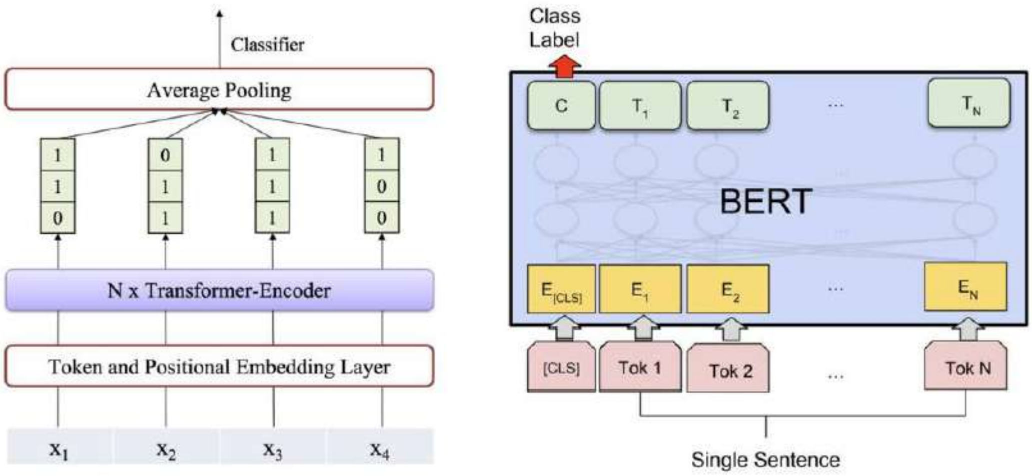
AI VIET NAM – COURSE 2023

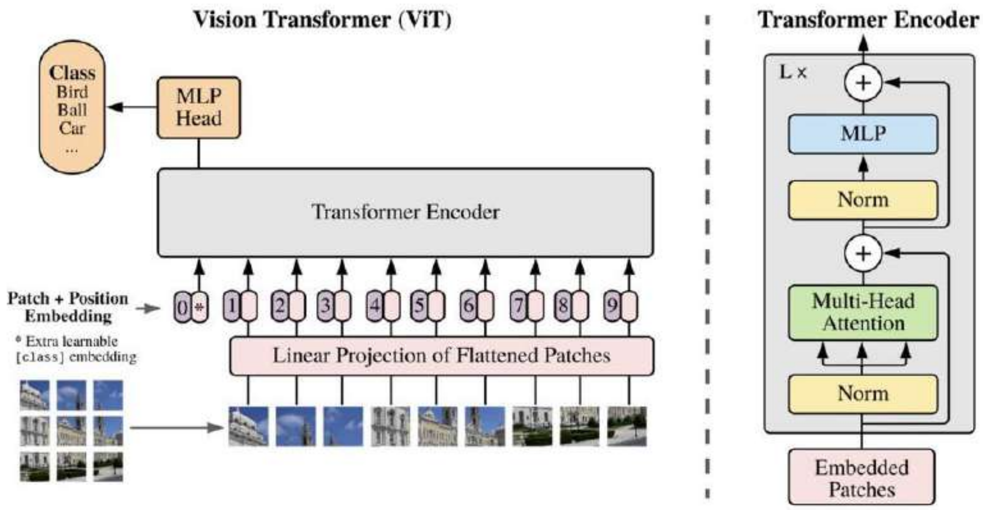
Exercise: Transformer Applications

Ngày 4 tháng 12 năm 2023

Phần 1. Transformer



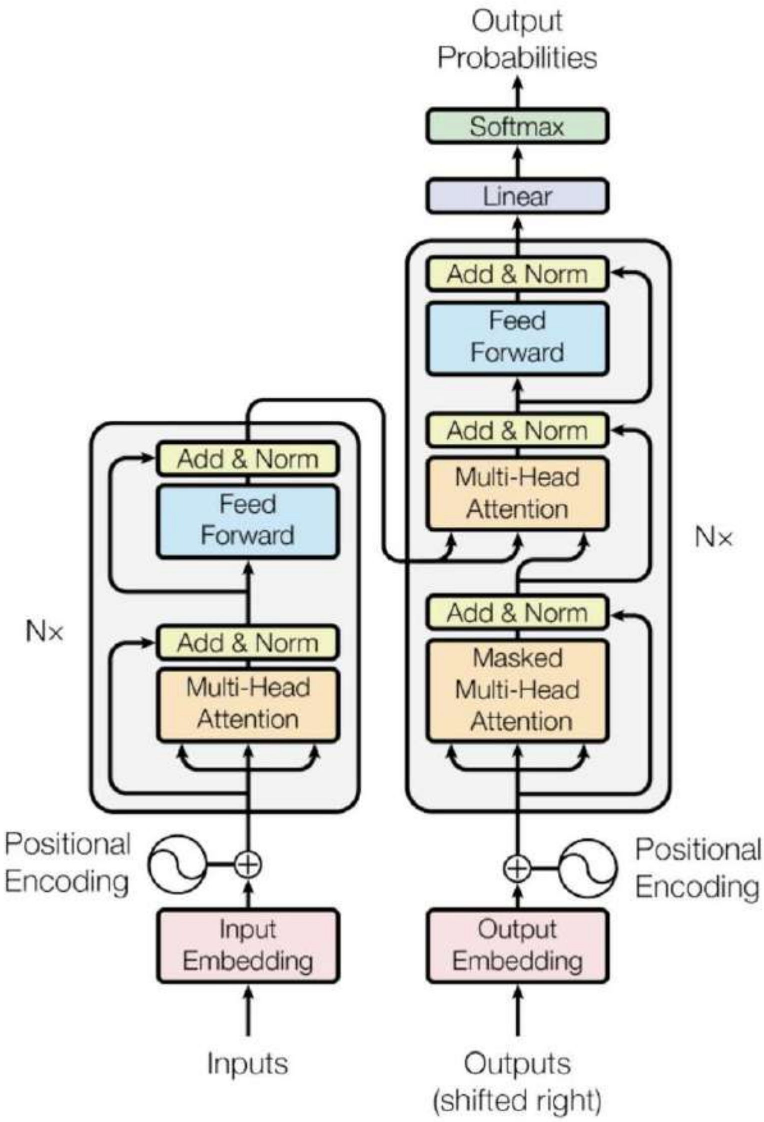
Hình 1: Mô hình Transformer-Encoder và BERT cho bài toán phân loại văn bản.



Hình 2: Mô hình Vision Transformer cho bài toán phân loại hình ảnh.

Mô hình Transformer ra đời với kỹ thuật cốt lõi và cơ chế Attention, đã đạt được những kết quả ấn tượng cho các bài toán về dữ liệu văn bản rồi từ đó mở rộng cho các kiểu dữ liệu như hình ảnh và âm thanh,... Trong phần này, chúng ta sẽ tìm hiểu các thành phần trong mô hình Transformer và ứng dụng cho bài toán phân loại văn bản.

1.1. Kiến trúc Transformer



Hình 3: Mô hình kiến trúc Transformer.

Kiến trúc Transformer gồm các thành phần:

- Input Embedding: Biểu diễn các token đầu vào (Thường được tách bởi Subword-based Tokenization) thành các Dense Vector.
- Positional Encoding: Biểu diễn vị trí (thứ tự) của các token trong câu. Thường được tính dựa vào hàm sinusoid hoặc được học trong quá trình huấn luyện mô hình.

- Các khối encoder: Để mã hoá các tokens đầu vào thành các contextual embedding. Bao gồm: Multi-Head Attention, Add - Normalization, Feed Forward
- Các khối decoder: nhận input là các token lịch sử và trạng thái mã hoá từ encoder, giải mã dự đoán token tiếp theo. Gồm: Masked Multi-Head Attention (dựa vào token lịch sử cửa decoder), Multi-Head Attention(dựa vào encoder và trạng thái hiện tại decoder), Add - Normalization, Feed Forward
- Language Model Head: Projection và Softmax dự đoán token tiếp theo vs xác suất lớn nhất.

1. Input Embedding, Positional Encoding

```
class TokenAndPositionEmbedding(nn.Module):
    def __init__(self, vocab_size, embed_dim, max_length, device='cpu'):
        super().__init__()
        self.device = device
        self.word_emb = nn.Embedding(
            num_embeddings=vocab_size,
            embedding_dim=embed_dim
        )
        self.pos_emb = nn.Embedding(
            num_embeddings=max_length,
            embedding_dim=embed_dim
        )

    def forward(self, x):
        N, seq_len = x.size()
        positions = torch.arange(0, seq_len).expand(N, seq_len).to(self.device)
        output1 = self.word_emb(x)
        output2 = self.pos_emb(positions)
        output = output1 + output2
        return output
```

2. Encoder

```
class TransformerEncoderBlock(nn.Module):
    def __init__(self, embed_dim, num_heads, ff_dim, dropout=0.1):
        super().__init__()
        self.attn = nn.MultiheadAttention(
            embed_dim=embed_dim,
            num_heads=num_heads,
            batch_first=True
        )
        self.ffn = nn.Sequential(
            nn.Linear(in_features=embed_dim, out_features=ff_dim, bias=True),
            nn.ReLU(),
            nn.Linear(in_features=ff_dim, out_features=embed_dim, bias=True)
        )
        self.layernorm_1 = nn.LayerNorm(normalized_shape=embed_dim, eps=1e-6)
        self.layernorm_2 = nn.LayerNorm(normalized_shape=embed_dim, eps=1e-6)
        self.dropout_1 = nn.Dropout(p=dropout)
        self.dropout_2 = nn.Dropout(p=dropout)

    def forward(self, query, key, value):
        attn_output, _ = self.attn(query, key, value)
        attn_output = self.dropout_1(attn_output)
        out_1 = self.layernorm_1(query + attn_output)
        ffn_output = self.ffn(out_1)
        ffn_output = self.dropout_2(ffn_output)
        out_2 = self.layernorm_2(out_1 + ffn_output)
        return out_2
```

```python

class TransformerEncoder(nn.Module):
    def __init__(self,
                 src_vocab_size, embed_dim, max_length, num_layers, num_heads, ff_dim,
                 dropout=0.1, device='cpu'
        ):
        super().__init__()
        self.embedding = TokenAndPositionEmbedding(
            src_vocab_size, embed_dim, max_length, device
        )
        self.layers = nn.ModuleList(
            [
                TransformerEncoderBlock(
                    embed_dim, num_heads, ff_dim, dropout
                ) for i in range(num_layers)
            ]
        )

    def forward(self, x):
        output = self.embedding(x)
        for layer in self.layers:
            output = layer(output, output, output)
        return output
```

3. Decoder

```python
class TransformerDecoderBlock(nn.Module):
    def __init__(self, embed_dim, num_heads, ff_dim, dropout=0.1):
        super().__init__()
        self.attn = nn.MultiheadAttention(
            embed_dim=embed_dim,
            num_heads=num_heads,
            batch_first=True
        )
        self.cross_attn = nn.MultiheadAttention(
            embed_dim=embed_dim,
            num_heads=num_heads,
            batch_first=True
        )
        self.ffn = nn.Sequential(
            nn.Linear(in_features=embed_dim, out_features=ff_dim, bias=True),
            nn.ReLU(),
            nn.Linear(in_features=ff_dim, out_features=embed_dim, bias=True)
        )
        self.layernorm_1 = nn.LayerNorm(normalized_shape=embed_dim, eps=1e-6)
        self.layernorm_2 = nn.LayerNorm(normalized_shape=embed_dim, eps=1e-6)
        self.layernorm_3 = nn.LayerNorm(normalized_shape=embed_dim, eps=1e-6)
        self.dropout_1 = nn.Dropout(p=dropout)
        self.dropout_2 = nn.Dropout(p=dropout)
        self.dropout_3 = nn.Dropout(p=dropout)

    def forward(self, x, enc_output, src_mask, tgt_mask):
        attn_output, _ = self.attn(x, x, x, attn_mask=tgt_mask)
        attn_output = self.dropout_1(attn_output)
        out_1 = self.layernorm_1(x + attn_output)

        attn_output, _ = self.cross_attn(
            out_1, enc_output, enc_output, attn_mask=src_mask
        )
        attn_output = self.dropout_2(attn_output)
        out_2 = self.layernorm_2(out_1 + attn_output)
```

```python

        ffn_output = self.ffn(out_2)
        ffn_output = self.dropout_2(ffn_output)
        out_3 = self.layernorm_2(out_2 + ffn_output)
        return out_3

class TransformerDecoder(nn.Module):
    def __init__(self,
            tgt_vocab_size, embed_dim, max_length, num_layers, num_heads, ff_dim,
            dropout=0.1, device='cpu'
        ):
        super().__init__()
        self.embedding = TokenAndPositionEmbedding(
            tgt_vocab_size, embed_dim, max_length, device
        )
        self.layers = nn.ModuleList(
            [
                TransformerDecoderBlock(
                    embed_dim, num_heads, ff_dim, dropout
                ) for i in range(num_layers)
            ]
        )

    def forward(self, x, enc_output, src_mask, tgt_mask):
        output = self.embedding(x)
        for layer in self.layers:
            output = layer(output, enc_output, src_mask, tgt_mask)
        return output
```

4. Transformer

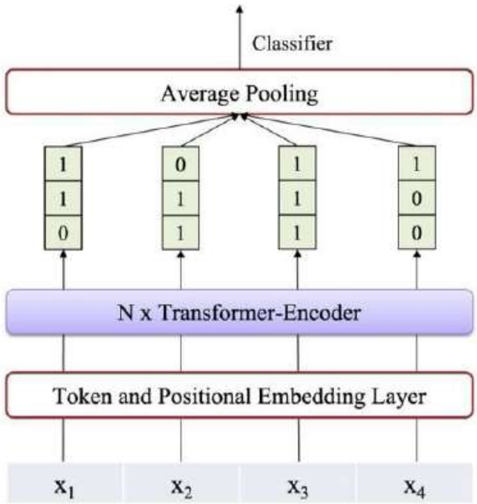
```python
class Transformer(nn.Module):
    def __init__(self,
            src_vocab_size, tgt_vocab_size,
            embed_dim, max_length, num_layers, num_heads, ff_dim,
            dropout=0.1, device='cpu'
        ):
        super().__init__()
        self.device = device
        self.encoder = TransformerEncoder(
            src_vocab_size, embed_dim, max_length, num_layers, num_heads, ff_dim
        )
        self.decoder = TransformerDecoder(
            tgt_vocab_size, embed_dim, max_length, num_layers, num_heads, ff_dim
        )
        self.fc = nn.Linear(embed_dim, tgt_vocab_size)

    def generate_mask(self, src, tgt):
        src_seq_len = src.shape[1]
        tgt_seq_len = tgt.shape[1]

        src_mask = torch.zeros(
            (src_seq_len, src_seq_len),
            device=self.device).type(torch.bool)

        tgt_mask = (torch.triu(torch.ones(
            (tgt_seq_len, tgt_seq_len),
            device=self.device)
        ) == 1).transpose(0, 1)
        tgt_mask = tgt_mask.float().masked_fill(
            tgt_mask == 0, float('-inf')).masked_fill(tgt_mask == 1, float(0.0))
```

```
        return src_mask, tgt_mask

    def forward(self, src, tgt):
        src_mask, tgt_mask = self.generate_mask(src, tgt)
        enc_output = self.encoder(src)
        dec_output = self.decoder(tgt, enc_output, src_mask, tgt_mask)
        output = self.fc(dec_output)
        return output
```

5. Thử nghiệm

```
batch_size = 128
src_vocab_size = 1000
tgt_vocab_size = 2000
embed_dim = 200
max_length = 100
num_layers = 2
num_heads = 4
ff_dim = 256

model = Transformer(
    src_vocab_size, tgt_vocab_size,
    embed_dim, max_length, num_layers, num_heads, ff_dim
)

src = torch.randint(
    high=2,
    size=(batch_size, max_length),
    dtype=torch.int64
)

tgt = torch.randint(
    high=2,
    size=(batch_size, max_length),
    dtype=torch.int64
)

prediction = model(src, tgt)
prediction.shape # batch_size x max_length x tgt_vocab_size
```

1.2. Text Classification



Hình 4: Phân loại văn bản sử dụng Transformer-Encoder

Ở phần này, chúng ta sử dụng mô hình Transformer-Encoder cho bài toán phân loại văn bản. Kiến trúc mô hình gồm các phần:

- Input Embedding và Positional Encoding
- Các lớp Encoder
- Lớp Average Pooling: lấy trung bình biểu diễn các từ thành biểu diễn cho câu
- Classifier: Linear layer

1. **Load Dataset**

```
# download
!git clone https://github.com/congnghia0609/ntc-scv.git
!unzip ./ntc-scv/data/data_test.zip -d ./data
!unzip ./ntc-scv/data/data_train.zip -d ./data
!rm -rf ./ntc-scv

# load data
import os
import pandas as pd

def load_data_from_path(folder_path):
    examples = []
    for label in os.listdir(folder_path):
        full_path = os.path.join(folder_path, label)
        for file_name in os.listdir(full_path):
            file_path = os.path.join(full_path, file_name)
            with open(file_path, "r", encoding="utf-8") as f:
                lines = f.readlines()
            sentence = " ".join(lines)
            if label == "neg":
                label = 0
            if label == "pos":
                label = 1
```

```
                data = {
                    'sentence': sentence,
                    'label': label
                }
                examples.append(data)
    return pd.DataFrame(examples)

folder_paths = {
    'train': './data/data_train/train',
    'valid': './data/data_train/test',
    'test': './data/data_test/test'
}

train_df = load_data_from_path(folder_paths['train'])
valid_df = load_data_from_path(folder_paths['valid'])
test_df = load_data_from_path(folder_paths['test'])
```

2. **Preprocessing**

```
import re
import string

def preprocess_text(text):
    # remove URLs https://www.
    url_pattern = re.compile(r'https?://\s+\wwww\.\s+')
    text = url_pattern.sub(r" ", text)

    # remove HTML Tags: <>
    html_pattern = re.compile(r'<[^<>]+>')
    text = html_pattern.sub(" ", text)

    # remove puncs and digits
    replace_chars = list(string.punctuation + string.digits)
    for char in replace_chars:
        text = text.replace(char, " ")

    # remove emoji
    emoji_pattern = re.compile("["
        u"\U0001F600-\U0001F64F"  # emoticons
        u"\U0001F300-\U0001F5FF"  # symbols & pictographs
        u"\U0001F680-\U0001F6FF"  # transport & map symbols
        u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
        u"\U0001F1F2-\U0001F1F4"  # Macau flag
        u"\U0001F1E6-\U0001F1FF"  # flags
        u"\U0001F600-\U0001F64F"
        u"\U00002702-\U000027B0"
        u"\U000024C2-\U0001F251"
        u"\U0001f926-\U0001f937"
        u"\U0001F1F2"
        u"\U0001F1F4"
        u"\U0001F620"
        u"\u200d"
        u"\u2640-\u2642"
        "]+", flags=re.UNICODE)
    text = emoji_pattern.sub(r" ", text)

    # normalize whitespace
    text = " ".join(text.split())

    # lowercasing
    text = text.lower()
```

```
    return text

train_df['sentence'] = [preprocess_text(row['sentence']) for index, row in train_df.
    iterrows()]
valid_df['sentence'] = [preprocess_text(row['sentence']) for index, row in valid_df.
    iterrows()]
test_df['sentence'] = [preprocess_text(row['sentence']) for index, row in test_df.
    iterrows()]
```

3. Representation

```
# !pip install -q torchtext==0.16.0

def yield_tokens(sentences, tokenizer):
    for sentence in sentences:
        yield tokenizer(sentence)


# word-based tokenizer
from torchtext.data.utils import get_tokenizer
tokenizer = get_tokenizer("basic_english")

# build vocabulary
from torchtext.vocab import build_vocab_from_iterator

vocab_size = 10000
vocabulary = build_vocab_from_iterator(
    yield_tokens(train_df['preprocess_sentence'], tokenizer),
    max_tokens=vocab_size,
    specials=["<pad>", "<unk>"]
)
vocabulary.set_default_index(vocabulary["<unk>"])

# convert torchtext dataset
from torchtext.data.functional import to_map_style_dataset

def prepare_dataset(df):
    # create iterator for dataset: (sentence, label)
    for index, row in df.iterrows():
        sentence = row['preprocess_sentence']
        encoded_sentence = vocabulary(tokenizer(sentence))
        label = row['label']
        yield encoded_sentence, label

train_dataset = prepare_dataset(train_df)
train_dataset = to_map_style_dataset(train_dataset)

valid_dataset = prepare_dataset(valid_df)
valid_dataset = to_map_style_dataset(valid_dataset)

test_dataset = prepare_dataset(test_df)
test_dataset = to_map_style_dataset(test_dataset)
```

4. Dataloader

```
import torch

seq_length = 100

def collate_batch(batch):
    # create inputs, offsets, labels for batch
    sentences, labels = list(zip(*batch))
```

```
    encoded_sentences = [
        sentence+([0]* (seq_length-len(sentence))) if len(sentence) < seq_length else
    sentence[:seq_length]
        for sentence in sentences
    ]

    encoded_sentences = torch.tensor(encoded_sentences, dtype=torch.int64)
    labels = torch.tensor(labels)

    return encoded_sentences, labels

from torch.utils.data import DataLoader

batch_size = 128

train_dataloader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle=True,
    collate_fn=collate_batch
)
valid_dataloader = DataLoader(
    valid_dataset,
    batch_size=batch_size,
    shuffle=False,
    collate_fn=collate_batch
)

test_dataloader = DataLoader(
    test_dataset,
    batch_size=batch_size,
    shuffle=False,
    collate_fn=collate_batch
)
```

5. **Trainer**

```
# train epoch
import time

def train_epoch(model, optimizer, criterion, train_dataloader, device, epoch=0,
    log_interval=50):
    model.train()
    total_acc, total_count = 0, 0
    losses = []
    start_time = time.time()

    for idx, (inputs, labels) in enumerate(train_dataloader):
        inputs = inputs.to(device)
        labels = labels.to(device)

        optimizer.zero_grad()

        predictions = model(inputs)

        # compute loss
        loss = criterion(predictions, labels)
        losses.append(loss.item())

        # backward
        loss.backward()
```

```
        optimizer.step()
        total_acc += (predictions.argmax(1) == labels).sum().item()
        total_count += labels.size(0)
        if idx % log_interval == 0 and idx > 0:
            elapsed = time.time() - start_time
            print(
                "| epoch {:3d} | {:5d}/{:5d} batches "
                "| accuracy {:8.3f}".format(
                    epoch, idx, len(train_dataloader), total_acc / total_count
                )
            )
            total_acc, total_count = 0, 0
            start_time = time.time()

    epoch_acc = total_acc / total_count
    epoch_loss = sum(losses) / len(losses)
    return epoch_acc, epoch_loss

# evaluate
def evaluate_epoch(model, criterion, valid_dataloader, device):
    model.eval()
    total_acc, total_count = 0, 0
    losses = []

    with torch.no_grad():
        for idx, (inputs, labels) in enumerate(valid_dataloader):
            inputs = inputs.to(device)
            labels = labels.to(device)

            predictions = model(inputs)

            loss = criterion(predictions, labels)
            losses.append(loss.item())

            total_acc += (predictions.argmax(1) == labels).sum().item()
            total_count += labels.size(0)

    epoch_acc = total_acc / total_count
    epoch_loss = sum(losses) / len(losses)
    return epoch_acc, epoch_loss


# train
def train(model, model_name, save_model, optimizer, criterion, train_dataloader,
    valid_dataloader, num_epochs, device):
    train_accs, train_losses = [], []
    eval_accs, eval_losses = [], []
    best_loss_eval = 100
    times = []
    for epoch in range(1, num_epochs+1):
        epoch_start_time = time.time()
        # Training
        train_acc, train_loss = train_epoch(model, optimizer, criterion,
    train_dataloader, device, epoch)
        train_accs.append(train_acc)
        train_losses.append(train_loss)

        # Evaluation
        eval_acc, eval_loss = evaluate_epoch(model, criterion, valid_dataloader,
    device)
```

```python
        eval_accs.append(eval_acc)
        eval_losses.append(eval_loss)

        # Save best model
        if eval_loss < best_loss_eval:
            torch.save(model.state_dict(), save_model + f'/{model_name}.pt')

        times.append(time.time() - epoch_start_time)
        # Print loss, acc end epoch
        print("-" * 59)
        print(
            "| End of epoch {:3d} | Time: {:5.2f}s | Train Accuracy {:8.3f} | Train Loss {:8.3f} "
            "| Valid Accuracy {:8.3f} | Valid Loss {:8.3f} ".format(
                epoch, time.time() - epoch_start_time, train_acc, train_loss, eval_acc, eval_loss
            )
        )
        print("-" * 59)

    # Load best model
    model.load_state_dict(torch.load(save_model + f'/{model_name}.pt'))
    model.eval()
    metrics = {
        'train_accuracy': train_accs,
        'train_loss': train_losses,
        'valid_accuracy': eval_accs,
        'valid_loss': eval_losses,
        'time': times
    }
    return model, metrics

# report
import matplotlib.pyplot as plt

def plot_result(num_epochs, train_accs, eval_accs, train_losses, eval_losses):
    epochs = list(range(num_epochs))
    fig, axs = plt.subplots(nrows = 1, ncols =2 , figsize = (12,6))
    axs[0].plot(epochs, train_accs, label = "Training")
    axs[0].plot(epochs, eval_accs, label = "Evaluation")
    axs[1].plot(epochs, train_losses, label = "Training")
    axs[1].plot(epochs, eval_losses, label = "Evaluation")
    axs[0].set_xlabel("Epochs")
    axs[1].set_xlabel("Epochs")
    axs[0].set_ylabel("Accuracy")
    axs[1].set_ylabel("Loss")
    plt.legend()
```

6. **Modeling**

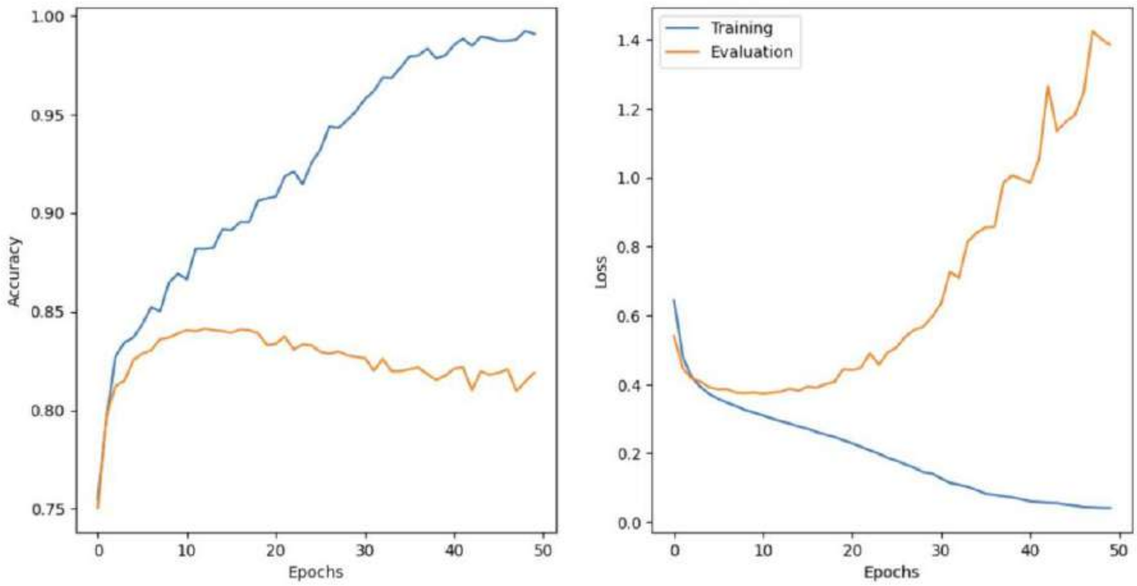
```python
class TransformerEncoderCls(nn.Module):
    def __init__(self,
                 vocab_size, max_length, num_layers, embed_dim, num_heads, ff_dim,
                 dropout=0.1, device='cpu'
        ):
        super().__init__()
        self.encoder = TransformerEncoder(
            vocab_size, embed_dim, max_length, num_layers, num_heads, ff_dim, dropout, device
        )
        self.pooling = nn.AvgPool1d(kernel_size=max_length)
```

```python
        self.fc1 = nn.Linear(in_features=embed_dim, out_features=20)
        self.fc2 = nn.Linear(in_features=20, out_features=2)
        self.dropout = nn.Dropout(p=dropout)
        self.relu = nn.ReLU()
    def forward(self, x):
        output = self.encoder(x)
        output = self.pooling(output.permute(0,2,1)).squeeze()
        output = self.dropout(output)
        output = self.fc1(output)
        output = self.dropout(output)
        output = self.fc2(output)
        return output
```

7. **Training**

```python
import torch.optim as optim

vocab_size = 10000
max_length = 100
embed_dim = 200
num_layers = 2
num_heads = 4
ff_dim = 128
dropout=0.1

model = TransformerEncoderCls(
    vocab_size, max_length, num_layers, embed_dim, num_heads, ff_dim, dropout
)

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

model = TransformerEncoderCls(
    vocab_size, max_length, num_layers, embed_dim, num_heads, ff_dim, dropout, device
)
model.to(device)

criterion = torch.nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.00005)

num_epochs = 50
save_model = './model'
os.makedirs(save_model, exist_ok = True)
model_name = 'model'

model, metrics = train(
    model, model_name, save_model, optimizer, criterion, train_dataloader,
    valid_dataloader, num_epochs, device
)
```

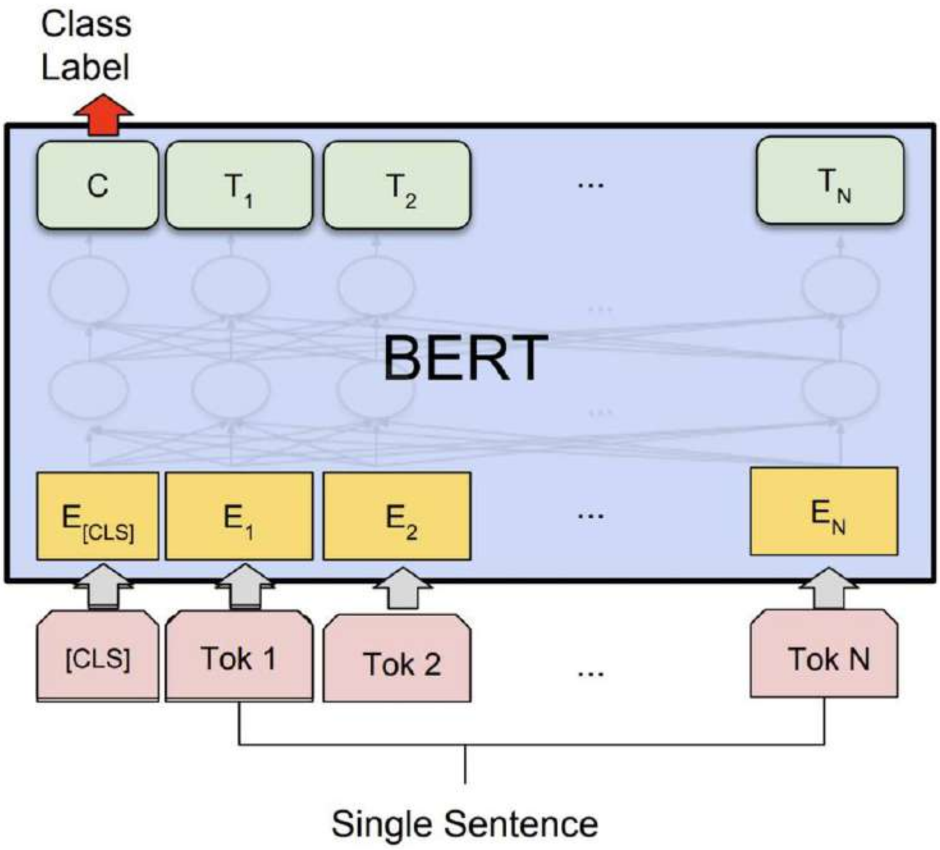
Kết quả training và accuracy trên tập test là 82.55



Hình 5: Quá trình huấn luyện bộ dữ liệu NTC-SCV với mô hình Transformer-Encoder.

Phần 2. Text Classification using BERT

Một trong những mô hình pretrained đầu tiên cho dữ liệu văn bản dựa vào kiến trúc mô hình Transformer được ứng dụng cho các downstream task khác nhau đó là BERT. Trong phần này chúng ta sẽ fine tuning BERT cho bài toán phân loại trên bộ dữ liệu NTC-SCV dựa vào thư viện transformers của huggingface.



Hình 6: Fine-Tuning BERT cho bài toán phân loại văn bản.

1. Load Dataset

```
# install libs
!pip install -q -U transformers datasets accelerate evaluate

# download
!git clone https://github.com/congnghia0609/ntc-scv.git
!unzip ./ntc-scv/data/data_test.zip -d ./data
!unzip ./ntc-scv/data/data_train.zip -d ./data
!rm -rf ./ntc-scv

# load data
import os
import pandas as pd

def load_data_from_path(folder_path):
    examples = []
```

```python
    for label in os.listdir(folder_path):
        full_path = os.path.join(folder_path, label)
        for file_name in os.listdir(full_path):
            file_path = os.path.join(full_path, file_name)
            with open(file_path, "r", encoding="utf-8") as f:
                lines = f.readlines()
            sentence = " ".join(lines)
            if label == "neg":
                label = 0
            if label == "pos":
                label = 1
            data = {
                'sentence': sentence,
                'label': label
            }
            examples.append(data)
    return pd.DataFrame(examples)

folder_paths = {
    'train': './data/data_train/train',
    'valid': './data/data_train/test',
    'test': './data/data_test/test'
}

train_df = load_data_from_path(folder_paths['train'])
valid_df = load_data_from_path(folder_paths['valid'])
test_df = load_data_from_path(folder_paths['test'])

# convert to Dataset Object
from datasets import Dataset, DatasetDict

raw_dataset = DatasetDict({
    'train': Dataset.from_pandas(train_df),
    'valid': Dataset.from_pandas(valid_df),
    'test': Dataset.from_pandas(test_df)
})
```

2. **Preprocessing**

```python
import re
import string

def preprocess_text(text):
    # remove URLs https://www.
    url_pattern = re.compile(r'https?://\s+\wwww\.\s+')
    text = url_pattern.sub(r" ", text)

    # remove HTML Tags: <>
    html_pattern = re.compile(r'<[^<>]+>')
    text = html_pattern.sub(" ", text)

    # remove puncs and digits
    replace_chars = list(string.punctuation + string.digits)
    for char in replace_chars:
        text = text.replace(char, " ")

    # remove emoji
    emoji_pattern = re.compile("["
        u"\U0001F600-\U0001F64F"  # emoticons
        u"\U0001F300-\U0001F5FF"  # symbols & pictographs
```

```
        u"\U0001F680-\U0001F6FF"  # transport & map symbols
        u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
        u"\U0001F1F2-\U0001F1F4"  # Macau flag
        u"\U0001F1E6-\U0001F1FF"  # flags
        u"\U0001F600-\U0001F64F"
        u"\U00002702-\U000027B0"
        u"\U000024C2-\U0001F251"
        u"\U0001f926-\U0001f937"
        u"\U0001F1F2"
        u"\U0001F1F4"
        u"\U0001F620"
        u"\u200d"
        u"\u2640-\u2642"
        "]+", flags=re.UNICODE)
    text = emoji_pattern.sub(r" ", text)

    # normalize whitespace
    text = " ".join(text.split())

    # lowercasing
    text = text.lower()
    return text

train_df['sentence'] = [preprocess_text(row['sentence']) for index, row in train_df.
    iterrows()]
valid_df['sentence'] = [preprocess_text(row['sentence']) for index, row in valid_df.
    iterrows()]
test_df['sentence'] = [preprocess_text(row['sentence']) for index, row in test_df.
    iterrows()]
```

```
# tokenization
from transformers import AutoTokenizer

model_name = "bert-base-uncased"

tokenizer = AutoTokenizer.from_pretrained(
    model_name,
    use_fast=True
)
max_seq_length = 100
max_seq_length = min(max_seq_length, tokenizer.model_max_length)

def preprocess_function(examples):
    # Tokenize the texts

    result = tokenizer(
        examples["sentence"],
        padding="max_length",
        max_length=max_seq_length,
        truncation=True
    )
    result["label"] = examples['label']

    return result

# Running the preprocessing pipeline on all the datasets
processed_dataset = raw_dataset.map(
    preprocess_function,
    batched=True,
    desc="Running tokenizer on dataset",
)
```

```python

# collator with padding max length
from transformers import DataCollatorWithPadding

data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
```

3. Modeling

```python
from transformers import AutoConfig, AutoModelForSequenceClassification

num_labels = 2

config = AutoConfig.from_pretrained(
    model_name,
    num_labels=num_labels,
    finetuning_task="text-classification"
)
model = AutoModelForSequenceClassification.from_pretrained(
    model_name,
    config=config
)
```

4. Metric

```python
import numpy as np
import evaluate

metric = evaluate.load("accuracy")
def compute_metrics(eval_pred):
    predictions, labels = eval_pred
    predictions = np.argmax(predictions, axis=1)
    result = metric.compute(predictions=predictions, references=labels)
    return result
```

5. Trainer

```python
from transformers import TrainingArguments, Trainer

training_args = TrainingArguments(
    output_dir="save_model",
    learning_rate=2e-5,
    per_device_train_batch_size=128,
    per_device_eval_batch_size=128,
    num_train_epochs=10,
    evaluation_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=processed_dataset["train"],
    eval_dataset=processed_dataset["valid"],
    compute_metrics=compute_metrics,
    tokenizer=tokenizer,
    data_collator=data_collator,
)

```

```
trainer.train()
```

6. Training

Kết quả training và accuracy trên tập test là 85.52

Epoch	Training Loss	Validation Loss	Accuracy
1	No log	0.423262	0.809400
2	No log	0.401464	0.824700
3	0.447100	0.392191	0.836700
4	0.447100	0.373473	0.842200
5	0.316700	0.396957	0.840800
6	0.316700	0.416141	0.842200
7	0.245100	0.454328	0.843700
8	0.245100	0.468748	0.845100
9	0.187800	0.486744	0.841400
10	0.187800	0.489360	0.842600

Hình 7: Quá trình huấn luyện bộ dữ liệu NTC-SCV dựa vào fine tuning BERT.

Phần 3. Vision Transformer

1. Load Dataset

```
import torch
import torchvision.transforms as transforms
from torch.utils.data import DataLoader, random_split
import torch.optim as optim
from torchvision.datasets import ImageFolder
from torch import nn
import math
import os
```

```
# download
!gdown 11Buzytn4vIh4x_0qz8MY29JMMdIqSzj-
!unzip ./flower_photos.zip

# load data
data_patch = "./flower_photos"
dataset = ImageFolder(root=data_patch)
num_samples = len(dataset)
classes = dataset.classes
num_classes = len(dataset.classes)

# split
TRAIN_RATIO, VALID_RATIO = 0.8, 0.1
n_train_examples = int(num_samples * TRAIN_RATIO)
n_valid_examples = int(num_samples * VALID_RATIO)
n_test_examples = num_samples - n_train_examples - n_valid_examples
train_dataset, valid_dataset, test_dataset = random_split(
    dataset,
    [n_train_examples, n_valid_examples, n_test_examples]
)
```

2. Preprocessing

```
# resize + convert to tensor
IMG_SIZE = 224

train_transforms = transforms.Compose([
    transforms.Resize((IMG_SIZE, IMG_SIZE)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(0.2),
    transforms.ToTensor(),
    transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
])

test_transforms = transforms.Compose([
    transforms.Resize((IMG_SIZE, IMG_SIZE)),
    transforms.ToTensor(),
    transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
])

# apply
train_dataset.dataset.transform = train_transforms
valid_dataset.dataset.transform = test_transforms
test_dataset.dataset.transform = test_transforms
```