$\frac{o_{t-2-p/4}}{c_t}$		$\frac{o_{t-4}}{c_t}$	$\frac{o_{t-3}}{c_t}$	$\frac{o_{t-2}}{c_t}$	$\frac{o_{t-1}}{c_t}$	$\frac{o_t}{c_t}$
$\frac{L_{t-2-p/4}}{C_t}$	•••	$\frac{L_{t-4}}{C_t}$	$\frac{L_{t-3}}{C_t}$	$\frac{L_{t-2}}{C_t}$	$\frac{L_{t-1}}{C_t}$	$\frac{L_t}{C_t}$
$\frac{H_{t-2-p/4}}{C_t}$	•••	$\frac{H_{t-4}}{C_t}$	$\frac{H_{t-3}}{C_t}$	$\frac{H_{t-2}}{C_t}$	$\frac{H_{t-1}}{C_t}$	$\frac{H_t}{C_t}$
$\frac{C_{t-2-p/4}}{C_t}$	•••	$\frac{C_{t-4}}{C_t}$	$\frac{c_{t-3}}{c_t}$	$\frac{c_{t-2}}{c_t}$	$\frac{C_{t-1}}{C_t}$	$\frac{c_t}{c_t}$



Known Predict

$\frac{o_{t-2-p/4}}{c_t}$	•••	$\frac{o_{t-4}}{c_t}$	$\frac{o_{t-3}}{c_t}$	$\frac{o_{t-2}}{c_t}$	$\frac{o_{t-1}}{c_t}$	$\frac{o_t}{c_t}$	$\frac{O_{t+1}}{C_t}$
$\frac{L_{t-2-p/4}}{C_t}$		$\frac{L_{t-4}}{C_t}$	$\frac{L_{t-3}}{C_t}$	$\frac{L_{t-2}}{C_t}$	$\frac{L_{t-1}}{C_t}$	$\frac{L_t}{C_t}$	$\frac{L_{t+1}}{C_t}$
$\frac{H_{t-2-p/4}}{C_t}$	•••	$\frac{H_{t-4}}{C_t}$	$\frac{H_{t-3}}{C_t}$	$\frac{H_{t-2}}{C_t}$	$\frac{H_{t-1}}{C_t}$	$\frac{H_t}{C_t}$	$\frac{H_{t+1}}{C_t}$
$\frac{C_{t-2-p/4}}{C_t}$	•••	$\frac{C_{t-4}}{C_t}$	$\frac{c_{t-3}}{c_t}$	$\frac{c_{t-2}}{c_t}$	$\frac{c_{t-1}}{c_t}$	$\frac{c_t}{c_t}$	$\frac{C_{t+1}}{C_t}$

Predict



Unknown

Change the approach: shift from predicting individual future prices to forecasting an integrated information entity encompassing both past and future prices.

We need to integrate future price information with past price information into a unified framework.

Method: PCA-Principal Component Analysis

1. Data Normalization and Segmentation

2. Input Data Matrix

$$[x_{11}, x_{12}, x_{13} \cdots x_{1p}]$$



$$X = \begin{bmatrix} x_{11} \cdots x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} \cdots x_{np} \end{bmatrix}$$

3. Data Centering

$$X_{\text{centered}} = X - \mu$$

$$X_{\text{centered}} = X - \mu = \begin{bmatrix} x_{11} - \mu_1 x_{12} - \mu_2 \cdots x_{1p} - \mu_p \\ x_{21} - \mu_1 x_{22} - \mu_2 \cdots x_{2p} - \mu_p \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} - \mu_1 x_{n2} - \mu_2 \cdots x_{np} - \mu_p \end{bmatrix}$$

$$x_{n1} - \mu_1 x_{n2} - \mu_2 \cdots x_{np} - \mu_p$$

4. Covariance Matrix

variance Matrix
$$C = \frac{1}{n} X_{\mathrm{centered}}^{\top} X_{\mathrm{centered}} = \begin{bmatrix} c_{11} c_{12} \cdots c_{1p} \\ c_{21} c_{22} \cdots c_{2p} \\ \vdots & \vdots & \vdots \\ c_{p1} c_{p2} \cdots c_{pp} \end{bmatrix}$$

5. Eigenvalue Computation

$$\det(C - \lambda I) = \begin{vmatrix} c_{11} - \lambda & c_{12} & \cdots & c_{1p} \\ c_{21} & c_{22} - \lambda \cdots & c_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ c_{p1} & c_{p2} & \cdots c_{pp} - \lambda \end{vmatrix} = 0$$

$$X_{\text{pca}} = X_{\text{centered}} W \in \mathbb{R}^{n \times k}$$



$$\begin{bmatrix} \tilde{x}_{11} \cdots \tilde{x}_{1k} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{n1} \cdots \tilde{x}_{nk} \end{bmatrix} = \begin{bmatrix} x_{11} \cdots x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} \cdots x_{np} \end{bmatrix} \begin{bmatrix} v_{11} \cdots v_{1k} \\ \vdots & \ddots & \vdots \\ v_{p1} \cdots v_{pk} \end{bmatrix}$$

$\frac{o_{t-2-p/4}}{c_t}$		$\frac{o_{t-4}}{c_t}$	$\frac{o_{t-3}}{c_t}$	$\frac{o_{t-2}}{c_t}$	$\frac{o_{t-1}}{c_t}$	$\frac{o_t}{c_t}$	$\frac{o_{t+1}}{c_t}$
$\frac{L_{t-2-p/4}}{C_t}$	•••	$\frac{L_{t-4}}{C_t}$	$\frac{L_{t-3}}{C_t}$	$\frac{L_{t-2}}{C_t}$	$\frac{L_{t-1}}{C_t}$	$\frac{L_t}{C_t}$	$\frac{L_{t+1}}{C_t}$
$\frac{H_{t-2-p/4}}{C_t}$		$\frac{H_{t-4}}{C_t}$	$\frac{H_{t-3}}{C_t}$	$\frac{H_{t-2}}{C_t}$	$\frac{H_{t-1}}{C_t}$	$\frac{H_t}{C_t}$	$\frac{H_{t+1}}{C_t}$
$\frac{C_{t-2-p/4}}{C_t}$		$\frac{c_{t-4}}{c_t}$	$\frac{c_{t-3}}{c_t}$	$\frac{c_{t-2}}{c_t}$	$\frac{c_{t-1}}{c_t}$		$\frac{c_{t+1}}{c_t}$

Future data points are projected by these eigenvectors, effectively distributing them into a transformed space where each dimension (eigenvector) encodes a distinct pattern of variability.

 $\left[\tilde{x}_{11},\tilde{x}_{12},\tilde{x}_{13}\cdots\tilde{x}_{1k}\right]$



 $[x_{11}, x_{12}, x_{13} \cdots x_{1p}] \cdots$

Principal Component Analysis

1. Calculate Row-wise Mean
$$m=\begin{bmatrix}m_1\\m_2\\\vdots\\m_n\end{bmatrix}_{m\times 1}$$
 $m_i=\frac{1}{k}\sum_{j=1}^k\sin(\tilde{x}_{ij})$

$$m_i = \frac{1}{k} \sum_{j=1}^k \sin(\tilde{x}_{ij})$$

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} \, \tilde{x}_{12} \cdots \tilde{x}_{1k} \\ \tilde{x}_{21} \, \tilde{x}_{22} \cdots \tilde{x}_{2k} \\ \vdots & \vdots & \ddots \vdots \\ \tilde{x}_{n1} \, \tilde{x}_{n2} \cdots \tilde{x}_{nk} \end{bmatrix}_{n \times k}$$

$$\begin{bmatrix} \|\tilde{x}_1\|_2 \\ \|\tilde{x}_2\|_2 \end{bmatrix}$$

$$n = \begin{bmatrix} \|\tilde{x}_1\|_2 \\ \|\tilde{x}_2\|_2 \end{bmatrix} \qquad \|\tilde{x}_i\|_2 = \sqrt{\sum_{j=1}^k \tilde{x}_{ij}^2}$$
 L2 Norm
$$\begin{bmatrix} \|\tilde{x}_1\|_2 \\ \vdots \\ \|\tilde{x}_n\|_2 \end{bmatrix}_{n \times 1}$$

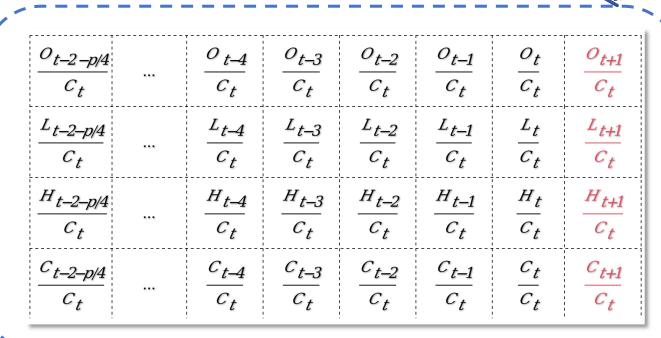
2. Compute Row-wise L2 Norm

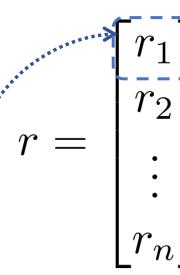
$$\left[\|\tilde{x}_n\|_2\right]_{n\times 1}$$

3. Dimensionality Reduction

$$r = m \odot n = \begin{bmatrix} m_1 \times \|\tilde{x}_1\|_2 \\ m_2 \times \|\tilde{x}_2\|_2 \\ \vdots \\ m_n \times \|\tilde{x}_n\|_2 \end{bmatrix}_{n \times 1}$$









Clustering