

① 3/22/2023

Learning a Linear System

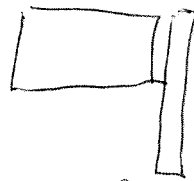
Suppose we want to minimize

$$\text{Loss: } \mathcal{L}(x, p) = \frac{1}{2} \|x - y\|^2 + \frac{\lambda}{2} \|p\|^2 \quad \text{for a known } y$$

$\uparrow \quad \uparrow \quad \uparrow$
 $\mathbb{R}^n \quad \mathbb{R}^L \quad \mathbb{R}^n$

$$\text{s.t. } f(x, p) = Ax + Bp = 0_n$$

$n \times n \quad n \quad n \times 1 \quad 1 \quad n$



lots of parameters

or



a few parameters

e.g. We have measurements y_1, \dots, y_n
that approximate x_1, \dots, x_n
or perhaps

$$\mathcal{L}(x, p) = y^T x + v^T p \quad \text{etc.}$$

Basic Loop

Start at x, p with $f(x, p) = 0$

(1) update p (e.g. Follow $-\nabla_p \mathcal{L}$)

(2) compute $f(x, p)$ (not 0 now)

(3) update x (f 0 again)

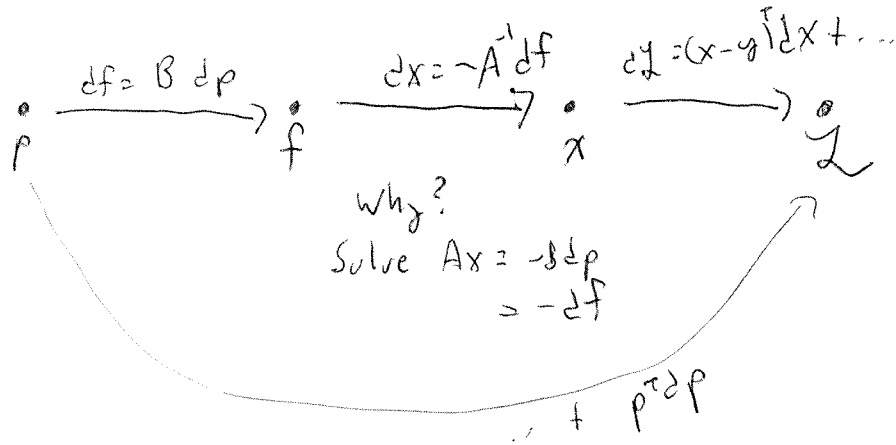
~~Repeat~~

(4) compute \mathcal{L}

Repeat

(2)

Write as a graph



$$\frac{dy}{dp} = (x-y)^T \underbrace{(-A^{-1})B}_{\text{Matrix} \setminus \text{matrix}} + p^T \quad \text{forward mode}$$

$$\nabla_p y = -B^T \underbrace{(A^{-T})}_{\text{Matrix} \setminus \text{vector}} (x-y) + p \quad \text{reverse mode}$$

You've seen this before: with one output
reverse is better because vector(Matrix)(Matrix)

(3)

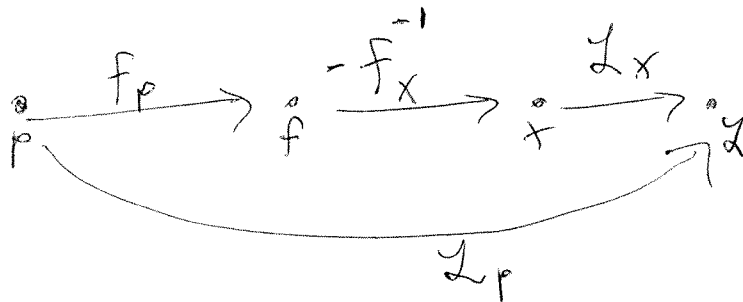
Generalize to non-linear problems

$$\min_{\substack{x, p \\ \uparrow \quad \uparrow \\ n \quad q}} \mathcal{L}(x, p) \quad \text{s.t.} \quad f(\substack{x, p \\ \uparrow \quad \uparrow \\ n \quad q}) = \substack{0 \\ \uparrow \\ n}$$

last example

For ease of notation write $f_x = \frac{\partial f}{\partial x}$ $n \times n$ matrix (was A)
 $f_p = \frac{\partial f}{\partial p}$ $n \times q$ matrix (was B)

$$\mathcal{L}_x = \frac{\partial \mathcal{L}}{\partial x} \quad 1 \times n \text{ matrix (was } (x-y)^T \text{)} \\ \mathcal{L}_p = \frac{\partial \mathcal{L}}{\partial p} \quad 1 \times q \text{ matrix (was } p^T \text{)}$$



$$\frac{d\mathcal{L}}{dp} = \mathcal{L}_x (-f_x^{-1}) f_p + \mathcal{L}_p$$

$$\nabla_p \mathcal{L} = - f_p^T \underbrace{f_x^{-T} \mathcal{L}_x^T}_{\lambda^T} + \mathcal{L}_p^T$$

Solve $f_x^T \lambda = \mathcal{L}_x^T$ λ is $1 \times n$

$$\nabla_p \mathcal{L} = \underbrace{1 \times n}_{\lambda^T} \underbrace{n \times q}_{f_p^T} + \underbrace{1 \times q}_{\mathcal{L}_p^T}$$

$\nabla_p \mathcal{L} = \mathcal{L}_p^T - f_p^T \lambda^T$

(4)

Learning a differential equation

A vector x is a "discrete function" as much as a
 $i \rightarrow x[i]$ for $i=1, \dots, n$ memory address
vector value

A cont function looks like
 $t \rightarrow u(t)$ on $[t_0, T]$ $u(t) \in \mathbb{R}^n$

Instead of

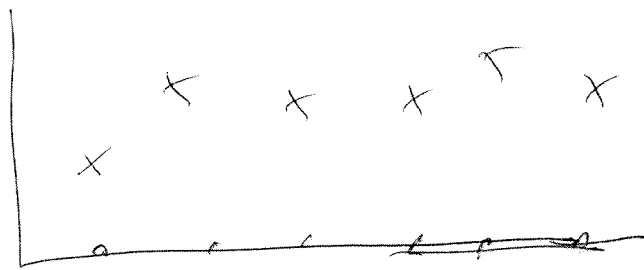
$$\mathcal{L}(x, p) = \frac{1}{2} \|x - y\|^2 + \frac{1}{2} \|p\|^2$$

we can have

$$\mathcal{L}(u, p) = \frac{1}{2} \int_{t_0}^T (u(t) - y(t))^2 dt + \frac{1}{2} \|p\|^2$$

or even

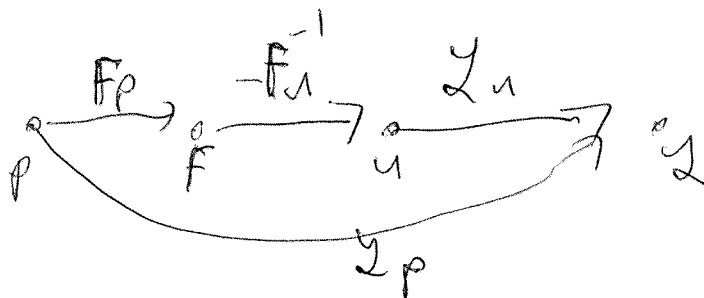
$$\sum (u(t_i) - y_i)^2$$



you know
these
values
what is p ?

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Need the analogs



$$F(u, p) = t \rightarrow u'(t) - f(u, p, t)$$

$$[t, T] \rightarrow \mathbb{R}$$

$$p \in \mathbb{R}^q$$

$$F_p: \text{continuous } \times \begin{matrix} q \\ \text{cont} \times \mathbb{R}^n \end{matrix}$$

$$F_p: \text{contin} \times \text{contin}$$

$$\begin{matrix} \text{cont} \times \mathbb{R}^n \\ [t_0, T] \end{matrix}$$

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To be more general

$$\text{let } \mathcal{L}(u, p) = \int_{t_0}^T g(u, p) dt$$

$$= \int_{t_0}^T g(u(t), p) dt$$

$\mathcal{L}_p = \frac{\partial \mathcal{L}}{\partial p} \rightarrow$ scalar function of $p \in \mathbb{R}^q$
row vector

$$\mathcal{L}(u, p + \varepsilon e_i) - \mathcal{L}(u, p) \approx \varepsilon (\mathcal{L}_p)_i$$

$$\text{and } \mathcal{L}_p(u, p) = \int_{t_0}^T g_p(u, p) dt$$

differentiate inside the integral

\mathcal{L}_u : If u were just a scalar
 \mathcal{L}_u would be $1 \times n$
so now \mathcal{L}_u is $1 \times (\text{continuous } n)$

that is given t & i we can obtain

$$\mathcal{L}_u : (t, i) \rightarrow \text{scalar}$$

$$\mathcal{L}(u + \varepsilon f(t - t_0) e^i, p) - \mathcal{L}(u, p)$$

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What is an inner product
on functions $u(t) : [t_0, T] \times \{1, \dots, n\} \rightarrow \mathbb{R}$

Well if $\langle u, v \rangle$ in \mathbb{R}^n is $\sum u_i v_i$

& $\langle f, g \rangle$ on $[t_0, T]$ is $\int f(t)g(t) dt$

$$\langle u(t), v(t) \rangle = \int_{t_0}^T u(t)^T v(t) dt$$

combines the best of
both worlds

$$F(u, p) = t \rightarrow u(t) - f(u, p, t)$$

to find an adjoint means to find
an operator on $\lambda(t)$ s.t

$$\langle \lambda(t), \frac{d}{dt}(u'(t) - f(u, p, t)) \rangle = \langle (\lambda^T(t), u(t)) \rangle$$

$$\int \lambda(t)^T \frac{d}{dt}(u'(t) - f(u, p, t)) dt$$

Suppose
 $u_p(t_0) = 0$
 $\lambda(T) = 0$

$$\text{Let } S = u_p$$

$$S' = u'_p \quad (\text{prime} = \frac{d}{dt})$$

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$$\int_{t_0}^{\tau} \lambda^T (s' - f_u s - f_p) dt$$

$$= \int_{t_0}^{\tau} \lambda^T s' dt - \int_{t_0}^{\tau} \lambda^T f_u s dt - \int_{t_0}^{\tau} \lambda^T f_p dt$$

$$= \left[\lambda^T s \right]_{t_0}^{\tau} - \int_{t_0}^{\tau} (\lambda^T)' s dt - \int_{t_0}^{\tau} \lambda^T (f_u s - f_p) dt$$

$$\uparrow$$

vanish

$$\lambda(\tau) = 0$$

$$s(t_0) = 0$$

$$\lambda^T = -\frac{\partial p^T}{\partial u} \lambda + \left(\frac{dy}{du} \right)^T$$

The adjoint is a difeq!