Transformerを詳しく学ぼう!



Section3



講座の内容

Section1. Transformerの概要

Section 2. Attention の仕組み



Section3. Transformerにおける埋め込み

Section 4. Transformer を組み立てる

今回の内容

- 1. Section3の概要
- 2. Token Embedding
- 3. Positional Encoding
- 4. Position-wise Feed-Forward Networks
- 5. Layer Normalization
- 6. 演習

教材の紹介

・Pythonの基礎:

python_basic

·Section3の教材

01_token_embedding.ipynb

02_positional_encoding.ipynb

03_positionwise_feed_forward.ipynb

04_layer_norm.ipynb

05_exercise.ipynb

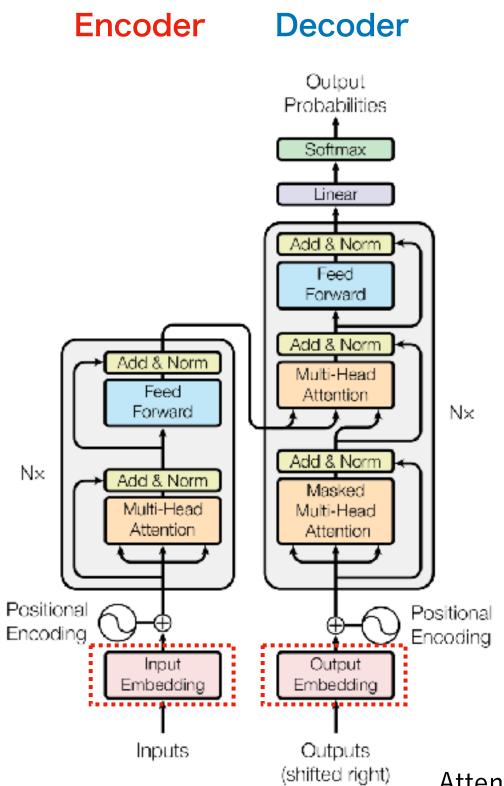
https://github.com/yukinaga/learning_transformer/

Section2演習の解答例

• 03_exercise.ipynb



Token Embedding



nn.Embedding()

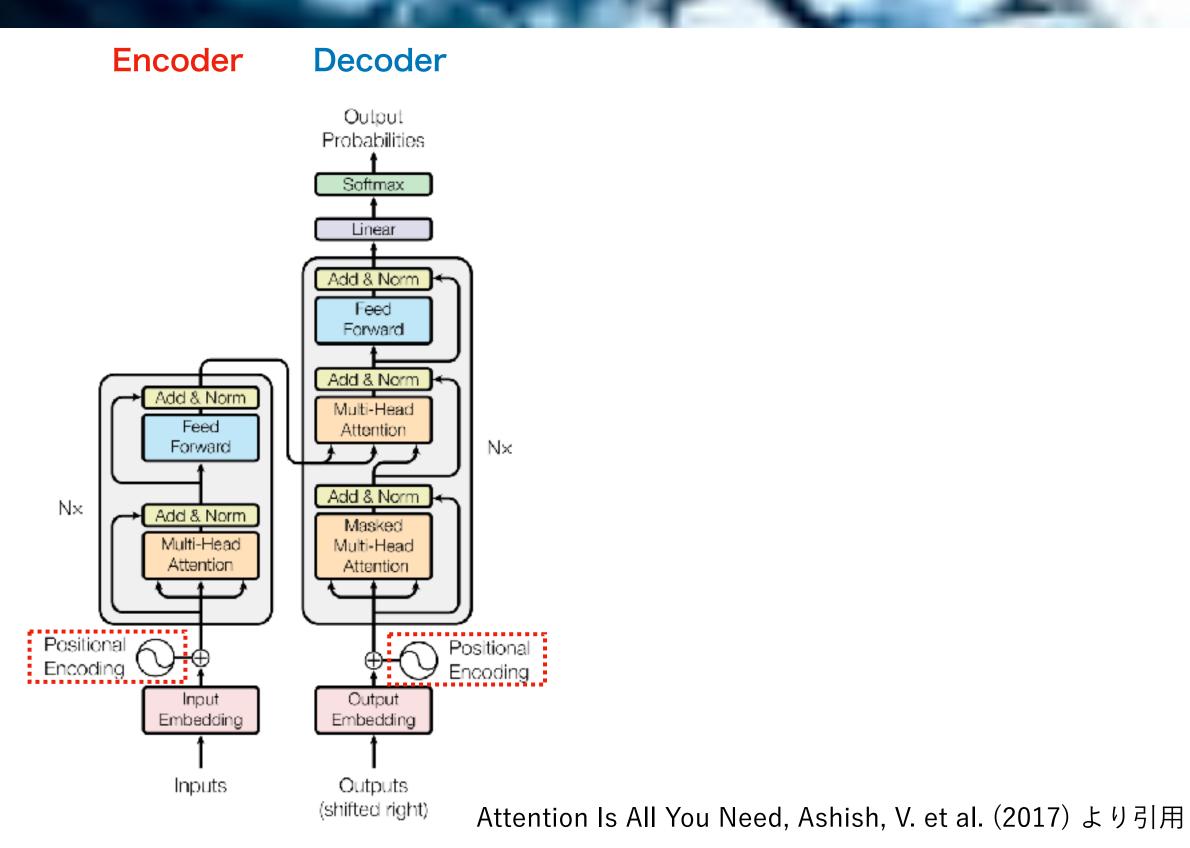
• https://pytorch.org/docs/stable/generated/torch.nn.Embedding

Token Embedding

•01_token_embedding.ipynb



Positional Encoding



Positional Encoding

Positional Encoding

→「単語の位置」の情報を加える

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

 $PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$

pos: 単語の位置 2i, 2i+1: Embedding の何番目の次元か d_{model}: 次元数

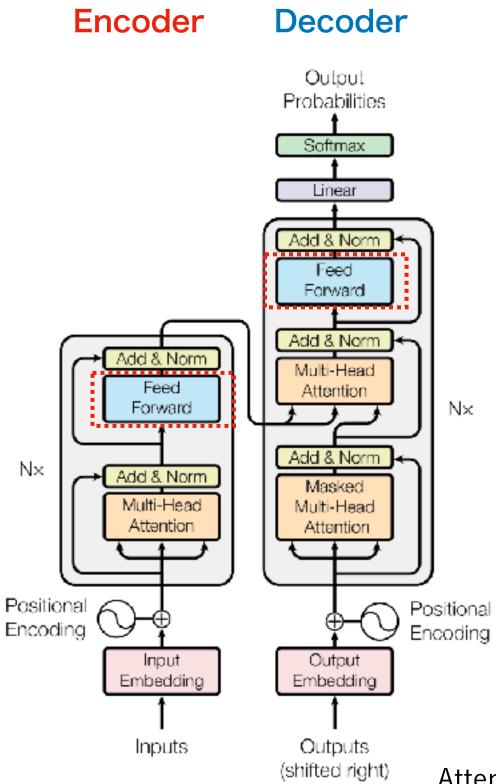
Positional Encoding

•02_positional_encoding.ipynb





Position-wise Feed-Forward Networks



Position-wise Feed-Forward Networks

Positionwise fully connected feed-forward network

- →2層の全結合ニューラルネットワーク
- → 単語の位置ごとに個別の順伝播ネットワーク
- →他単語との影響関係を排除
- → パラメータは全てのネットワークで共通

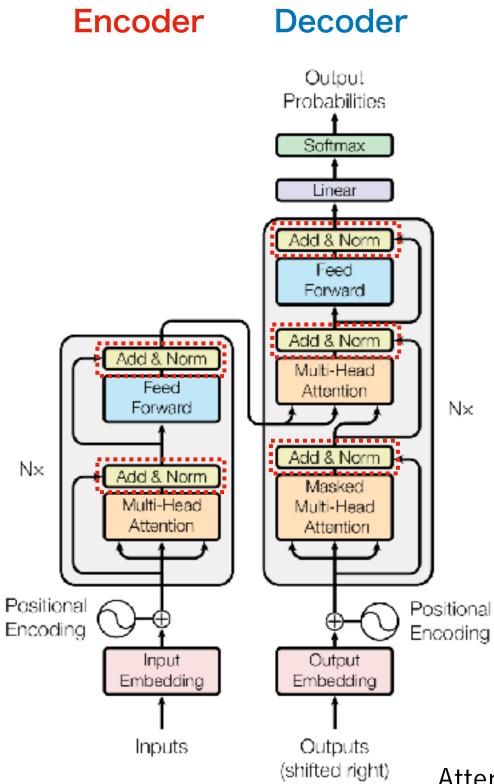
$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

Position-wise Feed-Forward Networks

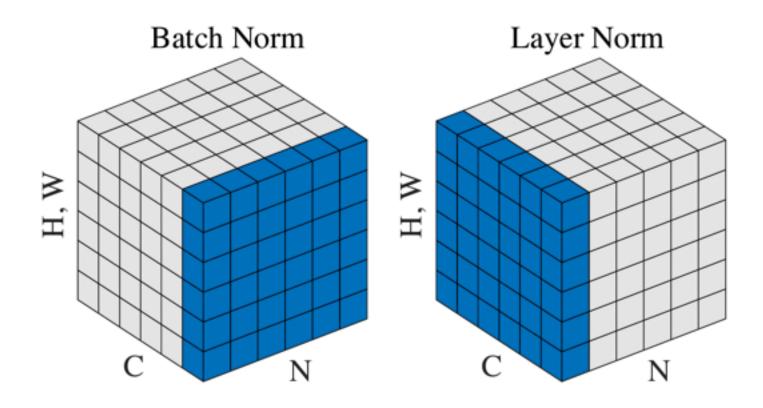
•03_positionwise_feed_forward.ipynb



Layer Normalization



Layer Normalization



Group Normalization, Yuxin Wu, et al. (2018) より引用

$$\mu^{l} = \frac{1}{H} \sum_{i=1}^{H} a_{i}^{l}$$
 $\sigma^{l} = \sqrt{\frac{1}{H} \sum_{i=1}^{H} (a_{i}^{l} - \mu^{l})^{2}}$

Layer Normalization, Jimmy Lei Ba, et al. (2016) より引用

Layer Normalization

•04_layer_norm.ipynb



演習

• 05_exercise.ipynb

次回の内容

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