Intro to Neural Networks

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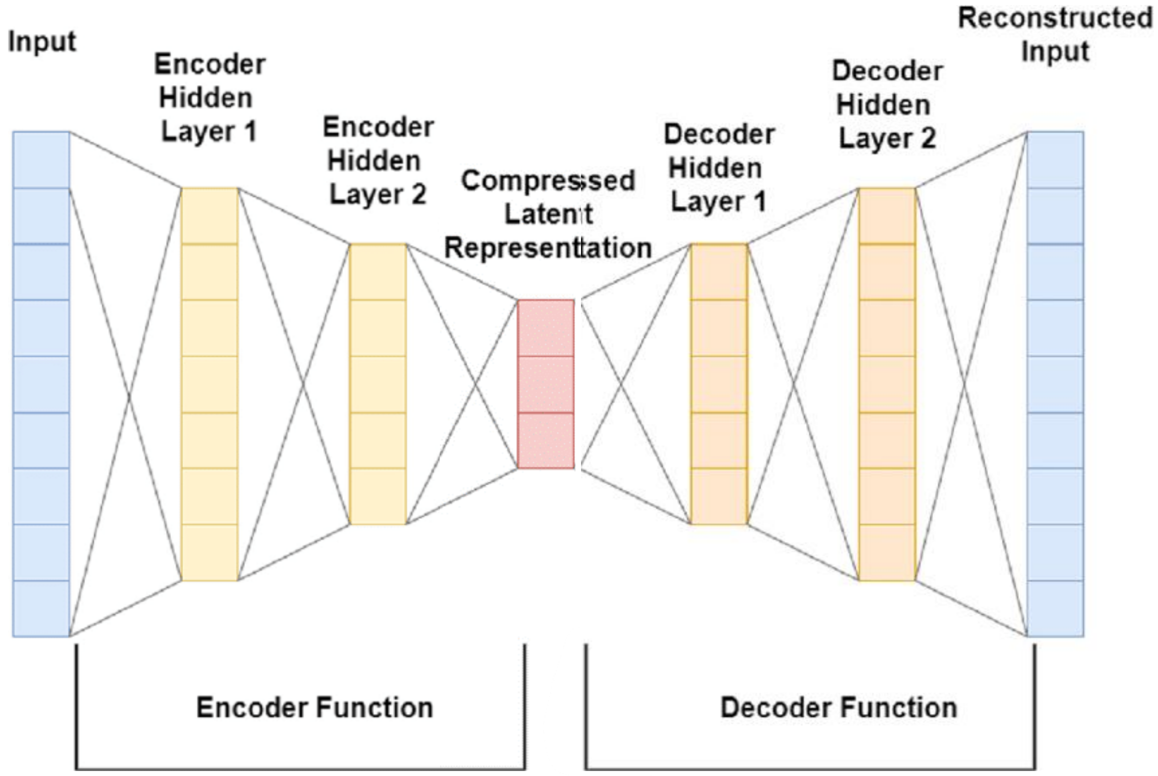
Auto-Encoders

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.



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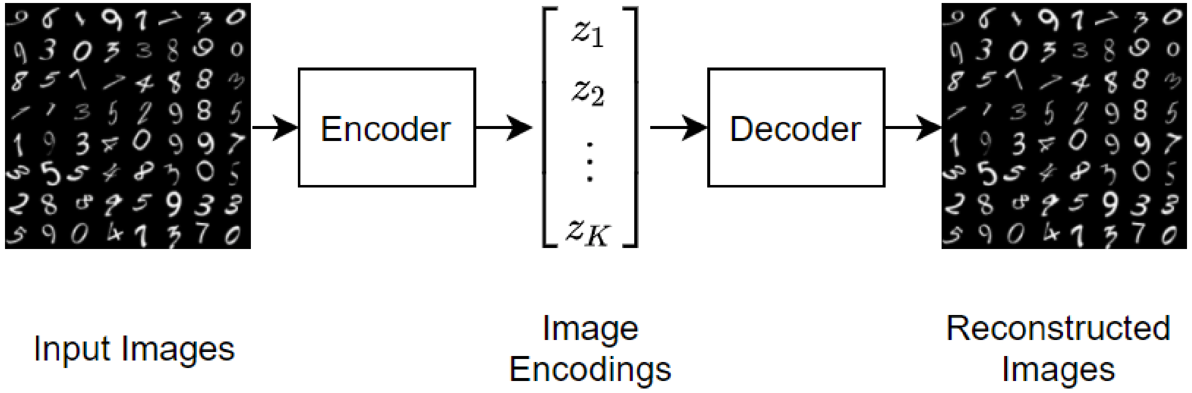
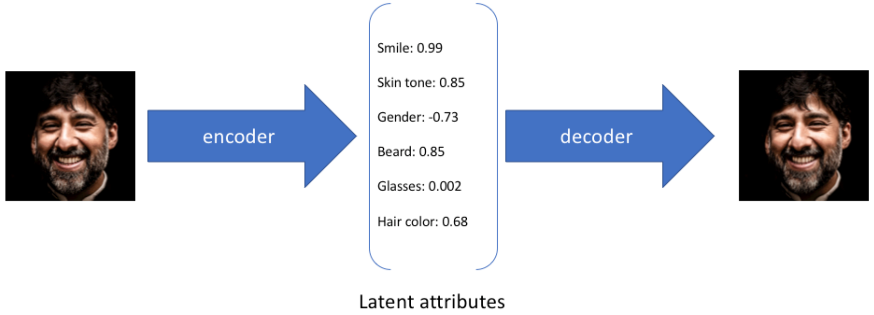


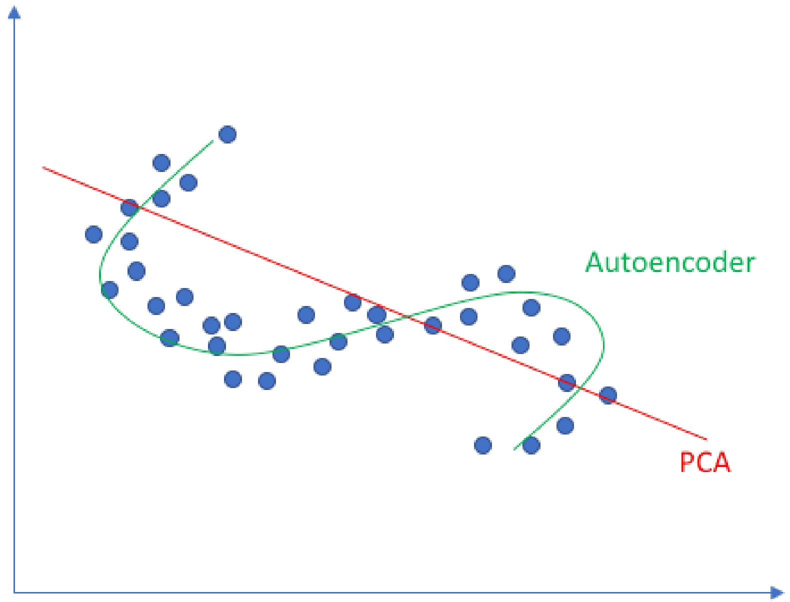


jeremyjordan

Auto-Encoder

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

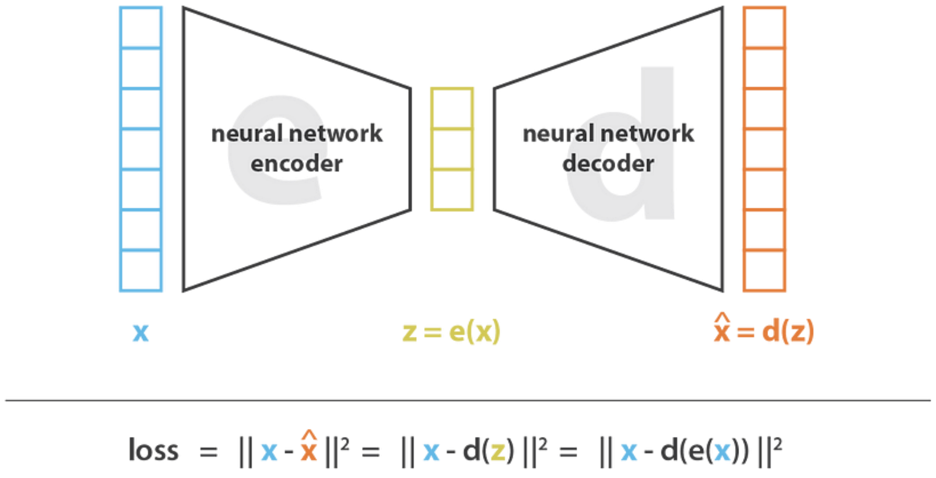
Linear vs nonlinear dimensionality reduction



Herminarto Nugroho

The Error Function

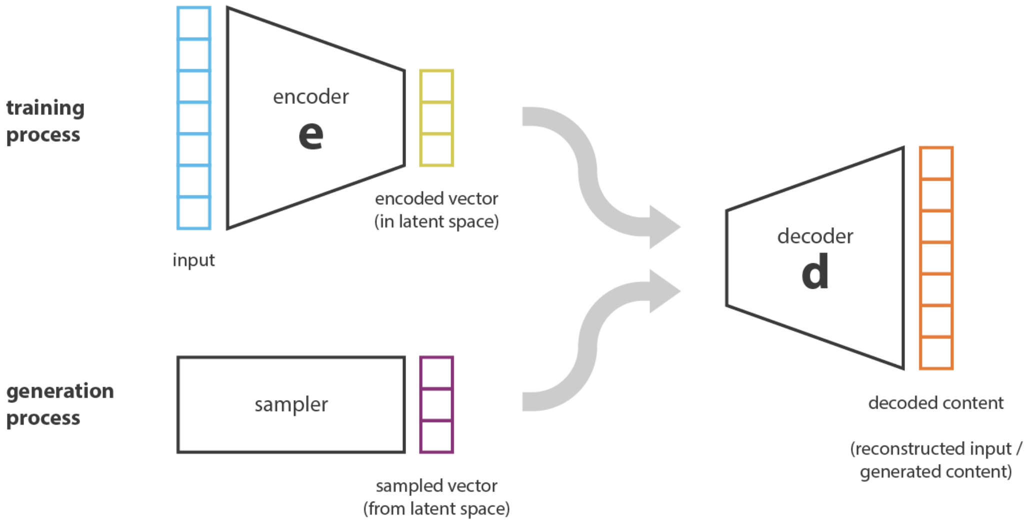
- The error is the *"reconstruction loss"*
  - The MSE between the input and the output.



Joseph Rocca

The Auto-Encoder as a Generator

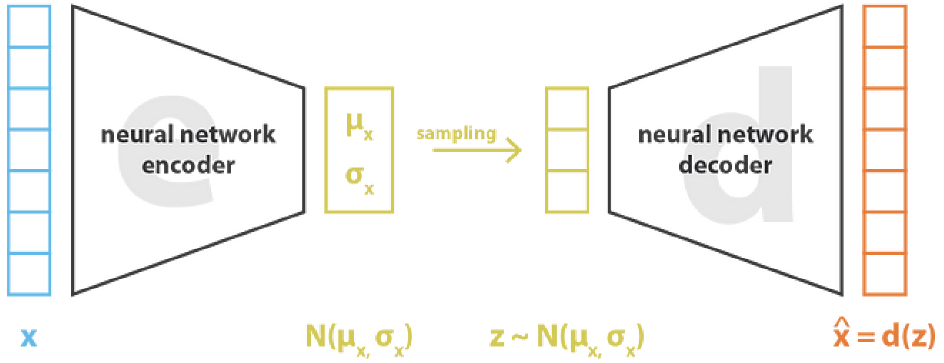
- Once the model is trained, we could use the decoder to generate new content!



Joseph Rocca

Variational Auto-Encoder

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

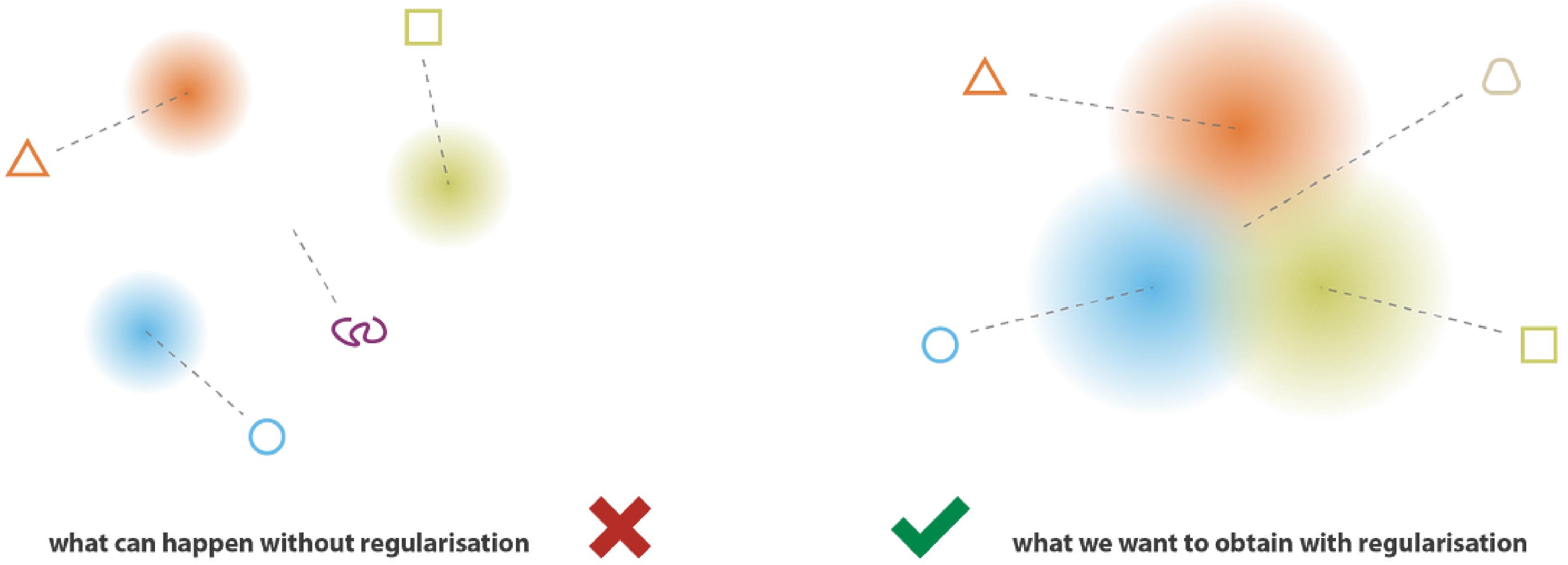


$$\text{loss} = \| x - \hat{x} \|^2 + \text{KL}[\, N(\mu_x, \sigma_x), N(0, I)\,] = \| x - d(z) \|^2 + \text{KL}[\, N(\mu_x, \sigma_x), N(0, I)\,]$$

[Joseph Rocca]

Variational Auto-Encoder

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



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Variational Auto-Encoder

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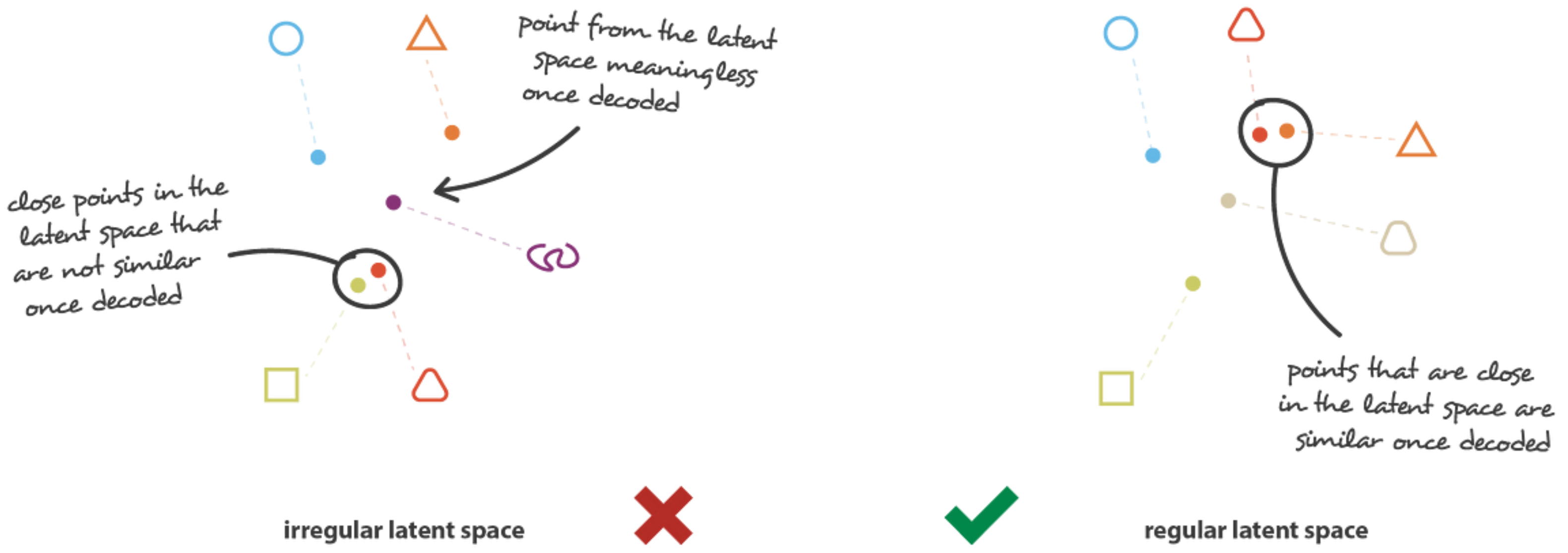
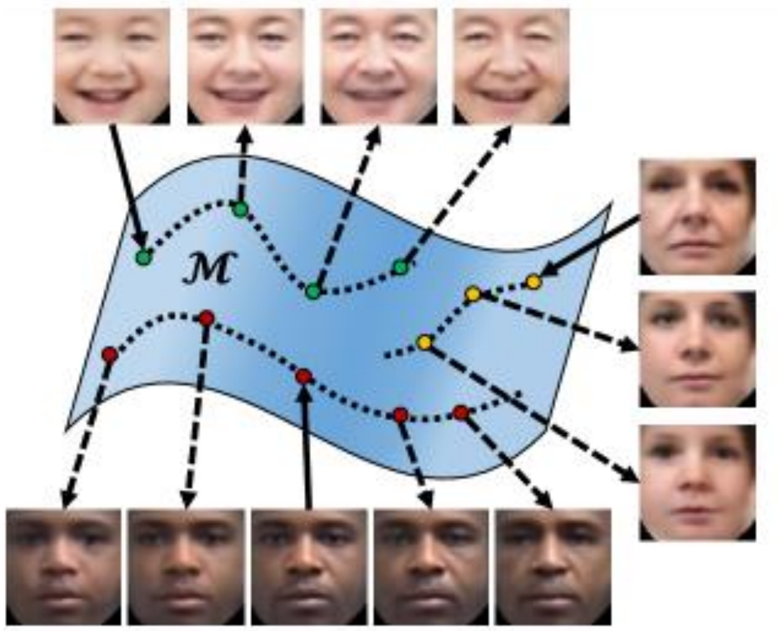


Joseph Rocca

Manipulating The Embedding

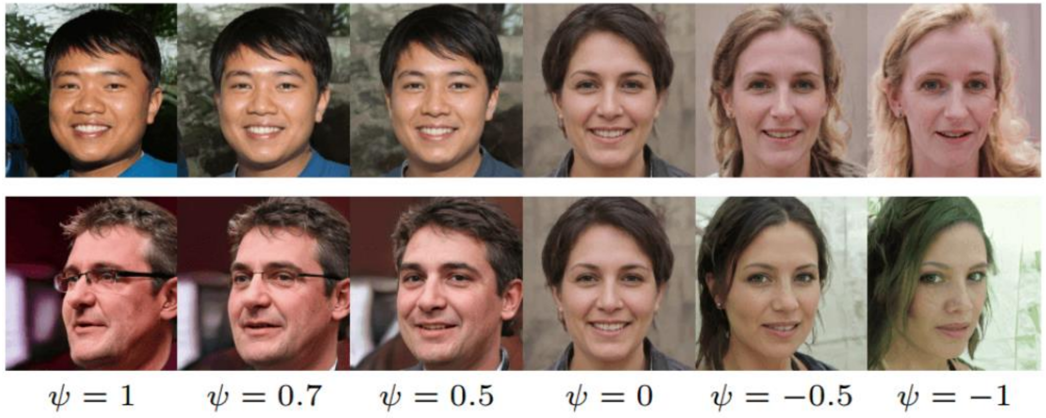
- Traversing the embedded space in certain specific directions will lead to interesting changes in the image:
  - Age, hair color, etc.
- This is similar to the concept of directionality in word embeddings.



Zhang et al.

Manipulating The Embedding

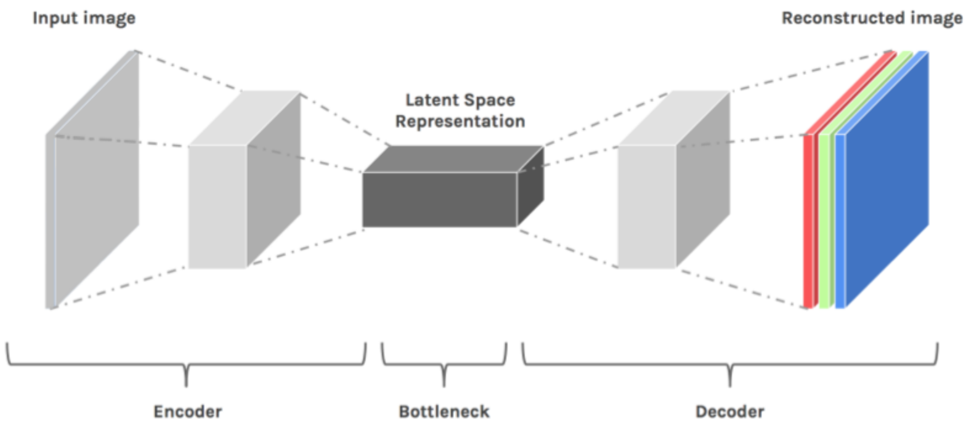
- Linear interpolation is not interesting.
- Interpolating between images using deep learning is much smoother (Demo, Video).
  - You can even styling an image (Demo)



Karras et al.

Image Modification

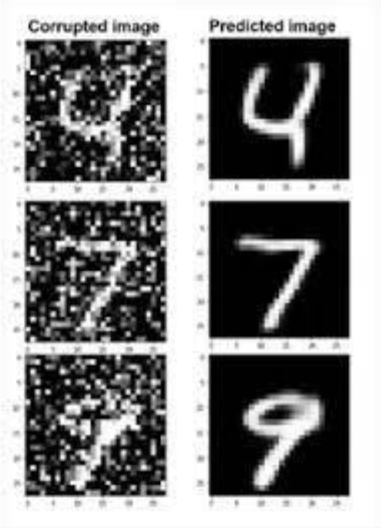
- Instead of reconstructing the image, you could modify it (e.g., BW to colored).
- The loss here would be simply the error between the original colored image and the generated colored image (e.g., MSE).

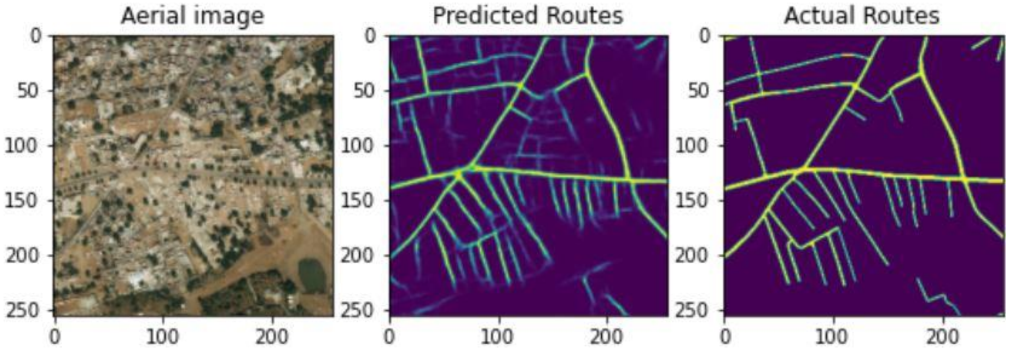


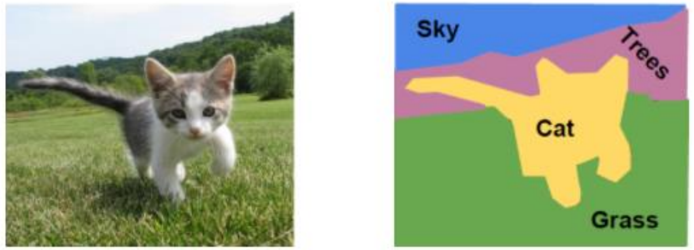
becominghuman.ai

Image Modification

[Sketch2pix]







Semantic segmentation

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

Debugging Neural Nets

Results are bad?

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

- Are you overfitting or underfitting?

How do I improve my results?

- Best way: Get more GOOD data
  - If not, clean-up existing data.
- Are you overfitting or underfitting?
  - Overfitting: get more data, use a less complex model, regularization, or transfer learning.
  - Underfitting: 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.