Pre Session Exercise

The company goal is to increase conversion rate: # conversions / total sessions.

In order to maximise the conversion rate, we should target maximising # of conversions.

In [1]:
```
%matplotlib notebook
#Importing the required libraries for the data analysis
import pandas as pd
import numpy as np
from matplotlib import pyplot
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, Bagging
Classifier
from sklearn.metrics import accuracy_score, f1_score, classification_report, con
fusion_matrix
import seaborn as sns
```

In [2]:
```
#Read the data(CSV file) from the local folder and saving it into a dataframe df
df = pd.read_csv("C:/Users/Shriya/Desktop/Insight Data Science/Pre Session Data
Exercise/conversion_data.csv")
```

Data Exploration and Visualization

In [3]:
```
#Previewing data in df - top 10 rows
df.head(10)
```

Out[3]:

	country	age	new_user	source	total_pages_visited	converted
0	UK	25	1	Ads	1	0
1	US	23	1	Seo	5	0
2	US	28	1	Seo	4	0
3	China	39	1	Seo	5	0
4	US	30	1	Seo	6	0
5	US	31	0	Seo	1	0
6	China	27	1	Seo	4	0
7	US	23	0	Ads	4	0
8	UK	29	0	Direct	4	0
9	US	25	0	Ads	2	0

The output above shows a snapshot of Conversion Data.

In [4]:
```
#Checking for nulls in any of the columns of df
df.apply(lambda x: sum(x.isnull()),axis=0)
```

Out[4]:
```
country              0
age                  0
new_user             0
source               0
total_pages_visited  0
converted            0
dtype: int64
```

After checking for nulls, no nulls were found!

In [5]:
```
#Checking for distinct values in all the columns of df starting with the ddependent variable - Converted

print (df['converted'].value_counts())
```

```
0    306000
1     10200
Name: converted, dtype: int64
```

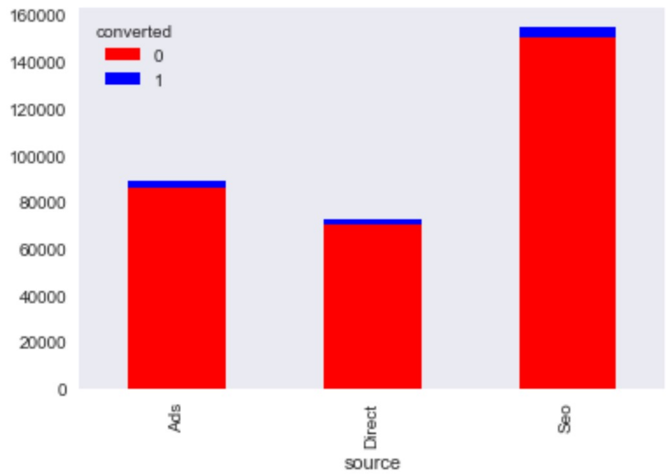
We can see the data set is skewed with converted = 0 comprising 96.77 % of the total while the data of intereset that is converted = 1 is less than 4% of the total.

In [6]:
```
print (df['source'].value_counts())
```

```
Seo       155040
Ads        88740
Direct     72420
Name: source, dtype: int64
```

The sources fall into 3 different categories - Seo, Ads, Direct. Assessing which source gains maximum conversions and which source has room for improvement.

In [7]:
```
%matplotlib inline
temp = pd.crosstab([df['source']], df['converted'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```



In [8]:
```
temp
```

Out[8]:

converted	0	1
source		
Ads	85680	3060
Direct	70380	2040
Seo	149940	5100

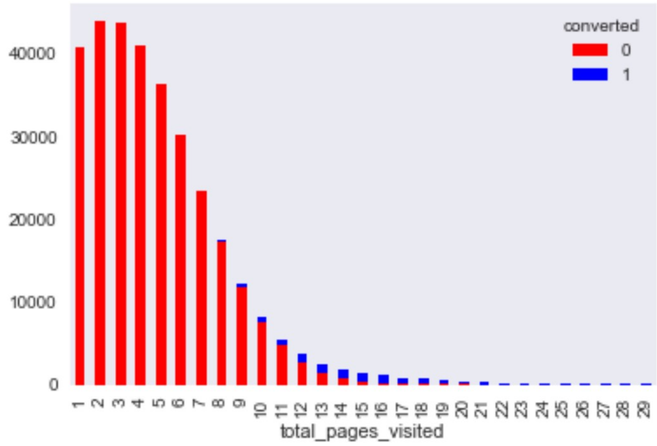
Seo as a source seems to be working the best and can be scaled up further. While Direct source shows room for improvement.

In [9]:
```
print (df['total_pages_visited'].value_counts())
```

```
2     43868
3     43829
4     41046
1     40739
5     36308
6     30261
7     23488
8     17522
9     12157
10     8074
11     5394
12     3615
13     2425
14     1811
15     1325
16     1100
17      845
18      722
19      565
20      405
21      296
22      180
23      113
24       46
25       39
26       17
27        7
29        2
28        1
Name: total_pages_visited, dtype: int64
```

Total number of pages visited by a user can fall anywhere between 1 to 29. It is a proxy for time spent on site and engagement during the session.

In [10]:
```
%matplotlib inline
temp = pd.crosstab([df['total_pages_visited']], df['converted'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```



In [11]:
```
temp
```

Out[11]:

converted	0	1
total_pages_visited		
1	40739	0
2	43858	10
3	43818	11
4	41014	32
5	36251	57
6	30157	104
7	23329	159
8	17255	267
9	11755	402
10	7580	494
11	4728	666
12	2731	884
13	1453	972
14	747	1064
15	344	981
16	141	959
17	65	780
18	28	694
19	6	559
20	1	404
21	0	296
22	0	180
23	0	113
24	0	46
25	0	39
26	0	17
27	0	7
28	0	1
29	0	2

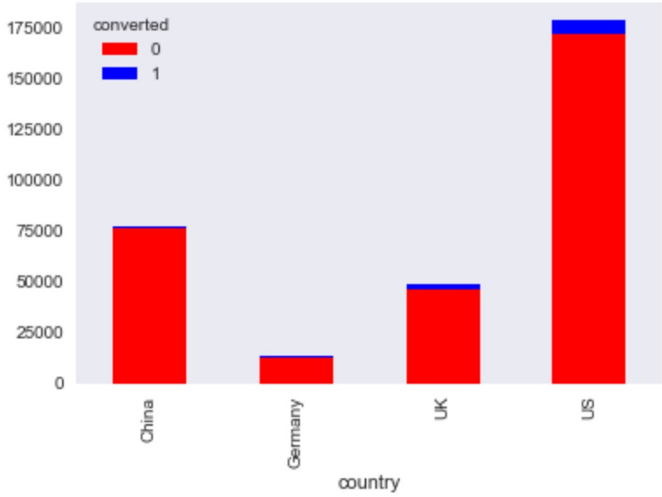
The plot shows that the likelihood of conversion increases with increase in time spent increases. So it would be fair to suggest that by increasing engagement the company is likely to increase conversion.

In [12]:
```
print (df['country'].value_counts())
```

```
US         178092
China       76602
UK          48450
Germany     13056
Name: country, dtype: int64
```

The users belong to 4 countries - US, China, UK, Germany. Majority of whom belong to US.

In [13]:
```
%matplotlib inline
temp = pd.crosstab([df['country']], df['converted'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```



In [14]:
```
temp
```

Out[14]:

converted	0	1
country		
China	76500	102
Germany	12240	816
UK	45900	2550
US	171360	6732

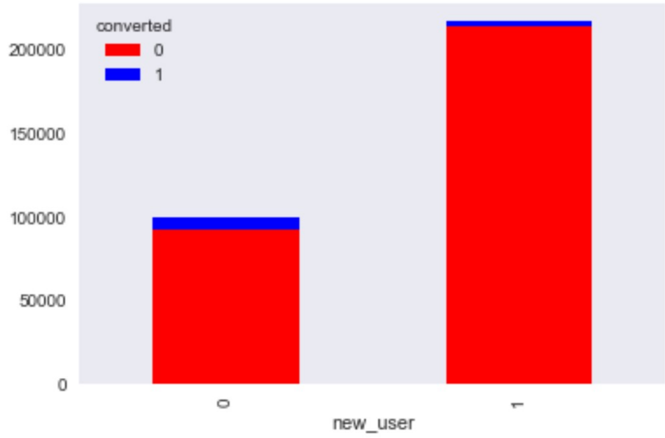
Users in US are more likely to be converted. Therefore, it would be advisable to scale up operations in US. On the other hand, users in China have the lowest conversions. Strategy in China does not seem to be working well and needs a modification.

In [15]:
```
print (df['new_user'].value_counts())
```

```
1    216744
0     99456
Name: new_user, dtype: int64
```

It can be seen that majority of users are return users.

In [16]:
```
%matplotlib inline
temp = pd.crosstab([df['new_user']], df['converted'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```



In [17]:
```
temp
```

Out[17]:

converted	0	1
new_user		
0	92295	7161
1	213705	3039

Surprisingly, return user are more likely to not convert.Therefore, there is a need to target the return users specifically by providing some sort of loyalty schemes. New users tend to convert.

In [18]:
```
print (df['age'].value_counts())
```

```
30     14346
28     14341
29     14158
27     14084
26     13931
31     13692
32     13507
25     13460
24     12960
33     12631
23     12336
34     12108
22     11701
35     11471
21     10966
36     10779
20     10156
37      9761
19      9349
38      8970
18      8466
39      8202
17      7597
40      7148
41      6401
42      5588
43      4904
44      4224
45      3634
46      2994
47      2504
48      2121
49      1629
50      1356
51      1093
52       935
53       627
54       520
55       394
56       286
57       247
58       165
59       127
60        94
61        71
62        59
63        35
64        27
65        15
66         9
67         5
68         5
69         3
70         2
77         1
79         1
111        1
73         1
72         1
123        1
Name: age, dtype: int64
```

In [19]:
```
ages = np.array(df['age'])
print("Mean age of users: ", ages.mean())
print("Standard deviation in the ages : ", ages.std())
print("Minimum age: ", ages.min())
print("Maximum age: ", ages.max())
```

```
Mean age of users:  30.569857685009488
Standard deviation in the ages :  8.271788721781903
Minimum age:  17
Maximum age:  123
```

Age of the users tend to be an average of 30 with a deviation of 8 years. Minimum age is 17 years. Maximum age is 123 years. This number seems to be an error so it would be advisable to drop such erroneous data.

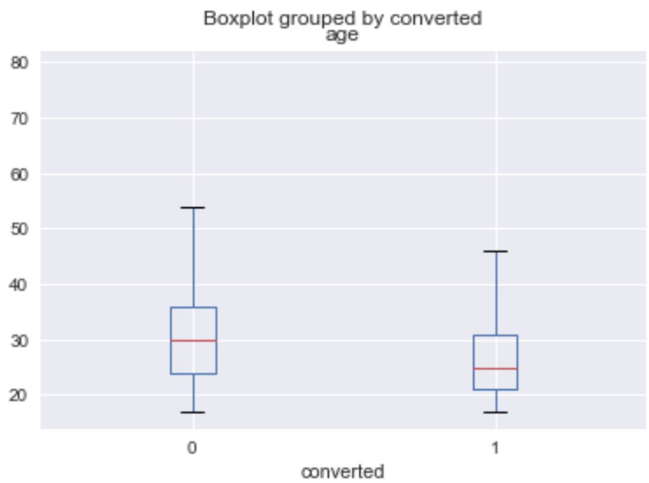
In [20]:
```
# drop unrealistic values of age -  eg : 111, 123
df = df[df["age"] <= 100]
```

In [21]:
```
ages = np.array(df['age'])
print("Mean age of users:       ", ages.mean())
print("Standard deviation in the ages :", ages.std())
print("Minimum age:    ", ages.min())
print("Maximum age:    ", ages.max())
```

```
Mean age of users:        30.569311001334608
Standard deviation in the ages : 8.268944520810427
Minimum age:     17
Maximum age:     79
```

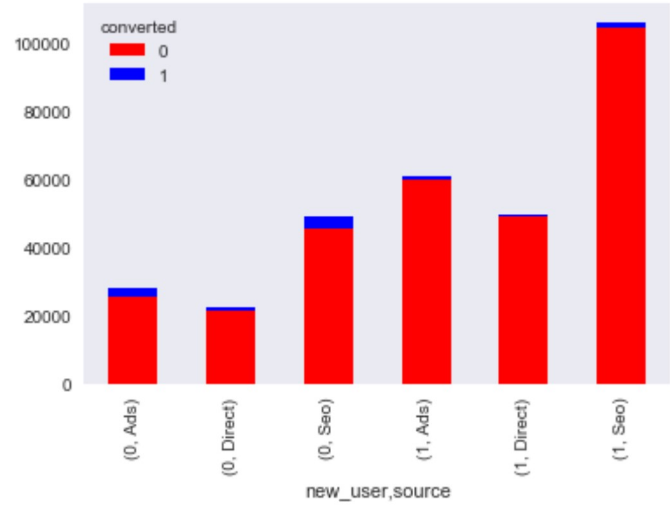
After dropping erroneous data, the maximum age now is 79 years. This number seems more realistic.

In [22]:
```
df.boxplot(column='age', by = 'converted')
pyplot.show()
```



The boxplot shows that the older users are more likely to not convert while their younger counterparts are more likely to convert.

In [23]:
```
temp = pd.crosstab([df['new_user'], df['source']], df['converted'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```

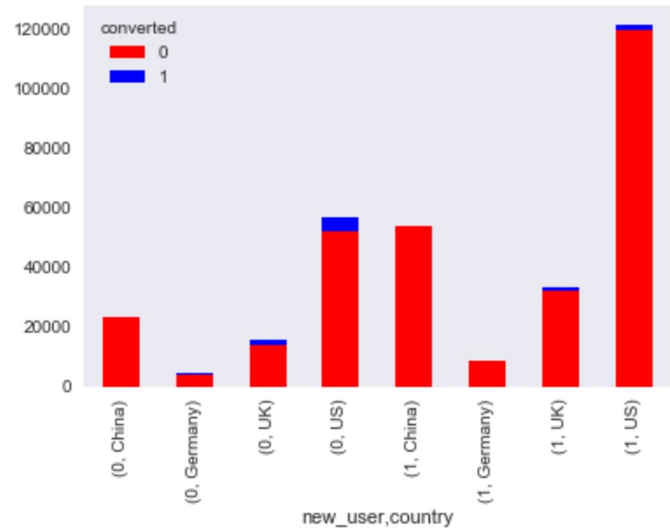


In [24]:
```
temp
```

Out[24]:

	converted	0	1
new_user	**source**		
0	**Ads**	25706	2184
	Direct	21291	1387
	Seo	45298	3588
1	**Ads**	59974	875
	Direct	49089	653
	Seo	104642	1511

In [25]:
```
temp = pd.crosstab([df['new_user'], df['country']], df['converted'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```

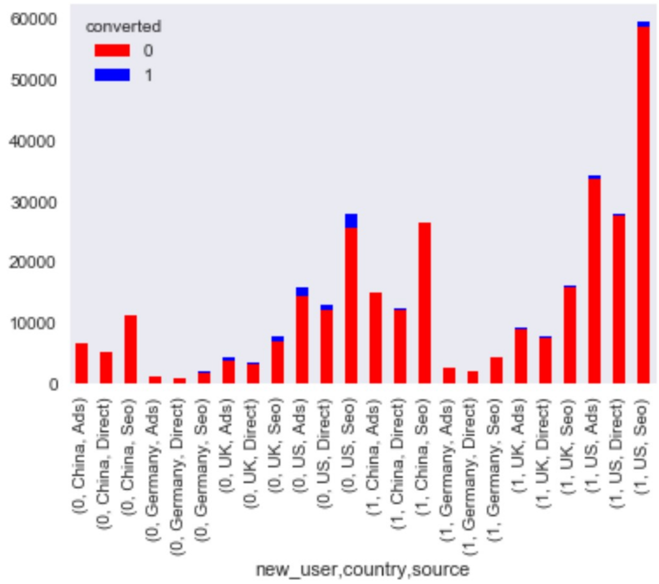


In [26]:
```
temp
```

Out[26]:

	converted	**0**	**1**
new_user	**country**		
0	**China**	23028	66
	Germany	3625	588
	UK	13738	1773
	US	51904	4732
1	**China**	53472	36
	Germany	8615	227
	UK	32162	776
	US	119456	2000

In [27]:
```
temp = pd.crosstab([ df['new_user'],df['country'],df['source']], df['converted
'])
temp.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
pyplot.show()
```



In [28]:
```
temp
```

Out[28]:

		converted	0	1
new_user	**country**	**source**		
0	**China**	**Ads**	6519	22
		Direct	5248	14
		Seo	11261	30
	Germany	**Ads**	1035	189
		Direct	797	105
		Seo	1793	294
	UK	**Ads**	3762	538
		Direct	3169	331
		Seo	6807	904
	US	**Ads**	14390	1435
		Direct	12077	937
		Seo	25437	2360
1	**China**	**Ads**	15010	10
		Direct	12191	10
		Seo	26271	16
	Germany	**Ads**	2474	62
		Direct	1914	48
		Seo	4227	117
	UK	**Ads**	9004	213
		Direct	7447	184
		Seo	15711	379
	US	**Ads**	33486	590
		Direct	27537	411
		Seo	58433	999

The plots above provide deeper understanding into the distribution of data across various combination of features helping us make an informed decision in order to optimize the conversion rate.

Prediction Models

The prediction at hand is a binary classification problem and the prediction is made for the "converted" column. Thus, in turn predicting conversion rate. As mentioned above, the data is skewed that is there is an uneven class distribution. Due to this reason, F-Score is being utilised as the evaluation metric instead of accuracy. F1 Score is needed as we seek to strike a balance between Precision and Recall. If a simple model predicts that the entire test sample of signed-in users during a session will not be converted, the model would still have a 96% accuracy. The model would also hope to improve on this accuracy.

In [29]:
```
#Predictiors - country, age, new_user, source, total_pages_visited
x = df.iloc[:, :-1]
#Dependent variable - converted
y = df.iloc[:, -1]
```

In [30]:
```
#Randomly split the data set into trainset : testset => Ratio = 0.67 : 0.33
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random
_state=1)
```

In [31]:
```
print(y_test.value_counts())
```

```
0    100964
1      3382
Name: converted, dtype: int64
```

In [32]:
```
print(y_train.value_counts())
```

```
0    205036
1      6816
Name: converted, dtype: int64
```

In [33]:
```
#Retrieving numerical value based predictors
x_train_numerical = x_train.select_dtypes(include = np.number).copy()
```

In [34]:
```
x_train_numerical_indices = x_train_numerical.index.values
y_train_numerical = y_train[y_train.index.isin(x_train_numerical_indices)]
```

In [35]:
```
x_test_numerical = x_test.select_dtypes(include = np.number).copy()
```

In [36]:
```
x_test_numerical_indices = x_test_numerical.index.values
y_test_numerical = y_test[y_test.index.isin(x_test_numerical_indices)]
```

In [37]:
```
x_selected = x_train.loc[:,x_train.nunique().sort_values()< 50]
cat_cols = list(x_selected.select_dtypes(['object']).columns.values)
x_categorical = x_selected[cat_cols].apply(lambda x: x.astype('category').cat.co
des)
```

In [38]:
```
x_train_selected = x_train_numerical.join(x_categorical)
```

In [39]:
```
x_test_selected = x_test.loc[:,x_test.nunique().sort_values() < 50]
cat_cols = list(x_test_selected.select_dtypes(['object']).columns.values)
x_test_categorical = x_test_selected[cat_cols].apply(lambda x:x.astype('category
').cat.codes)
x_test_selected = x_test_numerical.join(x_test_categorical)
```

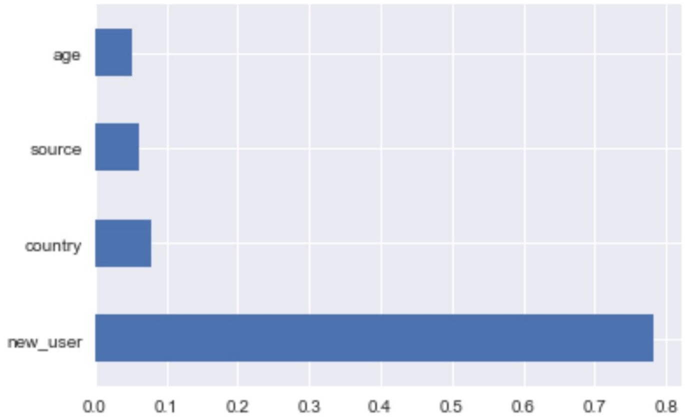
Starting with simpler classifier like Decision Tree and Logistic Regression. Decision Tree works well when predictors are cataegorical in nature like source, country, new_user. However, logistic regression is more robust to noise.

In [40]:
```
DTclf= DecisionTreeClassifier()
DTclf.fit(x_train_selected,y_train) #Fitting the model on the training data
```

Out[40]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [41]:
```
%matplotlib inline
#Plotting importance of each feature in the model
feat_importances = pd.Series(DTclf.feature_importances_, index=x_train.columns)
feat_importances.nlargest(4).plot(kind='barh')
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x23f80338940>



Whether user is new or returning seems to have the most sway on whether the user will convert or not.

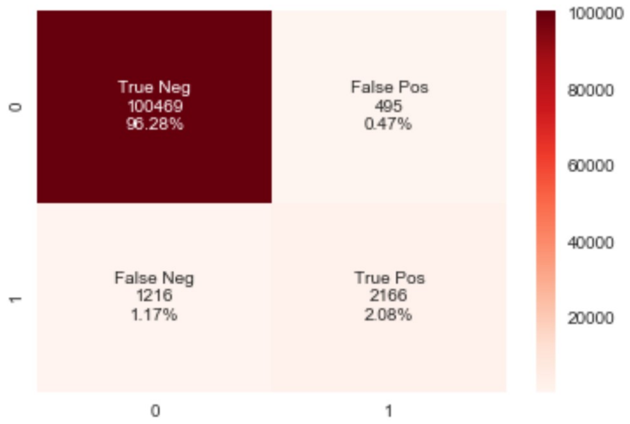
In [42]:
```
y_pred = DTclf.predict(x_test_selected) #Predicting on test set
accuracy = accuracy_score(y_test, y_pred) #Get Accuracy
print('Accuracy: %.2f' % (accuracy*100))
print('F-Score: %.2f' % f1_score(y_test, y_pred))#Get F-Score
print(classification_report(y_pred, y_test))
```

```
Accuracy: 98.36
F-Score: 0.72
              precision    recall  f1-score   support

           0       1.00      0.99      0.99    101685
           1       0.64      0.81      0.72      2661

   micro avg       0.98      0.98      0.98    104346
   macro avg       0.82      0.90      0.85    104346
weighted avg       0.99      0.98      0.98    104346
```

In [43]:
```
#Visualise confusion Matrix
cf_matrix = confusion_matrix(y_test,y_pred)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten()/n
p.sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,group_counts,gro
up_percentages)]
labels = np.asarray(labels).reshape(2,2)
```

In [44]:
```
%matplotlib inline
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Reds')
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x23f803ee860>



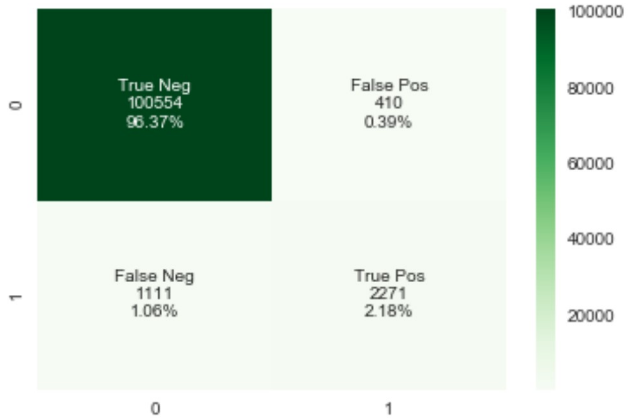
In [45]:
```
LRclf = LogisticRegression()
LRclf.fit(x_train_selected,y_train)
y_pred = LRclf.predict(x_test_selected)
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy: %.2f' % (accuracy*100))
print('F-Score: %.2f' % f1_score(y_test, y_pred))
print(classification_report(y_pred, y_test))
```

```
C:\Users\Shriya\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
33: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify
a solver to silence this warning.
  FutureWarning)

Accuracy: 98.54
F-Score: 0.75
              precision    recall  f1-score   support

           0       1.00      0.99      0.99    101665
           1       0.67      0.85      0.75      2681

   micro avg       0.99      0.99      0.99    104346
   macro avg       0.83      0.92      0.87    104346
weighted avg       0.99      0.99      0.99    104346
```

In [46]:
```
cf_matrix = confusion_matrix(y_test,y_pred)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten()/n
p.sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,group_counts,gro
up_percentages)]
labels = np.asarray(labels).reshape(2,2)
```

In [47]:
```
%matplotlib inline
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Greens')
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x23f8048dba8>



Logistic Regression model performs better than the Decision Tree model in terms of f-score and accuracy.

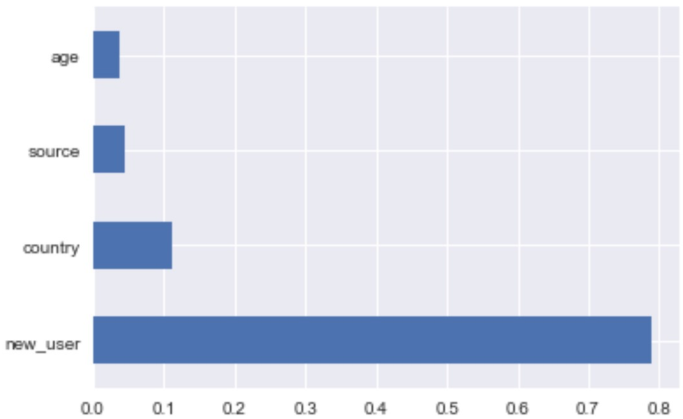
Ensemble models are explored next - Random Forest, Ada Boost and Bagging based clasifiers. Ensemble learning helps improve machine learning results by combining several models. This approach allows the production of better predictive performance compared to a single model.

In [48]:
```
RFclf = RandomForestClassifier(max_depth = 20,
                               n_estimators = 30,
                               n_jobs = -1)
RFclf.fit(x_train_selected,y_train)
```

Out[48]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=20, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=30, n_jobs=-1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [49]:
```
%matplotlib inline
feat_importances = pd.Series(RFclf.feature_importances_, index=x_train.columns)
feat_importances.nlargest(4).plot(kind='barh')
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x23f806f1898>



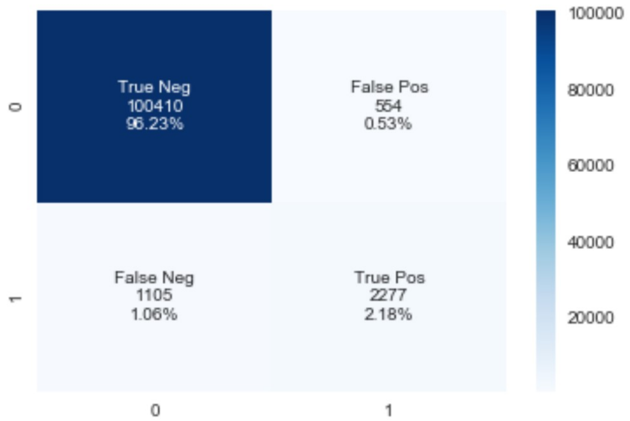
In [50]:
```
y_pred = RFclf.predict(x_test_selected)
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy: %.2f' % (accuracy*100))
print('F-Score: %.2f' % f1_score(y_test, y_pred))
print(classification_report(y_pred, y_test))
```

```
Accuracy: 98.41
F-Score: 0.73
              precision    recall  f1-score   support

           0       0.99      0.99      0.99    101515
           1       0.67      0.80      0.73      2831

   micro avg       0.98      0.98      0.98    104346
   macro avg       0.83      0.90      0.86    104346
weighted avg       0.99      0.98      0.98    104346
```

In [51]:
```
cf_matrix = confusion_matrix(y_test,y_pred)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten()/n
p.sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,group_counts,gro
up_percentages)]
labels = np.asarray(labels).reshape(2,2)
```

In [52]:
```
%matplotlib inline
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Blues')
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x23f8048d198>

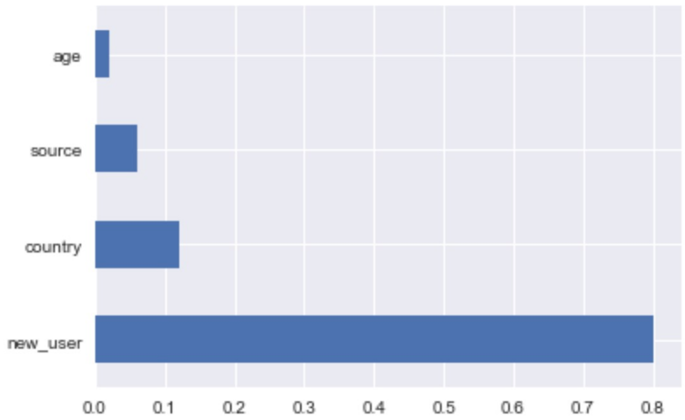


In [53]:
```
ABclf= AdaBoostClassifier()
ABclf.fit(x_train_selected,y_train)
y_pred = ABclf.predict(x_test_selected)
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy: %.2f' % (accuracy*100))
print('F-Score: %.2f' % f1_score(y_test, y_pred))
print(classification_report(y_pred, y_test))
```

```
Accuracy: 98.59
F-Score: 0.76
              precision    recall  f1-score   support

           0       1.00      0.99      0.99    101590
           1       0.69      0.85      0.76      2756

   micro avg       0.99      0.99      0.99    104346
   macro avg       0.84      0.92      0.88    104346
weighted avg       0.99      0.99      0.99    104346
```

In [54]:
```
%matplotlib inline
feat_importances = pd.Series(ABclf.feature_importances_, index=x_train.columns)
feat_importances.nlargest(4).plot(kind='barh')
```

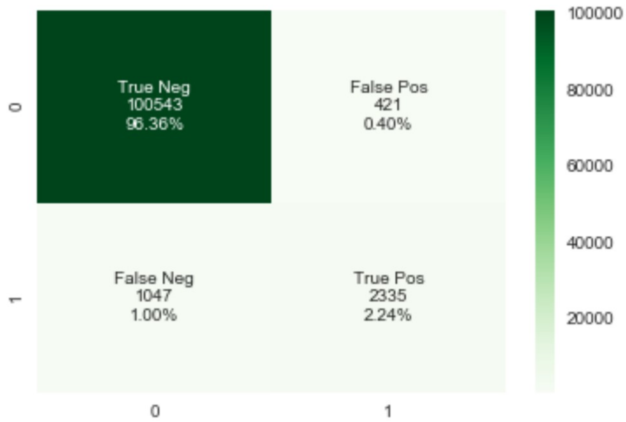
Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x23f80d1a978>



In [55]:
```
cf_matrix = confusion_matrix(y_test,y_pred)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten()/np.sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,group_counts,group_percentages)]
labels = np.asarray(labels).reshape(2,2)
```

In [56]:
```
%matplotlib inline
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Greens')
```

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x23f80328d68>



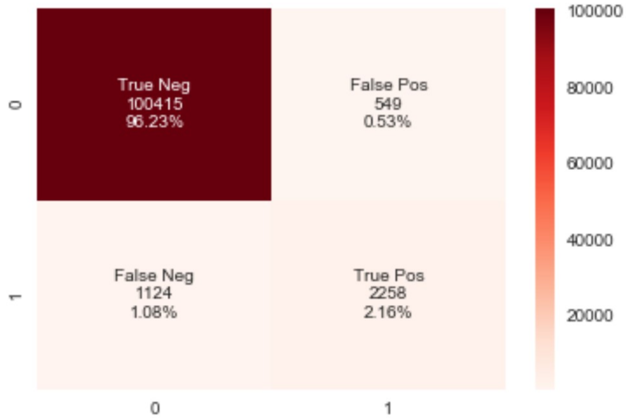
In [57]:
```
Bclf = BaggingClassifier()
Bclf.fit(x_train_selected,y_train)
y_pred = Bclf.predict(x_test_selected)
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy: %.2f' % (accuracy*100))
print('F-Score: %.2f' % f1_score(y_test, y_pred))
print(classification_report(y_pred, y_test))
```

```
Accuracy: 98.40
F-Score: 0.73
              precision    recall  f1-score   support

           0       0.99      0.99      0.99    101539
           1       0.67      0.80      0.73      2807

   micro avg       0.98      0.98      0.98    104346
   macro avg       0.83      0.90      0.86    104346
weighted avg       0.99      0.98      0.98    104346
```

In [58]:
```
cf_matrix = confusion_matrix(y_test,y_pred)
group_names = ['True Neg','False Pos','False Neg','True Pos']
group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]
group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten()/n
p.sum(cf_matrix)]
labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names,group_counts,gro
up_percentages)]
labels = np.asarray(labels).reshape(2,2)
```

In [59]:
```
%matplotlib inline
sns.heatmap(cf_matrix, annot=labels, fmt='', cmap='Reds')
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x23f8011c780>



AdaBoost model performs best out of the lot and achieves a F-Score of 0.76. Surprisingly, Random Forest and Bagging based classifiers perform worse than the simpler Logistic Regression classifier.

Recommendations

1. The most crucial ascpect in determining whether user will convert is whether they are repeat users. Repeat users are likely not to convert and new users are more likely to convert. It would be essential to attract more new users to the website in order to increase conversion rate. This should be supplemented by coming up with ideas to get return users to convert.

2. US provides the maximum number of converted users. Targeting the users based in US would be fruitful in efforts to increase conversion rate.

3. SEO is the most popular source for users that convert. It would be sensible to invest in potentially scaling it even further.

4. Users in China are least likely to convert even though it has the second largest user base. This seems to be a hindrance when trying to increase conversion rate. Users in China which are likely to convert are routed to website via SEO. Therefore, focusing on optimising this source specially in China would help increase conversion rate.

5. Younger user base is more likely to convert when compared to the older user base. Marketing should target older user base to increase popularity of the website in that age group and also increase their engagement. This would help increase the likelihood of them converting as increased engagement positively affects the chances of conversion.