Utilizing UNet for the Future Weather Prediction: Weather4cast 2021

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Abstract

This paper describes our experiments of UNet based deep convolutional neural network model applied on Weather4cast challenge 2021 stage 1. This challenge's task is to predict future weather patterns, which is composed of four target variables per pixel: temperature, convective rainfall rate, probability of occurrence of tropopause folding, and cloud mask. Given equal size of input and output weather image, we trained UNet shaped neural network model to make predictions for each target variable. Evaluation results show competitive performance compared to the baseline method.

Keywords

Weather forecast, deep learning, neural network

1. Introduction

In this paper, we describe our methods on Weather4cast 2021' stage 1 challenge. This challenge's task is to predict future 8 hours weather image given prior 1 hour's weather data [1]. Both input and output weather image have 256 x 256 pixels, and each pixel represents approximately 3km x 3km spatial area. Input weather image contains various weather-related variable measurements (For detailed explanation with regard to the input data variables, please see [1]). Target output variable to predict is temperature, convective rainfall rate, probability of occurrence of tropopause folding, and cloud mask.

Training data contains weather images acquired from 3 distinct regions worldwide, named R1, R2 and R3 (which corresponds to Nile region, Eastern Europe, and South West Europe, respectively) in this challenge. In the core challenge task, both training data and held out test data came from R1, R2 and R3 regions. In the transfer learning task, training data is same as core challenge task, but held out test data is coming from different regions, named R4, R5 and R6 (which corresponds to Central Maghreb, South Mediterranean and Central Europe).

Since input and output weather image has equal size (width and height), UNet [2] is a natural choice which shown effective performance in similar tasks [3], [4], [5], [6], [7]. We trained neural network model having UNet based architecture. Each convolution block is densely connected with subsequent layers like a DenseNet [8].

Evaluation results show competitive performance compared to the baseline methods for this task.

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2. Methods

2.1. Preprocessing data

Prediction takes prior 1 hour's weather data as input, and should produce prediction ranging to next 8 hours. Each weather image has 15 minutes interval, so input has 4 weather images, and output should have 32 weather images.

Input weather image contains various weather-related variables data per pixel. There are 9 continuous variables, and 16 discrete variables. Continuous variables are normalized to minimum 0.0, maximum 1.0 range, and discrete variables are converted into one-hot encoding vector.

In this study, recurrent model such as LSTM (long short term memory network) [9] was not utilized. So, time dimension is simply merged into feature channel dimension.

2.2. Model

We implemented UNet [2] based model, as described in Figure 1. Each dense block consists of 2 convolutional layers, which are densely connected as depicted in Figure 2 [8].

Each blue box represents dense convolution layers block with average pooling layer. Each orange box represents deconvolution layers. Green arrow represents skip connections between downsampling path and upsampling path.

We trained model for each of 4 target variables separately, but all of them have identical UNet with DenseNet model structure described above. For temperature, convective rainfall rate, probability of occurrence of tropopause folding, mean squared error is used as loss function. For cloud mask, since it can have only binary output (0 or 1), sigmoid loss is used instead.

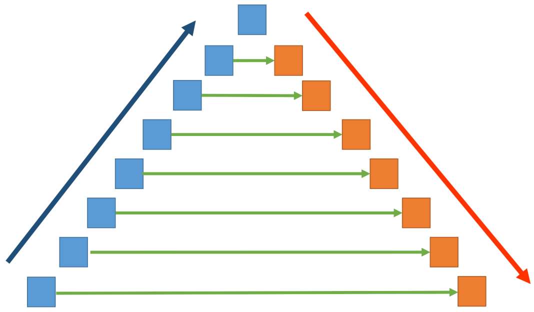

Figure 1: UNet model overall structure

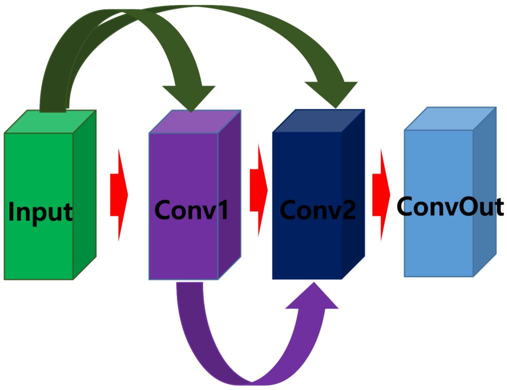

Figure 2: Dense convolution block structure: 2 convolutional layers are densely connected with each other

2.3. Training

Training data has 316 days weather images from R1, R2 and R3 region, time period ranging 2019-2020. Held-out test data is captured from separate time period (2020-2021).

In this study, we haven't tried to train region-specific model. All training weather images from different regions were merged and used together to train general model that can be used to apply on all regions.

We trained 1 model for the temperature prediction, 2 models for the convective rainfall rate prediction, 2 models for the probability of occurrence of tropopause folding prediction, and 3 models for the cloud mask prediction. When multiple models are trained for the same target variable, output prediction values are simply averaged to produce final output. Our experimentation code is publicly available at https://github.com/sungbinchoi/w4c_st1.

3. Results

Official evaluation metric for this challenge was mean squared error divided by mean squared error of the baseline prediction, which is taking last previous weather image as prediction output on all out timeframe, so baseline prediction output is scored as 1.0.

In this study, we trained only region-agnostic model. Same models used to produce prediction for the core task is used for the transfer learning task without any change. Our best evaluation results from held out test set was 0.507325 in the core challenge task and 0.465760 in the transfer learning task, which means roughly loss is halved compared to the baseline.

4. Conclusion

In this experiment, we used UNet for the weather forecast task. It showed competitive performance compared to the baseline.

In our study, we trained only region-agnostic model. In our preliminary experiment, it was not clear whether a region-specific model is more effective than the general model for the core challenge task. As a layperson, this was quite counterintuitive, because weather from R1 (Nile region) seems very different from R3 (South West Europe). We will explore more various research ideas and hope to find more effective methods in the next stage of the challenge.

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