Physics Informed Multi-frame Super Resolution for Weather Forecasts

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Abstract

The weather forecasts are typically made by costly numerical models and the computational costs scale in such a way that 4x resolution increase requires 10x more resources. We are provided with a calculated dataset of weather forecasts for a region made by a WRF model in two resoutions. Task of our work is to improve a low resolution forecast with the help of multi-frame super resolution methods with physics informed parts.

1. Introduction

Usually, when people ask what weather will be, they only want to know quite little — will it be rainy or sunny, cold or warm, windy or not at their town today (or tomorrow) and modern mathematical models can relatively easy do accurate prognoses for such things. However, weather forecasting is not limited to this. In many areas (aviation, energy generation) forecasts must be much more complex: include more parameters (wind speed, humidity, atmospheric pressure, etc) and have much higher resolution than one ”averaged” prediction per town.

Mathematical models that are used for this are usually large, complex and require lots of input information. Their development takes constantly increasing amount of scientific research, so there are many approaches of implementing methods of machine learning to this task (consider (Bochenek & Ustrnu, 2022) for review of the current state in the field).

Both classic and machine learning methods have limited resolutions — each model predicts ‘averaged’ weather over regions of certain size. That size can’t be decreased without risking the quality of predictions, because of the nature of meteorological data — it’s either observations that are exactly correct only for the point where they were made (e.g. traditional thermometer can measure air temperature only around itself, not 2 miles away) or some ‘averaged-over-area’ predictions that have their own resolutions (e.g. air temperature measurements made by infrared spectrometer on a satellite). Thus, to increase resolution means to unproportionally increase amount of input data. For example, doubling the resolution of a two-dimensional grid leads to, at least, an increase of four times in number of observation points, and each of them must be equipped with expensive hardware and well-trained specialists to operate and maintain it.

And so, a problem arises — we can measure atmospheric parameters in some regions and have to reconstruct them in between measurement points. This task in a certain way similar to ‘upscaling’ blurry photos and videos with deep neural networks that recently become very popular (Lee et al., 2022). Such methods were implemented for Super Resolution of weather forecast data (e.g. (Rodrigues et al., 2018)), but there are some issues.

First of all, meteorological data is very different from images, thus models must be trained from the scratch which requires a lot of data. And obtaining data in our domain is costly. Although they learn *some* underlying relationships exist in the data, sometimes those relationships are *not* the underlying physical principles that models are supposed to learn. Moreover, as it was shown in (Reichstein et al., 2019), there are no guarantee of good ability to ‘generalization’ (i.e. to work outside of the scenarios covered in training data).

Similar issues are arising in many different fields and to overcome them methods of Physics-Informed machine learning were introduced. These are numerous different techniques dedicated at incorporating into neural model knowledge about underlying physical laws by specially designed architecture or training procedure of a model (Kashinath et al., 2021). They have shown good results for many tasks.

Many attempts were made for weather super resolution but they mostly were intended for super resolution by a single frame. So a question remains — can the knowledge of development of atmospheric situation (data from several time-points) help us improve quality of prediction.

And thus, we aimed this project at creating a physics-informed neural model for multi-frame super resolution of weather forecast data.

This paper is divided as follows:

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- In Section 3 review recent advances in both physics-informed Machine Learning and ML fro weather forecasting.
- In Section 4 we describe the ideas and methods that we plan to use in our model.
- In Section 5 we provide a description of the used dataset.

Link to project's GitHub repository: https://github.com/ArGintum/featherweather

2. Preliminaries

Image Super Resolution (SR) is a low-level computer vision task, which aims at reconstructing a high-resolution (HR) image from its low-resolution (LR) counterpart. Multiple HR images may correspond to an identical LR image and due to it this problem is inherently ill-posed. To address it, numerous methods have been proposed, that can be split including into three main categories: interpolation-based methods (Zhang & Wu, 2006), reconstruction-based methods (Zhang et al., 2012), and methods based on neural models (Dong et al., 2015).

Neural-based methods and due to this are very popular nowadays. The benefits of deep learning based methods mainly come from its two key factors — depth and residual/dense connections.

As the depth of networks grows, the number of parameters increases and along with it grows the risk of overfitting. To reduce network parameters, some authors employ the recurrent structure in their model (e.g. (Tai et al., 2017)).

3. Related works

Physics informed methods in machine learning have been developed for a long time and there are various different types of them (we encourage our reader to refer to (Karniadakis et al., 2021) for complete overview) but they can be roughly split into two major categories: custom design of the network architecture or special choice of the loss function (and combinations of these two approaches also exist).

Methods centered around designing the network are aimed at 'engraving' the physical laws into model's architecture. In some cases, to implement them architecture is very straightforward. For example, in (Zhang et al., 2020) where to solve complex partial derivatives equation (PDE) authors propose neural model where stack of fully-connected layers emulates the solution (function) and loss function minimizes difference between parts of equation. Something similar was done in (Hy et al., 2018) to make physics informed model for prediction of qualities of complex organic molecules. This approach requires a lot of data to train and perfect knowledge of governing rules just to write the correct loss function and thus is hardly applicable to our problem, since physical processes behind the climate are very complex.

Another, but much less radical example of such approach is (Cheng et al., 2020) where authors implement specially designed convolutional blocks to construct deep network for weather forecasts super resolution. That model achieves SOTA results (as per it's publication date). This idea is very promising and interesting for our work, but proposed model is quite large (requires much data) and it is intended for single frame super resolution. There is another issue — local obstacles (e.g. high hills) may affect processes of weather formation around them, a thing that purely convolutional model may not be able to handle.

Architecture of MeshfreeFlowNet introduced in (Jiang et al., 2020) for modelling of turbulent flows proposes possible solution of such problem by concatenating coordinates of each position to its embedding (we will describe this idea more in the next section).

Second approach for inducing physics into model is choice of the loss function. According to it, loss function is considered as 'soft constraint' that helps model get 'right' learning bias. Usually loss function is constructed around some spectral methods, like Discrete Fourier Transform in conditional GAN in (Singh et al., 2019). In that work authors use it together with mean square error in loss function, a thing that we would like to avoid in our work, since usage of MSE at super resolution tasks recently received some critique for being too sensitive to small shifts or one-point outliers (Choi et al., 2019).

4. Methods

4.1. Single-frame super resolution

For super resolution of single-frame we use multi-layer convolutional network. The nature of CNN will help with maintaining translational symmetry and multiscale hierarchy of atmospheric processes. To further incorporate knowledge about underlying physical principals and governing laws into our model we consider implementing

1. *Gradient loss* (in a form used in (Serifi et al., 2021)) in the loss function as the reconstruction loss. As authors of that paper shows this loss function generalizes usual $l1$-loss and greatly helps it towards convergence. It helps to better approximate the structure of data. Gradient loss between two vector fields $\mathbf{v}$ and $\mathbf{w}$ is computed as

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

where λ usually set to 1.

2. *Position contextualization*. We concatenate output of convolutional part that gives the *context* of output (tensor of size $H_{out} \times W_{out} \times d_{out}$) with coordinates of each position (tensor of size $H_{out} \times W_{out} \times 2$). Then feed it stack of fully connected layers that will produce final result as it was suggested in (Jiang et al., 2020).

Position contextualization brings connection between prediction and exact locations for which they are made at the same time preserving benefits of convolutional network. CNN provides translational symmetry that is completely in line with underlying principles (at interesting for us scale laws of Nature are pretty much the same everywhere). But at the same time, local terrain peculiarities: high hills/ large bodies of water/etc, may significantly affect atmospheric processes around them and because of it knoweledge of exact position is important too.

4.2. Multi-frame super resolution

We have not a single observation, but data about situation development in progress. This may provide additional information for super resolution and we implemented in our model feed-forward connections over time-stamps.

Architecture of our model was inspired by model SRFBN (Li et al., 2019). Complete scheme of our model is presented at Figure 1. As activation functions in our network we used LeakyReLU.

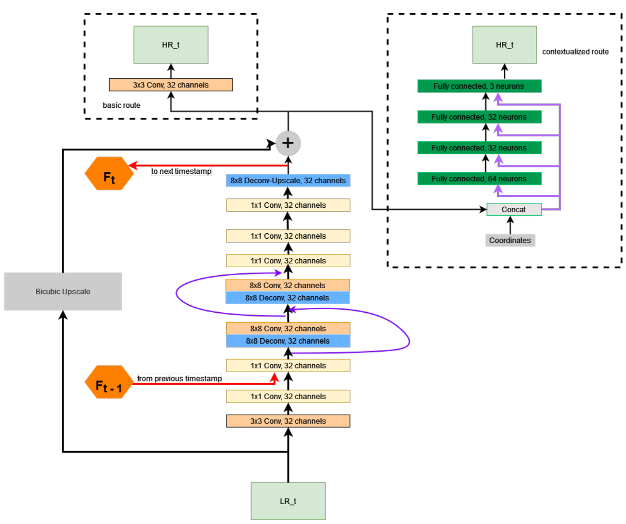

Figure 1. Architecture of implemented model. Skip connections are colored in pink. "Basic route" was used only for measuring importance of contextualizing approach, it isn't included in main model.

5. Data overview

After some initial experiments and proper examination of the dataset initially given to us we developed strong concerns regarding it - none of the models we trained on them regardless of architecture and hyperparameters was able to surpass quality of honest interpolation. And because of it we decided to switch to alternative dataset from the same domain.

The dataset we used contains data on wind velocity over continental United States. Data is publicly available at doi:10.22002/D1.2126 . It was originally obtained from USA National Renewable Energy Laboratory's (NREL) Wind Integration National Database Toolkit (WINDT). For our work we used only small subset of data with the size almost equal to the size of initially provided data (10,605 pairs against 10,495 pairs and same temporal resolution).

Each image covers a region 200 km $\times$ 200 km. The grid size for low resolution image is 8 km and 2 km for high resolution (thus, each piece low-resolution data is float array of shape 25×25). Data is generated for time points within 6 months interval in 2014. For each region, 256 snapshots made every 4 hours are available.

We preprocessed data by extracting actual wind speeds from PNG files and linearly scaling them to interval [0; 1].

Train set contains 8,448 pairs of corresponding high resolution image/small resolution image. Validation and Test sets contain 1,024 pairs each.

6. Experiments

6.1. Baselines and metrics

In our work we used following baselines:

- Bicubic Interpolation. This method does not include any trainable parameters, so we just apply it to all images from the Test set.
- SR-CNN (Dong et al., 2015). A classic convolutional model for image Super Resolution. We built and trained it from the scratch on our data according to procedure suggested by authors of the model. We used Adam optimizer with learning rate $1e-4$ ($1e-5$ for the last layer). We trained model for 200 epoch with batch size of 72 and chose best by performance on validation set.
- ESRGAN (Wang et al., 2018). Generative model for image Super Resolution. We obtained pretrained model from `https://github.com/github.com/xinntao/Real-ESRGAN` and fine-tuned it for our data according to procedure suggested by authors of the model. We left all the parameters

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.

standard and trained model for 100 epoch with batch size of 16 and chose best by performance on validation set.

- SRFBN (Li et al., 2019). Feedback Network for Image Super-Resolution. Deep network with elements of recurrence for image super resolution. We trained model from the start on our data using recomendations provided by authors of the original model.

As quality metrics we MSE, MAE and PSNR (peak signal to noise ratio) — classic quality metrics for image super resolution.

6.2. Training details

We did a grid search for hyperparameters of our model. To achieve result presented in Table 1, we used best discovered hyperparameters: batch size of 64 and Adam optimizer with learning rate 1e-3 for model in "basic" configuration (without contextualizing block) and 1e-4 for "contextualized" model. We trained our model for 200 epochs monitoring its performance on validation set.

6.3. Model results

Table 1 presents quality metrics of our model trained in different setups. They are following:

1. "Gradient loss" — Base model trained for single-frame image restoration with gradient loss
2. "Contextualized" — Contextualized model trained for single-frame image restoration with $l2$-loss.
3. "Both" — Contextualized model trained for single-frame image restoration with gradient-loss.
4. "Final" — Contextualized model trained for multi-frame image restoration with gradient-loss.

First three setups allow us to estimate the influence of each of the two methods of physically-informing.

Multi-framed model was trained using the data of 4 consequent time-stamps for each of the regions. Picture 2 shows an example of such image upsampling. As it can be seen

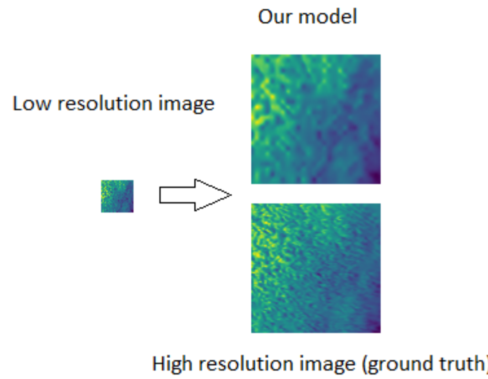

Figure 2. Example result of superresolutioning by our model

from Table 1, usage of physics informed methods allows to surpass baselines and slightly increase results (since our model is based on SFRBN we may assume that its quality is equal to quality of our model without physics-informed improvements). This improvement is nevertheless marginal.

7. Conclusion

In this research we explored the effect of physics-informed methods on super-resolutioning weather data (on the example of wind power data). We created deep convolutional multi-frame model for upscaling data and included two physics-informed methods — contextualization and gradient loss into it.

We trained our model in different setups and compared it against baselines in image super resolutioning. From the results that we achieved on our data we can not say that including 'physical knoweledge' into model helps improve its performance.

Small impact of including physics-informed methods may be caused by small size of dataset or small size of images.

An important challenge for us was to extract correct physical data from PNG-files and problems with initial dataset arised likely due to improper conversion (float-point numbers are converted to 3 single-byte integers w.r.t. some formula and super resolutioning over them as over 3 channels of standard RGB-image may be unjust).

We are planning to continue this research, did more research into the subject, use different data and explore more physics-informed approaches.

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