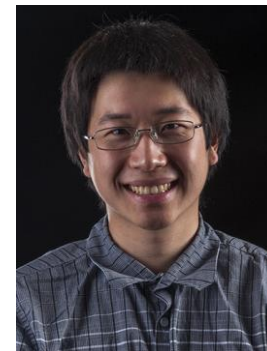


# Fast Fourier Sparsity Testing



GRIGORY YAROSLAVTSEV  
SAMSON ZHOU



The  
Alan Turing  
Institute



Carnegie  
Mellon  
University

# Fourier Expansion

For  $S \subseteq [n]$ , the characteristic function  $\chi_S(x): \{-1, +1\}^n \rightarrow \{-1, +1\}$  is defined as  $\chi_S(x) = \prod_{i \in S} x_i$

The Fourier expansion of a function  $f: \{-1, +1\}^n \rightarrow \mathbb{R}$  is the unique linear combination of multilinear polynomials:

$$f(x_1, \dots, x_n) = \sum_{S \subseteq [n]} \hat{f}(S) \chi_S(x)$$

Then we have the Fourier coefficient  $\hat{f}(S) = \langle f, \chi_S \rangle = E[f(x) \chi_S(x)]$

# Fourier Sparsity

$$f(x_1, x_2, x_3) = \text{Maj}_3(x_1, x_2, x_3) = \frac{1}{2}x_1 + \frac{1}{2}x_2 + \frac{1}{2}x_3 - \frac{1}{2}x_1x_2x_3$$

$$\begin{aligned} f(x_1, x_2, x_3, x_4, x_5, x_6) &= 6 + 6x_1x_2 \\ &= 3(x_1 + x_2)^2 - x_3^3x_4 + 2x_3x_4x_5^2 - x_3x_4^3x_6^4 \end{aligned}$$

A function is  $s$ -sparse if it has at most  $s$  nonzero Fourier coefficients

# Why Fourier Sparsity?

Fourier sparsity has applications in coding theory [GoldreichLevin89, AkaviaGoldwasserShafra03], learning theory [KushilevitzMansour93, LinialMansourNisan93], communication complexity [ShiZhang09]

If a function is known to be  $s$ -sparse, more efficient algorithms can often be run, e.g. sparse Fourier transform [HIKP12]

# Property Tester

Testing sparsity of Boolean functions under Hamming distance

[GOSSW11]

Non-tolerant test

Complexity  $O\left(s^{14} \log s + \frac{s^6}{\epsilon^2 \log s}\right)$

Reduction to testing under  $\ell_2$

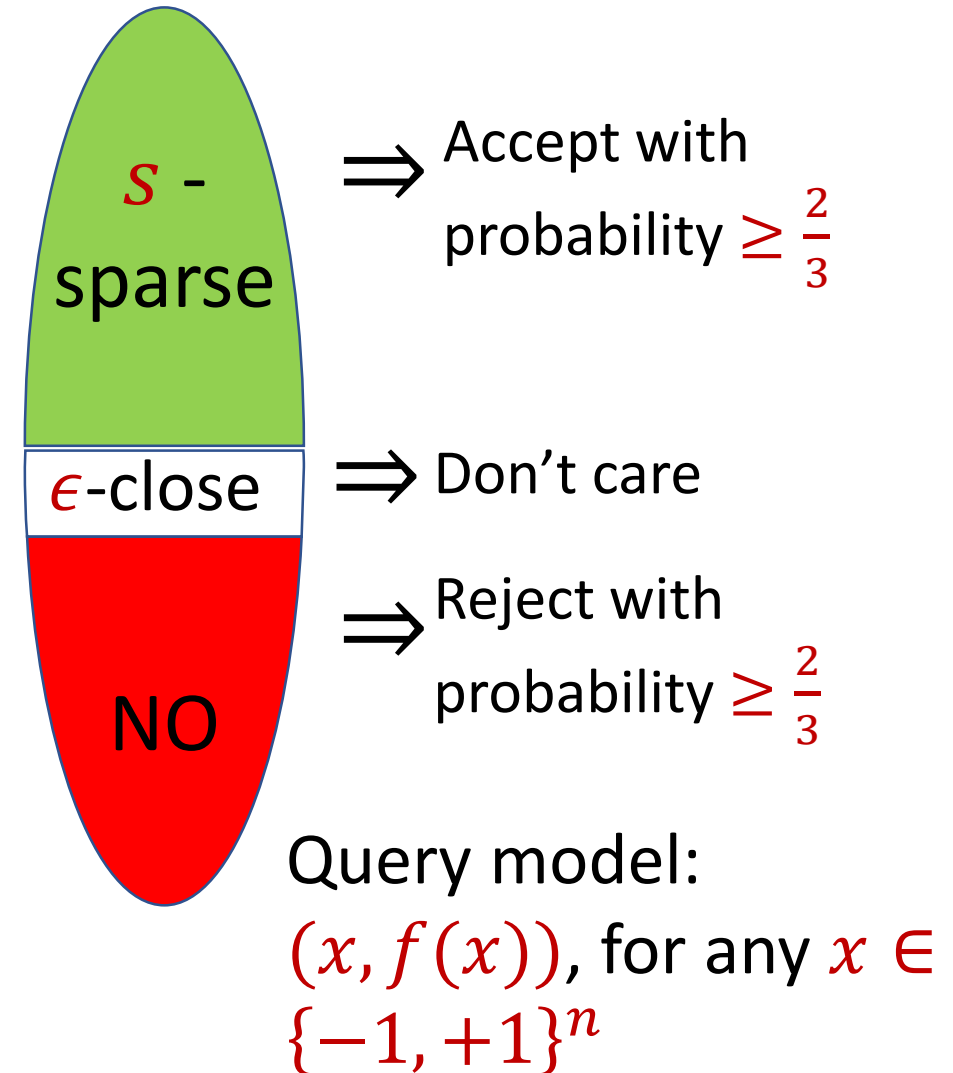
Lower bound  $\Omega(\sqrt{s})$

[WimmerYoshida13]

Tolerant test

Complexity  $\text{poly}\left(s, \frac{1}{\epsilon}\right)$

Our results give a tolerant test with almost quadratic improvement on [GOSSW11]



# Our Contributions

Upper bound: Algorithm that makes  $O\left(\frac{s}{\epsilon^4} \log \frac{1}{\epsilon}\right)$  non-adaptive queries to a (normalized) function  $f$  and approximates the  $\ell_2^2$  distance from  $f$  to the set of  $s$ -sparse functions. Translates to a tester.

Lower bound: Any algorithm that distinguishes whether  $f$  is  $s$ -sparse or at least  $\frac{1}{3}$  - far from  $s$ -sparse in  $\ell_2^2$  distance requires  $\Omega(\sqrt{s})$  queries

# Random Hashing [FGKP09]

If a subspace  $H$  of  $\{-1, +1\}^n$  is drawn randomly from subspaces of codimension  $d$ , then  $\Pr[b \in a + H] = \frac{1}{2^d}$  for distinct  $a, b \neq 0$

For an element  $a \in H^\perp$ , the projected function  $f|_{a+H}(z) = E_{x \in H^\perp} [f(x+z)\chi_a(x)]$  for each  $z \in \{-1, +1\}^n$

Poisson Summation Formula:  $\hat{f}|_{a+H}(\alpha) = \hat{f}(\alpha)$  if  $\alpha \in a + H$  and 0 otherwise

Define the total energy of  $f|_{a+H}$  as  $\sum_{\alpha \in a+H} \hat{f}(\alpha)^2 = \|\hat{f}|_{a+H}\|_2^2$

# Testing $s$ -Sparsity

$$\# \text{ } \img alt="recycling bin" data-bbox="225 285 315 465" = O(s^2) \Rightarrow \img alt="recycling bin with a red prohibition sign over it" data-bbox="665 225 805 515"/>$$

$$\sum_{\alpha \in a+H} \hat{f}(\alpha)^2 = E[\chi_a(z) f(x) f(x+z)], \text{ where } x \in \{-1, +1\}^n, z \in H^\perp \text{ [GOSSW11]}$$

The set of queries  $\{f(x+z)\}_{x \in H^\perp}$  can be used to compute  $f|_{a+H}(z)$  for each of the cosets  $a+H$  simultaneously



# Algorithm

Draw subspace  $H$  of codimension  $d = \log \frac{2s}{\epsilon^4}$  at random

Draw  $O\left(\frac{s}{\epsilon^4}\right)$  pairs  $(x, x + z)$ , where  $x \in \{-1, +1\}^n$ ,  $z \in H^\perp$

Estimate the energy  $y_{a+H}$  for each  $a \in H^\perp$

$$y_{a+H} += O\left(\frac{\epsilon^4}{s}\right) \chi_a(z) f(x) f(x + z)$$

Repeat  $\ell = O\left(\log \frac{1}{\epsilon}\right)$  times, take the largest sum of the energies in  $s$  buckets

$$\xi = \max_{S \in H^\perp, |S|=s} \sum_{a \in S} \text{median} \left( y_{a+H}^{(1)}, \dots, y_{a+H}^{(\ell)} \right)$$

# Analysis

Top  $s$  coefficients may collide in a bucket

Noise from non top  $s$  coefficients

Hashing error: Let  $y_1 \geq \dots \geq y_s$  be the energies of the top  $s$  buckets and  $f_1 \geq \dots \geq f_s$  be the energies of the top  $s$  Fourier coefficients. Then with probability at least  $15/16$ , the hashing error  $\sum y_i - f_i \leq 5\epsilon^2$

Estimation error: Let  $y_1 \geq \dots \geq y_s$  be the energies of the top  $s$  buckets and  $\hat{y}_i$  be the estimate of  $y_i$ . Then  $E_H[\sum_{i=1}^s |\hat{y}_i - y_i|^2] \leq \epsilon^2$

# Putting it all together

Let  $S^*$  be the set of  $s$  buckets that maximize the estimated energies

Define  $h$  to be  $f$  with only the  $s$  Fourier coefficients that are the largest Fourier coefficient in each bucket, but their energies is the energy of the entire bucket

$$\xi = \|h\|_2^2$$



# Putting it all together

Define  $f^*$  to be  $f$  with only the largest  $s$  Fourier coefficients

$$|\xi - \|f^*\|_2^2| = |\|h\|_2^2 - \|f^*\|_2^2| \leq 2\|f^* - h\|_2$$

Define  $g$  to be  $f$  with only the  $s$  Fourier coefficients that are the largest Fourier coefficient in each bucket

$$\text{Then } \|f^* - h\|_2 \leq \|f^* - g\|_2 + \|g - h\|_2 = O(\epsilon)$$



Hashing error   Estimation error

# Future Work?

Improve upper or lower bounds

Extensions to other domains (line, hypergrid)

Other properties that can be tested in  $\ell_2$ ?



# Hashing Error

Hashing error: Let  $y_1 \geq \dots \geq y_s$  be the energies of the top  $s$  buckets and  $f_1 \geq \dots \geq f_s$  be the energies of the top  $s$  Fourier coefficients. Then with probability at least  $15/16$ , the hashing error is at most  $5\epsilon^2$  (Essentially just avoid collisions)

Define  $y_i^*$  as the largest Fourier coefficient hashing into bucket  $i$

$$\sum y_i - f_i = \sum y_i - y_i^* + \sum y_i^* - f_i \leq \sum y_i - y_i^*$$

$E[\sum y_i - y_i^*] \leq \sqrt{\frac{2s}{2^d}}$ ,  $\text{Var}(\sum y_i - y_i^*) \leq \frac{2}{2^d}$  by Cauchy-Schwartz and Jensen, result holds by Chebyshev

# Estimation Error

Estimation error: Let  $y_1 \geq \dots \geq y_s$  be the energies of the top  $s$  buckets and  $\hat{y}_i$  be the estimate of  $y_i$ . Then  $E_H[\sum_{i=1}^s |\hat{y}_i - y_i|^2] \leq \epsilon^2$

For a fixed  $j \in [\ell]$ ,  $E_H[\sum_{i=1}^s |y_{i,j} - y_i|^2] \leq \frac{\epsilon^4}{s}$  (number of samples)

By Markov and counting,  $\Pr[|\hat{y}_i - y_i|^2 \geq \eta] \leq \left(\frac{2e\epsilon^4}{s\eta}\right)^{\ell/2}$

Result follows from integrating probability density function and Jensen