

The role of machine learning in ice sheet modeling

Presented on March 24th, 2022 by Kyle Blum

The goals this presentation:

- Discuss how we calibrate our ice sheet model
- Give a brief overview of why machine learning is a good way to solve this problem
- Describe how our neural net learns PISM
- Give a few details on the implementation of this neural net with pytorch

What we're looking at here is a classic inverse problem

$$G(m) = d$$

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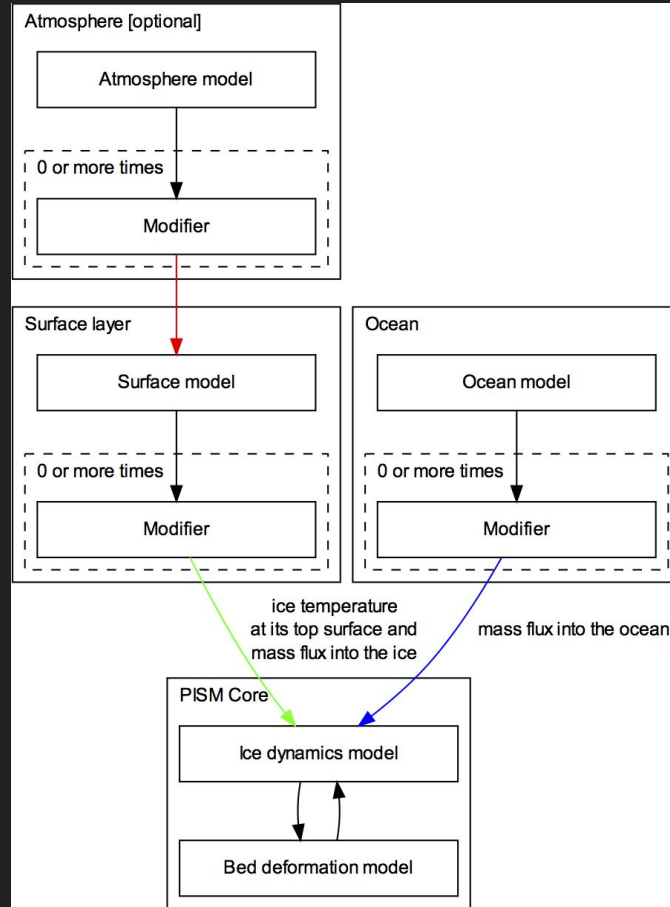
$$G = PISM$$

m = ice dynamics parms

d = velocity fields

Ice sheet modeling is expensive

G =

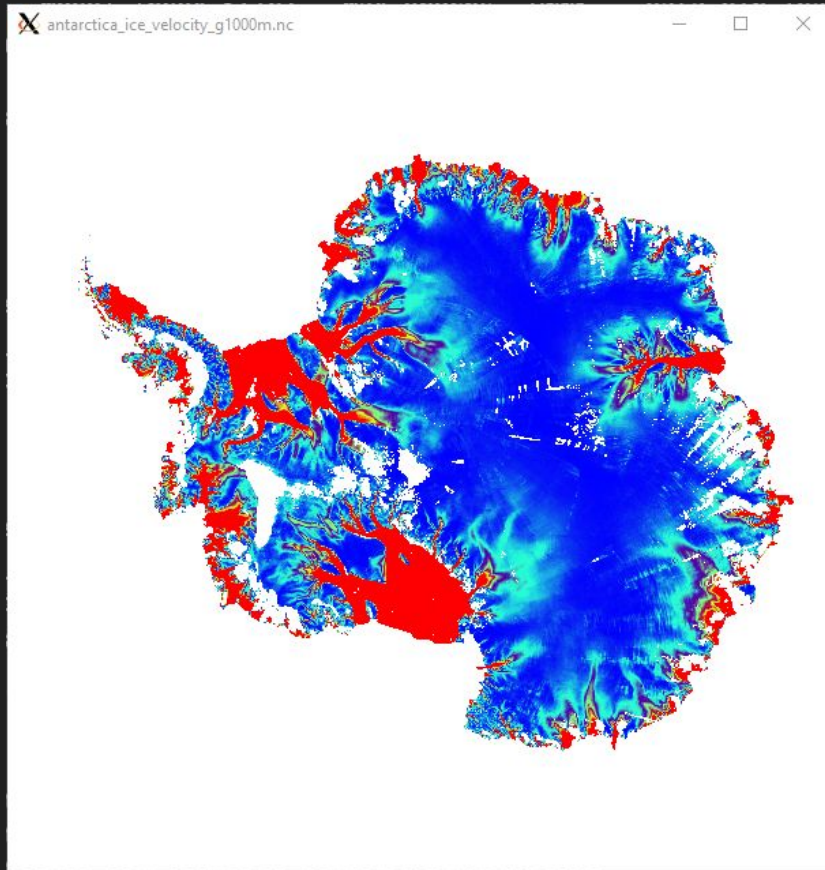


There are many (>500) model parameters that dictate our model

$$m = m_0 + m_1 + \dots + m_{510} \quad \longrightarrow$$

$$m_{\text{flow}} = m_0 + m_1 + \dots + m_7$$

We can represent surface flow with SVD



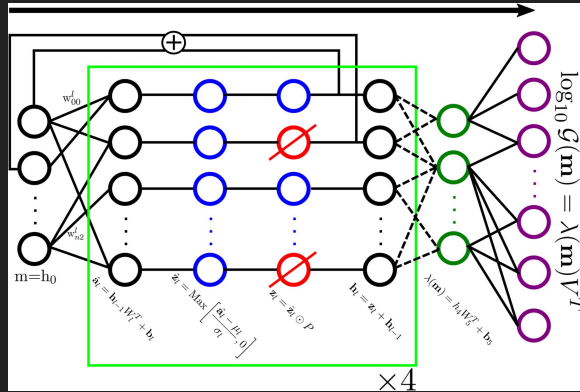
$d =$

$= USV^T$

Ice sheet modeling is expensive

G = **PISIM**
PARALLEL ICE SHEET MODEL

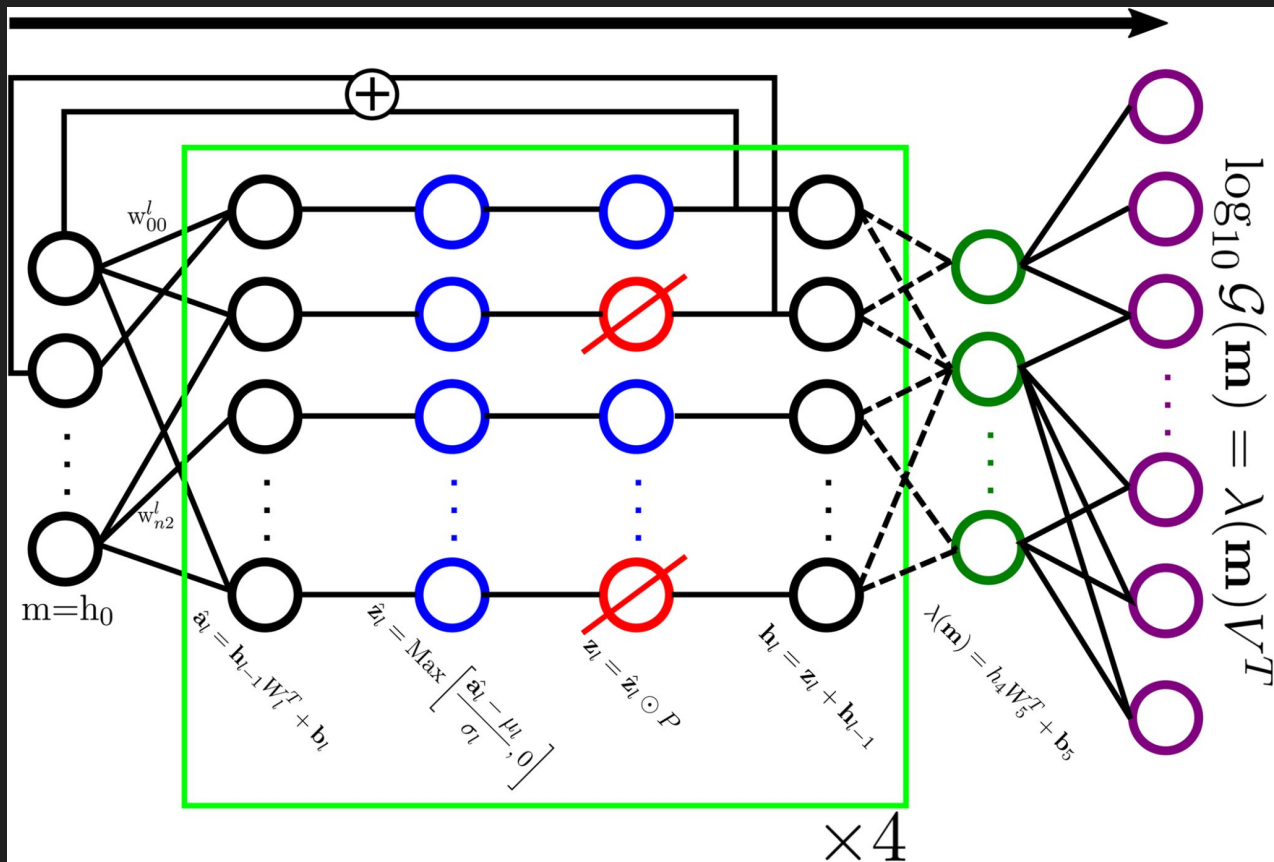
Model calibration doesn't have to be as expensive



$$= \mathbb{F} \cong \mathbb{G} =$$

PISIM
PARALLEL ICE SHEET MODEL

We implement an L=5 neural network with 128 nodes per layer



$$\hat{\mathbf{a}}_l = \mathbf{h}_{l-1} W_l^T + \mathbf{b}_l,$$

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$$\mathbf{z}_l = \hat{\mathbf{z}}_l \odot R,$$

$$\hat{\mathbf{a}}_l = \mathbf{h}_{l-1} W_l^T + \mathbf{b}_l,$$

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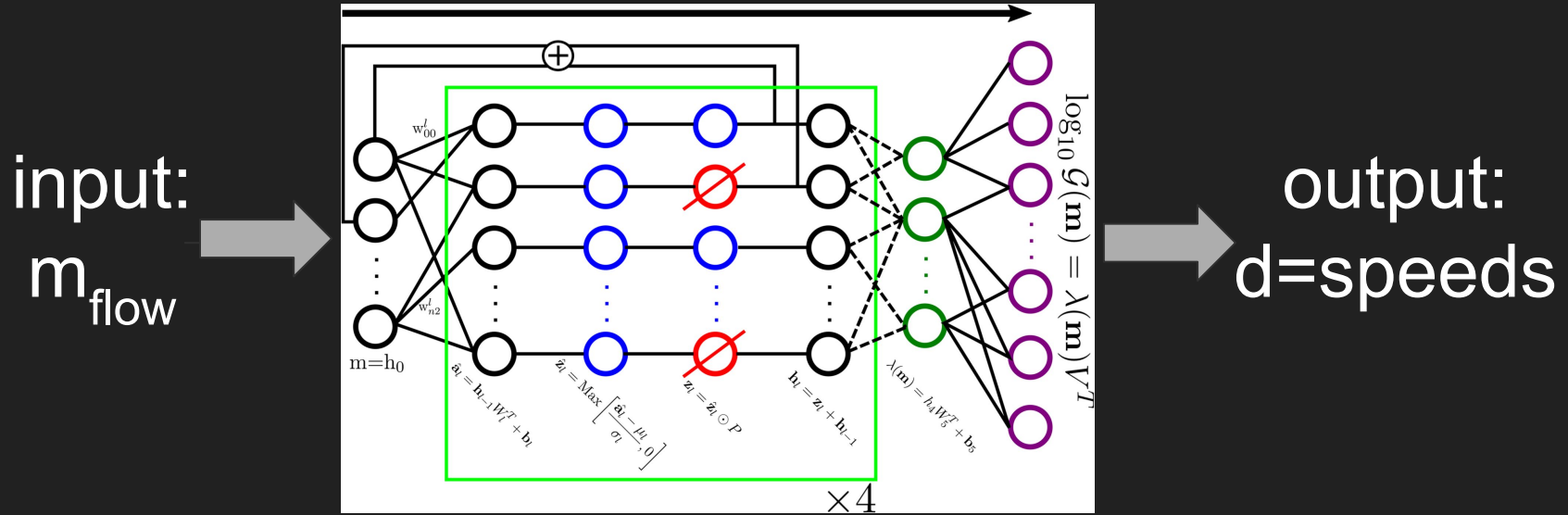
$$\hat{\mathbf{z}}_l = \text{ReLU}(\mathbf{a}_l),$$

$$\mathbf{z}_l = \hat{\mathbf{z}}_l \odot R,$$

$$\mathbf{h}_l = \mathbf{z}_l + \mathbf{h}_{l-1},$$

F is the approximate map from m_{flow} to surface ice speeds

F



To accrue training data we run the high fidelity model forward a bunch of times

$$G(m) = d_{\text{target}}$$

To train our surrogate model, we minimize this objective

$$I(\theta) \propto \sum_{i=1}^m [F(m_{flow,i}, \theta) - G(m_{flow,i})]^2$$

Let's pop open the hood



PyTorch Lightning

Bibliography

Brinkerhoff, Douglas, et al. "Constraining Subglacial Processes from Surface Velocity Observations Using Surrogate-Based Bayesian Inference." *Journal of Glaciology*, vol. 67, no. 263, 2021, pp. 385–403., <https://doi.org/10.1017/jog.2020.112>.

Khroulev, C., & the PISM Authors. (2022). PISM, a Parallel Ice Sheet Model. Zenodo. doi: 10.5281/zenodo.1199019

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I'm happy to take questions at this time

