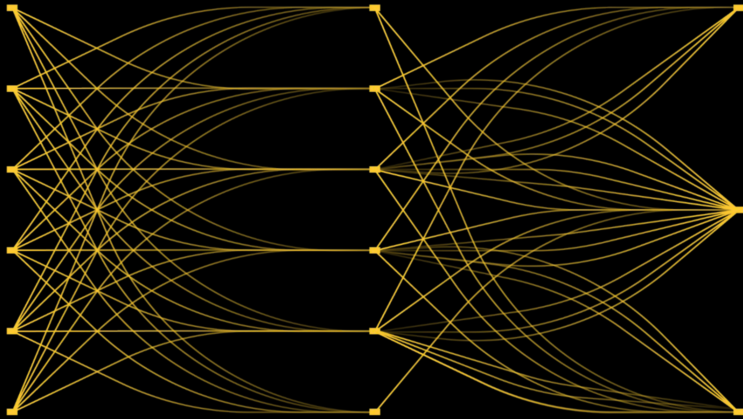
Diffusion on the Clouds: Short-Term Solar Energy Forecasting with Diffusion Models



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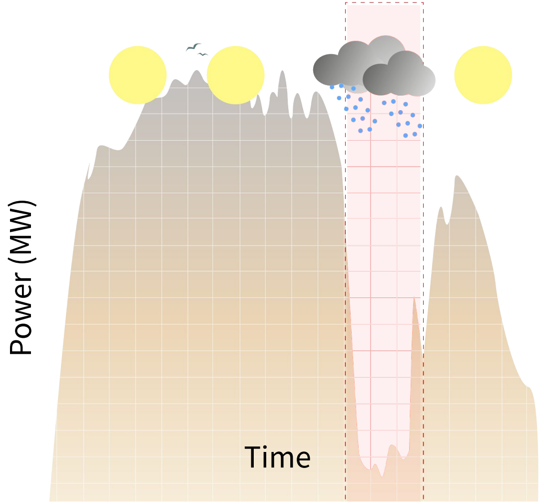
Motivation

Solar energy is variable at different timescales



PV production can **drop by up to 80%** in just a few minutes...

steadysun

Solar production forecasting services

Better predictability. Less risk. More renewables.

Motivation

Steadysun's existing forecasting solutions

steadymet

"day-ahead" Forecasting

6 hours to 15 days

Based on meteorological models

steadysat

"intraday" Forecasting

30 min to 6 hours

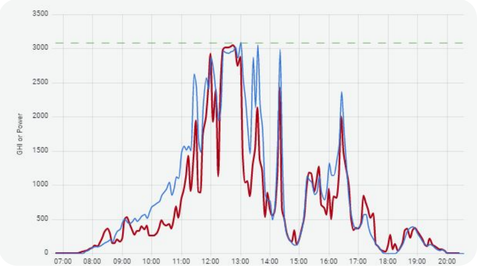
Based on satellite imagery

steadyeye

"very short-term" Forecasting

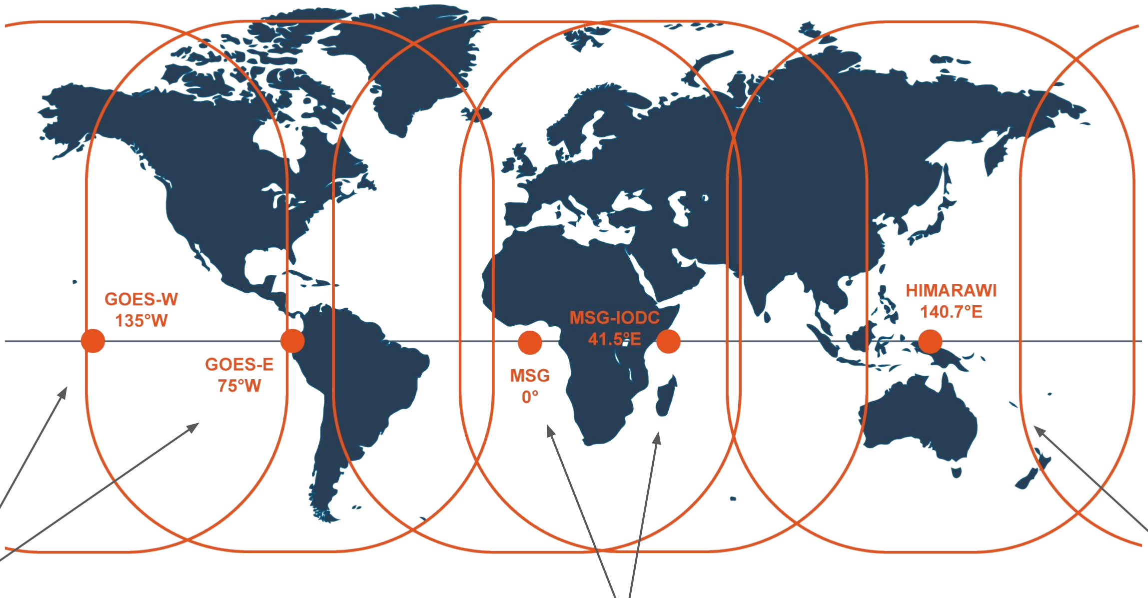
5 to 30 min

Use of a sky imager installed on site



Motivation

Satellite imagery



Every 10 min
@ 0.5km precision max

Every 15 min
@ 1km precision max

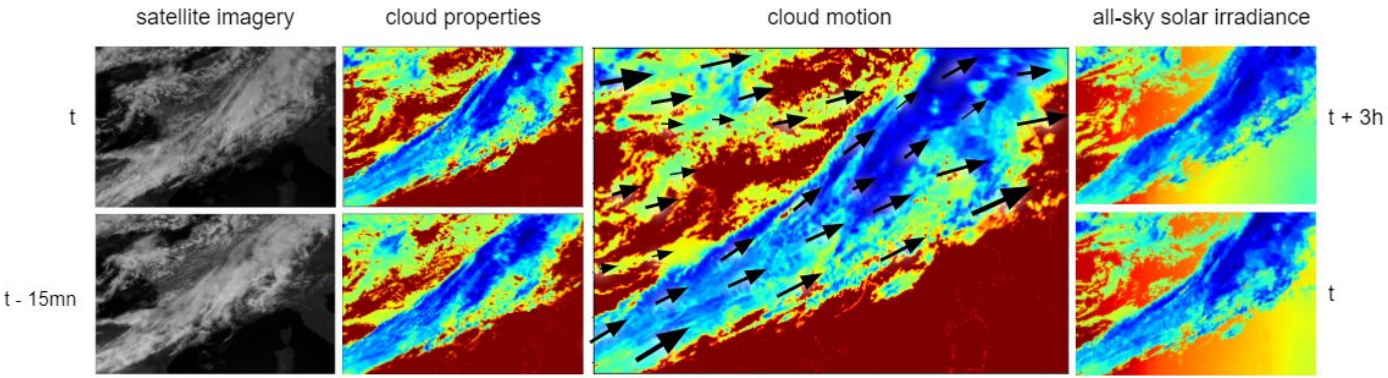
Every 10 min
@ 0.5km resolution max

Motivation

Challenge of forecasting clouds with satellite images

Optical Flow is used for cloud forecasting

- Clouds masks are derived using the six last satellite images
- Cloud movement is inferred based on those masks
- This movement is then applied to the current cloud mask, to simulate cloud movement up to 6 hours onwards



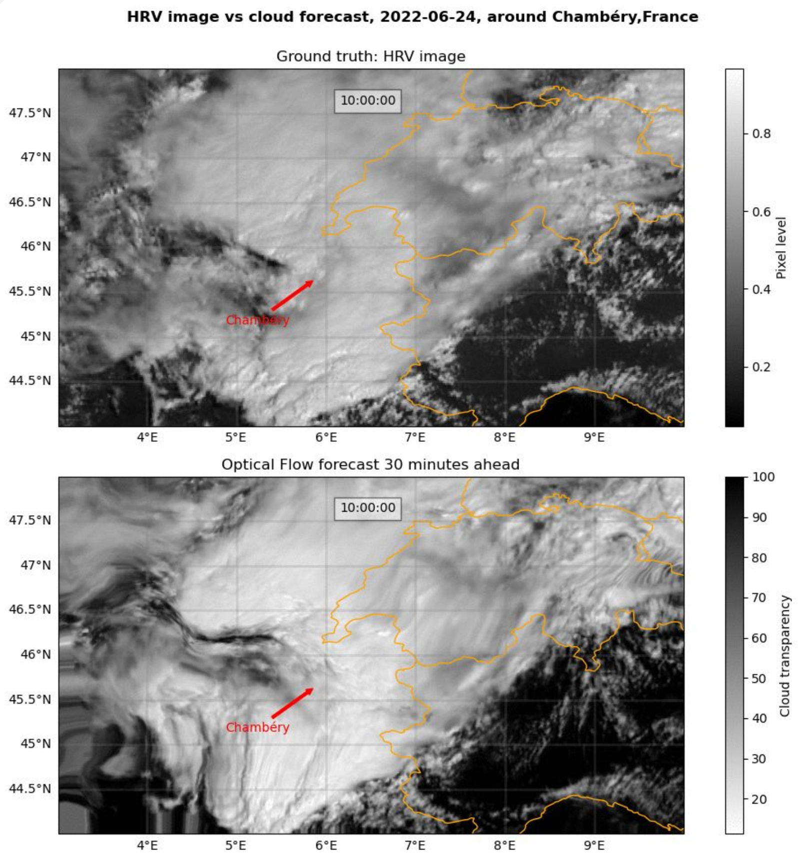
INCEPTION PROGRAM

Motivation

Challenge of forecasting clouds with satellite images

Optical Flow is great for advection

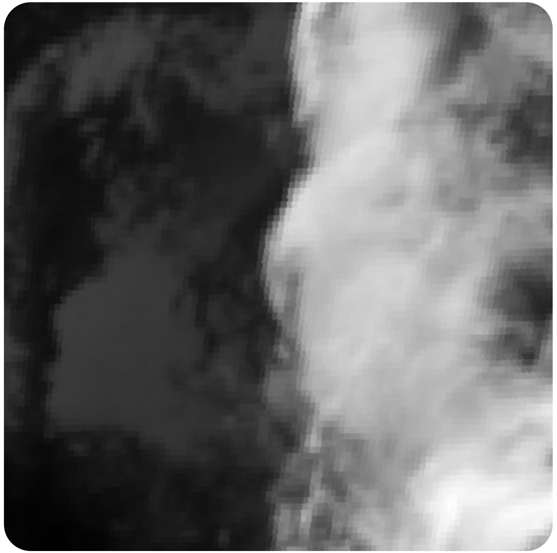
- Not so much for convection (local cloud formation or dissipation)…
- Boundaries problem
- Lots of parameters are difficult to optimize
- The more distant the horizon of forecast, the less accurate the result (1 pixel difference ~ 500m to 1km offset…)



Next frame prediction

Satellite images every 15 minutes

Next frame prediction



The cloud disappeared! 🤯

Denoising Diffusion Probabilistic Models*

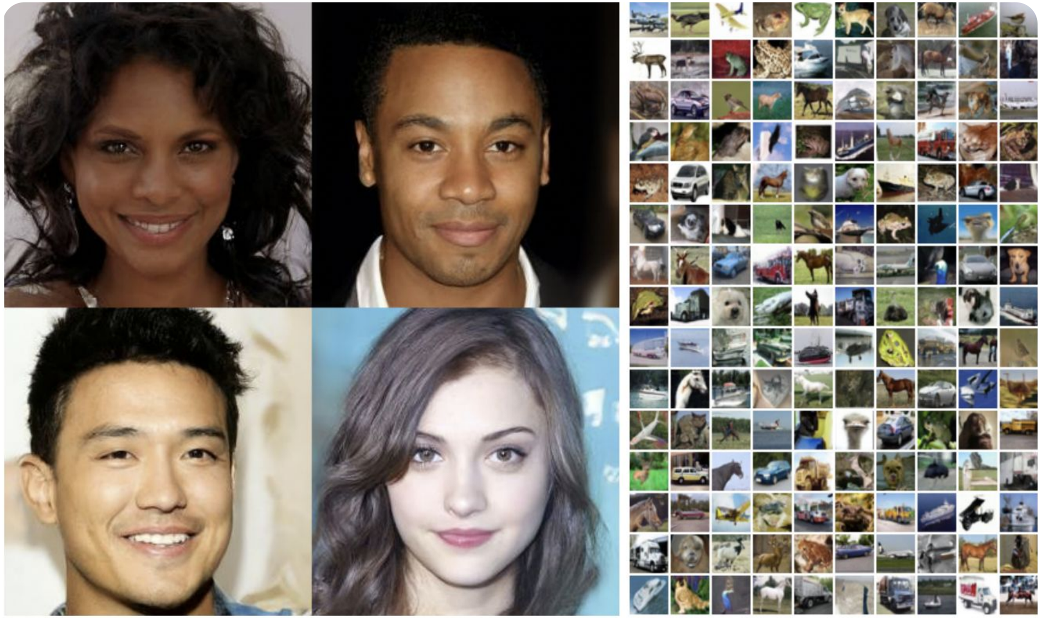


Figure 1: Generated samples on CelebA-HQ 256 × 256 (left) and unconditional CIFAR10 (right)

*https://arxiv.org/abs/2006.11239

- Capable models for image generation
- Can generate images that are sharp and detailed
- Extremely simple model, very easy to train

Denoising Diffusion Probabilistic Models*

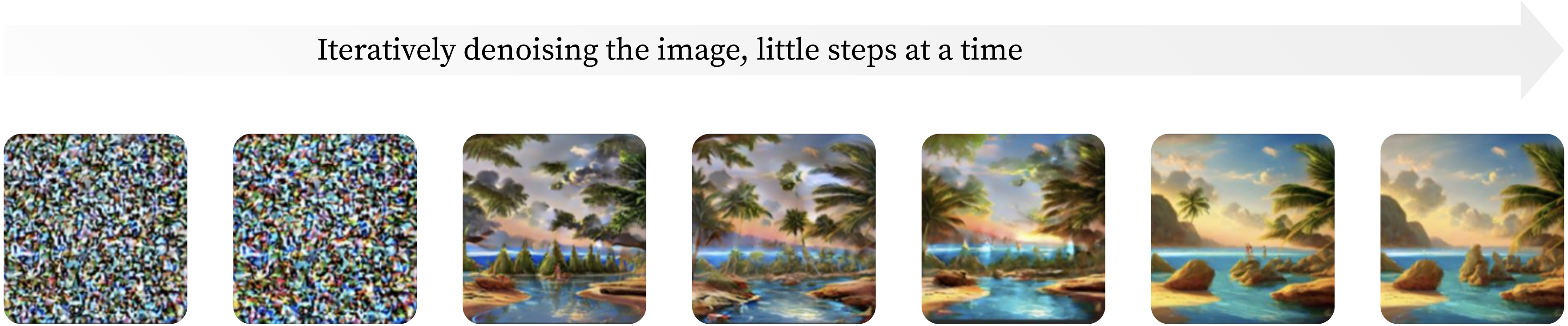
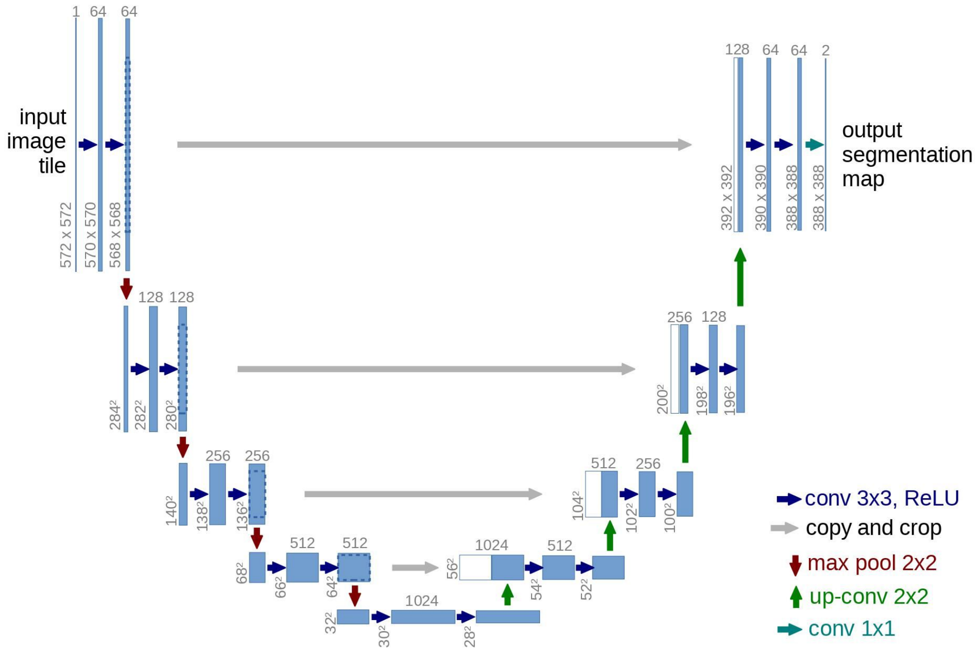


Image from "The Illustrated Stable Diffusion"

Denoising Diffusion Probabilistic Models

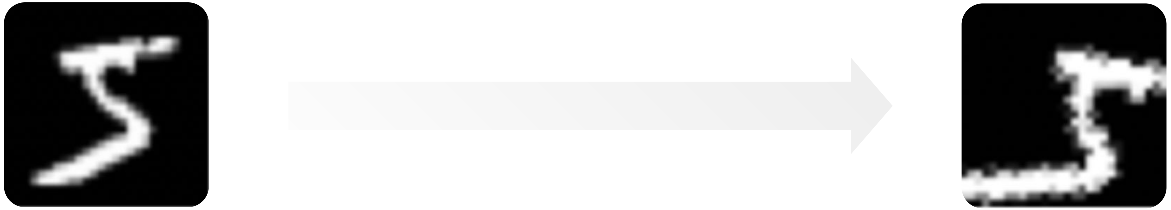


- The workhorse of the diffusion process: The UNet* architecture
- We train the UNet to predict the amount of noise on the image
- Battle tested architecture, upgraded with self-attention layers

*https://arxiv.org/abs/1505.04597

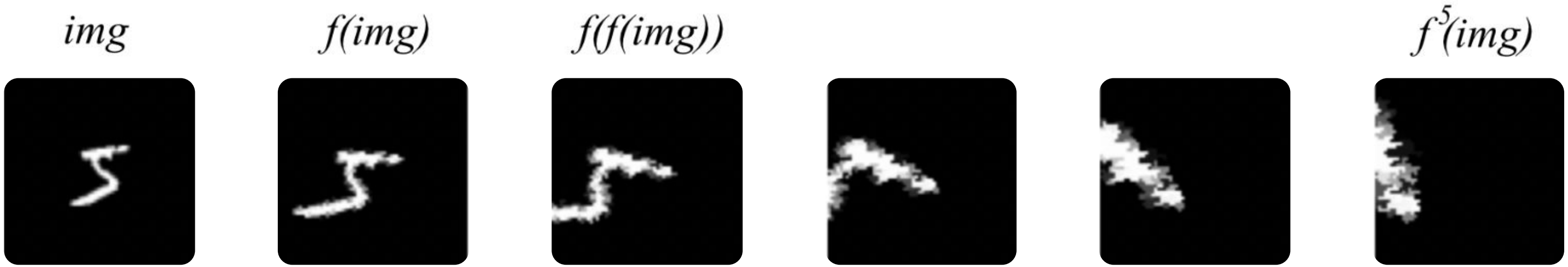
Diffusion for next frame-prediction?

A "simpler" problem: Moving MNIST



Applying affine transform iteratively
(translate, scale, rotate, shear)

A "simpler" problem: Moving MNIST



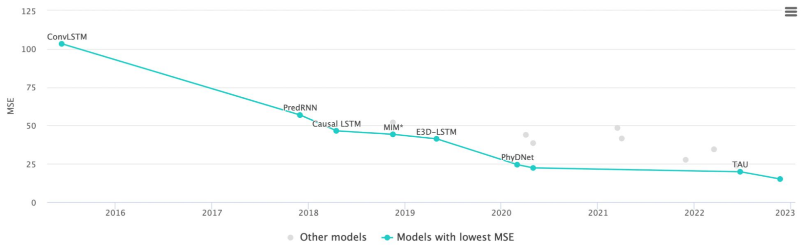

```
from torch.transforms import Affine

# setup values for angle, translate, scale and shear on config
affine_tfm = Affine(angle=angle, translate=translate, scale=scale, shear=shear)


def apply_n_times(affine_tfm, x, n=5):
    "Apply `tf` to `x` `n` times, return all values"
    sequence = [x]
    for n in range(n):
        sequence.append(tf(sequence[n]))
    return sequence
```

A “simpler” problem: Moving MNIST

Video Prediction on Moving MNIST

Leaderboard   Dataset

View MSE by Date



Filter: untagged

Edit Leaderboard

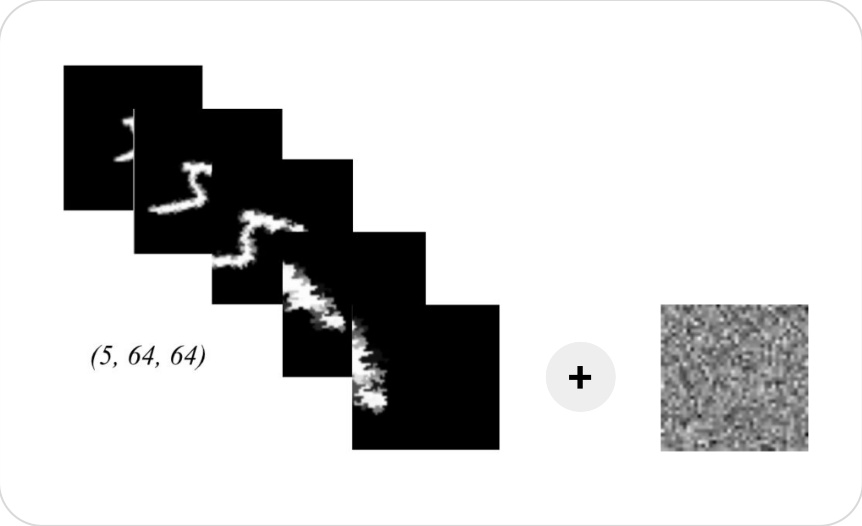
Rank	Model	MSE	MAE	SSIM	LPIPS	PSNR	Paper	Code	Result	Year	Tags
1	**SimVP+gSTA-Sx10**	15.05	49.8	0.967			SimVP: Towards Simple yet Powerful Spatiotemporal Predictive Learning			2022	
2	**TAU**	19.8	60.3	0.957			Temporal Attention Unit: Towards Efficient Spatiotemporal Predictive Learning			2022	
3	**CrevNet+ST-LSTM**	22.3		0.949			Efficient and Information-Preserving Future Frame Prediction and Beyond			2020	
4	**SimVP**	23.8		0.948			SimVP: Simpler yet Better Video Prediction			2022	

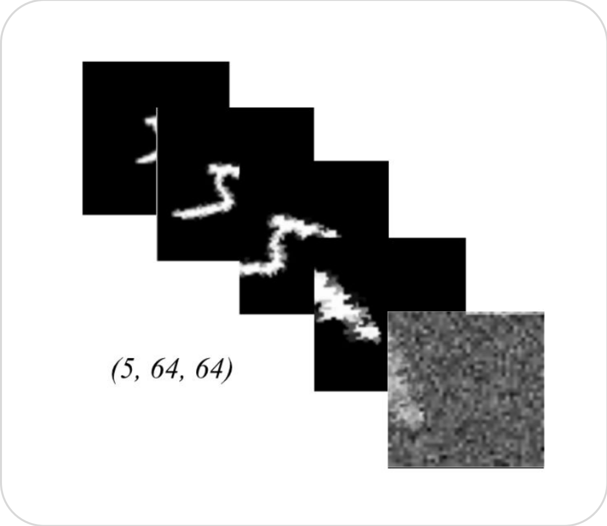
But what are the actual models?

A “simpler” problem: Moving MNIST

Stacking the images on the channel axis
to pass context to the model

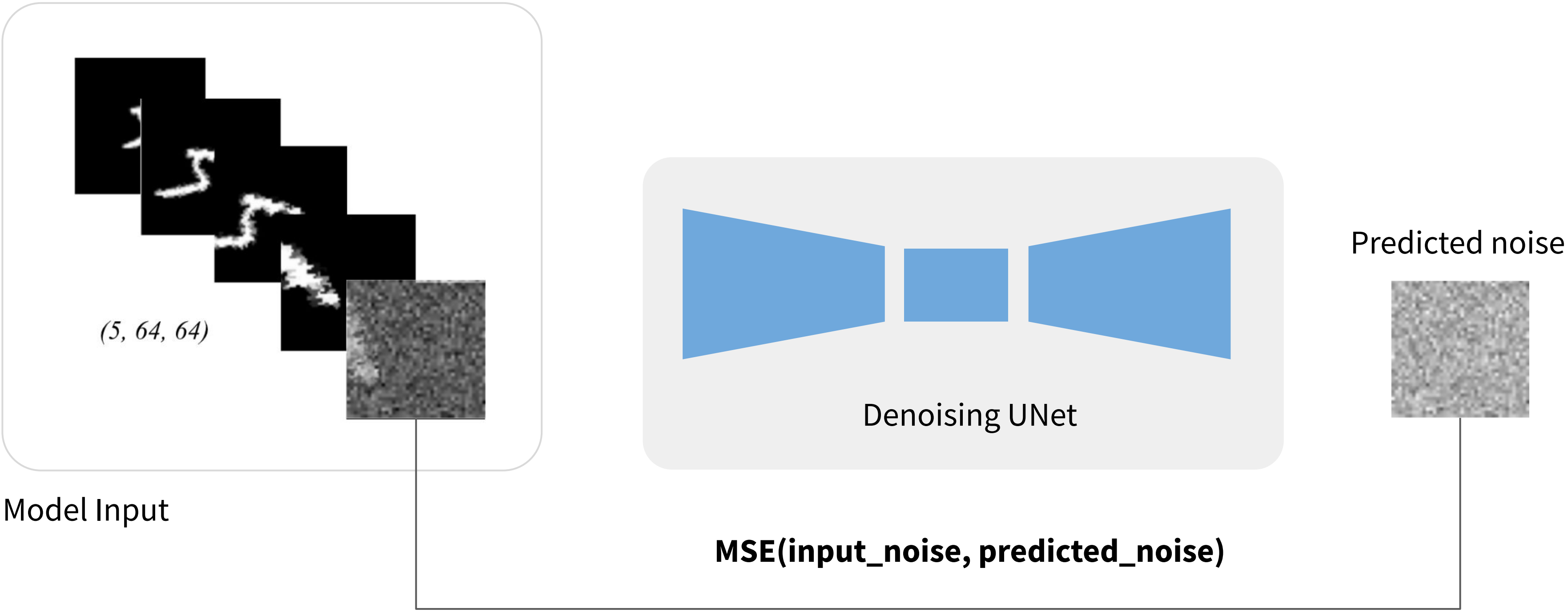
A “simpler” problem: Moving MNIST





Model input (past frames
and “future” noisy frame)

How to condition diffusion for next-frame prediction



The NVIDIA Deep Learning stack

vermilion-rocket-105

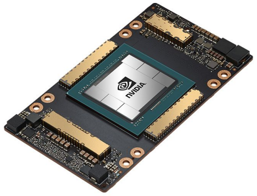
What makes this run special?

Privacy	PUBLIC
Tags	uvit
Author	capecape
State	finished
Start time	February 2nd, 2023 at 1:35:21 pm
Duration	4s
Run path	capecape/ddpm_clouds/my3bfqsh
Hostname	cape-a100-2
OS	Linux-5.15.0-1027-gcp-x86_64-with
Python version	3.10.8
Python executable	/home/tcapelle/mambaforge/envs/
Git repository	`git clone git@github.com:tcapelle/`
Git state	`git checkout -b "vermilion-rocket-`
Command	`<python with no main file>`
System Hardware	CPU count 6
	GPU count 1
	GPU type NVIDIA A100-SXM4-40GB

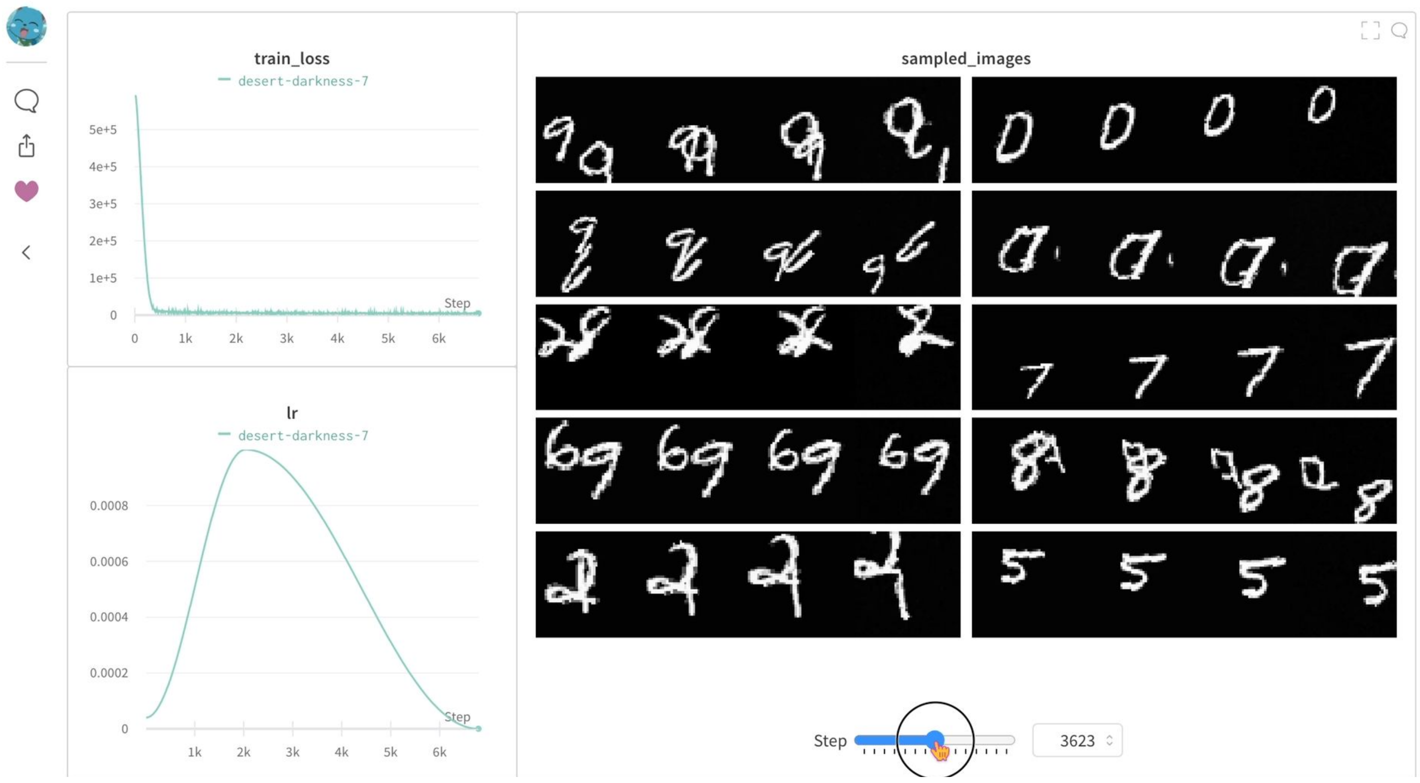
PyTorch | Accelerated with NVIDIA

Also, the best way to make use of the fastest possible configurations is to use **Nvidia NGC PyTorch** optimized containers.

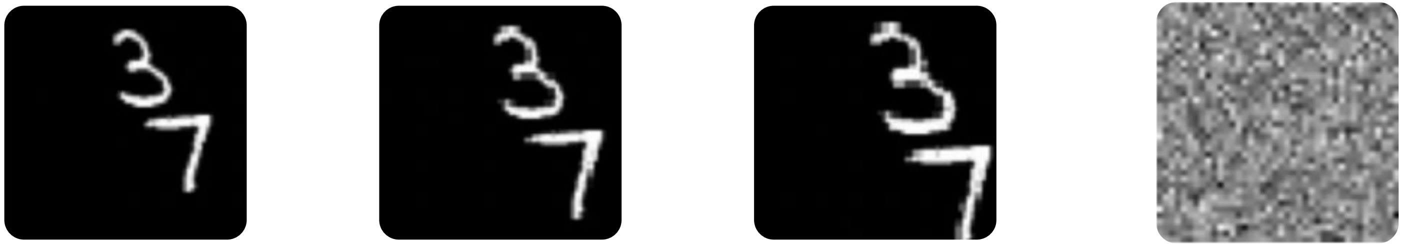
These models require lots of VRAM to go vroom vroom 😎



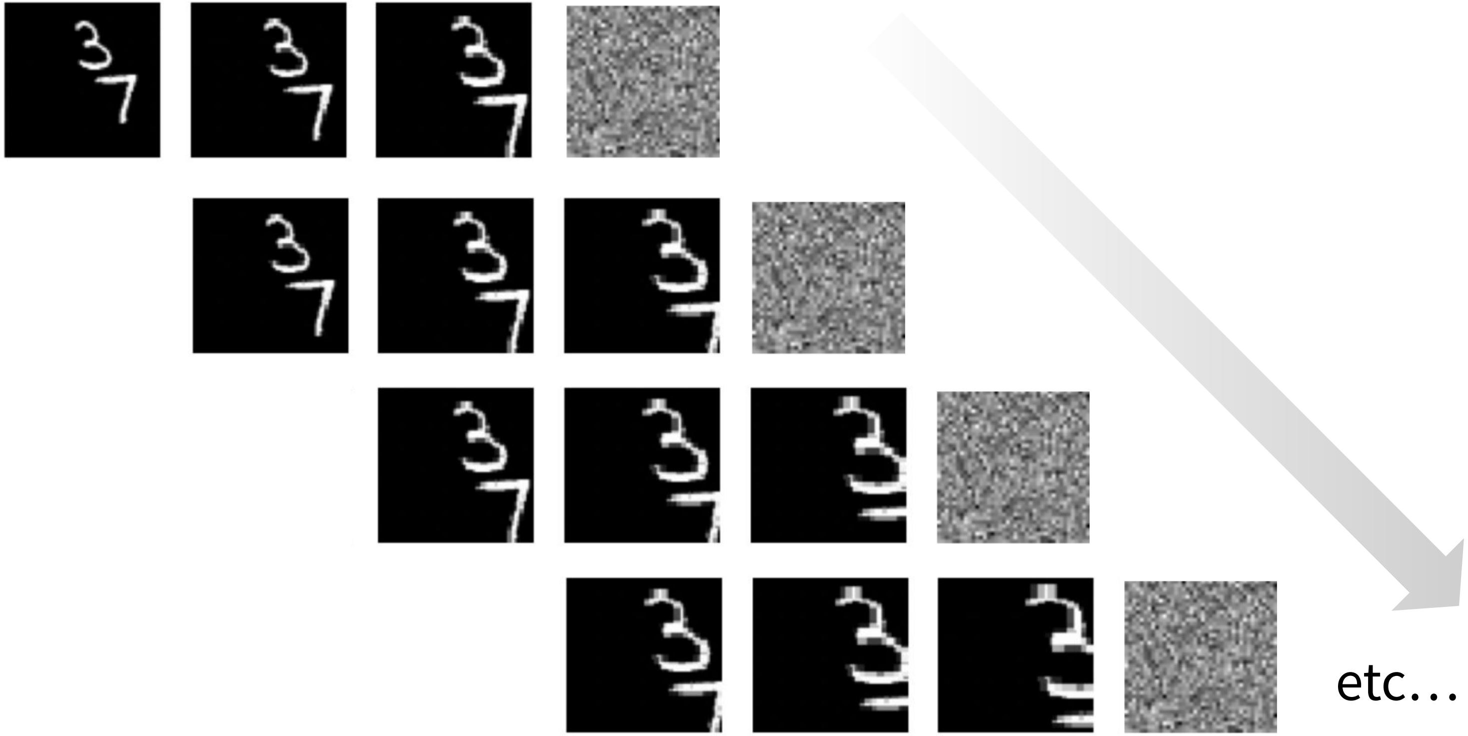
Looking at the loss is not enough...



Autoregressive model sampling



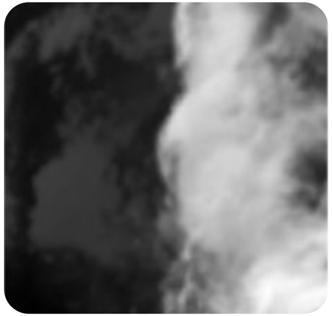
Autoregressive model sampling



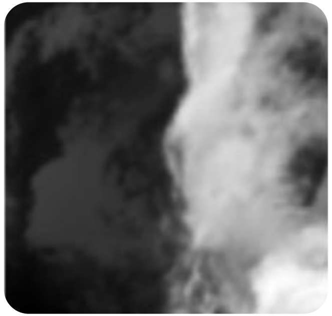
etc…

Let's check the results on the W&B workspace

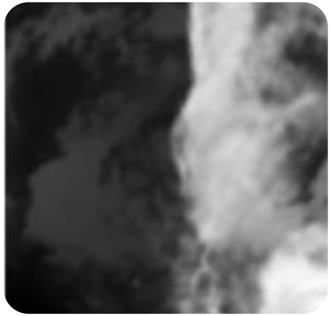
Back to our original problem



t-2



t-1



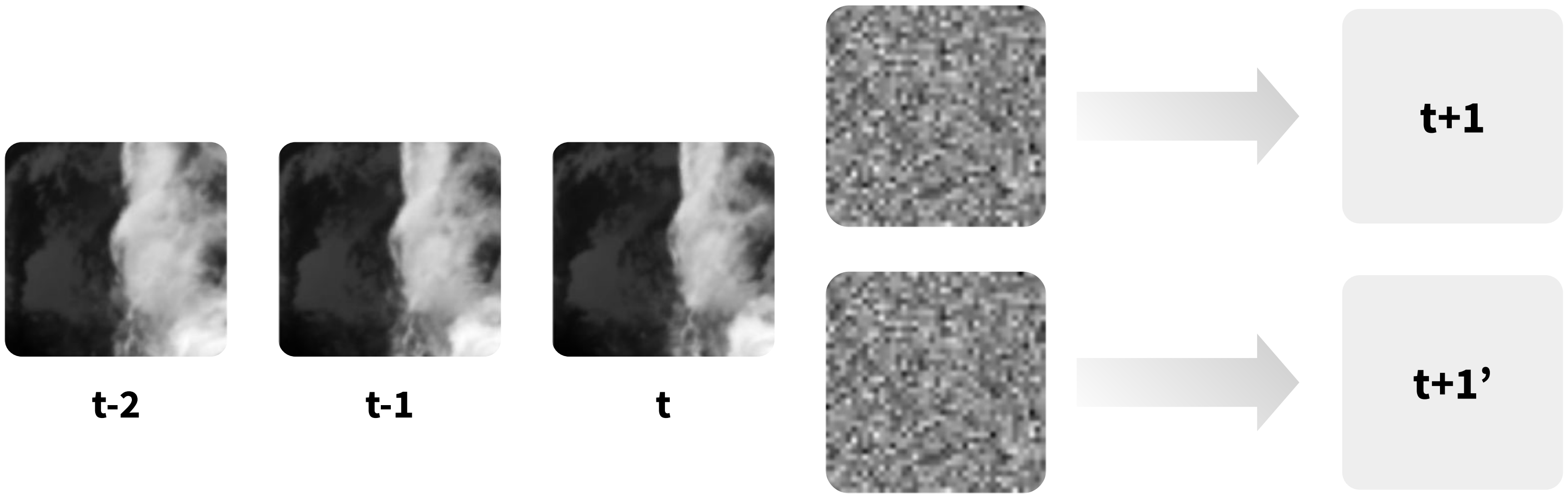
t

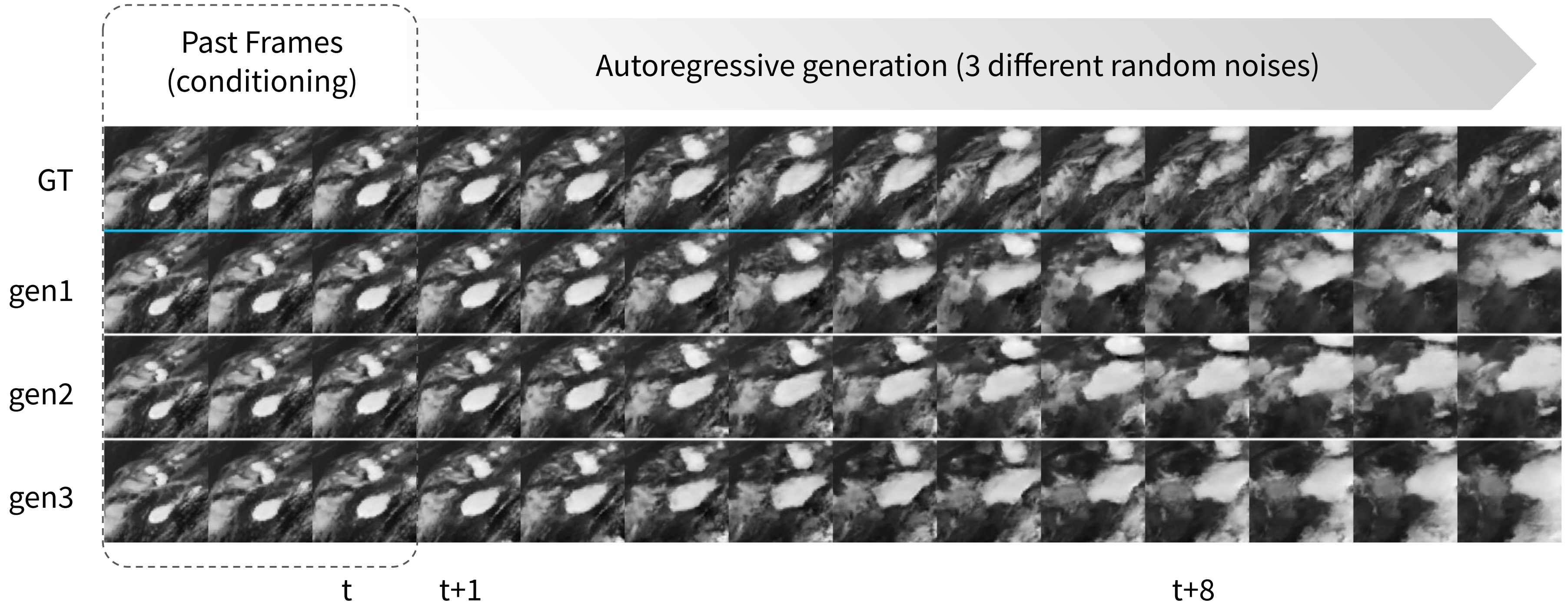
?

Satellite images every 15 minutes

Show me the results!

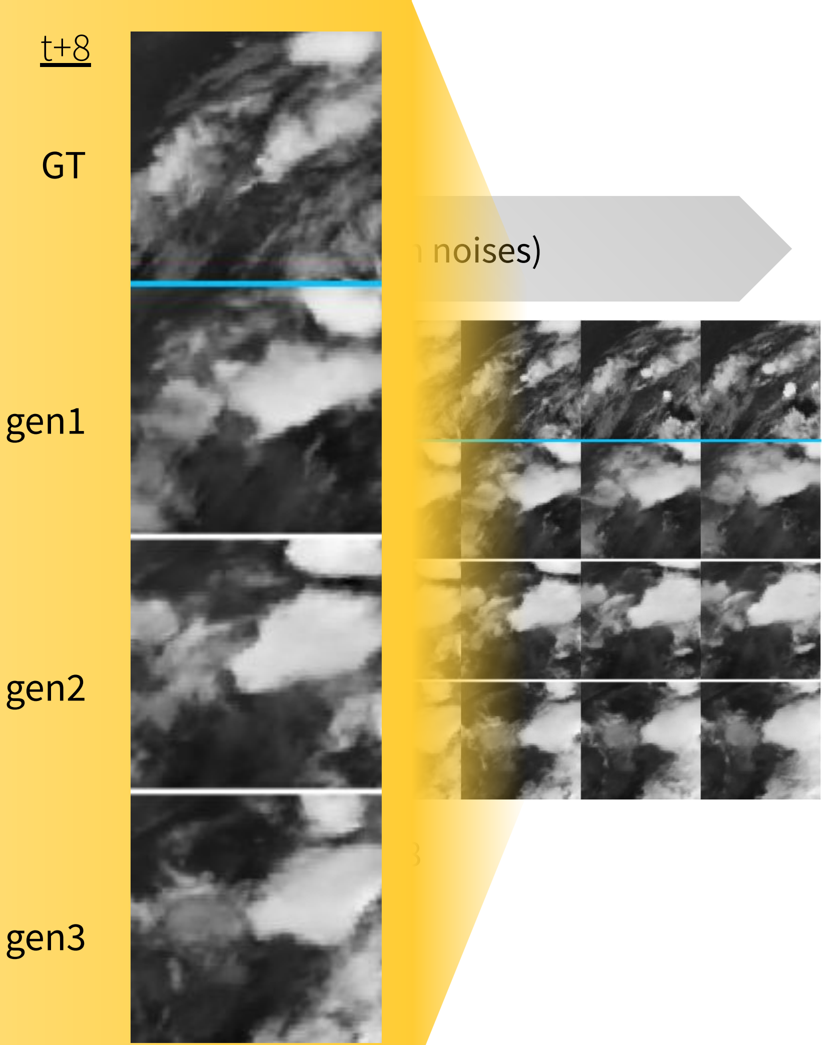
The prediction is *not* deterministic, different noises generate different futures




Past Frames
(conditioning)
Autoregressive generation (3 different random noises)
GT
gen1
gen2
gen3
t
t+1
t+8

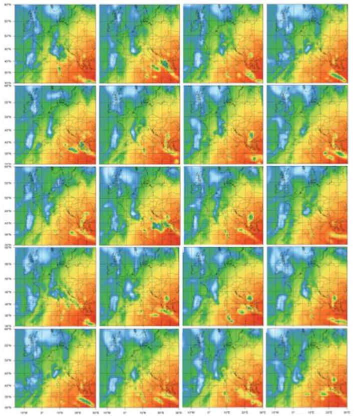
3 slightly different outcomes => enables stochastic model predictions

All predictions we identify the 2 cloud masses present in the GT.

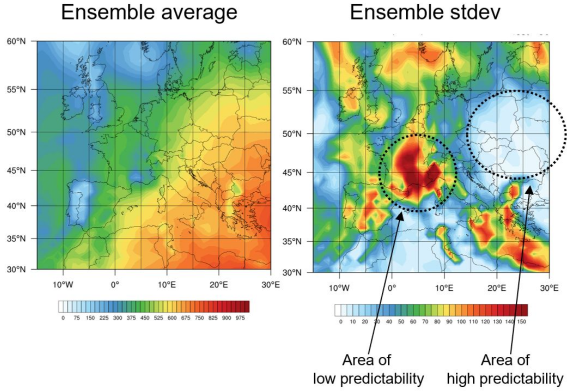


Non-deterministic forecasts

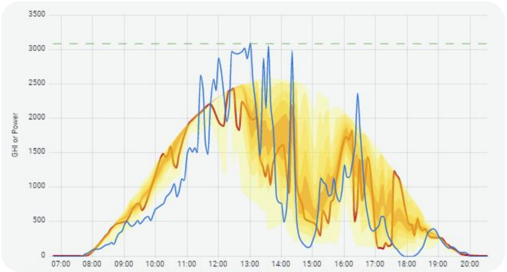
Usefulness for PV forecasts: confidence intervals



Different outcomes



Statistics on the ensemble



Forecast extraction

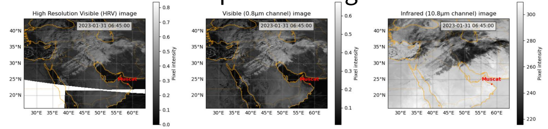
- With several different outcomes for a single run, we can provide **confidence intervals** using an **ensemble approach**
- These intervals account for the **chaotic nature of the atmosphere** and the associated **forecast uncertainty**
- They enable **anticipating corrective actions** to be made in case of erroneous forecasts

In the end...

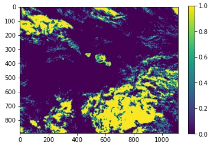
- Cloud forecasts are only a part of the problem of PV power forecasts
- Any errors in cloud movement/position/aspect can greatly affect the outcome of the forecast
- Other AI/DL models considered to deal with several or all the steps of the forecasting chain

Data preprocessing

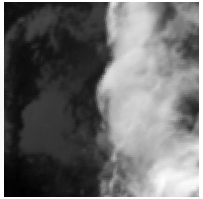
Multispectral images



Cloud detection

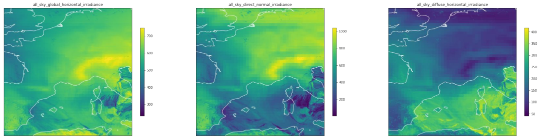


Cloud forecasts

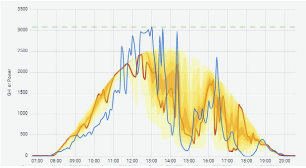


Irradiance computation

GHI DNI DHI



Powerplant forecast extraction



Conclusions and future work

- We are still on the early days of generative modelling and new models are coming out every day!
- NVIDIA ML focused (i.e. A100) GPUs and GPU-accelerated PyTorch enable the ability to train and tune large diffusion models
- This is a proof of concept, but the results look very promising
- The capabilities of diffusion models to generate realistic and possible future frames is impressive
- The most impressive results come from formation/dissipation of clouds, something that optical flow is not capable of doing
- No border issues
- High resolution capabilities
- We have to couple this model with the ground projections and energy conversion. We will first evaluate its performance as is on irradiance forecasts.
- Explore the possibilities of training end-to-end pipelines, to directly generate the timeseries results. Also, consider feeding the model with other data, like NWP model outputs and in-situ observations.

To learn more about the code and the experiments

wandb.me/gtc2023