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>
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Supervised Learning

- classification
- regression

but real world exit numerous unlabled datas

Unsupervised Learning

there exist three usual types of machine learning

- 'pure' reinforement learning

  interaction(交互) with the enviornment

  - need a few bits for some samples

- Supervised learning

  - 10 - 10,000 bits per sample

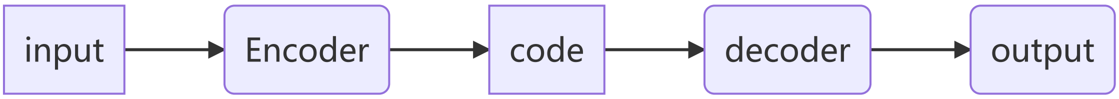
- Unsupervised/predictive learnign

  - millions bits per sample

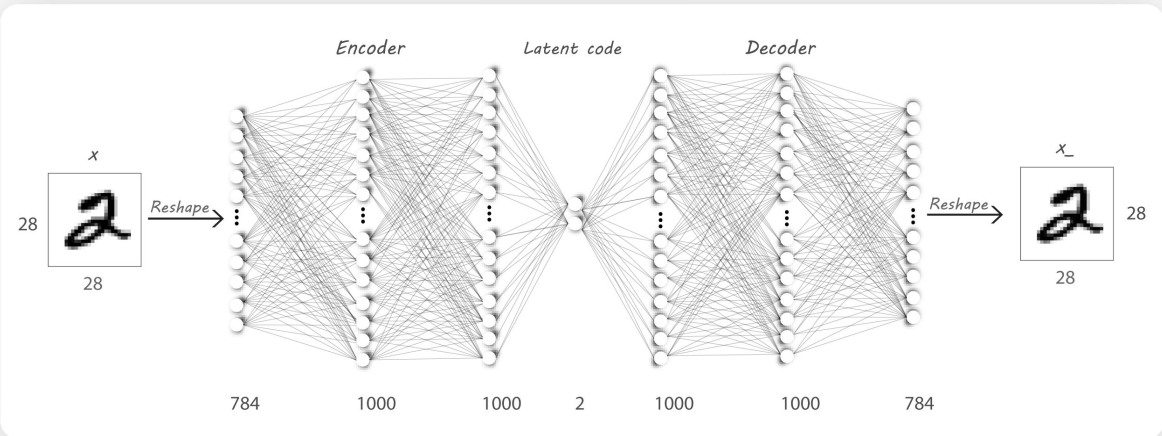
why we need unsupervised learning,

- - dimension reduction
  - Processing: Huge dimention, say 224 * 224, is hard to process(将224 * 224 降为低维)
  - Visualization: projector.tensorflow.org
  - Compression, denosing, super-resolution(超分辨率)

Auto-Encoder



the aim of auto encoder is reconstract(重建) the output same as the input via the encoder process and decoder process. Encoder process encode the input into a low dimension, and the decoder can be used for reform the result from the coded feature.



it could use to increase or decrease the feture by the **latent code** (井)

How to train?

- loss function for binary inputs(二进制文件，如 Mnist 数据集)
  - cross-entropy error function (reconstract loss) $f(x) \equiv \hat{x}$

$$l(f(x)) = -\sum_k (x_k log(\hat{x}) + (1 - x_k) log(\hat{x_k}))$$

- loss function for real-valued inputs
  - sum of square differences (reconstract loss)
  - we used a linear **activation function** at the output

$$l(f(x)) = \frac{1}{2}\sum_k(\hat{x_k} - x_k)^2$$

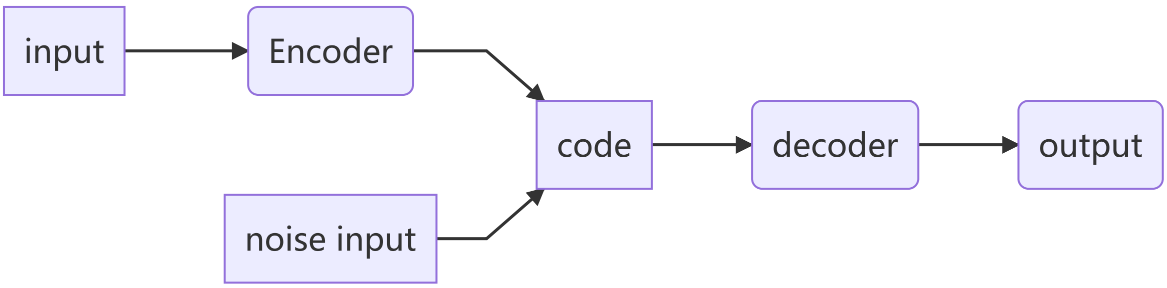
PCA V.S. Auto-Encoders

comparing to Auto-Encoders:

- PCA, which finds the directions of maximal variance in high-dimention data, select only those axes that have the largest variance.
- The linearity of PCA, however, places signicant limitations on the kinds of feature dimensions that can be extracted.(丢失很多信息)

Other Auto-Encoder

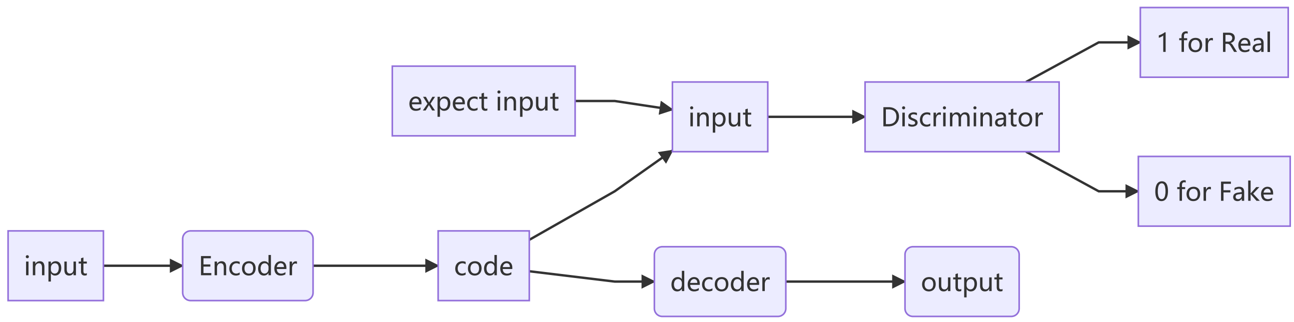
- Denosing AutoEncoder



- Dropout AutoEncders
- Adversarial AutoEncoders

Adversarial AutoEncoders

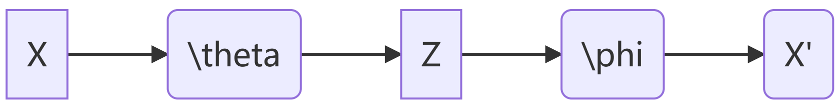
- distribution of higgen code



make the code submit to a specific ditribution.

Another Approach -- Variationnal Auto-Encoder

- Maximum likelihood similarity



$$l_i(\theta,\phi) = -E_{Z\sim q_\theta}(log[p_\phi(x_i|z))] + KL(q_\theta(z|x_i)||p(z))$$

$$KL(P||Q) = \int_{-\infty}^{\infty} p(x)log\frac{P(x)}{Q(x)}dx$$

for the first part , to reduced the reconstraction loss of auto encoders, KL use to describe the differce between two distribution, means to make the feature simular to the specific distribution.

Maximize Likelihood

realise the $E_{Z\sim q_\theta}(log[p_\phi(x_i|z))]$ part by:

- loss function for binary inputs(二进制文件，如 Mnist 数据集)
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$$l(f(x)) = -\sum_k (x_k log(\hat{x}) + (1 - x_k)log(\hat{x_k}))$$

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Minimize KL Divergence

$KL(q_\theta(z|x_i)||p(z))$

to calculate the $KL(q,p)$, we assume that

$$p(z_i) \sim N(\mu_1, \sigma_1^2)$$
$$q(z_i) \sim N(\mu_2, \sigma_2^2)$$

then,

$$\begin{aligned} KL(p,q) &= -\int p(x)log(q(x))dx + \int p(x)log(p(x))dx \\ &= \frac{1}{2}log(2\pi\sigma_2^2) + \frac{\sigma_1^2 + (\mu_1-\mu_2)^2}{2\sigma_2^2} - \frac{1}{2}(1 + log(2\pi\sigma_1^2)) \\ &= log\frac{\sigma_2}{\sigma_1} + \frac{\sigma_1^2 + (\mu_1-\mu_2)^2}{2\sigma_2^2} - \frac{1}{2} \end{aligned}$$

Though the loss function, what we get is not a determinate feature, rather a ditribution, so when we make a reconstraction, we have to make a 'sample' process to get a determinate feature vector. So, sample process is not differential.

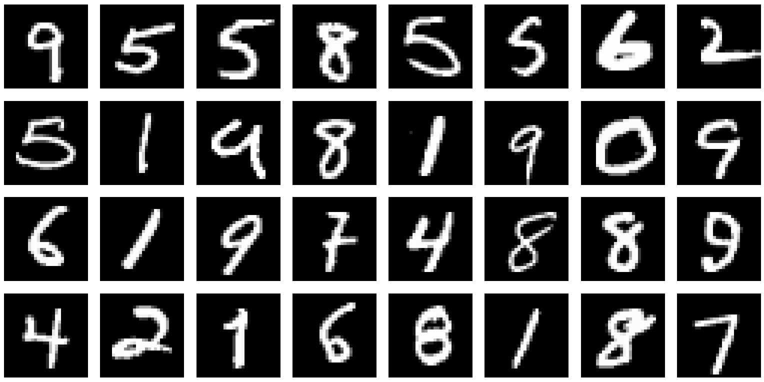
sample process is not differential

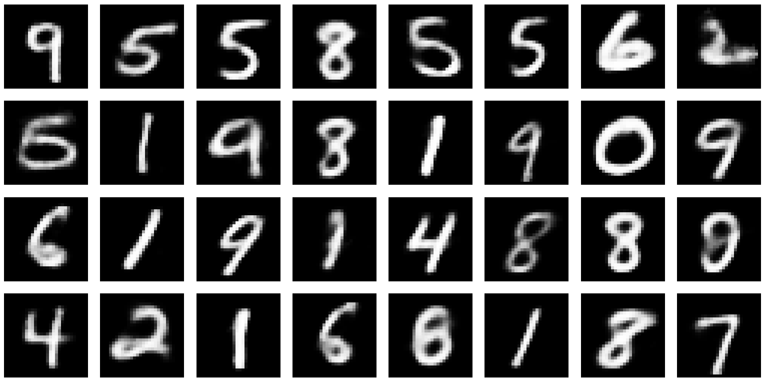
sample process is not differential, it hard to realize a back probagation. so ,we used a reparameterization trick

$$z \sim N(\mu, \sigma^2) \rightarrow z = \mu + \sigma \odot \epsilon, \quad \epsilon \sim N(0,1)$$

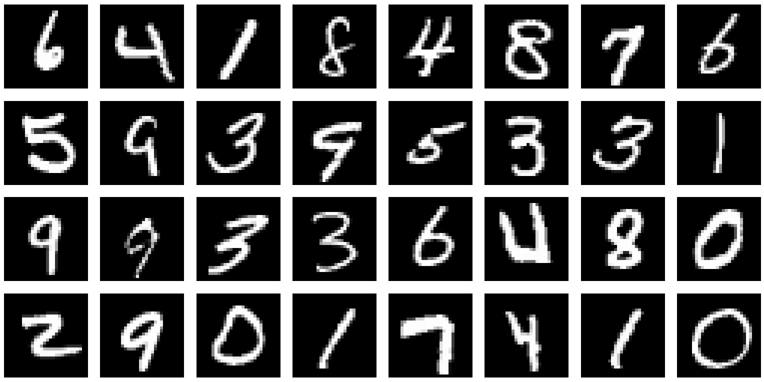
$\odot$ means dot product

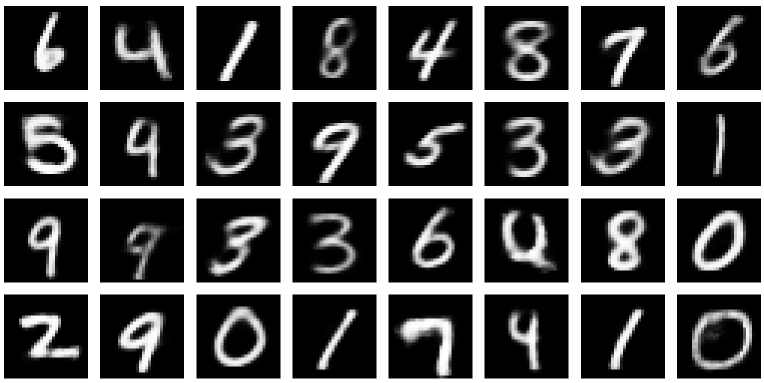
Result





the two pictures above are the origin pic and after AE pic





the two pictures above are the origin pic and after VAE pic