

Two examples of Machine Learning in Geoscience:

Self-Organizing Maps (SOMs) & Feed-Forward Networks (FFNs)

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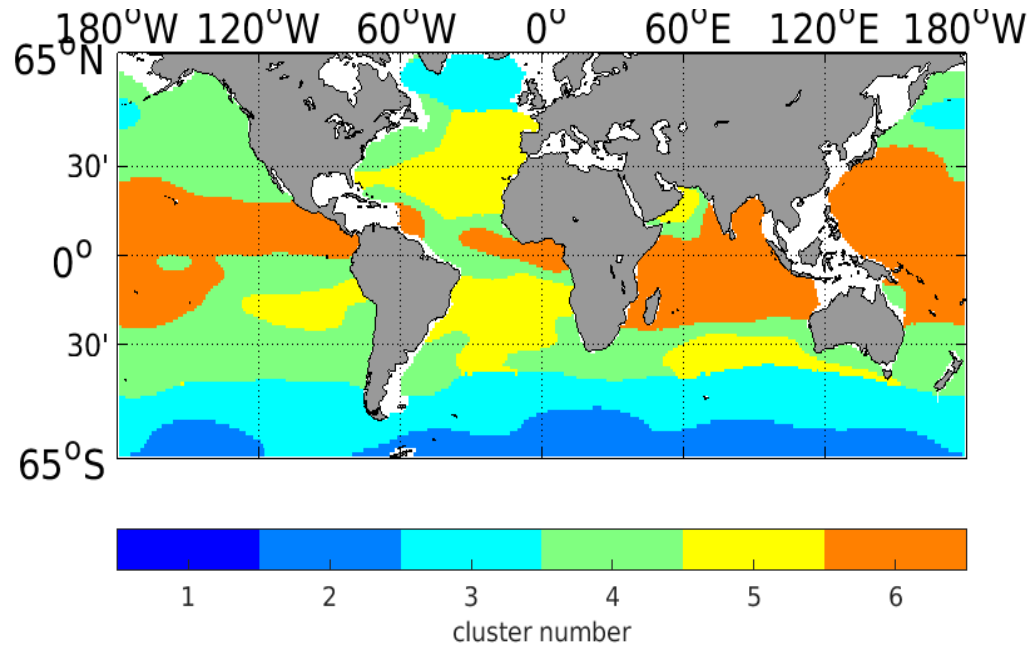
PhD candidate (she/her)

Observations, Analysis and Synthesis (OAS)
Director's Research Group (DRO)



Clustering: Self-Organising Maps (SOMs)

- SOMs to cluster data into regions of similar properties (Kohonen 1987, 2001)



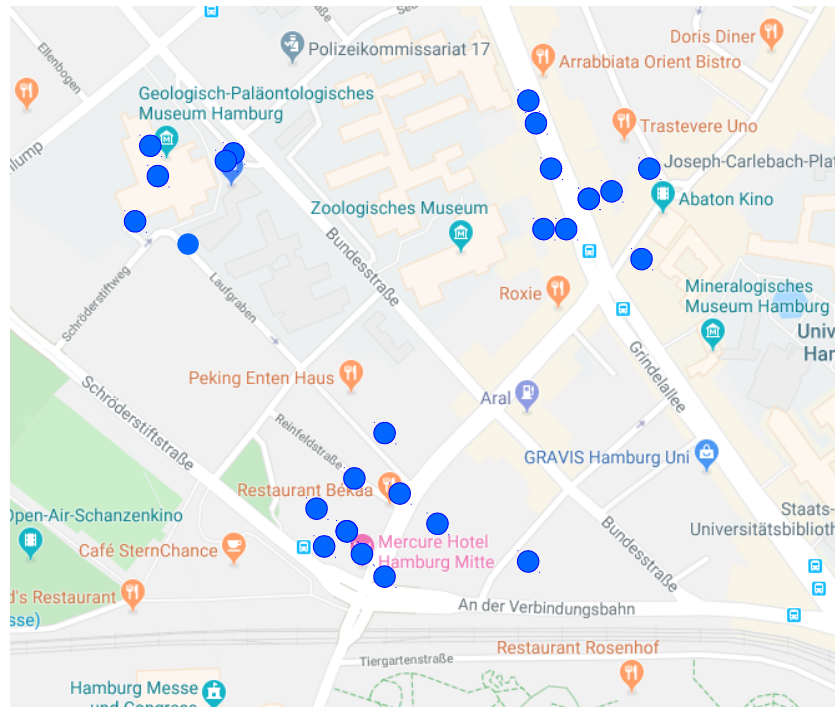
Where to build a pizzeria

- Giovanni wants to build three pizzerias near the MPI-M
- Where should he put them?



Where to build a pizzeria

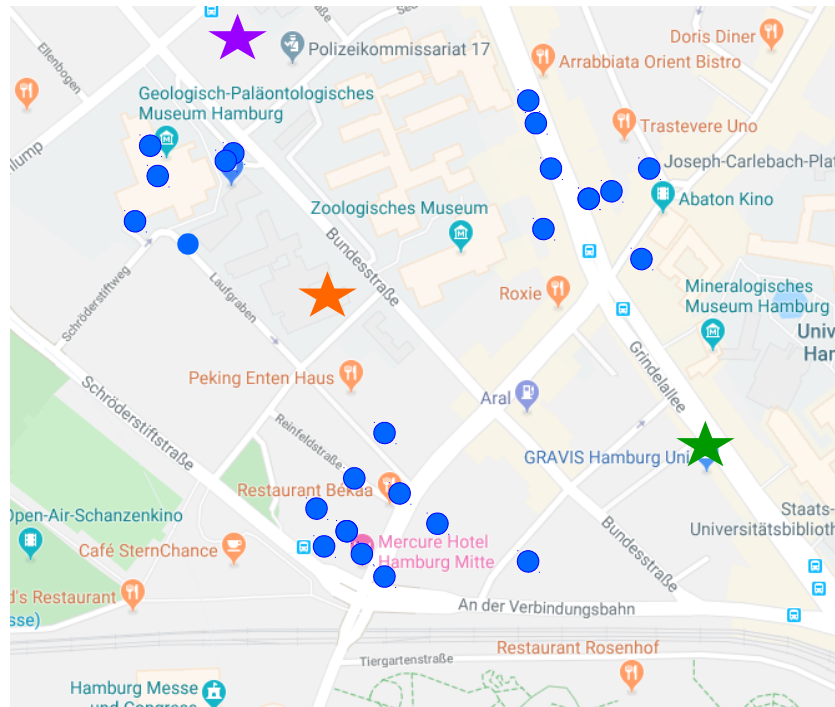
- Giovanni wants to build three pizzerias near the MPI-M
- Where should he put them?



● people who eat a lot of pizza

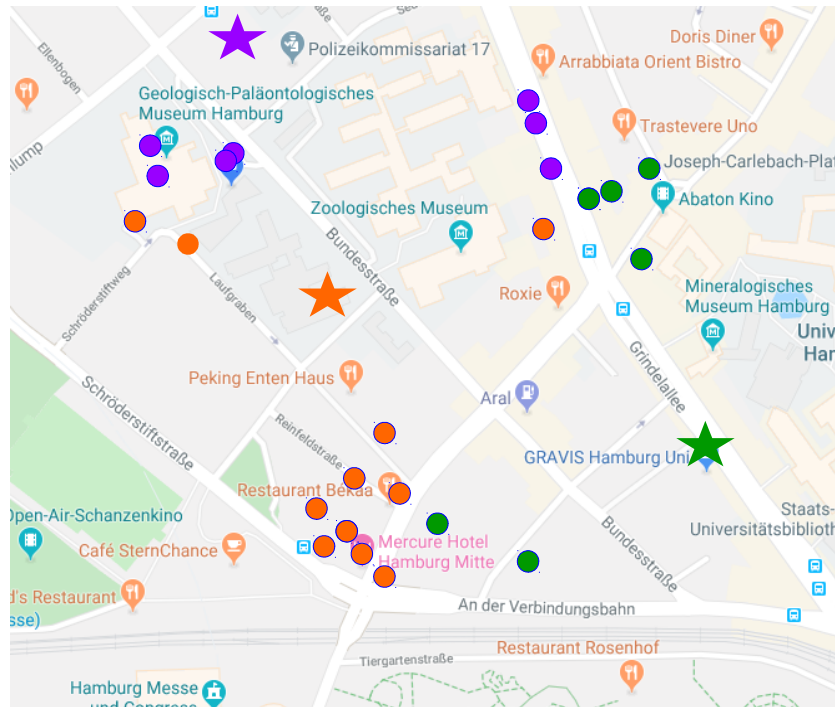
Where to build a pizzeria

- We start with three random locations for the pizzeria



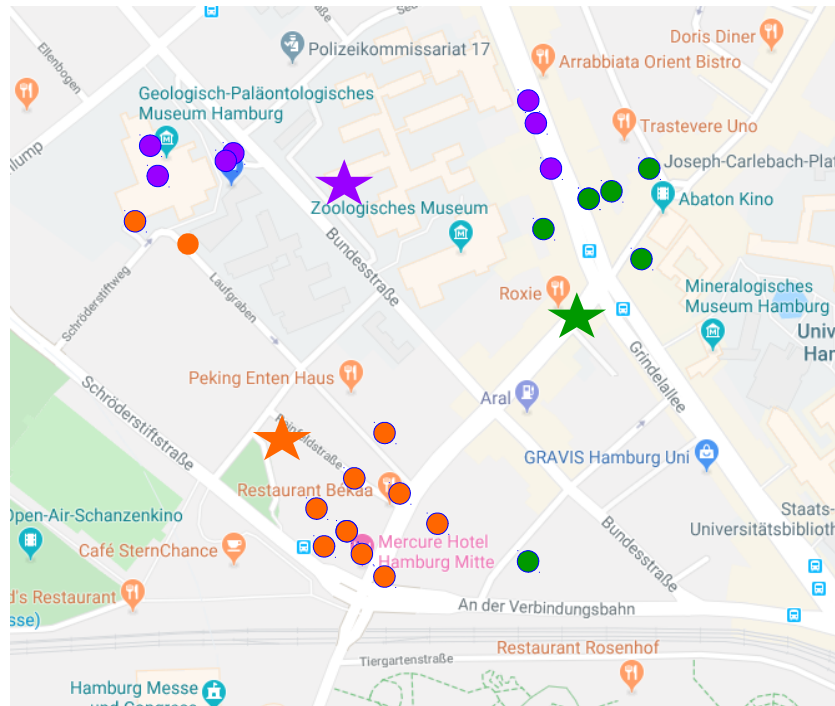
Where to build a pizzeria

- We start with three random locations for the pizzeria
- Everyone goes to the one that is closest



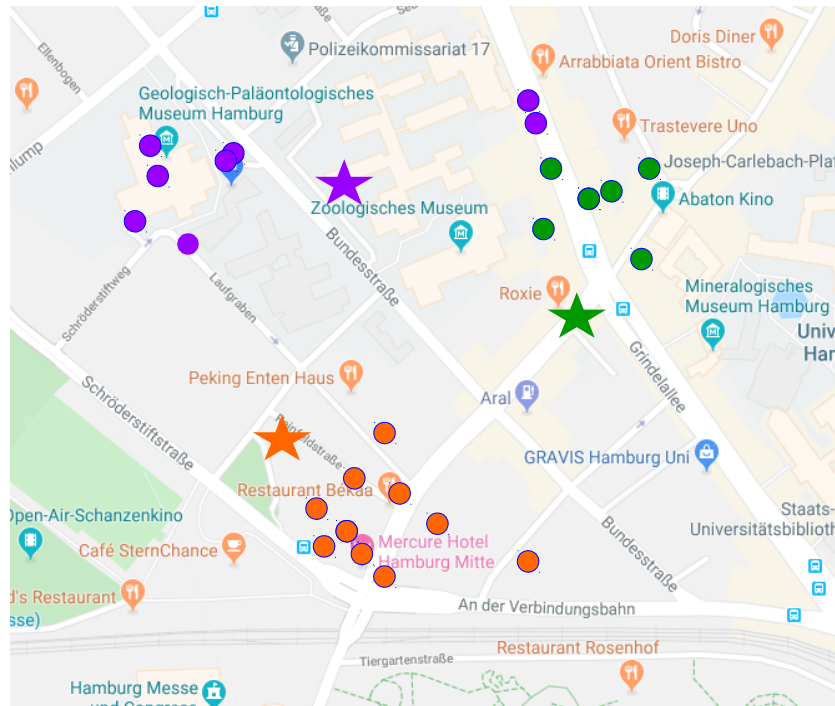
Where to build a pizzeria

- We move the pizzeria to the center of the houses



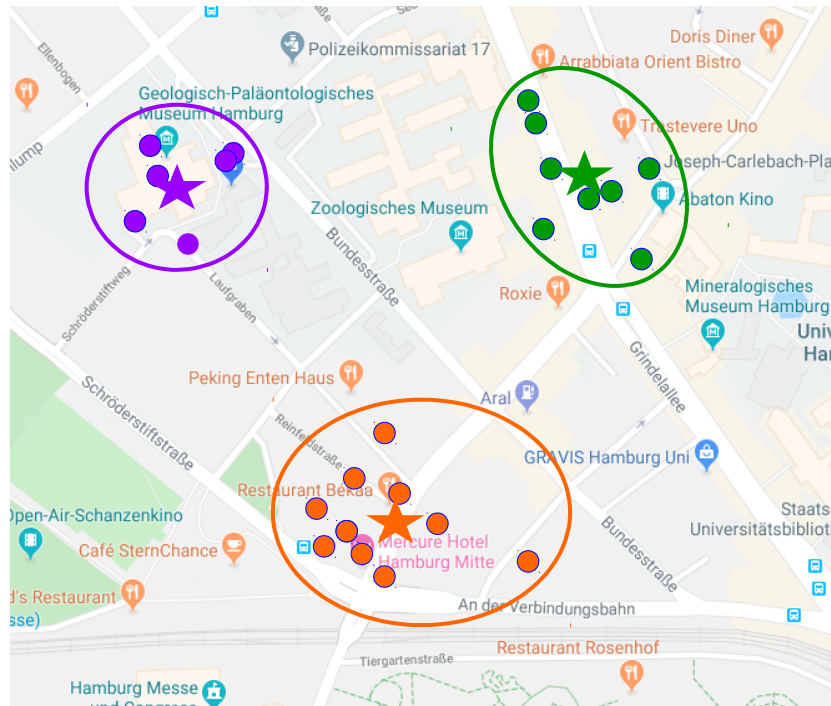
Where to build a pizzeria

- We re-adjust the closest pizzarias for each house



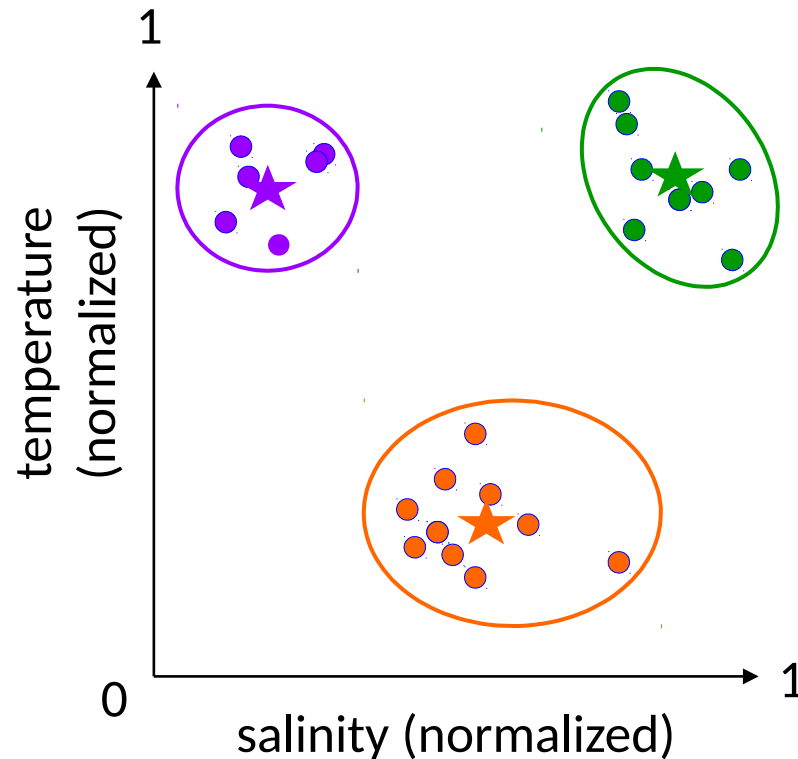
Where to build a pizzeria

- We repeat this process until the distances do not get smaller anymore



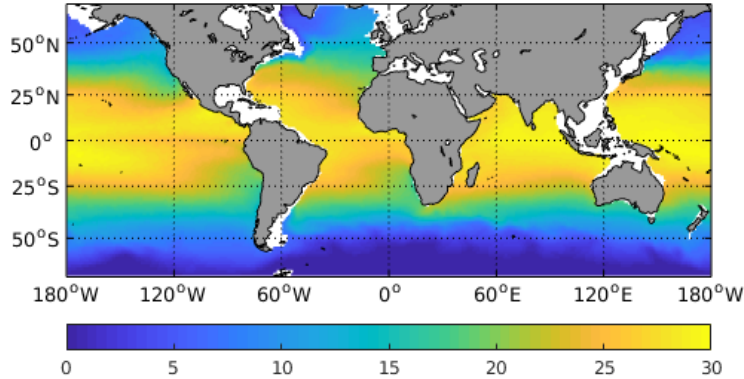
SOM-clustering with non-pizza variables

- We can e.g., use normalized temperature and salinity to cluster the ocean into water masses

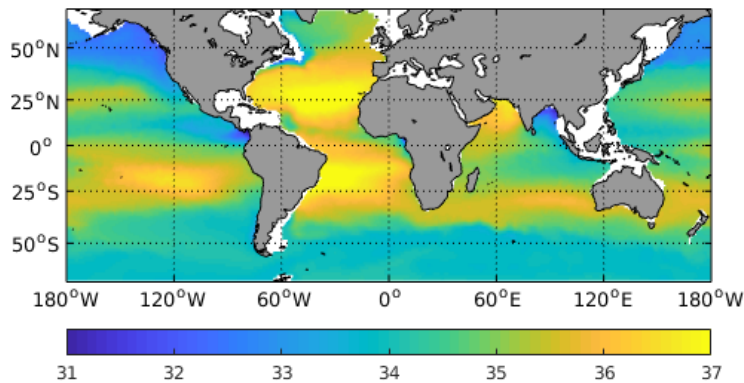


SOM-clustering with non-pizza variables

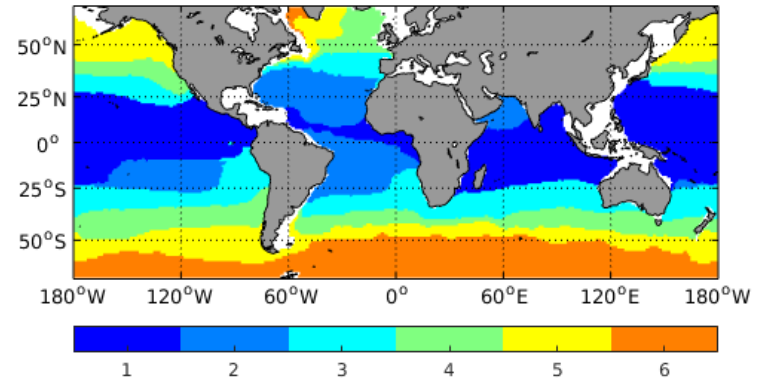
- Example: temperature and salinity at 10 m as input to SOMs



temperature (°C)



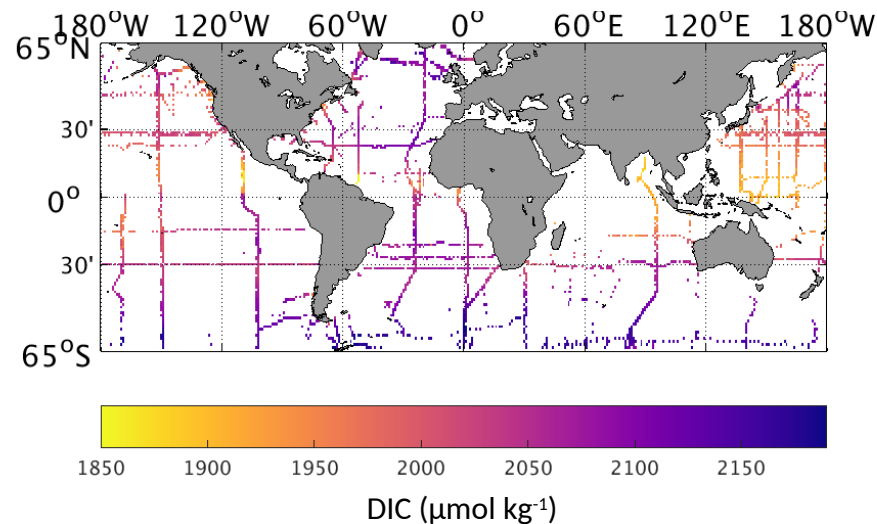
salinity



cluster number

Feed-Forward Networks (FFNs)

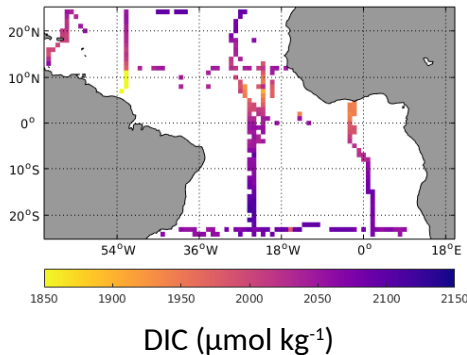
- FFNs compute and apply statistical relationships between multiple predictor and target variables **to approximate a function**
 - like a MLR, but the relationships don't have to be linear
- Here: from sparse data with gaps to mapped data



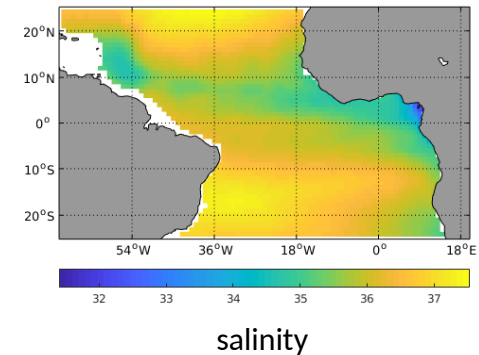
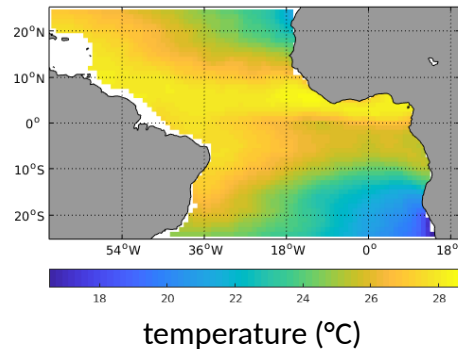
Feed-Forward Networks (FFNs)

- We have sparse ship data which we want to have mapped (target data)
- We need predictor data (mapped global data; e.g., temperature / salinity)
- The network establishes the statistical relationship between the predictor and the target data and then applies this relationship to map the target data

target data



predictor data



Establishing the relationship (training the FFN)

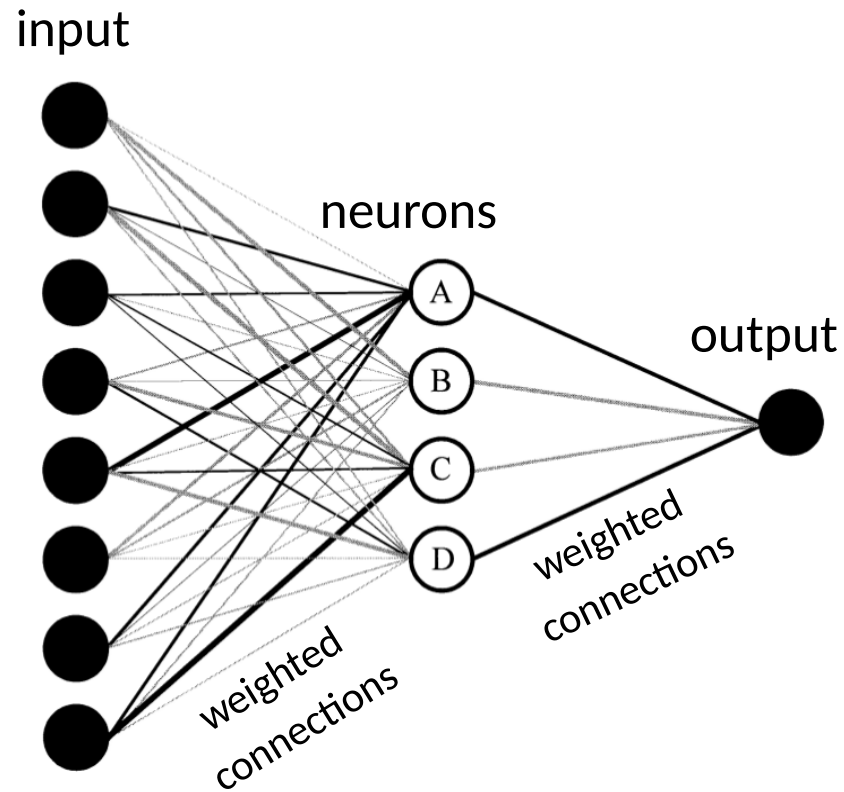
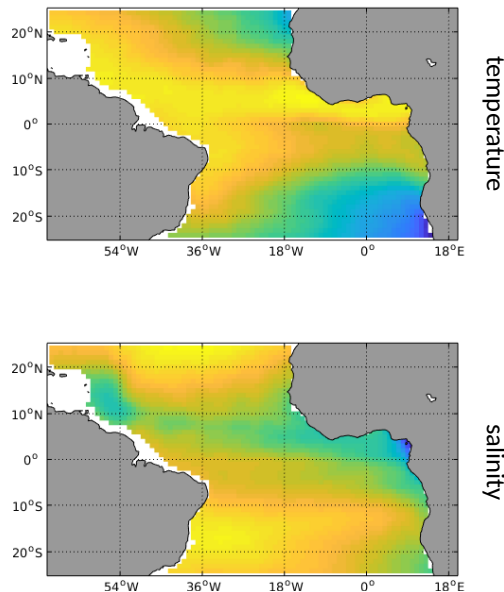


Figure adapted from Olden & Jackson, 2002

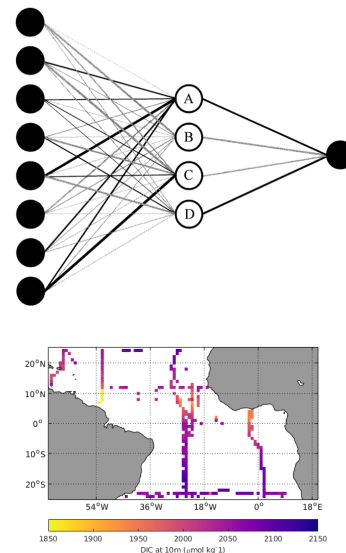
Applying the relationship

- Now the established relationship between the target data and the predictor data is applied to map the target data globally (disclaimer: the resulting field is not realistic, because of the simplified set-up, e.g. only SST and SSS as predictors; testing of the result is important)

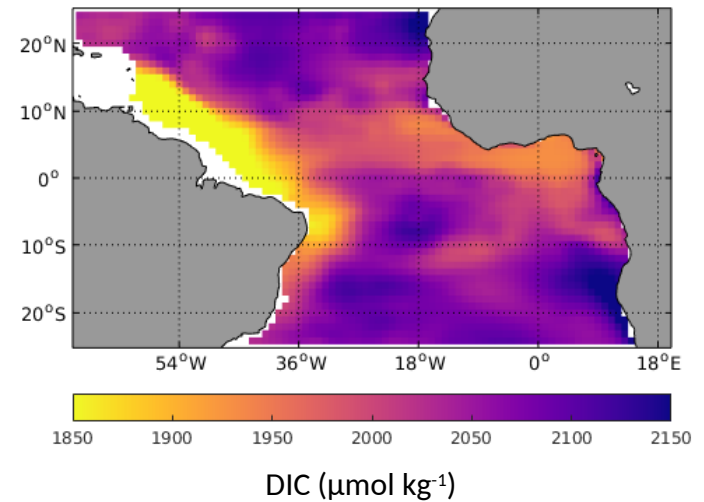
predictor data



trained network

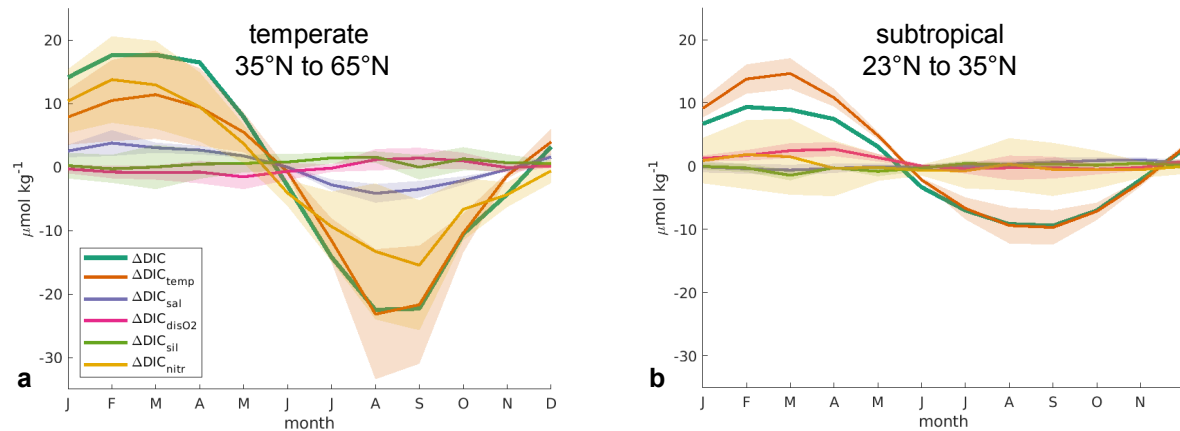


output



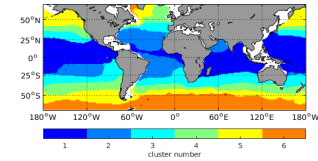
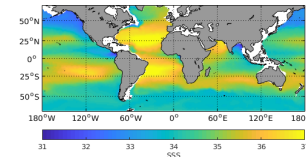
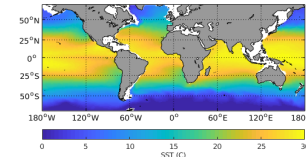
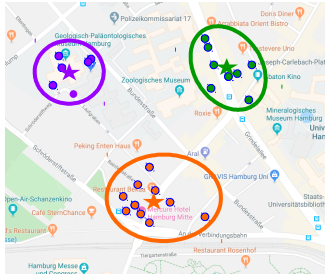
Understanding the resonse

- We can see how each of the predictors contributes to the FFN (Similar to profile method by Gevrey et al., (2003))
- We train the network as usual, and in the simulation-step, we hold one predictor constant in time, and vary the others (iteratively for all predictors)
- We get the change in DIC due to each predictor



Summary

- **SOMs can cluster data into (e.g., into regions of similar properties)**



- **FFNs can compute and apply statistical relationships between multiple predictor and target variables to approximate a function**

