Лабораторная работа № 8

Динамические сети

Воронов К.М., М8О-407Б-19

Целью работы является исследование свойств некоторых динамических нейронных сетей, алгоритмов обучения, а также применение сетей в задачах аппроксимации функций и распознавания динамических образов.

Вариант 19

[ ]:
```
import torch
import torch.nn as nn
import matplotlib.pyplot as plt
import numpy as np
from collections import deque
from torch.utils.data import DataLoader
```

[ ]:
```
!pip install matplotlib --upgrade
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/dist-
packages (3.6.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib) (1.4.4)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.8/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib) (1.0.6)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.8/dist-packages (from matplotlib) (4.38.0)
Requirement already satisfied: pyparsing>=2.2.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib) (3.0.9)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib) (7.1.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.8/dist-
packages (from matplotlib) (21.3)
Requirement already satisfied: numpy>=1.19 in /usr/local/lib/python3.8/dist-
packages (from matplotlib) (1.21.6)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
packages (from matplotlib) (0.11.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.7->matplotlib) (1.15.0)
```

[ ]:
```
class TDL(nn.Module):
    def __init__(self, in_dim, delays):
        super(TDL, self).__init__()
        self.in_dim = in_dim
        self.delays = delays
        self.queue = deque()
        self.clear()

    def clear(self):
        self.queue.clear()
        for i in range(self.delays):
            self.queue.append(torch.zeros(self.in_dim))


    def push(self, inputs):
        self.queue.appendleft(inputs)

    def forward(self, input = 0):
        return self.queue.pop()
```

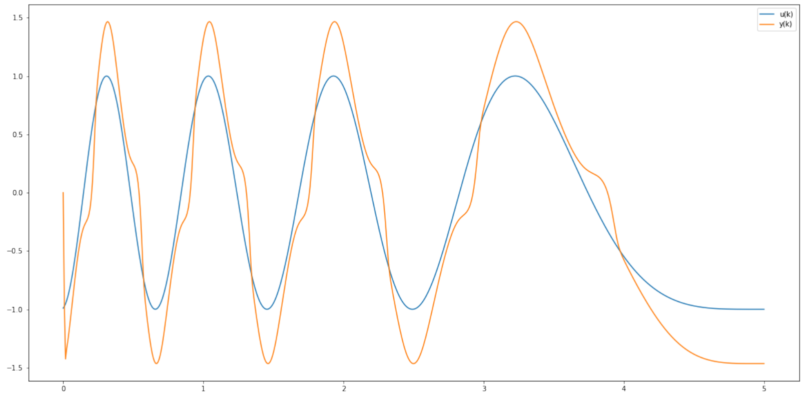
```
[ ]: class NARX(nn.Module):
         def __init__(self, in_dim, hi_dim, out_dim, delays1, delays2):
             super(NARX, self).__init__()
             self.in_dim = in_dim
             self.out_dim = out_dim
             self.hi_dim = hi_dim

             self.queue1 = TDL(in_dim, delays1)
             self.queue2 = TDL(out_dim, delays2)

             self.w1 = torch.nn.Parameter(torch.randn(in_dim, hi_dim))
             self.w2 = torch.nn.Parameter(torch.randn(hi_dim, out_dim))
             self.w3 = torch.nn.Parameter(torch.randn(out_dim, hi_dim))

             self.b1 = torch.nn.Parameter(torch.ones(hi_dim))
             self.b2 = torch.nn.Parameter(torch.ones(out_dim))

         def clear(self):
             self.queue1.clear()
             self.queue2.clear()

         def forward(self, inputs):
             out1 = torch.tanh(self.queue1() @ self.w1 + self.queue2() @ self.w3 + self.
      ↪b1)
             out2 = out1 @ self.w2 + self.b2

             self.queue1.push(torch.tensor(inputs))
             self.queue2.push(torch.tensor(out2))

             return out2
```

```
[ ]: def fun_u(k):
         return np.cos(k * k - 10 * k + 3)
```

```python

def fun_y(yk, uk):
    return yk / (1 + yk ** 2) + uk ** 3
```

[ ]:
```python
window_size = 3

narx = NARX(window_size, 24, window_size, 2, 2)

batch_size = 1
epochs = 500
optim = torch.optim.Adam(narx.parameters(), lr = 1e-4)
N = 600

tt = np.linspace(0, 5, N)
u = fun_u(tt)
y = [0]

for i in range(N - 1):
    y.append(fun_y(y[i], u[i]))
```

[ ]:
```python
figure = plt.figure(figsize = (20, 10))

plt.plot(tt, u, label = 'u(k)')
plt.plot(tt, y, label = 'y(k)')
plt.legend()
plt.show()
```



[ ]:
```python
data = [(np.array(u[i:i + window_size], dtype = np.float32), np.array(y[i:i +␣
↪window_size], dtype = np.float32)) for i in range(N - window_size + 1)]
data = DataLoader(data, batch_size = batch_size, shuffle = False)
```

[ ]:

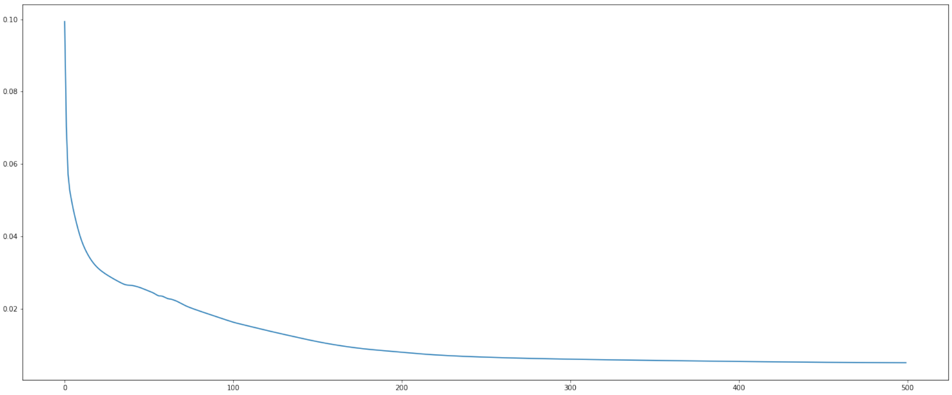
```
narx.train()
loss_epoch = []

for i in range(epochs):

    narx.clear()
    loss_1e = 0
    for x, lbl in data:

        out = narx(x)
        loss = nn.MSELoss()(out, lbl)
        optim.zero_grad()
        loss.backward()
        optim.step()

        loss_1e += loss.clone().detach().item()

    loss_epoch.append(loss_1e / (N - window_size))
    print("Loss ", i + 1, " = ", loss_epoch[-1])
```

```
<ipython-input-97-bd93cde4178f>:26: UserWarning: To copy construct from a
tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  self.queue1.push(torch.tensor(inputs))
<ipython-input-97-bd93cde4178f>:27: UserWarning: To copy construct from a
tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  self.queue2.push(torch.tensor(out2))
/usr/local/lib/python3.8/dist-packages/torch/nn/modules/loss.py:536:
UserWarning: Using a target size (torch.Size([1, 3])) that is different to the
input size (torch.Size([3])). This will likely lead to incorrect results due to
broadcasting. Please ensure they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
```

```
Loss  1  =  0.09938914751769722
Loss  2  =  0.07024632064602025
Loss  3  =  0.057242301936405095
Loss  4  =  0.05270695570977404
Loss  5  =  0.05009273008527302
Loss  6  =  0.04768173095913603
Loss  7  =  0.04558422845900718
Loss  8  =  0.04366181677527907
Loss  9  =  0.041875504201509754
Loss  10  =  0.04025777700846395
...
Loss  490  =  0.005062251109878617
Loss  491  =  0.005060207080146752
Loss  492  =  0.005058191643180352
Loss  493  =  0.005056086841639601
Loss  494  =  0.005054027688636549
Loss  495  =  0.0050518554234810255
Loss  496  =  0.005049715144164951
Loss  497  =  0.005047548008308582
Loss  498  =  0.005045304137775229
Loss  499  =  0.005043059682204208
Loss  500  =  0.005040877619271034
```

[ ]:

```python
ttt = np.arange(0, epochs, 1)
figure = plt.figure(figsize = (24, 10))
plt.plot(ttt, loss_epoch)

plt.show()
```



[ ]:

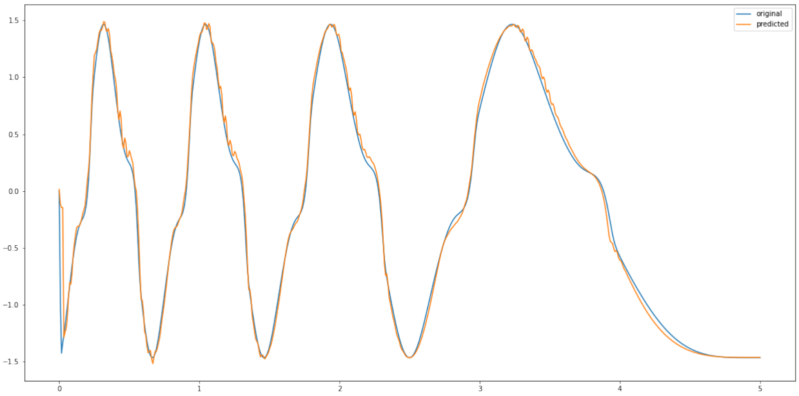
```python
narx.eval()
narx.clear()

predict = []

ii = 0
for x, _ in data:
    if ii == 0:
        predict = narx(x).detach().numpy()
    else:
        predict = np.append(predict, narx(x).detach().numpy().item(-1))
    ii = 1
```

```
<ipython-input-97-bd93cde4178f>:26: UserWarning: To copy construct from a
tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  self.queue1.push(torch.tensor(inputs))
<ipython-input-97-bd93cde4178f>:27: UserWarning: To copy construct from a
```

```
tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  self.queue2.push(torch.tensor(out2))
```

[ ]:

```python
figure = plt.figure(figsize = (20, 10))

plt.plot(tt, y, label = 'original')
plt.plot(tt, predict, label = 'predicted')
plt.legend()
plt.show()
```



Выводы

Выполнив данную лабораторную работу, я изучил строение сетей NARX и реализовал одну из них, продемонстрировав её работу на предсказывании значения функции по значениям другой функции.

[ ]:

```python

```