# Universality of distribution functions in random matrix theory

Arno Kuijlaars Katholieke Universiteit Leuven, Belgium

#### **Overview**

- **▲** Universality
  - **▲** Local eigenvalue statistics
  - ▲ Fluctuations of the largest eigenvalue
- ▲ Connections outside RMT
  - **▲** Zeros of Riemann zeta function
  - **▲ Non-intersecting Brownian paths**
  - **▲ Tiling problem**
- **▲** Unitary ensembles
  - **▲** Determinantal point process
  - **▲** Precise formulation of universality
  - **▲** Universality in regular cases
- ▲ Universality classes in singular cases
  - ▲ Singular cases I and II and Painlevé equations
  - ▲ Spectral singularity

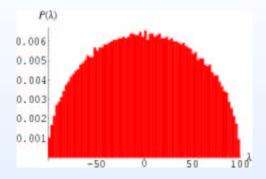
## Gaussian ensembles

- ▲ Simplest ensembles are Gaussian ensembles.
- ▲ Matrix entries have normal distribution with mean zero. The entries are independent up to the constraints that are imposed by the symmetry class.
  - **▲** Gaussian Unitary Ensemble GUE: complex Hermitian matrices
  - ▲ Gaussian Orthogonal Ensemble GOE: real symmetric matrices
  - ▲ Gaussian Symplectic Ensemble GSE: self-dual quaternionic matrices

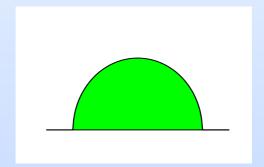
▲ Where are the eigenvalues?

# Wigner's semi-circle law

 $\blacktriangle$  Histogram of eigenvalues of large Gaussian matrix, size  $10^4 \times 10^4$ 



lacktriangle After scaling of eigenvalues with a factor  $\sqrt{n}$ , there is a limiting mean eigenvalue distribution, known as Wigner's semi-circle law



▲ This is special for Gaussian ensembles (non-universal). Other limiting distributions for Wishart ensembles, Jacobi ensembles,...

## **Universality 1: Local eigenvalue statistics**

- ▲ Global statistics of eigenvalues depend on the particular random matrix ensemble in contrast to local statistics. Distances distances between consecutive eigenvalues show regular behavior.
- ▲ Rescale eigenvalues around a certain value so that mean distance is one.



plot shows only a few rescaled eigenvalues of a very large GUE matrix

- ▲ This is the same behavior as seen in energy spectra in quantum physics.
- ▲ The repulsion between neighboring eigenvalues is very different from Poisson spacings.



## **Universality 1: Local eigenvalue statistics**

- ▲ This local behavior of eigenvalues is not special for GUE.
  - ▲ It holds for large class of unitary ensembles  $\boxed{\frac{1}{Z_n}e^{-n\operatorname{Tr} V(M)}dM}$  these are ensembles that have the same symmetry property as GUE.

Deift, Kriecherbauer, McLaughlin, Venakides, Zhou (1999)

- ▲ Local eigenvalue statistics is different for GOE and GSE which have different symmetry properties. Proof of universality for orthogonal and symplectic ensembles is more recent result

  Deift, Gioev (arxiv 2004)
- ▲ Universality fails at special points, such as end points of the spectrum, or points where eigenvalue density vanishes.
  - ▲ This gives rise to new universality classes.

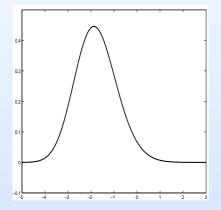
## Universality 2: Largest eigenvalue

- ▲ Fluctuations of the largest eigenvalues of random matrices also show a universal behavior (depending on the symmetry class).
- ▲ For  $n \times n$  GUE matrix, the largest eigenvalue grows like  $\sqrt{2n}$  and has a standard deviation of the order  $n^{-1/6}$ .
- ▲ Centered and rescaled largest eigenvalue

$$\sqrt{2}n^{1/6}\left(\lambda_{\max}-\sqrt{2n}\right)$$

converges in distribution as  $n \to \infty$  to a random variable with the Tracy-Widom distribution, described by Tracy, Widom in 1994.

- ▲ Same limit holds generically for unitary random matrix ensembles.
- ▲ Different TW-distributions for orthogonal and symplectic ensembles.



Density of Tracy-Widom distribution. The density is non-symmetric with top at -1.8 and different decay rates for  $x\to +\infty$  and  $x\to -\infty$ 

## **Tracy-Widom distribution**

- lacktriangle There is no simple formula for the Tracy-Widom distribution F(s).
- ▲ First formula is as a Fredholm determinant:

$$F(s) = \det(I - A_s)$$

where  $A_s$  is the integral operator acting on  $L^2(s,\infty)$  with kernel

$$\frac{\operatorname{Ai}(x)\operatorname{Ai}'(y) - \operatorname{Ai}'(x)\operatorname{Ai}(y)}{x - y}$$
 Airy kernel

and Ai is the Airy function.

Second formula

$$F(s) = \exp\left(-\int_{s}^{\infty} (x-s)q^{2}(x)dx\right)$$

where q(s) is a special solution of the Painlevé II equation

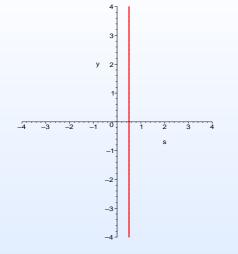
$$q''(s) = sq(s) + 2q^3(s)$$

### Limit laws outside RMT

- ▲ Distribution functions of random matrix theory appear in various other domains of mathematics and physics.
  - **▲ Number theory** 
    - $\blacktriangle$  Riemann zeta-function, L-functions, ...
  - **▲** Representation theory
    - ▲ Young tableaux, large classical groups, ...
  - Random combinatorial structures
    - ▲ random permutations, random tilings, ...
  - **▲ Growth models in statistical physics** 
    - ▲ last passage percolation, polynuclear growth, ...
- ▲ ..., as well as in applications in statistics, finance, information theory, ...

## Riemann zeta function

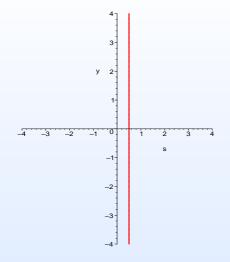
- $\blacktriangle$  The zeta function  $\zeta(s)=\sum\limits_{k=1}^{\infty}\frac{1}{k^s}$  has an analytic continuation to the complex plane.
- ▲ The non-trivial zeros of the zeta function are believed to be on the line  ${\rm Re}\,s=1/2$ . (Riemann hypothesis)



- ▲ Computational evidence: no non-real zeros have been found off the critical line.
- lacktriangleq 1,500,000,000 zeros have been found on the critical line.

## Riemann zeta function

- ▲ The zeta function  $\zeta(s) = \sum\limits_{k=1}^{\infty} \frac{1}{k^s}$  has an analytic continuation to the complex plane.
- ▲ The non-trivial zeros of the zeta function are believed to be on the line  ${\rm Re}\,s=1/2$ . (Riemann hypothesis)



▲ More computational evidence: Spacings between consecutive zeros on the critical line  ${\rm Re}\,s=1/2$  (after appropriate scaling) show the same behavior as the spacings between eigenvalues of a large GUE matrix

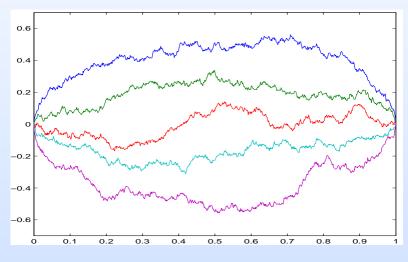


Zeros of  $\zeta(s)$  on the critical line have the same

local behavior as the eigenvalues of a large random matrix

## Non-intersecting Brownian motion paths

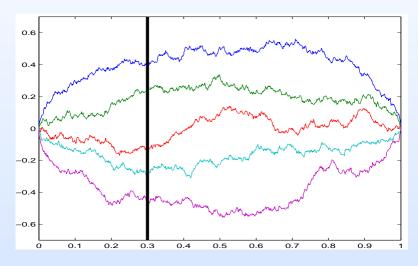
- ▲ Take n independent 1-dimensional Brownian motions with time in [0,1] conditioned so that:
  - ▲ All paths start and end at the same point.
  - ▲ The paths do not intersect at any intermediate time.



**Five non-intersecting Brownian bridges** 

## Non-intersecting Brownian motion

Remarkable fact: At any intermediate time the positions of the paths have exactly the same distribution as the eigenvalues of an  $n \times n$  GUE matrix (up to a scaling factor).

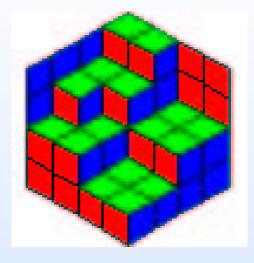


Positions of five non-intersecting Brownian paths behave the same as the eigenvalues of a  $5\times 5$  GUE matrix

▲ This interpretation is basic for the connection of random matrix theory with growth models of statistical physics.

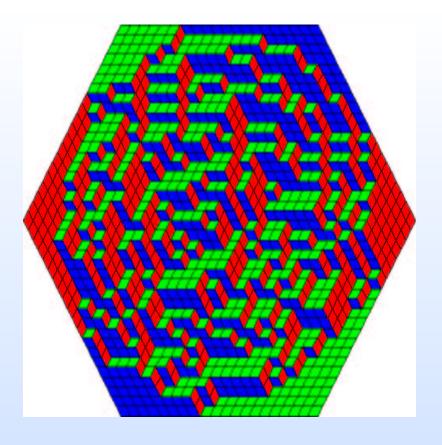
## A random tiling problem

Hexagonal tiling with rhombi.



- ▲ May also be viewed as packing of boxes in a corner.
- ▲ Take a tiling at random.
  - ▲ What does a typical tiling look like, if the number of rhombi increases?

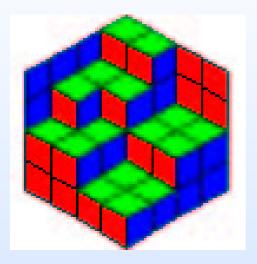
## Typical random tiling

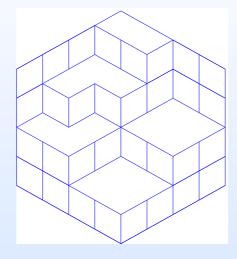


- **▲** Observation:
  - **▲** frozen regions near the corners,
  - **▲** disorder in the center.

# Non-intersecting random walk

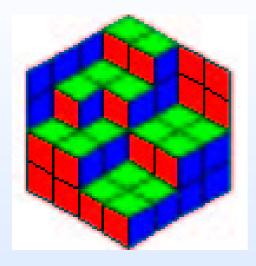
▲ Consider only blue and red rhombi.

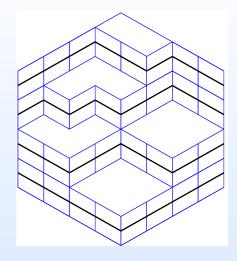




## Non-intersecting random walk

▲ We can connect the left and the right with non-intersecting paths.





- ▲ A random tiling is the same as a number of non-intersecting random walks.
- ▲ As size increases: Tracy-Widom distribution governs the transition between frozen region and disordered region.

Baik, Kriecherbauer, McLaughlin, Miller, (arxiv 2003)

## Other examples

▲ Longest increasing subsequence of random permutations

Baik, Deift, Johansson (1999)

▲ Polynuclear growth model (PNG)
Totally asymmetric exclusion process (TASEP)

Praehofer, Spohn, Ferrari

**Imamura, Sasamoto** 

Buses in Cuernavaca, Mexico

Krbalek, Seba

Baik, Borodin, Deift, Suidan

▲ Airplane boarding problem

**Bachmat** 

## Universality classes in unitary ensembles

lacktriangle Probability measure on  $n \times n$  Hermitian matrices

$$\frac{1}{Z_n}e^{-n\operatorname{Tr}V(M)}dM$$

where  $dM = \prod_j dM_{jj} \prod_{j < k} d\operatorname{Re} M_{jk} d\operatorname{Im} M_{jk}$ 

- ▲ This is a Gaussian ensemble for  $V(x) = \frac{1}{2}x^2$
- ▲ Joint eigenvalue density

$$\frac{1}{\tilde{Z}_n} \prod_{i < j} |x_i - x_j|^2 \prod_{j=1}^n e^{-nV(x_j)}$$

wher

## Determinantal point process

It is special about unitary ensembles that the eigenvalues follow a determinantal point process. This means means that there is a kernel  $K_n(x,y)$  so that all eigenvalue correlation functions are expressed as determinants

$$\mathcal{R}_m(x_1, x_2, \dots, x_k) = \det [K_n(x_i, x_j)]_{i,j=1,\dots,m}$$

 $\mathcal{R}_m(x_1,x_2,\dots,x_k) = \det\left[K_n(x_i,x_j)\right]_{i,j=1,\dots,m}$  \Lambda \int\_a^b K\_n(x,x)dx is expected number of eigenvalues in [a, b]

## Orthogonal polynomial kernel

Let  $P_{k,n}(x)$  be the kth degree monic orthogonal polynomial with respect to  $e^{-nV(x)}$ 

$$\int_{-\infty}^{\infty} P_{k,n}(x)P_{j,n}(x)e^{-nV(x)}dx = h_{k,n}\delta_{j,k}.$$

Correlation kernel is equal to

$$K_n(x,y) = e^{-\frac{1}{2}n(V(x)+V(y))} \sum_{k=0}^{n-1} \frac{1}{h_{k,n}} P_{k,n}(x) P_{k,n}(y)$$

$$= e^{-\frac{1}{2}n(V(x)+V(y))} \frac{h_{n,n}}{h_{n-1,n}} \frac{P_{n,n}(x) P_{n-1,n}(y) - P_{n-1,n}(x) P_{n,n}(y)}{x-y}$$

**Christoffel-Darboux formula** 

## **Asymptotical questions**

- lacktriangle All information is contained in the correlation kernel  $K_n$ .
- ▲ Asymptotic questions deal with the global regime

$$\rho_V(x) = \lim_{n \to \infty} \frac{1}{n} K_n(x, x)$$

- ▲ and with the local regime
  - lacktriangle Choose  $x^*$  and center and scale eigenvalues around  $x^*$

$$\lambda \mapsto (cn)^{\gamma}(\lambda - x^*)$$

▲ This is a determinantal point process with rescaled kernel

$$\frac{1}{(cn)^{\gamma}}K_n\left(x^* + \frac{x}{(cn)^{\gamma}}, x^* + \frac{y}{(cn)^{\gamma}}\right)$$

lacktriangle Determine  $\gamma$  and calculate limit of rescaled kernel. Limits turn out to be universal, depending only on the nature of  $x^*$  in the global regime.

## Global regime

 $\blacktriangle$  In limit  $n\to\infty$  , the mean eigenvalue density has a limit  $\rho=\rho_V$  which minimizes

$$\iint \log \frac{1}{|x-y|} \rho(x) \rho(y) dx dy + \int V(x) \rho(x) dx$$

among density functions  $\rho \geq 0$ ,  $\int \rho(x) dx = 1$ .

**▲** Equilibrium conditions

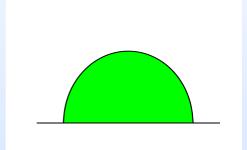
$$2\int\log\frac{1}{|x-y|}\rho(y)dy+V(x)=const \text{ on support of }\rho$$
 
$$2\int\log\frac{1}{|x-y|}\rho(y)dy+V(x)\geq const \text{ outside support }$$

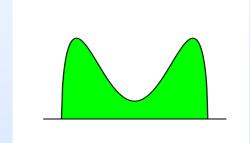
## Regular and singular cases

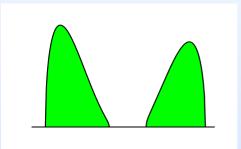
lacktriangle If V is real analytic, then

Deift, Kriecherbauer, McLaughlin (1998)

- lack supp(
  ho) is a finite union of disjoint intervals,
- lacktriangleq 
  ho(x) is analytic on the interior of each interval
- $ho(x) \sim |x-a|^{2k+1/2}$  at an endpoint a for some  $k=0,1,2,\ldots$



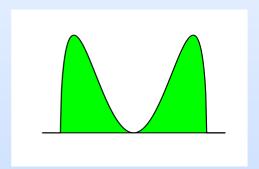


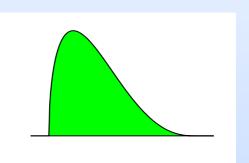


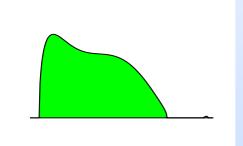
▲ Regular case: positive in interior, square root vanishing at endpoints, and strict inequality in

$$2\int \log \frac{1}{|x-y|} \rho(y) dy + V(x) > const$$
 outside the support of  $\rho$ 

- lacktriangle Singular cases correspond to possible change in number of intervals if parameters in the external field V change.
  - lacktriangle Singular case I: ho vanishes at an interior point
  - ▲ Singular case II:  $\rho$  vanishes to higher order than square root at an endpoint.
  - ▲ Singular case III: equality in equilibrium inequality somewhere outside the support







## Local regime

Limit of rescaled kernel

$$\frac{1}{(cn)^{\gamma}}K_n\left(x^* + \frac{x}{(cn)^{\gamma}}, x^* + \frac{y}{(cn)^{\gamma}}\right)$$

lacktriangle For  $x^*$  in the bulk, we take  $\gamma=1$ ,  $c=
ho(x^*)$ , and limit is the sine

kernel 
$$\frac{\sin \pi (x-y)}{\pi (x-y)}$$

Pastur, Shcherbina (1997), Bleher, Its (1999)

Deift, Kriecherbauer, McLaughlin, Venakides, Zhou (1999)

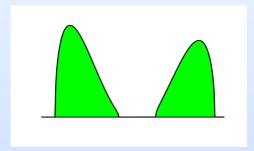
- Scaling limit of kernel follows from detailed asymptotics of the orthogonal polynomials  $P_{n,n}$  and  $P_{n-1,n}$  as  $n\to\infty$ , which is available in the GUE case since then the orthogonal polynomials are Hermite polynomials.
- For more general cases a powerful new technique was developed: steepest descent analysis of Riemann-Hilbert problems

## Regular endpoint

A For a regular endpoint of the support, we take  $\gamma=\frac{2}{3}$ , and the scaling limit is the Airy kernel

$$\frac{\operatorname{Ai}(x)\operatorname{Ai}'(y) - \operatorname{Ai}'(x)\operatorname{Ai}(y)}{x - y}$$

▲ This always gives rise to the Tracy Widom distribution for the fluctations of the extreme eigenvalues.



#### **Unitary ensemble**

$$\frac{1}{Z_n}e^{-n\operatorname{Tr}V(M)}dM$$

## Reference point $x^*$

- ▲ Regular interior point:
- ▲ Regular endpoint:
- ▲ Singular case I:
- ▲ Singular case II:
- ▲ Singular case III:

#### **Unitary ensemble**

$$\frac{1}{Z_n}e^{-n\operatorname{Tr}V(M)}dM$$

#### Reference point $x^*$

- ▲ Regular interior point: sine kernel
- ▲ Regular endpoint: Airy kernel
- ▲ Singular case I:
- ▲ Singular case II:
- ▲ Singular case III:

#### **Unitary ensemble**

$$\frac{1}{Z_n}e^{-n\operatorname{Tr}V(M)}dM$$

#### Reference point $x^*$

- ▲ Regular interior point: sine kernel
- Regular endpoint: Airy kernel
- lacktriangle Singular case I: kernels built out of  $\psi$  functions associated with the Hastings-Mcleod solution of Painlevé II Claeys, AK (2006)
- ▲ Singular case II:
- ▲ Singular case III:

#### **Unitary ensemble**

$$\frac{1}{Z_n}e^{-n\operatorname{Tr}V(M)}dM$$

#### Reference point $x^*$

- ▲ Regular interior point: sine kernel
- Regular endpoint: Airy kernel
- lacktriangle Singular case I: kernels built out of  $\psi$  functions associated with the Hastings-Mcleod solution of Painlevé II Claeys, AK (2006)
- ▲ Singular case II: second member of Painlevé I hierarchy

Claeys, Vanlessen (in progress)

▲ Singular case III:

#### **Unitary ensemble**

$$\frac{1}{Z_n}e^{-n\operatorname{Tr}V(M)}dM$$

#### Reference point $x^*$

- ▲ Regular interior point: sine kernel
- Regular endpoint: Airy kernel
- lacktriangle Singular case I: kernels built out of  $\psi$  functions associated with the Hastings-Mcleod solution of Painlevé II Claeys, AK (2006)
- ▲ Singular case II: second member of Painlevé I hierarchy

**Claeys, Vanlessen (in progress)** 

▲ Singular case III: ??

Extra factor in random matrix model

$$\frac{1}{Z_n} |\det M|^{2\alpha} e^{-n \operatorname{Tr} V(M)} dM$$

The extra factor does not change the global behavior but it does change the local behavior around the reference point  $x^{\ast}=0$ 

- ▲ Regular interior point:
- ▲ Regular endpoint:

- ▲ Singular case I:
- ▲ Singular case II:
- ▲ Singular case III:

Extra factor in random matrix model

$$\frac{1}{Z_n} |\det M|^{2\alpha} e^{-n \operatorname{Tr} V(M)} dM$$

The extra factor does not change the global behavior but it does change the local behavior around the reference point  $x^{\ast}=0$ 

▲ Regular interior point: Bessel kernel

AK, Vanlessen (2003)

▲ Regular endpoint:

- ▲ Singular case I:
- ▲ Singular case II:
- ▲ Singular case III:

#### Extra factor in random matrix model

$$\frac{1}{Z_n} |\det M|^{2\alpha} e^{-n \operatorname{Tr} V(M)} dM$$

The extra factor does not change the global behavior but it does change the local behavior around the reference point  $x^{\ast}=0$ 

▲ Regular interior point: Bessel kernel

AK, Vanlessen (2003)

**A** Regular endpoint: general Painlevé II with parameter  $2\alpha + \frac{1}{2}$ 

$$q'' = sq + 2q^3 - 2\alpha - \frac{1}{2}$$

Its, AK, Östensson (in progress)

- ▲ Singular case I:
- ▲ Singular case II:
- Singular case III:

#### Extra factor in random matrix model

$$\frac{1}{Z_n} |\det M|^{2\alpha} e^{-n \operatorname{Tr} V(M)} dM$$

The extra factor does not change the global behavior but it does change the local behavior around the reference point  $x^{\ast}=0$ 

▲ Regular interior point: Bessel kernel

AK, Vanlessen (2003)

A Regular endpoint: general Painlevé II with parameter  $2\alpha + \frac{1}{2}$ 

$$q'' = sq + 2q^3 - 2\alpha - \frac{1}{2}$$

Its, AK, Östensson (in progress)

- lacktriangle Singular case I: Painlevé II with parameter lpha Claeys, AK, Vanlessen (arxiv 2005)
- ▲ Singular case II:
- Singular case III:

#### Extra factor in random matrix model

$$\frac{1}{Z_n} |\det M|^{2\alpha} e^{-n \operatorname{Tr} V(M)} dM$$

The extra factor does not change the global behavior but it does change the local behavior around the reference point  $x^{\ast}=0$ 

▲ Regular interior point: Bessel kernel

AK, Vanlessen (2003)

A Regular endpoint: general Painlevé II with parameter  $2\alpha + \frac{1}{2}$ 

$$q'' = sq + 2q^3 - 2\alpha - \frac{1}{2}$$

Its, AK, Östensson (in progress)

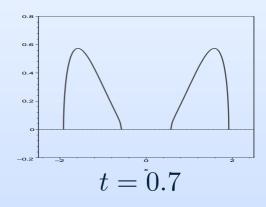
- lacktriangle Singular case I: Painlevé II with parameter lpha Claeys, AK, Vanlessen (arxiv 2005)
- ▲ Singular case II: ??
- ▲ Singular case III: ??

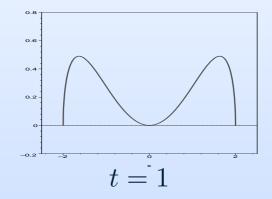
## Singular case I

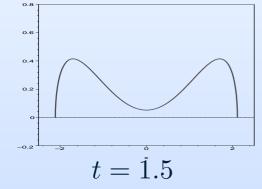
- Quartic external field  $V(x)=rac{1}{4}x^4-x^2$  is simplest singular case I.
- Transition from two-interval to one-interval. If

$$V_t(x) = \frac{1}{t} \left( \frac{1}{4} x^4 - x^2 \right)$$

then for t < 1: two intervals, and for t > 1: one interval







Consider singular case in double scaling limit where we rescale

eigenvalues

$$\lambda\mapsto (c_1n)^{1/3}(\lambda-x^*)$$
 and we let  $t o 1$  as  $n o\infty$ 

such that

$$n^{2/3}(t-1) = c_2 s$$

## Double scaling limit in singular case I

 $\blacktriangle$  One-parameter family of limiting kernels, depending on s , but independent of V

$$-\frac{\Phi_1(x;s)\Phi_2(y;s) - \Phi_2(x;s)\Phi_1(y;s)}{2\pi i(x-y)}$$

 $lack \Phi_1$  and  $\Phi_2$  satisfy a differential equation

$$\frac{d}{dx} \begin{pmatrix} \Phi_1 \\ \Phi_2 \end{pmatrix} = \begin{pmatrix} -4ix^2 - i(s+2q^2) & 4xq + 2ir \\ 4xq - 2ir & 4ix^2 + i(s+2q^2) \end{pmatrix} \begin{pmatrix} \Phi_1 \\ \Phi_2 \end{pmatrix}$$

with parameters s,q and r that are such that q=q(s) satisfies Painlevé II:

$$q^{\prime\prime}=sq+2q^3$$
 and  $r=r(s)=q^\prime(s)$ . for critical quartic  $V$ : Bleher, Its (2003)

for real analytic  $V\colon \mathbf{Claeys}, \mathbf{AK}$  (arxiv 2005)

for less smooth, even V: Shcherbina (arxiv 2006)

lacktriangle Our proof uses the fact that  $\Phi_1$  and  $\Phi_2$  solve a RH problem that can be used as a local parametrix in the steepest descent analysis.