

Islam Gamal

11

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Search by Images

Using Auto Encoders



The selected one to expand on.

Feature Detection

Using algorithms for matching image deformation such as blur, rotation, scale, and illumination change.
Such as **SIFT**, **PCA-SIFT** and **SURF**

Feature Detection

A set of algorithms is used to analyze image attributes ex (colour, shape, texture, luminosity, complexity, objects and regions). These attributes are stored for indexing and this can be used with keywords to refine searches on extremely large collections.

Search by Color

"Piximilar Multicolor Search process"

Given archive of images → create digital signature based colors (color histograms) → store the extracted signatures in database → whenever given a query image, extract its colors → find the most suitable matching image

Auto Encoder

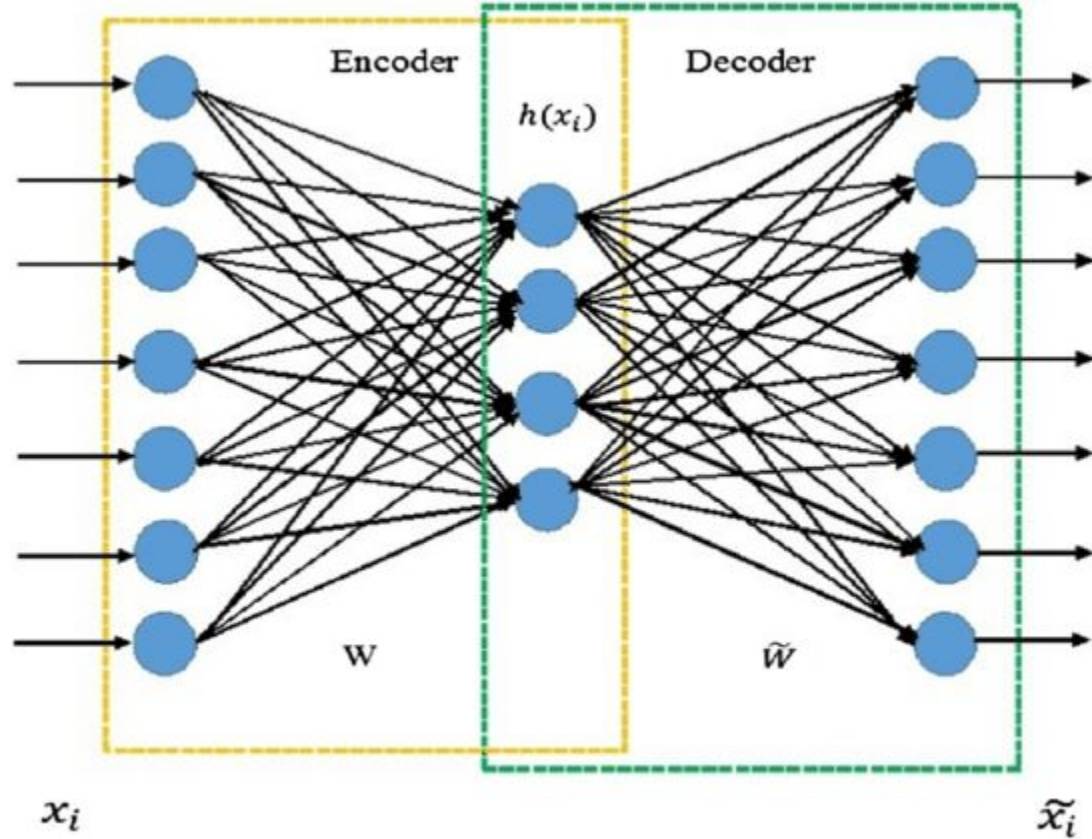
Encoding Images into 1D vector array and then finding the Nearest neighbours to a given query image.

Related work.

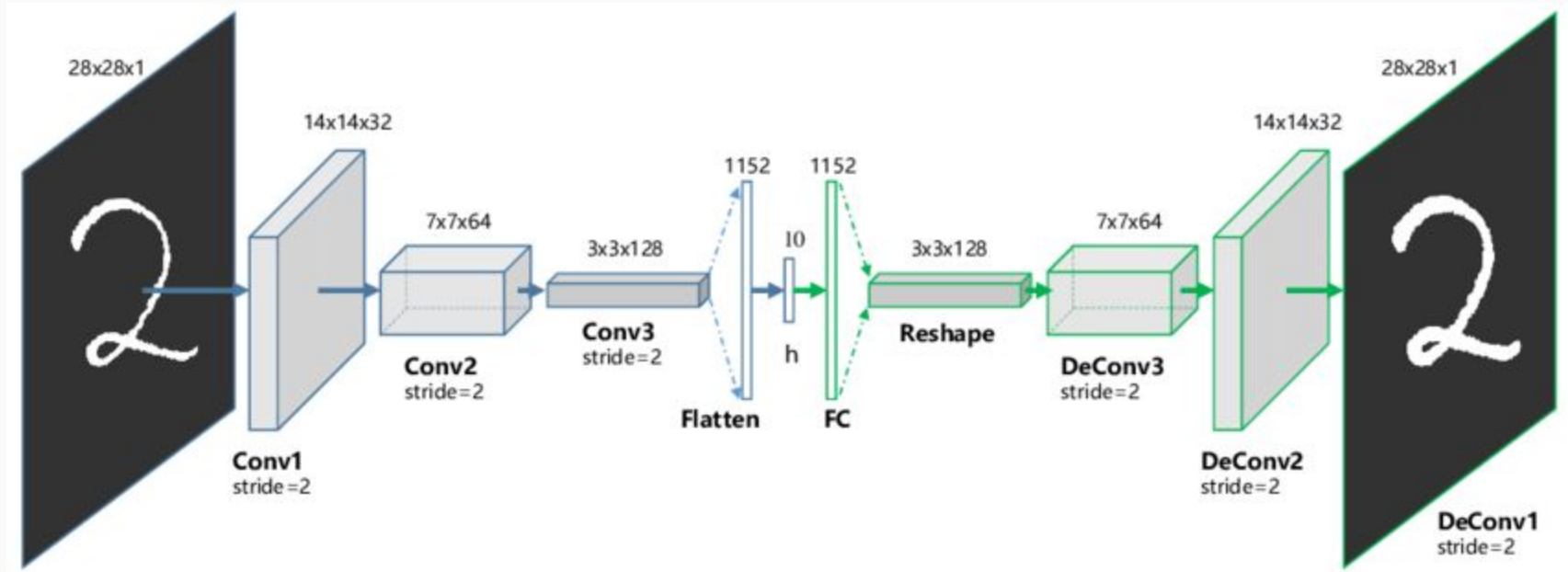
People Approaches to the Auto encoder.

1. Fully connected layers.
2. Fully convolutional way
 - a. Encoder : Conv + pooling
 - b. Decoder : Conv + Up sampling
3. Convolution , DeConvolution
 - a. Encoder : Accumulative convolutions layers + Pooling.
 - b. Decoder : Accumulative transpose convolutional layers.
4. Mix of 2 and 1

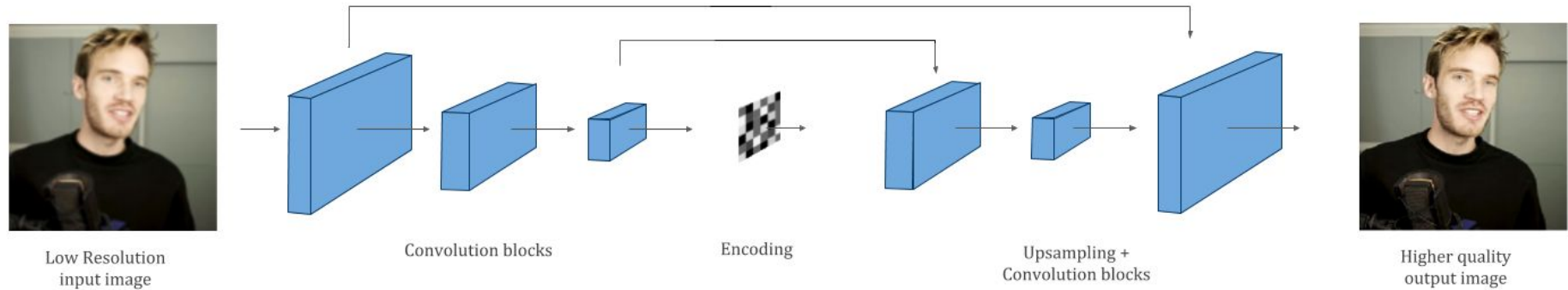
Fully Connected Layers Methodology - Architecture



Fully Convolutional way - Architecture



Convolutional + Up Sampling - Architecture

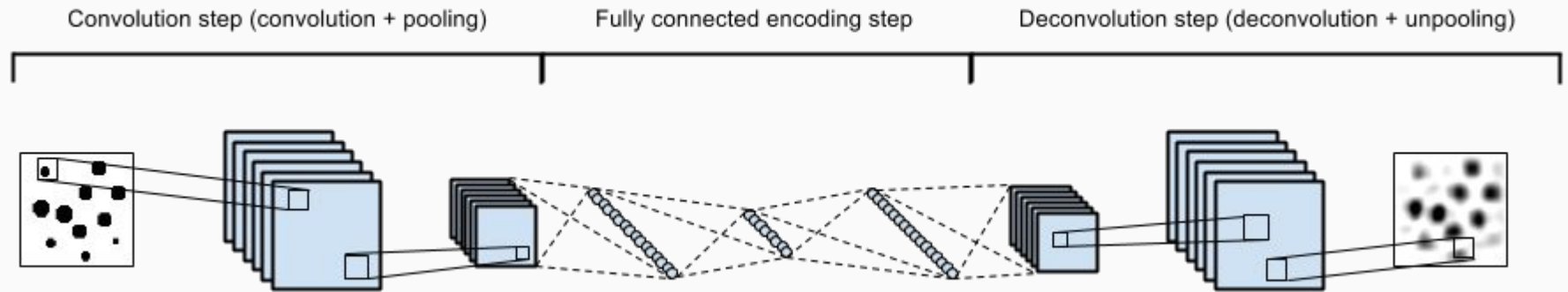


Our proposed solution/model and Difference from related work.

mixed approach with Convolutional Neural Networks (CNNs) and FC layers

- The **Encoder** consists of the following layers
 - ✓ Convolutional Layers.
 - ✓ Non-Linearity layers.
 - ✓ Rectification Layers (can use just ReLU).
 - ✓ Pooling layers (Average and Max pooling)
 - ✓ Fully connected layers.
 - ✓ Dropout layers.
- The **Decoder** consists of the following layers
 - ✓ FC layers (undos effect of last layer in encoder).
 - ✓ Transpose Convolution Layers (Reversing the encoder)

Model Architecture (CNN + FC + Trans Conv)

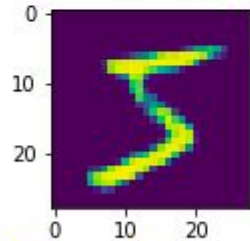
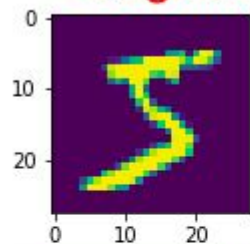


Applying the models on MNIST (Handwriting) dataset.

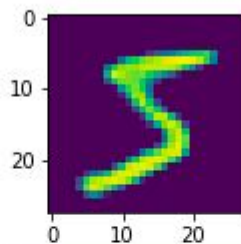
```
plt.xlabel("Reconstructed by conv + FC + up sampling")
```



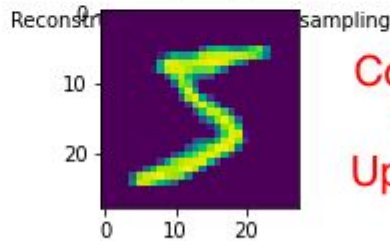
Original



Convolution +
DeConvolution



Convolution +
UpSampling



Convolution
+ FC +
UpSampling

| Approach \ MSE train loss by | Them | Winner | Us |
|------------------------------|--------|--------|--------|
| Fully Connected Only | 0.0214 | → | 0.0026 |
| Convolution + Up Sampling | 0.0407 | → | 0.0065 |
| Convolution + DeConvolution | 0.0297 | → | 0.0091 |
| Conv + FC + Up Sampling | 0.0173 | → | 0.0050 |

Them :

<https://towardsdatascience.com/aligning-hand-written-digits-with-convolutional-autoencoders-99128b83af8b>

<https://towardsdatascience.com/build-a-simple-image-retrieval-system-with-an-autoencoder-673a262b7921>

<https://medium.com/analytics-vidhya/building-a-convolutional-autoencoder-using-keras-using-conv2dtranspose-ca403c8d144e>

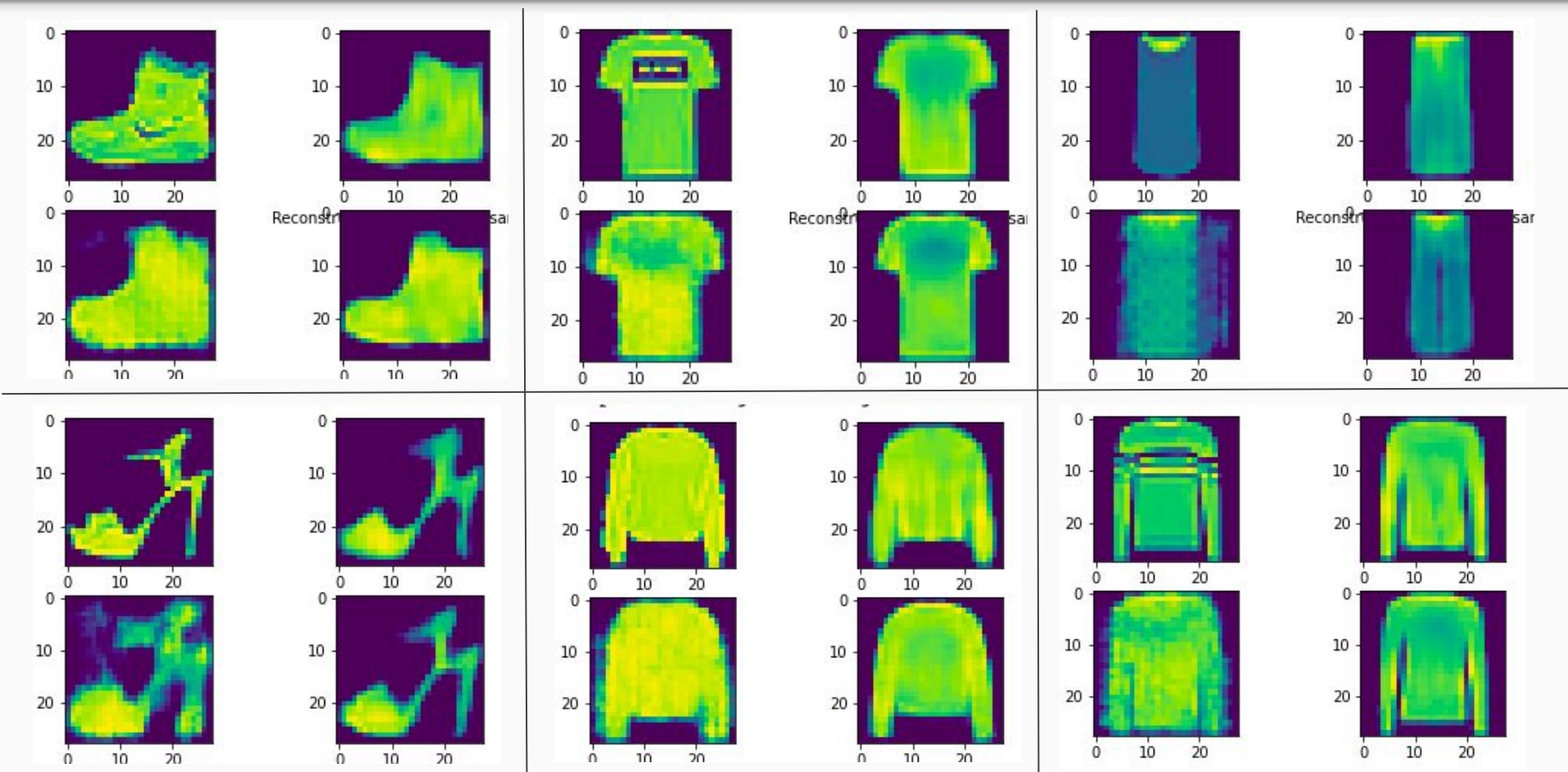
Confusing



Using a new dataset

MNIST for fashion

Applying the models on MNIST (Handwriting) dataset.



| Approach \ MSE train loss by | Them | Us (Fashion MNIST) | Us (HandWriting MNIST) |
|------------------------------|--------|--------------------|------------------------|
| Fully Connected Only | 0.0214 | 0.00543 | 0.0026 |
| Convolution + Up Sampling | 0.0407 | 0.0131 | 0.0065 |
| Convolution + DeConvolution | 0.0297 | 0.049 | 0.0091 |
| Conv + FC + Up Sampling | 0.0173 | 0.0091 | 0.0050 |

Them :

<https://towardsdatascience.com/aligning-hand-written-digits-with-convolutional-autoencoders-99128b83af8b>

<https://towardsdatascience.com/build-a-simple-image-retrieval-system-with-an-autoencoder-673a262b7921>

<https://medium.com/analytics-vidhya/building-a-convolutional-autoencoder-using-keras-using-conv2dtranspose-ca403c8d144e>

VAE

Variational Autoencoders

2. Using Variational autoencoders instead on normal autoencoders.

WHY?

Given a dataset that we want to encode it all, the resulted latent layers will be in a clustering form, not a continuous form, so if a target image contained some noise or error , there is a high probability that the produced vector will not be close to the original one , it may be considered as another cluster.

(Unsupervised learning)

VAE

Variational Autoencoders

2. Using Variational autoencoders instead on normal autoencoders.

BUT

With using Variational autoencoders, the encoded dataset will be in a continuous way since the latent layers has learnt a distribution in the input images.

So it will be more reasonable and confidential to use the nearest neighbour algorithms to find the target image from it's encoded version.

(Supervised learning)

VAE Model Architecture. (encoder)

Model: "encoder"

| Layer (type) | Output Shape | Param # | Connected to |
|----------------------------|--------------|---------|---------------------------------|
| encoder_input (InputLayer) | (None, 784) | 0 | |
| dense_4 (Dense) | (None, 512) | 401920 | encoder_input[0][0] |
| z_mean (Dense) | (None, 2) | 1026 | dense_4[0][0] |
| z_log_var (Dense) | (None, 2) | 1026 | dense_4[0][0] |
| z (Lambda) | (None, 2) | 0 | z_mean[0][0] z_log_var[0][0] |

Total params: 403,972

Trainable params: 403,972

Non-trainable params: 0

VAE Model Architecture. (decoder)

Model: "decoder"

| Layer (type) | Output Shape | Param # |
|-------------------------|--------------|---------|
| ===== | | |
| z_sampling (InputLayer) | (None, 2) | 0 |
| dense_5 (Dense) | (None, 512) | 1536 |
| dense_6 (Dense) | (None, 784) | 402192 |
| ===== | | |

Total params: 403,728

Trainable params: 403,728


Non-trainable params: 0

Evaluation Metrics

Reconstruction loss + K-L loss.

- Reconstruction loss → using (Cross Entropy) OR (mean square error)
- K-L loss → K-L Divergence Metric → rule.

Prior Latent Distribution



$D[p_\phi(z|x) || p(z)]$

- → $D[p_\phi(z|x) || p(z)] = -\frac{1}{2} \sum_{j=0}^{k-1} (\sigma_j^2 + \mu_j^2 - 1 - \log \sigma_j)$
 - KL-divergence between the two distributions
 - $N(\mu, \sigma)$ and $N(0, 1)$

- For two Gaussian distributions

KL(p,q) = $\log \frac{\sigma_2}{\sigma_1} + \frac{\sigma_1^2 + (\mu_1 - \mu_2)^2}{2\sigma_2^2} - \frac{1}{2}$

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From Dr. Moustafa Youssef Slides

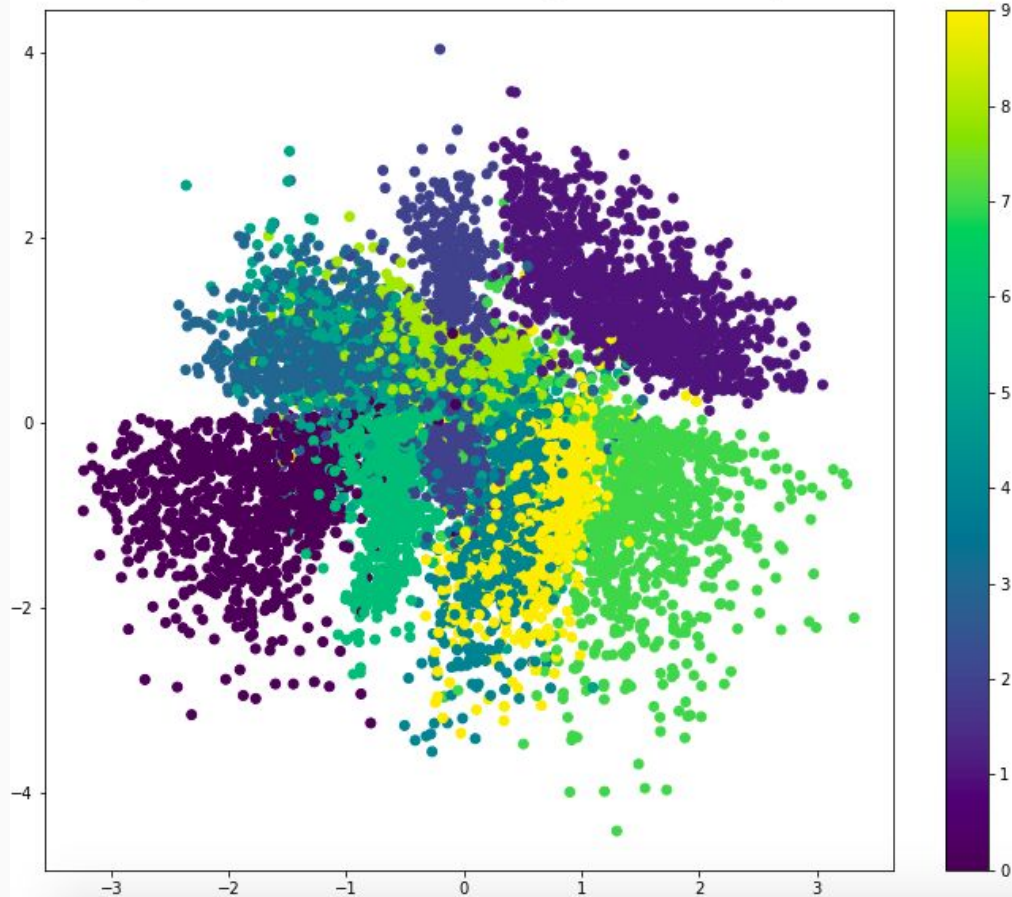
https://piazza.com/class_profile/get_resource/k6mquuyyw903ch/k9cp4lksi2a1n8

37.3252

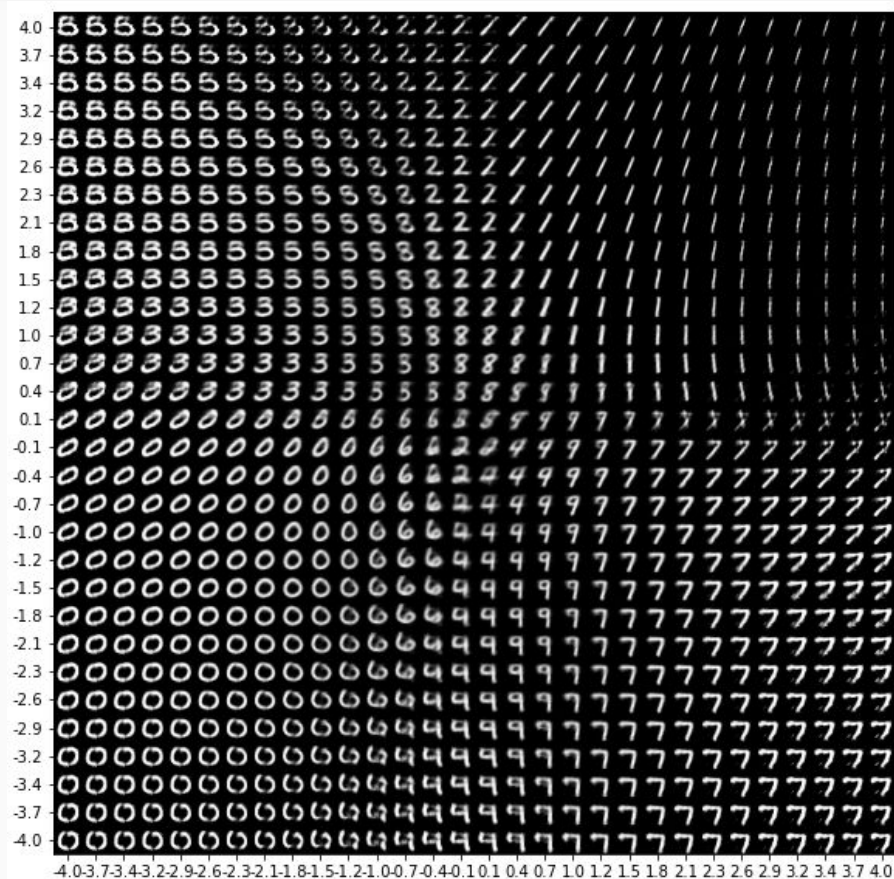
Evaluated Loss

Visualizations to the continuous distribution of the latent vectors.

100/60000 [=====] - 12s 193us/step - loss: 36.5084 - val_loss: 37.3252



Visualizations to the continuous distribution of the latent vectors. (Interpolation)



Another proposed solution/model and Difference from related work.

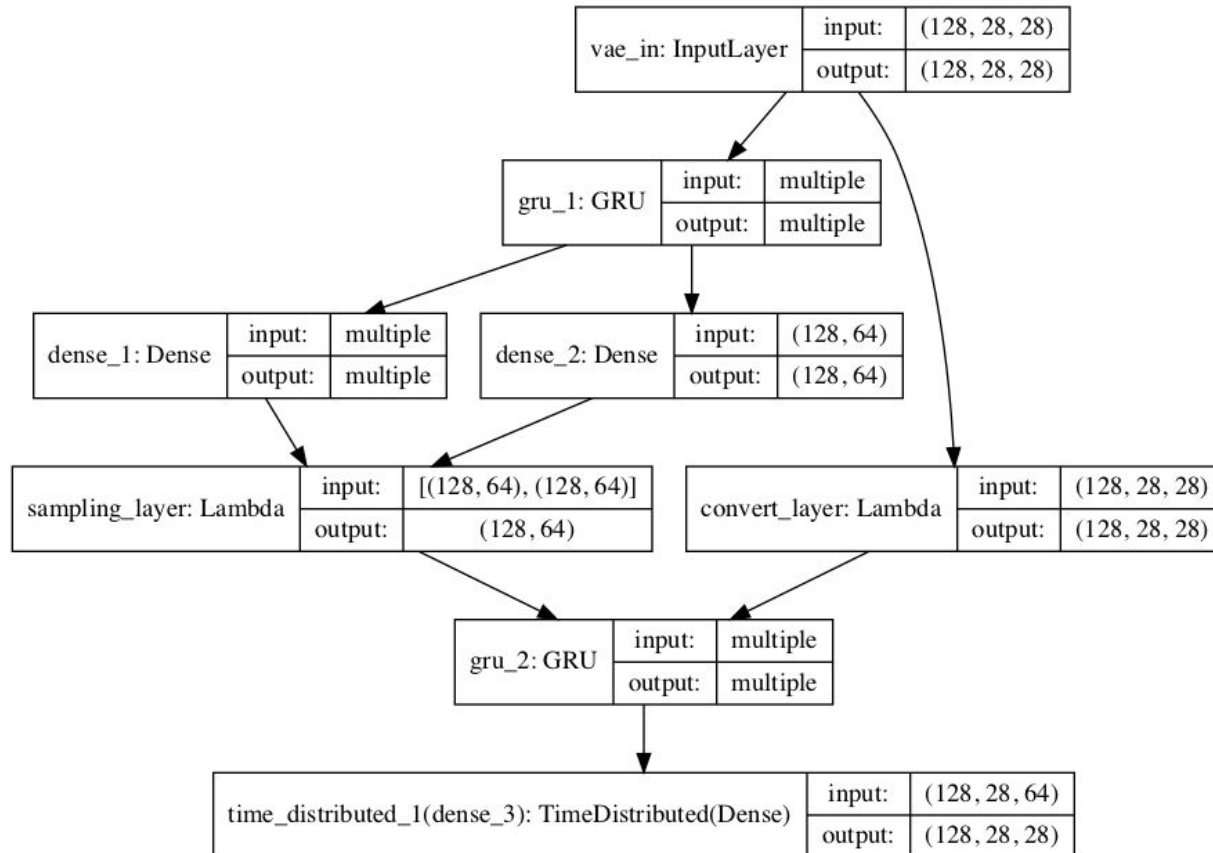
3. Third we will try to improve that by using Recurrent Neural Networks (**RNN**) instead of CNN:
 - LSTM network:
 - ✓ Each layer of LSTM has as many cells as the timesteps and using ReLU as activation function.
 - ✓ It takes 2d as input (each layer).
 - ✓ If the subsequent layer is also LSTM, we will duplicate this vector using “RepeatVector(timeSteps)” to get a 2D array for the next layer.

RNN architectures made no sense

Since there is no sequence in the input, they are just random consecutive numbers from 0 to 9 so it's not confidential to use the RNN for this type of problems except

1. Sorting the input in a circular way $\rightarrow 0, 1, 2, 3 \dots, 8, 9, 0, 1, 2 \dots$ and learn the natural counting pattern in order to identify whether an input sequence is in correct counting order or not.
2. Using videos instead of images and predicting the next frame to enhance the searching speed.

RNN (GRU) Model Architecture



67.4471

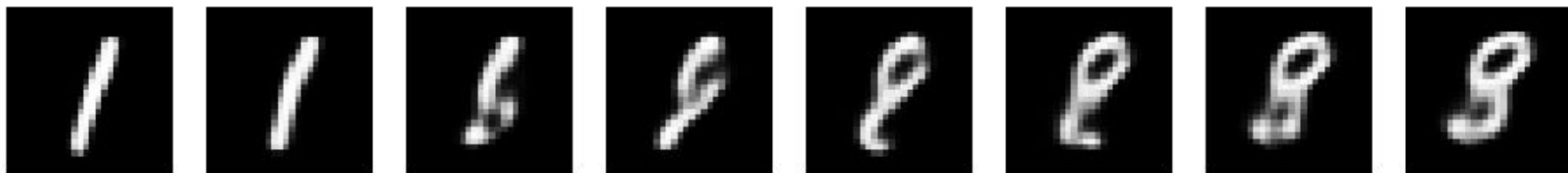
Evaluated Loss

Interpolation example (8 steps)

start original digits end



interpolated digits



Our proposed solution/model and Difference from related work.

4. Finally we will try to use the **Attention model** alongside RNN Encoder-Decoder model:

A potential issue with this encoder–decoder approach is that a neural network needs to be able to compress all the necessary information of a source information into a fixed-length vector. This may make it difficult for the neural network to cope with long or big images, especially those that are larger than the images in the training corpus.

Attention model is proposed as a solution to this limitation.

Achievements

- ✓ FC layers.
- ✓ Conv + Up Sampling.
- ✓ Conv + TransposeConv.
- ✓ Conv + FC + Up Sampling.
- ✓ Conv + FC + Transpose Conv.
- ✓ Using different datasets
- ✓ Variational AutoEncoders.
- ✓ RNNs + VAE
 - Attention Model
 - Apply nearest neighbour to be done.

What we have
achieved so far.

Thanks !