

CS6025 Report

Testing Monotonocity

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1 Introduction

In the class we have seen Monotonicity Testing(randomised) for boolean functions. We will further extend monotonicity testing for general functions $f : \Sigma^n \rightarrow \mathcal{Z}$ where Σ is a finite alphabet and \mathcal{Z} is finite range. We will also look on Unateness testing of a function $f : \{0, 1\}^n \rightarrow \{0, 1\}$.

2 Monotonicity

A function $f : \Sigma^n \rightarrow \mathcal{Z}$ is monotone if $f(x) \leq_{\mathcal{Z}} f(y)$ for every $x \prec_{\mathcal{Z}} y$. We will first show monotonicity testing for $f : \Sigma^n \rightarrow \{0, 1\}$ where $|\Sigma| > 2$ and later generalise it to any \mathcal{Z} .

Algorithm 1:

1. Uniform select $i \in \{1 \dots, n\}, \alpha \in \Sigma^{i-1}$ and $\beta \in \Sigma^{n-i}$
2. Select (k, l) according to distribution p .
3. If $f(\alpha k \beta) > f(\alpha l \beta)$ then *reject*

2.1 Idea

The analysis of the above algorithm entirely reduces to the analysis of the algorithm for $n = 1$ i.e. $g : \Sigma \rightarrow \{0, 1\}$. We will show that error in one iteration of the algorithm given above is upper bounded by performance of a function g . So bounding the error for the function will bound the error for $f : \Sigma^n \rightarrow \{0, 1\}$. So we will see different modifications of the algorithm for $n = 1$ and their performance will improve the main algorithm.

2.2 Lemmas and Propositions

Lemma 1. *Let A denotes a single iteration of the algorithm given above and $f : \Sigma^n \rightarrow \{0, 1\}$, then there exists a function $f_{i,\alpha,\beta} : \Sigma \rightarrow \{0, 1\}$ such that the following holds*

1. $\epsilon_M(f) \leq 2 \sum_i \mathbb{E}[\epsilon_M(f_{i,\alpha,\beta})]$
2. $\mathbb{E}_{i,\alpha,\beta}[Pr[A \text{ rejects } f_{i,\alpha,\beta}]] \leq Pr[A \text{ rejects } f]$

Hence we will focus on designing algorithms for the case $n = 1$. Note that we mentioned about the distribution p in the algorithm. We will analyse now for three different distributions and see the query complexity.

Algorithm 1.1 This is a modification of the algorithm we have given in the beginning. The distribution here is $p_1 : \Sigma \times \Sigma \rightarrow [0, 1]$ defined by $p_1(k, k+1) = \frac{1}{d-1}$ for $k = 1, \dots, d-1$.

Proposition 1 Let A_1 be a single iteration of the Algorithm 1 and $f' : \Sigma \rightarrow \{0, 1\}$. Then , $Pr[A_1 \text{ rejects } f'] \geq \frac{2}{d-1} \epsilon_M(f')$

Algorithm 1.2 The distribution used in this algorithm is $p_2 : \Sigma \times \Sigma \rightarrow [0, 1]$ which is uniform on the set P defined as follows

$$P = \{(k, l) \mid 0 < l - k \leq 2^t \text{ and } 2^t \text{ is the largest power of 2 which divides either } k \text{ or } l\}$$

Proposition 2 Let A_2 be the single iteration of the Algorithm 1.2 and $f' : \Sigma \rightarrow \{0, 1\}$. Then, $\Pr[A_2 \text{ rejects } f'] \geq \Omega(\frac{1}{\log d})\epsilon_M(f')$

Algorithm 1.3 The distribution used in this algorithm is uniformly chosen from the set P which is defines as follows.

$$P = \{(k, l) \mid 1 \leq k < l \leq d\}$$

Let $p_3 : \Sigma \times \Sigma \rightarrow [0, 1]$ defined by $p_3(k, l) = \frac{2}{d(d-1)}$

2.3 Main Theorem

Theorem 1. [GGL⁺00]

1. The query complexity of Algorithm 1.1 is $\mathcal{O}(\frac{nd}{\epsilon})$
2. The query complexity of Algorithm 1.2 is $\mathcal{O}(\frac{n \log d}{\epsilon})$
3. The query complexity of Algorithm 1.3 is $\mathcal{O}(\frac{n}{\epsilon})^2$

This follows from Lemma 1 and the propositions for each of the algorithms.

2.4 General Ranges

We will lose a factor of $|\mathcal{Z}|$ while extending to any ranges. The same algorithm will work. Let $f : \Sigma^n \rightarrow \{0, 1, \dots, b\}$ and $f_i : \Sigma^n \rightarrow \{0, 1\}$ where $f_i(x) = 1$ if $f(x) \geq i$ for $i = 0, 1, \dots, b$. Let $\delta_M^A(f)$ be the probability that the algorithm A observes a violating edge pair in f and $\epsilon_M(f)$ be the distance from the closest monotone function.

Lemma 2. Let $f : \Sigma^n \rightarrow \{0, 1, \dots, b\}$ and f_i as defined above

1. $\epsilon_M(f) \leq \sum_{i=1}^b \epsilon_M(f_i)$
2. $\delta_M^A(f) \geq \delta_M^A(f_i)$, for every i

We know that $\delta_M^A(f_i) \geq \epsilon_M(f_i)/F$ where F depends on Σ and n . From above lemma we get that

$$\delta_M^A(f) \geq \max\{\delta_M^A(f_i)\} \geq \frac{1}{b} \sum_{i=1}^b \delta_M^A(f_i) \geq \frac{1}{b} \sum_{i=1}^b \frac{\epsilon(f_i)}{F} \geq \frac{1}{b} \frac{\epsilon_M(f)}{F}$$

2.5 Recent Development

In 2013, Chakrabarty and Seshadhri [CS13] removed the dependence on the range size showing an $\mathcal{O}(\frac{d \log n}{\epsilon})$ - query monotonicity tester for any real valued function and then again in a different paper [CS13] they showed that any monotonicity tester (adaptive) with distance parameter ϵ must make $\Omega(\frac{d \log n}{\epsilon})$ queries.

3 Unateness

We will define unateness first. If $f(x_1, \dots, x_{i-1}, 1, x_{i+1} \dots x_n) / \text{gef}(x_1, \dots, x_{i-1}, 0, x_{i+1} \dots x_n)$ then f is called to be positive unate and if $f(x_1, \dots, x_{i-1}, 1, x_{i+1} \dots x_n) / \text{gef}(x_1, \dots, x_{i-1}, 0, x_{i+1} \dots x_n)$ then f is called to be negative unate. A function f is called to be unate if for every x_i , it is either positive or negative unate.

Algorithm

1. Sample $m = \mathcal{O}(\frac{n^{1.5}}{\epsilon})$ strings uniformly and m indices
2. From the chosen string x^j , obtain y^j by flipping one bit and check unateness.

3.1 Idea

If the function f is unate then the algorithm never makes mistake. We only need to analyse for the false positive. The authors tries to prove that if f is ϵ -far from being unate then the algorithm will reject with probability at least ϵ and end up showing that $\delta_M(f) \geq \frac{\epsilon_M(f)}{n}$

3.2 Main Theorem

Theorem 2. [GGL⁺00] *The algorithm given is a testing algorithm for unateness and if the function is unate then algorithm always accepts.*

Some more definitions

$\bar{\pi} = \pi_1 \dots \pi_n$ where π is a permutation $\{0, 1\}$ or $\{1, 0\}$

$x <_{\bar{\pi}} y$ iff $x_i <_{\pi_i} y_i$

$\epsilon_{M,\bar{\pi}}(f)$ = Min distance between f and any function g that is monotone with respect to π

$\delta_{M,\bar{\pi}} = x <_{\bar{\pi}} y$ but $f(x) > f(y)$ and the pair (x, y) differs only in 1 bit

$\epsilon_U(f)$ = minimum distance of f from set of unate functions

$\gamma_{i,\pi}(f)$ = fraction of strings that differ on single bit (i) and $x_i <_{\pi} y_i$ but $f(x) > f(y)$

Lemma 3. *For any function $f : \{0, 1\}^n \rightarrow \{0, 1\}$ and a permutation $\bar{\pi}$*

$$\delta_{M,\bar{\pi}}(f) \geq \frac{\epsilon_{M,\bar{\pi}}}{n}$$

Now we need to relate $\delta_{M,\bar{\pi}}(f)$ and behaviour of the given algorithm for unateness. The key observation in this follows from the following equation

$$\delta_{M,\bar{\pi}}(f) = \sum_{i=1}^n \gamma_{i,\pi_i}(f) = \sum_{i=1}^n \min_{\pi} \{\gamma_{i,\pi_i}(f)\}$$

This is clear from the definition of each of terms in the equation.

Lemma 4. $\sum_{i=1}^n \min_{\pi} \{\gamma_{i,\pi}\} \geq \frac{\epsilon_U(f)}{n}$

This follows from $\sum_{i=1}^n \min_{\pi} \{\gamma_{i,\pi}\} = \delta_{M,\bar{\pi}}(f) \geq \frac{\epsilon_{M,\bar{\pi}}}{n} \geq \frac{\epsilon_U(f)}{n}$

References

- [CS13] D Chakrabarty and C Seshadhri. Testing monotonicity. *STOC*, 2013.
- [GGL⁺00] Oded Goldreich, Shafi Goldwasser, Eric Lehman, Dana Ron, and Alex Samorodnitsky. Testing monotonicity. *Combinatorica*, 20(3):301–337, Mar 2000.