Spatially coherent postprocessing of cloud cover and precipitation using GANs

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Overview

- Part 1: cGAN postprocessing for hourly cloud cover which actually works\(^1\)
  - Reference forecasts: gEMOS or dense NN + ECC or Schaake shuffle
  - Univariate and multivariate calibration
  - Pros and cons of the different methods
- Part 2: cGAN postprocessing for precipitation which does not work yet
  - Reference forecasts: COSMO-E, spatially pooled COSMO-E, (similarity based) quantile regression

Dataset

• Predictors (subsampled)
  – Numerical forecasts (COSMO-E and IFS [+12h])
    • Training set: 05.2016 - 04.2018
    • Validation set: 05.2018 - 04.2019
    • Test set: 05.2019 - 04.2020

• Observations
  – EUMETSAT CM-SAF satellite data, 2 × 2 km resolution
Conditional GAN (cGAN)

CLCT_mean
CLCT_var
CLCH_mean
CLCL_mean
TCC_mean
TCC_var
HCC_mean
MCC_mean
LCC_mean
LCC_var
HPBL_mean
T_2M_mean

embeddings
init_time
lead_time
hour_of_day
month

61,206,094 parameters

COSMO-E

IFS

1,316,951 parameters

CLCT_mean
CLCT_var
CLCH_mean
CLCL_mean
TCC_mean
TCC_var
HCC_mean
MCC_mean
LCC_mean
LCC_var
HPBL_mean
T_2M_mean

init_time
lead_time
hour_of_day
month
High DJF CRPS in fog prone regions

gEMOS skill > COSMO-E skill, but not significantly in fog prone regions

denseNN and cGAN improve forecast skill compared to gEMOS
Multivariate verification

- p-variogram skill score
- cGAN performs best
- Schaake shuffle outperforms ECC for gEMOS and denseNN
Data efficiency

more data needed
Summary part 1

- Three approaches for post-processing cloud cover

<table>
<thead>
<tr>
<th></th>
<th>gEMOS</th>
<th>Dense NN</th>
<th>cGAN</th>
</tr>
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<tbody>
<tr>
<td>Interpretability</td>
<td>★★★★☆</td>
<td>★☆☆☆☆</td>
<td>★☆☆☆☆</td>
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<tr>
<td>Forecast skill</td>
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<td>★★★★☆</td>
<td>★★★☆☆</td>
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<tr>
<td>Calibration</td>
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<td>★★★☆☆</td>
<td>★★★★★</td>
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<tr>
<td>Realistic images</td>
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<td>Realistic videos¹</td>
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<td>Data efficiency</td>
<td>★★★★☆</td>
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</tbody>
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¹temporal consistency provided by ECC

★ raw model output
★★ model output with ECC
cGAN for precipitation

- Is cGAN model for cloud cover transferable to precipitation?
- Is it possible to include temporal dependence?
- Issues with skewness of precipitation
- Work with daily precipitation accumulations to simplify the problem
- Not transforming the data at all leads to ‘most realistic’ cGAN samples
  - Trade-off: training works only for simple generator architecture
Generator architecture

- 11th, 16th, and 21th member of ordered and spatially smoothed COSMO-E used as features
- no compression of features
- Temporal split and lead day dependent 2D convolutions

Graph generated using Netron
https://github.com/lutzroeder/Netron
Example forecasts

- **day 1**
  - COE CTRL
  - CGAN 1
  - CGAN 2
  - CombP

- **day 2**
  - COE CTRL
  - CGAN 1
  - CGAN 2
  - CombP

- **day 3**
  - COE CTRL
  - CGAN 1
  - CGAN 2
  - CombP

- **day 4**
  - COE CTRL
  - CGAN 1
  - CGAN 2
  - CombP

- **day 5**
  - COE CTRL
  - CGAN 1
  - CGAN 2
  - CombP

Precipitation [mm/d]

Reftime: 2019-06-04T00Z
CRPS and calibration

- rank histograms for lead day 3
- pooled: simple spatial pooling
- QR: quantile regression
- QR_sim: similarity / analog based QR
Brier score and AUC

BS

lead day

threshold 0 mm/d

threshold 10 mm/d

threshold 50 mm/d

AUC

COSMO-E
pooled
QR
QR_sim
cGAN
Summary part 2

- cGAN generates quite realistic looking precipitation fields
- cGAN skill in terms of CRPS is poor
- cGAN produces comparatively well calibrated forecasts
- cGAN resolution probably poor, issues with conditioning on features
- Probably, there is still a lot of room for improvement