# Fourier transforms of measures on the Brownian graph 

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## My co-authors



## Fourier transforms and dimension

The Fourier transform of a measure $\mu$ on $\mathbb{R}^{d}$ is a function $\hat{\mu}: \mathbb{R}^{d} \rightarrow \mathbb{C}$ defined by

$$
\hat{\mu}(x)=\int \exp (-2 \pi i x \cdot y) d \mu(y)
$$



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or (using Parseval and convolution formulae)

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$\ldots$ and so if $\mu$ is supported on $K$, then

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|\hat{\mu}(x)| \lesssim|x|^{-s / 2} \Rightarrow I_{s-}(\mu)<\infty \Rightarrow \operatorname{dim}_{\mathrm{H}} K \geqslant s
$$

## Simple example

For example, if $\mu$ is Lebesgue measure on the unit interval, then a quick calculation reveals that for $x \in \mathbb{R}$

$$
|\hat{\mu}(x)|=\left|\int_{0}^{1} \exp (-2 \pi i x y) d y\right| \leqslant \frac{1}{\pi}|x|^{-1}
$$



## Examples with no decay



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The middle 3rd Cantor set also supports no measures with Fourier decay!

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\end{gathered}
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Sets with equality are called Salem sets.


## Classical results on Brownian motion

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- Kahane proved in 1966 that such image sets are almost surely Salem.


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- Taylor proved in 1953 that


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- It remained open for a long time whether or not graphs are almost surely Salem.
- Kahane explicitly asked the question in 1993 (also asked by Shieh-Xiao in 2006).


## Our work on Brownian motion

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|\hat{\mu}(x)| \lesssim|x|^{-s / 2}
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for any $s>1$. Therefore $\operatorname{dim}_{F} G(B) \leqslant 1<3 / 2 \stackrel{\text { a.s. }}{=} \operatorname{dim}_{H} G(B)$.

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- Key idea: we proved a new slicing theorem for planar sets supporting measures with fast Fourier decay.
- the answer to Kahane's problem is geometric (not stochastic).


## Slicing theorems

## Theorem (Marstrand)

Suppose $K \subset \mathbb{R}^{2}$ has $\operatorname{dim}_{H} K>1$, then for almost all directions $\theta \in S^{1}$, Lebesgue positively many $y \in \mathbb{R}$ satisfy:

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## Theorem (F-Sahlsten, 2015)

Let $\mu$ be the push forward of Lebesgue measure on the graph of Brownian motion. Then almost surely

$$
|\hat{\mu}(x)| \lesssim|x|^{-1 / 2} \sqrt{\log |x|} \quad\left(x \in \mathbb{R}^{2}\right)
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and, in particular, $\operatorname{dim}_{F} G(B) \stackrel{\text { a.s. }}{=} 1$.

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This time our proof was stochastic (not geometric) and relied on techniques from Itô calculus, as well as adapting some of Kahane's ideas.

## Sketch proof

Write $x \in \mathbb{R}^{2}$ in polar coordinates as

$$
x=(u \cos \theta, u \sin \theta)
$$

and observe that

$$
\hat{\mu}(x)=\int_{0}^{1} \overbrace{\exp (-2 \pi i u(t \cos \theta+B(t) \sin \theta))}^{Z_{t}} d t .
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We must prove

$$
|\hat{\mu}(x)| \stackrel{\text { a.s. }}{\leqslant} C u^{-1 / 2} \sqrt{\log u}
$$

with $C$ independent of $\theta$.

## Sketch proof - case 1: $\theta$ close to 0

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where $T$ is chosen such that $Z_{T}=Z_{0}=1$ and the interval $(0, T)$ contains all 'full rotations'.

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where $T$ is chosen such that $Z_{T}=Z_{0}=1$ and the interval $(0, T)$ contains all 'full rotations'. Similar to Lebesgue case:

$$
\left|\int_{T}^{1} Z_{t} d t\right| \lesssim u^{-1 / 2}
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so it remains to consider the 'full rotations'.

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Recall that $Z_{t}=\exp \left(i X_{t}\right)$ where

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- apply the Burkholder-Davis-Gundy inequality and Euler's formula to obtain good estimates
- use Kahane's techniques to transform moment estimates back to an almost sure estimate for the Fourier transform


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## Thanks!!



