Exploring Randomly Wired Neural Networks for Climate Model Emulation

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- Modeling many emissions scenarios is important, but expensive.

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- Machine learning emulators can provide cheap, fast solutions. However, comparing emulators is difficult without standardized testing frameworks.
- Watson-Paris et al. (2022) introduced Climatebench, a standardized dataset and testing framework

ClimateBench

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  - Long-lived: CO_2, CH_4
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- Outputs: four predicted output variables (annual means)
  - Surface air temperature (TAS)
  - Diurnal temperature range (DTR)
  - Precipitation (PR)
  - 90th percentile of precipitation (PR90)

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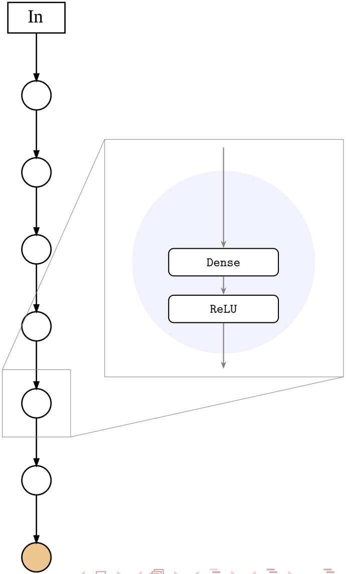
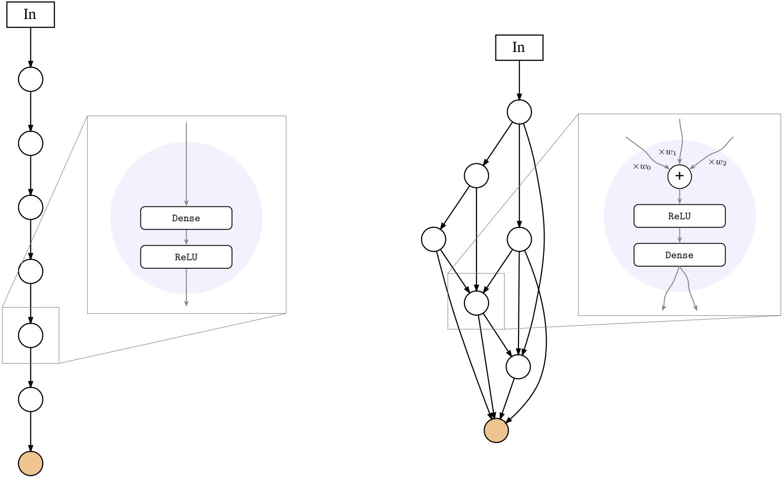
Multilayer Perceptron (MLP)

- Most basic type of neural network
- Information flows in one direction from one layer to the next
- White circle: hidden dense layer and activation function



RandDense Networks



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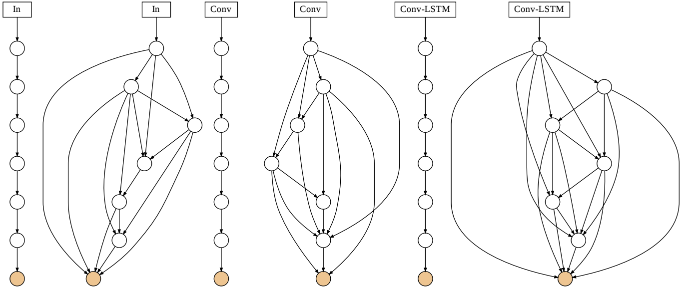
Experimental Setup

- Three baseline architectures: MLP, convolutional neural network (CNN), convolutional long short-term memory network (CNN-LSTM)
- 2-10 hidden layers, 1M and 10M parameters
- Generate 50 standard networks and 50 randomly wired networks for comparison

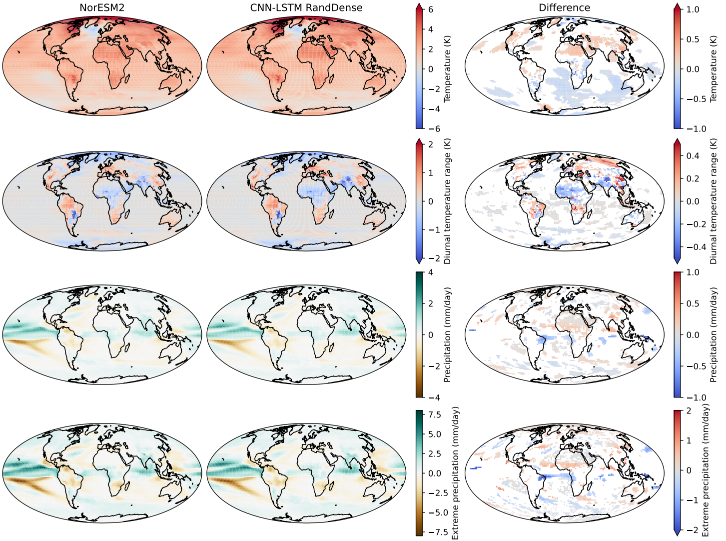


Results

		TAS	DTR	PR	PR90
MLP	Standard	1.928	15.62	4.663	5.651
	RandDense	**1.612**	**14.67**	**4.472**	**5.206**
CNN	Standard	**3.350**	23.15	9.235	10.30
	RandDense	3.353	**22.92**	**8.681**	**9.964**
CNN-LSTM	Standard	**0.262**	11.85	2.861	3.880
	RandDense	0.263	**11.66**	**2.775**	**3.810**
ClimateBench		0.327	16.78	3.175	4.339

Table 1: Best total RMSE performance for each model class and predicted variable across all generated models, along with the original CNN-LSTM model from Watson-Parris et al. (2022). Lower is better, and the better RMSE between the standard and RandDense models is bolded.

NorESM2 vs. CNN-LSTM RandDense



Summary and Conclusion

Key takeaways

- Randomization appears to provide performance benefits in multiple models!
- Same prediction speed as standard models
- Suggests replacing dense layers with randomly wired ones for the task of climate model emulation

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Thank you! Correspondence to wyik@hmc.edu.