# Introduction to Property Testing Lecture 5

Lecture by Dr. Reut Levi Typeset by Steven Karas

 $\begin{array}{c} 2020\text{-}05\text{-}20 \\ \text{Last edited } 22\text{:}25\text{:}53 \ 2020\text{-}05\text{-}20 \end{array}$ 

**Disclaimer** These notes are based on the lectures for the course Introduction to Property Testing, taught by Dr. Reut Levi at IDC Herzliyah in the spring semester of 2019/2020. Sections may be based on the lecture slides prepared by Dr. Reut Levi.

## 1 Agenda

- Monotonicity
- Graph properties

# 2 Testing Monotonicity

Consider  $f:[n] \to R_n$ , where  $R_n$  is an arbitrary totally ordered set. w.l.o.g. we may assume that the values of f are distinct (break ties according to index - i.e. augment f(i) to (f(i),i)). Note that we can consider f as an array filled with values.

## Algorithm 2

- 1. select  $i \in [n]$  u.a.r.
- 2. find f(i) in the array by performing a binary search.
- 3. accept iff f(i) is found

This has query complexity  $1 + \lceil \log n \rceil$ .

**Correctness** If our algorithm accepts w.p.  $\geq 1 - \delta$ , then f is  $\delta$ -close to monotone.

Note that the only random choice is i. We define that i is good (w.r.t. f) if the execution on i accepts. if i < j are both good, then f(i) < f(j). Let t be the first location where the binary search for i and j take different halves. If  $f(i) \le f(t)$  and f(j) > f(t), then it follows that f(i) < f(j).

Observe that the restriction of f to the set of good points is a monotone function. If we correct f on the non-good points we obtain a monotone function. There are  $\geq (1 - \delta) \cdot n$  good points thus f is  $\delta$ -close to monotone.

A related non-adaptive tester Observe that after selecting  $i \in [n]$ , the choice of queries can be determined a priori. If we search for the index i rather than the value, we can make these queries and check that there are no violations. Correctness follows similarly to above.

**2-query algorithm** There exists a 2-query POT for monotonicity with detection probability  $\delta/\lceil \log_2 n \rceil$ .

- 1. select  $i \in [n]$  u.a.r.
- 2. select one of the queries of the nonadaptive algorithm u.a.r.
- 3. reject iff we see a violation.

#### 3 Dense Graph Model

In the adjacency matrix model (a.k.a. the dense graph model), a k-vertex graph G = ([k], E) is represented by  $g:[k]\times[k]\to\{0,1\}$  such that g(u,v)=1 iff  $\{u,v\}\in E$ . We define the distance between G and G' as represented by q and q', respectively:

$$\delta(G,G') = \frac{|\{(u,v): g(u,v) \neq g'(u,v)\}|}{|V|^2}$$

We say that graph properties are sets of graphs that are closed under isomorphism. That is,  $\Pi$  is a graph property if  $\forall G = ([k], E)$  and every permutation of  $[k] : G \in \Pi$  iff  $a(G) \in \Pi$  where  $a(G) \overset{\textstyle \operatorname{def}}{=} ([k], \{\{a(u), a(v)\} : \{u, v\} \in E\}). \text{ In simple terms, the labels of the vertices do not matter,}$ only the structure of the edges.

#### 3.1Testing bipartiteness

We define a bipartite graph as a graph whose vertices can be partitioned into A, B such that every edge is in  $A \times B$ . <sup>2</sup>

**Algorithm** Given an input  $k, \varepsilon$ :

- 1. u.a.r. select  $\tilde{O}(1/\varepsilon^2)$  vertices denoted by R.
- 2. accept iff subgraph induced on R is bipartite.

This algorithm rejects graphs that are  $\varepsilon$ -far from being bipartite with probability  $\geq 2/3$ .

**Correctness** Assume G is  $\varepsilon$ -far from bipartite and we'll see that with probability  $\geq 2/3$ , G([R])is not bipartite. View R as a union of U and S (disjoint) where  $t = |U| = O(\frac{\log \frac{1}{\varepsilon}}{\varepsilon})$  and m = 0 $|S| = O(\frac{t}{\epsilon})$ . Consider all 2-partitions of U. For each 2-partition  $U_1, U_2$  of U consider the partial 2-partition of [k]: One side: all neighbors of  $U_1$  are opposite to  $U_1$ . The other side: all neighbors of  $U_2$  are opposite to  $U_2$ . If v is adjacent to both  $U_1$  and  $U_2$  place it opposite to  $U_2$ .

Denote  $N(v) \stackrel{\text{def}}{=} \{u : \{u, v\} \in E\}$  and  $N(X) \stackrel{\text{def}}{=} \bigcup_{v \in X} N(v)$ . Given a 2-partition  $U_1, U_2$  of U, define a possibly partial 2-partition of [k]:  $V_1, V_2$  where  $V_1 = V_1$  $N(U_2)$  and  $V_2 = N(U_1) \setminus V_1$ .

Define a vertex v as being high-degree if its degree  $\geq \frac{\varepsilon k}{6}$ . U is good if all but at most  $\frac{\varepsilon k}{6}$  of high-degree vertices are in N(U). With probability  $\geq 5/6$ , U is good. Proof follows from any vthat has high degree  $\Pr[N(v) \cap U = \emptyset] = (1 - (\varepsilon/6))^t < \varepsilon/36$  (due to Markov's inequality).

### References

[1] Oded Goldreich. Introduction to property testing. Cambridge University Press, 2017.

<sup>&</sup>lt;sup>1</sup>Sparse matrices are typically stored as lists of edges per vertex

<sup>&</sup>lt;sup>2</sup>There is no POT with constant query complexity, and we will likely have this as a question as part of the next homework set (exercise 8.5 in the book).