

## 1. Best approximants

Interpolation of data  $\mathcal{D} = \{(x_i, y_i = f(x_i)), i = 0, \dots, n\}$  by an approximant  $p(t)$  corresponds to the minimization problem

$$\min_p \|f - p\|,$$

in the discrete one-norm at the sample points  $x_i$

$$\|f\| = \|f\|_1 = \sum_{i=0}^n |f(x_i)|.$$

Different approximants are obtained upon changing the norm.

**THEOREM (EXISTENCE OF BEST APPROXIMANT).** *For any element  $f \in F$  in a normed vector space  $\mathcal{F} = (F, S, +, \cdot)$ , there exists a best approximant  $g \in G$  within a finite dimensional subspace  $G \subset F$  that is a solution of*

$$\min_{g \in G} \|f - g\|.$$

The argument underlying the above theorem is based upon constructing the closed and bounded subset of  $G$

$$K = \{g \in G \mid \|g - f\| \leq \|0 - f\| = \|f\|\} \subset G.$$

Since  $G$  is finite dimensional,  $K$  is compact, and the continuous mapping  $g \rightarrow \|g - f\|$  attains its extrema.

The two main classes of approximants  $g$  of real functions  $f: [a, b] \rightarrow \mathbb{R}$  that arise are:

**Approximants based upon sampling.** The vectors  $f = f(x)$ ,  $g = g(x)$  are constructed at sample points  $x \in \mathbb{R}^m$  and the best approximant solves the problem

$$\min_{g \in G} \|f - g\|.$$

Note that the minimization is carried out over the members of the subset  $G$ , not over the vectors  $g$ . The norm can include information on derivatives as in the norm

$$\|f\|_H = \|f\|_1 + \|f'\|_1,$$

arising in Hermite interpolation.

**Approximants over the function domain.** The norm is now expressed through an integral such as the  $p$ -norms

$$\|f\|_p = \left( \int_a^b |f(t)|^p dt \right)^{1/p}.$$

In general, the best approximant in a normed space is not unique. However, the best approximant is unique in a Hilbert space, and is further characterized by orthogonality of the residual to the approximation subspace.

**THEOREM (BEST APPROXIMANT IN HILBERT SPACE).** *For any element  $f \in F$  in a Hilbert space  $\mathcal{F} = (F, S, +, \cdot)$ , there exists a unique approximant  $g \in G$  within a finite dimensional subspace  $G \subset F$  that is a solution of*

$$\min_{g \in G} \|f - g\|,$$

and the residual  $f - g$  is orthogonal to  $G$ ,  $\forall h \in G$

$$(f - g, h) = 0.$$

Note that orthogonality of the residual  $(f - g, h) = 0$  implies  $(f, h) = (g, h)$  or that the best approximant is the projection of  $f$  onto  $G$ .

## 2. Two-norm approximants in Hilbert spaces

For Hilbert spaces with a norm induced by the scalar product

$$\|f\| = (f, f)^{1/2},$$

finding the best approximant reduces to a problem within  $\mathbb{R}^m$  (or  $\mathbb{C}^m$ ). Introduce a basis  $\mathcal{B} = \{b_1, b_2, \dots\}$  for  $\mathcal{F}$  such that any  $f \in F$  has an expansion

$$f(t) = \sum_{j=1}^{\infty} f_j b_j(t), f_j = (f, b_j)$$

Since  $G$  is finite dimensional, say  $n = \dim(G)$ , an approximant has expansion

$$g(t) = \sum_{j=1}^n g_j b_{s(j)}(t).$$

Note that the approximation may lie in an arbitrary finite-dimensional subspace of  $\mathcal{F}$ . Choosing the appropriate subset through the function  $s: \mathbb{N} \rightarrow \mathbb{N}$  is an interesting problem in itself, leading to the goal of selecting those basis functions that capture the largest components of  $f$ , i.e., the solution of

$$\min_{s \in \mathbb{N}^n} \sum_{j=1}^n |(f, b_{s(j)})|.$$

Approximate solutions of the basis component selection are obtained by processes such as greedy approximation or clustering algorithms. The approach typically adopted is to exploit the Bessel inequality

$$\sum_{i=1}^n f_{s(i)}^2 \leq \|f\|^2,$$

and select

$$s(1) = \arg \max_{i \in S} f_i^2,$$

eliminate  $s(1)$  from  $S$ , and search again. The  $k^{\text{th}}$ -step is

$$s(k) = \arg \max_{i \in S} f_i^2,$$

with  $S_k = S - \{s(1), \dots, s(k-1)\}$ .

Assuming  $s(j) = j$ , the orthogonality relation  $f - g \perp G$  leads to a linear system

$$(f - g, b_i) = 0 \Rightarrow \left( \sum_{j=1}^n g_j b_j, b_i \right) = \sum_{j=1}^n (b_i, b_j) g_j = (f, b_i) \Rightarrow \mathbf{B} \mathbf{g} = \mathbf{f}.$$

If the basis is orthonormal, then  $\mathbf{B} = \mathbf{I}$ , and the best approximant is simply given by the projection of  $f$  onto the basis elements. Note that the scalar product need not be the Euclidean discrete or continuous versions

$$(f, g) = \sum_{i=1}^n f_i g_i, (f, g) = \int_a^b f(t) g(t) dt.$$

A weighting function may be present as in

$$(f, g) = \mathbf{f}^T \mathbf{W} \mathbf{g}, (f, g) = \int_a^b f(t) g(t) w(t) dt,$$

discrete and continuous versions, respectively. In essence the appropriate measure  $\mu(t)$  for some specific problem

$$d\mu(t) = w(t) dt,$$

arises and might not be the Euclidean measure  $w(t) = 1$ .

### 3. Inf-norm approximants

In the vector space of continuous functions defined on a topological space  $X$  (e.g., a closed and bounded set in  $\mathbb{R}^n$ ), a norm can be defined by

$$\|f\| = \max_{x \in X} |f(x)|,$$

and the best approximant is found by solving the problem

$$\inf_{g \in G} \|f - g\| = \inf_{g \in G} \max_{x \in X} |f(x) - g(x)|.$$

The fact that  $g$  is the best approximant of  $f$  can be restated as 0 being the approximant of  $f - g$  since

$$\|f - g - 0\| \leq \|f - (g + h)\|.$$

A key role is played by the points where  $f(x) = g(x)$  leading to the definition of a critical set as

$$\text{crit}(f) = \mathcal{L}(f) = \{x \in X : |f(x)| = \|f\|\}.$$

When  $G = P_{n-1}$ , the space of polynomials of degree at most  $n - 1$ , with  $\dim P_{n-1} = n$ , the best approximant can be characterized by the number of sign changes of  $f(x) - g(x)$ .

**THEOREM (CHEBYSHEV ALTERNATION).** *The polynomial  $p \in P_{n-1}$  is the best approximant of  $f: [a, b] \rightarrow \mathbb{R}$  in the inf-norm*

$$\|f - p\|_\infty = \max_{a \leq x \leq b} |f(x) - p(x)|$$

if and only if there exist  $n + 1$  points  $a \leq x_0 < x_1 < \dots < x_n \leq b$  such that

$$f(x_i) - p(x_i) = s \cdot (-1)^i \|f - p\|_\infty,$$

where  $|s| = 1$ .

Recall that choosing  $x_i = \cos[(2i - 1)\pi / (2n)]$ , the roots of the  $T_n(\theta) = \cos(n\theta)$  Chebyshev polynomial (with  $x = \cos \theta$ ,  $a = -1$ ,  $b = 1$ ), leads to the optimal error bound in polynomial interpolation

$$|f(t) - p(t)| \leq \frac{\|f^{(n+1)}\|_\infty}{(n+1)! 2^n}.$$

The error bound came about from consideration of the alternation of signs of  $p(x_i) - q(x_j)$  at the extrema of the Chebyshev polynomial  $T_n$ ,  $x_i = \cos(i\pi / n)$ ,  $i = 0, 1, \dots, n$ , with  $p, q$  monic polynomials. The Chebyshev alternation theorem generalizes this observation and allows the formulation of a general approach to finding the best inf-norm approximant known as the Remez algorithm. The idea is that rather than seeking to satisfy the interpolation conditions

$$\mathbf{M}\mathbf{a} = \mathbf{y}$$

in the monomial basis

$$\mathbf{M} = \mathcal{M}_{n-1}(x) = [\mathbf{1} \ \mathbf{x} \ \dots \ \mathbf{x}^{n-1}] \in \mathbb{R}^{n \times n},$$

attempt to find  $n$  alternating-sign extrema points by considering the basis set

$$\mathbf{R} = \mathcal{R}_n(x) = [\mathbf{1} \ \mathbf{x} \ \dots \ \mathbf{x}^{n-1} \ \pm \mathbf{1}] \in \mathbb{R}^{(n+1) \times (n+1)}$$

with  $\pm \mathbf{1} = [+1 \ -1 \ +1 \ \dots]$ .

### Algorithm (Remez)

1. Initialize  $\mathbf{x} \in \mathbb{R}^{n+1}$  to Chebyshev maxima on interval  $[a, b]$
2. Solve  $\mathbf{R}\mathbf{c} = f(\mathbf{x})$ ,  $\mathcal{R}(\mathbf{x})$ ,  $\mathbf{c}^T = [\mathbf{a}^T \ c_{n+1}]$ ,  $\mathbf{a} \in \mathbb{R}^n$
3. Find the extrema  $\mathbf{y}$  of  $p(t) - f(t)$  with  $p(t) = a_0 + a_1 t + \dots + a_{n-1} t^{n-1}$
4. If  $p(y_i) - f(y_i)$  are approximately equal in absolute value and of opposite signs, return  $\mathbf{x}$
5. Otherwise set  $\mathbf{x} = \mathbf{y}$ , repeat