Business analytics project

You've done beautifully in the Practicum course, and you've been offered an internship in the analytical department at Yandex.Afisha. Your first task is to help optimize marketing expenses. You have:

- Server logs with data on Yandex.Afisha visits from June 2017 through May 2018
- Dump file with all orders for the period
- Marketing expenses statistics

You are going to study:

- How people use the product
- When they start to buy
- How much money each customer brings
- When they pay off

Step 1. Download the data and prepare it for analysis

In [2]:
```
#load libraries

import matplotlib.pyplot as plt
import matplotlib as mpl
import numpy as np
import pandas as pd
import seaborn as sns
import warnings; warnings.simplefilter('ignore')


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


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

In [3]:
```
visits = pd.read_csv('/datasets/visits_log_us.csv')
orders = pd.read_csv('/datasets/orders_log_us.csv')
costs = pd.read_csv('/datasets/costs_us.csv')
```

First step is to check file sizes and see if I can make them lighter by converting datatypes.

In [4]:
```
visits.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359400 entries, 0 to 359399
Data columns (total 5 columns):
Device       359400 non-null object
End Ts       359400 non-null object
Source Id    359400 non-null int64
Start Ts     359400 non-null object
Uid          359400 non-null uint64
dtypes: int64(1), object(3), uint64(1)
memory usage: 79.3 MB
```

In [5]:
```
visits.sample(5)
```

Out[5]:

	Device	End Ts	Source Id	Start Ts	Uid
205827	desktop	2018-05-18 10:55:00	5	2018-05-18 09:16:00	7654636749667288880
51568	desktop	2018-05-14 22:38:00	3	2018-05-14 22:35:00	15033293459920254393
79943	desktop	2017-06-02 12:48:00	3	2017-06-02 12:37:00	7225125819688884766
351306	desktop	2018-05-10 17:23:00	9	2018-05-10 17:22:00	4623183830589441118
137411	desktop	2018-05-24 22:53:00	5	2018-05-24 22:46:00	13031693977804575955

In [6]:
```
visits.Device.value_counts()
```

Out[6]:
```
desktop    262567
touch       96833
Name: Device, dtype: int64
```

In [7]:
```
visits['Device'] = visits['Device'].astype('category')
```

In [8]:
```
visits['End Ts']= pd.to_datetime(visits['End Ts'], format="%Y-%m-%d %H:%M:%S")
visits['Start Ts']= pd.to_datetime(visits['Start Ts'], format="%Y-%m-%d %H:%M:%S")
```

In [9]:
```
visits.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359400 entries, 0 to 359399
Data columns (total 5 columns):
Device       359400 non-null category
End Ts       359400 non-null datetime64[ns]
Source Id    359400 non-null int64
Start Ts     359400 non-null datetime64[ns]
Uid          359400 non-null uint64
dtypes: category(1), datetime64[ns](2), int64(1), uint64(1)
memory usage: 11.3 MB
```

Much better! Now let's rename the columns.

In [10]:
```
visits.columns = ['device', 'end_ts', 'source_id', 'start_ts', 'uid']
visits.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359400 entries, 0 to 359399
Data columns (total 5 columns):
device       359400 non-null category
end_ts       359400 non-null datetime64[ns]
source_id    359400 non-null int64
start_ts     359400 non-null datetime64[ns]
uid          359400 non-null uint64
dtypes: category(1), datetime64[ns](2), int64(1), uint64(1)
memory usage: 11.3 MB
```

Let's have a bit closer look at the data.

In [11]:
```
visits.describe(include='all')
```

Out[11]:

	device	end_ts	source_id	start_ts	uid
count	359400	359400	359400.000000	359400	3.594000e+05
unique	2	224760	NaN	224303	NaN
top	desktop	2017-11-24 16:51:00	NaN	2017-11-24 16:06:00	NaN
freq	262567	23	NaN	19	NaN
first	NaN	2017-06-01 00:02:00	NaN	2017-06-01 00:01:00	NaN
last	NaN	2018-06-01 01:26:00	NaN	2018-05-31 23:59:00	NaN
mean	NaN	NaN	3.750515	NaN	9.202557e+18
std	NaN	NaN	1.917116	NaN	5.298433e+18
min	NaN	NaN	1.000000	NaN	1.186350e+13
25%	NaN	NaN	3.000000	NaN	4.613407e+18
50%	NaN	NaN	4.000000	NaN	9.227413e+18
75%	NaN	NaN	5.000000	NaN	1.372824e+19
max	NaN	NaN	10.000000	NaN	1.844668e+19

This data doesn't seem to have any missing values or obvious nonsence. Looks pretty useful for closer analysis.

Now I repeat it with orders and costs tables.

In [12]:
```
orders.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50415 entries, 0 to 50414
Data columns (total 3 columns):
Buy Ts      50415 non-null object
Revenue     50415 non-null float64
Uid         50415 non-null uint64
dtypes: float64(1), object(1), uint64(1)
memory usage: 4.4 MB
```

In [13]:
```
orders.sample(5)
```

Out[13]:

	Buy Ts	Revenue	Uid
37009	2018-02-26 11:20:00	2.44	233786961902768308
2254	2017-06-29 16:48:00	1.83	3350212363338545294
47157	2018-05-13 17:53:00	5.50	12771443857325540846
33426	2018-02-07 15:47:00	1.77	2855826466565515337
16084	2017-11-04 13:42:00	20.78	11920452646463905188

In [14]:
```
orders['Buy Ts']= pd.to_datetime(orders['Buy Ts'], format="%Y-%m-%d %H:%M:%S")
```

In [15]:
```
orders.columns = ['buy_ts','revenue','uid']
orders.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50415 entries, 0 to 50414
Data columns (total 3 columns):
buy_ts      50415 non-null datetime64[ns]
revenue     50415 non-null float64
uid         50415 non-null uint64
dtypes: datetime64[ns](1), float64(1), uint64(1)
memory usage: 1.2 MB
```

In [16]:
```
orders.describe(include='all')
```

Out[16]:

	buy_ts	revenue	uid
count	50415	50415.000000	5.041500e+04
unique	45991	NaN	NaN
top	2018-05-31 10:13:00	NaN	NaN
freq	9	NaN	NaN
first	2017-06-01 00:10:00	NaN	NaN
last	2018-06-01 00:02:00	NaN	NaN
mean	NaN	4.999647	9.098161e+18
std	NaN	21.818359	5.285742e+18
min	NaN	0.000000	3.135781e+14
25%	NaN	1.220000	4.533567e+18
50%	NaN	2.500000	9.102274e+18
75%	NaN	4.890000	1.368290e+19
max	NaN	2633.280000	1.844617e+19

This data doesn't seem to have any missing values or obvious nonsense. Looks pretty useful for closer analysis.

In [17]:
```
costs.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2542 entries, 0 to 2541
Data columns (total 3 columns):
source_id    2542 non-null int64
dt           2542 non-null object
costs        2542 non-null float64
dtypes: float64(1), int64(1), object(1)
memory usage: 206.2 KB
```

In [18]:
```
costs.head()
```

Out[18]:

	source_id	dt	costs
0	1	2017-06-01	75.20
1	1	2017-06-02	62.25
2	1	2017-06-03	36.53
3	1	2017-06-04	55.00
4	1	2017-06-05	57.08

In [19]:
```
#transform dt column to datetime format
costs['dt']= pd.to_datetime(costs['dt'], format="%Y-%m-%d")
```

In [20]:
```
costs.describe(include='all')
```

Out[20]:

	source_id	dt	costs
count	2542.000000	2542	2542.000000
unique	NaN	364	NaN
top	NaN	2018-03-03 00:00:00	NaN
freq	NaN	7	NaN
first	NaN	2017-06-01 00:00:00	NaN
last	NaN	2018-05-31 00:00:00	NaN
mean	4.857199	NaN	129.477427
std	3.181581	NaN	156.296628
min	1.000000	NaN	0.540000
25%	2.000000	NaN	21.945000
50%	4.000000	NaN	77.295000
75%	9.000000	NaN	170.065000
max	10.000000	NaN	1788.280000

This data is already alright. I don't see any missing values or anything like that.

Step 2. Make reports and calculate metrics.

Product

How many people use it every day, week, and month?

In [21]:
```
visits.head()
```

Out[21]:

	device	end_ts	source_id	start_ts	uid
0	touch	2017-12-20 17:38:00	4	2017-12-20 17:20:00	16879256277535980062
1	desktop	2018-02-19 17:21:00	2	2018-02-19 16:53:00	104060357244891740
2	touch	2017-07-01 01:54:00	5	2017-07-01 01:54:00	7459035603376831527
3	desktop	2018-05-20 11:23:00	9	2018-05-20 10:59:00	16174680259334210214
4	desktop	2017-12-27 14:06:00	3	2017-12-27 14:06:00	9969694820036681168

In [22]:
```
visits['visit_date'] = visits.start_ts.dt.date.astype('datetime64[D]')
visits['visit_year'] = visits.visit_date.astype('datetime64[Y]')
visits['visit_month'] = visits.visit_date.astype('datetime64[M]')
visits['visit_week'] = visits.visit_date.astype('datetime64[W]')
```

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

Out[23]:

	device	end_ts	source_id	start_ts	uid	visit_date	visit_year	visit_month	visit_week
0	touch	2017-12-20 17:38:00	4	2017-12-20 17:20:00	16879256277535980062	2017-12-20	2017-01-01	2017-12-01	2017-12-14
1	desktop	2018-02-19 17:21:00	2	2018-02-19 16:53:00	104060357244891740	2018-02-19	2018-01-01	2018-02-01	2018-02-15
2	touch	2017-07-01 01:54:00	5	2017-07-01 01:54:00	7459035603376831527	2017-07-01	2017-01-01	2017-07-01	2017-06-29
3	desktop	2018-05-20 11:23:00	9	2018-05-20 10:59:00	16174680259334210214	2018-05-20	2018-01-01	2018-05-01	2018-05-17
4	desktop	2017-12-27 14:06:00	3	2017-12-27 14:06:00	9969694820036681168	2017-12-27	2017-01-01	2017-12-01	2017-12-21

In [24]:
```
#find duration of each visit
visits['duration'] = visits.end_ts - visits.start_ts
```

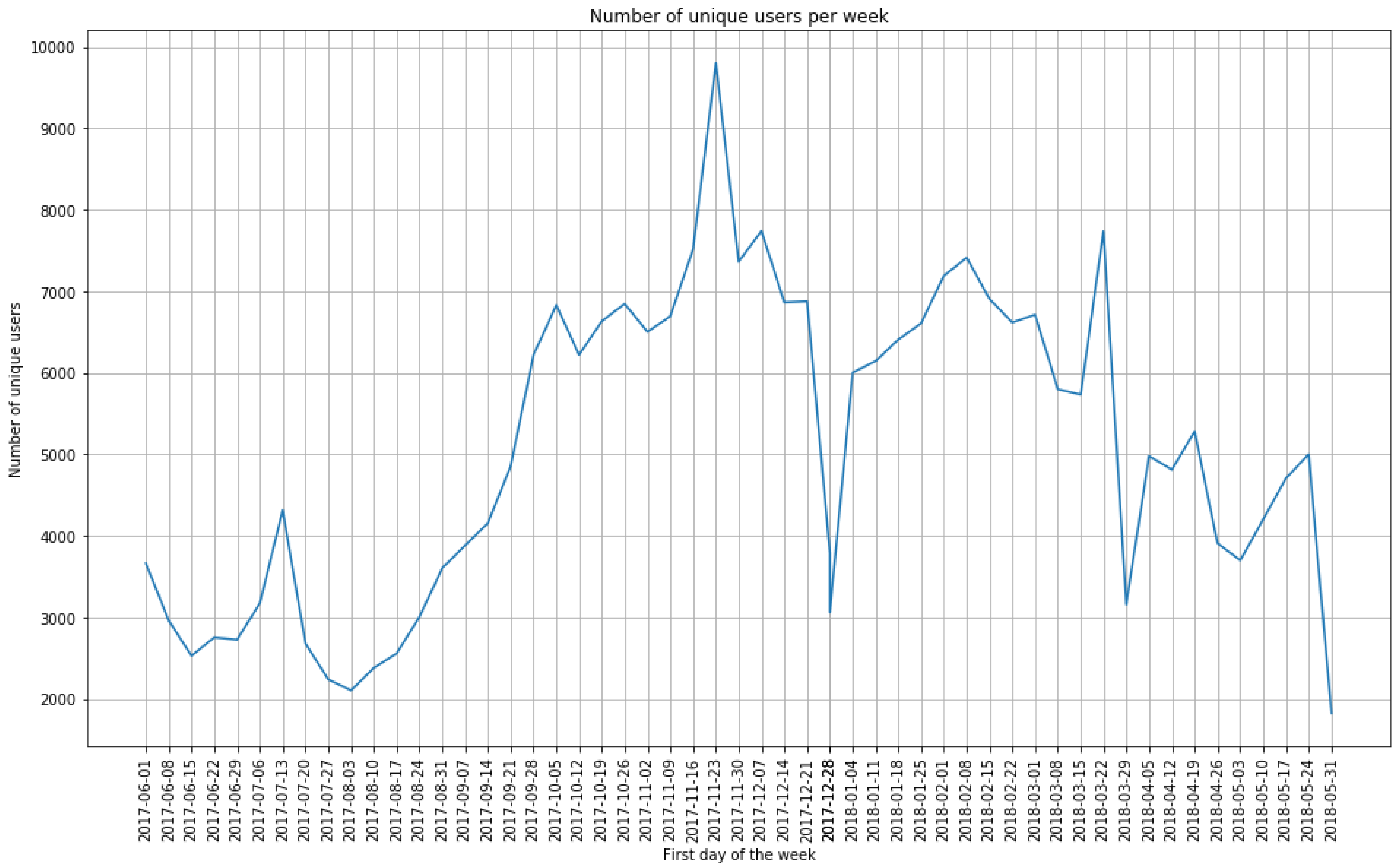
In [25]:
```
#get rid of 0 seconds visits
visits = visits.query('duration > "00:00:00"')
```

In [26]:
```python
dau_total = int(visits.groupby('visit_date').agg({'uid': 'nunique'}).mean())
wau_total = int(visits.groupby(['visit_year', 'visit_week']).agg({'uid': 'nunique'}).mean())
mau_total = int(visits.groupby(['visit_year', 'visit_month']).agg({'uid': 'nunique'}).mean())

print('Mean number of daily unique users:', dau_total )
print('Mean number of weekly unique users:', wau_total)
print('Mean number of monthly unique users:', mau_total )
print('Monthly sticky factor: {:.3f}'.format(dau_total / mau_total))
print('Weekly sticky factor: {:.3f}'.format(dau_total / wau_total))
```

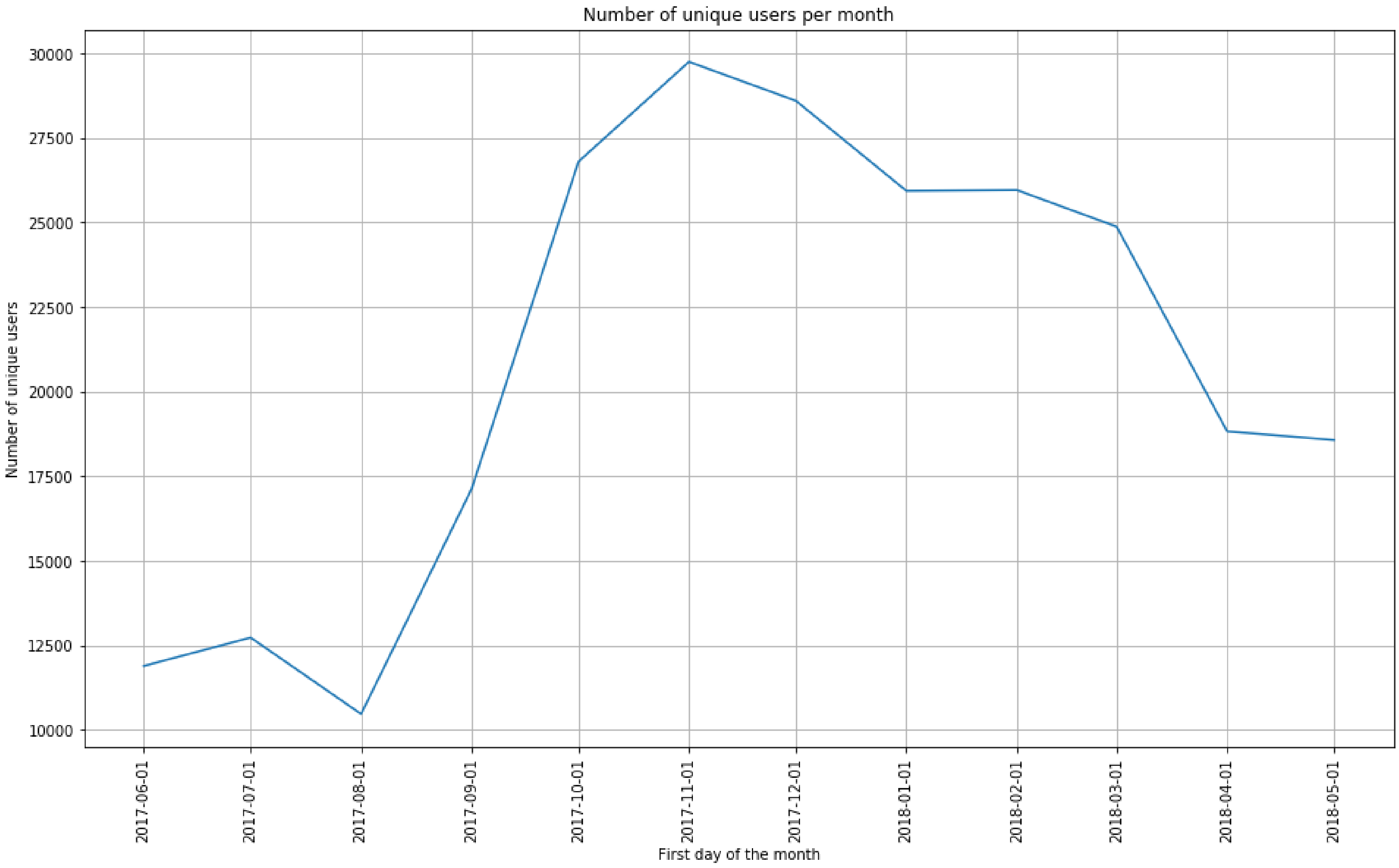
```
Mean number of daily unique users: 817
Mean number of weekly unique users: 5063
Mean number of monthly unique users: 20955
Monthly sticky factor: 0.039
Weekly sticky factor: 0.161
```

Let's have a deeper look at this data and plot graphs on how the average number of users changed throughout all this time. I'll make two charts: one per week, one per month.

In [27]:
```python
df = visits.groupby(['visit_year', 'visit_week']).agg({'uid': 'nunique'}).reset_index()
fig, ax = plt.subplots(figsize = (16,9))
ax.plot(df.visit_week, df.uid)

ax.set(xlabel='First day of the week', ylabel='Number of unique users',
       title='Number of unique users per week')
ax.grid()

plt.xticks(df.visit_week, rotation=90)
plt.show();
```



In [28]:
```
df = visits.groupby(['visit_year', 'visit_month']).agg({'uid': 'nunique'}).reset_index()
fig, ax = plt.subplots(figsize = (16,9))

ax.plot(df.visit_month, df.uid)
ax.set(xlabel='First day of the month', ylabel='Number of unique users',
       title='Number of unique users per month')
ax.grid()
plt.xticks(df.visit_month, rotation=90)
plt.show();
```



Conclusion

Amount of visitors have risen during autumn, but than it seems to have had some decline. It may be due to seasonal changes, or maybe something is wrong with the app, I'm going to check it later.

How many sessions are there per day? (One user might have more than one session.)

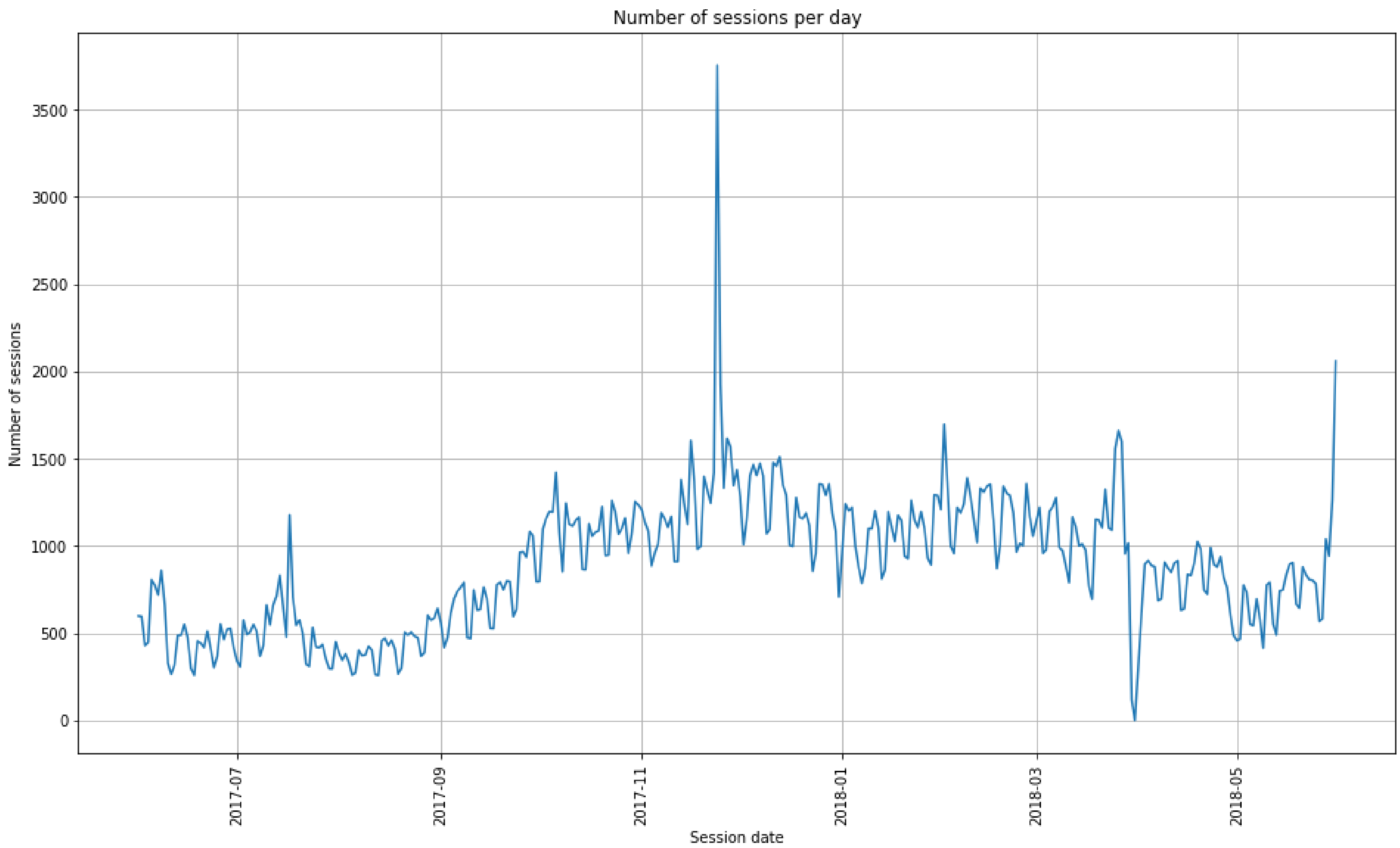
In [29]:
```
sessions_per_day = (visits.groupby(['visit_date', 'uid']) #group values by date and users
                    .agg({'start_ts':'nunique'}) #find for each user amount of sessions for each day
                    .reset_index()
                    .groupby('visit_date')[['start_ts']].sum().reset_index() #get sessions per day
)
sessions_per_day
```

Out[29]:

	visit_date	start_ts
0	2017-06-01	599
1	2017-06-02	596
2	2017-06-03	429
3	2017-06-04	447
4	2017-06-05	807
...	...	...
359	2018-05-27	582
360	2018-05-28	1041
361	2018-05-29	942
362	2018-05-30	1265
363	2018-05-31	2059

364 rows × 2 columns

In [30]:
```
df = sessions_per_day
fig, ax = plt.subplots(figsize = (16,9))

ax.plot(df.visit_date, df.start_ts)
ax.set(xlabel='Session date', ylabel='Number of sessions',
       title='Number of sessions per day')
ax.grid()
plt.xticks(rotation=90)
plt.show();
```



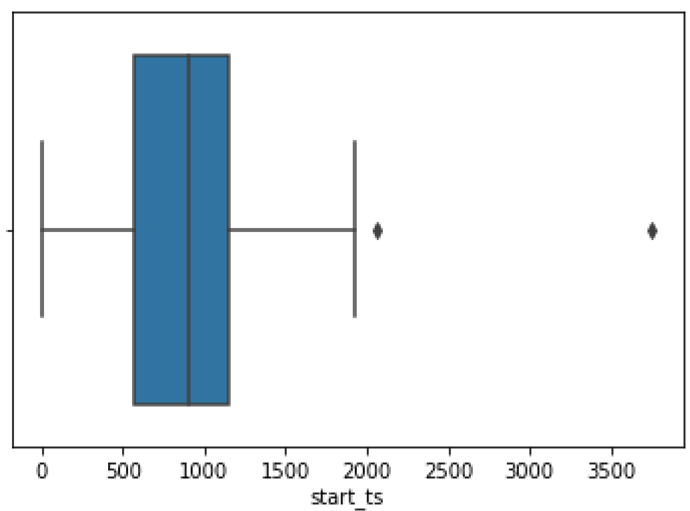
In [31]:
```
print('Average amount of sessions per day: {:.1f}'.format(sessions_per_day.start_ts.mean()))
print('Average sessions per day per user: {:.1f}'.format(sessions_per_day.start_ts.mean() /dau_total))
```

```
Average amount of sessions per day: 889.0
Average sessions per day per user: 1.1
```

I see from this analysis that average amount of sessions per day has changed throughout the year. But mostly it hasn't been much more than 1 session a day per user. But also There is some strange anomaly sometime in November with very high amount of sessions, let's build boxplot to check how the data is ditrbuted.

In [32]:
```
sns.boxplot(sessions_per_day.start_ts)
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb419d3350>



In [33]:
```
sessions_per_day.sort_values('start_ts',ascending=False).head()
```

Out[33]:

	visit_date	start_ts
176	2017-11-24	3755
363	2018-05-31	2059
177	2017-11-25	1925
245	2018-02-01	1698
298	2018-03-26	1663

In [34]:
```
#check amount of unique users for this date
visits[visits['visit_date'] == '2017-11-24'].nunique()
```

Out[34]:
```
device            2
end_ts         1068
source_id         7
start_ts       1021
uid            3090
visit_date        1
visit_year        1
visit_month       1
visit_week        1
duration        158
dtype: int64
```

It looks like something had happened on 24.11.2017. I'm not sure what was it. It could have been some event that caused lots of people to get to Yandex.Afisha or maybe some DDoS atack took place or something else. It would have been better to check this information with other departments.

Conclusion

On average there has been 889 sessions per day, amount of sessions have changed through the year, its raise looks simillar to raise of amount of unique users.

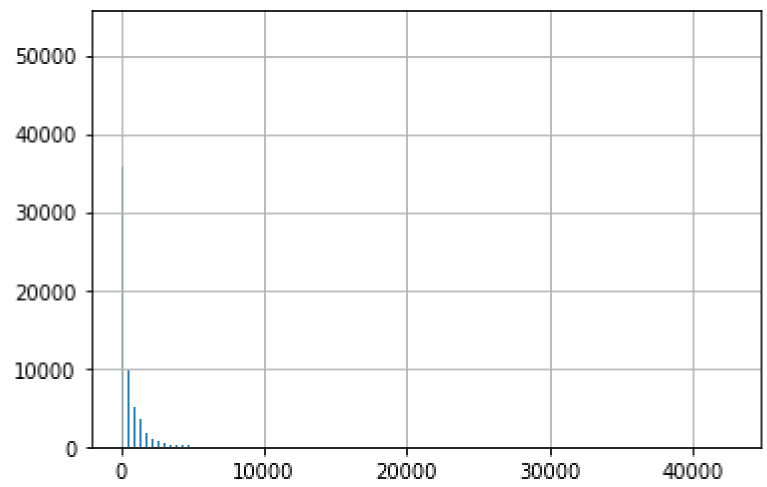
What is the length of each session?

As I have already calculated sessions' duration for each session, I don't need to do it now. I suppose that session duration should have somhow normal distribution or at least "normalish". Let's have a look at it.

In [35]:
```
#convert duration to seconds
visits['duration'] = visits.duration.dt.seconds
```

In [36]:
```
visits.duration.hist(bins='auto')
```

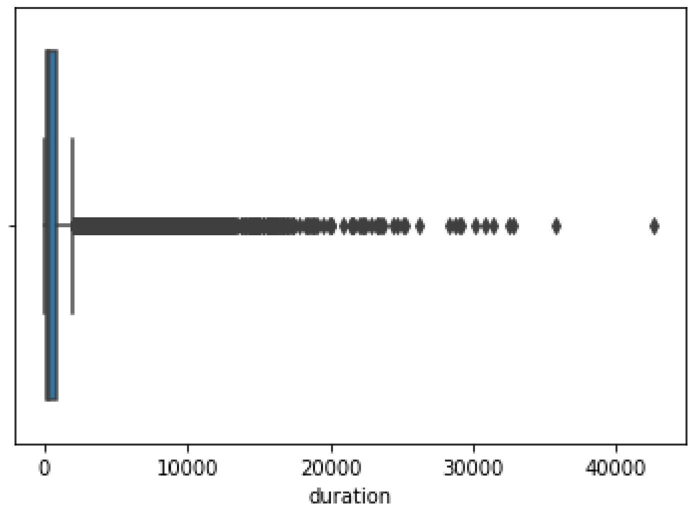
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb4075e3d0>



Not normal....

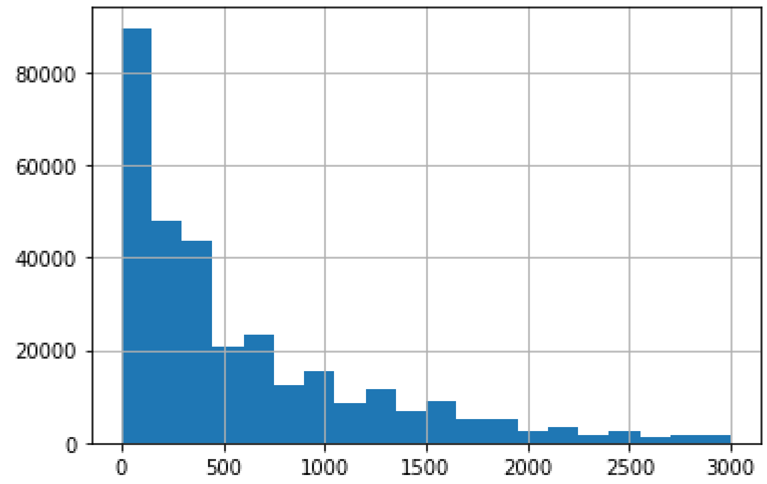
In [37]:
```
sns.boxplot(visits.duration)
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb4436c1d0>



```
In [38]: #let's plot it without outhlighers
visits.duration.hist(bins=20, range=(0,3000))
```

```
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb4199ae50>
```



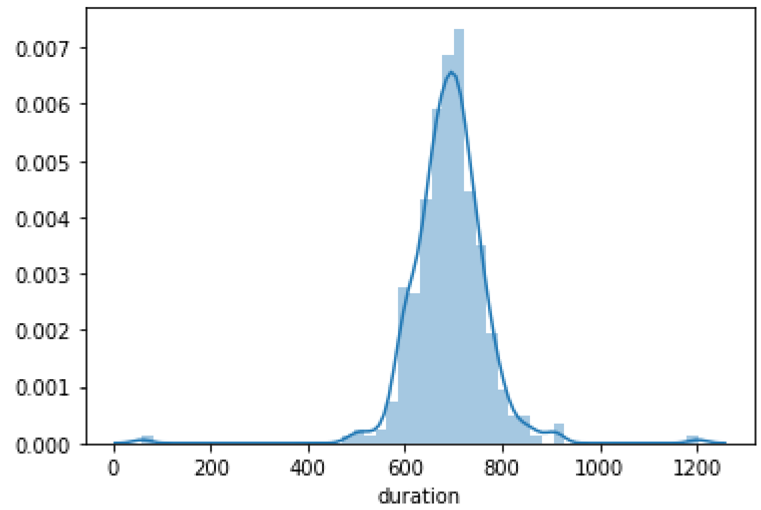

```
In [39]: visits.duration.describe()
```

```
Out[39]: count     323604.000000
mean         714.169516
std         1026.349417
min           19.000000
25%          120.000000
50%          360.000000
75%          900.000000
max        42660.000000
Name: duration, dtype: float64
```

So median lenth of a session is 360 seconds (6 minutes), while mean value is around 12 minutes. Let's calculate mean value for each day and then see distribution that way.

```
In [40]: df=visits.groupby('visit_date')['duration'].mean()
sns.distplot(df)
print ('Mean value of session length is: {:.2f}'.format(df.mean()))
```

```
Mean value of session length is: 691.41
```



Conclusion

Average lenght of a session is - 11.5 minutes, while median user usually spends on Yandex.Afisha around 6 minutes.

```
In [46]: visits.duration.value_counts()
```

```
Out[46]: 0    60
dtype: int64
```

How often do users come back?

To do this I'll calculate retention rate for all users, devided by cohorts. Here I will use months as cohort parameters.

In [104]:
```
#Add first visit date
visits['first_visit_date'] = visits.groupby('uid')['visit_date'].transform('min')
visits
```

Out[104]:

	device	end_ts	source_id	start_ts	uid	visit_date	visit_year	visit_month	visit_week	duration	first_visit_date
0	touch	2017-12-20 17:38:00	4	2017-12-20 17:20:00	16879256277535980062	2017-12-20	2017-01-01	2017-12-01	2017-12-14	1080	2017-12-20
1	desktop	2018-02-19 17:21:00	2	2018-02-19 16:53:00	104060357244891740	2018-02-19	2018-01-01	2018-02-01	2018-02-15	1680	2018-02-19
3	desktop	2018-05-20 11:23:00	9	2018-05-20 10:59:00	16174680259334210214	2018-05-20	2018-01-01	2018-05-01	2018-05-17	1440	2018-03-09
5	desktop	2017-09-03 21:36:00	5	2017-09-03 21:35:00	16007536194108375387	2017-09-03	2017-01-01	2017-09-01	2017-08-31	60	2017-09-03
6	desktop	2018-01-30 12:09:00	1	2018-01-30 11:13:00	6661610529277171451	2018-01-30	2018-01-01	2018-01-01	2018-01-25	3360	2017-06-29
...	...	...	...	...	...	...	...	...	...	...	...
359395	desktop	2017-07-29 19:07:19	2	2017-07-29 19:07:00	18363291481961487539	2017-07-29	2017-01-01	2017-07-01	2017-07-27	19	2017-07-29
359396	touch	2018-01-25 17:38:19	1	2018-01-25 17:38:00	18370831553019119586	2018-01-25	2018-01-01	2018-01-01	2018-01-25	19	2018-01-25
359397	desktop	2018-03-03 10:12:19	4	2018-03-03 10:12:00	18387297585500748294	2018-03-03	2018-01-01	2018-03-01	2018-03-01	19	2018-03-03
359398	desktop	2017-11-02 10:12:19	5	2017-11-02 10:12:00	18388616944624776485	2017-11-02	2017-01-01	2017-11-01	2017-11-02	19	2017-11-02
359399	touch	2017-09-10 13:13:19	2	2017-09-10 13:13:00	18396128934054549559	2017-09-10	2017-01-01	2017-09-01	2017-09-07	19	2017-09-10

323604 rows × 11 columns

In [105]:
```
#add month of the first visit
visits['first_visit_month'] = visits.first_visit_date.astype('datetime64[M]')
#calculate lifetime of each cohort
visits['cohort_lifetime'] = ((visits.visit_month - visits.first_visit_month)/np.timedelta64(1,'M')).round().astype(int
)
visits.cohort_lifetime.value_counts()
```

Out[105]:
```
0     242549
1      20817
2      13145
3      10624
4       8763
5       7414
6       6003
7       4624
8       3565
9       2719
10      1939
11      1442
Name: cohort_lifetime, dtype: int64
```

In [106]:
```
#create table for cohorts
cohorts = visits.groupby(['first_visit_month', 'cohort_lifetime']).agg({'uid':'nunique'}).reset_index()
cohorts.head()
```

Out[106]:

	first_visit_month	cohort_lifetime	uid
0	2017-06-01	0	11885
1	2017-06-01	1	900
2	2017-06-01	2	606
3	2017-06-01	3	710
4	2017-06-01	4	777

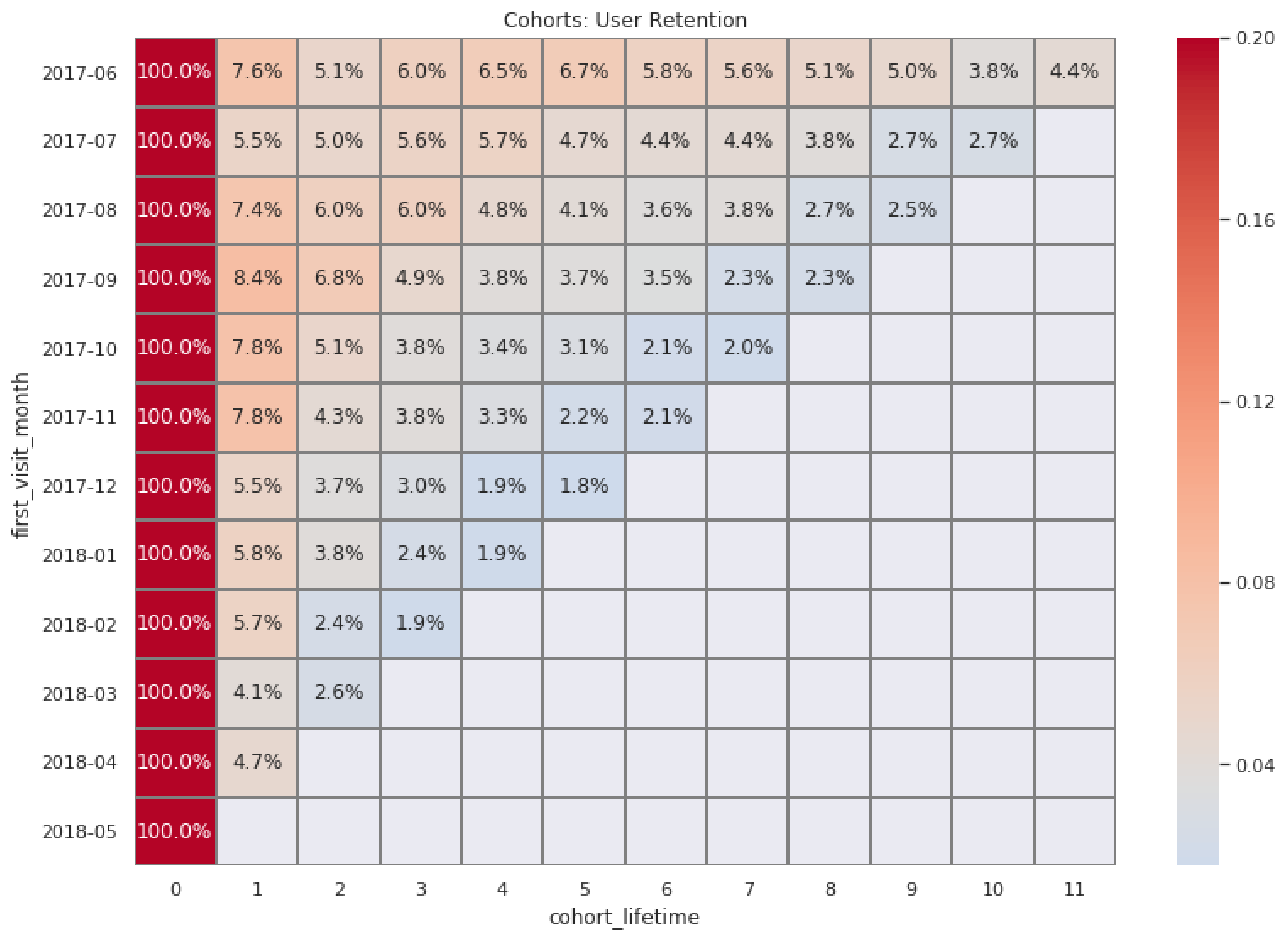
In [107]:
```
cohorts['cohort_users'] = cohorts.groupby('first_visit_month')['uid'].transform('max') #add column for all users of ea
ch cohort
cohorts['retention'] = cohorts['uid'] / cohorts['cohort_users'] #calculate retention
cohorts['first_visit_month'] = cohorts['first_visit_month'].dt.strftime('%Y-%m')
```

In [108]:
```
retention_pivot = cohorts.pivot_table(values='retention', index='first_visit_month',
                                      columns='cohort_lifetime', aggfunc='sum')
retention_pivot
```

Out[108]:

cohort_lifetime	0	1	2	3	4	5	6	7	8	9	10	11
first_visit_month												
2017-06	1.0	0.075726	0.050989	0.059739	0.065377	0.067480	0.057720	0.056121	0.050989	0.049727	0.038115	0.043921
2017-07	1.0	0.054545	0.050402	0.055645	0.056660	0.046512	0.044059	0.044059	0.037886	0.027315	0.027061	NaN
2017-08	1.0	0.074452	0.060451	0.060451	0.047970	0.041459	0.036249	0.037660	0.027133	0.024745	NaN	NaN
2017-09	1.0	0.083570	0.067769	0.049322	0.038083	0.036959	0.035372	0.022876	0.022744	NaN	NaN	NaN
2017-10	1.0	0.078129	0.050811	0.037811	0.033648	0.031184	0.020775	0.019798	NaN	NaN	NaN	NaN
2017-11	1.0	0.078183	0.042733	0.037824	0.032593	0.021729	0.020602	NaN	NaN	NaN	NaN	NaN
2017-12	1.0	0.054668	0.036518	0.030178	0.019453	0.017716	NaN	NaN	NaN	NaN	NaN	NaN
2018-01	1.0	0.057794	0.037817	0.024352	0.019249	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-02	1.0	0.056561	0.024290	0.019184	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-03	1.0	0.040760	0.025541	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-04	1.0	0.047485	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-05	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [109]:
```
sns.set(style='dark')
plt.figure(figsize=(13, 9))
plt.title('Cohorts: User Retention')
sns.heatmap(retention_pivot, annot=True, fmt='.1%',cmap='coolwarm', linewidths=1, linecolor='gray',
            center=0.035, vmax=0.2);
```



Conclusion

Usually from 4 to 8 percent of users come back to Yandex.Afisha on the second month. Wee see that first cohorts have higher return rate than the newest ones. For cohorts of March and April of 2018 only around 2% of users return on the third month. We actually see fall of return rates for all cohorts in the last months, maybe there has been less notifications or something has happened to the platform. I recommend to marketing departmant to check what changes with user notifications has been made and maybe turn them around.

Sales

When do people start buying?

Let's find date of first order for each user.

In [110]:
```
orders.head()
```

Out[110]:

	buy_ts	revenue	uid
0	2017-06-01 00:10:00	17.00	10329302124590727494
1	2017-06-01 00:25:00	0.55	11627257723692907447
2	2017-06-01 00:27:00	0.37	17903680561304213844
3	2017-06-01 00:29:00	0.55	16109239769442553005
4	2017-06-01 07:58:00	0.37	14200605875248379450

In [126]:
```
#create first orders table
user_orders = (orders
               .groupby('uid')[['buy_ts','revenue']]
               .agg({'buy_ts':'min', 'revenue':'sum'}).reset_index()
               .rename(columns={'buy_ts':'first_order','revenue':'total_revenue'})
              )
user_orders
```

Out[126]:

	uid	first_order	total_revenue
0	313578113262317	2018-01-03 21:51:00	0.55
1	1575281904278712	2017-06-03 10:13:00	3.05
2	2429014661409475	2017-10-11 18:33:00	73.33
3	2464366381792757	2018-01-28 15:54:00	2.44
4	2551852515556206	2017-11-24 10:14:00	10.99
...	...	...	...
36518	18445147675727495770	2017-11-24 09:03:00	3.05
36519	18445407535914413204	2017-09-22 23:55:00	0.88
36520	18445601152732270159	2018-03-26 22:54:00	4.22
36521	18446156210226471712	2018-02-18 19:34:00	9.78
36522	18446167067214817906	2017-10-17 10:16:00	7.94

36523 rows × 3 columns

Make a query for a dataframe that will only have info for first logins to Yandex Afisha.

In [127]:
```
first_visits = visits[visits['start_ts'] == visits.groupby('uid')['start_ts'].transform('min')]
```

Merge these two dataframes into one that will have all info needed for this analysis.

In [128]:
```
user_orders = user_orders.merge(first_visits[['uid','first_visit_date',
                                              'source_id','device']], on='uid', how='left')
user_orders
```

Out[128]:

	uid	first_order	total_revenue	first_visit_date	source_id	device
0	313578113262317	2018-01-03 21:51:00	0.55	2017-09-18	2.0	desktop
1	1575281904278712	2017-06-03 10:13:00	3.05	2017-06-03	10.0	touch
2	2429014661409475	2017-10-11 18:33:00	73.33	2017-10-11	3.0	desktop
3	2464366381792757	2018-01-28 15:54:00	2.44	2018-01-27	5.0	desktop
4	2551852515556206	2017-11-24 10:14:00	10.99	2017-11-24	5.0	desktop
...	...	...	...	...	...	...
36518	18445147675727495770	2017-11-24 09:03:00	3.05	NaT	NaN	NaN
36519	18445407535914413204	2017-09-22 23:55:00	0.88	2017-09-22	3.0	desktop
36520	18445601152732270159	2018-03-26 22:54:00	4.22	2017-08-07	2.0	desktop
36521	18446156210226471712	2018-02-18 19:34:00	9.78	2017-11-07	3.0	desktop
36522	18446167067214817906	2017-10-17 10:16:00	7.94	2017-10-17	5.0	desktop

36523 rows × 6 columns

In [129]:
```
user_orders.uid.nunique()
```

Out[129]: 36523

In [130]:
```
user_orders['first_order_date'] = user_orders.first_order.dt.date.astype('datetime64[D]')
user_orders['days_since_first_visit'] = (user_orders['first_order_date'] - user_orders['first_visit_date']).dt.days
user_orders.days_since_first_visit.value_counts()
```

Out[130]:
```
 0.0      25198
 1.0       1893
 2.0        644
 3.0        429
 4.0        367
          ...
-137.0        1
 271.0        1
-26.0         1
-180.0        1
-12.0         1
Name: days_since_first_visit, Length: 412, dtype: int64
```

In [131]:
```
#check amount negative values
user_orders.query('days_since_first_visit <0').shape[0] / user_orders.days_since_first_visit.shape[0]
```

Out[131]:
```
0.003970101032226269
```

Looks like there are some rows with negative values of days between first visit and first order, it may be some problem with log or something else on data collection side. I'll drop these values, so they won't affect further analysis.

In [132]:
```
user_orders = user_orders.query('days_since_first_visit >=0')
user_orders
```

Out[132]:

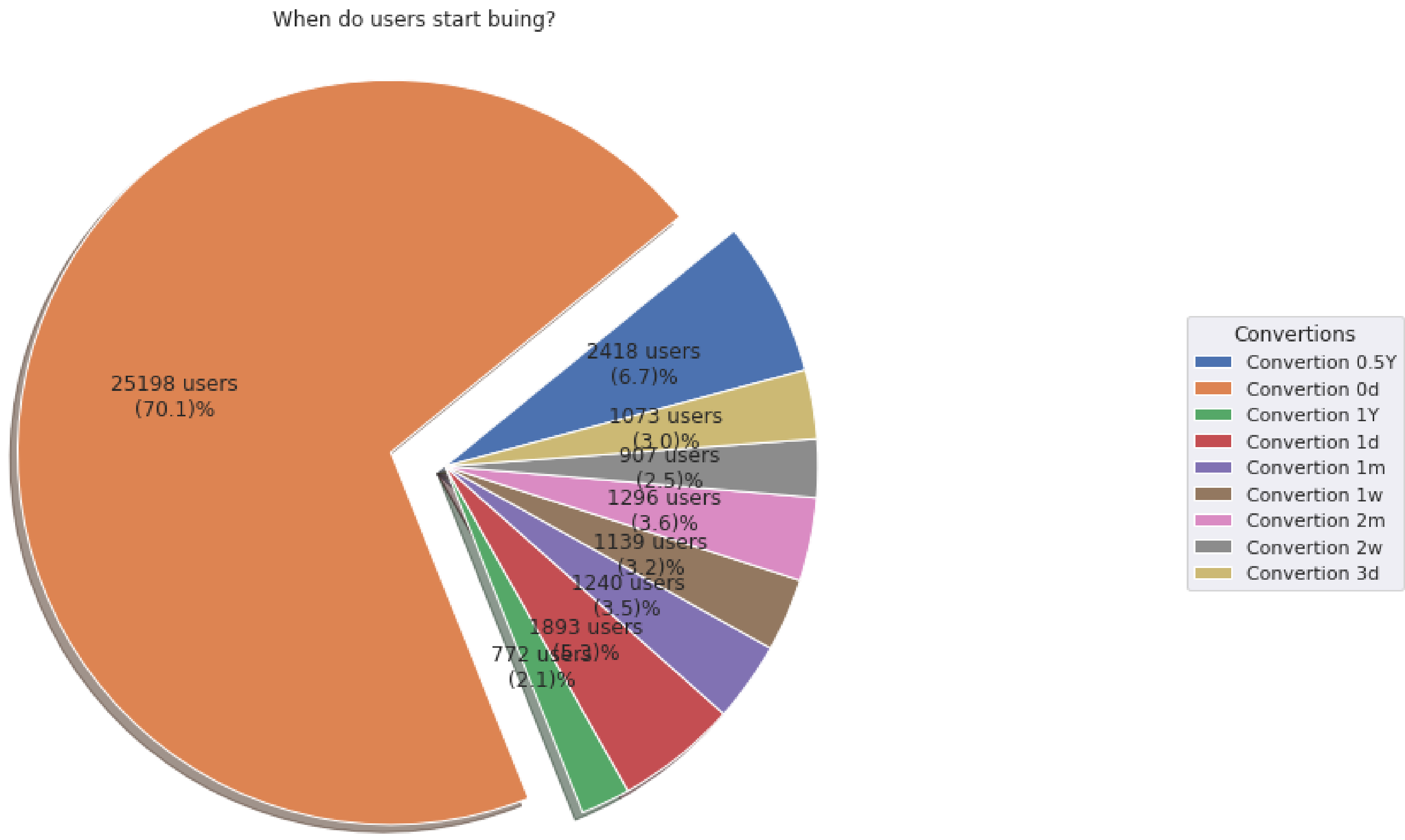
	uid	first_order	total_revenue	first_visit_date	source_id	device	first_order_date	days_since_first_visit
0	313578113262317	2018-01-03 21:51:00	0.55	2017-09-18	2.0	desktop	2018-01-03	107.0
1	1575281904278712	2017-06-03 10:13:00	3.05	2017-06-03	10.0	touch	2017-06-03	0.0
2	2429014661409475	2017-10-11 18:33:00	73.33	2017-10-11	3.0	desktop	2017-10-11	0.0
3	2464366381792757	2018-01-28 15:54:00	2.44	2018-01-27	5.0	desktop	2018-01-28	1.0
4	2551852515556206	2017-11-24 10:14:00	10.99	2017-11-24	5.0	desktop	2017-11-24	0.0
...	...	...	...	...	...	...	...	...
36517	18442290965339407211	2018-02-05 19:39:00	0.18	2018-02-05	3.0	touch	2018-02-05	0.0
36519	18445407535914413204	2017-09-22 23:55:00	0.88	2017-09-22	3.0	desktop	2017-09-22	0.0
36520	18445601152732270159	2018-03-26 22:54:00	4.22	2017-08-07	2.0	desktop	2018-03-26	231.0
36521	18446156210226471712	2018-02-18 19:34:00	9.78	2017-11-07	3.0	desktop	2018-02-18	103.0
36522	18446167067214817906	2017-10-17 10:16:00	7.94	2017-10-17	5.0	desktop	2017-10-17	0.0

35936 rows × 8 columns

In [133]:
```
def convertion_prog(days):
    if days == 0: return 'Convertion 0d'
    elif days == 1: return 'Convertion 1d'
    elif days <=3: return 'Convertion 3d'
    elif days <=7: return 'Convertion 1w'
    elif days <=14: return 'Convertion 2w'
    elif days <= 31: return 'Convertion 1m'
    elif days <=62: return 'Convertion 2m'
    elif days <=182: return 'Convertion 0.5Y'
    else: return 'Convertion 1Y'
```

In [134]:
```
user_orders['convertion'] = user_orders['days_since_first_visit'].apply(convertion_prog)
```

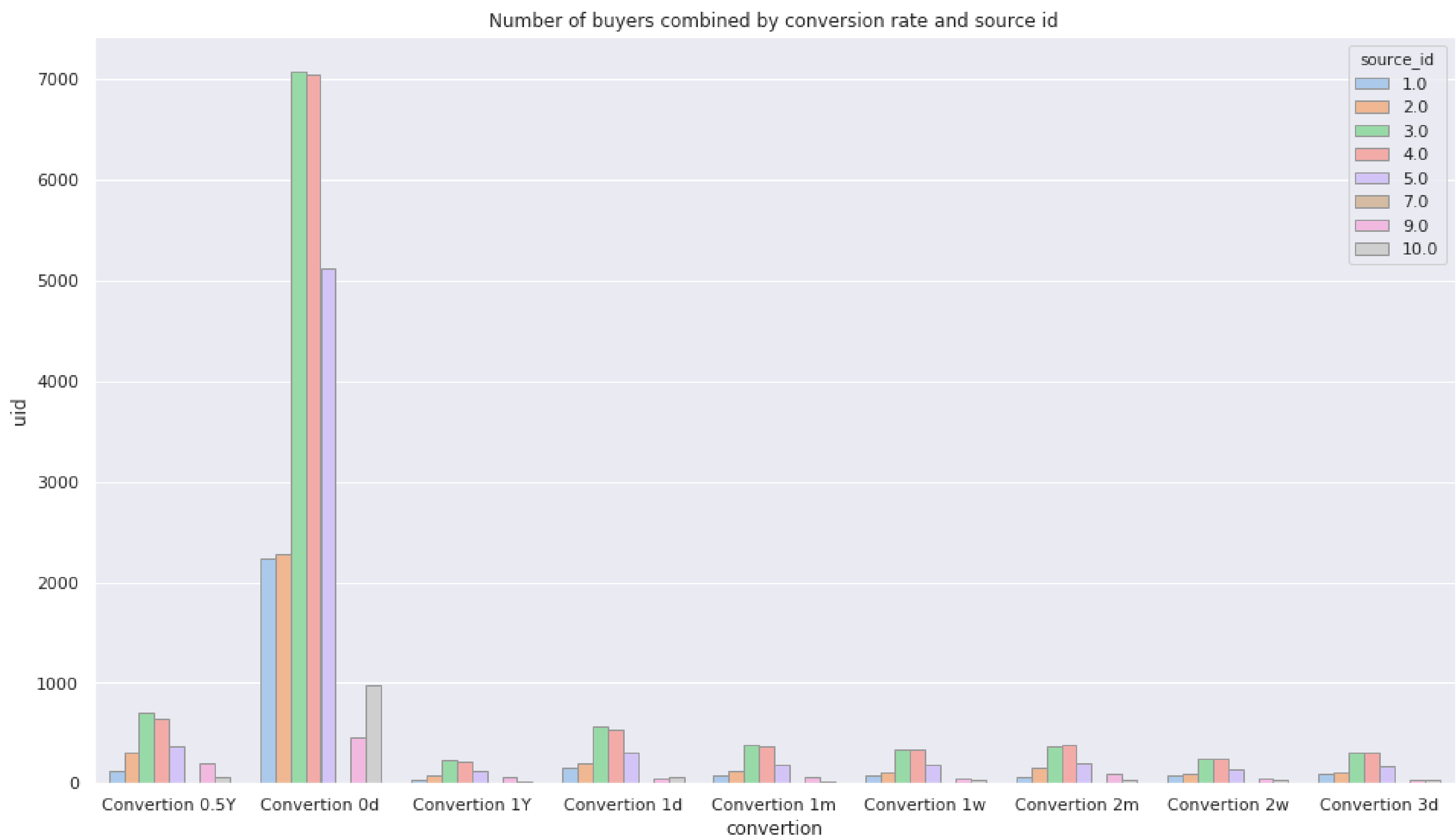
```
In [135]: df = user_orders.groupby('convertion')[['uid']].nunique().reset_index()

fig, ax = plt.subplots(figsize = (16,9))
my_explode = (0, 0.15, 0, 0, 0, 0, 0, 0, 0)
plt.pie(df['uid'], autopct=lambda p:"{:.0f} users\n({:.1f})%".format(p*sum(df['uid'])/100, p),
        startangle=15, shadow = True, explode=my_explode)
plt.title('When do users start buing?')
plt.axis('equal')
ax.legend(df['convertion'],
          title="Convertions",
          loc="center left",
          bbox_to_anchor=(1, 0, 0.5, 1))
plt.show()
```



Most of users that start buying usually make their first purchase on the day they register. Almost 70 percent of buyers act this way, so we should focus on getting our user to final step during his first day, becuase later it becomes less likely that he would buy.

```
In [136]: df = user_orders.groupby(['convertion','source_id'])[['uid']].nunique().reset_index()
fig, ax = plt.subplots(figsize=(16, 9))
ax.set_title('Number of buyers combined by conversion rate and source id')
plt.grid()
sns.barplot(x='convertion', y='uid', hue='source_id', data=df, palette="pastel", edgecolor=".6", ax=ax)
```

```
Out[136]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2ce7dd6450>
```



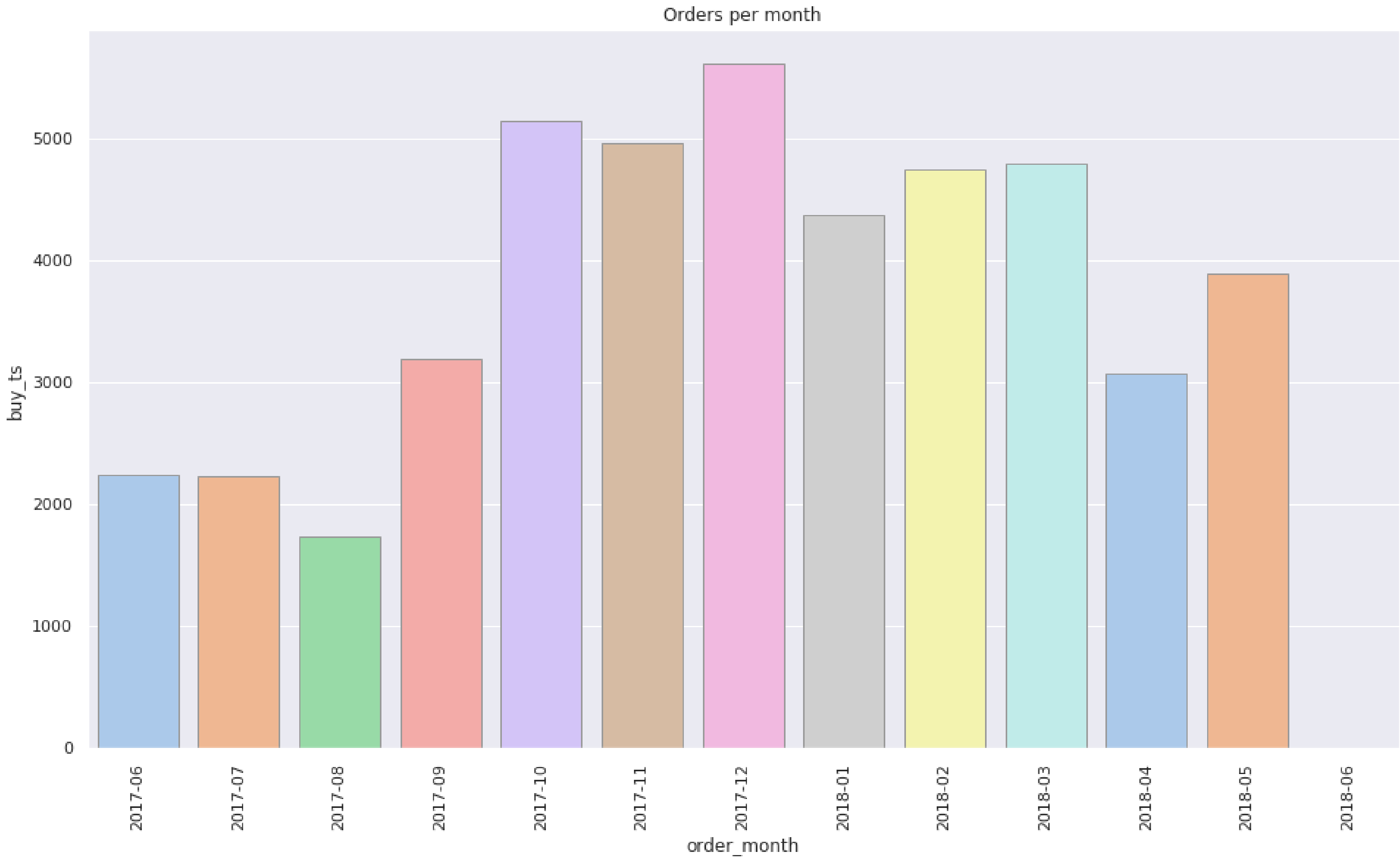
From here we can see that even though the scale is different, most effective ways to attract custumers stay the same. Most users who make purchase come from sources 3 and 4, while sources 10 and 7 show to be the most ineffective.

How many orders do they make during a given period of time?

For this I'll group all orders by the month they were made and will check how many orders were made each month.

In [138]:
```
orders['order_month'] = orders.buy_ts.astype('datetime64[M]')
orders_per_month = orders.groupby('order_month')[['buy_ts','revenue']].agg({'buy_ts':'nunique', 'revenue':'sum'}).rese
t_index()
orders_per_month['order_month'] = orders_per_month['order_month'].dt.strftime('%Y-%m')
fig, ax = plt.subplots(figsize=(16, 9))
plt.xticks(rotation=90)
ax.set_title('Orders per month')
ax.set(xlabel='Order Month', ylabel='Orders Per Month')
plt.grid()
sns.barplot(x='order_month', y='buy_ts', data=orders_per_month, palette="pastel", edgecolor=".6", ax=ax)
```

Out[138]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2ce77f6290>



Here I see that Yandex.Afisha definetly shows some success this year, bacause amount of orders have increased. I can't tell if we can expect same rise closer to the end of 2018, but the info is good.

Now let's check how many orders does a user make on average per month and what is average revenue per user per month.

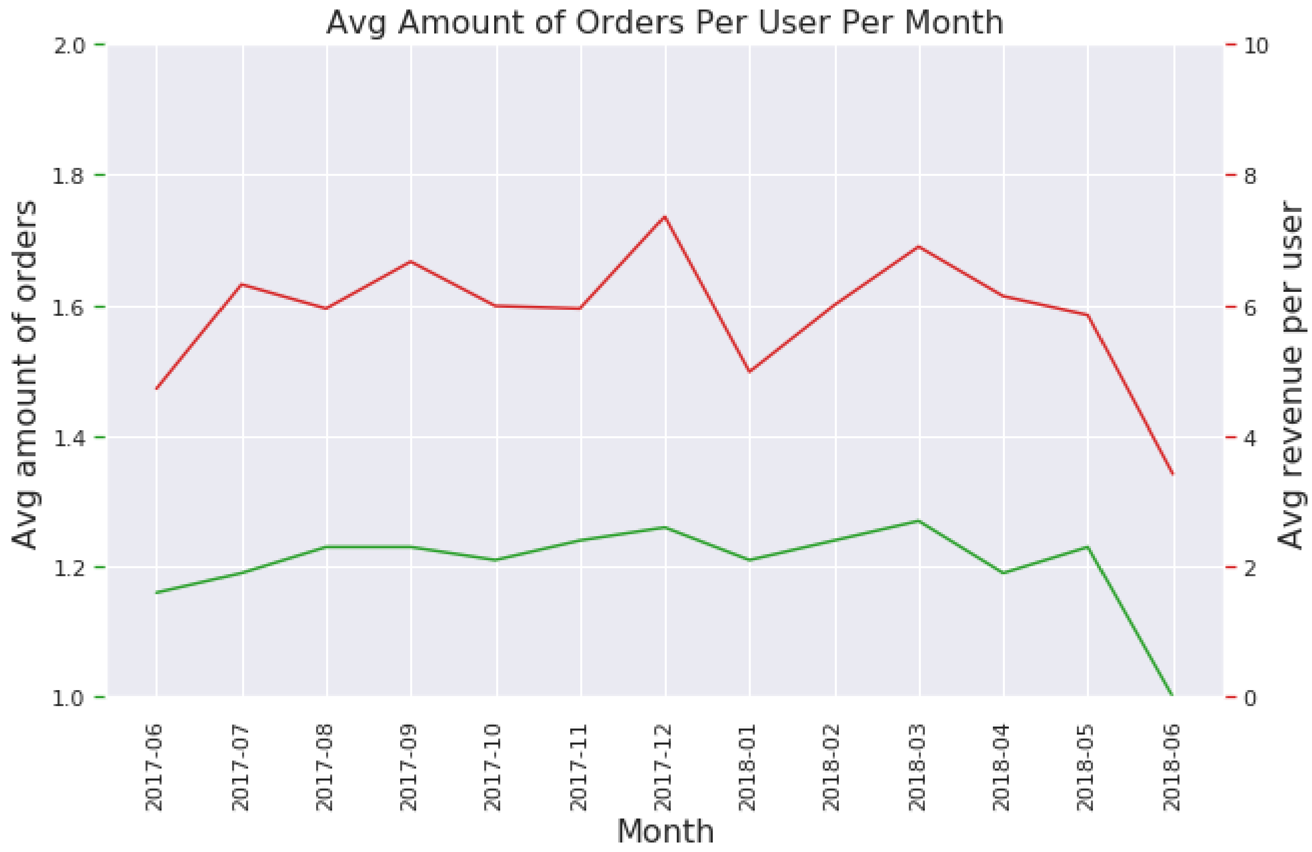
In [140]:
```
orders_per_user_per_month = (
    orders
    .groupby(['order_month','uid'])[['buy_ts', 'revenue']]
    .agg({'buy_ts':'nunique', 'revenue':'sum'})
    .reset_index()
)
```

In [144]:
```
orders_per_user_per_month = (orders_per_user_per_month
                             .groupby('order_month')[['buy_ts','revenue']].mean().round(2)
                             .reset_index()
                            )
orders_per_user_per_month['order_month'] = orders_per_user_per_month['order_month'].dt.strftime('%Y-%m')
orders_per_user_per_month
```

Out[144]:

	order_month	buy_ts	revenue
0	2017-06	1.16	4.72
1	2017-07	1.19	6.32
2	2017-08	1.23	5.95
3	2017-09	1.23	6.67
4	2017-10	1.21	5.99
5	2017-11	1.24	5.95
6	2017-12	1.26	7.36
7	2018-01	1.21	4.98
8	2018-02	1.24	6.00
9	2018-03	1.27	6.90
10	2018-04	1.19	6.14
11	2018-05	1.23	5.85
12	2018-06	1.00	3.42

In [145]:
```
fig, ax = plt.subplots(figsize=(10, 6))
ax.set_title('Avg Amount of Orders Per User Per Month',fontsize=16)
plt.xticks(rotation=90)
ax.tick_params(axis='y')
plt.grid()
#plot line chart for amount of orders per month
plt.ylim(1,2)
sns.lineplot(x='order_month', y='buy_ts', data=orders_per_user_per_month, sort=False, ax=ax, color = 'tab:green')
ax.set_xlabel('Month', fontsize=16)
ax.set_ylabel('Avg amount of orders',fontsize=16)
ax.tick_params(axis='y', color='tab:green')
#plot line chart for revenue per user per month
ax2 = ax.twinx()
plt.ylim(0,10)
sns.lineplot(x='order_month', y='revenue', data=orders_per_user_per_month, sort=False, ax=ax2, color = 'tab:red')
ax2.set_ylabel('Avg revenue per user', fontsize=16)
ax2.tick_params(axis='y', color='tab:red')
```



Conclution

Here I see that on average people make around 1.2 orders per month and it doesn't really change that much throughout the time. So we can suppose that making a user do more orders per month might be a tough task, maybe because there is a limited amount of events that he wants to visit in one month. So I thing for us it's useful to keep the users that we have on the folowing months.

What is the average purchase size?

I have already calculated average profit per user per month in previous section.

In [146]:
```
print ('Average purchase size for one user per month: {:.2f}'.format(orders_per_user_per_month.revenue.mean()))
```

```
Average purchase size for one user per month: 5.87
```

But I can also calulate the average purchase per month instead, and see how it has changed.

In [147]:
```
orders.head()
```

Out[147]:

	buy_ts	revenue	uid	order_month
0	2017-06-01 00:10:00	17.00	10329302124590727494	2017-06-01
1	2017-06-01 00:25:00	0.55	11627257723692907447	2017-06-01
2	2017-06-01 00:27:00	0.37	17903680561304213844	2017-06-01
3	2017-06-01 00:29:00	0.55	16109239769442553005	2017-06-01
4	2017-06-01 07:58:00	0.37	14200605875248379450	2017-06-01

In [148]:
```
orders.pivot_table(index='buy_ts', columns='order_month', values='revenue')
```

Out[148]:

order_month	2017-06-01	2017-07-01	2017-08-01	2017-09-01	2017-10-01	2017-11-01	2017-12-01	2018-01-01	2018-02-01	2018-03-01	2018-04-01	2018-05-01	2018-06-01
buy_ts													
2017-06-01 00:10:00	17.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2017-06-01 00:25:00	0.55	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2017-06-01 00:27:00	0.37	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2017-06-01 00:29:00	0.55	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2017-06-01 07:58:00	0.37	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2018-05-31 23:43:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.67	NaN
2018-05-31 23:50:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	5.22	NaN
2018-05-31 23:54:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.30	NaN
2018-05-31 23:56:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.67	NaN
2018-06-01 00:02:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.42

45991 rows × 13 columns

In [149]:
```
(orders
 .groupby('order_month')[['buy_ts','revenue']]
 .agg({'buy_ts': 'nunique', 'revenue':'sum'})
)
```

Out[149]:

order_month	buy_ts	revenue
2017-06-01	2245	9557.49
2017-07-01	2236	12539.47
2017-08-01	1737	8758.78
2017-09-01	3188	18345.51
2017-10-01	5136	27987.70
2017-11-01	4964	27069.93
2017-12-01	5604	36388.60
2018-01-01	4369	19417.13
2018-02-01	4746	25560.54
2018-03-01	4795	28834.59
2018-04-01	3075	16858.06
2018-05-01	3895	20735.98
2018-06-01	1	3.42

In [150]:
```
revenue_per_month = (
    orders
    .groupby('order_month')[['buy_ts','revenue']]
    .agg({'buy_ts': 'nunique', 'revenue':'sum'})
    .eval('avg_purchase = revenue / buy_ts')
    .reset_index()
)
```

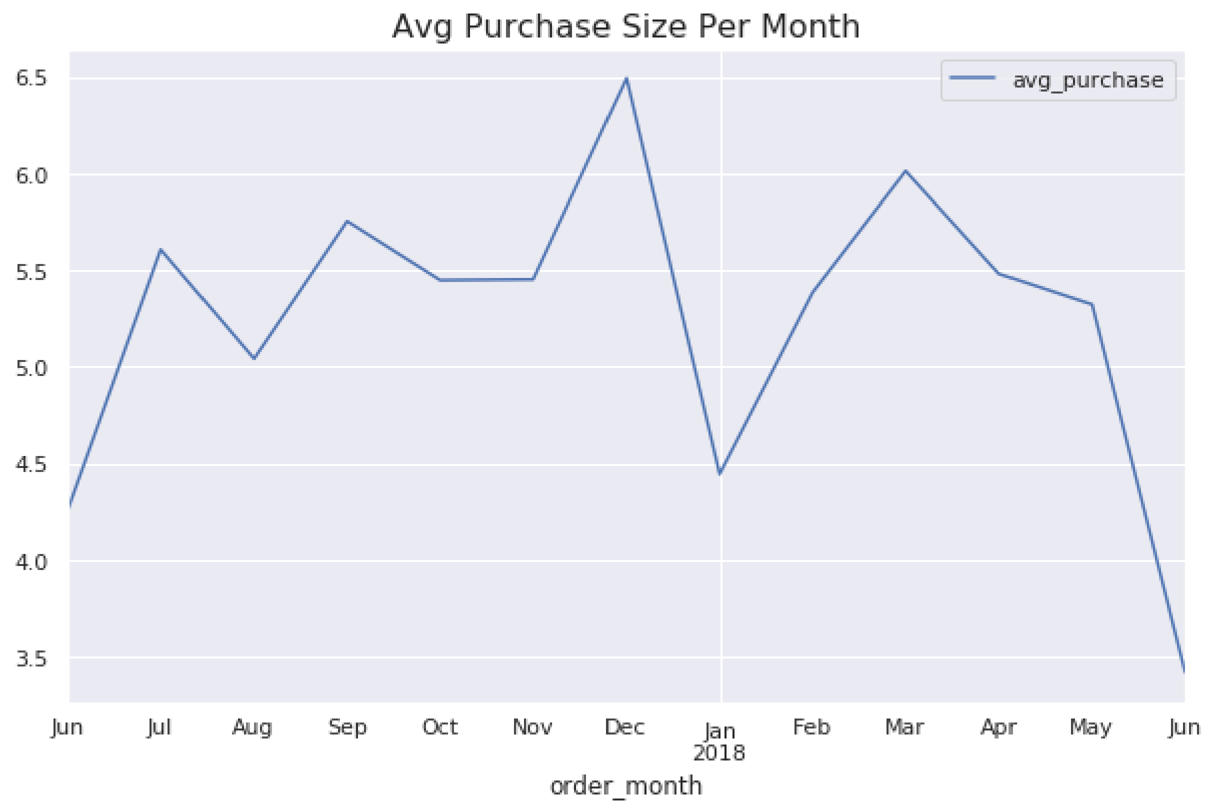
In [152]:
```
revenue_per_month
```

Out[152]:

	order_month	buy_ts	revenue	avg_purchase
0	2017-06-01	2245	9557.49	4.257234
1	2017-07-01	2236	12539.47	5.607992
2	2017-08-01	1737	8758.78	5.042476
3	2017-09-01	3188	18345.51	5.754551
4	2017-10-01	5136	27987.70	5.449319
5	2017-11-01	4964	27069.93	5.453249
6	2017-12-01	5604	36388.60	6.493326
7	2018-01-01	4369	19417.13	4.444296
8	2018-02-01	4746	25560.54	5.385702
9	2018-03-01	4795	28834.59	6.013470
10	2018-04-01	3075	16858.06	5.482296
11	2018-05-01	3895	20735.98	5.323743
12	2018-06-01	1	3.42	3.420000

In [153]:
```
fig, ax = plt.subplots(figsize=(10, 6))
ax.set_title('Avg Purchase Size Per Month',fontsize=16)
plt.grid()
revenue_per_month.plot(y='avg_purchase', x='order_month', ax=ax, grid=True)
```

Out[153]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2ce75bd1d0>



In [154]:
```
print ('Average purchase size: {:.2f}'.format(revenue_per_month.avg_purchase.mean()))
```

```
Average purchase size: 5.24
```

Conclusion

Average purchase fluctuated thorugh the year, we see that purchases sizes gut bigger by December and are very low for January. I suppose that in December lots of people buy tickets to children events and for company events for New Year, so maybe they buy in group, an that increases the average purchase size. In January there is a decrease in average purchase size which may be caused by the fact that there usually aren't any big events or concerts in the January, but I'm not certain about that:)

How much money do they bring? (LTV)

For this I'm going to use monthly cohorts like I did before with visits when I was calculating retention pivot.

In [155]:
```
#get for each user his first order month
orders['first_order_month'] = orders.groupby('uid')['buy_ts'].transform('min').astype('datetime64[M]')
orders
```

Out[155]:

	buy_ts	revenue	uid	order_month	first_order_month
0	2017-06-01 00:10:00	17.00	10329302124590727494	2017-06-01	2017-06-01
1	2017-06-01 00:25:00	0.55	11627257723692907447	2017-06-01	2017-06-01
2	2017-06-01 00:27:00	0.37	17903680561304213844	2017-06-01	2017-06-01
3	2017-06-01 00:29:00	0.55	16109239769442553005	2017-06-01	2017-06-01
4	2017-06-01 07:58:00	0.37	14200605875248379450	2017-06-01	2017-06-01
...	...	...	...	...	...
50410	2018-05-31 23:50:00	4.64	12296626599487328624	2018-05-01	2018-05-01
50411	2018-05-31 23:50:00	5.80	11369640365507475976	2018-05-01	2018-05-01
50412	2018-05-31 23:54:00	0.30	1786462140797698849	2018-05-01	2018-05-01
50413	2018-05-31 23:56:00	3.67	3993697860786194247	2018-05-01	2018-05-01
50414	2018-06-01 00:02:00	3.42	83872787173869366	2018-06-01	2018-06-01

50415 rows × 5 columns

Create dataframe for cohorts.

In [156]:
```
#create dataframe with amount of buyers for each month
cohort_sizes = (orders.groupby('first_order_month')
                .agg({'uid': 'nunique'})
                .reset_index()
                .rename(columns = {'uid': 'n_buyers'}, inplace = False)
               )
cohort_sizes
```

Out[156]:

	first_order_month	n_buyers
0	2017-06-01	2023
1	2017-07-01	1923
2	2017-08-01	1370
3	2017-09-01	2581
4	2017-10-01	4340
5	2017-11-01	4081
6	2017-12-01	4383
7	2018-01-01	3373
8	2018-02-01	3651
9	2018-03-01	3533
10	2018-04-01	2276
11	2018-05-01	2988
12	2018-06-01	1

In [157]:
```
cohorts = orders.groupby(['first_order_month','order_month']).agg({'revenue': 'sum'}).reset_index()
```

In [158]:
```
report = pd.merge(cohort_sizes, cohorts, on='first_order_month')
```

In [159]:
```
report
```

Out[159]:

	first_order_month	n_buyers	order_month	revenue
0	2017-06-01	2023	2017-06-01	9557.49
1	2017-06-01	2023	2017-07-01	981.82
2	2017-06-01	2023	2017-08-01	885.34
3	2017-06-01	2023	2017-09-01	1931.30
4	2017-06-01	2023	2017-10-01	2068.58
...	...	...	...	...
74	2018-03-01	3533	2018-05-01	1114.87
75	2018-04-01	2276	2018-04-01	10600.69
76	2018-04-01	2276	2018-05-01	1209.92
77	2018-05-01	2988	2018-05-01	13925.76
78	2018-06-01	1	2018-06-01	3.42

79 rows × 4 columns

Next step is to calculate LTV. We know that LTV is calculated based on gross profit, rather than on revenue, I need to find the gross profit by multiplying revenue by profitability. Second, LTV is a relative parameter, and it's easier to study for "mature" cohorts, so I'll make the columns show the cohort's age instead of the month of the order.

I don't have enough information to calculate margin rate by myself, but I'll use the value of 40% as an average for this calculation.

In [160]:

```
margin_rate = .4
report['gp'] = report['revenue'] * margin_rate
report['age'] = (report['order_month'] - report['first_order_month']) / np.timedelta64(1, 'M')
report['age'] = report['age'].round().astype('int')

#calculate LTV
report['ltv'] = report['gp'] / report['n_buyers']
report['first_order_month'] = report['first_order_month'].dt.strftime('%Y-%m')
report.head()
```

Out[160]:

	first_order_month	n_buyers	order_month	revenue	gp	age	ltv
0	2017-06	2023	2017-06-01	9557.49	3822.996	0	1.889766
1	2017-06	2023	2017-07-01	981.82	392.728	1	0.194131
2	2017-06	2023	2017-08-01	885.34	354.136	2	0.175055
3	2017-06	2023	2017-09-01	1931.30	772.520	3	0.381869
4	2017-06	2023	2017-10-01	2068.58	827.432	4	0.409012

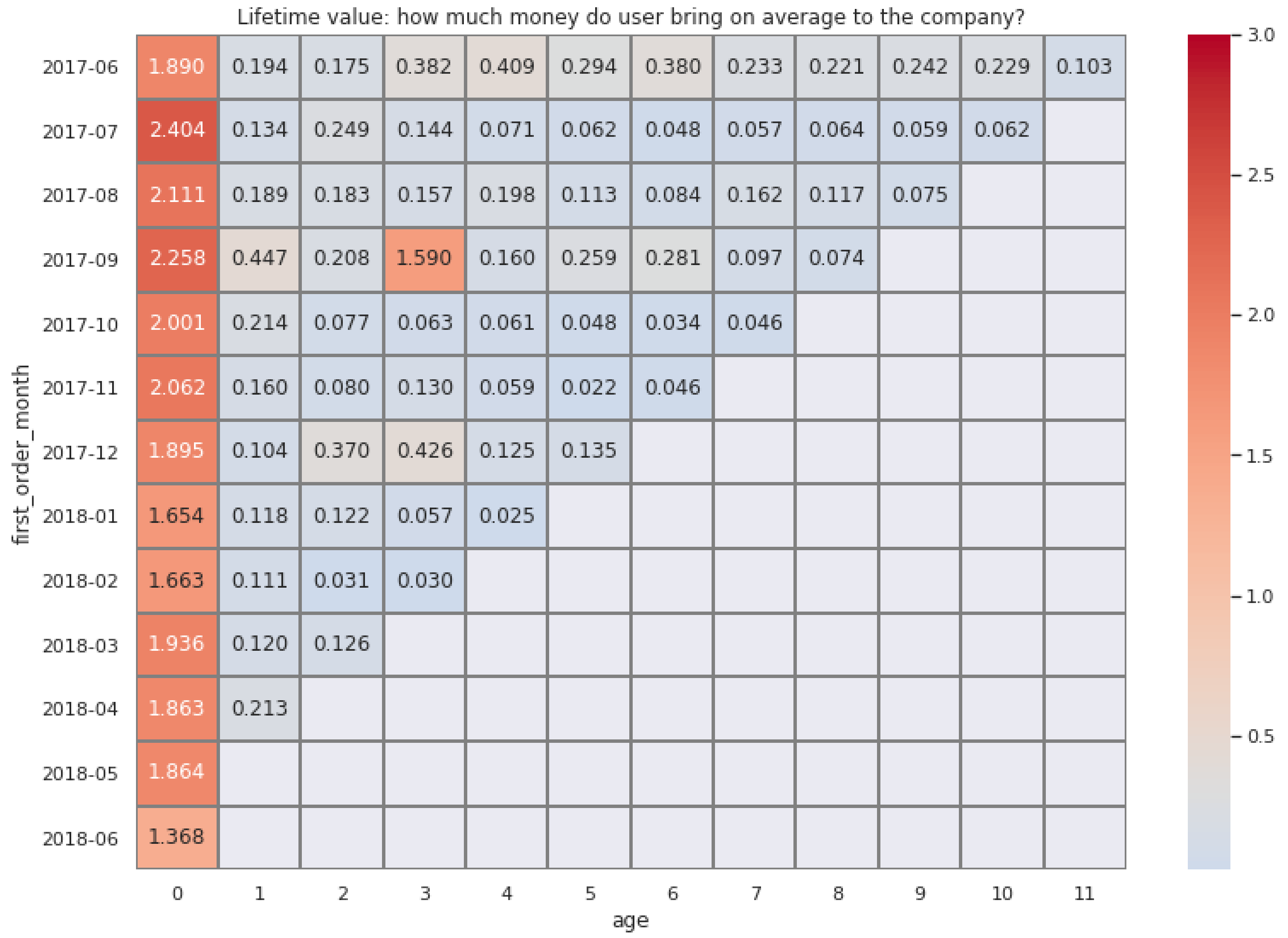
In [161]:

```
output = report.pivot_table(
    index='first_order_month',
    columns='age',
    values='ltv',
    aggfunc='mean').round(3)

output
```

Out[161]:

age	0	1	2	3	4	5	6	7	8	9	10	11
first_order_month												
2017-06	1.890	0.194	0.175	0.382	0.409	0.294	0.380	0.233	0.221	0.242	0.229	0.103
2017-07	2.404	0.134	0.249	0.144	0.071	0.062	0.048	0.057	0.064	0.059	0.062	NaN
2017-08	2.111	0.189	0.183	0.157	0.198	0.113	0.084	0.162	0.117	0.075	NaN	NaN
2017-09	2.258	0.447	0.208	1.590	0.160	0.259	0.281	0.097	0.074	NaN	NaN	NaN
2017-10	2.001	0.214	0.077	0.063	0.061	0.048	0.034	0.046	NaN	NaN	NaN	NaN
2017-11	2.062	0.160	0.080	0.130	0.059	0.022	0.046	NaN	NaN	NaN	NaN	NaN
2017-12	1.895	0.104	0.370	0.426	0.125	0.135	NaN	NaN	NaN	NaN	NaN	NaN
2018-01	1.654	0.118	0.122	0.057	0.025	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-02	1.663	0.111	0.031	0.030	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-03	1.936	0.120	0.126	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-04	1.863	0.213	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-05	1.864	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-06	1.368	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [162]:
```python
plt.figure(figsize=(13, 9))
plt.title('Lifetime value: how much money do user bring on average to the company?')
sns.heatmap(output, annot=True, fmt='.3f',cmap='coolwarm', linewidths=1, linecolor='gray',
            center=0.3, vmax=3);
```



Conclusion

1. On average one user doesn't bring a lot of money to Yandex.Afisha;
2. On average users bring most of the money during their first month;
3. There is one cohort that shows that on 4th month users have brought a comparable amount of money to their first month (I mean cohort of 2017-09);
4. Even when after a year users continue to come back to use the service, so we chouldn't disregard users from old cohorts.

Marketing

How much money was spent? Overall/per source/over time

In [163]:
```python
costs.head()
```

Out[163]:

	source_id	dt	costs
0	1	2017-06-01	75.20
1	1	2017-06-02	62.25
2	1	2017-06-03	36.53
3	1	2017-06-04	55.00
4	1	2017-06-05	57.08

In [164]:
```python
print ('Money spent overall: ', costs.costs.sum())
```

```
Money spent overall:  329131.62
```

Now let's check how the much money were spend over time

In [165]:
```python
costs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2542 entries, 0 to 2541
Data columns (total 3 columns):
source_id    2542 non-null int64
dt           2542 non-null datetime64[ns]
costs        2542 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(1)
memory usage: 59.7 KB
```

In [166]:
```
costs
```

Out[166]:

	source_id	dt	costs
0	1	2017-06-01	75.20
1	1	2017-06-02	62.25
2	1	2017-06-03	36.53
3	1	2017-06-04	55.00
4	1	2017-06-05	57.08
...	...	...	...
2537	10	2018-05-27	9.92
2538	10	2018-05-28	21.26
2539	10	2018-05-29	11.32
2540	10	2018-05-30	33.15
2541	10	2018-05-31	17.60

2542 rows × 3 columns

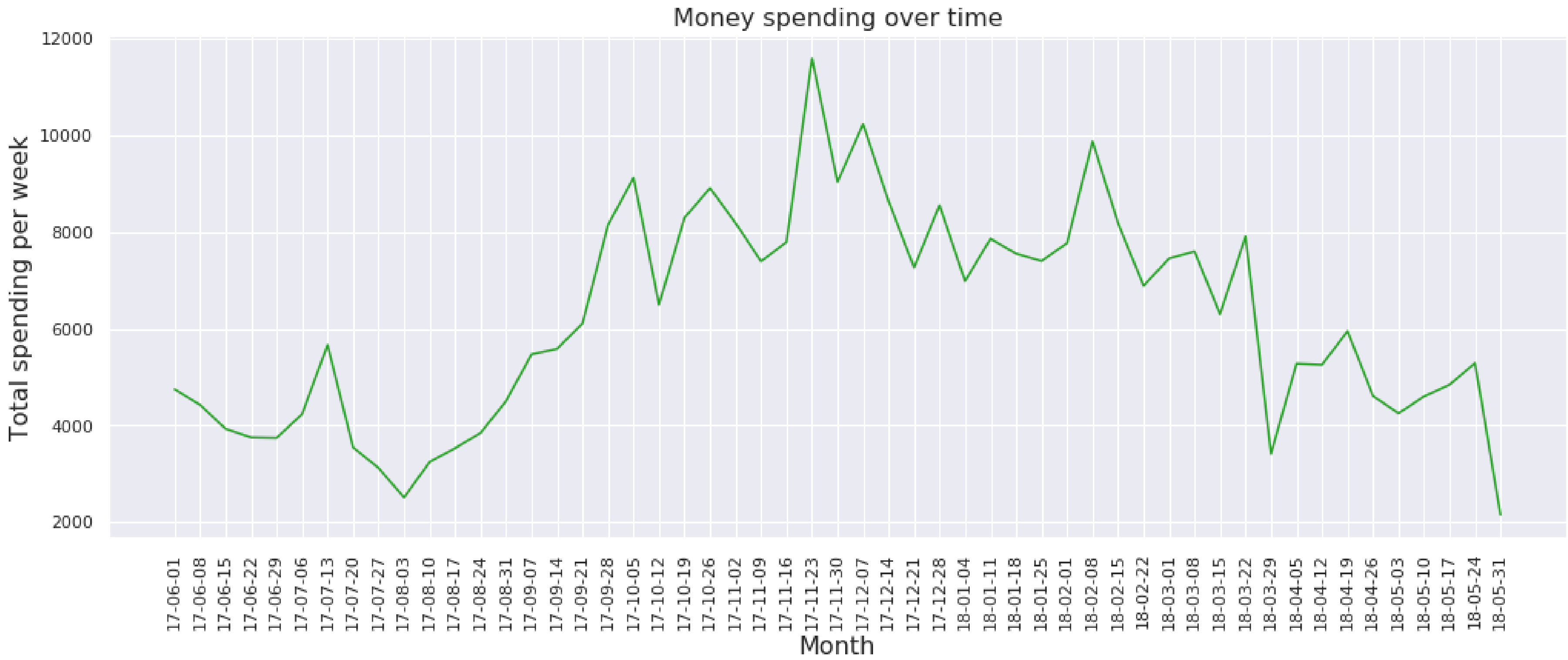
In [167]:
```
#group the data by week
costs['week_spending'] = costs.dt.astype('datetime64[W]')
costs['week_spending'] = costs['week_spending'].dt.strftime('%y-%m-%d')
costs_by_week = costs.groupby('week_spending')[['costs']].sum().reset_index()
costs_by_week.head()
```

Out[167]:

	week_spending	costs
0	17-06-01	4750.61
1	17-06-08	4427.52
2	17-06-15	3933.09
3	17-06-22	3753.14
4	17-06-29	3743.03

In [168]:
```
fig, ax = plt.subplots(figsize=(17, 6))
ax.set_title('Money spending over time',fontsize=16)
plt.xticks(rotation=90)
ax.tick_params(axis='y')
plt.grid()
#plot line chart for amount of orders per month
sns.lineplot(x='week_spending', y='costs', data=costs_by_week, sort=False, ax=ax, color = 'tab:green')
ax.set_xlabel('Month', fontsize=16)
ax.set_ylabel('Total spending per week',fontsize=16)
```

Out[168]: `Text(0, 0.5, 'Total spending per week')`



Here I see that amount of money spent on marketing has really fluctuated over time. Yandex.Afisha might be getting this decline of orders in recent months because money spending has fallen to much lower level. To make more further conclusions we'll need to see the data of previous years.

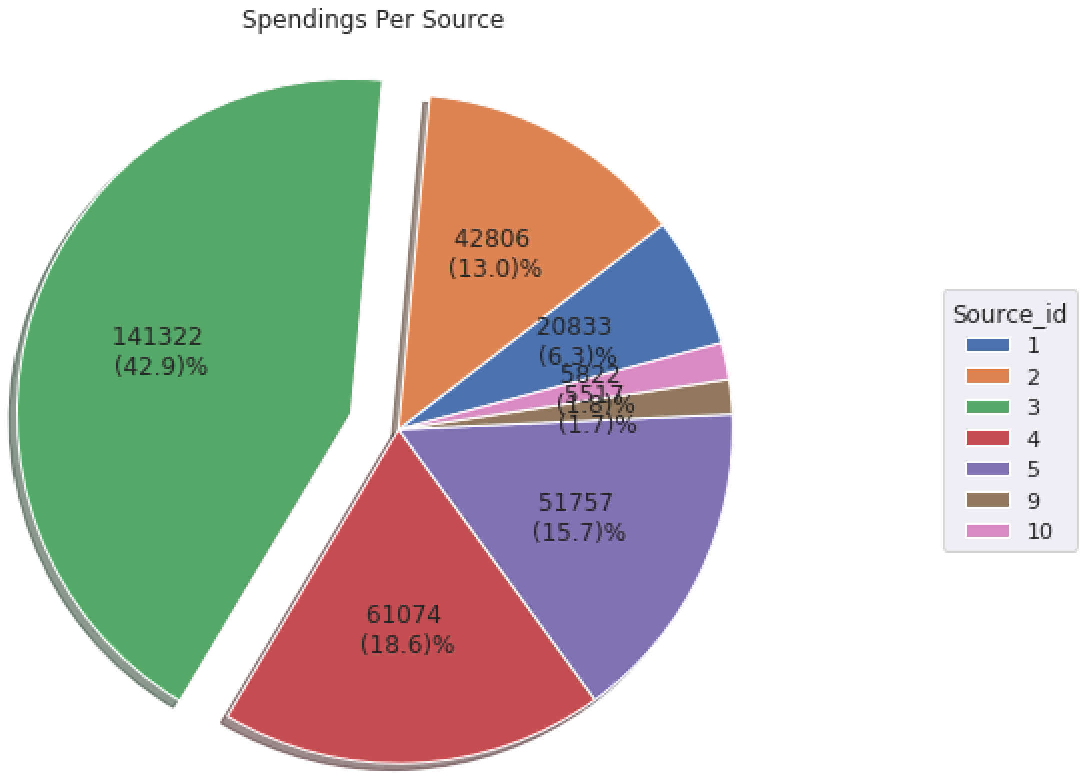
Now let's see what happened with spendings per source. First I'll check how spendings were generally distributed over sources.

In [169]:
```
costs_per_source = costs.groupby('source_id')[['costs']].sum().reset_index()
costs_per_source
```

Out[169]:

	source_id	costs
0	1	20833.27
1	2	42806.04
2	3	141321.63
3	4	61073.60
4	5	51757.10
5	9	5517.49
6	10	5822.49

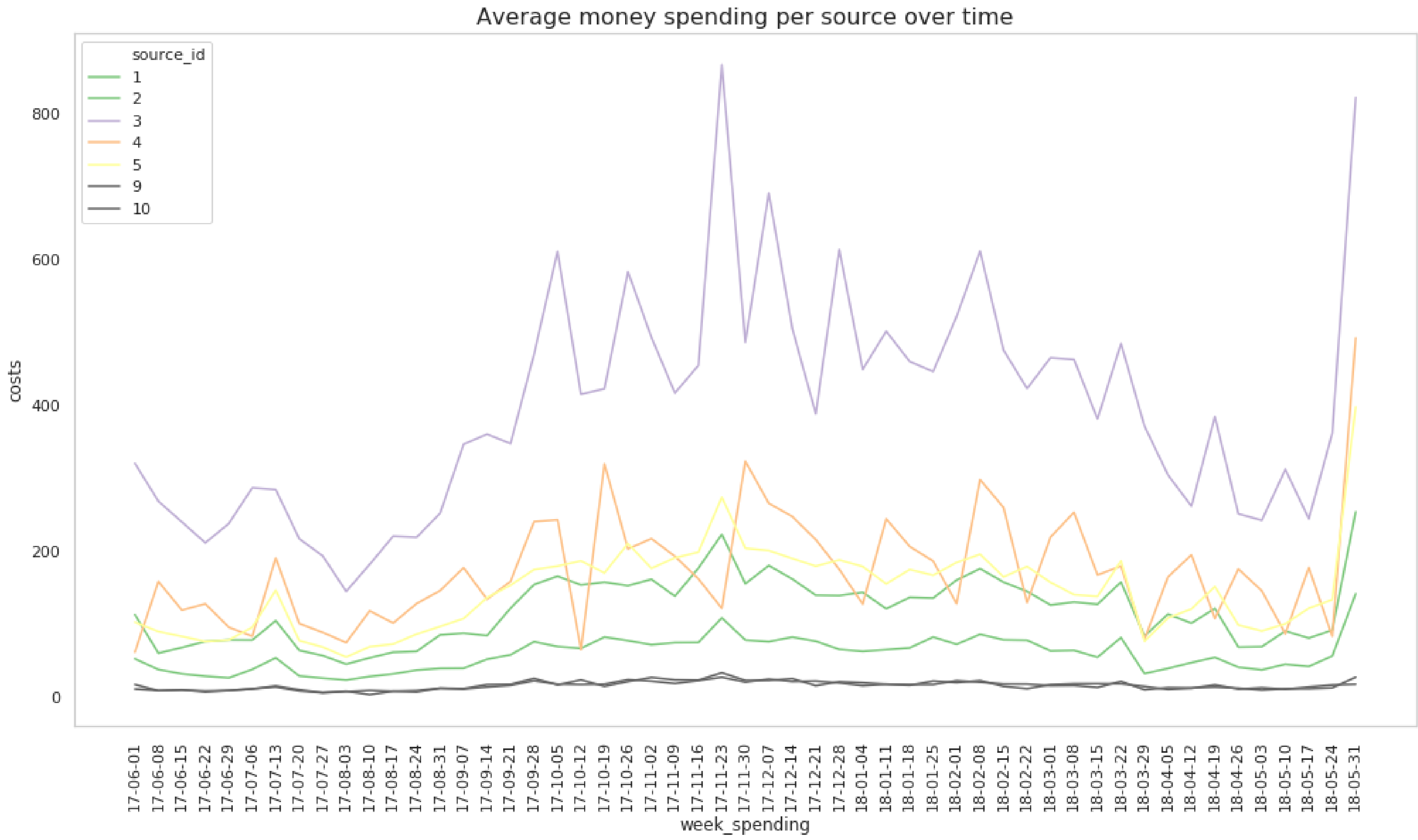
In [170]:
```
fig, ax = plt.subplots(figsize = (10,7))
my_explode = (0, 0, 0.15, 0, 0, 0, 0)
plt.pie(costs_per_source['costs'], autopct=lambda p:"{:.0f} \n({:.1f})%".format(p*sum(costs_per_source['costs'])/100,
p),
        startangle=15, shadow = True, explode=my_explode)
plt.title('Spendings Per Source')
plt.axis('equal')
ax.legend(costs_per_source['source_id'],
          title="Source_id",
          loc="center left",
          bbox_to_anchor=(1, 0, 0.5, 1))
plt.show()
```



Here I see that there are some sources that the source with most funding is source 3, while there are sources that get much less funding.

Now let's check how distribution of average money spending per source has changed over time.

In [171]:
```
df = costs.groupby(['week_spending','source_id'])[['costs']].mean().reset_index()

sns.set(style='whitegrid')
fig, ax = plt.subplots(figsize=(17, 9))
ax.set_title('Average money spending per source over time', fontsize=16)
plt.xticks(rotation=90)
plt.grid()
sns.lineplot(x="week_spending", y="costs", hue='source_id',estimator=None, palette='Accent', legend="full", data=df);
```



Looks like it mostly stayed the same. So now let's combine this with data on how many users came to Yandex.Afisha from different sources to see if spending makes sence. This info is already stored in visits table.

In [172]:
```
source_visits = visits.groupby('source_id')[['uid']].nunique().reset_index()
```

In [173]:
```
#now let's convert both tables to percentages and merge them
source_visits['perc_of_users'] = (source_visits['uid'] / source_visits.uid.sum() *100).round(2)
costs_per_source['perc_of_money_spent'] = (costs_per_source['costs'] / costs_per_source['costs'].sum() *100).round(2)
```

In [174]:
```
source_visits[['source_id','perc_of_users']].merge(costs_per_source[['source_id','perc_of_money_spent']],
                                                    on='source_id', how='outer')
```

Out[174]:

	source_id	perc_of_users	perc_of_money_spent
0	1	7.15	6.33
1	2	9.62	13.01
2	3	26.79	42.94
3	4	29.89	18.56
4	5	20.28	15.73
5	6	0.00	NaN
6	7	0.01	NaN
7	9	3.39	1.68
8	10	2.87	1.77

Conclusion

So from here it's obvious that there is some misdistribution of money. For example we spend 43 percent of spending on source 3 and 18,5 on source 4, while source 4 brings to Yandex.Afisha more users. That means that we spend on marketing of source 3 twice as much as on source 4, but we don't even get the same amount of users from that source. I suggest thta it would be good to refocus our more of our spendings to source 4 from source 3. Also we could add some more money to marketing source 5, it also brings to Yandex.Afisha many users, maybe this is worth looking into.

How much did customer acquisition from each of the sources cost?

In [176]:
```
users_per_source = visits.groupby('source_id')[['uid']].nunique().reset_index()
```

In [177]:
```
costs_per_source
```

Out[177]:

	source_id	costs	perc_of_money_spent
0	1	20833.27	6.33
1	2	42806.04	13.01
2	3	141321.63	42.94
3	4	61073.60	18.56
4	5	51757.10	15.73
5	9	5517.49	1.68
6	10	5822.49	1.77

In [178]:
```
users_per_source = users_per_source.merge(costs_per_source[['source_id','costs']],
                                          on='source_id', how='outer')
```

In [179]:
```
users_per_source['cost_per_user'] = (users_per_source.costs / users_per_source.uid)
users_per_source = users_per_source.sort_values('cost_per_user', ascending = False)
users_per_source
```

Out[179]:

	source_id	uid	costs	cost_per_user
2	3	67284	141321.63	2.100375
1	2	24152	42806.04	1.772360
0	1	17960	20833.27	1.159982
4	5	50921	51757.10	1.016420
3	4	75080	61073.60	0.813447
8	10	7208	5822.49	0.807782
7	9	8504	5517.49	0.648811
5	6	5	NaN	NaN
6	7	33	NaN	NaN

Conclusion

So here I see that the most expencive users to aquire come from source 3. While getting a user from source 4 (that brings almost the same amount of users) is more than 2 times less. So I keep my suggestions of rederecting more money spendings to source 4 because it brings the highest amount of users at very low cost.

How worthwhile where the investments? (ROI)

For this I will use data that I have created before for calculating LTV - *report* table.

In [181]:
```
report
```

Out[181]:

	first_order_month	n_buyers	order_month	revenue	gp	age	ltv
0	2017-06	2023	2017-06-01	9557.49	3822.996	0	1.889766
1	2017-06	2023	2017-07-01	981.82	392.728	1	0.194131
2	2017-06	2023	2017-08-01	885.34	354.136	2	0.175055
3	2017-06	2023	2017-09-01	1931.30	772.520	3	0.381869
4	2017-06	2023	2017-10-01	2068.58	827.432	4	0.409012
...	...	...	...	...	...	...	...
74	2018-03	3533	2018-05-01	1114.87	445.948	2	0.126224
75	2018-04	2276	2018-04-01	10600.69	4240.276	0	1.863039
76	2018-04	2276	2018-05-01	1209.92	483.968	1	0.212640
77	2018-05	2988	2018-05-01	13925.76	5570.304	0	1.864225
78	2018-06	1	2018-06-01	3.42	1.368	0	1.368000

79 rows × 7 columns

In [182]:
```
#get first_order_month column back to normal
report['first_order_month'] = pd.to_datetime(report['first_order_month'])
```

In [183]:
```
#calculate cost per month
costs
```

Out[183]:

	source_id	dt	costs	week_spending
0	1	2017-06-01	75.20	17-06-01
1	1	2017-06-02	62.25	17-06-01
2	1	2017-06-03	36.53	17-06-01
3	1	2017-06-04	55.00	17-06-01
4	1	2017-06-05	57.08	17-06-01
...	...	...	...	...
2537	10	2018-05-27	9.92	18-05-24
2538	10	2018-05-28	21.26	18-05-24
2539	10	2018-05-29	11.32	18-05-24
2540	10	2018-05-30	33.15	18-05-24
2541	10	2018-05-31	17.60	18-05-31

2542 rows × 4 columns

In [184]:
```
costs['month'] = costs.dt.astype('datetime64[M]')
monthly_costs = costs.groupby('month').sum()
```

In [185]:
```
report_ = pd.merge(report, monthly_costs, left_on='first_order_month', right_on='month')
report_['cac'] = report_['costs'] / report_['n_buyers']
report_.head()
```

Out[185]:

	first_order_month	n_buyers	order_month	revenue	gp	age	ltv	source_id	costs	cac
0	2017-06-01	2023	2017-06-01	9557.49	3822.996	0	1.889766	1020	18015.0	8.905091
1	2017-06-01	2023	2017-07-01	981.82	392.728	1	0.194131	1020	18015.0	8.905091
2	2017-06-01	2023	2017-08-01	885.34	354.136	2	0.175055	1020	18015.0	8.905091
3	2017-06-01	2023	2017-09-01	1931.30	772.520	3	0.381869	1020	18015.0	8.905091
4	2017-06-01	2023	2017-10-01	2068.58	827.432	4	0.409012	1020	18015.0	8.905091

In [186]:
```
#Calculate ROI
report_['roi'] = report_['ltv'] / report_['cac']
output = report_.pivot_table(
    index='first_order_month',
    columns='age',
    values='roi',
    aggfunc='mean')

output.cumsum(axis=1).round(2)
```

Out[186]:

age	0	1	2	3	4	5	6	7	8	9	10	11
first_order_month												
2017-06-01	0.21	0.23	0.25	0.30	0.34	0.38	0.42	0.44	0.47	0.50	0.52	0.53
2017-07-01	0.25	0.27	0.29	0.31	0.32	0.32	0.33	0.33	0.34	0.35	0.35	NaN
2017-08-01	0.20	0.21	0.23	0.24	0.26	0.27	0.28	0.30	0.31	0.31	NaN	NaN
2017-09-01	0.24	0.29	0.31	0.48	0.49	0.52	0.55	0.56	0.57	NaN	NaN	NaN
2017-10-01	0.24	0.26	0.27	0.28	0.29	0.29	0.30	0.30	NaN	NaN	NaN	NaN
2017-11-01	0.22	0.24	0.25	0.26	0.27	0.27	0.28	NaN	NaN	NaN	NaN	NaN
2017-12-01	0.22	0.23	0.27	0.32	0.33	0.35	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-01	0.17	0.18	0.19	0.20	0.20	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-02-01	0.19	0.20	0.20	0.20	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-03-01	0.22	0.24	0.25	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-04-01	0.19	0.21	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-05-01	0.25	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Here I see that none of the cohorts has actually showed any retern of marketing invesments. Cohort of 09.2017 shows to be the most profitable yet. Last cohorts don't chow any return of investments after their first month, seems like they don't come back at all. We should expect that we get some return of investments if user will continue using Yandex.Afisha after at least 2 years of usage, that seems to be really too long.

Step 3. Write a conclusion: advise marketing experts how much money to invest and where.

Based on performed analysis I can see that Yandex.Afisha doesn't bring lots of money in, while spendings are way up high. There are few things that I can recomend here to make investments worthwhile:

1. Most of users come from add sources 3 and 4, they bring simillar amount of users, but source 4 is almost twice cheaper and more effective. Therefore I recomend to focus spendings on source 4 and cut some money on marketing through source 3. It may also be usefull to try to redirect some money to source 5, because it's also showing to be really effective;
2. It takes really long time to get return of investments, average user can get ROI at around 0.5 only after a year, here I recomend to try to focus more on keeping existing custumers with notificatins and e-mails;
3. Most people spend most of their money during their first month, especially during first days after their first visit, so it's important to keep people there;
4. Check what has happened to website/app in last months, maybe there've been some design changes that made people less interested in the platform;
5. New users bring more money than old ones, it's important to focus on new users, because they bring really high percent of their money in the first month (actually more like first purchase).