Lecture 24: Recent Progress in Deep Learning: Few-shot Learning

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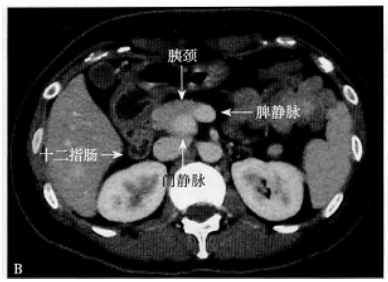
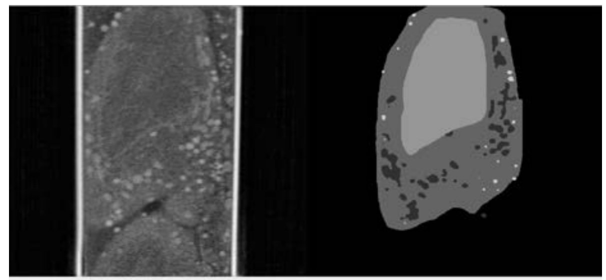
Real-world scenarios

- Data annotation is costly
  - Many specific domain and cross modality tasks



Medical image understanding
(image credit: 廖飞. 胰腺影像学. 2015.)

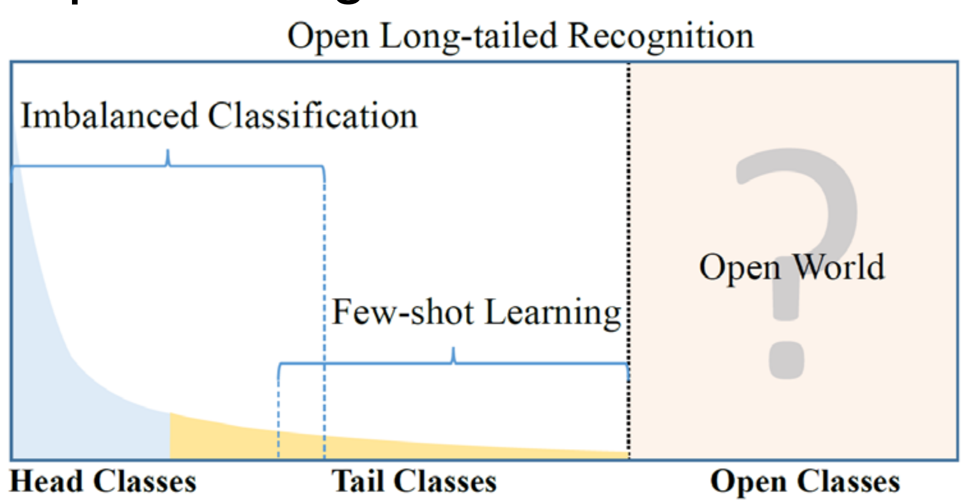


Biological image analysis
(Zhang and He, 2019)

A house cat laying on a couch beside a remote.

Vision & Language (MSCOCO)

- Visual concept learning in wild



(Liu et al CVPR 2019)

Challenges

- Limitation in naïve transfer learning
  - Insufficient instance variations of novel classes
  - Fine-tuning usually fails given a few examples per class

Image Credit: Ravi & Larochelle et al 2017

- Human (child) performance is much better
  - How do we achieve such data efficiency?
  - What representations are used?
  - What are the underlying learning algorithms?

Few-shot learning problem

- Learning from (very) limited annotated data
- Typical setting:
  - Classification using a few training examples per visual category
  - Formally, given a small dataset $D_{train} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{L}$
    - N categories $y_i \in \mathcal{Y}, |\mathcal{Y}| = N,$
    - K shot: each class has K examples, or $L = N \times K$
  - The goal is to learn a model *F* parametrized by θ to minimize

$$E_{D_{test}}\left[\text{loss}(y_i, F_\theta(x_i))\right]$$

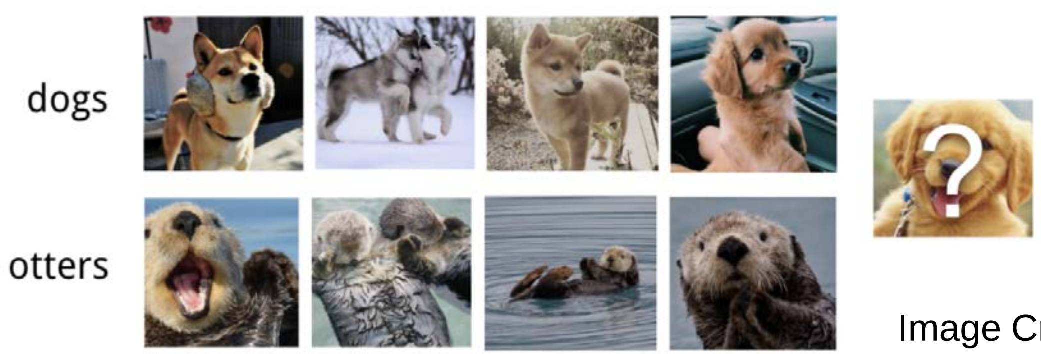


Image Credit: Weng, Lil-log, 2018

Few-shot learning problem

- For a single isolated task, this is difficult
  - But *if* we have access to many *similar* few-shot learning tasks, we can exploit such prior knowledge.
- Main idea is to consider task-level learning
  - Learn a representation shared by all those tasks
  - Learn an efficient classifier learning algorithm that can be applied to all the tasks

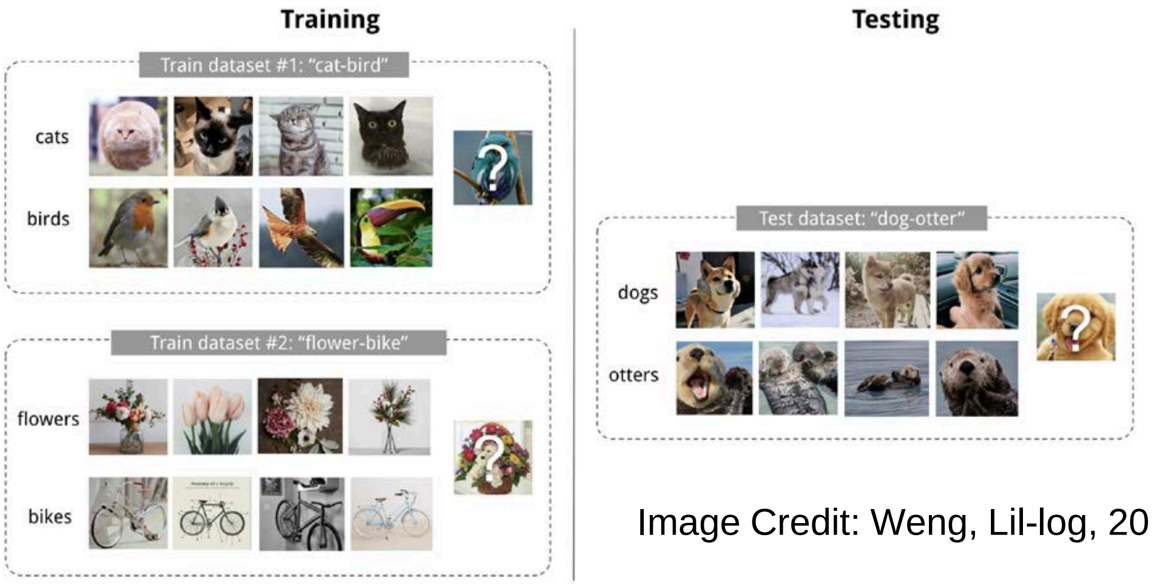


Image Credit: Weng, Lil-log, 2018

Main intuitions in few-shot learning

- Prior knowledge in different vision tasks
  - Similarity between visual categories
    - Feature representations, etc.
  - Similarity between visual recognition tasks
    - Learning a classifier, etc.

- Focusing on generic aspects of similar tasks
  - Generic visual representations
    - Not category-specific
  - Transferrable learning strategies
    - Very data-efficient

Meta-learning framework

- Problem formulation
  - Each few-shot classification problem as a task

    Each Task: $T \in \mathcal{T}$ $\quad T \sim P(T)$

  - Each task (or an *episode*) consists of

    $T = (D_{train}, D_{test}, \mathcal{Y}_T)$

  - Task-train (*support*) set

    $D_{train} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{L} \quad \forall y_i \in \mathcal{Y}_T$

  - Task-test set (query) D_{test}
  - For each task, we adopt an learning algorithm A_ϕ
    - to learn its own classifier F_θ via $F_\theta = A_\phi(D_{train})$
    - to perform well on the task-test set D_{test}

Meta-learning formulation

- Key assumptions:
  - The learning algorithm A_ϕ is shared across tasks
  - We can sample many tasks to learn a good A_ϕ

- A meta-learning strategy
  - Input: meta-training set $\mathcal{D}_{meta-train} = \{(D^{(n)}_{train}, D^{(n)}_{test})\}_{n=1}^{N}$
  - Output: algorithm parameter ϕ^*
  - Objective: good performance on meta-test set

$$\mathcal{D}_{meta-test} = \{(D'^{(n)}_{train}, D'^{(n)}_{test})\}_{n=1}^{N'}$$

  - Minimizing the empirical loss on the meta-training set

$$\min_\phi E_{\mathcal{D}_{meta-train}} \left[\mathrm{loss}(F_\theta^{(n)}, D^{(n)}_{test}) \right]$$

    - Each meta-train task $F_\theta^{(n)} = A_\phi(D^{(n)}_{train})$

Meta-learning formulation

- Analogy to standard supervised learning

Supervised-Learning	Train	Test	One data point
Meta-learning	Meta-training	Meta-testing	One task

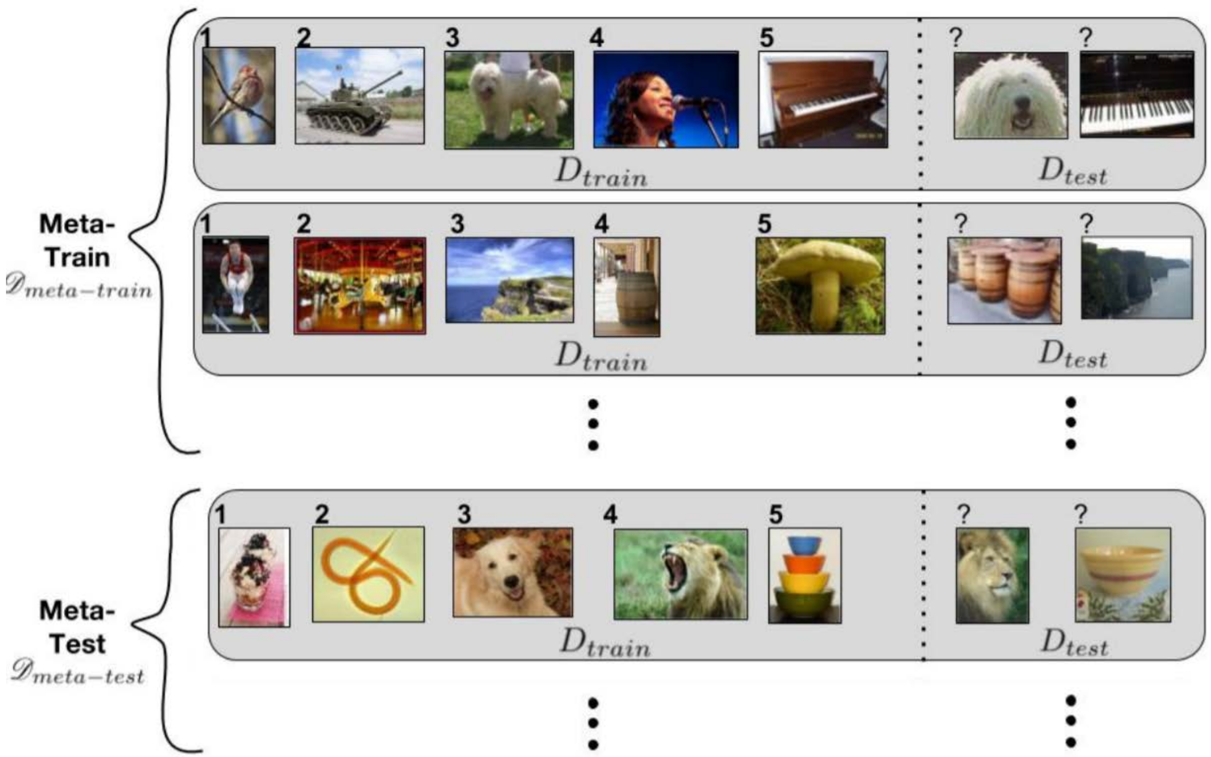
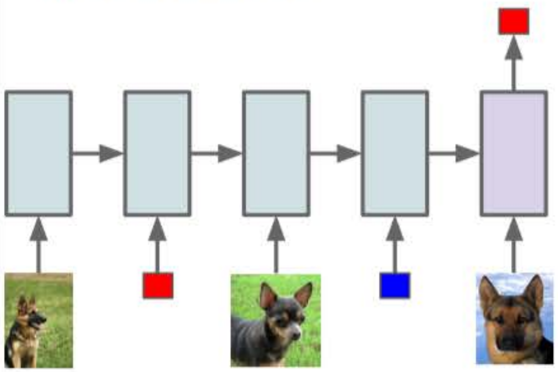


Image Credit: Ravi & Larochelle et al 2017

Overview of existing methods

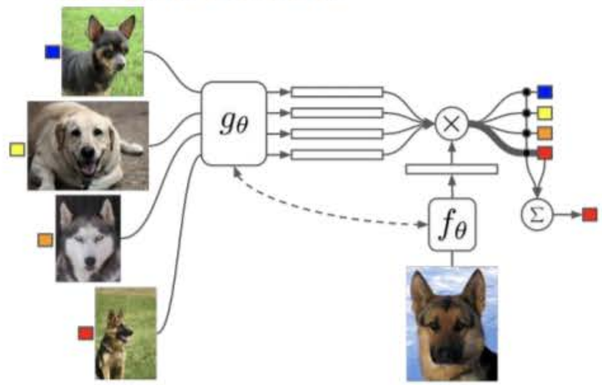
- Depending on the meta-learners used in few-shot tasks

Model Based



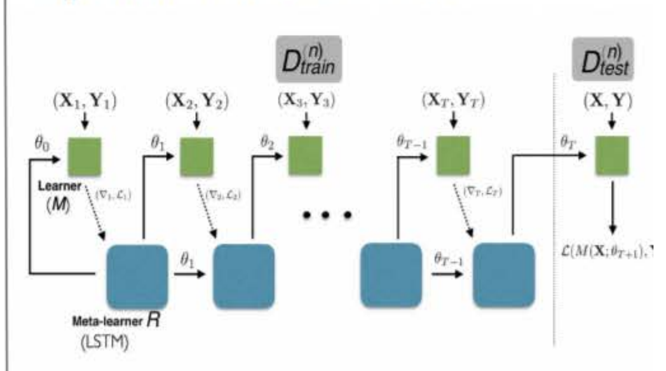
- Santoro et al. '16
- Duan et al. '17
- Wang et al. '17
- Munkhdalai & Yu '17
- Mishra et al. '17

Metric Based



- Koch '15
- Vinyals et al. '16
- Snell et al. '17
- Shyam et al. '17
- Sung et al. '17

Optimization Based



- Schmidhuber '87, '92
- Bengio et al. '90, '92
- Hochreiter et al. '01
- Li & Malik '16
- Andrychowicz et al. '16
- Ravi & Larochelle '17
- Finn et al. '17

Slide Credit: Vinyals, NIPS 2017

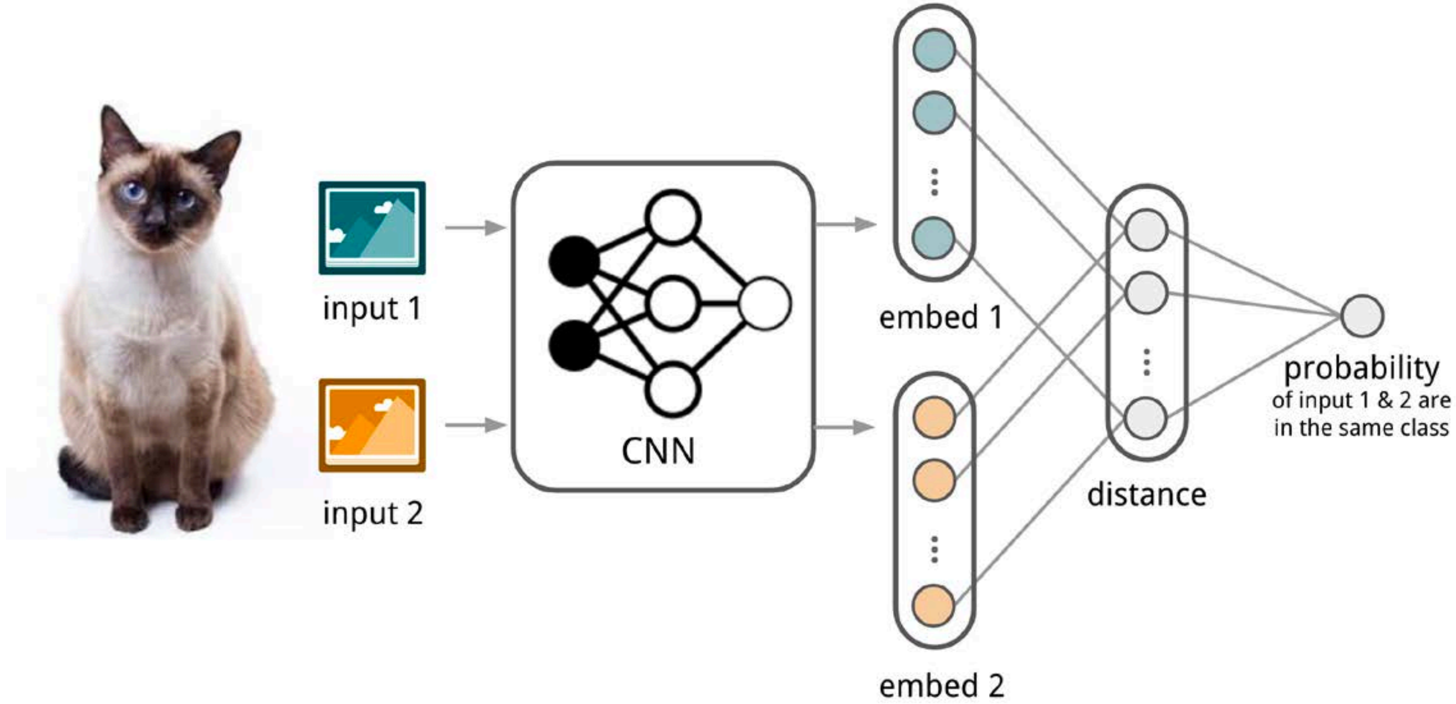
Metric-based methods

- Basic idea: Learn a generic distance metric

$$P_\theta(y|\mathbf{x}, D_{train}) = \sum_{(\mathbf{x}_i, y_i)\in D_{train}} k_\theta(\mathbf{x}, \mathbf{x}_i) y_i$$

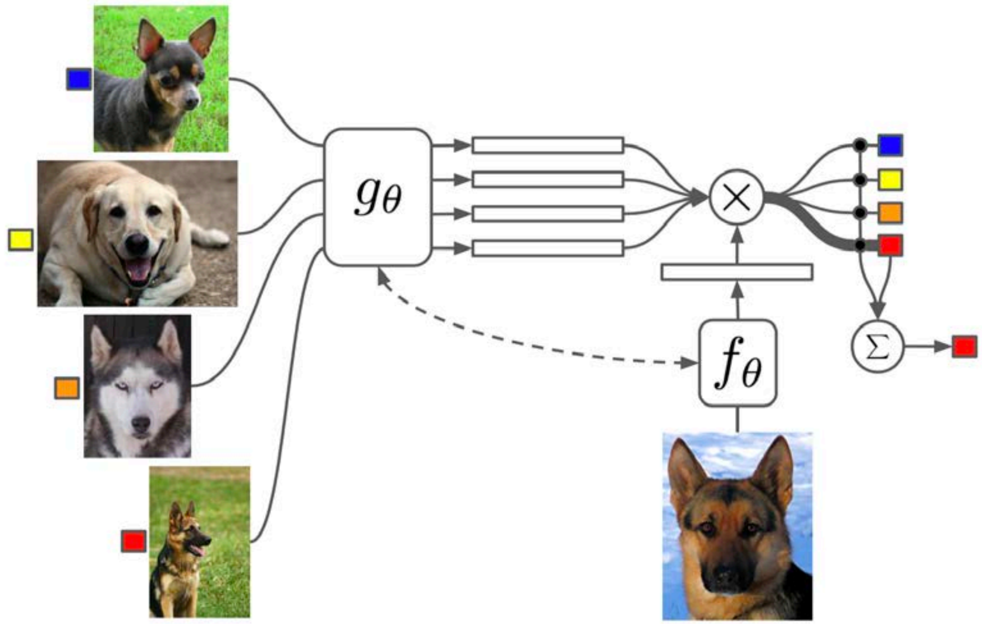
- Typical methods
  - Siamese network (Koch, Zemel & Salakhutdinov, 2015)
  - Matching network (Vinyals et al, 2016)
  - Relation network (Sung et al. 2018)
  - Prototypical network (Snell, Swersky & Zemel, 2017)

Siamese Neural Network



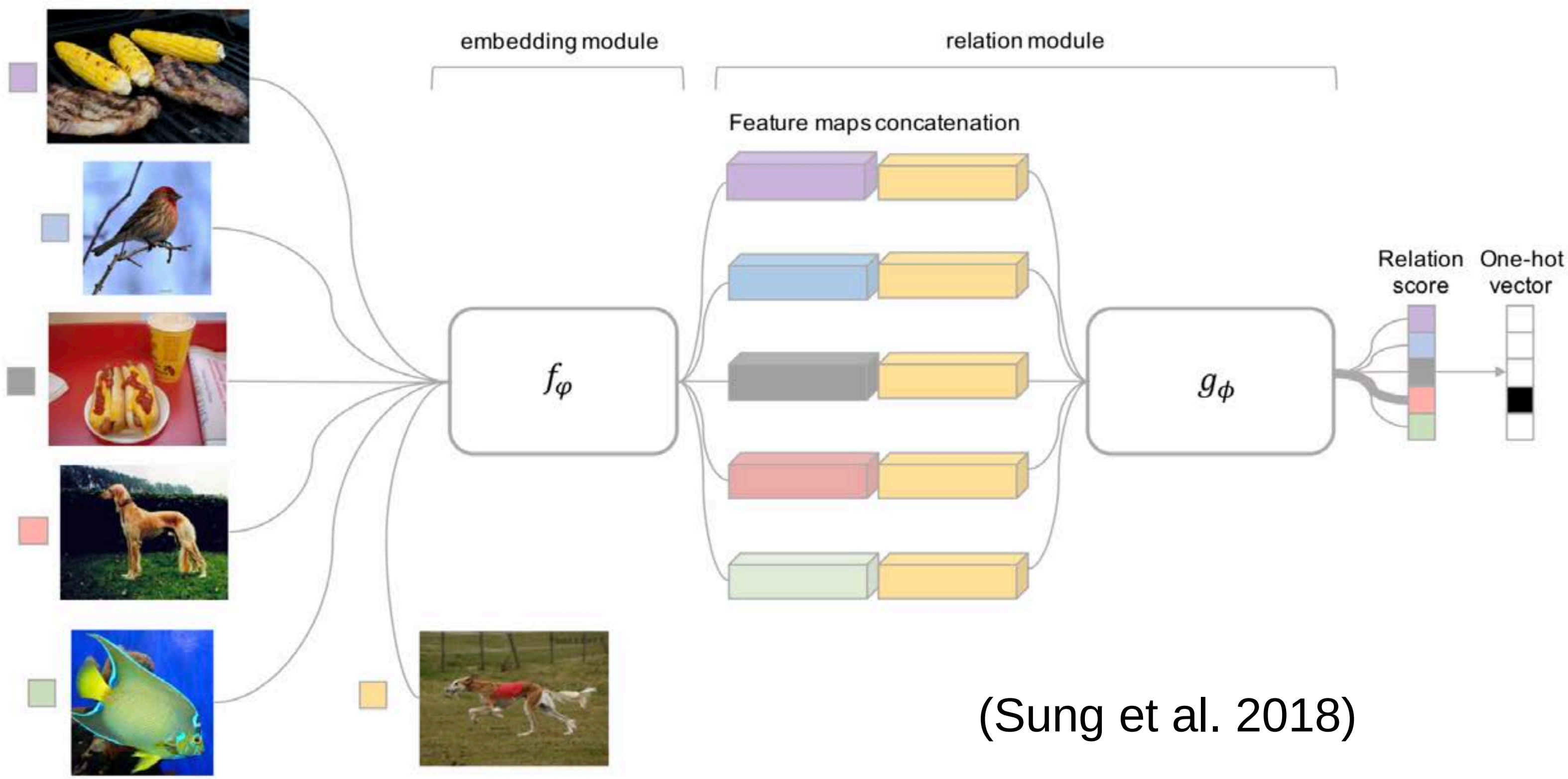
- The learned embedding can be generalized to unknown categories (Koch, Zemel & Salakhutdinov, 2015)

Matching Networks



- Full Contextual Embedding (Vinyals et al, 2016)
  - Encoding input in the context of the entire support set
  - The learned embedding can be adjusted based on the relationship with other support samples.

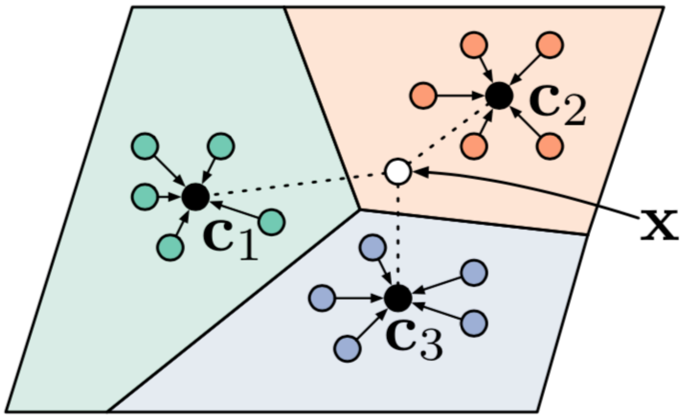
Relation Network



(Sung et al. 2018)

- Similar to Siamese network
- More complex metric learning $r_{ij} = g_\phi([\mathbf{x}_i, \mathbf{x}_j])$

Prototypical Networks



(a) Few-shot

$$\mathbf{v}_c = \frac{1}{|S_c|} \sum_{(\mathbf{x}_i, y_i) \in S_c} f_\theta(\mathbf{x}_i)$$

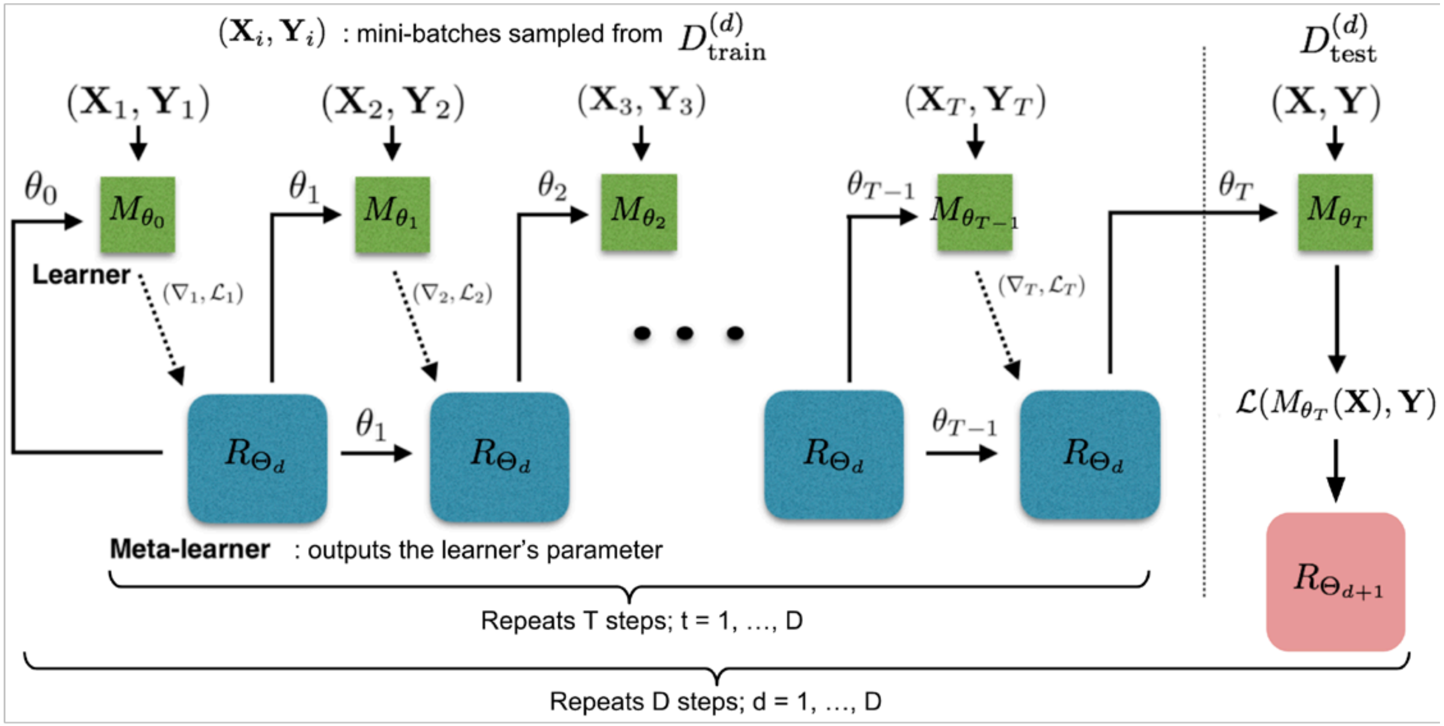
- Prototype vectors (Snell, Swersky & Zemel, 2017)

$$P(y = c|\mathbf{x}) = \mathrm{softmax}(-d_\varphi(f_\theta(\mathbf{x}), \mathbf{v}_c))$$

Optimization-based methods

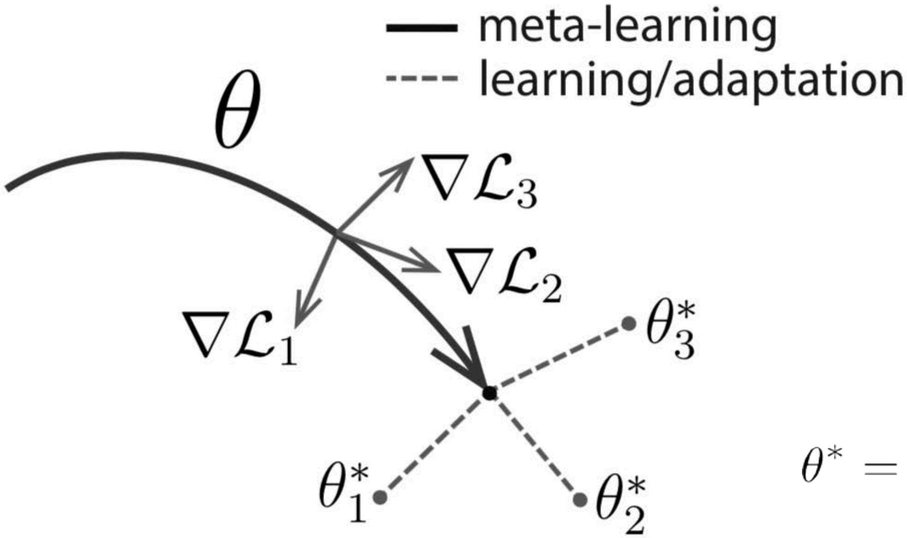
- Basic idea: Adjust the optimization in model learning so that the model can effectively learn from a few examples
- Typical methods
  - LSTM meta-learner (Ravi & Larochelle, 2017)
  - MAML (Finn, et al. 2017)
  - Reptile (Nichol, Achiam & Schulman, 2018)

LSTM meta-learner



- The optimization algorithm is explicitly modeled based on an LSTM meta-learner (Ravi & Larochelle, 2017)

MAML



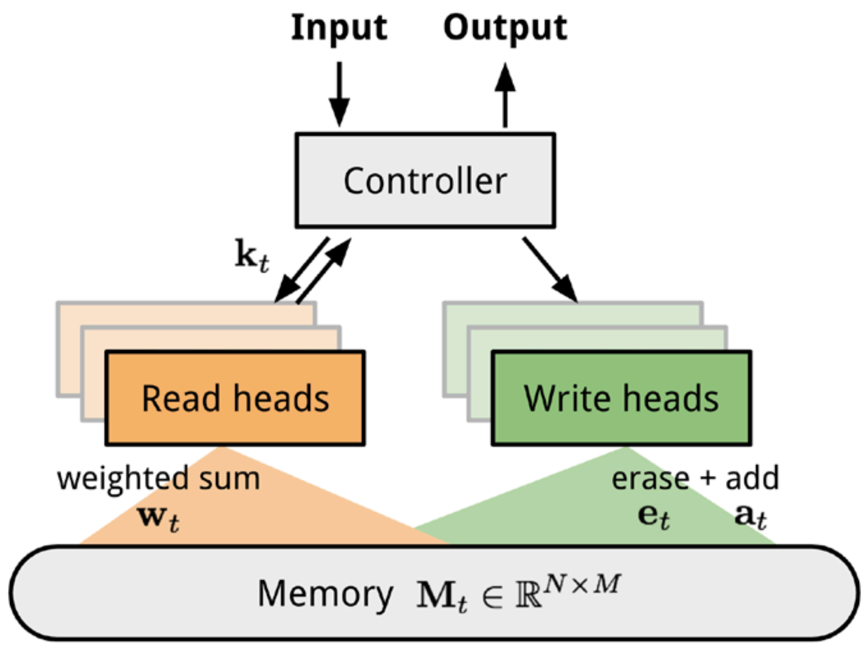
$$\theta^* = \arg\min_{\theta} \sum_{\tau_i \sim p(\tau)} \mathcal{L}^{(1)}_{\tau_i}\left(f_{\theta - \alpha \nabla_\theta \mathcal{L}^{(0)}_{\tau_i}(f_\theta)}\right)$$

- Model-Agnostic Meta-Learning (Finn, et al. 2017) aims to generate a fast gradient based learner

Model-based methods

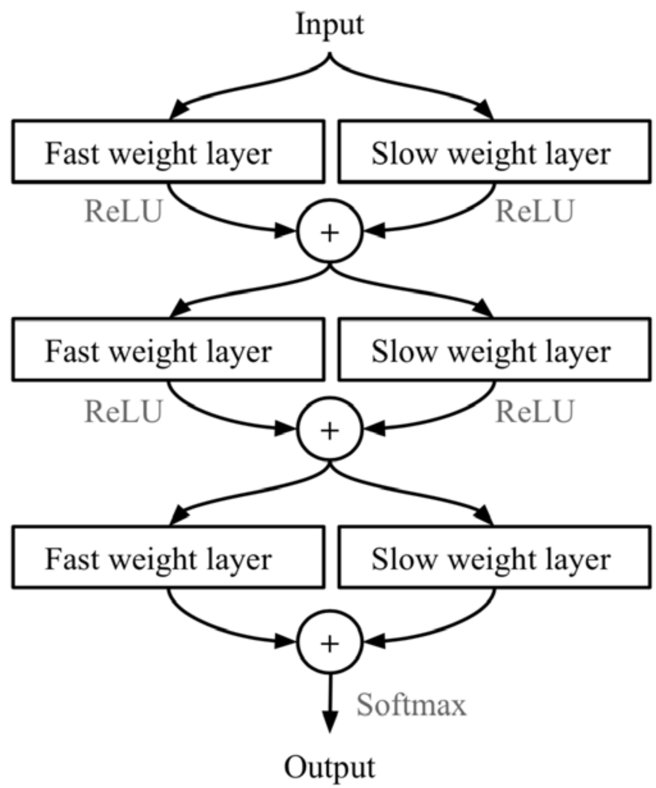
- Basic idea: Using a black-box neural network designed specifically for fast learning
- Typical methods
  - Memory-augmented network (Santoro et al., 2016)
  - Meta networks (Munkhdalai & Yu, 2017)
  - SNAIL (Mishra et al., 2018)

Memory-augmented network



- With an explicit storage buffer, it is easier for the network to rapidly incorporate new information.
- (Santoro et al., 2016) train it in a way that the memory can encode and capture information of new tasks fast and is easily and stably accessible.

Meta networks



- The MetaNet relies on “fast weights” to achieve rapid generalization across tasks (Munkhdalai & Yu, 2017)

Main limitations

- A global representation of inputs
  - Sensitive to nuisance parameters: background clutter, occlusions, etc.
- Mixed representation and predictor learning
  - Complex architecture, difficult to interpret
  - Sometimes slow convergence
- Focusing on classification tasks
  - Non-trivial to apply to other vision tasks: localization, segmentation, etc.

Our proposed solutions

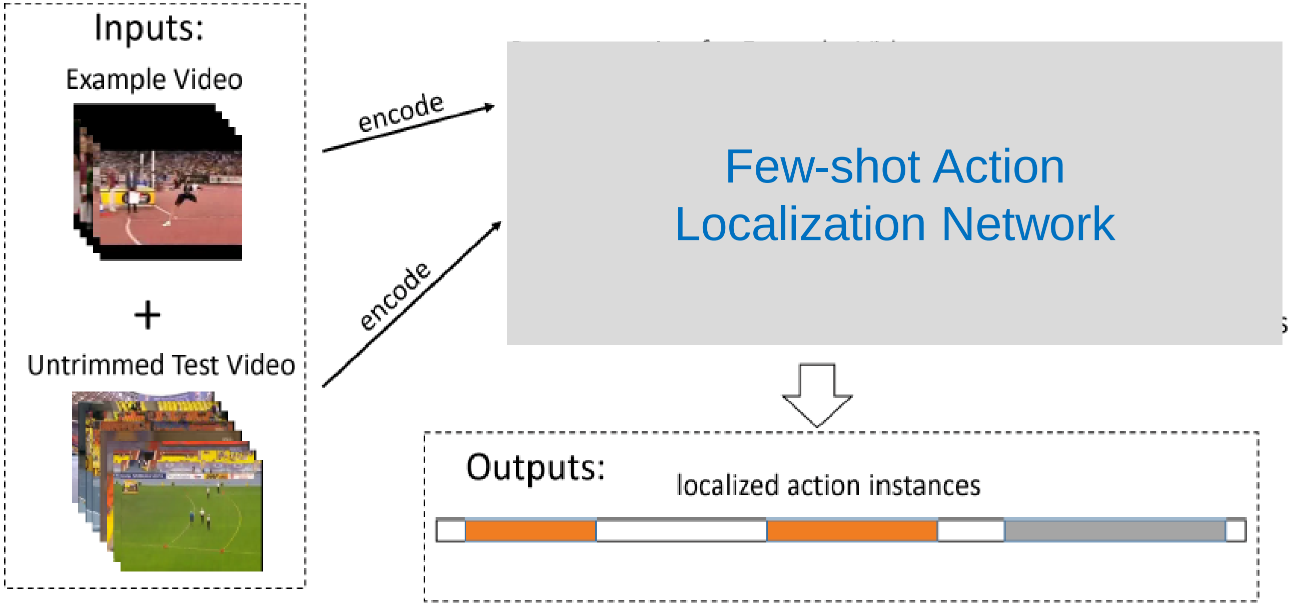
- Structure-aware data representation
  - Spatial/temporal representations for semantic objects/actions
- Decoupling representation and classifier learning
  - Improving representation learning
- Generalizing to other visual tasks
  - Instance localization and detection with few-shot learning

Temporal action localization

- Our goal: Jointly classify action instances and localize them in an untrimmed video
  - Important for detailed video understanding
  - Broad range of applications in video surveillance/analytics

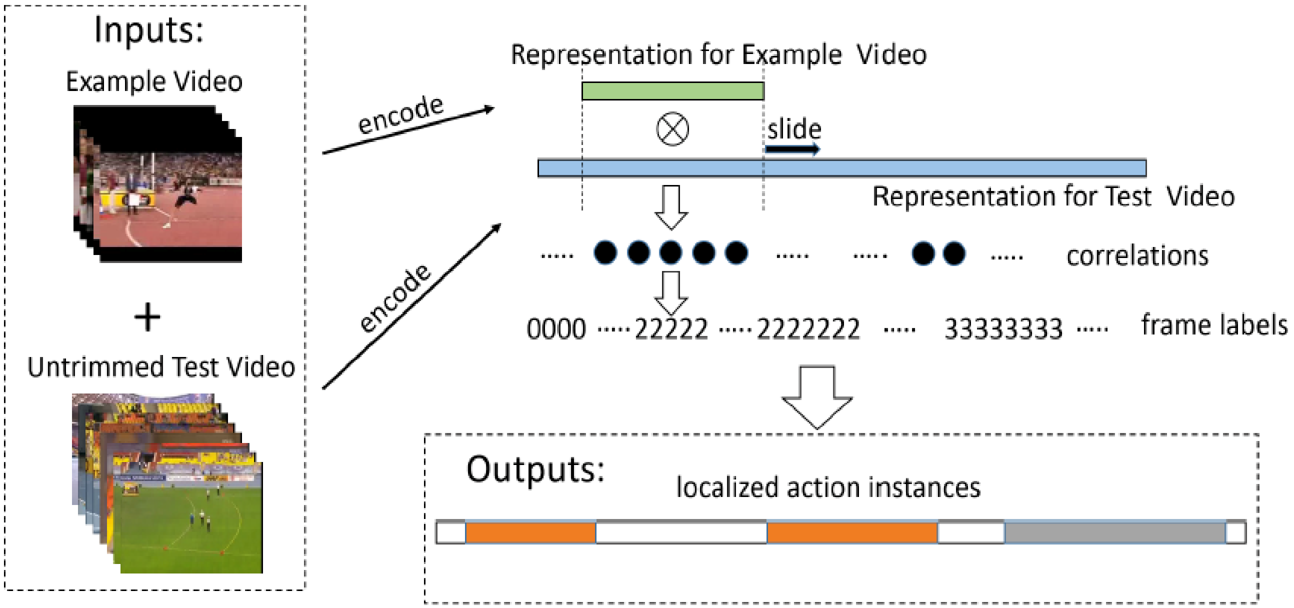
Our problem setting

- We conceptualize an example-based action localization strategy
  - Few-shot learning of action classes and
  - Being sensitive to action boundaries

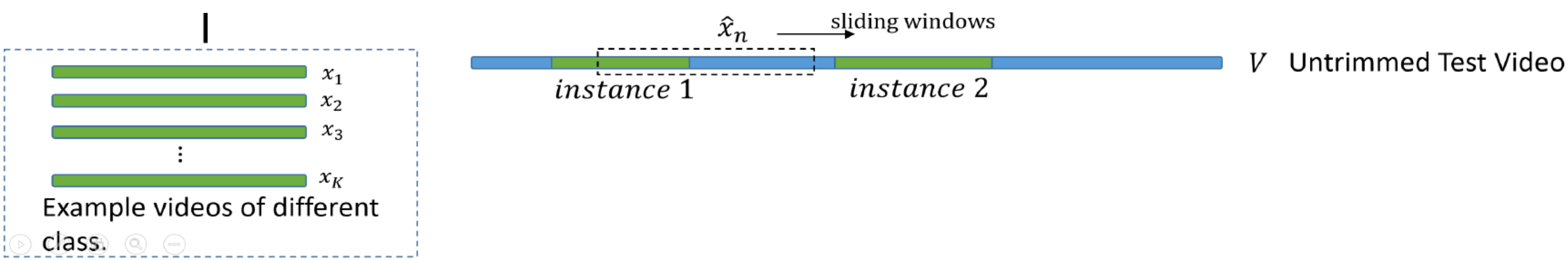


Main ideas

- Meta-learning problem formulation
  - Learning how to transfer the labels of a few action examples to a test video
    - Encode action instance into a structured representation
    - Learn to match (partial) action instances
    - Exploit the matching correlation scores



Overview of our method



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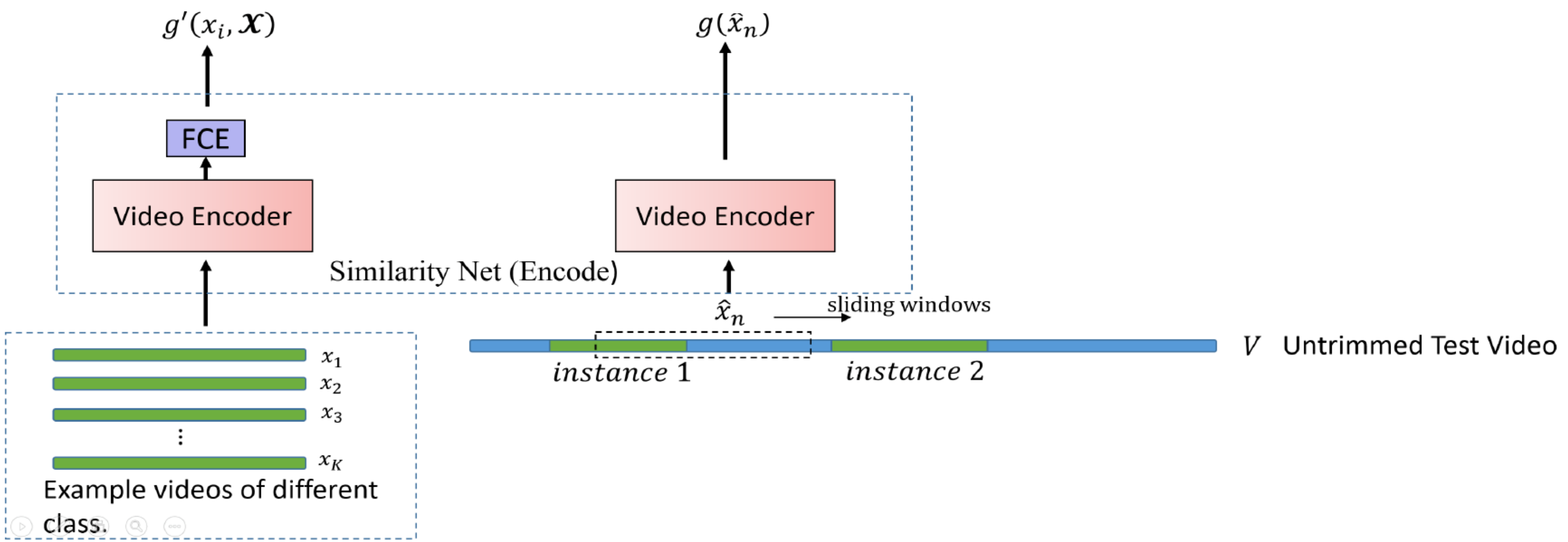

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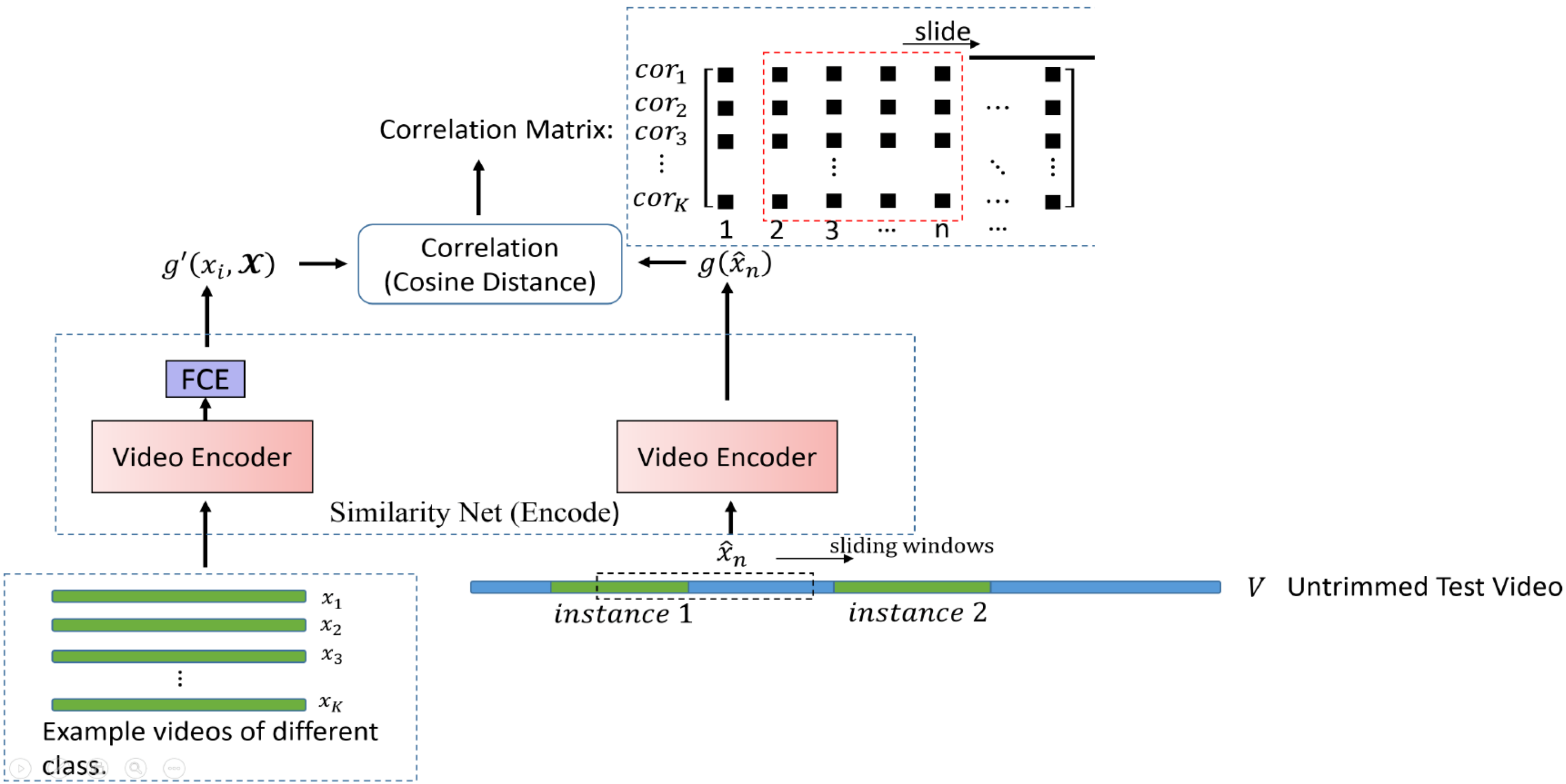

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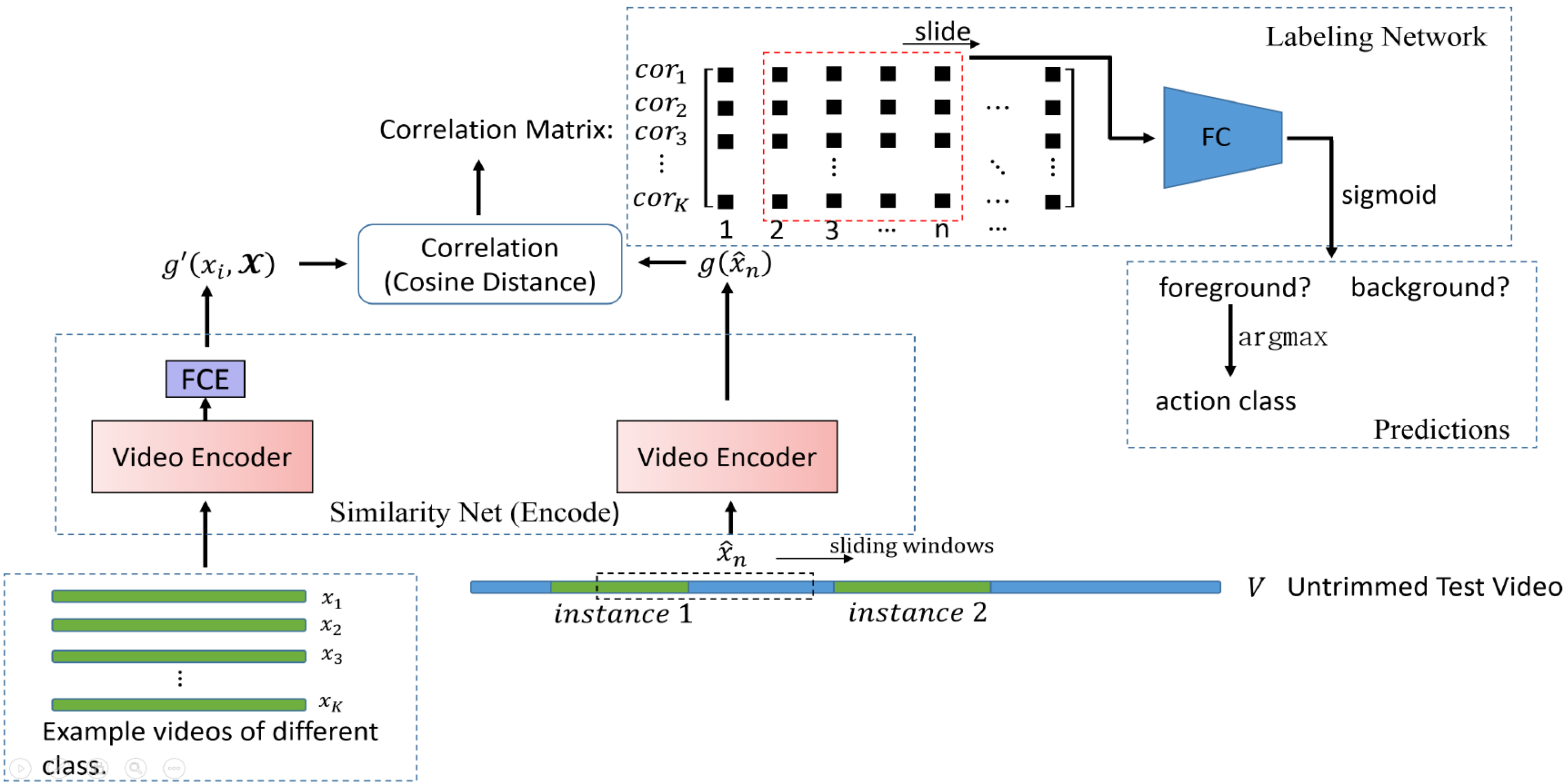
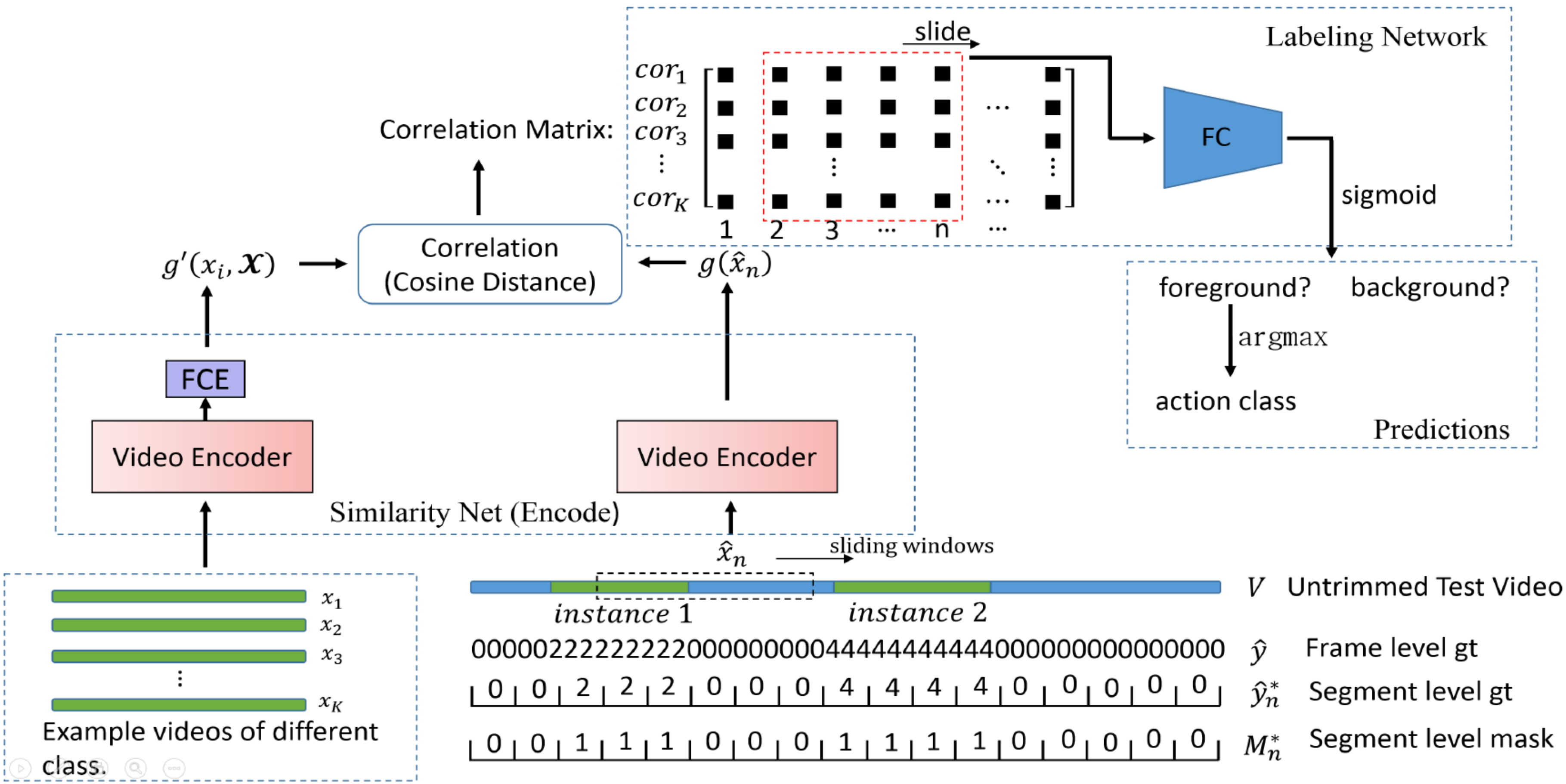
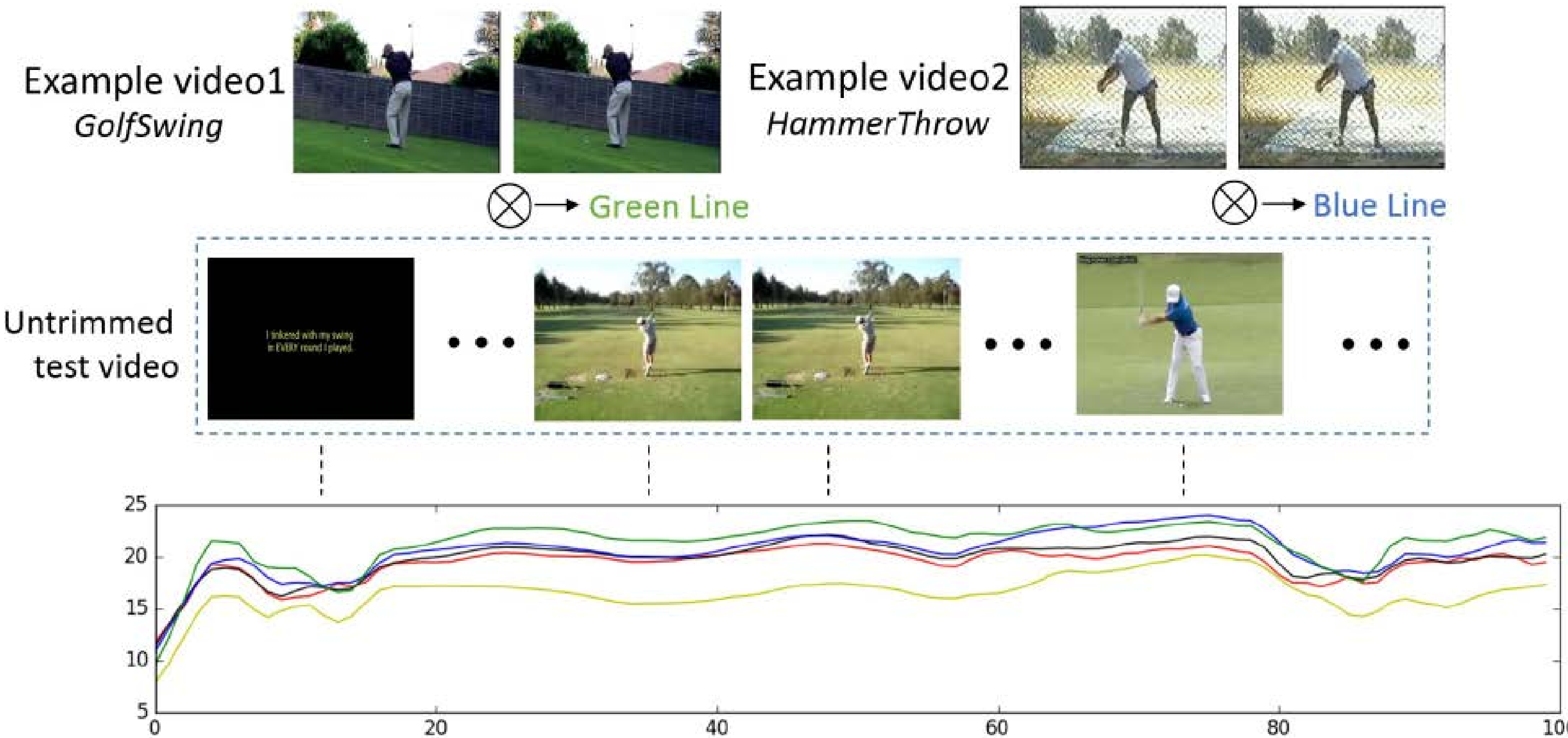


Overview of our method



Matching examples



Matching score trajectories

Meta-learning strategy

- Meta-training phase
  - Meta-training set $\mathcal{T}_{meta-train} = \{\mathcal{X}, \hat{\mathcal{X}}, \mathcal{L}(\mathcal{X}, \hat{\mathcal{X}}, \theta)\}$
  - Task-train (support set) $\mathcal{X} = \{x_i, y_i\}$
  - Task-test (query) $\hat{\mathcal{X}} = \{\hat{x}_j, \hat{y}_j\}$
  - Loss function $\mathcal{L}$
- Our loss function
  - Localization loss: foreground vs background (cross entropy)
  - Classification loss: action class (log loss)

$$L = \mathbb{E}_{\mathcal{T} \sim \mathcal{T}_{meta-train}}[L_{loc} + L_{cls}]$$

  - Ranking loss: replacing localization loss to encourage partial alignment

Experimental evaluation

- Few-shot performance summary
  - ~80 classes for meta-training and ~20 for meta-test

Fully supervised	mAP	Few-shot	mAP
Heilbron *et al.* [5]	13.5	Ours@1	13.6
Yeung *et al.* [49]	17.1	Ours@5	14.0
Yuan *et al.* [50]	17.8	Ours@15	14.7
S-CNN [35]	19.0	CDC@1	6.4
S-CNN + SST [4]	23.0	CDC@5	6.5
CDC [34]	23.3	CDC@15	6.8

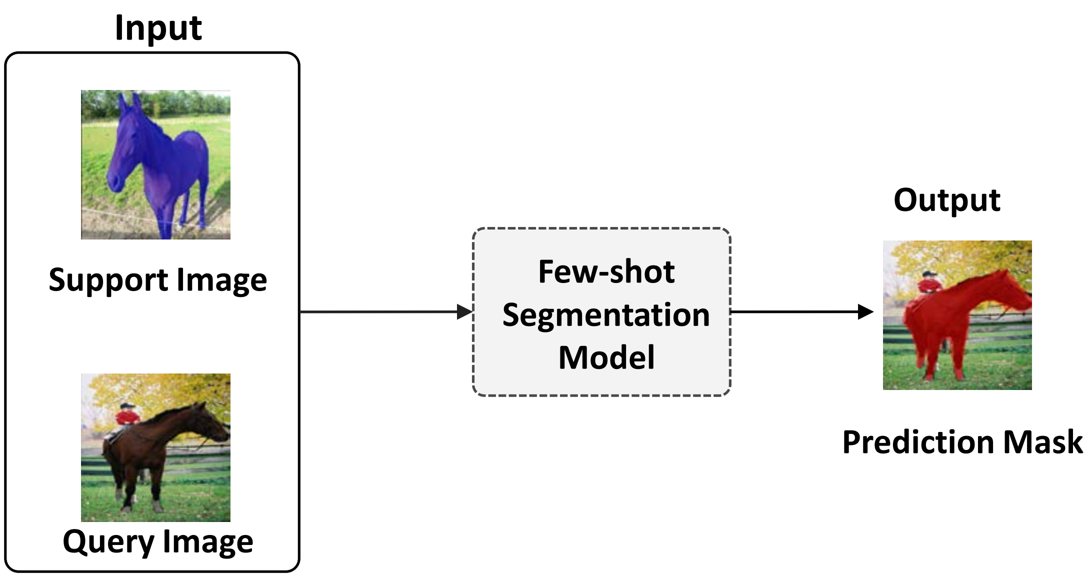
Thumos14

	mAP@0.5	Average mAP
TCN [8]	37.4	23.5
R-C3D [48]	-	26.8
Wang *et al.* [26]	42.2	14.8
Lin *et al.* [27]	48.9	32.2
Xiong *et al.* [47]	41.1	24.8
CDC [34]	43.8	22.7
Ours@1	22.3	9.8
Ours@5	23.1	10.0
CDC@1	8.2	2.4
CDC@5	8.6	2.5

ActivityNet

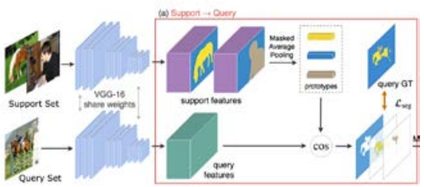
Problem Definition

- Few-shot semantic segmentation aims to segment **new** semantic objects in an image with only **a few annotated examples**.



Related Works

Prototype-Based Algorithm:



Wang et al. *ICCV19*
Dong et al. *BMVC18*

- Hard to model object's scale and appearance variations
- Easy to saturate with multi-shots

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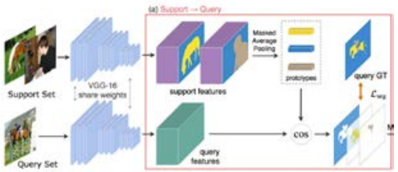
Related Works

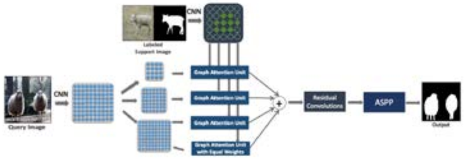
Prototype-Based Algorithm:



Wang et al. *ICCV19*
Dong et al. *BMVC18*

- Hard to model object's scale and appearance variations
- Easy to saturate with multi-shots

Parametric-Based Algorithm:



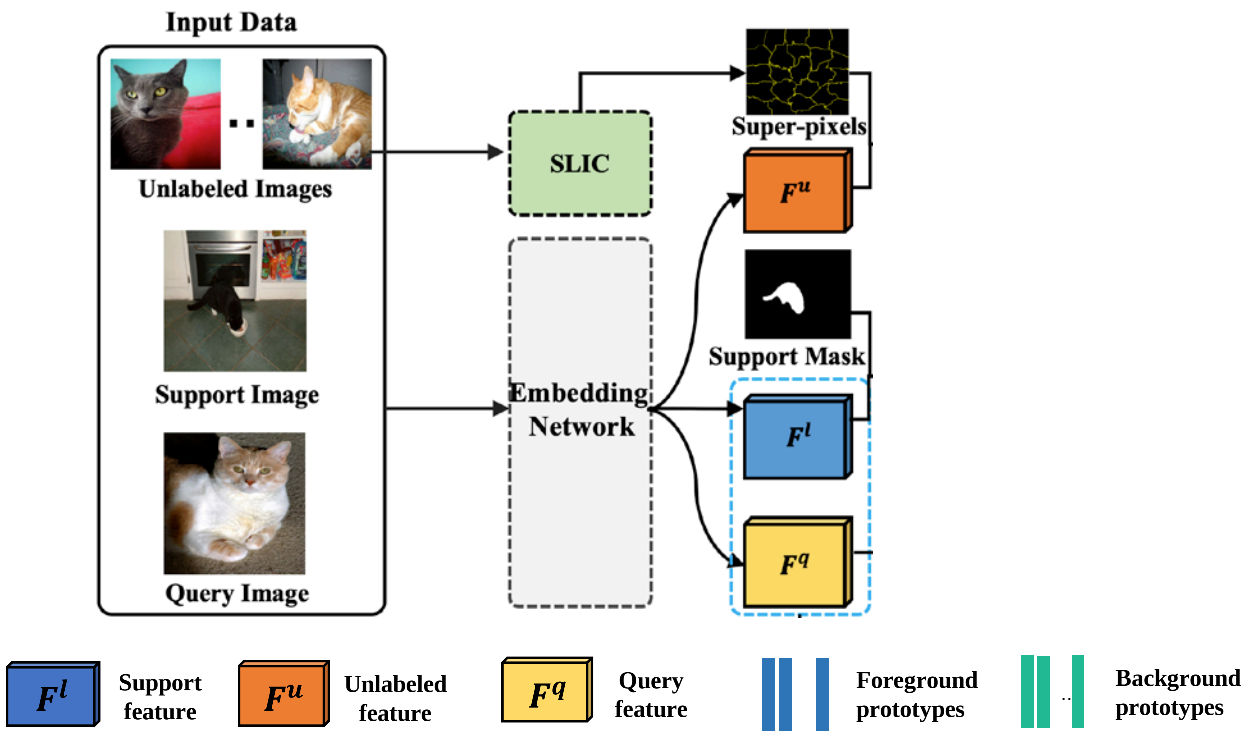
Zhang et al. *ICCV19*
Zhang et al. *CVPR19*

- Hard to adapt to multi-way few shot segmentation
- High model complexity

Challenges

Challenges	Our solutions
Global prototype representation lacks detailed information of novel objects.	Part-based prototype representation reserves more detailed information.
Large appearance & scale variation between support and query images.	Utilize the unlabeled images to handle variations.
Less effective to learn a good visual representation for segmentation.	Add semantic branch to learn a better visual representation.

Method



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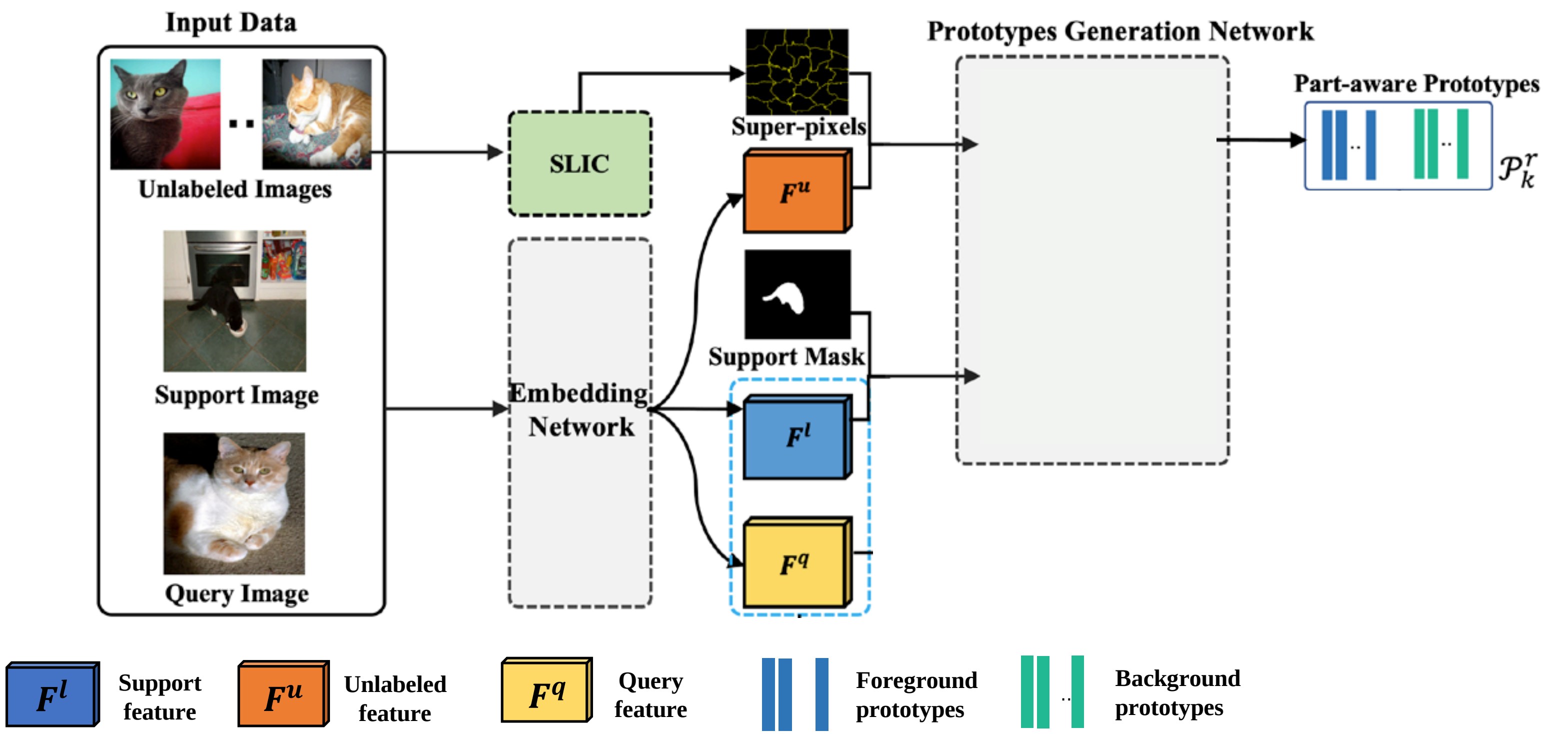
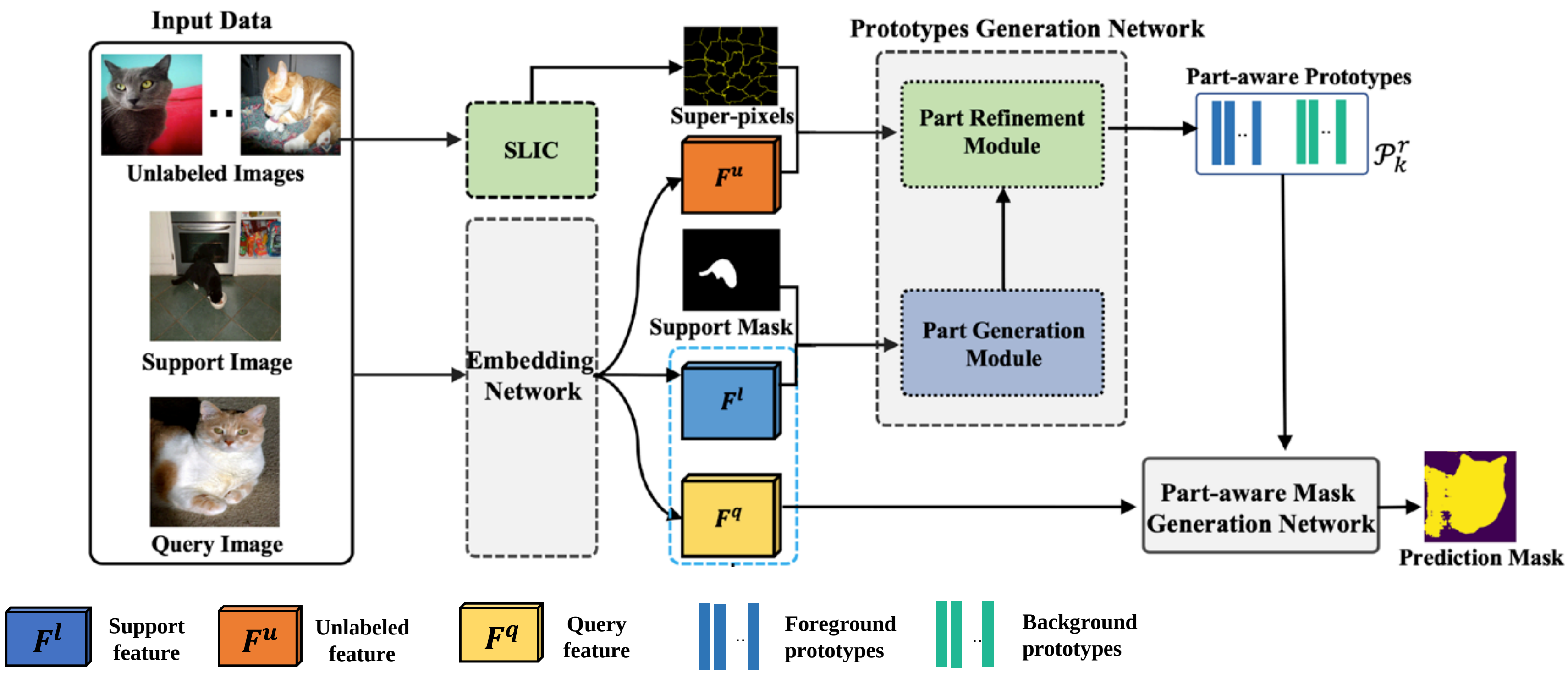
Method



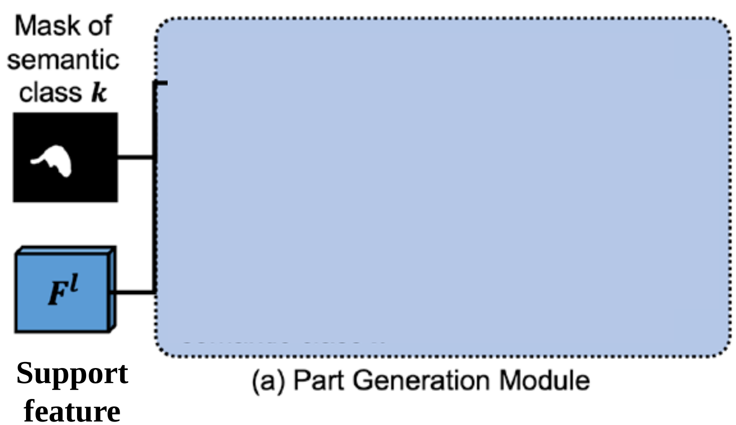
Input Data
Unlabeled Images
Support Image
Query Image
SLIC
Embedding Network
Super-pixels
F^u
Support Mask
F^l
F^q
Prototypes Generation Network
Part-aware Prototypes
$\mathcal{P}_k^r$
F^l
Support feature
F^u
Unlabeled feature
F^q
Query feature
Foreground prototypes
Background prototypes

Method


Input Data
Unlabeled Images
Support Image
Query Image
SLIC
Embedding Network
Super-pixels
F^u
Support Mask
F^l
F^q
Prototypes Generation Network
Part Refinement Module
Part Generation Module
Part-aware Prototypes
$\mathcal{P}_k^r$
Part-aware Mask Generation Network
Prediction Mask
F^l Support feature
F^u Unlabeled feature
F^q Query feature
Foreground prototypes
Background prototypes

Method

Part Generation Module



(a) Part Generation Module

Part Generation Module aims to generate **the initial part-aware prototypes** on support images.

- Build a set of part-aware prototypes to capture **fine-grained part-level variation.**
- Further augment each initial prototype with a **global context** of the semantic class.

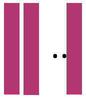
Method

Part Refinement Module

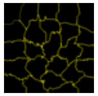
(b) Part Refinement Module

Part Refinement Module **further improve** part-aware prototypes representation with unlabeled images features.

Unlabeled image feature



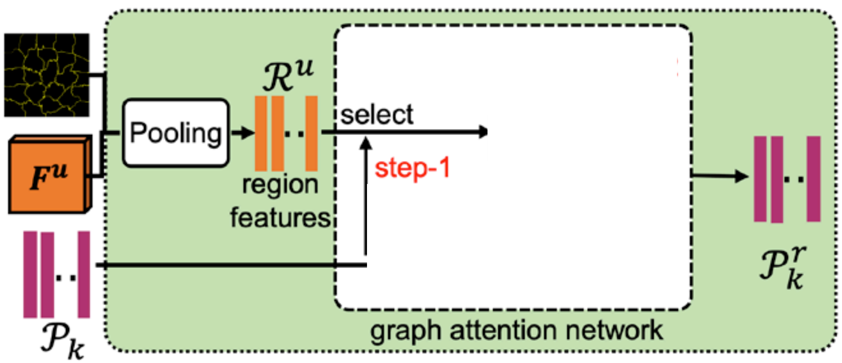
$\mathcal{P}_k$: part-aware prototypes



Unlabeled image superpixel

Method

Part Refinement Module

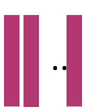


(b) Part Refinement Module

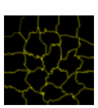
Part Refinement Module **further improve** part-aware prototypes representation with unlabeled images features.

Step-1: Relevant feature generation.

Unlabeled image feature



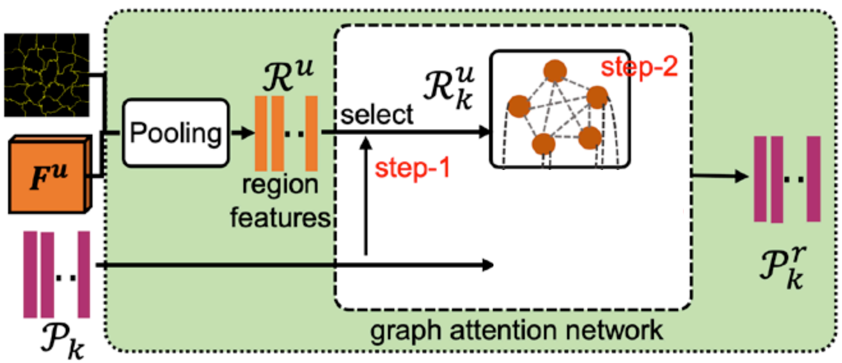
$\mathcal{P}_k$: part-aware prototypes



Unlabeled image superpixel

Method

Part Refinement Module



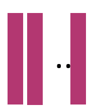
(b) Part Refinement Module

Part Refinement Module **further improve** part-aware prototypes representation with unlabeled images features.

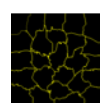
Step-1: Relevant feature generation.

Step-2: Unlabeled feature augmentation.

Unlabeled image feature



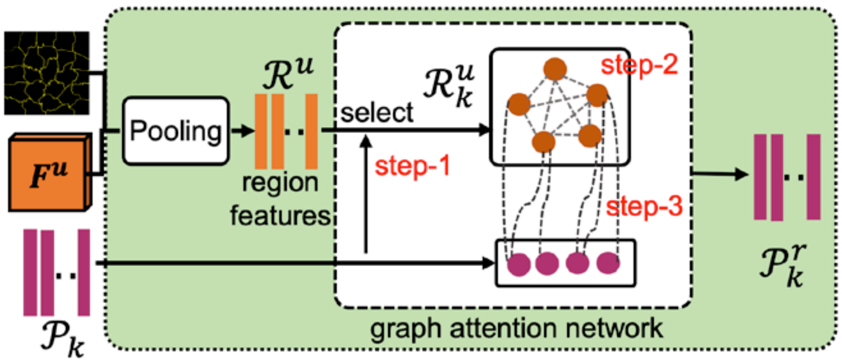
$\mathcal{P}_k$: part-aware prototypes



Unlabeled image superpixel

Method

Part Refinement Module



(b) Part Refinement Module

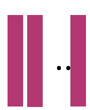
Part Refinement Module **further improve** part-aware prototypes representation with unlabeled images features.

Step-1: Relevant feature generation.

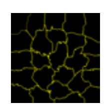
Step-2: Unlabeled feature augmentation.

Step-3: Part-aware prototype refinement.

Unlabeled image feature

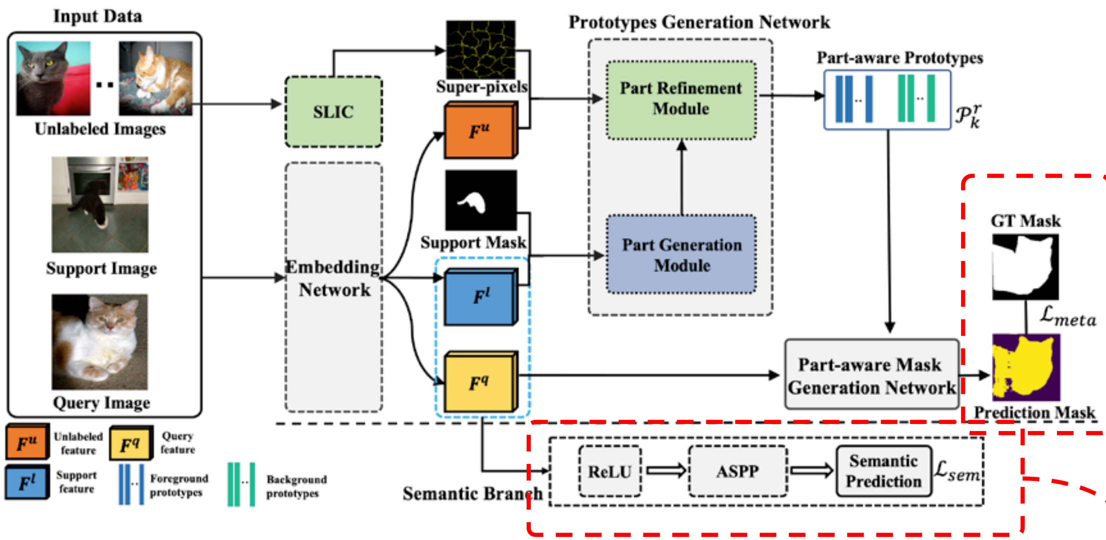


$\mathcal{P}_k$: part-aware prototypes



Unlabeled image superpixel

Model Learning



① $$\boldsymbol{L_{meta}} = \boldsymbol{L_{ce}}(\hat{Y}^q, Y^q) + \boldsymbol{L_{ce}}(\hat{Y}^l, Y^l)$$

- Y^q, Y^l are ground-truth mask.

② $$\boldsymbol{L_{sem}} = \boldsymbol{L_{ce}}(\hat{Y}^q_{sem}, Y^q_{sem}) + \boldsymbol{L_{ce}}(\hat{Y}^l_{sem}, Y^l_{sem})$$

- Y^q_{sem}, Y^l_{sem} are ground-truth mask over global semantic classes.

$$\boldsymbol{L_{full}} = \boldsymbol{L_{meta}} + \boldsymbol{\beta L_{sem}}$$

Results

COCO-20^i Performance (1-way)

Methods	Split	Backbone	1-shot fold-1	1-shot fold-2	1-shot fold-3	1-shot fold-4	1-shot mean	5-Shot fold-1	5-Shot fold-2	5-Shot fold-3	5-Shot fold-4	5-Shot mean
PANet [34]	A	VGG16	28.70	21.20	19.10	14.80	20.90	39.43	28.30	28.20	22.70	29.70
PANet* [34]	A	RN50	31.50	22.58	21.50	16.20	22.95	45.85	29.15	30.59	29.59	33.80
Our(**w/o** $\mathcal{S}^u$)	A	RN50	34.53	25.44	24.33	18.57	25.71	48.30	30.90	35.65	30.20	36.24
Our	A	RN50	**36.48**	**26.53**	**25.99**	**19.65**	**27.16**	**48.88**	**31.36**	**36.02**	**30.64**	**36.73**
FWB [21]	B	RN101	16.98	17.78	20.96	**28.85**	21.19	19.13	21.46	23.39	30.08	23.05
Our	B	RN50	**28.09**	**30.84**	**29.49**	27.70	**29.03**	**38.97**	**40.81**	**37.07**	**37.28**	**38.53**

Split A +4.21 +2.93

Split B +7.84 +15.48

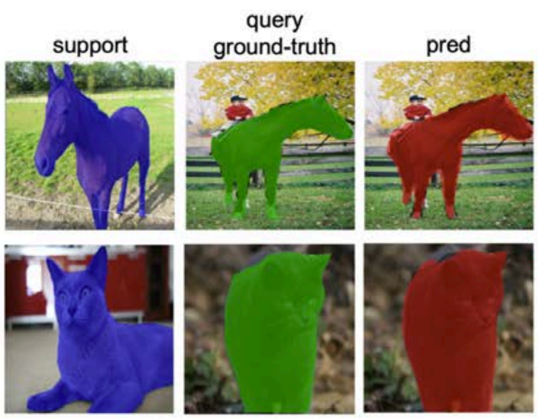
COCO-20^i Performance (2-way & 5-way)

Methods	Backbone	2-way, 1-shot fold-1	fold-2	fold-3	fold-4	mean	5-way, 1-shot fold-1	fold-2	fold-3	fold-4	mean
PANet [34]	VGG16	29.88	21.13	20.46	15.37	21.71	24.94	19.85	19.28	14.11	19.55
PANet* [34]	RN50	31.86	21.47	21.31	16.43	22.76	27.20	21.50	19.66	15.35	20.93
PPNet(**w/o** $\mathcal{S}^u$)	RN50	33.87	23.98	22.75	17.59	24.55	29.12	22.29	21.10	16.37	22.22
PPNet	RN50	**34.20**	**24.21**	**23.39**	**19.06**	**25.22**	**30.84**	**23.03**	**21.32**	**17.93**	**23.28**

+2.46 +2.35

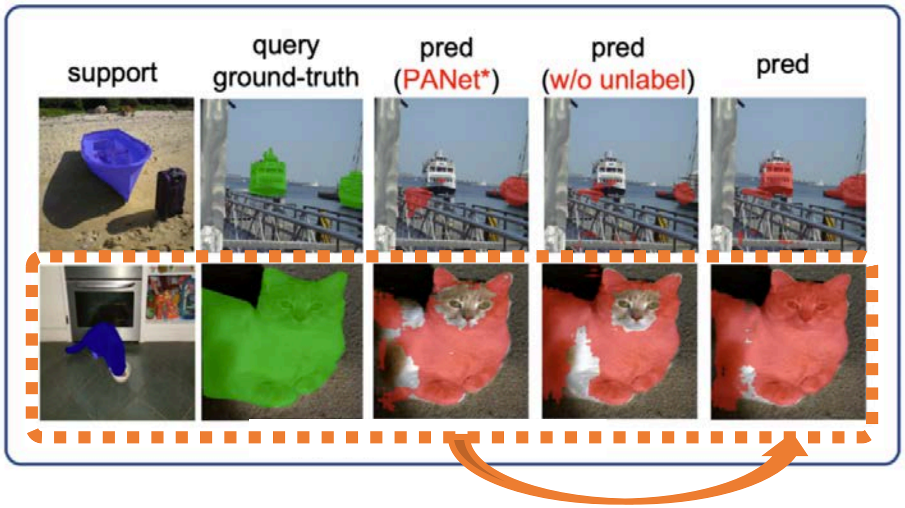
Visualization

Part visualization on Pascal 5^i (1-way)

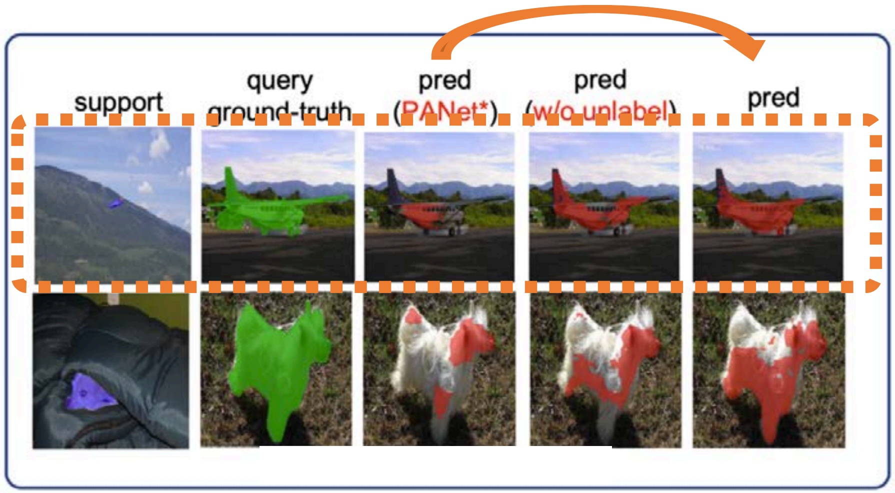


Visualization

Qualitative Visualization by utilizing unlabeled data on Pascal 5^i visualization (1-way)



Appearance Variations



Scale Variations