Sampling on Manifolds

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August 10, 2025

BACKGROUND AND DEFINITIONS

DEFINITION

Let $f: \mathbb{R}^d \to \mathbb{C}$. The Fourier transform of f is defined by

$$\hat{f}(m) = \int_{-\infty}^{\infty} f(x) \chi(-mx) dx, \quad \forall m \in \mathbb{R}^d.$$

where $\chi(t) = e^{(2\pi i t)}$.

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REMARK (FOURIER INVERSION AND PLANCHEREL)

We have

$$f(x) = \int_{-\infty}^{\infty} \widehat{f}(m)\chi(xm)dm, \quad \text{and} \quad \int_{-\infty}^{\infty} |f(x)|^2 dx = \int_{-\infty}^{\infty} |\widehat{f}(m)|^2 dm.$$

Uncertainty Principle: A Theory of Tradeoff

DEFINITION (SUPPORT)

Let $f: \mathbb{R}^d \to \mathbb{C}$, then the support of f is supp $(f) = \{x \in \mathbb{R}^d : f(x) \neq 0\}$.

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THEOREM (CLASSICAL UNCERTAINTY PRINCIPLE)

Let $f: \mathbb{R}^d \to \mathbb{C}$ be supported in a subset $E \subseteq \mathbb{R}^d$ and let \hat{f} be supported in a subset $S \subseteq \mathbb{R}^d$. Then

$$|E|\cdot |S|\geqslant c>0,$$

where $|\cdot|$ is the d-dimensional Lebesgue measure.

FIGURE: Uncertainty Principle

source: https://brilliant.org/wiki/heisenberg-uncertainty-principle/

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REDEFINING LOCALIZATION

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DEFINITION (CONCENTRATION)

Let (X, μ) be a measure space, and let $E \subset X$. We say that $f \in L^p(X, \mu)$ is L^p -concentrated on E at level ϵ if

$$\|f-\mathbf{1}_E f\|_{L^p(X)}\leqslant \epsilon \|f\|_{L^p(X)},\quad \text{for some } 0\leqslant \epsilon<1. \tag{1}$$

WHAT IS A MANIFOLD?

DEFINITION

An *n*-dimensional manifold is a topological space M such that each point $p \in M$ has a neighborhood homeomorphic to an open subset of \mathbb{R}^n .

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- ▶ Locally Euclidean, but the global shape can be curved or twisted.
- Hausdorff Space: the points can be "separated" in the topology
- ▶ Charts: coordinate maps from pieces of M to \mathbb{R}^n .
- Second Countable: there is a countable basis for the topology.
- ▶ Locally Euclidean: This means that $\forall p \in M$ there is some set open set $U \subset M$ where $p \in U$ and open $\hat{U} \subset \mathbb{R}^n$ such that $\mathbf{x} : U \to \hat{U}$ is a homeomorphism.
- ▶ Examples: \mathbb{R}^n , sphere S^n , torus \mathbb{T}^n .

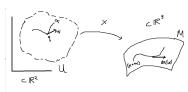
TANGENT SPACE IN \mathbb{R}^n

DEFINITION

A **derivation**, v, at a point $p \in M$, is a linear function which assigns each smooth function on M to a real number in $\mathbb R$ in such a way that the product rule holds (v(fg) = f(p)v(g) + g(p)v(f)). The set of all such derivations is the **Tangent Space**, T_pM . This captures the idea of tangent vectors to a manifold.

TANGENT SPACE IN FURTHER EXAMPLES

In the case of surfaces from \mathbb{R}^2 to \mathbb{R}^3 dealt with in the examples later, there is an easier interpretation. Take some point $p \in M$, $w \in \mathbb{R}^2$, and some chart covering that point $\mathbf{x}: U \to \hat{U}$ where $\mathbf{x}(q) = p$. Then take some curve $\alpha: (-\varepsilon, \varepsilon) \to M$ such that $\alpha(0) = q$ and $\alpha'(0) = v$. Then, define $d\mathbf{x}_p(w) := (\mathbf{x} \circ \alpha)'(0)$. Then the tangent space is at a point p is given by $T_pM:=d\mathbf{x}_p(\mathbb{R}^2)$.



 $\mathrm{Figure}\colon \mathsf{Showing}$ how vectors are "pushed forward" from \mathbb{R}^2 to \mathbb{R}^3

From Manifold to Riemannian Manifold

DEFINITION

A **Riemannian manifold** (M, g) is a manifold equipped with a smoothly varying inner product g_p on each tangent space T_pM .

In further examples, the surfaces we deal with all have the property that, given the chart $\mathbf{x}(u,v)$ that \mathbf{x}_u and \mathbf{x}_v are linearly independent and form a basis for the tangent space. Since the inner product is a bilinear form, this has a symmetric matrix associated with it given by:

$$g_p = \left[\begin{array}{cc} \langle \mathbf{x}_u, \mathbf{x}_u \rangle & \langle \mathbf{x}_u, \mathbf{x}_v \rangle \\ \langle \mathbf{x}_u, \mathbf{x}_v \rangle & \langle \mathbf{x}_v, \mathbf{x}_v \rangle \end{array} \right]$$

Evaluated such that $\mathbf{x}(u, v) = p$.

FROM MANIFOLD TO RIEMANNIAN MANIFOLD

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- ▶ g lets us measure lengths, angles, and volumes.
- Examples:
 - ▶ *S*² with the round metric.
 - ▶ Flat torus $\mathbb{T}^2 = \mathbb{R}^2/\mathbb{Z}^2$ with Euclidean metric.
- ▶ With g, we can define the Laplace–Beltrami operator.

LAPLACE-BELTRAMI OPERATOR

DEFINITION

Let (M,g) be a compact Riemannian manifold without boundary. The Laplace–Beltrami operator is

$$\Delta_{g} f = |g|^{-1/2} \, \partial_{i} \Big(|g|^{1/2} g^{ij} \partial_{j} f \Big) \,,$$

where (g^{ij}) is the inverse matrix and |g| its determinant.

- ▶ Self-adjoint and negative-definite on $L^2(M)$.
- Eigenfunctions e_j satisfy $\Delta_g e_j = -\lambda_j^2 e_j$.

EIGENVALUES, EIGENSPACES, AND MULTIPLICITY

• For each eigenvalue λ , the **eigenspace**

$$E_{\lambda} = \{e_j : \lambda_j = \lambda\}$$

has dimension $\#\{j : \lambda_j = \lambda\}$ (the multiplicity of λ).

• $\{e_j\}$ can be chosen orthonormal in $L^2(M)$:

$$\int_{M} e_{j}(x) \, \overline{e_{k}(x)} \, dV_{g}(x) = \delta_{jk}.$$

The pointwise sum

$$S_{\lambda}(x) = \sum_{j: \lambda_j = \lambda} |e_j(x)|^2$$

measures the total "energy density" of that eigenspace at x.

Uncertainty principle for compact manifolds without boundary

THEOREM

Let S be a finite subset of the set of eigenvalues of $\sqrt{-\Delta_g}$. Let $X_S = \{j : \lambda_j \in S\}$. Suppose that $f \in L^2(M)$ is not identically zero and that f is L^2 -concentrated in $E \subset M$ at level L with respect to the Riemannian volume density. Suppose also that \hat{f} is L^2 -concentrated on X_S at level L' with respect to the counting measure.

Then

$$\left(\frac{1}{\#X_S}\sum_{i\in X_S}\frac{1}{|E|}\int_{E}|e_j(x)|^2\,dx\right)^{-1}\leqslant \frac{|E|\cdot \#X_S}{(1-\epsilon-\epsilon')^2},$$

where

$$L = (1 - \epsilon^2)^{-1/2} \quad \text{and} \quad L' = (1 - \epsilon'^2)^{-1/2}.$$

THE MAIN EQUATION

MAIN EQUATION

For each eigenvalue λ ,

$$\sum_{j:\,\lambda_j=\lambda}|e_j(x)|^2\equiv c\quad\text{a.e. }x\in M,$$

with c independent of x.

This, thus will lead to the following relation:

RELATION

$$\frac{1}{\#\{j:\lambda_j\in S\}}\sum_{\lambda_j\in S}\frac{1}{|E|}\int_E \left|e_j(x)\right|^2=\frac{1}{|M|}$$

Combined with the aforementioned theorem, we get an alternative version of the uncertainty principle below:

ALTERED UNCERTAINTY PRINCIPLE

$$(1 - \epsilon - \epsilon')^2 \leqslant \frac{|E|}{|M|} \cdot \#X_S$$

STARTING SMALL: FAMILIES OF SURFACES

Our goal is to understand when the constant-sum property

$$S_{\lambda}(x) = \sum_{j: \lambda_j = \lambda} |e_j(x)|^2$$
 is constant in x

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holds.

- Rather than start with a general manifold, we first explore simple, symmetric surfaces:
 - ▶ Flat torus T².
 - ▶ Sphere S^2 .
 - Spheroids.

EXPERIMENTAL CHECK PLAN

- Choose a surface.
- **③** Evaluate $\sum_{j: \lambda_i = \lambda} |e_j(x)|^2$ on a grid for some fixed λ .
- Test if the range is constant.

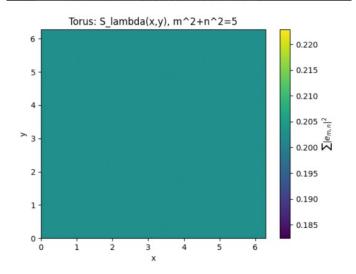


FIGURE: Sum over a torus

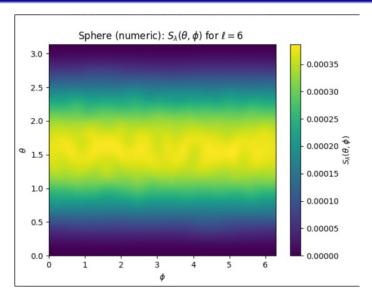


FIGURE: Sum over a sphere

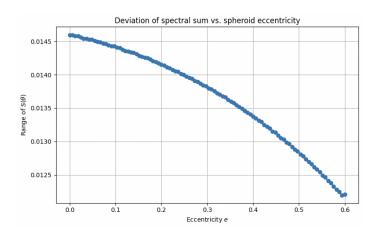


FIGURE: Sum over a spheroid

RESULTS

We conjecture that

$$\sum_{j:\,\lambda_j=\lambda}|e_j(x)|^2\equiv c\quad\text{a.e. }x\in M,$$

For this family of surfaces as we see that we stay somewhat constant throughout these three surfaces, but more data testing for other surfaces is needed before proving this conjecture.