

# Data Mining with Markowitz Portfolio Optimization in Higher Dimensions

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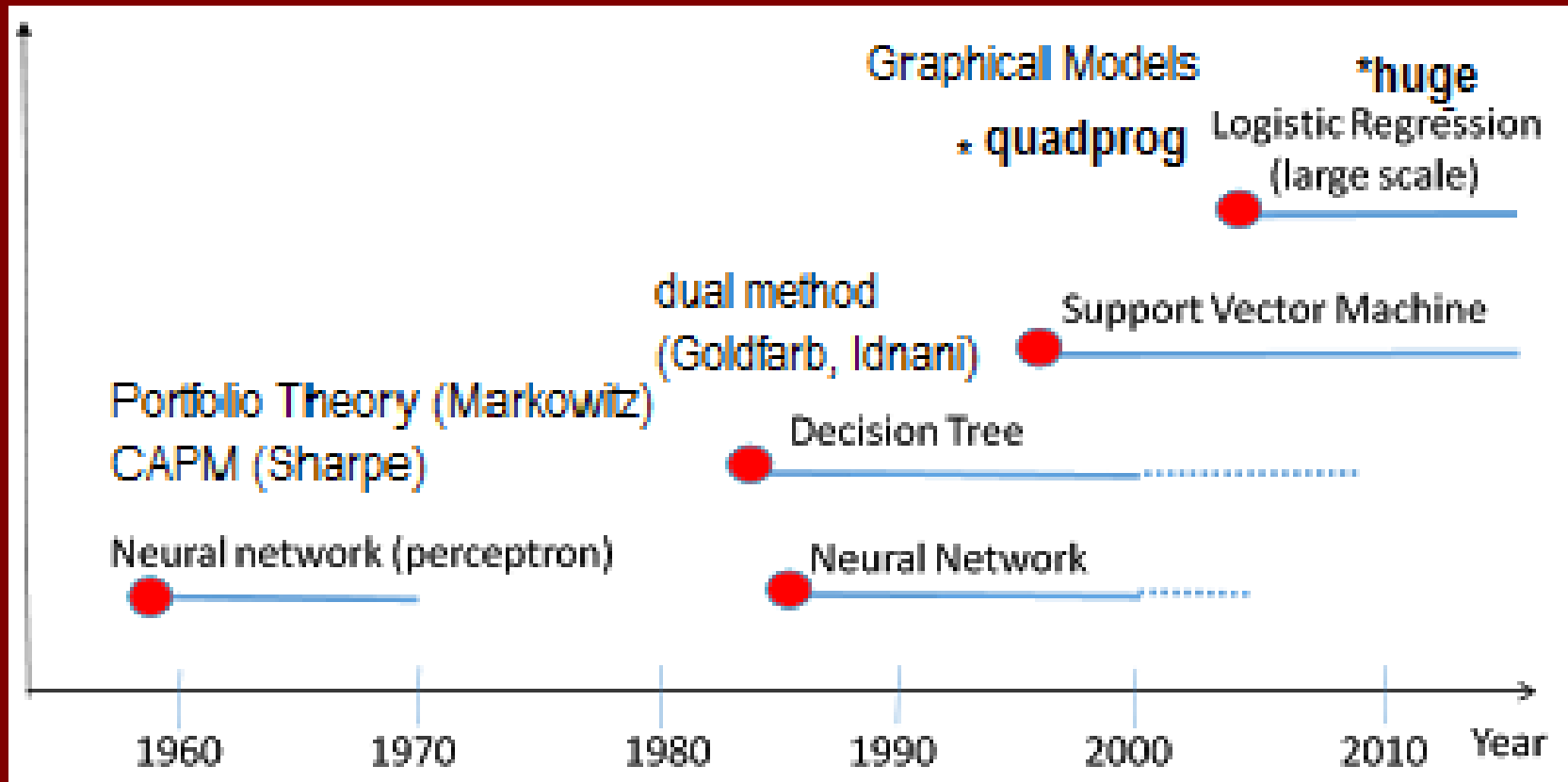
R in Finance, May, 2014

higher dimensional R-packages



Are they Data Mining cousins?

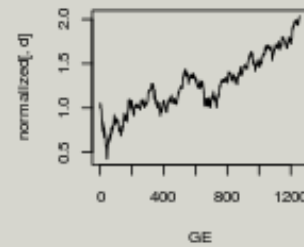
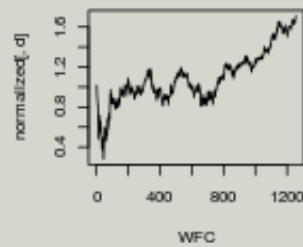
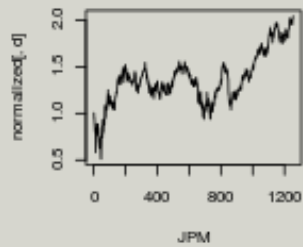
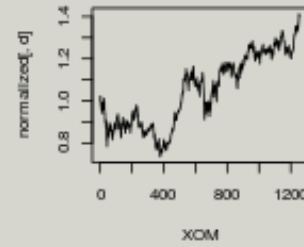
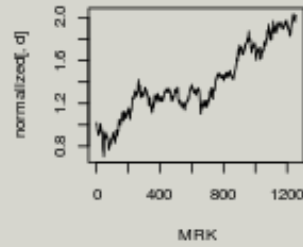
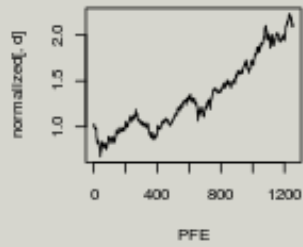
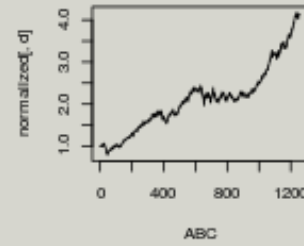
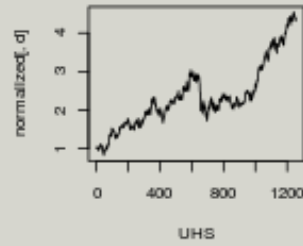
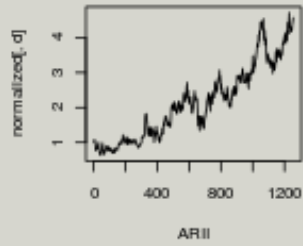
# Historical Timeline



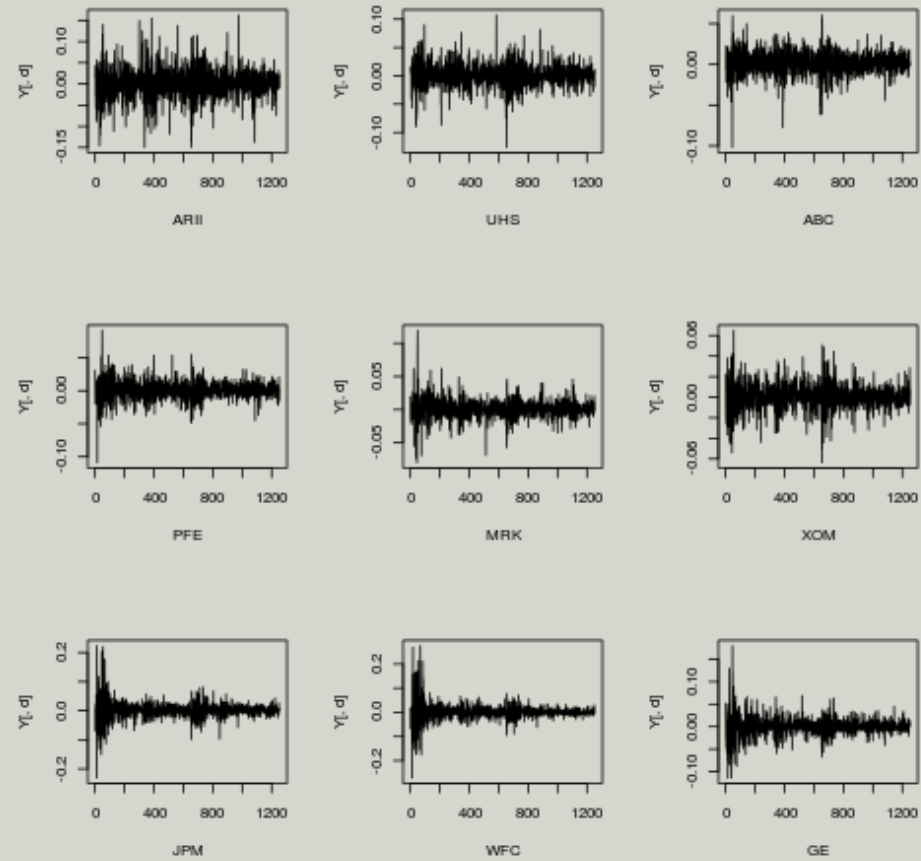
## Why Are These Techniques Important?

- Portfolio Theory and Graphical Models are Natural Tools for Market Uncertainty, Portfolio Complexity
- Tie together Machine Learning and Financial Analytics: looking for Comovement in Multivariate Gaussian distributed returns
- Given dataset:  $N$  Training vectors  $\times$   $p$  Dimensions
- Perform data mining where  $N \approx p$
- Inspect and clean dataset: split-adjust

Historical  $N + 1 = 1255$  prices for  $p = 9$  securities



Historical  $N = 1254$  log returns for  $p = 9$  securities



## Environment:

When we have  $p$  time series of stock prices:  $S_{ij}$  at time  $i$  for security  $j$ , log returns are  $R_{ij} = \ln(S_{ij}/S_{i-1j})$ .

The full matrix of log returns is:  $\mathbf{R} = \begin{bmatrix} R_{11} & R_{12} & \dots & R_{1p} \\ R_{21} & R_{22} & \dots & R_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ R_{N1} & R_{N2} & \dots & R_{Np} \end{bmatrix}$

We can find:  $E\{\mathbf{R}\} = \boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_p \end{bmatrix}$  and  $cov(\mathbf{R}) = \boldsymbol{\Sigma}_{p \times p}$

## Portfolio

## Optimization:

Find  $w = \begin{bmatrix} w_1 \\ \vdots \\ w_p \end{bmatrix}$  the *optimal weights* for the  $p$  securities given historical series of  $N \times p$  prices in order to forecast the best portfolio going forward:

$$\underset{w}{\operatorname{argmin}} w^T \Sigma w, \quad (1)$$

for each target level of return  $\mu_P$  where  $w^T \Sigma w$  is the return variance of the portfolio, weighted by the vector  $w$  where below are the weight sum, portfolio mean, and no short sales constraints:

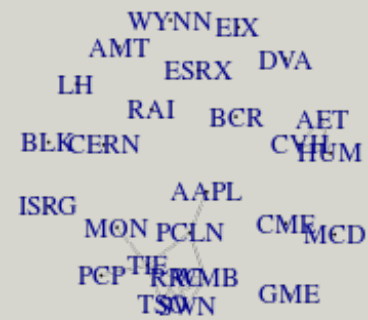
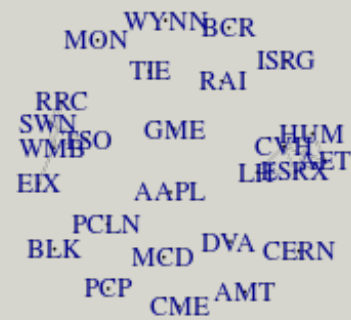
$$\begin{pmatrix} \mathbf{1}^T w \\ \mu^T w \end{pmatrix} = \begin{pmatrix} 1 \\ \mu_P \end{pmatrix}; w \geq 0 \quad (2)$$



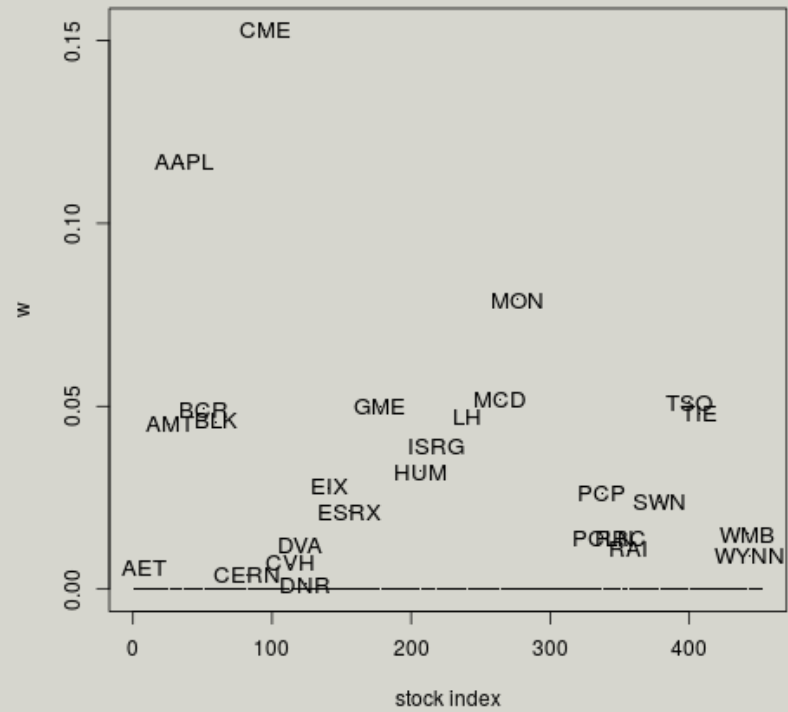
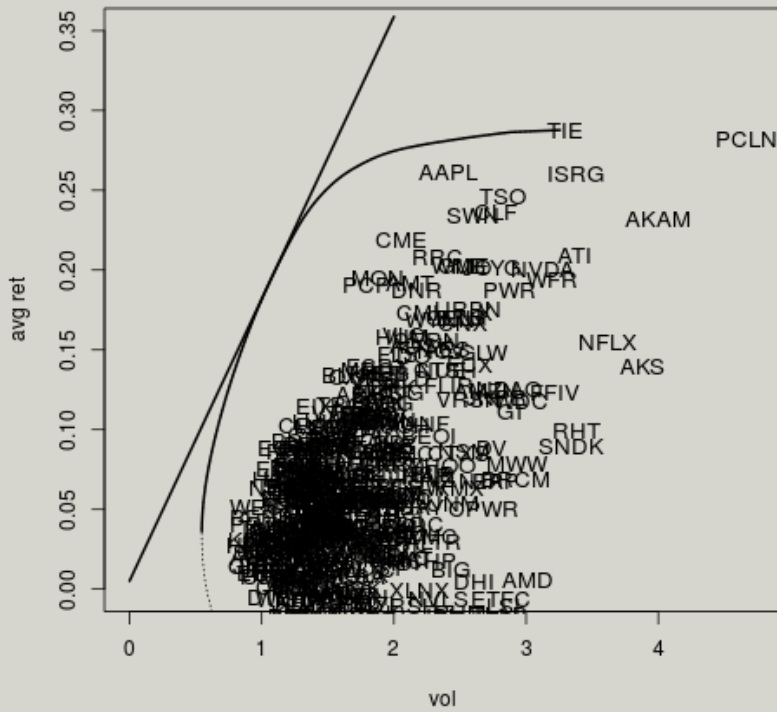
# Comovement Clusters for Weighted Stocks $p = 452$ securities

Huge lambda.min.ratio: 0.4  
NPN, Glasso

Cov Matrix Threshold: 1.7



Result Portfolio for  $p = 452$  securities: Favoring CME, AAPL



**Thank you!**

**References:**

- Ruppert, D., *Statistics and Data Analysis for Financial Engineering*, Springer Texts in Statistics. Springer, New York, ISBN 9781441977861, 2011.
- Zhao, T., Liu, H., Roeder, K., Lafferty, J., Wasserman, L., The huge Package for High-dimensional Undirected Graph Estimation in R, *Journal of Machine Learning Research* 13 (2012) 1059-1062, April 2012.