

### Final Event | March 09, 2023

# Heterogeneous Continual Learning

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- Continual Learning A Brief Overview
  - Semantic Segmentation
- Heterogeneous Continual Learning
  - Experimental Design
  - Results for Semantic Segmentation



# Continual Learning - A Brief Overview

## **Types of Continual Learning**



Class Incremental

Domain Incremental



## **Types of Continual Learning**



Domain Incremental



## **Concept Illustration of Class Incremental Continual Learning**





## **SoTA - CL Semantic Segmentation**



### MiB[1]

 addresses the issue of background shift along with catastrophic forgetting

### PLOP[2]

 addresses the issue of catastrophic forgetting using a multi-scale pooling distillation loss



[1] Cermelli et al. "Modeling the Background for Incremental Learning in Semantic Segmentation", CVPR 2020.[2] Douillard et al. "PLOP: Learning without Forgetting for Continual Semantic Segmentation", CVPR 2021.

#### Transfer Learning | Heterogeneous Continual Learning



## Dataset & Network

#### R&R3 Workshop (03.10.2022)

Category

Flat

Construction

Object

Nature

Sky

Human

Vehicle

Color



• Cityscapes Dataset [3]



• DeepLabv3 [4] with ResNet101 [5]

[3] Cordts et al. "The Cityscapes Dataset for Semantic Urban Scene Understanding", CVPR 2016. [4] Chen et al. "Rethinking Atrous Convolution for Semantic Image Segmentation", arXiv:1706.05587 [5] He et al. "Deep Residual Learning for Image Recognition", arXiv:1512.03385

#### Traffic light 7 Traffic sign 8 9 Vegetation 10 Terrain 11 Sky 12 Person 13 Rider 14 Car 15 Truck 16 Bus 17 Train Motorcycle 18 Bicycle 19

ID

1

2

3

4

5

6

Name

Road

Sidewalk

Building

Wall

Fence

Pole













# Heterogeneous Continual Learning

## Concept Illustration of Class Incremental Heterogeneous Continual Learning



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## Semantic Segmentation with Heterogeneous Continual Learning

### Definition:

 An incremental task add new class(es) but may also redefine previous information

### <u>Goals:</u>

- Defining suitable experiments
- Benchmark a Class Incremental Sem-Seg model

Increment [T1]: Car & Bicycle

Joint (Classes After Final Step): Vehicle(-cars), Human, Car & Bicycle



Initial classes [T0]: Vehicle & Human

A Sample

## **Classes in our Experiments**

- Original IDs and colors of Cityscapes [1]
- Color of superclass is the average of the sub-classes' color

ID	Name	Category	Color
12	Person	llumon	
13	Rider	Huilidii	
14	Car		
15	Truck	Vahiala	
16	Bus	venicle	
19	Bicycle		
20	Vehicle	Cuparalass	
21	Human	Superclass	

6 Selected Classes from Cityscapes + 2 Superclasses

10	) Name	Category	Color
1	Road	Flat	
2	Sidewalk	Flat	
3	Building		
4	Wall	Construction	
5	Fence		
6	Pole		
7	Traffic light	Object	
8	Traffic sign		
9	Vegetation	N .	
10	) Terrain	Nature	
1	1 Sky	Sky	
1	2 Person	11	
1	3 Rider	Human	
1-	4 Car		
1	5 Truck		
10	6 Bus	Vahiela	
1	7 Train	venicle	
1	8 Motorcycle		
1	9 Bicycle		

All 19 Classes of Cityscapes





# Experimental Design

## Experiment 1: 2 Tasks





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## Experiment 2: 7 Tasks





Joint: Car, Truck, Bus, Bicycle, Person, Rider

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## **Results: Joint Training**



•	Experiment 1:	2 Tasks			lo	U
	<ul> <li>Initial Task:</li> </ul>	Vehicle (Car, Truck, Bus), Human (Person, Rider)	ID	Class	Ex-1	Ex-2
	> (After)Final Task	Vehicle (Truck Bus) Human (Person Bider) Car Bicycle.	0	background	98.4	98.4
		The content of the co		person	-	63.9
			13	rider	-	39.8
•	Experiment 2:	7 Tasks	14	car	85.1	85.0
	Initial Task.	Vehicle (Car Truck Bur Biguele) Human (Derron Dider)	15	truck	-	58.1
		Vernete (Car, Truck, bus, bicycle), Human (Person, Rider)	16	bus	-	61.6
	(After)Final Task:	Car, Truck, Bus, Bicycle, Person, Rider	19	bicycle	54.8	55.3
			20	Vehicle	61.2	-

21

Joint

Human

mloU

\_

66.0

65.1

72.9

## **Results:** Naïve Training



Experiment 1:		BG	Vehicle	Human	Car	Bicycle	mloU
Initial Task ——	Task 0	98.5	86.5	64.2	-	-	83.1
(After)Final Task ——•	Task 1	96.5	0.0	0.0	84.3	35.1	43.2
	Joint	98.4	(61.2)	65.1	85.1	54.8	72.9

Experiment 2:		BG	Vehicle	Human	Car	Truck	Bus	Bicycle	Person	Rider	mloU
Initial Task ——•	Task 0	98.4	84.0	64.8	-	-	-	-	-	-	82.4
	Task 1	96.3	0.0	0.0	83.7	-	-	-	-	-	45.0
	Task 2	92.3	0.0	0.0	0.0	34.4	-	-	-	-	25.1
	Task 3	92.4	0.0	0.0	0.0	0.0	36.2	-	-	-	21.4
	Task 4	92.2	-	0.0	0.0	0.0	0.0	49.2	-	-	23.6
	Task 5	92.8	-	0.0	0.0	0.0	0.0	0.0	61.0	-	25.6
<sup>(After)</sup> Final Task ——•	Task 6	92.0	-	-	0.0	0.0	0.0	0.0	0.0	11.1	14.7
	Joint	98.4	-	-	85.0	58.1	61.6	55.3	63.9	39.8	66.0

## **Results: MiB**



<b>F</b> • • • • •					Naive         BG           Task 0         98.5           Task 1         96.5           Joint         98.4	Vehicle         Human           86.5         64.2           0.0         0.0           (61.2)         65.1	Car         Bicycle         mloU           -         -         83.1           84.3         35.1         43.2           85.1         54.8         72.9				
Experiment 1:		BG	Vehicle	Human	Car	Bicycle	mloU				
Initial Task ——>	Task 0	98.5	86.5	64.2	-	-	83.1				
<sup>(After)</sup> Final Task —→	Task 1	98.0	11.3	64.0	0.0	1.9	35.0				
	Joint	98.4	(61.2)	65.1	85.1	54.8	72.9	Naïve         BG         Ve           Task 0         98.4         8           Task 1         96.3         0	hicle         Human         Car           4.0         64.8         -           0.0         0.0         83.7	Truck         Bus         Bicycle           -         -         -         -           -         -         -         -	Person         Rider         mloU           -         -         82.4           -         -         45.0
								Task 2         92.3         0           Task 3         92.4         0           Task 4         92.2         1           Task 5         92.8         1           Task 6         92.0         1           Image: 1         92.4         1	0.0         0.0         0.0           0.0         0.0         0.0           -         0.0         0.0           -         0.0         0.0           -         0.0         0.0	34.4         -         -           0.0         36.2         -           0.0         0.0         49.2           0.0         0.0         0.0           0.0         0.0         0.0           0.0         0.0         5.2	-         -         25.1           -         -         21.4           -         -         23.6           61.0         -         25.6           0.0         11.1         14.7           62.0         20.8         60.0
Experiment 2:		BG	Vehicle	Human	Car	Truck	Bus	Bicycle	Person	Rider	mloU
Initial Task ——>	Task 0	98.4	84.0	64.8	-	-	-	-	-	-	82.4
_	Task 1	98.3	15.9	64.4	1.5	-	-	-	-	-	45.0
	Task 2	98.3	11.4	64.1	0.8	0.0	-	_	-	-	34.9
	Task 3	98.1	6.1	64.1	0.5	0.0	0.0	_	-	-	28.1
	Task 4	98.1	-	63.7	0.3	0.0	0.0	0.0	-	-	27.0
	Task 5	98.1	-	10.1	0.2	0.0	0.0	0.0	19.4	-	18.3
<sup>(After)</sup> Final Task —→	Task 6	98.0	-	-	0.1	0.0	0.0	0.0	22.9	0.0	17.3
	Joint	98.4	-	-	85.0	58.1	61.6	55.3	63.9	39.8	66.0

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## Results: Joint, Naïve & MiB



Experiment 1:

	mloU
Joint (Upper Baseline)	72.9
Naïve	43.2
MiB	35.0

Experiment 2:

	mloU
Joint (Upper Baseline)	66.0
Naïve	14.7
MiB	17.3

## Visual Comparison: Experiment 1 (2 Tasks)





Image



Ground Truth



Joint Baseline - Predictions



MiB - Predictions

Vehicles (Car, Truck, Bus), Humans (Person, Rider) → Vehicles (Truck, Bus), Humans (Person, Rider), Car, Bicycle

## Visual Comparison: Experiment 2 (7 Tasks)





Image



Ground Truth



Joint Baseline - Predictions



MiB - Predictions

Vehicles (Car, Truck, Bus, Bicycle), Humans (Person, Rider)  $\rightarrow$  Car, Truck, Bus, Bicycle, Person, Rider

## Summary & Conclusion



- Briefly presented the main concept of traditional Continual Learning (CL) for class incremental setting
- Showed the benchmarking results of two SoTA CL methods for Sem-Seg: MiB & PLOP
  - MiB performed better than PLOP for the Cityscapes dataset
- Introduced the new setting of CL where Label definitions can change over time (= ^ heterogeneous labels)
  - Heterogenous CL
- Designed experimental settings for Heterogenous CL
- Evaluated MiB for Heterogenous CL scenarios
- Current SoTA can not cope with the redefinition of labels in incremental learning!



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KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

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Supported by:

Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag