

Let's try directly learning using the task training set albeit its small size. Create a dataset and loader and train it with the earlier network and Train function.

```
[ ]: taskds = utils.MyDS(d_train[0],d_train[1])

[ ]: d_train_loader = torch.utils.data.
      ↳ DataLoader(dataset=taskds,batch_size=1,shuffle=True)

[ ]: net,losses,accs=models.Train(net,d_train_loader,lr=1e-1,epochs=10,verbose=True)
```

How does it do on the test set of the sampled task?

```
[ ]: models.accuracy(net,d_test[0],d_test[1])
```

5 CNP-based Meta-learning

```
[ ]: # optimisers from torch
import torch.optim as optim
import torch.nn.functional as F
```

```
[ ]: lossfn = torch.nn.NLLLoss()
```

Conditional Neural Process Network

2

```
[ ]: class CNP(nn.Module):
    def __init__(self,n_features=1,dims=[32,32],n_classes=2,lr=1e-4):
        super(CNP,self).__init__()
        self.n_features = n_features
        self.n_classes = n_classes
        dimL1 = [n_features]+dims
        dimL2=[n_features+n_classes*dims[-1]]+dims+[n_classes]
        self.mlp1 = models.MLP(dims=dimL1,task='embedding')
        self.mlp2 = models.MLP(dims=dimL2)
        self.optimizer=torch.optim.Adam(self.parameters(),lr=lr)
    def adapt(self,X,y):
        R = self.mlp1(X)
        m = torch.eye(self.n_classes)[y].transpose(0,1)/self.n_classes
        r = (m@R).flatten().unsqueeze(0)
        #r = (R.sum(dim=0)/X.shape[0]).unsqueeze(0)
        return r
    def forward(self,Y,r):
        rr = r.repeat(Y.shape[0],1)
```

Handwritten notes and diagrams for the CNP class:

- Arrows pointing to `self.mlp1` and `self.mlp2` with labels g and h .
- A diagram showing a Softmax layer: $g \rightarrow \text{Softmax} =$.

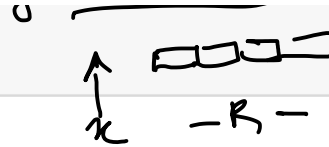
Handwritten notes and diagrams for the CNP class:

- Dimensions: $20, 32, 32$.
- Matrices: $R^{(1)}, R^{(2)}, R^{(3)}, R^{(4)}$.
- Weights: u_1, u_2, u_3, u_4 .
- Diagram showing a Softmax layer: $\text{Softmax} =$.

```

    p = self.mlp2(torch.cat((Y,rr),dim=1))
    return p
utils.hide_toggle('Class CNP')

```



Get a task dataset.

```
[ ]: meta_train_kloader=KShotLoader(meta_train_ds,shots=5,ways=2,num_tasks=1000)
```

```
[ ]: d_train,d_test = meta_train_kloader.get_task()
```

```
[ ]: net = CNP(n_features=20,dims=[32,64,32])
```

```
[ ]: print(net.mlp1,net.mlp2)
```

```
[ ]: r = net.adapt(d_train[0],d_train[1])
r
```

```
[ ]: net(d_train[0],r)
```

6 Putting it all together: CNP-based Meta-learning

Now let's put it together in a loop - CNP model-based meta-learning algorithm:

```
[ ]: # Redifning accuracy function so that it takes h - dataset context - as input
      ↳ since net requires it.
def accuracy(Net,X_test,y_test,h,verbose=True):
    #Net.eval()
    m = X_test.shape[0]
    y_pred = Net(X_test,h)
```

3

```

_, predicted = torch.max(y_pred, 1)
correct = (predicted == y_test).float().sum().item()
if verbose: print(correct,m)
accuracy = correct/m
#Net.train()
return accuracy

```

```
[ ]: classes_train = [i for i in range(5)]
classes_test = [i+5 for i in range(5)]
classes_train, classes_test
```



$$\begin{matrix} \rightarrow & \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \\ \rightarrow & \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \end{matrix} \quad \begin{matrix} 0 \\ 1 \\ 0 \\ 1 \end{matrix}$$

$$\begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} R^0 \\ R^1 \\ R^2 \\ R^3 \end{bmatrix}$$