

# Report about the result of recent experiments

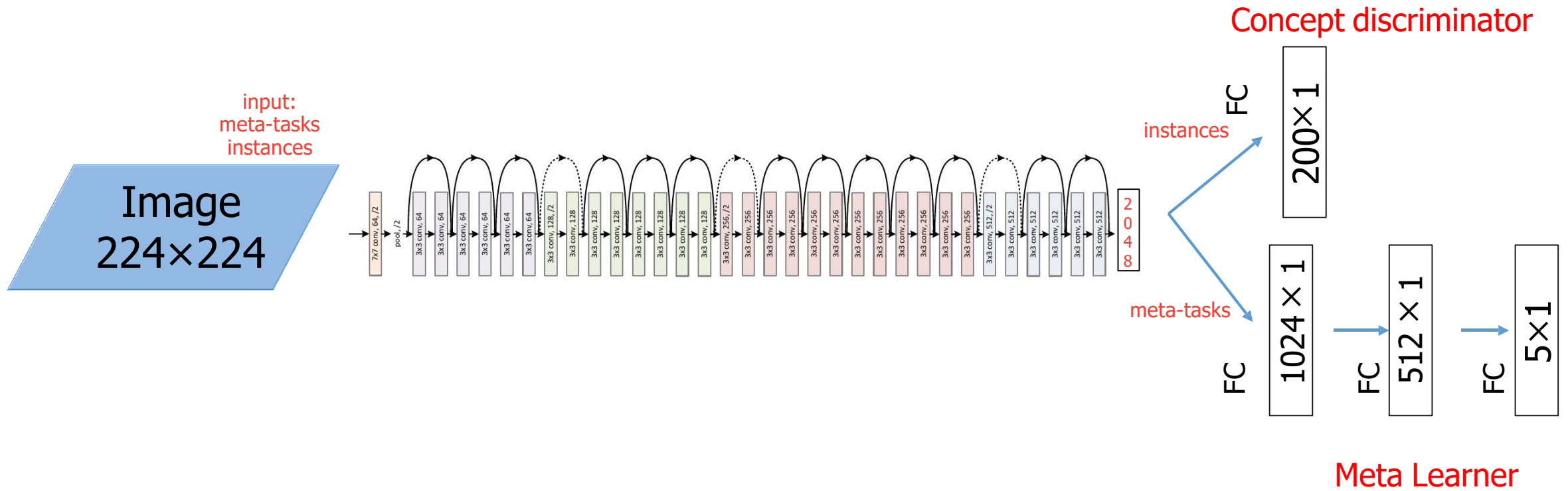
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# Contents

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1. Review of the paper ‘Learning to learn in the concept space’
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# 2. Model structure



# 2. Starting point of the experiment

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## Algorithm 2 Deep Meta-Learning with Meta-SGD

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- 1: **Input:** task distribution  $p(\mathcal{T})$ , labeled dataset  $\mathbb{D}$ , batch size  $n$  of tasks, batch size  $m$  of instances, learning rate  $\beta$
  - 2: **Output:**  $\theta_{\mathcal{G}}, \theta_{\mathcal{D}}, \theta_{\mathcal{M}} = \{\phi, \alpha\}$
  - 3: Initialize  $\theta_{\mathcal{G}}, \theta_{\mathcal{D}}, \phi, \alpha$
  - 4: **while** not done **do**
  - 5:   Sample  $n$  tasks  $\mathcal{T}_i \sim p(\mathcal{T})$  and  $m$  instances  $(\mathbf{x}_j, \mathbf{y}_j) \sim \mathbb{D}$
  - 6:   **for** each  $\mathcal{T}_i$  **do**
  - 7:      $\mathcal{L}_{\text{train}(\mathcal{T}_i)}(\phi, \theta_{\mathcal{G}}) \leftarrow \frac{1}{|\text{train}(\mathcal{T}_i)|} \sum_{(\mathbf{x}, \mathbf{y}) \in \text{train}(\mathcal{T}_i)} \ell(f_{\phi}(\mathcal{G}(\mathbf{x})), \mathbf{y});$
  - 8:      $\phi'_i \leftarrow \phi - \alpha \circ \nabla_{\phi} \mathcal{L}_{\text{train}(\mathcal{T}_i)}(\phi, \theta_{\mathcal{G}});$
  - 9:      $\mathcal{L}_{\text{test}(\mathcal{T}_i)}(\phi'_i, \theta_{\mathcal{G}}) \leftarrow \frac{1}{|\text{test}(\mathcal{T}_i)|} \sum_{(\mathbf{x}, \mathbf{y}) \in \text{test}(\mathcal{T}_i)} \ell(f_{\phi'_i}(\mathcal{G}(\mathbf{x})), \mathbf{y});$
  - 10:   **end for**
  - 11:    $(\theta_{\mathcal{G}}, \theta_{\mathcal{D}}, \phi, \alpha) \leftarrow (\theta_{\mathcal{G}}, \theta_{\mathcal{D}}, \phi, \alpha) - \beta \nabla \left[ \frac{1}{n} \sum_{i=1}^n \mathcal{L}_{\text{test}(\mathcal{T}_i)}(\phi'_i, \theta_{\mathcal{G}}) + \lambda \frac{1}{m} \sum_{j=1}^m \ell(\mathcal{D}(\mathcal{G}(\mathbf{x}_j)), \mathbf{y}_j) \right];$
  - 12: **end while**
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The generator plays a role of prior knowledge, but it learns by using the external dataset and the few-shot image recognition task. The experiment of the paper assume the datasets are similar. However, there is no scrutinizing step to guarantee that. **Will the unrelated dataset contaminate the prior knowledge?**

## 2.How we build the model

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- 1.The model structure is totally the same as shown before coded by PyTorch.
- 2.In order to update the three part of model simultaneously, we calculate and sum up the loss of Discriminator and meta-learner. Backward the grad of Discriminator and meta-learner.
3. In the output layer of Generator, we sum up the grad from Discriminator and meta-learner using parameter  $\lambda$ .
- 4.Modify the grad of Generator and then update the model.

# 3. Datasets

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101 classes of foods



CUB\_200(200 classes of birds)



# 3. Datasets

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1. Just use CUB\_200 meta-learner with the same architecture excluding Discriminator.
2. Selected 200 classes without any animals from ImageNet for Discriminator and CUB\_200 for meta-learner.
3. 101 classes of foods from Kaggle and CUB\_200 for meta-learner.
4. Randomly extracted 200 classes from ImageNet for Discriminator and CUB\_200 for meta-learner.



# Parameters setting

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1.learning-rate:0.001

2.inner-task:4

3.task:5 classes each with 5 samples

4.batch-size for discriminator:64

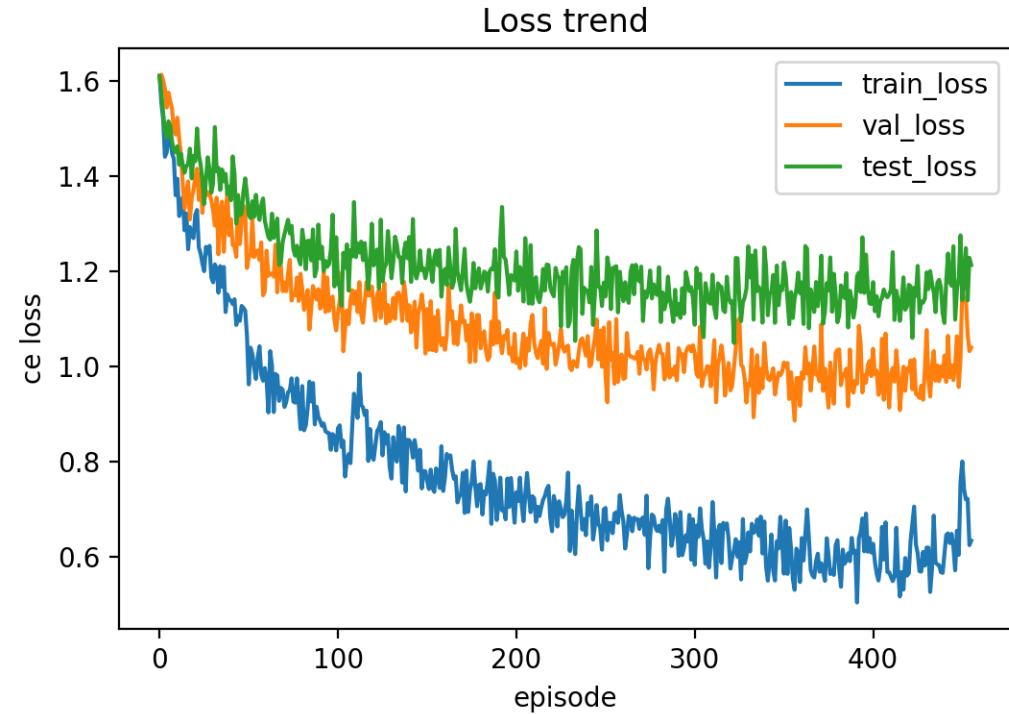
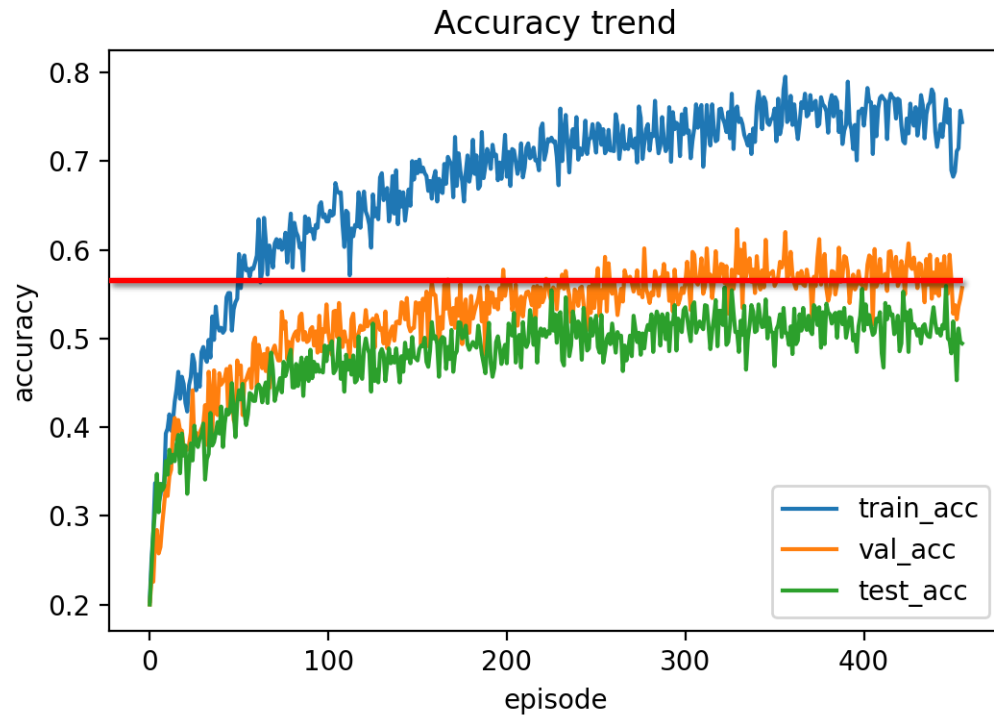
5.learning-rate decay:5000 epochs decay 50%

6. $\lambda$  :1

7.epochs:30000

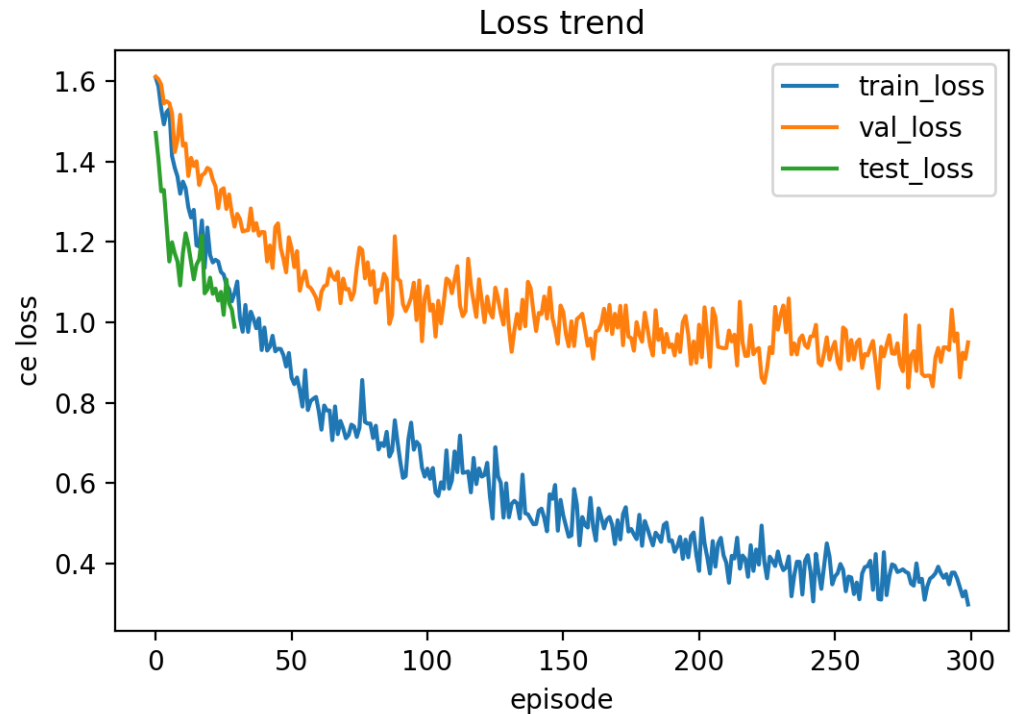
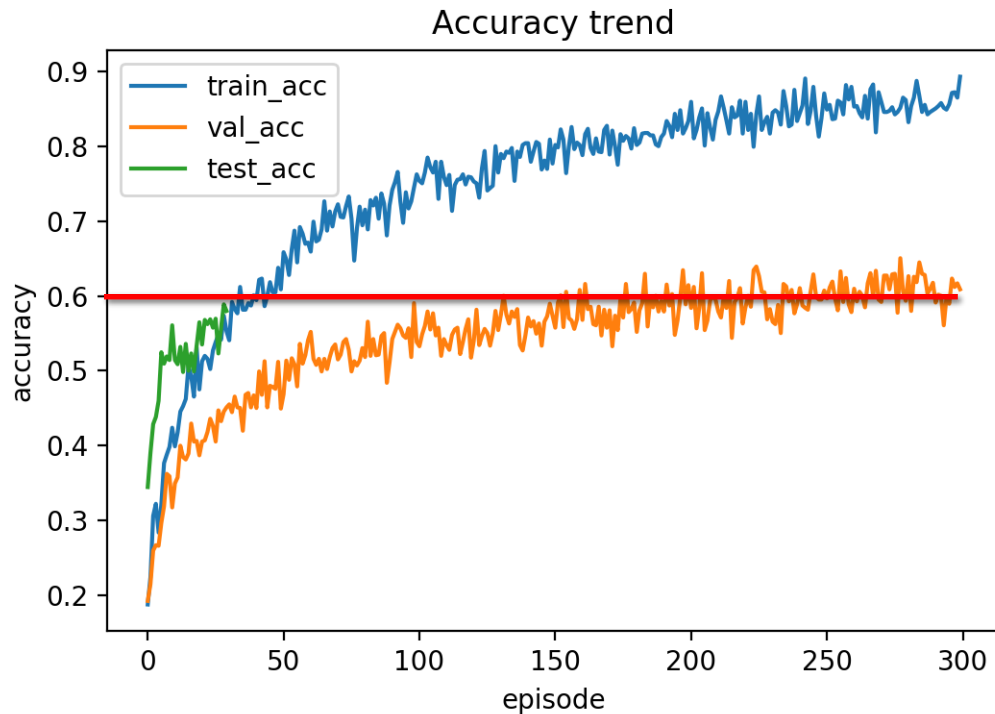


# 4. Result of original dataset



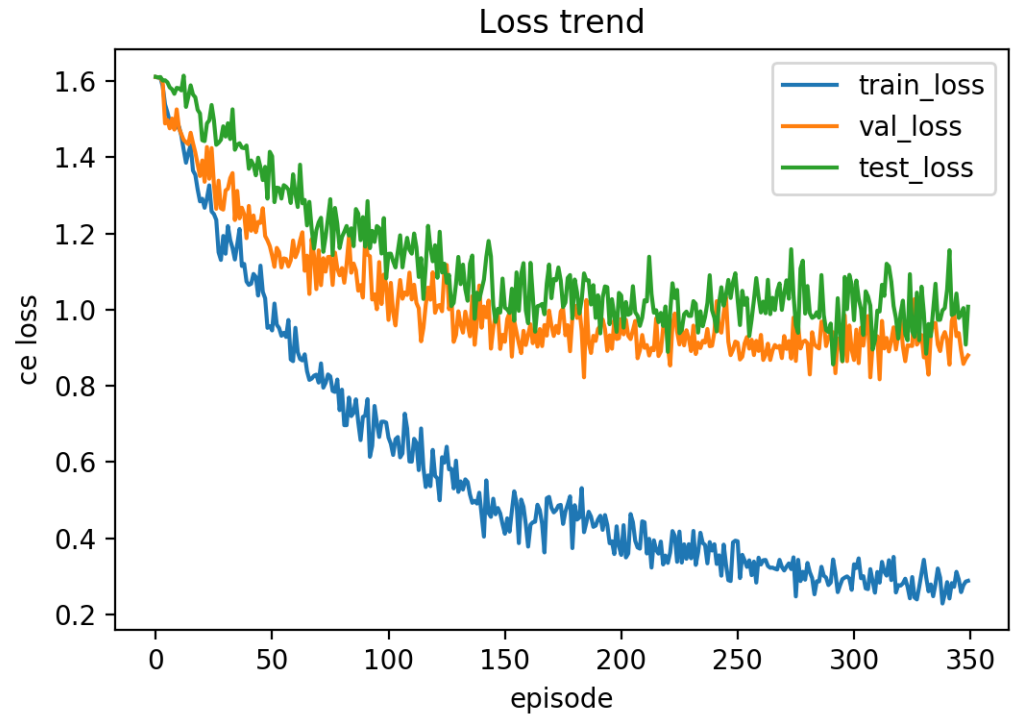
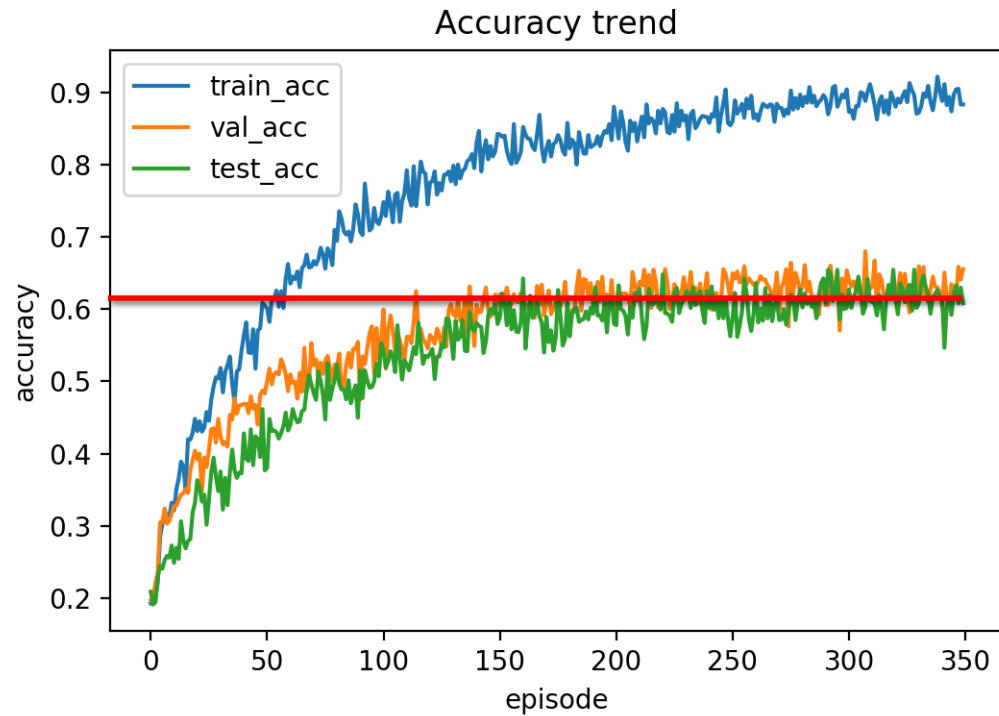
2. CUB\_200 for meta-learner.

# 4. Result of irrelative dataset



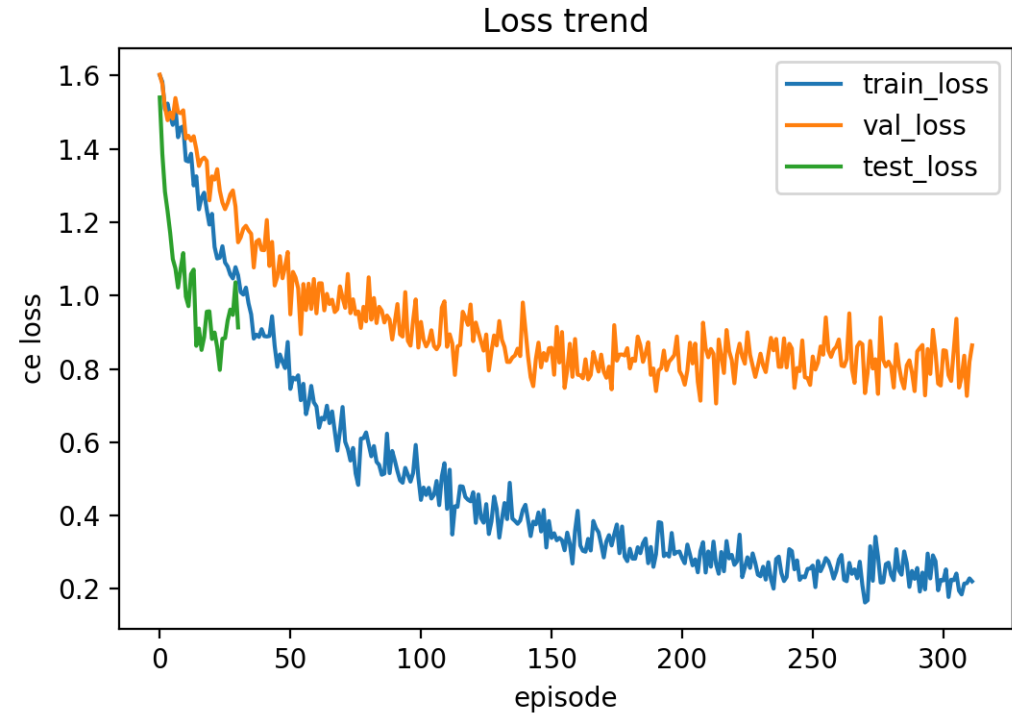
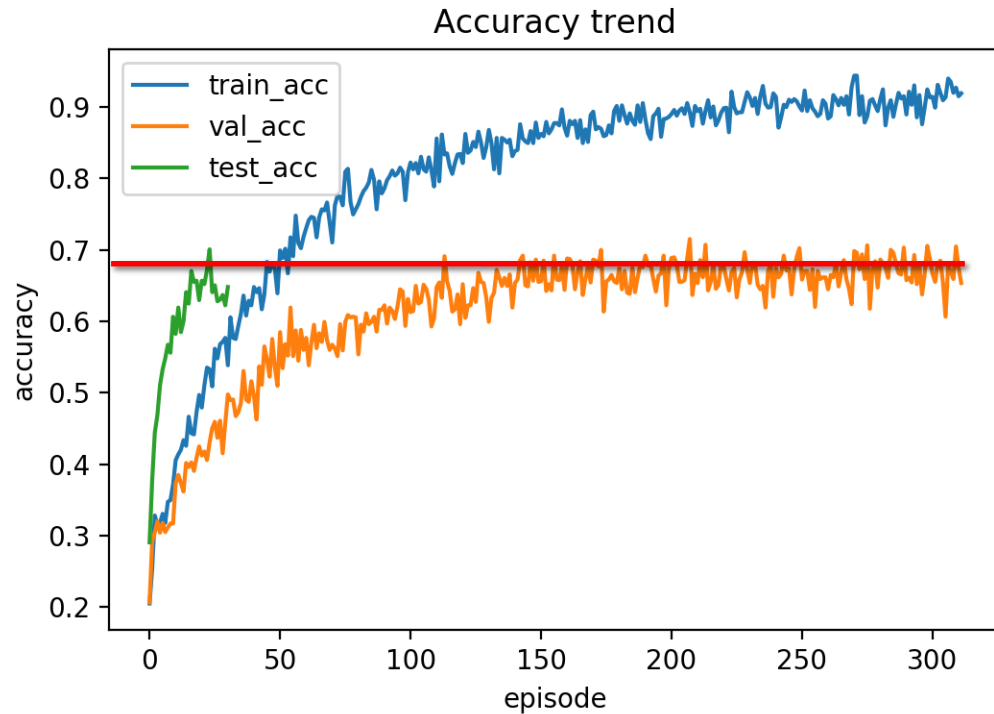
2. Selected 200 classes without any animals from ImageNet for Discriminator and CUB\_200 for meta-learner.

# 4. Result of irrelative dataset



2. Selected 101 kinds of food for Discriminator and CUB\_200 for meta-learner.

# 4. Result of relative dataset



2. Selected 200 classes with many animals from ImageNet for Discriminator and CUB\_200 for meta-learner.

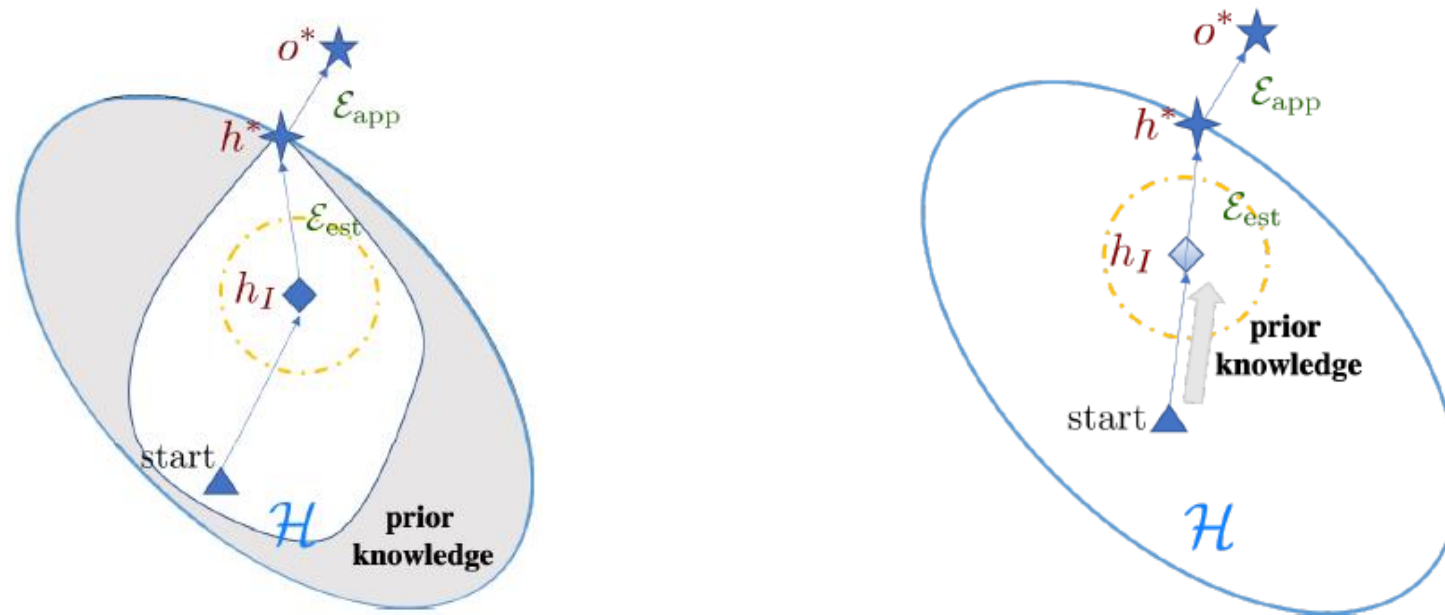
# Conclusion

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1. Relative external datasets make great contribution to model training.
2. Irrelative external datasets make very small contribution to Generator and meta-learner but not affect the performance.
3. Without external datasets, the model performs worse than the model with irrelative external datasets.

# 4. The uncertainty

1. the role of the shared parameter  $\theta$ . (Constrain the complexity of  $\mathcal{H}$  or help to search for  $\theta$ ?)



2.  $\theta_m$  aims to learn the sensitive parameters from the changing of tasks. As a result, the small change in grad and parameters will cause larger loss. (Is there any criterion in the small change will cause how big the loss change?)

# 5.Future work

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- 1.Using the attention mechanism to prove the correlation between two datasets.
- 2.Try to combining GAN with this model