



Semester: VIII

Subject: AIEB

Academic Year: 2024-25

## RUNNING THE GRAPHICAL LASSO (Glasso) Algorithm:

The following steps are followed to run glasso algorithm:

Step 1: Compute the sample covariance matrix  $S$  from given data.

Step 2: Solve the Graphical Lasso ~~optimization~~ optimization problem:

$$\hat{\Theta} = \arg \min_{\Theta} \left( \text{tr}(S\Theta) - \log \det(\Theta) + \lambda \sum_{i \neq j} |\Theta_{ij}| \right)$$

Step 3: Use  $L_1$  penalization to enforce sparsity, reducing overfitting.

Step 4: Tune regularization parameter  $\lambda$  to balance sparsity vs. accuracy.

Step 5: Interpret the sparse precision matrix to identify variable dependencies.

Example:

Using Glasso Algorithm extract estimated precision matrix for stock price data.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

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Semester: VIIISubject: AIFBAcademic Year: 2024-25

from sklearn.covariance import GraphicalLasso

import yfinance as yf

# Step 1: Download stock price data for selected assets.

stocks = ['AAPL', 'MSFT', 'GOOGL', 'AMZN', 'TSLA'] # Example stocks

data = yf.download(stocks, start='2022-01-01', end='2024-01-01')  
['Adj Close']# Step 2: Compute daily log returns

returns = np.log(data/data.shift(1)).dropna()

# Step 3: Apply Graphical Lasso to estimate a sparse precision matrix.

lambda\_value = 0.05 # Regularization parameter (tune as needed)

glasso = GraphicalLasso(alpha=lambda\_value)

glasso.fit(returns)

# Step 4: Extract estimated precision (inverse covariance) matrixprecision\_matrix = ~~glasso~~ glasso.precision\_

print("Estimated Precision Matrix:\n", glasso.precision\_)

Output:Estimated Precision Matrix:

```
[ [ 3e+03  -0  -0  -0  -0 ]  
  [ -0  1.4e+03  -0  -0  -0 ]  
  [ -0  -0  2.1e+03  -0  -0 ]  
  [ -0  -0  -0  2.7e+03  -0 ]  
  [ -0  -0  -0  -0  6.9e+02 ] ]
```





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### Interpretation of results:

- The **Non-zero elements** in the precision matrix indicate direct dependencies between asset returns.
  - **Zero elements** suggest that **two assets are conditionally independent**, given all others.
  - **Highly connected assets** → Stocks with similar risk exposure (eg. same industry)
  - **Sparse dependencies** - Diversified portfolio potential.
- This is how we run Graphical Lasso Algorithm.