Deep Learning for forecasting Thunderstorms on NE Italy

Agostino Manzato[1], Luca Foschiani[2], Davide Soldà[2], Pascal Horton[3], Giuseppe Serra[2], Agostino Dovier[2]

[1]OSMER - ARPA FVG (IT), [2]University of Udine (IT), [3]OCCR - University of Bern (CH)

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INTRODUCTION

- **Convolutional Neural Network** (CNN) are deep learning techniques normally used in image processing to detect objects. For example, Chen et al. 2016 used CNN for estimating tropical cyclone intensity from satellite images.
- Can we use CNN to analyze the meteorological model outputs and improve local forecasting? Gagne et al. (2019) used bidimensional CNN to detect the occurrence of hailstone > 25 mm inside WRF simulations, finding that CNN outperformed logistic regression.
- In this work we will use tridimensional and bidimensional CNN to estimate the 6-hours lightning probability in the Friuli Venezia Giulia region (FVG, NE Italy) starting from ECMWF IFS forecasts.

DOMAIN, TARGET AREA AND DATASETS

- ECMWF IFS "direct" outputs and derived fields during 2011-2018 April-September every 6h are standardized (in each gridpoin) and associated to $\log_{10}(1 + C2G\_Lights)$, where *C2G_Lights* is either the **total number** of cloud-to-ground lightnings (data from CESI/EUCLID) fallen inside the **whole FVG area**, or the partial number of lightnings fallen in one of the **5 subareas** in which FVG has been divided.
- Note that we tested two different domains: the **synoptic** domain (LON=[-5, 25] and LAT=[35, 55]) at 0.25 deg and the **mesoscale** domain (LON=[4, 18] and LAT=[42, 50]) at 0.125 deg. Training period: 2011, 2012, 2013, 2016. Validation: 2014, 2015. Test: 2017, 2018.
- Candidate predictors defined on 4 isobaric levels (500, 700, 850 and 925 hPa) are called 3D variables, while predictors defined on a single level (e.g. precipitation, 10 m wind, Lapse Rate, Maximum Buoyancy) are called 2D variables.

* Available only on the mesoscale domain.
** Available only on the synoptic domain.

3D variables	ID	Units
Geopotential	gh	[m]
relative humidity	r	[%]
Temperature	T	[K]
Zonal wind	u	[m/s]
meridional wind	v	[m/s]
vertical motion **	w	[Pa/s]
mixing ratio	q	[g/kg]
Equival. Pot. Temp.	Θ_e	[K]
Saturated Equival. Pot. Temp.	Θ_{es}	[K]

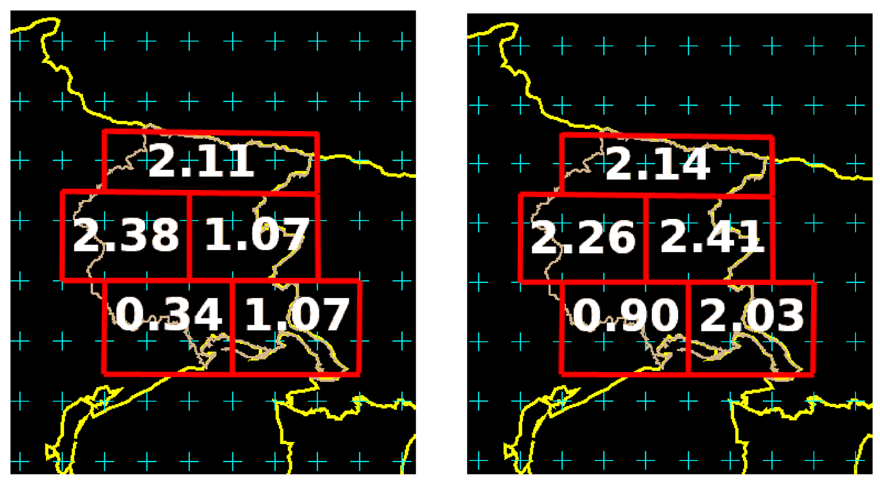
Table 1: 9 variables defined at 500, 700, 850 and 925 hPa.

2D variables	ID	Units
Temperature at 2 m *	2T	[K]
Convective precipitation *	cp	[m]
Total precipitation *	tp	[m]
Est-West wind at 10 m *	10U	[m/s]
North-South wind at 10 m *	10V	[m/s]
mean sea level pressure *	mslp	[Pa]
Zonal water vapor flux	Uflux	[kg/(s·m^2)]
Meridional water vapor flux	Vflux	[kg/(s·m^2)]
Maximum Buoyancy 925-700 hPa	MB925700	[K]
Maximum Buoyancy 925-500 hPa	MB925500	[K]
Maximum Buoyancy 850-500 hPa	MB850500	[K]
Temp. lapse rate 850-500 hPa	LRT850500	[K/km]
Temp. lapse rate 700-500 hPa	LRT700500	[K/km]
Θ_e lapse rate 850-500 hPa	LRΘ_e850500	[K/km]
Θ_e lapse rate Θ_e 700-500 hPa	LRΘ_e700500	[K/km]
Downdraft Potential 500-925 hPa	DP500925	[K]

Table 2: 16 variables defined only on a single level.

RESULTS AND VERIFICATION

- After many trials, the synoptic CNNs used all variables (precipitation not available), while the mesoscale CNNs used **all 2D variables** plus three 3D-var (T, v and Θ_e for all FVG, or plus gh, T and Θ_e for the 5 sub-areas).



Example of forecast using the mesoscale domain on the 5 sub-areas for the case of **10/08/2017**: on left the FLAS forecast; on right the real lightning observations.

- Results on the mesoscale are slightly better than those computed on the synoptic domain. For the latter we show only those for all FVG lightnings.

Metric	FLAS		AtmoSwing	
	Validation set	Test set	Validation set	Test set
γ	0.79	0.74	0.67	0.66
MSE	0.43	0.52	0.42	0.39
R	0.68	0.61	0.68	0.71

- AtmoSwing (using Θ_{es} at 925 and 850 hPa, MB925500 and w 700 hPa for the synoptic and *cp*, MB925500 and Θ_{es} 925 for the mesoscale) has R similar to FLAS, but the training phase takes few days (on Bern Univ. cluster) vs. few minutes (on Nvidia Tesla K40C GPU).
- For comparison, on the mesoscale all FVG lightnings, we developed a simple linear regression with maximum CP over FVG, or a CNN model using only the CP field, or a FLAS version without CP and TP.

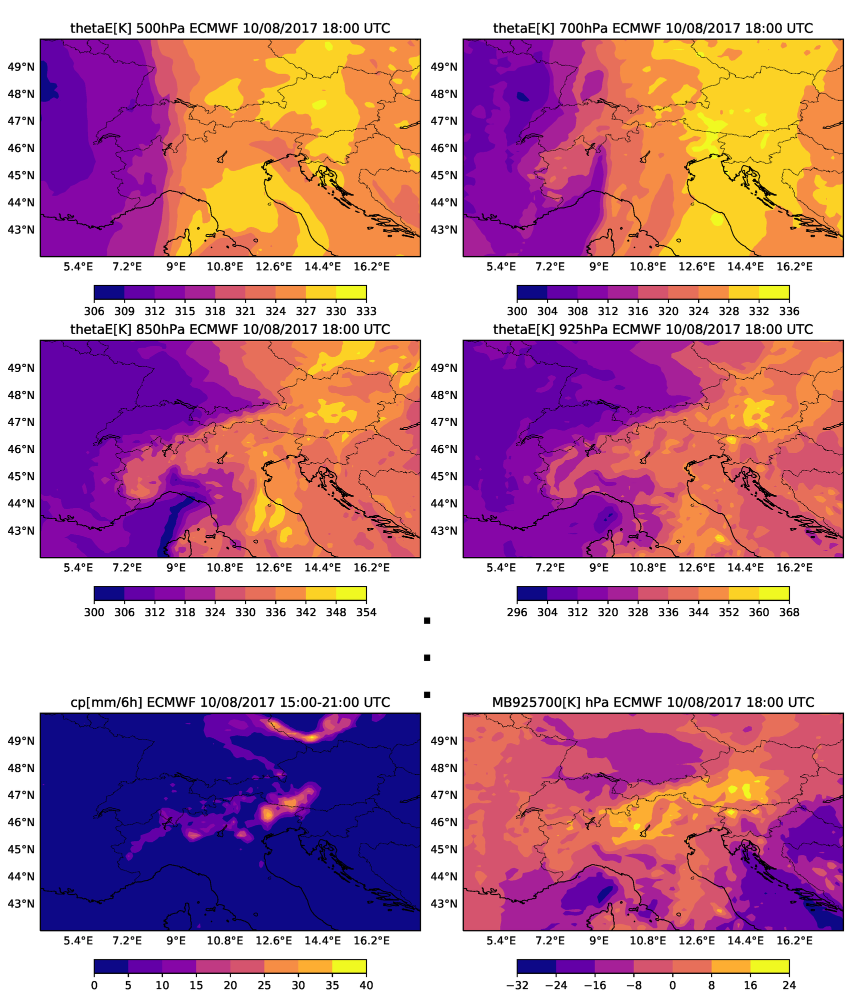
R for FVG total lightnings						R for FLAS on 5-areas				
dataset	FLAS	FLAS NoPrec	CNN-*cp*	LIN-*cp*	Atmo	W plain	E plain	W PreAlps	E PreAlps	Alps
validation	0.74	0.71	0.61	0.39	0.74	0.63	0.62	0.67	0.63	0.65
test	0.72	0.72	0.60	0.34	0.74	0.58	0.62	0.58	0.61	0.63

- From the correlation values shown above, a simple regression with maximum FVG CP gives very low performance, while the whole CP field used as only input of a CNN is much better. Atmo and FLAS have R=0.74. Removing the precipitation fields does not ruin it too much.

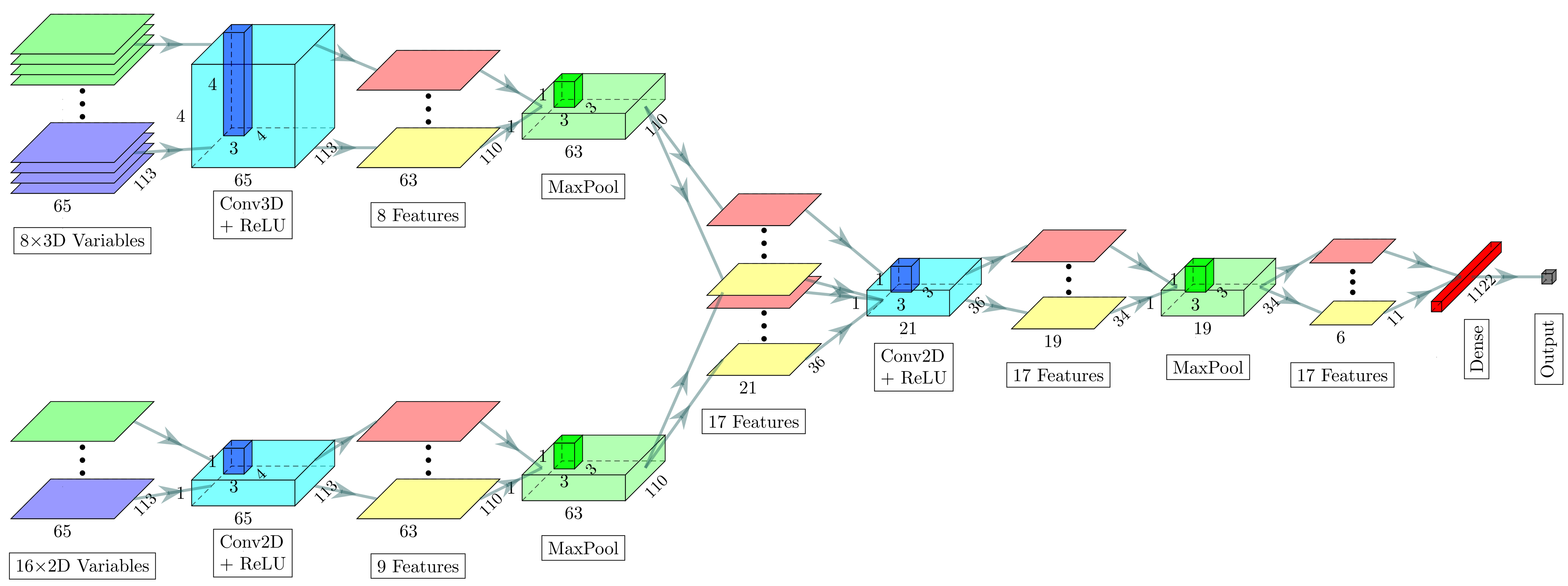
CONCLUSIONS

- CNNs are able to **squeeze** the big information embedded in many model-derived fields (even highly correlated) in order to extract useful features also for thunderstorm forecasting.

FLAS (Forecasting Lightning Activity System for Friuli Venezia Giulia) Convolutional Neural Network model, developed in Pytorch/CUDA



Some inputs for the 10/08/2017 case: above a 3D field (Θ_e) and below two 2D fields (Convective Precipitation and Maximum Buoyancy).



The proposed CNN, with two inputs layer (using a 3D CNN with kernel 3x4x4 for the 3D variables and a "normal" CNN with kernel 3x4 for the 2D variables) and their output features aggregated before the internal CNN. Convolutional blocks in cyan, Maximum-Pooling layer are green, while the output "dense" linear layer is red. Output is the estimated lightnings.

Comparison with "DMO" precipitation and AtmoSwing

For comparison, also a simple model based only on convective precipitation (linear model using the max CP in FVG, or a simplified CNN model using only the CP field) or based on the **analog method** have been developed. The analog method has been implemented by the AtmoSwing model (Horton 2019), that uses **Genetic Algorithms** as optimization method to select the relevant variables and their sub-domains, plus the number of analog cases to be compared. More details in ECSS2019-172 poster: Horton, P., Manzato, A., Soldà, D. and O. Martius, 2019: *Exploring potential predictor variables by means of genetic algorithms for thunderstorms forecasting with analog methods.*

CONCLUSIONS (cont.)

- To the author's knowledge, that is the first time that a 3D CNN has been used to look for **tridimensional tropospheric features**.
- Results on the mesoscale domain (at 0.125 deg and with more 2D predictors) are better than those found on the synoptic scale.
- AtmoSwing gives similar results (using only **few 2D predictors** on small sub-domains), but with much longer training periods.

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Agostino Manzato, OSMER - ARPA Friuli Venezia Giulia, 33057 Palmanova (UD), Italy agostino.manzato@meteo.fvg.it