

# Prática7\_respostas

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## 1 Prática 7

Aprendizado Dinâmico

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MBA em Ciências de Dados

Nesta prática vamos considerar redes dinâmicas para modelar a temperatura global dos dados em globaltemp.

### 1.Faça a leitura das bibliotecas.

```
[1]: import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
```

### 2. Leia os dados do arquivo globaltemp.csv.

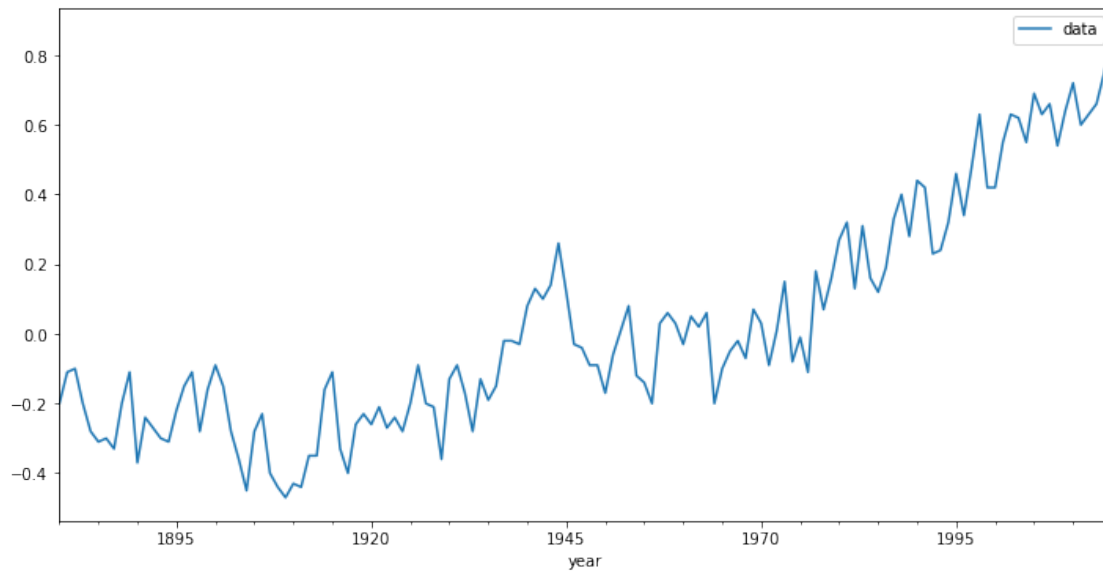
```
[2]: # Temperatura global

# Diferenças na média de temperatura global.
# Fonte: https://github.com/mjuez/pytsdatasets/

pkgdir = '/home/cibele/CibelePython/AprendizadoDinamico/Data'

df = pd.read_csv(f'{pkgdir}/globaltemp.csv', index_col=0,
                 parse_dates=True)
df.index = df.index
df.plot(figsize=(12,6))
```

```
[2]: <matplotlib.axes._subplots.AxesSubplot at 0x7fedb08a0690>
```



```
[3]: df.head()
```

```
[3]:          data
year
1880-01-01 -0.20
1881-01-01 -0.11
1882-01-01 -0.10
1883-01-01 -0.20
1884-01-01 -0.28
```

## 1.1

**3. Divida a base em treino e teste, deixando 14 dias para a previsão.**

```
[4]: len(df)
```

```
[4]: 136
```

```
[5]: len(df)-14
```

```
[5]: 122
```

```
[6]: train = df.iloc[:122]
     test  = df.iloc[122:]
```

```
[7]: train
```

```
[7]: data
      year
1880-01-01 -0.20
1881-01-01 -0.11
1882-01-01 -0.10
1883-01-01 -0.20
1884-01-01 -0.28
...
1997-01-01  0.48
1998-01-01  0.63
1999-01-01  0.42
2000-01-01  0.42
2001-01-01  0.55

[122 rows x 1 columns]
```

#### 4. Padronize os dados para a modelagem.

```
[8]: from sklearn.preprocessing import MinMaxScaler
```

```
[9]: scaler = MinMaxScaler()
```

```
[10]: scaler.fit(train)
```

```
[10]: MinMaxScaler(copy=True, feature_range=(0, 1))
```

```
[11]: scaled_train = scaler.transform(train)
      scaled_test = scaler.transform(test)
```

#### 5. Considere o gerador de séries temporais, com variados valores para os parâmetros `length` e `batch_size`.

```
[15]: from keras.preprocessing.sequence import TimeseriesGenerator
```

```
[16]: # defina o gerador
      n_input = 2
      n_features = 1
      generator = TimeseriesGenerator(scaled_train, scaled_train, length=n_input,
      ↪ batch_size=1)
```

```
[17]: len(scaled_train)
```

```
[17]: 122
```

```
[18]: len(generator) # n_input = 2
```

```
[18]: 120
```

```
[19]: # Qual é a aparência do primeiro lote?  
X,y = generator[0]
```

```
[20]: print(f'Dado o array: \n{X.flatten()}');  
print(f'Previsão: \n {y}');
```

```
Dado o array:  
[0.24545455 0.32727273]  
Previsão:  
[[0.33636364]]
```

## 6. Carregue as bibliotecas do keras para as redes dinâmicas.

```
[21]: from keras.models import Sequential  
from keras.layers import Dense  
from keras.layers import LSTM
```

## 7. Defina os lotes pra o processo iterativo.

```
[22]: # Vamos redefinir lotes de tamanho 21 para o procedimento iterativo  
# Veja mais informações sobre o tamanho do lote http://deeplearningbook.com.br/o-efeito-do-batch-size-no-treinamento-de-redes-neurais-artificiais/  
  
n_input = 7  
n_features = 1  
generator = TimeseriesGenerator(scaled_train, scaled_train, length=n_input,   
                                batch_size=1)
```

## 8. Defina o modelo. Ele pode ter uma camada LSTM e uma camada Dense. Teste alternativas.

```
[23]: # Defina o modelo  
model = Sequential()  
model.add(LSTM(100, activation='relu', input_shape=(n_input, n_features)))  
model.add(Dense(1))  
model.compile(optimizer='adam', loss='mse')
```

```
[24]: model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 100)	40800
dense (Dense)	(None, 1)	101

Total params: 40,901  
Trainable params: 40,901

Non-trainable params: 0

## 9. Faça o ajuste do modelo e observe a função de perda.

```
[25]: # Ajuste do modelo
```

```
model.fit_generator(generator, epochs=100)
```

WARNING:tensorflow:From <ipython-input-25-5e7daf52724a>:3: Model.fit\_generator (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future version.

Instructions for updating:

Please use Model.fit, which supports generators.

Epoch 1/100

115/115 [=====] - 1s 6ms/step - loss: 0.0438

Epoch 2/100

115/115 [=====] - 0s 3ms/step - loss: 0.0132

Epoch 3/100

115/115 [=====] - 0s 4ms/step - loss: 0.0125

Epoch 4/100

115/115 [=====] - 0s 3ms/step - loss: 0.0132

Epoch 5/100

115/115 [=====] - 0s 4ms/step - loss: 0.0123

Epoch 6/100

115/115 [=====] - 0s 3ms/step - loss: 0.0115

Epoch 7/100

115/115 [=====] - 0s 3ms/step - loss: 0.0112

Epoch 8/100

115/115 [=====] - 0s 3ms/step - loss: 0.0130

Epoch 9/100

115/115 [=====] - 0s 3ms/step - loss: 0.0117

Epoch 10/100

115/115 [=====] - 0s 3ms/step - loss: 0.0112

Epoch 11/100

115/115 [=====] - 0s 3ms/step - loss: 0.0115

Epoch 12/100

115/115 [=====] - 0s 3ms/step - loss: 0.0100

Epoch 13/100

115/115 [=====] - 0s 3ms/step - loss: 0.0114

Epoch 14/100

115/115 [=====] - 0s 3ms/step - loss: 0.0106

Epoch 15/100

115/115 [=====] - 0s 3ms/step - loss: 0.0100

Epoch 16/100

115/115 [=====] - 0s 3ms/step - loss: 0.0107

Epoch 17/100

115/115 [=====] - 1s 5ms/step - loss: 0.0101

Epoch 18/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0102  
Epoch 19/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0102  
Epoch 20/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0101  
Epoch 21/100  
115/115 [=====] - 0s 4ms/step - loss: 0.0102  
Epoch 22/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0102  
Epoch 23/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0104  
Epoch 24/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0099  
Epoch 25/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0098  
Epoch 26/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0097  
Epoch 27/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0102  
Epoch 28/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0092  
Epoch 29/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0104  
Epoch 30/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0096  
Epoch 31/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0098  
Epoch 32/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 33/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 34/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0089  
Epoch 35/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0094  
Epoch 36/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 37/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 38/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0089  
Epoch 39/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0090  
Epoch 40/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0090  
Epoch 41/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0087

Epoch 42/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 43/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0093  
Epoch 44/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0089  
Epoch 45/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0094  
Epoch 46/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 47/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0088  
Epoch 48/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0087  
Epoch 49/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0090  
Epoch 50/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0092  
Epoch 51/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0101  
Epoch 52/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 53/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0087  
Epoch 54/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 55/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 56/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 57/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0088  
Epoch 58/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0089  
Epoch 59/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0088  
Epoch 60/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 61/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 62/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0082  
Epoch 63/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 64/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0083  
Epoch 65/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085

Epoch 66/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0084  
Epoch 67/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 68/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0087  
Epoch 69/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 70/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0083  
Epoch 71/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0083  
Epoch 72/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0088  
Epoch 73/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0091  
Epoch 74/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0090  
Epoch 75/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 76/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0090  
Epoch 77/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0081  
Epoch 78/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 79/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 80/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0086  
Epoch 81/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0081  
Epoch 82/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 83/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0088  
Epoch 84/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0088  
Epoch 85/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 86/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0082  
Epoch 87/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 88/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0084  
Epoch 89/100  
115/115 [=====] - 0s 3ms/step - loss: 0.0078



```

Epoch 90/100
115/115 [=====] - 0s 3ms/step - loss: 0.0087
Epoch 91/100
115/115 [=====] - 0s 3ms/step - loss: 0.0080
Epoch 92/100
115/115 [=====] - 0s 3ms/step - loss: 0.0082
Epoch 93/100
115/115 [=====] - 0s 3ms/step - loss: 0.0082
Epoch 94/100
115/115 [=====] - 0s 3ms/step - loss: 0.0082
Epoch 95/100
115/115 [=====] - 0s 3ms/step - loss: 0.0082
Epoch 96/100
115/115 [=====] - 0s 3ms/step - loss: 0.0082
Epoch 97/100
115/115 [=====] - 0s 3ms/step - loss: 0.0080
Epoch 98/100
115/115 [=====] - 0s 4ms/step - loss: 0.0082
Epoch 99/100
115/115 [=====] - 0s 4ms/step - loss: 0.0080
Epoch 100/100
115/115 [=====] - 0s 3ms/step - loss: 0.0079

```

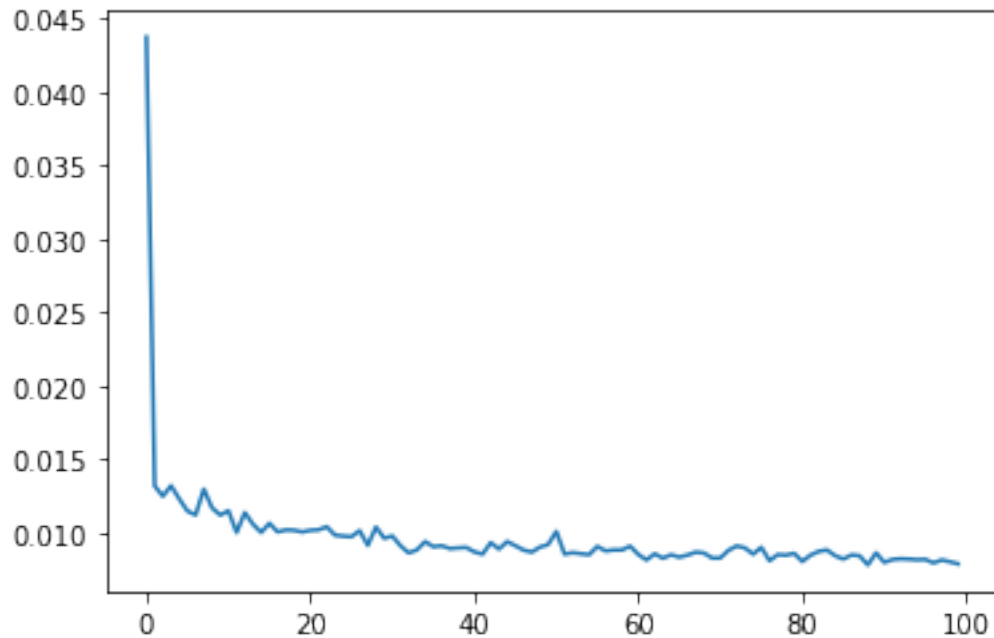
```
[25]: <tensorflow.python.keras.callbacks.History at 0x7fedadcfad90>
```

```
[26]: model.history.history.keys()
```

```
[26]: dict_keys(['loss'])
```

```
[27]: loss_per_epoch = model.history.history['loss']
      plt.plot(range(len(loss_per_epoch)),loss_per_epoch)
```

```
[27]: [<matplotlib.lines.Line2D at 0x7fed60436a50>]
```



## 10. Faça a previsão.

[28]: *# Vejamos passo a passo como é feita a previsão, a princípio para a próxima*  
*→ observação usando o tamanho do lote igual a 7*

```
first_eval_batch = scaled_train[-7:]
```

[29]: first\_eval\_batch

```
[29]: array([[0.84545455],
            [0.73636364],
            [0.86363636],
            [1.          ],
            [0.80909091],
            [0.80909091],
            [0.92727273]])
```

[30]: *# Agora vamos considerar as previsões para as próximas 21 observações e comparar*  
*→ com a base de teste*

```
test_predictions = []
```

```
first_eval_batch = scaled_train[-n_input:]
```

```
current_batch = first_eval_batch.reshape((1, n_input, n_features))
```

```
for i in range(len(test)):
```

```

    # obter a previsão de tempo 1 antecipadamente ([0] é para pegar apenas o
    → número em vez de [array])
    current_pred = model.predict(current_batch)[0]

    # previsão
    test_predictions.append(current_pred)

    # atualize a rodada para agora incluir a previsão e descartar o primeiro
    → valor
    current_batch = np.append(current_batch[:,1:,:], [[current_pred]], axis=1)

```

```
[31]: test_predictions
```

```

[31]: [array([0.8536765], dtype=float32),
       array([0.76443297], dtype=float32),
       array([0.8243903], dtype=float32),
       array([0.945121], dtype=float32),
       array([0.8264261], dtype=float32),
       array([0.8049556], dtype=float32),
       array([0.88539714], dtype=float32),
       array([0.84559166], dtype=float32),
       array([0.7754138], dtype=float32),
       array([0.7949036], dtype=float32),
       array([0.8879841], dtype=float32),
       array([0.81870073], dtype=float32),
       array([0.79119396], dtype=float32),
       array([0.8409509], dtype=float32)]

```

```
[32]: scaled_test
```

```

[32]: array([[1.          ],
             [0.99090909],
             [0.92727273],
             [1.05454545],
             [1.          ],
             [1.02727273],
             [0.91818182],
             [1.00909091],
             [1.08181818],
             [0.97272727],
             [1.          ],
             [1.02727273],
             [1.10909091],
             [1.21818182]])

```

## 11. Retorne da padronização.

```
[33]: true_predictions = scaler.inverse_transform(test_predictions)
```

```
[34]: true_predictions
```

```
[34]: array([[0.46904415],  
          [0.37087626],  
          [0.43682932],  
          [0.56963309],  
          [0.4390687 ],  
          [0.41545116],  
          [0.50393685],  
          [0.46015083],  
          [0.38295519],  
          [0.40439393],  
          [0.50678251],  
          [0.4305708 ],  
          [0.40031336],  
          [0.455046  ]])
```

```
[35]: # Possivelmente encontraremos warnings aqui  
test['Predictions'] = true_predictions
```

```
/home/cibele/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2:  
SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

## 12. Visualize os resultados, comparando as previsões com a base de teste.

```
[36]: test.plot(figsize=(12,8))
```

```
[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7fed60282c10>
```

