Gender_segmentation

May 25, 2020

Import relevant modules

[2]:
```
import pandas as pd
import numpy as np
import os,math,timeit,time,json
import matplotlib.pyplot as plt
import seaborn as sns
import dask.dataframe as dd

from sklearn import preprocessing
from sklearn.model_selection import␣
↪train_test_split,GridSearchCV,StratifiedKFold,RandomizedSearchCV
from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.feature_selection import SelectFromModel

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import␣
↪RandomForestClassifier,ExtraTreesClassifier,AdaBoostClassifier
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.naive_bayes import GaussianNB,MultinomialNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.ensemble import GradientBoostingClassifier
from xgboost.sklearn import XGBClassifier

# neural network
from keras import Sequential,models,regularizers,layers
from keras.models import load_model
from keras.layers import Dense,Dropout
from keras.callbacks import EarlyStopping
from keras.callbacks import ModelCheckpoint
```

```
Using TensorFlow backend.
```

Define required help functions

[3]:
```
def parse_json_file(filename):
    '''
       Convert a large json file into a Pandas Dataframe
    '''
    with open(filename,'rb') as json_file:
        data = json_file.readlines()
        # It converts all strings in list to actual json objects. This is␣
↪faster than pandas read_json
        data = list(map(json.loads, data))
    return pd.DataFrame(data)
```

[4]:
```
def list_to_string(colnames,dfname):
    '''
       Convert the list values in colnames into strings
    '''
    for col in colnames:
        dfname[col].fillna(value='',inplace=True)
        dfname[col]= [','.join(map(str, l)) for l in dfname[col] ]
    return dfname
```

[5]:
```
def dedup_data(df,keylist = []):
    ''' remove full row duplicates from the given dataframe    '''
    if not keylist:
        return df.drop_duplicates(keep='first')
    else:
        return df.drop_duplicates(subset = keylist,keep='first')
```

[6]:
```
def prep_Data(df):
    '''A generic function to load a given file, display basic analysis and␣
↪return a pandas dataframe'''

    percent_missing = df.isnull().sum() * 100 / len(df)
    missing_value_df = pd.DataFrame({'column_name': df.
↪columns,'percent_missing': percent_missing})
    missing_value_df.sort_values('percent_missing',ascending =False,␣
↪inplace=True)

    print('\n Basic Metadata \n')
    print(df.info())
    print('\n Missing values information \n')
    print(missing_value_df[missing_value_df.percent_missing>0])

    return df
```

[7]:
```python
def imputeNulls(df):
    ''' Find and impute null/missing values based on data type'''

    nullcols = df.columns[df.isna().any()].tolist()

    for c in nullcols:
        if df[c].dtype=='object':
            df[c] = df[c].fillna('')
        else:
            df[c] = df[c].fillna(0)

    print('\n List of columns with missing values now :',df.columns[df.isna().
↪any()].tolist())

    return df
```

[8]:
```python
def encode_cols(df,target_col=''):
    '''Encode all categorical columns'''
    #prepare list of all categorical variables in the dataset
    catlist = df.select_dtypes(include='object').columns.tolist()
    if target_col:
        catlist = [ c for c in catlist if c!=target_col]
        df[target_col] = df[target_col].apply(lambda x:0 if x=='F' else 1)


    label_encoder = preprocessing.LabelEncoder()
    df[catlist] = df[catlist].apply(label_encoder.fit_transform)


    return df
```

[9]:
```python
def scale_cols(df,scaler,excep_list):
    '''Scale continuous variables in data'''

    #prepare list of all continuos variables in the dataset
    contvars = df.select_dtypes(exclude='object').columns.tolist()
    contvars = [c for c in contvars if c not in excep_list]

    df[contvars] = scaler.fit_transform(df[contvars])
    return df
```

[10]:
```python
def class_dist(df,target_col):
    '''Produce a graph of target class distribution for analysis '''

    df1 = pd.crosstab(index = df[target_col], columns = "count")
    df1['percent'] = df1/df1.sum() * 100

```

```python
    print('\n Check target class distribution \n')
    print(df1)

    # graph of class distribution of the target variable
    df1.plot(kind='barh')
    plt.show()
    return None
```

[11]:
```python
def level_chk(df):
    '''Show the numbe rof levels of each feature in dataframe'''

    cols = df.select_dtypes(exclude='object').columns.tolist()
    nlevels = [ (c,df[c].nunique()) for c in cols]

    print(pd.DataFrame(sorted(nlevels,key = lambda x:x[1]),columns =␣
↪['col_name','n_levels']))
    return None
```

[12]:
```python
def reduce_dims(df,target_col):
        cols_retained = [ c for c in df.columns if c!=target_col]
        model = ExtraTreesClassifier(random_state=42,class_weight='balanced') #␣
↪for repeatability of results
        # send only 5k rows for quick response
        fsga = FSGA.FeatureSelectionGA(model,df.loc[:8000,cols_retained].values
                                       ,df.loc[:8000,target_col])
        pop = fsga.generate(100)
        new_retained = []
        prev_cols = len(cols_retained)

        for ind,val in enumerate(pop):
            if val:
                new_retained.append(cols_retained[ind])

        cols_retained = new_retained[:]
        print("\n Columns retained after Genetic Selection Algorithm are:␣
↪\n",cols_retained)
        print("\n {} columns retained out of {} \n".
↪format(len(cols_retained),prev_cols))
        return df[cols_retained+[target_col]]
```

[13]:
```python
def plot_feature_imp(df,target_col):
    '''
    Plot a feautre importance graph for analysis
    '''
```

```
    clf =␣
↪ExtraTreesClassifier(n_estimators=10,random_state=42,class_weight='balanced')␣
↪# for repeatability of results

    X = df[[c for c in df.columns if c!=target_col]]
    y = df[target_col]
    clf.fit(X,y)

    pd.Series(clf.feature_importances_, index=df.columns[1:]).plot.
↪bar(color='steelblue', figsize=(12, 18))
    plt.show()
    return clf,X,y
```

[14]:
```
def plot_corr(df):
    # Basic correlogram
    corr=df.corr()
    fig, ax = plt.subplots(figsize=(12,16))
    sns.heatmap(corr,xticklabels=corr.columns.values,yticklabels=corr.columns.
↪values,annot=True,ax=ax)
    plt.show()
    return None
```

[15]:
```
def create_Xy(df,target_col,imbalance = 'N'):
    '''
    Separate the predictors from the target
    '''
    # assign variables and target data
    y = df[target_col]
    X = df.loc[:,df.columns!=target_col]
    model_cols = X.columns # store the columns to be used as predictors

    if imbalance == 'Y':
        # use SMOTE-Synthetic Minority Over-sampling Technique to balance out␣
↪the target classes
        sm = SMOTE(random_state=42)
        X,y = sm.fit_resample(X, y)


    print('\n No: of predictor variables is: {} and no:of observations for␣
↪training is: {} \n'.format(X.shape[1],X.shape[0]))
    return X,y,model_cols
```

[43]:
```
def␣
↪creatNN(inp_cols,inp_rows,activation='relu',kernel_initializer='uniform',alpha=10,droporate
↪5):
    base_model = models.Sequential()
```

```
    '''
     Nh=Ns/( *(Ni+No))

     Ni= number of input neurons(inp_cols)
     No = number of output neurons(1)
     Ns = number of samples in training data set(inp_rows)
       = an arbitrary scaling factor usually 2-10 (alpha)

     OR Nh = 2/3 *(inp_cols+1)
     '''

    #Hidden Layer
    #base_model.add(layers.Dense(int(inp_rows/(alpha*(inp_cols+1))),␣
↪activation=activation, kernel_initializer=kernel_initializer                ␣
↪
    #                     ,kernel_regularizer=regularizers.l2(0.
↪001),input_dim=inp_cols))
    base_model.add(layers.Dense(int((2/3)*(inp_cols+1)+inp_cols),␣
↪activation=activation, kernel_initializer=kernel_initializer
                          ,kernel_regularizer=regularizers.l2(0.
↪0018),input_dim=inp_cols))
    base_model.add(layers.Dropout(droporate))

    #Output Layer
    base_model.add(layers.Dense(1, activation='sigmoid',␣
↪kernel_initializer=kernel_initializer))

    # compile model for a binary classification problem
    base_model.compile(optimizer ='rmsprop',loss='binary_crossentropy', metrics␣
↪=['accuracy'])

    return base_model
```

[17]:
```
def F1_score(model_obj,X,y,nn='N',n=10):
    '''Function to calculate the F1 score averaged over a n fold CV set'''
    SEED=42
    mean_f1 = 0.0
    n_cv=0
    skf = StratifiedKFold(n_splits=n,random_state=SEED,shuffle =True)

    if nn=='Y':
        for train_index, test_index in skf.split(X, y):
            n_cv+=1
            X_train, X_cv = X[train_index], X[test_index]
            y_train, y_cv = y[train_index], y[test_index]
```

```
            #fit and predict the target labels for a neural network
            #model_obj.fit(X_train, y_train,batch_size=10, epochs=5)
            # patient early stopping
            es = EarlyStopping(monitor='val_loss', mode='min', verbose=1,␣
↪patience=0)
            mc = ModelCheckpoint('best_model.h5', monitor='val_acc',␣
↪mode='max', verbose=1, save_best_only=True)
            # fit model, make sure to load the best model trained over the last␣
↪cv fold
            if n_cv>1:
                model_obj = load_model('best_model.h5')
            history = model_obj.fit(X_train, y_train, validation_data=(X_cv,␣
↪y_cv), epochs=10, callbacks=[es,mc])
            # evaluate the model
            _, train_acc = model_obj.evaluate(X_train, y_train, verbose=0)
            _, test_acc = model_obj.evaluate(X_cv, y_cv, verbose=0)
            print('Train: %.3f, Test: %.3f' % (train_acc, test_acc))
            # plot training history
            plt.plot(history.history['loss'], label='train')
            plt.plot(history.history['val_loss'], label='test')
            plt.legend()
            plt.show()

            preds = model_obj.predict(X_cv)
            preds = (preds>0.5).astype(int)

            # compute f1 metric for this CV fold
            f1_score = metrics.f1_score(y_cv, preds,average='macro')
            print("\n Best F1 score for CV fold no:{} was:{}\n".
↪format(n_cv,f1_score))
            mean_f1 += f1_score
        # load the saved model
        model_obj = load_model('best_model.h5')
        # evaluate the model
        _, train_acc = model_obj.evaluate(X_train, y_train, verbose=0)
        _, test_acc = model_obj.evaluate(X_cv, y_cv, verbose=0)
        print('\n Best Model has the following scores :\n')
        print('Train: %.3f, Test: %.3f' % (train_acc, test_acc))
    else:
        for train_index, test_index in skf.split(X, y):
            n_cv+=1
            X_train, X_cv = X[train_index], X[test_index]
            y_train, y_cv = y[train_index], y[test_index]
            #fit and predict the target labels
            model_obj.fit(X_train, y_train)
            preds = model_obj.predict(X_cv)
```

```
            # compute f1 metric for this CV fold
            f1_score = metrics.f1_score(y_cv, preds,average='macro')
            print("\n F1 score for CV fold no:{} was:{}\n".
↪format(n_cv,f1_score))
            mean_f1 += f1_score
    return  (mean_f1/n),model_obj
```

Stage 1: Load Data, Deduplicate and Merge the 3 separate datasets

[18]:
```
# 1. Process the urls data file

filename = 'Urls_data.txt'
df_urls_data =  parse_json_file(filename) # use helper JSON function to load␣
↪the file

df_urls_data = list_to_string(['alt_titles','entities','tags'],df_urls_data) #␣
↪convert list data to strings

df_urls_data = dedup_data(df_urls_data,keylist=['link']) # dedupe records based␣
↪on link
```

[19]:
```
df_urls_data.id.nunique()
# id column is not statistically significant as its generated by a system and␣
↪is unqiue for each observation
# We remove it at this stage itself as we know our Objective is Prediction
# we also drop the description column as it is just a shortened form of long␣
↪description and carries no extra info
df_urls_data.drop(['id','description'],axis=1,inplace=True)
```

Perform basic EDA on the processed Urls Data File

[20]:
```
df_urls_data.head() # note that columns with missing values show up as empty
```

[20]:
```
  alt_titles brand                             entities  \
0               ET                           Land Rover
1               ET
2               ET  Prime Minister Narendra Modi,Ganga
3               ET        Prime Minister Narendra Modi
4               ET  Sandip Sabharwal,Basant Maheshwari

                                                link  \
0  https://economictimes.indiatimes.com/industry/…
1  https://economictimes.indiatimes.com/auto-comp…
2  https://economictimes.indiatimes.com/news/poli…
3  https://economictimes.indiatimes.com/news/elec…
4  https://economictimes.indiatimes.com/markets/s…
```

```
                                    long_description tags  \
0  Default Agency Option of electrification The c…
1  Flipboard Google Plus Forget Tesla, this India…
2  Flipboard Google Plus Water quality of Ganga h…
3  Mar 04, 2019, 07.42 AM IST 0Comments PTI He to…
4  Mar 17, 2019, 10.38 AM IST 0Comments AP Tweets…

                                               title
0  Tata-owned JLR launches new luxury SUV- Range …
1  Forget Tesla, this Indian battery can change t…
2  Water quality of Ganga has worsened in 3 years…
3  Statements made by opposition are making enemi…
4  Tweet Buster: Top investment tips and what dis…
```

[21]:
```
# 2. Process the main Training data file with UserId and Gender information

df_userId_gender = pd.read_csv('UserIdToGender_Train.csv')
df_userId_gender = dedup_data(df_userId_gender,keylist=['userid']) # dedupe the data based on userid
```

Perform basic EDA on the processed URL to Gender Data File

[22]:
```
df_userId_gender.shape
```

[22]:
```
(229444, 2)
```

[23]:
```
df_userId_gender.head()
```

[23]:
```
    userid gender
0  4834460      M
1  4834437      M
2  4834411      F
3  4834405      M
4  4834352      M
```

[24]:
```
# 3. Process the part files with UserId and URL information

UserIdToUrl_part_files = [ f for f in os.listdir() if f.find('part',0,4)!=-1] # collect all filenames of the 11 part files

# this is lengthy process and takes around 15-18 minutes. This uses dask parallelized dataframes
# as they are faster than Pandas dataframes

start_time = timeit.default_timer()

file_list=[]
```

```
for f in UserIdToUrl_part_files:
    csv_f = dd.read_csv(f, usecols = range(2),low_memory=False)
    print('length of file{} is:{} '.format(f,len(csv_f)))
    file_list.append(csv_f)
df_userId_url = dd.concat(file_list,axis=0)

# convert the distributed dask dataframes to a pandas dataframe
df_userId_url = df_userId_url.compute()

df_userId_url=dedup_data(df_userId_url,keylist=['userid']) # dedupe the records

print('Elapsed Time approx :{} minutes'.format((timeit.default_timer() -␣
↪start_time)/60))
```

```
length of filepart-00000 is:4376400
length of filepart-00001 is:4714985
length of filepart-00002 is:4655516
length of filepart-00003 is:4515605
length of filepart-00004 is:4478587
length of filepart-00005 is:4566880
length of filepart-00006 is:4230262
length of filepart-00007 is:4665940
length of filepart-00008 is:4564013
length of filepart-00009 is:4376976
length of filepart-00010 is:4618130
length of filepart-00011 is:4696663
Elapsed Time approx :10.682767652266667 minutes
```

Perform basic EDA on the processed UserId to URL Data File

[25]:
```
df_userId_url.shape # note that a single userID may be attached to multiple URLs
```

[25]: (317828, 2)

[26]:
```
df_userId_url.head()
```

[26]:

	userid	url
0	2616607	http://timesofindia.indiatimes.com/
13	2316835	https://timesofindia.indiatimes.com/blogs/Swam…
89	3503424	http://nprssfeeds.indiatimes.com/feeds/appnavi…
97	3241218	https://timesofindia.indiatimes.com/interestin…
128	4121856	https://timesofindia.indiatimes.com/india

Now merge and deduplicate the individual datasets

[76]:
```
#1. First, merge gender UserID to UserID to URL data using UserId as the␣
↪key(Index)
```

```
df_train = df_userId_gender.set_index('userid')
df_userId_url = df_userId_url.set_index('userid')

# perform left outer join to retain all data in the training(UserID, Gender)␣
↪file
df_train = df_train.merge(df_userId_url, on='userid',how='outer')

df_train.reset_index(inplace=True)

df_train = dedup_data(df_train) # dedupe again after the join

#2. Next, merge UserID gender and URL file to URL data using url and link as␣
↪keys(Index)

df_train.set_index('url',inplace=True) # set index to key column for merge
df_urls_data.set_index('link',inplace = True) # set index to key column for␣
↪merge

# perform left outer join to retain all data in the training(UserID, Gender)␣
↪file
df_train = df_train.merge(df_urls_data,␣
↪right_on='link',left_index=True,how='outer')

df_train.reset_index(inplace=True)

df_train = dedup_data(df_train) # final dedupe again after all joins
```

[77]:
```
df_train.shape
```

[77]:
```
(394676, 9)
```

[78]:
```
df_train.drop('userid',1,inplace=True)
df_train.head()
```

[78]:
```
                                 link gender alt_titles          brand  \
0  http://timesofindia.indiatimes.com/      M             TIMES OF INDIA
1  http://timesofindia.indiatimes.com/      M             TIMES OF INDIA
2  http://timesofindia.indiatimes.com/      M             TIMES OF INDIA
3  http://timesofindia.indiatimes.com/      M             TIMES OF INDIA
4  http://timesofindia.indiatimes.com/      F             TIMES OF INDIA

  entities long_description tags                                        title
0                      NaN       India News, Latest Sports, Bollywood, World,
1                      NaN       India News, Latest Sports, Bollywood, World,
2                      NaN       India News, Latest Sports, Bollywood, World,
3                      NaN       India News, Latest Sports, Bollywood, World,
4                      NaN       India News, Latest Sports, Bollywood, World,
```

Stage 2: Preprocess, encode and make data ready for modelling

[79]:
```
target_col = 'gender'

df_train = prep_Data(df_train)
df_train = imputeNulls(df_train)
df_train = encode_cols(df_train,target_col=target_col)


scaler = MinMaxScaler()
df_train = scale_cols(df_train,scaler,[target_col])
```

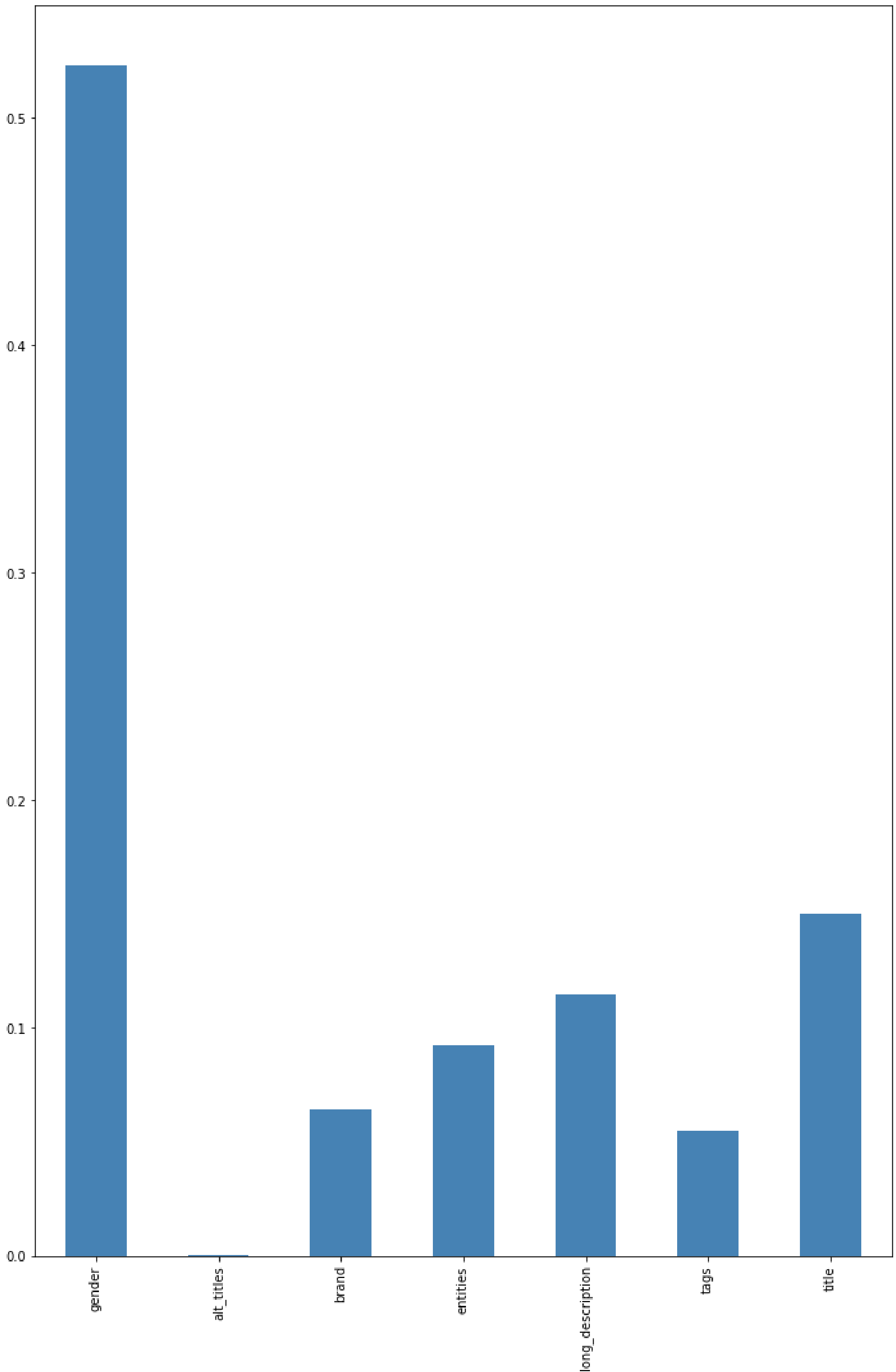
```
 Basic Metadata

<class 'pandas.core.frame.DataFrame'>
Int64Index: 394676 entries, 0 to 394675
Data columns (total 8 columns):
link                394676 non-null object
gender              229444 non-null object
alt_titles          256500 non-null object
brand               256159 non-null object
entities            256500 non-null object
long_description    123744 non-null object
tags                256500 non-null object
title               256500 non-null object
dtypes: object(8)
memory usage: 27.1+ MB
None

 Missing values information

                       column_name  percent_missing
long_description  long_description        68.646687
gender                      gender        41.865226
brand                        brand        35.096383
alt_titles              alt_titles        35.009983
entities                  entities        35.009983
tags                          tags        35.009983
title                        title        35.009983

 List of columns with missing values now : []
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:334:
DataConversionWarning: Data with input dtype int32 were all converted to float64
by MinMaxScaler.
  return self.partial_fit(X, y)
```

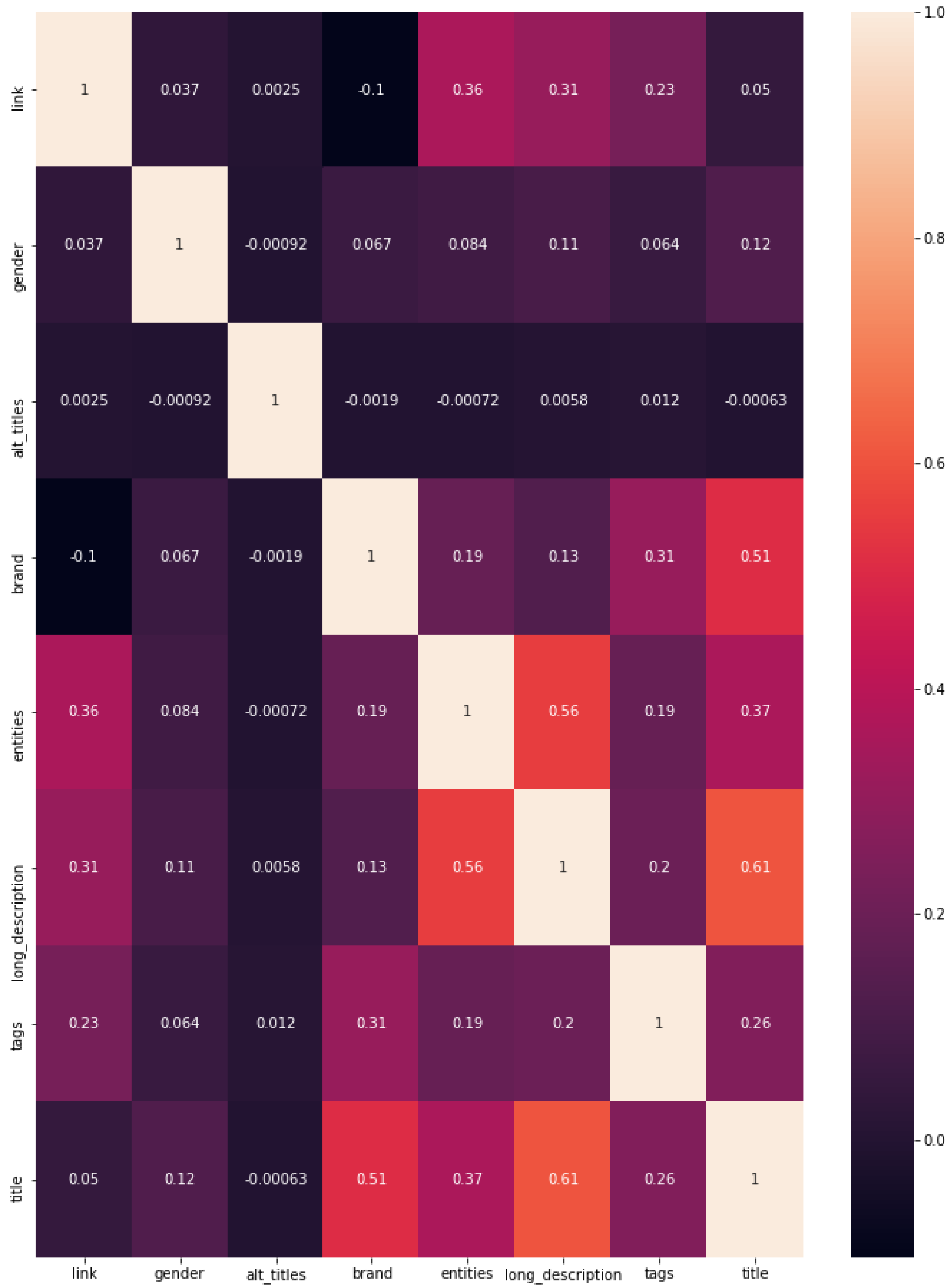
[80]:
```
df_train.head()
```

[80]:
```
      link  gender  alt_titles     brand  entities  long_description  tags  \
0  0.10354       1         0.0  0.759825       0.0               0.0   0.0
1  0.10354       1         0.0  0.759825       0.0               0.0   0.0
2  0.10354       1         0.0  0.759825       0.0               0.0   0.0
3  0.10354       1         0.0  0.759825       0.0               0.0   0.0
4  0.10354       0         0.0  0.759825       0.0               0.0   0.0

      title
0  0.261485
1  0.261485
2  0.261485
3  0.261485
4  0.261485
```

[58]:
```
# plot a graph of feature importance and view thresholds
pltclf,X1,y1 = plot_feature_imp(df_train,target_col)
```

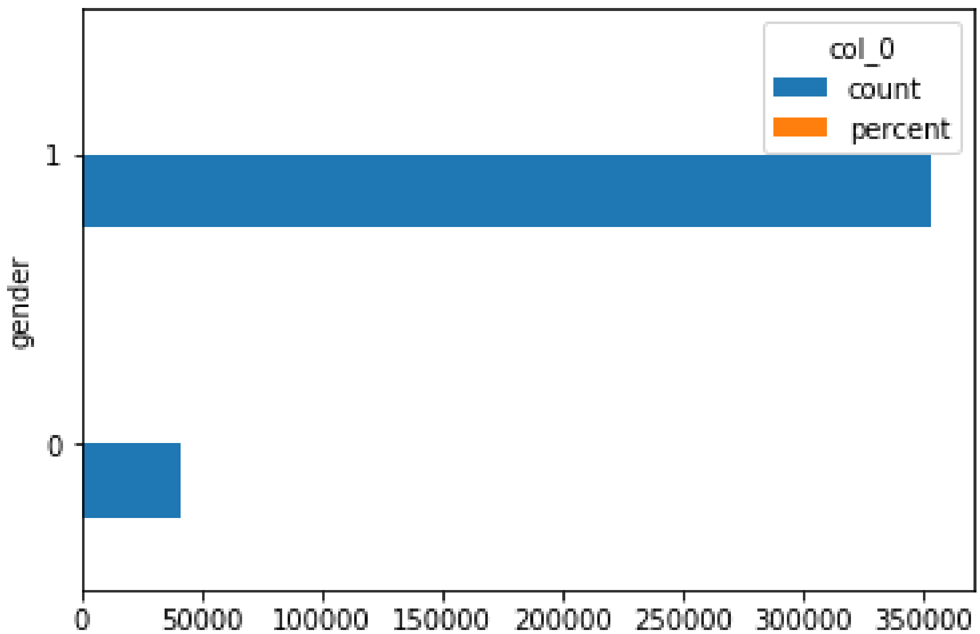

0.5
0.4
0.3
0.2
0.1
0.0
gender
alt_titles
brand
entities
long_description
tags
title

```
[59]: plot_corr(df_train)
```



[81]:
```
df_train.drop(['alt_titles','brand','entities'],1,inplace=True)
# view class distribution of target, this will affect sampling
class_dist(df_train,target_col)
```

```
Check target class distribution

col_0     count    percent
gender
0         41180  10.433875
1        353496  89.566125
```



[82]:
```
# class distribution is imbalanced , hence resampling is required
X,y,model_cols = create_Xy(df_train,target_col,imbalance = 'Y')
```

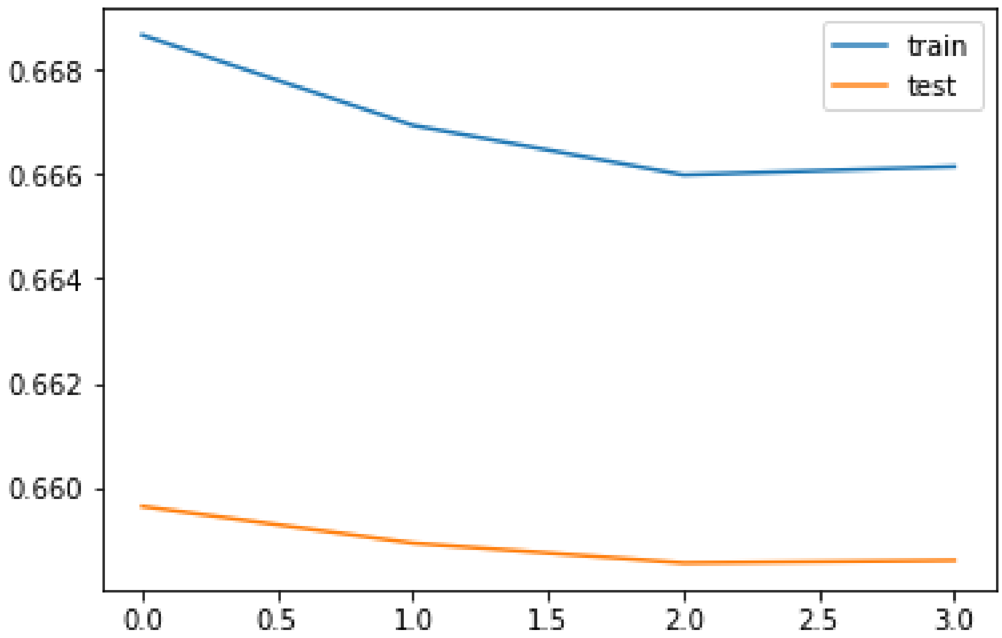
```
No: of predictor variables is: 4 and no:of observations for training is: 706992
```

Stage 3: Build and Train model for accuracy

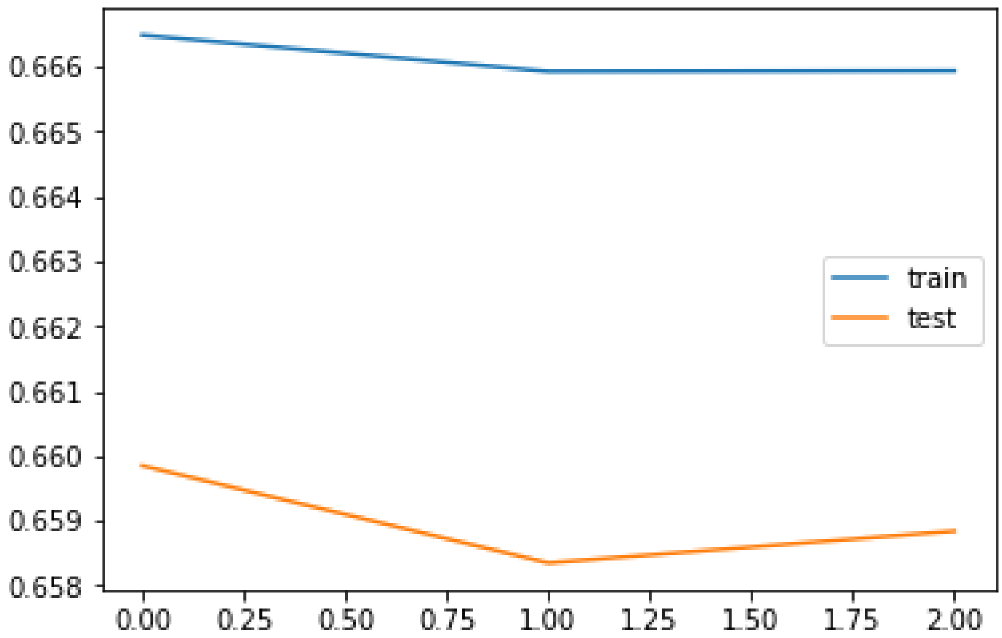
[83]:
```
# Initialize and train a Neural network Classfier model
neural_network = creatNN(len(model_cols),X.shape[0])
```

```python
# store it as the best model till now
best_clfname = 'neural_network'

# Create classifier, train it and test it.
start_time = timeit.default_timer()

# calculate accuracy
bestF1,best_clf = F1_score(neural_network,X,y,nn='Y')
print ("\nFinal F1 score: ", round(bestF1, 3), "\n- - - - - ", "\n")
print('Elapsed Training Time approx :{} minutes'.format((timeit.default_timer()␣
↪- start_time)/60))
```

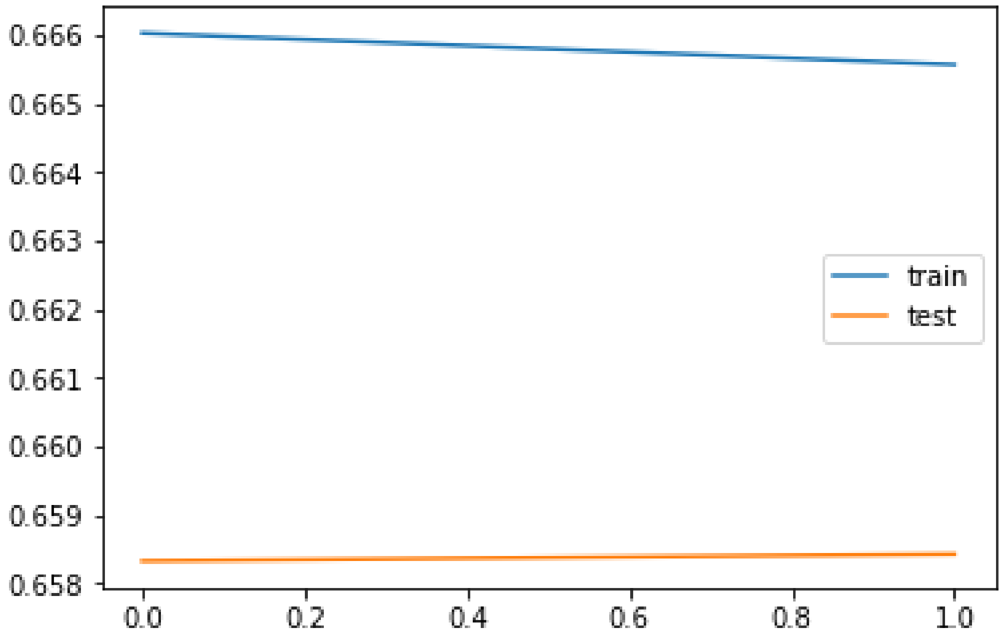
```
Train on 636292 samples, validate on 70700 samples
Epoch 1/10
636292/636292 [==============================] - 126s 198us/step - loss: 0.6687
- acc: 0.5907 - val_loss: 0.6596 - val_acc: 0.6011

Epoch 00001: val_acc improved from -inf to 0.60110, saving model to
best_model.h5
Epoch 2/10
636292/636292 [==============================] - 46s 72us/step - loss: 0.6669 -
acc: 0.5911 - val_loss: 0.6589 - val_acc: 0.6013

Epoch 00002: val_acc improved from 0.60110 to 0.60134, saving model to
best_model.h5
Epoch 3/10
636292/636292 [==============================] - 44s 69us/step - loss: 0.6660 -
acc: 0.5907 - val_loss: 0.6585 - val_acc: 0.6001

Epoch 00003: val_acc did not improve from 0.60134
Epoch 4/10
636292/636292 [==============================] - 42s 66us/step - loss: 0.6662 -
acc: 0.5906 - val_loss: 0.6586 - val_acc: 0.6004

Epoch 00004: val_acc did not improve from 0.60134
Epoch 00004: early stopping
Train: 0.600, Test: 0.600
```



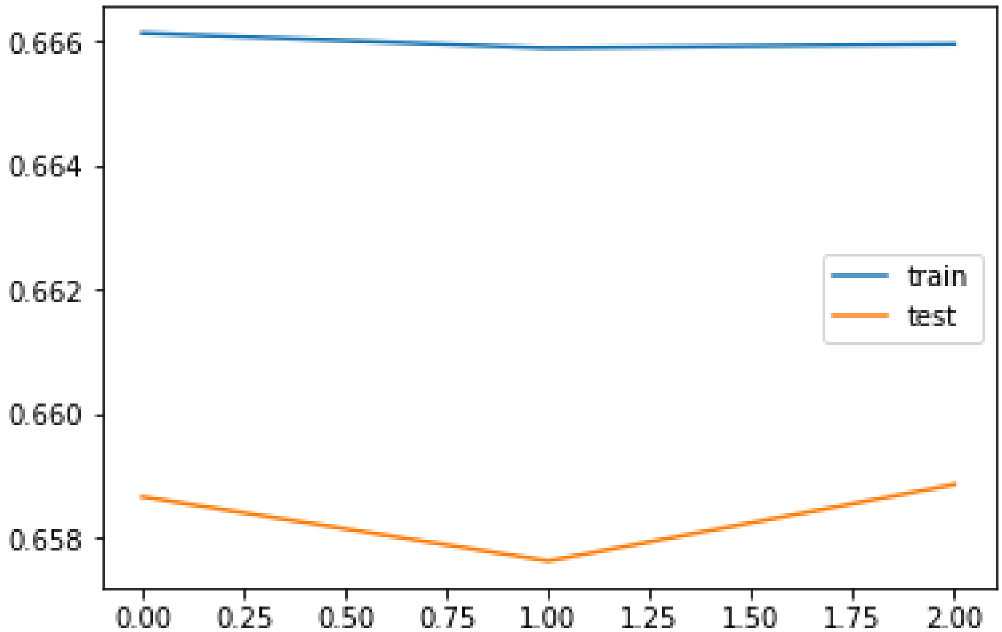

```
 Best F1 score for CV fold no:1 was:0.5712314248500121

Train on 636292 samples, validate on 70700 samples
Epoch 1/10
636292/636292 [==============================] - 43s 67us/step - loss: 0.6665 -
acc: 0.5913 - val_loss: 0.6598 - val_acc: 0.5967

Epoch 00001: val_acc improved from -inf to 0.59669, saving model to
best_model.h5
Epoch 2/10
636292/636292 [==============================] - 43s 67us/step - loss: 0.6659 -
acc: 0.5908 - val_loss: 0.6584 - val_acc: 0.5991

Epoch 00002: val_acc improved from 0.59669 to 0.59909, saving model to
best_model.h5
Epoch 3/10
636292/636292 [==============================] - 45s 70us/step - loss: 0.6659 -
acc: 0.5903 - val_loss: 0.6588 - val_acc: 0.5991

Epoch 00003: val_acc did not improve from 0.59909
Epoch 00003: early stopping
Train: 0.600, Test: 0.599
```



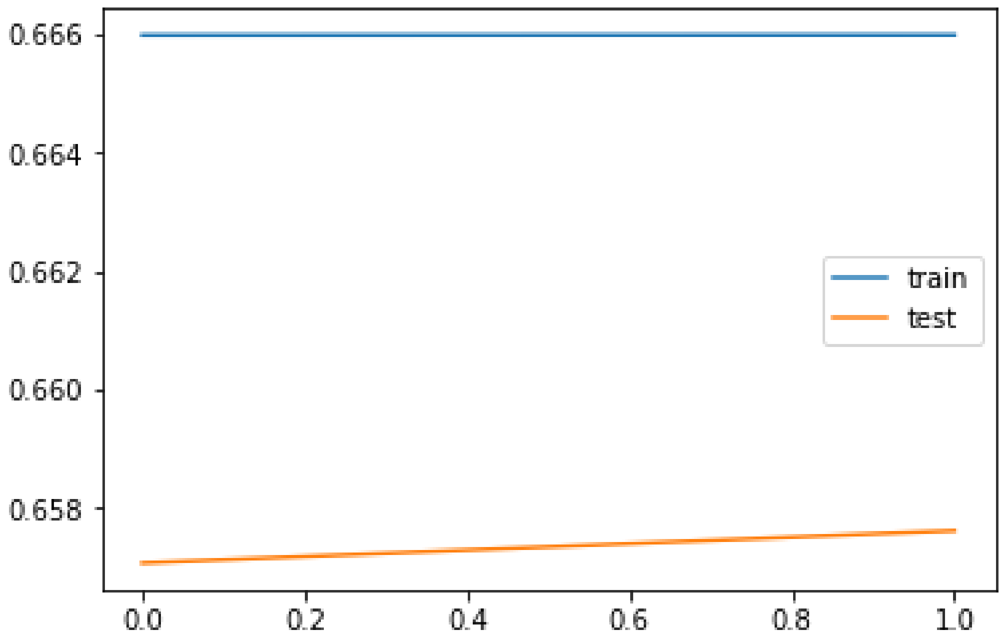

```
 Best F1 score for CV fold no:2 was:0.5696199831102413

Train on 636292 samples, validate on 70700 samples
Epoch 1/10
636292/636292 [==============================] - 45s 72us/step - loss: 0.6660 -
acc: 0.5901 - val_loss: 0.6583 - val_acc: 0.6000

Epoch 00001: val_acc improved from -inf to 0.59999, saving model to
best_model.h5
Epoch 2/10
636292/636292 [==============================] - 49s 77us/step - loss: 0.6656 -
acc: 0.5899 - val_loss: 0.6584 - val_acc: 0.5996

Epoch 00002: val_acc did not improve from 0.59999
Epoch 00002: early stopping
Train: 0.600, Test: 0.600
```




```
 Best F1 score for CV fold no:3 was:0.5701567380386918

Train on 636292 samples, validate on 70700 samples
Epoch 1/10
636292/636292 [==============================] - 45s 70us/step - loss: 0.6661 -
acc: 0.5901 - val_loss: 0.6587 - val_acc: 0.5980

Epoch 00001: val_acc improved from -inf to 0.59803, saving model to
best_model.h5
Epoch 2/10
636292/636292 [==============================] - 42s 65us/step - loss: 0.6659 -
acc: 0.5902 - val_loss: 0.6576 - val_acc: 0.6002

Epoch 00002: val_acc improved from 0.59803 to 0.60017, saving model to
best_model.h5
Epoch 3/10
636292/636292 [==============================] - 41s 65us/step - loss: 0.6660 -
acc: 0.5897 - val_loss: 0.6589 - val_acc: 0.6001

Epoch 00003: val_acc did not improve from 0.60017
Epoch 00003: early stopping
Train: 0.599, Test: 0.600
```

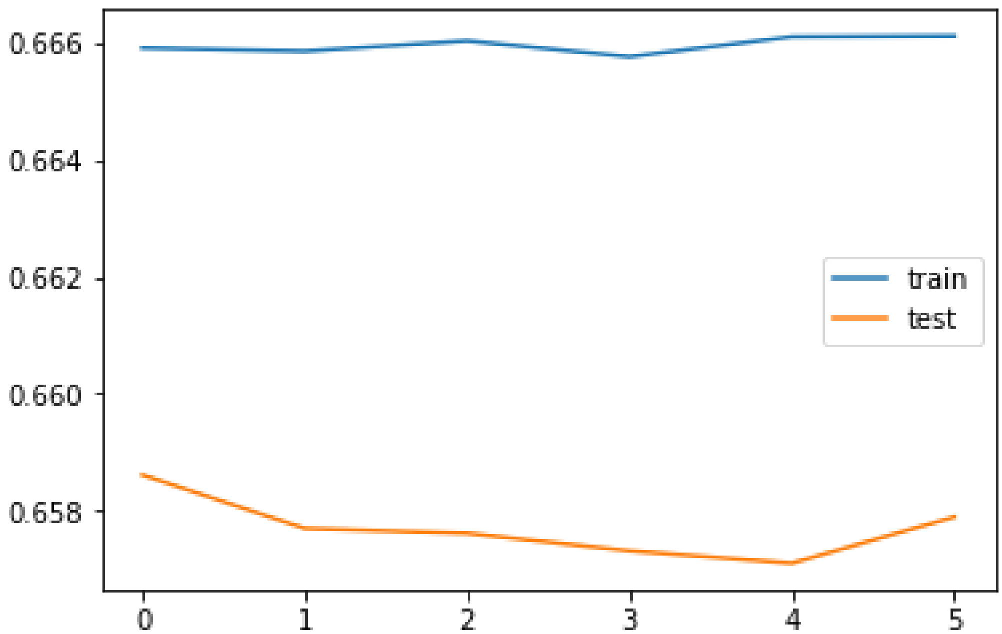



```
 Best F1 score for CV fold no:4 was:0.5711582090531219

Train on 636292 samples, validate on 70700 samples
Epoch 1/10
636292/636292 [==============================] - 47s 73us/step - loss: 0.6660 -
acc: 0.5899 - val_loss: 0.6571 - val_acc: 0.6023

Epoch 00001: val_acc improved from -inf to 0.60229, saving model to
best_model.h5
Epoch 2/10
636292/636292 [==============================] - 43s 67us/step - loss: 0.6660 -
acc: 0.5900 - val_loss: 0.6576 - val_acc: 0.6011

Epoch 00002: val_acc did not improve from 0.60229
Epoch 00002: early stopping
Train: 0.600, Test: 0.601
```



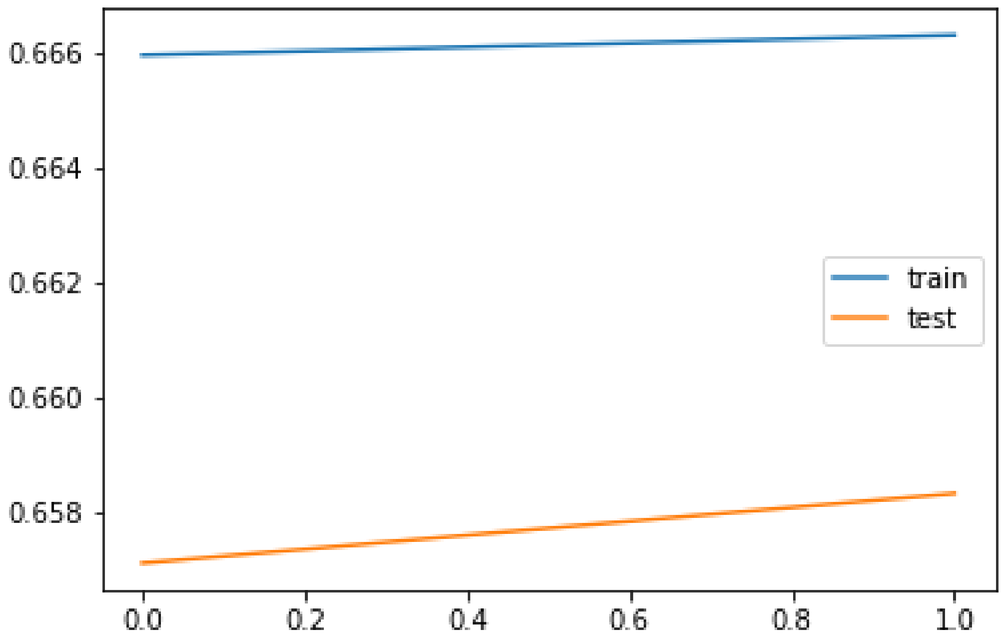

```
 Best F1 score for CV fold no:5 was:0.5725959089493943

Train on 636292 samples, validate on 70700 samples
Epoch 1/10
636292/636292 [==============================] - 44s 70us/step - loss: 0.6659 -
acc: 0.5899 - val_loss: 0.6586 - val_acc: 0.5971

Epoch 00001: val_acc improved from -inf to 0.59707, saving model to
best_model.h5
Epoch 2/10
636292/636292 [==============================] - 43s 68us/step - loss: 0.6659 -
acc: 0.5899 - val_loss: 0.6577 - val_acc: 0.6010

Epoch 00002: val_acc improved from 0.59707 to 0.60102, saving model to
best_model.h5
Epoch 3/10
636292/636292 [==============================] - 42s 65us/step - loss: 0.6660 -
acc: 0.5900 - val_loss: 0.6576 - val_acc: 0.6021

Epoch 00003: val_acc improved from 0.60102 to 0.60205, saving model to
best_model.h5
Epoch 4/10
636292/636292 [==============================] - 44s 69us/step - loss: 0.6658 -
acc: 0.5903 - val_loss: 0.6573 - val_acc: 0.6022
```

```
Epoch 00004: val_acc improved from 0.60205 to 0.60222, saving model to
best_model.h5
Epoch 5/10
636292/636292 [==============================] - 41s 65us/step - loss: 0.6661 -
acc: 0.5898 - val_loss: 0.6571 - val_acc: 0.6005

Epoch 00005: val_acc did not improve from 0.60222
Epoch 6/10
636292/636292 [==============================] - 42s 65us/step - loss: 0.6661 -
acc: 0.5894 - val_loss: 0.6579 - val_acc: 0.6024

Epoch 00006: val_acc improved from 0.60222 to 0.60243, saving model to
best_model.h5
Epoch 00006: early stopping
Train: 0.601, Test: 0.602
```



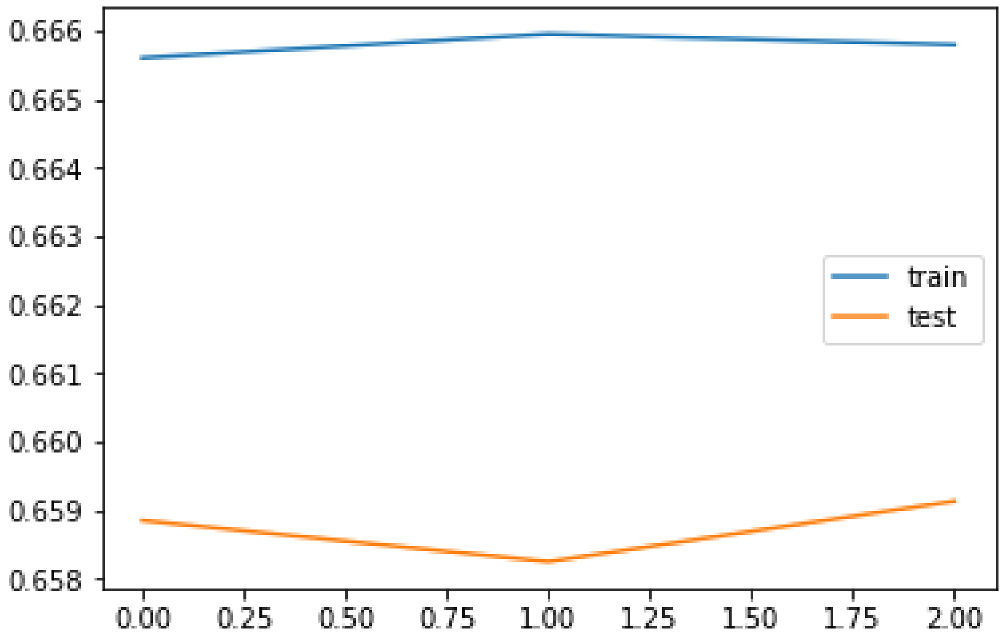

```
 Best F1 score for CV fold no:6 was:0.5766234421602597

Train on 636294 samples, validate on 70698 samples
Epoch 1/10
636294/636294 [==============================] - 49s 77us/step - loss: 0.6659 -
acc: 0.5900 - val_loss: 0.6571 - val_acc: 0.6032

Epoch 00001: val_acc improved from -inf to 0.60320, saving model to
best_model.h5
```

```
Epoch 2/10
636294/636294 [==============================] - 43s 68us/step - loss: 0.6663 -
acc: 0.5894 - val_loss: 0.6583 - val_acc: 0.5984

Epoch 00002: val_acc did not improve from 0.60320
Epoch 00002: early stopping
Train: 0.597, Test: 0.598
```



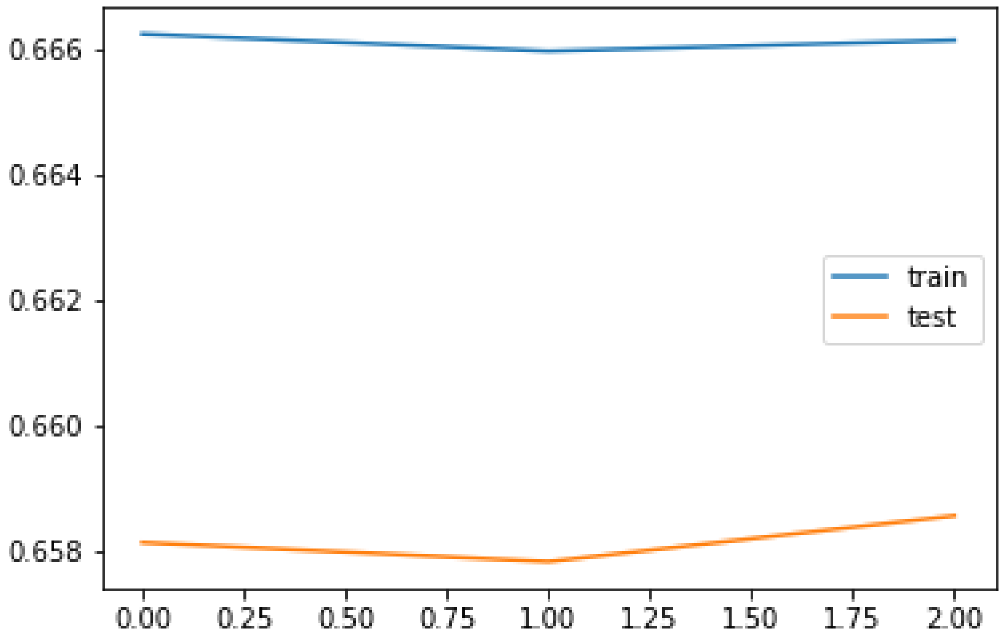

```
 Best F1 score for CV fold no:7 was:0.5663123146021577

Train on 636294 samples, validate on 70698 samples
Epoch 1/10
636294/636294 [==============================] - 47s 73us/step - loss: 0.6656 -
acc: 0.5900 - val_loss: 0.6589 - val_acc: 0.5996

Epoch 00001: val_acc improved from -inf to 0.59958, saving model to
best_model.h5
Epoch 2/10
636294/636294 [==============================] - 48s 75us/step - loss: 0.6659 -
acc: 0.5896 - val_loss: 0.6583 - val_acc: 0.6020

Epoch 00002: val_acc improved from 0.59958 to 0.60200, saving model to
best_model.h5
Epoch 3/10
636294/636294 [==============================] - 49s 76us/step - loss: 0.6658 -
```

```
acc: 0.5899 - val_loss: 0.6591 - val_acc: 0.5953

Epoch 00003: val_acc did not improve from 0.60200
Epoch 00003: early stopping
Train: 0.595, Test: 0.595
```



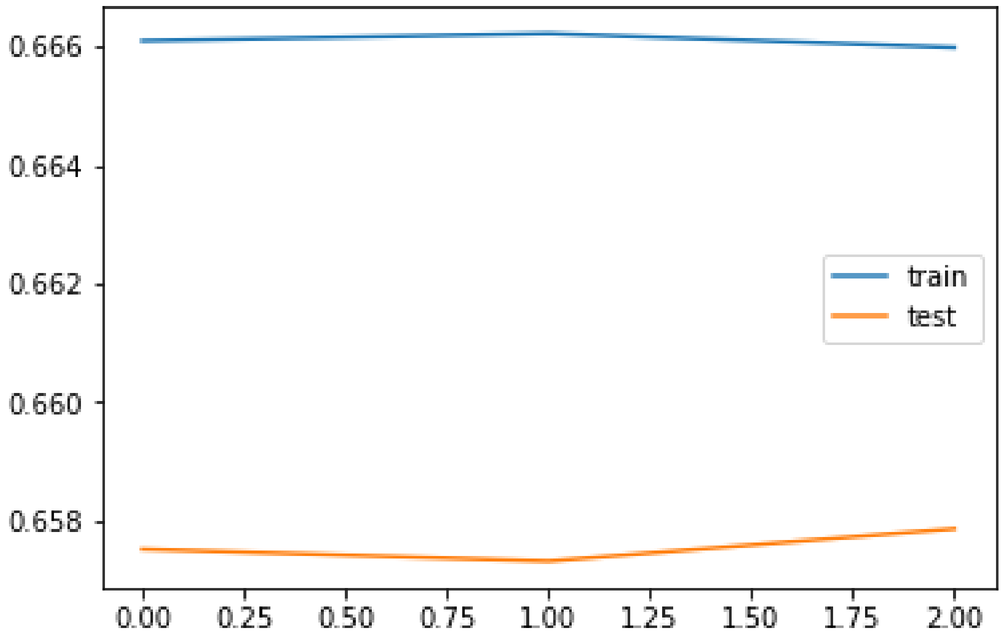

```
 Best F1 score for CV fold no:8 was:0.5622247585536473

Train on 636294 samples, validate on 70698 samples
Epoch 1/10
636294/636294 [==============================] - 46s 73us/step - loss: 0.6662 -
acc: 0.5897 - val_loss: 0.6581 - val_acc: 0.5990

Epoch 00001: val_acc improved from -inf to 0.59898, saving model to
best_model.h5
Epoch 2/10
636294/636294 [==============================] - 43s 67us/step - loss: 0.6660 -
acc: 0.5900 - val_loss: 0.6578 - val_acc: 0.6008

Epoch 00002: val_acc improved from 0.59898 to 0.60078, saving model to
best_model.h5
Epoch 3/10
636294/636294 [==============================] - 45s 71us/step - loss: 0.6661 -
acc: 0.5903 - val_loss: 0.6586 - val_acc: 0.5979
```

```
Epoch 00003: val_acc did not improve from 0.60078
Epoch 00003: early stopping
Train: 0.600, Test: 0.598
```




```
 Best F1 score for CV fold no:9 was:0.5692716859976159

Train on 636294 samples, validate on 70698 samples
Epoch 1/10
636294/636294 [==============================] - 46s 72us/step - loss: 0.6661 -
acc: 0.5896 - val_loss: 0.6575 - val_acc: 0.6002

Epoch 00001: val_acc improved from -inf to 0.60016, saving model to
best_model.h5
Epoch 2/10
636294/636294 [==============================] - 45s 70us/step - loss: 0.6662 -
acc: 0.5900 - val_loss: 0.6573 - val_acc: 0.5986

Epoch 00002: val_acc did not improve from 0.60016
Epoch 3/10
636294/636294 [==============================] - 42s 67us/step - loss: 0.6660 -
acc: 0.5900 - val_loss: 0.6579 - val_acc: 0.6012

Epoch 00003: val_acc improved from 0.60016 to 0.60118, saving model to
best_model.h5
Epoch 00003: early stopping
```

Train: 0.602, Test: 0.601




```
 Best F1 score for CV fold no:10 was:0.5751831571693857


 Best Model has the following scores :

Train: 0.602, Test: 0.601

Final F1 score:  0.57
- - - - -

Elapsed Training Time approx :31.098886277333317 minutes
```

Stage 4: use Best Model to predict segment on Test Data

[84]:
```
# Load the Testing data file with UserId and Actual Gender information
filename = 'UserId_Test.csv'
predictor = 'userid'

df_userId_Test = pd.read_csv(filename)
df_userId_Test = dedup_data(df_userId_Test)
df_userId_Test.shape
```

[84]: (88384, 1)

Prepare the Test File by taking information from previously loaded files

[85]:
```
#1. First, merge gender UserID to UserID to URL data using UserId as the␣
↪key(Index)

df_test = df_userId_Test.set_index('userid')

# perform left outer join to retain all data in the training(UserID, Gender)␣
↪file
df_test = df_test.merge(df_userId_url, on='userid',how='outer')

df_test.reset_index(inplace=True)

df_test = dedup_data(df_test) # dedupe again after the join

#2. Next, merge UserID gender and URL file to URL data using url and link as␣
↪keys(Index)

df_test.set_index('url',inplace=True) # set index to key column for merge

# perform left outer join to retain all data in the training(UserID, Gender)␣
↪file
df_test = df_test.merge(df_urls_data,␣
↪right_on='link',left_index=True,how='outer')

df_test.reset_index(inplace=True)

df_test = dedup_data(df_test,keylist=['userid']) # final dedupe again after all␣
↪joins
```

[86]:
```
df_test.userid.nunique()
```

[86]: 317828

Preprocess test data exactly as done for training

[87]:
```
df_test = prep_Data(df_test)
df_test = imputeNulls(df_test)
df_test = encode_cols(df_test)


scaler = MinMaxScaler()
df_test = scale_cols(df_test,scaler,[predictor,target_col])
```

```
 Basic Metadata

<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 317829 entries, 0 to 317828
Data columns (total 8 columns):
link                317829 non-null object
userid              317828 non-null float64
alt_titles          179653 non-null object
brand               179604 non-null object
entities            179653 non-null object
long_description    64549 non-null object
tags                179653 non-null object
title               179653 non-null object
dtypes: float64(1), object(7)
memory usage: 21.8+ MB
None

 Missing values information

                       column_name  percent_missing
long_description  long_description        79.690651
brand                        brand        43.490367
alt_titles              alt_titles        43.474950
entities                  entities        43.474950
tags                          tags        43.474950
title                        title        43.474950
userid                      userid         0.000315

 List of columns with missing values now : []

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:334:
DataConversionWarning: Data with input dtype int32 were all converted to float64
by MinMaxScaler.
  return self.partial_fit(X, y)
```

[88]:
```
df_test.userid.nunique()
```

[88]: 317829

[89]:
```
# predict classes and store in a column called 'gender'
df_test[target_col]= best_clf.predict(df_test[model_cols])

df_test[target_col] = df_test[target_col].apply(lambda x:'F' if x==0 else 'M')
#write the output file to disk
outfilename = 'application_test_predict.csv'
df_test[[predictor,target_col]].to_csv(outfilename,index=False)
```