Prototype networks for few-shot learning

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Summary

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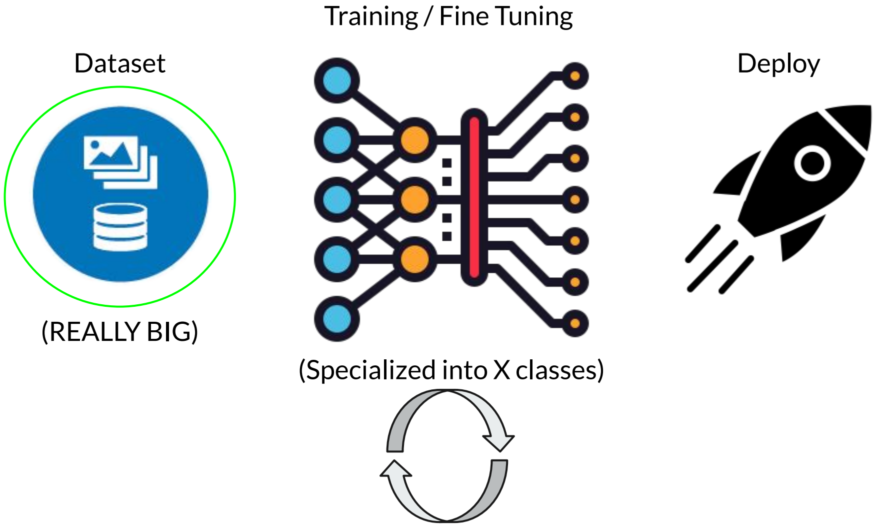
Intro

Challenge

‘classic’ Classification Task



Dataset

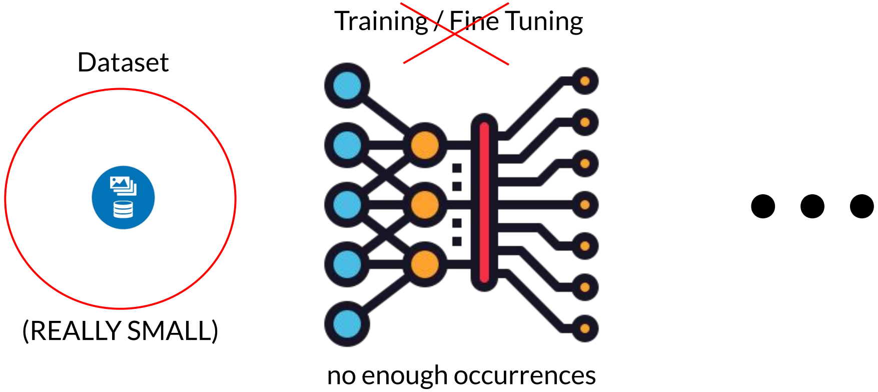
(REALLY BIG)

Training / Fine Tuning

(Specialized into X classes)

Deploy

Our Challenge Classification Task



Dataset

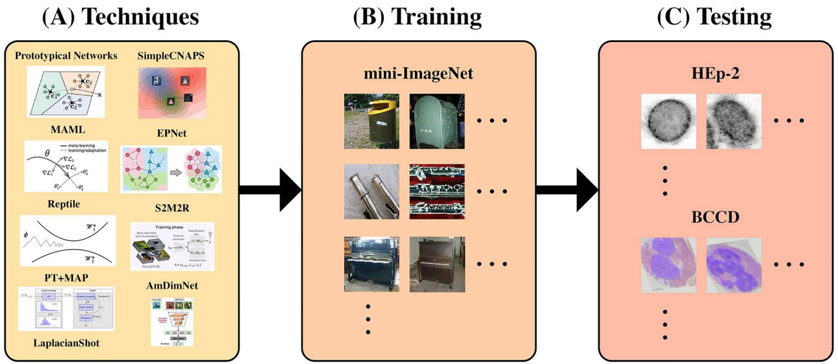
(REALLY SMALL)

~~Training / Fine Tuning~~

no enough occurrences

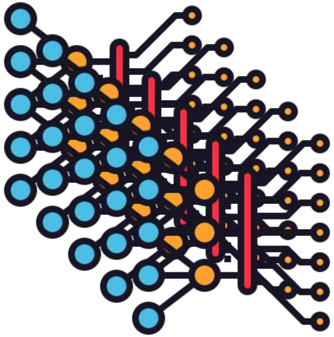
Few-shot learning

- A **meta-learning** technique to ‘learn to learn’
- Uses **small amount** of occurrences
- Can perform with **high accurancies**

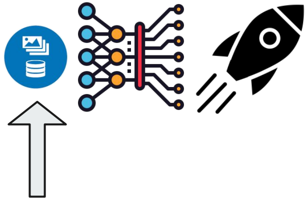


Dataset

Learn to learn



Learn + Deploy



small

Meta-learning definition

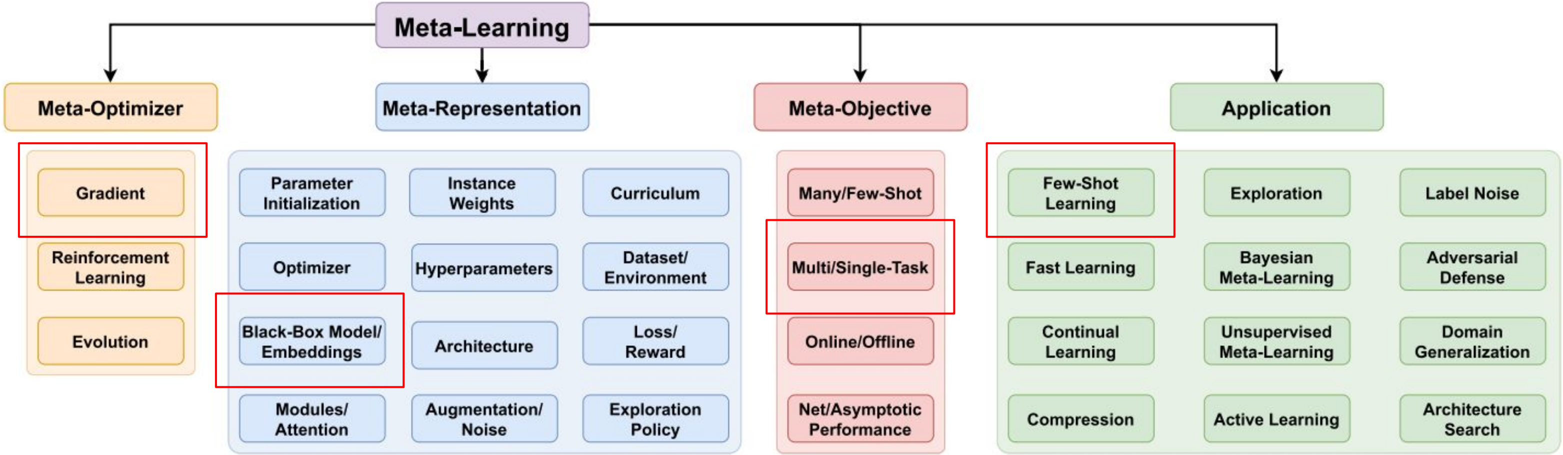


Fig. 1. Overview of the meta-learning landscape including algorithm design (meta-optimizer, meta-representation, meta-objective), and applications.

Meta-Learning in Neural Networks: A Survey, Hospedales, Antoniuou, Micarelli, Snorkey, 2022

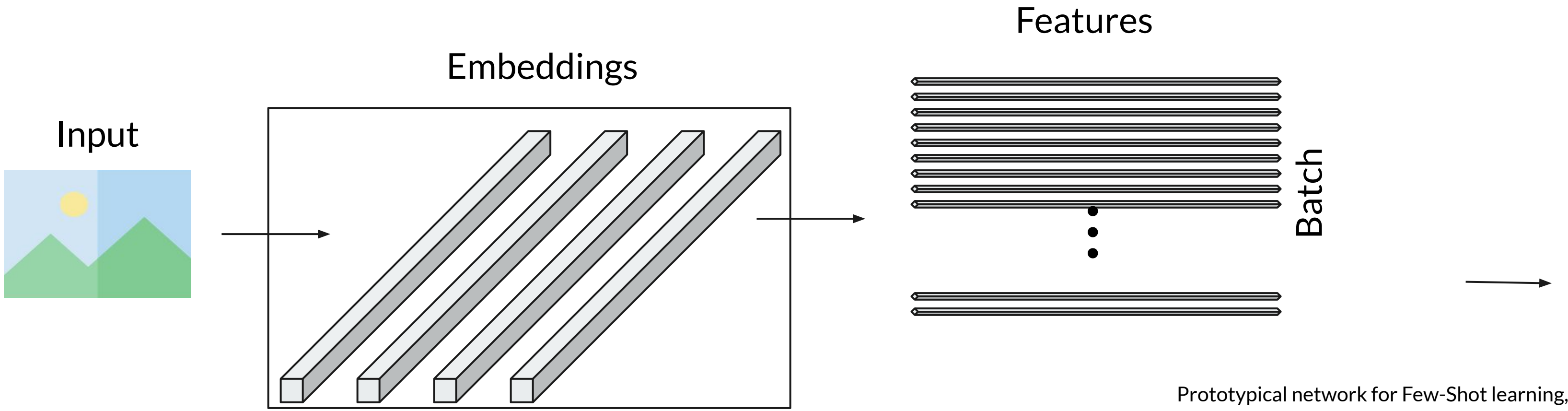
Project workflow

Datasets

- Omniglot: 1623 handwritten characters
  - 80 images per class
  - classes: (1032 train, 172 val, 464 test)
- Mini Imagenet: 100 objects
  - 600 images per class
  - classes: (64 train, 16 val, 20 test)
- Flowers102: 102 flowers
  - 40-120 images per class
  - classes: (64 train, 16 val, 22 test)

Prototypical Networks

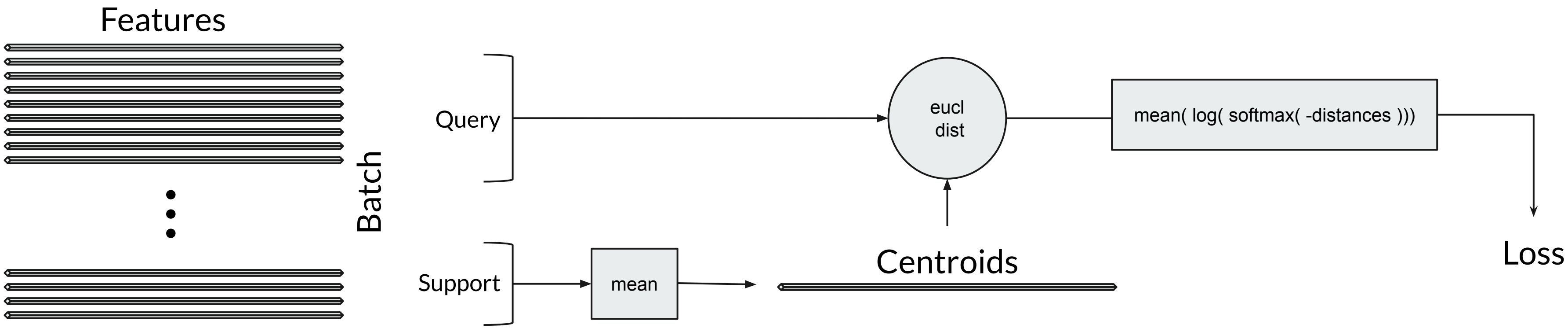
- Extracts features with a neural network
    - 4 CNN blocks: Conv out=64, ks=3 / BatchNorm2D / ReLu / MaxPool2D
- Learning: embeddings learning
    - Trained 100 episodes/iterations per epochs (200 ep) to learn embeddings



Prototypical network for Few-Shot learning, Snell, Swesky, Zemel, 2017

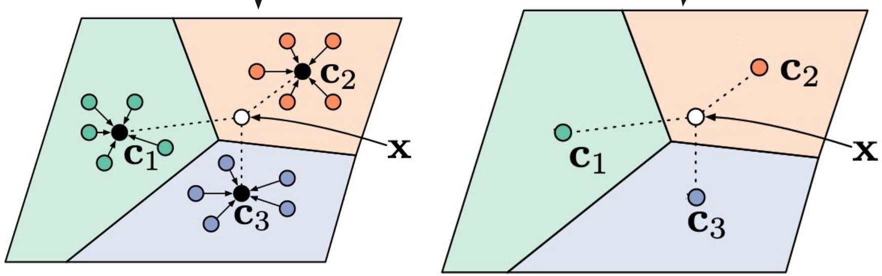
Prototypical Networks - centroids

- Use a small part of output as support, other as query
- Centroids are mean(support)
- Calculate distances between query and centroids
- Calculate loss as mean of log_softmax of negative distances



Prototypical Networks - NC, NS, NQ

- NC: how many classes to use per each iteration on batch (or ‘ways’)
- NS: how many examples to use as support for centroids calculus (or ‘shots’)
- NQ: how many examples to use as queries for centroids calculus (‘query’)
  - ○ 1 shots -> One-Shot Learning
  - ○ 5 shots -> Few-Shot Learning



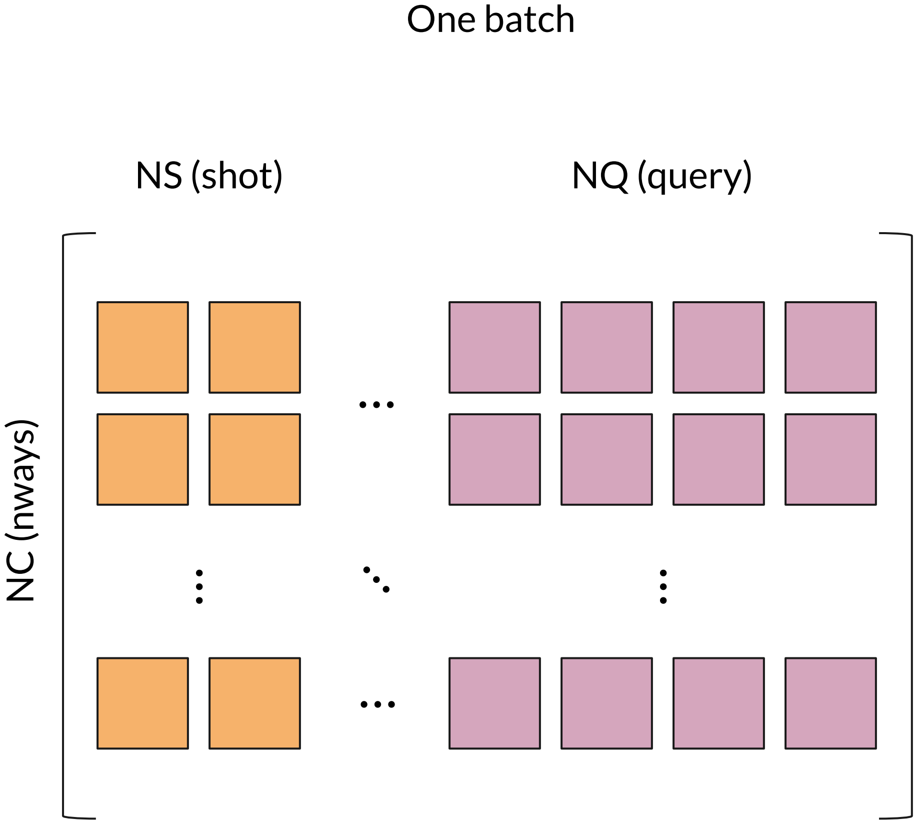
Loss, optimizer, scheduler

- Loss: mean(log_softmax(-distances(query, centroids), targets)
- Optimizer: Adam with lr=0.001
- Scheduler: StepLr with step_size=20, gamma = 0.5

Training skeleton

```
model = PrototypicalNet()
loss = loss_function(x, y, NC, NS, NQ)
optim = StepLr()

for epoch in epochs:
 for it in iterations:
  x, y = GetSample(NC, NS, NQ)
  out = model(x)
  ... loss
  backward()
 for it in iterations:
  .... eval ....
```



Code

All code is available at github

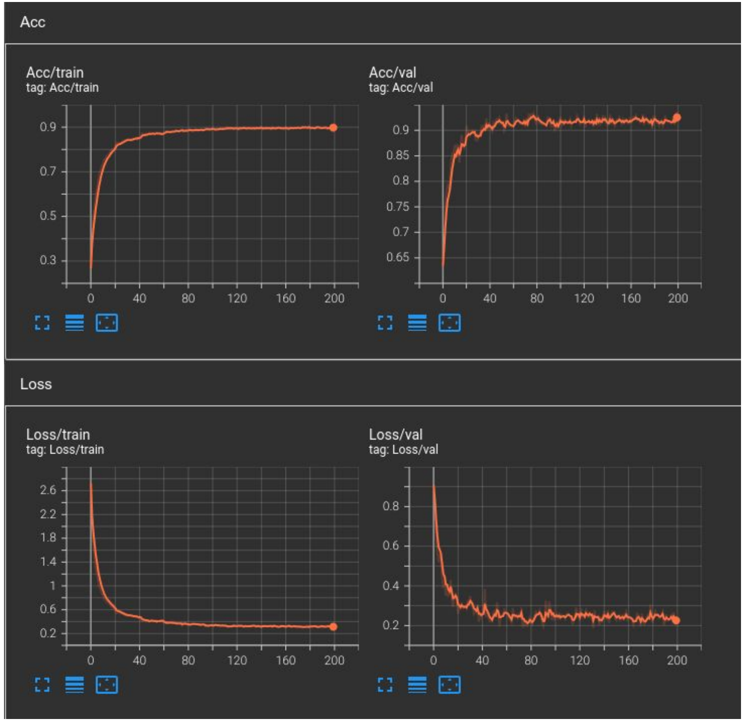
- Full hyperparams control
- 3 available datasets
- results and plots
- simple train.py and test.py scripts

```
python train.py --dataset mini_imagenet \
          --epochs 200 \
          --gpu \
          --train-num-class 30 \
          --test-num-class 5 \
          --number-support 5 \
          --train-num-query 15 \
          --episodes-per-epoch 100 \
          --adam-lr 0.001 \
          --opt-step-size 20 \
          --opt-gamma 0.5 \
          --distance-function "euclidean" \
          --save-each 5
```

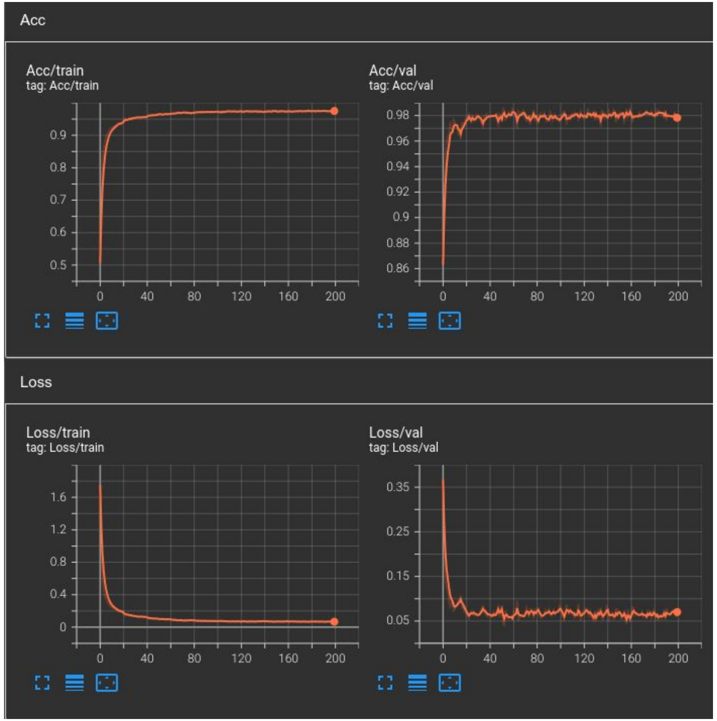
Experiments

Omniglot

1-shot

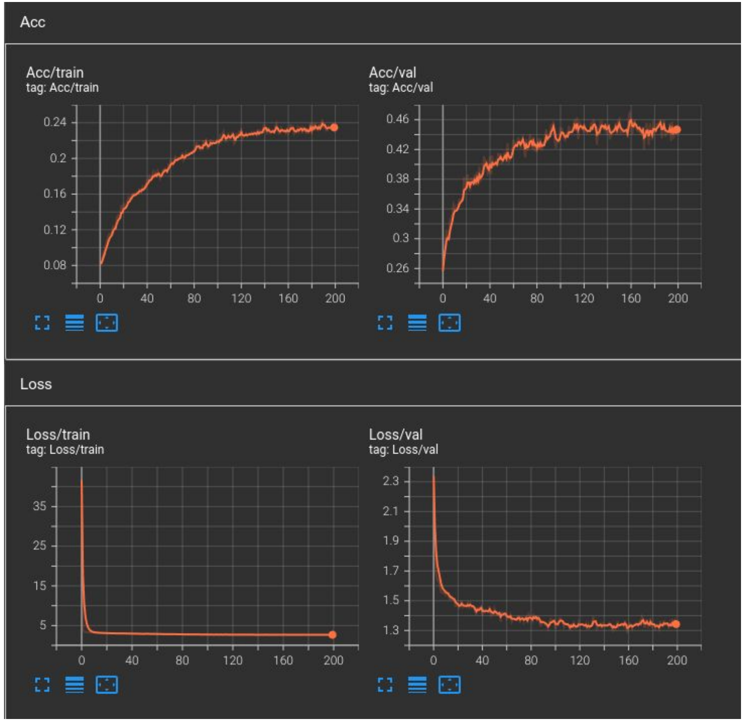


5-shot

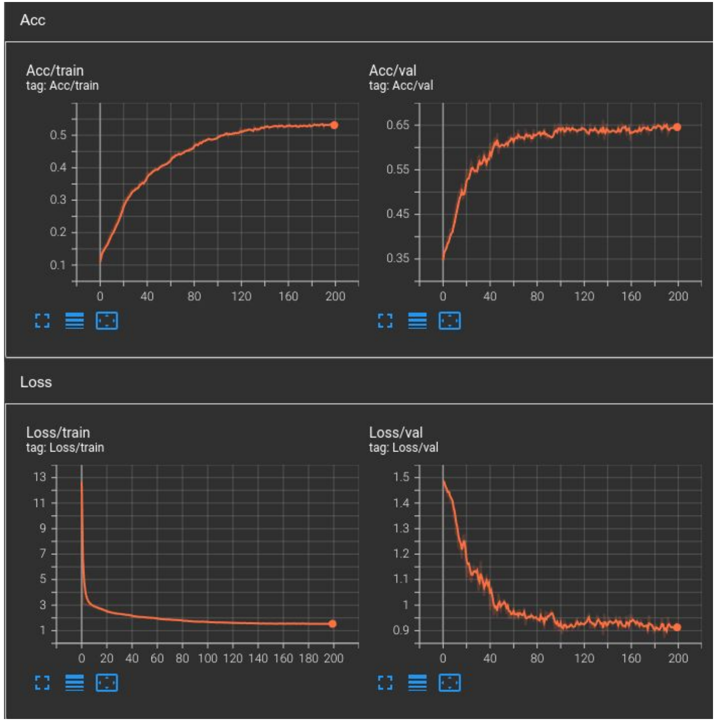


Mini Imagenet

1-shot

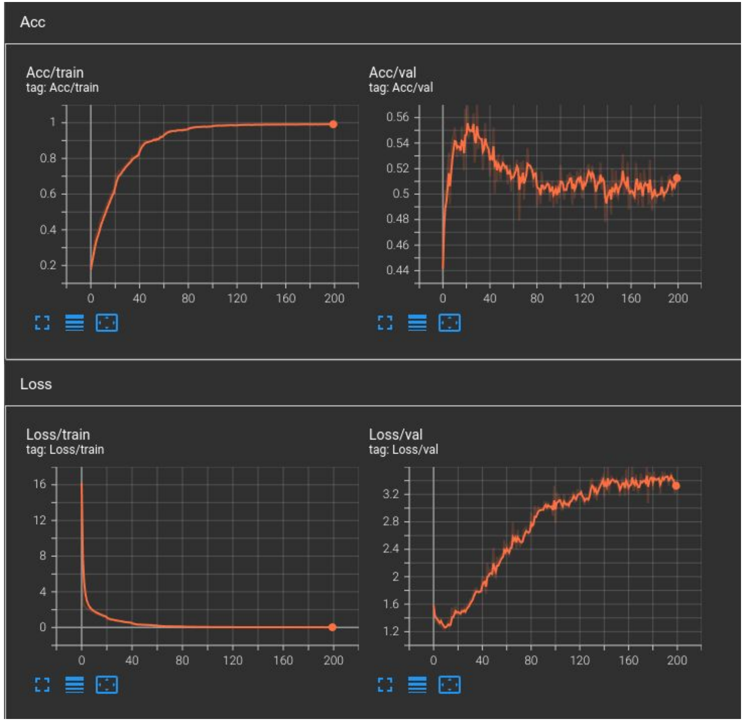


5-shot



Flowers 102

1-shot



Acc

Acc/train
tag: Acc/train

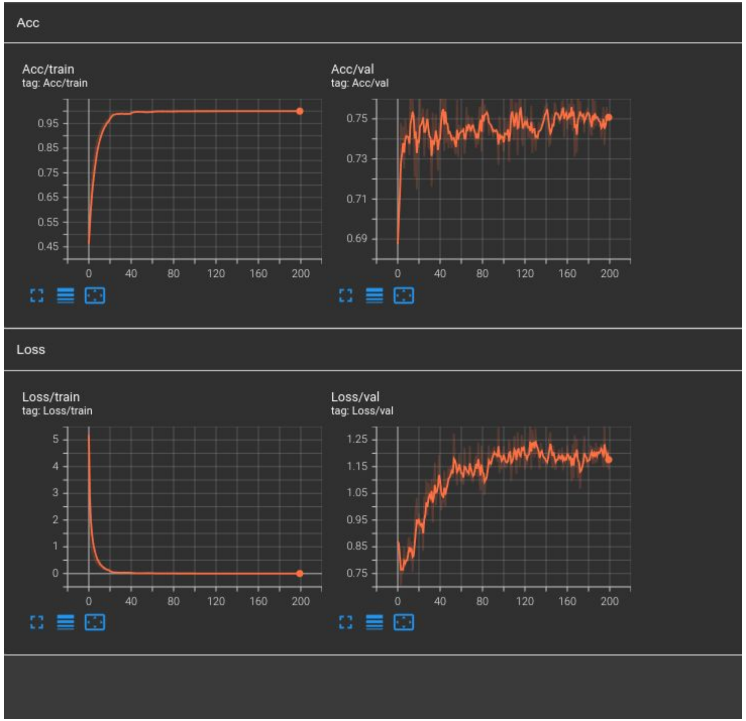
Acc/val
tag: Acc/val

Loss

Loss/train
tag: Loss/train

Loss/val
tag: Loss/val

5-shot



Acc

Acc/train
tag: Acc/train

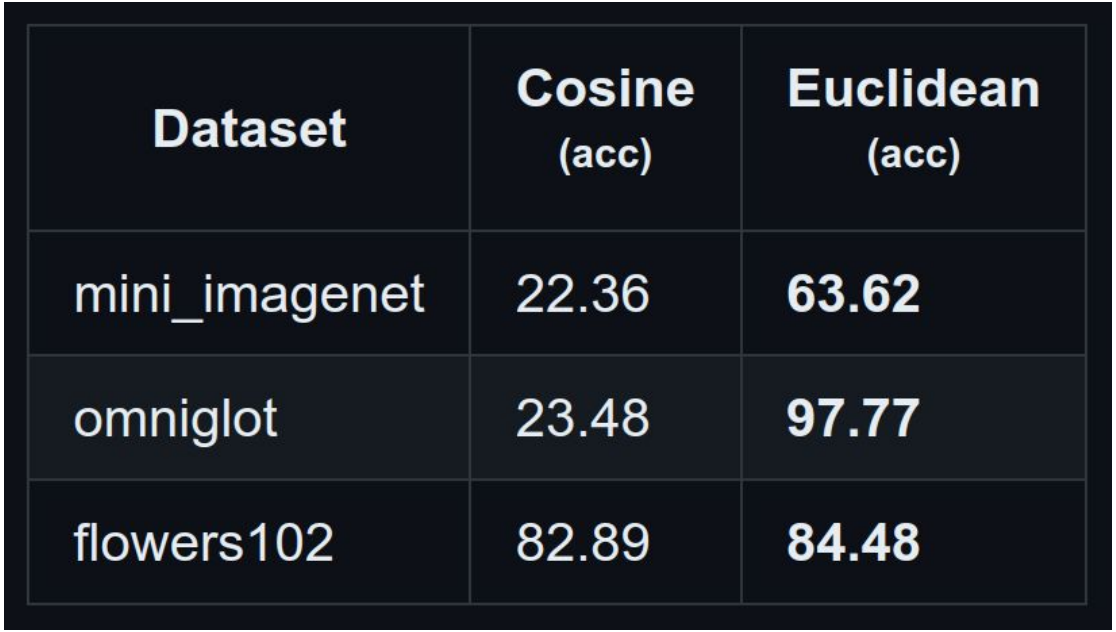
Acc/val
tag: Acc/val

Loss

Loss/train
tag: Loss/train

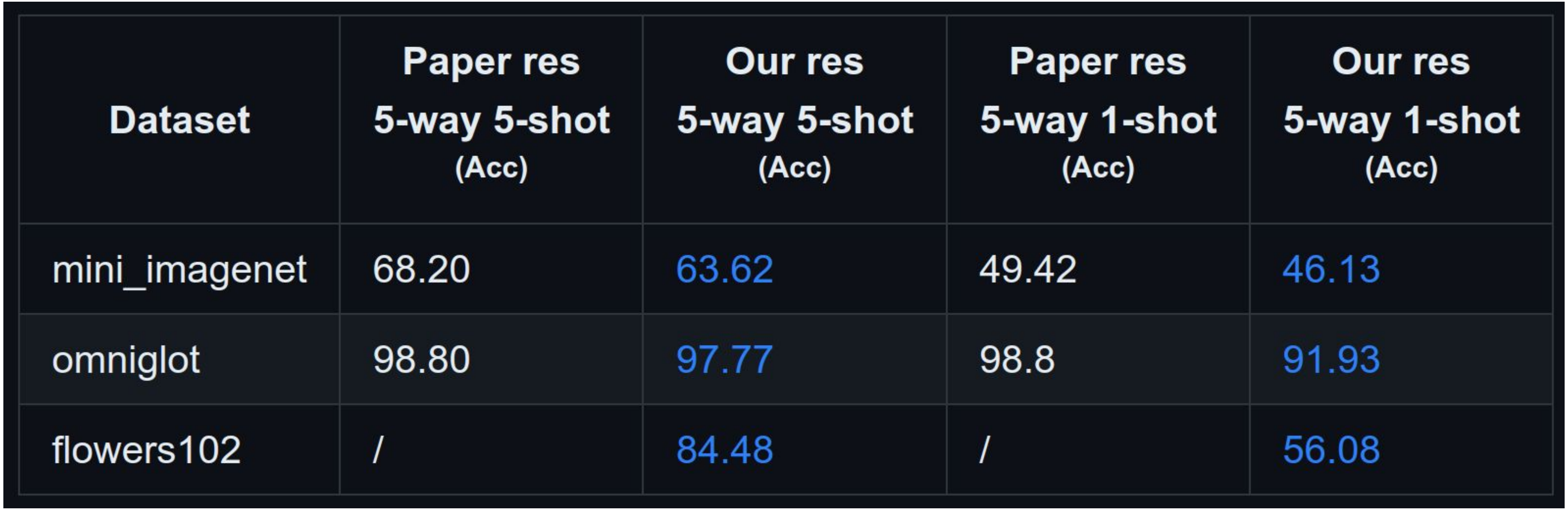
Loss/val
tag: Loss/val

Comparison - distance metric



Dataset	Cosine (acc)	Euclidean (acc)
mini_imagenet	22.36	**63.62**
omniglot	23.48	**97.77**
flowers102	82.89	**84.48**

Comparison - one vs few shot vs paper



Dataset	Paper res 5-way 5-shot (Acc)	Our res 5-way 5-shot (Acc)	Paper res 5-way 1-shot (Acc)	Our res 5-way 1-shot (Acc)
mini_imagenet	68.20	63.62	49.42	46.13
omniglot	98.80	97.77	98.8	91.93
flowers102	/	84.48	/	56.08

Conclusions

Conclusion

- Euclidean distance performs better than cosine similarity
- Paper results were correctly replicated

Future studies

- Add custom dataset option for training
- Implement proper torch.nn.Dataset and torch.nn.Sampler + torch.nn.DataLoader
- Try different fields than CV