Лабортаторная работа №6

По курсу "нейроинформатика"

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Цель работы:

Исследование свойств слоя Кохонена, карты Кохонена, а также сетей векторного квантования, обучаемых с уителем, алгоритма обучения, а также применение сетей в задачах кластреизации и классификации.

In [1]:
```
import numpy as np
import pylab
import copy
import sklearn as skl

import torch
import torch.nn as nn
from tqdm import tqdm
```

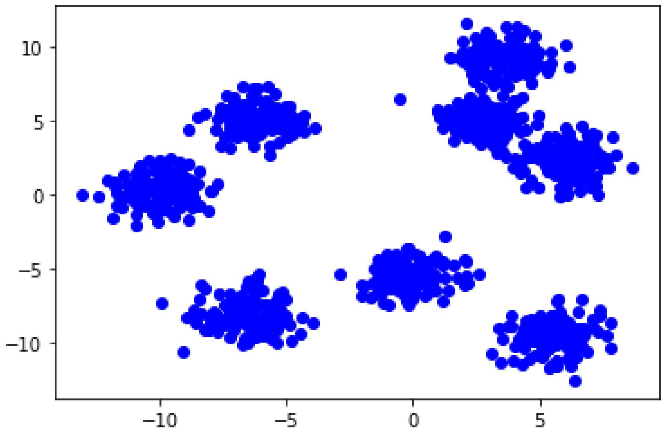
Задание 1. Слой Кохонена для кластеризации.

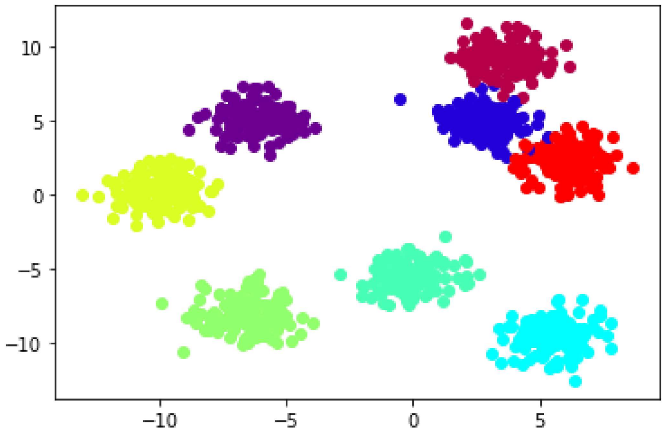
In [9]:
```
def plot_dataset(pts):
    for i in pts:
        pylab.plot(i[0],i[1],'o',color = [0,0,1])
    pylab.show()

def plot_dataset_by_classes(pts,lbls):
    for i in range(len(pts)):
        pylab.plot(pts[i][0],pts[i][1],'o',color = [lbls[i]/np.max(lbls),(lbls[i]%2 == 0
    pylab.show()

def plot_dataset_by_classes_cl(pts,lbls,centers):
    for i in range(len(pts)):
        pylab.plot(pts[i][0],pts[i][1],'o',color = [lbls[i]/np.max(lbls),(lbls[i]%2 == 0
    for i in centers:
        pylab.plot(i[0],i[1],'s',color = [0,0,0])
    pylab.show()
```

In [10]:
```
from sklearn.datasets import make_blobs
train_xx,y = make_blobs(n_samples=1000, centers=8, n_features=2,random_state = 10)
```

Сгенерированный датасет:

In [88]:
```
plot_dataset(train_xx)
plot_dataset_by_classes(train_xфx,y)
```





Слой Кохонена:

In [89]:
```
class cohonenLayer():
    def __init__ (self,classes):
        self.wts = np.random.random([classes,2])

    def train(self,inputs,n_epoch,lr = 0.5):

        for epoch in range(n_epoch):
            cur_elm = inputs[int(np.random.random()*len(inputs))]
            distances = np.zeros(len(self.wts))
            fфor i in range(len(self.wts)):
                dist = np.sqrt(((cur_elm - self.wts[i])**2).sum())
                distances[i] = dist
            self.wts[np.argmin(distances)] += lr*(cur_elm - self.wts[np.argmin(distances

    def predict(self,pt):
        res = np.zeros(len(self.wts))
        for i in range(len(self.wts)):
            res[i] = np.sqrt(((pt - self.wts[i])**2).sum())
        return np.argmin(res)
```

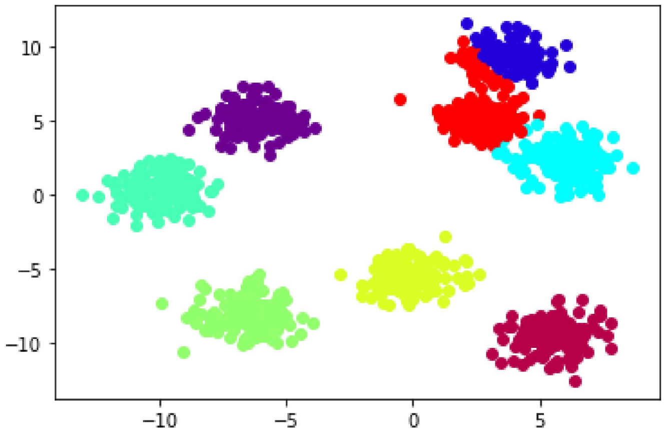
In [90]:
```
test_layer = cohonenLayer(8)
```

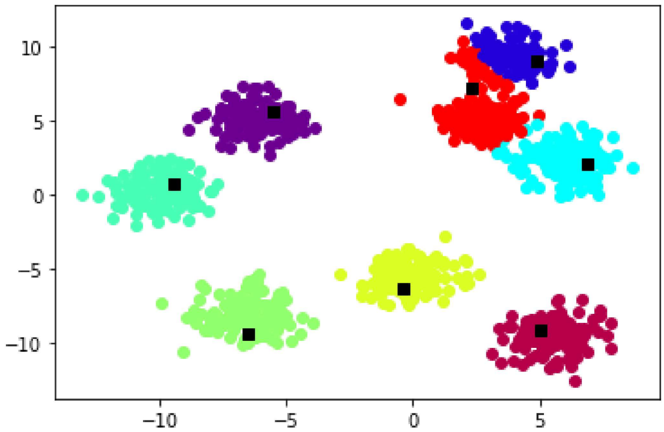
In [91]:
```
test_layer.train(train_xx,2000)
```

In [92]:
```
pred_lbl = []
for pt in train_xx:
    pred_lbl.append(test_layer.predict(pt))
pred_lbl = np.array(pred_lbl)
```

Результат кластеризации:

In [99]:
```
plot_dataset_by_classes(train_xx,pred_lbl)
plot_dataset_by_classes_cl(train_xx,pred_lbl,test_layer.wts)
```





Задание 2. Карта Кохонена

In [3]:
```
def visualise(matr): #представить двумерный массив в виде черно-белой картинки
    pylab.figure(figsize = (matr.shape[1]/10,matr.shape[0]/10))
    for i in range(matr.shape[0]):
        for j in range(matr.shape[1]):
            pylab.plot(j,matr.shape[0] - i,'s',color = (matr[i][j][0],matr[i][j][1],0))
    pylab.show()
```

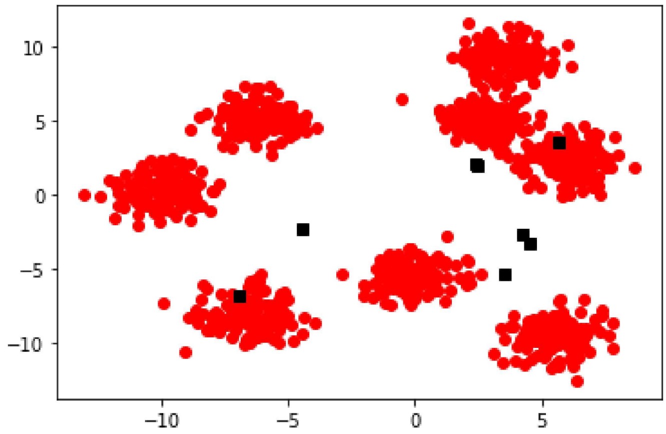
In [4]:
```
def h(t,dist):
    return np.exp(-dist)
```

In [5]:
```
class cohonenMap():
    def __init__(self,shape):
        self.shape = shape
        self.mesh = np.random.random([self.shape[0],self.shape[1],2])

    def expand(self,examples,n_epoch = 10, h = h, radius = 5):
        rad = radius
        for epoch in range(n_epoch):
            lr = n_epoch/(epoch + n_epoch)
            selected_node = examples[int(np.random.random()*len(examples))]
            tmp = self.mesh - selected_node

            tmp_norm = (np.abs(tmp).sum(axis = 2)) #не L2, но вроде норма

            min_val = np.min(tmp_norm)
            min_crd = np.argmin(tmp_norm)
            ril_min_crd = [int(min_crd / self.shape[0]),int(min_crd % self.shape[0])]

            for i in range(ril_min_crd[0] - rad,ril_min_crd[0] + rad):
                for j in range(ril_min_crd[1] - rad,ril_min_crd[1] + rad):
                    if(i >= 0 and j >= 0 and i < self.mesh.shape[0] and j < self.mesh.sh
                        dst = np.sqrt((ril_min_crd[0] - i)**2 + (ril_min_crd[1] - j)**2)

                        self.mesh[i,j] -= tmp[i,j]*h(epoch,dst/rad)*lr
                        #self.mesh[i,j] -= tmp[ril_min_crd[1],ril_min_crd[0]]*h(epoch,ds

            if(rad > 1):
                rad -= 1


    def plot(self):
        tmp = np.abs(self.mesh / np.max(np.abs(self.mesh)))
        visualise(tmp)
```

Нахождение центров кластеров

In [239]:
```
test_map = cohonenMap([2,4])
test_map.expand(train_xx,radius = 4, n_epoch = 10000)
```

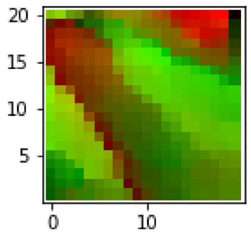
In [240]:
```
plot_dataset_by_classes_cl(train_xx,[1 for i in train_xx],test_map.mesh.reshape(8,2))
```



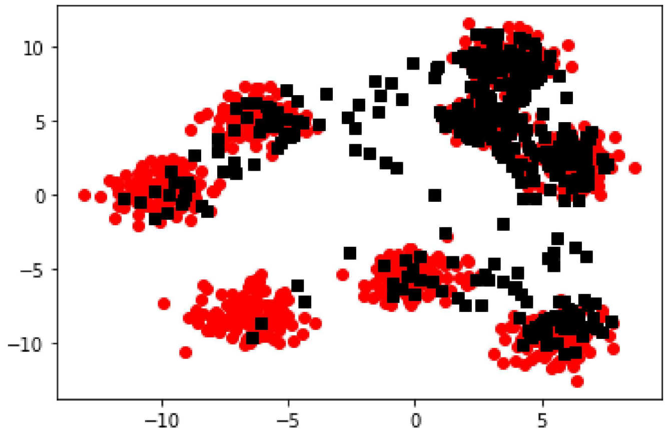
Карта большего размера

In [244]:
```
test_map = cohonenMap([20,20])
test_map.expand(train_xx,radius = 10, n_epoch = 10000)
```

In [245]:
```
test_map.plot()
```



In [246]:
```
plot_dataset_by_classes_cl(train_xx,[1 for i in train_xx],test_map.mesh.reshape(400,2))
```



Задание 3. Задача коммивояжера

In [211]:
```
class cohonenMap():
    def __init__(self,shape):
        self.shape = shape
        self.mesh = np.random.random([self.shape[0],self.shape[1],2])

    def expand(self,examples,n_epoch = 10, h = h, radius = 5):
        rad = radius
        for epoch in range(n_epoch):
            lr = n_epoch/(epoch + n_epoch)
            selected_node = examples[int(np.random.random()*len(examples))]
            tmp = self.mesh - selected_node

            tmp_norm = (np.abs(tmp).sum(axis = 2)) #не l2, но вроде норма

            min_val = np.min(tmp_norm)
            min_crd = np.argmin(tmp_norm)
            ril_min_crd = [int(min_crd / self.shape[1]),int(min_crd % self.shape[1])]

            #номер города в выходном слое
            no_outer = ril_min_crd[1]

            for i in range(ril_min_crd[0] - rad,ril_min_crd[0] + rad):
                for j in range(ril_min_crd[1] - rad,ril_min_crd[1] + rad):
                    #прохождение через границу
                    i = i % self.mesh.shape[0]
                    j = j % self.mesh.shape[1]
                    #if(i >= 0 and j >= 0 and i < self.mesh.shape[0] and j < self.mesh.s

                    dst = np.sqrt((ril_min_crd[0] - i)**2 + (ril_min_crd[1] - j)**2)

                    self.mesh[i,j] -= tmp[i,j]*h(epoch,dst/rad)*lr
                    #self.mesh[i,j] -= tmp[ril_min_crd[1],ril_min_crd[0]]*h(epoch,dst/ra


            if(rad > 1):
                rad -= 1

    def closest(self,vec):

        selected_node = vec
        tmp = self.mesh - selected_node

        tmp_norm = (np.abs(tmp).sum(axis = 2)) #не l2, но вроде норма

        min_val = np.min(tmp_norm)
        min_crd = np.argmin(tmp_norm)
        ril_min_crd = [int(min_crd / self.shape[1]),int(min_crd % self.shape[1])]

        #номер города в выходном слое
        return ril_min_crd


    def plot(self):
        tmp = np.abs(self.mesh / np.max(np.abs(self.mesh)))
        visualise(tmp)
```

In [283]:
```
cities = np.random.random([20,2])
```

In [284]:
```
test_map = cohonenMap([1,20])
test_map.expand(cities,radius = 5, n_epoch = 10000)
```

In [285]:
```
test_map.plot()
```

In [286]:
```
route = []
for x in cities:
    route.append(test_map.closest(x)[1])
route = np.array(route)
```

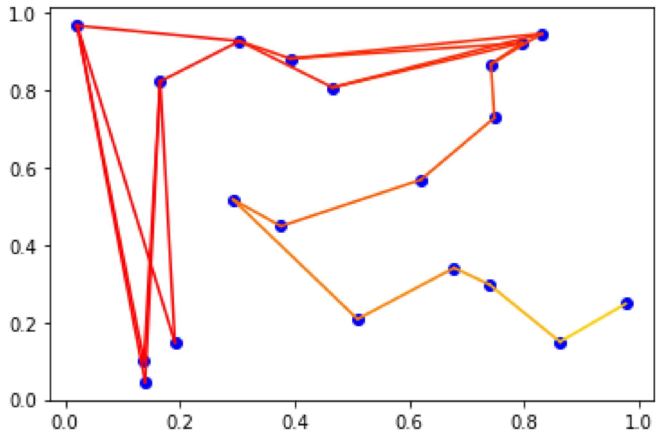
In [287]:
```
route
```

Out[287]:
```
array([ 9,  4,  1,  0,  1,  4,  3,  6, 12, 10, 16, 14,  8,  2,  0,  0, 18,
        3,  7,  5])
```

In [288]:
```
def display_route(cities,order):
    for i in cities:
        pylab.plot(i[0],i[1],'o',color = [0,0,1])

    for num in range(len(route)):
        for i in range(len(route)):
            if(route[i] == num):
                for numnext in range(num + 1,len(route)): #возможные индексы следующего
                    found = 0
                    for j in range(len(route)): #поиск города с соответствующим индексом
                        #print("-- {} {}\n".format(route[j],numnext))
                        if(route[j] == numnext):
                            print("{}:\t from node: {} \tto {} \t\t|\t ({}) -> ({})".for
                            found = 1
                            pylab.plot([cities[i][0],cities[j][0]],[cities[i][1],cities[

                    if(found == 1):
                        break



    pylab.show()
```

In [289]:
```
display_route(cities,route)
```

```
0:	from node: 3   to 2		|	([0.13918294 0.04510845]) -> ([0.16540
635 0.82354954])
0:	from node: 3   to 4		|	([0.13918294 0.04510845]) -> ([0.02069
403 0.96802678])
0:	from node: 14  to 2		|	([0.13713818 0.09950256]) -> ([0.16540
635 0.82354954])
0:	from node: 14  to 4		|	([0.13713818 0.09950256]) -> ([0.02069
403 0.96802678])
0:	from node: 15  to 2		|	([0.19114129 0.14737807]) -> ([0.16540
635 0.82354954])
0:	from node: 15  to 4		|	([0.19114129 0.14737807]) -> ([0.02069
403 0.96802678])
1:	from node: 2   to 13		|	([0.16540635 0.82354954]) -> ([0.30368
346 0.92790086])
1:	from node: 4   to 13		|	([0.02069403 0.96802678]) -> ([0.30368
346 0.92790086])
2:	from node: 13  to 6		|	([0.30368346 0.92790086]) -> ([0.46562
166 0.8078606 ])
2:	from node: 13  to 17		|	([0.30368346 0.92790086]) -> ([0.39189
83  0.88264813])
3:	from node: 6   to 1		|	([0.46562166 0.8078606 ]) -> ([0.83017
697 0.94696334])
3:	from node: 6   to 5		|	([0.46562166 0.8078606 ]) -> ([0.79664
982 0.92317549])
3:	from node: 17  to 1		|	([0.3918983  0.88264813]) -> ([0.83017
697 0.94696334])
3:	from node: 17  to 5		|	([0.3918983  0.88264813]) -> ([0.79664
982 0.92317549])
4:	from node: 1   to 19		|	([0.83017697 0.94696334]) -> ([0.74149
461 0.8683806 ])
4:	from node: 5   to 19		|	([0.79664982 0.92317549]) -> ([0.74149
461 0.8683806 ])
5:	from node: 19  to 7		|	([0.74149461 0.8683806 ]) -> ([0.74755
035 0.72931662])
6:	from node: 7   to 18		|	([0.74755035 0.72931662]) -> ([0.61922
165 0.56868409])
7:	from node: 18  to 12		|	([0.61922165 0.56868409]) -> ([0.37569
489 0.44868175])
8:	from node: 12  to 0		|	([0.37569489 0.44868175]) -> ([0.29199
364 0.51802053])
9:	from node: 0   to 9		|	([0.29199364 0.51802053]) -> ([0.50920
447 0.20808433])
10:	from node: 9   to 8		|	([0.50920447 0.20808433]) -> ([0.67743
487 0.34067109])
12:	from node: 8   to 11		|	([0.67743487 0.34067109]) -> ([0.73898
764 0.29750065])
14:	from node: 11  to 10		|	([0.73898764 0.29750065]) -> ([0.86180
122 0.14939888])
16:	from node: 10  to 16		|	([0.86180122 0.14939888]) -> ([0.97638
898 0.2478762 ])
```



Задание 4. LVQ сеть

Датасет для классификации:

In [273]:
```
data_c1 = [-0.3,-0.3,-1.1,-1.1,1.1,0.5,0,0.2,-0.7,-0.3,0.1,-0.3]
data_c2 = [1.4,0.3,-0.4,0.7,-0.5,-0.7,0.9,-0.5,-0.2,-0.5,0.7,-0.3]
data_lb = [1,1,1,1,1,1,1,1,-1,-1,1,-1]
```

In [274]:
```
examples = np.array([[data_c1[i],data_c2[i]] for i in range(len(data_c1))])
examples = examples / np.max(examples)
examples
```

Out[274]:
```
array([[-0.21428571,  1.        ],
       [-0.21428571,  0.21428571],
       [-0.78571429, -0.28571429],
       [-0.78571429,  0.5       ],
       [ 0.78571429, -0.35714286],
       [ 0.35714286, -0.5       ],
       [ 0.        ,  0.64285714],
       [ 0.14285714, -0.35714286],
       [-0.5       , -0.14285714],
       [-0.21428571, -0.35714286],
       [ 0.07142857,  0.5       ],
       [-0.21428571, -0.21428571]])
```

In [285]:
```
data_lb = np.array((np.array(data_lb) + 1) / 2)
data_lb
```

Out[285]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 0., 0., 1., 0.])
```

In [350]:
```python
class cohonenLayer(nn.Module):
    def __init__ (self,classes):
        super(cohonenLayer, self).__init__()
        self.wts = np.random.random([classes,2])

    def train(self,inputs,n_epoch,lr = 0.5):

        for epoch in range(n_epoch):
            cur_elm = inputs[int(np.random.random()*len(inputs))]
            distances = np.zeros(len(self.wts))
            for i in range(len(self.wts)):
                dist = np.sqrt(((cur_elm - self.wts[i])**2).sum())
                distances[i] = dist
            self.wts[np.argmin(distances)] += lr*(cur_elm - self.wts[np.argmin(distances

    def predict(self,pt):
        res = np.zeros(len(self.wts))
        for i in range(len(self.wts)):
            res[i] = np.sqrt(((pt - self.wts[i])**2).sum())
        return np.argmin(res)

    def __call__ (self,x):
        res = np.zeros(len(self.wts))
        for i in range(len(self.wts)):
            res[i] = np.sqrt(((x - self.wts[i])**2).sum())
        return torch.tensor(res,dtype = torch.float32)
```

Сеть состоит из слоя кохонена, который выволняет кластеризацию и линейного слоя, который определяет лейбл для каждого кластера:

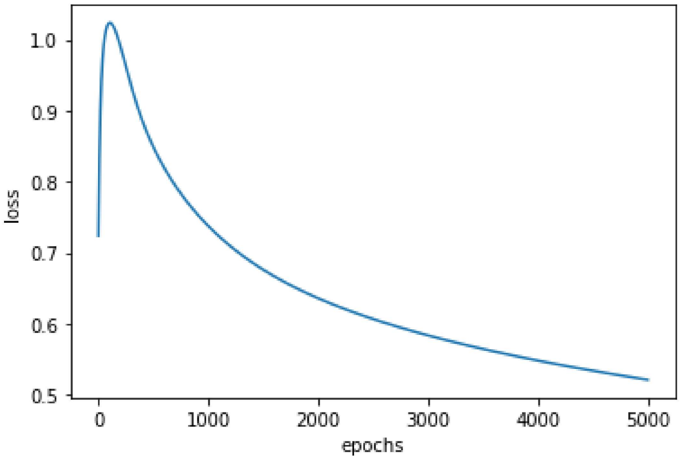
In [357]:
```python
model = torch.nn.Sequential(
    cohonenLayer(2),
    torch.nn.Linear(2,2),
    torch.nn.Softmax(0)
)
```

In [358]:
```python
def train(net,data_xx,data_lb,n_epochs,lr,
         optimiser = torch.optim.SGD,
         criterion = torch.nn.CrossEntropyLoss()
         ):

    optim = optimiser(model.parameters(),lr=lr)

    arr = []
    for i in tqdm(range(n_epochs)):
        for elm_ind in range(len(data_xx)):
            optim.zero_grad()

            loss = criterion(net(data_xx[elm_ind]),data_lb[elm_ind])
            loss.backward()
            optim.step()

        arr.append([i,
                    loss.detach().numpy(),
                   ])

    return np.array(arr)
```

In [359]:
```python
model[0].train(examples,5000)
arr = train(model,examples,torch.tensor(data_lb,dtype = torch.long),5000,0.01)
```

```
100%|██████████████████████████████████████████████████| 500
0/5000 [00:22<00:00, 220.55it/s]
```

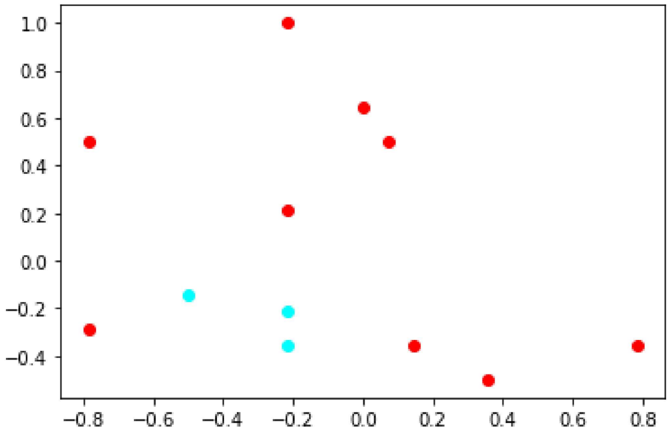
In [360]:
```
pylab.ylabel("loss")
pylab.xlabel("epochs")
pylab.plot(arr[:,0],arr[:,1])
pylab.show()
```



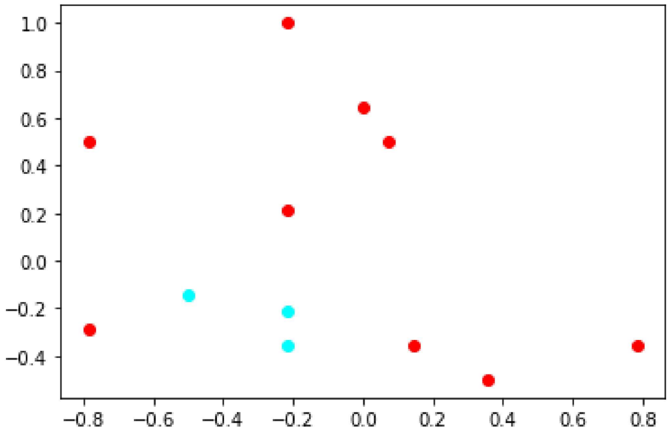
In [361]:
```
pred_lbl = []
for pt in examples:
    pred_lbl.append(np.argmax(model(pt).detach().numpy()))
pred_lbl = np.array(pred_lbl)
```

In [362]:
```
print("required result:")
plot_dataset_by_classes(examples,data_lb)
print("gained result:")
plot_dataset_by_classes(examples,pred_lbl)
```

```
required result:
```

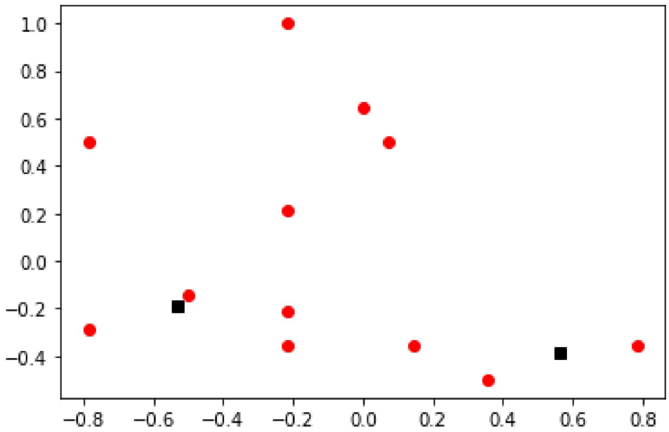



```
gained result:
```



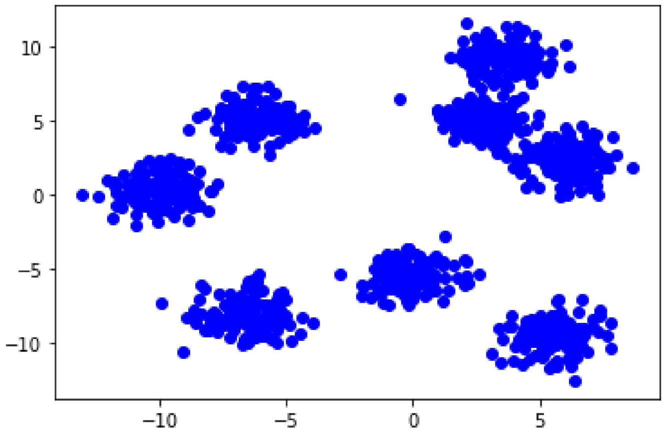
Центры кластеров, определенные слоем кохонена:

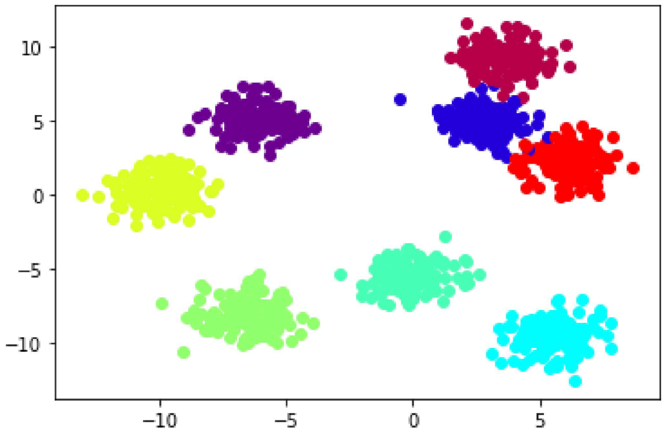
In [363]:
```
plot_dataset_by_classes_cl(examples,[1 for i in examples],model[0].wts)
```



Попробуем классифицировать датасет из задания 1.

In [365]:
```
plot_dataset(train_xx)
plot_dataset_by_classes(train_xx,y)
```



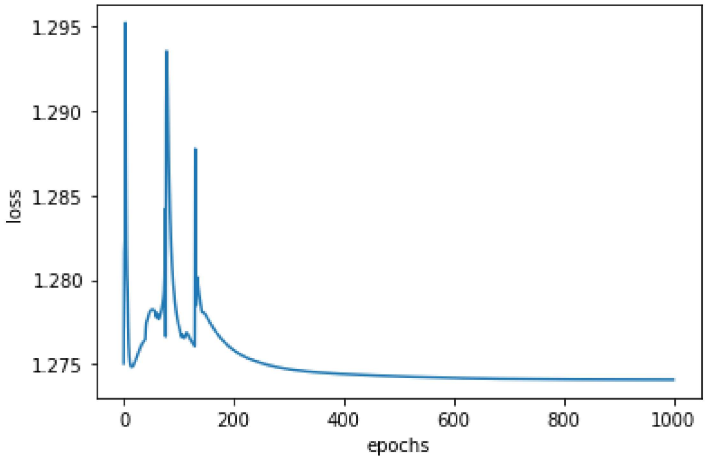


In [368]:
```
model = torch.nn.Sequential(
    cohonenLayer(8),
    torch.nn.Linear(8,8),
    torch.nn.Softmax(0)
)
```

In [369]:
```
model[0].train(train_xx,5000)
arr = train(model,train_xx,torch.tensor(y,dtype = torch.long),1000,0.01)
```

```
100%|████████████████████████████████████████| 1000/1000 [08:08<00:00,  2.05it/s]
```

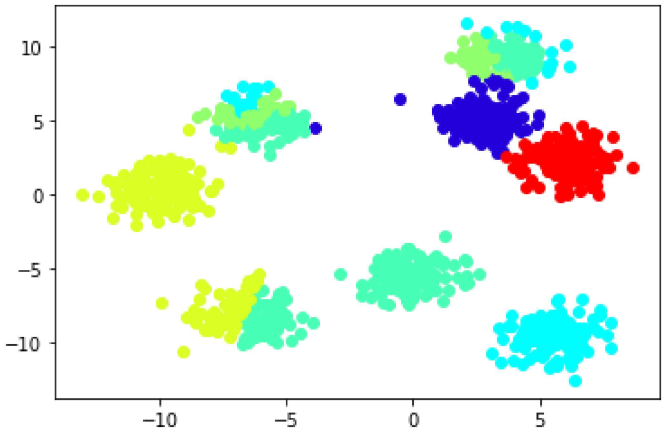
In [370]:
```
pylab.ylabel("loss")
pylab.xlabel("epochs")
pylab.plot(arr[:,0],arr[:,1])
pylab.show()
```

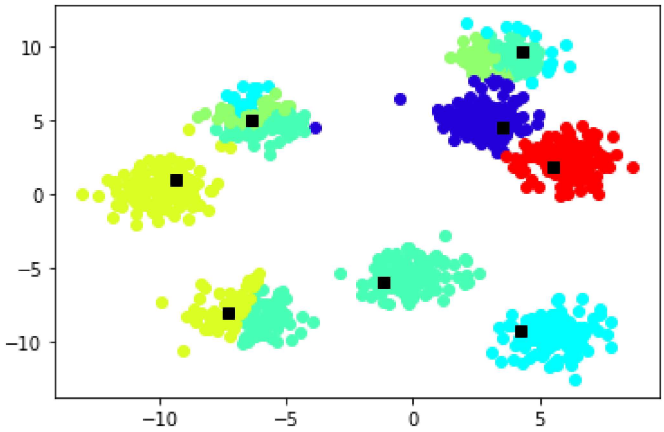


In [378]:
```
pred_lbl = []
for pt in train_xx:
    pred_lbl.append(np.argmax(model(pt).detach().numpy()))
pred_lbl = np.array(pred_lbl)
```

Результат классификации:

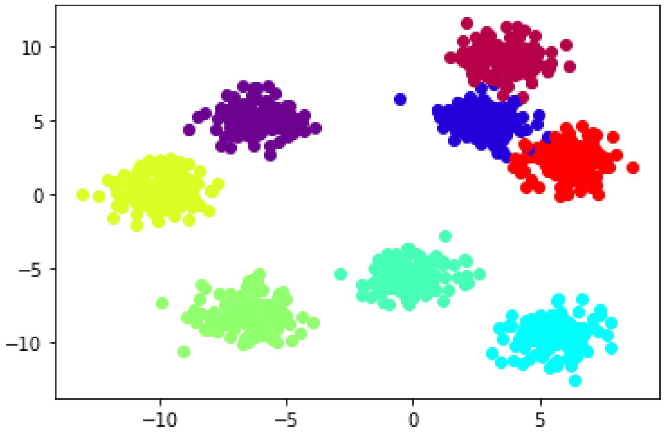
In [381]:
```
plot_dataset_by_classes(train_xx,pred_lbl)
plot_dataset_by_classes_cl(train_xx,pred_lbl,model[0].wts)
```





Настоящие классы:

In [382]:
```
plot_dataset_by_classes(train_xx,y)
```



Выводы

В ходе выполнения этой лабораторной работы я ознакомился со слоем Кохонена и картой Кохонена, получил опыт применения этих технологий для решения задачи кластеризации и классификации.

In [ ]:
```
```