Computer Engineering Department National University of Technology Islamabad, Pakistan

Introduction to Data Mining

Practice Exercise 03

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Practice Exercise 03

Understand and Analyse Weather Data.

Objective:

- Feature extraction and selection from time series- temperature data for complete year (365).

Equipment/Software Required:

- Python (Spyder 4.0 Anaconda Distribution)

Background:

Feature Extraction:

Feature Extraction aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features).
It is nowadays becoming quite common to be working with datasets of hundreds (or even thousands) of features. If the number of features becomes similar (or even bigger!) than the number of observations stored in a dataset then this can most likely lead to a Machine Learning model suffering from overfitting. To avoid this type of problem, it is necessary to apply either regularization or dimensionality reduction techniques (Feature Extraction).

- Feature Extraction techniques have many advantages such as:
- Accuracy improvements.
- Overfitting risk reduction.
- Speed up in training.
- Improved Data Visualization.
- Increase in explain-ability of our model.

Tasks:

- Generate hourly random temperature for each day between range 0 -50 C for 365 days.
  (hint: import random.uniform(low, high) function in python) and plot temperature for 365 days.
- Extract mean temperature per day (hint: 365 values of mean temperature) and plot mean feature.
- Calculate the variance of temperature per day (hint:365 values of variance use np.var() function in Python) and plot variance feature.
- Select the days that had highest variance of temperatures and print days for which variance> threshold.

Code:

```
# Feature extraction from Time Series Data

# importing neccessary python pakages

import matplotlib.pyplot as plt
import numpy as np
import random
import statistics
import pandas as pd
```

```
# defining function for generating random temperature values

def random_floats(low, high, size):
    return [random.uniform(low, high) for _ in range(size)]
print('\n')


# defining array for storing respective values

Temperature_yearly=np.array([])
Temperature=np.array([])
Temperature_mean=np.array([])
Temperature_var=np.array([])


# generating Time Series Temperature, Mean per day, Variance per day
for i in range(365):
    Temperature=random_floats(0, 50, 24)
    Temperature_yearly=np.append(Temperature_yearly,Temperature)
    Temperature_mean=np.append(Temperature_mean ,np.mean(Temperature))
    Temperature_var=np.append(Temperature_var, statistics.variance(Temperature))


# printing shape of respective arrays to confirm the total values
print(Temperature_yearly.shape)
print(Temperature_mean.shape)
print(Temperature_var.shape)


# intializing figure 1 for plotting Temperature values

plt.figure(1, figsize=(10,8))


# plotting temperature per year

plt.subplot(111)
plt.plot(Temperature_yearly, color='purple')
plt.xlabel("Time (One Year)")
plt.ylabel("Temperature")
plt.grid()


# intializing figure 2 for plotting Mean Temperature values

plt.figure(2, figsize=(8,6))


# plotting Mean temperature per day

plt.subplot(111)
plt.plot(Temperature_mean, color='brown')
plt.xlabel("Time (365 Days)")
plt.ylabel("Mean(average) Temperature per Day")
plt.grid()


# intializing figure 2 for plotting Mean Temperature values

plt.figure(3, figsize=(6,4))

# intializing figure 3 for plotting Variance Temperature values

plt.subplot(111)
plt.plot(Temperature_var, color='gray')
plt.xlabel("Time (365 Days)")
plt.ylabel("Variance Temperature per Day")
plt.grid()

# showing all graphs

plt.show()


# Selecting any random value of variances as threshold

threshold=random.choice(Temperature_var)
print("\n")
print("Threshold : ")
print("\n")
print(threshold)


# defining an array for saving variance values greater than threshold

days_above_threshold=np.array([])


# designing algorithm to sort out the day having variance values greater than Threshold

for i in Temperature_var:
        days_above_threshold=np.append(days_above_threshold,np.where(Temperature_var>threshold))

# printing variances above threshold
print("\n","Days above Threshold : ","\n")
print(days_above_threshold)



# converting days_above_threshold in DataFrame

day_above_DataFrame=pd.DataFrame(days_above_threshold)


# exporting days_above_threshold in .csv

day_above_csv=day_above_DataFrame.to_csv("D:\day_above_DataFrame.csv")
```

Output:

```
(8760,)
(365,)
(365,)
```

Threshold:

```
149.48455629372353
```

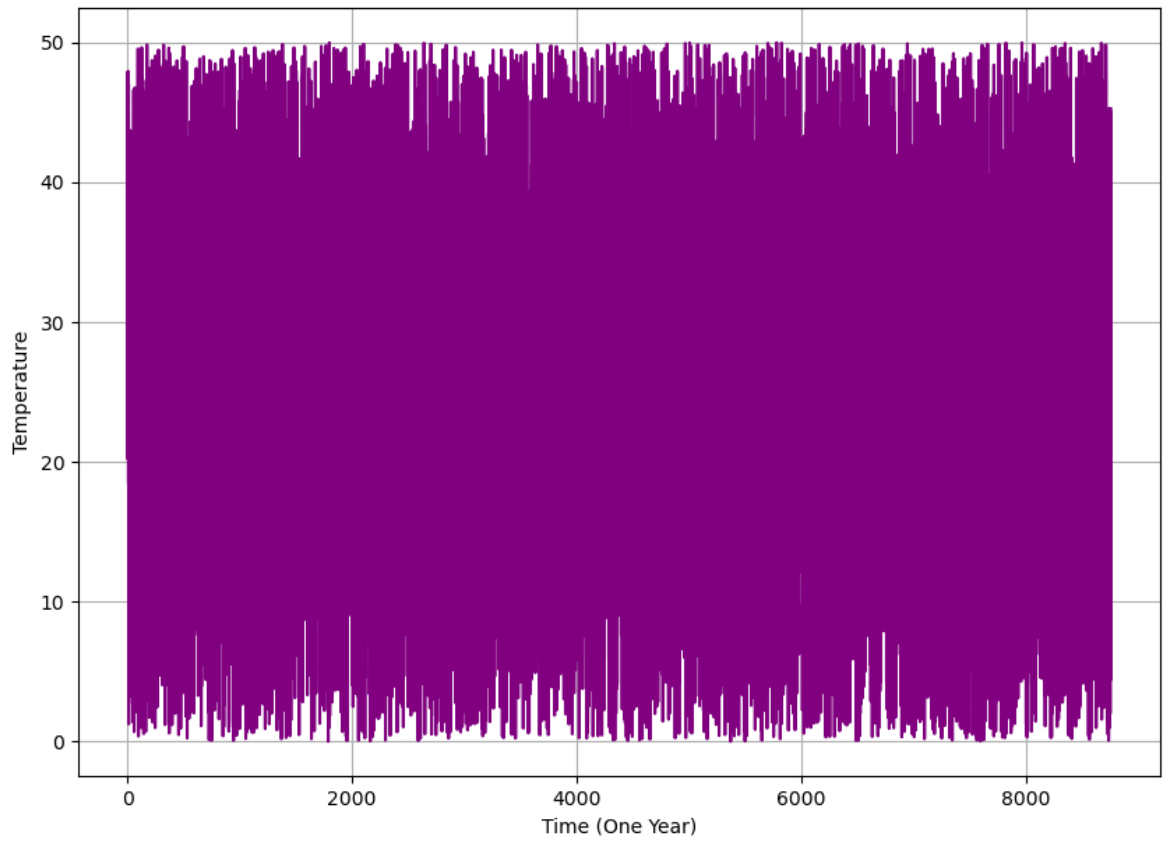
Days above Threshold:

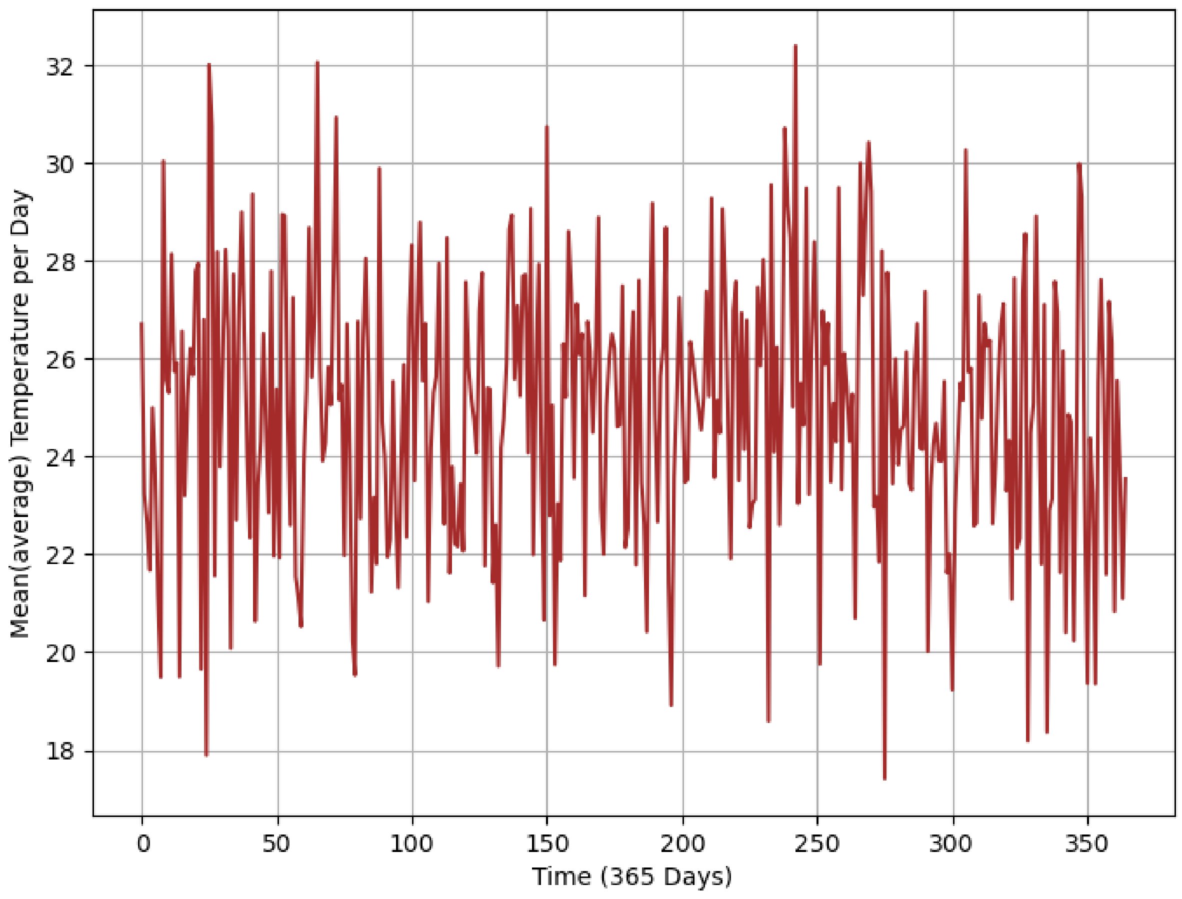
```
[  1.   3.  23. ... 353. 357. 361.]
```

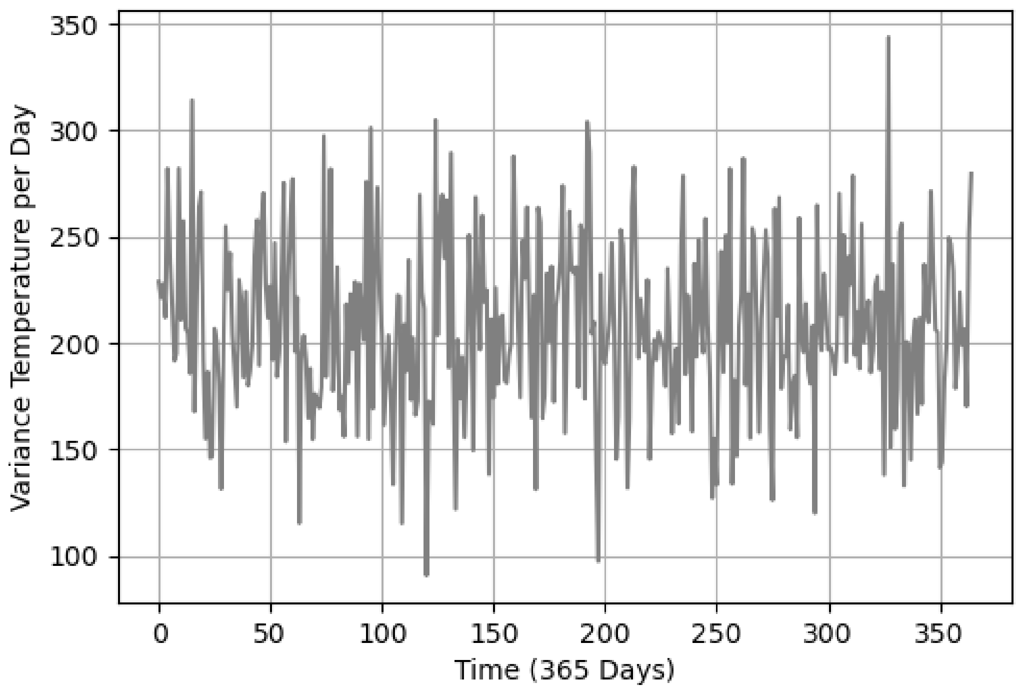
Note: as the array is so large so I am exporting **day_above_threshold** in **.csv** file and giving google drive link below:

https://drive.google.com/file/d/126vCq2nIpDdOhfrlKDRC-CqrdogWvL48/view?usp=sharing

please go through this link and acknowledge my complete results of array.




32
30
28
26
24
22
20
18
Mean(average) Temperature per Day
0
50
100
150
200
250
300
350
Time (365 Days)


350
300
250
200
150
100
Variance Temperature per Day
0
50
100
150
200
250
300
350
Time (365 Days)

Results and Discussions:

In this practical I learned to. Extract features from a random time series temperature data by classification using threshold value. And extract the days which are having variances above to the threshold. As we are choosing days and values randomly so the results are changing at each run of program. The main issue I faced in this practical is designing the algorithms for feature extraction. After completing this practical I realize that this could be very helpful in the field of time series big data manipulation.

The python packages I used in this practical: -

- ✓ NumPy
- ✓ SciPy
- ✓ matplotlib
- ✓ statistics
- ✓ pandas
- ✓ random

Conclusion:

Need of Feature Selection:

As discussed in class when we give our raw data to any machine learning algorithm so the outcome trained model results with very low efficiency because when we exquisite the real-world data so that data has so many irrelative and useless features which are not related with the objective we want to achieve by trained model. So that data actually called noise which can never let a model to achieve the accuracy we expect from model. We generally use to solve this problem by Feature Extraction Techniques.

In Feature Extraction method, we extract/select the optimal feature from our raw data by sub setting a group of features to give algorithm to achieve our expected task with high accuracy.