

Universal Behavior near Erdős-Rényi

Lorenzo Sadun

University of Texas at Austin

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Joint work with Rick Kenyon, Charles Radin and Kui Ren

Outline

1 Recap of graphs and graphons

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- Graphon entropy $s(g) = - \iint I_0(g(x, y)) dx dy$.
- $I_0(u) = \frac{1}{2} [u \ln(u) + (1 - u) \ln(1 - u)]$.

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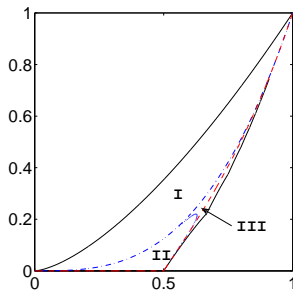
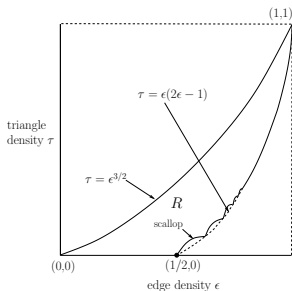
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- $S(e, e^3) = -I_0(e)$.
- What happens when t is only *close* to e^3 ?

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Phase portrait for edge-triangle model



Schematic Profile and Phase Portrait

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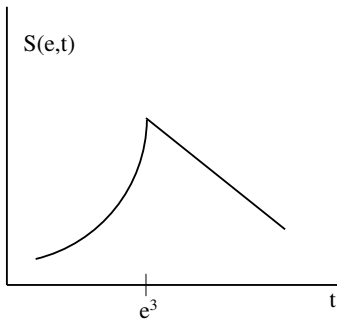
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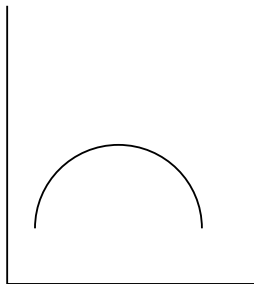
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- Other graph can be triangle, k -star, K_n , *anything*.
- Below ER, $S(e, e^3) - S(e, t)$ always goes as $(e^3 - t)^{2/n}$ for some $n > 2$. (Generically $n = 3$, but not always.)
- Caveat: for some graphs, density is minimized at ER. In those models, results below ER are moot.

$S(e, t)$ for fixed e



Not



Graphon just above ER curve

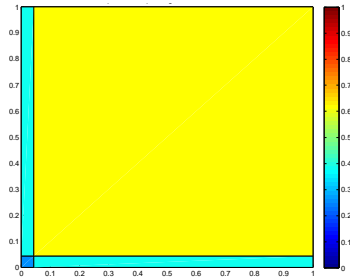


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- Break into sub-goals:
 - Get the most $|\Delta t|$ for the least $\|\Delta g\|$.
 - Get the most $\|\Delta g\|$ for the least $\|\Delta S\|$.
- Rewrite sub-goals as:
 - Maximize $|\Delta t|$ for fixed $\|\Delta g\|$.
 - Minimize $|\Delta S|$ for fixed $\|\Delta g\|$.

Use the L^2 norm

Treat g and Δg as integral kernels of operators on $L^2([0, 1])$.

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$$\begin{aligned}\|\Delta g\|^2 &= \iint (\Delta g(x, y))^2 dx dy \\ &= \iint \Delta g(x, y) \Delta g(y, x) dx dy \\ &= \text{Tr}(\Delta g^2).\end{aligned}$$

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Where $h(x) := \int_0^1 \Delta g(x, y) dy$.

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- Normalization: $\int_0^1 \alpha(x) dx = 0$, $\int_0^1 \alpha(x)^2 dx = 1$.

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- For $\Delta t > 0$, optimal Δg is rank 2 to lowest order, $\|\Delta g\|$ goes as $|\Delta t|^{1/2}$.
- Optimal solutions involve arbitrary functions $\alpha(x)$ or $h(x)$.
Picking the right function is at the heart of second goal.

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- With one class of exception, all higher-order terms are bounded by $\|\Delta g\|^3$.
- Exception is harmless, but requires a little more work.

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- Claim: That's achieved when $g_{1/2}(x, y)^2$ is constant.

A little Taylor Series

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- $I(u)$ is concave up as a function of $(u - \frac{1}{2})^2$.
- Since $\int (g - \frac{1}{2})^2$ is fixed, $s(g)$ is maximized by taking $(g - \frac{1}{2})^2$ constant.

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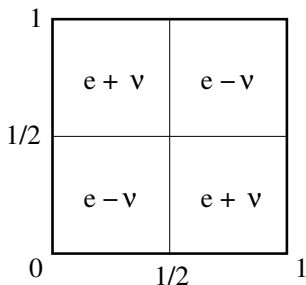
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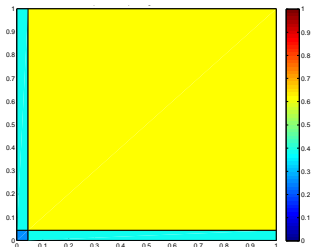
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- When $e > 1/2$, best seems to be asymmetric bipodal.

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Compromise between $\Delta g(x, y) = h(x) + h(y)$ and $|g(x, y) - 1/2|^2$ constant.

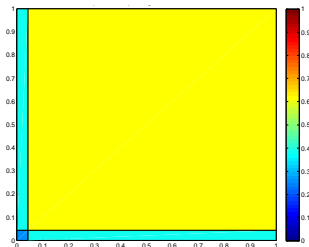
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Failure is only on tiny square of area $\sim \|\Delta g\|^4$.

What I showed you:

- For edge-triangle, as $t \rightarrow e^3$ from above, $|\Delta S| \sim |\Delta t|^1$.
- For edge-triangle, as $t \rightarrow e^3$ from below, $|\Delta S| \sim |\Delta t|^{2/3}$.
- For edge-triangle, the optimizing graphon takes a specific form just above the ER curve. Highly asymmetric bipodal.
 $\Delta g(x, y) \approx h(x) + h(y)$.

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 $\Delta g(x, y) \approx h(x) + h(y)$.
- The results above ER are *universal*, and apply to any model with edge density and one other graph density.
- Below ER, $|\Delta S|$ always goes as $|\Delta t|^{2/n}$ for some $n > 2$, since negative terms in $|\Delta t|$ are cubic or higher in Δg .