

Interpolation vs. Best Approx.

Given $f \in H$ and dictionary $\{e_1, \dots, e_N\} \subset H$, we can find the best approximation to f in $\text{span}\{e_1, \dots, e_N\}$ via QR decomp:

Algorithm: Compute best approx. via QR.

Step 1. QR decomposition of dictionary:

$$\begin{matrix} E & & Q & & R \\ \begin{bmatrix} | & & | \\ e_1 & \dots & e_N \\ | & & | \end{bmatrix} & = & \begin{bmatrix} | & & | \\ q_1 & \dots & q_N \\ | & & | \end{bmatrix} & \begin{bmatrix} \times & \dots & \times \\ 0 & \times & \dots & \times \\ \vdots & & \ddots & \\ 0 & \dots & 0 & \times \end{bmatrix} \end{matrix}$$

Step 2. Solve upper triangular system
 $Rc = Q^* f$

dictionary *ONB* *change of basis*

Question: What if we only have samples of $f: \Omega \rightarrow \mathbb{R}$ (continuous) at x_1, \dots, x_m ?
 $\subset \mathbb{R}^d$ *distinct*

$f_1 = f(x_1), \dots, f_m = f(x_m)$?

\Rightarrow Interpolate or otherwise "fit" data with dict.

Interpolation/Regression

How to choose combination of dictionary functions to interpolate/fit data?

$$f(x) \approx c_1 e_1(x) + \dots + c_N e_N(x)$$

Solve $M \geq N$ equations for c_1, \dots, c_N :

$$c_1 e_1(x_1) + c_2 e_2(x_1) + \dots + c_N e_N(x_1) = f(x_1)$$
$$\vdots$$

$$c_1 e_1(x_M) + c_2 e_2(x_M) + \dots + c_N e_N(x_M) = f(x_M)$$

Or in matrix notation, we have

Generalized Vandermonde

$$\begin{bmatrix} e_1(x_1) & e_2(x_1) & \dots & e_N(x_1) \\ e_1(x_2) & e_2(x_2) & \dots & e_N(x_2) \\ \vdots & \vdots & & \vdots \\ e_1(x_M) & e_2(x_M) & \dots & e_N(x_M) \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_M \end{bmatrix}$$
$$E_{N,M} \quad c = f$$

Case 1

If $N=M$ and $E_{N,M}$ is invertible, then $S_{N,M} = E \underline{c}$ will interpolate the data.

Case 2

If $N > M$ and $E_{N,M}$ has linearly indep. rows, then we can perform model regression on the data by solving in least-squares sense.

$$\Rightarrow E_{N,M} = Q_{N,M} R_{N,M} \Rightarrow \underline{c} = R_{N,M}^{-1} Q_{N,M}^* \underline{f}$$

Case 3

If $N < M$ and $E_{N,M}$ has linearly indep. rows, then there are many solutions! We often look for a minimum-norm solution or impose additional constraints on Model.

\Rightarrow Could also impose sparsity, smoothness, etc.

Question: What happens if x_1, \dots, x_M are not all distinct points in Ω ?

$\Rightarrow E_{N,M}$ has repeated rows. Must modify, Taylor?

Similar to Best-Fit approximations, the condition number of $E_{N,M}$ as $N, M \rightarrow \infty$ is typically the key factor in convergence.

$$N=M \quad K(E_N) = \|E_N\| \|E_N^{-1}\|$$

$$N \geq M \quad K(E_{N,M}^+ E_{N,M}) = \|E_{N,M}^+ E_{N,M}\| \|(E_{N,M}^+ E_{N,M})^{-1}\|$$

Polynomial Interpolation

To illustrate the basic analysis framework, consider $\{x_0, \dots, x_N\} \in [-1, 1]$ distinct and

$$E = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & x_0 & \dots & x_0^N \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_N & \dots & x_N^N \end{bmatrix}.$$

The Vandermonde matrix is invertible:

$$E_N = \begin{bmatrix} 1 & x_0 & \dots & x_0^N \\ 1 & x_1 & \dots & x_1^N \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_N & \dots & x_N^N \end{bmatrix}.$$

\Rightarrow Degree N polynomial interpolant through $N+1$ distinct points is unique

pf If p and p' are degree N and interpolate f at $N+1$ distinct points, then $p-p'$ is degree $\leq N$ and interpolates zero at $N+1$ points. The only deg $\leq N$ like this is the zero poly.
 $\Rightarrow p = p'$

For any $f: C[-1, 1] \rightarrow \mathbb{R}$ and any set of distinct points $X = \{x_0, \dots, x_n\}$, we define

$$p = P_X f$$

as the unique degree $\leq N$ interpolant of f on the set X .

The map $P_X: C[-1, 1] \rightarrow P_n$ is key to understanding the approximation qualities of polynomial interpolants on X :

P_x is linear: $P_x(f + \beta g) = P_x f + \beta P_x g$

P_x is onto \mathbb{P}_n : $p = P_x f \in \mathbb{P}_n$

$$P_x^2 = P_x : \quad p = P_x f \quad p = P_x p$$

These three properties make P_x a projection of $C[-1,1]$ onto \mathbb{P}_n . However, it is not, in general, an orthogonal projection! In particular,

$$\|P_x\| = \sup_{f \in C[-1,1]} \frac{\|P_x f\|}{\|f\|} > 1.$$

For "bad" interpolation points, $\|P_x\|$ can grow exponentially with n . For "good" point sets, $\|P_x\|$ grows modestly with n and $P_x f$ behaves similarly to the "best" (orthogonal) projection onto \mathbb{P}_n .