Research on Megaline plans

You work as an analyst for the telecom operator Megaline. The company offers its clients two prepaid plans, Surf and Ultimate. The commercial department wants to know which of the plans is more profitable in order to adjust the advertising budget.

You are going to carry out a preliminary analysis of the plans based on a relatively small client selection. You'll have the data on 500 Megaline clients: who the clients are, where they're from, which plan they use, and the number of calls they made and text messages they sent in 2018. Your job is to analyze clients' behavior and determine which prepaid plan is more profitable.

Step 1. Open the data file and study the general information

In [1]:
```
#load libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

from functools import reduce
from math import factorial
from scipy import stats as st
from statistics import mean

pd.set_option('display.max_columns', 500)
```

In [2]:
```
#load all data tables
data_calls = pd.read_csv('/datasets/megaline_calls.csv')
data_internet = pd.read_csv('/datasets/megaline_internet.csv')
data_messages = pd.read_csv('/datasets/megaline_messages.csv')
data_plans = pd.read_csv('/datasets/megaline_plans.csv')
data_users = pd.read_csv('/datasets/megaline_users1.csv')
```

In [3]:
```
print (data_calls.describe())
data_calls.head()
```

```
             user_id       duration
count  137735.000000  137735.000000
mean     1247.658046       6.745927
std       139.416268       5.839241
min      1000.000000       0.000000
25%      1128.000000       1.290000
50%      1247.000000       5.980000
75%      1365.000000      10.690000
max      1499.000000      37.600000
```

Out[3]:

	id	user_id	call_date	duration
0	1000_93	1000	2018-12-27	8.52
1	1000_145	1000	2018-12-27	13.66
2	1000_247	1000	2018-12-27	14.48
3	1000_309	1000	2018-12-28	5.76
4	1000_380	1000	2018-12-30	4.22

In [4]:
```
#turn call_date to date format
data_calls.call_date = pd.to_datetime(data_calls['call_date'], format='%Y-%m-%d')
data_calls.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 137735 entries, 0 to 137734
Data columns (total 4 columns):
id           137735 non-null object
user_id      137735 non-null int64
call_date    137735 non-null datetime64[ns]
duration     137735 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 4.2+ MB
```

This slice of data looks alright, all calls durations look realistic, all values are in right format.

In [5]:
```
print (data_internet.describe())
data_internet.head()
```

```
             user_id        mb_used
count  104825.000000  104825.000000
mean     1242.496361     366.713701
std       142.053913     277.170542
min      1000.000000       0.000000
25%      1122.000000     136.080000
50%      1236.000000     343.980000
75%      1367.000000     554.610000
max      1499.000000    1693.470000
```

Out[5]:

	id	user_id	session_date	mb_used
0	1000_13	1000	2018-12-29	89.86
1	1000_204	1000	2018-12-31	0.00
2	1000_379	1000	2018-12-28	660.40
3	1000_413	1000	2018-12-26	270.99
4	1000_442	1000	2018-12-27	880.22

In [6]:
```
data_internet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 104825 entries, 0 to 104824
Data columns (total 4 columns):
id              104825 non-null object
user_id         104825 non-null int64
session_date    104825 non-null object
mb_used         104825 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 3.2+ MB
```

In [7]:
```
#turn session_date to date format
data_internet['session_date'] = pd.to_datetime(data_internet['session_date'], format='%Y-%m-%d')
data_internet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 104825 entries, 0 to 104824
Data columns (total 4 columns):
id              104825 non-null object
user_id         104825 non-null int64
session_date    104825 non-null datetime64[ns]
mb_used         104825 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 3.2+ MB
```

Data for internet use looks alright, all amounts of mb used look realistic, and there are no missing values and all values are in the right format.

In [8]:
```
print (data_messages.describe())
data_messages.head()
```

```
            user_id
count  76051.000000
mean    1245.972768
std      139.843635
min     1000.000000
25%     1123.000000
50%     1251.000000
75%     1362.000000
max     1497.000000
```

Out[8]:

	id	user_id	message_date
0	1000_125	1000	2018-12-27
1	1000_160	1000	2018-12-31
2	1000_223	1000	2018-12-31
3	1000_251	1000	2018-12-27
4	1000_255	1000	2018-12-26

In [9]:
```
#turn message_date to date format
data_messages['message_date'] = pd.to_datetime(data_messages['message_date'], format='%Y-%m-%d')
data_messages.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 76051 entries, 0 to 76050
Data columns (total 3 columns):
id              76051 non-null object
user_id         76051 non-null int64
message_date    76051 non-null datetime64[ns]
dtypes: datetime64[ns](1), int64(1), object(1)
memory usage: 1.7+ MB
```

Data for messages sent looks fine, all amounts of mb used look realistic, and there are no missing values and all values are in the right format.

In [10]:
```
data_plans
```

Out[10]:

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute	plan_name
0	50	15360	500	20	10	0.03	0.03	surf
1	1000	30720	3000	70	7	0.01	0.01	ultimate

In [11]:
```
#I'll change indexes in this table for easier use
data_plans = data_plans.set_index('plan_name')
data_plans
```

Out[11]:

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute
plan_name							
surf	50	15360	500	20	10	0.03	0.03
ultimate	1000	30720	3000	70	7	0.01	0.01

In [12]:
```
data_users.head()
```

Out[12]:

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date
0	1000	Anamaria	Bauer	45	Atlanta-Sandy Springs-Roswell, GA MSA	2018-12-24	ultimate	NaN
1	1001	Mickey	Wilkerson	28	Seattle-Tacoma-Bellevue, WA MSA	2018-08-13	surf	NaN
2	1002	Carlee	Hoffman	36	Las Vegas-Henderson-Paradise, NV MSA	2018-10-21	surf	NaN
3	1003	Reynaldo	Jenkins	52	Tulsa, OK MSA	2018-01-28	surf	NaN
4	1004	Leonila	Thompson	40	Seattle-Tacoma-Bellevue, WA MSA	2018-05-23	surf	NaN

In [13]:
```
data_users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
user_id       500 non-null int64
first_name    500 non-null object
last_name     500 non-null object
age           500 non-null int64
city          500 non-null object
reg_date      500 non-null object
plan          500 non-null object
churn_date    34 non-null object
dtypes: int64(2), object(6)
memory usage: 31.4+ KB
```

Step 2. Prepare the data

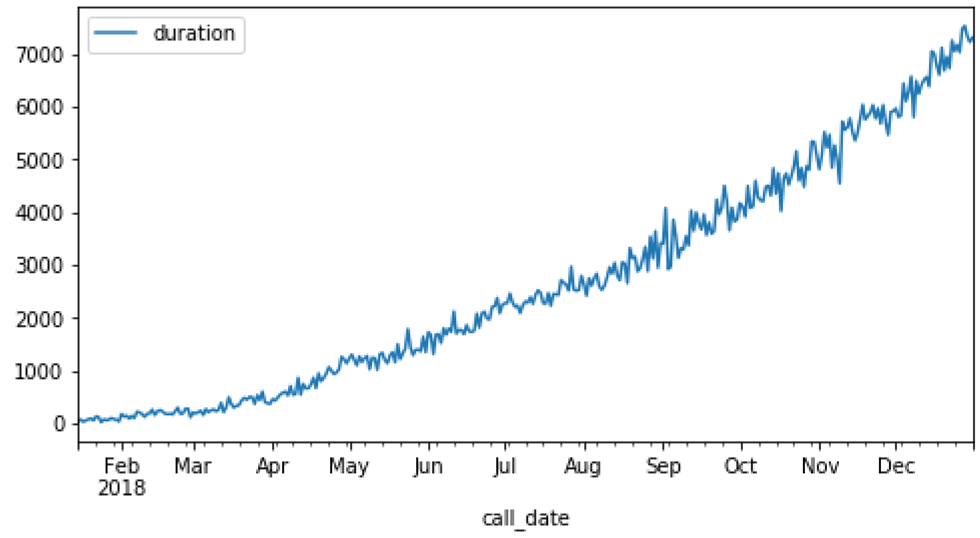
In [14]:
```
#convert registration date to data
data_users['reg_date'] = pd.to_datetime(data_users['reg_date'], format='%Y-%m-%d')
```

In [15]:
```
#Check the data for errors
```

In [16]:

```
#check if amount of calls is alright by creating a pivot table and
#have a look at how does amount of calls change throughout the year
(data_calls
 .pivot_table(index='call_date', values='duration', aggfunc='sum')
 .plot(y='duration', figsize=(8,4), style='-')
)
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3ebb82ddd0>



Looks like amount of calls has been incresing throughot the year, but maybe the same thing happened to amount of users. Let's check that by creating a pivot table that will have amount of unique user_ids for each month

In [17]:

```
#Looks like amount of calls has been incresing throughot the year, but maybe the same thing happened to amount of user
s
#Let's check that by creating a pivot table that will have amount of unique user_ids for each month
#firstly I need create new column with month, and actually I'm going to need it later
data_calls['month'] = data_calls['call_date'].dt.month
#then create a pivot table with unique values of user_id as values and month as index
data_calls.pivot_table (index='month', values='user_id', aggfunc=lambda x: len(x.dropna().unique()))
```

Out[17]:

	user_id
month	
1	6
2	15
3	35
4	71
5	104
6	141
7	179
8	230
9	277
10	337
11	403
12	460

Looks like there really are less people in our slice from begining of the year.

In [18]:

```
#Looks like there really are less people in our slice from begining of the year
#Now let's calculate amount of calls and calls durations for each user in each month
#I'll do it using pivot_table
dt_calls_grouped = (data_calls
                    .pivot_table(index=['user_id','month'], values=('duration'), aggfunc=('sum','count'))
                    .reset_index()
                   )
dt_calls_grouped.columns = ['user_id', 'month', 'calls_per_month', 'call_time_per_month']
dt_calls_grouped
```

Out[18]:

	user_id	month	calls_per_month	call_time_per_month
0	1000	12	16	116.83
1	1001	8	27	171.14
2	1001	9	49	297.69
3	1001	10	65	374.11
4	1001	11	64	404.59
...	...	...	...	...
2253	1498	12	39	324.77
2254	1499	9	41	330.37
2255	1499	10	53	363.28
2256	1499	11	45	288.56
2257	1499	12	65	468.10

2258 rows × 4 columns

In [19]:

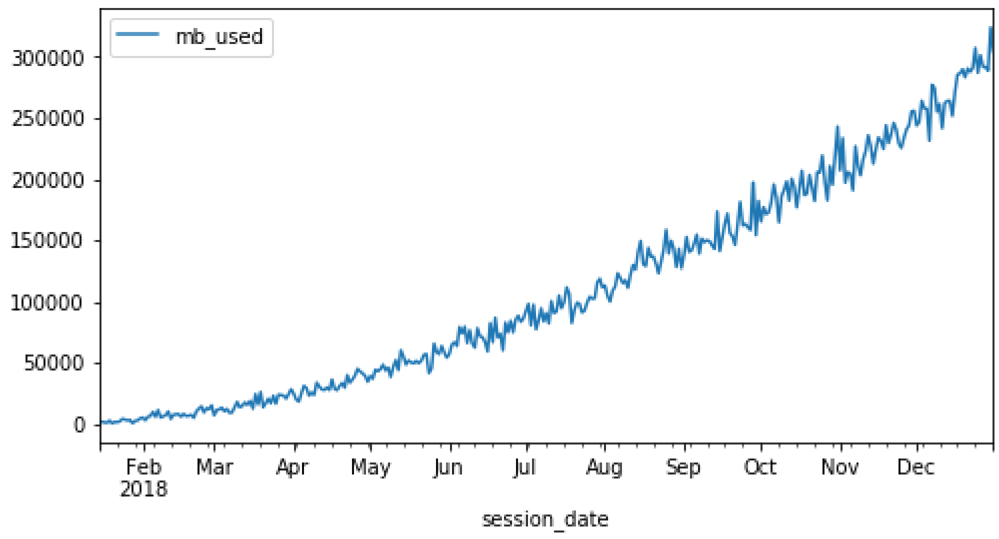
```
#Now let's check internet data
data_internet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 104825 entries, 0 to 104824
Data columns (total 4 columns):
id              104825 non-null object
user_id         104825 non-null int64
session_date    104825 non-null datetime64[ns]
mb_used         104825 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 3.2+ MB
```

In [20]:
```
data_internet['month'] = data_internet['session_date'].dt.month
(data_internet
 .pivot_table(index='session_date', values='mb_used', aggfunc='sum')
 .plot(y='mb_used', figsize=(8,4), style='-')
)
data_internet.pivot_table (index='month', values='user_id', aggfunc=lambda x: len(x.unique()))
```

Out[20]:

	user_id
month	
1	6
2	16
3	35
4	70
5	105
6	142
7	179
8	230
9	279
10	339
11	408
12	468



In [21]:
```
#looks like everything has the same dynamics as with data for calls
#now I'll count volume of data per month for each user

dt_internet_grouped = (data_internet
                       .pivot_table(index=['user_id','month'], values=('mb_used'), aggfunc=('sum'))
                       .reset_index()
                      )
dt_internet_grouped.columns = ['user_id', 'month', 'mb_per_month']
dt_internet_grouped
```

Out[21]:

	user_id	month	mb_per_month
0	1000	12	1901.47
1	1001	8	6919.15
2	1001	9	13314.82
3	1001	10	22330.49
4	1001	11	18504.30
...	...	...	...
2272	1498	12	23137.69
2273	1499	9	12984.76
2274	1499	10	19492.43
2275	1499	11	16813.83
2276	1499	12	22059.21

2277 rows × 3 columns

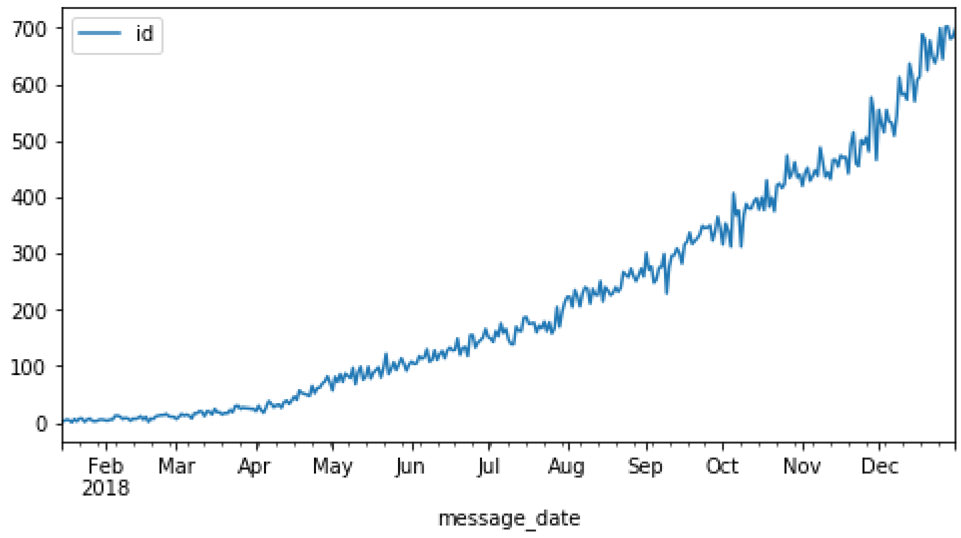
In [22]:
```
#now let's do the same for texts
data_messages.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 76051 entries, 0 to 76050
Data columns (total 3 columns):
id              76051 non-null object
user_id         76051 non-null int64
message_date    76051 non-null datetime64[ns]
dtypes: datetime64[ns](1), int64(1), object(1)
memory usage: 1.7+ MB
```

In [23]:
```
data_messages['month'] = data_messages['message_date'].dt.month
(data_messages
 .pivot_table(index='message_date', values='id', aggfunc='count')
 .plot(y='id', figsize=(8,4), style='-')
)
data_messages.pivot_table (index='month', values='user_id', aggfunc=lambda x: len(x.unique()))
```

Out[23]:

month	user_id
1	4
2	11
3	23
4	52
5	77
6	111
7	138
8	181
9	222
10	278
11	329
12	380



In [24]:
```
#looks like everything has the same dynamics as with data for calls and internet
#now I'll count amount of messages per month for each user

dt_messages_grouped = (data_messages
                      .pivot_table(index=['user_id','month'], values=('id'), aggfunc=('count'))
                      .reset_index()
                     )
dt_messages_grouped.columns = ['user_id', 'month', 'sms_per_month']
dt_messages_grouped
```

Out[24]:

	user_id	month	sms_per_month
0	1000	12	11
1	1001	8	30
2	1001	9	44
3	1001	10	53
4	1001	11	36
...	...	...	...
1801	1496	9	21
1802	1496	10	18
1803	1496	11	13
1804	1496	12	11
1805	1497	12	50

1806 rows × 3 columns

In [25]:
```
#merge all 3 tables together in united table
data_frames = [dt_calls_grouped, dt_internet_grouped, dt_messages_grouped]
dt_grouped = reduce(lambda left, right :pd.merge(left,right,on=['user_id','month'], how='outer', ),data_frames).fillna
(0)
dt_grouped
```

Out[25]:

	user_id	month	calls_per_month	call_time_per_month	mb_per_month	sms_per_month
0	1000	12	16.0	116.83	1901.47	11.0
1	1001	8	27.0	171.14	6919.15	30.0
2	1001	9	49.0	297.69	13314.82	44.0
3	1001	10	65.0	374.11	22330.49	53.0
4	1001	11	64.0	404.59	18504.30	36.0
...	...	...	...	...	...	...
2288	1349	10	0.0	0.00	13093.55	76.0
2289	1349	11	0.0	0.00	17128.26	72.0
2290	1349	12	0.0	0.00	13039.91	61.0
2291	1361	5	0.0	0.00	1519.69	2.0
2292	1482	10	0.0	0.00	0.00	2.0

2293 rows × 6 columns

```
In [26]: #Calculate profit for each user for each month. For this I will create a function

def calc_profit(dt, plans, users):
    #function for calculating profit based on a dataframe
    #function accepts 3 arguments: dataframe with spendings, dataframe with plans and info from them
    #and dataframe with information about users and their plans
    #function works only if plans for are set as indexes for plans dataframe
    #This function can work with different amount of plans without need to change anything.

    user_id = dt['user_id']

    #define extra payment variables
    extra_pay_calls = 0
    extra_pay_gb = 0
    extra_pay_sms = 0

    #get user plan from users dataframe
    plan = users.query('user_id == @user_id')['plan'].values[0]

    monthly_pay = plans.loc[plan,'usd_monthly_pay'] #calculate basic payment for the plan

    if dt['call_time_per_month'] > plans.loc[plan, 'minutes_included']: #calculate extra minutes payment
        extra_pay_calls = np.ceil(((dt['call_time_per_month'] - plans.loc[plan, 'minutes_included']))
        * plans.loc[plan, 'usd_per_minute'])


    if dt['mb_per_month'] > plans.loc[plan,'mb_per_month_included']:
    #here get value of used mb
    #then divide it by amount of mb in gb and round it up to nearest whole number.
    #Then it gets multiplied by price per extra gb
        extra_pay_gb = ((np.ceil((dt['mb_per_month'] - plans.loc[plan,'mb_per_month_included']) / 1024))
        * plans.loc[plan, 'usd_per_gb'])

    ##calculate extra sms payment
    if dt['sms_per_month'] > plans.loc[plan, 'messages_included']:
        extra_pay_sms = ((dt['sms_per_month'] - plans.loc[plan, 'messages_included']) * plans.loc[plan, 'usd_per_messa
ge'])

    return monthly_pay + extra_pay_calls + extra_pay_gb + extra_pay_sms

dt_grouped['profit'] = dt_grouped.apply(calc_profit, axis=1, args=(data_plans, data_users))
dt_grouped
```

Out[26]:

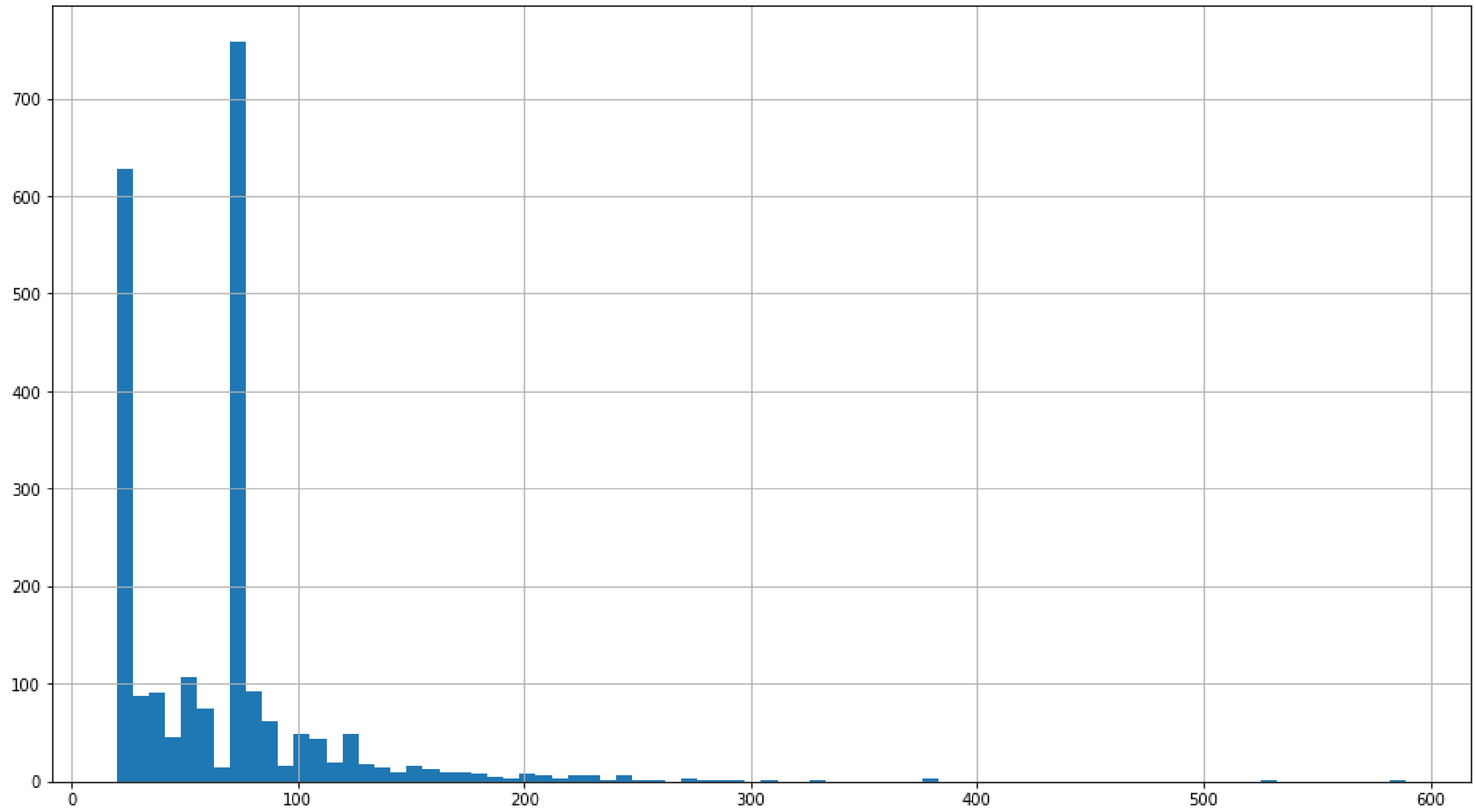
	user_id	month	calls_per_month	call_time_per_month	mb_per_month	sms_per_month	profit
0	1000	12	16.0	116.83	1901.47	11.0	70.00
1	1001	8	27.0	171.14	6919.15	30.0	20.00
2	1001	9	49.0	297.69	13314.82	44.0	20.00
3	1001	10	65.0	374.11	22330.49	53.0	90.09
4	1001	11	64.0	404.59	18504.30	36.0	60.00
...	...	...	...	...	...	...	...
2288	1349	10	0.0	0.00	13093.55	76.0	20.78
2289	1349	11	0.0	0.00	17128.26	72.0	40.66
2290	1349	12	0.0	0.00	13039.91	61.0	20.33
2291	1361	5	0.0	0.00	1519.69	2.0	20.00
2292	1482	10	0.0	0.00	0.00	2.0	70.00

2293 rows × 7 columns

Fixed the code, made it more readable, got rid of column alias that were not needed and passed extra dataframes as arguments.

In [27]:
```python
#Great! Now let's check how it generally looks
dt_grouped.profit.hist(bins='auto', figsize=(16,9))
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3ebad82150>



In [28]:
```python
#finally let's append plan for each user
dt_grouped = pd.merge(dt_grouped, data_users[['user_id','plan']], on='user_id')
dt_grouped
```

Out[28]:

	user_id	month	calls_per_month	call_time_per_month	mb_per_month	sms_per_month	profit	plan
0	1000	12	16.0	116.83	1901.47	11.0	70.00	ultimate
1	1001	8	27.0	171.14	6919.15	30.0	20.00	surf
2	1001	9	49.0	297.69	13314.82	44.0	20.00	surf
3	1001	10	65.0	374.11	22330.49	53.0	90.09	surf
4	1001	11	64.0	404.59	18504.30	36.0	60.00	surf
...	...	...	...	...	...	...	...	...
2288	1204	11	0.0	0.00	21346.95	42.0	70.00	ultimate
2289	1204	12	0.0	0.00	36730.05	78.0	112.00	ultimate
2290	1349	10	0.0	0.00	13093.55	76.0	20.78	surf
2291	1349	11	0.0	0.00	17128.26	72.0	40.66	surf
2292	1349	12	0.0	0.00	13039.91	61.0	20.33	surf

2293 rows × 8 columns

Replaced with merge:)

That's good that there most of the users spent 20 or 70 dollars. Let's check the big values for mistakes.

In [29]:
```python
dt_grouped.query('profit > 300')
```

Out[29]:

	user_id	month	calls_per_month	call_time_per_month	mb_per_month	sms_per_month	profit	plan
1101	1240	8	161.0	1038.88	49950.58	15.0	377.00	surf
1103	1240	10	162.0	1129.04	42128.84	9.0	309.00	surf
1330	1292	8	42.0	304.67	51809.35	0.0	380.00	surf
1332	1292	10	42.0	290.79	46868.75	0.0	330.00	surf
1334	1292	12	28.0	132.65	52034.66	0.0	380.00	surf
1726	1379	12	144.0	1045.24	70931.59	126.0	589.28	surf
2271	1121	12	0.0	0.00	66863.89	97.0	531.41	surf

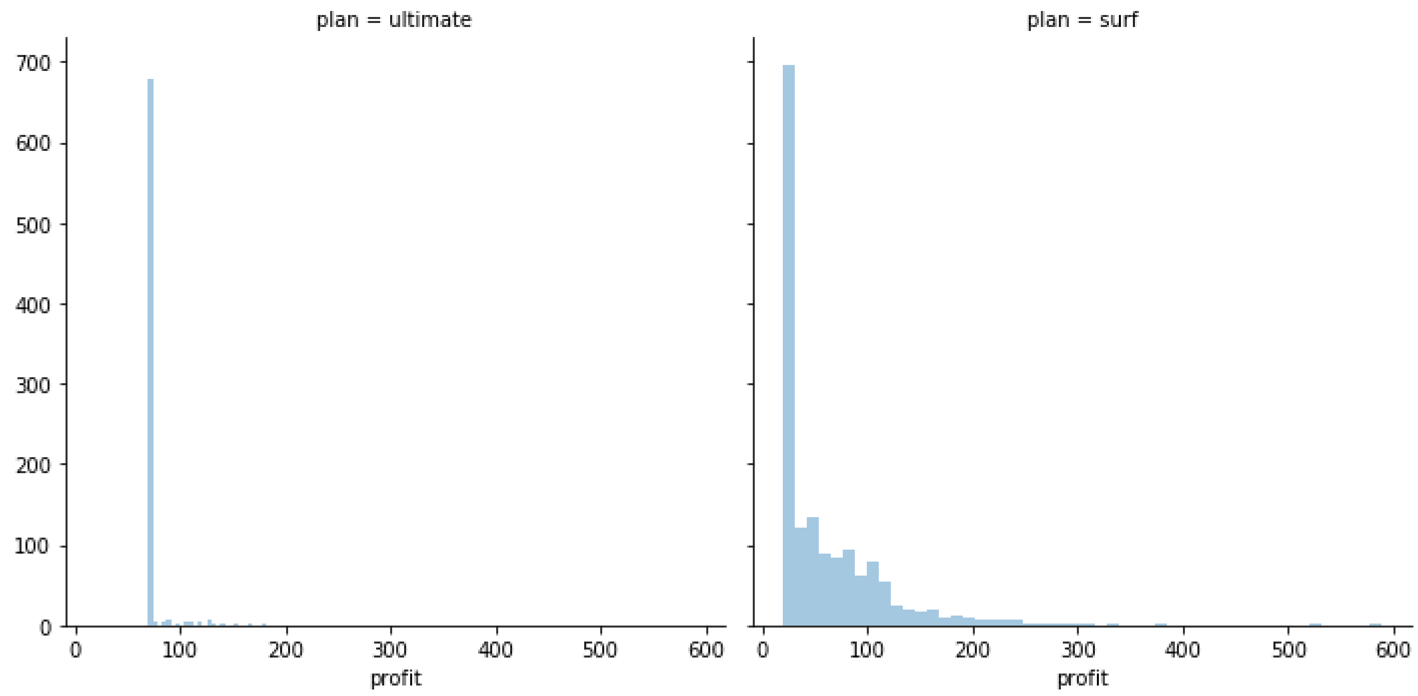
In [30]:
```
#Here I'll do manual calculations for user_id - 1121, his plan is surf:
selected_profit = 20 + np.ceil((((66863.89 - 15360)/1024))*10 + (97-50)*0.03
print (selected_profit)
if selected_profit == dt_grouped.query('user_id == 1121').profit.max():
    print ('Calculations are right!')
```

```
531.41
Calculations are right!
```

Now I'll make a histogram for profit for surf plan and for ultimate plan to see how they differ.

In [31]:
```
g = sns.FacetGrid(dt_grouped, col="plan", height=5, aspect=1)
g.map(sns.distplot, 'profit', kde=False)
```

Out[31]: <seaborn.axisgrid.FacetGrid at 0x7f3ebad56dd0>



From here I can see that most of users stay within their plans, but for surf plan we see more people needing more stuff that the plan provides and therefore more people are paying extra. While in ultimate plan it happends more rarely, and most people really stick to their plan.

Conclusion

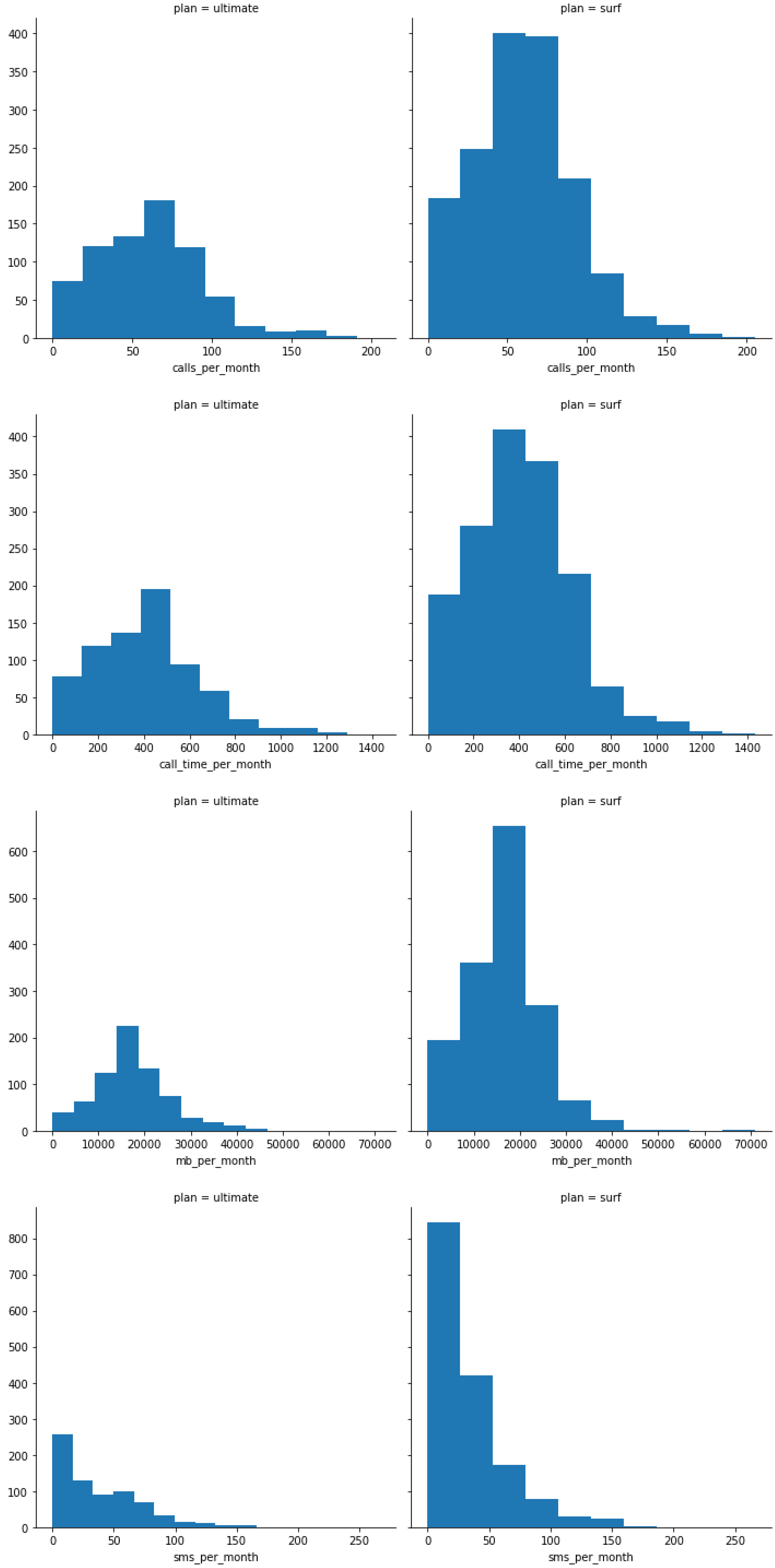
In this part of the project I have converted data to more usable format: I have grouped all the user data by user id and by month and have calculated overall spending for each user for each month. Having data aligned like this will make all further analysis much easier.

Step 3. Analyze the data

In [32]:

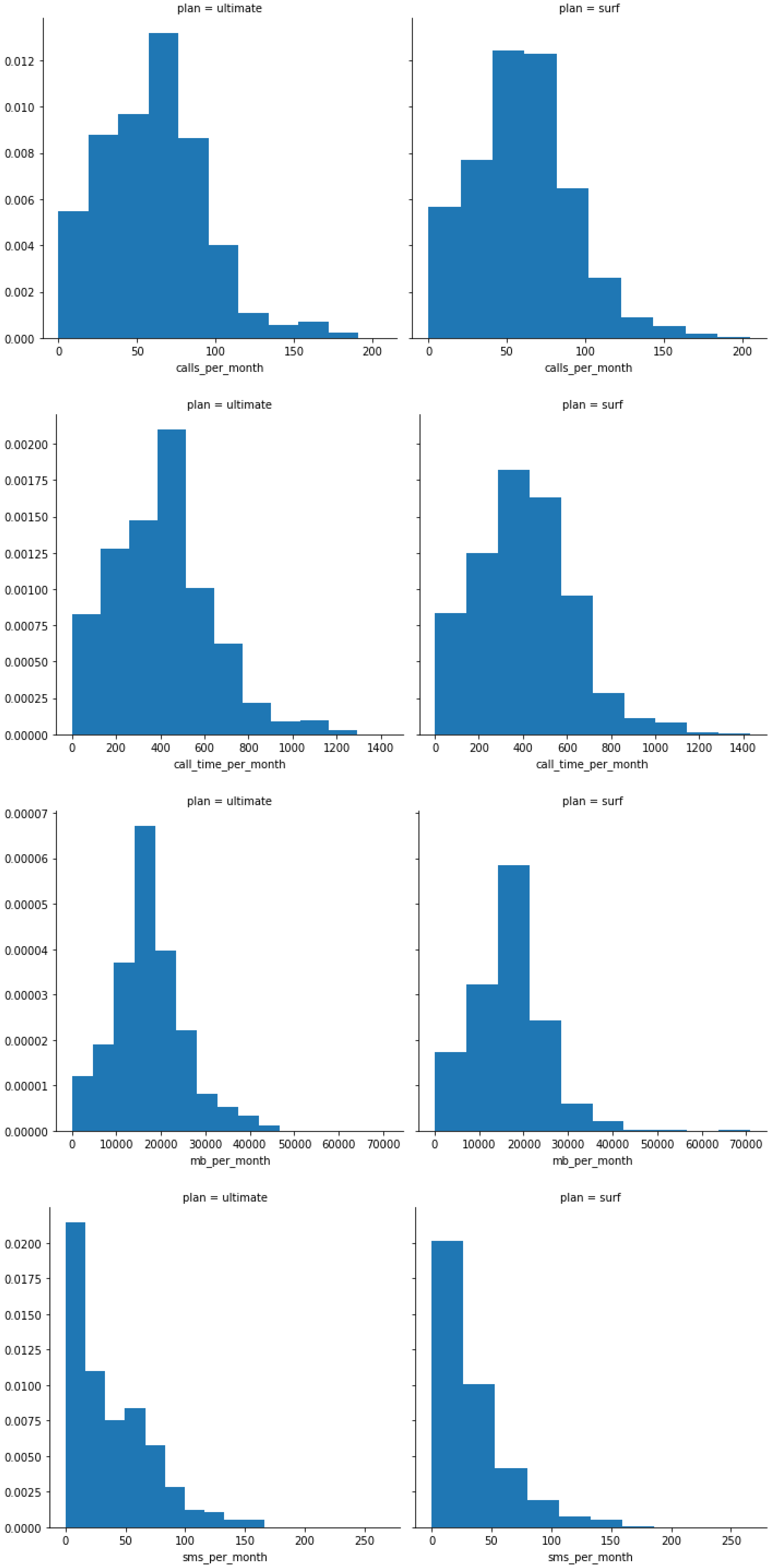
```
#Firstly I'm going to analize this plans in parallel by making histograms for them next to each other
#list of columns for analizing
analized_col = ['calls_per_month', 'call_time_per_month', 'mb_per_month', 'sms_per_month']


for col in analized_col:
    g = sns.FacetGrid(dt_grouped, col="plan", height=5, aspect=1) #create grid
    g.map(plt.hist, col); #print histogramm
```


plan = ultimate
plan = surf
calls_per_month
calls_per_month
plan = ultimate
plan = surf
call_time_per_month
call_time_per_month
plan = ultimate
plan = surf
mb_per_month
mb_per_month
plan = ultimate
plan = surf
sms_per_month
sms_per_month

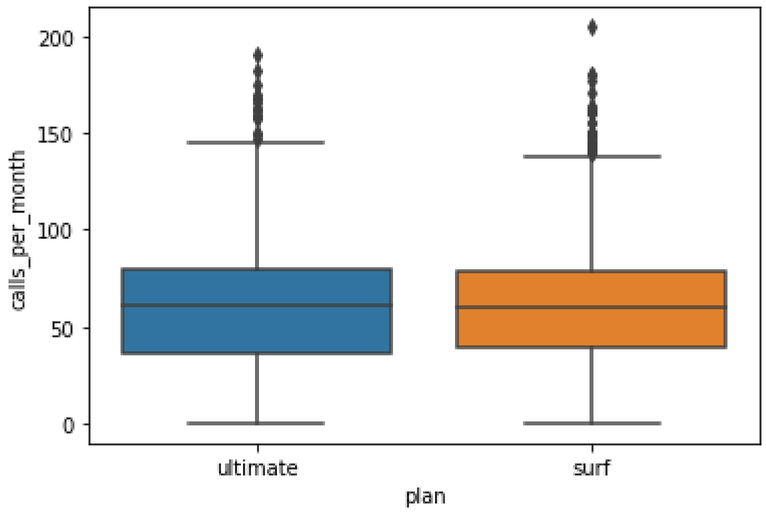
I see here that data differs in volume, but the shape is pretty alike. Now I'll print the same histograms, but showing densities.

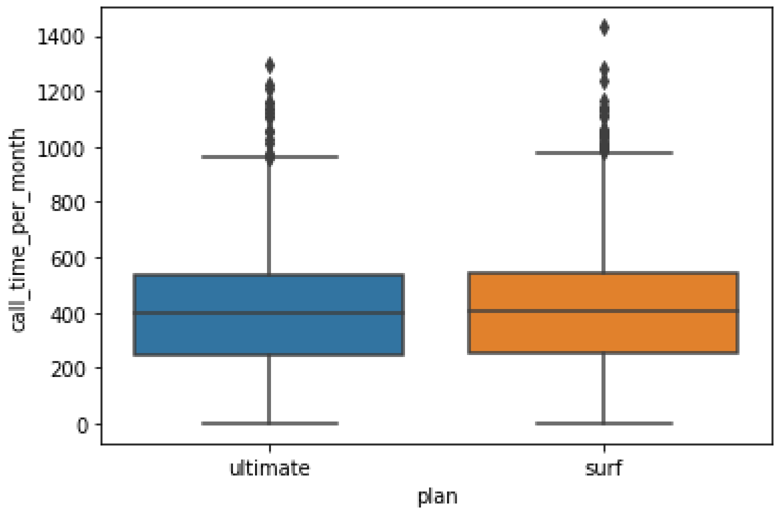
In [33]:
```
for col in analized_col:
    g = sns.FacetGrid(dt_grouped, col="plan", height=5, aspect=1) #create grid
    g.map(plt.hist, col, density=True); #print histogramm
```

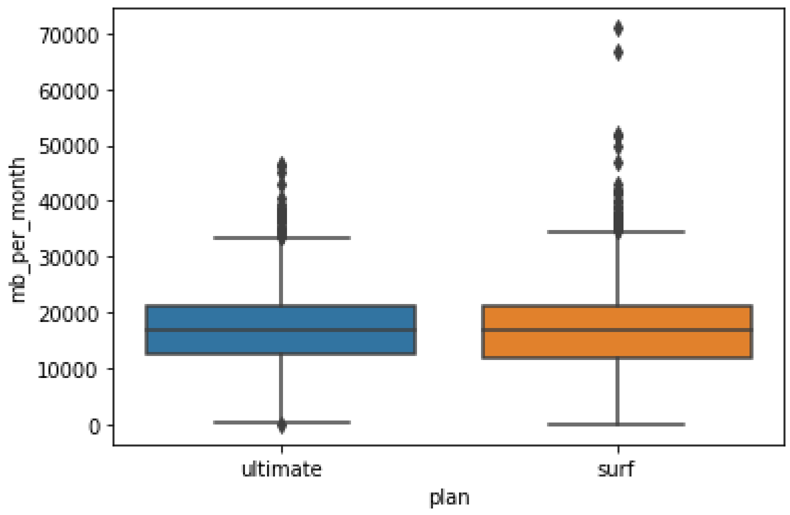

plan = ultimate
plan = surf
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0 50 100 150 200
calls_per_month
plan = ultimate
plan = surf
0.00000
0.00025
0.00050
0.00075
0.00100
0.00125
0.00150
0.00175
0.00200
0 200 400 600 800 1000 1200 1400
call_time_per_month
plan = ultimate
plan = surf
0.00000
0.00001
0.00002
0.00003
0.00004
0.00005
0.00006
0.00007
0 10000 20000 30000 40000 50000 60000 70000
mb_per_month
plan = ultimate
plan = surf
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
0.0200
0 50 100 150 200 250
sms_per_month

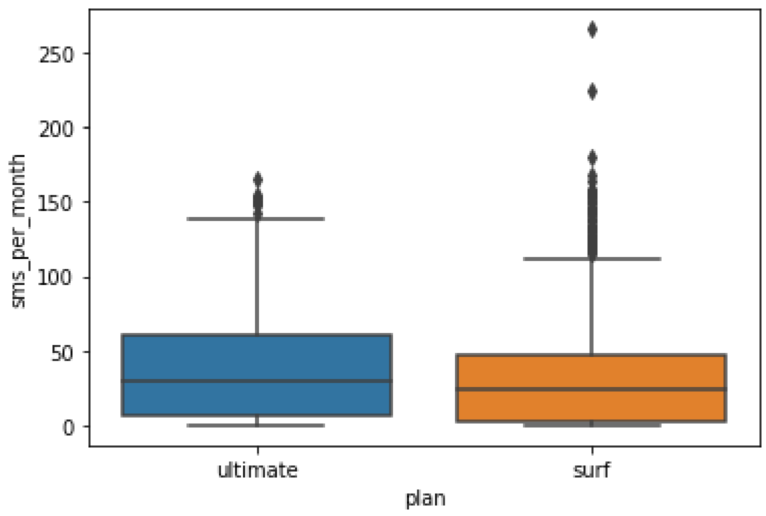
Yes here I see that the behavior of clients using different plan is very much alike, they spend pretty much the same amount of internet, send similar amount of sms and make similar amount of calls. Now let's check boxplots for each plan to see if we will be able to see differences there.

In [34]:
```
for col in analized_col:
    plt.figure(col)
    ax=sns.boxplot(x="plan", y=col, order=["ultimate", 'surf'], data=dt_grouped);
```







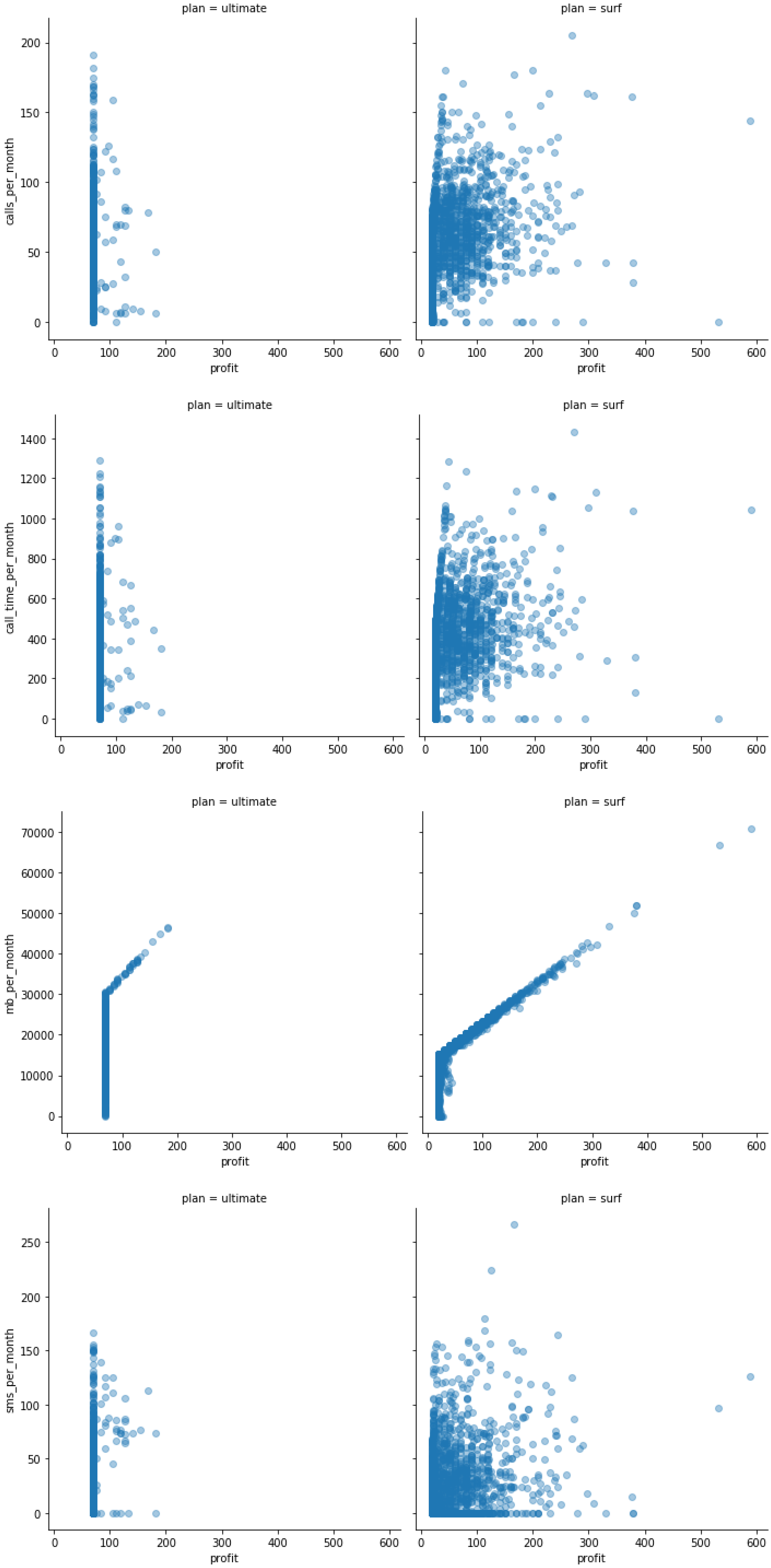


From here I see that even all the quantiles are very similar, only for internet I see that users of surf plan spend a bit less on average that users of ultimate plan. Also from these boxplots I see that there are more outliers for surf plan that in ultimate.

Now let's build some scatter plots with profit as x axis and internet/mb/sms as y axis to see which one is affecting the profit more often.

In [35]:

```
for col in analized_col:
    g = sns.FacetGrid(dt_grouped, col="plan", height=5, aspect=1) #create grid
    g.map(plt.scatter, "profit", col, alpha=.4); #print histogram
```


plan = ultimate
plan = surf
calls_per_month
0
50
100
150
200
profit
0
100
200
300
400
500
600
plan = ultimate
plan = surf
call_time_per_month
0
200
400
600
800
1000
1200
1400
profit
plan = ultimate
plan = surf
mb_per_month
0
10000
20000
30000
40000
50000
60000
70000
profit
plan = ultimate
plan = surf
sms_per_month
0
50
100
150
200
250
profit

From this plot I see that most of the uusers who are spending more money are purchasing extra mb. It's visual that there is no definite correlation between profit and sms, very little between profit and amount/length of calls and a definite correlation between profit mb used.

In [37]:
```
#describe for each plan
dt_grouped.query('plan =="ultimate"').describe()
```

Out[37]:

	user_id	month	calls_per_month	call_time_per_month	mb_per_month	sms_per_month	profit
count	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000	720.000000
mean	1253.330556	9.151389	60.626389	406.193083	17214.699694	37.551389	72.313889
std	150.915644	2.558495	33.242994	227.246499	7851.897435	34.767179	11.395108
min	1000.000000	1.000000	0.000000	0.000000	0.000000	0.000000	70.000000
25%	1126.000000	8.000000	36.000000	246.290000	12666.955000	7.000000	70.000000
50%	1241.500000	10.000000	61.000000	398.585000	16858.340000	30.000000	70.000000
75%	1401.000000	11.000000	80.000000	532.227500	21014.527500	61.000000	70.000000
max	1497.000000	12.000000	191.000000	1292.090000	46595.330000	166.000000	182.000000

In [38]:
```
#Find the minutes, texts, and volume of data the users of each plan require per month.
#Calculate the mean, dispersion, and standard deviation.
dt_optimal = (dt_grouped[['calls_per_month','call_time_per_month','mb_per_month','sms_per_month','plan']]
              .groupby('plan')
              .agg((('standart',np.std), ('mean',np.mean), ('var', np.var), ('required minimum',lambda x: (np.mean(x)
- 3*np.std(x))),
                    ('required maximum',lambda x: (np.mean(x) + 3*np.std(x)))
                   ))
             .round(2)
             .transpose()
             )
dt_optimal
```

Out[38]:

	plan	surf	ultimate
calls_per_month	standart	32.02	33.24
	mean	59.81	60.63
	var	1025.15	1105.10
	required minimum	-36.21	-39.03
	required maximum	155.84	160.29
call_time_per_month	standart	221.66	227.25
	mean	404.76	406.19
	var	49135.10	51640.97
	required minimum	-260.02	-275.07
	required maximum	1069.54	1087.46
mb_per_month	standart	8013.51	7851.90
	mean	16558.28	17214.70
	var	64216395.84	61652293.32
	required minimum	-7474.61	-6324.63
	required maximum	40591.18	40754.03
sms_per_month	standart	33.57	34.77
	mean	31.16	37.55
	var	1126.72	1208.76
	required minimum	-69.51	-66.68
	required maximum	131.83	141.78

If you only knew how hard it was to make it like that:)

In [39]:
```
data_plans
```

Out[39]:

plan_name	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute
surf	50	15360	500	20	10	0.03	0.03
ultimate	1000	30720	3000	70	7	0.01	0.01

Conclusion

Based on this data I'm able to make several conclusions:

- User behavior for ultimate plan and for surf plan is pretty alike, aside from amount of users signed to each one, average user of ultimate plan doesn't waste more of internet or calls or sms than user of surf plan.
- most of users of Surf plan go over the limit with amount of mb spent
- 99.7 of users of Ultimate plan don't spend that amount of everything that they have included.
- Most profit is recieved from extra mb that users are buying.
- Users of Ultimate plan are more likely to stany within their plan limits, there are much more outliers within users of Surf plan.

Step 4. Test the hypotheses

Here I'm going to test two hypotheeses:

1. The average profit from users of Ultimate and Surf calling plans differs.
2. The average profit from users in NY-NJ area is different from that of the users from other regions.

Let's start with the 1st one.

First thing I have to do is to make a null hypothesis. It will be:

The average profit from users of Ultimate plan equals the average profit from Surf calling plan.

In [40]:
```
ultimate = list(dt_grouped.query('plan == "ultimate"').profit)
surf = list(dt_grouped.query('plan == "surf"').profit)


alpha = .05 # critical statistical significance level
                        # if the p-value is less than alpha, we reject the hypothesis

print ('Average profit from users of Ultimate plan: {:.2f}'.format(mean(ultimate)))
print ('Average profit from users of Surf plan: {:.2f}'.format(mean(surf)))

print ('Variance of profit for users of ultimate plan {:.2f}'.format(np.var(ultimate)))
print ('Variance of profit for users of surf plan {:.2f}'.format(np.var(surf)))

results = st.ttest_ind(
    ultimate,
    surf)

print('p-value: ', results.pvalue)

if (results.pvalue < alpha):
        print("We reject the null hypothesis")
else:
        print("We can't reject the null hypothesis")
```

```
Average profit from users of Ultimate plan: 72.31
Average profit from users of Surf plan: 60.49
Variance of profit for users of ultimate plan 129.67
Variance of profit for users of surf plan 3056.57
p-value:  1.5047254582344138e-08
We reject the null hypothesis
```

Conclusion

Therefore we chave a reason to reject this hypothesis and assume that average profit from users of Ultimate plan differs from average profit from users of Surf plan.

Now let's check the second hypothesis. Null hyposthesis will be:

The average profit from users in NY-NJ area isn't different from that of the users from other regions.

In [41]:
```
data_users.head()
```

Out[41]:

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date
0	1000	Anamaria	Bauer	45	Atlanta-Sandy Springs-Roswell, GA MSA	2018-12-24	ultimate	NaN
1	1001	Mickey	Wilkerson	28	Seattle-Tacoma-Bellevue, WA MSA	2018-08-13	surf	NaN
2	1002	Carlee	Hoffman	36	Las Vegas-Henderson-Paradise, NV MSA	2018-10-21	surf	NaN
3	1003	Reynaldo	Jenkins	52	Tulsa, OK MSA	2018-01-28	surf	NaN
4	1004	Leonila	Thompson	40	Seattle-Tacoma-Bellevue, WA MSA	2018-05-23	surf	NaN

In [42]:
```
data_users.city.value_counts()
```

Out[42]:
```
New York-Newark-Jersey City, NY-NJ-PA MSA          80
Los Angeles-Long Beach-Anaheim, CA MSA             29
Dallas-Fort Worth-Arlington, TX MSA                21
Chicago-Naperville-Elgin, IL-IN-WI MSA             19
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA    17
                                                   ..
Greensboro-High Point, NC MSA                       1
Oxnard-Thousand Oaks-Ventura, CA MSA                1
Jacksonville, FL MSA                                1
Stockton, CA MSA                                    1
Raleigh-Cary, NC MSA                                1
Name: city, Length: 73, dtype: int64
```

In [43]:
```
def ny_nj (row):
#     function for finding out citizens of NY or NJ state
    if 'NY' in row.split(',')[1].split('-'): return True #if after "," there is NY return true
    elif 'NJ' in row.split(',')[1].split('-'): return True #if after "," there is NJ return true
    else: return False

data_users['new_yorker'] = data_users.city.apply(ny_nj)
```

In [44]:
```
#Let's check how many we have in our data
data_users.new_yorker.value_counts()
```

Out[44]:
```
False    403
True      97
Name: new_yorker, dtype: int64
```

In [45]:
```
#create lists with revenues for NYers and others
dt_grouped_new_york_check = pd.merge(dt_grouped, data_users[['user_id','new_yorker']], on='user_id')
dt_grouped_new_york_check
```

Out[45]:

	user_id	month	calls_per_month	call_time_per_month	mb_per_month	sms_per_month	profit	plan	new_yorker
0	1000	12	16.0	116.83	1901.47	11.0	70.00	ultimate	False
1	1001	8	27.0	171.14	6919.15	30.0	20.00	surf	False
2	1001	9	49.0	297.69	13314.82	44.0	20.00	surf	False
3	1001	10	65.0	374.11	22330.49	53.0	90.09	surf	False
4	1001	11	64.0	404.59	18504.30	36.0	60.00	surf	False
...	...	...	...	...	...	...	...	...	...
2288	1204	11	0.0	0.00	21346.95	42.0	70.00	ultimate	False
2289	1204	12	0.0	0.00	36730.05	78.0	112.00	ultimate	False
2290	1349	10	0.0	0.00	13093.55	76.0	20.78	surf	False
2291	1349	11	0.0	0.00	17128.26	72.0	40.66	surf	False
2292	1349	12	0.0	0.00	13039.91	61.0	20.33	surf	False

2293 rows × 9 columns

In [46]:
```
new_yorker = list(dt_grouped_new_york_check.query('new_yorker == True').profit) #profits only for new_yorkers
not_new_yorker = list(dt_grouped_new_york_check.query('new_yorker == False').profit) #the rest


#now let's check our hypothesis

print ('Average profit from residents of NY-NJ: {:.2f}'.format(mean(new_yorker)))
print ('Average profit from residents of other states: {:.2f}'.format(mean(not_new_yorker)))
print ('Variance of profit for users from NY-NJ {:.2f}'.format(np.var(new_yorker)))
print ('Variance of profit for users from other states {:.2f}'.format(np.var(not_new_yorker)))

alpha = .05 # critical statistical significance level

results = st.ttest_ind(
        new_yorker,
        not_new_yorker)

print('p-value: ', results.pvalue)

alpha = 0.05
if (results.pvalue < alpha):
        print("We reject the null hypothesis")
else:
        print("We can't reject the null hypothesis")
```

```
Average profit from residents of NY-NJ: 60.42
Average profit from residents of other states: 65.15
Variance of profit for users from NY-NJ 2026.72
Variance of profit for users from other states 2198.44
p-value:  0.05174064802570269
We can't reject the null hypothesis
```

Based on this conclusion we can't say that average profit from New Yorkers is different as from residents of other states (but we also can't say that it is definetly the same).

General conclusion

While analysing this slice of data I have made several interesting conclusions:

1. Behavior of people that use Ultimate and Surf plans are very alike. So we can suppose that users of Ultimate plan use it just for comfort and maybe because of status. It's possible to change the amount of services that they are getting without affecting the amount that they will use. So we can give it to marketing team, maybe they will find something to do with that.
2. First null theorie got rejected, so we know now that profit from Ultimate plan differs from profit from Surf plan (we can't definetly say which way, but it does for sure).
3. Second theory didn't get rejected, therefore we are not able to say if profit from residents of NY-NJ is definetly different from profit from other states.