In [1]:
```
'''Importing required libraries'''
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
pd.set_option('max_columns', None)
```

In [2]:
```
'''Setting data path and reading the data'''
dataPath = 'data/'
fileName = 'data_example.csv'
filePath = dataPath+fileName
data = pd.read_csv(filePath)
```

Let's have a look at the read data

In [3]:
```
data.head()
```

Out[3]:

	unique_id	date_registered	registration_platform	marketing_source	lifetime_banchees_spent	lifeti
0	105709319455	2020-01-01 00:03:29	iOS	organic	0.0	
1	105709319456	2020-01-01 00:15:34	Android	organic	0.0	
2	105709319456	2020-01-01 00:15:34	Android	organic	0.0	
3	105709319456	2020-01-01 00:15:34	Android	organic	0.0	
4	105709319456	2020-01-01 00:15:34	Android	organic	0.0	

In [4]:
```
"""Checking total number of unique players"""
len(data['unique_id'].unique())
```

Out[4]: 66720

The columns are as described in the problem description. For a `unique_id` , the `date_registered` , `registration_platform` , `marketing_source` , `lifetime_branchees_spent` , `lifetime_logindays` remain same irrespective session. Therefore, it makes sense to group the data by for these columns

In [5]:
```
np.all(data['session_number']==data['sessions_total'])
```

Out[5]: True

In [6]:
```
allColumns = list(data.columns)
groupByCols = ['unique_id','date_registered','registration_platform','marketing_source'
               'lifetime_banchees_spent','lifetime_logindays','active_four_we
```

In [7]:
```
groupData = data.groupby(groupByCols)
```

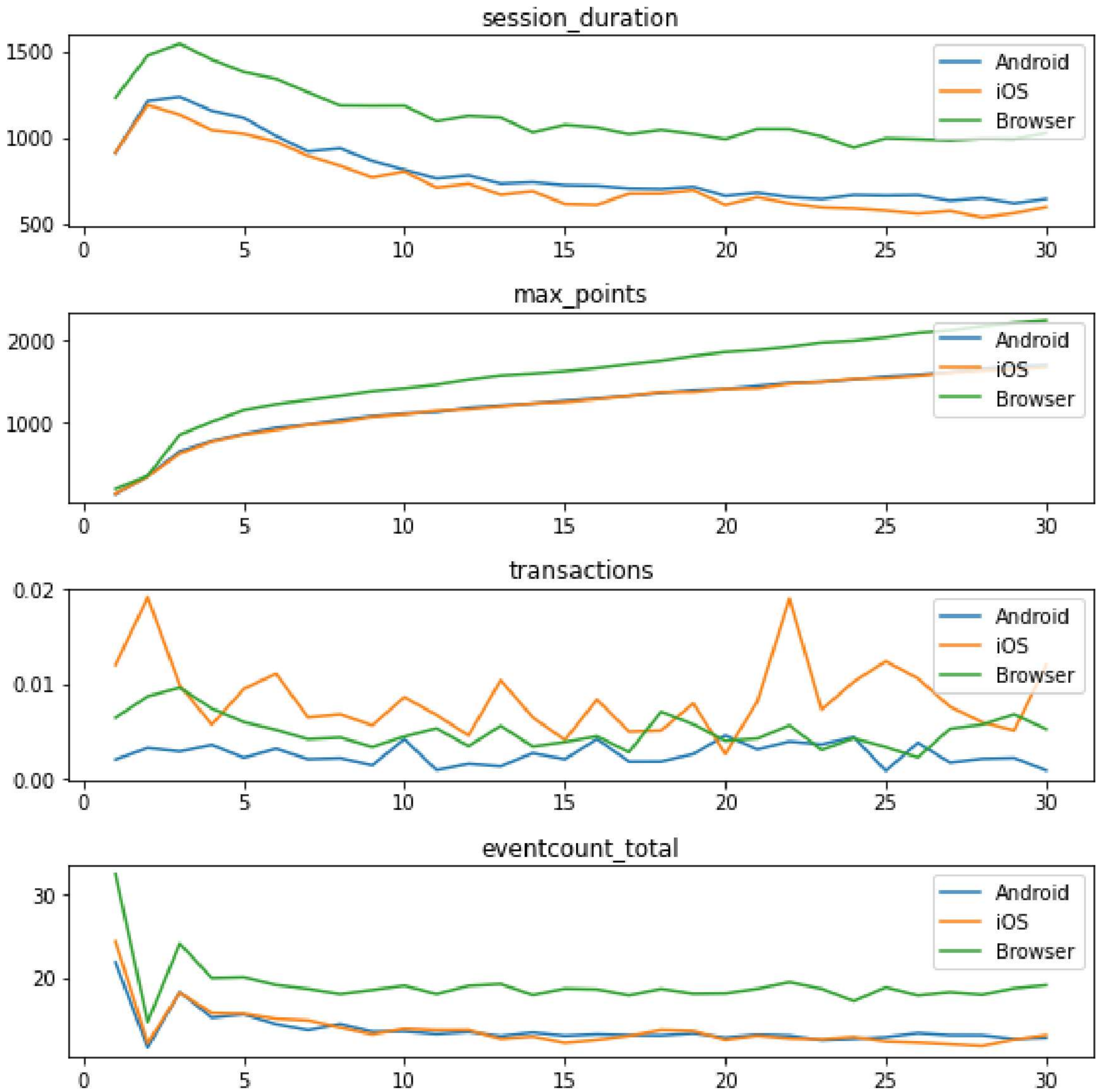
In [8]:
```
''' Properties dependant upon the session of a user are listed'''
elementsToAnalyze = ['session_duration','max_points', 'transactions', 'eventcount_total
                     'eventcount_message', 'eventcount_fight', 'eventcount_trade', 'eve
                     'eventcount_recruit', 'eventcount_ally', 'eventcount_research']
```

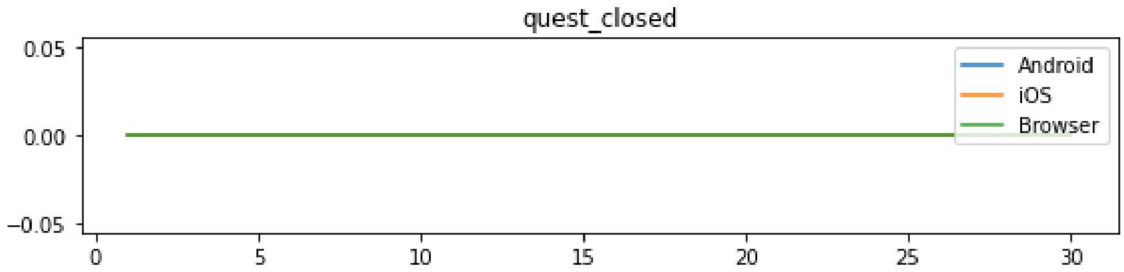
To analyse the user behaviour for first 30 sessions, the original data is grouped by `registration_platform` and `session_number`. This gives grouped information for each `session_number` per platform. An average of the attributes to be analyzed per session number, per platform is then calculated

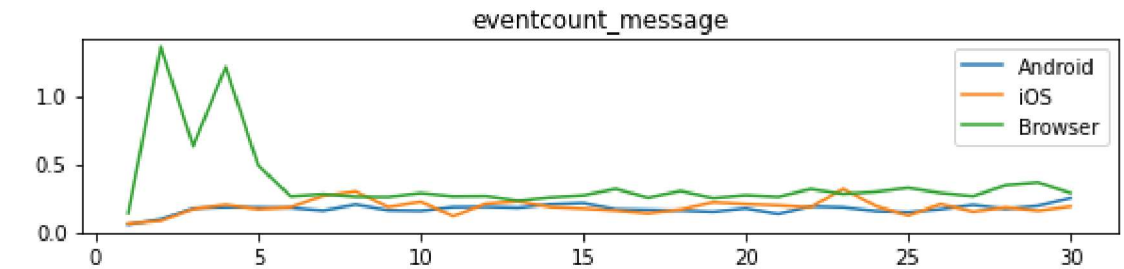
In [9]:
```
analysis = data.groupby(['registration_platform', 'session_number'])[elementsToAnalyze]
```

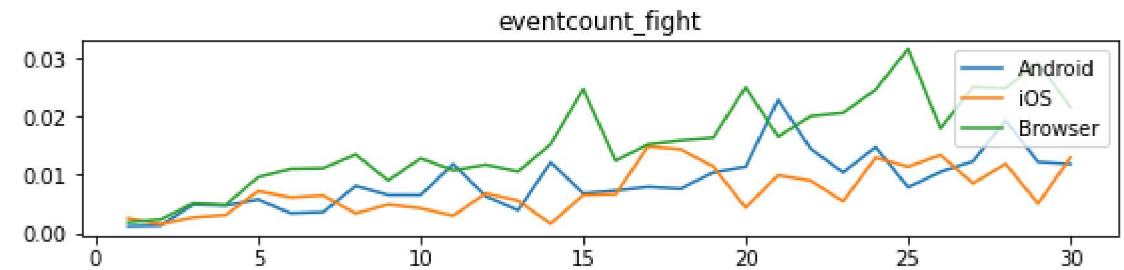
In [10]:
```
'''Writing out a plotting function'''

numToBeAnalysed = 30

def plotStuff(df, numToBeAnalysed, label=['session_duration','max_points'], platforms=[
    f, axes = plt.subplots(nrows = len(label),figsize=figsize)
    for ax_i in range(len(label)):
        ax = axes[ax_i]
        ax.set_title(label[ax_i])
        for plf in platforms:
            data = df.xs([plf]).loc[1:numToBeAnalysed][label[ax_i]]
            p = ax.plot(data)
        ax.legend(platforms, loc=1)
        ax.yaxis.labelpad = 25
    f.tight_layout()

    if save:
        plt.savefig(label[0]+'.png')
```

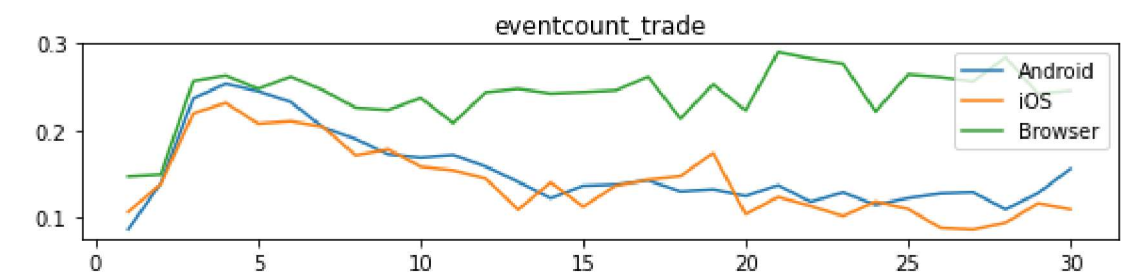
In [11]:
```
'''Plotting for all elements to be analyzed'''

nLabels = len(elementsToAnalyze)
nPlot = 4
for i in range(int(np.ceil(nLabels/nPlot))):
    plotStuff(analysis, 30, label=elementsToAnalyze[i*nPlot:(i+1)*nPlot], save=True)
```

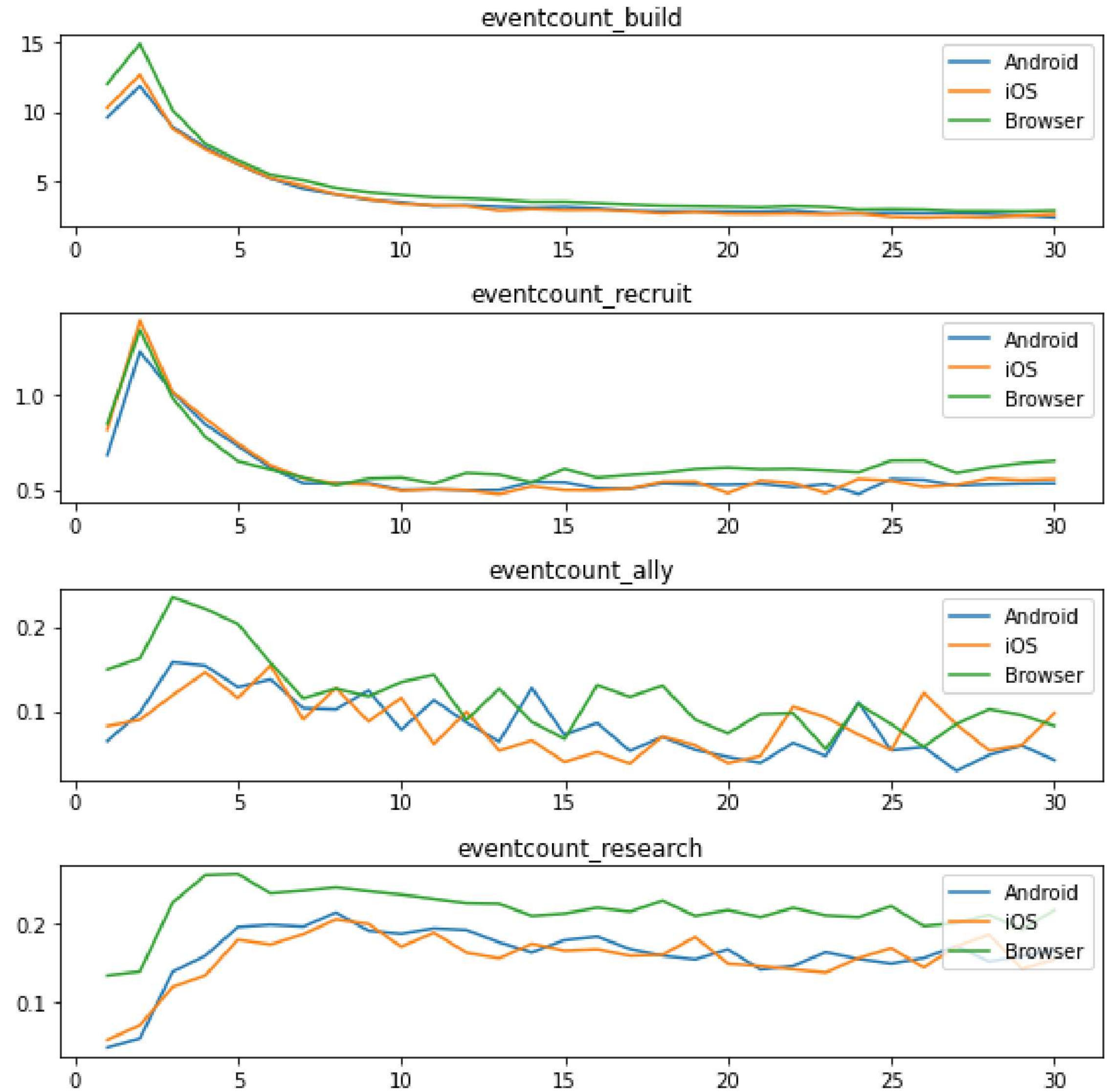

session_duration
Android
iOS
Browser
max_points
Android
iOS
Browser
transactions
Android
iOS
Browser
eventcount_total
Android
iOS
Browser


quest_closed
0.05
0.00
−0.05
0
5
10
15
20
25
30
Android
iOS
Browser


eventcount_message
1.0
0.5
0.0
0
5
10
15
20
25
30
Android
iOS
Browser


eventcount_fight
0.03
0.02
0.01
0.00
0
5
10
15
20
25
30
Android
iOS
Browser


eventcount_trade
0.3
0.2
0.1
0
5
10
15
20
25
30
Android
iOS
Browser



What can be seen from the above plots is as follows:

- In general, the mean session duration for browser is higher than either of the apps
- Maximum points, total event count, and individual event counts are generally more in browser than in apps. This could be since the session duration is longer, the player engagement is longer which leads to more event counts
- The mean session duration reduces gradually with increasing session number whereas the maximum points achieved increases. This could signify player's increasing familiarity or even advances in game leading to more points
- iOS users tend to conduct more transactions per session
- Total event counts are also higher for browser based users
- In earlier sessions, the amount of messages browser based players wrote is considerably high, but it reduced over time. Is it possible that because of having a keyboard and a larger typing setup, the browser based players found it easier to write texts. But reduced sending texts since it does not create much influence in the game?

- Amount of fights put up increases with increase number of sessions, maybe because it is required as one advances in the game
- All platform players traded resources in the beginning, but app based number of trades reduced over time whereas browser based didn't so much. Unlike messages, number of trades doesn't drop (for browser) which could mean that doing trades is important and influential. Is there need to improve at the trading interface in apps?
- Recruit and Build orders went down over time for all platforms. Similar trend as session duration
- Ally interaction numbers are a bit noisy, cannot infer much about the user behaviour, but the trend seems to go rather down
- Research was really low in the beginning but then it increased and stayed to level. Still, the numbers are more for browser based users which might be also due to more session duration leading to more event counts

For performing churn analysis, categorical data like registration platform and marketing sources are one-hot encoded.

In [12]:
```
dataReform = groupData['sessions_total'].max().to_frame()
dataReform['sessions_total'] = dataReform['sessions_total'].apply(lambda x:min(x,numToB
dataReform.reset_index(level=groupByCols[1:], inplace=True)
oneHotPlatform = pd.get_dummies(dataReform['registration_platform'],prefix='plt')
dataReform = dataReform.join(oneHotPlatform).drop(columns=['registration_platform'])
oneHotSource = pd.get_dummies(dataReform['marketing_source'],prefix='src')
dataReform = dataReform.join(oneHotSource).drop(columns=['marketing_source'])
dataReform.drop(columns=['date_registered'], inplace=True)
```

In [13]:
```
dataReform.head()
```

Out[13]:

	lifetime_banchees_spent	lifetime_logindays	active_four_weeks	sessions_total	plt_Android
unique_id					
105709319455	0.0	1	False	1	C
105709319456	0.0	5	False	30	1
105709319457	0.0	1	False	1	1
105709319458	0.0	1	False	1	C
105709319459	0.0	1	False	1	1

For session specific data of a particular player, a mean of each attribute for the a maximum of 30 sessions is calculated.

In [14]:
```
sessWise = groupData[elementsToAnalyze].apply(lambda x:np.mean(x[:numToBeAnalysed]))
sessWise.reset_index(level=groupByCols[1:], inplace=True)
sessWise.drop(columns=groupByCols[1:], inplace=True)
```

In [15]:
```
sessWise.head()
```

Out[15]:

unique_id	session_duration	max_points	transactions	eventcount_total	quest_closed	eventcount_m
105709319455	185.000000	0.0	0.0	9.0	0.0	
105709319456	593.366667	942.2	0.0	12.5	0.0	
105709319457	11.000000	0.0	0.0	4.0	0.0	
105709319458	8.000000	0.0	0.0	3.0	0.0	
105709319459	827.000000	0.0	0.0	25.0	0.0	

In [16]:

```
'''Join the player data with its mean session data'''
dataReform=dataReform.join(sessWise)
```

In [17]:

```
dataReform.head()
```

Out[17]:

unique_id	lifetime_banchees_spent	lifetime_logindays	active_four_weeks	sessions_total	plt_Android
105709319455	0.0	1	False	1	0
105709319456	0.0	5	False	30	1
105709319457	0.0	1	False	1	1
105709319458	0.0	1	False	1	0
105709319459	0.0	1	False	1	1

For performing churn analysis, a decision tree model is chosen for classification. A grid search cross validation is performed in order to find out the best maximum tree depth

In [18]:

```
from sklearn import tree
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import confusion_matrix, plot_confusion_matrix

def gridSearch(X, y, model, parameters, cv=None, n_jobs=4):

    clf = GridSearchCV(model(), trainableParams, n_jobs=4, cv=cv)
    clf.fit(X=X, y=y)
    bestModel = clf.best_estimator_
    print (clf.best_score_, clf.best_params_)
    return bestModel, clf

def testTrain(X, y, model, testSize=0.33, randomState=108):

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=testSize, rando
    accuracyTrain = model.score(X_train, y_train)
    accuracyTest = model.score(X_test, y_test)
    print("training accuracy: {} and testing accuracy: {}".format(accuracyTrain,accurac
    return (X_train, y_train), (X_test, y_test)
```

In [19]:

```
X = dataReform.drop(columns=['active_four_weeks'])
```

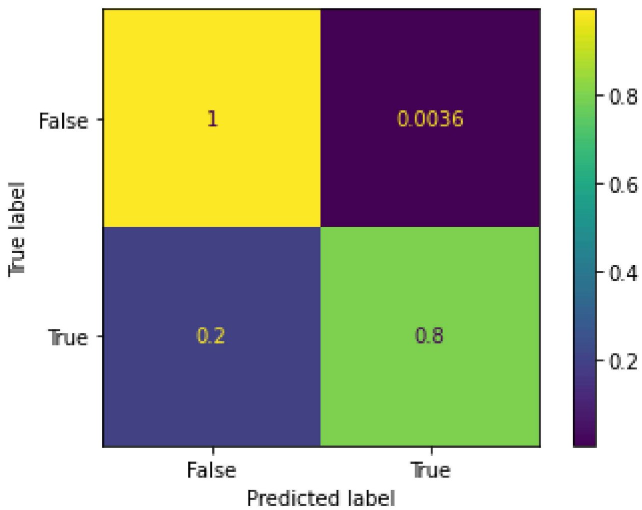
```
y = dataReform['active_four_weeks']
trainableParams = {'max_depth':range(3,10)}

bestModel,_ = gridSearch(X=X, y=y, model=tree.DecisionTreeClassifier, parameters=traina
(X_train, y_train),(X_test,y_test) = testTrain(X=X, y=y, model=bestModel)
```

```
0.9792116306954437 {'max_depth': 6}
training accuracy: 0.9817905239139189 and testing accuracy: 0.9805613588881824
```

The decision tree model was trained and the training & testing accuracy seem to be quite good. But this does not tell everything about a prediction. Therefore a normalized confusion matrix has been plotted for test data

In [20]:

```
fig = plot_confusion_matrix(bestModel, X_test, y_test, normalize='true')
#plt.savefig('confmatrix.png')
```



The confusion matrix plotted above gives more information about the predictions preformed by the model.

- True Positives = 0.8
- False Positives = 0.0036
- True Negatives = 0.9964
- False Negatives = 0.2

This states that with the given trained model, if a player is predicted to be True, then there is an 80% chance of a correct prediction. On the other hand, if a player is predicted to be False, it is 99.64% a right prediction

In [ ]: