

Expected Moments of the Spectral Measure for 2-Level Bipartite Graph Adjacency Matrices

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Motivation

- Introduced by Wigner to study spacings between energy levels of heavy nuclei

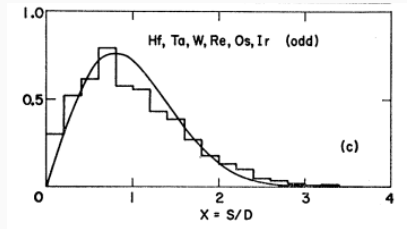


Figure 1: Energy levels of heavy nuclei

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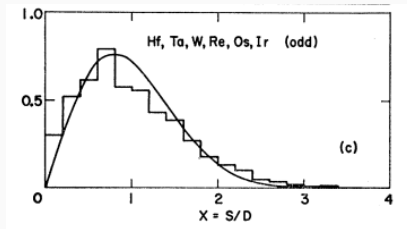


Figure 1: Energy levels of heavy nuclei

- Random matrices can be applied to a variety of spectra: zeroes of the Riemann Zeta function, heavy nuclei, bus arrivals.

Real, Symmetric Matrices

- Wigner showed that the eigenvalues of a **real, symmetric matrix** i.i.d.r.v entries converges to a semicircular distribution.

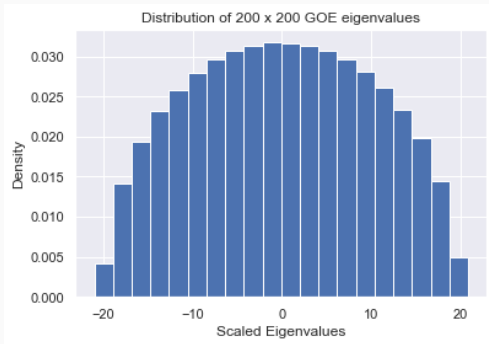


Figure 2: Distribution of eigenvalues

The McKay Ensemble

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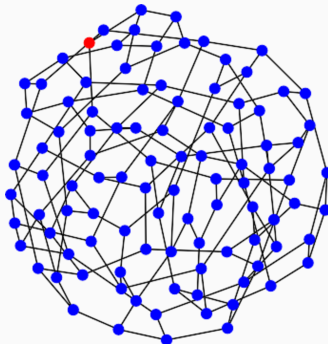


Figure 3: Random 3-regular graph on 100 vertices.

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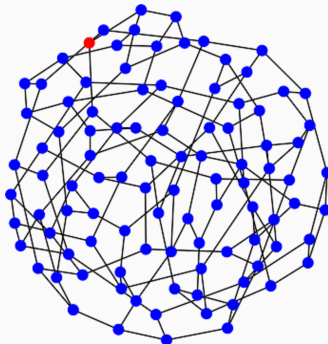


Figure 3: Random 3-regular graph on 100 vertices.

- Aside from trivial eigenvalue d , remaining eigenvalues admit a limiting distribution as $n \rightarrow \infty$, the Kesten-McKay distribution.

The McKay Law

- McKay: excluding trivial eigenvalue d , the empirical spectral distribution converges to

$$f(x) := \frac{d\sqrt{4(d-1) - x^2}}{2\pi(d^2 - x^2)} \quad \text{for } |x| \leq 2\sqrt{d-1}.$$

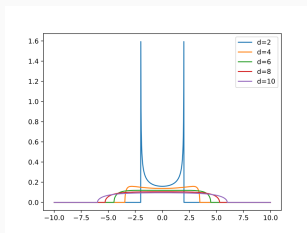


Figure 4: Kesten McKay Law

- Regular-graph analogue of semicircle law. Can create a new random matrix ensemble, similar to the ensemble of checkerboard matrices.

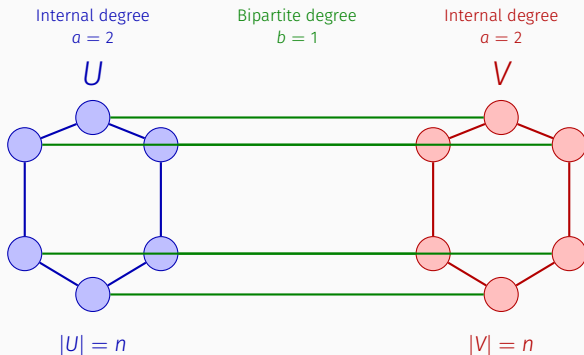
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($m_0 = 1, m_1 = 0, m_2 = d, m_3 = 0, m_4 = 2d^2 - d, \dots$)
- We considered a specific subset of the d -regular graphs.
- We impose a bipartite structure within the graph to observe how connectivity within the graph impacts the lower order terms of the moments.

Our Set Up

Consider two sets of vertices U, V , each with n vertices.
Consider a b -regular bipartite graph on U and V . Now within each of U and V impose $a = d - b$ -regularity.



Every vertex has degree $a + b = 2 + 1 = 3$

Let $A = (a_{ij})_{i,j=1}^N$ denote the adjacency matrix of G , and define the k th moment of its empirical spectral measure by

$$\mu_k(A) := \frac{1}{n} \sum_{i=1}^n \lambda_i^k = \frac{1}{n} \text{Tr}(A^k).$$

$$\text{Tr}(A^k) = \sum_{i=1}^n (A^k)_{ii}.$$

First and second moment

Corollary (1st moment)

For a random (a, b) -regular two-level bipartite graph,

$$\mathbb{E}[\mu_1(A)] = 0.$$

Corollary (2nd moment)

For a random (a, b) -regular two-level bipartite graph,

$$\mathbb{E}[\mu_2(A)] = d = a + b.$$

Proof of Lemma (2)

Because A is symmetric and its entries belong to $\{0, 1\}$,

$$\begin{aligned}\text{Tr}(A^2) &= \sum_{i=1}^N \sum_{j=1}^N a_{ij} a_{ji} \\ &= \sum_{i=1}^N d.\end{aligned}$$

Theorem

The expected moment for the (a,b) -regular two-level bipartite graph is

$$\mathbb{E}[\mu_k] = m_k(a + b) + \frac{R_k(a, b)}{N} + O(N^{-2}),$$

where

- m_k is the k^{th} moment of the Kesten-McKay distribution
- $R_k(a, b)$ is the expected number of Betti number $\beta = 1$ k -cycles

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- Decomposing the moment contribution by Betti number

$$\beta = |E| - |V| + 1:$$

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 - Represents a simple core c -cycle ($c \leq k$) decorated with tree tails.
- $\beta \geq 2$ (Multicyclic Diagrams):
 - Scale: $O(1/N^2)$ or smaller
 - Vanishes in the leading-order $1/N$ moment correction.

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- We count the number of ways to choose vertices and half-edges of the assigned vertices.
- For the probability, we will assume all a half-edges have uniform probability to connect to all of the remaining a half-edges in the same N_i set, and all b half-edges have uniform probability of connecting to the b half-edges in the opposite set.

Example of using half-edge technique for Betti one

Vertex choices:

$$n(n-1)(n-2) \cdot n.$$

Here $n(n-1)(n-2)$ chooses three ordered vertices in N_1 , and n chooses one vertex in N_2 .

Half-edge choices:

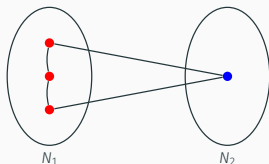
$$ab, \quad a(a-1), \quad ab, \quad b(b-1),$$

so their product is

$$a^3b^3(a-1)(b-1).$$

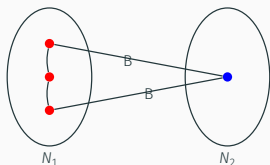
Contribution to the fourth moment

$$\frac{8n(n-1)(n-2) \cdot n a^3b^3(a-1)(b-1)}{(na-1)(na-2)(nb-1)nb} = 8ab(a-1)(b-1) + O\left(\frac{1}{N}\right).$$



Configuration 2.1

Example of using half-edge technique for Betti one



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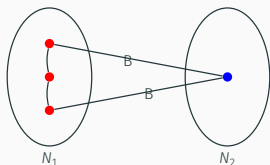
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$$\frac{8n(n-1)(n-2)na^3b^3(a-1)(b-1)}{(na-1)(na-2)(nb-1)nb}$$

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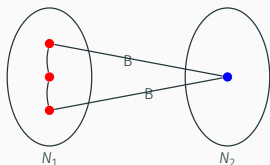
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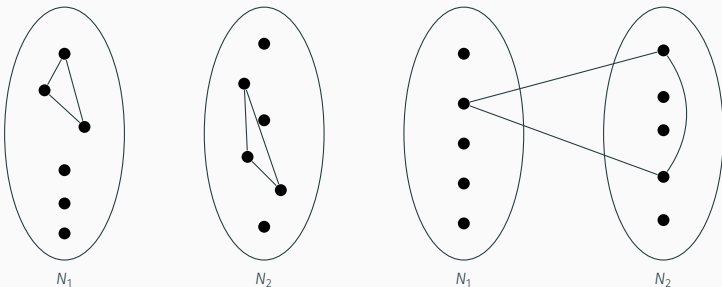
In general, the contribution corresponding to w is

$$a^{n_{BA}(w)}b^{n_{AB}(w)}(a-1)^{n_{AA}(w)}(b-1)^{n_{BB}(w)}.$$

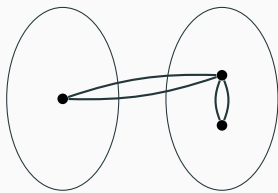
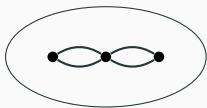
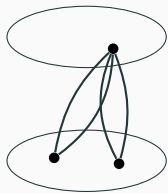
Third moment

We divide the triangles into three classes:

1. triangles whose three vertices lie in N_1 ;
2. triangles whose three vertices lie in N_2 ;
3. triangles having two vertices in one level and one vertex in the other level.



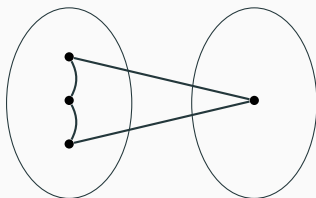
Fourth Moment: non-simple 4-cycles



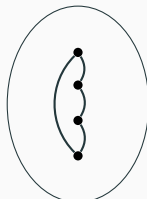
We compute the contributions manually in this case

- $2(b(b-1) + b^2)N$
- $2(a(a-1) + a^2)N$
- $4abN$

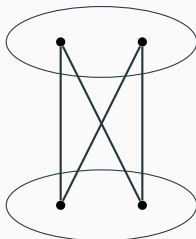
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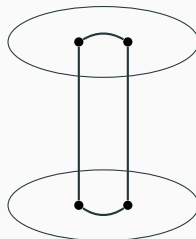
BAAB



AAAA



BBBB



ABAB

Third and Fourth Moments

Corollary

Let G be a random (a, b) -regular two-level graph on $N = 2n$ vertices, and let A be its adjacency matrix. For fixed a and b , as $N \rightarrow \infty$,

$$\mathbb{E}[m_3(A)] = \frac{2(a-1)^3 + 6ab(b-1)}{N} + O\left(\frac{1}{N^2}\right).$$

Moreover,

$$\begin{aligned}\mathbb{E}[m_4(A)] &= 2(a+b)^2 - (a+b) \\ &\quad + \frac{1}{N} \left[2(a-1)^4 + 2(b-1)^4 \right. \\ &\quad \quad \left. + 8a(a-1)b(b-1) + 4a^2b^2 \right] \\ &\quad + O\left(\frac{1}{N^2}\right).\end{aligned}$$

Considerations for Higher Order Moments

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- In general, we can count these cycles by breaking it up into a simple cycle and the number of excursion edges.
- We already know how to calculate the number of cycles, so we must count the number of symmetries that these tree-like excursions create.

Core Cycle Counts $B_s(a, b)$ via Parity Linear Recurrences

- Let $C_l(a, b)$ be the number of l -cycles.
- Windings around the cycle are accounted for via divisibility:

$$B_s(a, b) = \sum_{\substack{3 \leq l \leq s, \\ l|s}} 2l C_l(a, b)$$

- *Example* ($s = 6$): $B_6 = 12C_6 + 6C_3$ (includes twice-wound triangles!).

Excursion Counting

Definition: $h_{k,s}(d)$ counts length- k walks spending s steps on the core cycle and $k - s$ steps executing tree-like excursions.

Base Conditions ($k = 0$):

$$h_{0,0}(d) = 1, \quad h_{0,s}(d) = 0 \quad \text{for } s > 0$$

Step-by-Step Recurrence ($k \rightarrow k + 1$):

$$h_{k+1,0}(d) = d \cdot h_{k,1}(d) \quad (\text{Return to core root})$$

$$h_{k+1,1}(d) = h_{k,0}(d) + (d - 1)h_{k,2}(d) \quad (\text{Adjacent to core})$$

$$h_{k+1,s}(d) = h_{k,s-1}(d) + (d - 1)h_{k,s+1}(d) \quad \text{for } s \geq 2 \quad (\text{Deep tree excursions})$$

Parity Rule

$h_{k,s}(d) = 0$ whenever $k \not\equiv s \pmod{2}$.

Excursion Coefficients

Generating coefficients row-by-row via the 2D recurrence:

$k \setminus s$	0	1	2	3	4	5
0	1	0	0	0	0	0
1	0	1	0	0	0	0
2	d	0	1	0	0	0
3	0	$2d - 1$	0	1	0	0
4	$2d^2 - d$	0	$3d - 2$	0	1	0
5	0	$5d^2 - 6d + 2$	0	$4d - 3$	0	1

- **Tree Column ($s = 0$):** Gives the Kesten–McKay bulk moment $m_k(d)$.
- **Unicyclic Term ($s \geq 3$):** $h_{5,3}(d) = 4d - 3$, which directly multiplies $B_3(a, b) = 6C_3$ to form $6(4d - 3)C_3$ in $R_5(a, b)$.

The total count for the number of cycles then becomes:

$$R_k(a, b) = \sum_{s=3}^k h_{k,s}(d) B_s(a, b).$$

$$R_3(a, b) = 6C_3$$

$$R_4(a, b) = 8C_4$$

$$R_5(a, b) = 10C_5 + 6(4d - 3)C_3$$

$$R_6(a, b) = 12C_6 + 6C_3 + 8(5d - 4)C_4$$

Takeaways

- The lower order terms do depend on a and b , while the leading order term does not
- Closed walks with $\beta = k$ impact terms of order

$$\frac{1}{N^{k+i}}$$

where $i \geq 0$

Further Directions

- Generalize the work to higher moments and possibly to lower orders of N
- Further explore combinatorial interpretations of lower order terms
- Extend the analysis to other classes of graphs to gain further insight



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Thank You

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