

Trying to "fix" the adjoint

In today's final lecture, I will highlight two methods that attempt to address the "failure" of the adjoint to provide useful sensitivity information when the dynamics are chaotic.

- The first is relatively inexpensive and inaccurate and the other is relatively expensive and accurate.
- Consequently, the best "fix" for chaotic adjoints remains an open problem.

Ensemble Adjoint

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Average of Averages

The ensemble adjoint [LAH00] was the first idea proposed to deal with unstable adjoints that arise from chaotic dynamical systems. The idea is simple:

- adjoint is well-behaved over sufficiently short periods of time, even for chaotic problems.
- break the full simulation period into shorter periods, and compute the adjoint on each.
- use each adjoint to compute a sensitivity, and average this ensemble of sensitivities.

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Average of Averages (cont.)

The ensemble adjoint avoids the long-time instability problem because each time period is short and treated separately.

 the adjoints are independent; no continuity is enforced between periods.

Example: break [0,T] into P partitions of period $\Delta T = T/P$.

$$\Psi_{p}$$
 is the solution of $\frac{\partial T}{\partial n}^{T} + (\frac{\partial R}{\partial n})^{T} \Psi_{p} = 0$, $\forall t [T_{p+1}, T_{p}]$

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Average of Averages (cont.)

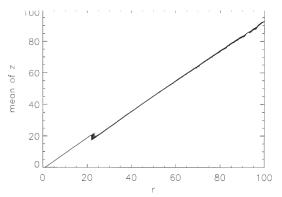
The final form of the total derivative with respect to α is

$$\frac{DJ}{D\alpha} = \sum_{p=1}^{P} \left(\frac{\partial J}{\partial \alpha} + \int_{T_{p-1}}^{T_p} (\psi_p, N'[\alpha])_{\Omega} dt \right)$$

- In principle, the ensemble approach is no more expensive than the convectional adjoint; in fact, it could be implemented in parallel with respect to the time partition.
- Unfortunately, the resulting sensitivities converge very slowly: the convergence rate with the number of samples P is slower than 1/P, i.e. worse than Monte-Carlo methods.

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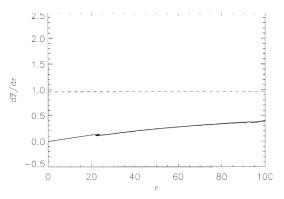
Results of the Ensemble Adjoint



Behavior of $\bar{z}=1/T\int_0^T z\,dt$, where z is from the Lorenz system, using T=131.36 [LAH00].

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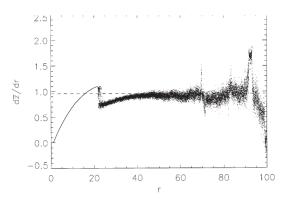
Results of the Ensemble Adjoint (cont.)



Ensemble-adjoint-based sensitivity $d\bar{z}/d\rho$ using P=1314 and $\Delta T=0.1.$ [LAH00].

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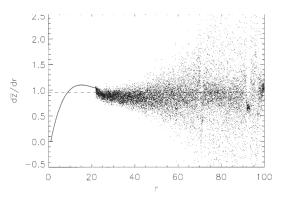
Results of the Ensemble Adjoint (cont.)



Ensemble-adjoint-based sensitivity $d\bar{z}/d\rho$ using P=299 and $\Delta T=0.44.$ [LAH00].

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Results of the Ensemble Adjoint (cont.)



Ensemble-adjoint-based sensitivity $d\bar{z}/d\rho$ using P=199 and $\Delta T=0.66.$ [LAH00].

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Least-Squares Shadowing

Shadowing Trajectory

The least-squares shadowing method for sensitivity analysis is quite different in its approach. The rough idea is as follows:

ullet Problem with chaotic system is that small perturbation of a parameter lpha leads to a large change in the state; recall

$$\|\Delta u(t)\| \approx e^{\lambda t} \|\Delta u_0\|$$

• Can we perturb the dynamics in such a way that the perturbed solution remains close to the reference solution?

This approach (perturbing the dynamics) is justified by the shadowing lemma:

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Shadowing Trajectory (cont.)

Theorem: Shadowing Lemma

For any $\delta>0$ and reference solution $u(t;\alpha)$, there exists an $\epsilon>0$, a smooth time transformation $\tau(t)$, and a solution $\tilde{u}(\tau(t);\alpha+\epsilon)$ such that

$$\|\tilde{u}(\tau(t); \alpha + \epsilon) - u(t; \alpha)\| < \delta, \quad \forall t,$$

 $\left|1 - \frac{d\tau}{dt}\right| < \delta, \quad \forall t.$

Requires uniform hyperbolicity and ergodicity.

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Shadowing Trajectory (cont.)

The shadow trajectory \tilde{u} can be approximated by solving the following least-squares optimization problem:

$$\begin{split} \min_{\tilde{u},\tau} J_{\epsilon}(\tilde{u},\tau) &= \frac{1}{2} \int_{0}^{T} \|\tilde{u}(\tau(t)) - u(t)\|^{2} \, dt + \frac{\mu}{2} \int_{0}^{T} \left(1 - \frac{d\tau}{dt}\right)^{2} \, dt, \\ \text{s.t.} \quad &\frac{d\tilde{u}}{d\tau} + N(\tilde{u};\alpha + \epsilon) = 0. \end{split}$$

- The first term in the objective forces the shadow trajectory to lie close to the reference
- \bullet The second term encourages the time transformation to be close to the identity; $\mu>0$ is a parameter
- \tilde{u} converges to a shadow trajectory as $T \to \infty$

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Tangent form of the LSS

Assuming we can obtain a shadow trajectory based on the parameter $\alpha+\epsilon$, the next step is to consider taking the limit $\epsilon\to 0$ in order to define the sensitivity $Du/D\alpha$.

Recall that the conventional direct (aka. tangent) sensitivity
$$Du/Da \equiv v$$
 satisfies
$$\frac{D}{Da} \left[\frac{du}{dt} + N(u, \alpha) \right] = \frac{dv}{dt} + N'[u]v + N'[\alpha] = 0$$

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Before we start taking limits, it will be helpful to express $d\tau/dt$ as a perturbation to the identity mapping:

$$\frac{d\tau}{dt}=1+\epsilon\eta(t).$$

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It will also be useful to keep in mind that

$$\lim_{\epsilon \to 0} \frac{\tilde{u} - u}{\epsilon} = \frac{Du}{D\alpha} \equiv v$$
here, this refers to
the LSS tangent sens.
(not conventional sens.)

First, we divide the objective J_{ϵ} by ϵ^2 and take the limit:

$$\lim_{\epsilon \to 0} \frac{J_{\epsilon}(\tilde{u}, \tau)}{\epsilon^{2}} = \lim_{\epsilon \to 0} \frac{1}{\epsilon^{2}} \frac{1}{2} \int_{0}^{T} (\tilde{u}(z) - u, \tilde{u}(z) - u) dt$$

$$+ \lim_{\epsilon \to 0} \frac{1}{\epsilon^{2}} \frac{u}{2} \int_{0}^{T} (1 - \frac{dz}{dt})^{2} dt$$

$$= \lim_{\epsilon \to 0} \frac{1}{2} \int_{0}^{T} (\frac{\overline{u} - u}{\epsilon}, \frac{\overline{u} - u}{\epsilon}) dt$$

$$+ \lim_{\epsilon \to 0} \frac{u}{2} \int_{0}^{T} \frac{e^{\epsilon} \eta(t)^{2}}{\epsilon^{2}} dt$$

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$$\lim_{\varepsilon \to 0} \frac{J_{\varepsilon}(\overline{n}, z)}{\varepsilon} = \frac{1}{2} \int_{0}^{T} (v, v) dt$$

$$+ \underbrace{\mu}_{Z} \int_{0}^{T} \eta(t)^{2} dt$$

$$= \frac{1}{2} \int_{0}^{T} \|v\|^{2} dt + \underbrace{\mu}_{Z} \int_{0}^{T} \eta(t)^{2} dt$$

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Similarly, we can determine the constraint on v by taking the difference between the dynamical systems, dividing by ϵ , and taking the limit:

$$\lim_{\epsilon \to 0} \frac{1}{\epsilon} \left[\underbrace{\frac{d\tilde{u}}{d\tau} + N(\tilde{u}; \alpha + \epsilon)}_{\bullet} - \underbrace{\frac{du}{dt} - N(u; \alpha)}_{\bullet} \right] = \mathbf{0}$$

First,
$$\frac{d\bar{u}}{d\tau} = \frac{d\bar{u}}{dt} \frac{dt}{d\tau} = \frac{1}{(1+\epsilon\eta(t))} \frac{d\bar{u}}{dt}$$

so,
$$\frac{1}{\varepsilon} \left(\frac{d\widetilde{u}}{d\tau} - \frac{du}{dt} \right) = \frac{1}{\varepsilon (1+\varepsilon \eta)} \left[\frac{d\widetilde{u}}{dt} - \frac{du}{dt} - \varepsilon \eta \frac{du}{dt} \right]$$

$$\lim_{\varepsilon \to 0} \frac{1}{(1+\varepsilon\eta)} \left[\frac{d}{dt} \left(\frac{\widetilde{u} - u}{\varepsilon} \right) - \eta \frac{du}{dt} \right] = \frac{dv}{dt} - \eta \frac{du}{dt}$$

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Furthermore,
$$\tilde{u} = u + \varepsilon v + O(\varepsilon^2)$$

$$\lim_{\varepsilon \to 0} \frac{1}{\varepsilon} \left[N(\tilde{u}; \alpha + \varepsilon) - N(u; \alpha) \right] \qquad O(\varepsilon^2)$$

$$= \lim_{\varepsilon \to 0} \frac{1}{\varepsilon} \left[N(u; \alpha) + N'[u] \varepsilon v + N'[\alpha] \varepsilon - N(u; \alpha) \right]$$

$$= N'[u] v + N'[u]$$

$$= N'[u] v + N'[u]$$

$$= \eta N(u; \alpha)$$

$$\frac{dv}{dt} + N'[u] v + N'[\alpha] - \eta \frac{du}{dt} = 0$$

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Definition: LSS, tangent form

The LSS tangent (i.e. direct) sensitivity is given by the solution to the least-squares problem

$$\min_{v,\eta} \quad \frac{1}{2} \int_0^T \|v(t)\|^2 \, dt + \frac{\mu}{2} \int_0^T \eta(t)^2 \, dt,$$

s.t.
$$\frac{dv}{dt} + N'[u]v + N'[\alpha] + \eta N(u, \alpha) = 0$$

* note the absence of I.C. on v

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- An adjoint version of the LSS can also be derived [WHB14]
- The LSS adjoint optimization statement is similar, but the constraint is replaced with the adjoint equation (with an LSS-specific term).

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Solving for the LSS tangent

The LSS tangent (and adjoint) optimization problem is "nice," because the constraint is linear and the objective is a convex quadratic.

 this guarantees a unique solution, which can be found by solving the (linear) first-order optimality conditions

Unfortunately, the linear system that must be solved is huge.

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Solving for the LSS tangent (cont.)

To obtain additional insight into the LSS problem, we now derive the first-order optimality conditions.

$$L(v, w, \eta) = \frac{1}{2} \int_{0}^{T} (v, v) dt + \underbrace{u}_{2} \int_{0}^{T} \eta(t)^{2} dt$$

$$+ \int_{0}^{T} (w, \frac{dv}{dt} + N'[u]v + N'[u] + \eta N(u) dt$$

$$D_{\nu}L\delta w = \int_{0}^{T} \left(\delta w, \frac{dv}{dt} + N'[u]v + N'[\alpha] + \eta N(u, \alpha)\right) dt = 0$$

$$\implies \frac{dv}{dt} + N'[u]v + N'[\alpha] + \eta N(u, \alpha) = 0$$

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Solving for the LSS tangent (cont.)

$$D_{\gamma}^{L} = \int_{0}^{\tau} (u \eta \delta \eta + w^{T} N(u, \alpha) \delta \eta) dt = 0$$

$$\Rightarrow u \eta(t) + w^{T} N(u, \alpha) = 0$$

$$\partial_{\nu} L \delta v = \int_{0}^{T} (\delta v^{T} v + w^{T} \frac{d}{dt} \delta v + w^{T} N' L w \int N' L w \int$$

$$= \int_{0}^{T} \left(\delta v_{3} - \frac{dw}{dt} + N' [u]^{*} w + v \right) dt$$

 $+ \left[w^{\mathsf{T}} \mathcal{S} \mathbf{v} \right]_{t=0}^{\mathsf{T}} = 0$

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Solving for the LSS tangent (cont.)

The LSS tangent solution v, time-dilation η , and multipliers w satisfy

$$\frac{dv}{dt} + N'[u]v + N'[\alpha] + \eta N(u, \alpha) = 0, \qquad \forall t \in [0, T]$$
$$\mu \eta + w^T N(u, \alpha) = 0, \qquad \forall t \in [0, T]$$
$$-\frac{dw}{dt} + N'[u]^* w + v = 0, \qquad \forall t \in [0, T],$$
$$w(0) = 0, \quad w(T) = 0.$$

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Solving for the LSS tangent (cont.)

The most notable aspect of the problem defining v is that it is a boundary-value problem in time.

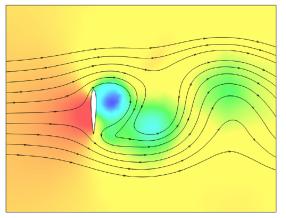
• To see this, one can eliminate v and η and obtain a second-order ODE in time for w with both initial and terminal conditions.

There have been limited uses of the LSS method, given the size of the linear system involved

- For example, in [BWND16] the authors solve for the chaotic flow around a 2D airfoil.
- Although the number of spatial DOF and time steps are relatively small, the memory requirements for the linear system is in the terabytes.

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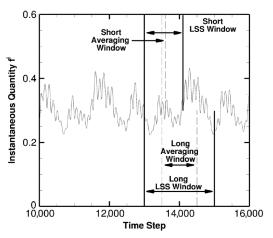
Results using LSS



Chaotic airfoil flow studied in [BWND16].

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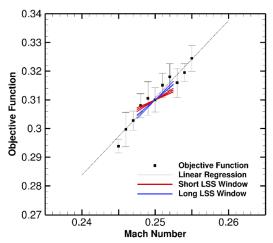
Results using LSS (cont.)



Definition of the LSS and averaging windows [BWND16].

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Results using LSS (cont.)



LSS-based sensitivities compared to trend [BWND16].

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References

- [BWND16] Patrick J. Blonigan, Qiqi Wang, Eric J. Nielsen, and Boris Diskin, Least Squares Shadowing Sensitivity Analysis of Chaotic Flow around a Two-Dimensional Airfoil, 54th AIAA Aerospace Sciences Meeting, American Institute of Aeronautics and Astronautics, January 2016.
- [LAH00] Daniel J. Lea, Myles R. Allen, and Thomas W. N. Haine, Sensitivity analysis of the climate of a chaotic system, Tellus A **52** (2000), no. 5, 523–532.
- [WHB14] Qiqi Wang, Rui Hu, and Patrick Blonigan, Least Squares Shadowing sensitivity analysis of chaotic limit cycle oscillations, Journal of Computational Physics **267** (2014), 210–224.