Zapier Monthly Active User Analysis

January 20, 2020

0.0.1 Importing modules and packages

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import psycopg2
import prophet
from fbprophet import Prophet
from fbprophet.plot import plot_plotly
import plotly.offline as py
import os
warnings.filterwarnings('ignore')
%matplotlib inline
py.init_notebook_mode()
color = sns.color_palette()
pd.set_option('display.float_format', lambda x: '%.3f' % x)
sns.set(rc={'figure.figsize':(8,5)})
```

0.0.2 Connecting to the Zapier database

- A view called **active_users_analysis** has been created in the **jchumley** schema using the *tasks_used_da table*.
- We'll use the *psycopg* odbc module to connect to the Redshift cluster. Pandas will be used extensively in conjunction with Postgres/Redshift queries.
- The user, password, host, and database parameters are loaded from a .bashrc file.

[2]:
```
port='5439'
user=os.environ['ZAP_USER']
password=os.environ['ZAP_PASS']
host=os.environ['ZAP_HOST']
db=os.environ['ZAP_DB']
conn = psycopg2.connect(user=user, password=password, host=host, port=port,␣
↪database=db)
```

0.0.3 Creating dataframe

- Let's create our first dataframe using pandas read_sql method.

[3]:
```
query = """
SELECT * FROM
jchumley.active_users_analysis
"""
df = pd.read_sql(query, conn)
df.head()
```

[3]:
```
         date  user_id  account_id  sum_tasks_used  cum_sum_tasks_used  \
0  2017-01-01        1           1              48                  48
1  2017-01-02        1           1              65                 113
2  2017-01-03        1           1              71                 184
3  2017-01-04        1           1              64                 304
4  2017-01-05        1           1              74                 406

   num_days_since_last_active  active  churned  month_num    month  dow_num  \
0                           0    True    False      1.000  January        0
1                           1    True    False      1.000  January        1
2                           1    True    False      1.000  January        2
3                           1    True    False      1.000  January        3
4                           1    True    False      1.000  January        4

         dow
0     Sunday
1     Monday
2    Tuesday
3  Wednesday
4   Thursday
```

- What is the shape of this dataset?

[4]:
```
df.shape
```

[4]:
```
(10547587, 12)
```

- There are ~10.5m rows and 12 columns.
- We'll also compute the ratio of missing values for each column.

[5]:
```
df_na = (df.isnull().sum() / len(df)) * 100
df_na = df_na.drop(df_na[df_na == 0].index).sort_values(ascending=False)
missing_data = pd.DataFrame({'Missing Ratio' :df_na})
missing_data.head()
```

[5]:
```
Empty DataFrame
Columns: [Missing Ratio]
```

```
Index: []
```

- Great, we don't have any null values!

0.1 Exploratory data analysis

0.1.1 Correlation Matrix

- Let's gain a deeper understanding of the associations between the features in this dataset. We'll use the pandas *corr* method to complete this task.

[6]:
```
df.corr()
```

[6]:
```
                          user_id  account_id  sum_tasks_used  \
user_id                     1.000       0.974          -0.022
account_id                  0.974       1.000          -0.019
sum_tasks_used             -0.022      -0.019           1.000
cum_sum_tasks_used          0.984       0.958          -0.022
num_days_since_last_active  0.021       0.020          -0.012
active                     -0.008      -0.008           0.004
churned                     0.007       0.006          -0.003
month_num                   0.108       0.108           0.001
dow_num                     0.002       0.002           0.000

                          cum_sum_tasks_used  num_days_since_last_active  \
user_id                                0.984                       0.021
account_id                             0.958                       0.020
sum_tasks_used                        -0.022                      -0.012
cum_sum_tasks_used                     1.000                       0.023
num_days_since_last_active             0.023                       1.000
active                                -0.009                      -0.760
churned                                0.008                       0.519
month_num                              0.096                       0.060
dow_num                                0.002                      -0.031

                          active  churned  month_num  dow_num
user_id                   -0.008    0.007      0.108    0.002
account_id                -0.008    0.006      0.108    0.002
sum_tasks_used             0.004   -0.003      0.001    0.000
cum_sum_tasks_used        -0.009    0.008      0.096    0.002
num_days_since_last_active -0.760   0.519      0.060   -0.031
active                     1.000   -0.873     -0.041   -0.000
churned                   -0.873    1.000      0.029    0.000
month_num                 -0.041    0.029      1.000    0.016
dow_num                   -0.000    0.000      0.016    1.000
```

- For this stage of analysis, the user_id and account_id columns will be ignored since they are unique identifiers.

- Notice that there is a strong negative association between the features active and churn which makes sense since they are mutually exclusive.

0.1.2 Active and churned users by month

- Let's take a look at counts of active and churned users.
- We'll run the following aggregate query to view churn and active user counts for each month in the dataset.

[7]:
```
query_month = """
SELECT month, month_num,
       count(CASE WHEN churned is TRUE then 1 END) as churned_count,
       count(CASE WHEN active is TRUE then 1 END) as active_count,
       ROUND(100.0*count(CASE WHEN churned is TRUE then 1 END)/count(*),2) as␣
 ↪churned_ratio,
       ROUND(100.0*count(CASE WHEN active is TRUE then 1 END)/count(*),2) as␣
 ↪active_ratio,
       count(*) as total_user_count
        FROM jchumley.active_users_analysis
       GROUP BY month, month_num
ORDER BY month_num;
"""
df_month = pd.read_sql(query_month, conn)
```

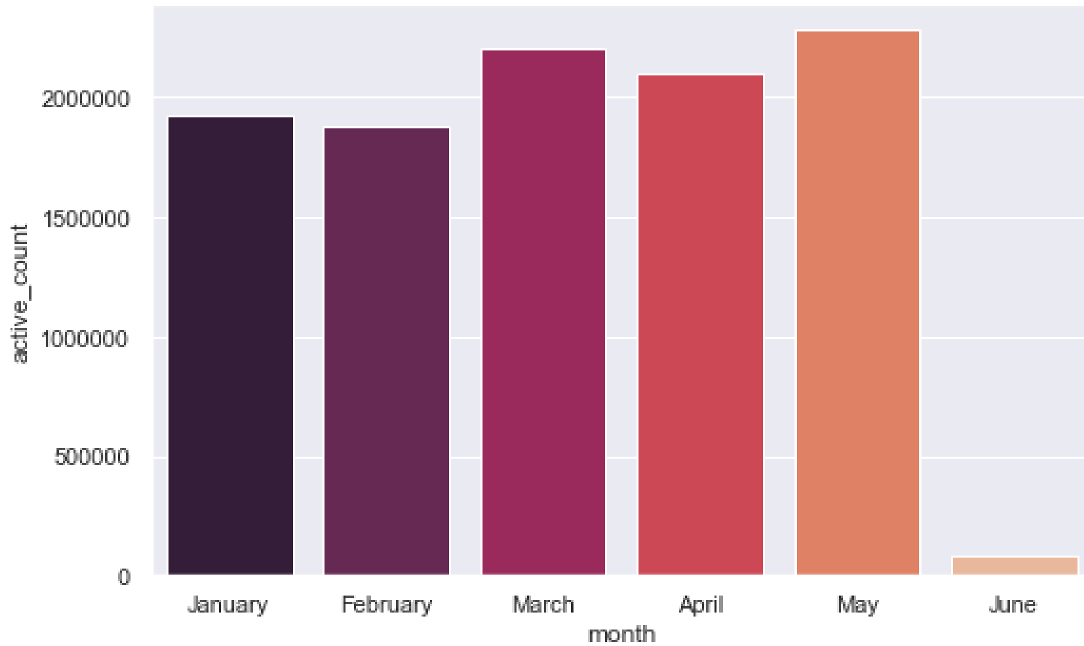
[8]:
```
df_month
```

[8]:
```
      month  month_num  churned_count  active_count  churned_ratio  \
0   January      1.000            120       1927467          0.010
1  February      2.000           8256       1881695          0.440
2     March      3.000          12974       2207687          0.580
3     April      4.000          12676       2100295          0.600
4       May      5.000          14207       2282399          0.620
5      June      6.000            964         83651          1.140

   active_ratio  total_user_count
0        99.990           1927587
1        99.560           1889981
2        99.300           2223331
3        99.170           2117882
4        99.070           2303880
5        98.500             84926
```

[9]:
```
sns.barplot(x='month', y='active_count', palette="rocket", data=df_month)
```

[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a374513d0>
```



- We can see that May had the highest count of active users. June has a very low count, perhaps because of data availability. Let's verify.

[10]:
```
query_june = """
SELECT month, COUNT(DISTINCT(date))
FROM jchumley.active_users_analysis
GROUP BY month"""
pd.read_sql(query_june, conn)
```

[10]:

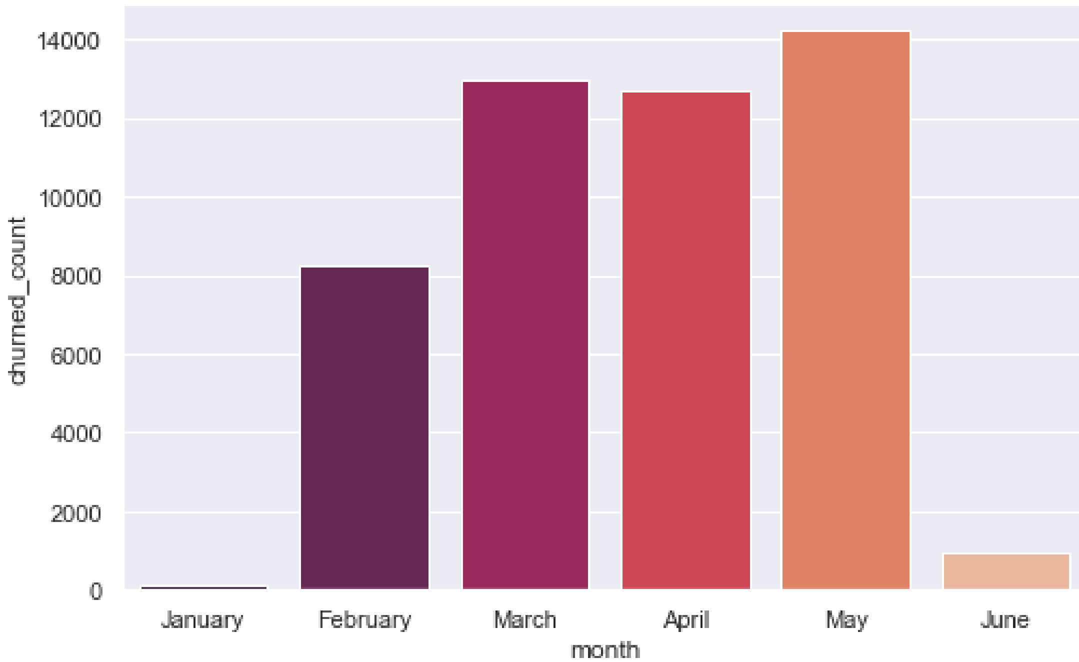
	month	count
0	January	31
1	June	1
2	May	31
3	April	30
4	February	28
5	March	31

- We can see that the dataset includes records from the first day of June 2017 but not other days in that month/year.

0.1.3 Churn by month

[11]:
```
sns.barplot(x='month', y='churned_count', palette="rocket", data=df_month)
```

[11]: `<matplotlib.axes._subplots.AxesSubplot at 0x1a38a6a310>`



- January's churn count would likely increase if records from 2016 were available.
- Potential factors contributing to June's relatively high churn count:

  1. Many users either chose to not renew or cancel their subscriptions on the first day of a given month.
  2. All June records are from the first day of the month.

0.1.4 Day of week analysis

- We'll run a query similar to the one used to compute aggregates by month.

[12]:
```
dow_query = """
SELECT dow, dow_num,
       count(CASE WHEN churned is TRUE then 1 END) as churned_count,
       count(CASE WHEN active is TRUE then 1 END) as active_count,
       ROUND(100.0*count(CASE WHEN churned is TRUE then 1 END)/count(*),2) as␣
 ↪churned_ratio,
       ROUND(100.0*count(CASE WHEN active is TRUE then 1 END)/count(*),2) as␣
 ↪active_ratio,
       count(*) as total_user_count
        FROM jchumley.active_users_analysis
       GROUP BY dow, dow_num
ORDER BY dow_num;
"""
df_dow = pd.read_sql(dow_query, conn)
```

[13]:
```
df_dow
```

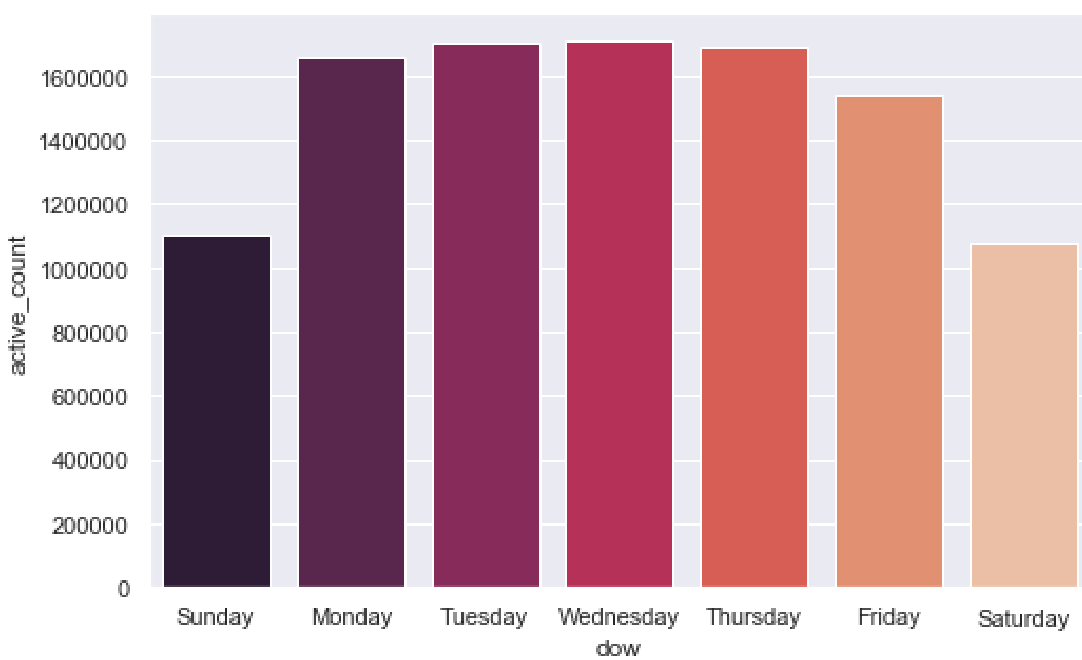
[13]:
```
         dow  dow_num  churned_count  active_count  churned_ratio  \
0     Sunday        0           3619       1102657          0.330
1     Monday        1           8207       1657615          0.490
2    Tuesday        2           8524       1703666          0.500
3  Wednesday        3           9268       1708853          0.540
4   Thursday        4           8773       1689305          0.520
5     Friday        5           6805       1540253          0.440
6   Saturday        6           4001       1080845          0.370

   active_ratio  total_user_count
0        99.570           1107429
1        99.370           1668200
2        99.340           1714992
3        99.300           1720901
4        99.320           1700834
5        99.420           1549246
6        99.530           1085985
```

0.1.5 Counts of active users by day of week

[14]:
```
sns.barplot(x='dow', y='active_count', palette="rocket", data=df_dow)
```

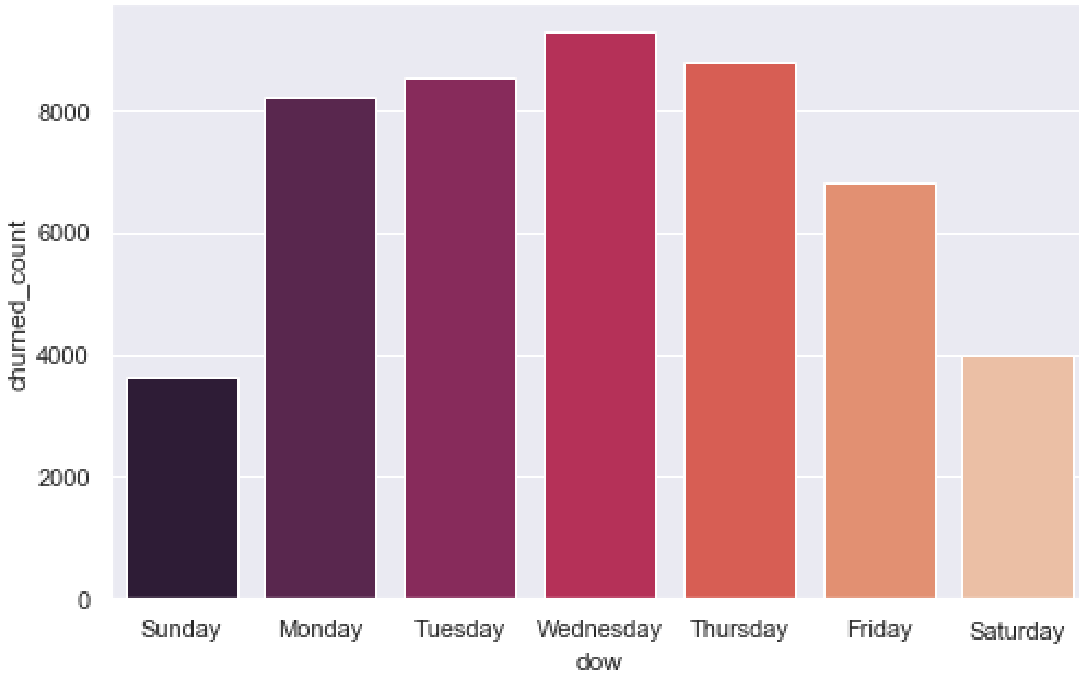
[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1a39d85550>



0.1.6 Counts of churned users by day of week

[15]:
```
sns.barplot(x='dow', y='churned_count', palette="rocket", data=df_dow)
```

[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1a3a400050>



- Since Zapier is a B2B platform, its users are expected to be most active while they are in the office.
- Recall that **churned** and **active** have a very strong negative association (see the correlation matrix above), so it's expected that churn is higher during normal business hours.

0.1.7 Power Users

- Let's see who the top 10 Zapier users based on the sum_tasks_used column.
- We'll query the view total_sum_tasks_used which has the cumulative total of sum of tasks used for each user from the tasks_used_da table.

[16]:
```
power_user_query = """SELECT user_id,  total_sum_tasks_used,
       ROUND(100.0*total_sum_tasks_used/(SELECT SUM(total_sum_tasks_used) as␣
 ↪total_sum_tasks_used_all_users
FROM jchumley.total_sum_tasks_used),2) pct_all_sum_tasks_used,
       RANK() OVER(ORDER BY total_sum_tasks_used DESC) as␣
 ↪user_rank_by_sum_tasks_used
FROM jchumley.total_sum_tasks_used
LIMIT 10"""
```

```
df_power_users = pd.read_sql(power_user_query, conn)
df_power_users
```

[16]:
```
   user_id  total_sum_tasks_used  pct_all_sum_tasks_used  \
0   541993              15878183                   3.120
1    19415              12574205                   2.470
2   558906               8282192                   1.630
3   645563               6153468                   1.210
4   103042               3872036                   0.760
5  1830742               3305466                   0.650
6   166842               3136333                   0.620
7   289586               2659815                   0.520
8   617995               2335859                   0.460
9   115417               2174002                   0.430

   user_rank_by_sum_tasks_used
0                            1
1                            2
2                            3
3                            4
4                            5
5                            6
6                            7
7                            8
8                            9
9                           10
```

- Would be interesting to dig deeper into metadata on these users (e.g, age, industry, gender, profession, etc.)

0.2 Timeseries forecasting

- We'll use Prophet to forecast active users and churn into the next 365 days. See https://facebook.github.io/prophet/ if you're not familiar with Prophet.
- Let's run another aggregate query against the active_users_analysis view, this time we'll group by date.

[17]:
```
user_aggregates_query = """
SELECT date as ds,
       count(CASE WHEN churned is TRUE then 1 END) as churned_count,
       count(CASE WHEN active is TRUE then 1 END) as active_count,
       ROUND(100.0*count(CASE WHEN churned is TRUE then 1 END)/count(*),2) as␣
 ↪churned_ratio,
       ROUND(100.0*count(CASE WHEN active is TRUE then 1 END)/count(*),2) as␣
 ↪active_ratio,
       count(*) as total_count
        FROM jchumley.active_users_analysis
       GROUP BY date
```

```
ORDER BY date"""
df_ts = pd.read_sql(user_aggregates_query, conn)
df_ts.head()
```

[17]:
```
           ds  churned_count  active_count  churned_ratio  active_ratio  \
0  2017-01-01              0         38903          0.000       100.000
1  2017-01-02              0         53046          0.000       100.000
2  2017-01-03              0         64350          0.000       100.000
3  2017-01-04              0         65926          0.000       100.000
4  2017-01-05              0         66304          0.000       100.000

   total_count
0        38903
1        53046
2        64350
3        65926
4        66304
```

0.2.1 Forecast of Active Users

- Let's create a timeseries forecast of counts of active users into June 2018.

[18]:
```
df_ts_active = df_ts.copy()
df_ts_active[['ds', 'y']] = df_ts[['ds', 'active_count']]
```

Instantiating and Prophet object and making predictions into June 2018.

[19]:
```
m = Prophet()
m.fit(df_ts_active)
active_users_future = m.make_future_dataframe(periods=365)
active_users_future.tail()
```

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
```

[19]:
```
            ds
512 2018-05-28
513 2018-05-29
514 2018-05-30
515 2018-05-31
516 2018-06-01
```

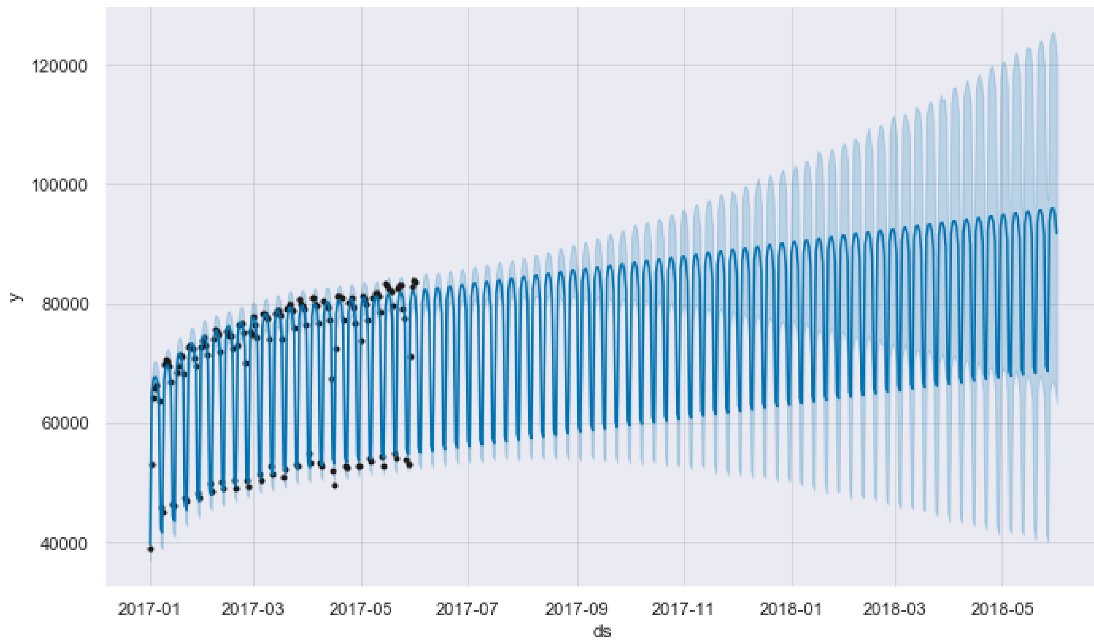
[20]:
```
active_users_forecast = m.predict(active_users_future)
active_users_forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

[20]:
```
            ds       yhat  yhat_lower  yhat_upper
512 2018-05-28  93785.262   65043.437  123242.307
513 2018-05-29  95813.956   66943.975  125219.928
```

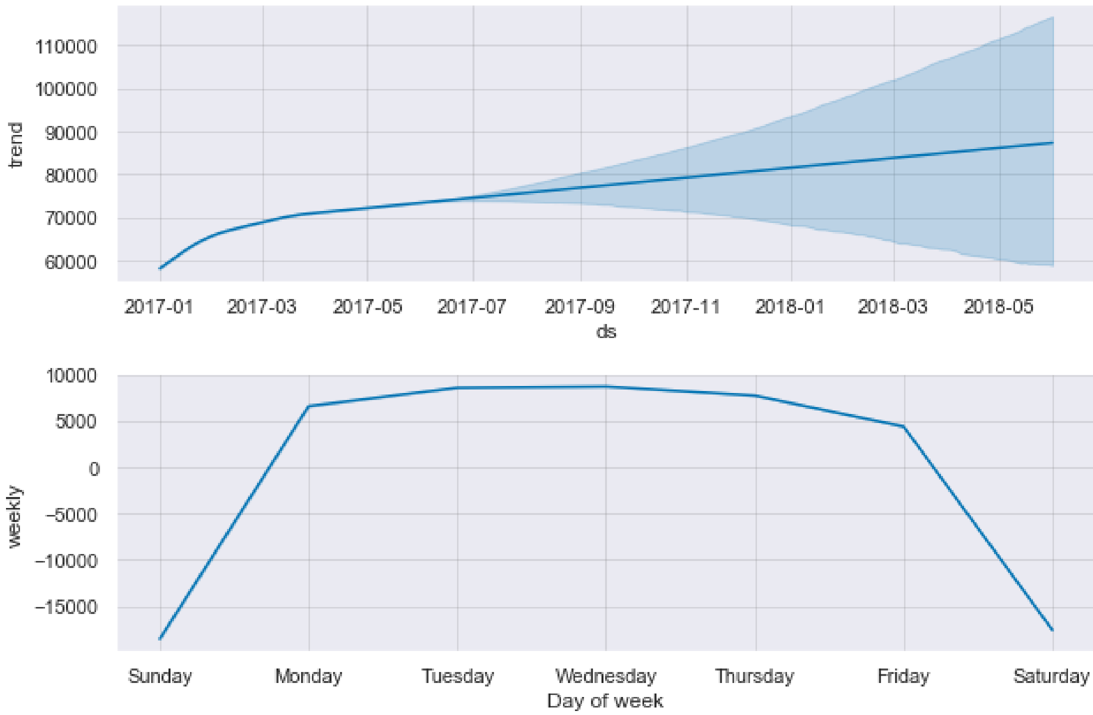
```
514 2018-05-30 95986.144   66981.395   125528.416
515 2018-05-31 95036.977   65946.426   124151.378
516 2018-06-01 91740.225   63269.911   121109.604
```

Visualizing our active users forecast

[21]:
```
fig = m.plot(active_users_forecast)
```



[22]:
```
fig2 = m.plot_components(active_users_forecast)
```



- The model is predicting a steady growth of active users into June 2018.
- The weekly plot component shown above aligns with our day of week analysis.

0.2.2 Forecast of Churned Users

Similarly, let's create a timeseries forecast of counts of churned users into June 2018.

[23]:
```
df_ts_churned = df_ts.copy()
df_ts_churned[['ds', 'y']] = df_ts[['ds', 'churned_count']]
df_ts_churned.head()
```

[23]:
```
           ds  churned_count  active_count  churned_ratio  active_ratio  \
0  2017-01-01              0         38903          0.000       100.000
1  2017-01-02              0         53046          0.000       100.000
2  2017-01-03              0         64350          0.000       100.000
3  2017-01-04              0         65926          0.000       100.000
4  2017-01-05              0         66304          0.000       100.000

   total_count  y
0        38903  0
1        53046  0
2        64350  0
3        65926  0
4        66304  0
```

Instantiating and Prophet object and making predictions

[24]:
```
m2=Prophet()
m2.fit(df_ts_churned)
churned_future = m2.make_future_dataframe(periods=365)
churned_future.tail()
```

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
```

[24]:

	ds
512	2018-05-28
513	2018-05-29
514	2018-05-30
515	2018-05-31
516	2018-06-01

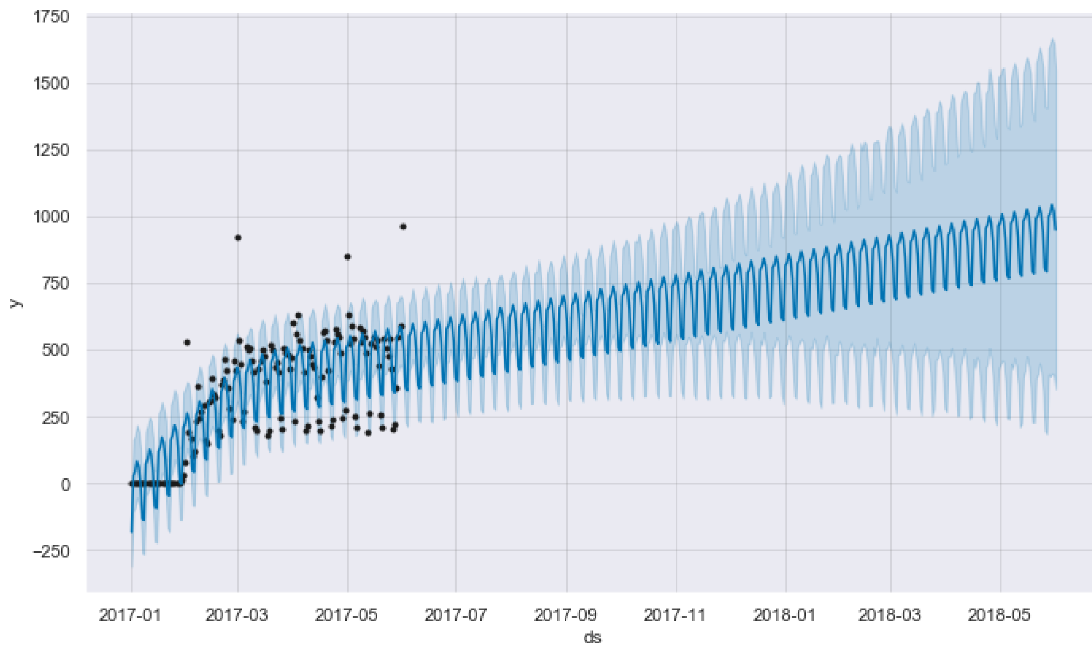
[25]:
```
churned_user_forecast = m2.predict(churned_future)
churned_user_forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

[25]:

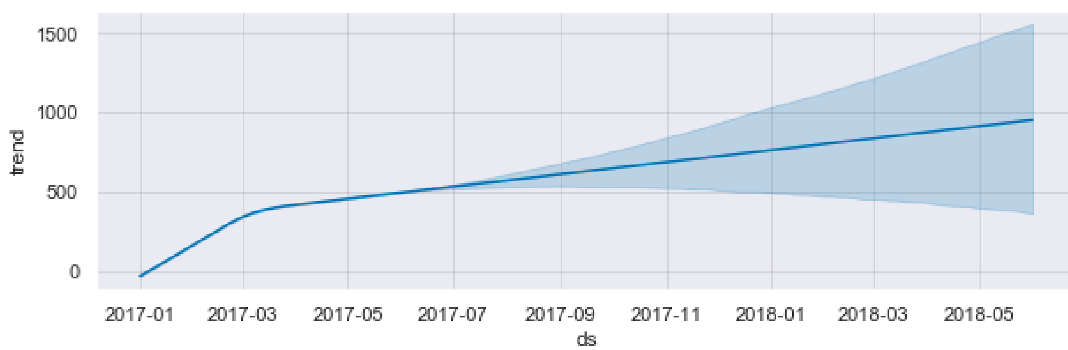
	ds	yhat	yhat_lower	yhat_upper
512	2018-05-28	999.565	408.261	1629.298
513	2018-05-29	1011.668	398.676	1647.355
514	2018-05-30	1043.238	411.981	1669.813
515	2018-05-31	1018.547	405.901	1648.968
516	2018-06-01	949.444	352.415	1545.710

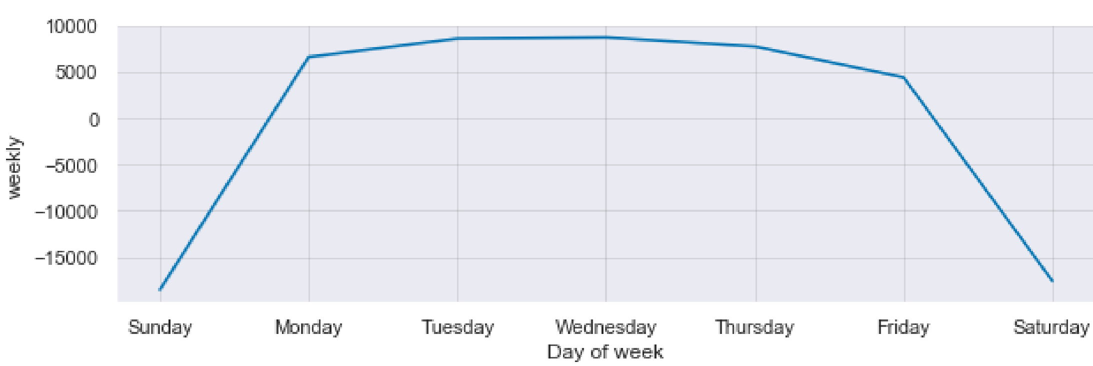
Visualizing out churned users forecast

[26]:
```
fig = m2.plot(churned_user_forecast)
```



[28]:
```
fig2 = m.plot_components(churned_user_forecast)
```





- Similar to the forecast of active users, churn is predicted to have steady growth into June 2018 but also at a higher rate.
- Unlike the active user plot, we can see outliers in churn at the end of each month. This could be due to a large number of users who are registered under monthly billing subscriptions.

0.2.3 Business recommendations

- Identify new data sources related to Zapier user metadata (e.g.,registration date, plan type, first usage date, acquisition channel, date of birth, gender, industry, etc.)
- Using additional data source combined with the task_used_da table, develop user metadata features
- Develop a logistic regression model to generate churn probability scores for each user
- Perform cohort analysis to group users by shared attributes
- For users who have churned, send out a survey to understand why they have decided to no longer use the Zapier platform
- Using the logistic regression model, identify high-value power users who are at risks of churn
- Run A/B testing experiments and compare churn rates between the test and control slices
- Reach out to users who are on monthly subscription plans prior to the end of the month via email or another communication channel with the goal of customer retention