Numerical Evaluation of Standard Distributions in Random Matrix Theory

A Review of Folkmar Bornemann's MATLAB Package and Paper

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Level Spacing Function

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Level Spacing Function

Definition (Gaussian Ensemble Spacing Function) Let $J \subset \mathbb{R}$ be an open interval.

 $E^{(n)}_{\beta}(k;J) \equiv \mathbb{P}(k \text{ eigenvalues of the } n \times n \text{ Gaussian } \beta \text{-ensemble lie in } J)$

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 $E_{\beta}^{(n)}(k;J) \equiv \mathbb{P}(k \text{ eigenvalues of the } n \times n \text{ Gaussian } \beta \text{-ensemble lie in } J)$

Let J = (0, s). Then $E_2(0; J)$ = probability no eigenvalues lie in (0, s).

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Fredholm Determinant

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It is well known that $E_2(0; J)$ can be represented as a Fredholm determinant:

Theorem (Gaudin 1961) Given $K_{sin}(x, y) = sinc(\pi(x - y)),$ $E_2(0, J) = det \left(I - K_{sin} \upharpoonright_{L_J^2}\right)$

Note the operator's restriction to square integrable functions over J. In general we will choose J = (0, s), and will notate $E_2(0, (0, s))$ as $E_2(0, s)$ as per Bornemann's conventions.

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Integral Formulation

Theorem (Jimbo, Miwa, Mori, Sato 1980)

$$E_2(0;s) = \exp\left(-\int_0^{\pi s} \frac{\sigma(x)}{x} dx\right)$$

where $\sigma(x)$ solves a particular form of the Painleve V equation:

$$(x\sigma'')^2 = 4(\sigma - x\sigma')(x\sigma - \sigma - (\sigma')^2), \quad \sigma(x) \approx \frac{x}{\pi} + \frac{x^2}{\pi^2} \quad (x \to 0)$$

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Tracy-Widom Distribution

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Tracy-Widom Distribution

Definition (Tracy-Widom Distribution)

Let $F_2(s) \equiv \mathbb{P}($ no eigenvalues of large-matrix limit GUE lie in $(s,\infty))$

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Determinantal Representation

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Determinantal Representation

Theorem (Bronk 1964)

Given

$$\mathcal{K}_{Ai}(x,y) = \frac{Ai(x)Ai'(y) - Ai'(x)Ai(y)}{x - y}$$

we have

$$F_2(s) = \det \left(I - K_{Ai} \restriction_{L^2_{(s,\infty)}}
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Integral Formulation

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Integral Formulation

Theorem (Tracy, Widom 1993)

$$F_2(s) = \exp\left(-\int_s^\infty (x-s)u(x)^2 dx\right)$$

where u(x) is the Hastings-McLeod (1980) solution to the Painleve II equation

$$u'' = 2u^3 + xu$$
, $u(x) \approx Ai(x)$ $(x \to \infty)$

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The common point of view, and why it's wrong.

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The common point of view, and why it's wrong.

Common point of view:

- Painleve formulation is somehow numerically "better behaved" than Fredholm determinant
- Solving initial value problem for numerical integration is easier to implement than Fredholm

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Bornemann's view:

- Numerical evaluation of Painleve transcendents is actually fairly involved. Stability is a major concern.
- There exists a simple, fast, accurate numerical method for evaluating Fredholm determinants
- Many multivariate functions (joint prob. dists.) have a nice representation as a Fredholm determinant, but no representation in terms of a nonlinear PDE.

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Straightforward Approach: Solving the IVP for Painleve

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All of the examples we are interested in take asymptotic IVP form:



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All of the examples we are interested in take asymptotic IVP form: Given an interval (a, b), we seek u(x) that solves

u''(x) = f(x, u(x), u'(x))

subject to either of the asymptotic one-sided conditions

$$u(x) \approx u_a(x) \quad (x \to a)$$

or

$$u(x) \approx u_b(x) \quad (x \to b)$$

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Problem 1: Must identify asympttic expansion of u(x) – not always easy.



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$$v''(x) = f(x, v(x), v'(x))$$
$$v(a_{+}) = u_{a}(a_{+}), \quad v'(a_{+}) = u'_{a}(a_{+})$$

or

$$v(b_{-}) = u_b(b_{-}), \quad v'(b_{-}) = u'_b(b_{-})$$

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Problem 2: Standard solution methods demonstrate numerical instability.

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$$v(x)'' = 2v(x)^3 + xv(x), \quad v(b_-) = Ai(b_-), \quad v'(b_-) = Ai'(b_-)$$

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Choosing $b_{-} \ge 8$ gives initial values accurate to machine precision (about 10^{-16} for IEEE doubles). Choose $b_{-} = 12$ yields these results:

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Stability Issues



method	reference	max. error	run time
IVP/Matlab's ode45	Edelman and Persson (2005)	$9.0 \cdot 10^{-5}$	11 sec
BVP/Matlab's bvp4c	Dieng (2005)	$1.5 \cdot 10^{-10}$	3.7 sec
BVP/spectral colloc.	Driscoll et al. (2008)	$8.1 \cdot 10^{-14}$	1.3 sec
Fredholm determinant	Bornemann (2010a)	$2.0\cdot10^{-15}$	0.69 sec

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Less Straightforward Approach: Solving the BVP for Painleve

Stability issues described in depth in Bornemann's paper lead to a BVP approach.

We use asymptotic expression $u_a(x)$ at $(x \rightarrow a)$ to infer asymptotic expression $u_b(x)$ at $(x \rightarrow b)$, or vice versa. Approximate u(x) by solving BVP:

$$v''(x) = f(x, v(x), v'(x)), \quad v(a_+) = u_a(a_+), \quad v(b_-) = u_b(b_-)$$

Requires four choices: values of a_+ , b_- , and order of asymptotic accuracy for $u_a(x)$ and $u_b(x)$

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Computing $F_2(s)$ via computation of u(x) via BVP methods:

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Computing $F_2(s)$ via computation of u(x) via BVP methods: By definition, $u(x) \approx \operatorname{Ai}(x)$ $(x \to \infty)$ so we take $u_b(x) = \operatorname{Ai}(x)$. Choose $a_+ = -10$, $b_- = 6$ (Dieng, 2005).

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Computing $F_2(s)$ via computation of u(x) via BVP methods: By definition, $u(x) \approx \operatorname{Ai}(x)$ $(x \to \infty)$ so we take $u_b(x) = \operatorname{Ai}(x)$. Choose $a_+ = -10$, $b_- = 6$ (Dieng, 2005). We need to choose a sufficiently accurate asymptotic expansion for $u_a(x)$. Tracy and Widom show

$$u(x) = \sqrt{-\frac{x}{2}} \left(1 + \frac{1}{8}x^{-3} - \frac{73}{128}x^{-6} + \frac{10657}{1024}x^{-9} + O(x^{-12}) \right), \quad (x \to -\infty)$$

so we'll use that for $u_a(x)$.

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Require turning asymptotic expansion at one endpoint into asymptotic endpoint at other point. Not easy!

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- Selecting appropriate a₊ and b₋ along with indices of truncation is a bit of a black art.
- Actually solving BVP requires choosing starting values for Newton iteration, discretizing the DE, choosing a good step size, etc.

Punchline: BVP approach is insufficiently "black-box" for us.

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Better Approach: Numerical Evaluation of Fredholm Determinants

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Choose your favorite quadrature rule (Clenshaw-Curtis is good) over nodes $x_j \in (a, b)$ and positive weights w_j : $\sum_{i=1}^m w_i f(x_i) \approx \int_a^b f(x) dx$

Better Approach: Numerical Evaluation of Fredholm Determinants

Choose your favorite quadrature rule (Clenshaw-Curtis is good) over nodes $x_j \in (a, b)$ and positive weights w_j : $\sum_{j=1}^m w_j f(x_j) \approx \int_a^b f(x) dx$ The Fredholm determinant

$$d(z) = \det \left(I - zK \upharpoonright_{L^2_{(a,b)}} \right)$$

has the approximation

$$egin{aligned} &\mathcal{A}_m = \mathcal{K}(x_i,y_j)_{i,j=1}^m \ &d_m(z) = \det\left(\delta_{ij} - z \cdot w_i^{1/2} \mathcal{A}_m w_j^{1/2}
ight) \end{aligned}$$

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We need the value at a single point z ∈ C.
 Compute LU of (I − zA_m), get determinant from ∏^m_{j=1} U_{jj}
 Computing d_m(z) for a single z takes O(m³) time.

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This is a standard Numerical Linear Algebra problem.

- ▶ We need the value at a single point $z \in \mathbb{C}$. Compute LU of $(I - zA_m)$, get determinant from $\prod_{j=1}^m U_{jj}$ Computing $d_m(z)$ for a single z takes $O(m^3)$ time.
- We need the value at many points, want d_m(z) as polynomial. Compute eigenvalues λ_j of A_m via QR (one-time cost of O(m³) time, but worse constant factor than LU in practice), then form

$$d_m(z) = \prod_{j=1}^m (1 - z\lambda_j)$$

Computing $d_m(z)$ takes O(m) time.

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Sample Matlab Code

The following code computes $F_2(0)$ to one unit of precision in the last decimal place:

```
>> m = 64; [w, x] = ClenshawCurtis(0, inf, m); w2 = sqrt(w);
>> [xi, xj] = ndgrid(x, x);
>> KAi = @AiryKernel;
>> F20 = det(eye(m) - (w2' * w2).*KAi(x, x))
F20 = 0.969372828355262
```

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Wrapup

- Computing Fredholm Determinants is faster, easier, and more stable than integrating Painleve IVP or BVP.
- Being able to handle things that are expressed in non-PDE form is useful.
- Bornemann uses the toolset to identify (and subsequently prove) several new results (omitted here for brevity) about distributions of the k-th largest eigenvalue in the soft-edge scaling limit of the GOE and GSE – the numerical code generates immediate insights!

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