Query Semantic Reconstruction for Background in Few-Shot Segmentation

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ABSTRACT

Few-shot segmentation (FSS) aims to segment unseen classes using a few annotated samples. Typically, a prototype representing the foreground class is extracted from annotated support image(s) and is matched to features representing each pixel in the query image. However, models learnt in this way are insufficiently discriminatory, and often produce false positives: misclassifying background pixels as foreground. Some FSS methods try to address this issue by using the background in the support image(s) to help identify the background in the query image. However, the backgrounds of theses images are often quite distinct, and hence, the support image background information is uninformative. This article proposes a method, QSR, that extracts the background from the query image itself, and as a result is better able to discriminate between foreground and background features in the query image. This is achieved by modifying the training process to associate prototypes with class labels including known classes from the training data and latent classes representing unknown background objects. This class information is then used to extract a background prototype from the query image. To successfully associate prototypes with class labels and extract a background prototype that is capable of predicting a mask for the background regions of the image, the machinery for extracting and using foreground prototypes is induced to become more discriminative between different classes. Experiments achieve state-of-the-art results for both 1-shot and 5-shot FSS on the PASCAL-5i and COCO-20i dataset. As QSR operates only during training, results are produced with no extra computational complexity during testing.

1. Introduction

The ability to segment objects is a long-standing goal of computer vision, and recent methods have achieved extraordinary results (He, Zhang, Ren and Sun, 2016; He, Deng, Zhou, Wang and Qiao, 2019; Long, Shelhamer and Darrell, 2015). These results depend on a large number of pixel-level annotations which are time-consuming and costly to produce. When facing the situation where few exemplars from a novel class are available, these methods overfit and perform poorly. To deal with this situation, few-shot segmentation (FSS) methods aim to predict a segmentation mask for a novel category using only a few images and their corresponding segmentation ground-truths.

Most current FSS algorithms (Zhang, Lin, Liu, Yao and Shen, 2019b; Siam, Oreshkin and Jagersand, 2019; Zhang, Lin, Liu, Guo, Wu and Yao, 2019a; Lu, He, Zhu, Zhang, Song and Xiang, 2021; Liu, Ding, Jiao, Ji and Ye, 2021; Li, Jampani, Sevilla-Lara, Sun, Kim and Kim, 2021; Wu, Shi, Lin and Cai, 2021; Zhang, Xiao and Qin, 2021) follow a similar sequence of steps. Features are extracted from support and query images by a shared convolutional neural network (CNN) which is pre-trained on ImageNet (Rusakovsky, Deng, Su, Krause, Satheesh, Ma, Huang, Karpathy, Khosla, Bernstein et al., 2015; Yang, Liu, Li, Jiao and Ye, 2020; Siam, Doraitswamy, Oreshkin, Yao and Jagersand, 2020; Zhang et al., 2019b). Then the support image ground-truth segmentation mask is used to identify and segment the foreground information in the support features. Generally, the object class is represented by a single foreground prototype feature vector (Wang, Liew, Zhou and Feng, 2019; Yang et al., 2020; Tian, Zhao, Shu, Yang, Li and Jia, 2020; Zhang et al., 2021; Li et al., 2021). Finally, a decoder is used to calculate the similarity of the foreground prototype and every pixel in the query feature-set to predict the locations occupied by the foreground object in the query image. This standard approach ignores the importance of background features that can be mined for negative samples in order to reduce false-positives, and hence, make the model more discriminative.

Some FSS methods (Yang et al., 2020; Boudiaf, Kervejac, Masud, Piantanida, Ayed and Dolz, 2021; Wang et al., 2019) extract background information from support images by using the support masks to identify the support image background. RPMMs (Yang et al., 2020) uses the Expectation-Maximization (EM) algorithm to mine more background information in the support images. MLC (Yang, Zhuo, Qi, Shi and Gao, 2021) extracts a global background prototype by averaging together the backgrounds extracted from the whole training data in an offline process, then updates this global background prototype with the support background during training. However, the same category object may appear against different backgrounds in different images. The background information extracted from or aligned with the support image(s) is, therefore, unlikely to be useful for segmenting the query image. Existing FSS methods ignore the fact that the background information of an image is most relevant for segmenting that specific image.

In this paper, we are motivated by the issue illustrated in Fig. 1 and design a method that can extract background information from the query image itself to make existing
FSS algorithms are more discriminative. Our method, Query Semantic Reconstruction (QSR), separates the feature extracted from a query image according to known classes and latent classes. Known classes are the categories that appear in the training data, like dog and cat in the example used in Fig. 1. Latent classes are unknown categories like mat and wall which are not explicitly labelled in the training data, but which can appear in the background in the training images. QSR learns to eliminate the foreground information according to the class labels. The remaining classes are used to define a prototype for the background of the query image that excludes contributions from the foreground class.

The extracted foreground and background prototypes are used as input to the prototype decoder module from the underlying, baseline, FSS method. The decoder produces predictions of foreground and background masks. The predictions are compared to a ground-truth mask and the loss is used to tune the parameters of the model. For these foreground and background prototypes to be effective at identifying the foreground and background regions of the query image, the whole model must be able to make the prototypes discriminative of features representing different semantics in the images. Hence, our method trains the underlying FSS method so that at test time it is able to more accurately segment images. Our method only predicts background masks during training to optimize the whole model. Hence, during testing the method is identical to that of the baseline.

The main contributions of our work are as follows:

1. To address the long-standing high false positive problem in FSS and to demonstrate that background information from the query image itself can be employed usefully for segmentation, we propose QSR that can be applied to many existing FSS algorithms to ensure they are better able to discriminate between foreground and background objects.

2. QSR improves existing FSS methods through optimized training. During testing our method is identical to the baseline, so no additional parameters or extra computation is needed at test-time.

3. We demonstrate the effectiveness of QSR using three different baselines methods: CaNet (Zhang et al., 2019b), ASGNet (Li et al., 2021) and PFENet (Tian et al., 2020). For the PASCAL-5i dataset, QSR improves mIOU results of 1-shot and 5-shot FSS by 1.0% and 1.5% for CaNet, 1.8% and 2.1% for ASGNet, and by 1.9% and 4.8% for PFENet. For the COCO-20i dataset, QSR improves ASGNet by 2.8% and 1.6%, PFENet by 4.5% and 3.8%.

4. Our method achieves new state-of-the-art performance on PASCAL-5i, with mIOU of 62.7% in 1-shot, and 66.7% in 5-shot. On the COCO-20i dataset, our method achieves strong results of 36.9% in 1-shot, and 41.2% in 5-shot.

2. Related Work

Semantic segmentation. Semantic segmentation requires the prediction of per-pixel class labels. The introduction of end-to-end trained fully convolutional networks (Long et al., 2015) has provided the foundation for recent success on this task. Additional innovations to improve segmentation accuracy further have included a multi-scale cascade model named U-Net (Ronneberger, Fischer and Brox, 2015), dilated convolution (Chen, Zhu, Papandreou, Schroff and Adam, 2018) and pyramid pooling (Zhao, Shi, Qi, Wang and
Few-shot learning. Few-shot learning (FSL) explores methods to enable models to quickly adapt to perform classification of new data. FSL methods can be categorized into generation, optimization or metric learning approaches. Generation methods (Hariharan and Girshick, 2017; Wang, Girshick, Hebert and Hariharan, 2018; Chen, Fu, Zhang, Jiang, Xue and Sigal, 2019; Liu, Sun, Han, Dou and Li, 2020) generate samples or features to augment the novel class data. Optimization approaches (Finn, Abbeel and Levine, 2017; Ravi and Larochelle, 2017) learn commonalities among different tasks, then a novel task can be fine-tuned on a few annotated samples based on the commonalities. Metric learning methods (Snell, Swersky and Zemel, 2017; Grant, Finn, Levine, Darrell and Griffiths, 2018) learn to produce a feature space that allows samples to be classified by comparing the distance between their features. Most FSL methods focus on image classification and cannot be easily adapted to produce the per-pixel labels required for segmentation.

Few-shot segmentation learning. The first FSS method (Shaban, Bansal, Liu, Essa and Boots, 2017) employed a two-branch comparison framework that has become the basis for FSS methods. PaNet (Wang et al., 2019) used prototype feature-vectors to represent support object classes, then compared their similarity with query features to make predictions. Other methods have improved different aspects of this process, for example, by extracting multiple prototypes representing different semantic classes (Yang et al., 2020; Li et al., 2021), by iteratively refining the predictions (Zhang et al., 2019b), or using a training-free prior mask generation method (Tian et al., 2020). Some methods extract information not only from support images, mining latent classes from the training dataset to search for more prototypes (Yang et al., 2021), or supplementing prototypes with support predictions (Zhang et al., 2021).

3. Problem Setting

Formally, we define a base dataset \( D_{\text{base}} \) with known classes \( C_{\text{known}} \). The FSS task is to use \( D_{\text{base}} \) to train a model which is able to segment new classes \( C_{\text{novel}} \), for which only a few annotated examples are available. The key point of FSS is that \( C_{\text{novel}} \notin C_{\text{known}} \). Specifically, \( D_{\text{base}} \) is a large set of image-mask pairs \((I_j, M_j)_{j=1}^{Num}\), where \( M_j \) is the semantic segmentation mask for the training image \( I_j \), and \( Num \) is the number of image-mask pairs. During testing, the model has access to a support set \( S = (I^1_j, M^1_j)_{j=1}^{Num} \in C_{\text{novel}} \), where \( M^1_j \) is the semantic segmentation mask for support image \( I^1_j \), and \( k \) is the number of image-mask pairs, which is small (typically either 1 or 5 for 1-shot and 5-shot tasks respectively). A query (or test) set \( Q = (I_q, M_q) \in C_{\text{novel}} \) is used to evaluate the performance of the model, where \( M_q \) is the ground-truth mask for image \( I_q \). The model uses the support set \( S \) to predict a segmentation mask, \( \hat{M}_f \), for each image \( I_q \) in query set \( Q \).

4. Method

4.1. Overview

Fig. 2 illustrates our method for 1-shot segmentation. Both support and query images are input into a shared CNN. In common with our baselines, CaNet (Zhang et al., 2019b), ASGNet (Li et al., 2021) and PFENet (Tian et al., 2020), we use a ResNet (He et al., 2017) pre-trained on ImageNet (Russakovsky et al., 2015) for this encoder backbone and choose features generated by block2 and block3. All parameter values in block2, block3, and earlier layers are fixed. These features are concatenated and encoded using a convolution layer. The convolution layer parameters are optimized by the loss function (details in Section 4.3). For CaNet (Zhang et al., 2019b) and ASGNet (Li et al., 2021), this layer has a 3 x 3 convolution kernel shared between support and query branches. For PFENet (Tian et al., 2020), two independent 1 x 1 convolution layers are defined for support and query features respectively. After the convolution layer, the CNN produces support features \( F \) and query features \( F_q \) of size \( d \times h \times w \), where \( d \) is the number of channels, and \( h, w \) are the height and width.

As for the baseline methods (Zhang et al., 2019b; Li et al., 2021; Tian et al., 2020), masked average pooling (MAP) was used to extract the foreground prototype \( P_f \):

\[
P_f = \frac{\sum_{i=1}^{ha} F_q(i) \cdot I[M_q(i) = 1]}{\sum_{i=1}^{ha} I[M_q(i) = 1]} \tag{1}
\]
where \(i\) indexes the spatial locations of features, and \(I[\cdot]\) is the indicator function, which equals 1 if the argument is True and 0 otherwise.

Global average pooling (GAP) was used to extract a query prototype \(P_q\) from the query features \(F_q\):

\[
P_q = \text{GAP}(F_q)
\]  

Both the foreground and query prototypes were input to our QSR method (defined in Section 4.2). QSR maps different regions of the query image to semantic classes, and uses this class information to generate a background prototype \(P_b\):

\[
P_b = \text{QSR}(P_q, P_f)
\]  

In Section 4.3, we describe how we utilise the prototype decoder module from the baseline FSS method. These modules are used to predict final semantic segmentation masks. The foreground prototype \(P_f\) is used to make a foreground prediction \(\hat{M}_f\) and the background prototype \(P_b\) is used for a background prediction \(\hat{M}_b\). The prototype decoder modules for foreground and background prediction are identical and share parameters. Our method only predicts a background mask during training. During testing the method is identical to the baseline and only uses the foreground prototype to predict the foreground mask.

In this paper, we limited ourselves to being consistent with the baselines: using a frozen backbone CNN and masked average pooling to extract a single foreground prototype. In addition, we also extract only one background prototype making is possible to share parameters in the decoder module that is applied to both the foreground and background prototype. Future work might usefully explore improved methods of representing foreground objects, for example, by using multiple prototypes.

### 4.2. Query Semantic Reconstruction

Our method assumes that images contain objects from known classes and latent classes. Known classes are ones corresponding to the labels provided in the training data and we define them as \(C^k = \{C_0^k, C_1^k, ..., C_{N_k}^k\}\). The number of known classes, \(N_k\), is defined by the training dataset, for example \(N_k = 15\) in PASCAL-5\(^{2}\) (Everingham, Van Gool, Williams, Winn and Zisserman, 2010). During training, the foreground class \(C_f\) is contained in \(C^k\). Latent classes are given the generic label of ‘background’ in the training data. However, we define multiple latent classes to represent possible background objects and they are defined as \(C^l = \{C_0^l, C_1^l, ..., C_{N_l}^l\}\). The number of latent classes, \(N_l\), is a hyper-parameter and the effects of different values were explored in experiments, the results of which are reported in Table 6. The background class must be a member of the set of latent classes or the set of known classes, excluding the class of the foreground object, which can be expressed as:

\[
C_b \in C^l \cup C^k \setminus C_f
\]  

![Figure 3: Query semantic reconstruction (QSR). A query prototype \(P_q\) is multiplied with the semantic class weights \(W_c\) (which are optimized by \(L_{\text{known}}\) and \(L_{\text{latent}}\)) to generate scores measuring the correlation between \(P_q\) and each class. The score for the current foreground class \(C_f\) is set to zero. The score \(S_b\) is multiplied with \(W_c\) to reconstruct a background prototype \(P_b\) eliminating any contribution from the foreground class. Note that the foreground class is one of the known classes, but is shown using a different colour for clarity.](image)

Mapping between prototype feature-vectors and classes is achieved using a layer of weights. A known class weight matrix \(W_k\) whose size is \(N_k \times d\) maps from the \(1 \times d\) prototype to the \(N_k\) known class labels. Hence, each row vector in \(W_k\) represents the corresponding category in \(C^k = \{C_0^k, C_1^k, ..., C_{N_k}^k\}\). In the same way, a latent class weight matrix \(W_l\), with size \(N_l \times d\), maps from a prototype to the latent categories in \(C^l = \{C_0^l, C_1^l, ..., C_{N_l}^l\}\). \(W_k\) and \(W_l\) are both randomly initialized.

The known class weights can be learnt directly from the training data. In each episode, \((P_f, C_f)\) is calculated from \((F_c, M_c)\), where \(C_f \in C^k\). \(P_f \times W_k\) is used as the prediction for the category of the foreground object. Cross-Entropy (CE) loss can then be used to update the known class weights to provide better representations of object class labels:

\[
L_{\text{known}} = \text{CE}(C_f, P_f \times W_k)
\]  

The true latent class labels are unknown, so learning the latent classes weights assumes that all categories (both known and latent) should be independent of each other. A possible method to achieve this is the application of contrastive loss (Zbontar, Jing, Misra, LeCun and Deny, 2021; Chen and He, 2021) to constrain each class representation to be independent by maximizing the orthogonality of their representations. A previous FSS method, ASR (Liu et al., 2021), has used contrastive loss to generate orthogonal semantic prototypes for foreground classes. In this paper, we apply the technique used in (Zbontar et al., 2021), a more efficient method, to constrain all class weights to be independent. Specifically, we define \(W_c\) as the concatenation of \(W_k\) and \(W_l\), \(i.e.\ W_c\) has size \((N_k + N_l) \times d\), we first calculate the cross-correlation matrix, \(W\), as:

\[
W = W_c \times W_c^T
\]  

The loss function for learning the latent class weights is defined as:

\[
L_{\text{latent}} = \sum_{i} (1 - W_{ii})^2 + \sum_{i} \sum_{j \neq i} W_{ij}^2
\]
where i, j index the spatial location of the cross-correlation matrix. The latent loss tries to make the cross-correlation matrix close to the identity matrix. This causes each category to be statistically independent of all others.

As illustrated in Fig. 3, a background score, $S_b$, is calculated to measure the correlation between each non-foreground class and the query image prototype:

$$S_b = (P_q \times W_c) \cdot 1[\mathcal{C}^f \cup \mathcal{C}^b \setminus C_f]$$  \hspace{1cm} (8)

where $P_q$ is the query prototype from Eq. (2). Finally the background prototype is calculated, by back-projecting the scores (which represent the classes predicted to be present in the background) through the weights that represent the classes:

$$P_b = \sum_{i=1}^{N_b + N_c} (W_c(i,:) \times S_b(i))$$  \hspace{1cm} (9)

where the colon means the whole dimension. This generates a prototype that represents a mixture of feature-vectors representing the classes believed to be present in the background of the query image.

In order to be able to share the same decoder with the baseline, $d$ is set to 256. However, such a large value may cause the background prototypes to be redundant. On PASCAL-$5^i$, the ratio between the class number ($N_b + N_c$) and $d$ in $W_c$ is 30:256, compared to about 8:1 in (Zbontar et al., 2021). Although these two ratios are used in unrelated tasks, and we also have the known loss to constrain the $W_b$ part of $W_c$, in future work it would be worth-while setting $d$ as a hyper-parameter that can be tuned for different datasets.

### 4.3. Prototypes Decoder Module

We use CaNet (Zhang et al., 2019b), ASGNet (Li et al., 2021) and PFENet (Tian et al., 2020) as baselines on which to test our method. These methods have been widely used as the underlying model enhanced by various previous techniques (Yang et al., 2020; Wu et al., 2021; Zhang et al., 2021). Unlike most previous methods that modify the structure of the baseline decoder network, we try to improve it through better training. Each baseline incorporates a prototype decoder module (called the Iterative Optimization Module in CaNet, FPN in ASGNet and the Feature Enrichment Module in PFENet) that takes as input the foreground prototype and query features, and outputs a predicted segmentation mask $\hat{M}_f$. In addition to using this module in the standard way, we also use it with the foreground prototype replaced by the background prototype, so that it outputs a background prediction $\hat{M}_b$. When predicting the background mask in the ASGNet baseline, we use only one background prototype ignoring its ability to use multiple prototypes. PFENet also uses a prior mask ($H$) to supplement $\hat{M}_f$ and this input is replaced by (1 - $H$) to predict $\hat{M}_b$ when using PFENet as the baseline.

Based on the two predicted segmentation masks, we define two loss functions which are consistent with those used by the baselines:

$$\mathcal{L}_{base}(f) = CE(\hat{M}_f, M_q)$$  \hspace{1cm} (10)

$$\mathcal{L}_{base}(b) = CE(\hat{M}_b, 1 - M_q)$$  \hspace{1cm} (11)

The overall loss combines the losses defined in Eqs. 5, 7, 10 and 11, as follows:

$$\mathcal{L} = \mathcal{L}_{base}(f) + \alpha \mathcal{L}_{base}(b) + \beta (\mathcal{L}_{known} + \mathcal{L}_{latent})$$  \hspace{1cm} (12)

where $\alpha$ and $\beta$ are parameters to balance the losses. Results for experiments investigating the effects of these hyper-parameters are reported in Table 7. When $\alpha = \beta = 0$, $\mathcal{L} = \mathcal{L}_{base}(f)$ and the whole method degenerates to the baseline.

For multi-shot tasks (i.e. when applied to k-shot FSS when $k > 1$), we use the same method as the corresponding baseline. Specifically, CaNet (Zhang et al., 2019b) designs an attention mechanism to fuse different features generated by each of the k support images. ASGNet (Li et al., 2021) uses super-pixels to generate multiple prototypes of support images. PFENet (Tian et al., 2020) averages the foreground prototypes from k support images together. As QSR obtains the background prototype from the query image, QSR is unaffected by the number of support images which makes QSR easy to integrate with different baseline methods.

### 5. Experiments

#### 5.1. Experimental Setup

**Datasets.** We evaluate our method on two benchmark datasets, PASCAL-$5^i$ (Shaban et al., 2017) and COCO-$20^i$ (Nguyen and Todorovic, 2019). PASCAL-$5^i$ includes the PASCAL VOC2012 (Everingham et al., 2010) and the extended SDS datasets (Hariharan, Arbeláez, Girshick and Malik, 2014). It contains 20 classes which are divided into 4 folds each containing 5 classes. COCO-$20^i$ is the MS-COCO dataset (Lin, Maire, Belongie, Hays, Perona, Ramanan, Dollár and Zitnick, 2014) with the 80 classes divided into 4 folds each containing 20 classes. Following previous standard practice (Zhang et al., 2019b; Tian et al., 2020), we use 4-fold cross validation to measure performance on both datasets: testing each fold in turn using a model that had been trained on the other three folds. A random sample of 1,000 query-support pairs is used to test each fold in PASCAL-$5^i$ and 20,000 in COCO-$20^i$.

**Implementation details.** As mentioned above, we use CaNet (Zhang et al., 2019b), ASGNet (Li et al., 2021) and PFENet (Tian et al., 2020) as baselines. The whole model is trained end-to-end. As QSR is only used in the training phase, the model is identical to the baseline during testing. The details specific to QSR were as follows: the class weights $W_c$ (Section 4.2) were initialized from the uniform distribution ($-\sqrt{1/d}, \sqrt{1/d}$). The loss weights $\alpha$ & $\beta$ (Eq. (12)) were set to 1.0 & 0.5 in PASCAL-$5^i$ and 1.0 & 0.1 in COCO-$20^i$. The motivation for reducing $\beta$ for COCO-$20^i$ was because this dataset has more categories. The number of latent classes $N_l$ (Section 4.2) was set to 15 in PASCAL-$5^i$
and 60 in COCO-20′ to make $N_i = N_k$ for each dataset. Consistent with the baselines, $d$ was set to 256. In common with many previous FSS methods (Siam et al., 2019; Zhang et al., 2019a; Lu et al., 2021; Liu et al., 2021; Li et al., 2021; Wu et al., 2021; Zhang et al., 2021), and the baselines, feature extraction was performed using a ResNet (He et al., 2015). During training, we used the methods and hyper-parameters used by the baselines. Specifically, for CaNet (Zhang et al., 2019b), weights were optimised using SGD with momentum of 0.9 and a weight decay of 0.0005. Training was performed for 200 epochs with a learning rate of 0.00025 and a batch size of 4. For ASGNet (Li et al., 2021), the model was trained with the SGD optimizer and an initial learning rate to 0.0025 with batch size 4 on Pascal-5′, and 0.005 with batch size 8 on COCO-20′. For PFENet (Tian et al., 2020), SGD was also used as the optimizer. The momentum was set to 0.9 and the weight decay to 0.0001. On PASCAL-5′, 200 epochs were used with a learning rate of 0.0025 and a batch size of 4. On COCO-20′, the PFENet baseline was trained for 50 epochs with a learning rate of 0.005 and a batch size 8. On both datasets, the learning rate was reduced following the “poly” policy (Chen, Papandreou, Kokkinos, Murphy and Yuille, 2017).

_Evaluation metrics._ Following standard practice, we use mean intersection over union (mIoU) as the primary evaluation metric. It computes the IoU for each individual foreground class and then calculates an average of these values over all classes (5 in PASCAL-5′ and 20 in COCO-20′). We also report the results of FB-IoU, which calculates the mean IoU for the foreground (i.e. for all objects ignoring class labels) and the background. We use false positive rate (FPR) which is defined as $FPR = \frac{FP}{FP + TN}$, where FP is the number of background pixels incorrectly labelled as foreground, and TN is the number of background pixels correctly labelled as background.

| Method          | 1-shot          | 5-shot          |
|-----------------|-----------------|-----------------|
|                 | P-5′ | P-5 | P-5′ | P-5 | P-5′ | P-5′ | Mean | P-5′ | P-5 | P-5′ | P-5′ | Mean |
| OSLSM (Shaban et al., 2017) | 33.6 | 55.3 | 40.9 | 33.5 | 40.8 | 35.9 | 58.1 | 42.7 | 39.1 | 43.9 |
| PANet (Wang et al., 2019) | 42.3 | 58.0 | 51.1 | 41.2 | 48.1 | 51.8 | 64.6 | 59.8 | 46.5 | 55.7 |
| RPMMs (Yang et al., 2020) | 55.2 | 66.9 | 52.6 | 50.7 | 56.3 | 56.3 | 67.3 | 54.5 | 51.0 | 57.3 |
| CWT (Lu et al., 2021) | 56.3 | 62.0 | 59.9 | 47.2 | 56.4 | 61.3 | 68.5 | 68.5 | 56.6 | 63.7 |
| ASR (Liu et al., 2021) | 53.8 | 69.6 | 51.6 | 52.8 | 56.9 | 56.2 | 70.6 | 53.9 | 53.4 | 58.5 |
| RePrI (Boudiaf et al., 2021) | 59.8 | 68.3 | 62.1 | 48.5 | 59.7 | 64.6 | 71.4 | 71.1 | 59.3 | 66.6 |
| MMNNet (Wu et al., 2021) | 58.0 | 70.0 | 58.0 | 55.0 | 60.2 | 60.0 | 70.6 | 56.3 | 60.3 | 61.8 |
| SCL (Zhang et al., 2021) | 63.0 | 70.0 | 56.5 | 57.7 | 61.8 | 64.5 | 70.9 | 57.3 | 58.7 | 62.9 |
| MLC (Yang et al., 2021) | 59.2 | 71.2 | 65.6 | 52.5 | 62.1 | 63.5 | 71.6 | 71.2 | 58.1 | 66.1 |
| CANet (Zhang et al., 2019b) | 52.5 | 65.9 | 51.3 | 51.9 | 55.4 | 55.5 | 67.8 | 51.9 | 53.2 | 57.1 |
| CANet+QSR (ours) | 56.1 | 66.3 | 51.5 | 52.3 | 56.4 | 59.3 | 68.7 | 52.8 | 53.6 | 58.6 |
| ASGNet (Li et al., 2021) | 58.8 | 67.9 | 56.8 | 53.7 | 59.3 | 63.7 | 70.6 | 64.2 | 57.4 | 63.9 |
| ASGNet+QSR (ours) | 62.0 | 68.4 | 57.8 | 56.1 | 61.1 | 66.5 | 71.2 | 65.1 | 61.0 | 60.0 |
| PFENet (Tian et al., 2020) | 61.7 | 69.5 | 55.4 | 56.3 | 60.8 | 63.1 | 70.7 | 55.8 | 57.9 | 61.9 |
| PFENet+QSR (ours) | 63.1 | 69.9 | 58.7 | 58.9 | 62.7 | 68.3 | 71.7 | 63.1 | 63.6 | 66.7 |

5.2. Comparison with the State-of-the-Art

Table 1 and Table 2 compare our method with other approaches on PASCAL-5′. When QSR is applied to PFENet, the method outperforms the previous state-of-the-art in both the 1-shot and 5-shot settings. For each baseline, the QSR method improves performance on every fold, and overall, for both 1-shot and 5-shot segmentation tasks. This is achieved with only a small increase in the number of learnable parameters, as indicated in the last column of the Table 2. These additional parameters are due to matrix $W_c$ (see Section 4.2), and are only used during training: at test time the proposed method uses an identical number of parameters as the corresponding baseline. The ability to improve performance for three existing FSS methods, suggests that QSR may have the potential to provide a general-purpose method of improving the accuracy of FSS approaches. Additional results using a different backbone architecture are shown in Table 3.
The performance of the proposed method improves on known classes, and $N$ classes, when using different numbers of latent data (15 in PASCAL-20). When $N=0$, there are no latent classes, only background prototypes created through the proposed method. As Table 9 shows, this is due to there being a diverse range of backgrounds against which objects from the same category can appear in different images. Extracting foreground and background information from different training images enables the decoder to be trained to correctly distinguish foreground objects from a larger variety of backgrounds.

Effects of loss weight. Table 7 shows the impact of different loss weights, $\alpha$ and $\beta$ (see Eq. (12)) on the results. When $\alpha = \beta = 0$, the loss function becomes equivalent to the baseline loss $L_{\text{base}}(f)$, the results produced are therefore identical to those of the baseline model. All combinations of non-zero values for $\alpha$ and $\beta$ produced mIoU results that were better than those of the baseline. For the loss weights tested, the best results were produced with $\alpha = 1$, meaning that the background and foreground information was weighted equally, and $\beta = 0.5$.

Background prototype from support images. Table 8 explores the effects of extracting background information from different images. In the baseline, background information was not used, and the results are the same as the underlying FSS method. For the results labelled ‘Support’, the background information was extracted from the support image, rather than the query image. This was achieved by replacing the query features $F_q$ in Eq. (3) with the support features $F_s$, but keeping other settings unchanged to allow for a fair comparison. It can be seen that this method produces little improvement over the baseline. For the results labelled ‘Query’, the background information was extracted from the query image. This is our proposed QSR method of extracting background prototypes, which produces a more significant improvement in the results. Hence, extracting background information from the query image is more effective than extracting it from the support image. We believe that this is due to there being a diverse range of backgrounds against which objects from the same category can appear in different images. Extracting foreground and background information from different training images enables the decoder to be trained to correctly distinguish foreground objects from a larger variety of backgrounds.

Importance of prototype reconstruction. Table 9 shows the effects of using different methods to extract the background prototypes. The results labelled ‘Mask’ used the query image segmentation masks (which are available during training) to obtain the background prototypes directly. Specifically, masked average pooling (Eq. (1)) was used to generate background prototypes replacing those generated by QSR in Eq. (3). The final loss function in Eq. (12) becomes $\mathcal{L} = \mathcal{L}_{\text{base}}(f) + \mathcal{L}_{\text{base}}(b)$. As Table 9 shows, this method improves the results compared to the baseline, which reinforces the idea that using background information can improve the training of the model. However, QSR provides a further improvement in the results, suggesting that the background prototypes created through the proposed method are more effective.
Table 5

| Method          | 1-shot | 5-shot | Mean | Backbone          |
|-----------------|--------|--------|------|-------------------|
| ASGNet          |        | -      | -    | -                 |
| ASGNet+QSR (ours) | 34.8   | 39.8   | 40.7 | 37.4              | ResNet50          |
| PFENet          | 34.3   | 33.0   | 32.3 | 30.1              | ResNet50          |
| PFENet+QSR (ours) | 34.1   | 38.4   | 35.5 | 32.3              | ResNet50          |
| PFENet+QSR (ours) | 33.6   | 41.0   | 39.2 | 33.8              | ResNet50          |

Table 6

| \(N_l\) | P-5^0 | P-5^1 | P-5^2 | P-5^3 | mean |
|---------|-------|-------|-------|-------|------|
| 0       | 62.2  | 69.3  | 57.7  | 58.4  | 61.9 |
| 15      | 63.1  | 69.9  | 58.7  | 58.9  | 62.7 |
| 30      | 63.6  | 69.5  | 57.7  | 58.6  | 62.4 |
| 45      | 61.8  | 69.5  | 57.2  | 57.5  | 61.5 |
| 60      | 61.6  | 69.1  | 58.0  | 57.7  | 61.6 |

Table 7

| \(\alpha\) | \(\beta\) | P-5^0 | P-5^1 | P-5^2 | P-5^3 | mean |
|-----------|-----------|-------|-------|-------|-------|------|
| 0.0       | 0.0       | 61.7  | 69.5  | 55.4  | 56.3  | 60.8 |
| 0.5       | 0.5       | 62.1  | 69.6  | 55.0  | 58.8  | 61.4 |
| 0.5       | 1.0       | 62.3  | 69.8  | 55.0  | 58.3  | 61.4 |
| 1.0       | 0.5       | 63.1  | 69.9  | 58.7  | 58.9  | 62.7 |
| 1.0       | 1.0       | 61.8  | 66.3  | 58.1  | 58.5  | 61.2 |

Table 8

| Method          | P-5^0 | P-5^1 | P-5^2 | P-5^3 | mean |
|-----------------|-------|-------|-------|-------|------|
| Baseline        | 61.7  | 69.5  | 55.4  | 56.3  | 60.8 |
| Support         | 62.1  | 69.8  | 54.5  | 57.1  | 60.9 |
| Query           | 63.1  | 69.9  | 58.7  | 58.9  | 62.7 |

Table 9

| Method          | P-5^0 | P-5^1 | P-5^2 | P-5^3 | mean |
|-----------------|-------|-------|-------|-------|------|
| Baseline        | 61.7  | 69.5  | 55.4  | 56.3  | 60.8 |
| Mask            | 63.4  | 69.5  | 54.9  | 57.4  | 61.3 |
| QSR             | 63.1  | 69.9  | 58.7  | 58.9  | 62.7 |

Figure 4: Visualized results of latent classes and background predictions. For each class, (a) the prediction results for three latent classes, (b) the final background prediction, (c) the query with foreground masks, (d) the support image with foreground masks.

5.4. Model Analysis

The following experiments to analyze QSR were performed with the PFENet baseline using the 1-shot setting in PASCAL-5.

What latent classes represent. Latent classes (see Section 4.2) are used to represent classes that are undefined in the training dataset, but may correspond to unlabelled background features. To visualise these latent classes we identified the three highest scores (see Eq. (8)) for latent classes. Then generated a background prototype for each of these high-scoring latent classes in turn, and used those prototypes to segment the image. The results for two example images are shown in Fig. 4. Since QSR only predicts the background in the training phase, the figure shows the results for two training images.

It can be seen that each latent class represents a certain area of the background. This shows that the latent weights do represent the unknown categories of the background. However, these categories do not correspond to meaningful categories, that might be given distinct labels by a human. This is because QSR constrains the latent classes to be statistically independent from each other and the known classes. This constraint does not force latent classes to correspond to specific background classes, but allows them to learn combinations of background features. It can also be seen that when the background prototype is generated using all non-foreground classes, in the way we propose, that this prototype does an excellent job of identifying almost all background regions in the two example images. This is even the case (as shown for the chair example) when the situation is challenging due to the object occupying a very small proportion of the image and both the background and
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Figure 5: Qualitative results for 1-shot FSS on PASCAL-5i (above the line) and COCO-20i (below the line). (a) Support images and ground-truths. (b) Query images and ground-truths. (c) Predictions of PFENet. (d) Predictions of PFENet+QSR.

foreground in the query image having little similarity with the support image.

False positive rate. QSR uses background information during training in order to make the model more discriminative and the foreground prototypes extracted during testing less likely to be matched with the background. The results shown in Table 10 demonstrate that QSR does indeed reduce the FPR compared to the corresponding baseline FSS algorithm.

Qualitative results. Fig. 5 shows some qualitative results. In the far right column above the line is an example of an unsuccessful segmentation, but a result where the false positive rate is reduced.

6. Conclusion

This paper proposes query semantic reconstruction (QSR) for few-shot segmentation. By associating the query image with semantics during training, QSR obtains background information from the query image to mine negative samples in order to make a more discriminative model that reduces false-positives. QSR improves the performance of three different baselines, and for one of them the improvement is sufficient to produce state-of-the-art results for both the 1-shot and 5-shot settings on PASCAL-5i. Future work might usefully explore improved methods of representing foreground objects or the use of background information at test time. In addition, due to limited computing resources, we did not tune the number of latent classes $N_l$ (see Section 4.2) on COCO-20i. Trying more $N_l$ may produce better performance.

Table 10

| Method       | P-5¹ | P-5² | P-5³ | mean |
|--------------|------|------|------|------|
| CaNet        | 10.9 | 7.9  | 9.8  | 10.1 | 9.7  |
| CaNet+QSR    | **7.4** | **7.1** | **9.7** | **8.9** | **8.3** |
| ASGNet       | 8.7  | 8.8  | 9.6  | 9.2  | 9.1  |
| ASGNet+QSR   | **6.2** | **7.8** | **8.8** | **8.2** | **7.8** |
| PFENet       | 5.8  | 7.7  | 7.6  | 8.6  | 7.4  |
| PFENet+QSR   | **5.2** | **7.9** | **6.9** | **6.0** | **6.5** |
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Conflict of Interest

The authors have no conflicts of interest/competing interests to declare that are relevant to the content of this article.

References

Boufias, M., Kervacz, H., Masud, Z.I., Piantanida, P., Ayed, I.B., Dolz, J., 2021. Few-shot segmentation without meta-learning: A good transductive inference is all you need?, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Chen, L.C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A.L., 2017. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence 40, 834–848.

Chen, L.C., Zhu, Y., Papandreou, G., Schroff, F., Adam, H., 2018. Encoder-decoder with atrous separable convolution for semantic image segmentation, in: Proceedings of the European conference on computer vision (ECCV), pp. 801–818.

Chen, X., He, K., 2021. Exploring simple siamese representation learning, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 15750–15758.

Chen, Z., Fu, Y., Zhang, Y., Jiang, Y.G., Xie, X., Sigal, L., 2019. Multi-level semantic feature augmentation for one-shot learning. IEEE Transactions on Image Processing 28, 4594–4605.

Everingham, M., Van Gool, L., Williams, C.K., Winn, J., Zisserman, A., 2010. The pascal visual object classes (voc) challenge. International journal of computer vision 88, 303–338.

Finn, C., Abbeel, P., Levine, S., 2017. Model-agnostic meta-learning for fast adaptation of deep networks, in: International Conference on Machine Learning, PMLR. pp. 1126–1135.

Grant, E., Finn, C., Levine, S., Darrell, T., Griffiths, T., 2018. Recasting gradient-based meta-learning as hierarchical bayes, in: 6th International Conference on Learning Representations, ICLR 2018.

Harirhan,B.,Arbelàez,P.,Girshick,R.,Malik,J.,2014.Simultaneousdetectionandsegmentation,in:EuropeanConferenceonComputerVision, Springer. pp. 297–312.

Harirhan,B.,Girshick,R.,2017.Low-shotvisualrecognitionbyshrinkingandhallucinatingfeatures, in: Proceedings of the IEEE International Conference on Computer Vision, pp. 3018–3027.

He, J., Deng, Z., Zhou, L., Wang, Y., Qiao, Y., 2019. Adaptive pyramid context network for semantic segmentation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7519–7528.

He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778.

Li, G., Jampali, V., Sevilla-Lara, L., Sun, D., Kim, J., Kim, J., 2021. Adaptive prototype learning and allocation for few-shot segmentation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Lin, T.Y., Mairé, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., Zitnick, C.L., 2014. Microsoft coco: Common objects in context, in: European conference on computer vision, Springer. pp. 740–755.

Liu, B., Ding, Y., Jiao, J., Ji, X., Ye, Q., 2021. Anti-aliasing semantic reconstruction for few-shot semantic segmentation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9747–9756.

Liu, J., Sun, Y., Han, C., Dou, Z., Li, W., 2020. Deep representation learning on long-tailed data: A learnable embedding augmentation perspective, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 2970–2979.

Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3431–3440.

Lu, Z., He, S., Zhu, X., Zhang, L., Song, Y.Z., Xiang, T., 2021. Simpler is better: Few-shot semantic segmentation with classifier weight transformer, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 8741–8750.

Nguyen, K., Todorovic, S., 2019. Feature weighting and boosting for few-shot segmentation, in: Proceedings of the IEEE International Conference on Computer Vision, pp. 622–631.

Ravi, S., Larochelle, H., 2017. Optimization as a model for few-shot learning, in: ICLR.

Ronneberger, O., Fischer, P., Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation, in: International Conference on Medical image computing and computer-assisted intervention, Springer. pp. 234–241.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., et al., 2015. Imagenet large scale visual recognition challenge. International journal of computer vision 115, 211–252.

Shaban, A., Bansal, S., Liu, Z., Essa, I., Boots, B., 2017. One-shot learning for semantic segmentation, in: BMVC.

Siam, M., Doria, W., Oreshkin, B.N., Yao, H., Jagersand, M., 2020. Weakly supervised few-shot object segmentation using co-attention with visual and semantic inputs, in: ICAI.

Siam, M., Oreshkin, B.N., Jagersand, M., 2019. Amp: Adaptive masked proxies for few-shot segmentation, in: Proceedings of the IEEE International Conference on Computer Vision, pp. 5249–5258.

Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

Snell, J., Swersky, K., Zemel, R., 2017. Prototypical networks for few-shot learning, in: Proceedings of the 31st International Conference on Neural Information Processing Systems, Curran Associates Inc., Red Hook, NY, USA. p. 4080–4090.

Tian, Z., Zhao, H., Shu, M.,Yang, Z., Li, R., Jia, J., 2020. Prior guided feature enrichment network for few-shot segmentation. IEEE Transactions on Pattern Analysis & Machine Intelligence.

Wang, K., Liew, J.H.,Zou, Y.,Zhou, D.,Feng,J.,2019.Panet:Few-shotimage segmentation with prototype alignment, in: Proceedings of the IEEE International Conference on Computer Vision, pp. 9197–9206.

Wang, Y.X., Girshick,R.,Hebert,M.,Harirhan,B.,2018.Low-shotlearningfromimaginarydata, in: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 7278–7286.

Wu, Z., Shi, X., Lin, G.,Cai,J.,2021.Learningmeta-classmemory for few-shot semantic segmentation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 517–526.

Yang, B., Liu, C., Li, B., Jiao, J., Ye, Q., 2020. Prototype mixture models for few-shot semantic segmentation, in: European Conference on Computer Vision, Springer. pp. 763–776.

Yang, L., Zhou, Q., Lin, G., Yao, Y., 2021. Mining latent classes for few-shot segmentation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pp. 8721–8730.

Zbontar, J., Jing, L., Misra, I., LeCun, Y., Deny, S., 2021. Barlow twins: Self-supervised learning via redundancy reduction. International Conference on Machine Learning (ICML).

Zhang, B., Xie, J., Qin, T., 2021. Self-guided and cross-guided learning for few-shot segmentation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 8312–8321.

Zhang, C., Lin, G., Liu, F., Guo, J., Wu, Q., Yao, R., 2019a. Pyramid graph networks with connection attentions for region-based one-shot semantic segmentation, in: Proceedings of the IEEE International Conference on Computer Vision, pp. 9587–9595.

Zhang, C., Lin, G., Liu, F., Yao, R., Shen, C., 2019b. 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, pp. 5217–5226.
Zhao, H., Shi, J., Qi, X., Wang, X., Jia, J., 2017. Pyramid scene parsing
network, in: Proceedings of the IEEE conference on computer vision
and pattern recognition, pp. 2881–2890.