Лабораторная работа №8

Рекуррентные нейронные сети для анализа временных рядов

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/)](https://www.kaggle.com/robervalt/sunspots/)

Задание 1

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

In [0]:

```
import warnings

warnings.filterwarnings('ignore')
```

In [2]:

```
from google.colab import drive

drive.mount('/content/drive', force_remount = True)
```

```
Mounted at /content/drive
```

In [0]:

```
BASE_DIR = '/content/drive/My Drive/Colab Files/mo-2'

import sys

sys.path.append(BASE_DIR)

import os
```

In [0]:

```
DATA_ARCHIVE_NAME = 'sunspots.zip'

LOCAL_DIR_NAME = 'sunspots'
```

In [0]:

```
from zipfile import ZipFile

with ZipFile(os.path.join(BASE_DIR, DATA_ARCHIVE_NAME), 'r') as zip_:
    zip_.extractall(LOCAL_DIR_NAME)
```

In [0]:

```
DATA_FILE_PATH = 'sunspots/Sunspots.csv'
```

In [0]:

```
import pandas as pd

all_df = pd.read_csv(DATA_FILE_PATH, parse_dates = ['Date'], index_col = 'Date')
```

In [8]:

```
print(all_df.shape)
```

```
(3252, 2)
```

In [9]:

```
all_df.keys()
```

Out[9]:

```
Index(['Unnamed: 0', 'Monthly Mean Total Sunspot Number'], dtype='object')
```

In [0]:

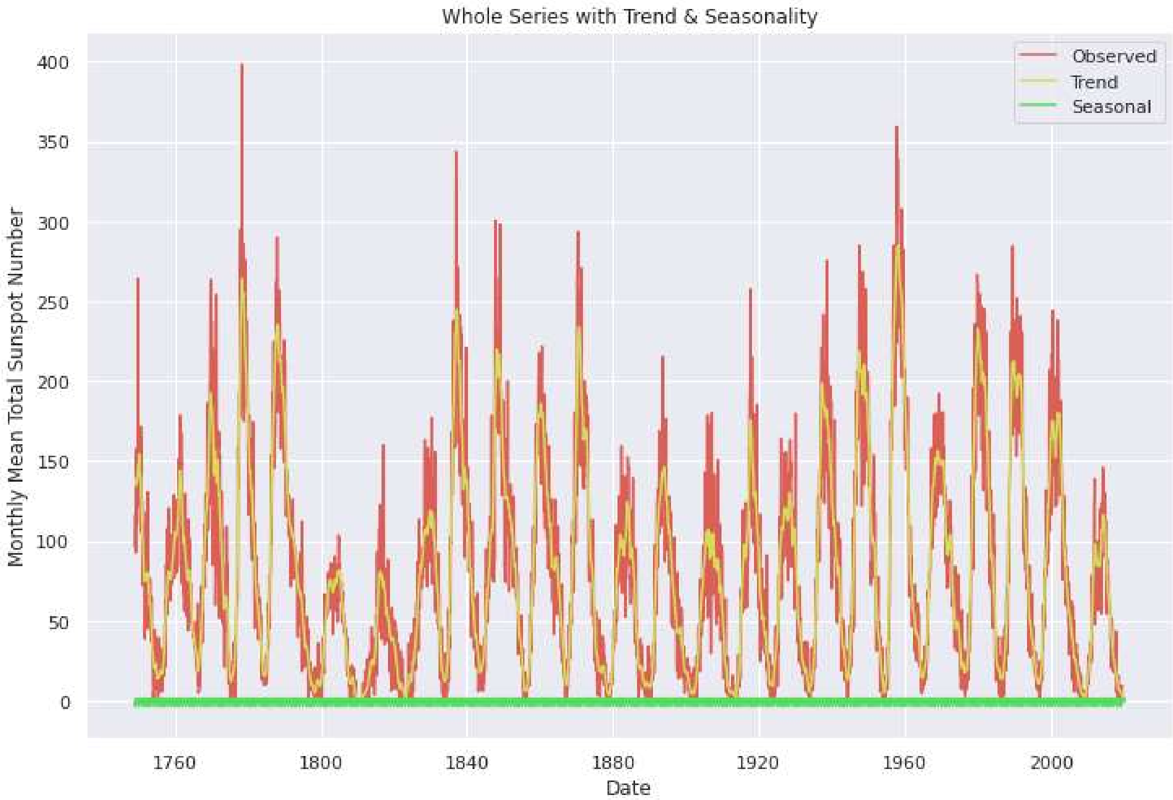
```
from statsmodels.tsa.seasonal import seasonal_decompose

additive = seasonal_decompose(all_df['Monthly Mean Total Sunspot Number'],
                              model = 'additive', extrapolate_trend = 'freq')
```

In [0]:

```
%matplotlib inline

import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import rcParams

rcParams['figure.figsize'] = 12, 8

sns.set()
sns.set_palette(sns.color_palette('hls'))

def plot_loss(_history):

    plt.plot(_history.history['loss'])
    plt.plot(_history.history['val_loss'])

    plt.title('Model loss')

    plt.ylabel('Loss')
    plt.xlabel('Epoch')

    plt.legend(['Train', 'Validation'], loc = 'right')

    plt.show()
```

In [12]:

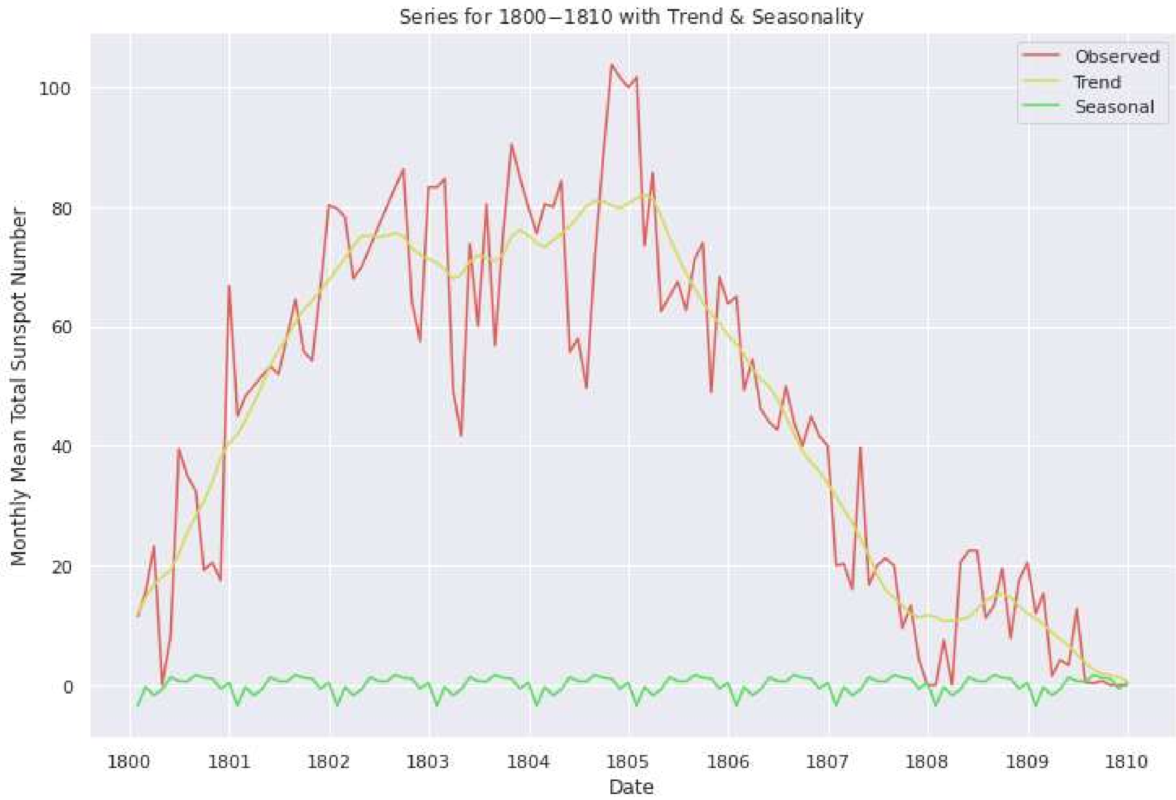
```
sns.lineplot(data = additive.observed, label = 'Observed')
sns.lineplot(data = additive.trend, label = 'Trend')
sns.lineplot(data = additive.seasonal, label = 'Seasonal')

plt.xlabel('Date')
plt.ylabel('Monthly Mean Total Sunspot Number')

plt.title('Whole Series with Trend & Seasonality')

plt.show()
```



Рассмотрим подробнее на небольшом промежутке:

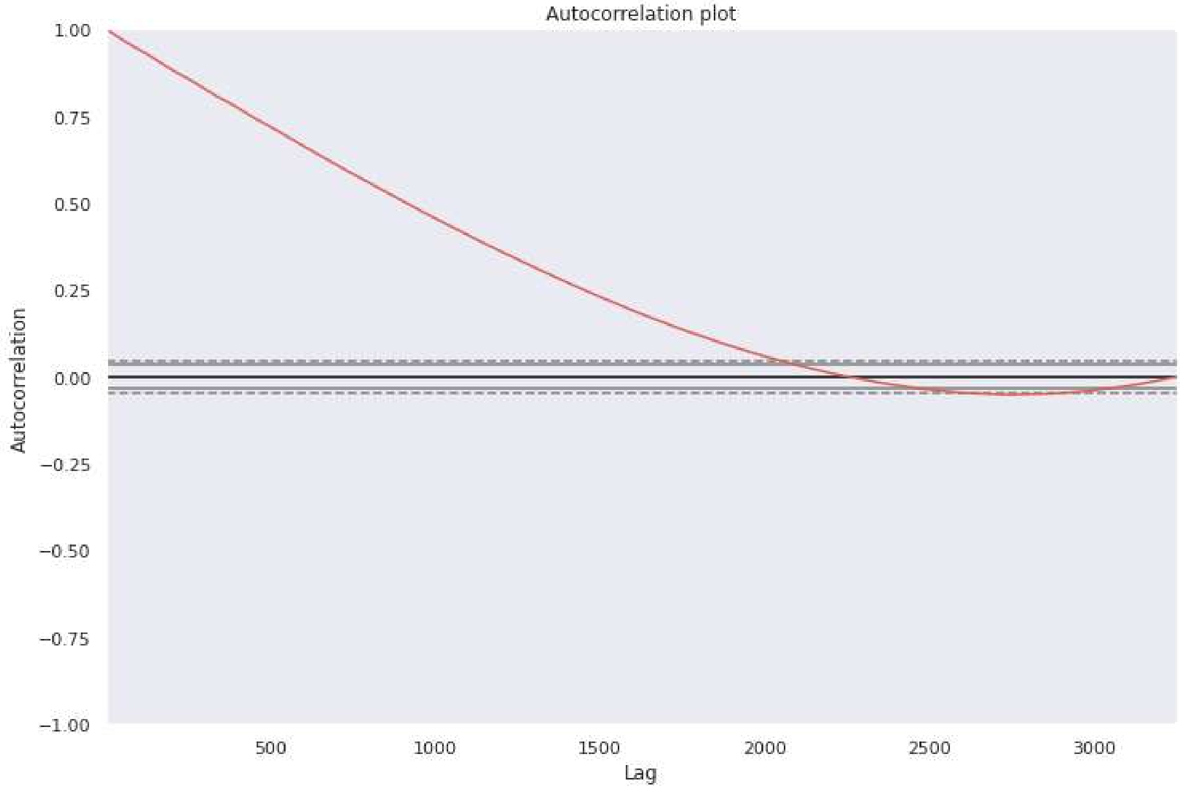
In [13]:

```
sns.lineplot(data = additive.observed['1800-01-01':'1810-01-01'], label = 'Observed')
sns.lineplot(data = additive.trend['1800-01-01':'1810-01-01'], label = 'Trend')
sns.lineplot(data = additive.seasonal['1800-01-01':'1810-01-01'], label = 'Seasonal')

plt.xlabel('Date')
plt.ylabel('Monthly Mean Total Sunspot Number')

plt.title('Series for 1800$-$1810 with Trend & Seasonality')

plt.show()
```



In [14]:

```
from pandas.plotting import autocorrelation_plot

autocorrelation_plot(all_df.values.tolist())

plt.title('Autocorrelation plot')

plt.show()
```



Задание 2

Для прогнозирования разделите временной ряд на обучающую, валидационную и контрольную выборки.

Этот шаг будет применён автоматически с помощью индексации массива данных и как параметр `validation_split` метода `model.fit()` .

Задание 3

Примените модель *ARIMA* для прогнозирования значений данного временного ряда.

In [0]:

```
! pip install pmdarima --quiet
```

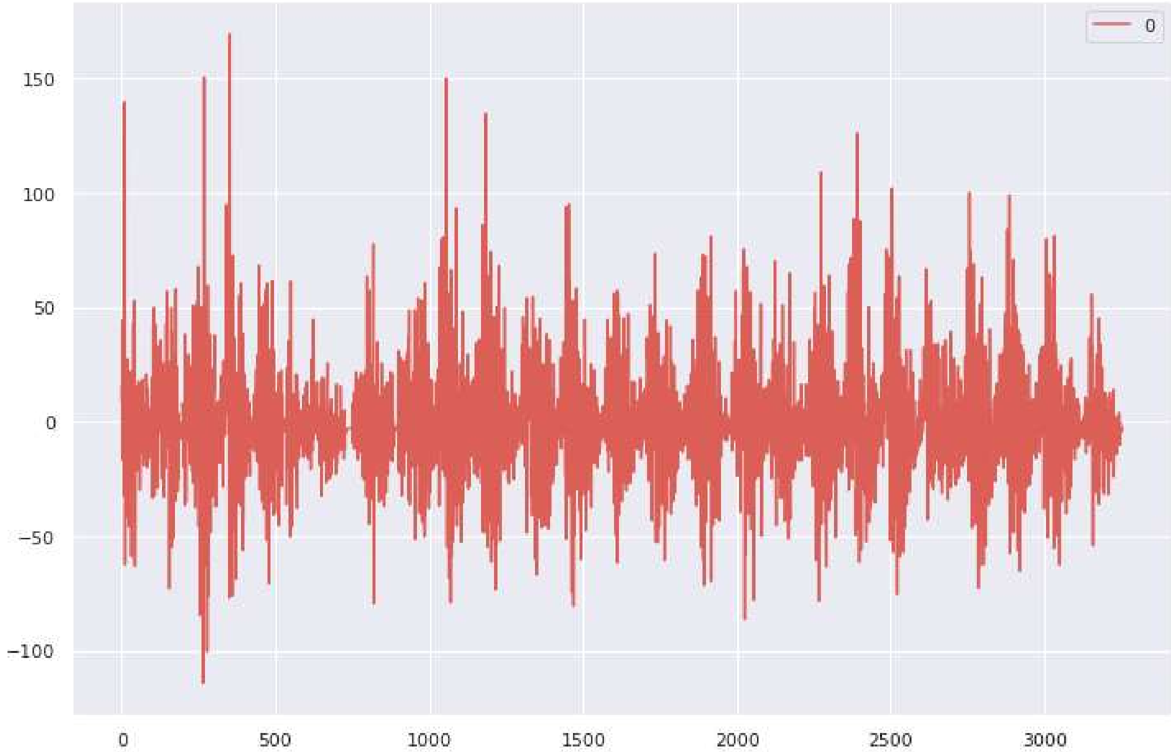
In [16]:

```
from statsmodels.tsa.arima_model import ARIMA

model = ARIMA(all_df['Monthly Mean Total Sunspot Number'].values,
              order = (1, 0, 2))

model_fit = model.fit(disp = 0)

print(model_fit.summary())
```

```
                              ARMA Model Results
============================================================================
==
Dep. Variable:                      y   No. Observations:                 32
52
Model:                     ARMA(1, 2)   Log Likelihood             -15098.8
79
Method:                       css-mle   S.D. of innovations              25.1
20
Date:                Mon, 20 Apr 2020   AIC                         30207.7
57
Time:                        04:10:50   BIC                         30238.1
92
Sample:                             0   HQIC                        30218.6
60

============================================================================
==
                 coef    std err          z      P>|z|      [0.025      0.97
5]
----------------------------------------------------------------------------
--
const         81.1334     11.977      6.774      0.000      57.660     104.6
07
ar.L1.y        0.9826      0.003    284.234      0.000       0.976       0.9
89
ma.L1.y       -0.4063      0.018    -22.947      0.000      -0.441      -0.3
72
ma.L2.y       -0.1140      0.017     -6.894      0.000      -0.146      -0.0
82
                                    Roots
============================================================================
=
                  Real          Imaginary           Modulus         Frequenc
y
----------------------------------------------------------------------------
-
AR.1            1.0177           +0.0000j            1.0177           0.000
0
MA.1            1.6743           +0.0000j            1.6743           0.000
0
MA.2           -5.2373           +0.0000j            5.2373           0.500
0
----------------------------------------------------------------------------
-
```

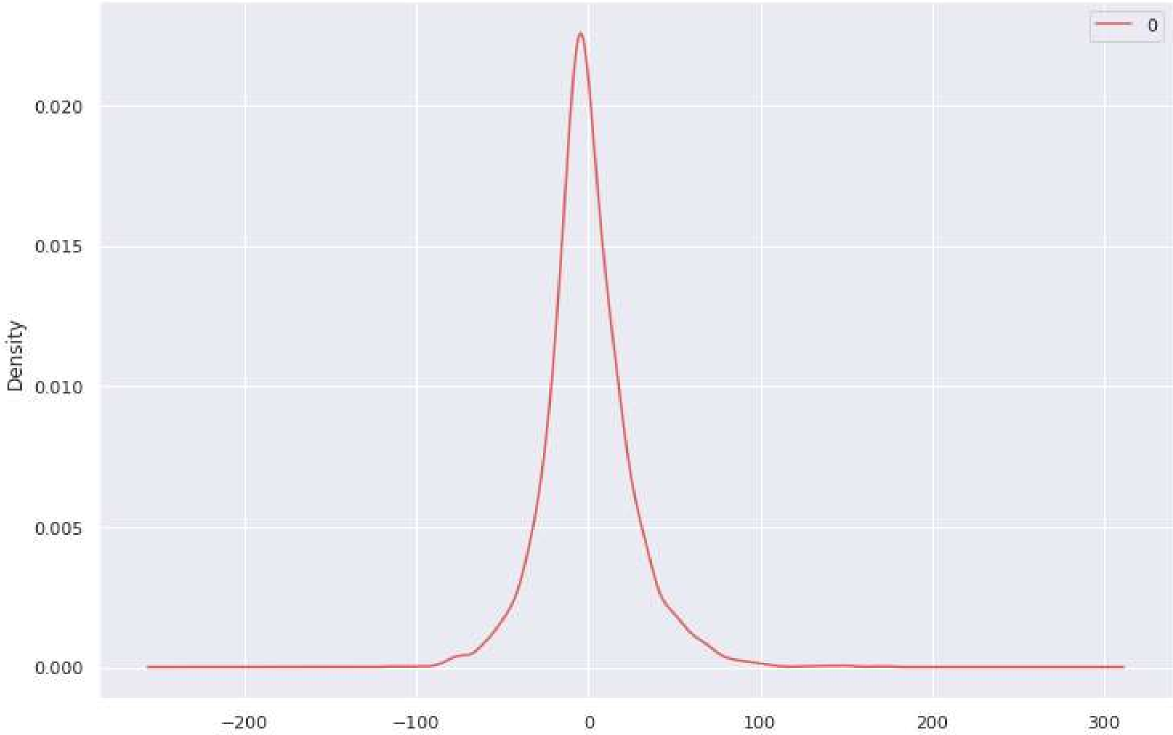
In [17]:

```
residuals = pd.DataFrame(model_fit.resid)

residuals.plot()

plt.show()
```



In [18]:

```
residuals.plot(kind = 'kde')

plt.show()
```



Задание 4

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

Сначала нужно создать датасет из данных.

In [0]:

```
TEST_PERIOD = 600
```

In [0]:

```
OBSERVATIONS_PER_CYCLE = 11 * 12
```

In [0]:

```
TIME_STEPS = OBSERVATIONS_PER_CYCLE
```

In [0]:

```
! pip install tensorflow-gpu --pre --quiet
```

In [0]:

```python
import tensorflow as tf

tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR)

from tensorflow import keras
```

In [0]:

```python
import numpy as np
from datetime import timezone

def timeseries_to_dataset(_X_ts, _time_steps):

    samples_n_ = len(_X_ts) - _time_steps

    _X_norm = tf.keras.utils.normalize(_X_ts).squeeze()

    print(_X_ts.shape, _X_norm.shape)

    X_ = np.zeros((samples_n_, _time_steps))
    y_ = np.zeros((samples_n_, ))

    for i in range(samples_n_):

        X_[i] = _X_norm[i:(i + _time_steps)]

        y_[i] = _X_norm[(i + _time_steps)]

    return X_[..., np.newaxis], y_
```

In [25]:

```python
X_as_ds, y_as_ds = timeseries_to_dataset(
    all_df['Monthly Mean Total Sunspot Number'].values,
    TIME_STEPS)

X, y = X_as_ds[:-TEST_PERIOD], y_as_ds[:-TEST_PERIOD]

X_test, y_test = X_as_ds[-TEST_PERIOD:], y_as_ds[-TEST_PERIOD:]
```

```
(3252,) (3252,)
```

In [26]:

```python
print(X.shape, X_test.shape, y.shape, y_test.shape)
```

```
(2520, 132, 1) (600, 132, 1) (2520,) (600,)
```

In [0]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

model = tf.keras.Sequential()

model.add(LSTM(2, activation = 'relu', return_sequences = True,
               input_shape = X.shape[-2:]))
model.add(LSTM(12, activation = 'relu'))
model.add(Dense(1))
```

In [28]:

```
model.compile(optimizer = 'adam',
              loss = 'mse')

model.summary()
```

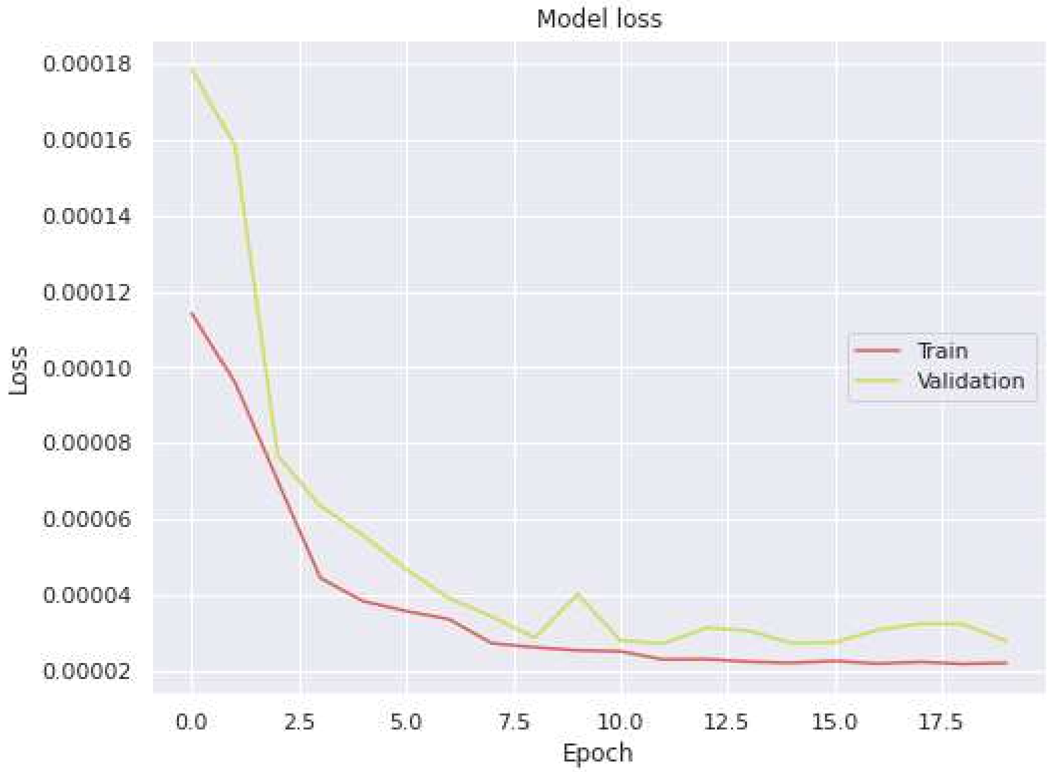
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 132, 2)            32
_________________________________________________________________
lstm_1 (LSTM)                (None, 12)                720
_________________________________________________________________
dense (Dense)                (None, 1)                 13
=================================================================
Total params: 765
Trainable params: 765
Non-trainable params: 0
_________________________________________________________________
```

In [0]:

```
history = model.fit(x = X, y = y, epochs = 20, validation_split = 0.15,
                    verbose = 0)
```

In [30]:

```
rcParams['figure.figsize'] = 8, 6

plot_loss(history)
```



In [31]:

```
results = model.evaluate(X_test, y_test)

print('Test mse:', results)
```

```
19/19 [==============================] - 0s 26ms/step - loss: 1.9438e-05
Test mse: 1.9438315575825982e-05
```

In [32]:

```
y_pred = model.predict(X_test[20][np.newaxis, ...])

print(y_pred, y_test[20])
```

```
[[0.01421428]] 0.011741172416758197
```

Задание 5

Сравните качество прогноза моделей.

Какой максимальный результат удалось получить на контрольной выборке?