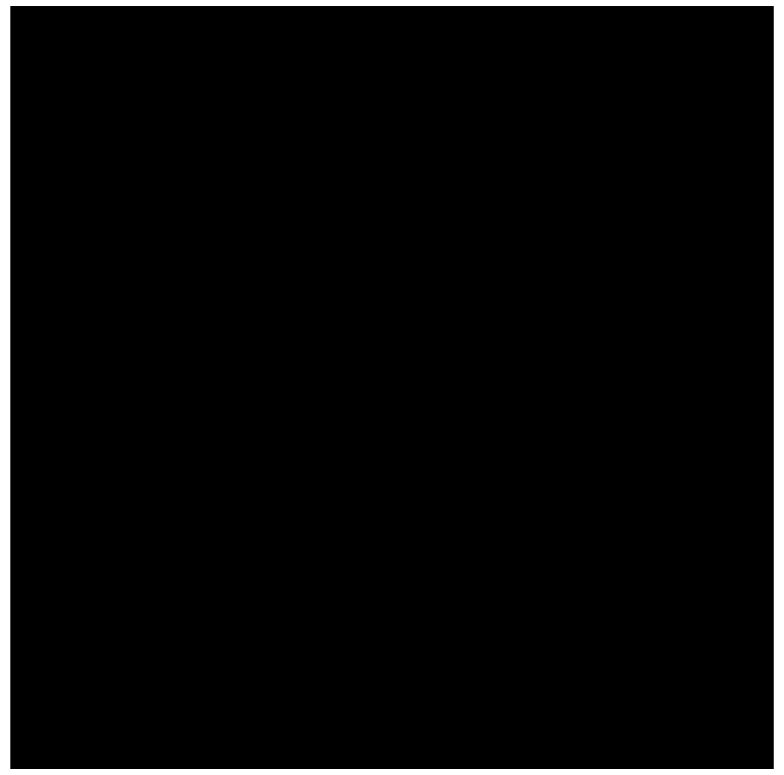


Step ground truth

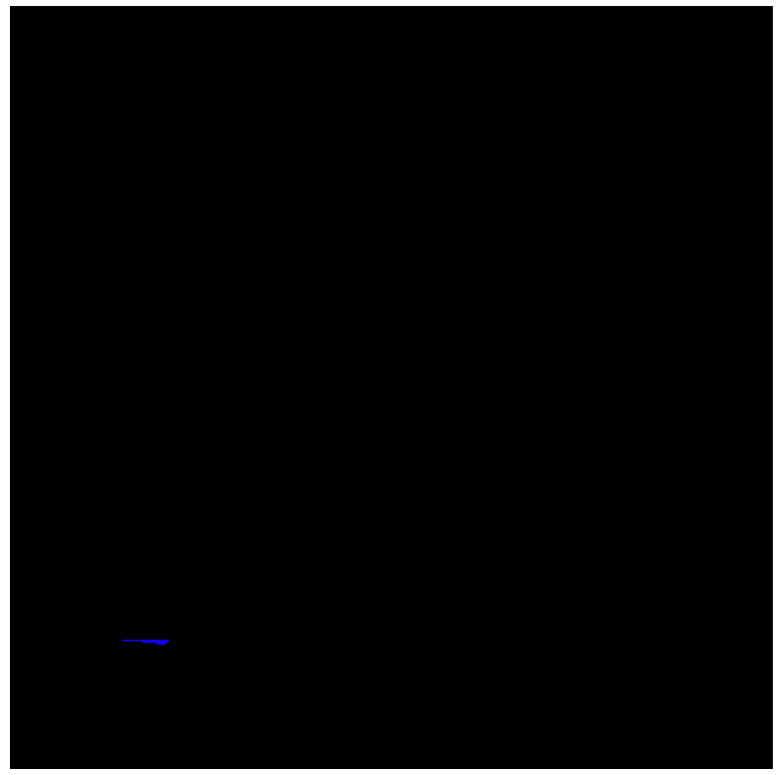


Known classes

100-10 classes - Step 5

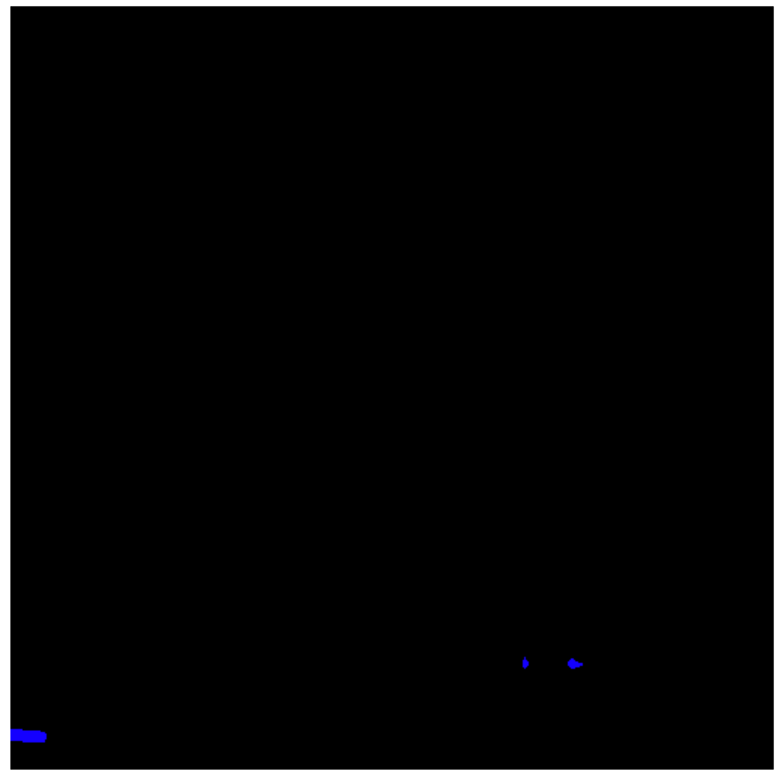


FT



LwF [1]

LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

3 Steps of 50 Classes
Example 1

Results

ADE 20K

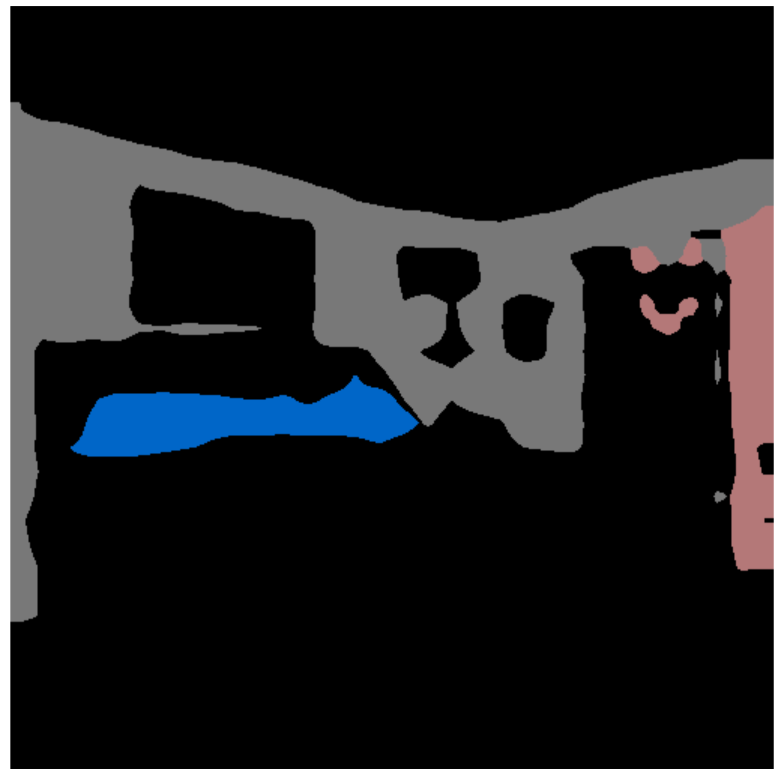
B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

Image

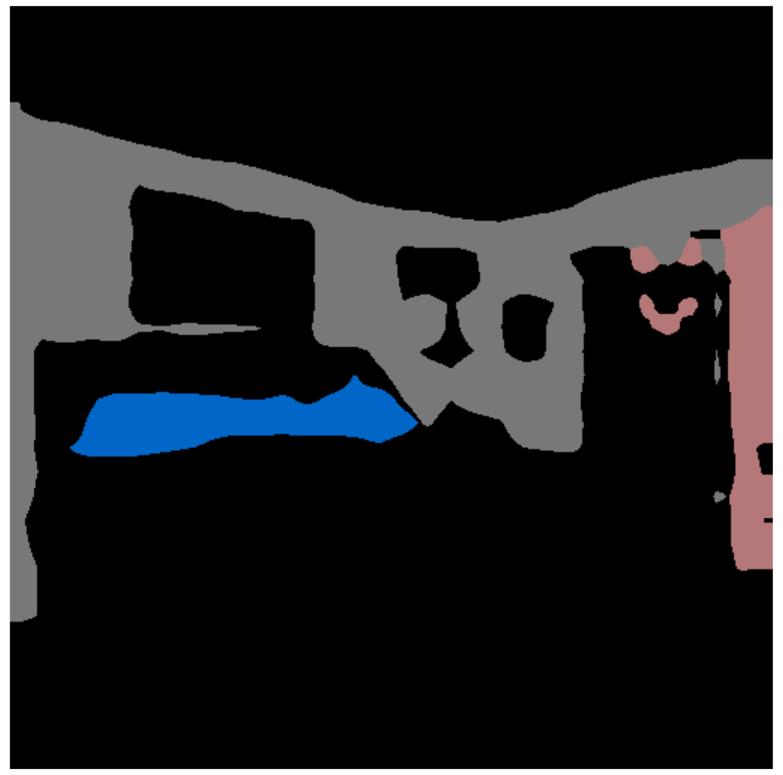
Step ground truth

Known classes

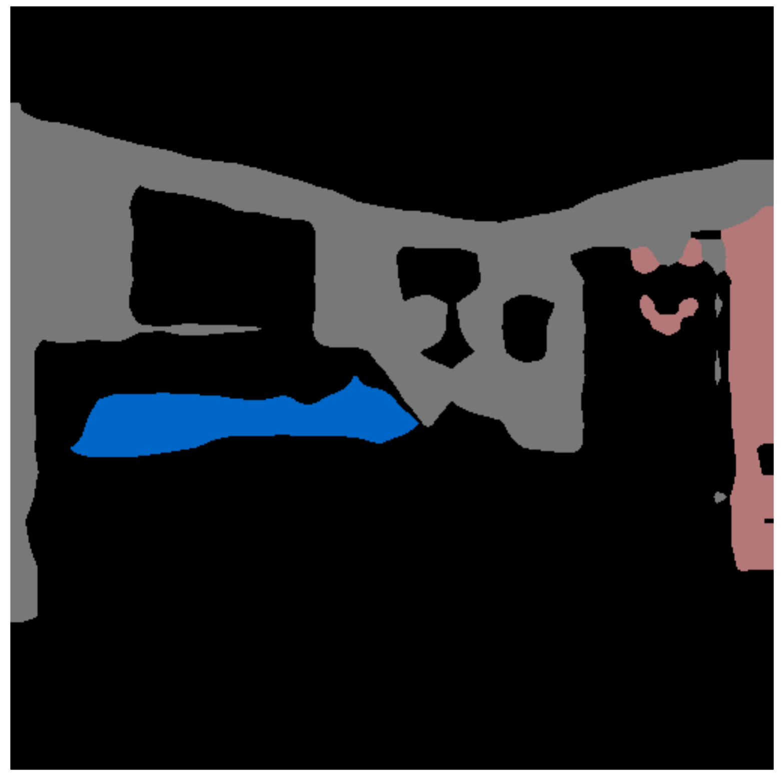
50 classes - Step 0



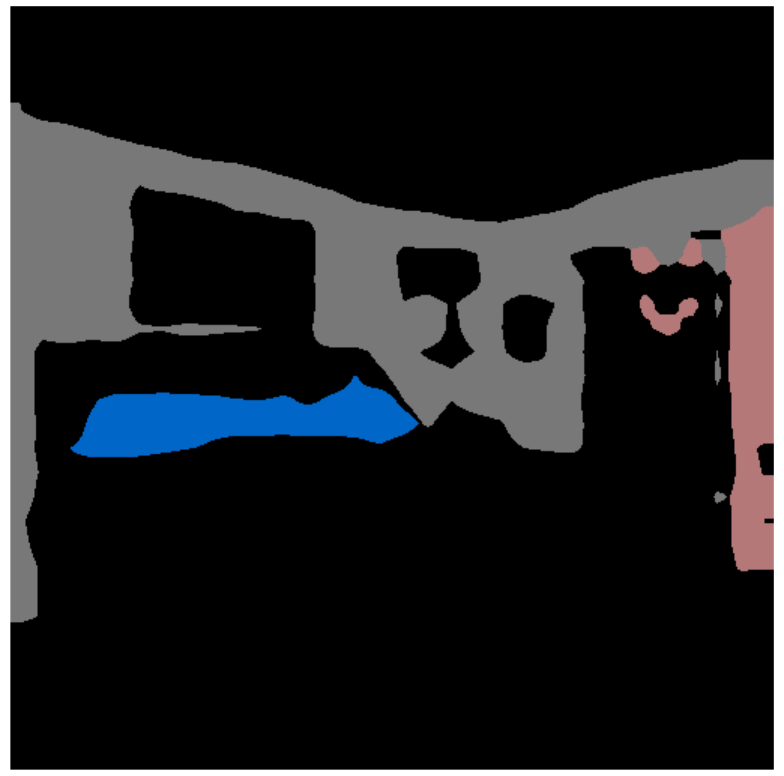
FT



LwF [1]



LwF-MC [5]



ILT [6]

MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.


Image


Step ground truth


Known classes

50 classes - Step 1


FT


LwF [1]


LwF-MC [5]


ILT [6]


MiB (Ours)

[1] Z. Li and D. Hoiem. *Learning without forgetting*. In IEEE T-PAMI, 40(12):2935–2947, 2017

[5] S.A. Rebuffi et al. *ICaRL: Incremental classifier and representation learning*. In CVPR, 2017

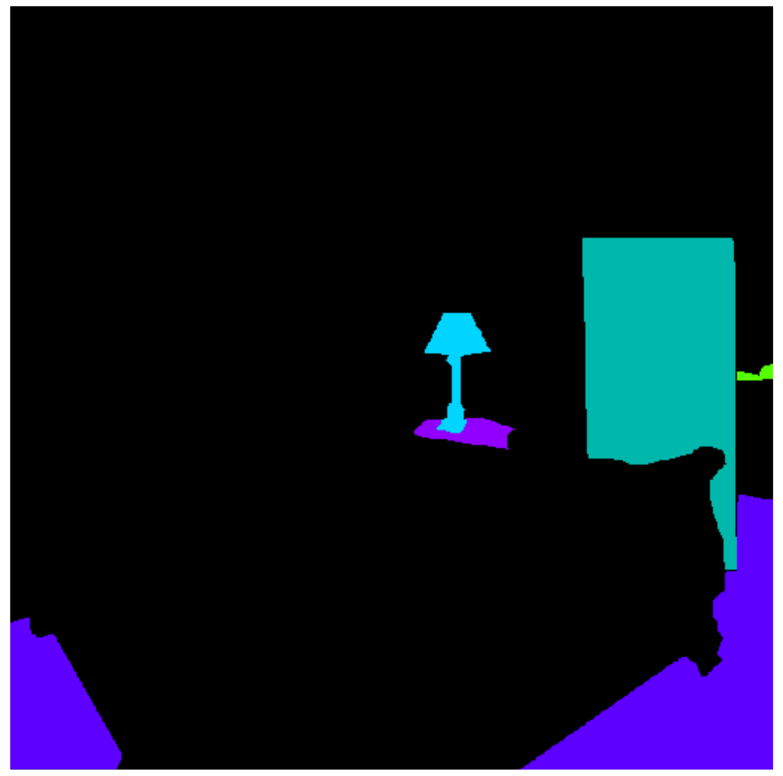
[6] U. Michieli and P. Zanuttigh. *Incremental learning techniques for semantic segmentation.* In ICCV Task-CV workshop, 2019

Results

ADE 20K

B. Zhou et al. *Scene parsing through ade20k dataset*. In CVPR, 2017.

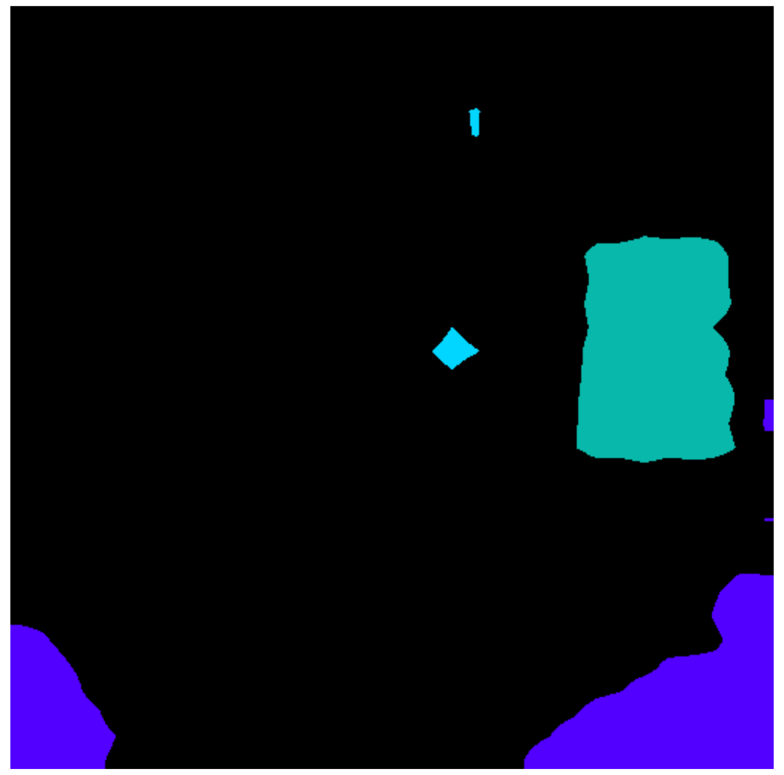
Image



Step ground truth

Known classes

50 classes - Step 2



FT

LwF [1]

LwF-MC [5]

ILT [6]

MiB (Ours)

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