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Variational Auto Encoders

Vae are used to generate outputs which are similar to the inputs

this is achieved with the help of an encoder and a decoder

to generate an out we need to specify a latent variable which helps in the creation of a specific input let it be z .

this latent variable is then used as an input to the function $f(z;v)$ where v is a learnable parameter, which produces an output similar to input, we generally prefer it to be a gaussian distribution which has mean $f(z;v)$ and variance $\sigma^2 I$ (identity matrix).

we sample z from a distribution in which each dimension is a gaussian distribution with mean 0 and sd 1

but sampling z from such distribution is difficult we would like to have a function $q(z/x)$ which provides the output(desired gaussian form) basing on the input x which helps in giving a better set of values of z which depend on x

this function q helps us in sampling z from a smaller set of values of z which helps us as it removes the difficulty of $p(x/z)$ being 0 most of the time and reducing computation difficulty

the above step is the encoding part which provides us with $q(z/x)$ (preferably gaussian) which outputs us with 1)mean 2)variance(a covariance matrix)

this is then used to sample(gaussian distr.) and then used as an input to $f(z)$ to produce the output

the main difficulty here is that during backprop the loss cannot travel back to the encoder part as we are sampling from a gaussian distribution

this problem is solved with the help of reparameterization

here we take the output from the encoder(mean, covariance matrix), then we sample from a standard normal distribution $N(0,1)$ (let the variable be r), then we provide the input to the decoder as $r \cdot \text{variance}(\text{from encoder}) + \text{mean}(\text{from encoder})$

by the above step of reparameterization trick we can form a direct link between the encoder and the decoder which can be used during backprop

now as the output is gaussian $T(f(z;v), \sigma^2 I)$ where σ is a hyperparameter the negative log likelihood is directly proportional to the square of the distance between $f(z)$ and x but as in the example given in the paper we need to keep the σ very small so as to make the output more similar to input