Machine Learning in Quantitative Portfolio Management

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Quants vs Fundamentals

- Quants
  - Financial assets’ actual historical and live prices in the market
  - All the available and needed information in order to model and forecast financial values and risks, is already incorporated in the market data.

Quants vs Fundamentals

- Fundamentals
  - Model the market through its internal properties and the economic agents' expectations (Rational Expectations Theory etc.)
  - Start with assumptions about the proper model's specifications and structure and then test the empirical evidence based on market data
  - Ending hypothesis is the belief or "bet" that the theoretical model is correct - any deviations from it, will be eliminated as the market will try to correct the errors and converge to the theoretical model's patterns

Asset Classes - Trading Assets

We used the following cumulative **returns** formula to rebase every asset on the unit base and to compare their overall dynamics with price returns terms :

$$P_{new} = 1 + \sum_{i=1}^{n} dlog(P_{old}),$$

where P_{new} are the new rebased “prices”, P_{old} are the raw time series data, and *dlog* is the operator that provides the returns of the raw assets prices.

Asset Classes - Trading Assets
Multi Asset Class Dataset

<u>Equities Markets</u>:

E-Mini S&P 500 (ES1 Index), E-Mini Nasdaq 100 (NQ1 Index), Eurex DJ Euro Stoxx 50 (VG1 Index), Cac40 (CF1 Index), Eurex Dax (GX1 Index), Ftse 100 (Z1 Index), Ibovespa (BZ1 Index), Swiss Market Index (SM1 Index), Mexican Market Index (IS1 Index), Australia Market Index (XP1 Index), Nikkei (NK1 Index), Topix (TP1 Index), Hang Seng (HI1 Index)

<u>Bonds Markets:</u>

a) ***Government Bond Futures*** : 10 Year U.S. T Note (TY1 Comdty), 2 Year U.S. T-Note (TU1 Comdty), Canadian Government 10 Year Note (CN1 Comdty), France Government Bond Future (CF1 Comdty), Eurex Euro Bund (RX1 Comdty), Eurex Euro Schatz (DU1 Comdty), Gilt UK (G1 Comdty), 5 Year T-Note (FV1 Comdty), Japan 10 Year Bond Futures (BJ1 Comdty), Australian 10 Year Bond (XM1 Comdty), Australian 3 Year Bond (YM1 Comdty), Euro Bobl (OE1 Comdty)

b) ***Corporate Bond Yields*** **:** The whole list with the 96 indices from the Category “BofA Merrill Lynch Index Yields”, in the FRED Database. (https://fred.stlouisfed.org/categories/32347)

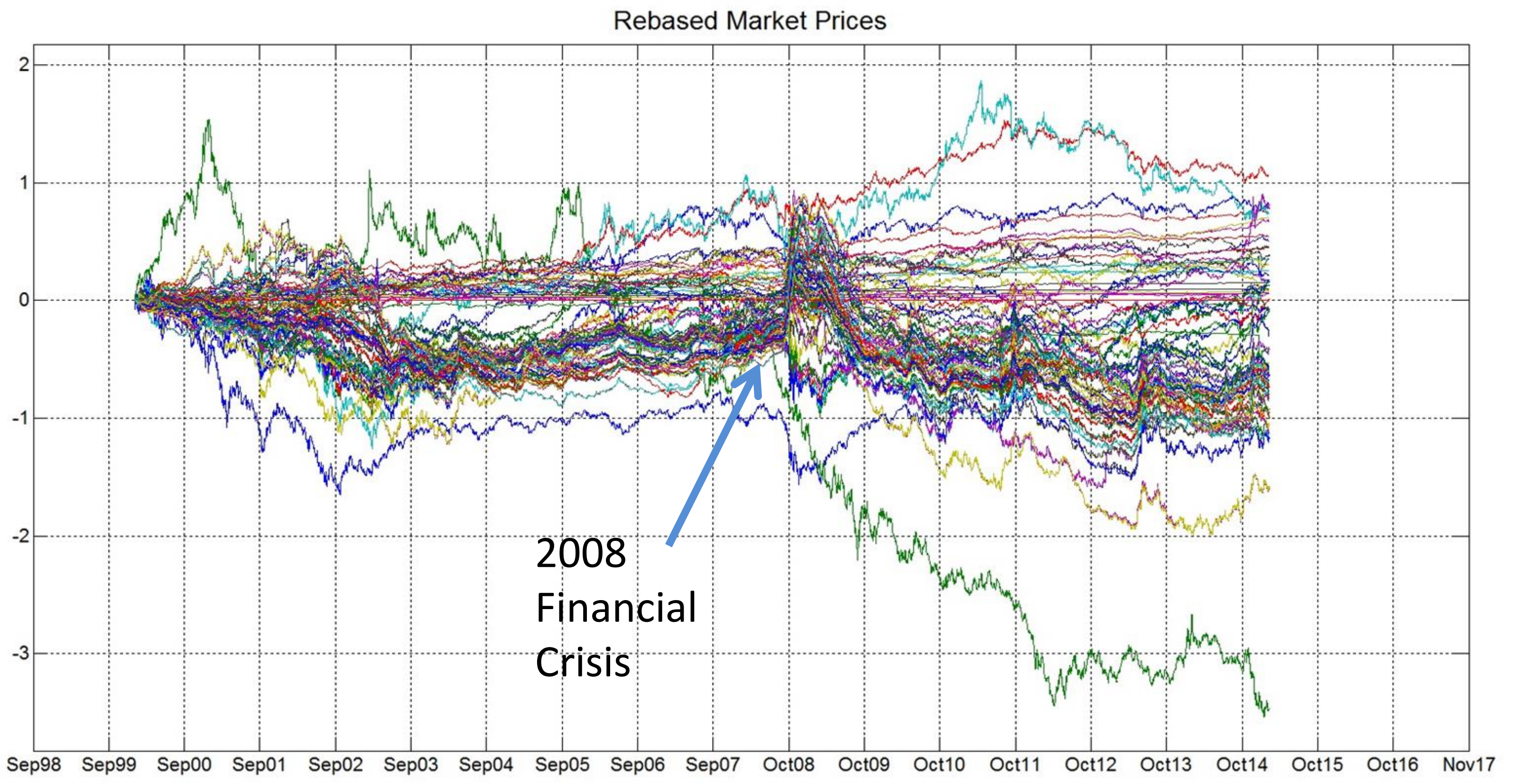
<u>Commodities Markets:</u>

Natural Gas (NG1 Comdty), Gold (GC1 Comdty), Silver (SI1 Comdty), Crude Oil (CL1 Comdty), Corn (ZC1 Comdty)

<u>FX Markets:</u>

EURUSD Curncy, USDJPY Curncy, EURJPY Curncy, EURCHF Curncy, GBPUSD Curncy, EURGBP Curncy, AUDUSD Curncy, AUDJPY Curncy, NZDUSD Curncy,EURAUD Curncy,USDRUB Curncy,USDCNH Curncy,USDMXN Curncy, USDINR Curncy

Asset Classes - Trading Assets
Multi Asset Class Dataset



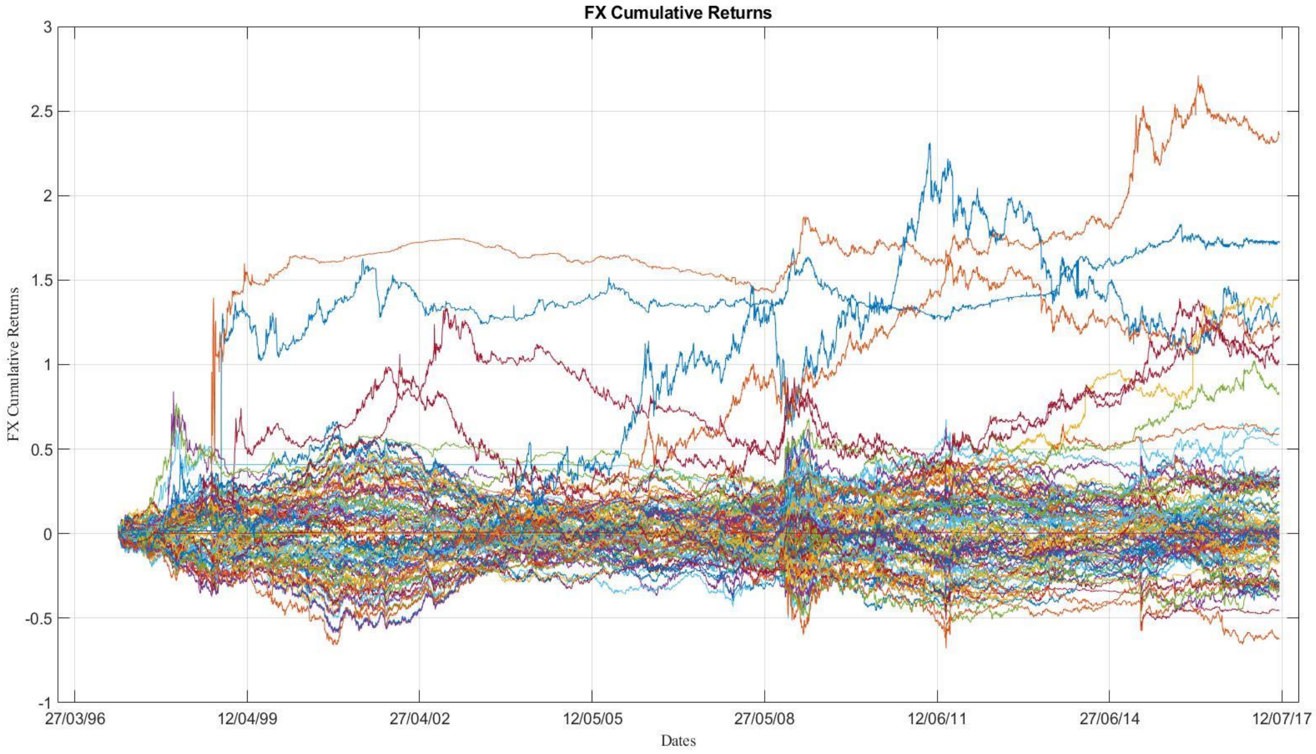
Asset Classes - Trading Assets
FX Asset Class Dataset only

Global FX Markets:

- The FX Dataset consists of one hundred (**100**) Foreign Exchange Pairs (Currencies), as obtained by the online eoddata.com Database, with spanning time period **01-01-1997** till **26-06-2017**. More specifically, the pairs under consideration are the following

- {'AUDCAD', 'AUDCHF', 'AUDEUR', 'AUDGBP', 'AUDHKD', 'AUDJPY', 'AUDNZD', 'AUDSGD', 'AUDUSD', 'CADAUD', 'CADCHF', 'CADGBP', 'CADHKD', 'CADJPY', 'CADNZD', 'CADSGD', 'CADUSD', 'CHFAUD', 'CHFCAD', 'CHFGBP', 'CHFHKD', 'CHFJPY', 'CHFNZD', 'CHFSGD', 'CHFUSD', 'EURAUD', 'EURCAD', 'EURCHF', 'EURGBP', 'EURHKD', 'EURJPY', 'EURNZD', 'EURSGD', 'EURUSD', 'GBPAUD', 'GBPCAD', 'GBPCHF', 'GBPEUR', 'GBPHKD', 'GBPJPY', 'GBPNZD', 'GBPSGD', 'GBPUSD', 'HKDAUD', 'HKDCAD', 'HKDCHF', 'HKDGBP', 'HKDJPY', 'HKDNZD', 'HKDSGD', 'HKDUSD', 'JPYAUD', 'JPYCAD', 'JPYCHF', 'JPYGBP', 'JPYHKD' ,'JPYNZD', 'JPYUSD', 'NZDAUD', 'NZDCAD', 'NZDCHF', 'NZDEUR', 'NZDGBP', 'NZDHKD', 'NZDJPY', 'NZDSGD', 'NZDUSD', 'SGDAUD', 'SGDCAD', 'SGDCHF', 'SGDGBP', 'SGDHKD', 'SGDJPY', 'SGDNZD', 'SGDUSD', 'USDAUD', 'USDBRL', 'USDCAD', 'USDCHF', 'USDCNY', 'USDDKK', 'USDEUR', 'USDGBP', 'USDHKD', 'USDIDR', 'USDINR', 'USDJPY', 'USDKRW', 'USDMXN', 'USDMYR', 'USDNOK', 'USDNZD', 'USDRUB', 'USDSEK', 'USDSGD', 'USDTHB', 'USDTWD', 'USDZAR', 'XAGUSD', 'XAUUSD'}

Asset Classes - Trading Assets
FX Asset Class Dataset only



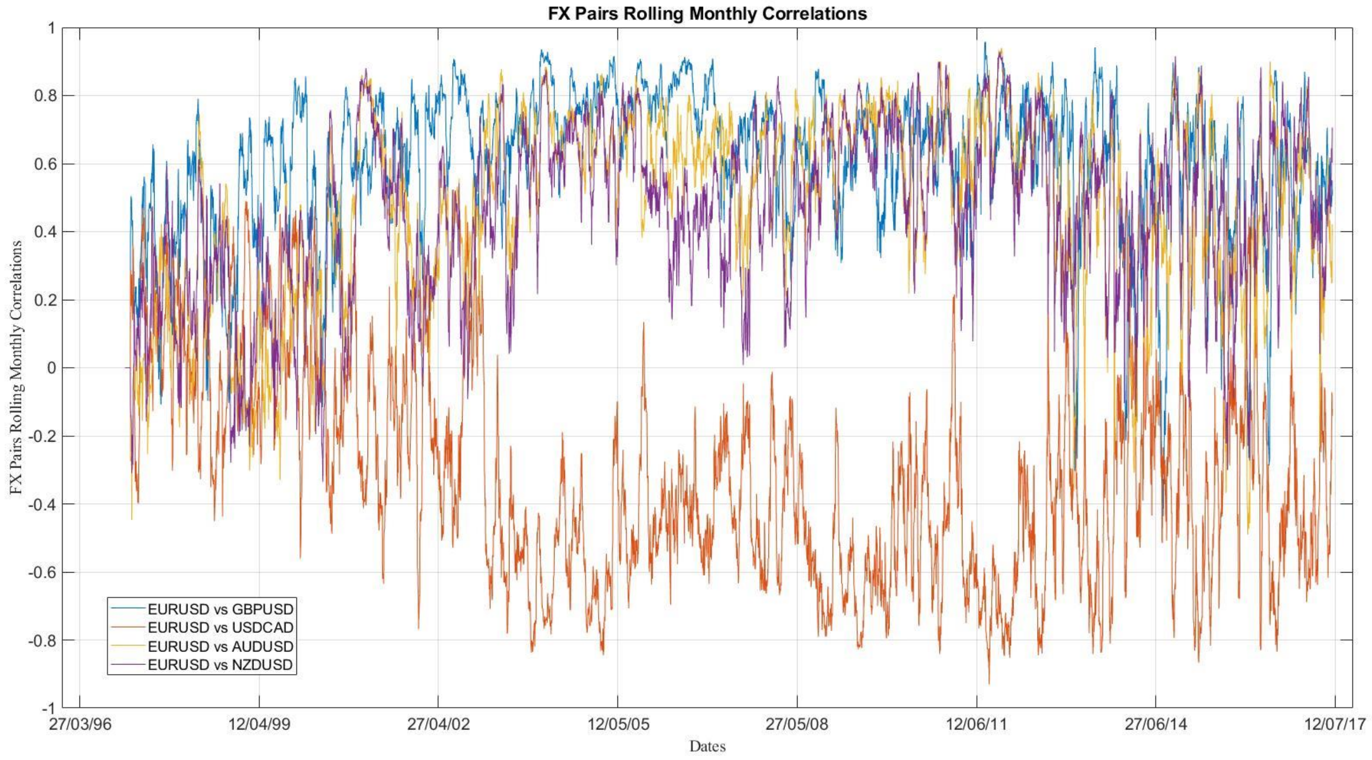
Portfolio Management

- Portfolio Diversification – Risk Management

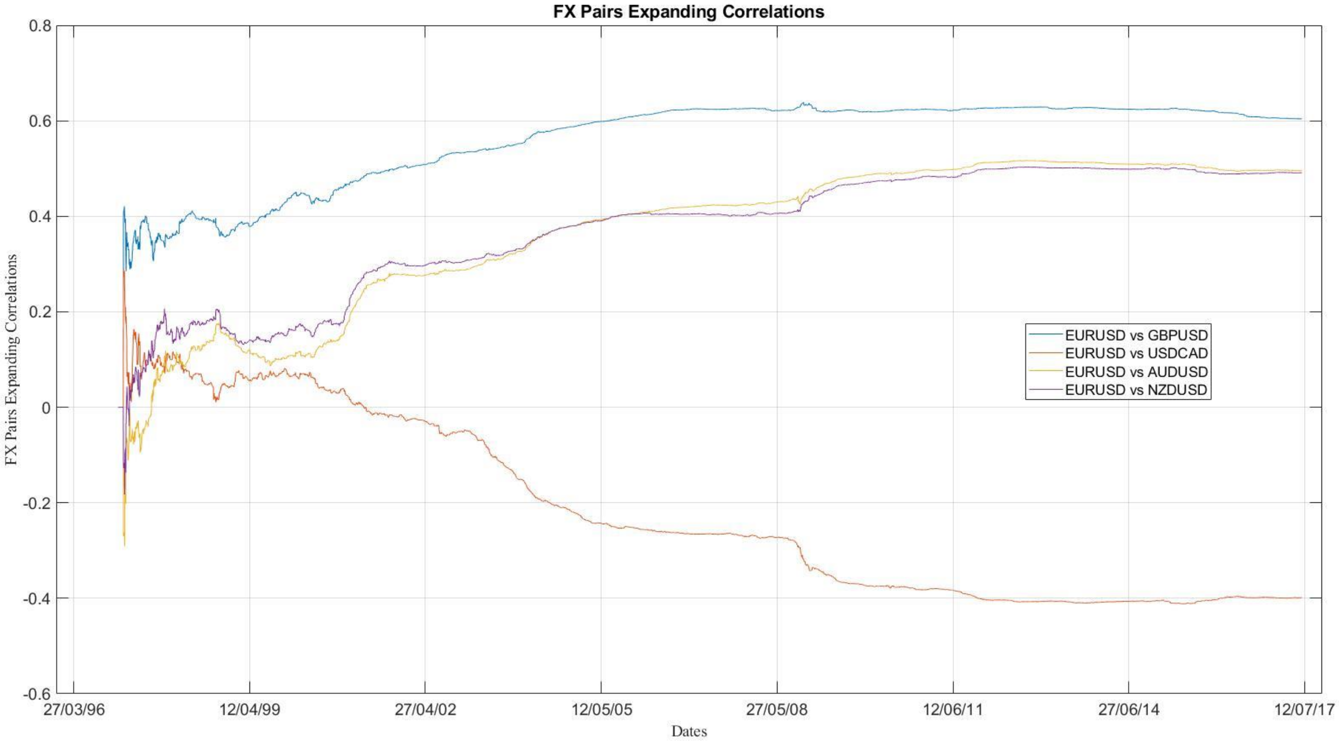
- Expected Return $$E(R_p) = \sum_i w_i E(R_i)$$

- Overall portfolio's risk, is given in terms of variance $$\sigma_p^2 = \sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij}$$

Portfolio Management



Portfolio Management



Portfolio Management

- Target = Consistent Profit Making

$$\Pi_t = \int_0^t W_t * d(R_t)\, dt,$$

→ d() and not dlog() ???

- where Wt are the weights invested in each asset in the portfolio and Rt are the **cumulative** returns of the trading assets in the portfolio.

Portfolio Management

- How do we select the trading weights in every step in time ?

- Are they functions of the correlations between the assets ?
  - noisy rolling correlations
  - not so noisy expanding correlations

- Which correlation measurement should we care for ? Is there only spatial correlation? What about temporal ones?

  - What if we 'shrinked', 'folded' or 'unfolded' the time of the trading assets dynamics ?

- Geometry – Manifold Learning – Machine Learning

Modeling and Forecasting

- Trading
- Model and forecast each asset individually
- Build equally weighted portfolios using the above models-assets pairs
- Difficulties :
  - How are all those correlated / connected ?
  - How can I perform risk management on the portfolio w/o knowing the ‘connections’ ?

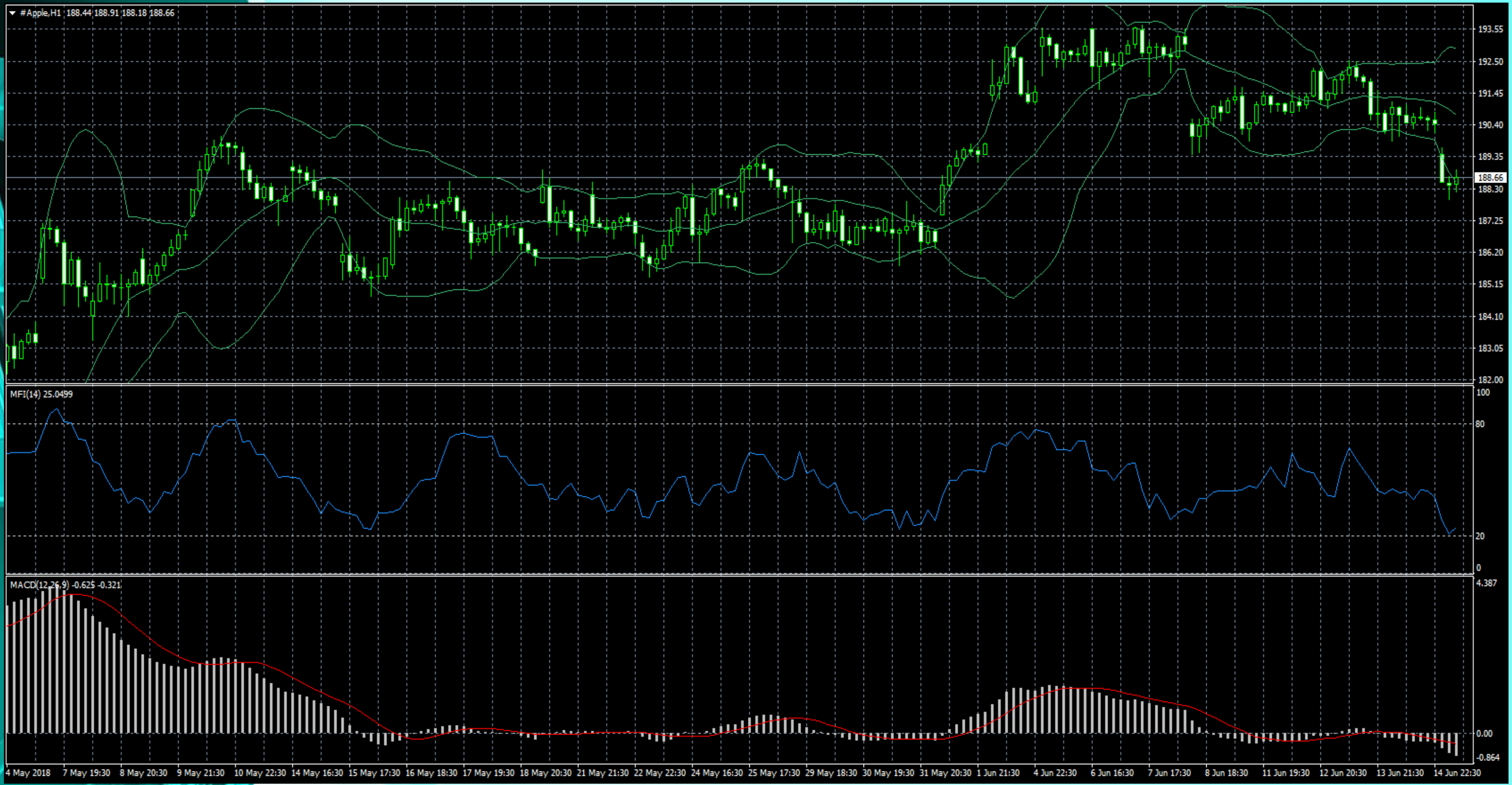
Modeling and Forecasting

- Technical Analysis

- ✓ Relative Strength Index
- ✓ Money Flow Index
- ✓ Stochastics
- ✓ MACD and
- ✓ Bollinger Bands
- ✓ and many others

Modeling and Forecasting

Modeling and Forecasting



Modeling and Forecasting
The Alchemists - Quants

$$S = \frac{E[R - R_f]}{\sqrt{\mathrm{var}[R]}}.$$

$$V_t = \mu t + v_0 e^{-\kappa t} + \sigma \int_0^t e^{\kappa(u-t)} dW_u.$$

$$dU_t = \kappa\,(\theta - U_t)\,dt + \sigma dW_t.$$

$$dx_t = \theta(\mu - x_t)\,dt + \sigma\,dW_t$$

$$U_t = e^{-\kappa t} u_0 + \theta(1 - e^{-\kappa t}) + \sigma \int_0^t e^{\kappa(s-t)} dW_s$$

$$d(V_t - \mu t) = -\kappa\,(V_t - \mu t)\,dt + \sigma dW_t.$$

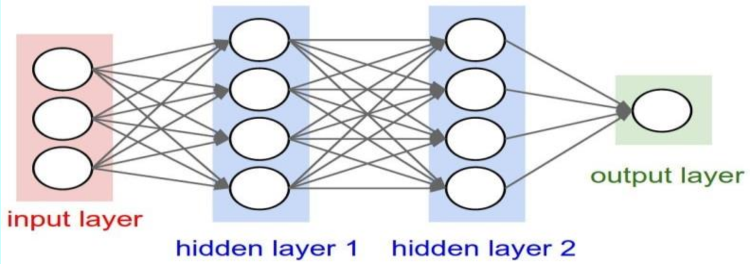
$$\Pi_t = \int_0^t W_t * d(ES_t)\,dt,$$

$$dS_t = \mu S_t\,dt + \sigma S_t\,dW_t$$

Modeling and Forecasting
The Alchemists – Quants – "Machined"

- <u>Unsupervised Machine Learning</u>
  - Feature Selection
    - PCA
    - Isomap
    - Diffusion Maps
    - K-means Clustering
    - Autoencoders
    - Boltzmann Machines etc.
    - "Linearization" of the Nonlinear Methods (PP PhD)
  - Portfolio Construction

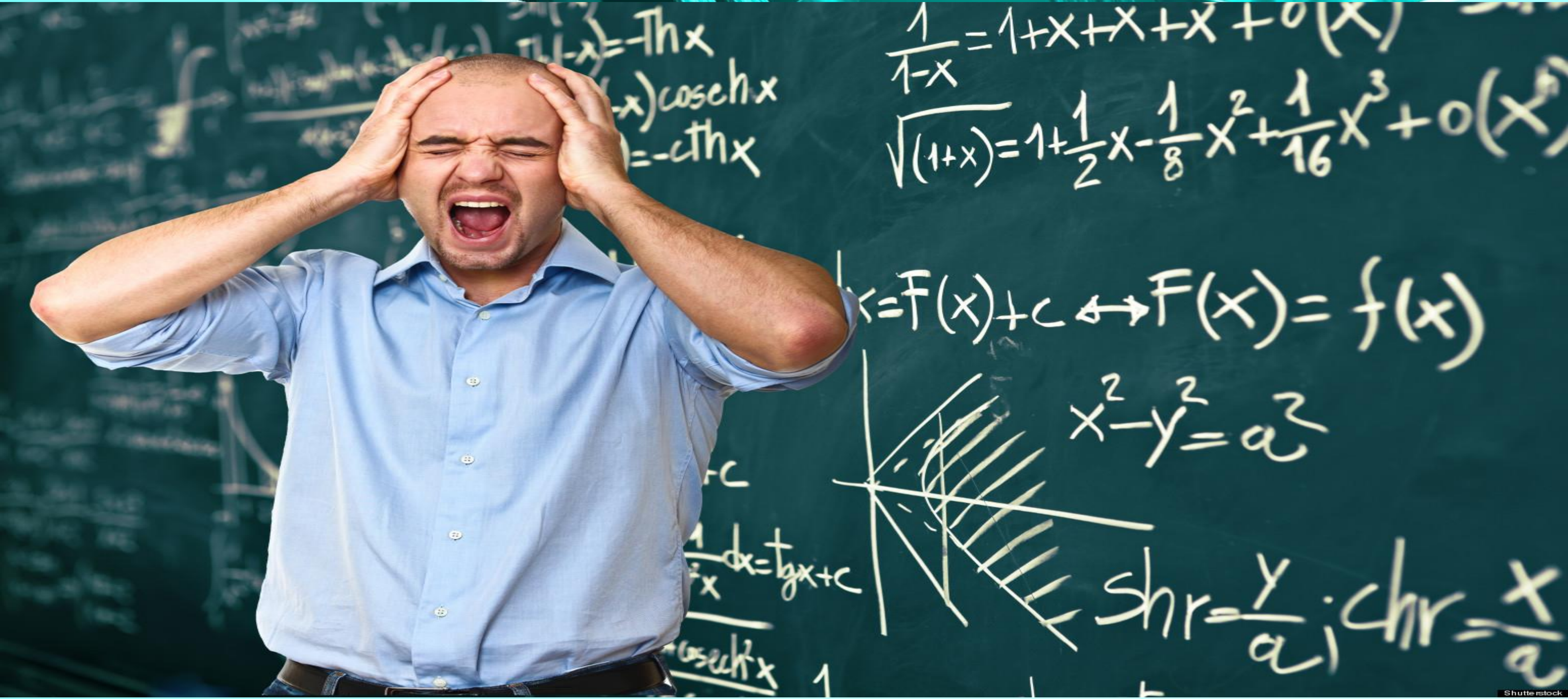
- <u>Supervised Machine Learning</u>
  - Labeling of what's right or wrong
    - Artificial Neural Networks (ANNs)
    - Recurrent Neural Networks (RNNs)
    - Convolution Neural Networks (CNNs)
  - Forecasting of the next price / on everything!



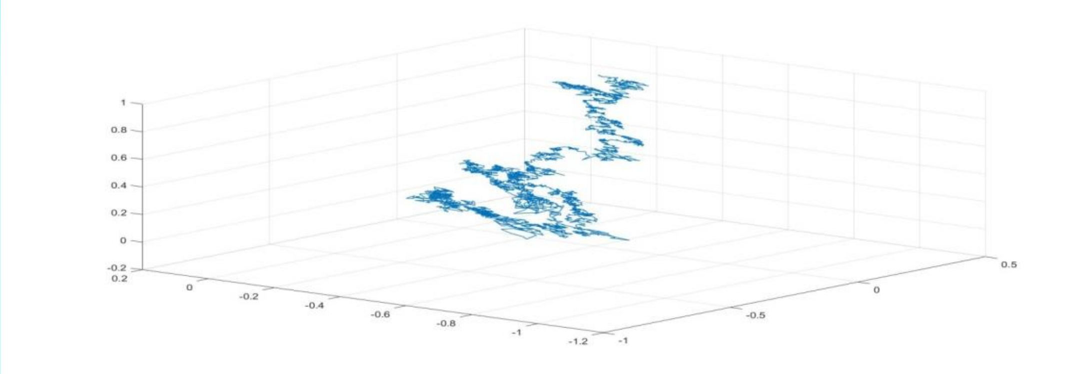
Neural Networks for Price Forecasting

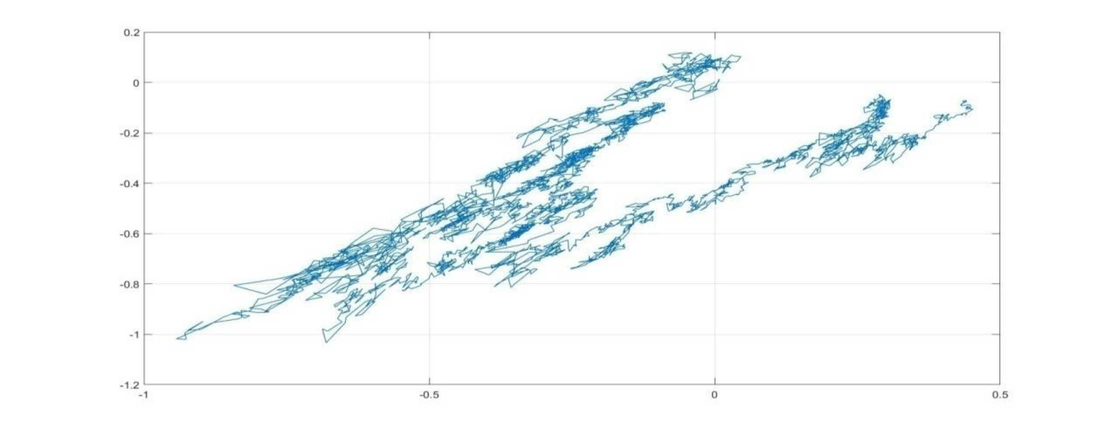
- Artificial Neural Networks (ANNs)
  - Neurons
  - Connections and weights
  - Back-Propagation Function
  - Learning Rule
- Recurrent Neural Networks (RNNs)
  - LSTM
  - Mostly for Time Series Analysis and Forecasting
- Convolutional Neural Networks (CNNs)
  - Image Processing
  - Voice and Video Processing

NOT EQUATIONS AGAIN – Let's Just Watch!



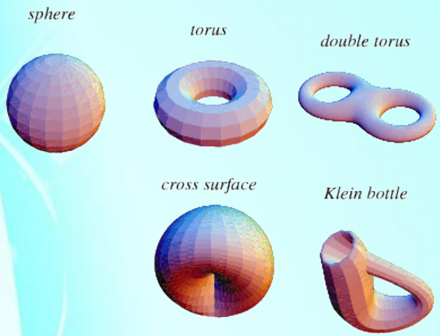
Modeling and Forecasting
Quants see "differently"

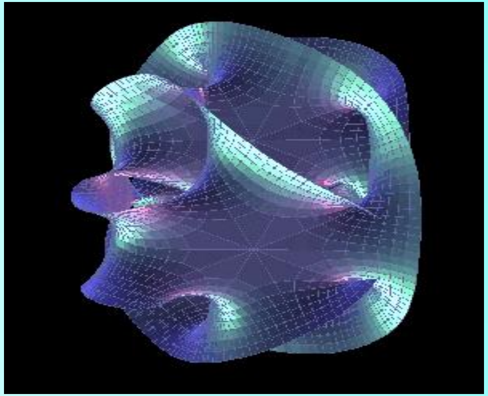


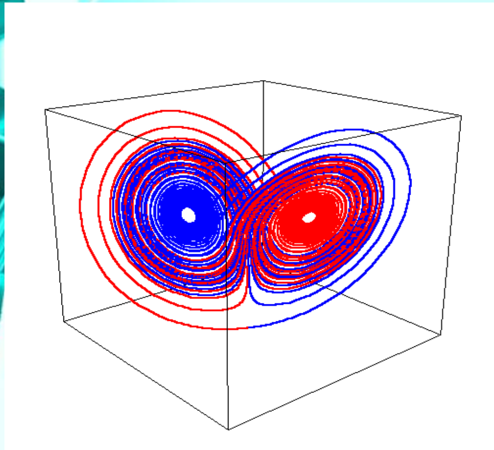


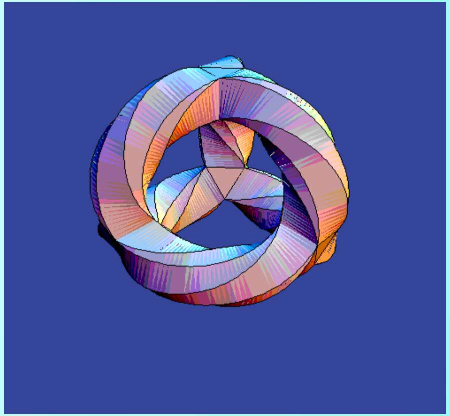
Maybe we can "fold", "twist", "bundle" time !! Let's Move to Topology / Geometry

Modeling and Forecasting







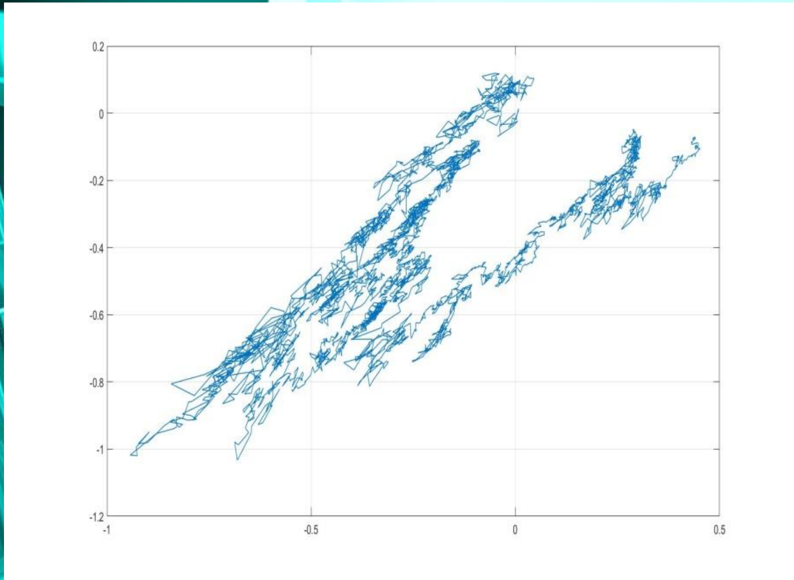


Modeling and Forecasting

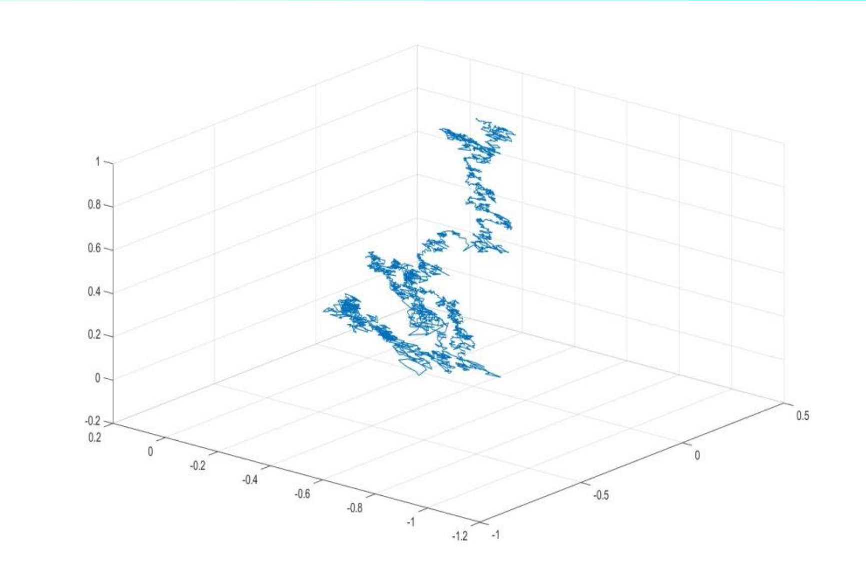
- Manifold
  - A topological space, which locally resembles Euclidean space near each of its points
- Assumption
  - the high-dimensional input space can be embedded in a lower-dimension manifold, and as such the property that locally each point lives in a Euclidean subspace, **enables us to do algebra**.

Modeling and Forecasting

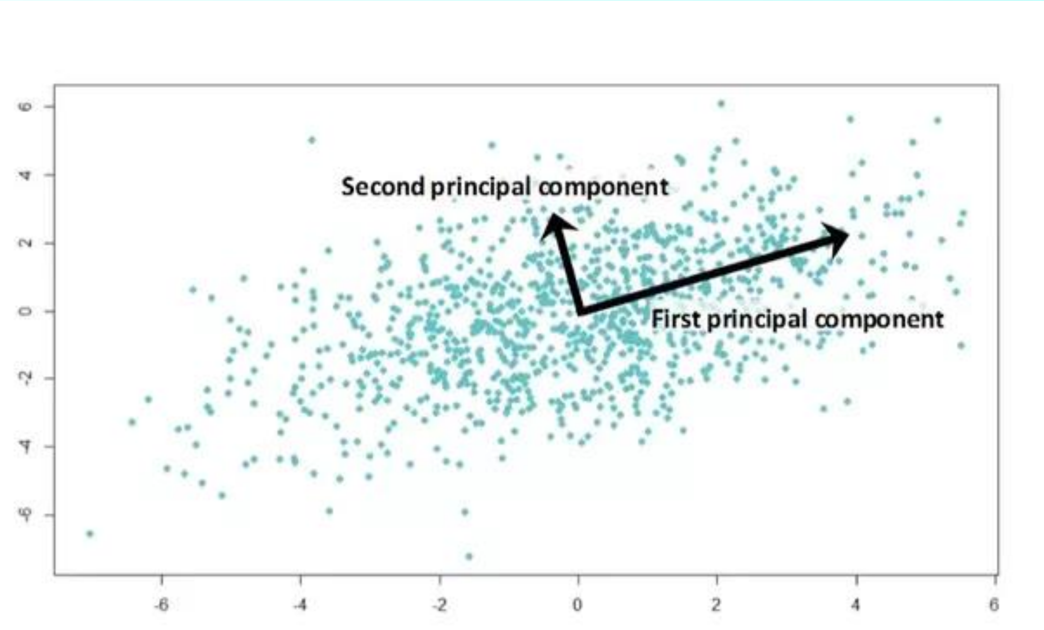
ES1 Index (x) vs VG1 Index (y)



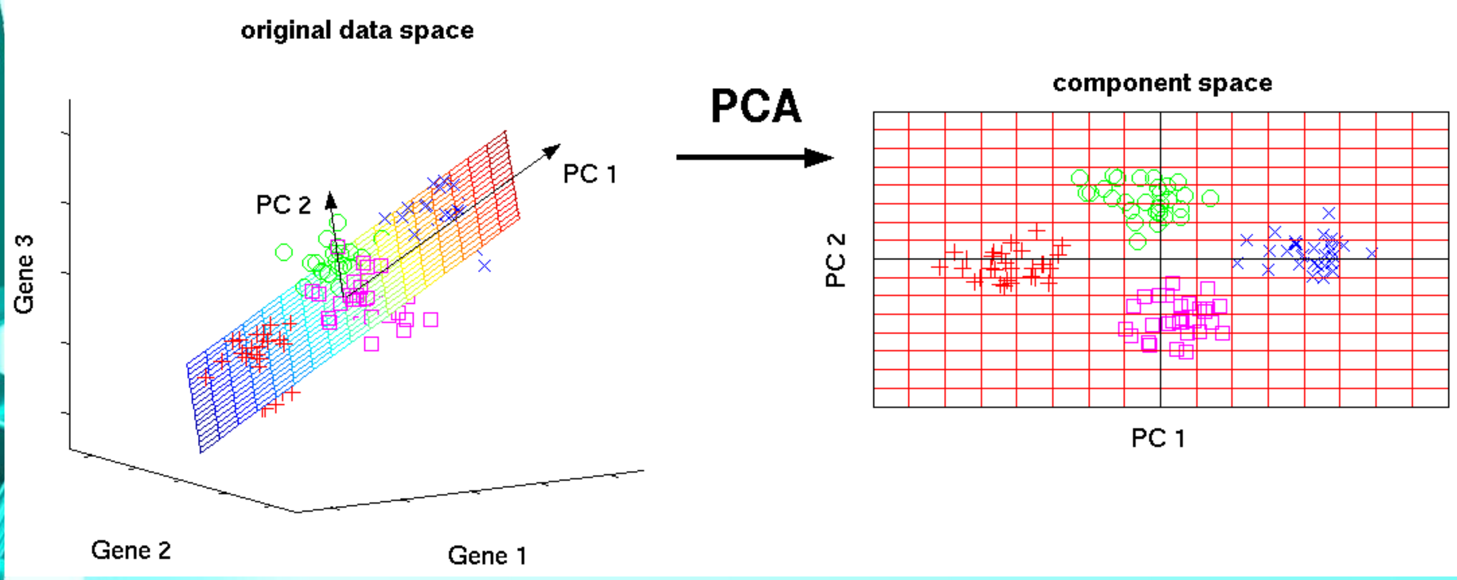
ES1 Index (x) vs VG1 Index(y) vs TY1 Comdty (z)



Modeling and Forecasting
PCA



Modeling and Forecasting PCA



Modeling and Forecasting
PCA

a. Input Space = the N input samples in the dataset (here N = 100 FX Pairs)

b. We compute the N = 100 mean vectors, as a single vector in R_m:

$$\vec{\mu} = \frac{1}{N}(\bar{x}_1 + \bar{x}_2 + \cdots + \bar{x}_{100}),$$

c. We compute **the covariance matrix** of the whole dataset, on the 'centered' dataset

$$B = [\vec{x}_1 - \vec{\mu}, \ldots, \vec{x}_{N=100} - \vec{\mu}],$$

as :

Modeling and Forecasting
PCA

$$S = \frac{1}{N-1}\; BB^T,$$

or written in matrix format :

$$S = \begin{bmatrix} S_1^2 & S_{12} & S_{13} & \cdots & S_{1N} \\ S_{21} & & \ddots & & S_{2N} \\ \vdots & & & & \vdots \\ S_{N1} & S_{N2} & S_{N3} & \cdots & S_N^2 \end{bmatrix}$$

where,

- $S_j^2 = \frac{1}{N}\sum_{i=1}^{N}(x_{ij} - \bar{x}_j)^2$, is the variance of the j-th variable,
- $S_{ij} = \frac{1}{N}\sum_{i=1}^{N}\left(x_{ij} - \bar{x}_j\right)(x_{ik} - \bar{x}_k)$, is the covariance between the j-th and the k-th variables

Alternatively, we can calculate the **correlation matrix**, as given below :

$$R = \begin{bmatrix} 1 & r_{12} & r_{13} & \cdots & r_{1N} \\ r_{21} & & \ddots & & r_{2N} \\ \vdots & & & & \vdots \\ r_{N1} & r_{N2} & r_{N3} & \cdots & 1 \end{bmatrix}$$

where,

$r_{jk} = \frac{S_{jk}}{S_j S_k} = \frac{\sum_{i=1}^{N}(x_{ij}-\bar{x}_j)(x_{ik}-\bar{x}_k)}{\sqrt{\sum_{i=1}^{N}(x_{ij}-\bar{x}_j)^2}\sqrt{\sum_{i=1}^{N}(x_{ik}-\bar{x}_k)^2}}$, the classical Pearson Correlation coefficient

Modeling and Forecasting
PCA

d. Perform eigenvalue decomposition on the Covariance or the Correlation Matrix to calculate $(e_1, e_2, \ldots, e_d)$ eigenvectors and corresponding $(\lambda_1, \lambda_2, \ldots, \lambda_d)$ eigenvalues :

$$\Sigma \boldsymbol{v} = \lambda \boldsymbol{v}, \qquad (7)$$

$$\boldsymbol{v} = Eigenvector, and\ \lambda = Eigenvalue$$

e. Sort the eigenvalues in decreasing order, and select m eigenvectors with the largest eigenvalues. In that way, we form a $d\ x\ m$ dimensional matrix W (columns = eigenvectors).

d. Project the data to the new coordinate system, performing the following projections:

$$y_{pca} = W_{pca}^T \times x, \qquad (8)$$

where x is a dx1-dimensional vector and y is its projection to the new coordinate system. Those are the projections, or as stated here our constructed portfolios, which we will trying to forecast in the work.

Modeling and Forecasting Metric

Find in wikipedia.com

Definition [edit]

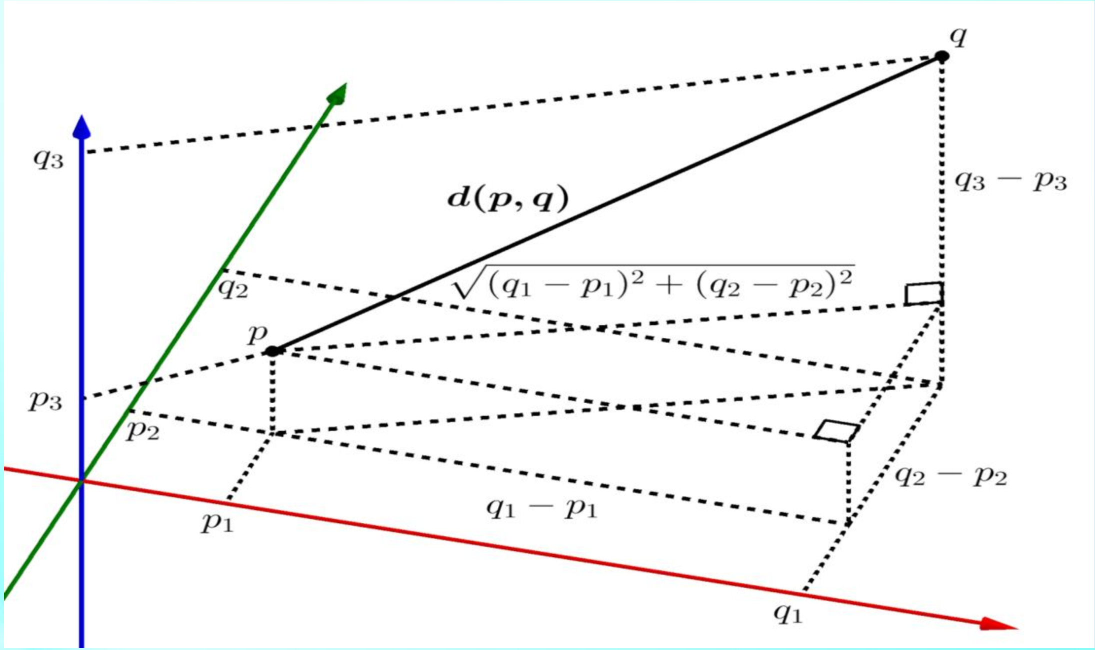
A **metric** on a set X is a function (called the *distance function* or simply **distance**)

$$d : X \times X \to [0, \infty),$$

where $[0, \infty)$ is the set of non-negative real numbers and for all $x, y, z \in X$, the following conditions are satisfied:

1.	$d(x, y) \geq 0$	non-negativity or separation axiom
2.	$d(x, y) = 0 \Leftrightarrow x = y$	identity of indiscernibles
3.	$d(x, y) = d(y, x)$	symmetry
4.	$d(x, z) \leq d(x, y) + d(y, z)$	subadditivity or triangle inequality

Modeling and Forecasting
Euclidean Metric



Modeling and Forecasting
PCA

- Variance – Covariance Matrix
  - Or Correlation Matrix
- Equivalence between the Cov(X,Y) and the Euclidean Distance
- Distance Correlation

Find in wikipedia.com

Distance correlation [edit]

The *distance correlation* [2][3] of two random variables is obtained by dividing their *distance covariance* by the product of their *distance standard deviations*. The distance correlation is

$$\mathrm{dCor}(X,Y) = \frac{\mathrm{dCov}(X,Y)}{\sqrt{\mathrm{dVar}(X)\,\mathrm{dVar}(Y)}},$$

and the *sample distance correlation* is defined by substituting the sample distance covariance and distance variances for the population coefficients above.

Modeling and Forecasting Metric

- Many many metrics
  - Discrete
  - Euclidean
  - Taxicab
  - Hamming Distance
  - Riemannian metric
  - Etc.
- Which is the ‘correct’ one?
- What are we actually looking for ???

Modeling and Forecasting
PCA

- Portfolio Construction
- Output eigenvectors of PCA = the trading weights applied into each trading asset
- We can define/construct portfolios out of them as follows :

$$Y_{pca}^{t} = \int_{0}^{t} y_{pca}^{t} = \int_{0}^{t} W_{pca}^{T} \times x$$

Modeling and Forecasting PCA - metric

- Portfolio Construction
  - "Out-of-sample" modeling and forecasting rationale
    - The trading weights Wpca should be calculated on an Ft-measurable rationale, i.e. with information set available up to time (t-1) if we wish to forecast the time (t) dynamics
  - "Noisy" and "Volatile" Trading Weights will cost Heavy Transaction Costs! Need them to be "smooth" and as stable as possible!
- **Target** : Need a Robust, Stable over time and Smooth Metric Dynamics
  - Can we stabilize the Variance – Covariance Matrix induced metric ?
- Alternatively, can we find another induced metric with such properties, but which can also be 'lifted' to Portfolio Trading Weights ???
- Working Papers :

(a) **Nonlinear Manifold Learning in Financial Markets Diffusion Maps "On the Metric Discovery and Portfolio Construction"**

Panagiotis Papaioannou[1], Constantinos Siettos[1,*] , Yannis Kevrekidis[2], Ronen Talmon[3], Athanasios Yannacopoulos[4]

(b) **PCA AND LLE ON FOREIGN EXCHNANGE MARKET FORECASTING AND PORTFOLIO MANAGEMENT**

Panagiotis Papaioannou[1], Constantinos Siettos[1,*] , Yannis Kevrekidis[2], Ronen Talmon[3], Athanasios Yannacopoulos[4]

Modeling and Forecasting "Shifting"

The methodology used to build the trading strategy is described below :

1. We apply Rolling PCA or LLE on the returns of the assets in the dataset, in a time window of 250 trading days (1 trading year), and we store at each step (day), the output coefficients of the three first eigenvectors (factors) F1, F2, F3, F4 and F5 that are used for reconstruction purposes:

$$\vec{C}_t$$

2. We shift the output coefficients of each factor by one day in the past

$$S(\vec{C}_t) = \vec{C}_{t-1}, \qquad (28)$$

where, S() is the shift operator

3. We then multiply the shifted coefficients with the initial assets' returns to get the out-of-sample ("tradable") Factors.

$$F_t^i = C_{t-1}^i * dlog(P_t), i = 1,2,3,4,5\ Factors\ (Projections), \quad (29)$$

and $dlog(P_t)$ are the assets' returns

Modeling and Forecasting "Shifting"

4. Considering the F_t^i as the return of a portfolio of assets at time tt, we want to see if simple time series analysis tools, e.g. the SDEs type of motions above or Exponential Moving Averages, are able to efficiently forecast its dynamics (for each of the three Factors = portfolios). We would like these factors to be 'smooth' over time, with no sudden 'holes', 'gaps' in them.

5. Being able to forecast the Factors as defined above, gives us the desired "tradability" of the constructed portfolios over time. More specifically, assume that a simple MA forecasts the Factor F^i efficiently, and it suggests that the Factor's level will increase from time t (today), to time t+1 (tomorrow), i.e.

$$F_{t+1}^i > F_t^i \xrightarrow{yields} C_t^i * dlog(P_{t+1}) > C_{t-1}^i * dlog(P_t), \quad (30)$$

Under the above construction of the Factors, we gain two crucial advantages

a. We only need information up until today in order to forecast future values of the portfolios, C_{t-1}^i and C_t^i, i.e. yesterday's PCA (or LLE's) coefficients multiplied by today's returns will be smaller than today's PCA (or LLE's) coefficients multiplied by tomorrow's returns.

b. We will be able to trade these portfolios in real world, by just investing the proposed allocations (coefficients) C_t^i on the assets today, in order to gain the $Portfolio\ Profit\ and\ Loss\ in\ time\ (t+1) = PnL_{t+1} = F_{t+1}^i - F_t^i$ (which will be statistically positive if the MA forecasts the Factors efficiently enough).

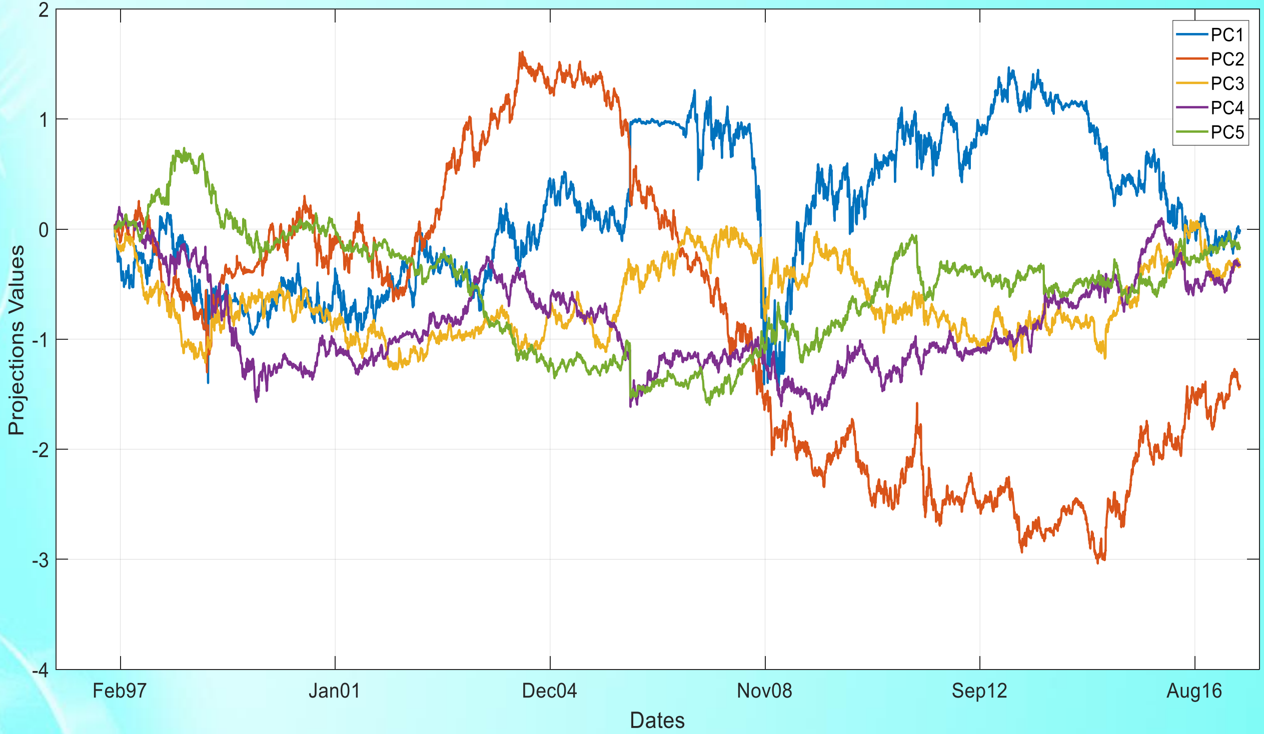
Modeling and Forecasting "Shifting"

6. Finally, we apply filters on investments allocations (coefficients), in order to

a. 'smooth' them up, using a Moving Average of Coeff-Lag = 25 days, so as to clear their noise and their sudden changes from time to time

b. trade only the allocations above a specific threshold, e.g. thr = 0.01 or 1% in absolute value, i.e. $Coeffs = 0, \forall\, Coeffs < thr$.

Modeling and Forecasting
PCA



Modeling and Forecasting PCA

- Forecasting the PCA Projections (Portfolios)
- Stationarity Tests on Projections! (ADF – KPSS)

Geometric Brownian Motion :

$$d\Pi_t = \mu \Pi_t dt + \sigma \Pi_t dW_t,$$

where W_t is a Wiener Process (or Bm), with mean = μ ("drift"), and σ the volatility term, each of which are constants. The Ito's solution for this process is given by the formula :

$$\Pi_t = \Pi_0 \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t\right),$$

Modeling and Forecasting PCA

- Forecasting the PCA Projections (Portfolios)

Mean Reversion Ornstein-Uhlenbeck Process :

$$d\Pi_t = k(\theta - \Pi_t)dt + \sigma\, dW_t, \qquad dW_t \sim N\left(0, \sqrt{dt}\right),$$

with Ito's solution being the :

$$\Pi_t = e^{-kt}\Pi_0 + \theta(1 - e^{-kt}) + \sigma \int_0^t e^{k(s-t)} dW_s,$$

Modeling and Forecasting PCA

- Forecasting the PCA Projections (Portfolios)

Trending Ornstein-Uhlenbeck Process :

$$(d\Pi_t - \mu t) = -k(\Pi_t - \mu t)\,dt + \sigma\, dW_t,$$

and the corresponding Ito's Solution :

$$\Pi_t = \mu t + \Pi_0 e^{-kt} + \sigma \int_0^t e^{k(u-t)}\, dW_u,$$

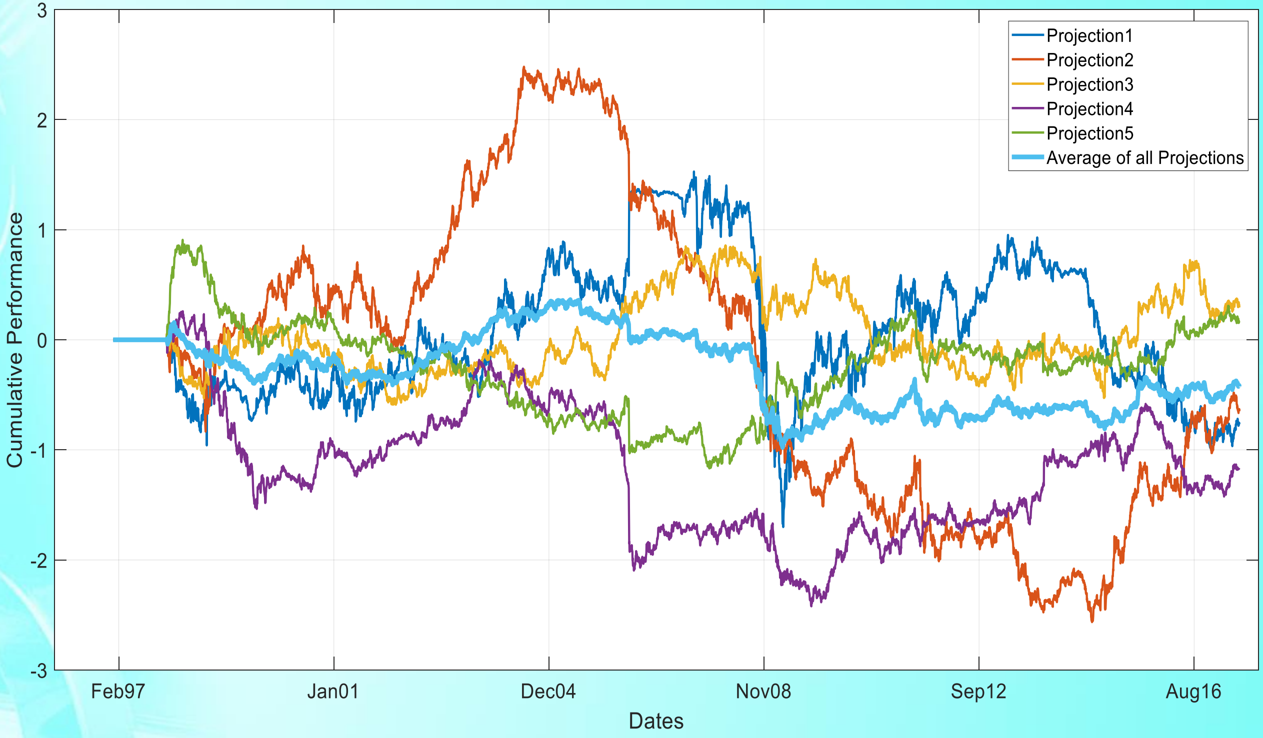
Modeling and Forecasting PCA

- Forecasting the PCA Projections (Portfolios)

  – Exponential Moving Average (Technical Analysis)

$$EMA(\Pi)_t = (\Pi_t * a) + (EMA(\Pi)_{t-1} * (1 - a),$$

Modeling and Forecasting PCA – OU Model Trading



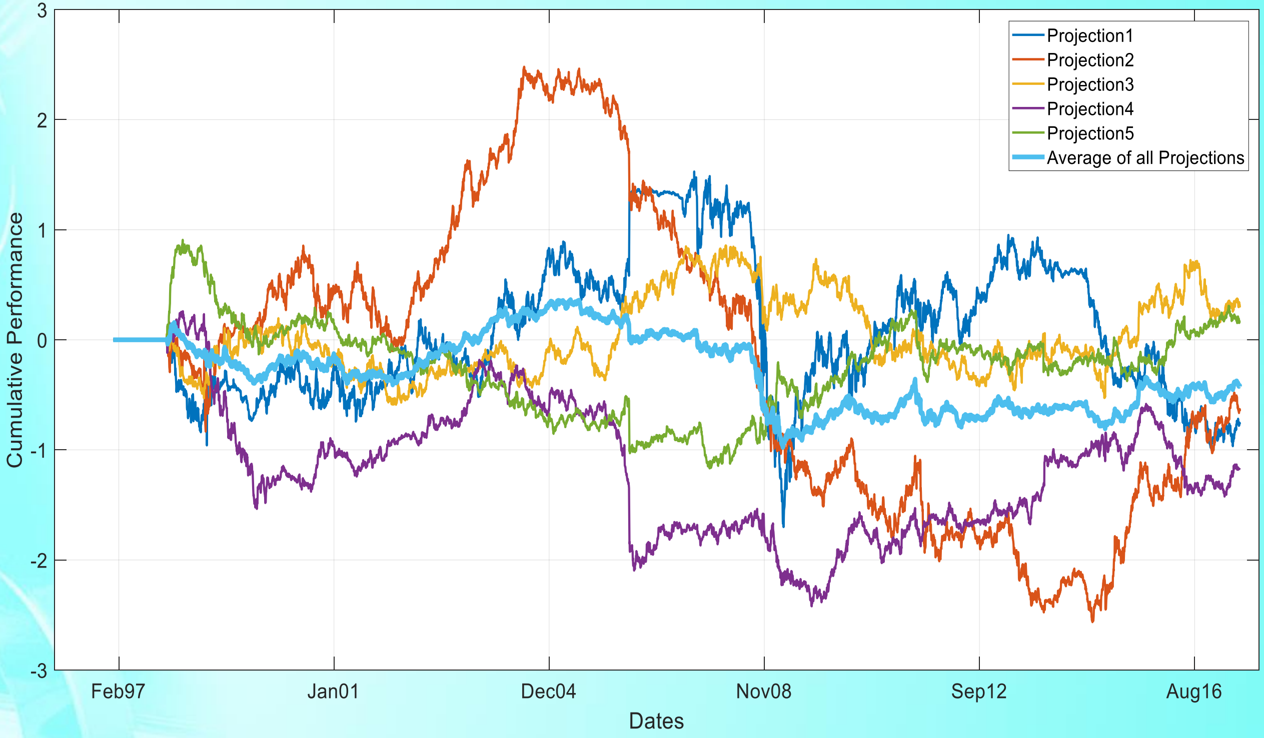
Modeling and Forecasting Sharpe Ratio

$$S = \frac{E[R - R_f]}{\sqrt{\mathrm{var}[R]}}.$$

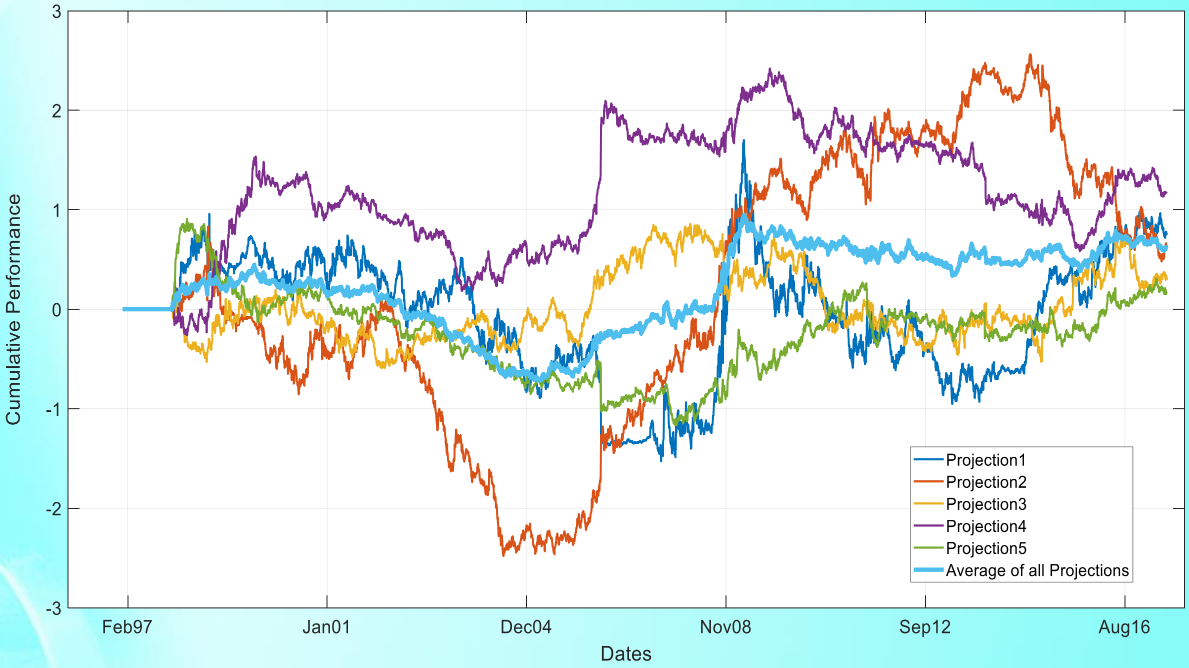
What does sharpe of 2 mean ?

Annualised Sharpe Ratio Commentary
sqrt(252) → 252 Trading Days in a year

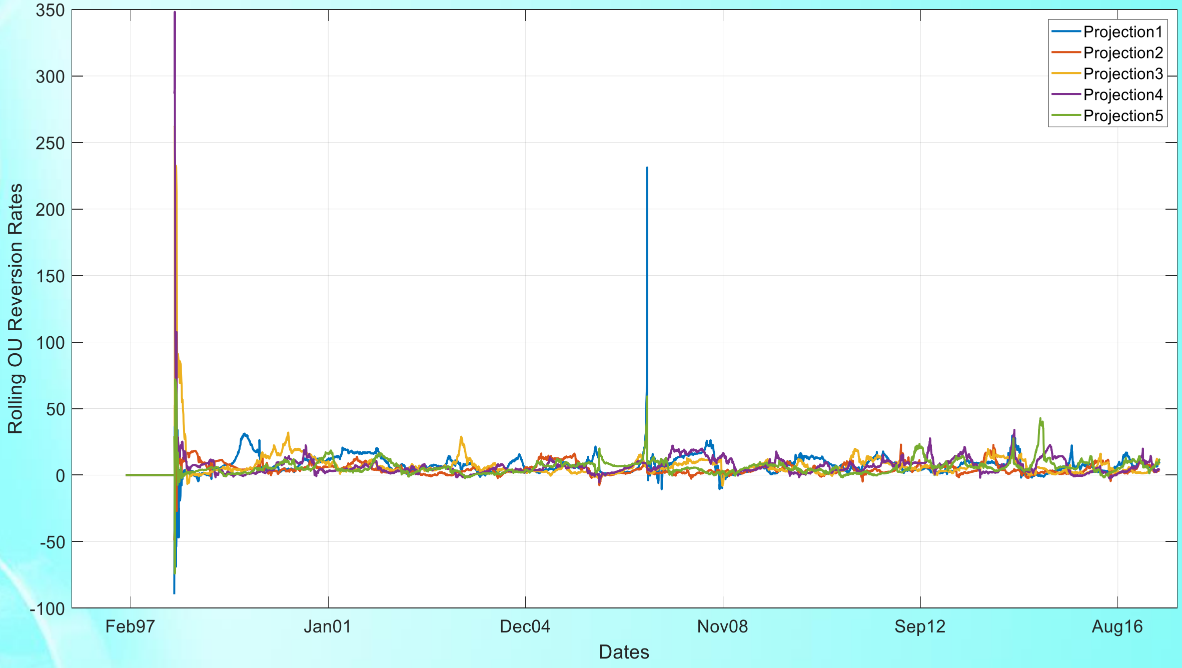
Modeling and Forecasting PCA – OU Model Trading



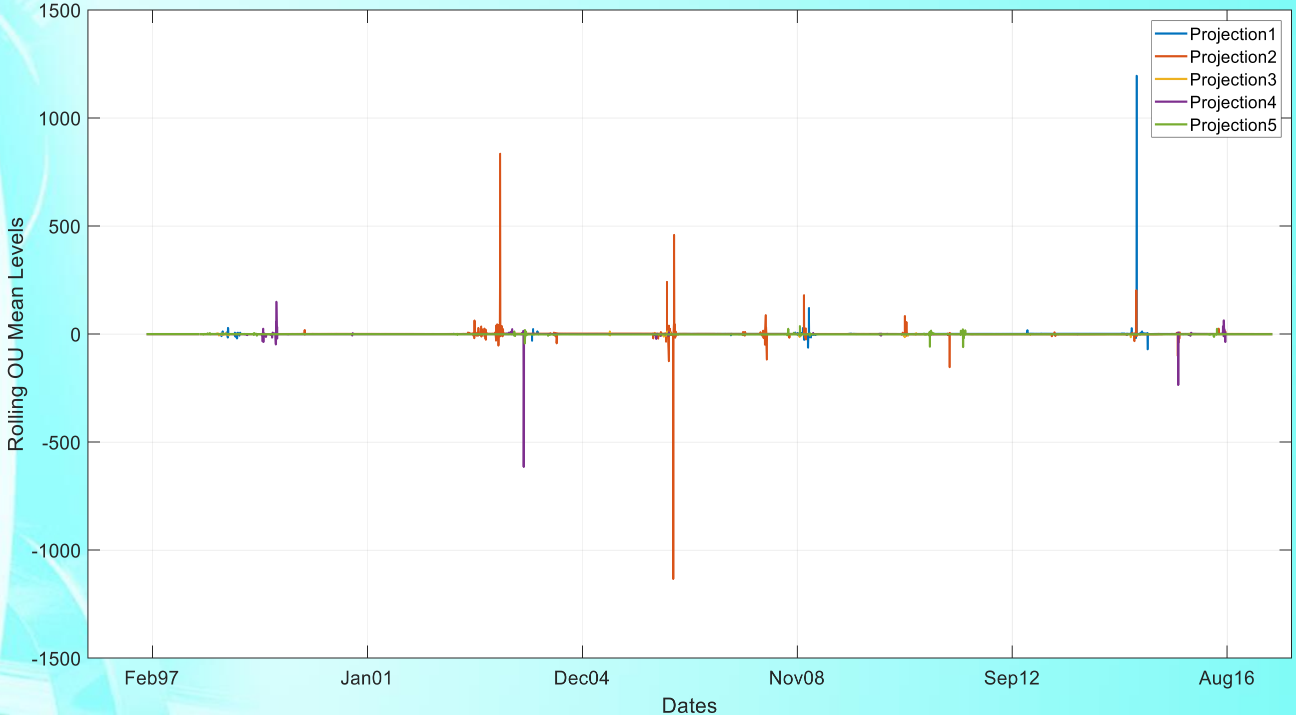
Modeling and Forecasting
PCA
OU Sharpe Optimized Model Trading



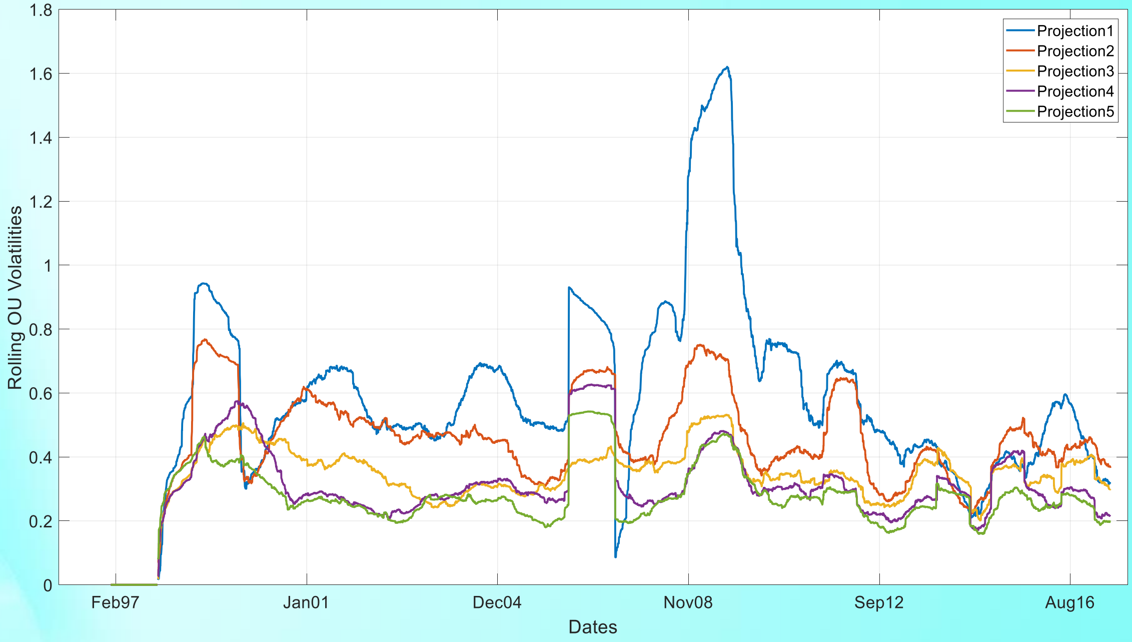
Modeling and Forecasting Rolling OU Reversion Rates on PCA Projections



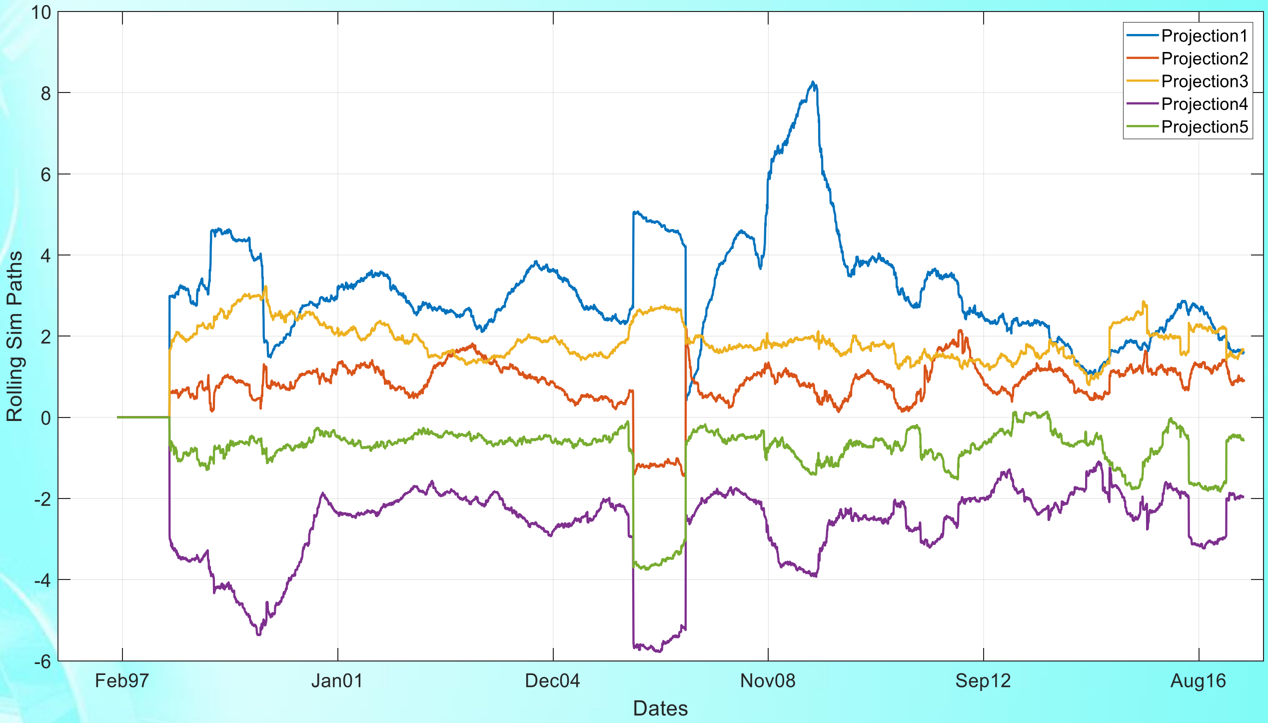
Modeling and Forecasting Rolling OU Mean Levels on PCA Projections



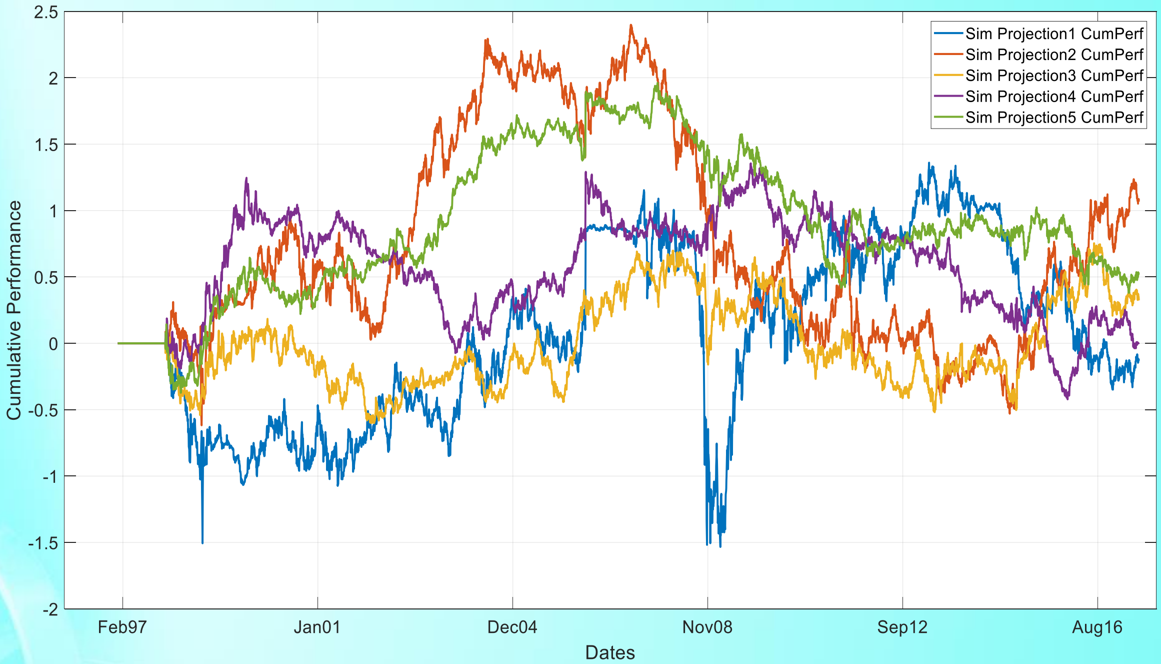
Modeling and Forecasting Rolling OU Volatility Levels on PCA Projections



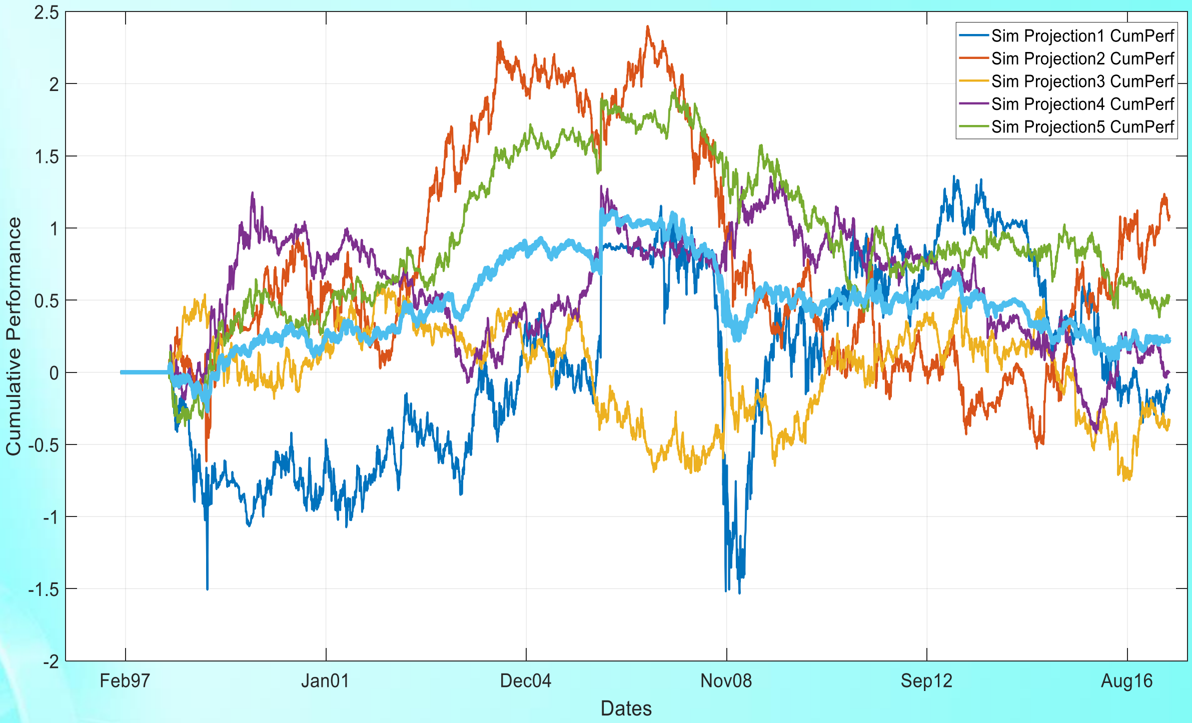
Modeling and Forecasting Simulated Gbm Multidimensional Market Model on the five PCA Projections



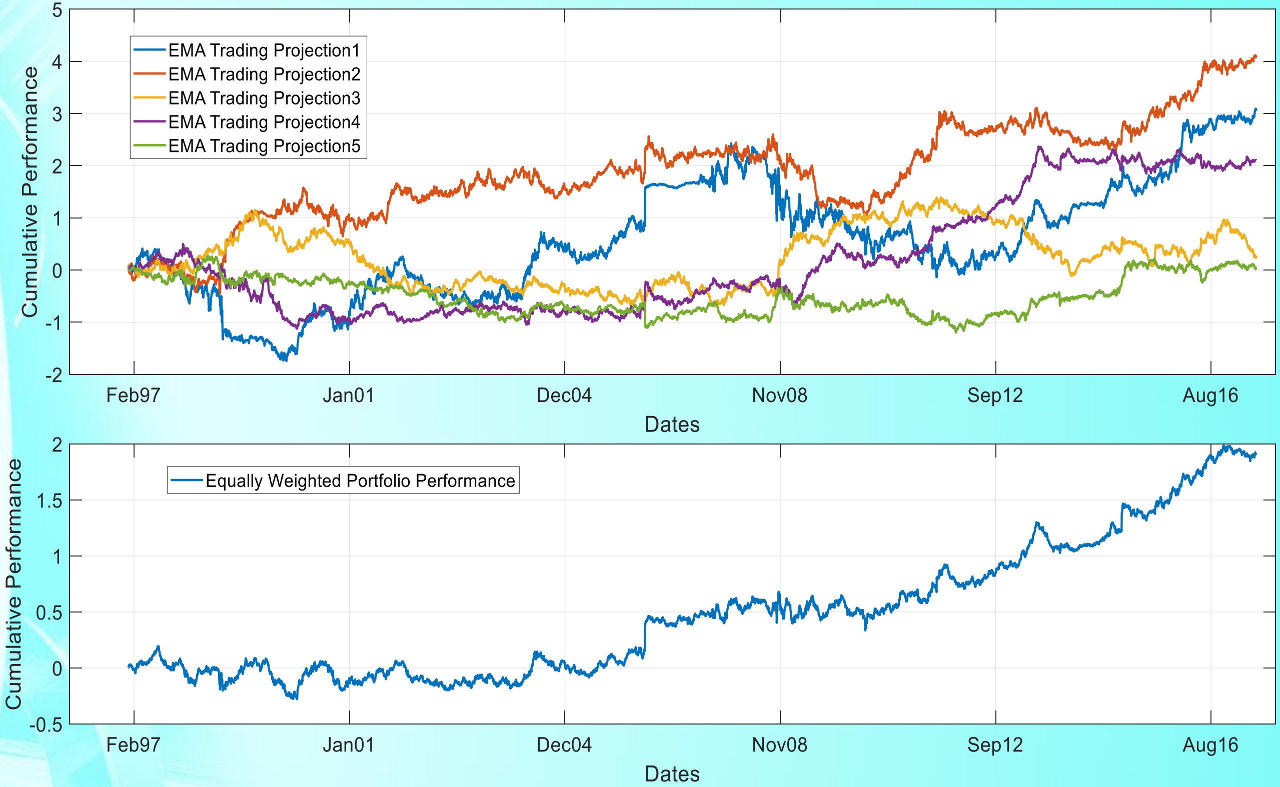
Modeling and Forecasting Directional Predictability curves after applying the Gbm Trading Strategy on the PCA Projections



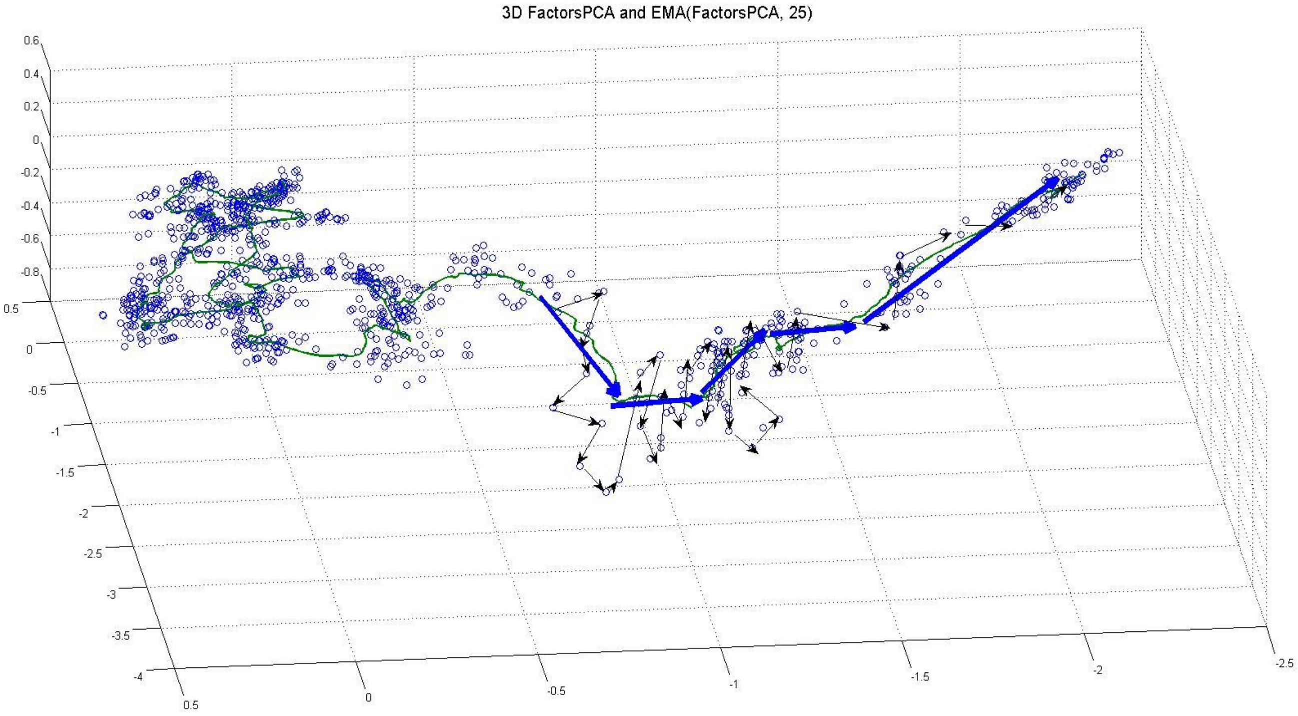
Modeling and Forecasting Optimized Directional Predictability curves (Gbm Trading Strategy on PCA Projections)



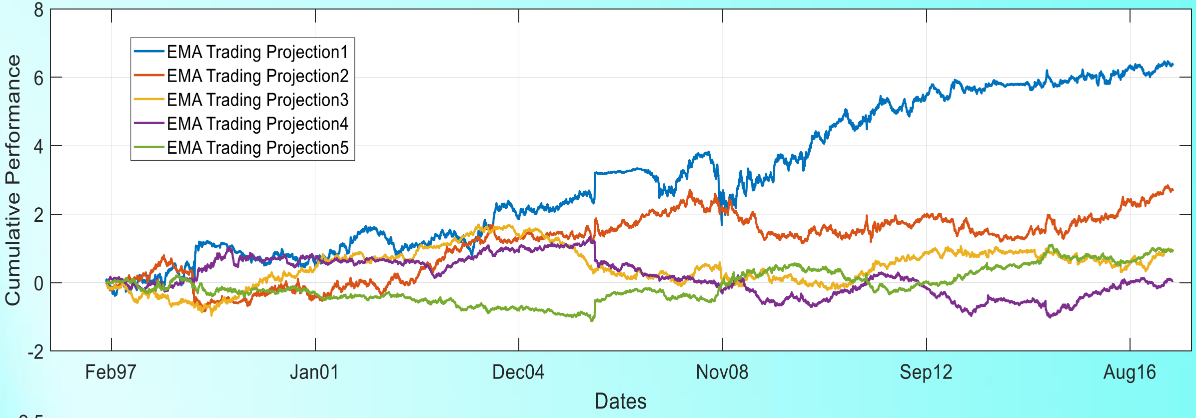
Modeling and Forecasting
(Upper) EMA with L = 3 Trading Days on PCA Projections, (Lower) Equally Weighted Portfolio of the generated PCA Projections EMA Trading

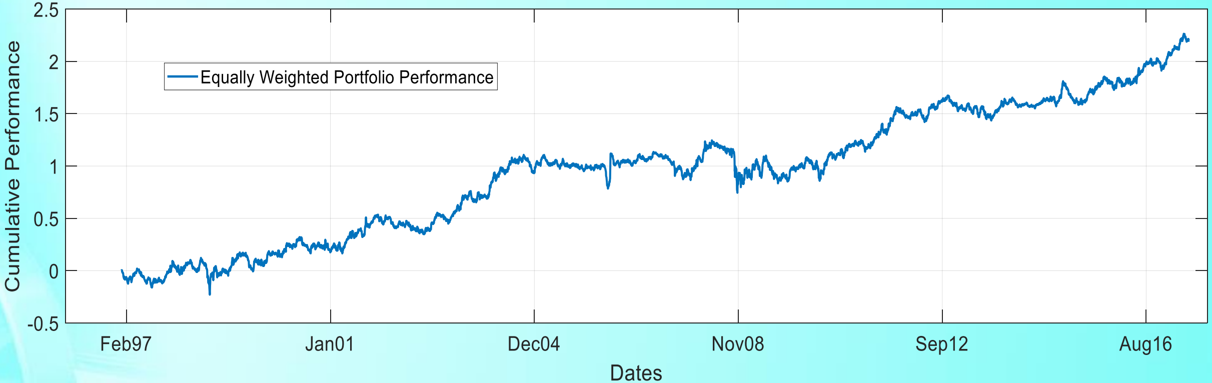


Modeling and Forecasting
(Upper) EMA with L = 25 Trading Days on PCA Projections, (Lower) Equally Weighted Portfolio of the generated PCA Projections EMA Trading

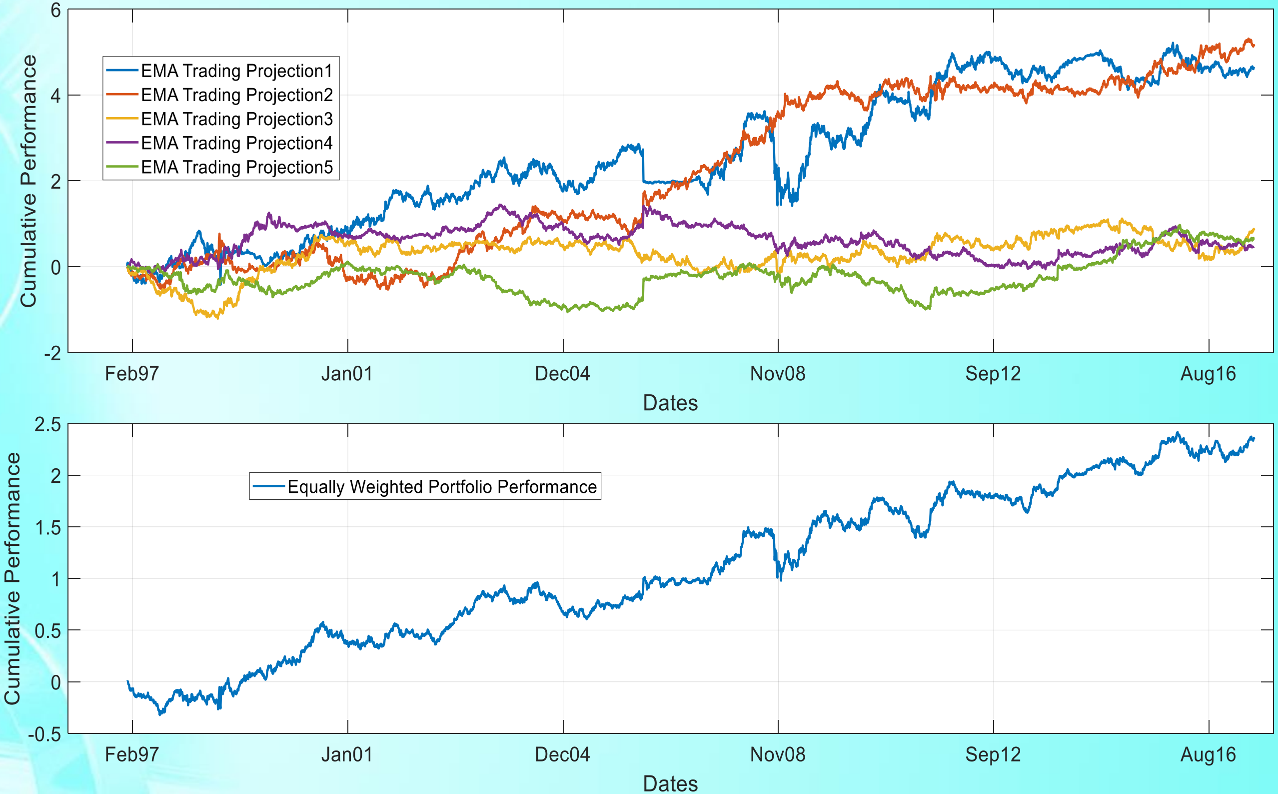


Modeling and Forecasting
(Upper) EMA with L = 25 Trading Days on PCA Projections, (Lower) Equally Weighted Portfolio of the generated PCA Projections EMA Trading



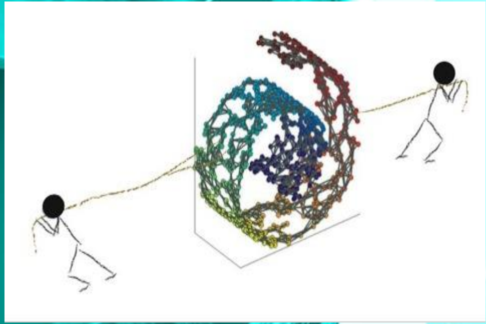


Modeling and Forecasting (Upper) EMA with L = 500 Trading Days on PCA Projections, (Lower) Equally Weighted Portfolio of the generated PCA Projections EMA Trading



Modeling and Forecasting More than PCA

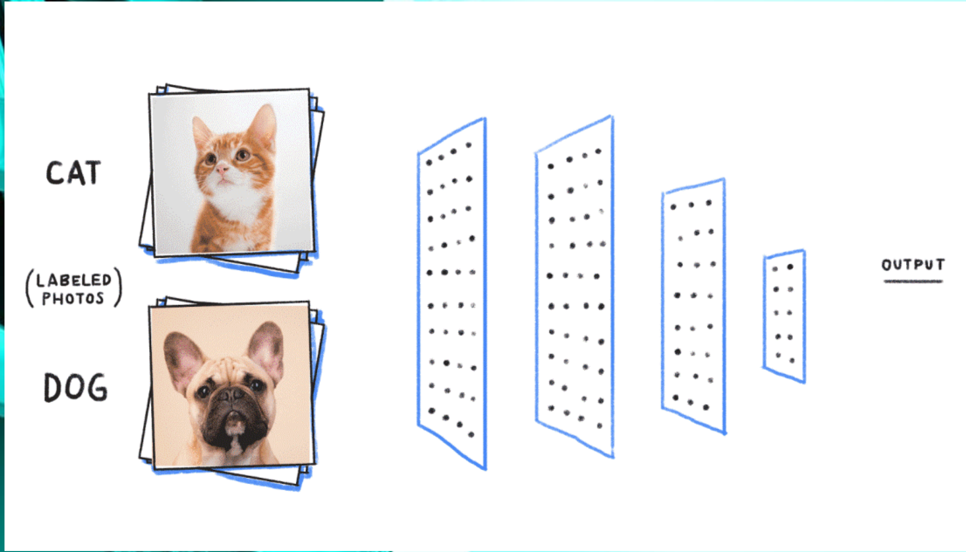
- **PCA**
  - Linear Manifold Learning Technique
  - Decomposition offers linear combinations (eigenvectors = portfolios' weights)
- **Local Linear Embedding**
  - Linear Manifold Learning Technique
  - Again decomposition (with some custom modifications) offers portfolio weights (linear combinations of assets)
- **Diffusion Maps**
  - NonLinear Technique
  - Decomposition is a nonlinear function of the input native space, e.g. Trading Assets, i.e. the output "implied" function could be f(x1, x2, x3) = 0.2 * x1^2 + 0.4 * x1*x2 + 0.4 * x3^3 * x2
  - How can we use such recognized pattern in order to Construct portfolios?
  - "Linearizers" : one of the previous working papers
    - Take the nonlinear projections and 'linearize' them locally in order to produce 'liftings'. Then use the linearized projections as the portfolio trading weights.
- K-NN, Autoencoders, Boltzmann Machines and many others!

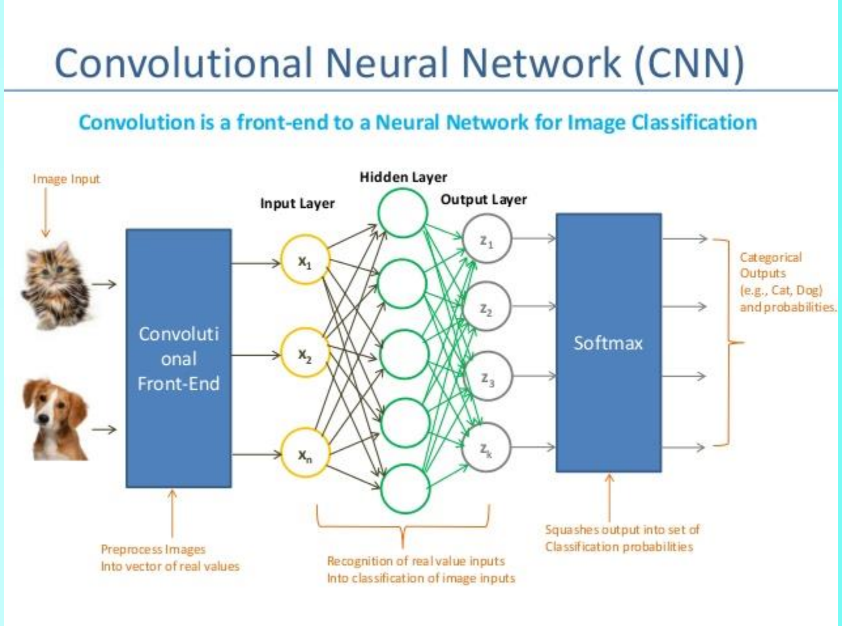


Unsupervised and Supervised Machine Learning

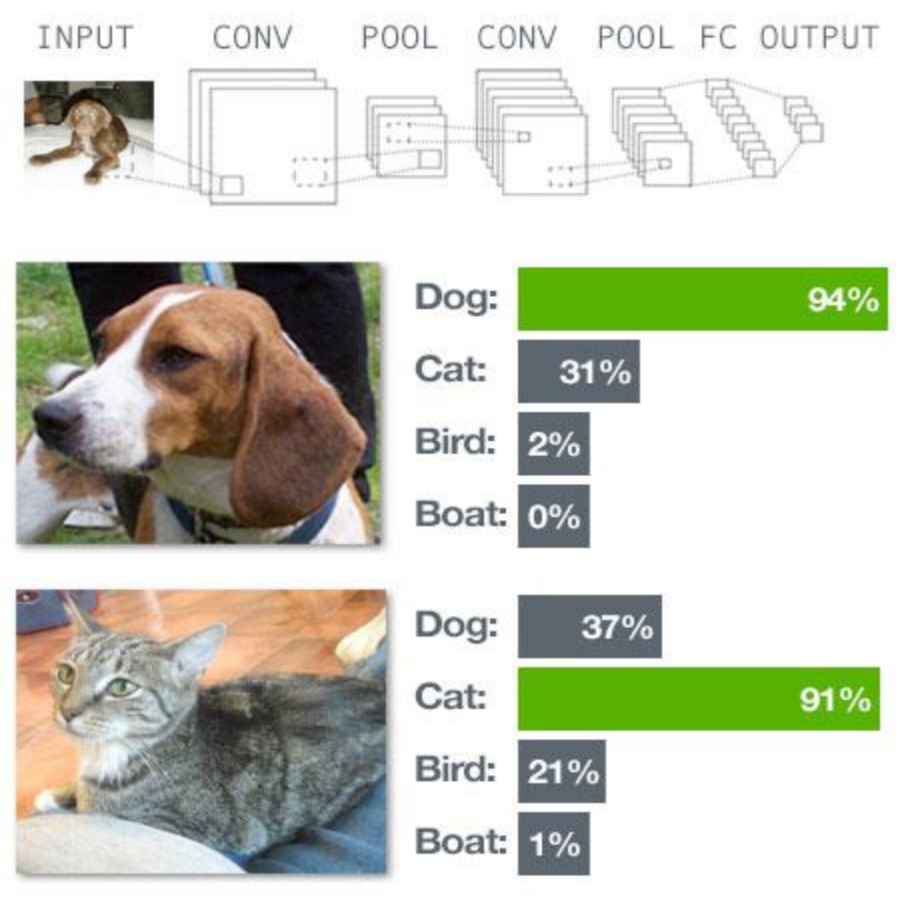
- **Use of ANNs, RNNs and CNNs to forecast the PCA, LLE or DMAPS projections**
- **ANNs and RNNs**
  – Inputs : ‘lagged’ Projections prices (t-N : t-1)
  – Outputs : Projections prices (t-N+1 : t)
  – Learning : BackPropagation and Online Learning (update weights in each step – no use of ‘Batching’)
- **CNNs**
  – Are used for image processing !?!
    - Photos pixels and labeling !?!
  – The several induced metrics (Covariance Matrix, Mahalanobis Distance, Diffusion Distance of DMAPS etc.) applied in rolling window, represent NxN pixeled photos (!), where N is the number of assets.
  – Folding or unfolding geometries, could also be represented as photos with N assets in a specific period (NxN pixeled photo at time t1), and M < N or M > N assets in another period (MxM pixeled photo at time t2)
  – Forecast the metric dynamics using the CNNs in our photos!
  – Obtain the “out-of-sample” trading weights!

Convolutional Neural Networks

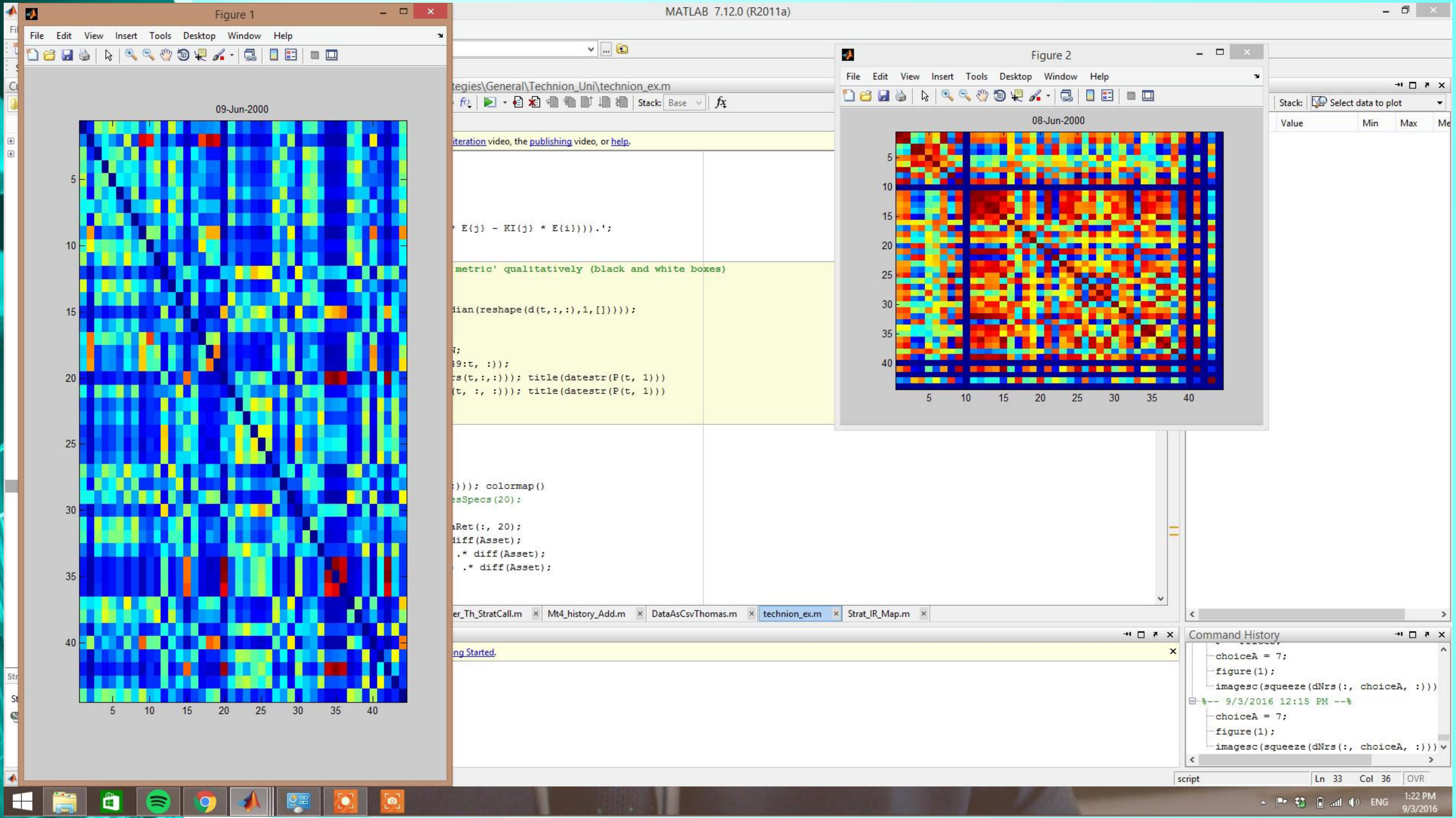




Convolutional Neural Networks



Metrics as Photos



Metrics as Photos

- Follow the ‘Dog’ and ‘Cat’ CNN rationale
- Is the previous or current metric ‘good’ or ‘bad’ for trading ?
- How much ? → get the pixel!
  - The pixel is the weight!


WHAT DO I
DO
NOW?


I don't know what I'm gonna do with my life.


FRIENDS
FRIENDS
MONEY!
FRIENDS
FRIENDS


HOW TO
MAKE
MONEY

LPs and Trading Platforms

LPs and Trading Platforms

Programming Languages

- Python
  - Free
  - Numerical, Matrix / Lin Algebra
    - Numpy
    - Pandas
    - etc
  - Machine Learning
    - Keras
    - Tensorflow
    - Scikit learn
    - etc

- Matlab
  - Need to pay
  - Matrix, Numerical etc
  - Machine Learning

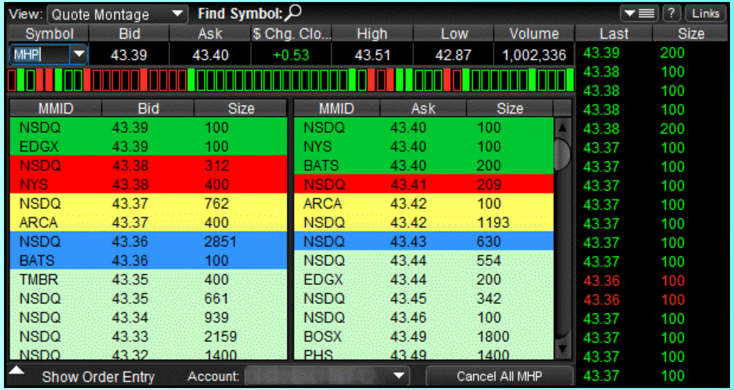
- C++ / C# / JAVA
  - Harder to manipulate stuff on numerical, matrix rationale
  - Faster (a lot)
  - Mostly used on more ‘executional’ base projects

Transaction Costs

Market Spread :
Bid/Ask Divergence

Liquid vs Il-Liquid Markets

Level 2 Quotes – Market Depth



View: Quote Montage | Find Symbol: | Links

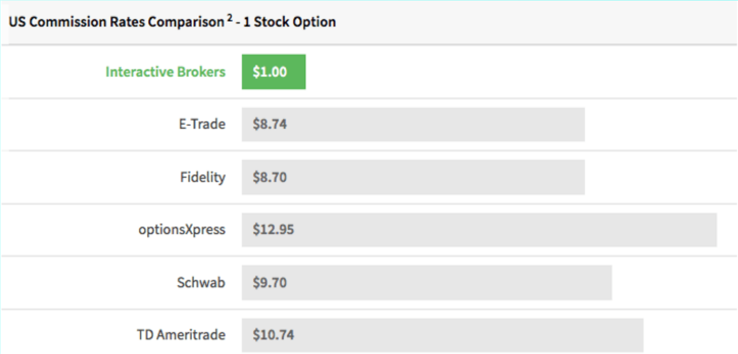
Symbol	Bid	Ask	$ Chg. Clo...	High	Low	Volume
MHP	43.39	43.40	+0.53	43.51	42.87	1,002,336

MMID	Bid	Size	MMID	Ask	Size
NSDQ	43.39	100	NSDQ	43.40	100
EDGX	43.39	100	NYS	43.40	100
NSDQ	43.38	312	BATS	43.40	200
NYS	43.38	400	NSDQ	43.41	209
NSDQ	43.37	762	ARCA	43.42	100
ARCA	43.37	400	NSDQ	43.42	1193
NSDQ	43.36	2851	NSDQ	43.43	630
BATS	43.36	100	NSDQ	43.44	554
TMBR	43.35	400	EDGX	43.44	200
NSDQ	43.35	661	NSDQ	43.45	342
NSDQ	43.34	939	NSDQ	43.46	100
NSDQ	43.33	2159	BOSX	43.49	1800
NSDQ	43.32	1400	PHS	43.49	1400

Last	Size
43.39	200
43.38	100
43.38	100
43.38	100
43.38	200
43.37	100
43.37	100
43.37	100
43.37	100
43.37	100
43.37	100
43.37	100
43.36	100
43.36	100
43.37	100
43.37	100
43.37	100
43.37	100

Show Order Entry | Account: | Cancel All MHP

Per Trade/Order Broker's
Commission Scheme



Transaction Costs

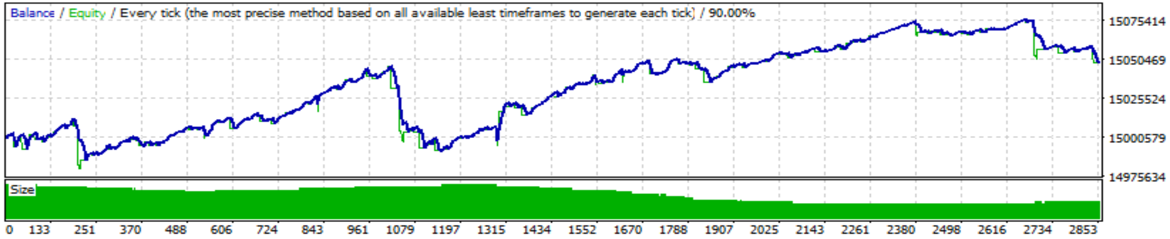
- Need to incorporate all Transaction Costs in the BackTests
- Market Spread is ‘Static’ – it is what it is, it cannot be negotiated
- Negotiate potential new Commission Schemes per Order / Trade / Volume with your Broker – they need flow/volume to ‘hear you’

Transaction Costs

Symbol	EURUSD (Euro vs US Dollar)
Period	5 Minutes (M5) 2017.01.02 00:00 - 2018.01.12 23:55 (2017.01.01 - 2018.04.06)
Model	Every tick (the most precise method based on all available least timeframes)

Market Spread = 0.1 Pips

Bars in test	76545	Ticks modelled	21032738	Modelling quality	90.00%
Mismatched charts errors	5				
Initial deposit	15000000.00			Spread	1
Total net profit	48610.99	Gross profit	408506.34	Gross loss	-359895.35
Profit factor	1.14	Expected payoff	17.06		
Absolute drawdown	19673.22	Maximal drawdown	59756.04 (0.40%)	Relative drawdown	0.40% (59756.04)
Total trades	2849	Short positions (won %)	1459 (61.89%)	Long positions (won %)	1390 (64.39%)
		Profit trades (% of total)	1798 (63.11%)	Loss trades (% of total)	1051 (36.89%)
	Largest	profit trade	1645.20	loss trade	-2025.00
	Average	profit trade	227.20	loss trade	-342.43
	Maximum	consecutive wins (profit in money)	38 (7325.30)	consecutive losses (loss in money)	21 (-9074.76)
	Maximal	consecutive profit (count of wins)	23868.22 (26)	consecutive loss (count of losses)	-23696.08 (12)
	Average	consecutive wins	9	consecutive losses	5



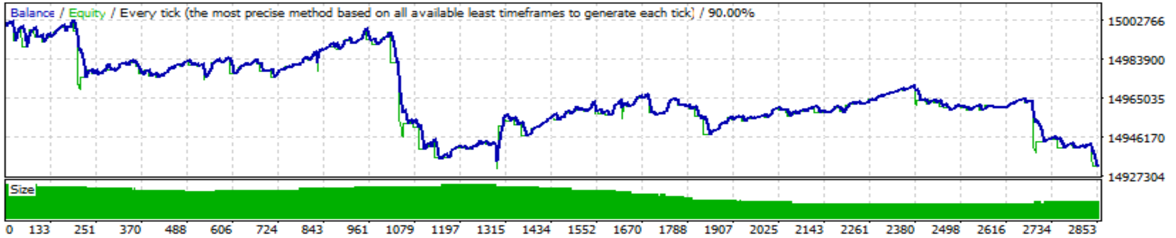
#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	2017.01.02 00:00	buy	1	1.90	1.05101	1.04049	1.06152		
2	2017.01.02 07:50	buy	2	1.90	1.05111	1.04059	1.06162		
3	2017.01.02 08:00	buy	3	1.90	1.05109	1.04057	1.06160		
4	2017.01.02 08:10	buy	4	1.90	1.05100	1.04048	1.06151		
5	2017.01.02 08:20	buy	5	1.90	1.05093	1.04041	1.06144		
6	2017.01.02 09:05	close	5	1.90	1.05199	1.04041	1.06144	201.40	15000201.40
7	2017.01.02 09:05	close	4	1.90	1.05199	1.04048	1.06151	188.10	15000389.50
8	2017.01.02 09:05	close	3	1.90	1.05199	1.04057	1.06160	171.00	15000560.50
9	2017.01.02 09:05	close	2	1.90	1.05199	1.04059	1.06162	167.20	15000727.70
10	2017.01.02 09:05	close	1	1.90	1.05199	1.04049	1.06152	186.20	15000913.90
11	2017.01.02 09:05	sell	6	1.90	1.05199	1.06252	1.04147		
12	2017.01.02 09:10	sell	7	1.90	1.05217	1.06270	1.04165		
13	2017.01.02 11:00	close	7	1.90	1.04889	1.06270	1.04165	623.20	15001537.10
14	2017.01.02 11:00	close	6	1.90	1.04889	1.06252	1.04147	589.00	15002126.10
15	2017.01.02 11:00	buy	8	1.90	1.04889	1.03839	1.05938		

Transaction Costs

Symbol	EURUSD (Euro vs US Dollar)
Period	5 Minutes (M5) 2017.01.02 00:00 - 2018.01.12 23:55 (2017.01.01 - 2018.04.06)
Model	Every tick (the most precise method based on all available least timeframes)

Market Spread = 3 pips (Retail Broker)

Bars in test	76545	Ticks modelled	21032738	Modelling quality	90.00%
Mismatched charts errors	5				
Initial deposit	15000000.00			Spread	30
Total net profit	-67804.51	Gross profit	337593.66	Gross loss	-405398.17
Profit factor	0.83	Expected payoff	-23.80		
Absolute drawdown	75588.40	Maximal drawdown	80733.67 (0.54%)	Relative drawdown	0.54% (80733.67)
Total trades	2849	Short positions (won %)	1459 (56.96%)	Long positions (won %)	1390 (58.56%)
		Profit trades (% of total)	1645 (57.74%)	Loss trades (% of total)	1204 (42.26%)
	Largest	profit trade	1593.00	loss trade	-2077.20
	Average	profit trade	205.22	loss trade	-336.71
	Maximum	consecutive wins (profit in money)	26 (22511.02)	consecutive losses (loss in money)	21 (-9654.76)
	Maximal	consecutive profit (count of wins)	22511.02 (26)	consecutive loss (count of losses)	-24331.48 (12)
	Average	consecutive wins	7	consecutive losses	5

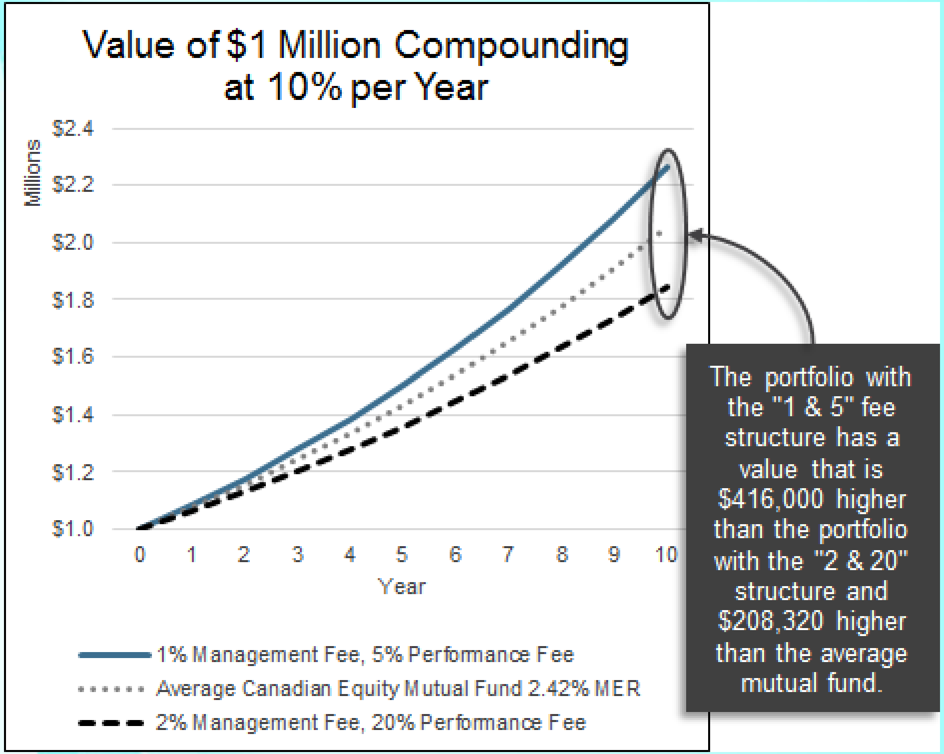


#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	2017.01.02 00:00	buy	1	1.90	1.05130	1.04049	1.06181		
2	2017.01.02 07:50	buy	2	1.90	1.05140	1.04059	1.06191		
3	2017.01.02 08:00	buy	3	1.90	1.05138	1.04057	1.06189		
4	2017.01.02 08:10	buy	4	1.90	1.05129	1.04048	1.06180		
5	2017.01.02 08:20	buy	5	1.90	1.05122	1.04041	1.06173		
6	2017.01.02 09:05	close	5	1.90	1.05199	1.04041	1.06173	146.30	15000146.30
7	2017.01.02 09:05	close	4	1.90	1.05199	1.04048	1.06180	133.00	15000279.30
8	2017.01.02 09:05	close	3	1.90	1.05199	1.04057	1.06189	115.90	15000395.20
9	2017.01.02 09:05	close	2	1.90	1.05199	1.04059	1.06191	112.10	15000507.30
10	2017.01.02 09:05	close	1	1.90	1.05199	1.04049	1.06181	131.10	15000638.40
11	2017.01.02 09:05	sell	6	1.90	1.05199	1.06281	1.04147		
12	2017.01.02 09:10	sell	7	1.90	1.05217	1.06299	1.04165		
13	2017.01.02 11:00	close	7	1.90	1.04918	1.06299	1.04165	568.10	15001206.50
14	2017.01.02 11:00	close	6	1.90	1.04918	1.06281	1.04147	533.90	15001740.40
15	2017.01.02 11:00	buy	8	1.90	1.04918	1.03839	1.05967		

Fund Management Costs

- Management Fees
- Performance Fees
- Fund Costs (operational costs)
  - Let's assume they are 'zero' or incorporated in the other fees, or even negligible

Fund Management Costs




THANK YOU