Hierarchical Approaches

Pawnesh Gautam, 07-05-2022

Referenced Papers:

1. Training of Convolutional Networks on Multiple Heterogeneous Datasets for Street Scene Semantic Segmentation

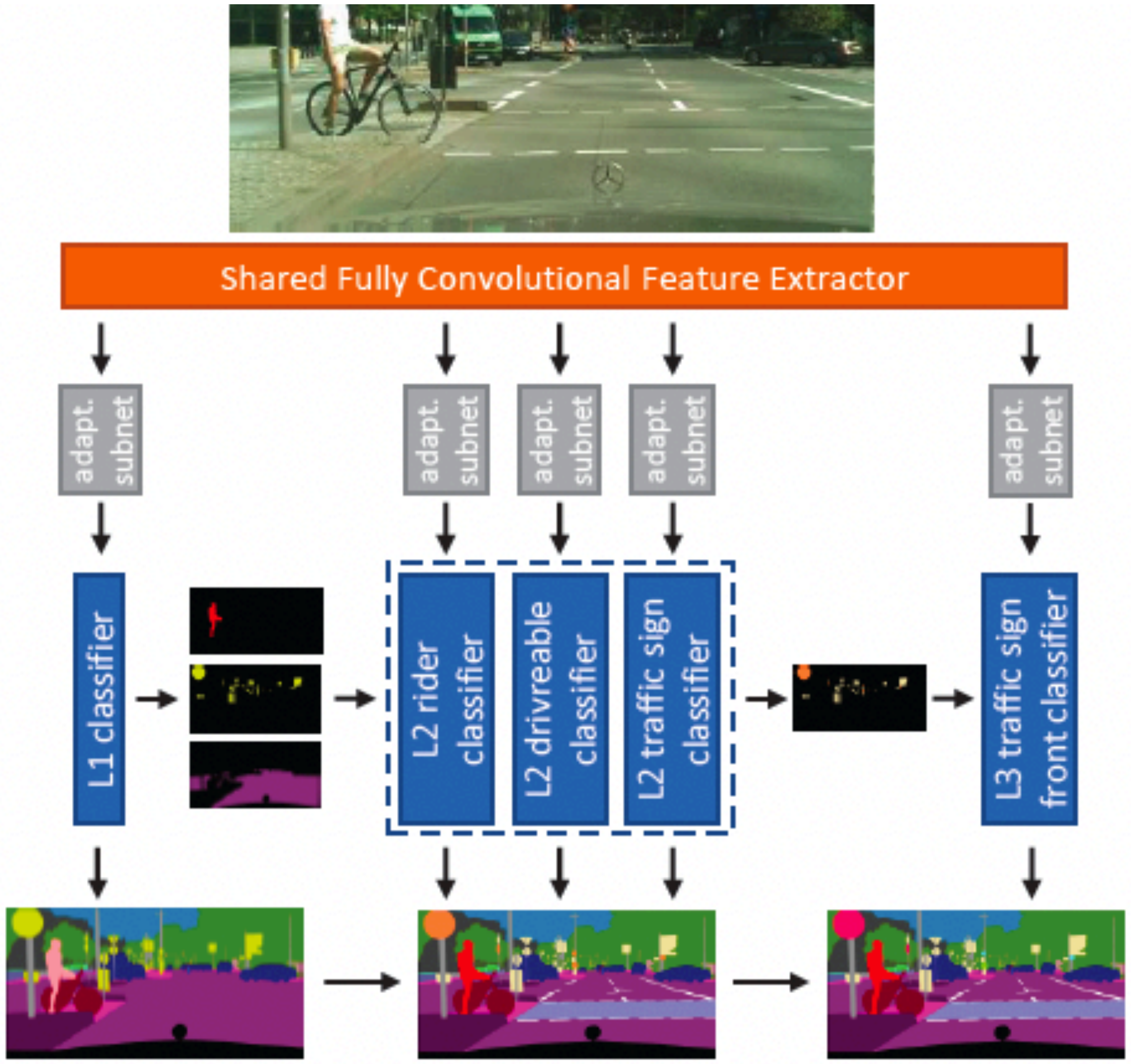
Meletis and Dubbelman: https://arxiv.org/pdf/1803.05675.pdf

- Datasets:
  - Training:
    - Cityscapes
    - GTSDB (traffic signs) non-pixel annotation
    - Mapillary Vistas

1. Training of Convolutional Networks on Multiple Heterogeneous Datasets for Street Scene Semantic Segmentation

Meletis and Dubbelman: https://arxiv.org/pdf/1803.05675.pdf

- Backbone: ResNet-50
- Same adaptation subnetworks
- Hybrid upsampling
- (2x2 learnable fractional strides convolutional layer, bilinear upsampling)
- Batch: 4 Cityscapes:Vistas:GTSDB = 1:2:1
- Input: 512x706
- Inference Time: 58 ms per frame
- Loss: Hierarchical loss



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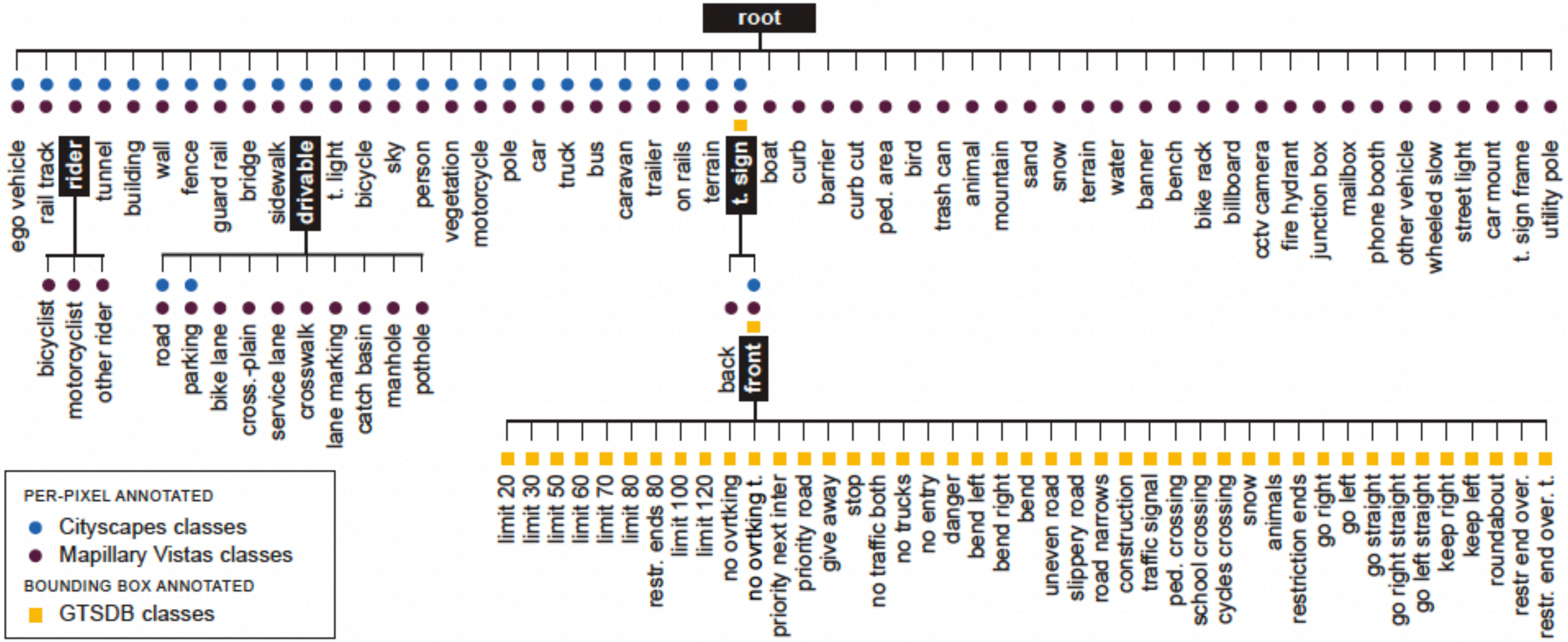
- 

Fig. 2. Three-level semantic label hierarchy combining 108 classes from Cityscapes, Mapillary Vistas and GTSDB dataset. Classes marked in black correspond to the L1, L2, and L3 classifiers of Fig. 1.

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- Both losses are accumulated per classifier to the so called hierarchical loss:

$$L^j = -\frac{1}{\left|P_1^j\right|} \sum_{p \in P_1^j} \log \sigma^{j,p}_{y^j,p} - \frac{1}{\left|P_2^j\right|} \sum_{p \in P_2^j} \log \sigma^{j,p}_{y^j,p} \,, \quad (1)$$

$$L^{total} = \sum_j \lambda^j \cdot L^j + regularizer \,.$$

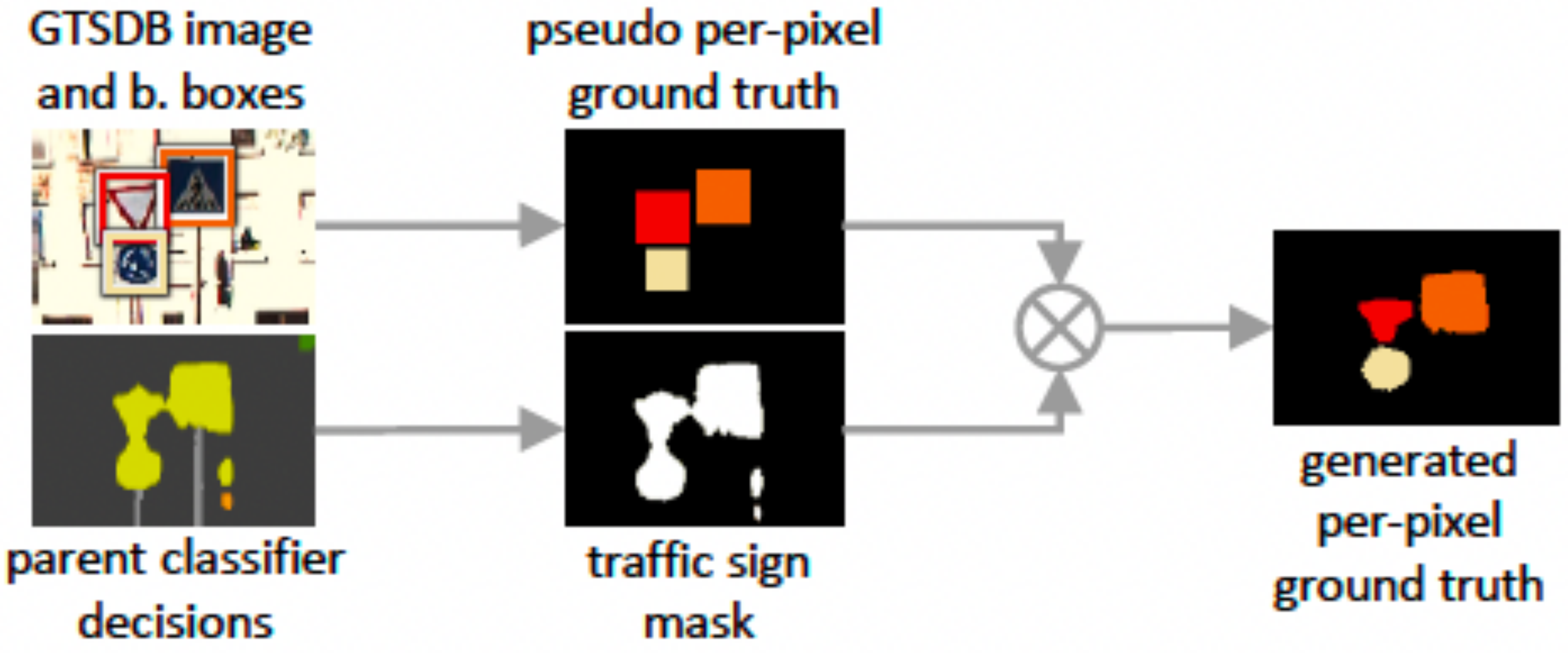

Fig. 3. Online procedure during training for generating per-pixel ground truth from bounding box labels.

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- TABLE II

FLAT CLASSIFICATION PERFORMANCE BASELINES ON PER-PIXEL ANNOTATED DATASETS.

Tested on	Same dataset			Cross-dataset
	Cityscapes	Vistas	GTSDB	Cityscapes Extended traffic sign classes
mPA (%)	53.6	36.5	25.4	19.1
mIoU (%)	46.2	29.6	17.2	3.0
Trained on	Cityscapes	Vistas	GTSDB	Cityscapes + GTSDB

TABLE III

PERFORMANCE OF OUR COMPLETE HIERARCHICAL CLASSIFICATION APPROACH ON 4 DATASETS.

Tested on	Same dataset			Cross-dataset
	Cityscapes classes	Vistas classes	GTSDB classes	Cityscapes Extended traffic sign classes
mPA (%)	66.6	38.9	57.7	29.7
mIoU (%)	57.3	31.9	41.5	8.3
Trained on	Cityscapes + Vistas + GTSDB			

2. MSeg: A composite Dataset for Multi-domain Semantic Segmentation

Lambert and Liu: https://arxiv.org/pdf/2112.13762.pdf

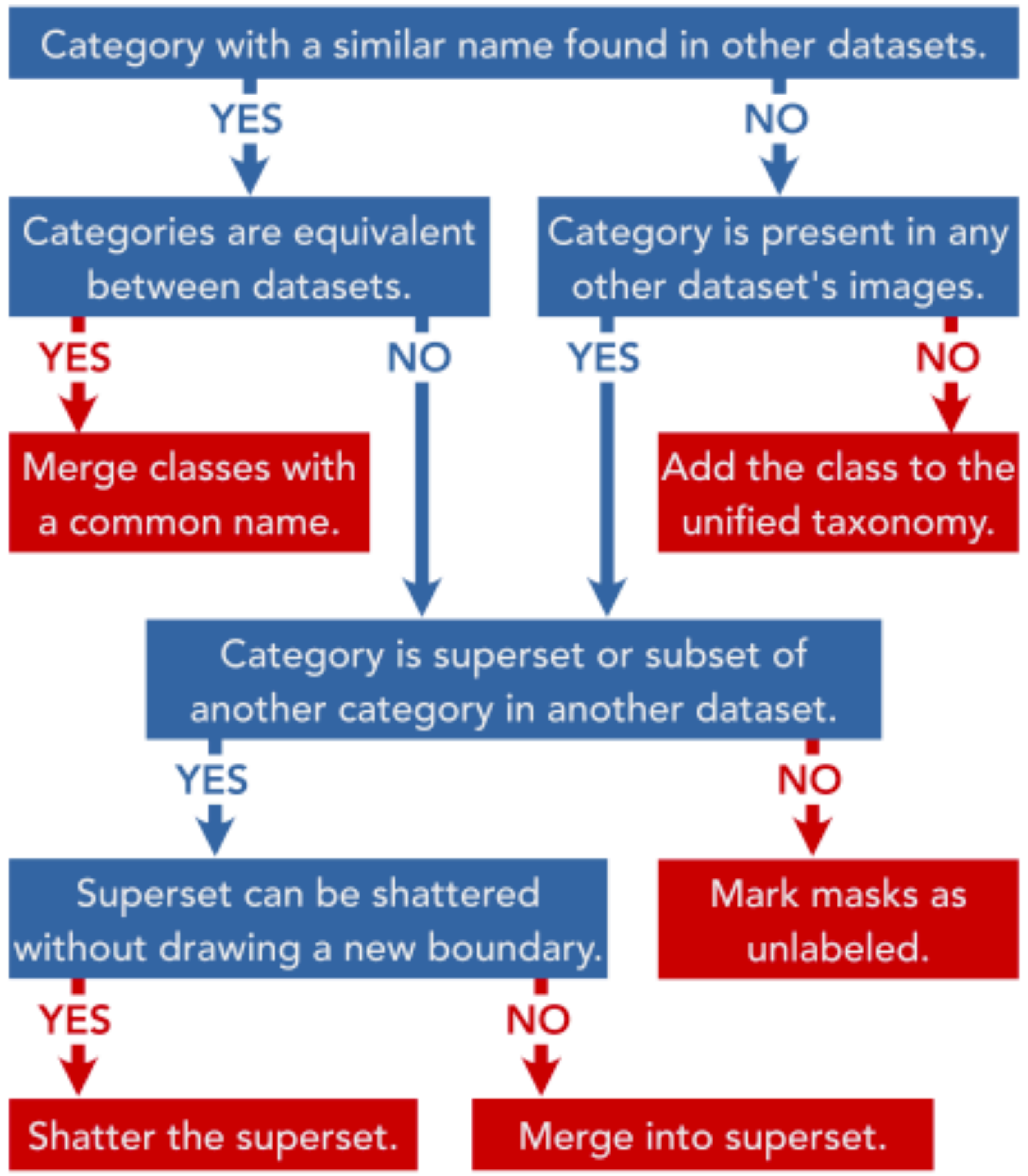

Fig. 2: Procedure for determining the set of categories in the MSeg taxonomy.

TABLE 1: Component datasets in MSeg.

Dataset name	Origin domain	# Images
Training & Validation		
COCO [10] + COCO Stuff [50]	Everyday objects	123,287
ADE20K [11]	Everyday objects	22,210
Mapillary [9]	Driving (Worldwide)	20,000
IDD [13]	Driving (India)	7,974
BDD [14]	Driving (United States)	8,000
Cityscapes [8]	Driving (Germany)	3,475
SUN RGBD [15]	Indoor	5,285
Test		
PASCAL VOC [51]	Everyday objects	1,449
PASCAL Context [52]	Everyday objects	5,105
CamVid [53]	Driving (U.K.)	101
WildDash-v1[1] [21]	Driving (Worldwide)	70
KITTI [54]	Driving (Germany)	200
ScanNet-20 [55]	Indoor	5,436

2. MSeg: A composite Dataset for Multi-domain Semantic Segmentation

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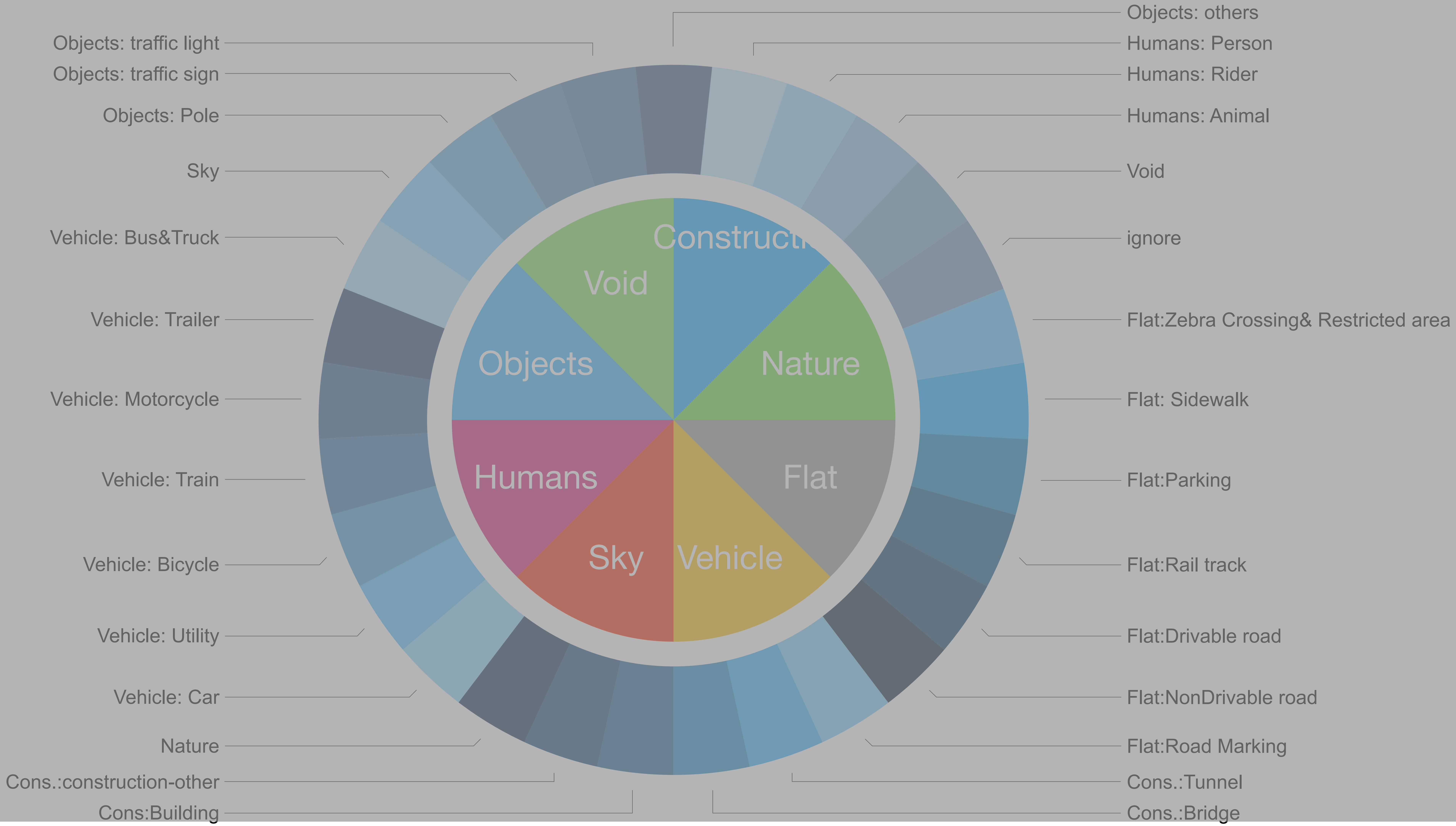
3. Autonomous driving datasets

- Cityscapes
- nuImages
- CamVid
- Mapillary
- IDD
- A2D2
- GTA-5

3. Autonomous driving datasets:
CityScape+CamVid+GTA5+nuScene+Mapillary+IDD+A2D2



Multi Domain Heterogeneous Dataset Hierarchical Semantic Segmentation Methods

Flat Network with hierarchical loss

- Loss function:
  - Loss of superclass (level 1)
  - Loss of level 2 classes
  - Loss of level 3 classes
  - Total loss = loss_level_1 + loss_level2 + loss_level3

Class Hierarchy

Vehicles	Small vehicles	Car	Pickup truck	
		Van		
		ego_vehicles		
	Large Vehicles	Truck	Train	
		Bus		
	two_wheelers	Motorcycle	Bicycle	
	other_vehicels	Caravan	trailer	Boat
		wheeled_slow	other_vehicles	Plane
Flat	normal_road	road	parking	rail_track
		sidewalk	curb	Pedestrian area
		Dirt track	runway	Crosswalk plain
		Bikelane	Service lane	Path
		Curb cut		
	road_marking	General marking	Zebra marking	manhole
		catch+basin	Pothole	all_road_marking
Construction	building_infra	Building	Grandstand	Stairs
		house	step_stair	stage
		stairway	Skyscraper	Column
		Wall	Bridge	tunnel
		fence	guard_rail	
	other_infra	Pier-dock	Canopy	Fountain
		Bannister	Barrier	awning-sunshade
		Hovel-hut		
Traffic_objects	pole_all	Pole	Utility pole	tower
	Sign	traffic_sign	Billboard	banner
		traffic_sign_frame	traffic_sign back	trade-brand
		picture	Poster	
	glowing_obj	street_light	Traffic light	Light-source

Level 1 super classes

Fine grained classes

	Other_obj	trashcan	phone_booth	cctv_camera
		junction_box	fyre_hydrant	mailbox
		bikerack		
Nature Objects	sky_ Vegetation	Tree	palm_tree	Sky
		plant	Vegetation	
	ground	terrain	Mountain	earth-ground
		soil-ground	hill	Field
		Rock		
	other_entities	Water	Snow	sand
		river	Lake	sea
		Water-fall	Swimming-pool	
Vulnerable_road_user VRU	Animal	ground_animal	Bird	
	Human	Motorcyclist	Bicyclist	other_rider
		Person		
Indoor_obj	furniture	Bed	cabinet	door
		Table	Chair	sofa
		Shelf	Armchair	desk
		drawers	Counter	Ward robe
		Coffee table	Ottoman	stool
		other_furniture	Book-case	box
		Swivel-chair	cradle	Case-showcase
		Seat	Bench	Window
	Bedroom obj	Cushion	Pillow	lamp
		rug	Mirror	curtain
		Flower	Blind	
		Blanket-cover	Apparel	Fireplace
				Ceiling
		Floor	Sconce	
	Bathroom obj	Bathtub	toilet	Towel
		Shower	shower_curtain	
	other_obj	Escalator	Flag	Clock

Level 1 super classes

Fine grained classes

		Radiator	Glass-drinking	plate
		Fan	tray	Vase
		pot	Bag	Tent
		Basket	barrel	Playing-toy
		Conveyerbelt	Chandelier	Book
		pool-billard	ball	Tank
		Sculpture	base	
	Electronic	Monitor	CRT-screen	screen-projector
		Television	Arcade machine	computer
		Screen		
	Kitchen_obj	hood_exhaust	Dishwasher	
		microwave	Food	Oven
		Washer	Buffet	Bottle
		Bar	Kitchen-island	Stove
		counter-top	Refrigerator	Sink

Level 1 super classes

Fine grained classes

Multi Heads Architecture: example

Level 1 Head

- Ignore
- Vehicles
- Flat
- Construction
- Traffic objects
- Nature objects
- VRU objects
- Indoor objects

Level 2 Head: Vehicles

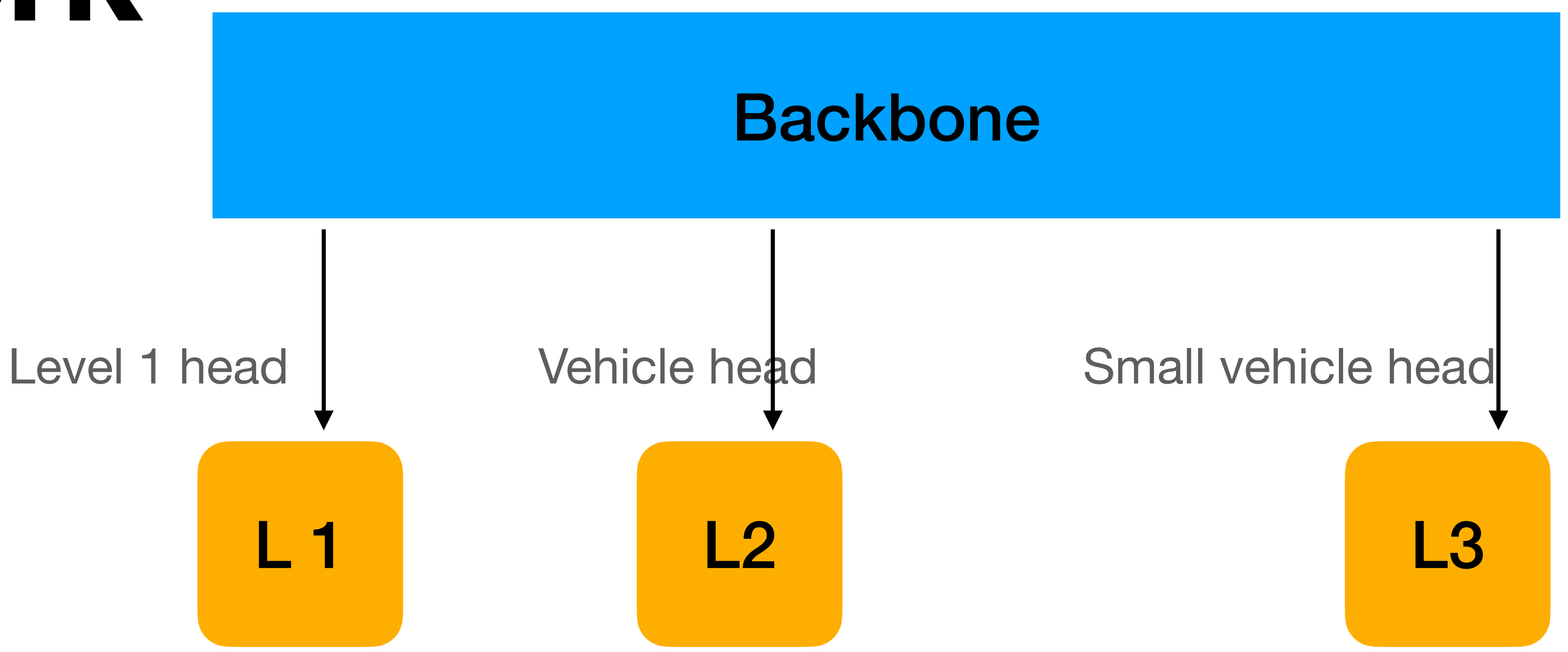
- Ignore
- Small vehicles
- Large vehicles
- Two wheelers vehicles
- Other vehicles

Level 3 Head: Small Vehicles

- Ignore
- Car
- pickup_truck
- Van
- ego_vehicle

Hierarchical Network

- Overview



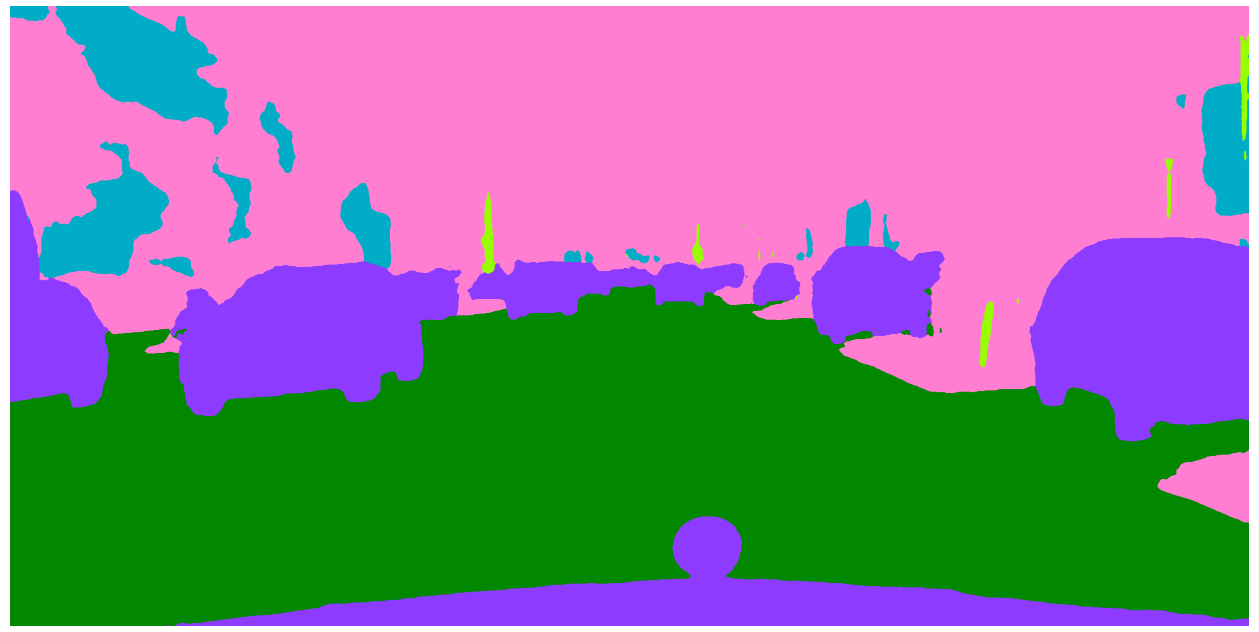
Example for level 1 vehicle class

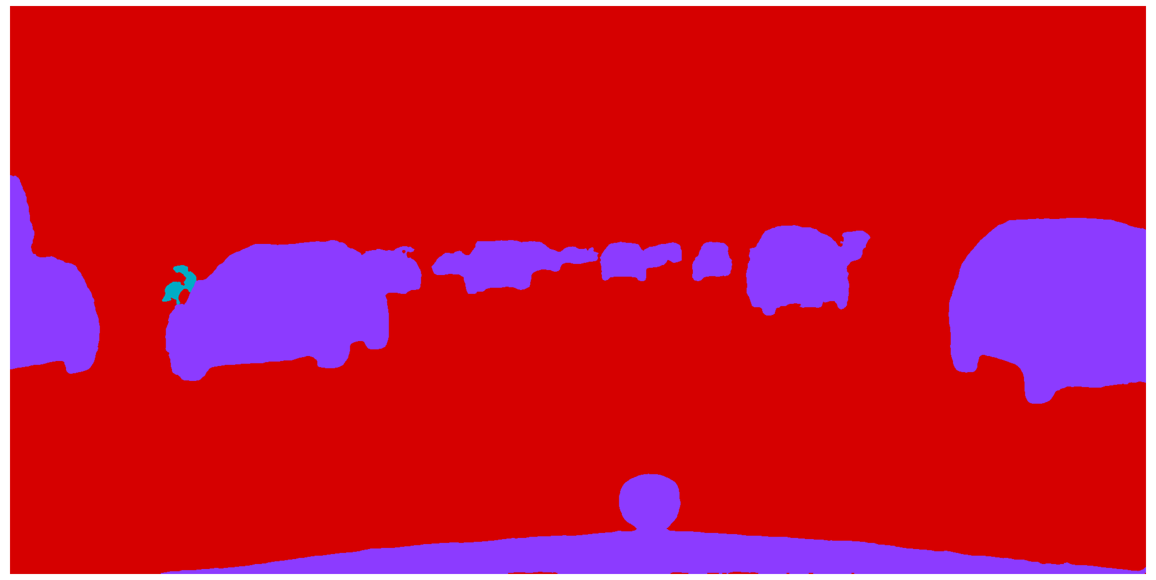
Prediction ->

…Vehicles …

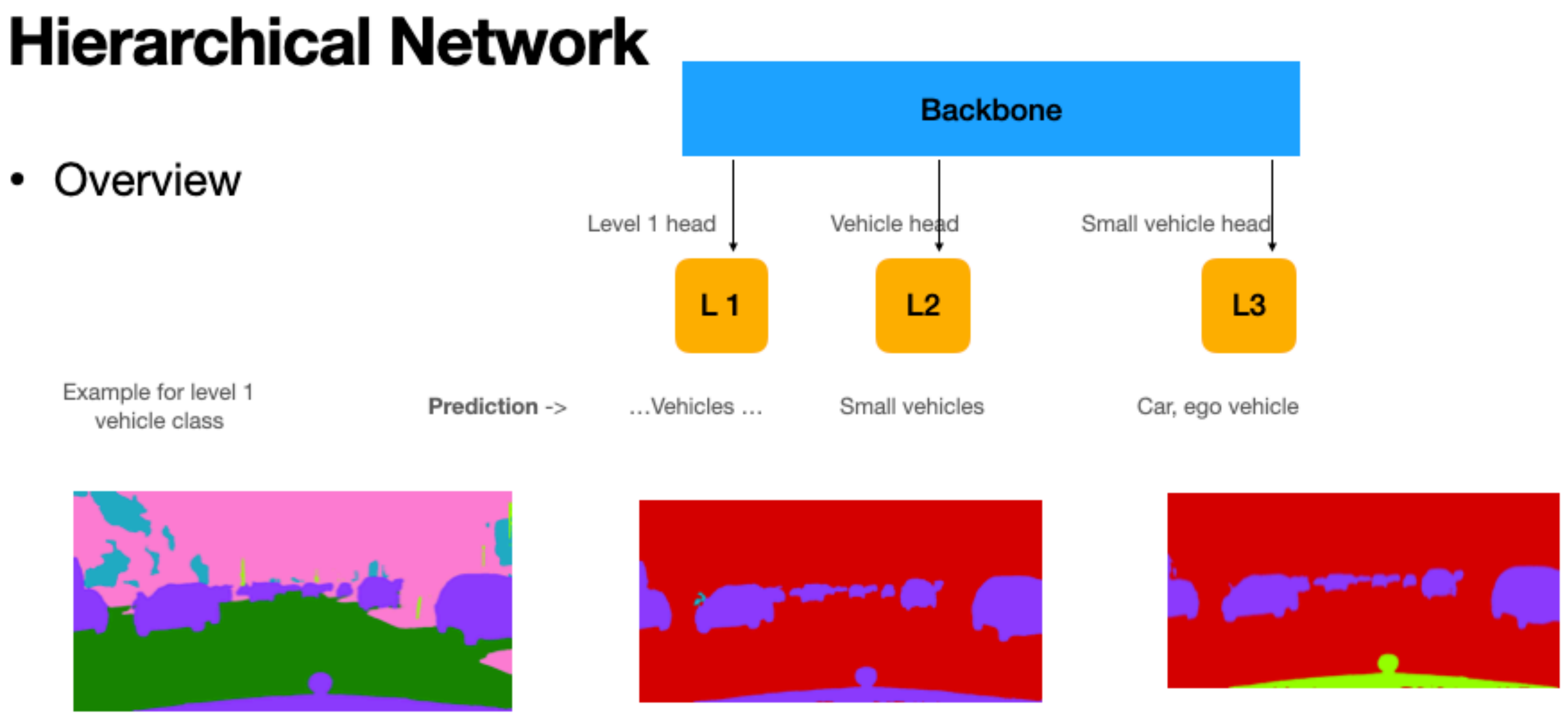
Small vehicles

Car, ego vehicle





Hierarchical N/W

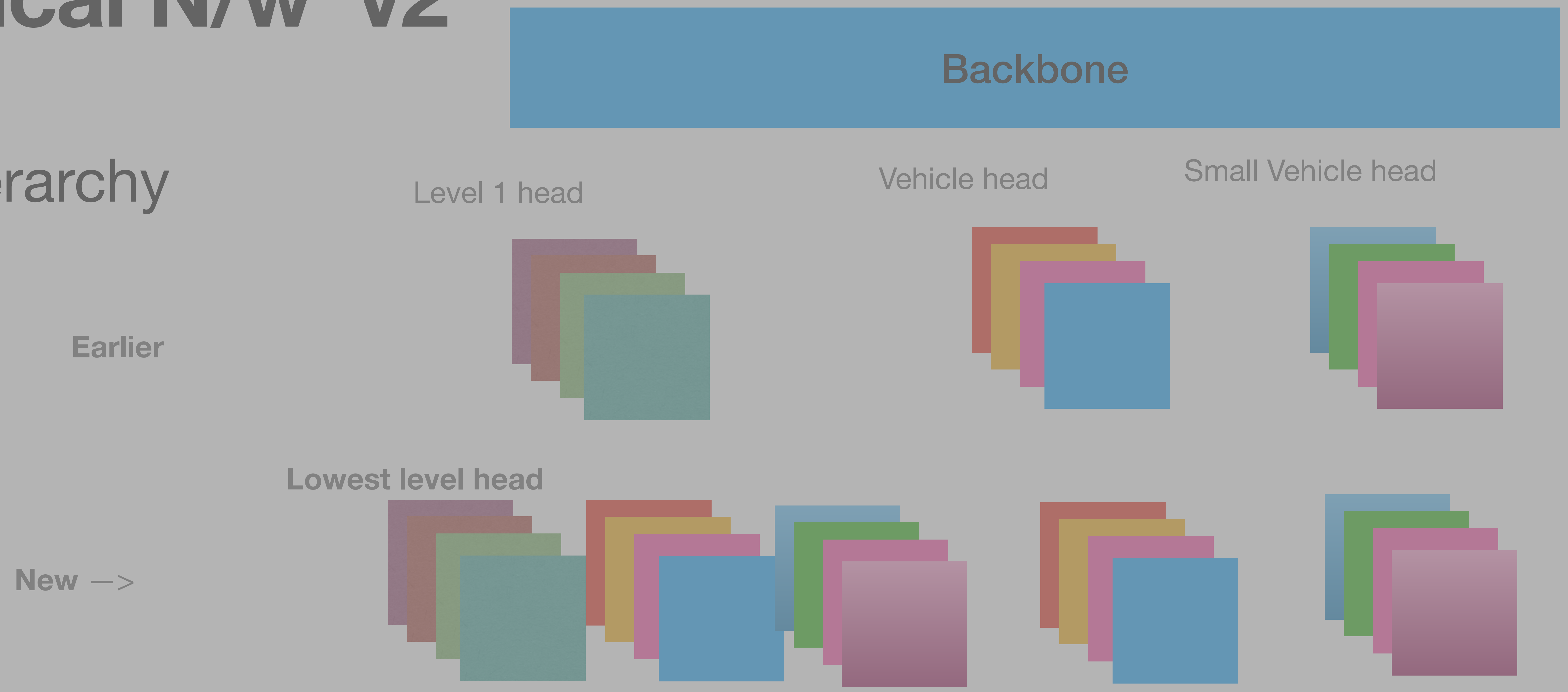


- Loss function: total loss
  - c1 * L1_loss + c2 * L2_loss + c3 * L3loss
- Discussion:
  - Everything relies on L1_head
    - solution: to improve mIOU -> class weights at L1 head
  - Loss function : other possibilites to connect all heads through loss function !!!
  - If L1 predicted negative: output is negative

- .
- .

Hierarchical N/w v2

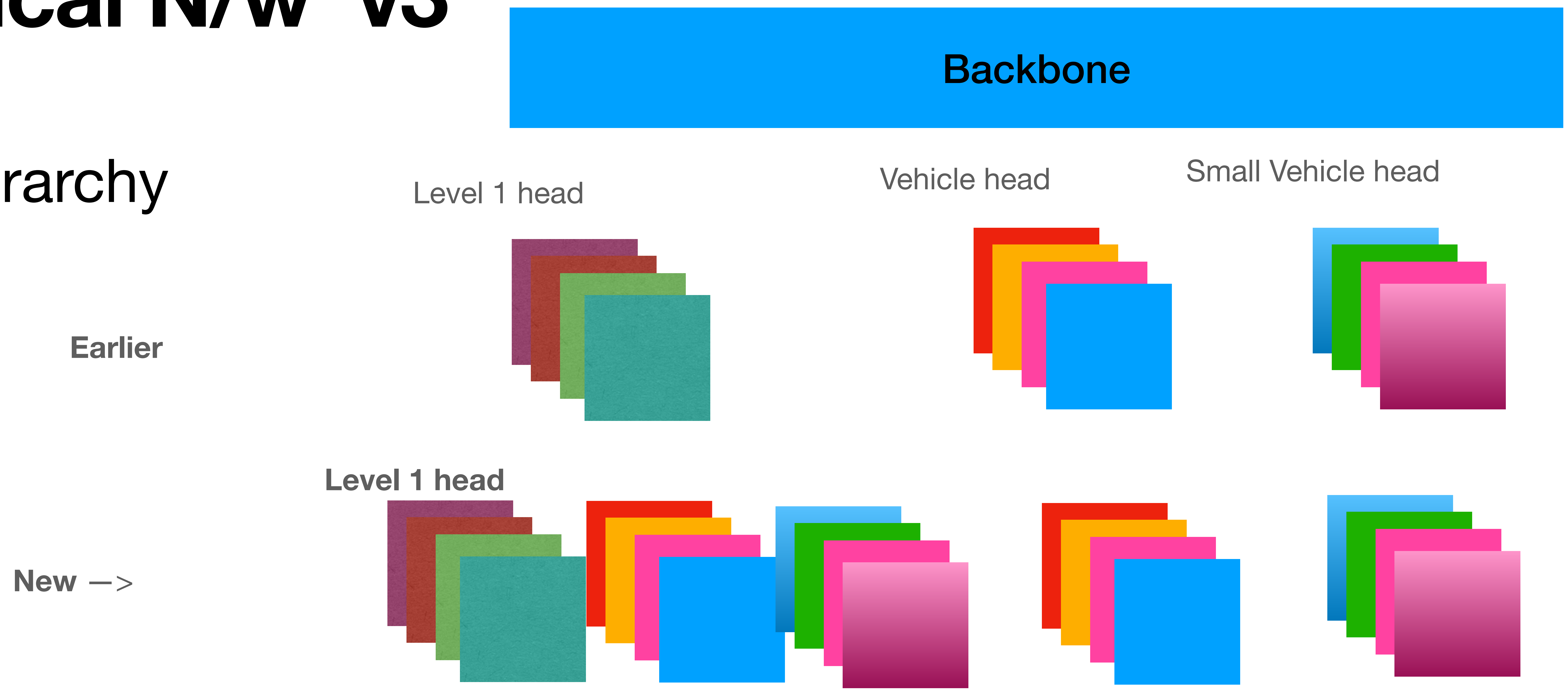
- Inverse Hierarchy



- Advantage:
    - Dependency over L1 head is reduced

Hierarchical N/w v3

- Inverse Hierarchy



- Advantage:
  - Level 1 is enriched with features!!

Results:

Comparison

	RVC2018_Best	RVC2020_1st	RVC2020_2nd	SingleDataset- mIoU	FlatMultiDataset-mIoU-1	FlatMultiDataset-mIoU-2	HierarchicalMultiDataset- mIoU	ImprovedHMDataset-mIoU
Evaluated on:		Test data	Test data	Validation data	Validation data			
Cityscapes	80.2	74.7	**80.7**	0.7399	0.7263		0	
Vistas		**40.4**	34.2	0.382	0.367		0	
Viper		**62.5**	40.7	0.496	**0.655**		0	
Wilddash	**59.1**	**45.4**	35.2	0.452	**0.554***		0	
Ade		31.1	**33.2**	0.386	0.304		0	
Scannet	48.0	**54.6**	48.5	-	**0.596**		0	
KiTTI	69.6	63.9	62.6					