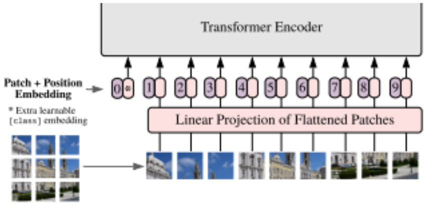
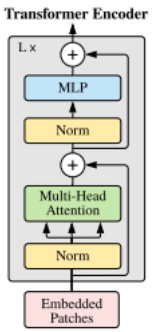
이론

0. 자연어 처리 모델에서 사용하는 Transformer를 이미지 분류에 적용시킨 Vision Transformer에 관한 논문입니다.

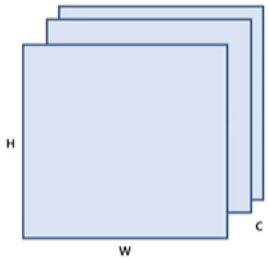
1. 이미지를 patch 단위로 쪼개 '토큰화'시키고, 이들을 Linear Projection 과정(벡터화 과정)을 거쳐 Position Embedding시켜 순서를 부여한 뒤 Transformer Encoder의 입력으로 들어가게 됩니다.



2. Transformer Encoder 내부에서는 먼저 Layer Normalization을 거치고, Multi-Head Attention을 지난 결과를 통과하지 않은 패치와 Skip Connection 시켜줍니다. 그리고 다시 Layer Nomalization, MLP를 거쳐 Skip Connection으로 다시 더해주는 것이 한 번 Transformer Encoder를 통과한 것입니다. 이러한 Transformer Encoder를 L번 반복합니다.

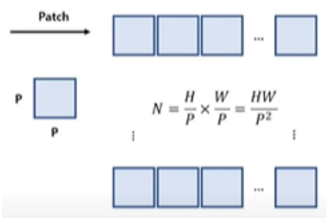


3. 만약 이미지가 (C,H,W) 크기



$\mathbf{x} \in \mathbb{R}^{H \times W \times C}$ 이며,

패치 사이즈가 (P,P)이면



총 패치의 개수 N = HW/P^2 이고,

패치의 차원은

$$\mathbf{x}_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$$

으로 이미지를 패치화합니다.

4. 각각의 n개의 patch를 D차원으로 벡터화하는데,그 결과가 n개의 xpE 입니다.

$$\mathbf{x}_p^1 \quad \cdots \quad \mathbf{x}_p^N \qquad \mathbf{x}_p^1\mathbf{E};\, \mathbf{x}_p^2\mathbf{E}; \cdots ;\, \mathbf{x}_p^N\mathbf{E}$$

5. n개의 벡터에 Position Embedding을 시켜줘야 하는데 Epos를 더해 z0를 생성합니다.

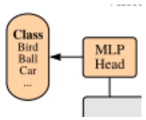
$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}};\, \mathbf{x}_p^1\mathbf{E};\, \mathbf{x}_p^2\mathbf{E}; \cdots ;\, \mathbf{x}_p^N\mathbf{E}] + \mathbf{E}_{pos},$$

6. z0가 Transformer Encoder 내부에서 1번 Encoding되는 과정은 다음과 같습니다.

$$\mathbf{z}'_\ell = \mathrm{MSA}(\mathrm{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1},$$
$$\mathbf{z}_\ell = \mathrm{MLP}(\mathrm{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell,$$

이러한 과정을 L번 반복합니다.

7. Encoding 과정을 L번 반복하고 그 결과값을 Layer Nomalization을 거치고 MLP head를 거쳐 softmax 결과에 따라 class로 나눠집니다.



이 때, mlp head의 입력은 D차원 벡터이며 (Transformer Encoder의 입출력 차원은 D차원이다),

구현

구현할 모델에서는 Layer의 개수를 12개, D의 크기를 64, MLP의 크기를 1024, Head 개수를 4로 설정하여 진행한다.

```
# tensorflow_addons를 사용하기 위해 설치해줘야 한다.
%pip install tensorflow_addons
```

```
Requirement already satisfied: tensorflow_addons in /usr/local/lib/python3.10/dist-packages (0.23.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorflow_addons) (23.2)
Requirement already satisfied: typeguard<3.0.0,>=2.7 in /usr/local/lib/python3.10/dist-packages (from tensorflow_addons) (2.13.3)
```

```
import numpy as np
import tensorflow as tf
import keras
from keras import layers         # vision transformer를 구성하는데 사용 (vit함수)
import tensorflow_addons as tfa
```

```
print(tf.__version__)   # tensorflow 2.14.0 버전을 사용한다.
```

```
2.14.0
```

데이터는 cifar100을 사용한다. 32 x 32 크기의 60000개의 이미지로 이루어져 있으며, 100개의 클래스로 분류(dolphin, fish ...) 되며 각각의 클래스는 600개의 이미지로 이루어져 있다. 또, 500개는 학습 데이터, 100개는 데이터 데이터로 이루어져 있어 총 50000개의 학습 데이터, 10000개의 테스트 데이터로 이루어져있다.

```
num_classes = 100        # cifar100 사용하므로 class를 100개로 지정
input_shape = (32,32,3)   # input shape는 32x32의 RGB 채널을 가진 이미지이다.

# 데이터 로드 (train과 test를 나눠서 로드한다)
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar100.load_data()

print(f"x_train shape : {x_train.shape}, y_train shape : {y_train.shape}")
print(f"x_test shape : {x_test.shape}, y_test shape : {y_test.shape}")
```

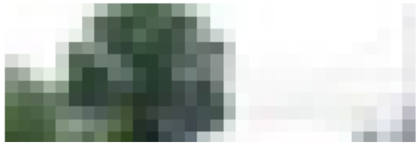
```
x_train shape : (50000, 32, 32, 3), y_train shape : (50000, 1)
x_test shape : (10000, 32, 32, 3), y_test shape : (10000, 1)
```

```
batch_size = 256

image_size = 224    # 16x16 이미지를 업사이징하여 224x224로 만들것이다.
patch_size = 32     # 패치 사이즈는 32x32,
num_patches = (image_size//patch_size)**2     # 패치의 개수는 이미지 크기를 패치사이즈로 나누고 제곱한다.
```

```
# D 차원으로 벡터화
projection_dim = 64   # D = 64
num_heads = 4

# mlp에서 사용하는 transformer unit (128, 64)
transformer_units = [
    projection_dim*2,
    projection_dim,
]

transformer_layers = 12         # layer의 개수
mlp_head_units = [2048, 1024]


# 이미지 업사이징, 전처리
data_augmentation = keras.Sequential(
    [
            layers.Normalization(),                         # Normalize
            layers.Resizing(image_size, image_size),        # 224 x 224
            layers.RandomFlip('horizontal'),
            layers.RandomRotation(factor=0.02),
            layers.RandomZoom(height_factor=0.2, width_factor=0.2),
    ],
    name = 'data_augmentation',
)

data_augmentation.layers[0].adapt(x_train)


# mlp 함수
def mlp(x, hidden_units, dropout_rate):
  for units in hidden_units:
      x = layers.Dense(units, activation=tf.nn.gelu)(x)   # 활성화함수로 gelu를 사용
      x = layers.Dropout(dropout_rate)(x)                 # dropout을 사용한다.
  return x


# 패치화하는 클래스
class Patches(layers.Layer):
  def __init__(self, patch_size):
    super().__init__()
    self.patch_size = patch_size

  def call(self, images):
    batch_size = tf.shape(images)[0]
    patches = tf.image.extract_patches(
        images = images,
        sizes = [1, self.patch_size, self.patch_size, 1],
        strides = [1, self.patch_size, self.patch_size, 1],
        rates = [1,1,1,1],
        padding = "VALID",    # padding 사용 X
    )
    patch_dims = patches.shape[-1]
    patches = tf.reshape(patches, [batch_size, -1, patch_dims])
    return patches
```

```python
import matplotlib.pyplot as plt

# 패치화 결과 확인
plt.figure(figsize=(4,4))
image = x_train[np.random.choice(range(x_train.shape[0]))]
plt.imshow(image.astype('uint8'))
plt.axis('off')

resized_image = tf.image.resize(
    tf.convert_to_tensor([image]), size = (image_size, image_size)
)

patches = Patches(patch_size)(resized_image)
print(f'Image size: {image_size} X {image_size}')
print(f'Patch size: {patch_size} X {patch_size}')
print(f'Patches per image: {patches.shape[1]}')
print(f'Elements per patch: {patches.shape[-1]}')
print(f'Shape of patch: {patches.shape}')

n = int(np.sqrt(patches.shape[1]))
plt.figure(figsize = (4,4))
for i, patch in enumerate(patches[0]):
  ax = plt.subplot(n, n, i+1)
  patch_img = tf.reshape(patch, (patch_size, patch_size, 3))
  plt.imshow(patch_img.numpy().astype('uint8'))
  plt.axis('off')
```

```
Image size: 224 X 224
Patch size: 32 X 32
Patches per image: 49
Elements per patch: 3072
Shape of patch: (1, 49, 3072)
```



```
# PatchEncoder를 class로 정의
# (Linear Projection -> Position Embedding)
class PatchEncoder(layers.Layer):
  def __init__(self, num_patches, projection_dim):
    super().__init__()
    self.num_patches = num_patches

    self.projection = layers.Dense(units=projection_dim)      # D차원으로 Linear Projection
    self.position_embedding = layers.Embedding(              # position embedding
        input_dim = num_patches, output_dim = projection_dim
    )

  def call(self, patch):
    positions = tf.range(start=0, limit=self.num_patches, delta=1)          # 0부터 patch개수만큼 1씩 증가하는 position
    encoded = self.projection(patch) + self.position_embedding(positions)   # position embedding 과정
    return encoded  # z0
```

```
# vision transformer
def vit():

  # 1) Patch화 ->  patch를 Linear Projection -> Position Embedding
  inputs = layers.Input(shape=input_shape)
  augmented = data_augmentation(inputs)     # inputs를 업사이징
  patches = Patches(patch_size)(augmented)  # patch 생성 (patches)
  encoded_patches = PatchEncoder(num_patches, projection_dim)(patches) # patch를 Linear Projection -> Position Embedding


  # 2) Transformer Encoder L번 반복
  for _ in range(transformer_layers):   # L번 반복

    x1 = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)       # 1) Norm

    attention_output = layers.MultiHeadAttention(                       # 2) Multi-Head Attention
        num_heads = num_heads, key_dim = projection_dim, dropout=0.1
    )(x1, x1)

    x2 = layers.Add()([attention_output, encoded_patches])              # 3) Skip Connection

    x3 = layers.LayerNormalization(epsilon=1e-6)(x2)                    # 4) Norm

    x3 = mlp(x3, hidden_units = transformer_units, dropout_rate = 0.1)  # 5) MLP

    encoded_patches = layers.Add()([x3, x2])                            # 6) Skip Connection
```

```
    # 3) MLP Head에 들어가기 전 레이어정규화
    representation = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)
    representation = layers.Flatten()(representation)
    representation = layers.Dropout(0.5)(representation)


    # 4) MLP Head
    features = mlp(representation, hidden_units = mlp_head_units, dropout_rate = 0.5)


    # 5) class화
    logits = layers.Dense(num_classes)(features)


    # 6) 모델 생성
    model = keras.Model(inputs=inputs, outputs = logits)

    return model


model = vit()
model.summary()
```

```
 dropout_33 (Dropout)        (None, 49, 128)              0          ['dense_35[0][0]']

 dense_36 (Dense)            (None, 49, 64)               8256       ['dropout_33[0][0]']

 dropout_34 (Dropout)        (None, 49, 64)               0          ['dense_36[0][0]']

 add_31 (Add)                (None, 49, 64)               0          ['dropout_34[0][0]',
                                                                      'add_30[0][0]']

 layer_normalization_33 (La  (None, 49, 64)               128        ['add_31[0][0]']
 yerNormalization)

 multi_head_attention_16 (M  (None, 49, 64)               66368      ['layer_normalization_33[0][0]
 ultiHeadAttention)                                                  ',
                                                                      'layer_normalization_33[0][0]
                                                                     ']

 add_32 (Add)                (None, 49, 64)               0          ['multi_head_attention_16[0][0
                                                                     ]',
                                                                      'add_31[0][0]']

 layer_normalization_34 (La  (None, 49, 64)               128        ['add_32[0][0]']
 yerNormalization)
```

```python
# 학습 / 테스트
num_epochs = 20
weight_decay = 0.001
learning_rate = 0.001

optimizer = tfa.optimizers.AdamW(
    learning_rate = learning_rate, weight_decay = weight_decay
)

model.compile(
    optimizer = optimizer,
    loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=[
        keras.metrics.SparseCategoricalAccuracy(name='accuracy'),
        keras.metrics.SparseTopKCategoricalAccuracy(5, name='top-5-accuracy'),
    ],
)

history = model.fit(
    x=x_train,
    y=y_train,
    batch_size = batch_size,
    epochs = num_epochs,
    validation_split = 0.1,
)
```

```
Epoch 1/20
176/176 [==============================] - 56s 188ms/step - loss: 4.2937 - accuracy: 0.0642 - top-5-accuracy: 0.2095 - val_loss: 3.7237 - val_accuracy: 0.1366 - val_top-5-accuracy: 0.3714
Epoch 2/20
176/176 [==============================] - 32s 184ms/step - loss: 3.7198 - accuracy: 0.1299 - top-5-accuracy: 0.3614 - val_loss: 3.3896 - val_accuracy: 0.1906 - val_top-5-accuracy: 0.4598
Epoch 3/20
176/176 [==============================] - 35s 200ms/step - loss: 3.4472 - accuracy: 0.1746 - top-5-accuracy: 0.4385 - val_loss: 3.1692 - val_accuracy: 0.2232 - val_top-5-accuracy: 0.5154
Epoch 4/20
176/176 [==============================] - 32s 180ms/step - loss: 3.2912 - accuracy: 0.2011 - top-5-accuracy: 0.4830 - val_loss: 3.0810 - val_accuracy: 0.2416 - val_top-5-accuracy: 0.5296
Epoch 5/20
```

```
176/176 [==============================] - 32s 181ms/step - loss: 3.1637 - accuracy: 0.2236 - top-5-accuracy: 0.5135 - val_loss: 2.9816 - val_accuracy: 0.2536 - val_top-5-accuracy: 0.5540
Epoch 6/20
176/176 [==============================] - 32s 184ms/step - loss: 3.0746 - accuracy: 0.2432 - top-5-accuracy: 0.5364 - val_loss: 2.9095 - val_accuracy: 0.2784 - val_top-5-accuracy: 0.5788
Epoch 7/20
176/176 [==============================] - 32s 180ms/step - loss: 3.0140 - accuracy: 0.2509 - top-5-accuracy: 0.5526 - val_loss: 2.8723 - val_accuracy: 0.2806 - val_top-5-accuracy: 0.5792
Epoch 8/20
176/176 [==============================] - 32s 181ms/step - loss: 2.9569 - accuracy: 0.2643 - top-5-accuracy: 0.5692 - val_loss: 2.8241 - val_accuracy: 0.2890 - val_top-5-accuracy: 0.5972
Epoch 9/20
176/176 [==============================] - 32s 181ms/step - loss: 2.9167 - accuracy: 0.2709 - top-5-accuracy: 0.5766 - val_loss: 2.8018 - val_accuracy: 0.2972 - val_top-5-accuracy: 0.5948
Epoch 10/20
176/176 [==============================] - 32s 182ms/step - loss: 2.8717 - accuracy: 0.2802 - top-5-accuracy: 0.5870 - val_loss: 2.7848 - val_accuracy: 0.3038 - val_top-5-accuracy: 0.6076
Epoch 11/20
176/176 [==============================] - 32s 183ms/step - loss: 2.8464 - accuracy: 0.2842 - top-5-accuracy: 0.5930 - val_loss: 2.7773 - val_accuracy: 0.3028 - val_top-5-accuracy: 0.6056
Epoch 12/20
176/176 [==============================] - 32s 182ms/step - loss: 2.8207 - accuracy: 0.2871 - top-5-accuracy: 0.5999 - val_loss: 2.7270 - val_accuracy: 0.3122 - val_top-5-accuracy: 0.6138
Epoch 13/20
176/176 [==============================] - 32s 184ms/step - loss: 2.7927 - accuracy: 0.2950 - top-5-accuracy: 0.6045 - val_loss: 2.7181 - val_accuracy: 0.3166 - val_top-5-accuracy: 0.6244
Epoch 14/20
176/176 [==============================] - 32s 183ms/step - loss: 2.7698 - accuracy: 0.2992 - top-5-accuracy: 0.6111 - val_loss: 2.7100 - val_accuracy: 0.3190 - val_top-5-accuracy: 0.6272
Epoch 15/20
176/176 [==============================] - 32s 182ms/step - loss: 2.7518 - accuracy: 0.3028 - top-5-accuracy: 0.6158 - val_loss: 2.6946 - val_accuracy: 0.3194 - val_top-5-accuracy: 0.6294
Epoch 16/20
176/176 [==============================] - 32s 185ms/step - loss: 2.7429 - accuracy: 0.3059 - top-5-accuracy: 0.6174 - val_loss: 2.6896 - val_accuracy: 0.3264 - val_top-5-accuracy: 0.6342
Epoch 17/20
176/176 [==============================] - 33s 185ms/step - loss: 2.7186 - accuracy: 0.3077 - top-5-accuracy: 0.6257 - val_loss: 2.6774 - val_accuracy: 0.3198 - val_top-5-accuracy: 0.6348
Epoch 18/20
176/176 [==============================] - 33s 186ms/step - loss: 2.7043 - accuracy: 0.3121 - top-5-accuracy: 0.6279 - val_loss: 2.6810 - val_accuracy: 0.3312 - val_top-5-accuracy: 0.6316
Epoch 19/20
176/176 [==============================] - 33s 187ms/step - loss: 2.6918 - accuracy: 0.3144 - top-5-accuracy: 0.6293 - val_loss: 2.6520 - val_accuracy: 0.3326 - val_top-5-accuracy: 0.6376
Epoch 20/20
176/176 [==============================] - 33s 186ms/step - loss: 2.6873 - accuracy: 0.3166 - top-5-accuracy: 0.6304 - val_loss: 2.6637 - val_accuracy: 0.3248 - val_top-5-accuracy: 0.6404
```

```python
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(history.history['loss'], 'b--', label='loss')
plt.plot(history.history['val_loss'], 'r-', label='val_loss')
plt.xlabel('Epochs')
plt.grid()
plt.legend()


plt.subplot(1,2,2)
plt.plot(history.history['accuracy'], 'b--', label='accuracy')
plt.plot(history.history['val_accuracy'], 'r-', label='val_accuracy')
plt.xlabel('Epochs')
plt.grid()
plt.legend()
```

<matplotlib.legend.Legend at 0x7cc0b4358670>