Distinguished Engineering

Transformer 4/5
- Transformer, revenge of the fallen
•••

BW

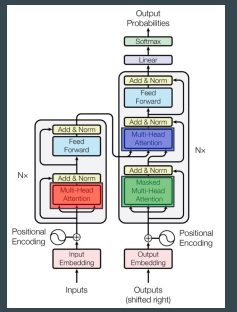
Plan

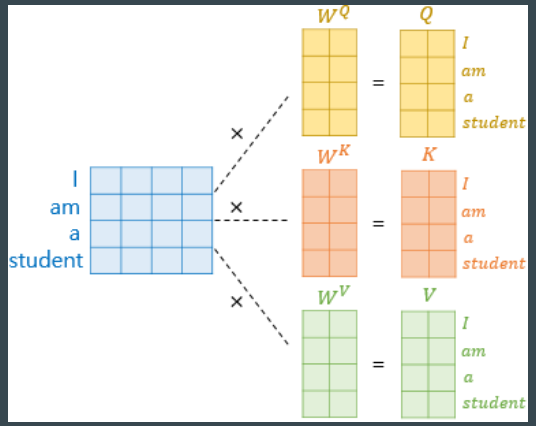
- Prologue, seq2seq
- **Attention, please**
- Transformer, a new hope
- Transformer, revenge of the fallen
- Transformer, vision

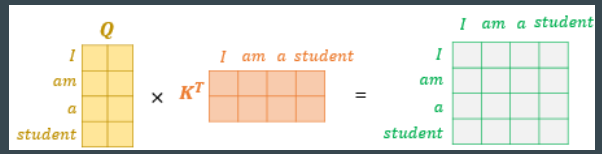
Transformer

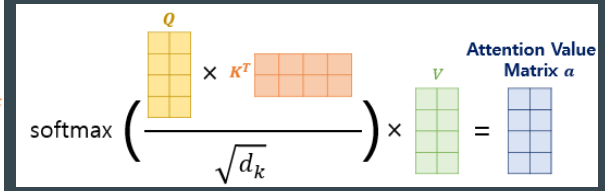
- Multi-head Attention

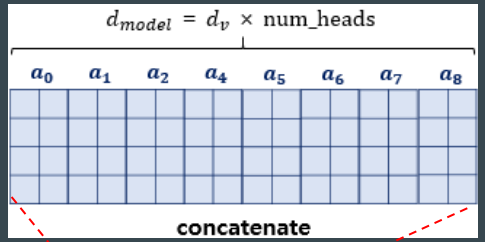
$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

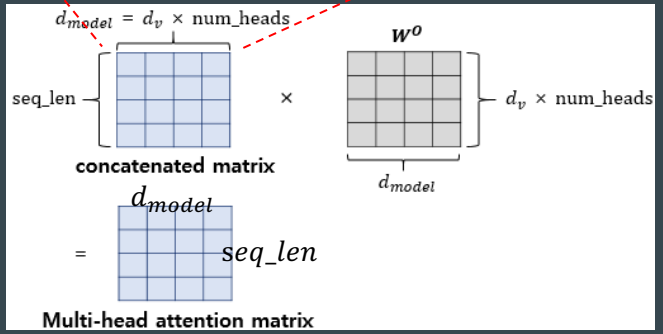


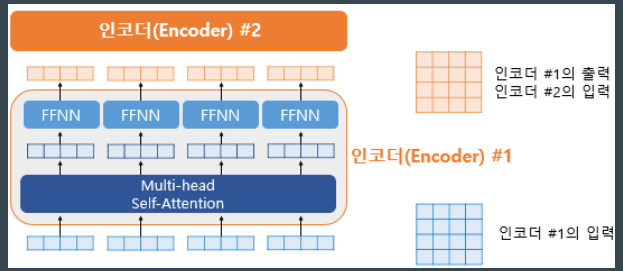






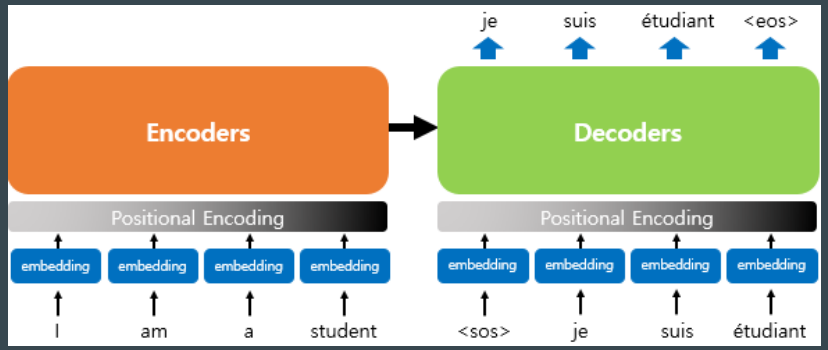


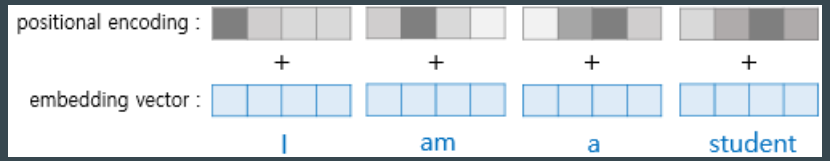




Transformer

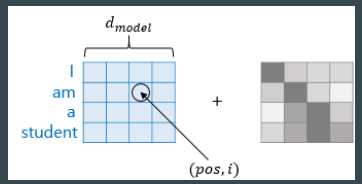
- Positional encoding

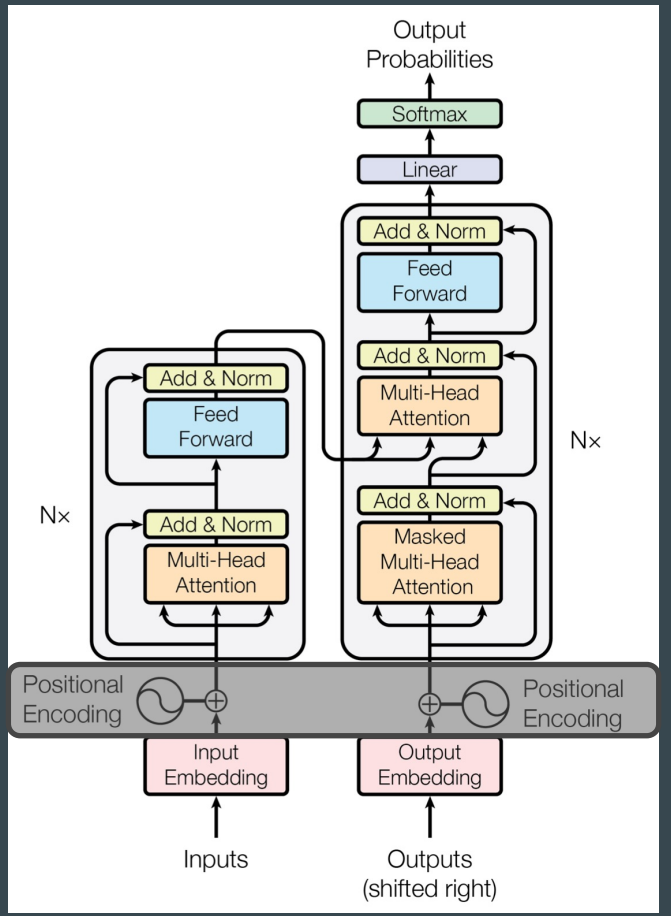




$$PE_{(pos,\,2i)} = sin(pos/10000^{2i/d_{model}})$$

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

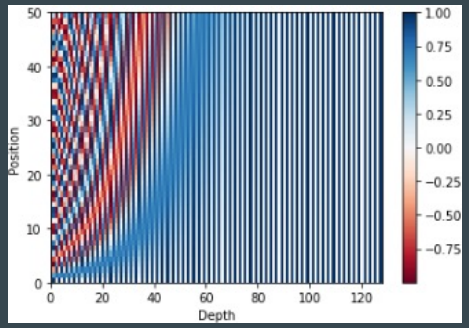




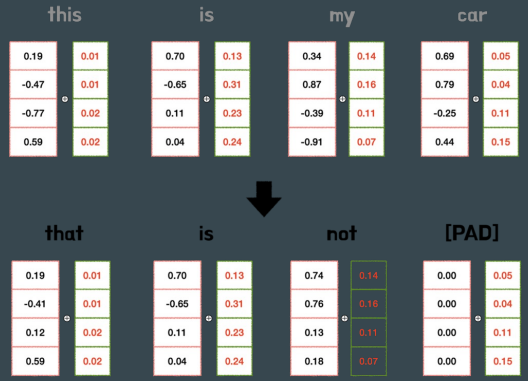
Transformer

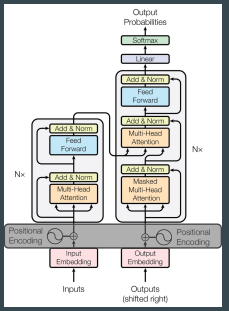
- Positional encoding

```
class PositionalEncoding(tf.keras.layers.Layer):
    def __init__(self, position, d_model):
        super(PositionalEncoding, self).__init__()
        self.pos_encoding = self.positional_encoding(position, d_model)

    def get_angles(self, position, i, d_model):
        angles = 1 / tf.pow(10000, (2 * (i // 2)) / tf.cast(d_model, tf.float32))
        return position * angles

    def positional_encoding(self, position, d_model):
        angle_rads = self.get_angles(
            position=tf.range(position, dtype=tf.float32)[:, tf.newaxis],
            i=tf.range(d_model, dtype=tf.float32)[tf.newaxis, :],
            d_model=d_model)

        # 배열의 짝수 인덱스(2i)에는 사인 함수 적용
        sines = tf.math.sin(angle_rads[:, 0::2])

        # 배열의 홀수 인덱스(2i+1)에는 코사인 함수 적용
        cosines = tf.math.cos(angle_rads[:, 1::2])

        angle_rads = np.zeros(angle_rads.shape)
        angle_rads[:, 0::2] = sines
        angle_rads[:, 1::2] = cosines
        pos_encoding = tf.constant(angle_rads)
        pos_encoding = pos_encoding[tf.newaxis, ...]

        print(pos_encoding.shape)
        return tf.cast(pos_encoding, tf.float32)

    def call(self, inputs):
        return inputs + self.pos_encoding[:, :tf.shape(inputs)[1], :]
```



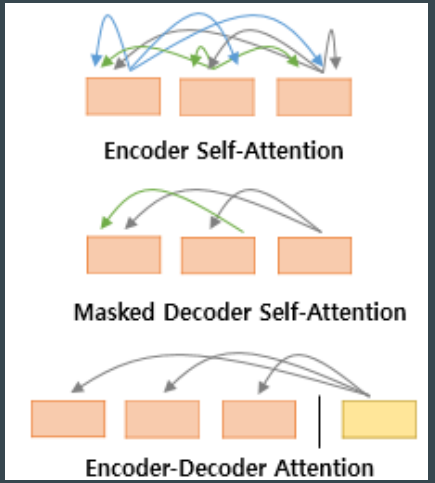
Positional Encoding Value
문장의 길이 50, 임베딩 벡터의 차원 128



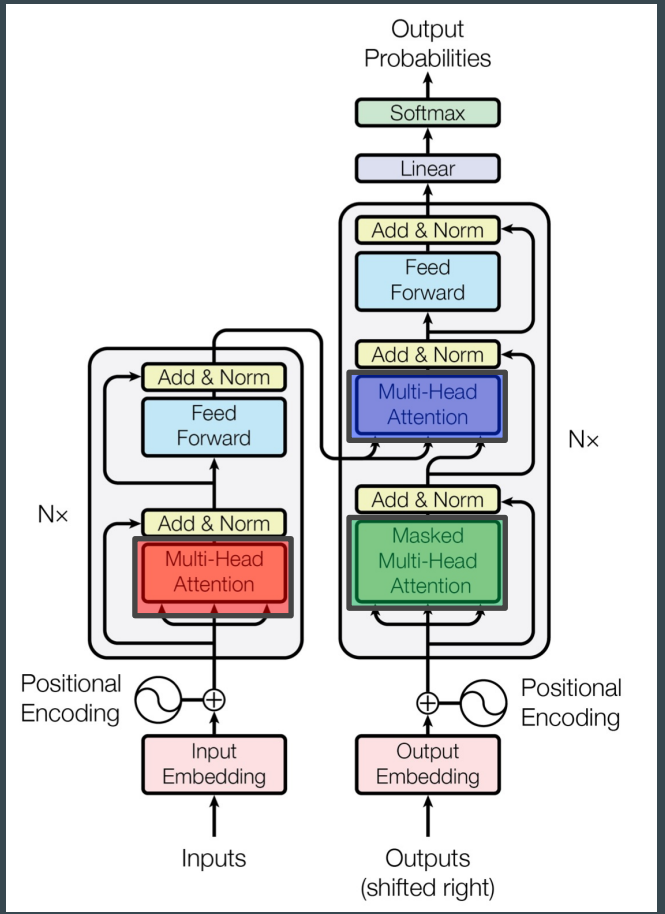


Transformer

- Attentions,

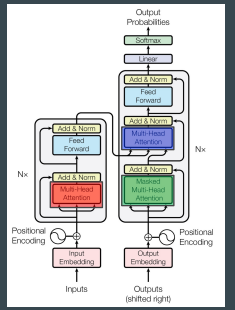


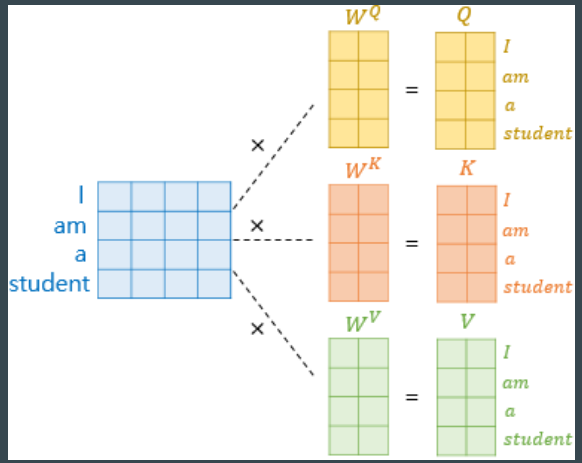
Encoder의 Self-Attention : Query = Key = Value
Decoder의 Masked Self-Attention : Query = Key = Value
Decoder의 Eocoder-Decoder Attention : Query : Decoder Vector /
Key = Value : Encoder Vector

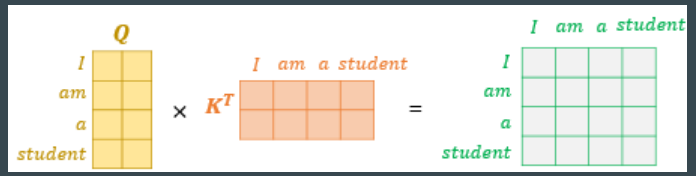


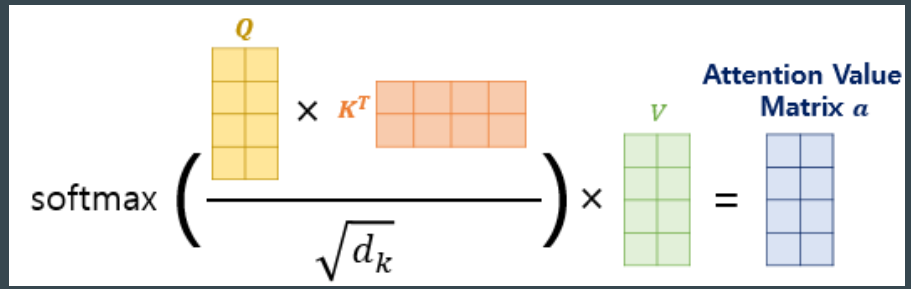
Transformer

- Scaled dot-product Attention → MATRIX!!!!





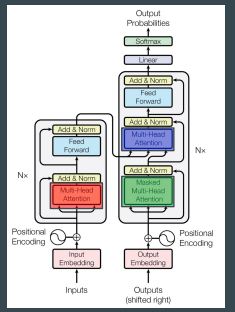




$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

Transformer

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

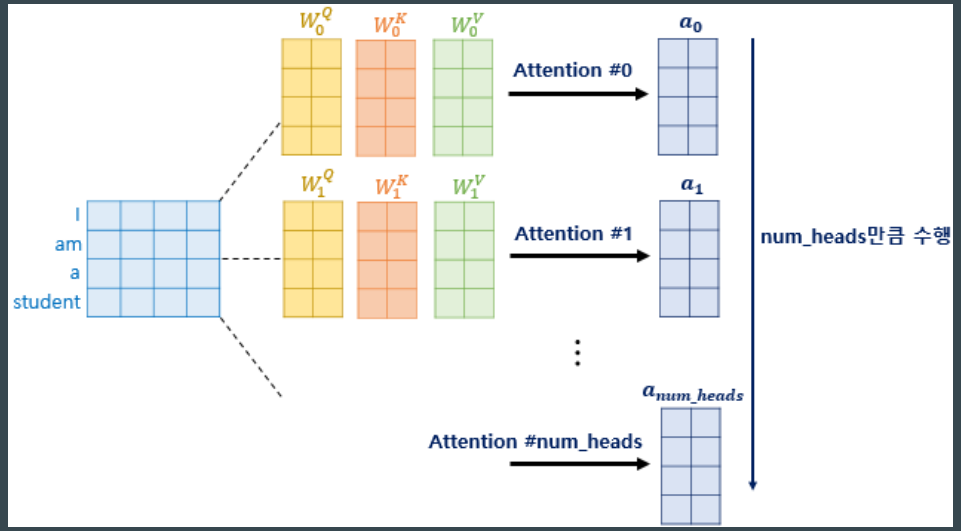


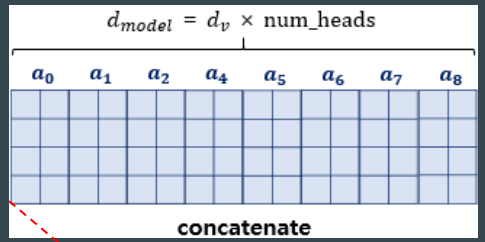
- **Encoder Self-Attention**

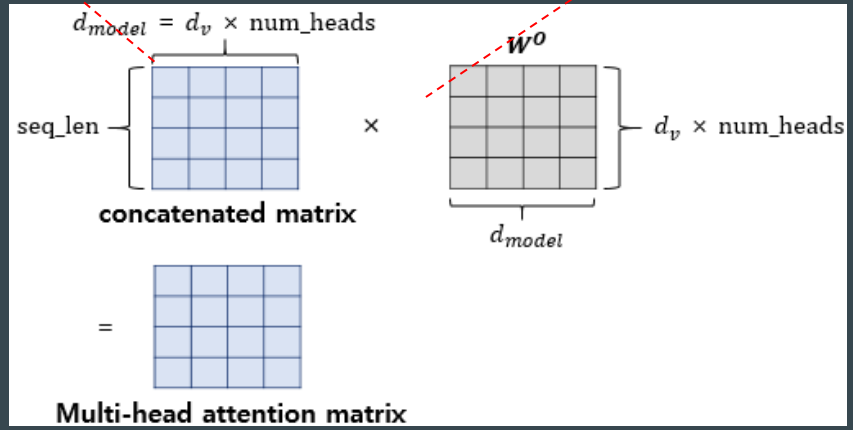
```
def scaled_dot_product_attention(query, key, value, mask):
    # query 크기 : (batch_size, num_heads, query의 문장 길이, d_model/num_heads)
    # key 크기 :   (batch_size, num_heads, key의 문장 길이,   d_model/num_heads)
    # value 크기 : (batch_size, num_heads, value의 문장 길이, d_model/num_heads)
    # padding_mask : (batch_size, 1, 1, key의 문장 길이)

    # Q와 K의 곱. 어텐션 스코어 행렬.
    matmul_qk = tf.matmul(query, key, transpose_b=True)

    # 스케일링
    # dk의 루트값으로 나눠준다.
    depth = tf.cast(tf.shape(key)[-1], tf.float32)
    logits = matmul_qk / tf.math.sqrt(depth)

    # 마스킹. 어텐션 스코어 행렬의 마스킹 할 위치에 매우 작은 음수값을 넣는다.
    # 매우 작은 값이므로 소프트맥스 함수를 지나면 행렬의 해당 위치의 값은 0이 된다.
    if mask is not None:
        logits += (mask * -1e9)

    # 소프트맥스 함수는 마지막 차원인 key의 문장 길이 방향으로 수행된다.
    # attention weight : (batch_size, num_heads, query의 문장 길이, key의 문장 길이)
    attention_weights = tf.nn.softmax(logits, axis=-1)

    # output : (batch_size, num_heads, query의 문장 길이, d_model/num_heads)
    output = tf.matmul(attention_weights, value)

    return output, attention_weights
```

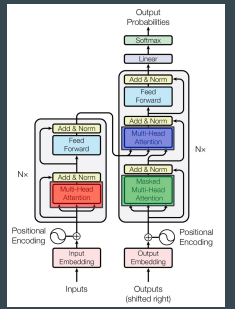
Transformer

- Multi-head Attention









Transformer

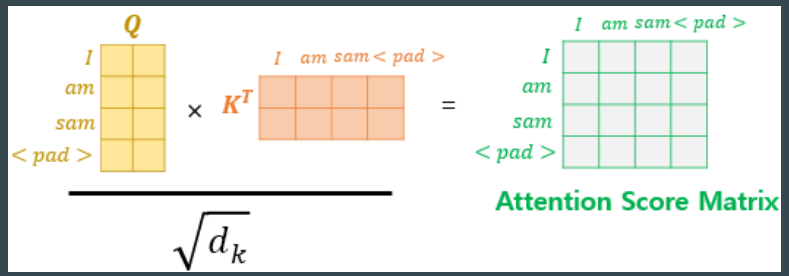
- Multi-head Attention

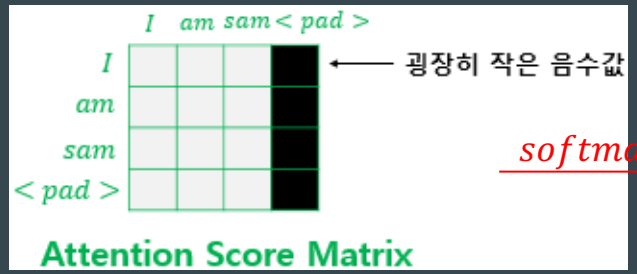
```
class MultiHeadAttention(tf.keras.layers.Layer):

    def __init__(self, d_model, num_heads, name="multi_head_attention"):
        super(MultiHeadAttention, self).__init__(name=name)
        self.num_heads = num_heads
        self.d_model = d_model

        assert d_model % self.num_heads == 0

        # d_model을 num_heads로 나눈 값.
        # 논문 기준 : 64
        self.depth = d_model // self.num_heads

        # WQ, WK, WV에 해당하는 밀집층 정의
        self.query_dense = tf.keras.layers.Dense(units=d_model)
        self.key_dense   = tf.keras.layers.Dense(units=d_model)
        self.value_dense = tf.keras.layers.Dense(units=d_model)

        # WO에 해당하는 밀집층 정의
        self.dense = tf.keras.layers.Dense(units=d_model)

        # num_heads 개수만큼 q, k, v를 split하는 함수
        def split_heads(self, inputs, batch_size):
            inputs = tf.reshape(
            inputs, shape=(batch_size, -1, self.num_heads, self.depth))

            return tf.transpose(inputs, perm=[0, 2, 1, 3])
```

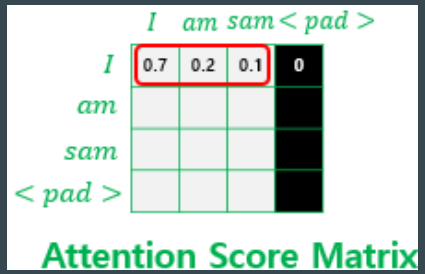
```
def call(self, inputs):
    query, key, value, mask = inputs['query'], inputs['key'], inputs['value'], inputs['mask']
    batch_size = tf.shape(query)[0]

    # 1. WQ, WK, WV에 해당하는 밀집층 지나기
    # q : (batch_size, query의 문장 길이, d_model)
    # k : (batch_size, key의 문장 길이, d_model)
    # v : (batch_size, value의 문장 길이, d_model)
    # 참고) 인코더(k, v)-디코더(q) 어텐션에서는 query 길이와
    #                     key, value의 길이는 다를 수 있다.
    query = self.query_dense(query)
    key   = self.key_dense(key)
    value = self.value_dense(value)

    # 2. 헤드 나누기
    # q : (batch_size, num_heads, query의 문장 길이, d_model/num_heads)
    # k : (batch_size, num_heads, key의 문장 길이, d_model/num_heads)
    # v : (batch_size, num_heads, value의 문장 길이, d_model/num_heads)
    query = self.split_heads(query, batch_size)
    key   = self.split_heads(key,   batch_size)
    value = self.split_heads(value, batch_size)

    # 3. 스케일드 닷 프로덕트 어텐션. 앞서 구현한 함수 사용.
    # (batch_size, num_heads, query의 문장 길이, d_model/num_heads)
    scaled_attention, _ = scaled_dot_product_attention(query, key, value, mask)
    # (batch_size, query의 문장 길이, num_heads, d_model/num_heads)
    scaled_attention = tf.transpose(scaled_attention, perm=[0, 2, 1, 3])

    # 4. 헤드 연결(concatenate)하기
    # (batch_size, query의 문장 길이, d_model)
    concat_attention = tf.reshape(scaled_attention,
                                  (batch_size, -1, self.d_model))

    # 5. WO에 해당하는 밀집층 지나기
    # (batch_size, query의 문장 길이, d_model)
    outputs = self.dense(concat_attention)

    return outputs
```

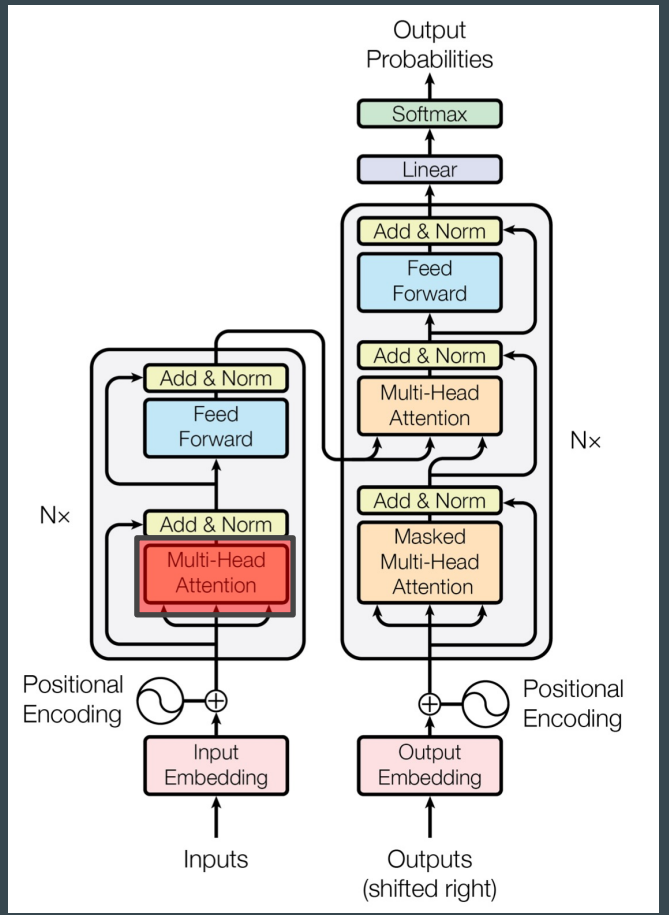
Transformer

- Padding Mask
  - Key의 경우에 <PAD> 토큰이 존재한다면 이에 대해서는 유사도를 구하지 않도록



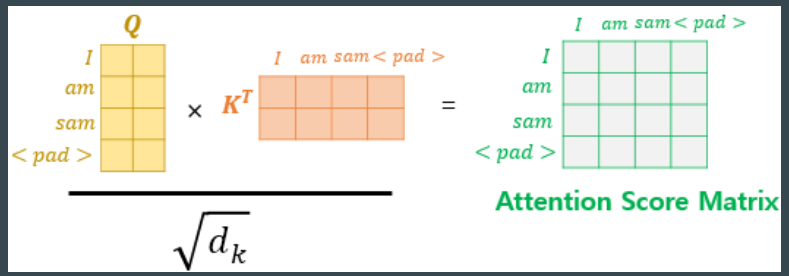


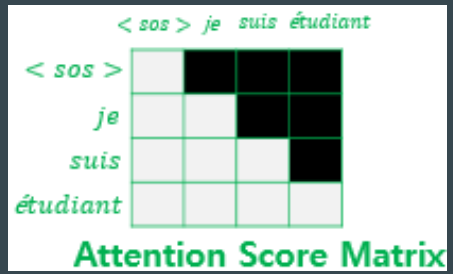


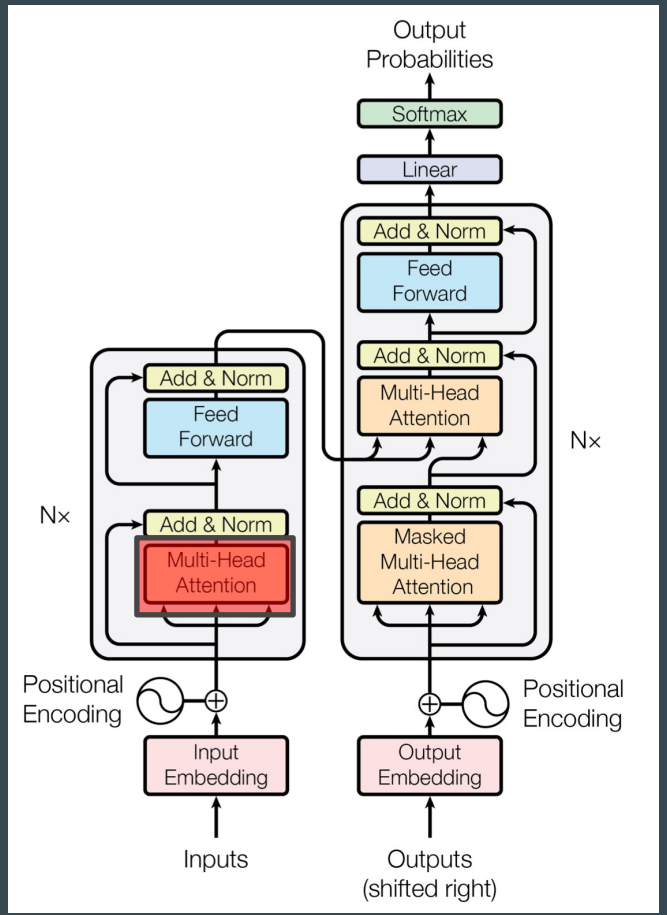


Transformer

- Look-ahead Mask
  - 현재 시점의 예측에서 현재 시점보다 미래에 있는 단어들을 참고하지 못하도록



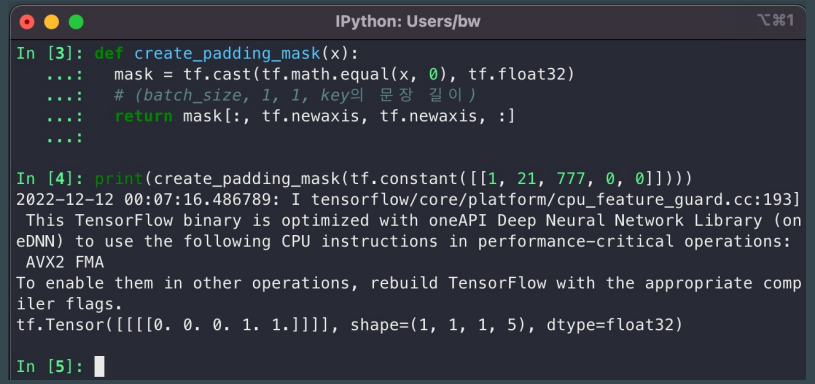




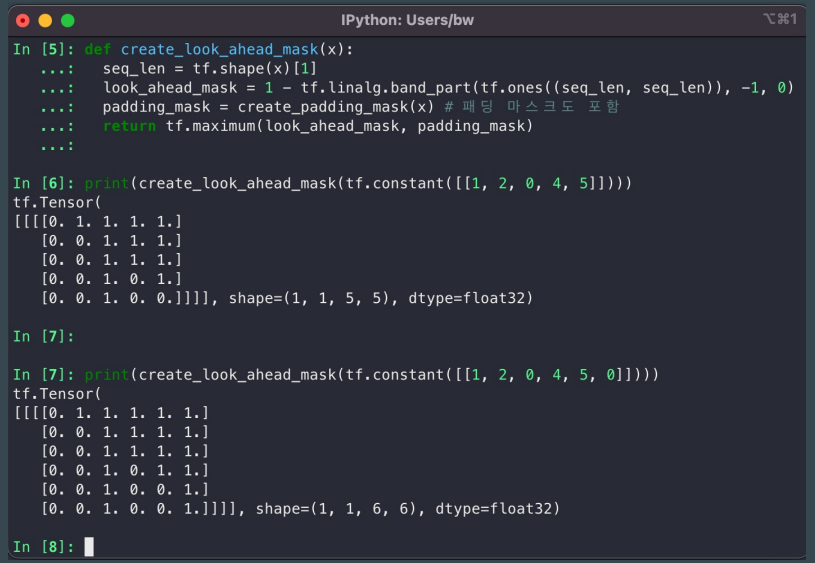
Transformer

- Padding & Look-ahead Mask

```python
# 인코더/디코더에서 문장의 끝을 Mask하는 함수
def create_padding_mask(x):
    mask = tf.cast(tf.math.equal(x, 0), tf.float32)
    # (batch_size, 1, 1, key의 문장 길이)
    return mask[:, tf.newaxis, tf.newaxis, :]
```

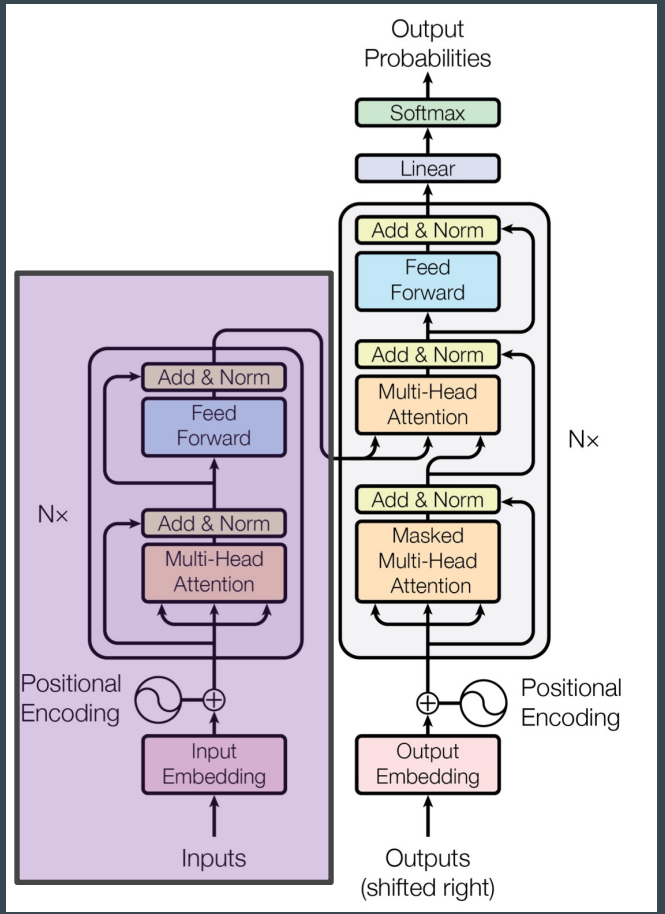



```python
# 디코더의 첫번째 서브층(sublayer)에서 미래 토큰을 Mask하는 함수
def create_look_ahead_mask(x):
    seq_len = tf.shape(x)[1]
    look_ahead_mask = 1 - tf.linalg.band_part(tf.ones((seq_len, seq_len)), -1, 0)
    padding_mask = create_padding_mask(x) # 패딩 마스크도 포함
    return tf.maximum(look_ahead_mask, padding_mask)
```



Transformer

- Encoder



Transformer

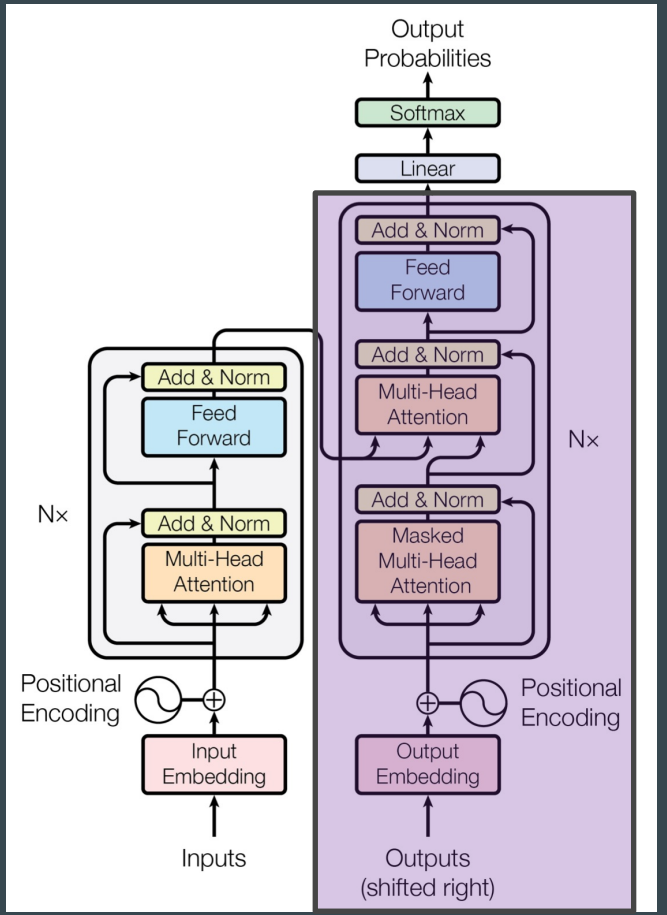
- Encoder

```
def encoder(vocab_size, num_layers, dff,
            d_model, num_heads, dropout,
            name="encoder"):
    inputs = tf.keras.Input(shape=(None,), name="inputs")

    # 인코더는 패딩 마스크 사용
    padding_mask = tf.keras.Input(shape=(1, 1, None), name="padding_mask")

    # 포지셔널 인코딩 + 드롭아웃
    embeddings  = tf.keras.layers.Embedding(vocab_size, d_model)(inputs)
    embeddings *= tf.math.sqrt(tf.cast(d_model, tf.float32))
    embeddings  = PositionalEncoding(vocab_size, d_model)(embeddings)
    outputs     = tf.keras.layers.Dropout(rate=dropout)(embeddings)

    # 인코더를 num_layers개 쌓기
    for i in range(num_layers):
        outputs = encoder_layer(dff=dff, d_model=d_model, num_heads=num_heads,
                                dropout=dropout, name="encoder_layer_{}".format(i),
                                )([outputs, padding_mask])

    return tf.keras.Model(inputs=[inputs, padding_mask], outputs=outputs, name=name)
```

```
def encoder_layer(dff, d_model, num_heads, dropout, name="encoder_layer"):
    inputs = tf.keras.Input(shape=(None, d_model), name="inputs")

    # 인코더는 패딩 마스크 사용
    padding_mask = tf.keras.Input(shape=(1, 1, None), name="padding_mask")

    # 멀티-헤드 어텐션 (첫번째 서브층 / 셀프 어텐션)
    attention = MultiHeadAttention(d_model, num_heads, name="attention")({
                        'query': inputs, 'key': inputs, 'value': inputs, # Q = K = V
                        'mask': padding_mask # 패딩 마스크 사용
                         })

    # 드롭아웃 + 잔차 연결과 층 정규화
    attention = tf.keras.layers.Dropout(rate=dropout)(attention)
    attention = tf.keras.layers.LayerNormalization(epsilon=1e-6)(inputs + attention)

    # 포지션 와이즈 피드 포워드 신경망 (두번째 서브층)
    outputs = tf.keras.layers.Dense(units=dff, activation='relu')(attention)
    outputs = tf.keras.layers.Dense(units=d_model)(outputs)

    # 드롭아웃 + 잔차 연결과 층 정규화
    outputs = tf.keras.layers.Dropout(rate=dropout)(outputs)
    outputs = tf.keras.layers.LayerNormalization(epsilon=1e-6)(attention + outputs)

     return tf.keras.Model(
                    inputs=[inputs, padding_mask], outputs=outputs, name=name).
```

Transformer

- Decoder



Transformer

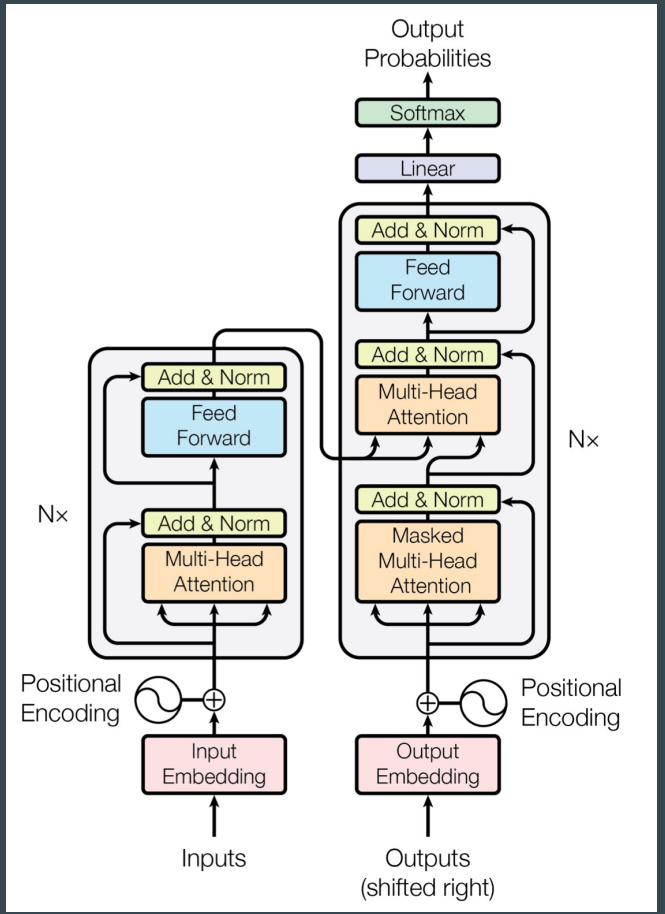
- Decoder

```
def decoder(vocab_size, num_layers, dff, d_model, num_heads, dropout, name='decoder'):
    inputs = tf.keras.Input(shape=(None,), name='inputs')
    enc_outputs = tf.keras.Input(shape=(None, d_model), name='encoder_outputs')

    # 디코더는 룩어헤드 마스크(첫번째 서브층)와 패딩 마스크(두번째 서브층) 둘 다 사용.
    look_ahead_mask = tf.keras.Input(shape=(1, None, None), name='look_ahead_mask')
    padding_mask = tf.keras.Input(shape=(1, 1, None), name='padding_mask')

    # 포지셔널 인코딩 + 드롭아웃
    embeddings = tf.keras.layers.Embedding(vocab_size, d_model)(inputs)
    embeddings *= tf.math.sqrt(tf.cast(d_model, tf.float32))
    embeddings = PositionalEncoding(vocab_size, d_model)(embeddings)
    outputs = tf.keras.layers.Dropout(rate=dropout)(embeddings)

    # 디코더를 num_layers개 쌓기
    for i in range(num_layers):
        outputs = decoder_layer(dff=dff, d_model=d_model, num_heads=num_heads,
                                dropout=dropout, name='decoder_layer_{}'.format(i),
                    )(inputs=[outputs, enc_outputs, look_ahead_mask, padding_mask])

    return tf.keras.Model(
            I               nputs=[inputs, enc_outputs, look_ahead_mask, padding_mask],
                            outputs=outputs,
                            name=name)
```

```
def decoder_layer(dff, d_model, num_heads, dropout, name="decoder_layer"):
    inputs = tf.keras.Input(shape=(None, d_model), name="inputs")
    enc_outputs = tf.keras.Input(shape=(None, d_model), name="encoder_outputs")

    # 룩어헤드 마스크(첫번째 서브층)
    look_ahead_mask = tf.keras.Input(
    shape=(1, None, None), name="look_ahead_mask")

    # 패딩 마스크(두번째 서브층)
    padding_mask = tf.keras.Input(shape=(1, 1, None), name='padding_mask')

    # 멀티-헤드 어텐션 (첫번째 서브층 / 마스크드 셀프 어텐션)
    attention1 = MultiHeadAttention(d_model, num_heads, name="attention_1")
                    (inputs={ 'query': inputs, 'key': inputs, 'value': inputs, # Q = K = V
                              'mask': look_ahead_mask # 룩어헤드 마스크.
                            })
    # 잔차 연결과 층 정규화
    attention1 = tf.keras.layers.LayerNormalization(epsilon=1e-6)(attention1 + inputs)

    # 멀티-헤드 어텐션 (두번째 서브층 / 디코더-인코더 어텐션)
    attention2 = MultiHeadAttention(d_model, num_heads, name="attention_2")
      (inputs={ 'query': attention1, 'key': enc_outputs, 'value': enc_outputs, # Q != K = V
                'mask': padding_mask # 패딩 마스크
      })
    # 드롭아웃 + 잔차 연결과 층 정규화
    attention2 = tf.keras.layers.Dropout(rate=dropout)(attention2)
    attention2 = tf.keras.layers.LayerNormalization(epsilon=1e-6)(attention2 + attention1)

    # 포지션 와이즈 피드 포워드 신경망 (세번째 서브층)
    outputs = tf.keras.layers.Dense(units=dff, activation='relu')(attention2)
    outputs = tf.keras.layers.Dense(units=d_model)(outputs)

    # 드롭아웃 + 잔차 연결과 층 정규화
    outputs = tf.keras.layers.Dropout(rate=dropout)(outputs)
    outputs = tf.keras.layers.LayerNormalization(epsilon=1e-6)(outputs + attention2)

    return tf.keras.Model(
                    inputs=[inputs, enc_outputs, look_ahead_mask, padding_mask],
                    outputs=outputs,
                    name=name)
```

Transformer

- All together



Transformer

```
def transformer(vocab_size, num_layers, dff, d_model, num_heads, dropout, name="transformer"):

    # 인코더의 입력
    inputs = tf.keras.Input(shape=(None,), name="inputs")

    # 디코더의 입력
    dec_inputs = tf.keras.Input(shape=(None,), name="dec_inputs")

    # 인코더의 패딩 마스크
    enc_padding_mask = tf.keras.layers.Lambda(create_padding_mask, output_shape=(1, 1, None),
                                              name='enc_padding_mask')(inputs)

    # 디코더의 룩어헤드 마스크(첫번째 서브층)
    look_ahead_mask = tf.keras.layers.Lambda(create_look_ahead_mask, output_shape=(1, None, None),
                                             name='look_ahead_mask')(dec_inputs)

    # 디코더의 패딩 마스크(두번째 서브층)
    dec_padding_mask = tf.keras.layers.Lambda(create_padding_mask, output_shape=(1, 1, None),
                                              name='dec_padding_mask')(inputs)

    # 인코더의 출력은 enc_outputs. 디코더로 전달된다.
    enc_outputs = encoder(vocab_size=vocab_size, num_layers=num_layers, dff=dff,
                          d_model=d_model, num_heads=num_heads, dropout=dropout,
                          )(inputs=[inputs, enc_padding_mask]) # 인코더의 입력은 입력 문장과 패딩 마스크

    # 디코더의 출력은 dec_outputs. 출력층으로 전달된다.
    dec_outputs = decoder(vocab_size=vocab_size, num_layers=num_layers, dff=dff,
                          d_model=d_model, num_heads=num_heads, dropout=dropout,
                          )(inputs=[dec_inputs, enc_outputs, look_ahead_mask, dec_padding_mask])

    # 다음 단어 예측을 위한 출력층
    outputs = tf.keras.layers.Dense(units=vocab_size, name="outputs")(dec_outputs)

    return tf.keras.Model(inputs=[inputs, dec_inputs], outputs=outputs, name=name)
```

Everything can be found in
https://wikidocs.net/book/2155
https://github.com/ukairia777/tensorflow-nlp-tutorial