Two Thoughts About Cointegration and the SVD

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Cointegration

Occurs when a linear combination of I(1) variables is I(0), and also in other more general cases.

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A drunk walking his dog.

Cointegration

Occurs when a linear combination of I(1) variables is I(0), and also in other more general cases.

- A drunk walking his dog.
- Any group hanging out with Thomas on a given night.

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Use R! Bernhard Pfaff

Analysis of Integrated and Cointegrated Time Series with R

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Second Edition

Springer

Computing and Testing Cointegration

VECM methods boil down to modeling variables *x* over time t = 1, 2, ..., T like

$$\Delta x_t = \Pi x_{t-1} + \epsilon_t,$$

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with the cointegration hypothesis that $rank(\Pi) \leq r$.

Computing and Testing Cointegration

Writing $\Pi = \alpha \beta^T$, $\alpha, \beta \in \mathbf{R}^{n \times r}$, the equations are often arranged in matrix form as a linear system:

$$X_0 = X_1 \beta \alpha^T + E,$$

where X_i arise from vectors x_t .

The Johansen method estimates

$$\min_{\beta\alpha^{T}} \| X_0 - X_1 \beta \alpha^{T} \|$$

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by maximum likelihood.

The Singular Value Decomposition (SVD)

Let $A \in \mathbf{R}^{m \times n}$, $m \ge n$. The SVD of A is:

$$\begin{array}{rcl} AV &=& U\Sigma, \\ V^TV &=& I = U^TU, \\ \Sigma &=& \mathsf{diag}(\sigma_1 \geq \sigma_2 \geq ... \geq \sigma_n \geq \mathbf{0}), \end{array}$$

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where $U \in \mathbb{R}^{m \times n}$, $\Sigma \in \mathbb{R}^{n \times n}$, $V \in \mathbb{R}^{n \times n}$ (thin version).

The Singular Value Decomposition

Note that the SVD:

- Always exists.
- Is (almost always) the most numerically-stable way to compute many things with matrices.
- Is a model-free way to consider data.

But, it's somewhat computationally expensive to compute.

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SVD and Cointegration (Doornik, O'Brien¹)

Solve $\min_{\beta\alpha^T} \|X_0 - X_1\beta\alpha^T\|$ by SVD(s) with:

- 1. Compute $X_j V_j = U_j \Sigma_j$,
- 2. Let $Z := U_1^T U_0$,
- 3. Compute $ZV_z = U_z \Sigma_z$.

They show that $\beta = T^{1/2} V_1 \Sigma^{\dagger} U_z$, and $\alpha = T^{1/2} V_0 \Sigma_0 Z^T U_z$.

¹Doornik, J.A. and O'Brien, R.J. (2002). Numerically Stable Cointegration Analysis, Computational Statistics and Data Analysis, 41, 185-193.

What about Large Data?

Doornik's approach can reliably detect numerical rank of large matrices in the presence of ill-conditioned data. But,

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- 1. We're generally not interested in trading huge sets.
- 2. Statistical interpretation difficult.

SVD Again

One approach builds a candidate set for cointegration by iterating:

- 1. Use SVD subset selection² to pick a few variables.
- 2. Project remaining variables into subspace defined by the selected set and choose among those with smallest norm.

That is if *K* is the set of selected columns in a matrix *A*, compute $A_K V_K = U_K \Sigma_K$ and choose additional columns *j* where $||U_K^T a_j||$ is small.

²Gene Golub and Charles Van Loan, Matrix Computations, Johns Hopkins University Press, 1996.

SVD Subset Selection, a Real Gem

Listing 1: SVD Subset Selection.

```
# Input matrix A
# Number of singular values n
# Number of output columns k<=n
# Returns an index subset of columns of A that *estimate*
   the k most
# linearly independent columns.
svdsubsel <- function(A, n, k=n)</pre>
 S \leq svd(A, n)
 Q \leq qr(t(S$v[,1:n]), LAPACK=TRUE)
Q$pivot[1:k]
```

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Example SVD Subset Selection



Performance

Wait, isn't it expensive to compute all these SVDs?

No! Note that many discussed computations require only partial SVDs.

Use the IRLB algorithm³.

- IRLB is perhaps the most efficient method to compute a few singular vectors of matrix.
- IRLB can find vectors associated with largest or smallest singular vectors.

³http://cran.r-project.org/web/packages/irlba/index.html

Summary

I advocate following Doornik's advice and using the SVD to solve the cointegration problem in a numerically stable way.

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Use the SVD to mine data for likely cointegrated sets.