

Sublinear Algorithms

LECTURE 6

Last time

- Communication complexity
- Testing with adversarial erasures

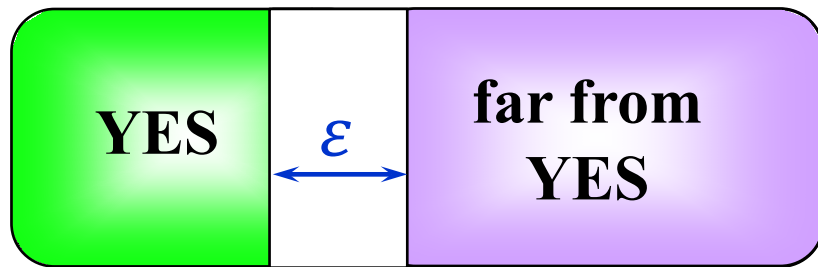
Today

- Other models of computation
- Streaming



Property Testing with Erasures

Property Tester [Rubinfeld Sudan 96,
Goldreich Goldwasser Ron 98]



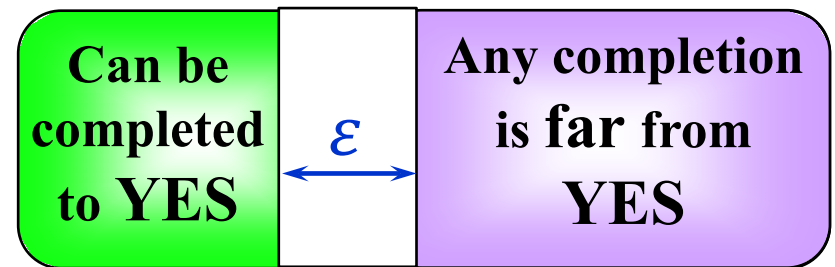
Accept with
probability
 $\geq 2/3$

Don't
care

Reject with
probability
 $\geq 2/3$

Erasure-Resilient Property Tester [Dixit
Raskhodnikova Thakurta Varma 16]

- $\leq \alpha$ fraction of the input is erased
adversarially



Accept with
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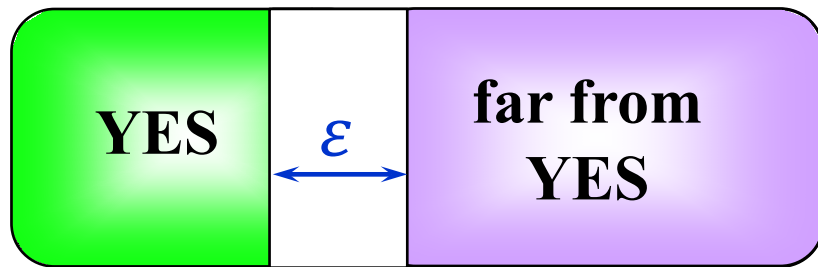
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Two objects are at distance ϵ = they differ in an ϵ fraction of places

Property Testing with Errors

Property Tester [Rubinfeld Sudan 96,
Goldreich Goldwasser Ron 98]



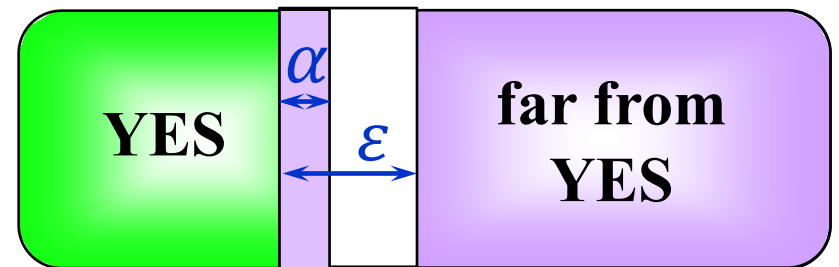
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Tolerant Property Tester
[Parnas Ron Rubinfeld 06]

- $\leq \alpha$ fraction of the input is wrong



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 $\geq 2/3$

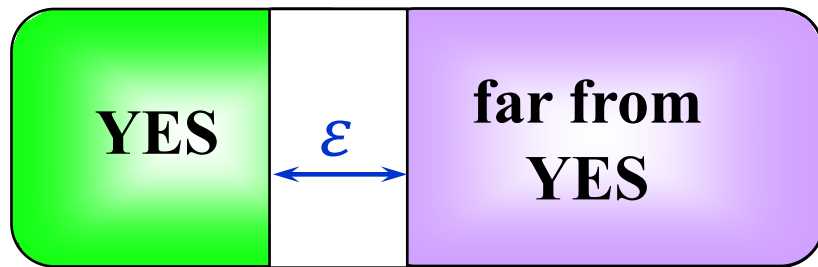
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Property Testing with Errors

Property Tester [Rubinfeld Sudan 96,
Goldreich Goldwasser Ron 98]



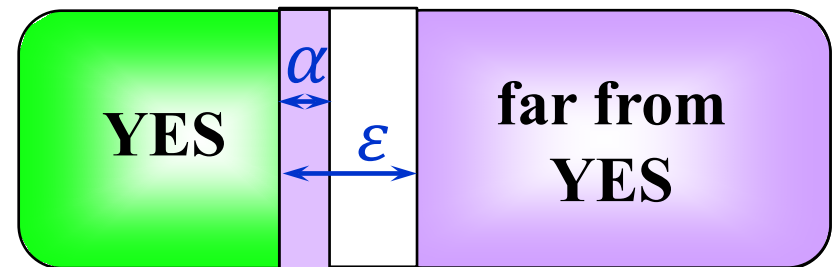
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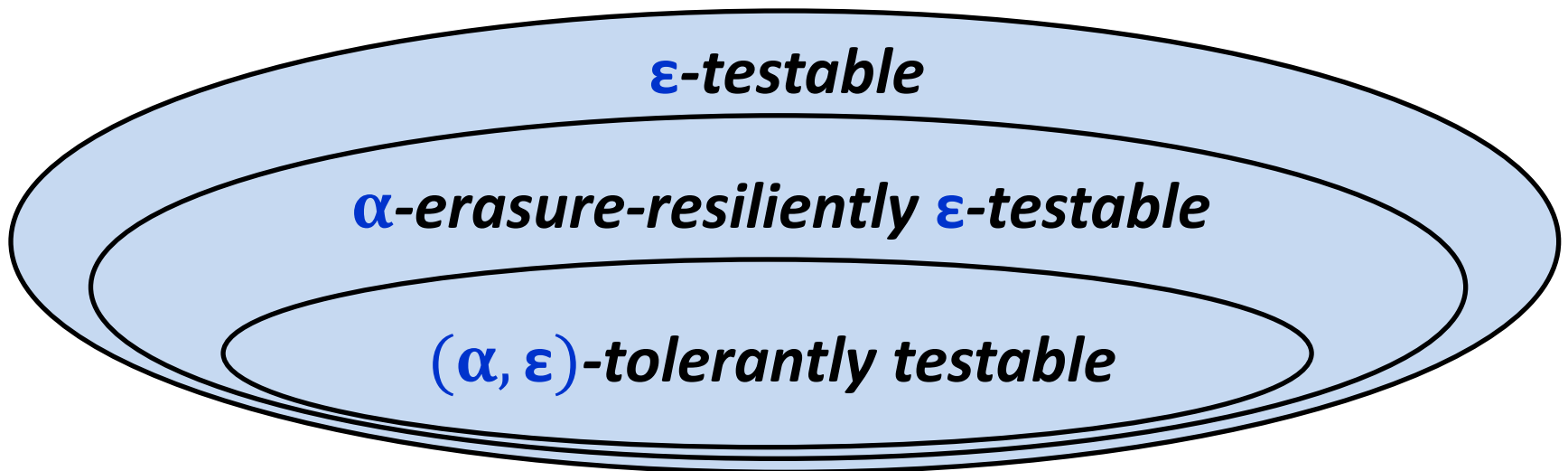
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Relationships Between Models

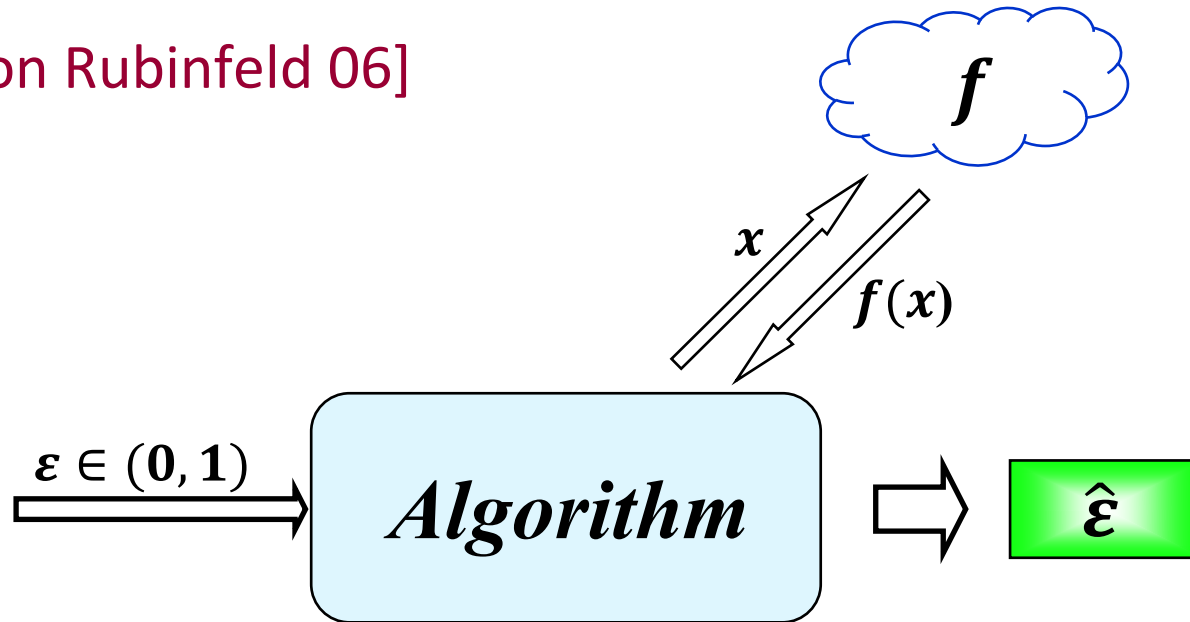
Containments are strict:

- [Fischer Fortnow 05]: standard vs. tolerant
- [Dixit R Thakurta Varma 16]: standard vs. erasure-resilient
- [R Ron-Zewi Varma 19]: erasure-resilient vs. tolerant



Distance Approximation for Boolean Functions

[Parnas Ron Rubinfeld 06]



Goal: Output $dist(f, \mathcal{P}) \pm \epsilon$

in sublinear time

Sublinear-Time “Restoration” Models

Local Decoding

Input: A slightly corrupted codeword

Requirement: Recover individual bits of the closest codeword with a constant number of queries per recovered bit.

Program Checking

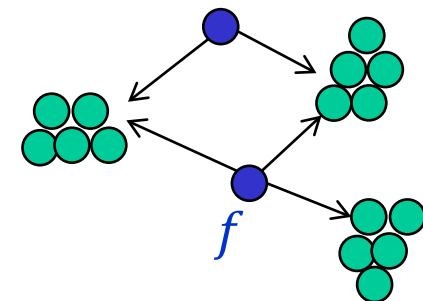
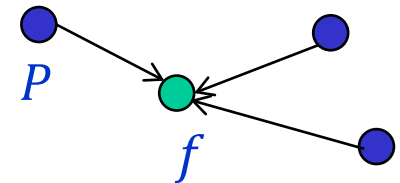
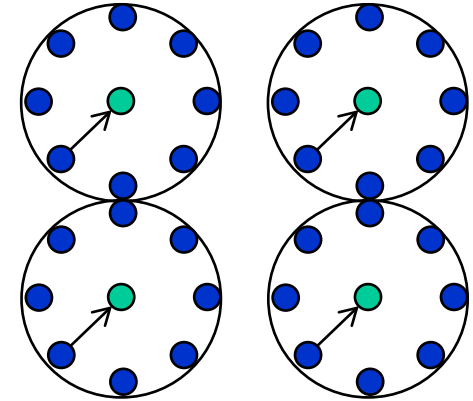
Input: A program P computing f correctly on most inputs.

Requirement: **Self-correct** program P : for a given input x , compute $f(x)$ by making a few calls to P .

Local Reconstruction

Input: Function f nearly satisfying some property P

Requirement: Reconstruct function f to ensure that the reconstructed function g satisfies P , changing f only when necessary. For each input x , compute $g(x)$ with a few queries to f .

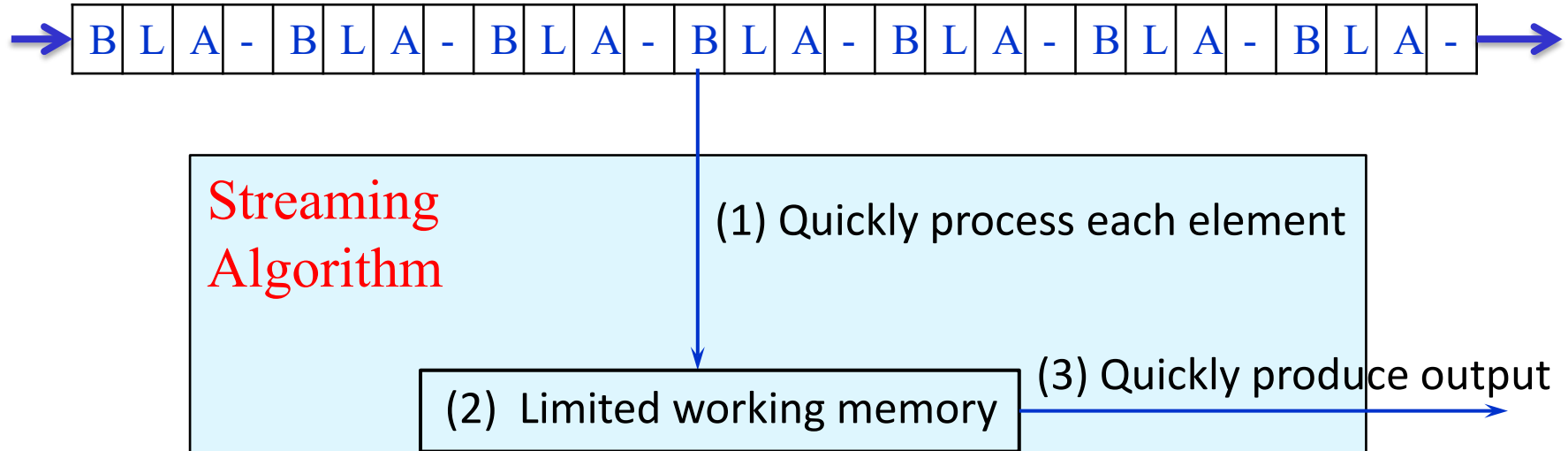


Generalization: Local Computation

[Rubinfeld Tamir Vardi Xie 2011]

- Compute the i -th character y_i of a legal output y .
- If there are several legal outputs for a given input, be consistent with one.
- **Example:** maximal independent set in a graph.

Data Stream Model [Alon Matias Szegedy 96]



Motivation: internet traffic analysis

Model the **stream** as m elements from $[n]$, e.g.,

$$\langle a_1, a_2, \dots, a_m \rangle = 3, 5, 3, 7, 5, 4, \dots$$

Goal: Compute a function of the stream, e.g., **median**, **number of distinct elements**, **longest increasing sequence**.

Streaming Puzzle



A stream contains $n - 1$ **distinct** elements from $[n]$ in arbitrary order.

Problem: Find the missing element, using $O(\log n)$ space.

Sampling from a Stream of Unknown Length

Warm-up: Find a uniform sample s from a stream $\langle a_1, a_2, \dots, a_m \rangle$ of *known* length m .

Sampling from a Stream of Unknown Length

Problem: Find a uniform sample s from a stream $\langle a_1, a_2, \dots, a_m \rangle$ of *unknown* length m

Algorithm (Reservoir Sampling)

1. Initially, $s \leftarrow a_1$
2. On seeing the t^{th} element, $s \leftarrow a_t$ with probability $1/t$

Analysis:

What is the probability that $s = a_i$ at some time $t \geq i$?

$$\begin{aligned}\Pr[s = a_i] &= \frac{1}{i} \cdot \left(1 - \frac{1}{i+1}\right) \cdot \dots \cdot \left(1 - \frac{1}{t}\right) \\ &= \frac{1}{i} \cdot \frac{i}{i+1} \cdot \dots \cdot \frac{t-1}{t} = \frac{1}{t}\end{aligned}$$

Space: $O(k (\log n + \log m))$ bits to get k samples.

Frequency Moments Estimation

Input: a stream $\langle a_1, a_2, \dots, a_m \rangle \in [n]^m$

- The **frequency vector** of the stream is $f = (f_1, \dots, f_n)$, where f_i is the number of times i appears in the stream
- The p -th frequency moment is $F_p = \|f\|_p^p = \sum_{i=1}^n f_i^p$

F_0 is the number of nonzero entries of f (# of distinct elements)

$F_1 = m$ (# of elements in the stream)

$F_2 = \|f\|_2^2$ is a measure of non-uniformity

used e.g. for anomaly detection in network analysis

$F_\infty = \max_i f_i$ is the most frequent element

Goal: Estimate F_p up to a multiplicative factor $(1 \pm \varepsilon)$ with probability $\geq 2/3$

Summary

Streaming Model

- Reservoir sampling
- Distinct Elements (approximating F_0)
- k -wise independent hashing