Impute Water Temperature in the Swiss River Network Using LSTMs

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Keywords: Water Temperature Dataset, Imputing Missing Data, LSTM, Recurrent Neural Network, Time Series.

Abstract: Switzerland is home to the sources of major European rivers. As the thermal regime of rivers is crucial for the environment, the Federal Office for the Environment has been collecting discharge and water temperature data at 81 river water stations for several decades. However, despite diligent collection 30% of the water temperature data is missing due to various reasons. These missing data are problematic in many ways – for instance, in predicting water temperatures based on different models. To tackle this problem, we propose to use LSTMs for water temperature imputing. In particular, we introduce three different scenarios – depending on the available input data – to impute possible data gaps. Then, we propose several methods for each scenario. For our empirical evaluation, we engineer a novel dataset (with ground truth) by artificially introducing gaps of sizes 2, 10, 30 and 60 days in the middle of 90-day sequences. A rather simple interpolation baseline achieves a competitive RMSE on gaps of two days. For larger gaps, however, this simple method clearly fails, and the novel, far more sophisticated models significantly outperform both interpolation and the current state of the art in this application.

1 INTRODUCTION

The thermal regime of rivers is important for several chemical and biological processes (Caissie, 2006). Moreover, due to the complexity and dependence of meteorological events, projections of future water temperature is both crucial and challenging (Piccolroaz et al., 2016). Improving the performance of predictive models is a crucial step of the overall simulation capabilities, especially when facing climate change.

Switzerland has a ubiquitous landscape of water bodies that consists of four major rivers (Rhine, Rhône, Inn, Ticino) with their corresponding tributaries. In the high alpine regions there are glaciers, snow fields and hydroelectric power plants. Within the lowlands there is agriculture, a multitude of medium and large cities as well as various lakes. All this substantially influences the water network and especially the temperature of the water bodies.

For instance, if inflowing water stays for a long time in a lake, the outflowing water corresponds to the surface layer of the lake. This layer is more affected by atmospheric exchange rather than the inflowing water (the solar radiation is absorbed by particles in the water, then converted into heat and finally exchanged with the water). Large cities (as a second example of influence) can warm up on sunny days and act as a boiler for rain water, which is then routed into the nearest body of water.

Furthermore, we have other effects such as ground water inflow or snow melt. Last but not least, on the water surface there is a direct exchange with the surrounding air. Hence, the water temperature is heavily dependent on the air temperature. All in all, we observe a fascinating network of water bodies with a high complexity.

The present paper researches the important and complex problem of water temperature imputation in case of missing data. The topic of water temperature imputing has been approached with diverse models such as spatiotemporal varying coefficients (Li et al., 2017), or by remotely sensed Land Surface Temperature (McNyset et al., 2015). In the present paper we propose to combine Deep Learning with the problem of imputing missing data in water temperature sequences. To this end, we use Long short-term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) networks for data imputation. LSTMs have

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Fankhauser, B., Bigler, V. and Riesen, K.
Impute Water Temperature in the Swiss River Network Using LSTMs.
DOI: 10.5220/0012358100003654

In *Proceedings of the 13th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2024)*, pages 732-738
ISBN: 978-989-758-684-2; ISSN: 2184-4313

shown promising results in the related task of water temperature prediction (Qiu et al., 2021; Jia et al., 2021).

LSTMs are a special type of a recurrent neural network (RNN) (Sherstinsky, 2020). An RNN in turn is a neural network that is applied to a time series on every time step. In addition to a standard RNN, an LSTM keeps track of a hidden state and a memory state, two vectors which are fed as inputs to the next time step and will be altered by the LSTM.

This paper is a continuation of the work on the Swiss River Network dataset where diverse open challenges have been presented (Fankhauser et al., 2023). In this previous publication, water temperatures are predicted by means of LSTMs on the basis of a graph based data structure. However, this prediction is – at least in past – based on incomplete data. We belief that improving data quality is an important part for any water temperature prediction model (and this is where the present work comes in).

The remainder of this paper is organized as follows. In Section 2, we describe the Swiss River Network and its missing data in more detail. In Section 3, we present several LSTM based methods to impute missing water temperature data. The proposed models mainly differ in the amount of input variables they actually use. These methods are then thoroughly evaluated in Section 4. Finally, we draw conclusions in Section 5.

2 THE SWISS RIVER NETWORK

The Federal Office of the Environment of Switzerland has been collecting water temperature and discharge data for more than half a century. For better monitoring of the climate change, about 30 additional water stations have been built during the period of 2002 to 2010 (see Fig. 1 for an overview of the Swiss River Network and the placement of the water stations). In the context of this project, we have also access to atmospheric measurements like the air temperature which is provided by air stations (operated by MeteoSwiss).

Recently, a graph structure has been introduced which represents the connectivity of both water and air stations (Fankhauser et al., 2023). The basic idea is to use information from neighboring air stations to make predictions for several target water stations. In the present paper, we reuse this connectivity but focus on the task of imputing missing data (rather than pure water temperature predictions). Similar to (Fankhauser et al., 2023) we work on temperatures of daily averages and we do not use data prior to 1980

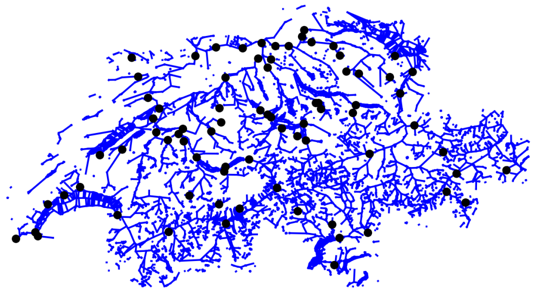


Figure 1: Overview of the Swiss River Network. Every blue line is a body of water. 81 water stations measure the water temperature and discharge (shown as black dots).

(due to the hydrological climate regime shift (Reid et al., 2016; Woolway et al., 2017)).

2.1 Missing Data

Sensor failure, scheduled maintenance or problems in the communication system are common causes for missing data in real world applications. In our particular application, dirt can clog the tube where the temperature sensor is placed in. Furthermore, temperature sensors are affected by drift and have to be calibrated regularly. A special case of missing data in our case is the time before construction of the water station: the water has been there but was not measured.

In our dataset we observe three types of missing data.

- Gaps in air temperature data. In our dataset, air temperature is nearly complete with only 1% missing data.
- Gaps in discharge data: For discharge data, 6% of the data is missing. Most water stations measured discharge before they were upgraded with a temperature sensor.
- Gaps in water temperature data. Overall, 30% of the data is missing.

In the present paper, we focus exclusively on the third category of missing data.

For a more detailed analysis of the missing data in the water temperature data, we show the frequencies of different gap sizes with histograms (see Fig. 2). We distinguish short gaps (up to 61 days), medium gaps (from 62 to 729 days), and long gaps (730 days or more). Short gaps are mostly due to unexpected events, while long gaps, on the other hand, are more likely due to operational decisions.

Regarding the histograms, it becomes clear that the most common gap size is two days (with more than 100 observations in total). Next, we observe several gaps ranging from 30 days to 6000 days. Of interest are ten gaps of exactly 365 days. Since they all occur in the same year, we suspect an artificial reason behind them. Furthermore, we observe relatively many gaps, which are larger than 6,000 days. These gaps correspond to the days before the construction of the newer stations, which were put into operation between 2002 and 2010.

3 METHODS FOR IMPUTING MISSING DATA

In this section, we present seven methods to impute missing water temperature data on the Swiss River Network. The methods are grouped by the number of input variables they have available (resulting in three groups). Each of the three groups represents a different scenario.

1. In the first scenario, we assume to have access to the water temperature of the target station only (i.e. the station with the gap). Water temperature data is available before and after the gap.
2. In the second scenario, we assume to have additionally access to air temperature data during the gap to use traditional models like Air2Stream (Toffolon and Piccolroaz, 2015).
3. In the third scenario, we assume to have access to all available input variables. Namely, we use the discharge data as well as the graph structure of the Swiss River Network to obtain water temperature measurements of neighboring stations.

The left side of Fig. 3 illustrates the three scenarios and in particular, which data the scenarios have at their disposal.

Before describing the individual methods of the three scenarios in more detail (in Sections 3.2, 3.3, and 3.4) we briefly describe the generalized architecture of the underlying model.

3.1 General Architecture

The available data is split into a part before the gap, auxiliary variables during the gap and a part after the gap. In general, each of the three parts are inputted to their own LSTM and then combined together. The LSTM working on auxiliary variables is used for estimating the values in the gap and thus called the main network. The right side of Fig. 3 shows the three possible LSTMs.

If a certain model has a ”Pr” in its identifier it uses an LSTM to encode the water temperature before the gap as initial state for the main network. The main network estimates the missing values of the gap. Its input depends on the scenario and is also implemented as an LSTM. If the data after the gap is used as well we add an additional LSTM and convert the main network into a bidirectional configuration (in this case the identifier of the model contains a ”Po”).

Note, however, that only two methods stemming from the first scenario make use of the water temperature data after the gap (since they have the least amount of information available). In theory, every method with the Pr-LSTM could be extended to the bidirectional setting to make use of the data after the gap. Yet, we focus on the unidirectional way for our methods as this allows the methods to fill gaps where only one side of the temporal direction is available, namely estimates in future or before construction time.

3.2 Scenario 1: Water Temperature Based Methods

The first group of methods has only access to the water temperature of the target station before and after the gap. We propose three methods.

Interpolation. The first method consists of a simple linear interpolation, i.e. the convex combination of the temperature of the last day before and the first day after the gap.

Pr2Gap. The second method is termed Pr2Gap and trains an LSTM on the water temperature before the gap in order to predict the missing values in the gap. During the gap, the LSTM is invoked and predicts each day of the gap as a day in future. Note that this method does not make use of the water temperature after the gap.

PrPo2Gap. The third method is termed PrPo2Gap and can be seen as an extension of the second method in a bidirectional configuration. It uses an LSTM on the water temperature before the gap and a second LSTM on the water temperature after the gap in opposite direction.

3.3 Scenario 2: Air Temperature Based Methods

In many real world scenarios, we have access to data of a near by air temperature station during the gap. Hence, the second group of methods has – in theory – access to the water temperature before and after the gap, as well as to neighboring air temperature stations. We propose two different methods (note that

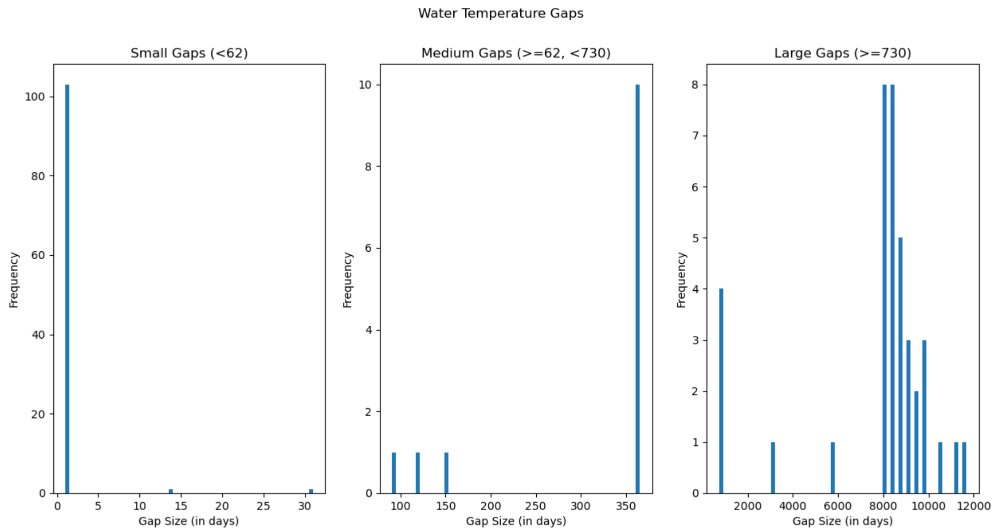


Figure 2: The distribution of gaps of different length in the water temperature data from 1980 to 2021 of the Swiss River Network. We observe that small gaps occur more frequently, but gaps of the medium and large category contribute much more to the overall 30% of missing data.

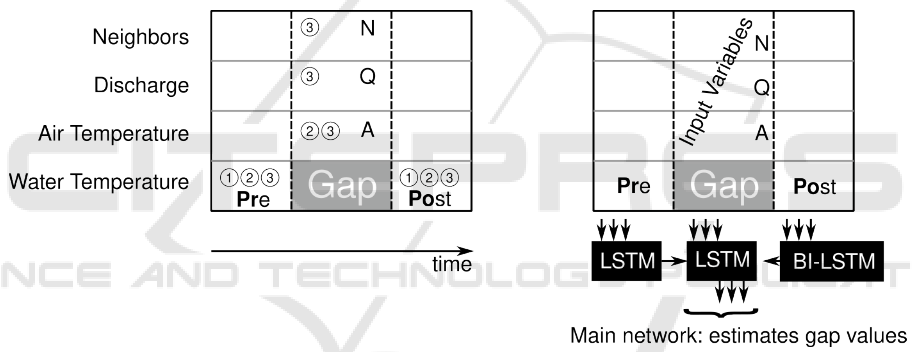


Figure 3: Overview of the three scenarios: On the left we see the data around the gap. Scenario 1 only uses water temperature from before and after the gap. Scenario 2 has additionally access to the air temperature during the gap and Scenario 3 might use all available data (i.e. additionally data from neighboring stations and discharge data). To the right we have the generalized architecture of the seven methods.

the identifiers of these methods now include the abbreviation A for air temperature).

A2Gap. The first method is termed A2Gap and models the air to water temperature relationship in the same way as Air2Stream (Toffolon and Piccolroaz, 2015) or corresponding LSTM versions (Qiu et al., 2021). The model uses the air temperature during the gap to estimate each day of the gap individually. No water temperature is taken into account (neither before nor after the gap), making this model independent of the gap size.

PrA2Gap. The second method is termed PrA2Gap and is similar to the A2Gap method but adds an additional LSTM to encode the previous water temperature. This encoded state is then fed to the A2Gap model as first initial state in order to make use of the available water temperature before the gap.

3.4 Scenario 3: Neighbor Based Methods

In this third scenario, we make use of all available data of the Swiss River Network. Additional to the previous two scenarios, we add discharge and use the Swiss River Network to determine neighboring stations. In particular, we use the water temperature of neighboring stations as input and refer to it as neighbor temperature. Note that the abbreviations of these methods now include a Q (for discharge) and an N (for neighbor temperature).

AQN2Gap. The first method of this group is the extension of the A2Gap method but uses more input variables. In particular, it has access to the air temperature, discharge and neighbor temperature during

the gap. However, this method does not use water temperature before or after the gap.
PrAQN2Gap. The second method of this group uses an additional LSTM to encode the water temperature before the gap. This encoded state is then used as initial state for the main network.
FCN-AQN2Gap. The third method is employed to compare the LSTM performance against a fully connected neural network (FCN). As we will use gaps of fixed size in our experiment, we can train an FCN fitting precisely the size of the gap and thus replace the LSTM of the main network with an FCN. It uses the same input data as the AQN2Gap model. This means it only relies on auxiliary variables during the gap. This method is interesting in practice as a trained FCN-AQN2Gap model for a gap size of k' can be used to fill any gap of size k as long as $k \leq k'$. Moreover, a gap of size $2k$ can be interpreted as two consecutive gaps of size k.

4 EXPERIMENTAL EVALUATION

4.1 Experimental Setup

As we do not have ground truth values for the actual gaps in the water temperature time series, we simulate artificial gaps in our experiment. To this end, we select gap-free sequences of 90 days and artificially introduce water temperature gaps in the middle of each sequence. In total, we select 412,436 sequences from 55 water stations for our evaluation. The sequences overlap in time. The inserted gaps are of length 2, 10, 30, and 60 days. We split the resulting sequences into disjoint sets for training, validation and testing (64%, 16% and 20% of the data, respectively). For each pair of method and station, we run a grid search over width and depth of the networks and the learning rate. The validation set is used to determine the best hyperparameters. The presented results are obtained on the untouched test set sequences.

For quantitative comparison we use the root mean square error (RMSE), formally defined by

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad , \tag{1}$$

where y_i is the ground truth value at the i-th position in the gap and $\hat{y}_i$ is the value estimated by the model. Obviously, the lower the RMSE the better the model.

Our code will be made publicly available for research purpose on the Git Repository of our research group[1].

4.2 Results and Discussion

For each method and water station we report the RMSE of the best model on the untouched test set. This results in 55 data points per method. Fig. 4 shows the results as box-plots diagram for all four gap sizes (2, 10, 30, and 60 days). In particular, the box-plots show the median RMSE for all eight methods with a horizontal line, the interquartile range (IQR), and the whiskers pointing to the smallest and largest elements still within 1.5 times the IQR (we also show possible outliers with circles).

For a gap size of two days, the results of linear interpolation are compatible to the best models. However, with larger gaps the performance of this rather simple method substantially deteriorates. The same holds for the other two methods of the first scenario.

The methods based on other auxiliary variables, which are accessible during the gap, namely air temperature, discharge and neighboring water temperature, maintain a constant performance independent of the size of the actual gap. The only exception is the FCN based method, which deteriorates slightly with increasing gap size.

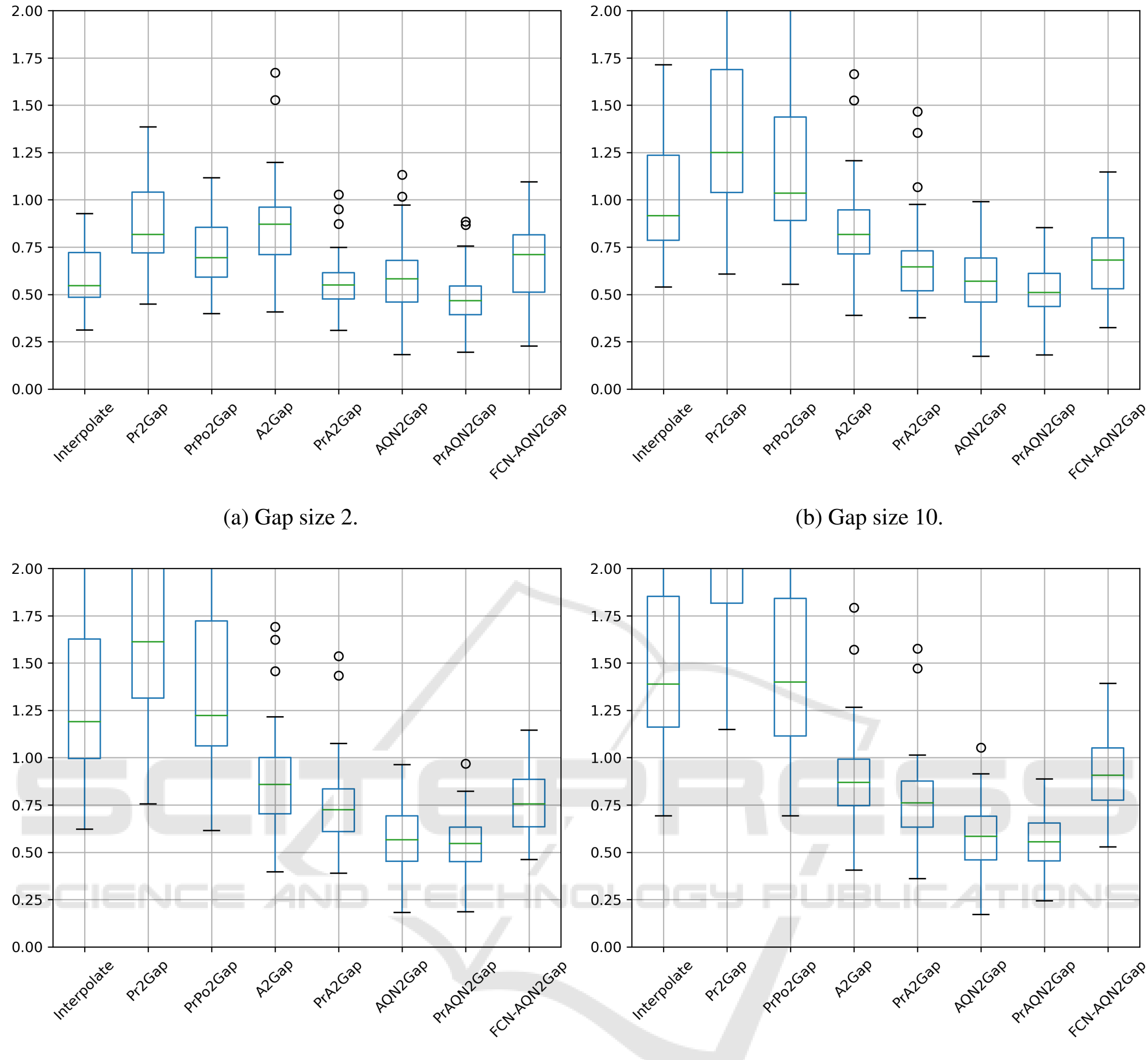
Adding neighboring water temperatures and discharge as input to the model, outperforms more traditional methods solely based on air temperature. The Pr-based variants, which encode the available water temperatures before the gap, constantly improve their counterparts that have no access to this information. Replacing the main network LSTM of the AQN2Gap model with a fully connected neural network decreases performance in our experimental setting.

The worst model is Pr2Gap, which performs poorly on all gap sizes and generally has the largest RMSE. Vice versa, we can report that on all tested gap sizes the PrAQN2Gap model achieves the best performance. This particular model is based on all available data (air and discharge data as well as water temperature of the neighboring stations) and achieves an RMSE of 0.47, 0.52, 0.54, and 0.55 on the data with gaps of 2, 10, 30, and 60 days, respectively.

5 CONCLUSIONS

After revisiting the hydrological data of the Swiss River Network (Fankhauser et al., 2023), we find that this real world application suffers from missing data (up to 30% of the data). Ignoring these gaps in the data is an unsatisfactory solution for both practition-

[1] https://github.com/Pattern-Recognition-Group-UniBe/swiss-river-network



(a) Gap size 2.

(b) Gap size 10.

(c) Gap size 30.

(d) Gap size 60.

Figure 4: Results of the experimental evaluation. Reported is the RMSE on the untouched test set sequences. The scale is cut off at a value of 2 in order to not distort the visual comparison.

ers as well as data analysts. For this reason, we address the task of data imputation in this paper.

We assume three different scenarios that could occur in real-world applications. That is, depending on the circumstances of the gap, one of the three introduced scenarios might occur. For each scenario different model architectures are proposed and researched. The different models differ primarily to the extent that they make use of different data (such as water temperature data before the gap or air temperatures or water temperatures of neighboring stations during the gap).

In order to evaluate the methods we run an experiment on a novel dataset with artificially created gaps of different sizes (2, 10, 30, and 60 days). The maximal gap size is rather small, but the stable results and constructions independent of the gap size allow us to extend our conclusions to larger gap sizes. In particular as some of the proposed techniques, viz. A2Gap, AQN2Gap, FCN-AQN2Gap, give consistently good results irrespective of the gap size.

Considering the results obtained, we can draw the following three main conclusions.

1. For small gaps of two days the interpolation method is performing well in respect of its simplicity, and we can recommend to use it.

2. For any gap size larger than ten days, however, more sophisticated models are necessary. The

model PrAQN2Gap performs the best in general. With an average RMSE close to 0.55 it outperforms current state of the art methods which are based solely on air temperature. To be fair, their experimental setup is slightly different and we introduce the A2Gap method as representable competitor.

3. In an ablation experiment, we replace the LSTM of the main network with a fully connected network. As the results of this particular model deteriorates with increasing gap size, we conclude that LSTMs seems to be beneficial for our task.

In future work we plan to impute missing data in discharge data and research the impact of the artificially created gap free dataset on water temperature prediction models. Another direction of work is to retrospectively investigate the measured data to find undetected outliers.

ACKNOWLEDGEMENTS

This project is supported by the Swiss National Science Foundation (SNSF) Grant Nr. PT00P2 206252. Data are kindly provided by the Federal Office for the Environment and MeteoSwiss. Calculations were performed on UBELIX (https://www.id.unibe.ch/hpc), the HPC cluster at the University of Bern.

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