Paper Reading

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Paper

MetaView: Few-shot Active Object Recognition

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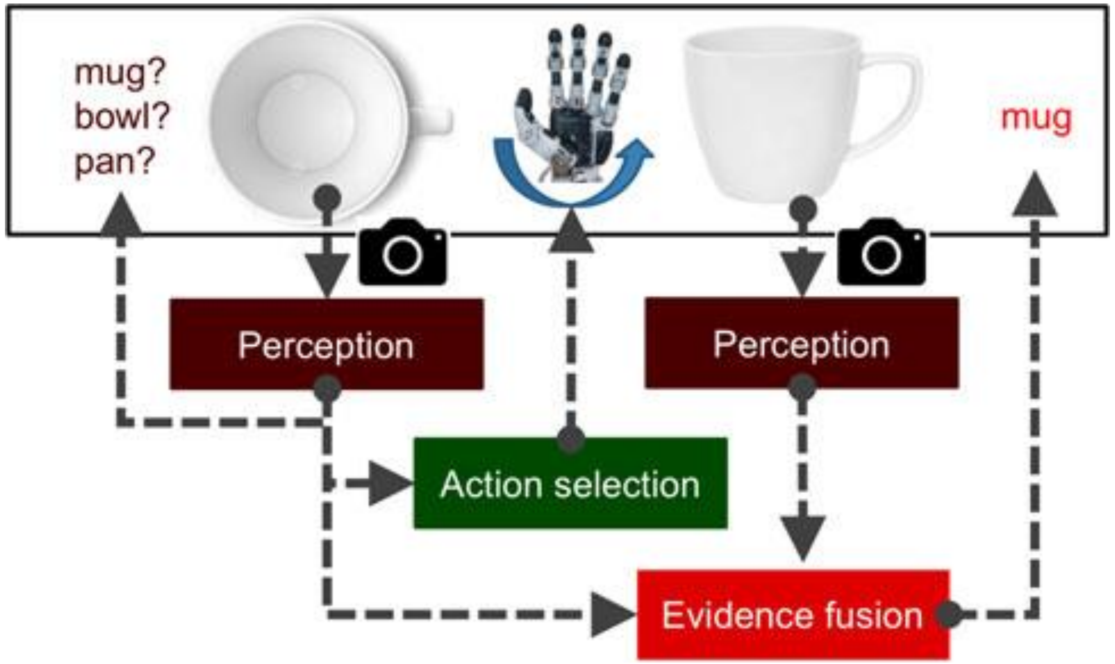
Key words: few-shot learning, active object recognition(AOR)

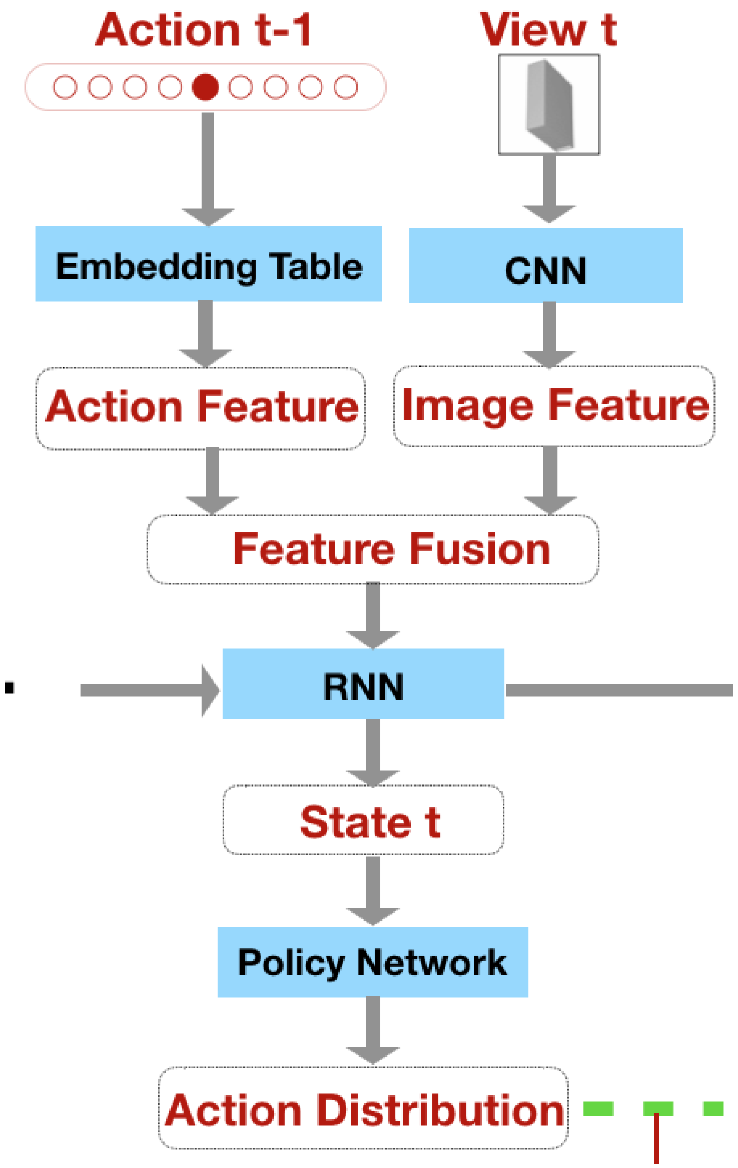
01

Why this paper?

1.1 Standard framework of AOR

Reinforcement Learning





(1) Select **camera moving strategy** with viewing history

(2) Use **RNN** to aggregate visual and action information

(3) Use aggregated information for **classification**

1.2 Comparison with previous works

Previous works	MetaView
rely on a massive amount of training data	learn view selection policies from **few samples**
testing categories have to be seen during training	recognize **new categories** in testing with few samples
category-level recognition: many training samples for each label	**instance-level** recognition: one training sample for each label

New problem of few-shot AOR: learning a way to learn from few-shot samples of new categories, rather than just learning to recognize.

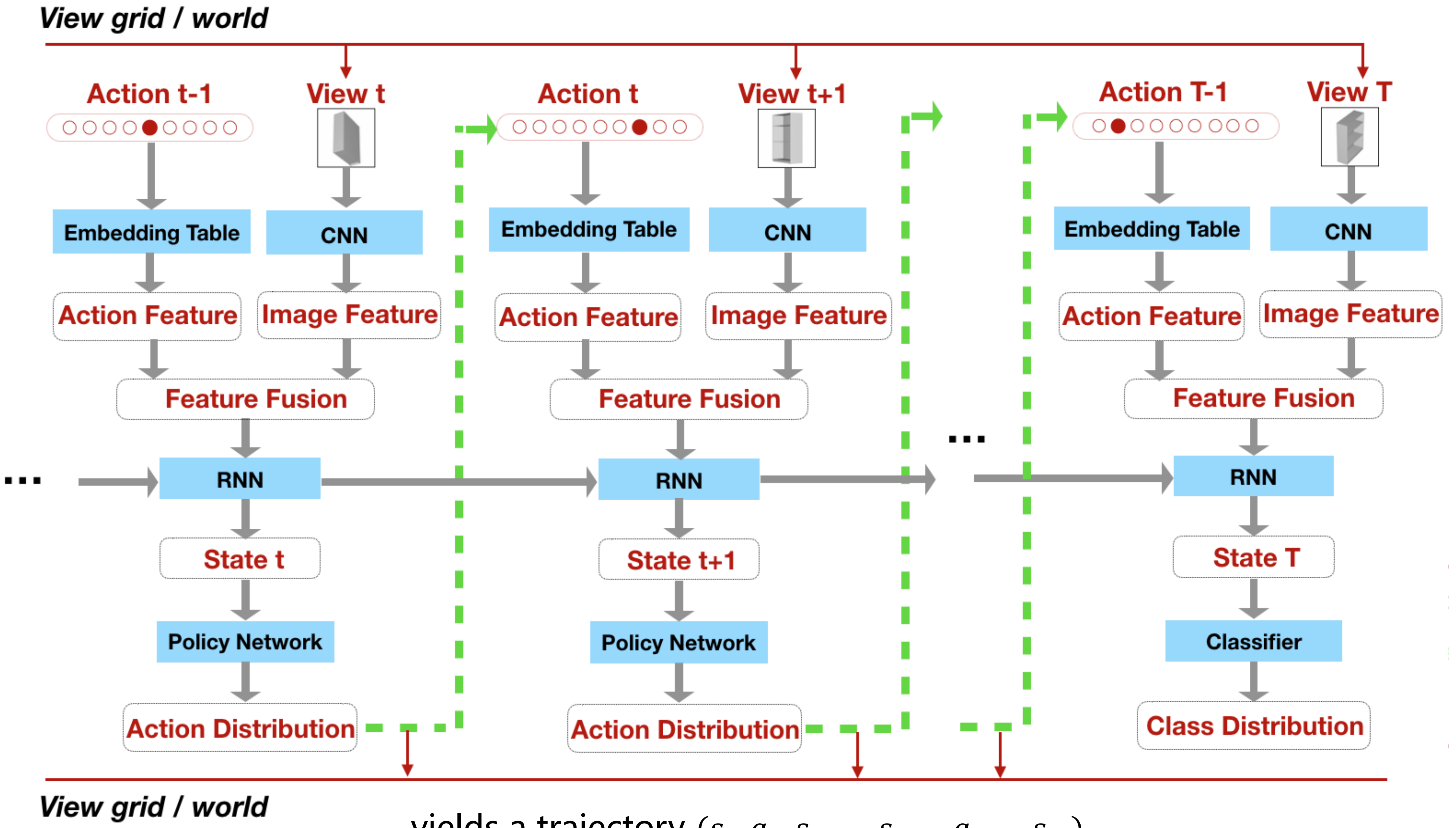
-> **Meta Learning**

02

Approaches of MetaView

2.1 AOR system – Pipeline

For a single object: **feed forward** process



yields a trajectory $(s_1, a_1, s_2, \ldots, s_{T-1}, a_{T-1}, s_T)$

2.1 AOR system – loss function

$$\boxed{\mathcal{L} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{policy} + \lambda_2 \mathcal{L}_{ent}}$$

- Classification loss: cross entropy between output and label y

$$\mathcal{L}_{cls} = -\sum_{c=1}^{C} y_c \log(f(s_T)_c)$$

- Policy loss: (REINFORCE algorithm) the sum of log action probabilities weighted by negative rewards, averaged over time steps

$$\mathcal{L}_{policy} = -\frac{1}{T-1}\sum_{t=1}^{T-1} \log \pi(a_t|s_t)R$$

- Entropy loss: minimize the negative policy entropy = maximize the entropy of action distribution (in order to encourage exploration)

$$\mathcal{L}_{ent} = \frac{1}{T-1}\sum_{t=1}^{T-1} \pi(a_t|s_t)\log \pi(a_t|s_t)$$

2.2 Few shot – Meta Learning

N-ways: N categories in training data
K-shot: K samples in each category

	Machine Learning	**Model-agnostic Meta-learning (MAML)**
Training unit	data	(1) N-way-K-shot tasks (2) data
Division	training, validation and test **dataset**	training, validation and testing **tasks** ※ Each task has its own training dataset (support set) and test dataset (query set)
Purpose	Find a mapping *f* between feature and labels	Output a function *f* that can be applied to a new task

2.2 Few shot – updating parameters in meta learning

- Meta-learning process can be divided into META-TRAIN, META-VALIDATION and META-TEST phases, in each of which several tasks are sampled.
- For each task T_i sampled from task distribution $P(T)$:

- Support set S_i: adapts θ via a single step of gradient descent,

$$\theta_i \leftarrow \theta - \alpha \nabla_\theta L_{S_i}(\theta)$$

$L_{S_i}(\theta)$ = average of the single object losses L over S_i

$$\mathscr{L} = \mathscr{L}_{cls} + \lambda_1 \mathscr{L}_{policy} + \lambda_2 \mathscr{L}_{ent}$$

- Query set Q_i: evaluates θ_i and produce query set loss $L_{Q_i}(\theta_i)$.

- After sampling a number of tasks for each epoch, $L_{Q_i}(\theta_i)$ are averaged together to actually update θ:

$$\theta \leftarrow \theta - \beta \nabla_\theta \mathbb{E}_{T_i \sim P(T)}[L_{Q_i}(\theta_i)]$$

03

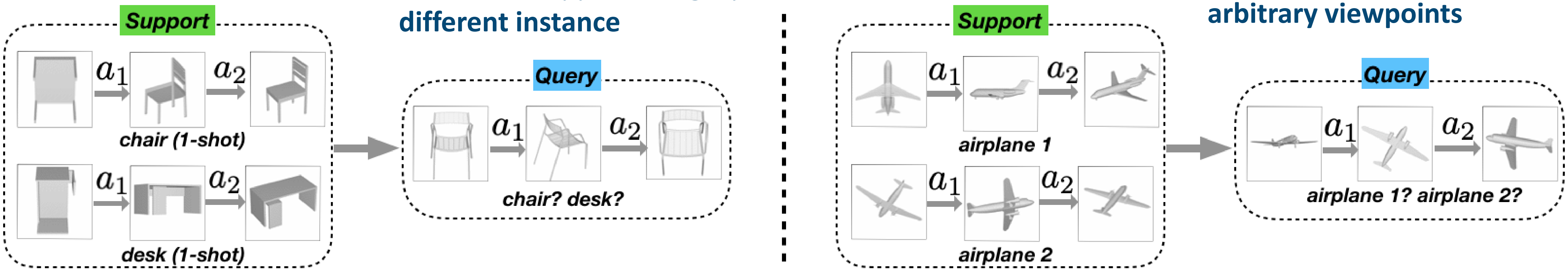
Experiments

3. Two kinds of experiments

- MetaView can solve both kind of recognition:

one of the support category, **different instance**

one of the support instances, **arbitrary viewpoints**

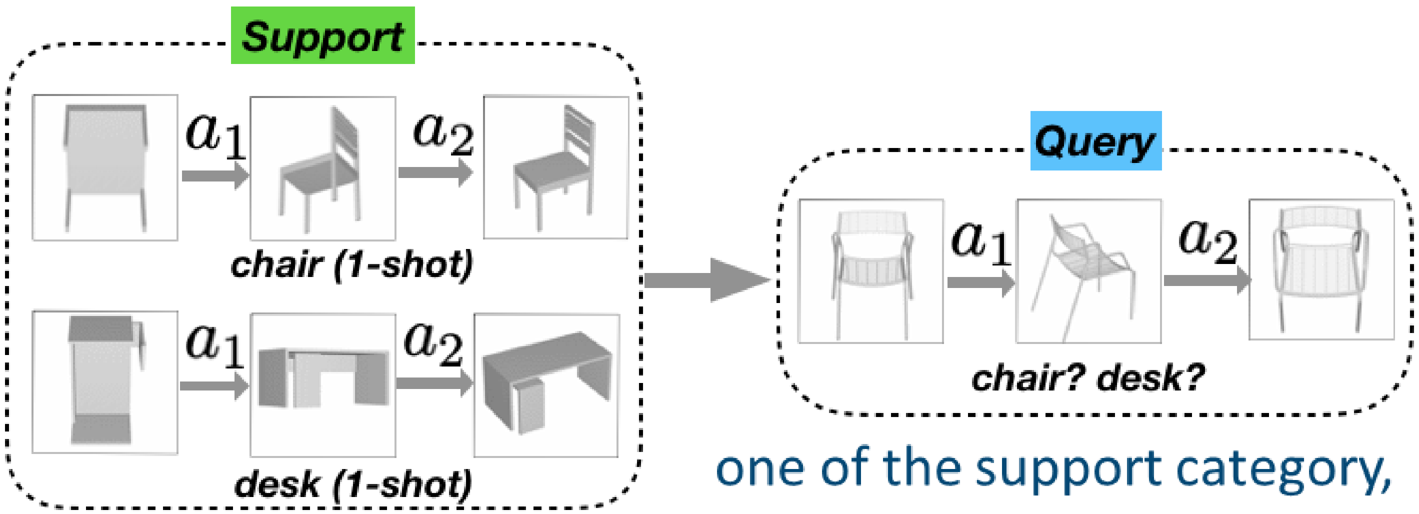


(a) Category-level Recognition.

(b) Instance-level Recognition.

- Support phase: view each sample for a limited budget to learn new category/instance
- Query phase: given the same budget, predict the label of a new sample which is belonging to one of the categories/instances in Support phase.

3.1 Category-level



one of the support category,
different instance

(a) Category-level Recognition.

- Aim: classify different categories with only few training sample.
- Dataset: ModelNet40

  (24 for META-TRAIN, 6 for META-VALIDATION and 10 for META-TEST)
- Set of tasks: 5-way-1-shot and 5-way-5-shot

  5-class-1-instance and 5-class-5-instance

3.1 Category-level

TABLE I: Category-level classification accuracy in METATEST

Method	*5way-1shot*	*5way-5shot*
LookAhead [13] (T=3)	38.67%	57.33%
RandomOneView (T=1)	43.84%	54.44%
RandomMultiView (T=3)	50.67%	70.42%
LargestMultiView (T=3)	53.59%	68.76%
MetaView (T=3)	**59.77%**	**74.54%**

- simply fine-tune the existing AOR method (trained by massive data) on few-shot performed badly
- view selection policy can be trained to improve performance

- Baselines:

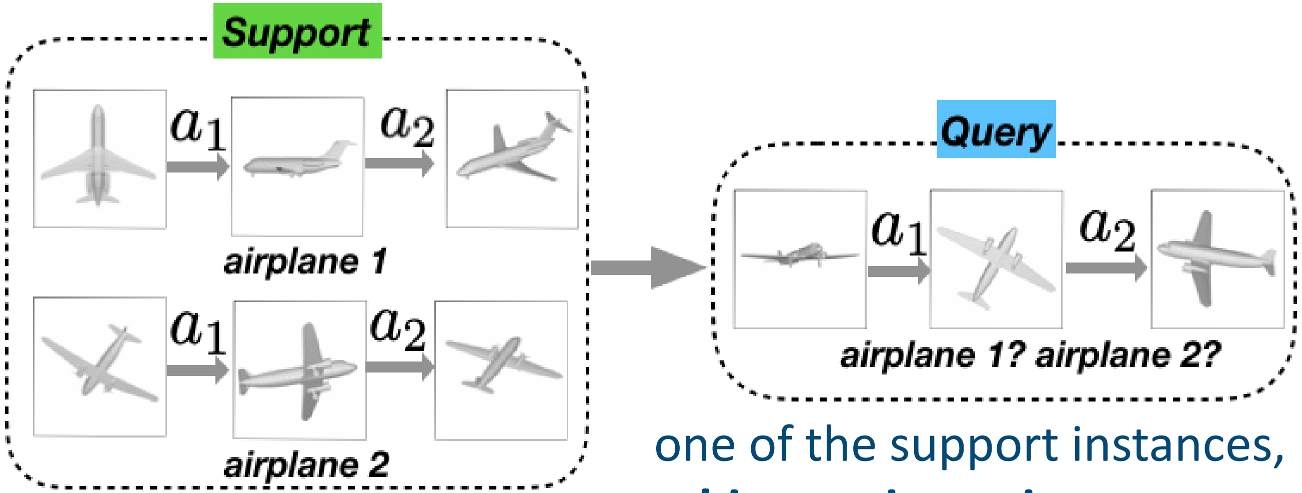
(1) LookAhead: state-of-the-art of AOR, fine-tuned and evaluated in META-TEST

(2) RandomOneView: meta-learning baseline, only use initial randomized view(T=1)

(3) RandomMultiView: use non-learnable random view selection policy

(4) LargestMultiView: chooses the largest allowable action every time

3.2 Instance-level - Intra-category Learning



one of the support instances,
arbitrary viewpoints

(b) Instance-level Recognition.

- Aim: few-shot learning for recognizing new instances within one category
- Dataset: airplane instances from ModelNet40

  (400 for META-TRAIN, 126 for META-VALIDATION and 200 for META-TEST)
- Set of tasks: 5-way-1-shot and 10-way-1-shot

  5-instance and 10 instance

3.2 Instance-level - Intra-category Learning

Fig3. Accuracy curves of intra-category learning

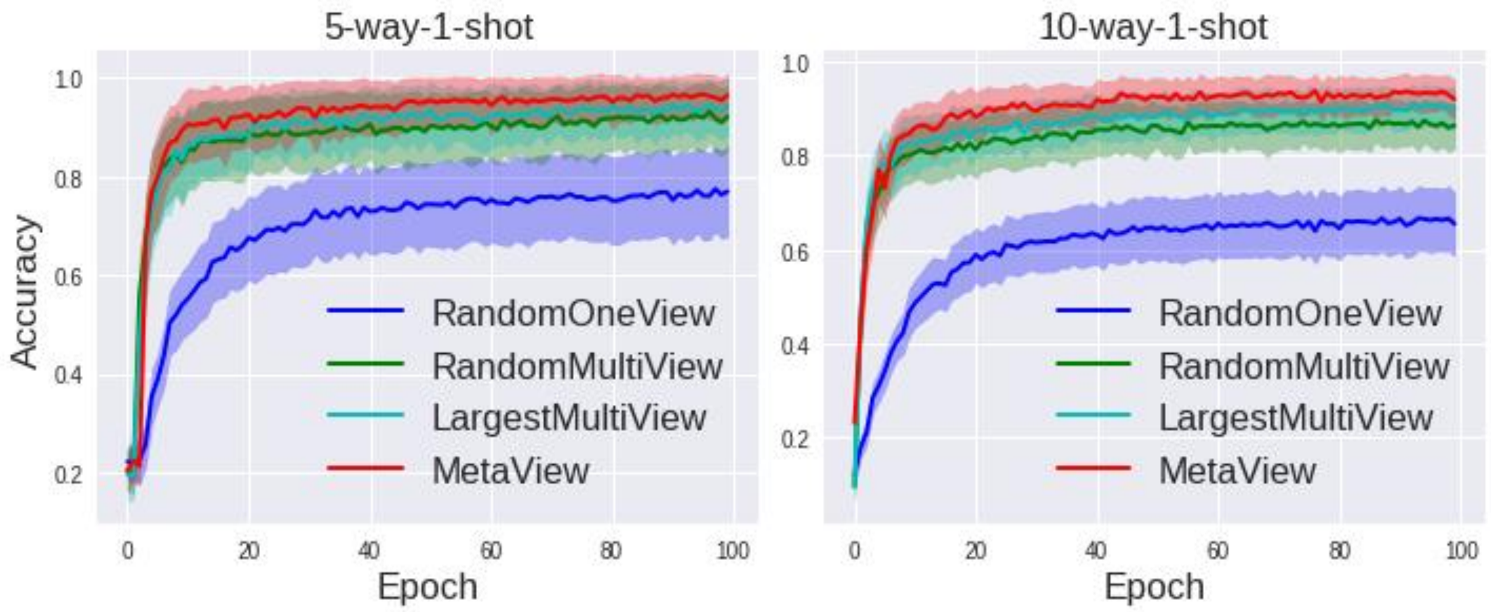


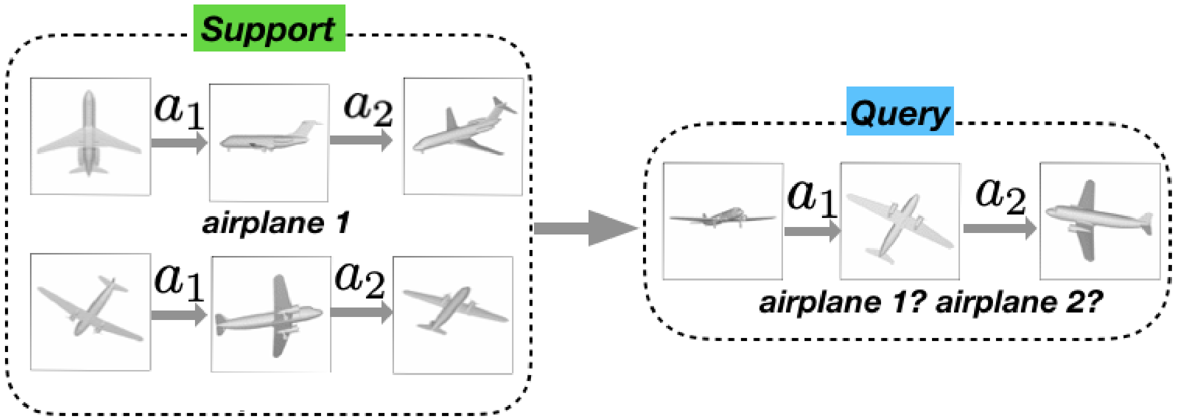
TABLE II: METATEST accuracy of intra-category learning

Task	*5-way-1-shot*	*10-way-1-shot*
RandomOneView (T=1)	75.24%	65.32%
RandomMultiView (T=3)	91.32%	85.10%
LargestMultiView (T=3)	93.03%	88.03%
MetaView (T=3)	**94.65%**	**91.73%**

- MetaView boosts the recognition accuracy even over other two high baselines which do not train policies
- Performance of Random-OneView is worse -> multiple views are necessary for better recognition

3.2 Instance-level - Inter-category Learning

META-TRAIN with airplane -> META-TEST with other category



- For each task, first sample one category, then sample instances.
- Support sets and Query sets contain the same instance, but the initial views are different

- <u>Aim</u>: whether can recognize instances of category A while only trained on instances of category B from few shots
- <u>Dataset</u>: ModelNet40 (not only airplane)

  (24 for META-TRAIN, 6 for META-VALIDATION and 10 for META-TEST)
- <u>Set of tasks</u>: 5-way-1-shot

  5-instance

3.2 Instance-level - Inter-category Learning

Fig4. Training curves for inter-category learning

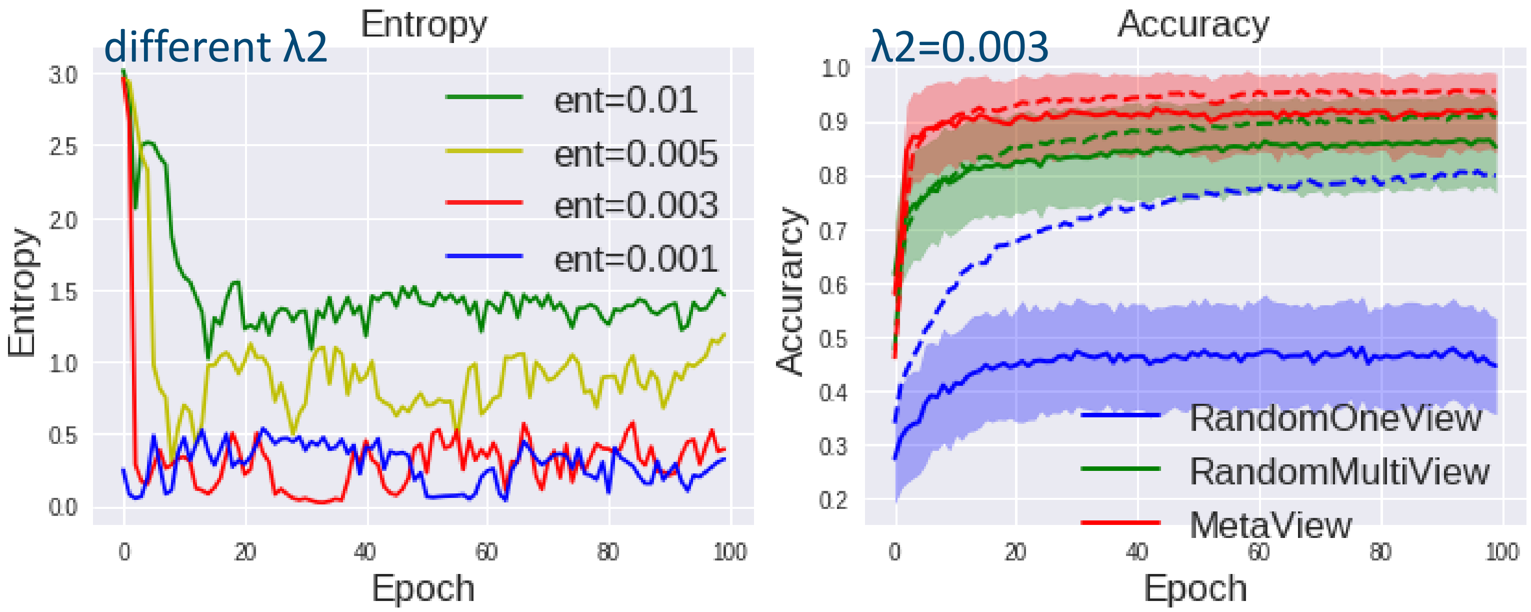


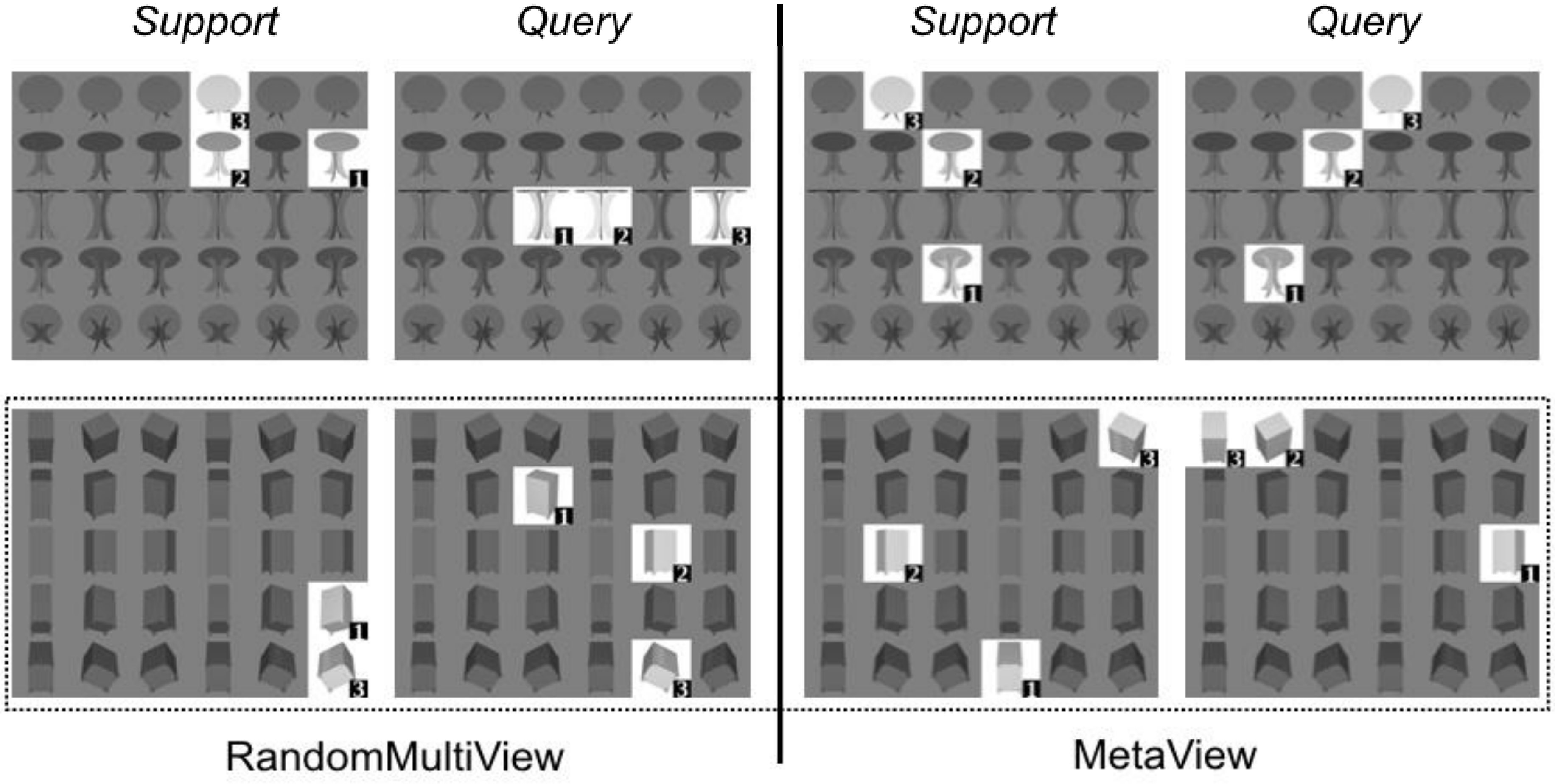
TABLE III: METATEST accuracy for inter-category learning

Task	*5-way-1-shot*
RandomOneView (T=1)	60.32%
RandomMultiView (T=3)	84.09%
LargestmMultiView (T=3)	86.29%
MetaView (T=3,λ_2=0.01)	92.33%
MetaView (T=3,λ_2=0.005)	90.90%
MetaView (T=3,λ_2=0.003)	**92.78%**
MetaView (T=3,λ_2=0.001)	90.55%

- Recognition of unknown category based on trained categories is possible.
- MetaView is better than baselines, regardless of the choice for λ2.
- The best performance appeared in λ2 = 0.003.

$$\mathscr{L} = \mathscr{L}_{cls} + \lambda_1 \mathscr{L}_{policy} + \lambda_2 \mathscr{L}_{ent}$$

3.2 Instance-level - View selection trajectories



30 views for the same instance in Support and Query

-> the learned policy does not always perform well

Meta View

- selected views in Support set: cover more diverse visual appearances
- selected views in paired Query set: (partially) match those in the support set

04

Conclusion

4. Innovation Points

- The proposed method is not novel, but is **the initial trial of few-shot AOR** and may enlighten further research works.
- To summarize, the main contributions of this work are:

1. Presented a new problem of AOR: few-shot learning setting, which can embrace more realistic applications.
2. Verified the performance of few-shot AOR: view selection policy learned from few-shot can boost the recognition accuracy, and trained model has the capability of fast adaptation to new categories.
3. Evaluated the performance in two levels: category-level and instance-level