

1st Place Solution of The Robust Vision Challenge (RVC) 2022

Semantic Segmentation Track

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Abstract

This report describes the winner solution to the semantic segmentation task of the Robust Vision Challenge on ECCV 2022. Our method adopts the FAN-B-Hybrid model as the encoder and uses Segformer as the segmentation framework. The model is trained on a combined dataset containing images from 9 datasets (ADE20K, Cityscapes, Mapillary Vistas, ScanNet, VIPER, Wilddash2, IDD, BDD, and COCO) with a simple dataset balancing strategy. All the original labels are projected to a 256-class unified label space, and the model is trained with naive cross-entropy loss. Without significant hyperparameters tuning or any specific loss weighting, our solution ranks 1st on all the required semantic segmentation benchmarks from multiple domains (ADE20K, Cityscapes, Mapillary Vistas, ScanNet, VIPER, and Wilddash2). Our method could be served as a strong baseline for the multi-domain segmentation task and our codebase could be helpful to future work. Code will be available at https://github.com/lambert-x/RVC_Segmentation.

1. Introduction

In the past few years, advances in deep learning have led to significant progress in visual recognition. However, the robustness of state-of-the-art deep learning models remains an open issue. On the one hand, real-world applications require models to be deployed “in the wild”. On the other hand, many current deep models have been shown to be brittle to distributional shifts and natural perturbations. This phenomenon raised considerable interest in open problems such as domain generalization and adaptation.

There is rich literature in domain generalization [18, 24] where popular methods include, but are not limited to: domain randomization, domain invariant representation learning, disentanglement learning and meta learning, etc. One approach related to this work is multi-dataset training [10], in which the authors show that a simple combination of multiple datasets with label space alignment can outperform strong domain generalization approaches.

Dataset	Scenes	#Images (train/val)	#Class (orig-proj)
COCO [3, 11]	Natural	118287/5000	201→133
ADE20K [22]	Natural	20210/2000	151→146
Cityscapes [6]	Driving	2975/500	34→31
Vistas [14]	Driving	18000/2000	66→64
BDD [20]	Driving	7000/1000	19→19
IDD [17]	Driving	6993/981	39→26
WildDash 2 [21]	Driving	3413/857	34→31
ScanNet [7]	Indoor	19466/5436	41→41
VIPER [16]	Artificial	13367/4959	32→32

Table 1. **Datasets overview.** A total of 9 datasets across natural, driving, indoor, and artificial scenes are used for training and validating the model. Class count denotes the number of classes in the original label space and the projected label space.

Another interesting trend is the recent surge of Vision Transformers (ViTs). Several works [1, 13, 15, 19] almost simultaneously pointed out that ViTs demonstrate surprisingly strong robustness to out-of-distribution scenarios. For example, SegFormer [19] demonstrates significantly better results over CNN-based strong methods in Cityscapes-C, a more challenging variant of Cityscapes contaminated by 16 types of natural corruption. More recently, [23] introduced the fully attentional network (FAN), a family of ViT backbones with state-of-the-art accuracy and robustness in both image classification and downstream tasks.

This report describes the winning solution to the RVC 2022 Semantic Segmentation track. This year, the challenge features benchmarking of a single semantic segmentation model on six datasets, spanning both indoor/outdoor and synthetic/real. Thus, it presents a great challenge to the generalization capability of a model over different domains. Our solution is inspired by the above advances in both multi-dataset training and ViTs, as will be detailed in the rest of the report.

2. Method

Backbone. We adopt FAN-B-Hybrid [23] as our backbone encoder due to its great robustness on multiple benchmarks

METHOD NAME	YEAR/RANK	ADE20K	RVC TEST DATASETS				
			CITYSCAPES	MAPILLARY	SCANNet	VIPER	WILDDASH-v2
MSEG1080_RVC [10]	2020 / 2nd	33.18	80.7	34.19	48.5	40.7	34.71
SN_RN152PYRX8_RVC [2]	2020 / 1st	31.12	74.7	40.43	54.6	62.5	42.29
FAN_NV_RVC (Ours)	2022 / 1st	43.46	82.0	55.27	58.6	69.8	47.5

Table 2. **Comparison with previous methods.** Measured by class mIoU. The best number in each column is highlighted in bold.

(ImageNet-C [9], Cityscapes-C, etc.). The backbone is initialized with the weight pretrained on ImageNet-22K and fine-tuned on ImageNet-1K (the checkpoint is provided in the official github repository¹).

Segmentation framework. We use SegFormer [19] as the segmentation framework. It uses simple but effective multilayer perceptron (MLP) decoders to fuse multi-level features (the outputs of the early Convolution blocks, last FAN Transformer block and the final class attention block output) and predict the semantic segmentation mask. The reader may refer to the official github of FAN (segmentation folder) for more details. Cross-entropy loss is used for training the model.

Training set. The model is trained on a combined dataset that contains all images from the training set from ADE20K, Cityscapes, Mapillary Vistas, ScanNet, VIPER, Wilddash2, IDD, BDD, and COCO. Table 1 is an overview of all the datasets involved. The datasets vary largely in size (COCO is more than 30 times larger than WildDash 2). To alleviate the dataset-imbalanced issue for better model generalization ability, we adopt a simple dataset resizing strategy - repeat each dataset ($120,000/\text{len}(\text{dataset})$) times.

Unified label space. We directly use the unified label space provided in the official RVC github repository² (with some minor corrections) which has 256 classes. This label space is naive and also noisy for relabeling some fine-grained classes in their original label space.

Post-processing. All predicted segmentation maps are projected from the unified label space to the original label space of each single dataset.

3. Implementation Details

We built our codebase with MMSegmentation [5]. The length of training process is 80,000 iterations while the first half training is without BDD and IDD datasets. Table 3 provides detailed information about the optimizer and hyperparameter settings. Training and testing data augmentations are detailed in Table 4 and Table 5. The model is trained on 64 V100 GPUs (32G), and the whole training procedure takes ~ 35 hours.

¹<https://github.com/NVlabs/FAN>

²https://github.com/ozendelait/rvc_devkit

Config	Setting
Optimizer	AdamW [12]
Learning rate	6e-5
Weight decay	0.01
Optimizer momentum	$\beta_1, \beta_2=0.9, 0.999$
Batch size	64
Learning rate schedule	Poly [4]
Warmup iters [8]	1500

Table 3. **Optimizer & hyper-parameters details.**

Operation	Setting
Resize	Scale: (2048, 1024), Ratio: (0.5, 2.0)
RandomCrop	Crop size: (1024, 1024)
RandomFlip	Prob: 0.5
PhotoMetricDistortion	Default

Table 4. **Training data augmentations.**

Operation	Setting
Resize	Scale: (2048, 1024)
Multi-scale	Ratios: (0.5, 0.75, 1.0, 1.25, 1.5, 1.75)
Flip	True

Table 5. **Testing data augmentations.**

4. Results

We compare our method with the winner solutions of RVC 2020 in Table 2. Our method makes solid improvements on all six benchmarks and beats them all by a large margin.

5. Conclusion

In this report, we describe the winning solution of the RVC 2022 Semantic Segmentation Track. Our result shows that Vision Transformer models (in our case, FAN), when coupled with multi-dataset training, exhibit strong robustness and generalization at scales in semantic segmentation. Our work again echoes recent discoveries of improved robustness and representation in ViTs. However, it is worth noting that the training computation and memory consumption have become important challenges as the data and label space become large. The efficiency on devices during deployment also presents another challenge for real-world applications of current ViT models.

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