# Intro to Neural Networks

BA865 – Mohannad Elhamod

BOSTON UNIVERSITY

# Auto-Encoders

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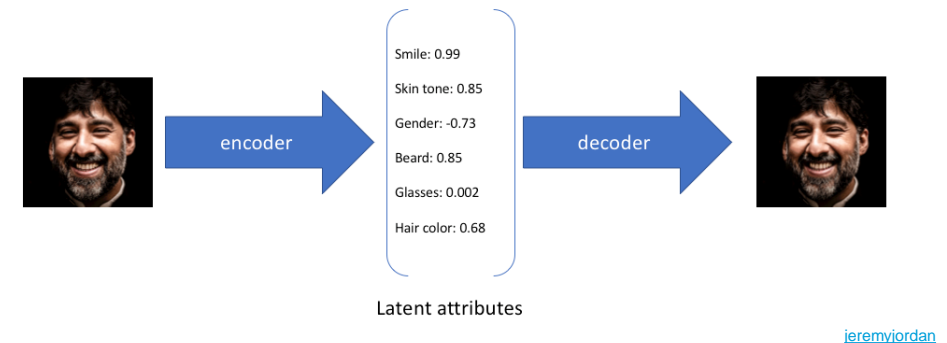
# Auto-Encoder

- Given an input, we want to learn a representation (i.e., code, embedding)
- This embedding is the compressed version of the data. It contains the "essential" information in the image.
- The embedding should be sufficient to obtain the desired reconstruction.

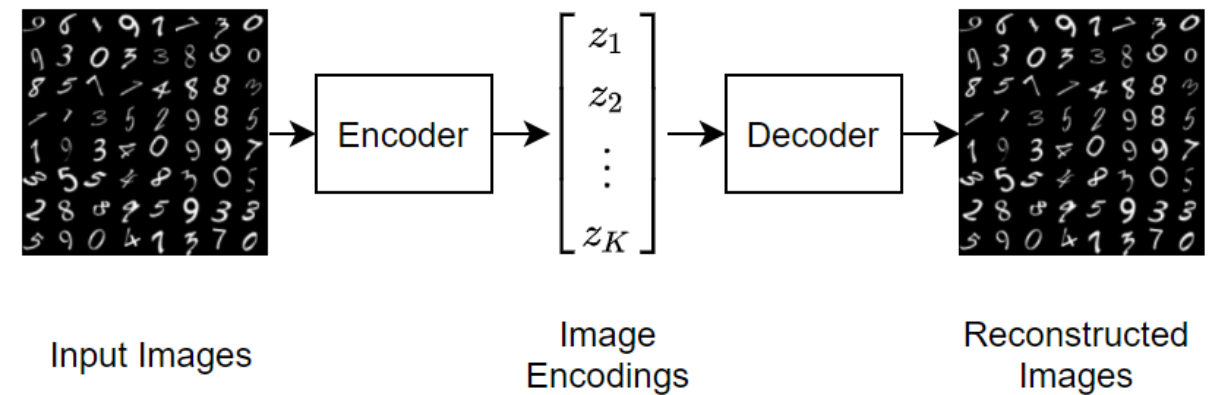**Boston University** Questrom School of Business

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Input Images        Image Encodings        Reconstructed Images



Latent attributes

jeremyjordan

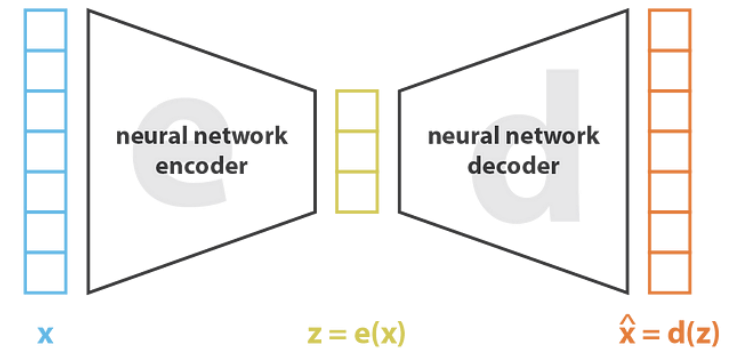**Boston University** Questrom School of Business
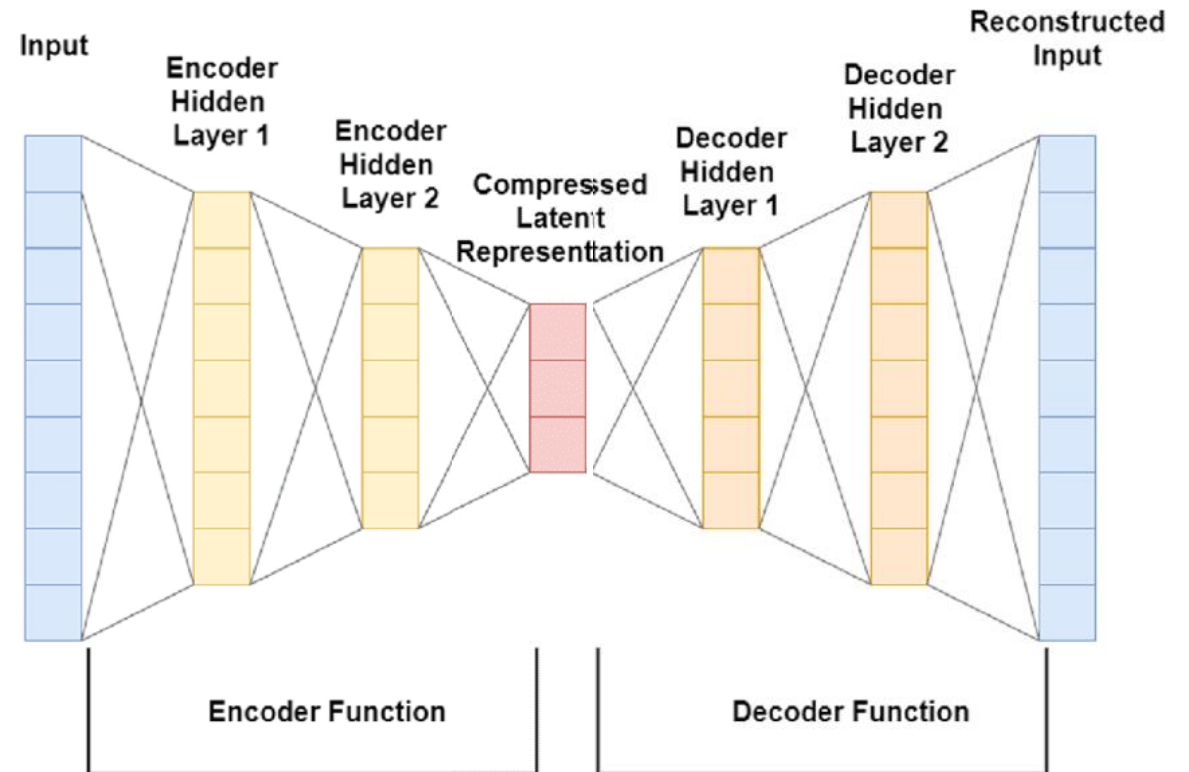
# Auto-Encoder

- The embedding is essentially a compressed form of the image.
- It is a *non-linear* dimensionality reduction method.

Linear vs nonlinear dimensionality reduction



Herminarto Nugroho

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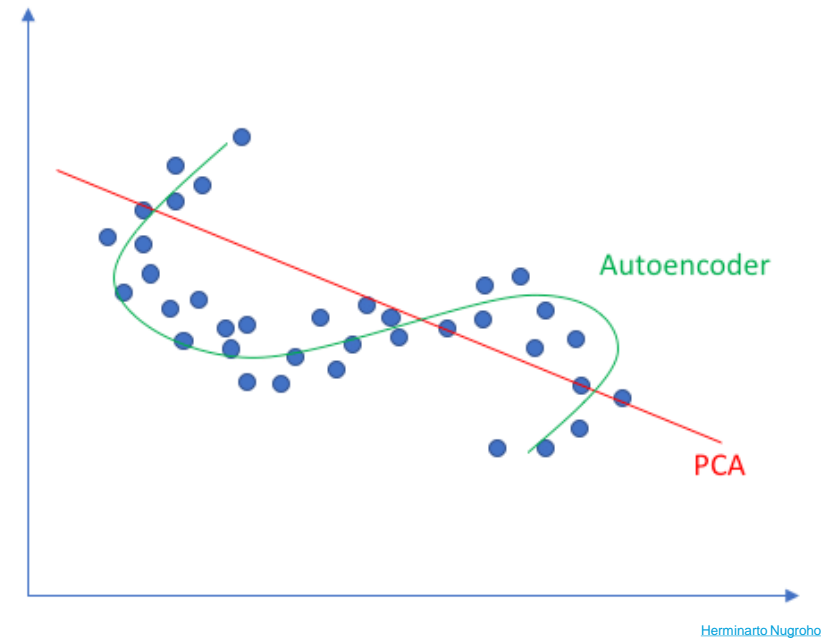
# The Error Function

- ## The error is the *"reconstruction loss"*
  - ### The MSE between the input and the output.



$$\text{loss} = || x - \hat{x} ||^2 = || x - d(z) ||^2 = || x - d(e(x)) ||^2$$
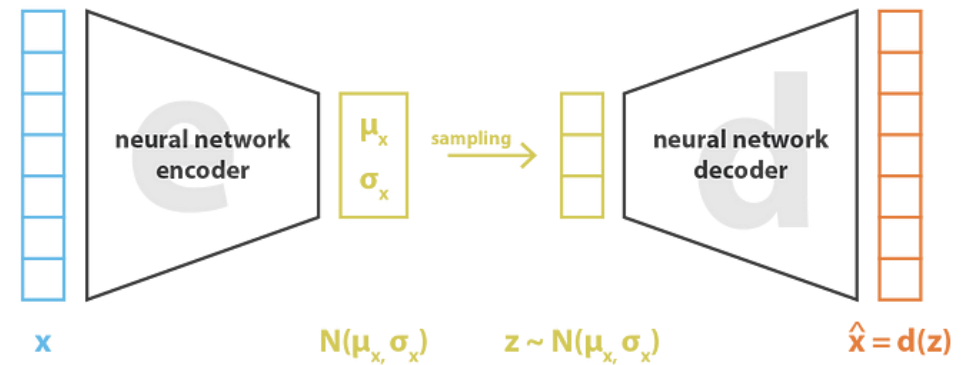
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# The Auto-Encoder as a Generator

- Once the model is trained, we could use the decoder to generate new content!



training process

encoder
**e**

input

encoded vector
(in latent space)

generation process

sampler

sampled vector
(from latent space)

decoder
**d**

decoded content

(reconstructed input /
generated content)
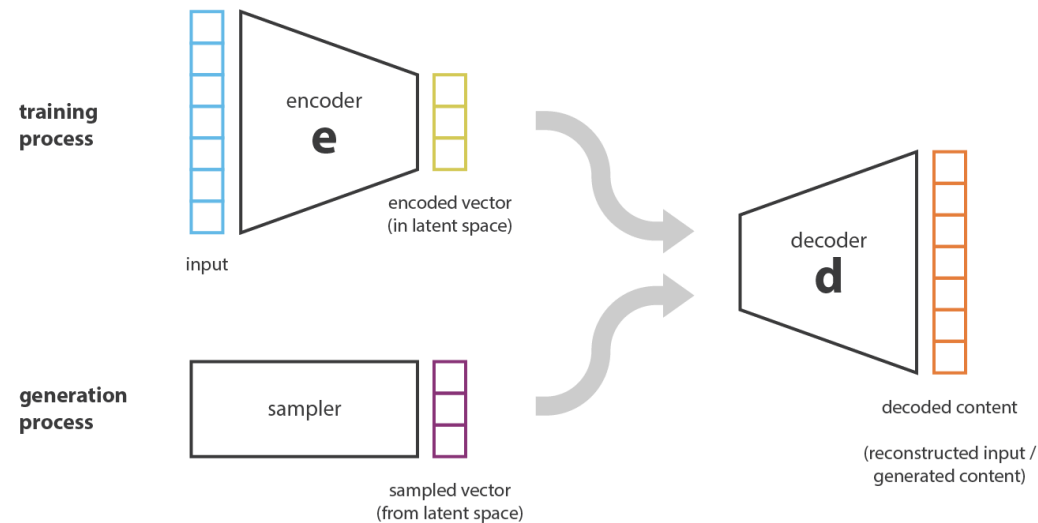
# Variational Auto-Encoder

- What if I want the embedding to follow a nice Gaussian distribution
- [Demo](#)



$$loss = \| x - \hat{x} \|^2 + KL[\, N(\mu_x, \sigma_x), N(0, I)\,] = \| x - d(z) \|^2 + KL[\, N(\mu_x, \sigma_x), N(0, I)\,]$$

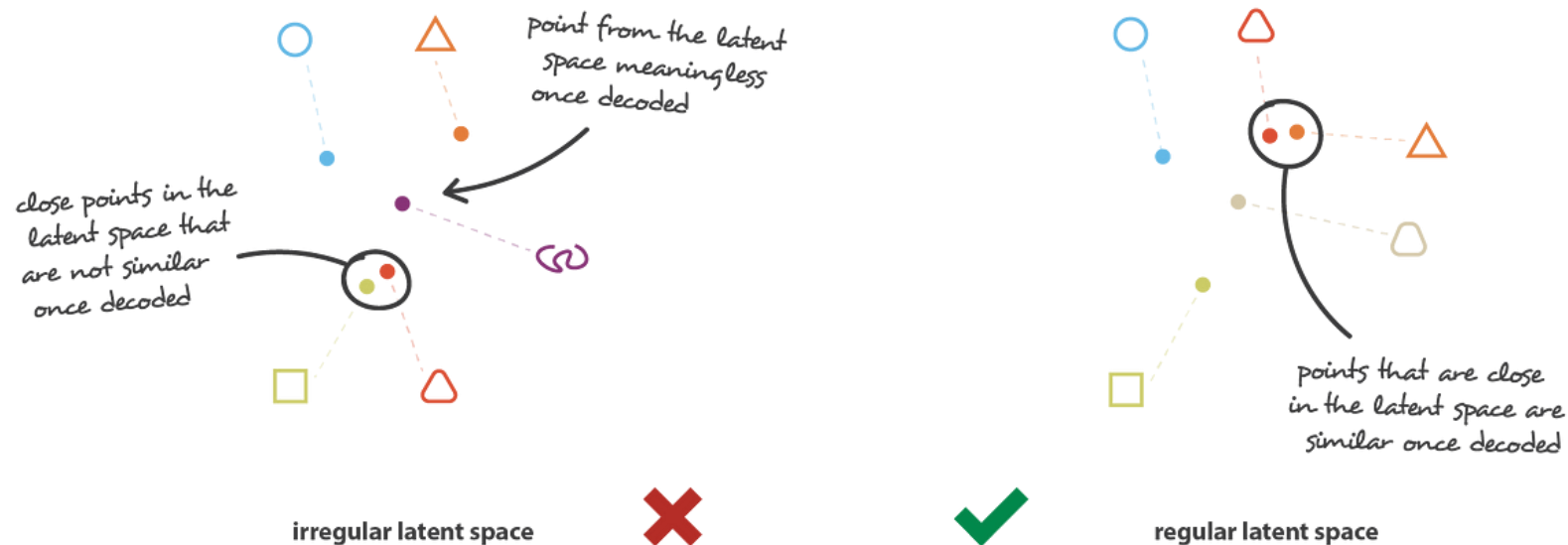Joseph Rocca

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# Variational Auto-Encoder

- Consequently, a traversal of the latent space would lead to smoother transitions in the reconstructed data.



what can happen without regularisation ❌    ✔️ what we want to obtain with regularisation

Joseph Rocca

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# Variational Auto-Encoder

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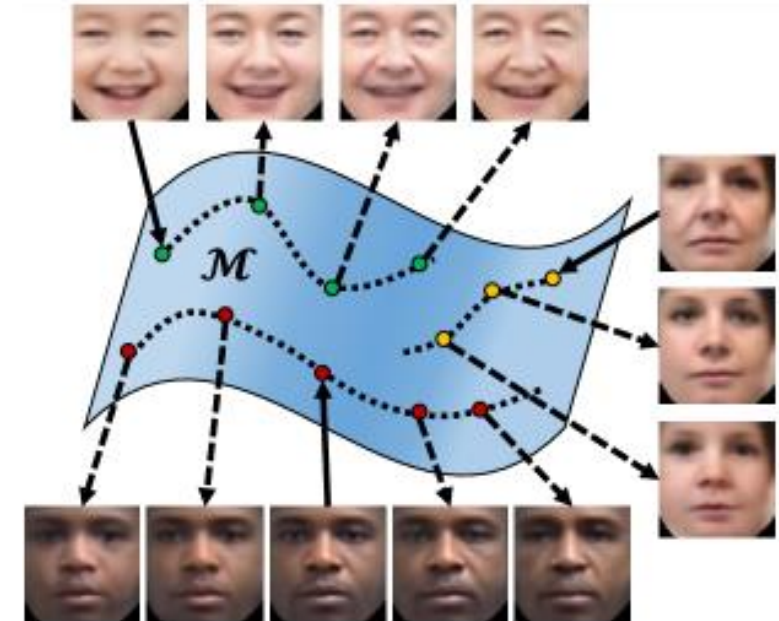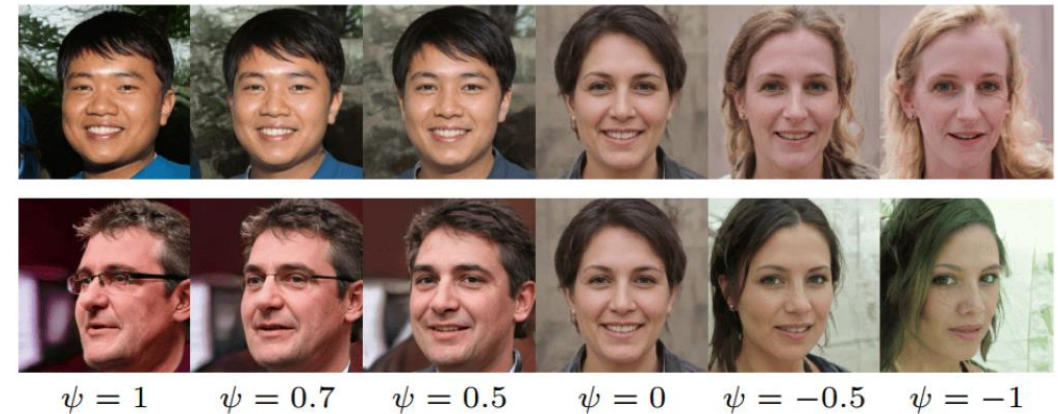
# Manipulating The Embedding

- Traversing the embedded space in certain specific directions will lead to interesting changes in the image:

  - Age, hair color, etc.

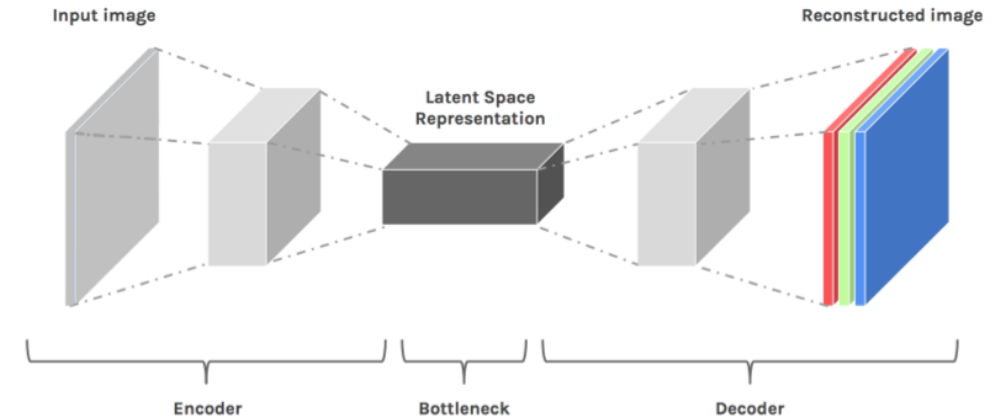- This is similar to the concept of directionality in word embeddings.



Zhang et al.

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# Manipulating The Embedding

- You could even interpolate between images ([Demo](#), [Video](#)).
  - Or even styling an image ([Demo](#))





$\psi = 1$    $\psi = 0.7$    $\psi = 0.5$    $\psi = 0$    $\psi = -0.5$    $\psi = -1$

[Karras et al.](#)

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# Image Modification

- Instead of reconstructing the image, you could modify it (e.g., BW to colored).
- The loss here would be simply the error between the original colored image and the generated colored image (e.g., MSE).



becominghuman.ai
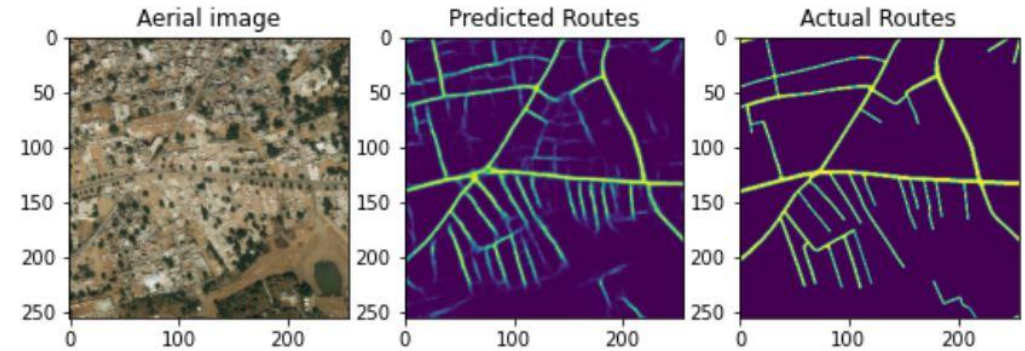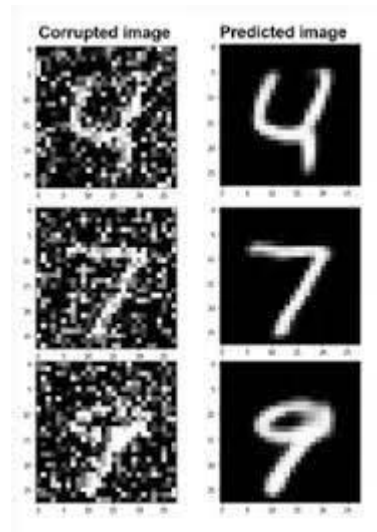
# Image Modification

Sketch2pix

IMAGE COLORING

Before | After

Corrupted image | Predicted image

Aerial image | Predicted Routes | Actual Routes

Semantic segmentation

- **Note: some of these models are more complex than just an auto-encoder. But the main idea of embedding/encoding applies**

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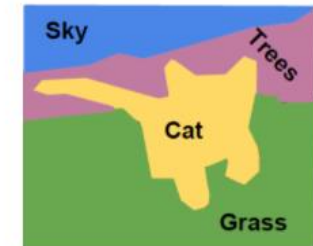UNIVERSITY

# Debugging Neural Nets

# Results are bad?

- Check against a benchmark!
  - paperswithcode.com
  - kaggle.com

- Are you overfitting or underfitting?

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# How do I improve my results?

- Best way: Get more **<u>GOOD</u>** data
  - If not, clean-up existing data.

- Are you overfitting or underfitting?
  - <u>Overfitting:</u> get more data, use a less complex model, regularization, or transfer learning.
  - <u>Underfitting:</u> get a more complex model.

- Keep it simple!
  - Start with a simple model, simple data, simple code.
  - Test by component (e.g., loss, forward pass, etc.).
  - Test by example (e.g., outliers).
  - Always use CPU in early development to avoid burning through compute units.

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