Build a self-attention Transformer model

In this notebook, we will build the Transformer model for the classification task. The main architecture of the Transformer is derived from the paper: https://arxiv.org/pdf/1706.03762.pdf, but to be able to perform text classification we have to re-build the model a bit by applying the Max or Avg Pooling according to https://arxiv.org/pdf/1705.02364.pdf, where instead of using hidden representations we will us the last Transfomer block output.

The Transformer is solely based on the self-attention mechanism, disposing recurrent units or convolution layers at all, thanks to which that architecture is superior in terms of the prediction quality and the training time. The Transformer allows for significantly more parallelization and keeps also the ability of discerning long-term dependencies. To increase the generalization performance of the model we will use the label smoothing method.

The model is going to be trained on the clean_review column from the training dataset. In the end, the model will be evaluated on the test set to determine the generalization error.

We will perform the hyperparameter fine-tuning and visualize model's learning curves to compare the model's performance while working on different set of parameters.

Building and training the model

Let's start with importing all indispensable libraries.

In [1]:

```
from batch_iterator import BatchIterator
from early_stopping import EarlyStopping
import pandas as pd
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch import device
from tqdm import tqdm_notebook
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
from tensorboardX import SummaryWriter
```

To train the model we will use the clean_review column from the training set as well as the label column.

In [2]:
```
# Import the dataset. Use clean_review and label columns
train_dataset = pd.read_csv('dataset/drugreview_feat_clean/train_feat_clean.c
                            usecols=['clean_review', 'rating'])

# Change columns order
train_dataset['label'] = train_dataset.rating >= 5
train_dataset = train_dataset[['clean_review', 'label']]
```

In [3]:
```
# Depict the first 5 rows of the training set
train_dataset = train_dataset.dropna()
train_dataset.head()
```

Out[3]:

	clean_review	label
2	young suffering severe extreme neck pain resul...	True
5	found work helping good nights sleep don'...	True
9	given medication gastroenterologist office wor...	False
12	recently laparoscopic hysterectomy know anesth...	True
13	mirena year experienced effects effects watch ...	False

To fine-tune the hyperparameters we will evaluate the model on a validation set.

In [4]:
```
# Import the dataset. Use clean_review and label columns
val_dataset = pd.read_csv('dataset/drugreview_feat_clean/val_feat_clean.csv',
                          usecols=['clean_review', 'rating'])

# Change columns order
val_dataset['label'] = val_dataset.rating >= 5
val_dataset = val_dataset[['clean_review', 'label']]
```

In [5]:
```
# Depict the first 5 rows of the validation set
val_dataset = val_dataset.dropna()
val_dataset.head()
```

Out[5]:

	clean_review	label
0	year old son took night went deep sea fishing ...	True
1	daughter epiduo grade junior year work wonders...	True
2	i've implant months day got totally felt ...	True
3	wanted wait days post couldn't results am...	True
4	colonoscopy best prep far morning took prep pm...	True

Now we will use the BatchIterator class to preprocess the text data and generate batches.

In [6]:
```
batch_size = 32
```

In [7]:
```
train_iterator = BatchIterator(train_dataset, batch_size=batch_size, vocab_cr
                               word2index=None, sos_token='<SOS>', eos_token=
                               pad_token='<PAD>', min_word_count=3, max_vocab
                               use_pretrained_vectors=False, glove_path='glov
                               weights_file_name='glove/weights.npy')
```

```
Trimmed vocabulary using as minimum count threashold: count = 3.00
8674/21861 tokens has been retained
Trimmed input strings vocabulary
Trimmed input sequences lengths to the length of: 58
Mapped words to indices
Batches created
```

In [8]:
```
val_iterator = BatchIterator(val_dataset, batch_size=batch_size, vocab_create
                             word2index=train_iterator.word2index, sos_token=
                             unk_token='<UNK>', pad_token='<PAD>', min_word_c
                             max_seq_len=0.9, use_pretrained_vectors=False, g
                             glove_name='glove.6B.100d.txt', weights_file_nam
```

```
Trimmed vocabulary using as minimum count threashold: count = 3.00
4655/11853 tokens has been retained
Trimmed input strings vocabulary
Trimmed input sequences lengths to the length of: 57
Mapped words to indices
Batches created
```

Now we will check out if the batches look correctly.

In [9]:
```
for batches in train_iterator:
    # Unpack the dictionary of batches
    input_seq, target, x_lengths = batches['input_seq'], batches['target'], b
    print('input_seq shape: ', input_seq.size())
    print('target shape: ', target.size())
    print('x_lengths shape: ', x_lengths.size())
    break
```

```
input_seq shape:  torch.Size([32, 4])
target shape:  torch.Size([32])
x_lengths shape:  torch.Size([32])
```

In [10]:

```
# Extract the maximum sequence length

max_len = 0

for batches in train_iterator:
    x_lengths = batches['x_lengths']
    if max(x_lengths) > max_len:
        max_len = int(max(x_lengths))
```

In [11]:

```
print('Maximum sequence length: {}'.format(max_len))
```

```
Maximum sequence length: 59
```

Let's start implementing the Transformer model.

In [12]:

```
class MultiHeadAttention(nn.Module):
    """Implementation of the Multi-Head-Attention.

    Parameters
    ----------
    dmodel: int
        Dimensionality of the input embedding vector.
    heads: int
        Number of the self-attention operations to conduct in parallel.
    """

    def __init__(self, dmodel, heads):

        super(MultiHeadAttention, self).__init__()

        assert dmodel % heads == 0, 'Embedding dimension is not divisible by 

        self.dmodel = dmodel
        self.heads = heads
        # Split dmodel (embedd dimension) into 'heads' number of chunks
        # each chunk of size key_dim will be passed to different attention he
        self.key_dim = dmodel // heads

        # keys, queries and values will be computed at once for all heads
        self.linear = nn.ModuleList([
            nn.Linear(self.dmodel, self.dmodel, bias=False),
            nn.Linear(self.dmodel, self.dmodel, bias=False),
            nn.Linear(self.dmodel, self.dmodel, bias=False)])

        self.concat = nn.Linear(self.dmodel, self.dmodel, bias=False)


    def forward(self, inputs):
        """ Perform Multi-Head-Attention.
```

```
        Parameters
        ----------
        inputs: torch.Tensor
            Batch of inputs - position encoded word embeddings ((batch_size,

        Returns
        -------
        torch.Tensor
            Multi-Head-Attention output of a shape (batch_size, seq_len, dmod
        """

        self.batch_size = inputs.size(0)

        assert inputs.size(2) == self.dmodel, 'Input sizes mismatch, dmodel={
            .format(self.dmodel, inputs.size(2))

        # Inputs shape (batch_size, seq_length, embedding_dim)
        # Map input batch allong embedd dimension to query, key and value vec
        # a shape of (batch_size, heads, seq_len, key_dim (dmodel // heads))
        # where 'heads' dimension corresponds o different attention head
        query, key, value = [linear(x).view(self.batch_size, -1, self.heads,
                             for linear, x in zip(self.linear, (inputs, input

        # Calculate the score (batch_size, heads, seq_len, seq_len)
        # for all heads at once
        score = torch.matmul(query, key.transpose(-2, -1)) / np.sqrt(self.key

        # Apply softmax to scores (batch_size, heads, seq_len, seq_len)
        soft_score = F.softmax(score, dim = -1)

        # Multiply softmaxed score and value vector
        # value input shape (batch_size, heads, seq_len, key_dim)
        # out shape (batch_size, seq_len, dmodel (key_dim * heads))
        out = torch.matmul(soft_score, value).transpose(1, 2).contiguous()\
            .view(self.batch_size, -1, self.heads * self.key_dim)

        # Concatenate and linearly transform heads to the lower dimensional s
        # out shape (batch_size, seq_len, dmodel)
        out = self.concat(out)

        return out


class PositionalEncoding(nn.Module):
    """Implementation of the positional encoding.

    Parameters
    ----------
    max_len: int
        The maximum expected sequence length.
    dmodel: int
        Dimensionality of the input embedding vector.
    dropout: float
```

```
        Probability of an element of the tensor to be zeroed.
    padding_idx: int
        Index of the padding token in the vocabulary and word embedding.

    """

    def __init__(self, max_len, dmodel, dropout, padding_idx):

        super(PositionalEncoding, self).__init__()

        self.dropout = nn.Dropout(dropout)

        # Create pos_encoding, positions and dimensions matrices
        # with a shape of (max_len, dmodel)
        self.pos_encoding = torch.zeros(max_len, dmodel)
        positions = torch.repeat_interleave(torch.arange(float(max_len)).unsq
        dimensions = torch.arange(float(dmodel)).repeat(max_len, 1)

        # Calculate the encodings trigonometric function argument (max_len, d
        trig_fn_arg = positions / (torch.pow(10000, 2 * dimensions / dmodel))

        # Encode positions using sin function for even dimensions and
        # cos function for odd dimensions
        self.pos_encoding[:, 0::2] = torch.sin(trig_fn_arg[:, 0::2])
        self.pos_encoding[:, 1::2] = torch.cos(trig_fn_arg[:, 1::2])

        # Set the padding positional encoding to zero tensor
        if padding_idx:
            self.pos_encoding[padding_idx] = 0.0

        # Add batch dimension
        self.pos_encoding = self.pos_encoding.unsqueeze(0)


    def forward(self, embedd):
        """Apply positional encoding.

        Parameters
        ----------
        embedd: torch.Tensor
            Batch of word embeddings ((batch_size, seq_length, dmodel = embed

        Returns
        -------
        torch.Tensor
            Sum of word embeddings and positional embeddings (batch_size, seq
        """

        # embedd shape (batch_size, seq_length, embedding_dim)
        # pos_encoding shape (1, max_len, dmodel = embedd_dim)
        embedd = embedd + self.pos_encoding[:, :embedd.size(1), :]
        embedd = self.dropout(embedd)
```

```
        # embedd shape (batch_size, seq_length, embedding_dim)
        return embedd


class LabelSmoothingLoss(nn.Module):
    """Implementation of label smoothing with the Kullback-Leibler divergence

    Example:
    label_smoothing/(output_size-1) = 0.1
    confidence = 1 - 0.1 = 0.9

    True labels      Smoothed one-hot labels
        |0|              [0.9000, 0.1000]
        |0|              [0.9000, 0.1000]
        |1|              [0.1000, 0.9000]
        |1|    label     [0.1000, 0.9000]
        |0|  smoothing   [0.9000, 0.1000]
        |1|    ---->     [0.1000, 0.9000]
        |0|              [0.9000, 0.1000]
        |0|              [0.9000, 0.1000]
        |0|              [0.9000, 0.1000]
        |1|              [0.1000, 0.9000]

    Parameters
    ----------
    output_size: int
         The number of classes.
    label_smoothing: float, optional (default=0)
        The smoothing parameter. Takes the value in range [0,1].

    """

    def __init__(self, output_size, label_smoothing=0):

        super(LabelSmoothingLoss, self).__init__()

        self.output_size = output_size
        self.label_smoothing = label_smoothing
        self.confidence = 1 - self.label_smoothing

        assert label_smoothing >= 0.0 and label_smoothing <= 1.0, \
        'Label smoothing parameter takes values in the range [0, 1]'

        self.criterion = nn.KLDivLoss()


    def forward(self, pred, target):
        """Smooth the target labels and calculate the Kullback-Leibler diverg

        Parameters
        ----------
        pred: torch.Tensor
            Batch of log-probabilities (batch_size, output_size)
```

```
        target: torch.Tensor
            Batch of target labels (batch_size, seq_length)

        Returns
        -------
        torch.Tensor
            The Kullback-Leibler divergence Loss.

        """
        # Create a Tensor of targets probabilities of a shape that equals 'pr
        # with label_smoothing/(output_size-1) value that will correspond to
        one_hot_probs = torch.full(size=pred.size(), fill_value=self.label_sm

        # Fill the tensor at positions that correspond to the true label from
        # with the modified value of maximum probability (confidence).
        one_hot_probs.scatter_(1, target.unsqueeze(1), self.confidence)

        # KLDivLoss takes inputs (pred) that contain log-probs and targets gi
        return self.criterion(pred, one_hot_probs)
```

In [13]:

```
class TransformerBlock(nn.Module):
    """Implementation of single Transformer block.

    Transformer block structure:
    x --> Multi-Head --> Layer normalization --> Pos-Wise FFNN --> Layer norm
      |   Attention   |                        |                 |
      |_______________|                        |_________________|
     residual connection                       residual connection

    Parameters
    ----------
    dmodel: int
        Dimensionality of the input embedding vector.
    ffnn_hidden_size: int
        Position-Wise-Feed-Forward Neural Network hidden size.
    heads: int
        Number of the self-attention operations to conduct in parallel.
    dropout: float
        Probability of an element of the tensor to be zeroed.
    """

    def __init__(self, dmodel, ffnn_hidden_size, heads, dropout):

        super(TransformerBlock, self).__init__()

        self.attention = MultiHeadAttention(dmodel, heads)
        self.layer_norm1 = nn.LayerNorm(dmodel)
        self.layer_norm2 = nn.LayerNorm(dmodel)

        self.ffnn = nn.Sequential(
                nn.Linear(dmodel, ffnn_hidden_size),
                nn.ReLU(),
```

```
                nn.Dropout(dropout),
                nn.Linear(ffnn_hidden_size, dmodel))


    def forward(self, inputs):
        """Forward propagate through the Transformer block.

        Parameters
        ----------
        inputs: torch.Tensor
            Batch of embeddings.

        Returns
        -------
        torch.Tensor
            Output of the Transformer block (batch_size, seq_length, dmodel)
        """
        # Inputs shape (batch_size, seq_length, embedding_dim = dmodel)
        output = inputs + self.attention(inputs)
        output = self.layer_norm1(output)
        output = output + self.ffnn(output)
        output = self.layer_norm2(output)

        # Output shape (batch_size, seq_length, dmodel)
        return output


class Transformer(nn.Module):
    """Implementation of the Transformer model for classification.

    Parameters
    ----------
    vocab_size: int
        The size of the vocabulary.
    dmodel: int
        Dimensionality of the embedding vector.
    max_len: int
        The maximum expected sequence length.
    padding_idx: int, optional (default=0)
        Index of the padding token in the vocabulary and word embedding.
    n_layers: int, optional (default=4)
        Number of the stacked Transformer blocks.
    ffnn_hidden_size: int, optonal (default=dmodel * 4)
        Position-Wise-Feed-Forward Neural Network hidden size.
    heads: int, optional (default=8)
        Number of the self-attention operations to conduct in parallel.
    pooling: str, optional (default='max')
        Specify the type of pooling to use. Available options: 'max' or 'avg'
    dropout: float, optional (default=0.2)
        Probability of an element of the tensor to be zeroed.
    """

    def __init__(self, vocab_size, dmodel, output_size, max_len, padding_idx=
```

```
                 ffnn_hidden_size=None, heads=8, pooling='max', dropout=0.2):

        super(Transformer, self).__init__()

        if not ffnn_hidden_size:
            ffnn_hidden_size = dmodel * 4

        assert pooling == 'max' or pooling == 'avg', 'Improper pooling type w

        self.pooling = pooling
        self.output_size = output_size

        self.embedding = nn.Embedding(vocab_size, dmodel)

        self.pos_encoding = PositionalEncoding(max_len, dmodel, dropout, padd

        self.tnf_blocks = nn.ModuleList()

        for n in range(n_layers):
            self.tnf_blocks.append(
                TransformerBlock(dmodel, ffnn_hidden_size, heads, dropout))

        self.tnf_blocks = nn.Sequential(*self.tnf_blocks)

        self.linear = nn.Linear(dmodel, output_size)


    def forward(self, inputs, input_lengths):
        """Forward propagate through the Transformer.

        Parameters
        ----------
        inputs: torch.Tensor
            Batch of input sequences.
        input_lengths: torch.LongTensor
            Batch containing sequences lengths.

        Returns
        -------
        torch.Tensor
            Logarithm of softmaxed class tensor.
        """
        self.batch_size = inputs.size(0)

        # Input dimensions (batch_size, seq_length, dmodel)
        output = self.embedding(inputs)
        output = self.pos_encoding(output)
        output = self.tnf_blocks(output)
        # Output dimensions (batch_size, seq_length, dmodel)

        if self.pooling == 'max':
            # Permute to the shape (batch_size, dmodel, seq_length)
            # Apply max-pooling, output dimensions (batch_size, dmodel)
```

```
            output = F.adaptive_max_pool1d(output.permute(0,2,1), (1,)).view(
        else:
            # Sum along the batch axis and divide by the corresponding length
            # Output shape: (batch_size, dmodel)
            output = torch.sum(output, dim=1) / input_lengths.view(-1,1).type

        output = self.linear(output)

        return F.log_softmax(output, dim=-1)


    def add_loss_fn(self, loss_fn):
        """Add loss function to the model.

        """
        self.loss_fn = loss_fn


    def add_optimizer(self, optimizer):
        """Add optimizer to the model.

        """
        self.optimizer = optimizer


    def add_device(self, device=torch.device('cpu')):
        """Specify the device.

        """
        self.device = device


    def train_model(self, train_iterator):
        """Perform single training epoch.

        Parameters
        ----------
        train_iterator: BatchIterator
            BatchIterator class object containing training batches.

        Returns
        -------
        train_losses: list
            List of the training average batch losses.
        avg_loss: float
            Average loss on the entire training set.
        accuracy: float
            Models accuracy on the entire training set.

        """
        self.train()

        train_losses = []
```

```
        losses = []
        losses_list = []
        num_seq = 0
        batch_correct = 0

        for i, batches in tqdm_notebook(enumerate(train_iterator, 1), total=l
            input_seq, target, x_lengths = batches['input_seq'], batches['tar

            input_seq.to(self.device)
            target.to(self.device)
            x_lengths.to(self.device)

            self.optimizer.zero_grad()

            pred = self.forward(input_seq, x_lengths)
            loss = self.loss_fn(pred, target)
            loss.backward()
            losses.append(loss.data.cpu().numpy())
            self.optimizer.step()

            losses_list.append(loss.data.cpu().numpy())

            pred = torch.argmax(pred, 1)

            if self.device.type == 'cpu':
                batch_correct += (pred.cpu() == target.cpu()).sum().item()

            else:
                batch_correct += (pred == target).sum().item()

            num_seq += len(input_seq)

            if i % 100 == 0:
                avg_train_loss = np.mean(losses)
                train_losses.append(avg_train_loss)

                accuracy = batch_correct / num_seq

                print('Iteration: {}. Average training loss: {:.4f}. Accuracy
                      .format(i, avg_train_loss, accuracy))

                losses = []

            avg_loss = np.mean(losses_list)
            accuracy = batch_correct / num_seq

        return train_losses, avg_loss, accuracy


    def evaluate_model(self, eval_iterator, conf_mtx=False):
        """Perform the one evaluation epoch.

        Parameters
```

```
        ----------
        eval_iterator: BatchIterator
            BatchIterator class object containing evaluation batches.
        conf_mtx: boolean, optional (default=False)
            Whether to print the confusion matrix at each epoch.

        Returns
        -------
        eval_losses: list
            List of the evaluation average batch losses.
        avg_loss: float
            Average loss on the entire evaluation set.
        accuracy: float
            Models accuracy on the entire evaluation set.
        conf_matrix: list
            Confusion matrix.

        """
        self.eval()

        eval_losses = []
        losses = []
        losses_list = []
        num_seq = 0
        batch_correct = 0
        pred_total = torch.LongTensor()
        target_total = torch.LongTensor()

        with torch.no_grad():
            for i, batches in tqdm_notebook(enumerate(eval_iterator, 1), tota
                input_seq, target, x_lengths = batches['input_seq'], batches[

                input_seq.to(self.device)
                target.to(self.device)
                x_lengths.to(self.device)

                pred = self.forward(input_seq, x_lengths)
                loss = self.loss_fn(pred, target)
                losses.append(loss.data.cpu().numpy())
                losses_list.append(loss.data.cpu().numpy())

                pred = torch.argmax(pred, 1)

                if self.device.type == 'cpu':
                    batch_correct += (pred.cpu() == target.cpu()).sum().item(

                else:
                    batch_correct += (pred == target).sum().item()

                num_seq += len(input_seq)

                pred_total = torch.cat([pred_total, pred], dim=0)
                target_total = torch.cat([target_total, target], dim=0)
```

```
                if i % 100 == 0:
                    avg_batch_eval_loss = np.mean(losses)
                    eval_losses.append(avg_batch_eval_loss)

                    accuracy = batch_correct / num_seq

                    print('Iteration: {}. Average evaluation loss: {:.4f}. Ac
                          .format(i, avg_batch_eval_loss, accuracy))

                    losses = []

            avg_loss_list = []

            avg_loss = np.mean(losses_list)
            accuracy = batch_correct / num_seq

            conf_matrix = confusion_matrix(target_total.view(-1), pred_total.

        if conf_mtx:
            print('\tConfusion matrix: ', conf_matrix)

        return eval_losses, avg_loss, accuracy, conf_matrix
```

In [14]:

```
# Initialize parameters
vocab_size = len(train_iterator.word2index)
dmodel = 64
output_size = 2
padding_idx = train_iterator.word2index['<PAD>']
n_layers = 4
ffnn_hidden_size = dmodel * 2
heads = 8
pooling = 'max'
dropout = 0.5
label_smoothing = 0.1
learning_rate = 0.001
epochs = 30

# Check whether system supports CUDA
CUDA = torch.cuda.is_available()

model = Transformer(vocab_size, dmodel, output_size, max_len, padding_idx, n_
                    ffnn_hidden_size, heads, pooling, dropout)

# Move the model to GPU if possible
if CUDA:
    model.cuda()

# Add loss function
if label_smoothing:
    loss_fn = LabelSmoothingLoss(output_size, label_smoothing)
```

```
else:
    loss_fn = nn.NLLLoss()

model.add_loss_fn(loss_fn)

optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
model.add_optimizer(optimizer)

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

model.add_device(device)

# Create the parameters dictionary and instantiate the tensorboardX SummaryWr
params = {'batch_size': batch_size,
          'dmodel': dmodel,
          'n_layers': n_layers,
          'ffnn_hidden_size': ffnn_hidden_size,
          'heads': heads,
          'pooling': pooling,
          'dropout': dropout,
          'label_smoothing': label_smoothing,
          'learning_rate': learning_rate}

train_writer = SummaryWriter(comment=f' Training, batch_size={batch_size}, dm
ffnn_hidden_size={ffnn_hidden_size}, heads={heads}, pooling={pooling}, dropou
label_smoothing={label_smoothing}, learning_rate={learning_rate}'.format(**pa

val_writer = SummaryWriter(comment=f' Validation, batch_size={batch_size}, dm
ffnn_hidden_size={ffnn_hidden_size}, heads={heads}, pooling={pooling}, dropou
label_smoothing={label_smoothing}, learning_rate={learning_rate}'.format(**pa

# Instantiate the EarlyStopping
early_stop = EarlyStopping(wait_epochs=3)

train_losses_list, train_avg_loss_list, train_accuracy_list = [], [], []
eval_avg_loss_list, eval_accuracy_list, conf_matrix_list = [], [], []

for epoch in range(epochs):

    try:
        print('\nStart epoch [{}/{}]'.format(epoch+1, epochs))

        train_losses, train_avg_loss, train_accuracy = model.train_model(trai

        train_losses_list.append(train_losses)
        train_avg_loss_list.append(train_avg_loss)
        train_accuracy_list.append(train_accuracy)

        _, eval_avg_loss, eval_accuracy, conf_matrix = model.evaluate_model(v

        eval_avg_loss_list.append(eval_avg_loss)
        eval_accuracy_list.append(eval_accuracy)
        conf_matrix_list.append(conf_matrix)
```

```
            print('\nEpoch [{}/{}]: Train accuracy: {:.3f}. Train loss: {:.4f}. E
                  .format(epoch+1, epochs, train_accuracy, train_avg_loss, eval_a

            train_writer.add_scalar('Training loss', train_avg_loss, epoch)
            val_writer.add_scalar('Validation loss', eval_avg_loss, epoch)

            if early_stop.stop(eval_avg_loss, model, delta=0.003):
                break

    finally:
        train_writer.close()
        val_writer.close()
```

```
Start epoch [1/30]

Iteration: 100. Average training loss: 0.1547. Accuracy: 0.728
Iteration: 200. Average training loss: 0.1432. Accuracy: 0.739
Iteration: 300. Average training loss: 0.1455. Accuracy: 0.742
Iteration: 400. Average training loss: 0.1451. Accuracy: 0.743

Iteration: 100. Average evaluation loss: 0.1322. Accuracy: 0.76

Epoch [1/30]: Train accuracy: 0.743. Train loss: 0.1469. Evaluation accuracy:
0.757. Evaluation loss: 0.1339

Start epoch [2/30]

Iteration: 100. Average training loss: 0.1413. Accuracy: 0.748
Iteration: 200. Average training loss: 0.1370. Accuracy: 0.751
Iteration: 300. Average training loss: 0.1373. Accuracy: 0.750
Iteration: 400. Average training loss: 0.1343. Accuracy: 0.749

Iteration: 100. Average evaluation loss: 0.1196. Accuracy: 0.79

Epoch [2/30]: Train accuracy: 0.750. Train loss: 0.1368. Evaluation accuracy:
0.781. Evaluation loss: 0.1212

Start epoch [3/30]

Iteration: 100. Average training loss: 0.1312. Accuracy: 0.748
Iteration: 200. Average training loss: 0.1259. Accuracy: 0.754
Iteration: 300. Average training loss: 0.1253. Accuracy: 0.760
Iteration: 400. Average training loss: 0.1254. Accuracy: 0.761

Iteration: 100. Average evaluation loss: 0.1140. Accuracy: 0.79

Epoch [3/30]: Train accuracy: 0.762. Train loss: 0.1263. Evaluation accuracy:
0.786. Evaluation loss: 0.1151

Start epoch [4/30]

Iteration: 100. Average training loss: 0.1239. Accuracy: 0.765
Iteration: 200. Average training loss: 0.1226. Accuracy: 0.770
Iteration: 300. Average training loss: 0.1185. Accuracy: 0.773
Iteration: 400. Average training loss: 0.1194. Accuracy: 0.773
```

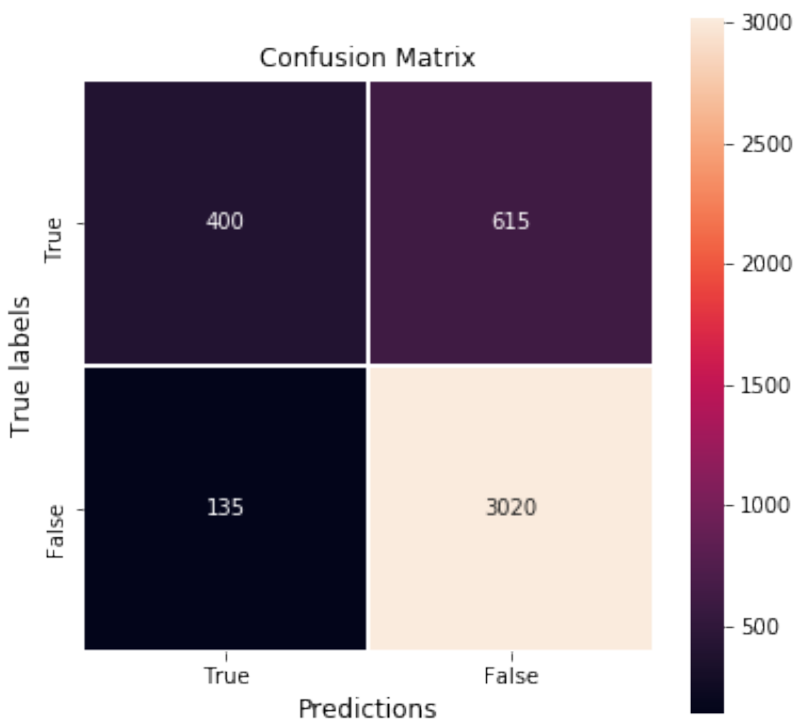
```
Iteration: 100. Average evaluation loss: 0.1082. Accuracy: 0.80

Epoch [4/30]: Train accuracy: 0.775. Train loss: 0.1203. Evaluation accuracy:
0.792. Evaluation loss: 0.1094

Start epoch [5/30]

Iteration: 100. Average training loss: 0.1188. Accuracy: 0.784
Iteration: 200. Average training loss: 0.1170. Accuracy: 0.787
Iteration: 300. Average training loss: 0.1160. Accuracy: 0.786
Iteration: 400. Average training loss: 0.1133. Accuracy: 0.786

Iteration: 100. Average evaluation loss: 0.1051. Accuracy: 0.80

Epoch [5/30]: Train accuracy: 0.787. Train loss: 0.1153. Evaluation accuracy:
0.802. Evaluation loss: 0.1063

Start epoch [6/30]

Iteration: 100. Average training loss: 0.1089. Accuracy: 0.795
Iteration: 200. Average training loss: 0.1097. Accuracy: 0.796
Iteration: 300. Average training loss: 0.1059. Accuracy: 0.800
Iteration: 400. Average training loss: 0.1097. Accuracy: 0.798

Iteration: 100. Average evaluation loss: 0.1023. Accuracy: 0.81

Epoch [6/30]: Train accuracy: 0.799. Train loss: 0.1081. Evaluation accuracy:
0.808. Evaluation loss: 0.1034

Start epoch [7/30]

Iteration: 100. Average training loss: 0.1100. Accuracy: 0.794
Iteration: 200. Average training loss: 0.1058. Accuracy: 0.800
Iteration: 300. Average training loss: 0.1029. Accuracy: 0.801
Iteration: 400. Average training loss: 0.1033. Accuracy: 0.804

Iteration: 100. Average evaluation loss: 0.1001. Accuracy: 0.82

Epoch [7/30]: Train accuracy: 0.805. Train loss: 0.1051. Evaluation accuracy:
0.818. Evaluation loss: 0.1014

Start epoch [8/30]

Iteration: 100. Average training loss: 0.1026. Accuracy: 0.816
Iteration: 200. Average training loss: 0.1052. Accuracy: 0.810
Iteration: 300. Average training loss: 0.1030. Accuracy: 0.811
Iteration: 400. Average training loss: 0.1002. Accuracy: 0.812

Iteration: 100. Average evaluation loss: 0.0985. Accuracy: 0.82

Epoch [8/30]: Train accuracy: 0.813. Train loss: 0.1024. Evaluation accuracy:
0.817. Evaluation loss: 0.1000

Start epoch [9/30]
```

```
Iteration: 100. Average training loss: 0.0984. Accuracy: 0.826
Iteration: 200. Average training loss: 0.0991. Accuracy: 0.823
Iteration: 300. Average training loss: 0.0987. Accuracy: 0.825
Iteration: 400. Average training loss: 0.0970. Accuracy: 0.827

Iteration: 100. Average evaluation loss: 0.0988. Accuracy: 0.82

Epoch [9/30]: Train accuracy: 0.827. Train loss: 0.0980. Evaluation accuracy:
0.812. Evaluation loss: 0.1006

Start epoch [10/30]

Iteration: 100. Average training loss: 0.0985. Accuracy: 0.825
Iteration: 200. Average training loss: 0.0963. Accuracy: 0.825
Iteration: 300. Average training loss: 0.0952. Accuracy: 0.826
Iteration: 400. Average training loss: 0.0936. Accuracy: 0.827

Iteration: 100. Average evaluation loss: 0.0970. Accuracy: 0.83

Epoch [10/30]: Train accuracy: 0.827. Train loss: 0.0956. Evaluation accuracy:
0.821. Evaluation loss: 0.0985

Start epoch [11/30]

Iteration: 100. Average training loss: 0.0938. Accuracy: 0.828
Iteration: 200. Average training loss: 0.0951. Accuracy: 0.828
Iteration: 300. Average training loss: 0.0938. Accuracy: 0.829
Iteration: 400. Average training loss: 0.0936. Accuracy: 0.830

Iteration: 100. Average evaluation loss: 0.0969. Accuracy: 0.83

Epoch [11/30]: Train accuracy: 0.832. Train loss: 0.0936. Evaluation accuracy:
0.828. Evaluation loss: 0.0985

Start epoch [12/30]

Iteration: 100. Average training loss: 0.0936. Accuracy: 0.833
Iteration: 200. Average training loss: 0.0913. Accuracy: 0.833
Iteration: 300. Average training loss: 0.0915. Accuracy: 0.835
Iteration: 400. Average training loss: 0.0904. Accuracy: 0.835

Iteration: 100. Average evaluation loss: 0.1003. Accuracy: 0.82

Epoch [12/30]: Train accuracy: 0.835. Train loss: 0.0914. Evaluation accuracy:
0.817. Evaluation loss: 0.1023

Start epoch [13/30]

Iteration: 100. Average training loss: 0.0894. Accuracy: 0.845
Iteration: 200. Average training loss: 0.0892. Accuracy: 0.842
Iteration: 300. Average training loss: 0.0896. Accuracy: 0.841
Iteration: 400. Average training loss: 0.0916. Accuracy: 0.840
```

```
Iteration: 100. Average evaluation loss: 0.1000. Accuracy: 0.83

Epoch [13/30]: Train accuracy: 0.841. Train loss: 0.0895. Evaluation accuracy:
0.824. Evaluation loss: 0.1018

Start epoch [14/30]

Iteration: 100. Average training loss: 0.0881. Accuracy: 0.843
Iteration: 200. Average training loss: 0.0880. Accuracy: 0.842
Iteration: 300. Average training loss: 0.0878. Accuracy: 0.844
Iteration: 400. Average training loss: 0.0844. Accuracy: 0.846

Iteration: 100. Average evaluation loss: 0.1015. Accuracy: 0.83

Epoch [14/30]: Train accuracy: 0.846. Train loss: 0.0868. Evaluation accuracy:
0.820. Evaluation loss: 0.1038

Training stoped by EarlyStopping
```

In [15]:

```
# Confusion matrix
plt.figure(figsize=(6,6))
ax = sns.heatmap(conf_matrix, fmt='d', annot=True, linewidths=1, square=True)
ax.set_xlabel('Predictions', size=12)
ax.set_ylabel('True labels', size=12)
ax.set_title('Confusion Matrix', size=12);
ax.xaxis.set_ticklabels(['True', 'False'])
ax.yaxis.set_ticklabels(['True', 'False'])
ax.set_ylim(2,0)
plt.show()
```



The generalization error

In [17]:
```
# Import the dataset. Use clean_review and label columns
test_dataset = pd.read_csv('dataset/drugreview_feat_clean/test_feat_clean.csv
                           usecols=['clean_review', 'rating'])

# Change columns order
test_dataset['label'] = test_dataset.rating >= 5
test_dataset = test_dataset[['clean_review', 'label']]
```

In [20]:
```
test_dataset = test_dataset.dropna()
test_dataset.head()
```

Out[20]:

	clean_review	label
2	given sample doctor mg hours lower abdominal g...	False
3	given medication post hysteroscopy suffered se...	True
4	loperamide helpful diarrhea fewer caplets help...	True
10	use claritin d seasonal allergies started taki...	True
15	worked immediate effects noticeable long term	True

In [21]:
```
test_iterator = BatchIterator(test_dataset, batch_size=256, vocab_created=Fal
                              word2index=train_iterator.word2index, sos_token
                              unk_token='<UNK>', pad_token='<PAD>', min_word_
                              max_seq_len=0.9, use_pretrained_vectors=False, 
                              glove_name='glove.6B.100d.txt', weights_file_na
```

```
Trimmed vocabulary using as minimum count threashold: count = 3.00
3069/8377 tokens has been retained
Trimmed input strings vocabulary
Trimmed input sequences lengths to the length of: 54
Mapped words to indices
Batches created
```

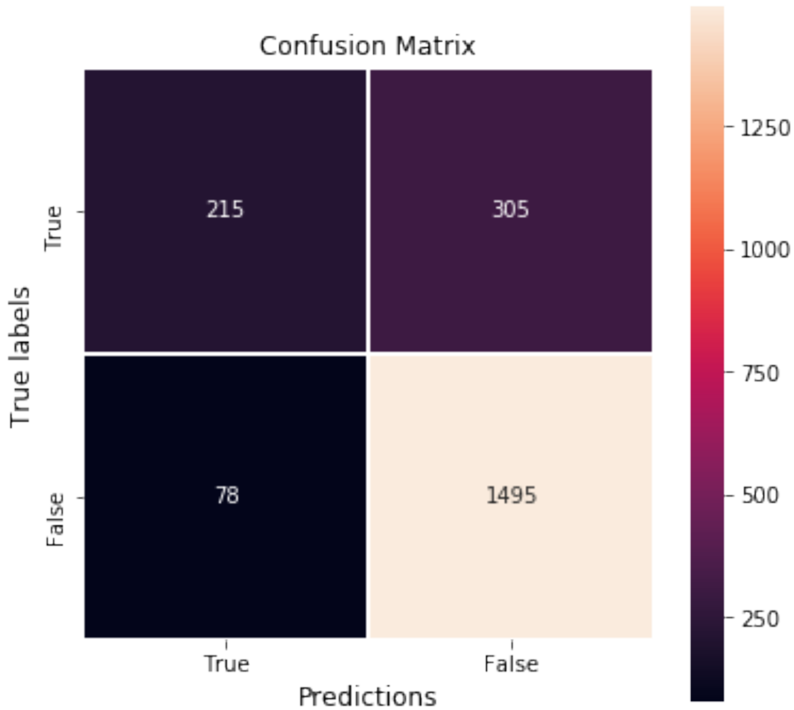
In [22]:
```
_, test_avg_loss, test_accuracy, test_conf_matrix = model.evaluate_model(test_
```

In [23]:
```
print('Test accuracy: {:.3f}. Test error: {:.3f}'.format(test_accuracy, test_
```

```
Test accuracy: 0.817. Test error: 0.105
```

In [24]:

```
# Confusion matrix
plt.figure(figsize=(6,6))
ax = sns.heatmap(test_conf_matrix, fmt='d', annot=True, linewidths=1, square='
ax.set_xlabel('Predictions', size=12)
ax.set_ylabel('True labels', size=12)
ax.set_title('Confusion Matrix', size=12);
ax.xaxis.set_ticklabels(['True', 'False'])
ax.yaxis.set_ticklabels(['True', 'False'])
ax.set_ylim(2,0)
plt.show()
```



In [ ]: