Learning What Not to Segment: A New Perspective on Few-Shot Segmentation

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Outline

- Introduction
- Related Work
- Framework
- Method
- Experiment
- Conclusion

Introduction

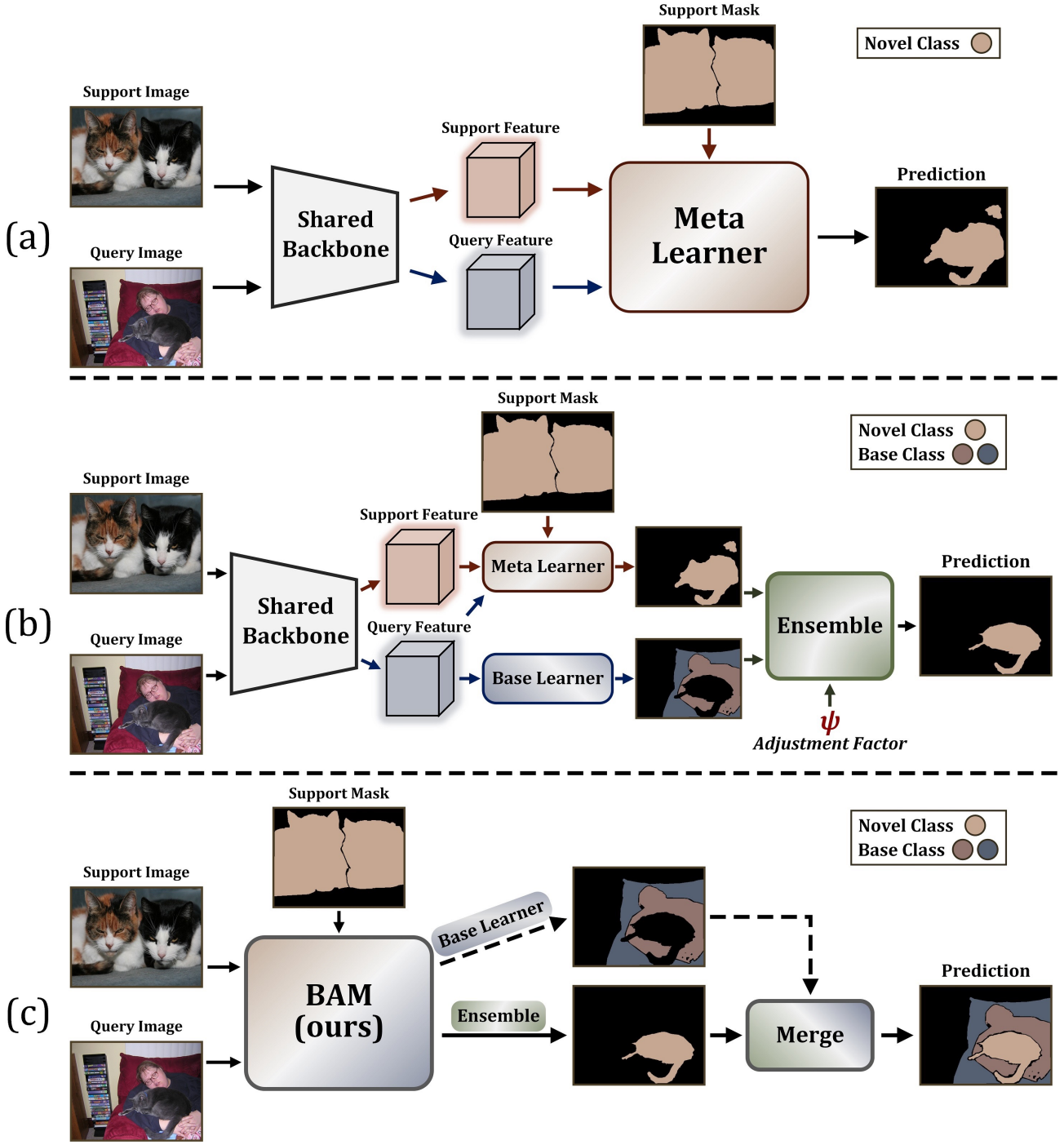
- Propose a simple but efficient scheme to address the bias problem by introducing **an additional branch to explicitly predict the regions of base classes** in the query images, which sheds light on future works.

- Propose to estimate the scene differences between the query-support image pairs through the **Gram matrix** for mitigating the adverse effects caused by the sensitivity of meta learner.

- Extend the proposed approach to a more challenging setting, **generalized FSS**, which simultaneously identifies the targets of base and novel classes.

Introduction

the proposed scheme is named BAM as it consists of two unique learners, base and the meta



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Related Work

- Pyramid Scene Parsing Network (PSPNet)
  - is served as the base learner
- Prior Guided Feature Enrichment Network for Few-Shot Segmentation(PFENet)
  - is served as the meta learner, where the FEM is replaced by ASPP

Related Work – PSPNet

Pyramid Scene Parsing Network

Hengshuang Zhao[1] Jianping Shi[2] Xiaojuan Qi[1] Xiaogang Wang[1] Jiaya Jia[1]
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CVPR 2017

Related Work – PSPNet

- Propose a **pyramid scene parsing network** to embed difficult scenery context features in an FCN based pixel prediction framework.

- Develop an **effective optimization strategy** for deep ResNet based on deeply supervised loss

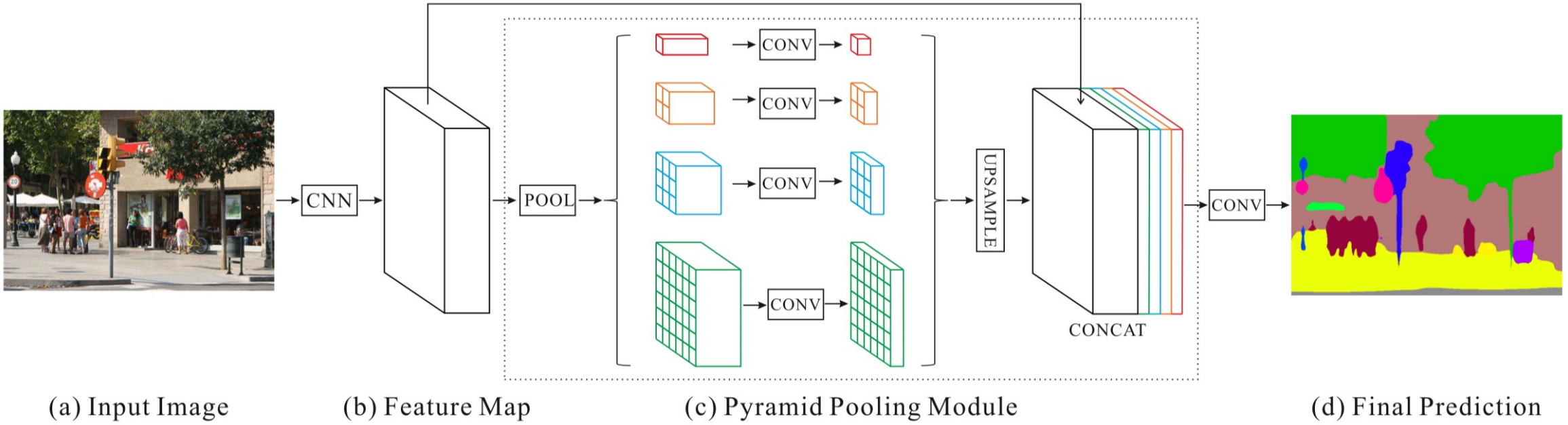
Related Work – PSPNet

- **Mismatched Relationship**: There exist co-occurrent visual patterns. For example, an airplane is likely to be in runway or fly in sky while not over a road.

- **Confusion Categories**: dataset that are confusing in classification. Examples are wall, house, building and skyscraper.

- **Inconspicuous Classes**: Several small-size things, like streetlight and signboard, are hard to find.

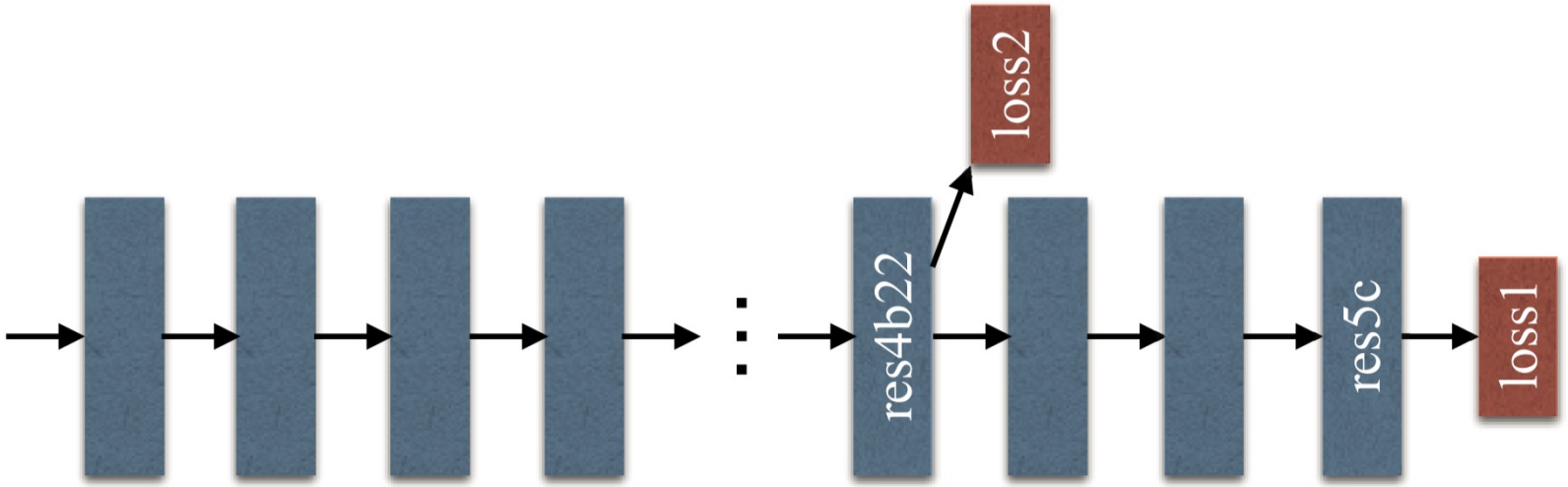
Related Work – PSPNet



- To summarize these observations, many errors related to **contextual relationship** and **global information** for different receptive fields.

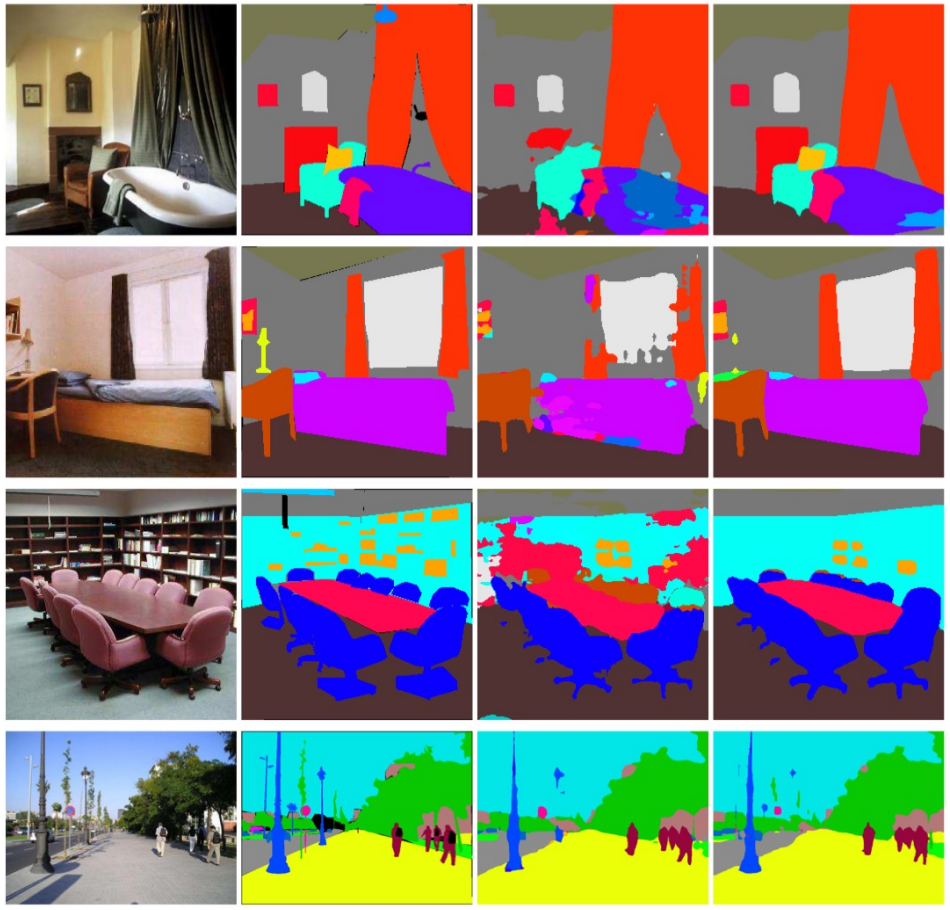
- A hierarchical global prior, containing information with different scales and varying among different sub-regions. Provides an **effective global contextual prior** for pixel-level scene parsing

Related Work – PSPNet



- Increasing depth of the network may introduce additional **optimization difficulty**
- Apart from the main branch using $softmax$ loss to train the final classifier, another classifier is applied after the fourth stage . The **auxiliary loss helps optimize the learning process**, while the master branch loss takes the most responsibility

Related Work – PSPNet



(a) Image (b) Ground Truth (c) Baseline (d) PSPNet

(a) Image (b) Ground Truth (c) Baseline (d) PSPNet

Figure 7. Visual improvements on PASCAL VOC 2012 data. PSP-Net produces more accurate and detailed results.

- Our baseline network is FCN and dilated network

Related Work – PSPNet – Contribution

- Proposed an effective pyramid scene parsing network for complex scene understanding
- The global pyramid pooling feature provides **additional contextual information**
- Also provided a deeply **supervised optimization strategy** for ResNet-based FCN network

Related Work – PFENet

Prior Guided Feature Enrichment Network for Few-Shot Segmentation

Zhuotao Tian, *Student Member, IEEE,* Hengshuang Zhao, *Member, IEEE,* Michelle Shu, *Student Member, IEEE,* Zhicheng Yang, *Member, IEEE,* Ruiyu Li, *Member, IEEE,* Jiaya Jia, *Fellow, IEEE*

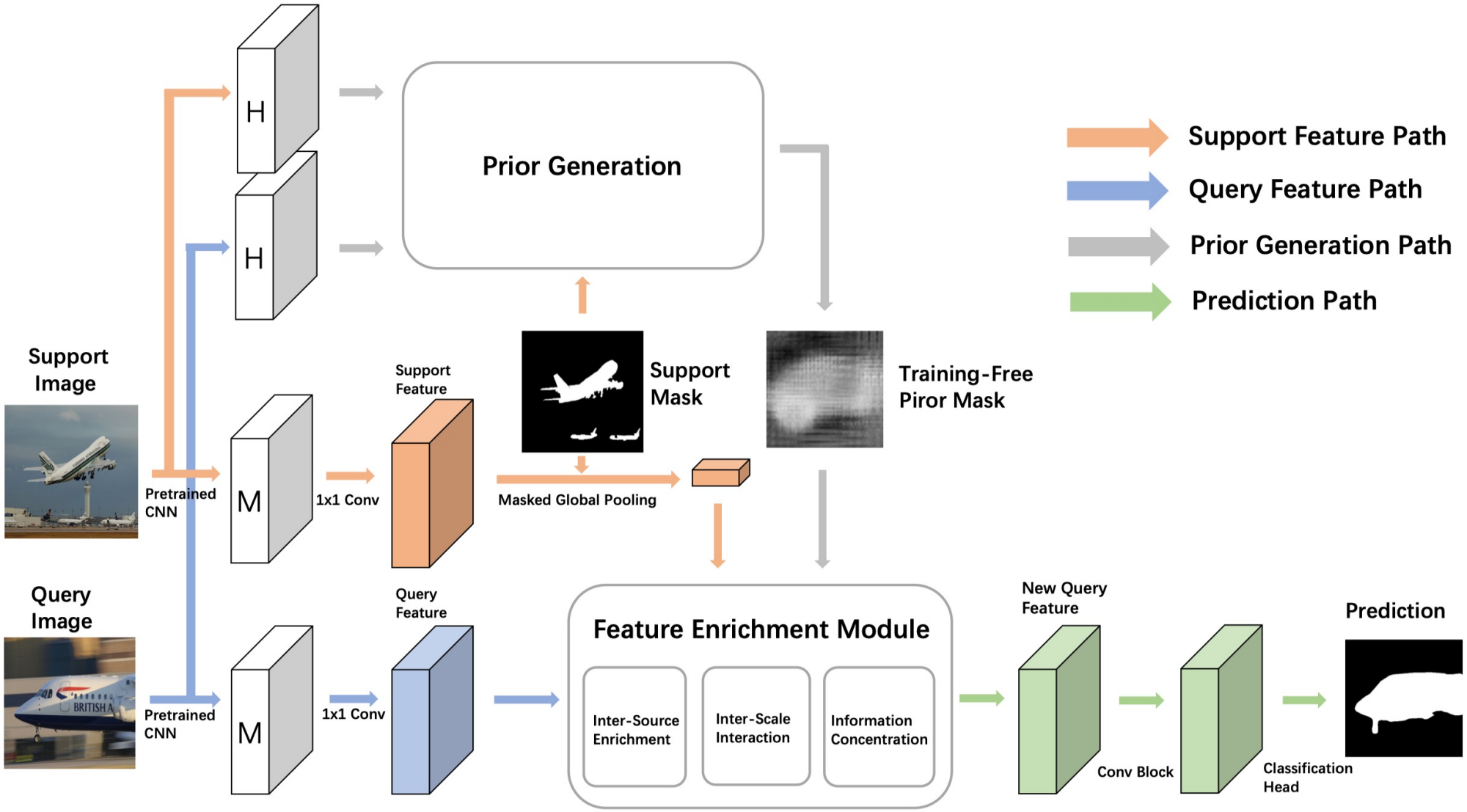
TPAMI 2020

Related Work – PFENet

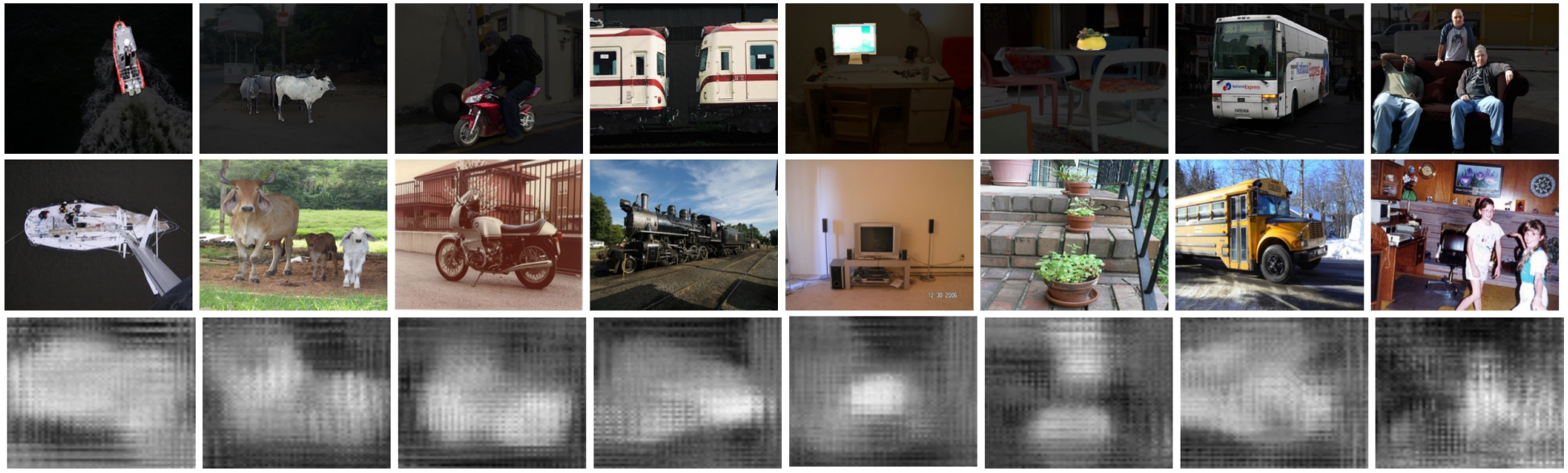
- Leverage high-level features and **propose training-free prior generation** to greatly improve prediction accuracy and retain high generalization

- By **incorporating the support feature** and **prior information**, our FEM helps adaptively **refine the query feature** with the conditioned inter-scale information interaction

Related Work – PFENet – Framework



Related Work – PFENet – Prior Generation



- High-level feature is **more class-specific** than the middle-level feature
- Exploit these features to **provide semantic cues** for final prediction

Related Work – PFENet – Prior Generation

$$X_Q = \mathcal{F}(I_Q), \quad X_S = \mathcal{F}(I_S) \odot M_S$$

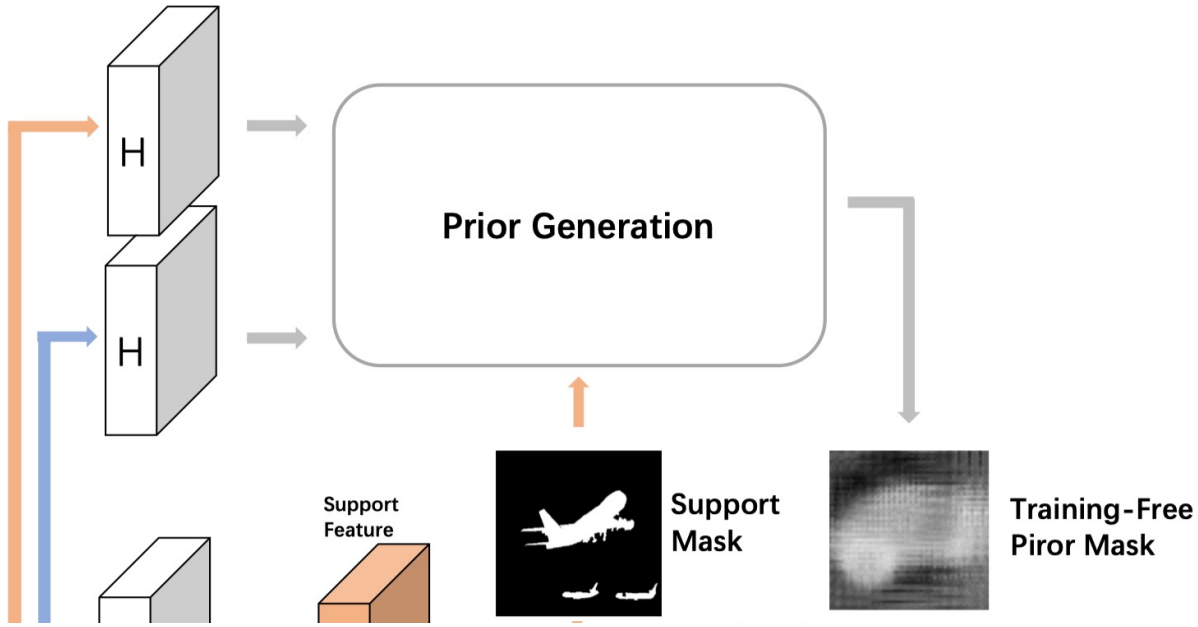
where $\odot$ is the Hadamard product

$$cos(x_q, x_s) = \frac{x_q^T x_s}{\|x_q\| \, \|x_s\|} \quad q, s \in \{1, 2, ..., hw\}$$

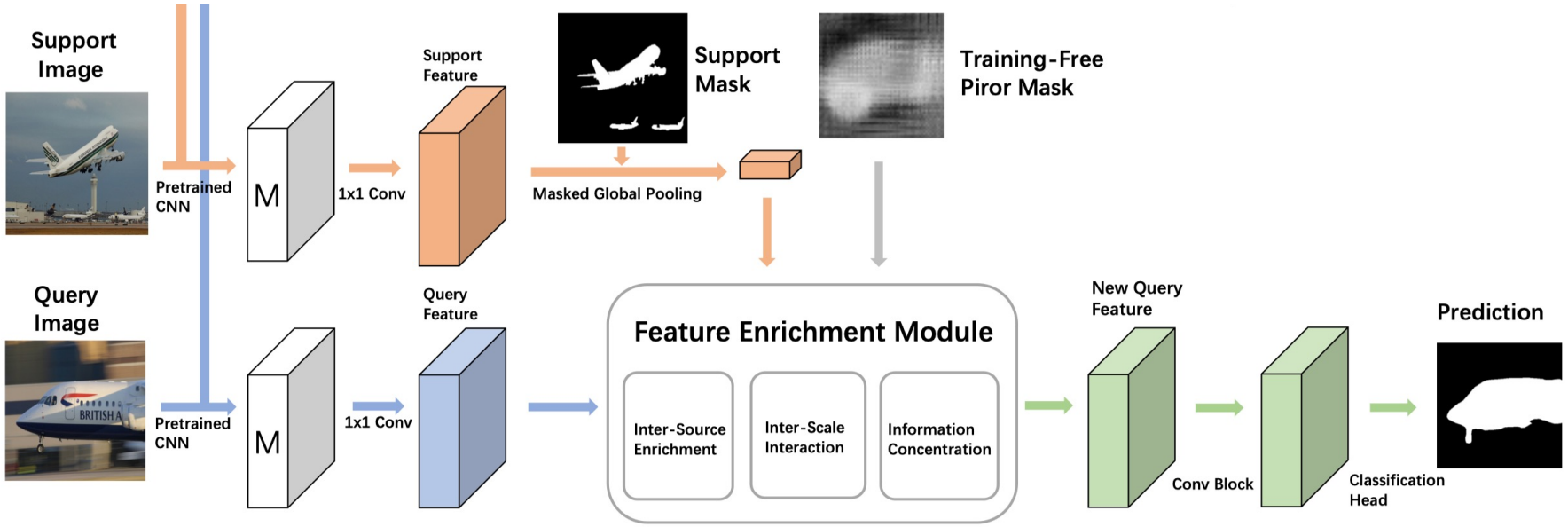
$$\begin{aligned} c_q &= \max_{s \in \{1,2,...,hw\}} (cos(x_q, x_s)), \\ C_Q &= [c_1, c_2, ..., c_{hw}] \in \mathbb{R}^{hw \times 1}. \end{aligned}$$

Reshaping $C_Q \in \mathbb{R}^{hw*1}$ into $Y_Q \in \mathbb{R}^{h*w*1}$

$$Y_Q = \frac{Y_Q - \min(Y_Q)}{\max(Y_Q) - \min(Y_Q) + \epsilon}$$



Related Work – PFENet – Feature Enrichment Module



- **horizontally** interact the query feature with the support features and prior masks in each scale
- **vertically** leverage the hierarchical relations to enrich coarse feature maps with essential information extracted from the finer feature via a **top-down information** path
- features projected into different scales are then collected to **form the new query feature**

Related Work – PFENet – Feature Enrichment Module

- **Inter-Source Enrichment**

$$X^i_{Q,m} = \mathcal{F}_{1\times1}(X^i_Q \oplus X^i_S \oplus Y^i_Q)$$

n different spatial sizes

- **Inter-Scale Interaction**

$$X^i_{Q,new} = \mathcal{M}(X^{Main,i}_{Q,m}, X^{Aux,i}_{Q,m})$$

- **Information Concentration**

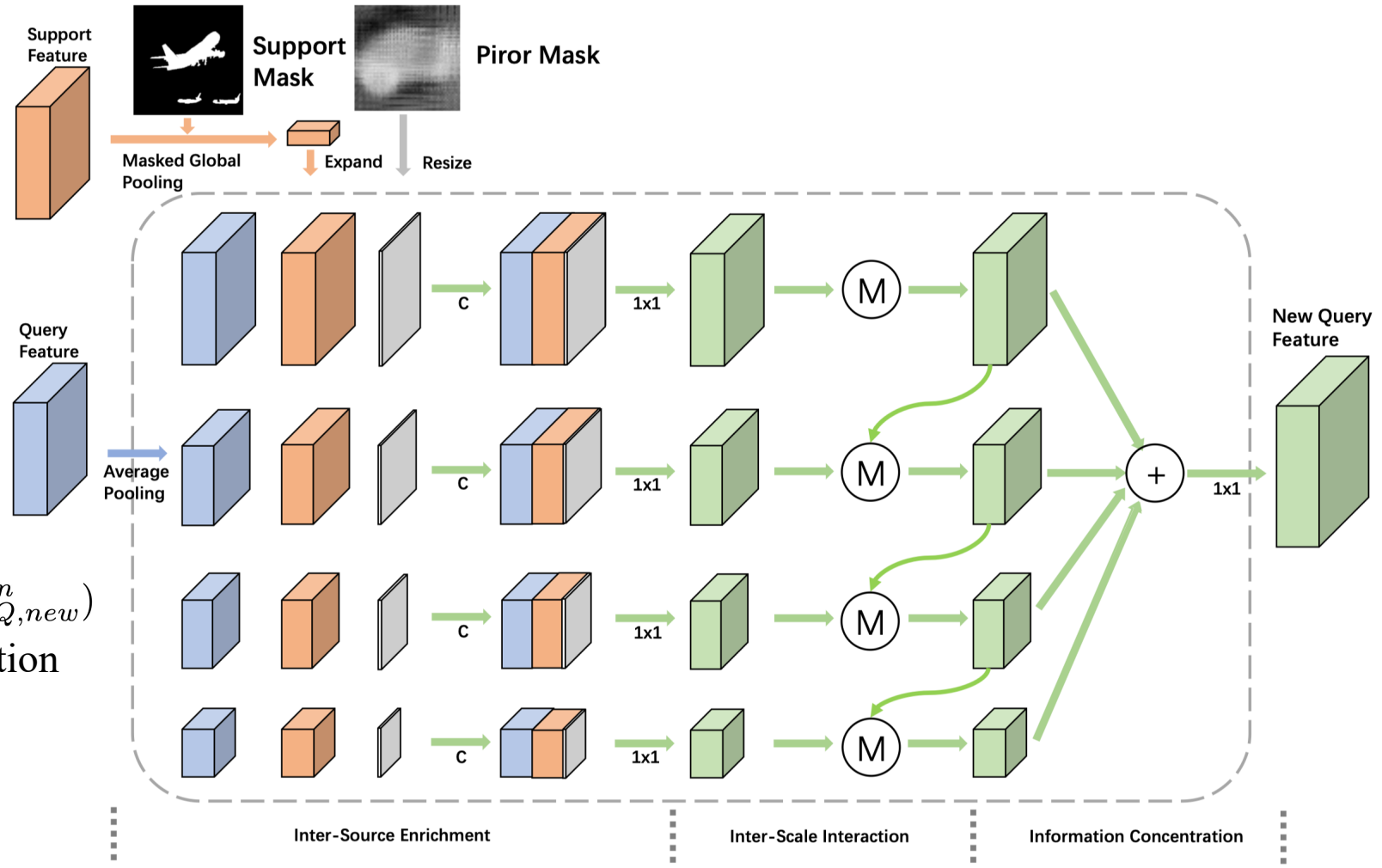
$$X_{Q,new} = \mathcal{F}_{1\times1}(X^1_{Q,new} \oplus X^2_{Q,new} \cdots \oplus X^n_{Q,new})$$

interpolation ,concatenation

- **Loss Function**

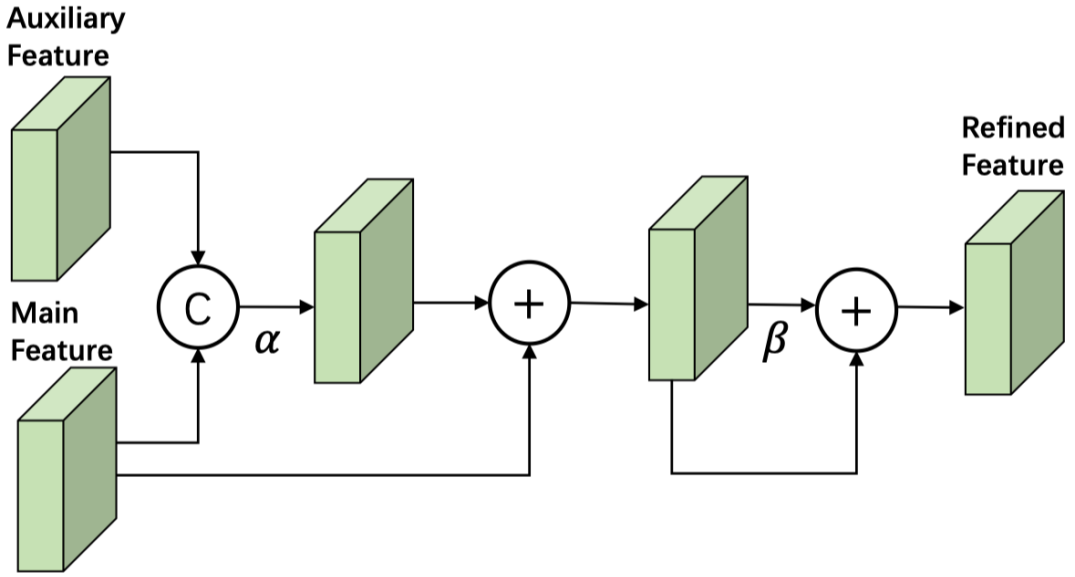
$$\mathcal{L} = \frac{\sigma}{n}\sum_{i=1}^{n}\mathcal{L}^i_1 + \mathcal{L}_2$$

intermediate supervision on $X^i_{Q,new}$



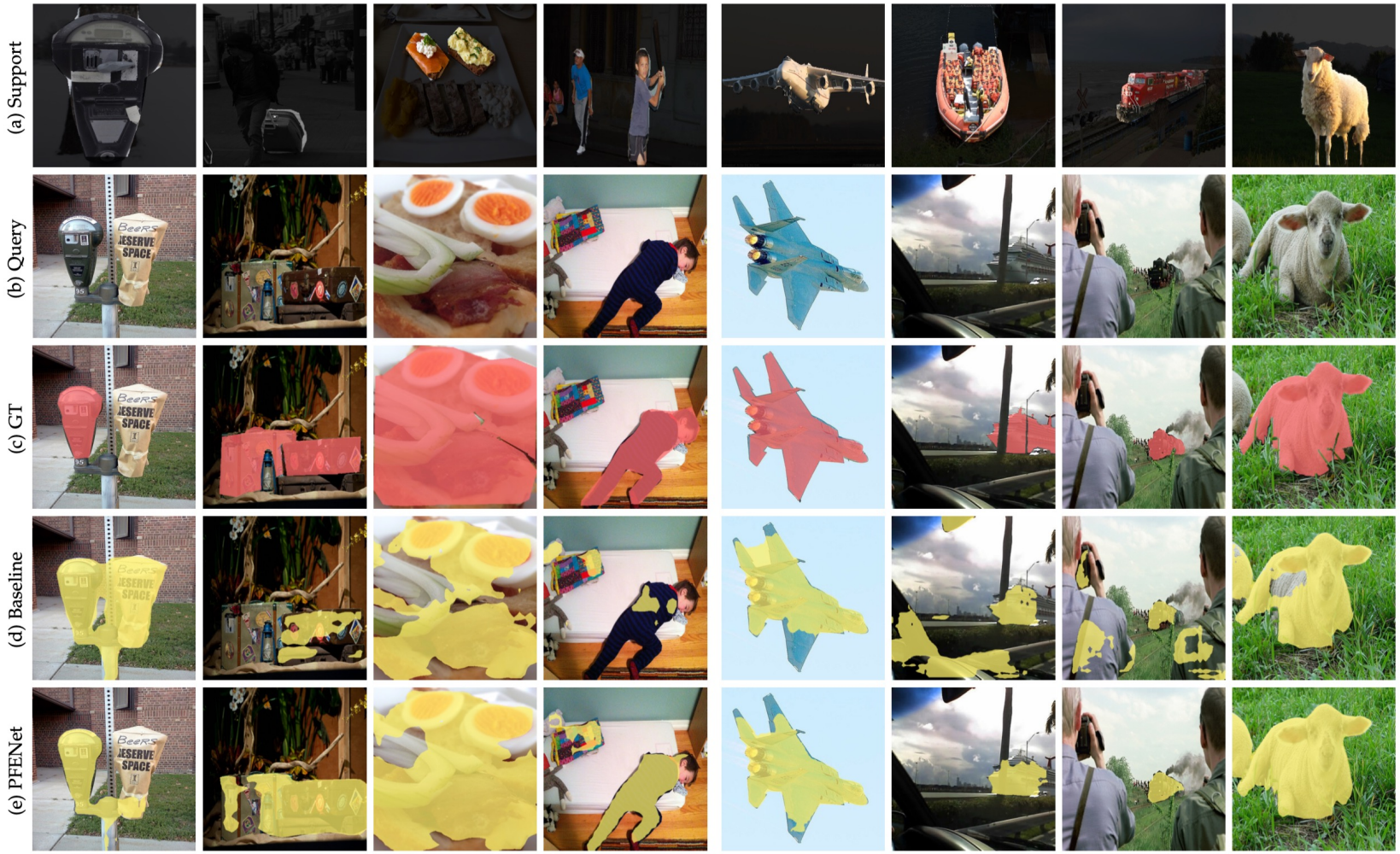
Related Work – PFENet – Inter-Scale Interaction

$$X_{Q,new}^{i} = \mathcal{M}(X_{Q,m}^{Main,i}, X_{Q,m}^{Aux,i})$$



- **Top-down path** adaptively passing information from finer features to the coarse ones
- M that interacts between different scales by selectively **passing useful information**
- α is a 1×1 convolution, β is two 3×3 convolutions

Related Work – PFENet – Result



- Baseline only has one scale size in FEM, not multi-scaled

Related Work – PFENet – Contribution

- presented PFENet with the proposed **prior generation** method and the **feature enrichment module (FEM)**
- The prior generation method leverages the cosine-similarity on pre-trained high-level features. Encourages the model to **localize the query targe**.
- FEM helps **solve the spatial inconsistency** by adaptively merging the query and support features at multiple scales with intermediate supervision and conditioned feature selection.

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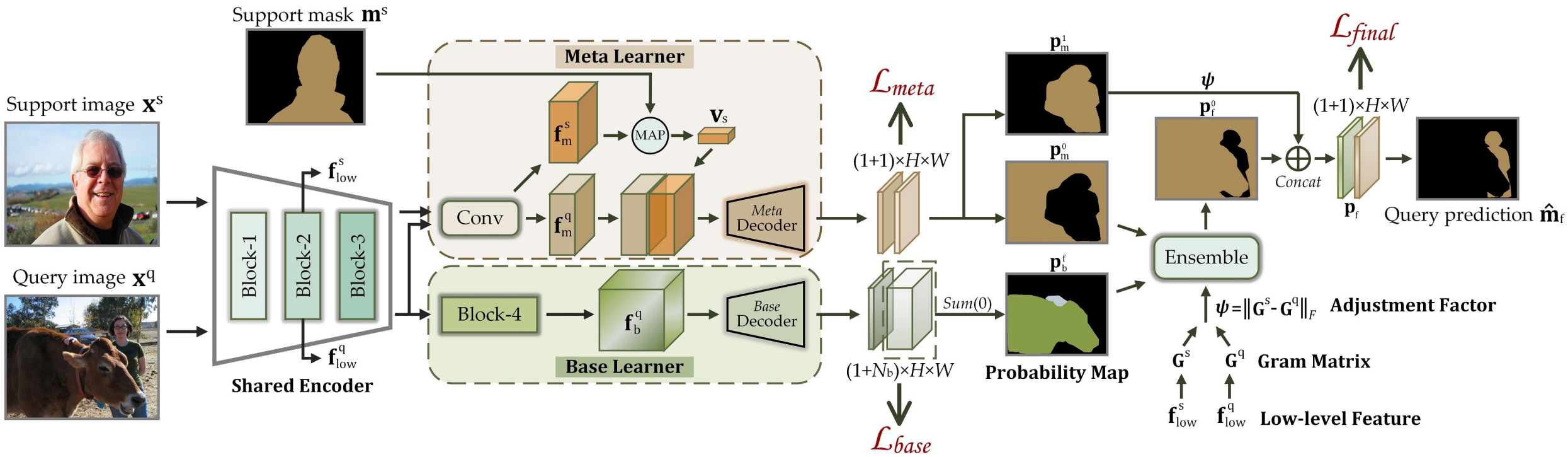
Framework


Support mask $\mathbf{m}^s$
Support image $\mathbf{x}^s$
Query image $\mathbf{x}^q$
Block-1
Block-2
Block-3
Block-4
$\mathbf{f}^s_{low}$
$\mathbf{f}^q_{low}$
Shared Encoder
Meta Learner
Conv
$\mathbf{f}^s_m$
$\mathbf{f}^q_m$
MAP
$\mathbf{v}_s$
Meta Decoder
$\mathbf{f}^q_b$
Base Decoder
Base Learner
$\mathcal{L}_{meta}$
$\mathcal{L}_{base}$
$\mathcal{L}_{final}$
$(1+1)\times H\times W$
$(1+N_b)\times H\times W$
Sum(0)
$\mathbf{p}^1_m$
$\mathbf{p}^0_m$
$\mathbf{p}^f_b$
Probability Map
ψ
$\mathbf{p}^0_f$
Concat
$\mathbf{p}_f$
Query prediction $\hat{\mathbf{m}}_f$
Ensemble
$\psi = \|\mathbf{G}^s - \mathbf{G}^q\|_F$
Adjustment Factor
$\mathbf{G}^s$
$\mathbf{G}^q$
Gram Matrix
$\mathbf{f}^s_{low}$
$\mathbf{f}^q_{low}$
Low-level Feature

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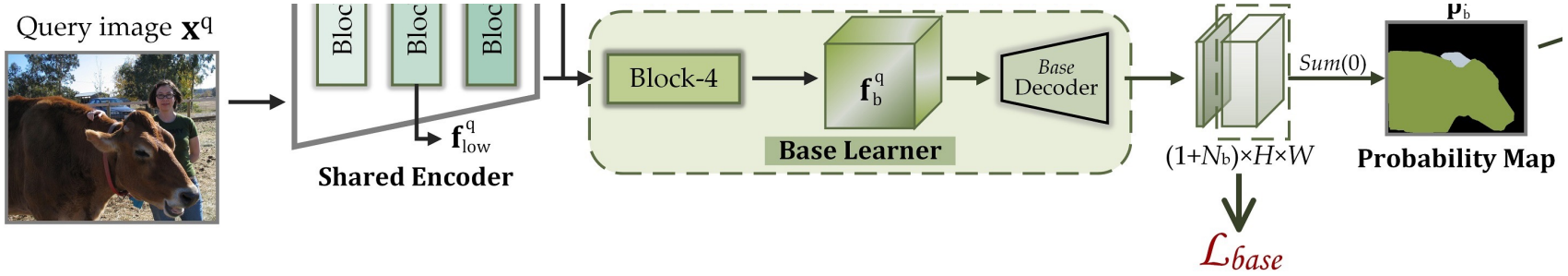
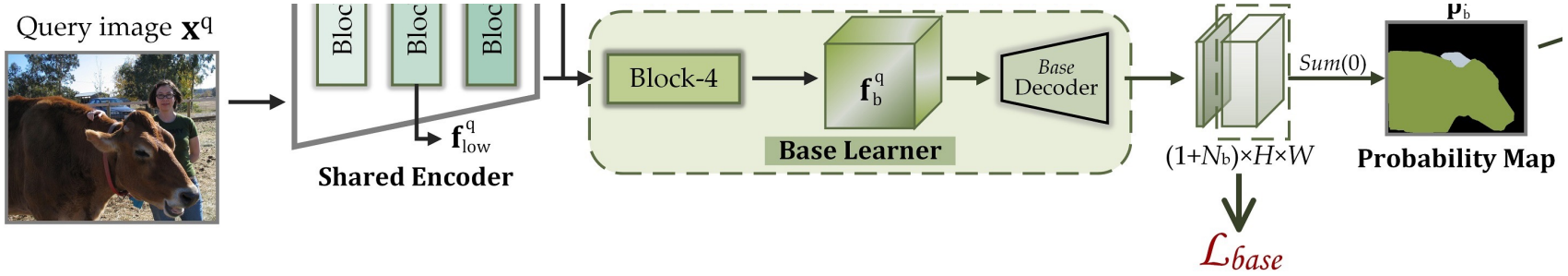
Methods – Base Learner



- Current FSS models are biased towards the seen classes, which impedes the recognition of novel concepts

- Add an additional branch, the base learner, to explicitly predict the regions of base classes in the query images

Methods – Base Learner

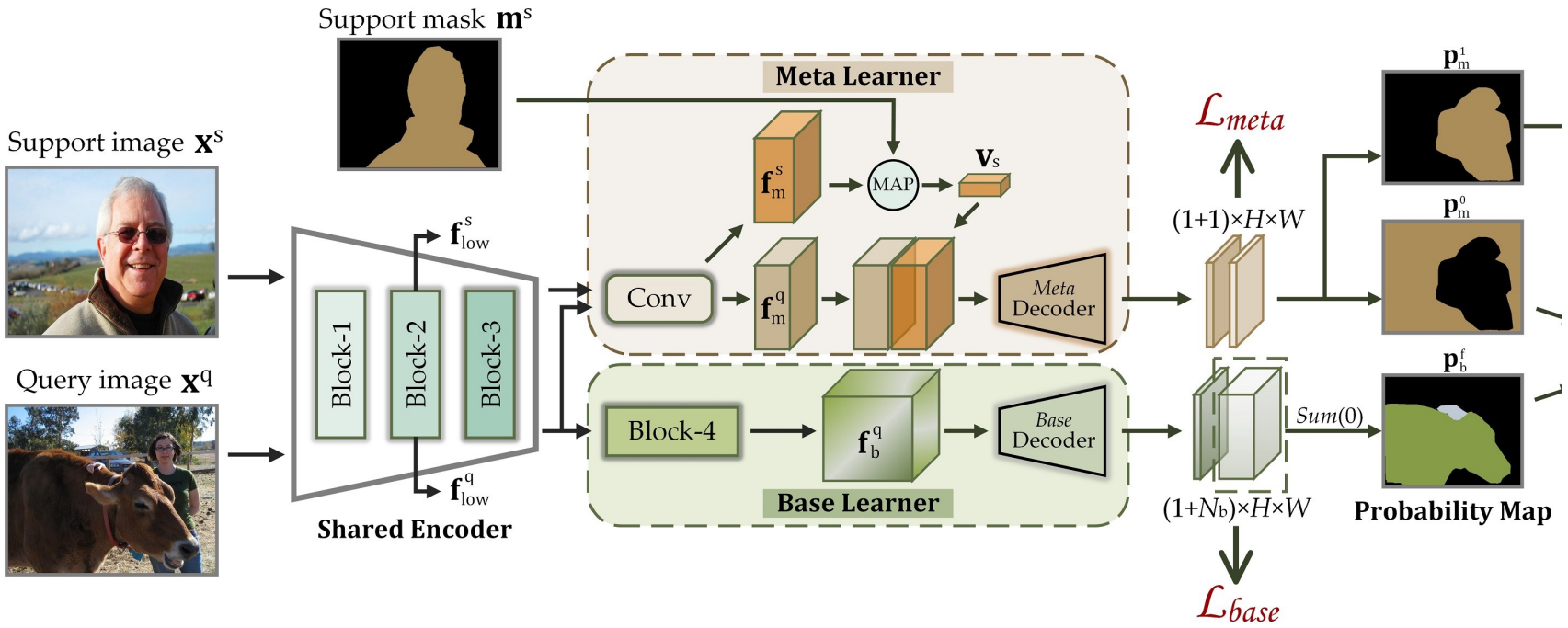


$$\mathbf{f}_{\mathrm{b}}^{\mathrm{q}} = \mathcal{F}_{\mathrm{conv}}\left(\mathcal{E}\left(\mathbf{x}^{\mathrm{q}}\right)\right) \in \mathbb{R}^{c\times h\times w}$$

$$\mathbf{p}_{\mathrm{b}} = \mathrm{softmax}\left(\mathcal{D}_{\mathrm{b}}\left(\mathbf{f}_{\mathrm{b}}^{\mathrm{q}}\right)\right) \in \mathbb{R}^{(1+N_{\mathrm{b}})\times H\times W}$$

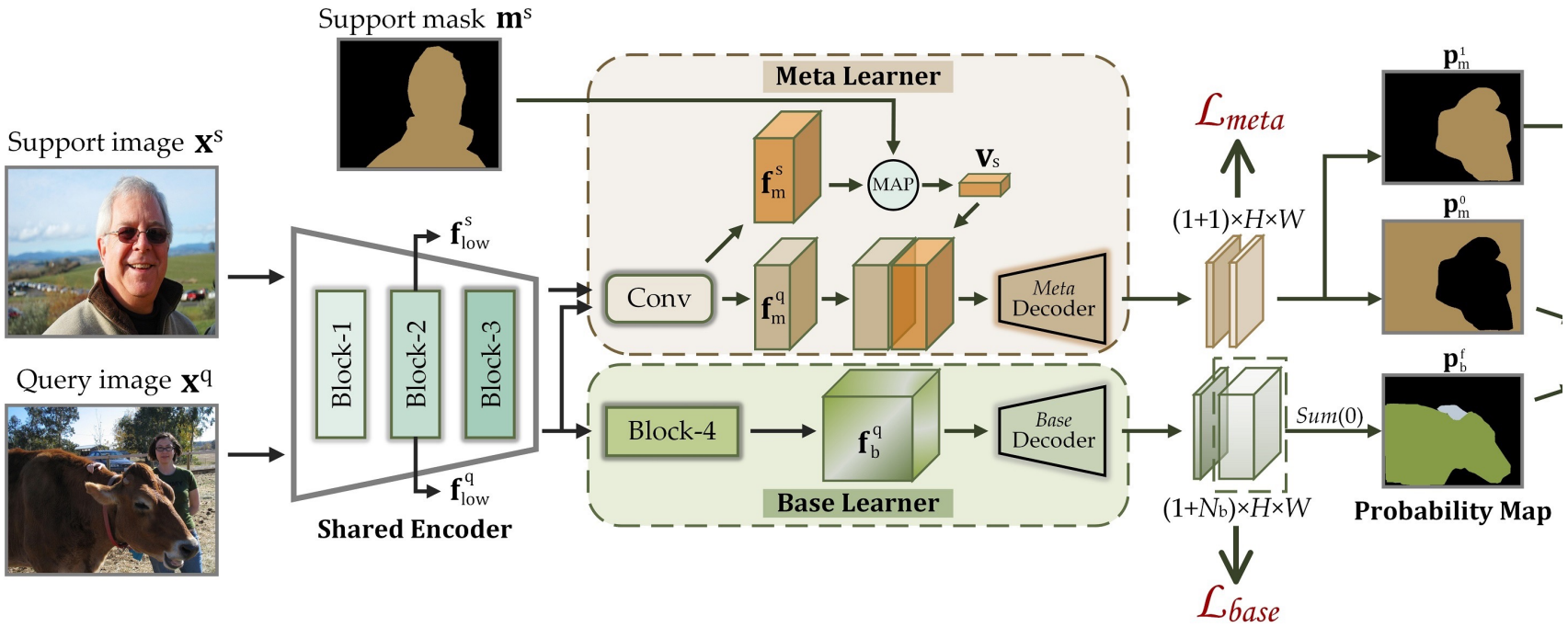
$$\mathcal{L}_{\mathrm{base}} = \frac{1}{n_{\mathrm{bs}}}\sum_{i=1}^{n_{\mathrm{bs}}} \mathrm{CE}\left(\mathbf{p}_{\mathrm{b};i}, \mathbf{m}_{\mathrm{b};i}^{\mathrm{q}}\right)$$

Methods – Meta Learner



- Given a support set $S = \{x^s, m^s\}$ and a query image x^q, the goal of the meta learner is to segment the objects in x^q that share the same category as the annotation mask m^s under the guidance of S.

Methods – Meta Learner



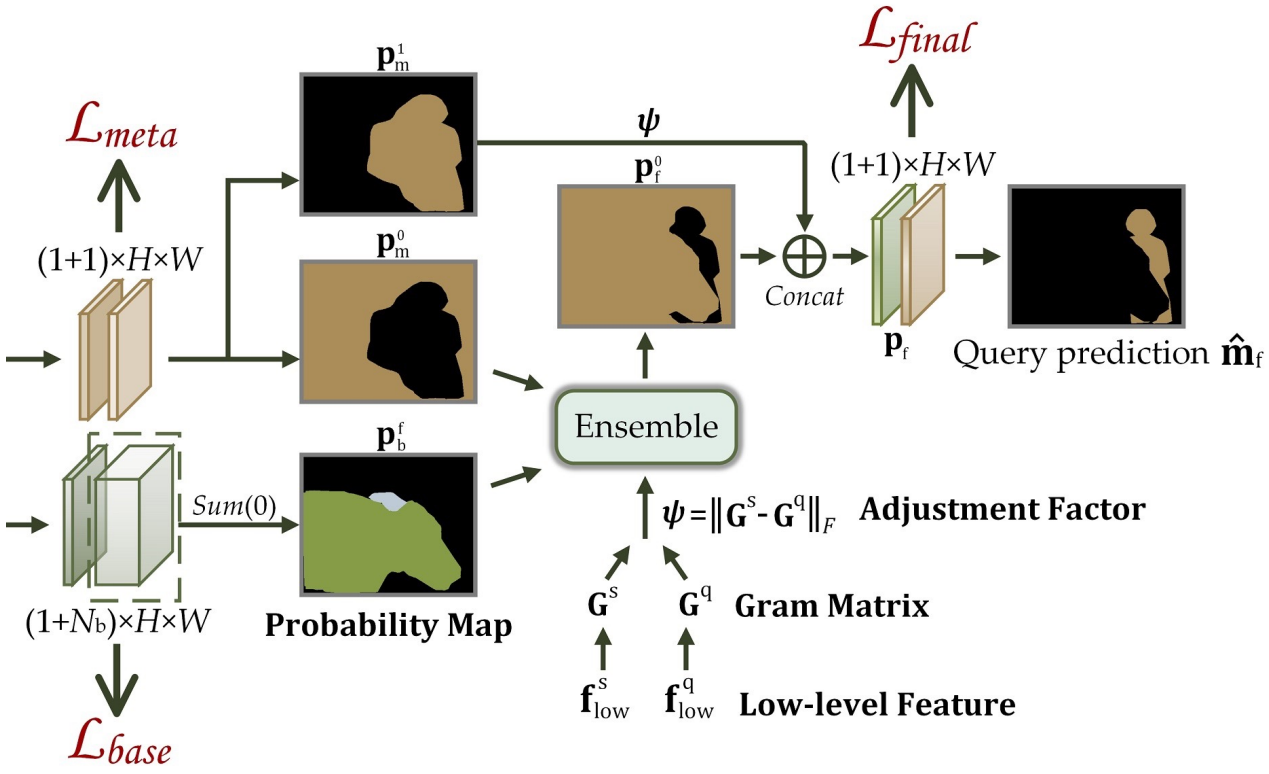
$$\mathbf{f}_{\mathrm{m}}^{\mathrm{s}} = \mathcal{F}_{1\times1}\left(\mathcal{E}\left(\mathbf{x}^{\mathrm{s}}\right)\right) \in \mathbb{R}^{c\times h\times w}$$

$$\mathbf{f}_{\mathrm{m}}^{\mathrm{q}} = \mathcal{F}_{1\times1}\left(\mathcal{E}\left(\mathbf{x}^{\mathrm{q}}\right)\right) \in \mathbb{R}^{c\times h\times w}$$

$$\mathbf{v}_{\mathrm{s}} = \mathcal{F}_{\mathrm{pool}}\left(\mathbf{f}_{\mathrm{m}}^{\mathrm{s}} \odot \mathcal{I}\left(\mathbf{m}^{\mathrm{s}}\right)\right) \in \mathbb{R}^{c}$$

$$\mathbf{p}_{\mathrm{m}} = \mathrm{softmax}\left(\mathcal{D}_{\mathrm{m}}\left(\mathcal{F}_{\mathrm{guidance}}\left(\mathbf{v}_{\mathrm{s}}, \mathbf{f}_{\mathrm{m}}^{\mathrm{q}}\right)\right)\right) \in \mathbb{R}^{2\times H\times W}$$

Methods – Ensemble

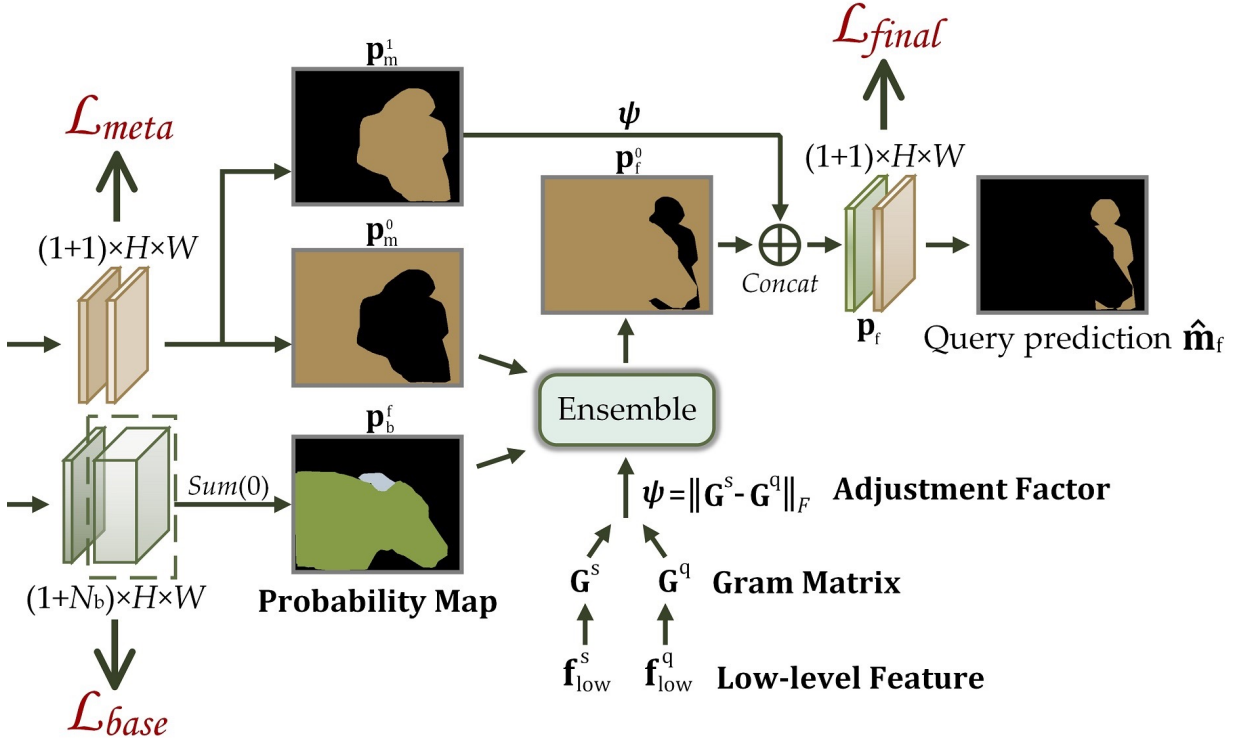


- Meta learners are typically sensitive to the quality of support images, we further propose to leverage the differences between query-support image pairs to **adjust the coarse predictions derived from meta learners**.

- **Integrate the probability maps generated by the base learner** to obtain the prediction of the background region relative to the few-shot task

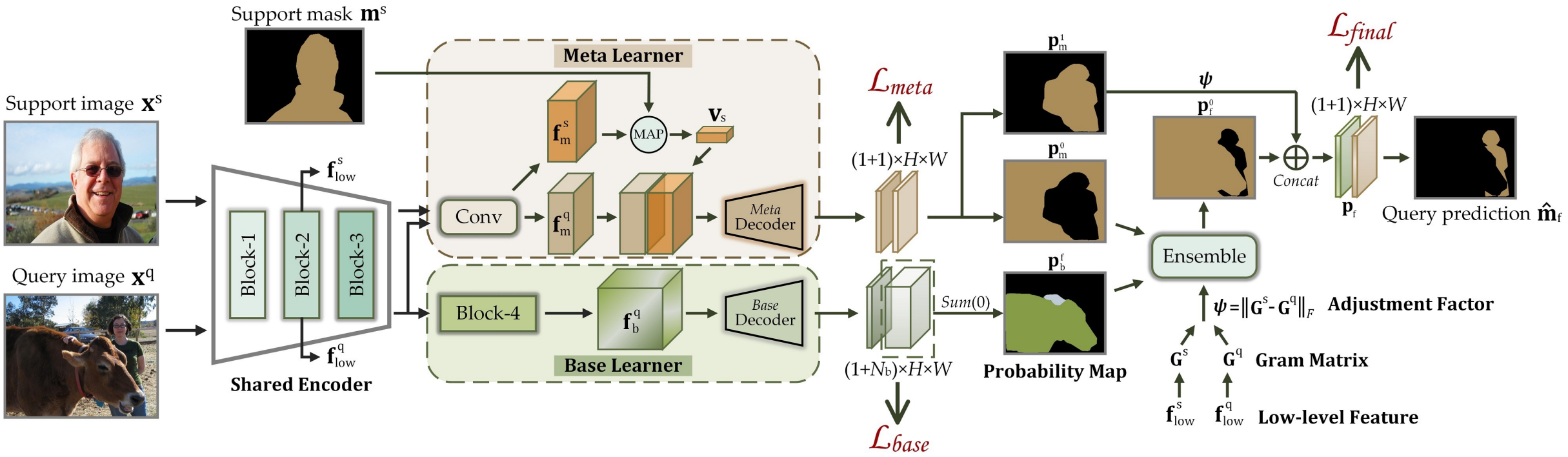
Methods – Ensemble

$$\mathbf{p}_{\mathrm{b}}^{\mathrm{f}} = \sum_{i=1}^{N_{\mathrm{b}}} \mathbf{p}_{\mathrm{b}}^{i}$$



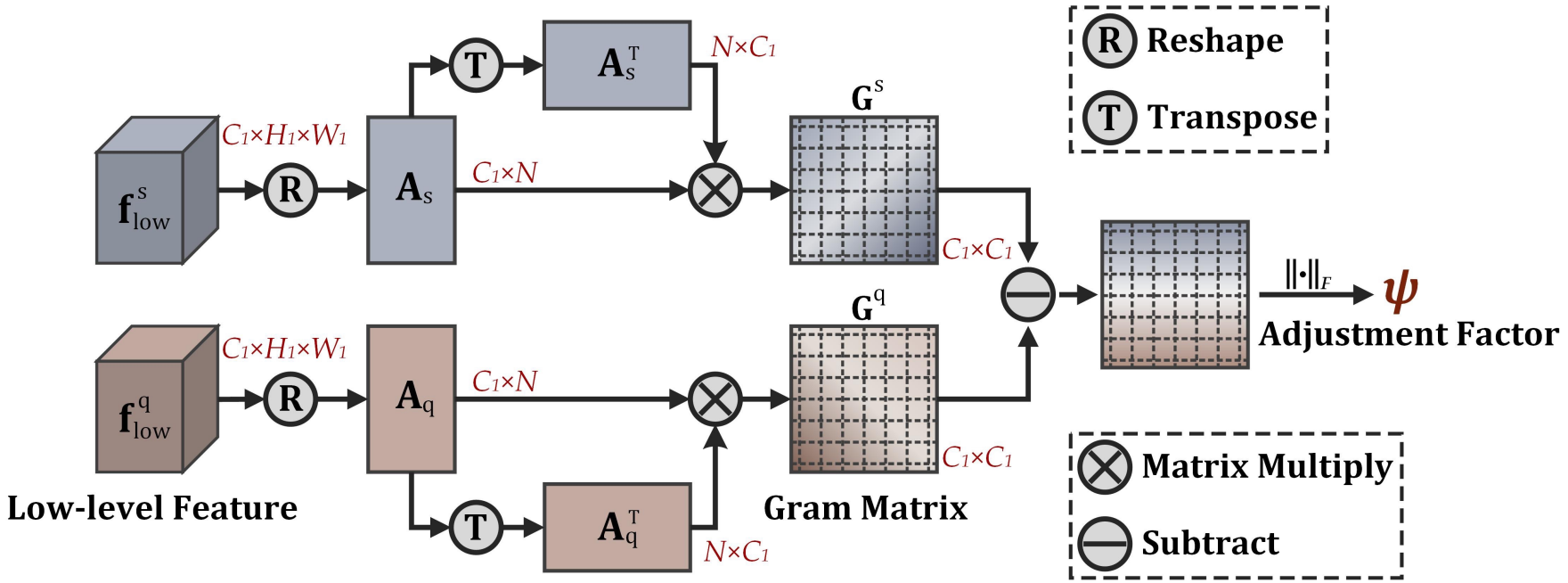
- the superscript of f stands for the foreground, and the subscript b stands for the base learner
- N_b represents the number of base categories

Methods – Ensemble



- we leverage the low-level features $f^s_{low}, f^q_{low} \in \mathbb{R}^{c_1 * H_1 * W_1}$ extracted from the fixed backbone network

Methods – Ensemble



$$\mathbf{A}_{\mathrm{s}} = \mathcal{F}_{\mathrm{reshape}}\left(\mathbf{f}^{\mathrm{s}}_{\mathrm{low}}\right) \in \mathbb{R}^{C_1 \times N},$$

$$\mathbf{G}^{\mathrm{s}} = \mathbf{A}_{\mathrm{s}}\mathbf{A}_{\mathrm{s}}^{\mathsf{T}} \in \mathbb{R}^{C_1 \times C_1},$$

$$\psi = \left\|\mathbf{G}^{\mathrm{s}} - \mathbf{G}^{\mathrm{q}}\right\|_F$$

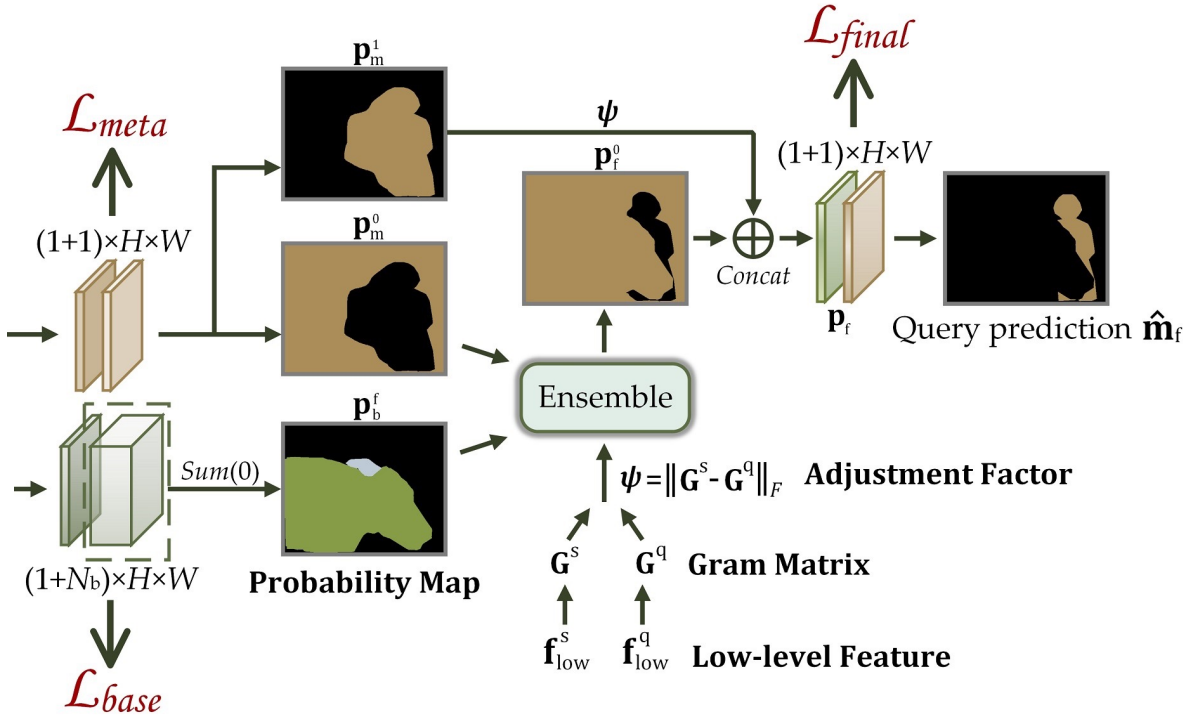
Methods – Ensemble

$$\mathbf{p}_{\mathrm{f}}^{0}=\mathcal{F}_{\mathrm{ensemble}}\left(\mathcal{F}_{\psi}\left(\mathbf{p}_{\mathrm{m}}^{0}\right),\mathbf{p}_{\mathrm{b}}^{\mathrm{f}}\right),$$

$$\mathbf{p}_{\mathrm{f}}=\mathbf{p}_{\mathrm{f}}^{0}\oplus\mathcal{F}_{\psi}\left(\mathbf{p}_{\mathrm{m}}^{1}\right),$$

$$\mathcal{L}=\mathcal{L}_{\mathrm{final}}+\lambda\mathcal{L}_{\mathrm{meta}},$$

$$\mathcal{L}_{\mathrm{final}}=\frac{1}{n_{\mathrm{e}}}\sum_{i=1}^{n_{\mathrm{e}}}\mathrm{BCE}\left(\mathbf{p}_{i}^{\mathrm{q}},\mathbf{m}_{i}^{\mathrm{q}}\right),$$



Methods – K-Shot setting

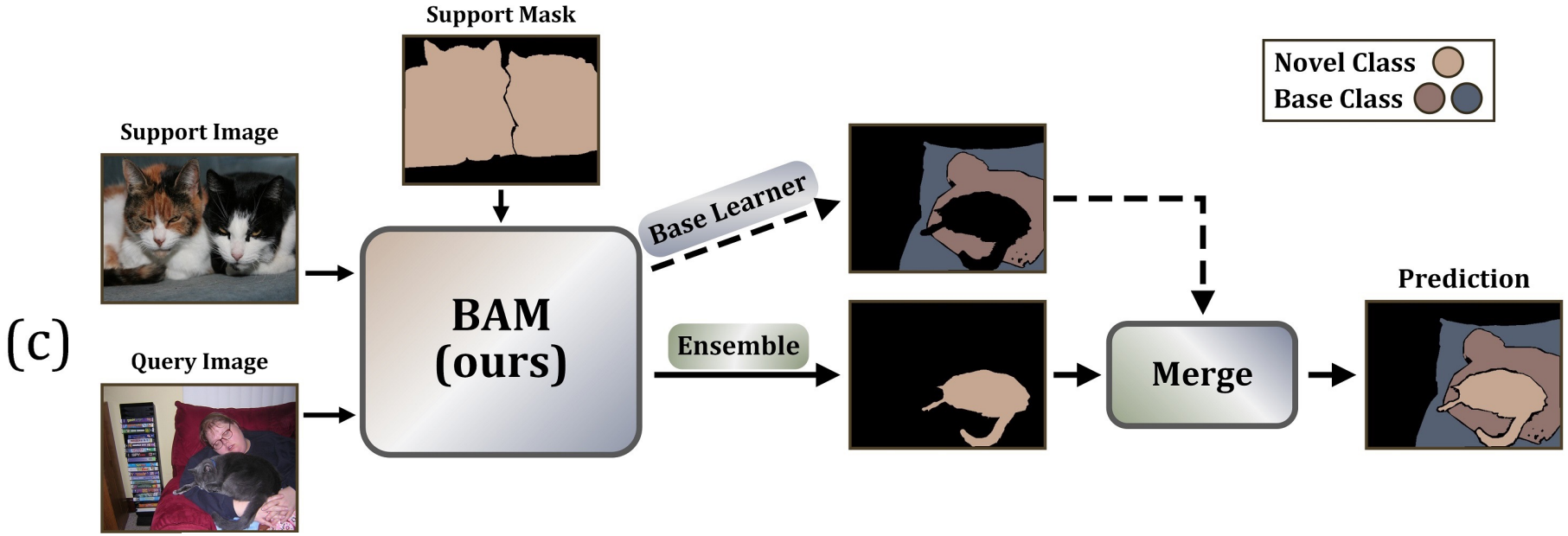
- the task is extended to the K-shot (K>1) setting, more than one annotated (support) images

- Two **FC layers** are applied to adaptively estimate the weight of each support image based on the adjustment factor ψ

$$\psi_{\mathrm{t}} \in \mathbb{R}^{K}$$

$$\eta = \mathrm{soft\,max}\left(\mathbf{w}_2^{\mathsf{T}}\mathrm{ReLU}\left(\mathbf{w}_1^{\mathsf{T}}\psi_{\mathrm{t}}\right)\right) \in \mathbb{R}^{K}$$

Methods – Extension to Generalized FSS



$$\hat{\mathbf{m}}_{\mathrm{g}}^{(x,y)} = \begin{cases} 1 & \mathbf{p}_{\mathrm{f}}^{1;(x,y)} > \tau \\ \hat{\mathbf{m}}_{\mathrm{b}}^{(x,y)} & \mathbf{p}_{\mathrm{f}}^{1;(x,y)} \leq \tau \text{ and } \hat{\mathbf{m}}_{\mathrm{b}}^{(x,y)} \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\hat{\mathbf{m}}_{\mathrm{b}} = \arg\max\left(\mathbf{p}_{\mathrm{b}}\right) \in \{0, 1, \ldots, N_{\mathrm{b}}\}^{H \times W}$$

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Experiments – Setup

- Evaluate the performance on two FSS datasets, namely **PASCAL-5i** and **COCO-20i**
- Divided into **four folds**, and the experiments are conducted in a cross validation manner. For each fold, we randomly sample **1,000 pairs** of support and query images for validation.
- Divided into two stages, **pretraining** and **meta-training**
- Standard **supervised learning** to train **the base learner**
- Jointly train **the meta learner** and **ensemble** module in an **episodic learning fashion**, and the parameters of the base learner are fixed in this stage.
- Two learners share the **same encoder** to extract the features of input images, which is also **not optimized** to facilitate generalization.

Experiments – Result

COCO-20i

Backbone	Method	1-shot					5-shot				
		Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	Mean
VGG16	FWB [38]	18.35	16.72	19.59	25.43	20.02	20.94	19.24	21.94	28.39	22.63
	PFENet [51]	35.40	38.10	36.80	34.70	36.30	38.20	42.50	41.80	38.90	40.40
	PRNet [32]	27.46	32.99	26.70	28.98	29.03	31.18	36.54	31.54	32.00	32.82
	Baseline	38.42	43.75	44.32	39.84	41.58	45.93	48.88	47.87	46.96	47.41
	BAM (ours)	**38.96**	**47.04**	**46.41**	**41.57**	**43.50**	**47.02**	**52.62**	**48.59**	**49.11**	**49.34**
ResNet50	HFA [31]	28.65	36.02	30.16	33.28	32.03	32.69	42.12	30.35	36.19	35.34
	ASGNet [23]	-	-	-	-	34.56	-	-	-	-	42.48
	HSNet [37]	36.30	43.10	38.70	38.70	39.20	43.30	51.30	48.20	45.00	46.90
	Baseline	41.92	45.35	43.86	41.24	43.09	46.98	51.87	49.49	47.81	49.04
	BAM (ours)	**43.41**	**50.59**	**47.49**	**43.42**	**46.23**	**49.26**	**54.20**	**51.63**	**49.55**	**51.16**

PASCAL-5i

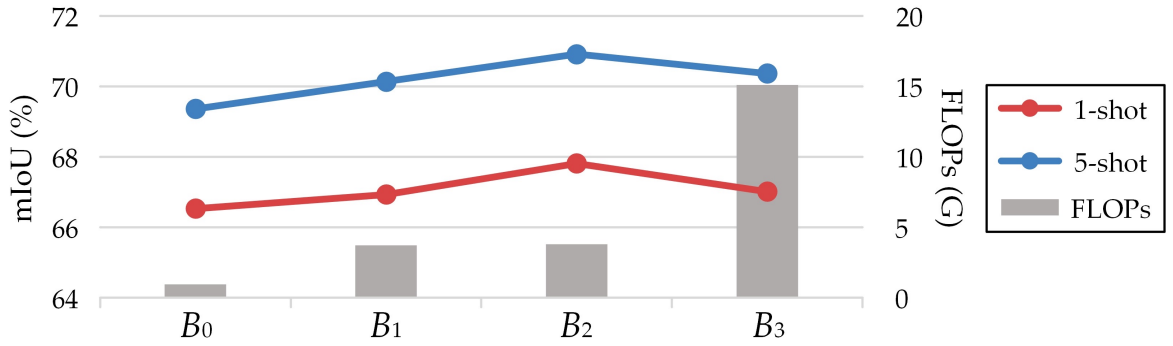
Backbone	Method	1-shot					5-shot				
		Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	Mean
VGG16	SG-One (TCYB'19) [67]	40.20	58.40	48.40	38.40	46.30	41.90	58.60	48.60	39.40	47.10
	PANet (ICCV'19) [56]	42.30	58.00	51.10	41.20	48.10	51.80	64.60	59.80	46.50	55.70
	FWB (ICCV'19) [56]	47.00	59.60	52.60	48.30	51.90	50.90	62.90	56.50	50.10	55.10
	CRNet (CVPR'20) [33]	-	-	-	-	55.20	-	-	-	-	58.50
	PFENet (TPAMI'20) [51]	56.90	68.20	54.40	52.40	58.00	59.00	69.10	54.80	52.90	59.00
	HSNet (ICCV'21) [37]	59.60	65.70	59.60	54.00	59.70	64.90	69.00	64.10	58.60	64.10
	Baseline	59.90	67.51	64.93	55.72	62.02	64.02	71.51	69.39	63.55	67.12
	BAM (ours)	**63.18**	**70.77**	**66.14**	**57.53**	**64.41**	**67.36**	**73.05**	**70.61**	**64.00**	**68.76**
ResNet50	CANet (ICCV'19) [66]	52.50	65.90	51.30	51.90	55.40	55.50	67.80	51.90	53.20	57.10
	PGNet (ICCV'19) [65]	56.00	66.90	50.60	50.40	56.00	57.70	68.70	52.90	54.60	58.50
	CRNet (CVPR'20) [33]	-	-	-	-	55.70	-	-	-	-	58.80
	PPNet (ECCV'20) [34]	48.58	60.58	55.71	46.47	52.84	58.85	68.28	66.77	57.98	62.97
	PFENet (TPAMI'20) [51]	61.70	69.50	55.40	56.30	60.80	63.10	70.70	55.80	57.90	61.90
	HSNet (ICCV'21) [37]	64.30	70.70	60.30	60.50	64.00	70.30	73.20	67.40	67.10	69.50
	Baseline	65.68	71.41	65.56	58.93	65.40	67.28	72.38	69.16	66.25	68.77
	BAM (ours)	**68.97**	**73.59**	**67.55**	**61.13**	**67.81**	**70.59**	**75.05**	**70.79**	**67.20**	**70.91**

Experiments – Comparison

Experiments – Ablation Study

- Two learners could be **trained jointly or separately**. In our experiments, the latter scheme exhibits better performance. Since base learner tends to **fix the parameters to enhance generalization**, while meta-learner tends to **update the parameters to extract more discriminative features**

- low-level features f_{low} to estimate ψ with ResNet50 backbone. B_i denotes the feature maps extracted from the i-th convolutional blocks. **B_2 features shows a better trade-off** between segmentation accuracy and computational complexity.



Outline

- Introduction
- Related Work
- Framework
- Method
- Experiment
- Conclusion

Conclusion

- Proposed a novel scheme **to alleviate the bias problem** of FSS models towards the seen concepts.

- The core idea of our scheme is to leverage the **base learner to identify the confusable (base) regions** in the query images and further refine the prediction of the meta learner.

- Moreover, extended the current task to a **more challenging generalized** setting and produced strong baseline results.