



A.Y.: 2024-25

Class/Sem: B.E.B.Tech/ Sem-VII

Sub: Quantitative Portfolio Management

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CSE (DS)

Experiment 10

Aim: Compare and analyze the Covariance Estimation for robust estimates

Objective:

- Understand the concept of robust covariance estimation.
- Compare and contrast different robust covariance estimators.
- Apply robust covariance estimation to real data sets.

Theory:

Covariance estimation is a fundamental statistical technique used to measure the relationship between variables in a dataset. However, standard covariance estimators can be highly sensitive to outliers and non-Gaussian data, leading to unreliable and biased results. In practical scenarios where data may be contaminated by noise or extreme observations, robust covariance estimation techniques are essential to obtain accurate and robust estimates.

Traditional covariance estimation methods, such as the sample covariance matrix, assume that the underlying data is normally distributed and free from outliers. However, real-world datasets often violate these assumptions, making the conventional estimators highly susceptible to influential observations. Outliers can substantially distort the covariance matrix, leading to unreliable parameter estimates, increased Type I errors, and reduced statistical power.

Robust covariance estimation addresses these issues by developing techniques that are resilient to the presence of outliers and deviations from normality. By downweighting or ignoring extreme observations, these methods provide more stable and accurate estimates of the covariance matrix.

Key Robust Covariance Estimation Techniques:

1. M-estimators: M-estimators are a class of robust estimators that minimize a certain objective function to estimate the covariance matrix. These estimators can be designed to be less influenced by extreme observations by incorporating robust weight functions. Examples of M-estimators for covariance estimation include the Minimum Covariance Determinant (MCD) and Tyler's M-estimator.

2. Minimum Volume Ellipsoid (MVE): The MVE method finds the smallest volume ellipsoid that contains a certain proportion of the data points. This approach is particularly useful for multivariate data with a significant number of outliers.

3. S-estimators: S-estimators are robust covariance estimators based on robust estimates of location and scale, such as the M-estimators of location and the median absolute deviation (MAD) of scale. The S-estimators provide an efficient way to compute robust covariance matrices in high-dimensional data settings.

4. Shrinkage Estimators: Shrinkage estimators strike a balance between the sample covariance matrix and a target matrix (e.g., diagonal matrix) by applying a shrinkage parameter. This technique improves the



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performance of covariance estimation when the sample size is relatively small compared to the number of variables.

Robust covariance estimation plays a vital role in modern statistical analysis, providing reliable and accurate estimates of the covariance matrix, even in the presence of outliers and non-Gaussian data. These techniques are essential in various fields where data may be contaminated or influenced by extreme observations, contributing to more robust and trustworthy statistical inference and decision-making processes. Researchers and practitioners are encouraged to use robust covariance estimation methods to enhance the robustness and validity of their statistical analyses.

Lab Experiment to be done by students:

1. Generate a data set with outliers.
2. Estimate the covariance matrix of the data set using the sample covariance matrix and the MCD estimator.
3. Compare the two covariance matrices.
4. Repeat steps 1-3 for different data sets with different levels of outlier

LINK: <https://colab.research.google.com/drive/1Bm8oi7tBi17o-8lrIHZSOyShE8CFGrqJ?usp=sharing>

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[1] # Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.covariance import MinCovDet

[2] # Function to generate a dataset with outliers
def generate_data(n_samples=100, n_features=2, outlier_fraction=0.1):
    np.random.seed(0)
    # Generate normal data
    data = np.random.normal(0, 1, (n_samples, n_features))
    # Introduce outliers
    n_outliers = int(n_samples * outlier_fraction)
    outliers = np.random.normal(10, 1, (n_outliers, n_features)) # Outliers with different mean
    return np.vstack((data, outliers))

[3] # Function to estimate covariance matrices
def estimate_covariance_matrices(data):
    sample_cov = np.cov(data, rowvar=False)
    mcd = MinCovDet().fit(data)
    mcd_cov = mcd.covariance_
    return sample_cov, mcd_cov

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[4] # Function to compare covariance matrices
def compare_covariance_matrices(sample_cov, mcd_cov):
    print("Sample Covariance Matrix:")
    print(sample_cov)
    print("\nMCD Covariance Matrix:")
    print(mcd_cov)

    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.title('Sample Covariance Matrix')
    plt.imshow(sample_cov, cmap='hot', interpolation='nearest')
    plt.colorbar()

    plt.subplot(1, 2, 2)
    plt.title('MCD Covariance Matrix')
    plt.imshow(mcd_cov, cmap='hot', interpolation='nearest')
    plt.colorbar()

    plt.show()

[5] # Main execution
n_samples = 100
n_features = 2
outlier_fraction = 0.1

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[5] # Main execution
n_samples = 100
n_features = 2
outlier_fraction = 0.1

[6] # Generate dataset
data = generate_data(n_samples, n_features, outlier_fraction)

[7] # Estimate covariance matrices
sample_cov, mcd_cov = estimate_covariance_matrices(data)

# Compare covariance matrices
compare_covariance_matrices(sample_cov, mcd_cov)

Sample Covariance Matrix:
[[10.1541896  8.39112713]
 [ 8.39112713  8.71787473]]

MCD Covariance Matrix:
[[ 1.05169203 -0.06191095]
 [-0.06191095  0.95088224]]

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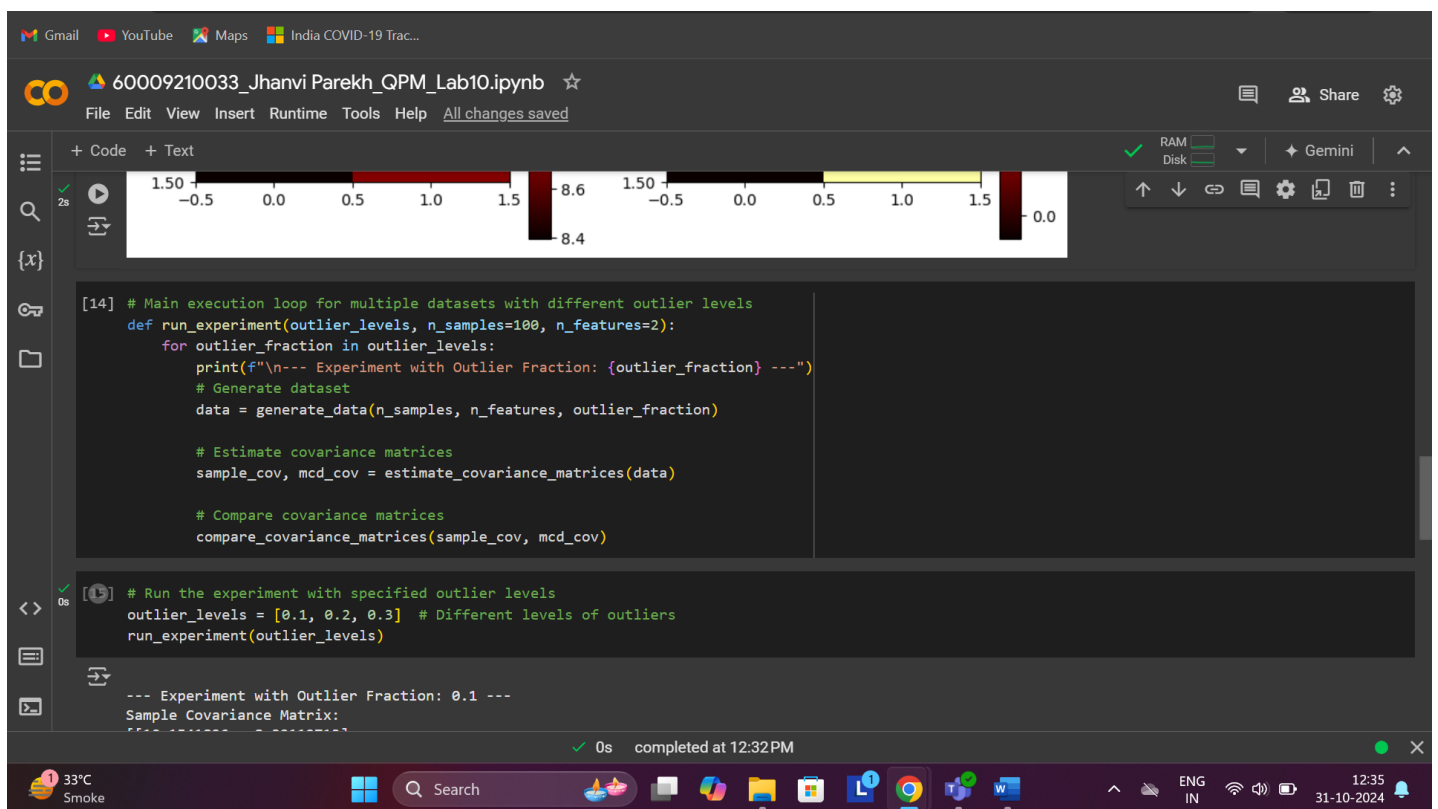
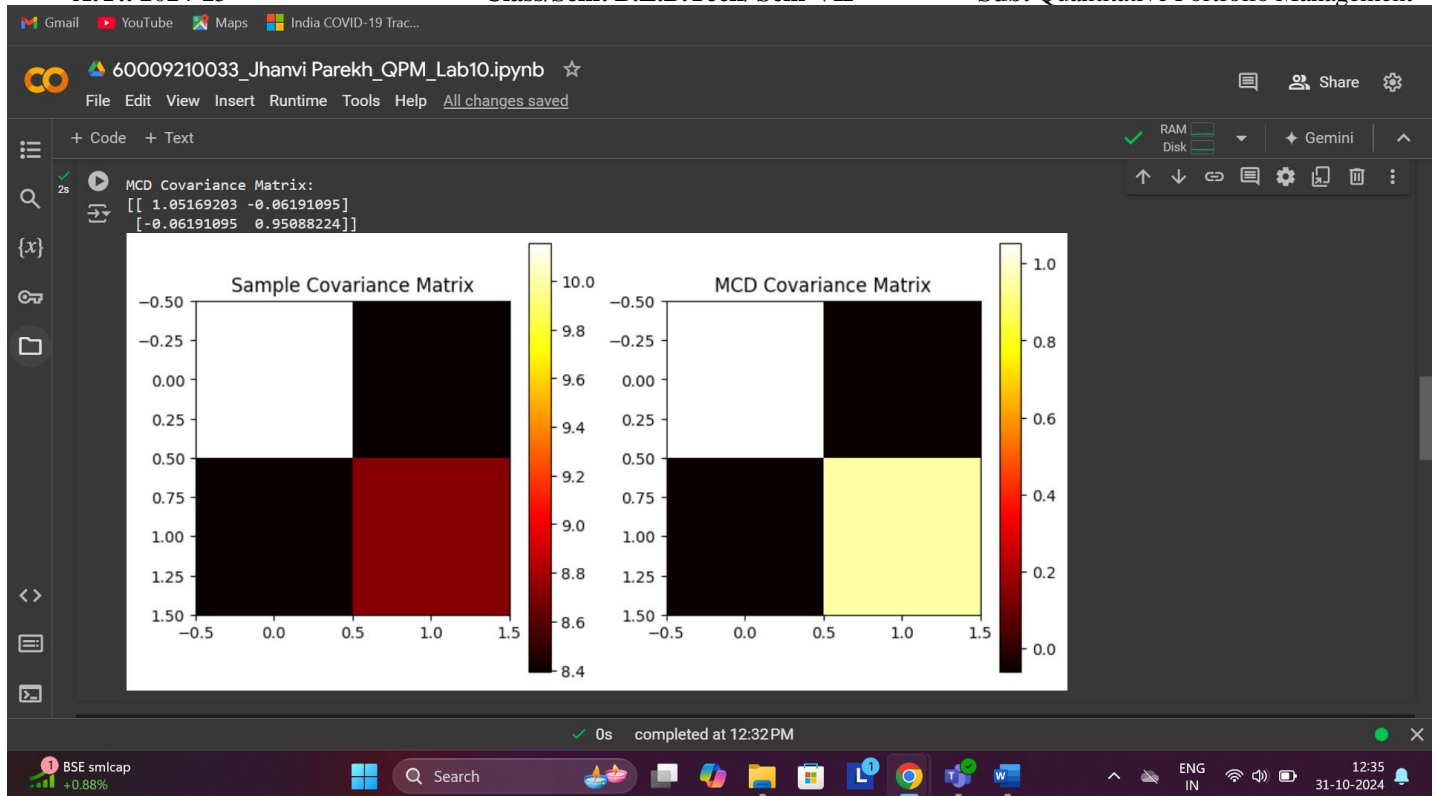
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[15] run_experiment(outlier_levels)

--- Experiment with Outlier Fraction: 0.1 ---
Sample Covariance Matrix:
[[10.1541896  8.39112713]
 [ 8.39112713  8.71787473]]

MCD Covariance Matrix:
[[ 1.05169203 -0.06191095]
 [-0.06191095  0.95088224]]

Difference between Sample and MCD Covariance Matrices:
[[9.10249758  8.45303808]
 [8.45303808  7.76699249]]

--- Experiment with Outlier Fraction: 0.2 ---
Sample Covariance Matrix:
[[15.04996875 13.56838561]
 [13.56838561 14.18309575]]

MCD Covariance Matrix:
[[ 1.04439794 -0.02492029]
 [-0.02492029  1.03188093]]

Difference between Sample and MCD Covariance Matrices:
[[14.0055708  13.59330591]
 [13.59330591 13.15121481]]

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[15] [[15.04996875 13.56838561]
      [13.56838561 14.18309575]]

MCD Covariance Matrix:
[[ 1.04439794 -0.02492029]
 [-0.02492029  1.03188093]]

Difference between Sample and MCD Covariance Matrices:
[[14.0055708  13.59330591]
 [13.59330591 13.15121481]]

--- Experiment with Outlier Fraction: 0.3 ---
Sample Covariance Matrix:
[[18.69994483 17.13264946]
 [17.13264946 17.57249576]]

MCD Covariance Matrix:
[[ 1.04439794 -0.02492029]
 [-0.02492029  1.03188093]]

Difference between Sample and MCD Covariance Matrices:
[[17.65554689 17.15756975]
 [17.15756975 16.54061483]]

[ ] Start coding or generate with AI.

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