Supervised and unsupervised machine learning for nowcasting, applied on radar data from central Transylvania region

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Radar Data Used

- **Reflectivity (R)**: size of water droplets
  - From 6 elevations
- **Velocity (V)**: velocity of water droplets
  - From 6 elevations
- **Vertically Integrated Liquid (VIL)**: derived product computed using other products from all elevations

$\Rightarrow$ 13 radar products used

Self Organizing-Maps

- A **SOM** is an *unsupervised learning* method, a type of ANN
- It has usually two layers: input layer and output layer
- The output layer (map) represents a low-dimensional representation of the input
- Preserves the topological relationships in the input space

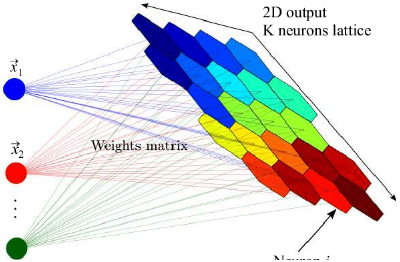


Figure: The structure of a SOM. [3]

SOM experiment example

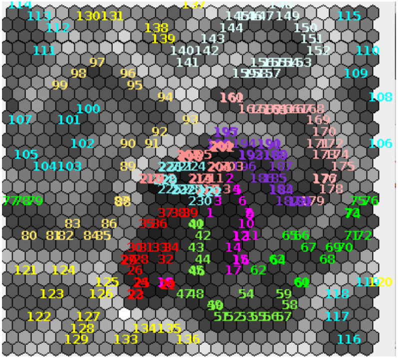


Figure: Visualization of the U-Matrix result of the SOM

- Idea: using Self Organizing Maps (SOMs) to uncover patterns in how radar data change over multiple time steps

Results:

- The values of the radar products clearly discriminate between calm weather and severe events.
- The meteorological products are smoothly changing in time, excepting situations when certain severe phenomena occur

Further SOM results

- *Reflectivity* (R), *particle velocity* (V) and *vertically integrated liquid* (VIL) represent the data better than using other sets of products.
- Values for radar products can be predicted from neighborhoods at previous time moments
- Predictions should work irrespective of the temporal window length or if there are meteorological events present or not.

Neighbourhood Data model

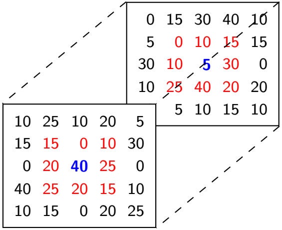


Figure: The data at time stamp $t-1$ (R01, R02, ...).

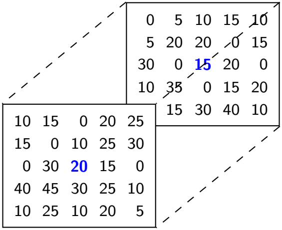


Figure: The data at time stamp t (R01, R02, ...).

Prediction intuition:

Values of data at one point at time step t is dependent on the data at time step $t-1$ for that point and its neighbourhood.

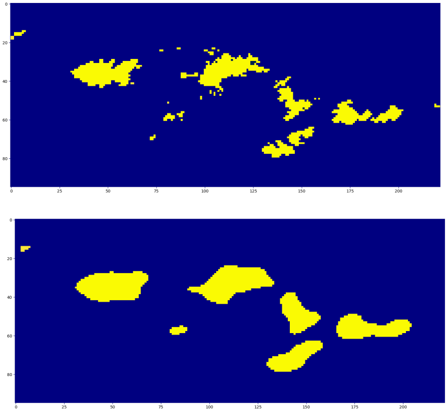
Rule Mining

- **Relational Association Rules** (RARs) express different type of relations between data attributes.
- RARs are mined using an algorithm called **Discovery of Relational Association Rules (DRAR)**
- We introduced a classifier model named **RadRAR**
  - Classifies whether values will be above 35 dBZ

Length	Rule	Confidence
2	$a_2 = a_3$	0.72
2	$a_4 > a_9$	0.68
2	$a_5 < a_6$	0.72
3	$a_1 > a_9 < a_2$	0.68
3	$a_1 > a_9 < a_3$	0.68
3	$a_1 > a_9 < a_5$	0.68
3	$a_1 > a_9 < a_7$	0.68
4	$a_1 > a_9 < a_6 > a_7$	0.68

Table: Example of mined RARs.

RadRAR Result



Comparison of the predicted data (bottom) with the real data (top) collected by the radar for the product R01 at 14:17 UTC.

The *NowDeepN* model

- We created a **Deep Neural Networks** regression model
- We created 13 models:
  - One model for each product (with the same architecture)
  - The input for one model would be **all** the data at that point and the neighbourhood

    => all models have the same input
  - The output for each model would be the value of the product that that model predicts

Intuition:

Using one network for each product would be more effective than using only one network for predicting all values, as the mapping learned by the model should be specific to each radar product.

Data Cleaning

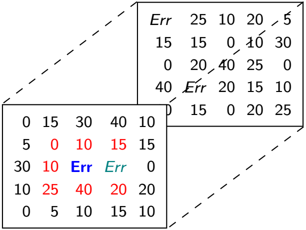


Figure: Uncleaned data highlighting the neghbourhood of error value at (3, 3).

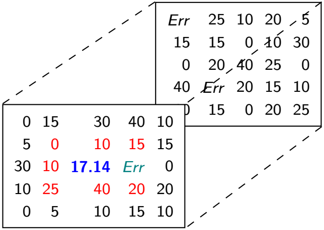


Figure: Same data after the correction of error value at (3, 3).

NowDeepN results

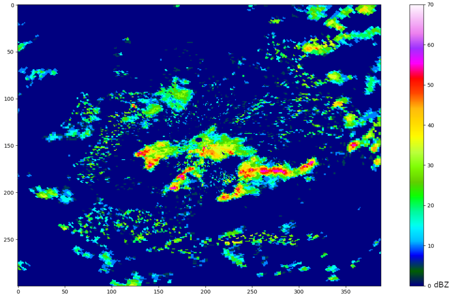


Figure: Real data for product R01 at 14:37:22 UTC.

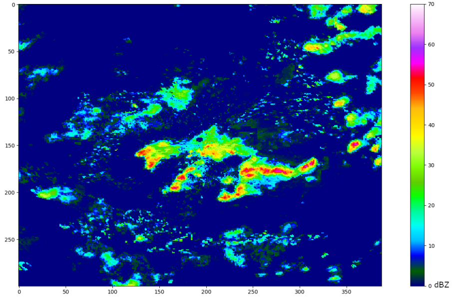


Figure: Predicted data for product R01 at 14:37:22 UTC.

The *XNow* model

- Predict all data for **one time step at once**
- View the data for one time step as an image with **13 channels**
  - Instead of Red/Green/Blue we have R01/R02/...
  - A point on the image represents a geographical location
- From image at time step $t-1$ predict the image at time step t
- Take advantage of powerful Computer Vision neural network models

XNow and *Xception*

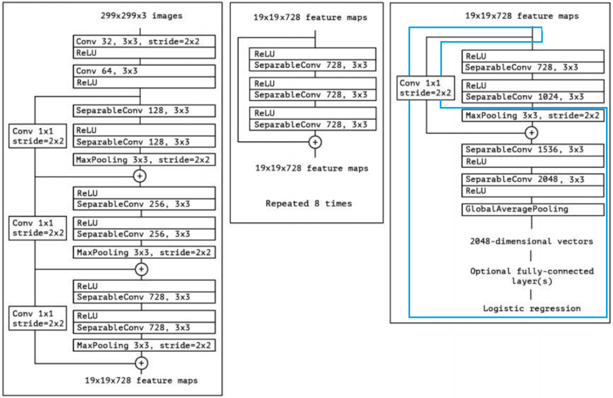


Figure: The original Xception [1], with a mark (the blue lines) on the part that we consider for replacement. [1]

[1] Image taken from [2]

XNow – results and comparison to related work

Measure	1	2	3	4	5	6	7	8	9	10	Average
RMSE	1.889	1.444	1.97	2.029	1.374	1.938	2.05	1.928	1.912	1.937	**1.847**

Table: RMSE values obtained during 10 runs of *XNow*.

Model	RMSE		
	Average	**Min**	**Max**
Our *XNow*	**1.85**	**1.37**	**2.03**
ANN [4]	> 1.80	> 1.67	> 1.88

Table: Comparison to related work [4].

Thank you!
Questions?

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