

OPTIMALITY CONDITIONS FOR FRACTIONAL LAPLACIAN

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1. GOALS

The goal of this note is to discuss the development of optimality conditions for an optimal control problem where the state equation (serving as a constraint) is the Fractional Laplacian. Here's the setup: we want to minimize the cost functional

$$\min J(u, z) = \frac{1}{2} \|u - u_d\|_{L^2(\Omega)}^2 + \frac{\lambda}{2} \|u\|_{L^2(\Omega)}^2,$$

subject to the state equation constraint

$$\begin{cases} (-\Delta)^s u(x) = z(x), & x \in \Omega \\ u(x) = 0, & x \in \mathbb{R}^n \setminus \Omega \end{cases}$$

Our parameters are as follows: $s \in (0, 1)$, $\lambda > 0$, and $u_d \in L^2(\Omega)$ are given, and the set of admissible controls is

$$Z_{\text{ad}} := \{\xi \in L^2(\Omega), a \leq \xi \leq b \text{ a.e.}\}$$

Finally, we note that the Fractional Laplacian $(-\Delta)^s$ is an operator of fractional type defined as

$$(-\Delta)^s u(x) := C(n, s) \int_{\mathbb{R}^n} \frac{u(x) - u(y)}{|x - y|^{n+2s}} dy$$

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2. THE STATE EQUATION

To have any hope of studying optimality conditions or the optimal control problem as a whole, we must first have well-posedness of the state equation.

Theorem 2.1. *Our state equation, a Dirichlet BVP for the Fractional Laplacian, has a unique solution, and there is a continuous dependence on the data (i.e., a stability estimate).*

Let's consider our function space. We define

$$X_0 := \tilde{H}^s(\Omega) = \left\{ u \in L^2(\Omega), \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{|u(x) - u(y)|^2}{|x - y|^{n+2s}} dy dx < \infty, u = 0 \text{ on } \mathbb{R}^n \setminus \Omega \right\} := \\ \{u \in L^2(\Omega), [u]_{\tilde{H}^s(\Omega)} < \infty, u = 0 \text{ on } \mathbb{R}^n \setminus \Omega\}$$

This space is Hilbert with the inner product

$$\langle u, v \rangle_{\tilde{H}^s(\Omega)} = \langle u, v \rangle_{L^2(\Omega)} + \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(v(x) - v(y))}{|x - y|^{n+2s}} dy dx$$

and the norm

$$\|u\|_{\tilde{H}^s(\Omega)} = \|u\|_{L^2(\Omega)} + \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{|u(x) - u(y)|^2}{|x - y|^{n+2s}} dy dx$$

That is, our state equation problem is posed on a Hilbert Space! Weak solutions of the Fractional Laplace Equation will satisfy the following for all $v \in \tilde{H}^s(\Omega)$ (see for instance [Ser]):

$$C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(v(x) - v(y))}{|x - y|^{n+2s}} dy dx = \int_{\mathbb{R}^n} z(x)v(x)dx,$$

of course with the same zero boundary condition as before. Clearly the left-hand side is a bi-linear form on $\tilde{H}^s(\Omega) \times \tilde{H}^s(\Omega)$ and the right-hand side is a linear form on $L^2(\Omega)$ (where z is taken as fixed data and v as a test function). In order to see that we are in a Lax-Milgram framework, we need to check some other properties of the bi-linear form. First, notice we have boundedness (continuity) through Cauchy-Schwarz:

$$\int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(v(x) - v(y))}{|x - y|^{n+2s}} dy dx \leq \left(\int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{|u(x) - u(y)|^2}{|x - y|^{n+2s}} dx dy \right)^{\frac{1}{2}} \left(\int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{|v(x) - v(y)|^2}{|x - y|^{n+2s}} dx dy \right)^{\frac{1}{2}}$$

The other thing to remark is that coercivity is immediate because of the equality

$$\int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{|u(x) - u(y)|^2}{|x - y|^{n+2s}} dx dy = [u]_{\tilde{H}^s(\Omega)}^2$$

Therefore, by the Lax-Milgram Theorem (see for instance Corollary 5.8 in [Bre]), there is a unique weak solution $u \in \tilde{H}^s(\Omega)$ to the Fractional Laplace Equation for any given data $z \in L^2(\Omega)$.

As for continuous dependence, set $v := u$ in the weak formulation:

$$C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{|u(x) - u(y)|^2}{|x - y|^{n+2s}} dx dy = \int_{\mathbb{R}^n} z(x)u(x) dx$$

Use the Cauchy-Schwarz Inequality on the RHS to conclude there exists a constant $C > 0$ (different from above) such that

$$[u]_{H^s(\Omega)}^2 \leq C \|z\|_{L^2(\Omega)} \|u\|_{L^2(\Omega)}$$

To proceed, we need the Fractional Poincaré Inequality

$$\|u\|_{L^2(\Omega)} \leq C [u]_{H^s(\Omega)}$$

We use it on the greater side of our to-be stability estimate to get

$$\begin{aligned} [u]_{H^s(\Omega)}^2 &\leq C \|z\|_{L^2(\Omega)} [u]_{H^s(\Omega)} \Rightarrow \\ [u]_{H^s(\Omega)} &\leq C \|z\|_{L^2(\Omega)}, \end{aligned}$$

which is certainly a stability estimate. We hence have well-posedness for our state equation.

3. REDUCED COST APPROACH

Henceforth let $S : L^2(\Omega) \rightarrow W^{s,2}(\Omega)$ be the control-to-state mapping. Then due to the well-posedness of the state equation, solving the original optimal control problem is equivalent to solving the **reduced problem**

$$\min \left\{ F(z) := \frac{1}{2} \|Sz - u_d\|_{L^2(\Omega)}^2 + \frac{\lambda}{2} \|z\|_{L^2(\Omega)}^2 \right\}$$

over $z \in Z_{\text{ad}}$, subject to the same constraint. Notice that our set Z_{ad} is non-empty, closed, convex, and bounded. Since the solution mapping S is continuous, F is continuous; since S is linear, F is convex. In fact, since $\lambda > 0$, F is strictly convex. With this mind we have a unique minimizer for the reduced problem over our desired domain, and in turn we have a unique minimizer for the original [constrained] optimal control problem. We have implicitly used the following theorem and corollary to reach this conclusion.

Theorem 3.1 (Projection Theorem). *Let $(Z, \|\cdot\|)$ be a Hilbert Space, $K \subset Z$ be closed and convex, and let $\xi \in Z$. Then there exists a projection onto K (i.e. a $z \in K$) so that*

$$\|\xi - z\| = \inf_{x \in K} \|\xi - x\|$$

Moreover, z can be characterized by the variational inequality

$$\langle \xi - z, x - z \rangle \geq 0$$

for all $x \in K$.

Corollary 3.2 (Direct Method as Projection). *Let $F : Z \rightarrow \mathbb{R}$ be convex and lower semi-continuous with K as before. Then $\exists \xi \in K$ so $F(\xi) \leq F(x)$ for all $x \in K$. If F is strictly convex, then the choice of ξ is unique.*

4. THE FORMAL LAGRANGIAN APPROACH

The calculations in this section are formal

We define the Lagrangian to be

$$L(u, z, p) = J(u, z) - \int_{\Omega} p(-\Delta^s u - z) dx$$

As always, a stationary point will satisfy the conditions $D_u L = 0$, $D_z L \geq 0$, and $D_p L = 0$ in the [linear] operator sense. From these we have the following relations:

$$\begin{aligned} \langle D_z L, z - h_z \rangle &= \langle \lambda z, z - h_z \rangle + \langle p, z - h_z \rangle \geq 0 \Rightarrow \langle z - \left(-\frac{1}{\lambda}\right) p, z - h_z \rangle \geq 0 \\ D_u L = 0 &\Rightarrow \langle u - u_d, h_u \rangle - \langle \Delta^s p, h_u \rangle = 0 \\ D_p L = 0 &\Rightarrow \langle -\Delta^s u - z, h_p \rangle = 0 \end{aligned}$$

In fact, the equalities tell us that necessary conditions for attaining a stationary point of the Lagrangian are

$$\begin{aligned} -\Delta^s p &= u - u_d \\ -\Delta^s u &= z \end{aligned}$$

And, based on our projection characterization, $z = \mathbb{P}_{Z_{\text{ad}}} \left(-\frac{1}{\lambda} p\right)$. For our particular choice of set Z_{ad} , $z = \max \left\{ a, \min \left\{ b, -\frac{1}{\lambda} p \right\} \right\}$. One advantage of this particular choice of Z_{ad} is that the projection formula is nice and easy to write concisely.

5. THE LAGRANGIAN APPROACH

We need to directly calculate criteria for which

$$\langle DF(z), h_z - z \rangle \geq 0$$

for all $h_z \in Z_{\text{ad}}$. To do this, we set up a difference quotient:

$$\begin{aligned} F(z+th) - F(z) &= \frac{1}{2} \|S(z+t(h-z)) - u_d\|_{L^2(\Omega)}^2 - \frac{1}{2} \|Sz - u_d\|_{L^2(\Omega)}^2 + \frac{\lambda}{2} \|z+th\|_{L^2(\Omega)}^2 - \frac{\lambda}{2} \|z\|_{L^2(\Omega)}^2 = \\ &= \frac{t}{2} \langle S(h-z), zSz - u_d \rangle + \frac{t^2}{2} \|S(h-z)\|_{L^2(\Omega)}^2 + \frac{\lambda}{2} \|z+th\|_{L^2(\Omega)}^2 - \frac{\lambda}{2} \|z\|_{L^2(\Omega)}^2 = \\ &= t \langle S^*(Sz - u_d), h - z \rangle + O(t^2) + \frac{\lambda}{2} \|z+th\|_{L^2(\Omega)}^2 - \frac{\lambda}{2} \|z\|_{L^2(\Omega)}^2 \end{aligned}$$

These quantities are all non-negative so long as z refers to a solution of the optimal control problem.

To actually obtain a derivative, we have to divide across by t and then send $t \rightarrow 0^+$. The latter two terms simply become $\lambda \langle z, h \rangle$ owing, for instance, to the example presented in Section 2.6 of [Trö]. As a result, we can combine the two terms and get the inequality

$$\langle S^*(Sz - u_d) + \lambda z, h_z - z \rangle \geq 0$$

In fact, the converse holds: that is, if the above inequality holds for all $h_z \in Z_{\text{ad}}$, then z is a solution to the optimal control. The convexity of the cost functional is crucial for this realization.

Remark 5.1. *The development of the variational inequality follows the statements and proofs of Lemma 2.21 and Theorem 2.22 in [Trö].*

Now, provided that $S \in B(L^2(\Omega))$, $p = S^*(Sz - u_d) \in L^2(\Omega)$, then it follows that

$$\left\langle z - \left(-\frac{1}{\lambda}p\right), z - h_z \right\rangle \geq 0$$

for all $z \in Z_{\text{ad}}$.

Thus by reduction, the task that remains is to characterize the adjoint. Let $u := Sz \in H_0^1(\Omega)$, then we want $\langle Sz, p \rangle = \langle z, S^*\varphi \rangle \forall z \in L^2(\Omega)$, and $\langle Sz, p \rangle = \langle u, \varphi \rangle$, where $\varphi = u - u_d$.

Now we claim that $p = S^*(Sz - u_d)$ for all $z \in Z_{\text{ad}}$ (where u was chosen to correspond to an arbitrary z via S). To see this, notice that since $u = Sz$, we have that for all $w \in H_0^s(\Omega)$,

$$\langle z, w \rangle = \langle u, w \rangle \Rightarrow \int_{\Omega} z w dx = C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(w(x) - w(y))}{|x - y|^{n+2s}} dx dy$$

so now, we set $z := u - u_d$ and $w := p$, and we obtain

$$\begin{aligned} \int_{\Omega} p(u - u_d) dx &= C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(p(x) - p(y))}{|x - y|^{n+2s}} dx dy \Rightarrow \\ \int_{\Omega} p(Sz - u_d) dx &= C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(p(x) - p(y))}{|x - y|^{n+2s}} dx dy \Rightarrow \end{aligned}$$

Since p satisfies the adjoint state equation $C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(v(x) - v(y))(p(x) - p(y))}{|x - y|^{n+2s}} dx dy = \int_{\Omega} (u - u_d)v dx$ over $v \in H^s(\Omega)$ by definition of the adjoint state equation (setting $v := u$)¹, we have

$$\begin{aligned} \langle \varphi, Sz \rangle &= \langle Sz, p \rangle \Rightarrow \\ \langle S^*\varphi, z \rangle &= \langle p, Sz \rangle \end{aligned}$$

for all $z \in L^2(\Omega)$, and so $p = S^*\varphi$ (as they agree in the weak sense). In summary, the optimality conditions are the following: for $u \in H_0^s(\Omega)$, the following hold for all $v, w \in H_0^s(\Omega)$:

$$\begin{aligned} C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(u(x) - u(y))(v(x) - v(y))}{|x - y|^{n+2s}} dx dy &= \int_{\Omega} z v dx \\ C(n, s) \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} \frac{(w(x) - w(y))(p(x) - p(y))}{|x - y|^{n+2s}} dx dy &= \int_{\Omega} (u - u_d) w dx \end{aligned}$$

¹also see Definition 3.4 in [D'Elia]

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