A Wild Bootstrap for Degenerate Kernel Tests

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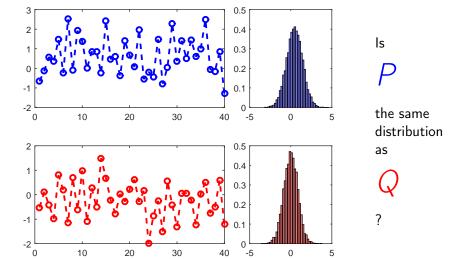


Arthur



Dino

Maximum Mean Discrepancy for Random Processes



Statistical Tests for Random Processes

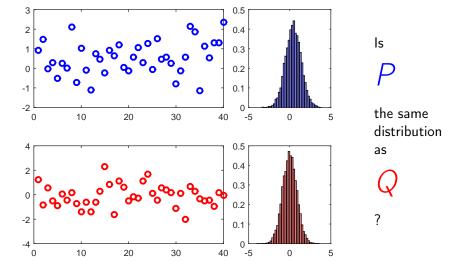
Where one can use Maximum Mean Discrepancy?

- ► Markov chains diagnostics
- ► Change point detection

Other tests

- ► Hilbert Schmidt Independence Criterion
 - ► Dependency structure in financial markets
 - ► Brain region activation
- ▶ Three Variables Interaction

Maximum Mean Discrepancy for i.i.d observations



Similarity

$$K_{P,P} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_1, X_n) \\ \vdots & \ddots & \vdots \\ k(X_n, X_1) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \ddots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix}$$

$$K_{Q,Q} = \begin{bmatrix} k(Y_1, Y_1) & \dots & k(Y_1, Y_n) \\ \vdots & \ddots & \vdots \\ k(Y_n, Y_1) & \dots & k(Y_n, Y_n) \end{bmatrix} =$$

$$K_{P,Q} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_1, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} =$$



Similarity

$$P \neq Q \Rightarrow \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} =$$

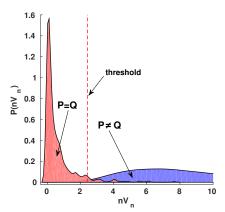
Similarity

$$P \neq Q \Rightarrow \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} =$$

$$P = Q \Rightarrow \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} =$$

Quantifying Similarity

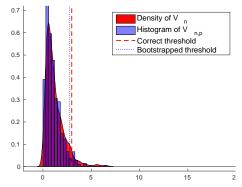
$$V_n = \overline{K_{P,P}} + \overline{K_{Q,Q}} - 2\overline{K_{P,Q}}$$



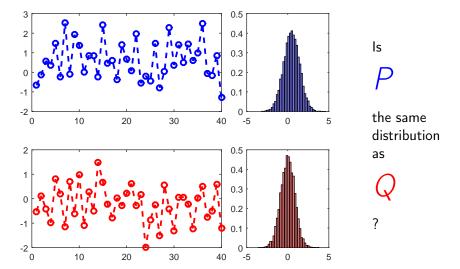
Putting Hands on V_n Distribution

Estimation of V_n via Permutation

$$\textit{V}_{\textit{n,p}} = \overline{\left[\begin{matrix} \textit{K}_{\textit{P},\textit{P}} & \textit{K}_{\textit{P},\textit{Q}} \\ \textit{K}_{\textit{Q},\textit{P}} & \textit{K}_{\textit{Q},\textit{Q}} \end{matrix} \right]} \odot \left[\begin{matrix} \textit{W}^\top \textit{W} \end{matrix} \right]$$



Back to the Difficult Problem



Memory of the Processes

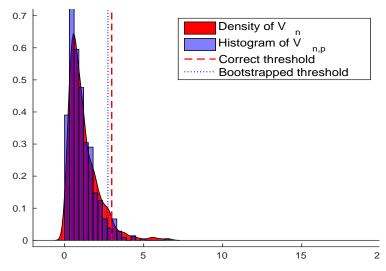


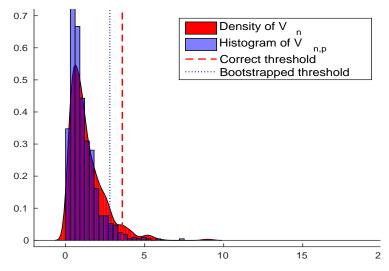
$$Q_t = \mathbf{0.14} Q_{t-1} + 0.98 \epsilon_t$$

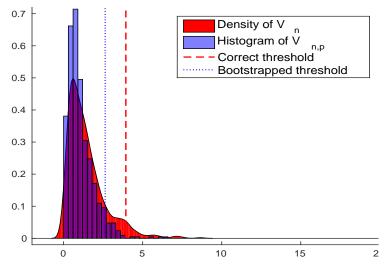
Processes with different memory

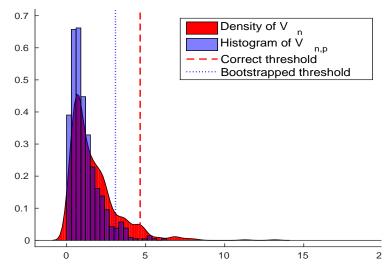
$$Z_t = \mathbf{0.97} Z_{t-1} + 0.22 \epsilon_t.$$

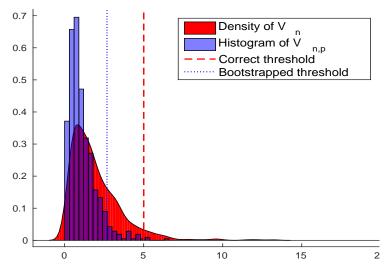
The distribution of the V-statistics is primary driven by memory

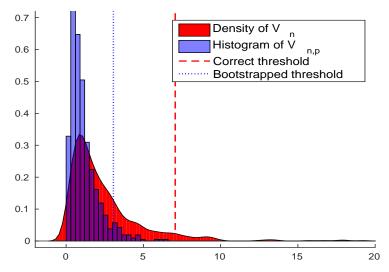


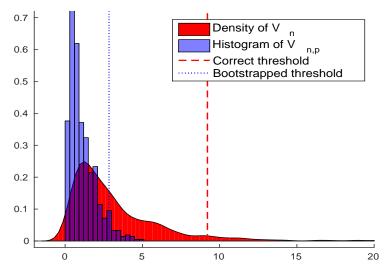


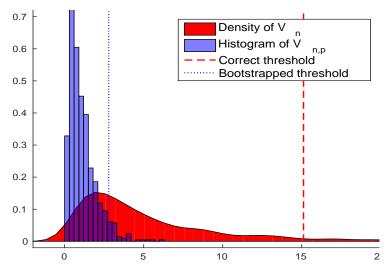












Similarity for Random Processes

$$K_{P,P} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_1, X_n) \\ \vdots & \ddots & \vdots \\ k(X_n, X_1) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(Y_1, Y_1) & \dots & k(Y_1, Y_n) \\ \vdots & \ddots & \vdots \\ k(Y_n, Y_1) & \dots & k(Y_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_1, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_1, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_1) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \ddots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \dots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \dots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \dots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \dots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \dots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, Y_1) & \dots & k(X_n, Y_n) \\ \vdots & \dots & \vdots \\ k(X_n, Y_n) & \dots & k(X_n, Y_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \dots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \dots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \dots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \dots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \dots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\ \vdots & \dots & \vdots \\ k(X_n, X_n) & \dots & k(X_n, X_n) \end{bmatrix} = \begin{bmatrix} k(X_1, X_1) & \dots & k(X_n, X_n) \\$$

Gram Matrices

$$P \neq Q \qquad \Rightarrow \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} =$$

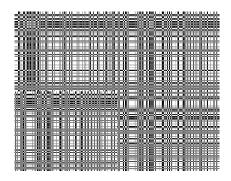
Gram Matrices

$$P \neq Q$$
 $\Rightarrow \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} =$

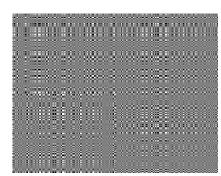
$$P = Q$$
 $\Rightarrow \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} =$

Permutation Test for Random Processes

If P = Q Permutation Approach Fails

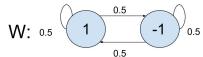


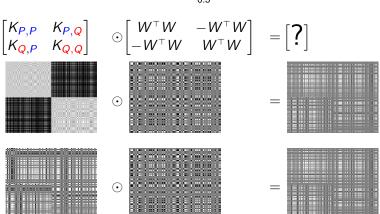




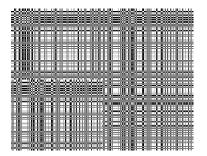
Matrix generated via permutation

Wild Bootstrap

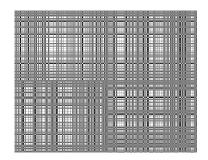




If P = Q the Wild Bootstrap Approach Works!

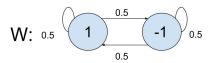


The actual matrix

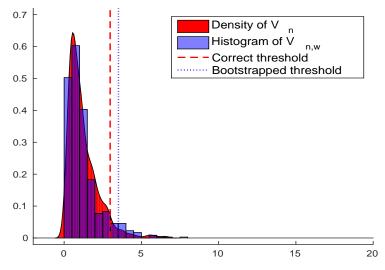


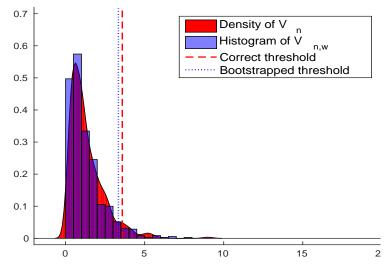
Matrix generated via **wild bootstrap**

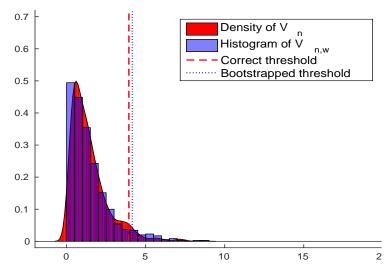
Estimation of V_n via the Wild Bootstrap

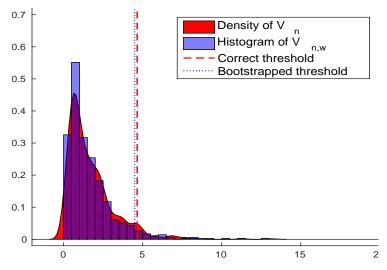


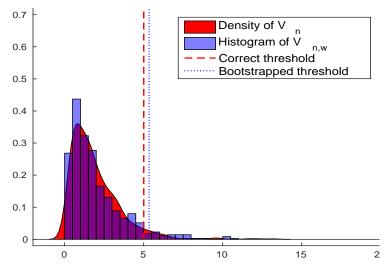
$$V_{n,w} = \begin{bmatrix} K_{P,P} & K_{P,Q} \\ K_{Q,P} & K_{Q,Q} \end{bmatrix} \odot \begin{bmatrix} W^{\top}W & -W^{\top}W \\ -W^{\top}W & W^{\top}W \end{bmatrix}$$

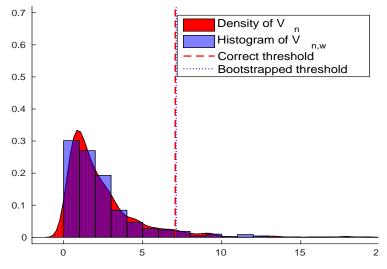


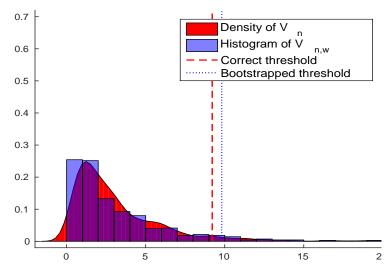


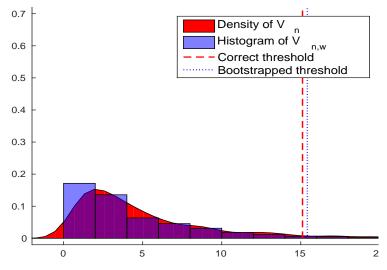




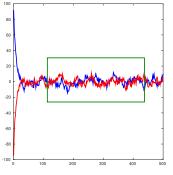








MCMC M.D. Experiment



Is P the same distribution as Q?

Test - MMD	Type one error	
Permutation	68 %	
Wild Bootstrap	6 %	

Indie Pop Group Predicts the Volume of the Dow Jones!





Indie Pop Group Predicts the Volume of the Dow Jones!





Test	p-value	Dependent
Permutation HSIC	0.003	Yes!

Indie Pop Group Predicts the Volume of the Dow Jones!





Test	p-value	Dependent
Permutation HSIC	0.003	Yes!
Wild Bootstrap HSIC	0.231	No