Exploring the Benefits of Machine Learning

Improving Stormflow Predictions using Long Short-Term Memory Networks

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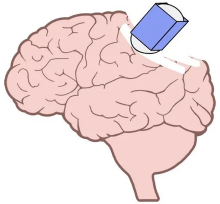
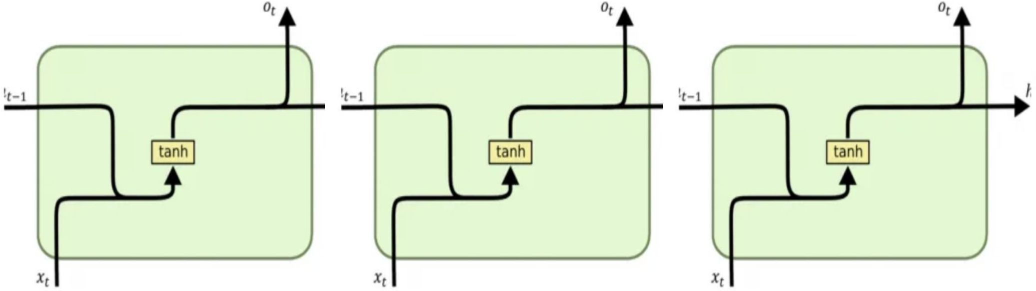
Recurrent Neural Networks (RNN)

- David Rumelhart, 1988
- (Artificial) Neural Network ((A)NN) modeling sequence data
- Layers: input, hidden (memory), output
- POOR LONG TERM MEMORY

Training Steps

1. Forward pass to make prediction
2. Performance check
3. Back propagate to determine weights





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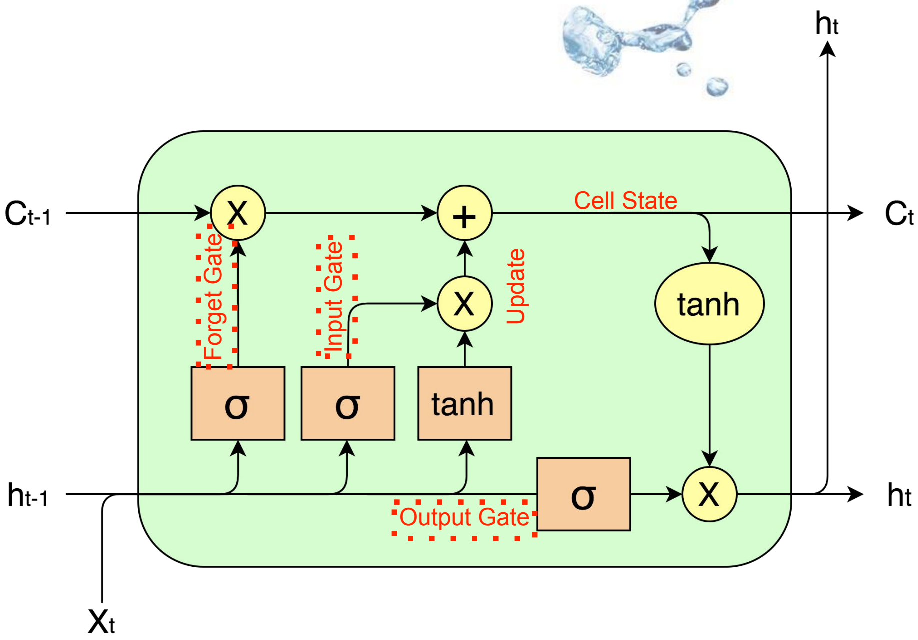
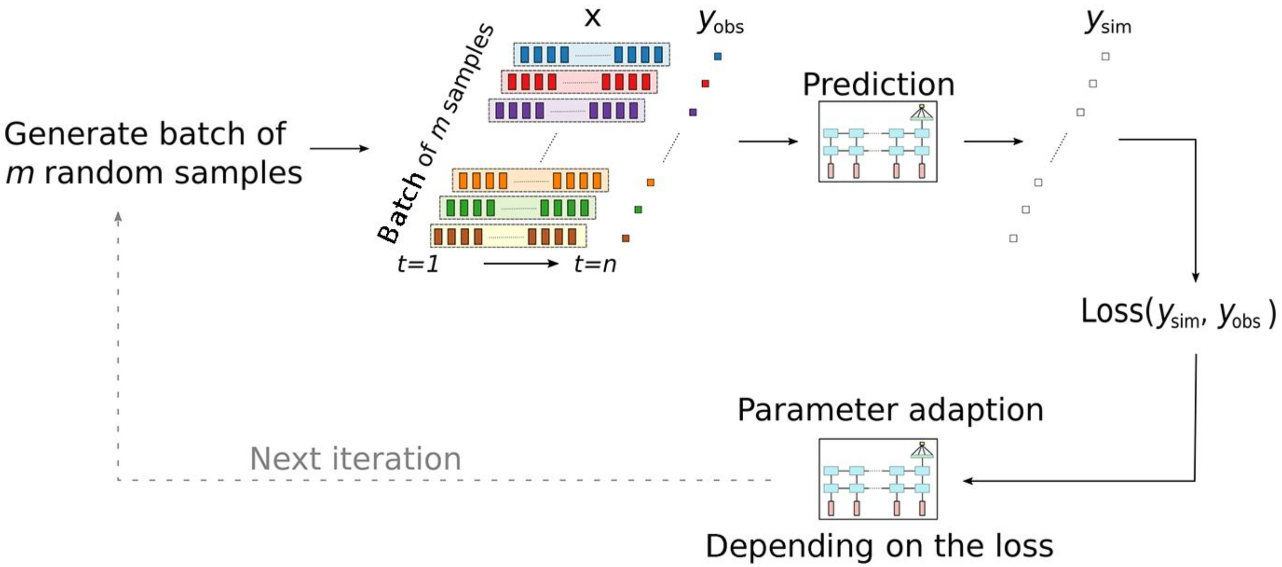
Long Short-Term Memory (LSTM)

- Hochreiter and Schmidhuber, 1997
- RNN + Cell State
- Flow of information is managed by *gates* to determine data relevancy
- Gates: Forget, Input & Output
- Note: both hidden & input layers (data) passed to *all* gates
- Recall: sigmoid (0,1)
- Cell state maintains info from *entire* sequence, hence…
- Long-term memory (e.g. snow)



LSTM Training



Kratzert, F., Klotz, D., Brenner, C., Schulz, K., and Herrnegger, M.: Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks, Hydrol. Earth Syst. Sci., 22, 6005–6022, https://doi.org/10.5194/hess-22-6005-2018, 2018.

Neural Hydrology

- Python library: train neural networks with emphasis on hydrological science & methods
- PyTorch: optimized tensor library for deep learning
- User def's configurations; I.e. no code manipulation
  - datasets
  - model design
  - training components

GitHub: https://github.com/neuralhydrology/neuralhydrology
Wiki: https://neuralhydrology.github.io/
Docs: neuralhydrology.readthedocs.io/
Tutorials: https://neuralhydrology.readthedocs.io/en/latest/tutorials
Frederik Kratzert: kratzert.github.io

What is BMI

Basic Model Interface: *A set of essential, "self-describing", functions used to **control** (e.g. advance-of-time) & **access** (i.e. query) the state of a model*

Developed by: **Community Surface Dynamics Modeling System (CSDMS)**

Models & Modules

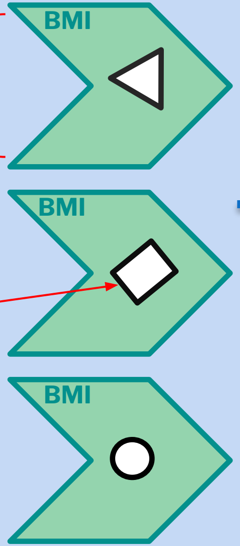
Modularize >> Single Uniform

Self-contained

Varies in:

- **Languages**
- **Units**
- **Variable Naming**

Extended to BMI

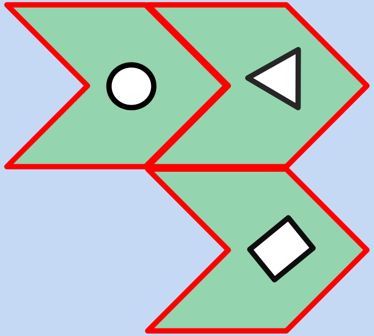


Model code is "wrapped" in BMI

Hydrologic predictions remain untouched

Exchange items are standardized

Model-coupling Framework



Plug-&-play

Exchange of information

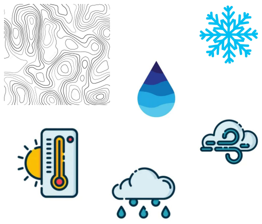
Extendable to external APIs

Workflow

Data → Train → BMI-LSTM → Package → NGen

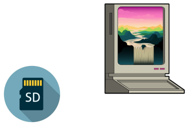
Data

Static & Dynamic



Train

NeuralHydrology



BMI-LSTM

Apply BMI Wrapper

- Extend model
- CudaLSTM

bmi

Package

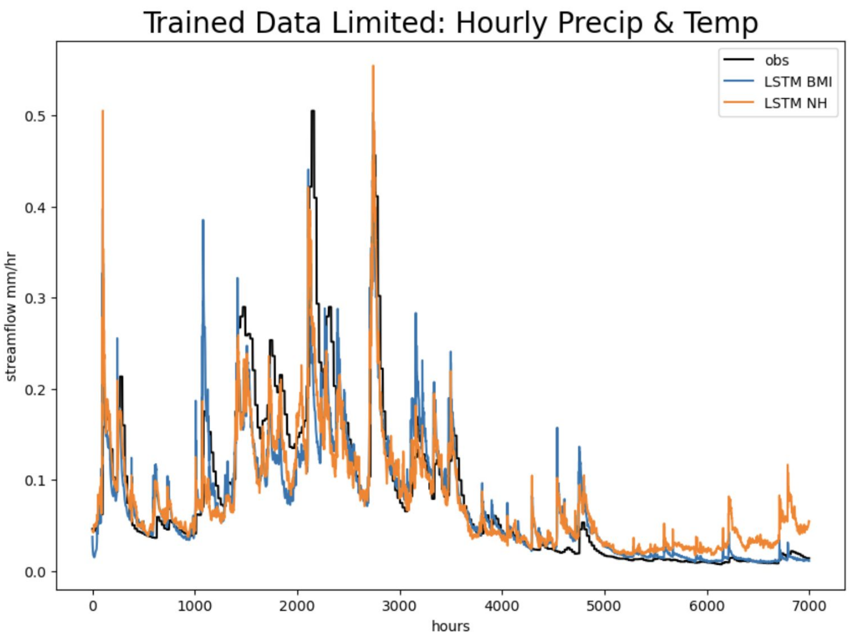
Framework Prep

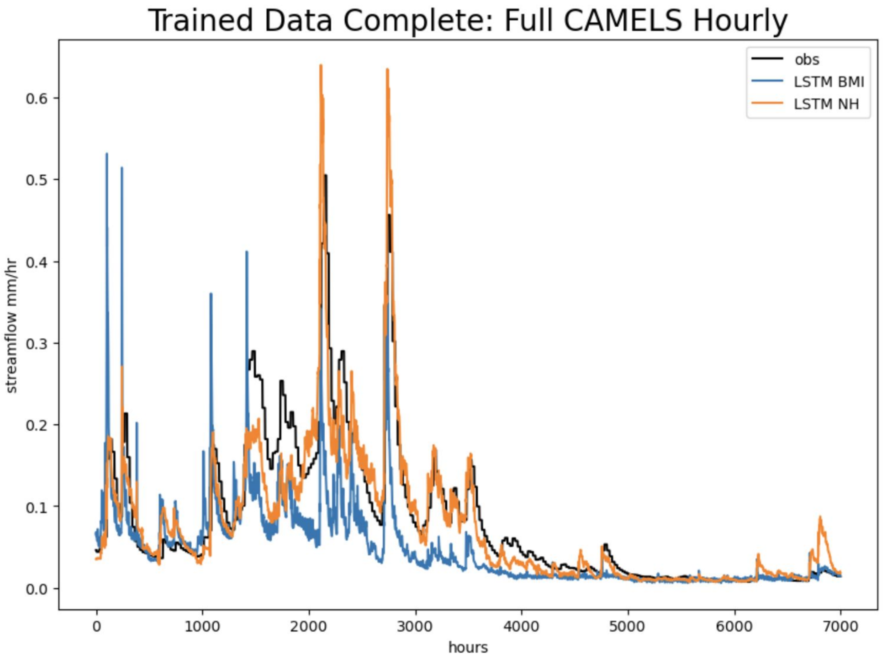
```
{
  "name": "bmi_python",
  "params": {
      "python_type": "lstm.bmi_LSTM",
      "model_type_name": "bmi_LSTM",
      "init_config": "./extern/lstm_py/
      "main_output_variable": "land_sur
      "uses_forcing_file": false,
      "variables_names_map" : {
          "streamflow_cms": "land_surfa
      "pytorch_model_path": "./data/lst
      "normalization_path": "./data/lst
      "initial_state_path": "./data/lst
      "useGPU": false
}
```

NGen

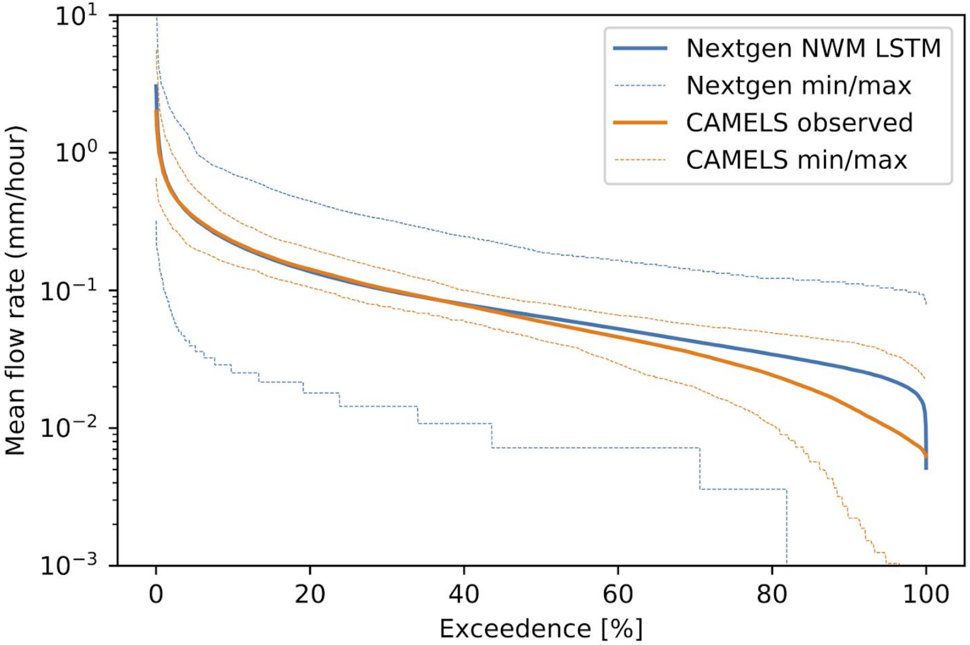
```
#### NextGen Output ####
NGen Framework 0.1.0
Building Nexus collection
Building Catchment collection
Catchment topology is dendridic.
Running Models
Running timestep 0
Running timestep 100
Running timestep 200
Running timestep 300
Running timestep 400
Running timestep 500
Running timestep 600
Running timestep 700
Finished 720 timesteps.
```

Sample Output

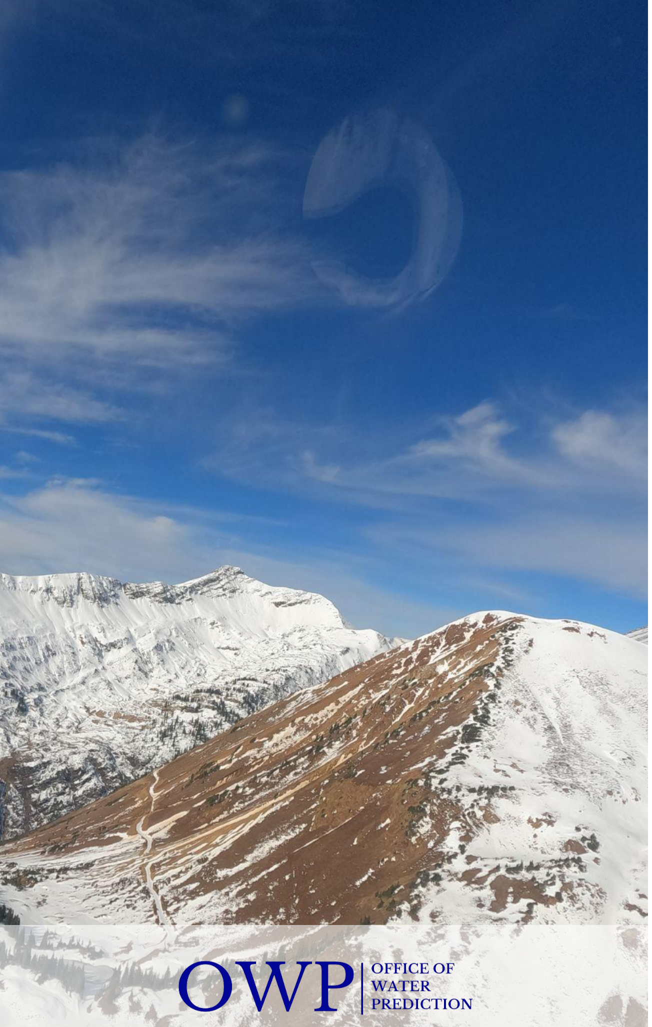




Sample Output: NGen



Animation and graphics thanks to Nels Frasier and Jonathon Frame



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Colorado SPLASH Soil Moisture Survey, October 2021

Next Steps

Training Data
- Updated Hydrofabric
- Varying inputs
- Multiple sources
- Time intervals
- Use different loss function(s)

```
dataset: hourly_camels_us
dynamic_inputs:
- total_precipitation
- temperature
epochs: 9
forcings: nldas_hourly
loss: NSE
metrics:
- NSE
- KGE
- Alpha-NSE
- Beta-NSE
model: cudalstm
static_attributes:
- elev_mean
- slope_mean
train_end_date: 30/09/2018
train_start_date: 01/10/1980
```

⊟ **Model Classes**
- BaseModel
- ARLSTM
- **CudaLSTM**
- CustomLSTM
- EA-LSTM
- EmbCudaLSTM
- GRU
- MC-LSTM
- MTS-LSTM
- ODE-LSTM

Model, etc.
- Merge of conceptual based models
- Explore other model classes;
  - CudaLSTM is most standard
  - CustomLSTM
- Backwards formulation
- Extreme events

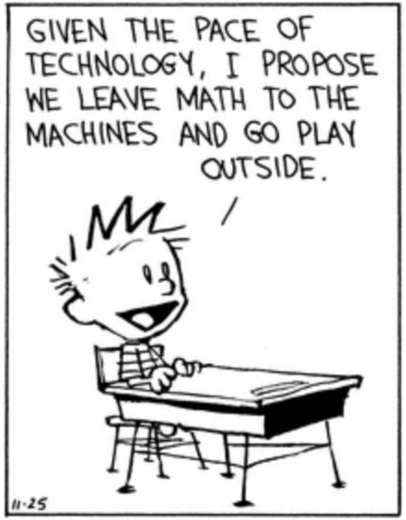
References

Kratzert, F., Klotz, D., Brenner, C., Schulz, K., and Herrnegger, M.: Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks, Hydrol. Earth Syst. Sci., 22, 6005–6022, https://doi.org/10.5194/hess-22-6005-2018, 2018.

Kratzert, F., Klotz, D., Hochreiter, S., and Nearing, G. S.: A note on leveraging synergy in multiple meteorological data sets with deep 400 learning for rainfall–runoff modeling, Hydrology and Earth System Sciences, 25, 2685–2703, https://doi.org/10.5194/hess-25-2685-2021, 2021.

Mulvaney, T. J.: On the use of self-registering rain and flood gauges in making observations of the relations of rainfall and of flood discharges in a given catchment, Proceedings Institution of Civil Engineers, Dublin, Vol. 4, 18–31, http://sources.nli.ie/Record/PS_UR_072021, 1850.

Frame, J. M., Kratzert, F., Klotz, D., Gauch, M., Shelev, G., Gilon, O., Qualls, L. M., Gupta, H. V., and Nearing, G. S.: Deep learning rainfall–runoff predictions of extreme events, Hydrol. Earth Syst. Sci., 26, 3377–3392, https://doi.org/10.5194/hess-26-3377-2022, 2022.



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Thank You!

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