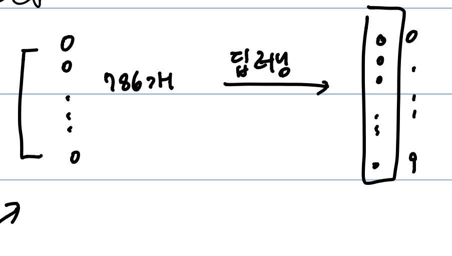
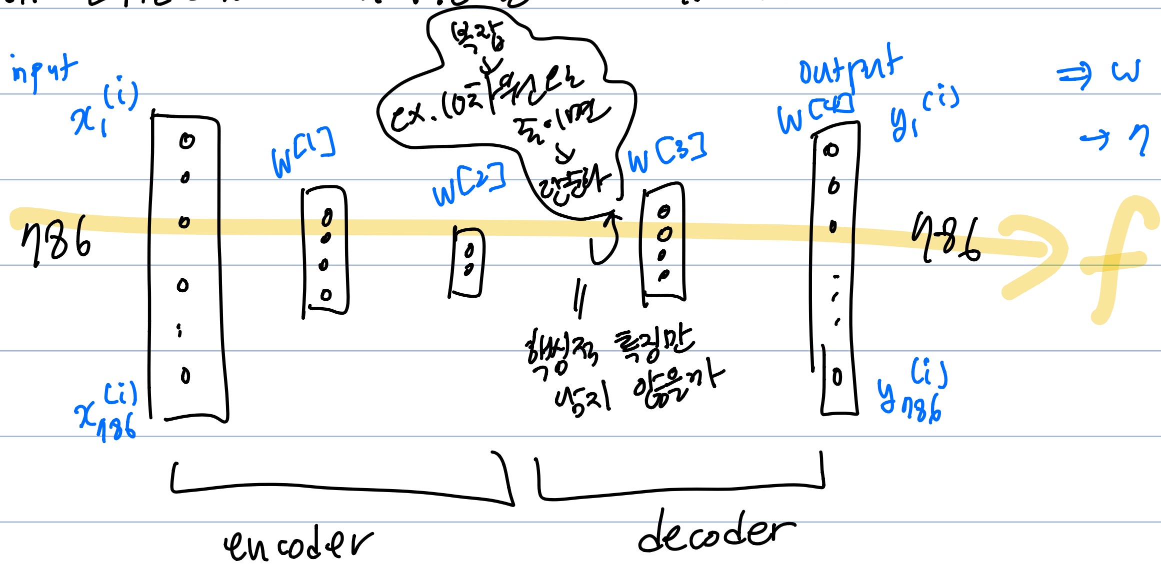
17.3 Autoencoder

outlayer (X) <핸즈온 7>

- data 복제

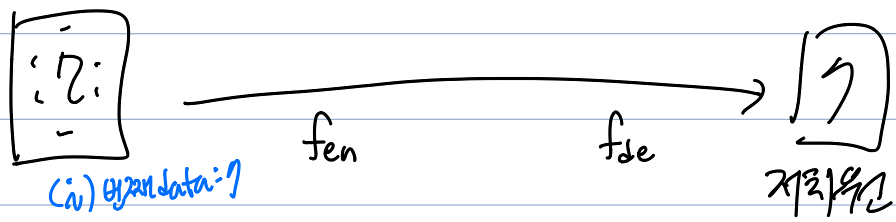


- PCA: 고차원 data → 저차원 표현 ≒ Autoencoder.



⇒ W 훈련

→ 7 똑바로 나오도록



저차원 image를 복원 : 목적.

loss fn: $(X - Y)^2$ 최소화.

encoder, decoder 합하면 f

$f_W(x^{(i)}) = y^{(i)}$ $\hat{w} = \underset{w}{\text{argmin}}$ ~~$\| y^{(i)} - f_w(x^{(i)}) \|_2$~~

$\| x^{(i)} - f_w(x^{(i)}) \|_2$

X 와 Y 거리

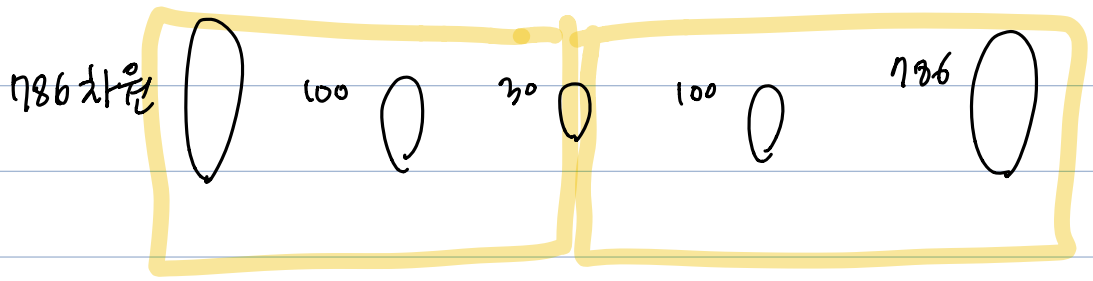
$\| (x_1, \dots, x_{786}) \| = \sqrt{x_1^2 + \dots + x_{786}^2}$

$y^{(i)} = f_{de}(f_{en}(x^{(i)}))$

$x^{(i)} \rightarrow$ $f_{en}(x^{(i)})$ 2차원 → 저장 → 쓰고싶을 때 decoder에 넣어주면 됨

‖

$f_{de}(z^{(i)})$



17.3.1 (679pg)

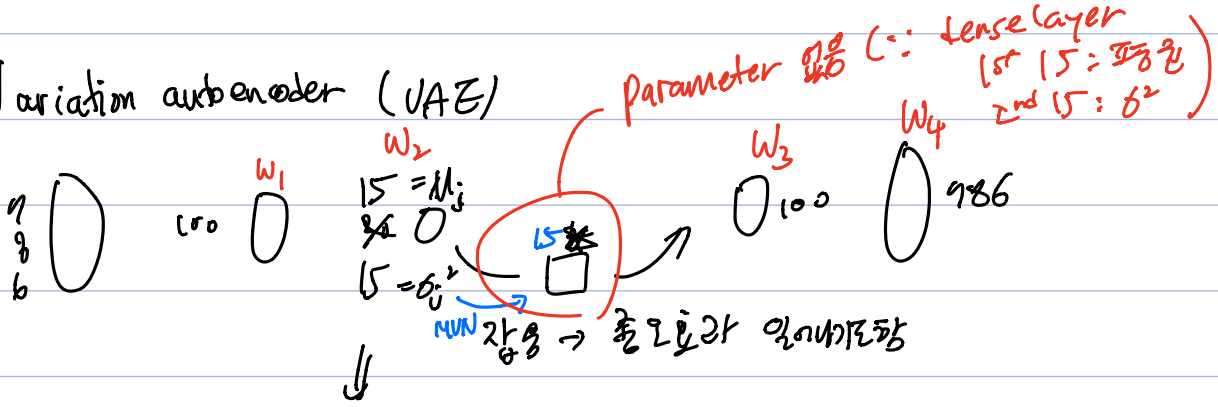
encoder = keras.models.Seq -- loss fun(측정함수)

p.431

17.3.2

fashion mnist data → 실습

17.8 Variation autoencoder (VAE)



$z \sim MVN((\mu_1, \cdots, \mu_{15}), \Sigma)$

$\Sigma = diag(\sigma_1^2, \cdots, \sigma_{15}^2)$

(다중정규 multinormal)

$\|x^{(i)} - f_{w,VAE}(x^{(i)})\|_2 \rightarrow w?$

p.699 ⇒ code

cod_size = 10 -

inputs = ··· Input (shape = [28,28])

z = ··· Flatten()(inputs)

z = Dense (150)(z)

z = Dense (100)(z)

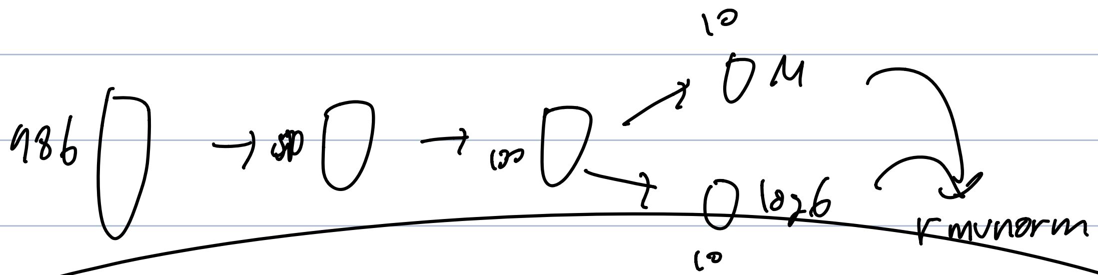
μ = Dense(10)(z)

log σ = Dense(10)(z)

codings = random Gaussian vnorm(μ, diag(exp(log σ)),

~~정의~~

encoder = keras.Model(input = input, output = codings]) ✓



h/w

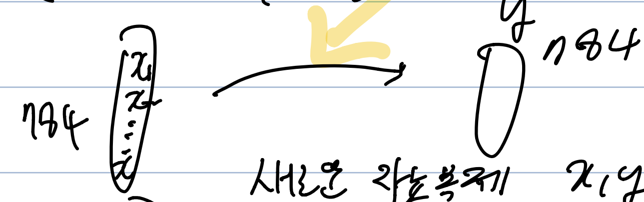
$$\left[\sum_{i=1}^{N} \| x^{(i)} - f(x^{(i)}) \|_2 + KL(rMVN, MVN(\mu_1 \cdots \mu_{10}), diag(--)) \right]$$

→ 공부 식 (17-3) 책 + google + youtube

[1]
* ① VAE Loss ftn 공부
  ② 17.8.1 fashion MNIST 실습 (VAE)
  ③ 17.3.3 fashion MNIST (Auto Encoder)

[2] 함수 세미나 ⇒ ~~발표~~ GAN 공부, T-SNE

[3] 자료적용. ex. 암 data, 간호 data, 보정시간 data



새로운 자료복제 x, y 둘다 복제

$y \sim x_1, \cdots, x_{784}$

(2차원, 3차원, 100차원, 200차원 → 예측결과)

☆ Tensorflow 잘써야함.