# Covariance Graphical Lasso Approach

April 16, 2021

## 1 Covariance Matrix Using Graphical Lasso Approach

### 1.1 Introduction

management of large-scale portfolios with high $p-$ dimensional finite number of assets is one of the most challenging task in the field of finance. One of the main contributing factors is due to the instability of the estimated covariance between assets or the precision matrix from the observed data of $n$ assets returns. In this article, we propose the use of the graphical lasso method for the estimation of the covariance matrix between assets. The graphical lasso is a sparse penalized maximum likelihood estimator for the concentration or precision matrix (inverse of the covariance matrix) of a multivariate distribution.

### 1.2 Motivation

Our main motivation for choosing a graphical method for estimation of covariance matrix stems from the fact that Graphical models are a powerful tool to estimate a high dimensional inverse covariance matrix, which can, in turn, be plugged into markowitz framework for computation of optimal portfolios for capital allocation.

### 1.3 Preliminaries

consider $X_1, X_2, ..., X_n$ from a multivariate gaussian distribution $N \sim (0, \Sigma)$ The objective is to estimate the precision matrix (covariance ) $\Theta = \Sigma^{-1}$ given a sample Covariance $S$

The graphical lasso estimator is such that $\widehat{\Theta} = argmin_{\Theta \geq 0}(tr(S\Theta) - logdet(\Theta) + \lambda \Sigma_{j \neq k}|\Theta_{jk}|)$

$tr$ is the trace, $dt$ is the determinant. By observation of the formulation, the $argmin$ exposes that this is a optimization problem and the $\Theta \geq 0$ reveals the positive definiteness of the output results

### 1.4 Method

For estimation, we use the coordinate descent procedure a optimization algorithm that successively minimizes along the coordinates directions to find the minimum of a function at each iteration.

### 1.5 Application

We use 16 stocks prices from yahoo finance for a 3 months period ending on the 15th of April 2021, our package is still on its infancy thus the method of approach is subject to vast changes, keep track to our twitter announcements for changes.

[9]:
```
#import yahoo finance
import yfinance as yf
#import pandas
import pandas as pd
#import our implementing package this will be accessed via QFish in the next␣
↪implementation
import lasso as ls
```

[10]:
```
# Retrieve Data
stocks = ['AAPL', 'AMZN', 'GOOG', 'JNJ',␣
↪'JPM','BAC','PEP','BAYP','JPM','V','BAC','MA','PYPL','C','TOT','EQNR']
tickers = yf.Tickers(stocks)
"""returns a named Tuple if Ticker Objects"""
history = tickers.history(period="3mo")['Close']
"""dataframe"""
df = pd.DataFrame(data=history)
```

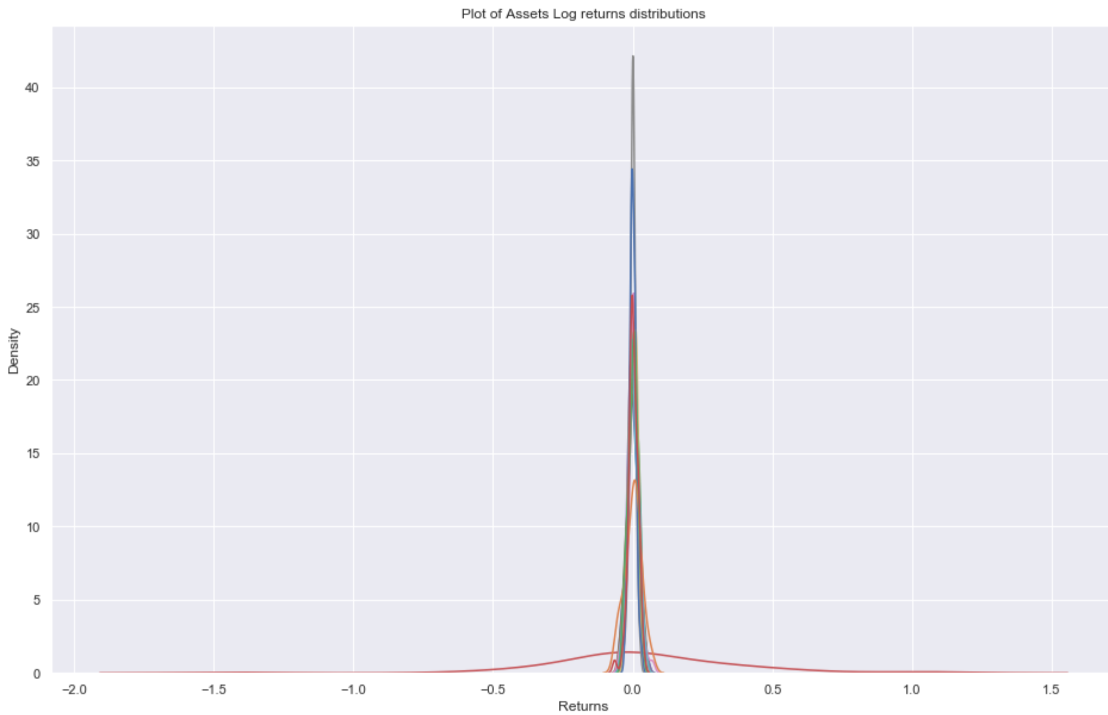
```
[*********************100%***********************]  14 of 14 completed
```

[11]:
```
# Initialize our package with the prices
ls = ls.Lasso(df)
```

[12]:
```
# List assets with initial index from 0 up to n-1
ls.assetsList()
```

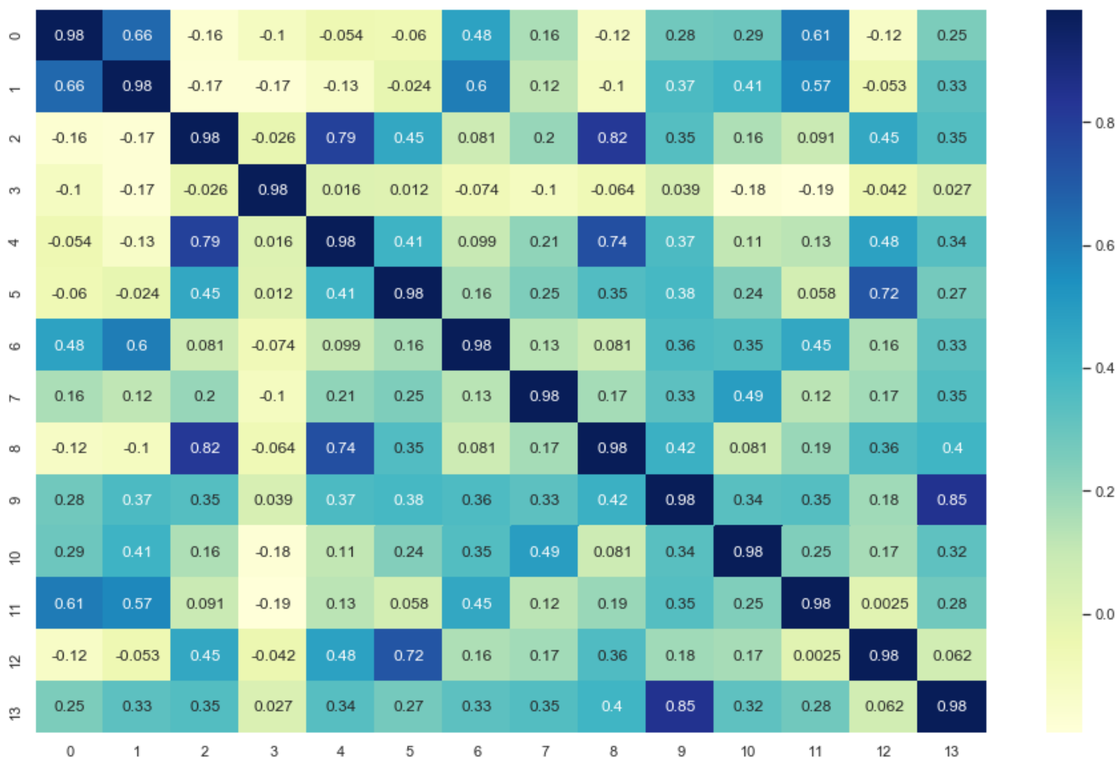
```
['AAPL', 'AMZN', 'BAC', 'BAYP', 'C', 'EQNR', 'GOOG', 'JNJ', 'JPM', 'MA', 'PEP',
'PYPL', 'TOT', 'V']
```

[13]:
```
# plot the normalized log returns distributions: Next package update will have␣
↪labels for the distributions
ls.plotDistros()
```

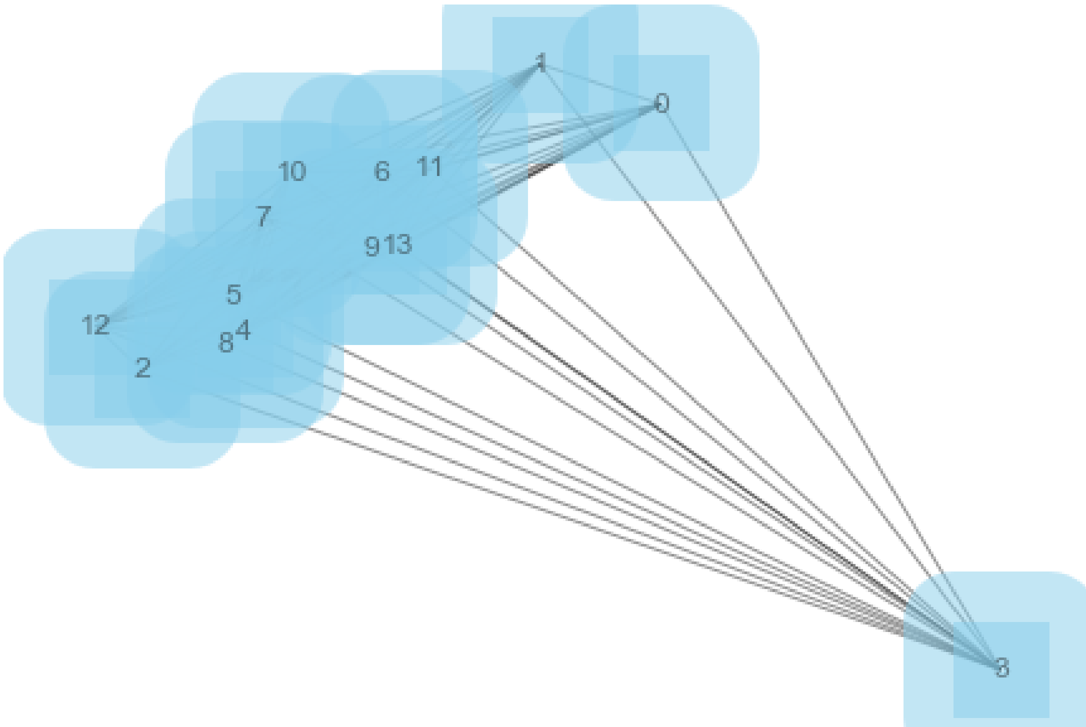



[14]:
```
# Plot Covariance heatmap and Values remember the indexing list is matched to
↪the output list above
ls.assetsList()
ls.covarianceMap()
```

```
['AAPL', 'AMZN', 'BAC', 'BAYP', 'C', 'EQNR', 'GOOG', 'JNJ', 'JPM', 'MA', 'PEP',
'PYPL', 'TOT', 'V']
```



[24]:
```
# Assets network graph
ls.CovarianceNetwork()
```




# 2 References

Wikipedia article on graphical lasso

Optimal Portfolio Using Factor Graphical Lasso

A Tutorial on Regularized Partial Correlation Networks

## 2.1 Contacts

Email

Twitter