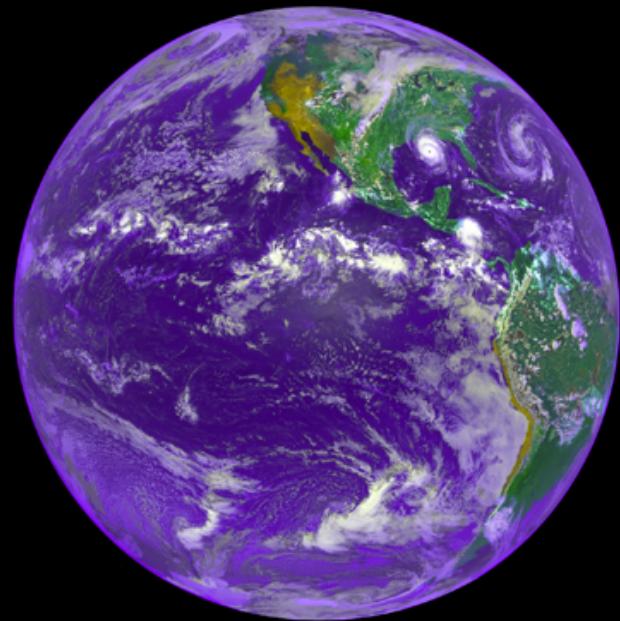


2013 Dolomites Research Week on Approximation

Kernel approximation on the sphere with applications to computational geosciences

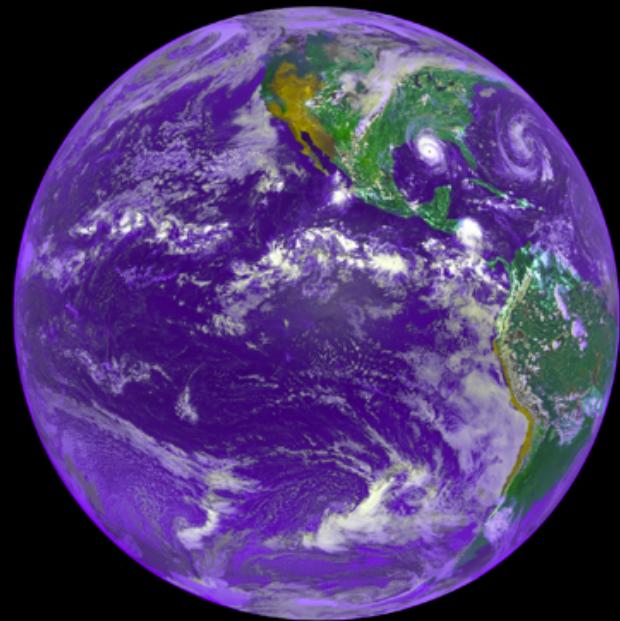


Grady B. Wright
Boise State University

*This work is supported by NSF grants DMS 0934581

2013 Dolomites Research Week on Approximation

Lecture 1:
Introduction to kernels and
approximation on the sphere



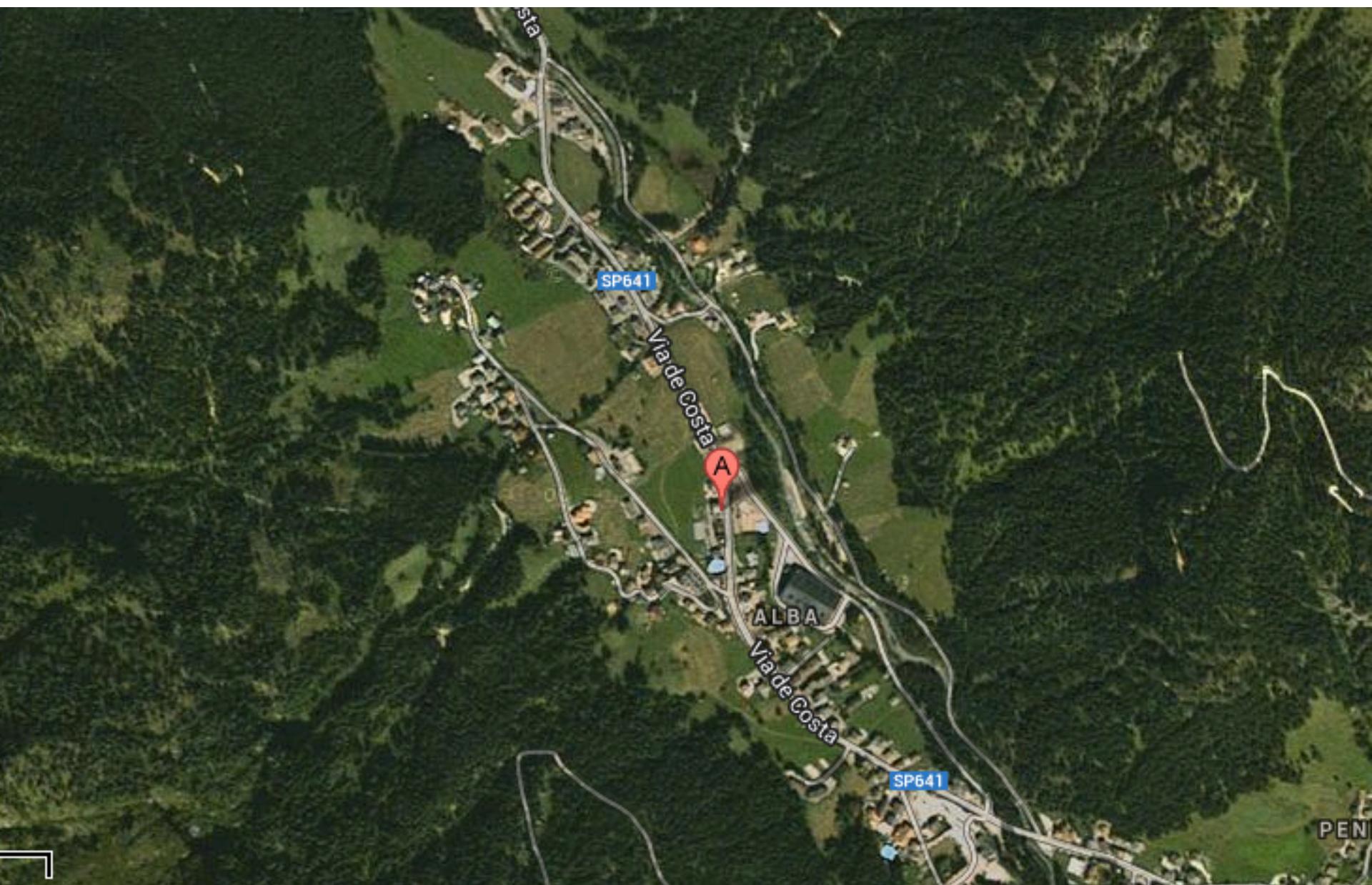
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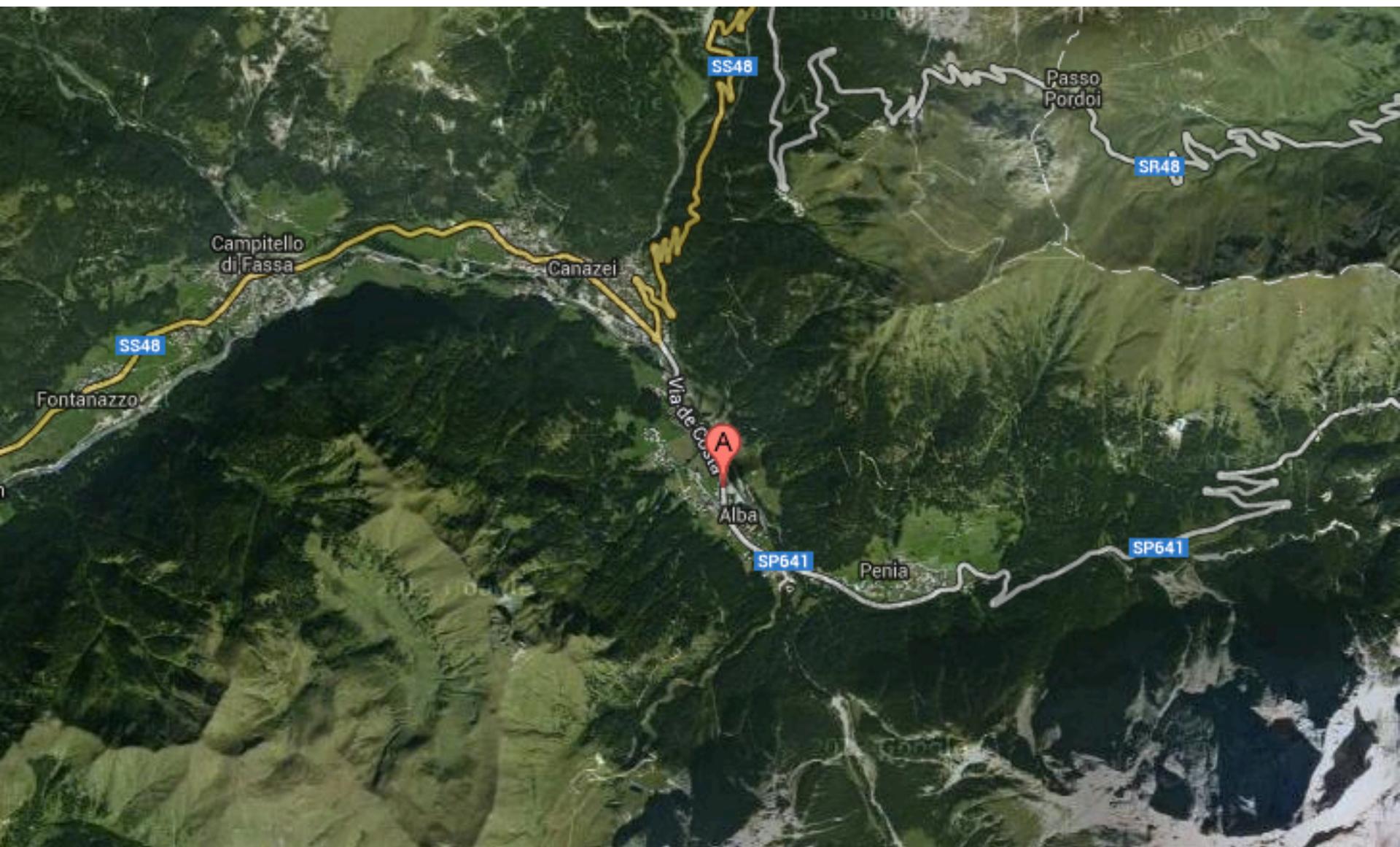
Overview

- Applications in spherical geometries
- Scattered data interpolation in \mathbb{R}^d
 - Positive definite radial kernels: radial basis functions (RBF)
 - Some theory
- Scattered data interpolation on the sphere \mathbb{S}^2
 - Positive definite (PD) zonal kernels
 - Brief review of spherical harmonics
 - Characterization of PD zonal kernels
 - Conditionally positive definite zonal kernels
 - Examples
- Error estimates:
 - Reproducing kernel Hilbert spaces
 - Sobolev spaces
 - Native spaces
 - Geometric properties of node sets
- Optimal nodes on the sphere

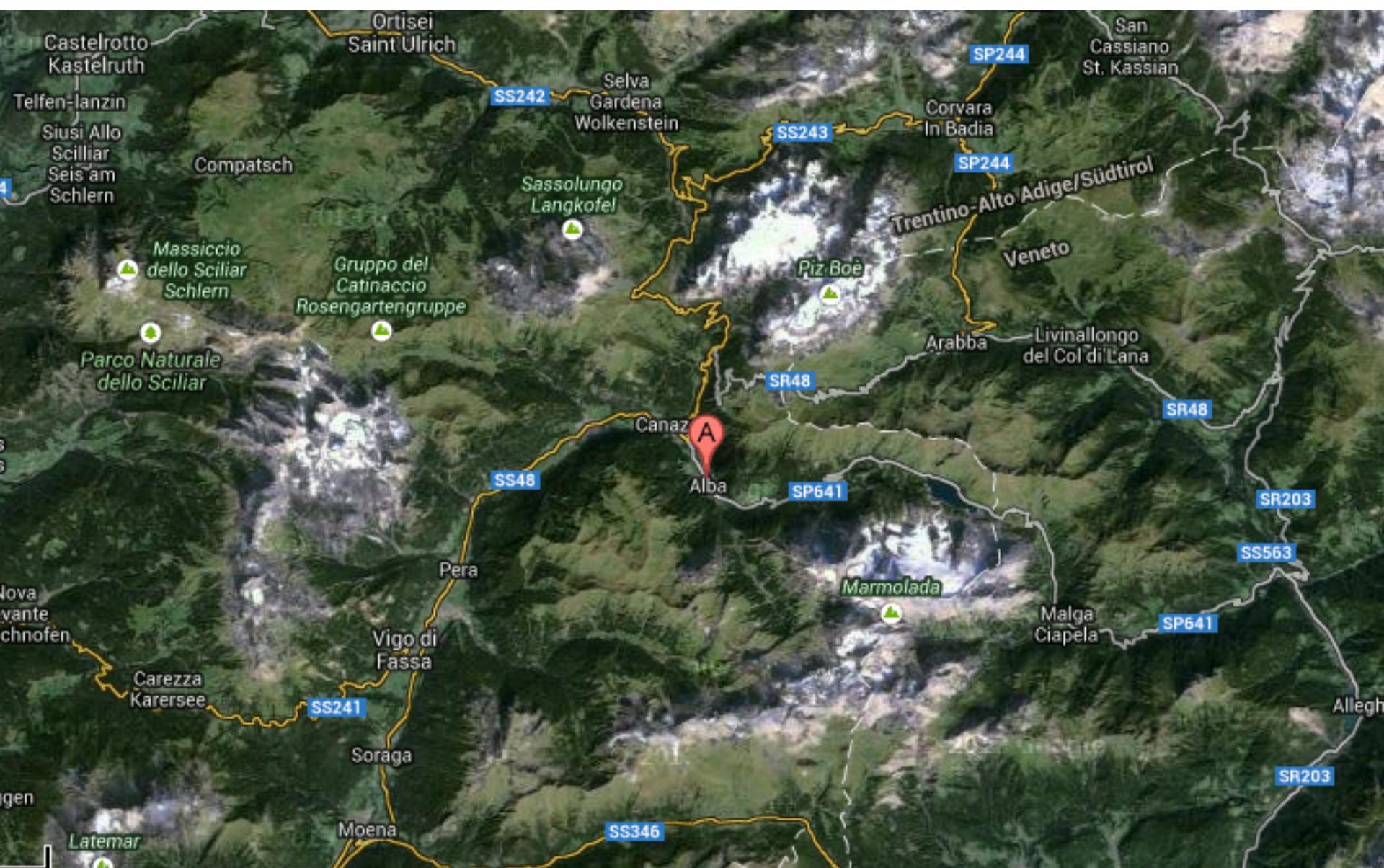
Where I am from



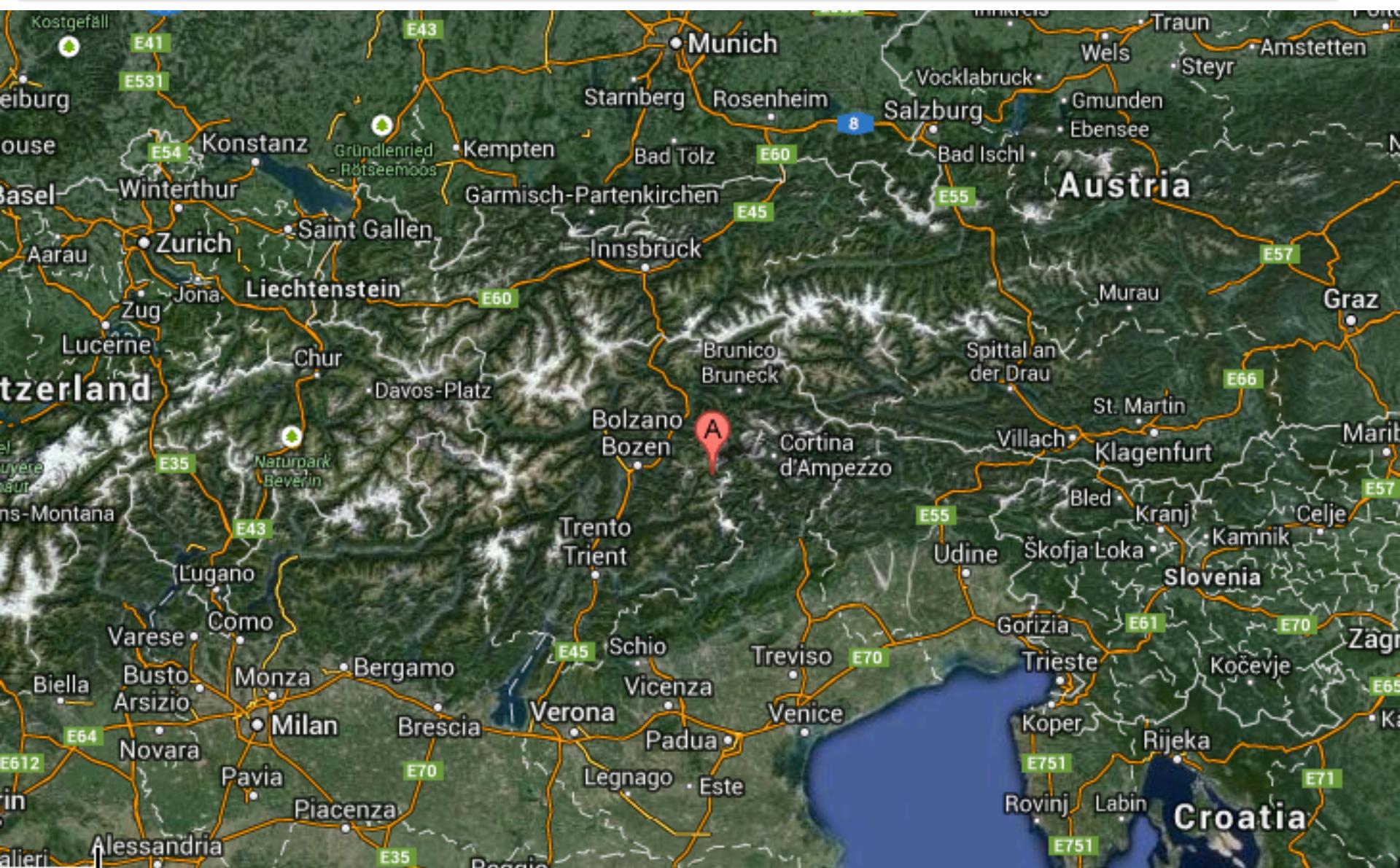
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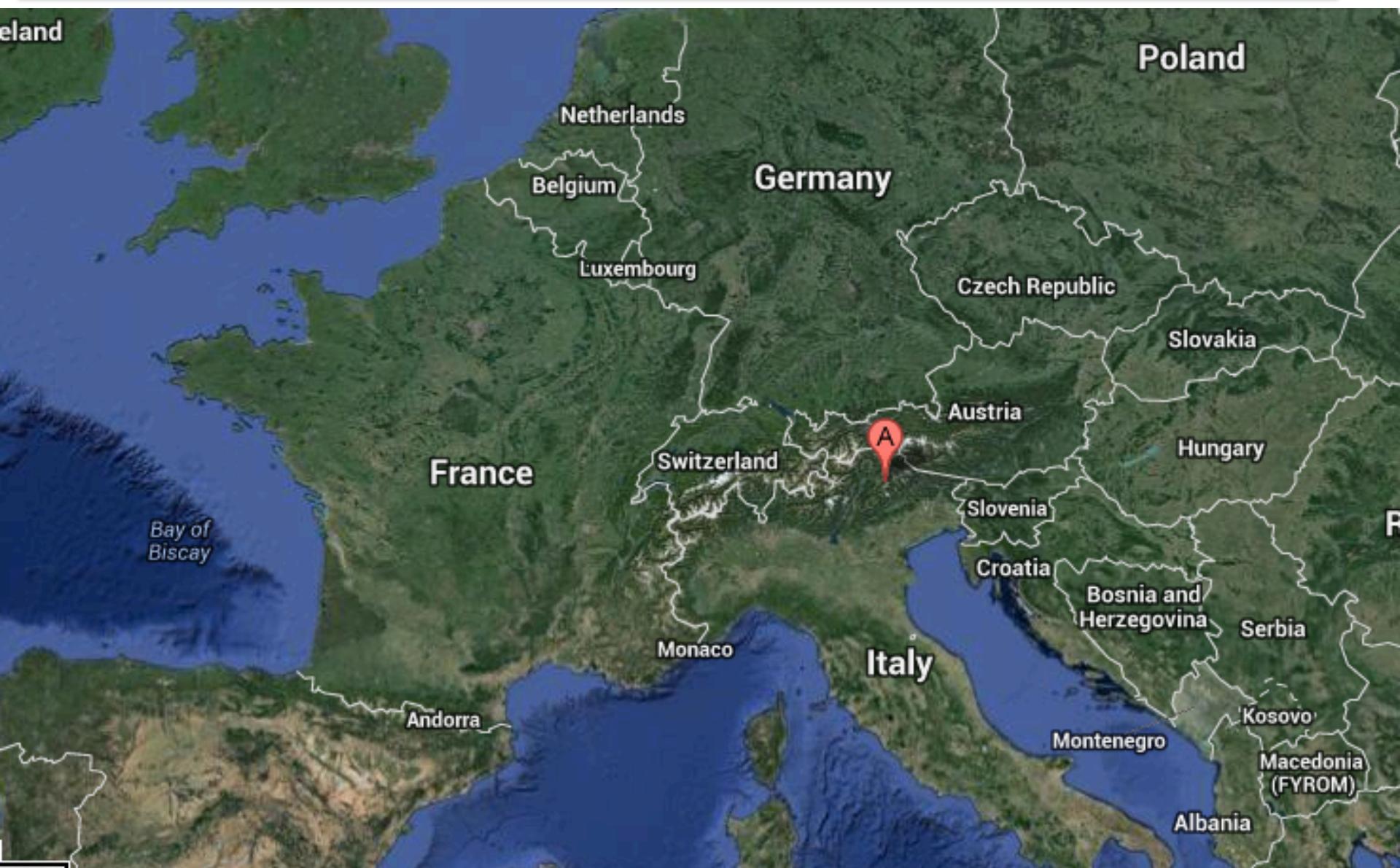
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Where I am from



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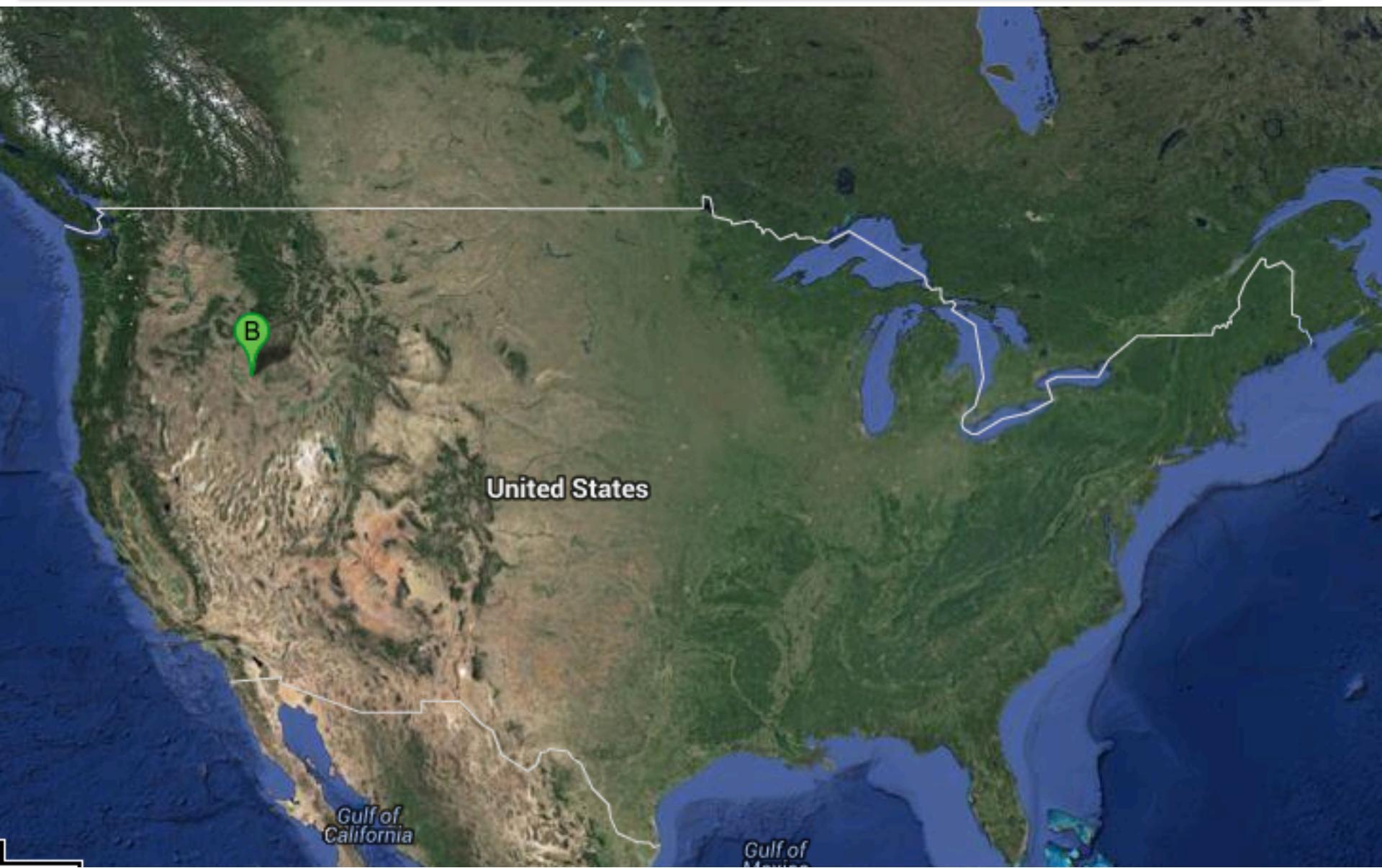
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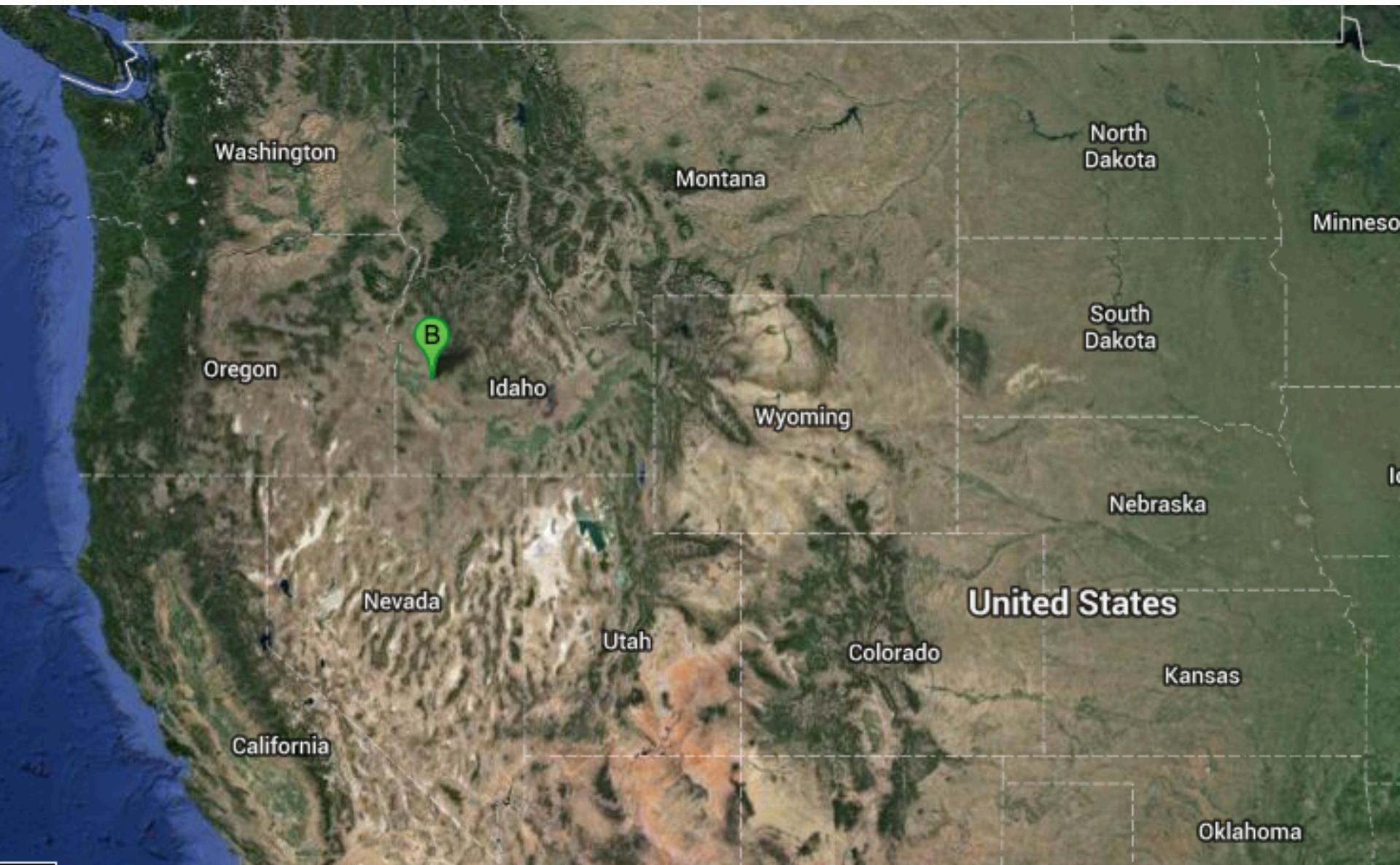
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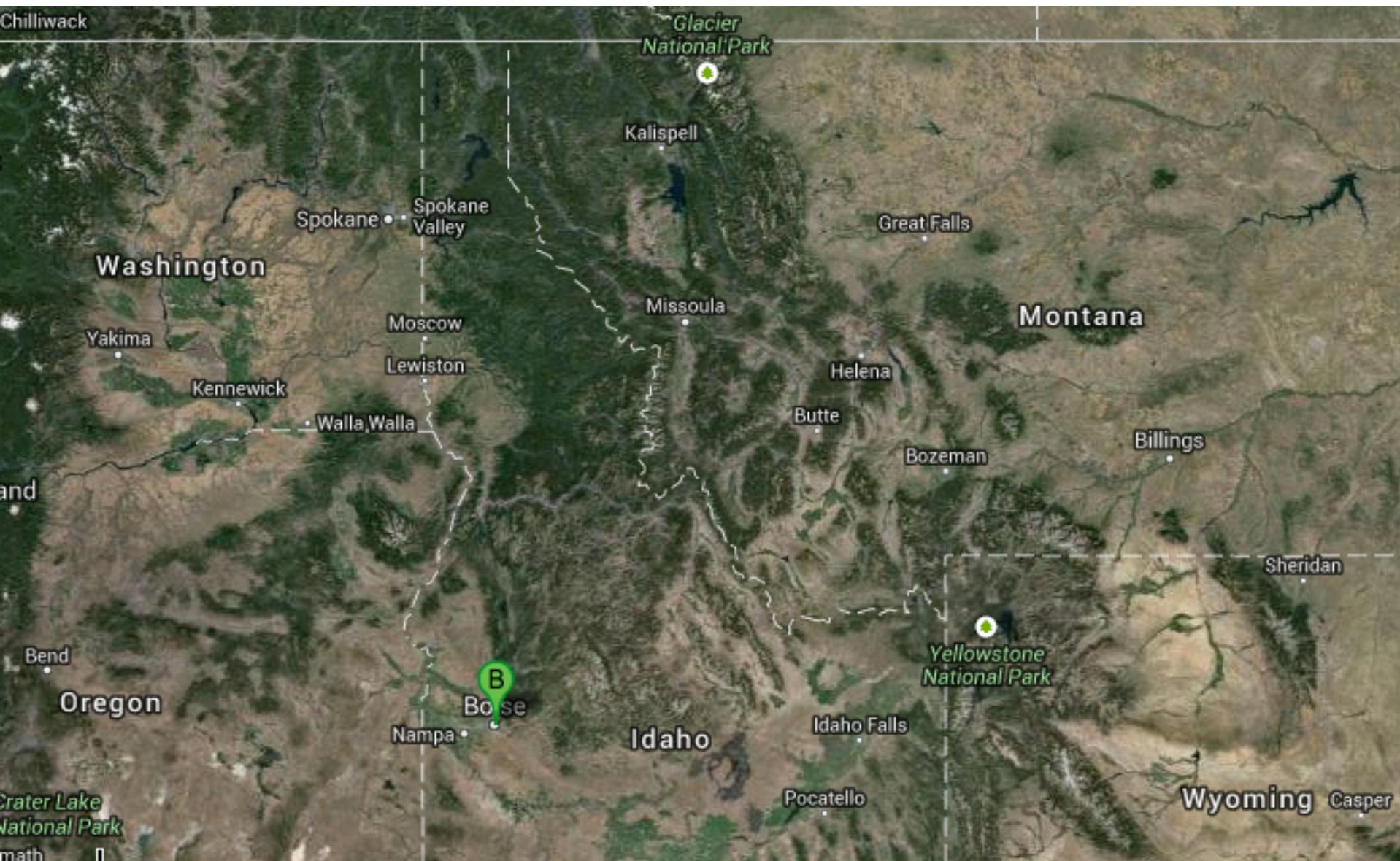
Where I am from



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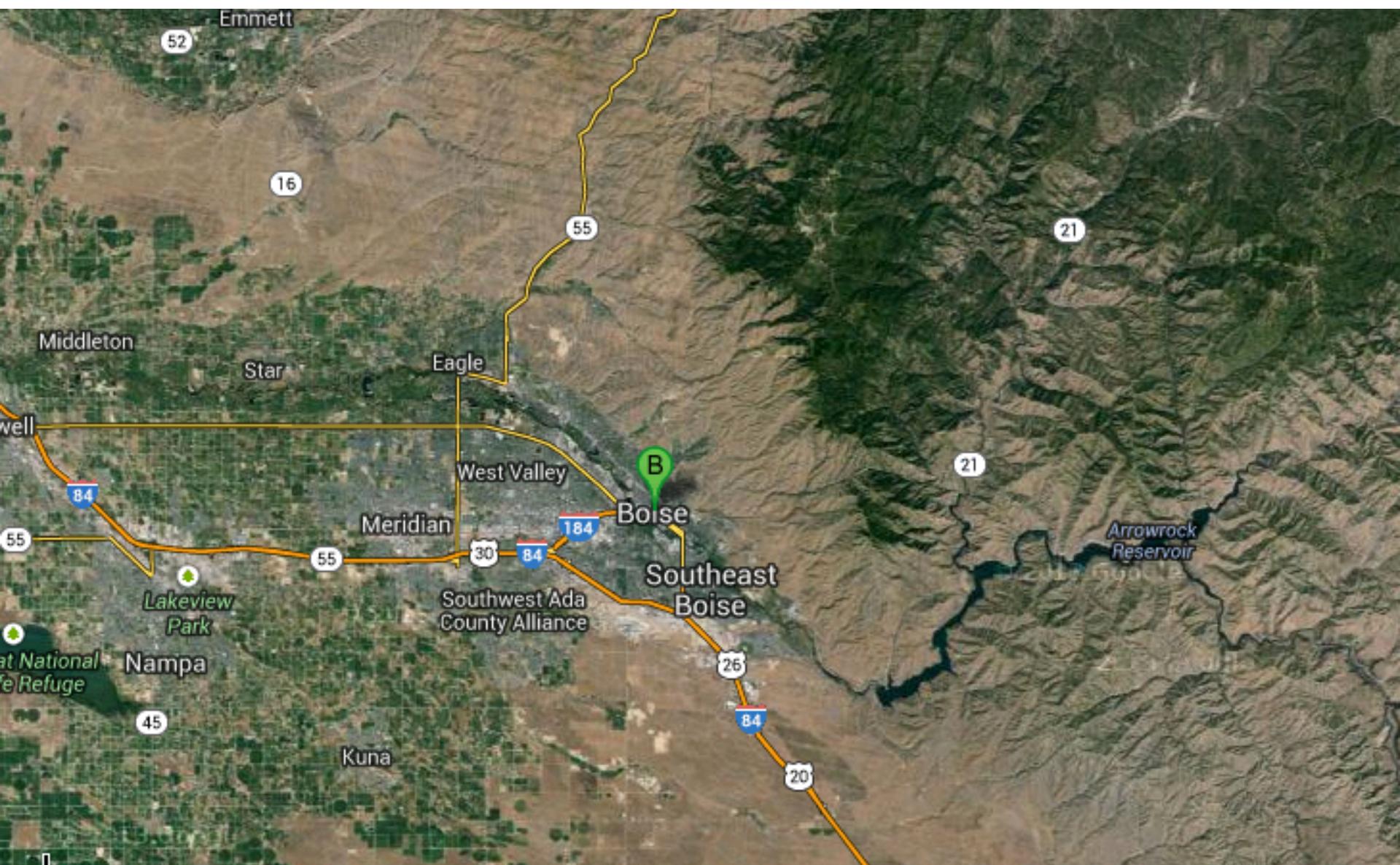
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DRWA 2013

Lecture 1



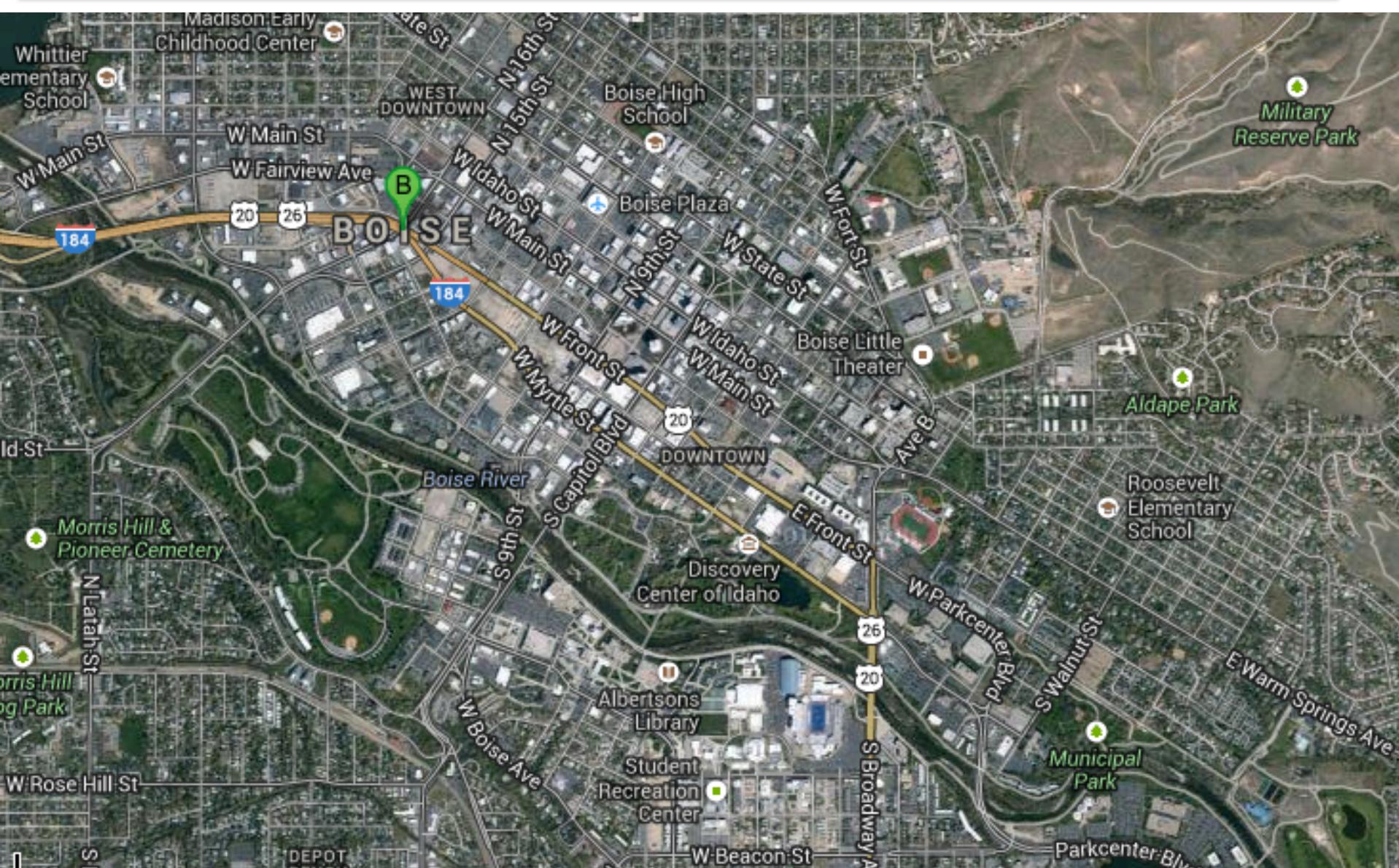
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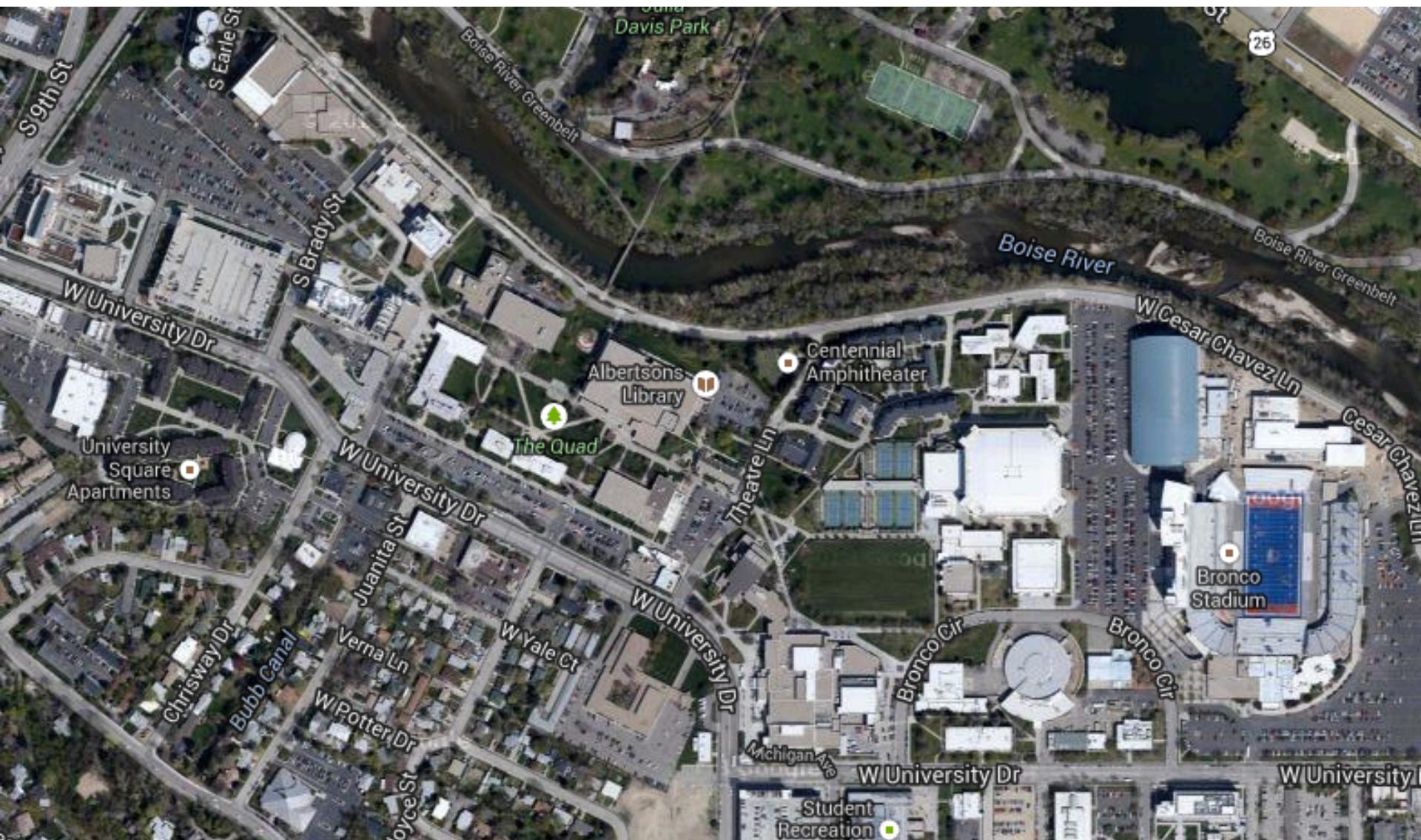
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DRWA 2013

Lecture 1



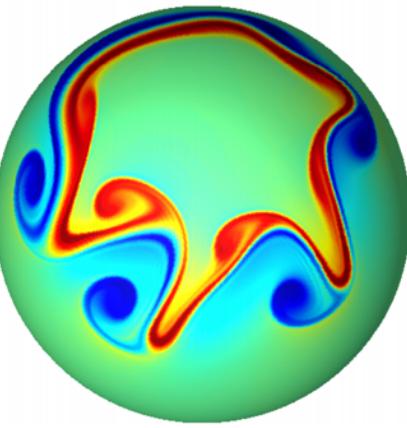
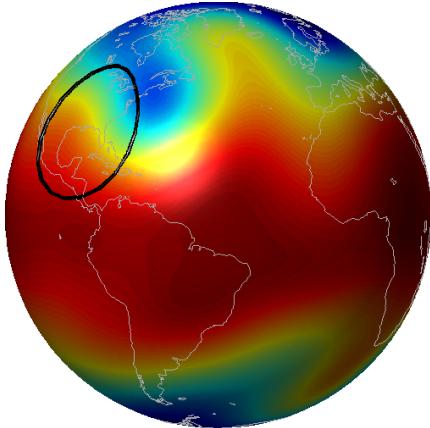
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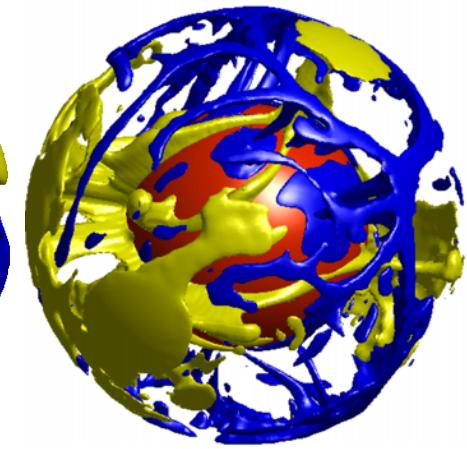
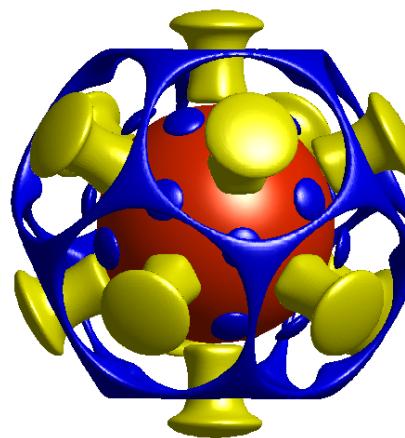
Applications in spherical geometries

- A visual overview: applications in the geosciences

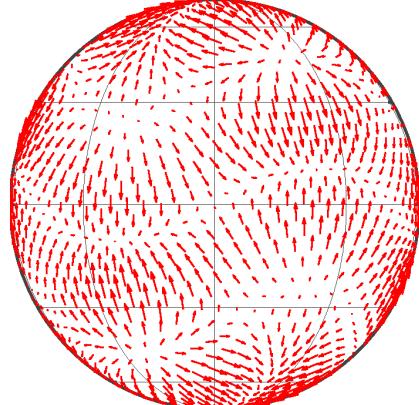
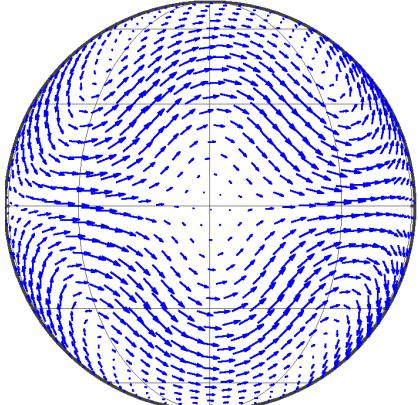
Shallow water flows:
numerical weather prediction



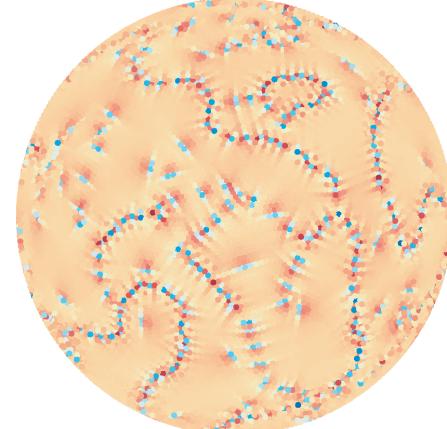
Rayleigh-Bénard Convection:
Mantle convection



Vector fields on the sphere



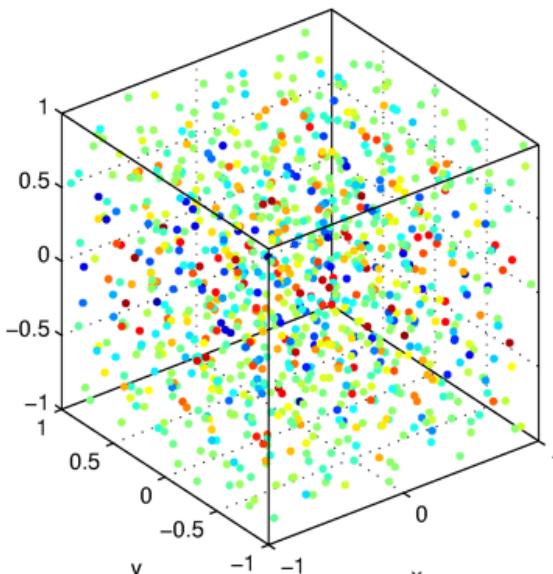
Numerical integration



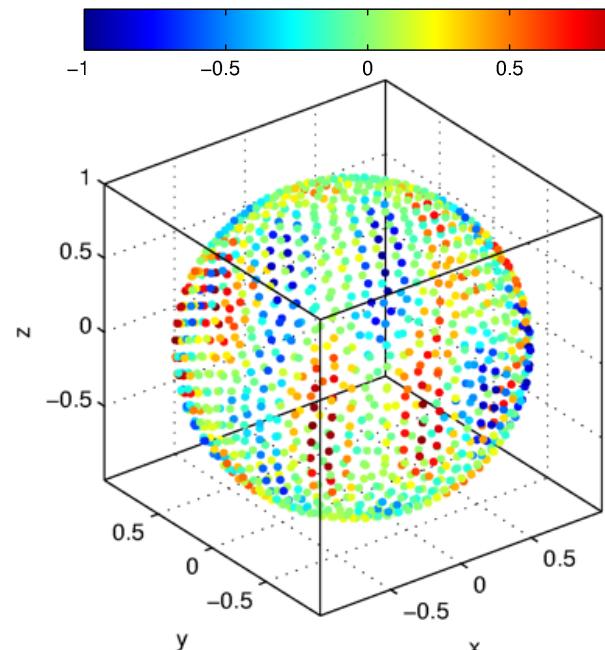
Interpolation with kernels

- Let $\Omega \subset \mathbb{R}^d$ and $X = \{\mathbf{x}_j\}_{j=1}^N$ a set of nodes on Ω .
- Consider a continuous target function $f : \Omega \rightarrow \mathbb{R}$ sampled at X : $f|_X$.

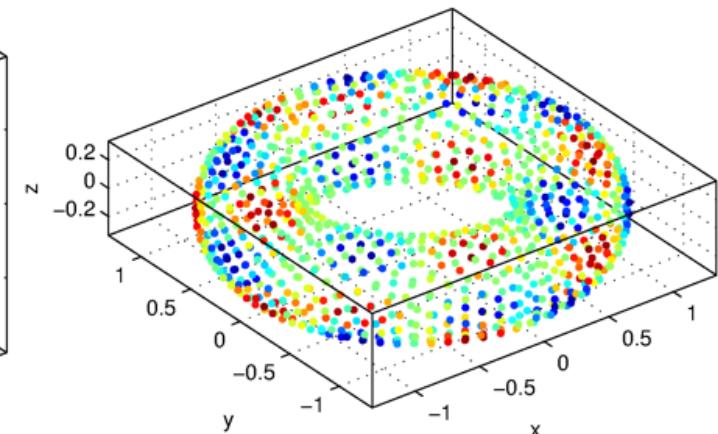
Examples:



$$\Omega = [-1, 1]^3$$



$$\Omega = \mathbb{S}^2$$



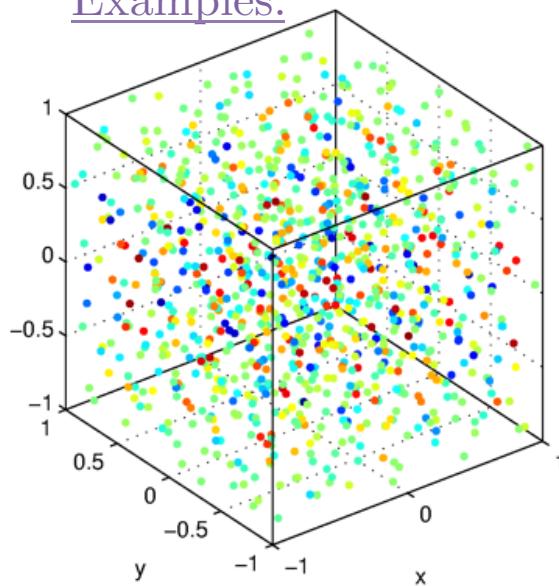
$$\Omega = \mathbb{T}^2$$

- Kernel interpolant to $f|_X$: $I_X f = \sum_{j=1}^N c_j \Phi(\cdot, \mathbf{x}_j)$

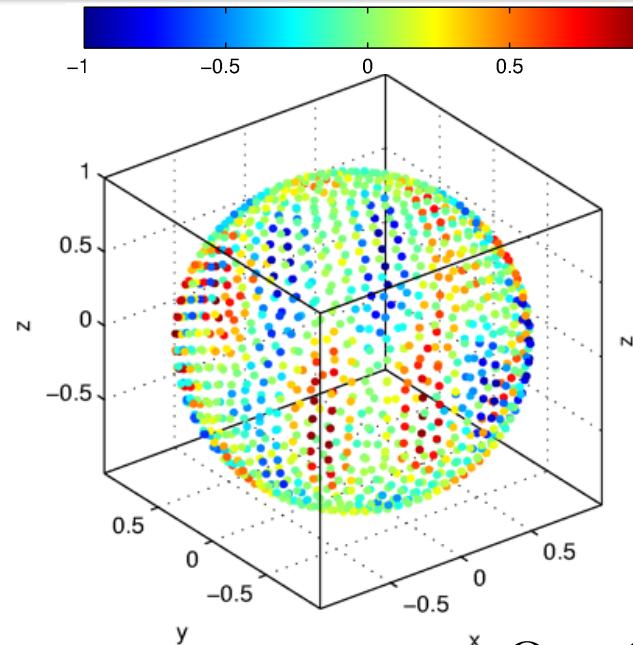
where $\Phi : \Omega \times \Omega \rightarrow \mathbb{R}$ and c_j come from requiring $I_X f|_X = f|_X$

Interpolation with kernels

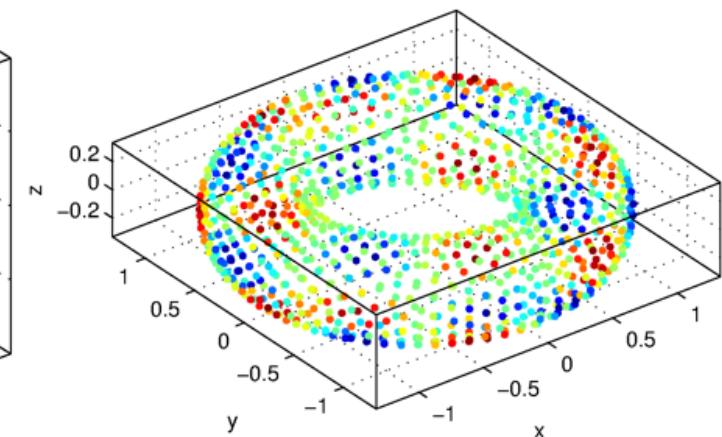
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$$I_X f = \sum_{j=1}^N c_j \Phi(\cdot, \mathbf{x}_j)$$



$$\Omega = \mathbb{T}^2$$

- Kernel interpolant to $f|_X$: $I_X f = \sum_{j=1}^N c_j \Phi(\cdot, \mathbf{x}_j)$
- Definition: Φ is a **positive definite kernel** on Ω if the matrix $A = \{\Phi(\mathbf{x}_i, \mathbf{x}_j)\}$ is positive definite for any distinct $X = \{\mathbf{x}_j\}_{j=1}^N \subset \Omega$, i.e.

$$\sum_{i=1}^N \sum_{j=1}^N b_i \Phi(\mathbf{x}_i, \mathbf{x}_j) b_j > 0, \text{ provided } \{b_i\}_{i=1}^N \not\equiv 0.$$

- In this case c_j are uniquely determined by X and $f|_X$.

Interpolation with kernels

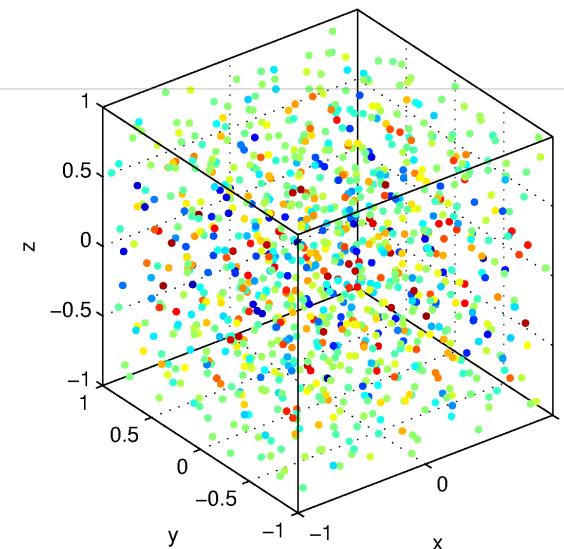
- Kernel interpolant to $f|_X$: $I_X f = \sum_j c_j \Phi(\cdot, \mathbf{x}_j)$.
- Some considerations for choosing the kernel $\Phi : \Omega \times \Omega \rightarrow \mathbb{R}$
 1. The kernel should be easy to compute.
 2. The kernel interpolant should be uniquely determined by X and $f|_X$.
 3. The kernel interpolant should accurately reconstruct f .

Interpolation with kernels

- Kernel interpolant to $f|_X$: $I_X f = \sum_j c_j \Phi(\cdot, \mathbf{x}_j)$.



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$$\Omega = [-1, 1]^3$$



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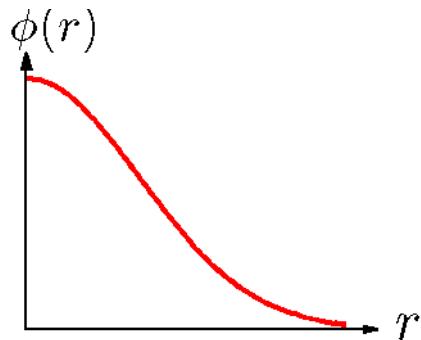


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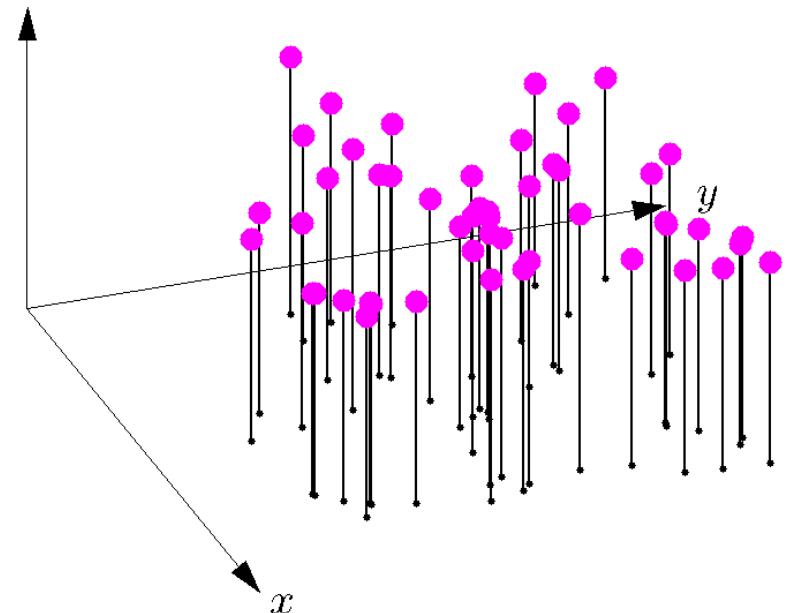
- Leads to radial basis function (RBF) interpolation.

Radial basis function (RBF) interpolation

Key idea: linear combination of **translates** and **rotations** of a single radial kernel:



$$f \quad X = \{\mathbf{x}_j\}_{j=1}^N \subset \Omega, \quad f|_X = \{\mathbf{f}_j\}_{j=1}^N$$



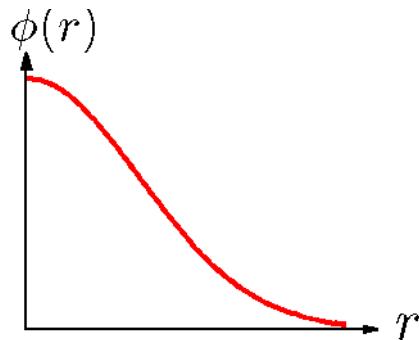
Basic RBF Interpolant for $\Omega \subseteq \mathbb{R}^2$

$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \phi(\|\mathbf{x} - \mathbf{x}_j\|)$$

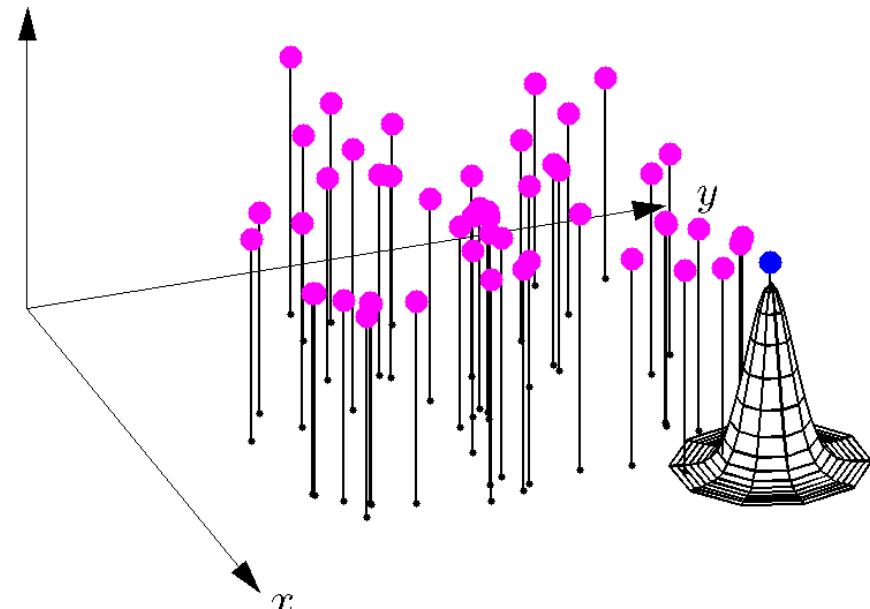
$$\text{where } \|\mathbf{x} - \mathbf{x}_j\| = \sqrt{(x - x_j)^2 + (y - y_j)^2}$$

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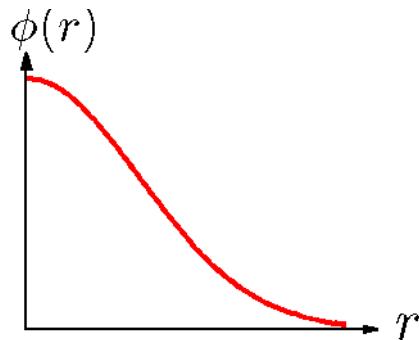
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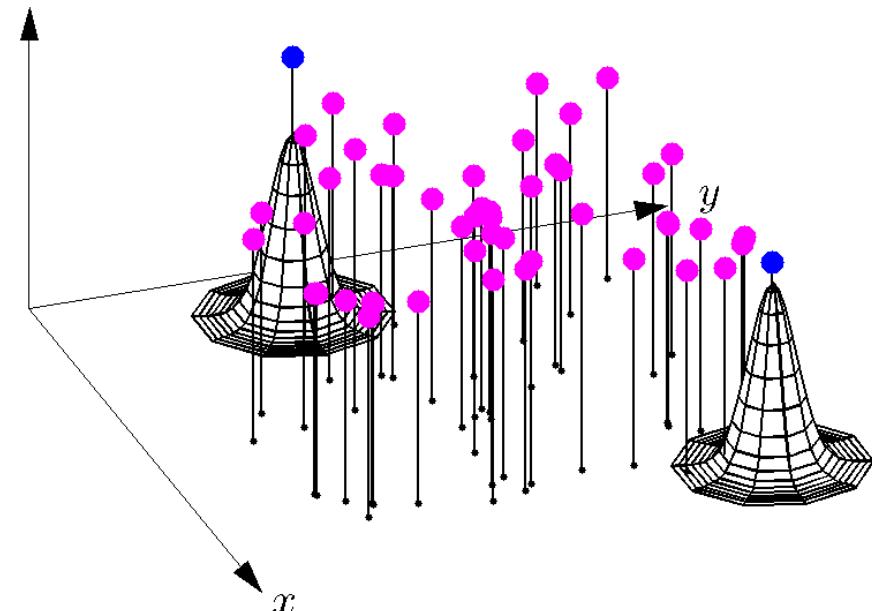
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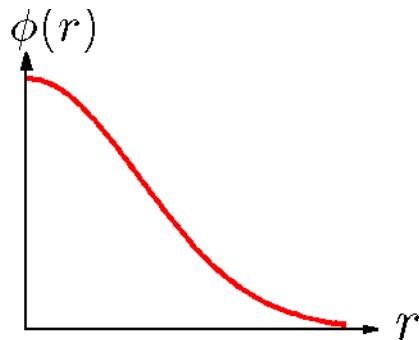
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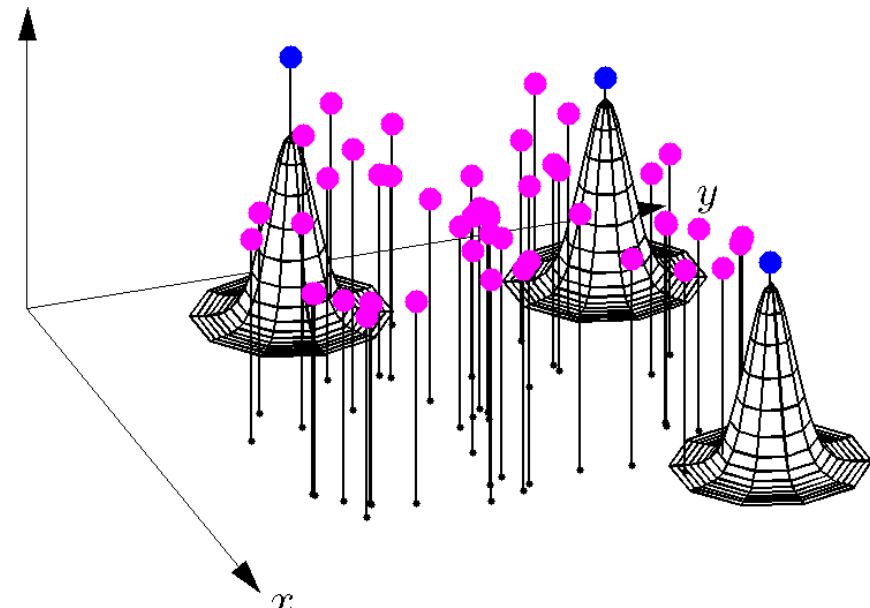
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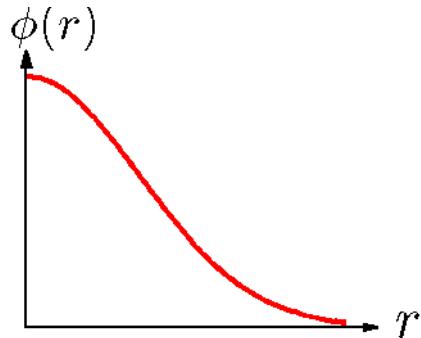
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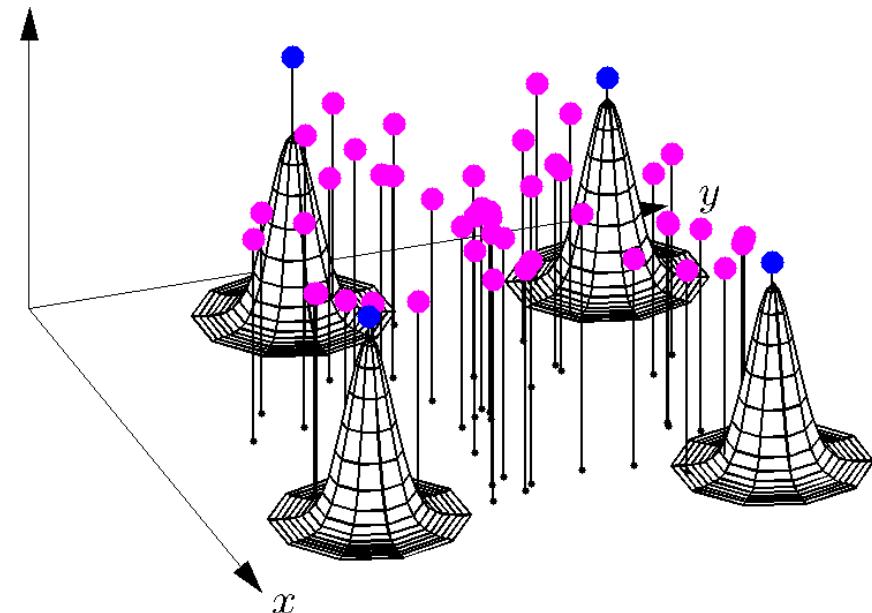
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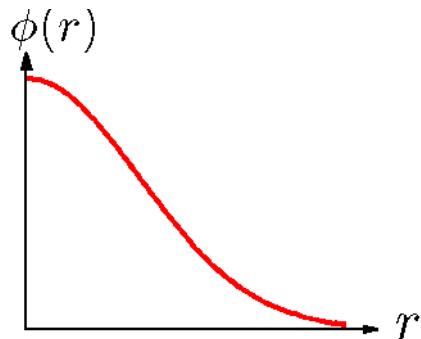
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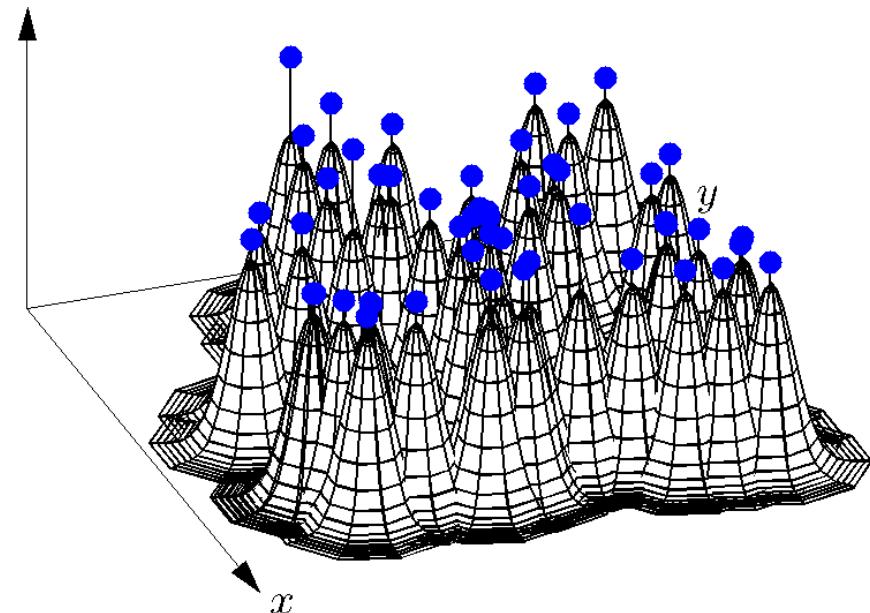
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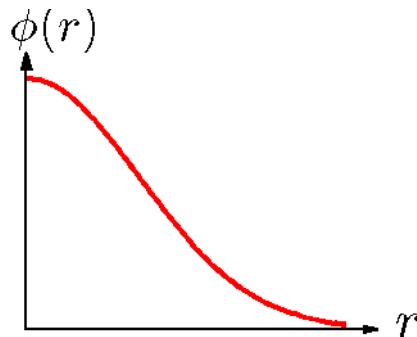
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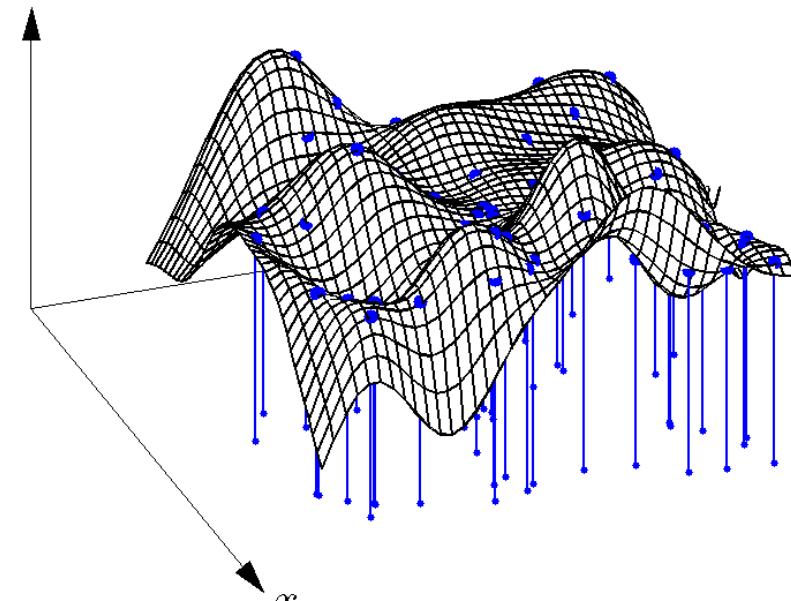
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Basic RBF Interpolant for $\Omega \subseteq \mathbb{R}^2$

$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \phi(\|\mathbf{x} - \mathbf{x}_j\|)$$

Linear system for determining the interpolation coefficients

$$\underbrace{\begin{bmatrix} \phi(\|\mathbf{x}_1 - \mathbf{x}_1\|) & \phi(\|\mathbf{x}_1 - \mathbf{x}_2\|) & \cdots & \phi(\|\mathbf{x}_1 - \mathbf{x}_N\|) \\ \phi(\|\mathbf{x}_2 - \mathbf{x}_1\|) & \phi(\|\mathbf{x}_2 - \mathbf{x}_2\|) & \cdots & \phi(\|\mathbf{x}_2 - \mathbf{x}_N\|) \\ \vdots & \vdots & \ddots & \vdots \\ \phi(\|\mathbf{x}_N - \mathbf{x}_1\|) & \phi(\|\mathbf{x}_N - \mathbf{x}_2\|) & \cdots & \phi(\|\mathbf{x}_N - \mathbf{x}_N\|) \end{bmatrix}}_{A_X} \underbrace{\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{bmatrix}}_c = \underbrace{\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}}_f$$

A_X is guaranteed to be **positive definite** if ϕ is positive definite.

Positive definite radial kernels

- Some results on positive definite radial kernels.

Theorem. If $\phi \in C[0, \infty)$ with $\phi(0) > 0$ and $\phi(\rho) < 0$ for some $\rho > 0$, then ϕ cannot be positive definite in \mathbb{R}^d for all d .

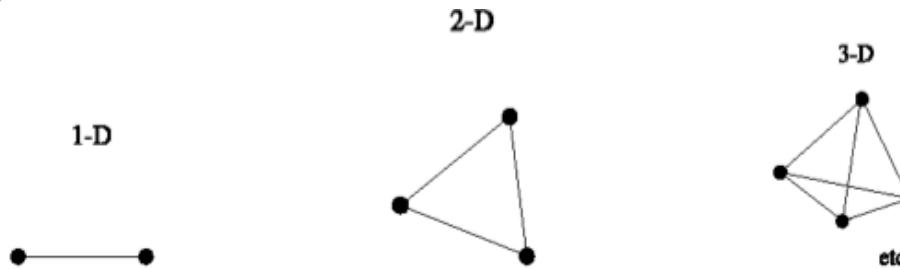
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Proof

Consider X to be the vertices of an m dimensional simplex with spacing ρ , i.e. $X = \{\mathbf{x}\}_{j=1}^{m+1} \subset \mathbb{R}^m$



Then

$$\begin{aligned} \sum_{i=1}^{m+1} \sum_{j=1}^{m+1} \phi(\|\mathbf{x}_i - \mathbf{x}_j\|) &= \sum_{i=1}^{m+1} \phi(0) + \sum_{i=1}^{m+1} \sum_{j=1, j \neq i}^{m+1} \phi(\rho) \\ &= (m+1)[\phi(0) + m\phi(\rho)]. \end{aligned}$$

Given $\phi(0) > 0$, we can find a ρ for which $\phi(\rho) < 0$ and an m to make this sum zero.

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Definition. A function $\Phi : [0, \infty) \rightarrow \mathbb{R}$ is said to be **completely monotone** on $[0, \infty)$ if

$$(1) \Phi \in C[0, \infty), \quad (2) \Phi \in C^\infty(0, \infty), \quad (3) (-1)^k \Phi^{(k)}(t) \geq 0, \quad t > 0, \quad k = 0, 1, \dots$$

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Theorem (Hausdorff-Bernstien-Widder). A function Φ is **completely monotone** if and only if it can be written in the form

$$\Phi(t) = \int_0^\infty e^{-st} d\gamma(s),$$

where $\gamma(s)$ is bounded, non-decreasing, and not concentrated at zero.

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Theorem (Schoenberg 1938). Let $\phi : [0, \infty) \rightarrow \mathbb{R}$ be a radial kernel and $\Phi(r) = \phi(\sqrt{r})$. Then ϕ is positive definite on \mathbb{R}^d , for all d , if and only if Φ is **completely monotone** on $[0, \infty)$ and not constant.

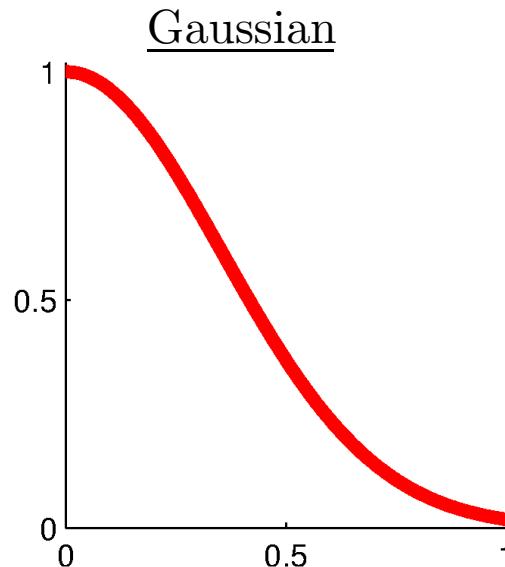
Proof: Use Bernstein-Hausdorff-Widder result and the fact the Gaussian is positive definite.

Positive definite radial kernels

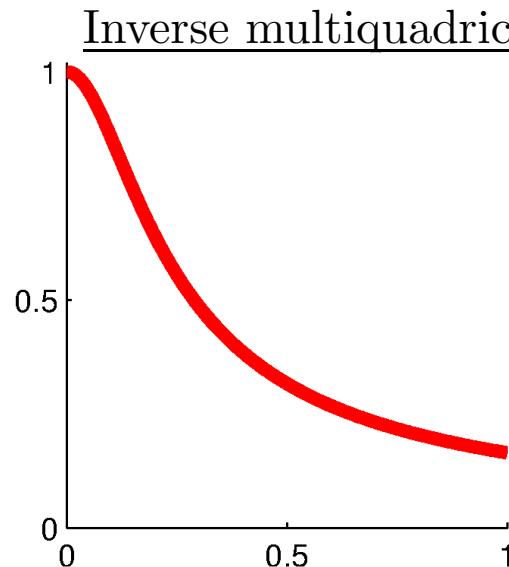
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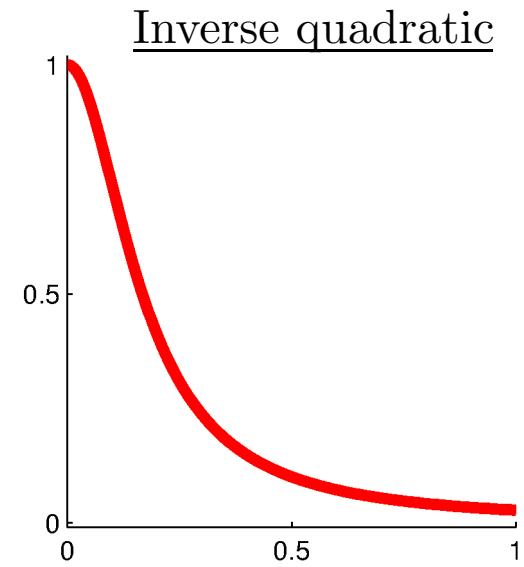
Examples:



$$\phi(r) = \exp(-(\varepsilon r)^2)$$



$$\phi(r) = \frac{1}{\sqrt{1 + (\varepsilon r)^2}}$$



$$\phi(r) = \frac{1}{1 + (\varepsilon r)^2}$$

Here ε is called the **shape parameter** (more on this later).

Positive definite radial kernels

- Results on dimensions specific positive definite radial kernels:

Theorem (General kernel). Let ϕ be a continuous kernel in $L_1(\mathbb{R}^d)$. Then ϕ is positive definite if and only if ϕ is bounded and its d -dimensional Fourier transform $\hat{\phi}(\boldsymbol{\omega})$ is non-negative and not identically equal to zero.

Remark: Related to Bochner's theorem (1933). Theorem and proof can be found in Wendland (2005).

- To make the result specific to radial kernels, we apply the d -dimensional Fourier transform and use radial symmetry to get (Hankel transform):

$$\hat{\phi}(\boldsymbol{\omega}) = \hat{\phi}(\|\boldsymbol{\omega}\|_2) = \frac{1}{\|\boldsymbol{\omega}\|_2^\nu} \int_0^\infty \phi(t) t^{d/2+1} J_\nu(\|\boldsymbol{\omega}\|_2 t) dt,$$

where $\nu = d/2 - 1$ and J_ν is the J -Bessel function of order ν .

- Note that if ϕ is positive definite on \mathbb{R}^d then it is positive definite on \mathbb{R}^k for any $k \leq d$.

Positive definite radial kernels

- Examples

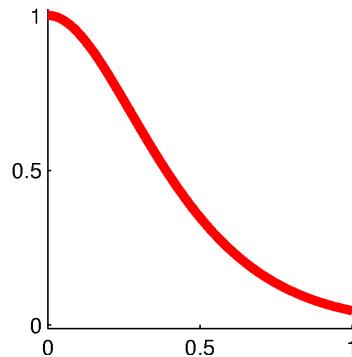
Finite-smoothness

Matérn

$$(\varepsilon r)^{\nu-d/2} K_{\nu-d/2}(\varepsilon r)$$

PD for $2\nu > d$

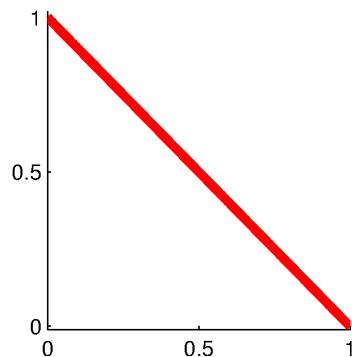
$$\text{Ex: } e^{-r}(r^2 + 3r + 3)$$



Truncated powers

$$(1 - \varepsilon r)_+^\ell$$

PD for $\ell \geq \lfloor d/2 \rfloor + 1$

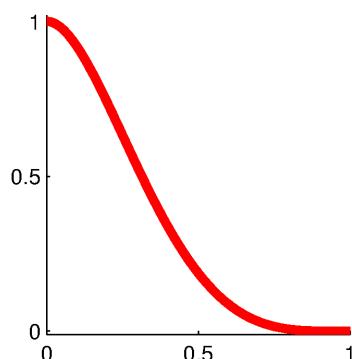


Wendland (1995)

$$(1 - \varepsilon r)_+^k p_{d,k}(\varepsilon r)$$

$p_{d,k}$ is a polynomial whose degree depends on d and k .

$$\text{Ex: } (1 - \varepsilon r)_+^4(4\varepsilon r + 1)$$

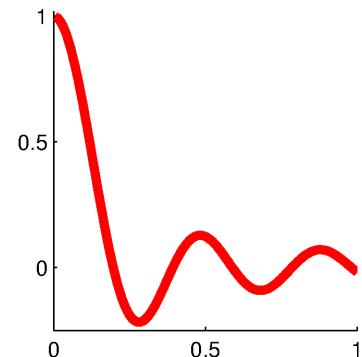


Infinite-smoothness

J-Bessel

$$\frac{J_{d/2-1}(\varepsilon r)}{(\varepsilon r)^{d/2}}$$

$$\text{Ex (d = 3): } \frac{\sin(\varepsilon r)}{\varepsilon r}$$

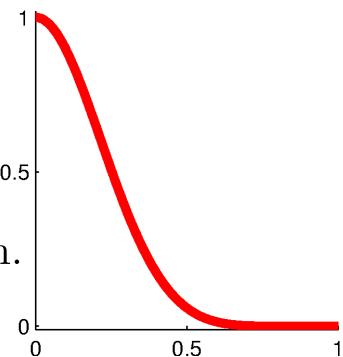


Platte

$$(\varphi * \varphi)(r)$$

φ is a $C^\infty(\mathbb{R})$ compactly supported radial function.

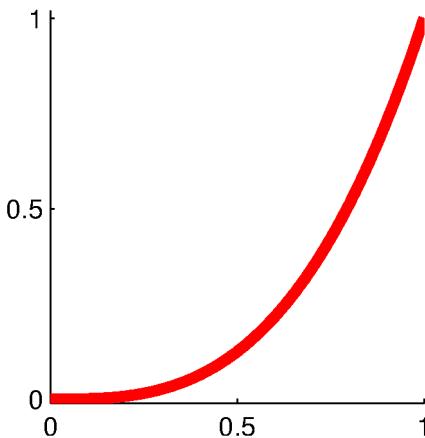
PD dimension depends on convolution dimension.



Conditionally positive definite kernels

- Discussion thus far does not cover many important radial kernels:

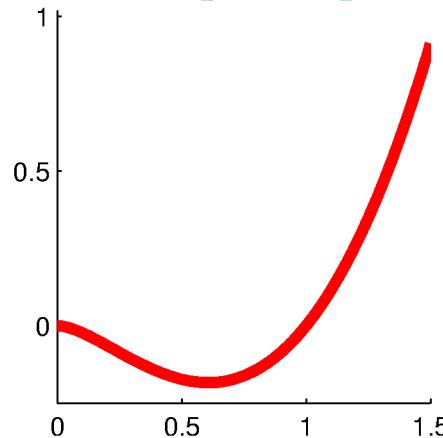
Cubic



$$\phi(r) = r^3$$

Cubic spline in 1-D

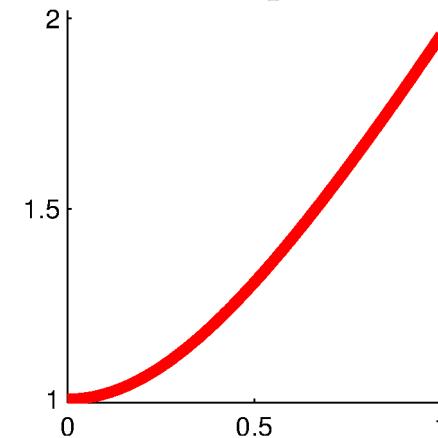
Thin plate spline



$$\phi(r) = r^2 \log r$$

Generalization of energy minimizing spline in 2D

Multiquadric



$$\phi(r) = \sqrt{1 + (\varepsilon r)^2}$$

Popular kernel and first used in any RBF application; Hardy 1971

- These can be covered under the theory of **conditionally positive definite kernels**.
- CPD kernels can be characterized similar to PD kernels but, using **generalized Fourier transforms**. We will not take this approach; see Ch. 8 Wendland 2005 for details.
- We will instead use a **generalization of completely monotone** functions.

Conditionally positive definite kernels

Definition. A continuous kernel $\phi : [0, \infty) \rightarrow \mathbb{R}$ is said to be **conditionally positive definite of order k** on \mathbb{R}^d if, for any distinct $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{R}^d$, and all $\mathbf{b} \in \mathbb{R}^N \setminus \{\mathbf{0}\}$ satisfying

$$\sum_{j=1}^N b_j p(\mathbf{x}_j) = 0$$

for all d -variate polynomials of degree $< k$, the following is satisfied:

$$\sum_{i=1}^N \sum_{j=1}^N b_i \phi(\|\mathbf{x}_i - \mathbf{x}_j\|) b_j > 0.$$

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$$\sum_{i=1}^N \sum_{j=1}^N b_i \phi(\|\mathbf{x}_i - \mathbf{x}_j\|) b_j > 0.$$

- Alternatively, ϕ is positive definite on the subspace $V_{k-1} \subset \mathbb{R}^N$:

$$V_{k-1} = \left\{ \mathbf{b} \in \mathbb{R}^N \middle| \sum_{j=1}^N b_j p(\mathbf{x}_j) = 0 \text{ for all } p \in \Pi_{k-1}(\mathbb{R}^d) \right\},$$

where $\Pi_m(\mathbb{R}^d)$ is the space of all d -variate polynomials of degree $\leq m$.

- The case $k = 0$, corresponds to standard positive definite kernels on \mathbb{R}^d .

Conditionally positive definite kernels

Definition. A continuous kernel $\Phi : [0, \infty) \rightarrow \mathbb{R}$ is said to be **completely monotone of order k** on $(0, \infty)$ if $(-1)^k \Phi^{(k)}$ is completely monotone on $(0, \infty)$.

Examples:

$k=1$

$$\Phi(t) = \sqrt{t} \quad \Phi(t) = \sqrt{1+t}$$

$k=2$

$$\Phi(t) = t^{3/2} \quad \Phi(t) = \frac{1}{2}t \log t$$

Conditionally positive definite kernels

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$\Phi(t) = \sqrt{t}$	$\Phi(t) = \sqrt{1+t}$		$\Phi(t) = t^{3/2}$
$\Phi(t) = \frac{1}{2}t \log t$			

Theorem (Micchelli (1986); Guo, Hu, & Sun (1993)). The radial kernel $\phi : [0, \infty)$ is **conditionally positive definite** on \mathbb{R}^d , for all d , if and only if $\Phi = \phi(\sqrt{\cdot})$ is **completely monotone of order k** on $(0, \infty)$ and $\Phi^{(k)}$ is not constant.

Remark:

- This is one of the BIG theorems that launched the RBF field.
- It says, for example, that linear, cubic, thin-plate splines, and the multiquadric are conditionally positive definite on \mathbb{R}^d for any d .
- Next, its consequences on RBF interpolation of scattered data...

Conditionally positive definite kernels

Definition. Let $\phi : [0, \infty) \rightarrow \mathbb{R}$ be continuous and $\{p_i(\mathbf{x})\}_{i=1}^n$ be a basis for $\Pi_{k-1}(\mathbb{R}^d)$ ($k > 1$). The **general RBF interpolant** for the distinct nodes $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{R}^d$ and some target, f , sampled on X , $\{f_j\}_{j=1}^N$ is

$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \phi(\|\mathbf{x} - \mathbf{x}_j\|) + \sum_{\ell=1}^n d_\ell p_\ell(\mathbf{x}),$$

where $I_X f(\mathbf{x}_i) = f_i$, $i = 1, \dots, N$ and $\sum_{j=1}^N c_j p_\ell(\mathbf{x}_j) = 0$, $\ell = 1, \dots, n$.

In linear system form, these constraints are

$$\begin{bmatrix} A & P \\ P^T & 0 \end{bmatrix} \begin{bmatrix} \underline{c} \\ \underline{d} \end{bmatrix} = \begin{bmatrix} \underline{f} \\ \underline{0} \end{bmatrix}, \text{ where } a_{i,j} = \phi(\|\mathbf{x}_i - \mathbf{x}_j\|), p_{i,\ell} = p_k(\mathbf{x}_i)$$

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Theorem (Micchelli (1986)). The above linear system is invertible for any distinct X , provided

- $\text{rank}(P) = n$ (i.e. X is unisolvant on $\Pi_{k-1}(\mathbb{R}^d)$),
- $\Phi = \phi(\sqrt{\cdot})$ is completely monotone of order k on $(0, \infty)$,
- $\Phi^{(k)}$ is not constant.

Conditionally positive definite kernels

Definition. Let $\phi : [0, \infty) \rightarrow \mathbb{R}$ be continuous and $\{p_i(\mathbf{x})\}_{i=1}^n$ be a basis for $\Pi_{k-1}(\mathbb{R}^d)$ ($k > 1$). The **general RBF interpolant** for the distinct nodes $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{R}^d$ and some target, f , sampled on X , $\{f_j\}_{j=1}^N$ is

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$$\begin{bmatrix} A & P \\ P^T & 0 \end{bmatrix} \begin{bmatrix} \underline{c} \\ \underline{d} \end{bmatrix} = \begin{bmatrix} \underline{f} \\ \underline{0} \end{bmatrix}, \text{ where } a_{i,j} = \phi(\|\mathbf{x}_i - \mathbf{x}_j\|), p_{i,\ell} = p_k(\mathbf{x}_i)$$

Example (Thin plate spline, \mathbb{R}^2). Let

- $\phi(r) = r^2 \log(r)$
- $p_1(x, y) = 1$, $p_2(x, y) = x$, and $p_3(x, y) = y$.

The system has a unique solution provided the nodes are not collinear.

Theorem (Micchelli (1986)). Suppose $\Phi = \phi(\sqrt{\cdot})$ is completely monotone of order 1 on $(0, \infty)$ and Φ' is not constant. Then for any distinct set of nodes $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{R}^d$, and any d , the matrix A with entries $a_{i,j} = \phi(\|\mathbf{x}_i - \mathbf{x}_j\|)$, $i, j = 1, \dots, N$, has $N - 1$ positive eigenvalues and 1 negative eigenvalue. Hence it is invertible.

Remark:

- This theorem means that for kernels like the popular multiquadric $\phi(r) = \sqrt{1 + (\varepsilon r)^2}$ the basic RBF interpolant

$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \phi(\|\mathbf{x} - \mathbf{x}_j\|)$$

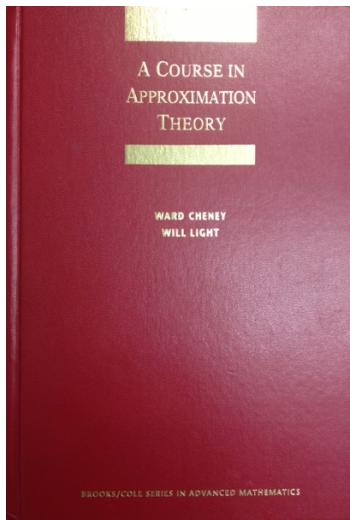
has a unique solution for any distinct set of nodes $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{R}^d$ and sampled target function f on X .

- Augmenting the RBF interpolant with polynomials is not necessary to guarantee uniqueness for order 1 CPD kernels.
- This theorem answered a conjecture from Franke (1983) regarding the multiquadric.

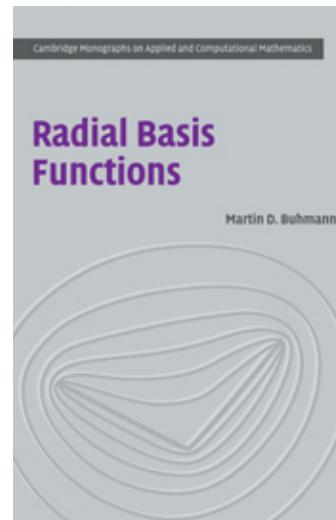
Radial basis function (RBF) interpolation

- Many good books to consult further on RBF theory and applications:

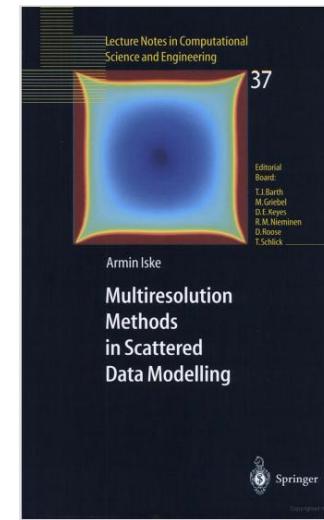
1999



2003



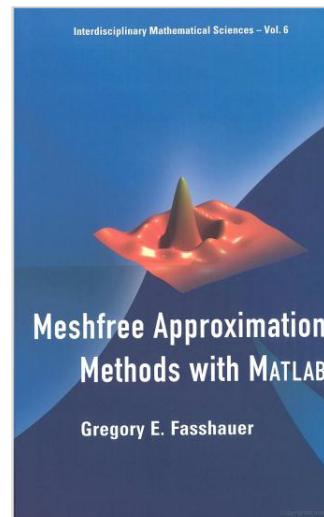
2004



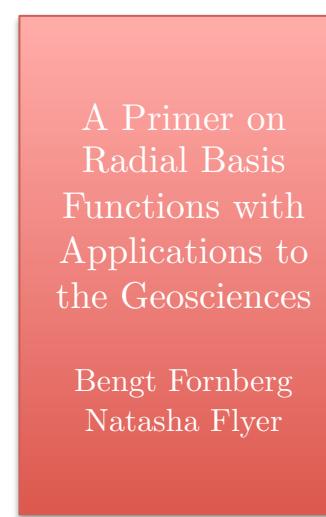
2005



2007

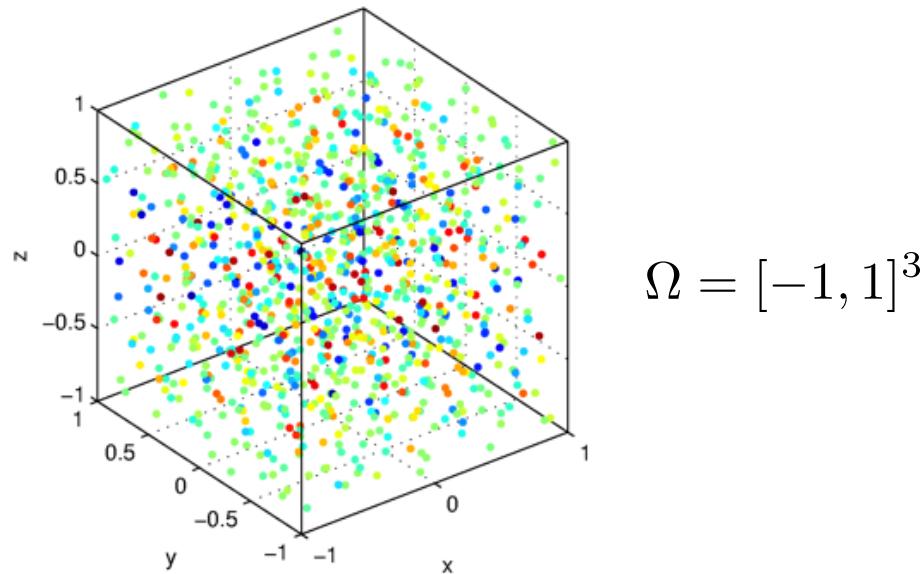


2014: SIAM



Interpolation with kernels (revisited)

- Kernel interpolant to $f|_X$: $I_X f = \sum_j c_j \Phi(\cdot, \mathbf{x}_j)$.
- Some considerations for choosing the kernel $\Phi : \Omega \times \Omega \rightarrow \mathbb{R}$
 1. The kernel should be easy to compute.
 2. The kernel interpolant should be uniquely determined by X and $f|_X$.
 3. The kernel interpolant should accurately reconstruct f .
- For problems like



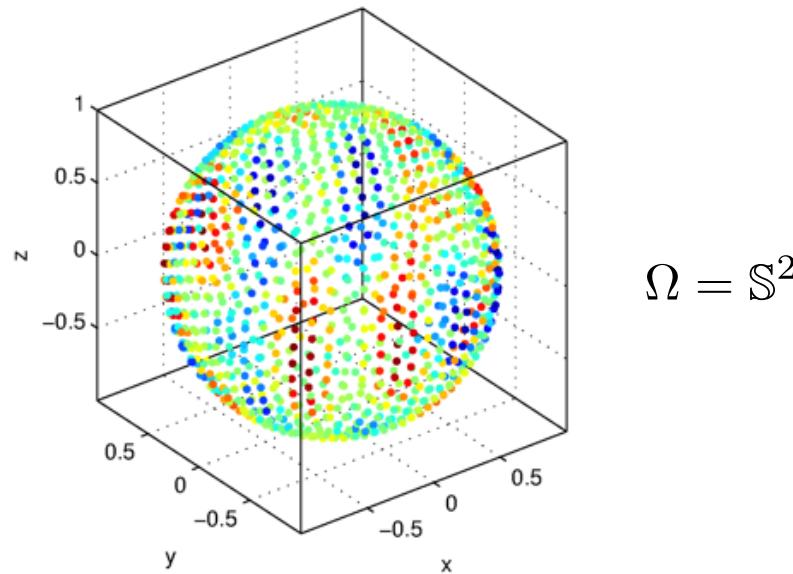
Obvious choice: ϕ is a (conditionally) positive definite radial kernel

$$\Phi(\mathbf{x}, \mathbf{x}_j) = \phi(\|\mathbf{x} - \mathbf{x}_j\|_2) = \phi(r)$$

- Leads to radial basis function (RBF) interpolation.

Interpolation with kernels on the sphere

- Kernel interpolant to $f|_X$: $I_X f = \sum_j c_j \Phi(\cdot, \mathbf{x}_j)$.
- Some considerations for choosing the kernel $\Phi : \Omega \times \Omega \rightarrow \mathbb{R}$
 1. The kernel should be easy to compute.
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 3. The kernel interpolant should accurately reconstruct f .
- For problems like



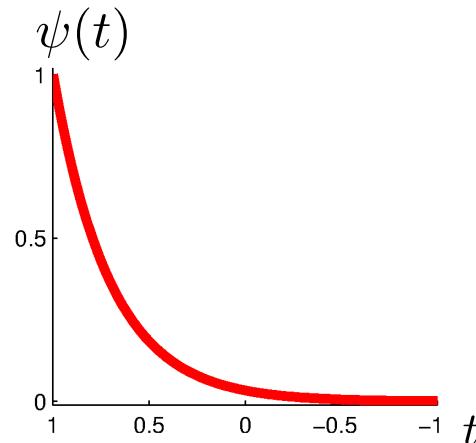
Obvious(?) choice: Φ is a (conditionally) positive definite zonal kernel:

$$\Phi(\mathbf{x}, \mathbf{x}_j) = \psi(\mathbf{x}^T \mathbf{x}_j) = \psi(t), \quad t \in [-1, 1]$$

- Analog of RBF interpolation for the sphere: **SBF interpolation**.

SBF interpolation

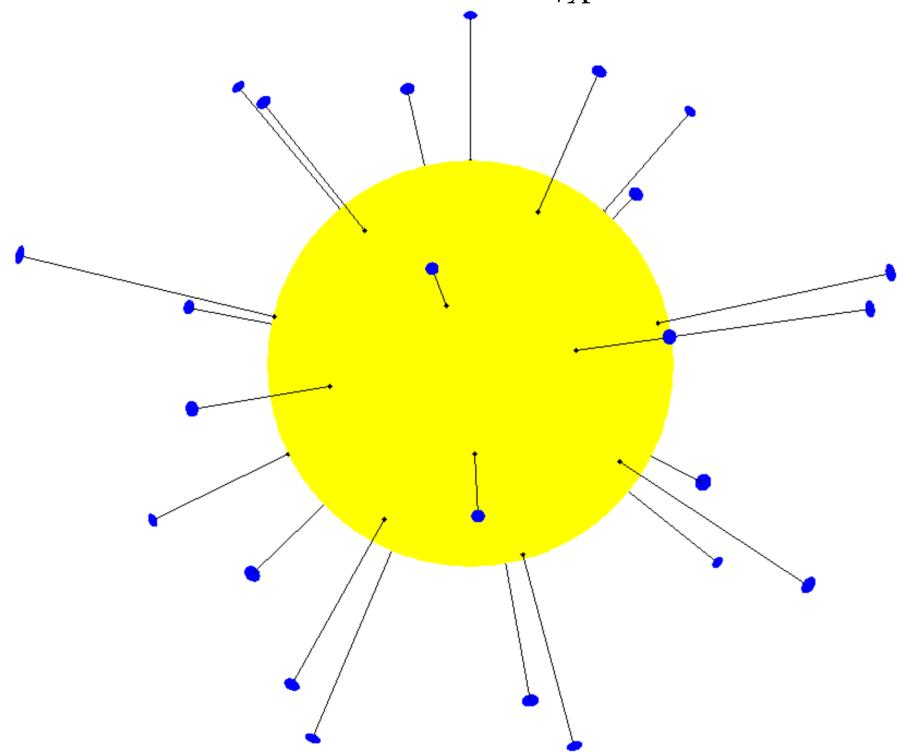
Key idea: linear combination of **translates** and **rotations** of a single zonal kernel on \mathbb{S}^2



Basic SBF Interpolant for \mathbb{S}^2

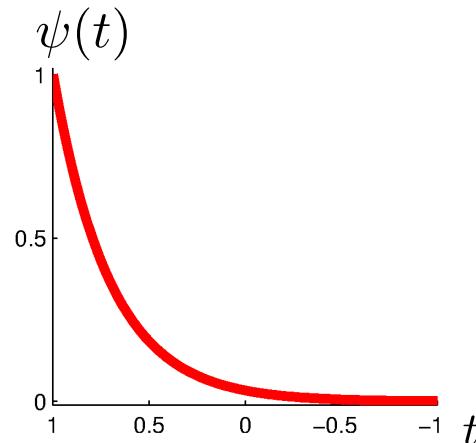
$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \psi(\mathbf{x}^T \mathbf{x}_j)$$

$$X = \{\mathbf{x}_j\}_{j=1}^N \subset \Omega, \quad f|_X = \{f_j\}_{j=1}^N$$



SBF interpolation

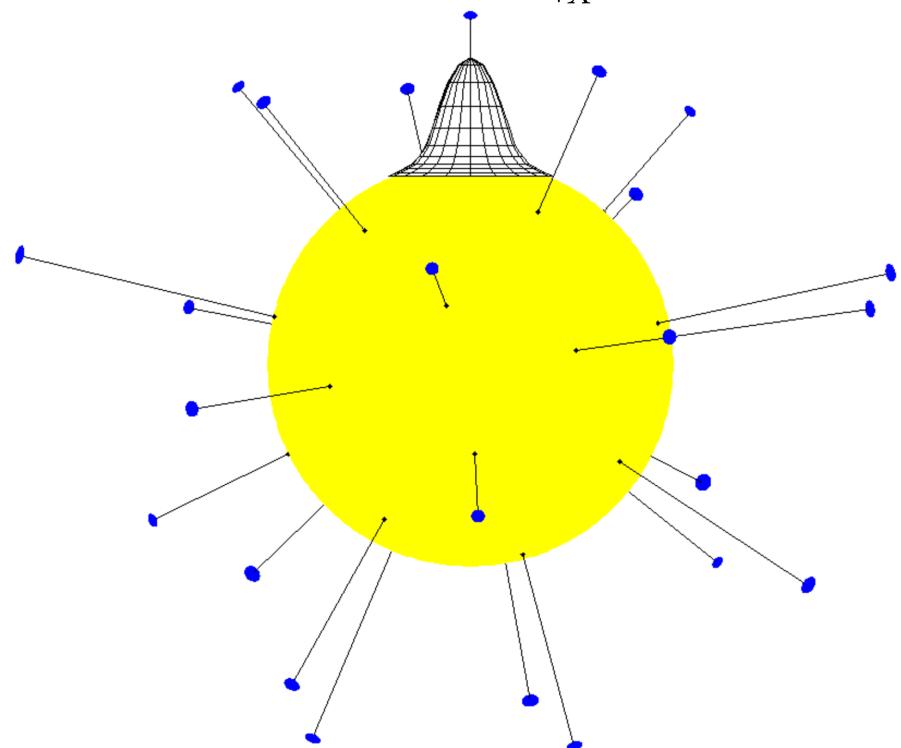
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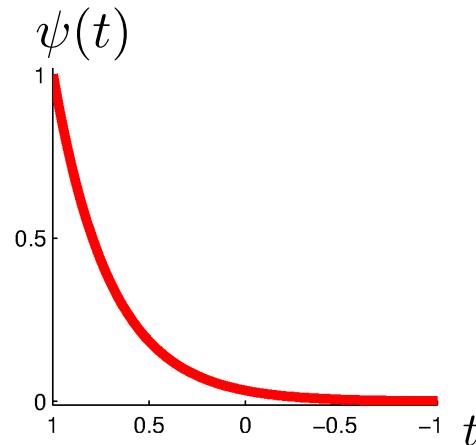
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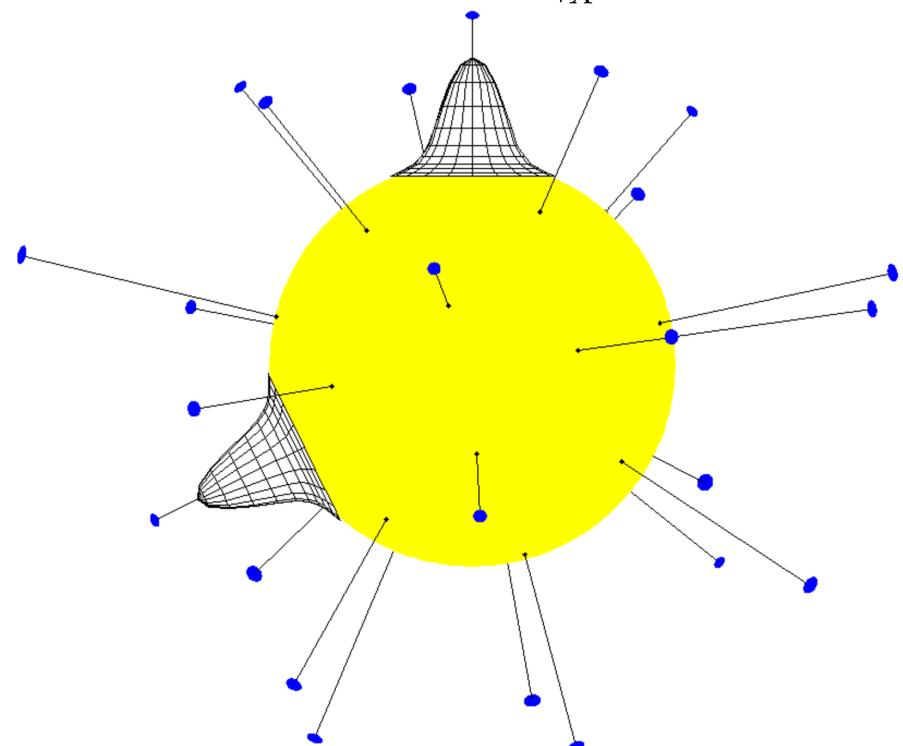
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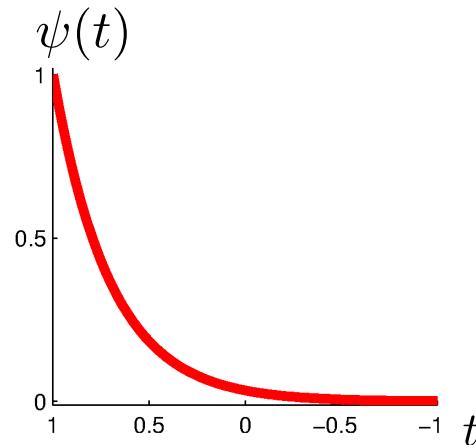
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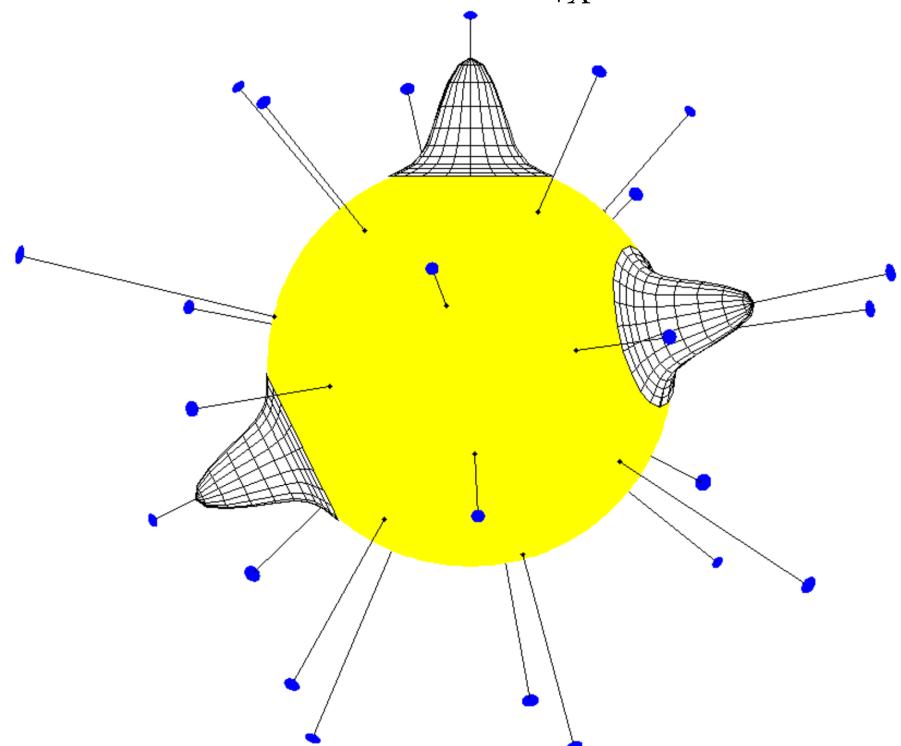
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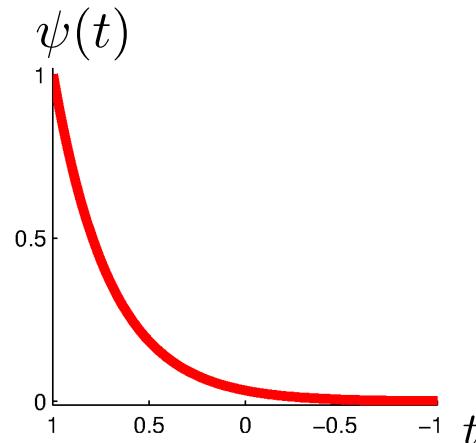
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SBF interpolation

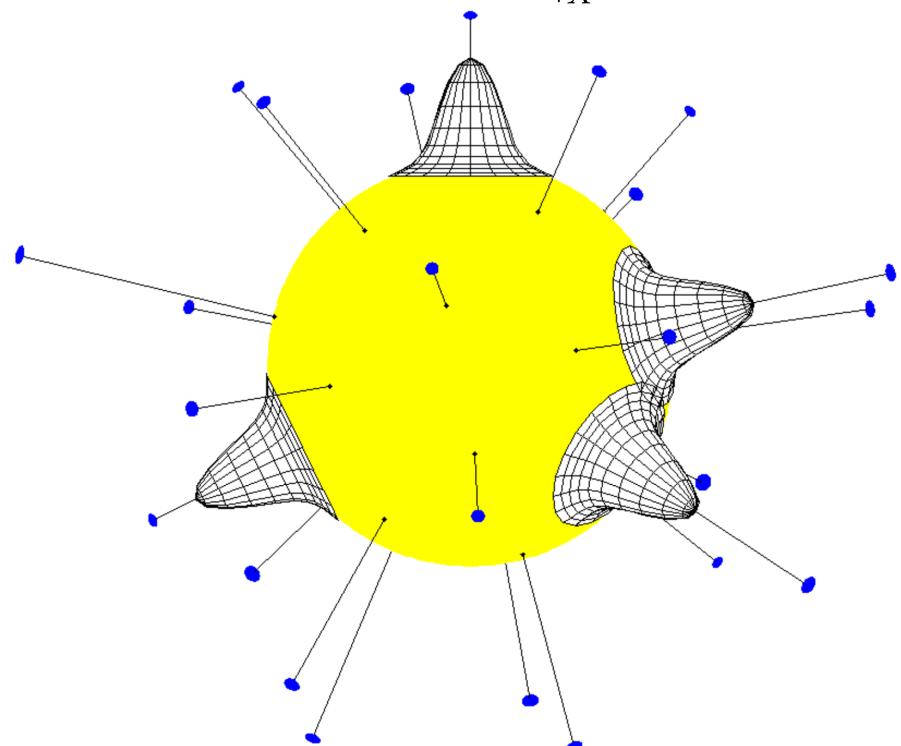
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Basic SBF Interpolant for \mathbb{S}^2

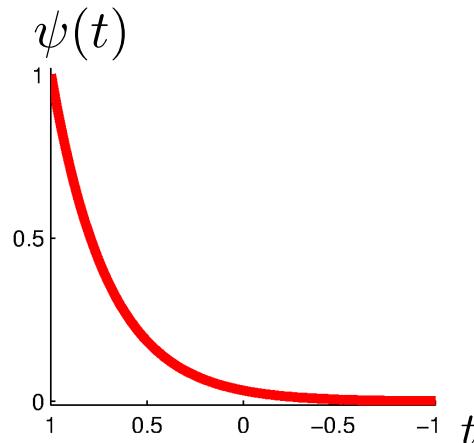
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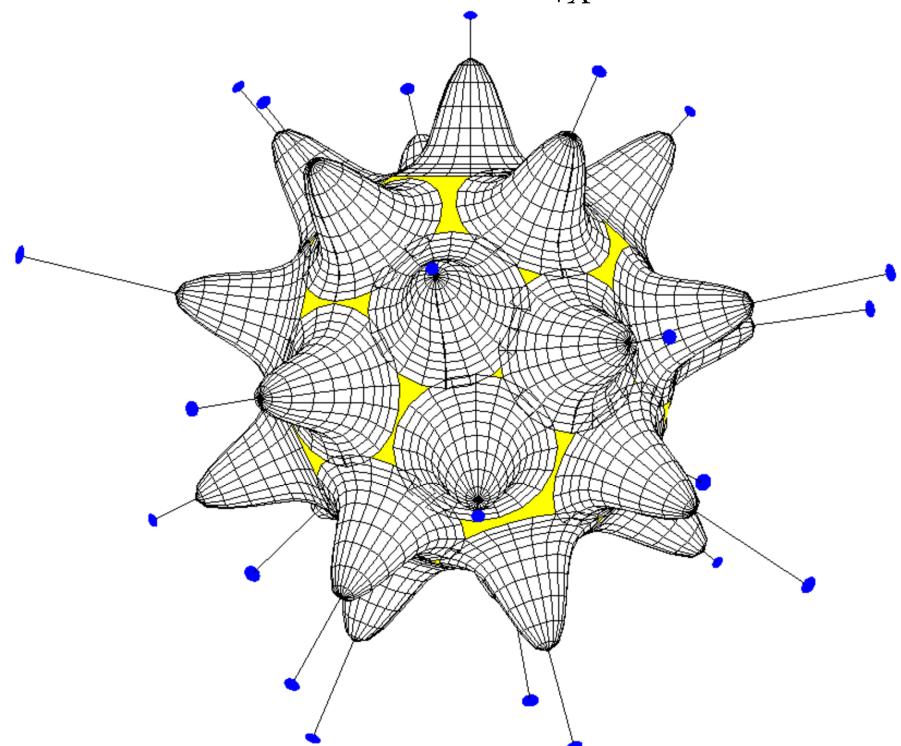
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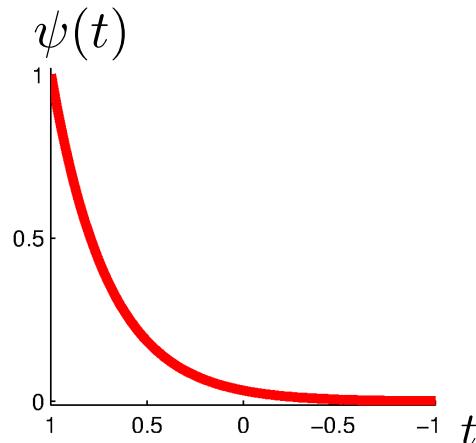
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SBF interpolation

Key idea: linear combination of **translates** and **rotations** of a single zonal kernel on \mathbb{S}^2



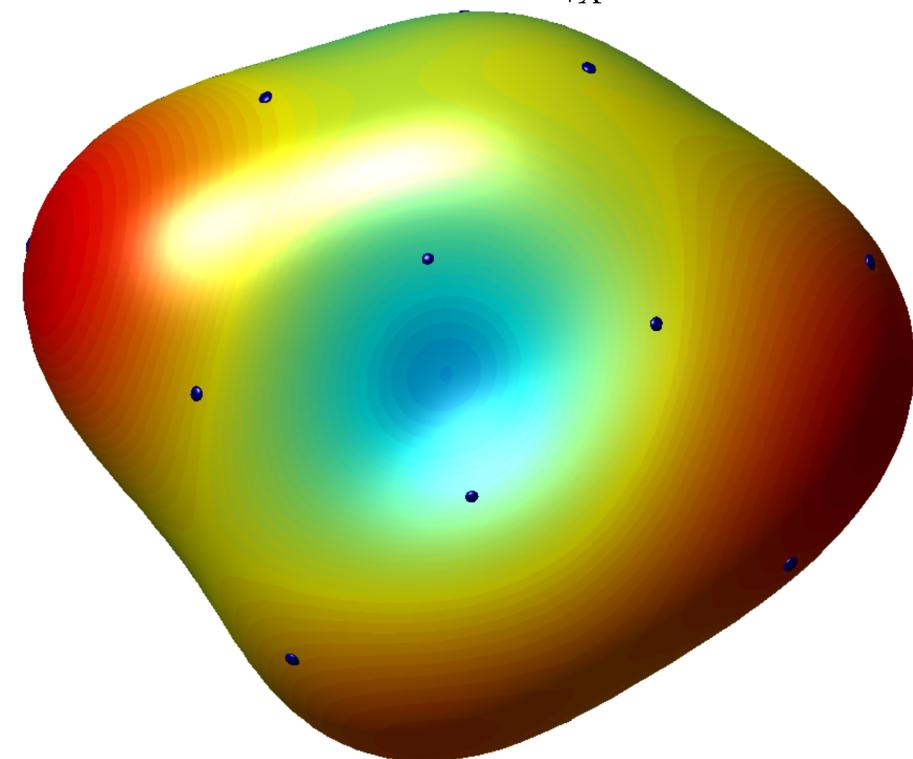
Basic SBF Interpolant for \mathbb{S}^2

$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \psi(\mathbf{x}^T \mathbf{x}_j)$$

Linear system for determining the interpolation coefficients

$$\underbrace{\begin{bmatrix} \psi(\mathbf{x}_1^T \mathbf{x}_1) & \psi(\mathbf{x}_1^T \mathbf{x}_2) & \cdots & \psi(\mathbf{x}_1^T \mathbf{x}_N) \\ \psi(\mathbf{x}_2^T \mathbf{x}_1) & \psi(\mathbf{x}_2^T \mathbf{x}_2) & \cdots & \psi(\mathbf{x}_2^T \mathbf{x}_N) \\ \vdots & \vdots & \ddots & \vdots \\ \psi(\mathbf{x}_N^T \mathbf{x}_1) & \psi(\mathbf{x}_N^T \mathbf{x}_2) & \cdots & \psi(\mathbf{x}_N^T \mathbf{x}_N) \end{bmatrix}}_{A_X} \underbrace{\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{bmatrix}}_c = \underbrace{\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}}_f$$

$$X = \{\mathbf{x}_j\}_{j=1}^N \subset \Omega, \quad f|_X = \{\underline{f}_j\}_{j=1}^N$$



A_X is guaranteed to be **positive definite** if ψ is a positive definite zonal kernel

Positive definite zonal kernels

Definition. A kernel $\Psi : \mathbb{S}^{d-1} \times \mathbb{S}^{d-1} \rightarrow \mathbb{R}$ is called radial or **zonal** on \mathbb{S}^{d-1} if $\Psi(\mathbf{x}, \mathbf{y}) = \psi(\mathbf{x}^T \mathbf{y})$, where $\psi : [-1, 1] \rightarrow \mathbb{R}$. In this case, ψ is simply referred to as the **zonal kernel** and no reference is made to Ψ .

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$$\sum_{i=1}^N \sum_{j=1}^N b_i \psi(\mathbf{x}_i^T \mathbf{x}_j) b_j > 0.$$

Remark: PD zonal kernels are sometimes called **spherical basis functions (SBFs)**.

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Remark: PD zonal kernels are sometimes called **spherical basis functions (SBFs)**.

- The study of positive definite kernels on \mathbb{S}^{d-1} started with Schoenberg (1940).
- Extension of this work, including to conditionally positive definite kernels, began in the 1990s (Cheney and Xu (1992)), and continues today.
- Our interest is strictly in \mathbb{S}^2 and we will only present results for this case.

Positive definite zonal kernels

- Any positive definite radial kernel ϕ on \mathbb{R}^3 is also positive definite on \mathbb{S}^2 .
- In fact, they are **positive definite zonal kernels**, since for $\mathbf{x}, \mathbf{y} \in \mathbb{S}^2$

$$\phi(\|\mathbf{x} - \mathbf{y}\|) = \phi\left(\sqrt{2 - 2\mathbf{x}^T \mathbf{y}}\right) = \psi(\mathbf{x}^T \mathbf{y})$$

- So, standard RBF methods can be used for problems on the sphere \mathbb{S}^2 .
- Cheney (1995) appears to have been the first to mathematically study the specialization of RBFs to the sphere.
- Many others have followed suit, e.g.
Fasshauer & Schumaker (1998); Baxter & Hubbert (2001); Levesley & Hubbert (2001);
Hubbert & Morton (2004); zu Castel & Filbir (2005); Narcowich, Sun, & Ward (2007);
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Positive definite zonal kernels

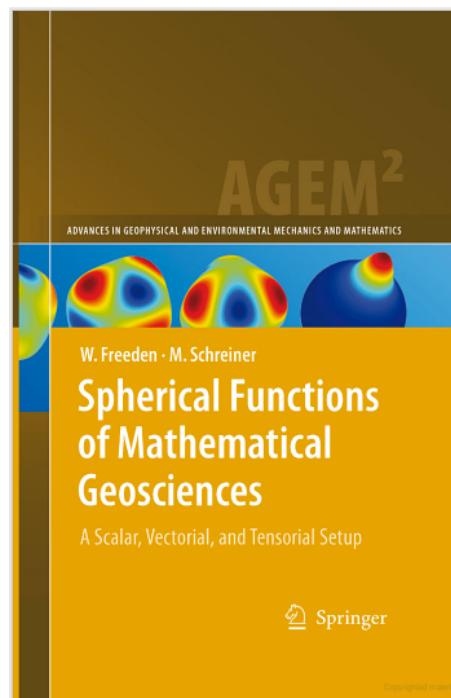
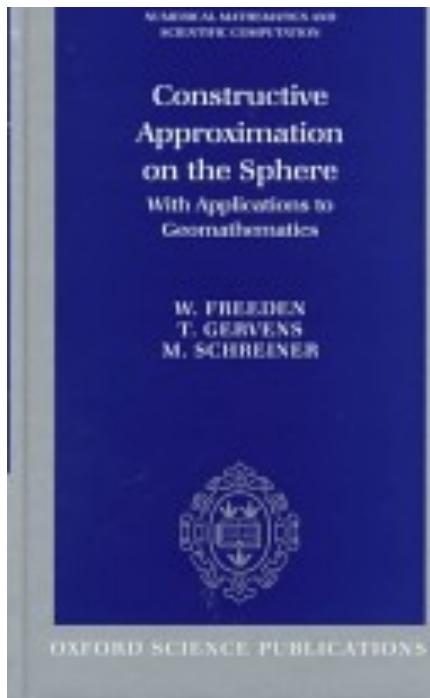
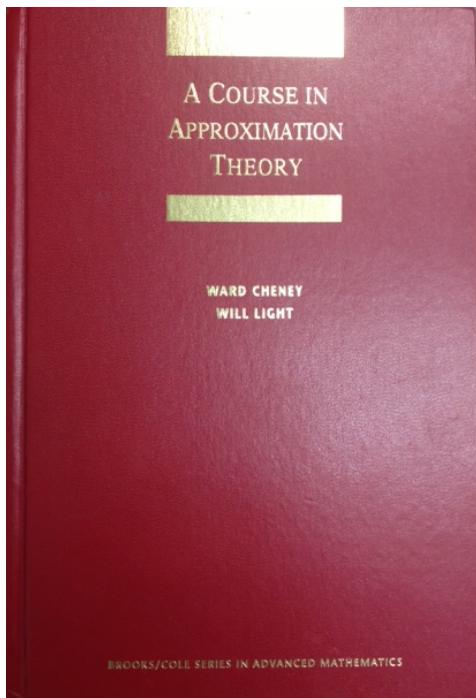
- Any positive definite radial kernel ϕ on \mathbb{R}^3 is also positive definite on \mathbb{S}^2 .
- In fact, they are **positive definite zonal kernels**, since for $\mathbf{x}, \mathbf{y} \in \mathbb{S}^2$

$$\phi(\|\mathbf{x} - \mathbf{y}\|) = \phi\left(\sqrt{2 - 2\mathbf{x}^T \mathbf{y}}\right) = \psi(\mathbf{x}^T \mathbf{y})$$

- So, standard RBF methods can be used for problems on the sphere \mathbb{S}^2 .
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- Is there any advantage to using a purely PD zonal kernel to a restricted PD radial kernel? (Baxter & Hubbert (2001))
- Personally, I have always used restricted radial kernels.

Positive definite zonal kernels

- Some references for the material to come:



- A good understanding of functions on the sphere requires one to be well-versed in spherical harmonics.
- Spherical harmonics are the analog of 1-D Fourier series for approximation on spheres of dimension 2 and higher.
- Several ways to introduce spherical harmonics (Freeden & Schreiner 2008)
- We will use the eigenfunction approach and restrict our attention to the 2-sphere.
- Following this we review some important results about spherical harmonics.

Overview of spherical harmonics

- Laplacian in spherical coordinates ($x = r \cos \theta \cos \varphi$, $y = r \cos \theta \sin \varphi$, $z = r \sin \theta$)

$$\Delta = \frac{1}{r^2} \frac{\partial}{\partial r} \left(r^2 \frac{\partial}{\partial r} \right) + \underbrace{\frac{1}{r^2} \left\{ \frac{\partial^2}{\partial \theta^2} - \tan \theta \frac{\partial}{\partial \theta} + \frac{1}{\cos^2 \theta} \frac{\partial^2}{\partial \varphi^2} \right\}}_{\Delta_s = \text{Laplace-Beltrami operator}}$$

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- **Spherical harmonics:** Set of all functions bounded at $\theta = \pm \frac{\pi}{2}$ or $z = \pm 1$ such that $\Delta_s Y = \lambda Y$.
- Solve using separation of variables to arrive at:

$$Y_\ell^m(\theta, \varphi) = a_\ell^{|m|} P_\ell^{|m|}(\cos \theta) e^{im\varphi}, \quad \ell = 0, 1, \dots, \quad m = -\ell, -\ell + 1, \dots, \ell - 1, \ell.$$

- Here P_ℓ^k , for $k = 0, 1, \dots$, $\ell = k, k+1, \dots$, are the **Associated Legendre functions**, given by Rodrigues' formula

$$P_\ell^k(z) = (1 - z^2)^{k/2} \frac{d^k}{dz^k} (P_\ell(z)),$$

where P_ℓ is the standard Legendre polynomial of degree ℓ .

- The a_ℓ^k are normalization factors (e.g. $a_\ell^k = \sqrt{((2\ell+1)(\ell-k)!)/(4\pi(\ell+m)!)}$)

Overview of spherical harmonics

- Each spherical harmonic satisfies $\Delta_s Y_\ell^m = -\ell(\ell + 1)Y_\ell^m$.
- For each $\ell = 0, 1, \dots$, there are $2\ell+1$ harmonics with eigenvalue $-\ell(\ell+1)$.

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- Real-form of spherical harmonics:

$$Y_\ell^m(\theta, \varphi) = Y_\ell^m(z, \varphi) = \begin{cases} \sqrt{2}a_\ell^m P_\ell^m(z) \cos(m\varphi) & m > 0, \\ a_\ell^0 P_\ell(z) & m = 0, \\ \sqrt{2}a_\ell^{|m|} P_\ell^{|m|}(z) \sin(m\varphi) & m < 0. \end{cases}$$

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- Can also be expressed purely in **Cartesian coordinates** ($\mathbf{x} = (x, y, z) \in \mathbb{S}^2$):

$$Y_\ell^m(\mathbf{x}) = Y_\ell^m(x, y, z) = \begin{cases} \sqrt{2}a_\ell^m Q_\ell^m(z)^{\frac{1}{2}} ((x + iy)^m + (x - iy)^m) & m > 0, \\ a_\ell^0 P_\ell(z) & m = 0, \\ \sqrt{2}a_\ell^{|m|} Q_\ell^{|m|}(z)^{\frac{1}{2i}} ((x + iy)^{-m} - (x - iy)^{-m}) & m < 0. \end{cases}$$

where $Q_\ell^m(z) = (-1)^m \frac{\partial^m}{\partial z^m} P_\ell(z)$.

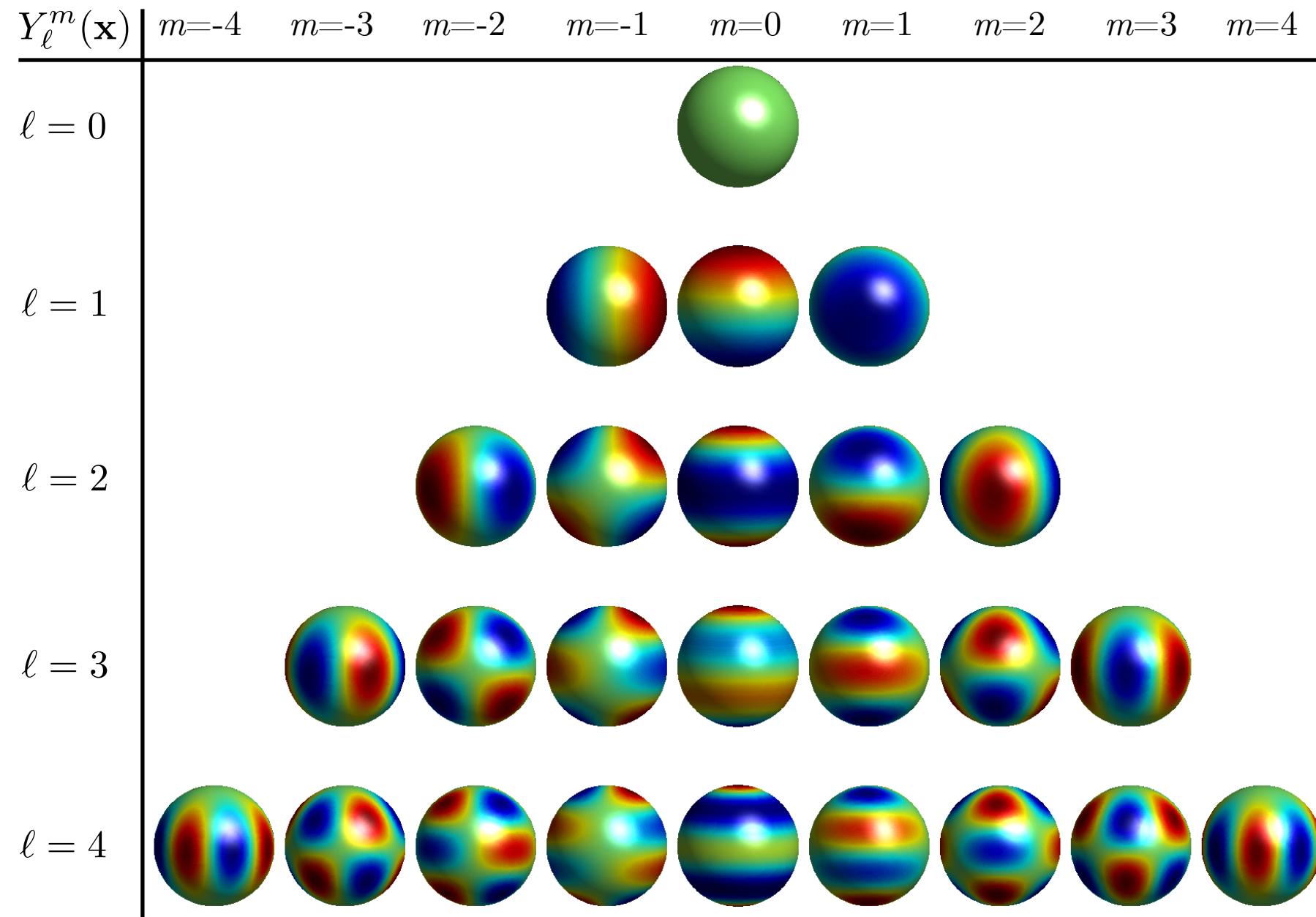
- We will sometimes switch notation from $Y_\ell^m(\theta, \varphi)$ to $Y_\ell^m(\mathbf{x})$.

Overview of spherical harmonics

- Spherical harmonics $Y_\ell^m(\mathbf{x})$ in Cartesian form, for $\ell = 0, 1, 2, 3$.

$m=-3$	$m=-2$	$m=-1$	$m=0$	$m=1$	$m=2$	$m=3$
			$\frac{1}{2\sqrt{\pi}} z$			
	$-\frac{1}{2} \sqrt{\frac{3}{2\pi}} y$			$-\frac{1}{2} \sqrt{\frac{3}{2\pi}} x$		
$-\frac{1}{8} \sqrt{\frac{35}{\pi}} (3x^2y - y^3)$	$\frac{1}{2} \sqrt{\frac{15}{2\pi}} xy$	$-\frac{1}{2} \sqrt{\frac{15}{2\pi}} yz$	$\frac{1}{4} \sqrt{\frac{5}{\pi}} (3z^2 - 1)$	$-\frac{1}{2} \sqrt{\frac{15}{2\pi}} xz$	$\frac{1}{4} \sqrt{\frac{15}{2\pi}} (x-y)(x+y)$	
	$\frac{1}{2} \sqrt{\frac{105}{2\pi}} xyz$	$-\frac{1}{4} \sqrt{\frac{7}{3\pi}} y \left(\frac{15z^2}{2} - \frac{3}{2} \right)$	$\frac{1}{2} \sqrt{\frac{7}{\pi}} \left(\frac{5z^3}{2} - \frac{3z}{2} \right)$	$-\frac{1}{4} \sqrt{\frac{7}{3\pi}} x \left(\frac{15z^2}{2} - \frac{3}{2} \right)$	$\frac{1}{4} \sqrt{\frac{105}{2\pi}} z(x^2 - y^2)$	$-\frac{1}{8} \sqrt{\frac{35}{\pi}} (x^3 - 3xy^2)$

Overview of spherical harmonics



Overview of spherical harmonics

- Spherical harmonics satisfy the $L_2(\mathbb{S}^2)$ orthogonality condition:

$$\int_{\mathbb{S}^2} Y_\ell^m(\mathbf{x}) Y_k^n(\mathbf{x}) d\mu(\mathbf{x}) = \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \int_{-\pi}^{\pi} Y_\ell^m(\theta, \varphi) Y_k^n(\theta, \varphi) \cos \theta d\varphi d\theta = \delta_{kl} \delta_{mn}$$

- They form a **complete orthonormal basis** for $L_2(\mathbb{S}^2)$.
- If $f \in L_2(\mathbb{S}^2)$ then

$$f(\mathbf{x}) = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} \hat{f}_\ell^m Y_\ell^m(\mathbf{x}), \text{ where } \hat{f}_\ell^m = \int_{\mathbb{S}^2} f(\mathbf{x}) Y_\ell^m(\mathbf{x}) d\mu(\mathbf{x}).$$

- There is no counter part to the fast Fourier transform (FFT) for computing the spherical harmonic coefficients \hat{f}_ℓ^m .
 - Fast methods of similar complexity ($\mathcal{O}(N \log N)$) have been developed, but have very large constants associated with them. So an actual computational advantage does not occur until N is extremely large.

Overview of spherical harmonics

- Two useful results on spherical harmonics we will use:
- **Addition theorem:** Let $\mathbf{x}, \mathbf{y} \in \mathbb{S}^2$, then for $\ell = 0, 1, \dots$

$$\frac{4\pi}{2\ell+1} \sum_{m=-\ell}^{\ell} Y_{\ell}^m(\mathbf{x}) Y_{\ell}^m(\mathbf{y}) = P_{\ell}(\mathbf{x}^T \mathbf{y}),$$

where P_{ℓ} is the standard Legendre polynomial of degree ℓ .

- **Funk-Hecke formula:** Let $f \in L_1(-1, 1)$ and have the Legendre expansion

$$f(t) = \sum_{k=0}^{\infty} a_k P_k(t), \text{ where } a_k = \frac{2k+1}{2} \int_{-1}^1 f(t) P_k(t) dt.$$

Then for any spherical harmonic Y_{ℓ}^m the following holds:

$$\int_{\mathbb{S}^2} f(\mathbf{x} \cdot \mathbf{y}) Y_{\ell}^m(\mathbf{x}) d\mu(\mathbf{x}) = \frac{4\pi a_{\ell}}{2\ell+1} Y_{\ell}^m(\mathbf{y}).$$

Theorems for positive definite zonal kernels

Definition. A **zonal kernel** $\psi : [-1, 1] \rightarrow \mathbb{R}$ is said to be a **positive definite zonal kernel** on \mathbb{S}^2 if for any distinct set of nodes $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$ and $\underline{b} \in \mathbb{R}^N \setminus \{0\}$ the matrix $A = \{\psi(\mathbf{x}_i^T \mathbf{x}_j)\}$ is positive definite, i.e.

$$\sum_{i=1}^N \sum_{j=1}^N b_i \psi(\mathbf{x}_i^T \mathbf{x}_j) b_j > 0.$$

Theorem (Schoenberg (1942)). If a zonal kernel $\psi : [-1, 1] \rightarrow \mathbb{R}$ is expressible in a Legendre series as

$$\psi(t) = \sum_{\ell=0}^{\infty} a_{\ell} P_{\ell}(t)$$

where $a_{\ell} > 0$ for $\ell \geq 0$ and $\sum_{\ell=0}^{\infty} a_{\ell} < \infty$ then ψ is a **positive definite zonal kernel** on \mathbb{S}^2 .

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Proof:

1. The condition $\sum_{\ell=0}^{\infty} a_{\ell} < \infty$ guarantees that $\psi \in C(\mathbb{S}^2)$.
2. Use the **addition theorem**: Let $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$ and $\underline{b} \in \mathbb{R}^N \setminus \{0\}$ then

$$\begin{aligned} \sum_{i=1}^N \sum_{j=1}^N b_i \psi(\mathbf{x}_i^T \mathbf{x}_j) b_j &= \sum_{i=1}^N \sum_{j=1}^N b_i b_j \sum_{\ell=0}^{\infty} a_{\ell} P_{\ell}(\mathbf{x}_i^T \mathbf{x}_j) \\ &= \sum_{\ell=0}^{\infty} \frac{4\pi a_{\ell}}{2\ell+1} \sum_{m=-\ell}^{\ell} \sum_{i=1}^N \sum_{j=1}^N b_i b_j Y_{\ell}^m(\mathbf{x}_i) Y_{\ell}^m(\mathbf{x}_j) \\ &= \sum_{\ell=0}^{\infty} \frac{4\pi a_{\ell}}{2\ell+1} \sum_{m=-\ell}^{\ell} \left| \sum_{j=1}^N b_j Y_{\ell}^m(\mathbf{x}_j) \right|^2 \geq 0 \end{aligned}$$

3. Show that the quadratic form must be strictly positive.

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- Necessary and sufficient conditions on the Legendre coefficients a_{ℓ} were only given in 2003 by Chen, Menegatto, & Sun.

- Their result says the set $\left\{ \ell \in \mathbb{N}_0 \mid a_{\ell} > 0 \right\}$ must contain infinitely many odd and infinitely many even integers.

Conditionally positive definite zonal kernels

- Similar to \mathbb{R}^d , we can define conditionally positive definite zonal kernels.

Definition. A continuous **zonal kernel** $\psi : [-1, 1] \rightarrow \mathbb{R}$ is said to be **conditionally positive definite of order k** on \mathbb{S}^2 if, for any distinct $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$, and all $\mathbf{b} \in \mathbb{R}^N \setminus \{\mathbf{0}\}$ satisfying

$$\sum_{j=1}^N b_j p(\mathbf{x}_j) = 0$$

for all spherical harmonics of degree $< k$, the following is satisfied:

$$\sum_{i=1}^N \sum_{j=1}^N b_i \psi(\|\mathbf{x}_i - \mathbf{x}_j\|) b_j > 0.$$

Theorem. If the Legendre expansion coefficients of $\psi : [-1, 1] \rightarrow \mathbb{R}$ satisfy $a_\ell > 0$ for $\ell \geq k$ and $\sum_{\ell=0}^{\infty} a_\ell < \infty$.

Proof: Use same ideas as the positive definite case.

Conditionally positive definite zonal kernels

Definition. Let $\psi : [-1, 1] \rightarrow \mathbb{R}$ be a continuous zonal kernel and $\{p_i(\mathbf{x})\}_{i=1}^{k^2}$ be a basis for the space of all spherical harmonics of degree $k - 1$. The **general SBF interpolant** for the distinct nodes $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$ and some target, f , sampled on X , $\{f_j\}_{j=1}^N$ is

$$I_X f(\mathbf{x}) = \sum_{j=1}^N c_j \psi(\mathbf{x}^T \mathbf{x}_j) + \sum_{\ell=1}^{k^2} d_\ell p_\ell(\mathbf{x}),$$

where $I_X f(\mathbf{x}_i) = f_i$, $i = 1, \dots, N$ and $\sum_{j=1}^N c_j p_\ell(\mathbf{x}_j) = 0$, $\ell = 1, \dots, k^2$.

In linear system form, these constraints are

$$\begin{bmatrix} A & P \\ P^T & 0 \end{bmatrix} \begin{bmatrix} \underline{c} \\ \underline{d} \end{bmatrix} = \begin{bmatrix} \underline{f} \\ \underline{0} \end{bmatrix}, \text{ where } a_{i,j} = \psi(\mathbf{x}_i^T \mathbf{x}_j), \quad p_{i,\ell} = p_\ell(\mathbf{x}_i)$$

Theorem. The above linear system is invertible for any distinct X , provided

- $\text{rank}(P) = k^2$,
- ψ is conditionally positive definite of order k .

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Example (Restricted thin plate spline, or surface spline). Let

- $\psi(t) = (1 - t) \log(2 - 2t)$
- $p_1(\mathbf{x}) = 1$, $p_2(\mathbf{x}) = x$, $p_3(\mathbf{x}) = y$, and $p_4(\mathbf{x}) = z$.

The system has a unique solution provided X are distinct.

Spherical Fourier coefficients

- More useful to work with a zonal kernels spherical Fourier coefficients $\hat{\psi}_\ell$. These are related to Legendre coefficients through the Funk-Hecke formula:

$$\psi(\mathbf{x}^T \mathbf{y}) = \sum_{\ell=0}^{\infty} \hat{\psi}(\ell) \sum_{m=-\ell}^{\ell} Y_\ell^m(\mathbf{x}) Y_\ell^m(\mathbf{y}) \implies \hat{\psi}(\ell) := \frac{4\pi a_\ell}{2\ell + 1}$$

- Error estimates for SBF interpolants are governed by the asymptotic decay of $\hat{\psi}_\ell$.
- Stable algorithms (RBF-QR) also work with $\hat{\psi}_\ell$ (more on this later...)
- Baxter & Hubbert (2001) computed $\hat{\psi}_\ell$ for many standard RBFs restricted to \mathbb{S}^2 .
- zu Castell & Filbir (2005) and Narcowich, Sun, & Ward (2007) linked the spherical Fourier coefficients of restricted RBFs to the standard Fourier coefficients in \mathbb{R}^3 :

$$\hat{\psi}_\ell = \int_0^\infty u \hat{\phi}(u) J_{\ell+1/2}(u) du,$$

where $\hat{\phi}$ is the Hankel transform of the RBF in \mathbb{R}^3 .

Examples of positive definite zonal kernels

- Examples of positive definite (PD) and order k conditionally positive definite (CPD(k)) zonal kernels with their spherical Fourier coefficients.

Name	Kernel ($r(t) = \sqrt{2 - 2t}$)	Fourier coefficients $\hat{\psi}_\ell$ ($0 < h < 1, \varepsilon > 0$)	Type
Legendre	$\psi(t) = (1 + h^2 - 2ht)^{-1/2}$	$\hat{\psi}_\ell = \frac{2\pi h^\ell}{\ell + 1/2}$	PD
Poisson	$\psi(t) = (1 - h^2)(1 + h^2 - 2ht)^{-3/2}$	$\hat{\psi}_\ell = 4\pi h^\ell$	PD
Spherical	$\psi(t) = 1 - r(t) + \frac{(r(t))^2}{2} \log\left(\frac{r(t) + 2}{r(t)}\right)$	$\hat{\psi}_\ell = \frac{2\pi}{(\ell + 1/2)(\ell + 1)(\ell + 2)}$	PD
Gaussian	$\psi(t) = \exp(-(\varepsilon r(t))^2)$	$\varepsilon^{2\ell} \frac{4\pi^{3/2}}{\varepsilon^{2\ell+1}} e^{-2\varepsilon^2} I_{\ell+1/2}(2\varepsilon^2)$	PD
IMQ	$\psi(t) = \frac{1}{\sqrt{1 + (\varepsilon r(t))^2}}$	$\varepsilon^{2\ell} \frac{4\pi}{(\ell + 1/2)} \left(\frac{2}{1 + \sqrt{4\varepsilon^2 + 1}} \right)^{2\ell+1}$	PD
MQ	$\psi(t) = -\sqrt{1 + (\varepsilon r(t))^2}$	$\varepsilon^{2\ell} \frac{2\pi(2\varepsilon^2 + 1 + (\ell + 1/2)\sqrt{1 + 4\varepsilon^2})}{(\ell + 3/2)(\ell + 1/2)(\ell - 1/2)} \left(\frac{2}{1 + \sqrt{4\varepsilon^2 + 1}} \right)^{2\ell+1}$	CPD(1)
TPS	$\psi(t) = (r(t))^2 \log(r(t))$	$\frac{8\pi}{(\ell + 2)(\ell + 1)\ell(\ell - 1)}$	CPD(2)
Cubic	$\psi(t) = (r(t))^3$	$\frac{18\pi}{(\ell + 5/2)(\ell + 3/2)(\ell + 1/2)(\ell - 1/2)(\ell - 3/2)}$	CPD(2)

- First three kernels are specific to \mathbb{S}^2 , while the last 5 are RBFs restricted to \mathbb{S}^2 .

- **Goal:** Present some known results on error estimates for SBF interpolants for target function of various smoothness.
- We will introduce (or review) some background notation and material that is necessary for the proofs of the estimates, but will not prove them.
 - Reproducing kernel Hilbert spaces (RKHS)
 - Sobolev spaces on \mathbb{S}^2 ;
 - Native spaces;
 - Geometric properties of node sets $X \subset \mathbb{S}^2$.
- Brief historical notes regarding SBF error estimates:
 - Earliest results appear to be Freedon (1981), but do not depend on ψ or target.
 - First Sobolev-type estimates were given in Jetter, Stöckler, & Ward (1999).
 - Since then many more results have appeared, e.g. Levesley, Light, Ragozin, & Sun (1999), v. Golitschek & Light (2001), Morton & Neamtu (2002), Narcowich & Ward (2002), Hubbert & Morton (2004,2004), Levesley & Sun (2005), Narcowich, Sun, & Ward (2007), [Narcowich, Sun, Ward, & Wendland \(2007\)](#), Sloan & Sommariva (2008), Sloan & Wendland (2009), Hangelbroek (2011).

Reproducing kernel Hilbert spaces

- Reproducing kernel Hilbert spaces (RKHS) play a key role deriving error estimates for SBF (and more generally RBF) interpolants.
- They allow one to view the interpolation problem as the solution to a particular **optimization problem**.

Definition. Let $\mathcal{F}(\Omega)$ be a **Hilbert space of functions** $f : \Omega \rightarrow \mathbb{R}$ with inner product $\langle \cdot, \cdot \rangle_{\mathcal{F}}$. If there exists a kernel $\Phi : \Omega \times \Omega \rightarrow \mathbb{R}$ such that for all $\mathbf{y} \in \Omega$

$$f(\mathbf{y}) = \langle f, \Phi(\cdot, \mathbf{y}) \rangle_{\mathcal{F}} \text{ for all } f \in \mathcal{F},$$

then \mathcal{F} is called a RKHS with **reproducing kernel** Φ .

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- The reproducing kernel Φ of a RKHS is **unique**.
- Existence of Φ is equivalent to the point evaluation functional $\delta_{\mathbf{y}} : \mathcal{F} \rightarrow \mathbb{R}$ being continuous. (Implied by **Reisz representation theorem**).
- Φ also satisfies the following:
 - (1) $\Phi(\mathbf{x}, \mathbf{y}) = \Phi(\mathbf{y}, \mathbf{x})$ for $x, y \in \Omega$;
 - (2) Φ is positive semi-definite on Ω .

Reproducing kernel Hilbert spaces

Example. The space spanned by all spherical harmonics of degree n with the standard $L_2(\mathbb{S}^2)$ inner product $\langle \cdot, \cdot \rangle_{L_2}$ is a RKHS with reproducing kernel

$$\Phi_n(\mathbf{x}, \mathbf{y}) = \sum_{k=0}^n \frac{2k+1}{4\pi} P_k(\mathbf{x}^T \mathbf{y}).$$

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$$\Phi_n(\mathbf{x}, \mathbf{y}) = \sum_{k=0}^n \frac{2k+1}{4\pi} P_k(\mathbf{x}^T \mathbf{y}).$$

Let $\mathbf{x}, \mathbf{y} \in \mathbb{S}^2$ and $f(\mathbf{x}) = \sum_{\ell=0}^n \sum_{m=-\ell}^{\ell} c_{\ell}^m Y_{\ell}^m(\mathbf{x})$ for some coefficients c_{ℓ}^m . Then

$$\begin{aligned} \langle f, \Phi_n(\cdot, \mathbf{y}) \rangle_{L_2} &= \int_{\mathbb{S}^2} f(\mathbf{x}) \Phi_n(\mathbf{x}, \mathbf{y}) d\mu(\mathbf{x}) \\ &= \int_{\mathbb{S}^2} \left(\sum_{\ell=0}^n \sum_{m=-\ell}^{\ell} c_{\ell}^m Y_{\ell}^m(\mathbf{x}) \right) \left(\sum_{k=0}^n \frac{2k+1}{4\pi} P_k(\mathbf{x}^T \mathbf{y}) \right) d\mu(\mathbf{x}) \\ &= \sum_{k=0}^n \frac{2k+1}{4\pi} \sum_{\ell=0}^n \sum_{m=-\ell}^{\ell} c_{\ell}^m \int_{\mathbb{S}^2} P_k(\mathbf{x}^T \mathbf{y}) Y_{\ell}^m(\mathbf{x}) d\mu(\mathbf{x}) \\ &= \sum_{k=0}^n \frac{2k+1}{4\pi} \sum_{m=-k}^k \frac{4\pi}{2k+1} c_k^m Y_k^m(\mathbf{y}) \quad (\text{Funk-Hecke formula}) \\ &= \sum_{k=0}^n \sum_{m=-k}^k c_k^m Y_k^m(\mathbf{y}) = f(\mathbf{y}) \end{aligned}$$

Sobolev spaces

- Sobolev spaces on \mathbb{S}^2 can be defined in terms of spherical Harmonics.

Definition. The Sobolev space of order τ on \mathbb{S}^2 is given by

$$H^\tau(\mathbb{S}^2) = \left\{ f \in L_2(\mathbb{S}^2) \middle| \|f\|_{H^\tau}^2 = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} (1 + \ell(\ell + 1))^\tau |\hat{f}_\ell^m|^2 < \infty \right\}.$$

Here $\|\cdot\|_{H^\tau}$ is a norm induced by the inner product

$$\langle f, g \rangle_{H^\tau} = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} (1 + \ell(\ell + 1))^\tau \hat{f}_\ell^m \hat{g}_\ell^m,$$

where $\hat{f}_\ell^m = \langle f, Y_\ell^m \rangle_{L_2} = \int_{\mathbb{S}^2} f(\mathbf{x}) Y_\ell^m(\mathbf{x}) d\mu(\mathbf{x})$.

- Compare to Sobolev spaces on \mathbb{R}^3 :

$$H^\beta(\mathbb{R}^3) = \left\{ f \in L_2(\mathbb{R}^3) \middle| \|f\|_{H^\beta}^2 = \int_{\mathbb{R}^3} (1 + \|\boldsymbol{\omega}\|^2)^\beta |\hat{f}(\boldsymbol{\omega})|^2 d\mathbf{x} < \infty \right\}.$$

- Sobolev spaces on \mathbb{S}^2 can be defined in terms of spherical Harmonics.

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$$H^\tau(\mathbb{S}^2) = \left\{ f \in L_2(\mathbb{S}^2) \middle| \|f\|_{H^\tau}^2 = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} (1 + \ell(\ell + 1))^\tau |\hat{f}_\ell^m|^2 < \infty \right\}.$$

- Sobolev embedding theorem implies $H^\tau(\mathbb{S}^2)$ is continuously embedded in $C(\mathbb{S}^2)$ for $\tau > 1$. Thus, $H^\tau(\mathbb{S}^2)$ is a RKHS.
- Can show the reproducing kernel is $\Phi_\tau(\mathbf{x}, \mathbf{y}) = \sum_{\ell=0}^{\infty} (1 + \ell(\ell + 1))^{-\tau} \frac{2\ell + 1}{4\pi} P_\ell(\mathbf{x} \cdot \mathbf{y})$.

- Each positive definite zonal kernel ψ naturally gives rise to a RKHS on \mathbb{S}^2 , which is called the native space of ψ .
- This is the natural space to understand approximation with shifts of ψ .

Definition. Let ψ be a positive definite zonal kernel with spherical Fourier coefficients $\hat{\psi}_\ell$, $\ell = 0, 1, \dots$. The native space \mathcal{N}_ψ of ψ is given by

$$\mathcal{N}_\psi = \left\{ f \in L_2(\mathbb{S}^2) \middle| \|f\|_{\mathcal{N}_\psi} = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} \frac{|\hat{f}_\ell^m|^2}{\hat{\psi}_\ell} < \infty \right\},$$

with inner product

$$\langle f, g \rangle_{\mathcal{N}_\psi} = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} \frac{\hat{f}_\ell^m \hat{g}_\ell^m}{\hat{\psi}_\ell}.$$

- A similar definition holds for conditionally positive definite kernels, but the inner product has to be slightly modified (see Hubbert, 2002).

- An important “optimality” result stems from $\mathcal{N}_\psi(\mathbb{S}^2)$ being a RKHS.
- Consider the following optimization problem:

Problem. Let $X = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$ be a distinct set of nodes on \mathbb{S}^2 and let $\{f_1, \dots, f_N\}$ be samples of some target function f on X . Find $s \in \mathcal{N}_\psi(\mathbb{S}^2)$ that satisfies $s(\mathbf{x}_j) = f_j$, $j = 1, \dots, N$ and has minimal native space norm $\|s\|_{\mathcal{N}_\psi}$, i.e.

$$\text{minimize} \left\{ \|s\|_{\mathcal{N}_\psi} \mid s \in \mathcal{N}_\psi(\mathbb{S}^2) \text{ with } s|_X = f|_X \right\}.$$

Solution: s is the unique SBF interpolant to $f|_X$ using the kernel ψ .

- SBF interpolants also have nice properties in their respective native spaces:
 1. $\|f - I_{\psi, X}f\|_{\mathcal{N}_\psi}^2 + \|I_{\psi, X}f\|_{\mathcal{N}_\psi}^2 = \|f\|_{\mathcal{N}_\psi}^2$
 2. $\|f - I_{\psi, X}f\|_{\mathcal{N}_\psi} \leq \|f\|_{\mathcal{N}_\psi}$

Native spaces

- Note **similarity** between Sobolev space $H^\tau(\mathbb{S}^2)$ and $\mathcal{N}_\psi(\mathbb{S}^2)$:

$$H^\tau(\mathbb{S}^2) = \left\{ f \in L_2(\mathbb{S}^2) \middle| \|f\|_{H^\tau}^2 = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} (1 + \ell(\ell+1))^\tau |\hat{f}_\ell^m|^2 < \infty \right\}$$

$$\mathcal{N}_\psi(\mathbb{S}^2) = \left\{ f \in L_2(\mathbb{S}^2) \middle| \|f\|_{\mathcal{N}_\psi} = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} \frac{|\hat{f}_\ell^m|^2}{\hat{\psi}_\ell} < \infty \right\}$$

- If $\hat{\psi}_\ell \sim (1 + \ell(\ell+1))^{-\tau}$, then it follows that $\mathcal{N}_\psi = H^\tau$, with equivalent norms.
- This is one reason we care about the asymptotic behavior of $\hat{\psi}_\ell$.
- For **RBFs restricted to \mathbb{S}^2** , we have the following nice result connecting the asymptotics of the spherical Fourier coefficients to the Fourier transform (Levesley & Hubbert (2001), zu Castell & Filbir (2005), Narcowich, Sun, & Ward (2007)):

If ψ is an SBF obtained by restricting an RBF ϕ to \mathbb{S}^2 and if $\hat{\phi}(\omega) \sim (1 + \|\omega\|_2^2)^{-(\tau+1/2)}$ then $\hat{\psi}_\ell \sim (1 + \ell(\ell+1))^{-\tau}$.

- Examples of radial kernels ϕ and their norm-equivalent native spaces \mathcal{N}_ψ when restricted to \mathbb{S}^2 :

Name	RBF (use $r = \sqrt{2 - 2t}$ to get SBF ψ)	$\mathcal{N}_\psi(\mathbb{S}^2)$
Matern	$\phi_2(r) = e^{-\varepsilon r}$	$H^{1.5}(\mathbb{S}^2)$
TPS(1)	$\phi(r) = r^2 \log(r)$	$H^2(\mathbb{S}^2)$
Cubic	$\phi(r) = r^3$	$H^{2.5}(\mathbb{S}^2)$
TPS(2)	$\phi(r) = r^4 \log(r)$	$H^3(\mathbb{S}^2)$
Wendland	$\phi_{3,2}(r) = (1 - \varepsilon r)_+^6 (3 + 18(\varepsilon r) + 15(\varepsilon r)^2)$	$H^{3.5}(\mathbb{S}^2)$
Matern	$\phi_5(r) = e^{-\varepsilon r} (15 + 15(\varepsilon r) + 6(\varepsilon r)^2 + (\varepsilon r)^3)$	$H^{4.5}(\mathbb{S}^2)$

- The spherical Fourier coefficients for all these restricted kernels have **algebraic decay rates**.
- For kernels with spherical Fourier coefficients with **exponential decay rates** (*e.g.* Gaussian and multiquadric) the Native spaces are no longer equivalent to Sobolev spaces.
- These natives spaces do satisfy: $\mathcal{N}_\psi(\mathbb{S}^2) \subset H^\tau(\mathbb{S}^2)$ for all $\tau > 1$.
- Error estimates for interpolants are directly linked to the native space of ψ .

Geometric properties of node sets

- The following properties for node sets on the sphere appear in the error estimates:
- Mesh norm

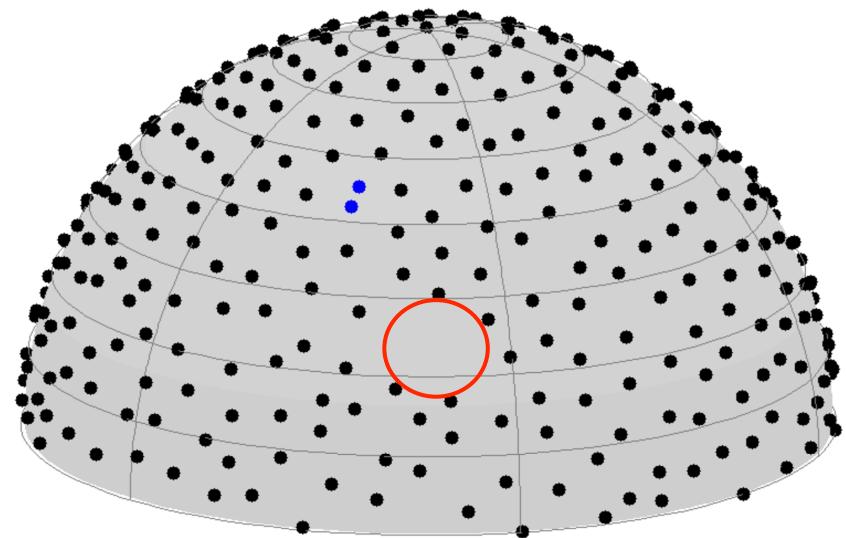
$$h_X = \sup_{\mathbf{x} \in \mathbb{S}^2} \text{dist}_{\mathbb{S}^2}(\mathbf{x}, X)$$

- Separation radius

$$q_X = \frac{1}{2} \min_{i \neq j} \text{dist}_{\mathbb{S}^2}(\mathbf{x}_i, \mathbf{x}_j)$$

- Mesh ratio

$$\rho_X = \frac{h_X}{q_X}$$



$$X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$$

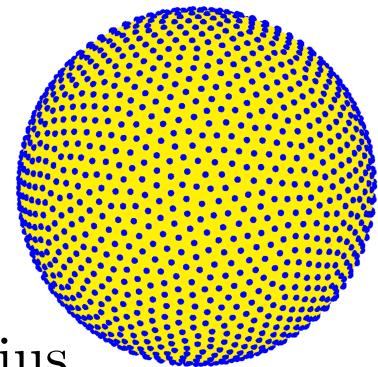
(Only part of the sphere is shown)

Interpolation error estimates

- We start with known error estimates for kernels of finite smoothness.
Jetter, Stöckler, & Ward (1999), Morton & Neamtu (2002), Hubbert & Morton (2004,2004), Narcowich, Sun, Ward, & Wendland (2007)

Notation:

- ψ is the SBF
- $\hat{\psi}_\ell \sim (1 + \ell(\ell + 1))^{-\tau}$, $\tau > 1$
- $\mathcal{N}_\psi(\mathbb{S}^2) = H^\tau(\mathbb{S}^2)$
- $I_X f$ is SBF interpolant of $f|_X$
- $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$
- h_X = mesh-norm
- q_X = separation radius
- $\rho_X = h_X/q_X$, mesh ratio



Theorem. Target functions in the native space.

If $f \in H^\tau(\mathbb{S}^2)$ then $\|f - I_X f\|_{L_p(\mathbb{S}^2)} = \mathcal{O}(h_X^{\tau-2(1/2-1/p)_+})$ for $1 \leq p \leq \infty$.
In particular,

$$\|f - I_X f\|_{L_1(\mathbb{S}^2)} = \mathcal{O}(h_X^\tau)$$

$$\|f - I_X f\|_{L_2(\mathbb{S}^2)} = \mathcal{O}(h_X^\tau)$$

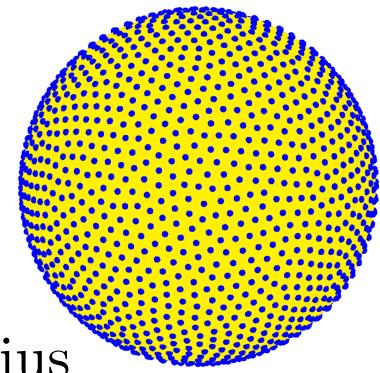
$$\|f - I_X f\|_{L_\infty(\mathbb{S}^2)} = \mathcal{O}(h_X^{\tau-1})$$

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Theorem. Target functions twice as smooth as the native space.

If $f \in H^{2\tau}(\mathbb{S}^2)$ then $\|f - I_X f\|_{L_p(\mathbb{S}^2)} = \mathcal{O}(h_X^{2\tau})$ for $1 \leq p \leq \infty$.

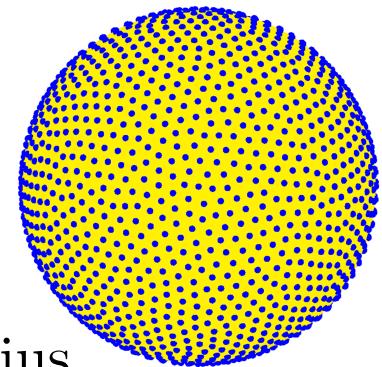
Remark. Known as the “doubling trick” from spline theory. (Schaback 1999)

Interpolation error estimates

- We start with known error estimates for kernels of finite smoothness.
Jetter, Stöckler, & Ward (1999), Morton & Neamtu (2002), Hubbert & Morton (2004,2004), Narcowich, Sun, Ward, & Wendland (2007)

Notation:

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- $\hat{\psi}_\ell \sim (1 + \ell(\ell + 1))^{-\tau}$, $\tau > 1$
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- $I_X f$ is SBF interpolant of $f|_X$
- $X = \{\mathbf{x}_j\}_{j=1}^N \subset \mathbb{S}^2$
- h_X = mesh-norm
- q_X = separation radius
- $\rho_X = h_X/q_X$, mesh ratio



Theorem. Target functions **rounger than the native space**.

If $f \in H^\beta(\mathbb{S}^2)$ for $\tau > \beta > 1$ then $\|f - I_X f\|_{L_p(\mathbb{S}^2)} = \mathcal{O}(\rho^{\tau-\beta} h_X^{\tau-2(1/2-1/p)_+})$ for $1 \leq p \leq \infty$.

Remark.

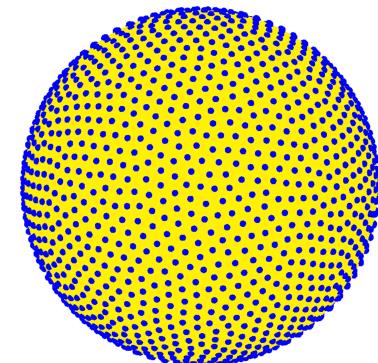
- (1) Referred to as “escaping the native space”. (Narcowich, Ward, & Wendland (2005, 2006)).
- (2) These rates are the best possible.

Interpolation error estimates

- Error estimates for **infinitely smooth kernels** (e.g. Gaussian, multiquadric).
Jetter, Stöckler, & Ward (1999)

Notation:

- ψ is the SBF
- $\hat{\psi}_\ell \sim \exp(-\alpha(2\ell + 1))$, $\alpha > 0$
- $\mathcal{N}_\psi(\mathbb{S}^2) = \left\{ f \in L_2(\mathbb{S}^2) \middle| \|f\|_{\mathcal{N}_\psi} = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{\ell} \frac{|\hat{f}_\ell^m|^2}{\hat{\psi}_\ell} < \infty \right\}$



Theorem. Target functions **in the native space**.

$$\text{If } f \in \mathcal{N}_\psi(\mathbb{S}^2) \text{ then } \|f - I_X f\|_{L_\infty(\mathbb{S}^2)} = \mathcal{O}(h_X^{-1} \exp(-\alpha/2h)).$$

Remarks:

- (1) This is called **spectral** (or **exponential**) convergence.
- (2) Function space may be small, but does include all **band-limited functions**.
- (3) Only known result I am aware of (too bad there are not more).
- (4) Numerical results indicate convergence is also fine for less smooth functions.

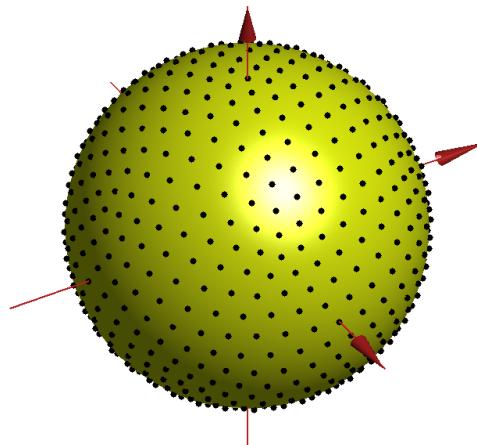
Optimal nodes

- If one has the freedom to choose the nodes, then the error estimates indicate they should be roughly as evenly spaced as possible.

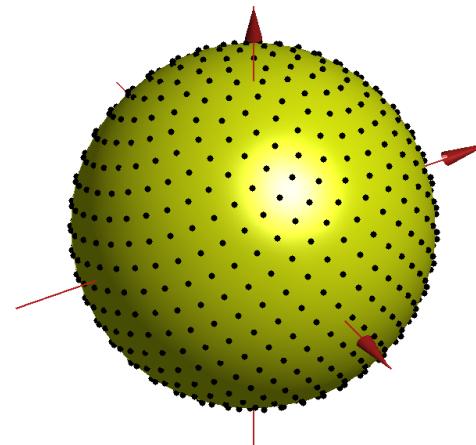
Examples:

Deterministic

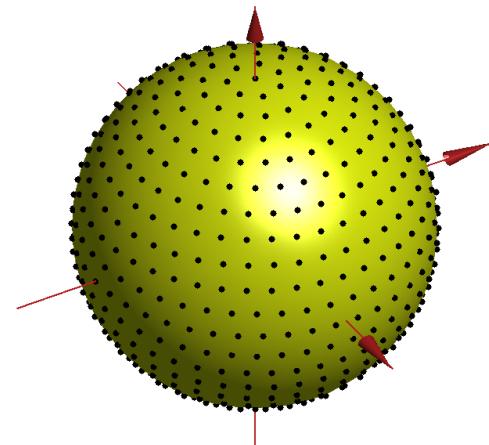
Icosahedral



Fibonacci



Equal area

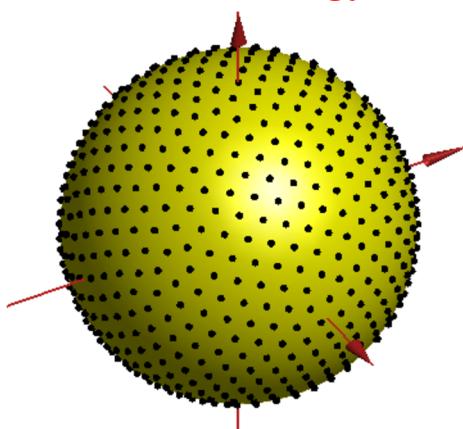


Swinbank & Purser (2006)

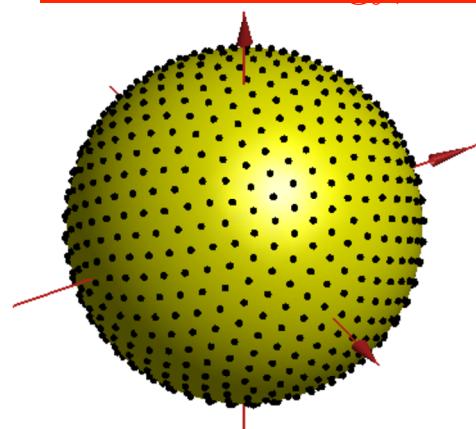
Saff & Kuijlaars (1997)

Non-deterministic

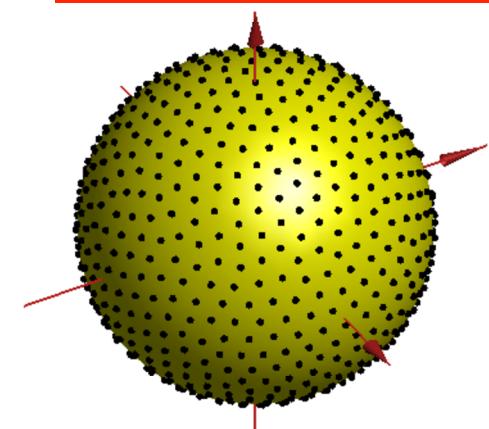
Minimum energy, $s=2$



Minimum energy, $s=3$



Maximal determinant



Hardin & Saff (2004)

Riesz energy: $\|\mathbf{x} - \mathbf{y}\|_2^{-s}$

Womersley & Sloan (2001)

Concluding remarks

- This was general background material for getting started in this area.
- There is still much more to learn and many interesting problems.
- Remainder of the lectures will focus on:
 - Approximation (and decomposition) of vector fields.
 - Better bases for certain kernels (better=more stable).
 - Fast algorithms for interpolation (with applications to quadrature)
 - Numerical solution of partial differential equations on spheres.
 - ❖ Focus: non-linear hyperbolic equations.
 - ❖ Global and local methods.
 - Problems in spherical shells.
 - ❖ Mantle convection (Rayleigh-Bénard convection).
 - ❖ Generalizations to other manifolds.
- ❖ If you have any questions or want to chat about research ideas, please come and talk to me.

Grazie per la vostra attenzione.