# A Manifold Learning Approach to Boundary Value Problems 

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April 8, 2021

Supported by NSF-DMS 1854204 and 1723175
Slides developed with Ryan Vaughn

## Boundary Value Problems on Embedded Manifolds

- Given points $\left\{x_{i}\right\}_{i=1}^{N} \subset \mathcal{M} \subset \mathbb{R}^{d}$
- Want to solve BVPs



## Boundary Value Problems on Embedded Manifolds

- Given points $\left\{x_{i}\right\}_{i=1}^{N} \subset \mathcal{M} \subset \mathbb{R}^{d}$
- Dimensions $m \equiv \operatorname{dim}(\mathcal{M})$ and $d$ arbitrary



## Boundary Value Problems on Embedded Manifolds

- Given points $\left\{x_{i}\right\}_{i=1}^{N} \subset \mathcal{M} \subset \mathbb{R}^{d}$
- Points come from a black-box:
- hard to mesh
- not uniformly distributed
- location of boundary unknown



## Mesh-free: Tools of the trade

Neumann Problem: Given $f \in H^{1}(\mathcal{M})^{*}, g \in L^{2}(\partial \mathcal{M})$,

$$
\left\{\begin{array}{lll}
-\Delta u+u & =f & \text { in } \mathcal{M} \\
\nabla u \cdot \eta & =g & \text { on } \partial \mathcal{M}
\end{array}\right.
$$

$\eta$ is the outward unit normal to $\partial \mathcal{M}$
Good news: Stokes' theorem still works on $\mathcal{M}$

$$
-\int_{\mathcal{M}} v \Delta u d x=\int_{\mathcal{M}} \nabla v \cdot \nabla u d x-\int_{\partial \mathcal{M}} v \nabla u \cdot \eta d s
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Weak-sense formulation: $\forall v \in H^{1}(\Omega)$

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\int_{\mathcal{M}} \nabla u \cdot \nabla v d x+\int_{\mathcal{M}} u v d x=\int_{\mathcal{M}} f v d x+\int_{\partial \mathcal{M}} g v d s
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Weak-sense formulation: $\forall v \in H^{1}(\Omega)$

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\begin{aligned}
& \qquad \int_{\mathcal{M}} \nabla u \cdot \nabla v d x+\int_{\mathcal{M}} u v d x=\int_{\mathcal{M}} f v d x+\int_{\partial \mathcal{M}} g v d s \\
& \text { Dirichlet Energy } \quad \text { Volume Integral } \quad \text { Boundary Integral }
\end{aligned}
$$

## Key to Manifold Learning

- Given $f: \mathcal{M} \rightarrow \mathbb{R}$, want to estimate $\int_{\mathcal{M}} f(x) d x$
- Assume $\left\{x_{i}\right\}_{i=1}^{N} \subset \mathcal{M} \subset \mathbb{R}^{d}$ are sampled from distribution $p$

$$
\lim _{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^{N} f\left(x_{i}\right)=\mathbb{E}_{X \sim p}[f(X)]=\int_{\mathcal{M}} f(x) p(x) d x
$$

- Step one is estimate the density $p$ so we can compute:

$$
\frac{1}{N} \sum_{i=1}^{N} \frac{f\left(x_{i}\right)}{p\left(x_{i}\right)}=\int_{\mathcal{M}} f(x) d x+\mathcal{O}\left(N^{-1 / 2}\right)
$$

## Key to Manifold Learning

- $L^{2}(\mathcal{M})$ inner product $\Rightarrow$ diagonal matrix $D_{i i}=\frac{1}{N_{p}\left(x_{i}\right)}$

$$
\vec{g}^{\top} D \vec{f}=\frac{1}{N} \sum_{i=1}^{N} \frac{g\left(x_{i}\right) f\left(x_{i}\right)}{p\left(x_{i}\right)}=\langle f, g\rangle_{L^{2}}+\mathcal{O}\left(N^{-1 / 2}\right)
$$

## Estimating the density

- Select a kernel function, eg. $k_{\epsilon}(x, y)=e^{-\|x-y\|^{2} / \epsilon^{2}}$
- Define a kernel matrix $K_{i j}=\frac{k_{\epsilon}\left(x_{i}, x_{j}\right)}{m_{0} \epsilon^{m} N}$

$$
\begin{aligned}
(K \vec{f})_{i} & \equiv \frac{\epsilon^{-m}}{m_{0} N} \sum_{j=1}^{N} k_{\epsilon}\left(x_{i}, x_{j}\right) f\left(x_{j}\right) \\
& =\frac{\epsilon^{-m}}{m_{0}} \int_{\mathcal{M}} k_{\epsilon}\left(x_{i}, y\right) f(y) p(y) d y+\mathcal{O}\left(\epsilon^{-m} N^{-1 / 2}\right) \\
& =f\left(x_{i}\right) p\left(x_{i}\right)+\mathcal{O}\left(\epsilon, \epsilon^{-m} N^{-1 / 2}\right)
\end{aligned}
$$

- Setting $f \equiv 1$ we have

$$
p_{i}=\sum_{j=1}^{N} K_{i j}=p\left(x_{i}\right)+\mathcal{O}\left(\epsilon, \epsilon^{-m} N^{-1 / 2}\right)
$$

## Density estimation on manifold $\mathcal{M} \subset \mathbb{R}^{d}$ without boundary

$$
\begin{aligned}
\mathbb{E}\left[\sum_{j=1}^{N} K_{i j}\right] & =\frac{1}{m_{0} \epsilon^{d}} \int_{y \in \mathcal{M}} h\left(\frac{\|x-y\|^{2}}{\epsilon^{2}}\right) p(y) d V(y) \\
(\text { decay of } h) & =\frac{1}{m_{0} \epsilon^{d}} \int_{\|x-y\|<\epsilon^{\alpha}} h\left(\frac{\|x-y\|^{2}}{\epsilon^{2}}\right) p(y) d V(y) \\
\left(y=\exp _{x}(\epsilon s)\right) & =\frac{1}{m_{0}} \int_{\|\epsilon s\|<\epsilon^{\alpha}} h\left(\|s\|^{2}+\mathcal{O}\left(\epsilon^{2} s_{i}^{4}\right)\right) p\left(\exp _{x}(\epsilon s)\right)\left(1+\mathcal{O}\left(\epsilon^{2} s_{i}^{2}\right)\right) d s \\
(\text { Taylor }) & =\frac{1}{m_{0}} \int_{\| s \mid<\epsilon \epsilon^{\alpha-1}} h\left(\|s\|^{2}\right)(p(x)+\epsilon \nabla p(x) \cdot s) d s+\mathcal{O}\left(\epsilon^{2}\right) \\
(\text { symmetry }) & =\frac{1}{m_{0}} \int_{\|s\|<\epsilon^{\alpha-1}} h\left(\|s\|^{2}\right) p(x) d s+\mathcal{O}\left(\epsilon^{2}\right) \\
(\alpha<1) & =p(x) \frac{1}{m_{0}} \int_{\mathbb{R}^{d}} h\left(\|s\|^{2}\right) d s+\mathcal{O}\left(\epsilon^{2}\right) \\
& =p(x)+\mathcal{O}\left(\epsilon^{2}\right)
\end{aligned}
$$

## Density estimation on manifold $\mathcal{M} \subset \mathbb{R}^{d}$ with boundary

Requires estimating the distance to boundary function

(Berry \& Sauer, [1])

## Kernel integral operator

$$
\begin{array}{cc}
\int_{\mathcal{M}} \nabla u \cdot \nabla v d x+\int_{\mathcal{M}} u v d x=\int_{\mathcal{M}} f v d x+\int_{\partial \mathcal{M}} g v d s \\
\text { Dirichlet Energy } \quad \text { Volume Integral } \quad \text { Boundary Integral }
\end{array}
$$

- Kernel, $K \Rightarrow$ Density, $p_{i} \approx p\left(x_{i}\right) \Rightarrow$ Volume, $D_{i i}=\frac{1}{N p_{i}}$
- To get Dirichlet Energy and Boundary Integral we dig deeper into kernel integral asymptotics


## Diffusion Maps (w/o Boundary)

## Proposition (Coifman, Lafon 2006 [2])

Let $\mathcal{M}$ be a compact Riemannian manifold without boundary and let $\epsilon$ be sufficiently small. Then we have uniformly in the variable $\epsilon$ :

$$
\begin{aligned}
\mathcal{K}_{\epsilon} f(x) & \equiv \epsilon^{-m} \int_{\mathcal{M}} k_{\epsilon}(x, y) f(y) d y \\
& =m_{0} f(x)+\epsilon^{2} m_{2}(f(x) \omega(x)-\Delta f(x))+\mathcal{O}\left(\epsilon^{3}\right)
\end{aligned}
$$

where $m_{0}$ and $m_{2}$ are constants depending on $k$ and $\omega(x)$ is a function depending on the curvature of $\mathcal{M}$.
(Uniformity in $\epsilon$ is crucial.)

## New Result (w/ Boundary)

Theorem (R. Vaughn, [8])
For $\epsilon$ sufficiently small, let $\operatorname{dist}(x, \partial \mathcal{M})<\epsilon$. Then:
$\mathcal{K}_{\epsilon} f(x)=m_{0}^{\partial}(x) f(x)+\epsilon m_{1}^{\partial}(x)\left(\left\langle\nabla f, \eta_{x}\right\rangle_{g}-\frac{m-1}{2} H(x) f(x)\right)+\mathcal{O}\left(\epsilon^{2}\right)$
where $m_{0}^{\partial}(x)$ and $m_{2}^{\partial}(x)$ are functions of the distance to the boundary and $H(x)$ is the mean curvature of the hypersurface parallel to $\partial M$ intersecting $x$.

## Isolating the Laplacian

$$
\begin{aligned}
\mathcal{K}_{\epsilon} f(x)= & f(x)+\epsilon m_{1}(\nabla f(x) \cdot \eta+H(x) f(x)) \\
& +\epsilon^{2} m_{2}(\omega(x) f(x)-\Delta f(x)) \\
f(x) \mathcal{K}_{\epsilon} 1(x)= & f(x)+\epsilon m_{1} H(x) f(x)+\epsilon^{2} m_{2} \omega(x) f(x)
\end{aligned}
$$

Subtract...

$$
\begin{aligned}
\mathcal{L}_{\epsilon} f(x) & \equiv \mathcal{K}_{\epsilon} f(x)-f(x) \mathcal{K}_{\epsilon} 1(x) \\
& =-\epsilon m_{1} \nabla f(x) \cdot \eta+\epsilon^{2} m_{2} \Delta f(x)
\end{aligned}
$$

The long-standing mystery...

$$
\begin{aligned}
\frac{1}{m_{2} \epsilon^{2}} \mathcal{L}_{\epsilon} f(x) & =\frac{\epsilon^{-m}}{m_{2} \epsilon^{2}} \int_{\mathcal{M}} k_{\epsilon}(x, y) f(y)-k_{\epsilon}(x, y) f(x) d y \\
& =\Delta f(x)-\frac{c \nabla f(x) \cdot \eta}{\epsilon}+\mathcal{O}(\epsilon)
\end{aligned}
$$

## Diffusion Maps Problems at the Boundary

Elements of proof:

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- Expand $\mathcal{K}_{\epsilon}$ in Riemannian normal coordinates.


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Elements of proof:

- Localize $\mathcal{K}_{\epsilon} f$ to a Riemannian normal coordinate neighborhood.
Normal coordinate charts shrink near the boundary.
- Expand $\mathcal{K}_{\epsilon}$ in Riemannian normal coordinates.

Can't apply Taylor's theorem without coordinates.

- Use radial symmetry of the domain to cancel all odd terms. Even if we could, the coordinates would be nonsymmetric.
- Addressed by "symmetrizing" normal coordinates near the boundary in $[3,4]$ and others.


## Diffusion Maps Solution at the Boundary

Solution: Use different coordinates near the boundary.

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Solution: Use different coordinates near the boundary.

## Semigeodesic coordinates

- Classical
- Less well-behaved
- Better for computations near hypersurfaces ( $\partial M)$.

Semigeodesic Coordinates



Properties of Semigeodesic Coordinates

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- Components of metric tensor are orthogonal $g_{i j}(0)=\delta_{i j}(0)$ (Same as normal coordinates)
- Radial symmetry in all but one direction (Different from normal coordinates)
- Christoffel symbols are nonzero at the origin (Different from normal coordinates)
- The coordinate norm does not parameterize geodesic distance (Different from normal coordinates)


## Semigeodesic Coordinates

Generalization for manifolds with boundary:


## Semigeodesic Expansion

- Volume measure in normal coordinates:

$$
\begin{aligned}
d \mathrm{Vol}= & \sqrt{|\operatorname{det} g|} d s^{1} \cdots d s^{m} \\
& =1-\frac{1}{6} \operatorname{Ric}(s, s)+\mathcal{O}\left(\|s\|_{g}^{3}\right) d s^{1} \cdots d s^{m}
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\end{aligned}
$$

- Volume measure in semigeodesic coordinates:

$$
d \operatorname{Vol}(u)=1+H(x) u^{m}+\mathcal{O}\left(\|u\|_{\text {sem }}^{2}\right)
$$

## Semigeodesic Expansion

- Distance comparison in normal coordinates (Smolyanov et al. [5] 2007)

$$
\|x-y\|_{\mathbb{R}^{d}}^{2}=\|s\|_{g}^{2}-\frac{1}{12}\|\Pi(s, s)\|_{g}^{2}+\mathcal{O}\left(\|s\|_{g}^{5}\right)
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$$

- Norm comparison in semigeodesic coordinates (V, 2020)

$$
\|x-y\|_{\mathbb{R}^{d}}^{2}=\|u\|_{\text {sem }}^{2}-\left\langle\Pi_{\partial \mathcal{M}_{b_{x}}}\left(u^{\top}, u^{\top}\right), u^{\perp}\right\rangle_{g}+\mathcal{O}\left(\|u\|_{\text {sem }}^{4}\right) .
$$

## Semigeodesic Expansion

Proposition (R. Vaughn, 2020)
For $\epsilon$ sufficiently small, let $x$ be a point in $N_{\epsilon}$. Then:

$$
\begin{aligned}
& \frac{1}{\epsilon^{m}} \int_{y \in \mathcal{M}} \\
& \quad k(\epsilon, x, y) f(y) d \mathrm{Vol}=m_{0}^{\partial}(x) f(x) \\
& \quad+\epsilon m_{1}^{\partial}(x)\left(\left\langle\nabla f, \eta_{x}\right\rangle_{g}-\frac{m-1}{2} H(x) f(x)\right) \\
& \quad+\mathcal{O}\left(\epsilon^{2}\right)
\end{aligned}
$$

where $m_{0}^{\partial}(x)$ and $m_{2}^{\partial}(x)$ are functions of the distance to the boundary and $H(x)$ is the mean curvature of the hypersurface parallel to $\partial M$ intersecting $x$.

The long-standing mystery...

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\begin{aligned}
\frac{1}{m_{2} \epsilon^{2}} \mathcal{L}_{\epsilon} f(x) & \equiv \frac{\epsilon^{-m}}{m_{2} \epsilon^{2}} \int_{\mathcal{M}} k_{\epsilon}(x, y) f(y)-k_{\epsilon}(x, y) f(x) d y \\
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& =\Delta f(x)-\frac{c \nabla f(x) \cdot \eta}{\epsilon}+\mathcal{O}(\epsilon)
\end{aligned}
$$

Solution: Analyze $\mathcal{L}_{\epsilon}$ in the weak-sense

## Main Result

Theorem (R. Vaughn, [8])
Assume $q$ is a uniform distribution for simplicity. Then for any smooth function $f$ and any smooth test function $\phi$, we have:

$$
\begin{aligned}
\mathcal{L}_{\epsilon} & \equiv \frac{\epsilon^{-m-2}}{m_{2}} \int_{\mathcal{M}} \phi \cdot\left(\mathcal{K}_{\epsilon} f-f \mathcal{K}_{\epsilon} 1\right) d \mathrm{Vol} \\
& =-\int_{\mathcal{M}}\langle\nabla \phi, \nabla f\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon) .
\end{aligned}
$$

## Elements of Proof



- $\mathcal{M}_{\epsilon}$ grows as $\epsilon \rightarrow 0$
- $N_{\epsilon}$ shrinks as $\epsilon \rightarrow 0$

The additional integral allows us to subdivide $\mathcal{M}$ into two regions for every $\epsilon$.

## Elements of Proof

$$
\int_{\mathcal{M}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}=\int_{\mathcal{M}_{\epsilon} \cup N_{\epsilon}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}
$$

## Elements of Proof

$$
\begin{aligned}
\int_{\mathcal{M}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol} & =\int_{\mathcal{M}_{\epsilon} \cup N_{\epsilon}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol} \\
& =\int_{\mathcal{M}_{\epsilon}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}+\int_{N_{\epsilon}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}
\end{aligned}
$$

## Elements of Proof

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\begin{aligned}
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& =\int_{\mathcal{M}_{\epsilon}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}-\int_{\partial \mathcal{M}}\langle\phi \nabla f, \eta\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon)
\end{aligned}
$$

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& =\int_{\mathcal{M}_{\epsilon}} \phi \Delta f d \mathrm{Vol}-\int_{\partial \mathcal{M}}\langle\phi \nabla f, \eta\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon)
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& =\int_{\mathcal{M}_{\epsilon}} \phi \Delta f d \mathrm{Vol}-\int_{\partial \mathcal{M}}\langle\phi \nabla f, \eta\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon) \\
& =-\int_{\mathcal{M}}\langle\nabla \phi, \nabla f\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon)
\end{aligned}
$$

## Elements of Proof

Hence,

$$
\vec{\phi}^{\top} L_{\epsilon} \vec{f} \approx \int_{\mathcal{M}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}=-\int_{\mathcal{M}}\langle\nabla \phi, \nabla f\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon)
$$

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Hence,

$$
\vec{\phi}^{\top} L_{\epsilon} \vec{f} \approx \int_{\mathcal{M}} \phi \mathcal{L}_{\epsilon} f d \mathrm{Vol}=-\int_{\mathcal{M}}\langle\nabla \phi, \nabla f\rangle_{g} d \mathrm{Vol}+\mathcal{O}(\epsilon)
$$

- The kernel based estimator does not converge pointwise
- But it converges to the variational form of $\Delta$ with Neumann B.C. in the weak sense.


## Boundary Integrals

Use distance-to-boundary function to estimate boundary integrals:

Theorem (R. Vaughn, [8])
For $f: \mathcal{M} \rightarrow \mathbb{R}, d_{\mathcal{M}}$ the intrinsic distance, and $h$ with fast decay we have,
$\frac{1}{\epsilon} \int_{x \in N_{\epsilon}} h\left(\frac{d_{\mathcal{M}}(x, \partial M)^{2}}{\epsilon^{2}}\right) f(x) d \mathrm{Vol}=\bar{m}_{0} \int_{x \in \partial \mathcal{M}} f(x) d \mathrm{Vol}_{\partial}+\mathcal{O}(\epsilon)$
where $\bar{m}_{0}=\int_{0}^{\infty} h(u) d u$.

## Mesh-free solver for BVPs on Embedded Manifolds

Weak-sense formulation:

$$
\begin{aligned}
& \qquad \int_{\mathcal{M}} \nabla u \cdot \nabla v d x+\int_{\mathcal{M}} u v d x=\int_{\mathcal{M}} f v d x+\int_{\partial \mathcal{M}} g v d s \\
& \text { Dirichlet Energy } \quad \text { Volume Integral } \quad \text { Boundary Integral }
\end{aligned}
$$



## Consequences

Manifold Learning:

- Diffusion Maps returns Neumann eigenfunctions [2]
- Our result rigorously explains this empirical phenomenon
- Eigenproblem, $\vec{v}^{\top} L_{\epsilon} \vec{v} \approx \int_{\mathcal{M}} \nabla \phi \cdot \nabla \phi d x$
- Natural boundary condition is Neumann
[1] Tyrus Berry and Timothy Sauer.
Density estimation on manifolds with boundary.
Computational Statistics \& Data Analysis, 107:1-17, 2017.
[2] Ronald R Coifman and Stéphane Lafon.
Diffusion maps.
Applied and computational harmonic analysis, 21(1):5-30, 2006.
[3] Amit Singer and H-T Wu.
Vector diffusion maps and the connection laplacian.
Communications on pure and applied mathematics, 65(8):1067-1144, 2012.
[4] Amit Singer and Hau-Tieng Wu.
Spectral convergence of the connection laplacian from random samples.
Information and Inference: A Journal of the IMA, 6(1):58-123, 2016.
[5] Oleg G Smolyanov, Heinrich v Weizsäcker, and Olaf Wittich.
Chernoff's theorem and discrete time approximations of brownian motion on manifolds.
Potential Analysis, 26(1):1-29, 2007.
[6] Nicolás García Trillos, Moritz Gerlach, Matthias Hein, and Dejan Slepčev.
Error estimates for spectral convergence of the graph laplacian on random geometric graphs toward the laplace-beltrami operator.
Foundations of Computational Mathematics, pages 1-61, 2019.
[7] Nicolás García Trillos and Dejan Slepčev.
A variational approach to the consistency of spectral clustering.
Applied and Computational Harmonic Analysis, 45(2):239-281, 2018.
[8] Ryan Vaughn, Tyrus Berry, and Harbir Antil.
Diffusion maps for embedded manifolds with boundary with applications to pdes, 2019.


# Density Estimation, Volume Integrals [1]: 

http://math.gmu.edu/~tberry/

Dirichlet energy \& boundary integrals [8]:
http://math.gmu.edu/~rvaughn5/

