Photographic Visualization of Weather Forecasts with Generative Adversarial Networks

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Outline

Motivation: Why Photographic Images?
Baseline and Evaluation Criteria
Method: Conditional GANs
Results
Conclusions and Future Work
Outdoor Weather Cameras

An information-dense yet accessible visualization of past and present weather:

- cloud type
- precipitation
- cloud area fraction
- radiation
- visibility
- snow cover
Visualization of Weather Forecasts

Screnshots of the MeteoSwiss smartphone app

Also use photographic images to visualize future weather conditions!
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Baseline: Analog Retrieval

$\hat{I}_t$  Retrieval of best matching individual images from annotated archive

$\hat{I}^{ind}_t$  Retrieval of best matching individual images from annotated archive

$\hat{I}^{seq}_t$  Retrieval of best matching sequence

$I_t$  Image sequence taken at Flüela, 10 to 16 UTC on July 2nd, 2020
I. Images should look real, no obvious artifacts
II. Match future atmospheric, ground and illumination conditions
III. Seamless transition from observation to forecast
IV. Visual continuity between consecutive images
Evaluation of Analog Retrieval

|                         | I. Realism | II. Matching conditions | III. Seamless transition | IV. Visual continuity |
|-------------------------|------------|-------------------------|--------------------------|-----------------------|
| Analog images           | 😊         | 😞                      | 😞                       | 😞                    |
| Analog sequence         | 😊         | 😞                      | 😞                       | 😊                    |

High information density of images → retrieving analogs is not feasible 😞
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Image Synthesis: A Regression Problem

Generate photographic image $\hat{I}_t$, given forecast $w_t$ of future weather conditions

$$G: w_t \mapsto \hat{I}_t$$

Generator $G(w; \theta)$ is a neural network, $\theta$ trained by minimizing expected loss

$$\arg\min_{\theta} \mathbb{E}_{w_t, I_t} [L(G(w; \theta), I_t)]$$
Goal: User should not be able to tell whether $I_t$ or $\hat{I}_t$ is the real image, even if they are not identical.

\[
\text{argmin}_\theta \mathbb{E}_{w_t,I_t}[L(G(w_t; \theta), I_t)]
\]

Forecast $w_t$ does not determine exact shapes and locations of clouds → Pixel-wise loss function is not appropriate, results in uniform sky:

$\hat{I}_t$ for $L_1$ loss

$I_t$
Generative Adversarial Networks Goodfellow et al., 2014

**Discriminator** $D: I \mapsto [0, 1]$ mimics user, learns loss function through adversarial training

**Generator** $G: z \mapsto I$, creates image $I$ from random input $z \sim \mathcal{N}(0, 1)$

$$\min_\theta \max_\eta \mathbb{E}_I[\log D(I; \eta)] + \mathbb{E}_z[\log\{1 - D(G(z; \theta); \eta)\}]$$

authenticate real images fool discriminator

spot fake images
Generator Architecture

- Conditional Generator Mirza and Osindero, 2014 transforms current image $I_0$
- Encoder-decoder with skip connections Ronneberger et al., 2015
- Spectral normalization applied to all convolution layers Miyato et al., 2018
Discriminator Architecture

- Conditional discriminator $D(I|I_0, w_0, w_t)$
- Two output heads: patch-level $D_p$ and pixel-l $D_{ij}$ Schonfeld et al., 2020
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Descriptor $w$: time of day, day of year, 31 COSMO-1 hourly output fields

Training: all pairs $(I_0, w_0)$ and $(I_t, w_t)$, $t \in [0, 10, 20, ..., 360 \text{ min}]$ of 2019

Test: Jan to Aug of year 2020 (until decommissioning of COSMO-1 at MCH)

Downscaled to 64 x 128 pixels to speed up training and conserve GPU memory
What is your first impression of the image?

- generated
- real
- generated
- real
I. Realism

Results of study with 5 professional users of MCH camera feeds:

| Actual  | Judgment | Actual  | Judgment | Actual  | Judgment |
|---------|----------|---------|----------|---------|----------|
| Real    | 57       | Real    | 52       | Real    | 57       |
| Generated | 43   | Generated | 32       | Generated | 49       |
| Generated | 18   | Generated | 23       | Generated | 18       |
| Generated | 32   | Generated | 43       | Generated | 26       |

Cevio: 59 % accuracy  
Etziken: 63 % accuracy  
Flüela: 55 % accuracy

User accuracy is not much better than random guessing 🙂
II. Matching Weather Conditions

Atmosphere: cloud cover, cloud type, visibility
Ground: dry, wet, frost, snow
Illumination: time of day, diffuse or direct
II. Matching Weather Conditions

| Camera   | Cloud cover | Cloud type | Visibility | Ground | Time of day | Diffuse/direct |
|----------|-------------|------------|------------|--------|-------------|----------------|
| Cevio    | 32          | 35         | 45         | 45     | 45          | 40             |
| Etziken  | 36          | 36         | 44         | 45     | 45          | 38             |
| Flüela   | 31          | 33         | 26         | 44     | 41          | 35             |

Example: Mismatch in cloud cover

but forecast $w_t$ predicted 100% cloud area fraction in medium troposphere
II. Matching Weather Conditions

| Camera | Atmosphere | | | Illumination | | Viz. failures |
|---|---|---|---|---|---|---|
| | Cloud cover | Cloud type | Visibility | Ground | Time of day | Diffuse/direct | |
| Cevio | 32 | 35 | 45 | 45 | 45 | 40 | 5 |
| Etziken | 36 | 35 | 44 | 45 | 45 | 38 | 2 |
| Flüela | 31 | 33 | 26 | 44 | 41 | 35 | 5 |

**Visualization failure**: forecast $w_t$ is accurate, but generated image $\hat{I}_t$ is inconsistent with it
Possible because $G$ is conditioned on $I_0$, compare to analog retrieval:
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Conclusions

- Photographic images can also visualize future weather conditions
- Look realistic, match predicted weather conditions, attain seamless transition from observation to forecast and visual continuity

Applications:
- Communicate localized forecasts in webcam feeds, smartphone app
- Provide similar service to communities and tourism organizations
• Use more accurate and descriptive weather descriptors
• Scale image size beyond 64 x 128 pixels e.g. Karras et al., 2018
• Improve transformations involving translations:

\[
I_t \quad I_t \quad I_t \quad I_t \quad I_t \quad I_t \quad I_t \quad I_t
\]

\[
\hat{I}_t \quad \hat{I}_t \quad \hat{I}_t \quad \hat{I}_t \quad \hat{I}_t \quad \hat{I}_t \quad \hat{I}_t \quad \hat{I}_t
\]

\[
t = 0 \quad t = 1 \text{ h} \quad t = 2 \text{ h} \quad t = 3 \text{ h} \quad t = 4 \text{ h} \quad t = 5 \text{ h} \quad t = 6 \text{ h}
\]

(including self-attention layers Zhang et al., 2019 did not help)
• Synthesize whole sequences to improve temporal evolution Wu et al., 2020
The pre-print of our paper is available at

https://arxiv.org/abs/2203.15601

Tensorflow code, trained models and results are available at

https://github.com/meteoswiss/photocast
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Bibliography

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. Advances in neural information processing systems, 27.
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
Karras, T., Aila, T., Laine, S., & Lehtinen, J. (2017). Progressive growing of gans for improved quality, stability, and variation. arXiv preprint arXiv:1710.10196.
Mirza, M., & Osindero, S. (2014). Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784.
Miyato, T., Kataoka, T., Koyama, M., & Yoshida, Y. (2018). Spectral normalization for generative adversarial networks. arXiv preprint arXiv:1802.05957.
Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241).
U. Schättler, G. Doms, and C. Schraff. (2021). COSMO-Model Version 6.00: A Description of the Non-hydrostatic Regional COSMO-Model - Part VI: Model Output and Data Formats for I/O.
Schröder, E., Schiele, B., & Khoreva, A. (2020). A u-net based discriminator for generative adversarial networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 8207-8216).
Wu, S., Xiao, X., Ding, Q., Zhao, P., Wei, Y., & Huang, J. (2020). Adversarial sparse transformer for time series forecasting. Advances in Neural Information Processing Systems, 33, 17105-17115.
Yun, S., Han, D., Oh, S. J., Chun, S., Choe, J., & Yoo, Y. (2019). Cutmix: Regularization strategy to train strong classifiers with localizable features. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 6023-6032).
Zhang, H., Goodfellow, I., Metaxas, D., & Odena, A. (2019, May). Self-attention generative adversarial networks. In International conference on machine learning (pp. 7354-7363). PMLR.
Generator Objectives to be Minimized

How much $G(I_0, z|w_0, w_t)$ struggles to fool the discriminator on the patch level

$$\mathbb{E}_{I_0, w_0, w_t} \mathbb{E}_z \left[ \sum_p \log[D_p(G(I_0, z|w_0, w_t)|I_0, w_0, w_t)] \right]$$

and on the pixel level

$$\mathbb{E}_{I_0, w_0, w_t} \mathbb{E}_z \left[ \sum_{ij} \log[D_{ij}(G(I_0, z|w_0, w_t)|I_0, w_0, w_t)] \right]$$

How similar two generated images look at the pixel level, given different random inputs $z_1, z_2 \sim \mathcal{N}(0, 1)$

$$-\mathbb{E}_{I_0, w_0, w_t} \mathbb{E}_{z_1, z_2} \left[ \sum_{ijc} \left| G_{ijc}(I_0, z_1|w_0, w_t) - G_{ijc}(I_0, z_2|w_0, w_t) \right| \right]$$
Discriminator Objectives to be Maximized

How well the patch head $D_p$ authenticates real images

$$\mathbb{E}_{I_0,w_0,t} \left[ \sum_p \log D_p(I_t|I_0,w_0,w_t) \right]$$

and spots generated images

$$\mathbb{E}_{I_0,w_0,t} \mathbb{E}_Z \left[ \sum_p \log \left[ 1 - D_p(G(I_0,z|w_0,w_t)|I_0,w_0,w_t) \right] \right]$$

How well the pixel head $D_{ij}$ can distinguish pixels of a cut-mix composite $C$

$$\mathbb{E}_C \left[ \sum_{ij} M_{ij} D_{ij}(C) + (1 - M_{ij}) \log(1 - D_{ij}(C)) \right]$$
Clouds in $I_0$ are still partially visible in the clear sky regions of $\hat{I}_t$.

→ Residual transformation learned by the generator does not fully cancel their appearance.
## Subset of COSMO-1 Output Fields

Schättler et al., 2021

| Abbreviation   | Unit     | Name                                                                                     |
|----------------|----------|------------------------------------------------------------------------------------------|
| ALB.RAD        | %        | Surface albedo for visible range, diffuse                                                |
| ASOB.S         | W/m²     | Net short-wave radiation flux at surface                                                 |
| ASWDIF.D.S     | W/m²     | Diffuse downward short-wave radiation at the surface                                     |
| ASWDIF.U.S     | W/m²     | Diffuse upward short-wave radiation at the surface                                       |
| ASWDIR.S       | W/m²     | Direct downward short-wave radiation at the surface                                      |
| ATHB.S         | W/m²     | Net long-wave radiation flux at surface                                                  |
| CLCH           | %        | Cloud area fraction in high troposphere (pressure below ca. 400 hPa)                     |
| CLCM           | %        | Cloud area fraction in medium troposphere (between ca. 400 and 800 hPa)                 |
| CLCL           | %        | Cloud area fraction in low troposphere (pressure above ca. 800 hPa)                      |
| CLCT           | %        | Total cloud area fraction                                                               |
| D.TD.2M        | K        | 2 m dew point depression                                                                |
| DD.10M         | °        | 10 m wind direction                                                                     |
| DURSUN         | s        | Duration of sunshine                                                                    |
| FF.10M         | m/s      | 10 m wind speed                                                                         |
| GLOB           | W/m²     | Downward shortwave radiation flux at surface                                            |
| H.SNOW         | m        | Snow depth                                                                              |
| HPBL           | m        | Height of the planetary boundary layer                                                  |
| PS             | Pa       | Surface pressure (not reduced)                                                         |
| RELHUM.2M      | %        | 2 m relative humidity (with respect to water)                                           |
| T.2M           | K        | 2 m air temperature                                                                     |
| TD.2M          | K        | 2 m dew point temperature                                                               |
| TOT_PREC       | kg/m²    | Total precipitation                                                                     |
| TOT_RAIN       | kg/m²    | Total precipitation in rain                                                             |
| TOT_SNOW       | kg/m²    | Total precipitation in snow                                                             |
| U.10M          | m/s      | 10 m grid eastward wind                                                                 |
| V.10M          | m/s      | 10 m grid northward wind                                                                |
| VMAX.10M       | m/s      | Maximum 10 m wind speed                                                                  |