

Supplemental Material CVPR2022 Paper

Unifying Panoptic Segmentation for Autonomous Driving

1. Unified Label Policy

Table 1 lists all WD2 labels including mappings to MVD, IDD, Cityscapes, and WD2_{eval} as well as each label’s supercategory and visualization color.

WD2	color	MVD	IDD	Cityscapes	WD2 _{eval}	WD2	color	MVD	IDD	Cityscapes	WD2 _{eval}
†	person	person	person	person	person	☞	pole	pole	pole	<i>pole</i>	pole
†	motorcyclist	motorcyclist	rider	rider	rider	☞	utilitypole	utilitypole	pole	<i>pole</i>	pole
†	bicyclist	bicyclist	rider	rider	rider	☞	trafficsignframe	trafficsignframe	pole	<i>pole</i>	pole
†	otherrider	otherrider	rider	rider	rider	☞	trafficsign	trafficsign	trafficsign	trafficsign	trafficsign
🚗	egovehicle	egovehicle	egovehicle	<i>egovehicle</i>	egovehicle	☞	billboard	billboard	billboard	<i>billboard</i>	billboard
🚗	dashcammount	carmount	egovehicle	<i>egovehicle</i>	egovehicle	☞	streetlight	streetlight	obsstrbarf.	<i>streetlight</i>	streetlight
🚗	car	car	car	car	car	☞	manhole	manhole	road	road	road
🚗	truck	truck	truck	truck	truck	☞	trafficsignfront	trafficsignfront	trafficsign	trafficsign	trafficsign
🚗	bus	bus	bus	bus	bus	☞	trafficsignback	trafficsignback	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	motorcycle	motorcycle	motorcycle	motorcycle	motorcycle	☞	trafficsignnany	<i>unlabeled</i>	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	bicycle	bicycle	bicycle	bicycle	bicycle	☞	otherbarrier	otherbarrier	wall	wall	wall
🚗	pickup	truck	truck	truck	pickup	☞	catchbasin	catchbasin	road	road	road
🚗	van	car	car	car	van	☞	manholesidewalk	manhole	sidewalk	sidewalk	sidewalk
🚗	autorickshaw	othervehicle	autorickshaw	motorcycle	motorcycle	☞	junctionbox	junctionbox	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	caravan	caravan	caravan	<i>caravan</i>	<i>unlabeled</i>	☞	mailbox	mailbox	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	trailer	trailer	trailer	<i>trailer</i>	<i>unlabeled</i>	☞	phonebooth	phonebooth	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	onrails	onrails	train	onrails	<i>unlabeled</i>	☞	bikerack	bikerack	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	othervehicle	othervehicle	vehiclef.	<i>dynamic</i>	<i>unlabeled</i>	☞	pothole	pothole	road	road	road
🚗	wheeledslow	wheeledslow	vehiclef.	<i>dynamic</i>	<i>unlabeled</i>	☞	trashcan	trashcan	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
🚗	boat	boat	<i>unlabeled</i>	<i>dynamic</i>	<i>unlabeled</i>	☞	bench	bench	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
▲	road	road	road	road	road	☞	banner	banner	obsstrbarf.	<i>dynamic</i>	<i>unlabeled</i>
▲	sidewalk	sidewalk	sidewalk	sidewalk	sidewalk	☞	firehydrant	firehydrant	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
▲	roadmarking	markinggeneral	road	road	roadmarking	☞	cctvcamera	cctvcamera	obsstrbarf.	<i>static</i>	<i>unlabeled</i>
▲	curb	curb	curb	sidewalk	sidewalk	🏠	building	building	building	building	building
▲	tramtrack	railtrack	road	road	road	🏠	wall	wall	wall	wall	wall
▲	bikelane	bikelane	road	road	road	🏠	fence	fence	fence	fence	fence
▲	bikelanesidewalk	bikelane	sidewalk	sidewalk	sidewalk	🏠	guardrail	guardrail	guardrail	<i>guardrail</i>	guardrail
▲	pedestrianarea	pedestrianarea	road	road	road	🏠	bridge	bridge	bridge	<i>bridge</i>	<i>unlabeled</i>
▲	crosswalkplain	crosswalkplain	road	road	road	🏠	tunnel	tunnel	tunnel	<i>tunnel</i>	<i>unlabeled</i>
▲	crosswalkzebra	crosswalkzebra	road	road	road	🌿	vegetation	vegetation	vegetation	vegetation	vegetation
▲	curbterrain	curb	curb	terrain	terrain	🌿	terrain	terrain	nondrivablef.	terrain	terrain
▲	servicelane	servicelane	road	road	road	🌿	groundanimal	groundanimal	<i>dynamic</i>	<i>dynamic</i>	<i>unlabeled</i>
▲	curbcut	curbcut	curb	sidewalk	sidewalk	🌿	bird	bird	<i>animal</i>	<i>dynamic</i>	<i>unlabeled</i>
▲	ground	<i>unlabeled</i>	<i>unlabeled</i>	<i>ground</i>	<i>unlabeled</i>	🌿	mountain	mountain	f.background	<i>static</i>	<i>unlabeled</i>
▲	parking	parking	parking	<i>parking</i>	<i>unlabeled</i>	☁	sky	sky	sky	sky	sky
▲	railtrack	railtrack	railtrack	<i>railtrack</i>	<i>unlabeled</i>	✖	dynamic	<i>unlabeled</i>	<i>unlabeled</i>	<i>dynamic</i>	<i>unlabeled</i>
▲	water	water	nondrivablef.	<i>ground</i>	<i>unlabeled</i>	✖	overlay	<i>unlabeled</i>	<i>rect.border</i>	<i>rect.border</i>	<i>unlabeled</i>
▲	sand	sand	drivablef.	<i>ground</i>	<i>unlabeled</i>	✖	outofroi	<i>unlabeled</i>	<i>outofroi</i>	<i>outofroi</i>	<i>unlabeled</i>
▲	snow	snow	<i>unlabeled</i>	<i>ground</i>	<i>unlabeled</i>	✖	static	<i>unlabeled</i>	<i>unlabeled</i>	<i>static</i>	<i>unlabeled</i>
☞	polegroup	pole	<i>polegroup</i>	<i>polegroup</i>	pole	✖	unlabeled	<i>unlabeled</i>	<i>unlabeled</i>	<i>unlabeled</i>	<i>unlabeled</i>

Table 1. Willdash2 label policy and mapping to MVD, IDD, CS, and WD2_{eval}. Bold labels have instance annotations, italic labels are not evaluated at their respective benchmark. Negative test cases do evaluate areas labeled as *unlabeled* in WD2_{eval} (see paper’s Section 4.2 on Negative Testing); Supercategories: † human; 🚗 vehicle; ▲ flat; ☞ object; 🏠 construction; 🌿 nature; ☁ sky; ✖ void

2. Category definitions

The WD2 label policy unifies MVD, IDD, and Cityscapes category labels (in addition to the new vehicle labels *pickup* and *van*). The definition for most labels can be found in existing label definitions. Others need clarification or clear rules for differentiation in borderline cases. This leads to the following category definitions:

- The categories *person*, *egovehicle*, *car*, *truck*, *bus*, *motorcycle*, *bicycle*, *caravan*, *trailer*, *onrails*, *road*, *sidewalk*, *ground*, *parking*, *railtrack*, *polegroup*, *billboard*, *streetlight*, *building*, *wall*, *fence*, *guardrail*, *bridge*, *tunnel*, *vegetation*, *terrain*, *sky*, *unlabeled*, *outofroi*, *static*, and *dynamic* are described in the supplemental material to the Cityscapes [1] paper.
- The categories *motorcyclist*, *bicyclist*, *otherrider*, *othervehicle*, *wheeledslow*, *boat*, *roadmarking* (==marking general) *curb*, *bikelane*, *pedestrianarea*, *crosswalkplain*, *crosswalkzebra*, *servicelane*, *curbcut*, *water*, *sand*, *snow*, *pole*, *utilitypole*, *trafficsign* (== traffic sign front), *manhole*, *pothole*, *trafficsignback*, *trafficsignframe*, *otherbarrier*, *catchbasin*, *junctionbox*, *mailbox*, *phonebooth*, *bikerack*, *trashcan*, *bench*, *banner*, *firehydrant*, *cctvcamera*, *groundanimal*, *bird*, *mountain*, *dashcammount* (== car mount) are described in the supplemental material to the MVD [2] paper.

	👤 human	🚗 vehicle	🏠 flat	🗑️ object	🏗️ construction	🌳 nature	☁️ sky	average
mvd100 PQ_{Cat}	46.0%	55.3%	71.6%	32.3%	52.8%	66.5%	79.5%	57.7%
mix150 PQ_{Cat}	49.7%	61.4%	86.2%	34.1%	62.5%	71.9%	87.3%	64.7%
mvd100 RQ_{Cat}	60.2%	67.0%	84.1%	48.2%	70.0%	82.1%	86.3%	71.1%
mix150 RQ_{Cat}	65.2%	73.6%	97.5%	50.9%	79.8%	87.1%	93.6%	78.2%
mvd100 SQ_{Cat}	76.4%	82.6%	85.1%	67.1%	75.4%	80.9%	92.2%	80.0%
mix150 SQ_{Cat}	76.2%	83.4%	88.4%	66.9%	78.2%	82.6%	93.3%	81.3%

Table 2. Per-supercategory PQ, RQ and SQ metrics evaluated on the hidden WD2 benchmark set for both models *mvd100* and *mix150* presented in the main paper.

- The labels *curb* and *curbterrain* both are described by the MVD *curb* label (i.e. curb stones; including all visible faces of a curb). If the curb encases an area labeled with terrain (or other vegetation), then the curb receives the *curbterrain* label. Otherwise use *curb*.
- The labels *bikelane* and *bikelanesidewalk* are both described by the MVD *curb* label. Use *bikelanesidewalk* if the bikelane is on a sidewalk. Otherwise use *bikelane*.
- The labels *manhole* and *manholesidewalk* are both described by the MVD *manhole* label. Use *manholesidewalk* if the manhole is on a sidewalk. Otherwise use *manhole*.
- The *traintrack* is described by the Cityscapes *traintrack* label (i.e. track of raised rails, not drivable by cars). The *tramtrack* label is used for the track area between embedded rails (drivable by cars) including the rails themselves.
- The *autorickshaw* category is described in the IDD [3] paper.
- The *trafficsignany* category is a fallback category used for cases where either *trafficsign* (=front) or *trafficsignback* could be correct.
- Vehicle class *pickup*: This label is used for light commercial vehicles (LCV) with an open cargo area. It only applies to motorized, car-sized vehicles with a visible un-roofed cargo area (also for open cages). Pickup trucks have regular car front wheels and a regular car wheelbase (distance). Cargo vehicles with larger tires or a truck motor housing (driver sitting above motor with a vertical windscreen and bonnet) retain the *truck* label.
- Vehicle class *van*: This label applies to motorized LCV without an open cargo area. Vans have a boxy shape with regular car tires and their wheel-base is typically larger than those of regular cars. The front of vans is often inclined but straight and they are distinctively higher (i.e. the van’s ceiling) than regular cars. Vehicles sold under the term “mini-van” with a regular car height remain at the *car* label. Hybrid vehicles with a fully separated, non-continuous, driver cabin are still labeled as *truck* (e.g. many ambulance vehicles, police, some delivery trucks).

3. Supercategory Scores

Table 2 shows individual per-supercategory scores of *mvd100* and *mix150* on the $WD2_{bench}$ set. Table 3 in the main paper contains the right-most column (arithmetic mean over all supercategories) denoted as PQ_{cat} .

4. Further Experiments

The following Table 3 mirrors the layout of Table 3 in the main paper. Experiments were conducted for WD2, Cityscapes, and IDD in the same way as for MVD: first 100 epochs on only the original dataset using the standard training label policy (plus *van* and *pickup*. This results in 66 labels for MVD, 29 for IDD, and 22 for Cityscapes. The validation results are calculated on the original validation dataset using the original training label policy while the WD2 benchmark evaluation remaps the algorithm outputs to the $WD2_{eval}$ label policy (26 labels) and reports the results for the hidden WD2 benchmark dataset. The models after 100 epochs are fine-tuned for 50 epochs using WD2 individually remapped to each of the dataset’s training label policies mixed with the same amount of frames from the original dataset (i.e. 50%/50% split). The model for the first column *wd2_100* uses only WD2 frames with the $WD2_{eval}$ label policy during training. The same train/val split is used both for *wd2_100* as well as in all fine-tunings.

	Original Validation					WD2 Benchmark						
	<i>PQ</i>	<i>SQ</i>	<i>RQ</i>	<i>PQ_{van}</i>	<i>PQ_{pickup}</i>	<i>PQ</i>	<i>SQ</i>	<i>RQ</i>	<i>PQ_{van}</i>	<i>PQ_{pickup}</i>	<i>PQ_{neg}</i>	<i>PQ_{cat}</i>
wd2_100	38.0%	75.6%	48.2%	36.9%	33.4%	37.0%	75.5%	47.7%	35.1%	37.3%	16.9%	61.1%
cs100	55.7%	76.4%	68.2%	53.7%	0.0%	10.7%	69.5%	15.0%	10.6%	0.0%	5.4%	22.8%
cs150	56.1%	77.4%	68.2%	55.2%	0.0%	32.2%	76.9%	41.1%	34.4%	41.1%	15.5%	58.4%
idd100	47.7%	75.6%	59.5%	48.8%	0.0%	15.3%	72.8%	20.1%	14.1%	0.0%	7.2%	35.7%
idd150	46.4%	75.7%	57.9%	40.4%	0.0%	29.4%	76.1%	37.7%	33.7%	33.7%	14.2%	54.8%
mvd100	35.1%	74.2%	43.9%	26.6%	29.9%	37.6%	75.6%	48.3%	34.0%	38.1%	17.1%	57.7%
mix150	34.1%	73.5%	42.8%	24.7%	29.7%	42.2%	77.5%	53.2%	38.9%	49.2%	21.1%	64.7%

Table 3. Comparison of performances for multiple models first trained on the respective original datasets (WD2, Cityscapes, IDD, MVD) and later fine-tuned for 50 additional epochs on a 50%/50% mixture of the original dataset and WD2. The left side shows results when evaluated on the original validation sets and the right side shows scores on the hidden WD2 benchmark set. The label policy on the left is not constant across the rows while the right side all evaluate using the same labels: $WD2_{eval}$. Results for MVD are duplicated from the main paper to improve comparability.

References

- [1] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3213–3223, 2016. [1](#)
- [2] Gerhard Neuhold, Tobias Ollmann, Samuel Rota Buló, and Peter Kotschieder. The mapillary vistas dataset for semantic understanding of street scenes. In *IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 4990–4999, 2017. [1](#)
- [3] Girish Varma, Anbumani Subramanian, Anoop Namboodiri, Manmohan Chandraker, and CV Jawahar. IDD: A dataset for exploring problems of autonomous navigation in unconstrained environments. In *IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1743–1751. IEEE, 2019. [2](#)