MULTICRITERIA OPTIMIZATION

Best Simultaneous Approximation of Functions

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Abstract. The problem we consider is to find (the) best approximation(s) to a given function simultaneously with respect to more than one criterion of proximity. Questions of existence, characterization, unicity and computation are examined. Examples are given.

Keywords: Best vectorial approximation(s), minimal projection norms, computational schemata

1. INTRODUCTION

Among other formulations of simultaneous approximation, the notion of a "Vectorially Minimal Approximation" is introduced, which is shown to be the natural setting for problems of simultaneity, both theoretically as well as computationally. For the above formulations of Multicriteria Optimization we propose 3 types of "models" and show their interrelationships in each "primal" and "dual" spaces. In particular, attention has been given to effective models suitable for numerical computation. A related problem situated in the "dual space" of approximation operators is to approximate the (non-linear) best approximation operator by projection operators. This approach, as a tool of "good" approximation of functions (in situations to be specified), is motivated by the following inequality, where the role of minimal projections, i.e. $min||P||$ is self-explanatory.

 $||f - Pf|| \le ||I - P||dist(f, Y) \le (1 + ||P||)dist(f, Y).$

Here again the approximation in the operator space is done simultaneously with respect to several norms. As just indicated, this reduces to finding "simultaneously" minimal projection norms. Examples are given and a "Zero in the Convex Hull" as well as a "Kolmogorov-type" characterization theorems are presented.

The tools used in this presentation are Elementary Optimization Theory, Computational Numerical Analysis and Elementary Functional Analysis.

2. VECTORIAL APPROXIMATION

Let $\|\cdot\|_a$, $\|\cdot\|_b$ be two norms defined on a linear space S and let $f \in S \sim K$ be a given function to be approximated by approximation $p \in K \subset S$. K is assumed to be a closed, convex, proper subset of S. Let $G(p) = (||f - p||_q, ||f - p||_b)$ and define the partial ordering \triangleright on $G(K)$ by

$$
G(p) \trianglelefteq G(q) \Longleftrightarrow \begin{cases} ||f - p||_a \leq ||f - q||_a \\ \text{and} \\ ||f - p||_b \leq ||f - q||_b \end{cases}
$$

We shall write $G(p) \triangleleft G(q)$ if and only if $G(p) \trianglelefteq G(q)$ and $G(p) \neq G(q)$.

Definition 2.1

We say that p is a best vec approximation if there does not exist a $q \in K$ such that $G(q) \triangleleft G(p)$.

Definition 2.2

The minimal set M is given by $M = \{G(p): p \in K \text{ is a best vec approximation} \}.$

There are some general geometric facts that are easy to verify. We cite some of them here:

- $\pi_1(G(K))$ has zero homotopy group.
- \bullet *M* is a convex, decreasing arc.

Let *A* is the 45° bisector of the $\|\cdot\|_a$, $\|\cdot\|_b$ orthogonal axes. *L* is the supporting line to $G(K)$ which makes 135° angle with $\|\cdot\|_a$ axes.

The proof of the following theorem is a consequence of the definitions, convexity and, in the case of $(P_m) = M \cup L$, the continuity of the best approximation operator. Sum here denotes the sum of two norms. Max means the maximum of two norms.

Theorem 2.1

Let p_s be a best sum approximation. Then $G(P_s) \subseteq M \cup L$. Similarly, if p_m denotes the best max approximation then $G(P_m) = M \cup L$ (assuming $M \cup L \neq \emptyset$).

Furthermore, we define the set D by

$$
D = \left\{ d : \inf_{q \in K} ||f - q||_a \le d \le \inf_{q \in B} ||f - q||_a \right\}
$$

where,

$$
B = \Big\{ r \in K : ||f - r||_b = \inf_{q \in K} ||f - q||_b \Big\}.
$$

Theorem 2.2

An element $p \in K$ is a best vectorial approximation if and only if there exists $d \in D$ and Φ ∈ S^{*} satisfying

$$
\|\Phi\|_{b} = 1
$$

$$
\Phi(f - b) = \|f - q\|_{a} \le d
$$

and

 $Re\Phi(p - q) \leq 0$ for all $q \in K$ satisfying $||f - q||_q \leq d$.

3. VECTORIALY MINIMAL PROJECTIONS

Let $\Lambda = \Lambda(X, V)$ be the space of all linear operators from a real or complex space X into a finite-dimensional subspace V, and let Π be the family of all operators in Λ with a given fixed action on V (e.g., the identity action corresponds to the family of projections onto V). Let X be equipped with norms $\|\cdot\|_i$, $i = 1, 2, ..., k$. Let X_i denote the normed space given by X with the norm $\lVert \cdot \rVert_i$, and define

 $||x||:=(||x||_1, ||x||_2, ..., ||x||_k).$

Define the partial ordering " \leq " on X by

 $||x|| \triangleq ||z|| \Leftrightarrow ||x||_i \leq ||z||_i$ for every $i = 1, 2, ..., k$. We write $||x|| \le ||z||$ if and only if $||x|| \le ||z||$ and $||x|| \ne ||z||$.

Definition 3.1

For $Q \in \Lambda$, let $||Q||_i$ denote the operator norm on X_i , let $||Q||: = (||Q||_1, ||Q||_2, ..., ||Q||_k)$ and define the partial ordering " \leq " on Λ by $||P|| \triangleq ||Q|| \Leftrightarrow ||P||_i \leq ||Q||_i$ for every $i = 1, 2, ..., k$. We write $||P|| \le ||Q||$ if and only if $||P|| \le ||Q||$ and $||P|| \ne ||Q||$. P is a vectorially minimal operator in Π if there no exist $Q \in \Pi$ such that $||Q|| \triangleleft$ $\|P\|$.

Notation

The minimal set *is given by*

 $M \coloneqq \{||P||: P \in \Pi \text{ is a vectorially minimal operator in } \Pi\}.$

Definition 3.2

For $i = 1, 2, ..., k$ $(x, y) \in S(X_i^{**}) \times S(X_i^{*})$ will be called an extremal pair for $Q \in \Lambda$, if $\langle Q_i^{**}x, y \rangle = ||Q||_i$, where $Q_i^{**}: X_i^{**} \to V$ is the second adjoint extension of Q to $X_i^{\ast\ast}$.

 $(S$ denotes the unit sphere).

Notation

Let $E(Q)$ be the set of all extremal pairs for Q. To each $(x, y) \in Q$ associate the rankone operator $y \otimes x$ from X_i to X_i^{**} given by $(y \otimes x)(z) = \langle z, y \rangle x$ for $\in X_i$, where *i* is the subscript associated with (x, y) .

Theorem 3.1 (Characterization)

P has vectorially minimal norm in Π if and only if the closed convex hull of $\{y \otimes x\}_{(x,y)\in E(P)}$ contains an operator E_P for which V is an invariant subspace, i.e.

$$
\boldsymbol{E}_{\boldsymbol{P}} = \int_{\boldsymbol{E}(\boldsymbol{P})} y \otimes x d\mu(x, y) : V \longrightarrow V.
$$

Theorem 3.2

P has vectorially minimal norm in Π if and only if there does not exist $D \in \Delta = \{D \in \Lambda : D = 0 \text{ in } V\}$ such that

$$
\sup_{(x,y)\in E(P)} Re\langle P_i^{**}x, y\rangle \overline{\langle D^{**}x, y\rangle} < 0.
$$

4. SOME SPECIAL CASES

We give some examples of Theorem 2.2. In the notation of this theorem, let $S = C[a, b],$

 $K = \prod_n [a, b]$ (the set of polynomials on $[a, b]$ of degree less than or equal to n), $\|\cdot\|$ is the supremum norm on [a, b] and $w_1, w_2 \in C[a, b]$ two (weight) functions, positive and continuous on $[a, b]$.

We introduce extreme points, for a given $f \in C[a, b]$ to be approximated, in connection with the next theorem, as follows:

$$
\begin{aligned}\n\overline{\underline{X}}_{+1} &= \{ x \in [a, b] : w_1(x) \big(f(x) - p(x) \big) = + \| w_1(f - p) \| \} \\
\overline{\underline{X}}_{+2} &= \{ x \in [a, b] : w_2(x) \big(f(x) - p(x) \big) = + \| w_2(f - p) \| \} \\
\overline{\underline{X}}_{-1} &= \{ x \in [a, b] : w_1(x) \big(f(x) - p(x) \big) = - \| w_1(f - p) \| \} \\
\overline{\underline{X}}_{-2} &= \{ x \in [a, b] : w_2(x) \big(f(x) - p(x) \big) = - \| w_2(f - p) \| \}.\n\end{aligned}
$$

$$
\overline{\underline{X}}_p = \overline{\underline{X}}_{+1} \cup \overline{\underline{X}}_{+2} \cup \overline{\underline{X}}_{-1} \cup \overline{\underline{X}}_{-2}
$$

The sign function $\sigma(x)$ on \underline{X}_p is defined by

$$
\sigma(x) = -1 \text{ when } x \in \underline{\overline{X}}_{-1} \cup \underline{\overline{X}}_{-2}
$$

and

$$
\sigma(x) = +1 when x \in \underline{\overline{X}}_{+1} \cup \underline{\overline{X}}_{+2}.
$$

Theorem 4.1 (Application)

Consider the Vectorial Chebyshev optimization, with w_1 and w_2 as defined above. Then p is a best vec approximation to f if and only if there exist $n + 2$ points $x_1 < x_2 < \cdots < x_{n+2} \in \overline{X}_p \subset [a, b]$ satisfying

$$
\sigma(x_i) = (-1)^{i+1} \sigma(x_1) \text{ for every } i = 1, 2, ..., n+2.
$$

Theorem 4.2

Each best vec approximation is unique; i.e. given $\mu \in M$ there is only one $p \in$ $\Pi_n[a, b]$ such that $G(p) = \mu$.

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Note that this uniqueness does not contradict the fact that the minimal set M has, in general, an infinite number of points, each of which corresponds to a (unique) best vectorial approximation. Likewise, the easily shown existence of M proves the existence of best solutions.

Theorem 4.3 (Application)

Let $X = C[a, b], K = \Pi_n[a, b], || \cdot ||_a$, $|| \cdot ||_b$ the sup and L_2 norms on $C[a, b]$ which we denote by $\|\cdot\|_{\infty}$ and $\|\cdot\|_{2}$ respectively.

Find the best vectorial approximation p_d whose error in Chebyshev norm equals a prescribed value $d \in P^+$, $|| f - p_1 ||_{\infty} \le d \le || f - p_2 ||_{\infty}$. It is clear that the desired polynomial p_d is the unique solution to the problem

$$
\min_{p \in \Pi_n} \|f - p\|_2
$$

subject to

$$
\|f - p\|_{\infty} \le d.
$$

Since the number of constraints here is infinite, we proceed by solving a sequence of quadratic programming problems, each with a finite number of constraints. The sequence of solutions $\{p_k\}$ is shown to converge to the theoretical solution p_d .

Algorithm Corresponding to Theorem 4.3

At the $k - th$ step we have from the preceding steps a finite set of points $X^k \subset$ $[a, b]$. We solve the quadratic program

$$
\min_{p\in \varPi_n} \lVert f-p\rVert_2
$$

subject to

$$
|| f(x) - p(x)||_{\infty} \le d, x \in X_k.
$$

Denoting by p_k the solution of this problem, we calculate a point $x_k \in [a, b]$ such that $|f(x_k) - p_k(x_k)| = || f - p_k ||_{\infty}.$

We form $X^{k+1} = X^k \cap \{x_k\}$ and proceed to the next cycle. At the beginning X^1 may be an arbitrary finite set, containing a maximum of $|f(x) - p_L(x)|$.

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