

# Expander Random Walks: A Fourier-Analytic Approach

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Based on joint works with

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# Outline

- 1 Spectral expanders
- 2 Question
- 3 Answers
- 4 Approach

# Spectral Expanders

Let  $G = (V, E)$  be a  $d$ -regular undirected graph on  $n$  vertices.

$$(\mathbf{W}_G)_{u,v} = \begin{cases} \frac{1}{d}, & uv \in E, \\ 0, & \text{otherwise.} \end{cases}$$

The eigenvalues of  $\mathbf{W}_G$  are real, satisfying

$$-1 \leq \lambda_n \leq \dots \leq \lambda_2 \leq \lambda_1 = 1.$$

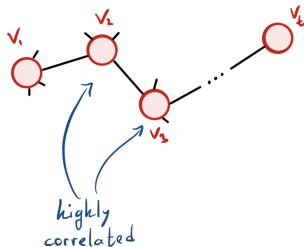
The **spectral expansion** of  $G$  is given by

$$\lambda(G) = \max(\lambda_2, -\lambda_n).$$

The smaller  $\lambda(G)$  is the better. The “best” spectral expanders, dubbed Ramanujan graphs, satisfy

$$\lambda = \frac{2\sqrt{d-1}}{d}.$$

# Expander random walks



$$v_1 \sim V$$

$$v_2 \sim N(v_1)$$

$$\vdots$$

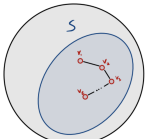
$$v_t \sim N(v_{t-1})$$

Meta question

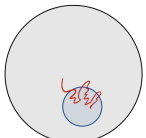
How random are random walks on expanders?

# Some pseudorandom properties

## The Expander hitting property (Ajtai-Komlós-Szemerédi'87)

$$\Pr \left[ \text{Diagram} \right] \leq (\mu(S) + \lambda)^t$$


## The Expander Chernoff bound (AKS'87, Gillman'98, Healy'08)

$$\Pr \left[ \text{Diagram} \right] < e^{-c(1-\lambda)\epsilon^2 t}$$


$$\Pr_{(v_1, \dots, v_t) \sim \text{RW}} \left[ \left| \frac{|\{v_1, \dots, v_t\} \cap S|}{t} - \mu \right| \geq \epsilon \right] \leq e^{-c(1-\lambda)\epsilon^2 t}$$

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# Question

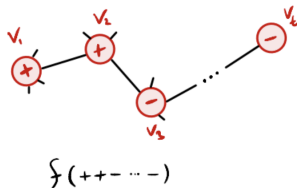
## Question

What test functions are fooled by a random walk on expanders?

For  $G = (V, E)$  and  $\text{val} : V \rightarrow \{\pm 1\}$  let  $\text{RW}_{G, \text{val}} \in \{\pm 1\}^t$  be the distribution  $\text{val}(v_1), \dots, \text{val}(v_t)$  where  $v_1, \dots, v_t$  is a random walk in  $G$ .

Given  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$  define

$$\mathcal{E}_{G, \text{val}}(f) = \left| \mathbb{E}[f(\text{RW}_{G, \text{val}})] - \mathbb{E}[f(\text{val}(V)^t)] \right|.$$



# Question

Recall

$$\mathcal{E}_{G,\text{val}}(f) = \left| \mathbb{E}[f(\text{RW}_{G,\text{val}})] - \mathbb{E}[f(\text{val}(V)^t)] \right|.$$

## Definition

For  $\lambda, \mu$  and  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$ , define

$$\mathcal{E}_{\lambda,\mu}(f) = \sup_{G,\text{val}} \mathcal{E}_{G,\text{val}}(f),$$

where

- $G = (V, E)$  ranges over all  $\lambda$ -spectral expanders; and
- $\text{val}$  ranges over all valuations with  $\mathbb{E}[\text{val}(V)] = \mu$ .



# Pseudorandom properties revisited

## The Expander hitting property (Ajtai-Komlós-Szemerédi'87)

$$\Pr \left[ \text{Diagram} \right] \leq (\mu(s) + \lambda)^t$$

$$\mathcal{E}_{\lambda, \mu}(\text{AND}_t) \leq (\mu + \lambda)^t.$$

## The Expander Chernoff bound (AKS'87, Gillman'98, Healy'08)

$$\Pr \left[ \text{Diagram} \right] < e^{-c(1-\lambda)\varepsilon^2 t}$$

$$\mathcal{E}_{\lambda, \mu}(\mathbf{1}_{[(\mu-\varepsilon)t, (\mu+\varepsilon)t]}) \leq e^{-c(1-\lambda)\varepsilon^2 t}.$$

# Other known results

CLT for expander random walks wrt CDF.

Theorem (Kipnis-Varadhan'86, Lezaud'01, Kloeckner'17)

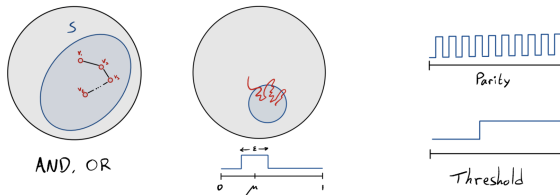
$$\mathcal{E}_{\lambda,\mu} \left( \sum_{i=1}^t x_i \geq k \right) = O \left( \frac{1}{(1-\lambda)^2 \sqrt{t}} \right).$$

Perhaps most surprising is

Theorem (Ta-Shma'17 (see also Alon'93, Wigderson-Rozenman'04))

$$\mathcal{E}_{\lambda,\mu}(\text{Parity}) \leq (\mu + 2\lambda)^{t/2}.$$

# What about other test functions?



What about other symmetric functions? Namely, CLT wrt TVD (raised independently by Guruswami-Kumar'20).

## Beyond symmetric functions.

- 1  **$AC^0$**  circuits.
- 2 Bounded-width (any order) read-once branching programs.
- 3 Low query complexity.

# Question

## Meta question

How random are random walks on expanders?

## Question

What test functions are fooled by a random walk on expanders?

## Question (formalized)

Given  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$ , bound  $\mathcal{E}_{\lambda, \mu}(f)$ .

## Remarks.

- For simplicity, we only consider  $\mu = 0$  and denote  $\mathcal{E}_{\lambda, \mu}$  by  $\mathcal{E}_{\lambda}$ .
- To bound  $\mathcal{E}_{\lambda}(f)$  it suffices to bound  $\mathcal{E}_{G, \text{val}}(f)$  for all relevant  $G, \text{val}$ . We fix  $G, \text{val}$  and write  $\mathcal{E}$  for  $\mathcal{E}_{G, \text{val}}$ .

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# Symmetric functions

## Theorem

For every symmetric function  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$ ,

$$\mathcal{E}_\lambda(f) = O(\lambda).$$

Further, the bound is tight for this class.

## Theorem

$$\mathcal{E}_\lambda(\mathbf{1}_w) = O\left(\frac{\lambda}{\sqrt{t}}\right),$$

$$\mathcal{E}_\lambda(\text{Majority}) = O\left(\frac{\lambda^2}{\sqrt{t}}\right).$$

# Beyond symmetric functions

## Theorem ( $\mathbf{AC}^0$ circuits)

For every  $f$  that is computable by a size- $s$  depth- $d$  circuit,

$$\varepsilon_\lambda(f) = O\left(\sqrt{\lambda} \cdot (\log s)^{2(d-1)}\right).$$

This is essentially tight.

## Theorem (Any order ROBP)

For every  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$  that is computable by any order width- $w$  ROBP,

$$\varepsilon_\lambda(f) = O\left(\sqrt{\lambda} \cdot (\log t)^{2w}\right).$$

For permutation ROBP,  $\varepsilon_\lambda(f) = O\left(\sqrt{\lambda} \cdot w^4\right).$

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# Our approach

## Our Approach

- 1 Bound  $\mathcal{E}(\chi_S) = |\mathbb{E}[\chi_S(\text{RW})]|$  for a general character

$$\chi_S(x_1, \dots, x_t) = \prod_{i \in S} x_i$$

with  $\emptyset \neq S \subseteq [t]$ .

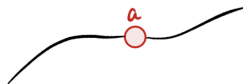
- 2 Expand  $f$  in the Fourier basis

$$f(x) = \sum_{S \subseteq [t]} \hat{f}(S) \chi_S(x).$$

- 3 Conclude that

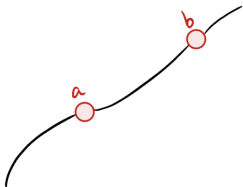
$$\mathcal{E}(f) \leq \sum_{\emptyset \neq S \subseteq [t]} |\hat{f}(S)| \mathcal{E}(\chi_S).$$

# Degree 1 characters



For every  $a \in [t]$ ,  $v_a$  is uniformly distributed over  $V$  and so  $\mathcal{E}(x_a) = 0$ .

# Degree 2 characters



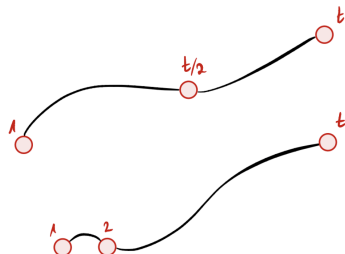
By the expander mixing lemma,

$$\mathcal{E}(x_a x_{a+1}) \leq \lambda.$$

The general case can be reduced to the above by considering  $G^{b-a}$ , and so

$$\mathcal{E}(x_a x_b) \leq \lambda^{b-a}.$$

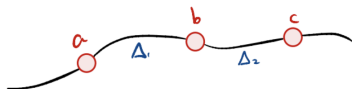
# Degree 3 characters



Test your intuition.

$$\varepsilon \left( \begin{array}{c} \text{node } 1 \\ \text{node } t/2 \\ \text{node } t \end{array} \right) \square \varepsilon \left( \begin{array}{c} \text{node } 1 \\ \text{node } 2 \\ \text{node } t \end{array} \right)$$

# Degree 3 characters



**Informally.** A random step on a  $\lambda$ -spectral expander  $G$  can be thought of as sampling a vertex uniformly at random with probability  $1 - \lambda$  and letting an adversary select a vertex with probability  $\lambda$ .

**Formally.**

$$W_G = J + E,$$

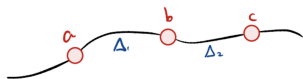
where  $J = (\frac{1}{n})_{i,j}$  and  $\|E\| = \max\{\|Ex\|_2 : \|x\|_2 = 1\} \leq \lambda$ .

**Informally.**

- Except with probability  $\lambda^{\Delta_1}$ ,  $b \mid a \sim V$ .
- Independent of that, e.w.p  $\lambda^{\Delta_2}$ ,  $c \mid b \sim V$ .

Thus, e.w.p.  $\lambda^{\Delta_1 + \Delta_2}$ , the bias is 0 and so  $\mathcal{E}(x_a x_b x_c) \leq \lambda^{\Delta_1 + \Delta_2}$ .

# Degree 3 characters



**Formally.** Let  $\mathbf{1} = \left( \frac{1}{\sqrt{n}}, \dots, \frac{1}{\sqrt{n}} \right)^T$ ,  $\mathbf{P} = \text{diag}(\text{val}(v))_{v \in V}$ . Observe that

$$\mathbb{E}_{\text{RW}}(\chi_{a,b,c}) = \mathbf{1}^T \mathbf{P} \mathbf{W}^{\Delta_2} \mathbf{P} \mathbf{W}^{\Delta_1} \mathbf{P} \mathbf{1}.$$

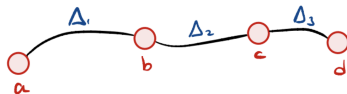
Now,  $\mathbf{W}^{\Delta_i} = \mathbf{J} + \mathbf{E}_i$ , with  $\|\mathbf{E}_i\| \leq \lambda^{\Delta_i}$ , and so

$$\begin{aligned} \mathbf{1}^T \mathbf{P} \mathbf{W}^{\Delta_2} \mathbf{P} \mathbf{W}^{\Delta_1} \mathbf{P} \mathbf{1} &= \mathbf{1}^T \mathbf{P} \mathbf{J} \mathbf{P} \mathbf{J} \mathbf{P} \mathbf{1} + \\ &\quad \mathbf{1}^T \mathbf{P} \mathbf{J} \mathbf{P} \mathbf{E}_1 \mathbf{P} \mathbf{1} + \\ &\quad \mathbf{1}^T \mathbf{P} \mathbf{E}_2 \mathbf{P} \mathbf{J} \mathbf{P} \mathbf{1} + \\ &\quad \mathbf{1}^T \mathbf{P} \mathbf{E}_2 \mathbf{P} \mathbf{E}_1 \mathbf{P} \mathbf{1}. \end{aligned}$$

As  $\mathbf{J} \mathbf{P} \mathbf{1} = (\mathbf{1} \mathbf{1}^T) \mathbf{P} \mathbf{1} = \mathbf{1} (\mathbf{1}^T \mathbf{P} \mathbf{1}) = \mathbf{0}$ , we have

$$\mathbb{E}_{\text{RW}}(\chi_{a,b,c}) = \mathbf{1}^T \mathbf{P} \mathbf{E}_2 \mathbf{P} \mathbf{E}_1 \mathbf{P} \mathbf{1} \implies \mathcal{E}(\chi_{a,b,c}) \leq \|\mathbf{P} \mathbf{E}_2 \mathbf{P} \mathbf{E}_1 \mathbf{P}\| \leq \lambda^{\Delta_1 + \Delta_2}.$$

# Degree 4 characters



$$\begin{aligned}\mathbb{E}_{\text{RW}}(\chi_{a,b,c,d}) &= \mathbf{1}^T \mathbf{P} \mathbf{W}^{\Delta_3} \mathbf{P} \mathbf{W}^{\Delta_2} \mathbf{P} \mathbf{W}^{\Delta_1} \mathbf{P} \mathbf{1} \\ &= \mathbf{1}^T \mathbf{P} \mathbf{E}_3 \mathbf{P} \mathbf{W}^{\Delta_2} \mathbf{P} \mathbf{E}_1 \mathbf{P} \mathbf{1}\end{aligned}$$

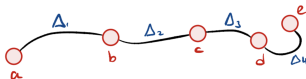
and so

$$\mathcal{E}(\chi_{a,b,c,d}) \leq \|\mathbf{P} \mathbf{E}_3 \mathbf{P} \mathbf{W}^{\Delta_2} \mathbf{P} \mathbf{E}_1 \mathbf{P}\| \leq \lambda^{\Delta_1 + \Delta_3}.$$

$$\mathcal{E}\left(\begin{array}{c} \text{---} \Delta_2 \text{---} \\ \text{---} \Delta_1 \text{---} \end{array}\right) \leq \lambda^2$$

$$\mathcal{E}\left(\begin{array}{c} \text{---} \Delta_1 \text{---} \\ \text{---} \Delta_2 \text{---} \end{array}\right) \leq \lambda^{t-2}$$

# Degree 5 characters



$$\begin{array}{cccccccccc}
 1^T & P & W^{\Delta_4} & P & W^{\Delta_3} & P & W^{\Delta_2} & P & W^{\Delta_1} & P & 1 \\
 E & & J & & J & & J & & E & & \\
 E & & J & & E & & E & & E & & \\
 E & & E & & J & & E & & E & & \\
 E & & E & & E & & E & & E & & 
 \end{array}$$

$$JPJ = (11^T)P(11^T) = 1(1^TP1)1^T = 0$$

and so

$$\mathcal{E}(\chi_{a,b,c,d,e}) \leq \lambda^{\Delta_1+\Delta_2+\Delta_4} + \lambda^{\Delta_1+\Delta_3+\Delta_4} + \lambda^{\Delta_1+\Delta_2+\Delta_3+\Delta_4} \approx \lambda^{\Delta_1+\min(\Delta_2,\Delta_3)+\Delta_4}.$$

$$\mathcal{E}\left(\begin{array}{c} \Delta_4 \\ \Delta_3 \\ \Delta_2 \\ \Delta_1 \end{array} \right) \leq \lambda^3$$





# Degree 6 characters

$$1^T P W^{\Delta_5} P W^{\Delta_4} P W^{\Delta_3} P W^{\Delta_2} P W^{\Delta_1} P 1$$

E	J	E	J	E
E	E	E	J	E
E	E	J	E	E
E	J	E	E	E
E	E	E	E	E

$$\mathcal{E}(\chi_{a,b,c,d,e,f}) \lesssim \lambda^{\Delta_1+\Delta_3+\Delta_5} + \lambda^{\Delta_1+\Delta_2+\Delta_4+\Delta_5}.$$



# Degree 7 characters

$1^T P W^{\Delta_6} P$	$W^{\Delta_5} P$	$W^{\Delta_4} P$	$W^{\Delta_3} P$	$W^{\Delta_2} P$	$W^{\Delta_1} P$	1
6	5	4	3	2		1
	E	J	E	J		
	J	E	E	J		
	J	E	J	E		

$$\xi \approx \lambda^{\Delta_1 + \Delta_6} \left( \lambda^{\Delta_3 + \Delta_5} + \lambda^{\Delta_3 + \Delta_4} + \lambda^{\Delta_2 + \Delta_4} \right)$$

# Degree 8 characters (this is addicting...)

$$1^T P W^{\Delta_7} P W^{\Delta_6} P W^{\Delta_5} P W^{\Delta_4} P W^{\Delta_3} P W^{\Delta_2} P W^{\Delta_1} P 1$$

7	6	5	4	3	2	1
	J	E	J	E	J	
	E	J	E	E	J	
	E	J	E	J	E	
	J	E	E	J	E	

# The $\lambda$ -tail

$$1^T P W^{\Delta_7} P W^{\Delta_6} P W^{\Delta_5} P W^{\Delta_4} P W^{\Delta_3} P W^{\Delta_2} P W^{\Delta_1} P 1$$

Handwritten diagram illustrating the product of matrices  $W^{\Delta_i}$  and  $P$  matrices, with brackets indicating the minimum of consecutive  $\Delta_i$  values:

- Brackets above the sequence:  $\min(\Delta_5, \Delta_6)$ ,  $\min(\Delta_3, \Delta_4)$ ,  $\min(\Delta_1, \Delta_2)$
- Brackets below the sequence:  $\min(\Delta_4, \Delta_5)$ ,  $\min(\Delta_2, \Delta_3)$

## Definition

Let  $S = \{s_1 < \dots < s_k\} \subseteq [t]$ ,  $k \geq 4$ , and let  $\Delta_i = s_{i+1} - s_i$ . Define

$$\Delta(S) = \sum_{i=1}^{k-2} \min(\Delta_i, \Delta_{i+1}).$$

For  $k = 2$ ,  $\Delta(S) = \Delta_1$ . For  $k = 3$ ,  $\Delta(S) = \Delta_1 + \Delta_2$ .

## Lemma

$$\mathcal{E}(\chi_S) \leq 2^{|S|} \cdot \lambda^{\frac{\Delta(S)}{2}}.$$

# Beyond symmetric functions

## Definition

A function  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$  has  $b$ -Fourier decay if

$$\forall k \in [n] \quad \sum_{\substack{S \subseteq [t] \\ |S|=k}} |\hat{f}(S)| \leq b^k.$$

## Known Fourier decay results.

- For size- $s$  depth- $d$  circuits,  $b = O((\log s)^{d-1})$  (Linial-Mansour-Nisan'93, Tal'17).
- For permutation width- $w$  ROBP,  $b \leq 2w^2$  (Reingold-Steinke-Vadhan'13).
- For general width- $w$  ROBP,  $b = O((\log t)^w)$  (Chattopadhyay-Hatami- Reingold-Tal'18).
- For every  $f$ ,  $b \leq \text{DT}(f)$ .

# Beyond symmetric functions

## Definition

A function  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$  has  $b$ -Fourier decay if

$$\forall k \in [t] \quad \sum_{\substack{S \subseteq [t] \\ |S|=k}} |\hat{f}(S)| \leq b^k.$$

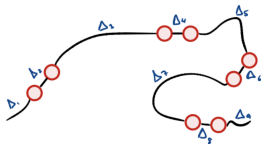
## Lemma

$$\mathcal{E}(f) = O(\sqrt{\lambda} \cdot b(f)^2).$$

# Symmetric functions

## Lemma (Main technical lemma)

$$\beta_k = \sum_{\substack{S \subseteq [t] \\ |S|=k}} \mathcal{E}(\chi_S) \lesssim 2^k \binom{t}{\lfloor \frac{k}{2} \rfloor} \lambda^{\lceil \frac{k}{2} \rceil}.$$



$$\Delta \left( \text{graph} \right) = \sum_{i=1}^{k-2} \underbrace{\min(\Delta_i, \Delta_{i+1})}_\lambda \cong \frac{k}{2}$$

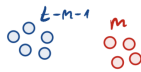
$$\mathcal{E}_\lambda \left( \text{graph} \right) \leq 2^k \cdot \lambda^{\Delta(\text{graph})} \leq 2^k \cdot \lambda^{k/2}$$

$$\# \left( \text{graph} \right) = \binom{t}{k/2}$$

# Symmetric functions

$$\beta_k = \sum_{\substack{s \in [k] \\ |s|=k}} \mathcal{E}(\chi_s) = \sum_{\substack{s \in [k] \\ |s|=k}} \underbrace{\left| 1^T P W^{\Delta_{k-1}} P \dots W^{\Delta_1} P 1 \right|}_{\wedge \sum \lambda^{\tau(s)}} \\ \tau \in \left\{ \begin{array}{c} E J E J \dots E J E \\ E E J E \dots E J E \\ \vdots \\ E J E E \dots J E E \end{array} \right\}$$

$$\Rightarrow \beta_k \leq \sum_{\tau} \sum_{\substack{s \in [k] \\ |s|=k}} \lambda^{\tau(s)} = \sum_{\tau} \sum_m c_m(\tau) \lambda^m$$



$$\tau: \underbrace{\quad}_E \underbrace{\quad}_J \underbrace{\quad}_E \underbrace{\quad}_E \dots \underbrace{\quad}_J \underbrace{\quad}_E$$



# Summary and open problems

## Summary.

- Expander random walks fool all symmetric functions.
- Stronger Fourier decay  $\implies$  better fooled by RW

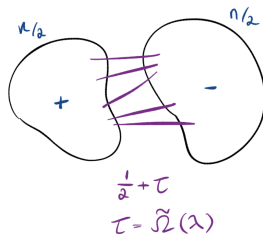
## Open problems.

- Tightness
- “Tailor-made” expanders
- Applications

Thanks!

# You cannot fool them all

## The cross cut function



$$f(x_1, \dots, x_t) = \text{Threshold}_{\frac{\tau}{2}t} \left( \sum_{i=1}^{t-1} x_i x_{i+1} \right).$$

We have that

$$\begin{aligned} |\mathbb{E}[f(U_t)]| &\leq e^{-\Omega(\tau^2 t)} \rightarrow 0, \\ |\mathbb{E}[f(\text{RW})]| &\geq 1 - e^{-\Omega(\tau^2 t)} \rightarrow 1. \end{aligned}$$

## Lemma

Let  $G = (V, E)$  be a Cayley graph on the Boolean hypercube and consider a labelling of  $V$  by an eigenvector corresponding to  $\lambda_2$ .

For  $f : \{\pm 1\}^t \rightarrow \{\pm 1\}$  define  $g : \{\pm 1\}^{2t} \rightarrow \{\pm 1\}$  by

$$g(x_1, \dots, x_{2t}) = f(x_1 x_2, x_3 x_4, \dots, x_{2t-1} x_{2t}).$$

Then,

$$\mathbb{E}[g(\text{RW})] = (T_\lambda f)(\mathbf{1}).$$