Лабораторная работа № 2

Линейная нейронная сеть. Правило обучения Уидроу-Хоффа

Цель работы: исследование свойств линейной нейронной сети и алгоритмов ее обучения, применение сети в задачах аппроксимации и фильтрации

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```
import numpy as np
import torch
import torch.nn as nn
import matplotlib.pyplot as plt
```

Аппроксимация функции

Создается временная последовательность X с использованием функции x(t), а затем формируются последовательности длиной D из временного ряда и соответствующие им последующие дискреты для обучения модели с заданным числом задержек D.

```
D = 5

def x(t):
    return np.sin(np.sin(t) * t**2 + 3*t - 10)

t = np.arange(2.5, 5, 0.01)
X = x(t).tolist()


sequences = [X[i:i+D] for i in range(0, len(X) - D)]
upcoming_points = [X[i] for i in range(D, len(X))]

assert len(sequences) == len(upcoming_points)
```

Определяется функция sync_shuffle, которая перемешивает два массива a и b с использованием одной и той же случайной перестановки, обеспечивая синхронное перемешивание элементов обоих массивов.

```
def sync_shuffle(a, b):
    assert len(a) == len(b)
    p = np.random.permutation(len(a))
    return a[p], b[p]
```

Обучающие данные sequences и upcoming_points синхронно перемешиваются с использованием функции sync_shuffle.

```
x_train, y_train = sync_shuffle(np.array(sequences),
np.array(upcoming_points))

x_train = torch.FloatTensor(x_train)
y_train = torch.FloatTensor(y_train)
```

Создание модели AdaptiveLinearNetwork, повторяет Perceptron из ЛР 1

```
class AdaptiveLinearNetwork(nn.Module):
    def __init__(self, in_features: int, out_features: int, bias: bool
= True):
        super().__init__()
        self.weights = nn.Parameter(torch.randn(in_features,
out_features))
        self.bias = bias
        if bias:
            self.bias_term = nn.Parameter(torch.randn(out_features))

    def forward(self, x):
        x = x @ self.weights
        if self.bias:
            x += self.bias_term
        return x
```

Создается экземпляр модели с числом входных признаков D и одним выходным признаком. Для обучения используется среднеквадратичная ошибка в качестве функции потерь, и оптимизатор стохастического градиентного спуска (SGD) с заданной скоростью обучения 0.05.

```
adaptiveLinearNetwork = AdaptiveLinearNetwork(D, 1)
loss_function = nn.MSELoss()
optimizer = torch.optim.SGD(adaptiveLinearNetwork.parameters(),
lr=0.05)
```

Определена функция fit, которая выполняет обучение модели. В каждой эпохе производится прямой проход, вычисляется и обновляется функция потерь, итерации отображаются с использованием tqdm. Возвращается список значений функции потерь на каждой эпохе.

```
def fit(model, x_train, y_train, criterion, optimizer, epochs):
    losses = []
    log_template = "\nEpoch {ep:03d} train_loss: {t_loss:0.4f}"
    for epoch in range(epochs):
        optimizer.zero_grad()
        outp = model(x_train)
```

```
        loss = criterion(outp.view(-1), y_train)

        loss.backward()
        losses.append(loss.detach().flatten()[0])
        optimizer.step()

        print(log_template.format(ep=epoch+1, t_loss=loss))
    return losses
```

Определена функция predict, которая использует обученную модель для выполнения предсказания на входных данных x_test. Модель переводится в режим оценки (eval), и с предсказаниями возвращается результат.

```
def predict(model, x_test):
    with torch.no_grad():
        model.eval()
        outp = model(x_test)
    return outp
```

Модель обучается на обучающих данных

```
losses = fit(adaptiveLinearNetwork, x_train, y_train, loss_function,
optimizer, 50)
```

```
Epoch 001 train_loss: 2.9362

Epoch 002 train_loss: 2.3250

Epoch 003 train_loss: 1.8679

Epoch 004 train_loss: 1.5167

Epoch 005 train_loss: 1.2413

Epoch 006 train_loss: 1.0219

Epoch 007 train_loss: 0.8452

Epoch 008 train_loss: 0.7016

Epoch 009 train_loss: 0.5843

Epoch 010 train_loss: 0.4881

Epoch 011 train_loss: 0.4090

Epoch 012 train_loss: 0.3438

Epoch 013 train_loss: 0.2900
```

```
Epoch 014 train_loss: 0.2456
Epoch 015 train_loss: 0.2088
Epoch 016 train_loss: 0.1784
Epoch 017 train_loss: 0.1533
Epoch 018 train_loss: 0.1324
Epoch 019 train_loss: 0.1152
Epoch 020 train_loss: 0.1009
Epoch 021 train_loss: 0.0890
Epoch 022 train_loss: 0.0791
Epoch 023 train_loss: 0.0709
Epoch 024 train_loss: 0.0641
Epoch 025 train_loss: 0.0584
Epoch 026 train_loss: 0.0537
Epoch 027 train_loss: 0.0497
Epoch 028 train_loss: 0.0464
Epoch 029 train_loss: 0.0436
Epoch 030 train_loss: 0.0412
Epoch 031 train_loss: 0.0392
Epoch 032 train_loss: 0.0376
Epoch 033 train_loss: 0.0361
Epoch 034 train_loss: 0.0349
Epoch 035 train_loss: 0.0338
Epoch 036 train_loss: 0.0329
Epoch 037 train_loss: 0.0321
Epoch 038 train_loss: 0.0314
Epoch 039 train_loss: 0.0308
```

```
Epoch 040 train_loss: 0.0302

Epoch 041 train_loss: 0.0297

Epoch 042 train_loss: 0.0293

Epoch 043 train_loss: 0.0289

Epoch 044 train_loss: 0.0285

Epoch 045 train_loss: 0.0281

Epoch 046 train_loss: 0.0278

Epoch 047 train_loss: 0.0275

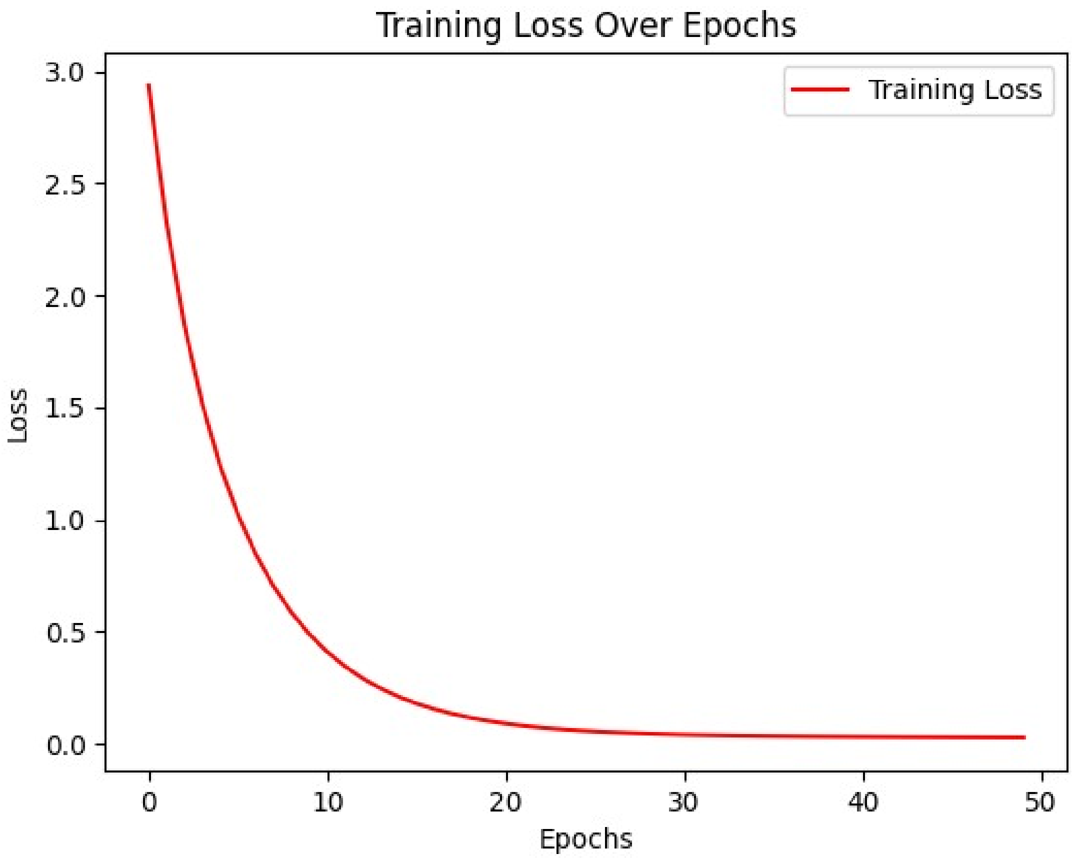
Epoch 048 train_loss: 0.0272

Epoch 049 train_loss: 0.0269

Epoch 050 train_loss: 0.0266
```

График функции потерь (ошибка - MSE)

```
plt.plot(losses, color='red', label='Training Loss')
plt.legend()
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training Loss Over Epochs')
plt.show()
```



Производится прогнозирование значений моделью для последующих точек временной последовательности. Предсказанные значения добавляются к списку X_PRED, а ошибки предсказания записываются в список errors.

```
X_PRED = X[:D]
errors = []

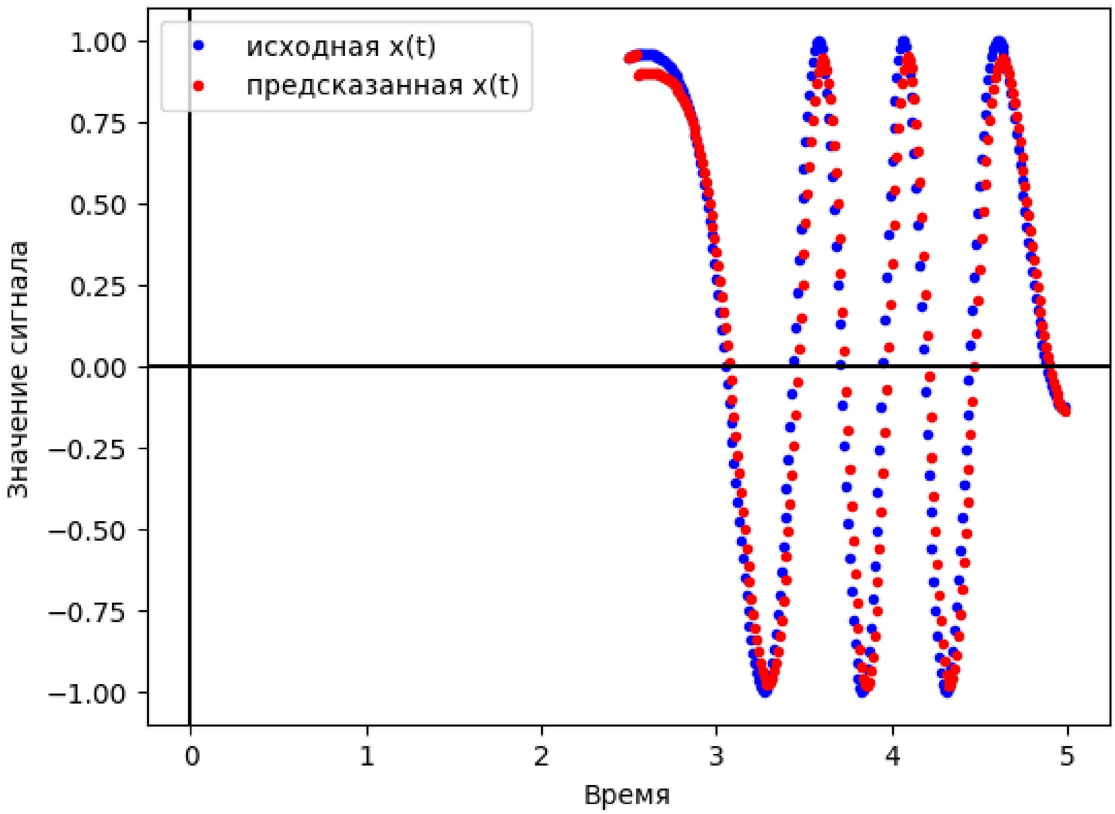
for i in range(0, len(upcoming_points)):
    x_test = torch.FloatTensor(np.array(sequences[i]))
    upcoming_point_pred = predict(adaptiveLinearNetwork, x_test)
    X_PRED += upcoming_point_pred.numpy().tolist()
    errors += (upcoming_point_pred -
upcoming_points[i]).numpy().tolist()
```

На графике синим цветом обозначены исходные значения временной последовательности x(t), а красным - предсказанные значения моделью AdaptiveLinearNetwork.

```
plt.plot(t, X, '.', color="blue", label='исходная x(t)')
plt.plot(t, X_PRED, '.', color="red", label='предсказанная x(t)')

plt.axhline(y=0, color='k')
plt.axvline(x=0, color='k')
```

```
plt.xlabel('Время')
plt.ylabel('Значение сигнала')
plt.legend()
plt.show()
```

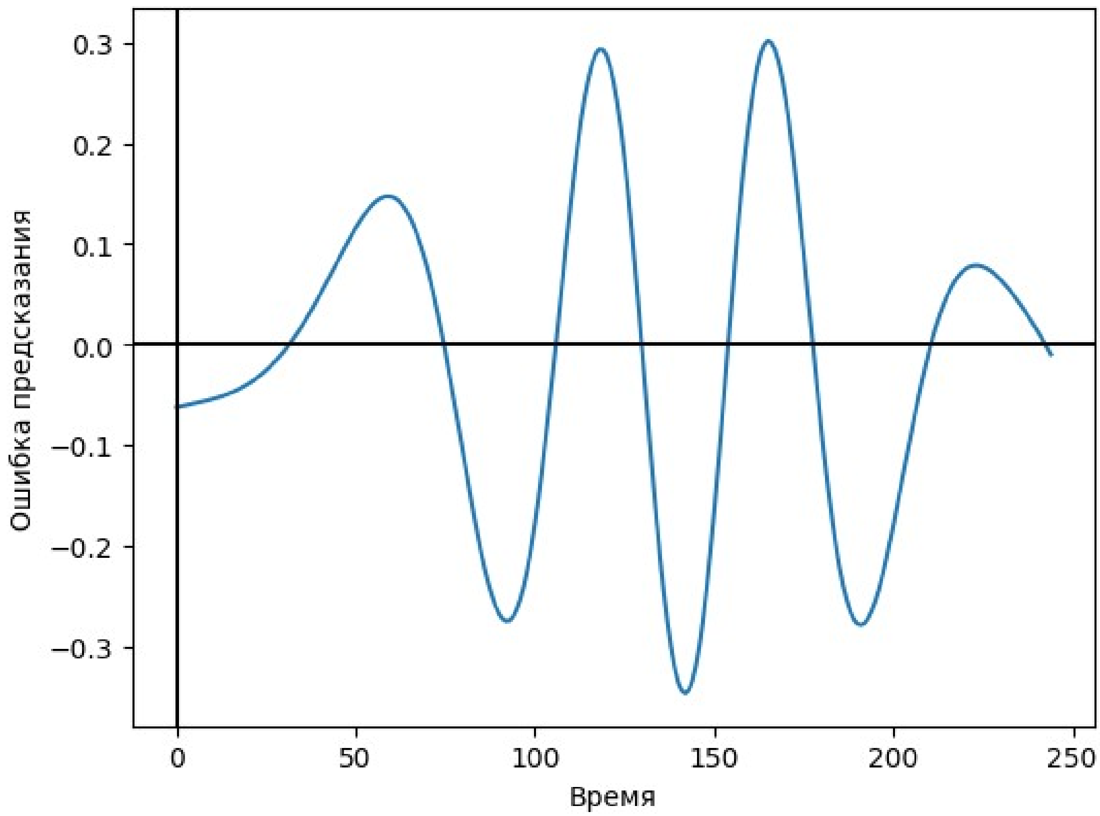


На этом графике отображены ошибки предсказания для каждого момента времени.

```
plt.plot(errors)

plt.axhline(y=0, color='k')
plt.axvline(x=0, color='k')

plt.xlabel('Время')
plt.ylabel('Ошибка предсказания')
plt.show()
```



Подавление помех

Создаются истинный сигнал X и зашумленный сигнал Y с использованием функций true_signal и noized_signal. Затем формируются последовательности из зашумленного сигнала Y длиной D и соответствующие им последующие дискреты истинного сигнала X для задачи подавления помех.

```
D = 4


def true_signal(t):
    return np.cos(np.cos(t) * t**2 + 5*t)


def noized_signal(t):
    return (1 / 5) * np.cos(np.cos(t) * t**2 + 5 * t + 4)


t = np.arange(0, 3.5, 0.01)
X = true_signal(t).tolist()
Y = noized_signal(t).tolist()


noized_sequences = [Y[i:i+D] for i in range(0, len(Y) - D)]
upcoming_points_true = [X[i] for i in range(D, len(X))]
```

```
assert len(noized_sequences) == len(upcoming_points_true)
```

Обучающие данные noized_sequences и upcoming_points_true синхронно перемешиваются с использованием функции sync_shuffle

```
x_train, y_train = sync_shuffle(np.array(noized_sequences),
np.array(upcoming_points_true))

x_train = torch.FloatTensor(x_train)
y_train = torch.FloatTensor(y_train)

adaptiveLinearNetwork2 = AdaptiveLinearNetwork(D, 1)
loss_function = nn.MSELoss()
optimizer = torch.optim.SGD(adaptiveLinearNetwork2.parameters(),
lr=0.05)

losses2 = fit(adaptiveLinearNetwork2, x_train, y_train, loss_function,
optimizer, 600)
```

```
Epoch 001 train_loss: 6.1653

Epoch 002 train_loss: 5.0690

Epoch 003 train_loss: 4.1804

Epoch 004 train_loss: 3.4600

Epoch 005 train_loss: 2.8759

Epoch 006 train_loss: 2.4022

Epoch 007 train_loss: 2.0178

Epoch 008 train_loss: 1.7058

Epoch 009 train_loss: 1.4523

Epoch 010 train_loss: 1.2464

Epoch 011 train_loss: 1.0789

Epoch 012 train_loss: 0.9426

Epoch 013 train_loss: 0.8315

Epoch 014 train_loss: 0.7409

Epoch 015 train_loss: 0.6668
```

```
Epoch 016 train_loss: 0.6061

Epoch 017 train_loss: 0.5564

Epoch 018 train_loss: 0.5154

Epoch 019 train_loss: 0.4816

Epoch 020 train_loss: 0.4537

Epoch 021 train_loss: 0.4304

Epoch 022 train_loss: 0.4109

Epoch 023 train_loss: 0.3946

Epoch 024 train_loss: 0.3808

Epoch 025 train_loss: 0.3690

Epoch 026 train_loss: 0.3589

Epoch 027 train_loss: 0.3502

Epoch 028 train_loss: 0.3426

Epoch 029 train_loss: 0.3359

Epoch 030 train_loss: 0.3299

Epoch 031 train_loss: 0.3246

Epoch 032 train_loss: 0.3198

Epoch 033 train_loss: 0.3154

Epoch 034 train_loss: 0.3113

Epoch 035 train_loss: 0.3075

Epoch 036 train_loss: 0.3040

Epoch 037 train_loss: 0.3006

Epoch 038 train_loss: 0.2975

Epoch 039 train_loss: 0.2945

Epoch 040 train_loss: 0.2916

Epoch 041 train_loss: 0.2888
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Epoch 042 train_loss: 0.2862

Epoch 043 train_loss: 0.2836

Epoch 044 train_loss: 0.2811

Epoch 045 train_loss: 0.2786

Epoch 046 train_loss: 0.2762

Epoch 047 train_loss: 0.2739

Epoch 048 train_loss: 0.2716

Epoch 049 train_loss: 0.2694

Epoch 050 train_loss: 0.2673

Epoch 051 train_loss: 0.2651

Epoch 052 train_loss: 0.2630

Epoch 053 train_loss: 0.2610

Epoch 054 train_loss: 0.2590

Epoch 055 train_loss: 0.2570

Epoch 056 train_loss: 0.2551

Epoch 057 train_loss: 0.2532

Epoch 058 train_loss: 0.2513

Epoch 059 train_loss: 0.2495

Epoch 060 train_loss: 0.2477

Epoch 061 train_loss: 0.2459

Epoch 062 train_loss: 0.2442

Epoch 063 train_loss: 0.2424

Epoch 064 train_loss: 0.2408

Epoch 065 train_loss: 0.2391

Epoch 066 train_loss: 0.2375

Epoch 067 train_loss: 0.2359
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Epoch 068 train_loss: 0.2343
Epoch 069 train_loss: 0.2328
Epoch 070 train_loss: 0.2313
Epoch 071 train_loss: 0.2298
Epoch 072 train_loss: 0.2283
Epoch 073 train_loss: 0.2269
Epoch 074 train_loss: 0.2254
Epoch 075 train_loss: 0.2240
Epoch 076 train_loss: 0.2227
Epoch 077 train_loss: 0.2213
Epoch 078 train_loss: 0.2200
Epoch 079 train_loss: 0.2187
Epoch 080 train_loss: 0.2174
Epoch 081 train_loss: 0.2162
Epoch 082 train_loss: 0.2149
Epoch 083 train_loss: 0.2137
Epoch 084 train_loss: 0.2125
Epoch 085 train_loss: 0.2113
Epoch 086 train_loss: 0.2102
Epoch 087 train_loss: 0.2090
Epoch 088 train_loss: 0.2079
Epoch 089 train_loss: 0.2068
Epoch 090 train_loss: 0.2057
Epoch 091 train_loss: 0.2047
Epoch 092 train_loss: 0.2036
Epoch 093 train_loss: 0.2026
```

```
Epoch 094 train_loss: 0.2016

Epoch 095 train_loss: 0.2006

Epoch 096 train_loss: 0.1996

Epoch 097 train_loss: 0.1986

Epoch 098 train_loss: 0.1977

Epoch 099 train_loss: 0.1968

Epoch 100 train_loss: 0.1959

Epoch 101 train_loss: 0.1950

Epoch 102 train_loss: 0.1941

Epoch 103 train_loss: 0.1932

Epoch 104 train_loss: 0.1924

Epoch 105 train_loss: 0.1915

Epoch 106 train_loss: 0.1907

Epoch 107 train_loss: 0.1899

Epoch 108 train_loss: 0.1891

Epoch 109 train_loss: 0.1883

Epoch 110 train_loss: 0.1875

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Epoch 113 train_loss: 0.1853

Epoch 114 train_loss: 0.1846

Epoch 115 train_loss: 0.1839

Epoch 116 train_loss: 0.1832

Epoch 117 train_loss: 0.1825

Epoch 118 train_loss: 0.1818

Epoch 119 train_loss: 0.1811
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Epoch 120 train_loss: 0.1805

Epoch 121 train_loss: 0.1799

Epoch 122 train_loss: 0.1792

Epoch 123 train_loss: 0.1786

Epoch 124 train_loss: 0.1780

Epoch 125 train_loss: 0.1774

Epoch 126 train_loss: 0.1768

Epoch 127 train_loss: 0.1762

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Epoch 129 train_loss: 0.1751

Epoch 130 train_loss: 0.1746

Epoch 131 train_loss: 0.1740

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Epoch 139 train_loss: 0.1700

Epoch 140 train_loss: 0.1695

Epoch 141 train_loss: 0.1691

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Epoch 146 train_loss: 0.1669

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Epoch 162 train_loss: 0.1611

Epoch 163 train_loss: 0.1608

Epoch 164 train_loss: 0.1605

Epoch 165 train_loss: 0.1602

Epoch 166 train_loss: 0.1599

Epoch 167 train_loss: 0.1596

Epoch 168 train_loss: 0.1593

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Epoch 171 train_loss: 0.1584
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Epoch 172 train_loss: 0.1582

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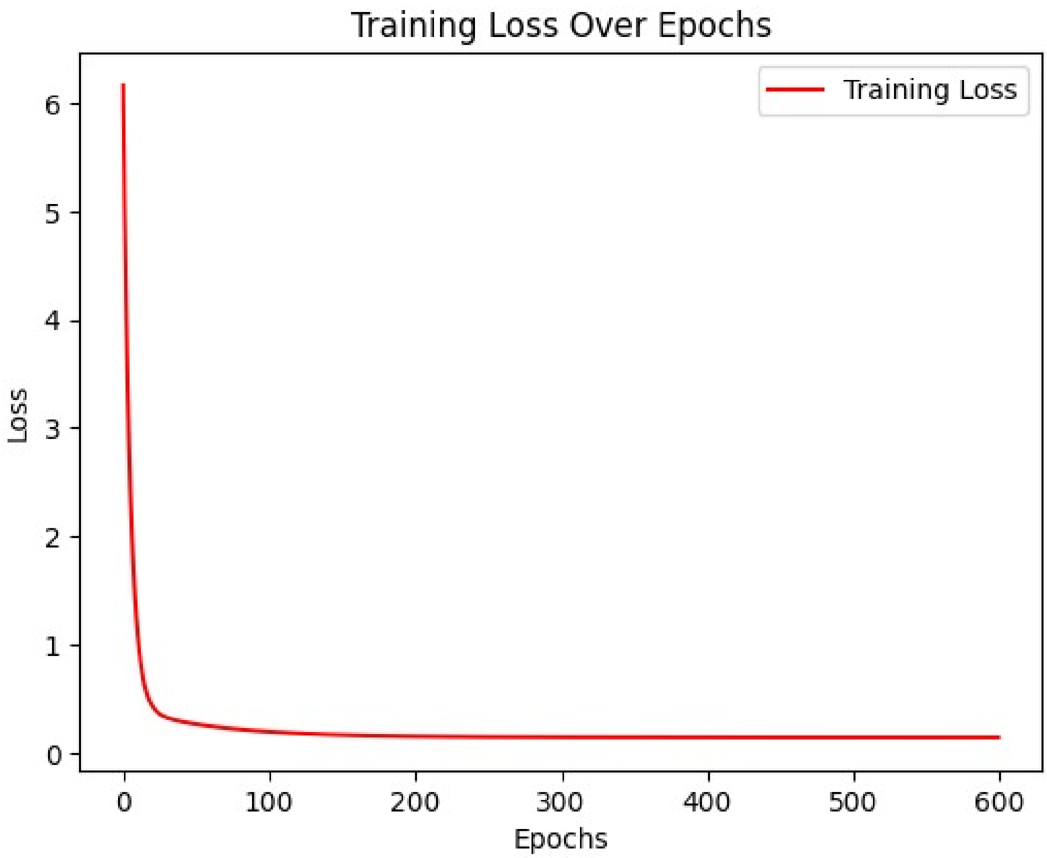
График функции потерь (ошибка - MSE)

```
plt.plot(losses2, color='red', label='Training Loss')
plt.legend()
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training Loss Over Epochs')
plt.show()
```



Выполняется предсказание на зашумленных данных noized_sequences. Предсказанные значения добавляются к списку X_PRED, и ошибки предсказания записываются в список errors2.

```
x_test = torch.FloatTensor(np.array(noized_sequences))
upcoming_points_pred = predict(adaptiveLinearNetwork2,
x_test).numpy().flatten().tolist()

X_PRED = X[:D] + upcoming_points_pred

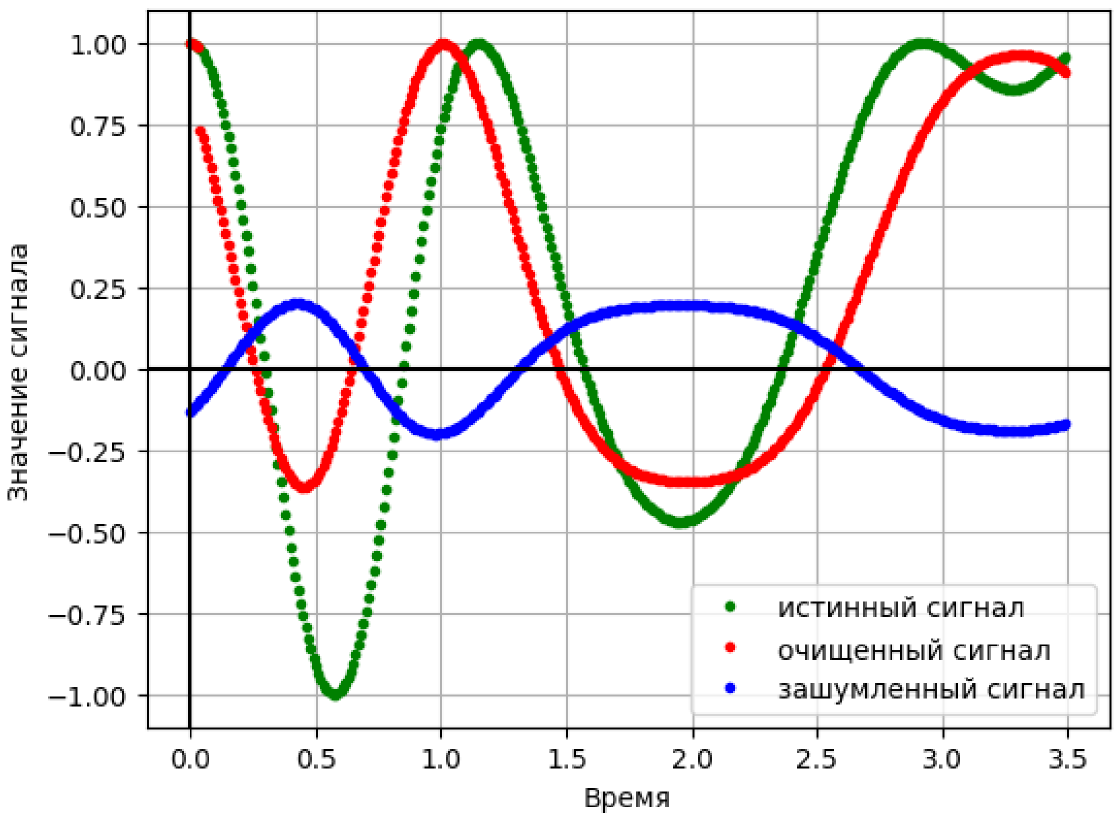
errors2 = [pred - true for pred, true in zip(upcoming_points_pred,
upcoming_points_true)]
```

На графике зеленым цветом обозначен истинный сигнал, красным - очищенный сигнал, предсказанный моделью, и синим - зашумленный сигнал.

```
plt.plot(t, X, '.', color="green", label='истинный сигнал')
plt.plot(t, X_PRED, '.', color="red", label='очищенный сигнал')
plt.plot(t, Y, '.', color="blue", label='зашумленный сигнал')

plt.grid(True, which='both')
plt.axhline(y=0, color='k')
plt.axvline(x=0, color='k')
```

```
plt.xlabel('Время')
plt.ylabel('Значение сигнала')
plt.legend()
plt.show()
```

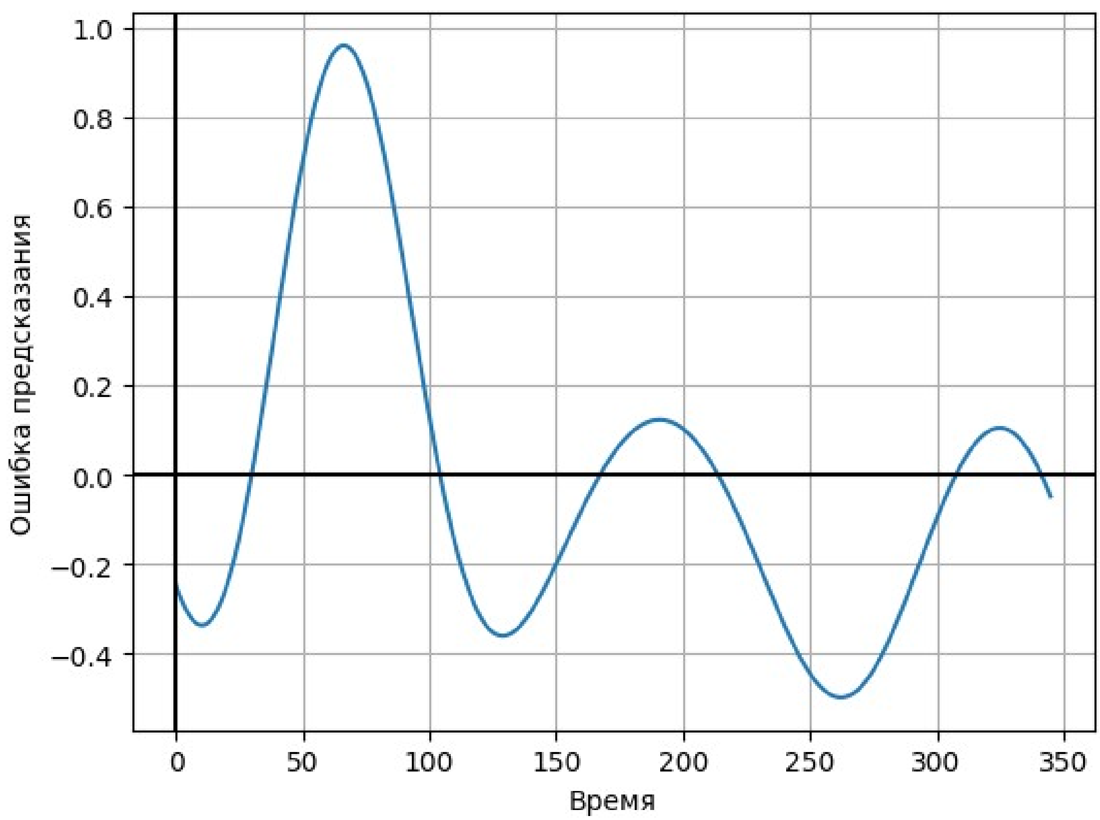


На графике отображены ошибки предсказания для каждого момента времени при решении задачи подавления помех.

```
plt.plot(errors2)

plt.grid(True, which='both')
plt.axhline(y=0, color='k')
plt.axvline(x=0, color='k')

plt.xlabel('Время')
plt.ylabel('Ошибка предсказания')
plt.show()
```



Выводы: В ходе выполнения лабораторной работы была успешно построена и обучена линейная нейросетевая модель для двух задач: аппроксимации функции и подавления помех в сигнале. После проведения обучения на 50 и 600 эпохах для каждой задачи соответственно, модель продемонстрировала хорошие результаты, что подтверждается анализом графиков и значений функции потерь.

Что я усвоил и из чего состояли задачи:

- Работа с временными последовательностями и задачами прогнозирования.
- Освоение процесса синхронного перемешивания данных для обучения модели.
- Изучение влияния числа эпох обучения на результаты модели в контексте двух различных задач: аппроксимации функции и подавления помех в сигнале.