Defining an adopted user **as a user who has logged into the product on three separate days in at least one sevenday period ,**
identify which factors predict future user adoption.
We suggest spending 1-2 hours on this, but you're welcome to spend more or less. Please send us a brief writeup of your findings (the more concise, the better no more than one page), along with any summary tables, graphs, code, or queries that can help us understand your approach. Please note any factors you considered or investigation you did, even if they did not pan out. Feel free to identify any further research or data you think would be valuable.

Analysis of the provided data shows that the age of the account, time since account was opened is the best predictor to determine whether the user is adopted. This feature is followed by the type of the account creation type. Following graph shows how different features contributed to determine the trend of user adoption. Capture.JPG
Results shows that the users who signed up early are more like to be adopted, the distribution of the account age is shown below:
Capture_1.JPG

I developed a model with a ROC_AUC of 0.65. To improve the performance of the model, We need to gather various other information of the users such as the demographic, education and financial information.

Please follow the following notebook to get insights into the coding and analysis.

Coding Section

```
### Importing Basic Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from datetime import date
from datetime import datetime
from datetime import timedelta


from sklearn.preprocessing import LabelEncoder


from google.colab import drive
drive.mount('/content/drive')
```

```
    Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=Tr
```

```
users=pd.read_csv('/content/drive/MyDrive/DS-SB/Take Home_1_challenge/takehome_users.csv', encoding='latin-1')
users.head()
```

	object_id	creation_time	name	email	creation_source	las
0	1	2014-04-22 03:53:30	Clausen August	AugustCClausen@yahoo.com	GUEST_INVITE	
1	2	2013-11-15 03:45:04	Poole Matthew	MatthewPoole@gustr.com	ORG_INVITE	
2	3	2013-03-19 23:14:52	Bottrill Mitchell	MitchellBottrill@gustr.com	ORG_INVITE	
3	4	2013-05-21 08:09:28	Clausen Nicklas	NicklasSClausen@yahoo.com	GUEST_INVITE	
4	5	2013-01-17 10:14:20	Raw Grace	GraceRaw@yahoo.com	GUEST_INVITE	

Next steps: Generate code with users View recommended plots

```
engagement=pd.read_csv('/content/drive/MyDrive/DS-SB/Take Home_1_challenge/takehome_user_engagement.csv')
engagement['time_stamp']=pd.to_datetime(engagement['time_stamp'], format='%Y-%m-%d %H:%M:%S')
engagement.head()
```

	time_stamp	user_id	visited
0	2014-04-22 03:53:30	1	1
1	2013-11-15 03:45:04	2	1
2	2013-11-29 03:45:04	2	1
3	2013-12-09 03:45:04	2	1
4	2013-12-25 03:45:04	2	1

```
engagement['date']=engagement['time_stamp'].dt.date
engagement.head()
```

	time_stamp	user_id	visited	date
0	2014-04-22 03:53:30	1	1	2014-04-22
1	2013-11-15 03:45:04	2	1	2013-11-15
2	2013-11-29 03:45:04	2	1	2013-11-29
3	2013-12-09 03:45:04	2	1	2013-12-09
4	2013-12-25 03:45:04	2	1	2013-12-25

```
#Determination of a adopted user
adopted_user=[]
for user_id in engagement['user_id'].unique():
    logins=engagement[engagement['user_id']==user_id]['date'].drop_duplicates().sort_values()
    logins=logins.diff(3).dropna()
    if len([date for date in logins if date<=timedelta(days=7)])>1:
        adopted_user.append(user_id)
```

```
len(adopted_user)
```

1265

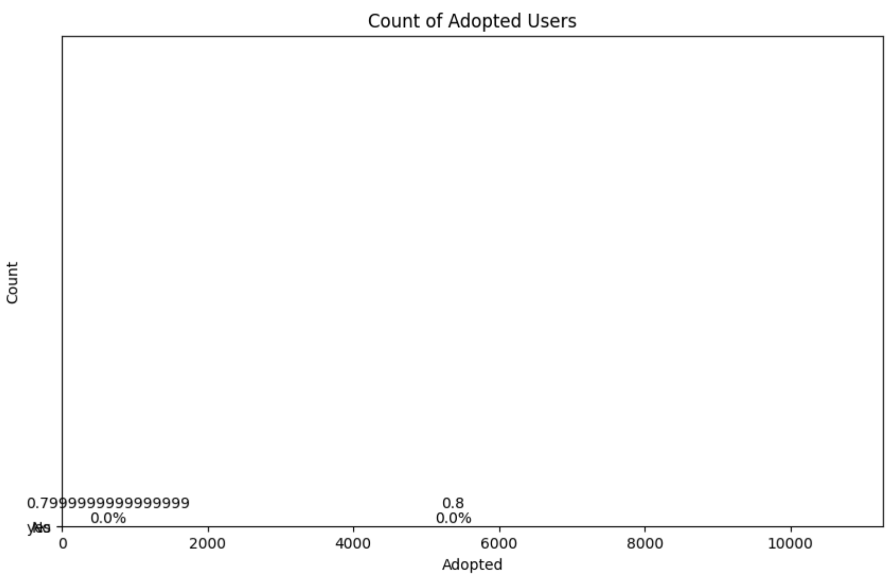
```
#adopted_user
```

```
users['adopted']=['yes' if i in adopted_user else 'No' for i in users['object_id'].values]
users.head()
```

	object_id	creation_time	name	email	creation_source	las
0	1	2014-04-22 03:53:30	Clausen August	AugustCClausen@yahoo.com	GUEST_INVITE	
1	2	2013-11-15 03:45:04	Poole Matthew	MatthewPoole@gustr.com	ORG_INVITE	
2	3	2013-03-19 23:14:52	Bottrill Mitchell	MitchellBottrill@gustr.com	ORG_INVITE	
3	4	2013-05-21 08:09:28	Clausen Nicklas	NicklasSClausen@yahoo.com	GUEST_INVITE	
4	5	2013-01-17 10:14:20	Raw Grace	GraceRaw@yahoo.com	GUEST_INVITE	

Next steps: Generate code with users View recommended plots

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))

# Create the count plot
ax = sns.countplot(users['adopted'])

# Set y-axis limit
plt.ylim([0, 12000])

# Annotate each bar with percentage
total = len(users)  # Total number of users
for p in ax.patches:
    height = p.get_height()
    ax.annotate('{:.1f}%'.format(100 * height / total), (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=10)
    ax.annotate('{}'.format(height), (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=10, xytext=(0, 10), textcoords='offset points')

# Add labels and title
plt.xlabel('Adopted')
plt.ylabel('Count')
plt.title('Count of Adopted Users')

# Show plot
plt.show()
```



Target is highly unbalanced, we might need to weighting factor during modelling.

Feature Generation

```
users['creation_time']=pd.to_datetime(users['creation_time'])
```

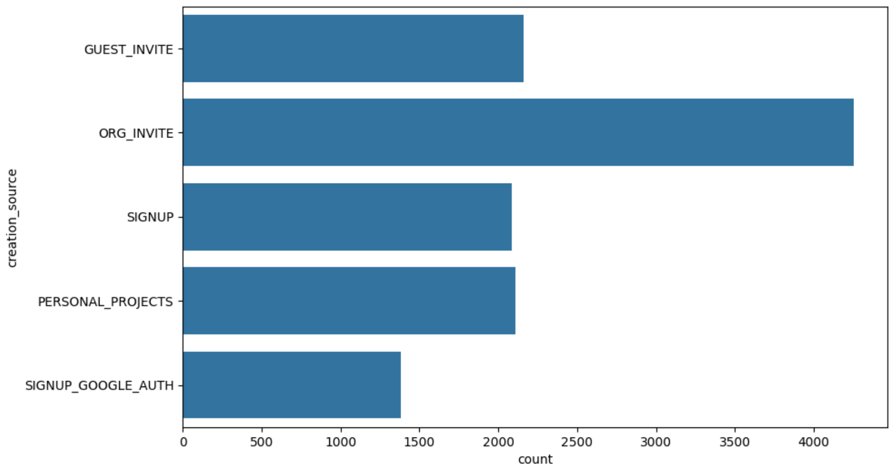
```
datetime.now()
```

```
datetime.datetime(2024, 3, 26, 6, 26, 6, 706834)
```

```
#Creating new feature from account creation time
account_age=datetime.now()-users['creation_time']
users['account_age']=account_age/np.timedelta64(1, 's')
```

```
plt.figure(figsize=(10,6))
sns.countplot(users['creation_source'])
```

    <Axes: xlabel='count', ylabel='creation_source'>



Missing Value

```
users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12000 entries, 0 to 11999
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   object_id                   12000 non-null  int64
 1   creation_time               12000 non-null  datetime64[ns]
 2   name                        12000 non-null  object
 3   email                       12000 non-null  object
 4   creation_source             12000 non-null  object
 5   last_session_creation_time  8823 non-null   float64
 6   opted_in_to_mailing_list    12000 non-null  int64
 7   enabled_for_marketing_drip  12000 non-null  int64
 8   org_id                      12000 non-null  int64
 9   invited_by_user_id          6417 non-null   float64
 10  adopted                     12000 non-null  object
 11  account_age                 12000 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(4), object(4)
memory usage: 1.1+ MB
```

Two features: last session creation time and invited by user contains missing values. Missing in invite by user should corresponds to the account that are not invited. Hence, let's impute the missing value by None for invited by user and mean value in last session creation time.

```
users['last_session_creation_time']=users['last_session_creation_time'].fillna(users['last_session_creation_time'].mean())
users['invited_by_user_id']=users['invited_by_user_id'].fillna('None')
```

Object_id and Org_id should be object.

```
users['object_id']=users['object_id'].astype('object')
users['org_id']=users['org_id'].astype('object')
```

```
users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12000 entries, 0 to 11999
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   object_id                   12000 non-null  object
 1   creation_time               12000 non-null  datetime64[ns]
 2   name                        12000 non-null  object
 3   email                       12000 non-null  object
 4   creation_source             12000 non-null  object
 5   last_session_creation_time  12000 non-null  float64
 6   opted_in_to_mailing_list    12000 non-null  int64
 7   enabled_for_marketing_drip  12000 non-null  int64
 8   org_id                      12000 non-null  object
 9   invited_by_user_id          12000 non-null  object
 10  adopted                     12000 non-null  object
 11  account_age                 12000 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(2), object(7)
memory usage: 1.1+ MB
```

```
users['org_id'].value_counts()
```

```
0      319
1      233
2      201
3      168
4      159
      ...
396      9
397      8
400      8
386      7
416      2
Name: org_id, Length: 417, dtype: int64
```

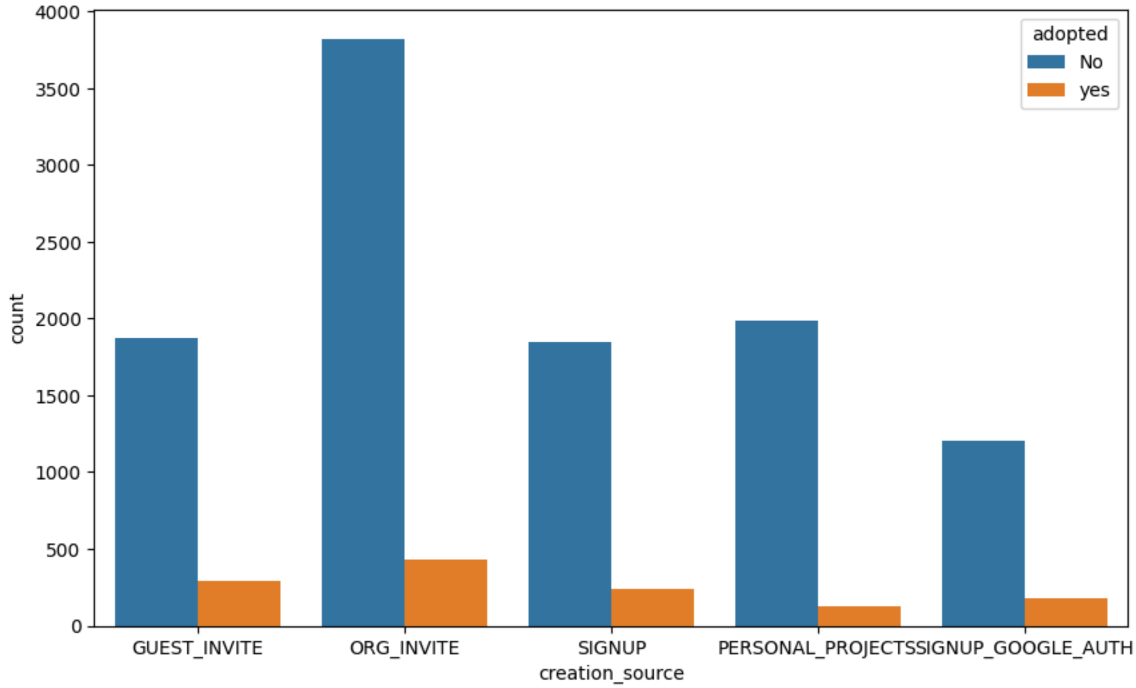
There are too many organization ids, hence, this feature will not be converted into dummy variable.

```
users['creation_source'].value_counts()
```

```
ORG_INVITE            4254
GUEST_INVITE          2163
PERSONAL_PROJECTS     2111
SIGNUP                2087
SIGNUP_GOOGLE_AUTH    1385
Name: creation_source, dtype: int64
```

```
plt.figure(figsize=(10,6))
sns.countplot(x='creation_source',data=users,hue='adopted')
```

```
<Axes: xlabel='creation_source', ylabel='count'>
```



Thus feature will be converted into dummy variable later.

```
users['invited_by_user_id'].value_counts()
```

```
None       5583
10741.0      13
2527.0       12
1525.0       11
2308.0       11
           ...
2071.0        1
1390.0        1
5445.0        1
8526.0        1
5450.0        1
Name: invited_by_user_id, Length: 2565, dtype: int64
```

There are too many values for invited_by_user, we can't convert each input into dummy variables. Let's create a new feature by classifying the inputs as if the user is invited by another user or not.

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```
# Create two DataFrames based on the condition
df1 = users[users['invited_by_user_id'] != 'None'].copy()
df2 = users[users['invited_by_user_id'] == 'None'].copy()

# Set the value of 'invited_by_user_id' column accordingly
df1['invited_by_user_id'] = 'yes'
df2['invited_by_user_id'] = 'no'

# Concatenate the DataFrames
users = pd.concat([df1, df2], ignore_index=True)

# Display the counts of the 'invited_by_user_id' column
print(users['invited_by_user_id'].value_counts())
```

```
yes    6417
no     5583
Name: invited_by_user_id, dtype: int64
```

Start coding or generate with AI.

Predictive model to determine if the user is adopted

Preprocessing and Train Data Development

```
users.columns
```

```
Index(['object_id', 'creation_time', 'name', 'email', 'creation_source',
       'last_session_creation_time', 'opted_in_to_mailing_list',
       'enabled_for_marketing_drip', 'org_id', 'invited_by_user_id', 'adopted',
       'account_age'],
      dtype='object')
```

```
#Selecting useful features only
df=users[['creation_source','opted_in_to_mailing_list','enabled_for_marketing_drip', 'invited_by_user_id', 'adopted','account_ag
df
```

	creation_source	opted_in_to_mailing_list	enabled_for_marketing_drip
0	GUEST_INVITE	1	C
1	ORG_INVITE	0	C
2	ORG_INVITE	0	C
3	GUEST_INVITE	0	C
4	GUEST_INVITE	0	C
...	...	...	..
11995	PERSONAL_PROJECTS	0	C
11996	PERSONAL_PROJECTS	0	C
11997	SIGNUP_GOOGLE_AUTH	0	C
11998	PERSONAL_PROJECTS	0	C
11999	SIGNUP	0	1

12000 rows × 6 columns

Next steps: Generate code with df View recommended plots

Encoding categorical features

Encoding features with boolen datatypes

```
le = LabelEncoder()
df['adopted']= le.fit_transform(df['adopted'])
df['invited_by_user_id']= le.fit_transform(df['invited_by_user_id'])
df.head()
```

```
<ipython-input-51-1cb4d01480e7>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view
  df['adopted']= le.fit_transform(df['adopted'])
<ipython-input-51-1cb4d01480e7>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view
  df['invited_by_user_id']= le.fit_transform(df['invited_by_user_id'])
```

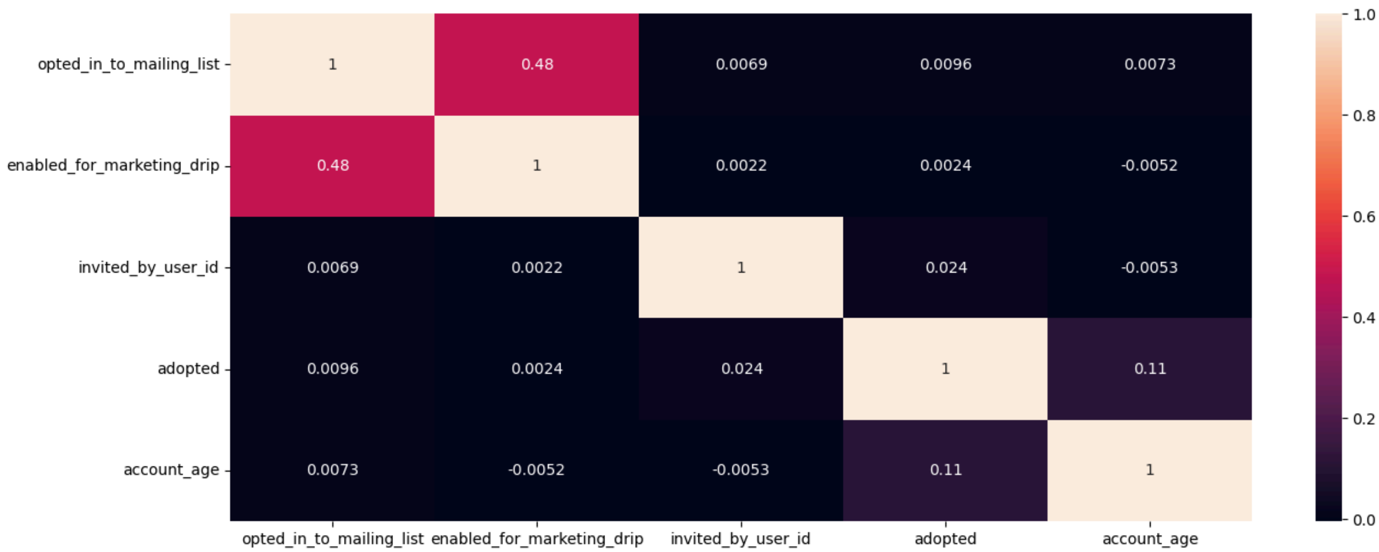
	creation_source	opted_in_to_mailing_list	enabled_for_marketing_drip	invited_by_user_id	adopted	account_age
0	GUEST_INVITE	1	0	1	0	3.132956e+08
1	ORG_INVITE	0	0	1	0	3.269473e+08
2	ORG_INVITE	0	0	1	0	3.476995e+08
3	GUEST_INVITE	0	0	1	0	3.423106e+08
4	GUEST_INVITE	0	0	1	0	3.530167e+08

Next steps: Generate code with df View recommended plots

Correlation within the features

```
plt.figure(figsize=(15,6))
sns.heatmap(df.corr(),annot=True)
```

```
<ipython-input-52-42c19d2e59ca>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a fu
  sns.heatmap(df.corr(),annot=True)
<Axes: >
```



Features are not highly correlated.

```
cat=df.select_dtypes('object').columns
cat
```

```
Index(['creation_source'], dtype='object')
```

```
dummies=pd.get_dummies(df['creation_source'],drop_first=True)
df=pd.concat([df,dummies], axis=1)
df=df.drop('creation_source', axis=1)
df.head()
```

	opted_in_to_mailing_list	enabled_for_marketing_drip	invited_by_user_id	adop
0	1	0	1	
1	0	0	1	
2	0	0	1	
3	0	0	1	
4	0	0	1	

Next steps: Generate code with df View recommended plots

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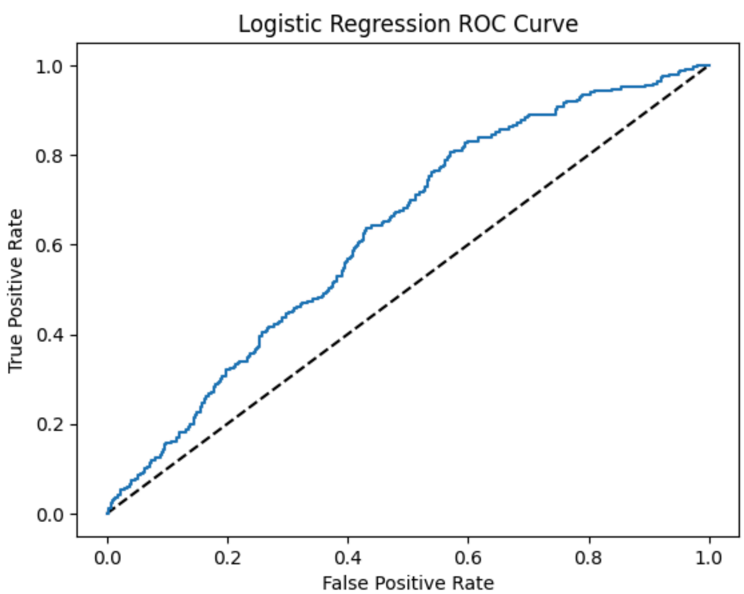
Data Scaling and Train/Test split

```
### Test train split and scaling
X=df.drop(['adopted'], axis=1).values
y=df['adopted'].values

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)

from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
X_train=scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)
```

Logistic Regression

```
# Training the Logistic Regression model on the Training set
from sklearn.linear_model import LogisticRegression
classifier_LR = LogisticRegression(random_state = 0)
classifier_LR.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier_LR.predict(X_test)

# Model evaluation matrices
from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

print('\n')
print('Train Data Metrics:')
y_pred = classifier_LR.predict(X_train)
print(confusion_matrix(y_train, y_pred))
print(classification_report(y_train, y_pred))


from sklearn.metrics import roc_auc_score
y_pred_prob = classifier_LR.predict_proba(X_test)[:,1]
y_pred_prob_train = classifier_LR.predict_proba(X_train)[:,1]

#ROC_AUC Curve
from sklearn.metrics import roc_curve
y_pred_prob = classifier_LR.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Logistic Regression')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.show()

print('ROC_AUC Score')
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
```

```
Test Data Metrics:
[[2153    0]
 [ 247    0]]
              precision    recall  f1-score   support

           0       0.90      1.00      0.95      2153
           1       0.00      0.00      0.00       247

    accuracy                           0.90      2400
   macro avg       0.45      0.50      0.47      2400
weighted avg       0.80      0.90      0.85      2400



Train Data Metrics:
[[8582    0]
 [1018    0]]
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      8582
           1       0.00      0.00      0.00      1018

    accuracy                           0.89      9600
   macro avg       0.45      0.50      0.47      9600
weighted avg       0.80      0.89      0.84      9600

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
  _warn_prf(average, modifier, msg_start, len(result))
```




```
ROC_AUC Score
roc_auc (test): 0.626
roc_auc (training): 0.635
```

```
#Feature importance LR
feature_importance_LR=abs(classifier_LR.coef_)[0]
features= df.drop(['adopted'], axis=1).columns
feature_importances_LR=pd.DataFrame(list(zip(features,feature_importance_LR/max(feature_importance_LR)*100)), columns=['features

feature_importances_LR.head(50)
```

	features	importance
3	account_age	100.000000
5	PERSONAL_PROJECTS	47.437034
4	ORG_INVITE	22.225939
2	invited_by_user_id	20.522806
7	SIGNUP_GOOGLE_AUTH	19.469596
0	opted_in_to_mailing_list	7.955123
6	SIGNUP	7.385012
1	enabled_for_marketing_drip	3.276962

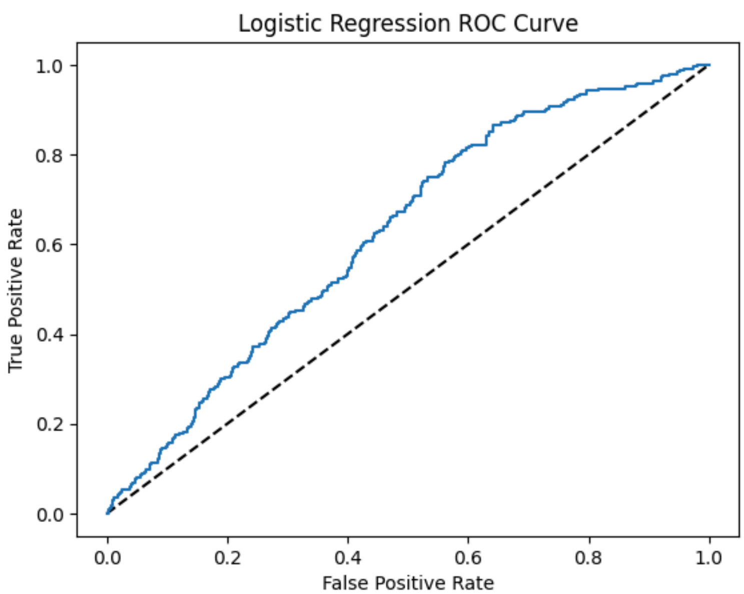
Next steps: Generate code with feature_importances_LR View recommended plots

Start coding or generate with AI.

Weighted Logistic Regression

```
# Training the Logistic Regression model on the Training set
from sklearn.linear_model import LogisticRegression
classifier_LR = LogisticRegression(random_state = 0, class_weight={0:1,1:10})
classifier_LR.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier_LR.predict(X_test)

# Model evaluation matrices
from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

print('\n')
print('Train Data Metrics:')
y_pred = classifier_LR.predict(X_train)
print(confusion_matrix(y_train, y_pred))
print(classification_report(y_train, y_pred))


from sklearn.metrics import roc_auc_score
y_pred_prob = classifier_LR.predict_proba(X_test)[:,1]
y_pred_prob_train = classifier_LR.predict_proba(X_train)[:,1]

#ROC_AUC Curve
from sklearn.metrics import roc_curve
y_pred_prob = classifier_LR.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label='Logistic Regression')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.show()

print('ROC_AUC Score')
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
```

```
Test Data Metrics:
[[1048 1105]
 [  72  175]]
              precision    recall  f1-score   support

           0       0.94      0.49      0.64      2153
           1       0.14      0.71      0.23       247

    accuracy                           0.51      2400
   macro avg       0.54      0.60      0.43      2400
weighted avg       0.85      0.51      0.60      2400



Train Data Metrics:
[[4214 4368]
 [ 285  733]]
              precision    recall  f1-score   support

           0       0.94      0.49      0.64      8582
           1       0.14      0.72      0.24      1018

    accuracy                           0.52      9600
   macro avg       0.54      0.61      0.44      9600
weighted avg       0.85      0.52      0.60      9600
```




```
ROC_AUC Score
roc_auc (test): 0.625
roc_auc (training): 0.635
```

Start coding or generate with AI.

L1 Regularized LR

```
from sklearn.linear_model import LogisticRegression
classifier_LR = LogisticRegression(solver='liblinear', random_state = 0, penalty='l1', class_weight={0:1,1:10})
classifier_LR.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier_LR.predict(X_test)
y_pred_train= classifier_LR.predict(X_train)

# Making the Confusion Matrix
from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))


print('\n')
print('Train Data Metrics:')
print(confusion_matrix(y_train, y_pred_train))
print(classification_report(y_train, y_pred_train))

from sklearn.metrics import roc_auc_score
y_pred_prob = classifier_LR.predict_proba(X_test)[:,1]
y_pred_prob_train = classifier_LR.predict_proba(X_train)[:,1]

print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
```

```
Test Data Metrics:
[[1048 1105]
 [  72  175]]
              precision    recall  f1-score   support

           0       0.94      0.49      0.64      2153
           1       0.14      0.71      0.23       247

    accuracy                           0.51      2400
   macro avg       0.54      0.60      0.43      2400
weighted avg       0.85      0.51      0.60      2400



Train Data Metrics:
[[4214 4368]
 [ 286  732]]
              precision    recall  f1-score   support

           0       0.94      0.49      0.64      8582
           1       0.14      0.72      0.24      1018

    accuracy                           0.52      9600
   macro avg       0.54      0.61      0.44      9600
weighted avg       0.85      0.52      0.60      9600

roc_auc (training): 0.635
roc_auc (test): 0.625
```

Random Forest classifier

```
from sklearn.ensemble import RandomForestClassifier

classifier_RF=RandomForestClassifier(random_state=0,class_weight={0:1,1:10})

classifier_RF.fit(X_train,y_train)

# Predicting the Test set results
y_pred = classifier_RF.predict(X_test)
y_pred_train=classifier_RF.predict(X_train)

# Making the Confusion Matrix
from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))


print('\n')
print('Train Data Metrics:')
print(confusion_matrix(y_train, y_pred_train))
```

```
print(confusion_matrix(y_train, y_pred_train))
print(classification_report(y_train, y_pred_train))


from sklearn.metrics import roc_auc_score
y_pred_prob = classifier_RF.predict_proba(X_test)[:,1]
y_pred_prob_train = classifier_RF.predict_proba(X_train)[:,1]

print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
```

```
Test Data Metrics:
[[1929  224]
 [ 214   33]]
              precision    recall  f1-score   support

           0       0.90      0.90      0.90      2153
           1       0.13      0.13      0.13       247

    accuracy                           0.82      2400
   macro avg       0.51      0.51      0.51      2400
weighted avg       0.82      0.82      0.82      2400



Train Data Metrics:
[[8582    0]
 [   3 1015]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      8582
           1       1.00      1.00      1.00      1018

    accuracy                           1.00      9600
   macro avg       1.00      1.00      1.00      9600
weighted avg       1.00      1.00      1.00      9600

roc_auc (training): 1.000
roc_auc (test): 0.562
```

XgBoost

```
import xgboost
from xgboost import XGBClassifier
classifier_xgb = XGBClassifier(random_stat=0, scale_pos_weight=10)

classifier_xgb.fit(X_train, y_train)


# Predicting the Test set results
y_pred = classifier_xgb.predict(X_test)
y_pred_train = classifier_xgb.predict(X_train)

# Making the Confusion Matrix
from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))


print('\n')
print('Train Data Metrics:')
print(confusion_matrix(y_train, y_pred_train))
print(classification_report(y_train, y_pred_train))

from sklearn.metrics import roc_auc_score
y_pred_prob = classifier_xgb.predict_proba(X_test)[:,1]
y_pred_prob_train = classifier_xgb.predict_proba(X_train)[:,1]

print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:160: UserWarning: [06:26:12] WARNING: /workspace/src/learner.cc:742:
Parameters: { "random_stat" } are not used.

  warnings.warn(smsg, UserWarning)
Test Data Metrics:
[[1269  884]
 [ 120  127]]
```

```
              precision    recall  f1-score   support

           0       0.91      0.59      0.72      2153
           1       0.13      0.51      0.20       247

    accuracy                           0.58      2400
   macro avg       0.52      0.55      0.46      2400
weighted avg       0.83      0.58      0.66      2400



Train Data Metrics:
[[5431 3151]
 [  53  965]]
              precision    recall  f1-score   support

           0       0.99      0.63      0.77      8582
           1       0.23      0.95      0.38      1018

    accuracy                           0.67      9600
   macro avg       0.61      0.79      0.57      9600
weighted avg       0.91      0.67      0.73      9600

roc_auc (training): 0.877
roc_auc (test): 0.595
```

LGBM

```
import lightgbm as lgb
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import mean_squared_error,roc_auc_score,precision_score, roc_auc_score


#converting the dataset into proper LGB format
d_train=lgb.Dataset(X_train, label=y_train)

#Specifying the parameter
params={}
params['learning_rate']=0.03
params['boosting_type']='gbdt' #GradientBoostingDecisionTree
params['objective']='binary' #Binary target feature
params['metric']='binary_logloss' #metric for binary classification
params['max_depth']=50,
params['scale_pos_weight']=10,

#train the model
clf=lgb.train(params,d_train,100) #train the model on 100 epocs

#prediction on the test set
y_pred_prob=clf.predict(X_test)
y_pred_prob_train=clf.predict(X_train)

y_pred= [1 if x >= 0.5 else 0 for x in y_pred_prob]
y_pred_train= [1 if x >= 0.5 else 0 for x in y_pred_prob_train]

from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))


print('\n')
print('Train Data Metrics:')
print(confusion_matrix(y_train, y_pred_train))
print(classification_report(y_train, y_pred_train))

print('\n')
print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
```

```
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leaves OR 2^max_depth > num_leaves. (num_leaves
[LightGBM] [Warning] Accuracy may be bad since you didn't explicitly set num_leaves OR 2^max_depth > num_leaves. (num_leaves
[LightGBM] [Info] Number of positive: 1018, number of negative: 8582
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.001477 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 269
[LightGBM] [Info] Number of data points in the train set: 9600, number of used features: 8
```

```
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.106042 -> initscore=-2.131827
[LightGBM] [Info] Start training from score -2.131827
Test Data Metrics:
[[ 993 1160]
 [  59  188]]
              precision    recall  f1-score   support

           0       0.94      0.46      0.62      2153
           1       0.14      0.76      0.24       247

    accuracy                           0.49      2400
   macro avg       0.54      0.61      0.43      2400
weighted avg       0.86      0.49      0.58      2400



Train Data Metrics:
[[3980 4602]
 [ 126  892]]
              precision    recall  f1-score   support

           0       0.97      0.46      0.63      8582
           1       0.16      0.88      0.27      1018

    accuracy                           0.51      9600
   macro avg       0.57      0.67      0.45      9600
weighted avg       0.88      0.51      0.59      9600



roc_auc (training): 0.756
roc_auc (test): 0.640
```

```
feature_importance_LGBM = clf.feature_importance()
features= df.drop(['adopted'], axis=1).columns
feature_importances_LGBM=pd.DataFrame(list(zip(features,feature_importance_LGBM/max(feature_importance_LGBM)*100)), columns=['fe

feature_importances_LGBM.head(50)
```

	features	importance
3	account_age	100.000000
4	ORG_INVITE	7.607699
0	opted_in_to_mailing_list	5.957837
5	PERSONAL_PROJECTS	5.774519
2	invited_by_user_id	5.637030
6	SIGNUP	4.995417
1	enabled_for_marketing_drip	4.124656
7	SIGNUP_GOOGLE_AUTH	3.391384

Next steps: Generate code with `feature_importances_LGBM` View recommended plots

LightGBM performs better than all other models. Hence, I will choose this as a final model.

Hyperparameter tuning

```
# Randomized CV
param_grid = {
    'n_estimators':list(np.arange(150,200,2)),
   'colsample_bytree': list(np.linspace(0,1,11)),
    'max_depth': list(np.arange(10,100,5)),
    'num_leaves': list(np.arange(25, 100, 25)),
    'reg_alpha': [0, 1, 2.5, 5, 10,15,20],
    'reg_lambda': [0,1,2.5,5,10,15,20],
    'min_split_gain': [0.3, 0.4, 0.8,1.5],
    'scale_pos_weight':[5,9,10,11,12,15],
    'subsample': list(np.arange(0.2,1,0.1)),
    'subsample_freq': list(np.arange(10,50,5))}
```

```
import lightgbm as lgb
```

```
import lightgbm as lgb
from sklearn.model_selection import RandomizedSearchCV

clf = lgb.LGBMClassifier(random_state=0)
gs = RandomizedSearchCV(
    estimator=clf, param_distributions=param_grid,
    n_iter=1000,
    scoring='roc_auc',
    cv=10,
    refit=True,
    random_state=0,
    verbose=True)



# Fit the object to our data
gs.fit(X_train, y_train)


print(gs.best_score_)
print(gs.best_params_)
```

```
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
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[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

Final Model

```
import lightgbm as lgb
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import mean_squared_error,roc_auc_score,precision_score, roc_auc_score


#converting the dataset into proper LGB format
d_train=lgb.Dataset(X_train,y_train)

#Specifying the parameter
params={}
params['subsample_freq']= 20,
params['subsample']= 0.9,
params['scale_pos_weight']= 5,
params['reg_lambda']= 1,
params['reg_alpha']= 10,
params['num_leaves']= 50,
params['min_split_gain']= 1.5,
params['max_depth']= 25,
params['colsample_bytree']= 0.5,
params['boosting_type']='gbdt'
params['objective']='binary'
params['metric']='binary_logloss',

#train the model
clf=lgb.train(params,d_train,194)

#prediction on the test set
y_pred_prob=clf.predict(X_test)
y_pred_prob_train=clf.predict(X_train)

y_pred= [1 if x >= 0.5 else 0 for x in y_pred_prob]
y_pred_train= [1 if x >= 0.5 else 0 for x in y_pred_prob_train]

from sklearn.metrics import classification_report,confusion_matrix
print('Test Data Metrics:')
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))


print('\n')
print('Train Data Metrics:')
print(confusion_matrix(y_train, y_pred_train))
print(classification_report(y_train, y_pred_train))

print('\n')
print("roc_auc (training): {0:.3f}".format(roc_auc_score(y_train, y_pred_prob_train)))
print("roc_auc (test): {0:.3f}".format(roc_auc_score(y_test, y_pred_prob)))
```

```
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] Stopped training because there are no more leaves that meet the split requirements
```