



# Some Notes on Finite and Hyperfinite model theory

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# Three seminal papers

1. Gaifman: Concerning measures on first order calculi, Israel J. Math 2 (1964), 1-18
2. Fagin: Probabilities on finite models, J. Symb. Logic 41 (1976), 50-58
3. Keisler: Hyperfinite model theory, in: R. O. Gandy, J. M. E. Hyland (eds.) Logic Colloquium 76, North-Holland (1977), 5-110

# Specifying probabilities on $\text{Sent}_L$

Gaifman: A probability on  $\text{Sent}_L$  is a function  $P : \text{Sent}_L \rightarrow [0, 1]$  such that:

- $P(\alpha \vee \beta) + P(\alpha \wedge \beta) = P(\alpha) + P(\beta)$
- $P(\neg\alpha) = 1 - P(\alpha)$
- $P(\alpha) = P(\beta)$ , if  $\vdash \alpha \leftrightarrow \beta$
- $P(\alpha) = 1$ , if  $\vdash \alpha$ .

A probability on  $L$  can be conceived as a non-trivial, non-negative, finitely-additive probability measure on the Lindenbaum-Tarski algebra of the sentences of  $L$ .

# Specifying probabilities on $\text{Sent}_L$

- Let  $(M, R)$  be a classical structure:

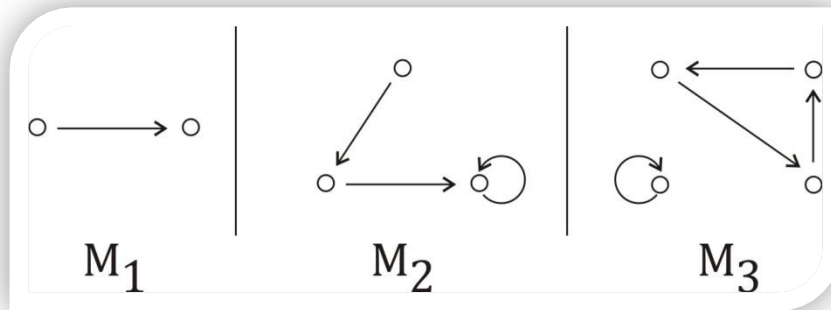
$$P_{\mathbf{M}} : \text{Sent}_L \rightarrow [0,1], P_{\mathbf{M}}(\varphi) = \begin{cases} 1, & \mathbf{M} \models \varphi \\ 0, & \mathbf{M} \not\models \varphi \end{cases}$$

- Let  $\mathfrak{M}$  be a set of classical structures with a probability  $m$  on the algebra of subsets of  $\mathfrak{M}$  generated by  $[\varphi]_{\mathfrak{M}} = \{\mathbf{M} \in \mathfrak{M} \mid \mathbf{M} \models \varphi\}$ :

$$P_{\mathfrak{M}} : \text{Sent}_L \rightarrow [0,1], P_{\mathfrak{M}}(\varphi) = \int_{\mathfrak{M}} P_{\mathbf{M}}([\varphi]_{\mathfrak{M}}) dm(\mathbf{M})$$

# Specifying probabilities on $\text{Sent}_L$

Example 1.  $L = \{B\}$ ,  $\text{ar}(B) = 2$



$$\begin{pmatrix} \mathbf{M}_1 & \mathbf{M}_2 & \mathbf{M}_3 \\ 5/8 & 1/4 & 1/8 \end{pmatrix}$$

$$P(\forall x \exists y Bxy) = \frac{1}{4} + \frac{1}{8} = \frac{3}{8}$$

$$P(\exists x \exists y (x \neq y \rightarrow Bxy)) = 1$$

# Probabilistic models

$$M \neq \emptyset, L(M) = \{B\} \cup \{c_a \mid a \in M\}$$

Classical model:

$$B^M : M \times M \rightarrow \{0,1\}$$

$$c_a^M = a, a \in M$$

$$J : \text{Atomic}_{L(M)} \rightarrow \{0,1\}$$

$$\hat{J} : \text{Sent}_{L(M)} \rightarrow \{0,1\}$$

Probabilistic models

$$\mathcal{P} : \text{Atomic}_{L(M)} \rightarrow [0,1]$$

is not sufficient (the values assigned to atomic sentences do not determine unique values for Boolean combinations of these sentences)!

# Probabilistic models

$$M \neq \emptyset, L(M) = \{B\} \cup \{c_a \mid a \in M\}$$

Classical model:

$$B^M : M \times M \rightarrow \{0,1\}$$

$$c_a^M = a, a \in M$$

Probabilistic models

$$\mathcal{P} : \text{Bool}_{L(M)} \rightarrow [0,1]$$

$$\mathcal{I} : \text{Atomic}_{L(M)} \rightarrow \{0,1\}$$

$$\hat{\mathcal{J}} : \text{Sent}_{L(M)} \rightarrow \{0,1\}$$

# Gaifman's condition

Theorem. If  $P : \text{Sent}_{L(M)} \rightarrow [0,1]$  is a probability, then

$$\begin{aligned} & \text{(G) } P(\exists x \alpha(x)) \\ &= \sup \{ P(\alpha(a_1) \vee \cdots \vee \alpha(a_k)) \mid k \in \mathbb{N}, a_1, \dots, a_k \in M \}. \end{aligned}$$

Theorem. Let  $(M, \mathcal{P})$  be a probabilistic model (i.e.,  $\mathcal{P} : \text{Bool}_{L(M)} \rightarrow [0,1]$ ). Then there is a unique probability  $\mathcal{P}^*$  which extends  $\mathcal{P}$  to  $\text{Sent}_{L(M)}$  and satisfies (G).

Theorem. Every probability on  $\text{Sent}_L$  has a probabilistic model whose power is  $\aleph_0 + |\text{Sent}_L|$ .



# Probabilistic models

Example 2.  $M = \{0,1\}$

$$\mathcal{P}(B00 \wedge B01 \wedge B10 \wedge B11) = p_1$$

$$\mathcal{P}(B00 \wedge B01 \wedge B10 \wedge \neg B11) = p_2$$

$$\vdots$$

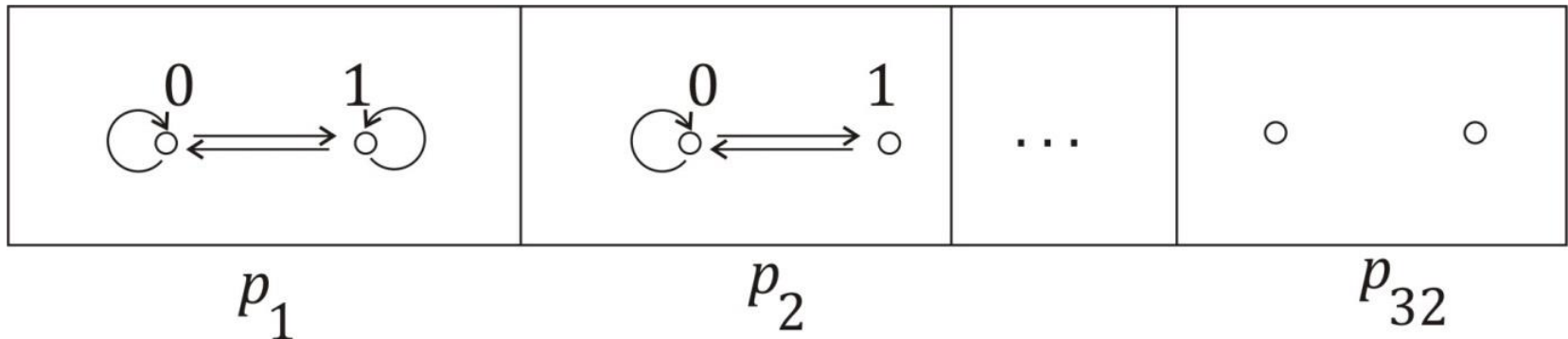
$$\mathcal{P}(\neg B00 \wedge \neg B01 \wedge \neg B10 \wedge \neg B11) = p_{32}$$

$$p_1 + p_2 + \cdots + p_{32} = 1$$

$$\mathcal{P} : \text{Sent}_{L(M)} \rightarrow [0,1]$$

# Probabilistic models

Example 2.  $M = \{0,1\}$



$$p_1 + p_2 + \dots + p_{32} = 1$$

$$\mathcal{P} : \text{Sent}_{L(M)} \rightarrow [0,1]$$

# Probabilistic models

Example 3.  $B : \{0,1\}^2 \rightarrow [0,1]$ ,  $\begin{pmatrix} B00 & B01 & B10 & B11 \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{3} & \frac{1}{6} \end{pmatrix}$

$$B00 \wedge B01 \wedge B10 \wedge B11 \mapsto \frac{1}{4} \cdot \frac{1}{2} \cdot \frac{1}{3} \cdot \frac{1}{6}$$

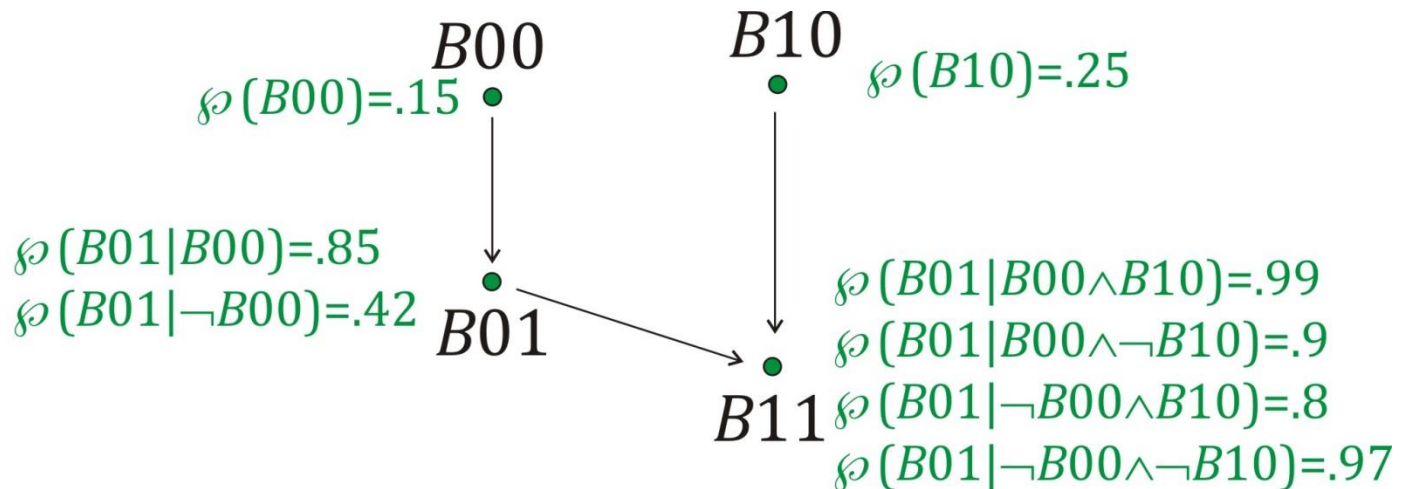
$$B00 \wedge B01 \wedge B10 \wedge \neg B11 \mapsto \frac{1}{4} \cdot \frac{1}{2} \cdot \frac{1}{3} \cdot \frac{5}{6}$$

$\vdots$

$$\neg B00 \wedge \neg B01 \wedge \neg B10 \wedge \neg B11 \mapsto \frac{3}{4} \cdot \frac{1}{2} \cdot \frac{2}{3} \cdot \frac{5}{6}$$

# Probabilistic models

Example 4.



$$\begin{aligned} & \mathcal{P}(B00 \wedge \neg B01 \wedge \neg B10 \wedge B11) \\ &= \mathcal{P}(B00) \cdot \mathcal{P}(\neg B01 | B00) \cdot \mathcal{P}(\neg B10) \cdot \mathcal{P}(B11 | B00 \wedge \neg B01) \\ &= 0.15 \cdot (1 - 0.85) \cdot (1 - 0.25) \cdot 0.9 \end{aligned}$$

# Random structure $M(n, p)$

Erdős, Rényi: On the Evolution of the Random graph,  
Mat. Kutató Int. Közl 5 (1960), 17-60

$$M = \{0, 1, \dots, n-1\}, \quad 0 \leq p \leq 1$$

Define  $\mathcal{P} : \text{Bool}_{L(M)} \rightarrow [0, 1]$  by:

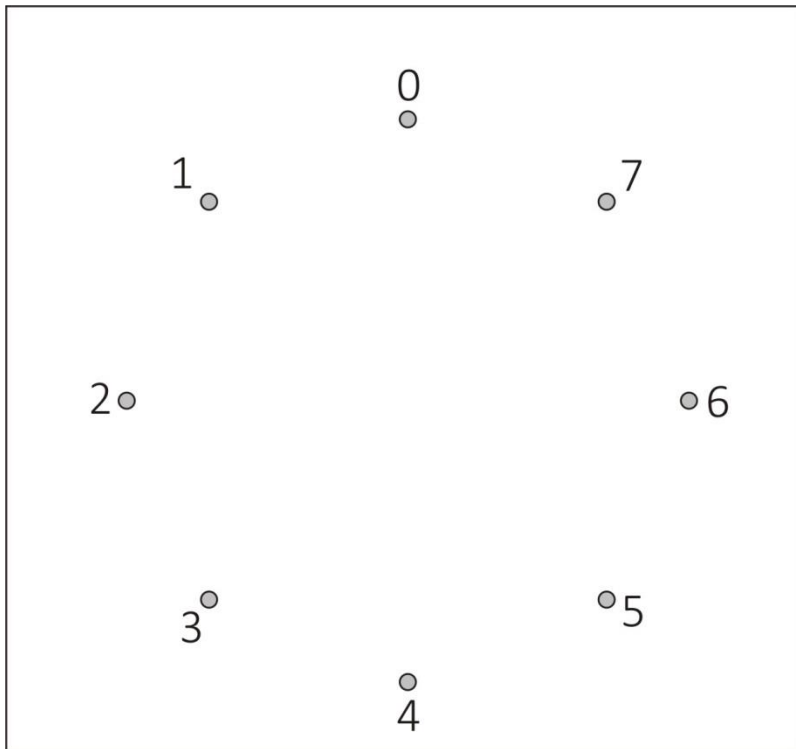
$\mathcal{P}(Bab) = p, a, b \in M$ , and these events are mutually independent.

$$\mathcal{P}\left(\bigwedge_{i=1}^k Ba_i b_i \wedge \bigwedge_{j=k+1}^n \neg Ba_j b_j\right) = p^k (1-p)^{n-k},$$

where sentences  $Ba_i b_i$  and  $Ba_j b_j$  are not identical.

# Random structure $M(8,0.5)$

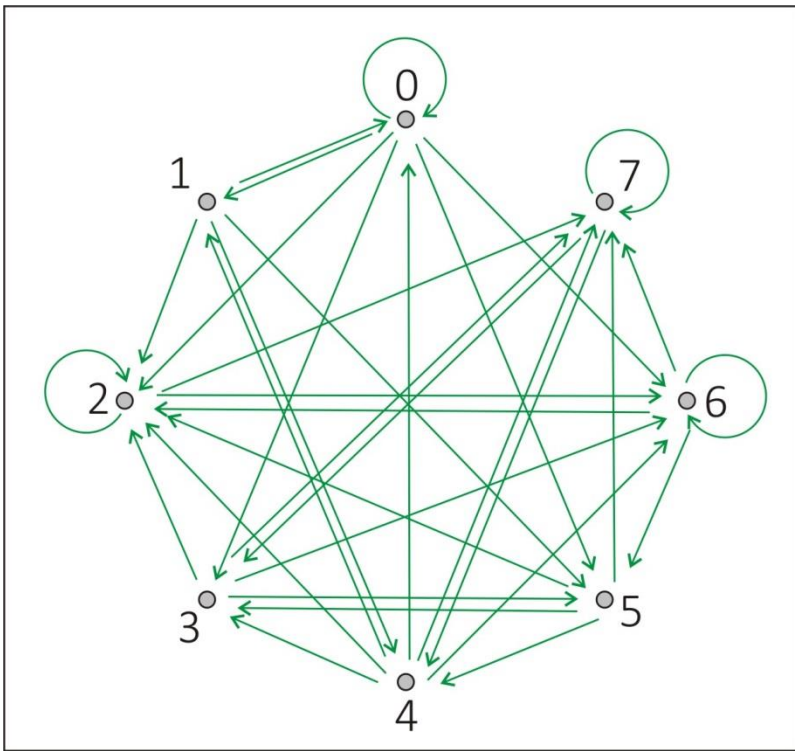
Example 5.



	0	1	2	3	4	5	6	7
0	H	H	H	H	T	H	H	T
1	H	T	H	T	H	H	T	T
2	T	T	H	T	T	T	H	T
3	T	T	H	T	T	H	H	H
4	H	H	H	H	T	T	H	T
5	T	T	T	H	H	T	T	H
6	T	T	H	T	T	H	H	H
7	T	T	T	H	H	T	T	H

# Random structure $M(8,0.5)$

Example 5.



	0	1	2	3	4	5	6	7
0	H	H	H	H	T	H	H	T
1	H	T	H	T	H	H	T	T
2	T	T	H	T	T	T	H	T
3	T	T	H	T	T	H	H	H
4	H	H	H	H	T	T	H	T
5	T	T	T	H	H	T	T	H
6	T	T	H	T	T	H	H	H
7	T	T	T	H	H	T	T	H

# Gaifman's simple example

Example 6: Let  $M$  an infinite set, and  $p$  a fixed number,  $0 < p < 1$ .

Define  $\mathcal{P} : \text{Bool}_{L(M)} \rightarrow [0,1]$  by:

- $\mathcal{P}(Bab) = p, a, b \in M,$
- $\mathcal{P}\left(\bigwedge_{i=1}^k Ba_i b_i \wedge \bigwedge_{j=k+1}^n \neg Ba_j b_j\right) = p^k (1 - p)^{n-k},$

where sentences  $Ba_i b_i$  and  $Ba_j b_j$  are not identical,

- $\mathcal{P}(a = b) = 0, a \neq b.$

Let  $\mathcal{P}^* : \text{Sent}_{L(M)} \rightarrow [0,1]$  be the extension of  $\mathcal{P}$  satisfying (G).



# Gaifman's simple example

Lemma. If  $\alpha, \beta \in \text{Sent}_{L(M)}$  and no constant occurs both in  $\alpha$  and  $\beta$  then

$$\mathcal{P}^*(\alpha \wedge \beta) = \mathcal{P}^*(\alpha) \cdot \mathcal{P}^*(\beta).$$

In particular, for every  $\sigma \in \text{Sent}_L$

$$\mathcal{P}^*(\sigma) = \mathcal{P}^*(\sigma \wedge \sigma) = (\mathcal{P}^*(\sigma))^2,$$

and hence  $\mathcal{P}^*(\sigma)$  is either 0 or 1.

$(M, \mathcal{P})$  determines a complete theory!

# The complete theory

Let  $V_n = \{v_0, v_1, \dots, v_{n-1}\}$  be a set of distinct variables.

A complete diagram  $\sigma(V_n)$  is a conjunction s.t. for every pair  $(v_i, v_j) \in V_n \times V_n$  either  $Bv_i v_j$  or  $\neg Bv_i v_j$  is a conjunct.

$$\begin{aligned}\sigma(V_3) = & Bv_0 v_0 \wedge \neg Bv_0 v_1 \wedge Bv_0 v_2 \wedge \\ & \wedge \neg Bv_1 v_0 \wedge Bv_1 v_1 \wedge Bv_1 v_2 \wedge \\ & \wedge Bv_2 v_0 \wedge \neg Bv_2 v_1 \wedge \neg Bv_2 v_2\end{aligned}$$

# The complete theory

A complete diagram  $\sigma(V_{n+1})$  extends another complete diagram  $\sigma'(V_n)$  if  $\vdash \sigma'(V_n) \rightarrow \sigma(V_{n+1})$ .

$$\begin{aligned}\sigma(V_3) = & Bv_0v_0 \wedge \neg Bv_0v_1 \wedge Bv_0v_2 \wedge \\ & \wedge \neg Bv_1v_0 \wedge Bv_1v_1 \wedge Bv_1v_2 \wedge \\ & \wedge Bv_2v_0 \wedge \neg Bv_2v_1 \wedge \neg Bv_2v_2\end{aligned}$$

extends

$$\begin{aligned}\sigma'(V_2) = & Bv_0v_0 \wedge \neg Bv_0v_1 \wedge \\ & \wedge \neg Bv_1v_0 \wedge Bv_1v_1\end{aligned}$$

# The complete theory

Let  $E$  be the set of all sentences  $\varepsilon_n$ :

$$\forall v_0 \dots v_{n-1} \left( \bigwedge_{i \neq j} v_i \neq v_j \wedge \sigma(V_n) \right. \\ \left. \rightarrow \exists v_n \bigwedge_i v_i \neq v_n \wedge \sigma'(V_{n+1}) \right)$$

Theorem.  $E$  is consistent and complete.

# The complete theory

The theory  $E$  has exactly one, up to isomorphism, countable model – the Rado graph.

That model is ‘most general’ in the sense that:

- every possible finite model is realized there as a submodel, and
- for every finite submodel every possible finite extension of it is realized.

# Probabilities on finite models

What is the probability that a certain sentence holds for a randomly chosen finite structure?










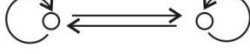


$\mathfrak{M}_n$  the class of all  $n$ -structures (on  $\{0, 1, \dots, n - 1\}$ ).

$$\mathfrak{M}_n[\sigma] = \{\mathbf{M} \in \mathfrak{M}_n \mid \mathbf{M} \models \sigma\}$$

$$P_n(\sigma) = \frac{|\mathfrak{M}_n[\sigma]|}{|\mathfrak{M}_n|}$$

# Specifying probabilities on $\text{Sent}_L$

Example 7.

○ ○	
○ → ○	○ ← ○
○ ↔ ○	
	
	
	
	
	
	
	

$$P_2(\forall x \exists y Bxy) = ?$$

# Specifying probabilities on $\text{Sent}_L$

Example 7.

○ ○	
○ → ○	○ ← ○
○ ↔ ○	
○ ↻ ○ ↻	
○ ↻ ○	○ ○ ↻
○ ↻ → ○ ↻	○ ↻ ← ○ ↻
○ ↻ → ○	○ ← ○ ↻
○ ↻ ← ○	○ → ○ ↻
○ ↻ ↔ ○ ↻	
○ ↻ ↔ ○	○ ↔ ○ ↻

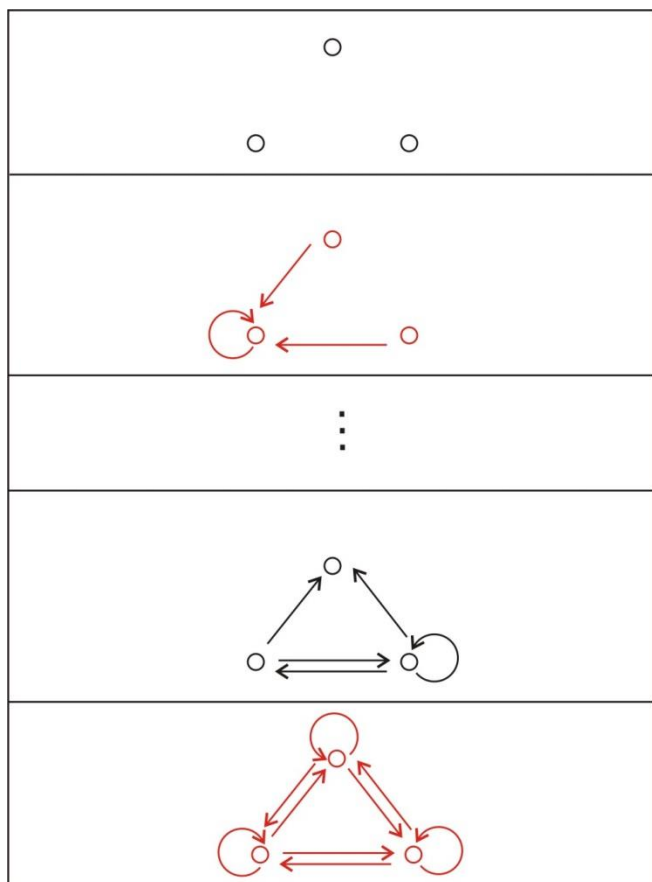
$$P_2(\forall x \exists y Bxy) = ?$$

$$P_2(\forall x \exists y Bxy) = \frac{9}{16} \approx 0.56$$



# Specifying probabilities on $\text{Sent}_L$

Example 7.



$$P_3(\forall x \exists y Bxy) = ?$$

# 0-1 law

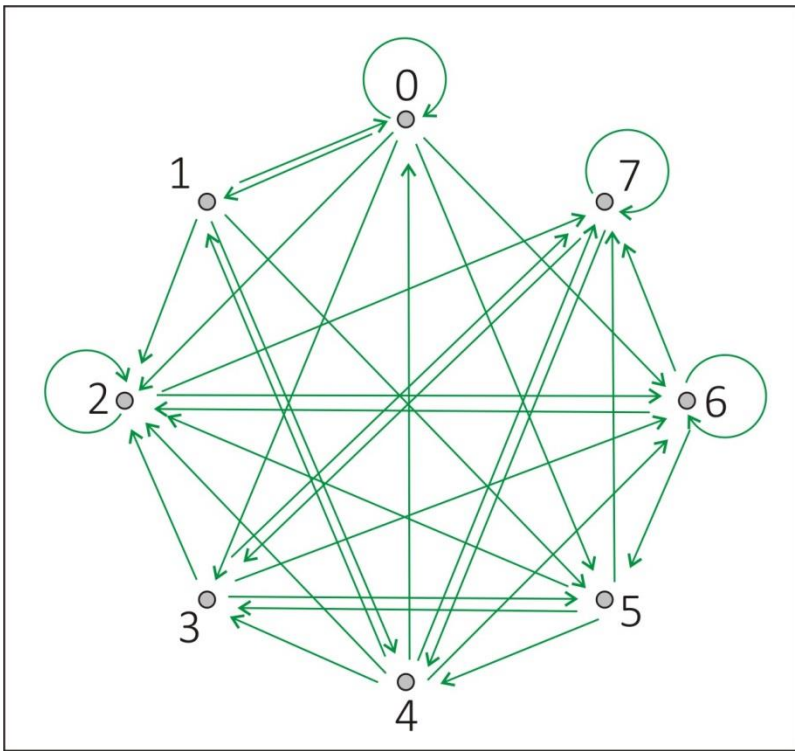
$$P_n(\sigma) = \frac{|\mathfrak{M}_n[\sigma]|}{|\mathfrak{M}_n|} \rightarrow ?, n \rightarrow \infty$$

The zero-one law.

$P_n(\sigma)$  converges to either **0** or **1**.

# Random structure $M = (8,0.5)$

Example 8.

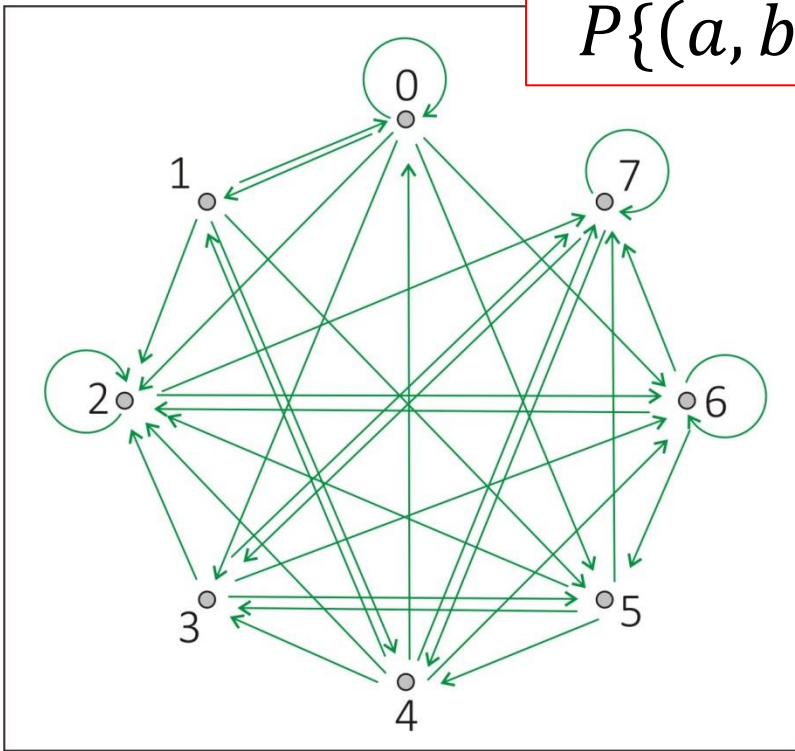


$\circ \quad \circ$	13
$\circ \longrightarrow \circ$	15,34, 45
$\circ \longleftrightarrow \circ$	14,35
$\circ \longrightarrow \circ$ $\circ \longleftarrow \circ$	07
$\circ \longrightarrow \circ$ $\circ$	16,17
$\circ \longrightarrow \circ$ $\circ \longrightarrow \circ$	02,27,67
$\circ \longrightarrow \circ$ $\circ$	03,05,25,56,57
$\circ \longleftarrow \circ$ $\circ$	04,12,23,24,36,46
$\circ \longrightarrow \circ$ $\circ \longrightarrow \circ$	26
$\circ \longrightarrow \circ$ $\circ \longrightarrow \circ$	01,37,47

# Random graph

$$\sigma(v_0, v_1) = (Bv_0v_0 \vee Bv_0v_1) \wedge (Bv_1v_0 \vee Bv_1v_1)$$

$$P\{(a, b) \in M \times M \mid \mathbf{M} \models \sigma[a, b]\} = ?$$



# Random graph

$$\sigma(v_0, v_1) = (Bv_0v_0 \vee Bv_0v_1) \wedge (Bv_1v_0 \vee Bv_1v_1)$$

$\circ \quad \circ$	13
$\circ \longrightarrow \circ$	15,34, 45
$\circ \longleftrightarrow \circ$	14,35
$\circ \curvearrowright \quad \circ \curvearrowright$	07
$\circ \curvearrowright \quad \circ$	16,17
$\circ \curvearrowright \longrightarrow \circ \curvearrowright$	02,27,67
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$\circ \curvearrowright \longleftrightarrow \circ$	01,37,47

$$P\{(a, b) \in M \times M \mid \mathbf{M} \models \sigma[a, b]\} = ?$$

$$\dots \models \forall x \exists y Bxy$$

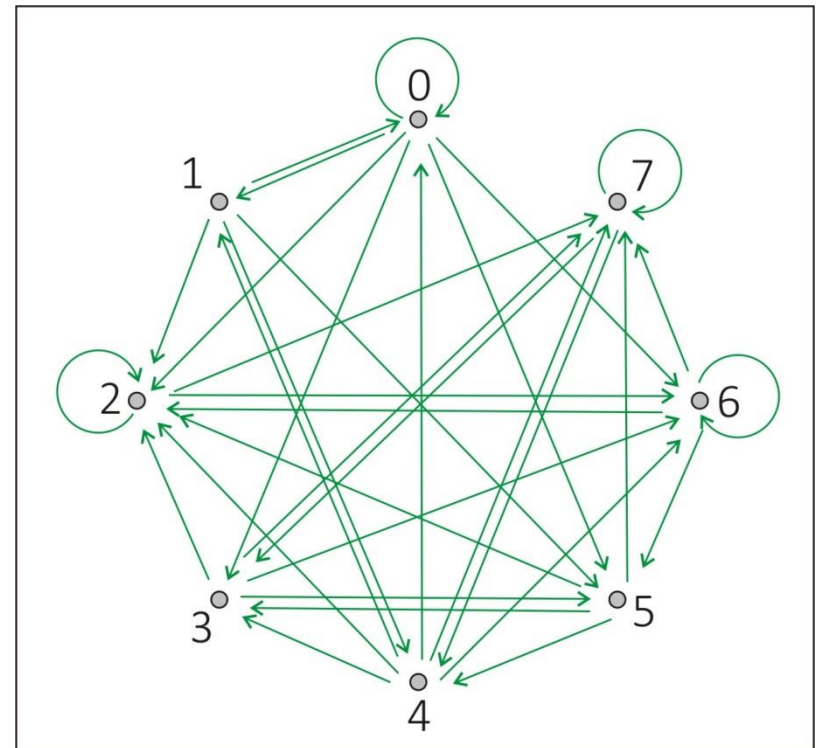
$$= \frac{16}{\binom{8}{2}} = \frac{16}{28} \approx 0.57$$

# Count models!

○	○
○ → ○	○ ← ○
○ ↔ ○	
○ ↻	○ ↻
○ ↻    ○	○    ○ ↻
○ ↻ → ○ ↻	○ ↻ ← ○ ↻
○ ↻ → ○	○ ← ○ ↻
○ ↻ ← ○	○ → ○ ↻
○ ↻ ↔ ○ ↻	
○ ↻ ↔ ○	○ ↔ ○ ↻

$$P_2(\forall x \exists y Bxy) \approx 0.56$$

# Count pairs!



$$P\{\sigma(v_0, v_1)\} \approx 0.57$$

# Count models vs. count tuples

Intuition: If  $H \gg n$ , then  $(H, 0.5)$  contains (almost) all  $n$ -structures as its substructures. Moreover, the distribution of  $n$ -structures inside  $(H, 0.5)$  is (almost) uniform.

# Hyperfinite model theory

Keisler: The purpose of hyperfinite model theory is to study and classify a type of models which arises in applied mathematics.

... [These] models have usually been either countable sequences of finite models or structures built upon the real numbers. Hyperfinite models provide a better source of infinite models which closely approximate large finite phenomena.

... Hyperfinite models deal with limiting behavior of finite models.



# Hyperfinite model theory

**Definition.** A hyperfinite probability space is a pair  $(M, \mu)$  where  $M$  is a nonempty hyperfinite set and  $\mu$  is an internal function  $\mu : M \rightarrow^*[0,1]$  such that  $\sum_{a \in M} \mu(a) = 1$ .

$\langle \mathfrak{M}_1, \mathfrak{M}_2, \mathfrak{M}_3, \dots \rangle_u$  - a hyperfinite set

$\langle \mathfrak{M}_1[\sigma], \mathfrak{M}_2[\sigma], \mathfrak{M}_3[\sigma], \dots \rangle_u \subseteq \langle \mathfrak{M}_1, \mathfrak{M}_2, \mathfrak{M}_3, \dots \rangle_u$

$\left\langle \frac{|\mathfrak{M}_1[\sigma]|}{|\mathfrak{M}_1|}, \frac{|\mathfrak{M}_2[\sigma]|}{|\mathfrak{M}_2|}, \frac{|\mathfrak{M}_3[\sigma]|}{|\mathfrak{M}_3|}, \dots \right\rangle_u \in {}^*[0,1]$

# Probability logic $L_{\omega P}$

Probability logic  $L_{\omega P}$  is like first-order logic, but instead of  $\forall$  and  $\exists$  it has probability quantifiers  $(P\vec{x} > r)$ ,  $r \in \mathbb{Q}$ .

$$\mathbf{M} \models (Px > r)\varphi(x) \text{ iff } \mu\{x \in M \mid \mathbf{M} \models \varphi(\vec{x})\} > r$$

# Logic and Probability

First-order logic	Probability logic	Probability theory
Downward Löwenheim- Skolem theorem	Elementary submodel theorem	Weak law of large numbers
The zero-one law	Elementary subsequence theorem	Strong law of large numbers

Thank you for your attention