Build a TextCNN model

In this notebook, we are going to build a Convolutional Neural Network model according to the following paper: https://arxiv.org/pdf/1408.5882.pdf (https://arxiv.org/pdf/1408.5882.pdf). The model will be trained on the top of the pre-trained Glove embeddings.

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
```

Now, we are going to load the tarining and validation sets, but we will use only the clean_review column and label column.

In [2]:
```
# Import the dataset. Use clean_review and label columns
train_dataset = pd.read_csv('dataset/drugreview_feat_clean/train_feat_
                            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

In [4]:
```
# Import the dataset. Use clean_review and label columns
val_dataset = pd.read_csv('dataset/drugreview_feat_clean/val_feat_clea
                          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

Below we will use the BatchIterator class defined in the *vocabulary* notebook to create the vocabulary, trim sequences in terms of the rare word occurrence and the length, map words to their numerical representation (word2index), furthermore BatchIterator sorts dataset examples, generates batches, performs sequence padding and enables to use it instance to iterate through all batches.

To create the weights matrix we have to set use_pretrained_vectors=True and supply the weight file path, Glove vectors file name and the directory and the name of the file to which we will export the prepared weights matrix. To use different word embeddings, simply pass on their file to the BatchIterator class.

In [6]:

```
train_iterator = BatchIterator(train_dataset, batch_size=128, vocab_cr
                               word2index=None, sos_token='<SOS>', eos
                               pad_token='<PAD>', min_word_count=3, ma
                               use_pretrained_vectors=True, glove_path
                               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: 47
Mapped words to indices
Start creating glove_word2vector dictionary
Extracted 7686/8678 of pre-trained word vectors.
992 vectors initialized to random numbers
Weights vectors saved into glove/weights.npy
Batches created
```

In [7]:

```
val_iterator = BatchIterator(val_dataset, batch_size=128, vocab_create
                             word2index=train_iterator.word2index, sos
                             unk_token='<UNK>', pad_token='<PAD>', mir
                             max_seq_len=0.7, use_pretrained_vectors=F
                             glove_name='glove.6B.100d.txt', weights_f
```

```
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: 46
Mapped words to indices
Batches created
```

We have to check out how batches that we created look like before we pass them into the model. For the record, the set of batches for input and output variables is returned as a dictionary, thus we will just look at the dictionary keys to find out how to extract particular variables.

In [8]:
```
for batches in train_iterator:
    print(batches.keys())
    break
```

```
dict_keys(['input_seq', 'target', 'x_lengths'])
```

Notice that the output batch has the dimensions: (batch_size, seq_len)

In [9]:
```
for batches in train_iterator:
    # Unpack the dictionary of batches
    input_seq, target, x_lengths = batches['input_seq'], batches['targ
    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([128, 9])
target shape:  torch.Size([128])
x_lengths shape:  torch.Size([128])
```

In [10]:
```
for batches in val_iterator:
    # Unpack the dictionary of batches
    input_seq, target, x_lengths = batches['input_seq'], batches['targ
    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([128, 31])
target shape:  torch.Size([128])
x_lengths shape:  torch.Size([128])
```

Next step is to build the TextCNN model.

In [11]:
```
class TextCNN(nn.Module):
    """Text Convolutional Neural Network.

    Parameters
    ----------
    conv_config: dict
        Dictionary of convolution layer settings (keys: 'num_channels'
```

```
        Number of channels corresponds to the number of filters.
    weight_matrix: numpy.ndarray
        Matrix of pre-trained word embeddings.
    output_size: int
        Number of classes.
    dropout: float, optional (default=0.5)
        Probability of an element of the tensor to be zeroed.

    """

    def __init__(self, conv_config, weights_matrix, output_size, dropo

        # Inherit everything from the nn.Module
        super(TextCNN, self).__init__()

        # Initialize attributes
        self.conv_config = conv_config
        self.output_size = output_size
        self.weights_matrix = weights_matrix
        self.dropout_p = dropout
        self.vocab_size, self.embedding_dim = self.weights_matrix.shap

        # Initialize layers
        self.embedding = nn.Embedding(self.vocab_size, self.embedding_

        # Load the weights to the embedding layer
        self.embedding.load_state_dict({'weight': torch.from_numpy(wei
        self.embedding.weight.requires_grad = False

        self.convolutions = nn.ModuleList([nn.Sequential(
            nn.Conv1d(self.embedding_dim, self.conv_config['num_channe
            nn.ReLU(),
            nn.AdaptiveMaxPool1d((1,)))\
                        for kernel in self.conv_config['kernel_sizes'

        self.dropout = nn.Dropout(self.dropout_p)
        self.linear = nn.Linear(self.conv_config['num_channels'] * ler



    def forward(self, input_seq):
        """Forward propagate through the neural network model.

        Parameters
        ----------
        input_seq: torch.Tensor
            Batch of input sequences.

        Returns
        -------
        torch.Tensor
```

```
        torch.Tensor
            Logarithm of softmaxed input tensor.

        """
        # Embeddings shapes
        # Input: (batch_size,  seq_length)
        # Output: (batch_size, embedding_dim, seq_length)
        emb_out = self.embedding(input_seq).permute(0,2,1)

        # Conv1d -> Relu -> AdaptiveMaxPool1d
        # Input: (batch_size, embedding_dim, seq_length)
        # Output: (batch_size, num_channels)

        conv_out = [conv(emb_out).squeeze(2) for conv in self.convolut

        # Concatenate the list of convolving outputs from the previous
        concat_out = torch.cat(conv_out, dim=1)

        concat_out = self.dropout(concat_out)
        out = self.linear(concat_out)
        return F.log_softmax(out, 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),
            input_seq, target, x_lengths = batches['input_seq'], batch

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

            self.optimizer.zero_grad()

            pred = self.forward(input_seq)
            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().it

            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
```

```
                accuracy = batch_correct / num_seq

                print('Iteration: {}. Average training loss: {:.4f}. A
                      .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
                input_seq, target, x_lengths = batches['input_seq'], b

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

```
                x_lengths.to(self.device)

                pred = self.forward(input_seq)
                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(

                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: {:.
                          .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

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

        return eval_losses, avg_loss, accuracy, conf_matrix
```

Now we will instantiate the model, add loss function, optimizer, and device to it and begin the training.

In [12]:
```
# Initialize parameters
```

```
conv_config = {'num_channels': 50, 'kernel_sizes': [1,2]}
output_size = 2
learning_rate = 0.001
epochs = 50
dropout = 0.8

# Load the weights matrix
weights = np.load('glove/weights.npy')

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

model = TextCNN(conv_config, weights, output_size, dropout)

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

model.add_loss_fn(nn.NLLLoss())

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)

# 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):

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

    train_losses, train_avg_loss, train_accuracy = model.train_model(t

    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_mode

    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}
          format(epoch+1, epochs, train_accuracy, train_avg_loss, eva
```

```
        .format(epoch+1, epochs, train_accuracy, train_avg_loss, eva

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

```
Epoch [29/50]: Train accuracy: 0.797. Train loss: 0.4396. Evaluatio
n accuracy: 0.799. Evaluation loss: 0.4402

Start epoch [30/50]
```

Training: 113/113 [00:01<00:00,

100% 69.08it/s]

```
Iteration: 100. Average training loss: 0.4380. Accuracy: 0.800
```

Evaluation: 33/33 [00:00<00:00,

100% 122.93it/s]

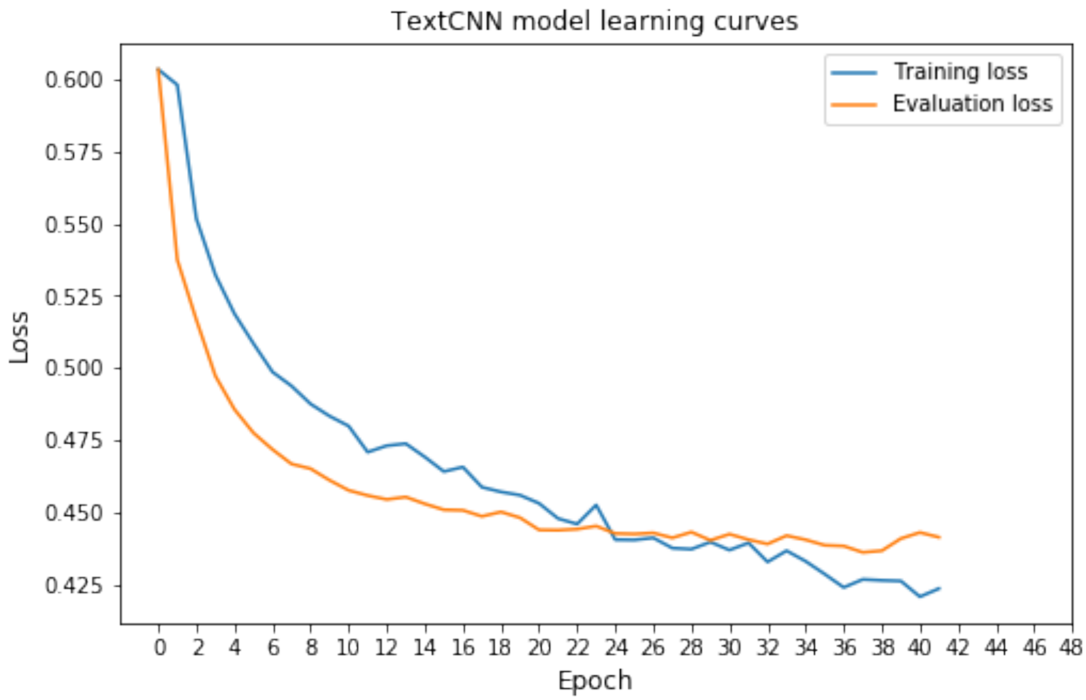
```
Epoch [30/50]: Train accuracy: 0.800. Train loss: 0.4368. Evaluatio
n accuracy: 0.796. Evaluation loss: 0.4423

Start epoch [31/50]
```

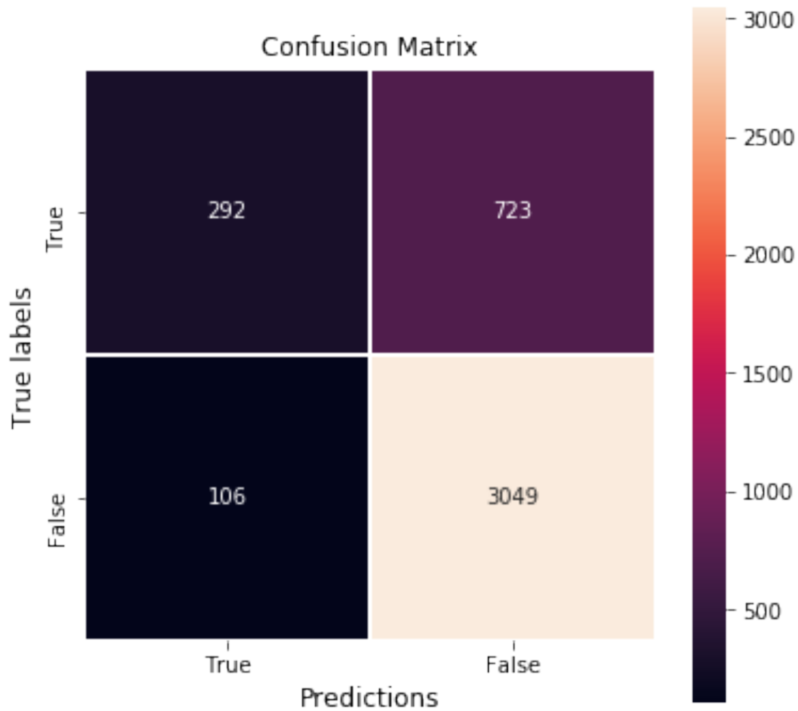
In [13]:

```
# Add the dataset initial loss
train_avg_loss_list.insert(0, train_losses_list[0][0])
eval_avg_loss_list.insert(0, train_losses_list[0][0])
```

In [14]:
```
# Plot the training and the validation learning curve
plt.figure(figsize=(8,5))
plt.plot(train_avg_loss_list, label='Training loss')
plt.plot(eval_avg_loss_list, label='Evaluation loss')
plt.xlabel('Epoch', size=12)
plt.ylabel('Loss', size=12)
plt.title('TextCNN model learning curves')
plt.xticks(ticks=range(0,49,2))
plt.legend()
plt.show()
```



In [15]:
```
# Confusion matrix
plt.figure(figsize=(6,6))
ax = sns.heatmap(conf_matrix, fmt='d', annot=True, linewidths=1, squar
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 model achieved the validation accuracy of 0.847, while the training accuracy was 0.833. The model's best state was saved to the *checkpoint.pt* file in the current directory.

The generalization error

In [16]:
```
# Import the dataset. Use clean_review and label columns
test_dataset = pd.read_csv('dataset/drugreview_feat_clean/test_feat_cl
                           usecols=['clean_review', 'rating'])

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

In [17]:
```
test_dataset = test_dataset.dropna()
test_dataset.head()
```

Out[17]:

	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 [18]:
```
test_iterator = BatchIterator(test_dataset, batch_size=256, vocab_crea
                              word2index=train_iterator.word2index, sc
                              unk_token='<UNK>', pad_token='<PAD>', mi
                              max_seq_len=0.9, use_pretrained_vectors=
                              glove_name='glove.6B.100d.txt', weights_
```

```
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
```

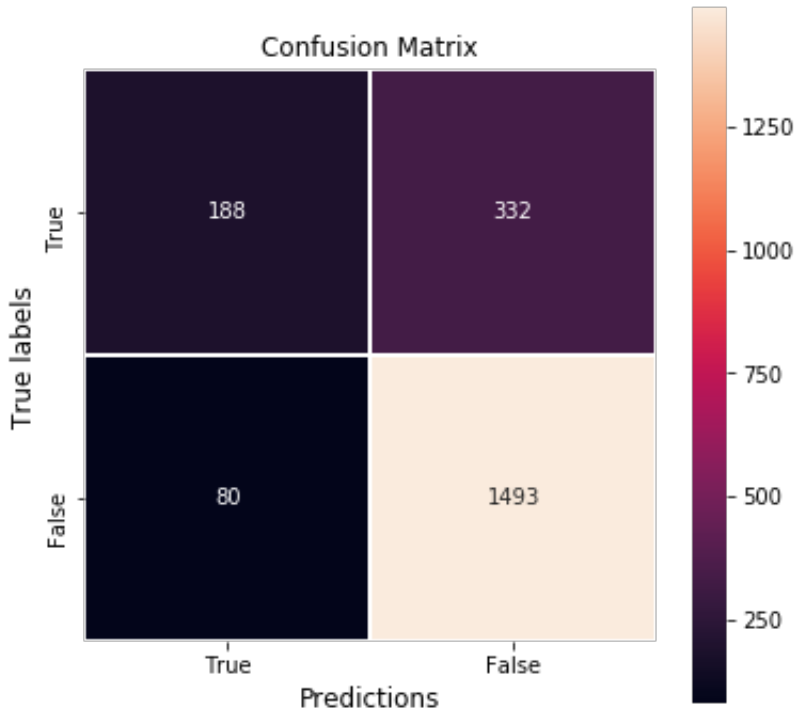
In [19]:
```
_, test_avg_loss, test_accuracy, test_conf_matrix = model.evaluate_moc
```

Evaluation: 100% 9/9 [00:00<00:00, 27.29it/s]

In [20]:
```
print('Test accuracy: {:.3f}. Test error: {:.3f}'.format(test_accuracy
```

```
Test accuracy: 0.774. Test error: 0.529
```

In [70]:
```
# Confusion matrix
plt.figure(figsize=(6,6))
ax = sns.heatmap(test_conf_matrix, fmt='d', annot=True, linewidths=1,
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 accuracy of the TextCNN model is 0.774. As we can see in the above plot of the confusion matrix the number of False negative predictions (332) is greater than the amount of False positive predictions (80) which is good.