

Solving Infinite-Dimensional Optimization Problems using Polynomial Approximation



Olivier Devolder, François Glineur and Yurii Nesterov: UCLouvain, CORE & INMA

What is infinite-dimensional optimization ?

Optimization problems where the decision variable belongs to a infinite-dimensional space i.e:

$$\inf_{x \in X} f(x)$$

$$x \in C$$

where X is a normed vector space of **infinite dimension**.

Furthermore, our interest is in **convex** optimization problems i.e. $f : X \rightarrow \mathbb{R}$ and $C \subset X$ must be convex.

Why infinite-dimensional optimization problems ?

- Domain of interest since the 17th century with the classical calculus of variations
- Natural generalization of many classical optimization problems to the continuous setting, for example network problems, supply problems, transportation problems, etc.
- Natural framework for Optimal Control problems using theory of PDE-constrained optimization
- Natural framework for Shape or Topology optimization problems

Studied problems class

Let X be a normed vector space and X' its topological dual. We consider the following class of infinite-dim. problems:

$$P^* = \inf_{x \in X} \langle f, x \rangle \quad (P)$$

$$\langle a_i, x \rangle = b_i \quad \forall i = 1, \dots, L$$

$$\langle c_t, x \rangle \leq d_t \quad \forall t \in T$$

$$\|x\|_X \leq M$$

where $f, a_i, c_t \in X'$, L is finite and T is a (possibly infinite) set.

All solvable convex optimization problems with closed feasible set can be included in this class (a closed convex set in a normed space is equal to the intersection of all closed half-spaces that contain it).

How to solve infinite-dimensional opt. prob.?

- Using infinite-dimensional algorithms whose *implementation* has been discretized
- Using a discretization of the *functions* in the original problem
- Our approach is different: using **polynomial approximation** by discretizing the description of elements of space X

Polynomial Approximation

Let $\{p_1, p_2, \dots, p_n, \dots\}$ be an infinite family of linearly independent elements of X , e.g. a basis of polynomials and $X_n = \text{span}\{p_1, p_2, \dots, p_n\}$. We consider the sequence of finite-dimensional optimization problems

$$P_n^* = \inf_{x \in X_n} \langle f, x \rangle \text{ s.t. } \langle a_i, x \rangle = b_i, \langle c_t, x \rangle \leq d_t, \|x\|_X \leq M \quad (P_n)$$

which are restrictions of problem (P) to the finite-dimensional subspaces X_n (e.g. spaces of polynomials of degree at most $n - 1$).

Why consider Polynomial Approximation ?

Polynomial approximation is useful if we can prove the following two properties:

1. The problem (P_n) can be solved in practice using existing (finite-dimensional) optimization methods.
2. The sequence of optimal values P_n^* converges to the optimal value of the original problem P^* when $n \rightarrow \infty$.

Resolution of the Polynomial Approximation

- When X is an Hilbert space: P_n is a convex quadratic problem.
- When $X = L^\infty([a, b])$ or $X = W^{k, \infty}([a, b])$ with $X_n = \text{span}\{1, t, \dots, t^{n-1}\}$: P_n is a semidefinite problem.
- $X = L^q([a, b])$ or $X = W^{k, q}([a, b])$ with q even and $X_n = \text{span}\{1, t, \dots, t^{n-1}\}$: P_n is a structured convex problem.

Conclusion: for these cases, we are **able to solve (P_n) in polynomial time** using interior-point methods.

Convergence of the Polynomial Approximation

Let $A : X \rightarrow \mathbb{R}^L$ defined by $(Ax)_i = \langle a_i, x \rangle$. If

1. $\cup X_n$ is dense in X
2. there exists N_1 and $x \in X_{N_1}$ such that $Ax = b$, $\|x\|_X < M$ and $\inf_{t \in T} \left(\frac{d_t - \langle c_t, x \rangle}{\|c_t\|_{X'}} \right) > 0$
3. there exist N_2 and $\sigma_{N_2} > 0$ such that $\|Ax - b\| \geq \sigma_{N_2} \inf_{\tilde{x} \in X_{N_2}, A\tilde{x} = b} \|x - \tilde{x}\|_X \quad \forall x \in X_{N_2}$

Then P_n^* **converges to P^* when $n \rightarrow \infty$** , with a rate of convergence that we can characterize quantitatively (i.e. give an upper bound).

In particular, if there are no inequality constraints, $P_n^* \rightarrow P^*$ in $O(E_n(x_{opt}))$ where x_{opt} is an optimal solution of (P) and $E_n(x_{opt})$ is its best polynomial approximation error in X_n .

Example of Numerical results

We take $X = L^2([-1, 1])$ and no inequality constraints, define the (relative) approximation error as $e_n = \frac{P_n^* - P^*}{P^*}$ and illustrate two cases:

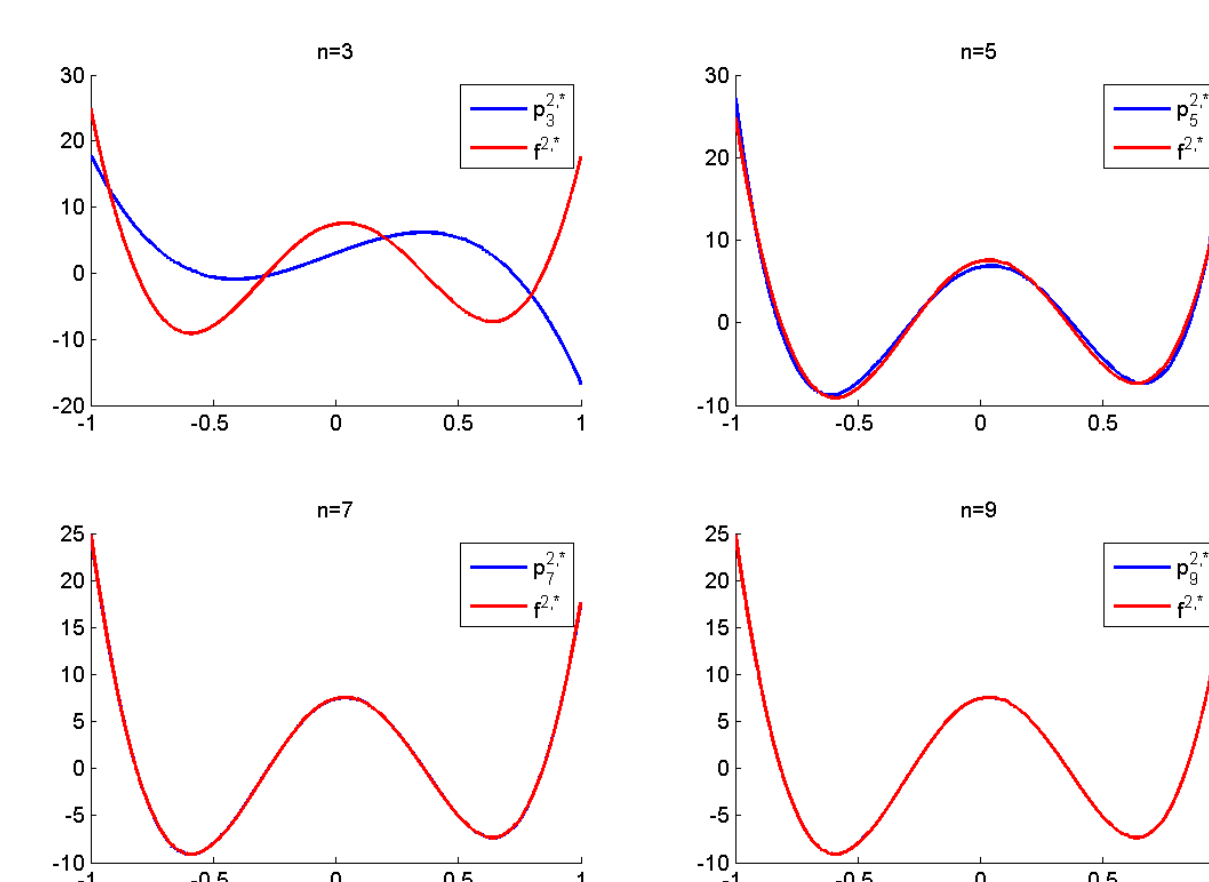
Problem data s.t. $x_{opt} \in C^\infty$
Convergence of the opt. values:

n	e_n
3	4,2119
5	0.0020408
7	4.5711×10^{-5}
9	2.27×10^{-7}

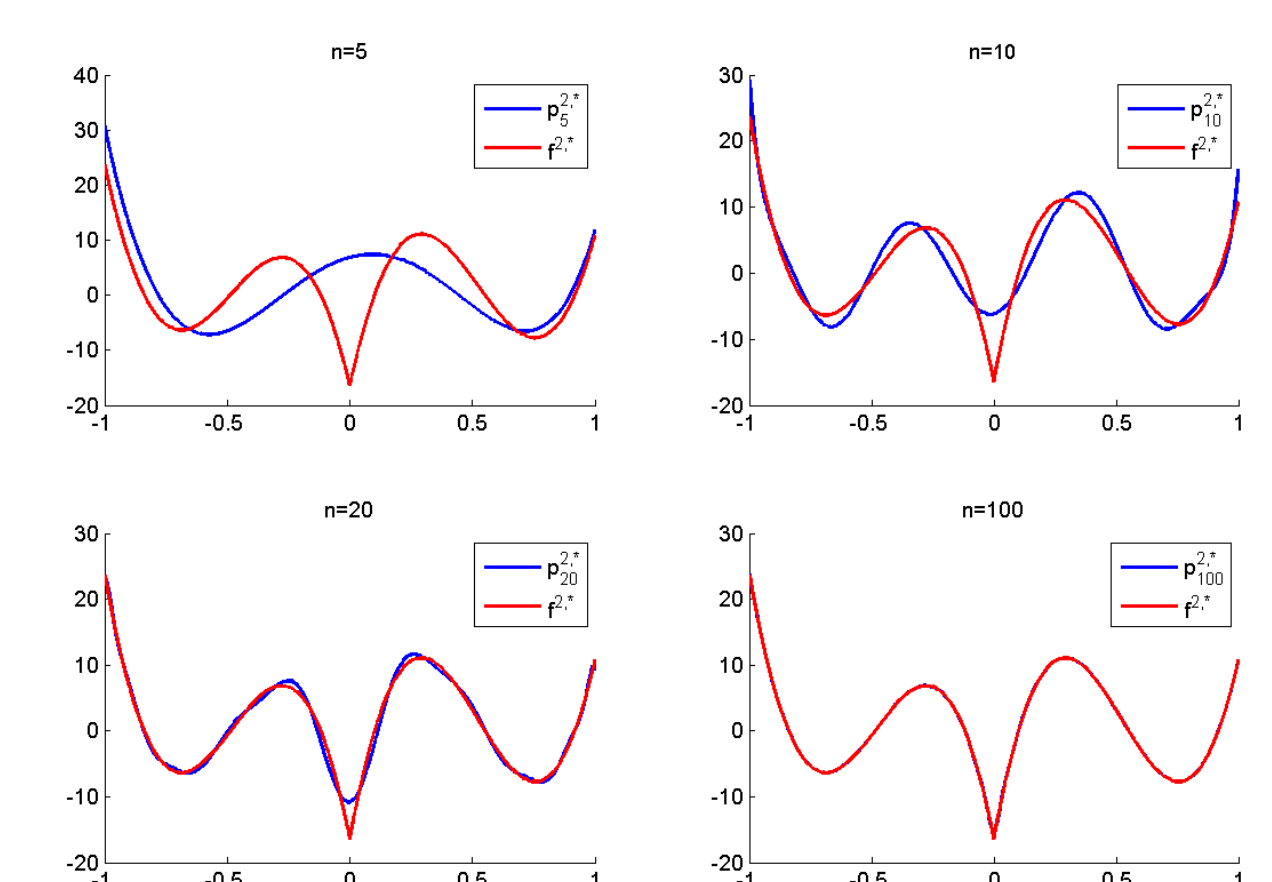
Problem data s.t. $x_{opt} \in C \setminus C^1$
Convergence of the opt. values:

n	e_n
5	0.50585
10	0.05980
20	0.0089009
100	8.4327×10^{-5}

Convergence of the opt. sol.:



Convergence of the opt. sol.:



Acknowledgements

The first author is an F.R.S-FNRS research fellow. This poster presents research results of the Belgian Network DYSCO, funded by the Interuniversity Attraction Poles Programme, initiated by the Belgian State, Science Policy Office. The scientific responsibility rests with its authors.