In [12]:

```
import tensorflow as tf
import matplotlib.pyplot as plt
import math
import random
import numpy as np
import pandas as pd
from copy import deepcopy
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import pickle
(x,y) ,(x_, y_)=tf.keras.datasets.mnist.load_data()
```

In [13]:

```
x=x.reshape(60000,784)
x_=x_.reshape(10000,784)
```

In [14]:

```
class Mnn():
    acti_fns = ['relu', 'sigmoid', 'linear', 'tanh', 'softmax','leaky_relu']
    weight_inits = ['zero', 'random', 'normal']

    def __init__(self, n_layers = 3, layer_sizes = [768,1,10], activation = "tanh", lea
        self.min_loss = 100000000
        self.weights = []
        self.biases = []
        self.n_layers = n_layers
        self.layer_sizes = layer_sizes
        self.convergence = convergence

        if activation not in self.acti_fns:
            raise Exception('Incorrect Activation Function')
        else:
            self.activation = activation

        self.learning_rate =learning_rate


        if weight_init not in self.weight_inits:
            raise Exception('Incorrect Weight Initialization Function')
        else:
            self.weight_init = weight_init


        self.batch_size = batch_size
        self.num_epochs = num_epochs

        if(weight_init=="zero"):
            for i in range(self.n_layers-1):
                weight = self.zero_init(shape =(self.layer_sizes[i],self.layer_sizes[i+
                self.weights.append(weight)
        elif(weight_init=="random"):
            for i in range(self.n_layers-1):
                weight = self.random_init((self.layer_sizes[i],self.layer_sizes[i+1]))
                self.weights.append(weight)
        elif(weight_init=="normal"):
            for i in range(self.n_layers-1):
```

```
                weight = self.normal_init((self.layer_sizes[i],self.layer_sizes[i+1]))
                self.weights.append(weight)
        else:
            raise Exception("Error in setting weights")

        for i in range(self.n_layers-1):
            bias = self.zero_init((1,self.layer_sizes[i+1]))
            self.biases.append(bias)

    def relu(self, X):
        return X*(X>0)

    def relu_grad(self, X):
        return np.array(X>0,dtype=int)

    def sigmoid(self, X):
        return 1/(1+np.exp(-X))

    def sigmoid_grad(self, X):
        return self.sigmoid(X)*(1-self.sigmoid(X))

    def linear(self, X):
        return X

    def linear_grad(self, X):
        return np.ones(X.shape)

    def tanh(self, X):
        return np.tanh(X)

    def tanh_grad(self, X):
        return 1 - np.tanh(X)**2

    def softmax(self, X):
        new_arr = []
        # print(type(X[0]))
        for i in X:
            # print(type(i))
            exponential = np.exp(i)
            total = exponential.sum()
            new_arr.append(exponential/total)
        return np.array(new_arr)

    def softmax_grad(self, X):
        return X*(1-X)

    def leaky_relu(self,z):
        return np.maximum(0.01 * z, z)
    def leaky_relu_gradient(self,z):
        grad = np.ones_like(z)
        grad[z < 0] = 0.01
        return grad

    def zero_init(self, shape):
        return np.zeros(shape)

    def random_init(self, shape):
        return np.random.rand(shape[0],shape[1])*0.01

    def normal_init(self, shape):
```

```
        return np.random.normal(size = shape)*0.01

    def activate(self, X):
        if(self.activation == "relu"):
            return self.relu(X)
        elif(self.activation == "sigmoid"):
            return self.sigmoid(X)
        elif(self.activation == "linear"):
            return self.linear(X)
        elif(self.activation == "tanh"):
            return self.tanh(X)
        elif(self.activation == "softmax"):
            return self.softmax(X)
        elif(self.activation=='leaky_relu'):
            return self.leaky_relu(X)
        else:
            print("error in activate fucntion")

    def activate_grad(self, X):
        if(self.activation == "relu"):
            return self.relu_grad(X)
        elif(self.activation == "sigmoid"):
            return self.sigmoid_grad(X)
        elif(self.activation == "linear"):
            return self.linear_grad(X)
        elif(self.activation == "tanh"):
            return self.tanh_grad(X)
        elif(self.activation == "softmax"):
            return self.softmax_grad(X)
        elif(self.activation=='leaky_relu'):
            return self.leaky_relu_gradient(X)
        else:
            print("error in activate fucntion grad")

    def cross_entropy(self, y_pred, y_true):
        ce =  -1*np.log(y_pred[np.arange(len(y_true)), y_true.argmax(axis=1)])
        return np.sum(ce)

    def forward(self, X):
        before_activation = []
        after_activation = []
        x = deepcopy(X)
        for i in range(self.n_layers-2):
            op = x.dot(self.weights[i]) + self.biases[i]
            before_activation.append(op)
            op = self.activate(op)
            after_activation.append(op)
            x = op
        op = x.dot(self.weights[-1]) + self.biases[-1]
        before_activation.append(op)
        op = self.softmax(op)
        after_activation.append(op)
        return before_activation, after_activation

    def backward(self, y, before_activation, after_activation):
        grads = []
        final_pred = after_activation[-1]
        loss = final_pred - y
        grads.append(loss)
        for layer in range(self.n_layers - 3, -1, -1):
```

```
            curr_error = loss.dot(self.weights[layer+1].T)
            grad = self.activate_grad(before_activation[layer])
            loss = curr_error*grad
            grads.append(loss)
        grads.reverse()
        return grads

    def fit(self, X, y, X_test=None, y_test=None):
        loss = []
        val_loss = []
        for epoch in range(self.num_epochs):
            for batch in range(0,len(X),self.batch_size):
                currX = X[batch:batch+self.batch_size,:]
                currY = y[batch:batch+self.batch_size,:]
                bef,aft = self.forward(currX)
                grads = self.backward(currY, bef, aft)
                zumm = currX
                for i in range(self.n_layers-1):
                    grad = zumm.T.dot(grads[i])/len(currX)
                    zumm = aft[i]
                    self.weights[i] = self.weights[i] - self.learning_rate*grad
                    self.biases[i] = self.biases[i] - self.learning_rate*np.sum(grads[i
            #cross entropy
            b,a = self.forward(X)
            loss.append(self.cross_entropy(a[-1],y)/len(y))
            if(loss[-1]<self.min_loss):
                self.min_loss = loss[-1]
            b,a = self.forward(X_test)
            val_loss.append(self.cross_entropy(a[-1],y_test)/len(y_test))
            print("epoch",epoch,", loss:",loss[-1])
            if(self.convergence != None):
                if((loss[-1] - self.min_loss > 0.1)):
                    print("Stopping iteration due to convergence (minima lost)")
                    break
                if(len(loss)>2 and epoch > self.num_epochs//5):
                    if(abs(loss[-2] - loss[-1]) < self.convergence):
                        print("Stopping iteration due to convergence")
                        break
        self.loss = loss
        self.val_loss = val_loss
        return self

    def predict_proba(self, X):
        return self.forward(X)[1][-1]

    def predict(self, X):
        return self.forward(X)[1][-1].argmax(axis=1)

    def score(self, X, y):
        y_pred = self.predict(X)
        c = 0
        for i in range(len(y_pred)):
            if(y[i][y_pred[i]]==1):
                c+=1
        return c/len(y_pred)
```

In [4]:

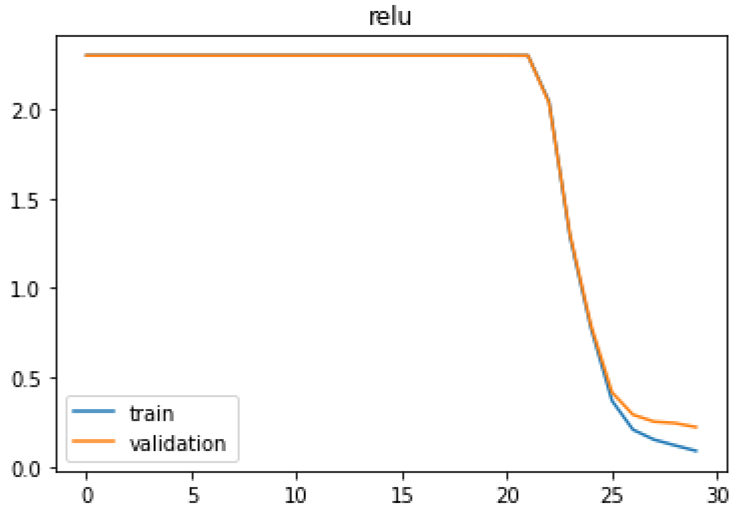
```
scaler = StandardScaler()
temp = np.zeros((y.size, int(y.max())+1))
```

```
temp[np.arange(y.size), y.astype(int)] = 1
y = temp
X_train, X_testval, y_train, y_testval = train_test_split(x, y, test_size=0.2)
X_train = scaler.fit_transform(X_train)
X_testval = scaler.transform(X_testval)
X_test, X_val, y_test, y_val = train_test_split(X_testval, y_testval, test_size=0.5)
```

In [5]:

```
nn_relu = Mnn(n_layers=6, layer_sizes=[784,256,128,64,32,10],activation="relu", weight_
nn_relu.fit(X_train,y_train,X_val,y_val)
plt.plot(nn_relu.loss,label="train")
plt.plot(nn_relu.val_loss, label="validation")
plt.title("relu")
plt.legend()
plt.show()
print(nn_relu.score(X_test,y_test))
pickle.dump(nn_relu,open("relu.pkl","wb"))
```

```
epoch 0 , loss: 2.301485468167068
epoch 1 , loss: 2.3014910598291354
epoch 2 , loss: 2.301490905197303
epoch 3 , loss: 2.301490450987469
epoch 4 , loss: 2.3014900140127703
epoch 5 , loss: 2.3014895386766074
epoch 6 , loss: 2.301488969463436
epoch 7 , loss: 2.301488342209451
epoch 8 , loss: 2.3014875580341907
epoch 9 , loss: 2.301486668487556
epoch 10 , loss: 2.301485601322965
epoch 11 , loss: 2.3014842597344063
epoch 12 , loss: 2.301482576527112
epoch 13 , loss: 2.301480403974597
epoch 14 , loss: 2.3014774934993234
epoch 15 , loss: 2.301473432540421
epoch 16 , loss: 2.30146746064785
epoch 17 , loss: 2.3014580087059384
epoch 18 , loss: 2.3014413849464583
epoch 19 , loss: 2.3014071511900944
epoch 20 , loss: 2.301314373930616
epoch 21 , loss: 2.3008293854275412
epoch 22 , loss: 2.044115591321575
epoch 23 , loss: 1.2855667701479911
epoch 24 , loss: 0.7743509769904707
epoch 25 , loss: 0.3681201011971479
epoch 26 , loss: 0.20577041826471873
epoch 27 , loss: 0.15008088636094283
epoch 28 , loss: 0.1177848184554482
epoch 29 , loss: 0.0869424084183926
```




```
0.9438333333333333
```

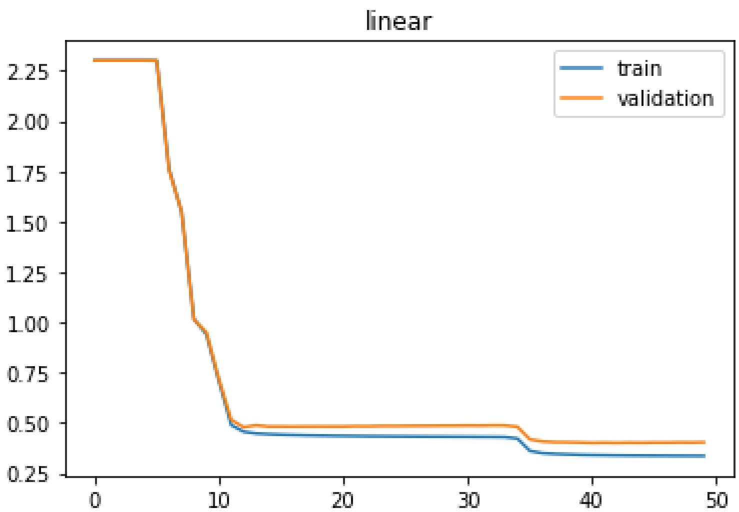
In [5]:

In [6]:

```
nn_linear = Mnn(n_layers=6, layer_sizes=[784,256,128,64,32,10],activation="linear", wei
nn_linear.fit(X_train,y_train,X_val,y_val)
plt.plot(nn_linear.loss,label="train")
plt.plot(nn_linear.val_loss, label="validation")
plt.title("linear")
plt.legend()
plt.show()
print(nn_linear.score(X_test,y_test))
pickle.dump(nn_relu,open("linear.pkl","wb"))
```

```
epoch 0 , loss: 2.3014743770020303
epoch 1 , loss: 2.3014683207667472
epoch 2 , loss: 2.301451211312131
epoch 3 , loss: 2.301421673684004
epoch 4 , loss: 2.3013559318304613
epoch 5 , loss: 2.3010836102793117
epoch 6 , loss: 1.76087097679784
epoch 7 , loss: 1.547689029074755
epoch 8 , loss: 1.0171809592654708
epoch 9 , loss: 0.94044575014983
epoch 10 , loss: 0.7089441259570743
epoch 11 , loss: 0.48935614177893505
epoch 12 , loss: 0.45623236355557084
epoch 13 , loss: 0.4473737377615199
epoch 14 , loss: 0.4439204681693736
epoch 15 , loss: 0.4415254511367745
epoch 16 , loss: 0.43976175889094876
epoch 17 , loss: 0.43834087212246525
epoch 18 , loss: 0.43726792756454713
epoch 19 , loss: 0.4361098891298429
epoch 20 , loss: 0.43524991365471405
epoch 21 , loss: 0.43461778449927996
epoch 22 , loss: 0.4338275307393148
epoch 23 , loss: 0.43335757808790853
epoch 24 , loss: 0.43287624009029135
epoch 25 , loss: 0.43237676228539074
epoch 26 , loss: 0.43202273546012576
```

```
epoch 27 , loss: 0.4315555104427561
epoch 28 , loss: 0.4313254701176669
epoch 29 , loss: 0.43089446189823777
epoch 30 , loss: 0.43080105251331063
epoch 31 , loss: 0.43028903675216473
epoch 32 , loss: 0.430153699727276
epoch 33 , loss: 0.42932451594457993
epoch 34 , loss: 0.42225066205371475
epoch 35 , loss: 0.3608284355574697
epoch 36 , loss: 0.34948795061907556
epoch 37 , loss: 0.345742140211505
epoch 38 , loss: 0.34354065020714764
epoch 39 , loss: 0.34128235191470013
epoch 40 , loss: 0.34005928672207075
epoch 41 , loss: 0.3393754208509637
epoch 42 , loss: 0.33843920231706887
epoch 43 , loss: 0.3378294420173866
epoch 44 , loss: 0.33725845371058083
epoch 45 , loss: 0.33696987559632574
epoch 46 , loss: 0.33659577640481425
epoch 47 , loss: 0.3362716421839427
epoch 48 , loss: 0.335922726706864
epoch 49 , loss: 0.33580556144378315
```



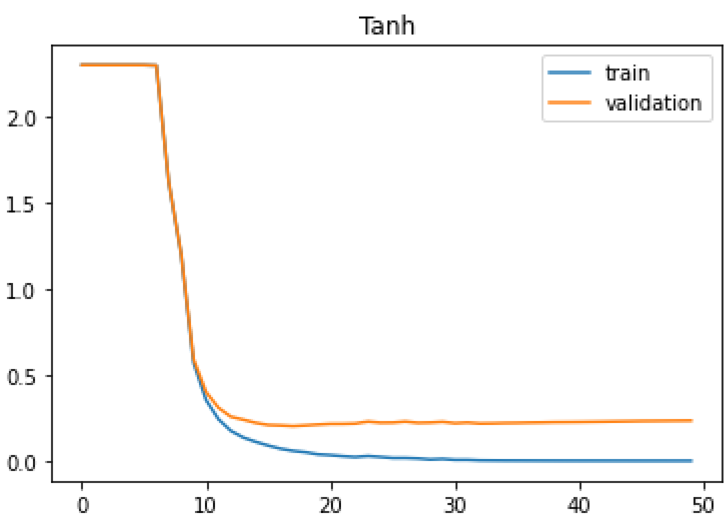

```
0.8953333333333333
```

In [7]:

```python
nn_tanh = Mnn(n_layers=6, layer_sizes=[784,256,128,64,32,10],activation="tanh", weight_
nn_tanh.fit(X_train,y_train,X_val,y_val)
plt.plot(nn_tanh.loss,label="train")
plt.plot(nn_tanh.val_loss, label="validation")
plt.title("Tanh")
plt.legend()
plt.show()
print(nn_tanh.score(X_test,y_test))
pickle.dump(nn_relu,open("tanh.pkl","wb"))
```

```
epoch 0 , loss: 2.3014791324174944
epoch 1 , loss: 2.301474560249197
epoch 2 , loss: 2.3014602297534545
epoch 3 , loss: 2.301436737236324
epoch 4 , loss: 2.301388973372883
epoch 5 , loss: 2.30123979718874
epoch 6 , loss: 2.2987188258083617
epoch 7 , loss: 1.6158673274699
```

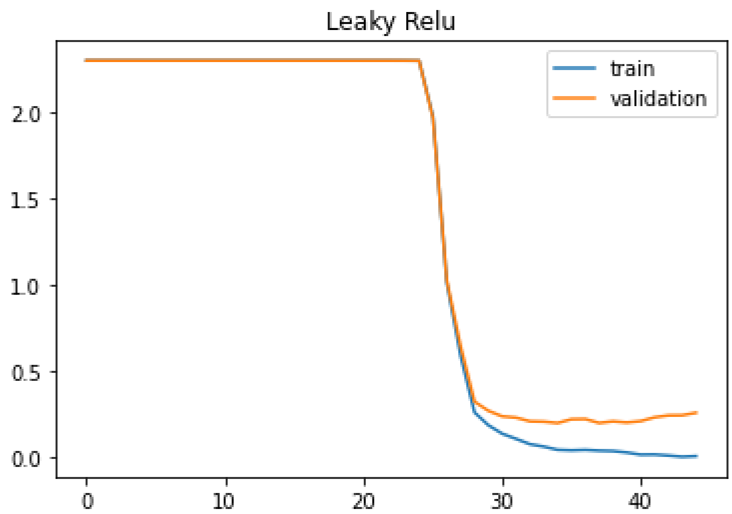
```
epoch 8 , loss: 1.1978121136680604
epoch 9 , loss: 0.5700305645876753
epoch 10 , loss: 0.3544210888180196
epoch 11 , loss: 0.2429075123586408
epoch 12 , loss: 0.17508900027785804
epoch 13 , loss: 0.13633924359281088
epoch 14 , loss: 0.11123053466653711
epoch 15 , loss: 0.08970456484319915
epoch 16 , loss: 0.07122716170432657
epoch 17 , loss: 0.05870631246229349
epoch 18 , loss: 0.05083698943907232
epoch 19 , loss: 0.038395486718069825
epoch 20 , loss: 0.033978345148395706
epoch 21 , loss: 0.027785233403186435
epoch 22 , loss: 0.022723888010002583
epoch 23 , loss: 0.028718273052217788
epoch 24 , loss: 0.023103260284369247
epoch 25 , loss: 0.01717384274230169
epoch 26 , loss: 0.017327664005036197
epoch 27 , loss: 0.014543090326300452
epoch 28 , loss: 0.008738866024971302
epoch 29 , loss: 0.011782979208425729
epoch 30 , loss: 0.006450093815754906
epoch 31 , loss: 0.00655764796803535
epoch 32 , loss: 0.0034119305448375528
epoch 33 , loss: 0.0028790288531064523
epoch 34 , loss: 0.0022787159746259587
epoch 35 , loss: 0.002071199693128376
epoch 36 , loss: 0.0018342195697517948
epoch 37 , loss: 0.001603746013866665
epoch 38 , loss: 0.0014294281916500417
epoch 39 , loss: 0.0013003424373838068
epoch 40 , loss: 0.0012054763505405393
epoch 41 , loss: 0.0011324749274237058
epoch 42 , loss: 0.001064982015578669
epoch 43 , loss: 0.0009747702556465967
epoch 44 , loss: 0.0009303291832054153
epoch 45 , loss: 0.0008425437217308922
epoch 46 , loss: 0.000813271351400861
epoch 47 , loss: 0.0007543321545629841
epoch 48 , loss: 0.0007232426202362238
epoch 49 , loss: 0.0007084263782989027
```




```
0.9573333333333334
```

In [8]:
```
nn_leaky_relu = Mnn(n_layers=6, layer_sizes=[784,256,128,64,32,10],activation="leaky_re
nn_leaky_relu.fit(X_train,y_train,X_val,y_val)
plt.plot(nn_leaky_relu.loss,label="train")
plt.plot(nn_leaky_relu.val_loss, label="validation")
plt.title("Leaky Relu")
plt.legend()
plt.show()
print(nn_leaky_relu.score(X_test,y_test))
pickle.dump(nn_leaky_relu,open("leaky_relu.pkl","wb"))
```

```
epoch 0 , loss: 2.301485763625222
epoch 1 , loss: 2.3014913605199743
epoch 2 , loss: 2.3014910537375197
epoch 3 , loss: 2.3014905082950907
epoch 4 , loss: 2.301489959975759
epoch 5 , loss: 2.3014893978496342
epoch 6 , loss: 2.3014888115636363
epoch 7 , loss: 2.3014881569671366
epoch 8 , loss: 2.3014874134275574
epoch 9 , loss: 2.301486569693447
epoch 10 , loss: 2.301485592124682
epoch 11 , loss: 2.3014844453194727
epoch 12 , loss: 2.3014830903819843
epoch 13 , loss: 2.30148145908657
epoch 14 , loss: 2.3014794678868937
epoch 15 , loss: 2.3014769807159823
epoch 16 , loss: 2.301473801883498
epoch 17 , loss: 2.3014695794920543
epoch 18 , loss: 2.3014637741941266
epoch 19 , loss: 2.3014552989625985
epoch 20 , loss: 2.30144197566639
epoch 21 , loss: 2.3014193392352937
epoch 22 , loss: 2.3013744116146975
epoch 23 , loss: 2.301255954120485
epoch 24 , loss: 2.3006454248305706
epoch 25 , loss: 1.9748497870101351
epoch 26 , loss: 1.0157410231502773
epoch 27 , loss: 0.5901380969914486
epoch 28 , loss: 0.262787590305588
epoch 29 , loss: 0.1885067648239623
epoch 30 , loss: 0.1392088226267297
epoch 31 , loss: 0.10938360683124872
epoch 32 , loss: 0.07854349054807441
epoch 33 , loss: 0.06432532463421434
epoch 34 , loss: 0.04587053571935216
epoch 35 , loss: 0.04279109867758852
epoch 36 , loss: 0.04542849800150416
epoch 37 , loss: 0.04076900478733739
epoch 38 , loss: 0.03870134013645452
epoch 39 , loss: 0.030181463818222336
epoch 40 , loss: 0.01752438283394341
epoch 41 , loss: 0.018299243009564967
epoch 42 , loss: 0.012630474467286093
epoch 43 , loss: 0.005339894070057351
epoch 44 , loss: 0.009057035335855425
```



0.9615

In [15]:

```
for i in [256,572,784]:
  print('Batch size{}',i)
  nn_sigmoid = Mnn(n_layers=6, layer_sizes=[784,256,128,64,32,10],activation="sigmoid",
  nn_sigmoid.fit(X_train,y_train,X_val,y_val)
  plt.plot(nn_sigmoid.loss,label="train")
  plt.plot(nn_sigmoid.val_loss, label="validation")
  plt.title("sigmoid")
  plt.legend()
  plt.show()
  print(nn_sigmoid.score(X_test,y_test))
  pickle.dump(nn_relu,open(str(i)+"sigmoid.pkl","wb"))
```

```
Batch size{} 256
epoch 0 , loss: 2.302071183759006
epoch 1 , loss: 2.3020683457017705
epoch 2 , loss: 2.302065522034392
epoch 3 , loss: 2.302062712114132
epoch 4 , loss: 2.302059915305505
epoch 5 , loss: 2.302057130996239
epoch 6 , loss: 2.3020543585968203
epoch 7 , loss: 2.302051597540037
epoch 8 , loss: 2.302048847280527
epoch 9 , loss: 2.3020461072943217
epoch 10 , loss: 2.302043377078394
epoch 11 , loss: 2.3020406561502087
epoch 12 , loss: 2.302037944047272
epoch 13 , loss: 2.3020352403266826
epoch 14 , loss: 2.3020325445646934
epoch 15 , loss: 2.3020298563562624
epoch 16 , loss: 2.3020271753146178
epoch 17 , loss: 2.3020245010708233
epoch 18 , loss: 2.3020218332733426
epoch 19 , loss: 2.3020191715876126
epoch 20 , loss: 2.3020165156956205
epoch 21 , loss: 2.3020138652954807
epoch 22 , loss: 2.30201122010102
epoch 23 , loss: 2.302008579841363
epoch 24 , loss: 2.3020059442605314
epoch 25 , loss: 2.3020033131170337
epoch 26 , loss: 2.3020006861834705
epoch 27 , loss: 2.3019980632461436
```

```
epoch 28 , loss: 2.3019954441046644
epoch 29 , loss: 2.301992828571573
epoch 30 , loss: 2.3019902164719634
epoch 31 , loss: 2.301987607643106
epoch 32 , loss: 2.301985001934085
epoch 33 , loss: 2.301982399205437
epoch 34 , loss: 2.3019797993287945
epoch 35 , loss: 2.3019772021865346
epoch 36 , loss: 2.30197460767144
epoch 37 , loss: 2.301972015686353
epoch 38 , loss: 2.3019694261438497
epoch 39 , loss: 2.30196683896591
epoch 40 , loss: 2.3019642540835967
epoch 41 , loss: 2.3019616714367412
epoch 42 , loss: 2.3019590909736327
epoch 43 , loss: 2.3019565126507184
epoch 44 , loss: 2.3019539364323025
epoch 45 , loss: 2.301951362290256
epoch 46 , loss: 2.301948790203731
epoch 47 , loss: 2.301946220158883
epoch 48 , loss: 2.301943652148594
epoch 49 , loss: 2.301941086172207
epoch 50 , loss: 2.301938522235263
epoch 51 , loss: 2.3019359603492444
epoch 52 , loss: 2.3019334005313286
epoch 53 , loss: 2.3019308428041354
epoch 54 , loss: 2.3019282871954974
epoch 55 , loss: 2.3019257337382206
epoch 56 , loss: 2.3019231824698587
epoch 57 , loss: 2.301920633432492
epoch 58 , loss: 2.3019180866725124
epoch 59 , loss: 2.3019155422404065
epoch 60 , loss: 2.3019130001905603
epoch 61 , loss: 2.3019104605810488
epoch 62 , loss: 2.3019079234734483
epoch 63 , loss: 2.3019053889326466
epoch 64 , loss: 2.301902857026654
epoch 65 , loss: 2.3019003278264307
epoch 66 , loss: 2.301897801405706
epoch 67 , loss: 2.301895277840818
epoch 68 , loss: 2.3018927572105397
epoch 69 , loss: 2.301890239595927
epoch 70 , loss: 2.301887725080161
epoch 71 , loss: 2.3018852137484003
epoch 72 , loss: 2.3018827056876314
epoch 73 , loss: 2.301880200986534
epoch 74 , loss: 2.3018776997353387
epoch 75 , loss: 2.3018752020256987
epoch 76 , loss: 2.301872707950562
epoch 77 , loss: 2.301870217604045
epoch 78 , loss: 2.3018677310813156
epoch 79 , loss: 2.3018652484784763
epoch 80 , loss: 2.3018627698924523
epoch 81 , loss: 2.301860295420885
epoch 82 , loss: 2.301857825162027
epoch 83 , loss: 2.3018553592146405
epoch 84 , loss: 2.301852897677901
epoch 85 , loss: 2.3018504406513056
epoch 86 , loss: 2.3018479882345795
epoch 87 , loss: 2.301845540527592
```

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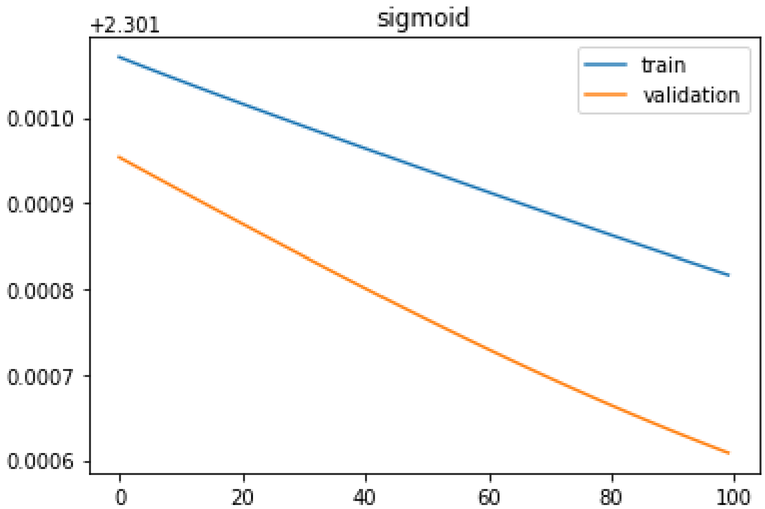
epoch 88 , loss: 2.3018430976302704
epoch 89 , loss: 2.301840659642521
epoch 90 , loss: 2.3018382266641515
epoch 91 , loss: 2.3018357987947966
epoch 92 , loss: 2.301833376133844
epoch 93 , loss: 2.3018309587803674
epoch 94 , loss: 2.301828546833062
epoch 95 , loss: 2.3018261403901756
epoch 96 , loss: 2.3018237395494543
epoch 97 , loss: 2.3018213444080793
epoch 98 , loss: 2.3018189550626107
epoch 99 , loss: 2.3018165716089363
```

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Batch size{} 572
epoch 0 , loss: 2.3018272099950163
epoch 1 , loss: 2.3018265831749227
epoch 2 , loss: 2.301825818585395
epoch 3 , loss: 2.301825054660981
epoch 4 , loss: 2.3018242914442513
epoch 5 , loss: 2.301823528936047
epoch 6 , loss: 2.301822767137208
epoch 7 , loss: 2.3018220060485652
epoch 8 , loss: 2.3018212456709484
epoch 9 , loss: 2.301820486005182
epoch 10 , loss: 2.301819727052087
epoch 11 , loss: 2.3018189688124804
epoch 12 , loss: 2.301818211287174
epoch 13 , loss: 2.301817454476977
epoch 14 , loss: 2.301816698382694
epoch 15 , loss: 2.301815943005126
epoch 16 , loss: 2.301815188345069
epoch 17 , loss: 2.301814434403316
epoch 18 , loss: 2.301813681180656
epoch 19 , loss: 2.3018129286778732
epoch 20 , loss: 2.301812176895749
epoch 21 , loss: 2.30181142583506
epoch 22 , loss: 2.3018106754965797
epoch 23 , loss: 2.3018099258810776
epoch 24 , loss: 2.301809176989317
epoch 25 , loss: 2.3018084288220617
epoch 26 , loss: 2.3018076813800676
epoch 27 , loss: 2.301806934664089
epoch 28 , loss: 2.3018061886748757
```

```
epoch 29 , loss: 2.301805443413174
epoch 30 , loss: 2.301804698879726
epoch 31 , loss: 2.3018039550752696
epoch 32 , loss: 2.30180321200054
epoch 33 , loss: 2.3018024696562676
epoch 34 , loss: 2.3018017280431797
epoch 35 , loss: 2.3018009871619993
epoch 36 , loss: 2.301800247013446
epoch 37 , loss: 2.3017995075982367
epoch 38 , loss: 2.301798768917082
epoch 39 , loss: 2.3017980309706907
epoch 40 , loss: 2.301797293759767
epoch 41 , loss: 2.3017965572850128
epoch 42 , loss: 2.301795821547124
epoch 43 , loss: 2.3017950865467953
epoch 44 , loss: 2.3017943522847157
epoch 45 , loss: 2.3017936187615717
epoch 46 , loss: 2.3017928859780463
epoch 47 , loss: 2.3017921539348176
epoch 48 , loss: 2.3017914226325615
epoch 49 , loss: 2.3017906920719486
epoch 50 , loss: 2.3017899622536473
epoch 51 , loss: 2.301789233178322
epoch 52 , loss: 2.301788504846633
epoch 53 , loss: 2.301787777259238
epoch 54 , loss: 2.30178705041679
epoch 55 , loss: 2.301786324319939
epoch 56 , loss: 2.301785598969331
epoch 57 , loss: 2.3017848743656097
epoch 58 , loss: 2.3017841505094134
epoch 59 , loss: 2.3017834274013773
epoch 60 , loss: 2.3017827050421342
epoch 61 , loss: 2.3017819834323126
epoch 62 , loss: 2.3017812625725362
epoch 63 , loss: 2.3017805424634283
epoch 64 , loss: 2.301779823105605
epoch 65 , loss: 2.3017791044996816
epoch 66 , loss: 2.301778386646269
epoch 67 , loss: 2.301777669545973
epoch 68 , loss: 2.301776953199399
epoch 69 , loss: 2.3017762376071462
epoch 70 , loss: 2.3017755227698125
epoch 71 , loss: 2.3017748086879894
epoch 72 , loss: 2.3017740953622683
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epoch 74 , loss: 2.3017726709814714
epoch 75 , loss: 2.301771959927558
epoch 76 , loss: 2.3017712496320692
epoch 77 , loss: 2.3017705400955797
epoch 78 , loss: 2.3017698313186554
epoch 79 , loss: 2.3017691233018645
epoch 80 , loss: 2.3017684160457668
epoch 81 , loss: 2.301767709550923
epoch 82 , loss: 2.301767003817886
epoch 83 , loss: 2.301766298847208
epoch 84 , loss: 2.301765594639438
epoch 85 , loss: 2.3017648911951207
epoch 86 , loss: 2.301764188514797
epoch 87 , loss: 2.3017634865990044
epoch 88 , loss: 2.301762785448278
```

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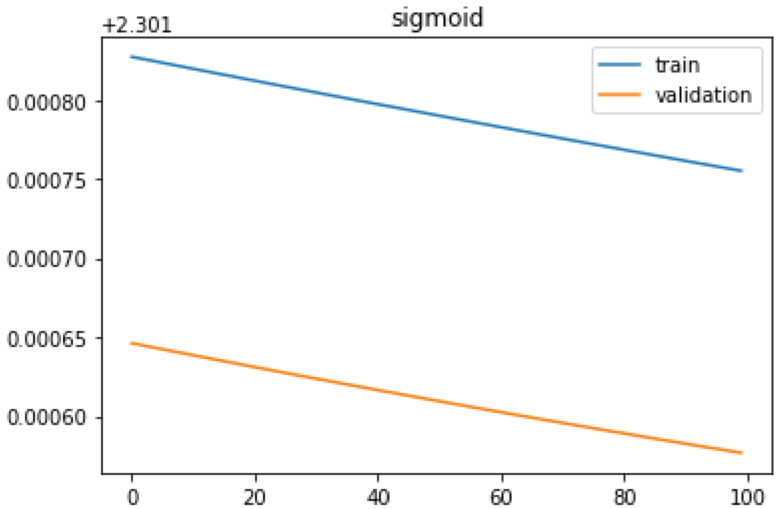
epoch 89 , loss: 2.301762085063148
epoch 90 , loss: 2.301761385444143
epoch 91 , loss: 2.301760686591787
epoch 92 , loss: 2.3017599885066
epoch 93 , loss: 2.3017592911891005
epoch 94 , loss: 2.3017585946398014
epoch 95 , loss: 2.3017578988592136
epoch 96 , loss: 2.3017572038478455
epoch 97 , loss: 2.3017565096061983
epoch 98 , loss: 2.3017558161347744
epoch 99 , loss: 2.301755123434069
```




```
0.09816666666666667
Batch size{} 784
epoch 0 , loss: 2.3016924090773765
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epoch 2 , loss: 2.301692364856191
epoch 3 , loss: 2.3016919570993806
epoch 4 , loss: 2.301691549724843
epoch 5 , loss: 2.301691142749785
epoch 6 , loss: 2.301690736174009
epoch 7 , loss: 2.3016903299972435
epoch 8 , loss: 2.301689924219217
epoch 9 , loss: 2.3016895188396584
epoch 10 , loss: 2.3016891138582993
epoch 11 , loss: 2.301688709274869
epoch 12 , loss: 2.301688305089099
epoch 13 , loss: 2.3016879013007183
epoch 14 , loss: 2.3016874979094597
epoch 15 , loss: 2.3016870949150543
epoch 16 , loss: 2.3016866923172348
epoch 17 , loss: 2.3016862901157324
epoch 18 , loss: 2.301685888310281
epoch 19 , loss: 2.3016854869006123
epoch 20 , loss: 2.301685085886461
epoch 21 , loss: 2.3016846852675608
epoch 22 , loss: 2.3016842850436445
epoch 23 , loss: 2.3016838852144472
epoch 24 , loss: 2.301683485779704
epoch 25 , loss: 2.3016830867391502
epoch 26 , loss: 2.3016826880925203
epoch 27 , loss: 2.301682289839551
epoch 28 , loss: 2.301681891979978
epoch 29 , loss: 2.301681494513538
```

```
epoch 30 , loss: 2.301681097439967
epoch 31 , loss: 2.3016807007590034
epoch 32 , loss: 2.3016803044703833
epoch 33 , loss: 2.301679908573846
epoch 34 , loss: 2.301679513069128
epoch 35 , loss: 2.301679117955969
epoch 36 , loss: 2.3016787232341067
epoch 37 , loss: 2.301678328903281
epoch 38 , loss: 2.301677934963231
epoch 39 , loss: 2.3016775414136963
epoch 40 , loss: 2.301677148254417
epoch 41 , loss: 2.301676755485133
epoch 42 , loss: 2.301676363105586
epoch 43 , loss: 2.3016759711155164
epoch 44 , loss: 2.301675579514665
epoch 45 , loss: 2.301675188302774
epoch 46 , loss: 2.301674797479585
epoch 47 , loss: 2.30167440704484
epoch 48 , loss: 2.3016740169982826
epoch 49 , loss: 2.301673627339654
epoch 50 , loss: 2.3016732380686986
epoch 51 , loss: 2.301672849185159
epoch 52 , loss: 2.3016724606887795
epoch 53 , loss: 2.301672072579304
epoch 54 , loss: 2.301671684856476
epoch 55 , loss: 2.3016712975200413
epoch 56 , loss: 2.3016709105697437
epoch 57 , loss: 2.3016705240053286
epoch 58 , loss: 2.3016701378265423
epoch 59 , loss: 2.3016697520331295
epoch 60 , loss: 2.3016693666248367
epoch 61 , loss: 2.30166898160141
epoch 62 , loss: 2.3016685969625965
epoch 63 , loss: 2.301668212708143
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epoch 65 , loss: 2.3016674453513035
epoch 66 , loss: 2.3016670622484128
epoch 67 , loss: 2.3016666795288723
epoch 68 , loss: 2.30166629719243
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epoch 70 , loss: 2.301665533667834
epoch 71 , loss: 2.30166515247918
epoch 72 , loss: 2.301664771672619
epoch 73 , loss: 2.3016643912479005
epoch 74 , loss: 2.301664011204777
epoch 75 , loss: 2.3016636315429966
epoch 76 , loss: 2.30166325226231
epoch 77 , loss: 2.301662873362468
epoch 78 , loss: 2.301662494843222
epoch 79 , loss: 2.301662116704322
epoch 80 , loss: 2.301661738945521
epoch 81 , loss: 2.3016613615665693
epoch 82 , loss: 2.30166098456722
epoch 83 , loss: 2.301660607947224
epoch 84 , loss: 2.301660231706334
epoch 85 , loss: 2.3016598558443033
epoch 86 , loss: 2.3016594803608843
epoch 87 , loss: 2.3016591052558306
epoch 88 , loss: 2.3016587305288954
epoch 89 , loss: 2.3016583561798325
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epoch 90 , loss: 2.301657982208395
epoch 91 , loss: 2.3016576086143385
epoch 92 , loss: 2.301657235397416
epoch 93 , loss: 2.3016568625573814
epoch 94 , loss: 2.3016564900939915
epoch 95 , loss: 2.301656118007001
epoch 96 , loss: 2.301655746296165
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epoch 98 , loss: 2.301655004001976
epoch 99 , loss: 2.3016546334181363
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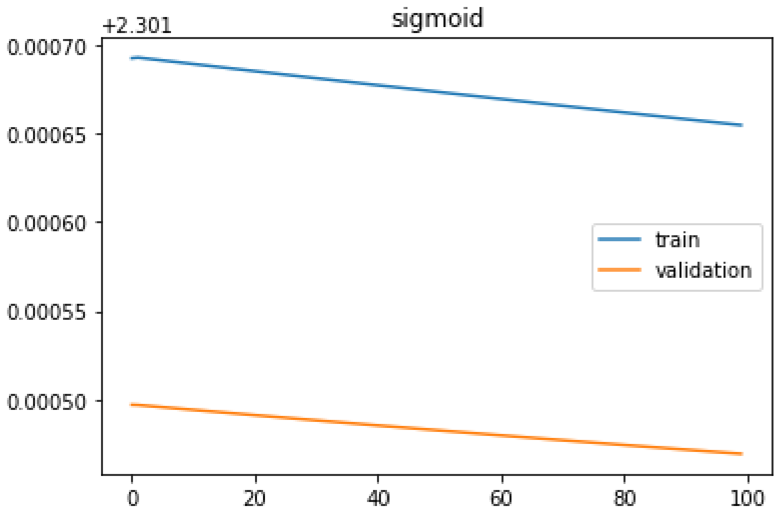


```
0.124
```

In [ ]: