MADRAS INSTITUTE OF TECHNOLOGY

DEPARTMENT OF COMPUTER TECHNOLOGY

SUBJECT: DEEP LEARNING

SUBJECT CODE: CS6005

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FINAL PROJECT REPORT

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Predictive Maintenance for Turbofan Aircraft Engines Using LSTM

ABSTRACT:

This project implements predictive maintenance for turbofan aircraft engines using LSTM networks. With a focus on enhancing reliability and efficiency in the aviation industry, the LSTM model predicts the Remaining Useful Life (RUL) of engine components. By leveraging advanced deep learning techniques, including data preprocessing and sequence generation, the project aims to optimize maintenance schedules, reduce downtime, and improve overall safety and operational success.

DATASET:

Data sets consist of multiple multivariate time series. Each data set is further divided into training and test subsets. Each time series is from a different engine i.e., the data can be considered to be from a fleet of engines of the same type. There are three operational settings that have a substantial effect on engine performance. These settings are also included in the data. The data is contaminated with sensor noise. The engine is operating normally at the start of each time series, and develops a fault at some point during the series. In the training set, the fault grows in magnitude until system failure. In the test set, the time series ends some time prior to system failure. The objective of the competition is to predict the number of remaining operational cycles before failure in the test set, i.e., the number of operational cycles after the last cycle that the engine will continue to operate. Also provided a vector of true Remaining Useful Life (RUL) values for the test data.

The data are provided with 26 columns of numbers, separated by spaces. Each row is a snapshot of data taken during a single operational cycle, each column is a different variable. The columns correspond to:

1) unit number
2) time, in cycles
3) operational setting 1
4) operational setting 2
5) operational setting 3
6) sensor measurement 1
7) sensor measurement 2

…

26) sensor measurement 26

IMPLEMENTATION:

```python
import keras
import keras.backend as K
from keras.layers import Activation
from keras.models import Sequential,load_model
from keras.layers import Dense, Dropout, LSTM

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
from sklearn import preprocessing
from tensorflow import keras
```

```python
# Setting seed for reproducibility
np.random.seed(1234)
PYTHONHASHSEED = 0
```

```python
# read training data - It is the aircraft engine run-to-failure data.
# read test data - It is the aircraft engine operating data without failure events recorded.
# read ground truth data - It contains the information of true remaining cycles for each
#  engine in the testing data.
train_df = pd.read_csv('/content/PM_train.txt', sep=" ", header=None)
test_df = pd.read_csv('/content/PM_test.txt', sep=" ", header=None)
truth_df = pd.read_csv('/content/PM_truth.txt', sep=" ", header=None)
```

```python
# Drop missing data columns(redundant)
train_df.drop(train_df.columns[[26, 27]], axis=1, inplace=True)
test_df.drop(test_df.columns[[26, 27]], axis=1, inplace=True)
truth_df.drop(truth_df.columns[[1]], axis=1, inplace=True)
```


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test_df.drop(test_df.columns[[26, 27]], axis=1, inplace=True)
truth_df.drop(truth_df.columns[[1]], axis=1, inplace=True)
```


```python
# Sorting and indicating columns
train_df.columns = ['id', 'cycle', 'setting1', 'setting2', 'setting3', 's1', 's2', 's3',
                     's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13', 's14',
                     's15', 's16', 's17', 's18', 's19', 's20', 's21']

train_df = train_df.sort_values(['id','cycle'])

test_df.columns = ['id', 'cycle', 'setting1', 'setting2', 'setting3', 's1', 's2', 's3',
                    's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13', 's14',
                    's15', 's16', 's17', 's18', 's19', 's20', 's21']
```

```python
train_df
```

	id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	...	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	521.66	2388.02	8138.62	8.4195	0.03	392	2388	100.0	39.06	23.4190
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	522.28	2388.07	8131.49	8.4318	0.03	392	2388	100.0	39.00	23.4236

<u>Data Preprocessing:</u>

We initiated the project by cleaning and transforming raw sensor data into sequences suitable for LSTM training. The code involved handling missing values, normalizing data, and preparing it for input into the neural network.

```python
# Data Preprocessing - Train data
# Data Labeling - generate column RUL(Remaining Usefull Life)
rul = pd.DataFrame(train_df.groupby('id')['cycle'].max()).reset_index()
rul.columns = ['id', 'max']
train_df = train_df.merge(rul, on=['id'], how='left')
train_df['RUL'] = train_df['max'] - train_df['cycle']
train_df.drop('max', axis=1, inplace=True)

# MinMax normalization (from 0 to 1)
train_df['cycle_norm'] = train_df['cycle']
cols_normalize = train_df.columns.difference(['id', 'cycle', 'RUL'])
min_max_scaler = preprocessing.MinMaxScaler()
norm_train_df = pd.DataFrame(min_max_scaler.fit_transform(train_df[cols_normalize]),
                             columns=cols_normalize,
                             index=train_df.index)
join_df = train_df[train_df.columns.difference(cols_normalize)].join(norm_train_df)
train_df = join_df.reindex(columns=train_df.columns)

print(train_df)
```

```
        id  cycle  setting1  setting2  setting3   s1        s2        s3  \
0        1      1  0.459770  0.166667       0.0  0.0  0.183735  0.406802
1        1      2  0.609195  0.250000       0.0  0.0  0.283133  0.453019
2        1      3  0.252874  0.750000       0.0  0.0  0.343373  0.369523
3        1      4  0.540230  0.500000       0.0  0.0  0.343373  0.256159
4        1      5  0.390805  0.333333       0.0  0.0  0.349398  0.257467
...    ...    ...       ...       ...       ...  ...       ...       ...
20626  100    196  0.477011  0.250000       0.0  0.0  0.686747  0.587312
20627  100    197  0.408046  0.083333       0.0  0.0  0.701807  0.729453
20628  100    198  0.522989  0.500000       0.0  0.0  0.665663  0.684979
20629  100    199  0.436782  0.750000       0.0  0.0  0.608434  0.746021
20630  100    200  0.316092  0.083333       0.0  0.0  0.795181  0.639634

             s4   s5  ...       s14       s15  s16       s17  s18  s19  \
0      0.309757  0.0  ...  0.199608  0.363986  0.0  0.333333  0.0  0.0
1      0.352633  0.0  ...  0.162813  0.411312  0.0  0.333333  0.0  0.0
```

```python
# Data Preprocessing - Test data
# MinMax normalization (from 0 to 1)
test_df['cycle_norm'] = test_df['cycle']
norm_test_df = pd.DataFrame(min_max_scaler.transform(test_df[cols_normalize]),
                            columns=cols_normalize,
                            index=test_df.index)
test_join_df = test_df[test_df.columns.difference(cols_normalize)].join(norm_test_df)
test_df = test_join_df.reindex(columns=test_df.columns)
test_df = test_df.reset_index(drop=True)

# We use the ground truth dataset to generate labels for the test data.
# generate column max for test data
rul = pd.DataFrame(test_df.groupby('id')['cycle'].max()).reset_index()
rul.columns = ['id', 'max']
truth_df.columns = ['more']
truth_df['id'] = truth_df.index + 1
truth_df['max'] = rul['max'] + truth_df['more']
truth_df.drop('more', axis=1, inplace=True)

# generate RUL for test data
test_df = test_df.merge(truth_df, on=['id'], how='left')
test_df['RUL'] = test_df['max'] - test_df['cycle']
test_df.drop('max', axis=1, inplace=True)

print(test_df)
```

```
        id  cycle  setting1  setting2  setting3   s1        s2        s3  \
0        1      1  0.632184  0.750000       0.0  0.0  0.545181  0.310661
1        1      2  0.344828  0.250000       0.0  0.0  0.150602  0.379551
2        1      3  0.517241  0.583333       0.0  0.0  0.376506  0.346632
3        1      4  0.741379  0.500000       0.0  0.0  0.370482  0.285154
4        1      5  0.580460  0.500000       0.0  0.0  0.391566  0.352082
...    ...    ...       ...       ...       ...  ...       ...       ...
13091  100    194  0.781609  0.500000       0.0  0.0  0.611446  0.619359
```

```python
# Window size extension to 60
sequence_length = 60

# function to reshape features into (samples, time steps, features)
def gen_sequence(id_df, seq_length, seq_cols):
    data_matrix = id_df[seq_cols].values
    num_elements = data_matrix.shape[0]
    for start, stop in zip(range(0, num_elements - seq_length), range(seq_length, num_elements)):
        yield data_matrix[start:stop, :]


# pick the feature columns
sensor_cols = ['s' + str(i) for i in range(1, 22)]
sequence_cols = ['setting1', 'setting2', 'setting3', 'cycle_norm']
sequence_cols.extend(sensor_cols)

# print(sequence_cols)
# val is a list of 192 - 60 = 142 bi-dimensional array (60 rows x 25 columns)
val = list(gen_sequence(train_df[train_df['id'] == 1], sequence_length, sequence_cols))
print(len(val))

# generator for the sequences
# transform each id of the train dataset in a sequence
seq_gen = (list(gen_sequence(train_df[train_df['id'] == id], sequence_length, sequence_cols))
           for id in train_df['id'].unique())

# generate sequences and convert to numpy array
seq_array = np.concatenate(list(seq_gen)).astype(np.float32)
print(seq_array.shape)
```

```
132
(14631, 60, 25)
```

LSTM Model Training:

- Designed and trained an LSTM-based neural network capable of capturing the complex temporal patterns inherent in turbofan engine data. The model was configured with two LSTM layers, dropout regularization, and a dense output layer for regression.
- Defines a custom metric r2_keras, which calculates the R-squared value. R-squared is a measure of how well the predicted values match the actual values.

- (nb_features) determine the number of features in the input data and (nb_out) determines the number of output units in the final layer.

```
[ ] # function to generate labels
    def gen_labels(id_df, seq_length, label):
        data_matrix = id_df[label].values
        num_elements = data_matrix.shape[0]
        return data_matrix[seq_length:num_elements, :]

    # generate labels
    label_gen = [gen_labels(train_df[train_df['id'] == id], sequence_length, ['RUL'])
                 for id in train_df['id'].unique()]

    label_array = np.concatenate(label_gen).astype(np.float32)
    print(label_array.shape)
    print(label_array[:10])
```

```
(14631, 1)
[[131.]
 [130.]
 [129.]
 [128.]
 [127.]
 [126.]
 [125.]
 [124.]
 [123.]
 [122.]]
```

```
[ ] # Modeling
    model_path = 'regression_model.h5'

    def r2_keras(y_true, y_pred):
        SS_res = K.sum(K.square(y_true - y_pred))
        SS_tot = K.sum(K.square(y_true - K.mean(y_true)))
        return (1 - SS_res / (SS_tot + K.epsilon()))
```

- This block checks if a trained model already exists at the specified path. If it does, it prints a message. Otherwise, it initializes a new model.
- The model architecture consists of two LSTM layers with dropout regularization to prevent overfitting.
- The final layer is a dense layer with a linear activation function since this is a regression problem (predicting numerical values).
- The model is compiled with a mean squared error loss function, RMSprop optimizer, and metrics including mean absolute error (mae) and the custom R-squared metric (r2_keras).

```python
# Network Architecture
# The first layer is an LSTM layer with 100 units followed by another LSTM layer with 60 units.
# Dropout is also applied after each LSTM layer to control overfitting.
# Final layer is a Dense output layer with single unit and linear activation
# since this is a regression problem.
nb_features = seq_array.shape[2]
nb_out = label_array.shape[1]

try:
    f = open(model_path)
    print("Trained model already exists")


except IOError:
    print("Initialize a model")
    model = Sequential()
    model.add(LSTM(
        input_shape=(sequence_length, nb_features),
        units=100,
        return_sequences=True))
    model.add(Dropout(0.3))
    model.add(LSTM(
        units=sequence_length,
        return_sequences=False))
    model.add(Dropout(0.3))
    model.add(Dense(units=nb_out))
    model.add(Activation("linear"))
    model.compile(loss='mean_squared_error', optimizer='rmsprop', metrics=['mae', r2_keras])

    print(model.summary())

    bs = 400
    # fit the network
    history = model.fit(seq_array, label_array, epochs=100, batch_size=bs, validation_split=0.1, verbose=1,
```

Model Summary & Training:

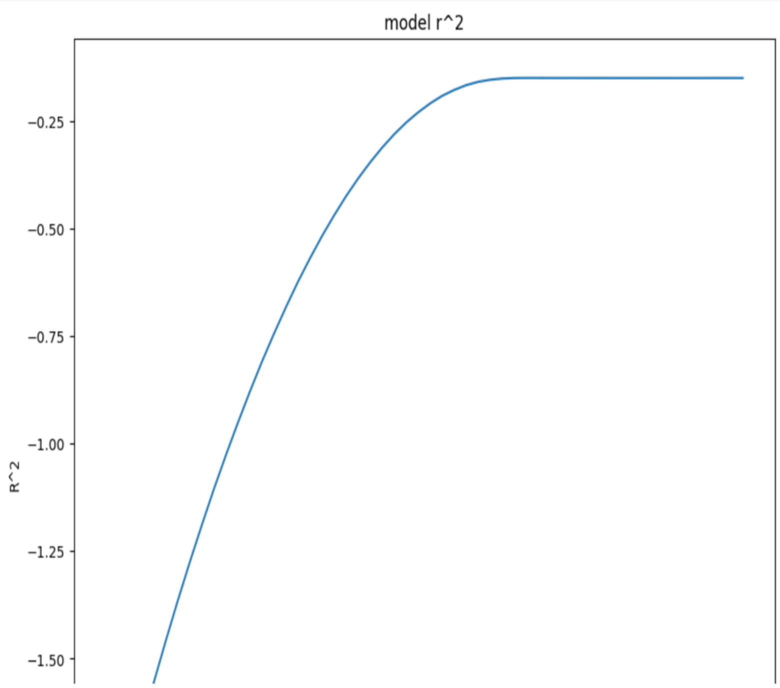
```
Initialize a model
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 60, 100)           50400

 dropout (Dropout)           (None, 60, 100)           0

 lstm_1 (LSTM)               (None, 60)                38640

 dropout_1 (Dropout)         (None, 60)                0

 dense (Dense)               (None, 1)                 61

 activation (Activation)     (None, 1)                 0

=================================================================
Total params: 89101 (348.05 KB)
Trainable params: 89101 (348.05 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
Epoch 1/100
33/33 [==============================] - 24s 587ms/step - loss: 7692.8169 - mae: 69.9096 - r2_keras: -1.6645 - val_loss: 10071.2383 - val_mae: 79.2196 - val_
Epoch 2/100
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This f
  saving_api.save_model(
33/33 [==============================] - 20s 622ms/step - loss: 7130.9102 - mae: 66.4162 - r2_keras: -1.4667 - val_loss: 9738.9863 - val_mae: 77.4406 - val_
Epoch 3/100
33/33 [==============================] - 18s 559ms/step - loss: 6865.6582 - mae: 64.7802 - r2_keras: -1.3743 - val_loss: 9435.2812 - val_mae: 75.8214 - val_
Epoch 4/100
33/33 [==============================] - 21s 634ms/step - loss: 6618.3130 - mae: 63.2534 - r2_keras: -1.2902 - val_loss: 9144.7920 - val_mae: 74.2793 - val_
Epoch 5/100
33/33 [==============================] - 19s 565ms/step - loss: 6380.8789 - mae: 61.7995 - r2_keras: -1.2082 - val_loss: 8861.9355 - val_mae: 72.7843 - val_
Epoch 6/100
```

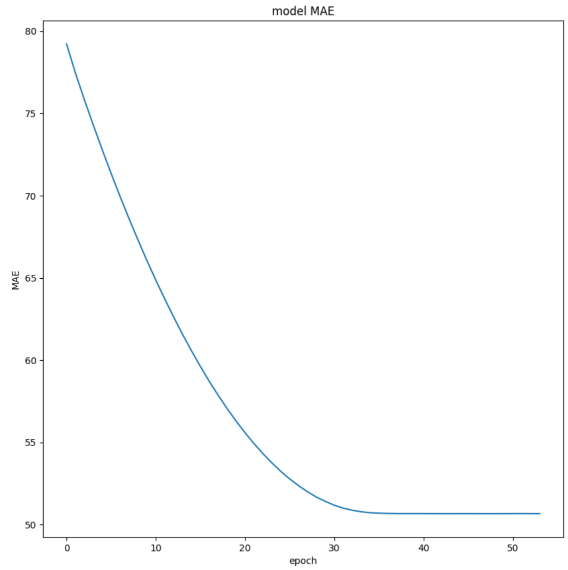
Visualization and Verification:

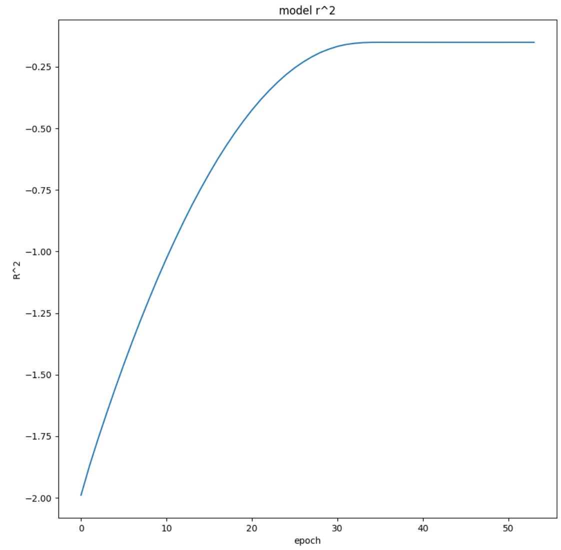
The project included visualizing model performance through plots of R-squared, MAE, and loss across epochs. Additionally, we verified predictions against actual data to ensure the model's effectiveness.

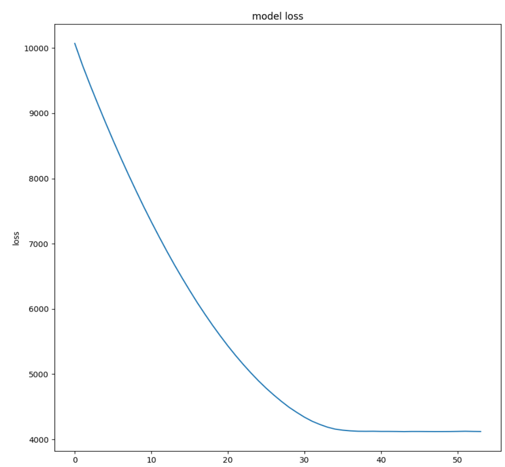
```
[ ] # summarize history for R^2
    fig_acc = plt.figure(figsize=(10, 10))
    plt.plot(history.history['val_r2_keras'])
    plt.title('model r^2')
    plt.ylabel('R^2')
    plt.xlabel('epoch')
    plt.show()
    fig_acc.savefig("model_r2.png")

    # summarize history for MAE
    fig_acc = plt.figure(figsize=(10, 10))
    plt.plot(history.history['val_mae'])
    plt.title('model MAE')
    plt.ylabel('MAE')
    plt.xlabel('epoch')
    plt.show()
    fig_acc.savefig("model_mae.png")

    # summarize history for Loss
    fig_acc = plt.figure(figsize=(10, 10))
    plt.plot(history.history['val_loss'])
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.show()
    fig_acc.savefig("model_regression_loss.png")
```

```
plt.show()
fig_acc.savefig("model_regression_loss.png")
```









Model Evaluation:

We evaluated the model using various metrics, including Mean Absolute Error (MAE) and R-squared (R^2), to assess its accuracy and reliability in predicting Remaining Useful Life (RUL).

```
[ ] # training metrics
    scores = model.evaluate(seq_array, label_array, verbose=1, batch_size=bs)
    print('\nMAE: {}'.format(scores[1]))
    print('\nR^2: {}'.format(scores[2]))

    y_pred = model.predict(seq_array, verbose=1, batch_size=bs)
    y_true = label_array

    test_set = pd.DataFrame(y_pred)
    test_set.to_csv('submit_train.csv', index=None)
```

```
37/37 [==============================] - 7s 201ms/step - loss: 3023.9824 - mae: 44.0437 - r2_keras: -0.0958

MAE: 44.0436897277832

R^2: -0.09582436084747314
37/37 [==============================] - 8s 199ms/step
```

```python
# Test data validation

# We pick the last sequence for each id in the test data
seq_array_test_last = [test_df[test_df['id'] == id][sequence_cols].values[-sequence_length:]
                       for id in test_df['id'].unique() if len(test_df[test_df['id'] == id]) >= sequence_length]

seq_array_test_last = np.asarray(seq_array_test_last).astype(np.float32)
print("seq_array_test_last")
# print(seq_array_test_last)
print(seq_array_test_last.shape)

# Similarly, we pick the labels
# print("y_mask")
y_mask = [len(test_df[test_df['id'] == id]) >= sequence_length for id in test_df['id'].unique()]
label_array_test_last = test_df.groupby('id')['RUL'].nth(-1)[y_mask].values
label_array_test_last = label_array_test_last.reshape(label_array_test_last.shape[0], 1).astype(np.float32)
# print(label_array_test_last.shape)

# if best iteration's model was saved then load and use it
if os.path.isfile(model_path):
    estimator = load_model(model_path, custom_objects={'r2_keras': r2_keras})

    # test metrics
    scores_test = estimator.evaluate(seq_array_test_last, label_array_test_last, verbose=2)
    print('\nMAE: {}'.format(scores_test[1]))
    print('\nR^2: {}'.format(scores_test[2]))

    y_pred_test = estimator.predict(seq_array_test_last)
    y_true_test = label_array_test_last


    pd.set_option('display.max_rows', 1000)
    test_print = pd.DataFrame()
    test_print['y_pred']  = y_pred_test.flatten()
```


```python
    test_print['y_pred']  = y_pred_test.flatten()
```


```python
    test_print['y_truth'] = y_true_test.flatten()
    test_print['diff'] = abs(y_pred_test.flatten() - y_true_test.flatten())
    test_print['diff(%)'] = abs(y_pred_test.flatten() - y_true_test.flatten())/y_true_test.flatten()
    print (test_print)



    test_set = pd.DataFrame(y_pred_test)
    test_set.to_csv('submit_test.csv', index=None)

    # Plot in blue color the predicted data and in green color the
    # actual data to verify visually the accuracy of the model.
    fig_verify = plt.figure(figsize=(12, 6))
    plt.plot(y_pred_test, color="blue")
    plt.plot(y_true_test, color="red")
    plt.title('prediction')
    plt.ylabel('value')
    plt.xlabel('row')
    plt.legend(['predicted', 'actual data'], loc='upper left')
    plt.show()
    fig_verify.savefig("model_regression_verify.png")
```

```
seq_array_test_last
(88, 60, 25)
3/3 - 1s - loss: 1747.5782 - mae: 36.1818 - r2_keras: -4.6432e-02 - 961ms/epoch - 320ms/step

MAE: 36.181819915771484

R^2: -0.04643185809254646
3/3 [==============================] - 1s 22ms/step
       y_pred  y_truth       diff    diff(%)
0   78.197372     69.0   9.197372   0.133295
1   78.197372     82.0   3.802628   0.046374
2   78.197372     91.0  12.802628   0.140688
```


```
seq_array_test_last
(88, 60, 25)
3/3 - 1s - loss: 1747.5782 - mae: 36.1818 - r2_keras: -4.6432e-02 - 961ms/epoch - 320ms/step

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1   78.197372     82.0   3.802628   0.046374
2   78.197372     91.0  12.802628   0.140688
```


```
3   78.197372     93.0  14.802628   0.159168
4   78.197365     91.0  12.802635   0.140688
5   78.197372     95.0  16.802628   0.176870
6   78.197365     96.0  17.802635   0.185444
7   78.197365     97.0  18.802635   0.193842
8   78.197365    124.0  45.802635   0.369376
9   78.197372     95.0  16.802628   0.176870
10  78.197380     83.0   4.802620   0.057863
11  78.197365     84.0   5.802635   0.069079
12  78.197365     50.0  28.197365   0.563947
13  78.197372     28.0  50.197372   1.792763
14  78.197365     87.0   8.802635   0.101180
15  78.197365     16.0  62.197365   3.887335
16  78.197372     57.0  21.197372   0.371884
17  78.197372    113.0  34.802628   0.307988
18  78.197380     20.0  58.197380   2.909869
19  78.197365    119.0  40.802635   0.342879
20  78.197372     66.0  12.197372   0.184809
21  78.197380     97.0  18.802620   0.193841
22  78.197365     90.0  11.802635   0.131140
23  78.197365    115.0  36.802635   0.320023
24  78.197372      8.0  70.197372   8.774672
25  78.197365     48.0  30.197365   0.629112
```