Our tensor notation is discussed in Section ?? of Bayesuvius. $\ell = \text{number of words}$ in a sentence segment. $\alpha \in [\ell], \ \ell \sim 100$ L = number of words in vocabulary, $\beta \in [L], \ L >> \ell$ $d = d_{\underline{q}} = d_{\underline{k}} = d_{\underline{v}} = 64$, hidden dimension per head, $\delta \in [d]$. $n_{\underline{h}} = 8$, number of heads, $\nu \in [n_{\underline{h}}]$ $D = n_{\underline{h}}d = 8(64) = 512$, hidden dimension for all heads. $\Delta \in [D]$ reshaping

$$T^{\nu,\delta} \to T^{\Delta(\nu,\delta)} \quad \left(T^{[n_{\underline{h}}],[d]} \to T^{[D]}\right)$$
 (1)

$$T^{\Delta(\nu,\delta)} \to T^{\nu,\delta} \quad (T^{[D]} \to T^{[n_{\underline{h}}],[d]})$$
 (2)

concatenation

$$T^{[n]} = (T^0, T^1, \dots, T^{n-1}) = (T^{\nu})_{\nu \in [n]}$$
(3)

Hadamard product (element-wise, entry-wise multiplication)

$$T^{[n]} * S^{[n]} = (T^{\nu} S^{\nu})_{\nu \in [n]} \tag{4}$$

Matrix multiplication ($T^{[n]} = T^{[n],[1]}$ is a column vector)

$$(T^{[n]})^T S^{[n]} = \text{scalar} \tag{5}$$

$$T^{[a],[b]}S^{[b],[c]} = \left[\sum_{\beta \in [b]} T^{\alpha,\beta}S^{\beta,\gamma}\right]_{\alpha \in [a],\gamma \in [c]}$$

$$(6)$$

$$e^{\delta,\alpha} = \sum_{\beta} E^{\delta,\beta} x^{\beta,\alpha} \quad \left(e^{[d],[\ell]} = E^{[d],[L]} x^{[L],[\ell]} \right) \tag{7}$$

$$Q^{\nu,\delta,\alpha} = \sum_{\delta'} W_{\underline{q}}^{\nu,\delta,\delta'} e^{\delta',\alpha} \quad \left(Q^{[D],[\ell]} = W_{\underline{q}}^{[D],[d]} E^{[d],[\ell]} \right) \tag{8}$$

$$K^{\nu,\delta,\alpha} = \sum_{\delta'} W_{\underline{k}}^{\nu,\delta,\delta'} e^{\delta',\alpha} \quad \left(K^{[D],[\ell]} = W_{\underline{k}}^{[D],[d]} E^{[d],[\ell]} \right) \tag{9}$$

$$V^{\nu,\delta,\alpha} = \sum_{\delta'} W^{\nu,\delta,\delta'}_{\underline{v}} e^{\delta',\alpha} \quad \left(V^{[D],[\ell]} = W^{[D],[d]}_{\underline{v}} E^{[d],[\ell]} \right) \tag{10}$$

$$B^{\nu,\alpha,\alpha'} = \frac{1}{\sqrt{d}} \sum_{\delta} Q^{\nu,\delta,\alpha} K^{\nu,\delta,\alpha'} \quad \left(B^{[n_h],[\ell],[\ell]} = \left[\frac{1}{\sqrt{d}} (Q^{\nu,[d],[\ell]})^T K^{\nu,[d],[\ell]} \right]_{\nu \in [n_h]} \right) \quad (11)$$

$$A^{[n_{\underline{h}}],[d],[\ell]} = \left[\sum_{\alpha} V^{\nu,[d],\alpha} \underbrace{\operatorname{softmax}(B^{\nu,\alpha,[\ell]})}_{(B^*)^{\nu,\alpha,[\ell]}} \right]_{\nu \in [n_h]}$$
(12)

$$= \left[V^{\nu,[d],[\ell]} (B^*)^{\nu,[\ell],[\ell]} \right]_{\nu \in [n_h]} \tag{13}$$

$$A^{[n_{\underline{h}}],[d],[\ell]} \to A^{[D],[\ell]} \tag{14}$$

• Positional Encoding Matrix

 $E_{pos}^{[d],[\ell]}$

$$E_{pos}^{\delta,\beta} = \begin{cases} \sin\left(\frac{\beta}{10^{4\delta/d}}\right) = \sin(2\pi\frac{\beta}{\lambda(\delta)}) & \text{if } \delta \text{ is even} \\ \cos\left(\frac{\beta}{10^{4(\delta-1)/d}}\right) = \cos(2\pi\frac{\beta}{\lambda(\delta)}) & \text{if } \delta \text{ is odd} \end{cases}$$
(15)

 $E_{pos}^{\delta,\beta}$ changes in phase by $\pi/2$ every time δ changes by 1. Its wavelength λ is independent of β , but increases rapidly with δ , from $\lambda(\delta=0)=2\pi*1$ to $\lambda(\delta=d)=2\pi*10^4$.

• ReLU

For a tensor T of arbitrary shape

$$ReLU(T) = (T)_{+} = max(0, T) \tag{16}$$

max element-wise

• Feed Forward neural net

$$F(x^{[1],[\ell]}) = ReLU(x^{[1],[\ell]}W_1^{[\ell],[d]} + b_1^{[1],[d]})W_2^{[d],[\ell]} + b_1^{[1],[\ell]}$$
(17)

$$F(x^{[\ell]}) = W_2^{[\ell],[d]} ReLU(W_1^{[d],[\ell]} x^{[\ell]} + b_1^{[d]}) + b_1^{[\ell]}$$
(18)

softmax

softmax() takes a vector and returns a vector of probabilities of the same length

$$x^{[n]} \to P^{[n]} \tag{19}$$

where

$$P^{\alpha} = \frac{\exp(x^{\alpha})}{\sum_{\alpha \in [n]} \exp(x^{\alpha})} \quad \left(P^{[n]} = \frac{\exp(x^{[n]})}{\|\exp(x^{[n]})\|_{0}}\right)$$
(20)

For example,

$$(1,0,0) \to (e,1,1)/norm$$
 (21)

$$(10,0,0) \to (e^{10},1,1)/norm \approx (1,0,0)$$
 (22)

For any $a \in \mathbb{R}$,

$$(a, a, a) \to (1, 1, 1)/3$$
 (23)