Temperature assimilation for convective flows by means of convolutional neural networks

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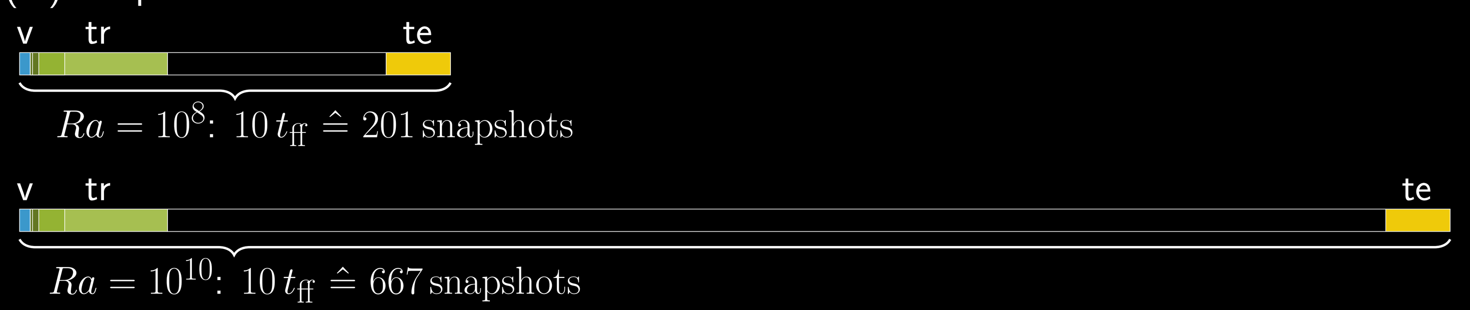
Objectives

Assimilation tasks in convective flows can be performed by various machine-learning [1, 2] and numerical [3] approaches. Here, we demonstrate the ability to retrieve temperature information from velocity fields of Rayleigh-Bénard convection using a purely data-driven approach based on convolutional neural networks. For this purpose, direct numerical simulations provided the ground truth data, which was downsampled to 64^3 grid points per domain. In order to augment the data and limit the size of the networks, the models were trained on windows clipped from the domain. The inference performance of different window sizes and shapes, as well as different training period lengths, was tested for $Ra = 10^8$, $Pr = 0.7$ and a more challenging case of $Ra = 10^{10}$, $Pr = 6.9$.

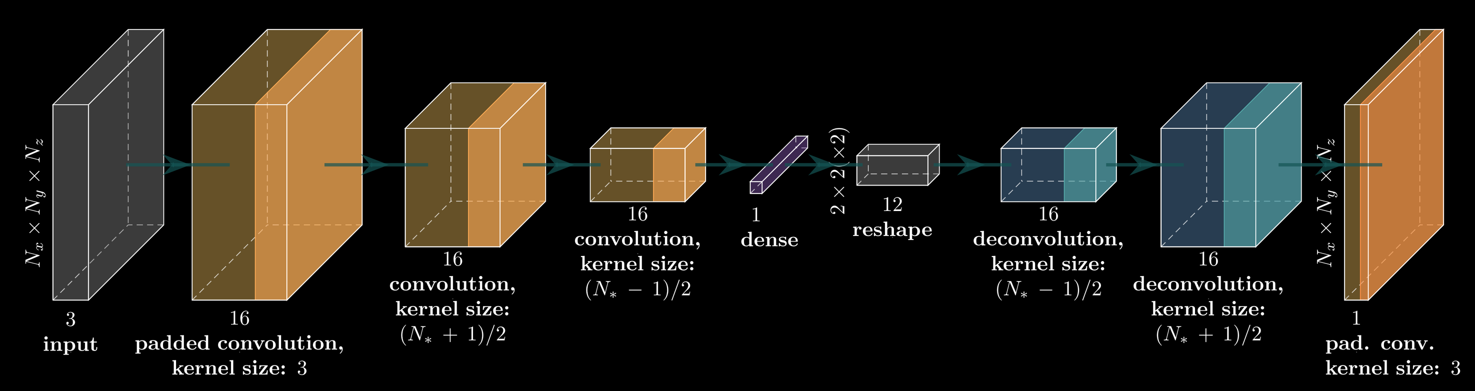
METHODOLOGY

In both cases, data was available for 10 free fall times (t_{ff}). The datasets consisted of 201 and 667 snapshots of the flow, respectively. The amount of training data (tr) was varied among the following numbers of snapshots (N_t): 1, 4, 16 and 64. In each case, the first 5 snapshots of the datasets were reserved for calculating the validation (v) metrics and the last 30 were used for testing (te) the performance of the models.



The input ($\boldsymbol{u}$) and output (T) data for the neural network were provided as windows of size $N_x \times N_y \times N_z$, clipped from the domain of 64^3 grid points. In the case of the 3D cubic window, these dimensions were set to 5, 7, 9 or 11. The same was used for the 2D window shapes, but with $N_x = 1$ for a vertical window and $N_z = 1$ for the horizontal one. The training data consisted of all window views of the domain generated with a step size of 2 in each direction.

Adapted to the window size, convolutional neural networks with an encoder-decoder architecture were defined as models for the different cases. Their structure is shown below, where N_* denotes the non-one dimensions of the in- and output windows. All layers were activated with ReLU functions, except for the last one, which was activated with a sigmoid function.



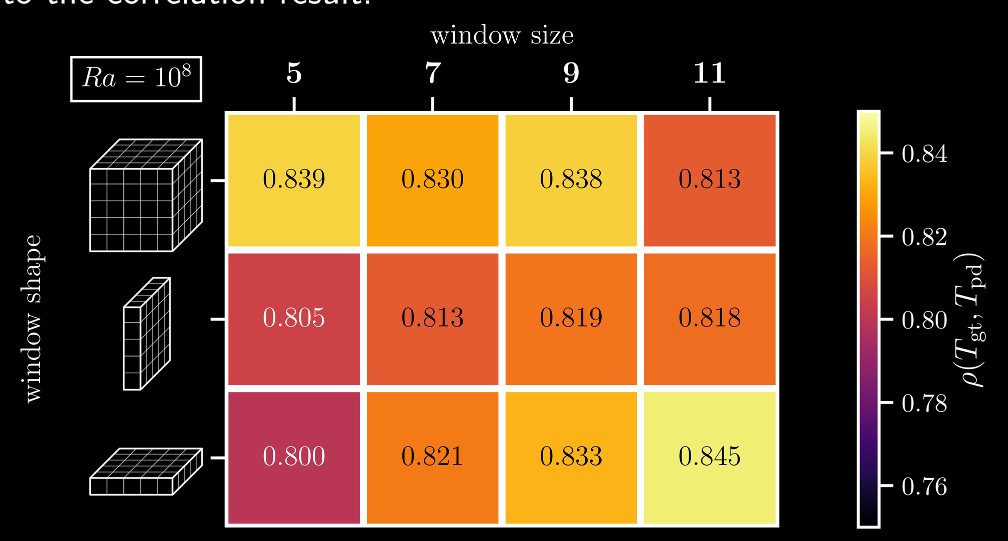
For inference, the temperature fields were reconstructed by averaging over all available window views. The overlapping windows result in averaging over up to $N_x \times N_y \times N_z$ different views for grid points more than half the window size away from the walls.

To account for the random weight initialization and the stochastic learning process, 3 training runs over 500 epochs (Adam optimizer on mean squared error loss function, learning rate 0.0025, batch size 512) were performed, from which the run with the best final validation loss was used for further analysis.

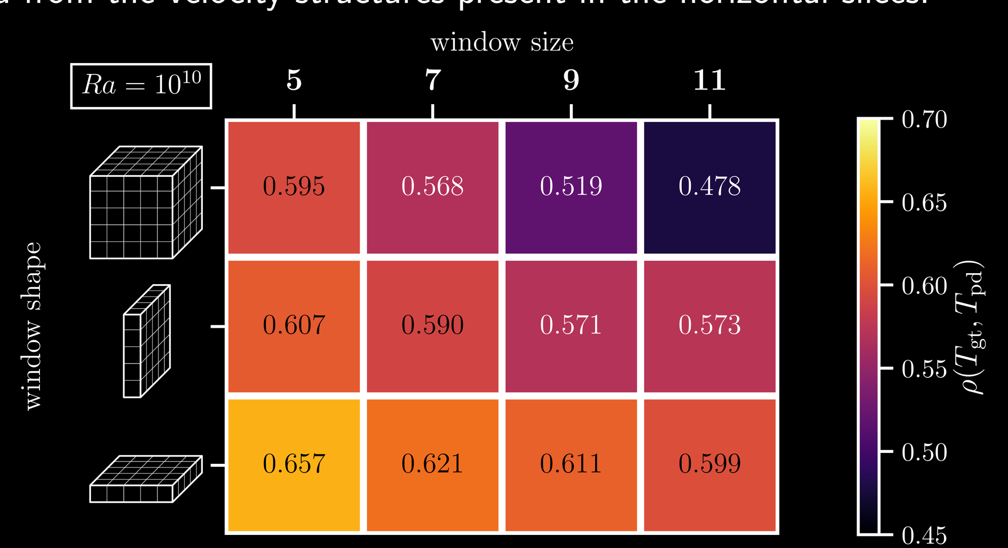
INFLUENCE OF WINDOW SIZE & SHAPE

First, the performance of varying the window size and shape is investigated. Correlation coefficients $\rho(T_{\mathrm{gt}}, T_{\mathrm{pd}})$ of the ground truth (gt) and predicted (pd) temperatures within the test interval were computed.

For $Ra = 10^8$, the best results were obtained for the smallest 3D window and the largest horizontal 2D window. This indicates that the flow structures within a horizontal slice are more valuable for temperature assimilation than those present in vertical slices. The advantages of larger windows – more information about the flow and more complex models – appear only for the 2D windows, since the reconstruction based on larger windows is also associated with a stronger smoothing effect, which is detrimental to the correlation result.



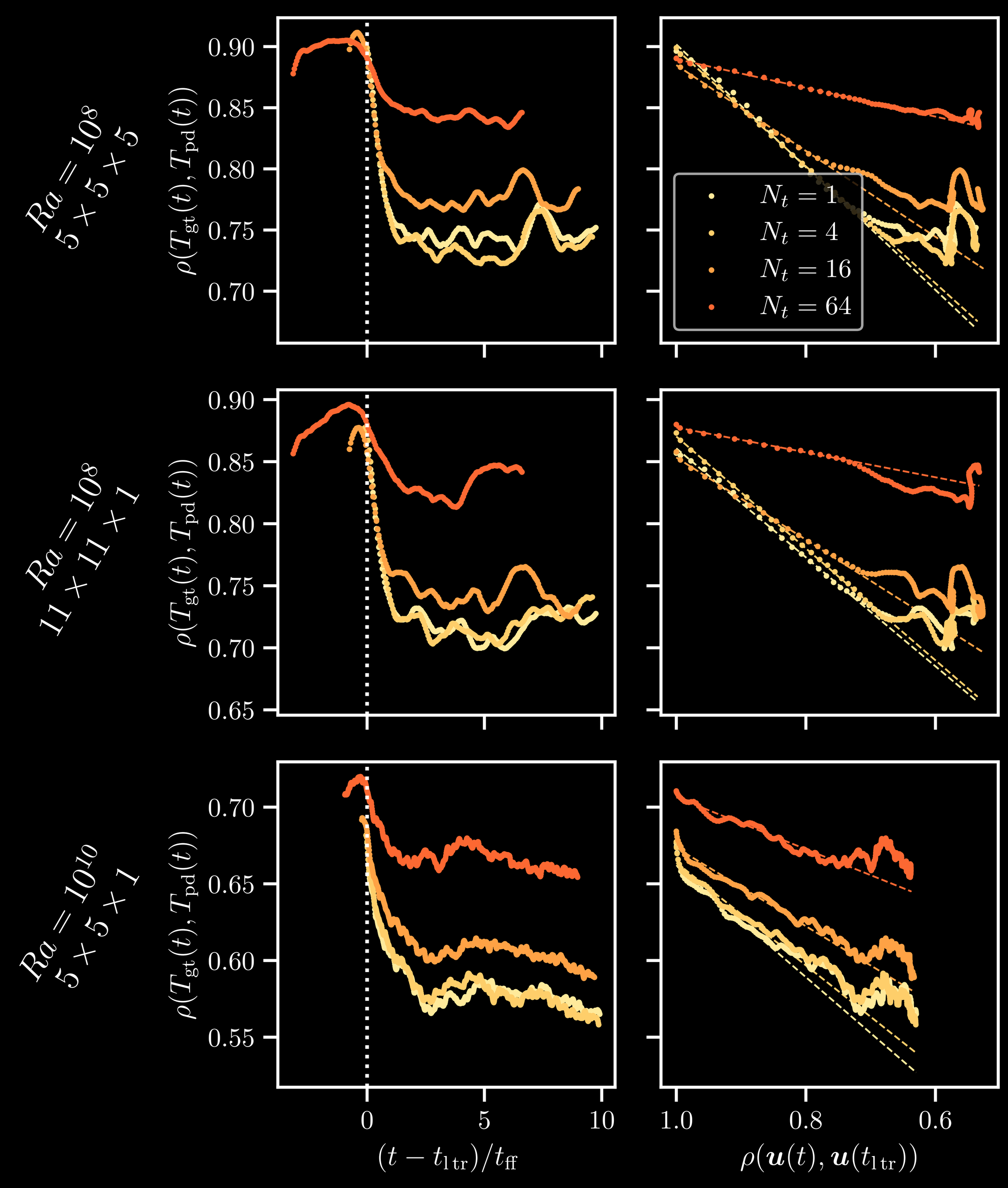
The detrimental smoothing effect of large windows is even more pronounced in the case of $Ra = 10^{10}$ and $Pr = 6.9$, which contains finer temperature than velocity structures. Therefore, the obtained correlation values are lower overall and the best results are obtained for the smallest window size of each shape. As for the lower Rayleigh number, the temperature information is more effectively assimilated from the velocity structures present in the horizontal slices.



INFLUENCE OF THE TRAINING PERIOD LENGTH

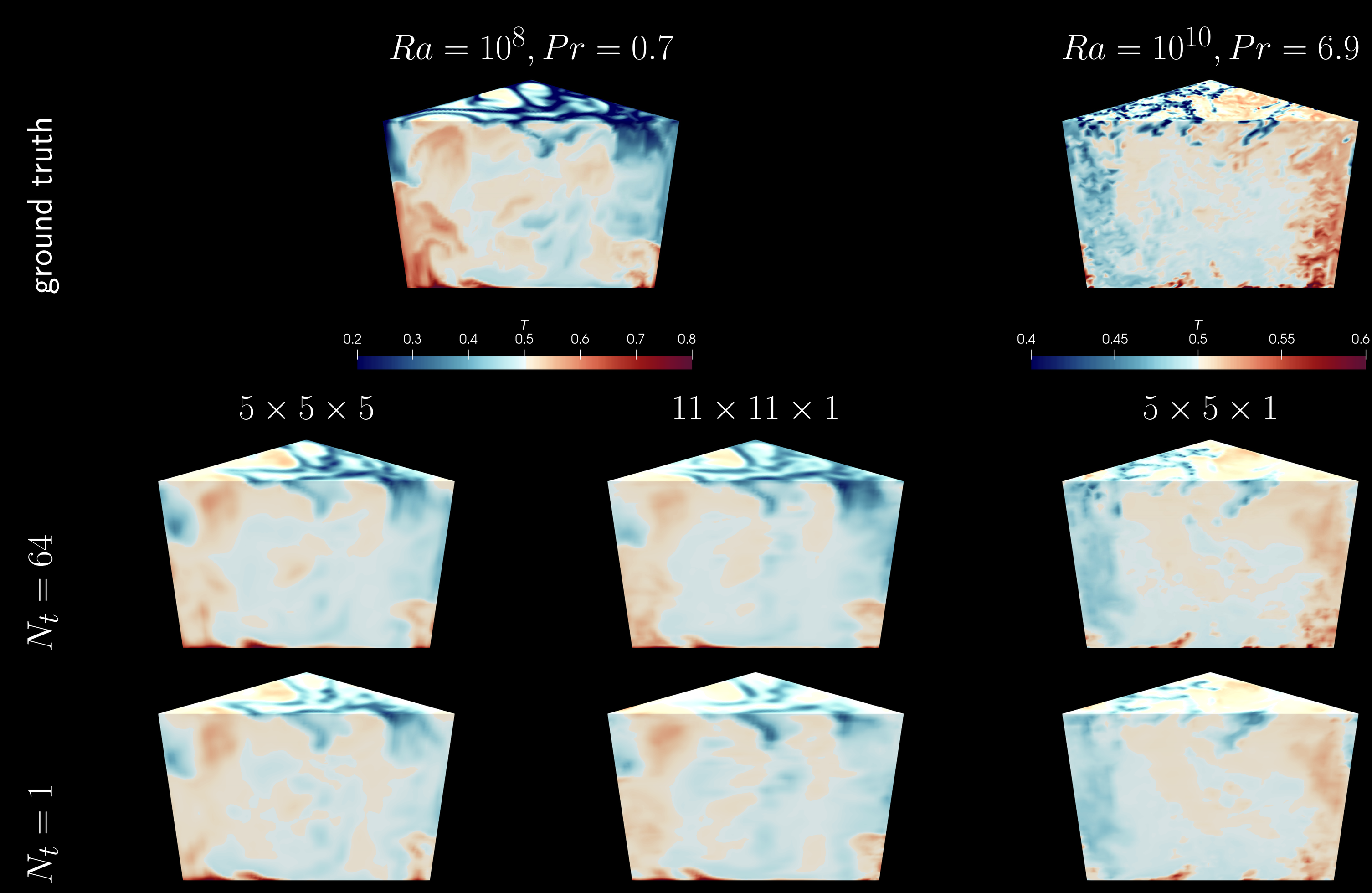
For the best window configurations, we examine the effect of the number of snapshots provided for training by plotting the time decay of the correlation coefficient $\rho(T_{\mathrm{gt}}(t), T_{\mathrm{pd}}(t))$. To account for the evolution of the velocity field, these correlation values are also plotted against the correlation coefficient $\rho(\boldsymbol{u}(t), \boldsymbol{u}(t_{1\,\mathrm{tr}}))$ of a velocity field to that of the last training snapshot at $t_{1\,\mathrm{tr}}$.

In all cases, a more training snapshots are beneficial for the assimilation performance. However, the differences between 1 and 4 snapshots are negligible, while they are producing robust results. Furthermore, the main performance drop is observed in the first $0.75\,t_{\mathrm{ff}}$ after the last training snapshot (this period was also used to fit the dashed lines in the plots on the right side). After that, it remains inconclusive whether the correlation values stabilize at these levels or continue to decay at a slow rate, as they also exhibit significant fluctuations.



RECONSTRUCTED TEMPERATURE FIELDS

The sample temperature fields illustrate the performance of selected models in reconstructing the last snapshot of the test interval. The main temperature structures are recovered by all models. However, they lack the ability to reconstruct the full extent of the temperature amplitudes and small structures due to the smoothing effect. Providing a larger number of snapshots mitigates these shortcomings.



CONCLUSION & OUTLOOK

Training the presented model architecture produces robust temperature predictions based on instantaneous velocity fields. The results highlight the advantages of horizontal planar domains and extended training data.

One application for this technique is to assimilate temperatures to long time sequences of measured velocity data, while equivalent direct numerical simulations cover only short time periods. In addition to refining the encoder-decoder architecture and tuning the hyperparameters, different reconstruction approaches will be tested to improve the quality of the determined temperature fields, since the smoothing caused by the overlapping windows is a major limiting factor.

REFERENCES

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