Neural Network For Letter Recoignition From Scratch

December 28, 2022

[1]:
```python
import numpy as np
import pandas as pd
from matplotlib import figure
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import OneHotEncoder
```

[2]:
```python
df= pd.read_csv('letter-recognition.data', header=None)
print(df.shape)
df.head()
```

```
(20000, 17)
```

[2]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	T	2	8	3	5	1	8	13	0	6	6	10	8	0	8	0	8
1	I	5	12	3	7	2	10	5	5	4	13	3	9	2	8	4	10
2	D	4	11	6	8	6	10	6	2	6	10	3	7	3	7	3	9
3	N	7	11	6	6	3	5	9	4	6	4	4	10	6	10	2	8
4	G	2	1	3	1	1	8	6	6	6	6	5	9	1	7	5	10

[3]:
```python
df.describe()
```

[3]:

	1	2	3	4	5 \
count	20000.000000	20000.000000	20000.000000	20000.00000	20000.000000
mean	4.023550	7.035500	5.121850	5.37245	3.505850
std	1.913212	3.304555	2.014573	2.26139	2.190458
min	0.000000	0.000000	0.000000	0.00000	0.000000
25%	3.000000	5.000000	4.000000	4.00000	2.000000
50%	4.000000	7.000000	5.000000	6.00000	3.000000
75%	5.000000	9.000000	6.000000	7.00000	5.000000
max	15.000000	15.000000	15.000000	15.00000	15.000000

	6	7	8	9	10 \
count	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000
mean	6.897600	7.500450	4.628600	5.178650	8.282050
std	2.026035	2.325354	2.699968	2.380823	2.488475
min	0.000000	0.000000	0.000000	0.000000	0.000000

```
25%       6.000000      6.000000      3.000000      4.000000      7.000000
50%       7.000000      7.000000      4.000000      5.000000      8.000000
75%       8.000000      9.000000      6.000000      7.000000     10.000000
max      15.000000     15.000000     15.000000     15.000000     15.000000

                11            12            13            14            15  \
count  20000.00000  20000.000000  20000.000000  20000.000000  20000.000000
mean       6.45400      7.929000      3.046100      8.338850      3.691750
std        2.63107      2.080619      2.332541      1.546722      2.567073
min        0.00000      0.000000      0.000000      0.000000      0.000000
25%        5.00000      7.000000      1.000000      8.000000      2.000000
50%        6.00000      8.000000      3.000000      8.000000      3.000000
75%        8.00000      9.000000      4.000000      9.000000      5.000000
max       15.00000     15.000000     15.000000     15.000000     15.000000

                16
count  20000.00000
mean       7.80120
std        1.61747
min        0.00000
25%        7.00000
50%        8.00000
75%        9.00000
max       15.00000
```

[4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 17 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       20000 non-null  object
 1   1       20000 non-null  int64
 2   2       20000 non-null  int64
 3   3       20000 non-null  int64
 4   4       20000 non-null  int64
 5   5       20000 non-null  int64
 6   6       20000 non-null  int64
 7   7       20000 non-null  int64
 8   8       20000 non-null  int64
 9   9       20000 non-null  int64
 10  10      20000 non-null  int64
 11  11      20000 non-null  int64
 12  12      20000 non-null  int64
 13  13      20000 non-null  int64
 14  14      20000 non-null  int64
 15  15      20000 non-null  int64
```

```
 16  16      20000 non-null  int64
dtypes: int64(16), object(1)
memory usage: 2.6+ MB
```

[5]:
```python
# label encoding the class labels
from sklearn.preprocessing import LabelEncoder
label_encoder= LabelEncoder()
df[0]= label_encoder.fit_transform(df[0])
print(df[0].unique())
df.head()
```

```
[19  8  3 13  6 18  1  0  9 12 23 14 17  5  2  7 22 11 15  4 21 24 16 20
 10 25]
```

[5]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	19	2	8	3	5	1	8	13	0	6	6	10	8	0	8	0	8
1	8	5	12	3	7	2	10	5	5	4	13	3	9	2	8	4	10
2	3	4	11	6	8	6	10	6	2	6	10	3	7	3	7	3	9
3	13	7	11	6	6	3	5	9	4	6	4	4	10	6	10	2	8
4	6	2	1	3	1	1	8	6	6	6	6	5	9	1	7	5	10

[6]:
```python
df_test= df[[0]]
print(df_test.shape)
df_test.head()
```

```
(20000, 1)
```

[6]:

	0
0	19
1	8
2	3
3	13
4	6

[7]:
```python
df_train= df.drop(0, axis=1, inplace=False)
print(df_train.shape)
df_train.head()
```

```
(20000, 16)
```

[7]:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	2	8	3	5	1	8	13	0	6	6	10	8	0	8	0	8
1	5	12	3	7	2	10	5	5	4	13	3	9	2	8	4	10
2	4	11	6	8	6	10	6	2	6	10	3	7	3	7	3	9
3	7	11	6	6	3	5	9	4	6	4	4	10	6	10	2	8
4	2	1	3	1	1	8	6	6	6	6	5	9	1	7	5	10

[8]:
```python
from sklearn.model_selection import train_test_split
```

[9]:
```
X_train, X_rem, y_train, y_rem = train_test_split(df_train, df_test,␣
↪train_size=0.8)

X_valid, X_test, y_valid, y_test = train_test_split(X_rem,y_rem, test_size=0.5)

print("x_train dataset size: ",X_train.shape)
print("y_train dataset size: ",y_train.shape)
print("x_validation dataset size: ",X_valid.shape)
print("y_validation dataset size: ",y_valid.shape)
print("x_test dataset size: ",X_test.shape)
print("y_test dataset size: ",y_test.shape)
```

```
x_train dataset size:  (16000, 16)
y_train dataset size:  (16000, 1)
x_validation dataset size:  (2000, 16)
y_validation dataset size:  (2000, 1)
x_test dataset size:  (2000, 16)
y_test dataset size:  (2000, 1)
```

[10]:
```
print("number of unique classes in the dataset is- ", len(df[0].unique()))
```

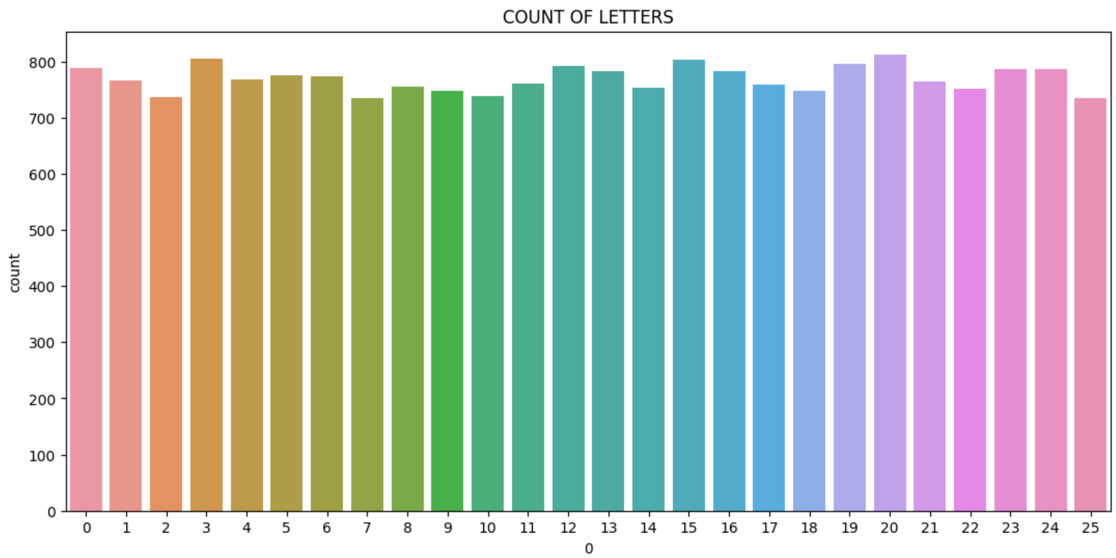
```
number of unique classes in the dataset is-  26
```

[11]:
```
df[0].value_counts()
```

[11]:
```
20    813
3     805
15    803
19    796
12    792
0     789
23    787
24    786
13    783
16    783
5     775
6     773
4     768
1     766
21    764
11    761
17    758
8     755
14    753
22    752
18    748
9     747
10    739
```

```
2     736
7     734
25    734
Name: 0, dtype: int64
```

[12]:
```
plt.figure(figsize = (13,6))
plt.title("COUNT OF LETTERS")
sns.countplot(x=0, data= df)
plt.show()
```



[13]:
```
# we can observe that the datset is balanced and dont have any null values so we␣
↪proceed with ot
```

1 Building the NN

[14]:
```
# it has 2 layers i.e. 1 input, 1 hidden and 1 output layer
# lets assume
# 40 neurons in the first hidden layer
# output layer is a 26 class softmax layer for multiclass classification
```

weight matrix between input layer and 1st hidden layer has size [16 x 40] bias vector between input layer and 1st hidden layer is of size [40 x 1]

weight matrix between 1st hidden layer and output softmax layer is [40 x 26] bias vector between 1st hidden layer and output softmax layer is of size [26 x 1]

[15]:
```
# converting all the datasets into arrays
x_train_arr = np.array(X_train)
```

```
y_train_arr = np.array(y_train)
x_test_arr = np.array(X_test)
y_test_arr = np.array(y_test)
x_valid_arr = np.array(X_valid)
y_valid_arr = np.array(y_valid)
```

[16]:
```
onehot= OneHotEncoder()
```

[17]:
```
y_train_arr = onehot.fit_transform(y_train_arr.reshape(-1,1))
y_train_arr = y_train_arr.toarray()
y_train_arr
```

[17]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

[18]:
```
y_test_arr = onehot.fit_transform(y_test_arr.reshape(-1,1))
y_test_arr = y_test_arr.toarray()
y_train_arr
```

[18]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

[19]:
```
y_valid_arr = onehot.fit_transform(y_valid_arr.reshape(-1,1))
y_valid_arr = y_valid_arr.toarray()
y_valid_arr
```

[19]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

[20]:
```
class activation_function:
    def __init__(self):
        self.name = None
        self.output = None
```

```
    def tanh(self, input_data):
        return np.tanh(input_data)

    def grad_tanh(self, input_data):
        return 1-np.tanh(input_data)**2

    def relu(self, x):
        self.output = np.maximum(0,x)
        return self.output

    def grad_relu(self, x):
        self.output[self.output>0] = 1
        return self.output

    def activation(self, name, x):
        self.name = name
        if self.name == "relu":
            return self.relu(x)
        elif self.name == "tanh":
            return self.tanh(x)

    def grad_activation(self,x):
        if self.name == "relu":
            return self.grad_relu(x)
        elif self.name == "tanh":
            return self.grad_tanh(x)
```

[21]:

```
# defining all three activation functions

def activation_relu(x):
    return np.maximum(0,x)

def activation_tanh(x):
    return np.tanh(x)

# def activation_softmax(x):
#     exp_values= np.exp(x - np.max(x, axis=1, keepdims=True))
#     probabilities= exp_values/ np.sum(exp_values, axis= 1, keepdims=True)
#     return probabilities
```

[22]:

```
#defining the gradients of both the activation functions for updating the weights

def gradient_relu(x):
    x[x>0]=1
    return x
```

```
def gradient_tanh(x):
    return (1- np.tanh(x)**2)

# def gradient_softmax(x):
#     jacobian= np.diag(x)
#     for i in range(len(jacobian)):
#         for j in range(len(jacobian)):
#             if i == j:
#                 jacobian[i][j] = x[i] * (1-x[i])
#             else:
#                 jacobian[i][j] = -x[i]*x[j]
#     return jacobian
```

[23]:
```
# #defining the adam optimizer for faster convergence

# def optimizer_adam(weight, alpha=0.001, beta1= 0.9, beta2= 0.999, epsilon=
↪1e-8):
#     t=0

#     m_t=0
#     v_t=0

#     m_t_hat= m_t
#     v_t_hat= v_t

#     num_steps=1000

#     while t in range(1,num_steps):
#         dw= compute_gradient(weight)

#         m_t= beta1*m_t+ (1-beta1)*dw
#         v_t= beta2*v_t+ (1-beta2)*dw*dw

#         m_t_hat= m_t/(1- beta1**t)
#         v_t_hat= v_t/(1-beta2**t)

#         weight= weight- alpha*(m_t_hat/(v_t_hat.sqrt()+ epsilon))

#     return weight
```

[24]:
```
#defining a layer

class layer:
    def __init__(self):
        self.input = None
        self.output = None
```

```
    # computes the output Y of a layer for a given input X
    def forward_propagation(self, input):
        pass

    # computes dE/dX for a given dE/dY (and update parameters if any)
    def backward_propagation(self, output_error, learning_rate):
        pass
```

[25]:

```
# the fully connected layer

class fully_connected_layer:
    def __init__(self, input_size, output_size):
        # xavier weight initialization
        # input_size = fan_in
        # output_size = fan_out
        self.weights = np.random.randn(input_size, output_size) / np.
 ↪sqrt(input_size)
        self.bias = np.random.randn(1,output_size)

    # returns output for a given input
    def forward_propagation(self, input_data):
        self.input = input_data.reshape(1,-1)
        self.output = np.dot(self.input, self.weights) + self.bias
        return self.output

    # computes dE/dW, dE/dB for a given output_error=dE/dY. Returns␣
 ↪input_error=dE/dX.
    def backward_propagation(self, output_gradient, learning_rate, optimizer, T):
        input_gradient = np.dot(output_gradient, self.weights.T)
        weights_gradient = np.dot(self.input.T, output_gradient)
        bias_gradient = output_gradient

        # updating the parameters
        self.weights = self.weights - (learning_rate * weights_gradient)
        self.bias = self.bias - (learning_rate * output_gradient)

        if optimizer=='adam':
            opt = AdamOptim(eta=learning_rate, beta1=0.9, beta2=0.999,␣
 ↪epsilon=1e-8)
            self.weights, self.bias = opt.update(t=T, w = self.weights, b = self.
 ↪bias, dw = weights_gradient, db = output_gradient)

        return input_gradient
```

[26]:

```
# # the actiation layer

# class activation_layer:
```

```
#     def __init__(self, activation, grad_activation):
#         self.activation = activation
#         self.grad_activation = grad_activation

#     # returns the activated input
#     def forward_propagation(self, input_data):
#         self.input = input_data
#         self.output = self.activation(self.input)
#         return self.output

#     # Returns input_error=dE/dX for a given output_error=dE/dY.
#     # learning_rate is not used because there is no "learnable" parameters.
#     def backward_propagation(self, output_gradient, learning_rate, optimizer,␣
 ↪T):
#         return self.grad_activation(self.input) * output_gradient
```

[27]:
```
# the activation layer

class activation_layer:
    def __init__(self, act_func):
        self.input = None
        self.output = None
        self.act_func = act_func
        self.act = activation_function()

    def forward_propagation(self, input_data):
        self.input = input_data
        self.output = self.act.activation(self.act_func, input_data)
        return self.output

    def backward_propagation(self, output_gradient, learning_rate, optimizer, T):
        return self.act.grad_activation(self.input)*output_gradient
```

[28]:
```
# defining the softmax activation layer
class softmax_layer:
    def __init__(self, input_size):
        self.input = None
        self.output = None
        self.input_size = input_size

    def forward_propagation(self, input_data):
        self.input = input_data
        exp = np.exp(self.input - np.max(self.input, axis=1, keepdims=True))
        exp_sum = np.sum(exp, axis=1, keepdims=True)
        self.output = exp/(exp_sum)
        return self.output
```

```
    def backward_propagation(self, output_data, learning_rate, optimizer, T):
        dz_x = np.zeros((self.input_size,self.input_size))
        for i in range(self.input_size):
            for j in range(self.input_size):
                if i == j:
                    dz_x[i,j] = self.output[0,i]*(1-self.output[0,i])
                else:
                    dz_x[i,j] = -self.output[0,i]*self.output[0,j]

        dl_x = np.dot(output_data,dz_x)
        return dl_x
```

[29]:
```
# defining the loss function
def cross_entropy_loss(y_true, y_pred):
    loss = np.sum(-np.log(y_pred+1e-20)*y_true)
    return loss

def grad_cross_entropy_loss(y_true, y_pred):
    grad_loss = -y_true/(y_pred + 1e-20)
    return grad_loss
```

[30]:
```
# defining the adam optimizer
class AdamOptim():
    def __init__(self, eta=0.01, beta1=0.9, beta2=0.999, epsilon=1e-8):
        self.m_dw, self.v_dw = 0, 0
        self.m_db, self.v_db = 0, 0
        self.beta1 = beta1
        self.beta2 = beta2
        self.epsilon = epsilon
        self.eta = eta
    def update(self, t, w, b, dw, db):
        ## dw, db are from current minibatch
        ## momentum beta 1
        # *** weights *** #
        self.m_dw = self.beta1*self.m_dw + (1-self.beta1)*dw
        # *** biases *** #
        self.m_db = self.beta1*self.m_db + (1-self.beta1)*db

        ## rms beta 2
        # *** weights *** #
        self.v_dw = self.beta2*self.v_dw + (1-self.beta2)*(dw**2)
        # *** biases *** #
        self.v_db = self.beta2*self.v_db + (1-self.beta2)*(db**2)

        ## bias correction
        m_dw_corr = self.m_dw/(1-self.beta1**t)
        m_db_corr = self.m_db/(1-self.beta1**t)
```

```
        v_dw_corr = self.v_dw/(1-self.beta2**t)
        v_db_corr = self.v_db/(1-self.beta2**t)
#         print(v_db_corr)

        ## update weights and biases
        w = w - self.eta*(m_dw_corr/(np.sqrt(v_dw_corr)+self.epsilon))
        b = b - self.eta*(m_db_corr/(np.sqrt(v_db_corr)+self.epsilon))
        return w, b
```

[31]:
```
class MLP:
    def __init__(self):
        self.layers = []
        self.loss = None
        self.grad_loss= None
        self.optimizer = None
        self.train_loss = []
        self.validation_loss = []
        self.train_accuracy= []
        self.validation_accuracy = []

    # add layer to network
    def add(self, layer):
        self.layers.append(layer)

    # set loss to use
    def use(self, loss, grad_loss):
        self.loss = loss
        self.grad_loss= grad_loss

    # predict output for given input
    def predict(self, input_data):
        # sample dimension first
        samples = len(input_data)
        result = []

        # run network over all samples
        for i in range(samples):
            # forward propagation
            output = input_data[i]
            for layer in self.layers:
                output = layer.forward_propagation(output)
            output= (output==np.max(output))*1
            result.append(output[0])

        return result

    # train the network
```

```
    def fit(self, x_train, y_train, x_valid, y_valid, epochs, learning_rate,␣
↪optimizer="adam"):
        # sample dimension first
        samples = len(x_train)
        self.optimizer= optimizer
        # training loop
        for i in range(epochs):
            err = 0
            for j in range(samples):
                # forward propagation
                output = x_train[j]
                for layer in self.layers:
                    output = layer.forward_propagation(output)

                # compute loss
                err += self.loss(y_train[j], output)

                # backward propagation
                error = self.grad_loss(y_train[j], output)
                for layer in reversed(self.layers):
                    error = layer.backward_propagation(error, learning_rate,␣
↪optimizer= self.optimizer, T=i+1)

            # training loss
            err /= samples
            self.train_loss.append(err)
            print("epoch- {}/{}, loss- {}".format(i,epochs,err))

            # accuracy for train set
            y_pred = self.predict(x_train)
            y_pred = onehot.inverse_transform(y_pred)
            y_pred = y_pred.flatten()

            y_true = y_train
            y_true = onehot.inverse_transform(y_true)
            y_true = y_true.flatten()

            self.train_accuracy.append(accuracy_score(y_pred, y_true))

            #Validation loss
            valid_samples= len(x_valid)
            err_valid= 0
            for j in range(valid_samples):
                output = x_valid[j]
                for layer in self.layers:
                    output = layer.forward_propagation(output)
                err_valid += self.loss(y_valid[j], output)
```

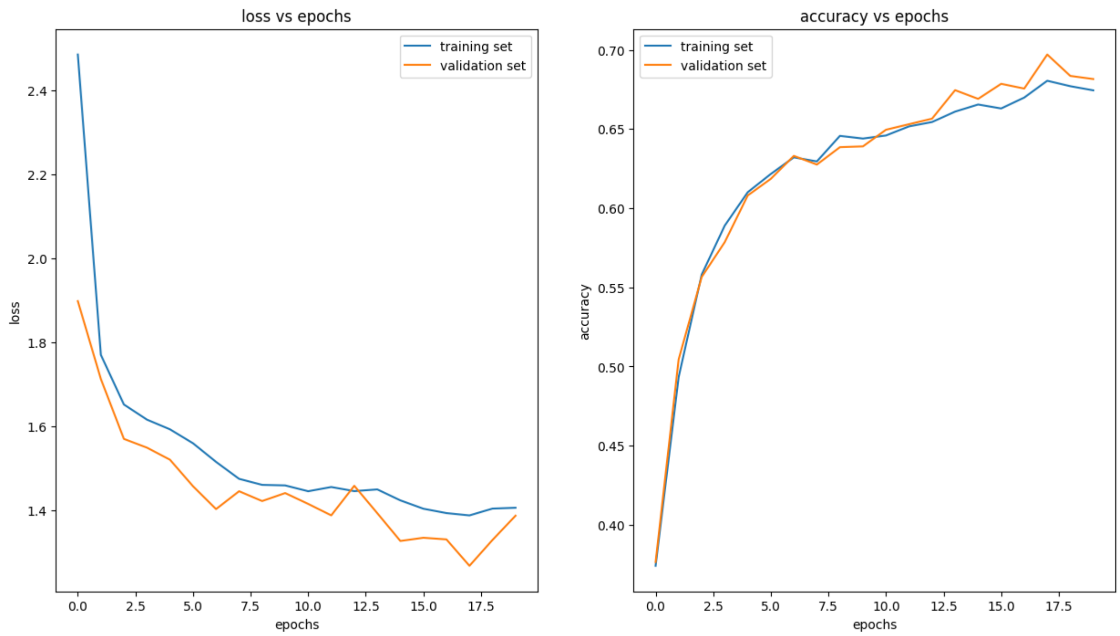
```
            err_valid /= valid_samples
            self.validation_loss.append(err_valid)

            # accuracy for validation set
            y_valid_pred = self.predict(x_valid)
            y_valid_pred = onehot.inverse_transform(y_valid_pred)
            y_valid_pred = y_valid_pred.flatten()

            y_valid_true = y_valid
            y_valid_true = onehot.inverse_transform(y_valid_true)
            y_valid_true = y_valid_true.flatten()

            self.validation_accuracy.append(accuracy_score(y_valid_pred,␣
↪y_valid_true))

    def plot(self):
        # plotting the graphs for loss vs epochs
        plt.figure(figsize=(15,8))
        plt.subplot(1,2,1)
        plt.plot(self.train_loss, label = "training set")
        plt.plot(self.validation_loss, label = "validation set")
        plt.title("loss vs epochs")
        plt.xlabel("epochs")
        plt.ylabel("loss")
        plt.legend()

        # plotting the graphs for accuracy vs epochs
        plt.subplot(1,2,2)
        plt.plot(self.train_accuracy, label = "training set")
        plt.plot(self.validation_accuracy, label = "validation set")
        plt.title("accuracy vs epochs")
        plt.xlabel("epochs")
        plt.ylabel("accuracy")
        plt.legend()
```

2 for tanh activation

[32]:
```
# neural network for tanh activation function
nn= MLP()
nn.add(fully_connected_layer(16, 40))
nn.add(activation_layer(act_func="tanh"))
#nn.add(activation_layer(activation_tanh, gradient_tanh))
nn.add(fully_connected_layer(40, 26))
nn.add(softmax_layer(26))
nn.use(cross_entropy_loss, grad_cross_entropy_loss)
```

```python
nn.fit(x_train_arr, y_train_arr, x_valid_arr, y_valid_arr,  epochs=20,␣
 ↪learning_rate=0.001, optimizer="adam")
nn.plot()

y_test_pred = np.array(nn.predict(x_test_arr))
y_test_pred = onehot.inverse_transform(y_test_pred)
y_test_true = onehot.inverse_transform(y_test_arr)
print("Accuracy on test set: ", accuracy_score(y_test_pred,y_test_true))
```

```
epoch- 0/20, loss- 2.4848552407795155
epoch- 1/20, loss- 1.770108385888565
epoch- 2/20, loss- 1.651964738313998
epoch- 3/20, loss- 1.6159811464985474
epoch- 4/20, loss- 1.5928636730328514
epoch- 5/20, loss- 1.5596862088299344
epoch- 6/20, loss- 1.5154159481811098
epoch- 7/20, loss- 1.4750465531988715
epoch- 8/20, loss- 1.460720551326636
epoch- 9/20, loss- 1.4594251237406901
epoch- 10/20, loss- 1.4455482761203344
epoch- 11/20, loss- 1.4556119168477015
epoch- 12/20, loss- 1.4458132059837878
epoch- 13/20, loss- 1.4498966800311928
epoch- 14/20, loss- 1.4238306677000039
epoch- 15/20, loss- 1.4039495491951772
epoch- 16/20, loss- 1.3935314119991875
epoch- 17/20, loss- 1.3880206577278735
epoch- 18/20, loss- 1.404275128613891
epoch- 19/20, loss- 1.4062536477525163
Accuracy on test set:  0.674
```

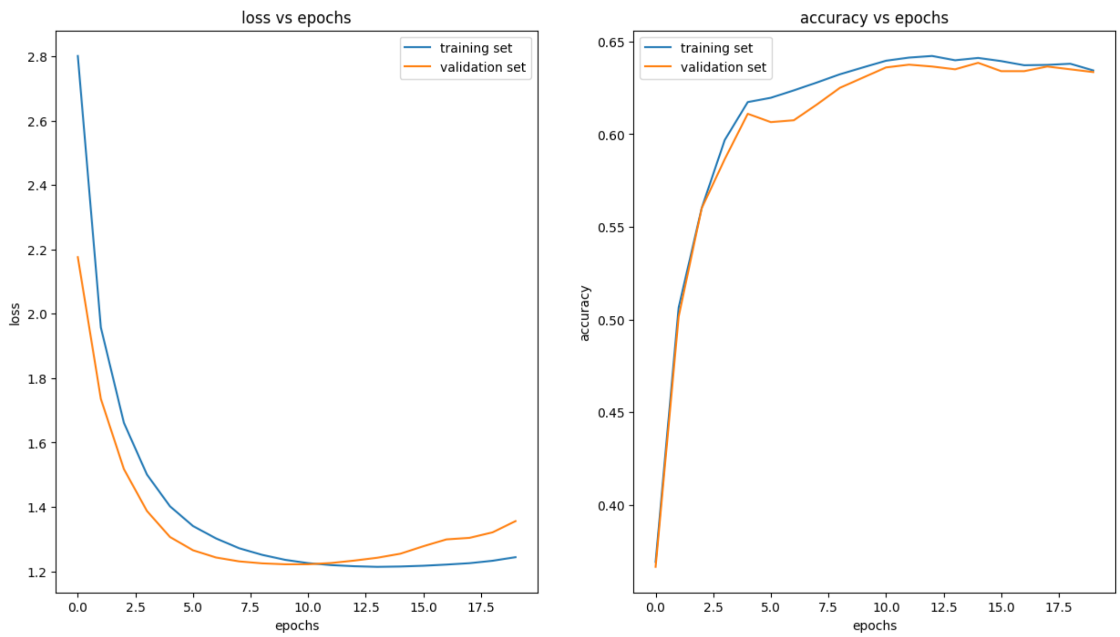


3 for relu activation

[37]:
```
# neural network for relu activation function
nn= MLP()
nn.add(fully_connected_layer(16, 40))
nn.add(activation_layer(act_func="relu"))
#nn.add(activation_layer(activation_relu, gradient_relu))
nn.add(fully_connected_layer(40, 26))
nn.add(softmax_layer(26))
nn.use(cross_entropy_loss, grad_cross_entropy_loss)
nn.fit(x_train_arr, y_train_arr, x_valid_arr, y_valid_arr,  epochs=20,␣
 ↪learning_rate=1e-4, optimizer="adam")
nn.plot()

y_test_pred = np.array(nn.predict(x_test_arr))
y_test_pred = onehot.inverse_transform(y_test_pred)
y_test_true = onehot.inverse_transform(y_test_arr)
print("Accuracy on test set: ", accuracy_score(y_test_pred,y_test_true))
```

```
epoch- 0/20, loss- 2.800645124648064
epoch- 1/20, loss- 1.9573487388589554
epoch- 2/20, loss- 1.6613207721119385
epoch- 3/20, loss- 1.5006014524197293
epoch- 4/20, loss- 1.4020208037404536
epoch- 5/20, loss- 1.3406659913878556
epoch- 6/20, loss- 1.3021977272718872
```

```
epoch- 7/20, loss- 1.2718083890888852
epoch- 8/20, loss- 1.2511874165531032
epoch- 9/20, loss- 1.2357377567541372
epoch- 10/20, loss- 1.2255004479148295
epoch- 11/20, loss- 1.2193503086813335
epoch- 12/20, loss- 1.215856510258434
epoch- 13/20, loss- 1.2139335391813948
epoch- 14/20, loss- 1.2149939346970002
epoch- 15/20, loss- 1.2173295336687786
epoch- 16/20, loss- 1.220953492865633
epoch- 17/20, loss- 1.225315314281561
epoch- 18/20, loss- 1.2328576003504141
epoch- 19/20, loss- 1.2439312460238066
Accuracy on test set:  0.635
```



4 for different learning rates on tanh activation

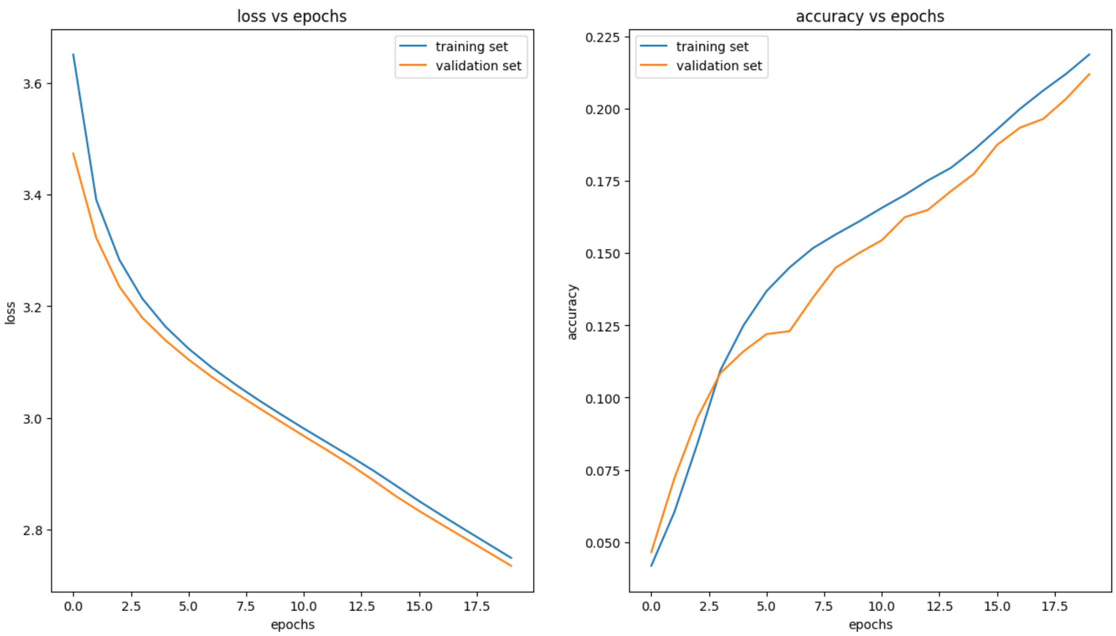
[34]:
```
lr=[1e-5,1e-4,0.001,0.01,0.1]
for i in lr:
    print("training for learning rate",i)
    print("----------------------------------")
    nn= MLP()
    nn.add(fully_connected_layer(16, 40))
    nn.add(activation_layer(act_func="tanh"))
    #nn.add(activation_layer(activation_relu, gradient_relu))
    nn.add(fully_connected_layer(40, 26))
```

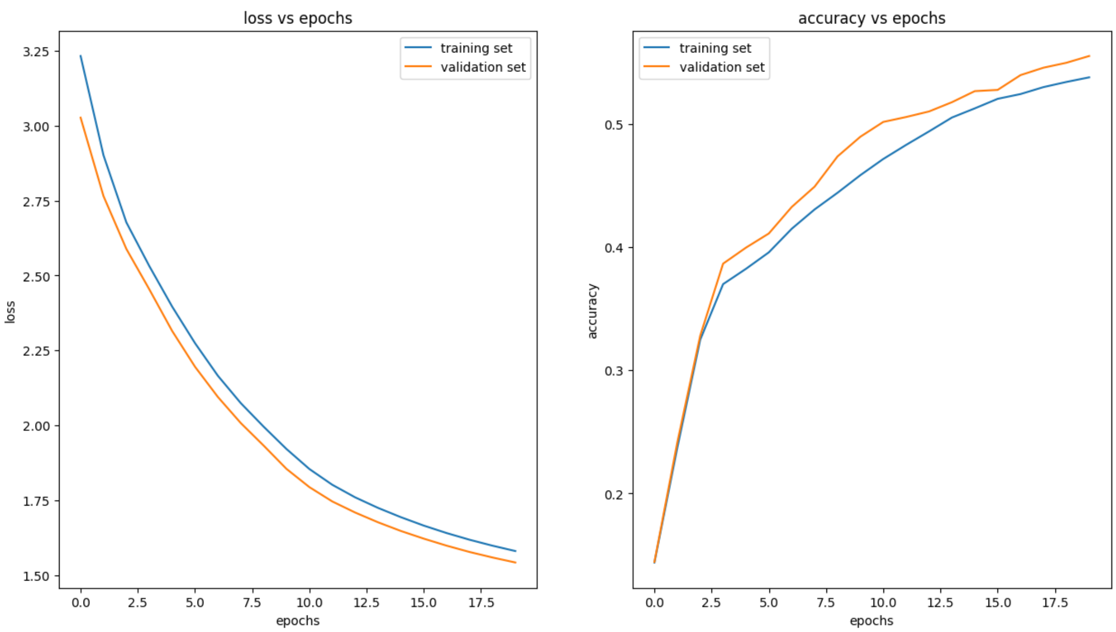
```
    nn.add(softmax_layer(26))
    nn.use(cross_entropy_loss, grad_cross_entropy_loss)
    nn.fit(x_train_arr, y_train_arr, x_valid_arr, y_valid_arr,  epochs=20,␣
↪learning_rate=i, optimizer="adam")
    nn.plot()

    y_test_pred = np.array(nn.predict(x_test_arr))
    y_test_pred = onehot.inverse_transform(y_test_pred)
    y_test_true = onehot.inverse_transform(y_test_arr)
    print("Accuracy on test set: ", accuracy_score(y_test_pred,y_test_true))
    print("\n")
```

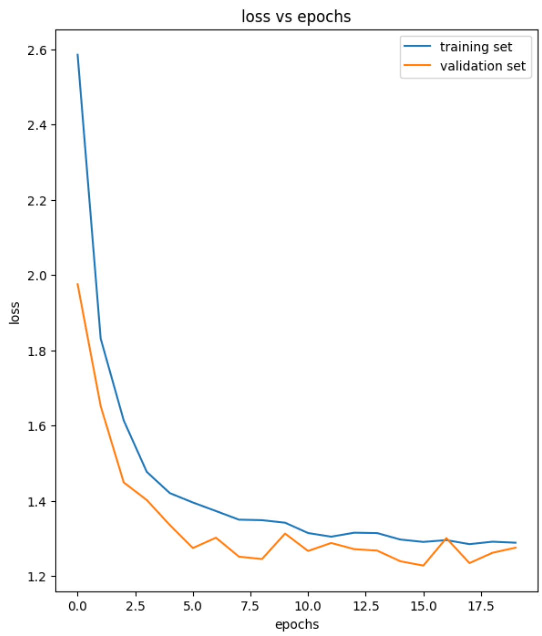
```
training for learning rate 1e-05
--------------------------------
epoch- 0/20, loss- 3.6507989615111143
epoch- 1/20, loss- 3.3902791159594217
epoch- 2/20, loss- 3.2832223832479825
epoch- 3/20, loss- 3.2134975221111484
epoch- 4/20, loss- 3.163537802493247
epoch- 5/20, loss- 3.1241895436310485
epoch- 6/20, loss- 3.0905104451033045
epoch- 7/20, loss- 3.060747430640881
epoch- 8/20, loss- 3.0330097263403415
epoch- 9/20, loss- 3.0065955798279407
epoch- 10/20, loss- 2.981069146093323
epoch- 11/20, loss- 2.956338682728828
epoch- 12/20, loss- 2.931674579740753
epoch- 13/20, loss- 2.9061196235062248
epoch- 14/20, loss- 2.878782635976009
epoch- 15/20, loss- 2.8511179212017197
epoch- 16/20, loss- 2.82498457217815
epoch- 17/20, loss- 2.7995995148710726
epoch- 18/20, loss- 2.774438691028938
epoch- 19/20, loss- 2.749230885574704
Accuracy on test set:  0.215


training for learning rate 0.0001
--------------------------------
epoch- 0/20, loss- 3.2320028393054367
epoch- 1/20, loss- 2.9010764373407216
epoch- 2/20, loss- 2.6771952234387153
epoch- 3/20, loss- 2.5319819371778136
epoch- 4/20, loss- 2.3966475123225788
epoch- 5/20, loss- 2.274682416329273
epoch- 6/20, loss- 2.1658703533141273
epoch- 7/20, loss- 2.0747467239867925
epoch- 8/20, loss- 1.996132584750352
```

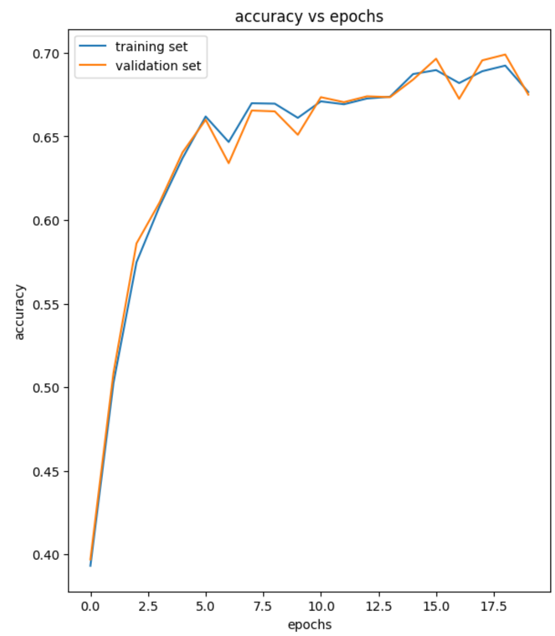
```
epoch- 9/20, loss- 1.9215871100361723
epoch- 10/20, loss- 1.8549408065297421
epoch- 11/20, loss- 1.8024457302338028
epoch- 12/20, loss- 1.760518797588856
epoch- 13/20, loss- 1.7253433051144413
epoch- 14/20, loss- 1.694341243537717
epoch- 15/20, loss- 1.666307184695178
epoch- 16/20, loss- 1.6414240956341197
epoch- 17/20, loss- 1.6191945131940597
epoch- 18/20, loss- 1.5993962889691378
epoch- 19/20, loss- 1.581512127587847
Accuracy on test set:  0.5445


training for learning rate 0.001
---------------------------------
epoch- 0/20, loss- 2.585573293003264
epoch- 1/20, loss- 1.831271402698168
epoch- 2/20, loss- 1.6137217545762945
epoch- 3/20, loss- 1.476979410185661
epoch- 4/20, loss- 1.4205451408626988
epoch- 5/20, loss- 1.3956305428458786
epoch- 6/20, loss- 1.3729319141755978
epoch- 7/20, loss- 1.3499768465582915
epoch- 8/20, loss- 1.3486021684000515
epoch- 9/20, loss- 1.3419190794052553
epoch- 10/20, loss- 1.314436708213282
epoch- 11/20, loss- 1.3047411350332974
epoch- 12/20, loss- 1.3153285458627295
epoch- 13/20, loss- 1.3143125338214823
epoch- 14/20, loss- 1.2971461882859967
epoch- 15/20, loss- 1.290838347161119
epoch- 16/20, loss- 1.2956511500705248
epoch- 17/20, loss- 1.2849351944787162
epoch- 18/20, loss- 1.2914247332617703
epoch- 19/20, loss- 1.2887430021721815
Accuracy on test set:  0.6865


training for learning rate 0.01
---------------------------------
epoch- 0/20, loss- 2.800153680157735
epoch- 1/20, loss- 2.5325232409537493
epoch- 2/20, loss- 2.3808311538502207
epoch- 3/20, loss- 2.2051589141338286
epoch- 4/20, loss- 2.2043700291283965
epoch- 5/20, loss- 2.211845481931634
epoch- 6/20, loss- 2.102422320430022
```

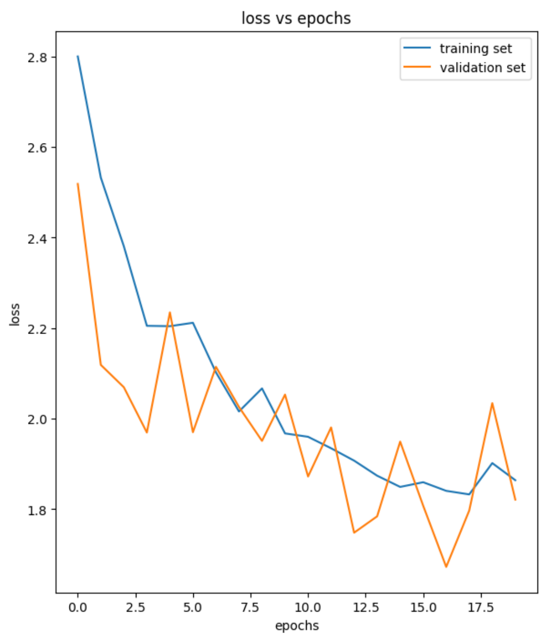
```
epoch- 7/20, loss- 2.0160011820139863
epoch- 8/20, loss- 2.0668799162578524
epoch- 9/20, loss- 1.9675458424502603
epoch- 10/20, loss- 1.9600399723680562
epoch- 11/20, loss- 1.9347114269485588
epoch- 12/20, loss- 1.9073709163780088
epoch- 13/20, loss- 1.8741254945618087
epoch- 14/20, loss- 1.849342603097563
epoch- 15/20, loss- 1.859689923432603
epoch- 16/20, loss- 1.8406772534425215
epoch- 17/20, loss- 1.8327936050019198
epoch- 18/20, loss- 1.9019239308223903
epoch- 19/20, loss- 1.8641683920966312
Accuracy on test set:  0.5815


training for learning rate 0.1
---------------------------------
epoch- 0/20, loss- 12.090184514752083
epoch- 1/20, loss- 10.499906073962102
epoch- 2/20, loss- 9.814617284393124
epoch- 3/20, loss- 9.405926745474895
epoch- 4/20, loss- 9.138706091613674
epoch- 5/20, loss- 8.955067089495921
epoch- 6/20, loss- 8.827011550890841
epoch- 7/20, loss- 8.737226127144089
epoch- 8/20, loss- 8.67645939920827
epoch- 9/20, loss- 8.636320598248565
epoch- 10/20, loss- 8.612367957695774
epoch- 11/20, loss- 8.601083653461352
epoch- 12/20, loss- 8.599667422579149
epoch- 13/20, loss- 8.606380383082977
epoch- 14/20, loss- 8.620142881410128
epoch- 15/20, loss- 8.638903191075485
epoch- 16/20, loss- 8.66203903653551
epoch- 17/20, loss- 8.688765201291044
epoch- 18/20, loss- 8.718437929029783
epoch- 19/20, loss- 8.750524642678858
Accuracy on test set:  0.042
```

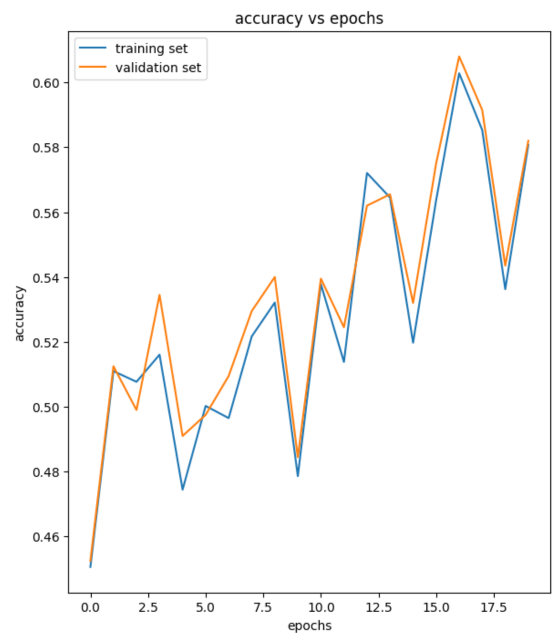

loss vs epochs
training set
validation set
loss
epochs
accuracy vs epochs
training set
validation set
accuracy
epochs

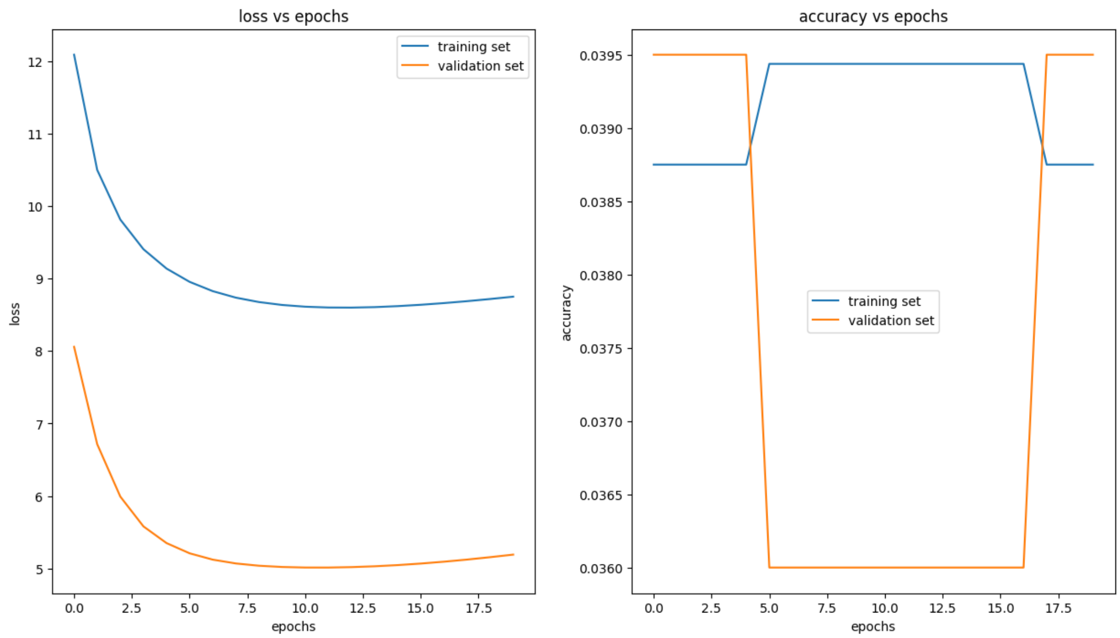

loss vs epochs
training set
validation set
loss
epochs
accuracy vs epochs
training set
validation set
accuracy
epochs


loss vs epochs
training set
validation set
loss
epochs


accuracy vs epochs
training set
validation set
accuracy
epochs


loss vs epochs
training set
validation set
loss
epochs


accuracy vs epochs
training set
validation set
accuracy
epochs



5 for different learning rates on relu activation

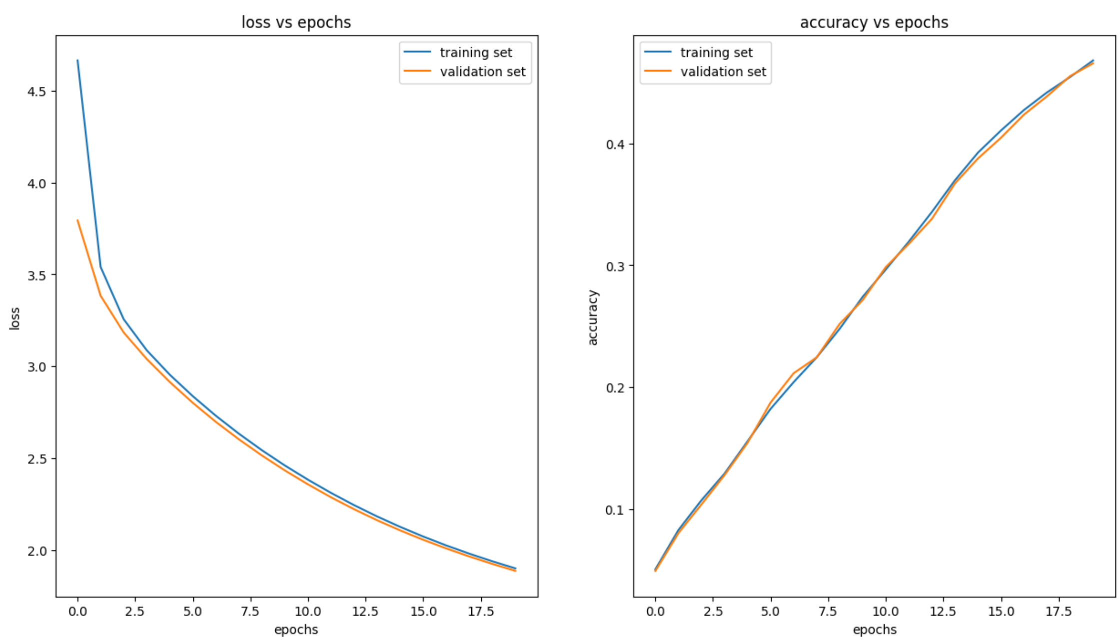
[35]:
```
lr=[1e-5,1e-4,0.001,0.01,0.1]
for i in lr:
    print("training for learning rate",i)
    print("----------------------------------")
    nn= MLP()
    nn.add(fully_connected_layer(16, 40))
    nn.add(activation_layer(act_func="relu"))
    #nn.add(activation_layer(activation_relu, gradient_relu))
    nn.add(fully_connected_layer(40, 26))
    nn.add(softmax_layer(26))
    nn.use(cross_entropy_loss, grad_cross_entropy_loss)
    nn.fit(x_train_arr, y_train_arr, x_valid_arr, y_valid_arr,  epochs=20,␣
↪learning_rate=i, optimizer="adam")
    nn.plot()

    y_test_pred = np.array(nn.predict(x_test_arr))
    y_test_pred = onehot.inverse_transform(y_test_pred)
    y_test_true = onehot.inverse_transform(y_test_arr)
    print("Accuracy on test set: ", accuracy_score(y_test_pred,y_test_true))
    print("\n")
```

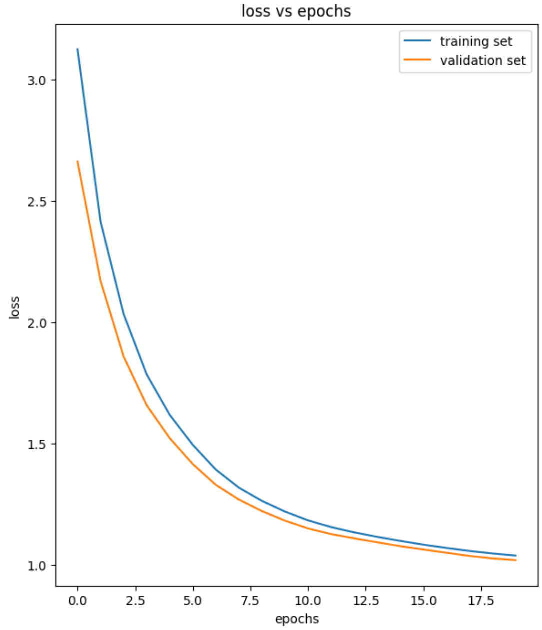
```
training for learning rate 1e-05
---------------------------------
epoch- 0/20, loss- 4.664039274644299
```

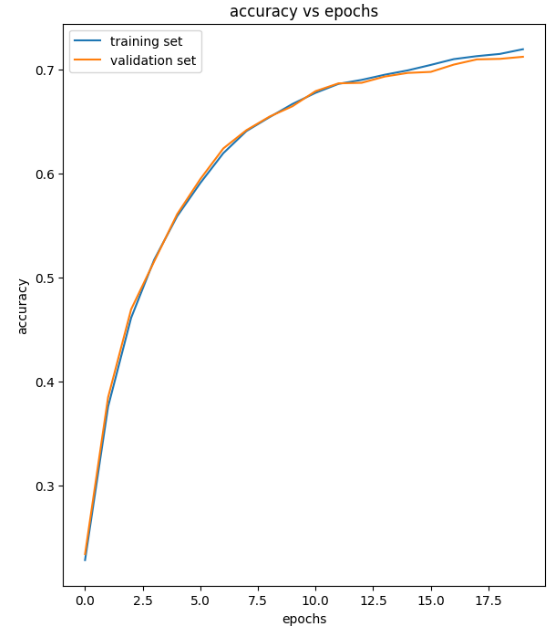
```
epoch- 1/20, loss- 3.540341895821613
epoch- 2/20, loss- 3.256182359364265
epoch- 3/20, loss- 3.0874346285416263
epoch- 4/20, loss- 2.954579316064428
epoch- 5/20, loss- 2.8376539498696904
epoch- 6/20, loss- 2.731186502791021
epoch- 7/20, loss- 2.6336030261319117
epoch- 8/20, loss- 2.543621969032915
epoch- 9/20, loss- 2.460210536802279
epoch- 10/20, loss- 2.383183119098905
epoch- 11/20, loss- 2.3114287125939277
epoch- 12/20, loss- 2.2448279374174707
epoch- 13/20, loss- 2.1833204236561405
epoch- 14/20, loss- 2.126685417249707
epoch- 15/20, loss- 2.074145279843294
epoch- 16/20, loss- 2.025608727264474
epoch- 17/20, loss- 1.9808416425968192
epoch- 18/20, loss- 1.9393367056019195
epoch- 19/20, loss- 1.9008196130734576
Accuracy on test set:  0.475


training for learning rate 0.0001
---------------------------------
epoch- 0/20, loss- 3.1264896716609902
epoch- 1/20, loss- 2.4160236187294015
epoch- 2/20, loss- 2.035261817105016
epoch- 3/20, loss- 1.786417148535075
epoch- 4/20, loss- 1.6194850399339846
epoch- 5/20, loss- 1.4959622072431815
epoch- 6/20, loss- 1.393900048439698
epoch- 7/20, loss- 1.3195611691100428
epoch- 8/20, loss- 1.2649386407476704
epoch- 9/20, loss- 1.2209092057265276
epoch- 10/20, loss- 1.1845287611648831
epoch- 11/20, loss- 1.1568863417914081
epoch- 12/20, loss- 1.1351921381055659
epoch- 13/20, loss- 1.1164237794398042
epoch- 14/20, loss- 1.1000326378147598
epoch- 15/20, loss- 1.0844872668132723
epoch- 16/20, loss- 1.07091943404348
epoch- 17/20, loss- 1.0586150092167474
epoch- 18/20, loss- 1.0481481013913445
epoch- 19/20, loss- 1.0395281525356364
Accuracy on test set:  0.7065


training for learning rate 0.001
```

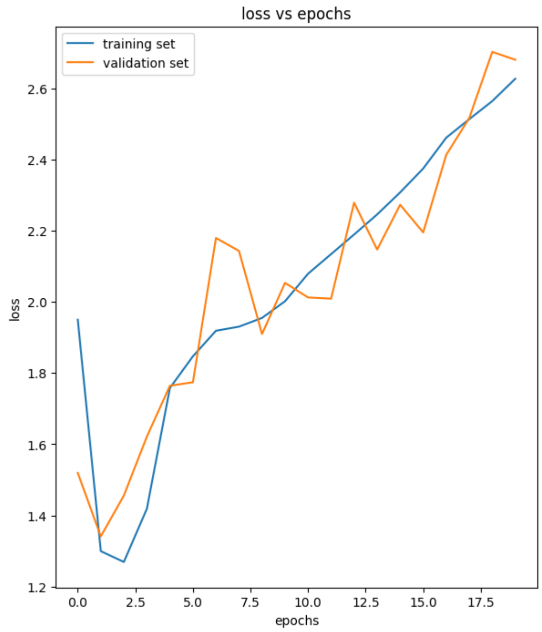
```
--------------------------------
epoch- 0/20, loss- 1.9497445642901394
epoch- 1/20, loss- 1.2993384825084473
epoch- 2/20, loss- 1.2690101114737204
epoch- 3/20, loss- 1.4184427706868088
epoch- 4/20, loss- 1.7578005204110492
epoch- 5/20, loss- 1.8468606362228392
epoch- 6/20, loss- 1.9187014761793975
epoch- 7/20, loss- 1.9301476383187912
epoch- 8/20, loss- 1.954684354422394
epoch- 9/20, loss- 2.0015675741810988
epoch- 10/20, loss- 2.0789265015996974
epoch- 11/20, loss- 2.1339791153075995
epoch- 12/20, loss- 2.189122715648856
epoch- 13/20, loss- 2.2454837146186017
epoch- 14/20, loss- 2.3074667264063744
epoch- 15/20, loss- 2.374467634050303
epoch- 16/20, loss- 2.4610298487075
epoch- 17/20, loss- 2.513137536375519
epoch- 18/20, loss- 2.5639378346840944
epoch- 19/20, loss- 2.6267847113492446
Accuracy on test set:  0.4175


training for learning rate 0.01
--------------------------------
epoch- 0/20, loss- 2.5788517836011904
epoch- 1/20, loss- 2.2929408644279645
epoch- 2/20, loss- 2.2326095191614663
epoch- 3/20, loss- 2.1993326158445803
epoch- 4/20, loss- 2.2087483499138463
epoch- 5/20, loss- 2.230298142261838
epoch- 6/20, loss- 2.218843048178565
epoch- 7/20, loss- 2.214882221150696
epoch- 8/20, loss- 2.2794222573451495
epoch- 9/20, loss- 2.303701260303057
epoch- 10/20, loss- 2.3083868867327473
epoch- 11/20, loss- 2.360445903204188
epoch- 12/20, loss- 2.315747718580962
epoch- 13/20, loss- 2.352287978797347
epoch- 14/20, loss- 2.351036021762887
epoch- 15/20, loss- 2.3689706779446227
epoch- 16/20, loss- 2.4134146906134775
epoch- 17/20, loss- 2.4151051006850994
epoch- 18/20, loss- 2.3850412245185364
epoch- 19/20, loss- 2.3806079852477118
Accuracy on test set:  0.565
```

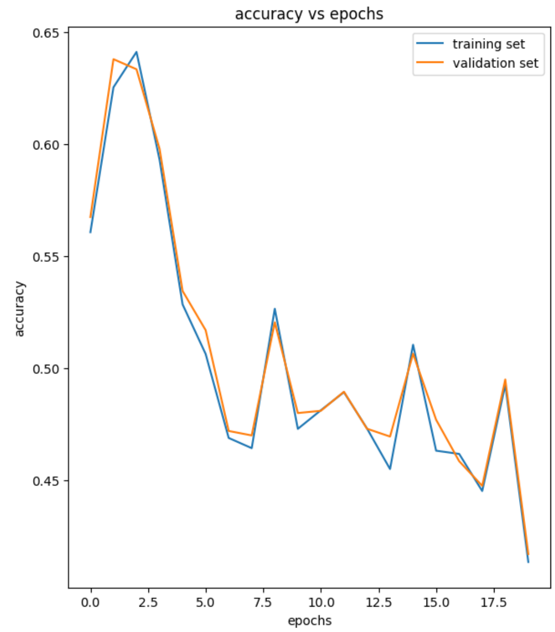
```
training for learning rate 0.1
---------------------------------
epoch- 0/20, loss- 38.90628817100049
epoch- 1/20, loss- 3.4125694713350985
epoch- 2/20, loss- 3.3861176871148966
epoch- 3/20, loss- 3.3730124479257944
epoch- 4/20, loss- 3.365337128801114
epoch- 5/20, loss- 3.3604704919884516
epoch- 6/20, loss- 3.3572651692551925
epoch- 7/20, loss- 3.355133953504586
epoch- 8/20, loss- 3.3537430802243335
epoch- 9/20, loss- 3.352887837873292
epoch- 10/20, loss- 3.3524351530959255
epoch- 11/20, loss- 3.3522944384550475
epoch- 12/20, loss- 3.352401659914012
epoch- 13/20, loss- 3.3527101028588313
epoch- 14/20, loss- 3.3531847573748714
epoch- 15/20, loss- 3.3537987649954952
epoch- 16/20, loss- 3.354531092717064
epoch- 17/20, loss- 3.355364965636401
epoch- 18/20, loss- 3.356286783956041
epoch- 19/20, loss- 3.3572853580800017
Accuracy on test set:  0.0315
```

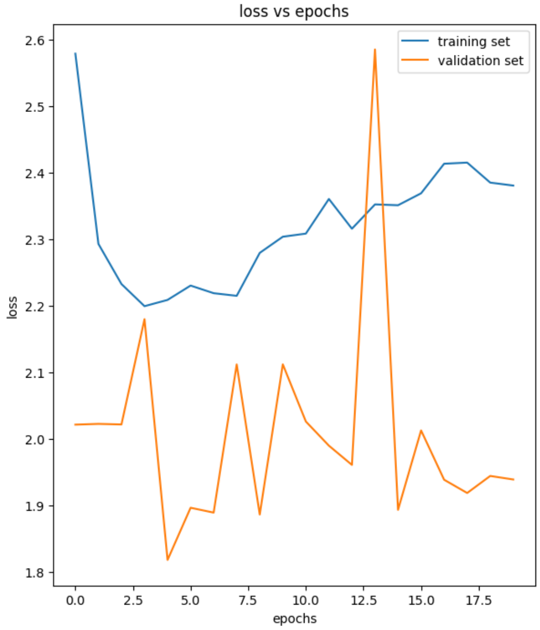


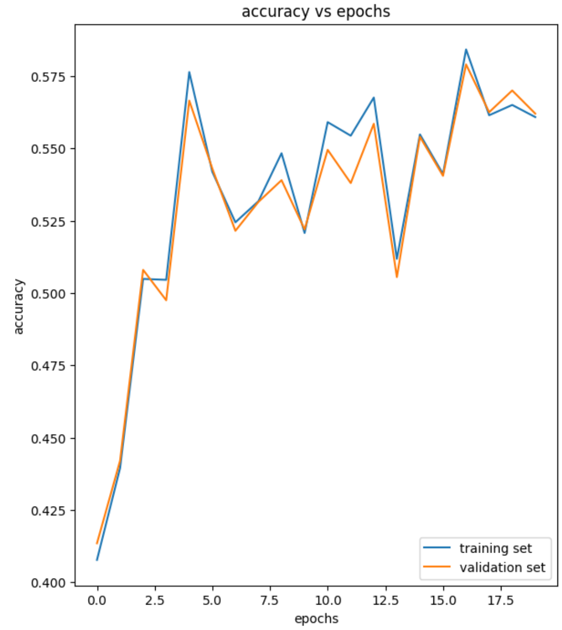

loss vs epochs
training set
validation set
loss
epochs

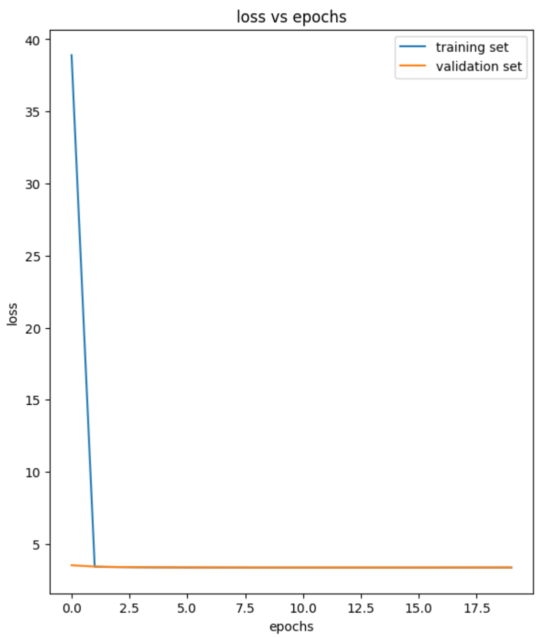

accuracy vs epochs
training set
validation set
accuracy
epochs

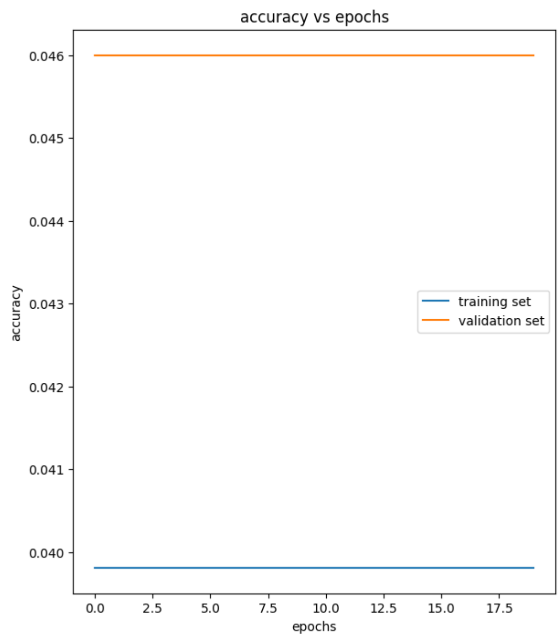

loss vs epochs
training set
validation set
loss
epochs


accuracy vs epochs
training set
validation set
accuracy
epochs


loss vs epochs
training set
validation set
loss
epochs


accuracy vs epochs
training set
validation set
accuracy
epochs


loss vs epochs
training set
validation set
loss
epochs


accuracy vs epochs
training set
validation set
accuracy
epochs

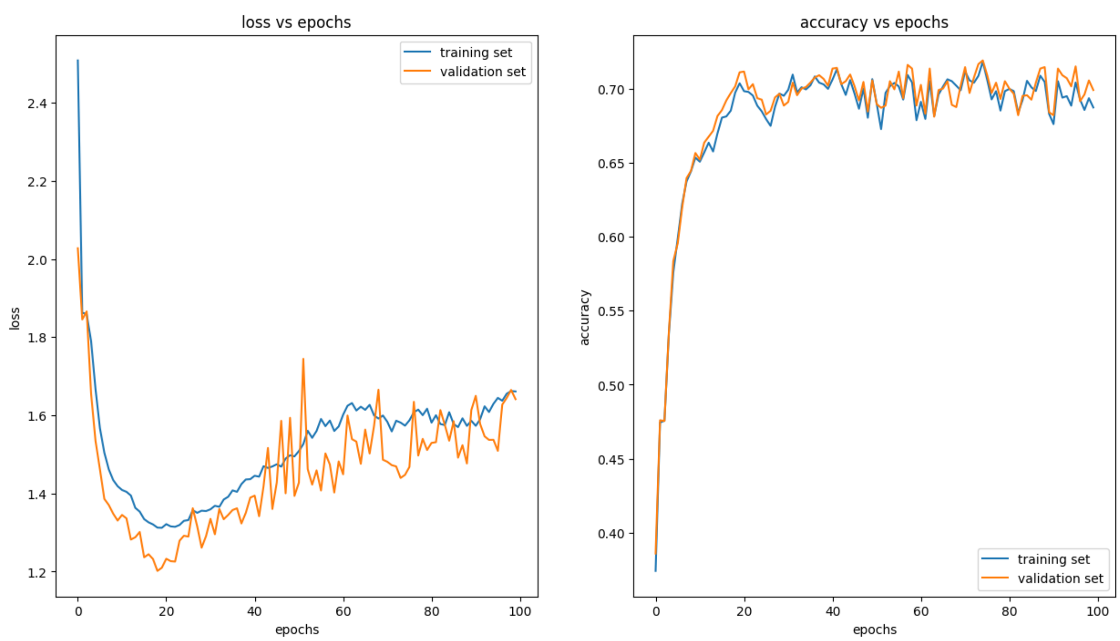
6 for different epochs on tanh activation

```
[38]: # lets run it for 100 epochs so that we can observe what is happening for all␣
     ↪the epochs between 20 and 100
     # neural network for tanh activation function
     nn= MLP()
     nn.add(fully_connected_layer(16, 40))
     nn.add(activation_layer(act_func="tanh"))
     #nn.add(activation_layer(activation_tanh, gradient_tanh))
     nn.add(fully_connected_layer(40, 26))
     nn.add(softmax_layer(26))
     nn.use(cross_entropy_loss, grad_cross_entropy_loss)
     nn.fit(x_train_arr, y_train_arr, x_valid_arr, y_valid_arr,  epochs=100,␣
     ↪learning_rate=0.001, optimizer="adam")
     nn.plot()

     y_test_pred = np.array(nn.predict(x_test_arr))
     y_test_pred = onehot.inverse_transform(y_test_pred)
     y_test_true = onehot.inverse_transform(y_test_arr)
     print("Accuracy on test set: ", accuracy_score(y_test_pred,y_test_true))
```

```
epoch- 0/100, loss- 2.5083383894457993
epoch- 1/100, loss- 1.862494219274102
epoch- 2/100, loss- 1.859269353058428
epoch- 3/100, loss- 1.7897892848493262
epoch- 4/100, loss- 1.6670168525369806
epoch- 5/100, loss- 1.5671354038545084
epoch- 6/100, loss- 1.504174246043134
epoch- 7/100, loss- 1.4618135603814795
epoch- 8/100, loss- 1.434236305329016
epoch- 9/100, loss- 1.4185731151648417
epoch- 10/100, loss- 1.4088692563745076
epoch- 11/100, loss- 1.4041577427653387
epoch- 12/100, loss- 1.3947059373933794
epoch- 13/100, loss- 1.3630910813052266
epoch- 14/100, loss- 1.3534617727820148
epoch- 15/100, loss- 1.3342925821242186
epoch- 16/100, loss- 1.3260759747736384
epoch- 17/100, loss- 1.3207539992364896
epoch- 18/100, loss- 1.3125294417135311
epoch- 19/100, loss- 1.312032116817627
epoch- 20/100, loss- 1.3214866073243292
epoch- 21/100, loss- 1.315682243804574
epoch- 22/100, loss- 1.3145655307803583
epoch- 23/100, loss- 1.3192780988413066
epoch- 24/100, loss- 1.3299791663405724
epoch- 25/100, loss- 1.3319387623831678
epoch- 26/100, loss- 1.357138070262373
```

```
epoch- 27/100, loss- 1.3504401593634185
epoch- 28/100, loss- 1.3558825960137624
epoch- 29/100, loss- 1.3549569719925176
epoch- 30/100, loss- 1.3594377434534792
epoch- 31/100, loss- 1.3684717927379018
epoch- 32/100, loss- 1.3657308543948155
epoch- 33/100, loss- 1.3844536920074386
epoch- 34/100, loss- 1.3914836814672764
epoch- 35/100, loss- 1.40782351115854
epoch- 36/100, loss- 1.404206684369323
epoch- 37/100, loss- 1.423957260504462
epoch- 38/100, loss- 1.4357782687157392
epoch- 39/100, loss- 1.4365907805142784
epoch- 40/100, loss- 1.445290594323743
epoch- 41/100, loss- 1.4429183119882876
epoch- 42/100, loss- 1.4696953877383216
epoch- 43/100, loss- 1.4653138667510746
epoch- 44/100, loss- 1.4690922553783947
epoch- 45/100, loss- 1.4746835543125512
epoch- 46/100, loss- 1.4686291973406667
epoch- 47/100, loss- 1.4892202837996047
epoch- 48/100, loss- 1.4976792152769425
epoch- 49/100, loss- 1.4948206664702868
epoch- 50/100, loss- 1.508604169954548
epoch- 51/100, loss- 1.5264147681023776
epoch- 52/100, loss- 1.5603928761102697
epoch- 53/100, loss- 1.542329678881554
epoch- 54/100, loss- 1.5599252949773672
epoch- 55/100, loss- 1.5906956581534368
epoch- 56/100, loss- 1.5722446125534717
epoch- 57/100, loss- 1.5865526798660587
epoch- 58/100, loss- 1.5599227160194389
epoch- 59/100, loss- 1.5714872162176285
epoch- 60/100, loss- 1.601489532084466
epoch- 61/100, loss- 1.6243578376099534
epoch- 62/100, loss- 1.631387137451445
epoch- 63/100, loss- 1.6123038017073656
epoch- 64/100, loss- 1.6220277429824603
epoch- 65/100, loss- 1.6140262343176162
epoch- 66/100, loss- 1.6267251630054298
epoch- 67/100, loss- 1.599705748892451
epoch- 68/100, loss- 1.5917657768223648
epoch- 69/100, loss- 1.5994445826426633
epoch- 70/100, loss- 1.5835260924243775
epoch- 71/100, loss- 1.5587780400876017
epoch- 72/100, loss- 1.5862024200151421
epoch- 73/100, loss- 1.5813871261313568
epoch- 74/100, loss- 1.5734797259767828
```

```
epoch- 75/100, loss- 1.587176553318264
epoch- 76/100, loss- 1.6078836383998318
epoch- 77/100, loss- 1.6145763727587612
epoch- 78/100, loss- 1.6003365976903736
epoch- 79/100, loss- 1.6169109294116213
epoch- 80/100, loss- 1.5812456187430421
epoch- 81/100, loss- 1.6001879995341592
epoch- 82/100, loss- 1.5776605381431168
epoch- 83/100, loss- 1.575021584627835
epoch- 84/100, loss- 1.6080562780049528
epoch- 85/100, loss- 1.5776439534206919
epoch- 86/100, loss- 1.569789429635737
epoch- 87/100, loss- 1.5922797398132431
epoch- 88/100, loss- 1.572955349533713
epoch- 89/100, loss- 1.5860103455637136
epoch- 90/100, loss- 1.573055343202307
epoch- 91/100, loss- 1.5901317812996927
epoch- 92/100, loss- 1.6230099808444323
epoch- 93/100, loss- 1.6084203990571568
epoch- 94/100, loss- 1.6294059000454038
epoch- 95/100, loss- 1.6446473757210134
epoch- 96/100, loss- 1.6373783759819138
epoch- 97/100, loss- 1.6552147859877746
epoch- 98/100, loss- 1.6621141059444748
epoch- 99/100, loss- 1.6611453152746687
Accuracy on test set:  0.683
```



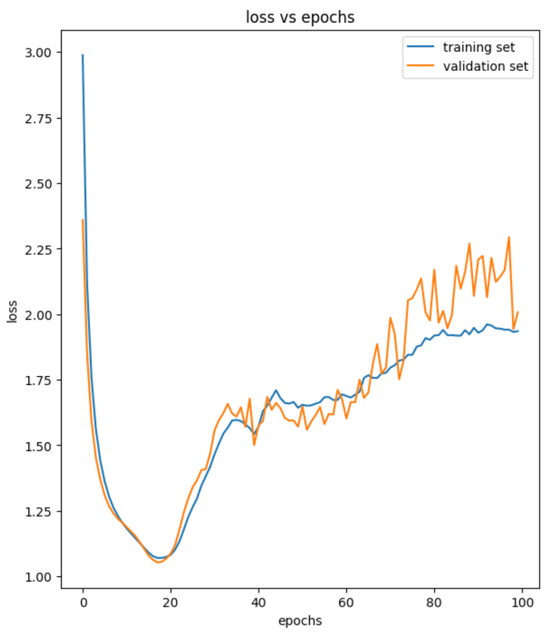
7 for different epochs on relu activation

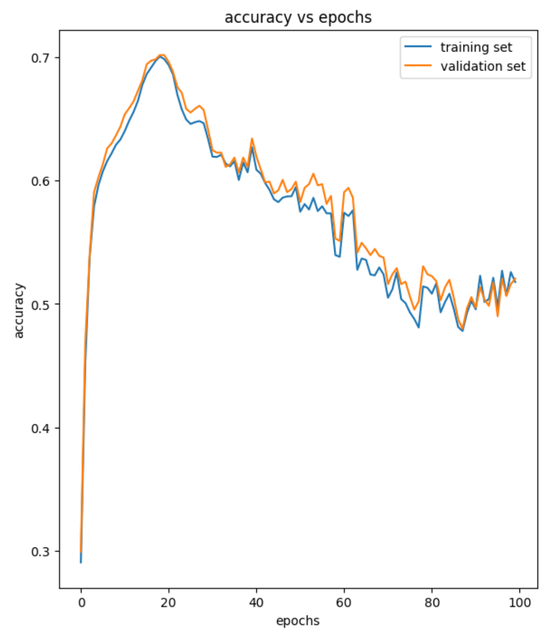
[39]:
```
# lets run it for 100 epochs so that we can observe what is happening for all␣
↪the epochs between 20 and 100
# neural network for tanh activation function
nn= MLP()
nn.add(fully_connected_layer(16, 40))
nn.add(activation_layer(act_func="relu"))
#nn.add(activation_layer(activation_tanh, gradient_tanh))
nn.add(fully_connected_layer(40, 26))
nn.add(softmax_layer(26))
nn.use(cross_entropy_loss, grad_cross_entropy_loss)
nn.fit(x_train_arr, y_train_arr, x_valid_arr, y_valid_arr,  epochs=100,␣
↪learning_rate=1e-4, optimizer="adam")
nn.plot()

y_test_pred = np.array(nn.predict(x_test_arr))
y_test_pred = onehot.inverse_transform(y_test_pred)
y_test_true = onehot.inverse_transform(y_test_arr)
print("Accuracy on test set: ", accuracy_score(y_test_pred,y_test_true))
```

```
epoch- 0/100, loss- 2.9884792852037654
epoch- 1/100, loss- 2.113862652356504
epoch- 2/100, loss- 1.759463925354568
epoch- 3/100, loss- 1.5623163976989092
epoch- 4/100, loss- 1.441973814711572
epoch- 5/100, loss- 1.3627454071201852
epoch- 6/100, loss- 1.3048068553075987
epoch- 7/100, loss- 1.2620756334812169
epoch- 8/100, loss- 1.2307569469413993
epoch- 9/100, loss- 1.2053166638904065
epoch- 10/100, loss- 1.1829633575528484
epoch- 11/100, loss- 1.1636753929978416
epoch- 12/100, loss- 1.1457332535655758
epoch- 13/100, loss- 1.1271035167026071
epoch- 14/100, loss- 1.1085508052583206
epoch- 15/100, loss- 1.0906723336778799
epoch- 16/100, loss- 1.0767276665691907
epoch- 17/100, loss- 1.070428385252438
epoch- 18/100, loss- 1.0703047058086363
epoch- 19/100, loss- 1.0737989161247021
epoch- 20/100, loss- 1.0818209878601366
epoch- 21/100, loss- 1.1012466393637723
epoch- 22/100, loss- 1.1325516638786413
epoch- 23/100, loss- 1.1778724890545886
epoch- 24/100, loss- 1.2256920166974854
epoch- 25/100, loss- 1.2634608351492673
epoch- 26/100, loss- 1.2967258859045598
```

```
epoch- 27/100, loss- 1.346000912051773
epoch- 28/100, loss- 1.3815850281039908
epoch- 29/100, loss- 1.4179833197163512
epoch- 30/100, loss- 1.465804479055009
epoch- 31/100, loss- 1.5067224531453733
epoch- 32/100, loss- 1.544306507465588
epoch- 33/100, loss- 1.5671798563167443
epoch- 34/100, loss- 1.5945198128103195
epoch- 35/100, loss- 1.5969278468485326
epoch- 36/100, loss- 1.5924839259890582
epoch- 37/100, loss- 1.5796826742605432
epoch- 38/100, loss- 1.5653434004237547
epoch- 39/100, loss- 1.5423338320589415
epoch- 40/100, loss- 1.5709006630753735
epoch- 41/100, loss- 1.629656109995847
epoch- 42/100, loss- 1.6514606375513885
epoch- 43/100, loss- 1.6817803377440712
epoch- 44/100, loss- 1.7098601818282364
epoch- 45/100, loss- 1.679425483283555
epoch- 46/100, loss- 1.6614759210784895
epoch- 47/100, loss- 1.6591222536192698
epoch- 48/100, loss- 1.665200350769158
epoch- 49/100, loss- 1.6431206317437204
epoch- 50/100, loss- 1.6546449922734967
epoch- 51/100, loss- 1.6509376891435212
epoch- 52/100, loss- 1.6522502761273388
epoch- 53/100, loss- 1.6587093281261787
epoch- 54/100, loss- 1.6644064191536572
epoch- 55/100, loss- 1.6833214480682657
epoch- 56/100, loss- 1.684075892386601
epoch- 57/100, loss- 1.6726669313748885
epoch- 58/100, loss- 1.6729470677838698
epoch- 59/100, loss- 1.6942009722376274
epoch- 60/100, loss- 1.6880536497880307
epoch- 61/100, loss- 1.6819840792617122
epoch- 62/100, loss- 1.6930929856515966
epoch- 63/100, loss- 1.704510889502957
epoch- 64/100, loss- 1.7571859829430043
epoch- 65/100, loss- 1.7672116706523893
epoch- 66/100, loss- 1.7572427424386927
epoch- 67/100, loss- 1.756441447464374
epoch- 68/100, loss- 1.7742967326961234
epoch- 69/100, loss- 1.776524370092036
epoch- 70/100, loss- 1.79617753228131
epoch- 71/100, loss- 1.8055971715976997
epoch- 72/100, loss- 1.8229772687416854
epoch- 73/100, loss- 1.8267710746031556
epoch- 74/100, loss- 1.845285428619157
```

```
epoch- 75/100, loss- 1.8450792971857672
epoch- 76/100, loss- 1.8763156725530323
epoch- 77/100, loss- 1.8812410202838281
epoch- 78/100, loss- 1.9089200764353194
epoch- 79/100, loss- 1.9026066778792041
epoch- 80/100, loss- 1.9187547021535636
epoch- 81/100, loss- 1.9203238853444295
epoch- 82/100, loss- 1.9399640845917359
epoch- 83/100, loss- 1.9199544543986087
epoch- 84/100, loss- 1.9201956225087153
epoch- 85/100, loss- 1.9184062158669166
epoch- 86/100, loss- 1.9180194939988522
epoch- 87/100, loss- 1.9391101290660304
epoch- 88/100, loss- 1.9232234762458822
epoch- 89/100, loss- 1.9482137079016997
epoch- 90/100, loss- 1.9292564630366065
epoch- 91/100, loss- 1.9385419097693577
epoch- 92/100, loss- 1.9616793154322212
epoch- 93/100, loss- 1.9567109167194676
epoch- 94/100, loss- 1.9459618471889641
epoch- 95/100, loss- 1.9448487839507769
epoch- 96/100, loss- 1.9410503508121828
epoch- 97/100, loss- 1.9411272654817069
epoch- 98/100, loss- 1.9321444982518572
epoch- 99/100, loss- 1.9356582689177622
Accuracy on test set:  0.519
```





so from the above analysis we ge that the best parameters for tanh are as follows- 1. learning rate- 0.001 or 1e-3 2. epoch- 100 epochs can be taken as test accuracy and generalization gap does not change significantly we get accuracy on test set- 68.31. learning rate- 0.0001 or 1e-4 2. epoch- we mus take 20 epochs because after that the loss increases and the accuracy decreases rapidly we get accuracy on test set- 63.5

8 finally we prefer tanh activation with learning rate 0.001 or 1e-3, number of epochs 100 and get test accuracy of 68.3%

[40]:
```
# code ended for Q.1.
```