实验五——多模态融合

Github仓库:

https://github.com/volcano26/Multimodal

实验环境: Autodl

CPU: 16 核心 内存: 120 GB

GPU: NVIDIA GeForce RTX 4090, 1

1.代码介绍

1) 数据预处理

```
def read_and_process_data(txt_filepath, output_csv_filepath):
    df_txt = pd.read_csv(txt_filepath, header=None, names=['guid', 'tag'],
dtype={'guid': str, 'tag': str})
    df_result = pd.DataFrame(columns=['guid', 'text', 'tag'])
    for index, row in df_txt.iterrows():
        guid = row['guid']
        txt_filename = f"{guid}.txt"
        txt_filepath = os.path.join('data', txt_filename)
        if os.path.exists(txt_filepath):
            with open(txt_filepath, 'rb') as txt_file:
                raw_data = txt_file.read()
                result = chardet.detect(raw_data)
                encoding = result['encoding']
            with open(txt_filepath, 'r', encoding=encoding, errors='replace') as
txt_file:
                text = txt_file.read().strip(",")
            df_result = df_result.append({'guid': guid, 'text': text, 'tag':
row['tag']}, ignore_index=True)
        else:
            print(f"Warning: Text file not found for guid {guid}")
    df_result['img_path'] = df_result['guid'].apply(lambda guid:
f'data/{guid}.jpg')
    df_result.to_csv(output_csv_filepath, index=False)
```

```
train_txt_filepath = 'train.txt'
train_csv_filepath = 'train.csv'
read_and_process_data(train_txt_filepath, train_csv_filepath)
train_df = pd.read_csv(train_csv_filepath)
```

```
train_set, val_set = train_test_split(train_df, test_size=0.2, random_state=42)

print(f'Training set shape: {train_set.shape}')

print(f'Validation set shape: {val_set.shape}')

train_train_csv_filepath = 'train_train.csv'
train_val_csv_filepath = 'train_val.csv'
train_set.to_csv(train_train_csv_filepath, index=False)
val_set.to_csv(train_val_csv_filepath, index=False)

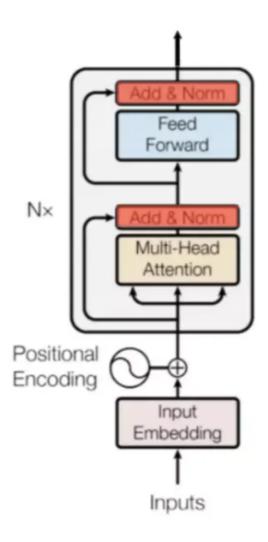
test_txt_filepath = 'test_without_label.txt'
test_csv_filepath = 'test.csv'
read_and_process_data(test_txt_filepath, test_csv_filepath, is_test=True)
```

这里我将txt文件进行数据的预处理,将其修改为csv文件的同时,在每个csv文件中添加**guid,其对应的text文本,其对应的img路径以及其tag标签**,以方便我后续对于其信息的处理效率(不需要每次寻找调用txt文件)

guid	•	text	tag	img_path
	1	How I feel to	positive	data/1.jpg
	2	grattis min g	positive	data/2.jpg
	3	RT @polynm	positive	data/3.jpg
	4	#escort We	positive	data/4.jpg
	6	RT @babesh	positive	data/6.jpg
	7	RT @deepik	positive	data/7.jpg
	9	Look at their	positive	data/9.jpg
	10	@ArrivaTW a	negative	data/10.jpg
	11	RT @Dthom	positive	data/11.jpg
	12	RT @cosy_co	positive	data/12.jpg
	14	RT @Chester	positive	data/14.jpg
	15	Awesome rec	positive	data/15.jpg
	16	RT @ VenusC	positive	data/16.jpg
	17	Love to party	positive	data/17.jpg
	18	RT @JoeyXcv	positive	data/18.jpg
	19	#depressed	negative	data/19.jpg
	21	Thank you t	positive	data/21.jpg
	22	Enraged by t	negative	data/22.jpg
	23	I am enthusi	positive	data/23.jpg
	24	Looking for	neutral	data/24.jpg
	25	RT @curiosit	neutral	data/25.jpg
	26	Waxwing tril	neutral	data/26.jpg
	27	RT @ Poshbi	neutral	data/27.jpg
	28	RT @ Beltrew	positive	data/28.jpg

而后以**20%验证集,80%训练集**的比例进行划分,形成train_train.csv,train_val.csv两个文件存储

2) bert模型介绍

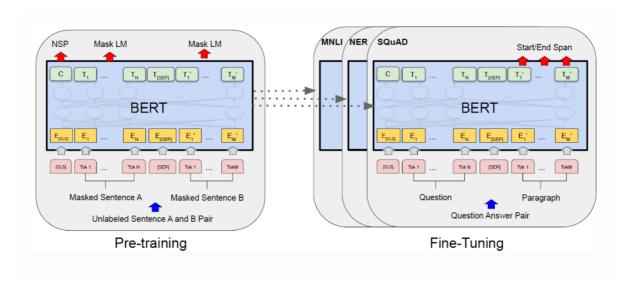


```
class BertModel(nn.Module):
    def __init__(self, num_labels, text_pretrained='./bert-base-uncased'):
        super().__init__()
        self.num_labels = num_labels
        self.text_encoder = AutoModel.from_pretrained(text_pretrained)
        self.classifier = nn.Linear(self.text_encoder.config.hidden_size,
num_labels)

def forward(self, text):
        output = self.text_encoder(text.input_ids,
attention_mask=text.attention_mask, return_dict=True)
        logits = self.classifier(output.last_hidden_state[:, 0, :])
        return logits
```

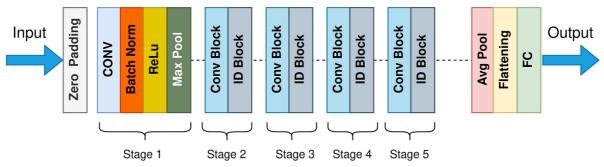
其中 logits = self.classifier(output.last_hidden_state[:, 0, :]) 这一行代码我使用的是 CLS embedding; 因为 [cLs] 所对应的Embedding被使用来代表句义的原理,所以比较适合于在进行 text文本(特别是单句话的情况使用)

我这里使用的预训练模型是 bert-base-uncased (这里很多遇到的问题会在后面讲)



3) resnet模型



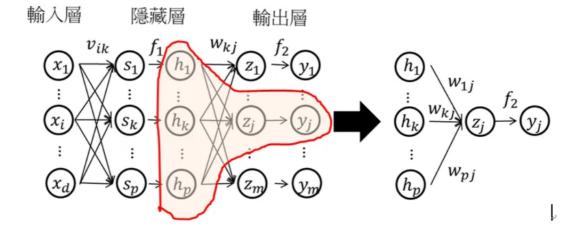


```
class ResNetDataset(Dataset):
    def __init__(self, df, label_to_id, train=False, text_field="text",
label_field="tag", image_path_field="img_path"):
        self.df = df.reset_index(drop=True)
        self.label_to_id = label_to_id
        self.train = train
        self.text_field = text_field
        self.label_field = label_field
        self.image_path_field = image_path_field
        # ResNet-50 settings
        self.img_size = 224
        self.mean, self.std = (
            0.48145466, 0.4578275, 0.40821073), (0.26862954, 0.26130258,
0.27577711)
        self.train_transform_func = transforms.Compose(
                [transforms.RandomResizedCrop(self.img_size, scale=(0.5, 1.0)),
                    transforms.RandomHorizontalFlip(),
                    transforms.ToTensor(),
                    transforms.Normalize(self.mean, self.std)
                    ])
        self.eval_transform_func = transforms.Compose(
                [transforms.Resize(256),
                    transforms.CenterCrop(self.img_size),
```

```
transforms.ToTensor(),
                transforms.Normalize(self.mean, self.std)
                ])
def __getitem__(self, index):
    text = str(self.df.at[index, self.text_field])
    label = self.label_to_id.get(self.df.at[index, self.label_field], -1)
    # self.label_to_id[self.df.at[index, self.label_field]]
    img_path = self.df.at[index, self.image_path_field]
    image = Image.open(IMG_FOLDER + '/' + img_path)
    if self.train:
      img = self.train_transform_func(image)
    else:
      img = self.eval_transform_func(image)
    return text, label, img
def __len__(self):
    return self.df.shape[0]
```

使用的是resnet-50模型;使用残差块来更好的进行图像的识别

4) 模型融合



```
class MML(nn.Module):
    def __init__(self, input_size1, input_size2, hidden_size, output_size):
        super().__init__()
        self.fc1 = nn.Linear(input_size1 + input_size2, hidden_size)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_size, output_size)

def forward(self, x1, x2):
        x = torch.cat((x1, x2), dim=1)
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x
```

```
class MMLmodel(nn.Module):
    def __init__(self, num_labels, text_pretrained='./bert-base-uncased',
hidden_size=512):
        super().__init__()
        self.text_encoder = AutoModel.from_pretrained(text_pretrained)
        self.visual_encoder = FeatureModel(output_layer='avgpool')
        self.image_hidden_size = 2048
        self.mlp_text = nn.Linear(self.text_encoder.config.hidden_size,
num_labels)
        self.mlp_image = nn.Linear(self.image_hidden_size, num_labels)
        self.mlp_both = MML(self.text_encoder.config.hidden_size,
self.image_hidden_size, hidden_size, num_labels)
    def forward(self, text, image, mode='both'):
        text_output = self.text_encoder(**text)
        text_feature = text_output.last_hidden_state[:, 0, :]
        img_feature = self.visual_encoder(image)
        if mode == 'text':
            logits = self.mlp_text(text_feature)
        elif mode == 'image':
            logits = self.mlp_image(img_feature)
        else: # 'both'
            logits = self.mlp_both(text_feature, img_feature)
        return logits
```

使用MLP,多层感知机进行模块的融合;多层感知机是一种**前向传递类神经网路**,利用到倒传递的技术达到监督式学习,将文本和图像的bert和resnet50两个模型相互交叉融合(这里一定要保证其输出的层数维度一致,不然矩阵乘法会报错)

2.遇到的问题

1) bert预训练模型下载

遇到直接使用代码超时

```
OSError: We couldn't connect to 'https://huggingface.co' to load this file, couldn't find it in the cached files and it looks like bert-base-uncased is not the path to a directory containing a file named config.json.
```

解决方案1: 登入官网下载其所需要的文件(pytorch或者tensorflow),而后将代码中的预训练模型改为本地链接

```
def __init__(self, num_labels, text_pretrained='./bert-base-uncased')
```

这样子操作我能够在本地电脑中运行,但是因为文件太大上传至服务器会有所丢失导致其bin文件不完整

```
OSError: Unable to load weights from pytorch checkpoint file for 'bert-base-uncased' at ... If you tried to load a PyTorch model from a TF 2.0 checkpoint, please set from_tf=True.
```

解决方案2:

```
pip install -∪ huggingface_hubCopy
```

输入命令

```
export HF_ENDPOINT=https://hf-mirror.comCopy
huggingface-cli download --resume-download --local-dir-use-symlinks False bert-base-uncased --local-dir bert-base-uncased
```

直接在云服务器上面下载

2) 读取txt文件数据时候报错

我代码先对于txt文件进行预处理,保存为csv文件,但其文本格式一直报错

使用 chardet 包先对于文本进行格式的判断,而后添加 errors='replace' 阻止其报错(只会有warning出现)

```
with open(txt_filepath, 'rb') as txt_file:
    raw_data = txt_file.read()
    result = chardet.detect(raw_data)
    encoding = result['encoding']

with open(txt_filepath, 'r', encoding=encoding, errors='replace') as
txt_file:
    text = txt_file.read().strip(",")
```

3.结果分析

1)只使用文本

可以看到只使用文本在验证集的准确率仅有0.2175

```
| 0/5 [00:00<?, ?it/s]
| 0/800 [00:00<?, ?it/s]
                               avg_epoch_loss = 0.751815449167043 learning rate = 9.045084971874738e-06
                                                                                                                               | 0/800 [00:00<?, ?it/s]
                               loss = 432, 0497868321836
                                                                                                                               0/800 [00:00<?, ?it/s]
  loss = 293.3832299914211
                                avg_epoch_loss = 0.3667290374892764
                                                                                                                               | 0/800 [00:00<?, ?it/s]
ch_loss = 195.63405899796635
                               avg_epoch_loss = 0.24454257374745794
                                                                          learning rate = 9.549150281252633e-07
                                                                                                                 Batch: 0%
                                                                                                                                     | 0/800 [00:00<?, ?it/s]
 _loss = 157.2573178196326
| 0/200 [00:00<?, ?it/s]
                                avg_epoch_loss = 0.19657164727454074
                                                                           learning rate = 0.0 469.0075559290126
```

2) 只使用图像

验证集准确率为0.71375

```
outodl-container-h52843h669-0h39a6ec^# nython main ny
                | 0/5 [00:00<?, ?it/s]
| 0/800 [00:00<?, ?it/s]
  ch_loss = 607.885859683156
                                                                                  learning rate = 9.045084971874738e-06
                                                                                                                                  Batch: 0%
                                                                                                                                                          | 0/800 [00:00<?, ?it/s]
                                        avg_epoch_loss = 0.7598573246039451
                                        avg_epoch_loss = 0.5483649862930179
   loss = 438.6919890344143
                                                                                  learning rate = 6.545084971874738e-06
                                                                                                                                  Batch: 0%
                                                                                                                                                         0/800 [00:00<?, ?it/s]
  ch_loss = 292.11121618561447
                                        avg_epoch_loss = 0.3651390202320181
                                                                                   learning rate = 3.4549150281252635e-06
                                                                                                                                                          | 0/800 [00:00<?, ?it/s]
                                                                                                                                                                  0/800 [00:00<?, ?it/s]
                                        avg_epoch_loss = 0.24469504673499615
                                                                                            learning rate = 9.549150281252633e-07
                                                                                                                                          Batch: 0%
          = 155.85070120729506
| 0/200 [00:00<?, ?it/s]
                                        avg_epoch_loss = 0.1948133765091188
                                                                                   learning rate = 0.0 464.2953635309823
        | 0/128 [00:00<?, ?it/s]
ntainer-b52843b669-0b39a6
```

3) 文本图像相互结合

验证集准确率为0.69875

```
utodl-container-b52843b669-0b39a6ec:~# python main.py
 t_decay: 0.01
p_steps: 0
 eq_length: 237
s: 0%|
                 | 0/10 [00:00<?, ?it/s]
| 0/800 [00:00<?, ?it/s]
                                        avg_epoch_loss = 0.7596877887286246
                                                                                  learning rate = 9.755282581475769e-06
                                                                                                                                 Batch: 0%
                                                                                                                                                        | 0/800 [00:00<?, ?it/s]
                                                                                                                                                        0/800 [00:00<?, ?it/s]
epoch loss = 429.7851064391434
                                        avg epoch loss = 0.5372313830489293
                                                                                  learning rate = 9.045084971874738e-06
                                                                                                                                         0%
                                                                                                                                Batch:
    _loss = 277.62029856815934
                                         avg_epoch_loss = 0.34702537321019916
                                                                                           learning rate = 7.938926261462366e-06
                                                                                                                                                  0%
                                                                                                                                                                 | 0/800 [00:00<?, ?it/s]
   th_loss = 155. 37706632027403
                                        avg_epoch_loss = 0.19422133290034252
                                                                                           learning rate = 6.545084971874738e-06
                                                                                                                                                                 | 0/800 [00:00<?, ?it/s]
                                                                                                                                         Batch:
  ch loss = 87 99552065017633
                                        avg epoch loss = 0.10999440081272041
                                                                                           learning rate = 5e-06
                                                                                                                       Ratch: 0%
                                                                                                                                               0/800 [00:00<?, ?it/s]
                                                                                           learning rate = 3.4549150281252635e-06
                                        avg_epoch_loss = 0.07515023048166768
                                                                                                                                                                 | 0/800 [00:00<?, ?it/s]
                                                                                                                                                                0/800 [00:00<?, ?it/s]
  och loss = 41, 44392206822522
                                        avg epoch loss = 0.051804902585281525
                                                                                           learning rate = 2.061073738537635e-06
 boch_loss = 31.22713000647491
= 8
                                        avg_epoch_loss = 0.039033912508093634
                                                                                           learning rate = 9.549150281252633e-07
                                                                                                                                                                 | 0/800 [00:00<?, ?it/s]
  och_loss = 24.504319305648096
                                                                                           learning rate = 2.447174185242324e-07
                                                                                                                                                                | 0/800 [00:00<?, ?it/s]
                                        avg_epoch_loss = 0.03063039913206012
                                                                                                                                                 0%
                                                                                                                                         Batch:
   ch_loss = 23.67398760310607
| 0/200 [00:00<?, ?i
                                        avg_epoch_loss = 0.029592484503882587
                                                                                           learning rate = 0.0 913.8805663757958
         | 0/128 [00:00<?, ?it/s]
ntainer-b52843b669-0b39a6ec:~#
```



可以看到其损失值已经趋近于平滑,基本上达到拟合状态

疑问点: 为什么使用多模态融合的结果反而不如单使用图像识别的准确率(个人猜测是因为单使用文本的准确率过低所以拉低了融合预测的准确率)