Singular Value Fine-tuning: Few-shot Segmentation requires Few-parameters Fine-tuning – Supplementary Material

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Appendix

A More details

Training Strategy: Different from the training strategy of previous methods, we set the learning rate to 0.015 and use an SGD optimizer with cosine learning rate decay when fine-tuning the backbone. Therefore, we compared the impact of different training strategies on benchmark datasets. As shown in Table 1, the new training strategy does not affect the performance of FSS models. Therefore, *different training strategies are NOT the key to the success of SVF*.

Table 1: Compare with different training strategy on Pascal-5^i training set in terms of mIoU for 1-shot segmentation.

Method	Backbone	Training Strategy	1-shot				
			Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline		original	65.60	70.28	64.12	60.27	65.07
baseline		ours	64.95	69.75	65.91	59.59	65.05
PFENet [9]	ResNet50	original	66.61	72.55	65.33	60.91	66.35
PFENet [9]		ours	65.58	72.49	66.12	60.30	66.12
BAM [3]		original	68.97	73.59	67.55	61.13	67.81
BAM [3]		ours	68.43	73.66	67.98	61.63	67.93

Table 2: Ablation study on the training trick.

Method	Backbone	Training Trick	1-shot				
			Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline		w/o	66.36	69.22	57.64	58.73	62.99
baseline		w	65.60	70.28	64.12	60.27	65.07
PFENet [9]		w/o	67.06	71.61	55.21	59.46	63.34
PFENet [9]	ResNet50	w	66.61	72.55	65.33	60.91	66.35
CyCTR [15]		w/o	67.80	72.80	58.00	58.00	64.20
CyCTR [15]		w	65.17	72.52	66.60	60.9	66.30
BAM [3]		w/o	68.37	72.05	57.55	60.38	64.59
BAM [3]		w	68.97	73.59	67.55	61.13	67.81

Training Tricks: Following the same setting of BAM [3], we remove some images containing novel classes of the test set from the training set. This is a novel trick in FSS to further improve the performance. In Table 2, we compared the effect of this trick on FSS models. The results show that this trick brings 2.0 mIoU improvement over the original FSS model on average. Especially on Flod-2, the trend of improvement is very obvious. It proves that removing images with novel classes of the test set from the training set prevents potential information leakage.

Table 3: Compare with different test image on COCO-20^i in terms of mIoU for 1-shot segmentation.

Method	backbone	test image	1-shot				
			Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	ResNet50	1000	38.91	46.07	42.67	39.71	41.84
baseline + SVF		1000	44.22	46.38	42.65	41.65	43.72
baseline		4000	37.19	45.30	42.90	38.49	40.97
baseline + SVF		4000	39.80	46.99	42.51	42.06	42.84
baseline		5000	36.59	45.17	43.34	38.73	40.96
baseline + SVF		5000	39.49	46.95	42.09	41.15	42.42

Test image of COCO-20^i: We found that the number of test sets used in previous work was different when testing on COCO. For example, BAM [3], HSNet [6] were tested with 1000 images, yet *Yang* [12] was tested with 4000 images, and CyCTR [15] was tested with 5000 images. This is very detrimental to the development of the community. In Table 3, we compare the different number of test images on COCO-20^i to observe changes in model performance. The experimental results show that as the number of test images increases, the performance of the baseline shows a downward trend. Therefore, we call on researchers to use the same training samples for a fair comparison. Meanwhile, SVF brings positive results in different numbers of test sets. It again shows the effectiveness of SVF.

B Compare with other SOTA methods.

To clear the doubts of dataset, we use the unprocessed training set to make a fair comparison with other SOTA methods, as show in Table4. It can be seen that baseline with SVF achieves best performance on both Pascal-5^i 1-shot and 5-shot settings. The experimental results prove that the advantages of SVF will not disappear due to the introduction of the training trick. Meanwhile, the experimental results prove that finetuning backbone is not only feasible in FSS, but also brings positive results to FSS models.

Table 4: Compare with SOTA on Pascal-5^i[8] in terms of mIoU for 1-shot and 5-shot segmentation.

Method	backbone	1-shot					5-shot				
		Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	Mean
PANet [10]	ResNet50	44.00	57.50	50.80	44.00	49.10	55.30	67.20	61.30	53.20	59.30
CANet [14]		52.50	65.90	51.30	51.90	55.40	55.50	67.80	51.90	53.20	57.10
PGNet [13]		56.00	66.90	50.60	50.40	56.00	57.70	68.70	52.90	54.60	58.50
RPMM [11]		55.20	66.90	52.60	50.70	56.30	56.30	67.30	54.50	51.00	57.30
PPNet [4]		47.80	58.80	53.80	45.60	51.50	58.40	67.80	64.90	56.70	62.00
CWT [5]		56.30	62.00	59.90	47.20	56.40	61.30	68.50	68.50	56.60	63.70
PFENet [9]		61.70	69.50	55.40	56.30	60.80	63.10	70.70	55.80	57.90	61.90
CyCTR [15]		67.80	72.80	58.00	58.00	64.20	71.10	73.20	60.50	57.50	65.60
baseline		66.36	69.22	57.64	58.73	62.99	70.75	72.92	58.86	65.56	67.02
baseline + SVF		66.88	70.84	62.33	60.63	**65.17**	71.49	74.04	59.38	67.43	**68.09**

C Detailed Ablation Study

Different finetune strategy: In Figure 1, we visualize the mIoU curve of different fine-tuning strategies. It can be seen that both layer-based and convolution-based fine-tuning methods bring over-fitting problems. This result shows that traditional fine-tuning methods are not suitable for few-shot segmentation tasks. Directly fine-tuning the parameters of backbone in few-shot learning affects the robustness of FSS models. Therefore, we propose a novel fine-tuning strategy, namely SVF. It decompose pre-trained parameters into three successive matrices via the Singular Value Decomposition (SVD). Then, It only fine-tunes the singular value matrices during the training phase. The experimental results show that SVF can effectively avoid over-fitting while bringing positive results to FSS model.

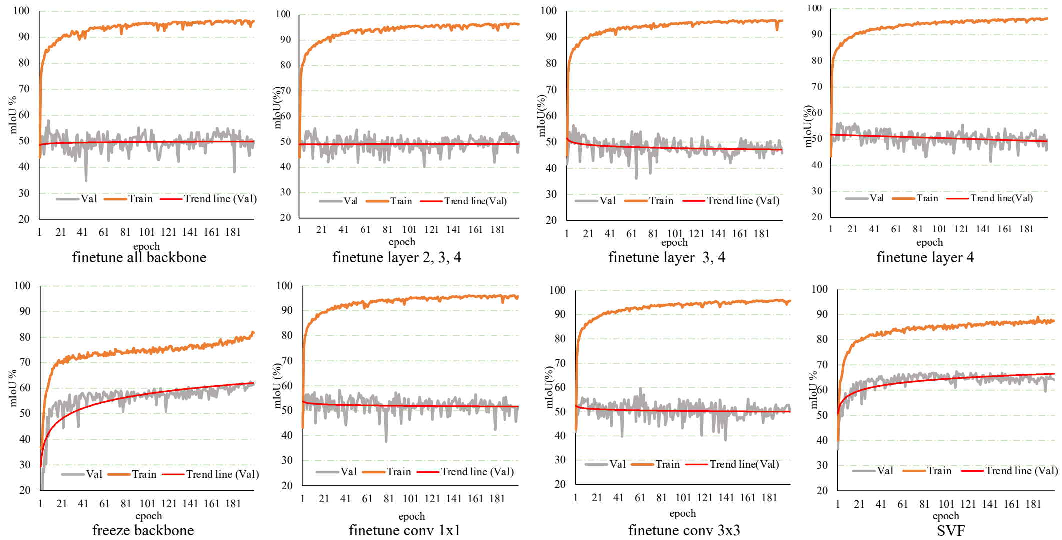


Figure 1: The mIoU curve of baseline with different finetune strategies on Pascal-5^i Fold-0.

Table 5: Ablation study of BN on Pascal-5^i under 1-shot setting. ✓represents fine-tuning this feature space. The best mean results are show in **bold**.

Method	BN	scale	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline			65.60	70.28	64.12	60.27	65.07
	✓		61.93	70.67	62.02	57.86	63.12$_{(-1.95)}$
	✓	✓	63.46	70.66	64.93	57.75	64.20$_{(-0.87)}$
		✓	67.42	71.57	67.99	61.57	**67.14**$_{(+2.07)}$

Sigular value subspace: In Figure 2, we visualize the changes of initial Top-30 largest singular values of all 3×3 convolutional in layer 3 after SVF. The experimental results show that the change of last 3x3 convolution is the most obvious, and the change of singular value gradually moderates as the network becomes shallower. To verify the above point, we visualize the singular value change map of all 3x3 convolutions of layer 2 in Figure 3. The variation of singular values in layer2 is more gradual. Furthermore we visualize the singular value changes from the 1×1 convolution of layer 3 and layer 2 in Figure 4 and Figure 5. where the 1×1 convolution is the last 1×1 convolution of each block in ResNet. This result is the same trend as 3×3 convolution. It shown that the information concerned by deep convolutions in pre-train backbone is not conducive to few-shot segmentation tasks. SVF improves the expressiveness of FSS model by focusing on adjusting distribution of singular value subspace in the deep convolution. Meanwhile, It proves that semantic cues in deep convolutions have the greatest impact on few-shot segmentation. In addition, Figure 6 shows the variation of all singular values. It can be easy seen that the change of singular values afterward tends to 0. Therefore, the change of top-30 singular values can describe the change of all singular values.

In Table 5, Table 6, Table 7, Table 8 and Tbale 9, we give more detail ablation study results. It contains the results for each flod in different ablation study.

D Discussion

D.1 Discussion on other SVD

In this section, we discuss the differences between other SVD-based methods [1, 7] and SVF. Both SVB [1] and *Hanie* [7] constrain the distribution of the singular values s where SVB [1] forces the singular value around 1 and *Hanie* [7] clamps the large singular values into a constant, hence serving as a regularization term. We did not pose an extra constraint on s, instead, encouraged the fully trainable singular values. As illustrated in SVB's Figure 1, the singular values of well-trained weights

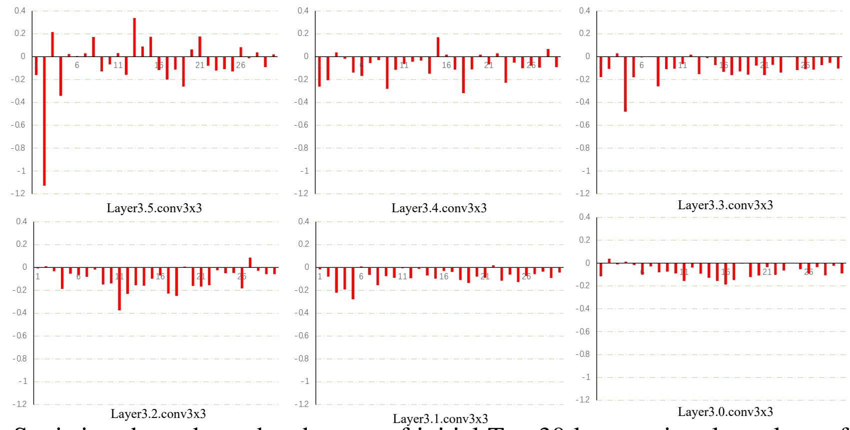


Figure 2: Statistics chart about the changes of initial Top-30 largest singular values of the 3×3 convolutional in layer3 after SVF.

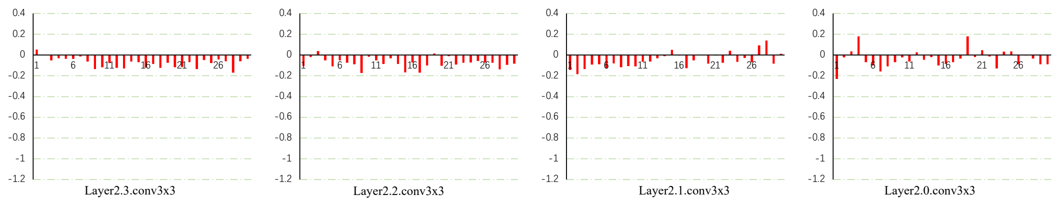


Figure 3: Statistics chart about the changes of initial Top-30 largest singular values of the 3×3 convolutional in layer2 after SVF.

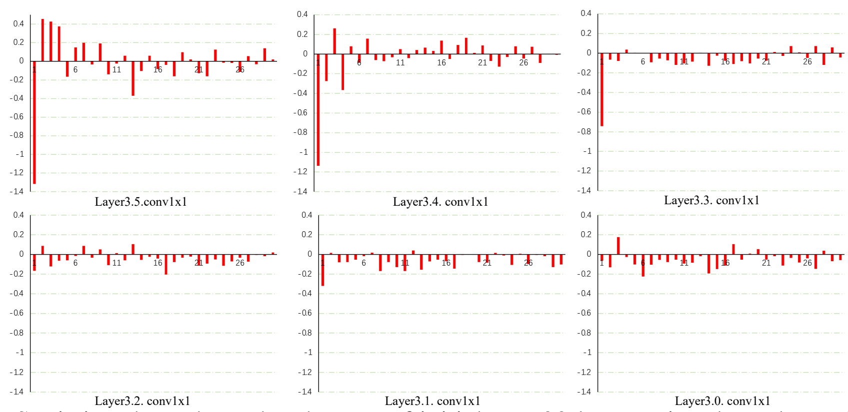


Figure 4: Statistics chart about the changes of initial Top-30 largest singular values of the 1×1 convolutional in layer3 after SVF.

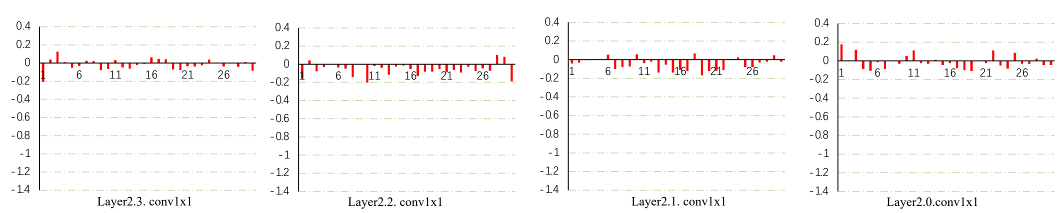
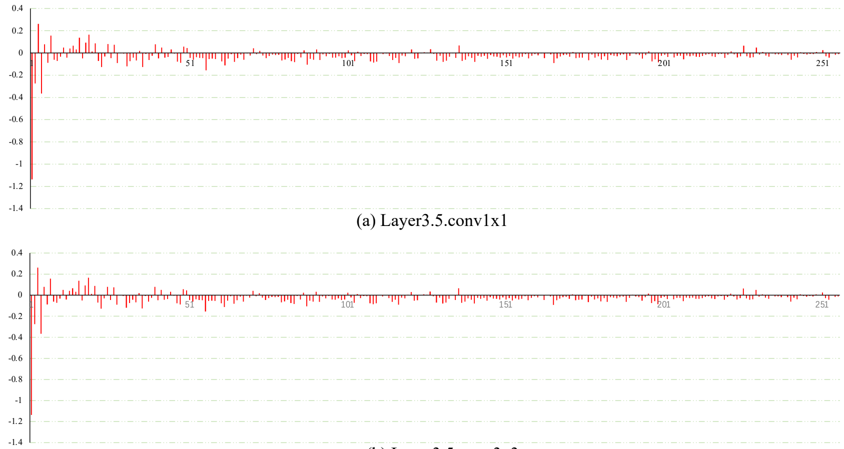


Figure 5: Statistics chart about the changes of initial Top-30 largest singular values of the 1×1 convolutional in layer2 after SVF.



(a) Layer3.5.conv1x1

(b) Layer3.5.conv3x3

Figure 6: Statistics chart about the changes of all singular values of the last 3×3 and 1×1 convolutional in layer3 after SVF.

Table 6: Comparative experiment with fine-tuning different layer of backbone on Pascal-5^i.

Method	layer	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	-	65.60	70.28	64.12	60.27	65.07
+fully fine-tune	1, 2, 3, 4	57.97	70.51	61.33	53.80	$60.90_{(-4.17)}$
+ part fine-tune	2, 3, 4	55.34	71.16	62.72	55.38	$61.15_{(-3.92)}$
	3, 4	56.85	71.44	61.72	54.32	$61.08_{(-3.99)}$
	4	56.19	70.63	59.98	55.50	$60.58_{(-4.49)}$
+SVF	2, 3, 4	**67.42**	**71.57**	**67.99**	**61.57**	**67.14**$_{(+2.07)}$

Table 7: Comparative experiment with fine-tuning different convolutional layer of backbone on Pascal-5^i.

Method	layer	3×3	1×1	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	-	-	-	65.60	70.28	64.12	60.27	65.07
+part fine-tune	2, 3, 4	✓	✓	55.34	71.16	62.72	55.38	$61.15_{(-3.92)}$
	2, 3, 4	✓		59.57	69.96	61.74	56.16	$61.86_{(-3.21)}$
	2, 3, 4		✓	58.30	70.50	62.04	55.63	$61.62_{(-3.45)}$
+SVF	2, 3, 4	-	-	67.42	71.57	67.99	61.57	$67.14_{(+2.07)}$

Table 8: Ablation study of SVF fine-tuning different subspace on Pascal-5^i.

Method	**U**	**S**	**V**	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	✓			58.14	70.06	60.91	55.24	61.09
		✓		67.42	71.57	67.99	61.57	67.14
			✓	53.87	70.63	63.65	55.36	60.88
	✓	✓		57.54	70.19	62.12	56.41	61.57
		✓	✓	53.30	71.21	62.24	54.92	60.42
	✓		✓	53.81	70.75	61.92	53.60	60.02
	✓	✓	✓	56.64	70.47	63.48	54.36	61.24

Table 9: Ablation study of SVF fine-tuning different layer on Pascal-5^i.

Method	layer	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline + SVF	4	68.28	71.04	65.59	59.91	66.21
	3, 4	67.21	71.88	68.12	61.57	67.20
	2, 3, 4	67.42	71.57	67.99	61.57	67.14
	1, 2, 3, 4	67.06	71.69	67.77	61.94	67.12

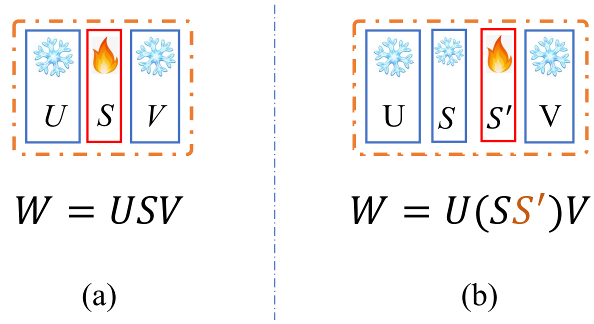


Figure 7: Different implementations of SVF.

Table 10: Comparing with only fine-tuning BN on Pascal-5^i.

Method	Backbone	Fine-tuning Method	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	ResNet-50	Freeze Backbone	65.60	70.28	64.12	60.27	65.07
		Fine-tuning BN scale (weight)	62.28	68.66	61.19	58.18	62.58
		Fine-tuning BN shift (bias)	61.62	70.10	64.80	55.19	62.93
		Fine-tuning BN (weight+bias)	61.93	70.67	62.02	57.86	63.12
		SVF	67.42	71.57	67.99	61.57	67.14

are widely spread around [0,2]. The strong regularization proposed in SVB [1] and *Hanie* [7] should damage the performance of pre-trained networks. Therefore, they turn to training from scratch, which is infeasible in the circumstance of few-shot segmentation. Our method coupled with pre-trained parameters can further exploit the capacity of the backbone, leading to superior results.

D.2 Discussion on different implementation

In this section, we provide a discussion on our SVF. The main idea of SVF is learning to change singular values in the backbone weights. It has different implementations. We show two possible ways to achieve SVF in Figure 7: (i) treat the single value matrix S as trainable parameters directly; (ii) freeze the original singular value matrix S and introduce another trainable singular value matrix $S^{'}$ (we use exponential function *exp* to keep it positive and initialize it with zeros), where the final singular value matrix is a product of S (frozen) and $S^{'}$ (trainable). In the second implementation, SVF keeps the backbone frozen (as all its weights are frozen) while introducing a small part of extra trainable parameters. It shares similarities with the recently proposed Visual Prompt Tuning (VPT) [2]. The difference between VPT and SVF is that VPT introduces the trainable parameters in the input space while SVF introduces them in the singular value space. Although SVF and VPT freeze the original backbone, they can produce optimization on the feature maps of the backbone. This property enables SVF to perform better in few-shot segmentation (FSS) and is the essential difference from the properties in previous SSF methods with frozen backbone (they do not change the feature maps of the backbone).

D.3 Discussion on success of SVF

In this section, we discuss the truly responsible for the success of SVF from three question. First, Does fine-tune another small part of parameters in the backbone work? We conduct experiments on Pascal-5^i with the 1-shot setting. We compare our SVF with methods that only fine-tune the

Table 11: introduce a new small part of parameters S' to verify the importance of singular values on Pascal-5^i.

Method	Backbone	Expression of weight	Fine-tune param	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	ResNet-50	W	-	65.60	70.28	64.12	60.27	65.07
		S'W	S'	60.96	71.99	62.54	58.58	63.52
		WS'	S'	62.82	71.69	62.84	61.13	64.62
		USV^T	S	67.42	71.57	67.99	61.57	**67.14**

Table 12: Compare with different implementations of SVF on Pascal-5^i 1-shot.

Method	Backbone	Expression of weight	Fine-tune param	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	ResNet-50	W	-	65.60	70.28	64.12	60.27	65.07
		USV^T	S	67.42	71.57	67.99	61.57	**67.14**
		USS'V^T	S'	67.16	71.58	68.59	61.08	67.10
		USS'V^T	S + S'	66.42	71.73	67.23	61.12	66.63

Table 13: Compare with other SVD-based methods on Pascal-5^i 1-shot.

Method	Backbone	Expression of weight	Fine-tune param	Fold-0	Fold-1	Fold-2	Fold-3	Mean
baseline	ResNet-50	W	-	65.60	70.28	64.12	60.27	65.07
		USV^T	S	67.42	71.57	67.99	61.57	**67.14**
		S'W	S'	60.96	71.99	62.54	58.58	63.52
		RS'R'W	S'	32.91	51.93	51.00	37.60	43.36

parameters in the BN layers. The results in Table 10 show that only fine-tuning the parameters in BN layers does not bring over-fitting in few-shot segmentation methods, but they perform worse than the conventional paradigm (freezing backbone). While our SVF outperform other methods by large margins.

Second, Is it really necessary to fine-tune the singular values? What if we introduce a new small part of parameters S', which is not in the singular value space, and only fine-tune the S'? To answer this question, we conduction two experiments, where the weight becomes S'W or WS', and only fine-tune the introduced small part of parameters S'. The results in Table 11 are consistence with Table 10. Both of them can avoid over-fitting but show slightly worse performance than the freezing backbone baseline. The above experimental results suggest that fine-tuning a small part of parameters is a good way to avoid over-fitting when fine-tuning the backbone in few-shot segmentation. But it is non-trivial to find such a small part of parameters that can bring considerable improvements.

Third, What causes the differences between SVF and WS' or S'W? In this question, we try to provide our understanding of what causes the superior performances of SVF over WS' and S'W. We conjecture that this may be related to the context that S or S' can access when fine-tuning the parameters. Assume that W has the shape of $[M, N]$. S and S' are diagonal matrices. S has the shape of [Rank, Rank], and S' has the shape of $[M, M]$ or $[N, N]$. When optimizing the parameters, S' only has relations on dimension M or dimension N in a channel-wise manner, while S can connect all channels on both dimension M and dimension N, as S is in the singular value space. This differences can affect the received gradients when training S or S', which results in different performance. To give more evidences, we design more variants of SVF and provide their results in Table 12.

Finaly, To verify whether SVF depends crucially on the singular value space, or simply on the number of effective updated parameters. we design a experiment: let R be a random rotation matrix, and set U=R' and V=RW, where W is the original weight matrix for the given layer. The formulation of the weight becomes RS'R'W. Note that S' is initialized with an identity matrix as done in previous experiments. During the fine-tuning, we only train S' while keep others frozen in the backbone. We provide the results in Table 13. Random rotation formulation gives poor results. In fact, if we set R as an identity matrix (identity matrix is a rotation matrix), RS'R'W = S'W. As shown in the table, S'W is much better than random RS'R'W. It seems that the selection of the rotation matrix R is critical to the final segmentation performance. Meanwhile, If we consider RS'R' (it is a diagonal matrix in the initialization stage) as a whole, RS'R is only related to one dimension of the weight W. Thus for the middle matrix S', it is also channel-aligned with respect to weight W.

In addition, if R is random initialized, we can not guarantee that RS'R' is a diagonal matrix when updating S' during training (we verify this phenomenon with the saved checkpoints when we finish the training). Note that the weight W is the one from the pre-trained backbone, which contains semantic clues or learned knowledge. The non-diagonal matrix RS'R' may bring unexpected transformation to the pre-trained weight W, leading to poor results.

E Code in PyTorch

In this section, we give the core code of SVF.

```python
import copy
import inspect

import torch
import torch.nn as nn


def d_nsvd(matrix, rank=1):
    U, S, V = torch.svd(matrix)
    S = S[:rank]
    U = U[:, :rank] # * S.view(1, -1)
    V = V[:, :rank] # * S.view(1, -1)
    V = torch.transpose(V, 0, 1)
    return U, S, V


class SVD_Conv2d(nn.Module):

    def __init__(self, in_channels, out_channels, kernel_size,
                 stride, padding, dilation, groups, bias,
                 padding_mode='zeros', device=None, dtype=None,
                 rank=1):
        super(SVD_Conv2d, self).__init__()
        factory_kwargs = {'device': device, 'dtype': dtype}
        self.conv_V = nn.Conv2d(
            in_channels, rank, kernel_size, stride, padding, dilation, groups, False)
        self.S = nn.Parameter(torch.empty((1, rank, 1, 1), **factory_kwargs))
        self.conv_U = nn.Conv2d(
            rank, out_channels, (1, 1), (1, 1), 0, (1, 1), 1, bias)

    def forward(self, x):
        x = self.conv_V(x)
        x = x.mul(self.S)
        output = self.conv_U(x)
        return output


class SVD_Linear(nn.Module):

    def __init__(self, in_features, out_features, bias, device=None, dtype=None, rank=1):
        super(SVD_Linear, self).__init__()
        factory_kwargs = {'device': device, 'dtype': dtype}
        self.fc_V = nn.Linear(in_features, rank, False)
        self.S = nn.Parameter(torch.empty((1, rank), **factory_kwargs))
        self.fc_U = nn.Linear(rank, out_features, bias)

    def forward(self, x):
        x = self.fc_V(x)
        x = x.mul(self.S)
        output = self.fc_U(x)
        return output


full2low_mapping_n = {
    nn.Conv2d: SVD_Conv2d,
    nn.Linear: SVD_Linear
}


def replace_fullrank_with_lowrank(model, full2low_mapping={}, layer_rank={}, lowrank_param_dict={},
                                  module_name=""):
    """Recursively replace original full-rank ops with low-rank ops.
    """
    if len(full2low_mapping) == 0 or full2low_mapping is None:
        return model
    else:
        for sub_module_name in model._modules:
            current_module_name = sub_module_name if module_name == "" else \
                module_name + "." + sub_module_name
            # has children
            if len(model._modules[sub_module_name]._modules) > 0:
                replace_fullrank_with_lowrank(model._modules[sub_module_name],
                                              full2low_mapping,
                                              layer_rank,
                                              lowrank_param_dict,
                                              current_module_name)
            else:
                if type(getattr(model, sub_module_name)) in full2low_mapping and \
                        current_module_name in layer_rank.keys():
                    _attr_dict = getattr(model, sub_module_name).__dict__
                    # use inspect.signature to know args and kwargs of __init__
                    _sig = inspect.signature(
```

```
                        type(getattr(model, sub_module_name)))
                    _kwargs = {}
                    for param in _sig.parameters.values():
                        if param.name not in _attr_dict.keys():
                            if 'bias' in param.name:
                                if getattr(model, sub_module_name).bias is not None:
                                    value = True
                                else:
                                    value = False
                            elif 'stride' in param.name:
                                value = 1
                            elif 'padding' in param.name:
                                value = 0
                            elif 'dilation' in param.name:
                                value = 1
                            elif 'groups' in param.name:
                                value = 1
                            elif 'padding_mode' in param.name:
                                value = 'zeros'
                            else:
                                value = None
                            _kwargs[param.name] = value
                        else:
                            _kwargs[param.name] = _attr_dict[param.name]
                    _kwargs['rank'] = layer_rank[current_module_name]
                    _layer_new = full2low_mapping[type(
                        getattr(model, sub_module_name))](**_kwargs)
                    old_module = getattr(model, sub_module_name)
                    old_type = type(old_module)
                    bias_tensor = None
                    if _kwargs['bias'] == True:
                        bias_tensor = old_module.bias.data
                    setattr(model, sub_module_name, _layer_new)
                    new_module = model._modules[sub_module_name]
                    if old_type == nn.Conv2d:
                        conv1 = new_module._modules["conv_U"]
                        conv2 = new_module._modules["conv_V"]
                        param_list = lowrank_param_dict[current_module_name]
                        conv1.weight.data.copy_(param_list[1])
                        conv2.weight.data.copy_(param_list[0])
                        new_module.scale.data.copy_(param_list[2])
                        if bias_tensor is not None:
                            conv2.bias.data.copy_(bias_tensor)
    return model


class DatafreeSVD(object):

    def __init__(self, model, global_rank_ratio=1.0,
                 excluded_layers=[], customized_layer_rank_ratio={}, skip_1x1=True, skip_3x3=True):
        # class-independent initialization
        super(DatafreeSVD, self).__init__()
        self.model = model
        self.layer_rank = {}
        model_dict_key = list(model.state_dict().keys())[0]
        model_data_parallel = True if str(
            model_dict_key).startswith('module') else False
        self.model_cpu = self.model.module.to(
            "cpu") if model_data_parallel else self.model.to("cpu")
        self.model_named_modules = self.model_cpu.named_modules()
        self.global_rank_ratio = global_rank_ratio
        self.excluded_layers = excluded_layers
        self.customized_layer_rank_ratio = customized_layer_rank_ratio
        self.skip_1x1 = skip_1x1
        self.skip_3x3 = skip_3x3

        self.low_rank_tol = 0.05
        self.param_lowrank_decomp_dict = {}
        registered_param_op = [nn.Conv2d, nn.Linear]

        for m_name, m in self.model_named_modules:
            if type(m) in registered_param_op and m_name not in self.excluded_layers:
                weights_tensor = m.weight.data
                tensor_shape = weights_tensor.squeeze().shape
                param_1x1 = False
                param_3x3 = False
                depthwise_conv = False
                if len(tensor_shape) == 2:
                    full_rank = min(tensor_shape[0], tensor_shape[1])
                    param_1x1 = True
                elif len(tensor_shape) == 4:
                    full_rank = min(
                        tensor_shape[0], tensor_shape[1] * tensor_shape[2] * tensor_shape[3])
                    if tensor_shape[2] == 1 and tensor_shape[3] == 1:
                        param_1x1 = True
                    else:
```

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                        param_3x3 = True
                else:
                    full_rank = 1
                    depthwise_conv = True

                if self.skip_1x1 and param_1x1:
                    continue
                if self.skip_3x3 and param_3x3:
                    continue
                if depthwise_conv:
                    continue

                self.layer_rank[m_name] = full_rank

    def decompose_layers(self):
        self.model_named_modules = self.model_cpu.named_modules()
        for m_name, m in self.model_named_modules:
            if m_name in self.layer_rank.keys():
                weights_tensor = m.weight.data
                tensor_shape = weights_tensor.shape
                if len(tensor_shape) == 1:
                    self.layer_rank[m_name] = 1
                    continue
                elif len(tensor_shape) == 2:
                    weights_matrix = m.weight.data
                    U, S, V = d_nsvd(weights_matrix, self.layer_rank[m_name])
                    self.param_lowrank_decomp_dict[m_name] = [
                        U, V, S.reshape(1, self.layer_rank[m_name])]
                elif len(tensor_shape) == 4:
                    weights_matrix = m.weight.data.reshape(tensor_shape[0], -1)
                    U, S, V = d_nsvd(weights_matrix, self.layer_rank[m_name])
                    self.param_lowrank_decomp_dict[m_name] = [
                        V.reshape(
                            self.layer_rank[m_name], tensor_shape[1], tensor_shape[2], tensor_shape[3]),
                        S.reshape(1, self.layer_rank[m_name], 1, 1),
                        U.reshape(tensor_shape[0],
                                  self.layer_rank[m_name], 1, 1)
                    ]

    def reconstruct_lowrank_network(self):
        self.low_rank_model_cpu = copy.deepcopy(self.model_cpu)
        self.low_rank_model_cpu = replace_fullrank_with_lowrank(
            self.low_rank_model_cpu,
            full2low_mapping=full2low_mapping_n,
            layer_rank=self.layer_rank,
            lowrank_param_dict=self.param_lowrank_decomp_dict,
            module_name=""
        )
        return self.low_rank_model_cpu


def resolver(
        model,
        global_low_rank_ratio=1.0,
        excluded_layers=[],
        customized_layers_low_rank_ratio={},
        skip_1x1=False,
        skip_3x3=False,
        tol=0.05
):
    lowrank_resolver = DatafreeSVD(model,
                                   global_rank_ratio=global_low_rank_ratio,
                                   excluded_layers=excluded_layers,
                                   customized_layer_rank_ratio=customized_layers_low_rank_ratio,
                                   skip_1x1=skip_1x1,
                                   skip_3x3=skip_3x3)
    lowrank_resolver.decompose_layers()
    lowrank_cpu_model = lowrank_resolver.reconstruct_lowrank_network()
    return lowrank_cpu_model


if __name__ == "__main__":
    origin_model = FSS_model
    final_model = resolver(origin_model)
```

References

[1] Kui Jia, Dacheng Tao, Shenghua Gao, and Xiangmin Xu. Improving training of deep neural networks via singular value bounding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4344–4352, 2017.

[2] Menglin Jia, Luming Tang, Bor-Chun Chen, Claire Cardie, Serge Belongie, Bharath Hariharan, and Ser-Nam Lim. Visual prompt tuning. *arXiv preprint arXiv:2203.12119*, 2022.

[3] Chunbo Lang, Gong Cheng, Binfei Tu, and Junwei Han. Learning what not to segment: A new perspective on few-shot segmentation. *arXiv preprint arXiv:2203.07615*, 2022.

[4] Yongfei Liu, Xiangyi Zhang, Songyang Zhang, and Xuming He. Part-aware prototype network for few-shot semantic segmentation. In *European Conference on Computer Vision*, pages 142–158. Springer, 2020.

[5] Zhihe Lu, Sen He, Xiatian Zhu, Li Zhang, Yi-Zhe Song, and Tao Xiang. Simpler is better: Few-shot semantic segmentation with classifier weight transformer. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 8741–8750, 2021.

[6] Juhong Min, Dahyun Kang, and Minsu Cho. Hypercorrelation squeeze for few-shot segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 6941–6952, 2021.

[7] Hanie Sedghi, Vineet Gupta, and Philip M Long. The singular values of convolutional layers. In *International Conference on Learning Representations*, 2018.

[8] Amirreza Shaban, Shray Bansal, Zhen Liu, Irfan Essa, and Byron Boots. One-shot learning for semantic segmentation. *arXiv preprint arXiv:1709.03410*, 2017.

[9] Zhuotao Tian, Hengshuang Zhao, Michelle Shu, Zhicheng Yang, Ruiyu Li, and Jiaya Jia. Prior guided feature enrichment network for few-shot segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2020.

[10] Kaixin Wang, Jun Hao Liew, Yingtian Zou, Daquan Zhou, and Jiashi Feng. Panet: Few-shot image semantic segmentation with prototype alignment. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 9197–9206, 2019.

[11] Boyu Yang, Chang Liu, Bohao Li, Jianbin Jiao, and Qixiang Ye. Prototype mixture models for few-shot semantic segmentation. In *European Conference on Computer Vision*, pages 763–778. Springer, 2020.

[12] Lihe Yang, Wei Zhuo, Lei Qi, Yinghuan Shi, and Yang Gao. Mining latent classes for few-shot segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 8721–8730, 2021.

[13] Chi Zhang, Guosheng Lin, Fayao Liu, Jiushuang Guo, Qingyao Wu, and Rui Yao. Pyramid graph networks with connection attentions for region-based one-shot semantic segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 9587–9595, 2019.

[14] Chi Zhang, Guosheng Lin, Fayao Liu, Rui Yao, and Chunhua Shen. Canet: Class-agnostic segmentation networks with iterative refinement and attentive few-shot learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5217–5226, 2019.

[15] Gengwei Zhang, Guoliang Kang, Yi Yang, and Yunchao Wei. Few-shot segmentation via cycle-consistent transformer. *Advances in Neural Information Processing Systems*, 34, 2021.