In [1]:

```
#importing all the required lib
import pandas as pd
import numpy as np
import os
import math
from collections import defaultdict
import matplotlib.pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer,CountVectorizer
from sklearn.model_selection import train_test_split
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.layers import SpatialDropout1D, LSTM, BatchNormalization,concatenate,Flatten,Embedding,
Dense,Dropout,MaxPooling2D,Reshape,CuDNNLSTM
from keras.models import Sequential
from keras import Model,Input
from keras.layers.convolutional import Conv2D,Conv1D
import keras.backend as k
from sklearn.metrics import roc_auc_score
import tensorflow as tf
import keras
from sklearn.utils import compute_class_weight
from keras.initializers import he_normal,glorot_normal
from keras.regularizers import l1,l2
from keras.callbacks import Callback, EarlyStopping, ModelCheckpoint,LearningRateScheduler
from time import time
from tensorflow.python.keras.callbacks import TensorBoard
from keras.callbacks import TensorBoard
from IPython.display import SVG, display
import pickle
from keras.layers import LeakyReLU
import warnings
warnings.filterwarnings("ignore")
```

```
Using TensorFlow backend.
```

In [2]:

```
%tensorflow_version 2.x
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
Found GPU at: /device:GPU:0
```

In [3]:

```
# Load the Drive helper and mount
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%
b&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2
www.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly
ttps%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
··········
Mounted at /content/drive
```

In [4]:

```
data = pd.read_csv("/content/drive/My Drive/Assignments/preprocessed_data.csv")
data.shape
```

Out[4]:

```
(109248, 9)
```

In [5]:

```
dbfile = open('/content/drive/My Drive/Assignments_DonorsChoose_2018/glove_vectors', 'rb')
db = pickle.load(dbfile)
```

In [6]:

```
print(db["good"].shape)
print(db["good"][0:10])
```

```
(300,)
[-0.069254  0.37668  -0.16958  -0.27482   0.25667  -0.20293  -4.1122
  0.02595  -0.27085  -0.87003 ]
```

Each word is represented as a 300X1 dim vector and we printed the first 10values of a word "good"

In [7]:

```
data.columns
```

Out[7]:

```
Index(['school_state', 'teacher_prefix', 'project_grade_category',
       'teacher_number_of_previously_posted_projects', 'project_is_approved',
       'clean_categories', 'clean_subcategories', 'essay', 'price'],
      dtype='object')
```

In [8]:

```
data['remaining_input'] = data['teacher_number_of_previously_posted_projects']  +\
                                data['price']
```

In [9]:

```
data.drop(["teacher_number_of_previously_posted_projects","price"],axis = 1 ,inplace = True)
```

In [10]:

```
data.columns
```

Out[10]:

```
Index(['school_state', 'teacher_prefix', 'project_grade_category',
       'project_is_approved', 'clean_categories', 'clean_subcategories',
       'essay', 'remaining_input'],
      dtype='object')
```

In [11]:

```
y=data["project_is_approved"]
data.drop("project_is_approved",axis = 1,inplace=True)
print(f"Target:{y.shape}\n Input {data.shape}")
```

```
Target:(109248,)
 Input (109248, 7)
```

Now let's investigate each features

In [12]:

```
cols = data.columns
for col in cols:
```

```
  print(f"{col}:{data[col].describe()}\n{data[col].unique()}")
  print("*"*100)
```

```
school_state:count     109248
unique         51
top            ca
freq        15388
Name: school_state, dtype: object
['ca' 'ut' 'ga' 'wa' 'hi' 'il' 'oh' 'ky' 'sc' 'fl' 'mo' 'mi' 'ny' 'va'
 'md' 'tx' 'ms' 'nj' 'az' 'ok' 'pa' 'wv' 'nc' 'co' 'dc' 'ma' 'id' 'al'
 'me' 'tn' 'in' 'la' 'ct' 'ar' 'ks' 'or' 'wi' 'ia' 'sd' 'ak' 'mn' 'nm'
 'nv' 'mt' 'ri' 'nh' 'wy' 'ne' 'de' 'nd' 'vt']
****************************************************************************************************

teacher_prefix:count     109248
unique           5
top            mrs
freq         57272
Name: teacher_prefix, dtype: object
['mrs' 'ms' 'mr' 'teacher' 'dr']
****************************************************************************************************

project_grade_category:count            109248
unique                   4
top         grades_prek_2
freq                 44225
Name: project_grade_category, dtype: object
['grades_prek_2' 'grades_3_5' 'grades_9_12' 'grades_6_8']
****************************************************************************************************

clean_categories:count                  109248
unique                      51
top         literacy_language
freq                    23655
Name: clean_categories, dtype: object
['math_science' 'specialneeds' 'literacy_language' 'appliedlearning'
 'math_science history_civics' 'literacy_language math_science'
 'appliedlearning music_arts' 'math_science appliedlearning'
 'math_science literacy_language' 'history_civics literacy_language'
 'appliedlearning health_sports' 'math_science music_arts'
 'appliedlearning literacy_language' 'music_arts' 'health_sports'
 'literacy_language specialneeds' 'math_science specialneeds'
 'appliedlearning history_civics' 'appliedlearning specialneeds'
 'health_sports literacy_language' 'literacy_language music_arts'
 'history_civics math_science' 'specialneeds health_sports'
 'literacy_language history_civics' 'health_sports specialneeds'
 'history_civics music_arts' 'math_science health_sports'
 'music_arts specialneeds' 'specialneeds music_arts'
 'health_sports history_civics' 'history_civics'
 'health_sports appliedlearning' 'history_civics specialneeds'
 'appliedlearning math_science' 'health_sports music_arts'
 'literacy_language health_sports' 'literacy_language appliedlearning'
 'music_arts health_sports' 'music_arts appliedlearning'
 'music_arts history_civics' 'health_sports math_science'
 'history_civics appliedlearning' 'history_civics health_sports'
 'health_sports warmth care_hunger' 'history_civics warmth care_hunger'
 'math_science warmth care_hunger' 'specialneeds warmth care_hunger'
 'warmth care_hunger' 'literacy_language warmth care_hunger'
 'music_arts warmth care_hunger' 'appliedlearning warmth care_hunger']
****************************************************************************************************

clean_subcategories:count       109248
unique             401
top            literacy
freq              9486
Name: clean_subcategories, dtype: object
['appliedsciences health_lifescience' 'specialneeds' 'literacy'
 'earlydevelopment' 'mathematics socialsciences' 'literacy mathematics'
 'appliedsciences history_geography' 'esl literacy'
 'appliedsciences mathematics' 'extracurricular visualarts'
 'appliedsciences earlydevelopment' 'environmentalscience literacy'
 'appliedsciences environmentalscience'
 'history_geography literature_writing' 'literacy literature_writing'
 'earlydevelopment gym_fitness' 'environmentalscience visualarts'
 'environmentalscience mathematics' 'appliedsciences visualarts'
 'earlydevelopment literacy' 'music' 'teamsports'
```

'health_lifescience mathematics' 'music performingarts'
'esl environmentalscience' 'college_careerprep esl'
'appliedsciences other' 'college_careerprep visualarts'
'literature_writing specialneeds' 'health_lifescience specialneeds'
'environmentalscience literature_writing' 'college_careerprep other'
'charactereducation socialsciences' 'literature_writing'
'earlydevelopment other' 'environmentalscience health_lifescience'
'other specialneeds' 'foreignlanguages' 'college_careerprep'
'literature_writing mathematics' 'health_wellness literature_writing'
'literacy specialneeds' 'literacy visualarts'
'health_lifescience visualarts' 'gym_fitness teamsports' 'mathematics'
'health_wellness teamsports' 'appliedsciences civics_government'
'economics mathematics' 'esl literature_writing'
'environmentalscience socialsciences' 'health_wellness'
'health_lifescience literature_writing' 'mathematics specialneeds'
'specialneeds teamsports' 'earlydevelopment visualarts'
'literacy socialsciences' 'esl' 'health_wellness specialneeds'
'history_geography music' 'earlydevelopment specialneeds' 'gym_fitness'
'appliedsciences literacy' 'communityservice earlydevelopment' 'other'
'charactereducation' 'esl mathematics' 'literacy performingarts'
'literature_writing visualarts' 'health_lifescience health_wellness'
'earlydevelopment literature_writing' 'literacy music'
'gym_fitness health_wellness' 'visualarts' 'charactereducation literacy'
'mathematics visualarts' 'music specialneeds' 'health_lifescience'
'history_geography literacy' 'literature_writing socialsciences'
'specialneeds visualarts' 'appliedsciences' 'environmentalscience'
'environmentalscience history_geography' 'health_wellness socialsciences'
'environmentalscience health_wellness' 'performingarts'
'appliedsciences literature_writing' 'extracurricular teamsports'
'charactereducation earlydevelopment' 'appliedsciences socialsciences'
'civics_government economics' 'extracurricular' 'health_wellness other'
'history_geography specialneeds' 'health_wellness literacy'
'communityservice extracurricular' 'charactereducation specialneeds'
'extracurricular literacy' 'environmentalscience specialneeds'
'college_careerprep literacy' 'esl specialneeds'
'appliedsciences specialneeds' 'music visualarts'
'college_careerprep communityservice' 'health_lifescience literacy'
'college_careerprep environmentalscience' 'charactereducation teamsports'
'financialliteracy mathematics' 'nutritioneducation visualarts'
'history_geography' 'foreignlanguages mathematics'
'literacy nutritioneducation' 'earlydevelopment health_wellness'
'charactereducation college_careerprep'
'history_geography socialsciences' 'appliedsciences college_careerprep'
'literacy other' 'literature_writing performingarts' 'other visualarts'
'college_careerprep specialneeds' 'college_careerprep literature_writing'
'esl foreignlanguages' 'nutritioneducation'
'charactereducation health_wellness' 'communityservice literacy'
'esl earlydevelopment' 'foreignlanguages literacy'
'history_geography visualarts' 'socialsciences visualarts'
'performingarts visualarts' 'appliedsciences foreignlanguages'
'civics_government literacy' 'esl health_lifescience'
'appliedsciences extracurricular' 'literature_writing parentinvolvement'
'esl history_geography' 'health_lifescience history_geography'
'extracurricular other' 'charactereducation other'
'charactereducation literature_writing' 'mathematics music'
'communityservice environmentalscience' 'communityservice visualarts'
'socialsciences' 'mathematics other' 'parentinvolvement visualarts'
'foreignlanguages literature_writing'
'charactereducation communityservice' 'charactereducation mathematics'
'health_wellness visualarts' 'extracurricular music'
'civics_government environmentalscience'
'health_lifescience nutritioneducation' 'appliedsciences music'
'esl socialsciences' 'appliedsciences parentinvolvement'
'charactereducation visualarts' 'foreignlanguages performingarts'
'literature_writing music' 'communityservice other'
'civics_government history_geography'
'appliedsciences charactereducation' 'performingarts teamsports'
'college_careerprep mathematics' 'health_wellness nutritioneducation'
'health_lifescience socialsciences' 'gym_fitness performingarts'
'college_careerprep history_geography'
'environmentalscience extracurricular' 'college_careerprep teamsports'
'esl visualarts' 'extracurricular gym_fitness'
'college_careerprep extracurricular' 'esl music'
'literature_writing other' 'extracurricular socialsciences'
'earlydevelopment environmentalscience' 'nutritioneducation other'
'extracurricular literature_writing' 'civics_government socialsciences'
'earlydevelopment music' 'music other' 'extracurricular specialneeds'

```
'performingarts socialsciences' 'communityservice specialneeds'
'charactereducation extracurricular'
'earlydevelopment health_lifescience' 'economics socialsciences'
'college_careerprep economics' 'gym_fitness literature_writing'
'communityservice' 'environmentalscience nutritioneducation'
'earlydevelopment mathematics' 'gym_fitness literacy'
'health_wellness mathematics' 'gym_fitness specialneeds'
'charactereducation environmentalscience' 'mathematics performingarts'
'college_careerprep health_wellness' 'college_careerprep performingarts'
'literacy parentinvolvement' 'economics other'
'history_geography mathematics' 'college_careerprep earlydevelopment'
'appliedsciences gym_fitness' 'appliedsciences teamsports'
'health_wellness history_geography'
'college_careerprep health_lifescience'
'charactereducation history_geography' 'socialsciences specialneeds'
'mathematics parentinvolvement' 'financialliteracy specialneeds'
'extracurricular mathematics' 'civics_government health_lifescience'
'parentinvolvement' 'health_wellness performingarts' 'esl other'
'environmentalscience other' 'earlydevelopment performingarts'
'communityservice performingarts' 'appliedsciences esl'
'communityservice history_geography' 'communityservice mathematics'
'health_lifescience music' 'economics literacy'
'college_careerprep financialliteracy' 'charactereducation music'
'college_careerprep music' 'college_careerprep parentinvolvement'
'economics financialliteracy' 'literacy teamsports'
'foreignlanguages specialneeds' 'extracurricular health_lifescience'
'extracurricular health_wellness' 'other socialsciences'
'nutritioneducation teamsports' 'civics_government'
'financialliteracy literacy' 'civics_government literature_writing'
'foreignlanguages other' 'civics_government visualarts'
'charactereducation health_lifescience' 'gym_fitness other'
'communityservice parentinvolvement' 'teamsports visualarts'
'foreignlanguages visualarts' 'other parentinvolvement'
'music teamsports' 'appliedsciences health_wellness'
'economics history_geography' 'earlydevelopment parentinvolvement'
'communityservice health_lifescience'
'foreignlanguages history_geography' 'history_geography other'
'charactereducation parentinvolvement' 'esl performingarts'
'communityservice literature_writing' 'charactereducation esl'
'civics_government communityservice' 'appliedsciences communityservice'
'parentinvolvement specialneeds' 'civics_government college_careerprep'
'communityservice health_wellness' 'charactereducation civics_government'
'esl health_wellness' 'health_lifescience other' 'health_wellness music'
'gym_fitness mathematics' 'earlydevelopment extracurricular'
'music socialsciences' 'economics' 'college_careerprep socialsciences'
'earlydevelopment socialsciences' 'parentinvolvement socialsciences'
'financialliteracy visualarts' 'performingarts specialneeds'
'health_lifescience parentinvolvement' 'foreignlanguages socialsciences'
'civics_government specialneeds' 'earlydevelopment nutritioneducation'
'civics_government financialliteracy' 'gym_fitness nutritioneducation'
'history_geography performingarts' 'esl financialliteracy'
'charactereducation performingarts' 'communityservice socialsciences'
'gym_fitness visualarts' 'foreignlanguages music'
'appliedsciences economics' 'charactereducation financialliteracy'
'literature_writing nutritioneducation' 'extracurricular performingarts'
'civics_government mathematics' 'environmentalscience parentinvolvement'
'mathematics nutritioneducation' 'environmentalscience foreignlanguages'
'college_careerprep nutritioneducation' 'gym_fitness health_lifescience'
'health_lifescience teamsports' 'gym_fitness music'
'nutritioneducation specialneeds' 'appliedsciences performingarts'
'esl nutritioneducation' 'foreignlanguages health_wellness'
'mathematics teamsports' 'civics_government esl'
'environmentalscience gym_fitness' 'gym_fitness history_geography'
'health_wellness parentinvolvement' 'civics_government extracurricular'
'financialliteracy' 'financialliteracy health_wellness'
'earlydevelopment history_geography' 'earlydevelopment teamsports'
'appliedsciences nutritioneducation' 'charactereducation gym_fitness'
'environmentalscience financialliteracy'
'earlydevelopment foreignlanguages' 'college_careerprep gym_fitness'
'communityservice financialliteracy' 'extracurricular nutritioneducation'
'nutritioneducation socialsciences' 'economics literature_writing'
'literature_writing teamsports' 'communityservice nutritioneducation'
'civics_government health_wellness' 'college_careerprep foreignlanguages'
'extracurricular history_geography' 'communityservice esl'
'economics health_lifescience' 'gym_fitness parentinvolvement'
'environmentalscience performingarts' 'environmentalscience music'
'economics environmentalscience' 'esl parentinvolvement'
```

```
 'charactereducation foreignlanguages' 'esl extracurricular'
 'health_wellness warmth care_hunger' 'economics specialneeds'
 'esl gym_fitness' 'charactereducation nutritioneducation'
 'civics_government performingarts' 'extracurricular parentinvolvement'
 'health_lifescience performingarts' 'history_geography teamsports'
 'economics music' 'civics_government foreignlanguages'
 'economics foreignlanguages' 'financialliteracy history_geography'
 'earlydevelopment economics' 'foreignlanguages gym_fitness'
 'economics nutritioneducation' 'communityservice music'
 'foreignlanguages health_lifescience' 'other teamsports'
 'history_geography warmth care_hunger' 'extracurricular foreignlanguages'
 'communityservice gym_fitness' 'music parentinvolvement'
 'earlydevelopment financialliteracy' 'gym_fitness socialsciences'
 'socialsciences teamsports' 'health_lifescience warmth care_hunger'
 'other performingarts' 'communityservice economics'
 'specialneeds warmth care_hunger' 'mathematics warmth care_hunger'
 'warmth care_hunger' 'literacy warmth care_hunger'
 'appliedsciences financialliteracy'
 'nutritioneducation warmth care_hunger'
 'environmentalscience warmth care_hunger' 'visualarts warmth care_hunger'
 'financialliteracy other' 'charactereducation warmth care_hunger'
 'civics_government teamsports' 'literature_writing warmth care_hunger'
 'earlydevelopment warmth care_hunger' 'other warmth care_hunger'
 'economics visualarts' 'charactereducation economics'
 'appliedsciences warmth care_hunger'
 'parentinvolvement warmth care_hunger' 'gym_fitness warmth care_hunger'
 'esl teamsports' 'environmentalscience teamsports'
 'financialliteracy literature_writing'
 'civics_government nutritioneducation' 'financialliteracy socialsciences'
 'parentinvolvement performingarts' 'civics_government parentinvolvement'
 'history_geography parentinvolvement' 'extracurricular financialliteracy'
 'financialliteracy health_lifescience' 'financialliteracy performingarts'
 'financialliteracy parentinvolvement'
 'financialliteracy foreignlanguages' 'esl economics'
 'parentinvolvement teamsports' 'college_careerprep warmth care_hunger']
**********************************************************************************************************

essay:count                                                    109248
unique                                                         108353
top       our students come diverse backgrounds blue col...
freq                                                                9
Name: essay, dtype: object
['i fortunate enough use fairy tale stem kits classroom well stem journals students really enjoyed
i would love implement lakeshore stem kits classroom next school year provide excellent engaging s
tem lessons my students come variety backgrounds including language socioeconomic status many not
lot experience science engineering kits give materials provide exciting opportunities students eac
h month i try several science stem steam projects i would use kits robot help guide science
instruction engaging meaningful ways i adapt kits current language arts pacing guide already teach
material kits like tall tales paul bunyan johnny appleseed the following units taught next school
year i implement kits magnets motion sink vs float robots i often get units not know if i teaching
right way using right materials the kits give additional ideas strategies lessons prepare students
science it challenging develop high quality science activities these kits give materials i need pr
ovide students science activities go along curriculum classroom although i things like magnets cla
ssroom i not know use effectively the kits provide right amount materials show use appropriate way
'
 'imagine 8 9 years old you third grade classroom you see bright lights kid next chewing gum birds
making noise street outside buzzing cars hot teacher asking focus learning ack you need break so s
tudents most students autism anxiety another disability it tough focus school due sensory overload
emotions my students lot deal school i think makes incredible kids planet they kind caring
sympathetic they know like overwhelmed understand someone else struggling they open minded
compassionate they kids someday change world it tough one thing time when sensory overload gets wa
y hardest thing world focus learning my students need many breaks throughout day one best items us
ed boogie board if classroom students could take break exactly need one regardless rooms school oc
cupied many students need something hands order focus task hand putty give sensory input need
order focus calm overloaded help improve motor skills make school fun when students able calm read
y learn when able focus learn retain they get sensory input need prevent meltdowns scary everyone
room this lead better happier classroom community able learn best way possible'
 'having class 24 students comes diverse learners some students learn best auditory means i class
twenty four kindergarten students my students attend title 1 school great majority english
language learners most students come low income homes students receive free breakfast lunch my stu
dents enthusiastic learners often faced many types hardships home school often safe by mobile
listening storage center students able reinforce enhance learning they able listen stories using m
obile listening center help reinforce high frequency words introduced in addition able listen stor
ies reinforce reading comprehension skills strategies amongst auditory experiences a mobile
listening center help keep equipment neat organized ready use help reinforce enhance literacy skil
ls numerous students able use center help increase student learning'
 ...
```

```
 'we title 1 school 650 total students our elementary school students third fifth grade beginning
formal training technology computing many theses children come rural farm backgrounds seen
agriculture action lives connect agriculture sustainability in elementary school students access s
ingle computer technology laboratory all 650 students rotate lab learn science mathematics compute
r programming web design reading computer processing using computers our students rely computing t
echnology currently access chromebooks due state budget issues students would greatly benefit curr
ent computers could use access programs activities google earth geographic information systems sof
tware software could used teach relationship agriculture sustainability these computers populate c
omputer lab currently no computers the old systems 11 years old removed network safety issues coul
d no longer updated repaired we would like teach children taking responsibility environment early
life there several effective ways three computer video games blockhood game students building home
s responsible way it teaches must take account resources water land energy also cityrain teaches b
uilding sustainable cities lastly stopdisasters org teaches planning anticipated potential disaste
rs building accordingly nannan'
 'i teach many different types students my classes full students want change world they unique way
i teach clinical health students grades 9th 12th our school loyal support one another students tak
e class learn health medical field opportunities available they want learn body systems help
others they motivated ready learn they hardworking strive excellence this cricket cutting machine
used making display boards health fair students put together community each group students chooses
different topic want inform community some topics include cancer fitness nutrition skeletal system
mental health blood pressure cpr first aid many each group conducts research creates display board
the cricket machine help enhance presentations community see learn important health care topics th
e health fair free anyone attend provides valuable information attends nannan'
 'my first graders eager learn world around they come school day full enthusiasm genuinely love le
arning our diverse class includes students variety cultural economic backgrounds many come homes p
arents not afford simply not know importance books important provide environment rich literature s
tudents learn love reading i want students lifelong learners reading best way i used magazines pas
t kids absolutely love the topics high interest children always correspond real world issues impor
tant kids learn the subscription also includes online resources videos printable worksheets skill
based games these materials expose students rigorous interesting nonfiction text spark curiosity w
orld around the topics allow teach nonfiction text standards using interesting materials they alwa
ys lead engaging discussions inspire students find additional information various topics nannan']
**************************************************************************************************

remaining_input:count    109248.000000
mean        309.272508
std         368.348015
min           0.900000
25%         113.987500
50%         219.720000
75%         391.595000
max       10157.000000
Name: remaining_input, dtype: float64
[778.05 217.03 339.   ... 313.96 381.87 288.73]
**************************************************************************************************
```

Splitting our data into train and test

In [13]:

```
# Split Train, CV and Test data (64, 16, 20)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data, y, test_size=0.2, stratify=y,random_state
=5)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.2, stratify=y_train,r
andom_state=5)

print('Train Data', X_train.shape, y_train.shape)
print('Cross-Validation Data', X_cv.shape, y_cv.shape)
print('Test Data', X_test.shape, y_test.shape)
```

```
Train Data (69918, 7) (69918,)
Cross-Validation Data (17480, 7) (17480,)
Test Data (21850, 7) (21850,)
```

In [14]:

```
from keras.utils import to_categorical
y_train = to_categorical(y_train)
y_cv = to_categorical(y_cv)
y_test = to_categorical(y_test)
```

In [15]:

```
y_train.shape
```

Out[15]:

```
(69918, 2)
```

Now let's prepare our features for embedding

Cateogrical Featurization

In [17]:

```
from sklearn.preprocessing import LabelEncoder
class LabelEncoderExt(object):
      def __init__(self):
         self.label_encoder = LabelEncoder()
      # self.classes_ = self.label_encoder.classes_
      def fit(self, data_list):

          self.label_encoder = self.label_encoder.fit(list(data_list) + ['Unknown'])
          self.classes_ = self.label_encoder.classes_
          return self
      def transform(self, data_list):

          new_data_list = list(data_list)
          for unique_item in np.unique(data_list):
              if unique_item not in self.label_encoder.classes_:
                      new_data_list = ['Unknown' if x==unique_item else x for x in new_data_list]
          return self.label_encoder.transform(new_data_list)
```

In [18]:

```
from keras.preprocessing import sequence
train_sch_state = X_train.school_state.values
test_sch_state = X_test.school_state.values
cv_sch_state = X_cv.school_state.values
# tokenizer = Tokenizer() #using the TOkenizer function creating an object tokenizer
# tokenizer.fit_on_texts(train_sch_state)#training on train data
# train_sch_state = tokenizer.texts_to_sequences(train_sch_state)#converting text to squences
# test_sch_state = tokenizer.texts_to_sequences(test_sch_state)
# cv_sch_state = tokenizer.texts_to_sequences(cv_sch_state)
# x_train_sch_state = sequence.pad_sequences(train_sch_state, maxlen = max_length, padding='post')
# x_test_sch_state = sequence.pad_sequences(test_sch_state, maxlen = max_length, padding='post')
# x_cv_sch_state = sequence.pad_sequences(cv_sch_state, maxlen = max_length, padding='post')
```

In [19]:

```
le1=LabelEncoderExt()
le1.fit(train_sch_state)
x_train_sch_state=le1.transform(train_sch_state)
x_cv_sch_state=le1.transform(cv_sch_state)
x_test_sch_state=le1.transform(test_sch_state)
```

In [20]:

```
train_proj_grade = X_train.project_grade_category.values
test_proj_grade = X_test.project_grade_category.values
cv_proj_grade = X_cv.project_grade_category.values
# tokenizer = Tokenizer()
# tokenizer.fit_on_texts(train_proj_grade)
# train_proj_grade = tokenizer.texts_to_sequences(train_proj_grade)
# test_proj_grade = tokenizer.texts_to_sequences(test_proj_grade)
# cv_proj_grade = tokenizer.texts_to_sequences(cv_proj_grade)
# x_train_proj_grade = sequence.pad_sequences(train_proj_grade, maxlen = max_length,
padding='post')
# x_test_proj_grade = sequence.pad_sequences(test_proj_grade, maxlen = max_length, padding='post')
# x_cv_proj_grade = sequence.pad_sequences(cv_proj_grade, maxlen = max_length, padding='post')
le1=LabelEncoderExt()
```

```
le1=LabelEncoderExt()
le1.fit(train_proj_grade)
x_train_proj_grade=le1.transform(train_proj_grade)
x_cv_proj_grade=le1.transform(cv_proj_grade)
x_test_proj_grade=le1.transform(test_proj_grade)
```

We can see that each state is converted into numeric using text to sequences
https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/text/Tokenizer

In [21]:

```
train_clean_cat = X_train.clean_categories.values
test_clean_cat = X_test.clean_categories.values
cv_clean_cat = X_cv.clean_categories.values
le1=LabelEncoderExt()
le1.fit(train_clean_cat)
x_train_clean_cat=le1.transform(train_clean_cat)
x_cv_clean_cat=le1.transform(cv_clean_cat)
x_test_clean_cat=le1.transform(test_clean_cat)
```

In [22]:

```
train_clean_sub_cat = X_train.clean_subcategories.values
test_clean_sub_cat = X_test.clean_subcategories.values
cv_clean_sub_cat = X_cv.clean_subcategories.values
le1=LabelEncoderExt()
le1.fit(train_clean_sub_cat)
x_train_clean_sub_cat=le1.transform(train_clean_sub_cat)
x_cv_clean_sub_cat=le1.transform(cv_clean_sub_cat)
x_test_clean_sub_cat=le1.transform(test_clean_sub_cat)
```

In [23]:

```
train_teacher_prefix = X_train.teacher_prefix.values
test_teacher_prefix = X_test.teacher_prefix.values
cv_teacher_prefix = X_cv.teacher_prefix.values
le1=LabelEncoderExt()
le1.fit(train_teacher_prefix)
x_train_teacher_prefix=le1.transform(train_teacher_prefix)
x_cv_teacher_prefix=le1.transform(cv_teacher_prefix)
x_test_teacher_prefix=le1.transform(test_teacher_prefix)
```

Numerical Featurization

In [24]:

```
X_train["remaining_input"] = X_train["remaining_input"].values.reshape(-1,1)
X_train["remaining_input"].shape
from sklearn.preprocessing import MinMaxScaler , StandardScaler

scalar = StandardScaler()
scalar.fit(X_train["remaining_input"].values.reshape(-1,1))
x_train_num = scalar.transform(X_train["remaining_input"].values.reshape(-1,1))
x_test_num = scalar.transform(X_test["remaining_input"].values.reshape(-1,1))
x_cv_num = scalar.transform(X_cv["remaining_input"].values.reshape(-1,1))
print(x_train_num.shape)
print(x_train_num)
```

```
(69918, 1)
[[-0.33347414]
 [-0.56713156]
 [ 3.04850062]
 ...
 [ 0.18106669]
 [-0.43048112]
 [-0.43015144]]
```

Text Data Vectorization

Text Data Vectorization

In [25]:

```
x_train_essay_text = X_train.essay.values.tolist()
x_test_essay_text = X_test.essay.values.tolist()
x_cv_essay_text = X_cv.essay.values.tolist()
print(len(max(x_train_essay_text)))
```

```
910
```

In [26]:

```
# tokenizing
# https://stackoverflow.com/questions/52126539/using-pretrained-gensim-word2vec-embedding-in-keras
# https://machinelearningmastery.com/develop-word-embedding-model-predicting-movie-review-
sentiment/
#t = Tokenizer()
#t.fit_on_texts(x_train_essay_text)
#vocab_size = len(t.word_index) + 1
#print(len(t.word_index))
```

In [ ]:

```
#vocab_size
```

In [27]:

```
#https://machinelearningmastery.com/use-word-embedding-layers-deep-learning-keras/
def padded(encoded_docs):
  max_length = 400
  padded_docs = pad_sequences(encoded_docs, maxlen=max_length, padding='post')
  return padded_docs
```

In [28]:

```
#https://stackoverflow.com/posts/51956230/revisions
t = Tokenizer()
t.fit_on_texts(x_train_essay_text)
vocab_size = len(t.word_index) + 1
print(vocab_size)
# integer encode the documents
encoded_docs = t.texts_to_sequences(x_train_essay_text)
essay_padded_train = padded(encoded_docs)
```

```
47243
```

In [29]:

```
vocab_size
```

Out[29]:

```
47243
```

In [30]:

```
essay_padded_train.shape
```

Out[30]:

```
(69918, 400)
```

In [31]:

```
#t = Tokenizer()
#t.fit_on_texts(x_cross.cleaned_essay)
#vocab_size = len(t.word_index) + 1
# integer encode the documents
```

```
# integer encode the documents
encoded_docs = t.texts_to_sequences(x_cv_essay_text)
essay_padded_cv = padded(encoded_docs)
```

In [32]:

```
#t = Tokenizer()
#t.fit_on_texts(x_test.cleaned_essay)
#vocab_size = len(t.word_index) + 1
# integer encode the documents
encoded_docs = t.texts_to_sequences(x_test_essay_text)
essay_padded_test = padded(encoded_docs)
```

In [33]:

```
print(essay_padded_train.shape)
print(essay_padded_test.shape)
print(essay_padded_cv.shape)
```

```
(69918, 400)
(21850, 400)
(17480, 400)
```

In [34]:

```
embedding_matrix = np.zeros((vocab_size, 300))
for word, i in t.word_index.items():
    embedding_vector = db.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

In [35]:

```
embedding_matrix.shape
```

Out[35]:

```
(47243, 300)
```

In [36]:

```
# https://stackoverflow.com/questions/41032551/how-to-compute-receiving-operating-characteristic-roc-and-auc-in-keras
def auroc(y_true, y_pred):
    # print(y_true, y_pred)
    return tf.py_function(roc_auc_score, (y_true, y_pred), tf.double)
```

In [46]:

```
from keras.optimizers import Adam
#input 1
input_1 = Input(shape=(400,))
x1 =Embedding(vocab_size, 300, weights=[embedding_matrix], input_length=400, trainable=False)(input_1)
#what are spartial dropouts - https://machinelearningmastery.com/how-to-reduce-overfitting-with-dropout-regularization-in-keras/
#https://stackoverflow.com/questions/50393666/how-to-understand-spatialdropout1d-and-when-to-use-it
x1 = LSTM(100,return_sequences=True, activation = 'relu',recurrent_dropout=0.5,kernel_regularizer=l2(0.001))(x1)
#x1= LeakyReLU(alpha = 0.3)(x1)
x1 = Flatten()(x1)

#input 2
input_2 = Input(shape=(1,))#school_state
x2 = Embedding(input_dim= 52, output_dim= min(52//2,50))(input_2)
x2 = Flatten()(x2)

#input 3
input_3 = Input(shape=(1,)) #project_grade
x3 = Embedding(input_dim = 52, output_dim= min(52//2,50))(input_3)
```

```
x3 = Embedding(input_dim = 52, output_dim= min(52//2,50))(input_3)
x3 = Flatten()(x3)

#input 4
input_4 = Input(shape=(1,)) #clean_categories
x4 = Embedding(input_dim=52,output_dim= min(52//2,50))(input_4)
x4 = Flatten()(x4)

#input 5
input_5 = Input(shape=(1,)) #clean_subcategories
x5 = Embedding(input_dim= 390, output_dim= min(390//2,50))(input_5)
x5 = Flatten()(x5)

#input 6
input_6 = Input(shape=(1,))#teacher_prefix
x6 = Embedding(input_dim= 6,output_dim= min(6//2,50))(input_6)
x6 = Flatten()(x6)

#input 7
input_7 = Input(shape=(1,)) #numerical
x7 = Dense(16,activation='relu',kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))
(input_7)

#merging all the inputs
concat = concatenate([x1,x2,x3,x4,x5,x6,x7])
x = BatchNormalization()(concat)

x = Dense(256,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(concat)
x= LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.6)(x)
x = Dense(128,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
x = LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.5)(x)
x = Dense(64,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
x = LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.5)(x)
x = Dense(32,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
x = LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.5)(x)
#x = Dense(16,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
#x = LeakyReLU(alpha = 0.3)(x)
output = Dense(2, activation = 'softmax')(x)

# model with all the inputs
model1 = Model([input_1, input_2, input_3, input_4, input_5, input_6, input_7], output)
model1.run_eagerly = True
#tensorboard = TensorBoard(log_dir="logs".format(time()))
tensorboard = TensorBoard(log_dir="/content/drive/My Drive/LSTM_Output/logs/{}".format(time()))
model1.compile(loss='categorical_crossentropy', optimizer=Adam(lr=0.0006,decay = 1e-4), metrics=[au
roc])
print(model1.summary())
```

```
Model: "model_4"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_22 (InputLayer)           (None, 400)          0
__________________________________________________________________________________________________
embedding_19 (Embedding)        (None, 400, 300)     14172900    input_22[0][0]
__________________________________________________________________________________________________
input_23 (InputLayer)           (None, 1)            0
__________________________________________________________________________________________________
input_24 (InputLayer)           (None, 1)            0
__________________________________________________________________________________________________
input_25 (InputLayer)           (None, 1)            0
__________________________________________________________________________________________________
input_26 (InputLayer)           (None, 1)            0
__________________________________________________________________________________________________
input_27 (InputLayer)           (None, 1)            0
__________________________________________________________________________________________________
lstm_4 (LSTM)                   (None, 400, 100)     160400      embedding_19[0][0]
__________________________________________________________________________________________________
embedding_20 (Embedding)        (None, 1, 26)        1352        input_23[0][0]
__________________________________________________________________________________________________
embedding_21 (Embedding)        (None, 1, 26)        1352        input_24[0][0]
__________________________________________________________________________________________________
embedding_22 (Embedding)        (None, 1, 26)        1352        input_25[0][0]
```

embedding_23 (Embedding)	(None, 1, 50)	19500	input_26[0][0]
embedding_24 (Embedding)	(None, 1, 3)	18	input_27[0][0]
input_28 (InputLayer)	(None, 1)	0	
flatten_19 (Flatten)	(None, 40000)	0	lstm_4[0][0]
flatten_20 (Flatten)	(None, 26)	0	embedding_20[0][0]
flatten_21 (Flatten)	(None, 26)	0	embedding_21[0][0]
flatten_22 (Flatten)	(None, 26)	0	embedding_22[0][0]
flatten_23 (Flatten)	(None, 50)	0	embedding_23[0][0]
flatten_24 (Flatten)	(None, 3)	0	embedding_24[0][0]
dense_19 (Dense)	(None, 16)	32	input_28[0][0]
concatenate_4 (Concatenate)	(None, 40147)	0	flatten_19[0][0] flatten_20[0][0] flatten_21[0][0] flatten_22[0][0] flatten_23[0][0] flatten_24[0][0] dense_19[0][0]
dense_20 (Dense)	(None, 256)	10277888	concatenate_4[0][0]
leaky_re_lu_13 (LeakyReLU)	(None, 256)	0	dense_20[0][0]
dropout_13 (Dropout)	(None, 256)	0	leaky_re_lu_13[0][0]
dense_21 (Dense)	(None, 128)	32896	dropout_13[0][0]
leaky_re_lu_14 (LeakyReLU)	(None, 128)	0	dense_21[0][0]
dropout_14 (Dropout)	(None, 128)	0	leaky_re_lu_14[0][0]
dense_22 (Dense)	(None, 64)	8256	dropout_14[0][0]
leaky_re_lu_15 (LeakyReLU)	(None, 64)	0	dense_22[0][0]
dropout_15 (Dropout)	(None, 64)	0	leaky_re_lu_15[0][0]
dense_23 (Dense)	(None, 32)	2080	dropout_15[0][0]
leaky_re_lu_16 (LeakyReLU)	(None, 32)	0	dense_23[0][0]
dropout_16 (Dropout)	(None, 32)	0	leaky_re_lu_16[0][0]
dense_24 (Dense)	(None, 2)	66	dropout_16[0][0]

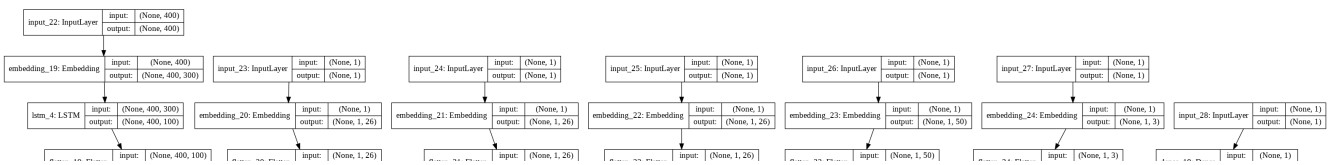
Total params: 24,678,092
Trainable params: 10,505,192
Non-trainable params: 14,172,900

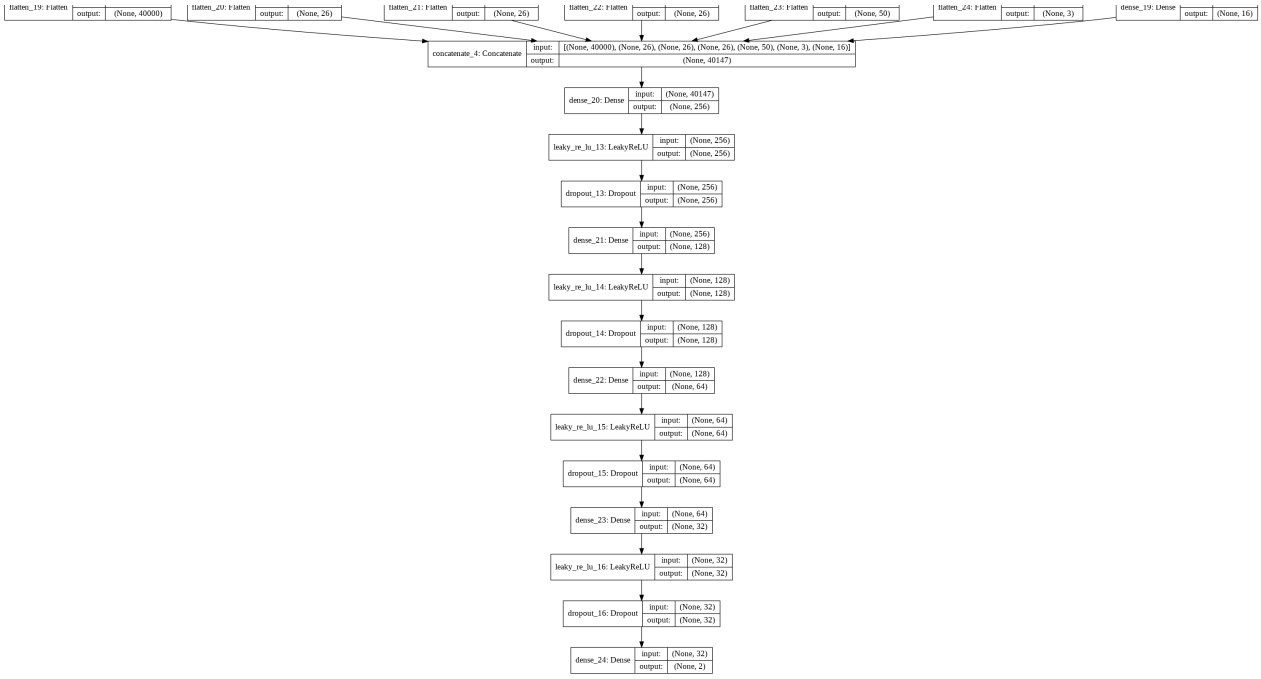
None

In [47]:

```
#https://machinelearningmastery.com/visualize-deep-learning-neural-network-model-keras/
from keras.utils.vis_utils import plot_model
plot_model(model1, to_file='/content/drive/My Drive/LSTM_Output/model_1.png', show_shapes=True,
show_layer_names=True)
```

Out[47]:





In [42]:

```
x_train = [essay_padded_train
,x_train_sch_state,x_train_proj_grade,x_train_clean_cat,x_train_clean_sub_cat,x_train_teacher_prefi
x,x_train_num]
x_test =
[essay_padded_test,x_test_sch_state,x_test_proj_grade,x_test_clean_cat,x_test_clean_sub_cat,x_test_
teacher_prefix,x_test_num]
x_cv = [essay_padded_cv
,x_cv_sch_state,x_cv_proj_grade,x_cv_clean_cat,x_cv_clean_sub_cat,x_cv_teacher_prefix,x_cv_num]
```

In [48]:

```
adam = keras.optimizers.Adam(lr=0.0006)
model1.compile(optimizer=adam, loss='categorical_crossentropy',metrics=[auroc])
```

In [49]:

```
from keras.callbacks import *
filepath="/content/drive/My Drive/LSTM_Output/model1/epochs:{epoch:03d}-val_acc:{val_auroc:.3f}.hd
f5"
checkpoint_1 = ModelCheckpoint(filepath, monitor='val_acc', verbose=1, mode='max')
```

In [50]:

```
filepath = "/content/drive/My Drive/weights_2.best.hdf5"
earlystopping1 = EarlyStopping(monitor='val_loss', patience=2, verbose=1)

#checkpoint2 = ModelCheckpoint(filepath, monitor='val_auc', verbose=1, save_best_only=True, mode='
max')
tensorboard = TensorBoard(log_dir="/content/drive/My Drive/LSTM_Output/logs/{}".format(time()))
callbacks_list = [checkpoint_1,tensorboard, earlystopping1]#, reduce_lr2]

history1= model1.fit(x_train, y_train, epochs=20, verbose=1, batch_size=300, validation_data=(x_cv
, y_cv),callbacks=callbacks_list)
#model2.save('/content/drive/My Drive/weights_2.best.hdf5')
```

```
Train on 69918 samples, validate on 17480 samples
Epoch 1/20
69918/69918 [==============================] - 180s 3ms/step - loss: 0.7282 - auroc: 0.6022 - val_
loss: 0.5247 - val_auroc: 0.7180

Epoch 00001: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:001-
val_acc:0.718.hdf5
Epoch 2/20
69918/69918 [==============================] - 174s 2ms/step - loss: 0.5044 - auroc: 0.7033 - val_
loss: 0.4768 - val auroc: 0.7261
```

```
Epoch 00002: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:002-
val_acc:0.726.hdf5
Epoch 3/20
69918/69918 [==============================] - 173s 2ms/step - loss: 0.4662 - auroc: 0.7279 - val_
loss: 0.4521 - val_auroc: 0.7323

Epoch 00003: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:003-
val_acc:0.732.hdf5
Epoch 4/20
69918/69918 [==============================] - 181s 3ms/step - loss: 0.4463 - auroc: 0.7451 - val_
loss: 0.4430 - val_auroc: 0.7354

Epoch 00004: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:004-
val_acc:0.735.hdf5
Epoch 5/20
69918/69918 [==============================] - 182s 3ms/step - loss: 0.4360 - auroc: 0.7534 - val_
loss: 0.4398 - val_auroc: 0.7371

Epoch 00005: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:005-
val_acc:0.737.hdf5
Epoch 6/20
69918/69918 [==============================] - 181s 3ms/step - loss: 0.4279 - auroc: 0.7656 - val_
loss: 0.4424 - val_auroc: 0.7337

Epoch 00006: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:006-
val_acc:0.734.hdf5
Epoch 7/20
69918/69918 [==============================] - 181s 3ms/step - loss: 0.4235 - auroc: 0.7738 - val_
loss: 0.4442 - val_auroc: 0.7320

Epoch 00007: saving model to /content/drive/My Drive/LSTM_Output/model1/epochs:007-
val_acc:0.732.hdf5
Epoch 00007: early stopping
```

In [51]:

```
from keras.optimizers import Adam
#input 1
input_1 = Input(shape=(400,))
x1 =Embedding(vocab_size, 300, weights=[embedding_matrix], input_length=400, trainable=False)(input
_1)
#what are spartial dropouts - https://machinelearningmastery.com/how-to-reduce-overfitting-with-dr
opout-regularization-in-keras/
#https://stackoverflow.com/questions/50393666/how-to-understand-spatialdropout1d-and-when-to-use-i
t
x1 = LSTM(100,return_sequences=True, activation = 'relu',recurrent_dropout=0.5,kernel_regularizer=l
2(0.001))(x1)
#x1= LeakyReLU(alpha = 0.3)(x1)
x1 = Flatten()(x1)

#input 2
input_2 = Input(shape=(1,))#school_state
x2 = Embedding(input_dim= 52, output_dim= min(52//2,50))(input_2)
x2 = Flatten()(x2)

#input 3
input_3 = Input(shape=(1,)) #project_grade
x3 = Embedding(input_dim = 52, output_dim= min(52//2,50))(input_3)
x3 = Flatten()(x3)

#input 4
input_4 = Input(shape=(1,)) #clean_categories
x4 = Embedding(input_dim=52,output_dim= min(52//2,50))(input_4)
x4 = Flatten()(x4)

#input 5
input_5 = Input(shape=(1,)) #clean_subcategories
x5 = Embedding(input_dim= 390, output_dim= min(390//2,50))(input_5)
x5 = Flatten()(x5)

#input 6
input_6 = Input(shape=(1,))#teacher_prefix
x6 = Embedding(input_dim= 6,output_dim= min(6//2,50))(input_6)
x6 = Flatten()(x6)
```

```
#input 7
input_7 = Input(shape=(1,)) #numerical
x7 = Dense(16,activation='relu',kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))
(input_7)

#merging all the inputs
concat = concatenate([x1,x2,x3,x4,x5,x6,x7])
x = BatchNormalization()(concat)

x = Dense(256,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(concat)
x= LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.6)(x)
x = Dense(128,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
x = LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.5)(x)
x = Dense(64,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
x = LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.5)(x)
x = Dense(32,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
x = LeakyReLU(alpha = 0.3)(x)
x = Dropout(0.5)(x)
#x = Dense(16,kernel_initializer=he_normal(),kernel_regularizer=l2(0.0001))(x)
#x = LeakyReLU(alpha = 0.3)(x)
output = Dense(2, activation = 'softmax')(x)

# model with all the inputs
model1 = Model([input_1, input_2, input_3, input_4, input_5, input_6, input_7], output)
model1.run_eagerly = True
#tensorboard = TensorBoard(log_dir="logs".format(time()))
tensorboard = TensorBoard(log_dir="/content/drive/My Drive/LSTM_Output/logs/{}".format(time()))
#model1.compile(loss='categorical_crossentropy', optimizer=Adam(lr=0.0006,decay = 1e-4), metrics=[
auroc])
#print(model1.summary())
model1.load_weights("/content/drive/My Drive/LSTM_Output/model1/epochs:005-val_acc:0.737.hdf5")
```

In [53]:

```
print("Auc for test data: %0.3f"%roc_auc_score(y_test,model1.predict(x_test)))
print("Auc for CV data: %0.3f"%roc_auc_score(y_cv,model1.predict(x_cv)))
print("Auc for train data: %0.3f"%roc_auc_score(y_train,model1.predict(x_train)))
```

```
Auc for test data: 0.752
Auc for CV data: 0.737
Auc for train data: 0.788
```

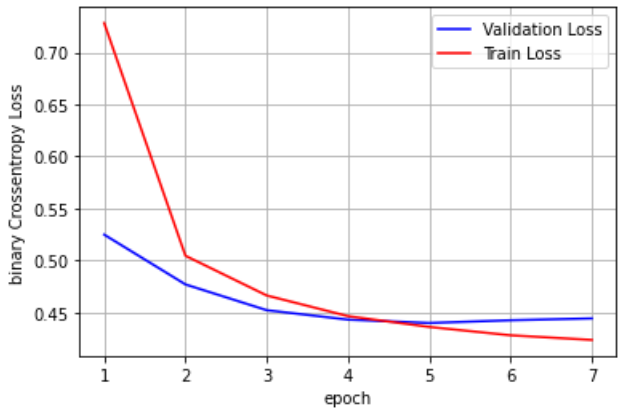
In [54]:

```
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

In [56]:

```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('binary Crossentropy Loss')

# list of epoch numbers
x = list(range(1,7+1))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
```

```
# for each key in histrory.histrory we will have a list of length equal to number of epochs


vy = history1.history['val_loss']
ty = history1.history['loss']
plt_dynamic(x, vy, ty, ax)
```

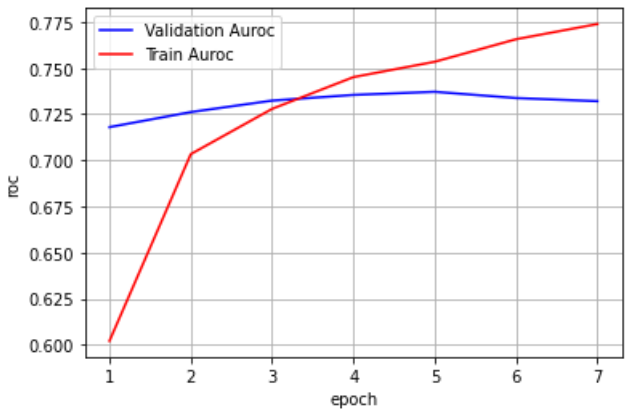


In [59]:

```
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Auroc")
    ax.plot(x, ty, 'r', label="Train Auroc")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

In [61]:

```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('roc')

# list of epoch numbers
x = list(range(1,7+1))

# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in histrory.histrory we will have a list of length equal to number of epochs


vy = history1.history['val_auroc']
ty = history1.history['auroc']
plt_dynamic(x, vy, ty, ax)
```



Observation

We can see that at first both the training and validation losses are decreasing but after epoch reaches to 5 validation loss increases again but training loss keeps on decreasing