Data Analysis Challenge: Relax Inc.

Relax Inc. makes productivity and project management software that's popular with both individuals and teams. It is considered a great company to work for.

Context

The data is available as two CSV files: + `takehome_user_engagement.csv` + `takehome_users.csv` The data has the following two tables: + A user table (`takehome_users`) with data on 12,000 users who signed up for the product in the last two years. This table includes: + `name`: the user's name + `object_id`: the user's id + `email`: email address + `creation_source`: how their account was created. This takes on one of 5 values: + `PERSONAL_PROJECTS`: invited to join another user's personal workspace + `GUEST_INVITE`: invited to an organization as a guest (limited permissions) + `ORG_INVITE`: invited to an organization (as a full member) + `SIGNUP`: signed up via the website + `SIGNUP_GOOGLE_AUTH`: signed up using Google Authentication (using a Google email account for their login id) + `creation_time`: when they created their account + `last_session_creation_time`: unix timestamp of last login + `opted_in_to_mailing_list`: whether they have opted into receiving marketing emails + `enabled_for_marketing_drip`: whether they are on the regular marketing email drip + `org_id`: the organization (group of users) they belong to + `invited_by_user_id`: which user invited them to join (if applicable). + A usage summary table (`takehome_user_engagement`) that has a row for each day that a user logged into the product.

Objective

Defining an "adopted user" as a user who has logged into the product on three separate days in at least one seven day period, **identify which factors predict future user adoption**.

Imports

In [1]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

import matplotlib.pyplot as plt
```

Load and Explore Data

In [2]:
```
# Load data
df_user = pd.read_csv("takehome_users.csv", encoding="ISO-8859-1")
print(f"\ndf_user.shape: {df_user.shape}\n")
print(f"\ndf_user.isnull().sum():\n\n{df_user.isnull().sum()}\n")
```

```
df_user.shape: (12000, 10)


df_user.isnull().sum():

object_id                        0
creation_time                    0
name                             0
email                            0
creation_source                  0
last_session_creation_time    3177
opted_in_to_mailing_list         0
enabled_for_marketing_drip       0
org_id                           0
invited_by_user_id            5583
dtype: int64
```

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

Out[3]:

	object_id	creation_time	name	email	creation_source	last_session_creati
0	1	2014-04-22 03:53:30	Clausen August	AugustCClausen@yahoo.com	GUEST_INVITE	1.3981
1	2	2013-11-15 03:45:04	Poole Matthew	MatthewPoole@gustr.com	ORG_INVITE	1.3962
2	3	2013-03-19 23:14:52	Bottrill Mitchell	MitchellBottrill@gustr.com	ORG_INVITE	1.3637
3	4	2013-05-21 08:09:28	Clausen Nicklas	NicklasSClausen@yahoo.com	GUEST_INVITE	1.3692
4	5	2013-01-17 10:14:20	Raw Grace	GraceRaw@yahoo.com	GUEST_INVITE	1.3588

In [4]:
```
df_eng = pd.read_csv("takehome_user_engagement.csv", parse_dates=["time_stamp"])
print(f"\ndf_eng.shape: {df_eng.shape}\n")
print(f"\ndf_eng.isnull().sum():\n\n{df_eng.isnull().sum()}\n")
```

```
df_eng.shape: (207917, 3)


df_eng.isnull().sum():

time_stamp    0
user_id       0
visited       0
dtype: int64
```

In [5]:
```
df_eng.head()
```

Out[5]:

	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

In [6]:
```
df_user = df_user.rename({"object_id":"user_id"}, axis=1)
df_user.head()
```

Out[6]:

	user_id	creation_time	name	email	creation_source	last_session_creation
0	1	2014-04-22 03:53:30	Clausen August	AugustCClausen@yahoo.com	GUEST_INVITE	1.398139
1	2	2013-11-15 03:45:04	Poole Matthew	MatthewPoole@gustr.com	ORG_INVITE	1.396238
2	3	2013-03-19 23:14:52	Bottrill Mitchell	MitchellBottrill@gustr.com	ORG_INVITE	1.363735
3	4	2013-05-21 08:09:28	Clausen Nicklas	NicklasSClausen@yahoo.com	GUEST_INVITE	1.369210
4	5	2013-01-17 10:14:20	Raw Grace	GraceRaw@yahoo.com	GUEST_INVITE	1.358850

Data Wrangling

In [7]:
```
# Determine 'adopted user'
df_agg = df_eng.set_index("time_stamp")

users = df_agg["user_id"].unique()
adoption = []

for i in users:
    id_filter = df_agg["user_id"] == i
    df_filter = df_agg[id_filter].resample("1D").count()
    df_filter = df_filter.rolling(window=7).sum()
    df_filter = df_filter.dropna()
    adoption.append(any(df_filter["visited"].values >= 3))
```

In [8]:
```
df_agg.head()
```

Out[8]:

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

In [9]:
```
np.sum(adoption)
```

Out[9]:
```
1597
```

In [10]:
```
# Create a dataframe with "user_id" and "adopted_user"
user_adoption = list(zip(users, adoption))

df_adopt = pd.DataFrame(user_adoption)
df_adopt.columns = ["user_id", "adopted_user"]

df = df_user.merge(df_adopt, on="user_id", how="left")
```

In [11]:
```
df.head()
```

Out[11]:

	user_id	creation_time	name	email	creation_source	last_session_creation
0	1	2014-04-22 03:53:30	Clausen August	AugustCClausen@yahoo.com	GUEST_INVITE	1.398139
1	2	2013-11-15 03:45:04	Poole Matthew	MatthewPoole@gustr.com	ORG_INVITE	1.396238
2	3	2013-03-19 23:14:52	Bottrill Mitchell	MitchellBottrill@gustr.com	ORG_INVITE	1.363735
3	4	2013-05-21 08:09:28	Clausen Nicklas	NicklasSClausen@yahoo.com	GUEST_INVITE	1.369210
4	5	2013-01-17 10:14:20	Raw Grace	GraceRaw@yahoo.com	GUEST_INVITE	1.358850

In [12]:
```
print(f"\ndf.shape: {df.shape}\n")
print(f"\ndf.isnull().sum():\n\n{df.isnull().sum()}\n")
```

```
df.shape: (12000, 11)


df.isnull().sum():

user_id                          0
creation_time                    0
name                             0
email                            0
creation_source                  0
last_session_creation_time    3177
opted_in_to_mailing_list         0
enabled_for_marketing_drip       0
org_id                           0
invited_by_user_id            5583
adopted_user                  3177
dtype: int64
```

In [13]:
```
df.adopted_user.sum()
```

Out[13]:
```
1597
```

There are 3177 missing values for `last_session_creation_time`. This means all these users never logged on and they are not `adopted_user`. The number of missing values of `adopted_user` is also same as 3177. We will assign `False` or `0` values to `adopted_user` feature for all these users.

In [14]:
```
# Mapping 'adopted_user'
df.loc[:, "adopted_user"] = df["adopted_user"].map({False:0, True:1, np.nan:0})
df.dropna(subset=["adopted_user"], inplace=True)
df["adopted_user"] = df["adopted_user"].astype(int)
```

In [15]:
```
df.isnull().sum()
```

Out[15]:
```
user_id                          0
creation_time                    0
name                             0
email                            0
creation_source                  0
last_session_creation_time    3177
opted_in_to_mailing_list         0
enabled_for_marketing_drip       0
org_id                           0
invited_by_user_id            5583
adopted_user                     0
dtype: int64
```

In [16]:
```
# Handling 'invited_by_user' missing values
# We will drop the 'invited_by_user_id' column before modeling
invite = lambda row: 0 if np.isnan(row) else 1
df["invited_by_user"] = df["invited_by_user_id"].apply(invite)
```

In [17]:
```
df.isnull().sum()
```

Out[17]:
```
user_id                         0
creation_time                   0
name                            0
email                           0
creation_source                 0
last_session_creation_time    3177
opted_in_to_mailing_list        0
enabled_for_marketing_drip      0
org_id                          0
invited_by_user_id           5583
adopted_user                    0
invited_by_user                 0
dtype: int64
```

In [18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12000 entries, 0 to 11999
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   user_id                     12000 non-null  int64  
 1   creation_time               12000 non-null  object 
 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_user                12000 non-null  int64  
 11  invited_by_user             12000 non-null  int64  
dtypes: float64(2), int64(6), object(4)
memory usage: 1.2+ MB
```

In [19]:
```
# Create a feature of user history
# Convert both time features into datetime
df['creation_time'] = pd.to_datetime(
    df['creation_time'], format='%Y-%m-%d %H:%M:%S')
df['last_session_creation_time'] = pd.to_datetime(
    df['last_session_creation_time'], unit='s')

# Calculate user history, defined as number of days between account creation
# and last use
df['history'] = df['last_session_creation_time'] - df['creation_time']
df['history'] = df['history'].dt.days
```

In [20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12000 entries, 0 to 11999
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   user_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   datetime64[ns]
 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_user                12000 non-null  int64
 11  invited_by_user             12000 non-null  int64
 12  history                     8823 non-null   float64
dtypes: datetime64[ns](2), float64(2), int64(6), object(3)
memory usage: 1.3+ MB
```

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
user_id                          0
creation_time                    0
name                             0
email                            0
creation_source                  0
last_session_creation_time    3177
opted_in_to_mailing_list         0
enabled_for_marketing_drip       0
org_id                           0
invited_by_user_id            5583
adopted_user                     0
invited_by_user                  0
history                       3177
dtype: int64
```

In [22]:
```
# Collect all the featuers that I think are relevant
df = df[["adopted_user", "history", "invited_by_user", "creation_source", \
         "opted_in_to_mailing_list", "enabled_for_marketing_drip"]]
```

In [23]:
```
df.head()
```

Out[23]:

	adopted_user	history	invited_by_user	creation_source	opted_in_to_mailing_list	enabled_for_mark
0	0	0.0	1	GUEST_INVITE	1	
1	1	136.0	1	ORG_INVITE	0	
2	0	0.0	1	ORG_INVITE	0	
3	0	1.0	1	GUEST_INVITE	0	
4	0	5.0	1	GUEST_INVITE	0	

In [24]:
```
df.shape
```

Out[24]:
```
(12000, 6)
```

In [25]:
```
df.isnull().sum()
```

Out[25]:
```
adopted_user                     0
history                       3177
invited_by_user                  0
creation_source                  0
opted_in_to_mailing_list         0
enabled_for_marketing_drip       0
dtype: int64
```

Now delete all the rows that has missing values in `history`.

In [26]:
```
df.dropna(inplace = True)
```

In [27]:
```
df.shape
```

Out[27]:
```
(8823, 6)
```

In [28]:
```
df.isnull().sum()
```

Out[28]:
```
adopted_user                  0
history                       0
invited_by_user               0
creation_source               0
opted_in_to_mailing_list      0
enabled_for_marketing_drip    0
dtype: int64
```

In [29]:
```
print(f"There were {df.adopted_user.sum()} adopted users out of {df.shape[0]} users
```

```
There were 1597 adopted users out of 8823 users.
```

This is an imbalance data set.

In [30]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8823 entries, 0 to 11999
Data columns (total 6 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   adopted_user                8823 non-null   int64
 1   history                     8823 non-null   float64
 2   invited_by_user             8823 non-null   int64
 3   creation_source             8823 non-null   object
 4   opted_in_to_mailing_list    8823 non-null   int64
 5   enabled_for_marketing_drip  8823 non-null   int64
dtypes: float64(1), int64(4), object(1)
memory usage: 482.5+ KB
```

In [31]:
```
df.head()
```

Out[31]:

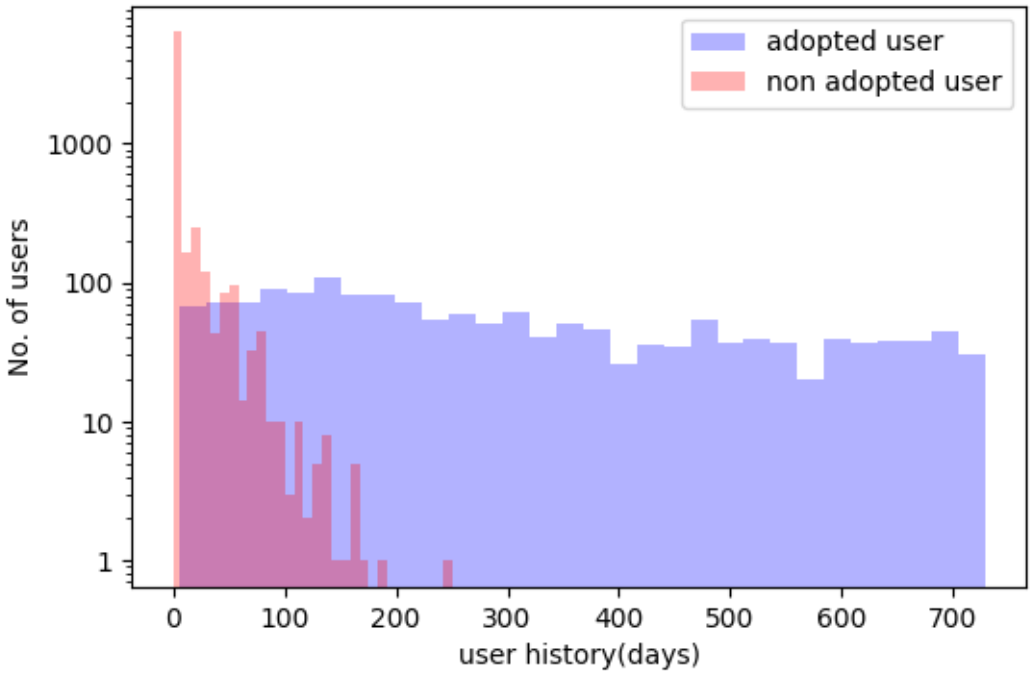
	adopted_user	history	invited_by_user	creation_source	opted_in_to_mailing_list	enabled_for_mark
0	0	0.0	1	GUEST_INVITE	1	
1	1	136.0	1	ORG_INVITE	0	
2	0	0.0	1	ORG_INVITE	0	
3	0	1.0	1	GUEST_INVITE	0	
4	0	5.0	1	GUEST_INVITE	0	

Exploratory Data Analysis

In [32]:
```
# Feature history and adopted user
def plot_hist_days(df, col, xlabel):

    plt.figure(dpi = 100)
    _ = plt.hist(df.loc[df['adopted_user']==1, col],
                 bins=30, alpha=0.3, color='b', label='adopted user')
    _ = plt.hist(df.loc[df['adopted_user']==0, col],
                 bins=30, alpha=0.3, color='r', label='non adopted user')
    _ = plt.yscale('log')
    _ = plt.legend()
    _ = plt.xlabel(xlabel)
    _ = plt.ylabel('No. of users')
    _ = plt.yticks([1, 10, 100, 1000], ['1', '10', '100', '1000'])
```

In [33]:
```
# Plot
plot_hist_days(df, 'history', 'user history(days)')
```



We see that users with long history are more likely to be adopted users.

Data Preprocessing and Modeling

In [34]:
```
# Make dummy variable for creation source
df = pd.get_dummies(df, columns = ['creation_source'])
```

In [35]:
```
df.head()
```

Out[35]:

	adopted_user	history	invited_by_user	opted_in_to_mailing_list	enabled_for_marketing_drip	creati
0	0	0.0	1	1	0	
1	1	136.0	1	0	0	
2	0	0.0	1	0	0	
3	0	1.0	1	0	0	
4	0	5.0	1	0	0	

In [36]:
```
df.shape
```

Out[36]:
```
(8823, 10)
```

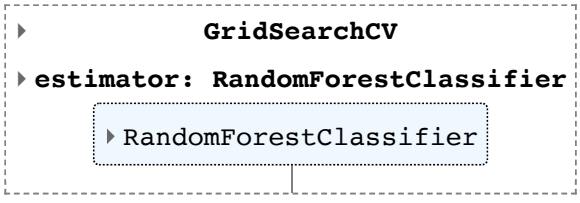
In [37]:
```
# Define features and target
X = df[df.columns[1:]]
y = df[df.columns[0]]

# Split training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.3

# Estimator
# Pass class_weight='balanced' because of imbalance data set
clf = RandomForestClassifier(random_state=42, class_weight='balanced')

# GridSearchCV to tune number of trees
params = {'n_estimators': [10, 50, 100, 200]}
rf_grid_cv = GridSearchCV(clf, params)
rf_grid_cv.fit(X_train, y_train)
```

Out[37]:



In [38]:
```
# Print best parameters and results

print(rf_grid_cv.best_params_)
print(rf_grid_cv.best_score_)
```

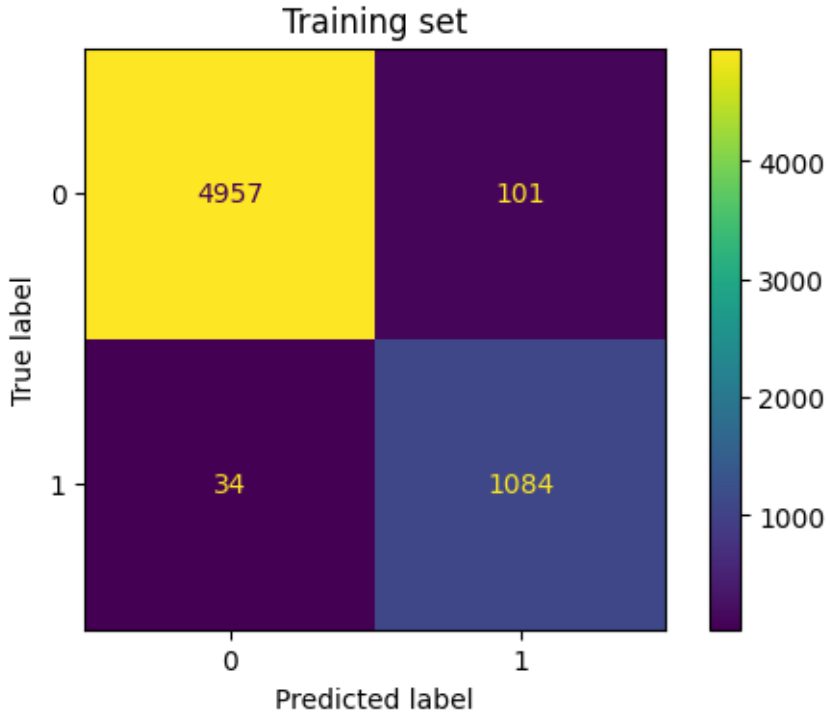
```
{'n_estimators': 10}
0.9530462639047208
```

In [39]:
```
# Train score
y_train_pred = rf_grid_cv.predict(X_train)
```

```
train_accuracy = accuracy_score(y_train, y_train_pred)
print(f"Train set accuracy: {train_accuracy}")
```

```
Train set accuracy: 0.9781411917098446
```

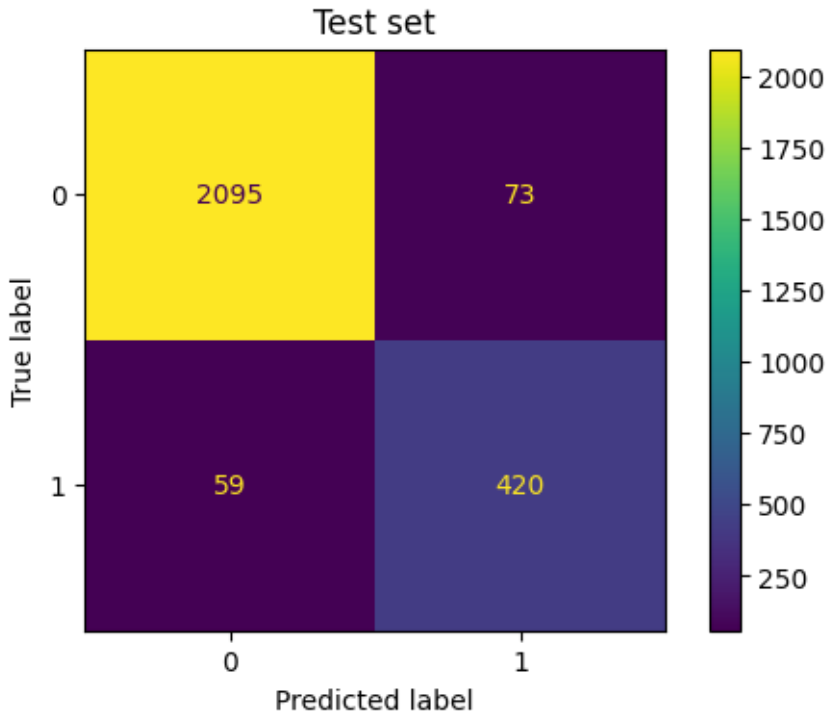
In [40]:
```
plt.figure(dpi = 100)
ax = plt.subplot(111)
cm = confusion_matrix(y_train, y_train_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(ax = ax)
plt.title(f"Training set")
plt.show()
```



In [41]:
```
# Test score
y_test_pred = rf_grid_cv.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
print(f"Test set accuracy: {test_accuracy}")
```

```
Test set accuracy: 0.9501322251605592
```

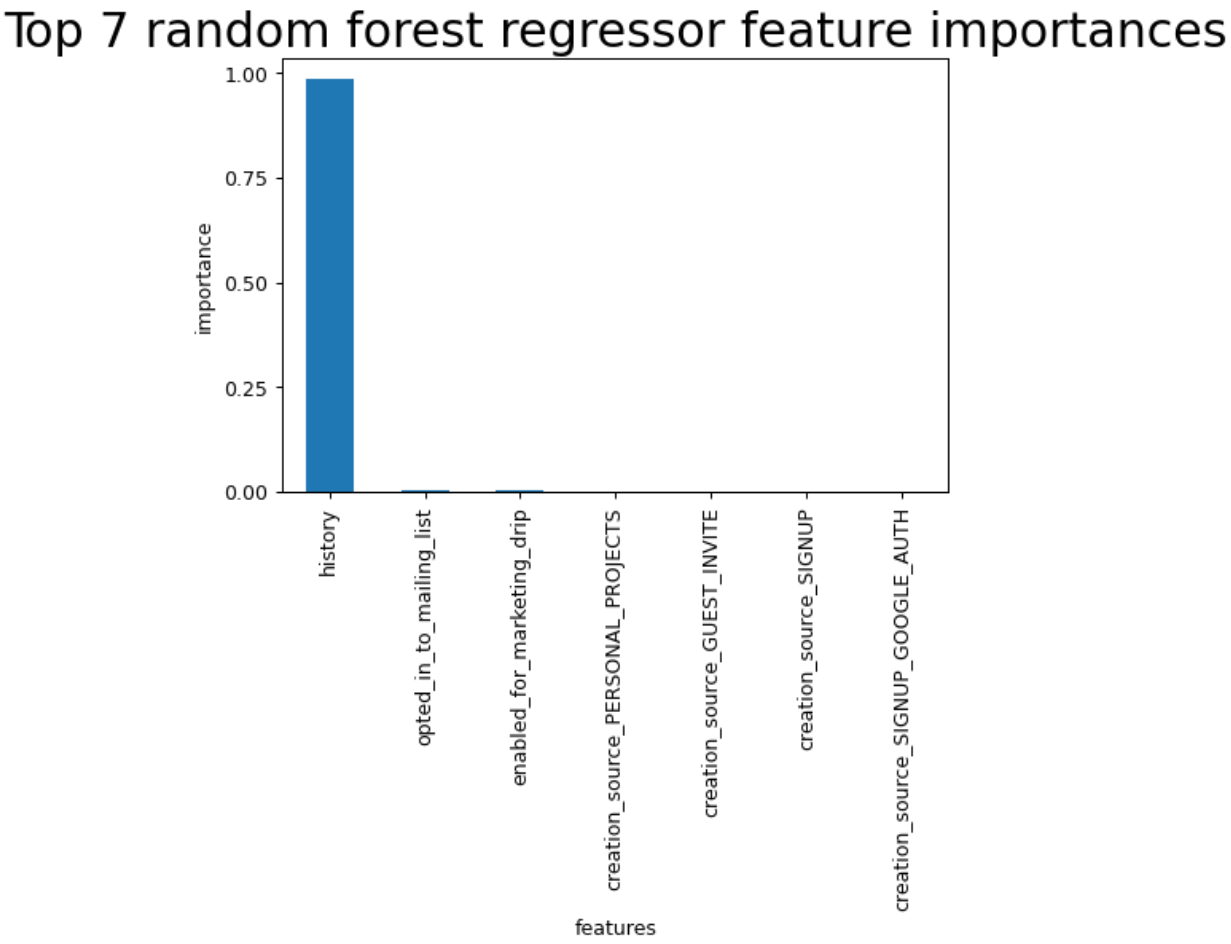
In [42]:
```
plt.figure(dpi = 100)
ax = plt.subplot(111)
cm = confusion_matrix(y_test, y_test_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(ax = ax)
plt.title(f"Test set")
plt.show()
```



The model performance is very good.

Refer to this stackoverflow response about how to extract the `feature_importances_`

In [43]:
```
# Feature importance
plt.subplots(dpi=90)
imps = rf_grid_cv.best_estimator_.feature_importances_
rf_feat_imps = pd.Series(imps, index=X_train.columns).sort_values(ascending=False)
rf_feat_imps[0:7].plot(kind='bar')
plt.rc('font', size=20)
plt.xlabel('features')
plt.ylabel('importance')
plt.title('Top 7 random forest regressor feature importances');
```



We can also print them.

In [44]:
```
# Print feature importance
imp = pd.Series(rf_grid_cv.best_estimator_.feature_importances_, index=X.columns)
imp = imp.sort_values(ascending=False)
print(imp)
```

```
history                                0.985502
opted_in_to_mailing_list               0.003657
enabled_for_marketing_drip             0.002600
creation_source_PERSONAL_PROJECTS      0.002130
creation_source_GUEST_INVITE           0.002088
creation_source_SIGNUP                 0.001532
creation_source_SIGNUP_GOOGLE_AUTH     0.001121
creation_source_ORG_INVITE             0.000725
invited_by_user                        0.000645
dtype: float64
```

Conclusions

The performance of our model is pretty good. The user history (`history`), a feature that we derived from other existing features, is the most important feature with a feature importance score of `0.99` . The rest of the features are hardly relevant. So, it is recommended to sketch out a plan that will encourage the existing users to log in and use the software once they create an account.