Advection Augmented Convolutional Neural Networks

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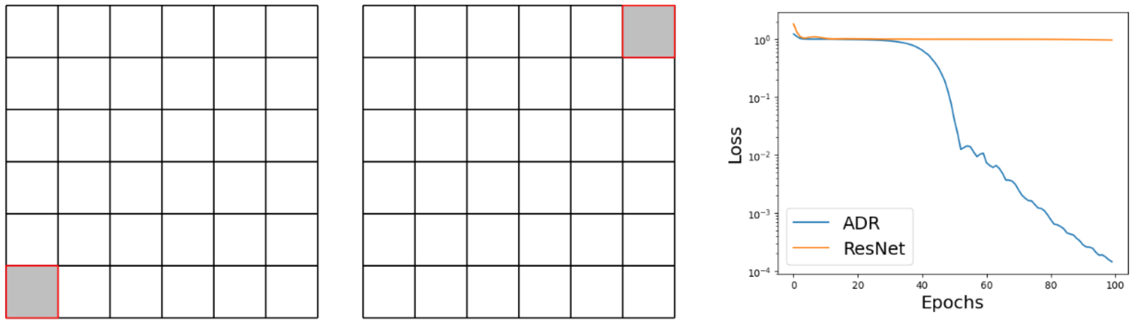
Project Page: https://github.com/Siddharth-Rout/deepADRnet

Paper: https://arxiv.org/abs/2406.19253

Introduction and Motivation

Convolutional Neural Networks (CNNs) struggle with tasks involving long-range information transport, which are common in applications like weather prediction and disease propagation.



(A) Source image (B) Target image (C) Convergence

Need for non-local operations in CNNs to handle such tasks efficiently

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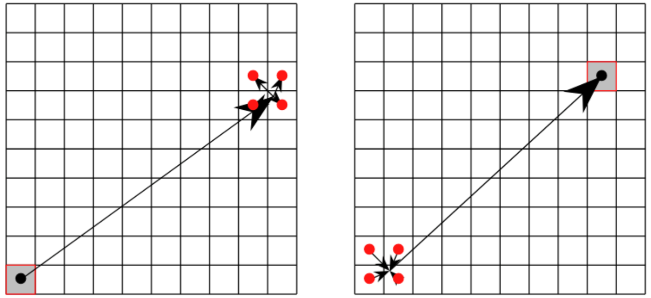
Key Ideas

NEURAL INFORMATION PROCESSING SYSTEMS

Augment CNNs with Advection, Diffusion, and Reaction (ADR) Process

- **Advection**: Non-local transport of information across the image.
- **Diffusion**: Smooths features locally between neighboring pixels.
- **Reaction**: Enables pointwise interaction among channels.

Semi-Lagrangian Push Operator: Allows efficient, non-local advection in a single step.



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ADR Network Structure

- **Overview**: Combines Advection, Diffusion, and Reaction within a CNN to capture complex transport processes in spatio-temporal data.

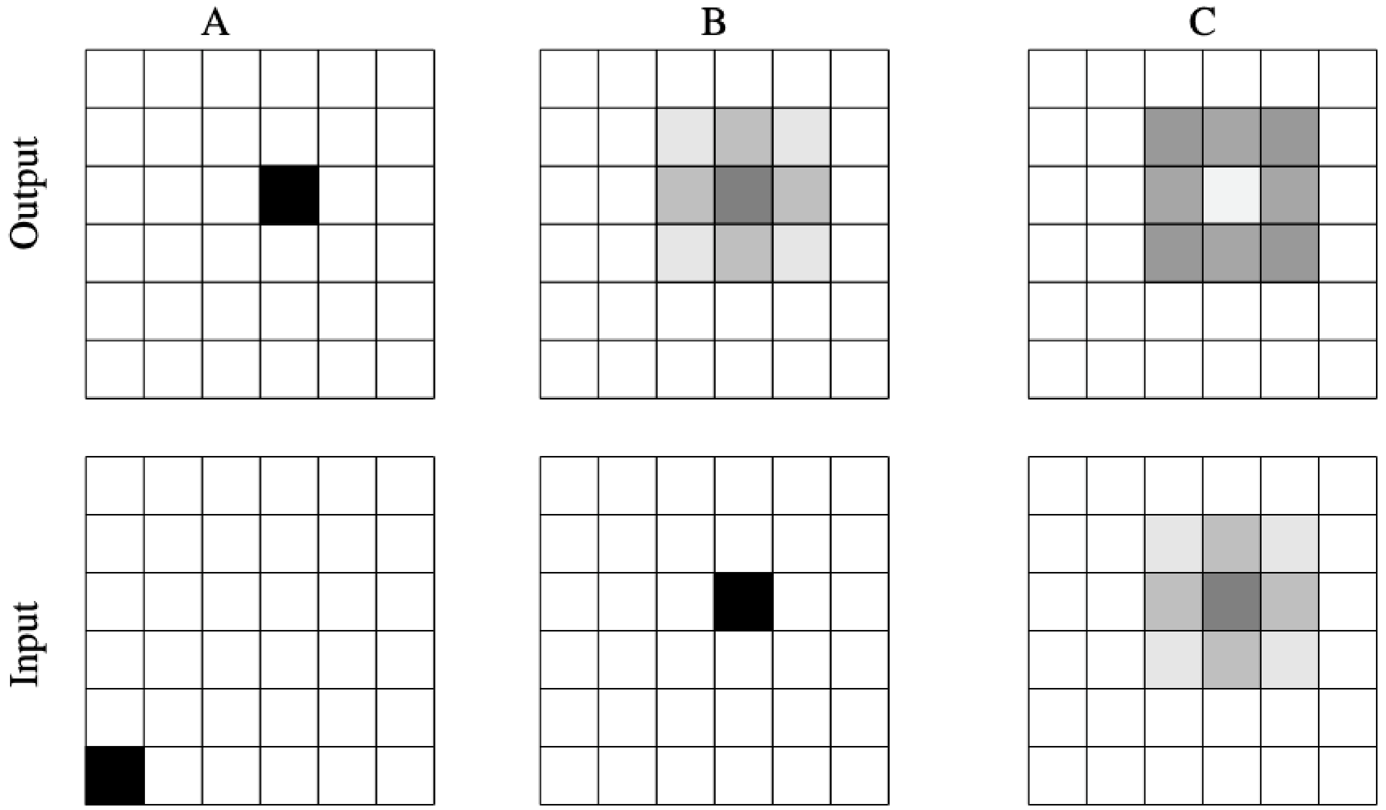
$$\frac{\partial \mathbf{I}(t,\mathbf{x})}{\partial t} = \underbrace{\kappa \Delta \mathbf{I}(t,\mathbf{x})}_{\text{Diffusion}} + \underbrace{\nabla \cdot (\mathbf{U}\mathbf{I}(t,\mathbf{x}))}_{\text{Advection}} + \underbrace{R(\mathbf{I}(t,\mathbf{x}),\boldsymbol{\theta})}_{\text{Reaction}}$$

Diffusion
Smooths information locally

Advection
Transports non-local information

Reaction
Pointwise Interaction

ADR Network Structure (Cont.)

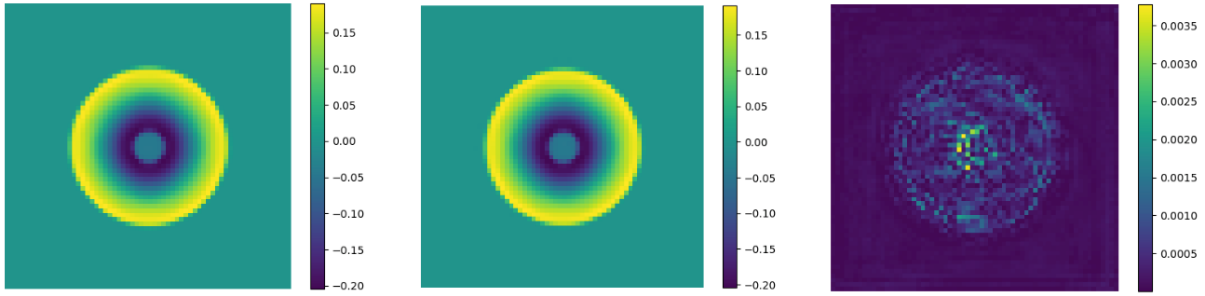


Advection: $t_k \to t_{k+1/3}$ Diffusion: $t_{k+1/3} \to t_{k+2/3}$ Reaction: $t_{k+2/3} \to t_{k+1}$

Experimental Results

Performance on Scientific Datasets

- **CloudCast dataset**
- **PDEBench SWE Dataset**



Ground-Truth Prediction Error

Prediction and error for the SWE problem using our ADRNet

Method	NRMSE ↓
UNet [52]	8.3e-2
PINN [52]	1.7e-2
MPP-AVIT-TI [36]	6.6e-3
ORCA-SWIN-B [47]	6.0e-3
FNO [52]	4.4e-3
MPP-AVIT-B [36]	**2.4e-3**
MPP-AVIT-L [36]	2.2e-3
ADRNet	**1.3e-4**

Results on PDEBench SWE Dataset

Method	SSIM (↑)	PSNR (↑)
AE-ConvLSTM [70]	0.66	8.06
MD-GAN [67]	**0.60**	**7.83**
TVL1 [56]	0.58	7.50
Persistent [70]	0.55	7.41
ADRNet	**0.83**	**38.17**

Results on CloudCast dataset

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Experimental Results (Cont.)

Moving MNIST, KITTI

✓Competitive on video prediction tasks

Method	MSE ↓	MAE ↓
MSPred [58]	34.4	-
MAU [6]	27.6	-
PhyDNet [19]	24.4	70.3
SimVP [53]	23.8	68.9
CrevNet [69]	22.3	-
TAU [54]	19.8	**60.3**
SwinLSTM [55]	**17.7**	-
IAM4VP [46]	**15.3**	**49.2**
ADRNet	**16.1**	**50.3**

Results on Moving MNIST

Method	MS-SSIM ($\times 10^{-2}$) ↑		LPIPS ($\times 10^{-2}$) ↓	
	$t+1$	$t+3$	$t+1$	$t+3$
SADM [2]	83.06	72.44	14.41	24.58
MCNET [59]	75.35	63.52	24.04	37.71
CorrWise [15]	82.00	N/A	17.20	N/A
OPT [66]	82.71	69.50	12.34	20.29
DMVFN (w/o R) [23]	**88.06**	**76.53**	**10.70**	**19.28**
DMVFN [23]	**88.53**	**78.01**	**10.74**	**19.27**
ADRNet	**85.86**	**83.62**	**7.54**	**9.26**

Results on KITTI

Limitations and Future Work

Limitations:

- Optimal for Scientific Data, Less effective for complex video prediction tasks requiring generative capabilities
- Niche Use Cases: Best suited for tasks requiring advection

Future Work:

- Enhanced Generative Capabilities: Adapt for evolving video features.