

Simple Video Generation using Neural ODEs

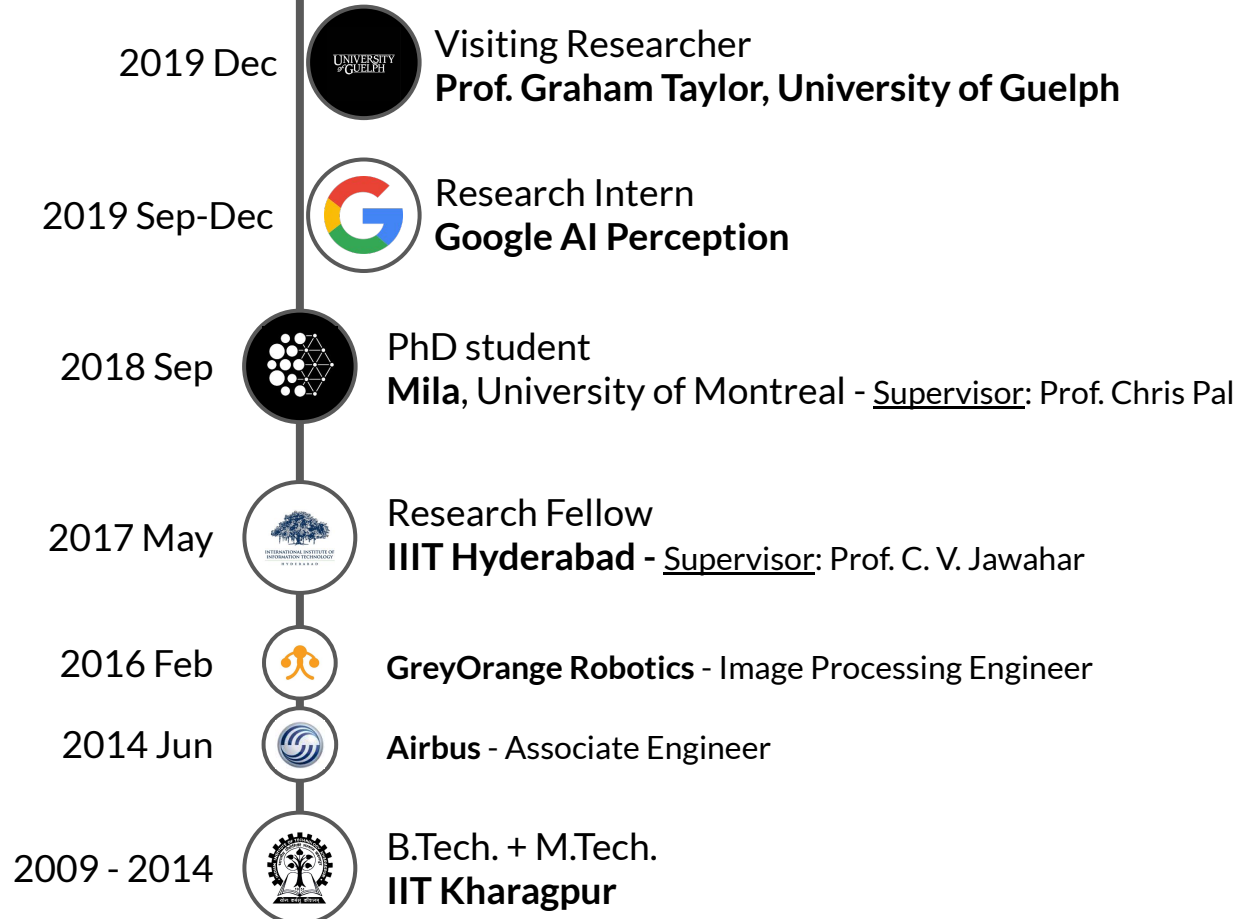
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NeurIPS 2019 Workshop

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Neural ODEs
can be trained to model
latent dynamics in video.

- Conditioned on m frames, generate next n frames

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Stochastic Adversarial Video Prediction:

<https://arxiv.org/abs/1804.01523>

High Fidelity Video Prediction with Large Stochastic Recurrent Neural Networks:

<https://arxiv.org/abs/1911.01655>

Improved Conditional VRNNs for Video Prediction - <https://arxiv.org/abs/1904.12165>

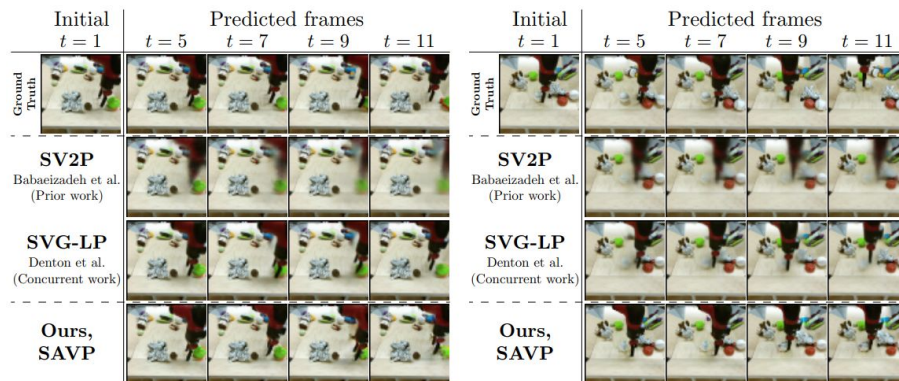


Fig. 1: **Example results.** We show example predictions for two video sequences comparing our method to prior and concurrent work. All methods are conditioned on two initial frames and predict 10 future frames (only some frames are shown). The predictions are stochastic, and we show the closest sample to the ground truth (out of 100 samples). While the prior SV2P method [1] produces blurry, unrealistic images, our method maintains sharpness and realism through time. We also compare to the concurrent SVG-LP method [2], which produces sharper predictions, but still blurs out objects in the background (left) or objects that interact with the robot arm such as the baseball (right).

What if we model the latent dynamics of a video using Neural ODEs?

3 Neural Ordinary Differential Equations

Neural Ordinary Differential Equations (Chen et al., 2018) (Neural ODEs) represent a family of parameterised algorithms designed to model the evolution across time of any system, of state $\xi(t)$ at an arbitrary time t , governed by continuous-time dynamics satisfying a Cauchy (or initial value) problem

$$\begin{cases} \xi(t_0) &= \xi_0 \\ \frac{\partial \xi}{\partial t}(t) &= f(\xi(t), t) \end{cases}$$

By approximating the differential with an estimator $f_\theta \simeq f$ parameterized by θ , such as a neural network, these methods allow to learn such dynamics (or, trajectories) from relevant data. Thus

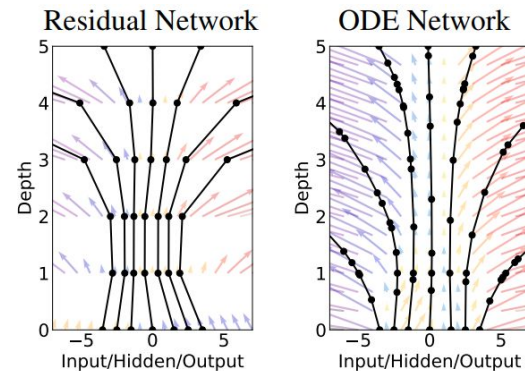
<https://arxiv.org/abs/1806.07366>

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Prev. video generation papers:

- train on generation

Neural ODE paper:

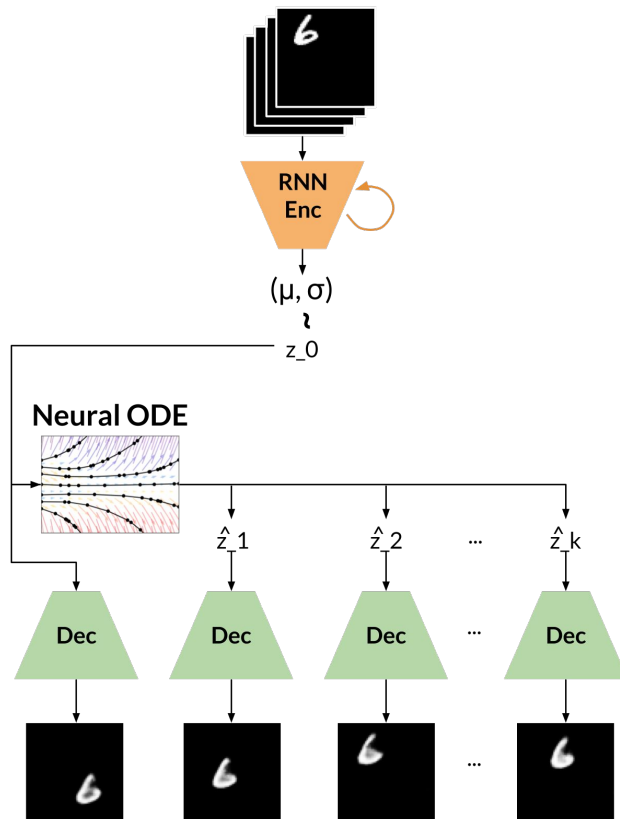
- replaces Residual layers with Neural ODE layer.

Ours:

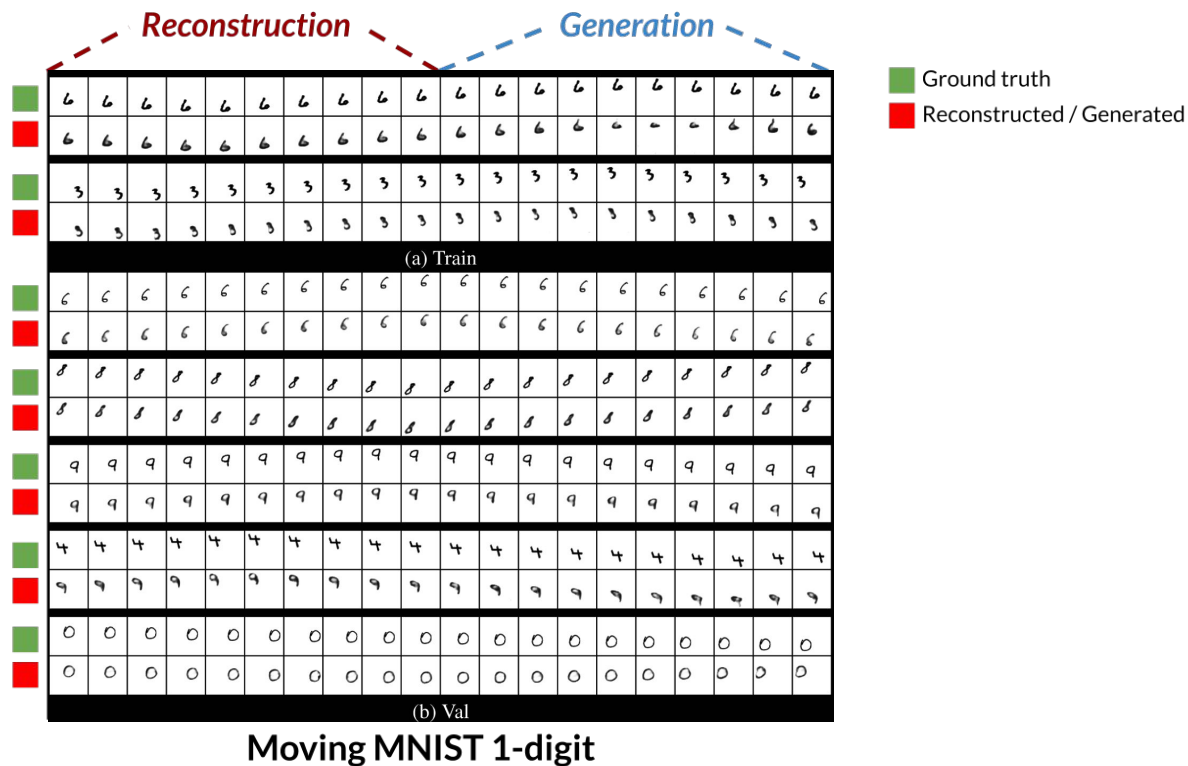
- **trains on only reconstruction.**
- **uses Neural ODE in latent space.**

<https://arxiv.org/abs/1806.07366>

Architecture

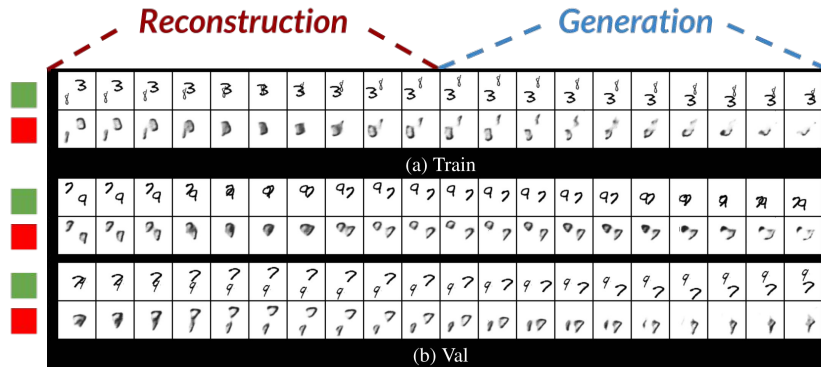


Results



Results

Ground truth
Reconstructed / Generated



Moving MNIST 2-digit

Simple Video Generation using Neural ODEs



- We study the use of Neural ODEs in video generation.
- We train an encoder-decoder architecture with a Neural ODE in latent space to generate video frames in future time steps.
- We show that Neural ODEs can model the latent dynamics in video for the 1-digit and 2-digit Moving MNIST dataset.
- We list the potential use cases and future steps in this direction.

Future (current) work

- Scaling up to natural datasets
- Visualization of latent space
- Evaluation using new video quality metrics (FVD, ...)

Links

Vikram Voleti - <https://voletiv.github.io>

[Paper](#)

[Mila](#)

Thank you.