

Data-driven sea-ice modelling with generative deep learning

Tobias Sebastian Finn

Charlotte Durand, Alban Farchi, Marc Bocquet, Pierre Rampal, Alberto Carrassi, Julien Brajard and others

This research was funded by Schmidt Sciences - a philanthropic initiative that seeks to improve societal outcomes through the development of emerging science and technologies



/

How to emulate what an ocean/sea-ice model is doing?



How to emulate what an ocean/sea-ice model is doing?



- 1. Faster version of the model
- 2. Adjoint for variational data assimilation (see Talk by Charlotte)
- 3. Possibility to improve the model by observations

How to emulate what an ocean/sea-ice model is doing?



- 1. Faster version of the model
- 2. Adjoint for variational data assimilation (see Talk by Charlotte)
- 3. Possibility to improve the model by observations

Our solution: Generative diffusion model

We need data, a lot of data ...



We need data, a lot of data ...



We need data, a lot of data ...



Regional setup



Lagrangian neXtSIM + ¼° NEMO (Boutin et al., 2023)

1995-2014: Training 2016-2018: Testing





 $\sim \mathcal{N}(\mathbf{0}, \mathbf{I})$















Neural network baseline works ...

Averaged over all variables



... but ensemble with generative performs best

Averaged over all variables









Deterministic model loses small-scale information ...



Deterministic model loses small-scale information ...



... generative model resolves the problems



... generative model resolves the problems



After 50 days



After 50 days



... generative model leads to consistent forecasts

After 50 days



... generative model leads to consistent forecasts

After 50 days





... generative model leads to consistent forecasts

After 50 days





Similar "physical" laws

The model generalizes to idealized cases

Simulation



Wind forcing



8

Goal: 12h prediction < 1 s, train/run on a single consumer GPU, linear scaling

Preliminary

Goal: 12h prediction < 1 s, train/run on a single consumer GPU, linear scaling

Preliminary 1.25 1.00 Persistence B0.75 W2U 0.50 Generative (1) Deterministic-like Generative (16) 0.25 0.00 0.0 2.5 5.0 7.5 10.012.5 15.0Lead time (days)

8

Goal: 12h prediction < 1 s, train/run on a single consumer GPU, linear scaling

Three-year long forecast: run in around 30 min

Goal: 12h prediction < 1 s, train/run on a single consumer GPU, linear scaling

Three-year long forecast: run in around 30 min



Goal: 12h prediction < 1 s, train/run on a single consumer GPU, linear scaling

Three-year long forecast: run in around 30 min



<u>Unlocks</u> improved data-driven modeling and can be also used for model error corrections

<u>Exhibits</u> physical consistent forecasts maintaing the sharpness + scaling laws

<u>Learns</u> efficient Arctic-wide models similar results + stable for several years

<u>Unlocks</u> improved data-driven modeling and can be also used for model error corrections

<u>Exhibits</u> physical consistent forecasts maintaing the sharpness + scaling laws

<u>Learns</u> efficient Arctic-wide models similar results + stable for several years



Paper

<u>Unlocks</u> improved data-driven modeling and can be also used for model error corrections

<u>Exhibits</u> physical consistent forecasts maintaing the sharpness + scaling laws

<u>Learns</u> efficient Arctic-wide models similar results + stable for several years

Do you have questions? (tobias.finn@enpc.fr)



Paper