

## Lecture 4: Solving the Lagrangian equation

Last time: convert the AD eq'n to Lagrangian coordinates:

$$\partial_t \Theta = \kappa \nabla_x \cdot (g^{-1} \nabla_x \Theta)$$

where  $\dot{x} = u(x, t)$ ,  $x(0) = X$

For instance, start with linearized velocity equation:  
("Filament" lecture)  $\rightarrow$  transpose

$$\partial_t \theta + x \cdot A^T(t) \cdot \nabla_x \theta = \kappa \Delta_x \theta$$

with  $u(x) = x \cdot A^T(t)$ ,  $\text{trace } A = 0$ .

Trajectories satisfy:  $\dot{x} = x \cdot A^T(t)$ ,  $x(0) = X$ ,

Try the solution:  $(\text{or } \dot{x} = A(t) \cdot x)$

$$x(t) = \exp\left(\int_0^t A(\tau) d\tau\right) \cdot X$$

The matrix exponential is defined from its Taylor series,

$$e^B = I + B + \frac{1}{2} B^2 + \dots$$

Check: with  $B(t) = \int_0^t A(\tau) d\tau$ ,  $\dot{B} = A(t)$ ,

$$\begin{aligned} \frac{d}{dt} \exp B(t) &= \frac{d}{dt} \left( I + B + \frac{1}{2} B^2 + \dots \right) \\ &= \dot{B} + \frac{1}{2} (\dot{B}B + B\dot{B}) + \dots \end{aligned}$$

If the commutator

$$[B, \dot{B}] = \int_0^t [A(t), A(\tau)] d\tau$$

vanishes  $\forall t \geq 0$ , i.e.,

$$(1) \quad [A(t_1), A(t_2)] = 0, \quad \forall t_1, t_2 \geq 0$$

then we're good, and

$$\frac{d}{dt} \exp B(t) = e^B \cdot \dot{B} = e^B \cdot A$$

$$x^i = (e^B)^i_j x^j$$

so the solution is indeed  $x = e^{B(t)} \cdot X$ .

Also we then have

$$X = e^{-B(t)} \cdot x$$

With indices:  $X^p = [e^{-B}]^p_i x^i$

$\leftarrow$  rows  
 $\nwarrow$  columns

This immediately gives the deformation gradient,

$$\frac{\partial X}{\partial x} = e^{-B(t)}, \quad \left( \frac{\partial X^p}{\partial x^i} = [e^{-B}]^p_i \right)$$

and the metric  $g^{pq} = [e^{-B}]^p_i [e^{-B}]^q_i$

$$[e^{-B}]^p_i [e^B]^i_q = \delta^p_q \quad \text{or} \quad [g^{-1}]^{pq} = ([e^{-B}][e^{-B}]^T)^{pq} \\ = [e^{-B} e^{-B^T}]^{pq}$$

It is not a given that

$$e^{-B} e^{-B^T} = e^{-(B+B^T)}$$

This requires  $[B(t), B^T(t)] = 0$

The matrix  $B$  is then called normal.

$$[B(t), B^T(t)] = \int_0^t [A(\tau), A^T(\sigma)] d\tau d\sigma,$$

$$(2) \text{ so } [A(t_1), A^T(t_2)] = 0 \quad \forall t_1, t_2 \geq 0$$

$\Rightarrow B(t)$  normal.

In general we assume (1) (so we can use the matrix exponential), but not (2).

Progress is made by using the singular value decomposition (SVD) of  $e^B$ .

$$e^B = UDV^T, \quad U, V \text{ orthogonal}$$
$$e^{-B} = UD^{-1}V^T, \quad D \text{ diagonal } > 0$$

$$[g_{pq}] = e^{B^T} e^B = VDU^T UDV^T = VD^2V^T$$

$$[g^{pq}] = VD^{-2}V^T \quad D = \begin{pmatrix} \Lambda_1 & & \\ & \ddots & \\ & & \Lambda_n \end{pmatrix}$$

We can also write this in dyad notation:

$$g^{pq} = \sum_{\sigma} V^p_{\sigma} \Lambda_{\sigma}^{-2} V^q_{\sigma}$$
$$= \Lambda_u^{-2} u^p u^q + \Lambda_m^{-2} m^p m^q + \Lambda_s^{-2} s^p s^q$$

where  $\Lambda_u \geq \Lambda_m \geq \Lambda_s$  (drop  $\Lambda_m$  in 2D)

Note that  $\det \sqrt{g} = \Lambda_u \Lambda_m \Lambda_s = 1$

In 2D,  $\Lambda_u = 1, \Lambda_s = \Lambda_u^{-1}$ .

We call the directions  $u$  *unstable*  
 $m$  *middle*  
 $s$  *stable*

Insert into the AD equation:

$$\partial_t \Theta = \kappa \nabla_X \cdot (g^{-1} \nabla_X \Theta)$$

$$= \kappa \nabla_X \cdot \left( (\Lambda_u^{-2} uu + \Lambda_m^{-2} mm + \Lambda_s^{-2} ss) \cdot \nabla_X \Theta \right)$$

$$= \left[ \Lambda_u^{-2} (u \cdot \nabla_X)^2 + \Lambda_m^{-2} (m \cdot \nabla_X)^2 + \Lambda_s^{-2} (s \cdot \nabla_X)^2 \right] \Theta$$

Use the orthogonal directions  $u, s$  to define coordinates  $(X, Y)$

$$u \cdot \nabla_X = \frac{\partial}{\partial X}, \quad s \cdot \nabla_X = \frac{\partial}{\partial Y}$$

In the most typical case,  $\Lambda_u$  and  $\Lambda_s$  are exponential in time.

$$\Lambda_s = e^{\lambda_s t} = e^{-\lambda t}, \quad \Lambda_u = e^{\lambda_u t} = e^{\lambda t}$$

(2D) (2D)

So we can make the approximation

$$\partial_t \Theta = n e^{2|\lambda_s|t} \frac{\partial^2 \Theta}{\partial Y^2} + O(e^{-2\lambda_m t})$$

$t \rightarrow \infty$

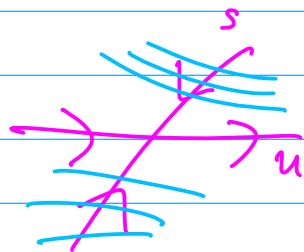
The equation has become one-dimensional

Now we can solve it exactly!

Note that diffusion starts to play a role when

$$n e^{2|\lambda_s|t} = 1 \Rightarrow t = \frac{1}{|\lambda_s|} \log n^{-1}$$

as claimed before.



gradients are amplified in the contracting direction.

Note: the " $t \rightarrow \infty$ " above should be taken with a grain of salt. It will often be the case that  $\partial_Y \Theta \rightarrow 0$  rapidly, allowing the other terms to take over.