Лабораторная работа №8. Рекуррентные нейронные сети для анализа временных рядов

Данные: Набор данных для прогнозирования временных рядов, который состоит из среднемесячного числа пятен на солнце, наблюдаемых с января 1749 по август 2017. Данные в виде csv-файла можно скачать на сайте Kaggle -> https://www.kaggle.com/robervalt/sunspots/ (https://www.kaggle.com/robervalt/sunspots/)

In [1]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
```

Загрузите данные. Изобразите ряд в виде графика. Вычислите основные характеристики временного ряда (сезонность, тренд, автокорреляцию).

In [2]:

```
data = pd.read_csv('/kaggle/input/sunspots/Sunspots.csv', usecols=[1,2], parse
_dates=[0], index_col=0, squeeze=True)
data.head()
```

Out[2]:

```
Date
1749-01-31     96.7
1749-02-28    104.3
1749-03-31    116.7
1749-04-30     92.8
1749-05-31    141.7
Name: Monthly Mean Total Sunspot Number, dtype: float64
```

In [3]:

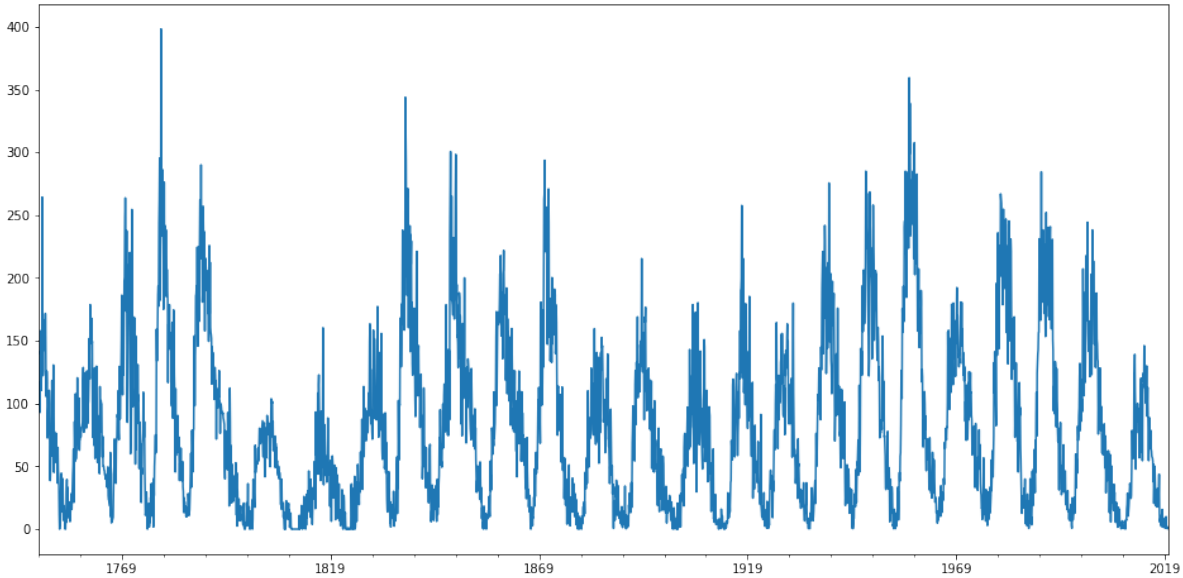
```
data.index = pd.DatetimeIndex(data.index.values,
                               freq=data.index.inferred_freq)
```

In [4]:

```
data.plot(figsize=(16, 8))
```

Out[4]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fc60d506860>

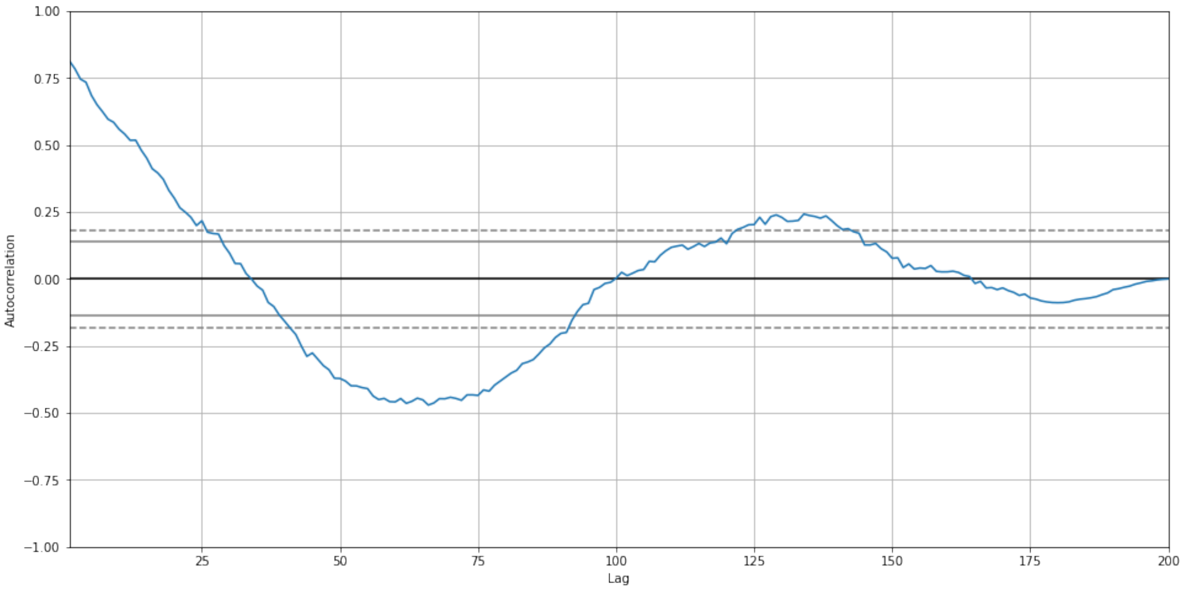


In [5]:

```
from pandas.plotting import autocorrelation_plot

plt.figure(figsize=(16, 8))
autocorrelation_plot(data[:200])
```

Out[5]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fc60b11e518>



In [6]:

```
from statsmodels.tsa.arima_model import ARIMA

model = ARIMA(data, order=(25,1,0), freq=data.index.inferred_freq)
model_fit = model.fit(disp=0)
print(model_fit.summary())
```

```
                                      ARIMA Model Results
==================================================================================
==============================
Dep. Variable:      D.Monthly Mean Total Sunspot Number   No. Obser
vations:                  3251
Model:                                   ARIMA(25, 1, 0)   Log Likel
ihood                -15038.442
Method:                                          css-mle   S.D. of i
nnovations               24.698
Date:                                   Sun, 19 Apr 2020   AIC
30130.883
Time:                                           14:17:17   BIC
30295.224
Sample:                                       02-28-1749   HQIC
30189.755
                                            - 12-31-2019
==================================================================================
============================================
                                                     coef    std err
z       P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
--------------------------------------------
const                                             -0.0216      0.317
-0.068      0.946      -0.643       0.600
ar.L1.D.Monthly Mean Total Sunspot Number         -0.4363      0.018
-24.880      0.000      -0.471      -0.402
ar.L2.D.Monthly Mean Total Sunspot Number         -0.3287      0.019
-17.208      0.000      -0.366      -0.291
ar.L3.D.Monthly Mean Total Sunspot Number         -0.2404      0.020
-12.049      0.000      -0.280      -0.201
ar.L4.D.Monthly Mean Total Sunspot Number         -0.1337      0.020
-6.556      0.000      -0.174      -0.094
ar.L5.D.Monthly Mean Total Sunspot Number         -0.0963      0.021
-4.697      0.000      -0.137      -0.056
ar.L6.D.Monthly Mean Total Sunspot Number         -0.0275      0.021
-1.336      0.181      -0.068       0.013
ar.L7.D.Monthly Mean Total Sunspot Number         -0.0237      0.021
-1.152      0.249      -0.064       0.017
ar.L8.D.Monthly Mean Total Sunspot Number         -0.0003      0.021
-0.014      0.989      -0.041       0.040
ar.L9.D.Monthly Mean Total Sunspot Number          0.0992      0.021
4.832      0.000       0.059       0.139
ar.L10.D.Monthly Mean Total Sunspot Number         0.1121      0.021
5.446      0.000       0.072       0.152
ar.L11.D.Monthly Mean Total Sunspot Number         0.1238      0.021
6.028      0.000       0.084       0.164
ar.L12.D.Monthly Mean Total Sunspot Number         0.1350      0.021
6.570      0.000       0.095       0.175
ar.L13.D.Monthly Mean Total Sunspot Number         0.1077      0.021
```

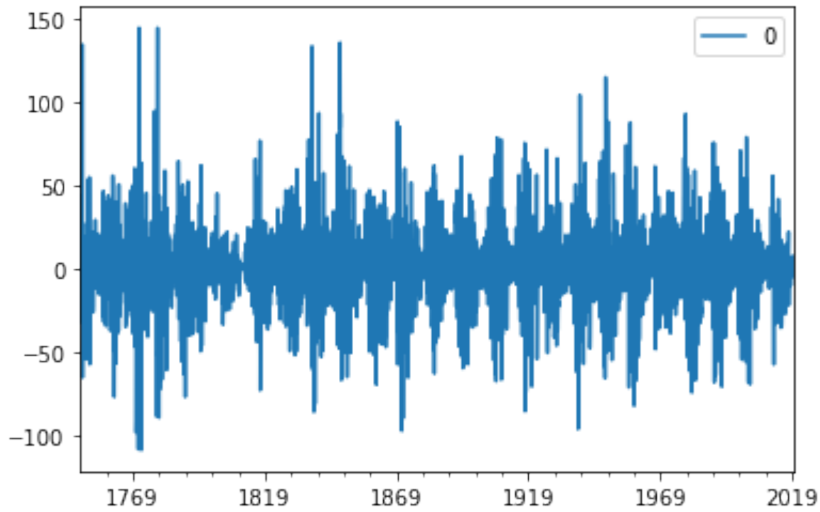
```
5.231      0.000       0.067       0.148
ar.L14.D.Monthly Mean Total Sunspot Number     0.1213      0.021
5.909      0.000       0.081       0.162
ar.L15.D.Monthly Mean Total Sunspot Number     0.1379      0.021
6.721      0.000       0.098       0.178
ar.L16.D.Monthly Mean Total Sunspot Number     0.0898      0.021
4.366      0.000       0.049       0.130
ar.L17.D.Monthly Mean Total Sunspot Number     0.0864      0.021
4.205      0.000       0.046       0.127
ar.L18.D.Monthly Mean Total Sunspot Number     0.0256      0.021
1.242      0.214      -0.015       0.066
ar.L19.D.Monthly Mean Total Sunspot Number     0.0207      0.021
1.004      0.316      -0.020       0.061
ar.L20.D.Monthly Mean Total Sunspot Number     0.0073      0.021
0.356      0.722      -0.033       0.048
ar.L21.D.Monthly Mean Total Sunspot Number    -0.0441      0.021
-2.143      0.032      -0.084      -0.004
ar.L22.D.Monthly Mean Total Sunspot Number    -0.0378      0.020
-1.851      0.064      -0.078       0.002
ar.L23.D.Monthly Mean Total Sunspot Number    -0.0007      0.020
-0.035      0.972      -0.040       0.039
ar.L24.D.Monthly Mean Total Sunspot Number    -0.0652      0.019
-3.400      0.001      -0.103      -0.028
ar.L25.D.Monthly Mean Total Sunspot Number     0.0050      0.018
0.282      0.778      -0.030       0.040
                                    Roots
===================================================================
============
                  Real          Imaginary           Modulus
Frequency
-------------------------------------------------------------------
------------
AR.1            -1.0817           -0.1497j            1.0920
-0.4781
AR.2            -1.0817           +0.1497j            1.0920
0.4781
AR.3            -1.0282           -0.4175j            1.1098
-0.4386
AR.4            -1.0282           +0.4175j            1.1098
0.4386
AR.5            -0.8887           -0.6480j            1.0999
-0.3997
AR.6            -0.8887           +0.6480j            1.0999
0.3997
AR.7            -0.6489           -0.8646j            1.0810
-0.3525
AR.8            -0.6489           +0.8646j            1.0810
0.3525
AR.9            -0.4182           -1.0145j            1.0973
-0.3122
AR.10           -0.4182           +1.0145j            1.0973
0.3122
AR.11           -0.1297           -1.1120j            1.1195
-0.2685
AR.12           -0.1297           +1.1120j            1.1195
0.2685
AR.13            1.0997           -0.0000j            1.0997
```

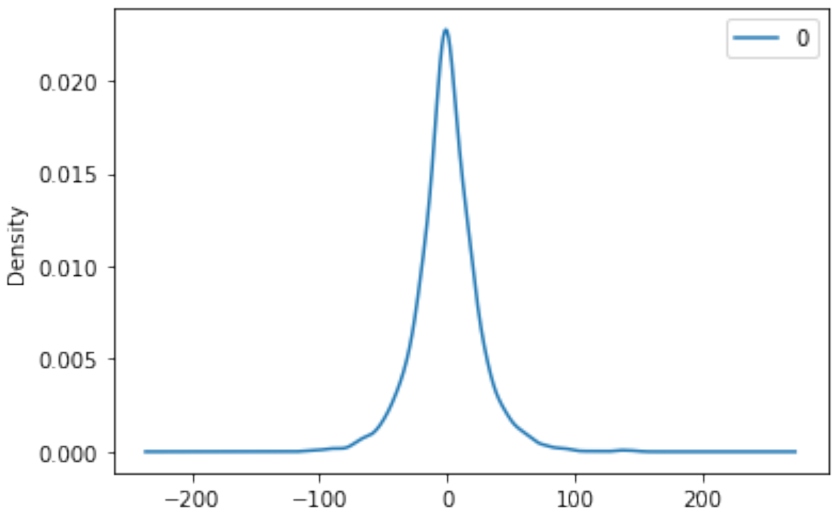
```
-0.0000
AR.14            1.2350          -0.0000j          1.2350
-0.0000
AR.15            0.9693          -0.4965j          1.0890
-0.0753
AR.16            0.9693          +0.4965j          1.0890
0.0753
AR.17            0.1610          -1.1519j          1.1631
-0.2279
AR.18            0.1610          +1.1519j          1.1631
0.2279
AR.19            0.8338          -0.7568j          1.1260
-0.1173
AR.20            0.8338          +0.7568j          1.1260
0.1173
AR.21            0.3766          -1.0714j          1.1357
-0.1962
AR.22            0.3766          +1.0714j          1.1357
0.1962
AR.23            0.6582          -0.9669j          1.1696
-0.1549
AR.24            0.6582          +0.9669j          1.1696
0.1549
AR.25           13.1733          -0.0000j         13.1733
-0.0000
------------------------------------------------------------------
------------
```

In [7]:

```
# plot residual errors
residuals = pd.DataFrame(model_fit.resid)
residuals.plot()
residuals.plot(kind='kde')
print(residuals.describe())
```

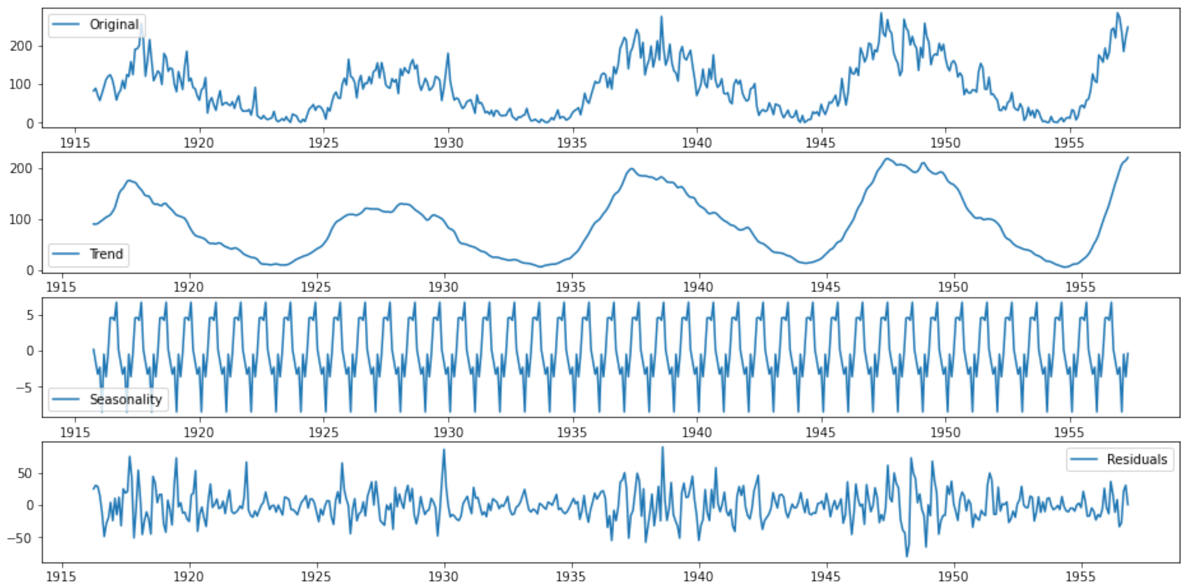
	0
count	3251.000000
mean	-0.013335
std	24.708216
min	-109.097567
25%	-12.867923
50%	-0.433795
75%	12.469070
max	144.989273





In [8]:

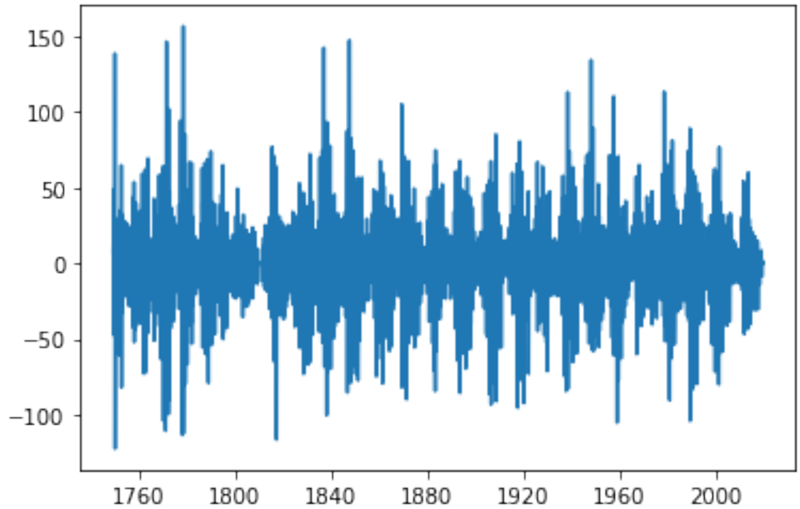
```
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(data[2000:2500])

trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plt.figure(figsize=(16, 8))
plt.subplot(411)
plt.plot(data[2000:2500], label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend, label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonality')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual, label='Residuals')
plt.legend(loc='best')
plt.show()
plt.tight_layout()
```




```
<Figure size 432x288 with 0 Axes>
```

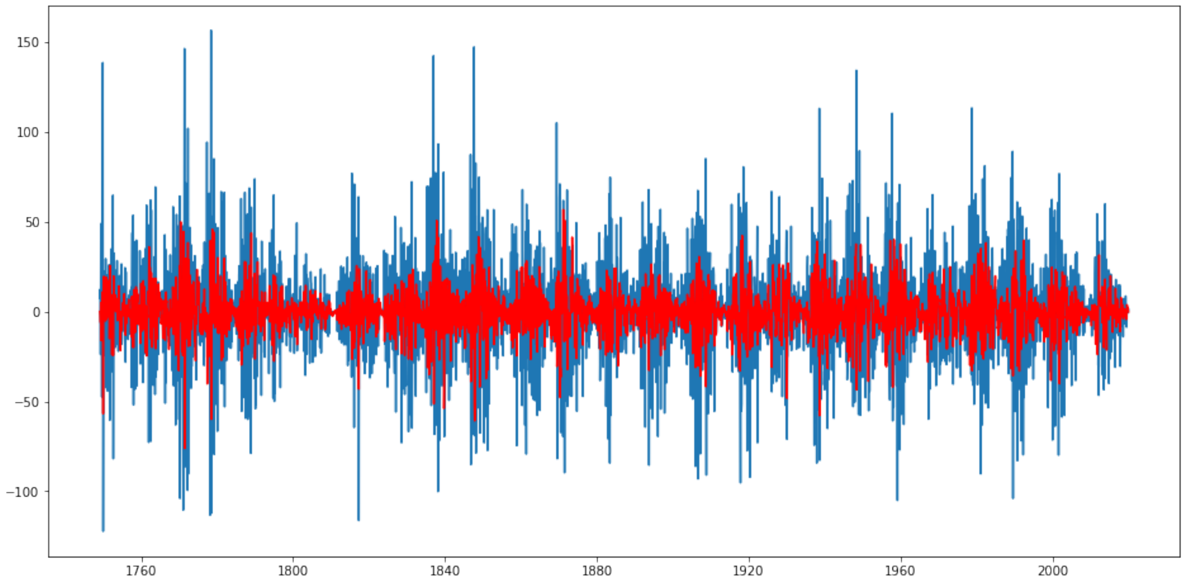
In [12]:

```
data_diff = data - data.shift()
plt.plot(data_diff)
plt.show()
```



In [14]:

```
plt.figure(figsize=(16, 8))
plt.plot(data_diff)
plt.plot(model_fit.fittedvalues, color='red')
plt.show()
```



Примените модель ARIMA для прогнозирования значений данного временного ряда.

In [126]:

```
from tqdm import tqdm
from sklearn.metrics import mean_squared_error

def evaluate_arima_model(X, order):
    # prepare training dataset
    train_size = int(len(X) * 0.8)
    train, test = X[0:train_size], X[train_size:]
    history = [x for x in train]
    # make predictions
    predictions = list()
    for t in tqdm(range(len(test))):
        model = ARIMA(history, order=order)
        model_fit = model.fit(disp=0)
        yhat = model_fit.forecast()[0]
        predictions.append(yhat)
        history.append(test[t])
    # calculate out of sample error
    error = mean_squared_error(test, predictions)
    return error, test, predictions
```

In [ ]:

```
mse, test, preds = evaluate_arima_model(data, order=(5,1,0))
```

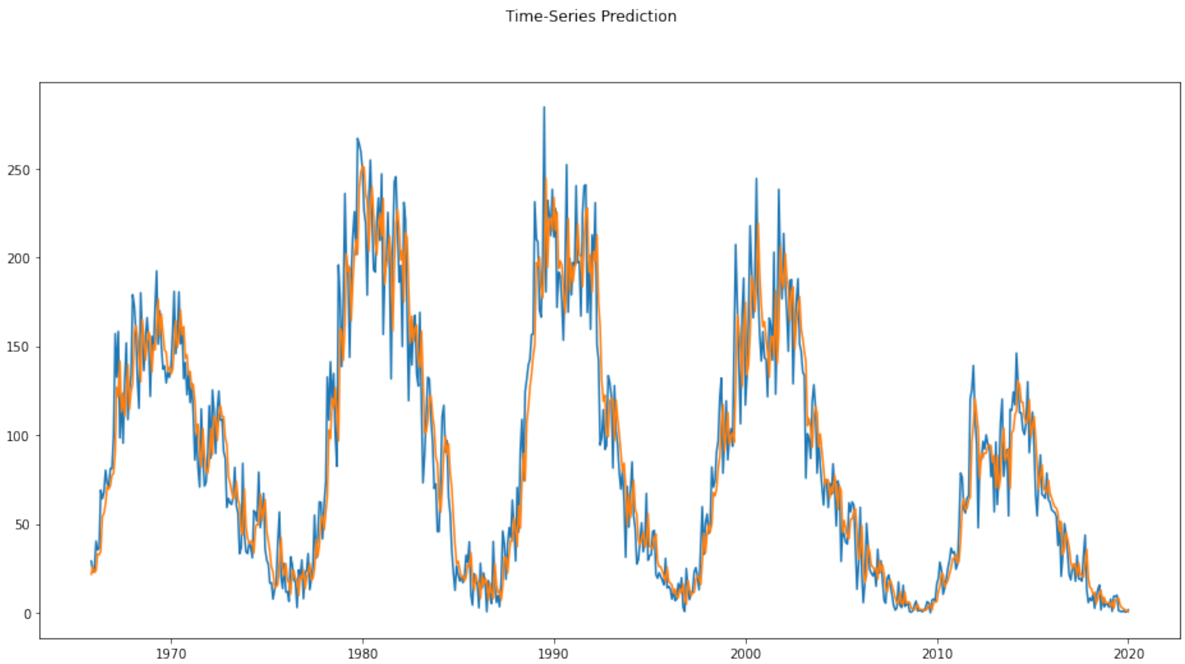
In [144]:

```
print(f'ARIMA MSE={mse:.3f}')
```

```
ARIMA MSE=538.131
```

In [145]:

```
preds = [x[0] for x in preds]
preds = pd.Series(preds, index=test.index)

plt.figure(figsize=(16, 8))

plt.plot(test)
plt.plot(preds)
plt.suptitle('Time-Series Prediction')
plt.show()
```



Повторите эксперимент по прогнозированию, реализовав рекуррентную нейронную сеть (с как минимум 2 рекуррентными слоями).

In [26]:

```
import torch
import torch.nn as nn
from torch.autograd import Variable
from sklearn.preprocessing import MinMaxScaler
```

In [25]:

```
def sliding_windows(data, seq_length):
    x = []
    y = []

    for i in range(len(data)-seq_length-1):
        _x = data[i:(i+seq_length)]
        _y = data[i+seq_length]
        x.append(_x)
        y.append(_y)

    return np.array(x),np.array(y)
```

In [49]:

```
sc = MinMaxScaler()
training_data = sc.fit_transform(data.values.reshape(-1, 1) )
```

In [51]:

```
seq_length = 30
x, y = sliding_windows(training_data, seq_length)
```

In [53]:

```
train_size = int(len(y) * 0.67)
test_size = len(y) - train_size

train_size, test_size
```

Out[53]:

```
(2158, 1063)
```

In [54]:

```
dataX = Variable(torch.Tensor(np.array(x)))
dataY = Variable(torch.Tensor(np.array(y)))

trainX = Variable(torch.Tensor(np.array(x[0:train_size])))
trainY = Variable(torch.Tensor(np.array(y[0:train_size])))

testX = Variable(torch.Tensor(np.array(x[train_size:len(x)])))
testY = Variable(torch.Tensor(np.array(y[train_size:len(y)])))
```

In [107]:

```
class LSTM(nn.Module):
    def __init__(self, num_classes, input_size, hidden_size, num_layers):
        super(LSTM, self).__init__()

        self.num_classes = num_classes
        self.num_layers = num_layers
        self.input_size = input_size
        self.hidden_size = hidden_size
        self.seq_length = seq_length

        self.lstm1 = nn.LSTM(input_size=input_size, hidden_size=hidden_size,
                            num_layers=num_layers, batch_first=True)
        self.fc1 = nn.Linear(hidden_size, 10)

        self.lstm2 = nn.LSTM(input_size=input_size, hidden_size=hidden_size,
                            num_layers=num_layers, batch_first=True)
        self.fc2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        h_0 = Variable(torch.zeros(
            self.num_layers, x.size(0), self.hidden_size))

        c_0 = Variable(torch.zeros(
            self.num_layers, x.size(0), self.hidden_size))

        # Propagate input through LSTM
        _, (h_out1, _) = self.lstm1(x, (h_0, c_0))
        h_out1 = h_out1.view(-1, self.hidden_size)
        out1 = self.fc1(h_out1)
        out1 = out1.reshape((out1.shape[0], out1.shape[1], 1))

        h_1 = Variable(torch.zeros(
            self.num_layers, out1.size(0), self.hidden_size))

        c_1 = Variable(torch.zeros(
            self.num_layers, out1.size(0), self.hidden_size))

        _, (h_out2, _) = self.lstm2(out1, (h_1, c_1))
        h_out2 = h_out2.view(-1, self.hidden_size)

        out2 = self.fc2(h_out2)

        return out2
```

In [146]:

```
num_epochs = 100
learning_rate = 0.01

input_size = 1
hidden_size = 2
num_layers = 1

num_classes = 1
```

In [147]:

```
model = LSTM(num_classes, input_size, hidden_size, num_layers)
```

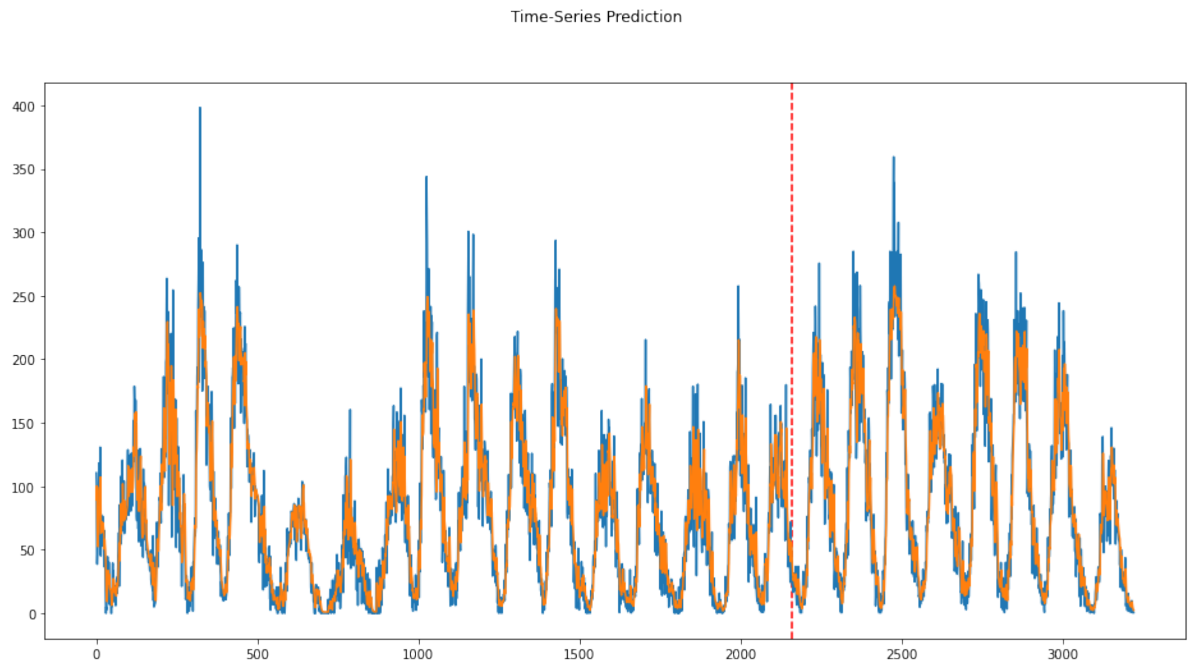
In [150]:

```
criterion = torch.nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

for epoch in range(num_epochs):
    outputs = model(trainX)
    optimizer.zero_grad()

    loss = criterion(outputs, trainY)
    loss.backward()

    optimizer.step()

    if (epoch+1) % 10 == 0:
      print(f'Epoch: {epoch+1}, loss: {loss.item():.5f}')
```

```
Epoch: 10, loss: 0.00481
Epoch: 20, loss: 0.00447
Epoch: 30, loss: 0.00424
Epoch: 40, loss: 0.00415
Epoch: 50, loss: 0.00409
Epoch: 60, loss: 0.00405
Epoch: 70, loss: 0.00403
Epoch: 80, loss: 0.00401
Epoch: 90, loss: 0.00401
Epoch: 100, loss: 0.00401
```

In [151]:

```
model.eval()
train_predict = model(dataX)

data_predict = train_predict.data.numpy()
dataY_plot = dataY.data.numpy()

data_predict = sc.inverse_transform(data_predict)
dataY_plot = sc.inverse_transform(dataY_plot)

plt.figure(figsize=(16, 8))
plt.axvline(x=train_size, c='r', linestyle='--')

plt.plot(dataY_plot)
plt.plot(data_predict)
plt.suptitle('Time-Series Prediction')
plt.show()
```



Вывод:

В данной лабораторной работе были построенны модели для прогнозированния временных рядов, использовались модель ARIMA и рекуррентная сеть с двумя рекуррентными слоями.