

Testing Continuous Distributions

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Testing probability distributions

- *General question:*
 - Test a given property of a given probability distribution
 - distribution is available by accessing only samples drawn from the distribution

Examples:

- is given probability uniform?
- are two prob. distributions independent?

Testing probability distributions

For more details/introduction:
see R. Rubinfeld's talk on Wednesday

- Typical result:
 - Given a probability distribution on n points, we can test if it's uniform after seeing $\sim \sqrt{n}$ random samples
- [Batu et al '01]

Testing = distinguish between uniform distribution and distributions which are ϵ -far from uniform

ϵ -far from uniform:

$$\sum_{x \in \Omega} |\Pr[x] - \frac{1}{n}| \geq \epsilon$$

Testing probability distributions

For more details/introduction:
see R. Rubinfeld's talk on Wednesday

- Typical result:
 - Given a probability distribution on n points, we can test if it's uniform after seeing $\sim \sqrt{n}$ random samples
- [Batu et al '01]
- What if distribution has infinite support?
 - Continuous probability distributions?

Testing continuous probability distributions

- Typical result:
 - Given a probability distribution on n points, we can test if it's uniform after seeing $\sim\sqrt{n}$ random samples
 - $\sim\sqrt{n}$ random samples are necessary
- Given a continuous probability distribution on $[0,1]$, can we test if it's uniform?
- Impossible
 - Follows from the lower bound for discrete case with $n \rightarrow \infty$

Testing continuous probability distributions

- More direct proof:
- Suppose tester A distinguishes in at most t steps between uniform distribution and ϵ -far from uniform
- D_1 - uniform distribution
- D_2 is $\frac{1}{2}$ -far from uniform and is defined as follows:
 - Partition $[0,1]$ into t^3 interval of identical length
 - Split each interval into two halves
 - Randomly choose one half:
 - the chosen half gets uniform distribution
 - the other half has zero probability
- In t steps, no interval will be chosen more than once in D_2

A cannot distinguish between D_1 and D_2

Testing continuous probability distributions

- What can be tested?
- First question:
test if the distribution is indeed continuous

Testing continuous probability distributions

- Test if a probability distribution is discrete
- Prob. distribution D on Ω is discrete on N points if there is a set $X \subseteq \Omega$, $|X| \leq N$, st. $\Pr_D[X]=1$
- D is ϵ -far from discrete on N points if
$$\forall X \subseteq \Omega, |X| \leq N$$
$$\Pr_D[X] < 1 - \epsilon$$

Testing if distribution is discrete on N points

- We repeatedly draw random points from D
- All what can we see:
 - Count frequency of each point
 - Count number of points drawn

For some D (eg, uniform or close):

- we need $\Omega(\sqrt{N})$ to see first multiple occurrence

Gives a hope that can be solved in sublinear-time

Testing if distribution is discrete on N points

Raskhodnikova et al '07 (Valiant'08):

Distinct Elements Problem:

- D discrete with each element with prob. $\geq 1/N$
- Estimate the support size

$\Omega(N^{1-o(1)})$ queries are needed to distinguish instances with $\leq N/100$ and $\geq N/11$ support size

Key step: two distributions that have identical first $\log^{\theta(1)}N$ moments

- their expected frequencies up to $\log^{\theta(1)}N$ are identical

Testing if distribution is discrete on N points

Raskhodnikova et al '07 (Valiant'08):

Distinct Elements Problem:

- D discrete with each element with prob. $\geq 1/N$
- Estimate the support size

$\Omega(N^{1-o(1)})$ queries are needed to distinguish instances with $\leq N/100$ and $\geq N/11$ support size

Corollary:

Testing if a distribution is discrete on N points requires $\Omega(N^{1-o(1)})$ samples

Testing if distribution is discrete on N points

- We repeatedly draw random points from D
- All what can we see:
 - Count frequency of each point
 - Count number of points drawn
- Can we get $O(N)$ time?

Testing if distribution is discrete on N points

- Testing if a distribution is discrete on N points:

- Draw a sample $S = (s_1, \dots, s_t)$ with $t = cN/\epsilon$
- If S has more than N distinct elements then **REJECT**
else **ACCEPT**

- If D is discrete on N points then we will accept D
- We only have to prove that
 - if D is ϵ -far from discrete on N points, then we will reject with probability $>2/3$

Testing if distribution is discrete on N points

- Testing if a distribution is discrete on N points:

- Draw a sample $S = (s_1, \dots, s_t)$ with $t = cN/\epsilon$
- If S has more than N distinct elements then **REJECT** else **ACCEPT**

Can we do better (if we only count distinct elements)?

D : has 1 point with prob. $1-4\epsilon$

$2N$ points with prob. $2\epsilon/N$

D is ϵ -far from discrete on N points

We need $\Omega(N/\epsilon)$ samples to see at least N points

Testing if distribution is discrete on N points

Assume D is ϵ -far from discrete on N points

Order points in Ω so that $\Pr[X_i] = p_i$ and $p_i \geq p_{i+1}$

$A = \{X_1, \dots, X_N\}$, $B =$ other points from the support

$$p_1 + p_2 + \dots + p_N < 1 - \epsilon$$

$\alpha =$ # points from A drawn by the algorithm

$\beta =$ # points from B drawn by the algorithm

We consider 3 cases (all bounds are with prob. > 0.99):

1) $p_N < \epsilon / 2N \rightarrow \beta > N$

- all points in B have small prob. \rightarrow not too many repetitions

2) $p_N \geq c N / \epsilon \rightarrow \beta \geq \epsilon / 2p_N$

- points in B have small prob. \rightarrow bound for #distinct points

3) $p_N \geq \epsilon / 2N \rightarrow \alpha \geq N - \epsilon / 2p_N$

- either many distinct points from A or p_N is very small (then β will be large)

Testing if distribution is discrete on N points

Assume D is ϵ -far from discrete on N points

Order points in Ω so that $\Pr[X_i] = p_i$ and $p_i \geq p_{i+1}$

$A = \{X_1, \dots, X_N\}$, $B =$ other points from the support

$\alpha = \#$ points from A drawn by the algorithm

$\beta = \#$ points from B drawn by the algorithm

Main ideas:

Case 2) $p_N \geq c N / \epsilon \rightarrow \beta \geq \epsilon/2p_N$

- Worst case: all points in B have uniform and maximum distrib. = p_N
- $Z_i =$ random variable: number of steps to get i th new point from B
- We have to prove that with prob. > 0.99 : $\sum_{i=1}^{\epsilon/2p_N} Z_i < t$
- Z_1, Z_2, \dots - geometric distribution: $E[Z_i] = \frac{1}{(r-i)p_N}$, $r =$ number of points in B

$$\sum_{i=1}^{\epsilon/2p_N} E[Z_i] \leq \frac{2}{p_N}$$

\rightarrow Markov gives with prob. ≥ 0.99 : $\sum_{i=1}^{\epsilon/2p_N} Z_i < t$

Testing if distribution is discrete on N points

- We repeatedly draw random points from D
- All what can we see:
 - Count frequency of each point
 - Count number of points drawn

By sampling $O(N/\epsilon)$ points one can distinguish between

- distributions discrete on N points and
- those ϵ -far from discrete on N points

The algorithm may fail with prob. $< 1/3$

Testing continuous probability distributions

- What can we test efficiently?
 - Complexity for discrete distributions should be “independent” on the support size
- Uniform distribution ... under some conditions
- Rubinfeld & Servedio'05:
 - testing monotone distributions for uniformity

Testing uniform distributions (discrete)

Rubinfeld & Servedio'05:

- Testing monotone distributions for uniformity

D : distribution on n -dimensional cube; $D: \{0,1\}^n \rightarrow \mathbb{R}$

$x, y \in \{0,1\}^n$, $x \preceq y$ iff $\forall i: x_i \leq y_i$

D is monotone if $x \preceq y \rightarrow \Pr[x] \leq \Pr[y]$

Goal: test if a monotone distribution is uniform

Rubinfeld & Servedio'05:

Testing if a monotone distribution on n -dimensional binary cube is uniform:

- Can be done with $O(n \log(1/\epsilon)/\epsilon^2)$ samples
- Requires $\Omega(n/\log^2 n)$ samples

Testing continuous probability distributions

Rubinfeld & Servedio'05:

- Testing monotone distributions for uniformity

D : distribution on n -dimensional cube; $D:\{0,1\}^n \rightarrow \mathbb{R}$

$x, y \in \{0,1\}^n$, $x \preceq y$ iff $\forall i: x_i \leq y_i$

D is monotone if $x \preceq y \rightarrow \Pr[x] \leq \Pr[y]$

Goal: test if a monotone distribution is uniform

D : distribution on n -dimensional cube;

density function $f:[0,1]^n \rightarrow \mathbb{R}$

$x, y \in [0,1]^n$, $x \preceq y$ iff $\forall i: x_i \leq y_i$

D is monotone if $x \preceq y \rightarrow f(x) \leq f(y)$

Testing continuous probability distributions

Lower bounds holds for continuous cubes

Upper bound: ???

- is it a function of the dimension or the support?

Rubinfeld & Servedio'05:

Testing if a monotone distribution on n -dimensional

binary cube is uniform:

- Can be done with $O(n \log(1/\epsilon)/\epsilon^2)$ samples
- Requires $\Omega(n/\log^2 n)$ samples

Testing monotone distributions for uniformity

D is ϵ -far from uniform if $\frac{1}{2} \int_{x \in \Omega} |f(x) - 1| dx \geq \epsilon$

To test uniformity, we need to characterize monotone distributions that are ϵ -far from uniform

On the high level:

- we follow approach of Rubinfeld & Servedio'05;
- details are quite different

Testing monotone distributions for uniformity

D is ϵ -far from uniform if $\frac{1}{2} \int_{x \in \Omega} |f(x) - 1| dx \geq \epsilon$

Key Technical Lemma:

Let $g: [0,1]^n$ be a monotone function with $\int_x g(x) dx = 0$ then

$$\int_x \|x\|_1 g(x) dx \geq \frac{1}{4} \int_x |g(x)| dx$$

Key Lemma follows from Key Technical Lemma with $g(x) = f(x) - 1$

Key Lemma:

If D is a monotone distribution on $[0,1]^n$ with density function f and which is ϵ -far from uniform then

$$E_f[\|x\|_1] = \int_x \|x\|_1 f(x) dx \geq \frac{n}{2} + \frac{\epsilon}{2}$$

Testing monotone distributions for uniformity

Key Lemma:

If D is a monotone distribution on $[0,1]^n$ with density function f and which is ϵ -far from uniform then

$$E_f[\|x\|_1] = \int_x \|x\|_1 f(x) dx \geq \frac{n}{2} + \frac{\epsilon}{2}$$

$$s = cn/\epsilon^2$$

Repeat 20 times

Draw a sample $S=(x_1, \dots, x_s)$ from $[0,1]^n$

If $\sum_i \|x_i\|_1 \geq s (n/2 + \epsilon/4)$ then REJECT and exit

ACCEPT

Testing monotone distributions for uniformity

Theorem:

The algorithm below tests if D is uniform.

It's complexity is $O(n/\epsilon^2)$.

Slightly better bound than the one by RS'05

$$s = cn/\epsilon^2$$

Repeat 20 times

Draw a sample $S=(x_1, \dots, x_s)$ from $[0,1]^n$

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Testing monotone distributions for uniformity

$$s = cn/\epsilon^2$$

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ACCEPT

Lemma 1: If D is uniform then

$$\Pr[\sum_i \|x_i\|_1 \geq s(n/2 + \epsilon/4)] \leq 0.01$$

Easy application of Chernoff bound

Lemma 2: If D is ϵ -far from uniform then

$$\Pr[\sum_i \|x_i\|_1 < s(n/2 + \epsilon/4)] \leq 12/13$$

By Key Lemma + Feige lemma

Testing monotone distributions for uniformity

$$s = cn/\epsilon^2$$

Repeat 20 times

Draw a sample $S=(x_1, \dots, x_s)$ from $[0,1]^n$

If $\sum_i \|x_i\|_1 \geq s(n/2 + \epsilon/4)$ then REJECT and exit
ACCEPT

Lemma 2: If D is ϵ -far from uniform then

$$\Pr[\sum_i \|x_i\|_1 < s(n/2 + \epsilon/4)] \leq 12/13$$

Proof:

D is ϵ -far from uniform $\rightarrow E[\sum_i \|x_i\|_1] \geq s(n+\epsilon)/2$

Feige's lemma: Y_1, \dots, Y_s independent r.v., $Y_i \geq 0$, $E[Y_i \leq 1] \rightarrow$

$$\Pr[\sum_i Y_i < s + 1/12] \geq 1/13$$

Choose $Y_i = 2 - 2\|x_i\|_1/(n+\epsilon)$

Then, Feige's lemma yields the desired claim

Testing monotone distributions for uniformity

Key Lemma:

If D is a monotone distribution on $[0,1]^n$ with density function f and which is ϵ -far from uniform then

$$E_f[\|x\|_1] = \int_x \|x\|_1 f(x) dx \geq \frac{n}{2} + \frac{\epsilon}{2}$$

$$s = cn/\epsilon^2$$

Repeat 20 times

Draw a sample $S=(x_1, \dots, x_s)$ from $[0,1]^n$

If $\sum_i \|x_i\|_1 \geq s (n/2 + \epsilon/4)$ then REJECT and exit

ACCEPT

Testing monotone distributions for uniformity

Key Lemma:

If D is a monotone distribution on $[0,1]^n$ with density function f and which is ϵ -far from uniform then

$$E_f[\|x\|_1] = \int_x \|x\|_1 f(x) dx \geq \frac{n}{2} + \frac{\epsilon}{2}$$

Key Technical Lemma:

Let $g:[0,1]^n$ be a monotone function with $\int_x g(x) dx = 0$ then

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Testing monotone distributions for uniformity

Key Technical Lemma:

Let $g:[0,1]^n$ be a monotone function with $\int_x g(x) dx = 0$ then

$$\int_x \|x\|_1 g(x) dx \geq \frac{1}{4} \int_x |g(x)| dx$$

Why such a bound:

Tight for $g(x) = \text{sgn}(x_1 - 1/2)$

$$\int_{x:x_1 > \frac{1}{2}} \|x\|_1 g(x) = \frac{1}{2} \int_{x:x_1 > \frac{1}{2}} (x_1 + \dots + x_n) = \frac{1}{2} \left(\frac{3}{4} + \frac{1}{2} + \dots + \frac{1}{2} \right) = \frac{n}{4} + \frac{1}{8} .$$

Similarly,

$$\int_{x:x_1 < \frac{1}{2}} \|x\|_1 g(x) = \frac{1}{2} \left(\frac{1}{4} + \frac{1}{2} + \dots + \frac{1}{2} \right) = \frac{n}{4} - \frac{1}{8} ,$$

and hence,

$$\int_x \|x\|_1 g(x) = \int_{x:x_1 > \frac{1}{2}} \|x\|_1 g(x) - \int_{x:x_1 < \frac{1}{2}} \|x\|_1 g(x) = \frac{1}{4} = \frac{1}{4} \cdot \int_x |g(x)| .$$

Testing monotone continuous distributions

Rubinfeld & Servedio'05:

Testing if a monotone distribution on n-dimensional
binary cube is uniform:

- Can be done with $O(n \log(1/\epsilon)/\epsilon^2)$ samples
- Requires $\Omega(n/\log^2 n)$ samples

Here:

Testing if a monotone distribution on n-dimensional
continuous cube is uniform :

- Can be done with $O(n/\epsilon^2)$ samples

Can be easily extended to $\{0,1,\dots,k\}^n$ cubes

Conclusions

- Testing continuous distributions is different from testing discrete distributions
- Continuous distributions are harder
- More examples when it's possible to test
 - Usually some additional conditions are to be imposed
- Tight(er) bounds?