Improving Deep Learning Precipitation Nowcasting by Using Prior Knowledge

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Introduction

In collaboration with Meteopress, we have achieved unparalleled quantitative performance of an operational precipitation nowcasting system (MWNet), building on the PhyDNet [1].

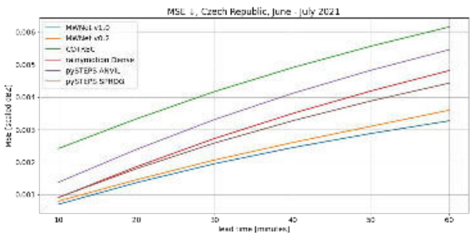

Figure 1:Comparison of prediction methods through summer 2021.

However, weather forecasting is not a competition, and there is room for improvement. We experiment with the utilization of prior knowledge of precipitation physics in the PhyDNet architecture to tackle the following persisting issues.

- Low explainability of system dynamics learned by DL model.
- Ignorance of hardly predictable high-frequency features caused by regression formulation of the learning problem.
- Quick performance decay with prolonged forecast times.

PhyDNet Architecture

PhyDNet [1] is a recurrent convolutional neural network designed for general video prediction that learns linear disentanglement between known physical and residual dynamics of the modeled system. The prediction is made in two branches.

- Physical branch (PhyCell) leverages physical prior to improve generalization and more effectively learn the precipitation dynamics described by PDEs.
- Residual branch (ConvLSTM) is a deep model that learns the complex unknown factors necessary for pixel-level prediction.

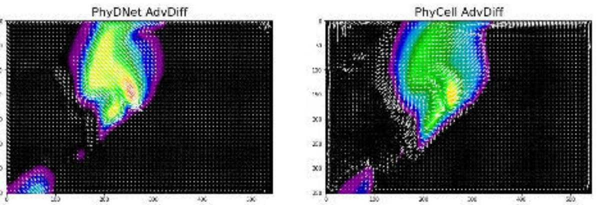

Figure 2:Advection field learned by the PhyCell.

Method

There are two possible drawbacks of the original PDE modeled by PhyCell.

- Referencing the non-linear advection term in Navier-Stokes equations for fluids, a linear PDE may not be sufficient for correct modeling of the atmosphere.
- It is difficult to interpret high-order derivatives in context of equations robustly describing physical phenomenons.

We study the effect of implementing the **advection-diffusion** equation into the PhyCell, where $\mathbf{h}^{(t)}$ is the hidden state representing precipitation at some time and $\mathbf{u}$ is a learned advection field.

$$\tilde{\mathbf{h}}^{(t+1)} = \mathbf{h}^{(t)} \underbrace{- c_0 \frac{\partial \mathbf{u}_x \mathbf{h}^{(t)}}{\partial x} - c_1 \frac{\partial \mathbf{u}_y \mathbf{h}^{(t)}}{\partial y}}_{\text{advection}} + \underbrace{c_2 \frac{\partial^2 \mathbf{h}^{(t)}}{\partial x^2} + c_3 \frac{\partial^2 \mathbf{h}^{(t)}}{\partial y^2}}_{\text{diffusion}}$$

Both PhyDNet and a separated PhyCell are trained, using different PhyCell designs. The dataset consists of $1\ \mathrm{km}^2$ and 10 minutes reflectivity data from above the Czech Republic in the time window from 23. 10. 2015 to 21. 7. 2020.

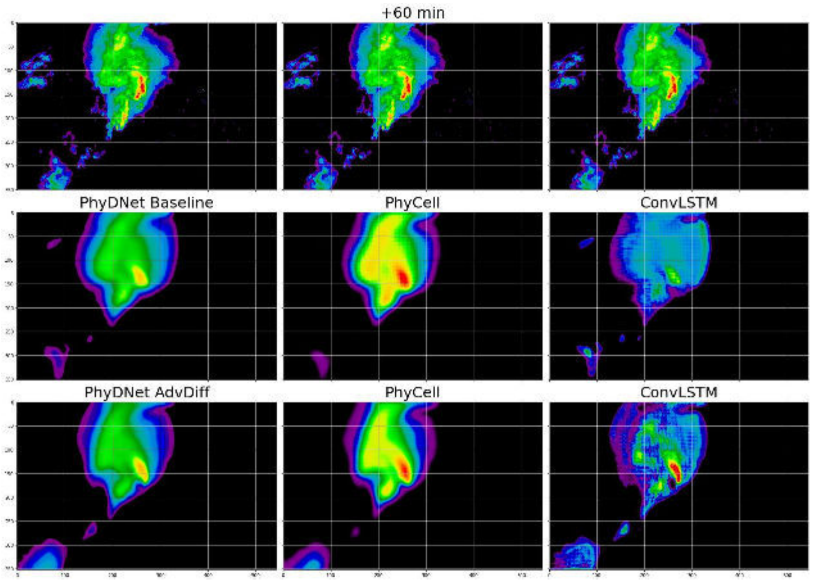

Figure 3:Visualization of partial predictions by PhyCell and the residual ConvLSTM.

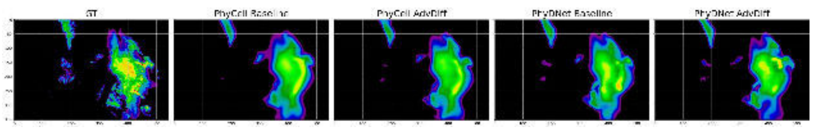

Figure 4:Visual comparison of predictions for 60 minutes lead time.

Experimental Results

- Learned $\mathbf{u}$ of PhyCell (Fig. 2) may be interpreted as local development vectors, while PhyDNet ignores directions.
- Empirically, in `PhyDNet AdvDiff` the residual part contributes more than in `PhyDNet Baseline` (Fig. 3).

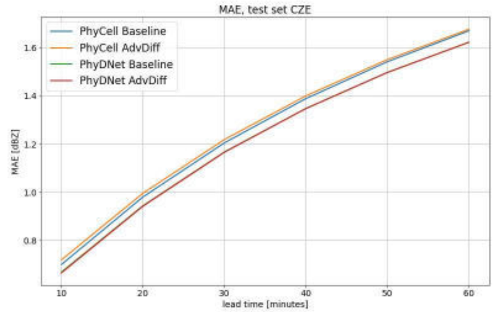

Figure 5:MAE on the test dataset.

- `PhyCell AdvDiff` reduces number of terms in it's PDE from 49 to 4, learning to predict precipitation effectively.
- Predictions of `PhyCell AdvDiff` are less smoothed and more physically sound (Fig. 4).
- In `PhyDNet AdvDiff` the residual ConvLSTM takes over the optimization, resulting in the quantitatively the same model as the baseline (Fig. 5), whose predictions are not distinguishable in general (Fig. 4).

Conclusion

The introduction of the advection-diffusion equation to PhyCell, resulted in a regularized model with predictions resembling actual dynamics in the atmosphere. However, results indicate that even if a part of PhyDNet is regularized with a physics prior and possibly learns the corresponding dynamics more effectively, the final predictions remain primarily decided by optimization of the loss function during training.

References

[1] Vincent Le Guen and Nicolas Thome.
Disentangling physical dynamics from unknown factors for unsupervised video prediction.
In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11474–11484, 2020.

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