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Few Shot Segmentation

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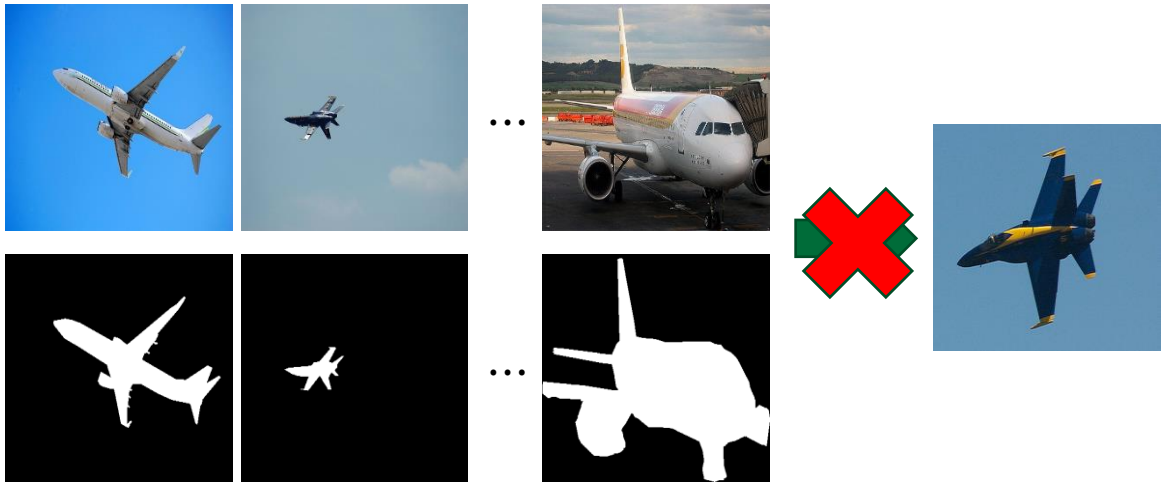
Motivation

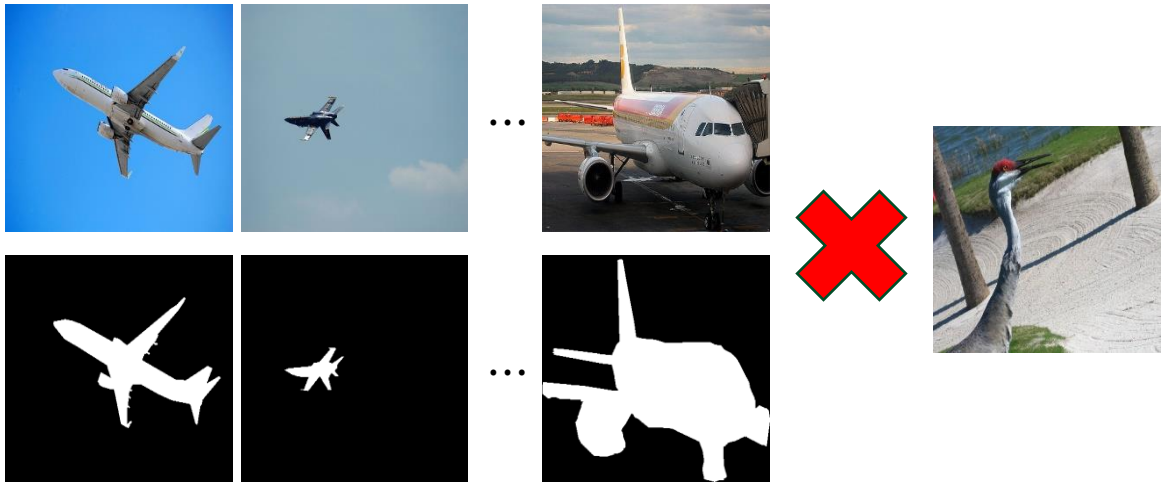
Defects of Deep-learning-based Segmentation

- Eager for large amount of samples of target
- Cannot segment unseen objects



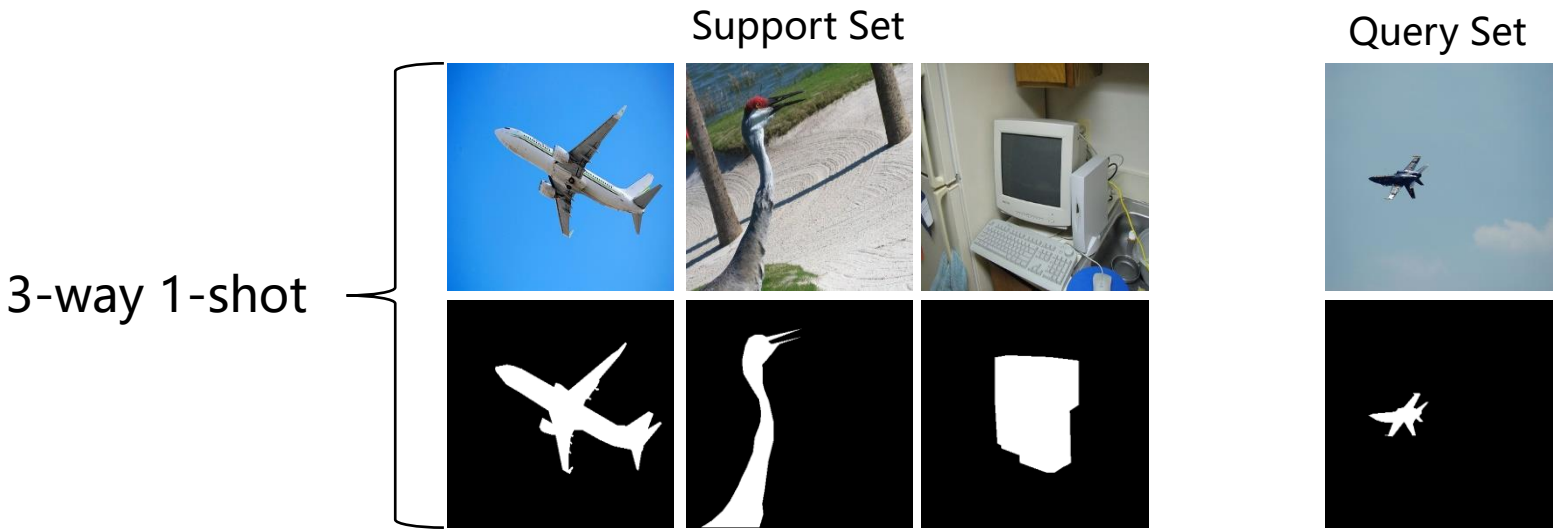
The aims of Few-shot Segmentation

- Segment unseen object with only a few references after training

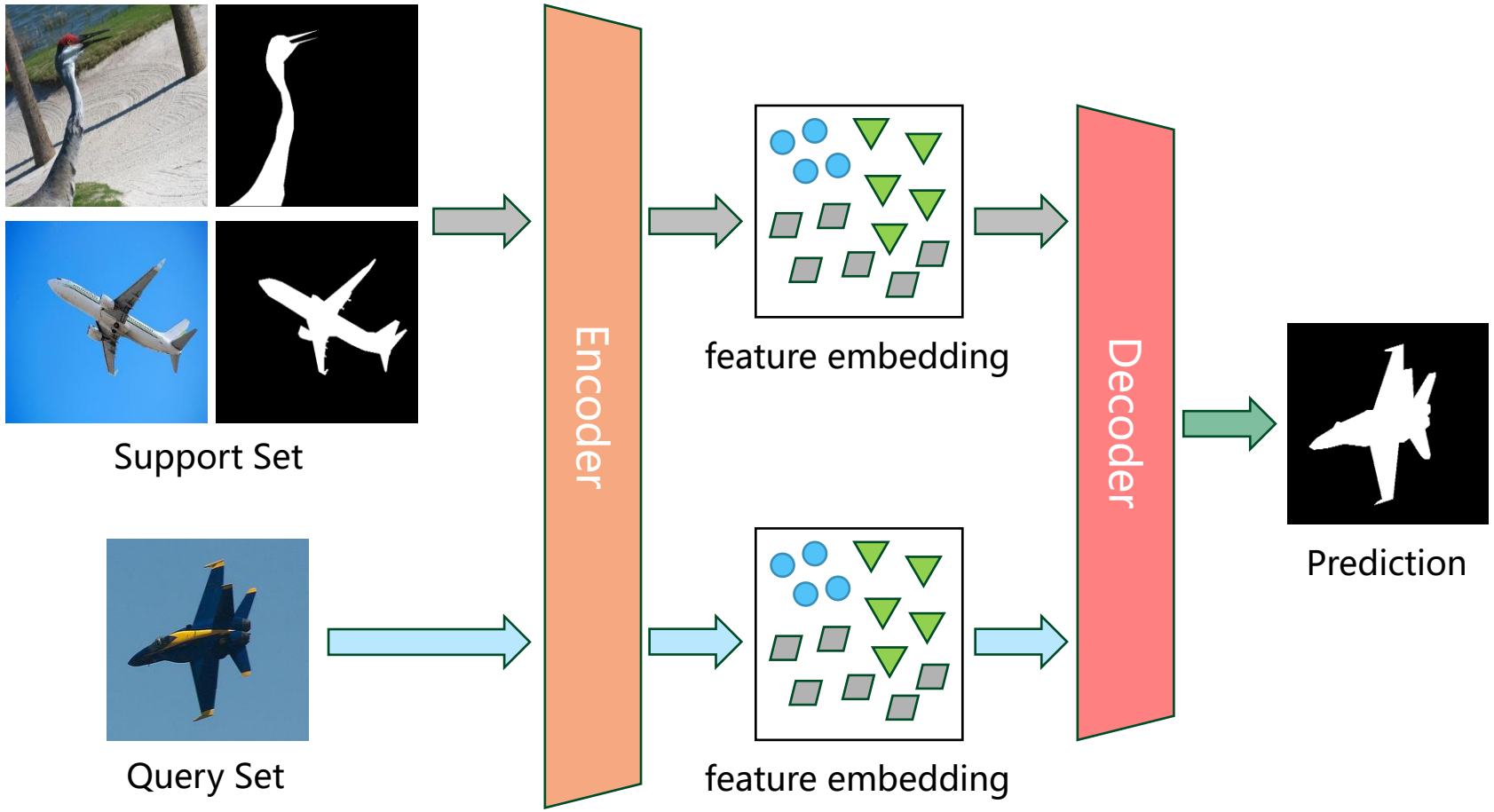


Implementation

- Divide classes C of dataset into seen C_{seen} and unseen C_{unseen}, $C_{seen} \cap C_{unseen} = \emptyset$
- $D_{train} = \{(S_i, Q_i)\}_{i=1}^{N_{train}}$, $D_{test} = \{(S_i, Q_i)\}_{i=1}^{N_{test}}$
- $S_i = \{(I_{c,k}, M_{c,k}) \mid c \in c_{seen}$ for training $else\ c \in c_{unseen}\}$, $Q_i = \{(I_{c,n}, M_{c,n})\}$
- (S_i, Q_i) called episode is the input to the model during training/testing stage



Implementation



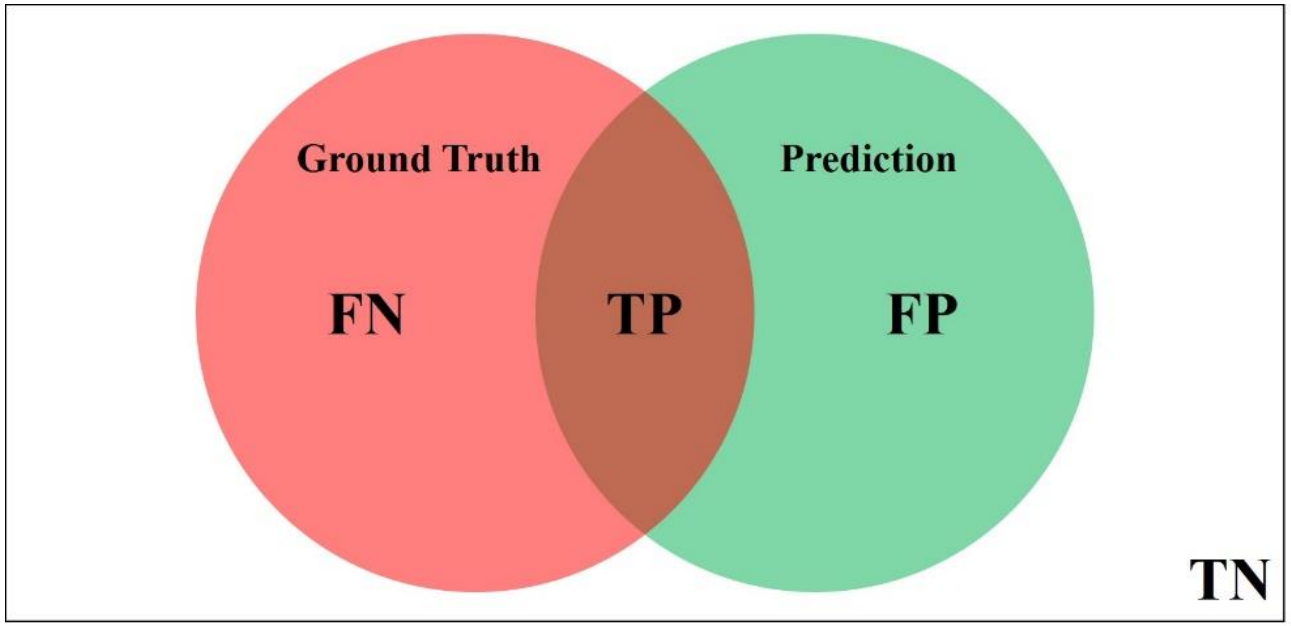
Dataset & Metric

Dataset:

- Pascal VOC 2012
- MS COCO

Metric:

- Mean Intersection over Union (mIoU)
- $mIoU = \frac{TP}{FP+FN+TP}$



Paper list

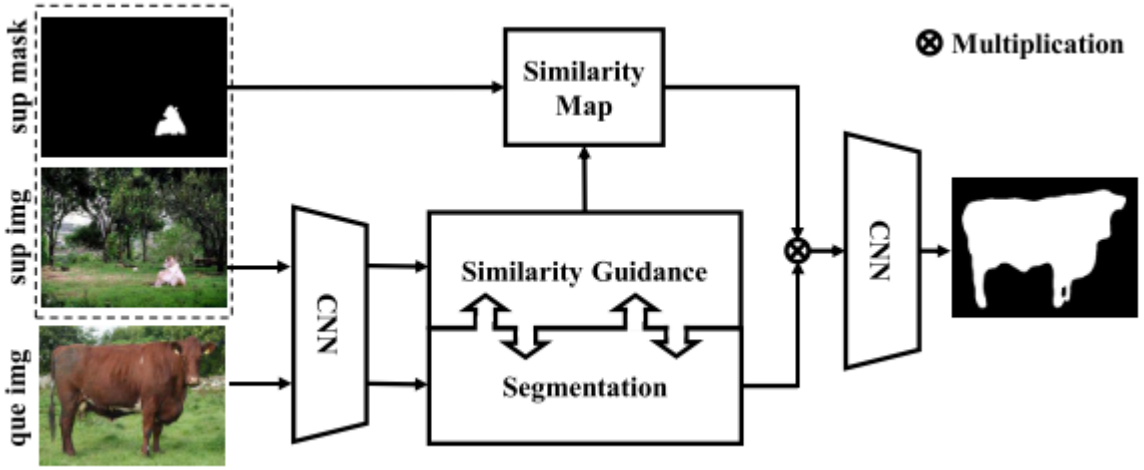
- SG-One: Similarity Guidance Network for One-Shot Semantic Segmentation (2018)
- PANet: Few-Shot Image Semantic Segmentation with Prototype Alignment (2019)
- Prior Guided Feature Enrichment Network for Few-Shot Segmentation (2020)
- Adaptive Prototype Learning and Allocation for Few-Shot Segmentation (2021)
- Edge-Labeling Graph Neural Network for Few-shot Learning (2019)

SG-One: Similarity Guidance Network for One-Shot Semantic Segmentation

SG-One

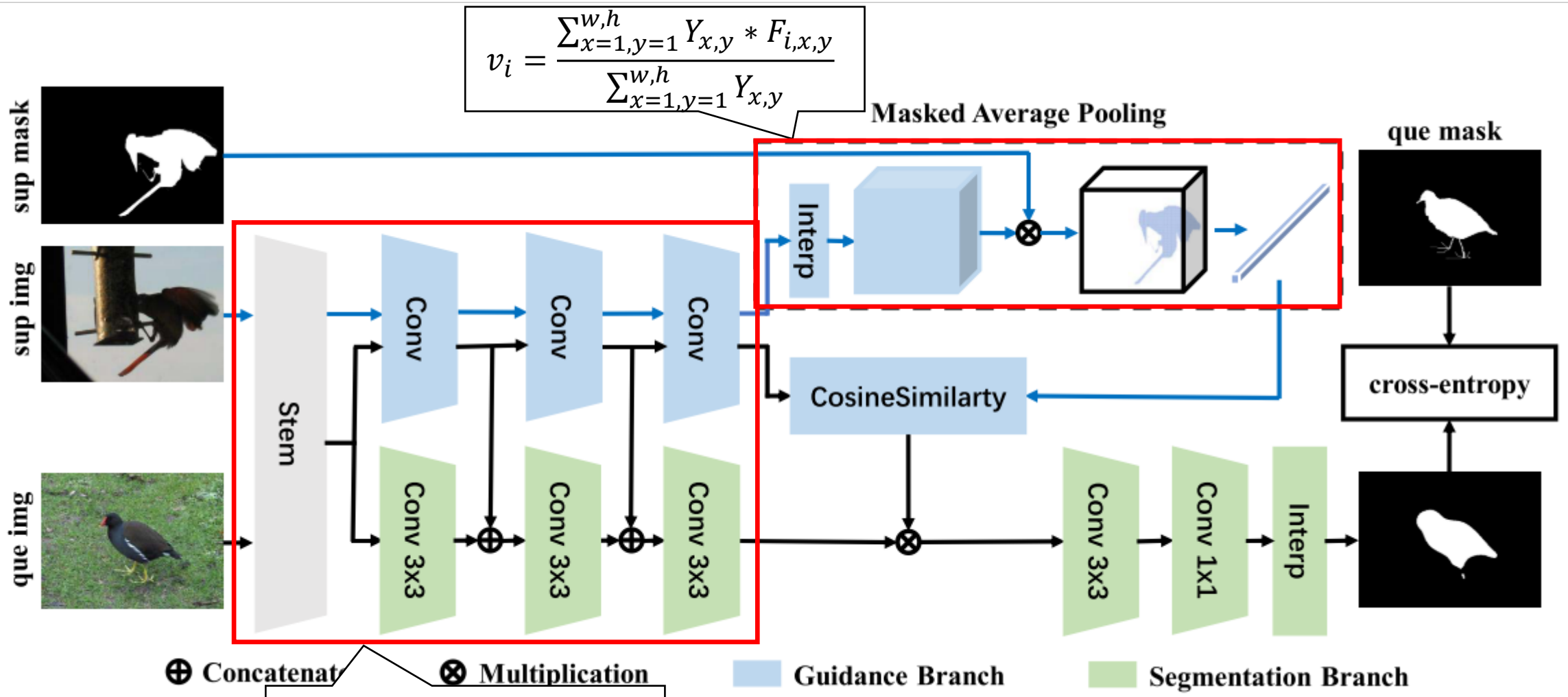
Key points:

- Masked Average Pooling strategy
- Build relationship between support and query with cosine similarity
- Unified network structure



SG-One

$$v_i = \frac{\sum_{x=1,y=1}^{w,h} Y_{x,y} * F_{i,x,y}}{\sum_{x=1,y=1}^{w,h} Y_{x,y}}$$



SG-One

K-shot Testing:

- Ensemble the K segmentation mask with equation:

$$\hat{Y}_{x,y} = max(\hat{Y}^1_{x,y}, \hat{Y}^2_{x,y}, \cdots, \hat{Y}^K_{x,y})$$

- Average the K representative vectors

MEAN IOU RESULTS OF ONE-SHOT SEGMENTATION ON THE PASCAL-5^i DATASET. THE BEST RESULTS ARE IN BOLD

Methods[1]	PASCAL-5^0	PASCAL-5^1	PASCAL-5^2	PASCAL-5^3	Mean
1-NN	25.3	44.9	**41.7**	18.4	32.6
LogReg	26.9	42.9	37.1	18.4	31.4
Siamese	28.1	39.9	31.8	25.8	31.4
OSVOS [37]	24.9	38.8	36.5	30.1	32.6
OSLSM [15]	33.6	55.3	40.9	33.5	40.8
co-FCN [16]	36.7	50.6	44.9	32.4	41.1
SG-One(Ours)	**40.2**	**58.4**	**48.4**	**38.4**	**46.3**

PANet: Few-Shot Image Semantic Segmentation with Prototype Alignment

PANet

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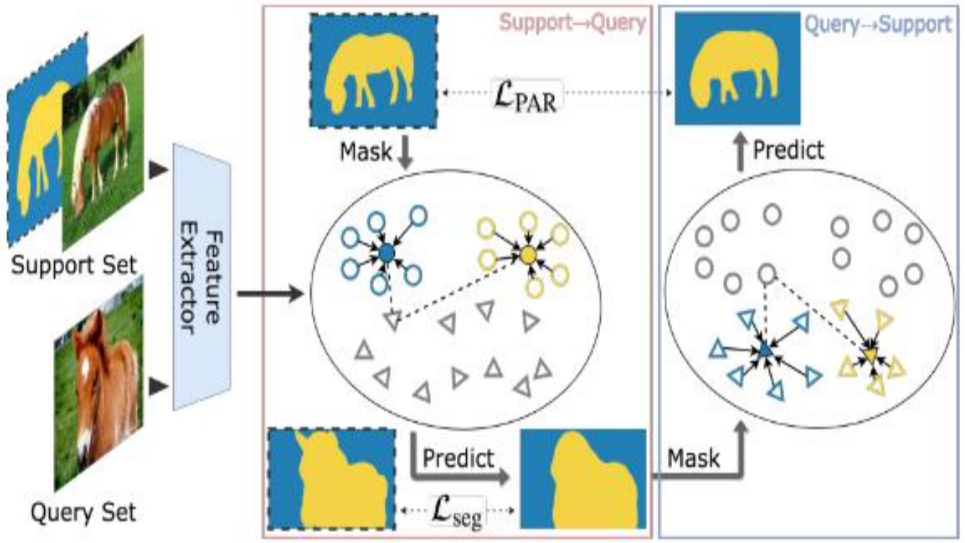
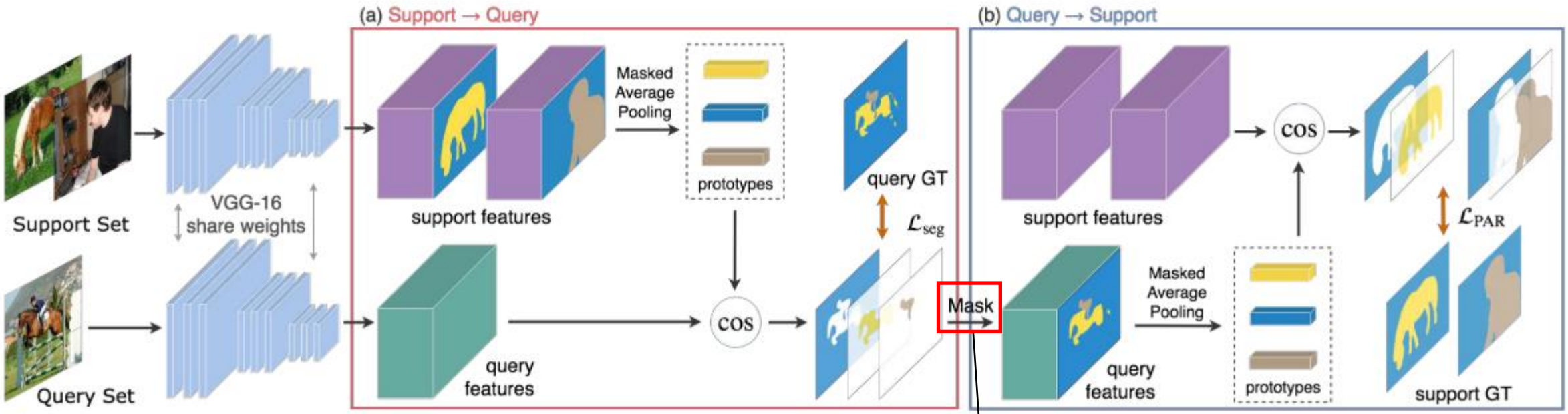
Key points:

- Propose a non-parametric metric learning to extract knowledge and perform segmentation
- Design a Prototype Alignment structure to fully exploit knowledge from the support



PANet


(a) Support → Query
(b) Query → Support
Support Set
Query Set
VGG-16
share weights
support features
Masked
Average
Pooling
prototypes
query GT
$\mathcal{L}_{seg}$
query
features
COS
Mask
support features
COS
$\mathcal{L}_{PAR}$
Masked
Average
Pooling
query
features
prototypes
support GT
$\widehat{M}_q^{(x,y)} = \underset{j}{\operatorname{argmin}} \widetilde{M}_{q;j}^{(x,y)}$

PANet

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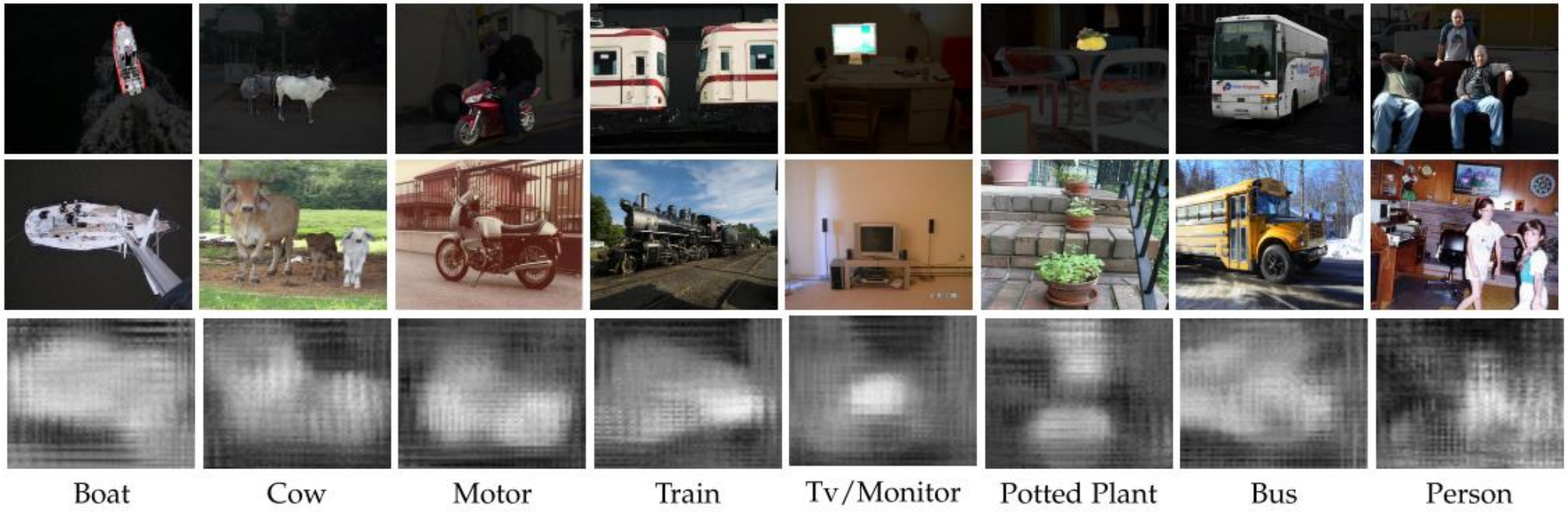
Method	1-shot					5-shot					Δ	#Params
	split-1	split-2	split-3	split-4	Mean	split-1	split-2	split-3	split-4	Mean	Mean	
OSLSM [21]	33.6	55.3	40.9	33.5	40.8	35.9	58.1	42.7	39.1	43.9	3.1	272.6M
co-FCN [16]†	36.7	50.6	44.9	32.4	41.1	37.5	50.0	44.1	33.9	41.4	0.3	34.2M
SG-One [28]	40.2	**58.4**	48.4	38.4	46.3	41.9	58.6	48.6	39.4	47.1	0.8	19.0M
PANet-init	30.8	40.7	38.3	31.4	35.3	41.6	52.7	51.6	40.8	46.7	**11.4**	14.7M
PANet	**42.3**	58.0	**51.1**	**41.2**	**48.1**	**51.8**	**64.6**	**59.8**	**46.5**	**55.7**	7.6	**14.7M**

Prior Guided Feature Enrichment Network for Few-Shot Segmentation

PFENet

PFENet mainly wants to solve following two problems:

- High-level features using in a few-shot model may cause performance drop
  - Using fixed high-level features to yield the prior mask
- Spatial Inconsistency
  - Proposing a FPN-like Feature Enrichment Module with residual blocks

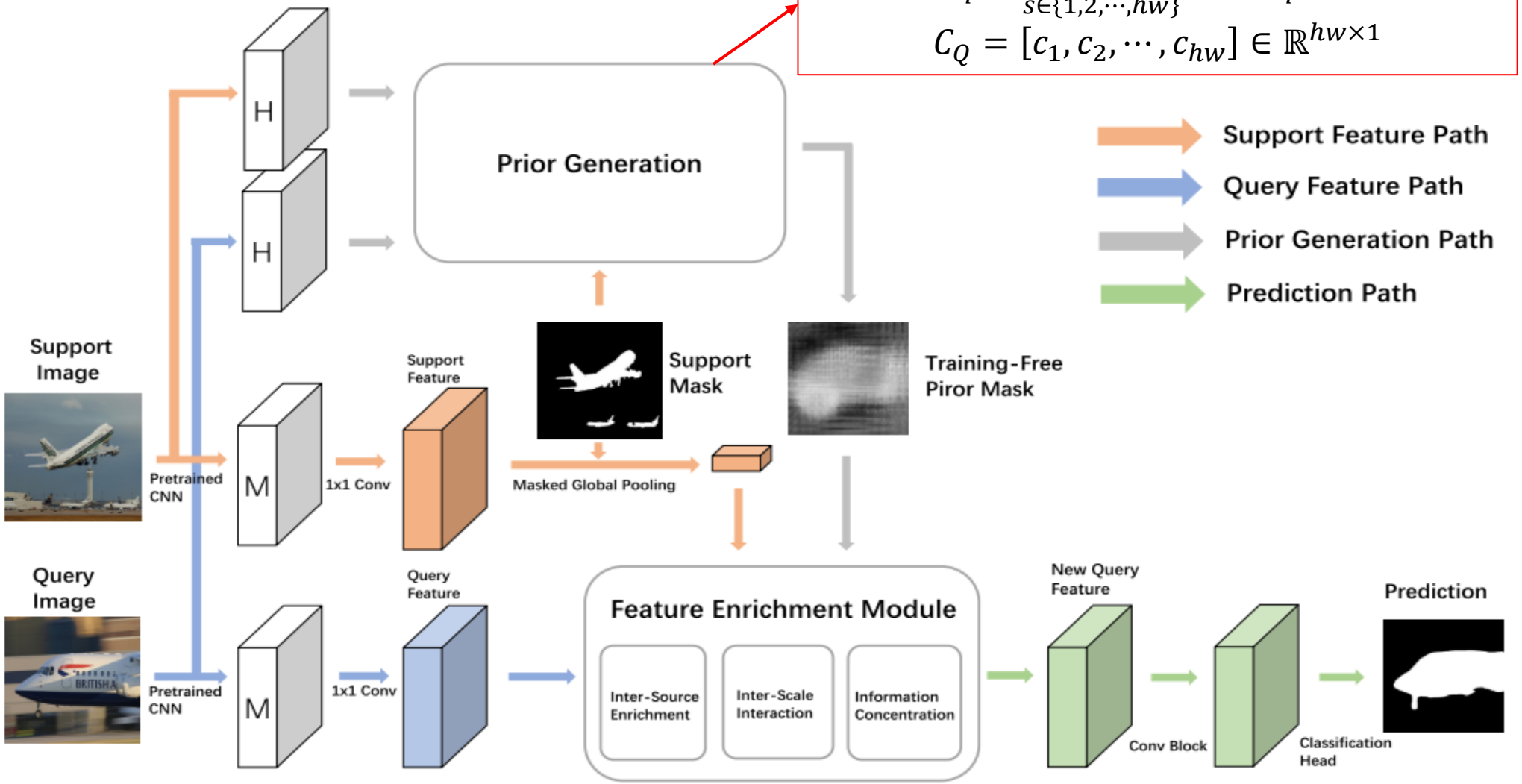


PFENet

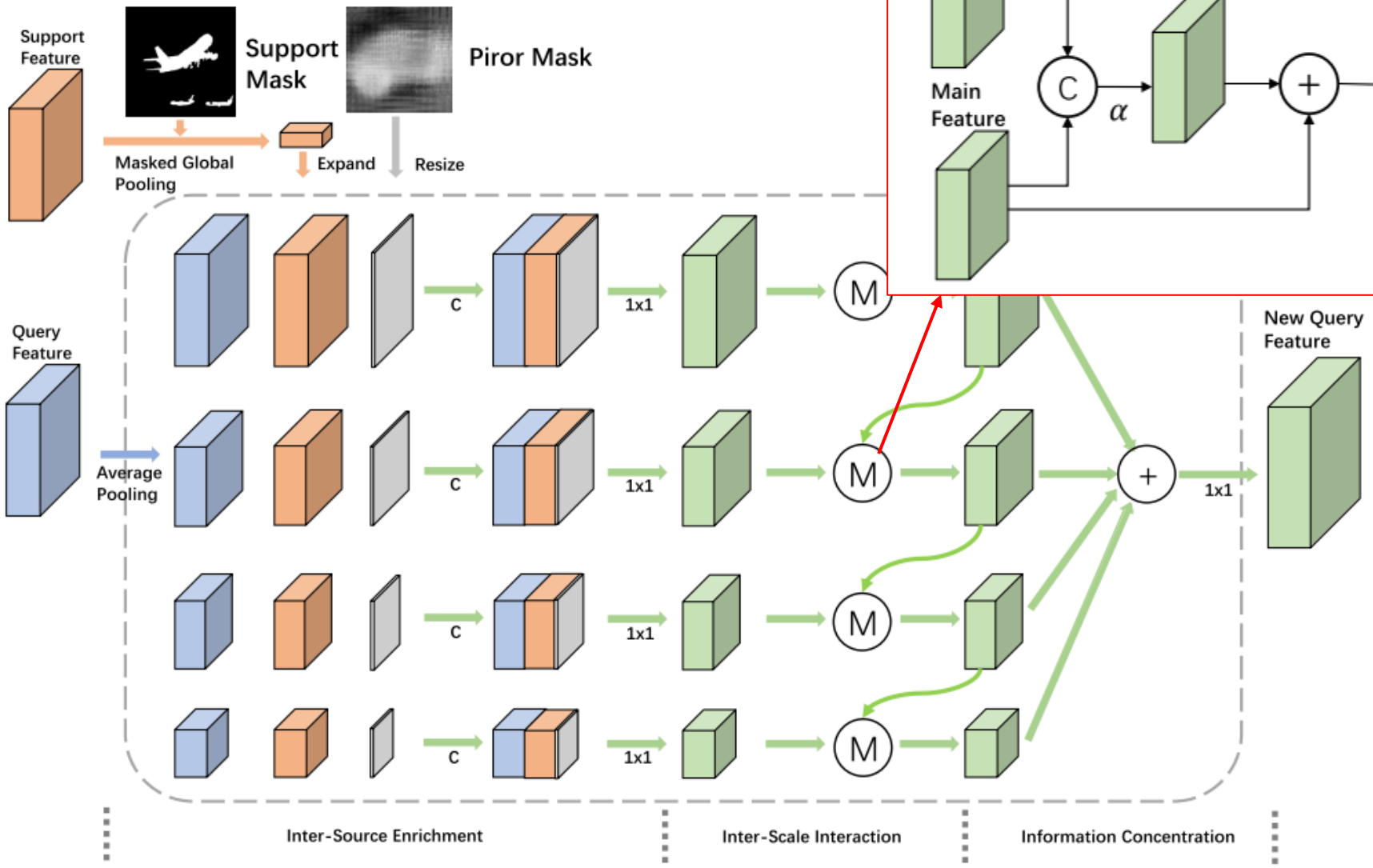
$$\cos(x_q, x_s) = \frac{x_q^T x_s}{\|x_q\|\|x_s\|} \quad q, s \in \{1,2,\cdots,hw\}$$

$$c_q = \max_{s\in\{1,2,\cdots,hw\}}(\cos(x_q, x_s))$$

$$C_Q = [c_1, c_2, \cdots, c_{hw}] \in \mathbb{R}^{hw\times 1}$$



PFENet


Support Feature
Support Mask
Piror Mask
Masked Global Pooling
Expand
Resize
Query Feature
Average Pooling
C
1x1
M
New Query Feature
Inter-Source Enrichment
Inter-Scale Interaction
Information Concentration
Auxiliary Feature
Main Feature
α
β
Refined Feature

PFENet

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Methods	1-Shot					5-Shot					Params
	Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	Mean	
VGG-16 Backbone											
$OSLSM_{2017}$ [33]	33.6	55.3	40.9	33.5	40.8	35.9	58.1	42.7	39.1	44.0	276.7M
$co\text{-}FCN_{2018}$ [29]	36.7	50.6	44.9	32.4	41.1	37.5	50.0	44.1	33.9	41.4	34.2M
$SG\text{-}One_{2018}$ [58]	40.2	58.4	48.4	38.4	46.3	41.9	58.6	48.6	39.4	47.1	19.0M
AMP_{2019} [35]	41.9	50.2	46.7	34.7	43.4	41.8	55.5	50.3	39.9	46.9	34.7M
$PANet_{2019}$ [45]	42.3	58.0	51.1	41.2	48.1	51.8	64.6	**59.8**	46.5	55.7	14.7M
$FWBF_{2019}$ [28]	47.0	59.6	52.6	48.3	51.9	50.9	62.9	56.5	50.1	55.1	-
Ours	**56.9**	**68.2**	**54.4**	**52.4**	**58.0**	**59.0**	**69.1**	54.8	**52.9**	**59.0**	**10.4M**
ResNet-50 Backbone											
$CANet_{2019}$ [54]	52.5	65.9	51.3	51.9	55.4	55.5	67.8	51.9	53.2	57.1	19.0M
$PGNet_{2019}$ [53]	56.0	66.9	50.6	50.4	56.0	54.9	67.4	51.8	53.0	56.8	17.2M
Ours	**61.7**	**69.5**	**55.4**	**56.3**	**60.8**	**63.1**	**70.7**	**55.8**	**57.9**	**61.9**	**10.8M**
ResNet-101 Backbone											
$FWBF_{2019}$ [28]	51.3	64.5	**56.7**	52.2	56.2	54.8	67.4	**62.2**	55.3	59.9	-
Ours	**60.5**	**69.4**	54.4	**55.9**	**60.1**	**62.8**	**70.4**	54.9	**57.6**	**61.4**	**10.8M**

Methods	*Backbone*	1-Shot					5-Shot				
		Fold-0	Fold-1	Fold-2	Fold-3	Mean	Fold-0	Fold-1	Fold-2	Fold-3	Mean
Class mIoU Evaluation											
$FWBF_{2019}$ [28]	VGG-16	18.4	16.7	19.6	25.4	20.0	20.9	19.2	21.9	28.4	22.6
Ours	VGG-16	**33.4**	**36.0**	**34.1**	**32.8**	**34.1**	**35.9**	**40.7**	**38.1**	**36.1**	**37.7**
$PANet_{2019}$† [45]	VGG-16	-	-	-	-	20.9	-	-	-	-	29.7
Ours†	VGG-16	**35.4**	**38.1**	**36.8**	**34.7**	**36.3**	**38.2**	**42.5**	**41.8**	**38.9**	**40.4**
$FWBF_{2019}$ [28]	ResNet-101	19.9	18.0	21.0	28.9	21.2	19.1	21.5	23.9	30.1	23.7
Ours	ResNet-101	**34.3**	**33.0**	**32.3**	**30.1**	**32.4**	**38.5**	**38.6**	**38.2**	**34.3**	**37.4**
Ours†	ResNet-101	36.8	41.8	38.7	36.7	38.5	40.4	46.8	43.2	40.5	42.7

Adaptive Prototype Learning and Allocation for Few-Shot Segmentation

Adaptive Prototype Learning and Allocation for Few-Shot Segmentation(CVPR2021)

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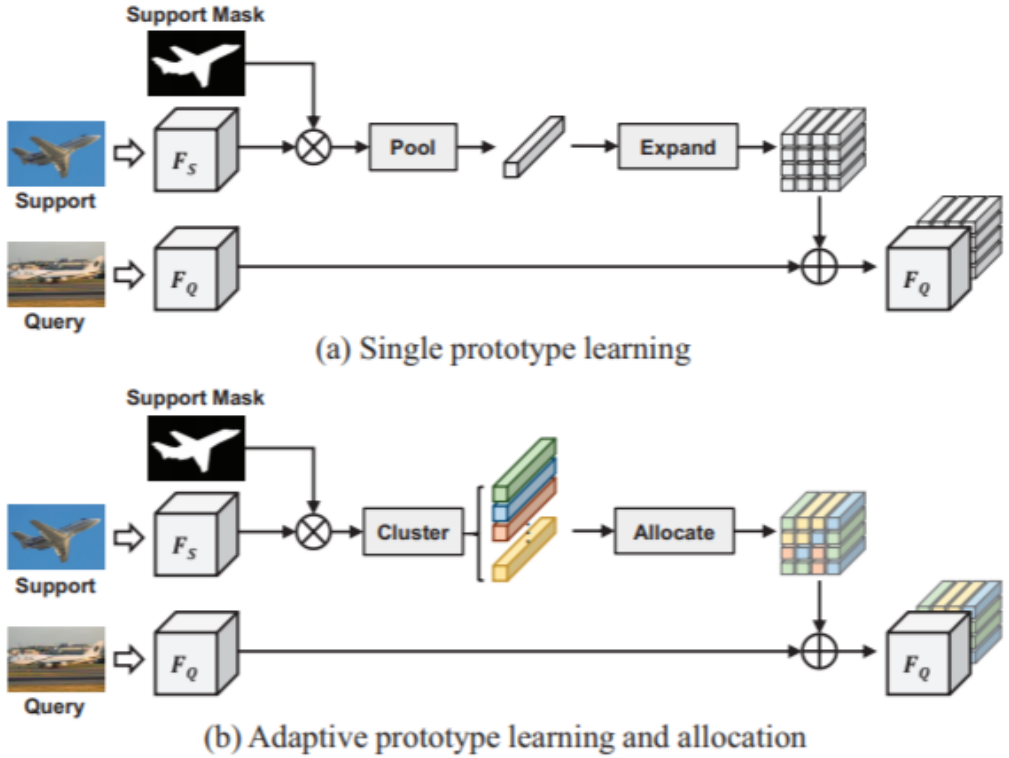
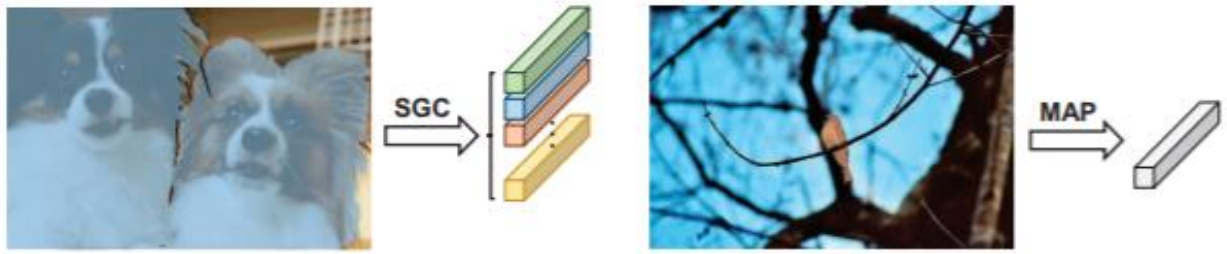
Motivation

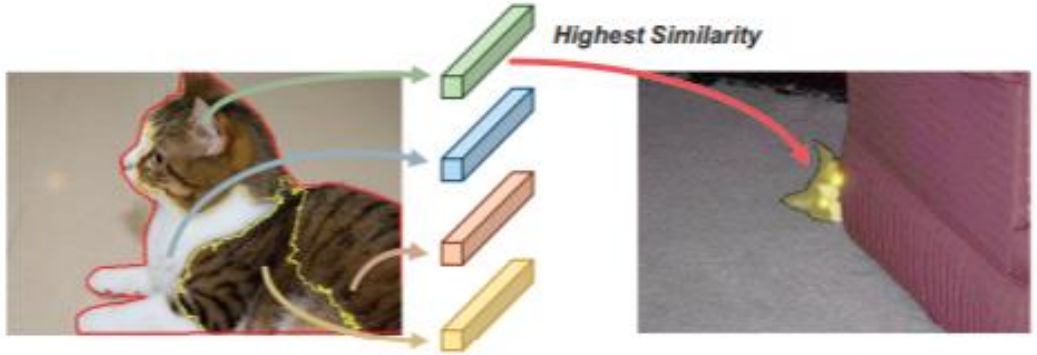
Using one prototype to represent all the information may lead to ambiguities



Adaptive Prototype Learning and Allocation for Few-Shot Segmentation



(a) SGC is adaptive to object scale variation



(b) GPA is adaptive to object shape variation

Adaptive Prototype Learning and Allocation for Few-Shot Segmentation

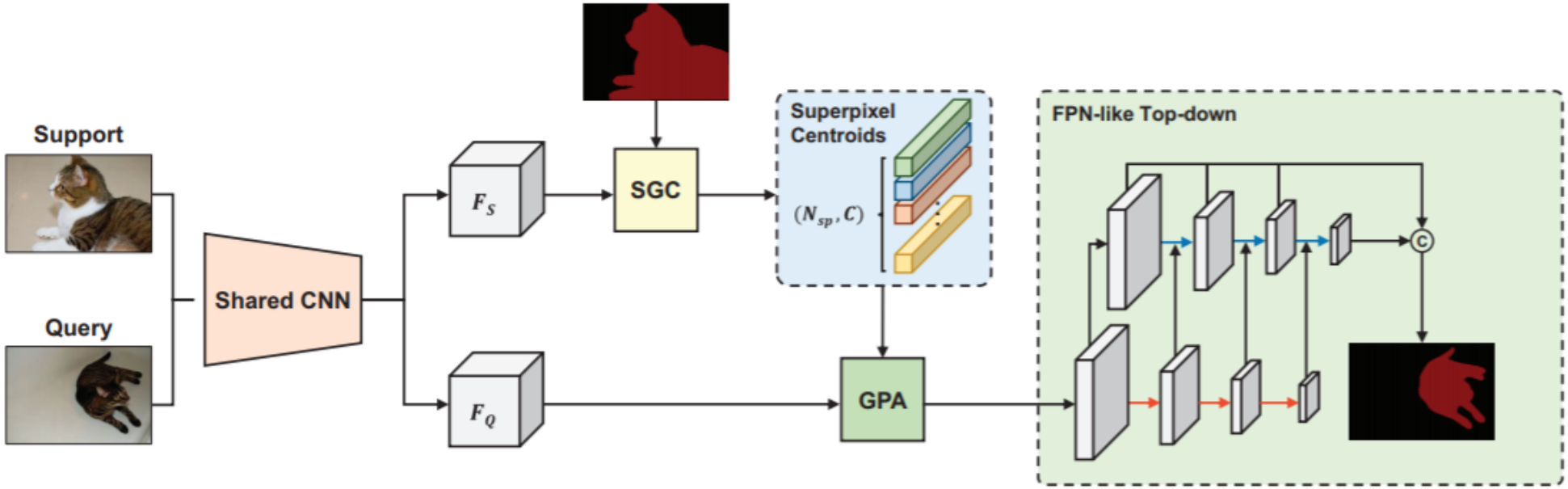


Figure 2. Overall architecture of the proposed Adaptive Superpixel-guided Network.

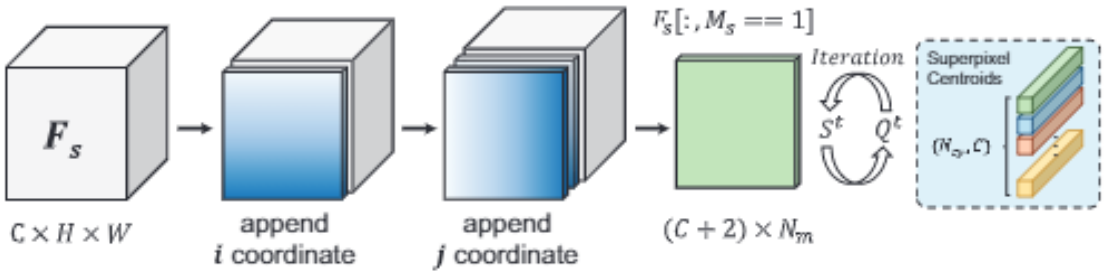
Super-pixel

Serve super-pixel centroids as prototypes

- concatenate the coordinates of each pixel with the support feature map
- Get foreground feature map with mask
- Iteration

$$D = \sqrt{(d_f)^2 + (d_s/r)^2}, \quad (1)$$

where d_f, d_s are the Euclidean distance for features and coordinate values, and r is a weighting factor. We filter



Adaptive Prototype Learning and Allocation for Few-Shot Segmentation

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Prototype Allocation

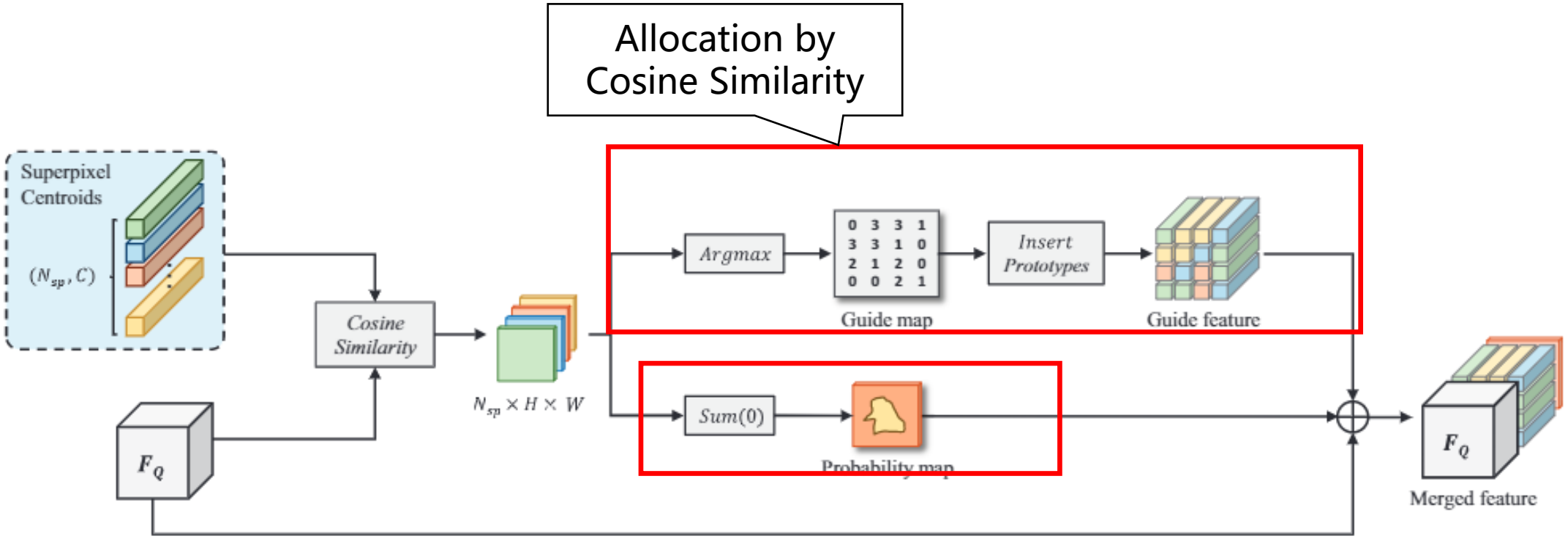

Figure 4. Illustration of proposed Guided Prototype Allocation.

Adaptability

Compute the number of prototypes with the number of pixels in the foreground

$$N_{sp} = \min(\left\lfloor \frac{N_m}{S_{sp}} \right\rfloor, N_{max}),$$

K-shot setting

Directly get all prototypes from K-shot

$$N_{sp} = max \sum_{i=1}^{k} N_{sp}^{i}$$

Adaptive Prototype Learning and Allocation for Few-Shot Segmentation

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Backbone	Methods	1-shot					5-shot					Δ
		s-0	s-1	s-2	s-3	mean	s-0	s-1	s-2	s-3	mean	
VGG-16	OSLSM [23]	33.60	55.30	40.90	33.50	40.80	35.90	58.10	42.70	39.10	43.95	3.15
	co-FCN [21]	36.70	50.60	44.90	32.40	41.10	37.50	50.00	44.10	33.90	41.40	0.30
	AMP [24]	41.90	50.20	46.70	34.40	43.40	40.30	55.30	49.90	40.10	46.40	3.00
	SG-One [42]	40.20	58.40	48.40	38.40	46.30	41.90	58.60	48.60	39.40	47.10	0.80
	PANet [32]	42.30	58.00	51.10	41.20	48.10	51.80	64.60	59.80	46.50	55.70	**7.60**
	FWB [20]	47.04	59.64	52.61	48.27	51.90	50.87	62.86	56.48	50.09	55.08	3.18
ResNet50	CANet† [40]	52.50	65.90	51.30	51.90	55.40	55.50	67.80	51.90	53.20	57.10	1.70
	PGNet† [39]	56.00	66.90	50.60	50.40	56.00	57.70	68.70	52.90	54.60	58.50	2.50
	RPMMs [34]	55.15	66.91	52.61	50.68	56.34	56.28	67.34	54.52	51.00	57.30	0.96
	SimPropNet [8]	54.82	67.33	54.52	52.02	57.19	57.20	68.50	58.40	56.05	60.04	2.85
	PPNet [18]	47.83	58.75	53.80	45.63	51.50	58.39	67.83	**64.88**	56.73	61.96	**10.46**
	PFENet [29]	**61.70**	**69.50**	55.40	**56.30**	**60.80**	63.10	**70.70**	55.80	**57.90**	61.90	1.10
	ASGNet (ours)	58.84	67.86	**56.79**	53.66	59.29	**63.66**	70.55	64.17	57.38	**63.94**	4.65
ResNet101	FWB [20]	51.30	64.49	56.71	52.24	56.19	54.84	67.38	62.16	55.30	59.92	3.73
	DAN† [31]	54.70	68.60	**57.80**	51.60	58.20	57.90	69.00	60.10	54.90	60.50	2.30
	PFENet [29]	**60.50**	**69.40**	54.40	**55.90**	**60.10**	62.80	70.40	54.90	**57.60**	61.40	1.30
	ASGNet (ours)	59.84	67.43	55.59	54.39	59.31	**64.55**	**71.32**	**64.24**	57.33	**64.36**	**5.05**

Edge-Labeling Graph Neural Network for Few-shot Learning

Edge-Labeling Graph Neural Network for Few-shot Learning (CVPR2019)

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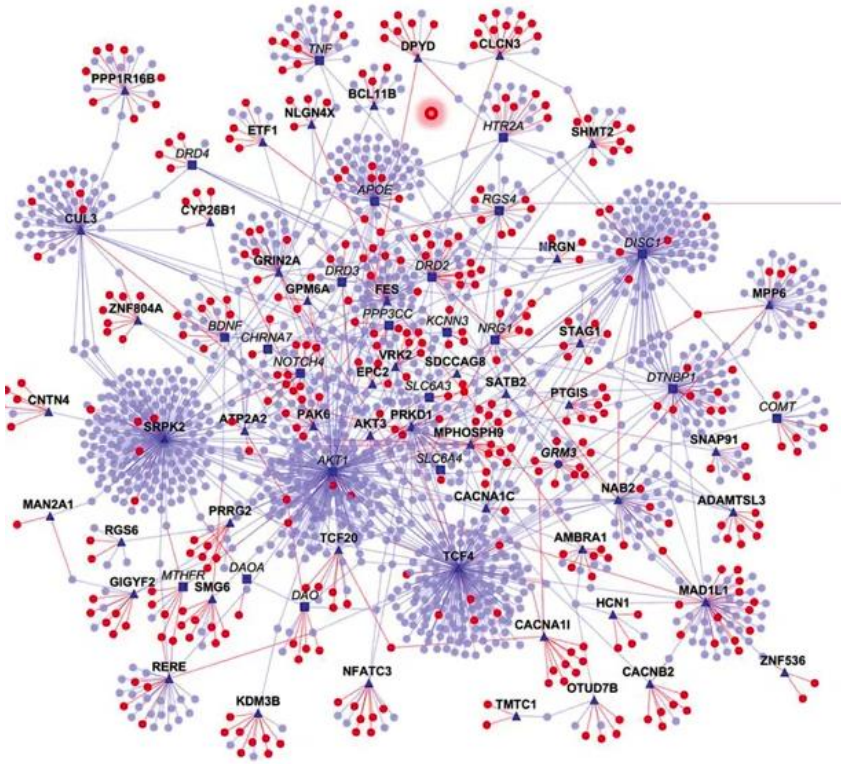
Graph Neural Network （GNN）

$$\mathbf{H} = F(\mathbf{H}, \mathbf{X})$$

$$\mathbf{O} = G(\mathbf{H}, \mathbf{X}_N)$$

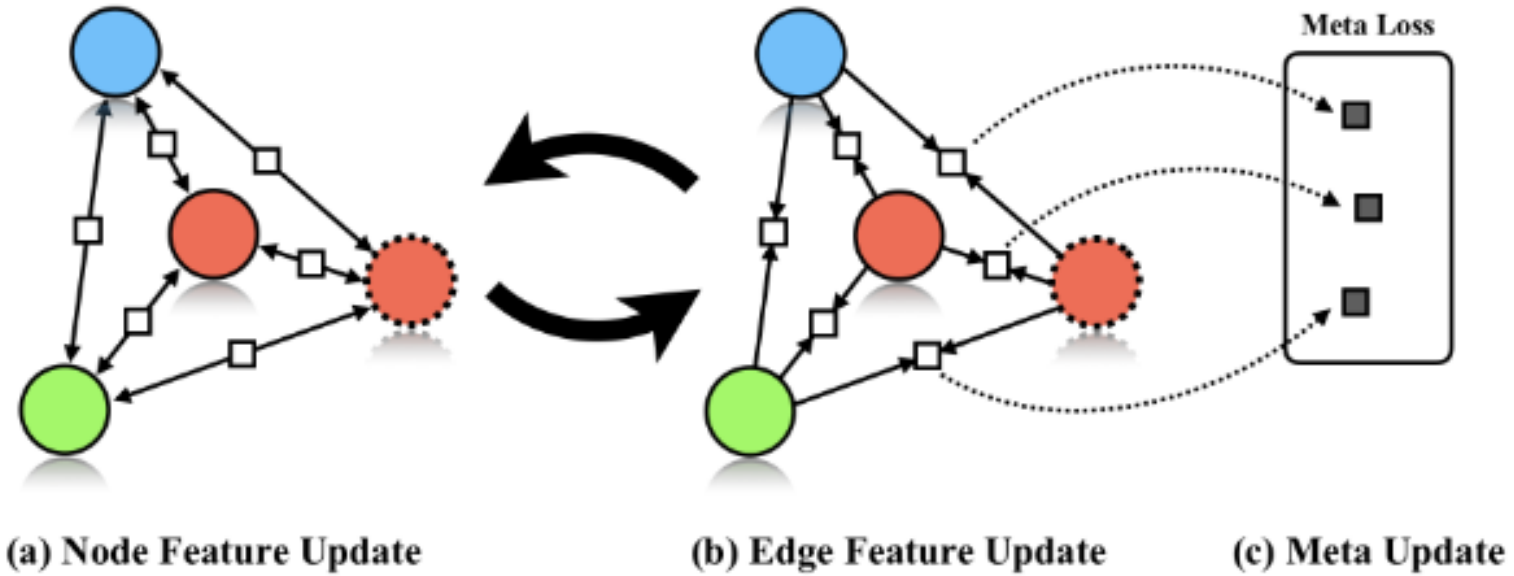
GCN

$$\mathbf{X}_s^{k+1} = \sigma\left(\left(\mathbf{I}_{|\mathcal{V}^s|} + \mathbf{D}_s^{-\frac{1}{2}}\mathbf{A}_s\mathbf{D}_s^{-\frac{1}{2}}\right)\mathbf{X}_s^k\mathbf{W}_s^k\right)$$



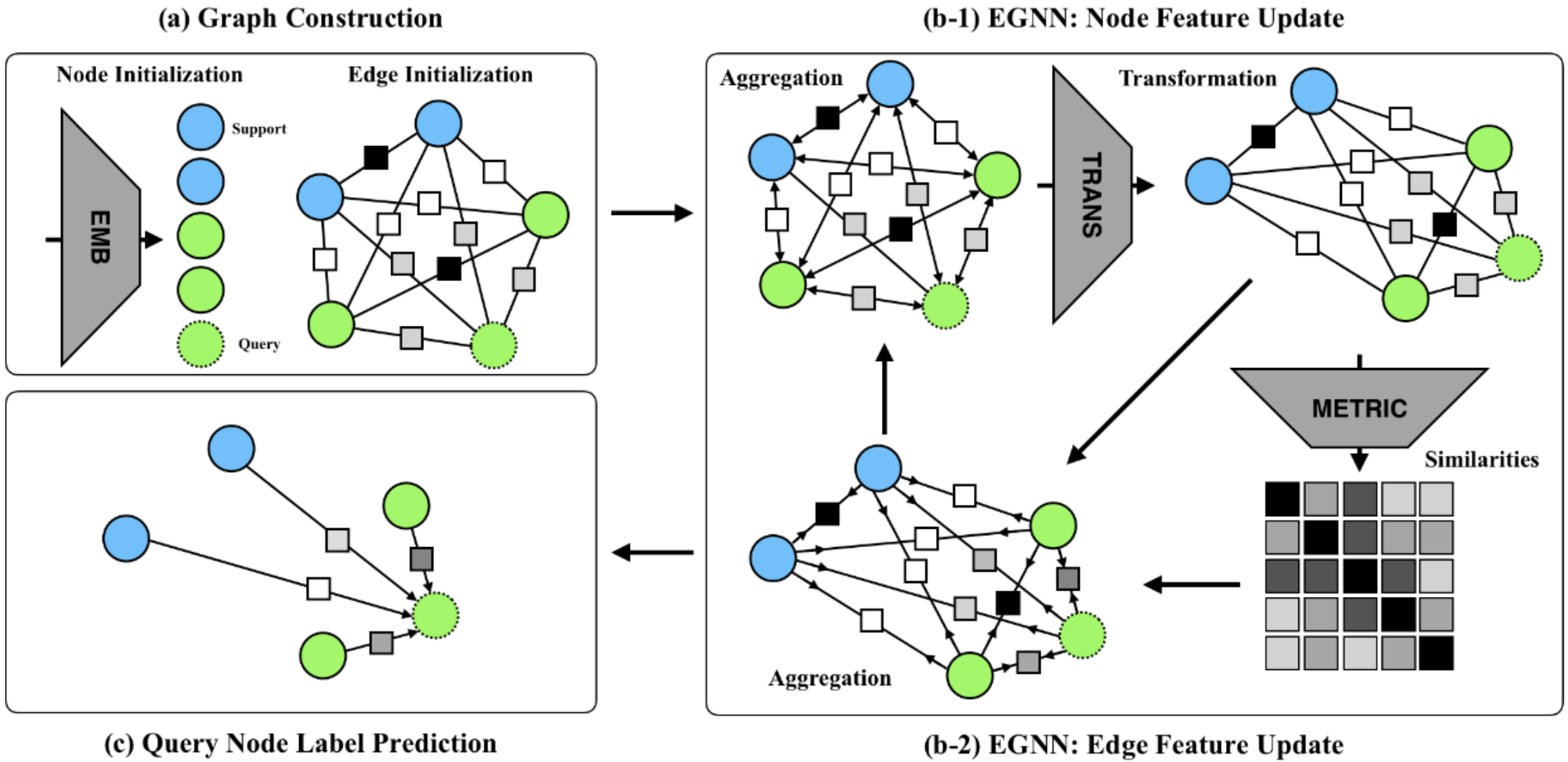
[1]Kipf and M. Welling. Semi-supervised classification with graph convolutional networks. ICLR, 2017.

Edge-Labeling Graph Neural Network for Few-shot Learning (CVPR2019)



Not suitable for few-shot learning

Edge-Labeling Graph Neural Network for Few-shot Learning (CVPR2019)



Edge-Labeling Graph Neural Network for Few-shot Learning (CVPR2019)

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Initial edge label

$$\mathbf{e}_{ij}^0 = \begin{cases} [1||0], & \text{if } y_{ij} = 1 \text{ and } i,j \leq N \times K, \\ [0||1], & \text{if } y_{ij} = 0 \text{ and } i,j \leq N \times K, \\ [0.5||0.5], & \text{otherwise,} \end{cases}$$

Node update

$$\mathbf{v}_i^\ell = f_v^\ell([\sum_j \tilde{e}_{ij1}^{\ell-1}\mathbf{v}_j^{\ell-1} || \sum_j \tilde{e}_{ij2}^{\ell-1}\mathbf{v}_j^{\ell-1}]; \theta_v^\ell),$$

Edge update

$$\bar{e}_{ij1}^\ell = \frac{f_e^\ell(\mathbf{v}_i^\ell, \mathbf{v}_j^\ell; \theta_e^\ell) e_{ij1}^{\ell-1}}{\sum_k f_e^\ell(\mathbf{v}_i^\ell, \mathbf{v}_k^\ell; \theta_e^\ell) e_{ik1}^{\ell-1} / (\sum_k e_{ik1}^{\ell-1})}, \quad (4)$$

$$\bar{e}_{ij2}^\ell = \frac{(1 - f_e^\ell(\mathbf{v}_i^\ell, \mathbf{v}_j^\ell; \theta_e^\ell)) e_{ij2}^{\ell-1}}{\sum_k (1 - f_e^\ell(\mathbf{v}_i^\ell, \mathbf{v}_k^\ell; \theta_e^\ell)) e_{ik2}^{\ell-1} / (\sum_k e_{ik2}^{\ell-1})}, \quad (5)$$

$$\mathbf{e}_{ij}^\ell = \bar{\mathbf{e}}_{ij}^\ell / \|\bar{\mathbf{e}}_{ij}^\ell\|_1, \quad (6)$$

Edge-Labeling Graph Neural Network for Few-shot Learning (CVPR2019)

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Algorithm 1: The process of EGNN for inference

Input: $\mathcal{G} = (\mathcal{V}, \mathcal{E}; \mathcal{T})$, where $\mathcal{T} = \mathcal{S} \bigcup \mathcal{Q}$,
$\mathcal{S} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N \times K}$, $\mathcal{Q} = \{\mathbf{x}_i\}_{i=N \times K+1}^{N \times K+T}$
Parameters: $\theta_{emb} \cup \{\theta_v^\ell, \theta_e^\ell\}_{\ell=1}^{L}$
Output: $\{\hat{y}_i\}_{i=N \times K+1}^{N \times K+T}$
Initialize: $\mathbf{v}_i^0 = f_{emb}(\mathbf{x}_i; \theta_{emb})$, $\mathbf{e}_{ij}^0$, $\forall i, j$
for $\ell = 1, \cdots, L$ **do**
  /* Node feature update */
  for $i = 1, \cdots, |V|$ **do**
    $\mathbf{v}_i^\ell \leftarrow \texttt{NodeUpdate}(\{\mathbf{v}_i^{\ell-1}\}, \{\mathbf{e}_{ij}^{\ell-1}\}; \theta_v^\ell)$
  end
  /* Edge feature update */
  for $(i, j) = 1, \cdots, |E|$ **do**
    $\mathbf{e}_{ij}^\ell \leftarrow \texttt{EdgeUpdate}(\{\mathbf{v}_i^\ell\}, \{\mathbf{e}_{ij}^{\ell-1}\}; \theta_e^\ell)$
  end
end
/* Query node label prediction */
$\{\hat{y}_i\}_{i=N \times K+1}^{N \times K+T} \leftarrow \texttt{Edge2NodePred}(\{y_i\}_{i=1}^{N \times K}, \{\mathbf{e}_{ij}^L\})$

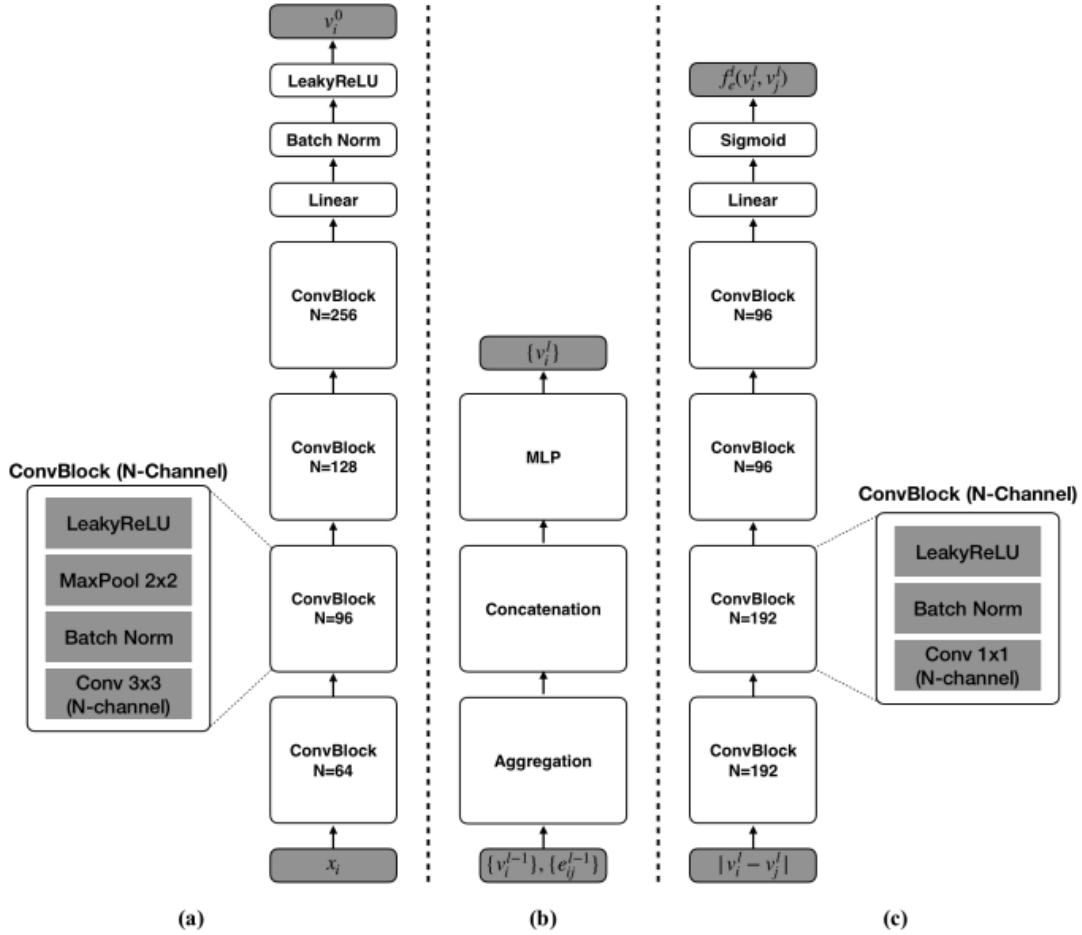

Figure 3: Detailed network architectures used in EGNN. (a) Embedding network f_{emb}. (b) Feature (node) transformation network f_v^ℓ. (c) Metric network f_e^ℓ.

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(a) *mini*ImageNet

Model	Trans.	5-Way 5-Shot
Matching Networks [2]	No	55.30
Reptile [46]	No	62.74
Prototypical Net [3]	No	65.77
GNN [6]	No	66.41
EGNN	No	**66.85**
MAML [4]	BN	63.11
Reptile + BN [46]	BN	65.99
Relation Net [5]	BN	67.07
MAML+Transduction [4]	Yes	66.19
TPN [12]	Yes	69.43
TPN (Higher K) [12]	Yes	69.86
EGNN+Transduction	Yes	**76.37**

(b) *tiered*ImageNet

Model	Trans.	5-Way 5-Shot
Reptile [46]	No	66.47
Prototypical Net [3]	No	69.57
EGNN	No	**70.98**
MAML [4]	BN	70.30
Reptile + BN [46]	BN	71.03
Relation Net [5]	BN	71.31
MAML+Transduction [4]	Yes	70.83
TPN [12]	Yes	72.58
EGNN+Transduction	Yes	**80.15**

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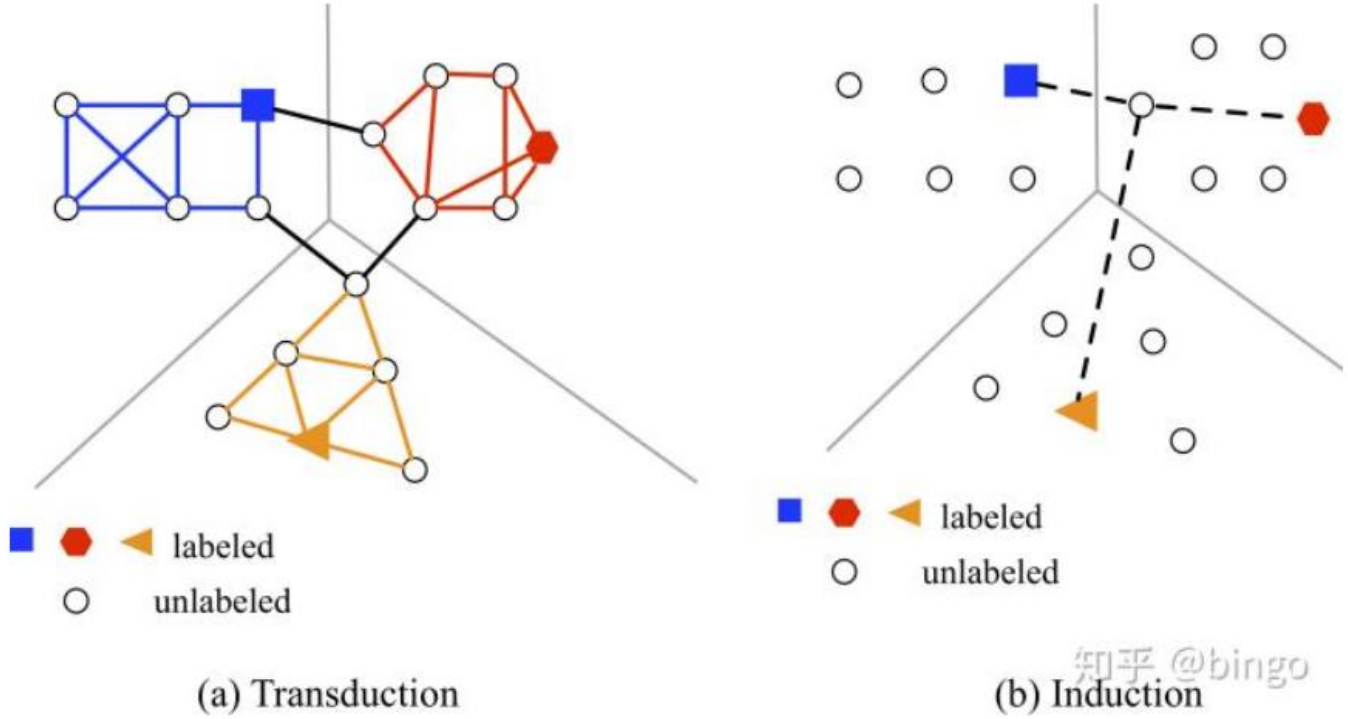
Transductive inference

Classify the entire test set at once to alleviate the low-data problem



[2]Liu Y, Lee J, Park M, et al. Learning to propagate labels: Transductive propagation network for few-shot learning[C]//7th International Conference on Learning Representations, ICLR 2019. 2019.

Edge-Labeling Graph Neural Network for Few-