Введение в искусственные нейронные сети

Урок 5. Рекуррентные нейронные сети

Практическое задание

1. Попробуйте обучить нейронную сеть LSTM на любом другом датасете (любимый временной ряд, текст на русском (другом языке) как генератор или классификатор, или прилагаемый набор airline-passengers - пасажиропоток для авиалиний). Опишите, какой результата вы получили? Что помогло вам улучшить ее точность?
2. *Попробуйте на numpy реализовать нейронную сеть архитектуры LSTM
3. *Предложите свои варианты решения проблемы исчезающего градиента в RNN

```
import numpy
import matplotlib.pyplot as plt
import pandas as pd
from pandas import read_csv
import math
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

```
from google.colab import files
import os
import datetime
```

```
numpy.random.seed(7)
```

Читаем данные из файла со значениями (набор airline-passengers - пасажиропоток для авиалиний)

```
files.upload()
!ls
```

Выбрать файлы Файл не выбран Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving airline-passengers.csv to airline-passengers (5).csv
'airline-passengers (1).csv'  'airline-passengers (4).csv'   logs2
'airline-passengers (2).csv'  'airline-passengers (5).csv'   sample_data
'airline-passengers (3).csv'   airline-passengers.csv
```

```
dataframe = pd.read_csv('/content/airline-passengers.csv', usecols=[1], engine='python')
```

```
dataset = dataframe.values
dataset = dataset.astype('float32')
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
```

```
type(dataframe)
```

```
pandas.core.frame.DataFrame
```

```
dataframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Passengers  144 non-null    int64
```

```
dtypes: int64(1)
memory usage: 1.2 KB
```

```
dataframe.columns
```

```
Index(['Passengers'], dtype='object')
```

```
dataframe.shape
```

```
(144, 1)
```

```
dataframe.isnull().sum()
```

```
Passengers    0
dtype: int64
```

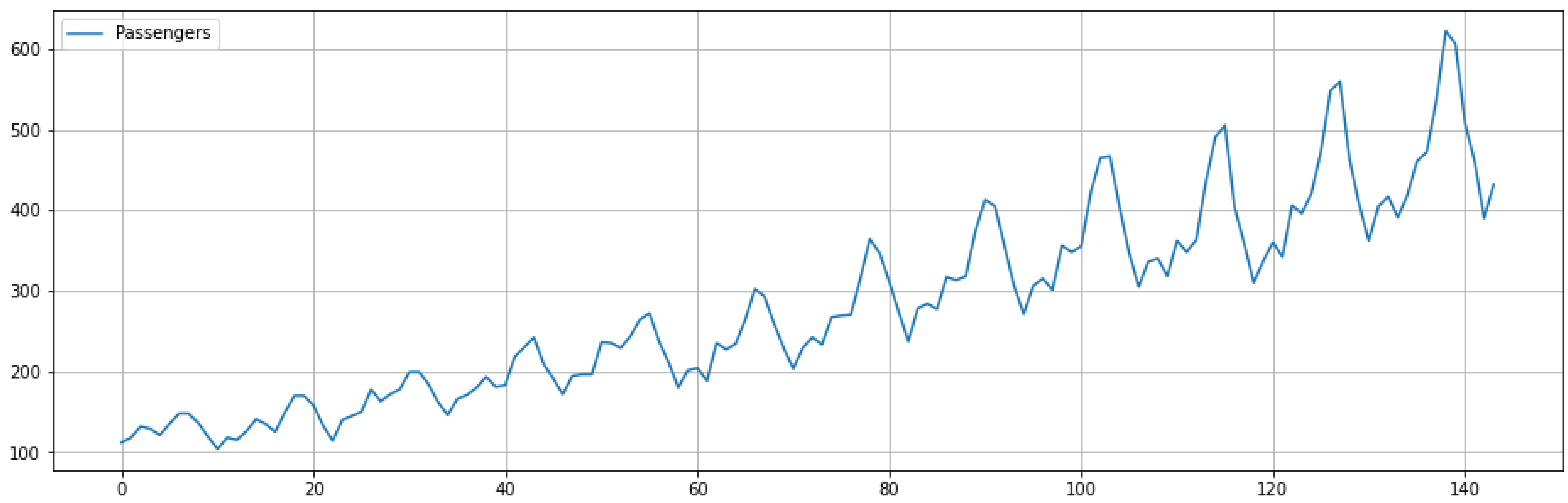
Данные о пасажиропотоке + индексы (Month)

```
dataframe.head()
```

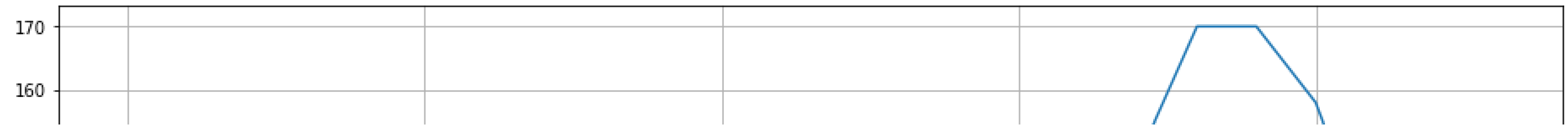
	Passengers
0	112
1	118
2	132
3	129
4	121

```
# dataframe.sort_index(ascending=True, inplace=True)
# dataframe.head()
```

```
dataframe.plot( figsize = (16,5))
# df['Passengers'].plot( figsize = (16,5))

plt.grid('On')
plt.show()
```




```
# dataframe['Passengers'][130:144].plot( figsize = (16,5))
dataframe['Passengers'][0:24].plot( figsize = (16,5))

plt.grid('On')
plt.show()
```



В данных отчётливо наблюдаются:

- тренд;
- периодичность (очевидно связанная с сезонностью);
- увеличение амплитуды колебаний пасажиропотока со временем.


```
dataframe.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Passengers	144.0	280.298611	119.966317	104.0	180.0	265.5	360.5	622.0

```
print(dataframe.shape)
```

```
(144, 1)
```

Создаем данные для обучения

```
def create_dataset(dataset, look_back=1):
  # разбиваем датасет на обучающую и тестовую выборки
    dataX, dataY = [], []
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return numpy.array(dataX), numpy.array(dataY)
```

Выделяем части на обучение и проверку (у нас временной ряд)

```
train_size = int(len(dataset) * 0.67)  # длина прошлого
test_size = len(dataset) - train_size  # длина тестового периода
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
```

```
look_back = 3

trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)
```

```
print(type(trainX))
trainX[:3]
```

```
<class 'numpy.ndarray'>
array([[0.01544401, 0.02702703, 0.05405405],
       [0.02702703, 0.05405405, 0.04826255],
       [0.05405405, 0.04826255, 0.03281853]], dtype=float32)
```

```
print(type(trainY))
print(len(trainY))
trainY
```

```
<class 'numpy.ndarray'>
92
array([0.04826255, 0.03281853, 0.05984557, 0.08494207, 0.08494207,
       0.06177607, 0.02895753, 0.        , 0.02702703, 0.02123553,
       0.04247104, 0.07142857, 0.05984557, 0.04054055, 0.08687258,
       0.12741312, 0.12741312, 0.10424709, 0.05598456, 0.01930502,
       0.06949806, 0.07915059, 0.08880308, 0.14285713, 0.11389962,
       0.13127413, 0.14285713, 0.18339768, 0.18339768, 0.15444016,
       0.11196911, 0.08108109, 0.1196911 , 0.12934363, 0.14671814,
       0.17181468, 0.14864865, 0.15250966, 0.22007722, 0.24324325,
       0.26640925, 0.2027027 , 0.16795367, 0.13127413, 0.17374519,
       0.17760617, 0.17760617, 0.25482625, 0.25289574, 0.24131274,
       0.26833975, 0.3088803 , 0.32432434, 0.25675675, 0.20656371,
       0.14671814, 0.18725869, 0.19305018, 0.16216215, 0.25289574,
```

```
       0.23745173, 0.25096524, 0.3088803 , 0.38223937, 0.36486486,
       0.2992278 , 0.24131274, 0.1911197 , 0.24131274, 0.26640925,
       0.24903473, 0.31467178, 0.3185328 , 0.32046333, 0.4073359 ,
       0.5019305 , 0.46911195, 0.40154442, 0.32818535, 0.25675675,
       0.3359073 , 0.34749034, 0.33397684, 0.41119692, 0.4034749 ,
       0.4131274 , 0.52123547, 0.5965251 , 0.58108103, 0.484556  ,
       0.3899614 , 0.3223938 ], dtype=float32)
```

```
print(type(testX))
testX[:3]
```

```
<class 'numpy.ndarray'>
array([[0.4073359 , 0.3803089 , 0.48648646],
       [0.3803089 , 0.48648646, 0.47104248],
       [0.48648646, 0.47104248, 0.484556  ]], dtype=float32)
```

```
# reshape input to be [samples, time steps, features]
trainX = numpy.reshape(trainX, (trainX.shape[0], trainX.shape[1], 1))
testX = numpy.reshape(testX, (testX.shape[0], testX.shape[1], 1))
```

```
print(type(trainX))
print(len(trainX))
trainX[:3]
```

```
<class 'numpy.ndarray'>
92
array([[[0.01544401],
        [0.02702703],
        [0.05405405]],

       [[0.02702703],
        [0.05405405],
        [0.04826255]],

       [[0.05405405],
        [0.04826255],
        [0.03281853]]], dtype=float32)
```

```
print(type(testX))
print(len(testX))
testX[:3]
```

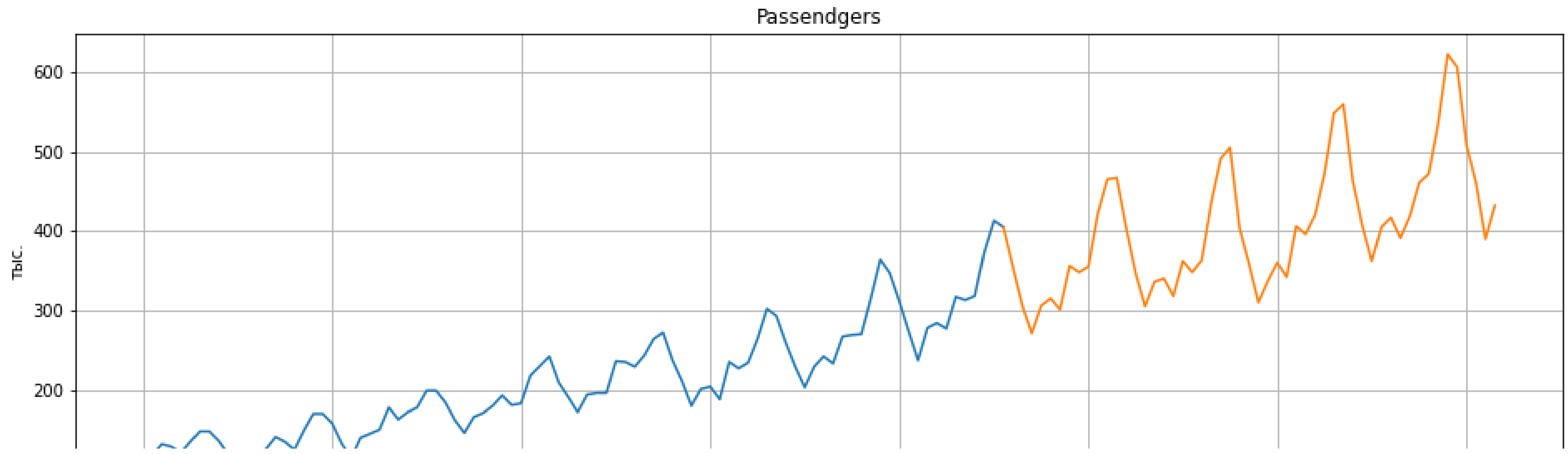
```
<class 'numpy.ndarray'>
44
array([[[0.4073359 ],
        [0.3803089 ],
        [0.48648646]],

       [[0.3803089 ],
        [0.48648646],
        [0.47104248]],

       [[0.48648646],
        [0.47104248],
        [0.484556  ]]], dtype=float32)
```

Посмотрим на данные для тренировки и теста

```
data = dataframe.copy()
```

Чтобы изменить содержимое ячейки, дважды нажмите на нее (или выберите "Ввод")

```
plt.figure(figsize=(16,5))
# plt.plot(data.index[xLen:yTrain.shape[0]+xLen],yTrain[:])
plt.plot(data.index[0:92],data[0:92])
plt.plot(data.index[91:144],data[91:144])
plt.grid('on')
plt.xlabel('t, месяцы')
plt.ylabel('тыс.')
#plt.title('Пассажиропоток в 1949-1969')
plt.title('Passendgers')
plt.show()
```



Строим сеть

t, месяцы

```
batch_size = 1

model = Sequential()
model.add(LSTM(4, batch_input_shape=(batch_size, look_back, 1), stateful=True))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')


# Обучаем
for i in range(100):
    model.fit(trainX, trainY, epochs=1, batch_size=batch_size, verbose=2, shuffle=False)
    model.reset_states()
```

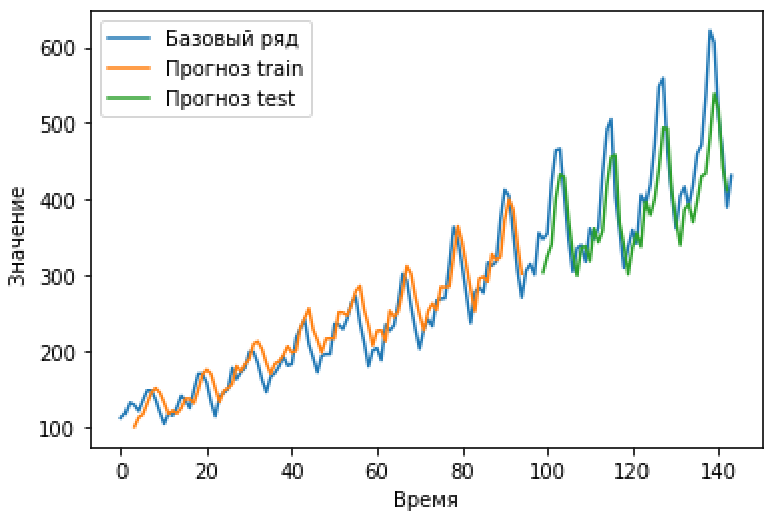
```
92/92 - 2s - loss: 0.0065 - 2s/epoch - 19ms/step
92/92 - 0s - loss: 0.0135 - 157ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0080 - 156ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0059 - 201ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0051 - 190ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0047 - 176ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0045 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0044 - 174ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 166ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 167ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 181ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0041 - 177ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0041 - 178ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 174ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0039 - 183ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0039 - 164ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0039 - 178ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0038 - 155ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0038 - 166ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0038 - 157ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0037 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0037 - 166ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0037 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0036 - 167ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0036 - 186ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0036 - 168ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0035 - 176ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0035 - 185ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0035 - 169ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0035 - 158ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0034 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0034 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0034 - 164ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0033 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0033 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0033 - 168ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0032 - 187ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0032 - 159ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0032 - 175ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0031 - 185ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0031 - 167ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0031 - 154ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0031 - 185ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0030 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0030 - 166ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0030 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0029 - 167ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0029 - 164ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0029 - 158ms/epoch - 2ms/step
```

```
92/92 - 0s - loss: 0.0029 - 176ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0028 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0028 - 176ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0028 - 160ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0027 - 167ms/epoch - 2ms/step
```

```
# Делаем предсказание на train
trainPredict = model.predict(trainX, batch_size=batch_size)
model.reset_states()
# Делаем предсказание на test
testPredict = model.predict(testX, batch_size=batch_size)


trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])


# Значение метрики на train и test
trainScore = math.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = math.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

```
Train Score: 24.92 RMSE
Test Score: 51.44 RMSE
```

```
trainPredictPlot = numpy.empty_like(dataset)
trainPredictPlot[:, :] = numpy.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict


testPredictPlot = numpy.empty_like(dataset)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] = testPredict



# Отобразим на графике данные и предсказания

plt.plot(scaler.inverse_transform(dataset),
         label='Базовый ряд')
plt.plot(trainPredictPlot,
         label='Прогноз train')
plt.plot(testPredictPlot,
         label='Прогноз test')

plt.xlabel('Время')
plt.ylabel('Значение ')

plt.legend()
plt.show()
```




```
look_back = 3

trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)


batch_size = 1

model1 = Sequential()
```

```
model1 = Sequential()
model1.add(LSTM(4, batch_input_shape=(batch_size, look_back, 1), stateful=True))

model.add(Flatten())·························#·(None,·n_Dense*n_lstm)
model.add(Dense(8,·activation="linear"))······#·(None,n_Dense)

model1.add(Dense(1))
model1.compile(loss='mean_squared_error', optimizer='adam')

# Обучаем
for i in range(100):
  model1.fit(trainX, trainY, epochs=1, batch_size=batch_size, verbose=2, shuffle=False)
  model1.reset_states()
```

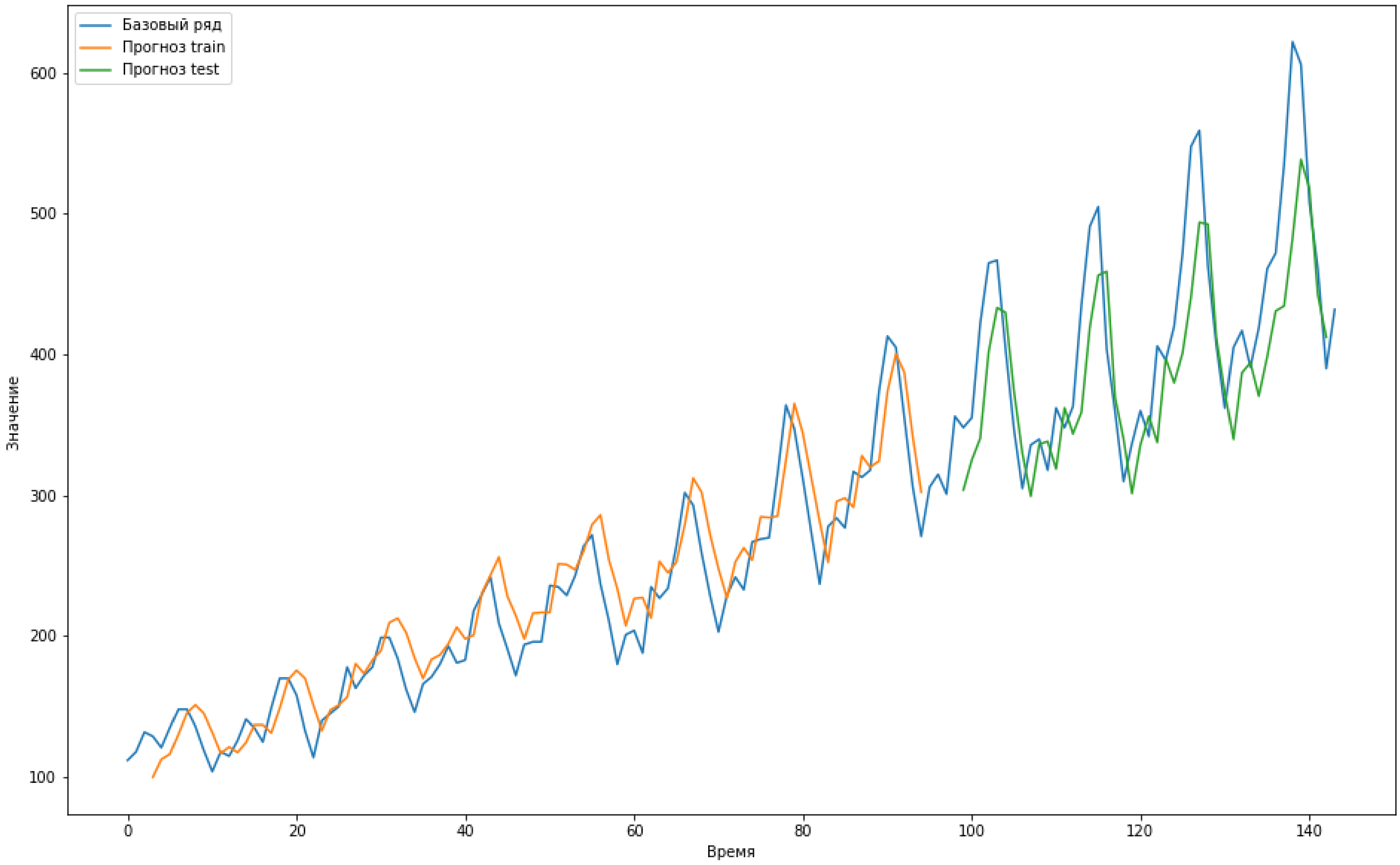
```
92/92 - 2s - loss: 0.0064 - 2s/epoch - 18ms/step
92/92 - 0s - loss: 0.0221 - 180ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0131 - 178ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0081 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0056 - 188ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0052 - 190ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0052 - 208ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0051 - 178ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0051 - 172ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0051 - 178ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0050 - 169ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0050 - 180ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0050 - 185ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0050 - 186ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0049 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0049 - 172ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0049 - 179ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0049 - 159ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0048 - 165ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0048 - 167ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0048 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0048 - 166ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0048 - 169ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0047 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0047 - 179ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0047 - 169ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0047 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0046 - 171ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0046 - 166ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0046 - 180ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0046 - 191ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0045 - 197ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0045 - 159ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0045 - 185ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0045 - 179ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0045 - 193ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0044 - 234ms/epoch - 3ms/step
92/92 - 0s - loss: 0.0044 - 223ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0044 - 204ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0044 - 175ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 182ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 174ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 164ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0043 - 181ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 165ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 173ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 161ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 168ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0042 - 176ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0041 - 180ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0041 - 176ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0041 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0041 - 170ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 182ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 185ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 204ms/epoch - 2ms/step
92/92 - 0s - loss: 0.0040 - 161ms/epoch - 2ms/step
```

```
# Делаем предсказание на train
trainPredict = model1.predict(trainX, batch_size=batch_size)
model.reset_states()
# Делаем предсказание на test
testPredict = model1.predict(testX, batch_size=batch_size)


trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
```

```
# Значение метрики на train и test
print('Модель 1')
print('Train Score: %.2f RMSE' % (trainScore))
print('Test Score: %.2f RMSE' % (testScore))

print('Модель 2')
trainScore1 = math.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore1))
testScore1 = math.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore1))
```

```
Модель 1
Train Score: 24.92 RMSE
Test Score: 51.44 RMSE
Модель 2
Train Score: 28.89 RMSE
Test Score: 62.51 RMSE
```

```
trainPredictPlot1 = numpy.empty_like(dataset)
trainPredictPlot1[:, :] = numpy.nan
trainPredictPlot1[look_back:len(trainPredict)+look_back, :] = trainPredict


testPredictPlot1 = numpy.empty_like(dataset)
testPredictPlot1[:, :] = numpy.nan
testPredictPlot1[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] = testPredict


plt.figure(figsize=(16,10))

# Отобразим на графике данные и предсказания (1-я млдель)

plt.plot(scaler.inverse_transform(dataset),
         label='Базовый ряд')
plt.plot(trainPredictPlot,
         label='Прогноз train')
plt.plot(testPredictPlot,
         label='Прогноз test')

plt.xlabel('Время')
plt.ylabel('Значение ')

plt.legend()
plt.show()
plt.figure(figsize=(16,10))
# Отобразим на графике данные и предсказания (2-я млдель)

plt.plot(scaler.inverse_transform(dataset),
         label='Базовый ряд')
plt.plot(trainPredictPlot1,
         label='Прогноз train')
plt.plot(testPredictPlot1,
         label='Прогноз test')

plt.xlabel('Время')
plt.ylabel('Значение ')

plt.legend()
plt.show()
```



Добавление 2-х слоёв Flatten и Dense в модель, позволило улучшить показатели модели.

Модель 1

Train Score: 24.92 RMSE

Test Score: 51.44 RMSE

Модель 2

Train Score: 28.89 RMSE

Test Score: 62.51 RMSE