Лабораторная работа №7. Рекуррентные нейронные сети для анализа текста

In [2]:

```
# TensorFlow и tf.keras
import tensorflow as tf
from tensorflow import keras
from keras import regularizers

import numpy as np
import matplotlib.pyplot as plt
import pdb
import os
import scipy.io
from sklearn.model_selection import train_test_split
import tarfile
from six.moves import cPickle as pickle
import zipfile
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import re
from collections import defaultdict
```

```
Using TensorFlow backend.
```

Задание 1. Загрузите данные. Преобразуйте текстовые файлы во внутренние структуры данных, которые используют индексы вместо слов.

In [ ]:

```
# загрузка и форматирование данных

# used only once
# !bash ../data/movie_reviews/preprocess_reviews.sh
```

Скрипт из открытого доступа (https://gist.github.com/aaronkub/09985a47740bda278712e1dd78e482cf (https://gist.github.com/aaronkub/09985a47740bda278712e1dd78e482cf)) объединяет все негативные рецензии и все позитивные в одни файлы. Он исправлен, чтобы файл был не один.

In [3]:

```
dataset_path = '../data/movie_reviews/aclImdb/data'

def extract_data(filename):
    dataset = []
    with open(os.path.join(dataset_path, filename)) as f:
        for lines in f.readlines():
            dataset.append(lines.strip())
    return dataset


train_pos_reviews = extract_data('full_pos_train.txt')
train_neg_reviews = extract_data('full_neg_train.txt')
test_pos_reviews = extract_data('full_pos_test.txt')
test_neg_reviews = extract_data('full_neg_test.txt')

train_labels = np.concatenate((np.ones(len(train_pos_reviews)), np.zeros(len(train_
test_labels = np.concatenate((np.ones(len(test_pos_reviews)), np.zeros(len(test_neg
```

In [17]:

```
print('Train positive lines: ', len(train_pos_reviews))
print('Train negative lines: ', len(train_neg_reviews))
print('Train labels: ', len(train_labels))
print('Test positive lines: ', len(test_pos_reviews))
print('Test negative lines: ', len(test_neg_reviews))
print('Test labels: ', len(test_labels))
```

```
Train positive lines:  12500
Train negative lines:  12500
Train labels:  25000
Test positive lines:  12500
Test negative lines:  12500
Test labels:  25000
```

https://towardsdatascience.com/sentiment-analysis-with-python-part-1-5ce197074184 (https://towardsdatascience.com/sentiment-analysis-with-python-part-1-5ce197074184)

Препроцессим данные и делаем их чище (убираем заглавные, знаки препинания и так далее).

In [4]:

```
REPLACE_NO_SPACE = re.compile("[.;:!\'?,\"()\[\]]")
REPLACE_WITH_SPACE = re.compile("(<br\s*/><br\s*/>)|(\-)|(\/)")

def preprocess_reviews(reviews):
    reviews = [REPLACE_NO_SPACE.sub("", line.lower()) for line in reviews]
    reviews = [REPLACE_WITH_SPACE.sub(" ", line) for line in reviews]

    return reviews

train_pos_reviews = preprocess_reviews(train_pos_reviews)
train_neg_reviews = preprocess_reviews(train_neg_reviews)
test_pos_reviews = preprocess_reviews(test_pos_reviews)
test_neg_reviews = preprocess_reviews(test_neg_reviews)
```

In [5]:

```
# https://stackoverflow.com/questions/51956000/what-does-keras-tokenizer-method-exa
# https://stackoverflow.com/questions/42943291/what-does-keras-io-preprocessing-seq

tokenizer = keras.preprocessing.text.Tokenizer(num_words=10000, split=' ')
tokenizer.fit_on_texts(train_pos_reviews + train_neg_reviews)

X = tokenizer.texts_to_sequences(train_pos_reviews + train_neg_reviews + test_pos_r
X = tf.keras.preprocessing.sequence.pad_sequences(X)

X_train, X_test = np.split(X, [25000])

y_train = train_labels
y_test = test_labels

X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size =
```

In [40]:

```
print('Train X: ', X_train.shape)
print('Valid X: ', X_valid.shape)
print('Test X: ', X_test.shape)
print('Train y: ', y_train.shape)
print('Valid y: ', y_valid.shape)
print('Test y: ', y_test.shape)
```

```
Train X:  (18750, 2176)
Valid X:  (6250, 2176)
Test X:  (25000, 2176)
Train y:  (18750,)
Valid y:  (6250,)
Test y:  (25000,)
```

Задание 2. Реализуйте и обучите двунаправленную рекуррентную сеть (LSTM или GRU). Какого качества классификации удалось достичь?

In [41]:

```
embedding_vector_length = 32

lstm_model = keras.models.Sequential([
    keras.layers.Embedding(10000, embedding_vector_length, input_length=X_train.sha
    keras.layers.LSTM(100),
    keras.layers.Dense(1, activation='sigmoid')
])

lstm_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 2176, 32)          320000    
_________________________________________________________________
lstm_1 (LSTM)                (None, 100)               53200     
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101       
=================================================================
Total params: 373,301
Trainable params: 373,301
Non-trainable params: 0
_________________________________________________________________
```

In [45]:

```
lstm_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy
lstm_model_history = lstm_model.fit(X_train, y_train, validation_data=(X_valid, y_v
```

```
Train on 18750 samples, validate on 6250 samples
Epoch 1/3
18750/18750 [==============================] - 945s 50ms/sample - los
s: 0.4725 - accuracy: 0.7867 - val_loss: 0.3591 - val_accuracy: 0.8494
Epoch 2/3
18750/18750 [==============================] - 947s 50ms/sample - los
s: 0.2834 - accuracy: 0.8877 - val_loss: 0.3431 - val_accuracy: 0.8530
Epoch 3/3
18750/18750 [==============================] - 909s 48ms/sample - los
s: 0.2064 - accuracy: 0.9218 - val_loss: 0.4535 - val_accuracy: 0.7906
```

In [46]:

```
test_loss, test_acc = lstm_model.evaluate(X_test, y_test, verbose=2)

print('\nТочность на проверочных данных:', test_acc)
```

```
25000/25000 - 310s - loss: 0.4565 - accuracy: 0.7914

Точность на проверочных данных: 0.7914
```

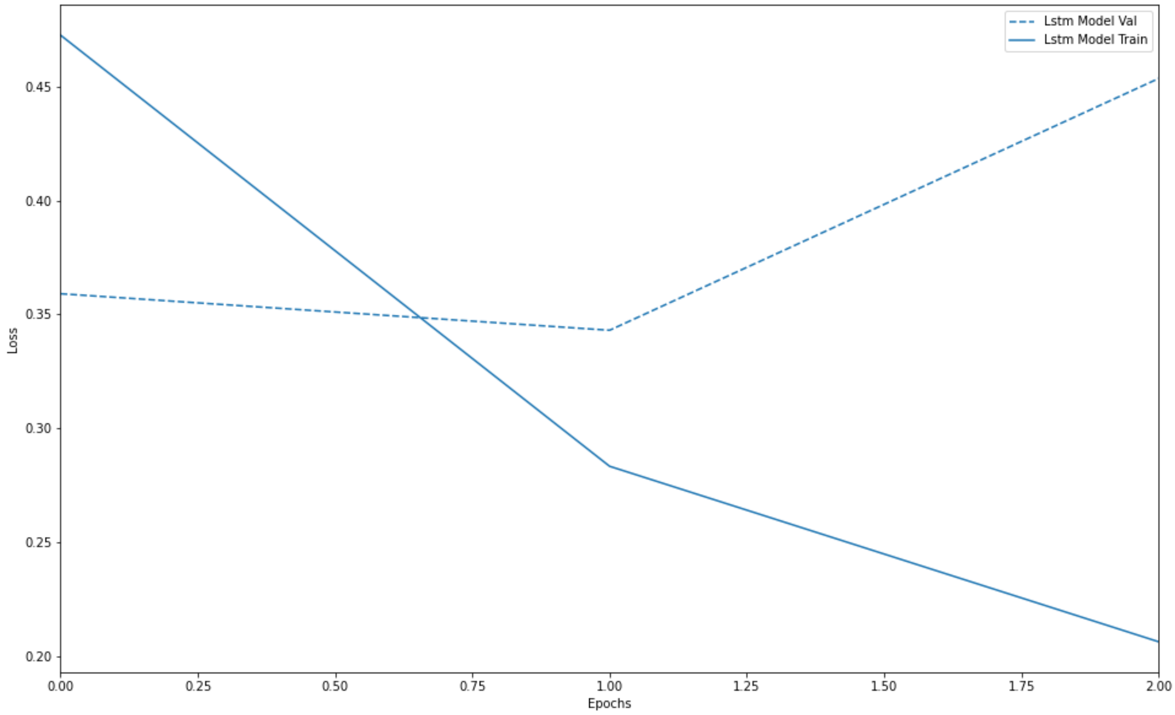
In [47]:

```
def plot_history(histories, key='binary_crossentropy'):
    plt.figure(figsize=(16,10))

    for name, history in histories:
        val = plt.plot(history.epoch, history.history['val_' + key],
                       '--', label=name.title()+' Val')
        plt.plot(history.epoch, history.history[key], color=val[0].get_color(),
                 label=name.title()+' Train')

    plt.xlabel('Epochs')
    plt.ylabel(key.replace('_',' ').title())
    plt.legend()
    plt.xlim([0,max(history.epoch)])
    plt.show()

plot_history([('lstm model', lstm_model_history)], key='loss')
```



Задание 3. Используйте индексы слов и их различное внутреннее представление (word2vec, glove). Как влияет данное преобразование на качество классификации?

In [6]:

```
def load_embeddings(filename):
    embeddings_index = {}

    with open(filename, 'r') as in_file:
        for line in in_file:
            values = line.split()

            try:
                word = values[0]
                embeddings_index[word] = np.asarray(values[1:], dtype=np.float32)
            except:
                pass

    return embeddings_index


def get_embedding_matrix(embedding, vocab):
    vocab_size = len(vocab) + 1
    weight_matrix = np.zeros((vocab_size, 300))

    for word, i in vocab.items():
        weight_matrix[i] = embedding.get(word)

    return weight_matrix


embedding = load_embeddings("../data/movie_reviews/glove/glove.840B.300d.txt")
weight_matrix = get_embedding_matrix(embedding, tokenizer.word_index)
```

In [9]:

```
vocab_size = len(tokenizer.word_index) + 1

glove_model = keras.models.Sequential([
    keras.layers.Embedding(vocab_size, 300, weights=[weight_matrix], trainable=Fals
    keras.layers.LSTM(100),
    keras.layers.Dense(1, activation='sigmoid')
])

glove_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, None, 300)         28131600  
_________________________________________________________________
lstm_1 (LSTM)                (None, 100)               160400    
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101       
=================================================================
Total params: 28,292,101
Trainable params: 160,501
Non-trainable params: 28,131,600
_________________________________________________________________
```

In [ ]:

```
glove_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accurac
glove_model_history = glove_model.fit(X_train, y_train, validation_data=(X_test, y_
```

In [ ]:

```
test_loss, test_acc = glove_model.evaluate(X_test, y_test, verbose=2)

print('\nТочность на проверочных данных:', test_acc)
```

In [ ]:

```
plot_history([('glove model', glove_model_history)], key='loss')
```

Задание 4.

Поэкспериментируйте со структурой сети (добавьте больше рекуррентных, полносвязных или сверточных слоев). Как это повлияло на качество классификации?

In [ ]:

```
embedding_vecor_length = 32

diff_model = keras.models.Sequential([
    keras.layers.Embedding(10000, embedding_vector_length, input_length=X_train.sha
    keras.layers.Conv1D(filters=32, kernel_size=3, padding='same', activation='relu
    keras.layers.MaxPooling1D(pool_size=2),
    keras.layers.Dropout(0.2),
    keras.layers.LSTM(100, dropout=0.2, recurrent_dropout=0.2),
    keras.layers.Dense(1, activation='sigmoid')
])

diff_model.summary()
```

In [ ]:

```
diff_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy
diff_model_history = diff_model.fit(X_train, y_train, validation_data=(X_test, y_te
```

In [ ]:

```
test_loss, test_acc = diff_model.evaluate(X_test, y_test, verbose=2)

print('\nТочность на проверочных данных:', test_acc)
```

In [ ]:

```
plot_history([('diff model', diff_model_history)], key='loss')
```