

Calculus of Variations, Lecture 8, 3/26/2013

1st half: optimization with a pde constraint
(The "adjoint eqn" method) Then another
looks at the Pontryagin Max Principle

2nd half: start multidimensional calc of varns,
by discussing nonlinear elasticity

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Consider the following question: for $a \in \mathbb{R}$,
let $u = u_a$ solve

$$\begin{aligned} -\Delta u + a u &= 1 && \text{in } D \\ u &= 0 && \text{at } \partial D \end{aligned}$$

where D is a fixed domain. Problem: find

$$\min_{a \in \mathbb{R}} \int_D |u_a - g|^2,$$

or more generally evaluate $f'(a)$ where

$$F(a) = \int_D |u_a - g|^2.$$

Why are we asking this?

- 1) Optimal control is pretty similar, except constraint is an ODE instead of a pde & the control is a function of s rather than constant
- 2) There are lots of situations where we're interested in pde's with parameters, & we may want to optimize some functional of the solution, or to know how it depends on the parameters.

Answer to the problem is this: given any $a \in \mathbb{R}$, we have

$$F'(a) = -2 \int_D u_a p_a$$

where $p = p_a$ solves $-\Delta p + ap = u_a - g$

Explanation: since $F(a) = \int_D |u_a - g|^2$ we have

$$F'(a) = \int_D 2(u_a - g) \dot{u}_a$$

where $\dot{u}_a = \frac{d}{da} u_a$. But differentiating the eqn gives

$$-\Delta \dot{u}_a + u_a + a \ddot{u}_a = 0 \text{ in } D.$$

$$\dot{u}_a = 0 \text{ at } \partial D$$

Now, multiply eqn for $p = p_a$ by \dot{u}_a to get

$$\int_D (u_a - g) \dot{u}_a = \int_D (-\Delta p_a + a p_a) \dot{u}_a$$

$$= \int_D (-\Delta \dot{u}_a + a \dot{u}_a) p_a$$

$$= - \int_D u_a p_a$$

We can derive the Pontryagin Max Prin by a very similar argument. The main differences, as noted earlier, are that the control is a fn and the eqn is an ode.

Concretely, as in lecture 7, $\max_{\alpha(s)} \int_0^T h(y(s), \alpha(s)) ds + g(y(T))$

with state eqn $y_s = f(y, \alpha)$. We want to take 1st var of the objective, so for any $\alpha(s)$ and $\dot{\alpha}(s)$ let

$$\alpha(s, \varepsilon) = \alpha(s) + \varepsilon \dot{\alpha}(s)$$

$$\dot{y}(s) = \frac{\partial}{\partial \varepsilon} \Big|_{\varepsilon=0} y(s, \varepsilon), \text{ etc.}$$

The optimality condition is of course that the

1st variation of the objective vanishes for all choices of $\dot{\alpha}(s)$ (I assume there are no piecewise restrictions on $\dot{\alpha}(s)$), ie

$$\int_t^T h_y \dot{y} + h_x \dot{\alpha} ds + g_y(y(T)) \dot{y}(T) = 0$$

for all $\dot{\alpha}(s)$. Differentiating the state eqn gives

$$\dot{y}_x = f_y \dot{y} + f_x \dot{\alpha} \rightarrow \dot{y}(t) = 0.$$

Making an inspired choice, we let $p(s)$ solve

$$p_s = -f_y(y(s), \alpha(s)) p(s) - h_y(y(s), \alpha(s)), \quad t \leq s \leq T$$

$$p(T) = g_y(y(T))$$

(secretly: $p(s)$ will be the $\pi(s)$ of the PMP, and 1st eqn says $p_s = -\nabla_y H$)

Then

$$\int_t^T p_s \dot{y} = \int_t^T -f_y \dot{y} p - h_y \dot{y}$$

$$\text{LHS} = g_y(y(T)) \dot{y}(T) - \cancel{p(T) \dot{y}(T)} - \int_t^T p \dot{y}_x$$

$$\text{RHS} = \int_t^T -p \dot{y}_x + f_x p \dot{\alpha} - h_y \dot{y}$$

So

$$g_y(y(\tau)) \dot{y}(\tau) = \int_t^T f_x p \dot{x} - h_y \dot{y}$$

Thus: 1st var of objective is

$$\begin{aligned} & \int_t^T h_y \dot{y} + h_x \dot{x} ds + g_y(y(\tau)) \dot{y}(\tau) \\ &= \int_t^T (h_x + f_x p) \dot{x}(s) ds. \end{aligned}$$

1st var = 0 for all $\dot{x}(s) \Leftrightarrow h_x + f_x p = 0$

$\Leftrightarrow x(s)$ achieves the
optimum at $y(s), p(s)$ of
 $H(p, x) = \max_{\alpha} \{ f(x, \alpha) \cdot p + h(x, \alpha) \}$

So: from this perspective $p(s)$ (formerly $\pi(s)$)
solves the "adjoint eqn" and the cond that
 x be optimal for defn of H is the optimality
condition.

Advantage of this viewpt: if you have guessed
 $x(s)$ and it isn't optimal, we can get a
better chance by "steepest descent", simply
taking $\dot{x}(s) = - (h_x + f_x p)$ along the path assoc
to $x(s)$.

Exercise related to the above :

(1) Returning to the calculation at the beginning of the section, suppose the pde is

$$-\Delta u + axu_x + byu_y = 1 \quad \text{in } D \\ u = 0 \quad \text{at } \partial D$$

where $D \subset \mathbb{R}^2$ and $a, b \in \mathbb{R}$. Consider once again

$$F(a, b) = \int_D |u - g|^2.$$

Use the "adjoint eqn" method to obtain expressions for $\frac{\partial F}{\partial a}$ and $\frac{\partial F}{\partial b}$.

(2) Now let's let the unknown coefficient be a function of x : given $a(x)$, defined on D , let $u = u_a$ solve

$$-\Delta u + a(x)u = 1 \quad \text{in } D \\ u = 0 \quad \text{at } \partial D$$

and consider

$$F[a] = \int_D |u_a - g|^2$$

where $g(x)$ is given. If $a(x, \varepsilon) = a(x) + \varepsilon \dot{a}(x)$, find an expression for $F = \left. \frac{d}{d\varepsilon} \right|_{\varepsilon=0} F[a(x, \varepsilon)]$. That's if

The form

$$\dot{F} = \int_D \varphi(x) \dot{a}(x) dx$$

where φ depends on $a(x)$ but not on $\dot{a}(x)$.
 $(\varphi$ is, essentially, the "gradient" of F
with respect to $a(x)$.)

We now shift focus toward multidimensional problems in the calculus of variations.

Recall our discussion (early in the semester) of existence: we showed that it's sufft (for pblm of form $\min \int W(Du)$ to have a soln) that W be convex, with L^p growth at ∞ .

In the scalar setting ($u: \mathbb{R}^n \rightarrow \mathbb{R}$) convexity is also a necessary condition for a robust existence theory. (we'll discuss this soon). But for $u: \mathbb{R}^n \rightarrow \mathbb{R}^m$ ($n > 1, m > 1$) convexity is not really the right condn (it is sufft but not necessary).

Moreover this matters, e.g. for elasticity.

(Good sources on this: Dacorogna's book, on reserve;
or Ball's 1977 article in Arch Ratiocinal Mech + Anal.)

The var'l pbm assoc elasticity is:

$$\min_{\substack{u| = u_0 \\ \partial \Omega}} \int_{\Sigma} W(F) \, dx$$

where

Σ = reference (undeformed body) $\subset \mathbb{R}^3$
(assumed stress-free)

$x: \Sigma \rightarrow \mathbb{R}^3$ deformation, takes $X \in \Sigma$ to
 $x(X)$ = deformed position

$F = \frac{\partial x}{\partial X}$ $n \times n$ matrix ("deformation gradient")

$W(RF) = W(F)$ for all $R \in SO(3)$.
("frame indifference").

Last condn $\Leftrightarrow W(F)$ depends only on $(F^T F)^{1/2}$, since
by polar decomp.

$$F = R (F^T F)^{1/2} \quad \begin{array}{l} \text{[eigs of } (F^T F)^{1/2} \text{ are} \\ \text{the "principal stretches"} \end{array}$$

rot pos def symm

whenever F is a 3×3 orientation-preserving lin map.
(There's also an obvious analogue of all this
for "2D elasticity".)

A bit more abt W :

- a) $F = I$ is a local min (since undeformed state is stress-free)
- b) $W \rightarrow \infty$ as $\det F \rightarrow 0$ and as $|F| \rightarrow \infty$
(large compression or extension should be difficult)
- c) if material is isotropic then $W(F) = W(FR)$
for all other R ; comes to $W(F)$ being a symmetric fn of the eigenvalues of $(F^T F)^{1/2}$ ("principal stretches")

Key pt for us: W cannot be a convex fn of F , since $SO(3)$ is not convex.

In fact, we expect W to be minimized at both

$$I \text{ and } R_0 = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

but $W = \infty$ at $\frac{1}{2}I + \frac{1}{2}R_0 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$!

So: for theory of elasticity we need a class of nonconvex var'l prbs where

- (1) minimizer is achieved
- (2) preceding properties of W are possible

For simplicity let's focus on analogous issue in 2D (so $x(x) : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ + F is 2×2 ; everything discussed above still applies).

Ball showed that the class of "polyconvex funs" has the desired properties (1) + (2)

In 2D, $W(F)$ is polyconvex (by defn) if it has the form

$$W(F) = g(F, \det F) \quad \text{with } g \text{ a convex fun of its 5 arguments.}$$

Key questions:

(i) is this class large enough to include reasonable elastic energies?

(ii) why is $\int W(F)$ lower semicontinuous when $W = g(F, \det F)$ with g convex?

Answer to (i): yes! The choice

$$W(F) = A(r_1^\alpha + r_2^\alpha - c) + g(\det F)$$

works, where $r_1 + r_2$ are eigs of $(F^T F)^{1/2}$ (so $\det F = r_1 r_2$) and g is convex; here $A + c$ are constants, g must

be convex, + the restrn $W = \min$ at $F = I$ places some restriction on them.

Polyconvexity of such W is due to

Lemma : a symmetric \ln of $v_1 + v_2$ determines a convex \ln of F if it is convex + increasing in each v_i

(Pf of Lemma is not trivial; see eg Ball's 1977 paper.)

Answer to (ii) : key pt is that $\det D\mathbf{x}$ is wly cont's under w_{loc} convergence in $W^{1,p}$ for $p > 2$.

More careful start: in this setting of maps $\mathbb{R}^2 \rightarrow \mathbb{R}^2$, $\det(\partial\mathbf{x}/\partial\mathbf{x})$ is quadratic in $\partial x_i/\partial x_\alpha$. So if a sequence $x^\circ(\mathbf{x})$ is bdd in $W^{1,p}$, $\det(\partial x^\circ/\partial\mathbf{x})$ is bdd in $L^{p/2}$. If $p > 2$, $p/2 > 1$, so this seq is precompact in w_{loc} topology on $L^{p/2}$. So (for a subsequence) $\det(\partial x^\circ/\partial\mathbf{x})$ converges wly to some $L^{p/2}$ fn. Our assertion is that The w_{loc} limit is $\det(\partial x^\infty/\partial\mathbf{x})$ (if $x^\circ \rightarrow x^\infty$ wly in $W^{1,p}$).

If we grant the assertion above then existence via direct method is easy. Need only prove lower semicontinuity.

1st pt: use Fenchel transform of Ψ , where
 $W = \Psi(F, \det F)$.

Evidently $\Psi(F, \det F) = \sup_{G, t} G \cdot F + t \cdot \det F - \Psi^*(G, t)$

So

$$\int \Psi(Dx, \det Dx) = \sup_{G(x), t(x)} \int G \cdot F(x) + t \cdot \det F - \Psi^*(G, t).$$

- sup of weakly compact lns

2nd pt: just use that a convex ful is lsc under weak convergence; so $F^\nu = \partial x^\nu / \partial X \rightarrow F^\infty = \partial x^\infty / \partial X$ and $\det F^\nu \rightarrow \det F^\infty$ weakly in $L^p \times L^{p/2}$ implies

$$\liminf \int \Psi(F^\nu, \det F^\nu) \geq \int \Psi(F^\infty, \det F^\infty)$$

when Ψ is convex (with appropriate growth).

It remains to explain The wh cent'y of $\det Dx$.
 Main pt:

(*) $\det D\mathbf{x}$ can be expressed as a divergence

[How could we have guessed this? Well,

$\int_L \det D\mathbf{x} = \text{area of image of } L$, if $\det D\mathbf{x} > 0$.

So integral depends only on bdry data. How else could this happen, but by $\det D\mathbf{x}$ being a divergence? Note corollary to the preceding: EL eqn for var'l ptm $\int_L \det D\mathbf{x}$ must be an identity. Therefore we say $\det D\mathbf{x}$ is a "null-Lagrangian".]

Pf of (*), via exterior calculus:

$$d(x_1 dx_2) = dx_1 \wedge dx_2 = (\det D\mathbf{x}) dX_1 \wedge dX_2.$$

Same pf, in coordinates:

$$\det D\mathbf{x} = \partial_1 x_1 \partial_2 x_2 - \partial_1 x_2 \partial_2 x_1$$

$$= \partial_1 (x_1 \partial_2 x_2) - \partial_2 (x_1 \partial_2 x_2)$$

To see why (*) implies ab convergence of $\det D\mathbf{x}^v$ to $\det D\mathbf{x}^\infty$ when $x^v \rightarrow x^\infty$ wly $W^p P$ ($p > 2$), it's sufft to prove convergence as distributions. So let

φ be smooth with cpt supp. Then

$$\int_{\Omega} (\det D\chi) \varphi = \int_{\Omega} -x_1 \partial_2 x_2 \partial_1 \varphi + x_1 \partial_1 x_2 \partial_2 \varphi$$

If $x^\nu \rightarrow x^\infty$ weakly $W^{1,p}$ then

$$\int_{\Omega} x_1^\nu \partial_2 x_2^\nu \partial_1 \varphi \rightarrow \int_{\Omega} x_1^\infty \partial_2 x_2^\infty \partial_1 \varphi$$

since $x_1^\nu \rightarrow x_1^\infty$ strongly in L^p (using Rellich)
 $\partial_2 x_2^\nu \rightarrow \partial_2 x_2^\infty$ weakly in L^p (by hypothesis)

+ similarly for the other term.

Ext'n of above descn to 3D elasticity: each
 2×2 minor is weakly cont's in $L^{p/2}$ under wle conv.
 in $W^{1,p}$ ($p > 2$); also the 3×3 det is weakly cont's
 in $L^{p/3}$ under wle conv in $W^{1,p}$ ($p > 3$).

Suggested exercises :

- (1) We showed that if $x^\nu \rightarrow x^\infty$ weakly in $W^{1,p}(\Omega)$, $p > 2$
 (for maps $\mathbb{R}^2 \rightarrow \mathbb{R}^2$; by defn this means $\int_{\Omega} |Dx^\nu|^p \leq C$
 with C indep of ν , and $\int_{\Omega} \langle Dx^\nu, \varphi \rangle \rightarrow \int_{\Omega} \langle Dx^\infty, \varphi \rangle$ for any
 L^p vector field φ on Ω) Then $\det Dx^\nu \rightarrow \det Dx^\infty$

wkly. $L^{p/2}$. When $\{x^n\}$ are more singular strange things can happen due to "cavitation." Explore this by considering the map $x^n: B_1 \rightarrow B_1'$ (where B_1 = unit ball in \mathbb{R}^2) such that

$$x^n(x) = \begin{cases} \frac{1-p_n}{p_n} X & \text{for } |X| \leq p_n \\ \left(\frac{1-2p_n}{1-p_n} + \frac{p_n}{1-p_n} |X| \right) \frac{X}{|X|} & \text{for } p_n \leq |X| < 1 \end{cases}$$

so x^n "blows up" B_{p_n} to B_{1-p_n} and "squashes" $B_1 \setminus B_{p_n}$ to $B_1 \setminus B_{1-p_n}$. (Here p_n can be any sequence $\{p_n\}$ converging to 0.)

- Show that $x^n(X) \rightarrow \frac{X}{|X|}$ a.e.
- Show that $\det Dx^n$ converges as a distribution to a point mass located at 0
- For which p does $\int |Dx^n|^p dX$ stay bounded as $n \rightarrow \infty$? $[B_1]$

[Comment: for additional examples, some similar and others rather different, see 37 of J Ball + F Murat, J Functional Analysis 58 (1984) 225-253. That section is independent of the rest of the paper.]

(2) Show that if $\int g(\det Du) dx$ is lower semicontinuous (for $S\subset \mathbb{R}^2$, $u:S \rightarrow \mathbb{R}^2$) then g must be convex.

Hint: it suffices to show that

$$g(\theta a + (1-\theta)b) \leq \theta g(a) + (1-\theta)g(b) \quad \text{for } 0 < \theta < 1$$

and $a, b \in \mathbb{R}$. Do this by considering $u_\varepsilon(x, y) = (u_1(x), u_2(y))$ defined by

$$u_1(x, y) = (\theta a + (1-\theta)b)x + \varepsilon g(x/\varepsilon)$$

$$u_2(x, y) = y$$

where $g: \mathbb{R} \rightarrow \mathbb{R}$ is periodic with period 1 such that

$$g(t) = \begin{cases} t(1-\theta)(a-b) & 0 < t < \theta \\ (t-\theta)\theta(a-b) & \theta < t < 1 \end{cases}$$

(3) It can be nontrivial to determine whether a given function $W(F)$ is polyconvex or not. As an example, show that in the 2×2 setting

$$W(F) = \begin{cases} 1 + |F|^2 & \text{if } \rho(F) \geq 1 \\ 2\rho(F) - 2|\det F| & \text{if } \rho(F) \leq 1 \end{cases}$$

is polyconvex, when $|F|^2 = \sum_{i,j=1}^2 |F_{ij}|^2$ and

$$\rho(F) = (|F|^2 + 2|\det F|)^{1/2}.$$

(This example arose as the "relaxation" of a nonconvex problem from "optimal designs", in my work with Strang in the 80's.)

Hint: show that $W(F) = g(F, \det F)$ where

$$g(F, t) = \max_{\alpha = \pm 1} \left\{ f\left(\left[|F|^2 + 2\alpha \det F\right]^{\frac{1}{2}}\right) - 2\alpha t \right\}.$$

in which

$$f(t) = \begin{cases} 1+t^2 & t \geq 1 \\ 2t & t \leq 1 \end{cases},$$

Then check that $g(F, t)$ is a convex function of F and t .