- NIPS
- KDD

机器学习与量化交易实战

第九课

- AAAI 2017
- IJCAI
- ICML

Dec.

- ~~A~~A 特征值

SVD

10

- w_i

- 5 paper

特征值 & 特征向量

$$A_{100\times100}\,\vec{x}_{100\times1} = \vec{u}_{100\times1}$$

$$f: \vec{x} \to \vec{u}$$

$A_{100\times100}$

mathmatical object

$a\vec{a}$

$\boxed{A_{100\times100}}$

$a \quad a+ib$ 复

$\boxed{A\vec{x}_{100\times1} = \lambda\vec{x}_{100\times1}}$

$\boxed{\vec{x} \parallel A\vec{x}}$

$A\vec{x}$

$(A-\lambda I)\vec{x}=0$

$A\vec{x} = \lambda\vec{x}$

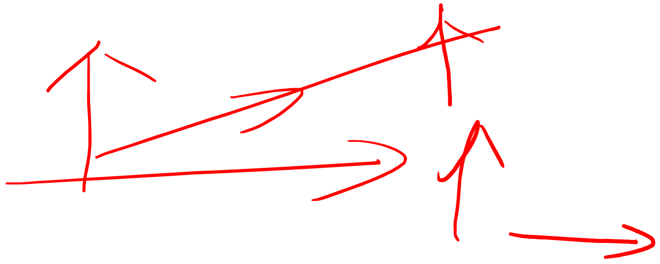
$A\vec{x} - \lambda\vec{x} = 0$

$(A_{n\times n} - \lambda I)\vec{x} = 0$

$(A_{3\times 3} - 6I)x = 0$

$\lambda \quad x$

$Ax = 2x$



$$\boxed{\det(A - \lambda I) = 0}$$

$$\left| \begin{bmatrix} 1-\lambda & 2 & 3 \\ 5 & 6-\lambda & 7 \\ 9 & 9 & 9-\lambda \end{bmatrix} \right| = 0$$

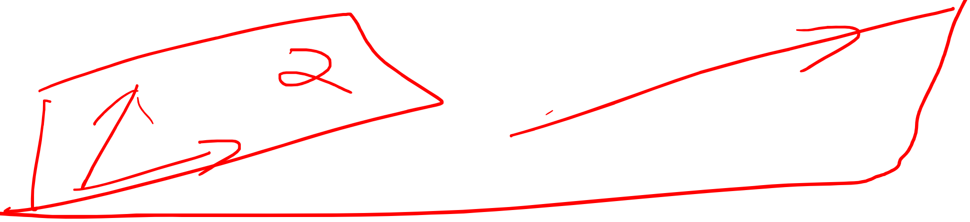
$1 \; \boxed{2} \; 2$

$\lambda \; : \; n$

$3 \times 3 \qquad Ax = \lambda x$

$1 \quad 2 \quad 6 \qquad Ax = 1x$

$\lambda = \underline{6, 6,} \; 2$



$\boxed{A = A^T}$ ① ② $\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}^T \neq \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$

$\lambda \in R$

$\lambda_i \rightarrow \vec{x}_i$ 互相垂直的

对于非对称 $A_{n \times n}$

$$\boxed{A = \underbrace{S}_{[\vec{x}_1, \vec{x}_2, \cdots]} \underbrace{\Lambda}_{} \underbrace{S^{-1}}_{}}$$

$[\vec{x}_1, \vec{x}_2, \cdots] \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} S^{-1}$

1 $\boxed{Ax = \lambda x}$ $\quad A = S\Lambda S^{-1}$

$$AS = A \cdot [\vec{x}_1, \vec{x}_2 \cdots \vec{x}_n]$$

$$= [\lambda_1 \vec{x}_1, \lambda_2 x_2, \cdots \lambda_n x_n]$$

矩阵乘法定义

$$= \underbrace{[\vec{x}_1, \vec{x}_2 \cdots]}_{} \cdot \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

$$= S\Lambda \Rightarrow \boxed{AS = S\Lambda}$$

$$\boxed{A = S\Lambda S^{-1}}$$

$\boxed{A = A^T}$ $\boxed{A = S\Lambda S^{-1}}$ S^{-1}

S: 正交矩阵 $S^{-1} = S^T$ $\boxed{A^{1000} = S\Lambda^{1000}S^{-1}}$

$\boxed{A = Q\Lambda Q^T}$ 谱定理

$\vec{x}_1$ λ A^k

$A^2 = A \cdot A$

$= S\Lambda \underbrace{S^{-1} S}_{} \Lambda S^{-1}$

$A = S\Lambda S^{-1}$ $A^2 = S\Lambda^2 S^{-1}$

MIT公开课 LA

$\boxed{\text{SVD}}$ 任意矩阵

$$\boxed{\begin{gathered} A = A^T \\ A = Q\Lambda Q^T \end{gathered}}$$

$$\boxed{A = U\Sigma V^T}$$

$Ax = \lambda x$

U：正交阵

Σ：对角

V^T：正交阵

$U, \Sigma, V = \mathrm{SVD}(m)$

$\vec{u}_1 \perp \vec{u}_2 \perp \vec{u}_3$ $\quad R^n$

A

$A = U\Sigma V^T$

$Ax = \lambda x$

$\vec{u}_i \perp$ $\quad A\vec{u}_i = \sigma_i v_i$ $\quad v_i$ $\quad \perp u_1$

A^TA

AA^T

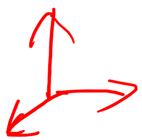
9 6 3 1 1 1 0.3 0.1

u_1 $\quad u_2$ $\quad u_3$

$$A = U\Sigma V^T$$

$\vec{x} =$

[3 6 9 2 5]



$u_1\ u_2 \ldots u_n$

[1 - - - -]

$$AU = A[\vec{u}_1, \vec{u}_2, \cdots \vec{u}_n]$$

$$AU = V\Sigma$$

$$= [\vec{w}_1, \vec{w}_2 \cdots \vec{w}_n]\begin{bmatrix}\sigma_1 & & \\ & \sigma_2 & \\ & & \sigma_n\end{bmatrix}$$

$$\boxed{\begin{aligned} Au_1 &= \sigma_1 v_1 \\ Au_2 &= \sigma_2 v_2 \end{aligned}}$$

$$A^TA = B \qquad B^T = A^TA = Q\Lambda Q^T$$

$$\boxed{A[\vec{u}_1, u_2 \cdots u_n] = [v_1\ v_2 \cdots v_n]\begin{bmatrix}\sigma_1 & & \\ & \ddots & \\ & & \sigma_2\end{bmatrix}}$$

$$AU = V\Sigma \qquad A^TA \qquad A\Lambda \qquad 4$$

$$\boxed{\underline{A} = V\Sigma U^{-1} = V\Sigma U^T}$$

Trick

$$\underline{A^T = U\Sigma V^T} \qquad AA^T = V\Sigma^2 V$$

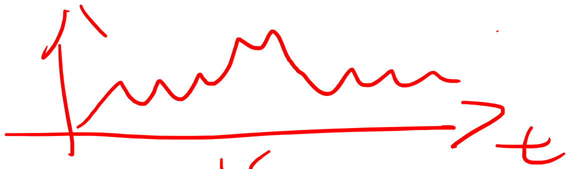
$$A^T \cdot A = U\Sigma \underbrace{V^T \cdot V}\Sigma U^T = U\Sigma^2 U^T$$

MIT 线性代数

Portfolio (N) (20)

— Stock i

$P_{i,t}$



招 招

t: $[P_{1t} \quad P_{2t} \quad P_{3t} \cdots P_{Nt}]$

$$r = \frac{P_t - P_{t-1}}{P_{t-1}}$$

t_1	t_2	t_3
2	6	7
9	8	10
15	20	

mean

var

$[r_{1t} \quad r_{2t} \quad \cdots \quad r_{nt}]$

$[\quad]$

$[\quad]$

$[\quad]$

M

$\vec{u} = [\quad]_N$

$\Sigma = [\quad]_{N\times N}$

协方差

t: $[r_1 \ r_2 \ \cdots \ r_N]$ Σ 协方差矩阵

t: $[w_1 \ w_2 \ \cdots \ w_N] = \vec{w}_{N\times 1}$ λ: 9 8 7 6 8

$\vec{x}$

$\mathrm{RISK} = \vec{w}^T \Sigma \vec{w}$

~~S+3~~

$[\ ]_{1\times N} [\ ]_{N\times N} [\ ]_{N\times 1}$

λ

$\vec{x}$

201511

Σ_{ε}

t_1 [r r r r]

t_2 [ ]

⋮

$\vec{u}$ M [ ]

5 5 6 7 9 $\longrightarrow$ $\bar{x}$ var

$\Sigma_{n\times n} = \Sigma^T$

$$\text{Risk} = w^T \Sigma w$$

Stanford

convex optimization

$$\min_{w} \; w^T \Sigma w$$

$$\text{s.t.} \quad w_1 + \cdots w_n = 1$$

$$\vec{w}^{*} = \frac{\Sigma^{-1} \cdot 1}{(\Sigma^{-1} \cdot 1)^T \cdot 1}$$

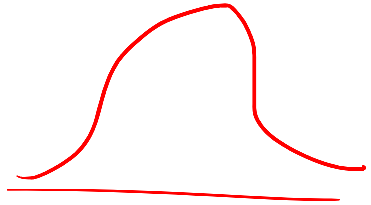
~~Ran~~

random
matrix
~~thear~~
theory

Pol =

[ ]

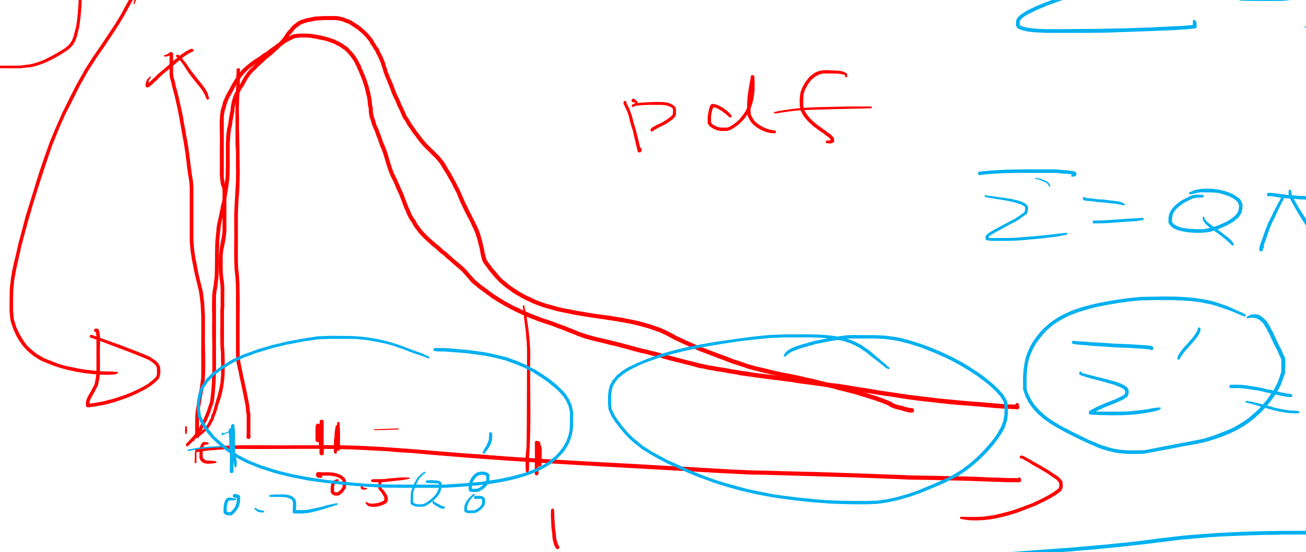
[0.1 0.25]



$\Sigma = \lambda$

pdf

$\Sigma = Q \Lambda Q^T$



~~Mar~~ Marchenko-Pastur

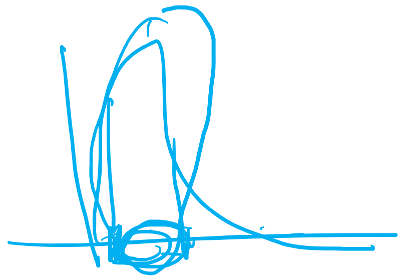
$\Sigma = \Sigma^T$

1) $SVD(\Sigma)^{100}$

$\lambda_1 \cdots \lambda_n$

$\Sigma = Q \Sigma Q^T$

100



Σ'

2) 60-70 $\lambda_1 \quad \lambda_2 \quad \lambda_5 \cdots \lambda_{100}$

$\lambda_i = 0 \qquad \lambda_i \in [\quad]$

3) $\Sigma' \longrightarrow$

$$-\ \sigma_1 = 2 \qquad \vec{x}_1 = [1,\ 1]$$

$$\sigma_2 = 2.5 \qquad \vec{x}_2 = [-1,\ 1]$$

$$A = A^T$$

σ

x

$$= \boxed{A = Q \Lambda Q^T = \begin{bmatrix} 1 & \cancel{-}1 \\ 1 & \cancel{\ }1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 2.5 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}}$$

$$\uparrow \qquad \uparrow$$

$$\vec{x}_1 \qquad \vec{x}_2$$

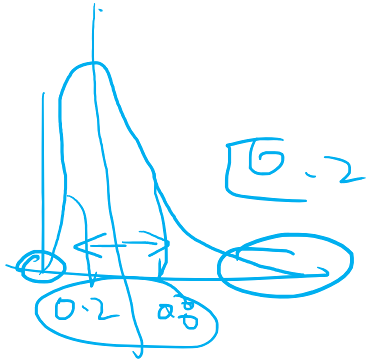
Σ 协方差

$\sigma_1 \quad \sigma_2 \quad \cdots \quad \sigma_n$

$x_1 \quad \cdots \quad x_n$

0.

1.



$[0.2 \quad 0.8]$

$\sigma_1 \quad \sigma \quad \sigma \quad \sigma \quad \sigma_j \quad \cdots$

$x \quad x \quad \cdots \quad x$

w

2. $\Sigma' = Q \Lambda Q^T$

3. $\Sigma' \to risk = w^T \Sigma' w$

$\lambda \to \vec{u} \to \vec{w}$

0.2
0.3
0.4

3 3

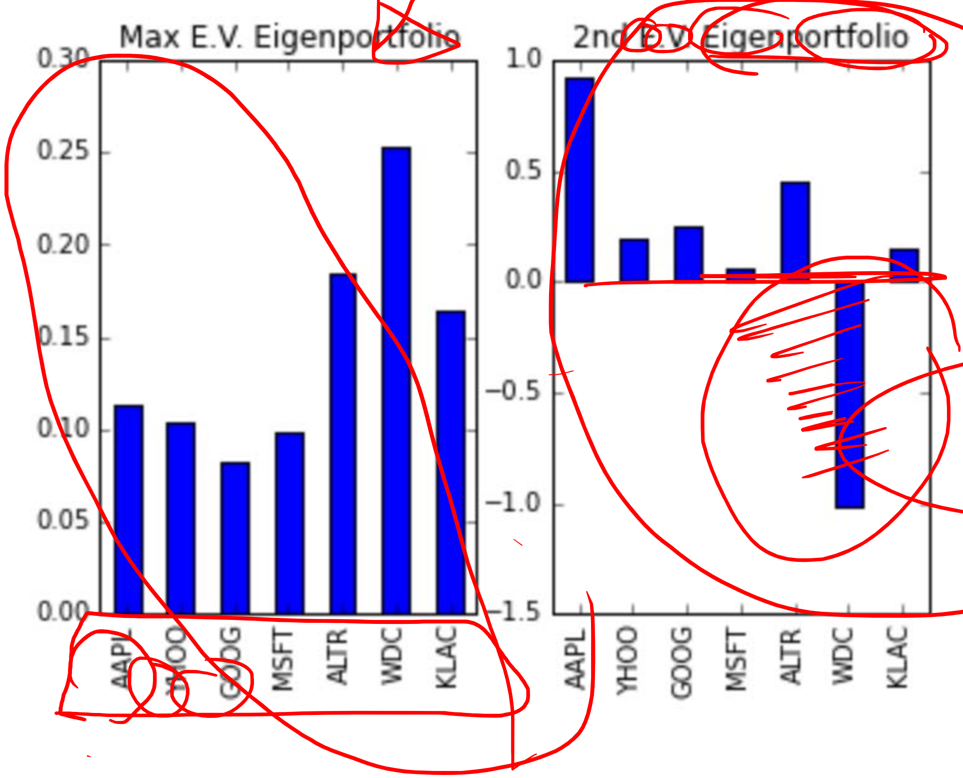
0.5

$\begin{bmatrix} 3 & 6.5 \\ 6 & 3 \end{bmatrix}$

$\downarrow$

λ : 0.2, 1.1

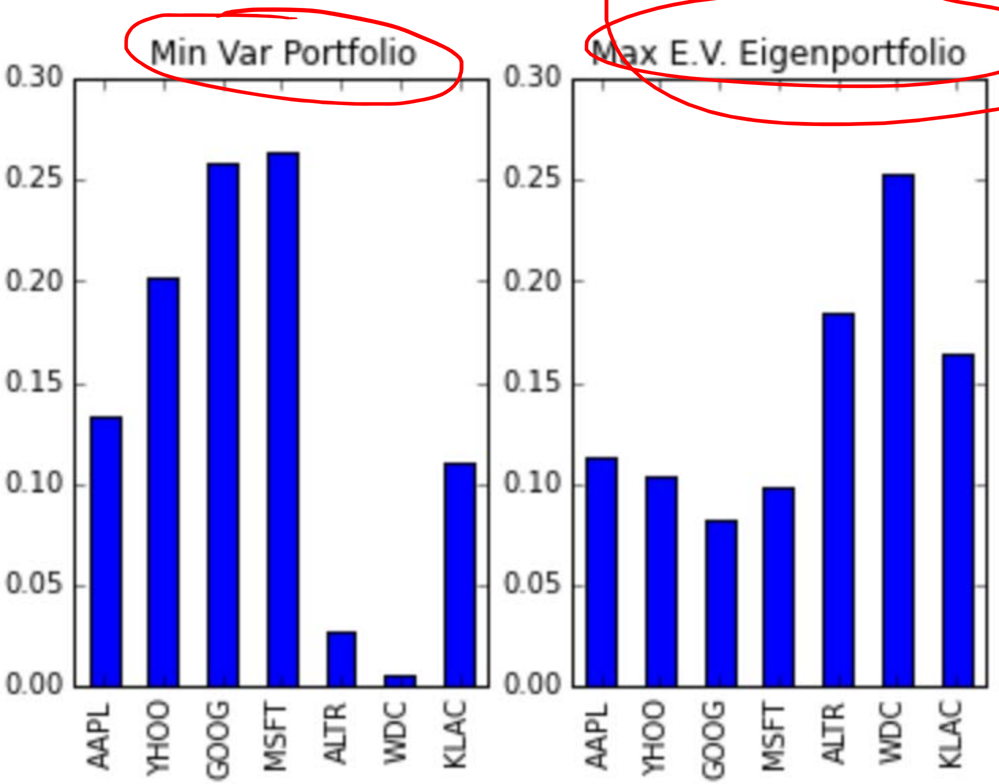
$\vec{x}$: $\begin{bmatrix} 0.2 \\ 0.8 \end{bmatrix}$ $\begin{bmatrix} 0.1 \\ 0.9 \end{bmatrix}$



short

sell

[illegible] var eingen

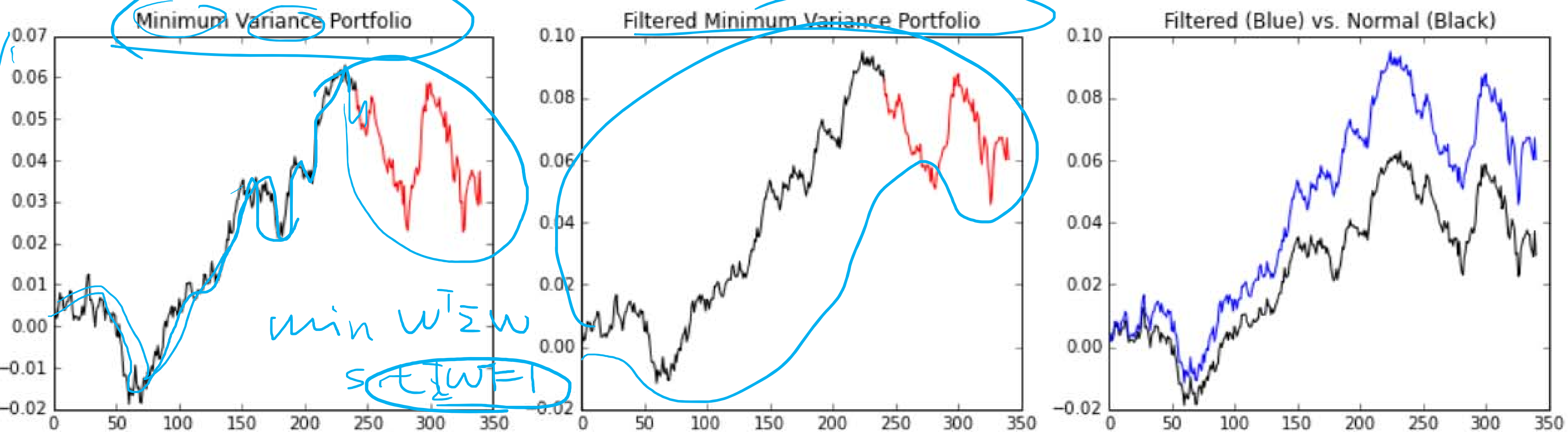


Min Var Portfolio
Max E.V. Eigenportfolio
0.30
0.25
0.20
0.15
0.10
0.05
0.00
AAPL
YHOO
GOOG
MSFT
ALTR
WDC
KLAC

$$A' = \omega$$

$$A = U \Sigma U^T$$

$$\omega \Sigma$$



$$\min w^T \Sigma w$$

$$\text{s.t. } \Sigma w = 1$$

Subject to $A' = Q \Lambda Q^T$

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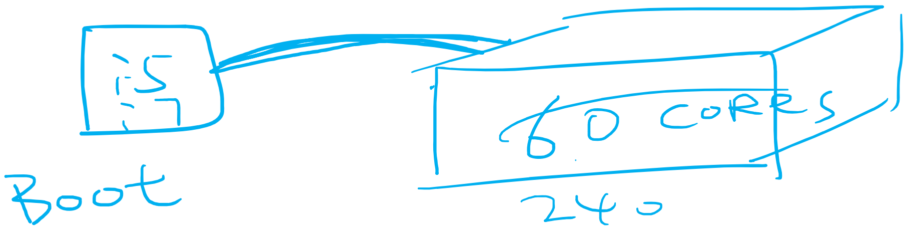
Symbol	Futures	Annualized Sharpe Ratio	Capability Ratio
PL	Platinum	3.29 (1.12)	12.51 (4.27)
NQ	E-mini NASDAQ 100 Futures Quotes	2.07 (2.11)	7.89 (8.03)
AD	Australian Dollar	1.48 (1.09)	5.63 (4.13)
BP	British Pound	1.29 (0.90)	4.90 (3.44)
ES	E-mini S&P 500 Futures Quotes	1.11 (1.69)	4.22 (6.42)

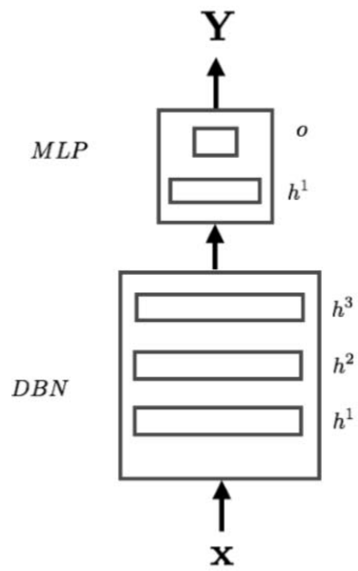
KNL

- The overall training dataset consists of the aggregate of feature training sets for each of the symbols. The training set of each symbol consists of price differences and engineered features including lagged prices differences from 1 to 100, moving price averages with window sizes from 5 to 100, and pair-wise correlations between the returns and the returns of all other symbols. The overall training set contains 9895 features. The motivation for including these features in the model is to capture memory in the historical data and co-movements between symbols



150612a.pdf
Deep Learning for Multivariate Financial Time Series

$$\mathbf{x} = \left\{ r_d^i(t), \ldots, r_d^i(t-19), r_m^i(t-2), \ldots, r_m^i(t-13), I(t = \mathrm{J}) \right\},$$



Model	Neurons	ϵ_p	ϵ_f	E_V (%)	E_T (%)
Naive	-	-	-	50.03	50.93
LReg	-	-	-	49.96	50.74
MLP	20	-	0.1	49.66	50.84
DBN	400	10^{-11}	10^{-3}	46.52	47.11

Table 5.5: *Result from DBN-MLP and benchmarks.*

ecbsp9.en.pdf

keras

gensim

~~Conclusion~~

NLTK

The reliability and accuracy of existing computational measures of investor sentiment leaves much to be desired. We therefore propose a direct and unambiguous measure of investor sentiment, namely the relative frequency of occurrence of two terms commonly used by investors in Twitter updates and Google search queries. Daily Twitter bullishness is indeed found to be a useful investor sentiment indicator. Our analysis shows a positive correlation between Twitter bullishness and Google bullishness on a weekly basis; furthermore, it finds that the former leads changes in the latter. In addition, the two indicators of bullishness from different data sources are found to be positively correlated to existing surveys of investor sentiment, such as the Daily Sentiment Index and the US Advisors' Sentiment Report of Investors Intelligence. More importantly, we find that daily Twitter bullishness leads stock index returns in the United States (Dow Jones, SP500, Russell 1000, Russell 2000), the United Kingdom (FTSE 100) and Canada (GPSTSE), but has only very modest predictive value in respect of the Chinese stock market, as expected. While high Twitter bullishness predicts an increase in stock returns, we observe that these return to fundamental values within a week. Our research thus appears to support the hypothesised role of "investor sentiment" in behavioural finance. We also note the strong positive linear correlation between Google bullishness and Chinese stock index prices (γ = 0.65, p = 0.01), with the former apparently leading the latter in extreme market conditions. This result suggests the merits of studying the predictive value of online information sources such as Weibo for the Chinese market; a topic that has received little interest in the literature.

16:10
DELL
23
x2
1400

17
64
1080

4
128
78
4T

10+

fora_gyula_krisztian.pdf

Indicator Name	Formula
EMA(N)	$EMA_t(N) = \frac{1}{N+1}\sum_{i=0}^{\infty} p_{(t-i)}(1-\frac{1}{N+1})^i$
MACD(N,M)	$MACD_t(N,M) = EMA_t(N) - EMA_t(M)$
K%	$\%K(N) = \frac{100(c_t - \max_{i=0..N}(p_t))}{(\max_{i=0..N}(p_t) - \min_{i=0..N}(p_t))}$
Arms Index	$\frac{NR_{Advances} \times VOL_{down}}{NR_{Declines} \times VOL_{up}}$

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