DLSC

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Task 3: Time Series Forecasting with Neural Operator

For task 3 we were asked to find future predictions of T_f and T_s at the spatial boundary, $x = 0$. We were provided with provided with measurements of the fluid and solid temperatures, $T^0_{f,i}, T^0_{s,i}, \quad i = 0, ..., 210$ taken from the top end of the storage and asked to use a method based on **Neural Operators** to predict the temperature for the next 34 time steps, with constant step sizes given by Δt. To solve this task I adapted the FNO-template from tutorial 10 to my problem. fortunately, only slight modifications in creating, normalising and loading the training data were necessary to make it work for this problem.

I trained my neural operator to predict, given 35 time values and corresponding fluid and solid temperatures, the fluid and solid values at the next 35 time points. I.e. I wanted my FNO to map, for example, $(t_i, T_{f,i}, T_s s, i)_i, \quad i \in \{0, .., 34\}$ to $(t_{i+35}, T_{f,i+35}, T_s s, i + 35)_i, \quad i \in \{0, .., 34\}$.

Hyperparameter tuning was fairly straightforward, I found that a time-point interval of length 35 was a good trade-off between number of possible Fourier-modes (which is approx. half the number of points in the second dim. of input tensors) and the maximum batch size. Additionally this approach allows us to predict the temperatures for the submission in one go, thus avoiding a potential cumulative error that a more fine-grained sliding window approach would incur, at least this was my conclusion from testing a couple approaches (NOTE: Included 3 different notebooks on task 3, but I used the second one to generate the submission). Some playing around with ADAM, the width parameter and regularisation quickly yielded good results for the training loss.