Lab 4

Transformer

Seoul National University

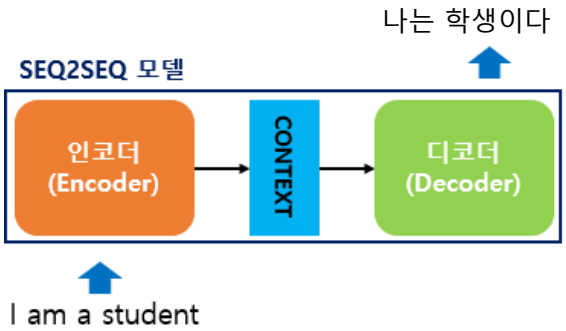
Human Interface Laboratory

Contents

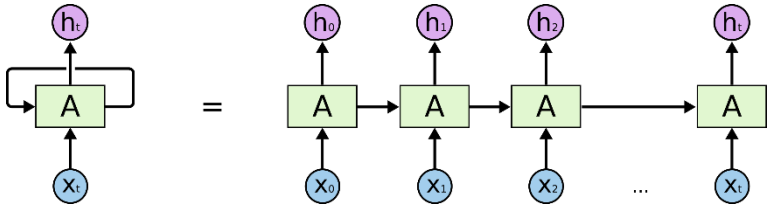
- **Intro**
  - Transformer 구조의 중요성
- **Transformer의 개념**
- **Transformer의 구현**
- **Pre-Trained Transformer 사용해보기**

Intro

- **Model Architecture for Seq2Seq**
  - Ex) 한국어 문장을 영어 문장으로 번역하는 AI 모델?
    - 영어 문장 -> 입력 벡터(인코딩)
    - 입력 벡터 – (AI 모델) -> 출력 벡터
    - 출력 벡터 -> 한국어 문장(디코딩)
  - Seq2Seq: Input Sequence -> context vector -> Output Sequence
  - RNN 문제: (특히) 긴 문장의 모델링이 어려움



https://wikidocs.net/160053



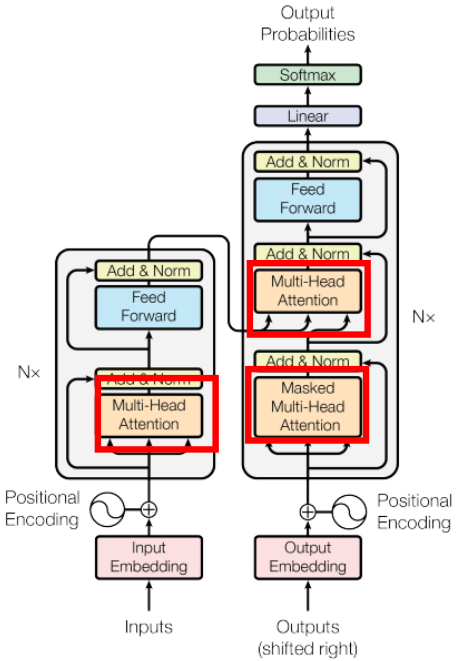
https://wikidocs.net/160053

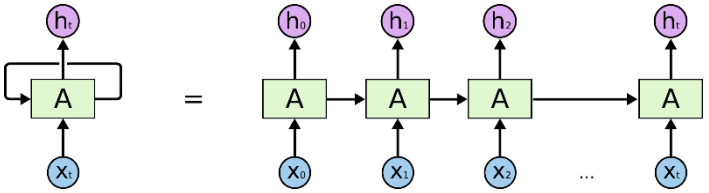
Intro

- **Transformer의 중요성**
  - Transformer는 RNN 대비 대체로 성능이 높은 Sequence Model
  - 최근 대부분의 생성모델에서 Transformer 구조를 활용

Transformer란

- **Transformer란**
  - 성능이 뛰어난 Sequence Model
  - Attention Mechanism이 핵심
    - Attention Mechanism을 통해 Input 정보를 보다 직접적으로 반영
    - cf) RNN: hidden state를 통해 Input 정보를 보다 간접적으로 반영



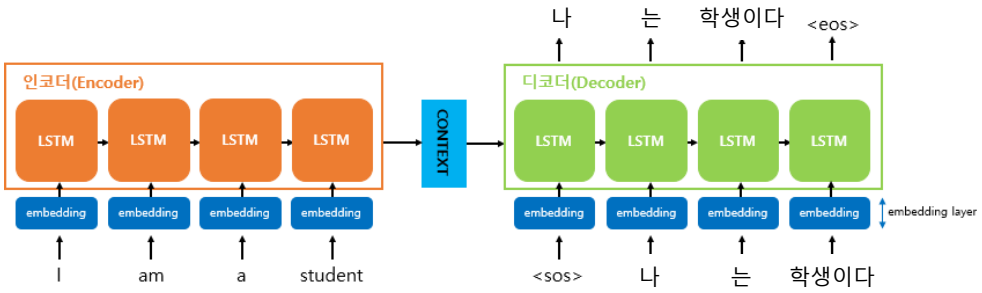


Vaswani, Ashish, et al. "Attention Is All You Need(NIPS)", 2017.

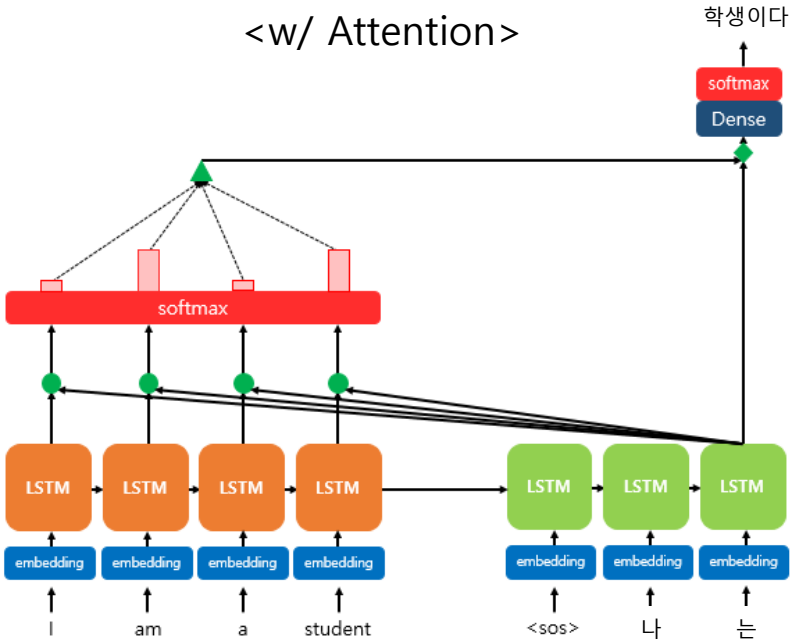
Transformer란

- **Attention**
  - Input Sequence에 대한 context vector를 생성하는 메커니즘
  - Sequence 각 Token간 연관성을 직접 반영하여 Input을 재조정
    - 모든 Token과의 연관성 반영 가능 => Long Sequence Modeling 용이

<w/o Attention>



<w/ Attention>



https://wikidocs.net/22893

Transformer란

- **Attention**
  - context vector는 각 Input token vector의 가중합(중요도에 차등)
  - 가중치는 Input sequence와 Target sequence 내 token간 연관도
    - Cross-Attention: Target Sequence가 Input Sequence와 다름
    - Self-Attention: Target Sequence가 Input Sequence 자기 자신임

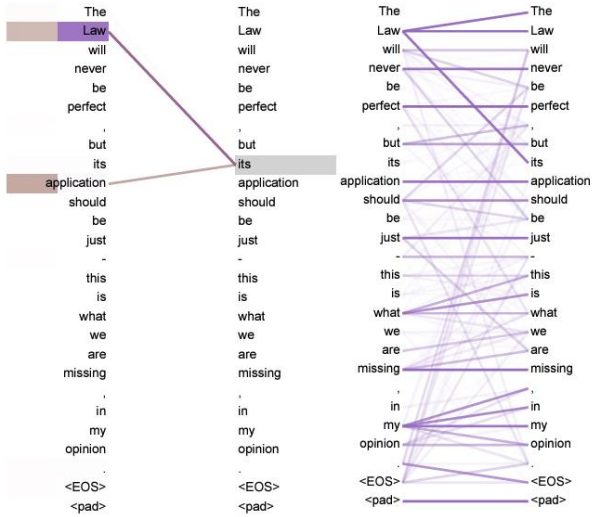
$$Context = Weight \cdot Input$$

$$Weight = softmax\left(\frac{Score}{\sqrt{d_{model}}}\right)$$

$$Score = Target \cdot Input^T$$

$$Context = Attention(Q, K, V) = softmax\left(\frac{Q \cdot K^T}{\sqrt{d_{model}}}\right) V$$

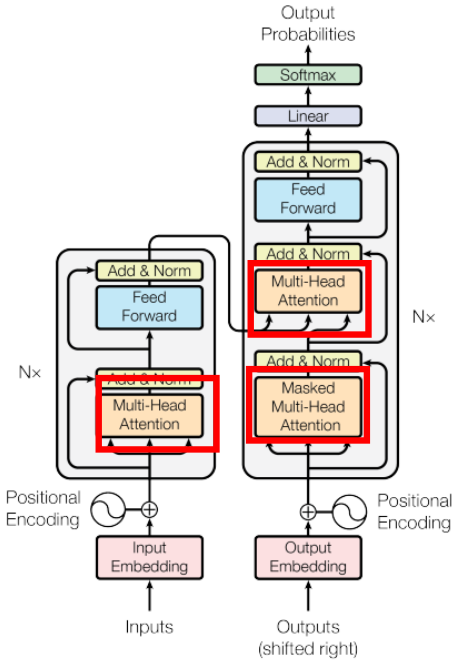
where $Q = Target,\ K = V = Input$

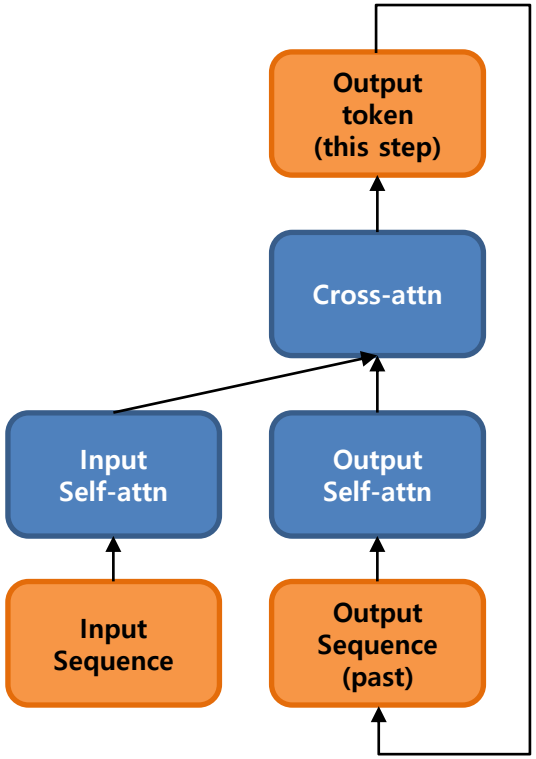


Vaswani, Ashish, et al. "Attention Is All You Need(NIPS)", 2017.

Transformer란

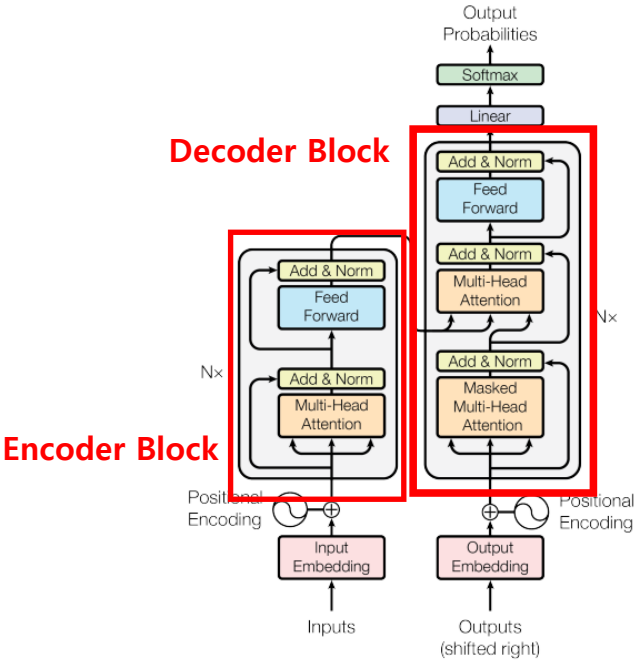
- **Transformer Architecture**
  - t번째 토큰 생성 시 세 종류의 Attention Mechanism 활용
    - Input Sequence에 대한 Self-Attention
    - Output Sequence($1 \sim (t-1)$번째)에 대한 Self-Attention
    - Input context vector와 Output context vector에 대한 Cross-Attention

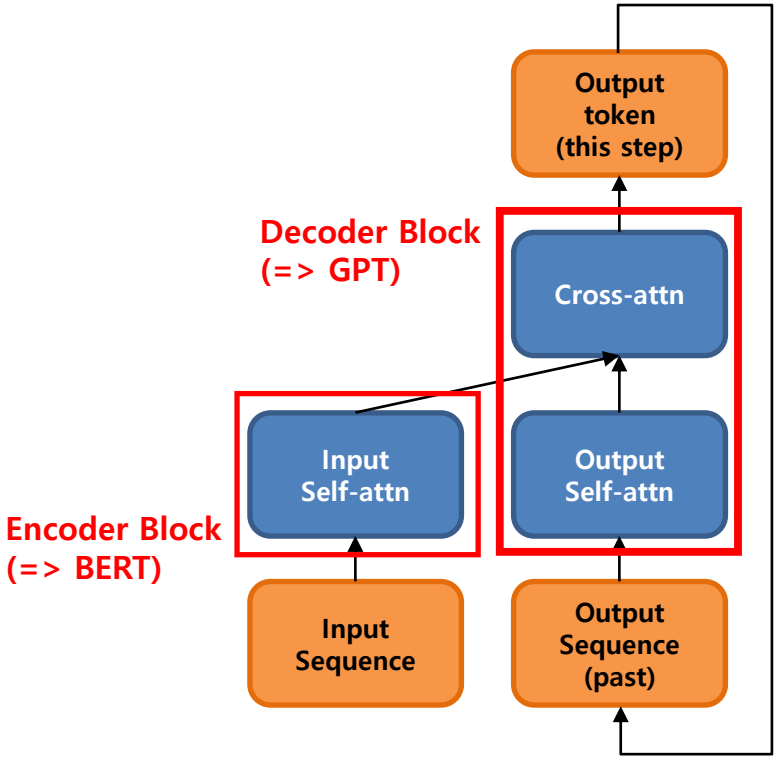




Transformer란

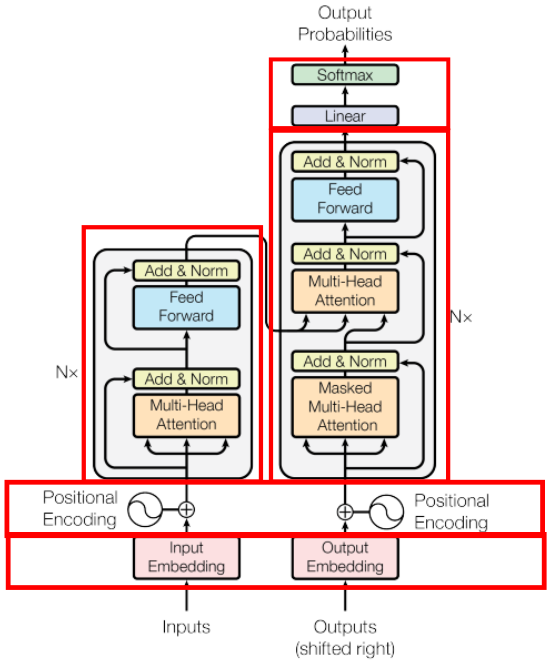
- **Transformer Architecture**
  - 기본적으로 N개의 Encoder Block과 Decoder Block으로 구성됨
    - Encoder Block만 특화: ex. BERT(주어진 문장의 Embedding 생성)
    - Decoder Block만 특화: GPT(언어 생성)

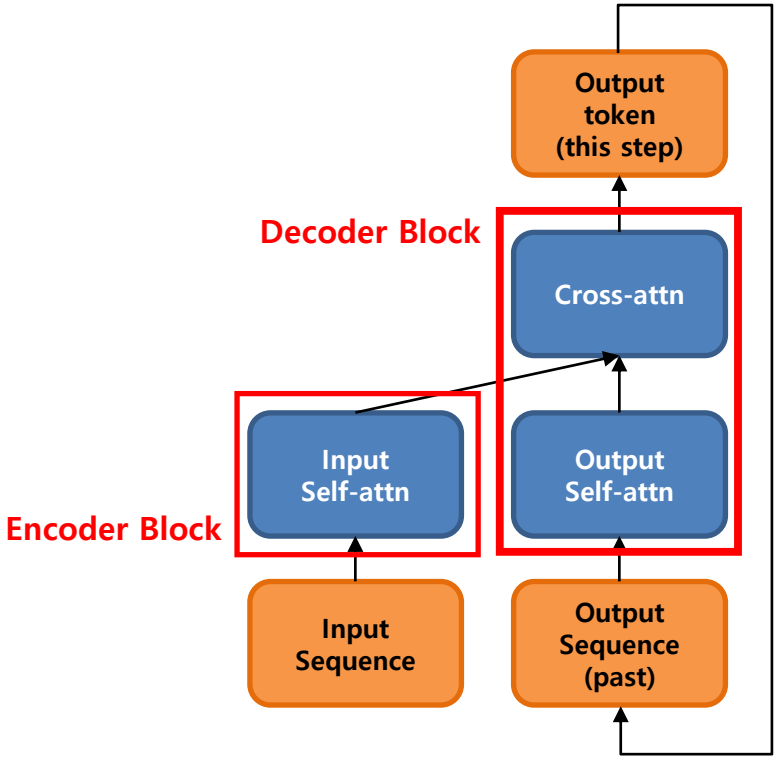




Transformer란

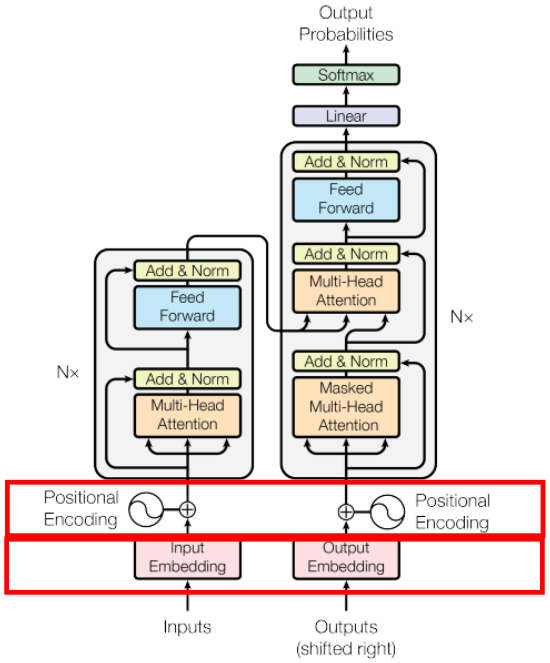
- **Implementation Details**
  - Positional Encoding
  - Encoder Block(N개 반복)
  - Decoder Block(N개 반복)
  - Computing Output Probabilities





Transformer란

- **Input/Output Embedding**
  - Sequence를 신경망이 연산할 수 있는 Embedding Vector로 변환
- **Positional Encoding**
  - 토큰 간 순서 정보를 sequence에 반영
    - Attention: Input Sequence의 모든 token을 동시에 처리하므로 순서 정보 소실
    - cf) RNN: Input Sequence의 순서에 따라 hidden state 순차적 갱신, 순서 정보 반영
  - Input Sequence에 Positional Encoding 값을 덧셈하는 방식으로 반영

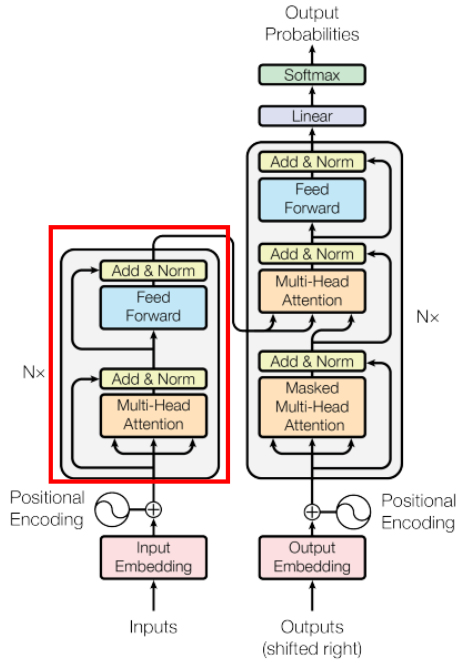


$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

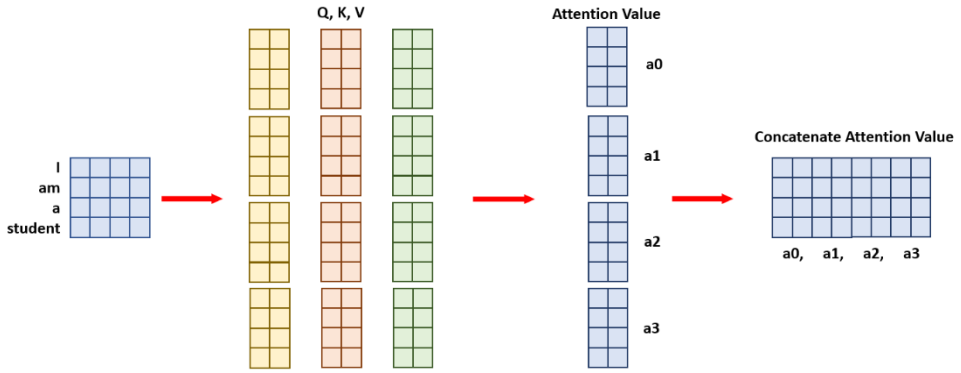
$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

Transformer란

- **Encoder Block**
  - Multi-Head Attention: 서로 다른 독립된 Attention을 수행한 뒤 이어붙임
    - 목적: 입력 데이터의 다양한 관계를 분담하여 학습
      - Ex. Head 1: 주어-목적어 관계, Head 2: 동사-목적어 관계…
    - 구현: Input sequence를 서로 다른 Linear Projection W_i로 변환시킴
      - 서로 다른 Linear Projection에 의한 독립적인 Attention 결과를 이어붙임(Concat)



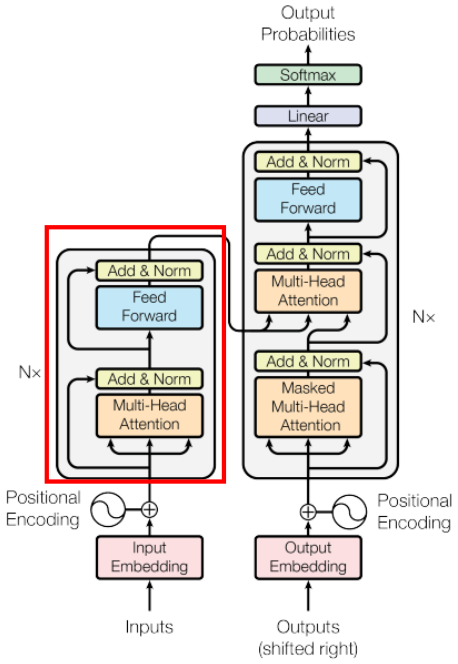
$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

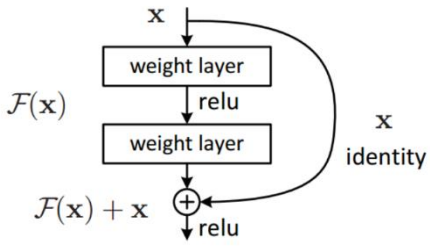


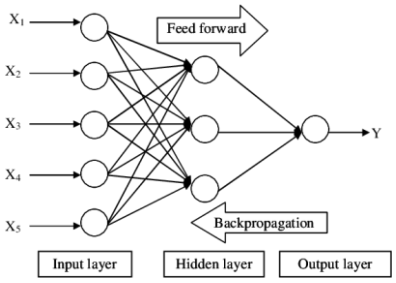
https://codingopera.tistory.com/44

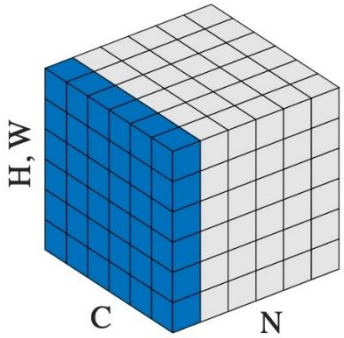
Transformer란

- **Encoder Block**
  - Skip Connection(Add): 원본 입력 정보를 그대로 전달해 중요 정보 소실 방지
  - Feedforward: 벡터 크기 조절, 학습 표현력 강화
  - Normalization: 입력 벡터의 평균과 분산을 조정해 학습 안정성 강화





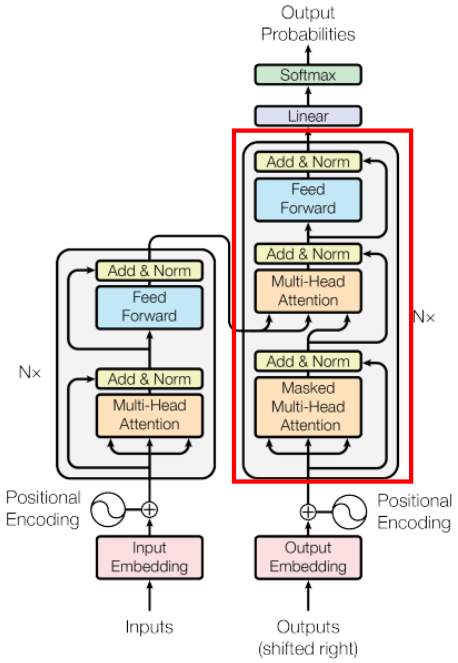


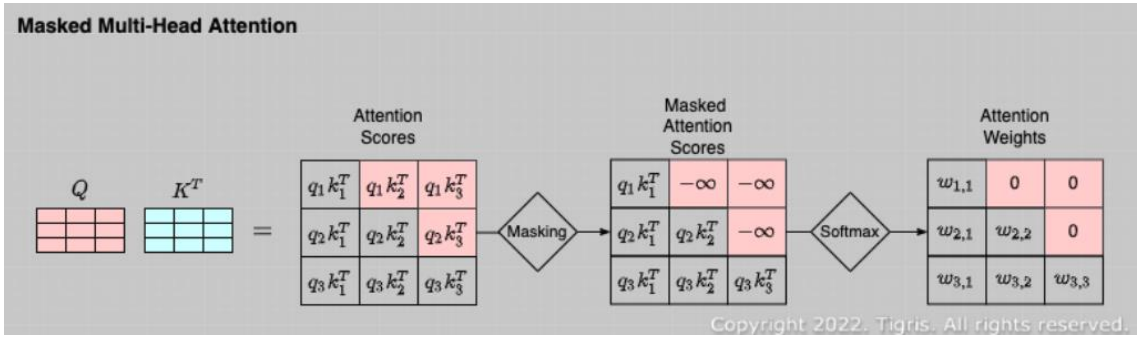


https://www.researchgate.net/figure/Architecture-of-a-typical-multilayer-feed-forward-neural-network_fig1_268380188

Transformer란

- **Decoder Block**
  - Masked Multi-Head Attention
    - Train 시 Output sequence에 대한 Self-Attention에 적용
    - t번째 token을 생성할 경우, output sequence에서 $(t+1)$번째부터의 토큰을 가림
    - Inference에서 t번째 token 생성 중 미래를 볼 수 없으므로 Train 시에도 맞춰줌
    - Mask: Input sequence와 미래 시점 token 간 연관도를 0으로 설정하여 구현

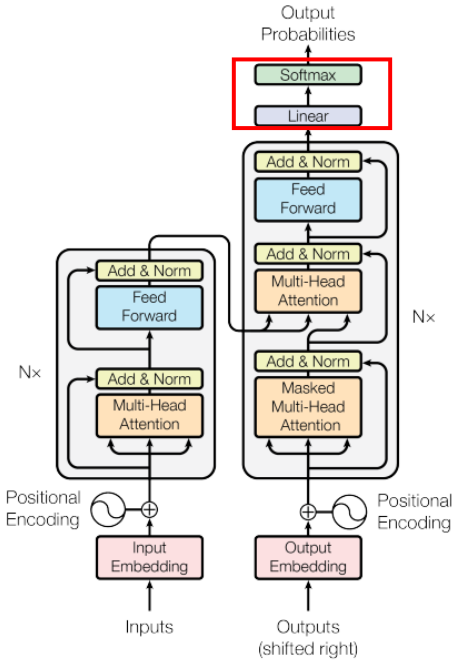




https://tigris-data-science.tistory.com/entry/%EC%B0%A8%EA%B7%BC%EC%B0%A8%EA%B7%BC-%EC%9D%B4%ED%95%B4%ED%95%98%EB%8A%94-Transformer4-Masked-Multi-Head-Attention%EA%B3%BC-Decoder

Transformer란

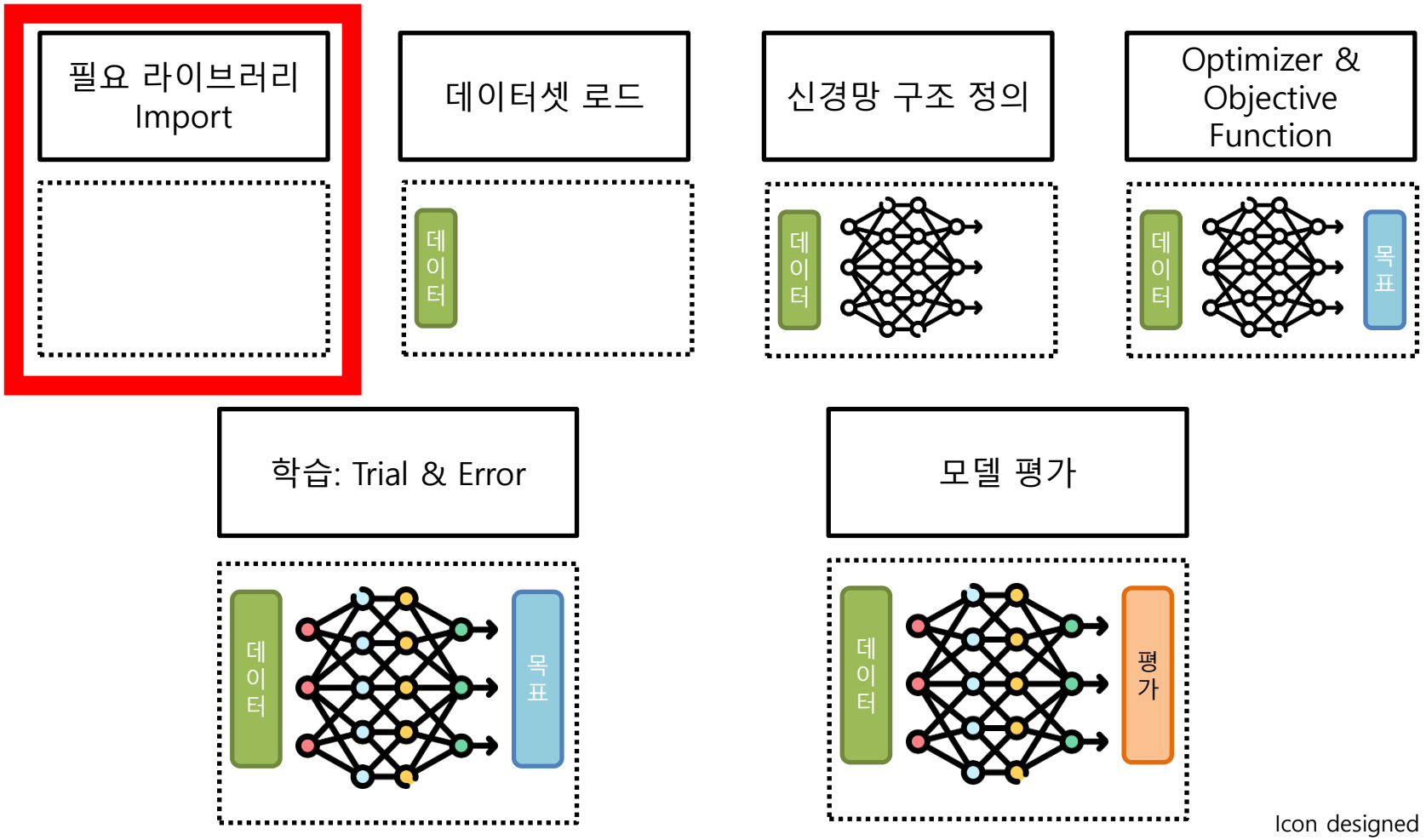
- **Compute Output probabilities**
  - Linear: 벡터 크기 조절
    - ex. 256차원 벡터를 알파벳 개수에 맞춰 26차원으로 변경
  - softmax: 주어진 벡터를 Discrete probability distribution으로 변환



$$\text{softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

Transformer 구현

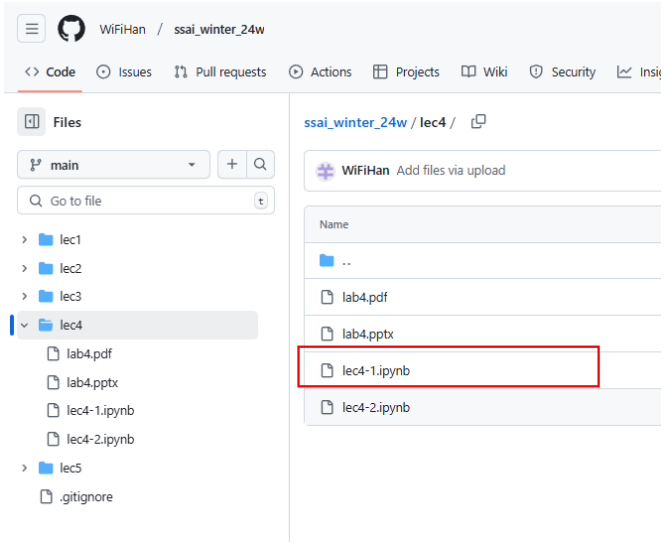
- **(Recall)딥러닝 코드의 대략적 구조**

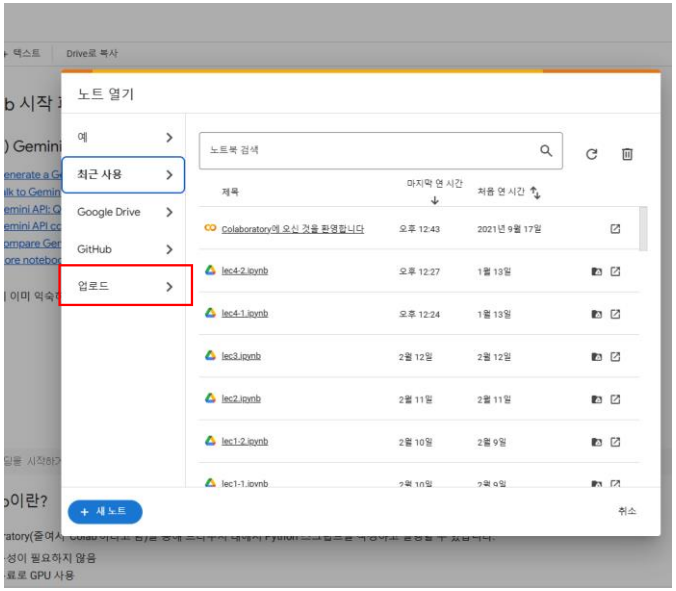


Icon designed by freepik

Transformer 구현

- **실습 준비**
  - https://github.com/WiFiHan/ssai_winter_24w에서
  - lec4 폴더의 lec4-1.ipynb 파일을 다운로드받고
  - colab.research.com에 업로드하여 실행
  - 런타임 유형을 T4 GPU로 설정할 것





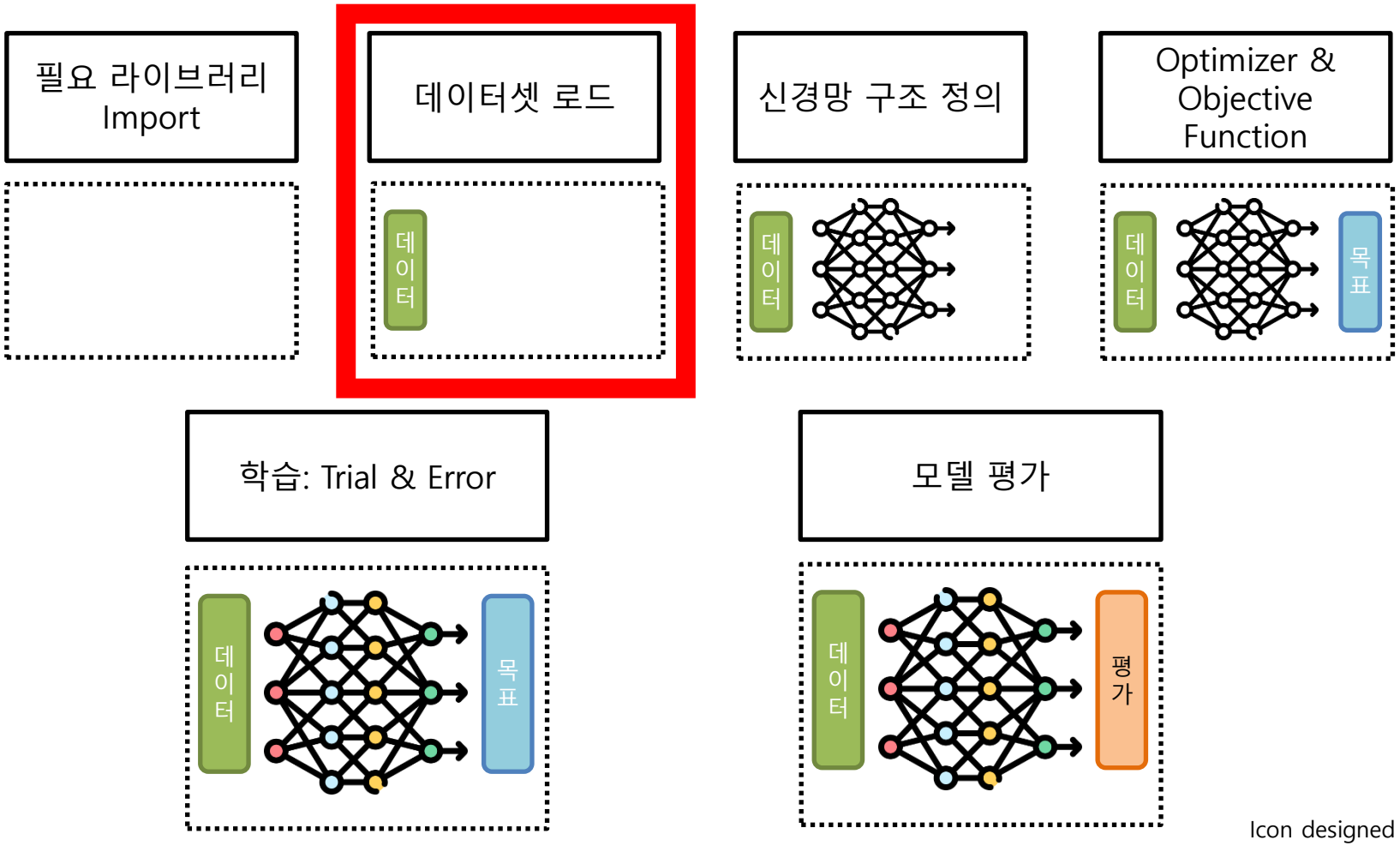
Transformer 구현

- 필요 라이브러리 Import

```
# %% Import Modules
import torch
import torch.nn as nn
import torch.nn.functional as F
import math
```

Transformer 구현

- **(Recall)딥러닝 코드의 대략적 구조**



Icon designed by freepik

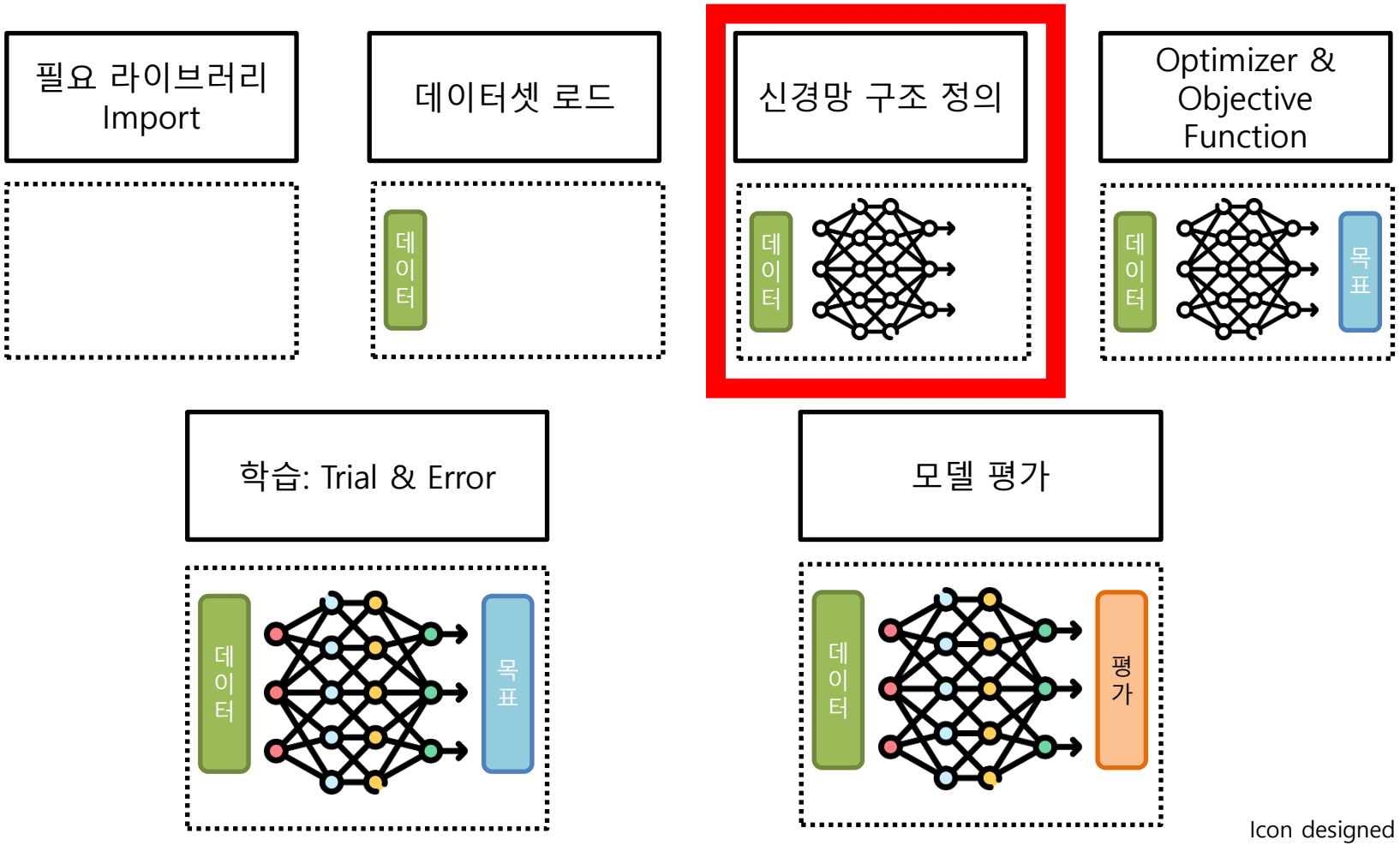
Transformer 구현

- 데이터셋 로드

```
# %% Dataset Preparation
vocab_size = 20
batch_size = 32
seq_len = 10
data_loader = [(torch.randint(0, vocab_size, (batch_size, seq_len)),
                torch.randint(0, vocab_size, (batch_size, seq_len))) for _ in range(100)]
```

Transformer 구현

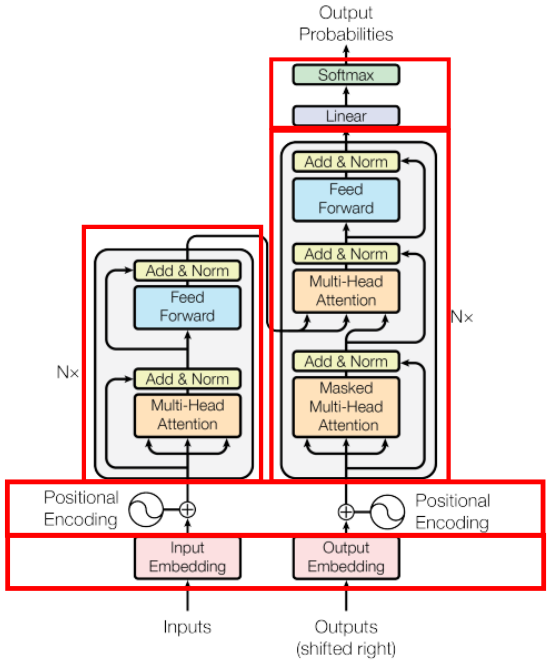
- **(Recall)딥러닝 코드의 대략적 구조**



Icon designed by freepik

Transformer 구현

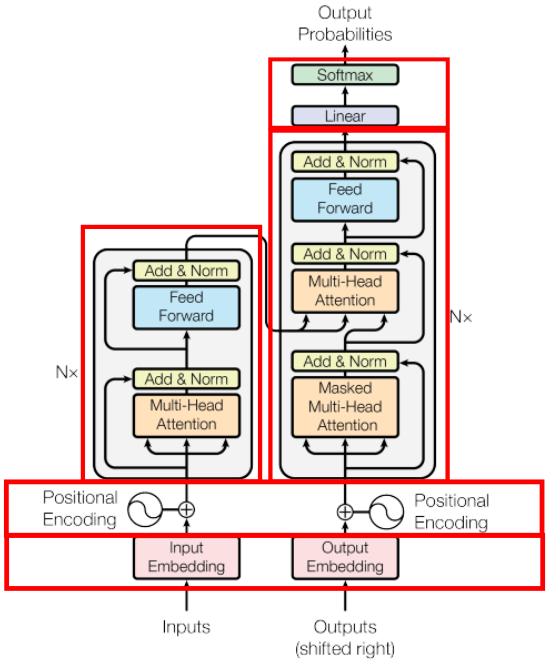
- **Transformer 신경망 구조의 구현**
  - Input/Output Sequence의 Embedding 획득
  - Positional Encoding
  - Encoder Block
  - Decoder Block
  - Computing Output Probabilities



Transformer 구현

- **Transformer 신경망 구조의 구현**
  - 전체적 구조

```python
# %% Transformer Model
class Transformer(nn.Module):
    def __init__(self, input_dim, output_dim, d_model, n_head, d_ff, num_layers, dropout):
        super(Transformer, self).__init__()
        self.src_embedding = nn.Embedding(input_dim, d_model)
        self.tgt_embedding = nn.Embedding(output_dim, d_model)
        self.positional_encoding = PositionalEncoding(d_model)

        self.encoder_layers = nn.ModuleList([EncoderLayer(d_model, n_head, d_ff, dropout)
for _ in range(num_layers)])
        self.decoder_layers = nn.ModuleList([DecoderLayer(d_model, n_head, d_ff, dropout)
for _ in range(num_layers)])
        self.fc_out = nn.Linear(d_model, output_dim)

    def forward(self, src, tgt, tgt_mask):
        src = self.src_embedding(src)
        src = self.positional_encoding(src)
        for layer in self.encoder_layers:
            src = layer(src, None)

        tgt = self.tgt_embedding(tgt)
        tgt = self.positional_encoding(tgt)
        for layer in self.decoder_layers:
            tgt = layer(tgt, src, tgt_mask)

        return self.fc_out(tgt)
```



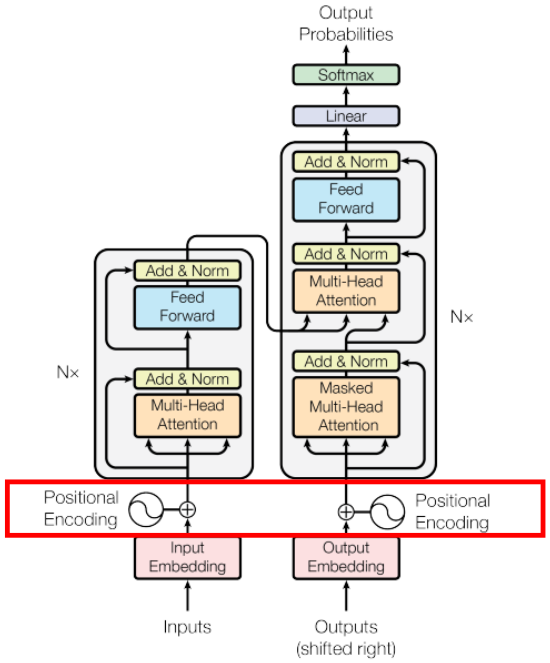
Transformer 구현

- **Transformer 신경망 구조의 구현**
  - Positional Encoding

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

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

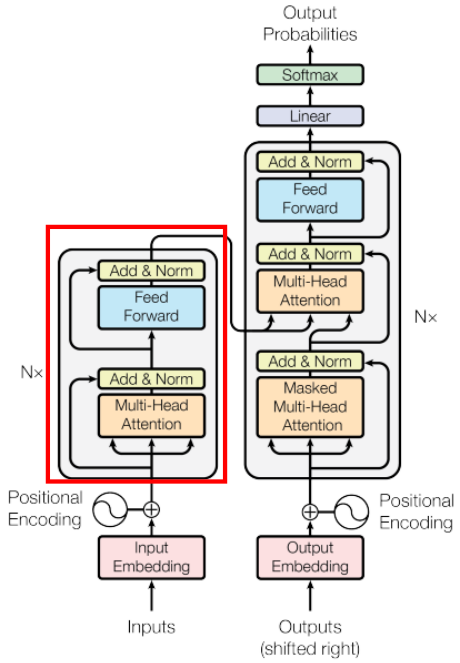
```python
# %% Positional Encoding
class PositionalEncoding(nn.Module):
    def __init__(self, d_model, max_len=5000):
        super(PositionalEncoding, self).__init__()
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len,
dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float()
* (-math.log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0)
        self.register_buffer('pe', pe)

    def forward(self, x):
        return x + self.pe[:, :x.size(1), :]
```



Transformer 구현

- **Transformer 신경망 구조의 구현**
  - Encoder Block의 전체적 구조

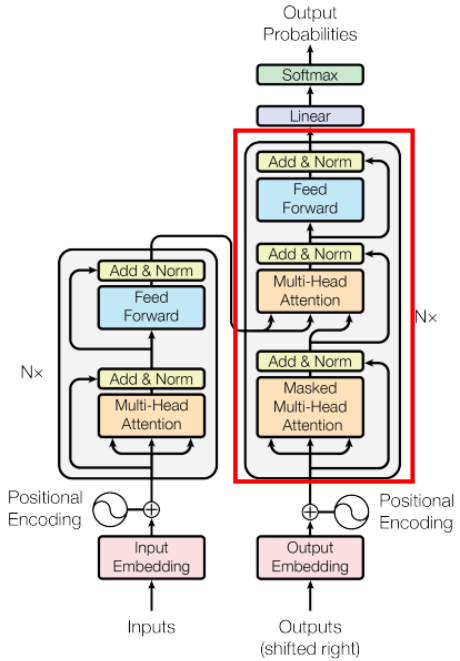
```python
# %% Encoder Block
class EncoderBlock(nn.Module):
    def __init__(self, d_model, n_head, d_ff, dropout):
        super(EncoderBlock, self).__init__()
        self.attn = MultiHeadAttention(d_model, n_head)
        self.ffn = FeedForward(d_model, d_ff, dropout)
        self.norm1 = nn.LayerNorm(d_model)
        self.norm2 = nn.LayerNorm(d_model)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x, mask):
        x = self.norm1(x + self.dropout(self.attn(x, x, x, mask)))
        x = self.norm2(x + self.dropout(self.ffn(x)))
        return x
```



Transformer 구현

- **Transformer 신경망 구조의 구현**
  - Decoder Block의 전체적 구조

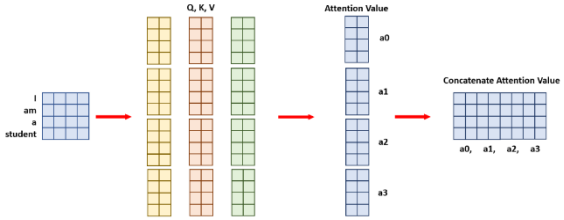
```python
# %% Decoder Block
class DecoderBlock(nn.Module):
    def __init__(self, d_model, n_head, d_ff, dropout):
        super(DecoderBlock, self).__init__()

        self.self_attn = MultiHeadAttention(d_model, n_head)
        self.norm1 = nn.LayerNorm(d_model)
        self.dropout1 = nn.Dropout(dropout)

        self.cross_attn = MultiHeadAttention(d_model, n_head)
        self.norm2 = nn.LayerNorm(d_model)
        self.dropout2 = nn.Dropout(dropout)

        self.ffn = FeedForward(d_model, d_ff, dropout)
        self.norm3 = nn.LayerNorm(d_model)
        self.dropout3 = nn.Dropout(dropout)

    def forward(self, tgt, memory, tgt_mask):
        tgt = self.norm1(tgt + self.dropout1(self.self_attn(tgt, tgt, tgt, tgt_mask)))
        tgt = self.norm2(tgt + self.dropout2(self.cross_attn(tgt, memory, memory)))
        tgt = self.norm3(tgt + self.dropout3(self.ffn(tgt)))
        return tgt
```



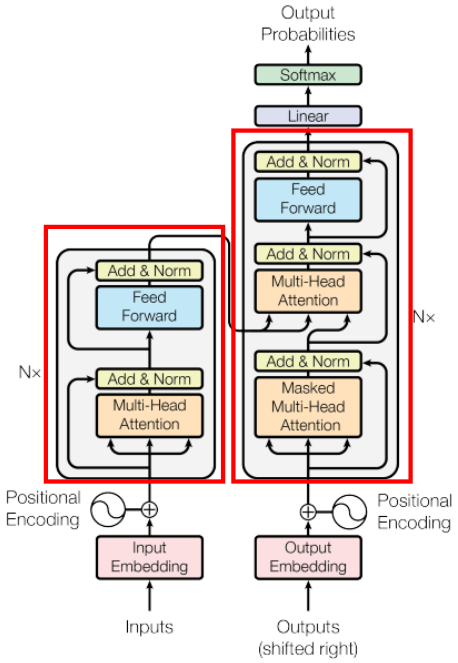
Transformer 구현

- **Transformer 신경망 구조의 구현**
  - Encoder/Decoder Block: Multi-Head Attention

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$



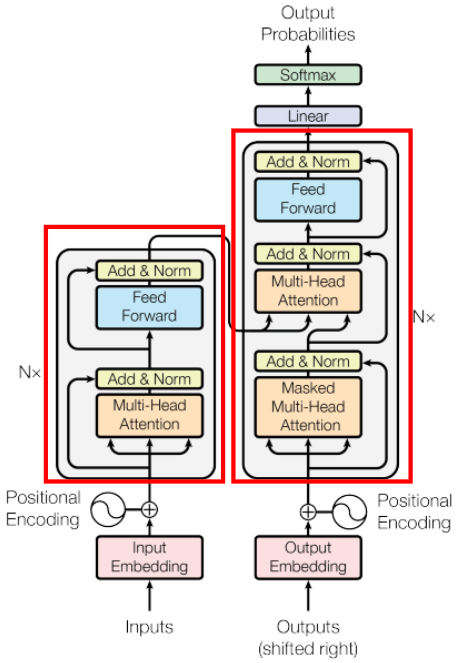

```python
# %% Multi-Head Attention
class MultiHeadAttention(nn.Module):
    def __init__(self, d_model, n_head):
        super(MultiHeadAttention, self).__init__()
        self.n_head = n_head
        self.attention = ScaleDotProductAttention()
        self.w_q = nn.Linear(d_model, d_model)
        self.w_k = nn.Linear(d_model, d_model)
        self.w_v = nn.Linear(d_model, d_model)
        self.w_concat = nn.Linear(d_model, d_model)

    def forward(self, q, k, v, mask=None):
        q, k, v = self.w_q(q), self.w_k(k), self.w_v(v)
        q, k, v = self.split(q), self.split(k), self.split(v)
        out, _ = self.attention(q, k, v, mask)
        out = self.concat(out)
        out = self.w_concat(out)
        return out

    def split(self, tensor):
        batch_size, length, d_model = tensor.size()
        d_tensor = d_model // self.n_head
        tensor = tensor.view(batch_size, length, self.n_head, d_tensor).transpose(1, 2)
        return tensor

    def concat(self, tensor):
        batch_size, head, length, d_tensor = tensor.size()
        d_model = head * d_tensor
        tensor = tensor.transpose(1, 2).contiguous().view(batch_size, length, d_model)
        return tensor
```



Transformer 구현

- **Transformer 신경망 구조의 구현**
  - Encoder/Decoder Block: Scaled Dot-Product Attention with mask

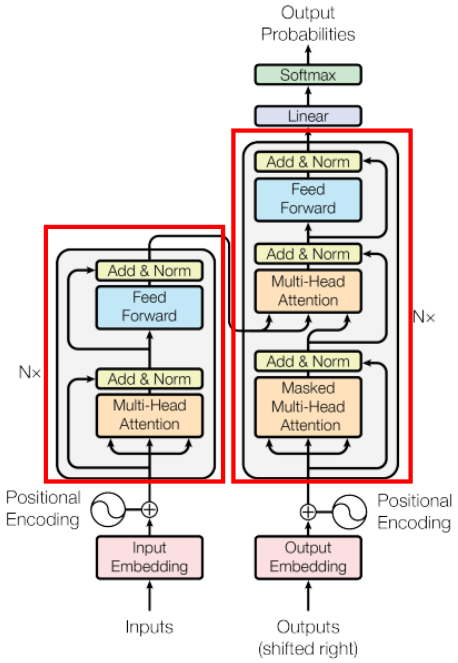
```python
# %% Scaled Dot-Product Attention
class ScaleDotProductAttention(nn.Module):
    def __init__(self):
        super(ScaleDotProductAttention, self).__init__()
        self.softmax = nn.Softmax(dim=-1)

    def forward(self, q, k, v, mask=None):
        score = torch.matmul(q, k.transpose(-2, -1)) / math.sqrt(q.size(-1))
        if mask is not None:
            score = score.masked_fill(mask == 0, -1e9)
        score = self.softmax(score)
        v = torch.matmul(score, v)
        return v, score
```



Transformer 구현

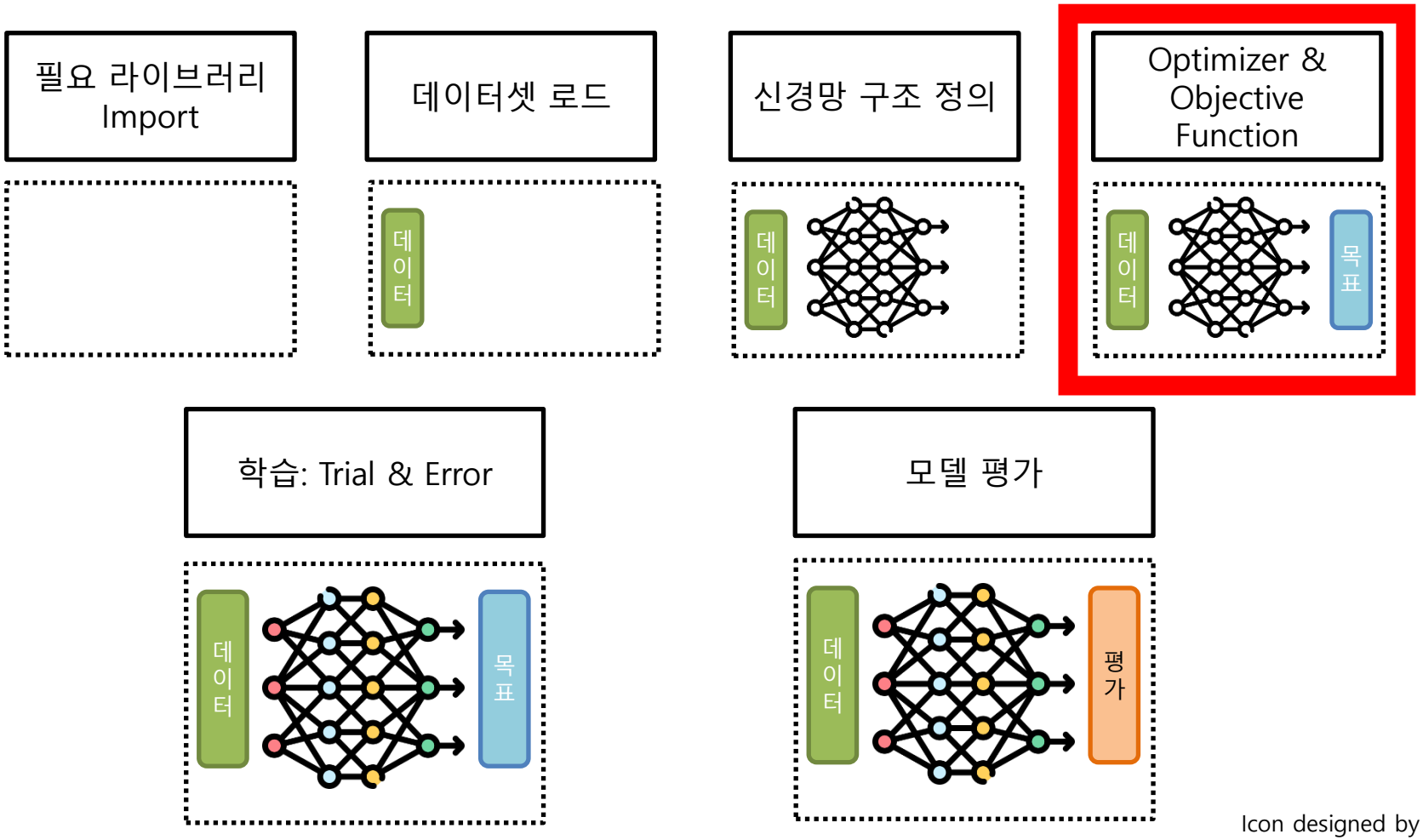
- **Transformer 신경망 구조의 구현**
  - Encoder/Decoder Block: Feedforward

```python
# %% Feed Forward Network
class FeedForward(nn.Module):
    def __init__(self, d_model, d_ff, dropout=0.1):
        super(FeedForward, self).__init__()
        self.linear1 = nn.Linear(d_model, d_ff)
        self.dropout = nn.Dropout(dropout)
        self.linear2 = nn.Linear(d_ff, d_model)

    def forward(self, x):
        return self.linear2(self.dropout(F.relu(self.linear1(x))))
```



Transformer 구현

- **(Recall)딥러닝 코드의 대략적 구조**



Icon designed by freepik

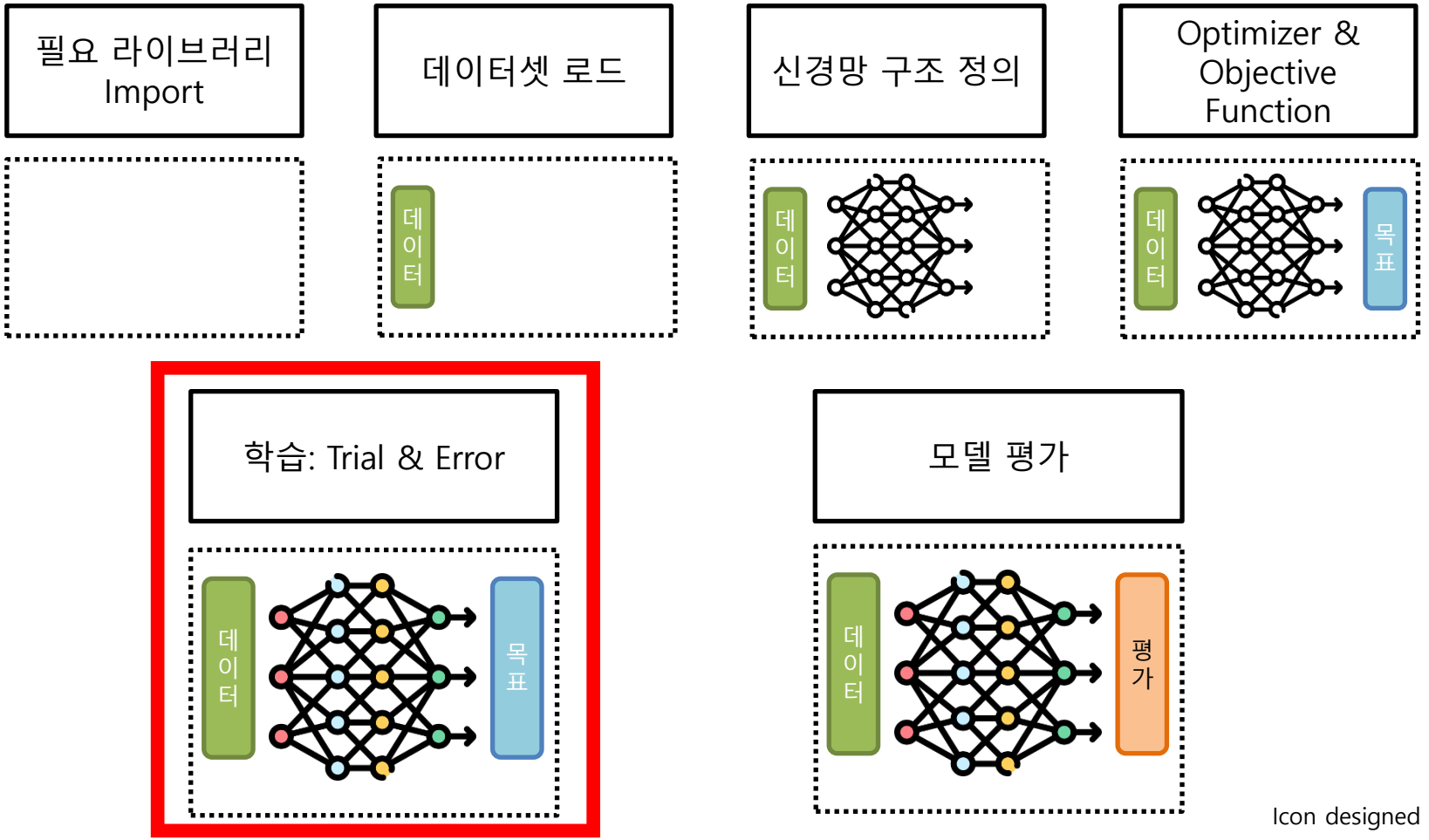
Transformer 구현

- **모델 호출 및 Optimizer & Loss Function**

```
d_model = 512
n_head = 8
d_ff = 2048
dropout = 0.1
num_layers = 6

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = Transformer(vocab_size, vocab_size, d_model, n_head, d_ff, num_layers,
dropout).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
criterion = nn.CrossEntropyLoss()
```

Transformer 구현

- **(Recall)딥러닝 코드의 대략적 구조**



Icon designed by freepik

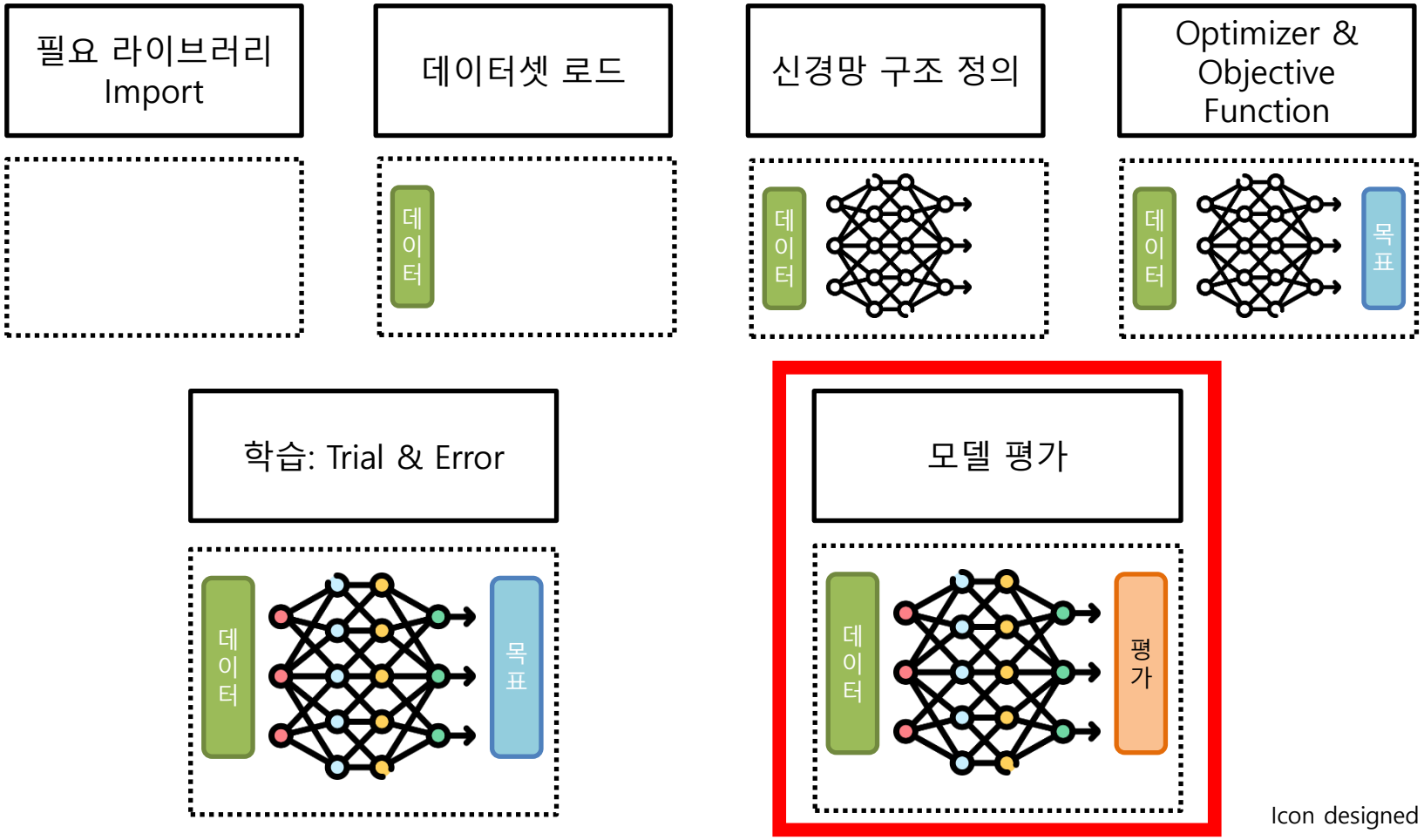
Transformer 구현

- 학습

```python
# %% Train Model Function
def train_model(model, data_loader, optimizer, criterion, device, num_epochs, seq_len):

    model.train()
    total_loss = 0

    for src, tgt in data_loader:
        src, tgt = src.to(device), tgt.to(device)
        mask = torch.tril(torch.ones((seq_len, seq_len), device=device))
        optimizer.zero_grad()
        output = model(src, tgt, mask)
        loss = criterion(output.view(-1, output.size(-1)), tgt.view(-1))
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    return total_loss / len(data_loader)
```

Transformer 구현

- **(Recall)딥러닝 코드의 대략적 구조**



Icon designed by freepik

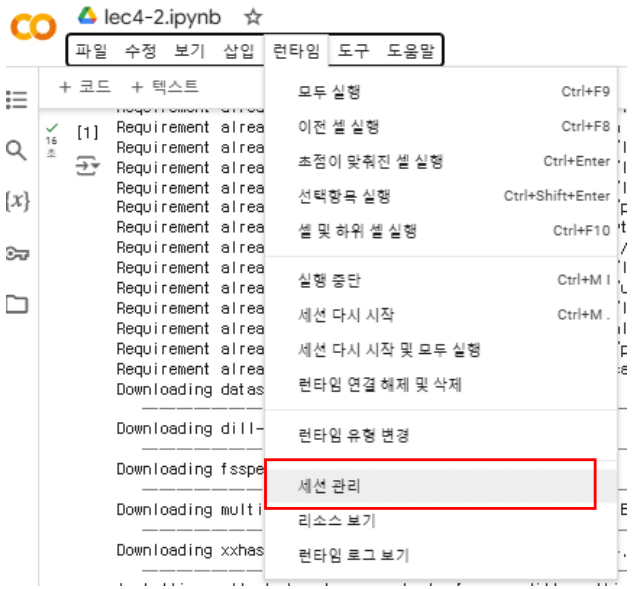
Transformer 구현

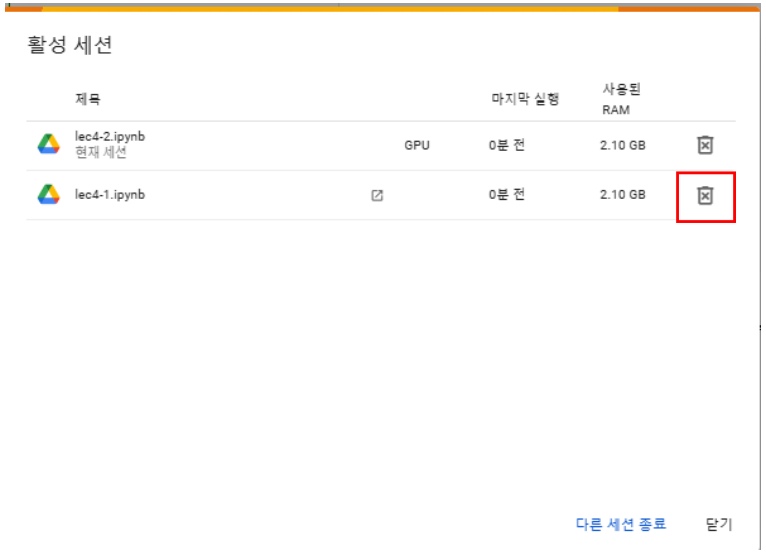
- 평가

```python
# %% Evaluate Model Function
def evaluate_model(model, data_loader, criterion, device, seq_len):

    model.eval()
    total_loss = 0

    with torch.no_grad():
        for src, tgt in data_loader:
            src, tgt = src.to(device), tgt.to(device)
            mask = torch.tril(torch.ones((seq_len, seq_len), device=device))
            output = model(src, tgt, mask)
            loss = criterion(output.view(-1, output.size(-1)), tgt.view(-1))
            total_loss += loss.item()

    return total_loss / len(data_loader)
```

Pretrained Transformer 사용해보기

- **Colab에서 실습코드 파일 실행**
  - https://github.com/WiFiHan/ssai_winter_24w 의 lec4/lec4-2.ipynb
  - 구글드라이브에서 lec4-2.ipynb 실행, 런타임 'T4 GPU'로 설정
  - 세션 관리에서 lec4-1.ipynb 파일 삭제

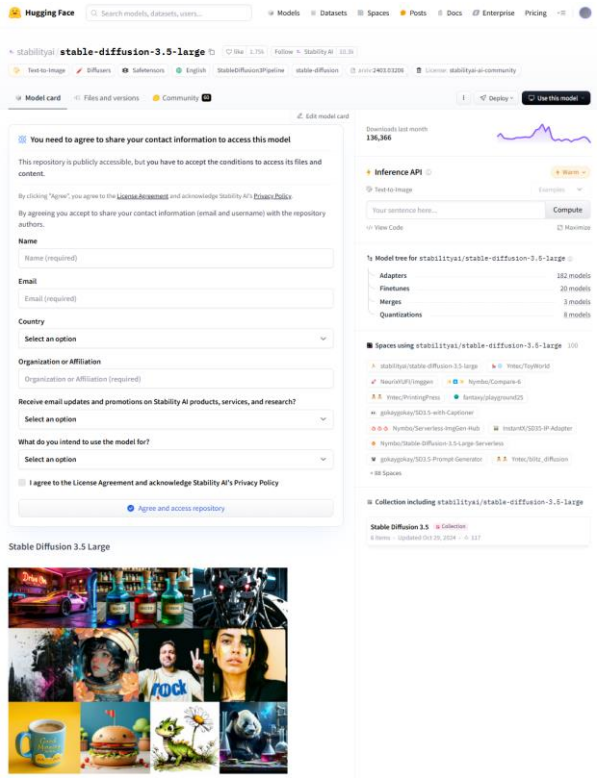




Pretrained Transformer 사용해보기

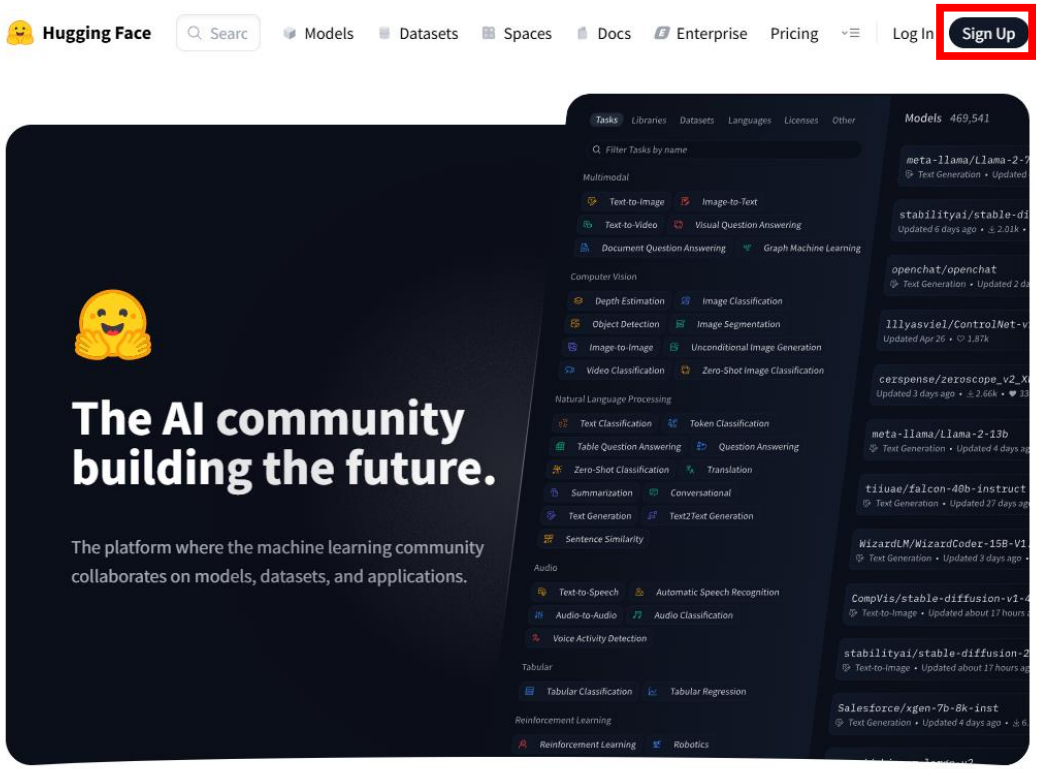
- **HuggingFace**
  - Pre-trained AI model을 간편하게 사용할 수 있는 오픈소스 플랫폼
  - Training, Inference의 간소화

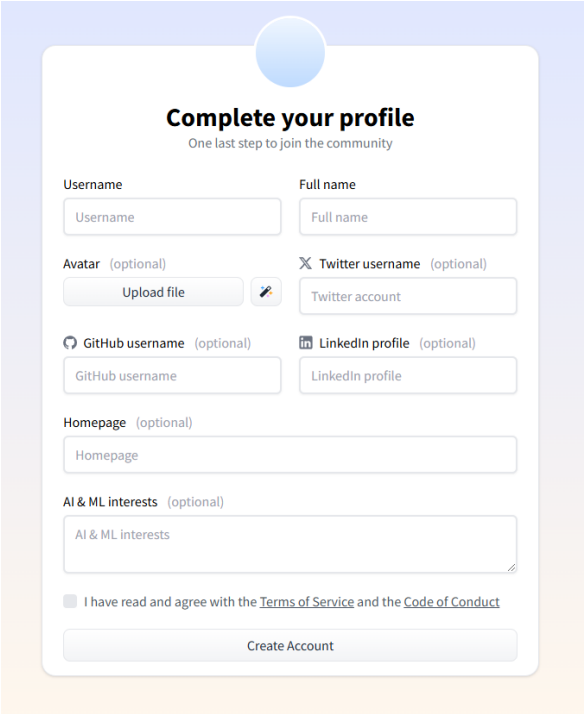
Hugging Face



Pretrained Transformer 사용해보기

- **HuggingFace 회원가입**
  - https://huggingface.co/ 에서 계정 생성





Pretrained Transformer 사용해보기

- 라이브러리 설치

```
! pip install transformers datasets sentencepiece accelerate
```

Pretrained Transformer 사용해보기

- **Inference 예제**
  - BERT(Transformer의 Encoder 구조 특화)를 활용한
  - 감정 분류 모델(긍정/부정 분류)

```python
import os
import torch
from transformers import AutoTokenizer, AutoModelForSequenceClassification, Trainer, TrainingArguments
from datasets import load_dataset

os.environ["WANDB_DISABLED"] = "true"  # for disabling wandb

# load pretrained tokenizer and model
model_name = "bert-base-uncased"
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2)

# example input
inputs = tokenizer("I want to submit paper...", return_tensors="pt")

# initial inference for example input: might be random
outputs = model(**inputs.to(model.device))
predictions = torch.nn.functional.softmax(outputs.logits, dim=-1)
labels = ["NEGATIVE", "POSITIVE"]
result = labels[torch.argmax(predictions)]
print(result)
```

Pretrained Transformer 사용해보기

- **Training(Fine-tuning) 예제**
  - IMDb(영화 리뷰 데이터셋)에서
  - BERT(Transformer의 Encoder 구조 특화) 기반
  - 감정 분류 모델(긍정/부정 분류) 훈련

```python
# load and preprocess dataset
dataset = load_dataset("imdb")  # IMDb 영화 리뷰 데이터셋
train_dataset = dataset["train"].shuffle(seed=42).select(range(1000))  # 일부 데이터로 실습
test_dataset = dataset["test"].shuffle(seed=42).select(range(200))

def preprocess_data(examples):
    return tokenizer(examples["text"], padding="max_length", truncation=True, max_length=512)

train_dataset = train_dataset.map(preprocess_data, batched=True)
test_dataset = test_dataset.map(preprocess_data, batched=True)
```

```python
# training configuration
training_args = TrainingArguments(
    output_dir="./results",
    evaluation_strategy="epoch",
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    num_train_epochs=3,
    weight_decay=0.01,
    logging_dir="./logs",
    logging_steps=10,
    save_strategy="epoch",
    report_to="none",
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=test_dataset,
    tokenizer=tokenizer
)
```

```python
# fine-tuning & evaluation
trainer.train()
results = trainer.evaluate()
print(results)
```

Pretrained Transformer 사용해보기

- **Fine-tuning 후 Inference**
  - IMDb(영화 리뷰 데이터셋)에서
  - BERT(Transformer의 Encoder 구조 특화) 기반
  - 감정 분류 모델(긍정/부정 분류) 훈련

```
# inference after fine-tuning
inputs = tokenizer("I want to submit paper...", return_tensors="pt")
outputs = model(**inputs.to(model.device))
predictions = torch.nn.functional.softmax(outputs.logits, dim=-1)
labels = ["NEGATIVE", "POSITIVE"]
result = labels[torch.argmax(predictions)]
print(result)
```

Closing

- **Summary**
  - Transformer란: Attention Mechanism을 활용한 Sequence Model
    - Attention: 서로 다른 두 Sequence의 token간 연관성을 직접 반영
    - 기본적으로 Encoder – Decoder 구조
      - 개량형으로 Encoder 특화(ex. BERT)와 Decoder 특화(ex. GPT) 있음
  - PyTorch를 활용한 Transformer 구현
  - HuggingFace를 활용한 Pre-trained model inference & training