The Transformer Architecture

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Today's Learning Outcomes

After today's class, you should be able to

- Explain **the building blocks** of the Transformer architecture to a non-technical person;
- Describe the Transformer architecture using **equations**, especially the self-attention block;
- **Implement** the Transformer architecture (in PyTorch or another framework that does automated differentiation).

Today's Programe

1. Quick recap quiz [5 min]
2. Lecture on the Transformer architecture [25 min]
3. Live coding session in PyTorch [45 min]
4. Lecture on architecture tweaks [15 min]

Architecture Tweaks

Activation Functions in the FF layer

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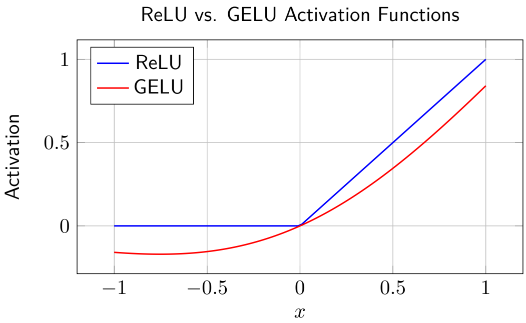
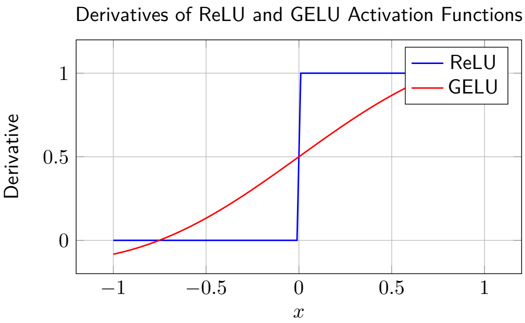
- LLaMA2 uses SwiGLU

$$\text{SwiGLU}(x, W, V, b, c, \beta) = \text{Swish}_\beta(xW + b) \otimes (xV + c)$$

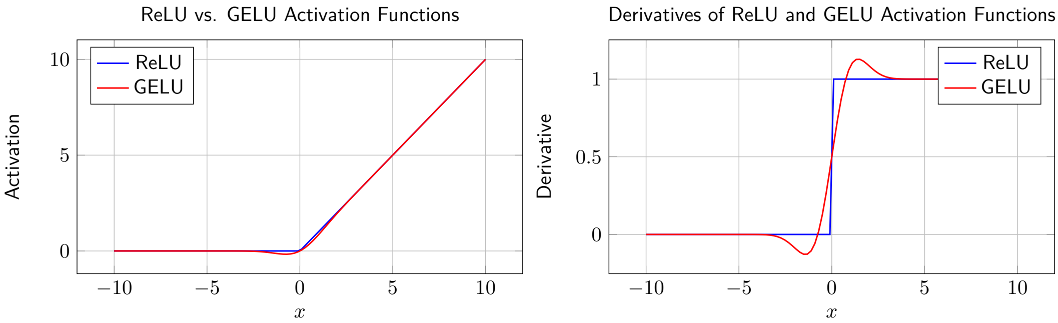
$$\text{Swish}_\beta(x) = x\,\text{sigmoid}(\beta x) = \frac{x}{1 + e^{-\beta x}}$$

ReLU vs. GELU [-1; 1]

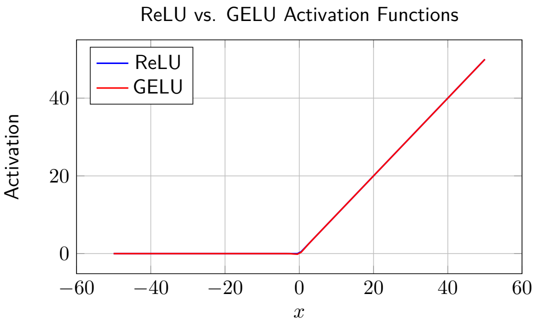


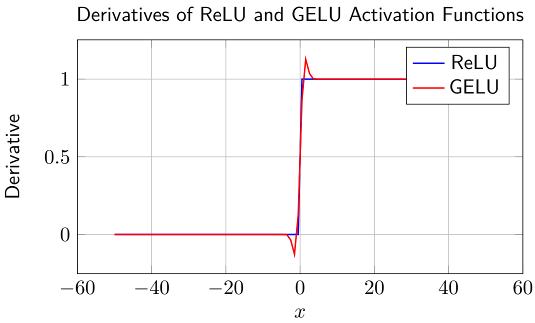


ReLU vs. GELU [-10; 10]

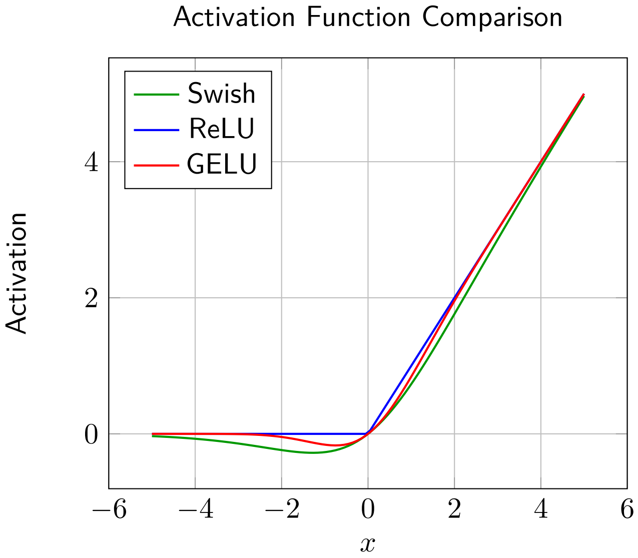


ReLU vs. GELU [-50; 50]





Swish activation function

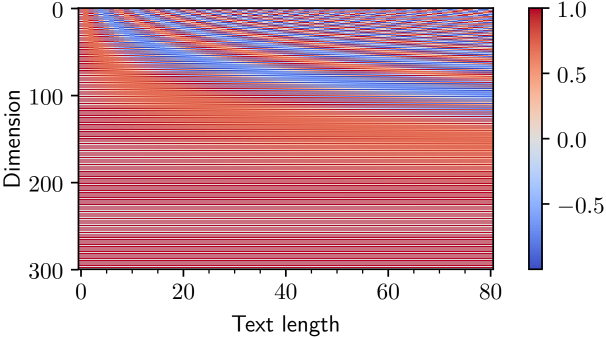


Position Embeddings

- Original 2017 paper: Sinusoidal absolute embeddings
- Often trained *absolute embeddings* embeddings (e.g., BERT or GPT-2 has that)
- Relative position encoding (e.g., T5)
- RoPE rotary positional encoding (e.g., BLOOM, LLaMA 2, PaLM, Gemma)

Sinusoidal Position Embeddings

$$\text{pos}(i) = \begin{cases} \sin\left(\frac{t}{10^4}^{\frac{i}{d}}\right), & \text{if } i \mod 2 = 0 \\ \cos\left(\frac{t}{10^4}^{\frac{i-1}{d}}\right), & \text{otherwise} \end{cases}$$



Rotary Position Embedding: Formulas

- Relative position embeddings: applied during QK multiplication

Jianlin Su, Yu Lu, Shengfeng Pan, Bo Wen, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *CoRR*, abs/2104.09864, 2021.
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- RoPE: Analytical version of relative position embeddings

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Rotary Position Embedding: Formulas

- Relative position embeddings: applied during QK multiplication
- RoPE: Analytical version of relative position embeddings
- Designed s.t.: when we multiply projection W_Q and W_K by the matrix position matrix, than $q_m^T k_n$ multiplication will have information about $m - n$

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Rotary Position Embedding: Formulas

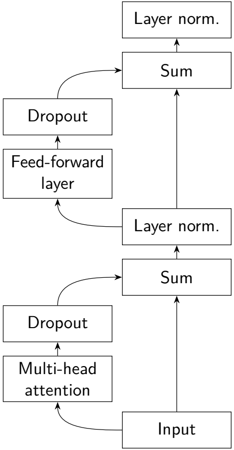
$$R^d_{\Theta,m} = \begin{pmatrix} \cos m\theta_1 & -\sin m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ \sin m\theta_1 & \cos m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cos m\theta_2 & -\sin m\theta_2 & \cdots & 0 & 0 \\ 0 & 0 & \sin m\theta_2 & \cos m\theta_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \cos m\theta_{d/2} & -\sin m\theta_{d/2} \\ 0 & 0 & 0 & 0 & \cdots & \sin m\theta_{d/2} & \cos m\theta_{d/2} \end{pmatrix}$$

$$\Theta = \{\theta_i = 10000^{-2(i-1)/d}, i \in [1, 2, ..., d/2]\}$$

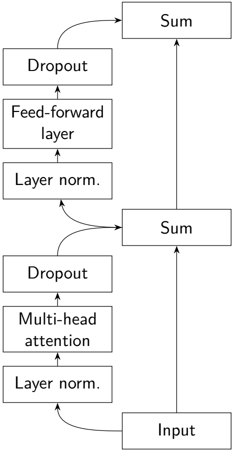
$$q_m^\intercal k_n = (R^d_{\Theta,m} W_q x_m)^\intercal (R^d_{\Theta,n} W_k x_n) = x^\intercal W_q R^d_{\Theta,n-m} W_k x_n$$

Pre- vs. Post-Layer Normalization

Original: Post-normalization



Now more common: Pre-normalization (Xiong et al., 2020)



Root Mean Square Layer Normalization

Instead of normalizing $\gamma \odot \left(\frac{x-\mu}{\sqrt{\sigma^2+\epsilon}}\right) + \beta$

$$\gamma \odot \left(\frac{x}{\mathsf{RMS}(x)}\right), +\beta \qquad \text{where } \mathsf{RMS}(x) = \sqrt{\frac{1}{d}\sum_{i=1}^{d} a_i^2}$$

It is faster and does approximately the same thing as the original layer norm.

Biao Zhang and Rico Sennrich. Root mean square layer normalization.
In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 12360–12371, 2019.
URL `https://proceedings.neurips.cc/paper/2019/hash/1e8a19426224ca89e83cef47f1e7f53b-Abstract.html`

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Ruibin Xiong, Yunchang Yang, Di He, Kai Zheng, Shuxin Zheng, Chen Xing, Huishuai Zhang, Yanyan Lan, Liwei Wang, and Tie-Yan Liu. On layer normalization in the transformer architecture. *CoRR*, abs/2002.04745, 2020. URL https://arxiv.org/abs/2002.04745.

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