Assignment_1_(NLP)

October 1, 2023

Import packages

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import torch
from tqdm.notebook import tqdm
import seaborn as sns
import os
import json

from transformers import BertTokenizerFast, BertModel
import torch
import torch.nn as nn
import torch.functional as F
from torch.optim import Adam
from time import strftime
from sklearn.metrics import classification_report, confusion_matrix

device = 'cuda' if torch.cuda.is_available() else 'cpu'
torch.cuda.empty_cache()
strftime = strftime("%Y-%m-%d_%H-%M-%S")
```

Load the IMDB dataset

link

[2]:
```
link_to_dataset = 'https://raw.githubusercontent.com/SagarParekh97/
↪NLP-Fall-2023/main/Assignment%201/IMDB%20Dataset.csv'

dataset = pd.read_csv(link_to_dataset)
print(dataset)
class_name = ['negative', 'positive']
```

```
                                                  review sentiment
0      One of the other reviewers has mentioned that …  positive
1      A wonderful little production. <br /><br />The…  positive
2      I thought this was a wonderful way to spend ti…  positive
3      Basically there's a family where a little boy …  negative
```

```
4      Petter Mattei's "Love in the Time of Money" is…  positive
…                                                  …         …
49995  I thought this movie did a down right good job…  positive
49996  Bad plot, bad dialogue, bad acting, idiotic di…  negative
49997  I am a Catholic taught in parochial elementary…  negative
49998  I'm going to have to disagree with the previou…  negative
49999  No one expects the Star Trek movies to be high…  negative

[50000 rows x 2 columns]
```

Divide the dataset into Training, Development, and Test sets

Training - 39723 reviews (80%)

Development - 4998 reviews (10%)

Test - 4995 reviews (10%)

[3]:
```python
# shuffle the dataset
dataset = dataset.sample(frac=1)
# split dataset according to the required size
train, development, test, _ = np.split(dataset, [39723, 39723 + 4998, 39723 +
 ↪4998 + 4995])

print(f'Length of train: {len(train)}\nLength of development:
 ↪{len(development)}\nLength of test: {len(test)}')
```

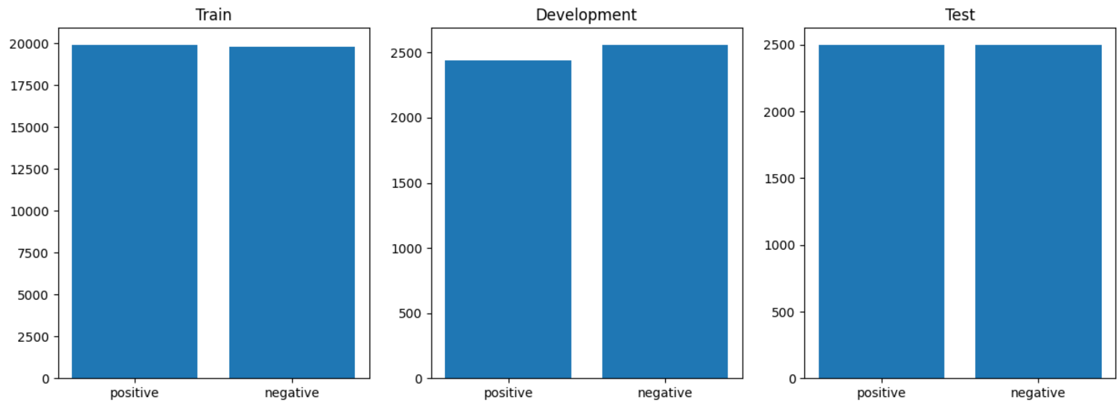
```
Length of train: 39723
Length of development: 4998
Length of test: 4995
```

```
/home/legion/miniconda3/envs/nlp/lib/python3.9/site-
packages/numpy/core/fromnumeric.py:59: FutureWarning: 'DataFrame.swapaxes' is
deprecated and will be removed in a future version. Please use
'DataFrame.transpose' instead.
  return bound(*args, **kwds)
```

Validate the datasets

[4]:
```python
_, ax = plt.subplots(1, 3, figsize=(15, 5))

ax[0].bar(['positive', 'negative'], [np.sum(train.sentiment == 'positive'), np.
 ↪sum(train.sentiment == 'negative')])
ax[0].set_title('Train')
ax[1].bar(['positive', 'negative'], [np.sum(development.sentiment ==
 ↪'positive'), np.sum(development.sentiment == 'negative')])
ax[1].set_title('Development')
ax[2].bar(['positive', 'negative'], [np.sum(test.sentiment == 'positive'), np.
 ↪sum(test.sentiment == 'negative')])
ax[2].set_title('Test')
```

[4]: Text(0.5, 1.0, 'Test')



Choosing the max length for tokens

[5]:
```
MODEL_NAME = 'bert-base-cased'

tokenizer = BertTokenizerFast.from_pretrained(MODEL_NAME)
# token_lens = []

# for txt in tqdm(dataset.review):
#     tokens = tokenizer.encode(txt, max_length=1000)
#     token_lens.append(len(tokens))
```

[6]:
```
# sns.displot(token_lens)
# plt.xlabel('Token count')
```

We find that the dataset contains reviews that are longer than 1000. But as we can see, most reviews have a length of around 200 tokens. So, we choose the max_length for the tokens to be 512 and truncate the reviews longer than that.

[7]:
```
MAX_LENGTH = 512
```

Toeknize the text using pre-trained BERT

0: negative sentiment 1: positive sentiment

[8]:
```
class Dataset(torch.utils.data.Dataset):
    def __init__(self, tokenizer, dataset: pd.DataFrame, device):
        self.tokenizer = tokenizer
        self.reviews = dataset.review.tolist()
        self.targets = dataset.sentiment.apply({'negative': 0, 'positive': 1}.
 ↪get).to_numpy()
        self.device = device
```

```
    def __len__(self):
        return len(self.reviews)

    def __getitem__(self, index):
        output = dict()
        tokens = tokenizer(self.reviews[index], max_length=MAX_LENGTH,␣
↪truncation=True,
                                padding='max_length')

        output['review'] = self.reviews[index]
        output['id'] = torch.tensor(tokens['input_ids'], dtype=torch.long)
        output['mask'] = torch.tensor(tokens['attention_mask'], dtype=torch.
↪long)
        output['token_type_id'] = torch.tensor(tokens['token_type_ids'],␣
↪dtype=torch.long)
        output['target'] = torch.tensor(self.targets[index], dtype=torch.long)

        return output

train_dataset = Dataset(tokenizer, train, device)
test_dataset = Dataset(tokenizer, test, device)
development_dataset = Dataset(tokenizer, development, device)
```

Sentiment Classifier

[9]:
```
torch.cuda.empty_cache()
class BERTClassifier(nn.Module):
    def __init__(self, dropout: float=0.3, output_size: int=2):
        super(BERTClassifier, self).__init__()
        self.bert = BertModel.from_pretrained(MODEL_NAME)
        self.d1 = nn.Dropout(dropout)
        self.l1 = nn.Linear(self.bert.config.hidden_size, output_size)
        self.activation = nn.ReLU()

        self.loss_fcn = nn.CrossEntropyLoss()

    def forward(self, ids, masks, targets):
        outputs = self.bert(input_ids=ids, attention_mask=masks)

        outputs = self.d1(outputs[1])
        outputs = self.l1(outputs)

        _, predictions = torch.max(outputs, axis=1)

        return predictions, self.loss(outputs, targets)

    def loss(self, outputs, targets):
```

```python
        return self.loss_fcn(outputs, targets)
```

Create functions to train and evaluate the model

[10]:
```python
def trainer(model, dataset, optimizer, epochs, params_dataLoader, device):
    dataset_loader = torch.utils.data.DataLoader(dataset, **params_dataLoader)

    training_loss = []
    training_accuracy = []
    for e in tqdm(range(epochs)):
        correct_predictions = 0
        for data in tqdm(dataset_loader):
            ids = data['id'].to(device)
            masks = data['mask'].to(device)
            targets = data['target'].to(device)

            prediction, loss = model(ids, masks, targets)
            training_loss.append(loss.item())
            correct_predictions += torch.sum(prediction == targets).cpu().
 ↪detach().numpy()

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        training_accuracy.append((e, correct_predictions / len(dataset)))

    # save the trained models
    model_checkpoint = dict()
    model_checkpoint['model_state_dict'] = model.state_dict()
    model_checkpoint['optimizer_state_dict'] = optimizer.state_dict()
    model_checkpoint['training_loss'] = training_loss
    model_checkpoint['training_accuracy'] = training_accuracy
    torch.save(model_checkpoint, f'./save_data/model_checkpoint_{strftime}.pth')
    return training_loss, training_accuracy
```

[11]:
```python
def eval(model, dataset, params_dataLoader, device):
    dataset_loader = torch.utils.data.DataLoader(dataset, **params_dataLoader)

    y_pred = []
    y_true = []
    for data in tqdm(dataset_loader):
        ids = data['id'].to(device)
        masks = data['mask'].to(device)
        targets = data['target'].to(device)
```

```
        y_true.append(targets.cpu().detach().numpy())
        with torch.no_grad():
            prediction, _ = model(ids, masks, targets)

            y_pred.append(prediction.cpu().detach().numpy().item())

    report = classification_report(y_true, y_pred, target_names=class_name)
    conf_mat = confusion_matrix(y_true, y_pred)

    return report, conf_mat
```

The BERT authors have some recommendations for fine-tuning:

```
Batch size: 16, 32
Learning rate (Adam): 5e-5, 3e-5, 2e-5
Number of epochs: 2, 3, 4
```

We use these values to guide our hyperparameters

[12]:

```
LR = 2e-5
TRAINING_BATCH_SIZE = 16
TEST_BATCH_SIZE = 1
EPOCHS = 5
DROPOUT = 0.3
N_CLASSES = 2
NUM_WORKERS = 4

params_dataLoader = {'batch_size': TRAINING_BATCH_SIZE,
                     'shuffle': True,
                     'num_workers': NUM_WORKERS}

model = BERTClassifier(dropout=DROPOUT, output_size=N_CLASSES).to(device)
optimizer = Adam(model.parameters(), lr=LR)
```

Train

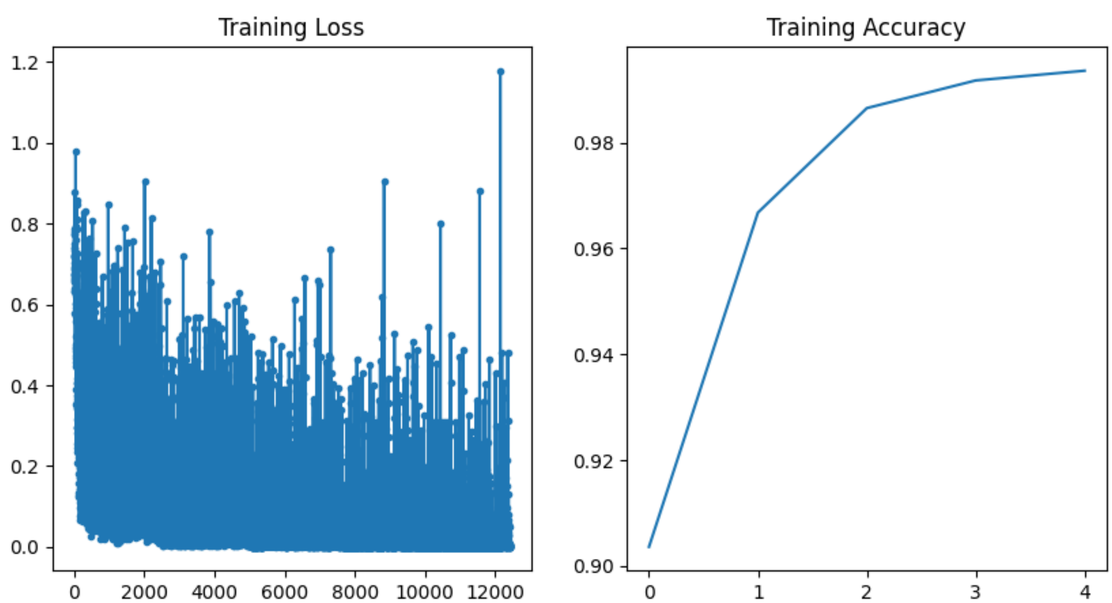
[13]:

```
training_loss, training_accuracy = trainer(model, train_dataset, optimizer,␣
 ↪EPOCHS, params_dataLoader, device)

fname = os.path.join(f'./save_data/training_loss_{strftime}.json')
with open(fname, 'w') as f:
    json.dump(training_loss, f)
fname = os.path.join(f'./save_data/training_accuracy_{strftime}.json')
with open(fname, 'w') as f:https://vt-collab.slack.com/files/U03BLL3DBB3/
 ↪F05VC7KD4DN/sim_pomdp.py?origin_team=T019P95SX32&origin_channel=D03ATE9ADFH
    json.dump(training_accuracy, f)

_, ax = plt.subplots(1, 2, figsize=(10, 5))
ax[0].plot(training_loss, marker='.')
```

```
ax[0].set_title('Training Loss')
ax[1].plot(*zip(*training_accuracy))
ax[1].set_title('Training Accuracy')
```

```
0%|          | 0/5 [00:00<?, ?it/s]

0%|          | 0/2483 [00:00<?, ?it/s]

0%|          | 0/2483 [00:00<?, ?it/s]

0%|          | 0/2483 [00:00<?, ?it/s]

0%|          | 0/2483 [00:00<?, ?it/s]

0%|          | 0/2483 [00:00<?, ?it/s]
```

[13]:
```
Text(0.5, 1.0, 'Training Accuracy')
```



Evaluate Train set

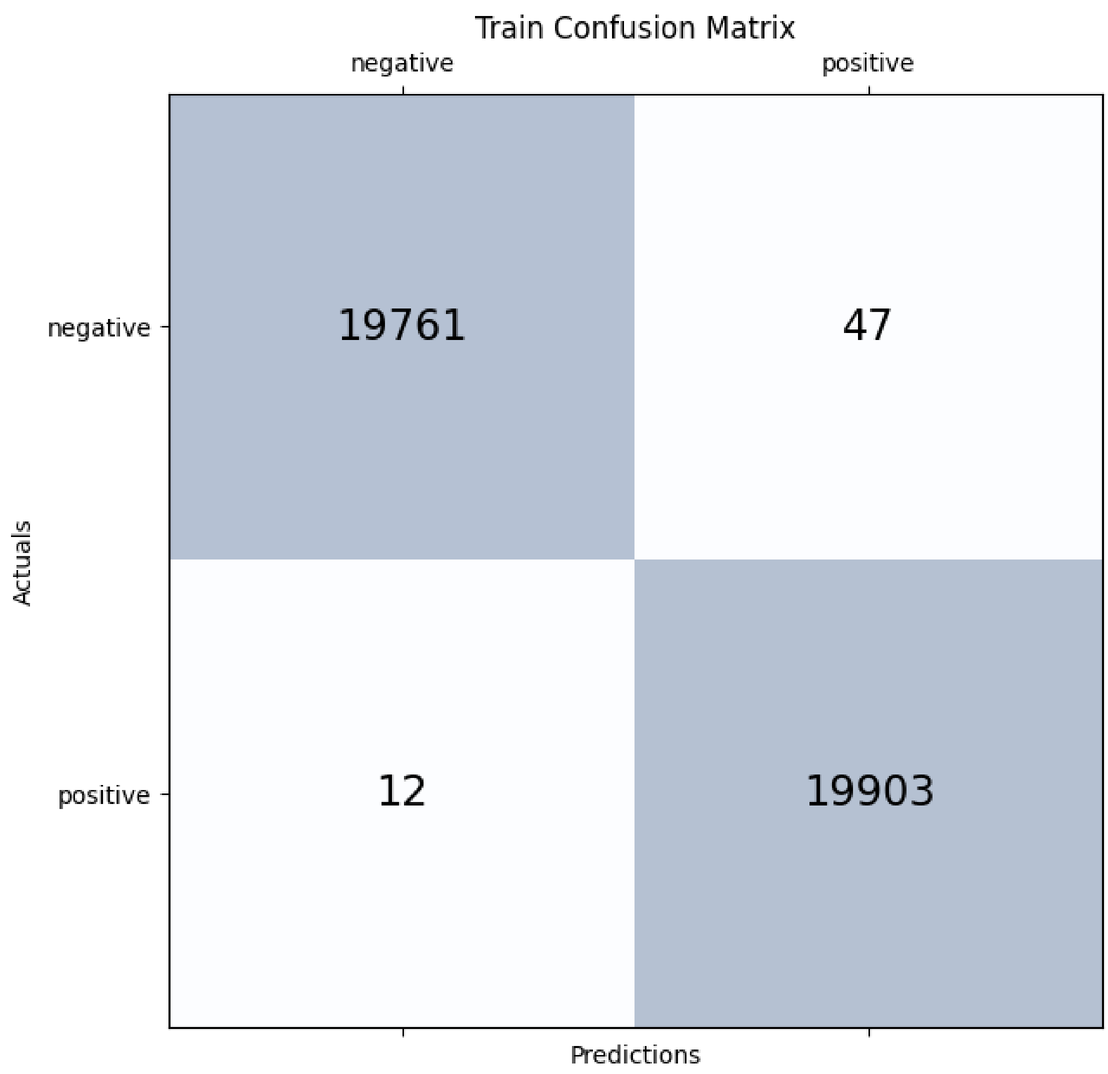
[14]:
```
params_dataLoader_eval = {'batch_size': TEST_BATCH_SIZE,
                          'shuffle': True,
                          'num_workers': NUM_WORKERS}
```

[15]:
```
train_report, train_conf_mat = eval(model, train_dataset,␣
 ↪params_dataLoader_eval, device)

_, ax = plt.subplots(1, 1, figsize=(7, 7))
ax.matshow(train_conf_mat, cmap=plt.cm.Blues, alpha=0.3)
for i in range(train_conf_mat.shape[0]):
```

```
    for j in range(train_conf_mat.shape[1]):
        ax.text(x=j, y=i, s=train_conf_mat[i, j], va='center', ha='center',␣
 ↪size='xx-large')
ax.set_xlabel('Predictions')
ax.set_ylabel('Actuals')
ax.set_xticks(range(len(class_name)))
ax.set_yticks(range(len(class_name)))
ax.set_xticklabels(class_name)
ax.set_yticklabels(class_name)
plt.title('Train Confusion Matrix')
```

```
  0%|          | 0/39723 [00:00<?, ?it/s]
```

[15]: Text(0.5, 1.0, 'Train Confusion Matrix')

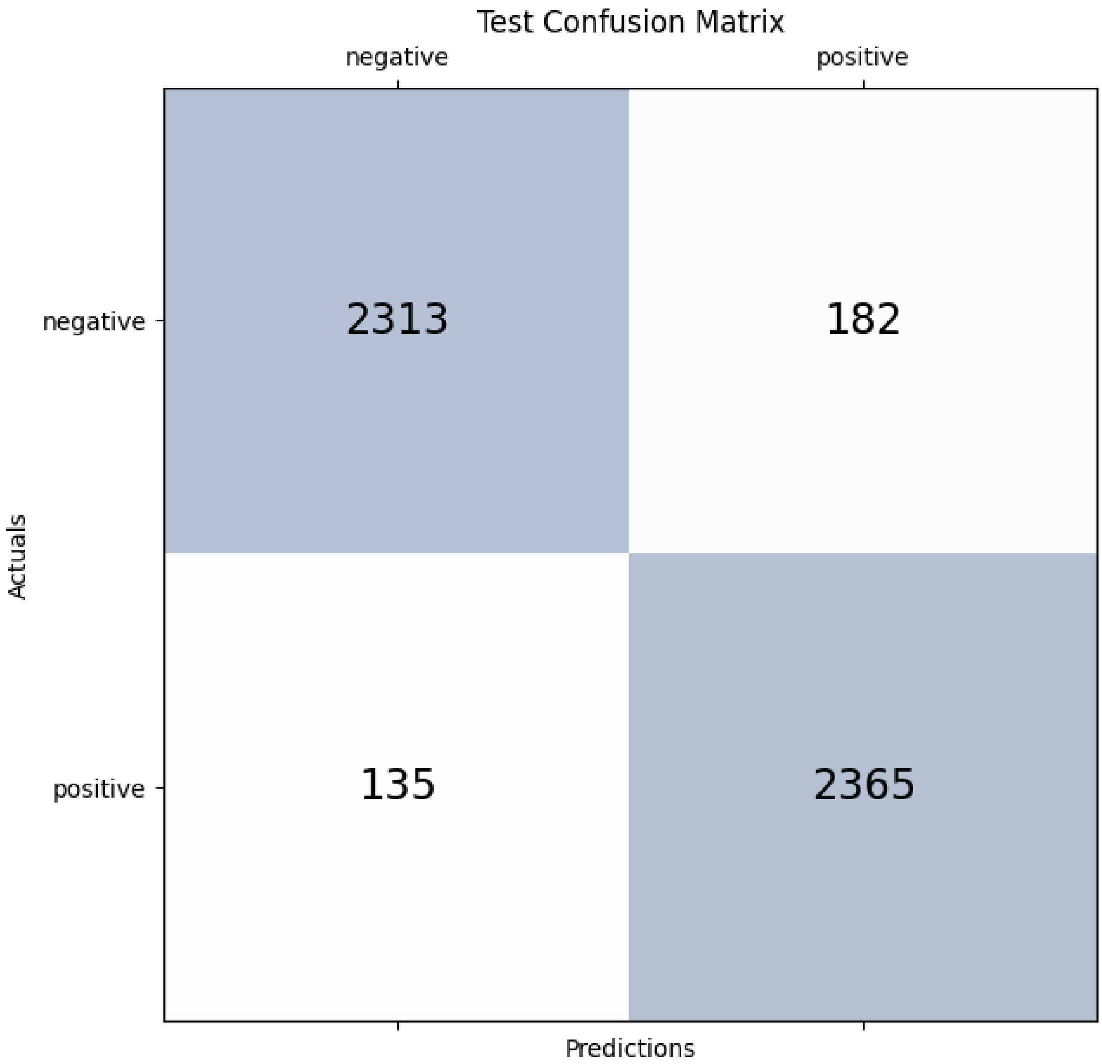


Test set

[16]:
```
test_report, test_conf_mat = eval(model, test_dataset, params_dataLoader_eval,␣
 ↪device)
_, ax = plt.subplots(1, 1, figsize=(7, 7))
ax.matshow(test_conf_mat, cmap=plt.cm.Blues, alpha=0.3)
for i in range(test_conf_mat.shape[0]):
    for j in range(test_conf_mat.shape[1]):
        ax.text(x=j, y=i, s=test_conf_mat[i, j], va='center', ha='center',␣
 ↪size='xx-large')
ax.set_xlabel('Predictions')
ax.set_ylabel('Actuals')
ax.set_xticks(range(len(class_name)))
ax.set_yticks(range(len(class_name)))
ax.set_xticklabels(class_name)
ax.set_yticklabels(class_name)
plt.title('Test Confusion Matrix')
```

```
 0%|          | 0/4995 [00:00<?, ?it/s]
```

[16]:
```
Text(0.5, 1.0, 'Test Confusion Matrix')
```



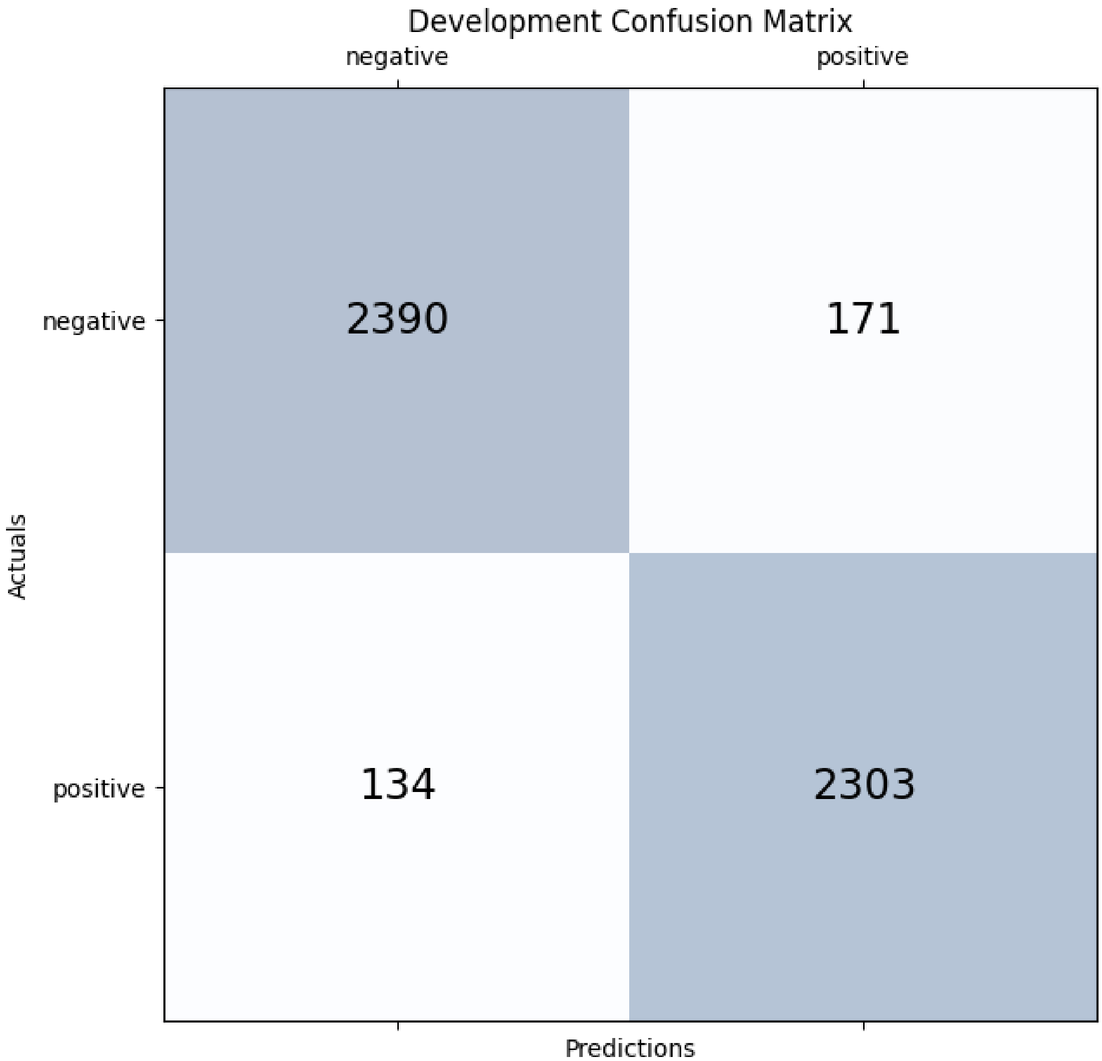
Development set

[17]:
```
devel_report, devel_conf_mat = eval(model, development_dataset,␣
  ↪params_dataLoader_eval, device)
_, ax = plt.subplots(1, 1, figsize=(7, 7))
ax.matshow(devel_conf_mat, cmap=plt.cm.Blues, alpha=0.3)
for i in range(devel_conf_mat.shape[0]):
    for j in range(devel_conf_mat.shape[1]):
        ax.text(x=j, y=i, s=devel_conf_mat[i, j], va='center', ha='center',␣
  ↪size='xx-large')
ax.set_xlabel('Predictions')
ax.set_ylabel('Actuals')
ax.set_xticks(range(len(class_name)))
ax.set_yticks(range(len(class_name)))
```

```
ax.set_xticklabels(class_name)
ax.set_yticklabels(class_name)
plt.title('Development Confusion Matrix')
```

```
0%|          | 0/4998 [00:00<?, ?it/s]
```

[17]: Text(0.5, 1.0, 'Development Confusion Matrix')



[ ]:

[ ]: