

# Wishart Random Matrices, Vicious Walkers and 2-d Yang-Mills Gauge Theory

Satya N. Majumdar

Laboratoire de Physique Théorique et Modèles Statistiques, CNRS,  
Université Paris-Sud, France

## WISHART RANDOM MATRICES

Wishart 1928, Tracy–Widom 1993,  
Johansson 2000 ....



## VICIOUS BROWNIAN WALKERS

de Gennes 1968, Fisher 1984, ...



## 2-d YANG–MILLS THEORY ON THE SPHERE

LARGE  $N$  PHASE TRANSITION (3rd order)

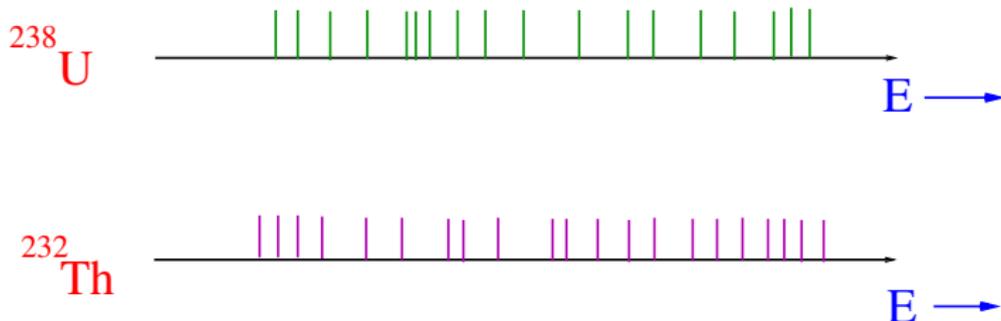
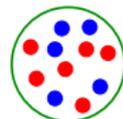
**LATTICE** (Wilson Action ) : Gross and Witten 1980, Wadia 1980....

**CONTINUUM** : Migdal 1975 , Rusakov 1990, Douglas and Kazakov 1993,  
Gross and Matytsin 1994....

# | : Wishart Random Matrices

# Random Matrices in Nuclear Physics

spectra of heavy nuclei



WIGNER ('50) : replace complex  $H$  by random matrix  
DYSON, GAUDIN, MEHTA, .....

# Applications of Random Matrices

**Physics:** nuclear physics, quantum chaos, disorder and localization, mesoscopic transport, optics/lasers, quantum entanglement, neural networks, gauge theory, QCD, matrix models, cosmology, string theory, statistical physics (growth models, interface, directed polymers...), ....

**Mathematics:** Riemann zeta function (number theory), Voiculescu's free probability theory, combinatorics and knot theory, determinantal points processes, integrable systems, ...

**Statistics:** multivariate statistics, principal component analysis (PCA), image processing, data compression, Bayesian model selection, ...

**Information Theory:** signal processing, wireless communications, ..

**Biology:** sequence matching, RNA folding, gene expression network

**Economics and Finance:** time series analysis,....

**Recent Ref:** [The Oxford Handbook of Random Matrix Theory](#)

ed. by G. Akemann, J. Baik and P. Di Francesco (2011)

Biometrika, 20, 32-52 (1928)

## THE GENERALISED PRODUCT MOMENT DISTRIBUTION IN SAMPLES FROM A NORMAL MULTIVARIATE POPU- LATION.

By **JOHN WISHART**, M.A., B.Sc. Statistical Department, Rothamsted  
Experimental Station.

### 1. *Introduction.*

For some years prior to 1915, various writers struggled with the problems that arise when samples are taken from uni-variate and bi-variate populations, assumed in most cases for simplicity to be normal. Thus "Student," in 1908\*, by considering the first four moments, was led by K. Pearson's methods to infer the distribution of standard deviations, in samples from a normal population. His results, for comparison with others to be deduced later, will be stated in the form

$$dp = \frac{1}{\Gamma(\frac{N-1}{2})} A^{\frac{N-1}{2}} \cdot e^{-Aa} \cdot a^{\frac{N-3}{2}} da \dots\dots\dots(1),$$

# John Wishart (1898-1956)



# SESSION IIB

## INTERPRETATION OF LOW ENERGY NEUTRON SPECTROSCOPY

CHAIRMAN—W. W. Havens, Jr.

### IIB1. DISTRIBUTION OF NEUTRON RESONANCE LEVEL SPACING.

E. P. WIGNER, *Princeton University*  
Presented by E. P. Wigner

The problem of the spacing of levels is neither a terribly important one nor have I solved it. That is really the point which I want to make very definitely. As we go up in the energy scale it is evident that the detailed analyses which we have seen for low energy levels is not possible, and we can only make

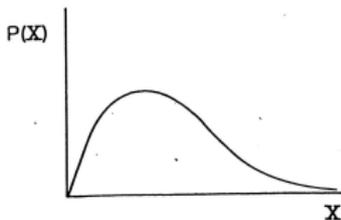


Fig. IIB1-1. Probability of a level spacing  $X$ .

our, that is a much more serious deviation and much less probable statistically.

Let me say only one more word. It is very likely that the curve in Figure 1 is a universal function. In other words, it doesn't depend on the details of the model with which you are working. There is one particular model in which the probability of the energy levels can be written down exactly. I mentioned this distribution already in Gatlinsburg. It is called the Wishart distribution. Consider a set of symmetric matrices in such a way that the diagonal element  $m_{11}$  has a distribution  $\exp(-m_{11}^2/4)$ . In other words, the probability that this diagonal element shall assume the value  $m_{11}$  is proportional to  $\exp(-m_{11}^2/4)$ . Then as I mentioned, and this was known a long time ago by Wishart, the probability for the characteristic roots to be  $\lambda_1, \lambda_2, \lambda_3 \dots \lambda_n$ , if  $M$  is an  $n$  dimensional matrix, is given by the expression:

probability that two successive roots have a distance  $X$ , then you have to integrate over all of them except two. This is very easy to do for the first integration, possible to do for the second integration, but when you get to the third, fourth and fifth, etc., integrations you have the same problem as in statistical mechanics, and presumably the solution of the problem will be accomplished by one of the methods of statistical mechanics. Let me only mention that I did integrate over all of them except one, and the result is  $\frac{1}{2\pi} \sqrt{4n - \lambda^2}$ . This is the probability that the root shall be  $\lambda$ . All I have to do is to integrate over one less variable than I have integrated over, but this I have not been able to do so far.

#### DISCUSSION

W. HAVENS: Where does one find out about a

to  
was  
for  
if  
the

the root shall be  $\lambda$ . All I have to do is to integrate over one less variable than I have integrated over, but this I have not been able to do so far.

## DISCUSSION

)]

**W. HAVENS:** Where does one find out about a Wishart distribution?

vs  
If  
a-

**E. WIGNER:** A Wishart distribution is given in S. S. Wilks book about statistics and I found it just by accident.

# Covariance Matrix

$$\mathbf{X} = \begin{array}{c} \text{phys.} \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{cc} \text{math} & \\ \left| \begin{array}{cc} X_{11} & X_{12} \\ X_{21} & X_{22} \\ X_{31} & X_{33} \end{array} \right| \end{array}$$

in general  
( $M \times N$ )

$$\mathbf{X}^t = \left( \begin{array}{ccc} X_{11} & X_{21} & X_{31} \\ X_{12} & X_{22} & X_{33} \end{array} \right)$$

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$$\mathbf{W} = \mathbf{X}^t \mathbf{X} = \left( \begin{array}{cc} X_{11}^2 + X_{21}^2 + X_{31}^2 & X_{11}X_{12} + X_{21}X_{22} + X_{31}X_{33} \\ X_{12}X_{11} + X_{22}X_{21} + X_{33}X_{31} & X_{12}^2 + X_{22}^2 + X_{33}^2 \end{array} \right)$$

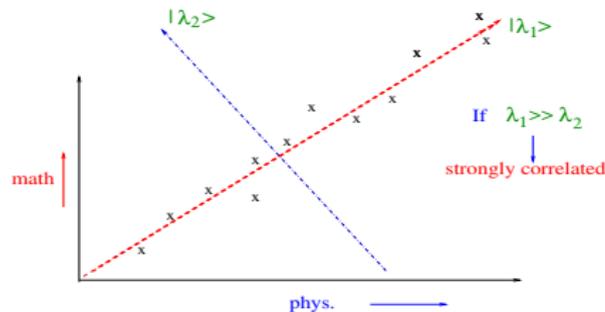
( $N \times N$ ) COVARIANCE MATRIX (unnormalized)

# Principal Component Analysis

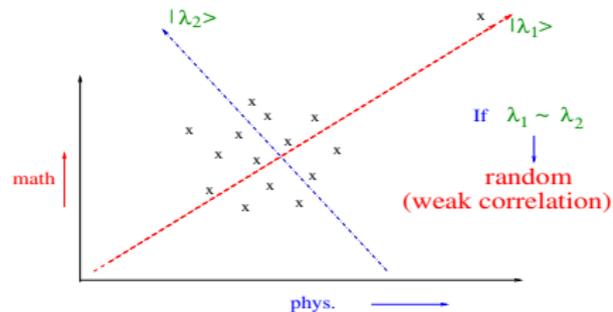
Consider  $N$  students and  $M = 2$  subjects (phys. and math.)

$X \rightarrow (N \times 2)$  matrix and  $W = X^t X \rightarrow 2 \times 2$  matrix

diagonalize  $W = X^t X \rightarrow [\lambda_1, \lambda_2]$



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data compression via 'Principal Component Analysis' (PCA)

→ practical method for image compression in computer vision

Null model → random data:  $X \rightarrow$  random  $(M \times N)$  matrix

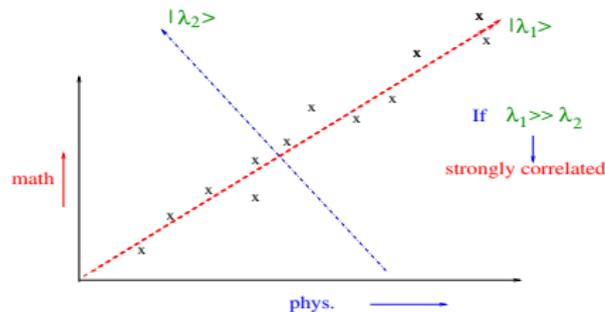
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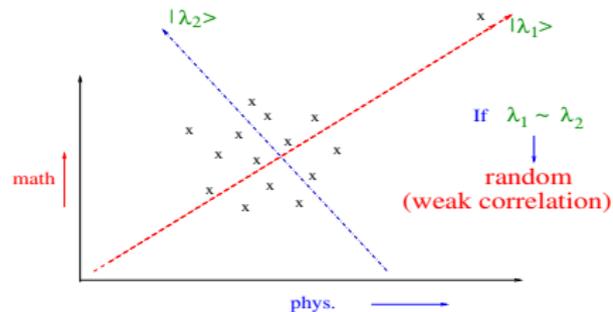
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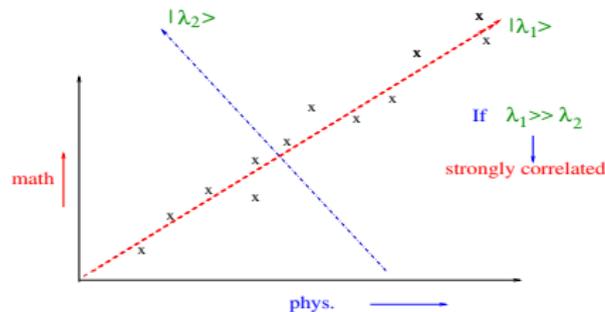
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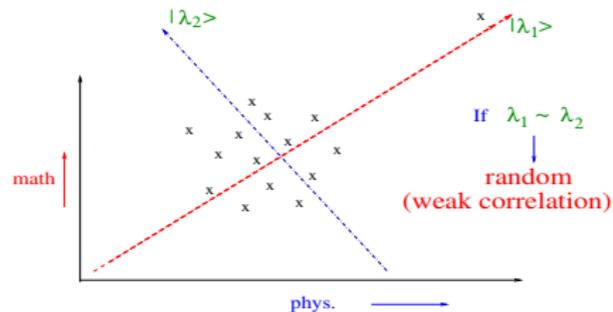
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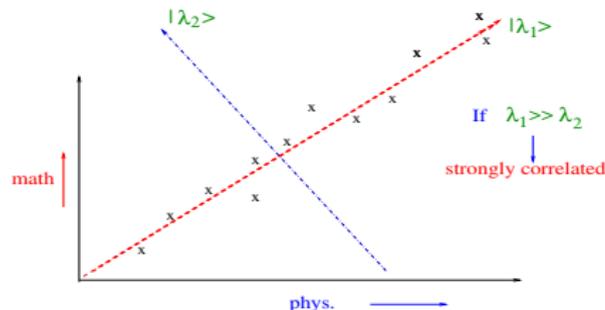
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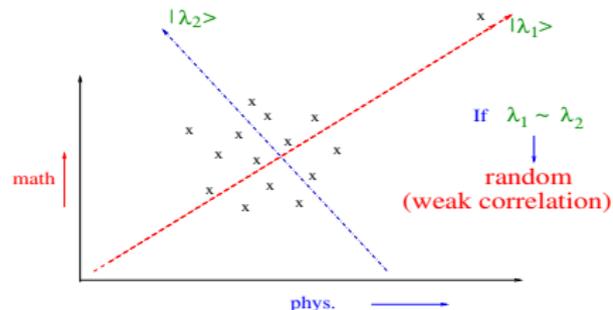
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# Random Data: Wishart Random Matrix

- Let  $X = [x_{i,j}] \rightarrow (M \times N)$  rectangular **data** matrix
- $W = X^\dagger X \rightarrow (N \times N)$  square **covariance** matrix (**Wishart**)
- Entries of  $X$  Gaussian:  $\Pr[X] \propto \exp\left[-\frac{\beta}{2}\text{Tr}(X^\dagger X)\right]$   
 $\beta = 1 \rightarrow$  **Real** entries,  $\beta = 2 \rightarrow$  **Complex**
- $N$  real eigenvalues of  $W$ :  $\lambda_1 \geq 0, \lambda_2 \geq 0, \dots, \lambda_N \geq 0$
- Joint distribution of eigenvalues (**James, 1960**):

$$P(\{\lambda_i\}) \propto \exp\left[-\frac{\beta}{2} \sum_{i=1}^N \lambda_i\right] \prod_i \lambda_i^{\frac{\beta}{2}(1+M-N)-1} \prod_{j < k} |\lambda_j - \lambda_k|^\beta$$

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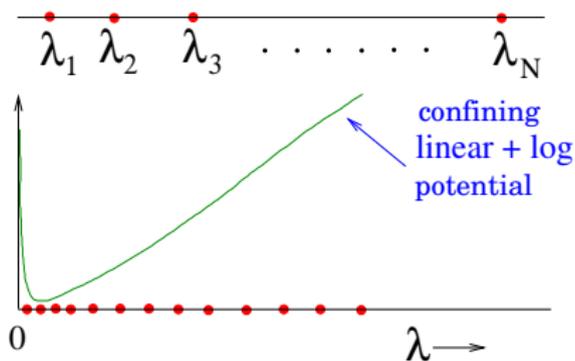
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# Coulomb Gas interpretation

- $P(\{\lambda_i\}) \propto \exp \left[ -\frac{\beta}{2} \left\{ \sum_{i=1}^N (\lambda_i - a \log \lambda_i) - \sum_{j \neq k} \log |\lambda_j - \lambda_k| \right\} \right]$

where  $a = M - N + 1 - \frac{2}{\beta}$

- 2-d Coulomb gas confined to a line (Dyson) with  $\beta \rightarrow$  inverse temp.



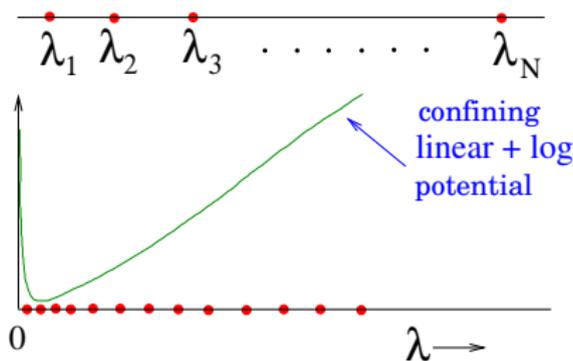
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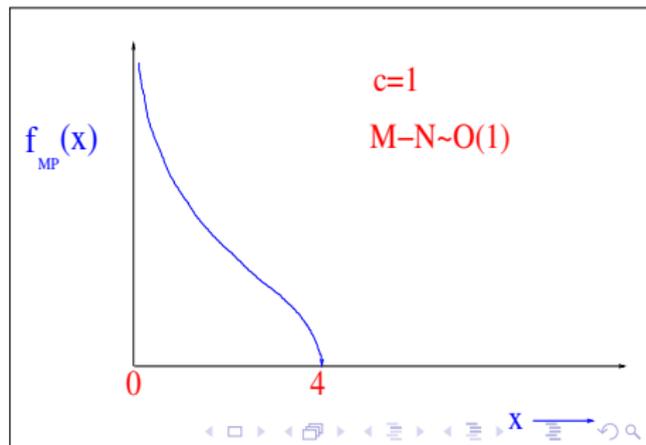
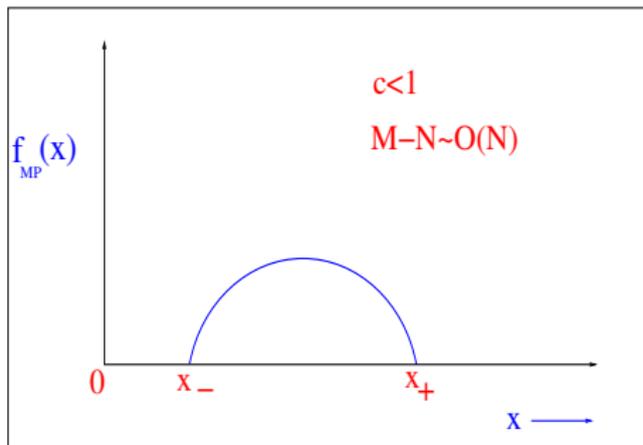
# Spectral Density: Marcenko-Pastur Law

- Av. density of states:  $\rho(\lambda, N) = \left\langle \frac{1}{N} \sum_{i=1}^N \delta(\lambda - \lambda_i) \right\rangle \xrightarrow{N \rightarrow \infty} \frac{1}{N} f_{\text{MP}}\left(\frac{\lambda}{N}\right)$

- Marcenko-Pastur law (1967):  $f_{\text{MP}}(x) = \frac{1}{2\pi x} \sqrt{(x_+ - x)(x - x_-)}$

$$x_{\pm} = \left(1 \pm \frac{1}{\sqrt{c}}\right)^2 \text{ where } c = N/M \leq 1$$

- for  $c = 1$  ( $M - N \sim O(1)$ ):  $f_{\text{MP}}(x) = \frac{1}{2\pi} \sqrt{\frac{4-x}{x}}$



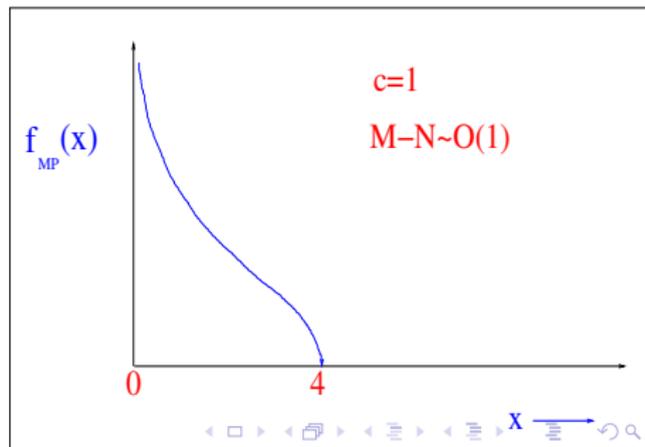
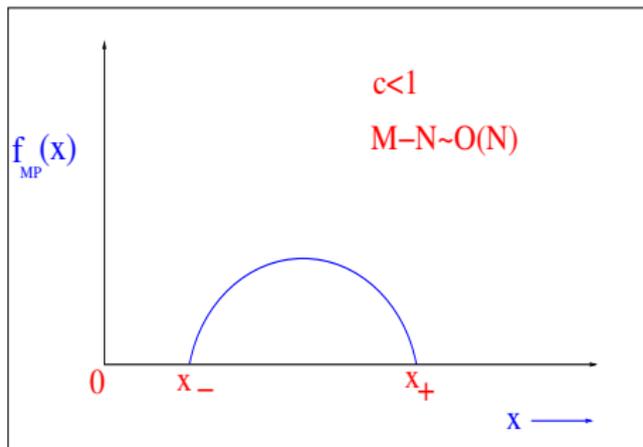
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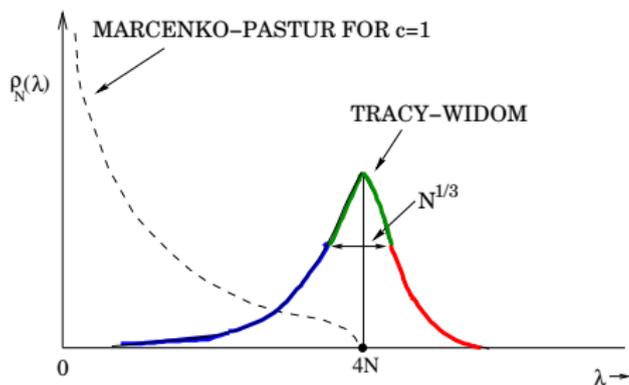
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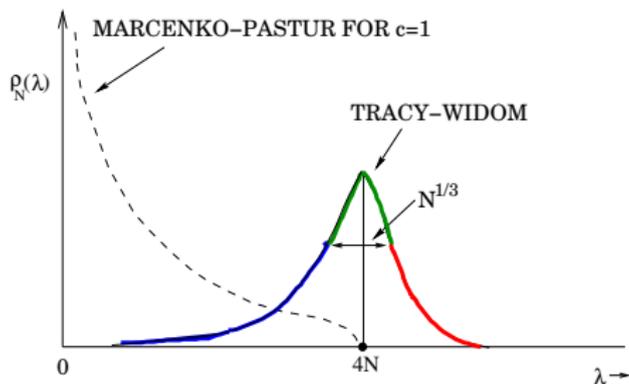
# Largest eigenvalue: Tracy-Widom distribution



Largest eigenvalue  $\lambda_{\max}$  fluctuates from sample to sample

- $\langle \lambda_{\max} \rangle = 4N$  ; typical fluctuation:  $|\lambda_{\max} - 4N| \sim N^{1/3}$  (small)
- typical fluctuations are distributed via Tracy-Widom, 1994 law  
(Johansson 2000, Johnstone, 2001)
- cumulative distribution:  $\text{Prob}[\lambda_{\max} \leq t, N] \rightarrow \mathcal{F}_\beta \left( \frac{t-4N}{2^{4/3} N^{1/3}} \right)$

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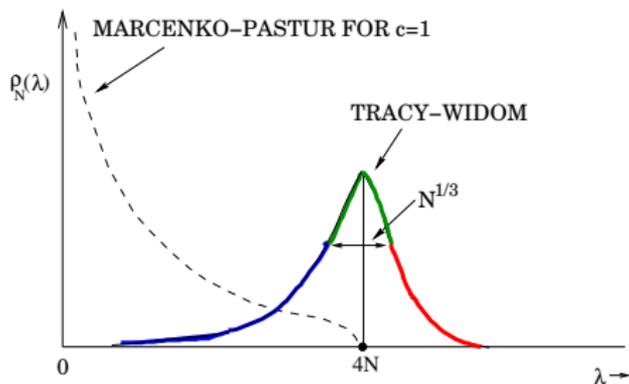
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# Tracy-Widom distribution (1994)

The scaling function  $\mathcal{F}_\beta(x)$  has the expression:

- $\beta = 1$ :  $\mathcal{F}_1(x) = \exp \left[ -\frac{1}{2} \int_x^\infty [(y-x)q^2(y) - q(y)] dy \right]$
- $\beta = 2$ :  $\mathcal{F}_2(x) = \exp \left[ - \int_x^\infty (y-x)q^2(y) dy \right]$

$$\frac{d^2 q}{dy^2} = 2q^3(y) + yq(y) \rightarrow \text{Painlevé equation}$$

- Note that  $\mathcal{F}_\beta(x) \rightarrow$  Cumulative distribution

$$\mathcal{F}_\beta(x) \rightarrow 0 \text{ (as } x \rightarrow -\infty)$$

$$\mathcal{F}_\beta(x) \rightarrow 1 \text{ (as } x \rightarrow \infty)$$

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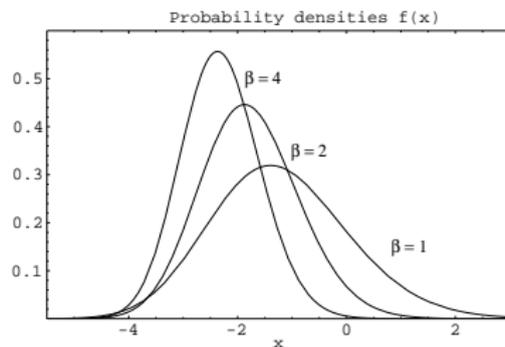
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$$\mathcal{F}_\beta(x) \rightarrow 0 \text{ (as } x \rightarrow -\infty)$$

$$\mathcal{F}_\beta(x) \rightarrow 1 \text{ (as } x \rightarrow \infty)$$

- Probability **density**:  $f_\beta(x) = \frac{d\mathcal{F}_\beta(x)}{dx} \rightarrow 0 \text{ (as } x \rightarrow \pm\infty)$

# Tracy-Widom distribution for $\lambda_{\max}$



- Tracy-Widom density  $f_{\beta}(x)$  depends explicitly on  $\beta$ .
- **Asymptotics:**  $f_{\beta}(x) \sim \exp\left[-\frac{\beta}{24}|x|^3\right]$  as  $x \rightarrow -\infty$   
 $\sim \exp\left[-\frac{2\beta}{3}x^{3/2}\right]$  as  $x \rightarrow \infty$

**Applications:** Growth models, Directed polymer, Sequence Matching.

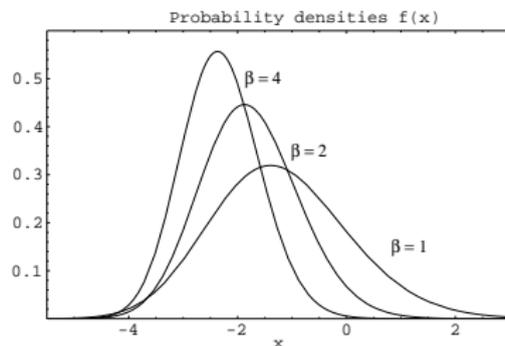
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(Baik, Deift, Johansson, Prahofer, Spohn, Johnstone,...)

[S.M., Les Houches lecture notes (2006)]



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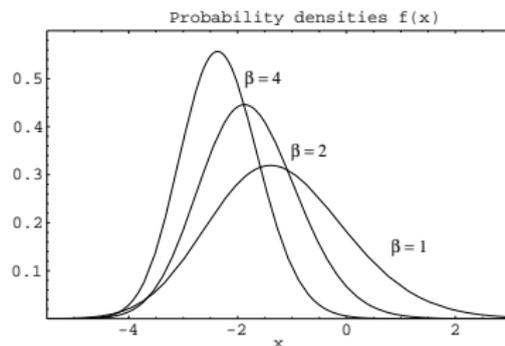
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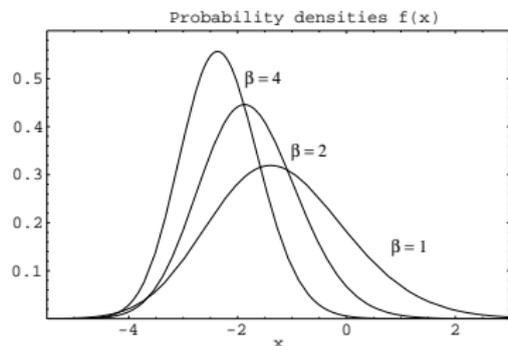
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...

(Baik, Deift, Johansson, Prahof, Spohn, Johnstone,....)

[S.M., Les Houches lecture notes (2006)]



# Two facts to remember:

For **Wishart** matrices with **complex** entries ( $\beta = 2$ )

- Joint distribution of eigenvalues:

$$P(\{\lambda_i\}) \propto \exp \left[ -\sum_{i=1}^N \lambda_i \right] \prod_i \lambda_i^{M-N} \prod_{j < k} |\lambda_j - \lambda_k|^2$$

- Largest eigenvalue  $\lambda_{\max}$  (centered and scaled) is distributed via

Tracy-Widom:  $\mathcal{F}_2(x)$

# II : Nonintersecting Brownian Motions

# Non-intersecting Brownian motions in 1-d

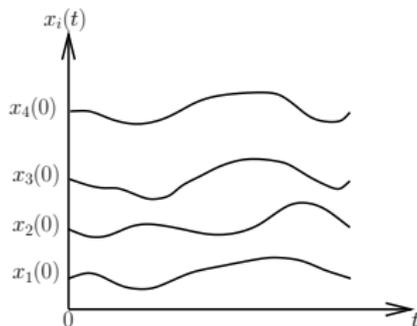
- $N$  Brownian motions in one-dimension

$$\dot{x}_i(t) = \zeta_i(t), \quad \langle \zeta_i(t) \zeta_j(t') \rangle = \delta_{i,j} \delta(t - t')$$

$$x_1(0) < x_2(0) < \dots < x_N(0)$$

- Non-intersecting condition

$$x_1(t) < x_2(t) < \dots < x_N(t), \\ \forall t \geq 0$$



P.-G. De Gennes, 1968, D. A. Huse and M. E. Fisher, 1984, ...

## Soluble Model for Fibrous Structures with Steric Constraints

P.-G. DE GENNES

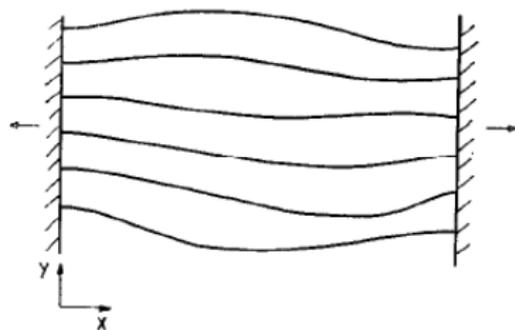


FIG. 1. Model for a two-dimensional fiber structure. The component chains are assumed to be attached to two plates I and F and placed under tension. The chains are bent by thermal fluctuations. Different chains cannot intersect each other.

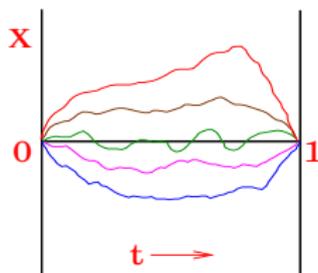
# Non-intersecting Brownian bridges in 1d

- $N$  Brownian bridges in one-dimension

$$\dot{x}_i(t) = \zeta_i(t), \quad \langle \zeta_i(t) \zeta_j(t') \rangle = \delta_{i,j} \delta(t-t'), \quad 0 \leq t \leq 1$$
$$x_i(0) = x_i(t=1) = 0$$

- Non-intersecting condition

$$x_1(t) < x_2(t) < \dots < x_N(t)$$
$$0 < \forall t < 1$$



watermelon

Reunion probability  $\rightarrow$  Comm.-Incomm. phase transition

Huse & Fisher, Fisher (1984), ..., Johansson (2002), Ferrari & Praehofer (2006), ...

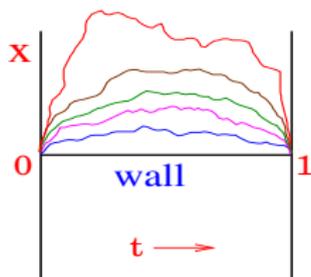
# Non-intersecting Brownian excursions in 1d

- $N$  Brownian excursions in one-dimension

$$\dot{x}_i(t) = \zeta_i(t), \quad \langle \zeta_i(t) \zeta_j(t') \rangle = \delta_{i,j} \delta(t-t'), \quad 0 \leq t \leq 1$$
$$x_i(0) = x_i(t=1) = 0 \quad x_i(t) > 0 \quad \text{for} \quad 0 < t < 1$$

- Non-intersecting condition

$$x_1(t) < x_2(t) < \dots < x_N(t)$$
$$0 < \forall t < 1$$



half-watermelon

watermelon "with a wall"

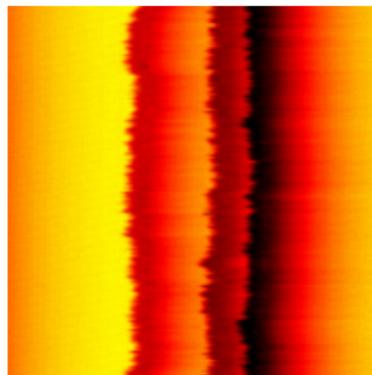
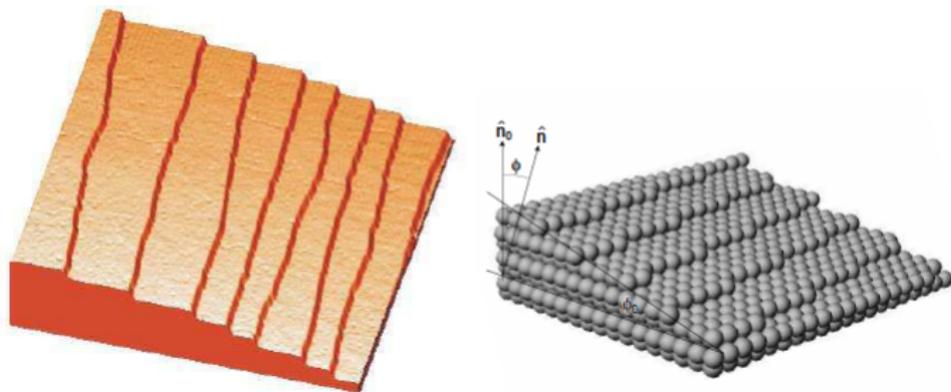
Katori & Tanemura (2004), Tracy & Widom (2007), ....

# Vicious Walkers in Physics

- P. G. de Gennes, *Soluble Models for fibrous structures with steric constraints* (1968)
- D. A. Huse and M. E. Fisher, *Commensurate melting, domain walls, and dislocations* (1984); M. E. Fisher, *Walks, Walls, Wetting and Melting* (1984)
- B. Duplantier *Statistical Mechanics of Polymer Networks of Any Topology* (1989)
- J. W. Essam, A. J. Guttmann, *Vicious walkers and directed polymer networks in general dimensions* (1995)
- H. Spohn, M. Praehofer, P. L. Ferrari et al. *Stochastic growth models* (2006)
- T. L. Einstein et. al., *Fluctuating step edges on vicinal surfaces* (2004–)
- ...

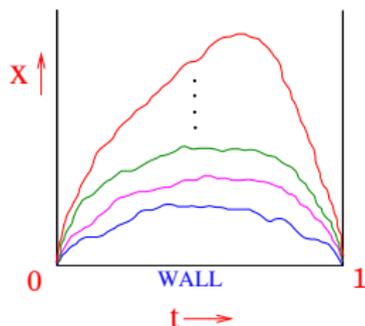
Connection between Vicious Walkers and Random Matrix Theory

# Fluctuating step edges: Maryland group



# Brownian excursions and Dyck paths

## HALF-WATERMELON



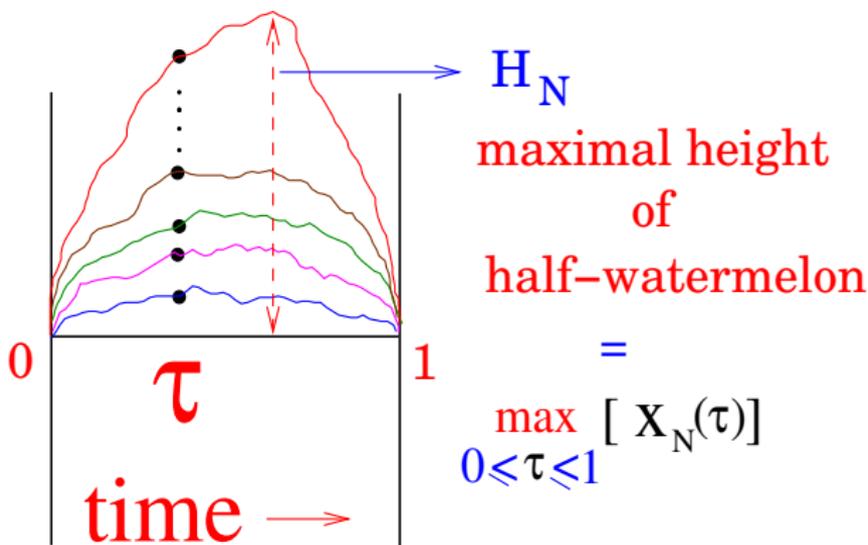
In presence of a **hard wall** at the origin  $\rightarrow$  **half-watermelons**

**Continuous** space-time: Non-intersecting Brownian **Excursions**

**Discrete** space-time: **Dyck paths** (combinatorial objects)

(Cardy, Katori, Tanemura, Krattenthaler, Fulmek, Feierl, Guttmann, Viennot, Tracy-Widom ...)

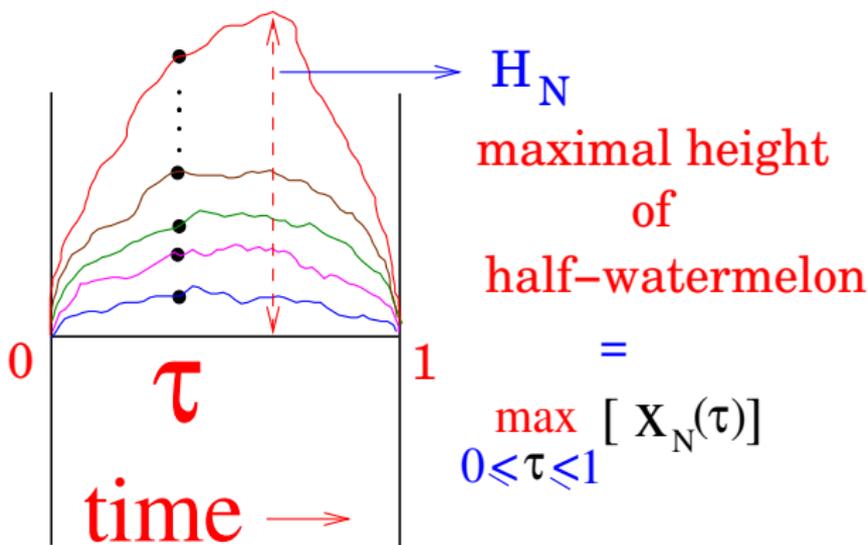
# Two questions



Q1: At fixed  $0 < \tau < 1$ , what is the joint distribution of positions  
 $P_{\text{joint}}(\{x_i\}|\tau)$ ?  $\Rightarrow$  local question

Q2: What is the probability distribution of the global maximal height  
 $\text{Prob.}[H_N \leq M, N] = F_N(M)$ ?  $\Rightarrow$  global question

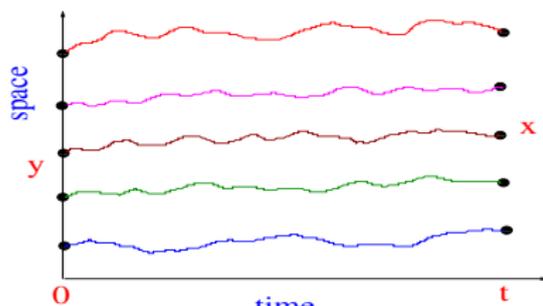
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# Method: Path Integral for free fermions



Propagator from  $\vec{y}$  at  $\tau = 0$  to  $\vec{x}$  at  $\tau = t$

$$G(\vec{x}, \vec{y}, t) = \int_{\vec{y}}^{\vec{x}} \mathcal{D}\vec{X}(\tau) \exp \left[ -\frac{1}{2} \int_0^t \sum_i \dot{x}_i^2(\tau) d\tau \right] \mathbf{1}_{x_1(\tau) < x_2(\tau) < \dots < x_N(\tau)}$$

$$= \langle \vec{x} | e^{-\hat{H}t} | \vec{y} \rangle; \text{ where } \hat{H} \equiv -\frac{1}{2} \sum_i \partial_{x_i}^2$$

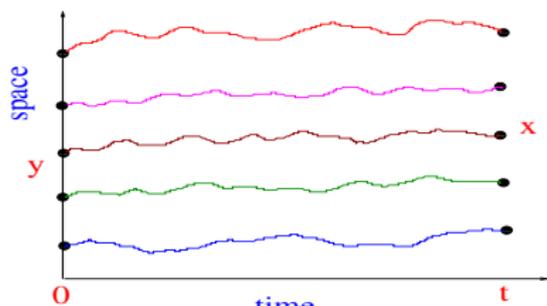
$$= \sum_E \psi_E(\vec{x}) \psi_E(\vec{y}) e^{-Et}$$

$\psi_E(\vec{x}) \equiv \det [\phi_{n_i}(x_j)] \rightarrow$  Slater determinant ( $N \times N$ )

Alternative methods:

- Lindstrom-Gessel-Viennot method (discrete lattice paths)
- Karlin-Mcgregor formula (continuous paths)

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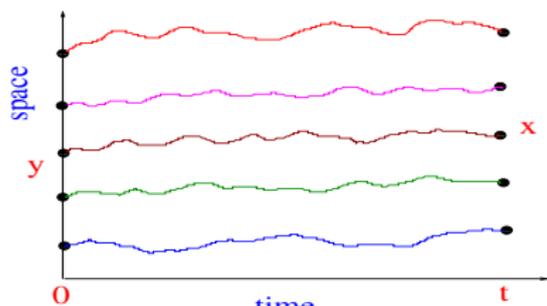
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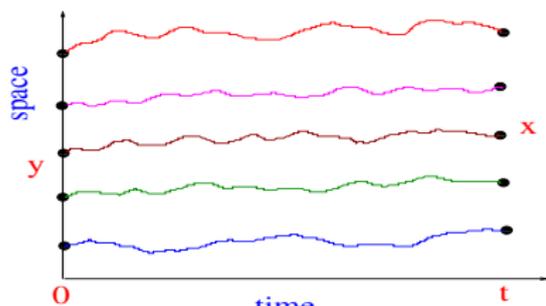
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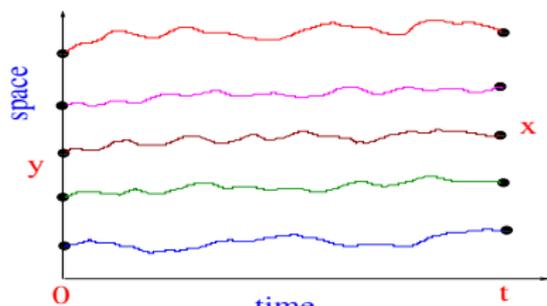
$$\begin{aligned} G(\vec{x}, \vec{y}, t) &= \int_{\vec{y}}^{\vec{x}} \mathcal{D}\vec{X}(\tau) \exp \left[ -\frac{1}{2} \int_0^t \sum_i \dot{x}_i^2(\tau) d\tau \right] \mathbf{1}_{x_1(\tau) < x_2(\tau) < \dots < x_N(\tau)} \\ &= \langle \vec{x} | e^{-\hat{H}t} | \vec{y} \rangle; \text{ where } \hat{H} \equiv -\frac{1}{2} \sum_i \partial_{x_i}^2 \\ &= \sum_E \psi_E(\vec{x}) \psi_E(\vec{y}) e^{-Et} \end{aligned}$$

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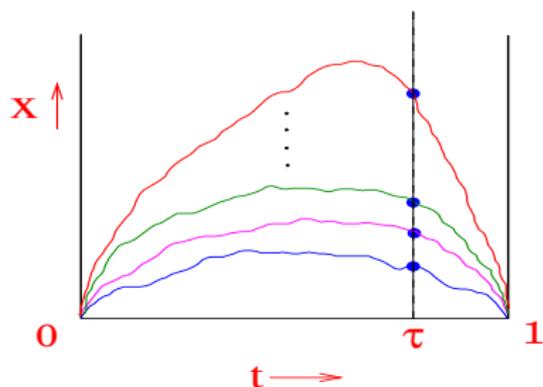
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# Q1: Joint distribution $\rightarrow$ Wishart eigenvalues



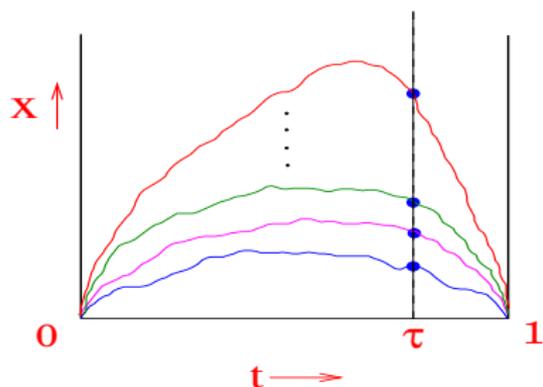
At fixed time  $0 < \tau < 1$ , let  
 $\{X_1, X_2, \dots, X_N\} \rightarrow$  positions of walkers

$$P_{\text{joint}}(\{X_i\}|\tau) \propto \prod_{i=1}^N x_i^2 \prod_{j < k} (x_j^2 - x_k^2)^2 \exp \left[ -\frac{1}{2\tau(1-\tau)} \sum_i x_i^2 \right]$$

(Schehr, S.M., Comtet, Randon-Furling, PRL, 101, 150601 (2008))

- $x_j^2 = \lambda_j \rightarrow$  eigenvalues of the Wishart matrix  $W = X^\dagger X$   
with  $\beta = 2$  and  $M - N = 1/2$

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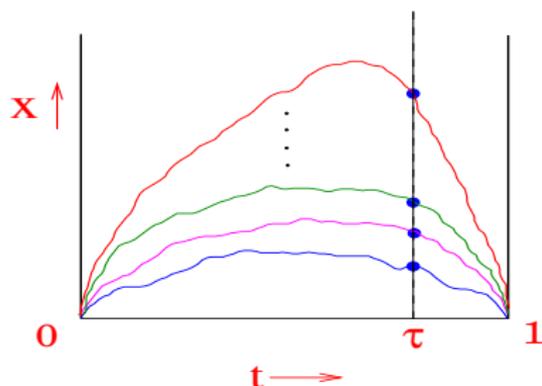
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# Top curve at fixed time: Tracy-Widom (GUE)



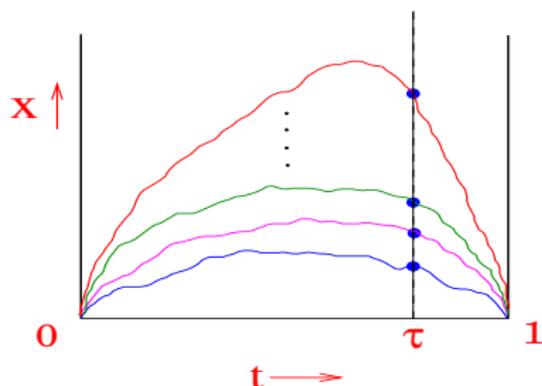
topmost curve at fixed time  $\tau$ :  $x_N^2(\tau) \rightarrow$   
**largest** eigenvalue of Wishart matrices

- largest eigenvalue of the Wishart GUE matrix (properly scaled for large  $N$ ) is distributed via the Tracy-Widom GUE law ([Johansson 2000](#), [Johnstone, 2001](#))
- This shows that the top position  $x_N(\tau)$  typically fluctuates for large  $N$  as

$$\frac{x_N(\tau)}{\sqrt{2\tau(1-\tau)}} = 2\sqrt{N} + 2^{-2/3} N^{-1/6} \chi_2$$

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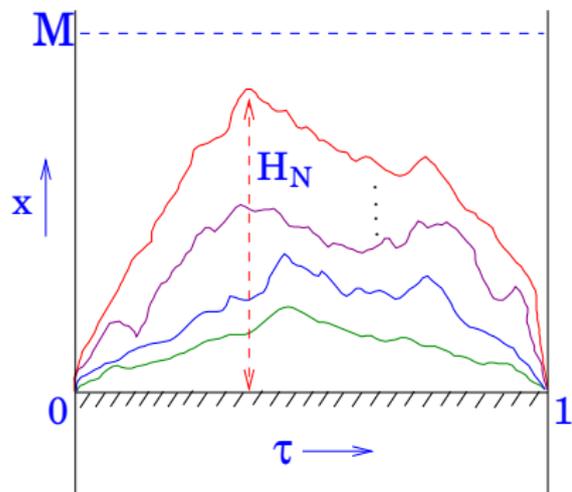
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## Q2: Maximal height of a watermelon with a wall



$H_N \rightarrow$  random variable

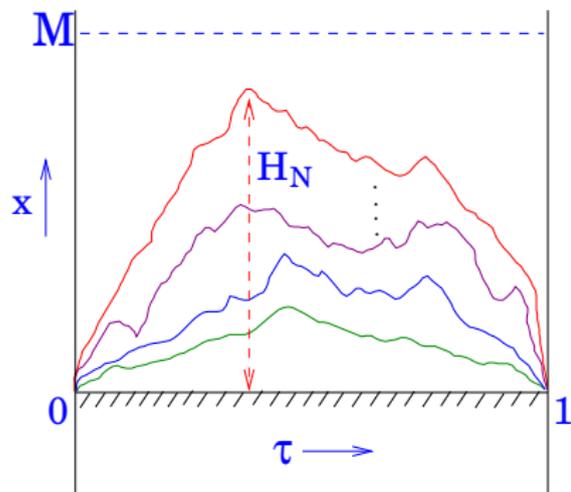
Q: What is its distribution

$\text{Prob}[H_N \leq M, N] = F_N(M)$  ?

$$N = 1: F_1(M) = \frac{\sqrt{2}\pi^{5/2}}{M^3} \sum_{k=1}^{\infty} k^2 e^{-\pi^2 k^2 / 2 M^2} \quad (\text{Chung '75, Kennedy '76})$$

$N = 2, F_2(M) \rightarrow$  complicated (Katori et. al., 2008)

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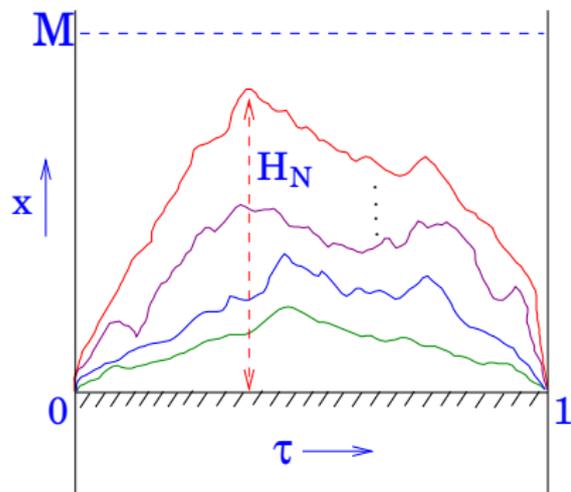
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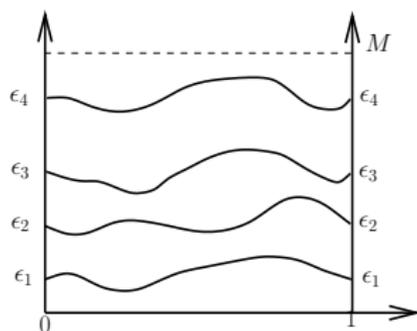
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# Exact result for all $N$ via Fermionic path integral



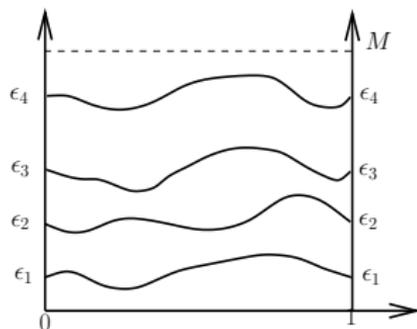
$$F_N(M) = \text{Proba}[x_N(\tau) \leq M, \forall \tau \in [0, 1]]$$

$$F_N(M) = \frac{R_M(1)}{R_\infty(1)}$$

$R_M(1) \equiv$  proba. that  $N$  walkers return to their initial positions at  $\tau = 1$

- $R_M(1) = \langle \vec{\epsilon} | e^{-\hat{H}} | \vec{\epsilon} \rangle = \sum_E |\psi_E(\vec{\epsilon})|^2 e^{-E}$
- $\hat{H} \equiv \sum_i [-\frac{1}{2} \partial_{x_i}^2 + V(x_i)]$
- potential  $V(x) = 0$  for  $0 < x < M$   
 $= \infty$  for  $x = 0, M$  (Absorbing b.c.)
- $\psi_E(\vec{\epsilon}) \equiv \det [\sin(n_j \pi \epsilon_j / M)] \rightarrow$  Slater determinant ( $N \times N$ )
- Energy  $E = \frac{\pi^2}{2M^2} (n_1^2 + n_2^2 + \dots + n_N^2)$

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Using Fermionic path-integral techniques we derived the full Prob. Dist. of  $H_N$  for all  $N$  exactly

Cumul. distr:  $F_N(M) = \text{Prob}[H_N \leq M]$

$$F_N(M) = \frac{B_N}{M^{2N^2+N}} \sum_{n_i=1,2,\dots} \prod_{i=1}^N n_i^2 \prod_{j<k} (n_j^2 - n_k^2)^2 \exp \left[ -\frac{\pi^2}{2M^2} \sum_i n_i^2 \right]$$

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$$B_N = \frac{\pi^{2N^2+N} 2^{N/2-N^2}}{\prod_{j=0}^{N-1} \Gamma(j+2)\Gamma(j+3/2)}$$

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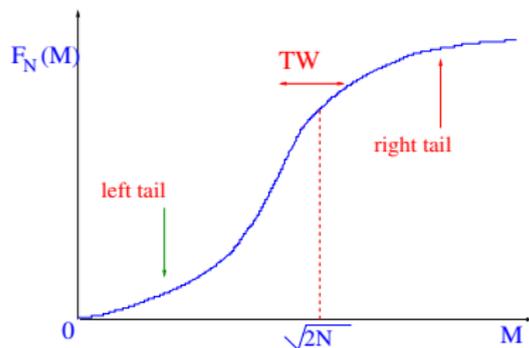
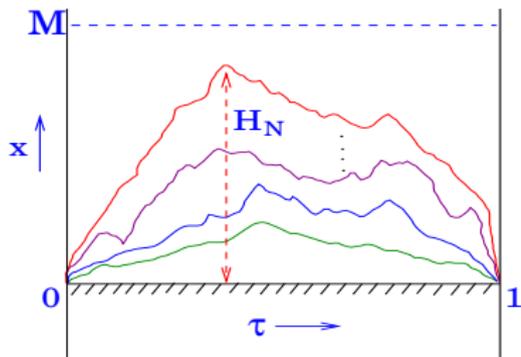
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# Asymptotic large $N$ results:



Cum. distr.  $F_N(M) = \text{Prob.}[H_N \leq M]$  behaves, for large  $N$  as:

$$\sim \exp \left[ -N^2 \phi_- \left( \frac{M}{\sqrt{2N}} \right) \right] \quad \text{for } \sqrt{2N} - M \sim O(\sqrt{N})$$

$$\sim \mathcal{F}_1 \left[ 2^{11/6} N^{1/6} (M - \sqrt{2N}) \right] \quad \text{for } |M - \sqrt{2N}| \sim O(N^{-1/6})$$

$$\sim 1 - B \exp \left[ -\beta N \phi_+ \left( \frac{M}{\sqrt{2N}} \right) \right] \quad \text{for } M - \sqrt{2N} \sim O(\sqrt{N})$$

# Asymptotic large $N$ results:

- where  $\mathcal{F}_1(x) \rightarrow$  **Tracy-Widom GOE**
- $\phi_{\pm}(x) \rightarrow$  left and right rate functions  $\implies$  explicitly computable  
(Schehr, S.M., Comtet, Forrester, 2011/2012)

Right rate function:

$$\phi_+(x) = 4x\sqrt{x^2-1} - 2\ln\left[2x\left(\sqrt{x^2-1}+x\right) - 1\right]$$

Left rate function:

$\phi_-(x) \rightarrow$  can be expressed in terms of elliptic functions

- In particular,

$$\phi_+(x) \simeq \frac{2^{9/2}}{3} (x-1)^{3/2} \quad \text{as } x \rightarrow 1^+$$

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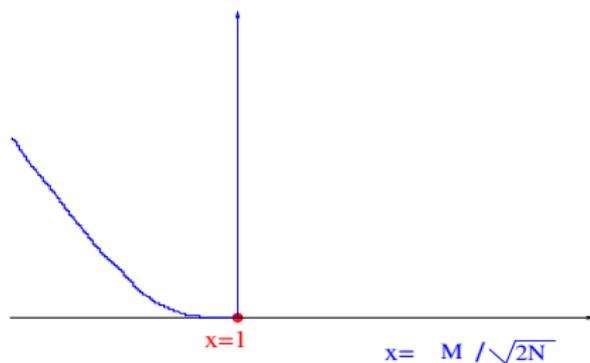
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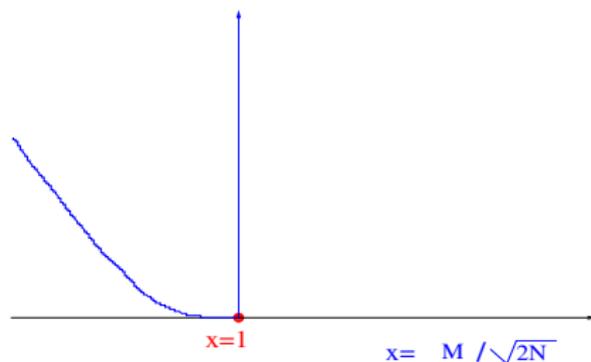


$$\lim_{N \rightarrow \infty} -\frac{1}{N^2} \ln F_N \left( M = \sqrt{2N} x \right) = \begin{cases} \phi_-(x), & x < 1 \\ 0, & x > 1. \end{cases}$$

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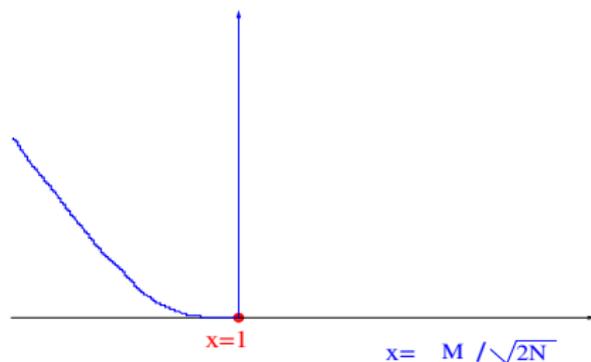


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## III : Yang-Mills gauge theory in 2-d

# Partition function of Yang-Mills theory in 2d

- Consider a 2-d manifold  $\mathcal{M}$ . At each point  $x$ : a pair of  $N \times N$  matrix

$$A_\mu(x) \ (\mu = 1, 2) \rightarrow \text{gauge field}$$

$$\text{Partition function: } \mathcal{Z}_{\mathcal{M}} = \int [DA_\mu] e^{-\frac{1}{4\lambda^2} \int \text{Tr}[F^{\mu\nu} F_{\mu\nu}] d^2x}$$

$$F_{\mu\nu} = \partial_\mu A_\nu - \partial_\nu A_\mu + i[A_\mu, A_\nu] \rightarrow \text{field strength}$$

$$\lambda \rightarrow \text{coupling strength}$$

- Under a local gauge transformation:

$$A_\mu \rightarrow S^{-1}(x)A_\mu S(x) - i S^{-1}(x)\partial_\mu S(x)$$

where  $S(x) \rightarrow N \times N$  matrix that depends on the underlying gauge group  $G$

Field strengths transform as  $F_{\mu\nu} \rightarrow S^{-1}(x)F_{\mu\nu}(x)S(x)$  that keeps the action gauge invariant.

Ex:  $G \equiv U(1)$  : electrodynamics

$G \equiv SU(2)$  : electro-weak interact<sup>o</sup>

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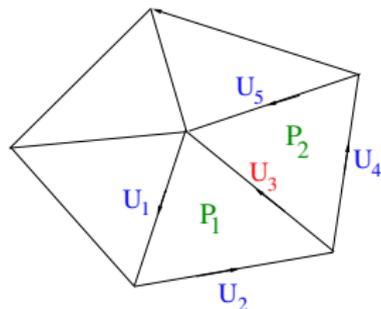
# Lattice Regularization:

Consider, for instance, the  $U(N)$  gauge theory

Regularization on the lattice:

$$\mathcal{Z}_{\mathcal{M}} = \int \prod_L dU_L \prod_{\text{plaquettes}} Z_P[U_P]$$

$$U_P = \prod_{L \in \text{plaquette}} U_L$$



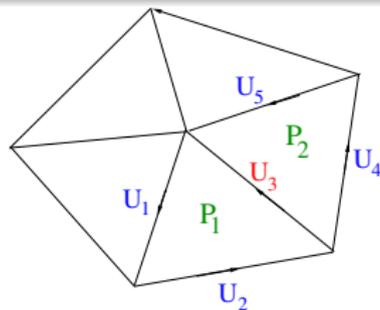
$Z_P \rightarrow$  **plaquette** partition function

(Wilson, '74, Migdal, '75)

# Heat-kernel action

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Wilson'74

- A common choice : **Wilson's action**

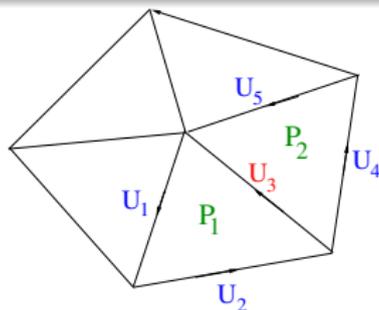
$$Z_P(U_P) = \exp \left[ b N \text{Tr}(U_P + U_P^\dagger) \right]$$

Exact solution of the Partition Function: (Gross & Witten, Wadia, '80)

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- **fixed point action** : invariance under decimation  $\Rightarrow$  **Migdal's recursion relation**

$$\int dU_3 Z_{P_1}(U_1 U_2 U_3) Z_{P_2}(U_4 U_5 U_3^\dagger) = Z_{P_1+P_2}(U_1 U_2 U_4 U_5)$$

$$Z_P(U_P) = \sum_R d_R \chi_R(U_P) \exp \left[ -\frac{A_P}{2N} C_2(R) \right]$$

Migdal'75, Rusakov'90

# Partition function of Yang-Mills theory on the $2d$ -sphere

- Partition function on  $\mathcal{M}$ , of genus  $g$ , computed with the heat-kernel action

$$\mathcal{Z}_{\mathcal{M}} = \sum_R d_R^{2-2g} \exp \left[ -\frac{A}{2N} C_2(R) \right]$$

# Partition function of Yang-Mills theory on the $2d$ -sphere

- Partition function on the **sphere** computed with the heat-kernel action

$$\mathcal{Z}_{\mathcal{M}} = \sum_R d_R^2 \exp \left[ -\frac{A}{2N} C_2(R) \right]$$

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- Partition function on the sphere computed with the heat-kernel action

$$\mathcal{Z}_{\mathcal{M}} = \sum_R d_R^2 \exp \left[ -\frac{A}{2N} C_2(R) \right]$$

- Irreducible representations  $R$  of  $G$  are labelled by the lengths of the Young diagrams:

- If  $G = U(N)$

$$\mathcal{Z}_{\mathcal{M}} = c_N e^{-A \frac{N^2-1}{24}} \sum_{n_1, \dots, n_N=0}^{\infty} \prod_{i < j} (n_i - n_j)^2 e^{-\frac{A}{2N} \sum_{j=1}^N n_j^2}$$

- If  $G = Sp(2N)$

$$\mathcal{Z}_{\mathcal{M}} = \hat{c}_N e^{A(N+\frac{1}{2})\frac{N+1}{12}} \sum_{n_1, \dots, n_N=0}^{\infty} \left( \prod_{j=1}^N n_j^2 \right) \prod_{i < j} (n_i^2 - n_j^2)^2 e^{-\frac{A}{4N} \sum_{j=1}^N n_j^2}$$

# Correspondence between $YM_2$ on the sphere and watermelons

- **Partition function** of  $YM_2$  on the sphere with gauge group  $Sp(2N)$

$$\mathcal{Z}_{\mathcal{M}} = \mathcal{Z}(A; Sp(2N))$$

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- **Cumulative distribution** of the **maximal height** of watermelons with a wall

$$F_N(M) = \frac{A_N}{M^{2N^2+N}} \sum_{n_1, \dots, n_N=0}^{+\infty} \left( \prod_{j=1}^N n_j^2 \right) \prod_{i<j} (n_i^2 - n_j^2)^2 e^{-\frac{\pi^2}{2M^2} \sum_{j=1}^N n_j^2}$$
$$\propto \mathcal{Z} \left( A = \frac{2\pi^2 N}{M^2}; Sp(2N) \right)$$

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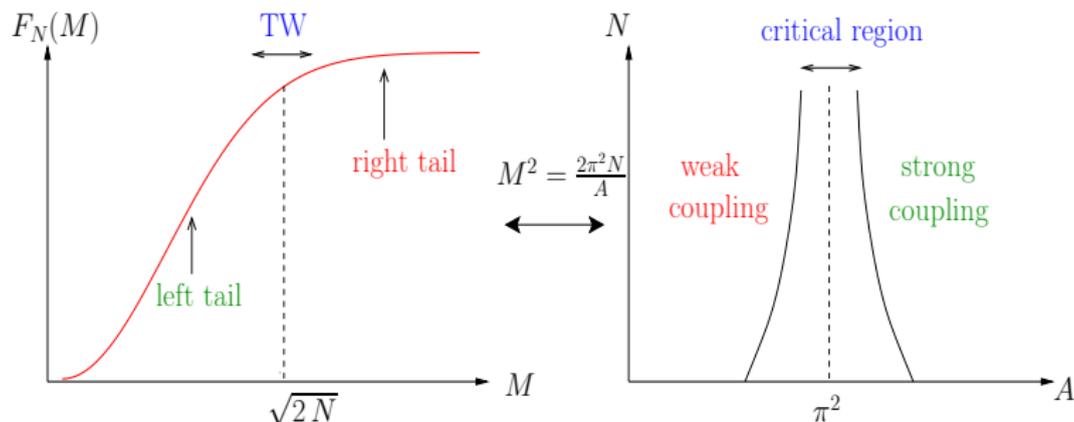
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# Large $N$ limit of $YM_2$ and consequences for $F_N(M)$

Weak-strong coupling transition (3-rd order) in  $YM_2$ , Douglas-Kazakov '93



Critical point  $A = A_c = \pi^2$  corresponds (using  $A = \frac{2\pi^2 N}{M^2}$ ):

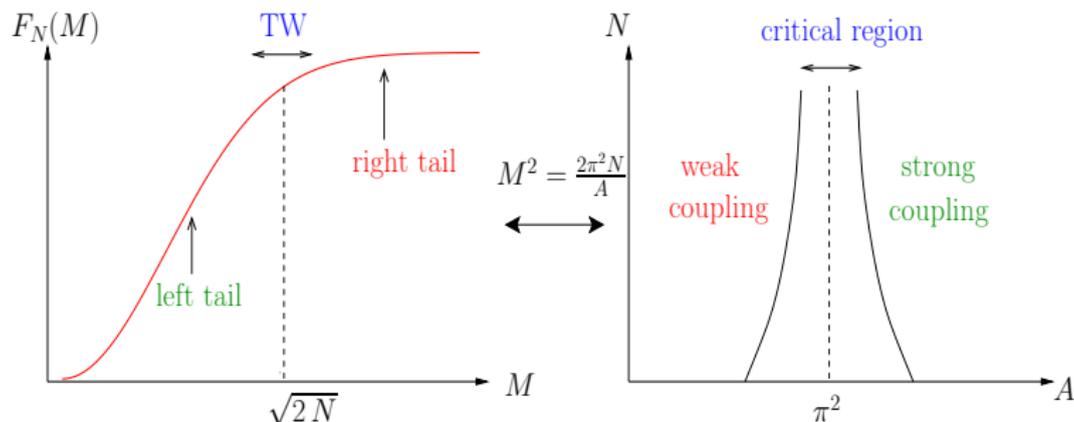
$$M = M_c = \sqrt{2N}$$

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Weak-strong coupling transition (3-rd order) in  $YM_2$ , Douglas-Kazakov '93



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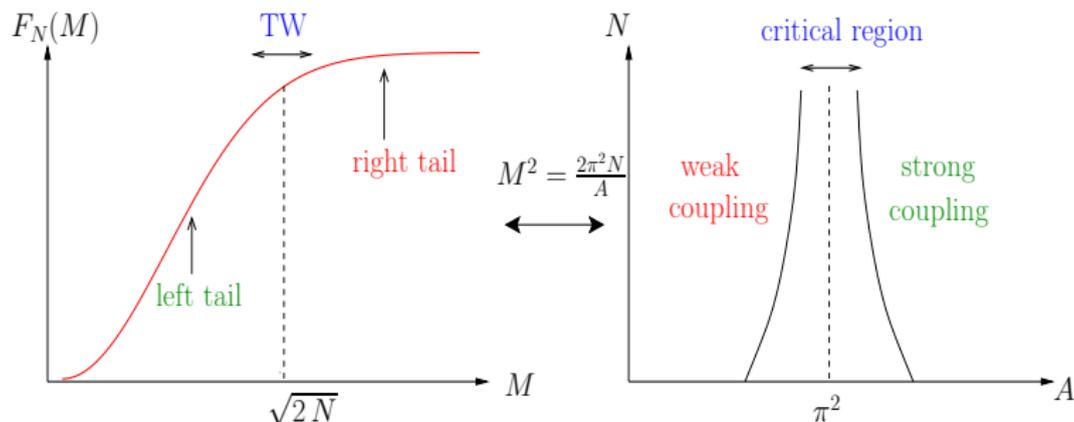
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- In the **critical** regime, "**double-scaling limit**", the method of orthogonal polynomials (Gross-Matysin '94, Crescimanno-Naculich-Schnitzer '96) shows

$$\frac{d^2}{dt^2} \log F_N\left(\sqrt{2N}(1 + t/(2^{7/3}N^{2/3}))\right) = -\frac{1}{2}\left(q^2(t) - q'(t)\right)$$
$$q''(t) = 2q^3(t) + tq(t), \quad q(t) \sim \text{Ai}(t), \quad t \rightarrow \infty$$

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$$\mathcal{F}_1(t) = \exp\left(-\frac{1}{2} \int_t^\infty ((s-t)q^2(s) + q(s)) ds\right)$$

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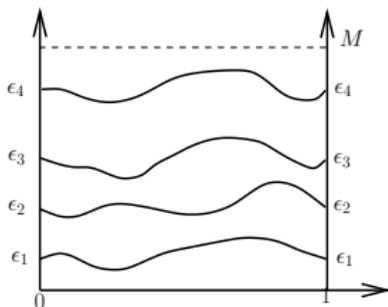
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- double scaling regime  $[A \sim A_c] \longleftrightarrow$  Tracy-Widom  $[M \sim \sqrt{2N}]$

Forrester, S. M., Schehr, '11

# Absorbing boundary condition $\rightarrow SP(2N)$

- Ratio of reunion probabilities for  $N$  vicious walkers on the segment  $[0, M]$  with **absorbing boundary conditions**



$$F_N(M) = \text{Proba}[X_N(\tau) \leq M, \forall \tau \in [0, 1]]$$

$$F_N(M) = \frac{R_M(1)}{R_\infty(1)}$$

$R_M(1) \equiv$  proba. that  $N$  walkers return to their initial positions at  $\tau = 1$

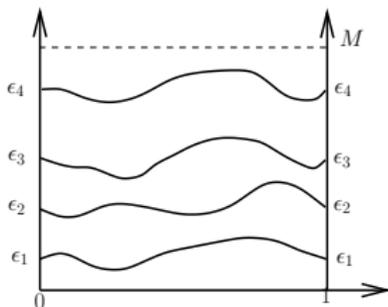
Related to  $YM_2$  on the sphere with **gauge group  $Sp(2N)$**

$$F_N(M) \propto \mathcal{Z} \left( A = \frac{2\pi^2 N}{M^2}; Sp(2N) \right)$$

limiting form of  $F_N(M)$ :  $\mathcal{F}_1 \rightarrow$  **Tracy-Widom (GOE)**

# Periodic boundary condition $\rightarrow U(N)$

- Ratio of reunion probabilities for  $N$  vicious walkers on the segment  $[0, M]$  with **periodic boundary conditions**



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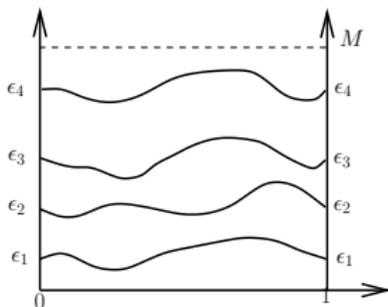
Related to  $YM_2$  on the sphere with **gauge group  $U(N)$**

$$F_N(M) \propto \mathcal{Z} \left( A = \frac{4\pi^2 N}{M^2}; U(N) \right)$$

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# Reflecting boundary condition $\rightarrow$ $SO(2N)$

- Ratio of reunion probabilities for  $N$  vicious walkers on the segment  $[0, M]$  with reflecting boundary conditions



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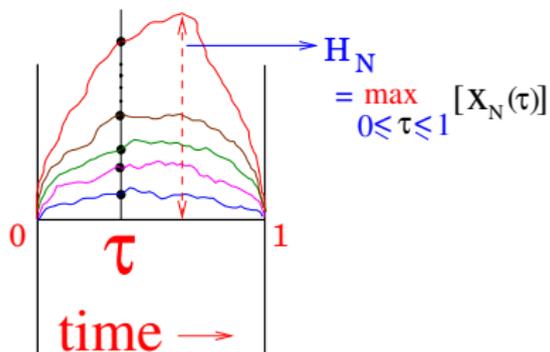
$R_M(1) \equiv$  proba. that  $N$  walkers return to their initial positions at  $\tau = 1$

Related to  $YM_2$  on the sphere with gauge group  $SO(2N)$

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# Summary



$x_i(\tau) \rightarrow$  trajectory of the  $i$ -th walker  
 $x_N(\tau) \rightarrow$  trajectory of the **top** path  
 $x_N(\tau)$  (centered and scaled)  
 $\rightarrow$  **Airy**<sub>2</sub> process minus a parabola

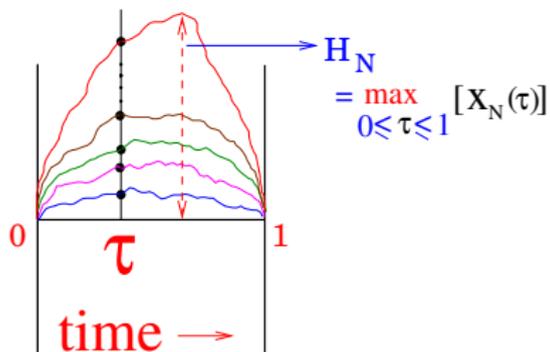
Prähofer & Spohn, '00

- At fixed time  $\tau$ , the marginal  $x_N(\tau)$  (centered and scaled)  
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- However, the maximal height  $H_N = \max_{0 \leq \tau \leq 1} [x_N(\tau)]$  (centered and scaled)  
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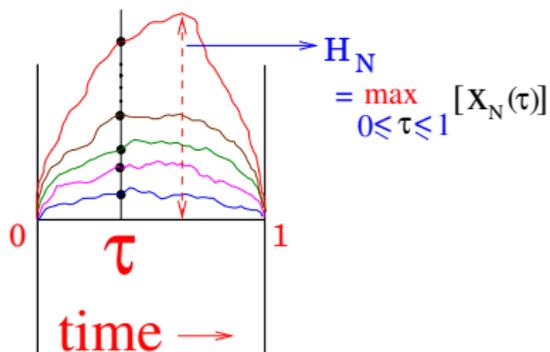
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## WISHART RANDOM MATRICES

Wishart 1928, Tracy–Widom 1993,  
Johansson 2000 ....



## VICIOUS BROWNIAN WALKERS

de Gennes 1968, Fisher 1984, ...



## 2-d YANG–MILLS THEORY ON THE SPHERE

LARGE  $N$  PHASE TRANSITION (3rd order)

**LATTICE** (Wilson Action ): Gross and Witten 1980, Wadia 1980....

**CONTINUUM** : Migdal 1975 , Rusakov 1990, Douglas and Kazakov 1993,  
Gross and Matytsin 1994....

# Collaborators and References

## Collaborators:

- O. Bohigas, A. Comtet, G. Schehr, P. Vivo (LPTMS, Orsay, France)
- P. J. Forrester (Univ. of Melbourne, Australia)
- C. Nadal (Oxford University, UK)
- J. Randon-Furling (Univ. Paris-1, France)
- M. Vergassola (Inst. Pasteur, Paris, France)

## References:

- P. Vivo, S. M., O. Bohigas, *J. Phys. A: Math. Theo.* **40**, 4317 (2007).
- S. M. & M. Vergassola, *Phys. Rev. Lett.* **102**, 060601 (2009).
- G. Schehr, S. M., A. Comtet, J. Randon-Furling, *Phys. Rev. Lett.* **101**, 150601 (2008).
- C. Nadal, S. M., *Phys. Rev. E* **79**, 061117 (2009).
- P. J. Forrester, S. M., G. Schehr, *Nucl. Phys. B* **844**, 500 (2011).
- G. Schehr, S. M., A. Comtet, P. J. Forrester, *J. Stat. Phys.* **150**, 491 (2013).

# Open Questions and related issues:

- **boundary conditions**  $\iff$  **gauge groups**  
deeper understanding needed
- Other interesting observables:
  - Joint distribution of the maximal height  $H_N = \max_{0 \leq \tau \leq 1} [x_N(\tau)]$  and the time  $\tau_M$  at which it occurs:  $P_N(H_N = M, \tau_M)$   
 $\implies$  Interesting relation to KPZ interfaces and  $(1+1)$ -d directed polymers

Rambeau & Schehr '11, Flores et. al. '12, Schehr '12, Quastel & Remenik, '12,  
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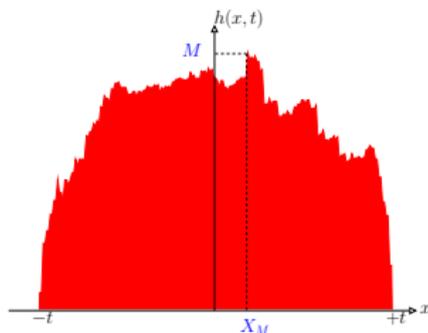
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# Consequences for curved stochastic growth



- Distribution of the height field  $h(0, t)$

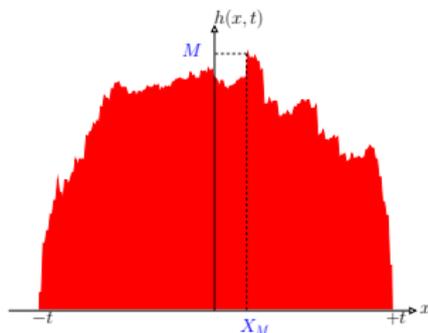
(Prähofer & Spohn,

'00)

$$\lim_{t \rightarrow \infty} P \left( \frac{h(0, t) - 2t}{t^{1/3}} \leq s \right) = \mathcal{F}_2(s)$$

$\mathcal{F}_2(s) \equiv$  **Tracy – Widom** distribution for  $\beta = 2$

# Consequences for curved stochastic growth



- Maximum  $M \equiv \max_{-t \leq x \leq t} h(x, t)$  (Forrester, S.M. and Schehr, NPB '11)

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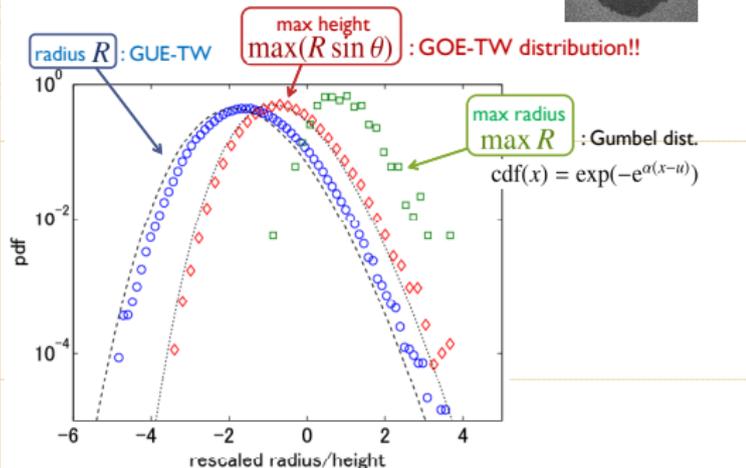
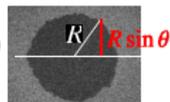
see also

- Krug *et al.* '92, Johansson '03 (indirect proof),
- G. M. Flores, J. Quastel, D. Remenik, arXiv:1106.2716

# Experiments on nematic liquid crystals

K. A. Takeuchi, M. Sano, Phys. Rev. Lett. **104**, 230601 (2010)

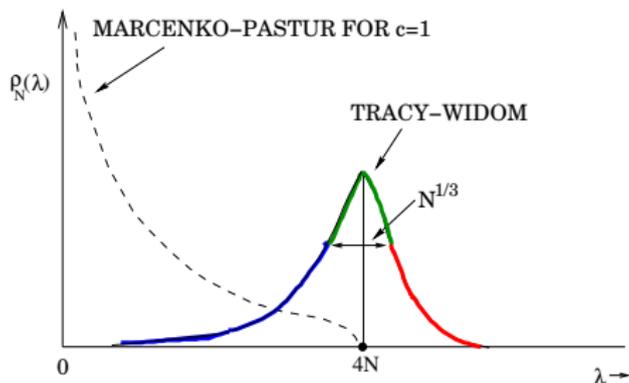
## Extreme-Value Statistics (circular)



Max heights of circular interfaces obey the GOE-TW dist.!

Courtesy of K. Takeuchi

# Probability of **Atypically** Large Deviations of $\lambda_{\max}$ :

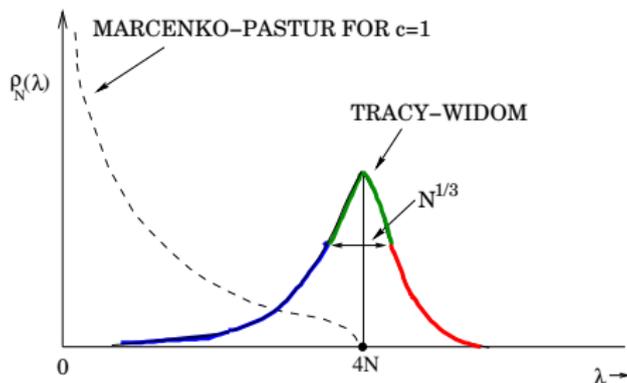


- Tracy-Widom law  $\text{Prob}[\lambda_{\max} \leq t, N] \rightarrow F_{\beta} \left[ \frac{t-4N}{24/3 N^{1/3}} \right]$  describes the prob. of **typical (small)** fluctuations of  $\sim O(N^{1/3})$  around the mean  $4N$ , i.e., when  $|\lambda_{\max} - 4N| \sim N^{1/3}$

- **Q:** the prob. of **large (atypical)** fluctuations (**red** and **blue**)?

$$|\lambda_{\max} - 4N| \sim O(N)$$

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# Exact Left and Right Large Deviation Functions

- For large deviation:  $t - 4N \sim O(N)$

$$P(\lambda_{\max} = t, N) \approx \begin{cases} \exp\left\{-\beta N^2 \Psi_-\left(\frac{4N-t}{N}\right)\right\} & \text{for } t \ll 4N \\ \exp\left\{-\beta N \Psi_+\left(\frac{t-4N}{N}\right)\right\} & \text{for } t \gg 4N \end{cases}$$

- $\Psi_-(x)$  and  $\Psi_+(x) \rightarrow$  computed exactly

(Vivo, S.M. and Bohigas 2007, S.M. and Vergassola 2009)

$$\Psi_-(x) \rightarrow \frac{x^3}{384} \text{ (as } x \rightarrow 0)$$

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matches respectively with the left and right tails of the Tracy-Widom behavior in the central peak

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- **Left** large deviation function:

$$\Psi_{-}(x) = \ln \left[ \frac{2}{\sqrt{4-x}} \right] - \frac{x}{8} - \frac{x^2}{64}; \quad x \geq 0$$

(Vivo, S.M., and Bohigas, 2007)

- **Right** large deviation function:

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$$P(\lambda_{\max} \leq t, N) \approx \begin{cases} \exp\{-\beta N^2 \Psi_-(\frac{4N-t}{N})\} & \text{for } t \ll 4N \\ 1 - A \exp\{-\beta N \Psi_+(\frac{t-4N}{N})\} & \text{for } t \gg 4N \end{cases}$$

$$\lim_{N \rightarrow \infty} -\frac{1}{\beta N^2} \ln [P(\lambda_{\max} \leq 4N - Nx, N)] = \begin{cases} \Psi_-(x) \sim x^3 & \text{as } x \rightarrow 0^- \\ 0 & \text{as } x \rightarrow 0^+ \end{cases}$$

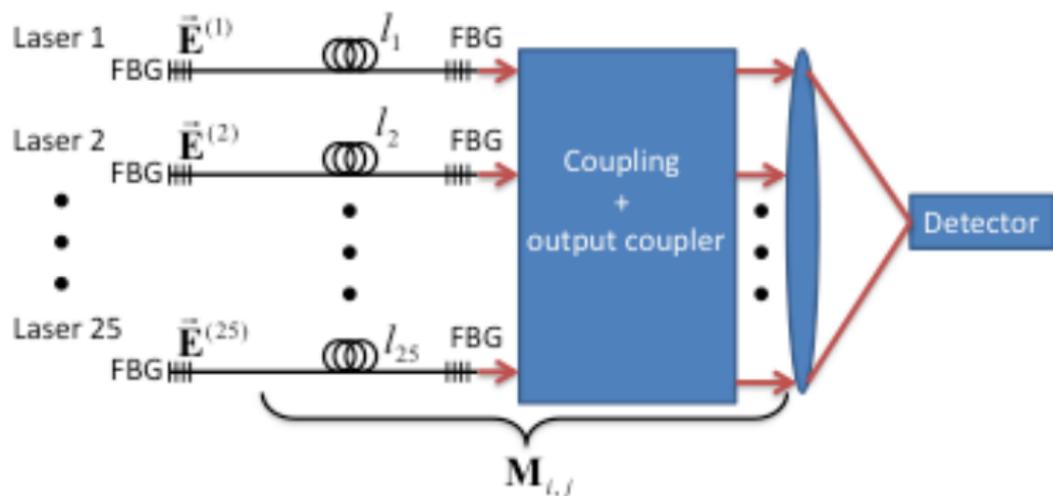
3-rd derivative  $\rightarrow$  discontinuous

## Measuring maximal eigenvalue distribution of Wigner-Dyson lasers

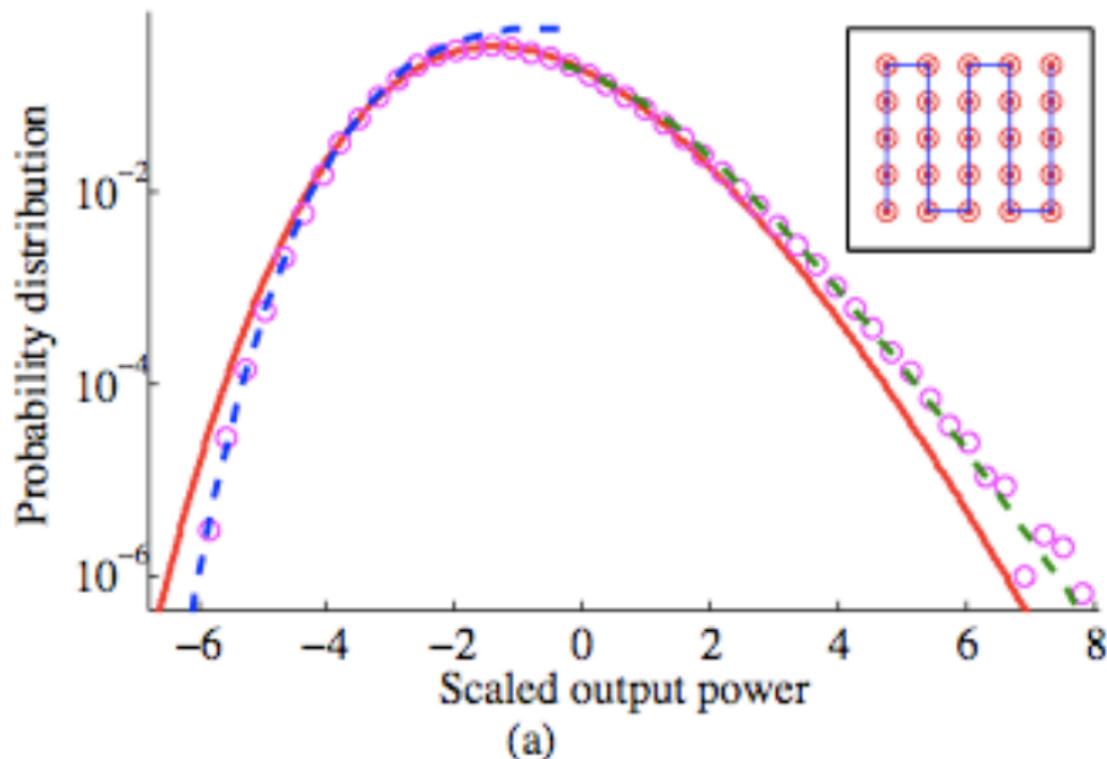
Moti Fridman, Rami Pugatch, Micha Nixon, Asher Peres  
*Weizmann Institute of Science, Dept. of Physics of Complex Systems*  
(Dated: May 30, 2014)

We determined the probability distribution of the combined eigenvalues of two coupled fiber lasers and show that it agrees well with the Tracy-Widom distribution for small deviations and the Vivo-Majumdar-Bohigas distributions of the largest eigenvalue for large deviations. This was achieved with 500,000 measurements from the fiber lasers, that continuously changes with varying coupling parameters. We show experimentally that for small deviations of the combined eigenvalues the Tracy-Widom distribution is correct, while for large deviations the Vivo-Majumdar-Bohigas distributions are correct.

# Experimental Verification with Coupled Lasers



# Experimental Verification with Coupled Lasers



Fridman et. al. arXiv:1012.1282

2

