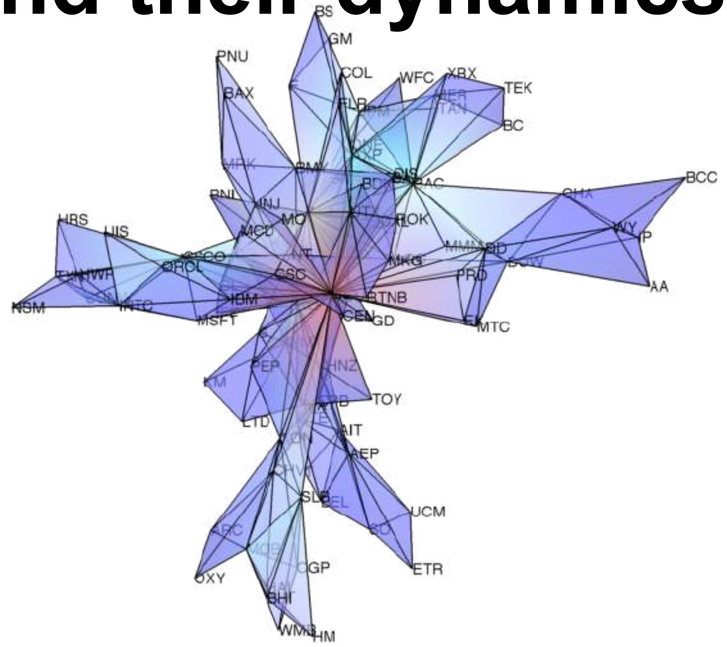
Machine learning for optimal portfolios: data-driven modeling of market states and their dynamics



Tomaso Aste

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The Financial Computing and Analytics research group investigates socio- economic systems using methods from computer science, applied mathematics, computational statistics and network theory.

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Research
- computational finance
- data-driven modelling
- artificial intelligence
- financial risk management
- blockchain technology
- digital economy
- systemic risk
- numerical pricing of derivatives
- agent-based simulation
- empirical finance
- market microstructure
- algorithmic trading
- high-frequency trading
- data science
- big data analytics
- network analysis
- machine learning
- price formation
- portfolio optimization

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Portfolio optimization

Aim:

- **maximize gains &**
- **minimize risk**

Mean-Variance approach

- *Maximize return's* ***mean***
- *Minimize return's* ***variance***

Exact solution:

$$\boldsymbol{W} = \Sigma^{-1}\,(c_1\mu + c_2\mathbf{1})$$

Optimal portfolio issues

1. Poor modeling
2. Parameter estimation error
3. Non-stationarity

- Unique and irreproducible observation set
- Error amplification via optimization

These are general issues not exclusive to the mean-variance approach

Market modeling: elliptical distribution family

- Aste, Tomaso. "Stress testing and systemic risk measures using multivariate conditional probability." Available at SSRN 3575512 (2020).
- Aste, Tomaso. "Topological regularization with information filtering networks." *arXiv preprint arXiv:2005.04692* (2020).

- Returns are not normal, a better modeling is by using elliptical family distribution
- Elliptical family distributions depend on
  - **mean** μ
  - **covariance** Σ
  - **other parameters** (i.e. degrees of freedom)
- With multivariate elliptical modeling, portfolios have location-scale distributions, therefore mean-variance portfolio optimization is consistent with elliptical distribution modeling

Parameter estimation

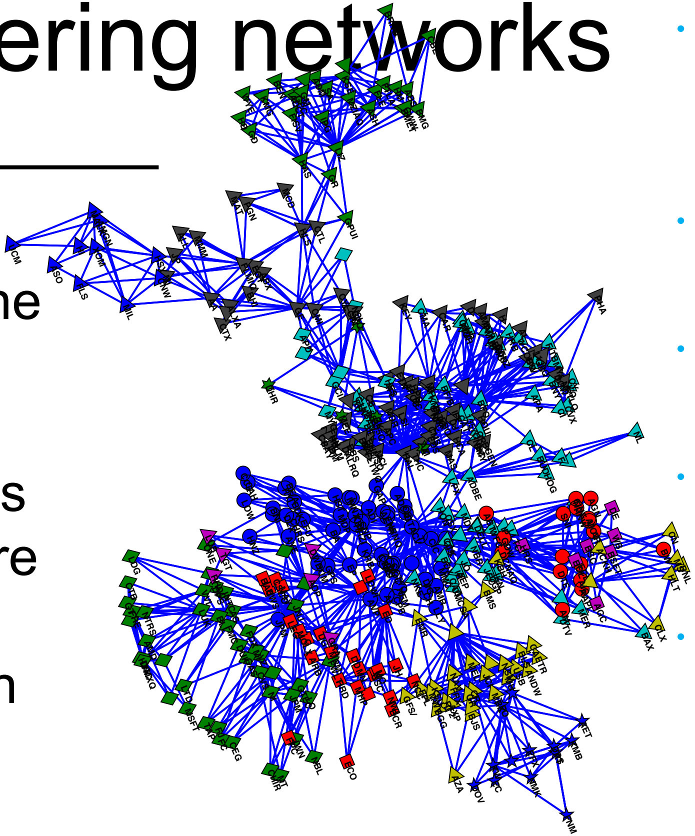
- Optimal portfolio mean-variance solution requires the estimation of:
  - **mean μ**
  - **covariance Σ**
- Sample estimators converge only asymptotically ($1/t^{1/2}$)
- Small observation sets and large number of variables yield to overfitting solutions (*curse of dimensionality*)
- Observation time is finite

Parameter estimation using L_0-norm regularization

- Barfuss, W., Massara, G.P., Di Matteo, T. and Aste, T., 2016. Parsimonious modeling with information filtering networks. Physical Review E, 94(6), p.062306.
- Aste, Tomaso. "Topological regularization with information filtering networks." *arXiv preprint arXiv:2005.04692* (2020).

- The dependency structure in a market can be captured using Information Filtering Networks
- These networks can be used to estimate the covariance from a sum of local low-dimensional covariance estimates
- This is a L_0-norm regularization
- Better performing than Lasso or Ridge estimates

Information filtering networks



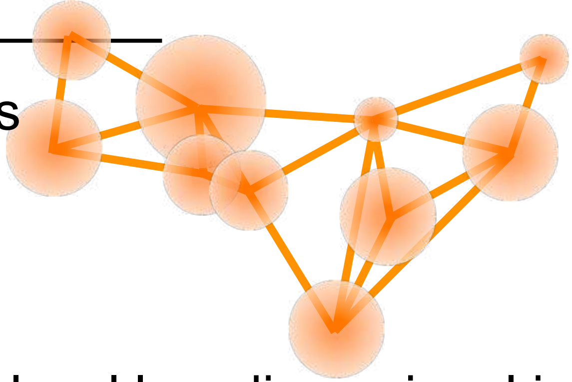
- IFN are networks constructed retaining the most relevant dependency links
- their structure describes well the market structure
- when they are clique-trees (chordal) they can be used for L0-norm regularization

- Tumminello, M., Aste, T., Di Matteo, T. and Mantegna, R.N., 2005. A tool for filtering information in complex systems. Proceedings of the National Academy of Sciences, 102(30), pp.10421-10426.
- Aste, T., Shaw, W. and Di Matteo, T., 2010. Correlation structure and dynamics in volatile markets. New Journal of Physics, 12(8), p.085009.
- Pozzi, F., Di Matteo, T. and Aste, T., 2013. Spread of risk across financial markets: better to invest in the peripheries. *Scientific reports*, *3*(1), pp.1-7.
- Guido Previde Massara, Tiziana Di Matteo and Aste, Tomaso Network filtering for big data: Triangulated maximally filtered graph Journal of complex Networks, 5 (2016) 161--178
- Massara, G.P. and Aste, T., 2019. Learning clique forests. arXiv preprint arXiv:1905.02266.

LoGo: **Lo**cal **Glo**bal approach to covariance estimation problem

- Massara, G.P. and Aste, T., 2019. Learning clique forests. arXiv preprint arXiv:1905.02266.
- Barfuss, W., Massara, G.P., Di Matteo, T. and Aste, T., 2016. Parsimonious modeling with information filtering networks. Physical Review E, 94(6), p.062306.
- Guido Previde Massara, Tiziana Di Matteo and Aste, Tomaso Network filtering for big data: Triangulated maximally filtered graph Journal of complex Networks, 5 (2016) 161--178

$\boldsymbol{\Sigma}^{-1}$ has non-zero elements where edges are present in the information filtering network



$\boldsymbol{\Sigma}^{-1}$ is given by the sum of local low-dimensional inverse covariances computed over the cliques and separators.

$$\boldsymbol{\Sigma}^{-1} = J_{i,j} = \sum_{\mathcal{C}\ s.t.\ \{i,j\}\in\mathcal{C}} \left(\boldsymbol{\Sigma}_{\mathcal{C}}^{-1}\right)_{i,j} - \sum_{\mathcal{S}\ s.t.\ \{i,j\}\in\mathcal{S}} (k(\mathcal{S})-1)\left(\boldsymbol{\Sigma}_{\mathcal{S}}^{-1}\right)_{i,j}$$

This solves the curse of dimensionality problem

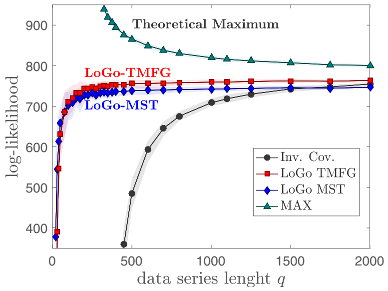
Problem 2: Results

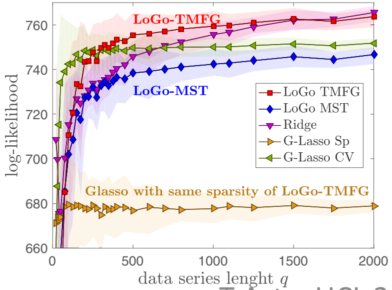
Sparse modeling yields to larger likelihoods

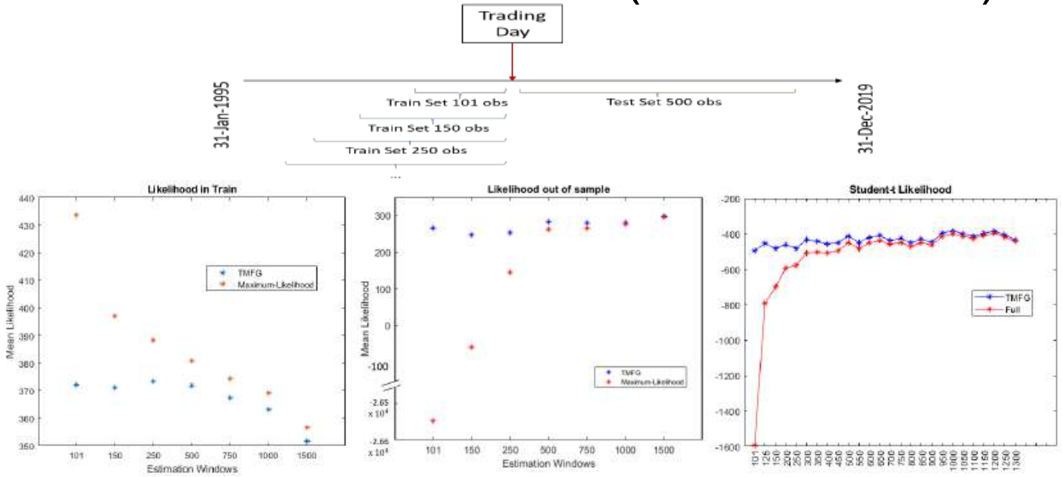
- Barfuss, W., Massara, G.P., Di Matteo, T. and Aste, T., 2016. Parsimonious modeling with information filtering networks. Physical Review E, 94(6), p.062306.
- Procacci, P.F. and Aste, T., 2021. Portfolio Optimization with Sparse Multivariate Modelling. arXiv preprint arXiv:2103.15232.

Likelihood comparison between models with full covariance (max likelihood) and sparse covariance (LoGo)

LoGo sparse models have larger likelihood than Glasso models, they can be computed in a fraction of computational time and have a more meaningful structure







Mean likelihoods from 100 tests computed form a randomly chosen trade day and with random sampling of 100 stocks over 342 US stocks over the period 1997-2016

Problem 3: setting

Non-stationarity

- Musmeci, N., Aste, T. & Di Matteo, T. Interplay between past market correlation structure changes and future volatility outbursts. Sci Rep 6, 36320 (2016). https://doi.org/10.1038/srep36320
- Aste, T., Shaw, W. and Di Matteo, T., 2010. Correlation structure and dynamics in volatile markets. New Journal of Physics, 12(8), p.085009.

- Model calibration needs observation sets that span long periods of time
- Markets change over time
- Models based on the past are not representing well the future
- The past cannot be treated as a consistent dataset
- Markets have both 'cyclical' dynamics and abrupt changes
- Some market states might repeat over time and others instead appear as new and unique

Time-clustering: Inverse Covariance Clustering (ICC)

- Procacci, P.F. and Aste, T., 2019. Forecasting market states. *Quantitative Finance*, *19*(9), pp.1491-1498.

- Market states are represented in terms of a mean $\boldsymbol{\mu}$ and a covariance $\boldsymbol{\Sigma}$
- Multivariate observations at each time-step can be gathered in a cluster together with other 'similar' observations
- Similarity is measured with a gain function
- Time-fragmentation must be penalized

Time-clustering: market states definition & gain function

- Procacci, P.F. and Aste, T., 2019. Forecasting market states. *Quantitative Finance*, *19*(9), pp.1491-1498.

$$\boxed{M_{t,k} = D_{t,k} + \gamma \mathbb{1}\{K_{t-1} \neq k\}}$$

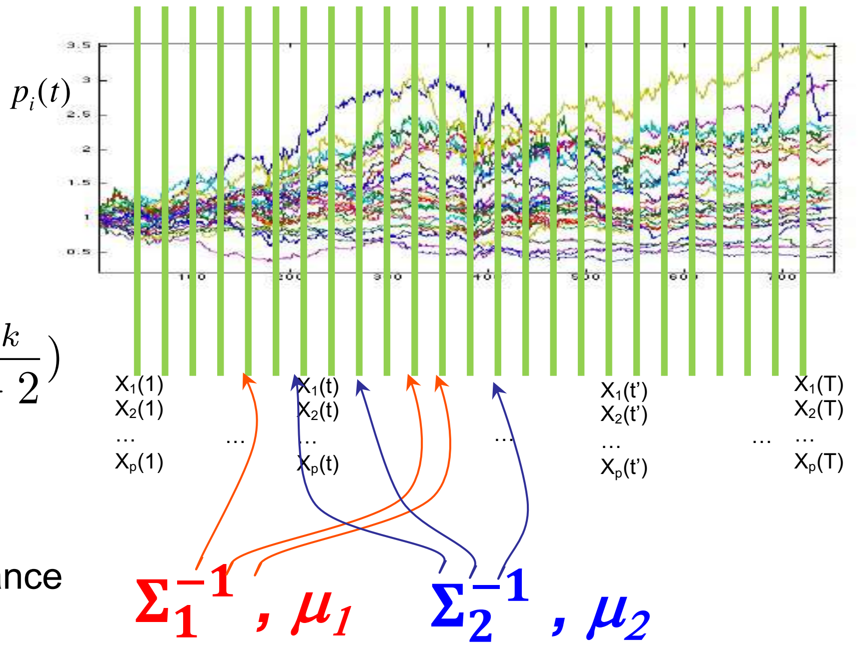
$$D_{t,k} = (X_t - \mu_k)^\top (X_t - \mu_k)$$

$$D_{t,k} = \mathcal{L}_{t,k} = 1/2(\log|\Sigma_k^{-1}| - d_{t,k}^2 - p\log(e\pi))$$

$$D_{t,k} = \mathcal{L}_{t,k}^{St} = \frac{1}{2}\log|\Sigma_k^{-1}| - \frac{\nu+p}{2}\log(1+\frac{d_{t,k}^2}{\nu-2})$$

$$D_{t,k} = c_1\log|\Sigma_k^{-1}| - c_2 d_{t,k}^2$$

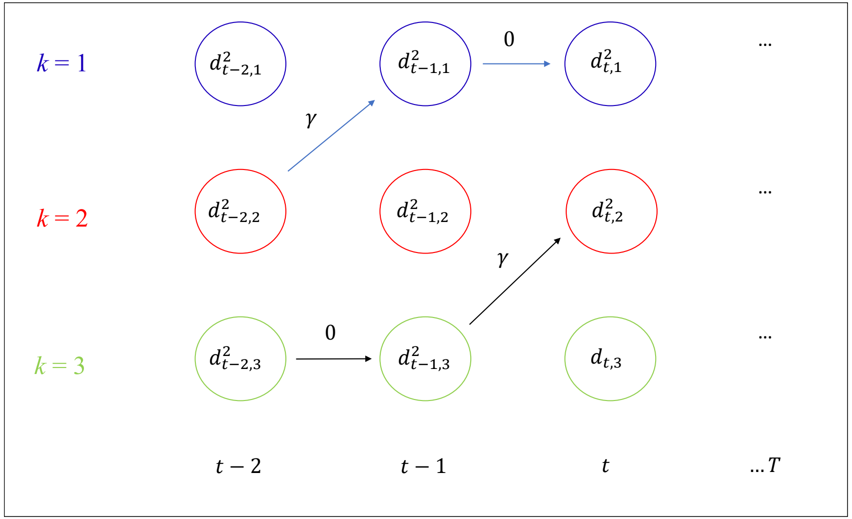
$$d_{t,k}^2 = (X_t - \mu_k)^\top \Sigma_k^{-1}(X_t - \mu_k)$$ Mahalanobis distance



Time-clustering: algorithm

- Procacci, P.F. and Aste, T., 2019. Forecasting market states. *Quantitative Finance*, *19*(9), pp.1491-1498.

- Assigning at random time steps to clusters
- Estimate covariance and mean for each cluster (using LoGo)
- Compute gain
- Reassign entries to cluster to maximize gain

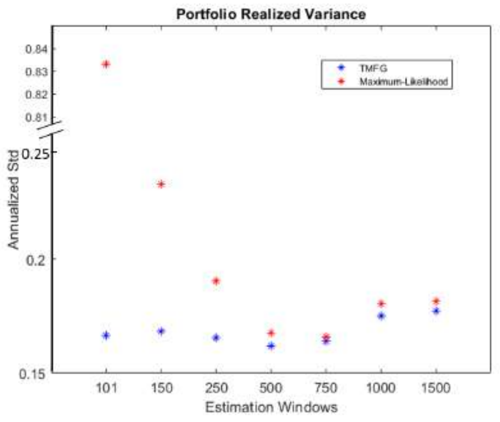


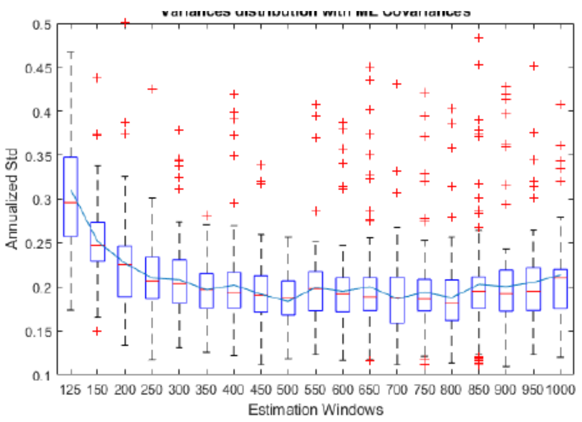
Use Viterbi path to make computation efficient

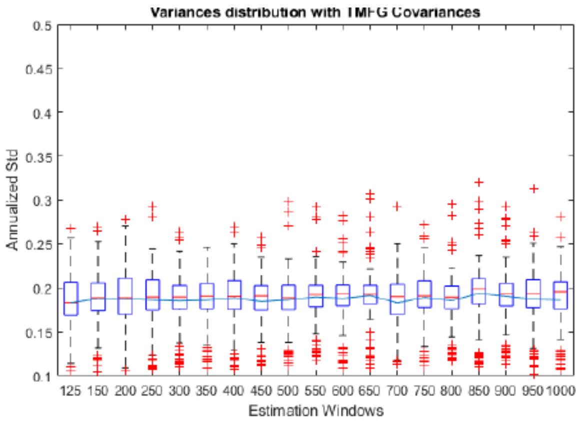
Effect of sparsification on portfolio performance

- Procacci, P.F. and Aste, T., 2021. Portfolio Optimization with Sparse Multivariate Modelling. arXiv preprint arXiv:2103.15232.

Sparse (Markowitz) portfolios constructed with sparse inverse covariances (LoGo-TMFG) have better performances than the ones with the full matrix





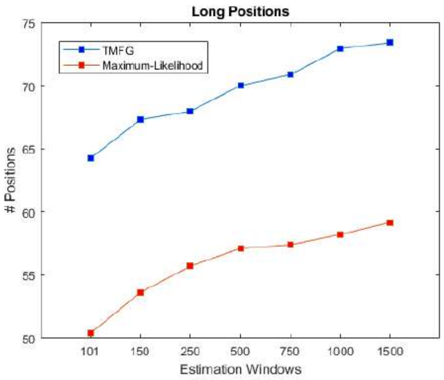


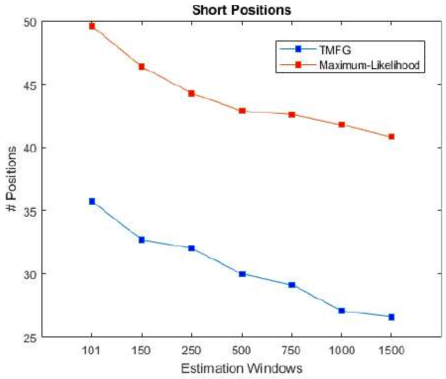
Results from 100 tests computed form a randomly chosen trade day and with random sampling of 100 stocks over 342 US stocks over the period 1997-2016

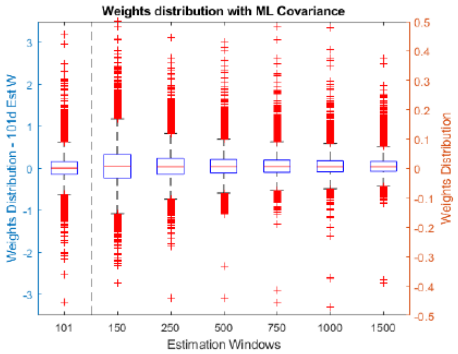
Effect of sparsification on portfolio composition

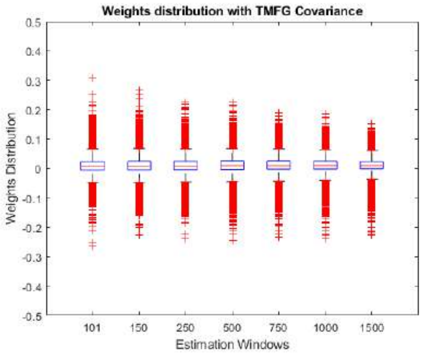
- Procacci, P.F. and Aste, T., 2021. Portfolio Optimization with Sparse Multivariate Modelling. arXiv preprint arXiv:2103.15232.

Sparse (Markowitz) portfolios constructed with sparse inverse covariances (LoGo-TMFG) have lower negative weights and narrower weight distribution







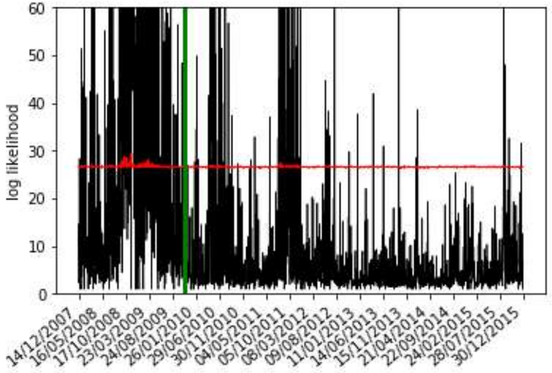


Results from 100 tests computed form a randomly chosen trade day and with random sampling of 100 stocks over 342 US stocks over the period 1997-2016

Sparse modeling and stationarity

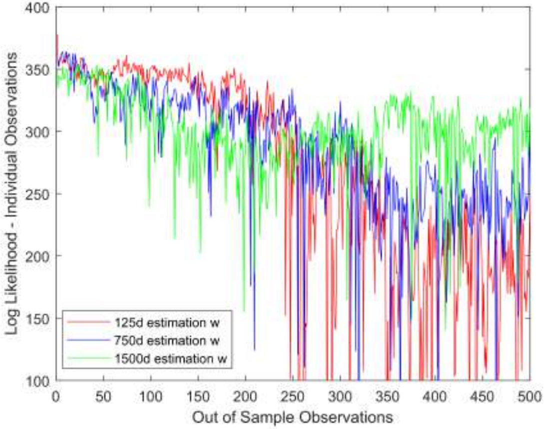
- Procacci, P.F. and Aste, T., 2019. Forecasting market states. *Quantitative Finance*, *19*(9), pp.1491-1498.
- Procacci, P.F. and Aste, T., 2021. Portfolio Optimization with Sparse Multivariate Modelling. arXiv preprint arXiv:2103.15232.

Modeling with sparse (LoGo) covariance is more consistent across time than modeling with full (ridge) estimator

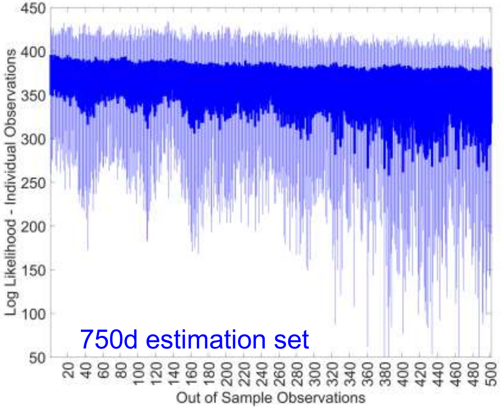


Results from 1 tests computed form a randomly chosen trade day and with random sampling of 100 stocks over 2490 US RIY index stocks traded between 02/01/1995 and 31/12/2015

Models (LoGo) trained on short estimation windows perform better on short out-of sample periods



Likelihood decreases with distance from the train set and variability increases



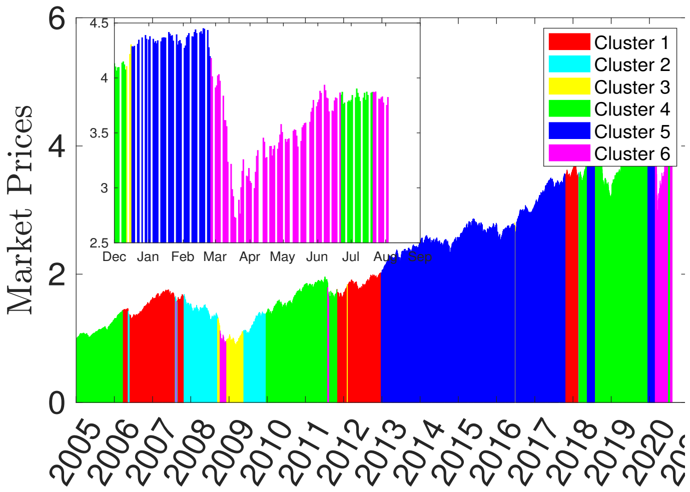
Results from 100 tests computed form a randomly chosen trade day and with random sampling of 100 stocks over 342 US stocks over the period 1997-2016

Problem 3: Results

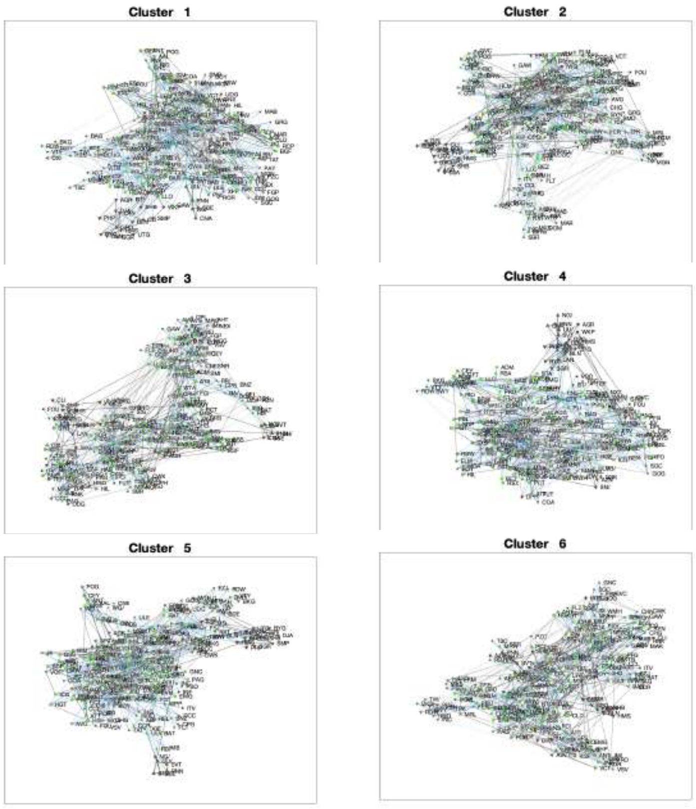
ICC clustering

- Isobel Seabrook, Fabio Caccioli, Tomaso Aste, An Information Filtering approach to stress testing: an applicationto FTSE markets (2021) preprint

- ICC clusters are representative of market states
- Different market periods are automatically gathered in clusters
- Example for 6 clusters obtained using likelihood gain function

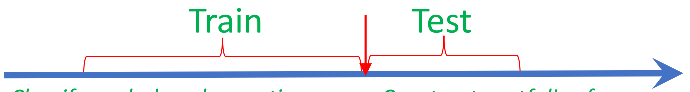


Average market price with color showing the clusters from FTSE 100 and 250 indices, from January 2005 to August 2020.



Effect of sparsification and clustering on portfolio performances

Yuanrong Wang & TA, Riding the Market Waves: Dynamic Portfolio Optimization with Inverse Covariance Clustering, 2021 preprint



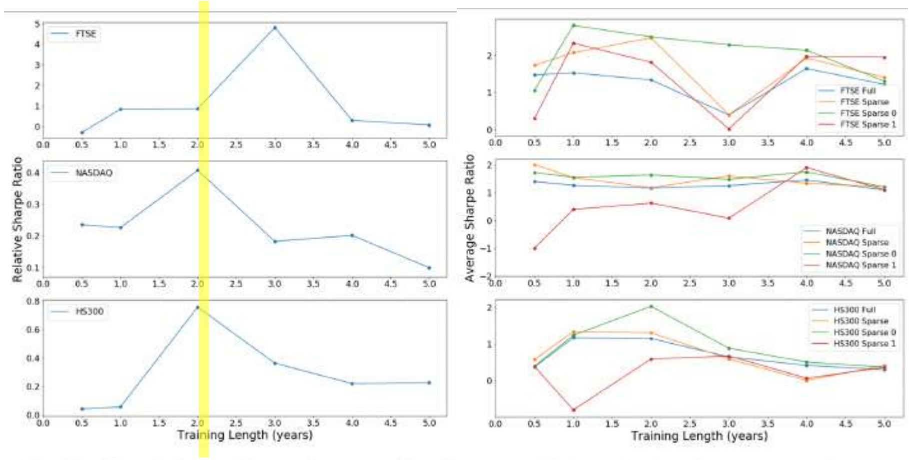
Classify each day observation into two clusters. Call '0' the one mostly present in the last part of the training period

Construct portfolios for both cluster's covariances

Portfolio optimizations:

- Markowitz's Mean Variance Optimisation
- Sequential Least Square (SLS)
- Critical Line Algorithm (CLA)

Chose 2 years



(a) Relative difference in Sharpe Ratio between the Sparse 0 and the Full

(b) Sharpe Ratio of the Full, Sparse, Sparse 0 and 1

Markets:
315 US NASDAQ stocks
229 UK FTSE stocks
129 Chinese HS300 stocks

Results are means for 100 samples with 100 random stocks

Optimal portfolio construction:

Market	Solver	State	Return (%)	(5,95)th percentile	Volatility	(5,95)th percentile	Sharpe	(5,95)th percentile
NASDAQ	SLS	Market	-5.10	(-171,206)	0.221	(0.14,0.4)	1.159	(-8.7,12.5)
NASDAQ	SLS	Full	0.62	(-192,190)	0.250	(0.13,0.57)	1.301	(-5.4,10.1)
NASDAQ	SLS	Sparse	-1.12	(-160,223)	0.225	(0.13,0.51)	1.559	(-7.4,10.3)
NASDAQ	SLS	Sparse 0	12.60	(-144,174)	0.205	(0.11,0.49)	2.432	(-5.0,12.6)
NASDAQ	SLS	Sparse 1	-22.98	(-181,218)	0.256	(0.14,0.59)	-0.083	(-8.7,7.8)
NASDAQ	CLA	Market	-1.67	(-171,208)	0.218	(0.14,0.4)	1.266	(-8.7,12.5)
NASDAQ	CLA	Full	4.34	(-192,198)	0.249	(0.13,0.57)	1.362	(-5.4,10.1)
NASDAQ	CLA	Sparse	2.95	(-160,223)	0.224	(0.13,0.51)	1.640	(-7.4,10.3)
NASDAQ	CLA	Sparse 0	20.17	(-169,171)	0.210	(0.12,0.36)	2.646	(-5.0,14.2)
NASDAQ	CLA	Sparse 1	-26.10	(-256,144)	0.257	(0.14,0.67)	-0.350	(-6.5,6.5)
NASDAQ	MM	Market	-5.39	(-171,206)	0.217	(0.14,0.4)	1.055	(-8.7,12.5)
NASDAQ	MM	Full	-3.05	(-228,196)	0.200	(0.12,0.43)	1.023	(-6.5,12.1)
NASDAQ	MM	Sparse	-4.45	(-231,196)	0.202	(0.12,0.45)	0.946	(-6.6,11.8)
NASDAQ	MM	Sparse 0	0.51	(-229,195)	0.202	(0.12,0.45)	1.194	(-7.1,12.6)
NASDAQ	MM	Sparse 1	-8.72	(-225,192)	0.210	(0.13,0.45)	0.617	(-7.1,11.1)
FTSE	SLS	Market	2.72	(-161,117)	0.126	(0.07,0.34)	1.661	(-9.2,15.4)
FTSE	SLS	Full	4.59	(-163,116)	0.126	(0.08,0.28)	2.090	(-8.7,14.1)
FTSE	SLS	Sparse	4.41	(-148,108)	0.123	(0.08,0.33)	2.295	(-8.9,14.2)
FTSE	SLS	Sparse 0	22.57	(-111,138)	0.103	(0.07,0.22)	4.038	(-7.1,18.8)
FTSE	SLS	Sparse 1	-10.79	(-199,118)	0.136	(0.09,0.4)	0.220	(-12.1,13.0)
FTSE	CLA	Market	2.72	(-161,117)	0.126	(0.07,0.34)	1.661	(-9.2,15.4)
FTSE	CLA	Full	4.55	(-163,116)	0.126	(0.08,0.28)	2.085	(-8.7,14.1)
FTSE	CLA	Sparse	4.42	(-148,108)	0.123	(0.08,0.33)	2.296	(-8.9,14.2)
FTSE	CLA	Sparse 0	25.08	(-111,146)	0.103	(0.07,0.21)	4.466	(-8.3,18.0)
FTSE	CLA	Sparse 1	-10.47	(-176,123)	0.130	(0.08,0.36)	0.228	(-11.0,13.7)
FTSE	MM	Market	2.72	(-161,117)	0.126	(0.07,0.34)	1.661	(-9.2,15.4)
FTSE	MM	Full	7.20	(-136,113)	0.122	(0.08,0.31)	1.942	(-9.0,12.6)
FTSE	MM	Sparse	7.03	(-149,138)	0.124	(0.07,0.32)	1.895	(-9.2,12.2)
FTSE	MM	Sparse 0	8.84	(-136,140)	0.122	(0.07,0.3)	2.095	(-9.2,12.8)
FTSE	MM	Sparse 1	5.02	(-142,137)	0.125	(0.08,0.32)	1.571	(-9.2,12.0)
HS300	SLS	Market	0.83	(-228,198)	0.197	(0.1,0.6)	1.392	(-7.7,10.8)
HS300	SLS	Full	18.57	(-250,216)	0.226	(0.12,0.42)	2.250	(-8.3,15.8)
HS300	SLS	Sparse	13.54	(-283,252)	0.216	(0.11,0.44)	2.273	(-8.1,15.3)
HS300	SLS	Sparse 0	39.53	(-165,276)	0.207	(0.11,0.42)	3.282	(-5.6,15.2)
HS300	SLS	Sparse 1	-21.42	(-289,176)	0.230	(0.13,0.44)	-0.126	(-8.3,7.9)
HS300	CLA	Market	0.83	(-228,198)	0.197	(0.1,0.6)	1.392	(-7.7,10.8)
HS300	CLA	Full	18.59	(-250,216)	0.226	(0.12,0.42)	2.252	(-8.3,15.8)
HS300	CLA	Sparse	13.60	(-283,252)	0.216	(0.11,0.44)	2.278	(-8.1,15.3)
HS300	CLA	Sparse 0	40.65	(-131,250)	0.208	(0.11,0.45)	3.715	(-5.3,18.8)
HS300	CLA	Sparse 1	-22.63	(-331,218)	0.247	(0.12,0.58)	-0.090	(-8.9,9.9)
HS300	MM	Market	0.83	(-228,198)	0.197	(0.1,0.6)	1.392	(-7.7,10.8)
HS300	MM	Full	-0.21	(-204,217)	0.185	(0.1,0.45)	0.939	(-8.8,10.2)
HS300	MM	Sparse	0.41	(-213,231)	0.185	(0.09,0.57)	0.936	(-8.7,10.1)
HS300	MM	Sparse 0	3.59	(-206,212)	0.182	(0.09,0.56)	1.144	(-8.3,11.2)
HS300	MM	Sparse 1	-4.45	(-219,227)	0.188	(0.09,0.45)	0.526	(-8.8,9.9)

Market	Solver	State	Return (%)	(5,95)th percentile	Volatility	(5,95)th percentile	Sharpe	(5,95)th percentile
NASDAQ	SLS	Market	0.13	(-112,137)	0.224	(0.154,**0.428**)	0.736	(-2.4,7.0)
NASDAQ	SLS	Full	6.73	(-105,113)	0.256	(0.164,0.745)	0.672	(-3.0,5.0)
NASDAQ	SLS	Sparse	5.92	(-135,120)	0.235	(0.155,0.743)	0.834	(-3.2,5.5)
NASDAQ	SLS	Sparse 0	**14.12**	(**-52**,116)	**0.220**	(0.124,0.784)	**1.340**	(-2.6,5.6)
NASDAQ	SLS	Sparse 1	-11.21	(-169,86)	0.272	(0.165,0.741)	-0.078	(-3.9,3.3)
NASDAQ	CLA	Market	0.13	(-112,137)	0.224	(0.154,**0.428**)	0.736	(-2.4,7.0)
NASDAQ	CLA	Full	7.22	(-105,113)	0.255	(0.165,0.715)	0.692	(-3.0,5.0)
NASDAQ	CLA	Sparse	7.12	(-135,120)	0.234	(0.154,0.736)	0.880	(-3.2,5.5)
NASDAQ	CLA	Sparse 0	**14.00**	(**-61**,116)	**0.214**	(0.144,0.712)	**1.409**	(-2.5,6.2)
NASDAQ	CLA	Sparse 1	-11.83	(-146,78)	0.263	(0.154,0.797)	0.011	(-4.1,3.7)
NASDAQ	MM	Market	0.13	(-112,137)	0.224	(0.154,**0.428**)	0.736	(-2.4,7.0)
NASDAQ	MM	Full	-1.34	(-123,101)	0.210	(0.144,0.666)	0.705	(-3.6,6.5)
NASDAQ	MM	Sparse	-1.92	(-125,97)	0.212	(0.146,0.672)	0.656	(-3.6,6.4)
NASDAQ	MM	Sparse 0	**0.41**	(**-111**,98)	**0.208**	(0.141,0.664)	**0.829**	(-3.5,6.6)
NASDAQ	MM	Sparse 1	-6.62	(-128,64)	0.224	(0.148,0.689)	0.445	(-3.9,5.7)
FTSE	SLS	Market	-0.68	(-69,64)	0.128	(0.100,0.252)	1.039	(-4.2,6.8)
FTSE	SLS	Full	5.02	(-56,79)	0.129	(0.106,0.242)	1.611	(-4.8,8.0)
FTSE	SLS	Sparse	6.07	(-53,73)	0.117	(0.105,0.208)	1.736	(-4.6,9.1)
FTSE	SLS	Sparse 0	**14.57**	(**-42**,74)	**0.107**	(0.082,**0.206**)	**2.607**	(-5.9,7.6)
FTSE	SLS	Sparse 1	2.27	(-88,66)	0.124	(0.111,0.225)	1.193	(-5.9,7.6)
FTSE	CLA	Market	10.14	(-86,40)	0.119	(0.084,**0.225**)	3.390	(-10.3,23.0)
FTSE	CLA	Full	11.22	(-79,35)	0.116	(0.108,0.264)	3.186	(-9.3,21.7)
FTSE	CLA	Sparse	11.23	(-73,36)	0.118	(0.973,0.266)	3.299	(-9.5,22.7)
FTSE	CLA	Sparse 0	**12.07**	(**-73**,37)	**0.111**	(0.077,0.272)	**3.437**	(-9.0,22.2)
FTSE	CLA	Sparse 1	9.31	(-76,39)	0.119	(0.087,0.265)	2.960	(-8.9,21.3)
FTSE	MM	Market	10.14	(-86,40)	0.119	(0.084,0.225)	3.389	(-10.3,23.0)
FTSE	MM	Full	15.59	(-47,37)	0.119	(0.087,0.225)	2.964	(-6.9,17.6)
FTSE	MM	Sparse	13.78	(-38,22)	0.110	(0.072,0.256)	3.261	(-9.2,18.0)
FTSE	MM	Sparse 0	**32.01**	(**-12**,61)	**0.101**	(0.071,**0.181**)	**5.378**	(-6.4,23.2)
FTSE	MM	Sparse 1	-7.47	(-69,23)	0.118	(0.095,0.246)	0.916	(-11.2,16.4)
HS300	SLS	Market	19.61	(-91,165)	0.217	(0.113,0.511)	1.541	(-3.3,6.0)
HS300	SLS	Full	20.02	(-127,168)	0.238	(0.164,0.423)	1.263	(-4.0,6.3)
HS300	SLS	Sparse	21.91	(-94,163)	0.229	(0.152,0.387)	1.530	(-4.1,7.1)
HS300	SLS	Sparse 0	**30.60**	(**-78**,182)	**0.215**	(0.125,**0.383**)	**1.925**	(-3.0,6.5)
HS300	SLS	Sparse 1	3.43	(-121,135)	0.255	(0.144,0.557)	0.584	(-3.9,5.5)
HS300	CLA	Market	19.61	(-91,165)	0.217	(0.113,0.511)	1.541	(-3.3,6.0)
HS300	CLA	Full	20.02	(-127,168)	0.238	(0.166,0.423)	1.267	(-4.0,6.3)
HS300	CLA	Sparse	21.91	(-94,163)	0.229	(0.155,**0.383**)	1.530	(-4.1,7.1)
HS300	CLA	Sparse 0	**31.90**	(**-54**,165)	**0.213**	(0.122,0.514)	**2.217**	(-2.3,7.8)
HS300	CLA	Sparse 1	4.99	(-110,138)	0.246	(0.145,0.437)	0.606	(-4.2,6.0)
HS300	MM	Market	**19.61**	(-91,165)	0.213	(0.113,0.511)	**1.541**	(-3.3,6.0)
HS300	MM	Full	16.20	(**-77**,139)	0.204	(0.115,0.466)	1.179	(-3.7,6.1)
HS300	MM	Sparse	16.92	(-79,143)	0.205	(0.112,0.463)	1.168	(-3.7,6.3)
HS300	MM	Sparse 0	18.73	(-78,150)	**0.201**	(0.111,**0.461**)	1.301	(-3.5,6.1)
HS300	MM	Sparse 1	13.93	(-80,130)	0.208	(0.114,0.462)	0.992	(-3.7,5.9)

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Centre and periphery of the network structure have different risk and performances

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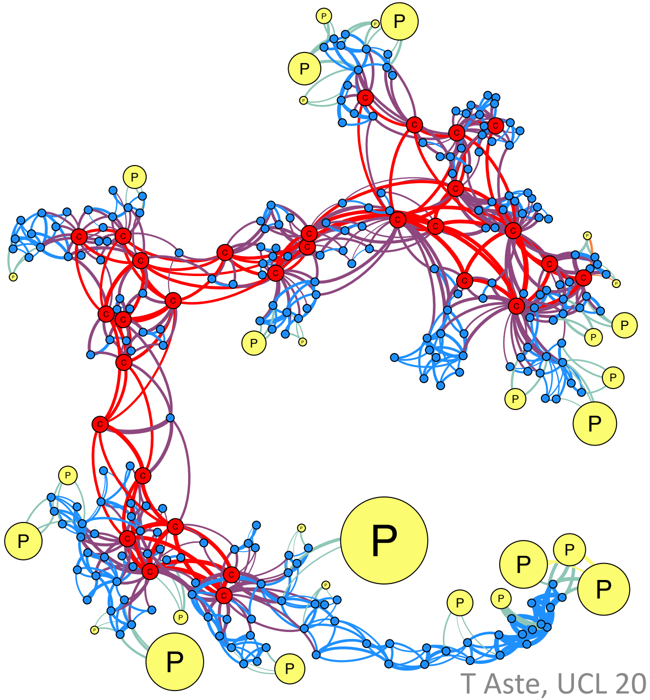
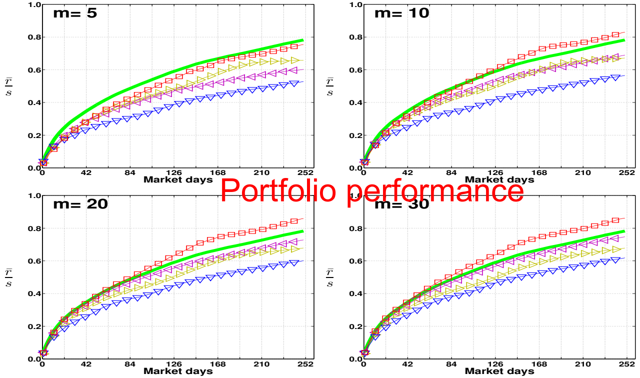
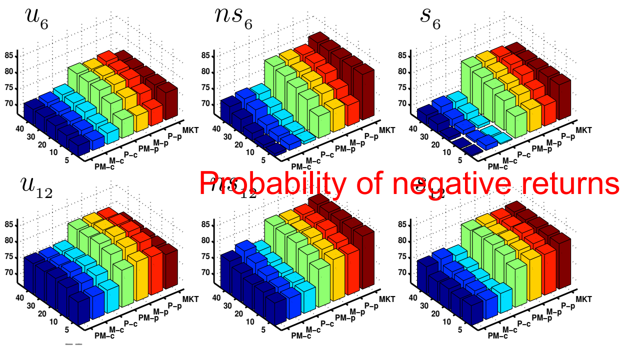


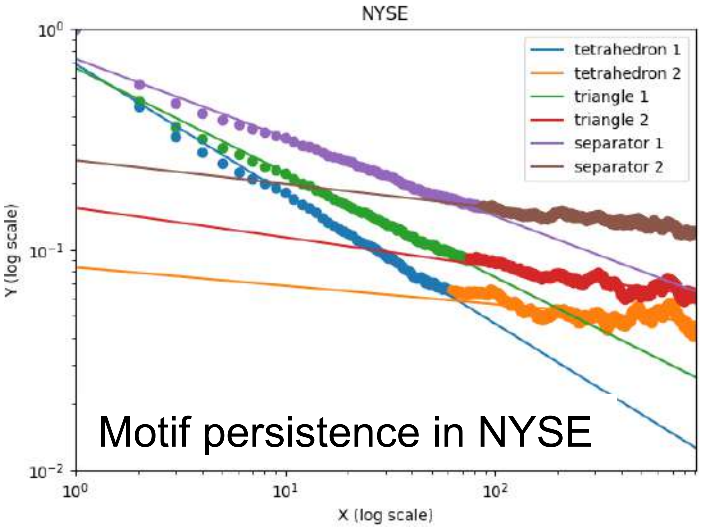


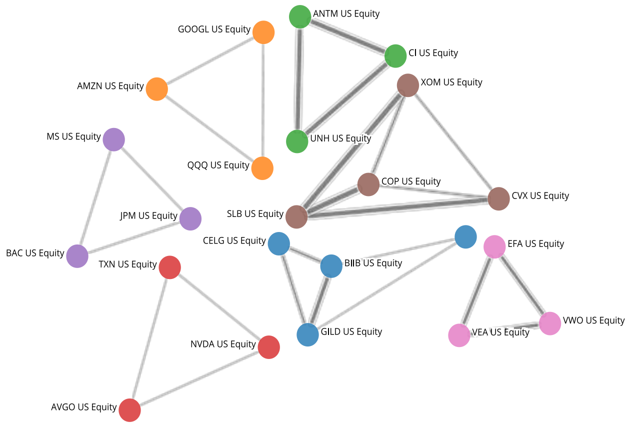


Other use of network: portfolios from persistent structures

- Turiel, J.D., Barucca, P. and Aste, T., 2020. Simplicial persistence of financial markets: filtering, generative processes and portfolio risk. arXiv preprint arXiv:2009.08794.
- Turiel, J.D. and Aste, T., 2019, December. Sector Neutral Portfolios: Long memory motifs persistence in market structure dynamics. In *International Conference on Complex Networks and Their Applications* (pp. 573-585). Springer, Cham.

The sparse network clique structure has long memory persistence





Experiments: 100 stocks NYSE, Germany, Italy, Israel, between 2012 and 2018

Conclusions and take-home message

1. Poor modeling
2. Parameter estimation error
3. Non-stationarity

- Unique and irreproducible observation set
- Error amplification via optimization

- Multivariate elliptical distribution family is appropriate for portfolio optimization (not exclusively mean-variance)
- LoGo sparse inverse covariance estimation largely improves model likelihood and portfolio performances
- ICC clustering is effective in handling non-stationarity
- A lot more can be done! *Collaborations welcome*

Links and references

LINKS

FCA Group Page:
http://fincomp.cs.ucl.ac.uk/introduction/

My articles:
https://scholar.google.co.uk/citations?user=27pUbTUAAAAJ&hl=en

Software:
TMFG & Clique Forests
https://github.com/cvborkulo/NetworkComparisonTest/pull/5
https://uk.mathworks.com/matlabcentral/fileexchange/56444-tmfg

RELEVANT PAPERS

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- "Stress testing and systemic risk measures using multivariate conditional probability." Aste, Tomaso Available at SSRN 3575512 (2020).
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- “Forecasting market states” Procacci, P.F. and Aste, T. Quantitative Finance, 19(9), pp.1491-1498 (2019)
- "Learning Clique Forests." Massara, Guido Previde, and Tomaso Aste. arXiv preprint arXiv:1905.02266 (2019).
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