

3/B/203

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Sym Tridiagonal Matrices

$$T = \begin{pmatrix} \alpha_1 & \beta_1 & & & \\ & \ddots & \ddots & & \\ & & \ddots & \beta_{n-1} & \\ & & & \beta_{n-1} & \alpha_n \end{pmatrix}$$

Classical: $w(x) \rightarrow \{ \pi_j(x) \} \rightarrow$ three term recurrence

Useful: Start with T

Classical: Continuous weight $w(x)$ For $n=0, 1, 2, \dots$

$$\begin{pmatrix} \alpha_1 & \beta_1 & & & \\ & \ddots & \ddots & & \\ & & \ddots & \beta_{n-1} & \\ & & & \beta_{n-1} & \alpha_n \end{pmatrix} \begin{pmatrix} \pi_0(x) \\ \vdots \\ \pi_{n-1}(x) \end{pmatrix} = x \begin{pmatrix} \pi_0(x) \\ \vdots \\ \pi_{n-1}(x) \end{pmatrix} - \beta_n \begin{pmatrix} 0 \\ \vdots \\ 0 \\ \pi_n(x) \end{pmatrix}$$

$$\pi_n(x) = \frac{(\beta_1 \dots \beta_n)}{\int_{\mathbb{R}} w(x) dx} \prod_{i=1}^n (x - \lambda_i)$$

 \rightarrow eigenvalues of sym tridiagonals are fast + often very accurate

Note $(T - xI)^{-1} \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix} = c \begin{pmatrix} \pi_0(x) \\ \vdots \\ \pi_n(x) \end{pmatrix}$ if

 x is not an eigenvalue

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Since we know $\pi_0(x) = \frac{1}{\int \omega(x) dx}$

we can compute the entire vector

$$\begin{pmatrix} \pi_0(x) \\ \vdots \\ \pi_m(x) \end{pmatrix}$$

$$T = Q \Lambda Q^T$$

with a solve.

Can do spectrally

~~$$M_{ij} = \sum \frac{q_{n,i} q_{n,j}}{\lambda_i - \lambda_j} Q^T \omega Q(n, i)$$~~

$$\sum \frac{q_{n,i}}{\lambda_i - x} q_i$$

I think faster & more accurate than other ways.

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For a discrete weight function say

$$w(x) = \sum_{i=1}^n q_i^2 \delta(x - x_i) \quad \left[\sum_{i=1}^n q_i^2 = 1 \right] \quad q_i \neq 0$$

Can only get finite tridiagonal

Lanczos construction:

Unstable:

$$K = [q \quad \Lambda q \quad \dots \quad \Lambda^{n-1} q]$$

$$QR = K$$

$$T = Q^* \Lambda Q^T$$

Stable:

$$v_0 = 0, \quad v_1 = q \\ \beta_0 = 0$$

For $j = 1 : \dots : n$

$$w_j \leftarrow \Lambda v_j$$

$$\alpha_j \leftarrow (w_j, v_j)$$

$$w_j \leftarrow w_j - \alpha_j v_j - \beta_j v_{j-1}$$

$$\beta_{j+1} \leftarrow \|w_j\|$$

$$v_{j+1} \leftarrow w_j / \beta_{j+1}$$

end

stop here when $j = n$

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Comment: Lanczos works for any \downarrow not just diagonal
Triangularizes a matrix
Generalizes Householder-reduction

Comment.

In discrete case π_0, \dots, π_{n-1} well defined
The orthonormalization not available

$$\int_{\mathcal{R}} \sum_{k=0}^n \pi_k(\lambda_j) \pi_k(\lambda_l) \rho_k^2 = \delta_{ij}$$

$0 \leq i, j \leq n-1$

Gauss-Quadrature

$w(x)$ & $w_1(x)$ agree on polynomials up to degree $2n-1$

Continuous Lanczos

$$L = \mathcal{K}$$

$$K = \sqrt{w(x)} [1 \ x \ x^2 \ \dots \ x^{n-1}] = QR$$

$$Q^* K Q^T = T$$

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Equilibrium Measure

$$e(x) = \sum_{k=1}^n \frac{1}{n} \delta(x - \lambda_k)$$

$$\sum q_i^2 \delta(x - \lambda_k) \rightarrow w(x)$$

$$\sum \delta(x - \lambda_k) \rightarrow e(x)$$

R & R^{-1} transfer to minimal bases

$$\int \frac{\pi_j(t) w(t)}{x-t} dt \quad \frac{1}{x-t} = \frac{1/x}{1-t/x}$$

$$= \int \left(\frac{1}{x} + \frac{t}{x^2} + \frac{t^2}{x^3} + \dots \right) \pi_j(t) w(t) dt$$

$$= \sum_{i=1}^{\infty} \frac{\text{coeff of } t^i \text{ in } \pi_j(t) w(t)}{x^{i+1}}$$

R_{ji}

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Orthogonal Polynomial Eigenvalue Density

$$w(x) \geq 0 \text{ on } I$$

$$\int_I \pi_i(x) \pi_j(x) w(x) dx = \delta_{ij}$$

Defn: We call the density

$$P(t_1, \dots, t_n) = c |\Delta|^\beta \prod_{i=1}^n w(t_i)$$

an orthogonal Polynomial (joint) Eigenvalue Density

when $\beta=2$, this is called a determinantal point process
or simply a determinantal process

$$p(t_1, \dots, t_n) = \det(k(t_i, t_j))_{1 \leq i, j \leq n} \quad \text{where } k(x, y) = \sum_{i=0}^{\infty} \pi_i(x) \pi_i(y) w(x)$$

Let $k = Y^T X$ "Gram Matrix"

$$X = \begin{bmatrix} \pi_0(t_1) & \dots & \pi_0(t_n) \\ \vdots & & \vdots \\ \pi_n(t_1) & & \pi_n(t_n) \end{bmatrix} \quad Y = \begin{bmatrix} w(t_1)^{1/2} \\ \vdots \\ w(t_n)^{1/2} \end{bmatrix}$$

$$p(t_1, \dots, t_n) = \det(k) = \det(A)^2 = \left(\text{Vandermonde} \right)^2 \cdot \prod w(t_i)$$

$$Y^T Y = I_p$$

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We say that A is an Orthogonal Polynomial Model if its eigenvalues have the corresponding joint density.

Preferred are explicit element related formulas.

Of course one can take $x \in \mathbb{R}^n$ with an orthogonal polynomial density $\pm \text{diag}(k)$ or $e^{\pm \text{diag}(k)} \phi$ are models, for any distribution on \mathcal{Q} , like Haar measure, but that seems like cheating.

Cauchy Binet

$$C = AB$$

$$\binom{C_{i_1 \dots i_p}}{K_{i_1 \dots i_p}} = \sum_{\substack{j_1 < j_2 < \dots < j_p}} A \binom{C_{i_1 \dots i_p}}{j_1 \dots j_p} B \binom{j_1 \dots j_p}{K_{j_1 \dots j_p}}$$

$$\det(A^T O A) = \sum_{\substack{A \text{ is } n \times p \\ n \geq p}} A \binom{C_{i_1 \dots i_p}}{1 \dots p}^2 d_{i_1} d_{i_2} \dots d_{i_p}$$

$$O = I \quad \text{pl}(A) = \binom{A \binom{C_{i_1 \dots i_p}}{1 \dots p}}{\leftarrow} \in \mathbb{R}^{\binom{p}{p}}$$

$$\det(A^T A) = \|\text{pl}(A)\|^2 = \text{Volume squared of parallelepiped} \\ \{Ax : 0 \leq x_i \leq 1\}$$

Generalized Euclidean formula:

$$\text{volume}^2 = \sum_{\binom{C}{C_p}} (\text{projections of value to all coordinate planes})^2$$

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$$d_i = \begin{cases} 1 & \text{if } i \in A \\ 0 & \text{if } i \notin A \end{cases}$$

$$\det(A^T O A) = \sum_{\substack{C_1, \dots, C_p \\ \text{all in } A}} A \binom{C_1 \dots C_p}{1 \dots p}^2$$

Let $Y^T Y = I$ "Tall skinny orthogonal"
 span is a unit cube

$$d_i = \begin{cases} 1+z & \text{if } i \in S \\ 1 & \text{if } i \notin S \end{cases}$$

$$Y^T D Y = I + z \sum_{\substack{S \subseteq \{i_1, \dots, i_p\} \\ i_1 < i_2 < \dots < i_p}} A \binom{i_1 \dots i_p}{1 \dots p}^2$$

$$d_i = z_i \text{ symbolic}$$

$$\det(A^T O A) = \sum A \binom{i_1 \dots i_p}{1 \dots p}^2 z_{i_1} \dots z_{i_p}$$

$$d_i = 1+z_i \text{ symbolic}$$

$$\sum_{k=0}^p \sum_{\substack{S \subseteq \{i_1, \dots, i_k\} \\ S \subseteq \{i_1, \dots, i_p\} \\ i_1 < i_2 < \dots < i_p}} \prod_{j=1}^k z_{i_j} A \binom{i_1 \dots i_p}{1 \dots p}^2$$

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$$= \sum A \begin{pmatrix} 1 & \dots & z_i \\ & \dots & \\ & & 1 \end{pmatrix}^2$$

$$+ \sum_{j \in \{i_1, \dots, i_p\}} z_j^2 A \begin{pmatrix} 1 & \dots & z_j \\ & \dots & \\ & & 1 \end{pmatrix}^2$$

$$+ \sum_{\substack{\{j_1, j_2\} \subset \{i_1, \dots, i_p\} \\ j_1 < j_2}} z_{j_1} z_{j_2} A \begin{pmatrix} 1 & \dots & z_{j_1} & \dots & z_{j_2} \\ & \dots & & \dots & \\ & & & & \\ & & & & \\ & & & & 1 \end{pmatrix}^2$$

$$\vdots$$
$$\sum_{i_1 < i_2 < \dots < i_p} z_{i_1} z_{i_2} \dots z_{i_p} A \begin{pmatrix} 1 & \dots & z_{i_1} & \dots & z_{i_2} & \dots & z_{i_p} \\ & \dots & & \dots & & \dots & \\ & & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & 1 \end{pmatrix}^2$$

$$= \det(A^T(I+A))$$

If $A = Y$ (i.e. $Y^T Y = I_p$) then $K = YY^T$

$$\det(Y^T(I + \text{diag}(z_i))Y) = \det(I_p + Y^T \text{diag}(z_i)Y)$$
$$= \det(I_n + K \text{diag}(z_i))$$

Let $f = \text{diag}(z_i)$ + we get

$$\det(I + Kf) \neq$$

$$Y = (\phi_0 \dots \phi_{p-1}) \quad \textcircled{5} \quad \varphi(\underbrace{t_1, \dots, t_p}_{1, \dots, p})^2 = \rho(t_1, \dots, t_p)$$

$$D = I + \delta(x-y)$$

$$\det(Y^T D Y) = 1 + \int_{\text{sum } x_i = y} \rho(t_1, \dots, t_p) dt_1 \dots dt_p$$

$$\begin{aligned} (Y^T D Y)_{ij} &= \delta_{ij} + \int \phi_i(x) \phi_j(x) \delta(x-y) dx \\ &= \delta_{ij} + \phi_i(y) \phi_j(y) \end{aligned}$$

$$1 + \sum_{i=1}^2 \phi_i^2(x) = 1 + \text{Prob}(\text{sum } x_i = y)$$

~~or~~ I

$$D(x, x) = 1 + F(x)$$

$$\det(Y^T (I + F) Y) = \prod_{i=1}^p E(\pi(F(t_i)))$$

$$\begin{aligned} \det(Y^T Y + Y^T F Y) \\ = \det(I + \frac{1}{p} F) &= \int \dots \int \pi(1 + F(t_i)) = E(\pi(1 + F)) \end{aligned}$$

$$K_p = Y Y^T \quad K_p(x, y) = \sum_{i=0}^{p-1} \phi_i(x) \phi_i(y)$$

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$$f(x) = \sum_{r=1}^n z_r \delta(x - y_r)$$

= 0 or z_r spike at y_r

analy to sum z_i on

$$1 + \sum z_i M_1(y_i, y_i)$$

$$+ \sum z_i z_j M_2(y_i, y_j; y_i, y_j)$$

;

;



$P(\text{all eigenvalues} < t)$

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In general

$$\det(I + Kf) = E(\prod [1 + f(x_i)])$$

Remark: All can be done continuously

$$f(x) \text{ can be } \sum_{r=1}^p z_r \delta(x - \theta_r) \text{ to set } p \text{ \lambda's to } z$$

J can be any interval

$$\det(I - KX_j) = \Pr(\text{no eig. in } J)$$

$$= \det\left[I - \left[\int_J \phi_i(x) \phi_i(x) dx\right]\right]$$

$$E(x, y) = \Pr \text{ no e.v. in } J = (x, y)$$

$$\text{I} \left(E(x+\Delta x, y) - E(x, y) \right) =$$

YES NO	YES NO	YES or NO
x	$x+\Delta x$	y
$x+\Delta x$		$y+\Delta y$

$$\text{II} \left(E(x+\Delta x, y+\Delta y) - E(x, y+\Delta y) \right)$$

YES	NO	NO
x	$x+\Delta x$	y
$x+\Delta x$		$y+\Delta y$

$$\text{I} - \text{II} =$$

YES	NO	YES
x	$x+\Delta x$	y
$x+\Delta x$		$y+\Delta y$