IFT6135 - Practical Assignment One

In [3]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import pickle as pickle
%matplotlib inline
```

Data Preparation ¶

Reading data and preparing the test, train and validation sets

In [4]:
```
input_size = 784
output_size = 10
```

In [5]:
```
class NN:
    ### __init__ Function to load the data and split the train set to train and v
    def __init__(self, mode, datapath=None, hidden_dims=None, hparams={}, model_p
        if mode=='train': assert (hidden_dims is not None) and bool(hparams)
        if mode=='test': assert model_path is not None
        self.mode = mode
        self.model_path = model_path
        self.lr = hparams.get('lr')
        self.weight_decay = hparams.get('weight_decay')
        self.num_epochs = hparams.get('num_epochs')
        self.Params = {}
        data = np.load(datapath)
        # Train data
        self.X_train = data['x_train'][:48000].reshape(48000, 784)
        self.y_train = data['y_train'][:48000]
        # Validation data
        self.X_valid = data['x_train'][48000:].reshape(12000, 784)
        self.y_valid = data['y_train'][48000:]
        self.X_test = data['x_test'].reshape(10000, 784)
        self.y_test = data['y_test']
        if (mode == 'train'):
            self.hidden_dims=(512,512)
            self.init_method = hparams['init_method']
            self.initialize_weights(hidden_dims)
        elif(mode == 'test'):
            with open(model_path,'rb') as f:
                self.Params = pickle.load(f)


    # Initialize the fucntion in three different ways : 1. Normal 2. Glorot 3. Ze
    def initialize_weights(self, dims):
        n_hidden = len(dims)
        num_nodes = [input_size] + list(dims) + [output_size]
        print('Initialization Method: %s' % self.init_method)
        print('--------------\n')
        for i in range(n_hidden + 1):
            self.Params['b%d'%(i+1)] = np.zeros(num_nodes[i+1])
            if self.init_method == 'Normal':
                self.Params['W%d'%(i+1)] = np.random.normal(0, 1,
                                                           (num_nodes[i+1], num_
            elif self.init_method == 'Glorot':
                D_Glorot = np.sqrt(6.0 / (num_nodes[i+1] + num_nodes[i]))
                self.Params['W%d'%(i+1)] = np.random.uniform(-D_Glorot, D_Glorot,
                                                           (num_nodes[i+1], num_
            elif self.init_method == 'Zeros':
                self.Params['W%d'%(i+1)] = np.zeros((num_nodes[i+1], num_nodes[i]

            else:
                raise ValueError('Invalid initialization type: %s' % self.init_me

    # Forward propagation
    def forward(self, x):
        N = x.shape[0]
        n_hidden = int(len(self.Params.keys()) / 2)
        h_cache_list = []
        a_cache_list = []
```

```
        h = x
        for i in range(n_hidden):
            h, h_cache = self.fc_forward(h, self.Params['W%d'%(i+1)], self.Params
            h_cache_list.append(h_cache)
            if i != (n_hidden-1):
                h, a_cache = self.relu_forward(h)
                a_cache_list.append(a_cache)
        scores = h
        cache = (N, n_hidden, a_cache_list, h_cache_list)
        return scores, cache

    # Backward function
    def backward(self, dloss, cache):
        (N, n_hidden, a_cache_list, h_cache_list) = cache
        dx = dloss
        grads = {}
        for i in range(n_hidden, 0, -1):
            dx, dW, db = self.fc_backward(dx, h_cache_list[i-1])
            grads['W%d'%i] = (dW / N) + (self.weight_decay * self.Params['W%d'%i]
            grads['b%d'%i] = (db / N)
            if i != 1:
                dx = self.relu_backward(dx, a_cache_list[i-2])
        return grads

    # Computes the forward pass for an affine (fully-connected) layer.
    def fc_forward(self, x, w, b):
        out = np.dot(x, w.T) + b
        cache = (x, w, b, out)
        return out, cache

    # Computes the backward pass for an affine (fully-connected) layer.
    def fc_backward(self, dupstream, cache):
        (x, w, b, out) = cache
        dx = np.dot(dupstream, w)
        dw = np.dot(dupstream.T, x)
        db = dupstream.sum(axis=0)
        return dx, dw, db

    ### Activation function
    def relu_forward(self, x):
        return np.maximum(0, x), x

    def relu_backward(self, dupstream, cache):
        return ((cache > 0) * dupstream)

    # The function to update parameters
    def update(self, grads):
        for param, grad in grads.items():
                self.Params[param] -= self.lr * grad

    ### Calculate Softmax and loss using cross entropy
    def softmax_loss(self, scores, label):
        sh_log = scores - np.max(scores, axis=1, keepdims=True)
        Z = np.sum(np.exp(sh_log), axis=1, keepdims=True)
        softmax = sh_log - np.log(Z)
        probs = np.exp(softmax)
        dim = scores.shape[0]
```

```
        loss = -np.sum(softmax[np.arange(dim), label]) / dim
        x = probs.copy()
        x[np.arange(dim), label] -= 1
        x /= dim
        return loss, x

    # Train function
    def train(self, mb_size=100):
        train_loss_hist = []
        val_loss_hist = []
        train_accuracies = []
        val_accuracies = []
        avg_loss = 0
        for ep in range(self.num_epochs):
            train_loss_epoch = 0
            train_data_size = 0
            correct_pred = 0
            batch_count = np.ceil(self.X_train.shape[0] / mb_size).astype('int')
            for i in range(batch_count):
                xi = self.X_train[i*mb_size:(i+1)*mb_size]
                yi = self.y_train[i*mb_size:(i+1)*mb_size]
                scores, cache = self.forward(xi)
                pred_train = np.argmax(scores, axis=1)
                train_loss, dloss = self.softmax_loss(scores, yi)
                correct_pred += (pred_train == yi).sum()
                grads = self.backward(dloss, cache)
                self.update(grads)
                train_loss_epoch += train_loss * len(yi)
                train_data_size += len(yi)

            scores_val,_ = self.forward(self.X_valid)
            pred_val = np.argmax(scores_val, axis=1)
            val_loss, _ = self.softmax_loss(scores_val, self.y_valid)

            train_loss_hist.append(train_loss_epoch / train_data_size)
            val_loss_hist.append(val_loss)
            train_acc = correct_pred / train_data_size
            val_acc = (pred_val == self.y_valid).mean()
            train_accuracies.append(train_acc)
            val_accuracies.append(val_acc)
            print('Epoch %d' % ep)
            print('Train: Loss: %.4f, Accuracy %.4f' % (train_loss_epoch / train_
            print('Validation: Loss: %.4f, Accuracy %.4f\n' % (val_loss, val_acc)

        train_history = {'train_loss_hist':train_loss_hist,
                         'val_loss_hist':val_loss_hist,
                         'train_accuracies':train_accuracies,
                         'val_accuracies':val_accuracies}
        if self.model_path is not None:
            with open(self.model_path, 'wb') as f:
                pickle.dump(self.Params, f)
        return train_history

    # Test function
    def test(self, x):
        scores,_ = self.forward(x)
        return scores
```

Helper Functions

In [18]:
```
def historyPlt(train_history):
    train_losses = train_history['train_loss_hist']
    train_accuracies = train_history['train_accuracies']
    valid_losses = train_history['val_loss_hist']
    valid_accuracies = train_history['val_accuracies']

    # Plotting the loss accuracy
    plt.figure(figsize=(12, 4))
    axis = plt.subplot(1, 2, 1)
    axis.plot(range(1, len(train_losses)+1), train_losses, label='train', color =
    axis.plot(range(1, len(valid_losses)+1), valid_losses, label='valid', color =
    axis.legend()
    axis.set_ylabel('Loss')
    axis.set_xlabel('Epochs')

    axis = plt.subplot(1, 2, 2)
    axis.plot(range(1, len(train_accuracies)+1), train_accuracies, label='train',
    axis.plot(range(1, len(valid_accuracies)+1), valid_accuracies, label='valid',
    axis.legend()
    axis.set_ylabel('Accuracy')
    axis.set_xlabel('Epochs')


def accuracy(scores, labels):
    preds = np.argmax(scores, axis=1)
    accuracy = (preds == labels).mean()
    return accuracy
```

1 .Train the model for 10 epochs 3 using the initialization methods above and record the average loss measured on the training data at the end of each epoch (10 values for each setup).

2. Compare the three setups by plotting the losses against the training time (epoch) and comment on the result.

For this part we trian the model using 3 different initialization approach.

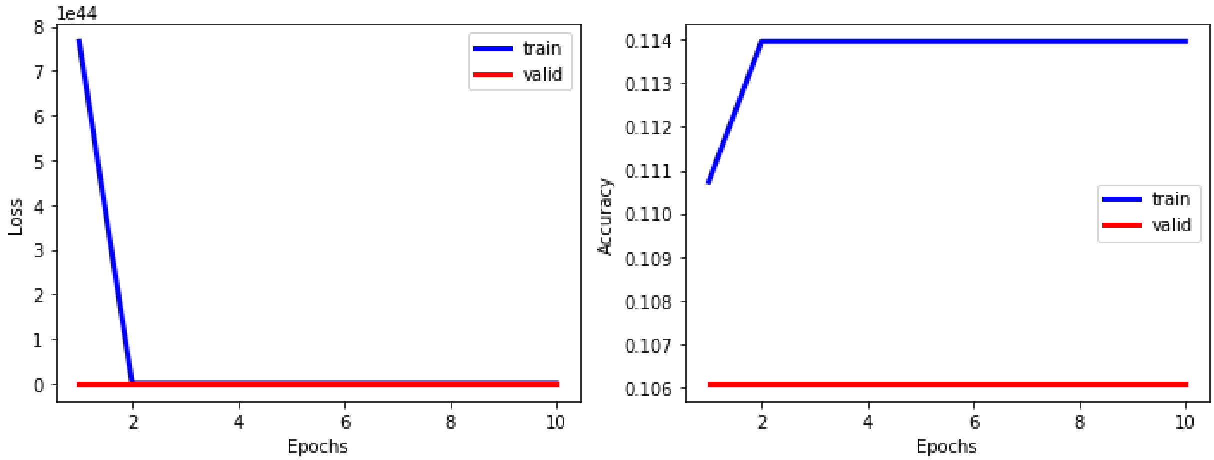
1.1. Initialization using Normal method

In [16]:
```
# Initiate hyperparameters
hparams = {'init_method': 'Normal',
           'lr': 1e-1,
           'weight_decay': 0,
           'num_epochs': 10}

# Initialize NN object
nn = NN(mode='train', datapath='./mnist.npz', hidden_dims=(512, 512), hparams=hpa
        model_path='Params.pkl')

# Start training
train_history_normal = nn.train()
print('Training done!')
```

```
Initialization Method: Normal
--------------

Epoch 0
Train: Loss: 766436245291446901776873926236796245558427648.0000, Accuracy 0.110
7
Validation: Loss: 2647632.1122, Accuracy 0.1061

Epoch 1
Train: Loss: 2.3023, Accuracy 0.1140
Validation: Loss: 2647632.1121, Accuracy 0.1061

Epoch 2
Train: Loss: 2.3022, Accuracy 0.1140
Validation: Loss: 2647632.1121, Accuracy 0.1061

Epoch 3
Train: Loss: 2.3021, Accuracy 0.1140
Validation: Loss: 2647632.1120, Accuracy 0.1061

Epoch 4
Train: Loss: 2.3020, Accuracy 0.1140
Validation: Loss: 2647632.1119, Accuracy 0.1061

Epoch 5
Train: Loss: 2.3019, Accuracy 0.1140
Validation: Loss: 2647632.1119, Accuracy 0.1061

Epoch 6
Train: Loss: 2.3018, Accuracy 0.1140
Validation: Loss: 2647632.1119, Accuracy 0.1061

Epoch 7
Train: Loss: 2.3017, Accuracy 0.1140
Validation: Loss: 2647632.1118, Accuracy 0.1061

Epoch 8
Train: Loss: 2.3017, Accuracy 0.1140
Validation: Loss: 2647632.1118, Accuracy 0.1061

Epoch 9
Train: Loss: 2.3016, Accuracy 0.1140
Validation: Loss: 2647632.1118, Accuracy 0.1061
```

```
Training done!
```

In [19]:
```
historyPlt(train_history_normal)
```



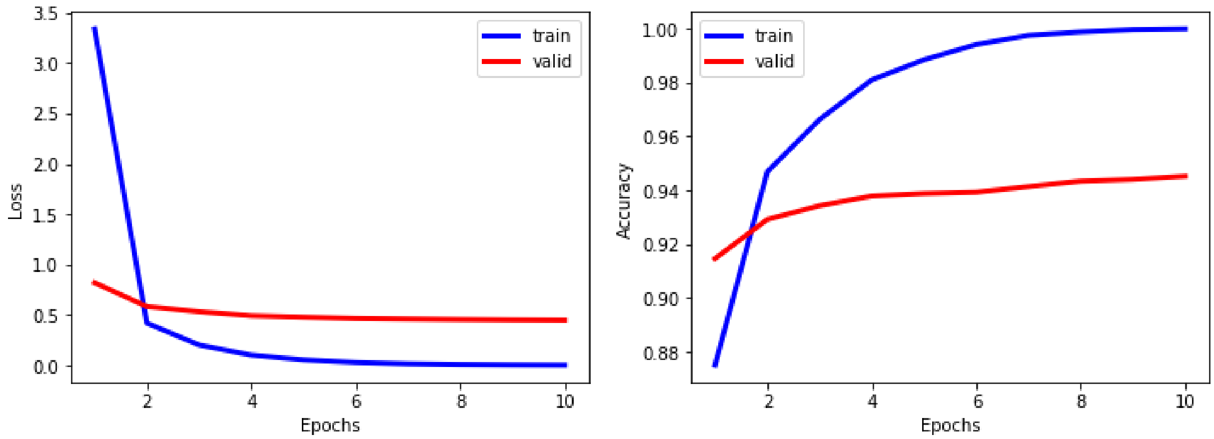
1.2. Initialization using Glorot method

In [5]:
```python
# Initiate hyperparameters
hparams = {'init_method': 'Glorot',
           'lr': 1e-1,
           'weight_decay': 0,
           'num_epochs': 10}

# Initialize NN object
nn = NN(mode='train', datapath='./mnist.npz', hidden_dims=(512, 512), hparams=hpa
        model_path='Params.pkl')

# Start training
train_history_glorot = nn.train()
print('Training done!')
```

```
Initialization Method: Glorot
--------------

Epoch 0
Train: Loss: 3.3376, Accuracy 0.8751
Validation: Loss: 0.8212, Accuracy 0.9147

Epoch 1
Train: Loss: 0.4210, Accuracy 0.9468
Validation: Loss: 0.5856, Accuracy 0.9292

Epoch 2
Train: Loss: 0.2038, Accuracy 0.9662
Validation: Loss: 0.5339, Accuracy 0.9343

Epoch 3
Train: Loss: 0.1037, Accuracy 0.9809
Validation: Loss: 0.4937, Accuracy 0.9378

Epoch 4
Train: Loss: 0.0559, Accuracy 0.9884
Validation: Loss: 0.4795, Accuracy 0.9387

Epoch 5
Train: Loss: 0.0304, Accuracy 0.9940
Validation: Loss: 0.4676, Accuracy 0.9393

Epoch 6
Train: Loss: 0.0163, Accuracy 0.9974
Validation: Loss: 0.4618, Accuracy 0.9413

Epoch 7
Train: Loss: 0.0093, Accuracy 0.9987
Validation: Loss: 0.4565, Accuracy 0.9433

Epoch 8
Train: Loss: 0.0055, Accuracy 0.9995
Validation: Loss: 0.4527, Accuracy 0.9440

Epoch 9
Train: Loss: 0.0037, Accuracy 0.9998
Validation: Loss: 0.4502, Accuracy 0.9452
```

```
Training done!
```

In [52]:
```
historyPlt(train_history_glorot)
```



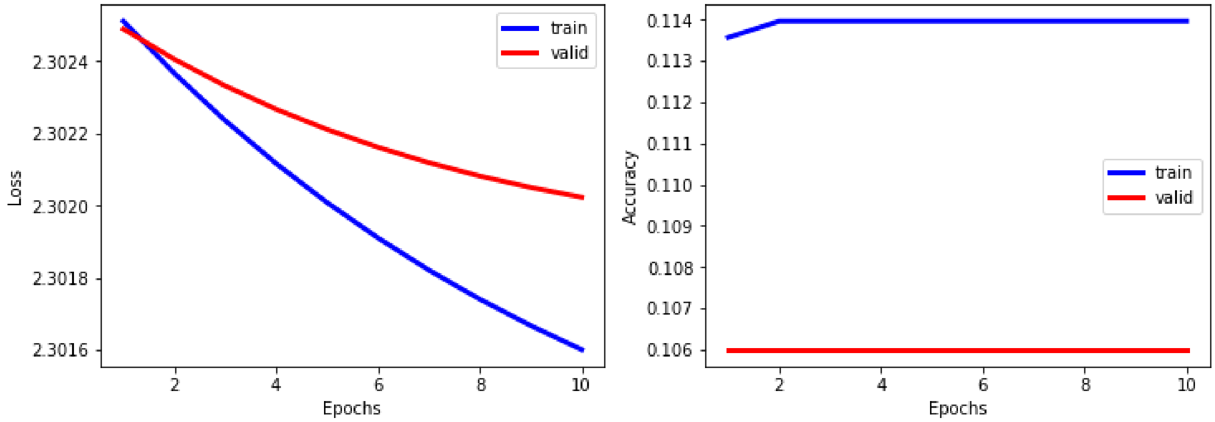
1.3. Initialization using Zero method

In [8]:
```
# Initiate hyperparameters
hparams = {'init_method': 'Zeros',
           'lr': 1e-1,
           'weight_decay': 0,
           'num_epochs': 10}

# Initialize NN object
nn = NN(mode='train', datapath='./mnist.npz', hidden_dims=(512, 512), hparams=hpa
        model_path='Params.pkl')

# Start training
train_history_zero = nn.train()
print('Training done!')
```

```
Initialization Method: Zeros
--------------

Epoch 0
Train: Loss: 2.3025, Accuracy 0.1136
Validation: Loss: 2.3025, Accuracy 0.1060

Epoch 1
Train: Loss: 2.3024, Accuracy 0.1140
Validation: Loss: 2.3024, Accuracy 0.1060

Epoch 2
Train: Loss: 2.3022, Accuracy 0.1140
Validation: Loss: 2.3023, Accuracy 0.1060

Epoch 3
Train: Loss: 2.3021, Accuracy 0.1140
Validation: Loss: 2.3023, Accuracy 0.1060

Epoch 4
Train: Loss: 2.3020, Accuracy 0.1140
Validation: Loss: 2.3022, Accuracy 0.1060

Epoch 5
Train: Loss: 2.3019, Accuracy 0.1140
Validation: Loss: 2.3022, Accuracy 0.1060

Epoch 6
Train: Loss: 2.3018, Accuracy 0.1140
Validation: Loss: 2.3021, Accuracy 0.1060

Epoch 7
Train: Loss: 2.3017, Accuracy 0.1140
Validation: Loss: 2.3021, Accuracy 0.1060

Epoch 8
Train: Loss: 2.3017, Accuracy 0.1140
Validation: Loss: 2.3021, Accuracy 0.1060

Epoch 9
Train: Loss: 2.3016, Accuracy 0.1140
Validation: Loss: 2.3020, Accuracy 0.1060
```

```
Training done!
```

In [53]:
```
historyPlt(train_history_zero)
```



Hyperparameter Search From now on, use the Glorot initialization method.

1. Find out a combination of hyper-parameters (model architecture, learning rate, nonlinearity, etc.) such that the average accuracy rate on the validation set (r(valid)) is at least 97%.

2. Report the hyper-parameters you tried and the corresponding r(valid).

```
For this question we have found two diffrent combination of hyper parameters and
initialization methods.
1. using Glorot
2. Using Normal initiation
```

Optimal Hyperparameter Search

In [67]:
```
# # Initiate hyperparameters
# hparams = {'init_method': 'Glorot',
#            'num_epochs': 3}

# for i in range(100):
#     lr = 10 ** np.random.uniform(-2, 0)
#     weight_decay = 10 ** np.random.uniform(-5, 0)

#     hparams['lr'] = lr
#     hparams['weight_decay'] = weight_decay
#     print('lr: %.6f'%lr)
#     print('weight_decay: %.6f'%weight_decay)
#     # Initialize NN object
#     nn = NN((512,512), mode='train', hparams=hparams, datapath='./mnist.npz')

#     # Start training
#     train_history = nn.train()


# print('Training done!')
```

Solution 1 : Hyperparameters Report :

```
For this question, we trained the model with the following parameters:
    • Initialization method : Glorot
    • learning rate : 0.14
    • batch size : 50
    • number of epochs : 10
    • weight_decay : 1e-3
    • number of neurons for l1, l2 : 600 * 250
    • Non linearity : ReLU
    • Optimizer : SGD
```

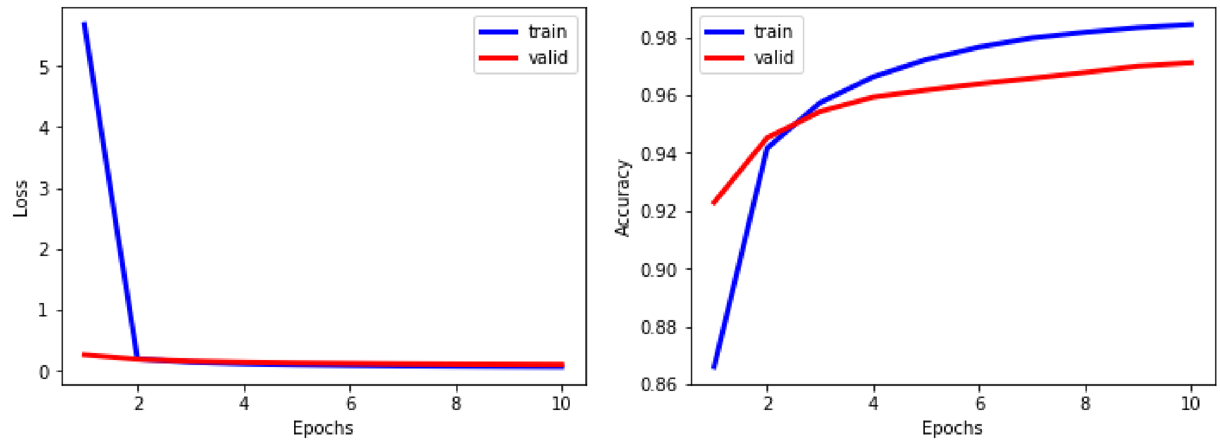
The case with at least 97% on accuracy rate on the validation set.

In [25]:
```
# Initiate hyperparameters
hparams = {'init_method': 'Glorot',
           'lr': 0.14,
           'weight_decay': 1e-3,
           'num_epochs': 10}

# Initialize NN object
nn = NN(mode='train', datapath='./mnist.npz', hidden_dims=(600, 250), hparams=hpa
        model_path='Params.pkl')

# Start training
train_history = nn.train()
print('Training done!')
```

```
Initialization Method: Glorot
--------------

Epoch 0
Train: Loss: 5.6846, Accuracy 0.8661
Validation: Loss: 0.2605, Accuracy 0.9229

Epoch 1
Train: Loss: 0.1918, Accuracy 0.9417
Validation: Loss: 0.1864, Accuracy 0.9453

Epoch 2
Train: Loss: 0.1393, Accuracy 0.9574
Validation: Loss: 0.1550, Accuracy 0.9543

Epoch 3
Train: Loss: 0.1131, Accuracy 0.9663
Validation: Loss: 0.1372, Accuracy 0.9593

Epoch 4
Train: Loss: 0.0964, Accuracy 0.9723
Validation: Loss: 0.1254, Accuracy 0.9617

Epoch 5
Train: Loss: 0.0849, Accuracy 0.9766
Validation: Loss: 0.1175, Accuracy 0.9639

Epoch 6
Train: Loss: 0.0767, Accuracy 0.9798
Validation: Loss: 0.1105, Accuracy 0.9658

Epoch 7
Train: Loss: 0.0714, Accuracy 0.9817
Validation: Loss: 0.1062, Accuracy 0.9678

Epoch 8
Train: Loss: 0.0671, Accuracy 0.9834
Validation: Loss: 0.1028, Accuracy 0.9700

Epoch 9
Train: Loss: 0.0642, Accuracy 0.9844
Validation: Loss: 0.1003, Accuracy 0.9712
```

```
Training done!
```

In [54]:
```
historyPlt(train_history)
```



Solution 2 : Hyperparameters Report :

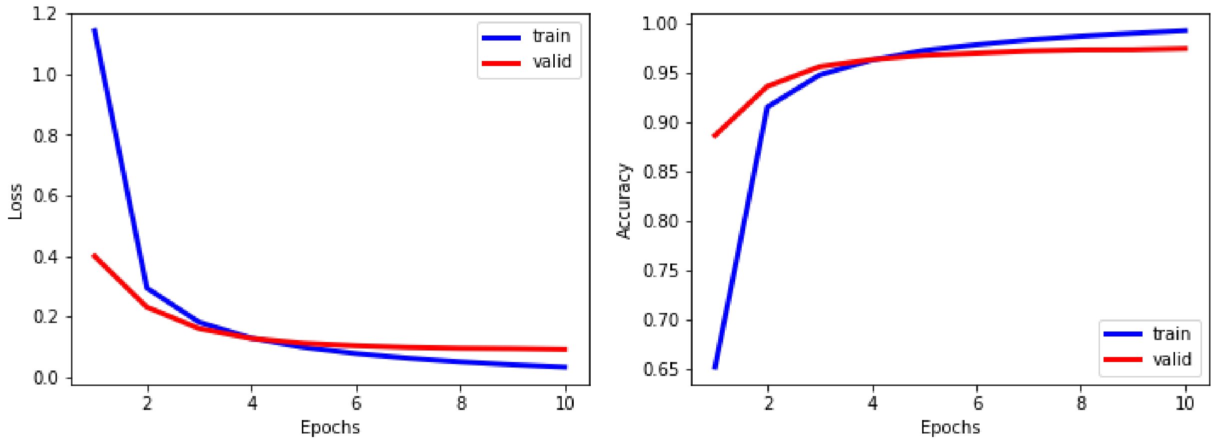
In [ ]:
```
For this question, we trained the model with the following parameters:
```
- Initialization method : Normal(mean = 0, sd = 0.001)
- learning rate : 0.14
- batch size : 50
- number of epochs : 10
- weight_decay : 0
- number of neurons for l1, l2 : 512 * 512
- Non linearity : ReLU
- Optimizer : SGD

In [33]:
```
# Initiate hyperparameters
hparams = {'init_method': 'Normal',
           'lr': 1e-1,
           'weight_decay': 0,
           'num_epochs': 10}

# Initialize NN object
nn = NN(mode='train', datapath='./mnist.npz', hidden_dims=(512, 512), hparams=hpa
        model_path='Params.pkl')

# Start training
train_history_normal_sd_001 = nn.train()
print('Training done!')
```

```
Initialization Method: Normal
--------------

Epoch 0
Train: Loss: 1.1431, Accuracy 0.6514
Validation: Loss: 0.3999, Accuracy 0.8858

Epoch 1
Train: Loss: 0.2952, Accuracy 0.9145
Validation: Loss: 0.2320, Accuracy 0.9355

Epoch 2
Train: Loss: 0.1824, Accuracy 0.9470
Validation: Loss: 0.1615, Accuracy 0.9554

Epoch 3
Train: Loss: 0.1302, Accuracy 0.9621
Validation: Loss: 0.1291, Accuracy 0.9626

Epoch 4
Train: Loss: 0.0998, Accuracy 0.9718
Validation: Loss: 0.1132, Accuracy 0.9669

Epoch 5
Train: Loss: 0.0793, Accuracy 0.9776
Validation: Loss: 0.1051, Accuracy 0.9690

Epoch 6
Train: Loss: 0.0639, Accuracy 0.9825
Validation: Loss: 0.0996, Accuracy 0.9713

Epoch 7
Train: Loss: 0.0519, Accuracy 0.9861
Validation: Loss: 0.0966, Accuracy 0.9725

Epoch 8
Train: Loss: 0.0424, Accuracy 0.9892
Validation: Loss: 0.0956, Accuracy 0.9726

Epoch 9
Train: Loss: 0.0344, Accuracy 0.9918
Validation: Loss: 0.0933, Accuracy 0.9738
```

```
Training done!
```

In [34]:
```
historyPlt(train_history_normal_sd_001)
```



Numerical Gradient

In [6]:
```
np.random.seed(7899)

hparams = {'init_method': 'Glorot',
           'lr': 1e-1,
          'weight_decay': 2e-3,
          'num_epochs': 10}

nn = NN(mode='train', datapath='./mnist.npz', hidden_dims=(512, 512), hparams=hpa
        model_path='Params.pkl')
xi = nn.X_train[0].reshape(-1,784)
yi = nn.y_train[0].reshape(-1,1)
```

```
Initialization Method: Glorot
--------------
```

In [13]:

```
max_diffs=[]
Ns=[np.float(i) for i in range(1,25)]
# Ns=[5e0,6e1,7e2,8e3,2e4]
for N in Ns:
    epsi = 1/N
    numerical_grad = []
    for i in range(0,10):

        nn.Params['W2'][0,i] += epsi
        scores,cache = nn.forward(xi)
        softmax_loss_plus, _ = nn.softmax_loss(scores, yi)

        nn.Params['W2'][0,i] -= 2*epsi
        scores,cache = nn.forward(xi)
        softmax_loss_min, _ = nn.softmax_loss(scores, yi)

        numerical_grad.append((softmax_loss_plus - softmax_loss_min) / (2*epsi))


        nn.Params['W2'][0,i] += epsi # reset original value
        scores,cache = nn.forward(xi)
        softmax_loss, dsoftmax = nn.softmax_loss(scores, yi)
        average_grads = nn.backward(dsoftmax, cache)
    diff = np.absolute(average_grads['W2'][0,:10] - numerical_grad)
    max_diffs.append(np.max(diff))
```

In [15]:

```
fig,ax = plt.subplots(1,1)
ax.plot(Ns,max_diffs)
ax.set_ylabel(" Max Diff ")
ax.set_xlabel("N")
plt.show()
```