UCLA Samueli School of Engineering

Towards Composable Latent Augmentation in Generative Models

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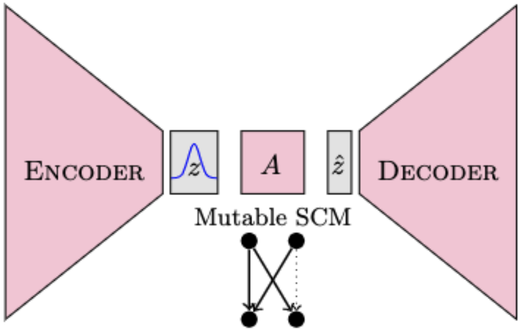
Contents

Causal Generative Modeling

Previous work: Causal Counterfactual Generative Models

- Used Causal VAE architecture compressing labelled images to a latent space[1,2]
- Learned adjacency matrix and functional relationships with only endogenous/exogenous (parent/child) priors
- Demonstrated ability to modify model and produce Out-of-Distribution counterfactual results on physics based dataset



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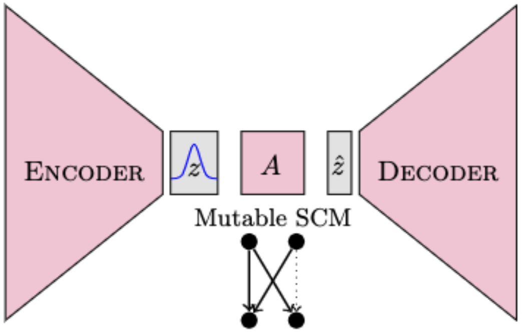
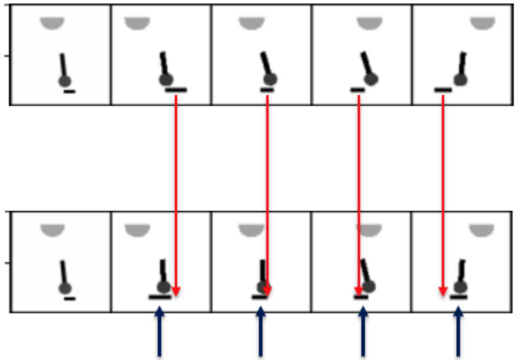
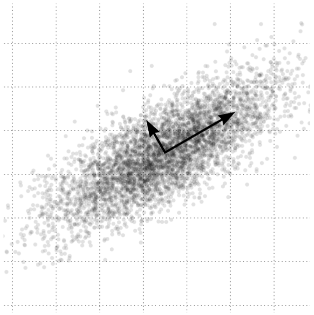
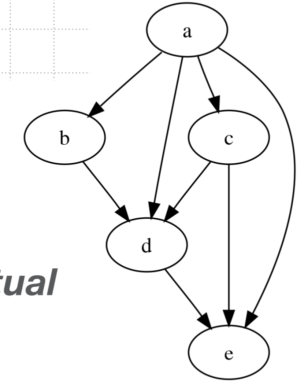




Causal Disentanglement Challenge

- **Causal Concepts are in a low dimensional space while images are relatively high-dimensional**
  - Compression is focused on ***minimum distortion, not interpretability***
    - orthogonal, variance preservation akin to PCA
- **Full causal disentanglement was not possible:**
  - Latent variables were not perfectly-aligned
  - Decoder learned some functional relationships
- **Fundamental Tension of Compression and Causality**
  - Subset of causal variables are usually highly correlated





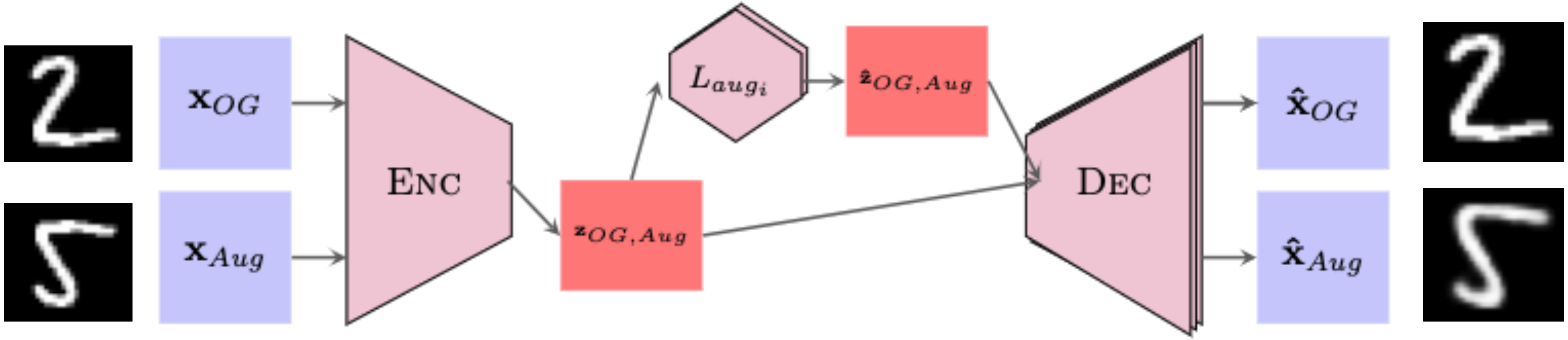
A pure information bottleneck is not the right solution for conceptual variables that are not independent (most of our causal priors)

Priors in Pre-processing

- **Data augmentation is a powerful technique to expand the train/test domain**
- **We don't augment naively, we augment based on priors**
  - We modify images along dimensions invariant to the classification interpretation
- **How might this perspective impact latent space research**
  - Can we better interpret and control the latent space?
  - Can we learn mappings between areas of the latent space?
  - Can we transfer certain properties of latent spaces between augmentations?

Latent Augmentation VAE (LAVAE)

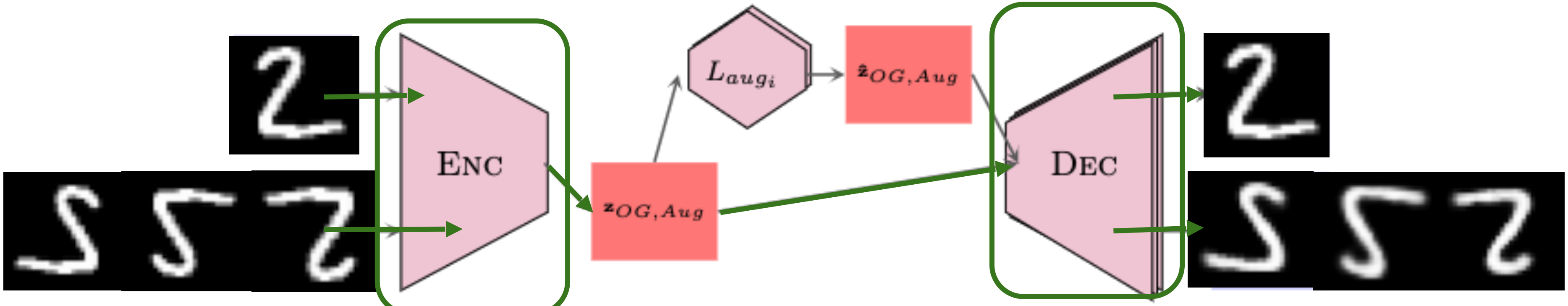
- **Similar architecture to VAE, but**
  - Includes learnable linear transformations between augmented latent spaces
  - Multiple decoder network heads for transferring latent spaces to new augmentations



Flip Up/Down

Training LAVAE

- **Training with Flip Left/Right and Flip Up/Down**
  - **Stage 1:** Populate latent space with original, two types of augmentations, and their composition
  - **Stage 2:** Learn L_{aug} linear transformations between latent spaces (original ->Aug_1, original -> Aug_2)
  - **Stage 3:** Transfer trained latent space by training new decoder on any other pair of augmentations *(X-direction shear and Canny edge-detect augmentations pictured)*



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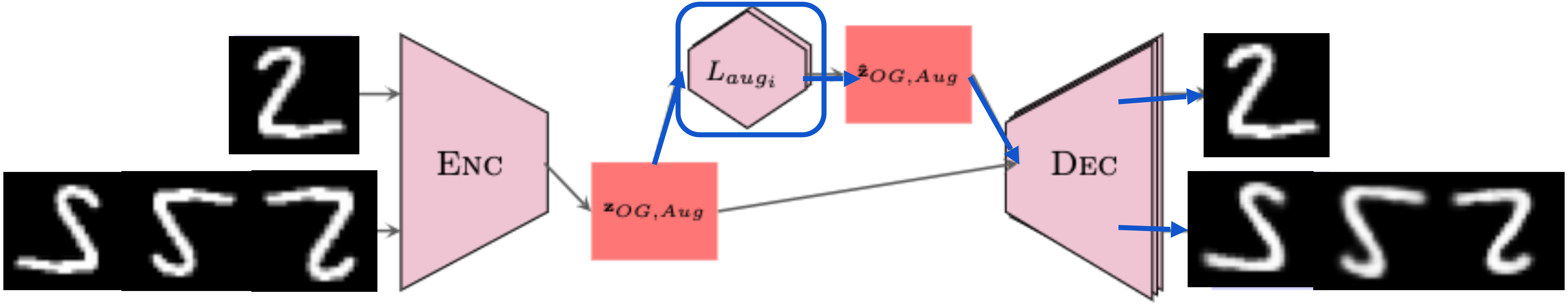

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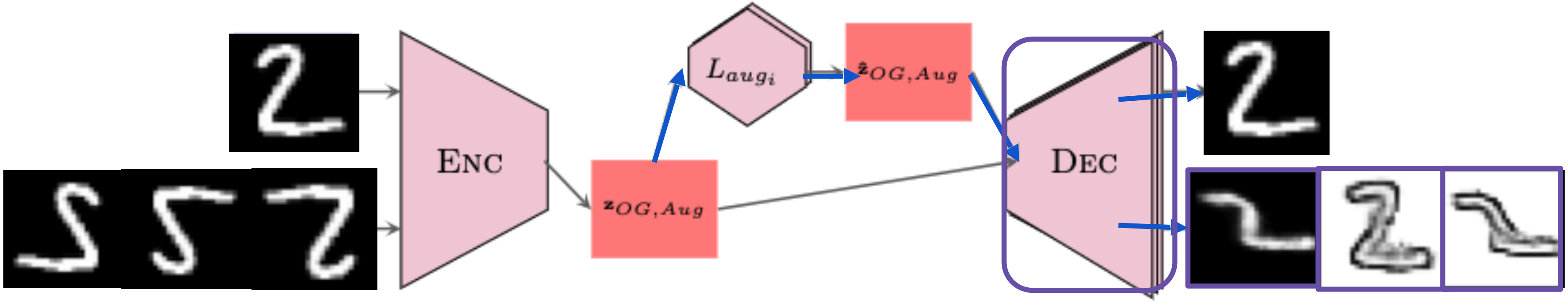


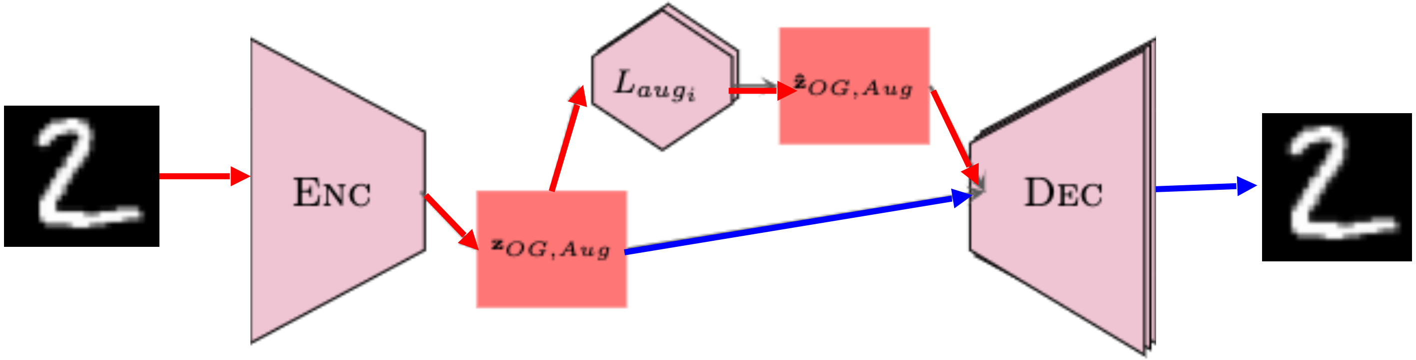
X-dir Shear, Canny Edge-Detect

LAVAE Capabilities

- Once trained, LAVAE offers tremendous flexibility for latent augmentation

Basic Reconstruction:

$$\hat{x}_i = DEC(ENC(x_i)) \mid i \in \{Orig, 1, 2, Compose\}$$



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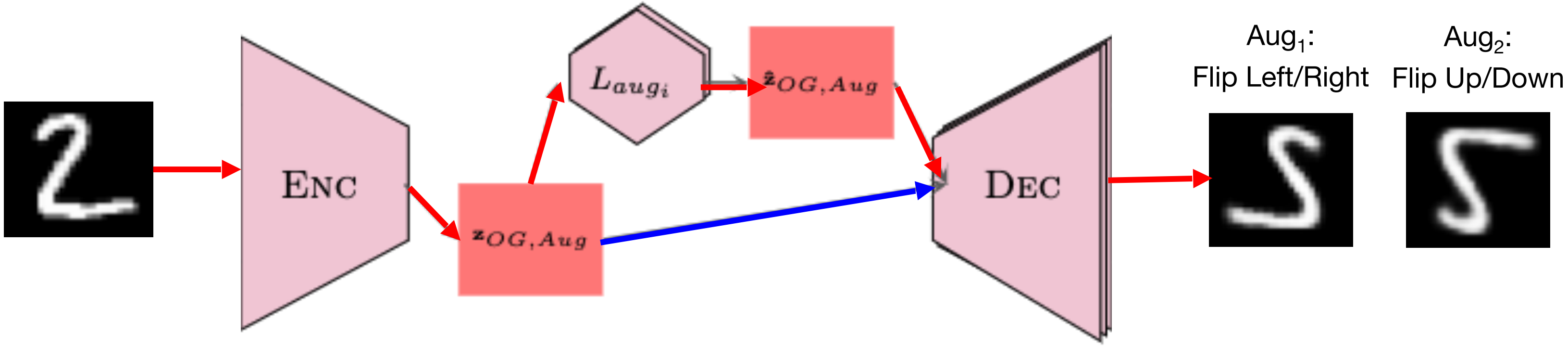
Latent Augmented Reconstructions:

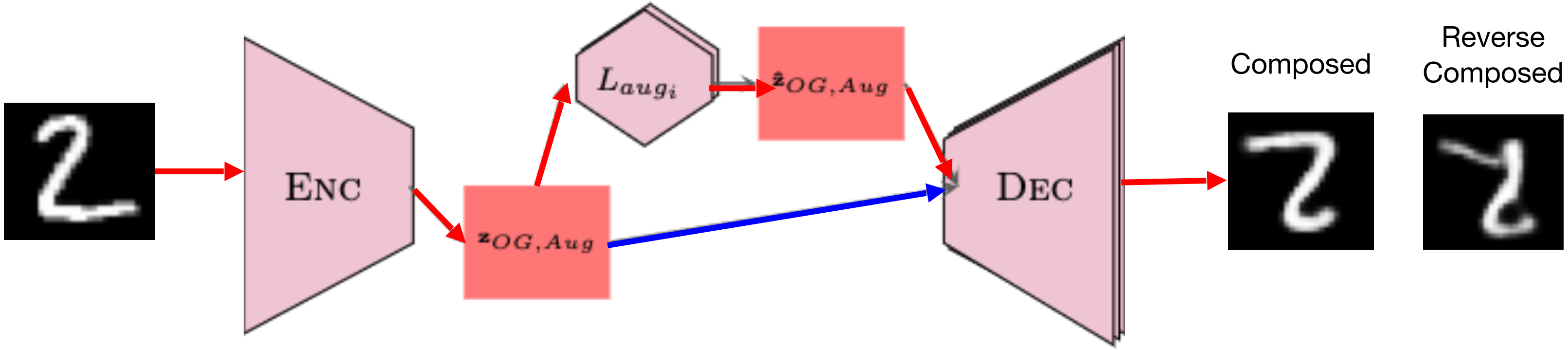
$$\hat{z}_i = ENC(x_{Orig}) \cdot L_{aug_i}$$
$$\hat{x}_i = DEC(\hat{z}_i) | i \in \{1, 2\}$$



LAVAE Capabilities

- **Once trained, LAVAE offers tremendous flexibility for latent augmentation Latent Composable Augmentations (*without explicit training*), and reverse composition with some loss:**

$$\hat{z_{compose}} = ENC(x_i) \cdot L_{aug_1} \cdot L_{aug_2}$$
$$\hat{z_{r\_compose}} = ENC(x_i) \cdot L_{aug_2} \cdot L_{aug_1}$$
$$\hat{x_{compose}} = DEC(\hat{z_{compose}}) \text{ and } \hat{x_{compose}} \approx DEC(\hat{z_{r\_compose}})$$

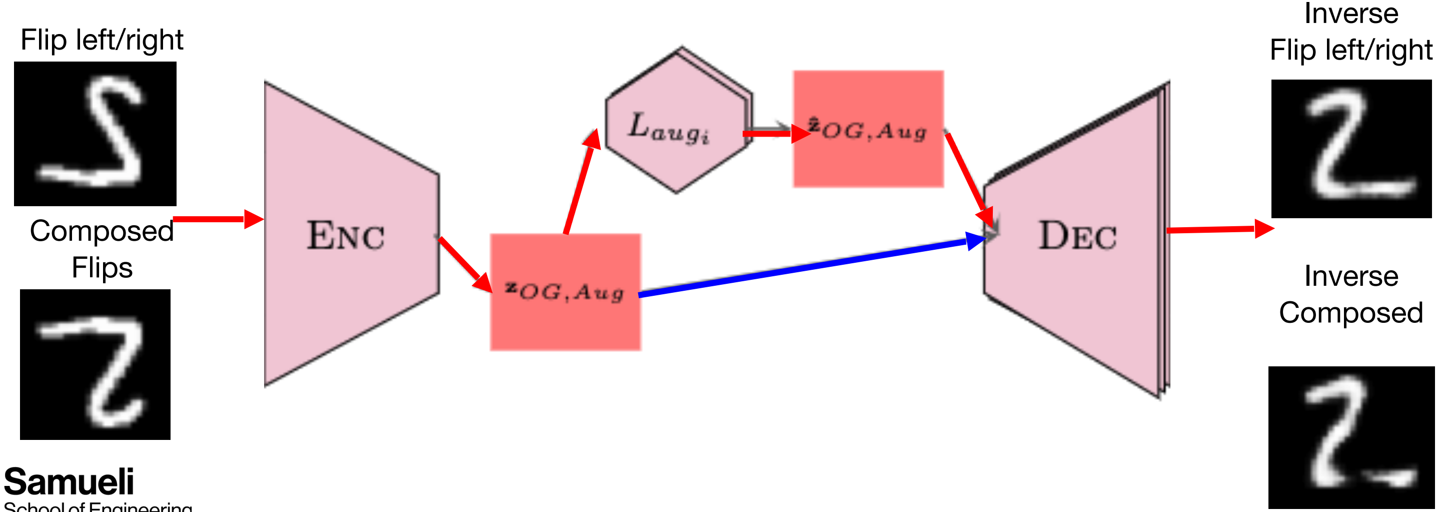


LAVAE Capabilities

- **Once trained, LAVAE offers tremendous flexibility for latent augmentation Inverse Augmentations to go from any input to any output**

$$\hat{x}_i = DEC(ENC(x_i) \cdot L_{aug_i}^{-1}) | i \in \{1, 2\}$$

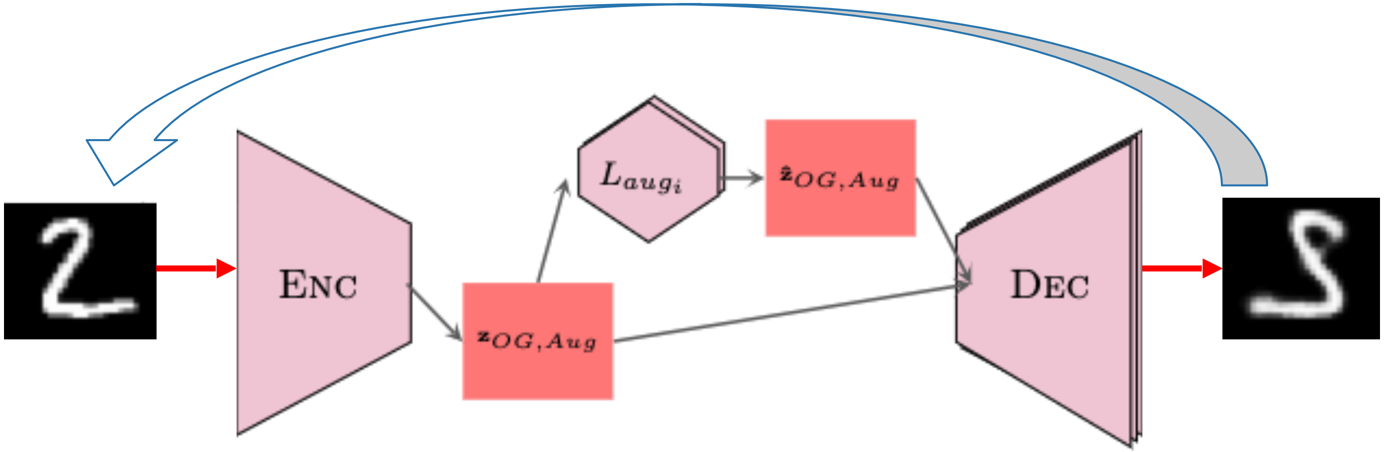
$$\hat{x_{Orig}} = DEC(ENC(x_{compose}) \cdot (L_{aug_1} \cdot L_{aug_2})^{-1})$$



LAVAE Capabilities cont.

- **We can also utilize LAVAE recursively**
  - Sometimes losses accumulate and repeated augmentations diverge and other times it is stable

$$\hat{x}_i = DEC(ENC(x_{Orig}) \cdot L_{aug_i})$$
$$for\ j\ in\ range:$$
$$\hat{\hat{x}}_i = DEC(ENC(\hat{x}_i) \cdot L_{aug_i})$$



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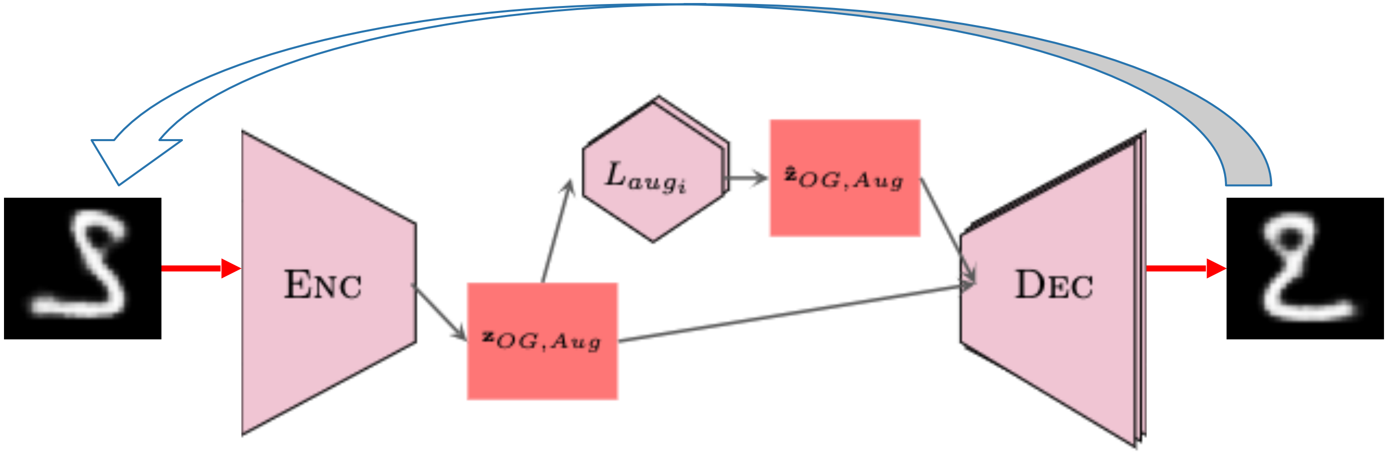
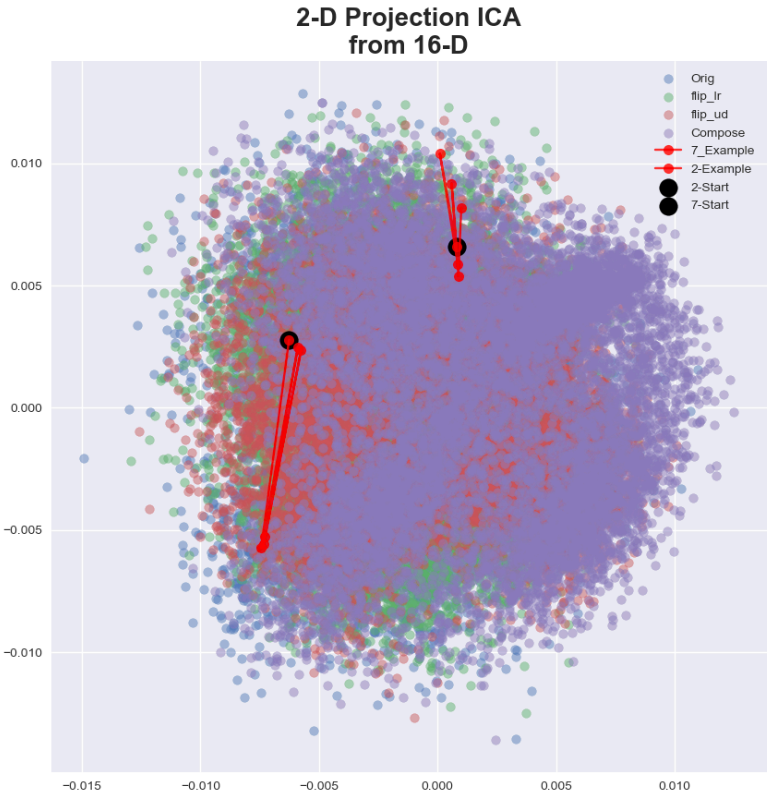
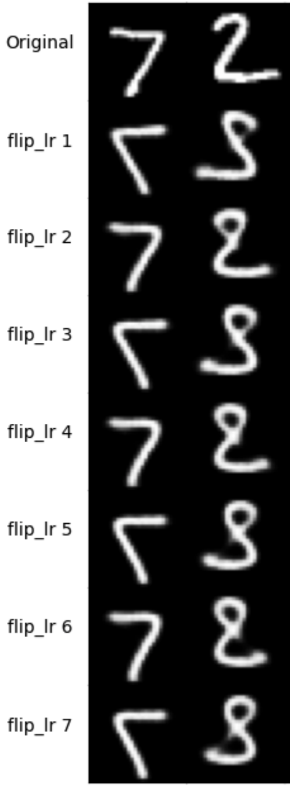


LAVAE Capabilities cont.

Repeated Flip left/right

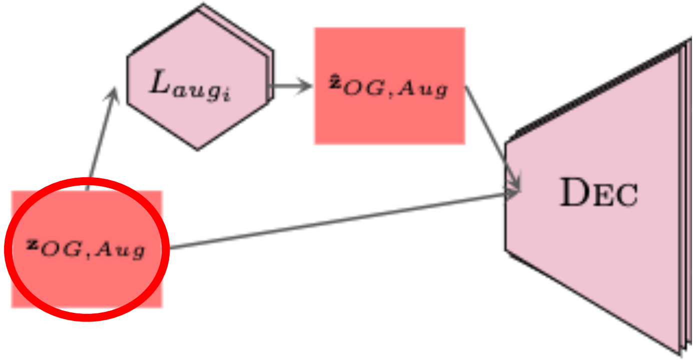
- 2 diverges (possibly to 8's)
- 7 is relatively stable showing minimal loss with repeated flip left/right 's

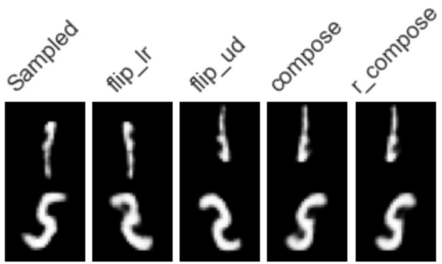




LAVAE Interpolation and Sampling

- **The LAVAE can still be sampled or interpolated like a standard VAE**
  - Sampling requires bounding box methods to find the original latent space (in 16-dims)
  - Interpolation between two points is uniformly spaced across latent dimensions





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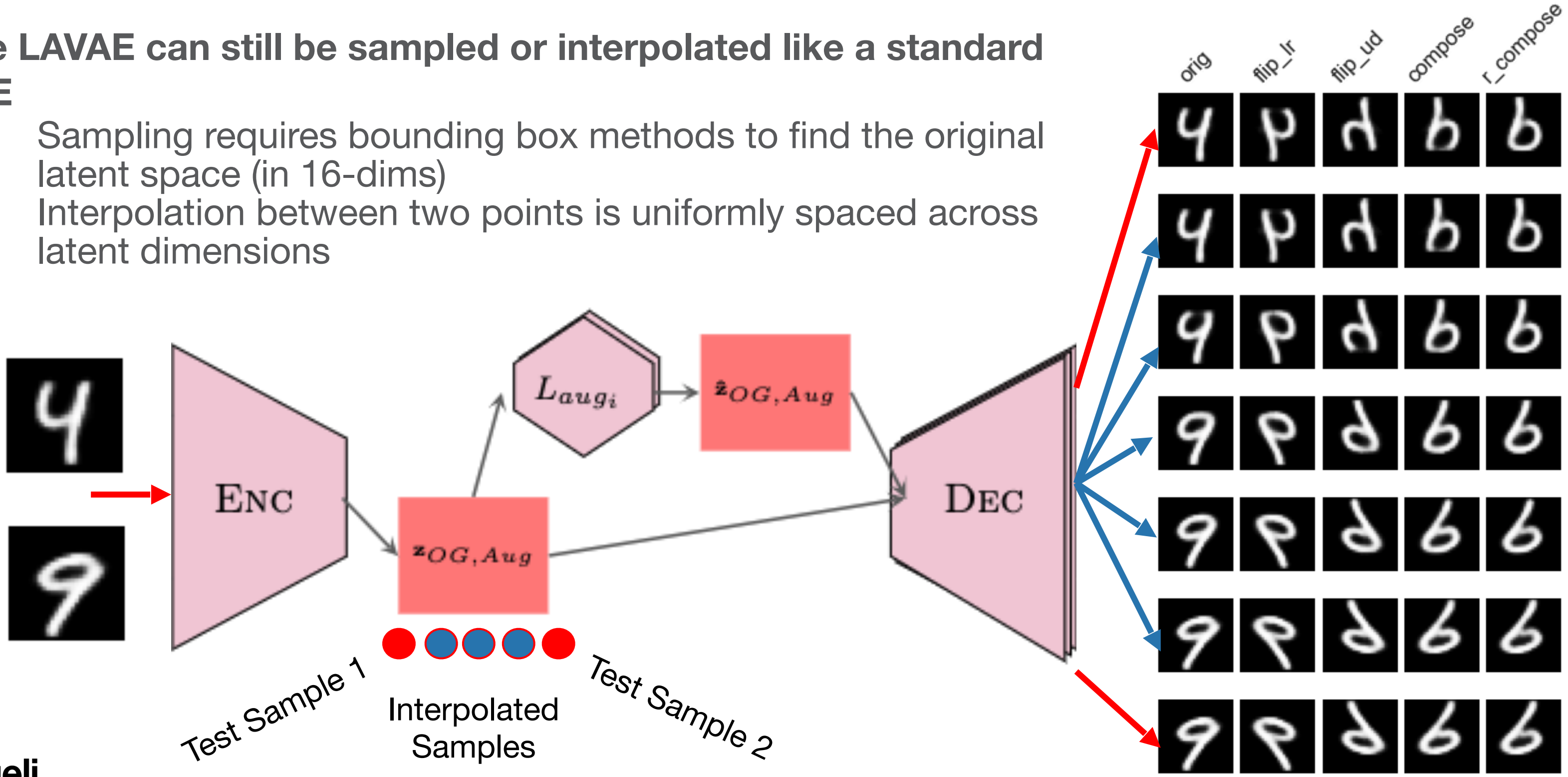
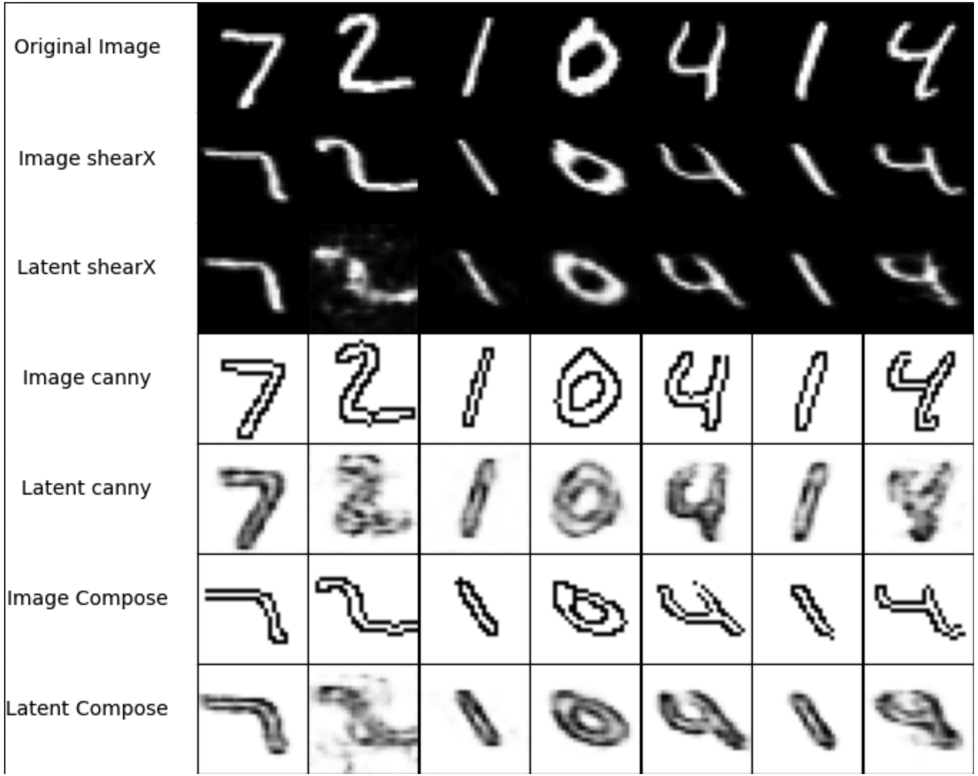


LAVAE Augmentation Transfer

- Finally, with LAVAE, we can transfer our latent space to any pair of augmentations:

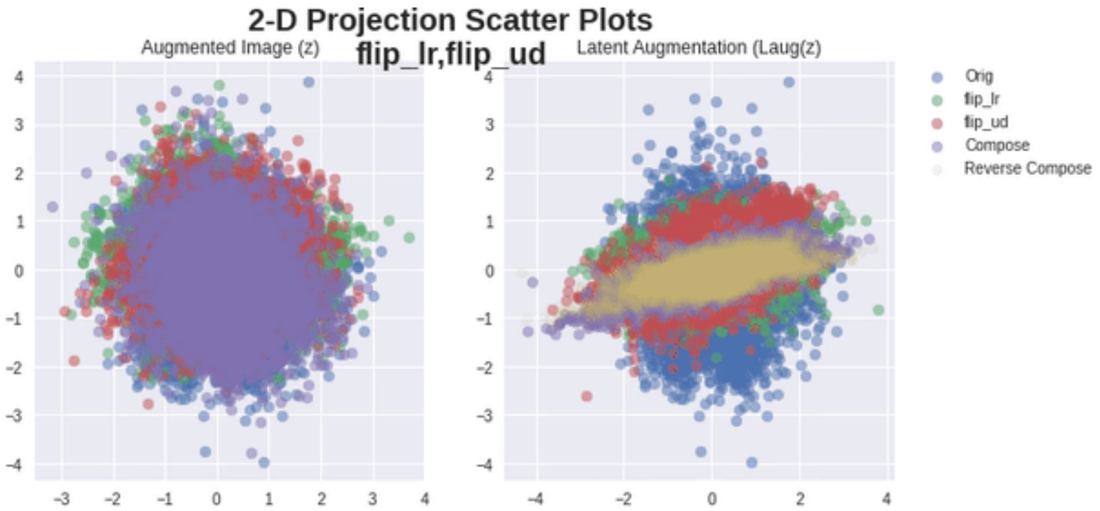
Flip left/right, flip up/down

X-direction Shear, Canny edge-detection



Exploring Latent Geometries

- The **choice of initial augmentation** impacts the latent space properties and how well they transfer to new augmentations
- We explore many augmentations pairs, using 2-D latent dimension or compressions (PCA, tSNE, ICA) to visualize the latent space and understand the geometries



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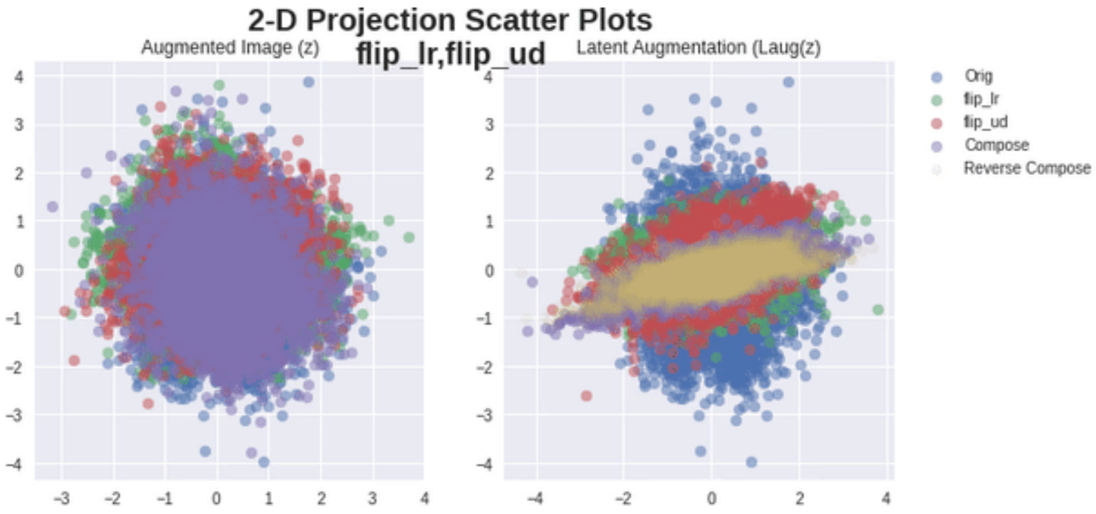
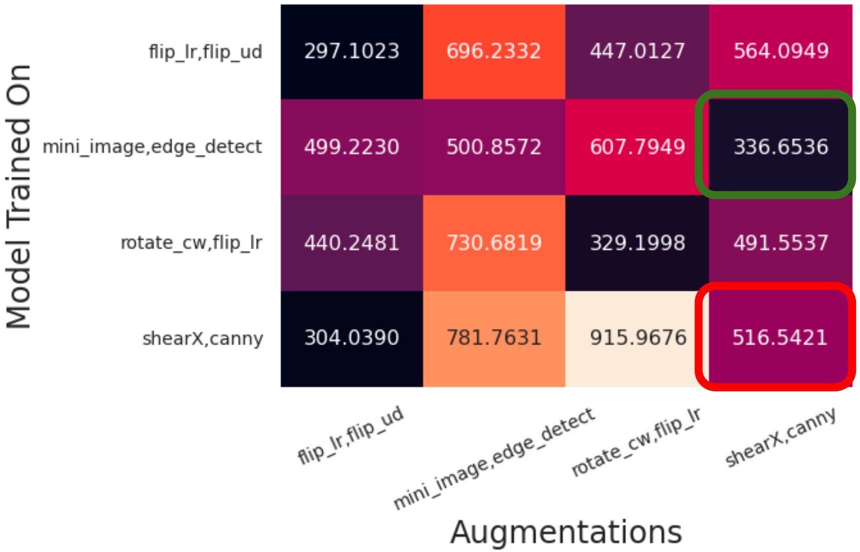
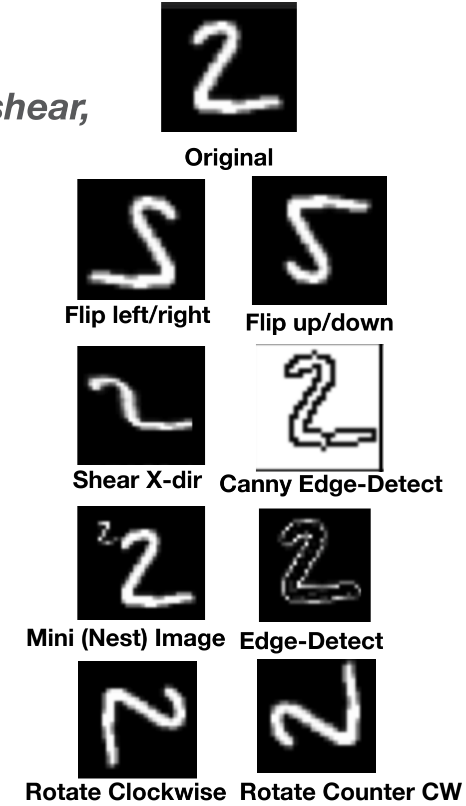


Tradeoff in Augmentation Pairs

The choice of initial augmentation impacts transfer performance:

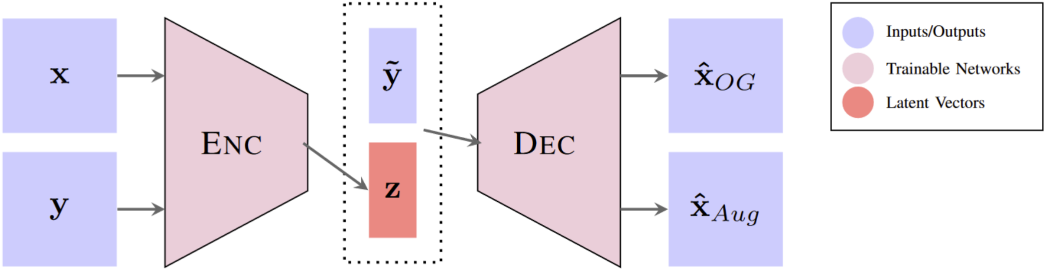
- Mini-Image, edge-detect pair ***performs better transferring to a shear, canny combo*** than training natively on shear,canny





LAVAE vs Conditional VAE (CVAE)

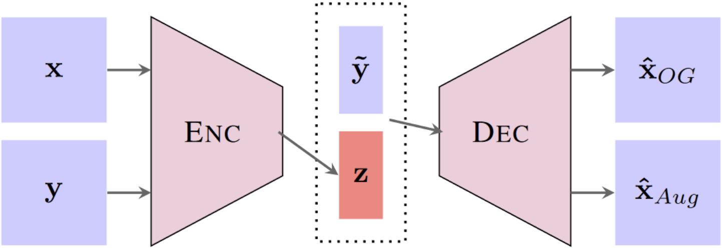
- **CVAE typically conditions on class to generate images within a class**
  - Idea: Enforce latent space partitioning done with conditioning increasing latent dimensions.
  - Can be modified to condition on class, augmentation or both
- **However, CVAE operates on a different philosophy than the LAVAE**
  - Uses same learned distribution, but no learned dependence between classes.
  - No latent space flexibility, meaning no augmentation interpolation.
- **CVAE either**
  - Does not preserve uniqueness (distributions are ind. on conditional)
  - Requires explicit training similar to LAVAE process

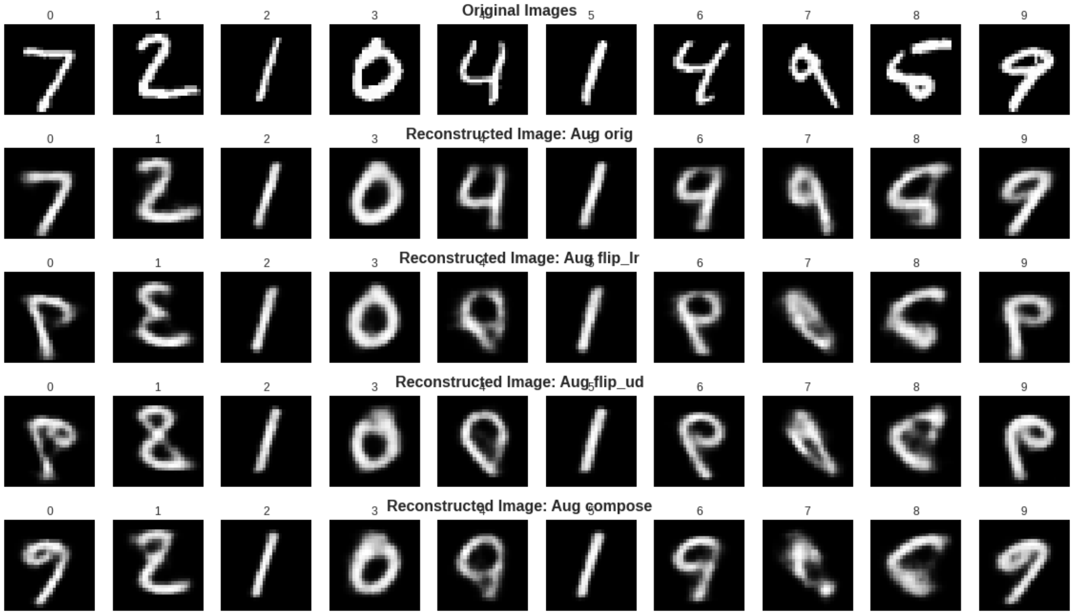


CVAE and Augmentations

CVAE: Class Change

- Suppose $\mathbf{y} \neq \tilde{\mathbf{y}}$
- Conditional does not change output based on augmentations of the original image

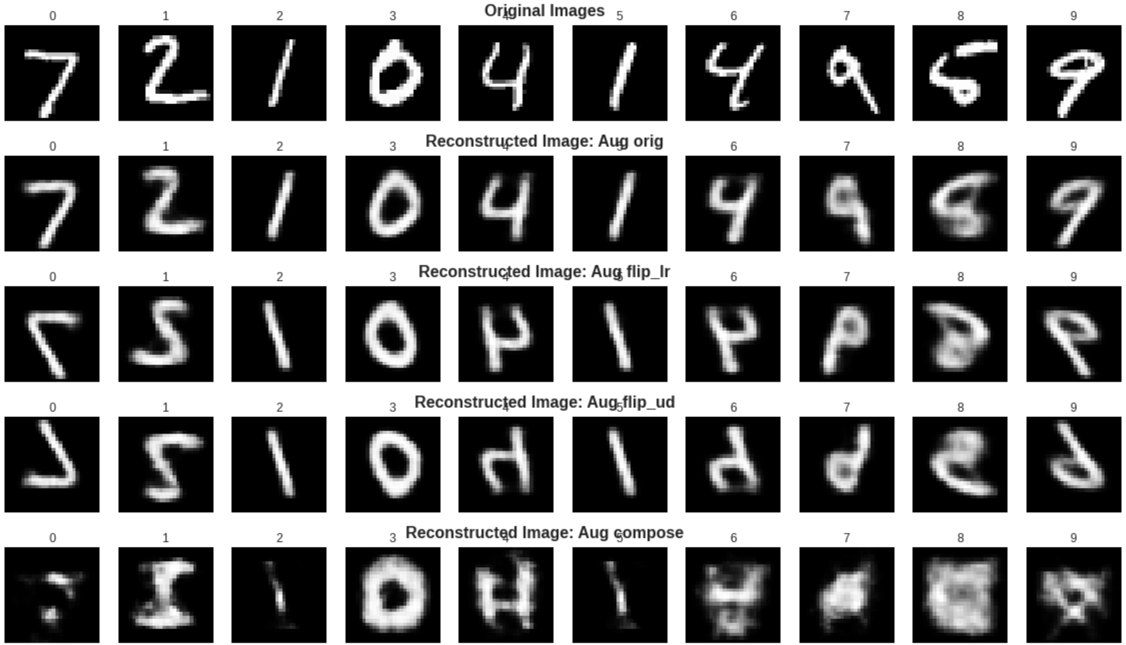




CVAE with LAVAE Training

Training the CVAE like LAVAE:

- Can teach CVAE to learn how to decode uniquely among augmentations.
- Composition does not emerge from training
- Can only input original images (not any-to-any)



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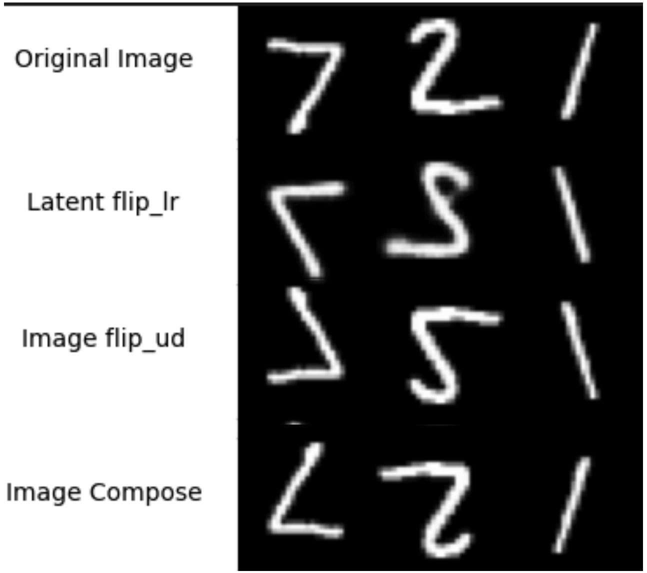
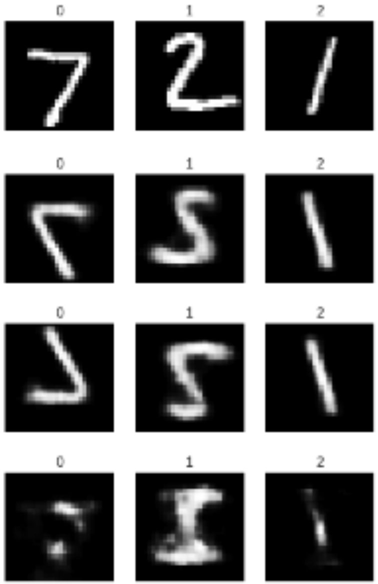
LAVAE



CVAE



Future Research

- Next phase, potentially **combine CVAE and LAVAE**, and **explore latent flow-based models** to better condition and partition based on dependencies of interest
- Utilize synthetic images with controlled variance instead of augmentation pairs to **construct latent space**
- **Use for causal models**
  - Better causal disentanglement
  - Explicit latent space partitioning and interpretability from priors

Thank You

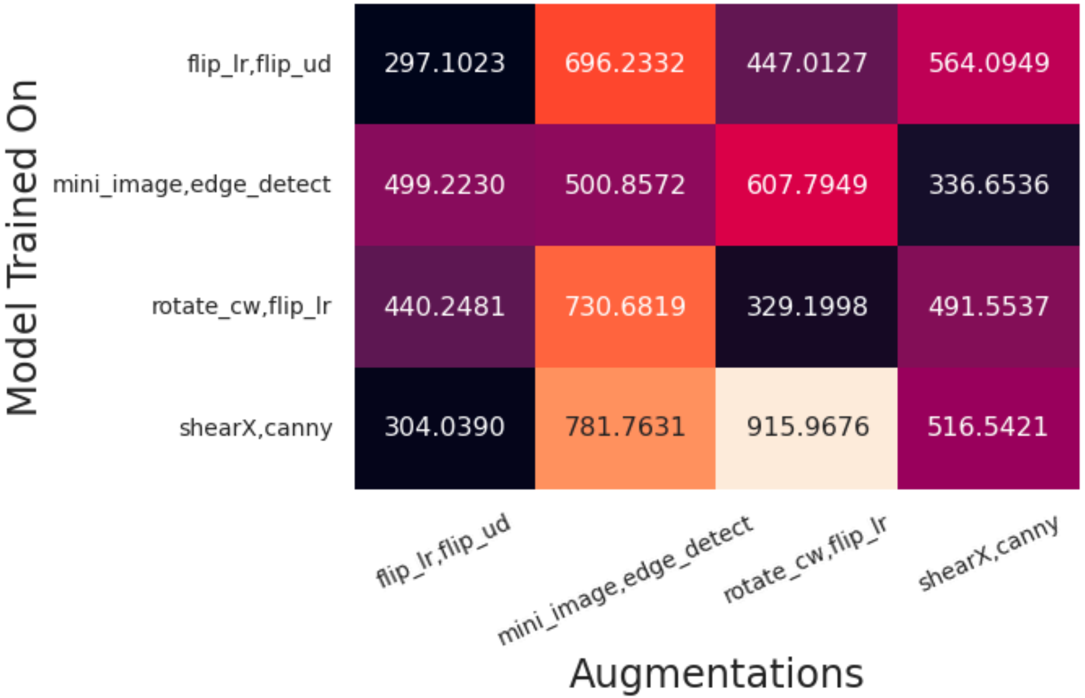
References

[1] S. Bhat, J. Jiang, O. Pooladzandi, and G. Pottie, “De-biasing generative models using counterfactual methods,” in 2022 Information Theory and Applications Workshop, 2022.

[2] M. Yang, F. Liu, Z. Chen, X. Shen, J. Hao, and J. Wang. CausalVAE: Disentangled representation learning via neural structural causal models. arXiv preprint arXiv:2004.08697, 2020.

Backup

Performance on other Augmentation Pairs



Enforcing Involutory Transformations

Training with Naturally Involutory Augmentations

- Flipping an image across any axis through the center of the image, notably horizontally and vertically.
- Rotating an image 180 degrees (composition of two orthogonal flips)

Training with Naturally Involutory Augmentations

- Partitions the latent space into augmentation regions.

Involutory Loss

$$L_{invol} = \| I - A^2 \|^2$$