Physics Informed Multi-frame Super Resolution for Weather Forecasts

Project report

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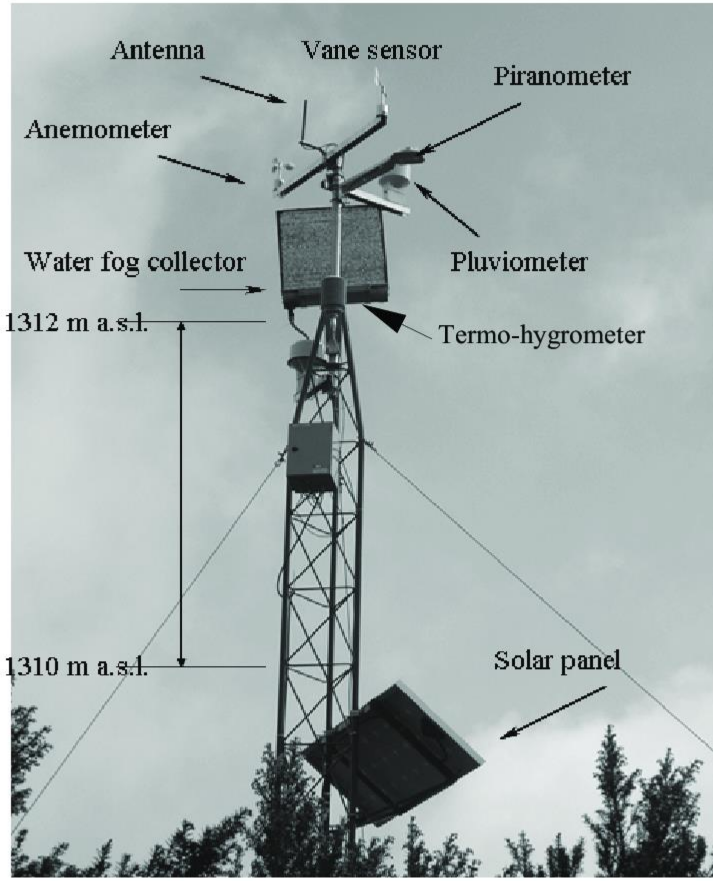
Why Upscaling the weather?

- Weather prediction and climate studies models (both classic and data-driven) require a lot of data
- Data is measured either *at some point* or averaged over large region (from satellite)
- To measure something away from observation station we need another observation station
- Data is gathered by very expensive and complex hardware
- Maybe we can calculate necessary data without measuring them?
- Proper mathematical models are extremely difficult



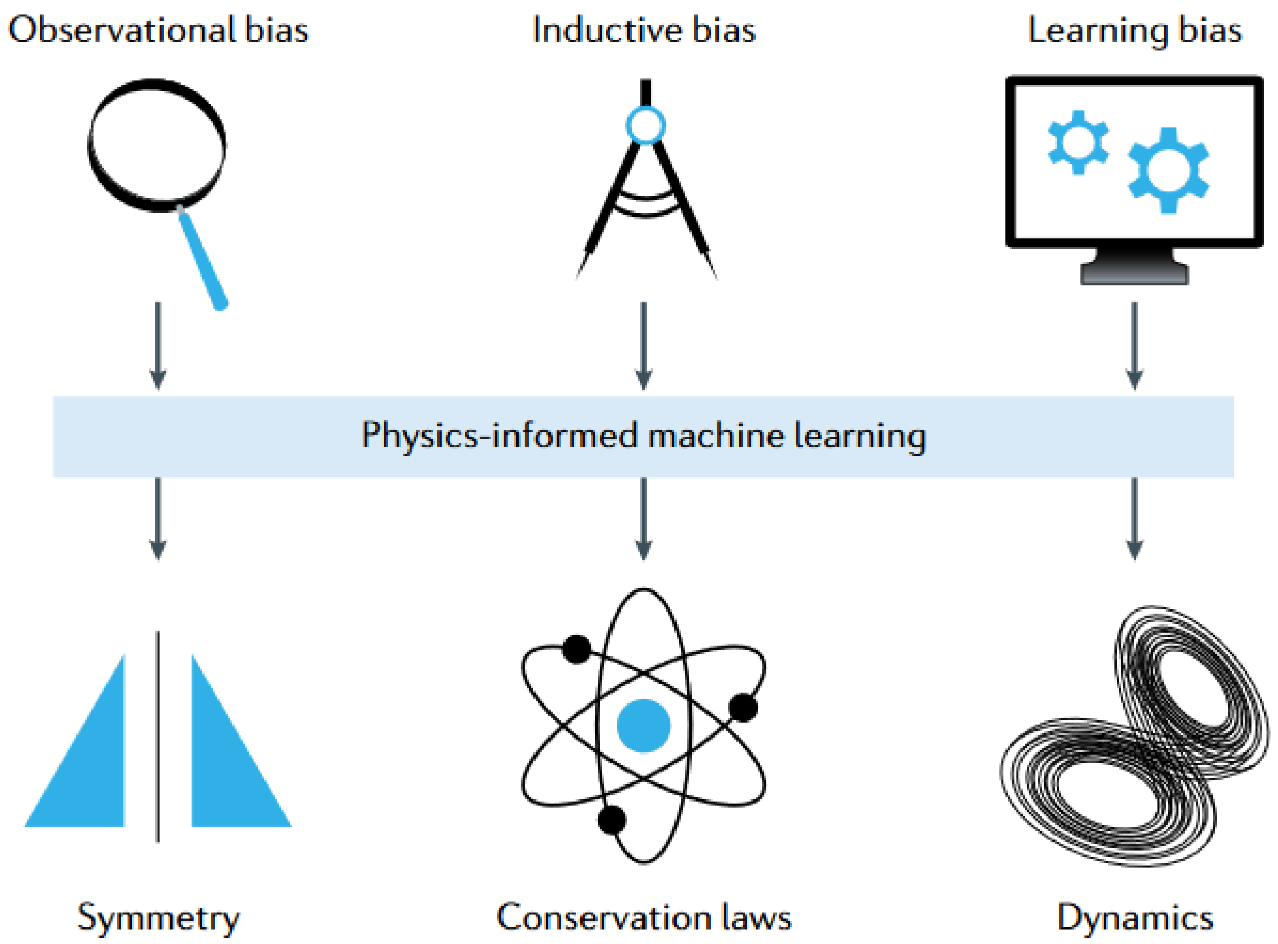
Inspiration - Deep Image Super Resolutioning

However…

1) Physics data are something different than just pixels

2) Need too much data to train

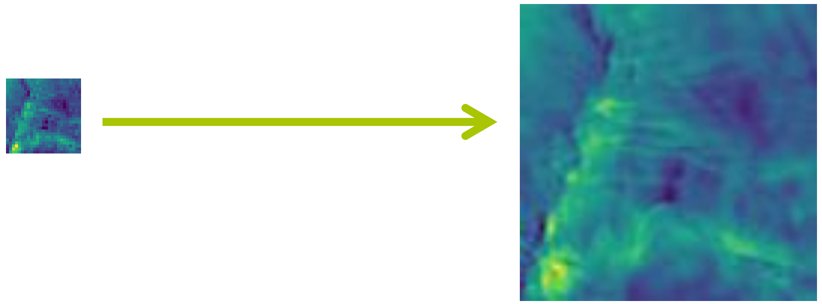
Physics-Informed Machine Learning



Dataset overwiev

Wind velocity measured over 256 small (200 x 200 km) in continental United States

1. Low resolution data – 25x25 measurements
2. High resolution data – 100x100 measurements
3. Data at each point --- one float number (expected to be). For display they were converted to RGB with respect to Viridis color scheme
4. Total 8448 pairs were used for training and 1024+1024 (validation/test) for inference



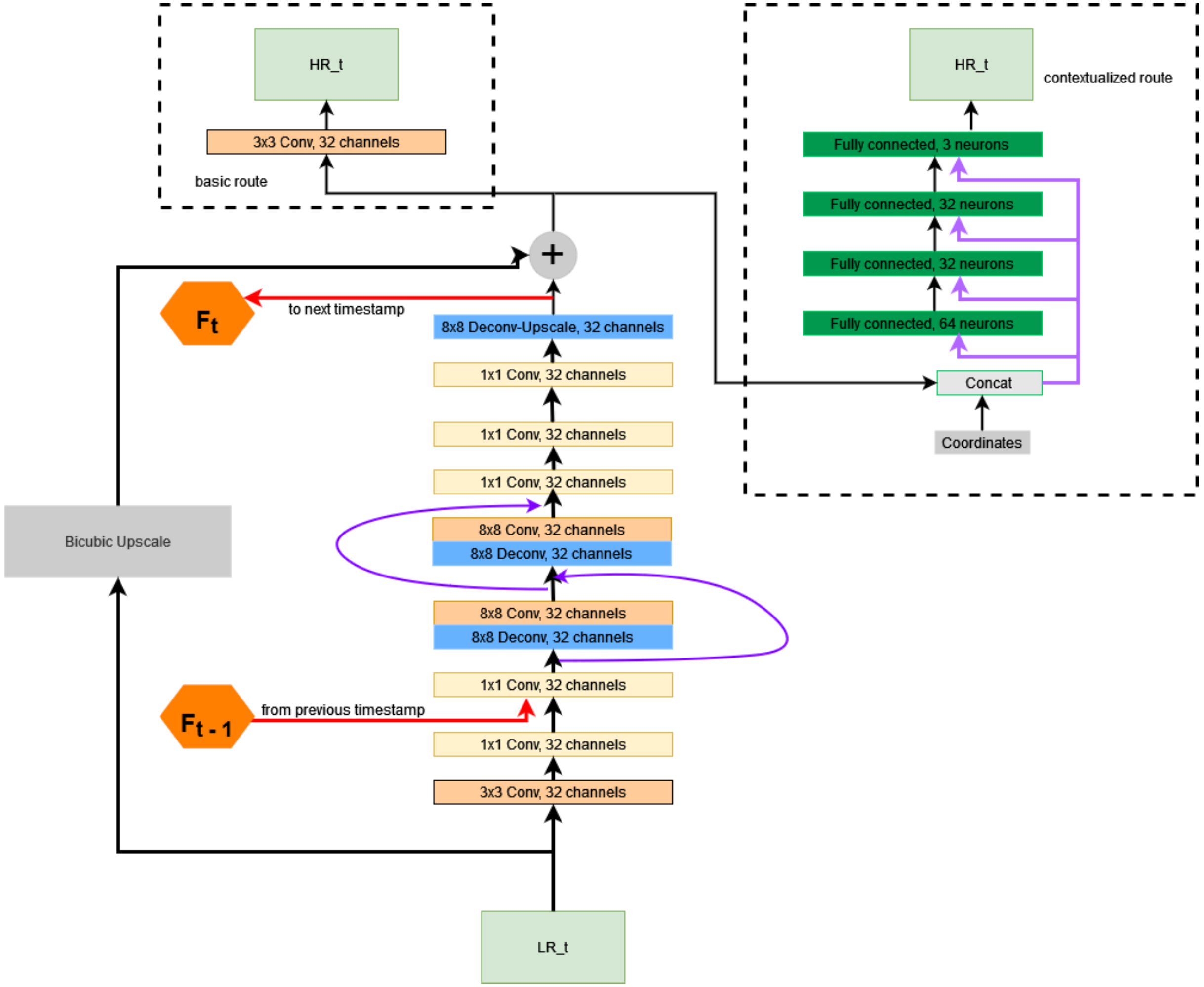
Implemented methods of Physics-Informing:

1) Gradient loss *(Serifi et. al., 2021)* – add to loss function term minimizing distance between gradients of vector fields

$$\mathcal{L}_{grad} = ||\mathbf{v} - \mathbf{w}||_1 + ||\nabla\mathbf{v} - \nabla\mathbf{w}||_1$$

2) Contextualization *(Jiang et. al., 2020)* – convolution models don’t pay much attention to actual positions, so we just add points coordinates as additional parameters to context representations and stack some fully-connected layers on top of it

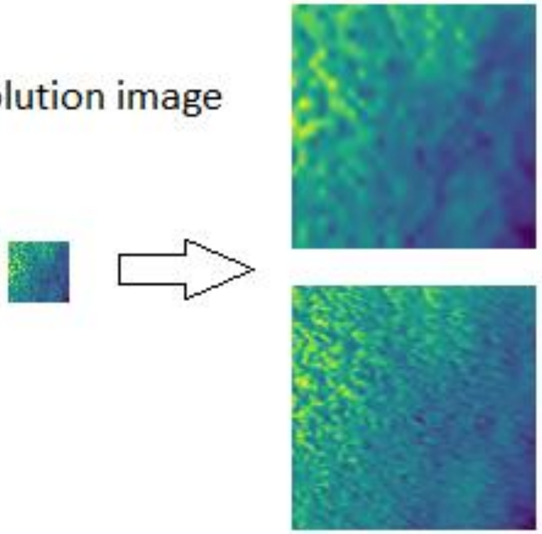
Model architecture



Results

Model	MSE	MAE	PSNR
Baselines			
Bicubic	7.2e-3	0.0604	22.404
SR-CNN	3.8e-3	0.0438	25.605
ESRGAN	5.6e-3	0.0533	23.795
SRFBN	3.8e-3	0.0428	25.820
Single frame model setups			
Gradient loss	3.7e-3	0.0426	25.838
Contextualized	3.7e-3	0.0427	25.854
Both	3.6e-3	0.0421	25.912
Multiframe setup			
Final	3.1e-3	0.0396	26.113

Table 1. Performance of models on Test data. **MSE**=mean square error. **MAE**=mean absolute error. **PSNR**=average peak signal to noise ratio.



Example of super-resolutioning. One parameter (wind velocity) is converted to color according to standard Matplotling pallete

References

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- Serifi, A., G¨unther, T., and Ban, N. Spatio-temporal downscaling of climate data using convolutional and error-predicting neural networks. Frontiers in Climate, 3:26, 2021.
- Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., and Yang, L. Physics-informed machine learning. Nature review Physics, 3:422–440, 2021
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