## Random Graphs — Assignment 3

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Question 1 (Alternative proof of zero-one law). The k-round Ehrenfeucht–Fraïssé game is played on a pair of graphs  $(G_1, G_2)$  by two players, Spoiler and Duplicator. We require both graphs to contain at least k vertices.

In the first round, Spoiler chooses a vertex on one of the graphs, and then Duplicator chooses a vertex on the other graph. We let  $a_1$  be the vertex chosen in  $G_1$ , and  $b_1$  be the vertex chosen in  $G_2$ .

In the second round, Spoiler again chooses a vertex on one of the graphs, and Duplicator chooses a vertex on the other graph. Both players are forced to choose vertices not already chosen (different from  $a_1, b_1$ ). We let  $a_2, b_2$  be the vertices chosen in  $G_1, G_2$ (respectively).

All subsequent rounds proceed in the same way. After k rounds, we end up with k vertices  $a_1, \ldots, a_k$  in  $G_1$  and k vertices  $b_1, \ldots, b_k$  in  $G_2$ . Duplicator's goal is that the following property is satisfied: for all i, j, there is an edge  $(a_i, a_j)$  in  $G_1$  iff there is an edge  $(b_i, b_j)$  in  $G_2$ . We say that *Duplicator wins* if Duplicator has a strategy which guarantees that her goal is fulfilled.

For every first-order formula  $\phi$  in the language of graphs, there is a constant k such that if Duplicator wins  $(G_1, G_2)$  then  $G_1 \vdash \phi$  (that is,  $\phi$  is satisfied for  $G_1$ ) iff  $G_2 \vdash \phi$ .

- (a) Show that for each k there is a function e(n) = o(1) such that if  $G_1 \sim G(n_1, 1/2)$ and  $G_2 \sim G(n_2, 1/2)$  then Duplicator wins  $(G_1, G_2)$  with probability at least  $1 - e(\min(n_1, n_2))$ .
- (b) Show that for each  $\phi$  there is a function e'(n) = o(1) such that for each n, either  $\Pr[G(n, 1/2) \vdash \phi] \leq e'(n)$  or  $\Pr[G(n, 1/2) \vdash \phi] \geq 1 e'(n)$ .
- (c) Show that for each  $\phi$ , either  $\Pr[G(n, 1/2) \vdash \phi] \to 0$  or  $\Pr[G(n, 1/2) \vdash \phi] \to 1$ .

Question 2 (Failure of zero-one law for colored graphs). A colored graph is a graph in which each vertex v has a color  $c(v) \in \mathbb{N}$ . Given a distribution  $\pi$  on  $\mathbb{N}$ , let  $G_{\pi}(n, 1/2)$  be the colored graph obtained by coloring each vertex in G(n, 1/2) according to  $\pi$  independently.

We say that two colored graphs  $G_1, G_2$  are *isomorphic* if there is an isomorphism f of graphs between  $G_1$  and  $G_2$  that respects the coloring, that is, c(v) = c(f(v)).

(a) Show that if  $G_1, G_2 \sim G_{\pi}(\aleph_0, 1/2)$  then almost surely,  $G_1$  and  $G_2$  are isomorphic (as colored graphs).

(b) Let  $\pi$  have a Poisson distribution with expectation 1:  $\Pr[\pi = k] = e^{-1}/k!$ . Show that

 $\Pr[G_{\pi}(k!, 1/2) \text{ contains a color appearing exactly once}] \to e^{-1-e^{-1}}.$ 

(c) The first-order language of colored graphs is defined similarly to the first-order language of graphs, together with the additional basic predicate c(x) = c(y). Show that the zero-one law doesn't hold for the first-order language of colored graphs with respect to the sequence  $G_{\pi}$ , where  $\pi$  is the distribution from the preceding item.

Choose one out of Question 3 and Question 4 (bonus if you do both).

Question 3 (Quasirandom permutations<sup>1</sup>). The symmetric group  $S_n$  consists of all permutations of  $[n] := \{1, \ldots, n\}$ . We think of permutations as sequences of length n.

For a permutation  $\pi \in S_n$  and a "pattern"  $\tau \in S_k$ , the density  $t(\pi, \tau)$  is the probability that if we sample k distinct indices  $i_1, \ldots, i_k \in [n]$  then the relative order of  $\pi(i_1), \ldots, \pi(i_k)$  is the same as  $\tau$ . For example,

$$t(13245, 123) = \frac{7}{10}, \quad t(13245, 213) = \frac{2}{10}, \quad t(13245, 132) = \frac{1}{10},$$

since 134, 135, 124, 125, 145, 345, 245 have relative order 123; 324, 325 have relative order 213; and 132 has relative order 132.

For each n, let  $\pi_n \in S_n$ . The sequence  $\vec{\pi}$  is k-quasirandom if for all  $\tau \in S_k$ ,

$$t(\pi_n, \tau) \to \frac{1}{k!}.$$

The sequence  $\vec{\pi}$  is quasirandom if it is k-quasirandom for each k. As an example, if  $\pi_n$  is chosen uniformly random permutation for each n, then  $\vec{\pi}$  is quasirandom almost surely.

- (a) Show that if  $\vec{\pi}$  is (k+1)-quasirandom then it is k-quasirandom.
- (b) Give an example of a 2-quasirandom sequence which is not 3-quasirandom.<sup>2</sup>

A permuton is a probability distribution  $\mu$  over  $[0,1]^2$  such that if  $(x,y) \sim \mu$  then the marginal distributions of x and y are uniform over [0,1]. Given a permuton  $\mu$ , for each nwe can draw a random permutation  $\pi \sim P(n,\mu)$  as follows. Let  $(x_1,y_1),\ldots,(x_n,y_n)$  be n independent samples of  $\mu$ . We arrange the  $x_i$  in order, and let  $\pi$  consist of the relative order of the  $y_i$ . (Since the marginal distributions are uniform over [0,1], almost surely all  $x_i$  and all  $y_i$  are distinct.) For example, if  $\mu$  is the uniform distribution over  $[0,1]^2$  then  $P(n,\mu)$  is a uniformly random permutation in  $S_n$ .

For  $\tau \in S_k$ , let  $t(\mu, \tau)$  be the probability that if we take k samples  $(x_i, y_i)$  from  $\mu$  and arrange the  $x_i$  in order, then the relative order of the  $y_i$  is  $\tau$ .

<sup>&</sup>lt;sup>1</sup>After Král' and Pikhurko, Quasirandom permutations are characterized by 4-point densities, GAFA vol. 23, pp. 570–579, 2013.

<sup>&</sup>lt;sup>2</sup>There are also examples of 3-quasirandom sequences which are not 4-quasirandom, but they are more complicated. One example is described in the paper of Král' and Pikhurko mentioned above, and another one in Cooper and Petrarca, Symmetric and asymptotically symmetric permutations.

(c) Show that  $\mathbb{E}_{\pi \sim P(n,\mu)}[t(\pi,\tau)] = t(\mu,\tau)$ . (In fact, more is true: if  $\pi_n \sim P(n,\mu)$  for each *n* independently, then almost surely  $t(\pi,\tau) \to t(\mu,\tau)$ .)

A permuton  $\mu$  is k-quasirandom if for each  $\tau \in S_k$ ,  $t(\mu, \tau) = 1/k!$ . A permuton  $\mu$  is quasirandom if it is k-quasirandom for all k. As in the case of individual distributions, it is not hard to show that a (k + 1)-quasirandom permuton is also k-quasirandom. Furthermore, if  $\mu$  is a (k-)quasirandom permuton and for each n we sample  $\pi_n \sim P(n, \mu)$ , then almost surely  $\vec{\pi}$  is (k-)quasirandom (where we think of  $\pi_n$  as a constant random variable).

In the rest of this exercise, we show that if  $\mu$  is a 4-quasirandom permuton, then it is in fact quasirandom (the constant 4 is optimal). This implies that if  $\vec{\pi}$  is a 4-quasirandom sequence of random permutations, then it is in fact quasirandom.

- (d) Let  $F_{\mu}(X, Y) = \Pr_{(x,y)\sim\mu}[x \le X, y \le Y]$  be the CDF of  $\mu$ . Show that  $\mathbb{E}_{(X,Y)\sim\mu}[F_{\mu}(X,Y)^{2}] = \Pr_{(x_{i},y_{i})\sim\mu}[x_{1}, x_{2} \le x_{3}; y_{1}, y_{2} \le y_{3}].$
- (e) Deduce that  $\mathbb{E}_{(X,Y)\sim\mu}[F_{\mu}(X,Y)^2] = 1/9$ , using only the fact that  $\mu$  is 3-quasirandom.
- (f) Show that

$$\mathbb{E}_{(X,Y)\sim\mu}[F_{\mu}(X,Y)XY] = \Pr_{(x_i,y_i)\sim\mu}[x_1,x_2 \le x_4; y_1,y_3 \le y_4].$$

Hint: if  $(x, y) \sim \mu$  then since the marginals x and y are uniform over [0, 1], then  $\Pr[x \leq X] = X$  and  $\Pr[y \leq Y] = Y$ .

- (g) Deduce that  $\mathbb{E}_{(X,Y)\sim\mu}[F_{\mu}(X,Y)XY] = 1/9$ , using the fact that  $\mu$  is 4-quasirandom.
- (h) Let  $\lambda$  be the permuton corresponding to two independent samples of the uniform distribution over [0, 1]. Show that  $\lambda$  is quasirandom and  $F_{\lambda}(X, Y) = XY$ .
- (i) Show that

$$\mathbb{E}_{(Z,W)\sim\lambda}[F_{\mu}(Z,W)^2] = \Pr_{(X_i,Y_i)\sim\mu}[x_1, x_2 \le x_3; y_1, y_2 \le y_4]$$

Hint: use two samples of  $\mu$  to generate one sample of  $\lambda$ .

- (j) Deduce that  $\mathbb{E}_{(Z,W)\sim\lambda}[F_{\mu}(Z,W)^2] = 1/9$ , using the fact that  $\mu$  is 4-quasirandom.
- (k) Show that

$$\mathbb{E}_{\substack{(Z,W)\sim\lambda}}[F_{\mu}(Z,W)ZW] = \Pr_{\substack{(x,y)\sim\mu\\(z_i,w_i)\sim\lambda}}[x,z_1 \le z_2; y,w_1 \le w_2] = \frac{1}{4} \mathbb{E}_{\substack{(X,Y)\sim\mu}}[(1-X^2)(1-Y^2)].$$

(1) Show that

$$A := \mathbb{E}_{(X,Y)\sim\mu} [F_{\mu}(X,Y)XY]^2 = \frac{1}{81}.$$

(m) Show that

$$B := \mathbb{E}_{(X,Y)\sim\mu} [F_{\mu}(X,Y)^2] \mathbb{E}_{(X,Y)\sim\mu} [X^2 Y^2] = \frac{4}{9} \mathbb{E}_{(Z,W)\sim\lambda} [F_{\mu}(Z,W) ZW] - \frac{1}{27}.$$

Hint: if  $(X, Y) \sim \mu$  then  $\mathbb{E}[X^2] = \mathbb{E}[Y^2] = 1/3$  since X, Y are individually uniform over [0, 1].

(n) Show that

$$C := \frac{4}{9} \sqrt{\mathbb{E}_{(Z,W)\sim\lambda} [F_{\mu}(Z,W)^2]} \sqrt{\mathbb{E}_{(Z,W)\sim\lambda} [Z^2 W^2]} - \frac{1}{27} = \frac{1}{81}$$

- (o) Explain why always  $A \leq B \leq C$ .
- (p) Since A = C = 1/81, both inequalities are tight. Show that this implies that  $F_{\mu}(XY) = XY$  and so  $\mu = \lambda$  is quasirandom.

Question 4 (Dijkstra's algorithm on the uniform weight distribution). In this question we will generalize the analysis of Dijkstra's algorithm from exponential weights to uniform weights. We will use U([0, 1]) to denote the uniform distribution over [0, 1], and Exp(1) to denote the unit mean exponential distribution, given by  $Pr[Exp(1) \ge t] = e^{-t}$ .

- (a) Let  $X \sim U([0,1])$  and  $Y = \log \frac{1}{1-X}$ . Show that  $Y \sim \text{Exp}(1)$ .
- (b) Consider the coupling (X, Y) from the preceding item. Show that

$$Y(1 - Y/2) \le X \le Y.$$

- (c) Suppose that  $w_1, w_2$  are two sets of edge weights that satisfy  $w_1(e) \leq Cw_2(e)$  for all edges e. Let  $d_1(x, y), d_2(x, y)$  be the shortest distance from x to y according to the two sets of edge weights. Show that  $d_1(x, y) \leq Cd_2(x, y)$ .
- (d) For a distribution  $\mathcal{D}$  supported on  $\mathbb{R}_+$ , let  $T_{\mathcal{D}}$  be the expected distance from vertex 1 to the farthest vertex, when weights are chosen according to  $\mathcal{D}$  independently. Show that

$$T_{U([0,1])} \le T_{Exp(1)}.$$

Proving a bound in the other direction is more tricky. For each edge e, we construct three different weights  $w_1(e), w_2(e), w_3(e)$  as follows. We choose  $w_1(e) \sim U([0, 1])$  and let  $w_2(e) = \log \frac{1}{1-w_1(e)}$ , so that  $w_2(e) \sim \text{Exp}(1)$ . For an  $\epsilon \in (0, 1/2)$  to be determined, we choose  $w_3(e) = \max(w_1(e), (1-\epsilon)w_2(e))$ .

- (e) We showed in class that  $T_{\text{Exp}(1)} \sim \frac{2 \log n}{n}$ . Let  $\delta = \omega(\frac{\log n}{n})$ . Show that with high probability, the shortest path tree for vertex 1 under edge weights  $w_1$  only contains edges of weight at most  $\delta$ .
- (f) Show that if  $\epsilon = \omega(\frac{\log n}{n})$  then with high probability, the shortest path trees for vertex 1 under  $w_1$  and under  $w_3$  are identical.

(g) Let  $\tau_1, \tau_2, \tau_3$  be the distances from vertex 1 to the farthest vertex under  $w_1, w_2, w_3$ , respectively. We showed in class that  $\mathbb{V}[\tau_2] = O(1/n^2)$ . Using Cauchy–Schwarz, show that if  $\delta = \omega(\frac{\log n}{n})$  then

$$\mathbb{E}[\tau_2 1_{\tau_2 > \delta}] = o(\mathbb{E}[\tau_2]).$$

(Here  $1_{\tau_2 > \delta}$  is the indicator variable for the event  $\tau_2 > \delta$ .)

(h) Show that if  $\epsilon = \omega(\frac{\log n}{n})$  then  $T_{U([0,1])} \ge (1 - \epsilon - o(1))T_{Exp(1)}$ , and conclude that  $T_{U([0,1])} \sim \frac{2\log n}{n}$ .