

Advances in Random Matrix Theory: Let there be tools

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Message

- ❖ Ingredient: Take Any important mathematics
- ❖ Then Randomize!
- ❖ This will have many applications!
- ❖ We can't keep this in the hands of specialists anymore: Need tools!

Tools

- ❖ So many applications ...
- ❖ Random matrix theory: catalyst for 21st century special functions, analytical techniques, statistical techniques
- ❖ In addition to mathematics and papers
 - ❖ Need tools for the novice!
 - ❖ Need tools for the engineers!
 - ❖ Need tools for the specialists!

Themes of this talk

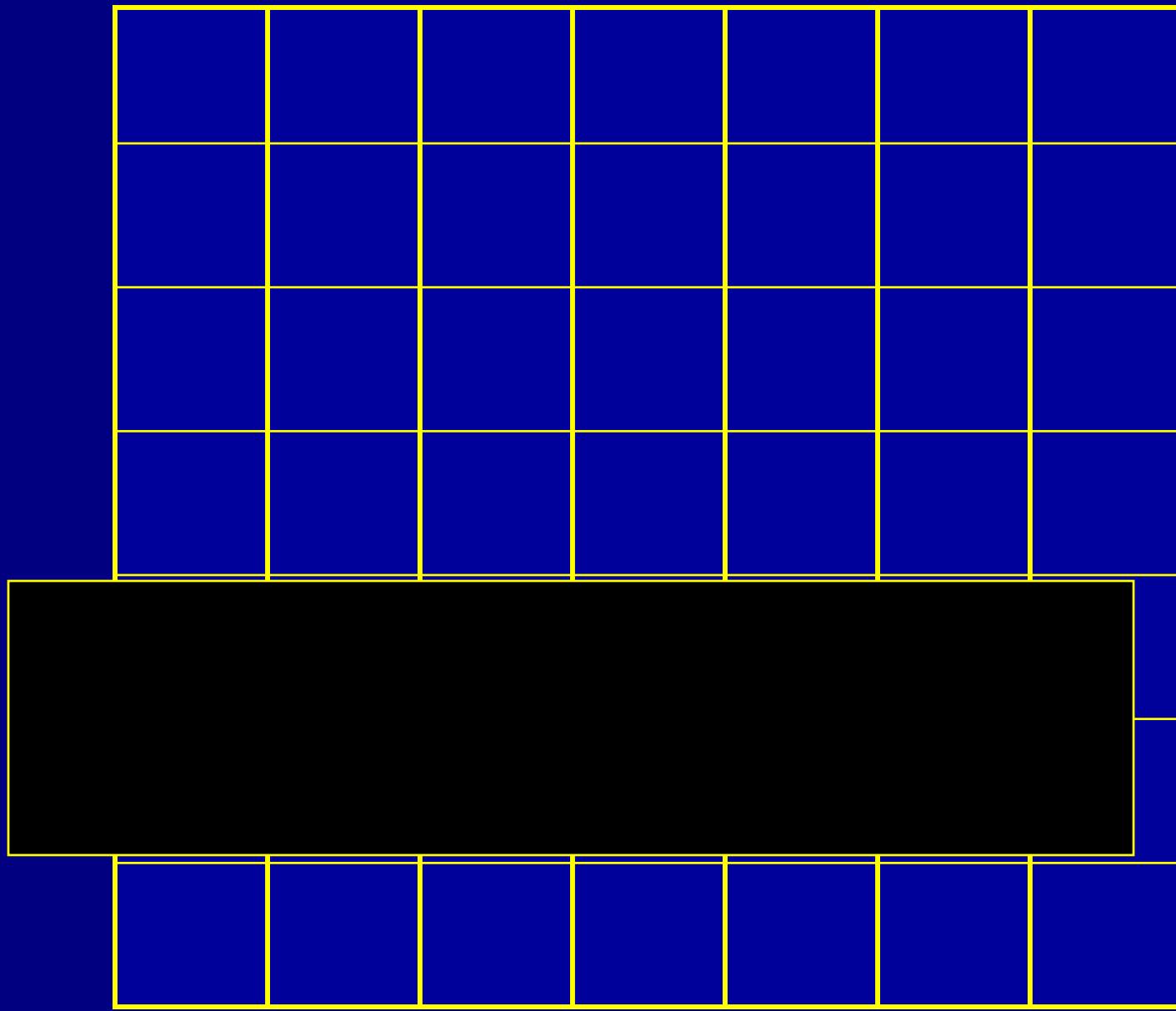
- ❖ Tools for general beta
 - ❖ What is beta? Think of it as a measure of (inverse) volatility in “classical” random matrices.
- ❖ Tools for complicated derived random matrices
- ❖ Tools for numerical computation and simulation

Wigner's Semi-Circle

- ❖ The classical & most famous random eig theorem
- ❖ Let $S = \text{random symmetric Gaussian}$
 - ❖ MATLAB: $A=\text{randn}(n); S=(A+A')/2;$
- ❖ S known as the Gaussian Orthogonal Ensemble
- ❖ Normalized eigenvalue histogram is a semi-circle

```
n=20; s=30000; d=.05; %matrix size, samples, sample dist  
e=[]; %gather up eigenvalues  
im=1; %imaginary(1) or real(0)  
for i=1:s,  
    a=randn(n)+im*sqrt(-1)*randn(n);a=(a+a')/(2*sqrt(2*n*(im+1)));  
    v=eig(a)'; e=[e v];  
end  
hold off; [m x]=hist(e,-1.5:d:1.5); bar(x,m*pi/(2*d*n*s));  
axis('square'); axis([-1.5 1.5 -1 2]); hold on;  
t=-1:.01:1; plot(t,sqrt(1-t.^2),'r');
```

sym matrix to tridiagonal form



General beta

G	$\chi_{6\beta}$	beta: 1: reals 2: complexes 4: quaternions
$\chi_{6\beta}$	G	$\chi_{5\beta}$
$\chi_{5\beta}$	G	$\chi_{4\beta}$
$\chi_{4\beta}$	G	$\chi_{3\beta}$
$\chi_{3\beta}$	G	$\chi_{2\beta}$
$\chi_{2\beta}$	G	χ_{β}
χ_{β}	G	

Bidiagonal Version corresponds
To Wishart matrices of Statistics

Tools

- ❖ Motivation: A condition number problem
- ❖ Jack & Hypergeometric of Matrix Argument
- ❖ MOPS: Ioana Dumitriu's talk
- ❖ The Polynomial Method
- ❖ The tridiagonal numerical 10^9 trick

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Numerical Analysis: Condition Numbers

- ❖ $\kappa(A)$ = “condition number of A ”
- ❖ If $A=U\Sigma V'$ is the svd, then $\kappa(A) = \sigma_{\max}/\sigma_{\min}$.
- ❖ Alternatively, $\kappa(A) = \sqrt{\lambda_{\max}(A'A)}/\sqrt{\lambda_{\min}(A'A)}$
- ❖ One number that measures digits lost in finite precision and general matrix “badness”
 - ❖ Small=good ☺
 - ❖ Large=bad ☹
- ❖ The condition of a random matrix???

Von Neumann & co.

- ❖ Solve $Ax=b$ via $x = \underbrace{(A^T A)^{-1} A^T}_{M \approx A^{-1}} b$
- ❖ Matrix Residual: $\|AM-I\|_2$
- ❖ $\|AM-I\|_2 \leq 200\kappa^2 n \varepsilon$
 ↑
 ≈
- ❖ How should we estimate κ ?
- ❖ Assume, as a model, that the elements of A are independent standard normals!

Von Neumann & co. estimates (1947-1951)

- ❖ “For a ‘random matrix’ of order n the expectation value has been shown to be about $\kappa \approx \infty$

Goldstine, von Neumann

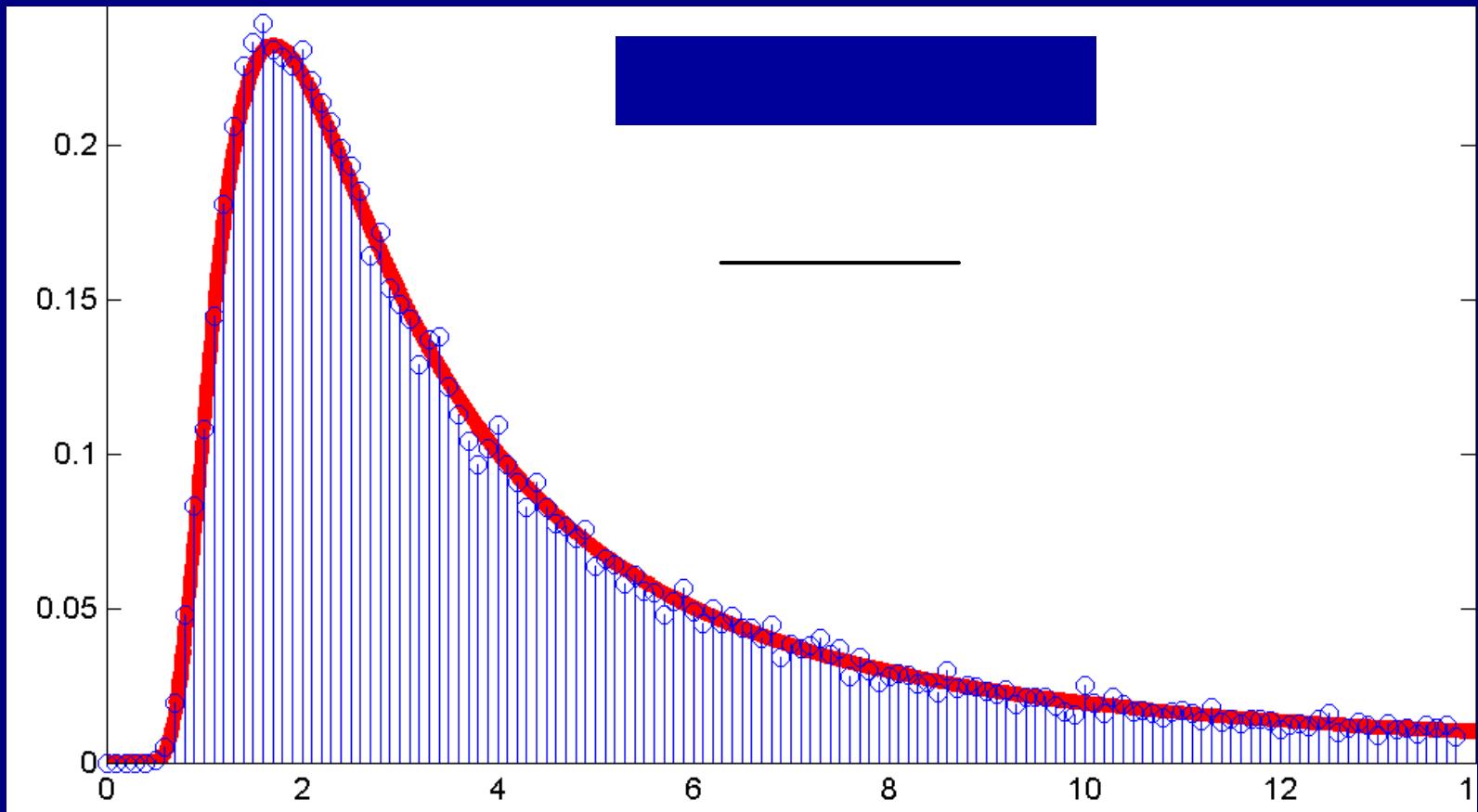
- ❖ “... we choose two different values of κ , namely n and $\sqrt{10n}$ ”
 $P(\kappa < n) \approx 0.02$
 $P(\kappa < \sqrt{10n}) \approx 0.44$

Bargmann, Montgomery, vN

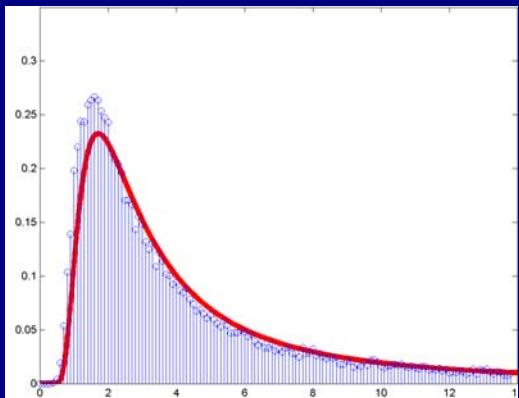
- ❖ “With a probability ~ 1 ... $\kappa < 10n$ ”
 $P(\kappa < 10n) \approx 0.80$

Goldstine, von Neumann

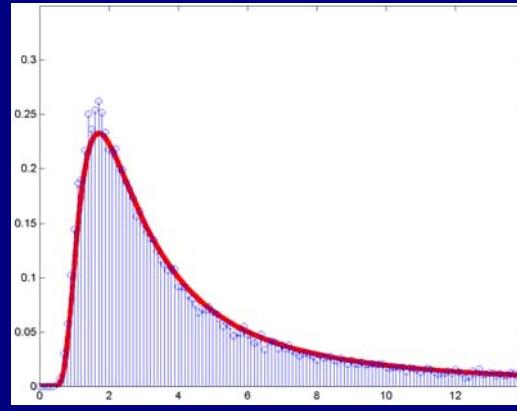
Random cond numbers, $n \rightarrow \infty$



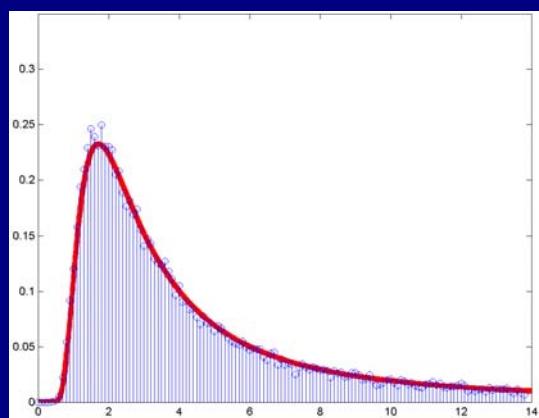
Finite n



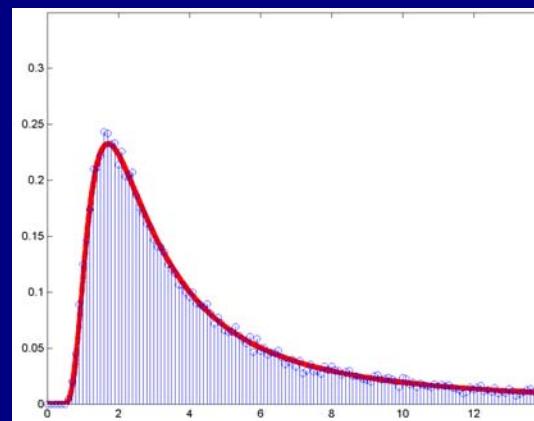
$n=10$



$n=25$

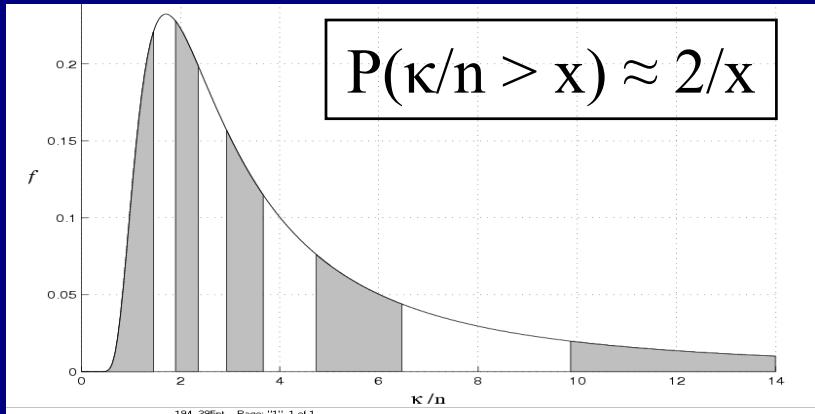


$n=50$

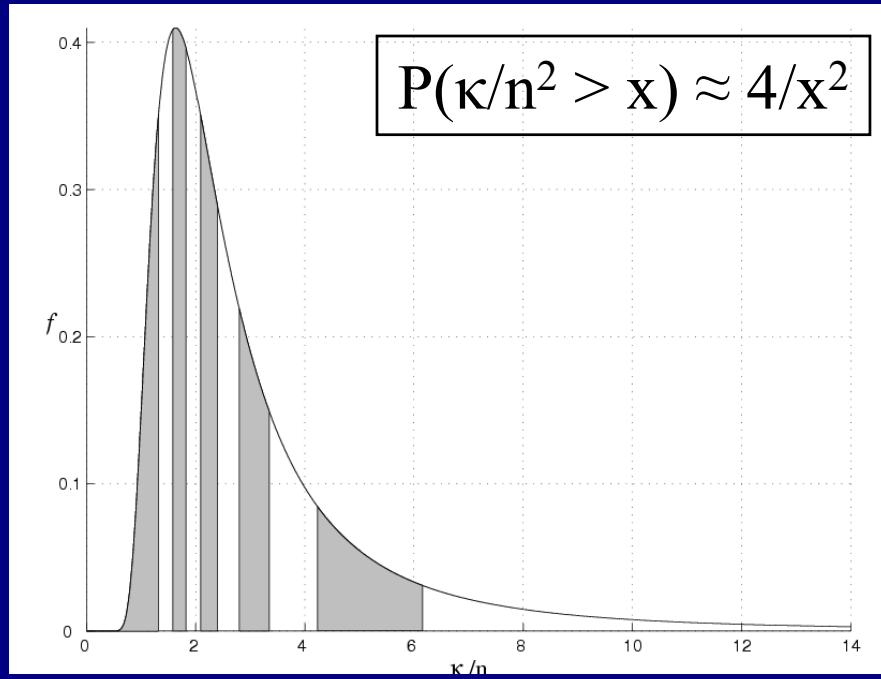


$n=100$

Condition Number Distributions



Real $n \times n$, $n \rightarrow \infty$

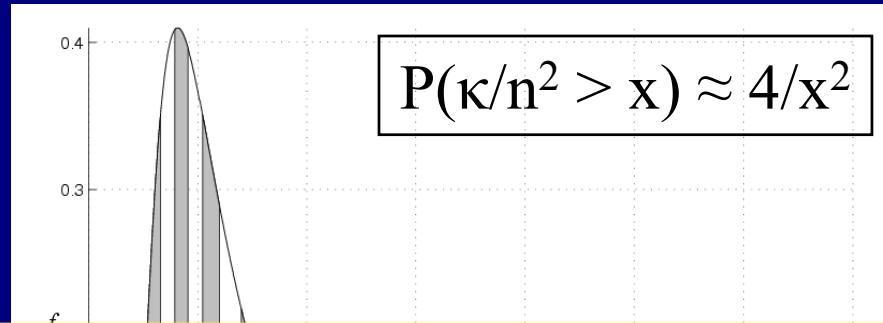
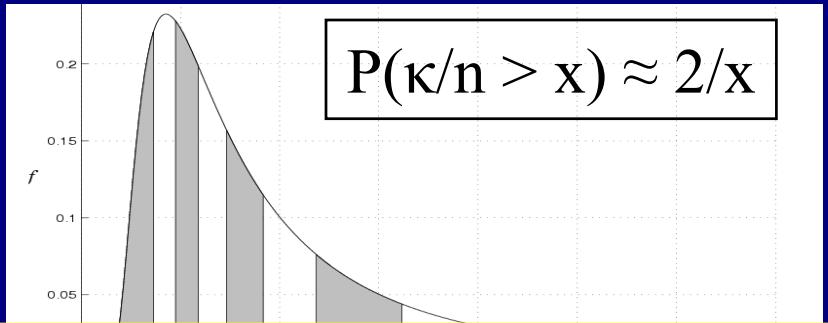


Generalizations:

- β : 1=real, 2=complex
- finite matrices
- rectangular: $m \times n$

Complex $n \times n$, $n \rightarrow \infty$

Condition Number Distributions



Square, $n \rightarrow \infty$: $P(\kappa/n^\beta > x) \approx (2\beta^{\beta-1}/\Gamma(\beta))/x^\beta$ (All Betas!!)

General Formula: $P(\kappa > x) \sim C\mu/x^{\beta(n-m+1)}$,

where $\mu = \beta(n-m+1)/2$ th moment of the largest eigenvalue of $W_{m-1,n+1}(\beta)$

and C is a known geometrical constant.

Density for the largest eig of W is known in terms of ${}_1F_1((\beta/2)(n+1), ((\beta/2)(n+m-1); -(x/2)I_{m-1})$ from which μ is available

Tracy-Widom law applies probably all beta for large m, n .
Johnstone shows at least beta=1,2.

Tools

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Multivariate Orthogonal Polynomials &

Hypergeometrics of Matrix Argument

- ❖ Ioana Dumitriu's talk
- ❖ The important special functions of the 21st century
- ❖ Begin with $w(x)$ on I
 - ❖ $\int p_\kappa(x)p_\lambda(x) \Delta(x)^\beta \prod_i w(x_i) dx_i = \delta_{\kappa\lambda}$
 - ❖ Jack Polynomials orthogonal for $w=1$ on the unit circle. Analogs of x^m

Multivariate Hypergeometric Functions

- Univariate

$${}_pF_q(a_1, \dots, a_p; b_1, \dots, b_q; x) \equiv \sum_{k=0}^{\infty} \frac{(a_1)_k \dots (a_p)_k}{k! (b_1)_k \dots (b_q)_k} \cdot x^k,$$

where $(a)_k = a(a+1)\dots(a+k-1)$.

- Hard problem to approximate. Slow convergence

Multivariate Hypergeometric Functions

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where $(a)_k = a(a+1)\dots(a+k-1)$.

- Hard problem to approximate. Slow convergence

- Multivariate

$$\begin{aligned} {}_pF_q^\alpha(a_1, \dots, a_p; b_1, \dots, b_q; x_1, \dots, x_n) \\ \equiv \sum_{k=0}^{\infty} \sum_{\kappa \vdash k} \frac{(a_1)_\kappa \dots (a_p)_\kappa}{k! (b_1)_\kappa \dots (b_q)_\kappa} \cdot C_\kappa^\alpha(x_1, \dots, x_n), \end{aligned}$$

where

– $(a)_\kappa \equiv \prod_{(i,j) \in \kappa} \left(a - \frac{i-1}{\alpha} + j - 1 \right)$ — Pochhammer symbol

– $C_\kappa^\alpha(x_1, x_2, \dots, x_n)$ is the “C” Jack Function

An Application—p.d.f. of λ_{\max} of a β -Laguerre matrix

Definition: $L = BB^T$, where

$$B = \begin{bmatrix} \chi_{2a} & & & \\ \chi_{\beta(n-1)} & \chi_{2a-\beta} & & \\ & \ddots & \ddots & \\ & & \chi_{\beta} & \chi_{2a-\beta(n-1)} \end{bmatrix},$$

and $k = a - \frac{\beta}{2}(n - 1) - 1$ is a nonnegative integer.

The p.d.f. of λ_{\max} is

$$f(x) = x^{kn} \cdot e^{-\frac{nx}{2}} \cdot {}_2F_0^{2/\beta}(-k, \beta \frac{n}{2} + 1; ; -\frac{2}{x}I_{n-1}).$$

Wishart (Laguerre) Matrices!

Plamen's clever idea

Idea: Update, do not Compute

$${}_pF_q^\alpha(a_{1:p}; b_{1:q}; x_{1:n}) \approx \sum_{k=0}^m \underbrace{\sum_{\kappa \vdash k} \frac{(a_1)_\kappa \dots (a_p)_\kappa}{k! (b_1)_\kappa \dots (b_q)_\kappa}}_{Q_\kappa} \cdot C_\kappa^\alpha(x_{1:n})$$

Store every computed Q_κ and C_κ^α .

If

$$\begin{aligned}\kappa &= (\kappa_1, \kappa_2, \dots, \kappa_i, \dots) \\ \nu &= (\kappa_1, \kappa_2, \dots, \kappa_i - 1, \dots)\end{aligned}$$

Then

$$\frac{Q_\kappa}{Q_\nu} = \frac{\prod_{j=1}^p (a_j + c)}{\prod_{j=1}^q (b_j + c)}, \text{ where } c = -\frac{i-1}{\alpha} + \kappa_i - 1;$$

Cost: $2(p+q)$ instead of $|\kappa|(p+q)$. 2

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Mops (Dumitriu etc.) Symbolic

Maple 8 - [Untitled (1) - [Server 1]]

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P Warning Courier New 10 B I U !!!

```

libname := "F:\maple-work\SF", "F:\maple-work\Jack", "Z:\MAPLE8\lib"
Warning, the protected name conjugate has been redefined and unprotected
|
[arm,conjugate,expjack,expjackj,expjackp,expjacks,gbinomial,ghypergeom,gsfact,hermite,issubpar,jack,jackcoeff,
 jackidentity,jackj,jackp,jacobi,jacobicoeff,laguerre,leg,lhook,par,p,sfact,subpar,tojack,uhook]
Warning, the name conjugate has been rebound

[Par,add_basis,char2sf,conjugate,dominate,dual_basis,evalsf,hooks,itensor,jt_matrix,ω,plethysm,scalar,sf2char,skew,
 subPar,θ,toe,toh,top,tos,varset,zee]
> tojack(1, m[9], 9);

$$C_9 - \frac{1}{8}C_{8,1} + \frac{1}{28}C_{7,1,1} - \frac{1}{56}C_{6,1,1,1} + \frac{1}{70}C_{5,1,1,1,1} - \frac{1}{56}C_{4,1,1,1,1,1} + \frac{1}{28}C_{3,1,1,1,1,1,1} - \frac{1}{8}C_{2,1,1,1,1,1,1,1}$$


$$+ C_{1,1,1,1,1,1,1,1}$$

> tojack(1/2, m[9], 9);

$$C_9 - \frac{1}{4}C_{8,1} + \frac{1}{28}C_{7,2} + \frac{1}{7}C_{7,1,1} - \frac{1}{42}C_{6,2,1} - \frac{1}{7}C_{6,1,1,1} + \frac{1}{70}C_{5,2,2} + \frac{1}{35}C_{5,2,1,1} + \frac{8}{35}C_{5,1,1,1,1} - \frac{3}{140}C_{4,2,2,1}$$


$$- \frac{2}{35}C_{4,2,1,1,1} - \frac{4}{7}C_{4,1,1,1,1,1} + \frac{1}{28}C_{3,2,2,2} + \frac{2}{35}C_{3,2,2,1,1} + \frac{4}{21}C_{3,2,1,1,1,1} + \frac{16}{7}C_{3,1,1,1,1,1,1}$$


$$- \frac{1}{7}C_{2,2,2,2,1} - \frac{2}{7}C_{2,2,2,1,1,1} - \frac{8}{7}C_{2,2,1,1,1,1,1} - 16C_{2,1,1,1,1,1,1,1} + 256C_{1,1,1,1,1,1,1,1}$$

> tojack(1/3, m[9], 9);

$$-\frac{27}{7}C_{2,2,2,2,1} + \frac{27}{140}C_{5,2,1,1} - \frac{1}{56}C_{6,3} + \frac{9}{28}C_{7,1,1,1} + \frac{81}{28}C_{3,2,1,1,1,1} - \frac{405}{56}C_{2,2,2,1,1,1} - \frac{3}{28}C_{6,2,1} - \frac{27}{56}C_{6,1,1,1}$$


$$- \frac{729}{28}C_{2,2,1,1,1,1,1} - \frac{27}{112}C_{4,2,2,1} + \frac{1}{28}C_{3,3,3} + \frac{81}{70}C_{5,1,1,1,1,1} - \frac{81}{140}C_{4,2,1,1,1,1} + \frac{9}{112}C_{3,3,2,1}$$


$$- \frac{243}{56}C_{4,1,1,1,1,1,1} - \frac{3}{112}C_{4,3,2} + \frac{3}{28}C_{7,2} + \frac{729}{28}C_{3,1,1,1,1,1,1} + C_9 + \frac{3}{28}C_{5,2,2} - \frac{2187}{8}C_{2,1,1,1,1,1,1,1}$$


```

Symbolic MOPS applications

Applications: eigenvalue statistics

Examples for Hermite:

⇒ Expectation of traces of powers:

$$\int_{\mathbb{R}^n} \left(\sum_{i=1}^n \lambda_i^4 \right) \prod_{i < j} |\lambda_i - \lambda_j|^{2/\alpha} e^{-\sum_{i=1}^n \lambda_i^2/2} = \frac{3\alpha^2 - 5\alpha + 3}{\alpha^2} n + \frac{5\alpha - 5}{\alpha^2} n^2 + \frac{2}{\alpha^2} n^3$$

⇒ Moments of the determinant:

$$\begin{aligned} \int_{\mathbb{R}^6} \prod_{i=1}^6 \lambda_i^3 \prod_{i < j} |\lambda_i - \lambda_j|^{2/\alpha} e^{-\sum_{i=1}^6 \lambda_i^2/2} &= \\ &= -75 \frac{25a^6 + 153a^5 + 472a^4 + 693a^3 + 610a^2 + 207a + 45}{a^9} \end{aligned}$$

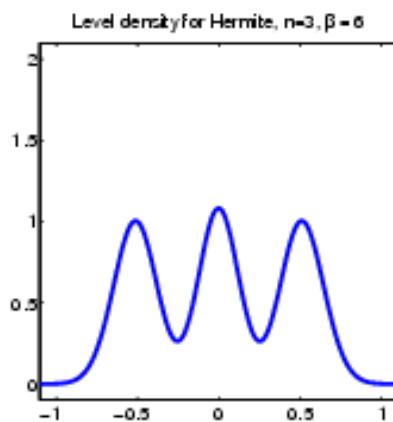
Symbolic MOPS applications

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Examples for Hermite:

⇒ Level densities:

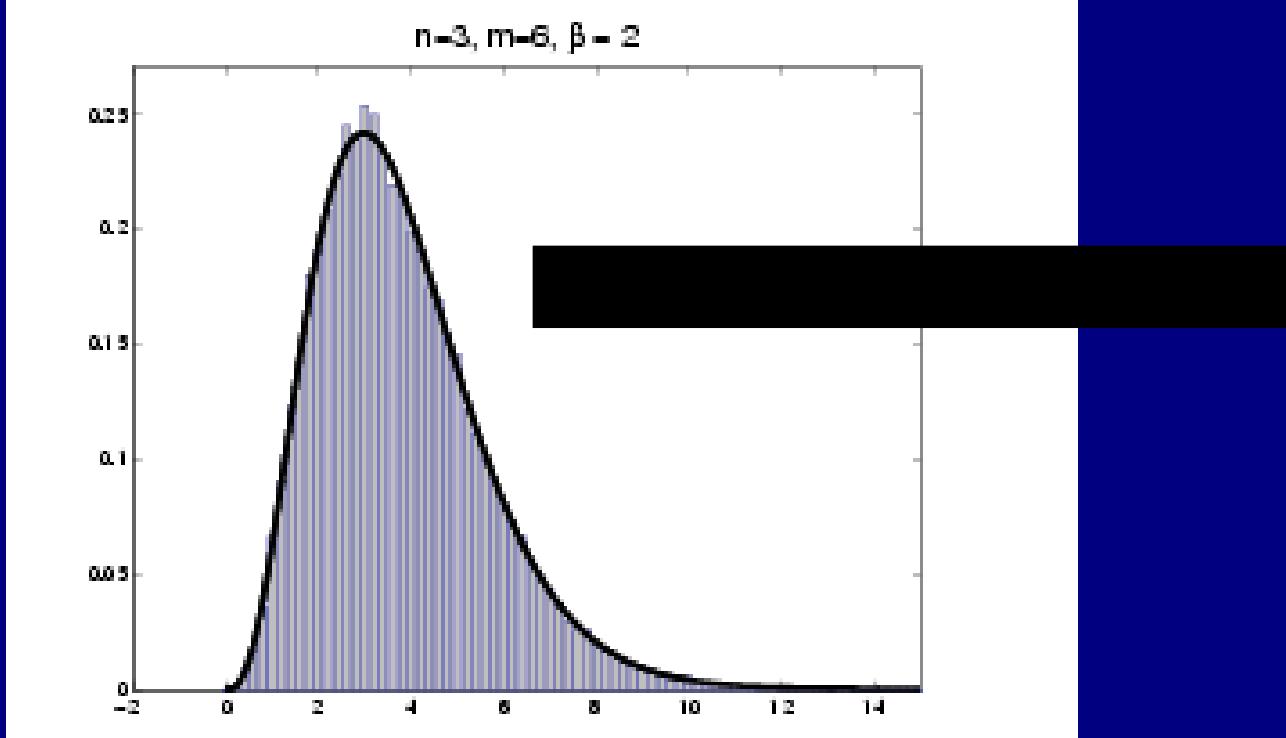
$$\int_{\mathbb{R}^2} \prod_{i=1}^2 |\lambda_i - x|^6 \prod_{i < j} |\lambda_i - \lambda_j|^6 e^{-\sum_{i=1}^2 \lambda_i^2/2} = \\ = \frac{3\sqrt{2}}{2240\sqrt{\pi}} e^{-18x^2} (80621568x^{12} + 26873856x^{10} + 8398080x^8 + 136080x^4 - 15120x^2 + 1015)$$



The exact level density for the 3×3 Hermite ensemble with $\alpha = 1/3$

Smallest eigenvalue statistics

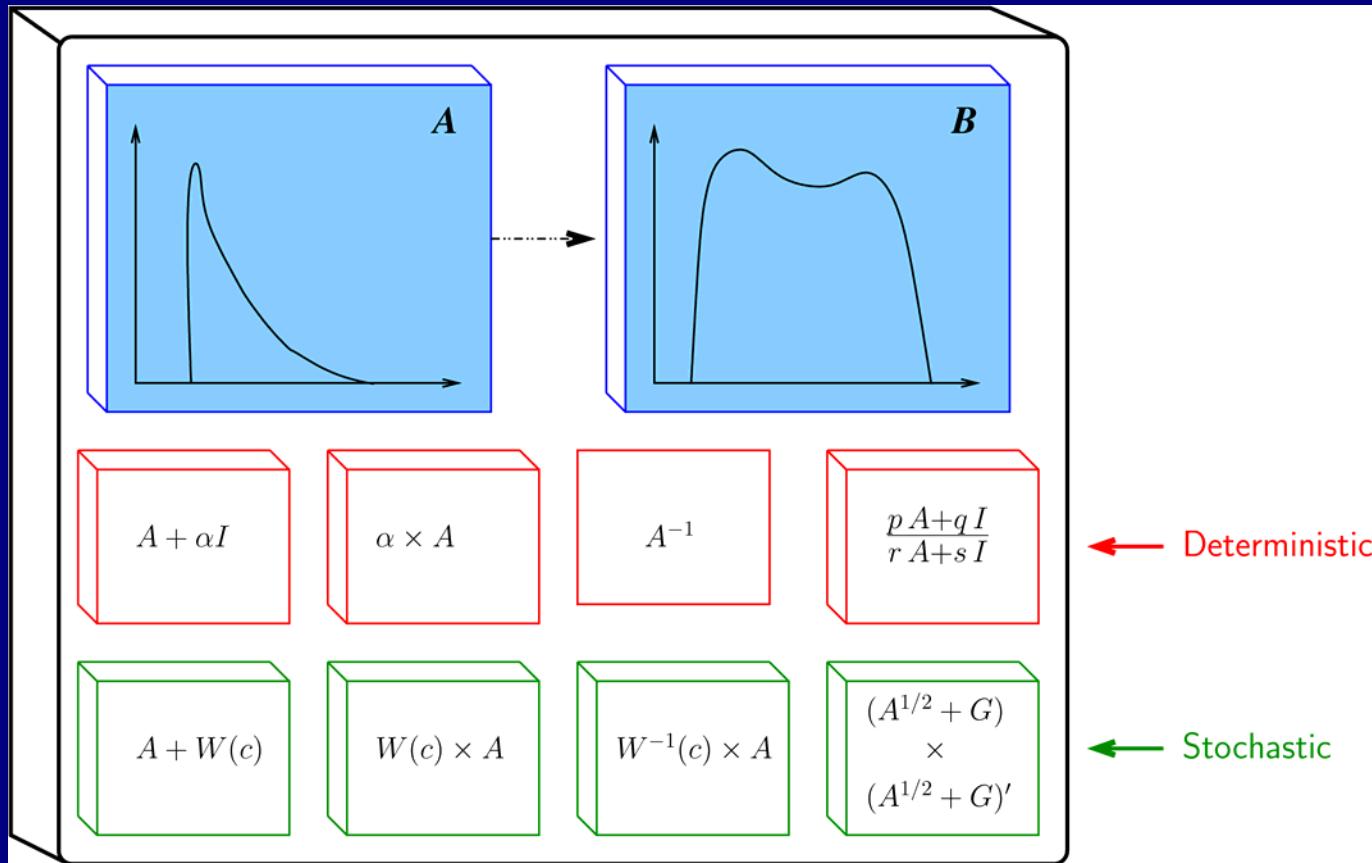
$$\rho(x) = x^9 e^{-3x/2} {}_2F_0(-3, 4; -2I_2/x);$$



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- ❖ MOPS: Ioana Dumitriu's talk
- ❖ The Polynomial Method -- Raj!
- ❖ The tridiagonal numerical 10^9 trick

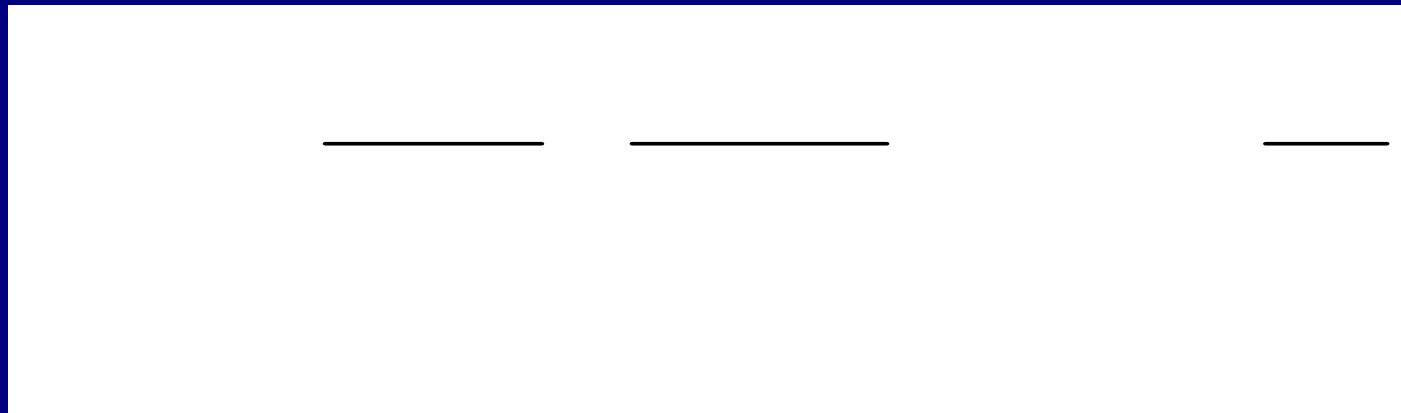
RM Tool – Raj!



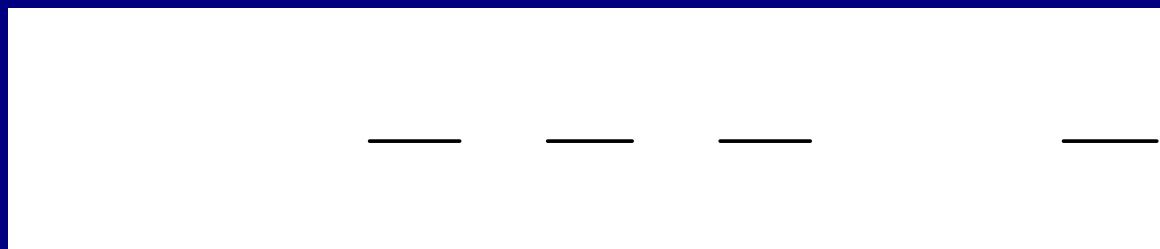
Courtesy of the Polynomial Method

	Delta	Semi-circle Hermite	Sample Covariance Laguerre	Regular graphs Jacobi
$f(x)$	$f_r(x) = \delta(x - r)$	$f_r(x) = \frac{2}{\pi r^2} \sqrt{r^2 - x^2}$	$f_r(x) = \frac{\sqrt{(x-r_1)(r_2-x)}}{2\pi xr}$ $r_1 = (1 - \sqrt{r})^2,$ $r_2 = (1 + \sqrt{r})^2, r \leq 1$	$f_r(x) = \frac{r(r-1)\sqrt{4-x^2}}{2\pi(r^2-(r-1)x^2)}$ $r \geq 2$
Moments	$m_k = r^k$	$m_{2k} = C_k(r/2)^{2k}$ $C_k = \text{"Catalan Number"} = \binom{2k}{k}/(k+1)$	$m_k = \sum_{j=0}^{k-1} \frac{r^j}{j+1} \binom{k}{j} \binom{k-1}{j}$ $\text{"Narayana Polynomials"} (m_k = C_k \text{ if } r = 1)$	$m_{2k} = \sum_{j=1}^k \binom{2k-j}{k} \frac{j}{2k-j} \left(\frac{r}{r-1}\right)^j$ $(m_{2k} = C_k, \text{ if } r = \infty)$
Support	$x = r$	$x = [-r, r]$	$x = [r_1, r_2]$	$ x \leq 2$
Cauchy Transform	$m(z) = 1/(r-z)$	$m(z) = \frac{2}{r^2}(\sqrt{z^2-r^2} - z)$	$m(z) = \frac{1}{2} + \frac{1-r}{2z} + i\pi f_r(z)$	$m(z) = \text{P.V. } m(z) + i\pi f_r(z)$
Inverse Transform	$z(m) = -\frac{1}{m} + r$	$z(m) = -\frac{1}{m} - \frac{mr^2}{4}$	$z(m) = -\frac{1}{m} + \frac{r}{1+m}$	$z(m) = -\frac{1}{m} + \frac{r}{2m} \left(1 - \sqrt{\frac{1+4m^2}{r-1}}\right)$
Symmetric Form	$mr - mz - 1 = 0$	$m^2r^2 + 4zm + 4 = 0$	$zm^2 + m(z+1-r) + 1 = 0$	$(r^2 - (r-1)z^2)m^2 + (r-1)(r-2)zm + (r-1)^2 = 0$
Principal Value	—	P.V. $m(z) = -\frac{2}{r^2}z$	P.V. $m(z) = \frac{1 + (1-r)/z}{2}$	P.V. $m(z) = \frac{(r-1)(r-2)z/2}{(r-1)z^2 - r^2}$
R-Transform	$R(m) = r$	$R(m) = -mr^2/4$	$R(m) = r/(1+m)$	$R(m) = \frac{r}{2m} \left(1 - \sqrt{1 + \frac{4m^2}{r-1}}\right)$

The Riemann Zeta Function

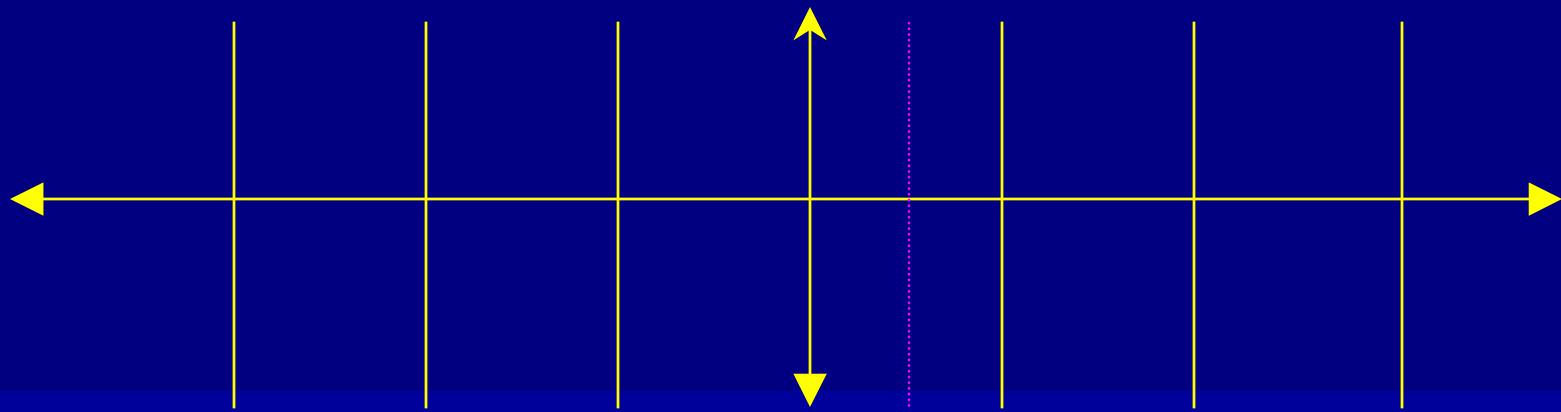
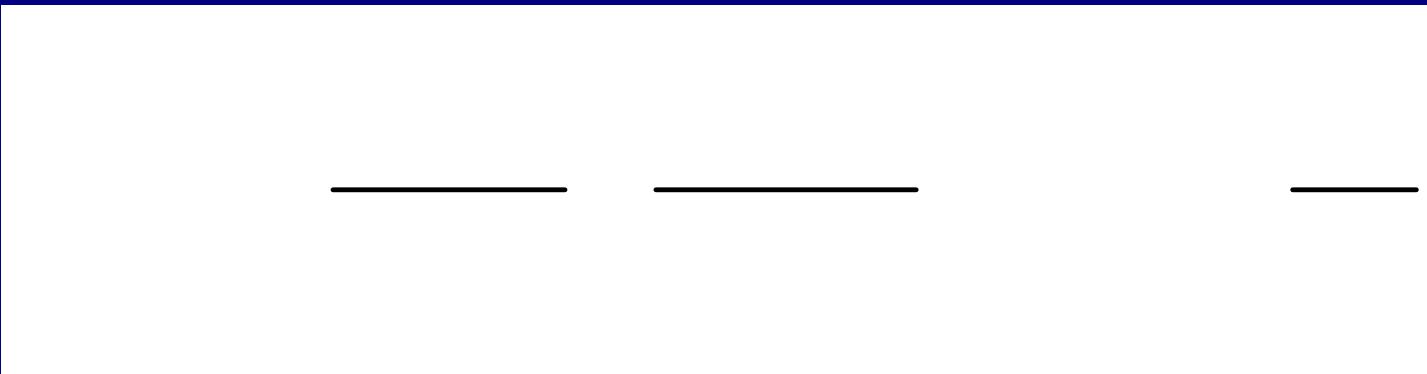


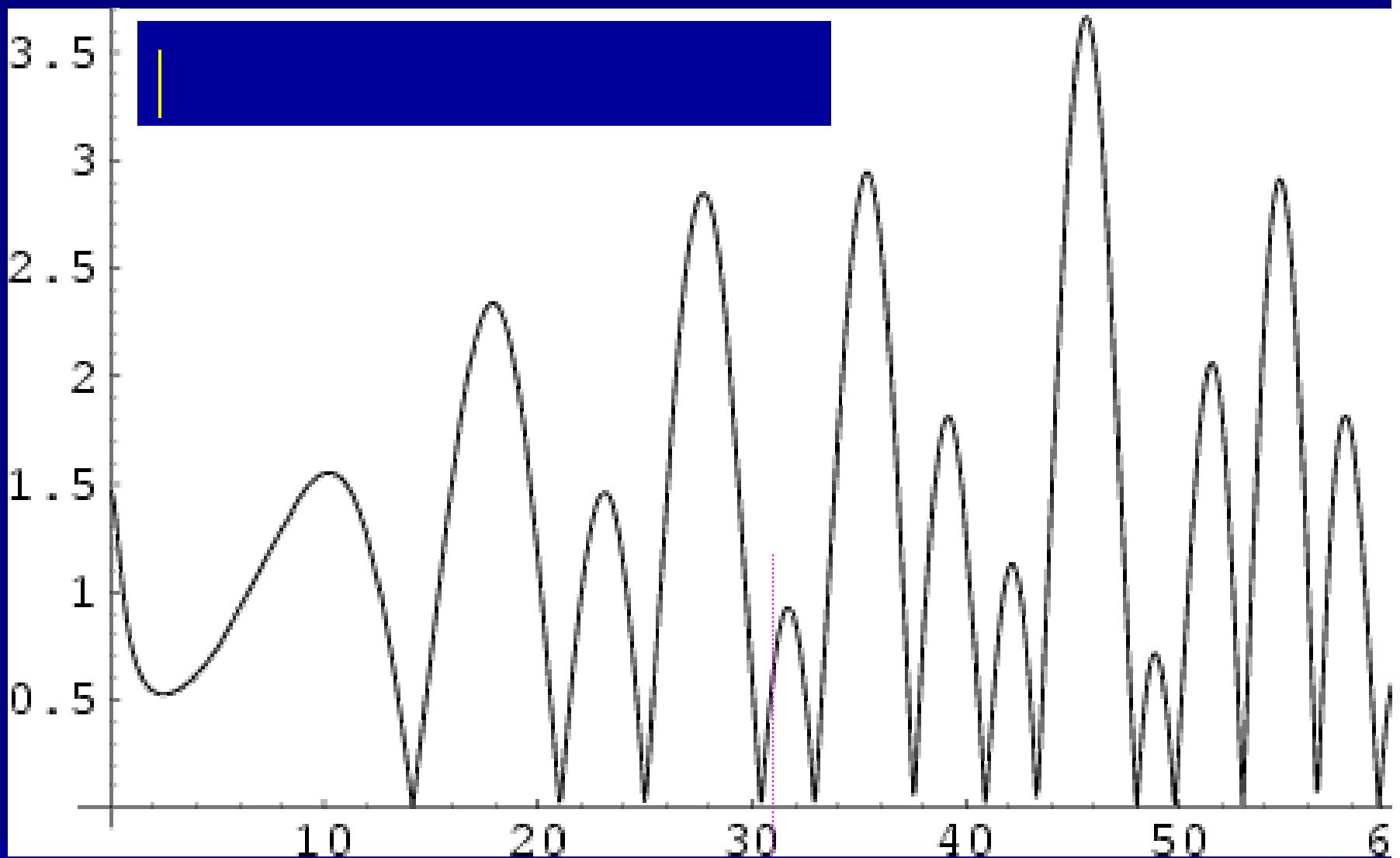
On the real line with $x > 1$, for example



May be analytically extended to the complex plane,
with singularity only at $x = 1$.

The Riemann Hypothesis





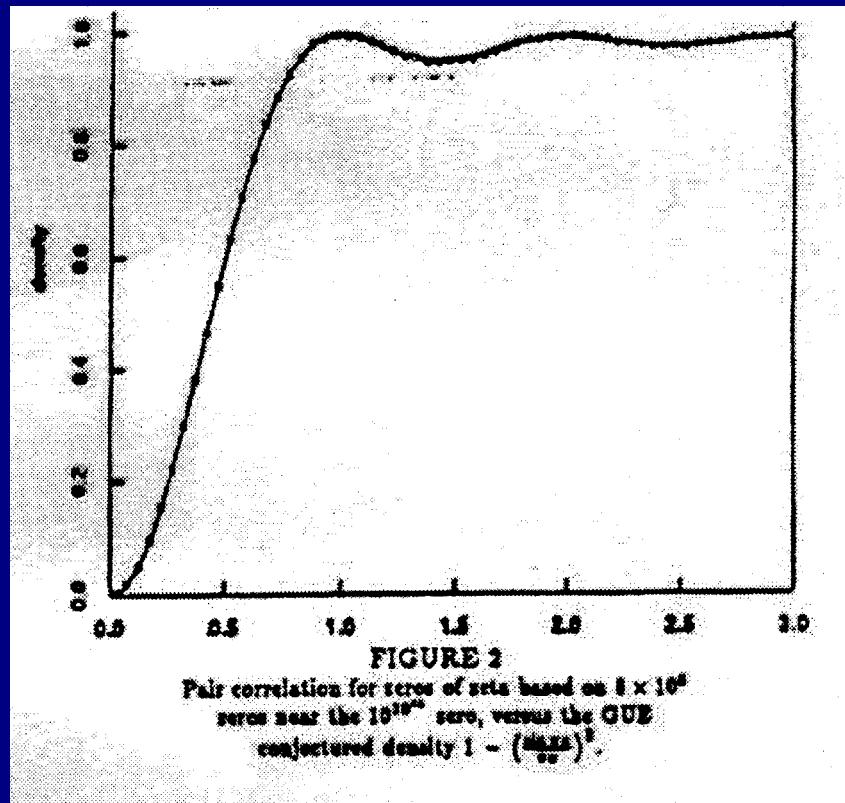
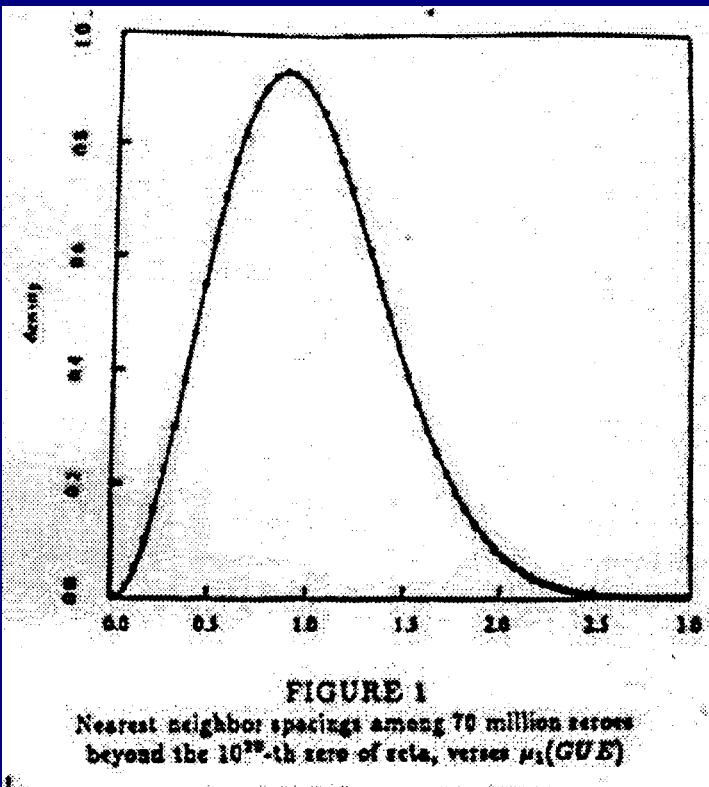
Computation of Zeros

- ❖ Odlyzko's fantastic computation of 10^{k+1} through $10^{k+10,000}$ for $k=12,21,22$.

See http://www.research.att.com/~amo/zeta_tables/

Spacings behave like the eigenvalues of
 $A = \text{randn}(n) + i * \text{randn}(n); S = (A + A') / 2;$

Nearest Neighbor Spacings & Pairwise Correlation Functions



Painlevé Equations

$$\text{I}) \quad y'' = 6y^2 + t,$$

$$\text{II}) \quad y'' = 2y^3 + ty + \alpha,$$

$$\text{III}) \quad y'' = \frac{1}{y}y'^2 - \frac{y'}{t} + \frac{\alpha y^2 + \beta}{t} + \gamma y^3 + \frac{\delta}{y},$$

$$\text{IV}) \quad y'' = \frac{1}{2y}y'^2 + \frac{3}{2}y^3 + 4ty^2 + 2(t^2 - \alpha)y + \frac{\beta}{y},$$

$$\text{V}) \quad y'' = \left(\frac{1}{2y} + \frac{1}{y-1} \right) y'^2 - \frac{1}{t}y' + \frac{(y-1)^2}{t} \left(\alpha y + \frac{\beta}{y} \right) \\ + \gamma \frac{y}{t} + \delta \frac{y(y+1)}{y-1},$$

$$\text{VI}) \quad y'' = \frac{1}{2} \left(\frac{1}{y} + \frac{1}{y-1} + \frac{1}{y-t} \right) y'^2 - \left(\frac{1}{t} + \frac{1}{t-1} + \frac{1}{y-t} \right) y' \\ + \frac{y(y-1)(y-t)}{t^2(t-1)^2} \left[\alpha - \beta \frac{t}{y^2} + \gamma \frac{t-1}{(y-1)^2} + \left(\frac{1}{2} - \delta \right) \frac{t(t-1)}{(y-t)^2} \right]$$

Spacings

- ❖ Take a large collection of consecutive zeros/eigenvalues.
- ❖ Normalize so that average spacing = 1.
- ❖ Spacing Function = Histogram of consecutive differences (the $(k+1)$ st – the k th)
- ❖ Pairwise Correlation Function = Histogram of all possible differences (the k th – the j th)
- ❖ Conjecture: These functions are the same for random matrices and Riemann zeta

Tools

- ❖ Motivation: A condition number problem
- ❖ Jack & Hypergeometric of Matrix Argument
- ❖ MOPS: Ioana Dumitriu's talk
- ❖ The Polynomial Method
- ❖ The tridiagonal numerical 10^9 trick

Everyone's Favorite Tridiagonal

$$\frac{1}{n^2} \begin{pmatrix} -2 & 1 & & & \\ 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & 1 \\ & & & 1 & -2 \end{pmatrix}$$

$$\boxed{\frac{d^2}{dx^2}}$$

Everyone's Favorite Tridiagonal

$$\frac{1}{n^2} \begin{pmatrix} -2 & 1 & & & \\ 1 & -2 & 1 & & \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & 1 \\ & & & 1 & -2 \end{pmatrix} + (\beta n)^{1/2} \begin{pmatrix} G & & & \\ & G & & \\ & & G & \\ & & & G \end{pmatrix}$$

$$\boxed{\frac{d^2}{dx^2}}$$

+

$$\boxed{\frac{dW}{\beta^{1/2}}}$$

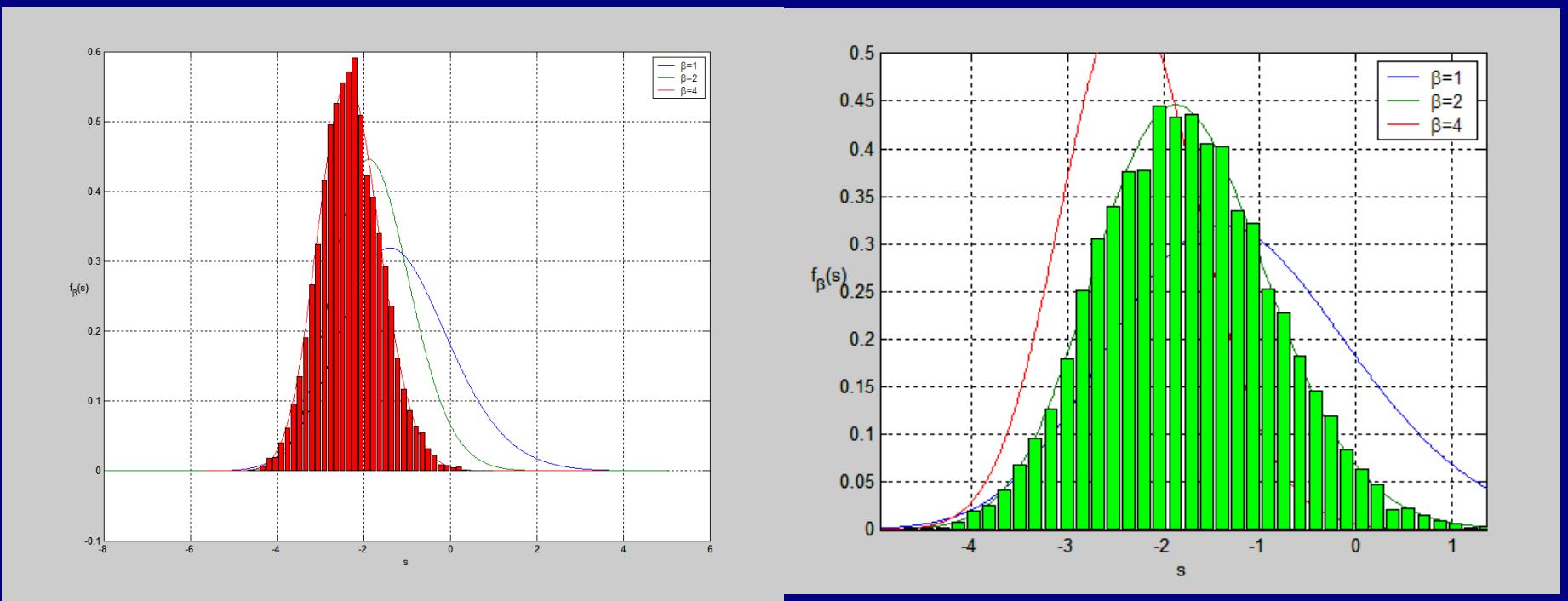
Stochastic Operator Limit

$$\frac{d^2}{dx^2} - x + \frac{2}{\sqrt{\beta}} dW ,$$

$$H_n^\beta \sim \frac{1}{2\sqrt{n\beta}} \begin{pmatrix} N(0,2) & \chi_{(n-1)\beta} & & & \\ \chi_{(n-1)\beta} & N(0,2) & \chi_{(n-2)\beta} & & \\ & \ddots & \ddots & \ddots & \\ & & \chi_{2\beta} & N(0,2) & \chi_\beta \\ & & & \chi_\beta & N(0,2) \end{pmatrix},$$

$$H_n^\beta \approx H_n^\infty + \frac{2}{\sqrt{\beta}} G_n ,$$

Largest Eigenvalue Plots



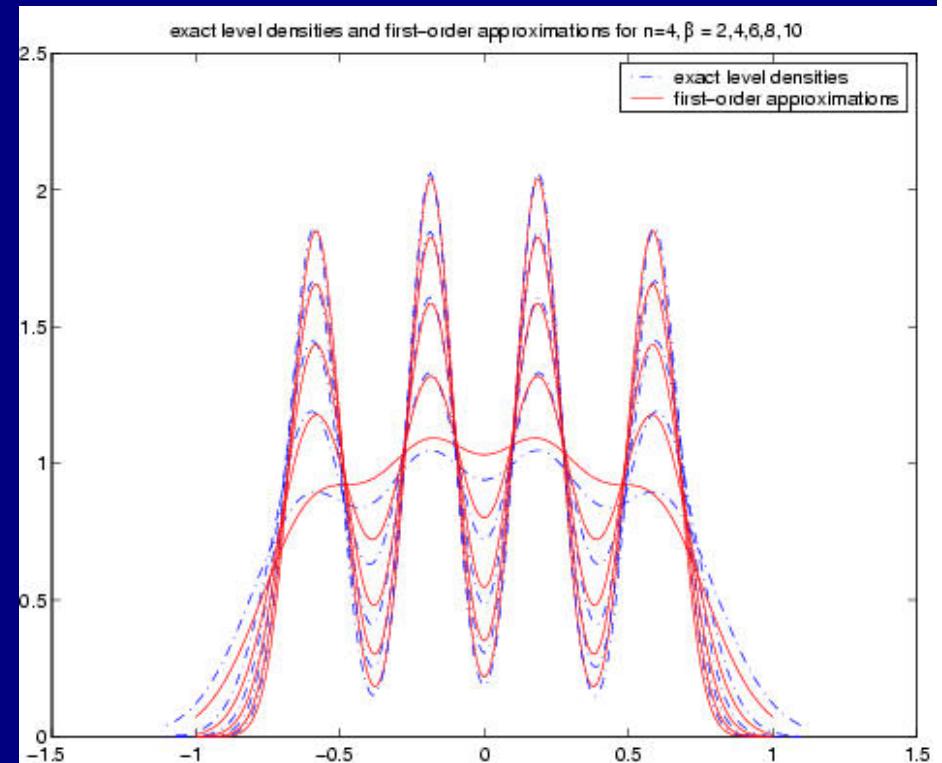
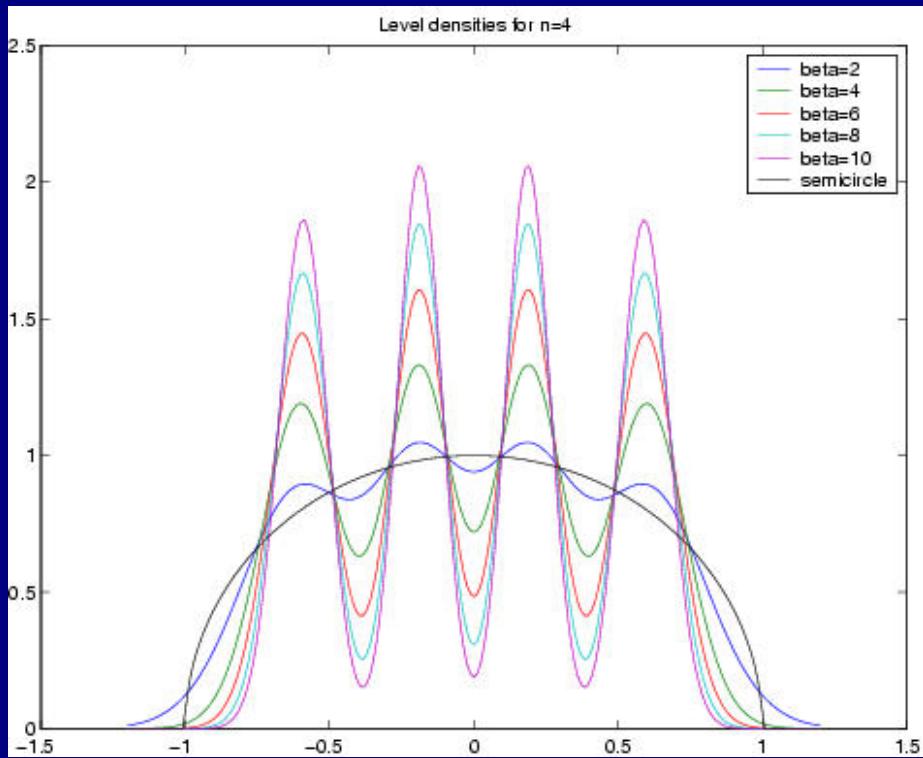
MATLAB

```
beta=1; n=1e9; opts.disp=0;opts.issym=1;
alpha=10; k=round(alpha*n^(1/3)); % cutoff parameters
d=sqrt(chi2rnd( beta*(n:-1:(n-k-1))))';
H=spdiags( d,1,k,k)+spdiags(randn(k,1),0,k,k);
H=(H+H')/sqrt(4*n*beta);
eigs(H,1,1,opts)
```

Tricks to get $O(n^9)$ speedup

- Sparse matrix storage (Only $O(n)$ storage is used)
- Tridiagonal Ensemble Formulas (Any beta is available due to the tridiagonal ensemble)
- The Lanczos Algorithm for Eigenvalue Computation (This allows the computation of the extreme eigenvalue faster than typical general purpose eigensolvers.)
- The shift-and-invert accelerator to Lanczos and Arnoldi (Since we know the eigenvalues are near 1, we can accelerate the convergence of the largest eigenvalue)
- The ARPACK software package as made available seamlessly in MATLAB (The Arnoldi package contains state of the art data structures and numerical choices.)
- The observation that if $k = 10n^{1/3}$, then the largest eigenvalue is determined numerically by the top $k \times k$ segment of n . (This is an interesting mathematical statement related to the decay of the Airy function.)

Level Densities



Open Problems

The distribution for general beta
Seems to be governed by a convection-diffusion equation

Random matrix tools!