

# Computation and Logic on Dynamic Random Graphs

Wesley Calvert

Southern Illinois University

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## Theorem (0-1 Law)

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## Definition

The theory of the random graph is the set of all sentences in the language of graphs which are true for almost all finite graphs.

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## Proof.

Back-and-forth



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*The theory of the random graph is properly simple.*



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- “There's nothing random in it!”
- “A model of that theory isn't a random graph!”
- “You mean your random graphs can be infinite?”
- “Maybe a better name would be 'random theory of graphs.' ”

Here's what they're used to as a random graph:

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### Proposition

*The theory of the random graph is the almost-sure theory of  $G_p(\omega)$  if  $p \in (0, 1)$ .*

## Definition

Continuous first-order logic is a logic taking truth values on  $[0, 1]$ , and having all continuous functions on  $[0, 1]$  for its Boolean connectives and sup and inf for its quantifiers. We typically also include a metric  $d$  in the signature.



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## Proposition (Ben Yaacov-Berenstein-Henson-Usvyatsov)

*Any continuous function  $[0, 1]^n \rightarrow [0, 1]$  can be approximated by  $(\div, \neg = x \mapsto 1 - x, \frac{1}{2})$ .*

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- Some distinguished uniformly continuous predicates  $R : M^n \rightarrow [0, 1]$ .

## Example

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- $R(x, y) = 1 - p$  if  $x \neq y$
- $R(x, x) = 1$ .

Note that this is a continuous structure, and “is” the Erdős-Renyi random graph  $G_p(n)$ .



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- 3 We say that a randomized Turing machine  $M$  *rejects*  $n$  with *probability*  $p$  if and only if  $\mu\{x \in 2^\omega : M^x(n) \downarrow = 1\} = p$ .

## Definition

The continuous atomic diagram  $D(\mathcal{M})$  of a continuous structure  $\mathcal{M}$  is the set of pairs  $(\varphi, p)$ , where  $\varphi$  is an atomic CFO formula (in  $\mathcal{M}$  with unary distance) and the truth value of  $\varphi$  in  $\mathcal{M}$  is equal to  $p$ .

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## Definition

A probabilistically computable structure  $\mathcal{M}$  is a continuous structure equipped with a randomized Turing machine which, for any pair  $(\varphi, p) \in D(\mathcal{M})$ , accepts  $\varphi$  with probability equal to  $p$ .

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## Theorem

*Classically computable structures are to  $\text{RCA}_0$  as probabilistically computable structures are to  $\text{ACA}_0$ .*



Note that the Erdős-Renyi random graph we described earlier is probabilistically computable.

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The FaceBook friend graph.

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### Example

Consider the reactions catalyzed by *E. Coli*. Make a node for each collection of reactants and products, and a connection for any two that share a metabolite (intermediate compound).

Major features we want to capture:

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- 2 Non-homogeneity [number of vertices of degree  $k$  proportional to  $\frac{1}{k^\beta}$  for fixed  $\beta$ ]



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- Infinitely many predicates  $(E_i)_{i \in \omega}$ , interpreted as the edge set at stage  $i$ .

## Definition

Let  $G_0$  be a finite graph with vertex set  $V_*$  and edge set  $E_*$ . The preferential attachment graph  $G(p, G_0)$  is the random graph process with  $V_0 = V_*$ , with  $E_0 = E_*$ , and with the following property:

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- For each  $t > 0$ , we form  $G_t$  by independently
  - With probability  $p$  let  $V_t$  consist of  $V_{t-1}$  plus a single new element  $v$ , and independently choose a vertex  $u$  in proportion to its degree in  $G_{t-1}$ , setting  $E_t = E_{t-1} \cup \{(u, v)\}$ .

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  - With probability  $p$  let  $V_t$  consist of  $V_{t-1}$  plus a single new element  $v$ , and independently choose a vertex  $u$  in proportion to its degree in  $G_{t-1}$ , setting  $E_t = E_{t-1} \cup \{(u, v)\}$ .
  - Otherwise, independently choose two vertices  $u, v$  with probability proportional to their degrees in  $G_{t-1}$ , and set  $V_t = V_{t-1}$  and  $E_t = E_{t-1} \cup \{(u, v)\}$ .

## Proposition

*There is an effective procedure which, given  $\sigma \in 2^\omega$ , will produce an index for the sample path corresponding to  $\sigma$ ; that is, for the uniformly computable sequence of (classical) relations  $(V_i^\sigma, E_i^\sigma)_{i \in \omega}$ .*

## Lemma

*For any  $p \in [0, 1]$ , there exists an infinite uniformly computable sequence of subsets  $(S_i^p)_{i \in \omega}$  of  $2^\omega$  which are independent, such that  $S_i^p$  has probability  $p$ .*

## Lemma

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## Lemma

*For any positive integer  $n$ , there exist infinite independent uniformly computable sequences of tuples  $(Q_t^n)_{t \in \omega}$  and  $(P_t^n)_{t \in \omega}$ , where each  $Q_t^n$  and each  $P_t^n$  has the form  $(Q_{t,k}^n)_{k < n}$  and the  $Q_{t,k}^n$  are disjoint subsets of  $2^\omega$ , each with measure  $\frac{1}{n}$ .*



Proof of Proposition.

Start with  $G_0$ .

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## Theorem

*For any  $p \in [0, 1]$  and any finite graph  $G_0$ , there is a probabilistically computable random graph process of form  $G(p, G_0)$ .*

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## Proof.

Take the Turing machine we just built, and let it work over all oracles.  $\square$

## Problem

What is  $Th(G(p, G_0))$ ?

## Proposition

*The axioms of preferential attachment are neither complete nor categorical.*



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## Proof.

Do the same construction as before, but arrange that individual numbers have small probability of coming in as vertices at stage  $t$ . □

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Preferential attachment  $\beta \geq 2$  (generally)

Metabolic Networks  $\beta \approx 1.5$ .

## Definition

Let  $G_0$  be a finite graph with vertex set  $V_*$  and edge set  $E_*$ . The duplication graph  $B(p, G_0)$  is the random graph process with  $V_0 = V_*$ , with  $E_0 = E_*$ , and with the following property: For each  $t > 0$ , we form  $G_t$  by

- Independently selecting a vertex  $v_t$  from  $V_{t-1}$  uniformly at random, add a new vertex  $y_t$ , and
- For each neighbor  $u$  connected to  $v_t$  at stage  $t - 1$ , we independently attach  $u$  to  $y_t$  with probability  $p$ .

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And it has all the same issues with completeness.

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