Time-Series Forecasting with Deep Learning for Predictive Maintenance

This notebook is the Kaggle notebook version of the notebook I uploaded in [my Github](https://github.com/jegun19/predictive_maintenance)

Select one machine

In this step, we will take a look at the overall characteristic of the data, and then select one machine that we want to analyze and use for doing the predictive maintenance task.

In [1]:

*# Load all csv datas using pandas*

import os

import pandas as pd

WORKING\_DIR = "/kaggle/input/microsoft-azure-predictive-maintenance/"

df\_tele = pd.read\_csv(WORKING\_DIR + 'PdM\_telemetry.csv')

df\_fail = pd.read\_csv(WORKING\_DIR + 'PdM\_failures.csv')

df\_err = pd.read\_csv(WORKING\_DIR + 'PdM\_errors.csv')

df\_maint = pd.read\_csv(WORKING\_DIR + 'PdM\_maint.csv')

In [2]:

*# print the top 5 rows from the failure dataframe*

df\_fail.head(n=5)

Out[2]:

|  | datetime | machineID | failure |
| --- | --- | --- | --- |
| 0 | 2015-01-05 06:00:00 | 1 | comp4 |
| 1 | 2015-03-06 06:00:00 | 1 | comp1 |
| 2 | 2015-04-20 06:00:00 | 1 | comp2 |
| 3 | 2015-06-19 06:00:00 | 1 | comp4 |
| 4 | 2015-09-02 06:00:00 | 1 | comp4 |

For simplicity purpose, we will select a single machine that we are going to use for analysis. In this notebook, we will select machine number 11.

In [3]:

df\_sel = df\_tele.loc[df\_tele['machineID'] == 11].reset\_index(drop=True)

df\_sel.head(n=5)

Out[3]:

|  | datetime | machineID | volt | rotate | pressure | vibration |
| --- | --- | --- | --- | --- | --- | --- |
| 0 | 2015-01-01 06:00:00 | 11 | 164.039259 | 389.699577 | 113.619975 | 29.775109 |
| 1 | 2015-01-01 07:00:00 | 11 | 180.325510 | 409.788550 | 97.506203 | 40.512160 |
| 2 | 2015-01-01 08:00:00 | 11 | 146.917119 | 420.626012 | 97.087205 | 33.420937 |
| 3 | 2015-01-01 09:00:00 | 11 | 164.895416 | 426.409611 | 86.494413 | 40.263365 |
| 4 | 2015-01-01 10:00:00 | 11 | 174.330072 | 471.774231 | 109.277816 | 39.931749 |

Then, we will look into the error and failure record and then filter it only to show records belonging to machine number 11.

In [4]:

*# Check failure record of machine 11*

sel\_fail = df\_fail.loc[df\_fail['machineID'] == 11]

pd.DataFrame(sel\_fail)

Out[4]:

|  | datetime | machineID | failure |
| --- | --- | --- | --- |
| 58 | 2015-01-20 06:00:00 | 11 | comp2 |
| 59 | 2015-02-19 06:00:00 | 11 | comp3 |
| 60 | 2015-04-20 06:00:00 | 11 | comp2 |
| 61 | 2015-04-20 06:00:00 | 11 | comp3 |
| 62 | 2015-10-02 06:00:00 | 11 | comp3 |
| 63 | 2015-12-16 06:00:00 | 11 | comp3 |

In [5]:

*# Check error record of machine 11*

sel\_err = df\_err.loc[df\_err['machineID'] == 11]

pd.DataFrame(sel\_err).head()

Out[5]:

|  | datetime | machineID | errorID |
| --- | --- | --- | --- |
| 360 | 2015-01-19 06:00:00 | 11 | error2 |
| 361 | 2015-01-19 06:00:00 | 11 | error3 |
| 362 | 2015-02-15 01:00:00 | 11 | error4 |
| 363 | 2015-02-18 06:00:00 | 11 | error4 |
| 364 | 2015-02-26 23:00:00 | 11 | error4 |

From the explanation regarding the difference between failure and error in Kaggle, it is described that error refers to non-breaking events while failure refers to events that cause the machine to fail. Then, we will see in chronological plot how does the two events relate to each other.

In [6]:

import matplotlib.pyplot as plt

import matplotlib.dates as mdates

fig, ax = plt.subplots()

*# For a simpler plot, we will use two different values in the y-axis to differentiate between error and failure*

y\_category = list()

for iter **in** range(0, len(sel\_fail)):

y\_category.append('Failure')

for iter **in** range(0, len(sel\_err)):

y\_category.append('Error')

*# Get timestamp from error and selected failure*

df\_timestamp = pd.concat([sel\_fail['datetime'], sel\_err['datetime']], ignore\_index=True, axis=0)

df\_plot = pd.DataFrame({"timestamp": df\_timestamp, "category": y\_category})

df\_plot.loc[:, 'timestamp'] = pd.to\_datetime(df\_plot.loc[:, 'timestamp'])

df\_plot.sort\_values(by=['timestamp'], inplace=True, ignore\_index=True)

*# Plot the data with timestamp as x-axis*

ax.scatter('timestamp', 'category', data = df\_plot)

yearfmt = mdates.DateFormatter('%Y-%m-**%d**')

ax.xaxis.set\_major\_formatter(yearfmt)

ax.tick\_params(axis='x', rotation=45)

ax.grid()

From the plot above, we can see that failures are oftentimes preceded by error in the machine. However, not all error result in immediate failures. Some time may passes before the failure in machine occurs. Thus, in the next step, we are going to focus on the failure data and check which feature is affected by machine's failure.

Feature check

Here, we will select the time window from the failure record, then plot each feature and check their response in the event of failures.

In [7]:

*# Change datatype of the timestamp column from object to datetime*

df\_sel.loc[:, 'datetime'] = pd.to\_datetime(df\_sel.loc[:, 'datetime'])

*# Select the date to check from failure records*

st = df\_sel.loc[df\_sel['datetime'] == "2015-02-19"].index.values[0]

*# Then, filter the telemetry data by the date and allow 7 days before and after*

*# the error occurs to observe any abnormalities.*

select = df\_sel.loc[st-7\*24:st + 7\*24,:]

*# Plot volt and rotation feature*

fig, ax = plt.subplots(nrows=2, sharex=True)

ax[0].plot('datetime', 'volt', data=select)

ax[0].set\_ylabel("Volt")

ax[1].plot('datetime', 'rotate', data=select)

ax[1].tick\_params(axis='x', rotation=45)

ax[1].set\_xlabel("Timestamp")

ax[1].set\_ylabel("Rotation")

Out[7]:

Text(0, 0.5, 'Rotation')

linkcode

As we observe volt and rotation readings, no noticeable anomalies are shown around the period of 2015-02-19. Then, next we will check both pressure and vibration features by plotting them.

In [8]:

*# Plot pressure and vibration feature*

fig, ax = plt.subplots(nrows=2, sharex=True)

ax[0].plot('datetime', 'pressure', data=select)

ax[0].set\_ylabel("Pressure")

ax[1].plot('datetime', 'vibration', data=select)

ax[1].tick\_params(axis='x', rotation=45)

ax[1].set\_xlabel("Timestamp")

ax[1].set\_ylabel("Vibration")

Out[8]:

Text(0, 0.5, 'Vibration')

Between pressure and vibration, abnormality around the period of 2015-02-19 is more noticeable. Thus, in the next step, we will use \*\*pressure\*\* as feature and predictor.

Check autocorrelation and partial autocorrelation

In time-series data, it is beneficial to check the autocorrelation and partial autocorrelation function of the data that will influence our model selection and parameter selection.

In [9]:

*# Import plotting function*

from statsmodels.graphics.tsaplots import plot\_acf, plot\_pacf

*# Autocorrelation plot*

plot\_acf(df\_sel['pressure'], lags = 40)

plt.show()

From the autocorrelation plot, we can see that the data is positively correlated up to lags of 40, where the autocorrelation value itself is quite low, indicating that the data does not have a strong autocorrelation properties.

In [10]:

*# Partial autocorrelation plot*

plot\_pacf(df\_sel['pressure'], lags = 40)

plt.show()

From the partial autocorrelation plot, the correlation between values of two different points in time is also quite weak, decaying to zero starting in the 15th lags. This information will be used in determining the lag in the model.

Model Selection

Prepare data input and output

In this notebook, we will use LSTM model, one of the famous prediction model in time-series forecasting task. To use it, first we need to provide input and output data in the correct format.

For our experiment, we will use training data of 1 month containing 2015-02-19 period where failure happened to predict another failure which occurs at 2015-04-20 according to the failure record. The feature used will be the pressure reading and timestamp (one-hot encoded).

In [11]:

import numpy as np

from sklearn.preprocessing import MinMaxScaler

from sklearn.model\_selection import train\_test\_split

*# Select the date to check from failure records*

st\_train = df\_sel.loc[df\_sel['datetime'] == "2015-02-19"].index.values[0]

*# Then, filter the data to include approximately one month window*

start\_period = st\_train - 14\*24

end\_period = st\_train + 14\*24

def create\_feature(start, end):

*# create features from the selected machine*

pressure = df\_sel.loc[start: end, 'pressure']

timestamp = pd.to\_datetime(df\_sel.loc[start: end, 'datetime'])

timestamp\_hour = timestamp.map(lambda x: x.hour)

timestamp\_dow = timestamp.map(lambda x: x.dayofweek)

*# apply one-hot encode for timestamp data*

timestamp\_hour\_onehot = pd.get\_dummies(timestamp\_hour).to\_numpy()

*# apply min-max scaler to numerical data*

scaler = MinMaxScaler()

pressure = scaler.fit\_transform(np.array(pressure).reshape(-1,1))

*# combine features into one*

feature = np.concatenate([pressure, timestamp\_hour\_onehot], axis=1)

X = feature[:-1]

y = np.array(feature[5:,0]).reshape(-1,1)

return X, y, scaler

X, y, pres\_scaler = create\_feature(start\_period, end\_period)

Then, we need to shape the input further into a sequence (3-dimensional numpy array). We will use a function to return input and output sequence where each input sequence consists of 5-points observation. Simply put, observations of the \*\*past five hours\*\* will be used to predict the sensor reading for the next \*\*one hour\*\* .

In [12]:

def shape\_sequence(arr, step, start):

out = list()

for i **in** range(start, arr.shape[0]):

low\_lim = i

up\_lim = low\_lim + step

out.append(arr[low\_lim: up\_lim])

if up\_lim == arr.shape[0]:

*# print(i)*

break

out\_seq = np.array(out)

return out\_seq

*# Shape the sequence according to the length specified*

X\_seq = shape\_sequence(X, 5, 0)

y\_seq = shape\_sequence(y, 1, 0)

*# Separate the input and output for train and validation*

X\_train, X\_val, y\_train, y\_val = train\_test\_split(X\_seq, y\_seq, test\_size=0.2, shuffle=False)

print("Training data shape = ", X\_train.shape)

print("Validation data shape = ", X\_val.shape)

Training data shape = (534, 5, 25)

Validation data shape = (134, 5, 25)

Create prediction model

Create a simple 2-layer LSTM model with input shape matching the shape of the data sequence provided.

In [13]:

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import LSTM, Dense, Dropout

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.losses import MeanSquaredError

from tensorflow.keras.callbacks import ModelCheckpoint

import tensorflow.keras.losses as loss

def create\_model(X\_train, y\_train):

shape = X\_train.shape[1]

feat\_length = X\_train.shape[2]

model = Sequential()

model.add(LSTM(shape, activation='tanh', input\_shape=(shape, feat\_length), return\_sequences=True))

model.add(LSTM(shape, activation='tanh', input\_shape=(shape, feat\_length), return\_sequences=False))

model.add(Dense(shape, activation='relu'))

model.add(Dense(1, activation='linear'))

model.compile(optimizer=Adam(lr=0.035),

loss=loss.mean\_squared\_error)

model.fit(X\_train, y\_train, verbose=1, epochs=500)

return model

model = create\_model(X\_train, y\_train)

User settings:

KMP\_AFFINITY=granularity=fine,verbose,compact,1,0

KMP\_BLOCKTIME=0

KMP\_DUPLICATE\_LIB\_OK=True

KMP\_INIT\_AT\_FORK=FALSE

KMP\_SETTINGS=1

KMP\_WARNINGS=0

Effective settings:

KMP\_ABORT\_DELAY=0

KMP\_ADAPTIVE\_LOCK\_PROPS='1,1024'

KMP\_ALIGN\_ALLOC=64

KMP\_ALL\_THREADPRIVATE=128

KMP\_ATOMIC\_MODE=2

KMP\_BLOCKTIME=0

KMP\_CPUINFO\_FILE: value is not defined

KMP\_DETERMINISTIC\_REDUCTION=false

KMP\_DEVICE\_THREAD\_LIMIT=2147483647

KMP\_DISP\_NUM\_BUFFERS=7

KMP\_DUPLICATE\_LIB\_OK=true

KMP\_ENABLE\_TASK\_THROTTLING=true

KMP\_FORCE\_REDUCTION: value is not defined

KMP\_FOREIGN\_THREADS\_THREADPRIVATE=true

KMP\_FORKJOIN\_BARRIER='2,2'

KMP\_FORKJOIN\_BARRIER\_PATTERN='hyper,hyper'

KMP\_GTID\_MODE=3

KMP\_HANDLE\_SIGNALS=false

KMP\_HOT\_TEAMS\_MAX\_LEVEL=1

KMP\_HOT\_TEAMS\_MODE=0

KMP\_INIT\_AT\_FORK=true

KMP\_LIBRARY=throughput

KMP\_LOCK\_KIND=queuing

KMP\_MALLOC\_POOL\_INCR=1M

KMP\_NUM\_LOCKS\_IN\_BLOCK=1

KMP\_PLAIN\_BARRIER='2,2'

KMP\_PLAIN\_BARRIER\_PATTERN='hyper,hyper'

KMP\_REDUCTION\_BARRIER='1,1'

KMP\_REDUCTION\_BARRIER\_PATTERN='hyper,hyper'

KMP\_SCHEDULE='static,balanced;guided,iterative'

KMP\_SETTINGS=true

KMP\_SPIN\_BACKOFF\_PARAMS='4096,100'

KMP\_STACKOFFSET=64

KMP\_STACKPAD=0

KMP\_STACKSIZE=8M

KMP\_STORAGE\_MAP=false

KMP\_TASKING=2

KMP\_TASKLOOP\_MIN\_TASKS=0

KMP\_TASK\_STEALING\_CONSTRAINT=1

KMP\_TEAMS\_THREAD\_LIMIT=4

KMP\_TOPOLOGY\_METHOD=all

KMP\_USE\_YIELD=1

KMP\_VERSION=false

KMP\_WARNINGS=false

OMP\_AFFINITY\_FORMAT='OMP: pid %P tid %i thread %n bound to OS proc set {%A}'

OMP\_ALLOCATOR=omp\_default\_mem\_alloc

OMP\_CANCELLATION=false

OMP\_DEFAULT\_DEVICE=0

OMP\_DISPLAY\_AFFINITY=false

OMP\_DISPLAY\_ENV=false

OMP\_DYNAMIC=false

OMP\_MAX\_ACTIVE\_LEVELS=1

OMP\_MAX\_TASK\_PRIORITY=0

OMP\_NESTED: deprecated; max-active-levels-var=1

OMP\_NUM\_THREADS: value is not defined

OMP\_PLACES: value is not defined

OMP\_PROC\_BIND='intel'

OMP\_SCHEDULE='static'

OMP\_STACKSIZE=8M

OMP\_TARGET\_OFFLOAD=DEFAULT

OMP\_THREAD\_LIMIT=2147483647

OMP\_WAIT\_POLICY=PASSIVE

KMP\_AFFINITY='verbose,warnings,respect,granularity=fine,compact,1,0'

2022-01-16 09:36:31.158578: I tensorflow/core/common\_runtime/process\_util.cc:146] Creating new thread pool with default inter op setting: 2. Tune using inter\_op\_parallelism\_threads for best performance.

/opt/conda/lib/python3.7/site-packages/keras/optimizer\_v2/optimizer\_v2.py:356: UserWarning: The `lr` argument is deprecated, use `learning\_rate` instead.

"The `lr` argument is deprecated, use `learning\_rate` instead.")

2022-01-16 09:36:31.778067: I tensorflow/compiler/mlir/mlir\_graph\_optimization\_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2)

Epoch 1/500

17/17 [==============================] - 4s 7ms/step - loss: 0.0500

Epoch 2/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0220

Epoch 3/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0215

Epoch 4/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0211

Epoch 5/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0206

Epoch 6/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0208

Epoch 7/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0198

Epoch 8/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0184

Epoch 9/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0180

Epoch 10/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0170

Epoch 11/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0175

Epoch 12/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0183

Epoch 13/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0162

Epoch 14/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0164

Epoch 15/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0152

Epoch 16/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0164

Epoch 17/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0168

Epoch 18/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0157

Epoch 19/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0150

Epoch 20/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0152

Epoch 21/500

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Epoch 22/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0149

Epoch 23/500

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Epoch 24/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0147

Epoch 25/500

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Epoch 26/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0148

Epoch 27/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0156

Epoch 28/500

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Epoch 29/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0150

Epoch 30/500

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Epoch 31/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0147

Epoch 32/500

17/17 [==============================] - 0s 15ms/step - loss: 0.0143

Epoch 33/500

17/17 [==============================] - 0s 10ms/step - loss: 0.0142

Epoch 34/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0141

Epoch 35/500

17/17 [==============================] - 0s 10ms/step - loss: 0.0153

Epoch 36/500

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Epoch 37/500

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Epoch 38/500

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Epoch 39/500

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Epoch 40/500

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Epoch 41/500

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Epoch 42/500

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Epoch 43/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0147

Epoch 44/500

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Epoch 45/500

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Epoch 46/500

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Epoch 47/500

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Epoch 48/500

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Epoch 50/500

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Epoch 51/500

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Epoch 52/500

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Epoch 55/500

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Epoch 56/500

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Epoch 57/500

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Epoch 58/500

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Epoch 59/500

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Epoch 61/500

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Epoch 62/500

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Epoch 63/500

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Epoch 64/500

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Epoch 65/500

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Epoch 66/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0130

Epoch 67/500

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Epoch 70/500

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Epoch 74/500

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Epoch 76/500

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Epoch 77/500

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Epoch 78/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0127

Epoch 79/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0125

Epoch 80/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0121

Epoch 81/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0124

Epoch 82/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0127

Epoch 83/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0125

Epoch 84/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0123

Epoch 85/500

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Epoch 86/500

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Epoch 87/500

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Epoch 88/500

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Epoch 89/500

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Epoch 90/500

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Epoch 91/500

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Epoch 93/500

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Epoch 94/500

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Epoch 95/500

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Epoch 96/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0115

Epoch 97/500

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Epoch 98/500

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Epoch 99/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0115

Epoch 100/500

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Epoch 101/500

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Epoch 102/500

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Epoch 103/500

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Epoch 104/500

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Epoch 105/500

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Epoch 106/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0151

Epoch 107/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0123

Epoch 108/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0115

Epoch 109/500

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Epoch 110/500

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Epoch 111/500

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Epoch 112/500

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Epoch 113/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0116

Epoch 114/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0116

Epoch 115/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0107

Epoch 116/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0104

Epoch 117/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0107

Epoch 118/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0114

Epoch 119/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0110

Epoch 120/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0105

Epoch 121/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0100

Epoch 122/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0100

Epoch 123/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0104

Epoch 124/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0109

Epoch 125/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0100

Epoch 126/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0093

Epoch 127/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0098

Epoch 128/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0093

Epoch 129/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0102

Epoch 130/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0097

Epoch 131/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0093

Epoch 132/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0104

Epoch 133/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0093

Epoch 134/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0093

Epoch 135/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0102

Epoch 136/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0093

Epoch 137/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0090

Epoch 138/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0090

Epoch 139/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0094

Epoch 140/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0109

Epoch 141/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0126

Epoch 142/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0110

Epoch 143/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0102

Epoch 144/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0106

Epoch 145/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0096

Epoch 146/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0093

Epoch 147/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0096

Epoch 148/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0090

Epoch 149/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0086

Epoch 150/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0084

Epoch 151/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0091

Epoch 152/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0096

Epoch 153/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0081

Epoch 154/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0086

Epoch 155/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0085

Epoch 156/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0081

Epoch 157/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0078

Epoch 158/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0078

Epoch 159/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0074

Epoch 160/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0078

Epoch 161/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0077

Epoch 162/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0091

Epoch 163/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0079

Epoch 164/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0075

Epoch 165/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0076

Epoch 166/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0072

Epoch 167/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0075

Epoch 168/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0071

Epoch 169/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0073

Epoch 170/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0069

Epoch 171/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0078

Epoch 172/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0073

Epoch 173/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0075

Epoch 174/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0076

Epoch 175/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0073

Epoch 176/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0071

Epoch 177/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0077

Epoch 178/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0075

Epoch 179/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0068

Epoch 180/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0067

Epoch 181/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0067

Epoch 182/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0067

Epoch 183/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0064

Epoch 184/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0067

Epoch 185/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0078

Epoch 186/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0071

Epoch 187/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0072

Epoch 188/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0070

Epoch 189/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0066

Epoch 190/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0060

Epoch 191/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0071

Epoch 192/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0073

Epoch 193/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0065

Epoch 194/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0066

Epoch 195/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0070

Epoch 196/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0081

Epoch 197/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0069

Epoch 198/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0066

Epoch 199/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0066

Epoch 200/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0059

Epoch 201/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0053

Epoch 202/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0055

Epoch 203/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0058

Epoch 204/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0059

Epoch 205/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0056

Epoch 206/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0066

Epoch 207/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0059

Epoch 208/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0061

Epoch 209/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0057

Epoch 210/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0054

Epoch 211/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0057

Epoch 212/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0055

Epoch 213/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0057

Epoch 214/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0062

Epoch 215/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0069

Epoch 216/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0058

Epoch 217/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0055

Epoch 218/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0055

Epoch 219/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0063

Epoch 220/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0058

Epoch 221/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0054

Epoch 222/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0053

Epoch 223/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0052

Epoch 224/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0048

Epoch 225/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0050

Epoch 226/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0046

Epoch 227/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0043

Epoch 228/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0044

Epoch 229/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0050

Epoch 230/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0067

Epoch 231/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0094

Epoch 232/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0085

Epoch 233/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0074

Epoch 234/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0062

Epoch 235/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0062

Epoch 236/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0062

Epoch 237/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0065

Epoch 238/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0055

Epoch 239/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0054

Epoch 240/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0054

Epoch 241/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0050

Epoch 242/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0052

Epoch 243/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0048

Epoch 244/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0046

Epoch 245/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0048

Epoch 246/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0050

Epoch 247/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0055

Epoch 248/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0048

Epoch 249/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0044

Epoch 250/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0050

Epoch 251/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0049

Epoch 252/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 253/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 254/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 255/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0046

Epoch 256/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 257/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0049

Epoch 258/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0052

Epoch 259/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0053

Epoch 260/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0046

Epoch 261/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0042

Epoch 262/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0044

Epoch 263/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0040

Epoch 264/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 265/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0036

Epoch 266/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0036

Epoch 267/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0045

Epoch 268/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0044

Epoch 269/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0038

Epoch 270/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0039

Epoch 271/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0042

Epoch 272/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0038

Epoch 273/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0033

Epoch 274/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0038

Epoch 275/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0037

Epoch 276/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0038

Epoch 277/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0034

Epoch 278/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 279/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0040

Epoch 280/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 281/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0038

Epoch 282/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0038

Epoch 283/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 284/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 285/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 286/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 287/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 288/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 289/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 290/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0032

Epoch 291/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 292/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0042

Epoch 293/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0042

Epoch 294/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0038

Epoch 295/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0043

Epoch 296/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 297/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0043

Epoch 298/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0041

Epoch 299/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0044

Epoch 300/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 301/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0041

Epoch 302/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 303/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 304/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 305/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0042

Epoch 306/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0046

Epoch 307/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 308/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 309/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 310/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0036

Epoch 311/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0040

Epoch 312/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0041

Epoch 313/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0040

Epoch 314/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0034

Epoch 315/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 316/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 317/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 318/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0035

Epoch 319/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 320/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 321/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0044

Epoch 322/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 323/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0038

Epoch 324/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 325/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0047

Epoch 326/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0049

Epoch 327/500

17/17 [==============================] - 0s 10ms/step - loss: 0.0042

Epoch 328/500

17/17 [==============================] - 0s 10ms/step - loss: 0.0039

Epoch 329/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0034

Epoch 330/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0033

Epoch 331/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0036

Epoch 332/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0035

Epoch 333/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0032

Epoch 334/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 335/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0027

Epoch 336/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0030

Epoch 337/500

17/17 [==============================] - 0s 11ms/step - loss: 0.0030

Epoch 338/500

17/17 [==============================] - 0s 8ms/step - loss: 0.0029

Epoch 339/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 340/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0036

Epoch 341/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 342/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 343/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0030

Epoch 344/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 345/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0028

Epoch 346/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0029

Epoch 347/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0032

Epoch 348/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 349/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0026

Epoch 350/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0030

Epoch 351/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0044

Epoch 352/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0042

Epoch 353/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0038

Epoch 354/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0034

Epoch 355/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0033

Epoch 356/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0032

Epoch 357/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0036

Epoch 358/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 359/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0026

Epoch 360/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0024

Epoch 361/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0024

Epoch 362/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0026

Epoch 363/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0028

Epoch 364/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0026

Epoch 365/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0028

Epoch 366/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 367/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0027

Epoch 368/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0029

Epoch 369/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0029

Epoch 370/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0027

Epoch 371/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0027

Epoch 372/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0027

Epoch 373/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0027

Epoch 374/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 375/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0029

Epoch 376/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0036

Epoch 377/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0034

Epoch 378/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0028

Epoch 379/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0028

Epoch 380/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0029

Epoch 381/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0027

Epoch 382/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 383/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 384/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 385/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0034

Epoch 386/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0034

Epoch 387/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 388/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 389/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 390/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 391/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 392/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0032

Epoch 393/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0032

Epoch 394/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0032

Epoch 395/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 396/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0026

Epoch 397/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0022

Epoch 398/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0021

Epoch 399/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0022

Epoch 400/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0020

Epoch 401/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0022

Epoch 402/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0024

Epoch 403/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0028

Epoch 404/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0028

Epoch 405/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 406/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 407/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0029

Epoch 408/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 409/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0037

Epoch 410/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0040

Epoch 411/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0045

Epoch 412/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0034

Epoch 413/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 414/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0034

Epoch 415/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 416/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0029

Epoch 417/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 418/500

17/17 [==============================] - 0s 5ms/step - loss: 0.0029

Epoch 419/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0026

Epoch 420/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0026

Epoch 421/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0026

Epoch 422/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 423/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0043

Epoch 424/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0050

Epoch 425/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0048

Epoch 426/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0047

Epoch 427/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0036

Epoch 428/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0040

Epoch 429/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0037

Epoch 430/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0040

Epoch 431/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 432/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0028

Epoch 433/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0024

Epoch 434/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0026

Epoch 435/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0026

Epoch 436/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0022

Epoch 437/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0025

Epoch 438/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0025

Epoch 439/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0029

Epoch 440/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0029

Epoch 441/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0041

Epoch 442/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 443/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0032

Epoch 444/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0028

Epoch 445/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0026

Epoch 446/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0022

Epoch 447/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0022

Epoch 448/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0020

Epoch 449/500

17/17 [==============================] - 0s 9ms/step - loss: 0.0016

Epoch 450/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0015

Epoch 451/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0014

Epoch 452/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0014

Epoch 453/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0018

Epoch 454/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0016

Epoch 455/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0016

Epoch 456/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0021

Epoch 457/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0018

Epoch 458/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0021

Epoch 459/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0022

Epoch 460/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0027

Epoch 461/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0020

Epoch 462/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0019

Epoch 463/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 464/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0039

Epoch 465/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0035

Epoch 466/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 467/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0037

Epoch 468/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 469/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 470/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 471/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0032

Epoch 472/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0055

Epoch 473/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0054

Epoch 474/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0064

Epoch 475/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0052

Epoch 476/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0043

Epoch 477/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0042

Epoch 478/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0034

Epoch 479/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0033

Epoch 480/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0033

Epoch 481/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0030

Epoch 482/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0036

Epoch 483/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0033

Epoch 484/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0034

Epoch 485/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0031

Epoch 486/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0024

Epoch 487/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0024

Epoch 488/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0031

Epoch 489/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0024

Epoch 490/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0023

Epoch 491/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0026

Epoch 492/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0023

Epoch 493/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0020

Epoch 494/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0022

Epoch 495/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0022

Epoch 496/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0020

Epoch 497/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0021

Epoch 498/500

17/17 [==============================] - 0s 7ms/step - loss: 0.0018

Epoch 499/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0016

Epoch 500/500

17/17 [==============================] - 0s 6ms/step - loss: 0.0013

Check validation result

We will check the model's performance with validation data.

In [14]:

*# Predict validation data using the trained model*

y\_pred = model.predict(X\_val)

mse = MeanSquaredError()

val\_err = mse(y\_val.reshape(-1,1), y\_pred)

print("Validation error = ", val\_err.numpy())

*# Return the value using inverse transform to allow better observation*

plt.plot(pres\_scaler.inverse\_transform(y\_val.reshape(-1,1)), 'k', label='Original')

plt.plot(pres\_scaler.inverse\_transform(y\_pred.reshape(-1,1)), 'r', label='Prediction')

plt.ylabel("Pressure")

plt.xlabel("Datapoint")

plt.title("Validation data prediction")

plt.legend()

plt.show()

Validation error = 0.027960692

Check test result

From the plot, we can see that some of the data points are inaccurate, which can be caused by the highly fluctuating nature of the hourly data points. Next, we will see whether the model can predict the sensor reading correctly in the event of anomalies. We are going to pick another date where failure occurred (2015-04-20).

In [15]:

*# Select the date where another failure occurred*

st\_test = df\_sel.loc[df\_sel['datetime'] == "2015-04-20"].index.values[0]

*# Then, filter the data to include approximately two-weeks window*

start\_period\_test = st\_test - 7\*24

end\_period\_test = st\_test + 7\*24

X\_test, y\_test, test\_scaler = create\_feature(start\_period\_test, end\_period\_test)

*# Shape the sequence*

X\_test\_seq = shape\_sequence(X\_test, 5, 0)

y\_test\_seq = shape\_sequence(y\_test, 1, 0)

*# Predict the testing data*

y\_pred\_test = model.predict(X\_test\_seq)

test\_err = mse(y\_test\_seq.reshape(-1,1), y\_pred\_test)

print("Testing error = ", test\_err.numpy())

*# Select first 200 datapoints to allow for better plotting*

*# Return the value using inverse transform to allow better observation*

plt.plot(test\_scaler.inverse\_transform(y\_pred\_test[:200].reshape(-1, 1)), 'r', label='Prediction')

plt.plot(test\_scaler.inverse\_transform(y\_test\_seq[:200].reshape(-1, 1)), 'k', label='Original')

plt.ylabel("Pressure")

plt.xlabel("Datapoints")

plt.legend()

plt.show()

Testing error = 0.039156154

We observe that the model can predict the sensor reading even in the event of machine failure. The key here is to make sure that the training data that we use to train include past failure event as well.

Further Steps

Now that we know how to construct a time-series forecasting model to predict anomalies, there are several possible steps on how to develop a complete predictive maintenance solution:

* Develop machine learning / deep learning model to predict the chance of machine breakdown by feeding it prediction results from our developed time-series forecasting model.
* Look into signal processing algorithm to smoothen the signal before feeding it to time-series forecasting model, which could improve model's performance.
* Use bigger subset of data in training process and check how does the model change, better or worse?
* Do hyperparameter optimization to further optimize the performance of time-series forecasting model.

Conclusion

In this notebook, we have looked into an example predictive maintenance data from Kaggle, do some prior analysis on it, and construct a time-series forecasting model that will predict sensor reading values in the future. Hopefully, this notebook could provide some insights regarding how to implement time-series forecasting with deep learning in predictive maintenance.

clc;

clear;

close all;

format long;

data = readmatrix("ĐÀ NẴNG.xlsx");

%data = rows2vars(data);

figure;

plot(data);

%%Divide Data: Training and Testing

numTimeStepsTrain = floor(0.9\*numel(data));

dataTrain = data(1:numTimeStepsTrain+1);

dataTest = data(numTimeStepsTrain+1:end);

%%Standardize Data

mu = mean(dataTrain);

sig = std(dataTrain);

dataTrainStandardized = (dataTrain - mu) / sig;

XTrain = dataTrainStandardized(1:end-1);

YTrain = dataTrainStandardized(2:end);

%%Define LSTM Network

numFeatures = 1;

numResponses = 1;

numHiddenUnits = 200;

layers = [ ...

sequenceInputLayer(numFeatures)

lstmLayer(numHiddenUnits)

fullyConnectedLayer(numResponses)

regressionLayer];

%%Training Options

options = trainingOptions('adam', ...

'MaxEpochs',250, ...

'GradientThreshold',1, ...

'InitialLearnRate',0.005, ...

'LearnRateSchedule','piecewise', ...

'LearnRateDropPeriod',125, ...

'LearnRateDropFactor',0.2, ...

'Verbose',0, ...

'Plots','training-progress');

%%Train Network

net = trainNetwork(XTrain,YTrain,layers,options);

%%Forecast Future Time Steps

dataTestStandardized = (dataTest - mu) / sig;

XTest = dataTestStandardized(1:end-1);

net = predictAndUpdateState(net,XTrain);

[net,YPred] = predictAndUpdateState(net,YTrain(end));

numTimeStepsTest = numel(XTest);

for i = 2:numTimeStepsTest

[net,YPred(:,i)] = predictAndUpdateState(net,YPred(:,i-1),'ExecutionEnvironment','cpu');

end

%%Unstandardize the predictions using the parameters calculated earlie.

YPred = sig\*YPred + mu;

%%RMSE and MAE Calculation

YTest = dataTest(2:end);

rmse = sqrt(mean((YPred-YTest).^2));

%%Plot results

figure;

plot(dataTrain(1:end-1));

hold on;

idx = numTimeStepsTrain:(numTimeStepsTrain+numTimeStepsTest);

plot(idx,[data(numTimeStepsTrain) YPred],'.-');

hold off;

xlabel("Day");

ylabel("Cases");

title("Forecast");

legend(["Observed" "Forecast"]);

figure;

subplot(2,1,1);

plot(YTest);

hold on;

plot(YPred,'.-');

hold off;

legend(["Observed" "Forecast"]);

ylabel("Cases");

title("Forecast");

%display(YPred);

%------------------------------------------------------------------

%do lech trung binh (%)

for i= 1:length(YPred)

data1(i) = abs(YTest(i)-YPred(i))/YTest(i);

end

AVR = mean(data1);

display(floor(AVR\*100));

%--------------------------------------------------------------------

subplot(2,1,2);

stem(YPred - YTest);

xlabel("Day");

ylabel("Error");

title("RMSE = " + rmse);

net = resetState(net);

net = predictAndUpdateState(net,XTrain);

YPred = [];

numTimeStepsTest = numel(XTest);

for i = 1:numTimeStepsTest

[net,YPred(:,i)] = predictAndUpdateState(net,XTest(:,i),'ExecutionEnvironment','cpu');

end

YPred = sig\*YPred + mu;

rmse = sqrt(mean((YPred-YTest).^2));

figure;

subplot(2,1,1)

plot(YTest);

hold on;

plot(YPred,'.-');

hold off;

legend(["Observed" "Predicted"]);

ylabel("Cases");

title("Forecast with Updates");

subplot(2,1,2);

stem(YPred - YTest);

xlabel("Day");

ylabel("Error");

title("RMSE = " + rmse);