Problem 1

In [1]:
```
import numpy as np
import mltools as ml
import matplotlib.pyplot as plt
```

In [2]:
```
# Data Loading
X = np.genfromtxt('data/X_train.txt', delimiter=None)
Y = np.genfromtxt('data/Y_train.txt', delimiter=None)
X,Y = ml.shuffleData(X,Y)
# print(type(X), type(Y)) # class 'numpy.ndarray'
# X.shape (200000, 14) Y.shape (200000,)
```

1. Print the minimum, maximum, mean, and the variance of all of the features.

In [3]:
```
print("minimum of features: ",X.min(axis=0))
print("maximum of features: ",X.max(axis=0))
print("mean of features: ",X.mean(axis=0))
print("variance of features: ",X.var(axis=0))
```

```
minimum of features:  [ 1.9300e+02  1.9000e+02  2.1497e+02  2.0542e+02  1.0000e+01
0.0000e+00
  0.0000e+00  0.0000e+00  6.8146e-01  0.0000e+00  0.0000e+00  0.0000e+00
  1.0074e+00 -9.9990e+02]
maximum of features:  [2.5300e+02 2.5050e+02 2.5250e+02 2.5250e+02 1.7130e+04 1.2338e
+04
 9.2380e+03 3.5796e+01 1.9899e+01 1.1368e+01 2.1466e+01 1.4745e+01
 2.7871e+02 7.8250e+02]
mean of features:  [2.41797220e+02 2.28228260e+02 2.41796298e+02 2.33649299e+02
 2.86797959e+03 8.84073295e+02 1.73553355e+02 3.04719572e+00
 6.35196722e+00 1.92523232e+00 4.29379349e+00 2.80947178e+00
 1.03679146e+01 7.87334450e+00]
variance of features:  [8.26945619e+01 9.09573945e+01 3.57255796e+01 9.52608539e+01
 1.06194180e+07 3.25702985e+06 7.40656134e+05 7.42244277e+00
 6.33229913e+00 4.28448703e+00 4.04684087e+00 1.98218303e+00
 1.66679252e+02 1.41079679e+03]
```

In [4]:
```
Xt, Xva, Yt, Yva = ml.splitData(X, Y)
#Xt, Yt = Xtr[:5000], Ytr[:5000] # subsample for efficiency (you can go higher)
XtS, params = ml.rescale(Xt) # Normalize the features
XvS, _ = ml.rescale(Xva, params) # Normalize the features
```

Print the min, maximum, mean, and the variance of the rescaled features.

In [5]:
```
print("Xtrain:")
print("minimum of features: ",XtS.min(axis=0))
print("maximum of features: ",XtS.max(axis=0))
print("mean of features: ",XtS.mean(axis=0))
print("variance of features: ",XtS.var(axis=0))
print("Xval:")
print("minimum of features: ",XvS.min(axis=0))
print("maximum of features: ",XvS.max(axis=0))
```

```
print("mean of features: ",XvS.mean(axis=0))
print("variance of features: ",XvS.var(axis=0))
```

```
Xtrain:
minimum of features:  [ -5.31562307  -4.01664032  -4.49633405  -2.89673811  -0.875967
2
  -0.48825006  -0.20113904  -1.11634769  -2.25580688  -0.93080255
  -2.13504853  -1.9930641   -0.72736273 -27.19147853]
maximum of features:  [ 1.23326723  2.33869552  1.79296911  1.93402145  4.38385234
6.34499675
 10.52072852 11.97345415  5.39061316  4.57071943  8.54037977  8.46444146
 20.85009005 20.89807723]
mean of features:  [-1.41302876e-13 -4.70445072e-15 -3.43683321e-13 -8.90671413e-13
 -6.39377440e-17  8.97532049e-16 -5.09733922e-16 -4.97252701e-14
  1.02976110e-13  3.47608040e-14  4.25285675e-14  7.13267635e-14
 -7.83458576e-15 -5.25653184e-15]
variance of features:  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
Xval:
minimum of features:  [ -5.37065576  -4.01664032  -4.49633405  -2.89673811  -0.875967
2
  -0.48825006  -0.20113904  -1.11634769  -2.1784456   -0.93080255
  -2.13504853  -1.9930641   -0.72583204 -27.19147853]
maximum of features:  [ 1.23326723  2.18112521  1.79296911  1.93402145  4.38385234
6.34499675
 10.52072852  9.4217546   5.39061316  4.57071943  7.27321349  8.46444146
 20.85009005 19.29275375]
mean of features:  [ 0.001145   -0.00440564 -0.00382347 -0.00100637  0.01048434  0.00
691434
  0.00145792 -0.01027963  0.00208692  0.00454986  0.00166142 -0.00259864
 -0.00026031 -0.00762704]
variance of features:  [1.00896923 1.0184885  1.01644672 1.01466979 1.01184084 0.9952
0251
 0.98851681 0.96256959 1.01247061 1.01724118 1.00442639 0.98516964
 1.03143655 1.13477852]
```

Problem 2

2-1

In [6]:

```
def train_tree(md=15, mp=2,mlf=1):
    learner = ml.dtree.treeClassify(XtS, Yt, maxDepth=md, minParent=mp, minLeaf=mlf)
    probs = learner.predictSoft(XvS)
    t_auc = learner.auc(XtS, Yt)
    v_auc = learner.auc(XvS, Yva)
    return (t_auc, v_auc, learner.sz)
```

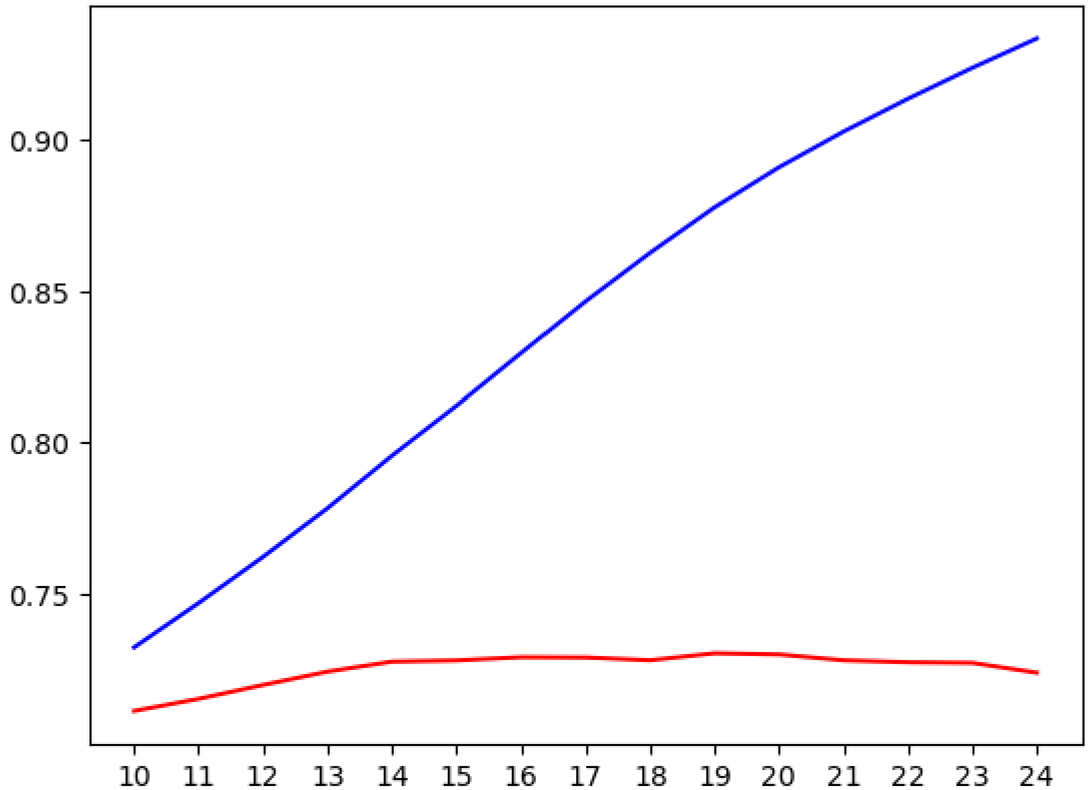
In [7]:

```
def draw_line(line1, line2, r1,r2):
    plt.figure(1)
    plt.xticks(list(range(0,r2-r1)), list(range(r1,r2)))
    plt.plot(line1,'b-',line2,'r-')
    plt.draw()
```

In [8]:

```
Train_AUC = []
Val_AUC = []
sz1 = []
for i in range(10,25):
```

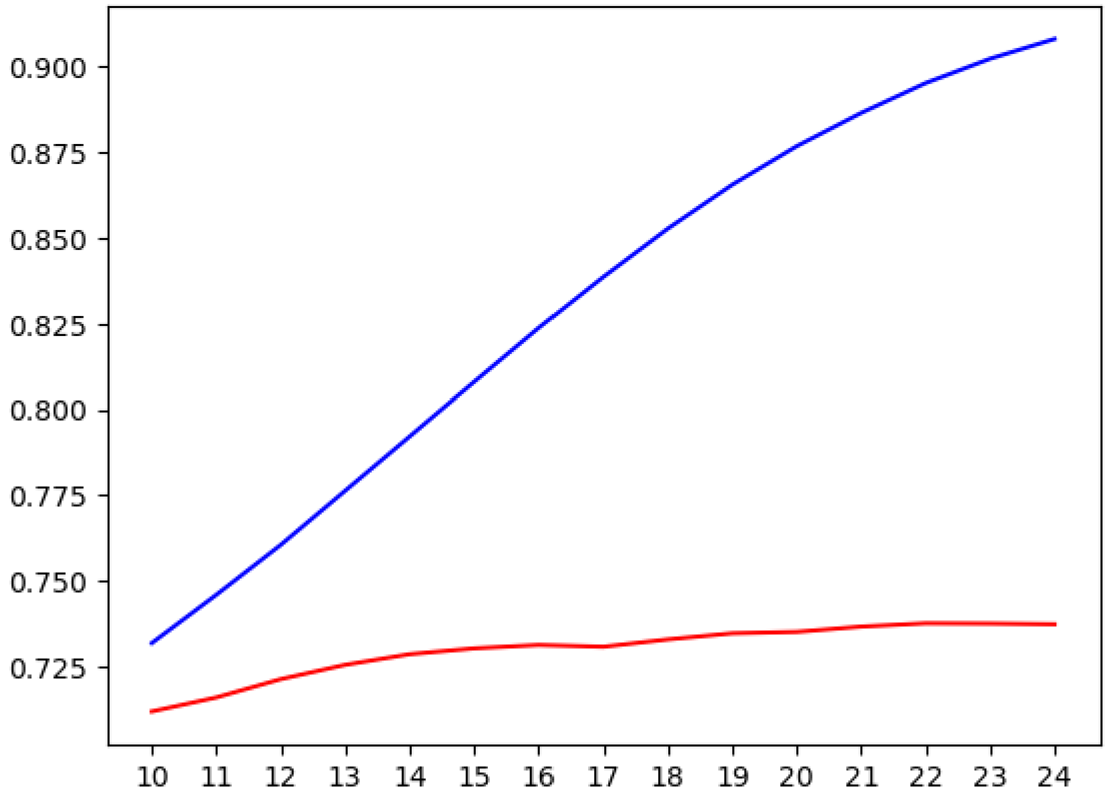
```
    t,v,s = train_tree(md=i)
    Train_AUC.append(t)
    Val_AUC.append(v)
    sz1.append(s)
#print("{0:>15}: {1:.4f}".format('Train AUC', t_auc))
#print("{0:>15}: {1:.v 4f}".format('Validation AUC', v_auc))

draw_line(Train_AUC,Val_AUC,10,25)
```



2-2

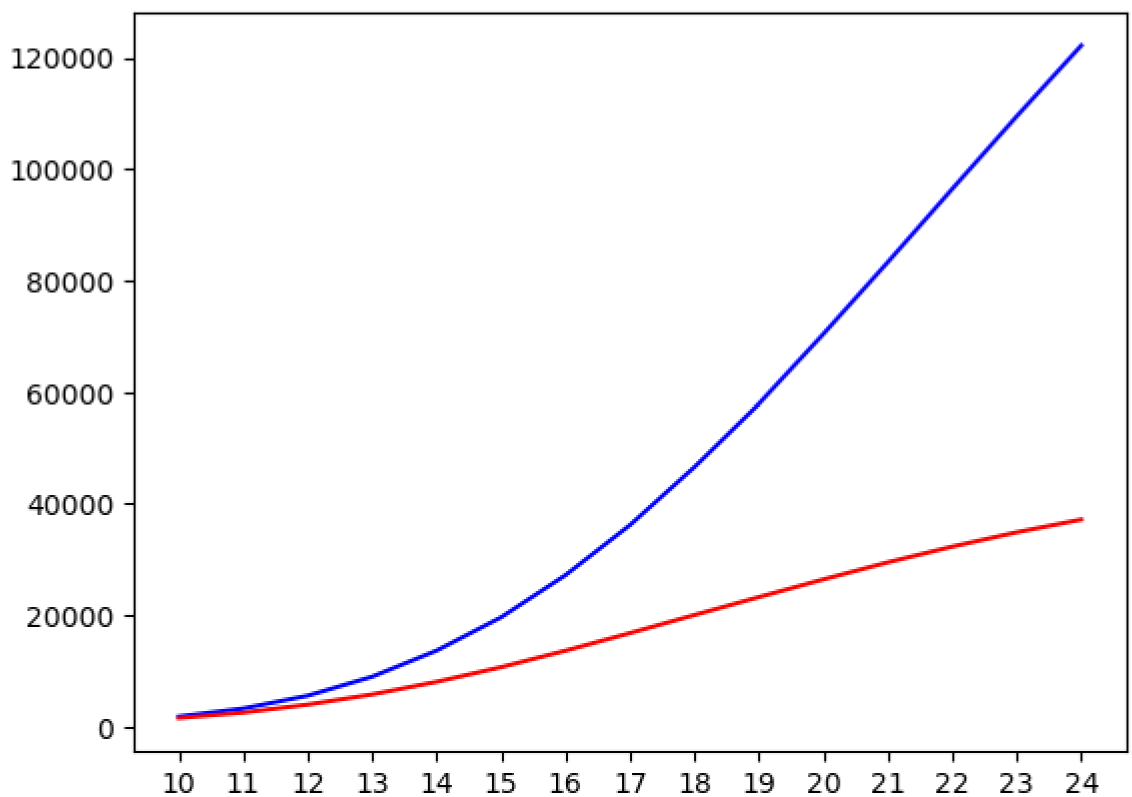
I changed minLeaf from 1 to 5

In [9]:
```
Train_AUC = []
Val_AUC = []
sz2 = []
for i in range(10,25):
    t,v,s = train_tree(mlf=5,md=i)
    Train_AUC.append(t)
    Val_AUC.append(v)
    sz2.append(s)
#print("{0:>15}: {1:.4f}".format('Train AUC', t_auc))
#print("{0:>15}: {1:.v 4f}".format('Validation AUC', v_auc))

draw_line(Train_AUC,Val_AUC,10,25)
```



In [10]:

```
draw_line(sz1,sz2,10,25)
```



blue line: sz1 (number of nodes = 1), red line: sz2 (number of nodes = 5)

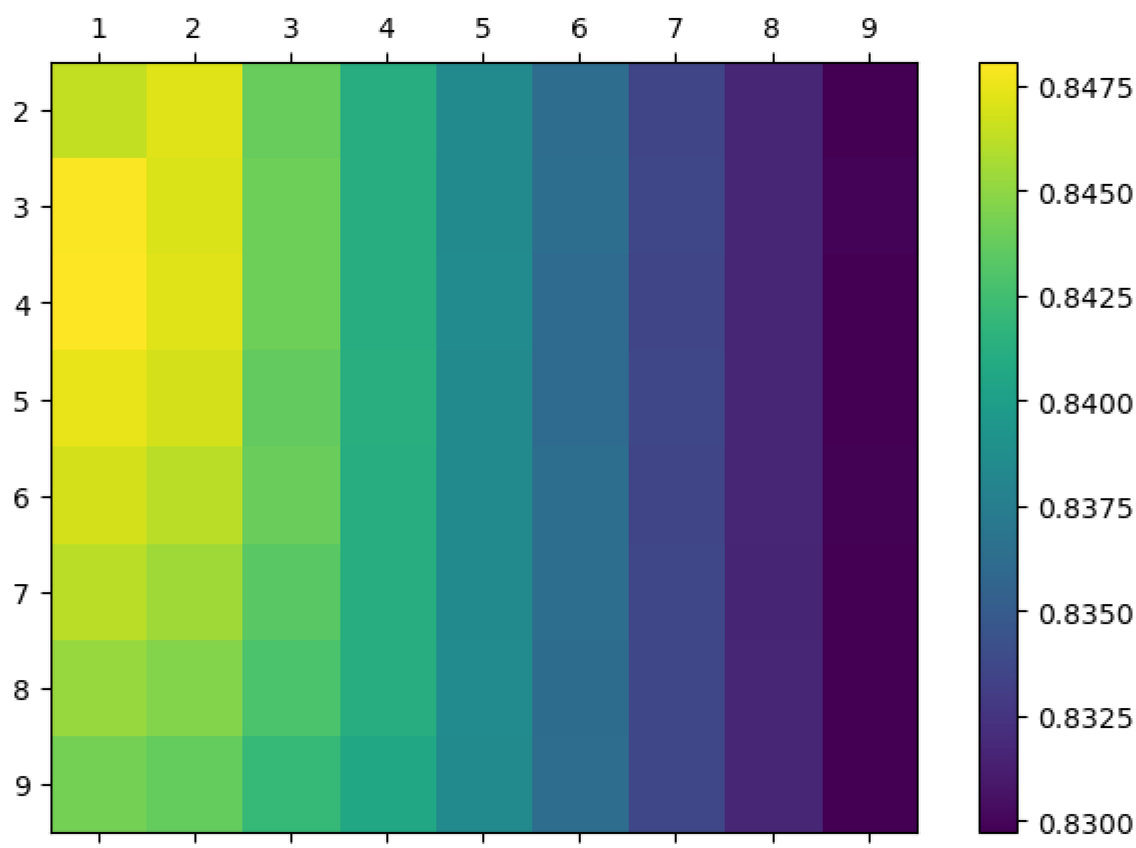
2-3

In [11]:
```
minParents = range(2,10,1) # Or something else
minLeaves = range(1,10,1) # Or something else
tr_auc = np.zeros((len(minParents),len(minLeaves)))
va_auc = np.zeros((len(minParents),len(minLeaves)))

for i,p in enumerate(minParents):
    for j,l in enumerate(minLeaves):
        t,v,_ = train_tree(md=17,mp=p,mlf=l)
        tr_auc[i][j] = t # train learner using k and a
        va_auc[i][j] = v
```

In [12]:
```
def plot_auc(auc):
    f, ax = plt.subplots(1, 1, figsize=(8, 5))
    cax = ax.matshow((auc), interpolation='nearest')
    f.colorbar(cax)
    ax.set_xticklabels(['']+list(minLeaves))
    ax.set_yticklabels(['']+list(minParents))

    plt.show()
```

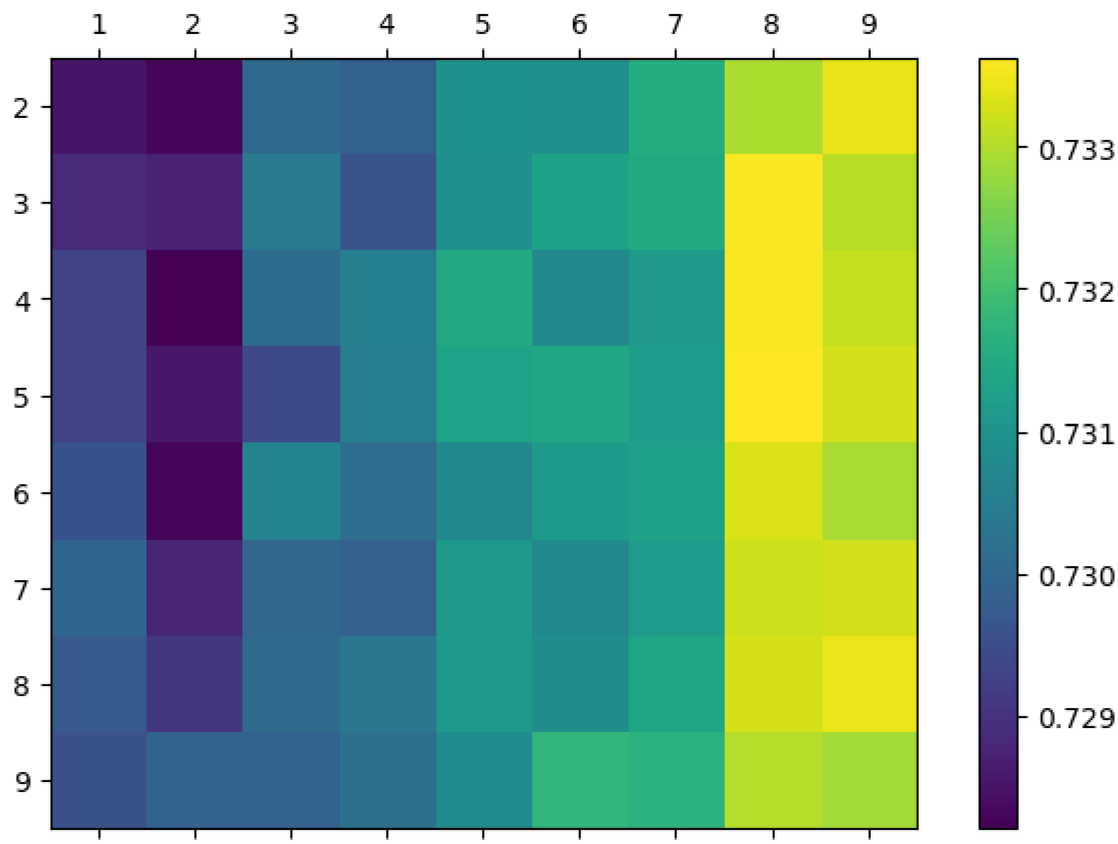
In [13]:
```
plot_auc(tr_auc)
```

```
C:\Users\henry\AppData\Local\Temp\ipykernel_4592\2982939589.py:5: UserWarning: FixedF
ormatter should only be used together with FixedLocator
  ax.set_xticklabels(['']+list(minLeaves))
C:\Users\henry\AppData\Local\Temp\ipykernel_4592\2982939589.py:6: UserWarning: FixedF
ormatter should only be used together with FixedLocator
  ax.set_yticklabels(['']+list(minParents))
```



In [14]:
```
plot_auc(va_auc)
```

```
C:\Users\henry\AppData\Local\Temp\ipykernel_4592\2982939589.py:5: UserWarning: FixedF
ormatter should only be used together with FixedLocator
  ax.set_xticklabels(['']+list(minLeaves))
C:\Users\henry\AppData\Local\Temp\ipykernel_4592\2982939589.py:6: UserWarning: FixedF
ormatter should only be used together with FixedLocator
  ax.set_yticklabels(['']+list(minParents))
```



After this experiment, I recommended using minparents=5 and minleaves=3 ot 5, for this give us best results in validation auc

Problem 3

In [15]:
```
import numpy as np
from datetime import datetime

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader

from torchvision import datasets, transforms

%matplotlib inline
import matplotlib.pyplot as plt

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

In [16]:
```
torch.cuda.is_available()
```

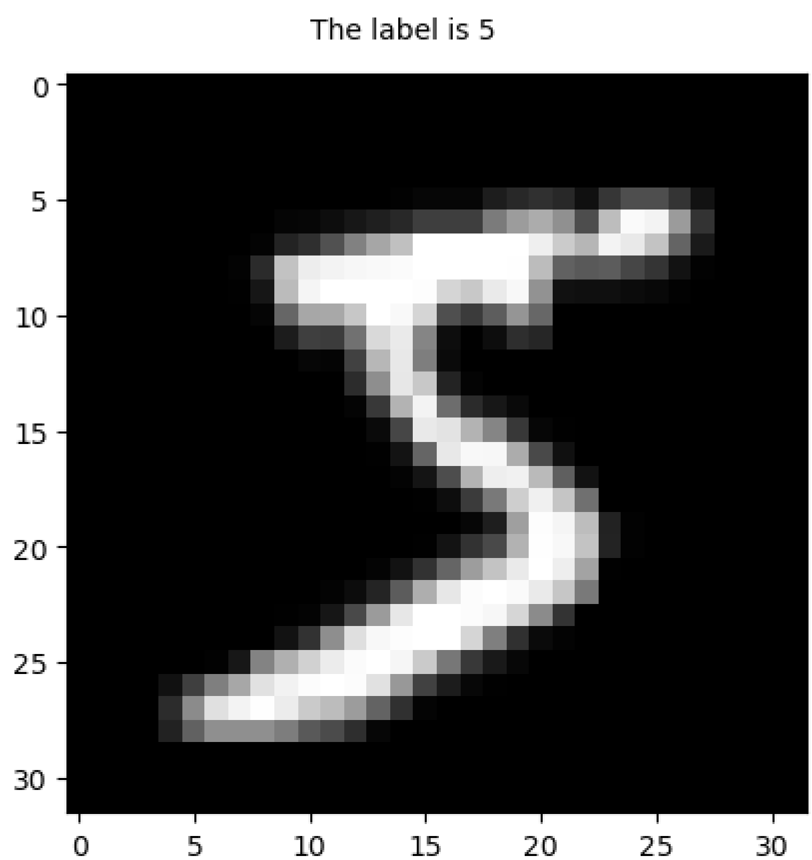
Out[16]:
```
True
```

In [17]:
```
# define transforms
transforms = transforms.Compose([transforms.Resize((32, 32)),
                                 transforms.ToTensor()])

# download and create datasets
train_dataset = datasets.MNIST(root='mnist_data',
                               train=True,
                               transform=transforms,
                               download=True)

valid_dataset = datasets.MNIST(root='mnist_data',
                               train=False,
                               transform=transforms)
```

3.1.1

In [18]:
```
plt.imshow(train_dataset[0][0].squeeze(), cmap='gray')
plt.text(10, -2, 'The label is ' + str(train_dataset[0][1]))
```

Out[18]:
```
Text(10, -2, 'The label is 5')
```



In [19]:
```
train_dataset[0][0].shape
```

Out[19]:
```
torch.Size([1, 32, 32])
```

In [20]:
```
# hyper parameters
RANDOM_SEED = 42
LEARNING_RATE = 0.001
BATCH_SIZE = 32
N_EPOCHS = 15

IMG_SIZE = 32
N_CLASSES = 10
```

3.1.2

In [21]:
```
# define the data loaders
train_loader = DataLoader(dataset=train_dataset,
                          batch_size=BATCH_SIZE, #32 imgs at once
                          shuffle=True)

valid_loader = DataLoader(dataset=valid_dataset,
                          batch_size=BATCH_SIZE,
                          shuffle=True)
```

3.1.3

In [22]:
```
def train(train_loader, model, criterion, optimizer):
    '''
    Train one epoch.
    '''

    model.train()
    running_loss = 0

    for X, y_true in train_loader:
        X = X.to(device)
        y_true = y_true.to(device)
        #X.shape 32,1,32,32
        #y.shape 32

        optimizer.zero_grad()

        # Forward pass
        y_hat, _ = model(X)

        loss = criterion(y_hat, y_true)
        running_loss += loss.item() * X.size(0)

        # Backward pass
        loss.backward()
        optimizer.step()

    epoch_loss = running_loss / len(train_loader.dataset)
    return model, optimizer, epoch_loss
```

3.1.4

In [23]:
```
def validate(valid_loader, model, criterion):
    '''
    Function for the validation step of the training loop.
    Returns the model and the loss on the test set.
    '''

    model.eval()
    running_loss = 0

    for X, y_true in valid_loader:

        X = X.to(device)
        y_true = y_true.to(device)

        # Forward pass and record loss

        y_hat, _ = model(X)
        loss = criterion(y_hat, y_true)
        running_loss += loss.item() * X.size(0)

    epoch_loss = running_loss / len(valid_loader.dataset)

    return model, epoch_loss
```

In [24]:
```
def training_loop(model, criterion, optimizer, train_loader, valid_loader, epochs, pri
    '''
    Function defining the entire training loop
    '''

    # set objects for storing metrics
    best_loss = 1e10
    train_losses = []
    valid_losses = []
    train_accs = []
    valid_accs = []

    # Train model
    for epoch in range(0, epochs):

        # training
        model, optimizer, train_loss = train(train_loader, model, criterion, optimizer
        train_losses.append(train_loss)

        # validation
        with torch.no_grad():
            model, valid_loss = validate(valid_loader, model, criterion)
            valid_losses.append(valid_loss)

        if epoch % print_every == (print_every - 1):

            train_acc = get_accuracy(model, train_loader,)
            train_accs.append(train_acc)
            valid_acc = get_accuracy(model, valid_loader)
            valid_accs.append(valid_acc)

            print(f'{datetime.now().time().replace(microsecond=0)} '
                  f'Epoch: {epoch}\t'
                  f'Train loss: {train_loss:.4f}\t'
                  f'Valid loss: {valid_loss:.4f}\t'
```

```
                  f'Train accuracy: {100 * train_acc:.2f}\t'
                  f'Valid accuracy: {100 * valid_acc:.2f}')

    performance = {
        'train_losses':train_losses,
        'valid_losses': valid_losses,
        'train_acc': train_accs,
        'valid_acc':valid_accs
    }

    return model, optimizer, performance
```

3.1.5

In [25]:

```
def get_accuracy(model, data_loader):
    '''
    Function for computing the accuracy of the predictions over the entire data_loader
    '''

    correct_pred = 0
    n = 0

    with torch.no_grad():
        model.eval()
        for X, y_true in data_loader:
            X = X.to(device)
            y_true = y_true.to(device)

            y_hat,y_prob = model(X)

            # print("yhat:",y_hat) #val from nnet
            # print("yprob:",y_prob) #normalized
            predicted_labels = torch.argmax(y_prob, 1)
            # print("predicted_labels:", predicted_labels)

            n += y_true.size(0) # 32, same as y_true.shape[0]
            correct_pred += torch.eq(predicted_labels, y_true).sum()

    return float(correct_pred / n)



def plot_performance(performance):
    '''
    Function for plotting training and validation losses
    '''

    # temporarily change the style of the plots to seaborn
    plt.style.use('seaborn')

    fig, ax = plt.subplots(1, 2, figsize = (16, 4.5))
    for key, value in performance.items():
        if 'loss' in key:
            ax[0].plot(value, label=key)
        else:
            ax[1].plot(value, label=key)
    ax[0].set(title="Loss  over epochs",
            xlabel='Epoch',
```

```python
            ylabel='Loss')
    ax[1].set(title="accuracy over epochs",
            xlabel='Epoch',
            ylabel='Accuracy')
    ax[0].legend()
    ax[1].legend()
    plt.show()

    # change the plot style to default
    plt.style.use('default')
```

3.2.1

In [26]:
```python
class LeNet5(nn.Module):

    def __init__(self, n_classes):
        super(LeNet5, self).__init__()

        self.layer1 = nn.Sequential( # use nn.Sequential to build several mini-models
            # in_channels, out_channels, kernel_size, stride
            nn.Conv2d(1, 6, (5,5), 1),
            nn.Tanh(),
            #kernel size, stride
            nn.AvgPool2d(2, 2)
        )
        self.layer2 = nn.Sequential(
            nn.Conv2d(6, 16, (5,5), 1),
            nn.Tanh(),
            nn.AvgPool2d(2, 2)
        )
        self.layer3 = nn.Sequential(
            nn.Conv2d(16,120,(5,5),1),
            nn.Tanh()
        )
        self.fc = nn.Sequential(
            nn.Linear(120, 84),
            nn.Tanh(),
            nn.Linear(84, n_classes)
        )


    def forward(self, x):
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = torch.flatten(x, 1)
        logits = self.fc(x)

        probs = F.softmax(logits, dim=1)
        return logits, probs
```

3.2.2

In [27]:
```python
class MLP(nn.Module):

    def __init__(self, layers):
```

```
        super(MLP, self).__init__()

        self.layer = nn.Sequential(
            nn.Flatten(),
            nn.Linear(layers[0],layers[1]),
            nn.Tanh(),
            nn.Linear(layers[1],layers[2]),
            nn.Tanh(),
            nn.Linear(layers[2],layers[3]),
            nn.Tanh(),
            nn.Linear(layers[3],layers[4])
        )
    def forward(self, x):
        logits = self.layer(x)
        probs = F.softmax(logits, dim=1)
        return logits, probs
```

3.3.1

In [28]:

```
torch.manual_seed(RANDOM_SEED)

LeNet5_model = LeNet5(N_CLASSES).to(device)
optimizer = torch.optim.Adam(LeNet5_model.parameters(), lr=LEARNING_RATE)
criterion = nn.CrossEntropyLoss()
```

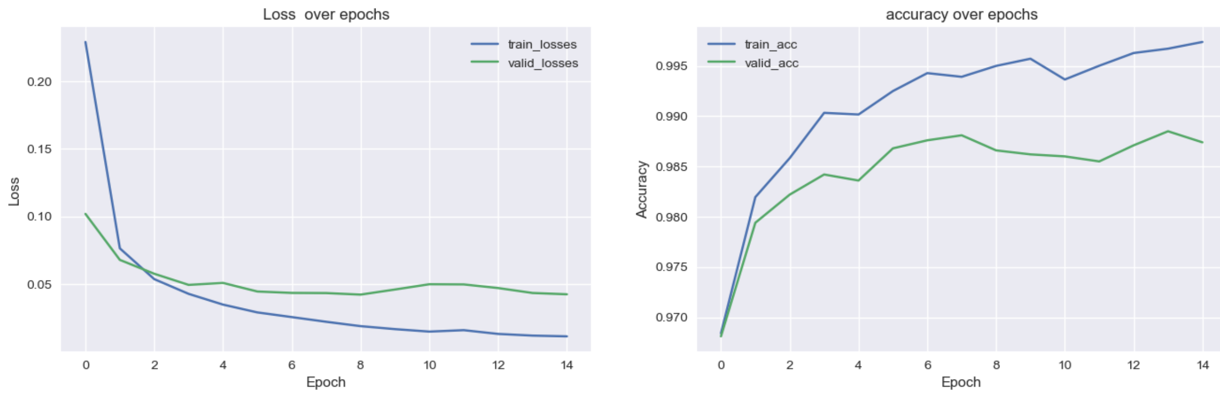
In [29]:

```
LeNet5_model, optimizer, performance_1 = training_loop(LeNet5_model, criterion, optimi
```

```
15:29:15 Epoch: 0       Train loss: 0.2290      Valid loss: 0.1020      Train accurac
y: 96.84        Valid accuracy: 96.81
15:29:39 Epoch: 1       Train loss: 0.0766      Valid loss: 0.0680      Train accurac
y: 98.19        Valid accuracy: 97.94
15:30:02 Epoch: 2       Train loss: 0.0538      Valid loss: 0.0578      Train accurac
y: 98.58        Valid accuracy: 98.22
15:30:26 Epoch: 3       Train loss: 0.0429      Valid loss: 0.0496      Train accurac
y: 99.03        Valid accuracy: 98.42
15:30:49 Epoch: 4       Train loss: 0.0350      Valid loss: 0.0510      Train accurac
y: 99.02        Valid accuracy: 98.36
15:31:12 Epoch: 5       Train loss: 0.0292      Valid loss: 0.0447      Train accurac
y: 99.25        Valid accuracy: 98.68
15:31:35 Epoch: 6       Train loss: 0.0258      Valid loss: 0.0436      Train accurac
y: 99.43        Valid accuracy: 98.76
15:31:59 Epoch: 7       Train loss: 0.0223      Valid loss: 0.0435      Train accurac
y: 99.39        Valid accuracy: 98.81
15:32:22 Epoch: 8       Train loss: 0.0191      Valid loss: 0.0424      Train accurac
y: 99.50        Valid accuracy: 98.66
15:32:45 Epoch: 9       Train loss: 0.0169      Valid loss: 0.0462      Train accurac
y: 99.57        Valid accuracy: 98.62
15:33:08 Epoch: 10      Train loss: 0.0151      Valid loss: 0.0500      Train accurac
y: 99.37        Valid accuracy: 98.60
15:33:32 Epoch: 11      Train loss: 0.0161      Valid loss: 0.0499      Train accurac
y: 99.50        Valid accuracy: 98.55
15:33:55 Epoch: 12      Train loss: 0.0133      Valid loss: 0.0472      Train accurac
y: 99.63        Valid accuracy: 98.71
15:34:18 Epoch: 13      Train loss: 0.0121      Valid loss: 0.0436      Train accurac
y: 99.67        Valid accuracy: 98.85
15:34:41 Epoch: 14      Train loss: 0.0116      Valid loss: 0.0426      Train accurac
y: 99.74        Valid accuracy: 98.74
```

In [30]:
```
plot_performance(performance_1)
```

```
C:\Users\henry\AppData\Local\Temp\ipykernel_4592\1716291042.py:35: MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated since 3.6, as they no longer correspond to the styles shipped by seaborn. However, they will remain available as 'seaborn-v0_8-<style>'. Alternatively, directly use the seaborn API instead.
  plt.style.use('seaborn')
```



The loss of training data is dropping from 0.2 to 0.01, while the loss of testing data is dropping from 0.1 to 0.04

The accuracy of training data is rising from 0.968 to 0.997, while the loss of testing data is rising from 0.968 to 0.987

3.3.2

In [31]:
```
torch.manual_seed(RANDOM_SEED)
layers = [1024, 256, 64, 16, N_CLASSES]
MLP_model = MLP(layers).to(device)
print(MLP_model)
optimizer = torch.optim.Adam(MLP_model.parameters(), lr=LEARNING_RATE)
criterion = nn.CrossEntropyLoss()
```

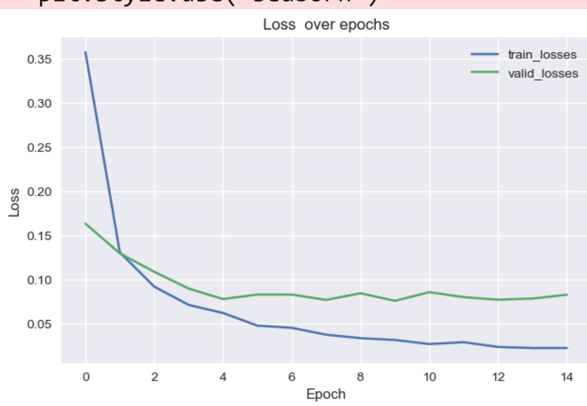
```
MLP(
  (layer): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=1024, out_features=256, bias=True)
    (2): Tanh()
    (3): Linear(in_features=256, out_features=64, bias=True)
    (4): Tanh()
    (5): Linear(in_features=64, out_features=16, bias=True)
    (6): Tanh()
    (7): Linear(in_features=16, out_features=10, bias=True)
  )
)
```

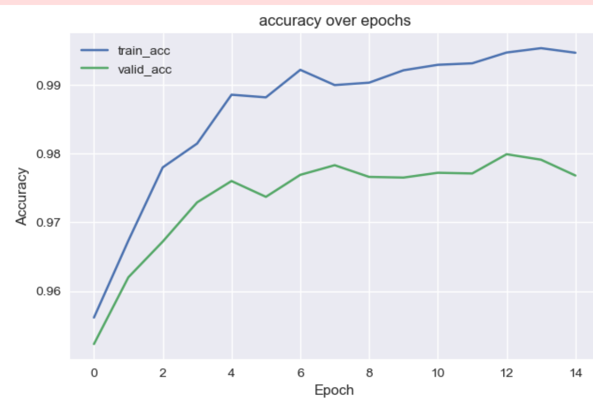
In [32]:
```
MLP_model, optimizer, performance_2 = training_loop(MLP_model, criterion, optimizer, t
```

```
15:35:02 Epoch: 0       Train loss: 0.3575      Valid loss: 0.1636      Train accurac
y: 95.61        Valid accuracy: 95.23
15:35:23 Epoch: 1       Train loss: 0.1311      Valid loss: 0.1300      Train accurac
y: 96.73        Valid accuracy: 96.20
15:35:43 Epoch: 2       Train loss: 0.0923      Valid loss: 0.1091      Train accurac
y: 97.80        Valid accuracy: 96.72
15:36:03 Epoch: 3       Train loss: 0.0717      Valid loss: 0.0901      Train accurac
y: 98.15        Valid accuracy: 97.29
15:36:24 Epoch: 4       Train loss: 0.0625      Valid loss: 0.0782      Train accurac
y: 98.86        Valid accuracy: 97.60
15:36:44 Epoch: 5       Train loss: 0.0482      Valid loss: 0.0834      Train accurac
y: 98.82        Valid accuracy: 97.37
15:37:06 Epoch: 6       Train loss: 0.0457      Valid loss: 0.0833      Train accurac
y: 99.22        Valid accuracy: 97.69
15:37:27 Epoch: 7       Train loss: 0.0380      Valid loss: 0.0773      Train accurac
y: 99.00        Valid accuracy: 97.83
15:37:48 Epoch: 8       Train loss: 0.0340      Valid loss: 0.0848      Train accurac
y: 99.03        Valid accuracy: 97.66
15:38:09 Epoch: 9       Train loss: 0.0320      Valid loss: 0.0763      Train accurac
y: 99.21        Valid accuracy: 97.65
15:38:30 Epoch: 10      Train loss: 0.0274      Valid loss: 0.0861      Train accurac
y: 99.29        Valid accuracy: 97.72
15:38:51 Epoch: 11      Train loss: 0.0294      Valid loss: 0.0804      Train accurac
y: 99.31        Valid accuracy: 97.71
15:39:11 Epoch: 12      Train loss: 0.0241      Valid loss: 0.0775      Train accurac
y: 99.47        Valid accuracy: 97.99
15:39:32 Epoch: 13      Train loss: 0.0228      Valid loss: 0.0789      Train accurac
y: 99.53        Valid accuracy: 97.91
15:39:52 Epoch: 14      Train loss: 0.0229      Valid loss: 0.0832      Train accurac
y: 99.47        Valid accuracy: 97.68
```

In [33]:
```
plot_performance(performance_2)
```

```
C:\Users\henry\AppData\Local\Temp\ipykernel_4592\1716291042.py:35: MatplotlibDeprecat
ionWarning: The seaborn styles shipped by Matplotlib are deprecated since 3.6, as the
y no longer correspond to the styles shipped by seaborn. However, they will remain av
ailable as 'seaborn-v0_8-<style>'. Alternatively, directly use the seaborn API instea
d.
  plt.style.use('seaborn')
```





The loss of training data is dropping from 0.35 to 0.02, while the loss of testing data is dropping from 0.16 to 0.08

The accuracy of training data is rising from 0.95 to 0.994, while the loss of testing data is between 0.95 and 0.98

3.4.1 3.4.2

In [34]:
```
def find_trainable_parameter(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)
```

In [35]:
```
print("number of trainable parameters of LeNet:", find_trainable_parameter(LeNet5_mode
print("number of trainable parameters of MLP:",find_trainable_parameter(MLP_model))
```

```
number of trainable parameters of LeNet: 61706
number of trainable parameters of MLP: 280058
```

3.4.3

LeNet has better performance than MLP in terms of prediction accuracy on the test data. The final accuracy is about 0.985~0.99 on LeNet and is lower than 0.98 on MLP. LeNet has better performance because it uses convolution layers to focus on small areas to collect patterns in the picture; while MLP don't, it will waste a lot of neurons on calculating relationships between two distant points in the graph. Hence, LeNet can give us better performance.

4. Statement of Collaboration

Sabina Yang- Discussed about implementation fo LeNet5 in pytorch

In [ ]:
```

```