```
In [1]:
        import pandas as pd
        import numpy as np
        %matplotlib inline
        import seaborn as sns
        import matplotlib.pyplot as plt
        import os
        from sklearn.preprocessing import LabelEncoder,StandardScaler, OneHotEncoder
        from scipy.sparse import csr matrix, hstack
        from sklearn.linear model import LogisticRegression
        from sklearn.model selection import StratifiedKFold
        from sklearn.metrics import log loss
        from sklearn.feature extraction.text import TfidfTransformer,TfidfVectorizer,C
        ountVectorizer
        from sklearn.cluster import KMeans
        from xgboost import XGBClassifier
        from sklearn.calibration import CalibratedClassifierCV
        import warnings
        warnings.filterwarnings("ignore")
In [2]:
        from keras.models import Sequential
        from keras.layers import Dense, Dropout, Activation, BatchNormalization
        from keras.wrappers.scikit learn import KerasClassifier
        from keras.utils import np utils
        from keras.optimizers import SGD,Adagrad
```

from keras.layers.advanced_activations import PReLU
from sklearn.model_selection import train_test_split
from keras.callbacks import EarlyStopping,TensorBoard

Using TensorFlow backend.

from statistics import mean

LOADING THE DATA

```
In [3]: gatrain = pd.read_csv("gender_age_train.csv",index_col='device_id')
    gatest = pd.read_csv("gender_age_test.csv",index_col='device_id')
    phone=pd.read_csv("phone_brand_device_model.csv")
    app_label=pd.read_csv('app_labels.csv')
    label_cat=pd.read_csv("label_categories.csv")
    app_events=pd.read_csv("app_events.csv", dtype={'is_active':bool})
    events = pd.read_csv('events.csv', parse_dates=['timestamp'],index_col='event_id')
To [4]: ##www.ins.dvmlis.sto.device.id/s
```

```
In [4]: #removing duplicate device id's
phone = phone.drop_duplicates('device_id',keep='first').set_index('device_id')
```

```
In [5]: print(gatrain.shape)
    print(gatest.shape)
    print(app_label.shape)
    print(label_cat.shape)
    print(app_events.shape)
    print(events.shape)

(74645, 3)
    (112071, 0)
    (186716, 2)
    (459943, 2)
    (930, 2)
    (32473067, 4)
    (3252950, 4)
```

SPLITTING THE DATA

SOME DEVICES HAVE EVENTS INFORMATION AND SOME DEVICES DOES NOT HAVE EVENT INFORMATION.

1. SO WE DIVIDE THE DATA INTO TRAIN AND TEST IN BOTH EVENTS AND NO EVENTS DATA.

```
In [6]:
        #https://docs.scipy.org/doc/numpy/reference/generated/numpy.in1d.html
        mask=np.in1d(gatrain.index,events["device_id"].values)
        gatrain events= gatrain[mask]
        mask=np.in1d(gatest.index,events["device id"].values)
        gatest events= gatest[mask]
In [7]:
        #https://docs.scipy.org/doc/numpy/reference/generated/numpy.in1d.html
        mask=np.in1d(gatrain.index,events["device id"].values,invert=True)
        gatrain noevents= gatrain[mask]
        mask=np.in1d(gatest.index,events["device id"].values,invert=True)
        gatest noevents= gatest[mask]
In [8]:
        #Each row of is given by a unique integer as an identifier
        gatrain['trainrow'] = np.arange(gatrain.shape[0])
        gatest['testrow'] = np.arange(gatest.shape[0])
        gatrain_events['trainrow']=np.arange(gatrain_events.shape[0])
        gatest events['testrow']=np.arange(gatest events.shape[0])
        gatrain_noevents['trainrow']=np.arange(gatrain_noevents.shape[0])
        gatest noevents['testrow']=np.arange(gatest noevents.shape[0])
```

```
In [9]: print("train data with events information:",gatrain_events.shape)
    print("train data without events information:",gatrain_noevents.shape)
    print("test data with events information:",gatest_events.shape)
    print("test data without events information:",gatest_noevents.shape)

    train data with events information: (23309, 4)
    train data without events information: (51336, 4)
    test data with events information: (35194, 1)
    test data without events information: (76877, 1)
```

VECTORIZING PHONE BRAND

```
In [10]: brandencoder = LabelEncoder().fit(phone.phone_brand)
    phone['brand'] = brandencoder.transform(phone['phone_brand'])
    nbrand=len(brandencoder.classes_)

In [11]: import pickle
    with open('brandencoder','wb') as fp:
        pickle.dump(brandencoder,fp)
```

VECTORIZING PHONE MODEL

FEATURES USING APP ID'S

Out[14]:

	device_id	арр	size	trainrow	testrow
0	-9222956879900151005	548	18	5145.0	NaN
1	-9222956879900151005	1096	18	5145.0	NaN
2	-9222956879900151005	1248	26	5145.0	NaN
3	-9222956879900151005	1545	12	5145.0	NaN
4	-9222956879900151005	1664	18	5145.0	NaN

```
In [15]: import pickle
with open('appencoder','wb') as fp:
    pickle.dump(appencoder,fp)
```

FEATURES USING APP LABELS

```
In [18]: import pickle
with open('labelencoder','wb') as fp:
    pickle.dump(labelencoder,fp)
```

Out[19]:

	device_id	label	size	trainrow	testrow
0	-9222956879900151005	117	1	5145.0	NaN
1	-9222956879900151005	120	1	5145.0	NaN
2	-9222956879900151005	126	1	5145.0	NaN
3	-9222956879900151005	138	2	5145.0	NaN
4	-9222956879900151005	147	2	5145.0	NaN

FEATURES USING TIME FEATURE

```
In [20]:
         #we are processing timestamp feature to get hour and day and dividing into 4 b
          events['hour'] = events['timestamp'].map(lambda x:pd.to_datetime(x).hour)
          events['hourbin'] = [1 \text{ if } ((x>=1)&(x<=6)) \text{ else } 2 \text{ if } ((x>=7)&(x<=12)) \text{ else } 3 \text{ if }
          ((x>=13)&(x<=18)) else 4 for x in events['hour']]
In [21]:
          events.hour=events.hour.astype(str)
          events.hourbin=events.hourbin.astype(str)
In [22]: | hourjoin = events.groupby("device_id")["hour"].apply(lambda x: " ".join('0'+st
          r(s) for s in x)
In [23]: | hourbinjoin=events.groupby("device_id")["hourbin"].apply(lambda x: " ".join(
          '0'+str(s) for s in x))
In [24]:
          daysjoin=events['timestamp'].dt.day_name()
          events['day']=daysjoin.map({'Sunday':0,'Monday':1,'Tuesday':2,'Wednesday':3,'T
          hursday':4,'Friday':5,'Saturday':6})
          daysjoin = events.groupby("device_id")["day"].apply(lambda x: " ".join("0"+str
In [25]:
          (s) for s in x)
```

FEATURES USING LATITUDE AND LONGITUDE

```
In [26]: median_lat = events.groupby("device_id")["latitude"].agg('median')
In [27]: median_lon=events.groupby("device_id")["longitude"].agg('median')
```

WE ARE CLUSTERING MEDIAN LATITUDES AND LONGITUDES IN TO 10 CLUSTERS

```
In [28]: com=pd.concat([median_lat, median_lon], axis=1)
    kmeans = KMeans(n_clusters=10, random_state=0).fit(com)
    clustered_geo_features=pd.Series(kmeans.labels_)
    clustered_geo_features.index=median_lon.index
```

FEATURES BASED ON ACTIVE APPS AND APP COUNT

```
In [29]: apps = app_events.groupby("event_id")["is_active"].apply(lambda x: " ".join(st
    r(s) for s in x))

In [30]: events["apps_active"] = events.index.map(apps)
    active_apps_events = events.groupby("device_id")["apps_active"].apply(lambda x
    : " ".join(str(s) for s in x if str(s)!='nan'))
```

MODELLING

ONE HOT ENCODING OF PHONE BRAND

ONE HOT ENCODING OF PHONE MODEL

ONE HOT ENCODING OF DEVICE APPS

ONE HOT ENCODING OF APP CATEGORY

```
In [36]: #hstacking all the features
         Xtrain = hstack((Xtr_brand, Xtr_model, Xtr_app, Xtr_label), format='csr')
         Xtest = hstack((Xte_brand, Xte_model, Xte_app, Xte_label), format='csr')
         print('Train data shape:',Xtrain.shape)
         print('Test data shape:',Xtest.shape)
         Train data shape: (74645, 21527)
         Test data shape: (112071, 21527)
In [37]: #applying applying label encoding on target variable
         targetencoder = LabelEncoder().fit(gatrain.group)
         y = targetencoder.transform(gatrain.group)
         nclasses = len(targetencoder.classes )
In [38]:
         import pickle
         with open('classlabel','wb') as fp:
             pickle.dump(y,fp)
In [39]: |#splitting data into train and validation
         from sklearn.calibration import CalibratedClassifierCV
         from sklearn.model selection import train test split
         xtr, xcv, ytr, ycv = train_test_split(Xtrain, y,stratify=y,test_size=0.15)
         print(xtr.shape,ytr.shape)
         print(xcv.shape,ycv.shape)
         (63448, 21527) (63448,)
         (11197, 21527) (11197,)
```

LOGISTIC REGRESSION

```
In [35]: | from sklearn.svm import LinearSVC
         from sklearn.calibration import CalibratedClassifierCV
         cv_log_error = []
         for i in alpha:
            print('for c = ',i)
            SGD = LogisticRegression(class_weight = 'balanced',penalty = '12',C = i)
            clf = SGD.fit(xtr,ytr)
            calib sgd = CalibratedClassifierCV(clf,method = 'sigmoid')
            calib_sgd.fit(xtr,ytr)
            y cv pred = calib sgd.predict proba(xcv)
            #cv_log_error.append(log_loss(y_cv,y_cv_pred))
            print('for c = ',i ,'the log loss is :',log_loss(ycv,y_cv_pred))
         for c = 1e-05
         for c = 1e-05 the log loss is : 2.4240490121671416
         for c = 0.0001
         for c = 0.0001 the log loss is : 2.4239127140248673
         for c = 0.001
         for c = 0.001 the log loss is : 2.421898251247192
         for c = 0.01
         for c = 0.01 the log loss is : 2.4034478389221365
         for c = 0.1
         for c = 0.1 the log loss is : 2.408299979523952
         for c = 1
         for c = 1 the log loss is : 2.4181286899702306
        for c = 10
         for c = 10 the log loss is : 2.42395984079844
         for c = 100
         for c = 100 the log loss is : 2.4254481618915733
         for c = 1000
         for c = 1000 the log loss is : 2.425641919967717
```

WE CHOSE OUR BEST C TO BE 0.01

```
In [36]: clf = LogisticRegression(C=0.01, class_weight='balanced', multi_class='multino
    mial', solver='lbfgs')
    clf.fit(xtr, ytr)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(xcv, ycv)

    predict_y = sig_clf.predict_proba(xtr)
    loss=log_loss(ytr, predict_y)
    print("The train log loss for best C is:",loss)
    predict_y = sig_clf.predict_proba(xcv)
    loss=log_loss(ycv, predict_y)
    print("The validation log loss for best C is:",loss)
```

The train log loss for best C is: 2.4145317866106
The validation log loss for best C is: 2.354060651561517

MODELLING USING DEVICES WITHOUT EVENTS

```
In [40]: Xtrain whole = hstack((Xtr brand, Xtr model), format='csr')
         targetencoder = LabelEncoder().fit(gatrain.group)
         y = targetencoder.transform(gatrain.group)
In [41]: | gatest_noevents['model']=phone['model']
         gatest noevents['brand']=phone['brand']
In [42]:
         gatest_noevents_model = csr_matrix((np.ones(gatest_noevents.shape[0]),
                                 (gatest noevents.testrow, gatest noevents.model)))
         gatest_noevents_brand= csr_matrix((np.ones(gatest_noevents.shape[0]),
                                 (gatest noevents.testrow, gatest noevents.brand)))
In [43]: xtest_noevents=hstack((gatest_noevents_brand, gatest_noevents_model), format=
          csr')
In [44]: | print("xtrain shape:", Xtrain_whole.shape)
         print("ytrain shape:",y.shape)
         print("xtest shape:",xtest_noevents.shape)
         xtrain shape: (74645, 1798)
         ytrain shape: (74645,)
         xtest shape: (76877, 1798)
In [42]: | xtr, xcv, ytr, ycv = train_test_split(Xtrain_whole, y,stratify=y,test_size=0.1
         5,random state=18)
```

LOGISTIC REGRESSION

```
In [43]: alpha = [0.001,0.01,0.02,0.1,0.15,1,10]
            for i in alpha:
                clf = LogisticRegression(C=i, class weight='balanced', multi class='multin
            omial',solver='lbfgs')
                clf.fit(xtr, ytr)
                #Using Model Calibration
                sig clf = CalibratedClassifierCV(clf, method="sigmoid")
                sig_clf.fit(xtr, ytr)
                predict y = sig clf.predict proba(xcv)
                print('For values of C = ', i, "The validation log loss is:",log_loss(ycv,
            predict_y))
            For values of C = 0.001 The validation log loss is: 2.4030020103020036
            For values of C = 0.01 The validation log loss is: 2.39641152579951
            For values of C = 0.02 The validation log loss is: 2.3940695248817785
            For values of C = 0.1 The validation log loss is: 2.3896730084069544
            For values of C = 0.15 The validation log loss is: 2.3891201368497037
            For values of C = 1 The validation log loss is: 2.39105667945638
            For values of C = 10 The validation log loss is: 2.398847882073424
WE CHOSE OUR BEST C TO BE 0.15
   In [44]: | clf = LogisticRegression(C=0.15, class weight='balanced', multi class='multino
            mial', solver='lbfgs')
            clf.fit(xtr, ytr)
            sig clf = CalibratedClassifierCV(clf, method="sigmoid")
            sig clf.fit(xtr, ytr)
            predict y = sig clf.predict proba(xtr)
            loss=log loss(ytr, predict y)
            print("The train log loss for best C is:",loss)
            predict y = sig clf.predict proba(xcv)
            loss=log_loss(ycv, predict_y)
            print("The validation log loss for best C is:",loss)
            The train log loss for best C is: 2.362802878894095
            The validation log loss for best C is: 2.3891201368497037
   In [45]: #predicting for test data
            no events pred lr=sig clf.predict proba(xtest noevents)
```

OBSERVATIONS:

In [46]: #saving the model

from sklearn.externals import joblib as jobl

np.save('lr noevents', no events pred lr)

from joblib import dump

FOR LOGISTIC REGRESSION MODEL TRAIN LOGLOSS IS 2.3628 AND VALIDATION LOSS IS 2.3891

NEURAL NETWORKS

```
#https://www.kagqle.com/c/talkingdata-mobile-user-demographics/discussion/2342
def noevents_nn_model1(input_shape):
    model = Sequential()
    model.add(Dense(256, input_dim=input_shape))
    model.add(PReLU())
    model.add(BatchNormalization())
    model.add(Dropout(0.5))
    model.add(Dense(64))
    model.add(PReLU())
    model.add(BatchNormalization())
    model.add(Dropout(0.5))
    model.add(Dense(12))
    model.add(Activation('softmax'))
    model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
    return model
```

WARNING: Logging before flag parsing goes to stderr.

W0408 12:30:09.095427 11128 deprecation_wrapper.py:119] From c:\users\navee\a ppdata\local\programs\python\python37\lib\site-packages\keras\backend\tensorf low_backend.py:74: The name tf.get_default_graph is deprecated. Please use t f.compat.v1.get default graph instead.

W0408 12:30:09.523084 11128 deprecation_wrapper.py:119] From c:\users\navee\a ppdata\local\programs\python\python37\lib\site-packages\keras\backend\tensorf low_backend.py:517: The name tf.placeholder is deprecated. Please use tf.comp at.v1.placeholder instead.

W0408 12:30:09.580778 11128 deprecation_wrapper.py:119] From c:\users\navee\a ppdata\local\programs\python\python37\lib\site-packages\keras\backend\tensorf low_backend.py:4138: The name tf.random_uniform is deprecated. Please use tf. random.uniform instead.

W0408 12:30:09.785201 11128 deprecation_wrapper.py:119] From c:\users\navee\a ppdata\local\programs\python\python37\lib\site-packages\keras\backend\tensorf low_backend.py:133: The name tf.placeholder_with_default is deprecated. Pleas e use tf.compat.v1.placeholder_with_default instead.

W0408 12:30:09.803154 11128 deprecation.py:506] From c:\users\navee\appdata\l ocal\programs\python\python37\lib\site-packages\keras\backend\tensorflow_back end.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_pr ob is deprecated and will be removed in a future version. Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - k eep prob`.

W0408 12:30:09.902594 11128 deprecation_wrapper.py:119] From c:\users\navee\a ppdata\local\programs\python\python37\lib\site-packages\keras\optimizers.py:7 90: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train. Optimizer instead.

W0408 12:30:09.918372 11128 deprecation_wrapper.py:119] From c:\users\navee\a ppdata\local\programs\python\python37\lib\site-packages\keras\backend\tensorf low_backend.py:3295: The name tf.log is deprecated. Please use tf.math.log in stead.

Layer (type)	Output	Shape	Param #
dense_1 (Dense)	(None,	256)	460544
p_re_lu_1 (PReLU)	(None,	256)	256
batch_normalization_1 (Batch	(None,	256)	1024
dropout_1 (Dropout)	(None,	256)	0
dense_2 (Dense)	(None,	64)	16448
p_re_lu_2 (PReLU)	(None,	64)	64
batch_normalization_2 (Batch	(None,	64)	256
dropout_2 (Dropout)	(None,	64)	0
dense_3 (Dense)	(None,	12)	780
activation_1 (Activation)	(None,	12)	0

Total params: 479,372 Trainable params: 478,732 Non-trainable params: 640

In [49]: early_stop=EarlyStopping(monitor='val_loss',patience=5,restore_best_weights=Tr ue)

```
In [50]:
         def noevents average nn 1(state):
             Takes a list of Random Seeds, splits the data into Train and CV based on S
         eed, trains model and takes average of
             predictions while testing
             model list=[]
             loss list=[]
             avg cv loss=0
             for i in range(len(state)):
                 xtr, xcv, ytr, ycv = train_test_split(Xtrain_whole, y,stratify=y,test_
         size=0.15,random state=state[i])
                 ytr=np_utils.to_categorical(ytr)
                 ycv=np utils.to categorical(ycv)
                 model=noevents nn model1(xtr.shape[1])
                 model.fit(xtr, ytr, batch_size=256, epochs=20, verbose=1, validation_d
         ata=(xcv, ycv),callbacks=[early stop])
                 model.save('saved_models/no_events/nn '+str(i+1))
                 pred=model.predict_proba(xcv)
                 cv loss=log loss(ycv, pred)
                 print("Validation Log Loss of Model in Current Run: ",cv loss)
                 model list.append(model)
                 loss list.append(cv loss)
             avg cv loss=mean(loss list)
             print("Average CV Loss of "+str(len(state))+" Runs :",avg_cv_loss)
             return(model list)
```

```
In [51]: random_seeds=[9,18,42,86,103]
model_list_1= noevents_average_nn_1(random_seeds)
```

W0408 12:30:10.290519 11128 deprecation.py:323] From c:\users\navee\appdata\l ocal\programs\python\python37\lib\site-packages\tensorflow\python\ops\math_gr ad.py:1250: add_dispatch_support.<locals>.wrapper (from tensorflow.python.op s.array_ops) is deprecated and will be removed in a future version. Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where

```
Train on 63448 samples, validate on 11197 samples
Epoch 1/20
acc: 0.1041 - val loss: 2.4166 - val acc: 0.1458
Epoch 2/20
acc: 0.1316 - val loss: 2.3994 - val acc: 0.1516
Epoch 3/20
63448/63448 [============= ] - 4s 56us/step - loss: 2.4185 -
acc: 0.1435 - val loss: 2.3957 - val acc: 0.1517
Epoch 4/20
acc: 0.1521 - val loss: 2.3947 - val acc: 0.1516
acc: 0.1560 - val loss: 2.3926 - val acc: 0.1566
Epoch 6/20
acc: 0.1593 - val loss: 2.3907 - val acc: 0.1553
Epoch 7/20
acc: 0.1592 - val loss: 2.3904 - val acc: 0.1561
Epoch 8/20
acc: 0.1642 - val_loss: 2.3926 - val_acc: 0.1551
Epoch 9/20
acc: 0.1660 - val_loss: 2.3933 - val_acc: 0.1521
Epoch 10/20
acc: 0.1693 - val_loss: 2.3940 - val_acc: 0.1537
Epoch 11/20
acc: 0.1686 - val loss: 2.3960 - val acc: 0.1566
Epoch 12/20
63448/63448 [============= ] - 4s 58us/step - loss: 2.3553 -
acc: 0.1709 - val loss: 2.3966 - val acc: 0.1561
Validation Log Loss of Model in Current Run: 2.3904335856160874
Train on 63448 samples, validate on 11197 samples
Epoch 1/20
63448/63448 [============== ] - 4s 68us/step - loss: 2.8901 -
acc: 0.1050 - val loss: 2.4086 - val acc: 0.1483
Epoch 2/20
acc: 0.1304 - val loss: 2.3965 - val acc: 0.1503
Epoch 3/20
63448/63448 [============= ] - 4s 58us/step - loss: 2.4164 -
acc: 0.1452 - val loss: 2.3923 - val acc: 0.1521
Epoch 4/20
acc: 0.1511 - val loss: 2.3910 - val acc: 0.1545
acc: 0.1551 - val loss: 2.3895 - val acc: 0.1581
Epoch 6/20
acc: 0.1602 - val loss: 2.3875 - val acc: 0.1590
```

```
Epoch 7/20
63448/63448 [=======================] - 14s 220us/step - loss: 2.3763
- acc: 0.1614 - val_loss: 2.3882 - val_acc: 0.1587
Epoch 8/20
- acc: 0.1650 - val_loss: 2.3906 - val_acc: 0.1540
Epoch 9/20
- acc: 0.1648 - val_loss: 2.3915 - val_acc: 0.1565
Epoch 10/20
acc: 0.1676 - val_loss: 2.3943 - val_acc: 0.1588
Epoch 11/20
acc: 0.1698 - val loss: 2.3937 - val acc: 0.1561
Validation Log Loss of Model in Current Run: 2.387496891607927
Train on 63448 samples, validate on 11197 samples
Epoch 1/20
acc: 0.1012 - val loss: 2.4104 - val acc: 0.1475
acc: 0.1306 - val loss: 2.3929 - val acc: 0.1573
Epoch 3/20
acc: 0.1447 - val_loss: 2.3902 - val_acc: 0.1551
Epoch 4/20
acc: 0.1521 - val loss: 2.3881 - val acc: 0.1549
Epoch 5/20
acc: 0.1558 - val loss: 2.3872 - val acc: 0.1529
Epoch 6/20
acc: 0.1597 - val loss: 2.3859 - val acc: 0.1531
Epoch 7/20
acc: 0.1631 - val loss: 2.3872 - val acc: 0.1536
acc: 0.1632 - val loss: 2.3876 - val acc: 0.1551
Epoch 9/20
acc: 0.1644 - val loss: 2.3884 - val acc: 0.1557
Epoch 10/20
acc: 0.1673 - val_loss: 2.3891 - val_acc: 0.1536
Epoch 11/20
acc: 0.1707 - val_loss: 2.3897 - val_acc: 0.1515
Validation Log Loss of Model in Current Run: 2.385876258398855
Train on 63448 samples, validate on 11197 samples
Epoch 1/20
acc: 0.1037 - val_loss: 2.4114 - val_acc: 0.1472
Epoch 2/20
```

```
acc: 0.1277 - val loss: 2.3947 - val acc: 0.1546
Epoch 3/20
acc: 0.1449 - val loss: 2.3922 - val acc: 0.1599
Epoch 4/20
acc: 0.1498 - val loss: 2.3902 - val acc: 0.1589
Epoch 5/20
63448/63448 [============= ] - 4s 61us/step - loss: 2.3904 -
acc: 0.1559 - val loss: 2.3872 - val acc: 0.1592
acc: 0.1580 - val loss: 2.3859 - val acc: 0.1575
Epoch 7/20
acc: 0.1630 - val loss: 2.3859 - val acc: 0.1604
Epoch 8/20
acc: 0.1643 - val loss: 2.3878 - val acc: 0.1576
Epoch 9/20
63448/63448 [============= ] - 4s 61us/step - loss: 2.3672 -
acc: 0.1657 - val loss: 2.3892 - val acc: 0.1540
Epoch 10/20
acc: 0.1685 - val_loss: 2.3910 - val_acc: 0.1550
Epoch 11/20
acc: 0.1702 - val_loss: 2.3938 - val_acc: 0.1551
Epoch 12/20
acc: 0.1705 - val_loss: 2.3955 - val_acc: 0.1526
Validation Log Loss of Model in Current Run: 2.3858903664887627
Train on 63448 samples, validate on 11197 samples
Epoch 1/20
acc: 0.1052 - val loss: 2.4110 - val acc: 0.1477
Epoch 2/20
63448/63448 [============= ] - 4s 64us/step - loss: 2.4786 -
acc: 0.1328 - val loss: 2.3959 - val acc: 0.1496
Epoch 3/20
acc: 0.1452 - val loss: 2.3928 - val acc: 0.1547
Epoch 4/20
acc: 0.1505 - val_loss: 2.3921 - val_acc: 0.1572
Epoch 5/20
acc: 0.1569 - val loss: 2.3900 - val acc: 0.1582
acc: 0.1582 - val loss: 2.3888 - val acc: 0.1557
Epoch 7/20
63448/63448 [============= ] - 4s 64us/step - loss: 2.3790 -
acc: 0.1607 - val loss: 2.3890 - val acc: 0.1558
Epoch 8/20
acc: 0.1645 - val loss: 2.3896 - val acc: 0.1553
```

```
Epoch 9/20
       acc: 0.1646 - val loss: 2.3901 - val acc: 0.1586
       Epoch 10/20
       acc: 0.1682 - val loss: 2.3915 - val acc: 0.1549
       Epoch 11/20
       acc: 0.1698 - val_loss: 2.3907 - val_acc: 0.1541
       Validation Log Loss of Model in Current Run: 2.3887528186292855
       Average CV Loss of 5 Runs : 2.3876899841481833
In [52]: avg pred=np.zeros((xtr.shape[0],12))
        for i in range(len(model list 1)):
           train_pred=model_list_1[i].predict_proba(xtr)
           avg_pred+=train pred
        avg pred/=len(model list 1)
        print("Train Average Log-Loss: ",log_loss(ytr, avg_pred))
       Train Average Log-Loss: 2.3528577585587853
In [53]: | avg_pred=np.zeros((xcv.shape[0],12))
        for i in range(len(model list 1)):
           cv_pred=model_list_1[i].predict_proba(xcv)
           avg pred+=cv pred
        avg pred/=len(model list 1)
        print("Validation Average Log-Loss: ",log loss(ycv, avg pred))
       Validation Average Log-Loss: 2.3577544682106013
In [54]: | avg pred=np.zeros((xtest noevents.shape[0],12))
        for i in range(len(model_list_1)):
           test pred=model list 1[i].predict proba(xtest noevents)
           avg pred+=test pred
        avg pred/=len(model list 1)
In [55]: #saving the model
       np.save('nn1_noevents_1',avg_pred)
```

OBSERVATIONS: USING NEURAL NETWORK WE GOT TRAIN LOSS OF 2.3528 AND TEST LOSS OF 2.3577

MODEL 2

```
In [57]: model_sum=noevents_nn_model2(xtr.shape[1],12)
    model_sum.summary()
```

W0408 12:35:07.644370 11128 nn_ops.py:4224] Large dropout rate: 0.82 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead of keep_prob. Please e nsure that this is intended.

Layer (type)	Output Shape	Param #
dense_19 (Dense)	(None, 500)	899500
p_re_lu_13 (PReLU)	(None, 500)	500
dropout_13 (Dropout)	(None, 500)	0
dense_20 (Dense)	(None, 12)	6012
activation_7 (Activation)	(None, 12)	0

Total params: 906,012 Trainable params: 906,012 Non-trainable params: 0

```
In [59]:
         def noevents average nn 2(state):
             Takes a list of Random Seeds, splits the data into Train and CV based on S
         eed, trains model and takes average of
             predictions while testing
             model list=[]
             loss list=[]
             avg cv loss=0
             for i in range(len(state)):
                 xtr, xcv, ytr, ycv = train test split(Xtrain whole, y,stratify=y,test
         size=0.15,random state=state[i])
                 ytr=np_utils.to_categorical(ytr)
                 ycv=np utils.to categorical(ycv)
                 model=noevents nn model2(xtr.shape[1],12)
                 #logdir = os.path.join("logs", "noevents_nn1."+str(i+1))
                 #t callback=TensorBoard(log dir=logdir)
                 model.fit(xtr, ytr, batch size=256, epochs=30, verbose=1, validation d
         ata=(xcv, ycv),callbacks=[early stop])
                 pred=model.predict_proba(xcv)
                 cv loss=log loss(ycv, pred)
                 print("Validation Log Loss of Model in Current Run: ",cv_loss)
                 model list.append(model)
                 loss list.append(cv loss)
             avg cv loss=mean(loss list)
             print("Average CV Loss of "+str(len(state))+" Runs :",avg cv loss)
             return(model list)
```

```
In [60]: random_seeds=[9,18,42,86,103]
model_list_2= noevents_average_nn_2(random_seeds)
```

W0408 12:35:07.760055 11128 nn_ops.py:4224] Large dropout rate: 0.82 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead of keep_prob. Please e nsure that this is intended.

```
Train on 63448 samples, validate on 11197 samples
Epoch 1/30
acc: 0.1345 - val loss: 2.4168 - val acc: 0.1427
Epoch 2/30
acc: 0.1416 - val loss: 2.4114 - val acc: 0.1440
Epoch 3/30
63448/63448 [============= ] - 4s 65us/step - loss: 2.4089 -
acc: 0.1452 - val loss: 2.4081 - val acc: 0.1444
Epoch 4/30
acc: 0.1462 - val_loss: 2.4059 - val_acc: 0.1466
acc: 0.1482 - val loss: 2.4042 - val acc: 0.1478
Epoch 6/30
acc: 0.1497 - val loss: 2.4030 - val acc: 0.1485
Epoch 7/30
acc: 0.1504 - val loss: 2.4020 - val acc: 0.1499
Epoch 8/30
acc: 0.1518 - val_loss: 2.4011 - val_acc: 0.1501
Epoch 9/30
acc: 0.1528 - val loss: 2.4004 - val acc: 0.1501
Epoch 10/30
acc: 0.1534 - val_loss: 2.3998 - val_acc: 0.1496
Epoch 11/30
acc: 0.1557 - val loss: 2.3993 - val acc: 0.1508
Epoch 12/30
63448/63448 [============== ] - 4s 64us/step - loss: 2.3928 -
acc: 0.1564 - val loss: 2.3988 - val acc: 0.1516
Epoch 13/30
acc: 0.1562 - val loss: 2.3984 - val acc: 0.1527
Epoch 14/30
acc: 0.1576 - val_loss: 2.3980 - val_acc: 0.1525
Epoch 15/30
acc: 0.1600 - val loss: 2.3976 - val acc: 0.1522
Epoch 16/30
acc: 0.1568 - val_loss: 2.3972 - val_acc: 0.1523
Epoch 17/30
acc: 0.1580 - val loss: 2.3969 - val acc: 0.1525
Epoch 18/30
63448/63448 [============= ] - 4s 71us/step - loss: 2.3882 -
acc: 0.1584 - val loss: 2.3966 - val acc: 0.1522
Epoch 19/30
```

```
acc: 0.1594 - val loss: 2.3963 - val acc: 0.1520
Epoch 20/30
acc: 0.1595 - val_loss: 2.3961 - val_acc: 0.1520
Epoch 21/30
acc: 0.1593 - val loss: 2.3958 - val acc: 0.1523
Epoch 22/30
63448/63448 [============= ] - 4s 70us/step - loss: 2.3851 -
acc: 0.1607 - val loss: 2.3955 - val acc: 0.1541
Epoch 23/30
acc: 0.1607 - val loss: 2.3953 - val acc: 0.1546
Epoch 24/30
acc: 0.1634 - val loss: 2.3951 - val acc: 0.1545
Epoch 25/30
acc: 0.1618 - val loss: 2.3949 - val acc: 0.1544
Epoch 26/30
63448/63448 [============= ] - 4s 69us/step - loss: 2.3830 -
acc: 0.1630 - val_loss: 2.3947 - val acc: 0.1545
Epoch 27/30
acc: 0.1638 - val loss: 2.3945 - val acc: 0.1545
Epoch 28/30
acc: 0.1633 - val_loss: 2.3943 - val_acc: 0.1537
Epoch 29/30
acc: 0.1627 - val_loss: 2.3941 - val_acc: 0.1533
Epoch 30/30
acc: 0.1627 - val loss: 2.3939 - val acc: 0.1535
W0408 12:37:17.340040 11128 nn_ops.py:4224] Large dropout rate: 0.82 (>0.5).
```

In TensorFlow 2.x, dropout() uses dropout rate instead of keep prob. Please e nsure that this is intended.

```
Validation Log Loss of Model in Current Run: 2.393906689524874
Train on 63448 samples, validate on 11197 samples
Epoch 1/30
acc: 0.1355 - val loss: 2.4170 - val acc: 0.1474
Epoch 2/30
acc: 0.1423 - val loss: 2.4108 - val acc: 0.1508
acc: 0.1463 - val loss: 2.4070 - val acc: 0.1512
Epoch 4/30
acc: 0.1459 - val loss: 2.4043 - val acc: 0.1525
Epoch 5/30
acc: 0.1461 - val loss: 2.4023 - val acc: 0.1523
Epoch 6/30
acc: 0.1494 - val loss: 2.4007 - val acc: 0.1519
Epoch 7/30
acc: 0.1514 - val loss: 2.3995 - val acc: 0.1533
Epoch 8/30
acc: 0.1524 - val loss: 2.3984 - val acc: 0.1539
acc: 0.1536 - val loss: 2.3975 - val acc: 0.1550
Epoch 10/30
63448/63448 [============== ] - 4s 66us/step - loss: 2.3961 -
acc: 0.1511 - val loss: 2.3968 - val acc: 0.1567
Epoch 11/30
acc: 0.1546 - val loss: 2.3962 - val acc: 0.1563
Epoch 12/30
acc: 0.1534 - val loss: 2.3956 - val acc: 0.1554
acc: 0.1554 - val loss: 2.3951 - val acc: 0.1560
Epoch 14/30
acc: 0.1543 - val loss: 2.3946 - val_acc: 0.1568
Epoch 15/30
acc: 0.1583 - val_loss: 2.3942 - val_acc: 0.1560
Epoch 16/30
acc: 0.1568 - val_loss: 2.3938 - val_acc: 0.1558
Epoch 17/30
acc: 0.1580 - val_loss: 2.3935 - val_acc: 0.1567
Epoch 18/30
acc: 0.1583 - val loss: 2.3931 - val acc: 0.1566
Epoch 19/30
```

```
acc: 0.1578 - val loss: 2.3928 - val acc: 0.1570
acc: 0.1599 - val loss: 2.3926 - val acc: 0.1569
Epoch 21/30
63448/63448 [============= ] - 4s 65us/step - loss: 2.3859 -
acc: 0.1611 - val loss: 2.3923 - val acc: 0.1565
Epoch 22/30
acc: 0.1582 - val loss: 2.3920 - val acc: 0.1565
Epoch 23/30
acc: 0.1599 - val loss: 2.3918 - val acc: 0.1566
Epoch 24/30
acc: 0.1597 - val loss: 2.3916 - val acc: 0.1572
Epoch 25/30
acc: 0.1605 - val loss: 2.3914 - val acc: 0.1581
acc: 0.1634 - val loss: 2.3912 - val acc: 0.1582
Epoch 27/30
acc: 0.1626 - val loss: 2.3910 - val acc: 0.1579
Epoch 28/30
acc: 0.1630 - val loss: 2.3908 - val acc: 0.1576
Epoch 29/30
acc: 0.1622 - val loss: 2.3906 - val acc: 0.1583
Epoch 30/30
acc: 0.1615 - val loss: 2.3904 - val acc: 0.1580
W0408 12:39:25.408527 11128 nn ops.py:4224] Large dropout rate: 0.82 (>0.5).
```

In TensorFlow 2.x, dropout() uses dropout rate instead of keep prob. Please e nsure that this is intended.

```
Validation Log Loss of Model in Current Run: 2.390445421803921
Train on 63448 samples, validate on 11197 samples
Epoch 1/30
acc: 0.1345 - val loss: 2.4160 - val acc: 0.1410
Epoch 2/30
acc: 0.1418 - val loss: 2.4098 - val acc: 0.1418
acc: 0.1459 - val loss: 2.4060 - val acc: 0.1454
Epoch 4/30
acc: 0.1464 - val loss: 2.4033 - val acc: 0.1460
Epoch 5/30
acc: 0.1479 - val loss: 2.4013 - val acc: 0.1468
Epoch 6/30
acc: 0.1489 - val loss: 2.3997 - val acc: 0.1474
Epoch 7/30
acc: 0.1505 - val loss: 2.3984 - val acc: 0.1482
Epoch 8/30
acc: 0.1534 - val loss: 2.3973 - val acc: 0.1498
acc: 0.1518 - val loss: 2.3963 - val acc: 0.1509
Epoch 10/30
63448/63448 [============== ] - 4s 66us/step - loss: 2.3955 -
acc: 0.1547 - val loss: 2.3955 - val acc: 0.1514
Epoch 11/30
acc: 0.1541 - val loss: 2.3948 - val acc: 0.1516s: 2.3950 - acc: 0.
Epoch 12/30
acc: 0.1543 - val loss: 2.3942 - val acc: 0.1518
acc: 0.1568 - val loss: 2.3936 - val acc: 0.1534
Epoch 14/30
acc: 0.1557 - val_loss: 2.3930 - val_acc: 0.1522
Epoch 15/30
acc: 0.1572 - val_loss: 2.3926 - val_acc: 0.1528
Epoch 16/30
acc: 0.1594 - val_loss: 2.3921 - val_acc: 0.1540
Epoch 17/30
acc: 0.1590 - val_loss: 2.3917 - val_acc: 0.1548
Epoch 18/30
acc: 0.1588 - val loss: 2.3914 - val acc: 0.1552
Epoch 19/30
```

```
acc: 0.1582 - val loss: 2.3910 - val acc: 0.1558
acc: 0.1610 - val loss: 2.3906 - val acc: 0.1564
Epoch 21/30
63448/63448 [============== ] - 4s 68us/step - loss: 2.3872 -
acc: 0.1605 - val loss: 2.3903 - val acc: 0.1565
Epoch 22/30
acc: 0.1602 - val loss: 2.3900 - val acc: 0.1562
Epoch 23/30
acc: 0.1587 - val loss: 2.3898 - val acc: 0.1563
Epoch 24/30
acc: 0.1604 - val loss: 2.3895 - val acc: 0.1570
Epoch 25/30
acc: 0.1617 - val loss: 2.3893 - val acc: 0.1571
acc: 0.1613 - val loss: 2.3890 - val acc: 0.1575
Epoch 27/30
63448/63448 [============= ] - 4s 67us/step - loss: 2.3841 -
acc: 0.1627 - val loss: 2.3888 - val acc: 0.1587
Epoch 28/30
acc: 0.1614 - val loss: 2.3886 - val acc: 0.1587
Epoch 29/30
acc: 0.1623 - val loss: 2.3884 - val acc: 0.1588
Epoch 30/30
acc: 0.1621 - val loss: 2.3882 - val acc: 0.1591
W0408 12:41:34.231742 11128 nn ops.py:4224] Large dropout rate: 0.82 (>0.5).
```

In TensorFlow 2.x, dropout() uses dropout rate instead of keep prob. Please e nsure that this is intended.

```
Validation Log Loss of Model in Current Run: 2.3882187361524307
Train on 63448 samples, validate on 11197 samples
Epoch 1/30
acc: 0.1353 - val loss: 2.4162 - val acc: 0.1448
Epoch 2/30
acc: 0.1429 - val loss: 2.4099 - val acc: 0.1463
acc: 0.1448 - val loss: 2.4060 - val acc: 0.1465
Epoch 4/30
acc: 0.1465 - val loss: 2.4033 - val acc: 0.1468
Epoch 5/30
acc: 0.1489 - val loss: 2.4012 - val acc: 0.1498
Epoch 6/30
acc: 0.1497 - val loss: 2.3996 - val acc: 0.1523
Epoch 7/30
acc: 0.1519 - val loss: 2.3983 - val acc: 0.1525
Epoch 8/30
acc: 0.1509 - val loss: 2.3973 - val acc: 0.1539
acc: 0.1526 - val loss: 2.3964 - val acc: 0.1549
Epoch 10/30
63448/63448 [============== ] - 4s 65us/step - loss: 2.3949 -
acc: 0.1536 - val loss: 2.3956 - val acc: 0.1552
Epoch 11/30
acc: 0.1560 - val loss: 2.3950 - val acc: 0.1560
Epoch 12/30
acc: 0.1548 - val loss: 2.3944 - val acc: 0.1553
acc: 0.1545 - val loss: 2.3939 - val acc: 0.1563
Epoch 14/30
acc: 0.1554 - val loss: 2.3934 - val_acc: 0.1558
Epoch 15/30
acc: 0.1581 - val_loss: 2.3930 - val_acc: 0.1560
Epoch 16/30
acc: 0.1572 - val_loss: 2.3926 - val_acc: 0.1565
Epoch 17/30
acc: 0.1579 - val_loss: 2.3923 - val_acc: 0.1558
Epoch 18/30
acc: 0.1571 - val loss: 2.3920 - val acc: 0.1569
Epoch 19/30
```

```
acc: 0.1584 - val_loss: 2.3917 - val_acc: 0.1570
Epoch 20/30
acc: 0.1569 - val loss: 2.3914 - val acc: 0.1567
Epoch 21/30
63448/63448 [============= ] - 4s 68us/step - loss: 2.3863 -
acc: 0.1608 - val loss: 2.3911 - val acc: 0.1574
Epoch 22/30
acc: 0.1600 - val loss: 2.3909 - val acc: 0.1583
Epoch 23/30
acc: 0.1595 - val_loss: 2.3907 - val_acc: 0.1596
Epoch 24/30
acc: 0.1606 - val loss: 2.3904 - val acc: 0.1591
Epoch 25/30
acc: 0.1606 - val loss: 2.3902 - val acc: 0.1595
acc: 0.1598 - val loss: 2.3900 - val acc: 0.1597
Epoch 27/30
63448/63448 [============= ] - 4s 65us/step - loss: 2.3826 -
acc: 0.1624 - val loss: 2.3898 - val acc: 0.1591
Epoch 28/30
acc: 0.1607 - val loss: 2.3897 - val acc: 0.1592 loss
Epoch 29/30
acc: 0.1615 - val loss: 2.3895 - val acc: 0.1592
Epoch 30/30
acc: 0.1615 - val loss: 2.3893 - val acc: 0.1595
Validation Log Loss of Model in Current Run: 2.389341872515844
Train on 63448 samples, validate on 11197 samples
Epoch 1/30
acc: 0.1354 - val_loss: 2.4152 - val_acc: 0.1402
Epoch 2/30
acc: 0.1441 - val_loss: 2.4097 - val_acc: 0.1409
acc: 0.1448 - val loss: 2.4065 - val acc: 0.1443
Epoch 4/30
63448/63448 [============== ] - 4s 66us/step - loss: 2.4052 -
acc: 0.1470 - val loss: 2.4043 - val acc: 0.1445
Epoch 5/30
acc: 0.1481 - val loss: 2.4025 - val acc: 0.1454
Epoch 6/30
acc: 0.1482 - val_loss: 2.4012 - val_acc: 0.1457
Epoch 7/30
```

```
acc: 0.1515 - val loss: 2.4002 - val acc: 0.1467
Epoch 8/30
acc: 0.1530 - val loss: 2.3993 - val acc: 0.1483
Epoch 9/30
acc: 0.1520 - val loss: 2.3985 - val acc: 0.1502
Epoch 10/30
acc: 0.1554 - val loss: 2.3979 - val acc: 0.1521
Epoch 11/30
acc: 0.1554 - val loss: 2.3973 - val acc: 0.1528
Epoch 12/30
acc: 0.1571 - val loss: 2.3967 - val acc: 0.1532
Epoch 13/30
acc: 0.1566 - val loss: 2.3963 - val acc: 0.1536
Epoch 14/30
acc: 0.1557 - val loss: 2.3958 - val acc: 0.1540
Epoch 15/30
acc: 0.1583 - val_loss: 2.3954 - val_acc: 0.1534
Epoch 16/30
acc: 0.1577 - val_loss: 2.3950 - val_acc: 0.1541
Epoch 17/30
acc: 0.1594 - val_loss: 2.3946 - val_acc: 0.1545
Epoch 18/30
acc: 0.1599 - val loss: 2.3943 - val acc: 0.1541
Epoch 19/30
acc: 0.1597 - val_loss: 2.3940 - val_acc: 0.1550
Epoch 20/30
63448/63448 [============== ] - 5s 75us/step - loss: 2.3867 -
acc: 0.1590 - val_loss: 2.3937 - val_acc: 0.1548
Epoch 21/30
acc: 0.1595 - val_loss: 2.3934 - val_acc: 0.1543
acc: 0.1615 - val loss: 2.3931 - val acc: 0.1544
Epoch 23/30
63448/63448 [============== ] - 5s 74us/step - loss: 2.3850 -
acc: 0.1609 - val loss: 2.3929 - val acc: 0.1545
Epoch 24/30
acc: 0.1603 - val loss: 2.3926 - val acc: 0.1546
Epoch 25/30
acc: 0.1611 - val_loss: 2.3924 - val_acc: 0.1550
Epoch 26/30
```

```
acc: 0.1623 - val loss: 2.3922 - val acc: 0.1547
        Epoch 27/30
        acc: 0.1622 - val loss: 2.3919 - val acc: 0.1559
        Epoch 28/30
        acc: 0.1615 - val loss: 2.3917 - val acc: 0.1575
        Epoch 29/30
       63448/63448 [============= ] - 5s 71us/step - loss: 2.3817 -
        acc: 0.1609 - val loss: 2.3915 - val acc: 0.1576
        Epoch 30/30
        acc: 0.1625 - val loss: 2.3913 - val acc: 0.1578
       Validation Log Loss of Model in Current Run: 2.391342581548126
       Average CV Loss of 5 Runs : 2.390651060309039
In [61]: | avg pred=np.zeros((xtr.shape[0],12))
        for i in range(len(model list 2)):
           train pred=model list 2[i].predict proba(xtr)
           avg pred+=train pred
        avg_pred/=len(model_list_2)
        print("Train Average Log-Loss: ",log_loss(ytr, avg_pred))
        Train Average Log-Loss: 2.3770776429186817
In [62]: avg pred=np.zeros((xcv.shape[0],12))
        for i in range(len(model list 2)):
           cv_pred=model_list_2[i].predict_proba(xcv)
           avg pred+=cv pred
        avg pred/=len(model list 2)
        print("Validation Average Log-Loss: ",log_loss(ycv, avg_pred))
       Validation Average Log-Loss: 2.3788470152956647
In [63]: | avg pred=np.zeros((xtest noevents.shape[0],12))
        for i in range(len(model list 2)):
           test pred=model list 2[i].predict proba(xtest noevents)
           avg pred+=test pred
        avg pred/=len(model list 2)
In [64]: #saving the model
        np.save('nn2_noevents_1',avg_pred)
```

OBSERVATIONS: 1.THE TRAIN AND VALIDATION LOSS FOR THE MODEL ARE 2.377 AND 2.378 RESPECTIVELY.

XGBOOST

```
In [65]: #https://www.kaqqle.com/c/talkingdata-mobile-user-demographics/discussion/2342
         xgb = XGBClassifier(n estimators=350, n jobs=-1,learning rate=0.05, colsample
         bytree=0.7, max depth=5,subsample=0.7,objective='multi:softprob',num class=12,
         eval metric='mlogloss')
         xgb.fit(xtr, ytr)
         #Using Model Calibration
         clf = CalibratedClassifierCV(xgb, method="sigmoid")
         clf.fit(xtr, ytr)
         pred y=clf.predict proba(xtr)
         print("Train Log Loss :",log_loss(ytr, pred_y))
         pred y=clf.predict proba(xcv)
         print("Validation Log Loss :",log_loss(ycv, pred_y))
         Train Log Loss: 2.3718148085004658
         Validation Log Loss: 2.3929110310146204
In [66]: no events pred lr=clf.predict proba(xtest noevents)
In [67]: #saving the model
         np.save('xgb_noevents_1.npy',no_events_pred_lr)
```

OBSERVATIONS: THE TRAIN AND VALIDATION LOSS ARE 2.3718 AND 2.3929 RESPECTIVELY. THESE ARE NOT AS GOOD AS THE NEURAL NETWORK MODEL.

MODELLING USING DEVICES WITH EVENTS

ONE HOT ENCODING OF PHONE BRAND

Train Brand One-hot Shape: (23309, 131) Test Brand One-hot Shape: (35194, 131)

ONE HOT ENCODING OF PHONE MODEL

Train Brand One-hot Shape: (23309, 1667) Test Brand One-hot Shape: (35194, 1667)

ONE HOT ENCODING OF DEVICE APPS

```
In [47]: #Since the Deviceapps has both train and test columns merged to create Train A
         pps One-Hot we will Drop all Nan of Train Row
         #Once we remove Nan in Train Rows we will get the Apps in Train Data and we cr
         eate CSR Matrix for those rows
         d = deviceapps.dropna(subset=['trainrow'])
         Xtr_events_app = csr_matrix((np.ones(d.shape[0]), (d.trainrow, d.app)),
                               shape=(gatrain events.shape[0],napps))
         #Since the Deviceapps has both train and test columns merged to create Test Ap
         ps One-Hot we will Drop all Nan of Test Row
         #Once we remove Nan in Test Rows we will get the Apps in Test Data and we crea
         te CSR Matrix for those rows
         d = deviceapps.dropna(subset=['testrow'])
         Xte events app = csr matrix((np.ones(d.shape[0]), (d.testrow, d.app)),
                               shape=(gatest events.shape[0],napps))
         print("Train Event Apps One-hot Shape: ",Xtr_events_app.shape)
         print("Test Event Apps One-hot Shape: ",Xte events app.shape)
```

Train Event Apps One-hot Shape: (23309, 19237) Test Event Apps One-hot Shape: (35194, 19237)

ONE HOT ENCODING OF DEVICE LABELS

Train Event Labels One-hot Shape: (23309, 492) Test Event Labels One-hot Shape: (35194, 492)

TFIDF FEATURES FOR HOURS

BOW FOR HOURS

```
In [51]: gatrain_events["hourjoin"]=gatrain_events.index.map(hourjoin)
    gatest_events["hourjoin"]=gatest_events.index.map(hourjoin)

    vectorizer=CountVectorizer()
    vectorizer.fit(gatrain_events['hourjoin'].values)

    X_tr_hourjoin_onehot = vectorizer.transform(gatrain_events['hourjoin'].values)
    X_te_hourjoin_onehot = vectorizer.transform(gatest_events['hourjoin'].values)
    print("After vectorizations")
    print("Train Event Hours One-hot Shape: ",X_tr_hourjoin_onehot.shape)
    print("Test Event Hours One-hot Shape: ",X_te_hourjoin_onehot.shape)

After vectorizations
    Train Event Hours One-hot Shape: (23309, 24)
    Test Event Hours One-hot Shape: (35194, 24)

In [52]: import pickle
    with open('hour_bow','wb') as fp:
        pickle.dump(vectorizer,fp)
```

ONE HOT ENCODING OF HOUR BIN

```
In [53]: gatrain_events["hourbinjoin"]=gatrain_events.index.map(hourbinjoin)
    gatest_events["hourbinjoin"]=gatest_events.index.map(hourbinjoin)

    vectorizer=CountVectorizer(binary=True)
    vectorizer.fit(gatrain_events['hourbinjoin'].values)

    X_tr_hourbinjoin_onehot = vectorizer.transform(gatrain_events['hourbinjoin'].values)

    X_te_hourbinjoin_onehot = vectorizer.transform(gatest_events['hourbinjoin'].values)

    print("Train Event Hours One-hot Shape: ",X_tr_hourbinjoin_onehot.shape)

    print("Test Event Hours One-hot Shape: ",X_te_hourbinjoin_onehot.shape)

Train Event Hours One-hot Shape: (23309, 4)
    Test Event Hours One-hot Shape: (35194, 4)

In [54]: import pickle
    with open('hour_bin_bow','wb') as fp:
        pickle.dump(vectorizer,fp)
```

TFIDF FEATURES FOR DAY

```
In [55]: gatrain_events["daysjoin"]=gatrain_events.index.map(daysjoin)
    gatest_events["daysjoin"]=gatest_events.index.map(daysjoin)

    vectorizer=TfidfVectorizer()
    vectorizer.fit(gatrain_events['daysjoin'].values)

    X_tr_daysjoin_tfidf = vectorizer.transform(gatrain_events['daysjoin'].values)
    X_te_daysjoin_tfidf = vectorizer.transform(gatest_events['daysjoin'].values)
    print("After vectorizations")
    print("Train Event days TF-IDF Shape: ",X_tr_daysjoin_tfidf.shape)
    print("Test Event days TF-IDF Shape: ",X_te_daysjoin_tfidf.shape)

After vectorizations
    Train Event days TF-IDF Shape: (23309, 7)
    Test Event days TF-IDF Shape: (35194, 7)

In [56]: import pickle
    with open('day_tfidf','wb') as fp:
        pickle.dump(vectorizer,fp)
```

STANDARDIZING LATITUDE AND LONGITUDE

```
In [57]: gatrain events["latitude"]=gatrain events.index.map(median lat)
         gatest events["latitude"]=gatest events.index.map(median lat)
         scaler=StandardScaler()
         scaler.fit(gatrain events['latitude'].values.reshape(-1,1))
         X tr event lat = scaler.transform(gatrain events['latitude'].values.reshape(-1
         ,1))
         X te event lat = scaler.transform(gatest events['latitude'].values.reshape(-1,
         1))
         print("Train Event Latitude Standardized Shape: ",X_tr_event_lat.shape)
         print("Test Event Latitude Standardized Shape: ",X_te_event_lat.shape)
         Train Event Latitude Standardized Shape:
                                                   (23309, 1)
         Test Event Latitude Standardized Shape:
                                                   (35194, 1)
In [58]: | import pickle
         with open('lat_scaler','wb') as fp:
             pickle.dump(scaler,fp)
In [59]: | gatrain_events["longitude"]=gatrain_events.index.map(median_lon)
         gatest events["longitude"]=gatest events.index.map(median lon)
         scaler=StandardScaler()
         scaler.fit(gatrain_events['longitude'].values.reshape(-1,1))
         X tr event lon = scaler.transform(gatrain events['longitude'].values.reshape(-
         1,1))
         X te event lon = scaler.transform(gatest events['longitude'].values.reshape(-1
         ,1))
         print("Train Event longitude Standardized Shape: ",X_tr_event_lon.shape)
         print("Test Event longitude Standardized Shape: ",X te event lon.shape)
         Train Event longitude Standardized Shape: (23309, 1)
         Test Event longitude Standardized Shape: (35194, 1)
In [60]:
         import pickle
         with open('lon_scaler','wb') as fp:
             pickle.dump(scaler,fp)
```

ONE HOT ENCODING OF CLUSTERED FEATURES

```
In [61]:
         gatrain events["locationbin"]=gatrain events.index.map(clustered geo features)
         gatest events["locationbin"]=gatest events.index.map(clustered geo features)
         #gatrain events.locationbin=gatrain events.locationbin.astype(str)
         #gatest events.locationbin=gatest events.locationbin.astype(str)
         vectorizer= OneHotEncoder()
         vectorizer.fit(gatrain events['locationbin'].values.reshape(-1,1))
         X_tr_clus = vectorizer.transform(gatrain_events['locationbin'].values.reshape(
         -1,1))
         X_te_clus = vectorizer.transform(gatest_events['locationbin'].values.reshape(-
         1,1))
         print("Train Event locationbin Shape: ",X tr clus.shape)
         print("Test Event locationbin Shape: ",X_te_clus.shape)
         Train Event locationbin Shape: (23309, 10)
         Test Event locationbin Shape: (35194, 10)
In [62]: import pickle
         with open('clustered features','wb') as fp:
             pickle.dump(vectorizer,fp)
```

TFIDF FEATURE FOR APP IS_ACTIVE

```
In [63]:
         #Mapping The Values the values to train and test dataframes
         gatrain events['apps active']=gatrain events.index.map(active apps events)
         gatest_events['apps_active']=gatest_events.index.map(active_apps_events)
         vectorizer=TfidfVectorizer()
         vectorizer.fit(gatrain events['apps active'].values)
         X tr active = vectorizer.transform(gatrain events['apps active'].values)
         X_te_active = vectorizer.transform(gatest_events['apps_active'].values)
         print("Train Apps Active TF-IDF Shape: ",X tr active.shape)
         print("Test Apps Active TF-IDF Shape: ",X te active.shape)
         Train Apps Active TF-IDF Shape: (23309, 2)
         Test Apps Active TF-IDF Shape: (35194, 2)
         import pickle
In [64]:
         with open('isactive_tfidf','wb') as fp:
             pickle.dump(vectorizer,fp)
```

```
In [65]: #creating final data matrix
         X_train_events=hstack((Xtr_events_brand,Xtr_events_model,Xtr_events_labels,X_t
         r hourjoin tfidf,X tr hourbinjoin onehot,X tr daysjoin tfidf,X tr event lat,X
         tr event lon,Xtr events app,X tr active,X tr clus),format='csr')
         X_test_events =hstack((Xte_events_brand,Xte_events_model,Xte_events_labels,X_t
         e hourjoin tfidf,X te hourbinjoin onehot,X te daysjoin tfidf,X te event lat,X
         te_event_lon,Xte_events_app,X_te_active,X_te_clus),format='csr')
         print(X_train_events.shape)
         print(X test events.shape)
         (23309, 21576)
         (35194, 21576)
In [81]: #label encoding target variable
         targetencoder = LabelEncoder().fit(gatrain events.group)
         y = targetencoder.transform(gatrain events.group)
In [82]: print("xtrain shape:",X_train_events.shape)
         print("ytrain shape:",y.shape)
         print("xtest shape:",X_test_events.shape)
         xtrain shape: (23309, 21576)
         ytrain shape: (23309,)
         xtest shape: (35194, 21576)
In [83]: | xtr, xcv, ytr, ycv = train_test_split(X_train_events, y,stratify=y,test_size=
         0.2, random state=9)
In [84]:
        #one hot encoding target variable
         ytr=np_utils.to_categorical(ytr)
         ycv=np utils.to categorical(ycv)
```

NEURAL NETWORK 1

```
In [85]:
         def events nn model1(input dim,output dim):
             model = Sequential()
             model.add(Dropout(0.15, input_shape=(input_dim,)))
             model.add(Dense(240, init='uniform'))
             model.add(PReLU(init='zero'))
             model.add(Dropout(0.8))
             model.add(Dense(240, init='uniform'))
             model.add(PReLU(init='zero', weights=None))
             model.add(Dropout(0.35))
             model.add(Dense(260, init='uniform'))
             model.add(PReLU(init='zero', weights=None))
             model.add(Dropout(0.40))
             model.add(Dense(output_dim, init='uniform'))
             model.add(Activation('softmax'))
             opt = Adagrad(lr=0.008, epsilon=1e-08)
             model.compile(loss='categorical_crossentropy',
                           optimizer=opt,
                           metrics=['accuracy'])
             return model
```

Layer (type)	Output	Shape	Param #
dropout_19 (Dropout)	(None,	21576)	0
dense_31 (Dense)	(None,	240)	5178480
p_re_lu_19 (PReLU)	(None,	240)	240
dropout_20 (Dropout)	(None,	240)	0
dense_32 (Dense)	(None,	240)	57840
p_re_lu_20 (PReLU)	(None,	240)	240
dropout_21 (Dropout)	(None,	240)	0
dense_33 (Dense)	(None,	260)	62660
p_re_lu_21 (PReLU)	(None,	260)	260
dropout_22 (Dropout)	(None,	260)	0
dense_34 (Dense)	(None,	12)	3132
activation_13 (Activation)	(None,	12)	0
	======		======

Total params: 5,302,852 Trainable params: 5,302,852 Non-trainable params: 0

```
In [88]:
         def events average nn 1(state):
             Takes a list of Random Seeds, splits the data into Train and CV based on S
         eed, trains model and takes average of
             predictions while testing
             model list=[]
             loss list=[]
             avg cv loss=0
             for i in range((state)):
                 model=events nn model1(xtr.shape[1],12)
                 model.fit(xtr, ytr, batch_size=149, epochs=20, verbose=1, validation_d
         ata=(xcv, ycv),callbacks=[early_stop])
                 model.save('saved models/events/nn1'+str(i+1))
                 pred=model.predict_proba(xcv)
                 cv_loss=log_loss(ycv, pred)
                 print("Validation Log Loss of Model in Current Run: ",cv loss)
                 model list.append(model)
                 loss_list.append(cv_loss)
             avg cv loss=mean(loss list)
             print("Average CV Loss of "+str((state))+" Runs :",avg_cv_loss)
             return(model list)
```

In [89]: model_list_2=events_average_nn_1(10)

```
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1883 - val loss: 2.1078 - val acc: 0.2602
Epoch 2/20
- acc: 0.2401 - val loss: 2.0377 - val acc: 0.2969
Epoch 3/20
- acc: 0.2699 - val loss: 2.0073 - val acc: 0.3012
Epoch 4/20
- acc: 0.2880 - val loss: 1.9709 - val acc: 0.3215
- acc: 0.2924 - val loss: 1.9530 - val acc: 0.3220
Epoch 6/20
- acc: 0.3013 - val loss: 1.9505 - val acc: 0.3168
Epoch 7/20
- acc: 0.3127 - val loss: 1.9464 - val acc: 0.3220
Epoch 8/20
- acc: 0.3130 - val_loss: 1.9306 - val_acc: 0.3271
Epoch 9/20
- acc: 0.3241 - val_loss: 1.9241 - val_acc: 0.3265
Epoch 10/20
- acc: 0.3339 - val_loss: 1.9207 - val_acc: 0.3275
Epoch 11/20
- acc: 0.3383 - val loss: 1.9211 - val acc: 0.3235
Epoch 12/20
- acc: 0.3423 - val loss: 1.9186 - val acc: 0.3241
Epoch 13/20
- acc: 0.3439 - val loss: 1.9126 - val acc: 0.3263
Epoch 14/20
- acc: 0.3502 - val_loss: 1.9149 - val_acc: 0.3271
Epoch 15/20
- acc: 0.3559 - val loss: 1.9189 - val acc: 0.3239
Epoch 16/20
- acc: 0.3608 - val_loss: 1.9151 - val_acc: 0.3275
Epoch 17/20
18647/18647 [============== ] - 14s 769us/step - loss: 1.7690
- acc: 0.3661 - val loss: 1.9180 - val acc: 0.3265
Epoch 18/20
- acc: 0.3677 - val loss: 1.9137 - val acc: 0.3299
Validation Log Loss of Model in Current Run: 1.9136059269573138
Train on 18647 samples, validate on 4662 samples
```

```
Epoch 1/20
- acc: 0.1749 - val_loss: 2.1252 - val_acc: 0.2578
Epoch 2/20
- acc: 0.2389 - val_loss: 2.0454 - val_acc: 0.2898
Epoch 3/20
- acc: 0.2671 - val_loss: 2.0079 - val_acc: 0.2997
Epoch 4/20
- acc: 0.2822 - val_loss: 1.9727 - val_acc: 0.3104
Epoch 5/20
- acc: 0.2914 - val loss: 1.9737 - val acc: 0.2992
- acc: 0.3011 - val_loss: 1.9551 - val_acc: 0.3142
Epoch 7/20
- acc: 0.3040 - val_loss: 1.9462 - val_acc: 0.3187
Epoch 8/20
- acc: 0.3159 - val_loss: 1.9417 - val_acc: 0.3142
Epoch 9/20
- acc: 0.3202 - val loss: 1.9305 - val acc: 0.3263
Epoch 10/20
- acc: 0.3278 - val loss: 1.9242 - val acc: 0.3230
Epoch 11/20
- acc: 0.3388 - val_loss: 1.9216 - val_acc: 0.3213
Epoch 12/20
- acc: 0.3354 - val_loss: 1.9225 - val_acc: 0.3230
Epoch 13/20
- acc: 0.3428 - val loss: 1.9212 - val acc: 0.3248
Epoch 14/20
- acc: 0.3436 - val loss: 1.9160 - val acc: 0.3237
Epoch 15/20
- acc: 0.3552 - val_loss: 1.9194 - val_acc: 0.3256
Epoch 16/20
- acc: 0.3569 - val loss: 1.9148 - val acc: 0.3267
Epoch 17/20
- acc: 0.3638 - val loss: 1.9220 - val acc: 0.3263
Epoch 18/20
18647/18647 [================ ] - 14s 773us/step - loss: 1.7692
- acc: 0.3698 - val loss: 1.9197 - val acc: 0.3245
Epoch 19/20
- acc: 0.3698 - val_loss: 1.9213 - val_acc: 0.3280
```

```
Epoch 20/20
- acc: 0.3712 - val loss: 1.9354 - val acc: 0.3170
Validation Log Loss of Model in Current Run: 1.9367125339164373
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1819 - val loss: 2.1559 - val acc: 0.2606
Epoch 2/20
- acc: 0.2369 - val loss: 2.0460 - val acc: 0.2821
Epoch 3/20
- acc: 0.2664 - val_loss: 2.0131 - val_acc: 0.3039
Epoch 4/20
- acc: 0.2797 - val loss: 1.9821 - val acc: 0.3091
Epoch 5/20
- acc: 0.2885 - val loss: 1.9650 - val acc: 0.3183
- acc: 0.3041 - val loss: 1.9557 - val acc: 0.3117
Epoch 7/20
18647/18647 [================ ] - 15s 826us/step - loss: 1.9425
- acc: 0.3070 - val loss: 1.9472 - val acc: 0.3164
Epoch 8/20
- acc: 0.3133 - val loss: 1.9398 - val acc: 0.3179
Epoch 9/20
- acc: 0.3286 - val loss: 1.9343 - val acc: 0.3196
Epoch 10/20
- acc: 0.3281 - val loss: 1.9219 - val acc: 0.3237
Epoch 11/20
- acc: 0.3326 - val loss: 1.9303 - val acc: 0.3224
- acc: 0.3402 - val loss: 1.9159 - val acc: 0.3252
Epoch 13/20
- acc: 0.3404 - val loss: 1.9160 - val acc: 0.3256
Epoch 14/20
- acc: 0.3530 - val_loss: 1.9152 - val_acc: 0.3228
Epoch 15/20
- acc: 0.3559 - val_loss: 1.9149 - val_acc: 0.3252
Epoch 16/20
- acc: 0.3582 - val_loss: 1.9145 - val_acc: 0.3280
Epoch 17/20
- acc: 0.3673 - val_loss: 1.9227 - val_acc: 0.3207
Epoch 18/20
```

```
- acc: 0.3645 - val_loss: 1.9206 - val_acc: 0.3248
Epoch 19/20
- acc: 0.3730 - val loss: 1.9182 - val acc: 0.3256
Epoch 20/20
- acc: 0.3700 - val_loss: 1.9221 - val_acc: 0.3241
Validation Log Loss of Model in Current Run: 1.9237789996264
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1854 - val loss: 2.1432 - val acc: 0.2492
Epoch 2/20
- acc: 0.2450 - val loss: 2.0251 - val acc: 0.2846
Epoch 3/20
- acc: 0.2733 - val loss: 1.9900 - val acc: 0.3140
Epoch 4/20
- acc: 0.2837 - val loss: 1.9835 - val acc: 0.3050
Epoch 5/20
- acc: 0.2962 - val_loss: 1.9566 - val_acc: 0.3097
Epoch 6/20
- acc: 0.3058 - val_loss: 1.9504 - val_acc: 0.3164
Epoch 7/20
- acc: 0.3111 - val_loss: 1.9408 - val_acc: 0.3218
Epoch 8/20
- acc: 0.3185 - val loss: 1.9395 - val acc: 0.3170
Epoch 9/20
- acc: 0.3255 - val_loss: 1.9258 - val_acc: 0.3263
Epoch 10/20
- acc: 0.3336 - val loss: 1.9244 - val acc: 0.3215
Epoch 11/20
- acc: 0.3321 - val_loss: 1.9246 - val_acc: 0.3260
Epoch 12/20
18647/18647 [============== ] - 15s 799us/step - loss: 1.8423
- acc: 0.3433 - val loss: 1.9187 - val acc: 0.3271
Epoch 13/20
- acc: 0.3447 - val loss: 1.9206 - val acc: 0.3297
Epoch 14/20
- acc: 0.3446 - val loss: 1.9190 - val acc: 0.3303
Epoch 15/20
- acc: 0.3534 - val_loss: 1.9267 - val_acc: 0.3286
Epoch 16/20
```

```
- acc: 0.3625 - val loss: 1.9182 - val acc: 0.3286
Epoch 17/20
- acc: 0.3649 - val loss: 1.9229 - val acc: 0.3265
Epoch 18/20
- acc: 0.3613 - val loss: 1.9256 - val acc: 0.3280
Epoch 19/20
- acc: 0.3694 - val loss: 1.9255 - val acc: 0.3269
Epoch 20/20
- acc: 0.3700 - val loss: 1.9282 - val acc: 0.3290
Validation Log Loss of Model in Current Run: 1.9296700733280108
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1793 - val_loss: 2.1393 - val_acc: 0.2435
Epoch 2/20
- acc: 0.2361 - val_loss: 2.0347 - val_acc: 0.2958
Epoch 3/20
- acc: 0.2644 - val loss: 2.0083 - val acc: 0.3014
Epoch 4/20
- acc: 0.2768 - val loss: 1.9843 - val acc: 0.3093
Epoch 5/20
- acc: 0.2908 - val loss: 1.9700 - val acc: 0.3054
Epoch 6/20
- acc: 0.3003 - val loss: 1.9472 - val acc: 0.3220
Epoch 7/20
18647/18647 [=============== ] - 15s 814us/step - loss: 1.9395
- acc: 0.3113 - val loss: 1.9389 - val acc: 0.3220
Epoch 8/20
- acc: 0.3163 - val loss: 1.9315 - val acc: 0.3185
Epoch 9/20
- acc: 0.3158 - val loss: 1.9310 - val acc: 0.3200
Epoch 10/20
- acc: 0.3274 - val_loss: 1.9207 - val_acc: 0.3284
Epoch 11/20
- acc: 0.3352 - val loss: 1.9191 - val acc: 0.3239
Epoch 12/20
- acc: 0.3363 - val loss: 1.9195 - val acc: 0.3245
Epoch 13/20
- acc: 0.3419 - val loss: 1.9163 - val acc: 0.3220
Epoch 14/20
- acc: 0.3492 - val_loss: 1.9152 - val_acc: 0.3256
```

```
Epoch 15/20
- acc: 0.3524 - val loss: 1.9180 - val acc: 0.3245
Epoch 16/20
- acc: 0.3543 - val_loss: 1.9127 - val_acc: 0.3252
Epoch 17/20
- acc: 0.3616 - val_loss: 1.9160 - val_acc: 0.3198
Epoch 18/20
- acc: 0.3665 - val_loss: 1.9178 - val_acc: 0.3224
Epoch 19/20
- acc: 0.3685 - val loss: 1.9203 - val acc: 0.3237
Epoch 20/20
- acc: 0.3699 - val loss: 1.9194 - val acc: 0.3181
Validation Log Loss of Model in Current Run: 1.9203065615975894
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1833 - val loss: 2.1179 - val acc: 0.2531
Epoch 2/20
- acc: 0.2436 - val loss: 2.0570 - val acc: 0.2999
Epoch 3/20
- acc: 0.2684 - val loss: 2.0122 - val acc: 0.2956
Epoch 4/20
- acc: 0.2828 - val loss: 1.9793 - val acc: 0.3085
Epoch 5/20
- acc: 0.2916 - val loss: 1.9699 - val acc: 0.3074
Epoch 6/20
- acc: 0.3028 - val loss: 1.9496 - val acc: 0.3175
- acc: 0.3117 - val loss: 1.9357 - val acc: 0.3226
Epoch 8/20
- acc: 0.3162 - val loss: 1.9444 - val acc: 0.3202
Epoch 9/20
- acc: 0.3256 - val_loss: 1.9258 - val_acc: 0.3220
Epoch 10/20
- acc: 0.3282 - val_loss: 1.9217 - val_acc: 0.3260
Epoch 11/20
- acc: 0.3336 - val_loss: 1.9173 - val_acc: 0.3220
Epoch 12/20
- acc: 0.3406 - val_loss: 1.9168 - val_acc: 0.3260
Epoch 13/20
```

```
- acc: 0.3428 - val_loss: 1.9159 - val_acc: 0.3299
Epoch 14/20
- acc: 0.3477 - val loss: 1.9157 - val acc: 0.3310
Epoch 15/20
- acc: 0.3492 - val loss: 1.9182 - val acc: 0.3248
Epoch 16/20
- acc: 0.3532 - val loss: 1.9158 - val acc: 0.3299
Epoch 17/20
- acc: 0.3604 - val loss: 1.9173 - val acc: 0.3252
Epoch 18/20
- acc: 0.3606 - val loss: 1.9219 - val acc: 0.3318
Epoch 19/20
- acc: 0.3723 - val loss: 1.9194 - val acc: 0.3312
Validation Log Loss of Model in Current Run: 1.9162446622131852
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1842 - val_loss: 2.1195 - val_acc: 0.2492
Epoch 2/20
- acc: 0.2474 - val_loss: 2.0474 - val_acc: 0.2846
Epoch 3/20
- acc: 0.2675 - val_loss: 2.0180 - val_acc: 0.3050
Epoch 4/20
- acc: 0.2795 - val loss: 1.9816 - val acc: 0.3093
Epoch 5/20
- acc: 0.2919 - val_loss: 1.9607 - val_acc: 0.3181
Epoch 6/20
- acc: 0.3009 - val_loss: 1.9576 - val_acc: 0.3160
Epoch 7/20
- acc: 0.3098 - val_loss: 1.9380 - val_acc: 0.3183
18647/18647 [============= ] - 15s 827us/step - loss: 1.9204
- acc: 0.3166 - val loss: 1.9344 - val acc: 0.3177
Epoch 9/20
- acc: 0.3209 - val loss: 1.9388 - val acc: 0.3196
Epoch 10/20
- acc: 0.3278 - val loss: 1.9261 - val acc: 0.3226
Epoch 11/20
- acc: 0.3238 - val_loss: 1.9327 - val_acc: 0.3192
Epoch 12/20
```

```
- acc: 0.3381 - val loss: 1.9199 - val acc: 0.3198
Epoch 13/20
- acc: 0.3446 - val loss: 1.9195 - val acc: 0.3278
Epoch 14/20
- acc: 0.3457 - val loss: 1.9163 - val acc: 0.3258
Epoch 15/20
- acc: 0.3570 - val loss: 1.9186 - val acc: 0.3190
Epoch 16/20
- acc: 0.3513 - val loss: 1.9140 - val acc: 0.3258
Epoch 17/20
- acc: 0.3599 - val loss: 1.9201 - val acc: 0.3280
Epoch 18/20
- acc: 0.3600 - val loss: 1.9189 - val acc: 0.3280
Epoch 19/20
- acc: 0.3639 - val loss: 1.9219 - val acc: 0.3241
Epoch 20/20
- acc: 0.3744 - val_loss: 1.9277 - val_acc: 0.3288
Validation Log Loss of Model in Current Run: 1.9291087886768443
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1868 - val loss: 2.1600 - val acc: 0.2544
Epoch 2/20
- acc: 0.2411 - val loss: 2.0484 - val acc: 0.2924
Epoch 3/20
18647/18647 [=============== ] - 15s 801us/step - loss: 2.0696
- acc: 0.2671 - val loss: 2.0009 - val acc: 0.3012
Epoch 4/20
- acc: 0.2752 - val loss: 1.9805 - val acc: 0.3130
Epoch 5/20
- acc: 0.2919 - val loss: 1.9656 - val acc: 0.3142
Epoch 6/20
- acc: 0.2947 - val_loss: 1.9542 - val_acc: 0.3138
Epoch 7/20
- acc: 0.3078 - val loss: 1.9513 - val acc: 0.3172
- acc: 0.3176 - val loss: 1.9395 - val acc: 0.3179
Epoch 9/20
- acc: 0.3221 - val loss: 1.9298 - val acc: 0.3237
Epoch 10/20
- acc: 0.3229 - val_loss: 1.9223 - val_acc: 0.3263
```

```
Epoch 11/20
- acc: 0.3328 - val_loss: 1.9291 - val_acc: 0.3205
Epoch 12/20
- acc: 0.3430 - val_loss: 1.9208 - val_acc: 0.3252
Epoch 13/20
- acc: 0.3397 - val_loss: 1.9176 - val_acc: 0.3241
Epoch 14/20
- acc: 0.3475 - val_loss: 1.9153 - val_acc: 0.3273
Epoch 15/20
- acc: 0.3520 - val loss: 1.9165 - val acc: 0.3275
- acc: 0.3559 - val_loss: 1.9136 - val_acc: 0.3258
Epoch 17/20
- acc: 0.3539 - val_loss: 1.9172 - val_acc: 0.3273
Epoch 18/20
- acc: 0.3601 - val_loss: 1.9187 - val_acc: 0.3288
Epoch 19/20
- acc: 0.3718 - val_loss: 1.9194 - val_acc: 0.3243
Epoch 20/20
- acc: 0.3698 - val loss: 1.9172 - val acc: 0.3254
Validation Log Loss of Model in Current Run: 1.9185632223832525
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1805 - val loss: 2.1186 - val acc: 0.2585
Epoch 2/20
- acc: 0.2459 - val loss: 2.0371 - val acc: 0.2932
- acc: 0.2646 - val loss: 2.0051 - val acc: 0.3042
Epoch 4/20
- acc: 0.2790 - val loss: 1.9902 - val acc: 0.3003
Epoch 5/20
- acc: 0.2886 - val_loss: 1.9915 - val_acc: 0.3093
Epoch 6/20
- acc: 0.2961 - val_loss: 1.9557 - val_acc: 0.3119
Epoch 7/20
- acc: 0.3049 - val_loss: 1.9508 - val_acc: 0.3117
- acc: 0.3195 - val_loss: 1.9425 - val_acc: 0.3179
Epoch 9/20
```

```
- acc: 0.3202 - val_loss: 1.9295 - val_acc: 0.3245
Epoch 10/20
- acc: 0.3247 - val loss: 1.9276 - val acc: 0.3233
Epoch 11/20
- acc: 0.3282 - val loss: 1.9285 - val acc: 0.3202
Epoch 12/20
- acc: 0.3369 - val loss: 1.9211 - val acc: 0.3235
Epoch 13/20
18647/18647 [============== ] - 16s 858us/step - loss: 1.8450
- acc: 0.3390 - val_loss: 1.9177 - val_acc: 0.3325
Epoch 14/20
- acc: 0.3487 - val loss: 1.9146 - val acc: 0.3293
Epoch 15/20
- acc: 0.3525 - val loss: 1.9188 - val acc: 0.3228
Epoch 16/20
- acc: 0.3501 - val loss: 1.9145 - val acc: 0.3327
Epoch 17/20
- acc: 0.3560 - val loss: 1.9213 - val acc: 0.3218
Epoch 18/20
- acc: 0.3637 - val loss: 1.9174 - val acc: 0.3312
Epoch 19/20
- acc: 0.3664 - val loss: 1.9251 - val acc: 0.3267
Epoch 20/20
- acc: 0.3765 - val loss: 1.9242 - val acc: 0.3250
Validation Log Loss of Model in Current Run: 1.9258740875150422
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1882 - val_loss: 2.1619 - val_acc: 0.2218
Epoch 2/20
- acc: 0.2425 - val_loss: 2.0396 - val_acc: 0.2928
18647/18647 [============== ] - 15s 818us/step - loss: 2.0685
- acc: 0.2666 - val loss: 2.0111 - val acc: 0.2939
Epoch 4/20
- acc: 0.2806 - val loss: 1.9822 - val acc: 0.3035
Epoch 5/20
- acc: 0.2895 - val loss: 1.9584 - val acc: 0.3140
Epoch 6/20
- acc: 0.3015 - val_loss: 1.9478 - val_acc: 0.3218
Epoch 7/20
```

```
- acc: 0.3083 - val loss: 1.9474 - val acc: 0.3172
     Epoch 8/20
     - acc: 0.3167 - val loss: 1.9349 - val acc: 0.3168
     Epoch 9/20
     - acc: 0.3262 - val loss: 1.9282 - val acc: 0.3230
     Epoch 10/20
     - acc: 0.3325 - val loss: 1.9207 - val acc: 0.3245
     - acc: 0.3251 - val loss: 1.9225 - val acc: 0.3280
     Epoch 12/20
     - acc: 0.3355 - val loss: 1.9233 - val acc: 0.3194
     Epoch 13/20
     - acc: 0.3401 - val loss: 1.9188 - val acc: 0.3230
     Epoch 14/20
     - acc: 0.3439 - val loss: 1.9197 - val acc: 0.3256
     Epoch 15/20
     - acc: 0.3522 - val_loss: 1.9379 - val_acc: 0.3220
     Epoch 16/20
     - acc: 0.3601 - val_loss: 1.9163 - val_acc: 0.3237
     Epoch 17/20
     - acc: 0.3550 - val_loss: 1.9128 - val_acc: 0.3218
     Epoch 18/20
     - acc: 0.3607 - val loss: 1.9208 - val acc: 0.3192
     Epoch 19/20
     - acc: 0.3693 - val_loss: 1.9202 - val_acc: 0.3209
     Epoch 20/20
     - acc: 0.3757 - val loss: 1.9192 - val acc: 0.3228
     Validation Log Loss of Model in Current Run: 1.9209416287566417
     Average CV Loss of 10 Runs : 1.9234806484970717
     avg pred=np.zeros((xtr.shape[0],12))
In [90]:
     for i in range(len(model list 2)):
       train_pred=model_list_2[i].predict_proba(xtr)
       avg pred+=train pred
     avg pred/=len(model list 2)
     print("Train Average Log-Loss: ",log_loss(ytr, avg_pred))
```

Train Average Log-Loss: 1.5406584936512548

OBSERVATIONS: 1.THE TRAIN AND VALIDATION LOSSES ARE 1.5406 AND 1.9074 RESPECTIVELY.

1. BOTH TRAIN AND VALIDATIONN LOSSES DECREASED AS WE ADDED MORE FEATURES.

NEURAL NETWORK 2

```
In [94]: def events_nn_model2(input_dim,output_dim):
    model = Sequential()
    model.add(Dropout(0.4, input_shape=(input_dim,)))
    model.add(Dense(75))
    model.add(PReLU())
    model.add(Dropout(0.30))
    model.add(Dense(50, init='normal', activation='tanh'))
    model.add(PReLU())
    model.add(Dropout(0.20))
    model.add(Dense(output_dim, init='normal', activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adadelta', metrics=['accuracy'])
    return model
```

```
In [95]: model_sum=events_nn_model2(xtr.shape[1],12)
    model_sum.summary()
```

Layer (type)	Output	Shape	Param #
dropout_63 (Dropout)	(None,	21576)	0
dense_75 (Dense)	(None,	75)	1618275
p_re_lu_52 (PReLU)	(None,	75)	75
dropout_64 (Dropout)	(None,	75)	0
dense_76 (Dense)	(None,	50)	3800
p_re_lu_53 (PReLU)	(None,	50)	50
dropout_65 (Dropout)	(None,	50)	0
dense_77 (Dense)	(None,	12)	612
Total params: 1,622,812 Trainable params: 1,622,812	:=====:	=======================================	======

Total params: 1,622,812 Trainable params: 1,622,812 Non-trainable params: 0

```
In [96]: def events average nn 2(state):
             model_list=[]
             loss_list=[]
             avg_cv_loss=0
             for i in range((state)):
                 model=events nn model2(xtr.shape[1],12)
                 model.fit(xtr, ytr, batch_size=149, epochs=20, verbose=1, validation_d
         ata=(xcv, ycv),callbacks=[early_stop])
                 model.save('saved_models/events/nn2'+str(i+1))
                 pred=model.predict_proba(xcv)
                 cv_loss=log_loss(ycv, pred)
                 print("Validation Log Loss of Model in Current Run: ",cv loss)
                 model list.append(model)
                 loss_list.append(cv_loss)
             avg cv loss=mean(loss list)
             print("Average CV Loss of "+str((state))+" Runs :",avg_cv_loss)
             return(model list)
```

In [97]: model_list_2=events_average_nn_2(10)

```
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1686 - val loss: 2.1600 - val acc: 0.2454
Epoch 2/20
- acc: 0.2397 - val loss: 2.0982 - val acc: 0.2683
Epoch 3/20
- acc: 0.2597 - val loss: 2.0512 - val acc: 0.2861
Epoch 4/20
- acc: 0.2799 - val loss: 1.9799 - val acc: 0.3166
Epoch 5/20
- acc: 0.2851 - val loss: 1.9927 - val acc: 0.3027
Epoch 6/20
- acc: 0.2986 - val loss: 1.9650 - val acc: 0.3162
Epoch 7/20
18647/18647 [============== ] - 12s 650us/step - loss: 1.9787
- acc: 0.3034 - val loss: 1.9700 - val acc: 0.3142
Epoch 8/20
18647/18647 [================ ] - 13s 712us/step - loss: 1.9568
- acc: 0.3110 - val_loss: 1.9337 - val_acc: 0.3233
Epoch 9/20
- acc: 0.3102 - val_loss: 1.9785 - val_acc: 0.3140
Epoch 10/20
- acc: 0.3182 - val_loss: 1.9467 - val_acc: 0.3164
Epoch 11/20
- acc: 0.3227 - val loss: 1.9328 - val acc: 0.3187
Epoch 12/20
- acc: 0.3324 - val_loss: 1.9169 - val_acc: 0.3278
Epoch 13/20
18647/18647 [=============== ] - 12s 636us/step - loss: 1.8862
- acc: 0.3372 - val_loss: 1.9572 - val_acc: 0.3102
Epoch 14/20
- acc: 0.3404 - val_loss: 1.9572 - val_acc: 0.3190
Epoch 15/20
- acc: 0.3413 - val loss: 1.9490 - val acc: 0.3181
Epoch 16/20
- acc: 0.3522 - val_loss: 1.9303 - val_acc: 0.3301
Epoch 17/20
18647/18647 [============== ] - 12s 637us/step - loss: 1.8272
- acc: 0.3567 - val loss: 1.9427 - val acc: 0.3260
Validation Log Loss of Model in Current Run: 1.9168982927262757
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1774 - val loss: 2.1513 - val acc: 0.2424
```

```
Epoch 2/20
- acc: 0.2451 - val_loss: 2.1517 - val_acc: 0.2480
Epoch 3/20
- acc: 0.2651 - val_loss: 2.0919 - val_acc: 0.2662
Epoch 4/20
- acc: 0.2813 - val_loss: 2.0846 - val_acc: 0.2656
Epoch 5/20
- acc: 0.2892 - val_loss: 1.9836 - val_acc: 0.2969
Epoch 6/20
- acc: 0.2990 - val loss: 1.9386 - val acc: 0.3202
- acc: 0.3070 - val_loss: 1.9354 - val_acc: 0.3256
Epoch 8/20
- acc: 0.3137 - val_loss: 1.9509 - val_acc: 0.3149
Epoch 9/20
- acc: 0.3227 - val_loss: 1.9435 - val_acc: 0.3267
Epoch 10/20
- acc: 0.3233 - val loss: 1.9459 - val acc: 0.3164
Epoch 11/20
- acc: 0.3277 - val loss: 1.9223 - val acc: 0.3271
Epoch 12/20
- acc: 0.3343 - val_loss: 1.9331 - val_acc: 0.3237
Epoch 13/20
18647/18647 [=============== ] - 12s 645us/step - loss: 1.8700
- acc: 0.3377 - val loss: 1.9246 - val acc: 0.3256
Epoch 14/20
- acc: 0.3458 - val loss: 1.9147 - val acc: 0.3194
Epoch 15/20
- acc: 0.3460 - val loss: 1.9315 - val acc: 0.3239
Epoch 16/20
- acc: 0.3515 - val_loss: 1.9360 - val_acc: 0.3166
Epoch 17/20
- acc: 0.3571 - val loss: 1.9337 - val acc: 0.3175
Epoch 18/20
- acc: 0.3591 - val loss: 1.9263 - val acc: 0.3192
Epoch 19/20
- acc: 0.3687 - val loss: 1.9415 - val acc: 0.3243
Validation Log Loss of Model in Current Run: 1.9146637250839105
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
```

```
- acc: 0.1779 - val loss: 2.1846 - val acc: 0.2179
Epoch 2/20
- acc: 0.2411 - val loss: 2.1458 - val acc: 0.2432
Epoch 3/20
- acc: 0.2660 - val loss: 2.0299 - val acc: 0.2906
Epoch 4/20
- acc: 0.2783 - val loss: 1.9921 - val acc: 0.3048
Epoch 5/20
- acc: 0.2928 - val loss: 1.9691 - val acc: 0.3190
Epoch 6/20
- acc: 0.2929 - val loss: 1.9847 - val acc: 0.3085
Epoch 7/20
- acc: 0.3035 - val loss: 1.9432 - val acc: 0.3269
- acc: 0.3111 - val loss: 1.9360 - val acc: 0.3243
Epoch 9/20
- acc: 0.3190 - val loss: 1.9513 - val acc: 0.3166
Epoch 10/20
- acc: 0.3220 - val loss: 1.9388 - val acc: 0.3318
Epoch 11/20
- acc: 0.3197 - val loss: 1.9370 - val acc: 0.3190
Epoch 12/20
- acc: 0.3329 - val loss: 1.9213 - val acc: 0.3260
Epoch 13/20
- acc: 0.3355 - val loss: 1.9198 - val acc: 0.3284
- acc: 0.3384 - val loss: 1.9149 - val acc: 0.3282
Epoch 15/20
- acc: 0.3399 - val loss: 2.0072 - val acc: 0.3027
Epoch 16/20
- acc: 0.3463 - val_loss: 1.9377 - val_acc: 0.3213
Epoch 17/20
- acc: 0.3504 - val_loss: 1.9421 - val_acc: 0.3185
Epoch 18/20
- acc: 0.3583 - val_loss: 1.9414 - val_acc: 0.3183
Epoch 19/20
- acc: 0.3615 - val loss: 1.9322 - val acc: 0.3248
Validation Log Loss of Model in Current Run: 1.9148988088457843
```

```
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1656 - val loss: 2.2334 - val acc: 0.2186
Epoch 2/20
- acc: 0.2360 - val loss: 2.0562 - val acc: 0.2891
Epoch 3/20
- acc: 0.2592 - val loss: 2.0043 - val acc: 0.3052
- acc: 0.2803 - val loss: 2.0205 - val acc: 0.2855
Epoch 5/20
- acc: 0.2885 - val loss: 1.9720 - val acc: 0.3106
Epoch 6/20
- acc: 0.2969 - val loss: 1.9922 - val acc: 0.3087
Epoch 7/20
- acc: 0.3036 - val loss: 1.9450 - val acc: 0.3222
Epoch 8/20
- acc: 0.3114 - val_loss: 1.9403 - val_acc: 0.3260
Epoch 9/20
18647/18647 [============== ] - 12s 620us/step - loss: 1.9409
- acc: 0.3160 - val_loss: 1.9493 - val_acc: 0.3192
Epoch 10/20
- acc: 0.3214 - val_loss: 1.9250 - val_acc: 0.3254
Epoch 11/20
- acc: 0.3275 - val loss: 1.9665 - val acc: 0.3119
Epoch 12/20
- acc: 0.3238 - val_loss: 1.9375 - val_acc: 0.3222
Epoch 13/20
- acc: 0.3334 - val loss: 1.9965 - val acc: 0.3033
Epoch 14/20
- acc: 0.3372 - val_loss: 1.9428 - val_acc: 0.3198
Epoch 15/20
- acc: 0.3452 - val loss: 1.9319 - val acc: 0.3250
Validation Log Loss of Model in Current Run: 1.924992392238362
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
18647/18647 [=============== ] - 13s 717us/step - loss: 2.3289
- acc: 0.1720 - val loss: 2.2337 - val acc: 0.2199
Epoch 2/20
18647/18647 [================ ] - 11s 615us/step - loss: 2.1578
- acc: 0.2379 - val loss: 2.0511 - val acc: 0.2840
Epoch 3/20
- acc: 0.2662 - val_loss: 2.0087 - val_acc: 0.3014
```

```
Epoch 4/20
- acc: 0.2805 - val_loss: 1.9674 - val_acc: 0.3134
Epoch 5/20
- acc: 0.2923 - val_loss: 1.9848 - val_acc: 0.3054
Epoch 6/20
- acc: 0.2985 - val_loss: 1.9581 - val_acc: 0.3119
Epoch 7/20
- acc: 0.3022 - val_loss: 1.9736 - val_acc: 0.3072
Epoch 8/20
- acc: 0.3069 - val loss: 1.9595 - val acc: 0.3106
- acc: 0.3132 - val_loss: 1.9356 - val_acc: 0.3220
Epoch 10/20
- acc: 0.3230 - val_loss: 1.9294 - val_acc: 0.3263
Epoch 11/20
- acc: 0.3273 - val_loss: 1.9277 - val_acc: 0.3245
Epoch 12/20
- acc: 0.3307 - val loss: 1.9205 - val acc: 0.3256
Epoch 13/20
- acc: 0.3382 - val loss: 1.9471 - val acc: 0.3097
Epoch 14/20
- acc: 0.3381 - val_loss: 1.9324 - val_acc: 0.3220
Epoch 15/20
18647/18647 [=============== ] - 11s 592us/step - loss: 1.8502
- acc: 0.3446 - val_loss: 1.9301 - val_acc: 0.3200
Epoch 16/20
18647/18647 [============== ] - 11s 593us/step - loss: 1.8359
- acc: 0.3487 - val loss: 1.9358 - val acc: 0.3215
Epoch 17/20
- acc: 0.3550 - val loss: 1.9568 - val acc: 0.3192
Validation Log Loss of Model in Current Run: 1.9205034403254269
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1669 - val_loss: 2.2163 - val_acc: 0.2059
Epoch 2/20
- acc: 0.2406 - val_loss: 2.0946 - val_acc: 0.2604
Epoch 3/20
- acc: 0.2653 - val_loss: 2.0344 - val_acc: 0.2962
- acc: 0.2804 - val_loss: 2.0642 - val_acc: 0.2786
Epoch 5/20
```

```
- acc: 0.2901 - val loss: 1.9781 - val acc: 0.3115
Epoch 6/20
- acc: 0.2989 - val loss: 1.9830 - val acc: 0.2973
Epoch 7/20
- acc: 0.3011 - val loss: 1.9472 - val acc: 0.3218
Epoch 8/20
- acc: 0.3077 - val loss: 1.9288 - val acc: 0.3301
Epoch 9/20
18647/18647 [============== ] - 11s 607us/step - loss: 1.9335
- acc: 0.3180 - val loss: 1.9576 - val acc: 0.3222
Epoch 10/20
- acc: 0.3243 - val loss: 1.9331 - val acc: 0.3220
Epoch 11/20
- acc: 0.3272 - val loss: 1.9319 - val acc: 0.3260
Epoch 12/20
- acc: 0.3313 - val loss: 1.9712 - val acc: 0.2984
Epoch 13/20
- acc: 0.3369 - val loss: 1.9516 - val acc: 0.3106
Validation Log Loss of Model in Current Run: 1.928770428193403
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1728 - val_loss: 2.1944 - val_acc: 0.2411
Epoch 2/20
- acc: 0.2447 - val loss: 2.1698 - val acc: 0.2282
Epoch 3/20
- acc: 0.2667 - val_loss: 2.0212 - val_acc: 0.2979
Epoch 4/20
- acc: 0.2830 - val loss: 1.9823 - val acc: 0.3140
Epoch 5/20
- acc: 0.2899 - val_loss: 1.9797 - val_acc: 0.3052
18647/18647 [============== ] - 12s 662us/step - loss: 1.9951
- acc: 0.2960 - val loss: 1.9542 - val acc: 0.3196
Epoch 7/20
- acc: 0.3051 - val loss: 1.9474 - val acc: 0.3125
Epoch 8/20
- acc: 0.3098 - val loss: 1.9606 - val acc: 0.3082
Epoch 9/20
- acc: 0.3130 - val_loss: 1.9435 - val_acc: 0.3241
Epoch 10/20
```

```
- acc: 0.3176 - val loss: 1.9461 - val acc: 0.3175
Epoch 11/20
- acc: 0.3251 - val loss: 2.0473 - val acc: 0.2718
Epoch 12/20
- acc: 0.3305 - val loss: 1.9139 - val acc: 0.3303
Epoch 13/20
- acc: 0.3320 - val loss: 1.9116 - val acc: 0.3260
Epoch 14/20
- acc: 0.3397 - val loss: 1.9259 - val acc: 0.3192
Epoch 15/20
- acc: 0.3463 - val loss: 1.9211 - val acc: 0.3230
Epoch 16/20
- acc: 0.3506 - val loss: 1.9176 - val acc: 0.3237
Epoch 17/20
- acc: 0.3564 - val loss: 1.9421 - val acc: 0.3164
Epoch 18/20
- acc: 0.3565 - val_loss: 1.9458 - val_acc: 0.3149
Validation Log Loss of Model in Current Run: 1.9115930246656696
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1744 - val loss: 2.1997 - val acc: 0.2201
Epoch 2/20
- acc: 0.2438 - val_loss: 2.1573 - val_acc: 0.2544
Epoch 3/20
- acc: 0.2650 - val loss: 2.0144 - val acc: 0.2883
Epoch 4/20
- acc: 0.2830 - val loss: 1.9886 - val acc: 0.3097
Epoch 5/20
- acc: 0.2884 - val loss: 1.9824 - val acc: 0.3127
Epoch 6/20
- acc: 0.3021 - val loss: 1.9594 - val acc: 0.3164
Epoch 7/20
- acc: 0.3092 - val loss: 1.9480 - val acc: 0.3228
- acc: 0.3129 - val loss: 1.9532 - val acc: 0.3125
Epoch 9/20
- acc: 0.3221 - val loss: 1.9327 - val acc: 0.3218
Epoch 10/20
- acc: 0.3187 - val_loss: 1.9317 - val_acc: 0.3196
```

```
Epoch 11/20
- acc: 0.3277 - val_loss: 1.9359 - val_acc: 0.3196
Epoch 12/20
- acc: 0.3313 - val_loss: 1.9373 - val_acc: 0.3183
Epoch 13/20
- acc: 0.3375 - val_loss: 1.9235 - val_acc: 0.3235
Epoch 14/20
- acc: 0.3381 - val_loss: 1.9196 - val_acc: 0.3284
Epoch 15/20
- acc: 0.3430 - val loss: 1.9149 - val acc: 0.3263
- acc: 0.3504 - val_loss: 1.9246 - val_acc: 0.3226
Epoch 17/20
- acc: 0.3532 - val_loss: 1.9464 - val_acc: 0.3157
Epoch 18/20
- acc: 0.3595 - val_loss: 1.9433 - val_acc: 0.3121
Epoch 19/20
- acc: 0.3649 - val_loss: 1.9347 - val_acc: 0.3207
Epoch 20/20
- acc: 0.3654 - val loss: 1.9322 - val acc: 0.3220
Validation Log Loss of Model in Current Run: 1.9148608428341785
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1681 - val loss: 2.1805 - val acc: 0.2250
Epoch 2/20
- acc: 0.2419 - val loss: 2.0904 - val acc: 0.2692
- acc: 0.2621 - val loss: 2.0280 - val acc: 0.2932
Epoch 4/20
- acc: 0.2840 - val loss: 1.9859 - val acc: 0.3121
Epoch 5/20
- acc: 0.2846 - val_loss: 2.1284 - val_acc: 0.2486
Epoch 6/20
- acc: 0.2977 - val_loss: 1.9518 - val_acc: 0.3093
Epoch 7/20
- acc: 0.3061 - val_loss: 1.9466 - val_acc: 0.3213
- acc: 0.3130 - val_loss: 1.9381 - val_acc: 0.3205
Epoch 9/20
```

```
- acc: 0.3175 - val_loss: 1.9406 - val_acc: 0.3226
Epoch 10/20
- acc: 0.3276 - val loss: 1.9258 - val acc: 0.3239
Epoch 11/20
- acc: 0.3251 - val loss: 1.9281 - val acc: 0.3338
Epoch 12/20
- acc: 0.3299 - val loss: 1.9254 - val acc: 0.3267
Epoch 13/20
- acc: 0.3359 - val loss: 1.9725 - val acc: 0.3157
Epoch 14/20
- acc: 0.3433 - val loss: 1.9183 - val acc: 0.3269
Epoch 15/20
- acc: 0.3471 - val loss: 1.9429 - val acc: 0.3102
Epoch 16/20
- acc: 0.3536 - val loss: 1.9477 - val acc: 0.3119
Epoch 17/20
- acc: 0.3521 - val loss: 2.0130 - val acc: 0.2992
Epoch 18/20
- acc: 0.3610 - val loss: 1.9446 - val acc: 0.3170
Epoch 19/20
- acc: 0.3641 - val loss: 1.9429 - val acc: 0.3200
Validation Log Loss of Model in Current Run: 1.918339006581988
Train on 18647 samples, validate on 4662 samples
Epoch 1/20
- acc: 0.1693 - val_loss: 2.2421 - val_acc: 0.1918
Epoch 2/20
- acc: 0.2400 - val_loss: 2.1214 - val_acc: 0.2576
Epoch 3/20
- acc: 0.2640 - val_loss: 1.9978 - val_acc: 0.3016
18647/18647 [============== ] - 11s 576us/step - loss: 2.0478
- acc: 0.2780 - val loss: 1.9853 - val acc: 0.3115
Epoch 5/20
- acc: 0.2827 - val loss: 1.9697 - val acc: 0.3177
Epoch 6/20
- acc: 0.2980 - val loss: 1.9509 - val acc: 0.3198
Epoch 7/20
- acc: 0.3025 - val_loss: 1.9436 - val_acc: 0.3226
Epoch 8/20
```

```
- acc: 0.3095 - val loss: 1.9513 - val acc: 0.3123
       Epoch 9/20
       - acc: 0.3139 - val loss: 1.9394 - val acc: 0.3263
       Epoch 10/20
       - acc: 0.3160 - val loss: 1.9418 - val acc: 0.3215
       Epoch 11/20
       - acc: 0.3258 - val loss: 1.9427 - val acc: 0.3138
       Epoch 12/20
       - acc: 0.3323 - val loss: 1.9222 - val acc: 0.3297
       Epoch 13/20
       - acc: 0.3368 - val loss: 1.9412 - val acc: 0.3198
       Epoch 14/20
       - acc: 0.3409 - val loss: 1.9385 - val acc: 0.3175
       Epoch 15/20
       - acc: 0.3436 - val_loss: 1.9255 - val acc: 0.3271
       Epoch 16/20
       - acc: 0.3465 - val loss: 1.9400 - val acc: 0.3226
       Epoch 17/20
       - acc: 0.3562 - val_loss: 1.9394 - val_acc: 0.3275
       Validation Log Loss of Model in Current Run: 1.9222252802920925
       Average CV Loss of 10 Runs : 1.918774524178709
In [98]: | avg pred=np.zeros((xtr.shape[0],12))
       for i in range(len(model list 2)):
          train_pred=model_list_2[i].predict_proba(xtr)
          avg_pred+=train pred
       avg pred/=len(model list 2)
       print("Train Average Log-Loss: ",log_loss(ytr, avg_pred))
       Train Average Log-Loss: 1.7068032853037864
In [99]: | avg_pred=np.zeros((xcv.shape[0],12))
       for i in range(len(model list 2)):
          cv_pred=model_list_2[i].predict_proba(xcv)
          avg pred+=cv pred
       avg pred/=len(model list 2)
       print("Validation Average Log-Loss: ",log_loss(ycv, avg_pred))
       Validation Average Log-Loss: 1.9012935504651483
       avg pred=np.zeros((X test events.shape[0],12))
In [100]:
       for i in range(len(model list 2)):
          test_pred=model_list_2[i].predict_proba(X_test_events)
          avg pred+=test pred
       avg pred/=len(model list 2)
```

```
In [101]: np.save('nn2_events_1',avg_pred)
```

OBSERVATIONS:

THE TRAIN AND VALIDATION LOSSES ARE 1.7068 AND 1.9012 RESPECTIVELY.

XGBOOST

```
In [102]: ytr.shape
Out[102]: (18647, 12)
In [103]: | xtr, xcv, ytr, ycv = train_test_split(X_train_events, y,stratify=y,test_size=
          0.2, random state=9)
In [104]: | ytr.shape
Out[104]: (18647,)
In [105]: xgb = XGBClassifier(n_estimators=350, n_jobs=-1,learning_rate=0.05, colsample_
          bytree=0.7, max depth=5,subsample=0.7,objective='multi:softprob',num class=12,
          eval_metric='mlogloss')
          xgb.fit(xtr, ytr)
          #Using Model Calibration
          clf = CalibratedClassifierCV(xgb, method="sigmoid")
          clf.fit(xtr, ytr)
          pred_y=clf.predict_proba(xtr)
          print("Train Log Loss :",log_loss(ytr, pred_y))
          pred_y=clf.predict_proba(xcv)
          print("Validation Log Loss :",log_loss(ycv, pred_y))
          Train Log Loss: 1.2839666002195145
          Validation Log Loss: 2.057339870807861
In [106]: events pred xgb=clf.predict proba(X test events)
In [107]: | np.save('xgb events 1.npy',events pred xgb)
```

OBSERVATIONS: THE TRAIN AND VALIDATION LOSSES ARE 1.2839 AND 2.0573 RESPECTIVELY.

LOGISTIC REGRESSION

```
In [108]: # Train a Logistic regression+Calibration model using text features whicha re
             on-hot encoded
            alpha = [0.001, 0.01, 0.02, 0.1, 0.15, 1, 10]
            for i in alpha:
                clf = LogisticRegression(C=i, class weight='balanced', multi class='multin
            omial',solver='lbfgs')
                clf.fit(xtr, ytr)
                #Using Model Calibration
                sig clf = CalibratedClassifierCV(clf, method="sigmoid")
                sig_clf.fit(xtr, ytr)
                predict y = sig clf.predict proba(xcv)
                print('For values of C = ', i, "The validation log loss is:",log loss(ycv,
             predict y))
            For values of C = 0.001 The validation log loss is: 2.0982561817893224
            For values of C = 0.01 The validation log loss is: 2.019844834880824
            For values of C = 0.02 The validation log loss is: 2.0160115578199274
            For values of C = 0.1 The validation log loss is: 2.043084585773688
            For values of C = 0.15 The validation log loss is: 2.055436921152977
            For values of C = 1 The validation log loss is: 2.1074612177933965
            For values of C = 10 The validation log loss is: 2.13818998200252
WE CHOSE OUR BEST C TO BE 0.02
  In [109]: clf = LogisticRegression(C=0.02, class weight='balanced', multi class='multino
            mial', solver='lbfgs')
            clf.fit(xtr, ytr)
            sig clf = CalibratedClassifierCV(clf, method="sigmoid")
            sig clf.fit(xtr, ytr)
            predict_y = sig_clf.predict_proba(xtr)
            loss=log loss(ytr, predict y)
            print("The train log loss for best C is:",loss)
```

```
predict y = sig clf.predict proba(xcv)
loss=log loss(ycv, predict y)
print("The validation log loss for best C is:",loss)
```

The train log loss for best C is: 1.840631737548809 The validation log loss for best C is: 2.0160115578199274

```
In [110]:
          events pred lr=clf.predict proba(X test events)
In [111]: | #saving the model
          np.save('lr_events_1.npy',events_pred_lr)
```

OBSERVATIONS: WE GOT TRAIN AND VALIDATION LOSS AS 1.84 AND 2.0160 RESPECTIVELY.

MODEL ENSEMBLING

MACHINE LEARNING MODELS

WE USE LOGISTIC REGRESSION AND XGBOOST WITH EVENTS AND WITHOUTS DATA AND WE CONCATENATE THE RESULTS.

```
In [112]: | lr1=np.load("lr_noevents.npy")
           lr2=np.load("lr_events_1.npy")
           xgb1=np.load("xgb noevents 1.npy")
           xgb2=np.load("xgb events 1.npy")
In [113]:
          w1 = 0.5
          w2 = 0.5
           w3 = 0.3
           w4 = 0.5
           test1=(w1*lr1)+(w2*xgb1)
          test2=(w3*1r2)+(w4*xgb2)
In [114]: | gatrain=pd.read_csv('gender_age_train.csv',index_col = 'device_id')
           targetencoder = LabelEncoder().fit(gatrain.group)
           y = targetencoder.transform(gatrain.group)
           nclasses = len(targetencoder.classes )
In [115]: pred 1 = pd.DataFrame(test1, index = gatest noevents.index, columns=targetenco
           der.classes )
           pred 2 = pd.DataFrame(test2, index = gatest events.index, columns=targetencode
           r.classes )
           final_pred=pd.concat([pred_1,pred_2], axis=0)
           final pred.shape
Out[115]: (112071, 12)
In [116]: final_pred.to_csv('ml_final.csv',index=True)
```

ENSEMBLING NEURAL NETS

WE ARE TAKING ONLY NEURAL NETWORK 1 FOR DEVICES WITHOUT EVENTS AND FOR DEVICES WITH EVENTS WE ARE TAKING AVERAGE OF BOTH NETWORKS.

```
In [118]: w1=0.5
          w2 = 0.5
          test1=(1*noevents nn1)
          test2=(0.5*events nn1)+(0.5*events nn2)
In [119]:
          gatrain=pd.read_csv('gender_age_train.csv',index_col = 'device_id')
In [120]: | targetencoder = LabelEncoder().fit(gatrain.group)
          y = targetencoder.transform(gatrain.group)
          nclasses = len(targetencoder.classes )
In [121]: pred 1 = pd.DataFrame(test1, index = gatest noevents.index, columns=targetenco
          der.classes )
          pred_2 = pd.DataFrame(test2, index = gatest_events.index, columns=targetencode
          r.classes )
          final pred 1=pd.concat([pred 1,pred 2], axis=0)
          final pred 1.shape
Out[121]: (112071, 12)
In [122]: | final_pred_1.to_csv('dl_sub_1.csv',index=True)
```

RESULT

```
In [124]: from prettytable import PrettyTable

Result = PrettyTable()
Result.field_names = ["Model", "Data", "TRAIN LOSS"," Validation loss"]
Result.add_row(["Logistic Regression", "without events", 2.3628,2.3891])
Result.add_row(["XGboost", "without events", 2.3718,2.3929])
Result.add_row(["Avg Neural Network-1", "without events", 2.3528,2.3577])
Result.add_row(["Avg Neural Network-2", "without events", 2.3770,2.3788])

Result.add_row(["Logistic Regression", "WITH events", 1.8406,2.0160])
Result.add_row(["XGboost", "WITH events", 1.2839,2.0573])
Result.add_row(["Avg Neural Network-1", "WITH events", 1.5406,1.9074])
Result.add_row(["Avg Neural Network-2", "WITH events", 1.7068,1.9012])
Result.add_row(['LOGISTIC REGRESSION','FULL DATA',2.4145,2.3540])

print(Result)
```

Model	•	•	Validation loss
XGboost Network-1 XGboost XG	without events without events without events without events WITH events WITH events WITH events WITH events WITH events FULL DATA	2.3628 2.3718 2.3528 2.377 1.8406 1.2839 1.5406 1.7068 2.4145	2.3891 2.3929 2.3577 2.3788 2.016 2.0573 1.9074 1.9012 2.354

REFERENCES

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2. https://www.kaggle.com/c/talkingdata-mobile-user-demographics/discussion/23424)
(https://www.kaggle.com/c/talkingdata-mobile-user-demographics/discussion/23424)

In []:	
In []:	