	Лабортаторная работа №4 По курсу "нейроинформатика" студент: Гаврилов М.С. группа: М8О-406Б-19 вариант: 11 Цель работы:
In [1]:	Цель работы: Исследование свойств некоторых видов сетей с радиальными базисными элементами, алгоритмов обучения, а также применение сетей в задачах классификации и аппроксимации функции. import numpy as np import pylab import torch import torch.nn as nn import copy
	<pre>import random import sklearn as skl import sklearn.metrics from tqdm import tqdm #визуал для циклов 1. Классификация точек Области: • Эллипс. a = 0.4, b = 0.15, alph = pi/3, x0 = -0.2, y0 = -0.18</pre>
In [2]:	 Эплипс. a = 0.4, b = 0.5, alph = -pi/3, x0 = -0.2, y0 = -0.18 Эплипс. a = 1, b = 1, alph = 0, x0 = 0, y0 = 0 # Уравнение эллипса в параметрическом виде. def ellipse(t,inp_arr):
In [3]:	x = x0 + t ** 2 / (2. * p) y = y0 + t return x, y # Функция вращения фигуры на заданный угол. def rotate(pt, alpha): x,y = pt xr = x * np.cos(alpha) - y * np.sin(alpha) yr = x * np.sin(alpha) + y * np.cos(alpha) return xr, yr ellipse1 = [0.4,0.15,-0.2,-0.18] ellipse2 = [0.4,0.5,-0.2,-0.18]
In [4]:	<pre>ellipse3 = [1,1,0,0] ell_arr_1 = [] for t in range(0,1000,1): ell_arr_1.append(rotate(ellipse(t/100,ellipse1),np.pi/3)) ell_arr_1 = np.array(ell_arr_1) ell_arr_2 = [] for t in range(0,1000,1): ell_arr_2.append(rotate(ellipse(t/100,ellipse2),-np.pi/3)) ell_arr_2 = np.array(ell_arr_2) ell_arr_3 = []</pre>
In [5]:	<pre>for t in range(0,1000,1): ell_arr_3.append(ellipse(t/100,ellipse3)) ell_arr_3 = np.array(ell_arr_3) pylab.xlabel("x",color = "grey") pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1]) pylab.show()</pre>
	1.00 0.75 0.50 0.25 > 0.00
	-0.50 -0.75 -1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00
In [6]:	Функции для построения датасета: def in_ellipse(ell_arr,pt,rot = 0): a,b,x0,y0 = ell_arr pt = rotate(pt,-rot) return (((pt[0]-x0)*(pt[0]-x0))/(a*a) + ((pt[1]-y0)*(pt[1]-y0))/(b*b) < 1) def make_dataset_on(sel_cnt = 1000,class_cnt = 500): data_X = [] data_L = [] for i in range (sel_cnt):
	<pre>pt = random.random()*10 choose = random.random()*3 if(choose > 2): data_X.append(rotate(ellipse(pt,ellipse1),np.pi/3)) data_L.append(0) continue if(choose > 1): data_X.append(rotate(ellipse(pt,ellipse2),-np.pi/3)) data_L.append(1) continue if(choose >= 0):</pre>
	<pre>data_X.append(ellipse(pt,ellipse3)) data_L.append(2) continue return np.array(data_X),np.array(data_L) def make_dataset_in(sel_cnt = 30000,class_cnt = 500): class_cnt = [0,0,0] data_X = [] data_L = [] for i in range (30000): pt = [(random.random()*2)-1,(random.random()*2)-1]</pre>
	<pre>if(in_ellipse(ellipse1,pt,np.pi/3) and class_cnt[0] < 1000): data_X.append(pt) data_L.append(0) class_cnt[0] += 1 continue if(in_ellipse(ellipse2,pt,-np.pi/3) and class_cnt[1] < 1000): data_X.append(pt) data_L.append(1) class_cnt[1] += 1 continue if(in_ellipse(ellipse3,pt) and class_cnt[2] < 1000):</pre>
In [8]:	<pre>data_X.append(pt) data_L.append(2) class_cnt[2] += 1 continue data_X = np.array(data_X) data_L = np.array(data_L) return np.array(data_X),np.array(data_L) def calculate_wts(data_L): class_wts = [] for i in range(np.max(data_L) + 1):</pre>
In [14]:	<pre>class_wts.append(1 - (data_L == i).mean()) class_wts = torch.tensor(class_wts,dtype = torch.float32) return class_wts Oбучающие функции def accuracy_mult(testRS,testLB): return (np.argmax(testRS,axis = 1) == testLB).mean() def train(net,trainXX,trainLB,n_epochs,batch_size,lr,</pre>
	accuracy = accuracy_mult): #функция, производящая обучение сети arr = [] optim = optimiser(model.parameters(),lr=lr) num_batches = len(trainXX)/batch_size for i in tqdm(range(n_epochs)): for j in range(int(num_batches)): batchXX = trainXX[j*batch_size : (j+1)*batch_size]
	<pre>batchLB = trainLB[j*batch_size : (j+1)*batch_size] optim.zero_grad() loss = criterion(model(batchXX),batchLB) loss.backward() optim.step() #трэйсинг обучения arr.append([i,</pre>
	<pre>def plot_learning(arr): pylab.grid() pylab.xlabel("epochs",color = "grey") pylab.ylabel("loss",color = "grey") pylab.plot(arr[:,0],arr[:,1]) pylab.show() pylab.axis([0,len(arr),0,1]) pylab.xlabel("epochs",color = "grey") pylab.ylabel("accuracy",color = "grey") pylab.plot(arr[:,0],arr[:,2]) pylab.show()</pre>
In [10]:	Классификация датасета с точками на эллипсах data_X,data_L = make_dataset_on(sel_cnt = 1000,class_cnt = 500) train_X = torch.tensor(data_X,dtype = torch.float32) train_L = torch.tensor(data_L) Демонстрация точек датасета: pylab.xlabel("x",color = "grey")
	<pre>pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1]) for i in range(len(data_X)): if(data_L[i] == 0): pylab.plot(data_X[i,0],data_X[i,1],'bo') if(data_L[i] == 1): pylab.plot(data_X[i,0],data_X[i,1],'ro') if(data_L[i] == 2): pylab.plot(data_X[i,0],data_X[i,1],'go')</pre>
	1.00
	-0.25 -0.50 -0.75 -1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00
In [12]: In [13]:	<pre>class myRBF(nn.Module): definit(self, in_features, out_features, bias=True): super()init() self.in_features = in_features self.out_features = out_features self.bias = bias</pre>
	<pre>self.weight = torch.nn.Parameter(torch.randn(out_features, in_features)) self.bias = torch.nn.Parameter(torch.randn(out_features)) def forward(self, input): x, y = input.shape if y != self.in_features: sys.exit(f'Wrong Input Features. Please use tensor with {self.in_features} Input Features') output = input @ self.weight.t() + self.bias return output</pre> RBF-МОДУЛЬ:
In [80]:	<pre>class myRBF(nn.Module): definit(self, in_features, out_features): super()init() self.in_features = in_features self.out_features = out_features self.wts_mean = torch.nn.Parameter(torch.randn(out_features,in_features)) self.wts_area = torch.nn.Parameter(torch.randn(out_features)) def forward(self, input):</pre>
In [82]:	<pre>x, y = input.shape if y != self.in_features:</pre>
In [102	model = torch.nn.Sequential(myRBF(2,30), nn.Tanh(), myRBF(30,40), nn.Tanh(), myRBF(40,3), nn.Softmax(dim = 1)) arr = train(model,train_X,train_L,1000,50,0.05,criterion = torch.nn.CrossEntropyLoss(weight = class_wts)) 100%
In [103	
	1.1
	0.8 0.7 0 200 400 600 800 1000 epochs
	0.8 0.6 0.4
	0.2 0.0 0.0 0.0 0.0 0.0 0.0 0.0
	precision recall f1-score support 0 0.80 1.00 0.89 337 1 1.00 0.80 0.89 348 2 1.00 0.94 0.97 315 accuracy macro avg 0.93 0.92 0.92 1000 weighted avg 0.93 0.91 0.91 1000
	0 - 1 0 0 - 0.8 - 0.8 - 0.6 - 0.4
In [104	2 - 0.057 0 0.94 0.0 Predicted label Графическая демонстрация классификации: print("blue - correct \nred - wrong\n")
	<pre>pylab.xlabel("x",color = "grey") pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1]) for i in range(len(data_X)): if(data_L[i] == torch.argmax(model(train_X[i].reshape(1,2)))): pylab.plot(data_X[i,0],data_X[i,1],'bo') else: pylab.plot(data_X[i,0],data_X[i,1],'ro')</pre>
	pylab.show() blue - correct red - wrong 1.00 0.75 0.50 0.25
	> 0.00 -0.25 -0.50 -0.75 -1.00
In [105	<pre>print("Correct Labels") pylab.xlabel("x",color = "grey") pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1])</pre> <pre>for i in range(len(data_X)):</pre>
	<pre>if(data_L[i] == 0): pylab.plot(data_X[i,0],data_X[i,1],'bo') if(data_L[i] == 1): pylab.plot(data_X[i,0],data_X[i,1],'ro') if(data_L[i] == 2): pylab.plot(data_X[i,0],data_X[i,1],'go') pylab.show() print("Predicted Labels") pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1])</pre>
	<pre>pylab.ylabel("y",color = "grey") pylab.grid() for i in range(len(data_X)): if(torch.argmax(model(train_X[i].reshape(1,2))) == 0): pylab.plot(data_X[i,0],data_X[i,1],'bo') if(torch.argmax(model(train_X[i].reshape(1,2))) == 1): pylab.plot(data_X[i,0],data_X[i,1],'ro') if(torch.argmax(model(train_X[i].reshape(1,2))) == 2): pylab.plot(data_X[i,0],data_X[i,1],'go') pylab.show()</pre> Correct Labels
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	<pre>data_X,data_L = make_dataset_in(sel_cnt = 1000,class_cnt = 500) train_X = torch.tensor(data_X,dtype = torch.float32) train_L = torch.tensor(data_L) print("blue - correct \nred - wrong\n") pylab.xlabel("x",color = "grey") pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1])</pre>
	<pre>for i in range(len(data_X)): if(data_L[i] == torch.argmax(model(train_X[i].reshape(1,2)))): pylab.plot(data_X[i,0],data_X[i,1],'bo') else: pylab.plot(data_X[i,0],data_X[i,1],'ro') pylab.show() blue - correct red - wrong</pre>
	1.00 0.75 0.50 0.25 > 0.00
In [108	-0.50 -0.75 -1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 x print("Correct Labels") pylab.xlabel("x",color = "grey")
	<pre>pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_2[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1]) for i in range(len(data_X)): if(data_L[i] == 0): pylab.plot(data_X[i,0],data_X[i,1],'bo') if(data_L[i] == 1): pylab.plot(data_X[i,0],data_X[i,1],'ro') if(data_L[i] == 2): pylab.plot(data_X[i,0],data_X[i,1],'go')</pre>
	<pre>pylab.show() print("Predicted Labels") pylab.plot(ell_arr_1[:,0],ell_arr_1[:,1]) pylab.plot(ell_arr_2[:,0],ell_arr_3[:,1]) pylab.plot(ell_arr_3[:,0],ell_arr_3[:,1]) pylab.xlabel("x",color = "grey") pylab.ylabel("y",color = "grey") pylab.grid() for i in range(len(data_X)): if(torch.argmax(model(train_X[i].reshape(1,2))) == 0): pylab.plot(data_X[i,0],data_X[i,1],'bo') if(torch.argmax(model(train_X[i].reshape(1,2))) == 1):</pre>
	<pre>pylab.plot(data_X[i,0],data_X[i,1],'ro') if(torch.argmax(model(train_X[i].reshape(1,2))) == 2): pylab.plot(data_X[i,0],data_X[i,1],'go') pylab.show() Correct Labels 1.00 0.75 0.50</pre>
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	0.25 > 0.00 -0.25 -0.50 -0.75
In [15]:	-1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 2. Аппроксимация функции tin [0,4], h = 0.02 def func(t): return np.cos(t**2)
	<pre>return np.cos(t**2) line = np.array([[i/1000,func(i/1000)] for i in range (0,4000)]) pylab.xlabel("x",color = "grey") pylab.ylabel("sin(x)",color = "grey") pylab.grid() pylab.plot(line[:,0],line[:,1]) pylab.show()</pre> 1.00
	0.75 0.50 0.25 0.00 -0.25 -0.50
In [18]:	-0.50 -0.75 -1.00 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
	<pre>def make_dataset(line,ln = 200): train_X = [] train_Y = []</pre>
In [19]: In [32]:	<pre>def make_dataset(line,ln = 200): train_X = [] train_Y = [] for j in range(ln): i = int(random.random()*len(line)) train_X.append([i/1000]) train_Y.append([line[i][1]]) train_Y = torch.tensor(train_X,dtype = torch.float32) train_Y = torch.tensor(train_Y,dtype = torch.float) return train_X,train_Y train_X,train_Y = make_dataset(line) test_X,test_Y = make_dataset(line,ln = 1000)</pre>
	<pre>def make_dataset(line,ln = 200): train_X = [] train_Y = [] for j in range(ln): i = int(random.random()*len(line)) train_X.append([i/1000]) train_Y.append([line[i][1]]) train_X = torch.tensor(train_X,dtype = torch.float32) train_Y = torch.tensor(train_Y,dtype = torch.float) return train_X,train_Y</pre> train_X,train_Y = make_dataset(line)
	<pre>def make_dataset(line,ln = 200): train_X = [] train_Y = [] for j in range(ln): i = int(random.random()*len(line)) train_X.append([i/1000]) train_Y.append([line[i][1]]) train_X = torch.tensor(train_X,dtype = torch.float32) train_Y = torch.tensor(train_Y,dtype = torch.float) return train_X,train_Y train_X,train_Y = make_dataset(line) test_X,test_Y = make_dataset(line,ln = 1000) pylab.xlabel("x",color = "grey") pylab.ylabel("y",color = "grey") pylab.grid() pylab.plot(train_X,train_Y,'yo',label = "train points") pylab.show() 1.00 0.75</pre>

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EBIBOQ B ходе выполнения этой лабораторной работы я получил опыт работы с RBF-сетями. а также научился создавать собственствой в руюгећ. Я решил задану классификации точек в двухмерном пространстве и задану аппрохомащим функцию с помо	pylab. xlabel ("x", color = "grey") pylab. ylabel ("y", color = "grey") pylab. ylabel ("y", color = "grey") pylab. plot (test X, model (test X), detach(), numpy(), 'go', label = "predixted on test") pylab. plot (lane(:,0), line(:,1), label = "true line") pylab. plot(pend()) pylab. slow() 1.00 0.75 0.50 0.25 0.00 0.75 0.50 0.75 0.50 0.75 0.75 0.7	Dylab. xlabel("x", color = "grey") pylab. ylabel("y", color = "grey") pylab. ylabel("y", color = "grey") pylab. plot(test X, model(test X), detach().numpy(), 'go', label = "predixted on test") pylab. plot(test X, model(test X), detach().numpy(), 'go', label = "predixted on test") pylab. plot(test X, model(test X), detach().numpy(), 'go', label = "predixted on test") pylab. show() 1.00 0.75 0.50 0.25 0.00 0.75 0.75 0.70 0.75 0.75 0.75 0.7	pylab.plot(tr pylab.plot(tr pylab.plot(lr pylab.legend pylab.show()	rain_X,model ine[:,0],lin	(train_X).deta	= "true poi	nts")),'yo',lab	pel = "predi	cted poin	ts")	
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