**What has been done and plans for the next week:**

The UNet model has been implemented as described in the V2V paper. As soon as the dataset is available, the reconstruction performance of the model will be observed. This should be important because a bad reconstruction model could extract poor features and overlook correlations between parameters. This could lead to a suboptimal input subset selection.

UNets proved to be effective in spatio-temporal prediction in comparison to other architectures. My research implies that UNets are capable of modeling spatial characteristics but struggle in capturing temporal characteristics. This will be examined further after the data is first analyzed independently focusing on spatial characteristics. Mainly the idea of adding earlier time steps into the decision process.

In addition to the extracted features of the parameters, we will also observe the prediction behavior of different input/output combinations. To achieve this, the model will be trained applying random dropout to the input layer. The final model trained by this method will be called the probe predictor similar to the probe denoiser in the original paper.

The V2V model forces the resolution into 1x512 in the 4th Conv layer but the original UNet by Ronneberger downsizes by half as usual. If our priority is prediction behavior and finding the best input subset, what would be the reason to force the resolution into 1D scale? The effect of the bridge part is to be observed further by trying different resolutions.

**Architectural ideas for the future:** At the moment our base model does not have any normalization except the one applied on the input at the start. So, Batch Normalization in-between layers might prove useful. Dropout in hidden layers for regularization is another option. But this could harm our main purpose, because additional dropouts may change the effect of the isolated dropout at the start. This is just an assumption which must be tested.

**Motivation and the purpose of our work:** **I wanted to outline this early to organize my future plans.**

Discovering patterns from meteorological data is significant for many subjects. Not only can it be used for short to middle-term weather prediction, it can also help us understand the order of our climate and how it transforms in the long term.

Our Networks might learn correlations present in the data but those correlations may not always be representative of our understanding of that system. We cannot treat these models as black boxes, because as long as the decision process of the model is not explained, scientists will be discouraged to use these models (when they don't know if it is consistent with atmospheric behavior --> no trust). Explaining the decision process will make it easier for them to improve their theories.

There are two main Visualization methods:

1- Feature Visualization, where we construct an input that maximizes a certain node or a layer, to see what that node or layer represents. (Which areas does a node/layer examine the most?)

2- Explaining Decisions, where given a specific input, we create a heatmap that shows which areas of the input affected the decision of the model the most. These heatmaps are created separately for each input.

In this work, we will try to find a subset of meteorological parameters that predict the remaining parameters with the best accuracy. To do that we will develop a UNet model (or additional models) that extract features of every parameter and use those to predict others.

Then we will use LRP to gain an understanding of the correlation between the parameters and explain the decision process of these models. Mainly focusing on the spatial patterns. Multiple heatmaps of different timesteps will be reduced into a single model to get a more compact representation of the decision process.

**RELATED WORK:**

LRP was first applied in geosciences very recently. Since then, there have been many works on identifying patterns of climate with the help of LRP applied to neural network models. A. Toms showed a pattern matching of the LRP method with already discovered common climate patterns to prove that neural networks can learn fundamental dynamics of the atmosphere. (ENSO pattern, El Nino, La Nina). A. Barnes identified climate patterns of forced change with the help of LRP and other methods.

More applications of LRP on specific climate patterns should be observed. These patterns will give a general idea about what to look for in the heatmaps.