

Key definitions of Lecture 1:

- $t(F, G) := \underset{\substack{\text{random } f: \\ V(F) \rightarrow V(G)}}{P} \left[\forall xy \in E(F) \quad f(x)f(y) \in E(G) \right]$

(homomorphism density of F in G)

- (G_n) converges to $\phi: G \rightarrow \mathbb{R}$ if

$$\forall F \quad \lim_{n \rightarrow \infty} t(F, G_n) = \phi(F)$$

- $LIM := \{ \text{such } \phi \} \subseteq [0, 1]^G$

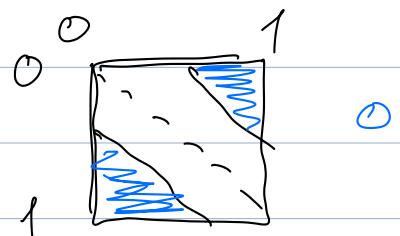
4 Graphon

Kernel: measurable bounded fn $W: [0, 1]^2 \rightarrow \mathbb{R}$
 which is symmetric ($W(x, y) = W(y, x)$)

graphon: Kernel which is $[0, 1]$ -valued

$$W := \{ \text{Kernels} \}$$

$$W_0 := \{ \text{graphons} \}$$



Ex constant- p , xy , $\frac{1}{1+x-y}$

Non-examples: $x+y$, $\max\{x-y, 0\}$

(HWM) density of $F \in \mathcal{F}_K := \{\text{Graphs on } \underbrace{\{1, \dots, K\}}_{\{1, \dots, n\}}\}$

$$|\mathcal{F}_K| = 2^{\binom{K}{2}}$$

$$t(F, W) := \int_{[0, 1]^K} dx_1 \dots dx_K \prod_{ij \in E(F)} W(x_i, x_j)$$

$$\begin{array}{l} t(K_2, W) = \int_{[0, 1]^2} W(x, y) dx dy \\ \text{---} \end{array}$$

Thm 4.1 (Lovász-Szegedy '06)

$$\text{LIM} = \{t(-, W) : W \in \mathcal{W}_0\}$$

"2": $\phi_W(-) := t(-, W)$:

- normalised ($\phi_W(K_1) = \int 1 = 1$)
- multiplicative ($\phi_W(F \sqcap H) = \phi_W(F) \phi_W(H)$)

⊗

$$\phi_W^\uparrow(F) = \sum_{\substack{F' : V(F') = V(F) \\ E(F') \supseteq E(F)}} (-1)^{e(F') - e(F)} \cdot \int \prod_{ij \in E(F')} W(x_i, x_j)$$

$$= \int_{[0,1]^K} dx_1 \dots dx_K \prod_{\substack{i,j \in E(F) \\ i \neq j}} W(x_i, x_j) \prod_{ij \in E(\bar{F})} (1 - W(x_i, x_j)) \geq 0$$

!!

$$t_{\text{ind}}(F, W)$$

Thm 3.2 $\Rightarrow \phi_W \in \text{LIM}$.

- pick $x_1, \dots, x_n \in [0,1]$
- connect i to j with prob $W(x_i, x_j)$
- (all independent)

Random sample $G(n, W)$ $\xrightarrow{\text{equivalent}}$

- rnd graph in \mathcal{F}_n (ie on E_h)
- $\mathbb{P}[G(n, W) = F] = t_{\text{ind}}(F)$

$$\mathbb{E}(t_{\text{ind}}(F, G(n, W))) = t_{\text{ind}}(F, W)$$

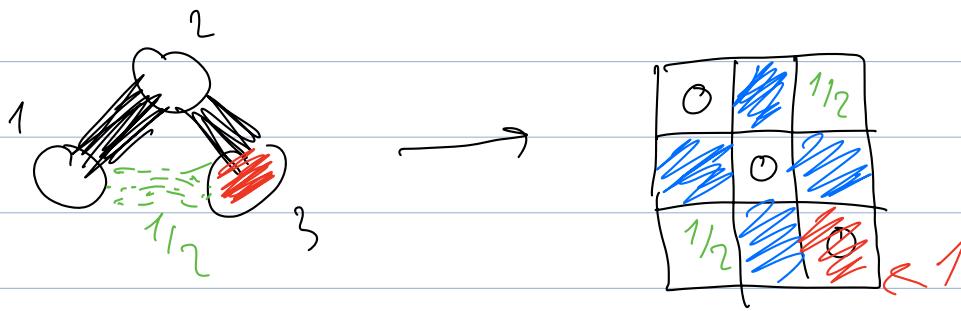
$v(F) = n$

Concentration: With prob 1, if $G_n \sim G(n, W)$, then $(\mathbf{q}_n) \xrightarrow{\text{w}} W$. \square

(G_n) converges to W : $\forall F \quad t(F, G_n) \xrightarrow{} t(F, W)$

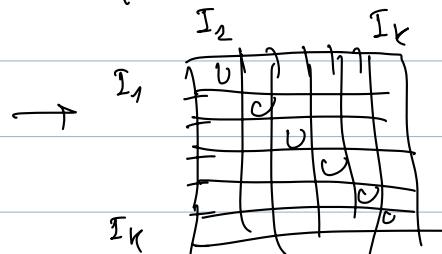
Ex $(K_n) \xrightarrow{\text{1}} 1, (\bar{K}_n) \xrightarrow{\text{0}},$

C $(K_{n/2, n/2}) \xrightarrow{\quad}$ 



$\mathcal{G}(1), \mathcal{G}(2), \mathcal{G}(3)$

$$v(\mathcal{G}) = r$$



W_G

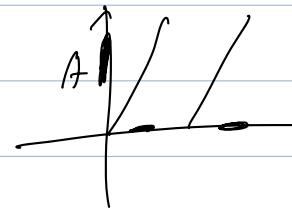


If measure-preserving $\psi: [0, 1] \rightarrow [0, 1]$

the pull-back $W^\psi(x, y) := W(\psi(x), \psi(y))$

satisfies $t(F, W^\psi) = t(F, W)$

Ex $\psi: x \mapsto 2x \bmod 1$



$$W^\psi : \begin{array}{|c|c|} \hline w & w \\ \hline w & w \\ \hline \end{array}$$

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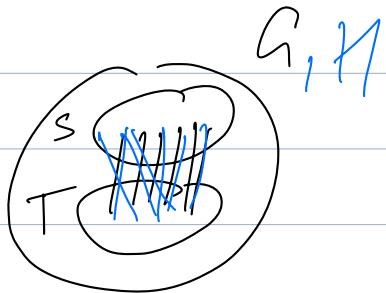
Borgs-Chayes-Lovász '10

Cut-norm of kernel W is

$$\|W\|_{\square} := \sup_{S, T \subseteq \{0, 1\}} \left| \int_{S \times T} W(x, y) dx dy \right|$$

$$V(H) = V(G) = [n]$$

$$\|W_G - W_H\|_D \sim \frac{1}{n^2} \sup_{T, S \subseteq C_n} |e_a(S, T) - e_b(S, T)|$$



Cut distance: $\delta_D(w, u) = \inf_{m.p. \psi} \|w - u^\psi\|_D$

conv in cent dist. \Leftrightarrow hom. dens. conv.

+ compactness

LDP for $G(n, p)$ uses W_0
 (Chatterjee-Varadhan '11)

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