

Learning Physical Models that Can Respect Conservation Laws

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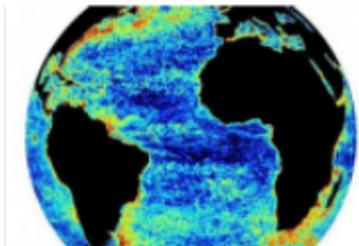
$$\left. \begin{aligned} \mathcal{F}u(t, x) &= 0, \quad x \in \Omega, \\ u(0, x) &= u_0(x), \quad x \in \Omega, \\ u(t, x) &= g(t, x), \quad x \in \partial\Omega, \end{aligned} \right\}, \forall t \geq 0,$$

Conservation Law

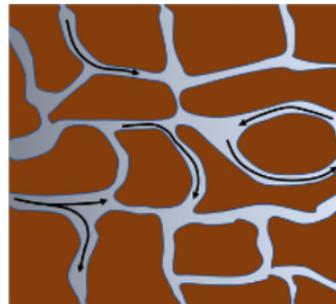
$$\mathcal{F}u = u_t + \nabla \cdot F(u)$$



Aerodynamics



Ocean & Climate



Reservoir Modeling

$$u_t + \nabla \cdot F(u) = 0$$

$$\int_{\Omega} u(t, x) d\Omega = \int_{\Omega} u_0(x) d\Omega - \int_0^t \int_{\Gamma} F(u) \cdot n d\Gamma dt$$

1D

$$\underbrace{\int_{\Omega} u(t, x) d\Omega}_{\mathcal{G}u(t,x)} = \underbrace{\int_{\Omega} u_0(x) d\Omega + \int_0^t (F_{\text{in}} - F_{\text{out}}) dt}_{b(t)}$$

$$F_{\text{in}} = F(u, t, x_0)|_{u=g(t,x_0)}$$

$$F_{\text{out}} = F(u, t, x_N)|_{u=g(t,x_N)}$$

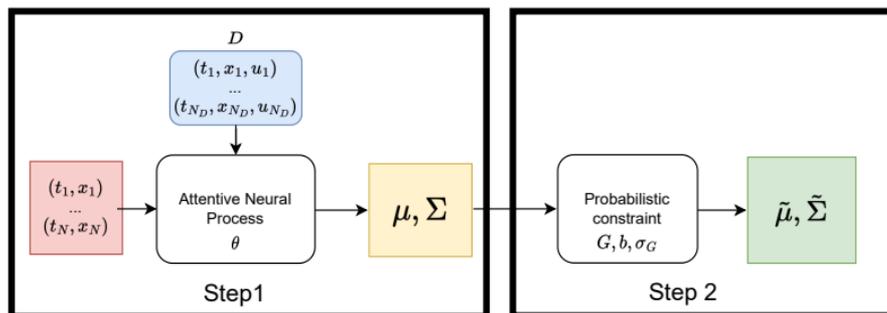
$$\Omega = [x_0, x_N]$$

Algorithm PROBCONSERV

- 1: **Input:** Constraint matrix G , constraint value b , non-zero noise σ_G and input points $(t_1, x_1), \dots, (t_N, x_N)$
 - 2: **Step 1:** Calculate black-box prediction over output grid:
 $\mu, \Sigma = f_\theta((t_1, x_1), \dots, (t_N, x_N); D)$
 - 3: **Step 2:** Calculate $\tilde{\mu}$ and $\tilde{\Sigma}$ according to Equation 1.
 - 4: **Output:** $\tilde{\mu}, \tilde{\Sigma}$
-

$$\begin{aligned}\tilde{\mu} &= \mu - \Sigma G^T (\sigma_G^2 I + G \Sigma G^T)^{-1} (G \mu - b) \\ \tilde{\Sigma} &= \Sigma - \Sigma G^T (\sigma_G^2 I + G \Sigma G^T)^{-1} G \Sigma\end{aligned}\tag{1}$$

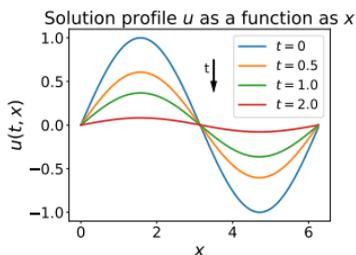
$b = Gu + \sigma_G \epsilon$



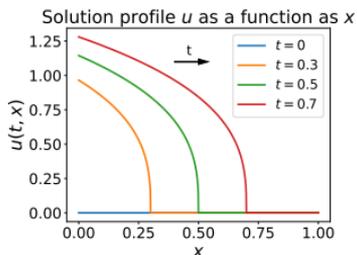
Schematic for the instantiation of our framework PROBCONSERV with the ANP (PROBCONSERV-ANP) as the data-driven black box model in Step 1

GPME as a Parameterized Family of Equations

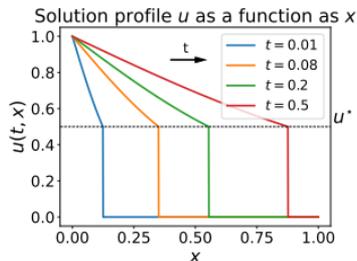
$$u_t = \nabla \cdot (k(u)\nabla u)$$



(a) Diffusion equation $k = 1$



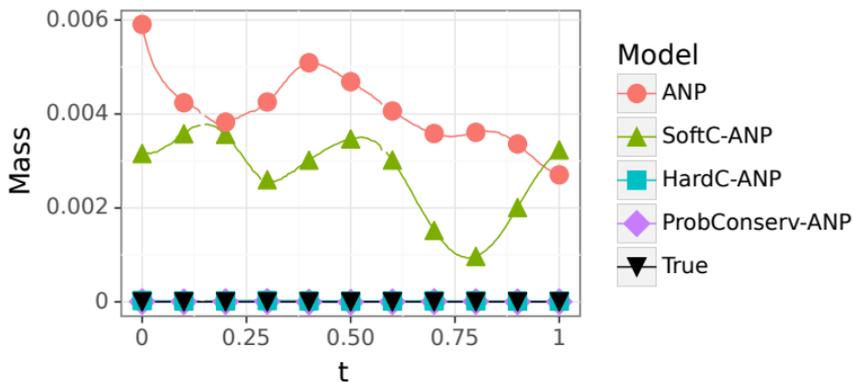
(b) PME $k(u) = u^3$



(c) Stefan discontin. $k(u)$

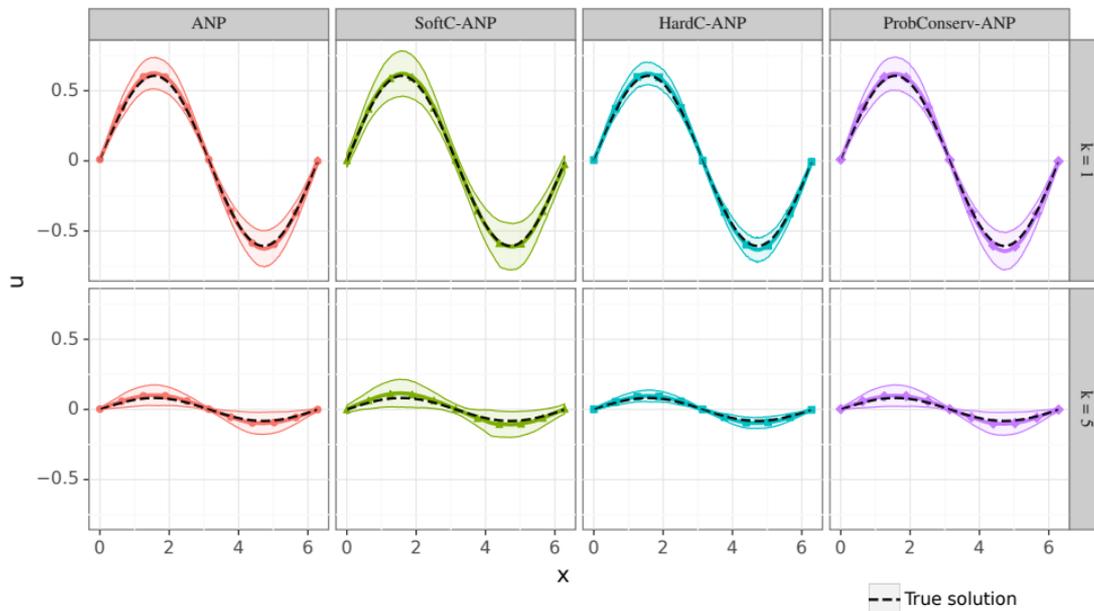
Illustration of the “easy-to-hard” paradigm for the GPME

Diffusion Equation: Violation of Conservation of Mass



True mass is **zero** over time: zero net flux from domain boundaries

Diffusion Equation: Solution Profiles and UQ

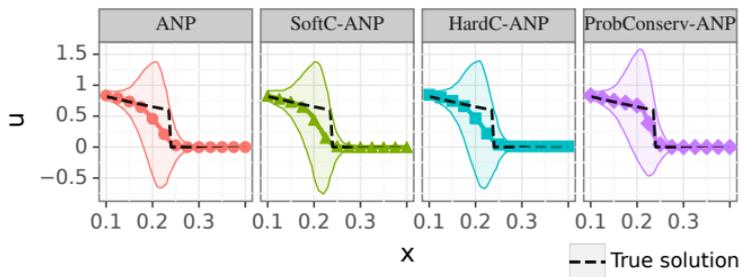


“Easy” problem: uncertainty is relatively **homoscedastic**

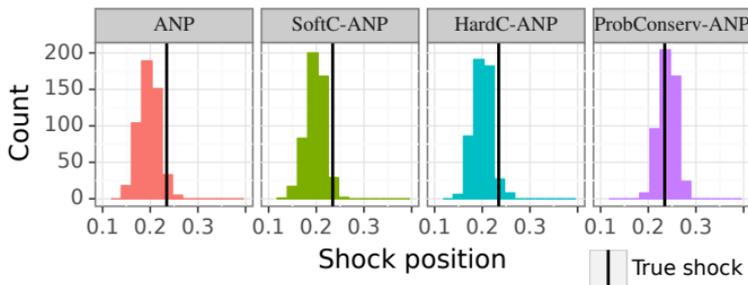
	CE	LL	MSE
ANP	4.68 (0.10)	2.72 (0.02)	1.71 (0.41)
SOFTC-ANP	3.47 (0.17)	2.40 (0.02)	2.24 (0.78)
HARDC-ANP	0 (0.00)	3.08 (0.04)	1.37 (0.33)
PROBCONSERV-ANP	0 (0.00)	2.74 (0.02)	1.55 (0.33)

Mean and standard error for CE $\times 10^{-3}$ (*should be zero*), LL (*higher is better*), MSE $\times 10^{-4}$ (*lower is better*) over $n_{\text{test}} = 50$ runs with variable diffusivity parameter $k \in [1, 5]$ and test-time parameter value $k = 1$

Stefan Equation: Solution Profile and Downstream Task



(a) Solution profile



(b) Posterior of the shock position

“Hard” problem: Uncertainty is highly **heteroscedastic** with largest magnitude near the shock location

	CE	LL	MSE
ANP	-1.30 (0.01)	3.53 (0.00)	5.38 (0.01)
SOFTC-ANP	-1.72 (0.04)	3.57 (0.01)	6.81 (0.15)
HARDC-ANP	0 (0.00)	2.33 (0.06)	5.18 (0.02)
PROBCONSERV-ANP	0 (0.00)	3.56 (0.00)	1.89 (0.01)

Mean and standard error for CE $\times 10^{-2}$ (*should be zero*), LL (*higher is better*), and MSE $\times 10^{-3}$ (*lower is better*) over $n_{\text{test}} = 50$ runs at time $t = 0.05$ with variable parameter $u^* \in [0.55, 0.7]$ and test-time parameter value $u^* = 0.6$

3X decrease in MSE

Thank you!

Hansen, D., Maddix, D.C., Alizadeh, S., Gupta, G., Mahoney, M.W., [Learning Physical Models that Can Respect Conservation Laws](#)," *Proceedings of the 40th International Conference on Machine Learning*, PMLR 202, 2023.

Code: <https://github.com/amazon-science/probconserv>

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