Local Kesten–McKay law for random regular graphs

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Random regular graph

 $G_{N,d}$ is the set of *d*-regular graphs on *N* vertices (without loops and multiedges). The random regular graph is the uniform probability measure on $G_{N,d}$.



Adjacency matrix $A_{ij} := \mathbf{1}_{i \sim j}$. Trivial eigenvalue d.

Normalized adjacency matrix $H := A/\sqrt{d-1}$.

Focus in this talk: d fixed (large) and $N \to \infty$. (Earlier results for $d \ge (\log N)^4$.)

Background: Kesten-McKay law

For $d \ge 3$ fixed, asymptotically almost surely as $N \to \infty$,



Weak convergence (η fixed).

Background: Numerical evidence for random matrix statistics

Numerical evidence that local eigenvalue statistics of random regular graphs are governed by Gaussian Orthogonal Ensemble (GOE).



Eigenvalue gaps for random 3-regular graphs on 2000 vertices (figure from Jakobson-Miller-Rivin-Rudnick)



2.85

250

2.75

N= 2000

Numerical results: Jakobson-Miller-Rivin-Rudnick; Newland-Terras; Oren-Smilansky.

Extensive predictions: Smilansky et al.

Results for $d \in [N^{\varepsilon}, N^{2/3-\varepsilon}]$: Bauerschmidt-Huang-Knowles-Yau (eigenvalue gaps).

Background: Eigenvector delocalization

Random regular graphs have only nonlocalized eigenvectors (with high probability). For example, all eigenvectors v obey

$$\|v\|_{\infty} = O\left(\frac{1}{(\log N)^c}\right).$$

Stronger results are also known, and such estimates actually hold for regular graphs under the deterministic assumption of local tree-like structure (later). References: Brooks–Lindenstrauss, Dumitriu–Pal, Geisinger.

The eigenvectors v of the GOE are uniform on the sphere and therefore (whp)

$$\|v\|_{\infty} = O\left(\sqrt{\frac{\log N}{N}}\right).$$

Similar estimates are now also known for much more general random matrices.

Example result: Eigenvector delocalization

Background: the eigenvectors v of the GOE satisfy (whp)

$$\|v\|_{\infty} = O\left(\sqrt{\frac{\log N}{N}}\right).$$

Theorem (Bauerschmidt-Huang-Yau 2016)

Fix $d \ge 10^{40}$. Then the eigenvectors v of a random d-regular graph satisfy (whp)

$$\|\mathbf{v}\|_{\infty} = O\left(\frac{(\log N)^{100}}{\sqrt{N}}\right),$$

simultaneously for all eigenvectors v with eigenvalues $|\lambda| < 2\sqrt{d-1} - \varepsilon$.

Preliminaries: Green's function

Green's function (resolvent): $G_{ij}(z) = (H - z)_{ij}^{-1}$ for $z \in \mathbb{C}_+ = \{ \operatorname{Im} z > 0 \}$.

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Spectral density:



• Eigenvectors: if Hv = Ev then

$$\|v\|_{\infty} \leqslant \sqrt{\eta \max_{i} \lim G_{ii}(E+i\eta)}$$
 for any $\eta > 0$

• We are interested in $z = E + i\eta$ close to the spectrum: $\eta \approx 1/N$.

Preliminaries: Local geometric structure of random regular graph

In a random *d*-regular graph, up to radius $R = c \log_d N$, with high probability:



Most *R*-balls have no cycles.



All *R*-balls have few cycles.

Let G(z) = (A/√d − 1 − z)⁻¹ be the Green's function of the d-regular tree;
 and G⁽ⁱ⁾(z) be that the graph from which vertex i is removed.



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Since $G_{ji}^{(i)}(z)$ is independent of $i \sim j$, the second equation closes:

$$G_{jj}^{(i)}(z)=m_{sc}(z), \hspace{1em} ext{where} \hspace{1em} m_{sc}(z)=-\Big(z+m_{sc}(z)\Big)^{-1},$$

and

$$G_{ii}(z)=m_d(z), \quad ext{where } m_d(z)=-\left(1+rac{d}{d-1}m_{sc}(z)
ight)^{-1}.$$

Preliminaries: Kesten-McKay law

Locally tree-like structure \rightarrow Kesten–McKay law: For $z \in \mathbb{C}_+$ fixed,

$$rac{1}{N}\operatorname{Tr}(G(z)) o m_d(z)$$

Equivalent:

$$\frac{1}{N}\sum_{j}\delta_{\lambda_{j}}\longrightarrow\rho_{d}^{KM}(x):=\left(1+\frac{1}{d-1}-\frac{x^{2}}{d}\right)^{-1}\frac{\sqrt{[4-x^{2}]_{+}}}{2\pi}.$$





For the infinite tree, the off-diagonal elements can be computed in the same way:

$$G_{ij}(z) = m_d(z) \left(-rac{m_{sc}(z)}{\sqrt{d-1}}
ight)^{{
m dist}(i,j)}$$

Here $|m_{sc}(z)| \leq 1$ and $|m_d(z)| \leq 1 + O(1/d)$ uniformly in $z \in \mathbb{C}_+$. In particular, the Green's function decays exponentially and is approximately given by

$$G_{ij}(z) \approx (d-1)^{-\operatorname{dist}(i,j)/2}.$$

Preliminaries: Local semicircle law

For random Wigner matrices (i.i.d. entries):

Semicircle law (Wigner): For $z \in \mathbb{C}_+$ fixed (whp)

 $rac{1}{N}\operatorname{Tr}(G(z)) o m_{sc}(z).$

Local semicircle law (Erdős–Schlein–Yau): For Im $z \gg 1/N$ (whp)

$$\max_{i} |G_{ii}(z) - m_{sc}(z)| \ll 1.$$
 (+)

(+) implies for example that any eigenvector v satisfies

$$\|v\|_{\infty} \leqslant \sqrt{(\operatorname{\mathsf{Im}} z)(m_{sc}(z) + o(1))} \approx rac{1}{\sqrt{N}}$$

and that spectral density is concentrated on scale $\gg 1$. Such estimates are fundamental in understanding local statistics (Erdős–Schlein–Yau; Tao–Vu).

(+) is not true for random *d*-regular graphs with fixed *d* (even with $m_{sc} \rightsquigarrow m_d$).

Local and global structure

General intuition:

Random regular graphs are locally given by (almost deterministic) tree-like graphs which are glued together randomly.

The local structure is given by tree-like neighborhoods.

- Our proof uses that the tree-like structure is valid for radii $\ell \approx \log_d \log N$.
- For $d \gg \log N$, we only need $\ell = 1$: this is the constraint that each vertex has exactly d neighbors.

The boundaries of such neighborhoods have $\gg \log N$ edges. This permits the use of concentration estimates.



The global structure is partially captured by invariance (reversibility) under switching dynamics.



Definition: tree extension



- Recall: most neighborhoods in a random regular graph look locally like a regular tree, but some neighborhoods can have a bounded number of cycles.
- We condition on a large ball $\mathcal{T} = \mathcal{B}_{\ell}(1, \mathcal{G})$ of radius $\ell = c \log_d \log N$ that has only a bounded number of cycles. Its boundary has size $\Omega(\log N)^c$.

Definition: tree extension



- We replace the graph outside the ball by infinite trees attached to the boundary. We call this graph the tree extension or TE(*T*).
- Thus TE(*T*) is an infinite graph for which we understand the Green's function very well (expanding the bounded number of cycles about a tree graph).

Main result

Let $\mathcal{E}_r(i, j, \mathcal{G})$ be the union of all paths $i \to j$ of length at most $r = c \log_d \log N$.



Theorem (Bauerschmidt-Huang-Yau 2016)

Fix $d \ge 10^{40}$. Then simultaneously for all $z \in \mathbb{C}$ with $\operatorname{Im} z \ge N^{-1}(\log N)^{200}$ and $|z \pm 2| \ge 1/(\log N)$, and simultaneously for all $i, j \in \llbracket N \rrbracket$, with high probability,

$$G_{ij}(\mathcal{G};z) = \underbrace{G_{ij}(\mathsf{TE}(\mathcal{E}_r(i,j,\mathcal{G});z))}_{P_{ij}(\mathcal{E}_r(i,j,\mathcal{G});z)} + O((\log N)^{-C}).$$

Implies ℓ^{∞} eigenvector delocalization and local Kesten–McKay law.

Initial estimates for Im $z = \Omega(1)$.

For z far from the spectrum, the random walk picture for $G_{ii}(z)$ is valid.



- Decay. For z away from the spectrum, $G_{ij}(z)$ decays exponentially in dist(i, j) with rate at least Im z: relevant walks are of length less than 1/Im z.
- Geometry. Locally tree-like structure implies (deterministically) that most pairs of vertices on the boundary are far from each other.

Multiscale approach for $\text{Im } z \ll 1$.

For $\text{Im } z \ll 1$ the random walk expansion would be highly oscillatory and involve very long paths which we cannot control. Thus we do not use it.



- Multiscale approach. Use estimates for some $z \in \mathbb{C}_+$ to get same estimates for $z \varepsilon i$ with slightly lower probability, say $\varepsilon = N^{-3}$. Iterate to $\text{Im } z \approx 1/N$.
- The main difficulty is to get this improvement.

Boundary resampling



Condition on $\mathcal{B}_{\ell}(1,\mathcal{G})$.

Pair boundary edges of ball with random edges from graph.

Call this pairing the resampling data **S**.

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- This defines the switched graph $\tilde{\mathcal{G}} = \mathcal{T}_{\mathsf{S}}(\mathcal{G})$.
- Outer boundary vertices of $\mathcal{B}_{\ell}(1, \tilde{\mathcal{G}})$ are random under the randomness of **S**.

Use of randomness of boundary resampling

We use the randomness of the boundary in the switched graph to obtain two key estimates for the switched graph.

- (a) Improved decay of the Green's function between most pairs of distinct boundary vertices.
- (b) Concentration of a certain average of the diagonal elements Green's function over the boundary.

These estimates ultimately allow us to obtain a more precise expansion of the Green's function in the interior and advance the iteration.



Use of randomness (a): Improved decay estimate

- For the tree and the tree extensions, we have $P_{ij}(z) \approx (d-1)^{-d(i,j)/2}$.
- Our goal is to prove that the tree extension is accurate up to distance r.
- For distances > r, we do not have an estimate better than $(d-1)^{-r/2}$.

Problem:

There are $\approx (d-1)^{2\ell} = (d-1)^r$ pairs of boundary vertices.

Even if all paths between these pairs are much longer than r, the previous estimate is not sufficient to bound their contribution.

Upshot:

■ We need a better estimate for the Green's function between distinct boundary vertices. We obtain these using that the boundary is essentially random.

Use of randomness (a): Improved decay estimate

Example. Fix a vertex x. Assume Im $G_{xx}(z) \leq 2$ and Im $z \gg (\log N)^{200}/N$. Then

$$\frac{1}{N}\sum_{b=1}^{N}|G_{xb}(z)|^{2}=\frac{\mathrm{Im}\ G_{xx}(z)}{N\,\mathrm{Im}\ z}\ll(\log N)^{-200}.$$

Let b_1, \ldots, b_μ be independent uniformly random vertices, with say $\mu = (\log N)^5$, independent of the graph. Then (Markov's inequality and union bound)

$$|G_{xb_i}| \leq M(\log N)^{-100} \ll d^{-3r/2}, \qquad M = (\log N)^2$$

holds for all but at most $\omega' = \log N$ indices *i* with probability at least

$$\binom{\mu}{\omega'}M^{-2\omega'}\ll N^{-c\log\log N}.$$

Upshot:

If the boundary ∂B_ℓ(1, G) was independent of the remainder of G, the Green's function between most pairs of vertices would have to be very small.

Use of randomness (b): Concentration estimate



There are μ boundary edges $l_1a_1, \ldots, l_{\mu}a_{\mu}$ in original graph \mathcal{G} .

In the switched graph $\tilde{\mathcal{G}}$, the new boundary edges have random endpoints conditioned on \mathcal{G} .

Pretend the boundary edges are uniformly random independently of \mathcal{G} .

Then

 $\frac{1}{\mu} \sum_{k=1}^{\mu} G_{a_k a_k}^{(l_k)} \quad \text{is the average of } \mu \gg \log N \text{ independent random variables}.$

Thus it concentrates near its mean

$$Q(\mathcal{G}) = rac{1}{\mathsf{Nd}} \sum_{i \sim j} \mathsf{G}_{jj}^{(i)}(\mathcal{G}).$$

For the infinite tree, recall that $G_{ii}^{(i)}(z) = m_{sc}(z)$ solves $m_{sc}^2 + zm_{sc} + 1 = 0$.

Use of randomness (b): Concentration estimate



- But the boundary edges are of course not independent in *G*.
- In the switched graph \$\tilde{\mathcal{G}}\$ the new boundary vertices are random and independent conditioned on \$\mathcal{G}\$.
- Remove conditioned neighborhood T to remove correlations.

Proposition

Conditioned on \mathcal{G} , with high probability in the resampling data,

$$\frac{1}{\mu}\sum_{k=1}^{\mu}\left(G_{\tilde{a}_k\tilde{a}_k}(\tilde{\mathcal{G}}^{(\mathbb{T})}) - P_{\tilde{a}_k\tilde{a}_k}(\mathcal{E}_r(\tilde{a}_k, \tilde{a}_k, \tilde{\mathcal{G}}^{(\mathbb{T})}))\right) \approx Q(\tilde{\mathcal{G}}) - m_{sc}$$

Self-consistent estimate

By resolvent expansion and the decay estimates to bound off-diagonal terms:

$$ilde{G}_{11}- ilde{P}_{11}=rac{1}{d-1}\sum_{k\in\llbracket 1,\mu
brace} ilde{P}_{1l_k}^2(ilde{G}^{(\mathbb{T})}_{ ilde{a}_k ilde{a}_k}- ilde{P}^{(\mathbb{T})}_{ ilde{a}_k ilde{a}_k})+O\left(d^{-(r+\ell+2)/2}
ight).$$

If 1 has a tree neighborhood, explicitly P
₁₁ = m_d and P
_{1lk} = m²_dm^{2ℓ}_{sc}/(d − 1)^ℓ.
 Use the concentration estimate to replace the sum above:

$$ilde{G}_{11}-P_{11}=m_d^2m_{sc}^{2\ell}rac{d}{d-1}(Q(ilde{\mathcal{G}})-m_{sc})+ ext{error}.$$

- Similar (somewhat less explicit) estimates hold if the neighborhood of 1 is not a tree but has (few) cycles.
- Using reversibility this estimate can be pulled back from the switched graph to the original graph. Analogous estimates hold for all other vertices.
- These implies a self-consistent estimate for the averaged quantity $Q(\mathcal{G}) m_{sc}$.
- This estimate implies the improved estimates for the Green's function.

Induction (simplified)

■ Let $\Omega(z) \subset G_{N,d}$ is a set of graphs which have locally tree-like structure and satisfy the estimate of the main theorem:

$$|G_{ij}(\mathcal{G};z) - P_{ij}(\mathcal{G};z)| \leqslant d^{-r/2}.$$

Initial estimates imply that

$$\mathbb{P}\left(\bigcap_{|z|\geqslant 2d}\Omega(z)
ight)=1-o(N^{-\omega+\delta}).$$

Let $\Omega^{-}(z) \subset G_{N,d}$ be the set of graphs with a slightly improved bound:

$$|G_{ij}(\mathcal{G};z)-P_{ij}(\mathcal{G};z)|\leqslant \frac{1}{2}d^{-r/2}$$

Lipschitz continuity of Green's function implies that $\Omega^{-}(z) \subset \Omega(z - i/N^3)$. Thus it suffices to prove that $\mathbb{P}(\Omega(z) \setminus \Omega^{-}(z)) \ll N^{-3}$ say.

Induction (simplified)

Fix a radius for the local resampling $r = c \log_d \log N$ and a center vertex, say 1.

Define the set $\Omega'_1(z)$ of graphs satisfying improved estimates near 1:

 $G_{1x}(\mathcal{G};z) = P_{1x}(\mathcal{G};z) + (...) + O(d^{-(r+1)/2}),$ (...)

Proposition

For any graph $\mathcal{G} \in \Omega(z)$, with high probability the switched graph is improved near 1:

$$\mathbb{P}\bigg[T_{\mathsf{S}}(\mathcal{G})\in\Omega_1'(z)\ \Big|\ \mathcal{G}\bigg]=1-O(N^{-D}).$$



- Reversibility of switchings implies that $\mathbb{P}(\Omega(z) \setminus \Omega'_1(z)) = o(N^{-\omega+\delta})$.
- Union bounds give $\mathbb{P}(\Omega^{-}(z)) = 1 o(N^{-\omega+7+\delta})$.

Conclusion

- Random matrix type delocalization estimates for eigenvectors and control of spectral density on all mesoscopic scales for bounded degree regular graphs.
- Simultaneous use of local graph structure and global randomness.
- Method is robust.
- Many interesting questions remain.