CS584 Assignment 4 David Fu

In [19]:
```
import os
import pandas as pd
import re
import math
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn import metrics
from keras.utils import to_categorical
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Model, Sequential
from keras.layers import Dense, Activation, BatchNormalization, Flatten,
Dropout, Embedding, Input, LSTM
from keras.layers.convolutional import Conv1D, MaxPooling1D
from keras.layers.merge import concatenate
from keras import optimizers
from keras.utils.vis_utils import plot_model
import keras.backend as backend
from sklearn.neural_network import MLPClassifier
import numpy as np
import matplotlib.pyplot as plt
```

Text Processing functions

In [2]:
```
"""
READS Text File and return all of body as a string
"""
def read_input(input_path:str) -> str:
    file_data = open(input_path , 'r')

    return file_data.read()


file1 = read_input('./a4-data/q1/28054-0.txt')
file2 = read_input('./a4-data/q1/pg1661.txt')
file3 = read_input('./a4-data/q1/pg31100.txt')
```

In [3]:
```
"""
Text pre-processing function
"""
def preprocess(doc, label, sample_size):

    paragraphs = doc.split('\n\n')
    data_set = [paragraph.strip() for paragraph in paragraphs if len(par
agraph) > sample_size]
    data = [re.sub('[\W_]+', ' ', sample.lower().strip()) for sample in
data_set]
    size = len(data)

    label_array = np.ones((size,)) * label
    df = pd.DataFrame({'paragraph': data, 'category':label_array })
    print('The total number of examples for category ' + str(label)+ ' i
s: ' + str(size))
    return df, size

df1, num1 = preprocess(file1, 0, 400)
df2, num2 = preprocess(file2, 1, 95)
df3, num3 = preprocess(file3, 2, 810)
```

```
The total number of examples for category 0 is: 1367
The total number of examples for category 1 is: 1397
The total number of examples for category 2 is: 1381
```

In [4]:
```
df = pd.concat([df1,df2,df3])
X = df['paragraph']
y = df['category']
df
```

Out[4]:

	paragraph	category
0	this ebook is for the use of anyone anywhere i...	0.0
1	part i book i the history of a family chapter ...	0.0
2	alexey fyodorovitch karamazov was the third so...	0.0
3	he was married twice and had three sons the el...	0.0
4	immediately after the elopement adelaïda ivano...	0.0
...	...	...
1376	elinor s marriage divided her as little from h...	2.0
1377	willoughby could not hear of her marriage with...	2.0
1378	creating the works from public domain print ed...	2.0
1379	1 c the project gutenberg literary archive fou...	2.0
1380	1 f 2 limited warranty disclaimer of damages e...	2.0

4145 rows × 2 columns

In [5]:
```
paragraphs = X.values
categorys = y

sentences_train, sentences_test, y_train, y_test = train_test_split(para
graphs, categorys, test_size=0.20, random_state=11)
X_train, X_val, y_train, y_val = train_test_split(sentences_train, y_tra
in, test_size=0.05, random_state=5)

tokenizer = Tokenizer(num_words=3000)
tokenizer.fit_on_texts(X_train)

X_train = tokenizer.texts_to_sequences(X_train)
X_validation = tokenizer.texts_to_sequences(X_val)
X_test = tokenizer.texts_to_sequences(sentences_test)

vocab_size = len(tokenizer.word_index) + 1

maxlen = 100

X_train = pad_sequences(X_train, padding='post', maxlen=maxlen)
X_validation = pad_sequences(X_validation, padding='post', maxlen=maxlen
)
X_test = pad_sequences(X_test, padding='post', maxlen=maxlen)

label_train = to_categorical(y_train)
label_validation = to_categorical(y_val)
label_test = to_categorical(y_test)
```

In [6]:
```
print('Shape of x_train: ' + str(X_train.shape))
print('Shape of label_train: ' + str(label_train.shape))
print('Shape of x_validation: ' + str(X_validation.shape))
print('Shape of y_validation: ' + str(label_validation.shape))
print('Shape of x_test: ' + str(X_test.shape))
print('Shape of y_test: ' + str(label_test.shape))
```

```
Shape of x_train: (3150, 100)
Shape of label_train: (3150, 3)
Shape of x_validation: (166, 100)
Shape of y_validation: (166, 3)
Shape of x_test: (829, 100)
Shape of y_test: (829, 3)
```

In [7]:

```
inputs = Input(shape=(maxlen,))
embedding = Embedding(vocab_size, 100)(inputs)

# layer 1
conv1 = Conv1D(filters=12, kernel_size=4, activation='relu')(embedding)
drop1 = Dropout(0.2)(conv1)
pool1 = MaxPooling1D(pool_size=3)(drop1)
flat1 = Flatten()(pool1)

# layer 2
conv2 = Conv1D(filters=12, kernel_size=2, activation='sigmoid')(embeddin
g)
drop2 = Dropout(0.3)(conv2)
pool2 = MaxPooling1D(pool_size=3)(drop2)
flat2 = Flatten()(pool2)

# layer 3
conv3 = Conv1D(filters=12, kernel_size=5, activation='softmax')(embeddin
g)
drop3 = Dropout(0.4)(conv3)
pool3 = MaxPooling1D(pool_size=3)(drop3)
flat3 = Flatten()(pool3)

# layer 4
conv4 = Conv1D(filters=12, kernel_size=3, activation='relu')(embedding)
drop4 = Dropout(0.5)(conv4)
pool4 = MaxPooling1D(pool_size=3)(drop4)
flat4 = Flatten()(pool4)

# merge
network = concatenate([flat1, flat2, flat3, flat4])

# interpretation
dense1 = Dense(10, activation='relu')(network)
outputs = Dense(3, activation='softmax')(dense1)
cnn_model = Model(inputs=[inputs], outputs=outputs)
# compile
opt = optimizers.Adam(learning_rate=0.001)
cnn_model.compile(loss='categorical_crossentropy', optimizer=opt, metric
s=['accuracy'])
# summarize
print(cnn_model.summary())
```

```
WARNING:tensorflow:From /Users/jig728/opt/anaconda3/lib/python3.7/site-
packages/keras/backend/tensorflow_backend.py:4070: The name tf.nn.max_p
ool is deprecated. Please use tf.nn.max_pool2d instead.

Model: "model_1"
_______________________________________________________________________
___________________________
Layer (type)                    Output Shape         Param #     Connec
ted to
=======================================================================
===========================
input_1 (InputLayer)            (None, 100)          0

_______________________________________________________________________
___________________________
embedding_1 (Embedding)         (None, 100, 100)     1675500     input_
1[0][0]

_______________________________________________________________________
___________________________
conv1d_1 (Conv1D)               (None, 97, 12)       4812        embedd
ing_1[0][0]

_______________________________________________________________________
___________________________
conv1d_2 (Conv1D)               (None, 99, 12)       2412        embedd
ing_1[0][0]

_______________________________________________________________________
___________________________
conv1d_3 (Conv1D)               (None, 96, 12)       6012        embedd
ing_1[0][0]

_______________________________________________________________________
___________________________
conv1d_4 (Conv1D)               (None, 98, 12)       3612        embedd
ing_1[0][0]

_______________________________________________________________________
___________________________
dropout_1 (Dropout)             (None, 97, 12)       0           conv1d
_1[0][0]

_______________________________________________________________________
___________________________
dropout_2 (Dropout)             (None, 99, 12)       0           conv1d
_2[0][0]

_______________________________________________________________________
___________________________
dropout_3 (Dropout)             (None, 96, 12)       0           conv1d
_3[0][0]

_______________________________________________________________________
___________________________
dropout_4 (Dropout)             (None, 98, 12)       0           conv1d
_4[0][0]

_______________________________________________________________________
___________________________
max_pooling1d_1 (MaxPooling1D)  (None, 32, 12)       0           dropou
t_1[0][0]

_______________________________________________________________________
___________________________
max_pooling1d_2 (MaxPooling1D)  (None, 33, 12)       0           dropou
t_2[0][0]

_______________________________________________________________________
```

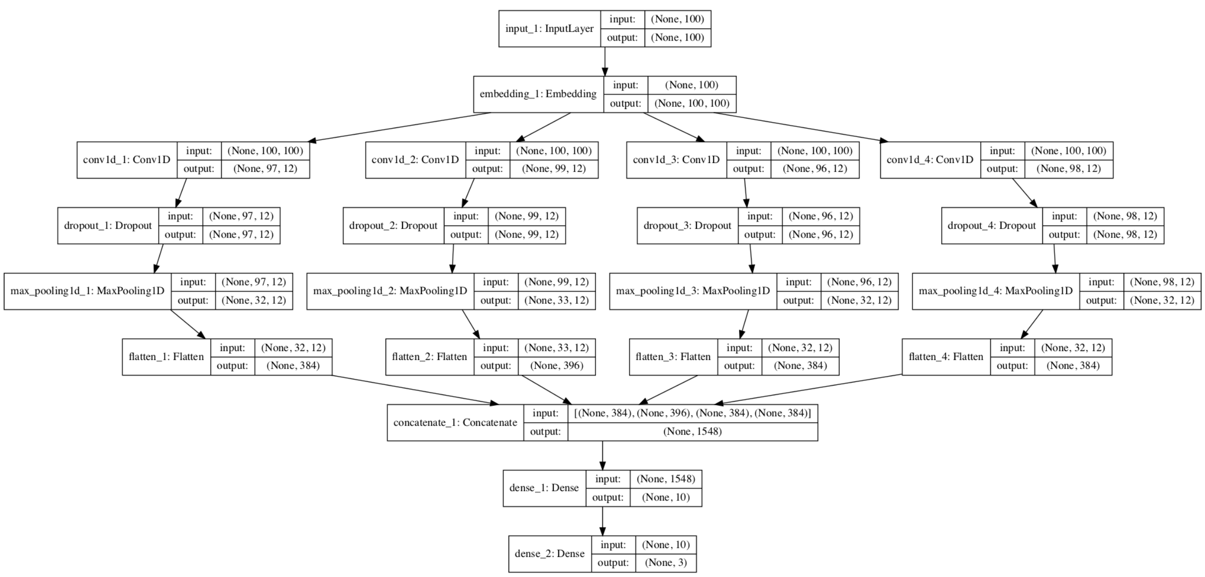
```
_________________________________________________________________
max_pooling1d_3 (MaxPooling1D)  (None, 32, 12)       0           dropou
t_3[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
max_pooling1d_4 (MaxPooling1D)  (None, 32, 12)       0           dropou
t_4[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
flatten_1 (Flatten)             (None, 384)          0           max_po
oling1d_1[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
flatten_2 (Flatten)             (None, 396)          0           max_po
oling1d_2[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
flatten_3 (Flatten)             (None, 384)          0           max_po
oling1d_3[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
flatten_4 (Flatten)             (None, 384)          0           max_po
oling1d_4[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
concatenate_1 (Concatenate)     (None, 1548)         0           flatte
n_1[0][0]
                                                                 flatte
n_2[0][0]
                                                                 flatte
n_3[0][0]
                                                                 flatte
n_4[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
dense_1 (Dense)                 (None, 10)           15490       concat
enate_1[0][0]
__________________________________________________________________________________________________
_________________________________________________________________
dense_2 (Dense)                 (None, 3)            33          dense_
1[0][0]
==================================================================================================
===========================
Total params: 1,707,871
Trainable params: 1,707,871
Non-trainable params: 0
__________________________________________________________________________________________________
_________________________________________________________________
None
```

In [8]:
```
lstm_model = Sequential()
lstm_model.add(Embedding(vocab_size, 100)(inputs))
lstm_model.add(LSTM(30))
lstm_model.add(Dense(3, activation='relu'))
print(lstm_model.summary())
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 100, 10)           30
_________________________________________________________________
lstm_1 (LSTM)                (None, 30)                4920
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 93
=================================================================
Total params: 5,043
Trainable params: 5,043
Non-trainable params: 0
_________________________________________________________________
None
```

In [16]:
```
plot_model(cnn_model, show_shapes=True, to_file='classification_model.pn
g')
```

Out[16]:



In [10]:
```
def perplexity(predict, label):
    return backend.exp(backend.categorical_crossentropy(predict, label))
```

In [11]:
```
result1 = cnn_model.fit([X_train], label_train, epochs=100, validation_d
ata=([X_validation], label_validation), batch_size=32)
```

```
WARNING:tensorflow:From /Users/jig728/opt/anaconda3/lib/python3.7/site-
packages/keras/backend/tensorflow_backend.py:422: The name tf.global_va
riables is deprecated. Please use tf.compat.v1.global_variables instea
d.

Train on 3150 samples, validate on 166 samples
Epoch 1/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.9123
- accuracy: 0.5171 - val_loss: 0.8515 - val_accuracy: 0.4940
Epoch 2/100
3150/3150 [==============================] - 3s 951us/step - loss: 0.63
05 - accuracy: 0.7432 - val_loss: 0.5959 - val_accuracy: 0.8313
Epoch 3/100
3150/3150 [==============================] - 3s 954us/step - loss: 0.43
87 - accuracy: 0.9000 - val_loss: 0.5252 - val_accuracy: 0.8795
Epoch 4/100
3150/3150 [==============================] - 3s 941us/step - loss: 0.36
28 - accuracy: 0.9248 - val_loss: 0.5005 - val_accuracy: 0.8735
Epoch 5/100
3150/3150 [==============================] - 3s 954us/step - loss: 0.28
74 - accuracy: 0.9667 - val_loss: 0.4495 - val_accuracy: 0.8735
Epoch 6/100
3150/3150 [==============================] - 3s 965us/step - loss: 0.23
91 - accuracy: 0.9854 - val_loss: 0.4348 - val_accuracy: 0.8976
Epoch 7/100
3150/3150 [==============================] - 3s 957us/step - loss: 0.19
68 - accuracy: 0.9937 - val_loss: 0.3855 - val_accuracy: 0.9036
Epoch 8/100
3150/3150 [==============================] - 3s 969us/step - loss: 0.17
33 - accuracy: 0.9952 - val_loss: 0.3368 - val_accuracy: 0.9277
Epoch 9/100
3150/3150 [==============================] - 3s 966us/step - loss: 0.15
12 - accuracy: 0.9962 - val_loss: 0.3237 - val_accuracy: 0.9096
Epoch 10/100
3150/3150 [==============================] - 3s 957us/step - loss: 0.13
39 - accuracy: 0.9965 - val_loss: 0.2915 - val_accuracy: 0.9337
Epoch 11/100
3150/3150 [==============================] - 3s 971us/step - loss: 0.11
95 - accuracy: 0.9968 - val_loss: 0.3018 - val_accuracy: 0.9157
Epoch 12/100
3150/3150 [==============================] - 3s 993us/step - loss: 0.10
86 - accuracy: 0.9971 - val_loss: 0.2782 - val_accuracy: 0.9277
Epoch 13/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0952
- accuracy: 0.9975 - val_loss: 0.2820 - val_accuracy: 0.9398
Epoch 14/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0871
- accuracy: 0.9981 - val_loss: 0.2475 - val_accuracy: 0.9398
Epoch 15/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0791
- accuracy: 0.9978 - val_loss: 0.2513 - val_accuracy: 0.9157
Epoch 16/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0727
- accuracy: 0.9975 - val_loss: 0.2355 - val_accuracy: 0.9398
Epoch 17/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0662
- accuracy: 0.9978 - val_loss: 0.2322 - val_accuracy: 0.9458
```

```
Epoch 18/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0611
- accuracy: 0.9981 - val_loss: 0.2552 - val_accuracy: 0.9398
Epoch 19/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0577
- accuracy: 0.9981 - val_loss: 0.2574 - val_accuracy: 0.9157
Epoch 20/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0528
- accuracy: 0.9978 - val_loss: 0.2141 - val_accuracy: 0.9337
Epoch 21/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0485
- accuracy: 0.9987 - val_loss: 0.2367 - val_accuracy: 0.9096
Epoch 22/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0481
- accuracy: 0.9981 - val_loss: 0.2079 - val_accuracy: 0.9398
Epoch 23/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0414
- accuracy: 0.9981 - val_loss: 0.2191 - val_accuracy: 0.9398
Epoch 24/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0390
- accuracy: 0.9984 - val_loss: 0.2162 - val_accuracy: 0.9337
Epoch 25/100
3150/3150 [==============================] - 5s 1ms/step - loss: 0.0350
- accuracy: 0.9987 - val_loss: 0.2446 - val_accuracy: 0.9337
Epoch 26/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0327
- accuracy: 0.9990 - val_loss: 0.2130 - val_accuracy: 0.9458
Epoch 27/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0313
- accuracy: 0.9987 - val_loss: 0.2106 - val_accuracy: 0.9518
Epoch 28/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0295
- accuracy: 0.9987 - val_loss: 0.2019 - val_accuracy: 0.9337
Epoch 29/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0270
- accuracy: 0.9990 - val_loss: 0.2226 - val_accuracy: 0.9458
Epoch 30/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0267
- accuracy: 0.9987 - val_loss: 0.1952 - val_accuracy: 0.9458
Epoch 31/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0267
- accuracy: 0.9981 - val_loss: 0.1998 - val_accuracy: 0.9398
Epoch 32/100
3150/3150 [==============================] - 5s 2ms/step - loss: 0.0248
- accuracy: 0.9984 - val_loss: 0.1916 - val_accuracy: 0.9518
Epoch 33/100
3150/3150 [==============================] - 5s 1ms/step - loss: 0.0230
- accuracy: 0.9987 - val_loss: 0.2260 - val_accuracy: 0.9217
Epoch 34/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0212
- accuracy: 0.9990 - val_loss: 0.2380 - val_accuracy: 0.9398
Epoch 35/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0201
- accuracy: 0.9990 - val_loss: 0.2369 - val_accuracy: 0.9398
Epoch 36/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0192
- accuracy: 0.9990 - val_loss: 0.2414 - val_accuracy: 0.9217
```

```
Epoch 37/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0183
- accuracy: 0.9990 - val_loss: 0.2374 - val_accuracy: 0.9458
Epoch 38/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0172
- accuracy: 0.9987 - val_loss: 0.2979 - val_accuracy: 0.8976
Epoch 39/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0164
- accuracy: 0.9990 - val_loss: 0.2399 - val_accuracy: 0.9398
Epoch 40/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0142
- accuracy: 0.9994 - val_loss: 0.2428 - val_accuracy: 0.9337
Epoch 41/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0134
- accuracy: 0.9994 - val_loss: 0.2474 - val_accuracy: 0.9337
Epoch 42/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0127
- accuracy: 0.9994 - val_loss: 0.2514 - val_accuracy: 0.9398
Epoch 43/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0121
- accuracy: 0.9994 - val_loss: 0.2517 - val_accuracy: 0.9337
Epoch 44/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0116
- accuracy: 0.9994 - val_loss: 0.2474 - val_accuracy: 0.9398
Epoch 45/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0111
- accuracy: 0.9994 - val_loss: 0.2522 - val_accuracy: 0.9398
Epoch 46/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0106
- accuracy: 0.9994 - val_loss: 0.2467 - val_accuracy: 0.9458
Epoch 47/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0102
- accuracy: 0.9994 - val_loss: 0.2464 - val_accuracy: 0.9458
Epoch 48/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0097
- accuracy: 0.9994 - val_loss: 0.2494 - val_accuracy: 0.9337
Epoch 49/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0094
- accuracy: 0.9994 - val_loss: 0.2466 - val_accuracy: 0.9458
Epoch 50/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0090
- accuracy: 0.9994 - val_loss: 0.2442 - val_accuracy: 0.9458
Epoch 51/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0086
- accuracy: 0.9994 - val_loss: 0.2486 - val_accuracy: 0.9398
Epoch 52/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0083
- accuracy: 0.9994 - val_loss: 0.2539 - val_accuracy: 0.9337
Epoch 53/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0080
- accuracy: 0.9994 - val_loss: 0.2501 - val_accuracy: 0.9458
Epoch 54/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0077
- accuracy: 0.9994 - val_loss: 0.2532 - val_accuracy: 0.9458
Epoch 55/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0075
- accuracy: 0.9994 - val_loss: 0.2476 - val_accuracy: 0.9398
```

```
Epoch 56/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0107
- accuracy: 0.9994 - val_loss: 0.2737 - val_accuracy: 0.9277
Epoch 57/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0344
- accuracy: 0.9917 - val_loss: 0.3484 - val_accuracy: 0.9337
Epoch 58/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0114
- accuracy: 0.9978 - val_loss: 0.5816 - val_accuracy: 0.9036
Epoch 59/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0181
- accuracy: 0.9965 - val_loss: 0.3788 - val_accuracy: 0.9277
Epoch 60/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0097
- accuracy: 0.9981 - val_loss: 0.4653 - val_accuracy: 0.9096
Epoch 61/100
3150/3150 [==============================] - 3s 1ms/step - loss: 0.0206
- accuracy: 0.9952 - val_loss: 0.3906 - val_accuracy: 0.9157
Epoch 62/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0057
- accuracy: 0.9997 - val_loss: 0.6265 - val_accuracy: 0.9036
Epoch 63/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0024
- accuracy: 0.9984 - val_loss: 0.5306 - val_accuracy: 0.9157
Epoch 64/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0056
- accuracy: 0.9984 - val_loss: 0.4776 - val_accuracy: 0.9337
Epoch 65/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0111
- accuracy: 0.9978 - val_loss: 0.4806 - val_accuracy: 0.9157
Epoch 66/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0013
- accuracy: 0.9990 - val_loss: 0.3960 - val_accuracy: 0.9398
Epoch 67/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9994 - val_loss: 0.4221 - val_accuracy: 0.9277
Epoch 68/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0012
- accuracy: 0.9994 - val_loss: 0.4221 - val_accuracy: 0.9337
Epoch 69/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9994 - val_loss: 0.4153 - val_accuracy: 0.9398
Epoch 70/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0010
- accuracy: 0.9994 - val_loss: 0.4181 - val_accuracy: 0.9398
Epoch 71/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9990 - val_loss: 0.4093 - val_accuracy: 0.9398
Epoch 72/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9994 - val_loss: 0.4280 - val_accuracy: 0.9398
Epoch 73/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9994 - val_loss: 0.4182 - val_accuracy: 0.9398
Epoch 74/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0010
- accuracy: 0.9994 - val_loss: 0.4315 - val_accuracy: 0.9398
```

```
Epoch 75/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9994 - val_loss: 0.4207 - val_accuracy: 0.9398
Epoch 76/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.6248
e-04 - accuracy: 0.9990 - val_loss: 0.4243 - val_accuracy: 0.9398
Epoch 77/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.3306
e-04 - accuracy: 0.9994 - val_loss: 0.4240 - val_accuracy: 0.9398
Epoch 78/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0017
- accuracy: 0.9994 - val_loss: 0.4714 - val_accuracy: 0.9217
Epoch 79/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0012
- accuracy: 0.9994 - val_loss: 0.3859 - val_accuracy: 0.9458
Epoch 80/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0015
- accuracy: 0.9994 - val_loss: 0.4618 - val_accuracy: 0.9277
Epoch 81/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.6244
e-04 - accuracy: 0.9994 - val_loss: 0.4157 - val_accuracy: 0.9398
Epoch 82/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9990 - val_loss: 0.5883 - val_accuracy: 0.9036
Epoch 83/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0011
- accuracy: 0.9990 - val_loss: 0.4193 - val_accuracy: 0.9398
Epoch 84/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.6432
e-04 - accuracy: 0.9990 - val_loss: 0.4229 - val_accuracy: 0.9398
Epoch 85/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.4333
e-04 - accuracy: 0.9990 - val_loss: 0.4243 - val_accuracy: 0.9398
Epoch 86/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.5201
e-04 - accuracy: 0.9994 - val_loss: 0.4251 - val_accuracy: 0.9398
Epoch 87/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0047
- accuracy: 0.9984 - val_loss: 0.5355 - val_accuracy: 0.9096
Epoch 88/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0100
- accuracy: 0.9978 - val_loss: 0.4550 - val_accuracy: 0.9217
Epoch 89/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.4329
e-04 - accuracy: 0.9994 - val_loss: 0.4158 - val_accuracy: 0.9398
Epoch 90/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0016
- accuracy: 0.9990 - val_loss: 0.5176 - val_accuracy: 0.9458
Epoch 91/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.7061
e-04 - accuracy: 0.9990 - val_loss: 0.4812 - val_accuracy: 0.9337
Epoch 92/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.6945
e-04 - accuracy: 0.9994 - val_loss: 0.5114 - val_accuracy: 0.9337
Epoch 93/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.5348
e-04 - accuracy: 0.9990 - val_loss: 0.5100 - val_accuracy: 0.9337
```

```
Epoch 94/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.3910
e-04 - accuracy: 0.9990 - val_loss: 0.5075 - val_accuracy: 0.9398
Epoch 95/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.3397
e-04 - accuracy: 0.9987 - val_loss: 0.5028 - val_accuracy: 0.9398
Epoch 96/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.4708
e-04 - accuracy: 0.9994 - val_loss: 0.5029 - val_accuracy: 0.9398
Epoch 97/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.4557
e-04 - accuracy: 0.9994 - val_loss: 0.5005 - val_accuracy: 0.9398
Epoch 98/100
3150/3150 [==============================] - 4s 1ms/step - loss: 8.9951
e-04 - accuracy: 0.9997 - val_loss: 0.4598 - val_accuracy: 0.9398
Epoch 99/100
3150/3150 [==============================] - 4s 1ms/step - loss: 0.0028
- accuracy: 0.9990 - val_loss: 0.5190 - val_accuracy: 0.9277
Epoch 100/100
3150/3150 [==============================] - 4s 1ms/step - loss: 9.3919
e-04 - accuracy: 0.9994 - val_loss: 0.5724 - val_accuracy: 0.9157
```

In [ ]:

```
lstm_model.compile(loss='categorical_crossentropy', optimizer=opt, metri
cs=[perplexity])

lstm_model.fit(X_train, label_train, epochs=100, batch_size=16)
```

In [15]:

```
cnn_loss = cnn_model.evaluate([X_test], label_test)
print('loss = ' + str(cnn_loss[0]))
print('accuracy = ' + str(cnn_loss[1]))
```

```
829/829 [==============================] - 0s 209us/step
loss = 0.293167890999938
accuracy = 0.9565742015838623
```

In [ ]:

```
lstm_loss = lstm_model.evaluate(X_test, label_test)
loss = lstm_loss[0]
perplexity_test = lstm_loss[1]
print('loss = ' + str(loss))
print('perplexity = ' + str(perplexity_test))
```

In [20]:
```
# Report the recall and precision for each category on the test sets
y_pred_NN = cnn_model.predict([X_test], batch_size=32, verbose=1)
y_pred_bool = np.argmax(y_pred_NN, axis=1)
print(classification_report(y_test, y_pred_bool))
```

```
829/829 [==============================] - 0s 210us/step
              precision    recall  f1-score   support

         0.0       0.93      0.97      0.95       278
         1.0       0.99      0.92      0.95       273
         2.0       0.95      0.97      0.96       278

    accuracy                           0.96       829
   macro avg       0.96      0.96      0.96       829
weighted avg       0.96      0.96      0.96       829
```

Classification Report from HW1

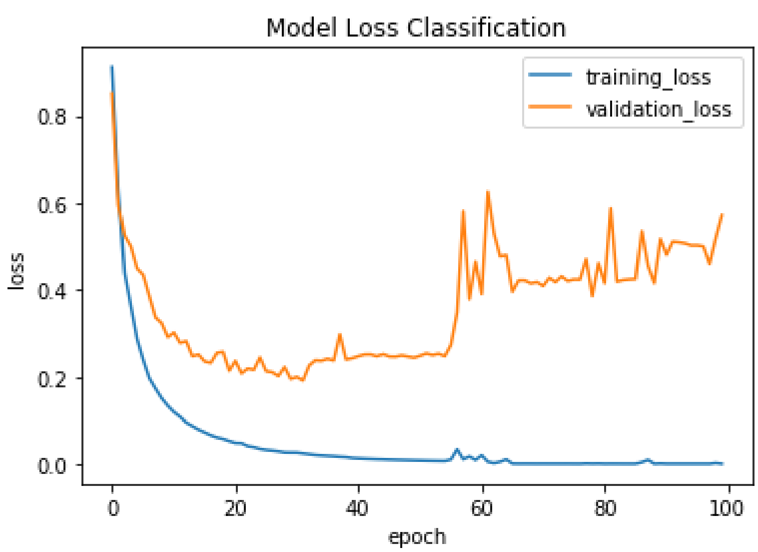
Mini-Batch	precision	recall	f1-score	support
0	1.00	0.97	0.98	62
1	0.93	1.00	0.97	70
2	1.00	0.95	0.97	60
accuracy			0.97	192
macro avg	0.98	0.97	0.97	192
weighted avg	0.98	0.97	0.97	192

SGD	precision	recall	f1-score	support
0	0.95	1.00	0.98	62
1	1.00	0.83	0.91	70
2	0.87	1.00	0.93	60
accuracy			0.94	192
macro avg	0.94	0.94	0.94	192
weighted avg	0.94	0.94	0.94	192

MLP	precision	recall	f1-score	support
0	0.98	1.00	0.99	62
1	1.00	1.00	1.00	70
2	1.00	1.00	1.00	60
micro avg	0.99	1.00	1.00	192
macro avg	0.99	1.00	1.00	192
weighted avg	0.99	1.00	1.00	192
samples avg	1.00	1.00	1.00	192

MLP2	precision	recall	f1-score	support
0	0.07	0.06	0.07	62
1	0.95	1.00	0.97	70
2	1.00	0.92	0.96	60
micro avg	0.69	0.67	0.68	192
macro avg	0.67	0.66	0.67	192
weighted avg	0.68	0.67	0.67	192
samples avg	0.52	0.67	0.57	192

In [21]:
```
plt.plot(result1.history['loss'])
plt.plot(result1.history['val_loss'])
plt.title('Model Loss Classification')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training_loss', 'validation_loss'], loc='upper right')
plt.show()
```



When comparing the four different models using TF-IDF and Word Embedded Vectors it seems the precision and recall accuracy is not as high as the standard model given the parameters provided, additional tweaking will be need to finally find maximum accuracy and effiency. There might be missing model for the network process. Given the dataset it seems more balenced in terms of sample and weight. There are more options but limited to overfitting process.

2. Sentiment Analysis

In [22]:
```
with open('./a4-data/q2/negative.review', encoding="utf8", errors='ignor
e') as f:
    negative = [line.strip() for line in f.readlines()]
with open('./a4-data/q2/positive.review', encoding="utf8", errors='ignor
e') as f:
    positive = [line.strip() for line in f.readlines()]
```

In [23]:
```
# Define a function to extract the review text from <review_text>
def review_text_extract(text_list):
    reviews = []
    for i in range(len(text_list)):
        if text_list[i] == '<review_text>':
            k = 1
            while text_list[i+k] != '</review_text>':
                k += 1
            review = ''.join(text_list[i+1:i+k])
            reviews.append(review)
    return reviews
```

In [24]:
```
#confirm number of review extracted
positive_reviews = review_text_extract(positive)
print(len(positive_reviews))

negative_reviews = review_text_extract(negative)
print(len(negative_reviews))
```

```
1000
1000
```

In [25]:
```
def review_to_df(p,n):
    cate_array_positive = np.ones((len(p),))
    cate_array_negative = np.zeros((len(n),))
    df_positive = pd.DataFrame({'reviews': p, 'category':cate_array_posi
tive})
    df_negative = pd.DataFrame({'reviews': n, 'category':cate_array_nega
tive})
    df = pd.concat([df_positive,df_negative])
    return df

df2 = review_to_df(positive_reviews,negative_reviews)
df2
```

Out[25]:

	reviews	category
0	Bridget Jones, modern day woman, brillant and ...	1.0
1	I am ordering copies for all 23 middle school ...	1.0
2	As a casual piano player and a Broadway fanati...	1.0
3	This is one of the best biographies I have eve...	1.0
4	I read this book many, many years ago on a ver...	1.0
...	...	...
995	This book provides excellent information about...	0.0
996	I really didn't enjoy this book. I am half It...	0.0
997	This book is a place to start at best. The ma...	0.0
998	I was barely able to finish this book. Armstro...	0.0
999	"The Burning" was a big letdown after reading ...	0.0

2000 rows × 2 columns

In [26]:
```
def process_review(df):
    X = df.iloc[:,0]
    y = df.iloc[:,1]
    sentences = X.values
    y = y
    sentences_train, sentences_test, y_train,y_test = train_test_split(s
entences, y, test_size=0.1, random_state=11)
    X_train, X_val, y_train, y_val = train_test_split(sentences_train, y
_train, test_size=0.1, random_state=4)

    tokenizer = Tokenizer(num_words=500)
    tokenizer.fit_on_texts(X_train)

    X_train = tokenizer.texts_to_sequences(X_train)
    X_validation = tokenizer.texts_to_sequences(X_val)
    X_test = tokenizer.texts_to_sequences(sentences_test)

    # Adding 1 because of reserved 0 index
    vocab_size = len(tokenizer.word_index) + 1

    maxlen = 100

    X_train = pad_sequences(X_train, padding='post', maxlen=maxlen)
    X_validation = pad_sequences(X_validation, padding='post', maxlen=ma
xlen)
    X_test = pad_sequences(X_test, padding='post', maxlen=maxlen)

    print('Shape of x_train: ' + str(X_train.shape))
    print('Shape of y_train: ' + str(y_train.shape))
    print('Shape of x_validation: ' + str(X_validation.shape))
    print('Shape of y_validation: ' + str(y_val.shape))
    print('Shape of x_test: ' + str(X_test.shape))
    print('Shape of y_test: ' + str(y_test.shape))
    return X_train, y_train, X_validation, y_val, X_test, y_test, (vocab
_size, maxlen)
```

In [ ]:

In [37]:
```
    inputs = Input(shape=(maxlen,))
    embedding = Embedding(vocab_size, 20)(inputs)
    # layer 1
    conv1 = Conv1D(filters=6, kernel_size=3, activation='relu')(embeddin
g)
    drop1 = Dropout(0.5)(conv1)
    pool1 = MaxPooling1D(pool_size=3)(drop1)
    flat1 = Flatten()(pool1)
    # layer 2
    conv2 = Conv1D(filters=12, kernel_size=4, activation='softmax')(embe
dding)
    drop2 = Dropout(0.5)(conv2)
    pool2 = MaxPooling1D(pool_size=3)(drop2)
    flat2 = Flatten()(pool2)
    # merge
    merged = concatenate([flat1,flat2])
    # interpretation
    drop3 = Dropout(0.5)(merged)
    dense1 = Dense(10, activation='relu')(drop3)
    outputs = Dense(2, activation='softmax')(dense1)
    sen_model = Model(inputs=[inputs], outputs=outputs)
    # compile
    sen_model.compile(loss='binary_crossentropy', optimizer=opt, metrics
=['accuracy'])
    # summarize
    print(sen_model.summary())
```

```
Model: "model_3"
______________________________________________________________________________
______________________________
Layer (type)                    Output Shape         Param #     Connec
ted to
==============================================================================
==============================
input_3 (InputLayer)            (None, 100)          0
______________________________________________________________________________
______________________________
embedding_4 (Embedding)         (None, 100, 20)      416500      input_
3[0][0]
______________________________________________________________________________
______________________________
conv1d_7 (Conv1D)               (None, 98, 6)        366         embedd
ing_4[0][0]
______________________________________________________________________________
______________________________
conv1d_8 (Conv1D)               (None, 97, 12)       972         embedd
ing_4[0][0]
______________________________________________________________________________
______________________________
dropout_8 (Dropout)             (None, 98, 6)        0           conv1d
_7[0][0]
______________________________________________________________________________
______________________________
dropout_9 (Dropout)             (None, 97, 12)       0           conv1d
_8[0][0]
______________________________________________________________________________
______________________________
max_pooling1d_7 (MaxPooling1D)  (None, 32, 6)        0           dropou
t_8[0][0]
______________________________________________________________________________
______________________________
max_pooling1d_8 (MaxPooling1D)  (None, 32, 12)       0           dropou
t_9[0][0]
______________________________________________________________________________
______________________________
flatten_7 (Flatten)             (None, 192)          0           max_po
oling1d_7[0][0]
______________________________________________________________________________
______________________________
flatten_8 (Flatten)             (None, 384)          0           max_po
oling1d_8[0][0]
______________________________________________________________________________
______________________________
concatenate_3 (Concatenate)     (None, 576)          0           flatte
n_7[0][0]
                                                                 flatte
n_8[0][0]
______________________________________________________________________________
______________________________
dropout_10 (Dropout)            (None, 576)          0           concat
enate_3[0][0]
______________________________________________________________________________
______________________________
dense_6 (Dense)                 (None, 10)           5770        dropou
```

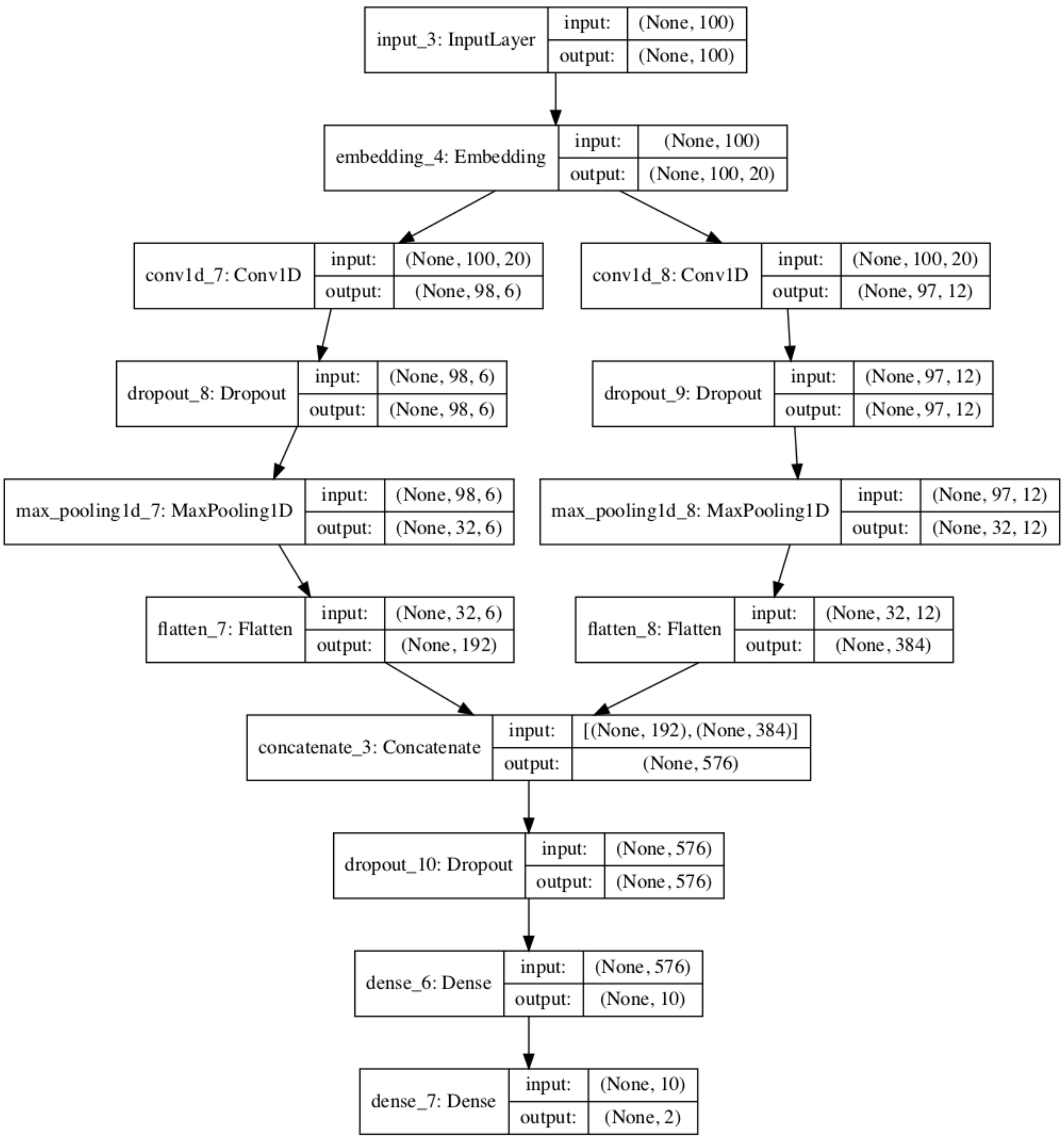
```
t_10[0][0]
__________________________________________________________________________________________________
dense_7 (Dense)                 (None, 2)            22          dense_
6[0][0]
==================================================================================================
Total params: 423,630
Trainable params: 423,630
Non-trainable params: 0
__________________________________________________________________________________________________
None
```

In [38]:
```
x_train, y_train, x_val, y_val,x_test, y_test, (vocab_size, maxlen) = pr
ocess_review(df2)
y_train = to_categorical(y_train)
y_val = to_categorical(y_val)
y_test_c = to_categorical(y_test)

plot_model(sen_model, show_shapes=True, to_file='sentiment_model.png')
```

```
Shape of x_train: (1620, 100)
Shape of y_train: (1620,)
Shape of x_validation: (180, 100)
Shape of y_validation: (180,)
Shape of x_test: (200, 100)
Shape of y_test: (200,)
```

Out[38]:



In [39]:
```
result2 = sen_model.fit([x_train], y_train, epochs=100, validation_data=
([x_val], y_val), batch_size=8)
```

```
Train on 1620 samples, validate on 180 samples
Epoch 1/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6954
- accuracy: 0.4889 - val_loss: 0.6929 - val_accuracy: 0.5167
Epoch 2/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4957 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 3/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4981 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 4/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4846 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 5/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4846 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 6/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4883 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 7/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4883 - val_loss: 0.6935 - val_accuracy: 0.4833
Epoch 8/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4833 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 9/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4784 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 10/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 11/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 12/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4784 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 13/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4846 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 14/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 15/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4920 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 16/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4994 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 17/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4957 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 18/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4796 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 19/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
```

```
- accuracy: 0.4907 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 20/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4907 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 21/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 22/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4907 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 23/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 24/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4944 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 25/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4846 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 26/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4846 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 27/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 28/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4957 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 29/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 30/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4883 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 31/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4907 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 32/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6935
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 33/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 34/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4870 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 35/100
1620/1620 [==============================] - 2s 2ms/step - loss: 0.6933
- accuracy: 0.4981 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 36/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6934
- accuracy: 0.4870 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 37/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.4846 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 38/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
```

```
- accuracy: 0.4735 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 39/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.4784 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 40/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 41/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 42/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6932
- accuracy: 0.4907 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 43/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6932
- accuracy: 0.4932 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 44/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 45/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.4870 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 46/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.4809 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 47/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 48/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.4994 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 49/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 50/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 51/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 52/100
1620/1620 [==============================] - 3s 2ms/step - loss: 0.6933
- accuracy: 0.4932 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 53/100
1620/1620 [==============================] - 2s 2ms/step - loss: 0.6934
- accuracy: 0.4710 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 54/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 55/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4969 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 56/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 57/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
```

```
- accuracy: 0.4920 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 58/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 59/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4870 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 60/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4833 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 61/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4772 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 62/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4969 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 63/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4932 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 64/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 65/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 66/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4932 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 67/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4895 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 68/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4772 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 69/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4833 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 70/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4932 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 71/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 72/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4957 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 73/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4895 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 74/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4895 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 75/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4858 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 76/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
```

```
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 77/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 78/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4809 - val_loss: 0.6932 - val_accuracy: 0.4833
Epoch 79/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4858 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 80/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4932 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 81/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 82/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4747 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 83/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4883 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 84/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4907 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 85/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4809 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 86/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 87/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 88/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 89/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4920 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 90/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4895 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 91/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4870 - val_loss: 0.6934 - val_accuracy: 0.4833
Epoch 92/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6934
- accuracy: 0.4969 - val_loss: 0.6935 - val_accuracy: 0.4833
Epoch 93/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4932 - val_loss: 0.6931 - val_accuracy: 0.5167
Epoch 94/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6932
- accuracy: 0.4994 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 95/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
```

```
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 96/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4895 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 97/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.4846 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 98/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 99/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6933 - val_accuracy: 0.4833
Epoch 100/100
1620/1620 [==============================] - 2s 1ms/step - loss: 0.6933
- accuracy: 0.5019 - val_loss: 0.6932 - val_accuracy: 0.4833
```

In [43]:
```
loss_and_acc = sen_model.evaluate([x_test], y_test_c)
print('loss = ' + str(loss_and_acc[0]))
print('accuracy = ' + str(loss_and_acc[1]))
```

```
200/200 [==============================] - 0s 158us/step
loss = 0.6931491518020629
accuracy = 0.5
```

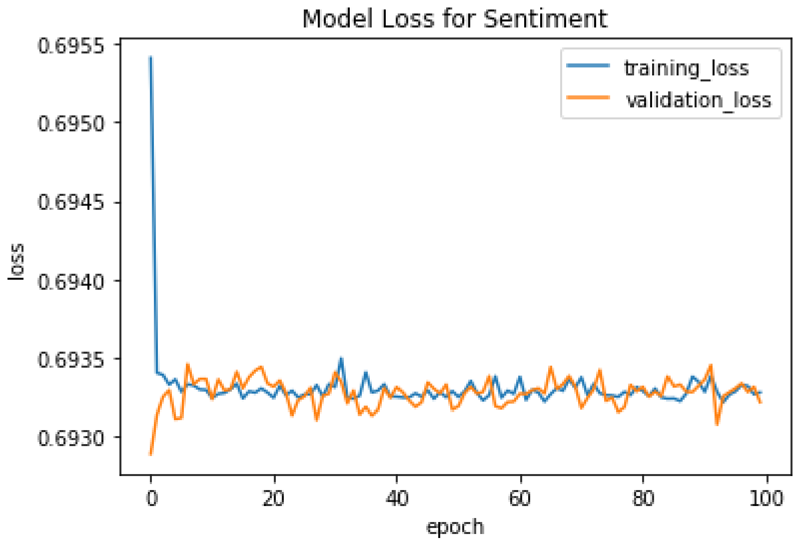
In [44]:
```
y_pred_NN = sen_model.predict([x_test], batch_size=8, verbose=1)
y_pred_bool = np.argmax(y_pred_NN, axis=1)
print(classification_report(y_test, y_pred_bool))
```

```
200/200 [==============================] - 0s 341us/step
              precision    recall  f1-score   support

         0.0       0.00      0.00      0.00       100
         1.0       0.50      1.00      0.67       100

    accuracy                           0.50       200
   macro avg       0.25      0.50      0.33       200
weighted avg       0.25      0.50      0.33       200
```

In [45]:
```
plt.plot(result2.history['loss'])
plt.plot(result2.history['val_loss'])
plt.title('Model Loss for Sentiment')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['training_loss', 'validation_loss'], loc='upper right')
plt.show()
```



When comparing LSTM vs CNN model for sentiment in the binary perspective CNN seems to overfit quite a bit due to limited dataset, and LSTM have a better precision and recall value

In [ ]: