Project Description

The goal of the project is to conduct the research to help optimize marketing expenses, based on the data from the analytical department at Yandex.Afisha for the period from June 2017 through May 2018.

Available data:

- 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

Objects of study:

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

Download the data and prepare it for analysis

In [1]:

```
home = %pwd
print(home)
if home != 'C:/Users/Coami':

    !pip install -Uq matplotlib --user
    !pip install -Uq numpy --user
    !pip install -Uq pandas --user
    !pip install -Uq plotly --user

    !pip install -Uq seaborn --user
    !pip install -Uq sidetable --user
```

```
C:\Users\Sophie\Personal_proj
```

```
  WARNING: The script f2py.exe is installed in 'C:\Users\Sophie\AppData\Roaming\Python\P
ython39\Scripts' which is not on PATH.
  Consider adding this directory to PATH or, if you prefer to suppress this warning, use
--no-warn-script-location.
ERROR: pip's dependency resolver does not currently take into account all the packages t
hat are installed. This behaviour is the source of the following dependency conflicts.
daal4py 2021.5.0 requires daal==2021.4.0, which is not installed.
scipy 1.7.3 requires numpy<1.23.0,>=1.16.5, but you have numpy 1.23.4 which is incompati
ble.
numba 0.55.1 requires numpy<1.22,>=1.18, but you have numpy 1.23.4 which is incompatibl
e.
```

In [2]:

```
#importing libraries

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import datetime
import random
   # !pip install -Uq seaborn --user
    #!pip install -Uq plotly --user
```

```
    # !pip install plotly
    # !pip install -Uq plotly --user
import sys
    #!conda install --yes --prefix {sys.prefix} plotly
import plotly as px
import plotly.express as px
```

Optimize the data for analysis.

In [4]:
```
try:
    visits = pd.read_csv('visits_log_us.csv', nrows=500)
except:
    visits = pd.read_csv('/datasets/visits_log_us.csv', nrows=500)

visits.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Device     500 non-null    object
 1   End Ts     500 non-null    object
 2   Source Id  500 non-null    int64
 3   Start Ts   500 non-null    object
 4   Uid        500 non-null    uint64
dtypes: int64(1), object(3), uint64(1)
memory usage: 113.1 KB
```

In [5]:
```
visits['Device'].value_counts()
```

Out[5]:
```
desktop    363
touch      137
Name: Device, dtype: int64
```

In [6]:
```
visits['Source Id'].value_counts()
```

Out[6]:
```
4     159
3     122
5      92
2      52
1      39
9      19
10     17
Name: Source Id, dtype: int64
```

In [7]:
```
try:
    visits = pd.read_csv(
    'visits_log_us.csv',
    dtype={'Device': 'category','Source Id':'category'},
    parse_dates=['Start Ts', 'End Ts'])
except:
    visits = pd.read_csv(
    '/datasets/visits_log_us.csv',
    dtype={'Device': 'category','Source Id':'category'},
    parse_dates=['Start Ts', 'End Ts'])


visits=visits.rename(columns={"Device": "device", "End Ts": "end_ts","Source Id":"source
visits.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359400 entries, 0 to 359399
Data columns (total 5 columns):
 #   Column     Non-Null Count   Dtype
```

```
---  ------     --------------   -----
 0   device     359400 non-null  category
 1   end_ts     359400 non-null  datetime64[ns]
 2   source_id  359400 non-null  category
 3   start_ts   359400 non-null  datetime64[ns]
 4   uid        359400 non-null  uint64
dtypes: category(2), datetime64[ns](2), uint64(1)
memory usage: 8.9 MB
```

In [8]:
```python
try:
    orders = pd.read_csv('/datasets/orders_log_us.csv', nrows=500)

except:
    orders = pd.read_csv('orders_log_us.csv', nrows=500)
orders.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Buy Ts   500 non-null    object
 1   Revenue  500 non-null    float64
 2   Uid      500 non-null    uint64
dtypes: float64(1), object(1), uint64(1)
memory usage: 45.0 KB
```

In [9]:
```python
orders.head()
```

Out[9]:

	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 [10]:
```python
try:
    orders = pd.read_csv(
    '/datasets/orders_log_us.csv',
    parse_dates=['Buy Ts'],)

except:
    orders = pd.read_csv(
    'orders_log_us.csv',
    parse_dates=['Buy Ts'],)

orders=orders.rename(columns={"Buy Ts": "buy_ts","Revenue":"revenue","Uid":"uid"})

orders.info(memory_usage='deep')
```

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

In [11]:
```
try:
    costs = pd.read_csv('costs_us.csv', nrows=500)
except:
    costs = pd.read_csv('/datasets/costs_us.csv', nrows=500)

costs.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   source_id  500 non-null    int64  
 1   dt         500 non-null    object 
 2   costs      500 non-null    float64
dtypes: float64(1), int64(1), object(1)
memory usage: 40.7 KB
```

In [12]:
```
costs['source_id'].value_counts()
```

Out[12]:
```
1    363
2    137
Name: source_id, dtype: int64
```

In [13]:
```
costs['costs'].describe()
```

Out[13]:
```
count    500.000000
mean      65.715440
std       35.374315
min        5.800000
25%       41.390000
50%       59.345000
75%       81.542500
max      272.590000
Name: costs, dtype: float64
```

In [14]:
```
try:
    costs = pd.read_csv(
    '/datasets/costs_us.csv',
    dtype={'source_id':'category'},
    parse_dates=['dt'],
)

except:
    costs = pd.read_csv(
    'costs_us.csv',
    dtype={'source_id':'category'},
    parse_dates=['dt'],
)

costs.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2542 entries, 0 to 2541
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype         
---  ------     --------------  -----         
 0   source_id  2542 non-null   category      
 1   dt         2542 non-null   datetime64[ns]
 2   costs      2542 non-null   float64       
dtypes: category(1), datetime64[ns](1), float64(1)
memory usage: 43.0 KB
```

Conclusion

The data was uploaded.

All dates within the data were changed to the date datatype. Columns were renamed for convenience. The source and devices information was read as categorical datatype due to the memory limitations.

Make reports and calculate metrics

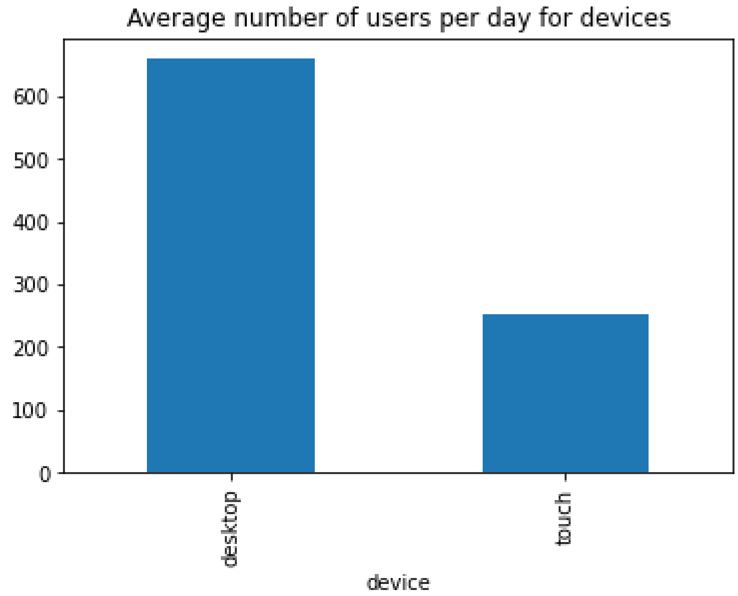
Product

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

In [15]:
```
visits['session_year']  = visits['start_ts'].dt.year
visits['session_month'] = visits['start_ts'].dt.month
visits['session_week']  = visits['start_ts'].dt.week
visits['session_date'] = visits['start_ts'].dt.date
mau_total = (
    visits.groupby(['session_year', 'session_month'])
    .agg({'uid': 'nunique'})
    .mean()
)
dau_total = (
    visits.groupby(['session_year', 'session_date'])
    .agg({'uid': 'nunique'})
    .mean()
)

wau_total = (
    visits.groupby(['session_year', 'session_week'])
    .agg({'uid': 'nunique'})
    .mean()
)
print(int(dau_total),'people used it every day')
print(int(wau_total),'people used it every week')
print(int(mau_total),'people used it every month')
```

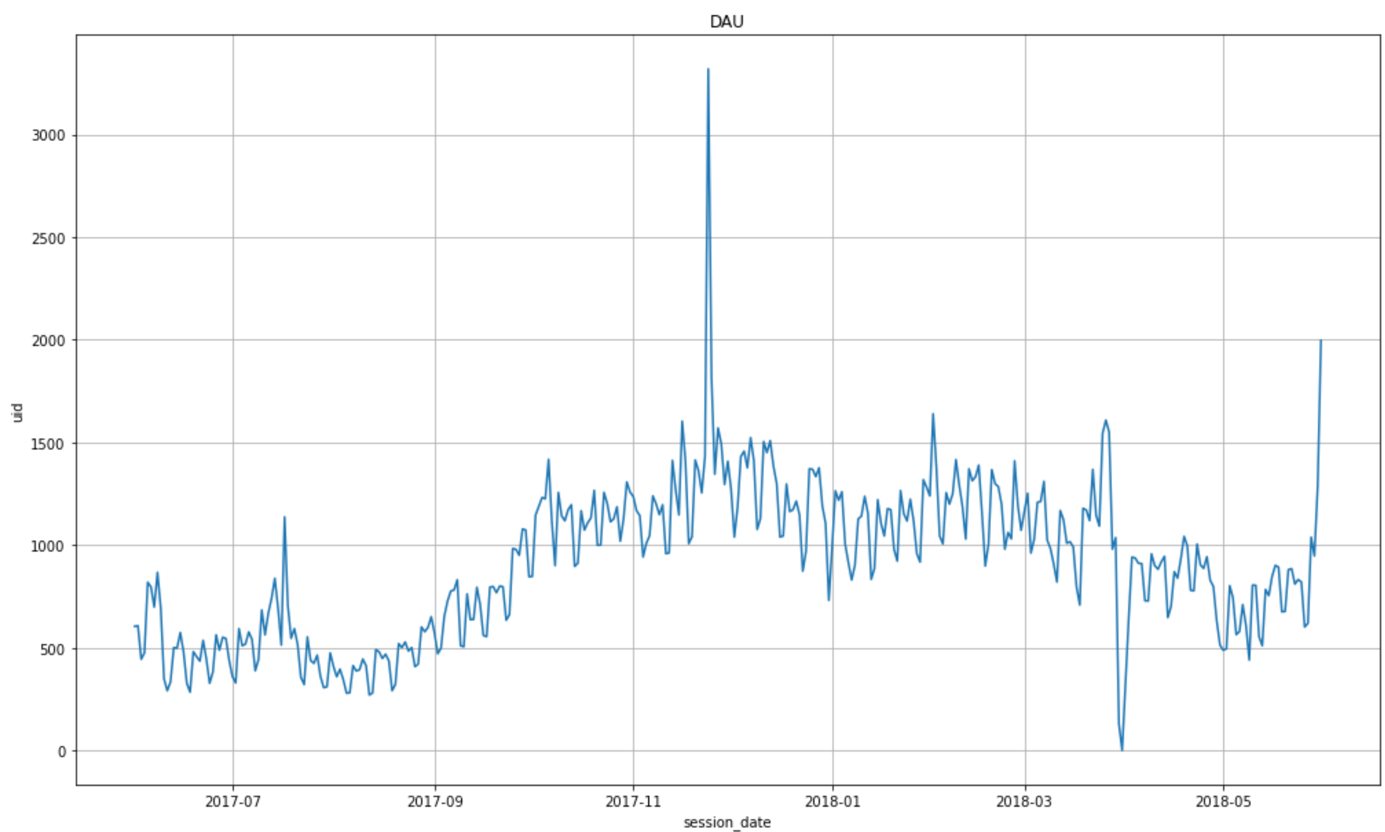
```
C:\Users\Sophie\AppData\Local\Temp\ipykernel_4048\3328251206.py:3: FutureWarning: Serie
s.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalenda
r().week instead.
  visits['session_week']  = visits['start_ts'].dt.week
907 people used it every day
5716 people used it every week
23228 people used it every month
```

In [16]:
```
visits.pivot_table(index='session_date', columns='device', values='uid', aggfunc='nuniqu
plt.title('Average number of users per day for devices')
plt.show()
```



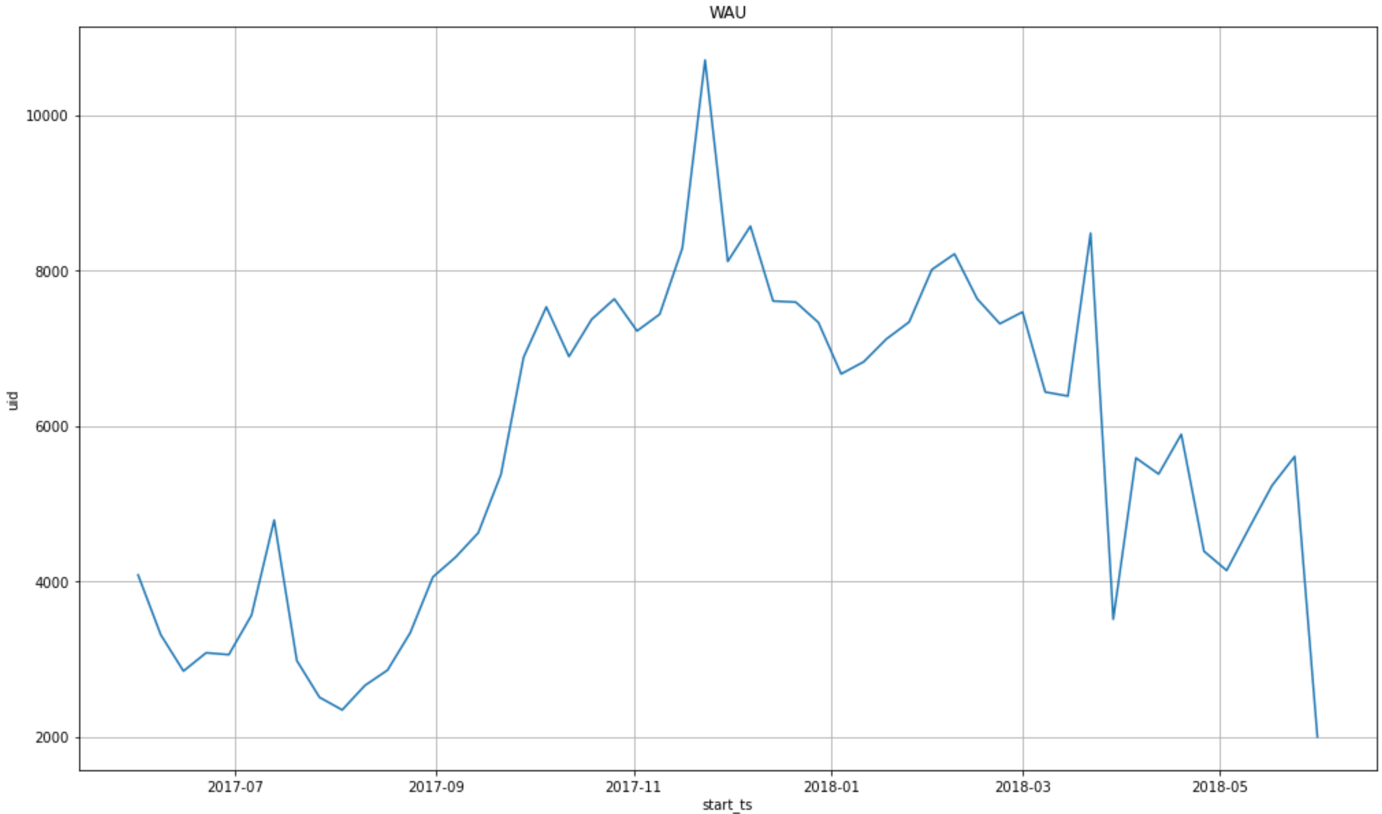
Number of the desktop version users are significantly exceed the number of mobile version users.

In [17]:
```
dau_= visits.pivot_table(index=('session_year','session_date'),values='uid',aggfunc=pd.S
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=dau_, x="session_date", y="uid") # hue="platform",markers ="o")
plt.title('DAU')
plt.grid()
plt.show()
```



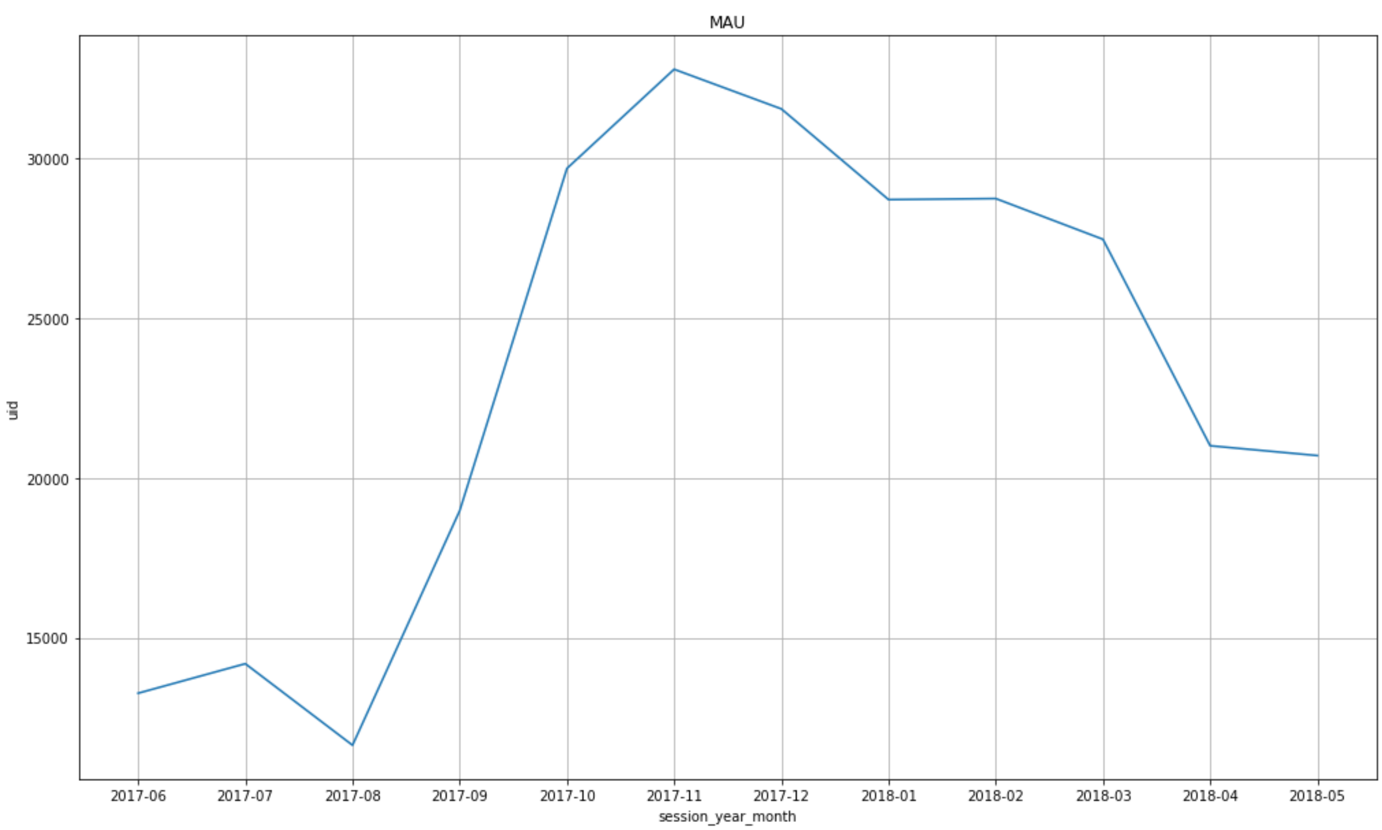
We can see the rise starting from September with noticeable peaks and outliers in the data.

In [18]:
```
wau_= visits.groupby([visits['start_ts'].astype('datetime64[W]')]).agg({'uid': 'nunique'
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=wau_, x="start_ts", y="uid") # hue="platform",markers ="o")
plt.title('WAU')
plt.grid()
plt.show()
```



The graph correlates with the DAU graph, we see rise at autumn with significant peaks.

In [19]:
```
visits['session_year_month'] = visits['start_ts'].dt.strftime('%Y-%m')
mau_= visits.pivot_table(index='session_year_month',values='uid',aggfunc=pd.Series.nuniq
mau_
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=mau_, x="session_year_month", y="uid") # hue="platform",markers ="o")
plt.grid()
plt.title('MAU')
plt.show()
```



The overall tendencies are that the most visitors are in November-December, and after the number of visitors start to decline.

In [20]:
```
sticky_wau=dau_total/wau_total*100
sticky_mau=dau_total/mau_total*100
print('Sticky factor for week:',int(sticky_wau),'%')
print('Sticky factor for month:',int(sticky_mau),'%')
```

```
Sticky factor for week: 15 %
Sticky factor for month: 3 %
```

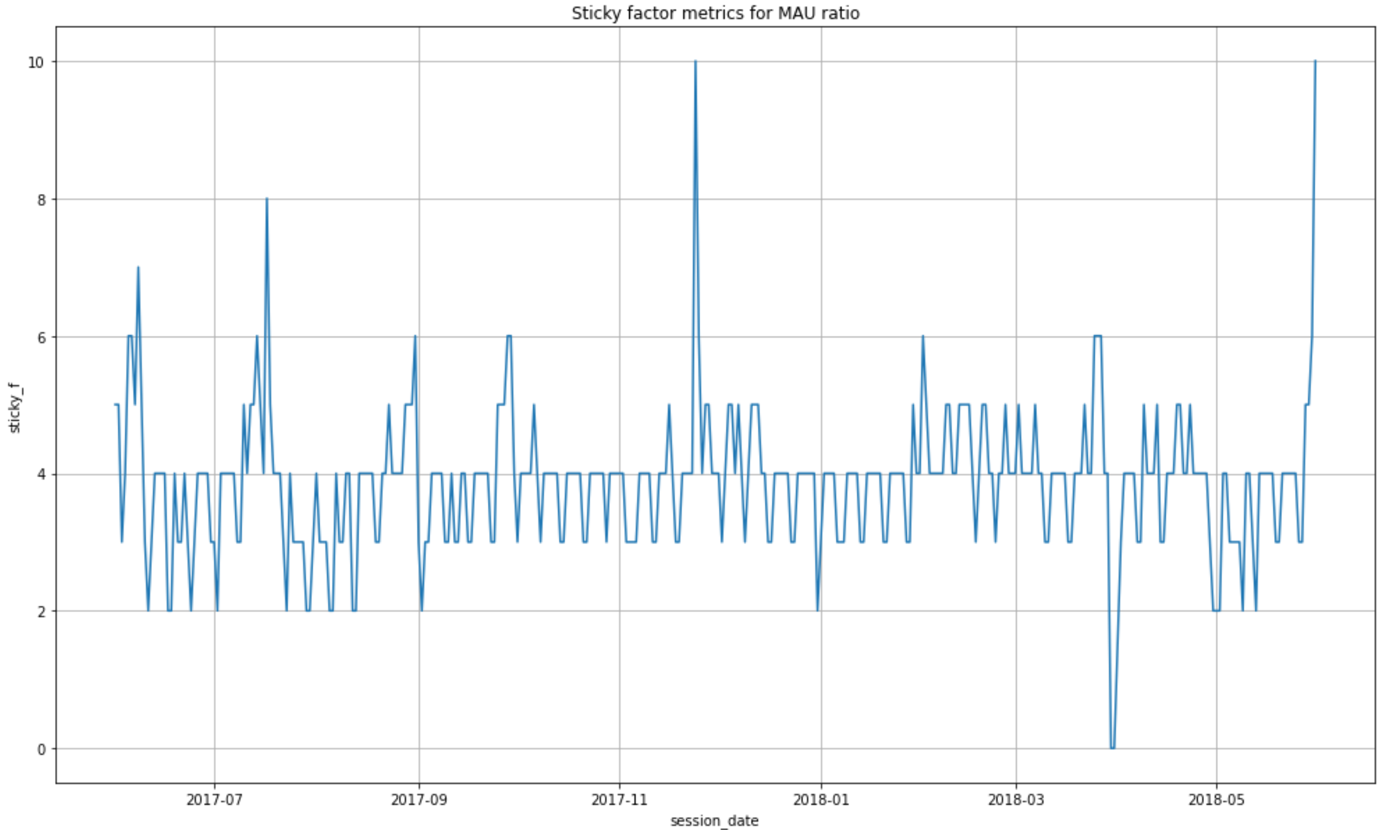
In [21]:
```
dau_['session_date']=dau_['session_date'].astype('datetime64')
dau_['session_year_month'] = dau_['session_date'].dt.strftime('%Y-%m')

sticky_mau_=dau_.merge(mau_, how = 'left', left_on='session_year_month', right_on='sessi
sticky_mau_['sticky_f']=round(sticky_mau_['uid_x']/sticky_mau_['uid_y']*100)
sticky_mau_
```

Out[21]:

	session_year	session_date	uid_x	session_year_month	uid_y	sticky_f
0	2017	2017-06-01	605	2017-06	13259	5.0
1	2017	2017-06-02	608	2017-06	13259	5.0
2	2017	2017-06-03	445	2017-06	13259	3.0
3	2017	2017-06-04	476	2017-06	13259	4.0
4	2017	2017-06-05	820	2017-06	13259	6.0
...	...	...	...	...	...	...
359	2018	2018-05-27	620	2018-05	20701	3.0
360	2018	2018-05-28	1039	2018-05	20701	5.0
361	2018	2018-05-29	948	2018-05	20701	5.0
362	2018	2018-05-30	1289	2018-05	20701	6.0
363	2018	2018-05-31	1997	2018-05	20701	10.0

364 rows × 6 columns

In [22]:
```
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=sticky_mau_, x="session_date", y="sticky_f")
plt.title('Sticky factor metrics for MAU ratio')
plt.grid()
plt.show()
```

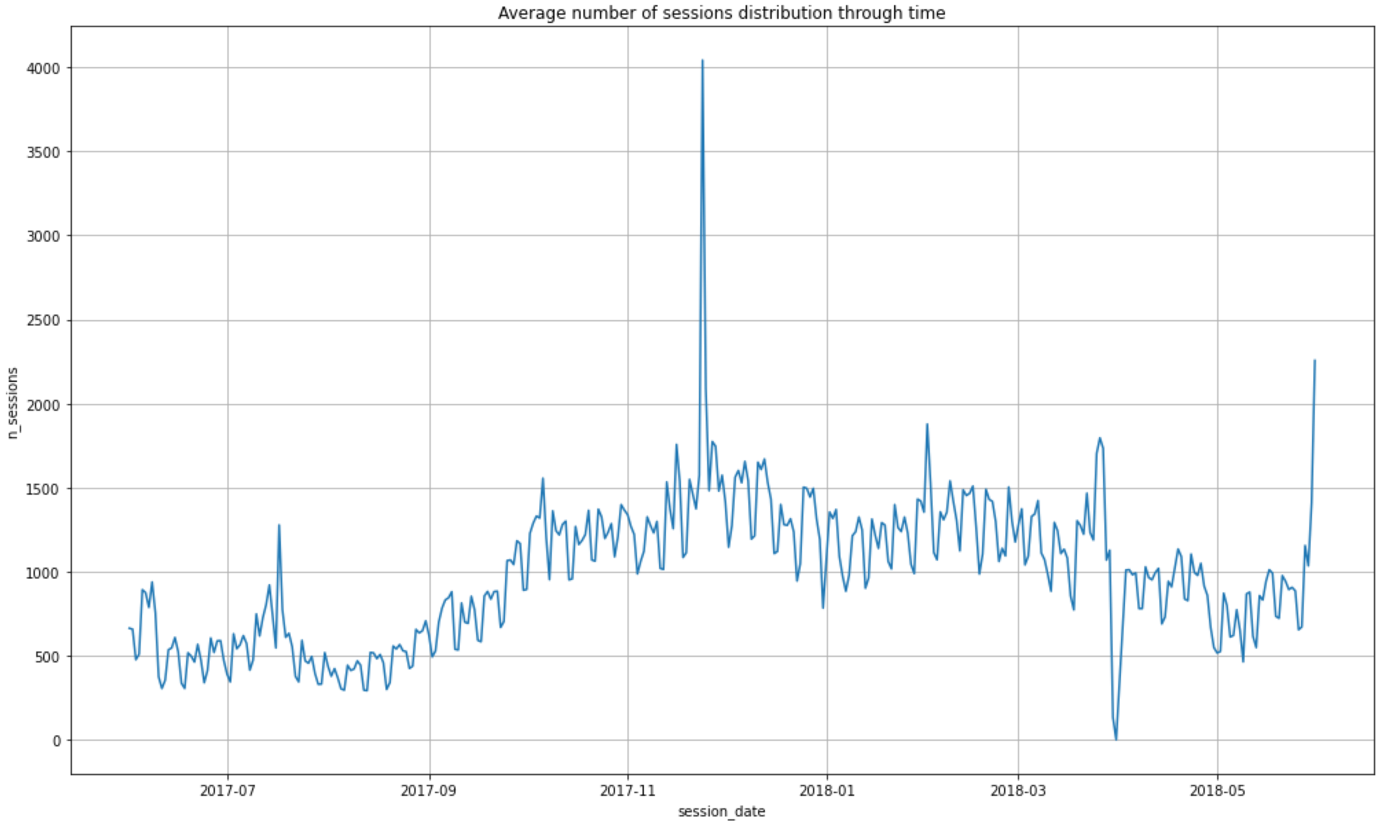


How many sessions are there per day?

In [23]:
```
sessions_per_user = visits.groupby(['session_date']).agg(
    {'uid': ['count', 'nunique']}
).reset_index()
sessions_per_user.columns = ['session_date','n_sessions', 'n_users']
sessions_per_user['sessions_per_user'] = (
    sessions_per_user['n_sessions'] / sessions_per_user['n_users']
)

print(sessions_per_user)
```

```
     session_date  n_sessions  n_users  sessions_per_user
0      2017-06-01         664      605           1.097521
1      2017-06-02         658      608           1.082237
2      2017-06-03         477      445           1.071910
3      2017-06-04         510      476           1.071429
4      2017-06-05         893      820           1.089024
..            ...         ...      ...                ...
359    2018-05-27         672      620           1.083871
360    2018-05-28        1156     1039           1.112608
361    2018-05-29        1035      948           1.091772
362    2018-05-30        1410     1289           1.093871
363    2018-05-31        2256     1997           1.129695

[364 rows x 4 columns]
```

In [24]:
```
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=sessions_per_user, x="session_date", y="n_sessions")
plt.title('Average number of sessions distribution through time')
plt.grid()
plt.show()
```



Number of sessions correlates with number of users. Rise in November-December.

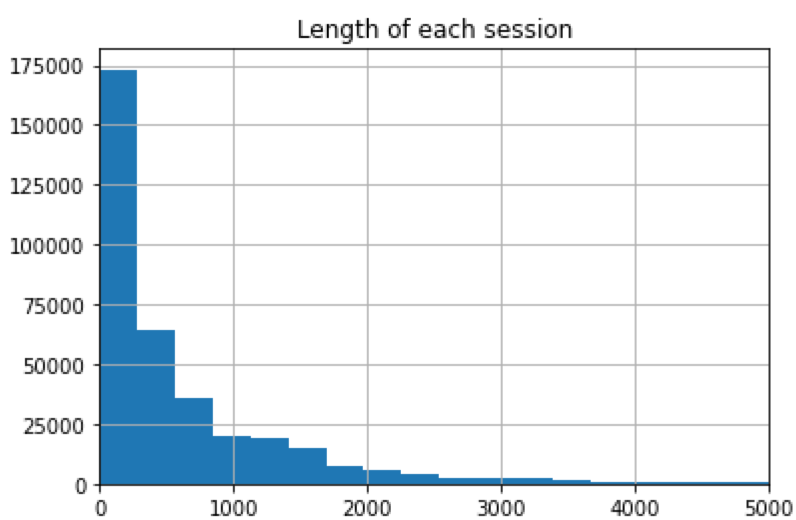
In [25]:
```
print("The average number of sessions per day: {0:.2f} ".format(sessions_per_user['n_ses
```

```
The average number of sessions per day: 987.36
```

What is the length of each session?

In [26]:
```
visits['session_duration_sec'] = (
    visits['end_ts'] - visits['start_ts']
).dt.seconds
visits['session_duration_sec'].hist(bins=300)
asl=visits['session_duration_sec'].mode()[0]
print('Average session length:',asl)
plt.title('Length of each session')
plt.xlim(0,5000)
plt.show()
```

```
Average session length: 60
```



We have unnaturally long sessions in the data, but the average session is around 1 minute.

How often do users come back?

```
In [27]: user_activity=visits[['uid','source_id','device','start_ts']]
first_activity_date = user_activity.groupby(['uid'])['start_ts'].min()
first_activity_date.name = 'first_activity_date'
user_activity = user_activity.join(first_activity_date, on='uid')
user_activity['activity_month']= user_activity['start_ts'].dt.strftime('%Y-%m')
user_activity['first_activity_month']= user_activity['first_activity_date'].dt.strftime(
user_activity
```

Out[27]:

	uid	source_id	device	start_ts	first_activity_date	activity_month	first_activity_mo
0	16879256277535980062	4	touch	2017-12-20 17:20:00	2017-12-20 17:20:00	2017-12	2017
1	104060357244891740	2	desktop	2018-02-19 16:53:00	2018-02-19 16:53:00	2018-02	2018
2	7459035603376831527	5	touch	2017-07-01 01:54:00	2017-07-01 01:54:00	2017-07	2017
3	16174680259334210214	9	desktop	2018-05-20 10:59:00	2018-03-09 20:05:00	2018-05	2018
4	9969694820036681168	3	desktop	2017-12-27 14:06:00	2017-12-27 14:06:00	2017-12	2017
...	...	...	...	...	...	...	
359395	18363291481961487539	2	desktop	2017-07-29 19:07:00	2017-07-29 19:07:00	2017-07	2017
359396	18370831553019119586	1	touch	2018-01-25 17:38:00	2018-01-25 17:38:00	2018-01	2018
359397	18387297585500748294	4	desktop	2018-03-03 10:12:00	2018-03-03 10:12:00	2018-03	2018
359398	18388616944624776485	5	desktop	2017-11-02 10:12:00	2017-11-02 10:12:00	2017-11	2017
359399	18396128934054549559	2	touch	2017-09-10 13:13:00	2017-09-10 13:13:00	2017-09	2017

359400 rows × 7 columns

```
In [28]: user_activity['activity_month']=pd.to_datetime(user_activity['activity_month'])
user_activity['first_activity_month']=pd.to_datetime(user_activity['first_activity_month
user_activity.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359400 entries, 0 to 359399
Data columns (total 7 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
```

```
 0   uid                    359400 non-null  uint64
 1   source_id              359400 non-null  category
 2   device                 359400 non-null  category
 3   start_ts               359400 non-null  datetime64[ns]
 4   first_activity_date    359400 non-null  datetime64[ns]
 5   activity_month         359400 non-null  datetime64[ns]
 6   first_activity_month   359400 non-null  datetime64[ns]
dtypes: category(2), datetime64[ns](4), uint64(1)
memory usage: 14.4 MB
```

In [29]:
```
user_activity['cohort_lifetime'] = (
    user_activity['activity_month'] - user_activity['first_activity_month']
)
user_activity['cohort_lifetime'] = user_activity[
    'cohort_lifetime'
] / np.timedelta64(1, 'M')
user_activity['cohort_lifetime'] = user_activity['cohort_lifetime'].round().astype(int)

user_activity
```

Out[29]:

	uid	source_id	device	start_ts	first_activity_date	activity_month	first_activity_mo
0	16879256277535980062	4	touch	2017-12-20 17:20:00	2017-12-20 17:20:00	2017-12-01	2017-12
1	104060357244891740	2	desktop	2018-02-19 16:53:00	2018-02-19 16:53:00	2018-02-01	2018-02
2	7459035603376831527	5	touch	2017-07-01 01:54:00	2017-07-01 01:54:00	2017-07-01	2017-07
3	16174680259334210214	9	desktop	2018-05-20 10:59:00	2018-03-09 20:05:00	2018-05-01	2018-03
4	9969694820036681168	3	desktop	2017-12-27 14:06:00	2017-12-27 14:06:00	2017-12-01	2017-12
...	...	...	...	...	...	...	
359395	18363291481961487539	2	desktop	2017-07-29 19:07:00	2017-07-29 19:07:00	2017-07-01	2017-07
359396	18370831553019119586	1	touch	2018-01-25 17:38:00	2018-01-25 17:38:00	2018-01-01	2018-01
359397	18387297585500748294	4	desktop	2018-03-03 10:12:00	2018-03-03 10:12:00	2018-03-01	2018-03
359398	18388616944624776485	5	desktop	2017-11-02 10:12:00	2017-11-02 10:12:00	2017-11-01	2017-11
359399	18396128934054549559	2	touch	2017-09-10 13:13:00	2017-09-10 13:13:00	2017-09-01	2017-09

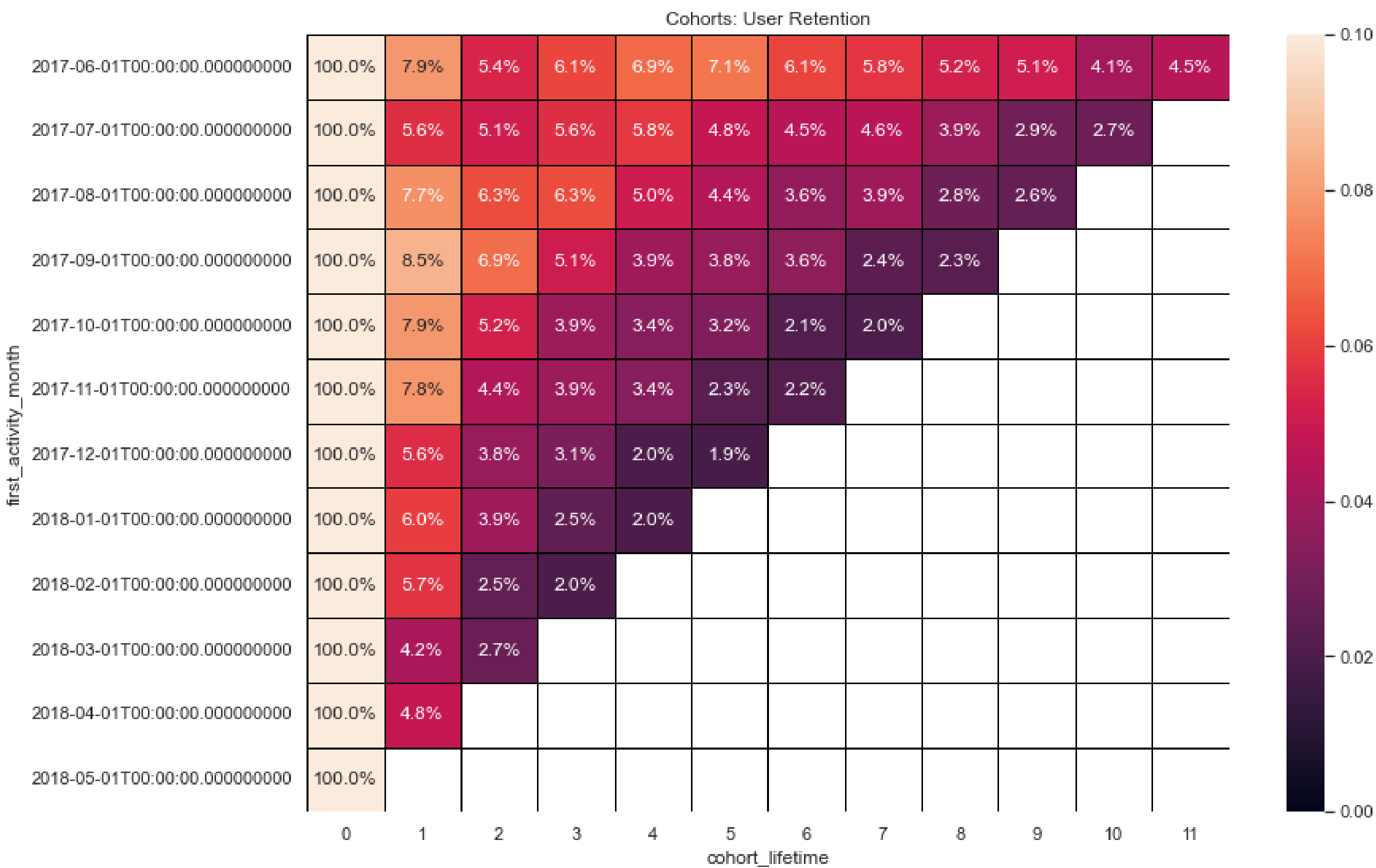
359400 rows × 8 columns

In [30]:
```
cohorts = user_activity.groupby(['first_activity_month', 'cohort_lifetime']).agg({'uid':
```

```
initial_users_count =cohorts[cohorts['cohort_lifetime']== 0][
    ['first_activity_month', 'uid']
]

initial_users_count =initial_users_count.rename(
    columns={'uid': 'cohort_users'}
)

cohorts =cohorts.merge(initial_users_count, on='first_activity_month')


cohorts['retention'] = cohorts['uid'] / cohorts['cohort_users']

retention_pivot = cohorts.pivot_table(
    index='first_activity_month',
    columns='cohort_lifetime',
    values='retention',
    aggfunc='sum',
)
retention_pivot
sns.set(style='white')
plt.figure(figsize=(13, 9))
plt.title('Cohorts: User Retention')
sns.heatmap(
    retention_pivot, annot=True, fmt='.1%', linewidths=1, linecolor='black', vmin= 0, vm
)
```

Out[30]:

```
<AxesSubplot:title={'center':'Cohorts: User Retention'}, xlabel='cohort_lifetime', ylabe
l='first_activity_month'>
```



first_activity_month	0	1	2	3	4	5	6	7	8	9	10	11
2017-06-01T00:00:00.000000000	100.0%	7.9%	5.4%	6.1%	6.9%	7.1%	6.1%	5.8%	5.2%	5.1%	4.1%	4.5%
2017-07-01T00:00:00.000000000	100.0%	5.6%	5.1%	5.6%	5.8%	4.8%	4.5%	4.6%	3.9%	2.9%	2.7%	
2017-08-01T00:00:00.000000000	100.0%	7.7%	6.3%	6.3%	5.0%	4.4%	3.6%	3.9%	2.8%	2.6%		
2017-09-01T00:00:00.000000000	100.0%	8.5%	6.9%	5.1%	3.9%	3.8%	3.6%	2.4%	2.3%			
2017-10-01T00:00:00.000000000	100.0%	7.9%	5.2%	3.9%	3.4%	3.2%	2.1%	2.0%				
2017-11-01T00:00:00.000000000	100.0%	7.8%	4.4%	3.9%	3.4%	2.3%	2.2%					
2017-12-01T00:00:00.000000000	100.0%	5.6%	3.8%	3.1%	2.0%	1.9%						
2018-01-01T00:00:00.000000000	100.0%	6.0%	3.9%	2.5%	2.0%							
2018-02-01T00:00:00.000000000	100.0%	5.7%	2.5%	2.0%								
2018-03-01T00:00:00.000000000	100.0%	4.2%	2.7%									
2018-04-01T00:00:00.000000000	100.0%	4.8%										
2018-05-01T00:00:00.000000000	100.0%											

Conclusion

1. **Based on the average amount of visitors throughout the year we can see that visits start to increase in autumn with the peak on November-December, and then slowly drops till reaches the minimum in summer with occasional peaks. We can assume that it's connected with the seasons**

of the events, for example, most theatre productions open in autumn, but summer usually is the "dead" season. Also, there are usually a lot of holidays during autumn and winter.
2. Each user has one session per day on average. The dynamic of how many sessions per day is coincidental with the DAU.
3. We have anomaly long sessions within the data. The median session is 1 minute.
4. The highest retention belongs to the June cohort. A lot of people use the platform and stick to it through the autumn and winter. As it was mentioned before, it might be because events are seasonal.

Sales

When do people start buying?

In [31]:
```
orders_=orders.pivot_table(index='uid',values='buy_ts', aggfunc = 'min').reset_index()
orders_.head()
orders_.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36523 entries, 0 to 36522
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   uid     36523 non-null  uint64
 1   buy_ts  36523 non-null  datetime64[ns]
dtypes: datetime64[ns](1), uint64(1)
memory usage: 570.8 KB
```

In [32]:
```
visits_=visits.pivot_table(index='uid',values='start_ts', aggfunc = 'min').reset_index()
visits_.head(10)
visits_.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 228169 entries, 0 to 228168
Data columns (total 2 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   uid       228169 non-null  uint64
 1   start_ts  228169 non-null  datetime64[ns]
dtypes: datetime64[ns](1), uint64(1)
memory usage: 3.5 MB
```

In [33]:
```
buys=orders_.merge(visits_[['uid','start_ts']], on='uid')
buys['conversion']=buys['buy_ts'] - buys['start_ts']
buys['conversion'] = buys[
    'conversion'
] / np.timedelta64(1, 'D')
buys['conversion'] = buys['conversion'].round().astype(int)

buys
```

Out[33]:

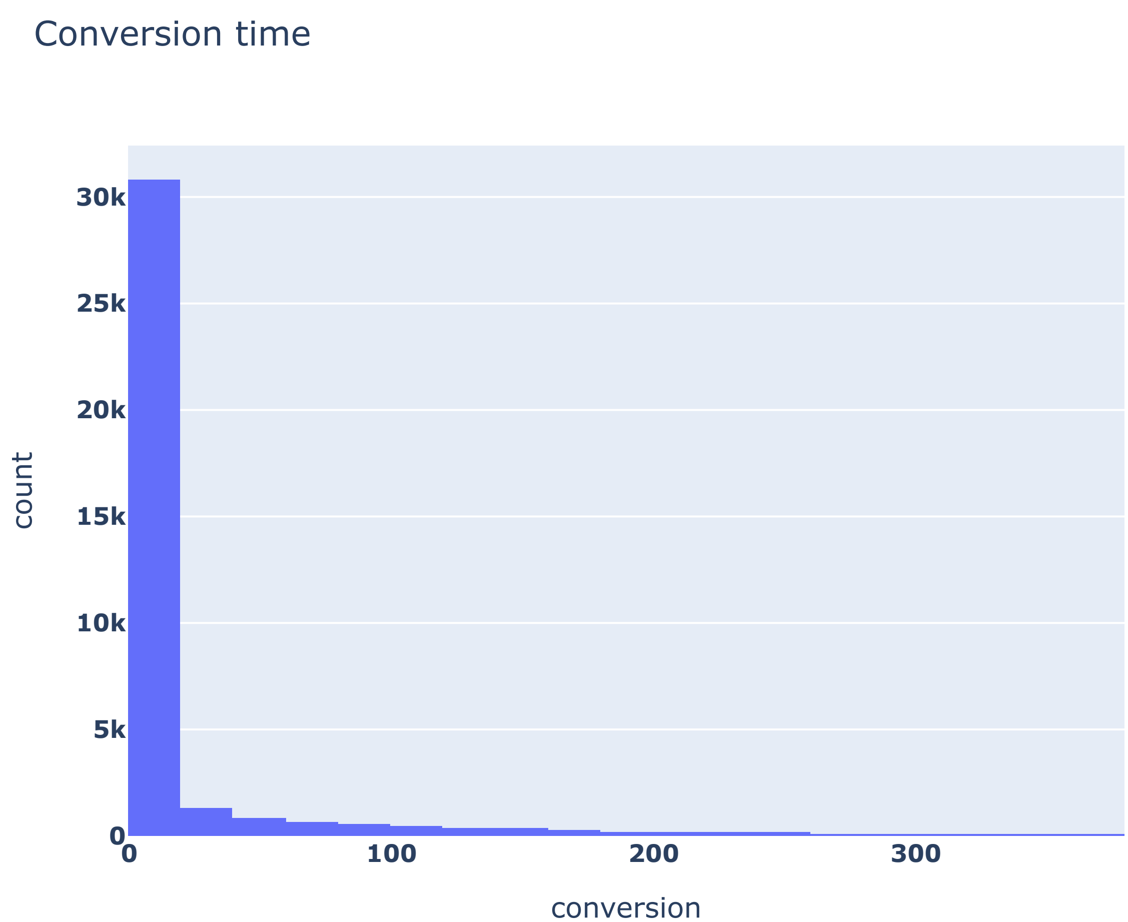
	uid	buy_ts	start_ts	conversion
0	313578113262317	2018-01-03 21:51:00	2017-09-18 22:49:00	107
1	1575281904278712	2017-06-03 10:13:00	2017-06-03 10:13:00	0
2	2429014661409475	2017-10-11 18:33:00	2017-10-11 17:14:00	0
3	2464366381792757	2018-01-28 15:54:00	2018-01-27 20:10:00	1
4	2551852515556206	2017-11-24 10:14:00	2017-11-24 10:14:00	0

...	...	...	...	...
36518	18445147675727495770	2017-11-24 09:03:00	2017-08-20 13:30:00	96
36519	18445407535914413204	2017-09-22 23:55:00	2017-09-22 23:48:00	0
36520	18445601152732270159	2018-03-26 22:54:00	2017-08-07 11:51:00	231
36521	18446156210226471712	2018-02-18 19:34:00	2017-11-07 10:01:00	103
36522	18446167067214817906	2017-10-17 10:16:00	2017-10-17 10:05:00	0

36523 rows × 4 columns

In [34]:
```
import plotly.express as px
```

In [35]:
```
fig = px.histogram(buys, x="conversion",nbins=30,title='Conversion time')

fig.show()
```



Most of the orders were made within the short time after the usage of the website.

In [36]:
```
buys['conversion'].median()
```

Out[36]:
```
0.0
```

In [37]:
```
print(' The overall conversion is {:.1%}'.format(buys['uid'].nunique()/visits_['uid'].nu
```

```
 The overall conversion is 16.0%
```

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

In [38]:
```
#defining cohort month through first purchase
orders['month']=orders['buy_ts'].astype('datetime64[M]')
first_order_date = orders.groupby(['uid'])['buy_ts'].min()
first_order_date.name = 'first_order_date'
orders=orders.join(first_order_date, on='uid')
orders['first_order_month'] = orders['first_order_date'].astype('datetime64[M]')

orders.head()
```

Out[38]:

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

In [39]:
```
orders.sample(5)
```

Out[39]:

	buy_ts	revenue	uid	month	first_order_date	first_order_month
33340	2018-02-07 09:54:00	3.67	1631356693099033031	2018-02-01	2018-02-07 09:54:00	2018-02-01
12254	2017-10-11 20:16:00	6.11	4148716401875468484	2017-10-01	2017-10-11 20:16:00	2017-10-01
43657	2018-04-10 12:10:00	4.89	3971030471691518392	2018-04-01	2018-04-10 12:10:00	2018-04-01
45602	2018-04-26 14:19:00	1.98	6093855166159309373	2018-04-01	2017-07-11 23:19:00	2017-07-01
28026	2018-01-04 13:44:00	2.44	13719347206112370408	2018-01-01	2018-01-04 13:44:00	2018-01-01

In [40]:
```
#let's define cohort size
cohort_sizes = orders.groupby('first_order_month').agg({'uid': 'nunique'}).reset_index()
cohort_sizes.columns=['first_order_month','cohort_size']
cohort_sizes.head()
```

Out[40]:

	first_order_month	cohort_size
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

In [41]:
```
#calculating number of purchases for cohort and month
cohort=orders.groupby(['first_order_month','month'])['revenue'].count().reset_index()
cohort.columns=['first_order_month','month','orders']
#merge cohort with cohort size
cohort=cohort.merge(cohort_sizes,on=['first_order_month'])
cohort['age_month'] = ((cohort['month'] - cohort['first_order_month']) / np.timedelta64(
cohort['orders_per_buyer']=cohort['orders']/cohort['cohort_size']
cohort.head()
```

Out[41]:

	first_order_month	month	orders	cohort_size	age_month	orders_per_buyer
0	2017-06-01	2017-06-01	2354	2023	0.0	1.163618
1	2017-06-01	2017-07-01	177	2023	1.0	0.087494
2	2017-06-01	2017-08-01	174	2023	2.0	0.086011
3	2017-06-01	2017-09-01	226	2023	3.0	0.111715
4	2017-06-01	2017-10-01	292	2023	4.0	0.144340

In [42]:
```
cohort_piv=cohort.pivot_table(
    index='first_order_month',
    columns='age_month',
    values='orders_per_buyer',
    aggfunc='sum'
).cumsum(axis=1)

cohort_piv.round(2).fillna('')
```

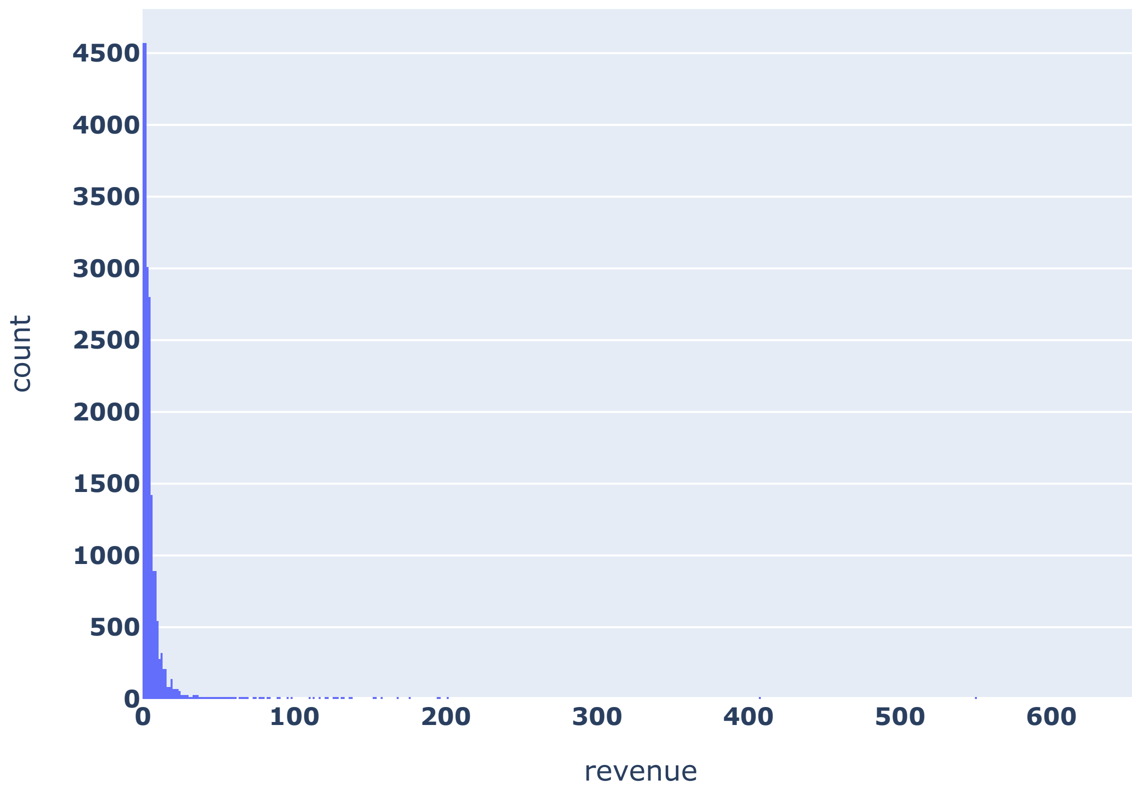
Out[42]:

age_month	0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0
first_order_month												
2017-06-01	1.16	1.25	1.34	1.45	1.59	1.7	1.84	1.92	2.03	2.1	2.15	2.19
2017-07-01	1.14	1.19	1.25	1.31	1.34	1.39	1.42	1.44	1.47	1.49	1.51	
2017-08-01	1.12	1.2	1.27	1.33	1.39	1.44	1.47	1.53	1.56	1.6		
2017-09-01	1.14	1.22	1.28	1.35	1.37	1.42	1.46	1.48	1.5			
2017-10-01	1.14	1.22	1.25	1.28	1.31	1.34	1.35	1.38				
2017-11-01	1.18	1.28	1.32	1.37	1.41	1.42	1.45					
2017-12-01	1.15	1.21	1.26	1.3	1.32	1.34						
2018-01-01	1.12	1.19	1.24	1.25	1.28							
2018-02-01	1.12	1.18	1.21	1.22								
2018-03-01	1.17	1.22	1.27									
2018-04-01	1.10	1.18										
2018-05-01	1.09											
2018-06-01	1.00											

What is the average purchase size?

In [43]:
```
avg_check=orders.groupby(['uid'])['revenue'].mean().reset_index()
fig = px.histogram(avg_check, x="revenue", title='Average purchase size')
fig.show()
```

Average purchase size



Most of the purchase sizes are within 10.

In [44]:
```
avg_cohort=orders.groupby(['first_order_month','month'])['revenue'].mean().reset_index()
avg_cohort['age_month'] = ((avg_cohort['month'] - avg_cohort['first_order_month']) / np.
avg_cohort.head()
```

Out[44]:

	first_order_month	month	revenue	age_month
0	2017-06-01	2017-06-01	4.060106	0.0
1	2017-06-01	2017-07-01	5.547006	1.0
2	2017-06-01	2017-08-01	5.088161	2.0
3	2017-06-01	2017-09-01	8.545575	3.0
4	2017-06-01	2017-10-01	7.084178	4.0

In [45]:
```
avg_cohort_piv=avg_cohort.pivot_table(
    index='first_order_month',
    columns='age_month',
    values='revenue',
    aggfunc='mean'
)

avg_cohort_piv.round(2).fillna('')
```

Out[45]:

age_month	0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0
first_order_month												
2017-06-01	4.06	5.55	5.09	8.55	7.08	6.83	6.97	6.76	5.28	8.01	12.04	6.04

2017-07-01	5.29	6.45	9.99	6.64	4.72	3.66	3.79	5.45	5.35	11.79	5.65
2017-08-01	4.72	5.99	6.28	6.62	7.96	6.27	5.89	7.11	8.7	5.6	
2017-09-01	4.97	13.17	8.35	62.57	15.43	15.32	16.77	11.21	7.79		
2017-10-01	4.37	7.41	5.13	5.59	5.1	5.07	4.28	4.01			
2017-11-01	4.37	4.1	4.47	6.28	4.44	3.73	4.6				
2017-12-01	4.11	4.23	20.07	26.08	15.95	14.11					
2018-01-01	3.69	4.44	6.45	7.52	2.71						
2018-02-01	3.71	4.58	3.45	3.87							
2018-03-01	4.14	5.97	6.33								
2018-04-01	4.25	6.2									
2018-05-01	4.29										
2018-06-01	3.42										

In [46]:
```
orders['revenue'].mean()
```

Out[46]:
```
4.999646930476993
```

How much money do they bring? (LTV)

In [47]:
```
orders.head(10)
```

Out[47]:

	buy_ts	revenue	uid	month	first_order_date	first_order_month
0	2017-06-01 00:10:00	17.00	10329302124590727494	2017-06-01	2017-06-01 00:10:00	2017-06-01
1	2017-06-01 00:25:00	0.55	11627257723692907447	2017-06-01	2017-06-01 00:25:00	2017-06-01
2	2017-06-01 00:27:00	0.37	17903680561304213844	2017-06-01	2017-06-01 00:27:00	2017-06-01
3	2017-06-01 00:29:00	0.55	16109239769442553005	2017-06-01	2017-06-01 00:29:00	2017-06-01
4	2017-06-01 07:58:00	0.37	14200605875248379450	2017-06-01	2017-06-01 07:58:00	2017-06-01
5	2017-06-01 08:43:00	0.18	10402394430196413321	2017-06-01	2017-06-01 08:43:00	2017-06-01
6	2017-06-01 08:54:00	1.83	12464626743129688638	2017-06-01	2017-06-01 08:54:00	2017-06-01
7	2017-06-01 09:22:00	1.22	3644482766749211722	2017-06-01	2017-06-01 09:22:00	2017-06-01
8	2017-06-01 09:22:00	3.30	17542070709969841479	2017-06-01	2017-06-01 09:22:00	2017-06-01
9	2017-06-01 09:23:00	0.37	1074355127080856382	2017-06-01	2017-06-01 09:23:00	2017-06-01

In [48]:
```
#get the revenue per cohort in each month
ltv_cohort=orders.groupby(['first_order_month','month'])['revenue'].sum().reset_index()
ltv_cohort.columns = ['first_order_month','month','revenue']
```

```
#merge with the cohort size
ltv_cohort=ltv_cohort.merge(cohort_sizes,on=['first_order_month'])
ltv_cohort['age']=((ltv_cohort['month'] - ltv_cohort['first_order_month']) / np.timedelt
ltv_cohort['ltv']=ltv_cohort['revenue']/ltv_cohort['cohort_size']
ltv_cohort
```

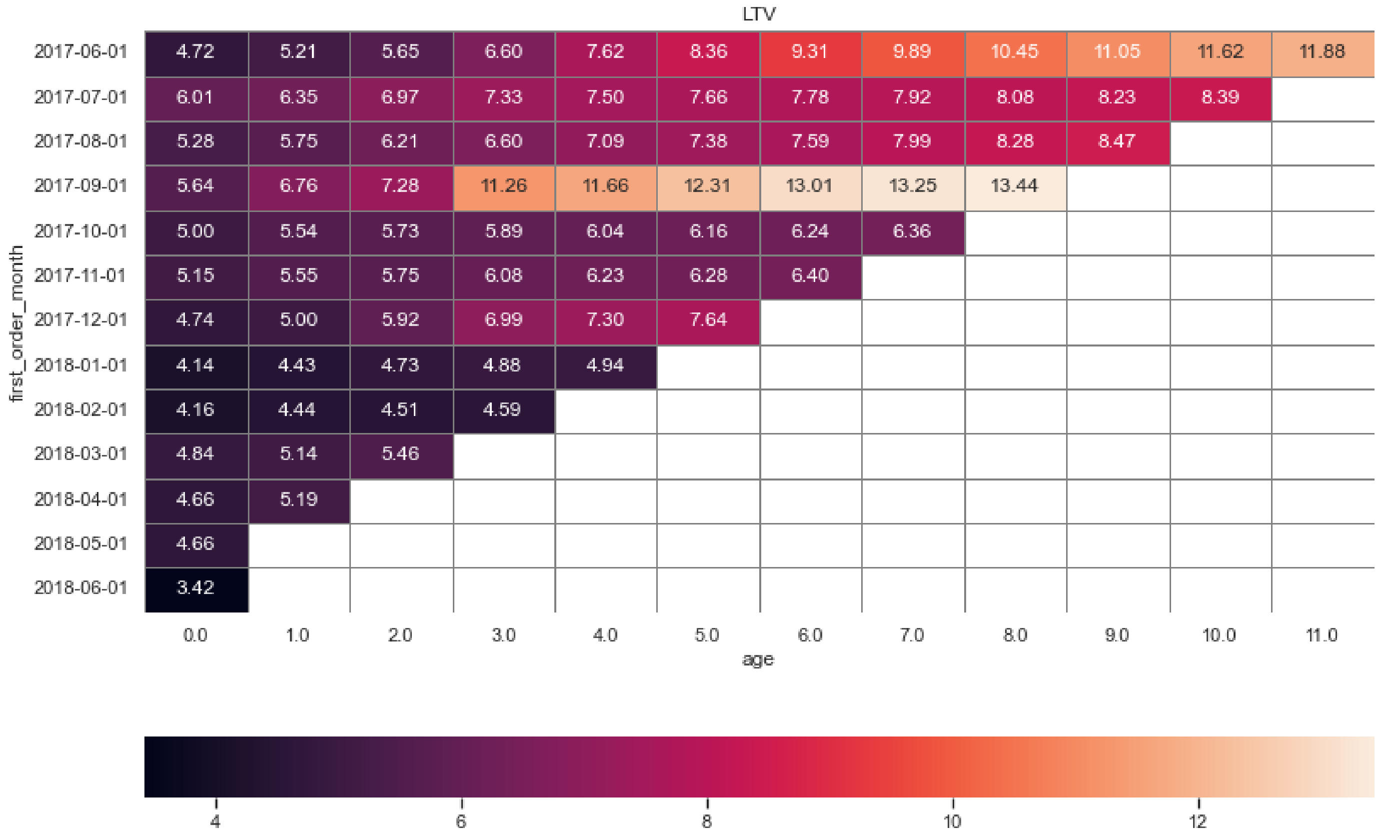
Out[48]:

	first_order_month	month	revenue	cohort_size	age	ltv
0	2017-06-01	2017-06-01	9557.49	2023	0.0	4.724414
1	2017-06-01	2017-07-01	981.82	2023	1.0	0.485329
2	2017-06-01	2017-08-01	885.34	2023	2.0	0.437637
3	2017-06-01	2017-09-01	1931.30	2023	3.0	0.954671
4	2017-06-01	2017-10-01	2068.58	2023	4.0	1.022531
...	...	...	...	...	...	...
74	2018-03-01	2018-05-01	1114.87	3533	2.0	0.315559
75	2018-04-01	2018-04-01	10600.69	2276	0.0	4.657597
76	2018-04-01	2018-05-01	1209.92	2276	1.0	0.531599
77	2018-05-01	2018-05-01	13925.76	2988	0.0	4.660562
78	2018-06-01	2018-06-01	3.42	1	0.0	3.420000

79 rows × 6 columns

In [49]:

```
ltv_cohort_piv=ltv_cohort.pivot_table(
    index='first_order_month',
    columns='age',
    values='ltv',
    aggfunc='sum'
).cumsum(axis=1)
plt.figure(figsize=(13, 9))
ltv_cohort_piv.index=ltv_cohort_piv.index.astype(str)
sns.heatmap(ltv_cohort_piv, annot=True, fmt='.2f', linewidths=1, linecolor='grey', cbar_
            ).set(title ='LTV')
plt.figure(figsize=(13, 9))
plt.show()
```




```
<Figure size 936x648 with 0 Axes>
```

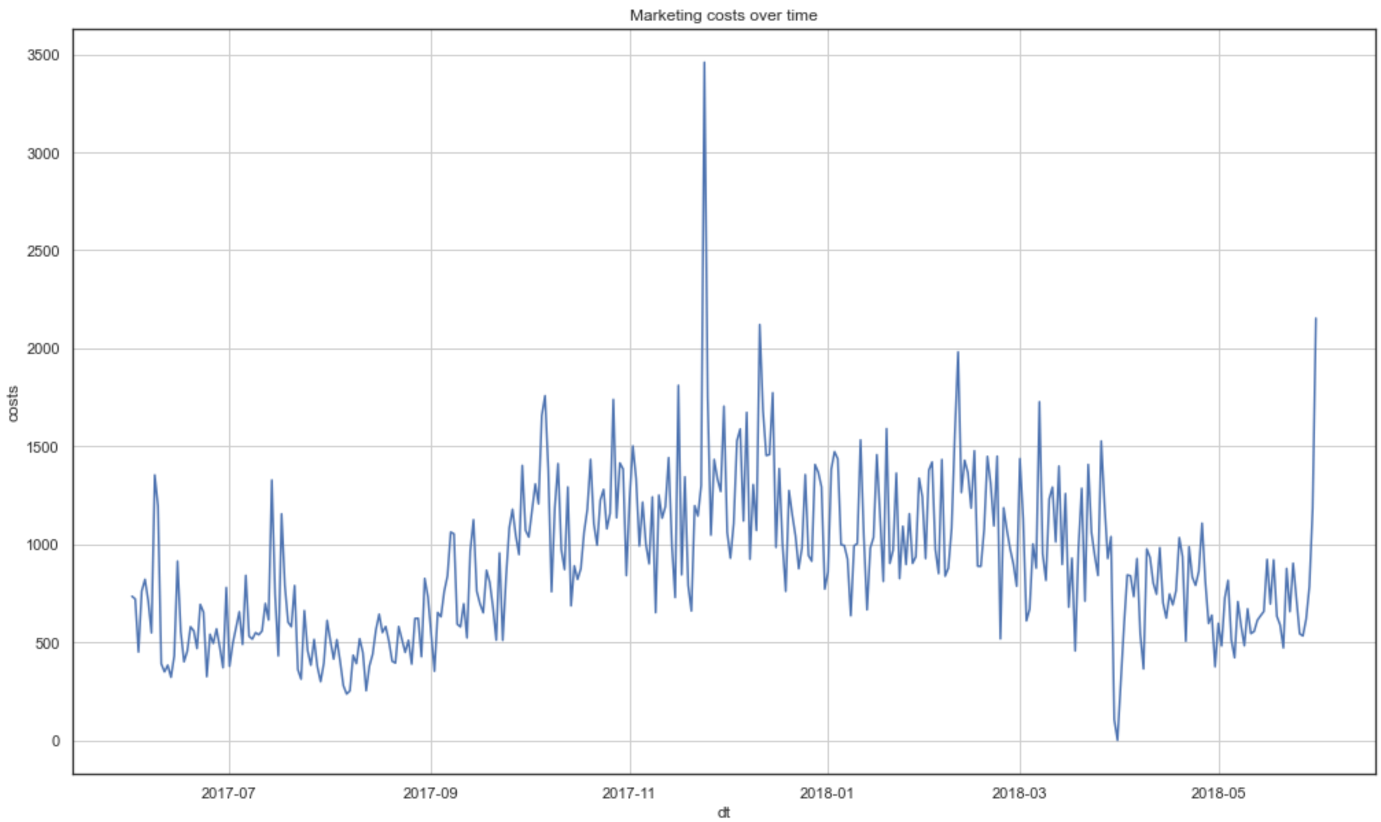
Conclusion

1. **People start buying the same day they start using the service. The overall conversion is 16%.**
2. **On average people make one or two purchases each month.**
3. **The average purchase size is around 5. The most profitable time is at the end of the year, it correlates with all that was mentioned above, autumn months and December are the most profitable. Also, people seem to spend most money several months after using the service.**
4. **The most profitable cohort are September one followed by summer users.**

Marketing

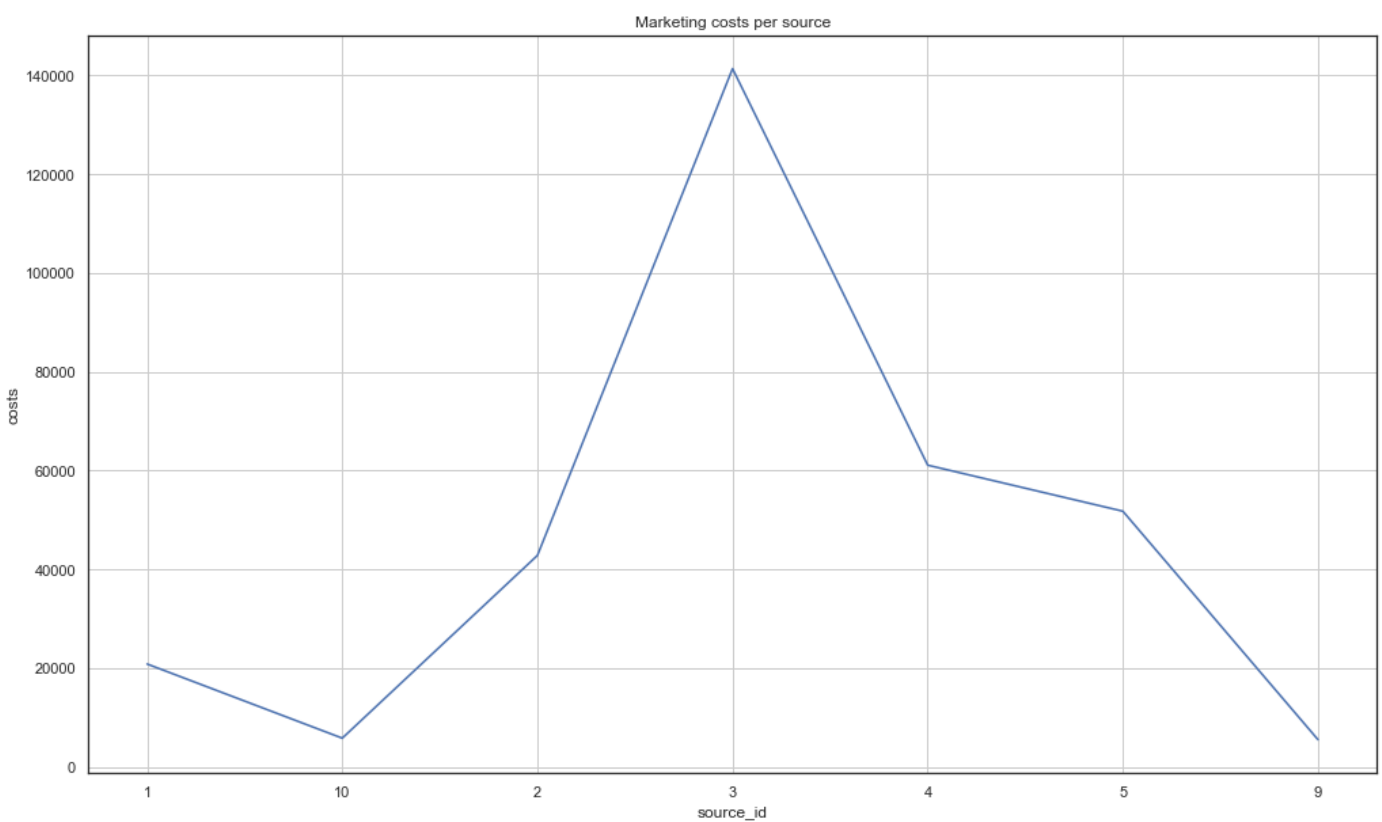
How much money was spent? Overall/per source/over time

In [50]:
```
costs_=costs.sort_values(by=['dt','source_id'])
costs_.head()
costs_dt=costs_.groupby(['dt']).sum().reset_index()
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=costs_dt, x="dt", y="costs")
plt.title('Marketing costs over time')
plt.grid()
plt.show()
```



The most money on the marketing was spent in November-December.

In [51]:
```
costs_s=costs_.groupby(['source_id']).sum().reset_index()
fig,ax=plt.subplots(figsize=(17,10))
sns.lineplot(data=costs_s, x="source_id", y="costs")
plt.title('Marketing costs per source')
plt.grid()
plt.show()
```



Sources 3,4 and 5 are the most expansive.

In [52]:
```
print('Total marketing cost is {}'.format(costs['costs'].sum()))
```

```
Total marketing cost is 329131.62
```

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

In [53]:
```
orders
```

Out[53]:

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

50415 rows × 6 columns

In [54]:
```
costs['costs_month']=costs['dt'].astype('datetime64[M]')
costs
```

Out[54]:

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

2541	10	2018-05-31	17.60	2018-05-01

2542 rows × 4 columns

In [55]:
```
costs_by_month=costs.groupby(['costs_month'])['costs'].sum().reset_index()
costs_by_month.head()
```

Out[55]:

	costs_month	costs
0	2017-06-01	18015.00
1	2017-07-01	18240.59
2	2017-08-01	14790.54
3	2017-09-01	24368.91
4	2017-10-01	36322.88

In [56]:
```
customers_per_moth=orders.groupby(['first_order_month'])['uid'].nunique().reset_index()
customers_per_moth.columns=['costs_month','customers']
customers_per_moth.head()
```

Out[56]:

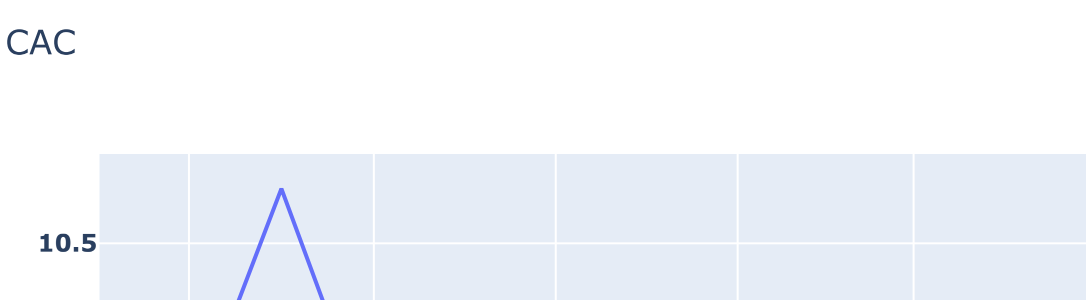
	costs_month	customers
0	2017-06-01	2023
1	2017-07-01	1923
2	2017-08-01	1370
3	2017-09-01	2581
4	2017-10-01	4340

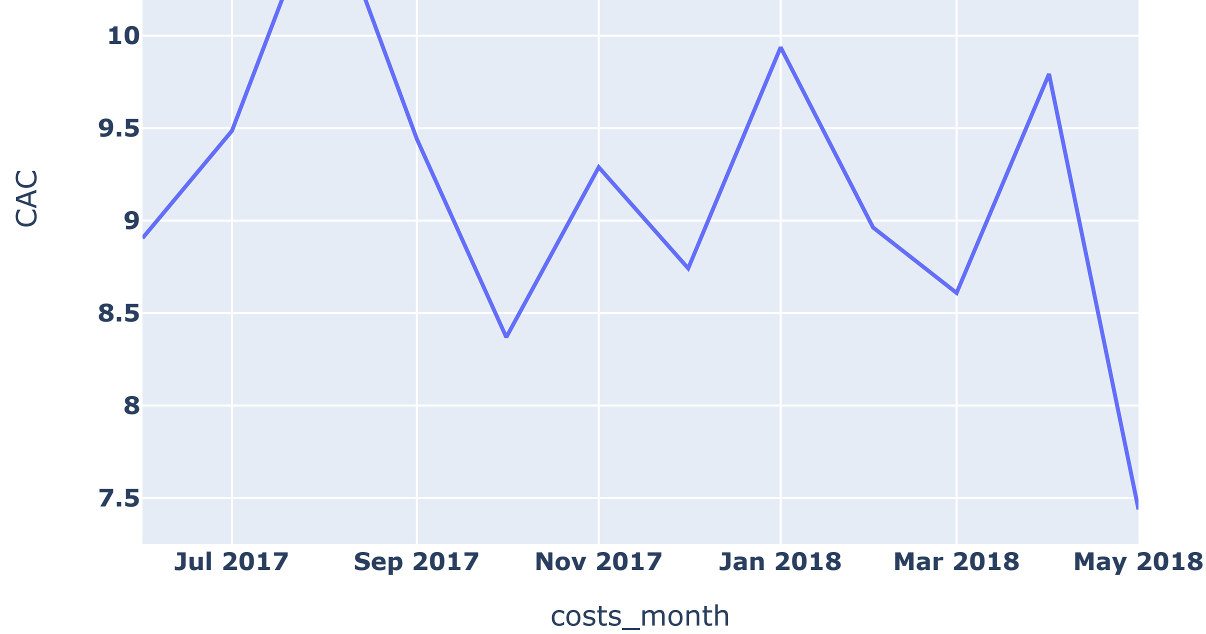
In [57]:
```
CAC_per_month=costs_by_month.merge(customers_per_moth,how='left',on=['costs_month'])
CAC_per_month['CAC']=CAC_per_month['costs']/CAC_per_month['customers']
CAC_per_month.head()
```

Out[57]:

	costs_month	costs	customers	CAC
0	2017-06-01	18015.00	2023	8.905091
1	2017-07-01	18240.59	1923	9.485486
2	2017-08-01	14790.54	1370	10.796015
3	2017-09-01	24368.91	2581	9.441654
4	2017-10-01	36322.88	4340	8.369327

In [58]:
```
fig = px.line(CAC_per_month, x="costs_month", y="CAC", title='CAC')
fig.show()
```





The highest CAC was during July-August period.

CAC per source

In [59]:
```
visits
```

Out[59]:

	device	end_ts	source_id	start_ts	uid	session_year	session_month	session_we
0	touch	2017-12-20 17:38:00	4	2017-12-20 17:20:00	16879256277535980062	2017	12	
1	desktop	2018-02-19 17:21:00	2	2018-02-19 16:53:00	104060357244891740	2018	2	
2	touch	2017-07-01 01:54:00	5	2017-07-01 01:54:00	7459035603376831527	2017	7	
3	desktop	2018-05-20 11:23:00	9	2018-05-20 10:59:00	16174680259334210214	2018	5	
4	desktop	2017-12-27 14:06:00	3	2017-12-27 14:06:00	9969694820036681168	2017	12	
...	...	...	...	...	...	...	...	
359395	desktop	2017-07-29 19:07:19	2	2017-07-29 19:07:00	18363291481961487539	2017	7	
359396	touch	2018-01-25 17:38:19	1	2018-01-25 17:38:00	18370831553019119586	2018	1	
359397	desktop	2018-03-03 10:12:19	4	2018-03-03 10:12:00	18387297585500748294	2018	3	
359398	desktop	2017-	5	2017-	18388616944624776485	2017	11	

		11-02 10:12:19		11-02 10:12:00				
359399	touch	2017-09-10 13:13:19	2	2017-09-10 13:13:00	18396128934054549559	2017	9	

359400 rows × 11 columns

In [60]:
```
visits.groupby(['uid'])['source_id'].nunique().head()
```

Out[60]:
```
uid
11863502262781      1
49537067089222      1
297729379853735     1
313578113262317     1
325320750514679     1
Name: source_id, dtype: int64
```

In [61]:
```
first_source=visits.sort_values('start_ts').groupby('uid').first()['source_id'].reset_in
first_source.columns=['uid','first_source']
first_source.head()
```

Out[61]:

	uid	first_source
0	11863502262781	3
1	49537067089222	2
2	297729379853735	3
3	313578113262317	2
4	325320750514679	5

In [62]:
```
purchase=orders.merge(first_source,on=['uid'],how='left')
purchase.head()
```

Out[62]:

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

In [63]:
```
costs_by_month_source=costs.groupby(['costs_month','source_id'])['costs'].sum().reset_in
costs_by_month_source.head()
```

Out[63]:

	costs_month	source_id	costs
0	2017-06-01	1	1125.61
1	2017-06-01	10	314.22
2	2017-06-01	2	2427.38

3	2017-06-01	3	7731.65
4	2017-06-01	4	3514.80

In [64]:
```
customers_per_moth_source=purchase.groupby(['first_order_month','first_source'])['uid'].
customers_per_moth_source.columns=['costs_month','source_id','customers']
customers_per_moth_source.head()
```

Out[64]:

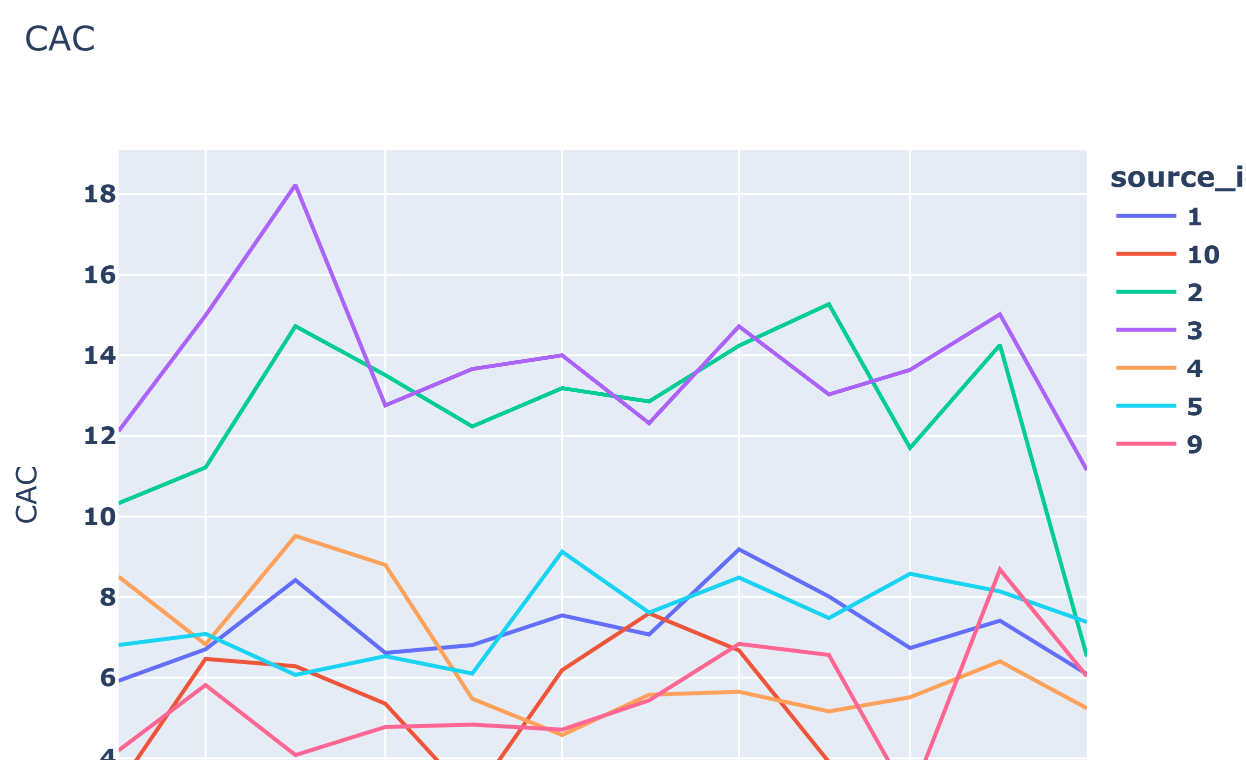
	costs_month	source_id	customers
0	2017-06-01	1	190
1	2017-06-01	10	95
2	2017-06-01	2	235
3	2017-06-01	3	638
4	2017-06-01	4	413

In [65]:
```
CAC_per_month_source=costs_by_month_source.merge(customers_per_moth_source,how='left',on
CAC_per_month_source['CAC']=CAC_per_month_source['costs']/CAC_per_month_source['customer
CAC_per_month_source.head()
```

Out[65]:

	costs_month	source_id	costs	customers	CAC
0	2017-06-01	1	1125.61	190	5.924263
1	2017-06-01	10	314.22	95	3.307579
2	2017-06-01	2	2427.38	235	10.329277
3	2017-06-01	3	7731.65	638	12.118574
4	2017-06-01	4	3514.80	413	8.510412

In [66]:
```
#plotting cac dynamics
fig = px.line(CAC_per_month_source, x="costs_month", y="CAC",color='source_id',title='CA
fig.show()
```



Sources 2 and 3 are the most expensive for the customer's acquirement. CAC for sources 9 and 10 are beneath the average.

How worthwhile where the investments? (ROI)

ROI per cohort

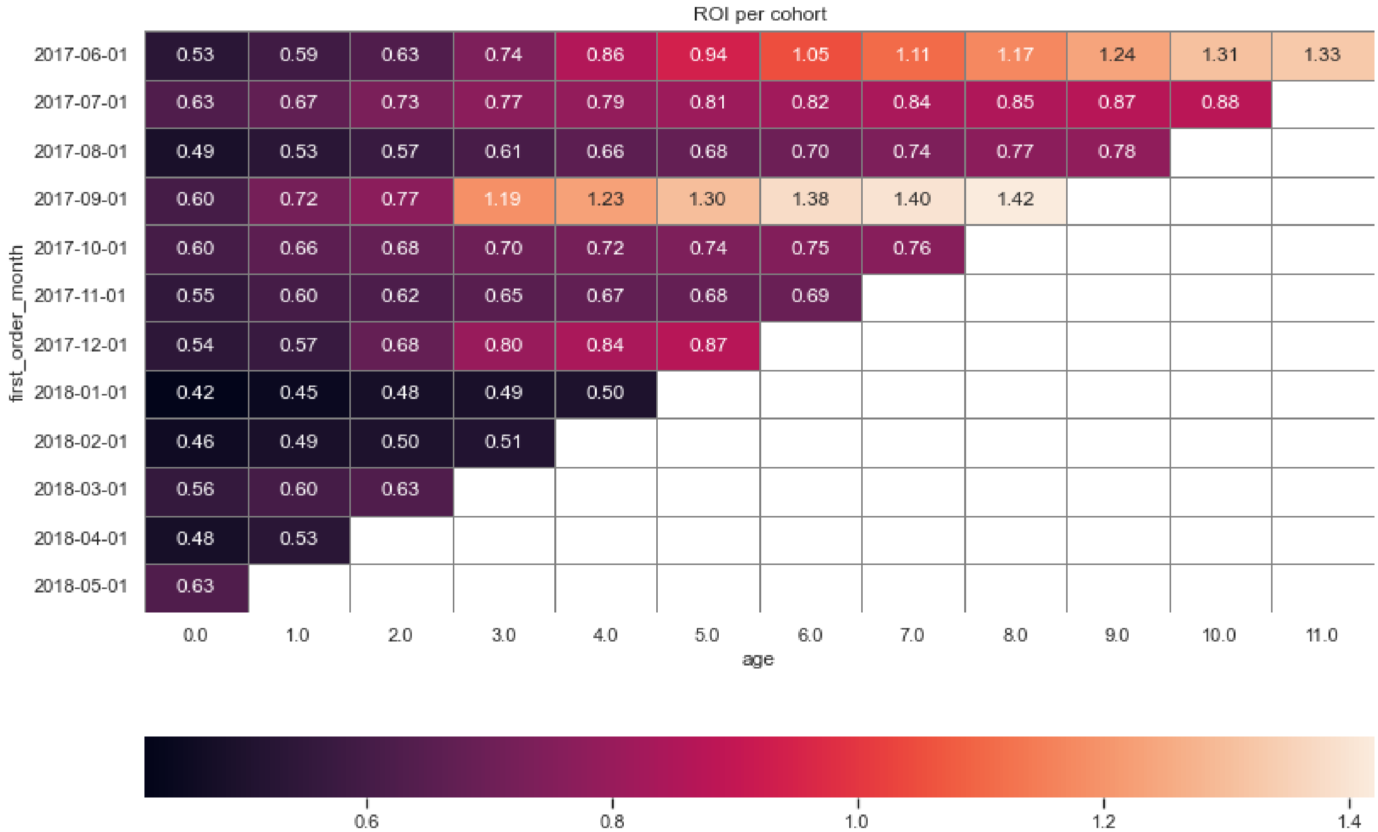
In [67]:
```
CAC_per_month_ROI=CAC_per_month[['costs_month','CAC']]
CAC_per_month_ROI.columns=['first_order_month','CAC']
ROI=ltv_cohort.merge(CAC_per_month_ROI,on=['first_order_month'],how='left')
ROI.head()
```

Out[67]:

	first_order_month	month	revenue	cohort_size	age	ltv	CAC
0	2017-06-01	2017-06-01	9557.49	2023	0.0	4.724414	8.905091
1	2017-06-01	2017-07-01	981.82	2023	1.0	0.485329	8.905091
2	2017-06-01	2017-08-01	885.34	2023	2.0	0.437637	8.905091
3	2017-06-01	2017-09-01	1931.30	2023	3.0	0.954671	8.905091
4	2017-06-01	2017-10-01	2068.58	2023	4.0	1.022531	8.905091

In [68]:
```
ROI['ROI']=ROI['ltv']/ROI['CAC']
roi_piv = ROI.pivot_table(
    index='first_order_month', columns='age', values='ROI', aggfunc='mean'
).cumsum(axis=1).round(2)
```

In [69]:
```
roi_piv.index=roi_piv.index.astype(str)
plt.figure(figsize=(13, 9))
sns.heatmap(roi_piv, annot=True, fmt='.2f', linewidths=1, linecolor='grey', cbar_kws= {'
            ).set(title ='ROI per cohort')
plt.show()
```



ROI per source

In [70]:

```
ltv_per_source=purchase.groupby(['first_source'])['uid','revenue'].agg({'uid':'nunique',
ltv_per_source.columns=['source_id','customers','revenue']
ltv_per_source['ltv']=ltv_per_source['revenue']/ltv_per_source['customers']
ltv_per_source
```

```
C:\Users\Sophie\AppData\Local\Temp\ipykernel_4048\1304129202.py:1: FutureWarning:

Indexing with multiple keys (implicitly converted to a tuple of keys) will be deprecate
d, use a list instead.
```

Out[70]:

	source_id	customers	revenue	ltv
0	1	2899	31090.55	10.724577
1	10	1329	4450.33	3.348631
2	2	3506	46923.61	13.383802
3	3	10473	54511.24	5.204931
4	4	10296	56696.83	5.506685
5	5	6931	52624.02	7.592558
6	6	0	0.00	NaN
7	7	1	1.22	1.220000
8	9	1088	5759.40	5.293566

In [71]:

```
roi_per_source=costs_s.merge(ltv_per_source,on=['source_id'])
roi_per_source['cac']=roi_per_source['costs']/roi_per_source['customers']
roi_per_source['romi']=roi_per_source['ltv']/roi_per_source['cac']
roi_per_source
```

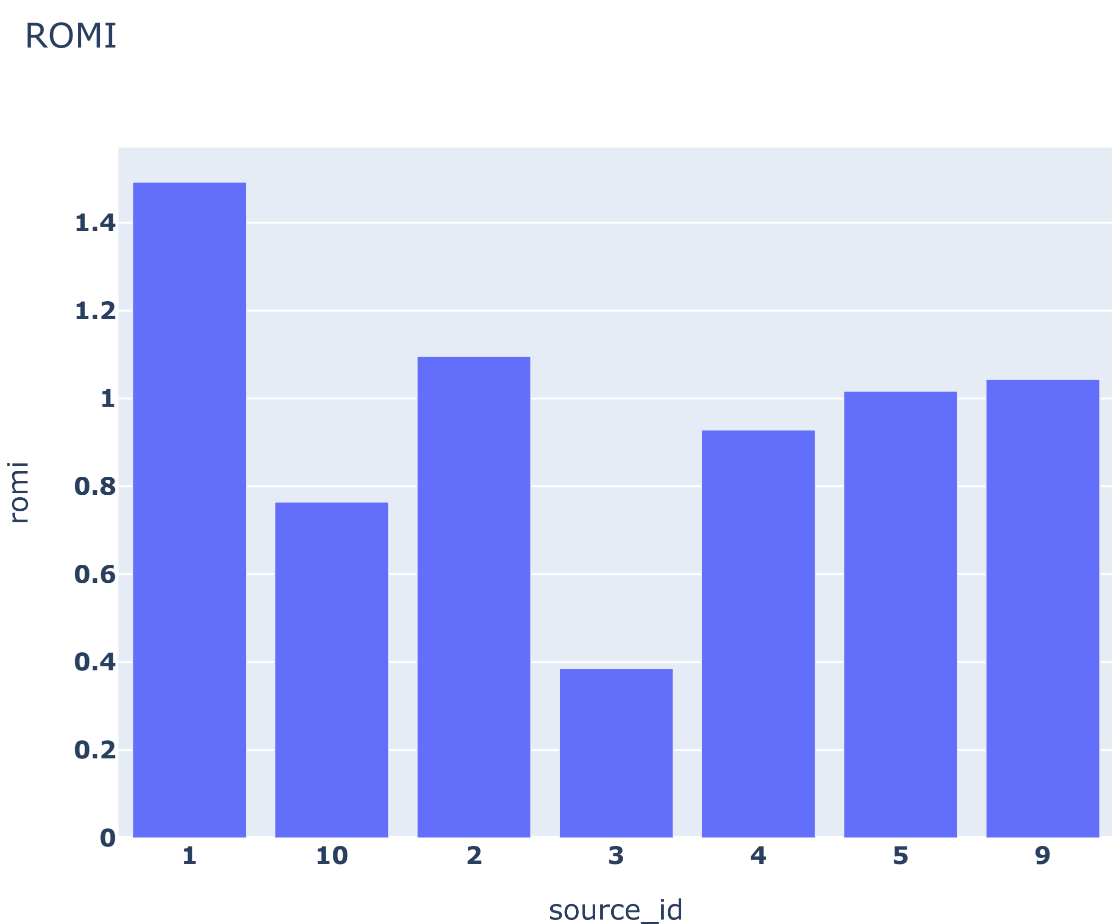
source_id	costs	customers	revenue	ltv	cac	romi

Out[71]:

0	1	20833.27	2899	31090.55	10.724577	7.186364	1.492351
1	10	5822.49	1329	4450.33	3.348631	4.381106	0.764335
2	2	42806.04	3506	46923.61	13.383802	12.209367	1.096191
3	3	141321.63	10473	54511.24	5.204931	13.493901	0.385725
4	4	61073.60	10296	56696.83	5.506685	5.931779	0.928336
5	5	51757.10	6931	52624.02	7.592558	7.467479	1.016750
6	9	5517.49	1088	5759.40	5.293566	5.071222	1.043844

In [72]:

```
fig = px.bar(roi_per_source, x='source_id', y='romi', title='ROMI')
fig.update_xaxes(type='category')
fig.show()
```



We are intrested on ROMI above 1: sources 1,2,4,5,9. Sources 10 and 3 are signigicantly below 1.

Conclusion

1. **Marketing costs correlate with the seasonal buying peaks. The most money is spent on the source 3. 2.The costs of marketing per customer are highest for sources 3 and 2. 3.Only expenses on sources 1,2,5 and 9 are profitable.**

In [ ]:

In [ ]:

Conclusion

As a result of the conducted research, I would recommend focusing marketing expenses on source 1, since it's the cheapest and the most profitable one.

We also see that people prefer using a desktop version of the service. So it might be worth checking if a mobile version of the website is easy to work with and/or functioning correctly.

Overall we see that interest in our service is seasonal and strongly correlated with the number of events throughout the year. Therefore we might correct our expenses on marketing depending on the season.

In [ ]: