

# Determining Optimal Test Functions for the 2-Level Densities of $L$ -functions

Jason Zhao<sup>1</sup>

In collaboration with Elżbieta Bołdyriew<sup>2</sup> Fangu Chen<sup>3</sup>  
Charles Devlin VI<sup>4</sup> Steven J Miller<sup>5</sup>

<sup>1</sup>UCLA, reavered@g.ucla.edu

<sup>2</sup>Colgate University, eboldyriew@colgate.edu

<sup>3</sup>University of Michigan, fangu@umich.edu

<sup>4</sup>University of Michigan, chatrick@umich.edu

<sup>5</sup>Williams College, sjml@williams.edu

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## Random Matrix Theory (RMT)

- Ensembles of matrices (e.g. real symmetric, Hermitian) with entries drawn from probability distribution.
- Study distribution of normalized eigenvalues for given ensemble.

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### Katz-Sarnak density conjecture

Behavior of zeros of  $L$ -functions associated with cuspidal new forms well-modeled by RMT models.

## 1-level Density

Assume Riemann hypothesis for  $L(s, f)$ . Then there are order  $\log c_f$  low-lying non-trivial zeros  $s = 1/2 + i\gamma_f$ .

### Test functions

We say  $\phi : \mathbb{R}^n \rightarrow [0, \infty)$  is a test function if it is even, Schwartz class, Fourier transform  $\widehat{\phi}$  compactly supported, and  $\phi(0) > 0$ .

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### 1-level density

$$D(f; \phi) := \sum_{\gamma_f} \phi \left( \frac{\gamma_f}{2\pi} \log(c_f) \right)$$

This measures the density of zeros of  $L(s, f)$  near the central point  $s = 1/2$ .

## 1-level Density

Impossible to calculate  $D(f; \phi)$  explicitly in practice, so take averages over finite subsets of  $\mathcal{F}$ :

$$\mathcal{F}(Q) := \{f \in \mathcal{F} : c_f \leq Q\}$$

$$\mathbb{E}(\mathcal{F}(Q); \phi) := \frac{1}{|\mathcal{F}(Q)|} \sum_{f \in \mathcal{F}} D(f; \phi)$$

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### 1-level density theorem

If  $\mathcal{F}$  is complete in a certain spectral sense, then

$$\lim_{Q \rightarrow \infty} \mathbb{E}(\mathcal{F}(Q); \phi) = \int_{\mathbb{R}} \phi(x) W(\mathcal{F})(x) dx$$

where  $W(\mathcal{F})$  is a distribution depending on  $\mathcal{F}$ .

## 1-level Density

From RMT,  $W(\mathcal{F})$  is dependent on a symmetry group  $G = G(\mathcal{F})$  of  $\mathcal{F}$ . Write  $W(\mathcal{F}) = W_{1,G}$ .



## 1-level Density

From RMT,  $W(\mathcal{F})$  is dependent on a symmetry group  $G = G(\mathcal{F})$  of  $\mathcal{F}$ . Write  $W(\mathcal{F}) = W_{1,G}$ . Some examples:

$$W_{1,O}(x) = 1 + \frac{1}{2}\delta(x)$$

$$W_{1,SO(\text{Even})}(x) = 1 + \frac{\sin(2\pi x)}{2\pi x}$$

$$W_{1,SO(\text{Odd})}(x) = 1 - \frac{\sin(2\pi x)}{2\pi x} + \delta(x)$$

$$W_{1,Sp}(x) = 1 - \frac{\sin(2\pi x)}{2\pi x}$$

## *n*-level Density

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$$D_n(f; \Phi) := \sum_{\substack{\gamma_{j,f} \\ |j| \text{ distinct}}} \Phi \left( \frac{\gamma_{1,f}}{2\pi} \log(c_f), \dots, \frac{\gamma_{n,f}}{2\pi} \log(c_f) \right)$$

where  $\Phi : \mathbb{R}^n \rightarrow [0, \infty)$  is a test function.

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### $n$ -level density theorem

If  $\mathcal{F}$  is complete in a certain spectral sense, then

$$\lim_{Q \rightarrow \infty} \mathbb{E}_n(\mathcal{F}(Q); \Phi) = \int_{\mathbb{R}^n} \Phi(x) W_n(\mathcal{F})(x_1, \dots, x_n) dx_1 \dots dx_n$$

where  $W_n(\mathcal{F})$  is a distribution depending on  $\mathcal{F}$ .

## Katz-Sarnak Determinants

Set  $K_\epsilon(x, y) := \frac{\sin(\pi(x-y))}{\pi(x-y)} + \epsilon \frac{\sin(\pi(x+y))}{\pi(x+y)}$ ,  $\epsilon \in \{0, \pm 1\}$ .  $n$ -level weights for classical compact groups are:

$$W_{n, \text{SO}(\text{Even})}(x) = \det (K_1(x_i, x_j))_{i, j \leq n}$$

$$W_{n, \text{SO}(\text{Odd})}(x) = \det (K_{-1}(x_i, x_j))_{i, j \leq n} + \sum_{k=1}^n \delta(x_k) \det (K_{-1}(x_i, x_j))_{i, j \neq k}$$

$$W_{n, \text{O}}(x) = \frac{1}{2} W_{n, \text{SO}(\text{Even})}(x) + \frac{1}{2} W_{n, \text{SO}(\text{Odd})}(x)$$

$$W_{n, \text{U}}(x) = \det (K_0(x_i, x_j))_{i, j \leq n}$$

$$W_{n, \text{Sp}}(x) = \det (K_{-1}(x_i, x_j))_{i, j \leq n}$$

## The optimization problem

### Quantities of interest

- AveRank( $\mathcal{F}(Q)$ ), the average order of vanishing at the central point  $s = \frac{1}{2}$  for  $\mathcal{F}(Q)$ .
- WeightedAveRank( $\mathcal{F}(Q)$ ), the weighted average order of vanishing at the central point for  $\mathcal{F}(Q)$ .

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### Bounds and an optimization problem

$$\lim_{Q \rightarrow \infty} \text{AveRank}(\mathcal{F}(Q)) \leq \frac{\int_{\mathbb{R}} \phi(x) W_{1,G}(x) dx}{\phi(0)}$$

$$\lim_{Q \rightarrow \infty} \text{WeightedAveRank}(\mathcal{F}(Q)) \leq \frac{\int_{\mathbb{R}^n} \Phi(x) W_{n,G}(x) dx}{\Phi(0)}$$

We want to minimize the right hand sides.

## Old results: 1-level densities

### Main Idea

Reduce the optimization problem to a differential equations problem via functional analysis.

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### Main Result 1 [ILS00], [FM15]

A 1-level optimal test function  $\phi$  for  $\text{supp } \hat{\phi} \subseteq [-2\sigma, 2\sigma]$  exists for each classical compact group.



## New results: 2-level densities

### Main Idea

Restrict domain to only those test functions which are products of single variable test functions

$\Phi(x, y) = \phi_1(x)\phi_2(y)$  for fixed admissible  $\phi_1(x)$ .

## New results: 2-level densities

### Main Idea

Restrict domain to only those test functions which are products of single variable test functions

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### Main Result 2

Can view the problem as a one-variable integration of  $\phi_2$  against a function of the form  $\delta + m$ , i.e. analogous to 1-level case.

## Fixed test function and resulting estimates

Let

$$\phi_1(x) = \left( \frac{\sin(2\pi x)}{2\pi x} \right)^2 .$$

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Family	Naive	Optimal
SO(E)	$\frac{5}{12} \approx 0.4166$	$\frac{1}{96} \left( 54\sqrt{3} \cot\left(\frac{2}{\sqrt{3}}\right) - 5 \right) \approx 0.3784$
SO(O)	$\frac{13}{12} \approx 1.0833$	$\frac{1}{32} \left( 33 + 2\sqrt{3} \cot\left(\frac{2}{\sqrt{3}}\right) \right) \approx 1.079$
O	$\frac{3}{4} \approx 0.75$	$\frac{1}{24} \left( 13 + 6\sqrt{3} \cot\left(\frac{2}{\sqrt{3}}\right) \right) \approx 0.733$
U	$\frac{1}{2} \approx 0.5$	$\frac{1}{12} (4 + 3 \cot(1)) \approx 0.4939$
Sp	$\frac{1}{12} \approx 0.0833$	$\frac{1}{32} (3 + 2 \cot(2)) \approx 0.06515$

## Applications to Order of Vanishing

$\Pr(N)$  := probability that  $L(s, f)$  has zero of order  $N$  at  $s = 1/2$ .

$$\sum_{N=2}^{\infty} 2\Pr(N) \leq \sum_{N=0}^{\infty} N(N-1)\Pr(N) \leq \frac{\int_{\mathbb{R}^2} \Phi(x, y) W_{2, \mathcal{G}}(x, y) dx dy}{\Phi(0, 0)}$$

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$$\Pr(0) + \Pr(1) \geq \begin{cases} 1 - \frac{13 + 6\sqrt{3} \cot\left(\frac{2}{\sqrt{3}}\right)}{48} \approx 0.633493 & W_{2,0} \\ 1 - \frac{54\sqrt{3} \cot\left(\frac{2}{\sqrt{3}}\right) - 5}{192} \approx 0.810776 & W_{2,SO(\text{Even})} \\ 1 - \frac{33 + 2\sqrt{3} \cot\left(\frac{2}{\sqrt{3}}\right)}{64} \approx 0.460457 & W_{2,SO(\text{Odd})} \\ 1 - \frac{4 + 3 \cot(1)}{24} \approx 0.753072 & W_{2,U} \\ 1 - \frac{3 + 2 \cot(2)}{64} \approx 0.967427 & W_{2,Sp} \end{cases}$$

## Key observations

### Observation 1

Ahiezer's Theorem and the Paley-Wiener theorem give a correspondence between test functions and  $L^2$

$\phi$  test function with  $\text{supp}(\hat{\phi}) \subseteq [-2\sigma, 2\sigma]$



$$\hat{\phi}(\xi) = (g * \check{g})(\xi) \text{ for } g \in L^2[-\sigma, \sigma]$$

where  $\check{g}(\xi) = \overline{g(-\xi)}$ .



## Key observations

### Observation 2

By Plancharel's theorem

$$\frac{\int_{\mathbb{R}} \phi(x) W_{1,G}(x) dx}{\phi(0)} = \frac{\int_{\mathbb{R}} \hat{\phi}(\xi) \widehat{W_{1,G}}(\xi) d\xi}{\int_{\mathbb{R}} \hat{\phi}(\xi) d\xi}.$$

### Observation 3

The Fourier transforms of the 1-level distributions  $W_{1,G}$  take the form

$$\widehat{W_{1,G}}(\xi) = \delta(\xi) + m_G(\xi)$$

where  $m_G$  is a real-valued even step function.

## Step 1: Convert to minimization over $L^2$

Define compact, self-adjoint linear operator

$$K : L^2[-\sigma, \sigma] \rightarrow L^2[-\sigma, \sigma]$$

$$(Kg)(x) := \int_{-\sigma}^{\sigma} m(x-y)g(y) dy.$$

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Let  $\text{supp } \hat{\phi} \subseteq [-2\sigma, 2\sigma]$ , then

$$\frac{\int_{\mathbb{R}} \hat{\phi}(\xi) \widehat{W_{1,G}}(\xi) d\xi}{\int_{\mathbb{R}} \hat{\phi}(\xi) d\xi} = \frac{\int_{\mathbb{R}} (g * \check{g})(\xi) (\delta(\xi) + m(\xi)) d\xi}{\int_{\mathbb{R}} (g * \check{g})(\xi) d\xi}$$

**Step 1: Convert to minimization over  $L^2$** 

$$\begin{aligned} &= \frac{\langle g, g \rangle_{L^2} + \int_{-\sigma}^{\sigma} \int_{-\sigma}^{\sigma} m(\xi - y) g(y) dy \overline{g(\xi)} d\xi}{|\langle \mathbf{1}, g \rangle_{L^2}|^2} \\ &= \frac{\langle g, g \rangle_{L^2} + \langle Kg, g \rangle_{L^2}}{|\langle \mathbf{1}, g \rangle_{L^2}|^2} \\ &= \frac{\langle (I + K)g, g \rangle_{L^2}}{|\langle \mathbf{1}, g \rangle_{L^2}|^2}. \end{aligned}$$

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### Equivalent optimization problem

Minimize the functional  $R : L^2[-\frac{1}{2}, \frac{1}{2}] \rightarrow \mathbb{R}$  given by

$$R(g) := \frac{\langle (I + K)g, g \rangle_{L^2}}{|\langle \mathbf{1}, g \rangle_{L^2}|^2}.$$

## Step 2: Fredholm theory

Some observations:

- $R(g) \geq \lim_{Q \rightarrow \infty} \text{AveRank}(\mathcal{F}(Q)) \geq 0.$
- Spectral Theorem  $\implies$  orthonormal basis of eigenvectors of  $K$ , eigenvalues  $\lambda_j$ .
- $\lambda_j \geq -1.$

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### Case 1: Eigenvalue $(-1)$

Let  $f_0 \in L^2[-\frac{1}{2}, \frac{1}{2}]$  not orthogonal to  $\mathbf{1}$  and  $(I + K)f_0 = 0,$

$$R(f_0) = \frac{\langle (I + K)f_0, f_0 \rangle_{L^2}}{|\langle \mathbf{1}, f_0 \rangle_{L^2}|^2} = 0.$$

## Step 2: Minimization

Case 2:  $\lambda_j > -1$  for all  $j$

More functional analysis!



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More functional analysis!

- $\ker(I + K) = \{0\}$  (all eigenvalues  $> -1$ ).
- By Fredholm Theory, exists unique  $f_0 \in L^2[-\frac{1}{2}, \frac{1}{2}]$  satisfying  $(I + K)f_0 = \mathbf{1}$ .
- $A := \langle \mathbf{1}, f_0 \rangle = \langle (I + K)f_0, f_0 \rangle_{L^2} > 0$ .

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- $A := \langle \mathbf{1}, f_0 \rangle = \langle (I + K)f_0, f_0 \rangle_{L^2} > 0$ .

For  $g = f_0 + h \in L^2[-\frac{1}{2}, \frac{1}{2}]$  with  $\langle \mathbf{1}, g \rangle_{L^2} \neq 0$ , WLOG  $\langle \mathbf{1}, g \rangle_{L^2} = A$ . Then  $\langle \mathbf{1}, h \rangle_{L^2} = 0$ , so

$$\begin{aligned} R(g) &= \frac{\langle \mathbf{1}, f_0 \rangle_{L^2} + \langle (I + K)h, h \rangle_{L^2} + \langle \mathbf{1}, h \rangle_{L^2} + \langle h, \mathbf{1} \rangle_{L^2}}{|A|^2} \\ &= \frac{A + \langle (I + K)h, h \rangle_{L^2} + 0 + 0}{|A|^2} \geq \frac{1}{A} = R(f_0) \end{aligned}$$

## Challenges

Larger support and higher level densities give better estimates on the average order of vanishing. Two main obstructions:

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Larger support and higher level densities give better estimates on the average order of vanishing. Two main obstructions:

1. Small support does not detect non-constant kernels, e.g.  $\widehat{W}_{1,Sp}(x) = \delta(x) - \frac{1}{2}\mathbf{1}_{[-1,1]}(x)$ .
2.  $\widehat{W}_{n,G}$  more complicated and higher dimensional integral operators not as well-understood.

## Simplifications

### A restricted optimization problem

Fix a test function  $\phi_1$  with  $\text{supp } \hat{\phi}_1 \subseteq [-1, 1]$ , we want to minimize

$$\frac{\int_{[-1,1]^2} \hat{\phi}_1(\xi_1) \hat{\phi}_2(\xi_2) \widehat{W}_{2,G}(\xi) d\xi_1 d\xi_2}{\phi_1(0)\phi_2(0)}$$

over test functions  $\phi_2$  with  $\text{supp}(\hat{\phi}_2) \subset [-1, 1]$ .

## Example: Unitary

The 2-level distributions:

$$W_{2,U}(x) = 1 - \frac{\sin^2(\pi(x_1 - x_2))}{\pi^2(x_1 - x_2)^2},$$

$$\widehat{W}_{2,U}(\xi) = \delta(\xi_1)\delta(\xi_2) + \delta(\xi_1 + \xi_2)(|\xi_1| - 1)\mathbf{1}(\xi_1).$$

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For  $\phi_1$  arbitrary,

$$\begin{aligned} \tilde{V}_{\phi_1,U}(\xi_2) &= \frac{1}{\phi_1(\mathbf{0})} \int_{\mathbb{R}} \hat{\phi}_1(\xi_2) \widehat{W}_{2,U}(\xi) d\xi_1 \\ &= \frac{\hat{\phi}_1(\mathbf{0})}{\phi_1(\mathbf{0})} \delta(\xi_2) + \frac{\hat{\phi}_1(-\xi_2)}{\phi_1(\mathbf{0})} (|\xi_2| - \mathbf{1})\mathbf{1}(\xi_2) \\ &= \mathbf{c}_{\phi_1,U} \delta(\xi_2) + \tilde{m}_{\phi_1,U}(\xi_2) \end{aligned}$$



## Recovering the 1-level set-up

For each classical compact group  $G$ ,

$$V_{\phi_1, G}(\xi_2) := \delta(\xi_2) + m_{\phi_1, G}(\xi_2), \quad m_{\phi_1, G}(\xi_2) := \frac{\tilde{m}_{\phi_1, G}(\xi_2)}{c_{\phi_1, G}}.$$

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### Optimization problem rehashed

Minimize

$$\frac{\int_{[-1, 1]} \hat{\phi}_2(\xi_2) V_{\phi_1, G}(\xi_2) d\xi_2}{\phi_2(\mathbf{0})}$$

over test functions  $\phi_2$  with  $\text{supp } \hat{\phi}_2 \subseteq [-1, 1]$ .

## Collect the 1-level goodies

There exists a unique  $g_{\phi_1, G} \in L^2[-1/2, 1/2]$  satisfying

$$1 = g_{\phi_1, G}(x) + \int_{-1/2}^{1/2} m_{\phi_1, G}(x - y) g_{\phi_1, G}(y) dy.$$

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Moreover,

$$\frac{c_{\phi_1, G}}{\langle \mathbf{1}, g_{\phi_1, G} \rangle_{L^2}} = \inf_{\phi_2} \frac{\int_{[-1, 1]} \hat{\phi}_2(\xi_2) V_{\phi_1, G}(\xi_2) d\xi_2}{\phi_2(0)}.$$

## Choosing $\phi_1$

Natural choice of test function is the Fourier pair

$$\phi_1(x) = \left( \frac{\sin(2\pi x)}{2\pi x} \right)^2, \quad \widehat{\phi}_1(\xi) = (1 - |\xi|)\mathbf{1}_{[-1,1]}(\xi)$$

### Key observation

Kernels take the form of quadratic polynomials in  $|x|$  on  $[-1, 1]$ , i.e.

$$m_{\phi_1, G}(x) = (a + b|x| + c|x|^2)\mathbf{1}_{[-1,1]}(x).$$

## Differentiation under the integral

Exercise for the reader, order one term:

$$\frac{d}{dx} \int_{-1/2}^{1/2} |x - y| g(y) dy = \int_{-1/2}^x g(y) dy - \int_x^{1/2} g(y) dy,$$

$$\frac{d^2}{dx^2} \int_{-1/2}^{1/2} |x - y| g(y) dy = 2g(x)$$

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Order two term:

$$\frac{d}{dx} \int_{-1/2}^{1/2} (x - y)^2 g(y) dy = \int_{-1/2}^{1/2} (2x - 2y) g(y) dy,$$

$$\frac{d^2}{dx^2} \int_{-1/2}^{1/2} (x - y)^2 g(y) dy = 2 \int_{-1/2}^{1/2} g(y) dy.$$

**Example:  $W_{2,U}$** 

We want to find  $g \in L^2[-1/2, 1/2]$  obeying

$$1 = g(x) - \int_{-\frac{1}{2}}^{\frac{1}{2}} (1 - |x - y|)^2 g(y) dy.$$



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$$0 = g''(x) - 4g(x) + 2 \int_{-\frac{1}{2}}^{\frac{1}{2}} g(y) dy$$

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Assuming evenness, solutions take the form

$$g(x) = A \cos(2x) + C.$$

**Optimal  $g_{\phi_1, G}$  for  $\text{supp } \widehat{\phi}_1, \text{supp } \widehat{\phi}_2 \subseteq [-1, 1]$**

$$g_{\phi_1, \text{SO(Even)}}(x) = \frac{216 \cos(4x/\sqrt{3}) + 36\sqrt{3} \sin(2/\sqrt{3})}{162 \cos(2/\sqrt{3}) - 5\sqrt{3} \sin(2/\sqrt{3})},$$

$$g_{\phi_1, \text{SO(Odd)}}(x) = \frac{8 \cos(4x/\sqrt{3}) + 12\sqrt{3} \sin(2/\sqrt{3})}{11\sqrt{3} \sin(2/\sqrt{3}) + 2 \cos(2/\sqrt{3})},$$

$$g_{\phi_1, \text{U}}(x) = \frac{6 \cos(2x) + 6 \sin(1)}{3 \cos(1) + 4 \sin(1)},$$

$$g_{\phi_1, \text{O}}(x) = \frac{36 \cos(4x/\sqrt{3}) + 18\sqrt{3} \sin(2/\sqrt{3})}{18 \cos(2/\sqrt{3}) + 13\sqrt{3} \sin(2/\sqrt{3})},$$

$$g_{\phi_1, \text{Sp}}(x) = \frac{8 \cos(4x) + 12 \sin(2)}{2 \cos(2) + 3 \sin(2)}$$

## Iterating $\phi_k$

### Some terminology

Fix a test function  $\phi$  with  $\text{supp } \hat{\phi}_1 \subseteq [-1, 1]$ . We say  $\psi$  is *optimal* for  $\phi$  if  $\psi$  minimizes

$$\frac{\int_{[-1,1]^2} \phi(x)\psi(y)W_{2,G}(x,y) dx dy}{\phi(0)\psi(0)}$$

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- Recall correspondence between  $L^2$  and test functions: optimal  $\phi$  takes the form  $g * \check{g}$ .
- To improve bounds, we iterate  $\phi_k$ : finding optimal  $\phi_3$  for  $\phi_2$ , finding optimal  $\phi_4$  for  $\phi_3$ , etc.

## Example: Unitary

Define

$$(Kg)(x) := \int_{-\sigma}^{\sigma} m_{U, \phi_2}(x - y)g(y) dy.$$



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Summing five terms gives the new bound

$$c_{G,\phi} \left( \sum_{n=0}^5 (-1)^n \int_{-1/2}^{1/2} K^n(1)(x) dx \right)^{-1} \approx 0.4888$$

## References I

-  Jesse Freeman and Steven J. Miller.  
Determining optimal test functions for bounding the average rank in families of  $L$ -functions, 2015.
-  Henryk Iwaniec, Wenzhi Luo, and Peter Sarnak.  
Low lying zeros of families of  $L$ -functions.  
*Publications Mathématiques de l'IHÉS*, 91:55–131, 2000.