Augmentation of brain MRIs using disentanglement and neural network expressivity

Status Seminar

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Pathology Segmentation in Human Brain MRIs

Task

Highlight abnormal regions in human brain MRIs

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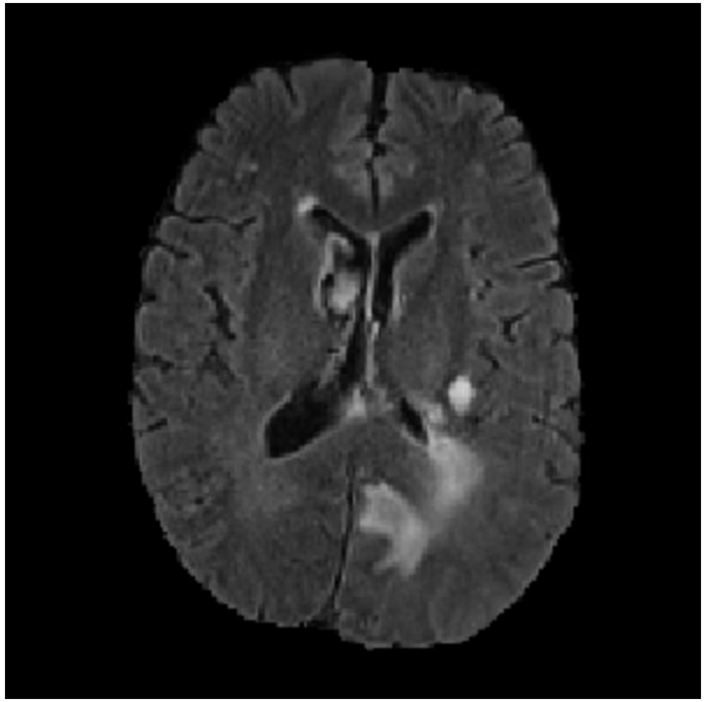

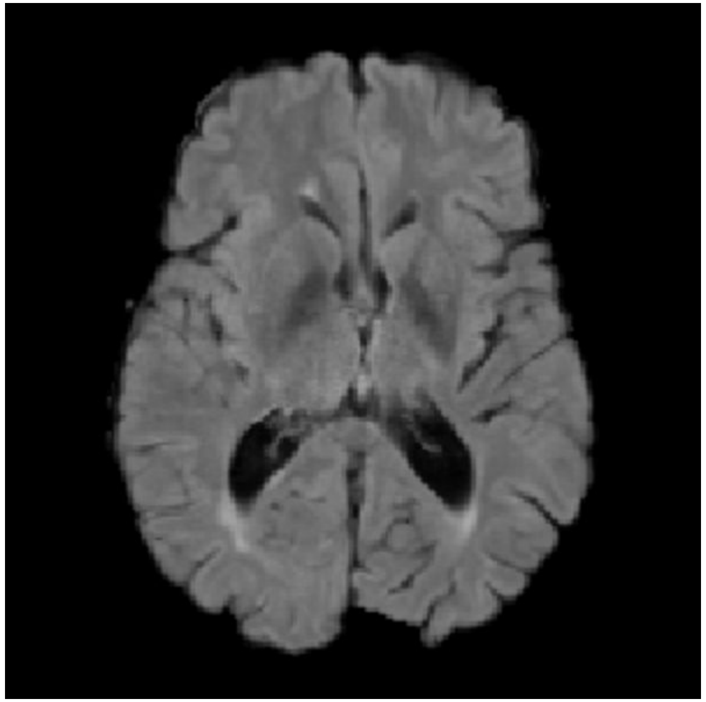

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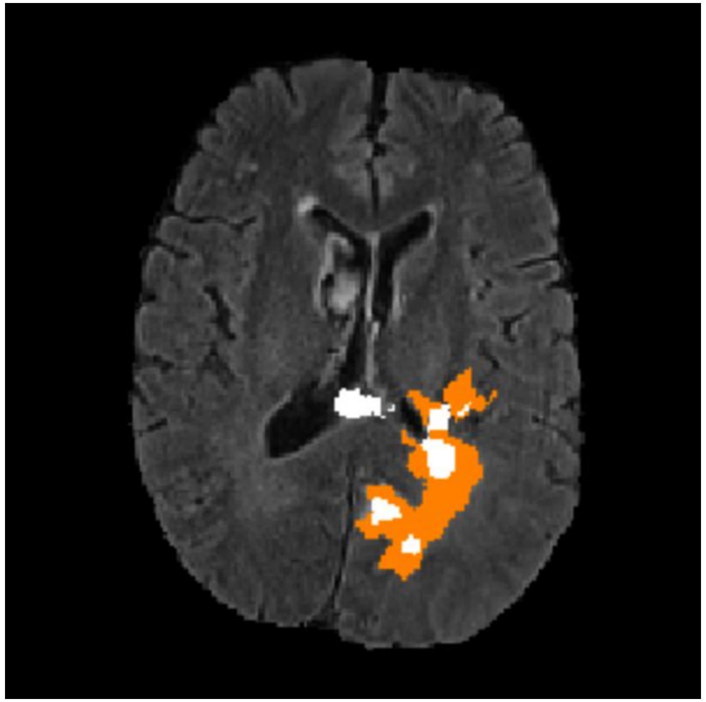

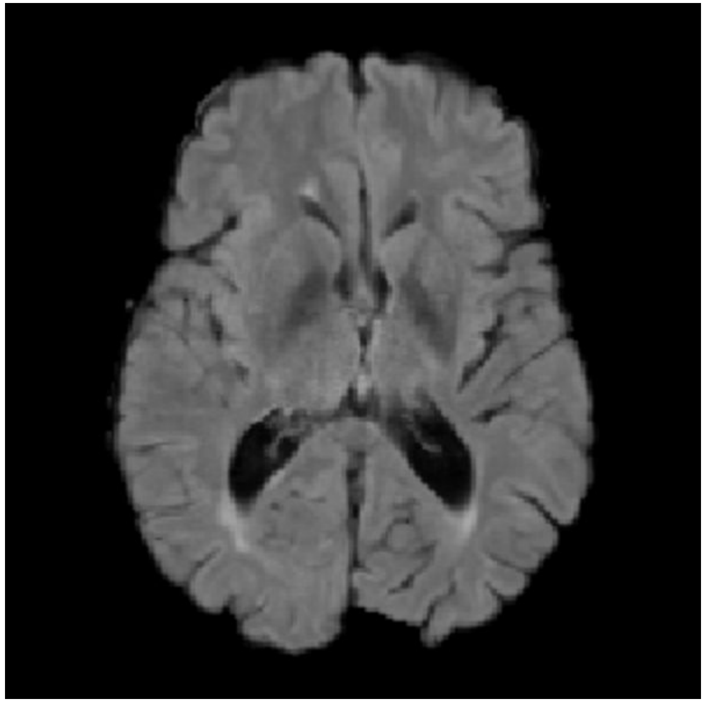

High-grade glioma (BraTS2019)

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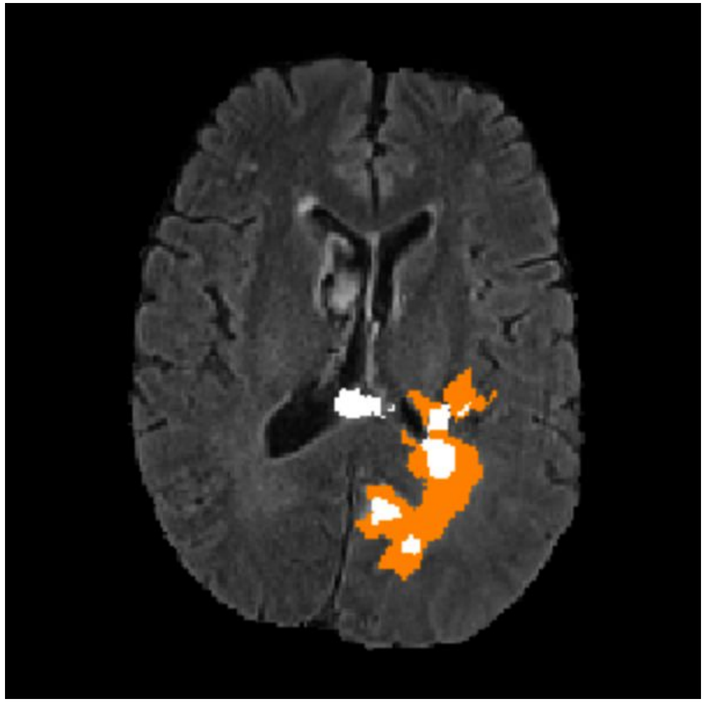

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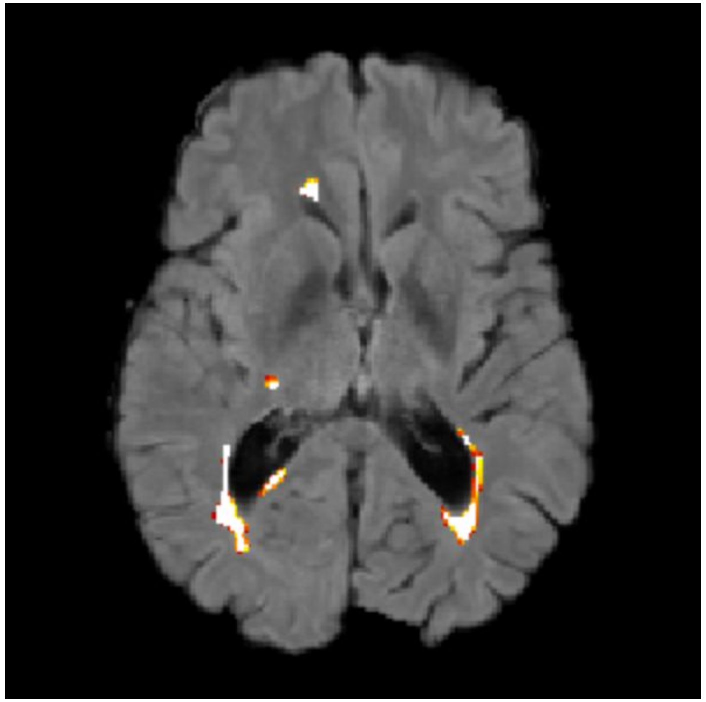

Multiple sclerosis (MSSEG-2015)

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  - Corruption (cutout, cutmix)
  - Intensification (gamma, bias-field)
  - Deformation (affine, elastic, diffeomorphic)

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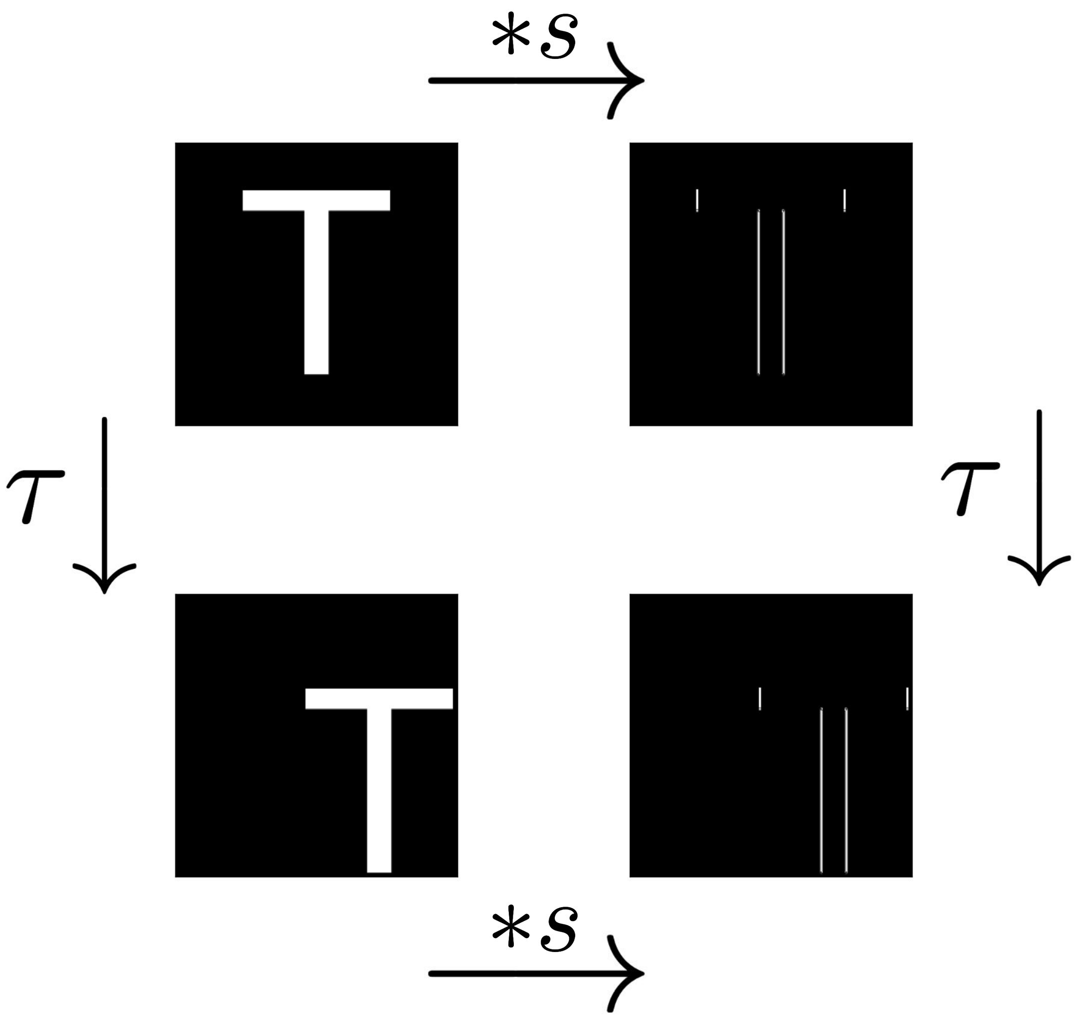
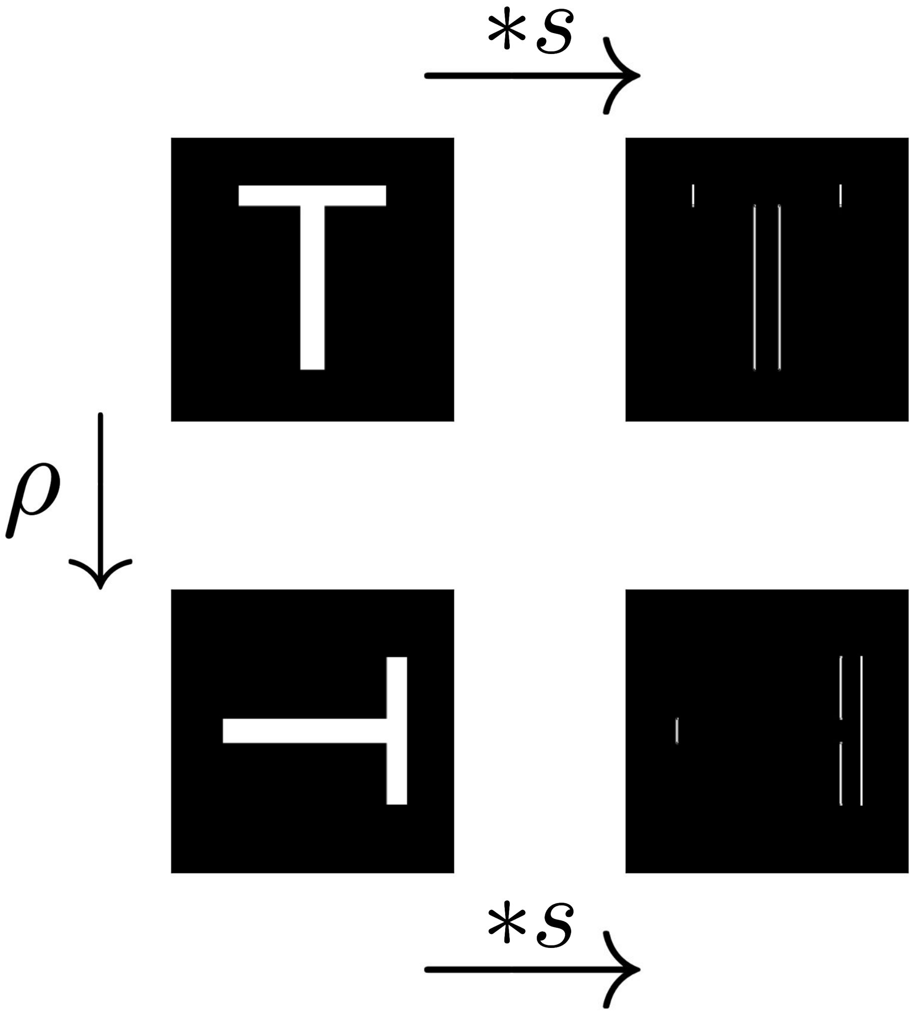
Translation equivariance in convolutional neural networks



Finite group-equivariant convolutional neural networks



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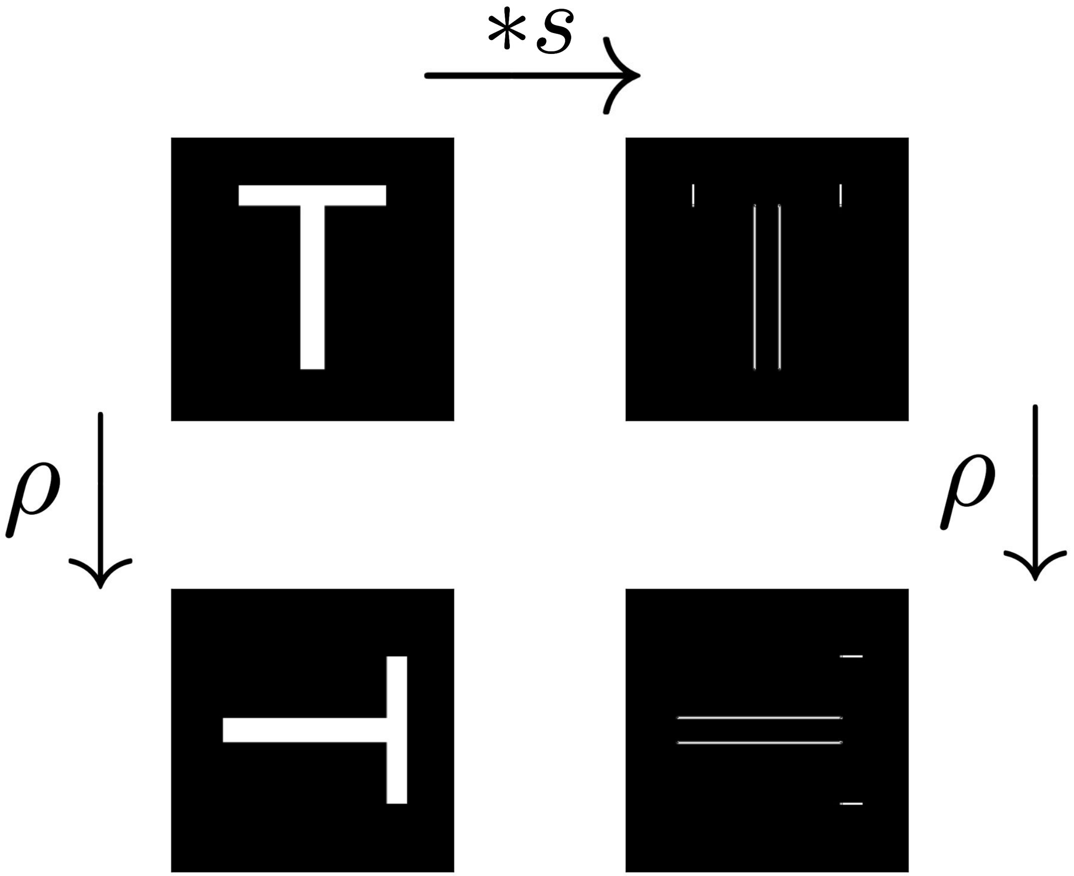

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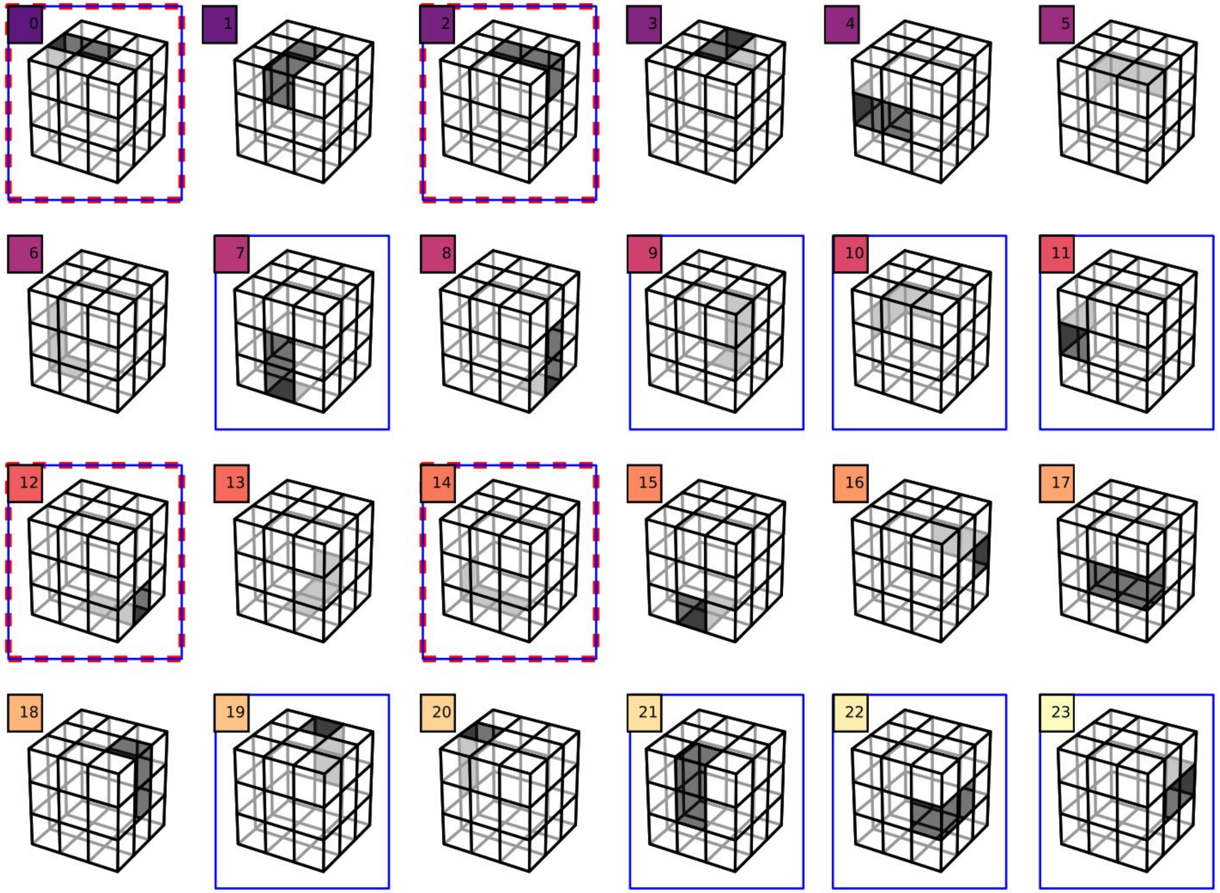

Source: https://openaccess.thecvf.com/content_ECCV_2018/papers/Daniel_Worrall_CubeNet_Equivariance_to_ECCV_2018_paper.pdf

Open source implementations of G-CNNs

e2cnn
https://github.com/QUVA-Lab/e2cnn

e3nn
https://github.com/e3nn/e3nn

Open source implementations of G-CNNs

GrouPy
https://github.com/tscohen/GrouPy

CubeNet
https://github.com/danielewworrall/cubenet

Harmonic Networks
https://github.com/danielewworrall/harmonicConvolutions

TensorFlow/Keras Implementation of G-CNNs

TensorFlow/Keras Implementation of G-CNNs

```
class CyclicFour3D(Group):
    """Class for a reducible three-dimensional representation of a cyclic group of any order. This
    group is called 'p4' in the equivariance literature.
    """

    def __init__(self, axes=(0, 1,), name=None):
        group_tuple = (Group.get_matrix([[1, 0, 0], [0, 1, 0], [0, 0, 1]]),
                       Group.get_matrix([[0, -1, 0], [1, 0, 0], [0, 0, 1]]),
                       Group.get_matrix([[-1, 0, 0], [0, -1, 0], [0, 0, 1]]),
                       Group.get_matrix([[0, 1, 0], [-1, 0, 0], [0, 0, 1]]),)
        self.generator = group_tuple[1]
```

TensorFlow/Keras Implementation of G-CNNs

```
class Octahedral3D(Group):
    """Class for a three-dimensional representation of the octahedral group (a.k.a the group
    of symmetries of the cube, or the fourth symmetric group).
    """
    def __init__(self, inversion=False, name=None):
        self.generators = (Group.get_matrix([[0, 0, 1],
                                             [1, 0, 0],
                                             [0, 1, 0]]),
                           Group.get_matrix([[0, 1, 0],
                                             [-1, 0, 0],
                                             [0, 0, 1]]),)
        group_tuple = ops.generate(self.generators, 6, 3, 24)
```

TensorFlow/Keras Implementation of G-CNNs

```
class GroupConv3D(Layer):
    """Implementation of an equivariant 3D convolution layer. This implementation maps out of
    Euclidean space and into an output_group of choice.
    """

    def __init__(self, n_channels_in, n_channels_out, kernel_size=3,
                 strides=(1, 1, 1, 1, 1,), padding="SAME", input_group=Trivial(3),
                 output_group=Trivial(3), activation=None, trainable=True):
```

TensorFlow/Keras Implementation of G-CNNs

```
class GroupUNet3D(ks.Model):
    """The complete U-net segmentation model"""

    def __init__(self, group, num_classes, n_channels_in, patch_size=(96, 96, 96,),
                 c_factor=1.0, out_act='softmax', kernel_reg=regularizers.l2(1e-6),
                 filters=12, depth=4, LReLU_alpha=0.01, kernel_size=3,
                 max_pool=2, dropout=0.2, padding='same', rotation_params=(False,),
                 blur_params=(False,), transform_params=(False,), cut_off=0.9,
                 trainable=True, label_smoothing=False, label_smoothing_neighbours=5,
                 val_samples=1):
```

Group U-Net on Truncated BraTS2019

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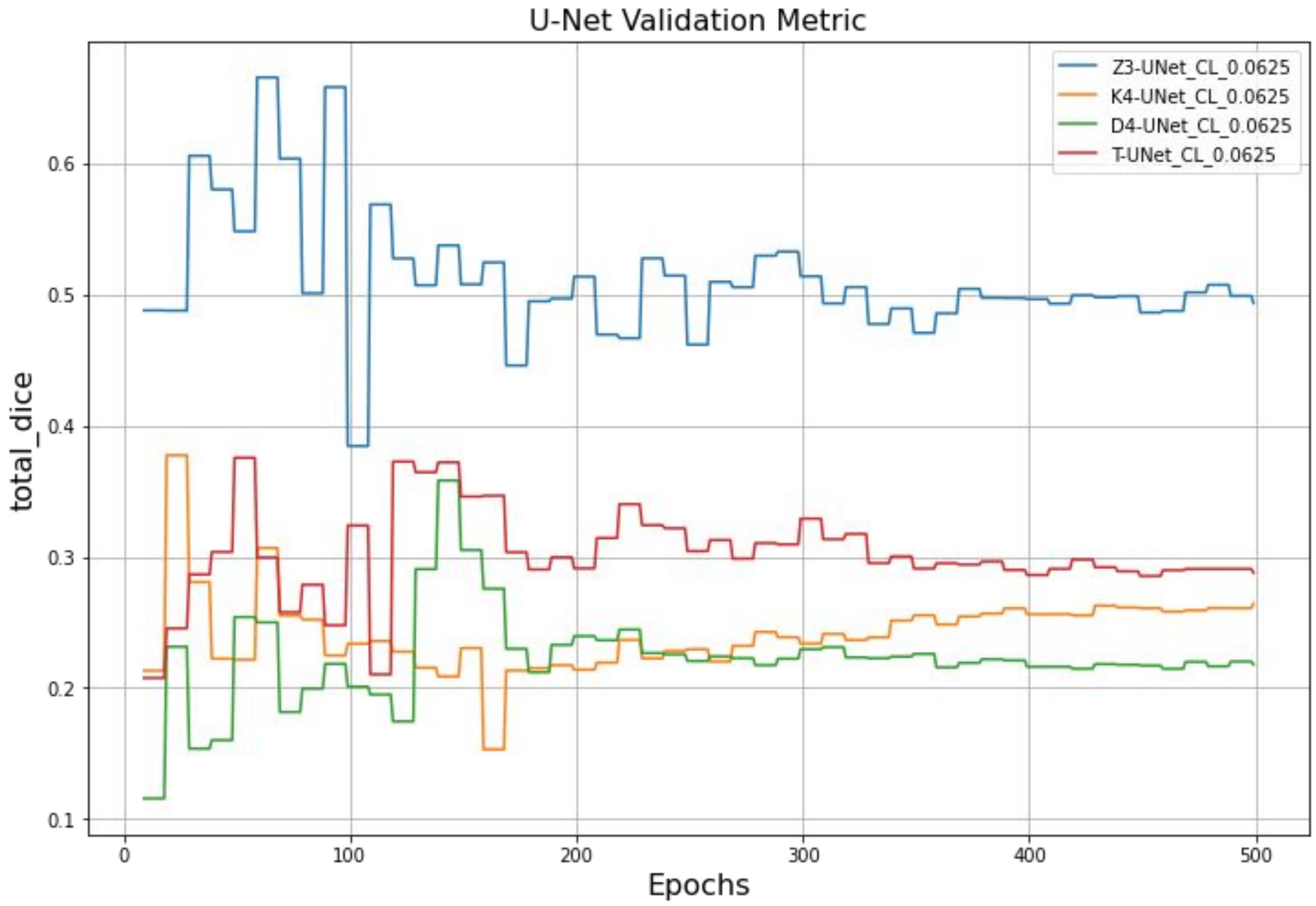

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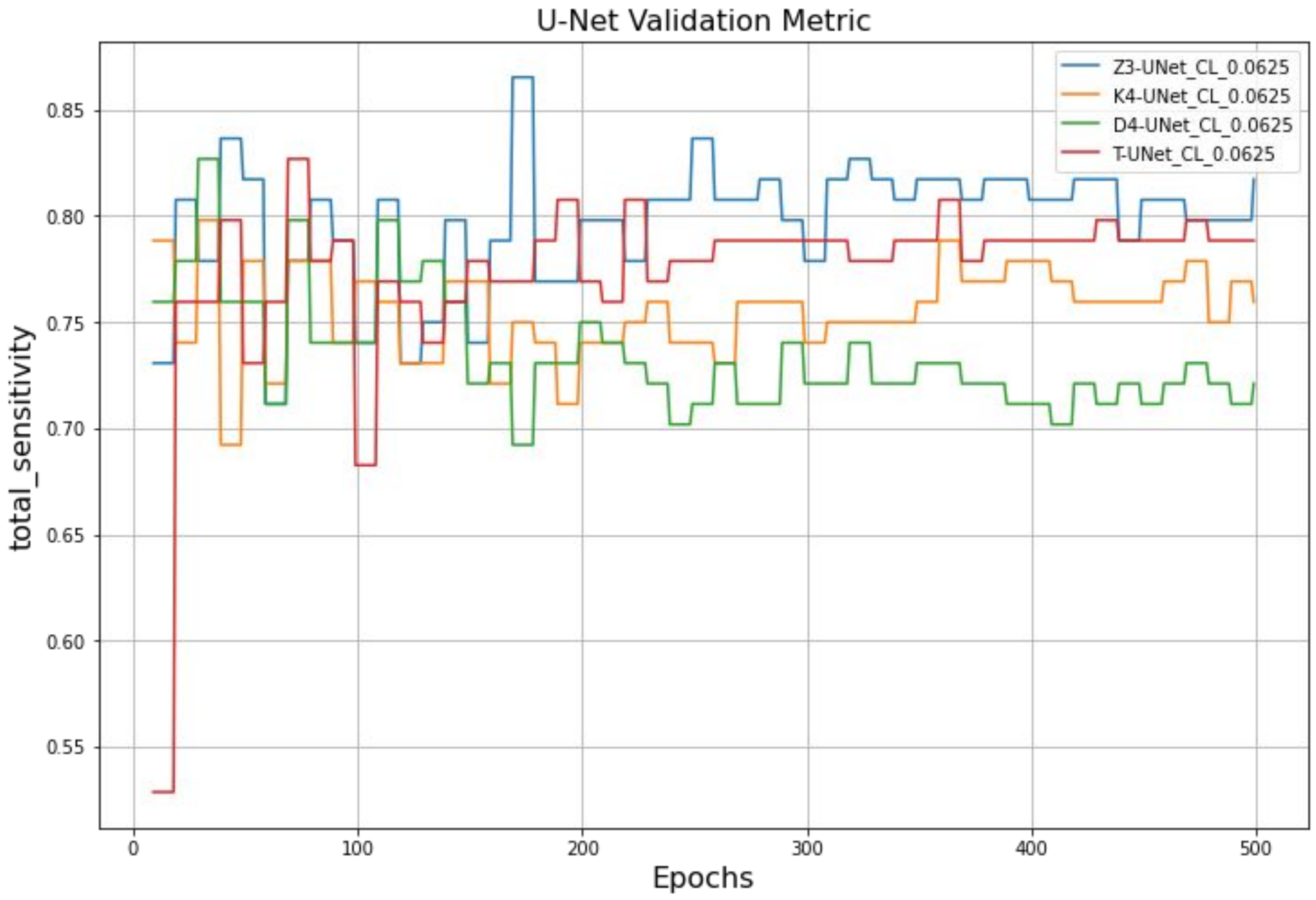

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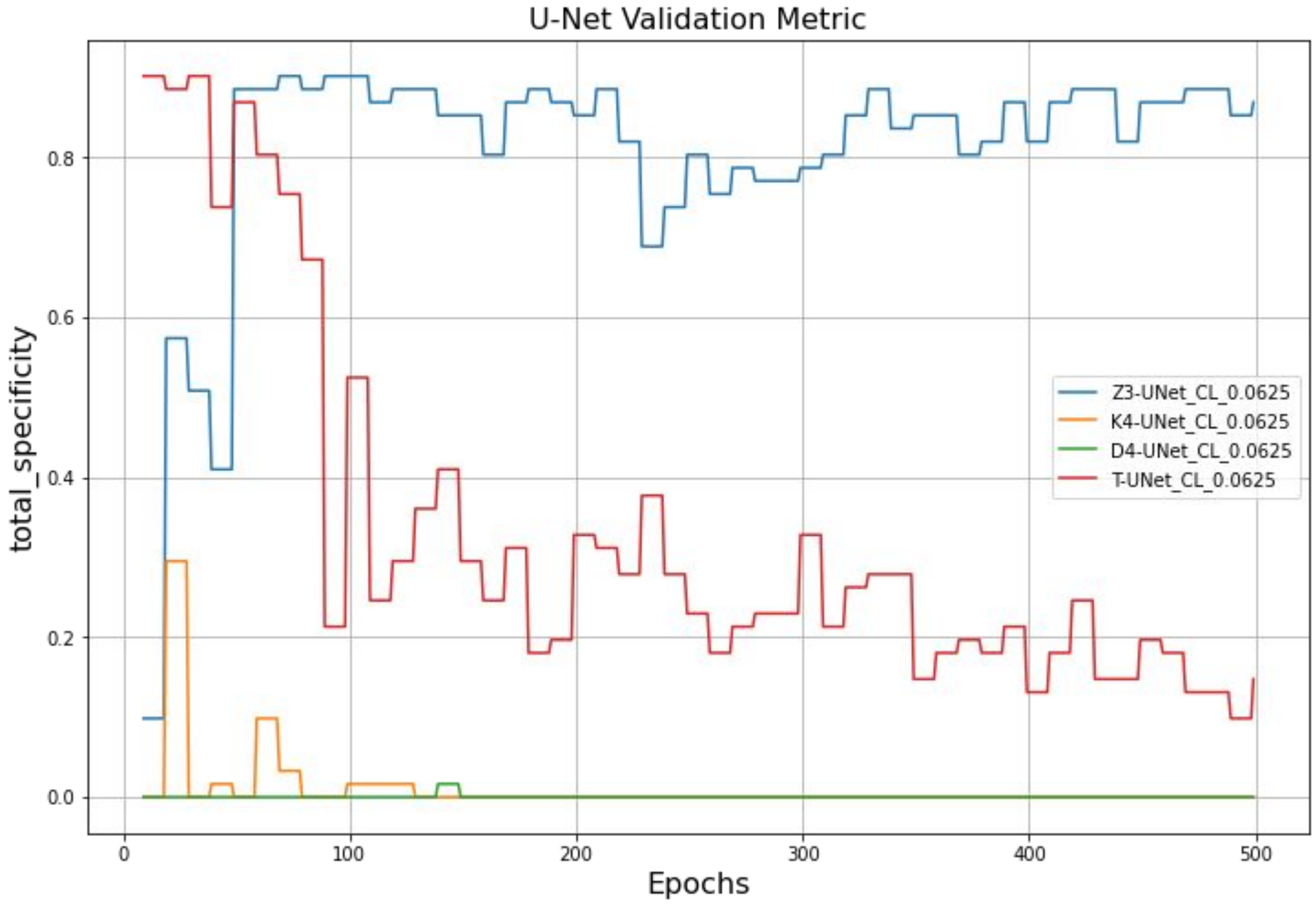

Group U-Net on Truncated BraTS2019

Possible cause
Not enough effective parameters in equivariant U-Nets

Example
Equivariance group: C4
Baseline U-Net: 12 filters in the first layer
C4 U-Net: 3 filters in the first layer

Inferred Transformation VAE for Spatial Augmentation

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PADDIT (Orbes-Arteaga, et al. 2019)
Bayesian inference of a template MRI

$$p(I_k | \mathbf{v}_k, I_T, \sigma) = \frac{1}{(2\pi)^{V/2}\sigma^V} \exp\left(-\frac{\|I_T - I_k \circ \mathrm{Exp}(\mathbf{v}_k)\|^2}{2\sigma^2}\right)$$

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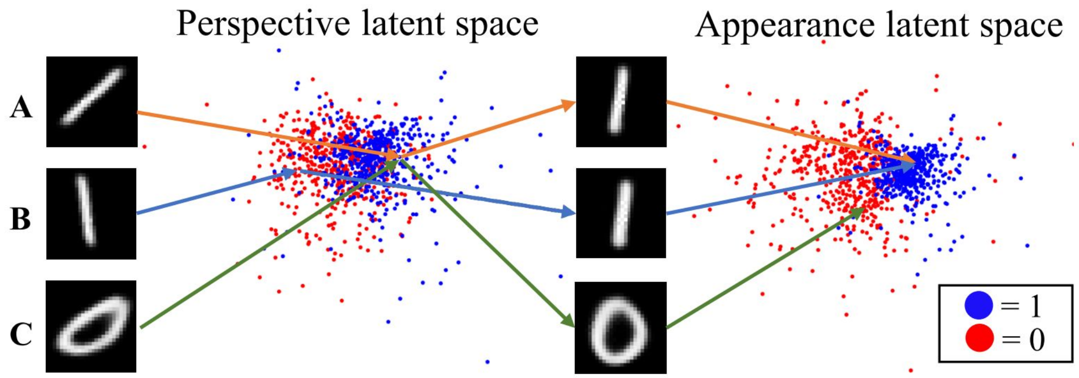
IT-VAE (Detlefsen and Hauberg, 2019)
Unsupervised disentanglement of shape and appearance



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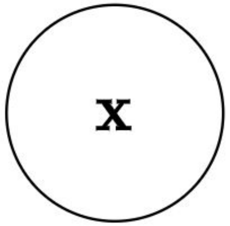

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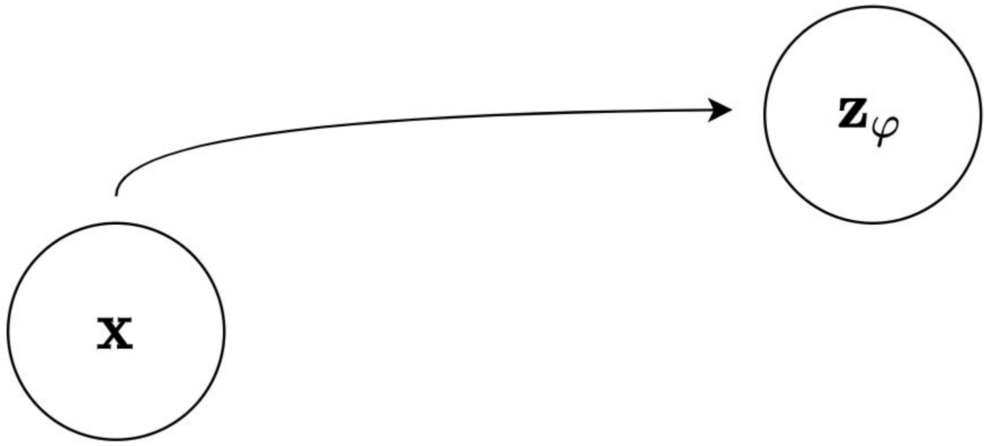

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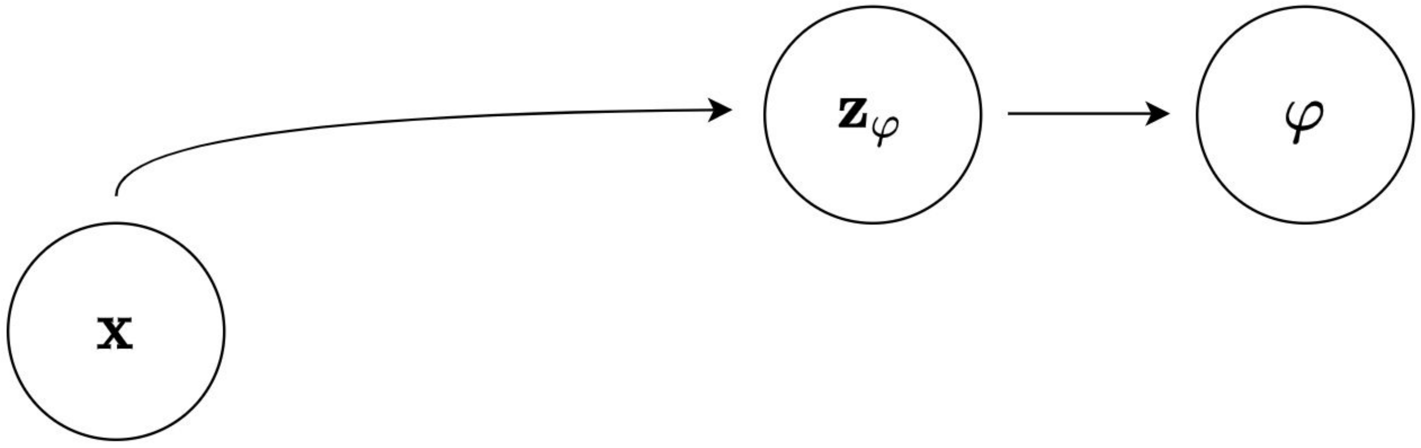

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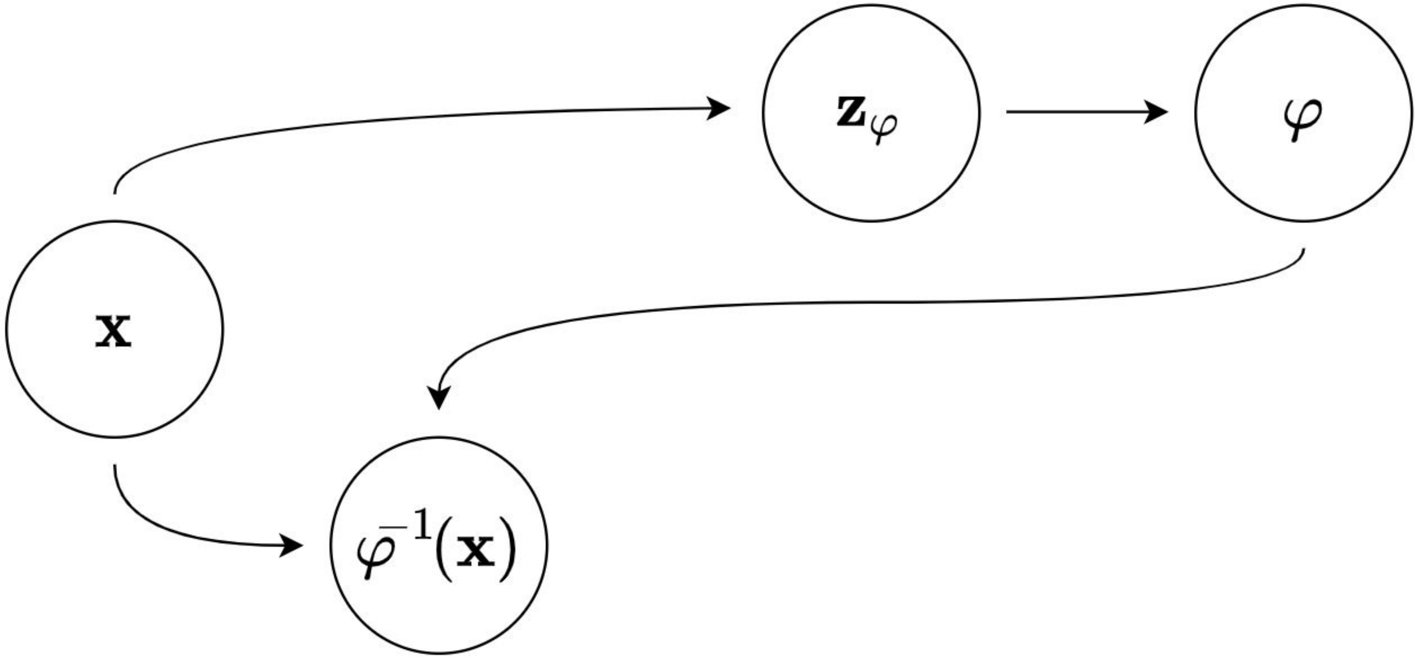

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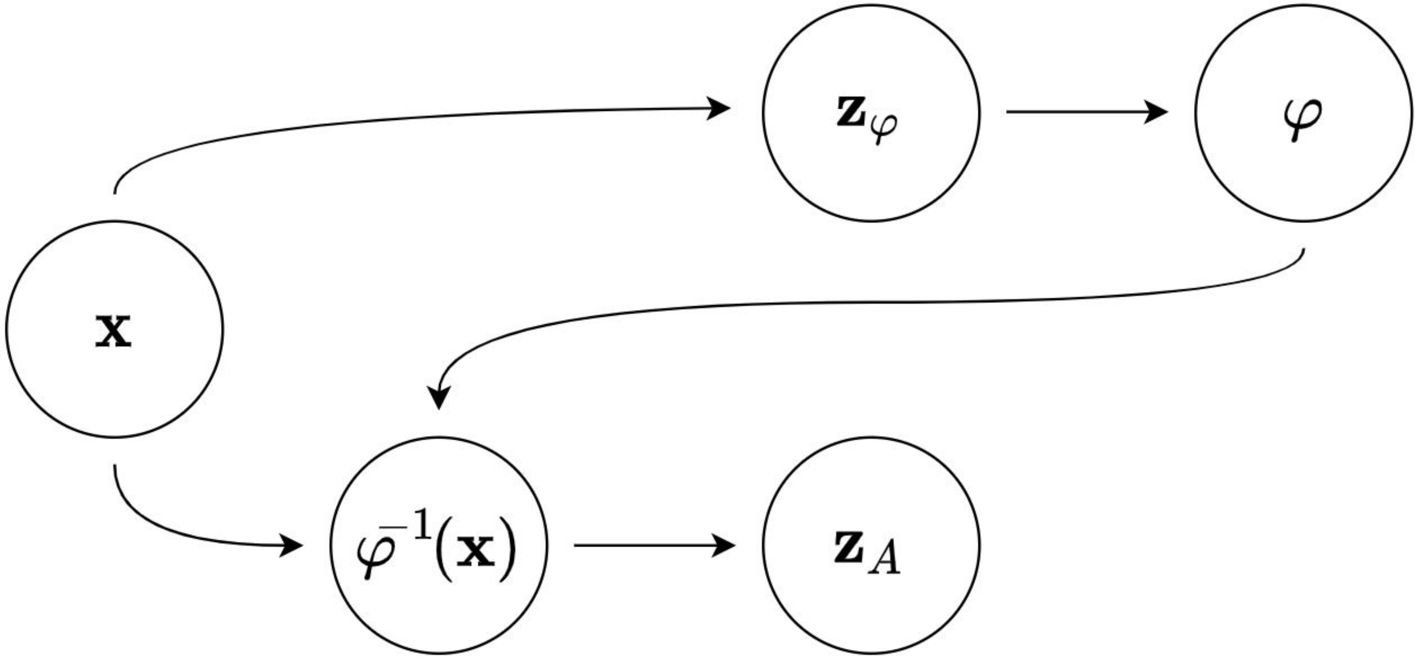

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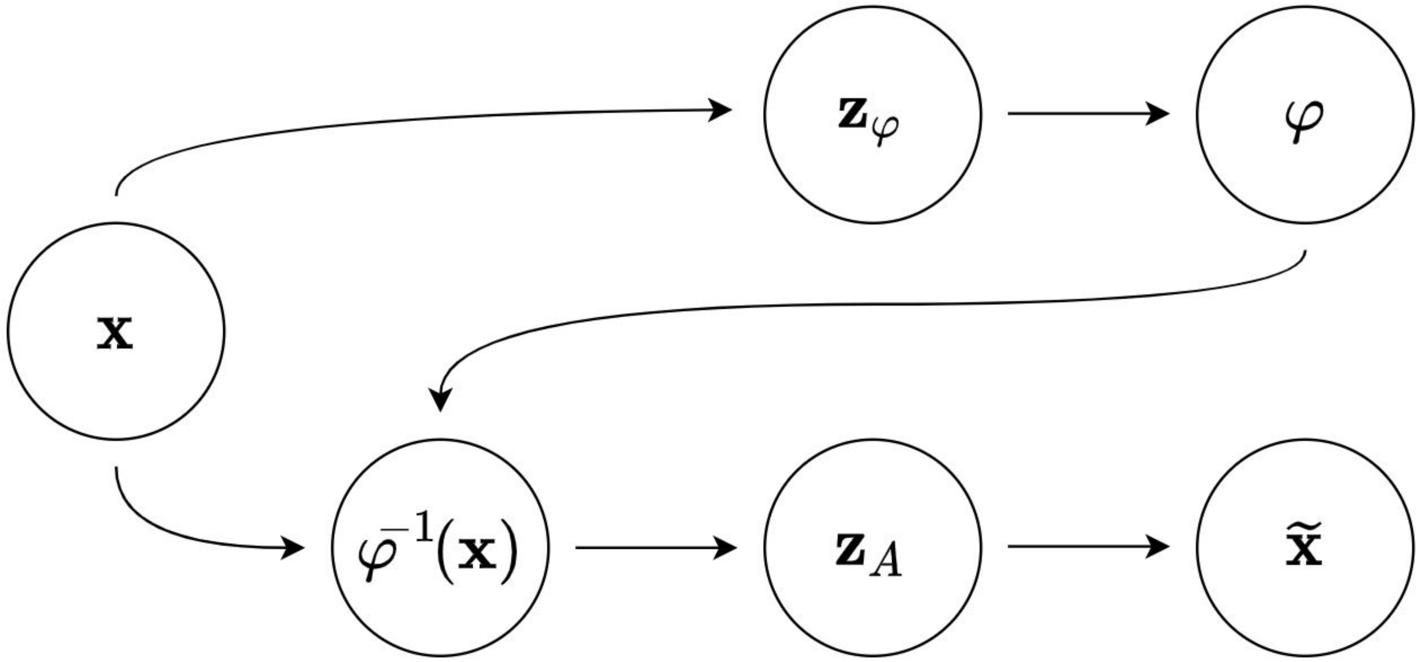

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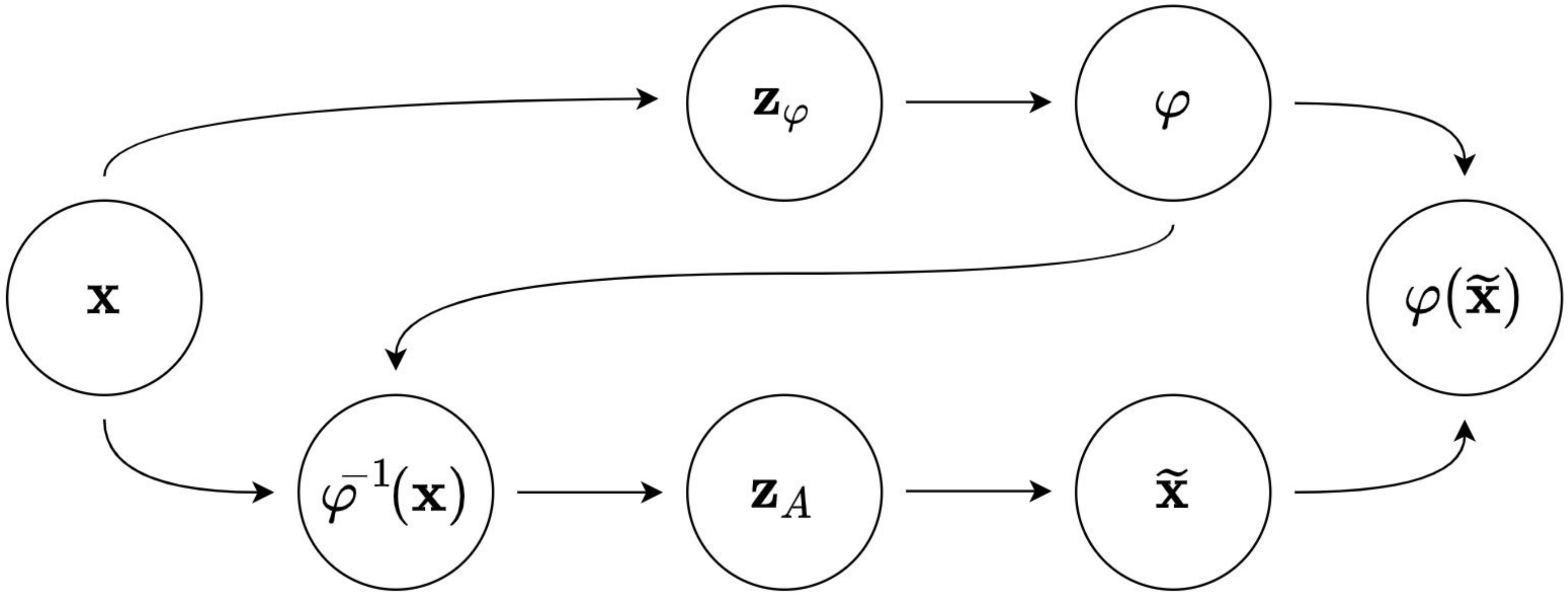

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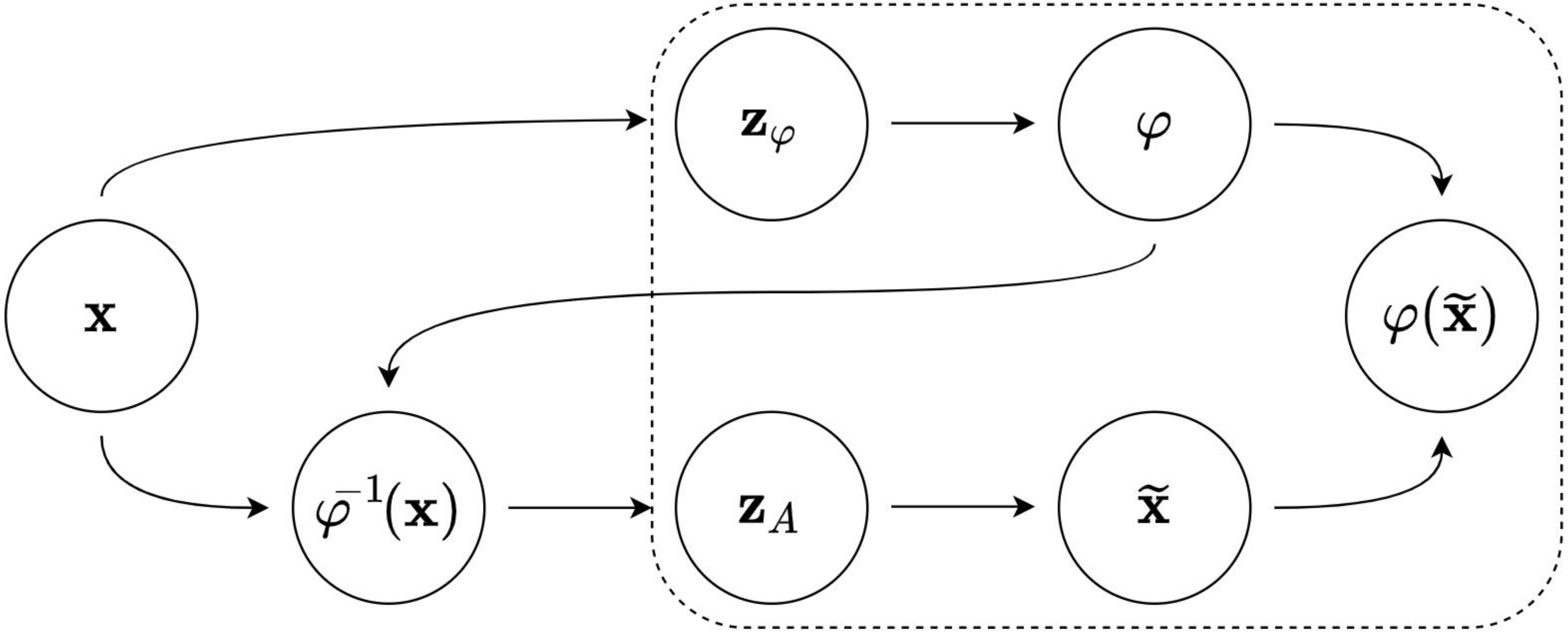

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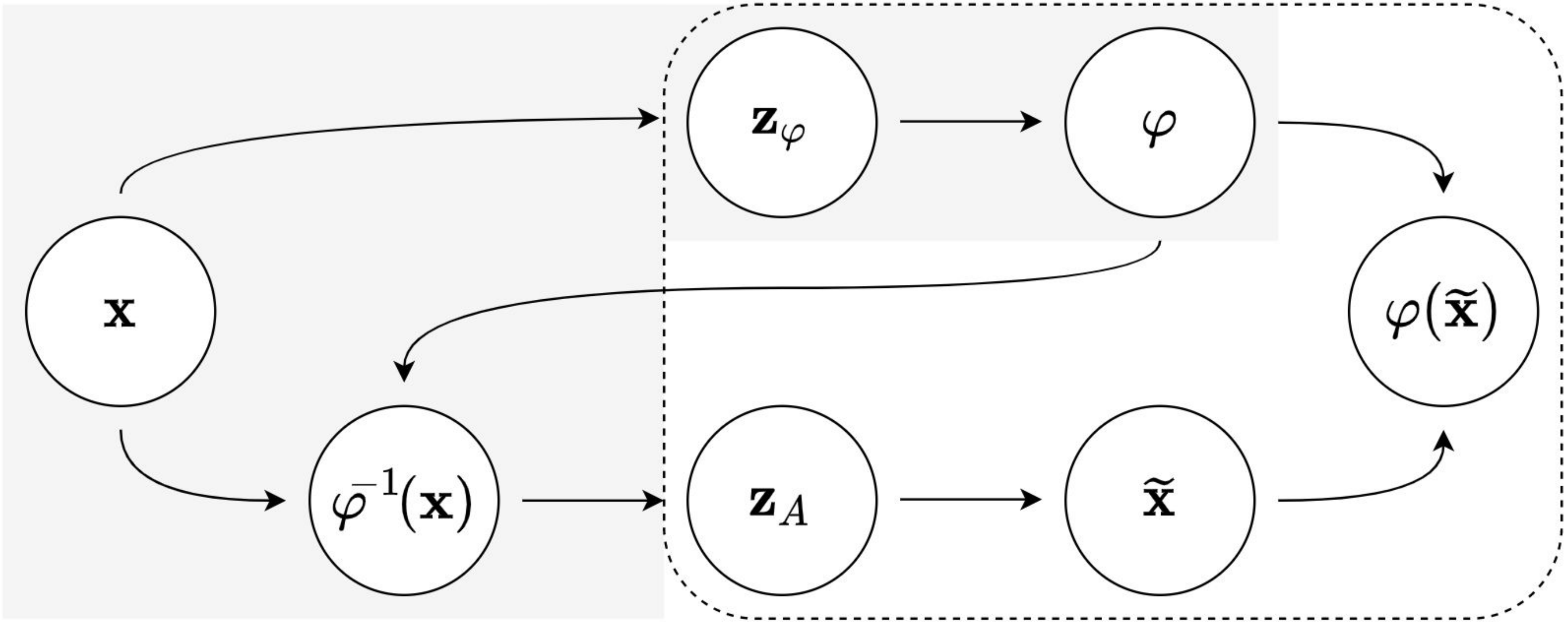

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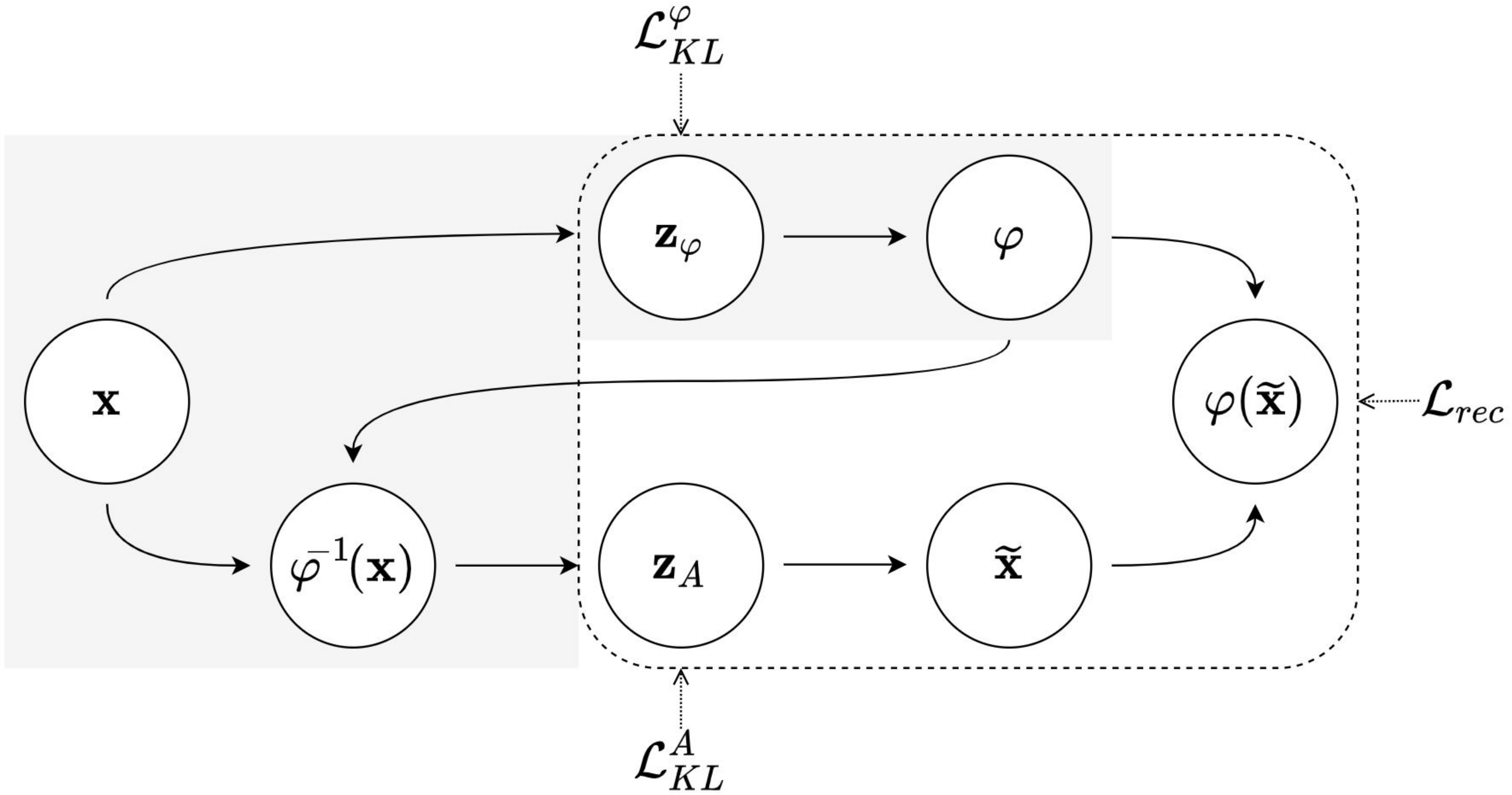

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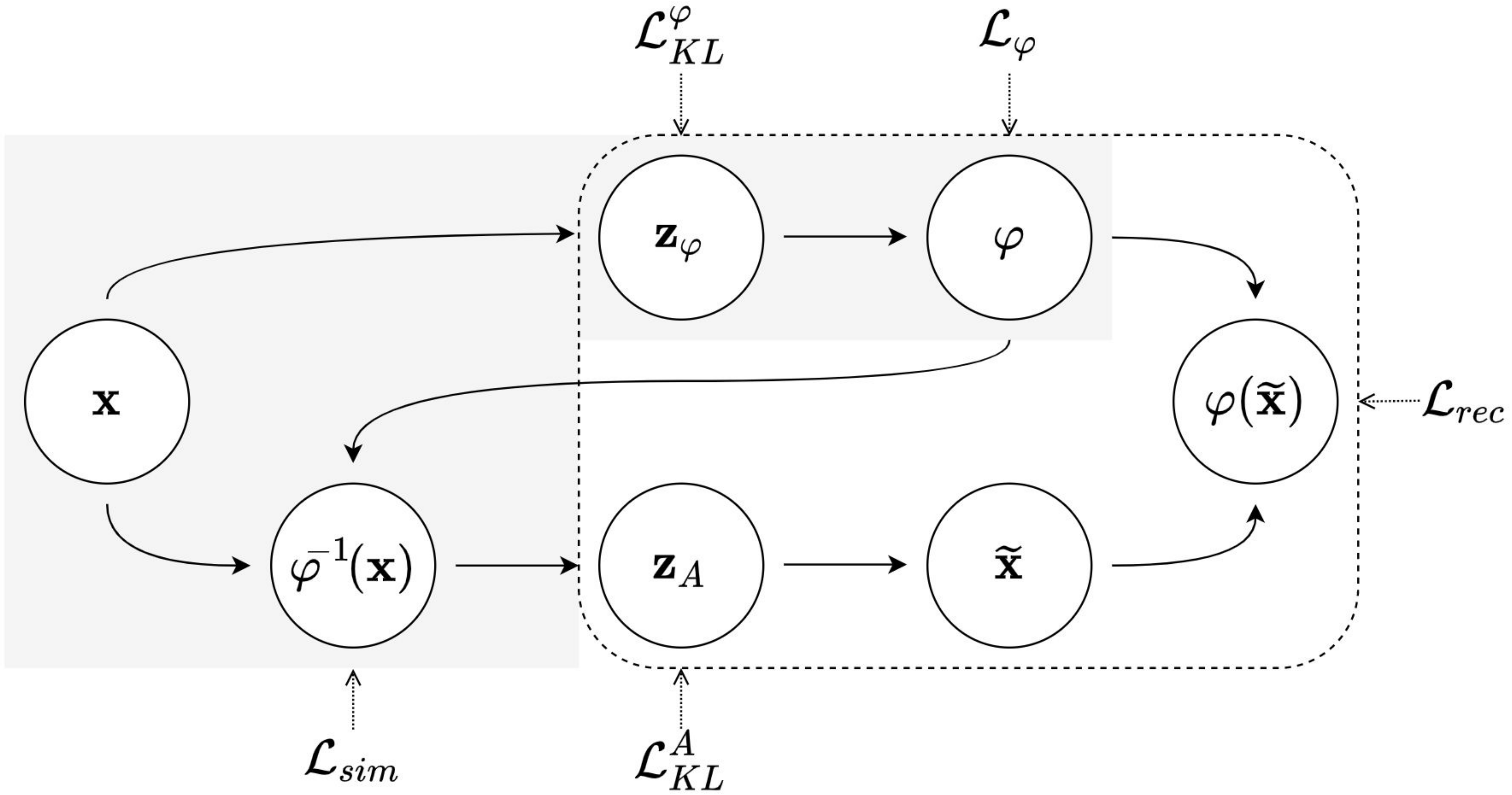
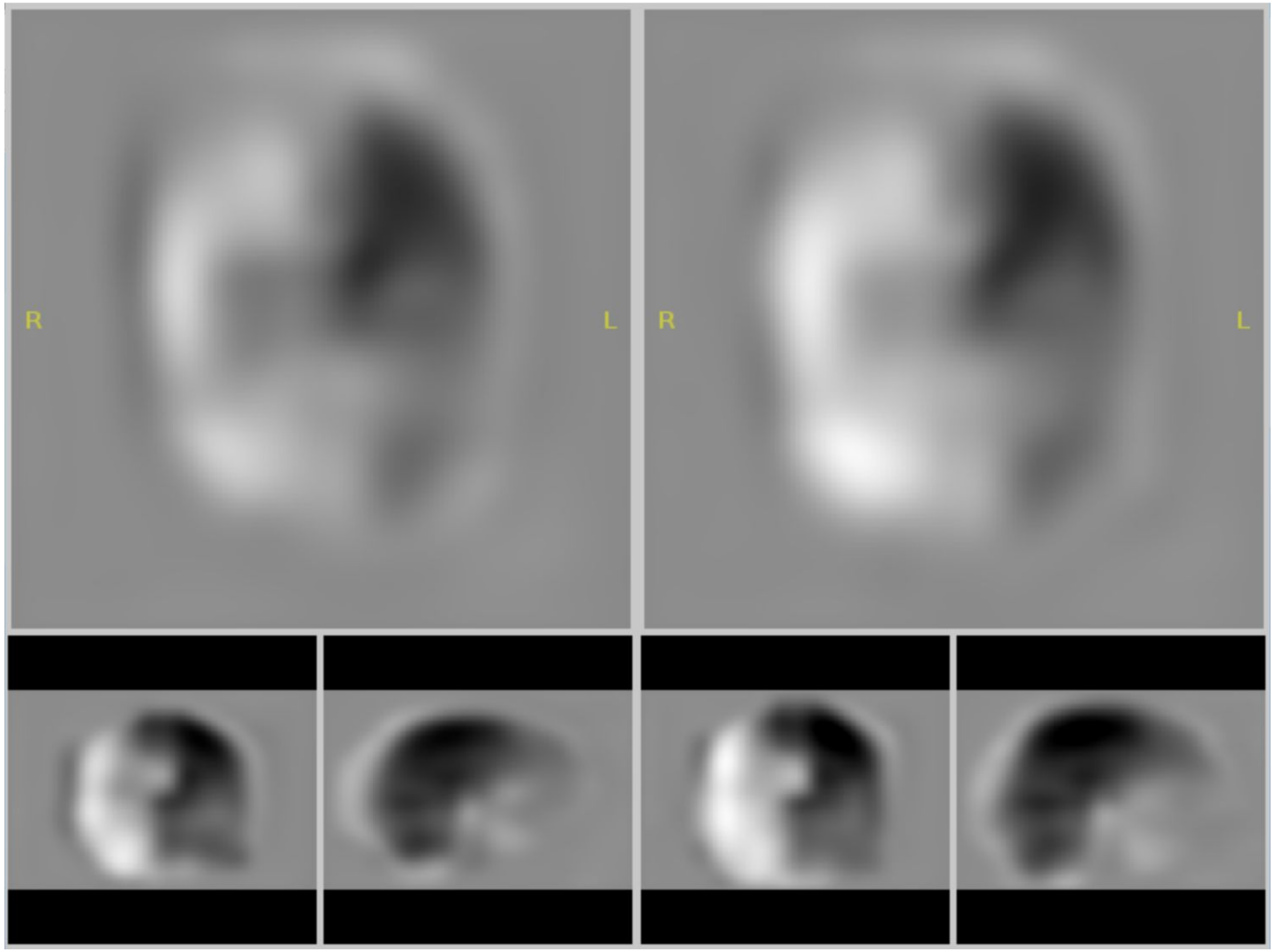


Decoded samples from conditional latent space distributions



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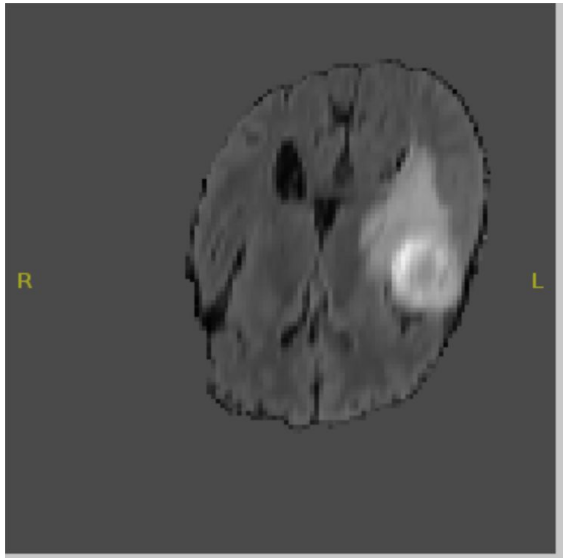
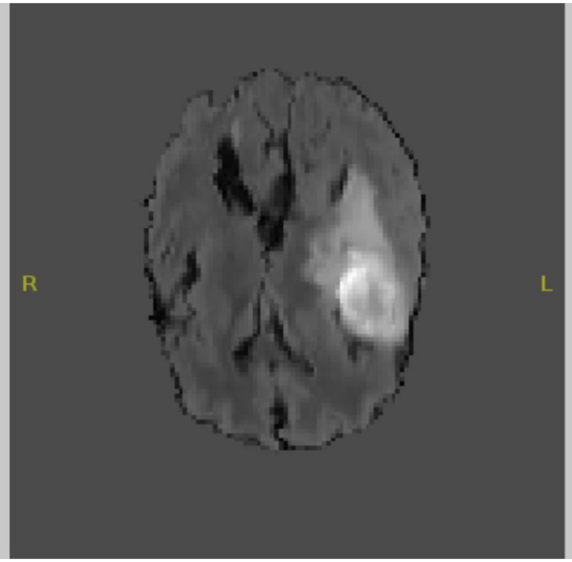
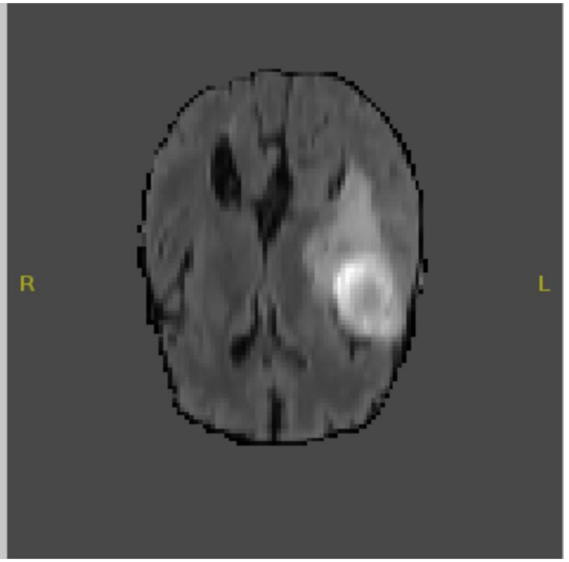


Affine



Elastic



IT-VAE

Inferred Transformation VAE for Spatial Augmentation

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  - Naive latent space sampling
  - Instance-specific latent space sampling
  - Mixed-instance latent space sampling
- How well can an IT-VAE perform unsupervised groupwise registration?
  - This works for small datasets, but for MRIs?
  - Deformable autoencoders work for MRIs but are unconditioned

Thanks!

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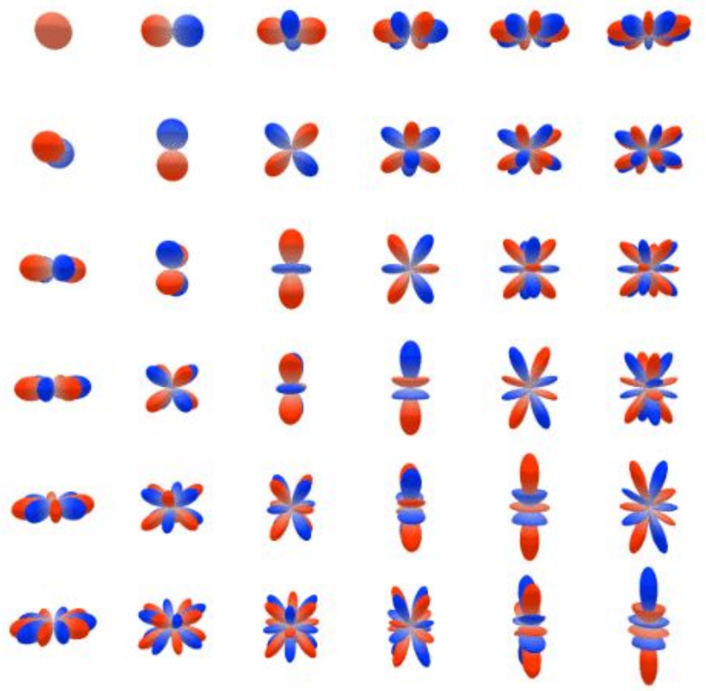
Equivariance with 3D harmonic filters



$$f(\rho,\theta,\phi)=\sum_{n=0}^{N}h_n(\rho)\sum_{m=-n}^{n}C_n[m]Y_{n,m}(\theta,\phi),$$

Sources: https://github.com/e3nn/e3nn, https://doi.org/10.1016/j.media.2020.101756

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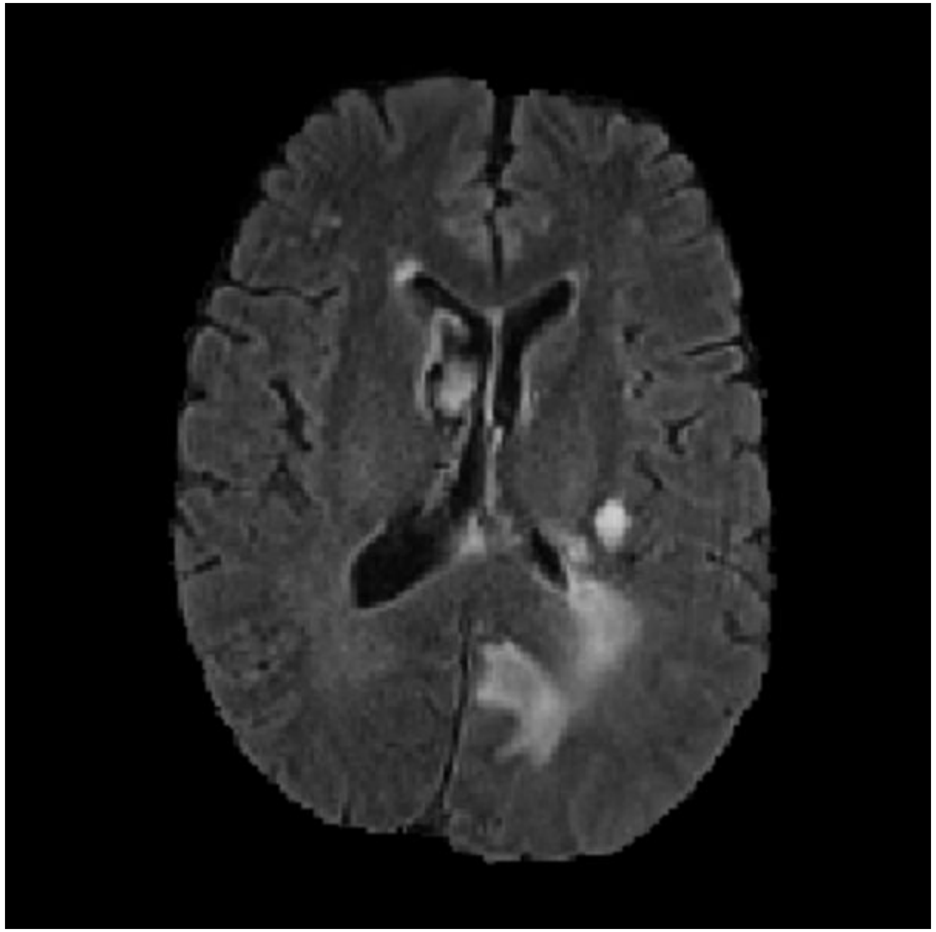

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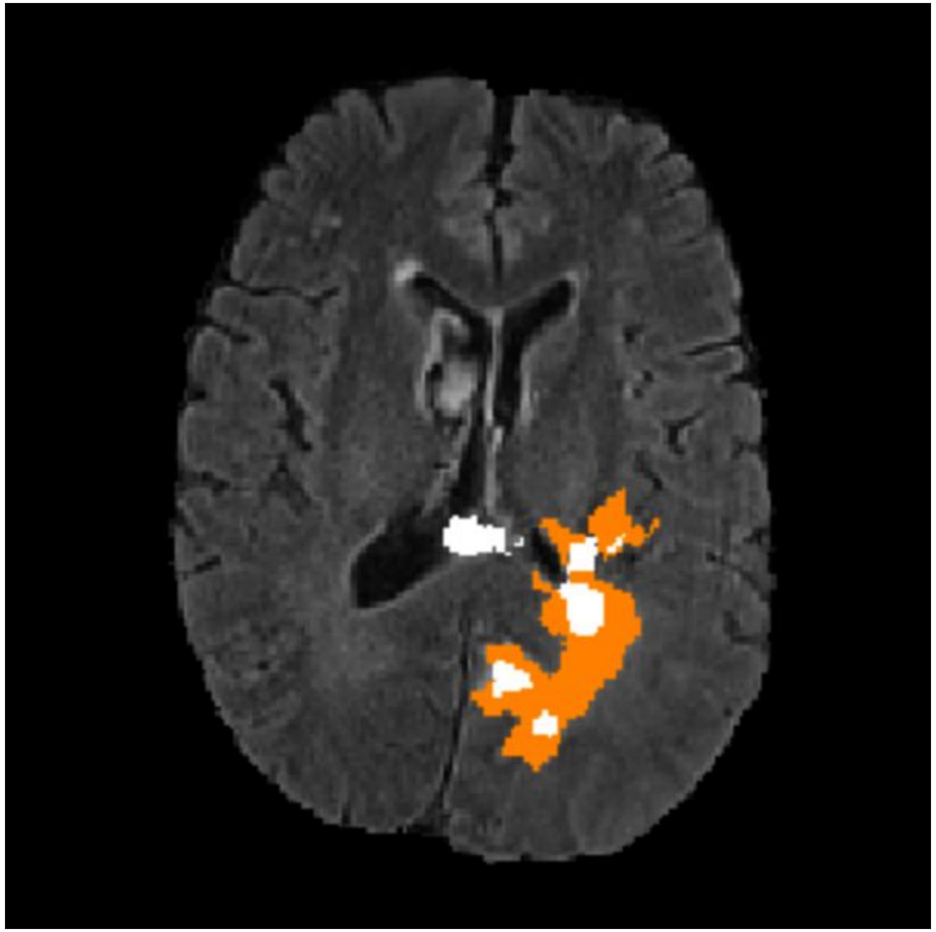

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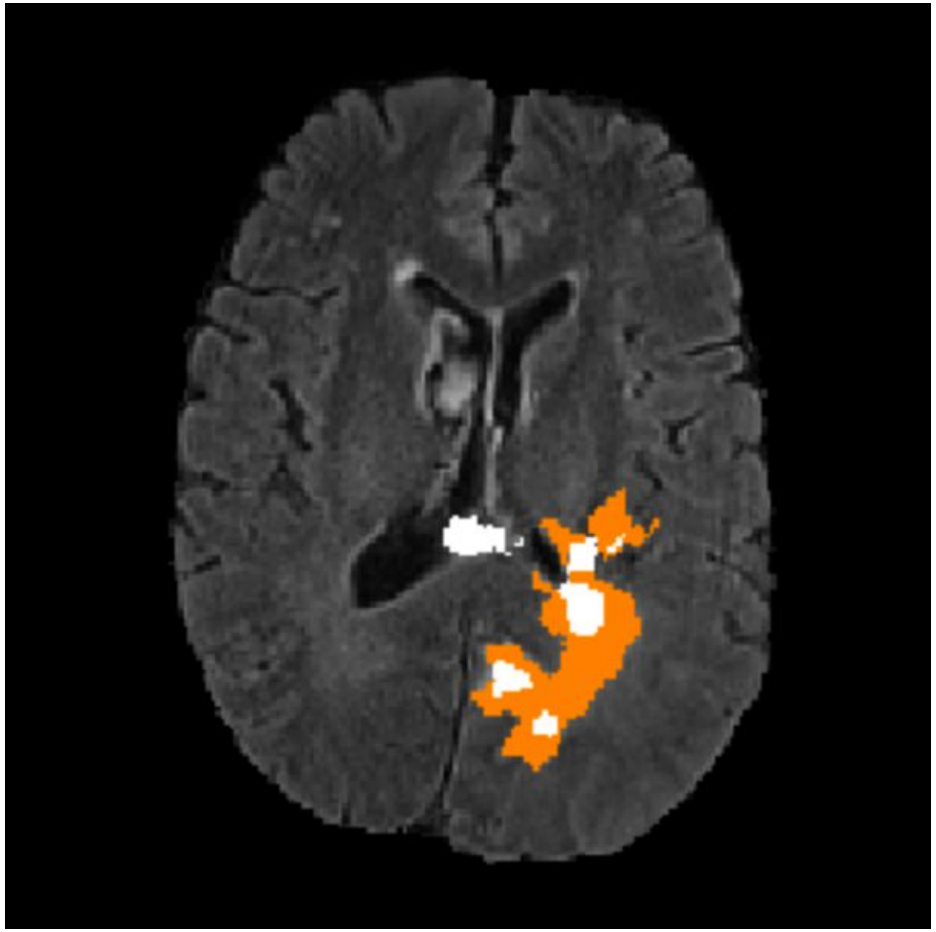

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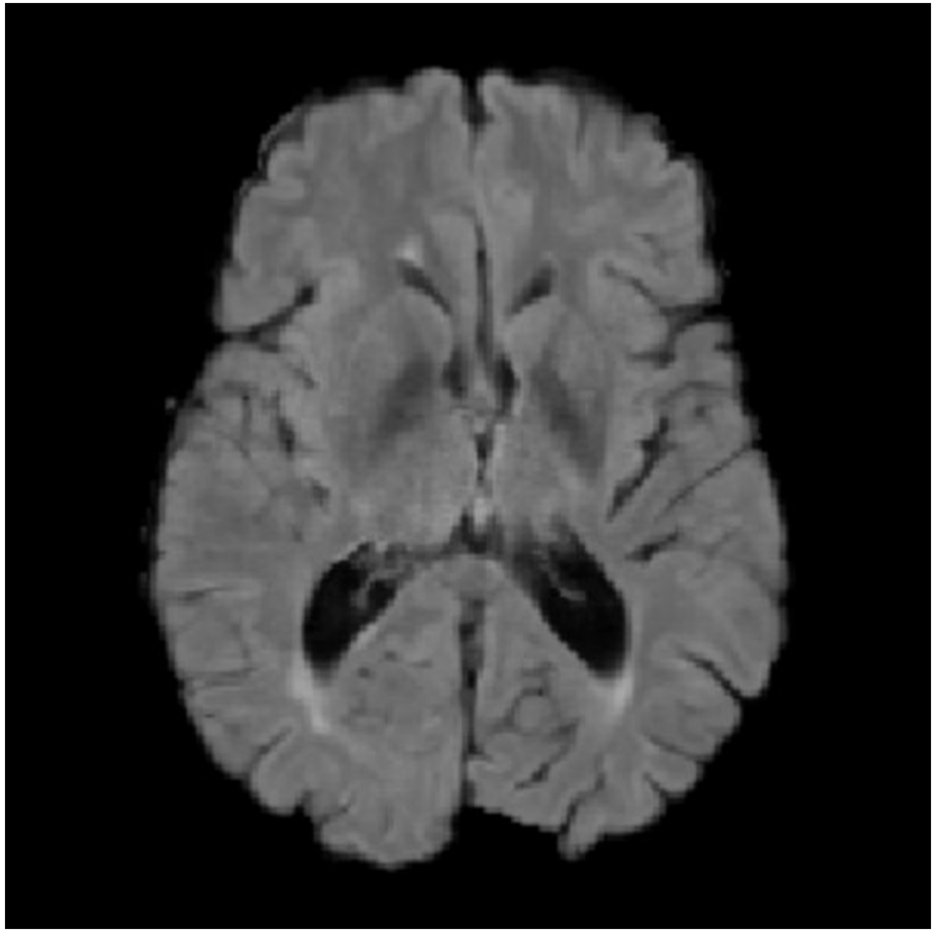

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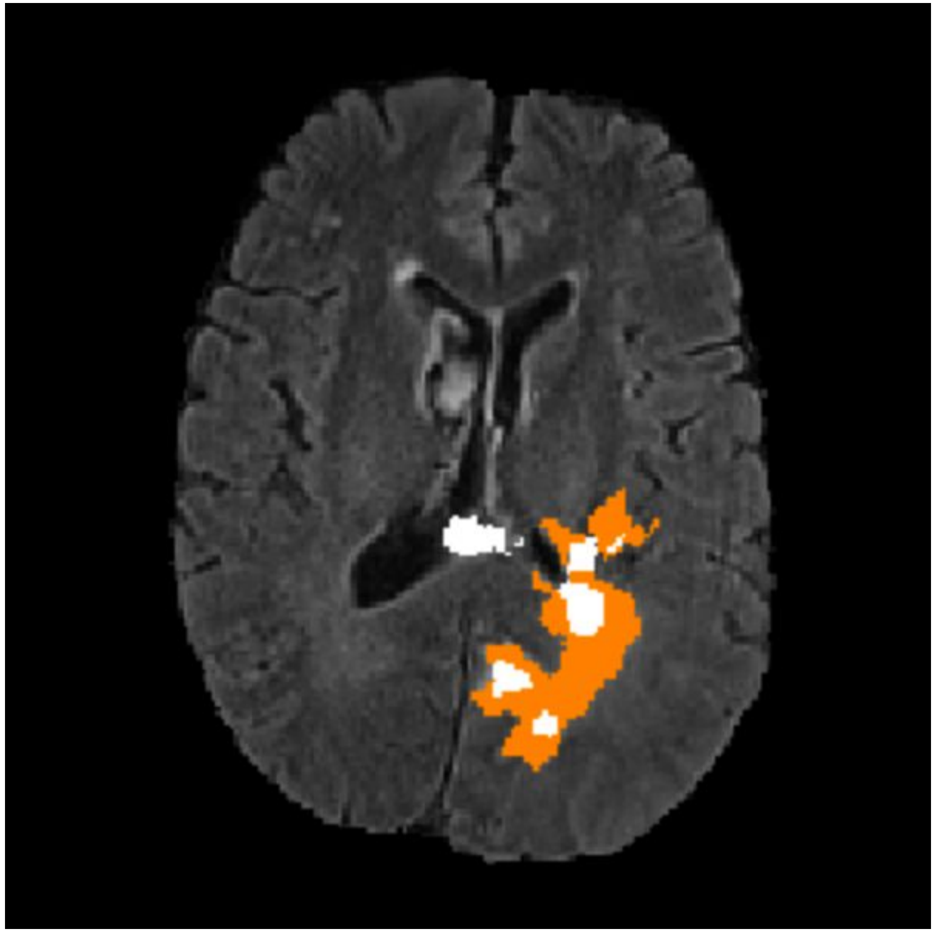

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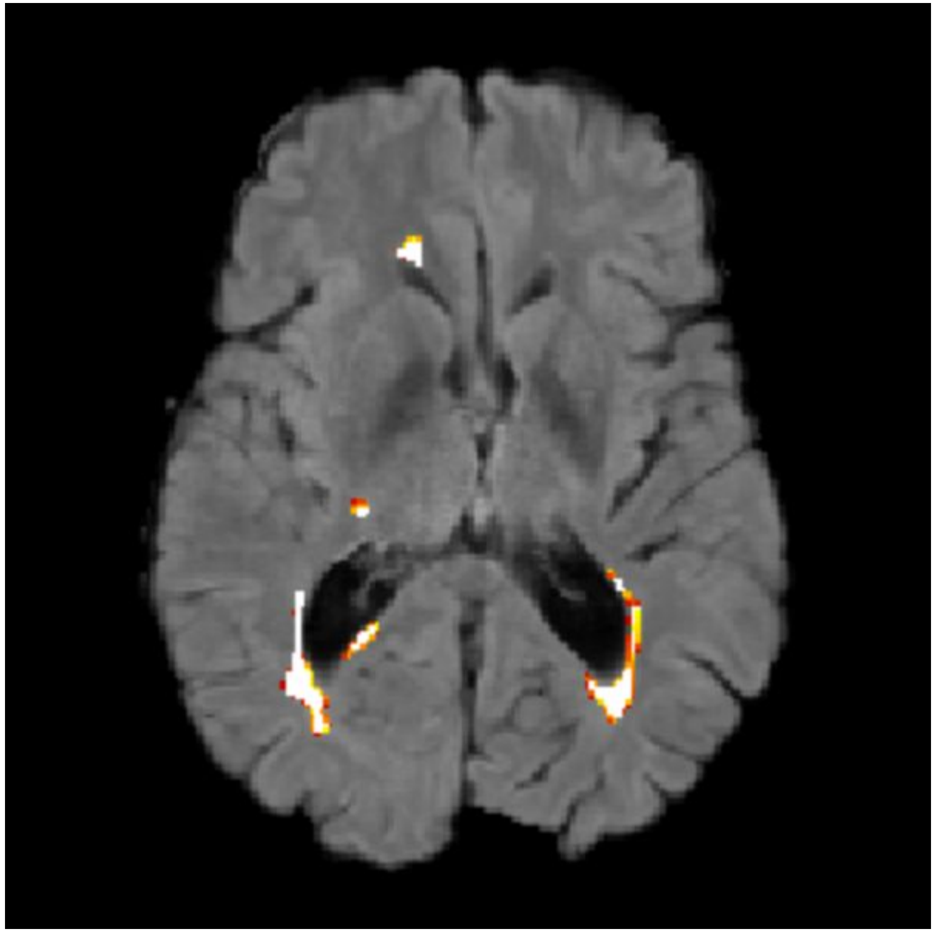

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