

Sparse and group regression models in portfolio optimization

Project Supervisor: Professor Mahesan Niranjan
Second Examiner: Professor Vladimiro Sassone

Abstract Portfolio Optimization

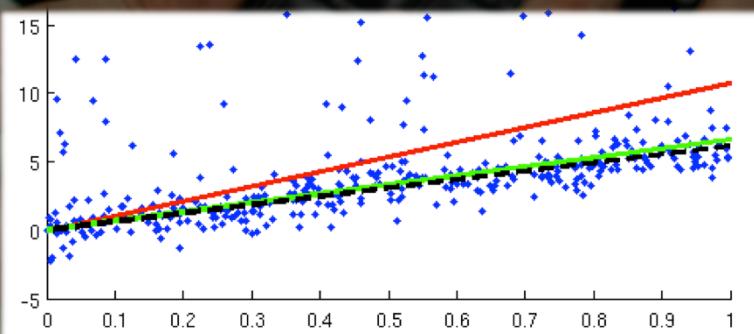
Choose Portfolio
(Market Index)



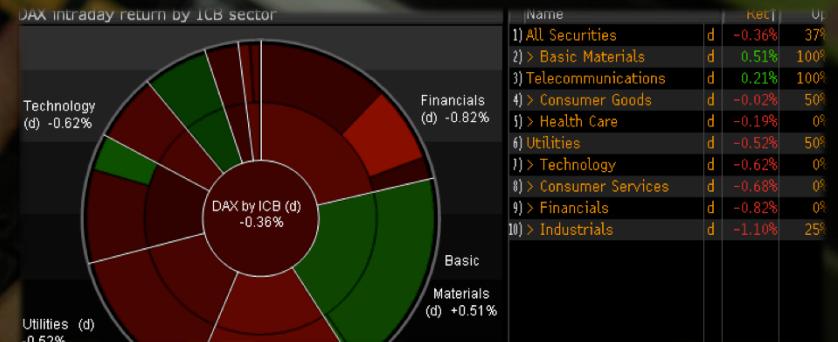
Portfolio Selection
(Optimization - Index Tracking)



Numerous Approaches
(Revenue, Tracking Error, Cost, etc)



Stock Groups/Classifications
(Industry, Sector, Rating, Type, etc)



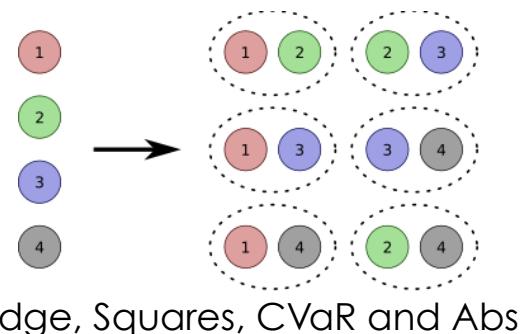
Initial Goals

(Semester 1) Portfolio Selection - Forward Search

Model Selection through a Greedy Forward Search approach.

**Simultaneous pursuit of out-of-sample performance
and sparsity in index tracking portfolios**

Akiko Takeda · Mahesan Niranjan ·
Jun-ya Gotoh · Yoshinobu Kawahara



(Semester 2) Portfolio Selection – Sparse Regression Models

Group Level Regression model approach.



**Pathways-Driven Sparse Regression Identifies Pathways
and Genes Associated with High-Density Lipoprotein
Cholesterol in Two Asian Cohorts**

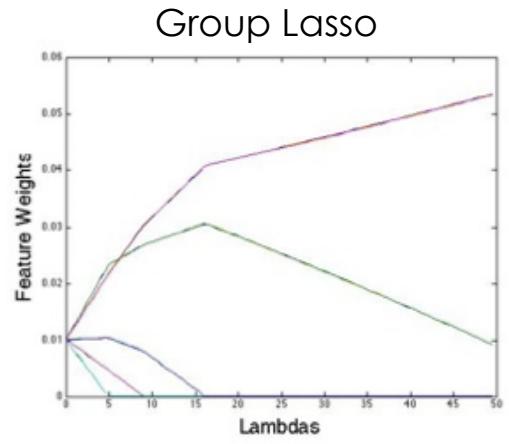
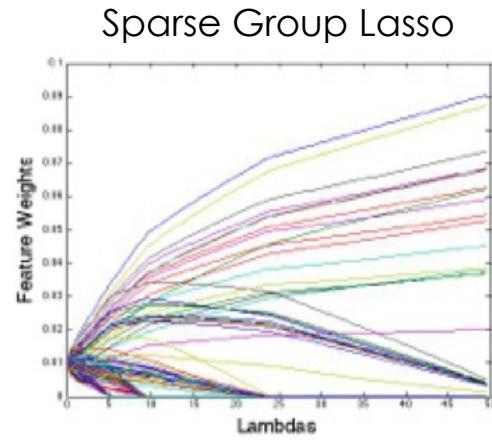
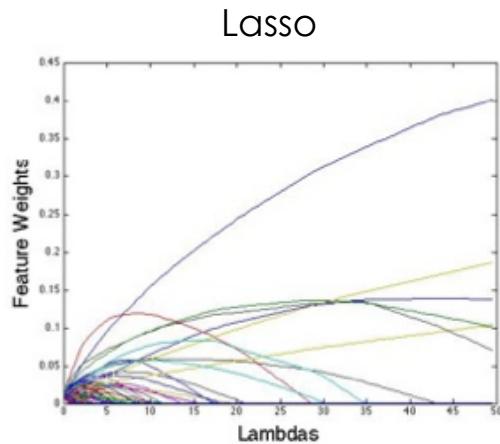
Matt Silver^{1,2*}, Peng Chen³, Ruoying Li⁴, Ching-Yu Cheng^{3,5,6}, Tien-Yin Wong^{5,6}, E-Shyong Tai^{3,4}, Yik-Ying Teo^{3,7,8,9,10}, Giovanni Montana^{1*}

Lasso, Group Lasso & Sparse Group Lasso

Intuition

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_{1,1} & \dots & \mathbf{R}_{1,n} \\ \dots & \dots & \dots \\ \mathbf{R}_{T,1} & \dots & \mathbf{R}_{T,n} \end{bmatrix} = \text{Returns} \quad \boldsymbol{\pi} = \begin{bmatrix} \pi_1 \\ \dots \\ \pi_n \end{bmatrix} = \text{Weights} \quad \mathbf{R}^T \boldsymbol{\pi} = \mathbf{I} = \begin{bmatrix} \mathbf{I}_1 \\ \dots \\ \mathbf{I}_T \end{bmatrix} = \text{Index}$$

$$\min_{\boldsymbol{\pi}} \|\mathbf{I} - \mathbf{R}^T \boldsymbol{\pi}\|_2^2 + \lambda \sum_{g=1}^m \sqrt{p_g} \|\bar{\boldsymbol{\pi}}_g\|_2 + \lambda |\boldsymbol{\pi}|$$



Research Objectives

Design, implement and test regression models

Implement feature level and group level regression models (Ridge, Squares, SGL, etc.)

Evaluate performance: Feature vs. group level approach

Present visual and intuitive results in order to provide concrete conclusions

Encourage Research in group sparsity models

Multiple Sparse Group Regression concept proposed to encourage further research

Build an intuitive, reusable programming library

Provide the code used for the implementation in a presentable and structured manner

Motivation

Opportunity to contribute
to current research



Novel approach to
portfolio optimization



Successful applications
in genetics



Extremely relevant to
previous and future projects



Main Challenges

Financial Concepts



Machine Learning Understanding

Equation 8 - α -Sparse Group Lasso

$$\min_{\pi \in \mathbb{R}^n} \frac{1}{2n} \left\| I - \sum_{g=1}^m R_g^T \bar{\pi}_g \right\|_2^2 + (1-\alpha)\lambda \sum_{g=1}^m \sqrt{p_g} \|\bar{\pi}_g\|_2 + \alpha\lambda \|\pi\|_1$$

Equation 1 - Tracking Error

$$\frac{1}{T} \sqrt[1/\varphi]{\left| \sum_{t=1}^T |I_t - R_t^T \pi| \right|^{\varphi}}$$

Equation 2 - CVaR

$$\min_{\pi, \alpha, z} \alpha + \frac{1}{(1-\beta)T} \sum_{t=1}^T z_t$$

Equation 7 - Group Lasso

$$\min_{\pi \in \mathbb{R}^n} \frac{1}{2} \left\| I_t - \sum_{g=1}^m R_{g,t}^T \bar{\pi}_g \right\|_2^2 + \lambda \sum_{g=1}^m \sqrt{p_g} \|\bar{\pi}_g\|_2$$

Equation 3 - Abs

$$\min_{\pi} \|I - R^T \pi\|_1$$

Equation 5 - Ridge

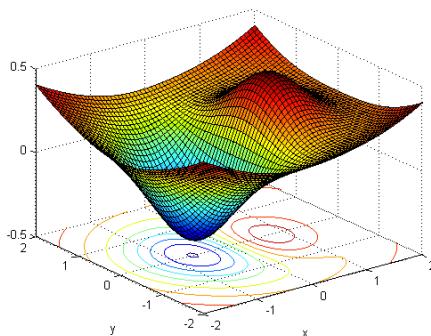
$$\min_{\pi} f^r(\pi) = \sum_{t=1}^T |I_t - R_t^T \pi| + \lambda \|\pi\|_2^2$$

Equation 6 - Lasso

$$\min_{\pi} \sum_{t=1}^T |I_t - R_t^T \pi| + \lambda |\pi|$$

Programming

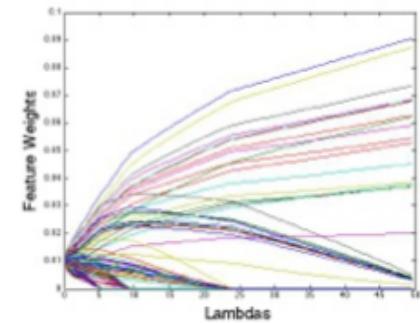
Convex Programming Libraries



Matrix Notation Algorithms

$$\begin{array}{ll} \text{loop} & \text{branch} \rightarrow \\ \downarrow & \\ 1 & 2 \quad 3 \quad 4 \quad 5 \quad 6 \\ 1 & \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \\ 2 & \begin{bmatrix} 0 & -1 & 1 & 1 & 0 & 0 \end{bmatrix} \\ 3 & \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

Implementation of ZCSGL



Achievements

Zero-Constrained Sparse Group Lasso

$$\min_{\pi \in \mathbb{R}^n} \|I - R^T \text{sum}(\hat{\pi}, 2)\| + \lambda_1 \text{sum}\left(\sqrt{p^T * \sqrt{\text{sum}(\hat{\pi} \cdot \hat{\pi}, 2, 2)}}\right) + \lambda_2 \|\text{sum}(\hat{\pi}, 2)\|_1$$

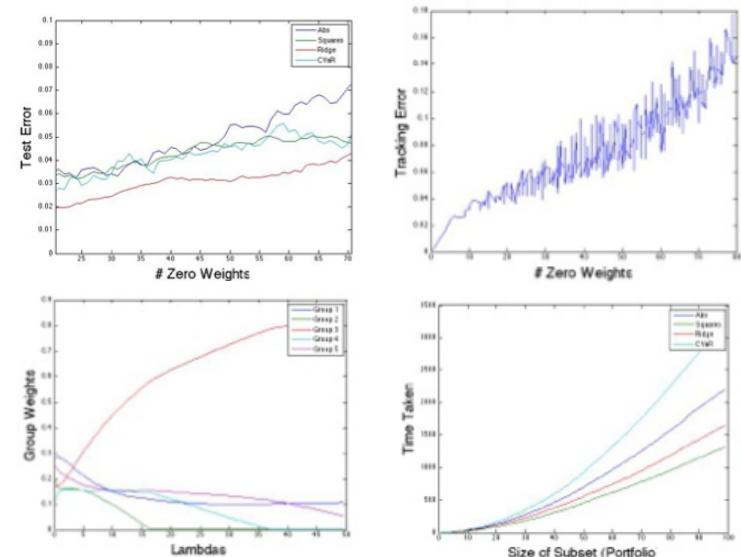
$$\text{s.t. } \pi_i > 0 \wedge \hat{\pi}[\sim \Psi_g, g] = 0$$

Algorithmic Implementations

- Time Series Modeling (p.6)
- Lasso, Ridge, Squares, Abs
- Spectral Clustering Algorithm
- Zero-Constrained-GL (p. 16)
- Zero-Constrained-SGL (p. 16)

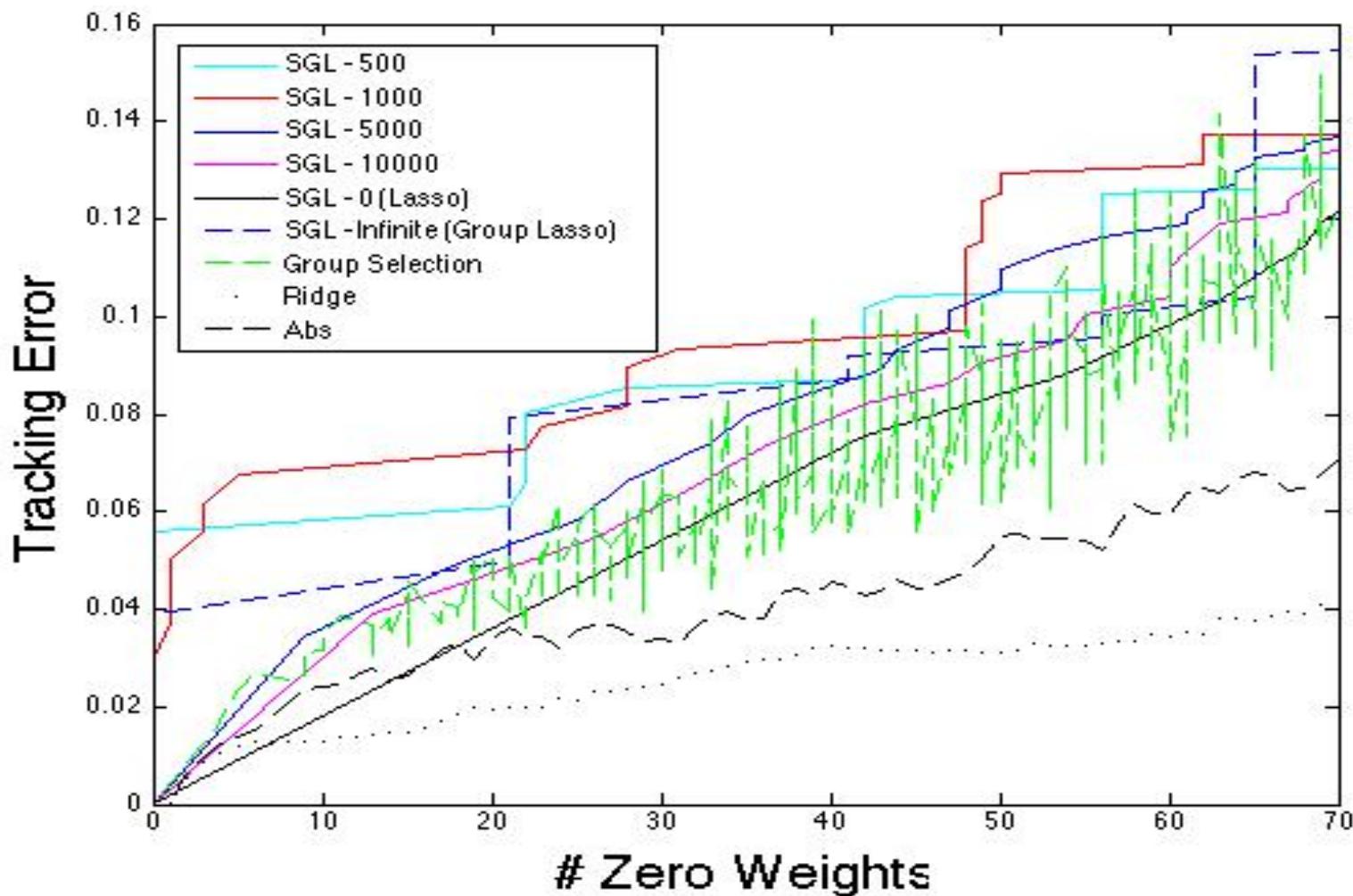
Screenshot of a GitHub repository page for "axsauze / sparse". The repository has 54 commits, 1 branch, 0 releases, and 1 contributor. The master branch is selected. The repository description is: "The effects of sparse and group-feature regression models in portfolio optimization." The commit history shows several additions related to window tests and data processing.

File	Commit Message	Date
data	added tests and main	12 days ago
functions	Added window test	10 days ago
helperfuncs	tiding up	12 days ago
saveworkspaces	Added window test	10 days ago
tests	Added window test	10 days ago
LICENSE.txt	licence modified	12 days ago



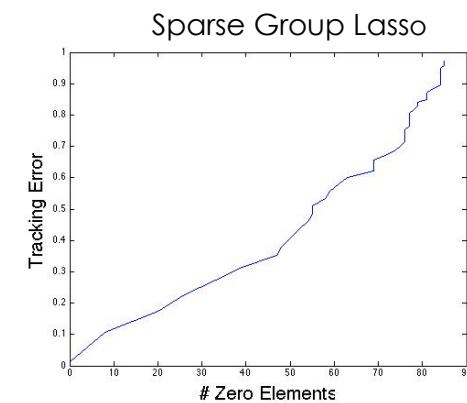
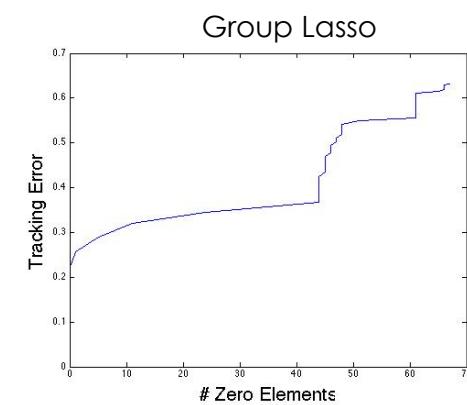
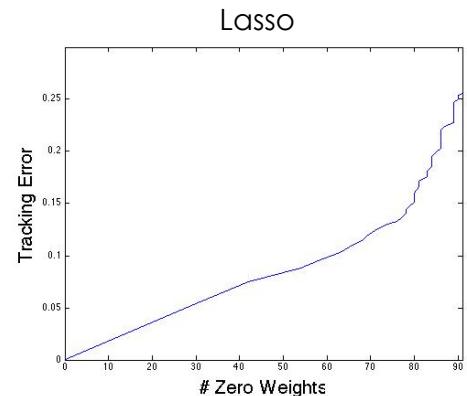
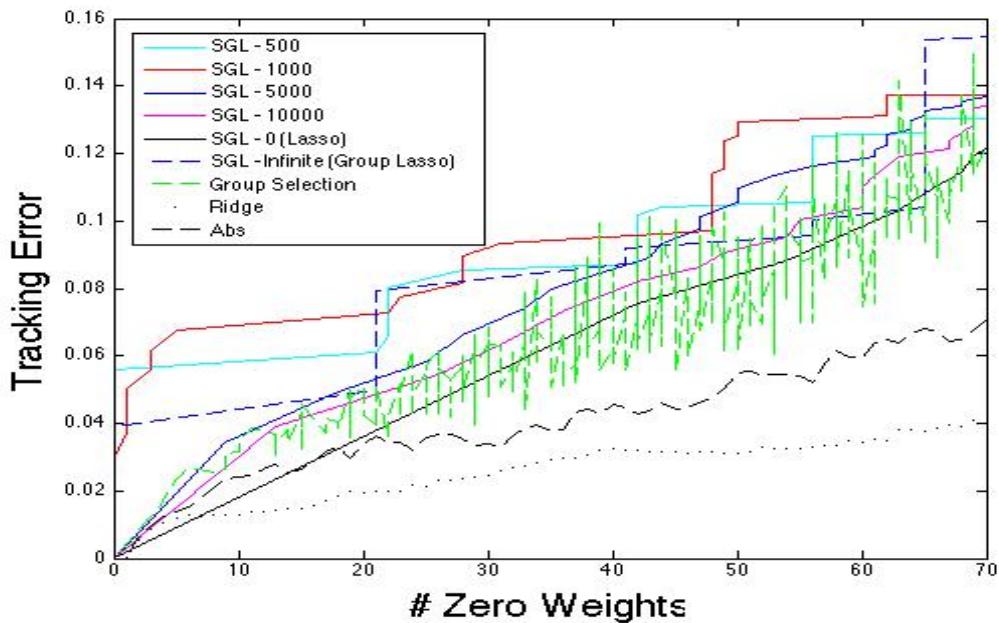
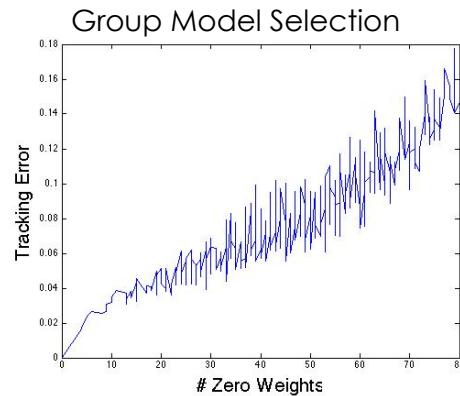
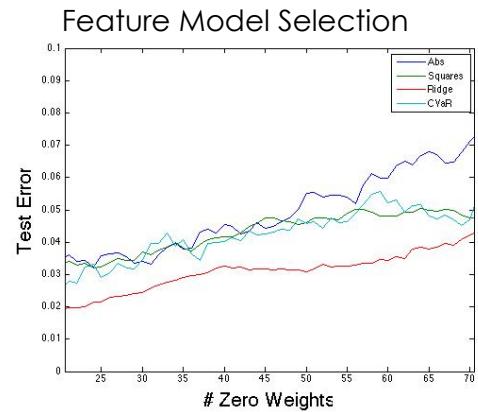
Final Results

(Tracking Error – All Data p.18-22)



Final Results

(Tracking Error – All Data p.18-22)



Expansion

Observation

Modelling chaotic systems such as financial stock markets requires consideration of complex correlations between groups of stocks.

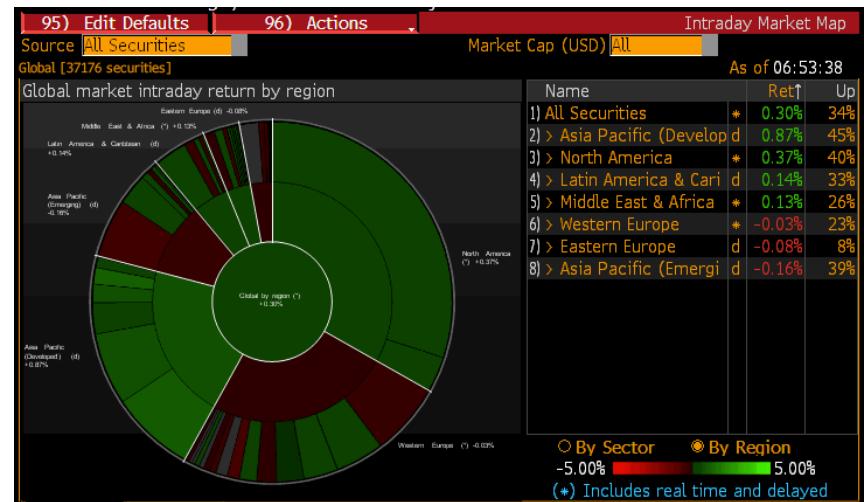
Objective

Enable regression models to induce sparsity based on multiple groupings of the data.

Proposed Solution

Multiple-SGL Concept

$$\min_{\boldsymbol{\pi} \in \mathbb{R}^n} K \|\mathbf{I} - \mathbf{R}^T \boldsymbol{\pi}\| + \lambda_1 \sqrt{\hat{p}} * \sqrt{\text{sum}(\boldsymbol{\pi}[\boldsymbol{\psi}]^2, 2)} + \lambda_2 \|\boldsymbol{\pi}\|_1$$



Professional Opinion

Denver Trouton

*FX Options Applications Lead
Bloomberg LP*

Bloomberg

“Several Teams working on similar principles”

- Multi-asset class support (equities, FX, commodities, bonds, CDS, IRS)
- Support for portfolios of composite securities (e.g. ETFs, mutual funds, indices)
- Efficient frontier optimization
- Long-only as well as long-short optimization
- Risk (volatility), Value-at-Risk, Conditional Value-at-Risk goal and/or constraints, possibly relative to benchmark
- Weight constraints on groups of securities (e.g. sectors, countries, issuers, ratings, etc)
- Bounding number of trades, buy, sells, positions, longs, shorts (potentially per grouping)

Bloomberg Portfolio Optimizer

Alper Atamtürk, Sridhar Gollamudi, Kevin He

December 17, 2013

Version 2.10.4

Thank you very much!

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