Part 3:
Designing the Interfaces
…

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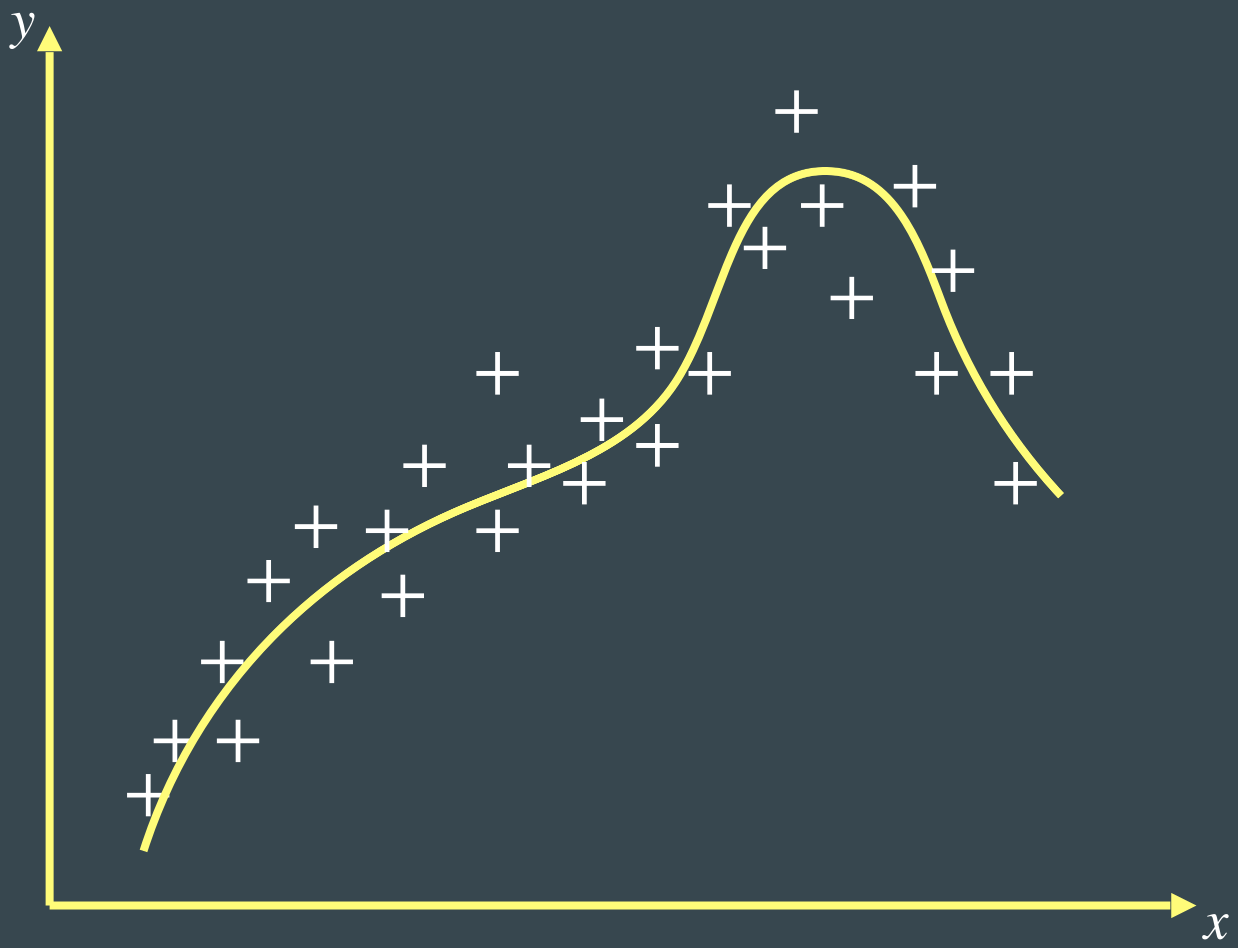
Regression: value to value



$x \in (-\infty, +\infty)$

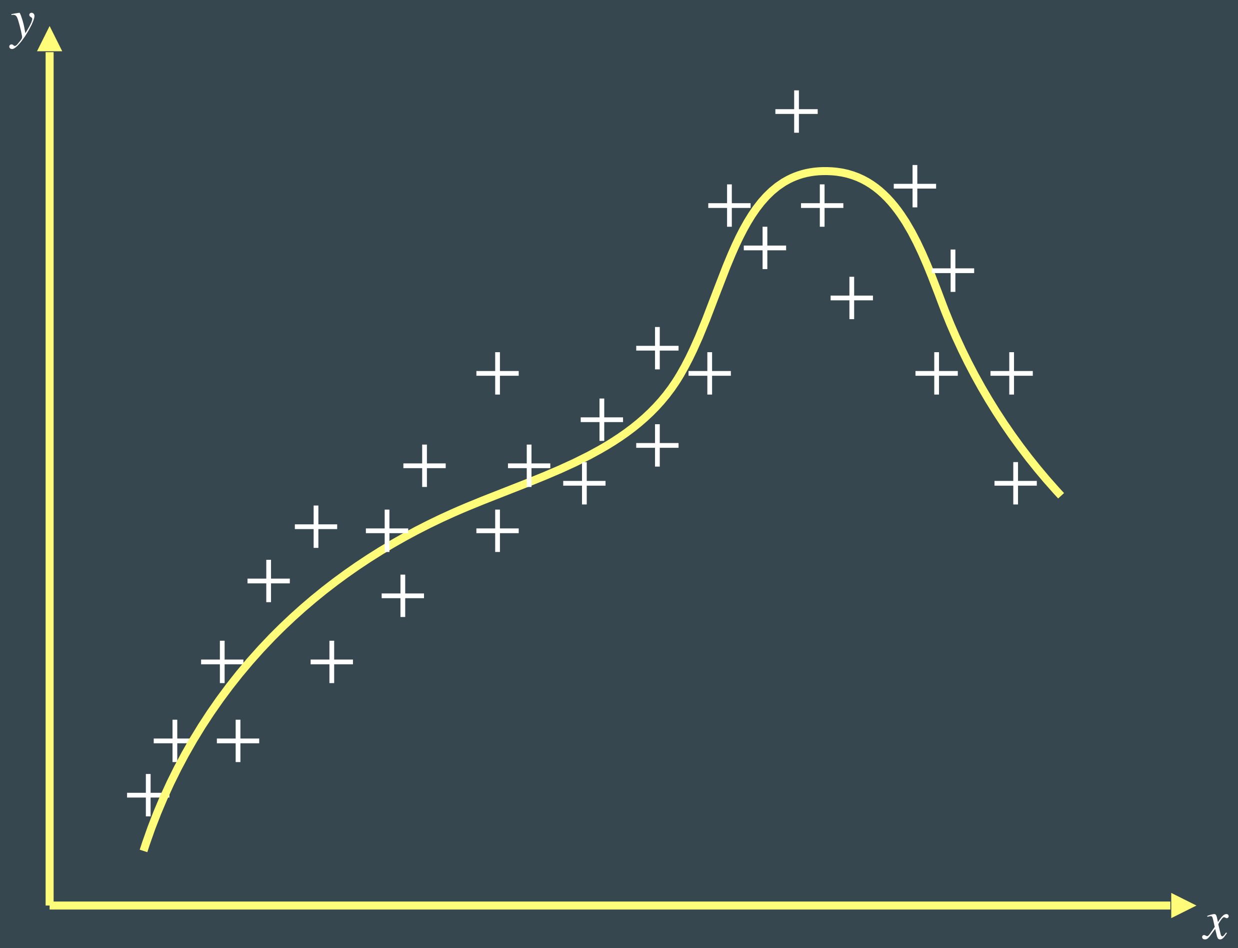
$y \in (-\infty, +\infty)$

$L(y_s, \hat{y}_s)$

$SE(y_s, \hat{y}_s) = (y_s - \hat{y}_s)^2$

$AE(y_s, \hat{y}_s) = \ y_s - \hat{y}_s$

Regression: vector to vector



$\mathbf{x} \in \mathbb{R}^N$ $\mathbf{y} \in \mathbb{R}^N$

$L(\mathbf{y}_s, \hat{\mathbf{y}}_s)$

$SE(\mathbf{y}_s, \hat{\mathbf{y}}_s) = \|y_s - \hat{y}_s\|_2^2$

$AE(\mathbf{y}_s, \hat{\mathbf{y}}_s) = \|y_s - \hat{y}_s\|_2$

Classification: Binary

$\mathbf{x} \in \mathbb{R}^N$ $\qquad y \in \mathbb{R}$ $\qquad p \in (0,1)$

Cat: Yes or No? (1 / 0)

$$\mathbf{x} \rightarrow \boxed{\text{Network}} \rightarrow y \rightarrow \sigma \rightarrow p$$

$$\sigma(z) = \frac{1}{1 + \exp(-z)} \qquad \sigma'(z) = \sigma(z)(1 - \sigma(z))$$

$$BCE(p_s, t_s) = -\, t_s \log p_s - (1 - t_s)\log(1 - p_s)$$

$$\frac{\partial\, BCE\left(\sigma(z_s), t_s\right)}{\partial z_s} = \left(t - \sigma(z_s)\right)$$

Classification: Binary

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$$\frac{\partial\ BCE\left(\sigma(z_s), t_s\right)}{\partial z_s} = \left(t - \sigma(z_s)\right)$$

$$MSE(p_s, t_s) = \left(\sigma(z_s) - t_s\right)^2$$

$$\frac{\partial\ MSE\left(\sigma(z_s), t_s\right)}{\partial z_s} = \left(t - \sigma(z_s)\right) \sigma(z_s)(1 - \sigma(z_s))$$

Classification: Complementary Multiclass

$\mathbf{x} \in \mathbb{R}^N$ $\qquad$ $\mathbf{y} \in \mathbb{R}$ $\qquad$ $p \in (0,1)$

$$\mathbf{x} \rightarrow \boxed{\text{Network}} \rightarrow \begin{bmatrix} y_{cat} \\ y_{dog} \\ y_{mouse} \end{bmatrix} \rightarrow \sigma \rightarrow \begin{bmatrix} p_{cat} \\ p_{dog} \\ p_{mouse} \end{bmatrix}$$

$$\sigma(z) = \frac{1}{1 + \exp(-z)} \qquad \sigma'(z) = \sigma(z)(1 - \sigma(z))$$

$$BCE(p_s, t_s) = -\, t_s \log p_s - (1 - t_s)\log(1 - p_s)$$

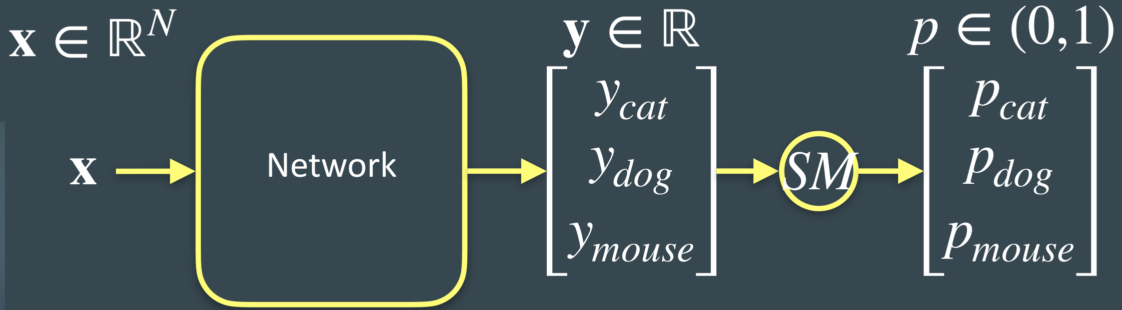
$$\frac{\partial\, BCE\left(\sigma(z_s), t_s\right)}{\partial z_s} = \left(t - \sigma(z_s)\right)$$

Cat: Yes or No? (1 / 0)

Dog: Yes or No? (1 / 0)

Mouse: Yes or No? (1 / 0)

Classification: Adversarial Multiclass



$$SM_c = \frac{\exp(z_c)}{\sum_{k=1}^{K} \exp(z_k)}$$

$$\sigma'(z) = \sigma(z)(1 - \sigma(z))$$

$$CE(p_s, t_s) = -\sum_{c=1}^{C} t_c \log p_c$$

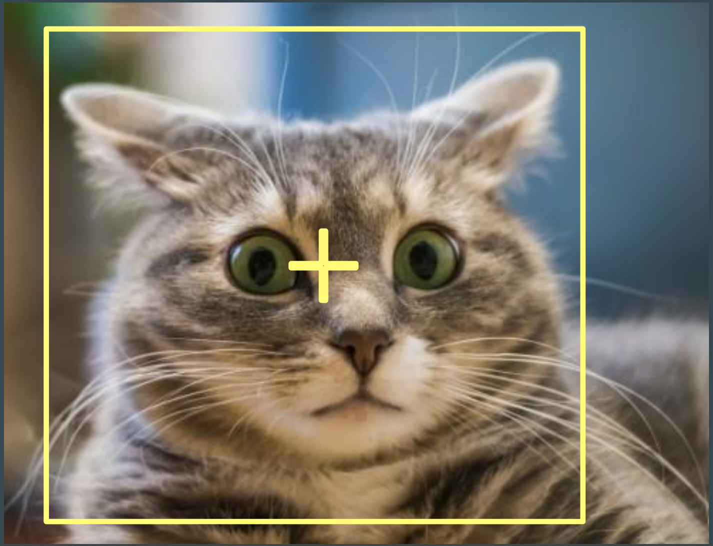
$$\frac{\partial\ CE\left(\mathbf{SM(z)}, \mathbf{t}\right)}{\partial \mathbf{z}} = \left(\mathbf{t} - \mathbf{SM}\right)$$

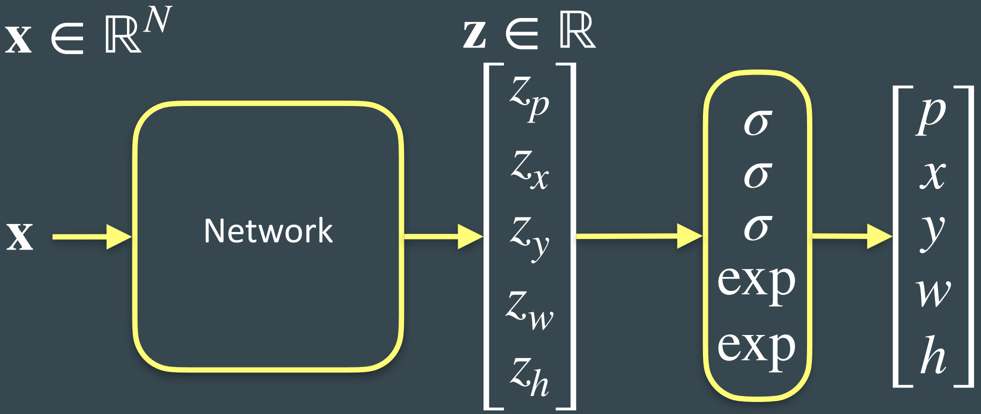
Cat: Yes or No? (1 / 0)

Dog: Yes or No? (1 / 0)

Mouse: Yes or No? (1 / 0)

Detection: One Object





$p: \quad BCE(p, I)$

$x: \quad BCE(x, \hat{x})$

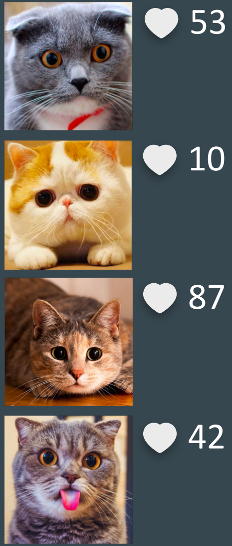
$y: \quad BCE(y, \hat{y})$

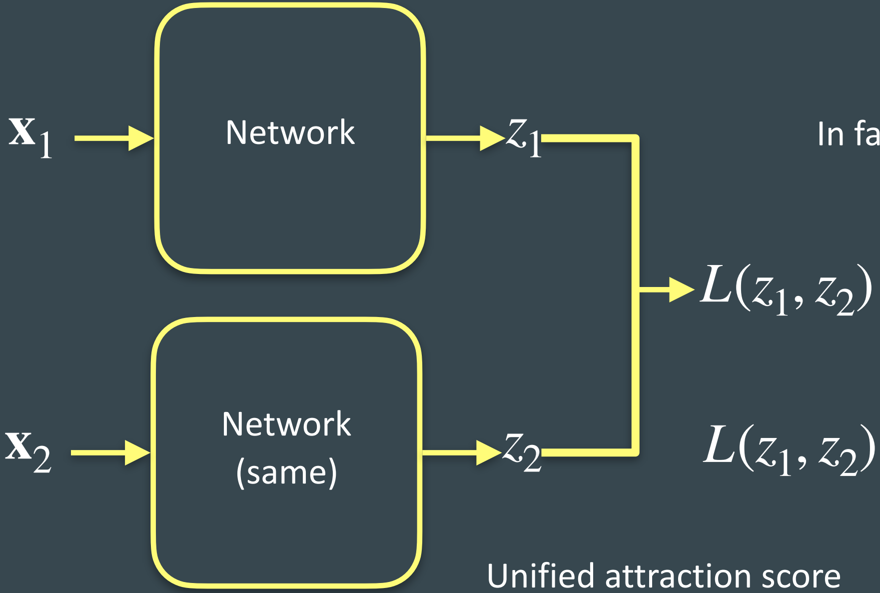
$w: \quad MSE(\log w - \log \hat{w})$

$h: \quad MSE(\log h - \log \hat{h})$

$$\begin{aligned} L = {} & BCE(p, I) + \\ & I \cdot BCE(x, \hat{x}) + \\ & I \cdot BCE(y, \hat{y}) + \\ & I \cdot MSE(\log w, \log \hat{w}) + \\ & I \cdot MSE(\log h, \log \hat{h}) \end{aligned}$$

Learning to Rank



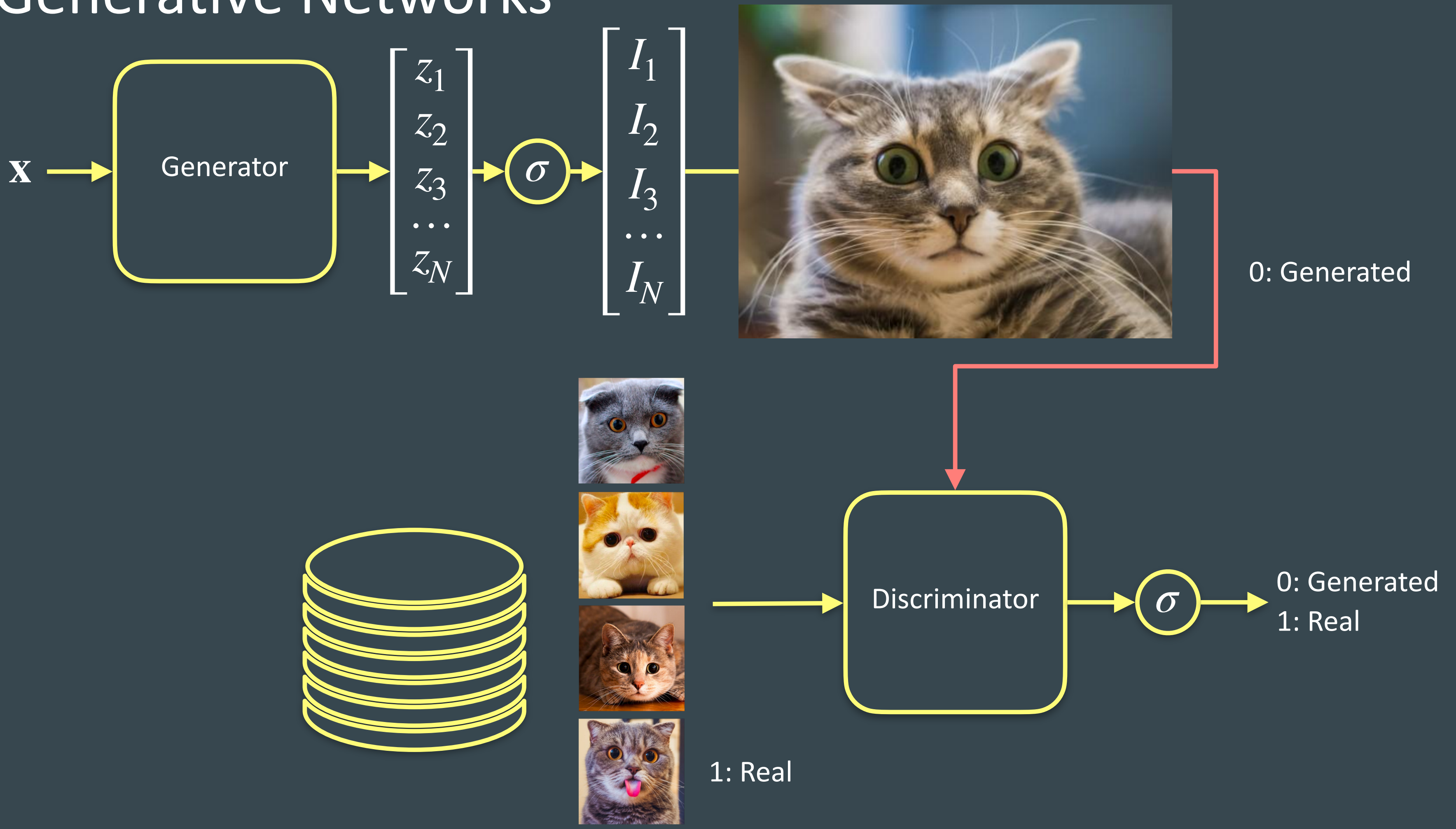


In fact, image #2 has more likes than #1

$$L(z_1, z_2) = \max\left(0,\ M - \quad z_2 - z_1 \quad\right)$$

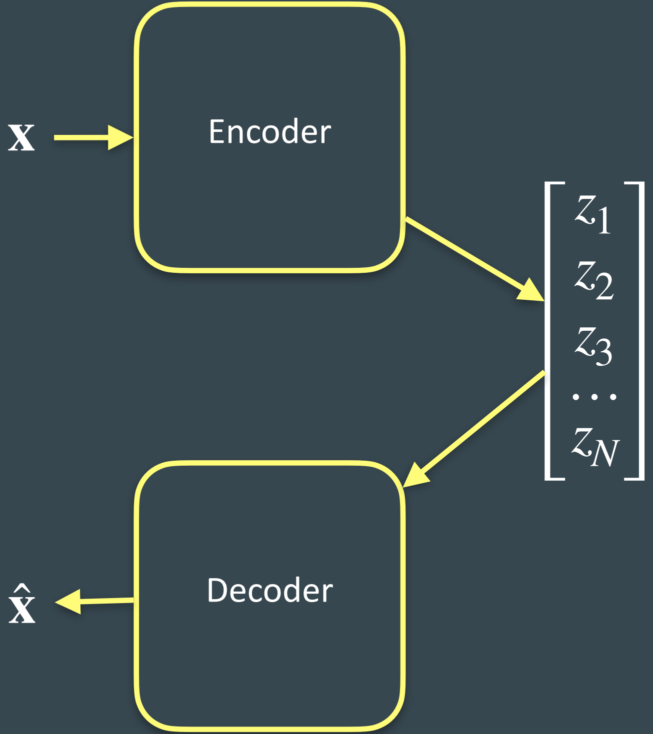
Unified attraction score

Generative Networks



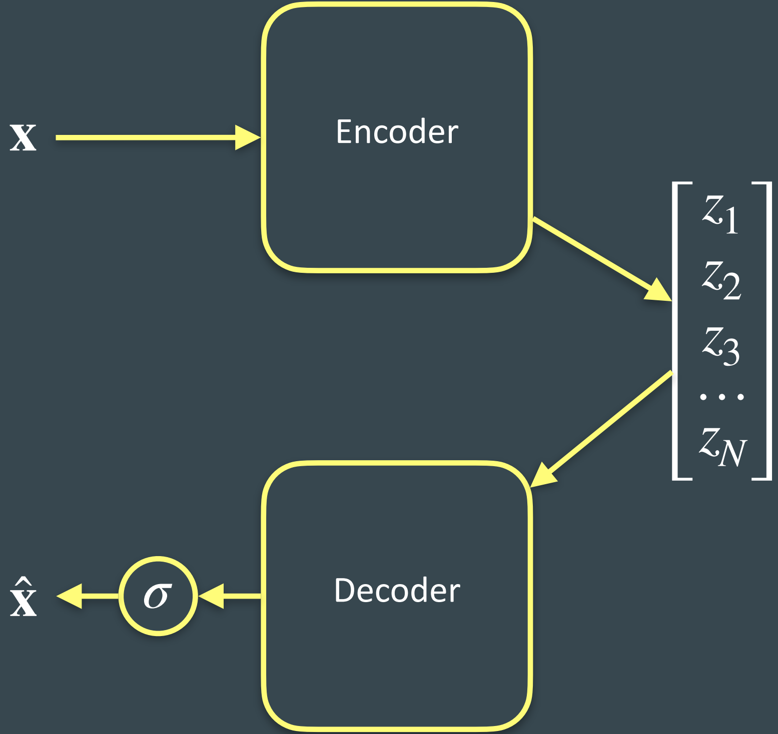
AutoEncoders: Dimensionality Compression

$$L(I^1, I^2) = \sum_{pix} MSE(I^1_{pix}, I^2_{pix})$$

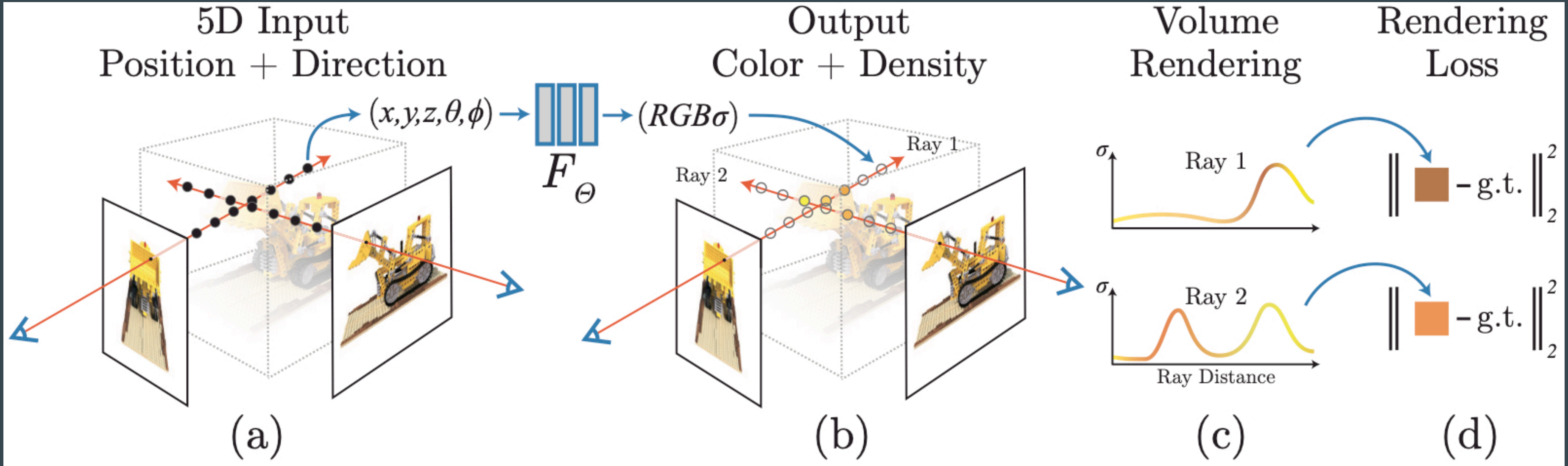


AutoEncoders: Dimensionality Compression

$$L(I^1, I^2) = \sum_{pix} BCE(I^1_{pix}, I^2_{pix})$$



Neural Radiance Fields



- Use the Neural Network as 3D model of an object!

Summary

- Binary Classification
- Multiclass Classification
- Regression
- Joint Regression and Classification: Detection
- Ranking
- Generative Adversarial Networks
- Autoencoders
- Neural Radiance Fields