



CInC Flow: Characterizable Invertible 3×3 Convolution

Sandeep Nagar¹ Marius Dufraisse² Girish Varma¹

¹Machine Learning Lab, International Institute of Information Technology, Hyderabad, India

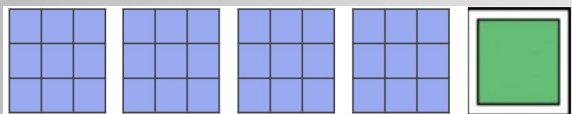
²Computer Science Dept., École Normale Supérieure (ENS), Paris-Saclay, France

uai
2021

Goal: derive necessary and sufficient conditions on a padded CNN for it to be invertible. also proposed a coupling method.

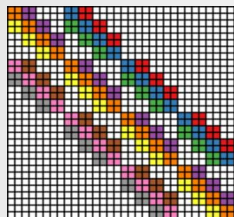
-- Standard Convolution: $y = M\hat{x}$

x : input, y : output, M : Convolution matrix



Kernels (3×3)

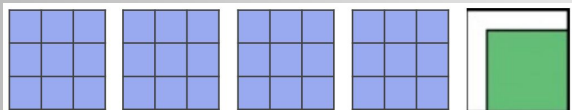
std. padded input (x)



M

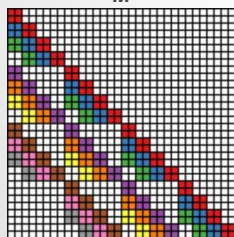
0
1
2
3
4
5
6
7
8
 \vec{x}

-- Convolution with specific padded input



kernels (3×3)

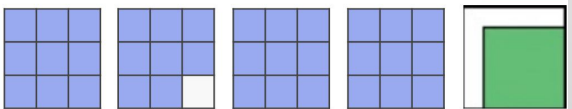
input(padded x)



M

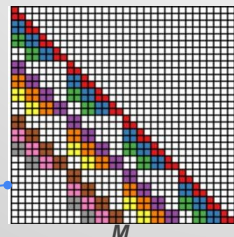
0
1
2
3
4
5
6
7
8
 \vec{x}

-- Convolution with specific padded input and masked kernels (Proposed method)



masked kernels (3×3)

input(padded x)



M

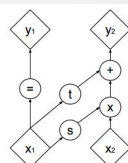
0
1
2
3
4
5
6
7
8
 \vec{x}

ensure
invertibility

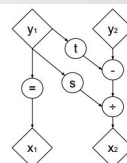
triangular

--Coupling Layers: we propose to use a modified version of the coupling layer designed to have a bigger receptive field.

-Affine Coupling

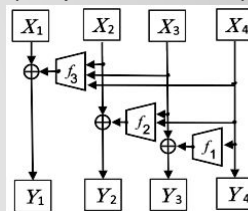


(a) Forward propagation



(b) Inverse propagation

-Quad Coupling
(Proposed method)



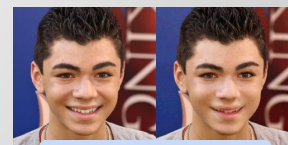
expressive
coupling
mechanism

--Image generation

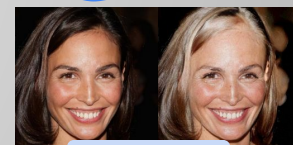
-Interpretability



removing glasses

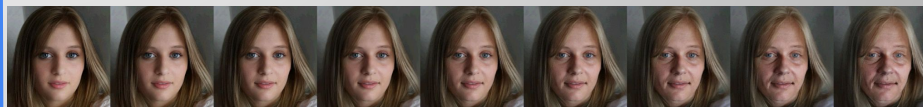


visage shape



hair colour

-modifying the age parameter



	Filters	Padding	Receptive Field	Matrix	Observations $n = \#in, out \text{ channels}$.
CInC (Ours) Convolution					<p>#learnable parameters $9n^2 - n(n-1)/2$ #convs = 1 Invertibility is guaranteed in training since diagonal entries of matrix are 1s.</p>
Autoregressive Convolutions					<p>#learnable parameters $5n^2$ #convs = 1 Number of learnable parameters are reduced by almost 50% resulting in lesser expressive power.</p>
Emerging Convolutions					<p>#learnable parameters $10n^2$ #convs = 2 Having more convolutions will increase runtime during generation as well as latent vector computation passes.</p>

Germain et al., Made: Masked autoencoder for distribution estimation. ICLR 2015. Kingma et al., Improved variational inference with inverse autoregressive flow, NIPS 2016.

Hoogeboom et al. Emerging Convolutions for Generative Normalizing Flows. ICLR, 2019.