Dette kan integreres med model

1 Data pipeline

The deep learning system can be disassembled into two parts working in tangent. The deep learning architecture which propagates fields containing information through its weights, and the dataloader which structures the dataset into trainable samples. This section will describe the process from raw data to ready sample, with the following Section (1) containing a rundown and results of the model architecture.

The data pipeline is made such that it constitutes models of three different lead times (one, two and three day lead time). A quick overview of the pipeline is as such. The raw data used are Sea Ice Charts, OSI-SAF and AA. For the Sea Ice Charts, ice charts from the bulletin date and valid date are selected. From AA, relevant meteorological fields are selected and daily means are computed (more details in following sections). Finally, from OSI-SAF a sea ice trend is computed. For a given bulletin date, the data fetched above is stored in a .hdf5 file, such that each sample (bulletin date) is represented by its own .hdf5 file. Furthermore, a dataloader object is initialized with a list of .hdf5 files, with the list containing filenames of the samples constituting a data subset such as train, validation or test data. This processes is visualized in Figure (1).

1.1 Data sources

Data sources used are Sea Ice charts from Nick initiated at 15:00 as well as Arome Arctic initiated at 18:00 Dinessen et al. (2020); Müller et al. (2017). For a given date, the current Ice Chart is used as a predictor for the model, while the Ice Chart drawn two days later is supplied as the model target.

1.1.1 Sea Ice Charts

The Sea Ice Charts used are a derived dataset of the Sea Ice Charts presented in a previous section. The present Ice Chart dataset has been postprocessed by Nick Hughes of the National Ice Service, such that they are presented on a 1km Arome Arctic grid. Furthermore, the Ice Charts does not feature a land-mask, which has been replaced with interpolated values resulting in a spatially consistent dataset where all values present are according to the WMO Sea Ice Concentration intervals JCOMM Expert Team on Sea Ice (2014).

label sections

Say thanks in acknowledgements

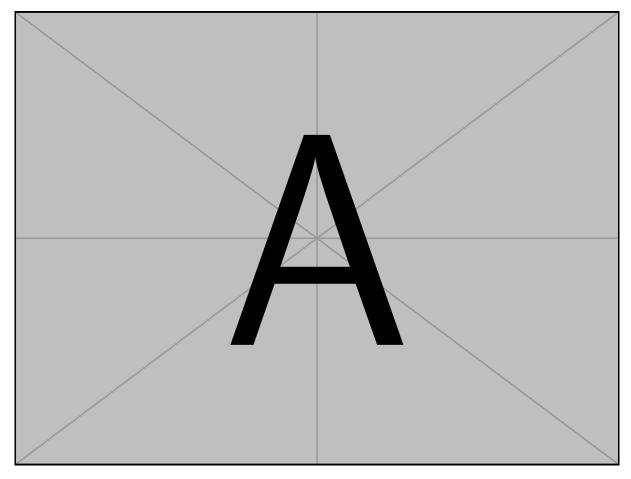


Figure 1: *PLACEHOLDER* uncomment to render, Unfinished figure showing the data pipeline, where four sources are merged into one sample,fed into the U-Net, trained against Target Ice Charts and output a predicted Ice Chart

1.2 AROME-Arctic

The Arome Arctic data is structured such that the period between forecast initialization and machine learning forecast lead time is stored as a mean product in the temporal dimension at intervals [0 - 18, 42, 66]. This ensures that temporal AA information is encoded into a single field up until 12:00 UTC of the publishing date of the target ice chart. The 4d variables used from AA are T2M, uwind and vwind. Finally, the land sea mask present in AA is fetched and used as a predictor, though this land sea mask is also used for validation purposes given the case where no other SIC-product is considered.

1.3 OSI-SAF

A linear SIC trend of variable temporal length is computed from 12.5km OSI-SAF data . In the case of OSI-SAF, the product is scheduled to be published daily at 15:00 UTC . However, given operational concerns of the developed forecasting system, where the availability of data is essential for the model to run, the previous day OSI-SAF trend is utilized. .

OSI-SAF SSMIS is a continously developed operational product, where changes are not required to act retroactively on the data. As such, the Sea Ice Concentration used for few samples with t2m runs and many data samples no t2m differ due to the introduction of a filtered ice concentration variable 10/05-2017 Tonboe et al. (2017). Thus, the filtered ice concentration will be used when the training data spans 2019-2020, and the unfiltered ice concentration will be used when the training data spans 2011 - 2018 to assert that there is no sudden shift in the ice concentration trend which can negatively impact the training period.

References

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Müller, M., Batrak, Y., Kristiansen, J., Køltzow, M. A. Ø., Noer, G., and Korosov, A.: Characteristics of a Convective-Scale Weather Forecasting System for the European Arc-

Mention how when using Osi Saf trend as predictor, the trend up to but not including the forecast start date is used. This is to make the model ready

for

operational use, as the Osi Saf daily product is

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