In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
from sklearn.metrics import roc_curve, auc
```

In [2]:

```
#reading in the data
all_data = pd.read_csv('/home/amybirdee/hobby_projects/health_first/all_data.csv', deli
miter = ',')
```

In [3]:

```
all_data.head()
```

Out[3]:

	user_id	goals	gender	motivation	challenge	trigger	age	height
0	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
1	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
2	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
3	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
4	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2

In [4]:

```
#won't need the customer id for the analysis so dropping this
all_data_edited = all_data.drop('user_id', axis = 1)
```

In [5]:

```
#target variable is churned_after_six - this needs to be a binary column so changing to 0/1
all_data_edited['churned_after_six'] = all_data_edited['churned_after_six'].replace({'Churn': 1, 'No churn': 0})
all_data_edited.reset_index(drop = True).head(10)
```

Out[5]:

	goals	gender	motivation	challenge	trigger	age	height	weight	churned_after_six
0	medium	F	looks	motivation	tired	25	156.2	99.3	NaN
1	medium	F	looks	motivation	tired	25	156.2	99.3	NaN
2	medium	F	looks	motivation	tired	25	156.2	99.3	NaN
3	medium	F	looks	motivation	tired	25	156.2	99.3	NaN
4	medium	F	looks	motivation	tired	25	156.2	99.3	NaN
5	high	F	health	motivation	emotions	66	154.9	60.3	0.0
6	high	F	health	motivation	emotions	66	154.9	60.3	0.0
7	high	F	health	motivation	emotions	66	154.9	60.3	0.0
8	high	F	health	motivation	emotions	66	154.9	60.3	0.0
9	high	F	health	motivation	emotions	66	154.9	60.3	0.0

In [6]:

```
#counting how many 0s and 1s we have in churn column - 21197 instances of no churn and
 2218 instances of churn
print(all_data_edited.churned_after_six.value_counts())
```

```
0.0    21197
1.0     2218
Name: churned_after_six, dtype: int64
```

In [7]:

```
#creating dummy values for all categorical variables to use in model
all_data_dummy = pd.get_dummies(all_data_edited)
all_data_dummy.reset_index(drop = True).head()
```

Out[7]:

	age	height	weight	churned_after_six	week_number	sentiment	questions_asked	emojis
0	25	156.2	99.3	NaN	0	1.026933	0.0	
1	25	156.2	99.3	NaN	0	0.295621	0.0	
2	25	156.2	99.3	NaN	0	0.069245	0.0	
3	25	156.2	99.3	NaN	3	0.141559	0.0	
4	25	156.2	99.3	NaN	3	0.109137	0.0	

5 rows × 37 columns

In [8]:

```
#checking datatypes
all_data_dummy.dtypes
```

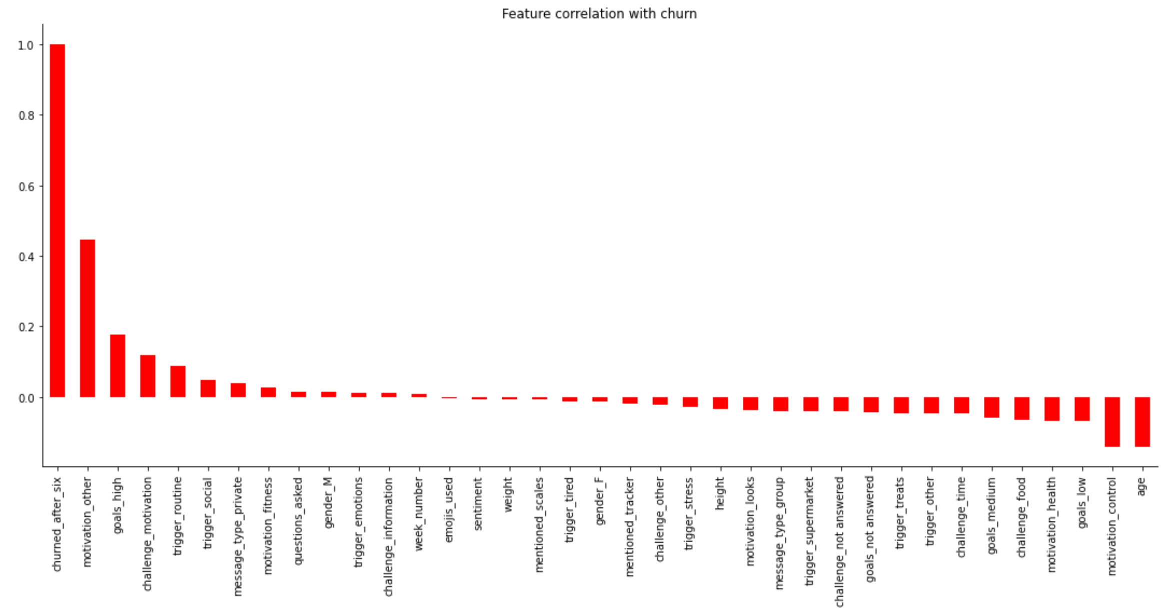
Out[8]:

```
age                         int64
height                    float64
weight                    float64
churned_after_six         float64
week_number                 int64
sentiment                 float64
questions_asked           float64
emojis_used               float64
mentioned_scales          float64
mentioned_tracker         float64
goals_high                  uint8
goals_low                   uint8
goals_medium                uint8
goals_not answered          uint8
gender_F                    uint8
gender_M                    uint8
motivation_control          uint8
motivation_fitness          uint8
motivation_health           uint8
motivation_looks            uint8
motivation_other            uint8
challenge_food              uint8
challenge_information       uint8
challenge_motivation        uint8
challenge_not answered      uint8
challenge_other             uint8
challenge_time              uint8
trigger_emotions            uint8
trigger_other               uint8
trigger_routine             uint8
trigger_social              uint8
trigger_stress              uint8
trigger_supermarket         uint8
trigger_tired               uint8
trigger_treats              uint8
message_type_group          uint8
message_type_private        uint8
dtype: object
```

Correlation analysis

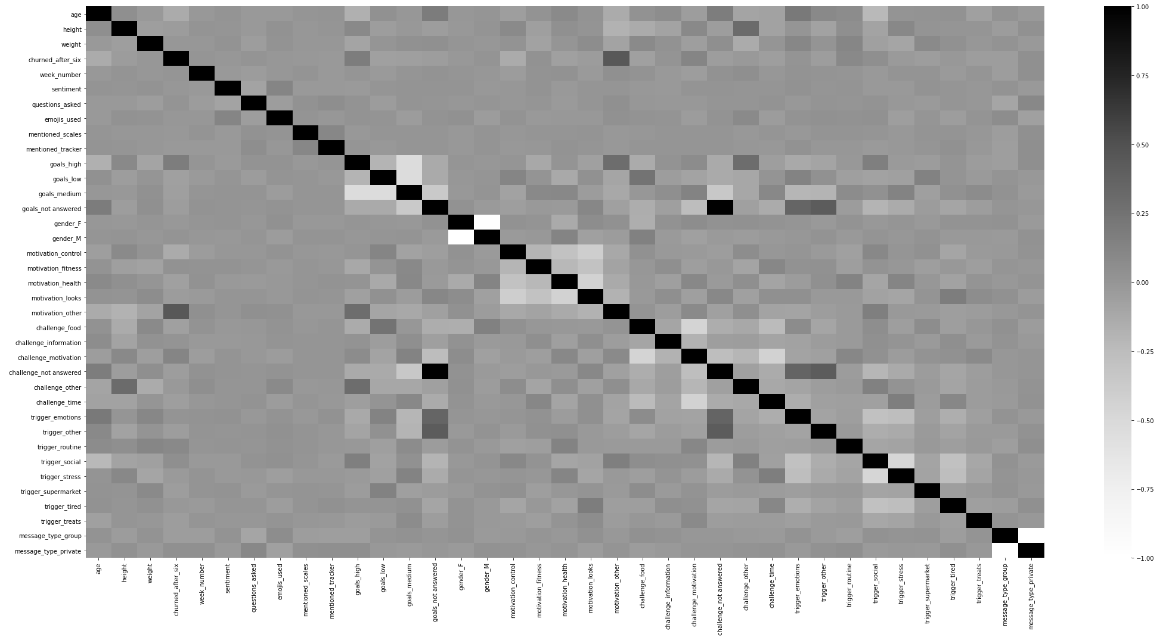
In [9]:

```
#plot correlations between target feature (churn) and all other variables - a lack of m
otivation and overly ambitious goals
#have the highest correlation with churn. Age, more achievable ambitions and a health m
otivation has the lowest correlation
fig = plt.figure(figsize = (15,8))
ax = plt.subplot()
all_data_dummy.corr()['churned_after_six'].sort_values(ascending = False).plot(kind =
'bar', color = 'red')
plt.title('Feature correlation with churn', fontsize = 12)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10)
plt.tight_layout()
plt.savefig('churn_correlation')
```



In [10]:

```
#plotting correlations on a heatmap
fig, ax = plt.subplots(figsize = (30,15))
sns.heatmap(all_data_dummy.corr(), cmap = 'Greys')
plt.tight_layout()
plt.savefig('heatmap')
```



In [11]:

```
#splitting data into known and unknown data. The known data will be used to train the m
odel
known_data = all_data_dummy[all_data_dummy['churned_after_six'].notnull()]

unknown_data = all_data_dummy[all_data_dummy['churned_after_six'].isnull()]

unknown_data.head()
```

Out[11]:

	age	height	weight	churned_after_six	week_number	sentiment	questions_asked	emojis
0	25	156.2	99.3	NaN	0	1.026933	0.0	
1	25	156.2	99.3	NaN	0	0.295621	0.0	
2	25	156.2	99.3	NaN	0	0.069245	0.0	
3	25	156.2	99.3	NaN	3	0.141559	0.0	
4	25	156.2	99.3	NaN	3	0.109137	0.0	

5 rows × 37 columns

In [12]:

```
#splitting the data into independent and dependent variables for the known data

y = known_data.churned_after_six.values

X = known_data.drop('churned_after_six', axis = 1)

#saving the X value columns to a separate list for reassigning after scaling the data
known_data_columns = X.columns
```

In [13]:

```
#categorical variables are scaled but also need to scale the numerical variables, e.g.
 age, height, weight

#instantiate the MinMaxScaler
scaler = MinMaxScaler()

#fit the scaler to X to transform the data. Converting to dataframe as well - otherwise
it would be a NumPy array
X = pd.DataFrame(scaler.fit_transform(X))

#reassign the column names
X.columns = known_data_columns

X.head()
```

Out[13]:

	age	height	weight	week_number	sentiment	questions_asked	emojis_used	mentic
0	0.86	0.103734	0.021833	0.000000	0.547588	0.0	0.0	
1	0.86	0.103734	0.021833	0.000000	0.573724	0.0	0.0	
2	0.86	0.103734	0.021833	0.000000	0.523439	0.0	0.0	
3	0.86	0.103734	0.021833	0.000000	0.847878	0.0	0.0	
4	0.86	0.103734	0.021833	0.166667	0.480026	0.0	0.0	

5 rows × 36 columns

In [14]:

```
#splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
= 42)
```

In [15]:

```
#checking shape of training and testing sets - all 7043 records are there
print('X_train shape:', X_train.shape)
print('X_test shape:', X_test.shape)
print('y_train shape:', y_train.shape)
print('y_test shape:', y_test.shape)
```

```
X_train shape: (18732, 36)
X_test shape: (4683, 36)
y_train shape: (18732,)
y_test shape: (4683,)
```

Fitting and evaluating logisitic regression model

In [16]:

```
#fitting the model. Liblinear is and algorithim which will help optimise the results.
logistic_model = LogisticRegression(solver = 'liblinear')
logistic_model.fit(X_train, y_train)
```

Out[16]:

```
LogisticRegression(solver='liblinear')
```

In [17]:

```
#predicting the churn values for X_train and X_test
y_pred_train = logistic_model.predict(X_train)
y_pred_test = logistic_model.predict(X_test)
```

In [18]:

```
#evaluating the model - finding the residual differences between train data and predict
ed train data
residuals = np.abs(y_train - y_pred_train)

#print value counts of predicted values
print(pd.Series(residuals).value_counts())

print('')

#print normalised value counts for predicted values - 93% of churn predictions were cor
rect on the train data set
print(pd.Series(residuals).value_counts(normalize = True))
```

```
0.0    17450
1.0     1282
dtype: int64

0.0    0.931561
1.0    0.068439
dtype: float64
```

In [19]:

```
#evaluating the model for the test data - finding the residual differences between test data and predicted test data
residuals_test = np.abs(y_test - y_pred_test)

#print value counts of predicted values
print(pd.Series(residuals_test).value_counts())

print('')

#print normalised value counts for predicted values - 93% of churn predictions were correct on the test data set
print(pd.Series(residuals_test).value_counts(normalize = True))
```

```
0.0    4360
1.0     323
dtype: int64

0.0    0.931027
1.0    0.068973
dtype: float64
```

In [20]:

```
#printing the confusion matrix - we are trying to limit false negatives (i.e. when we predict a customer will not churn
#but they do). When trying to limit false negatives we want to optimise on recall rather than precision

#158 = true positive, 4202 = true negative, 294 = false negative, 29 = false positive
matrix = confusion_matrix(y_test, y_pred_test)
print('Confusion matrix \n', matrix)
```

```
Confusion matrix
 [[4202   29]
 [ 294  158]]
```

In [21]:

```
#visualising the confusion matrix with labels
y_test_df = pd.Series(y_test)
y_pred_test_df = pd.Series(y_pred_test)

pd.crosstab(y_test_df, y_pred_test_df, rownames = ['True'], colnames = ['Predicted'], margins = True).reset_index()
```

Out[21]:

Predicted	True	0.0	1.0	All
0	0	4202	29	4231
1	1	294	158	452
2	All	4496	187	4683

In [22]:

```
#concatenating the series into a dataframe and adding a new row to describe what the re
sult is in each. The function uses
#if statements to define the result

results = pd.concat([y_test_df, y_pred_test_df], axis = 1).rename(columns = {0: 'actua
l', 1: 'prediction'})

def regression_results(row):
    if row['actual'] == 1 and row['prediction'] == 1:
        return 'actual = churn and prediction = churn - True positive'
    if row['actual'] == 0 and row['prediction'] == 0:
        return 'actual = no churn and prediction =  no churn - True negative'
    if row['actual'] == 0 and row['prediction'] == 1:
        return 'actual = no churn but prediction = churn - False positive'
    if row['actual'] == 1 and row['prediction'] == 0:
        return 'actual = churn but prediction = no churn - False negative'

#applying the above function to a new row
results['result'] = results.apply(lambda row: regression_results(row), axis = 1)
print(results.head())
```

```
   actual  prediction                                             result
0     0.0         0.0  actual = no churn and prediction =  no churn -...
1     0.0         0.0  actual = no churn and prediction =  no churn -...
2     0.0         0.0  actual = no churn and prediction =  no churn -...
3     0.0         0.0  actual = no churn and prediction =  no churn -...
4     0.0         0.0  actual = no churn and prediction =  no churn -...
```

In [23]:

```
#grouping the results to compare with the confustion matrix
results_grouped = results.groupby('result').size()
results_grouped
```

Out[23]:

```
result
actual = churn and prediction = churn - True positive           158
actual = churn but prediction = no churn - False negative       294
actual = no churn and prediction =  no churn - True negative   4202
actual = no churn but prediction = churn - False positive        29
dtype: int64
```

In [24]:

```
#printing out the scores for precision, recall, accuracy and F1 for y_test and y_pred_t
est
print(metrics.classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.99      0.96      4231
         1.0       0.84      0.35      0.49       452

    accuracy                           0.93      4683
   macro avg       0.89      0.67      0.73      4683
weighted avg       0.93      0.93      0.92      4683
```

In [25]:

```
#another way to print the scores, pos_label tells sklearn what class you want to print
 - we want 1 as that's the 'will
#churn' class. We want to optimise recall but the score is showing just 0.34 on the tra
ining set and 0.35 on the testing
#set. Hopefully AUC score will be better

precision_train = precision_score(y_train, y_pred_train, pos_label = 1)
precision_test = precision_score(y_test, y_pred_test, pos_label = 1)

recall_train = recall_score(y_train, y_pred_train, pos_label = 1)
recall_test = recall_score(y_test, y_pred_test, pos_label = 1)

accuracy_train = accuracy_score(y_train, y_pred_train)
accuracy_test = accuracy_score(y_test, y_pred_test)

f1_train = f1_score(y_train, y_pred_train, pos_label = 1)
f1_test = f1_score(y_test, y_pred_test, pos_label = 1)

print('Precision train: ', round(precision_train, 2))
print('Precision test: ', round(precision_test, 2))
print('')
print('Recall train: ', round(recall_train, 2))
print('Recall test: ', round(recall_test, 2))
print('')
print('Accuracy train: ', round(accuracy_train, 2))
print('Accuracy test: ', round(accuracy_test, 2))
print('')
print('F1 train: ', round(f1_train, 2))
print('F1 test: ', round(f1_test, 2))
print('')
```

```
Precision train:  0.84
Precision test:  0.84

Recall train:  0.34
Recall test:  0.35

Accuracy train:  0.93
Accuracy test:  0.93

F1 train:  0.48
F1 test:  0.49
```

In [26]:

```
#calculating probabilities scores for test and train sets
prob_train = logistic_model.predict_proba(X_train)
prob_test = logistic_model.predict_proba(X_test)

#keeping probabilities for positive outcome only (the threshold is 0.5 which means, if
 the predicted probability of the
#class for an instance is less than 0.5, that instance is predicted to be in class 0 (t
he negative class). If the
#probability of the class for an instance is equal or greater than 0.5, the instance is
classified as class 1.)
prob_train_churn = prob_train[:, 1]
prob_test_churn = prob_test[:, 1]

#calculate false positive rate (fpr), true positive rate (tpr) and thresholds for train
set
train_fpr, train_tpr, train_thresholds = roc_curve(y_train, prob_train_churn)

#calculate false positive rate (fpr), true positive rate (tpr) and thresholds for test
 set
test_fpr, test_tpr, test_thresholds = roc_curve(y_test, prob_test_churn)
```

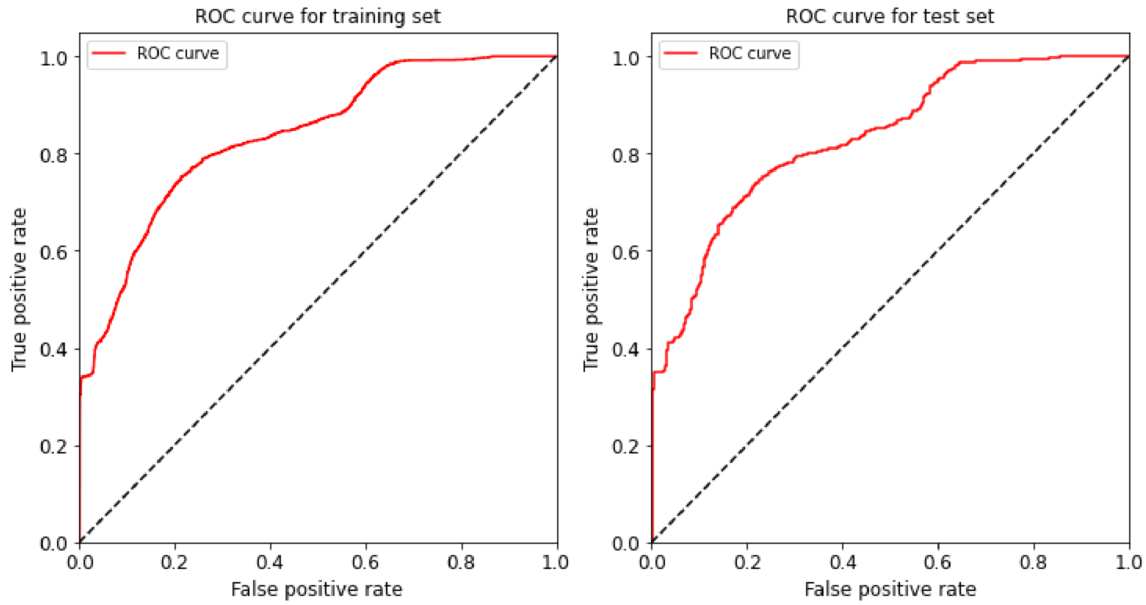
In [27]:

```
#calculating AUC (Area Under Curve) - this gives a single numeric metric to evaluate th
e model. An AUC value of 1 would
#represent a perfect classifier. If AUC = 0.5 the classifier only has 50% preision. AUC
scores above 0.8 so pretty good.

auc_train = auc(train_fpr, train_tpr)
auc_test = auc(test_fpr, test_tpr)
print('Training AUC: ', round(auc_train, 2))
print('Testing AUC: ', round(auc_test, 2))
```

```
Training AUC:  0.84
Testing AUC:  0.83
```

In [28]:

```
#plotting an ROC (Receiver Operator Characteristic) curve to evaluate the model perform
ance visually. It illustrates the
#true positive rate against the false positive rate of our classifier. Best performing
 models will have an ROC curve that
#hugs the upper left corner of the graph. This would represent that we correctly classi
fy the positives much more often
#than we incorrectly classify them.

#the ROC curve dips slightly for both the train and test sets which suggests a dip in m
odel performance but it's still
#above the diagonal line

fig = plt.figure(figsize = (12, 6))
ax = plt.subplot(1, 2, 1)
plt.plot(train_fpr, train_tpr, label = 'ROC curve', color = 'red')

#plotting diagonal line from zero which represents a model that guesses incorrectly for
every correct guess
plt.plot([0, 1], [0, 1], color = 'black', linestyle = 'dashed')
plt.xlim([0, 1])
plt.ylim([0, 1.05])

plt.legend()
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel('False positive rate', fontsize = 12)
plt.ylabel('True positive rate', fontsize = 12)
plt.title('ROC curve for training set', fontsize = 12)

ax = plt.subplot(1, 2, 2)
plt.plot(test_fpr, test_tpr, label = 'ROC curve', color = 'red')

#plotting diagonal line from zero which represents a model that guesses incorrectly for
every correct guess
plt.plot([0, 1], [0, 1], color = 'black', linestyle = 'dashed')
plt.xlim([0, 1])
plt.ylim([0, 1.05])

plt.legend()
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.xlabel('False positive rate', fontsize = 12)
plt.ylabel('True positive rate', fontsize = 12)
plt.title('ROC curve for test set', fontsize = 12)
plt.savefig('ROC_curves')
```



Predictions for unknown data

In [29]:

```
#need to fit the unknown data on the logistic model. First droppping the churn column

X_unknown = unknown_data.drop('churned_after_six', axis = 1)

#saving the X value columns to a separate list for reassigning after scaling the data
X_unknown_columns = X_unknown.columns
```

In [30]:

```
#scaling the numerical variables

#Already instantiated the scaler above - below code scales the data using the original
 scaler.
#Converting to dataframe as well - otherwise it would be a NumPy array
X_unknown = pd.DataFrame(scaler.transform(X_unknown))

#reassign the column names
X_unknown.columns = X_unknown_columns
X_unknown.head()
```

Out[30]:

	age	height	weight	week_number	sentiment	questions_asked	emojis_used	mentic
0	0.04	0.130705	0.337893	0.0	0.774553	0.0	0.0	
1	0.04	0.130705	0.337893	0.0	0.556447	0.0	0.0	
2	0.04	0.130705	0.337893	0.0	0.488932	0.0	0.0	
3	0.04	0.130705	0.337893	0.5	0.510499	0.0	0.0	
4	0.04	0.130705	0.337893	0.5	0.500830	0.0	0.0	

5 rows × 36 columns

In [31]:

```
#predicting for unknown users - the model has predicted no churn for all users...
predictions_unknown = logistic_model.predict(X_unknown)
predictions_unknown
```

Out[31]:

```
array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0.])
```

In [32]:

```
#converting predictions into a dataframe
predictions = pd.DataFrame(predictions_unknown, columns = ['predictions'])
predictions.head()
```

Out[32]:

	predictions
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

In [33]:

```
#filtering for the 10 unknown users
all_data_unknown = all_data[all_data['churned_after_six'].isnull()].reset_index(drop =
True)
```

In [34]:

```
#concatenating all data and predictions tables
all_data_unknown = pd.concat([all_data_unknown, predictions], axis = 1)
all_data_unknown.head()
```

Out[34]:

	user_id	goals	gender	motivation	challenge	trigger	age	height
0	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
1	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
2	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
3	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2
4	5a2e417806d240124a6185a0	medium	F	looks	motivation	tired	25	156.2

In [35]:

```
#separating out predictions for all users - model predicts all users will not churn
user_predictions = all_data_unknown.groupby(['user_id'])['predictions'].value_counts().
to_frame()
user_predictions
```

Out[35]:

		predictions
user_id	**predictions**	
5a2e417806d240124a6185a0	**0.0**	5
5ca8f158540a036b663a34df	**0.0**	12
5cba40489203684bd4c4e04f	**0.0**	54
5cbc31e194b8d6115731aed9	**0.0**	75
5cc929eba4cedc162e6df3c2	**0.0**	29
5cd520832925a912cbdd6061	**0.0**	21
5cd69b69fb622f12c5a74008	**0.0**	66
5cd89558f2f52212d094bd8e	**0.0**	2
5cd976930b932012b968558e	**0.0**	15
5ce050278ff304131108e204	**0.0**	17

In [ ]:

```
```