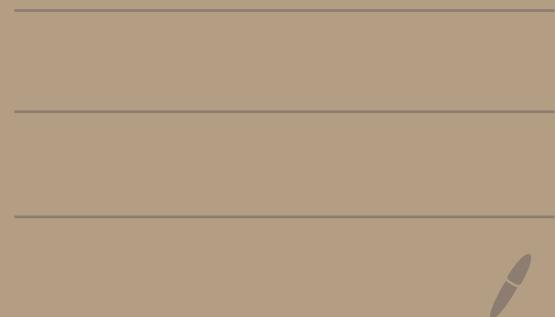


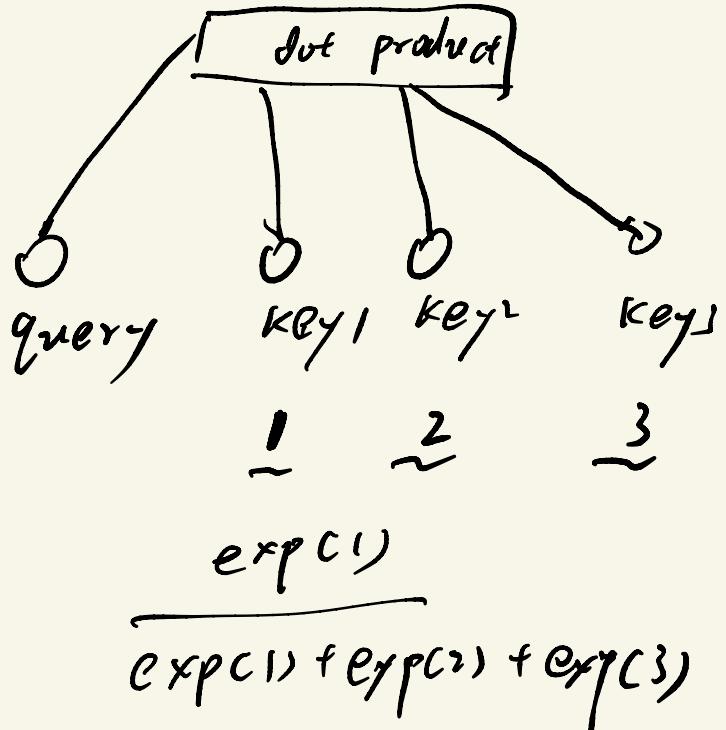
Lecture 20 transformer & VAE



$N \times$

$$\Phi \begin{bmatrix} q_1^\top \\ q_2^\top \\ q_3^\top \\ \vdots \\ q_n^\top \end{bmatrix} \times K^\top \begin{bmatrix} k_1 & k_2 & \dots & k_m \end{bmatrix}$$

$n \times m$ $\begin{bmatrix} q_1^\top k_1 & q_1^\top k_2 & \dots & \dots \\ q_2^\top k_1 & q_2^\top k_2 & \dots & \dots \end{bmatrix}$



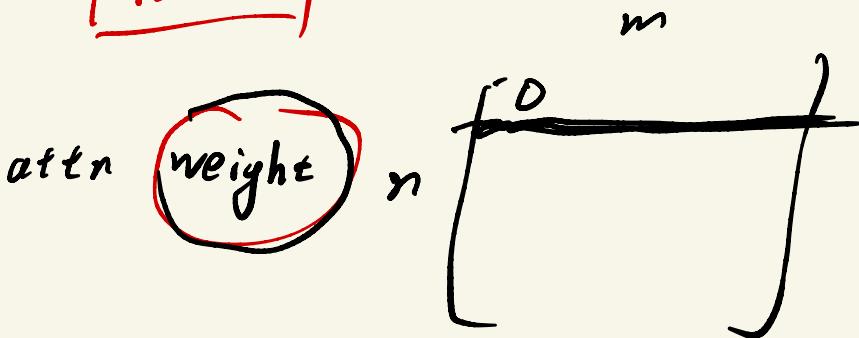
1092.

(x_1, x_2, x_3)

(y_1, y_2, y_3)

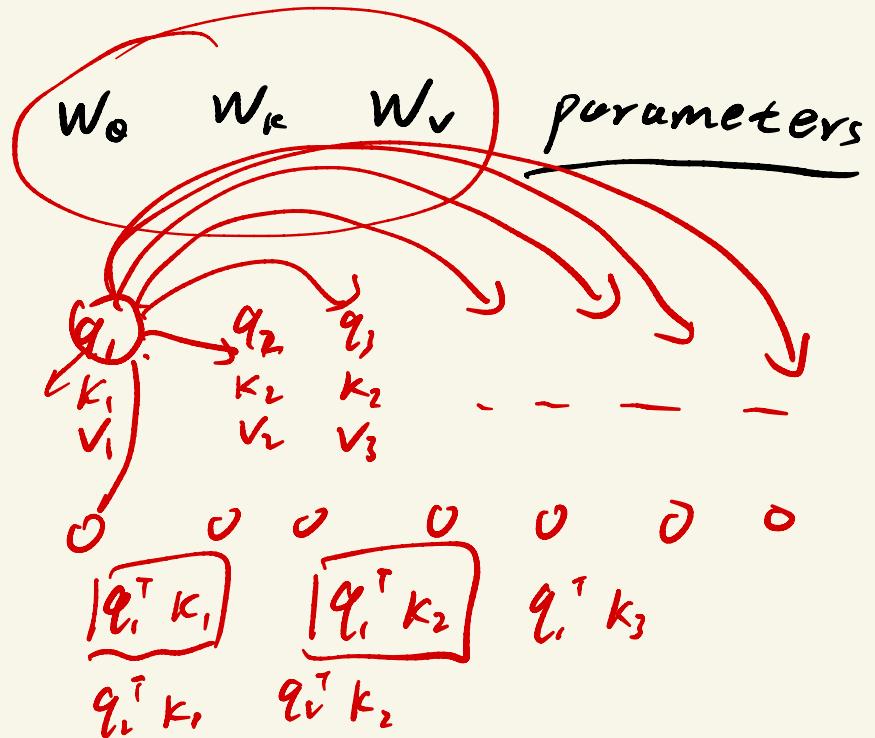
$$\underbrace{x_1 y_1 + x_2 y_2 + x_3 y_3}_{J}$$

$n \times m$



$$[w_1 \ w_2 \ \dots \ w_m]$$

$$(w_1 \vec{v}_1 + w_2 \vec{v}_2 + \dots + w_m \vec{v}_m)$$



$$\text{Softmax} \left(\frac{\mathbf{Q}'\mathbf{K}}{\sqrt{d_k}} \right) \vee$$

$$\mathbf{Q} \in \mathbb{R}^{n \times d}$$

$$\mathbf{K} \in \mathbb{R}^{m \times d}$$

$$n = m$$

$n = \text{sequence length}$

$$\boxed{n \times n}$$

h

$z_0 \quad z_1 \quad z_7$

Cross attention :

Q : from x
 (K, V) from encoder output

output : [1 3 4 2 5]

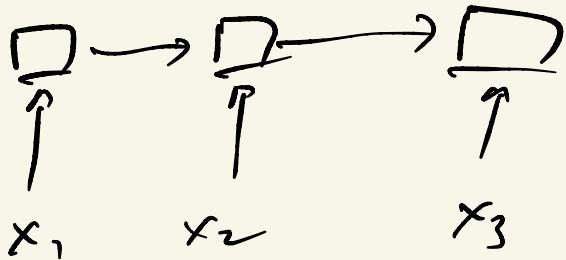
after shuffle : [3 4 1 2 5]

I give an apple to you

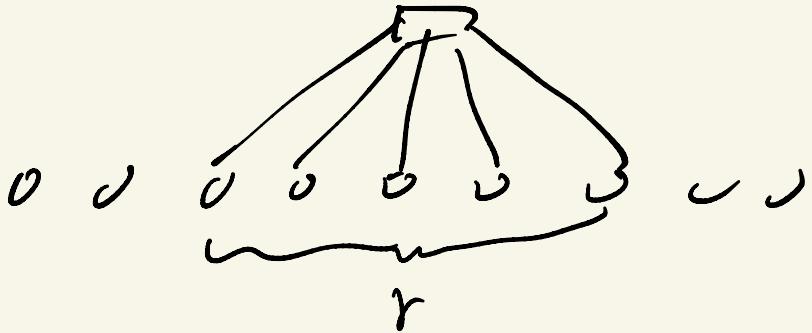
you give an

RNN

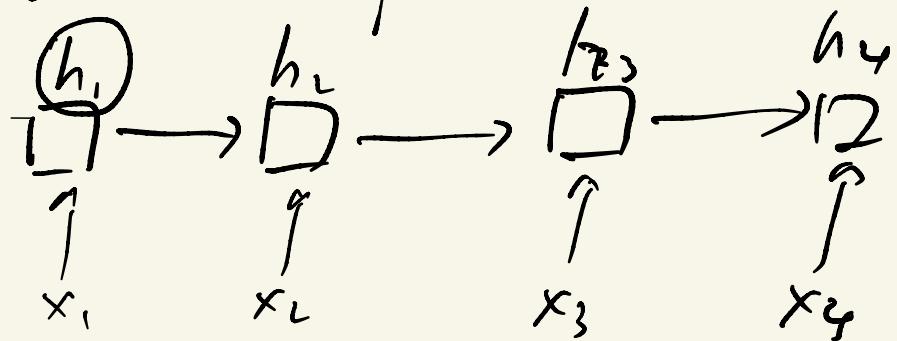
$$\begin{matrix} d_0 \\ d_1 \\ d_2 \end{matrix} = f(2)$$



$x_3 \quad x_2 \quad x_1$



Sequential operation $O(n)$



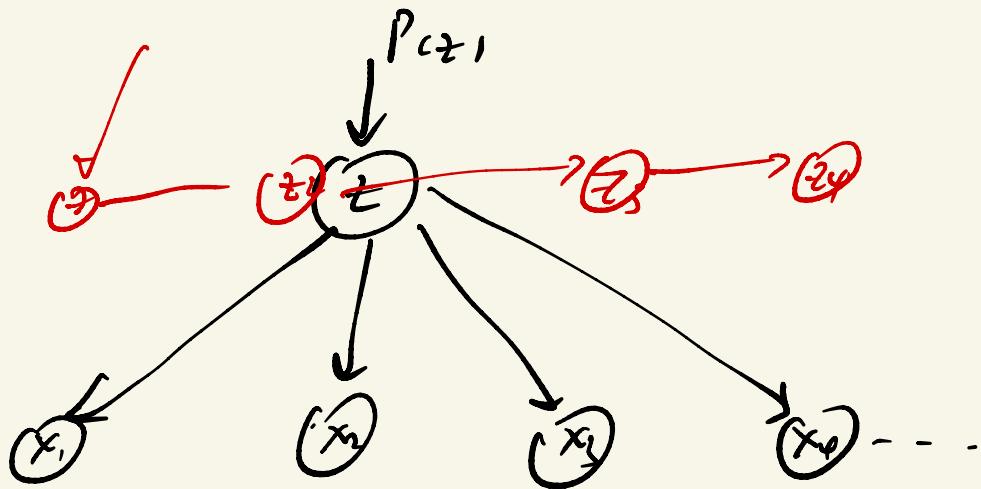
$$P(x_1, x_2, \dots, x_n)$$

$$= P(x_1) P(x_2|x_1) P(x_3|x_1, x_2)$$

$$\dots P(x_n|x_1, \dots, x_{n-1})$$

$$= P(x_1) P(x_2) f(x_3) \dots f(x_n)$$

$$[x_1 \perp x_2 \perp x_3]$$

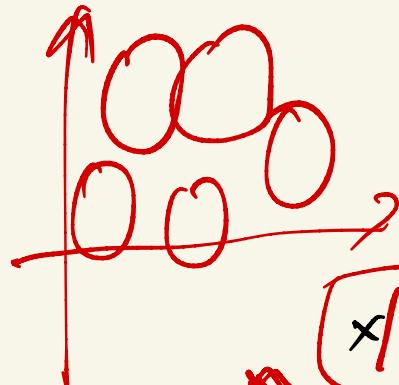


$$z \sim P(z)$$

$$P(x_1|z), P(x_2|z), P(x_3|z), \dots$$

$x_1 \perp x_2$?

$$x \sim P(x, f(z; \theta))$$



$P \rightarrow \text{Gaussian}$

$$P(x) = \int_z P(z) P(x|z)$$

Diagram illustrating the decomposition of the probability density function $P(x)$ into a latent variable z and a conditional distribution $P(x|z)$. The latent variable z follows a Gaussian distribution $N(0, 1)$. The conditional distribution $P(x|z)$ is also Gaussian, with mean $f(z; \theta)$ and variance σ^2 .

$$P(x) = \int_z P(z) P(x|z)$$

not Gaussian

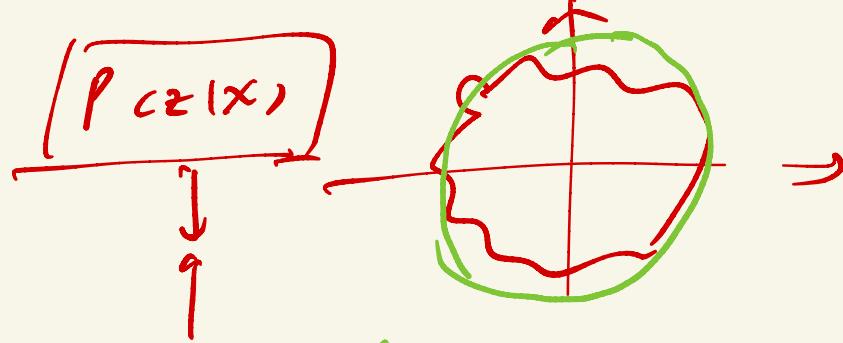
$$= E_{z \sim p_{Lz}} [P(x|z)]$$

$P(z|x)$ & $P(z) P(x|z)$

ELBO:

$$\boxed{E_{z \sim p_{(z|x)}} \log P(x, z; \theta)}$$

Sample $z \sim p_{(z|x)}$



simple $q(z|x)$ $q(z, \phi)$

easy to sample z from $q(z|x)$

$$d[q(z|x), P(z|x)]$$

$$\log P(x; \theta) \geq \bar{E}LB_0$$



unrelated to Q

when $Q = P_{(Z|X)}$

$$\log P(x) = \bar{E}LB_0$$

$$\bar{E}LB_0 = (\log P(x)) - KL(Q_{(Z|x)} || P_{(Z|x)})$$

$$Q_{(Z|x)} = P_{(Z|x)}$$

$$\arg \min_{\psi} \underbrace{KL(Q_{(Z|x); \psi} || P_{(Z|x)})}_{KL=0}$$

$P(z|x)$ exact inference

$q(z|x) \rightarrow P(z|x)$, variational inference

MLE by $P(x)$

$q(z|x; \phi)$ simple

$\tilde{z} \sim q(z|x; \phi)$