Нейроинформатика. Лабораторная работа №2

Линейная нейронная сеть. Правило обучения Уидроу-Хоффа

Целью работы является исследование свойств линейной нейронной сети и алгоритмов ее обучения, применение сети в задачах аппроксимации и фильтрации.

Выполнил Пивницкий Д.С. \ М8о-406Б-19

In [9]:
```
import tensorflow as tf
from tensorflow import keras
from keras import layers
import numpy as np
import matplotlib.pyplot as plt
import time
```

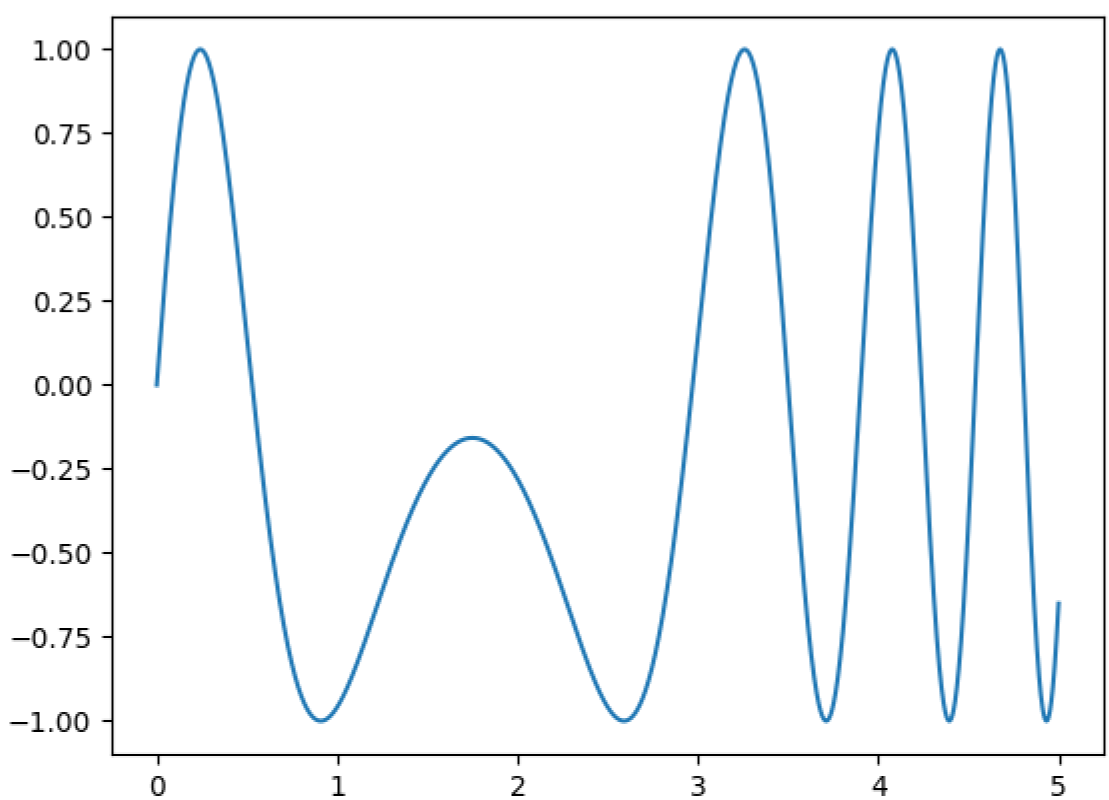
Прогнозирование

In [10]:
```
def func(t: float):
    return np.sin(-2*t**2 + 7*t)
```

In [11]:
```
h = 0.001
t = (0, 5)
D = 5
ans_x = np.arange(t[0],t[1] + h, h)
ans = func(ans_x)
```

In [12]:
```
plt.plot(ans_x, ans)
```

Out[12]:
```
[<matplotlib.lines.Line2D at 0x7f46bc3d22b0>]
```



Готовим датасет

In [13]:
```
X = [ans[i:i+D].tolist() for i in range(0, len(ans) - D)]
y = [ans[i] for i in range(D, len(ans))]
```

Создаем модель

In [14]:
```
predictor =  keras.Sequential([
        layers.Dense(1,input_dim=D, activation="linear", name="pred"),
    ]
)
predictor.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 pred (Dense)                (None, 1)                 6

=================================================================
Total params: 6
Trainable params: 6
Non-trainable params: 0
_________________________________________________________________
```

Компилируем модель

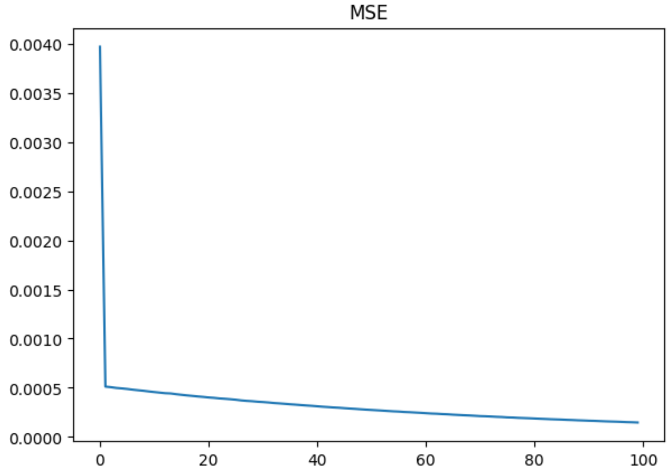
In [15]:
```
opt = keras.optimizers.SGD(learning_rate=0.1)
predictor.compile(loss='mse', optimizer=opt, metrics=['mae'])
```

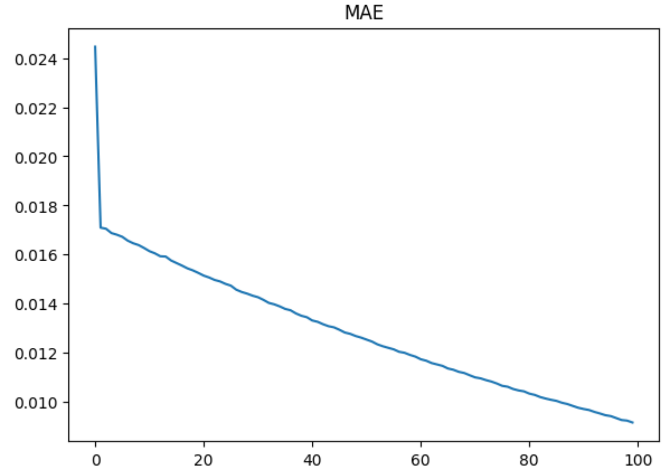
Тренеруем модель

In [16]:
```
epochs = 100
time_start = time.time()
hist = predictor.fit(
    X,
    y,
    epochs=epochs,
    verbose=0,
    shuffle=True
    )
time_finish = time.time()
mse_loss, mae_loss = predictor.evaluate(X, y, verbose=0)

print(f'Fit time: {(time_finish - time_start):.{2}f}s')
print(f'Result MSE: {mse_loss}')
print(f'Result MAE: {mae_loss}')

fig, ax = plt.subplots(1, 2)
fig.set_figwidth(15)

ax[0].set_title('MSE')
ax[1].set_title('MAE')

ax[0].plot(range(epochs), hist.history['loss'])
ax[1].plot(range(epochs), hist.history['mae'])
```

```
Fit time: 15.70s
Result MSE: 0.00016457519086543471
Result MAE: 0.010006273165345192
```

Out[16]:
```
[<matplotlib.lines.Line2D at 0x7f469c41dfd0>]
```





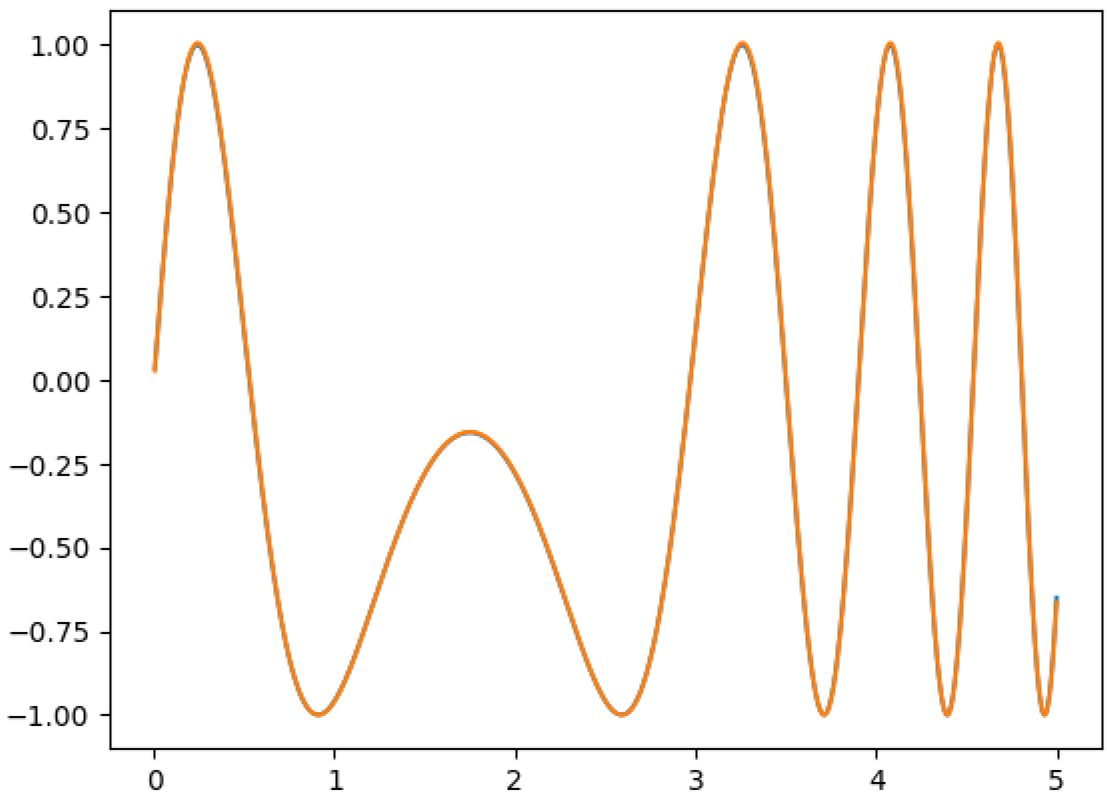
Получаем предсказания модели

In [17]:
```
my_ans = predictor.predict(X).flatten()
```

```
157/157 [==============================] - 0s 625us/step
```

In [9]:
```
plt.plot(ans_x[D:], y)
plt.plot(ans_x[D:], my_ans)
```

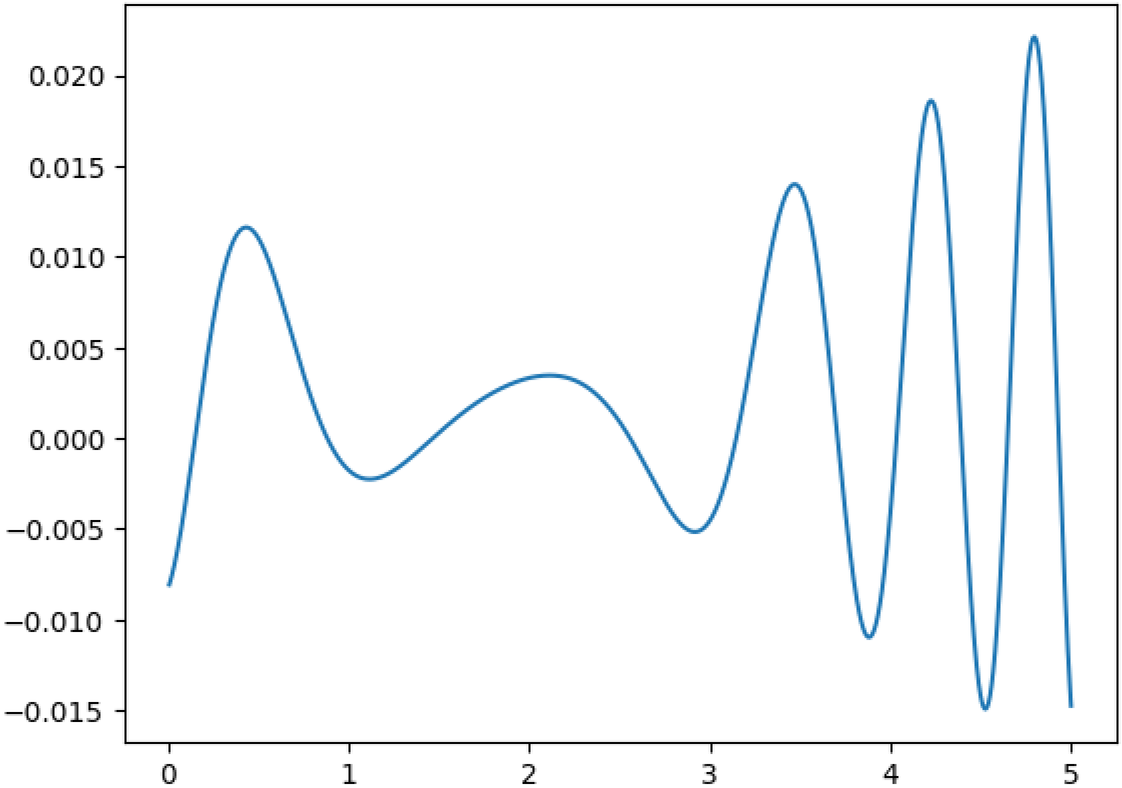
Out[9]:
```
[<matplotlib.lines.Line2D at 0x7fb3f5b2a640>]
```



Находим абсолютное отклонение

In [10]:
```
errors = my_ans - y
plt.plot(ans_x[D:], errors)
```

Out[10]:
```
[<matplotlib.lines.Line2D at 0x7fb3f52a0dc0>]
```



Зашумленный сигнал в чистый

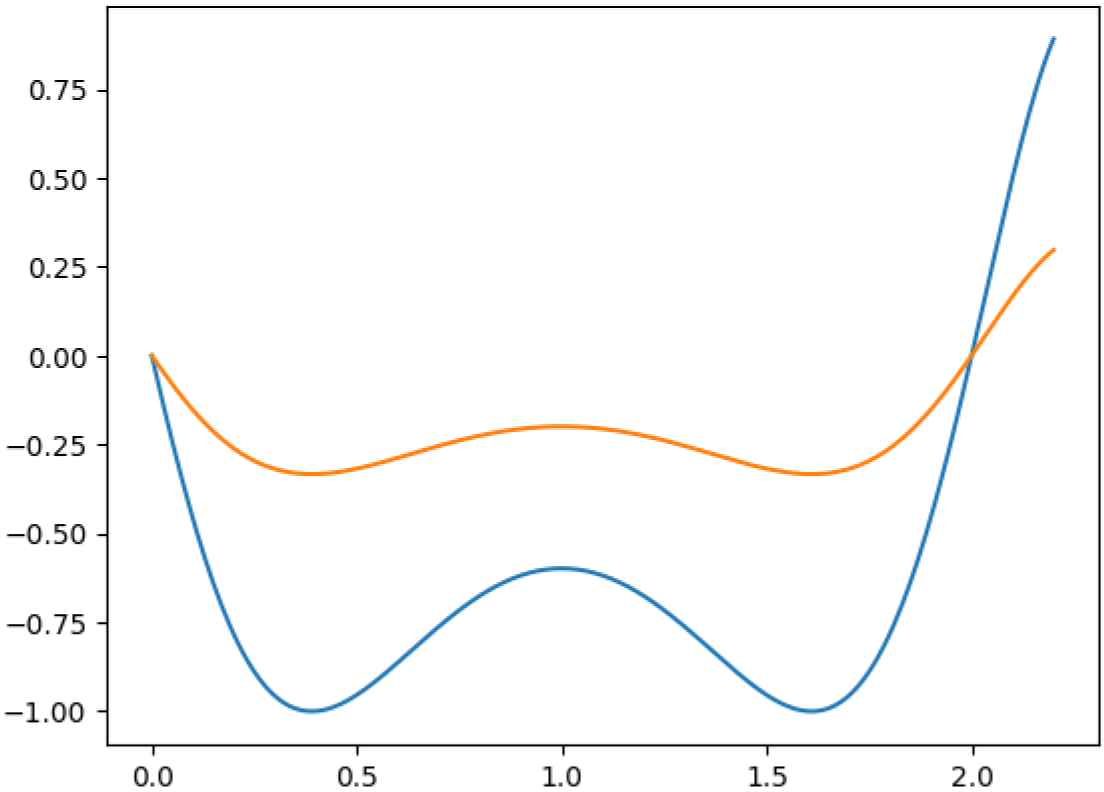
In [19]:
```
def noized(t):
    return np.sin(2.5*t**2 - 5*t)

def resl_sig(t):
    return np.sin(2.5*t**2 - 5*t + 4*np.pi)/3
```

In [20]:
```
h = 0.01
t = (0, 2.2)
D = 4
```

In [21]:
```
x_points = np.arange(t[0], t[1] + h, h)
noized_points = noized(x_points)
real_points = resl_sig(x_points)
```

In [22]:
```
plt.plot(x_points, noized_points)
plt.plot(x_points, real_points)
```

Out[22]:
```
[<matplotlib.lines.Line2D at 0x7f469c6da250>]
```



Готовим датасет

In [23]:
```
X = [noized_points[i:i+D].tolist() for i in range(0, len(noized_points) - D)]
y = [real_points[i] for i in range(D, len(real_points))]
```

Создаем модель

In [50]:
```
predictor =  keras.Sequential([
        layers.Dense(1,input_dim=D, activation="linear", name="pred"),
    ]
)
predictor.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 pred (Dense)                (None, 1)                 5

=================================================================
Total params: 5
Trainable params: 5
Non-trainable params: 0
_________________________________________________________________
```

Компилируем модель

In [51]:
```
opt = keras.optimizers.SGD(learning_rate=0.1)
predictor.compile(loss='mse', optimizer=opt, metrics=['mae'])
```

Тренеруем модель

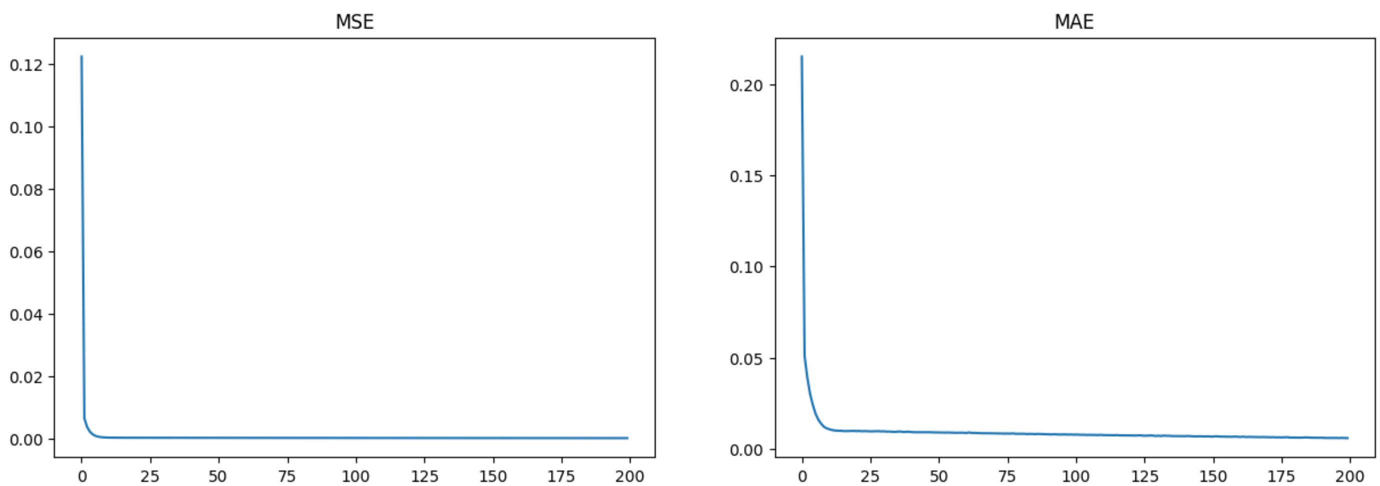
In [52]:
```
epochs = 200
time_start = time.time()
hist = predictor.fit(
    X,
```

```
    y,
    epochs=epochs,
    verbose=0,
    shuffle=True
    )
time_finish = time.time()
mse_loss, mae_loss = predictor.evaluate(X, y, verbose=0)

print(f'Fit time: {(time_finish - time_start):.{2}f}s')
print(f'Result MSE: {mse_loss}')
print(f'Result MAE: {mae_loss}')

fig, ax = plt.subplots(1, 2)
fig.set_figwidth(15)

ax[0].set_title('MSE')
ax[1].set_title('MAE')

ax[0].plot(range(epochs), hist.history['loss'])
ax[1].plot(range(epochs), hist.history['mae'])
```

```
Fit time: 4.24s
Result MSE: 7.184427522588521e-05
Result MAE: 0.005919293500483036
```

Out[52]:

```
[<matplotlib.lines.Line2D at 0x7f467825f9a0>]
```



Рисуем сигнал

In [53]:

```
my_denoized = predictor.predict(X).flatten()
```

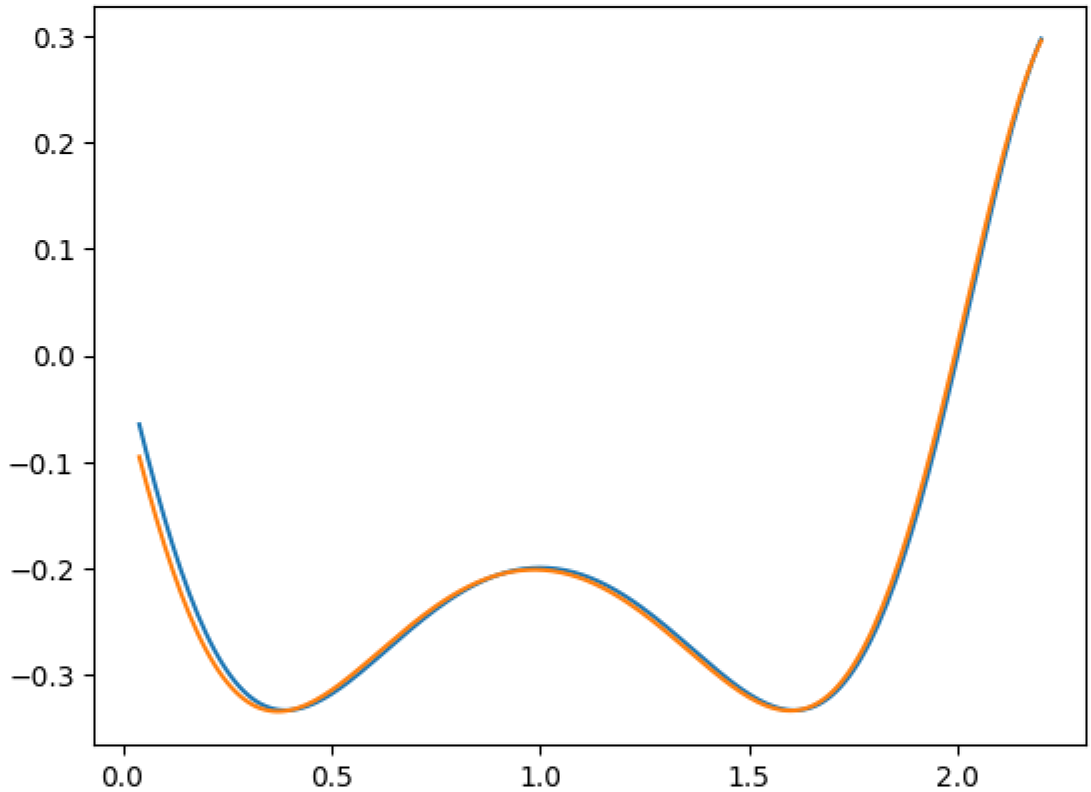
```
7/7 [==============================] - 0s 809us/step
```

In [54]:

```
plt.plot(x_points[D:], y)
plt.plot(x_points[D:], my_denoized)
```

Out[54]:

```
[<matplotlib.lines.Line2D at 0x7f46781a55e0>]
```



Находим абсолютное отконение

In [55]:
```
errors = my_denoized - y
plt.plot(x_points[D:], errors)
```

Out[55]:
```
[<matplotlib.lines.Line2D at 0x7f4678178ac0>]
```