TEDTALK ANALYSIS - Final DL Project - 2017

Data description

TED-LIUM Corpus

The TED-LIUM corpus was made from audio talks and their transcriptions available on the TED website. We have prepared and filtered these data in order to train acoustic models to participate to the International Workshop on Spoken Language Translation 2011 (the LIUM English/French SLT system reached the first rank in the SLT task).

More details are given in this paper:

A. Rousseau, P. Deléglise, and Y. Estève, "Enhancing the TED-LIUM Corpus with Selected Data for Language Modeling and More TED Talks", in Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14), May 2014.

Contents:

- 1495 audio talks in NIST sphere format (SPH)
- 1495 transcripts in STM format
- Dictionary with pronunciation (159848 entries)
- Selected monolingual data for language modeling from WMT12 publicly available corpora

In [17]:

```
import requests
from ipywidgets import Image
Image(value=requests.get('https://i.elitestatic.com/content/uploads/201
7/05/08083847/couple-talks-about-rape-ted-talk.jpg').content)
```

```
Widget Javascript not detected.  It may not be installed or enabled pro
perly.
```

In [63]:
```
import numpy as np
import pandas as pd
import glob
from texttable import Texttable

from keras.datasets import imdb
from keras.preprocessing.text import Tokenizer
from keras.utils import to_categorical
from keras.preprocessing.text import text_to_word_sequence, one_hot
from keras.preprocessing.sequence import pad_sequences
from keras.models import Model, Sequential
from keras.layers import Dense, Embedding, Flatten, LSTM , concatenate,
Dense, Dropout, Activation,Conv1D, GlobalMaxPooling1D

from sklearn.model_selection import train_test_split, cross_val_score, G
ridSearchCV
from sklearn.linear_model import SGDClassifier
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.metrics import confusion_matrix

from sklearn.naive_bayes import GaussianNB
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransf
ormer

from time import time
from pprint import pprint

%matplotlib inline
```

Cleaning & Preprocessing text data

Since, I am given only the text data of Tedtalk and no other information, which means there is no target variable present. However, the tendency of the project is to have a supervised learning model, I'm interested in defining the explanatory variables for the context of Tedtalk speech. And in this case, the classification is whether the speech is from "male" or "female" voice.

In [64]:
```
# female = pd.DataFrame
y = []
y_test = []

def preprocess(df, tag='train'):
    df   = df.drop(df.columns[[0, 1]], axis=1)
    str_ = ""
    str_ = df.columns[0].replace('female>', '').replace('male>', '')
    df   = df.rename(index=str, columns={df.columns[0]: "sentences"})# r
ename column

    #supervised labels male or female
    female = df['sentences'].str.contains('female>')
    male = df['sentences'].str.contains('male>')
    if tag == 'train':
        if female[0] == True:
            y.append(0) #female
        else:
            y.append(1) #male
    else:
        if female[0] == True:
            y_test.append(0) #female
        else:
            y_test.append(1) #male

    #truncate redundant tag word
    df['sentences'] = df['sentences'].str.replace('female>', '') # trunc
ate female>
    df['sentences'] = df['sentences'].str.replace('male>', '') # truncat
e male>
    pd.options.display.max_colwidth = 400
    df['col1'] = 'A' # set a random name for column
    df = df.groupby('col1')['sentences'].apply(' '.join).reset_index()
    return str_ + df.drop(labels='col1',axis=1).loc[0][0]
```

Load all tedtalk transcripts

In [65]:
```
path = 'TedTalk/train/stm'
allFiles = glob.glob(path + "/*.stm")
frame = pd.DataFrame()
X = []
X_test = []
for i,file_ in enumerate(allFiles):
    df = pd.read_csv(file_)
    try:
        content_extracted = preprocess(df, tag='train')
        X.append(content_extracted)
    except:
        pass

path = 'TedTalk/test/stm'
allFiles1 = glob.glob(path + "/*.stm")
for i,file_ in enumerate(allFiles1):
    df1 = pd.read_csv(file_)
    try:
        content_extracted = preprocess(df1, tag='test')
        X_test.append(content_extracted)
    except:
        pass
```

In [66]:
```
len(y)
```

Out[66]: 1492

In [67]:
```
print(len(allFiles))
```

1495

In [68]:
```
len(X)
```

Out[68]: 1492

In [69]:
```
y[:5]
```

Out[69]: [0, 0, 1, 1, 0]

```
In [70]: X[0]
```

```
Out[70]: " today because of i first learned that my son had been in the world tr
ade center on the morning of september eleventh two thousand and one  w
e didn 't know if he had perished yet until thirty six hours later at t
he time  we knew that it was political  we were afraid of what our coun
try was going to do in the name of our son my husband orlando and i  an
d our family and when i saw it and yet through the shock  the terrible
 shock and the terrible  explosion in our lives literally  we were not
 vengeful  on six counts of conspiracy to commit terrorism  and the u s
government called for a death penalty for him if convicted  my husband
 and i spoke out  in opposition to that publicly through that and throu
gh human rights  groups we were brought together with several other vic
tims families when i saw aicha in the media  coming over when her son w
as indicted and i thought what a brave woman someday i want to meet tha
t woman when i 'm stronger i was still in deep grief i knew i didn 't h
ave the strength i knew i would find her someday or we would find each
 other because when people heard that my son  was a victim i got immedi
ate sympathy  but when people learned what her son was accused of she d
idn 't get that sympathy but her suffering is equal to mine so we met i
n november two thousand and two and aicha will now tell you how that ca
me about  introduced me to five families and i saw phyllis and i watche
d  and i saw in her eyes that she was a mother just like me  i was marr
ied when i was fourteen i lost a child when i was fifteen a second chil
d when i was sixteen so the story with zacarias was too much really  so
that 's why i decided to tell my story so that my suffering is somethin
g positive for other women  all the women all the mothers  it 's up to
 us women because we are women because we love our children  it 's not
 against women it 's for us for us women for  i talk against violence a
gainst terrorism i go to schools to talk to young muslim  girls so they
don 't accept to be married against their will very young  so if i can
 save one of the young girls and avoid that they get married and suffer
as much as i did well this is something  i have learned so much  family
members but we were all so nervous why does she want to meet us  and th
en she was nervous why did we want to meet her what did we want from ea
ch other  before we knew each others names or anything we had embraced
and wept then we sat in a circle  with support with help from people ex
perienced in this kind of reconciliation and aicha started and she said
  i don 't know if my son is guilty or innocent but i want to tell you
 how sorry i am for what happened to your families  i know what it is t
o suffer  and i feel that if there is a crime a person should be tried
 fairly and punished  but  she reached out to us in that way and it was
i 'd like to say it was an ice breaker and what happened then is we all
told our stories  and we all connected as human beings by the end of th
e afternoon it was about three hours after lunch  we 'd felt as if we
 'd known each other forever now what i learned from her is a woman not
only who could be so generous under these present circumstances and wha
t it was then and what was being done to her son but the life she 's ha
d i never had met  someone with such a hard life from such a totally di
fferent culture and environment from my own  being afraid of the other
 but making that step  and then realizing hey this wasn 't so hard who
 else can i meet that i don 't know or that i 'm so different from  so
 aicha do you have  a couple of words for conclusion because our time i
s up  i wanted to say that we have to try to know other people the othe
r  and i hope that someday we 'll all live together in peace and respec
ting each other this is what i wanted to say"
```

Baseline

In [71]:
```
def prediction_summary(estimator, X, y):
    p = estimator.predict(X)
    correct_predictions = sum(p == y)
    incorrect_predictions = len(y) - correct_predictions

    # set up confusion matrix table
    label_list = [0, 1]
    cm = confusion_matrix(y, list(p), labels=label_list)
    y1 = [i for i in y if i == 0]

    t = Texttable()
    t.set_cols_align(["c", "l"])
#     t.set_chars(['_', '', '', '='])
    t.add_rows([['Data Outputs','Value'],
                ['    # of correct predictions: ', str(correct_predictio
ns)],
                ['  # of incorrect predictions: ', str(incorrect_predict
ions)] ,
                ['                    Accuracy: ', str(100.0 * correct_p
redictions / (correct_predictions + incorrect_predictions))],
                ["  Total actual female labels:", len(y1)],
                ["    Total actual male labels:", len(y) - len(y1)],
                ['              Labels in data:', label_list],
                ['            Confusion matrix', 'Columns: Predicted lab
els'],
                ['         Rows: actual labels', cm ]])
    t.set_cols_align(array=[0,"r"])
    t.set_cols_align(array=[1,"l"])
    print (t.draw())
```

Bag of words + TfidfTransform classifier

- tf-idf(t,d) = tf(t,d) × idf(t).

In [72]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 random_state=42)

# Convert a collection of text documents to a matrix of token counts
count_vect = CountVectorizer()
X_train_counts = count_vect.fit_transform(x_train)

#Transform a count matrix to a normalized tf-idf representation
tf_transformer = TfidfTransformer(use_idf=False)
X_train_tf = tf_transformer.fit_transform(X_train_counts)

print(len(x_train),len(y_train))
clf = GaussianNB().fit(X=X_train_tf.toarray(), y=y_train)
X_new_counts = count_vect.transform(x_train)

X_new_tfidf = tf_transformer.transform(X_new_counts)
predictions = clf.predict(X_new_tfidf.toarray())

correct_predictions = sum(predictions == y_train)
incorrect_predictions = len(y_train) - correct_predictions
print('# of correct predictions: ' + str(correct_predictions))
print('# of incorrect predictions: ' + str(incorrect_predictions))
print('Percent correct: ' + str(100.0 * correct_predictions / (correct_p
redictions + incorrect_predictions)))
```

```
1193 1193
# of correct predictions: 1189
# of incorrect predictions: 4
Percent correct: 99.6647108131
```

In [73]:
```
prediction_summary(clf, X_new_tfidf.toarray(), y_train)
```

```
+---------------------------------+---------------------------+
|          Data Outputs           |           Value           |
+=================================+===========================+
|     # of correct predictions:   | 1189                      |
+---------------------------------+---------------------------+
|   # of incorrect predictions:   | 4                         |
+---------------------------------+---------------------------+
|                       Accuracy: | 99.665                    |
+---------------------------------+---------------------------+
|   Total actual female labels:   | 392                       |
+---------------------------------+---------------------------+
|     Total actual male labels:   | 801                       |
+---------------------------------+---------------------------+
|                 Labels in data: | [0, 1]                    |
+---------------------------------+---------------------------+
|              Confusion matrix   | Columns: Predicted labels |
+---------------------------------+---------------------------+
|           Rows: actual labels   | [[392   0]                |
|                                 |  [  4 797]]               |
+---------------------------------+---------------------------+
```

MultinomialNB

In [74]:

```
# Naive Bayes classifier is a general term which refers to conditional i
ndependence of each of the features in the model,
# while Multinomial Naive Bayes classifier is a specific instance of a N
aive Bayes classifier
# which uses a multinomial distribution for each of the features.
# Naive Bayes classification is the best suited for this kind of text an
alysis and brings the most
# favorable results.
# It considers word occurrence in a single document
from sklearn.naive_bayes import MultinomialNB

x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.33, random_state=42)

# clean data: remove empty row
x_train = [x for x in x_train if x is not None]
x_test = [x for x in x_test if x is not None]

# feature extraction
count_vect = CountVectorizer()
count_vect.fit(x_train)

# turns the text into a sparse matrix
x_train_counts = count_vect.transform(x_train)

# train with MultinomialNB
nb = MultinomialNB()
nb.fit(x_train_counts, y_train)
```

Out[74]:

```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

In [75]:

```python
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

plt.figure(num=None, figsize=(7,8), dpi=100, facecolor='w',
edgecolor='k')
img = mpimg.imread('transform_text_data')
plt.imshow(img)
plt.axis('off')
print('\nAn example of tranformed x_train ')
plt.show()
```

```
An example of tranformed x_train
```

Term	Document						
	d1	*d2*	*d3*	*d4*	*d5*	*d6*	*d7*
t1	2	1	0	0	0	0	0
t2	1	2	0	0	0	0	1
t3	3	1	0	0	1	1	0
t4	0	0	1	2	1	1	1
t5	0	0	1	1	1	1	1
t6	0	0	1	1	0	0	0

Evaluate test data

In [76]:

```python
prediction_summary(nb, count_vect.transform(x_test), y_test)
```

```
+---------------------------------+----------------------------+
|          Data Outputs           |           Value            |
+=================================+============================+
|     # of correct predictions:   | 357                        |
+---------------------------------+----------------------------+
|   # of incorrect predictions:   | 136                        |
+---------------------------------+----------------------------+
|                       Accuracy: | 72.414                     |
+---------------------------------+----------------------------+
|   Total actual female labels:   | 152                        |
+---------------------------------+----------------------------+
|     Total actual male labels:   | 341                        |
+---------------------------------+----------------------------+
|                Labels in data:  | [0, 1]                     |
+---------------------------------+----------------------------+
|              Confusion matrix   | Columns: Predicted labels  |
+---------------------------------+----------------------------+
|           Rows: actual labels   | [[ 44 108]                 |
|                                 |  [ 28 313]]                |
+---------------------------------+----------------------------+
```

SVM

In [77]:
```
count_vect = CountVectorizer()
count_vect.fit(x_train)

svm_clf = SGDClassifier()
svm_clf.fit(count_vect.transform(x_train), y_train)
```

Out[77]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None, epsilon=
0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', n_iter=5, n_jobs=1,
       penalty='l2', power_t=0.5, random_state=None, shuffle=True,
       verbose=0, warm_start=False)
```

In [78]:
```
prediction_summary(svm_clf, count_vect.transform(x_test), y_test)
```

```
+---------------------------------+---------------------------+
|          Data Outputs           |           Value           |
+=================================+===========================+
|     # of correct predictions:   | 292                       |
+---------------------------------+---------------------------+
|   # of incorrect predictions:   | 201                       |
+---------------------------------+---------------------------+
|                      Accuracy:  | 59.229                    |
+---------------------------------+---------------------------+
|   Total actual female labels:   | 152                       |
+---------------------------------+---------------------------+
|     Total actual male labels:   | 341                       |
+---------------------------------+---------------------------+
|                Labels in data:  | [0, 1]                    |
+---------------------------------+---------------------------+
|               Confusion matrix  | Columns: Predicted labels |
+---------------------------------+---------------------------+
|          Rows: actual labels    | [[102  50]                |
|                                 |  [151 190]]               |
+---------------------------------+---------------------------+
```

In [87]:
```
p = Pipeline(steps=[('counts', CountVectorizer(ngram_range=(1, 2))),
                ('feature_selection', SelectKBest(chi2, k='10000')),
                ('multinomialnb', MultinomialNB())])

p.fit(x_train, y_train)
```

Out[87]:
```
Pipeline(steps=[('counts', CountVectorizer(analyzer='word', binary=Fals
e, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 2), preprocessor=None, stop_words=None,
        str...i2 at 0x125320d08>)), ('multinomialnb', MultinomialNB(alp
ha=1.0, class_prior=None, fit_prior=True))])
```

Pipeline + Feature Selection

In [88]:

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
# p = Pipeline(steps=[('counts', CountVectorizer(ngram_range=(1, 2))),
#                      ('feature_selection', SelectKBest(chi2, k=10000)),
 # Select features according to the k highest scores.
#                      ('tfidf', TfidfTransformer()),
#                      ('clf', SGDClassifier())])
# p = Pipeline(steps=[('counts', CountVectorizer()),
#                 ('feature_selection', SelectKBest(chi2, k='5000')),
#                 ('multinomialnb', MultinomialNB())])
parameters = {
    'counts__max_df': (0.5, 0.75,1.0),
    'counts__min_df': (0,1,2),
#     'counts__token_pattern': ('(?u)\b\w\w+\b', '(?u)\b\w\w+\b'),
    'counts__lowercase' : (True, False),
    'counts__ngram_range': ((1,1), (1,2)),
#     'feature_selection__k': (1000, 10000, 100000)

    }
# p.fit(x_train, y_train)
grid_search = GridSearchCV(p, parameters, n_jobs=-1, verbose=1)

grid_search.fit(x_train, y_train)

# print("Best score: %0.3f" % grid_search.best_score_)
# print("Best parameters set:")
# best_parameters = grid_search.best_estimator_.get_params()
# for param_name in sorted(parameters.keys()):
#     print("\t%s: %r" % (param_name, best_parameters[param_name]))
# print("Performing grid search...")
# print("pipeline:", [name for name, _ in p.steps])
# print("parameters:")
# pprint(parameters)
# t0 = time()
# grid_search.fit(x_train, y_train)
# print("done in %0.3fs" % (time() - t0))
# print()

# print("Best score: %0.3f" % grid_search.best_score_)
# print("Best parameters set:")
# best_parameters = grid_search.best_estimator_.get_params()
# for param_name in sorted(parameters.keys()):
#     print("\t%s: %r" % (param_name, best_parametders[param_name]))
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits

[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   55.3s
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed:  2.6min finished
```

Out[88]:
```
GridSearchCV(cv=None, error_score='raise',
       estimator=Pipeline(steps=[('counts', CountVectorizer(analyzer='w
ord', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 2), preprocessor=None, stop_words=None,
        str...i2 at 0x125320d08>)), ('multinomialnb', MultinomialNB(alp
ha=1.0, class_prior=None, fit_prior=True))]),
       fit_params={}, iid=True, n_jobs=-1,
       param_grid={'counts__max_df': (0.5, 0.75, 1.0), 'counts__min_d
f': (0, 1, 2), 'counts__lowercase': (True, False), 'counts__ngram_rang
e': ((1, 1), (1, 2))},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring=None, verbose=1)
```

In [89]:
```python
print("Best score: %0.3f" % grid_search.best_score_)
print("Best parameters set:")
best_parameters = grid_search.best_estimator_.get_params()
for param_name in sorted(parameters.keys()):
    print("\t%s: %r" % (param_name, best_parameters[param_name]))
```

```
Best score: 0.715
Best parameters set:
        counts__lowercase: True
        counts__max_df: 1.0
        counts__min_df: 2
        counts__ngram_range: (1, 2)
```

In [91]:
```python
grid_search.best_estimator_
```

Out[91]:
```
Pipeline(steps=[('counts', CountVectorizer(analyzer='word', binary=Fals
e, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=2,
        ngram_range=(1, 2), preprocessor=None, stop_words=None,
        str...i2 at 0x125320d08>)), ('multinomialnb', MultinomialNB(alp
ha=1.0, class_prior=None, fit_prior=True))])
```

Cross validate pipeline

In [92]:
```
scores = cross_val_score(p, x_test, y_test, cv=20)
print("scores:",list(scores))
print("mean  :",scores.mean())
```

```
scores: [0.69230769230769229, 0.68000000000000005, 0.68000000000000005,
0.64000000000000001, 0.71999999999999997, 0.76000000000000001, 0.680000
00000000005, 0.76000000000000001, 0.68000000000000005, 0.68000000000000
005, 0.71999999999999997, 0.71999999999999997, 0.70833333333333337, 0.6
25, 0.79166666666666663, 0.75, 0.70833333333333337, 0.6666666666666666
3, 0.75, 0.75]
mean  : 0.708115384615
```

In [ ]:
```
grid_search.best_estimator_
```

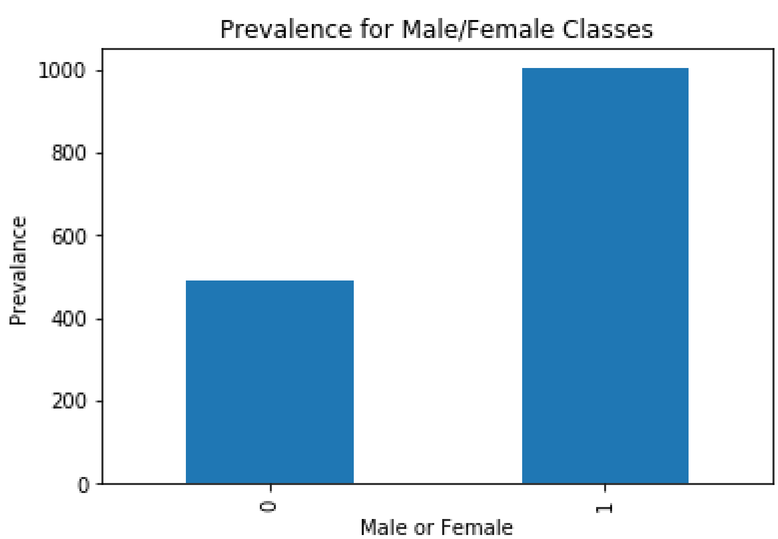
In [ ]:
```
len(max(X))
```

Checking Imbalance

In [12]:
```
import pandas as pd

s = pd.Series(y)
print(s.value_counts().sort_index())
axes = s.value_counts().sort_index().plot(kind='bar')
axes.set_xlabel('Male or Female')
axes.set_ylabel('Prevalance')
axes.set_title('Prevalence for Male/Female Classes')
```

```
0     491
1    1001
dtype: int64
```

Out[12]: <matplotlib.text.Text at 0x12815c7f0>



Preparing the text data

In [13]:
```
MAX_NB_WORDS = 20000
MAX_SEQUENCE_LENGTH = 2000
EMBEDDING_DIM = 50
hidden_dims = 250
VALIDATION_SPLIT = 0.2
```

Tokenize training set

In [14]:
```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

tokenizer = Tokenizer(nb_words=MAX_NB_WORDS)
tokenizer.fit_on_texts(X)
sequences = tokenizer.texts_to_sequences(X)

word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))

data = pad_sequences(sequences, maxlen=MAX_SEQUENCE_LENGTH)

labels = to_categorical(np.asarray(y))
print('Shape of data tensor:', data.shape)
print('Shape of label tensor:', labels.shape)
```

```
/Users/Tai/anaconda3/envs/dl/lib/python3.6/site-packages/keras/preproce
ssing/text.py:89: UserWarning: The `nb_words` argument in `Tokenizer` h
as been renamed `num_words`.
  warnings.warn('The `nb_words` argument in `Tokenizer` '
```

```
Found 39753 unique tokens.
Shape of data tensor: (1492, 2000)
Shape of label tensor: (1492, 2)
```

In [15]:
```
# split the data into a training set and a validation set
indices = np.arange(data.shape[0])
np.random.shuffle(indices)
data = data[indices]
labels = labels[indices]
nb_validation_samples = int(VALIDATION_SPLIT * data.shape[0])

x_train = data[:-nb_validation_samples]
y_train = labels[:-nb_validation_samples]
x_test = data[-nb_validation_samples:]
y_test = labels[-nb_validation_samples:]
```

Preparing embedding layers

In [16]:
```
import os
BASE_DIR = ''
GLOVE_DIR = BASE_DIR + 'glove.6B/'
TEXT_DATA_DIR = BASE_DIR + '/20_newsgroup/'
embeddings_index = {}
f = open(os.path.join(GLOVE_DIR, 'glove.6B.100d.txt'))
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()

print('Found %s word vectors.' % len(embeddings_index))
```

```
Found 400000 word vectors.
```

In [17]:
```
embedding_matrix = np.zeros((len(word_index) + 1, EMBEDDING_DIM))
for word, i in word_index.items():
    embedding_vector = word_index.get(word)
    if embedding_vector is not None:
        # words not found in embedding index will be all-zeros.
        embedding_matrix[i] = embedding_vector
```

Build DL model

In [18]:
```
from keras.layers import Input, Embedding, LSTM, Dense, Conv1D, Flatten,
 MaxPooling1D, MaxPool2D
from keras.models import Model

def cnn_model():
    embedding_layer = Embedding(len(word_index) + 1,
                                EMBEDDING_DIM,
                                weights=[embedding_matrix],
                                input_length=MAX_SEQUENCE_LENGTH,
                                trainable=False)

    sequence_input = Input(shape=(MAX_SEQUENCE_LENGTH,), dtype='int32')
    embedded_sequences = embedding_layer(sequence_input)
    x = Conv1D(128, 5, activation='relu')(embedded_sequences)
    x = MaxPooling1D(5)(x)
    x = Conv1D(128, 5, activation='relu')(x)
    x = MaxPooling1D(5)(x)
    x = Conv1D(128, 5, activation='relu')(x)
    x = MaxPooling1D(35)(x)  # global max pooling
    x = Flatten()(x)
    x = Dense(128, activation='relu')(x)
    preds = Dense(2, activation='softmax')(x)

    model = Model(sequence_input, preds)
    return model
# model_test.summary()
```

In [19]:
```
cnn_model().summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         (None, 2000)              0         
_________________________________________________________________
embedding_1 (Embedding)      (None, 2000, 50)          1987700   
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 1996, 128)         32128     
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 399, 128)          0         
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 395, 128)          82048     
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 79, 128)           0         
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 75, 128)           82048     
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 2, 128)            0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 256)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896     
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 258       
=================================================================
Total params: 2,217,078.0
Trainable params: 229,378.0
Non-trainable params: 1,987,700.0
_________________________________________________________________
```

In [20]:
```
# Setting the class weight as a methodology to handle imbalance class
from sklearn.utils import class_weight
class_weight = class_weight.compute_class_weight('balanced',
np.unique(y), y)
class_weight
```

Out[20]:
```
array([ 1.51934827,  0.74525475])
```

Overfitting model

In [21]:
```
from keras.metrics import categorical_accuracy,sparse_categorical_accura
cy,top_k_categorical_accuracy,binary_accuracy


model0 = cnn_model()
model0.compile(optimizer='rmsprop', loss='categorical_crossentropy', met
rics=[top_k_categorical_accuracy])
model0.fit(x_train[:5], y_train[:5], validation_split = .1,
               epochs=10, batch_size=64, class_weight=class_weight)
```

```
Train on 4 samples, validate on 1 samples
Epoch 1/10
4/4 [==============================] - 0s - loss: 1.0603 - top_k_catego
rical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_a
ccuracy: 1.0000
Epoch 2/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 3/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 4/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 5/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 6/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 7/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 8/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 9/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
Epoch 10/10
4/4 [==============================] - 0s - loss: 12.0886 - top_k_categ
orical_accuracy: 1.0000 - val_loss: 1.1921e-07 - val_top_k_categorical_
accuracy: 1.0000
```

Out[21]:
```
<keras.callbacks.History at 0x1341e08d0>
```

Metrics test

In [30]:
```
metrics = ['acc', binary_accuracy, categorical_accuracy, sparse_categori
cal_accuracy, top_k_categorical_accuracy]
def test_metric(metrics):
    acc = []
    models = []
    for metric in metrics:
        model = cnn_model()
        model.compile(optimizer='rmsprop', loss='categorical_crossentrop
y', metrics=[metric])
        model.fit(x_train, y_train, validation_split = .2,
                       epochs=10, batch_size=64, class_weight=class_weig
ht)
        models.append(model)
        scores = model.evaluate(x_test,y_test)
        acc.append([metric, scores])
        print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
    return acc, models
```

In [31]:

```
acc_list, model_list = test_metric(metrics)
```

```
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 12s - loss: 4.7781 - acc: 0.
6618 - val_loss: 5.3365 - val_acc: 0.6611
Epoch 2/10
955/955 [==============================] - 11s - loss: 5.0701 - acc: 0.
6702 - val_loss: 5.3369 - val_acc: 0.6611
Epoch 3/10
955/955 [==============================] - 12s - loss: 5.0659 - acc: 0.
6733 - val_loss: 5.5325 - val_acc: 0.6485
Epoch 4/10
955/955 [==============================] - 12s - loss: 5.0612 - acc: 0.
6733 - val_loss: 5.3390 - val_acc: 0.6653
Epoch 5/10
955/955 [==============================] - 12s - loss: 5.0494 - acc: 0.
6754 - val_loss: 5.3381 - val_acc: 0.6653
Epoch 6/10
955/955 [==============================] - 12s - loss: 5.0498 - acc: 0.
6733 - val_loss: 5.3391 - val_acc: 0.6653
Epoch 7/10
955/955 [==============================] - 12s - loss: 5.0496 - acc: 0.
6743 - val_loss: 5.3384 - val_acc: 0.6653
Epoch 8/10
955/955 [==============================] - 12s - loss: 5.0488 - acc: 0.
6743 - val_loss: 5.3394 - val_acc: 0.6611
Epoch 9/10
955/955 [==============================] - 12s - loss: 4.9811 - acc: 0.
6764 - val_loss: 5.3387 - val_acc: 0.6653
Epoch 10/10
955/955 [==============================] - 12s - loss: 5.0484 - acc: 0.
6733 - val_loss: 5.3392 - val_acc: 0.6611
298/298 [==============================] - 1s

acc: 67.45%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 12s - loss: 10.3988 - binary
_accuracy: 0.3325 - val_loss: 10.5695 - val_binary_accuracy: 0.3389
Epoch 2/10
955/955 [==============================] - 12s - loss: 10.6672 - binary
_accuracy: 0.3277 - val_loss: 10.5704 - val_binary_accuracy: 0.3389
Epoch 3/10
955/955 [==============================] - 12s - loss: 10.6672 - binary
_accuracy: 0.3277 - val_loss: 10.5713 - val_binary_accuracy: 0.3389
Epoch 4/10
955/955 [==============================] - 13s - loss: 10.6672 - binary
_accuracy: 0.3277 - val_loss: 10.5713 - val_binary_accuracy: 0.3389
Epoch 5/10
955/955 [==============================] - 13s - loss: 10.6673 - binary
_accuracy: 0.3257 - val_loss: 10.5758 - val_binary_accuracy: 0.3389
Epoch 6/10
955/955 [==============================] - 13s - loss: 10.6672 - binary
_accuracy: 0.3277 - val_loss: 10.5762 - val_binary_accuracy: 0.3389
Epoch 7/10
955/955 [==============================] - 14s - loss: 10.6672 - binary
_accuracy: 0.3277 - val_loss: 10.5744 - val_binary_accuracy: 0.3389
Epoch 8/10
```

```
955/955 [==============================] - 12s - loss: 10.6672 - binary
_accuracy: 0.3277 - val_loss: 10.5762 - val_binary_accuracy: 0.3389
Epoch 9/10
955/955 [==============================] - 12s - loss: 10.6673 - binary
_accuracy: 0.3277 - val_loss: 10.5735 - val_binary_accuracy: 0.3389
Epoch 10/10
955/955 [==============================] - 12s - loss: 10.6673 - binary
_accuracy: 0.3277 - val_loss: 10.5681 - val_binary_accuracy: 0.3389
298/298 [==============================] - 1s

binary_accuracy: 32.55%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 14s - loss: 10.0314 - catego
rical_accuracy: 0.3497 - val_loss: 10.5777 - val_categorical_accuracy:
 0.3389
Epoch 2/10
955/955 [==============================] - 14s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5754 - val_categorical_accuracy:
 0.3389
Epoch 3/10
955/955 [==============================] - 12s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5715 - val_categorical_accuracy:
 0.3389
Epoch 4/10
955/955 [==============================] - 12s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5702 - val_categorical_accuracy:
 0.3389
Epoch 5/10
955/955 [==============================] - 12s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5691 - val_categorical_accuracy:
 0.3389
Epoch 6/10
955/955 [==============================] - 12s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5679 - val_categorical_accuracy:
 0.3389
Epoch 7/10
955/955 [==============================] - 13s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5777 - val_categorical_accuracy:
 0.3389
Epoch 8/10
955/955 [==============================] - 12s - loss: 10.6674 - catego
rical_accuracy: 0.3277 - val_loss: 10.5681 - val_categorical_accuracy:
 0.3389
Epoch 9/10
955/955 [==============================] - 13s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5708 - val_categorical_accuracy:
 0.3389
Epoch 10/10
955/955 [==============================] - 13s - loss: 10.6672 - catego
rical_accuracy: 0.3277 - val_loss: 10.5646 - val_categorical_accuracy:
 0.3389
298/298 [==============================] - 1s

categorical_accuracy: 32.55%
Train on 955 samples, validate on 239 samples
Epoch 1/10
```

```
955/955 [==============================] - 14s - loss: 10.1381 - sparse
_categorical_accuracy: 0.0649 - val_loss: 10.5705 - val_sparse_categori
cal_accuracy: 0.0000e+00
Epoch 2/10
955/955 [==============================] - 14s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5738 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 3/10
955/955 [==============================] - 12s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5758 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 4/10
955/955 [==============================] - 12s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5789 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 5/10
955/955 [==============================] - 12s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5822 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 6/10
955/955 [==============================] - 12s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5840 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 7/10
955/955 [==============================] - 12s - loss: 10.6671 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5859 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 8/10
955/955 [==============================] - 15s - loss: 10.6671 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5878 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 9/10
955/955 [==============================] - 15s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5900 - val_sparse_cate
gorical_accuracy: 0.0000e+00
Epoch 10/10
955/955 [==============================] - 14s - loss: 10.6672 - sparse
_categorical_accuracy: 0.0000e+00 - val_loss: 10.5918 - val_sparse_cate
gorical_accuracy: 0.0000e+00
298/298 [==============================] - 1s

sparse_categorical_accuracy: 0.00%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 13s - loss: 5.1771 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.3366 - val_top_k_categorical_
accuracy: 1.0000
Epoch 2/10
955/955 [==============================] - 13s - loss: 6.0978 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 6.3693 - val_top_k_categorical_
accuracy: 1.0000
Epoch 3/10
955/955 [==============================] - 13s - loss: 6.2471 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 6.6587 - val_top_k_categorical_
accuracy: 1.0000
Epoch 4/10
955/955 [==============================] - 15s - loss: 6.4141 - top_k_c
```

```
ategorical_accuracy: 1.0000 - val_loss: 6.6591 - val_top_k_categorical_
accuracy: 1.0000
Epoch 5/10
955/955 [==============================] - 15s - loss: 6.4309 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 6.6594 - val_top_k_categorical_
accuracy: 1.0000
Epoch 6/10
955/955 [==============================] - 16s - loss: 8.4552 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 10.5967 - val_top_k_categorical
_accuracy: 1.0000
Epoch 7/10
955/955 [==============================] - 15s - loss: 10.6672 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.5966 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 8/10
955/955 [==============================] - 13s - loss: 10.6672 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.5966 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 9/10
955/955 [==============================] - 13s - loss: 10.6672 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.5966 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 10/10
955/955 [==============================] - 14s - loss: 10.6672 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.5966 - val_top_k_categorica
l_accuracy: 1.0000
298/298 [==============================] - 1s

top_k_categorical_accuracy: 100.00%
```

In [36]:

```python
for i in acc_list:
    print(i)
```

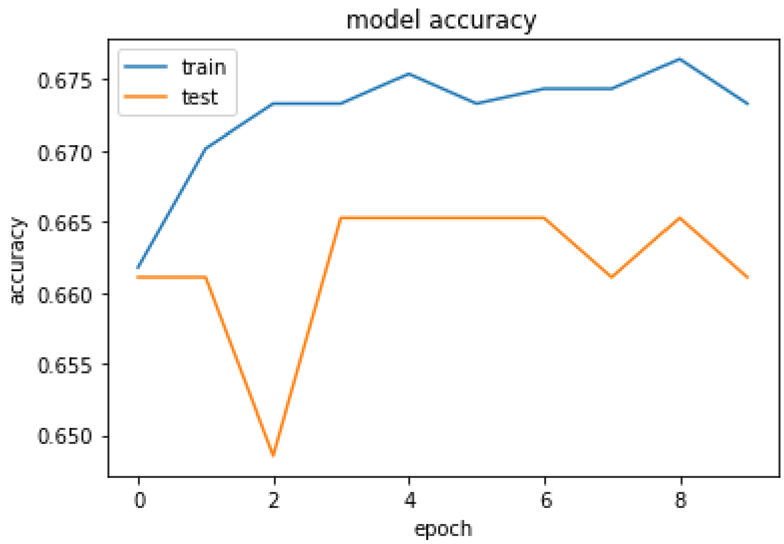
```
['acc', [5.125252920509185, 0.67449664349523963]]
[<function binary_accuracy at 0x1231b4ea0>, [10.772753619507656, 0.3255
0335575470191]]
[<function categorical_accuracy at 0x1231b4f28>, [10.772751571348049,
 0.32550335575470191]]
[<function sparse_categorical_accuracy at 0x1231c7048>, [10.77274143295
8002, 0.0]]
[<function top_k_categorical_accuracy at 0x1231c70d0>, [10.772738053494
653, 1.0]]
```

In [48]:

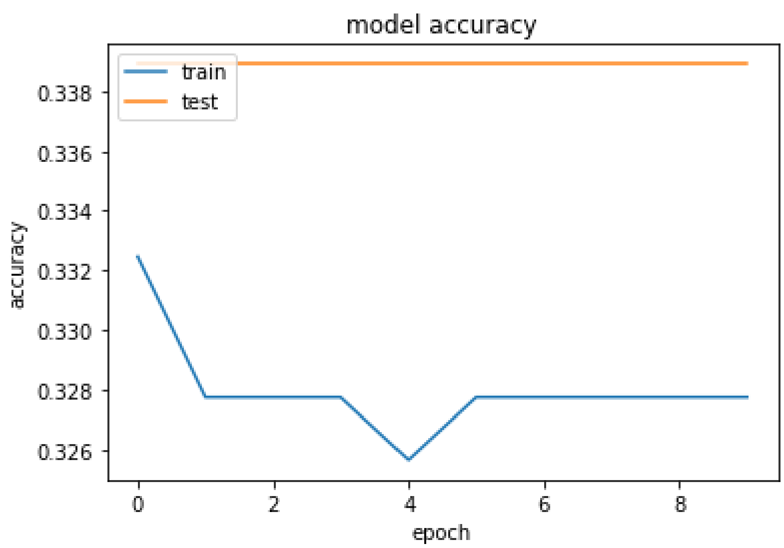
```python
metrics = ['acc', 'binary_accuracy', 'categorical_accuracy', 'sparse_cat
egorical_accuracy', 'top_k_categorical_accuracy']
```

In [49]:
```
count=0
for i,metric in enumerate(metrics):
    print("Model", count , ":",metric)
    plot_acc(model_list[count], metric)
    count += 1
    plt.show()
```

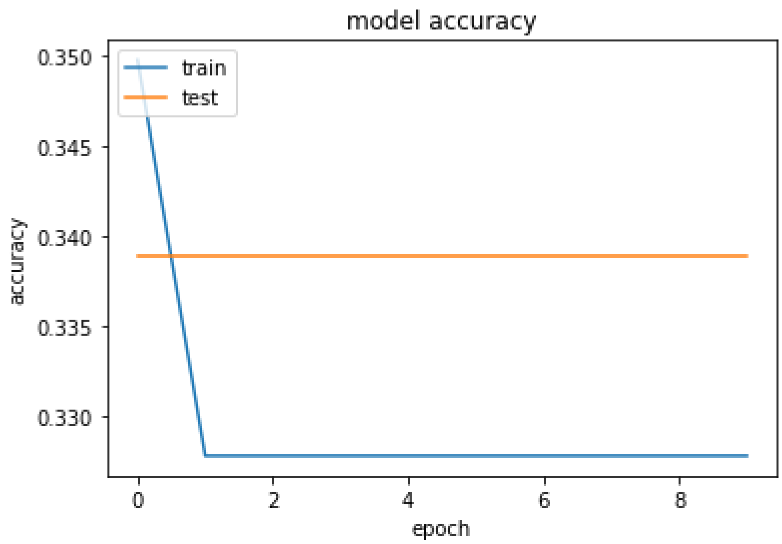
```
Model 0 : acc
acc
```



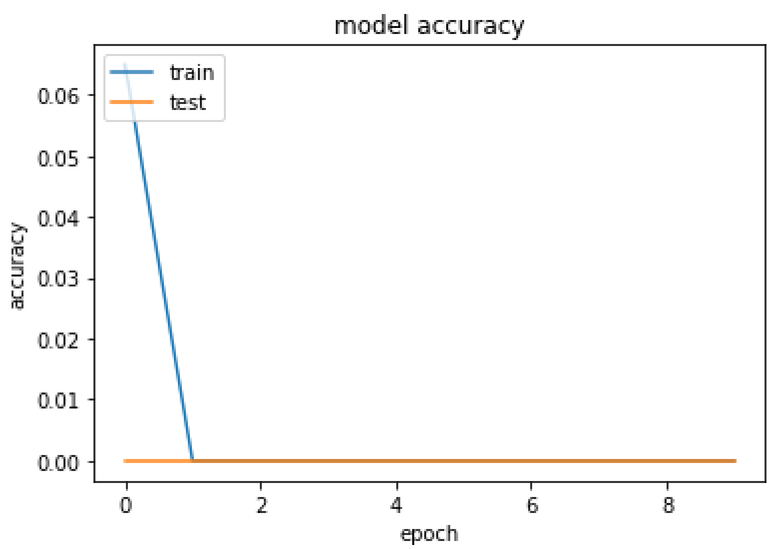

```
Model 1 : binary_accuracy
binary_accuracy
```



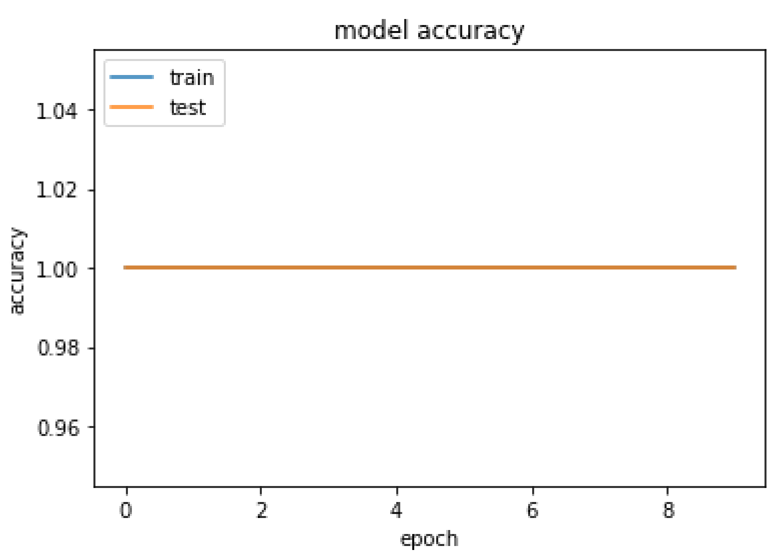

```
Model 2 : categorical_accuracy
categorical_accuracy
```



Model 3 : sparse_categorical_accuracy
sparse_categorical_accuracy



Model 4 : top_k_categorical_accuracy
top_k_categorical_accuracy



In [172]:
```
for metric in ['acc', binary_accuracy, categorical_accuracy, sparse_cate
gorical_accuracy, top_k_categorical_accuracy]:
model0 = cnn_model()
model0.compile(optimizer='rmsprop', loss='categorical_crossentropy', met
rics=[sparse_categorical_accuracy, top_k_categorical_accuracy])
model0.fit(x_train, y_train, validation_split = .2,
               epochs=2, batch_size=64, class_weight=class_weight)
```

```
Train on 955 samples, validate on 239 samples
Epoch 1/2
955/955 [==============================] - 14s - loss: 0.6339 - sparse_
categorical_accuracy: 0.9822 - top_k_categorical_accuracy: 1.0000 - val
_loss: 0.7313 - val_sparse_categorical_accuracy: 1.0000 - val_top_k_cat
egorical_accuracy: 1.0000
Epoch 2/2
955/955 [==============================] - 12s - loss: 0.6220 - sparse_
categorical_accuracy: 1.0000 - top_k_categorical_accuracy: 1.0000 - val
_loss: 0.6626 - val_sparse_categorical_accuracy: 1.0000 - val_top_k_cat
egorical_accuracy: 1.0000
```

Out[172]:
```
<keras.callbacks.History at 0x168efda90>
```

In [179]:

```
model0 = cnn_model()
model0.compile(optimizer='rmsprop', loss='categorical_crossentropy', met
rics=['acc', binary_accuracy, categorical_accuracy])
model0.fit(x_train, y_train, validation_split = .2,
               epochs=10, batch_size=64, class_weight=class_weight)
```

```
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 14s - loss: 0.6294 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6699 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 2/10
955/955 [==============================] - 12s - loss: 0.6200 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6608 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 3/10
955/955 [==============================] - 14s - loss: 0.6281 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6612 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 4/10
955/955 [==============================] - 13s - loss: 0.6168 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6591 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 5/10
955/955 [==============================] - 13s - loss: 0.6155 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6626 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 6/10
955/955 [==============================] - 13s - loss: 0.6115 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6572 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 7/10
955/955 [==============================] - 13s - loss: 0.6159 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6584 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 8/10
955/955 [==============================] - 14s - loss: 0.6107 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6713 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 9/10
955/955 [==============================] - 13s - loss: 0.5987 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.7463 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
Epoch 10/10
955/955 [==============================] - 14s - loss: 0.6046 - acc: 0.
6880 - binary_accuracy: 0.6880 - categorical_accuracy: 0.6880 - val_los
s: 0.6516 - val_acc: 0.6234 - val_binary_accuracy: 0.6234 - val_categor
ical_accuracy: 0.6234
```

```
Out[179]: <keras.callbacks.History at 0x16c399f98>
```

In [177]:
```
scores = model0.evaluate(x_test,y_test)
print("\n%s: %.2f%%" % (model0.metrics_names[1], scores[1]*100))
```

```
298/298 [==============================] - 1s

sparse_categorical_accuracy: 100.00%
```

Fitting with different hyperparameters

In [240]:
```
def multiple_hyper_train(x_train, y_train, x_test, y_test):
    model_list= []
    for i,loss_func in enumerate(['categorical_crossentropy','binary_cro
ssentropy']):
        for j,optimizer in enumerate(['rmsprop']):
            model = cnn_model()
            model.compile(optimizer=optimizer,loss=loss_func, metrics=[t
op_k_categorical_accuracy, sparse_categorical_accuracy])
            model.fit(x_train, y_train, validation_split = 0.2, epochs=1
0, batch_size=128)
            model_list.append(model)
            scores = model.evaluate(x_test,y_test)
            print('---------------------------------------------')
            print(loss_func, "+", optimizer)
            print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*10
0))
            print('---------------------------------------------')
    return model_list
```

In [241]:
```
models = multiple_hyper_train(x_train, y_train, x_test, y_test)
```

```
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 14s - loss: 4.6406 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.9309 - val
_loss: 4.8734 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 2/10
955/955 [==============================] - 11s - loss: 5.0571 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 1.0000 - val
_loss: 4.8733 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 3/10
955/955 [==============================] - 11s - loss: 5.0537 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 1.0000 - val
_loss: 4.8733 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 4/10
955/955 [==============================] - 12s - loss: 5.0500 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 1.0000 - val
_loss: 4.8733 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 5/10
955/955 [==============================] - 13s - loss: 5.0329 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.9874 - val
_loss: 4.8744 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 6/10
955/955 [==============================] - 11s - loss: 5.0315 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.9979 - val
_loss: 4.8735 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 7/10
955/955 [==============================] - 11s - loss: 5.0312 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 1.0000 - val
_loss: 4.8748 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 8/10
955/955 [==============================] - 13s - loss: 5.0284 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.9990 - val
_loss: 4.8749 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 9/10
955/955 [==============================] - 13s - loss: 5.0292 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.9969 - val
_loss: 4.8736 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
Epoch 10/10
955/955 [==============================] - 11s - loss: 5.0525 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 1.0000 - val
_loss: 4.8735 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_cat
egorical_accuracy: 1.0000
298/298 [==============================] - 1s
------------------------------------------
categorical_crossentropy + rmsprop

top_k_categorical_accuracy: 100.00%
------------------------------------------
```

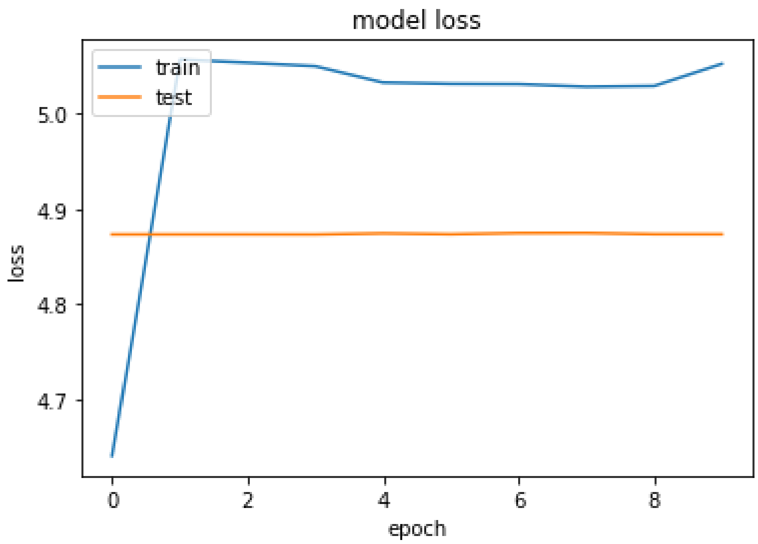
```
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 13s - loss: 9.4197 - top_k_c
ategorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0984 - val
_loss: 10.7747 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_ca
tegorical_accuracy: 0.0000e+00
Epoch 2/10
955/955 [==============================] - 11s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0000e+00
 - val_loss: 10.7779 - val_top_k_categorical_accuracy: 1.0000 - val_spa
rse_categorical_accuracy: 0.0000e+00
Epoch 3/10
955/955 [==============================] - 11s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0042 - va
l_loss: 10.7798 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0000e+00
Epoch 4/10
955/955 [==============================] - 11s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0178 - va
l_loss: 10.7829 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0000e+00
Epoch 5/10
955/955 [==============================] - 13s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0157 - va
l_loss: 10.7860 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0000e+00
Epoch 6/10
955/955 [==============================] - 12s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0188 - va
l_loss: 10.7895 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0251
Epoch 7/10
955/955 [==============================] - 11s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0209 - va
l_loss: 10.7906 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0251
Epoch 8/10
955/955 [==============================] - 11s - loss: 10.6902 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0209 - va
l_loss: 10.7919 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0251
Epoch 9/10
955/955 [==============================] - 11s - loss: 10.6901 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0209 - va
l_loss: 10.7934 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0251
Epoch 10/10
955/955 [==============================] - 11s - loss: 10.6901 - top_k_
categorical_accuracy: 1.0000 - sparse_categorical_accuracy: 0.0209 - va
l_loss: 10.7950 - val_top_k_categorical_accuracy: 1.0000 - val_sparse_c
ategorical_accuracy: 0.0251
298/298 [==============================] - 1s
------------------------------------------
binary_crossentropy + rmsprop

top_k_categorical_accuracy: 100.00%
------------------------------------------
```

Visualization

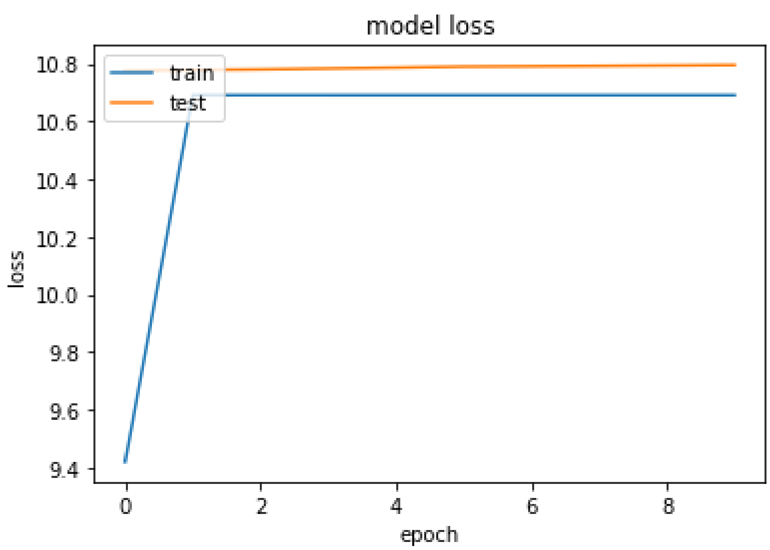
In [46]:
```
import matplotlib.pyplot as plt
%matplotlib inline

def plot_acc(model, metric):
    #summarize history for accuracy
    print(str(metric))
    plt.plot(model.history.history[str(metric)])
    plt.plot(model.history.history['val_' + str(metric)])
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')

def plot_loss(model):
    #summarize history for loss
    plt.plot(model.history.history['loss'])
    plt.plot(model.history.history['val_loss'])
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
```

In [255]:
```
count=0
for i,loss_func in enumerate(['categorical_crossentropy','binary_crossen
tropy']):
    for j,optimizer in enumerate(['rmsprop']):
        print("Model", count , ":",loss_func,"+", optimizer)
        plot_loss(models[count])
        count += 1
        plt.show()
```

```
Model 0 : categorical_crossentropy + rmsprop
```




```
Model 1 : binary_crossentropy + rmsprop
```



K-fold cross validation to handle imbalance classes

In [265]:
```
from sklearn.model_selection import StratifiedKFold
def kfold_cv(x_train, y, labels):
    # fix random seed for reproducibility
    seed = 7
    np.random.seed(seed)
    #############################################
    # define 10-fold cross validation test harness
    # The folds are made by preserving the percentage of samples for eac
h class.
    #############################################
    kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=seed)
    cvscores = []
    models = []

    for train, test in kfold.split(data, y):
        # create model
        model = cnn_model()
        # Compile model
        model.compile(loss='categorical_crossentropy', optimizer='rmspro
p', metrics=[top_k_categorical_accuracy])
        # Fit the model
        model.fit(data[train], labels[train], verbose=1, validation_spli
t=.2,
                                      epochs=10, batch_size=128, class_w
eight=class_weight)
        models.append(model)

        # evaluate the model
        scores = model.evaluate(data[test], labels[test], verbose=1)
        print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
        cvscores.append(scores[1] * 100)
    print("Mean:",np.mean(cvscores), "STD:",np.std(cvscores))
    return (models, cvscores)
```

In [266]:

```
k = kfold_cv(data, y, labels)
```

```
Train on 953 samples, validate on 239 samples
Epoch 1/10
953/953 [==============================] - 14s - loss: 5.8522 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2749 - val_top_k_categorical_
accuracy: 1.0000
Epoch 2/10
953/953 [==============================] - 11s - loss: 5.1053 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2772 - val_top_k_categorical_
accuracy: 1.0000
Epoch 3/10
953/953 [==============================] - 11s - loss: 5.1096 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2835 - val_top_k_categorical_
accuracy: 1.0000
Epoch 4/10
953/953 [==============================] - 11s - loss: 5.1071 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2749 - val_top_k_categorical_
accuracy: 1.0000
Epoch 5/10
953/953 [==============================] - 11s - loss: 5.0960 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2757 - val_top_k_categorical_
accuracy: 1.0000
Epoch 6/10
953/953 [==============================] - 11s - loss: 5.0926 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2782 - val_top_k_categorical_
accuracy: 1.0000
Epoch 7/10
953/953 [==============================] - 11s - loss: 5.0920 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2797 - val_top_k_categorical_
accuracy: 1.0000
Epoch 8/10
953/953 [==============================] - 12s - loss: 5.0915 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2802 - val_top_k_categorical_
accuracy: 1.0000
Epoch 9/10
953/953 [==============================] - 13s - loss: 5.0912 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2858 - val_top_k_categorical_
accuracy: 1.0000
Epoch 10/10
953/953 [==============================] - 12s - loss: 5.0913 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.2895 - val_top_k_categorical_
accuracy: 1.0000
300/300 [==============================] - 1s
top_k_categorical_accuracy: 100.00%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 14s - loss: 4.6972 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9408 - val_top_k_categorical_
accuracy: 1.0000
Epoch 2/10
955/955 [==============================] - 11s - loss: 4.9883 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9407 - val_top_k_categorical_
accuracy: 1.0000
Epoch 3/10
955/955 [==============================] - 11s - loss: 4.9854 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9406 - val_top_k_categorical_
accuracy: 1.0000
Epoch 4/10
```

```
955/955 [==============================] - 11s - loss: 4.9822 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9406 - val_top_k_categorical_
accuracy: 1.0000
Epoch 5/10
955/955 [==============================] - 11s - loss: 4.9796 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9509 - val_top_k_categorical_
accuracy: 1.0000
Epoch 6/10
955/955 [==============================] - 11s - loss: 4.9840 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9406 - val_top_k_categorical_
accuracy: 1.0000
Epoch 7/10
955/955 [==============================] - 11s - loss: 4.9851 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9405 - val_top_k_categorical_
accuracy: 1.0000
Epoch 8/10
955/955 [==============================] - 11s - loss: 4.9811 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9405 - val_top_k_categorical_
accuracy: 1.0000
Epoch 9/10
955/955 [==============================] - 11s - loss: 4.9792 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9409 - val_top_k_categorical_
accuracy: 1.0000
Epoch 10/10
955/955 [==============================] - 11s - loss: 4.9783 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.9412 - val_top_k_categorical_
accuracy: 1.0000
298/298 [==============================] - 1s
top_k_categorical_accuracy: 100.00%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 13s - loss: 9.6366 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 10.1303 - val_top_k_categorical
_accuracy: 1.0000
Epoch 2/10
955/955 [==============================] - 11s - loss: 10.7486 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1303 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 3/10
955/955 [==============================] - 11s - loss: 10.7486 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1303 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 4/10
955/955 [==============================] - 11s - loss: 10.7487 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1302 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 5/10
955/955 [==============================] - 11s - loss: 10.7486 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1303 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 6/10
955/955 [==============================] - 11s - loss: 10.7487 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1302 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 7/10
955/955 [==============================] - 11s - loss: 10.7486 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1302 - val_top_k_categorica
```

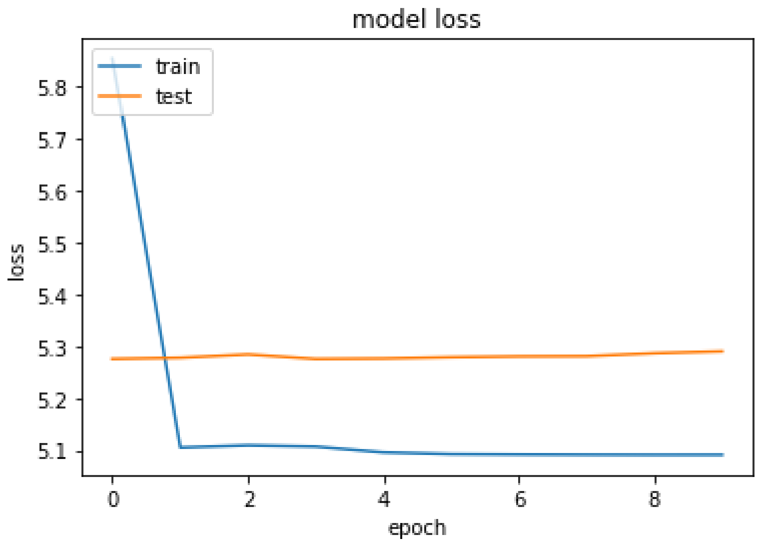
```
l_accuracy: 1.0000
Epoch 8/10
955/955 [==============================] - 11s - loss: 10.7486 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1302 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 9/10
955/955 [==============================] - 11s - loss: 10.7487 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1302 - val_top_k_categorica
l_accuracy: 1.0000
Epoch 10/10
955/955 [==============================] - 11s - loss: 10.7487 - top_k_
categorical_accuracy: 1.0000 - val_loss: 10.1302 - val_top_k_categorica
l_accuracy: 1.0000
298/298 [==============================] - 1s
top_k_categorical_accuracy: 100.00%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 13s - loss: 4.7907 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 2/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 3/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 4/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 5/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 6/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 7/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 8/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 9/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
Epoch 10/10
955/955 [==============================] - 11s - loss: 4.9604 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.4068 - val_top_k_categorical_
accuracy: 1.0000
298/298 [==============================] - 1s
```

```
top_k_categorical_accuracy: 100.00%
Train on 955 samples, validate on 239 samples
Epoch 1/10
955/955 [==============================] - 14s - loss: 4.8264 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7440 - val_top_k_categorical_
accuracy: 1.0000
Epoch 2/10
955/955 [==============================] - 12s - loss: 4.9354 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7440 - val_top_k_categorical_
accuracy: 1.0000
Epoch 3/10
955/955 [==============================] - 12s - loss: 4.9305 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7223 - val_top_k_categorical_
accuracy: 1.0000
Epoch 4/10
955/955 [==============================] - 12s - loss: 4.9630 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7959 - val_top_k_categorical_
accuracy: 1.0000
Epoch 5/10
955/955 [==============================] - 13s - loss: 4.9070 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7463 - val_top_k_categorical_
accuracy: 1.0000
Epoch 6/10
955/955 [==============================] - 14s - loss: 4.9207 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7440 - val_top_k_categorical_
accuracy: 1.0000
Epoch 7/10
955/955 [==============================] - 14s - loss: 4.9163 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7526 - val_top_k_categorical_
accuracy: 1.0000
Epoch 8/10
955/955 [==============================] - 16s - loss: 4.9128 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7441 - val_top_k_categorical_
accuracy: 1.0000
Epoch 9/10
955/955 [==============================] - 16s - loss: 4.9156 - top_k_c
ategorical_accuracy: 1.0000 - val_loss: 5.7482 - val_top_k_categorical_
accuracy: 1.0000
Epoch 10/10
955/955 [==============================] - 1379s - loss: 4.9114 - top_k
_categorical_accuracy: 1.0000 - val_loss: 5.7503 - val_top_k_categorica
l_accuracy: 1.0000
298/298 [==============================] - 1s
top_k_categorical_accuracy: 100.00%
Mean: 100.0 STD: 0.0
```

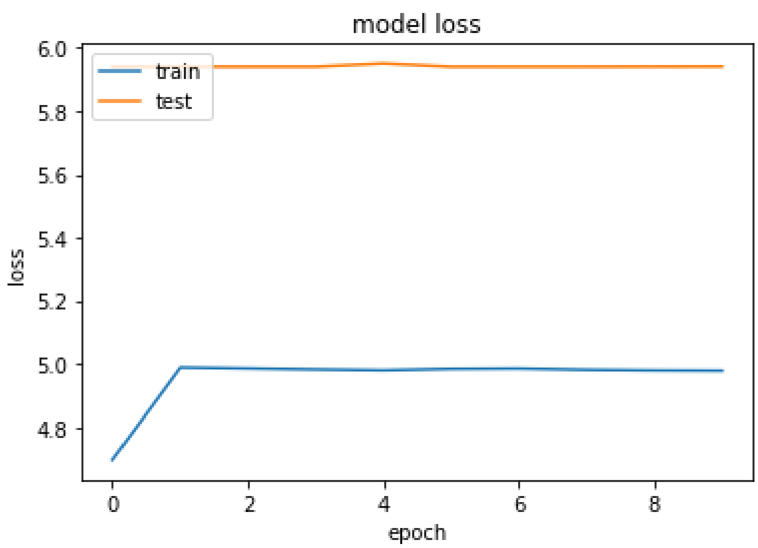
In [269]:

```
count=0
for i,loss_func in enumerate(range(5)):
    print("Model", count , ":",loss_func,"+", optimizer)
    plot_loss(k[0][count])
    count += 1
    plt.show()
```

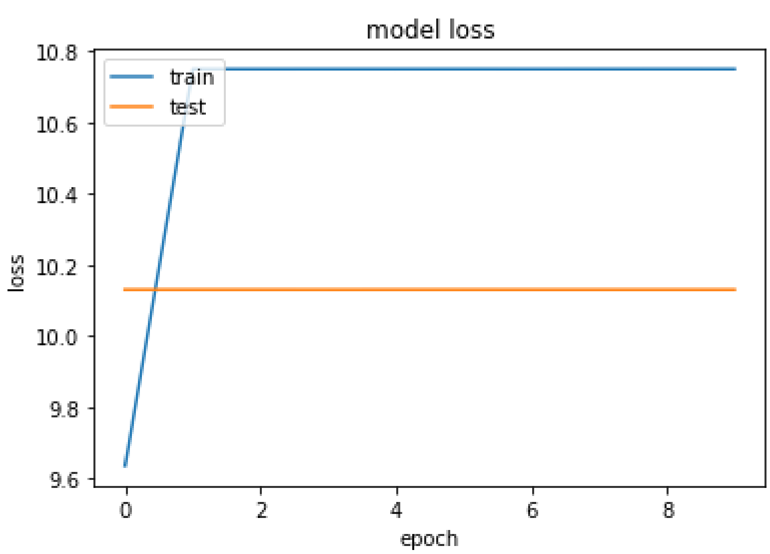
Model 0 : 0 + rmsprop



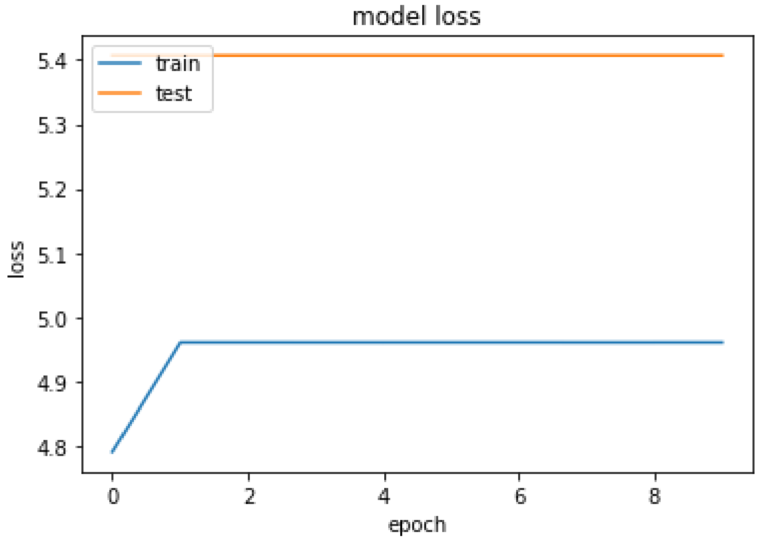
Model 1 : 1 + rmsprop



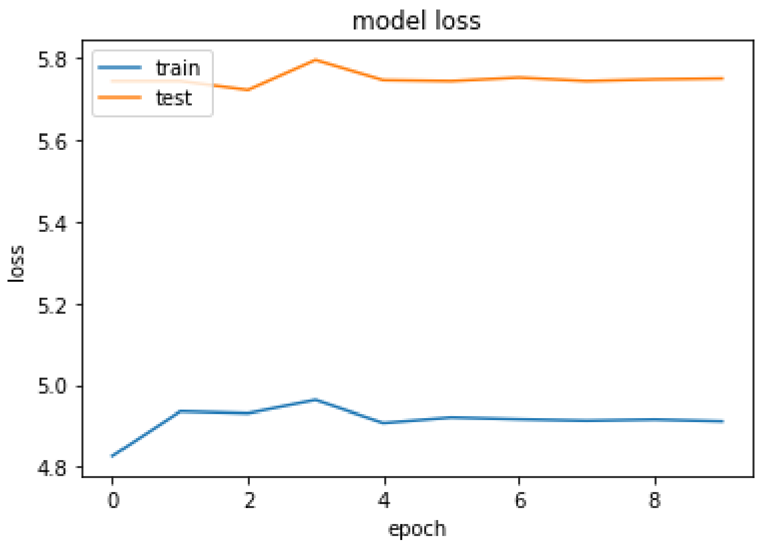
Model 2 : 2 + rmsprop



Model 3 : 3 + rmsprop



Model 4 : 4 + rmsprop



In [268]:
```
k[0]
```

Out[268]:
```
[<keras.engine.training.Model at 0x19e6f4fd0>,
 <keras.engine.training.Model at 0x19f411d30>,
 <keras.engine.training.Model at 0x19e600630>,
 <keras.engine.training.Model at 0x1a043b978>,
 <keras.engine.training.Model at 0x1a436ae80>]
```

Conclusion:

The goal of the project is aim to show the great performance of using deep learning in text classification for a supervised dataset of TedTalk transcripts whether the speech is from a male voice or female voice. The training/learning is gone through two comparable methodologies which is a baseline model using scikit learn versus a strong deep learning model using keras modules. The evaluation showed that the accuracy for baseline model is about 99.7% while with the right metric evaluation(in this case, it's k-top-categorical-accuracy), deep learning model is able to predict correctly 100%. This shows that deep learning model is really powerful in advanced contexts.

Q&A

- What was the biggest challenge/obstacle/hurdle?

During the training, the challenges are scattered through each step, the biggest challenge is during the training proccess. Since putting the wrong hyperparameters would yield a significant wrong result, it did take time and tests to investigate the optimized result.

- If you had two more weeks what would you do?

If there are additional time for this project, I would likely to explore with more complex classification rather than just male and female. It can be subject/topic classification such as science, math, environment, english,... .

- Does it scale?

Yes, the model is able to be flexible for adjusting size of all keras parameters such as embedding dimension, MAX_SEQUENCE_LENGTH

- How would you turn your project in a data product?

To do so, the input data must have to be formatted in same way with the Tedtalk transcript document. The input data will then be able to preprocessed. All parameters in keras would have been set to be bigger or smaller upon the size of dataset or user's choice.

- Why does your deep learning model beat your baseline?

Deep learning is able to adjust weight by using different optimizers, by doing so, accuracy is slightly improved but it will results in high tradeoff with loss.

- What are the tradeoffs between your baseline and your deep learning model? Would you put your deep learning model into production over your baseline? Why or why not?

Even though multiple loss functions have been tested, the training still shows high loss tradeoff with accuracy. Because of this, the model maybe not be considered as a perfect model for data production.

- What evidence can you provide that your model has generalized correctly?

Evaluation for test data always reach 100% for every repeat test.

- Are your results significant? Yes, they are.
- What hyperparameters mattered? Which didn't?

Metrics is the most important hyperparameter among others. For the imbalance dataset, the wrong metrics had leaded to the significant incorrect predictions.

- Why did or didn't you use accuracy as your evaluation metric? I start by testing with different metrics and it appears that k-top-categorical-accuracy showed the top result. Its algorithm works by calculate how often a target class is within the top-k predictions.

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In [ ]:
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