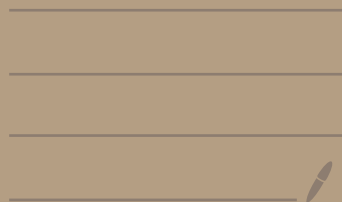


# Universality and delocalization of band matrix

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Joint work with  
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Recall Wigner Random Matrix:

$$H = H^\dagger, \quad H_{ij} \text{ i.i.d. } \mathbb{E}(H_{ij}) = 0, \quad \mathbb{E}(|H_{ij}|^2) = 1/N$$

$$1 \leq i, j \leq N$$

In the last 10 years, we have seen many variations.

- \* Not identical distribution
- \* Not mean zero
- \* Not uniform variance
- \* Not quite independent
- \* With spikes (like E. R graph)

In a Wigner random band matrix, we have the properties 1, 3, 5, but the most important is that it is a **Non-mean-field** model.

$$H_{xy} = 0, \quad a.s. \quad \text{if } |x - y| \gg W$$

In a system with size length  $L$ , there is no interaction between  $x$  and  $y$ , if the distance between them is much greater than  $W$  (interaction scale).

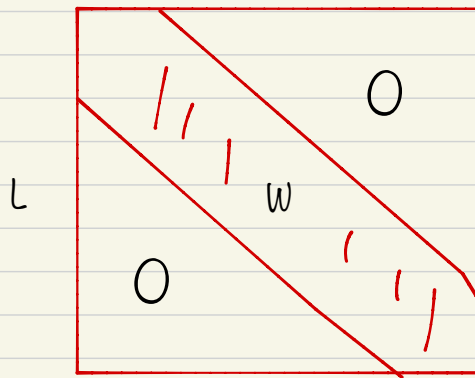
$W$  is called band width

A more precise definition:

$$H = H^\dagger, \quad H_{ij} \text{ i.d.} \quad \mathbb{E}(H_{xy}) = 0, \quad \mathbb{E}(|H_{xy}|^2) = S_{xy}$$

$$1 \leq x, y \leq (\mathbb{Z}_N)^d$$

$$\sum_x S_{xy} = 1, \quad S_{xy} = O(1/W), \quad S_{xy} = 0 \text{ if } \|x - y\| \gg W$$



The interesting case is

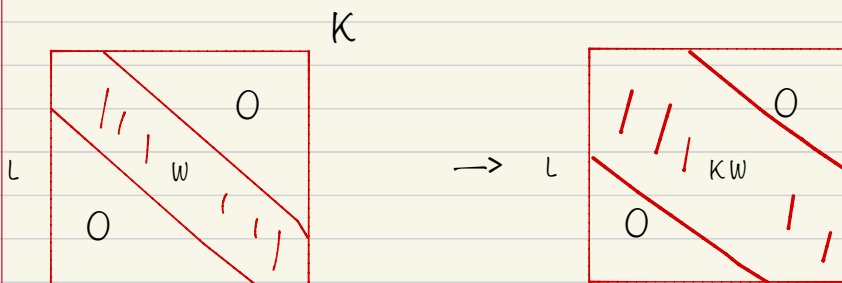
$$W = L^a, \quad 0 \leq a \leq 1$$

Global statistics: 2009 Erdos, Yau and Y:

Semi-Circle law holds up to scale  $W^{\{-d\}}$ .



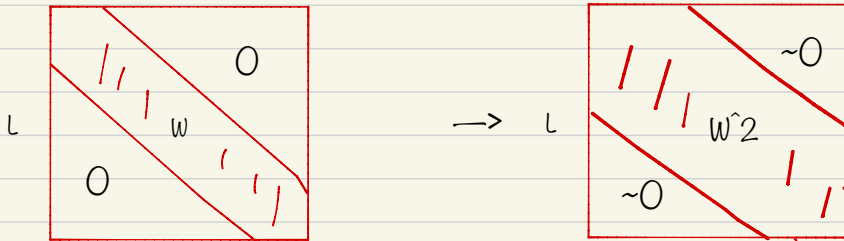
Interest property : ...



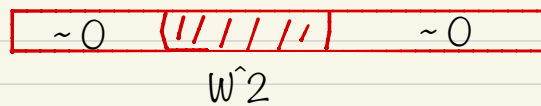
But it could be still a band matrix, even if the power  $K$  is very very large.

$$d=1$$

$K \rightarrow \text{infinity}$



The reason is that in this case most eigenvectors of  $H$  are localized in the scale of  $\hat{w}^2$ :



Recall:

$$H^k = \sum_{\alpha} \lambda_{\alpha}^k v_{\alpha}^{\dagger} v_{\alpha}$$

On the other hand, physicists want to know why sometimes it is **delocalized**

30 years ago, numerical calculations (P.R.L) and non-rigorous super symmetry (P.R.L) arguments showed that there is a phase transition between localization and delocalization.

## Random Band Matrix Conjecture (bulk)

$$d = 1 \quad W \sim L^{1/2}$$

$$d = 2 \quad W \sim (\log L)^{1/2}$$

$$d \geq 3 \quad W \gg 1 \quad (W \geq 3)$$

It is also the threshold for local statistics:

Small  $W$

Poisson distribution

Large  $W$

RM distribution (Sine-kernel)

The main new work for this talk is: 2020, Yau, Yang and Y  
Delocalization of eigenvectors holds if

$$d \geq 10, \quad W = L^a, \quad a > 0$$

## A quick review on previous results

### Universality part:

$W \sim L$                       Bourgade, Erdos, Yau and Y 2015

$W \gg L^{3/4}$                       Bourgade, Yau, Yang and Y 2017-18

### Localization part:    for $d=1$ Gaussian band matrices

$W \ll L^{1/8}$                       J. Schenker

$W \ll L^{1/7}$                       R. Peled, J. Schenker, M. Shamir and S. Sodin

For delocalization part:  $d=1$

$$W \gg L^{6/7}$$

Erdos and Knowles

$$W \gg L^{4/5}$$

Erdos, Knowles, Yau and Y.

$$W \gg L^{7/9}$$

Y. He and M. Marcozzi

$$W \gg L^{3/4}$$

Bourgade, Yau, Yang and Y

For Edge eigenvector:

$$W \sim L^{5/6},$$

S. Sodin (moment method)



For supersymmetry:

When the entries are Gaussian with some specific covariance profile, one can apply supersymmetry techniques

$$W \sim L$$

T. Shcherbina 2014

$$W \sim L^{\wedge}(6/7)$$

Bao and Erdos 2017

$$W \sim L^{\wedge}(1/2)$$

T. Shcherbina and M. Shcherbina 2017, 2019

$$W \sim L^{\wedge}(1/2)$$

M. Disertori, M. Lohmann, S. Sodin 2018

For delocalization,  $d \geq 1$ ,  $W = \hat{L} a$

$$a > \frac{6}{d+6}$$

L. Erdos and A. Knowles

$$a > \frac{d+2}{2d+2}$$

L. Erdos, A. Knowles, Yau and Y

$$a > \frac{d+1}{2d+1}$$

Y. He and M. Marozzi

$$a > \frac{2}{2d+2}$$

Yang and Y. 2019-2020

## Main new result of this talk

$$a > 0, d \geq 10$$

Yau, Yang and Y 2020

Hope to finish the proof for  $d \geq 6$  in the next year.

## Resolvent Tool

$$G = (H - z)^{-1}, \quad z \in \mathbb{C}$$

Delocalization of eigenvectors is implied by the following sense of delocalization of resolvent:

$$\exists \eta > 0, \quad s.t. \quad \forall E \in (-2, 2), \quad \forall \ell \ll L$$

$$\max_x \frac{\sum_{|y-x| \leq \ell} |G_{xy}(z)|^2}{\sum |G_{xy}(z)|^2} \ll 1, \quad z = E_0 + i\eta$$

Usually people choose  $\eta \sim W^2/L^2$

When  $\eta$  is larger, the above inequality does not hold.

But actually resolvent **polynomially decays**

(slower than power of  $d$ )

$$|G_{xy}|^2 \sim L/W^2, \quad d = 1$$

$$|G_{xy}|^2 \sim 1/W^2, \quad d = 2$$

$$|G_{xy}|^2 \sim \frac{1}{W^d + W^2 |x - y|^{d-2}}, \quad d \geq 3$$



$$\max \sim W^{-d}, \quad \min \sim \frac{1}{W^2 L^{d-2}}$$

The main contribution comes from  $|x-y| \sim L$  (min part)

Therefore, really we need to **prove this profile** for delocalization.

Previous tool / work

$$L_{\max} : \max_{x \neq y} |G_{xy}| \sim W^{-d/2} \quad (\text{highly non-trivial})$$

$$L_2 : \sum_y |G_{xy}|^2 \sim 1/\eta$$

In this work, we need to

$$\begin{aligned} G_{xy} \sim & (W^{-d/2} - \text{term}) + (W^{-d} - \text{term}) + (W^{-3d/2} - \text{term}) \\ & + (\dots) + (W^{-kd/2} - \text{term}) + (\dots) \\ & + (W^{-2}|x-y|^{-d+2} - \text{term}) \end{aligned}$$

Actually, we do (term by term) prove these terms are **zeros**,  
except the last one.

## Universal - Expansion

We expand the resolvent with  
some resolvent identities  
some conditional expectation tricks  
and a well designed rule on expansion order,  
(which will be the main component of the first paper in this series)

Why Universal:

There is a large universal expansion, for  $W = \hat{L}^a$ , for fixed  $a > 0$ ,  
we will only use a subpart of the whole expansion.

$$\mathcal{P}_a \subset \mathcal{P}_{a'}, \quad a \geq a'$$

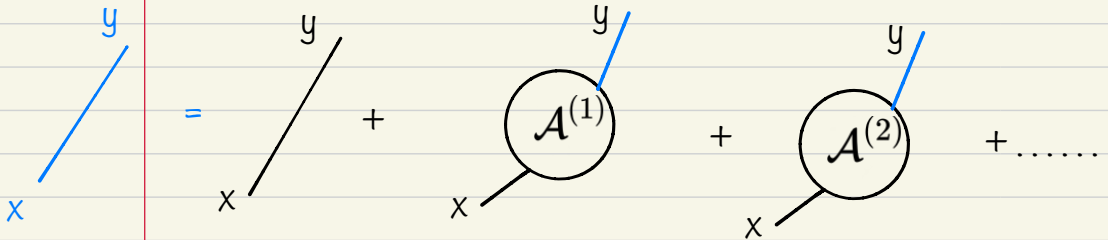
The limit expansion has a very clear fractal structure

$$\lim_{a \rightarrow 0} \mathcal{P}_a = \mathcal{P}_0$$

Different  $W$  cases share the same expansion is a very important property  
for our proof. (You will see soon)

$$T_{xy} := \sum_{y': |y'-y| \sim W} |G_{xy'}|^2$$

$$T = B + B \cdot \mathcal{A} \cdot T, \quad B = S(I - S)^{-1}, \quad S_{xy} = \mathbb{E}|H_{xy}|^2$$



(B has the profile as above)

$$\|B\|_{L_1 \rightarrow L_\infty} \sim \eta^{-1}$$

Here  $\mathcal{A}^{(k)}$  is the sub graphs with  $\sum_{z'} \mathcal{A}_{zz'}^{(k)} \sim (W^{-d/2})^k$

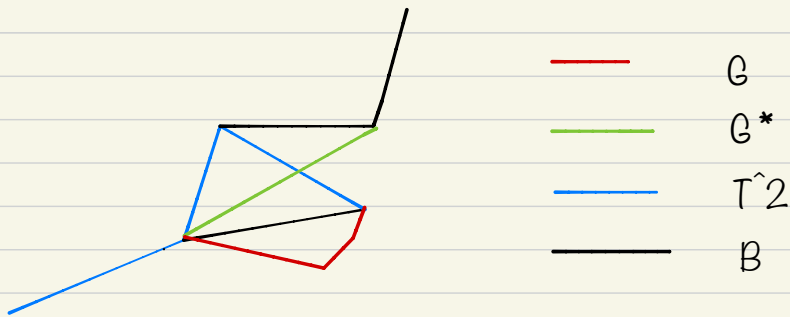
With some non-trivial cancellation (i.e.,  $\mathcal{Z}$  lemma idea), one can show

$\hat{A}^1$  term is zero.

Therefore, it would be an *effective* expansion if

$$\eta^{-1} W^{-d} \ll 1, \quad i.e., \quad L \ll W^{\frac{d+2}{2}}$$

## Complexity of the expansion



Even for such simple case:

Each free index:  $K^d$

Each  $G$  edge.  $K^{(-d/2+1)}$  if  $|x-y| \sim K$

Each  $B, T$  edge.  $K^{(-d+2)}$

Expansion seems not a good idea, since one extra edge can not cancel the factor contributed by one free index.

The expansion does not produce enough edges .

The more expansion (with no correct plan),  
the messier (out of control) the graphs will be.



## The number of graphs

k-th order:  $A^{\wedge}(k)$  has about  $(2k)^{\wedge}(3k)$  graphs.

k=2, with some simplification,

there are about hundreds of graphs

k=3, with help of computer (Matlab),

it took iMac 1 hr on computation and me 1 month in coding

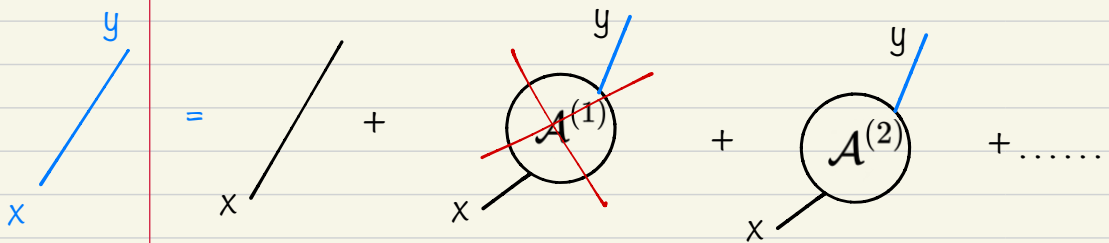
k=4, computer basically never stop

Due to shortage of time,

I will only focus on **one of main novelty** in the proof.

The whole proof is composed of 3 papers (or more).

## SUM ZERO



Sum up  $x$  and  $y$

$$L^d \eta^{-1}$$

$$L^d \eta^{-1}$$

$$\eta^{-2} \sum_{zz'} \mathcal{A}_{zz'}^{(2)}$$

It turns out if we choose

$$L^2/W^2 \cdot W^{-3d/2} \ll 1, \quad L^2/W^2 \cdot W^{-d} \gg 1$$

Then

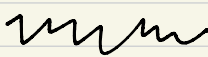
$$L^2/W^2 \sum_{z'} \left( \mathcal{A}^{(2)} \right)^{z'}_{z} \ll 1$$

$$\begin{array}{c} \text{Diagram 1} \\ \text{Diagram 2} \end{array} \Rightarrow L^2/W^2 \sum_{z'} \left( \text{Diagram 3} \right)^{z'} = 0$$

SUM ZERO

Example:

$$\sum_{z''} \left( \text{Diagram 1} \right)^{z''} - \sum_{z''} \left( \text{Diagram 2} \right)^{z''}$$

 S-edge

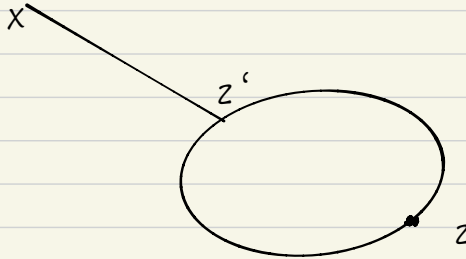
Why is Universal so important:

For certain  $L$ , we obtain the **sum zero property** of some  $\hat{A}(k)$

From sum zero property, we know the **cancellation** between the graphs in  $\hat{A}(k)$

Since for other (larger)  $L$ 's, we use **same** graphs, so in those cases,  $\hat{A}(k)$  also has **sum zero** property for larger  $L$  case.

Why is it so important ?



$$\sum_{z'} B_{xz'} \mathcal{A}_{z'z} = \sum_{z'} (B_{xz'} - B_{xz} - \partial_z B_{xz}(z' - z)) \mathcal{A}_{z'z}$$

Thanks