Turnover analysis and prediction (for pdf)

November 11, 2018

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# https://stackoverflow.com/questions/21137150/format-suppress-scientific-notation-fro
# pandas print without 'e'
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# style of plots is 'ggplot'
plt.style.use('ggplot')
```

1 Loading (pandas)

In [2]:
```
# https://ru.stackoverflow.com/questions/769110/pandas-%D0%BF%D1%80%D0%B8-%D1%87%D1%82
# 'decimal' is about ',' and '.' in numbers
df = pd.read_csv('orders_st.csv', sep=';', decimal=',')

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2851174 entries, 0 to 2851173
Data columns (total 4 columns):
id_o      int64
id_u      int64
o_date    object
price     float64
dtypes: float64(1), int64(2), object(1)
memory usage: 87.0+ MB
None
            id_o       id_u               price
count 2851174.00 2851174.00          2851174.00
mean  3109378.45 1899114.02       1888562486.56
std   2263497.69 1771364.72    3188914143473.47
min       129.00       0.00            -1605.10
25%   1034214.75  425886.50             576.80
```

```
50%   2787853.00 1310122.00             1084.30
75%   5061009.75 3069821.00             1934.80
max   7488720.00 6455922.00 5384615384615380.00
```

Out[2]:

	id_o	id_u	o_date	price
0	129	1	26.04.2013 15:33:35	1029.00
1	130	155	26.04.2013 16:14:06	140.00
2	131	1	26.04.2013 16:43:30	463.40
3	132	1	26.04.2013 17:20:17	663.60
4	133	1	29.04.2013 12:00:02	1739.50

2 Lossless compression

In [3]:
```
# https://stackoverflow.com/questions/15891038/change-data-type-of-columns-in-pandas
# change numeric types to more compact types
df['id_o'] = pd.to_numeric(df['id_o'], downcast='unsigned')
df['id_u'] = pd.to_numeric(df['id_u'], downcast='unsigned')

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2851174 entries, 0 to 2851173
Data columns (total 4 columns):
id_o      uint32
id_u      uint32
o_date    object
price     float64
dtypes: float64(1), object(1), uint32(2)
memory usage: 65.3+ MB
None
            id_o       id_u               price
count 2851174.00 2851174.00          2851174.00
mean  3109378.45 1899114.02       1888562486.56
std   2263497.69 1771364.72    3188914143473.47
min       129.00       0.00            -1605.10
25%   1034214.75  425886.50              576.80
50%   2787853.00 1310122.00             1084.30
75%   5061009.75 3069821.00             1934.80
max   7488720.00 6455922.00 5384615384615380.00
```

Out[3]:

	id_o	id_u	o_date	price
0	129	1	26.04.2013 15:33:35	1029.00
1	130	155	26.04.2013 16:14:06	140.00
2	131	1	26.04.2013 16:43:30	463.40

```
3   132     1  26.04.2013 17:20:17  663.60
4   133     1  29.04.2013 12:00:02 1739.50
```

3 Delete 2013 year

In [4]:
```
# https://pandas.pydata.org/pandas-docs/version/0.22/generated/pandas.Series.str.conta
# search indexes of rows in column 'o_date' wirh regexp '2013'
rows_with_2013 = df[df['o_date'].str.contains('2013')].index

# check first year is 2013
df.head(len(rows_with_2013) + 2)
```

Out[4]:

	id_o	id_u	o_date	price
0	129	1	26.04.2013 15:33:35	1029.00
1	130	155	26.04.2013 16:14:06	140.00
2	131	1	26.04.2013 16:43:30	463.40
3	132	1	26.04.2013 17:20:17	663.60
4	133	1	29.04.2013 12:00:02	1739.50
5	134	44	16.05.2013 14:08:45	743.40
6	135	1	16.05.2013 16:23:53	5439.00
7	137	160	16.05.2013 23:07:46	969.50
8	138	1	17.05.2013 9:42:44	12035.10
9	141	176	22.05.2013 16:28:47	576.80
10	142	179	23.05.2013 14:32:09	355.60
11	143	180	23.05.2013 14:35:29	527.80
12	144	181	26.05.2013 12:48:48	1120.00
13	145	1	28.05.2013 12:26:20	15847.30
14	146	1	28.05.2013 12:28:25	4415.60
15	148	194	30.05.2013 16:44:05	877.80
16	149	194	03.06.2013 13:59:28	259.00
17	150	203	04.06.2013 17:22:41	6127.80
18	151	204	04.06.2013 18:12:11	1260.00
19	152	209	05.06.2013 17:08:56	1955.10
20	153	219	07.06.2013 14:29:08	4415.60
21	154	159	07.06.2013 16:33:58	4415.60
22	155	220	07.06.2013 18:21:46	2267.30
23	156	222	08.06.2013 16:35:03	1820.00
24	157	223	08.06.2013 18:15:39	1491.70
25	158	226	08.06.2013 22:45:23	711.20
26	160	240	11.06.2013 1:14:20	963.90
27	161	244	11.06.2013 13:22:25	991.20
28	162	245	11.06.2013 15:25:57	2945.60
29	163	160	11.06.2013 18:22:52	835.10
...	...	...	...	...
32339	33934	66341	31.12.2013 0:57:15	1933.40
32340	33935	66343	31.12.2013 1:50:56	1383.20
32341	33936	65594	31.12.2013 2:51:06	1617.70

```
32342  33937  58751   31.12.2013 4:21:13  3515.40
32343  33938  66347   31.12.2013 5:09:44  4323.90
32344  33939  66348   31.12.2013 5:19:44  1016.40
32345  33940  66351   31.12.2013 8:32:41  1696.10
32346  33941  43972  31.12.2013 10:24:57  3467.80
32347  33942  66354  31.12.2013 10:34:04   484.40
32348  33943  66355  31.12.2013 10:53:03  1712.90
32349  33944  66356  31.12.2013 11:43:06   565.60
32350  33945  11508  31.12.2013 11:47:39   348.60
32351  33946  66357  31.12.2013 11:55:06  1087.80
32352  33947  66361  31.12.2013 12:34:15   657.30
32353  33948  66362  31.12.2013 12:53:58  1660.40
32354  33949  66364  31.12.2013 12:55:33   807.80
32355  33950  66365  31.12.2013 13:02:12  3887.80
32356  33951  66371  31.12.2013 14:17:23  1696.10
32357  33952  65713  31.12.2013 15:02:53  1502.90
32358  33953  66376  31.12.2013 15:05:44  2436.70
32359  33954   6324  31.12.2013 15:20:23   226.10
32360  33955  65594  31.12.2013 15:36:24  1659.00
32361  33956  66379  31.12.2013 16:15:11  1481.20
32362  33957  66074  31.12.2013 16:33:21  1389.50
32363  33958  42542  31.12.2013 18:06:37   608.30
32364  33959  48690  31.12.2013 18:40:32  3467.80
32365  33960  66382  31.12.2013 19:54:35  1233.40
32366  33961  65512  31.12.2013 22:45:34  1696.10
32367  33962  66388   01.01.2014 6:26:10  2893.10
32368  33963  66400  01.01.2014 12:38:26   560.00

[32369 rows x 4 columns]
```

In [5]:
```
# http://qaru.site/questions/15871022/delete-pandas-df-row-using-mask-based-on-the-las
# https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reset_index.
# drop rows with '2013' and reset index
df.drop(rows_with_2013, inplace=True)
df.reset_index(inplace=True, drop=True)

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818807 entries, 0 to 2818806
Data columns (total 4 columns):
id_o      uint32
id_u      uint32
o_date    object
price     float64
dtypes: float64(1), object(1), uint32(2)
```

```
memory usage: 64.5+ MB
None
            id_o       id_u      price
count 2818807.00 2818807.00 2818807.00
mean  3144883.47 1920443.91    1709.89
std   2251933.61 1770220.57    2506.41
min     33962.00       0.00   -1605.10
25%   1088052.50  440634.00     576.10
50%   2829083.00 1334140.00    1082.90
75%   5091384.50 3097147.00    1934.80
max   7488720.00 6455922.00  630074.90
```

Out[5]:

	id_o	id_u	o_date	price
0	33962	66388	01.01.2014 6:26:10	2893.10
1	33963	66400	01.01.2014 12:38:26	560.00
2	33964	66403	01.01.2014 13:02:34	4415.60
3	33965	66407	01.01.2014 13:47:19	1841.70
4	33966	66408	01.01.2014 14:07:46	845.60

4 Filtration (negative prices)

In [6]:
```
# check negative numbers or 0 in 'price'
negative_price = df[df['price'] <= 0]
negative_price
```

Out[6]:

	id_o	id_u	o_date	price
308699	386407	155823	14.04.2015 14:40:48	0.00
315358	393066	390698	20.04.2015 14:06:09	0.00
583765	820384	189642	22.10.2015 20:26:36	-1.40
687207	1049151	447755	01.12.2015 8:35:40	0.00
735608	1155915	471946	17.12.2015 23:56:55	-1605.10
735609	1155918	471946	17.12.2015 23:56:56	-90.30
847707	1401600	272316	20.02.2016 12:27:58	-2.10
948985	1615909	926637	13.04.2016 15:52:49	0.00
954212	1627392	428359	15.04.2016 10:13:30	-10.50
1024881	1784326	215957	23.05.2016 19:41:56	0.00
1025522	1785877	222822	24.05.2016 6:08:31	-13.30
1026802	1788679	1299090	24.05.2016 13:19:52	0.00
1029982	1795945	219291	24.05.2016 20:11:24	0.00
1072560	1909788	1516077	15.06.2016 19:52:32	0.00
1072655	1910028	148205	15.06.2016 20:36:53	0.00
1073125	1911224	222993	15.06.2016 23:29:51	0.00
1073902	1913217	1516077	16.06.2016 12:07:03	0.00
1074633	1915034	222993	16.06.2016 17:10:59	0.00
1075748	1917944	1538592	17.06.2016 9:33:52	0.00
1075761	1917974	1538592	17.06.2016 9:41:55	0.00
1076899	1920959	1370859	17.06.2016 20:10:29	0.00

```
1077665  1922886   503770  18.06.2016 10:25:23     0.00
1077678  1922922   503770  18.06.2016 10:30:57     0.00
1077717  1923020   186744  18.06.2016 10:52:59     0.00
1077734  1923060   797349  18.06.2016 11:04:31     0.00
1077954  1923605   469751  18.06.2016 13:22:15     0.00
1078068  1923899  1538592  18.06.2016 14:20:23     0.00
1078244  1924346   469751  18.06.2016 16:12:51     0.00
1078261  1924391  1512744  18.06.2016 16:18:35     0.00
1079000  1926315   390645   19.06.2016 0:44:08     0.00
1079008  1926333   390645   19.06.2016 1:01:23     0.00
1079015  1926351   390645   19.06.2016 1:09:43     0.00
1079741  1928217  1598373  19.06.2016 15:47:43     0.00
1080084  1929096   504534  19.06.2016 19:46:17     0.00
1080446  1930028   453428  19.06.2016 23:46:34     0.00
1080793  1930895   503770   20.06.2016 9:57:33     0.00
1080800  1930910   503770  20.06.2016 10:03:40     0.00
1081309  1932257   873550  20.06.2016 14:18:20     0.00
1081312  1932263   873550  20.06.2016 14:20:04     0.00
1092468  1958901   209907  23.06.2016 10:58:30     0.00
1092822  1959825   139548  23.06.2016 12:40:06     0.00
1092843  1959888   139548  23.06.2016 12:45:45     0.00
1092855  1959924      175  23.06.2016 12:51:14     0.00
1104860  1993533   777072  30.06.2016 23:20:54     0.00
1181659  2219955    73149  11.08.2016 14:59:33   -25.90
1207485  2288917   225869  23.08.2016 11:40:29     0.00
1578146  3360763  2682535  16.12.2016 21:38:42     0.00
1943561  4489341  1292160  26.04.2017 19:34:33    -0.70
2357771  5832513  4854405  17.10.2017 19:55:19  -142.10
2641822  6895681  3764611  26.12.2017 15:26:25     0.00
2772225  7322035  3764611  04.02.2018 20:12:25     0.00
2797767  7412173  3764611  12.02.2018 15:22:55     0.00
```

In [7]:
```
# drop rows with negative price and reset index
df.drop(negative_price.index, inplace=True)
df.reset_index(inplace=True, drop=True)

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818755 entries, 0 to 2818754
Data columns (total 4 columns):
id_o      uint32
id_u      uint32
o_date    object
price     float64
dtypes: float64(1), object(1), uint32(2)
```

```
memory usage: 64.5+ MB
None
            id_o       id_u      price
count 2818755.00 2818755.00 2818755.00
mean  3144900.19 1920462.33    1709.92
std   2251942.24 1770225.85    2506.42
min     33962.00       0.00       0.70
25%   1088029.50  440634.00     576.10
50%   2829134.00 1334163.00    1082.90
75%   5091412.50 3097187.00    1934.80
max   7488720.00 6455922.00  630074.90
```

Out[7]:

	id_o	id_u	o_date	price
0	33962	66388	01.01.2014 6:26:10	2893.10
1	33963	66400	01.01.2014 12:38:26	560.00
2	33964	66403	01.01.2014 13:02:34	4415.60
3	33965	66407	01.01.2014 13:47:19	1841.70
4	33966	66408	01.01.2014 14:07:46	845.60

5 Lossless compression

In [8]:
```
# https://stackoverflow.com/questions/15891038/change-data-type-of-columns-in-pandas
# change 'price' to more compact dtype
df['price'] = pd.to_numeric(df['price'], downcast='float')

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818755 entries, 0 to 2818754
Data columns (total 4 columns):
id_o      uint32
id_u      uint32
o_date    object
price     float32
dtypes: float32(1), object(1), uint32(2)
memory usage: 53.8+ MB
None
            id_o       id_u      price
count 2818755.00 2818755.00 2818755.00
mean  3144900.19 1920462.33    1709.75
std   2251942.24 1770225.85    2501.63
min     33962.00       0.00       0.70
25%   1088029.50  440634.00     576.10
50%   2829134.00 1334163.00    1082.90
75%   5091412.50 3097187.00    1934.80
```

```
max   7488720.00 6455922.00  630074.88
```

Out[8]:

	id_o	id_u	o_date	price
0	33962	66388	01.01.2014 6:26:10	2893.10
1	33963	66400	01.01.2014 12:38:26	560.00
2	33964	66403	01.01.2014 13:02:34	4415.60
3	33965	66407	01.01.2014 13:47:19	1841.70
4	33966	66408	01.01.2014 14:07:46	845.60

6 Filtration (outliers)

In [9]:
```
# https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.quantile.html
# calculate quantile of 'price'
alpha1 = 0.3173
alpha2 = 0.0455
alpha3 = 0.0027

quantile_of_price = df['price'].quantile(1 - alpha3)
print(quantile_of_price)

indexes_with_big_price = df[df['price'] > quantile_of_price]
indexes_with_big_price['price'].count()
```

```
18195.099609375
```

Out[9]: 7601

In [10]:
```
# drop rows with outliers in 'price' and reset index
# df.drop(indexes_with_big_price.index, inplace=True)
# df.reset_index(inplace=True, drop=True)

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818755 entries, 0 to 2818754
Data columns (total 4 columns):
id_o      uint32
id_u      uint32
o_date    object
price     float32
dtypes: float32(1), object(1), uint32(2)
memory usage: 53.8+ MB
None
            id_o       id_u      price
```

```
count 2818755.00 2818755.00 2818755.00
mean  3144900.19 1920462.33    1709.75
std   2251942.24 1770225.85    2501.63
min     33962.00       0.00       0.70
25%   1088029.50  440634.00     576.10
50%   2829134.00 1334163.00    1082.90
75%   5091412.50 3097187.00    1934.80
max   7488720.00 6455922.00  630074.88
```

Out[10]:

	id_o	id_u	o_date	price
0	33962	66388	01.01.2014 6:26:10	2893.10
1	33963	66400	01.01.2014 12:38:26	560.00
2	33964	66403	01.01.2014 13:02:34	4415.60
3	33965	66407	01.01.2014 13:47:19	1841.70
4	33966	66408	01.01.2014 14:07:46	845.60

7 Extracting data (year, month, type of order)

In [11]:
```
# https://stackoverflow.com/questions/26763344/convert-pandas-column-to-datetime
# https://pandas.pydata.org/pandas-docs/stable/generated/pandas.to_datetime.html
# https://docs.python.org/3/library/datetime.html#strftime-and-strptime-behavior
# change df['o_date'] to datetime64 type
df['o_date'] = pd.to_datetime(df['o_date'], format='%d.%m.%Y %H:%M:%S')

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818755 entries, 0 to 2818754
Data columns (total 4 columns):
id_o      uint32
id_u      uint32
o_date    datetime64[ns]
price     float32
dtypes: datetime64[ns](1), float32(1), uint32(2)
memory usage: 53.8 MB
None
            id_o       id_u      price
count 2818755.00 2818755.00 2818755.00
mean  3144900.19 1920462.33    1709.75
std   2251942.24 1770225.85    2501.63
min     33962.00       0.00       0.70
25%   1088029.50  440634.00     576.10
50%   2829134.00 1334163.00    1082.90
75%   5091412.50 3097187.00    1934.80
```

```
max   7488720.00 6455922.00  630074.88
```

Out[11]:

	id_o	id_u	o_date	price
0	33962	66388	2014-01-01 06:26:10	2893.10
1	33963	66400	2014-01-01 12:38:26	560.00
2	33964	66403	2014-01-01 13:02:34	4415.60
3	33965	66407	2014-01-01 13:47:19	1841.70
4	33966	66408	2014-01-01 14:07:46	845.60

In [12]:
```
# https://stackoverflow.com/questions/13648774/get-year-month-or-day-from-numpy-datet
# extracting year and month from 'o_date'
df['year'] = df['o_date'].apply(lambda x: x.year)
df['month'] = df['o_date'].apply(lambda x: x.month)

df['year'] = pd.to_numeric(df['year'], downcast='unsigned')
df['month'] = pd.to_numeric(df['month'], downcast='unsigned')

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818755 entries, 0 to 2818754
Data columns (total 6 columns):
id_o      uint32
id_u      uint32
o_date    datetime64[ns]
price     float32
year      uint16
month     uint8
dtypes: datetime64[ns](1), float32(1), uint16(1), uint32(2), uint8(1)
memory usage: 61.8 MB
None
            id_o       id_u      price       year      month
count 2818755.00 2818755.00 2818755.00 2818755.00 2818755.00
mean  3144900.19 1920462.33    1709.75    2016.13       7.14
std   2251942.24 1770225.85    2501.63       1.04       3.73
min     33962.00       0.00       0.70    2014.00       1.00
25%   1088029.50  440634.00     576.10    2015.00       4.00
50%   2829134.00 1334163.00    1082.90    2016.00       8.00
75%   5091412.50 3097187.00    1934.80    2017.00      11.00
max   7488720.00 6455922.00  630074.88    2018.00      12.00
```

Out[12]:

	id_o	id_u	o_date	price	year	month
0	33962	66388	2014-01-01 06:26:10	2893.10	2014	1
1	33963	66400	2014-01-01 12:38:26	560.00	2014	1
2	33964	66403	2014-01-01 13:02:34	4415.60	2014	1

```
3  33965  66407 2014-01-01 13:47:19 1841.70  2014      1
4  33966  66408 2014-01-01 14:07:46  845.60  2014      1
```

In [13]:
```python
# dict for 'order_checking'
# dict remembers id_u that have already been mentioned
memory_dict = {}

# check that the order is secondary


def order_checking(id_u):
    if id_u in memory_dict:
        return True
    else:
        memory_dict[id_u] = True
        return False


# extracting type of order (primary or secondary)
# primary == False
# secondary == True
df['type_of_order'] = df['id_u'].apply(order_checking)

print((df.info()))
print((df.describe()))
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2818755 entries, 0 to 2818754
Data columns (total 7 columns):
id_o             uint32
id_u             uint32
o_date           datetime64[ns]
price            float32
year             uint16
month            uint8
type_of_order    bool
dtypes: bool(1), datetime64[ns](1), float32(1), uint16(1), uint32(2), uint8(1)
memory usage: 64.5 MB
None
            id_o       id_u      price       year      month
count 2818755.00 2818755.00 2818755.00 2818755.00 2818755.00
mean  3144900.19 1920462.33    1709.75    2016.13       7.14
std   2251942.24 1770225.85    2501.63       1.04       3.73
min     33962.00       0.00       0.70    2014.00       1.00
25%   1088029.50  440634.00     576.10    2015.00       4.00
50%   2829134.00 1334163.00    1082.90    2016.00       8.00
75%   5091412.50 3097187.00    1934.80    2017.00      11.00
```

```
max   7488720.00 6455922.00  630074.88    2018.00      12.00
```

Out[13]:

	id_o	id_u	o_date	price	year	month	type_of_order
0	33962	66388	2014-01-01 06:26:10	2893.10	2014	1	False
1	33963	66400	2014-01-01 12:38:26	560.00	2014	1	False
2	33964	66403	2014-01-01 13:02:34	4415.60	2014	1	False
3	33965	66407	2014-01-01 13:47:19	1841.70	2014	1	False
4	33966	66408	2014-01-01 14:07:46	845.60	2014	1	False

8 Create pivot table (pandas)

In [14]:
```
# http://datareview.info/article/svodnyie-tablitsyi-v-python/
# https://pandas.pydata.org/pandas-docs/stable/generated/pandas.pivot_table.html
# create pivot table
pivot_table = pd.pivot_table(
    df,
    values='price',
    index=['year', 'month'],
    columns='type_of_order',
    aggfunc=[sum, len, 'mean'])

pivot_table
```

Out[14]:

		sum		len		mean	
type_of_order		False	True	False	True	False	True
year	month						
2014	1	6423418.50	2032559.88	4252.00	1417.00	1510.68	1434.41
	2	8451002.00	3960493.50	5059.00	2462.00	1670.49	1608.65
	3	14074470.00	5820574.00	7843.00	3348.00	1794.53	1738.52
	4	16400423.00	6907740.50	9221.00	4131.00	1778.59	1672.17
	5	20539852.00	6420844.50	11037.00	4054.00	1861.00	1583.83
	6	20957374.00	6727202.50	10222.00	4127.00	2050.22	1630.05
	7	21804286.00	8517702.00	11341.00	4980.00	1922.61	1710.38
	8	22223320.00	9624635.00	11464.00	5530.00	1938.53	1740.44
	9	22448120.00	10557109.00	11895.00	6731.00	1887.19	1568.43
	10	24694082.00	12879703.00	13326.00	8331.00	1853.08	1546.00
	11	34954440.00	17306228.00	20268.00	11620.00	1724.61	1489.35
	12	61015552.00	22865338.00	32804.00	14799.00	1860.00	1545.06
2015	1	24514220.00	16835278.00	12966.00	11400.00	1890.65	1476.78
	2	21557034.00	13505176.00	10885.00	9161.00	1980.43	1474.20
	3	32331540.00	19133576.00	16108.00	12093.00	2007.17	1582.20
	4	35679052.00	25908756.00	18890.00	16933.00	1888.78	1530.07
	5	35957504.00	26613584.00	19417.00	17992.00	1851.86	1479.19
	6	32579852.00	27272084.00	17231.00	18820.00	1890.77	1449.10
	7	34647104.00	31175280.00	21313.00	25406.00	1625.63	1227.08
	8	31613558.00	29812126.00	18334.00	22280.00	1724.31	1338.07
	9	32533032.00	35137752.00	20479.00	28248.00	1588.60	1243.90

```
      10        47044912.00  48897904.00 27908.00 35255.00 1685.71 1386.98
      11        63512740.00  63003668.00 38201.00 47453.00 1662.59 1327.71
      12        68728160.00  55910324.00 43158.00 41192.00 1592.48 1357.31
2016  1         37363248.00  37100144.00 20533.00 26003.00 1819.67 1426.76
      2         35078232.00  38348920.00 19490.00 25585.00 1799.81 1498.88
      3         42500080.00  46138320.00 25496.00 34020.00 1666.93 1356.21
      4         48771428.00  58423036.00 26871.00 40861.00 1815.02 1429.80
      5         37647688.00  45898736.00 20844.00 33838.00 1806.16 1356.43
      6         40793704.00  48972796.00 23158.00 36787.00 1761.54 1331.25
      7         41407548.00  45674416.00 22859.00 34365.00 1811.43 1329.10
      8         46673332.00  60697256.00 26213.00 40961.00 1780.54 1481.83
      9         55187888.00  62459340.00 29232.00 40911.00 1887.93 1526.71
      10        78635816.00  84179952.00 40390.00 49366.00 1946.91 1705.22
      11       101677168.00  95775288.00 57243.00 58037.00 1776.24 1650.25
      12       106247248.00  92991832.00 68636.00 59531.00 1547.98 1562.07
2017  1         66105144.00  70219112.00 34053.00 42089.00 1941.24 1668.35
      2         61464244.00  62878320.00 32398.00 38251.00 1897.16 1643.83
      3         77804168.00  87442392.00 40200.00 50139.00 1935.43 1744.00
      4         69457496.00  79844960.00 36117.00 47521.00 1923.12 1680.20
      5         71123928.00  74342688.00 35773.00 44147.00 1988.20 1683.98
      6         57656320.00  60055816.00 30100.00 34286.00 1915.49 1751.61
      7         56580652.00  53455012.00 28746.00 29878.00 1968.30 1789.11
      8         68182504.00  63281120.00 35272.00 34816.00 1933.05 1817.59
      9         78248736.00  74804632.00 37846.00 38175.00 2067.56 1959.52
      10        94404680.00  91157752.00 46094.00 46633.00 2048.09 1954.79
      11       115573696.00 102259000.00 60015.00 54326.00 1925.75 1882.32
      12       145474992.00 105412472.00 85062.00 62575.00 1710.22 1684.58
2018  1        102072000.00  95449120.00 53776.00 51644.00 1898.10 1848.21
      2         56037568.00  48915456.00 28962.00 27246.00 1934.87 1795.33
```

9 View pilot table (matplotlib)

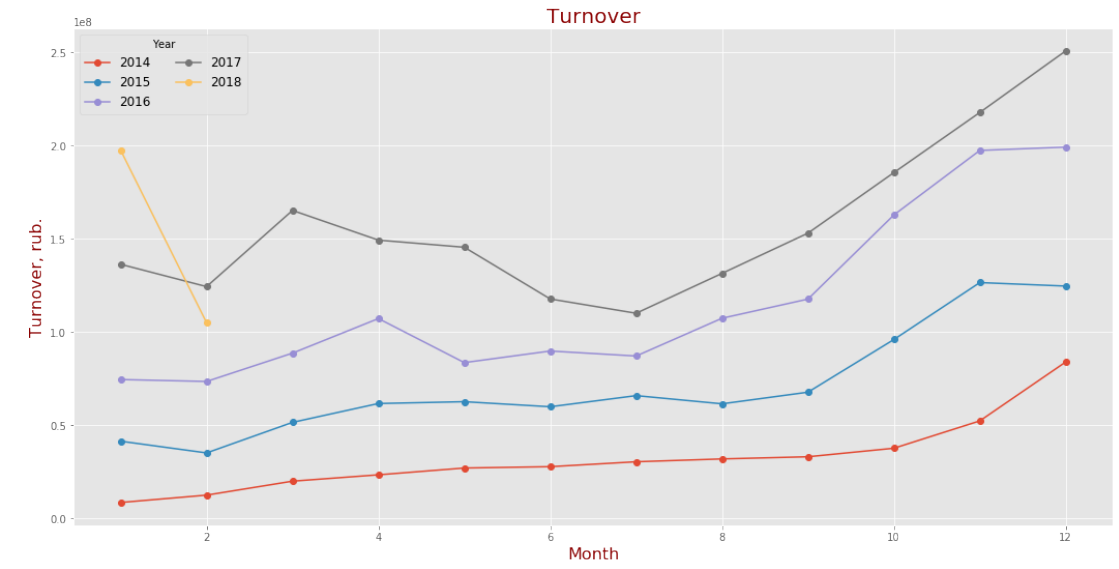
In [15]:
```
# https://www.digitalocean.com/community/tutorials/data-analysis-and-visualization-wi
# https://matplotlib.org/api/_as_gen/matplotlib.pyplot.plot.html?highlight=plot#matpl
# https://stackoverflow.com/questions/37970424/what-is-the-difference-between-drawing
# https://matplotlib.org/gallery/subplots_axes_and_figures/figure_title.html


def custom_plot(axes,
                chart_type,
                items,
                comparison_dict=None,
                ylabel='Item',
                xlabel='Month',
                title='Custom plot',
                xdata=None):
```

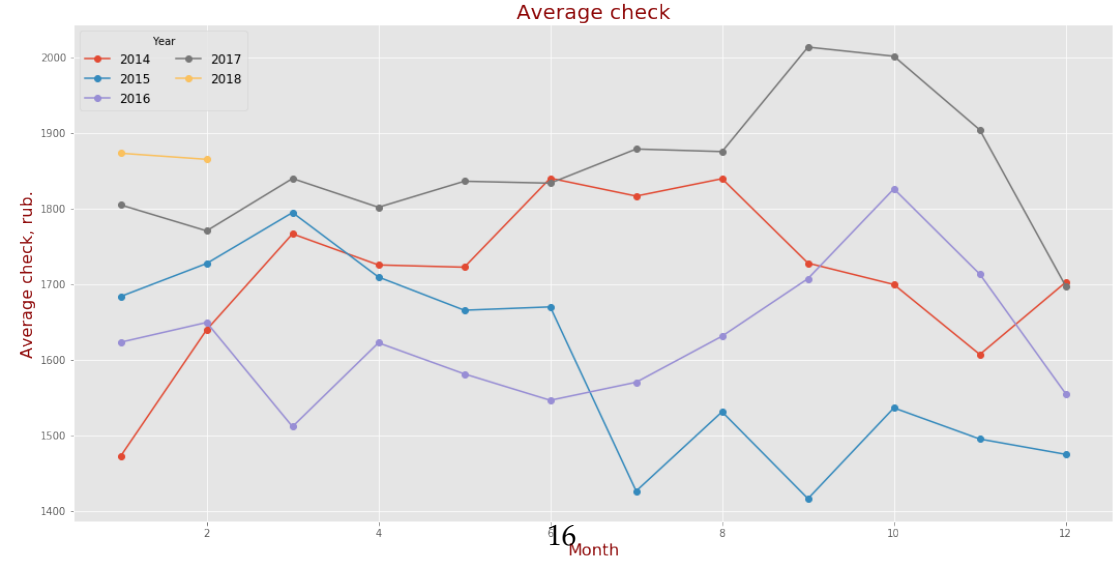
```
title_style = {
    'family': 'sans-serif',
    'color': 'darkred',
    'weight': 'normal',
    'size': 20
}

axes_lables_style = {
    'family': 'sans-serif',
    'color': 'darkred',
    'weight': 'normal',
    'size': 16
}

subplot_number = {'sum': 0, 'len': 1, 'mean': 2}

sum_table = None
if not (chart_type == 'comparison'):
    sum_table = pivot_table[(chart_type, False)] \
        + pivot_table[(chart_type, True)]

if chart_type == 'mean':
    sum_table /= 2

if chart_type == 'comparison':
    axes.set_title(title, fontdict=title_style)
    axes.set_xlabel(xlabel, fontdict=axes_lables_style)
    axes.set_ylabel(ylabel, fontdict=axes_lables_style)
else:
    axes[subplot_number[chart_type]].set_title(title, fontdict=title_style)
    axes[subplot_number[chart_type]].set_xlabel(
        xlabel, fontdict=axes_lables_style)
    axes[subplot_number[chart_type]].set_ylabel(
        ylabel, fontdict=axes_lables_style)

if chart_type == 'comparison':
    for item in items:
        axes.plot(xdata, comparison_dict[item], 'o-', label=item)

    axes.legend(
        loc='best',
        title='Comparison item',
        #title_fontsize = 'x-large',
        fontsize='large')
else:
    for item in items:
        axes[subplot_number[chart_type]].plot(
            sum_table[item], 'o-', label=item)
```

```
                axes[subplot_number[chart_type]].legend(
                    loc='best',
                    title='Year',
                    #title_fontsize = 'x-large',
                    fontsize='large',
                    ncol=2)
```

In [16]:
```
titles = {
    'sum': 'Turnover',
    'len': 'The number of orders',
    'mean': 'Average check'
}

labels = {
    'sum': 'Turnover, rub.',
    'len': 'The number of orders',
    'mean': 'Average check, rub.'
}

years = [_ for _ in range(2014, 2019)]

fig, axes = plt.subplots(3, figsize=(18, 30))
fig.suptitle('Order history monthly', fontsize=24, y=0.92)

custom_plot(axes, 'sum', years, ylabel=labels['sum'], title=titles['sum'])
custom_plot(axes, 'len', years, ylabel=labels['len'], title=titles['len'])
custom_plot(axes, 'mean', years, ylabel=labels['mean'], title=titles['mean'])

plt.show()
```

Order history monthly





10 Commodity circulation prediction

https://axd.semestr.ru/index/season.php
http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-2.html

10.0.0.1 Seasonal Prediction Technique:

1. To present graphically the actual values of the phenomenon being studied, in order to find out whether there is a seasonal wave, to identify the nature of the trend;
2. Calculate seasonality indicators (12-month amounts, 12-month average, centered averages, seasonality indicators, seasonality indices);
3. Determine the seasonality index:
   A. The method of constant average:
      a. The method of absolute differences,
      b. The method of relative differences,
      c. Index method (the calculation of the seasonal index using this formula does not take into account the presence of a trend);
   B. Moving average method,
   C. The method of analytical alignment;
4. Calculate the parameters of the equation describing the trend of the phenomenon under study;
5. Build a forecast:
   A. Formalized methods:
      a. Extrapolation methods:
         i. Moving average method,
         ii. Exponential smoothing method,
         iii. Least squares method;
      b. Modeling methods:
         i. Information modeling methods (patent and publication),
         ii. Statistical modeling method,
         iii. Logical modeling method (predictive analogy, “goal tree”);
   B. Intuitive methods;
6. Calculate its error:
   A. The average absolute score,
   B. Average square estimate,
   C. Average relative error.

```
In [17]: # https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.values.html
         # extracting monthly turnover/factual values of the dynamic series
         # from pivot table
         total_monthly_turnover = pivot_table[('sum', False)] \
             + pivot_table[('sum', True)]
```

```
        # change total_monthly_turnover from pandas dataframe to numpy array
        total_monthly_turnover = total_monthly_turnover.values

        # how many months do we drop when calculating the AA forecast
        AA_bias = 8

        # extracting monthly turnover/factual values of the dynamic series
        # (column 3) without second half of 2017 from pivot table
        monthly_turnover = pivot_table[('sum', False)][:-AA_bias] \
            + pivot_table[('sum', True)][:-AA_bias]

        # change monthly_turnover from pandas dataframe to numpy array
        monthly_turnover = monthly_turnover.values

        print((type(total_monthly_turnover)))
        print((total_monthly_turnover.shape))
        print(total_monthly_turnover)

        print((type(monthly_turnover)))
        print((monthly_turnover.shape))
        print(monthly_turnover)
```

```
<class 'numpy.ndarray'>
(50,)
[8.45597800e+06 1.24114960e+07 1.98950440e+07 2.33081640e+07
 2.69606960e+07 2.76845760e+07 3.03219880e+07 3.18479560e+07
 3.30052280e+07 3.75737840e+07 5.22606680e+07 8.38808880e+07
 4.13494960e+07 3.50622080e+07 5.14651160e+07 6.15878080e+07
 6.25710880e+07 5.98519360e+07 6.58223840e+07 6.14256840e+07
 6.76707840e+07 9.59428160e+07 1.26516408e+08 1.24638480e+08
 7.44633920e+07 7.34271520e+07 8.86384000e+07 1.07194464e+08
 8.35464240e+07 8.97664960e+07 8.70819680e+07 1.07370592e+08
 1.17647232e+08 1.62815776e+08 1.97452448e+08 1.99239072e+08
 1.36324256e+08 1.24342560e+08 1.65246560e+08 1.49302464e+08
 1.45466624e+08 1.17712136e+08 1.10035664e+08 1.31463624e+08
 1.53053376e+08 1.85562432e+08 2.17832704e+08 2.50887456e+08
 1.97521120e+08 1.04953024e+08]
<class 'numpy.ndarray'>
(42,)
[8.45597800e+06 1.24114960e+07 1.98950440e+07 2.33081640e+07
 2.69606960e+07 2.76845760e+07 3.03219880e+07 3.18479560e+07
 3.30052280e+07 3.75737840e+07 5.22606680e+07 8.38808880e+07
 4.13494960e+07 3.50622080e+07 5.14651160e+07 6.15878080e+07
 6.25710880e+07 5.98519360e+07 6.58223840e+07 6.14256840e+07
 6.76707840e+07 9.59428160e+07 1.26516408e+08 1.24638480e+08
 7.44633920e+07 7.34271520e+07 8.86384000e+07 1.07194464e+08
 8.35464240e+07 8.97664960e+07 8.70819680e+07 1.07370592e+08
```

```
 1.17647232e+08 1.62815776e+08 1.97452448e+08 1.99239072e+08
 1.36324256e+08 1.24342560e+08 1.65246560e+08 1.49302464e+08
 1.45466624e+08 1.17712136e+08]
```

10.0.1 2. and 3. Calculate seasonality indicators and determine the seasonality index

https://4analytics.ru/sezonnost/kak-rasschitat-indeksi-sezonnosti-i-piki-v-excel.html

3.A.c. The method of constant average (Index method)

```
In [18]: # calculate average turnover by month
         average_turnover_by_month = []

         for month_id in range(12):
             tmp_amount = 0

             for idx in range(month_id, len(monthly_turnover), 12):
                 tmp_amount += monthly_turnover[idx]

             number_of_years = (len(monthly_turnover) - month_id) // 12
             average_turnover_by_month.append(tmp_amount / number_of_years)

         print(len(average_turnover_by_month), '=', 12, ', yes? OK')
         average_turnover_by_month
```

```
12 = 12 , yes? OK
```

```
Out[18]: [86864374.0,
          81747805.33333333,
          108415040.0,
          113797633.33333333,
          106181610.66666667,
          98338381.33333333,
          61075446.666666664,
          100322116.0,
          109161622.0,
          148166188.0,
          188114762.0,
          203879220.0]
```

```
In [19]: # calculate seasonality indices without trend
         seasonality_indices_without_trend = []

         average_turnover_for_all_time = monthly_turnover.sum() \
             / len(monthly_turnover)

         seasonality_indices_without_trend = average_turnover_by_month \
```

```
            / (average_turnover_for_all_time / 100)

        print(len(seasonality_indices_without_trend), '=', 12, ', yes? OK')
        seasonality_indices_without_trend
```

```
12 = 12 , yes? OK
```

```
Out[19]: array([105.1824299 ,  98.98687353, 131.27772433, 137.79540494,
                128.57330694, 119.07608867,  73.95510486, 121.47815551,
                132.18174638, 179.41163868, 227.78461244, 246.87349689])
```

http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-6.html

3.B. Moving average method

```
In [20]: # calculate 12-month amounts (column 4), 12-month average (column 5)
         _12_month_amounts = []
         _12_month_average = []

         # first iteration of the algorithm
         _12_month_amounts.append(monthly_turnover[:12].sum())
         _12_month_average.append(_12_month_amounts[0] / 12)

         for idx in range(12, len(monthly_turnover)):
             tmp_amount = _12_month_amounts[idx - 12] \
                 - monthly_turnover[idx - 12] \
                 + monthly_turnover[idx]

             _12_month_amounts.append(tmp_amount)
             _12_month_average.append(_12_month_amounts[idx - 12] / 12)

         print(len(_12_month_amounts), '=', len(monthly_turnover) - 11, ', yes? OK')
         print(len(_12_month_average), '=', len(_12_month_amounts), ', yes? OK')
         print(_12_month_amounts)
         _12_month_average
```

```
31 = 31 , yes? OK
31 = 31 , yes? OK
[387606460.0, 420500000.0, 443150720.0, 474720800.0, 513000450.0, 548610800.0, 580778200.0, 616
```

```
Out[20]: [32300538.666666668,
          32300538.666666668,
          35041666.666666664,
          36929226.666666664,
          39560066.666666664,
          42750037.333333336,
          45717568.0,
```

```
 48398181.333333336,
 51356549.333333336,
 53821360.0,
 56710154.666666664,
 61574240.0,
 67762218.66666667,
 71158682.66666667,
 73918176.0,
 77115253.33333333,
 80213029.33333333,
 84013589.33333333,
 85761536.0,
 88254421.33333333,
 90026048.0,
 93854794.66666667,
 98019498.66666667,
 103592245.33333333,
 109503584.0,
 115720298.66666667,
 120875370.66666667,
 125118314.66666667,
 131502325.33333333,
 135011328.0,
 140171349.33333334]
```

In [21]:
```
# calculate centered averages (column 6)
centered_average = []

for idx in range(len(_12_month_average) - 1):
    centered_average.append(
        (_12_month_average[idx] + _12_month_average[idx + 1]) / 2)

print(len(centered_average), '=', len(_12_month_average) - 1, ', yes? OK')
centered_average
```

```
30 = 30 , yes? OK
```

Out[21]:
```
[32300538.666666668,
 33671102.666666664,
 35985446.666666664,
 38244646.666666664,
 41155052.0,
 44233802.66666667,
 47057874.66666667,
 49877365.333333336,
 52588954.66666667,
 55265757.33333333,
```

```
 59142197.33333333,
 64668229.333333336,
 69460450.66666667,
 72538429.33333334,
 75516714.66666666,
 78664141.33333333,
 82113309.33333333,
 84887562.66666666,
 87007978.66666666,
 89140234.66666666,
 91940421.33333334,
 95937146.66666667,
 100805872.0,
 106547914.66666666,
 112611941.33333334,
 118297834.66666667,
 122996842.66666667,
 128310320.0,
 133256826.66666666,
 137591338.6666667]
```

In [22]:
```
# calculate seasonality indicators (column 7)
seasonality_indicators = []

for idx in range(len(centered_average)):
    seasonality_indicators.append(
        100 * monthly_turnover[idx + 6] / centered_average[idx])

print(len(seasonality_indicators), '=', len(centered_average), ', yes? OK')
seasonality_indicators
```

```
30 = 30 , yes? OK
```

Out[22]:
```
[93.87455829426003,
 94.58542630838306,
 91.7182668475052,
 98.24586517293837,
 126.98481829156722,
 189.6307415215971,
 87.8694507410251,
 70.29683257260527,
 97.86297584009782,
 111.43936312776003,
 105.79770590419727,
 92.55230368453776,
 94.76239121435395,
 84.68019581418378,
```

```
 89.61033898084833,
 121.96512206679992,
 154.07539779746952,
 146.82772844995654,
 85.58225709997723,
 82.37262586819008,
 96.40852055554352,
 111.73405476863601,
 82.8785291396517,
 84.24988539741295,
 77.32924854055737,
 90.76293940843729,
 95.6506113891357,
 126.89219074506244,
 148.17435844687682,
 144.80495206364927]
```

In [23]:
```
# calculate seasonality indices
seasonality_indices = []

for month_id in range(12):
    tmp_amount = 0

    for idx in range(month_id, len(centered_average), 12):
        tmp_amount += seasonality_indicators[idx]

    number_of_years = (len(centered_average) - month_id) // 12
    seasonality_indices.append(tmp_amount / number_of_years)


seasonality_indices[6:], seasonality_indices[:6] = \
    seasonality_indices[:6], seasonality_indices[6:]

print(len(seasonality_indices), '=', 12, ', yes? OK')
seasonality_indices
```

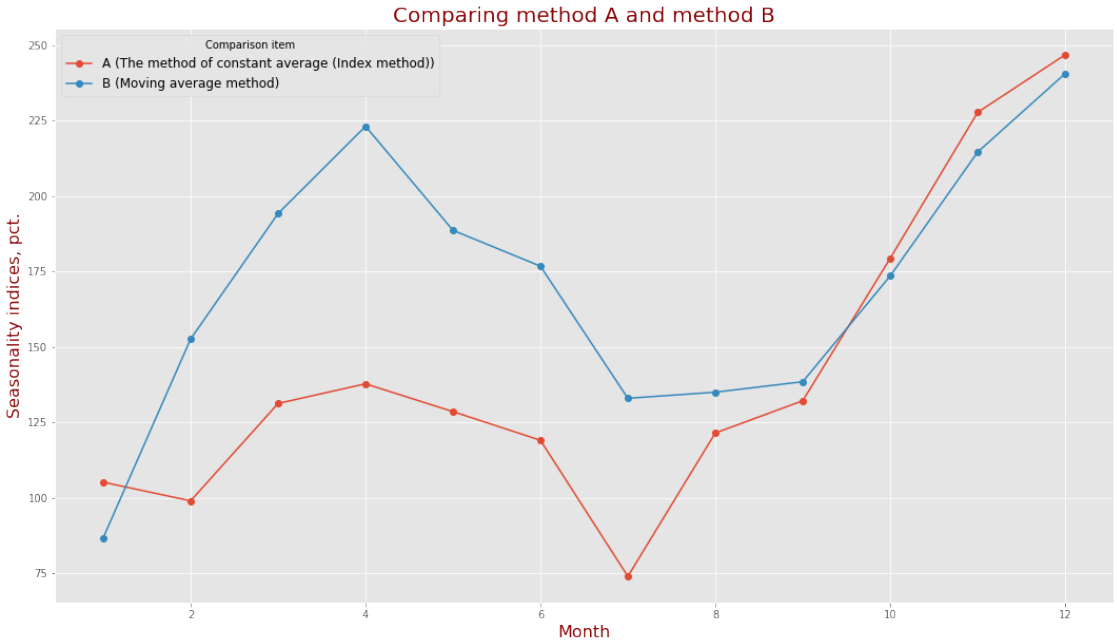
```
12 = 12 , yes? OK
```

Out[23]:
```
[86.72585392050117,
 152.66945844079535,
 194.27149639564135,
 223.17341789639605,
 188.67623504384898,
 176.8021890819507,
 132.98309902458567,
 135.01428076550206,
 138.48960860874462,
```

```
 173.55158899240035,
 214.61728726795678,
 240.63171101760145]
```

Method comparison (matplotlib)

In [24]:
```
# comparing method A (The method of constant average (Index method))
# and method B (Moving average method)
comparison_table = {
    'A (The method of constant average (Index method))':
    seasonality_indices_without_trend,
    'B (Moving average method)':
    seasonality_indices
}

methods = [
    'A (The method of constant average (Index method))',
    'B (Moving average method)'
]

fig, axes = plt.subplots(figsize=(18, 10))

custom_plot(
    axes,
    'comparison',
    methods,
    comparison_table,
    ylabel='Seasonality indices, pct.',
    xdata=[_ for _ in range(1, 13)],
    title='Comparing method A and method B')

plt.show()
```



Conclusion In the period from February to October there is a positive trend. In the period from September to November, there is almost no trend. In the period from October to February, there is a negative trend. The trend peak is observed in April.

10.0.2 4. Calculate the parameters of the equation describing the trend of the phenomenon under study (for 5.A.a.iii.)

In [25]:
```
# http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-6.html
# calculate 'a'
n = len(monthly_turnover)
X = np.array([_ for _ in range(1, n + 1)])
X_2 = np.array([_**2 for _ in range(1, n + 1)])
Yf_X = X * monthly_turnover

print(len(X), '=', n, ', yes? OK')
print(X)
print(len(X_2), '=', n, ', yes? OK')
print(X_2)
print(len(Yf_X), '=', n, ', yes? OK')
print(Yf_X)

X_sum = X.sum()
monthly_turnover_sum = monthly_turnover.sum()
a = (Yf_X.sum() - X_sum * monthly_turnover_sum / n) \
    / (X_2.sum() - X_sum**2 / n)
```

```
        print('a =', a)
```

```
42 = 42 , yes? OK
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42]
42 = 42 , yes? OK
[   1    4    9   16   25   36   49   64   81  100  121  144  169  196
  225  256  289  324  361  400  441  484  529  576  625  676  729  784
  841  900  961 1024 1089 1156 1225 1296 1369 1444 1521 1600 1681 1764]
42 = 42 , yes? OK
[8.45597800e+06 2.48229920e+07 5.96851320e+07 9.32326560e+07
 1.34803480e+08 1.66107456e+08 2.12253916e+08 2.54783648e+08
 2.97047052e+08 3.75737840e+08 5.74867348e+08 1.00657066e+09
 5.37543448e+08 4.90870912e+08 7.71976740e+08 9.85404928e+08
 1.06370850e+09 1.07733485e+09 1.25062530e+09 1.22851368e+09
 1.42108646e+09 2.11074195e+09 2.90987738e+09 2.99132352e+09
 1.86158480e+09 1.90910595e+09 2.39323680e+09 3.00144499e+09
 2.42284630e+09 2.69299488e+09 2.69954101e+09 3.43585894e+09
 3.88235866e+09 5.53573638e+09 6.91083568e+09 7.17260659e+09
 5.04399747e+09 4.72501728e+09 6.44461584e+09 5.97209856e+09
 5.96413158e+09 4.94390971e+09]
a = 3644032.441779434
```

```
In [26]: # http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-6.html
         # calculate 'b'
         b = (monthly_turnover_sum - a * X_sum) / n

         print('b =', b)
```

```
b = 4237793.168408836
```

10.0.3 5.A.a.iii. Build a forecast by least squares method

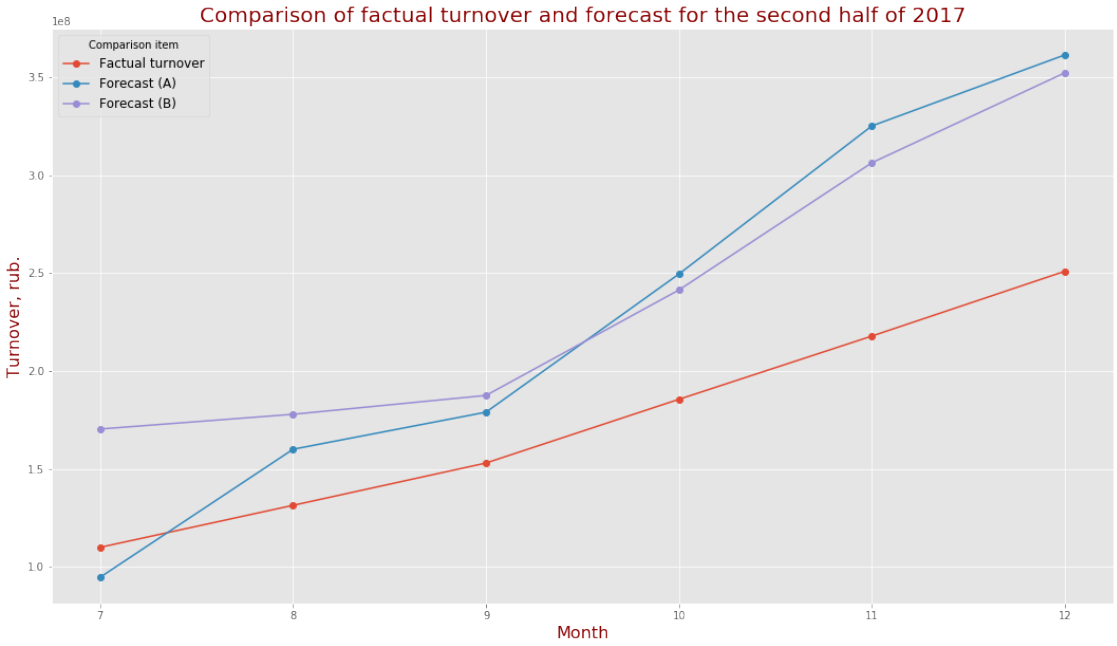
```
In [27]: # http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-6.html
         # building a forecast for the second half of 2017
         forecast_A = []
         forecast_B = []

         for month in range(6, 12):
             forecast_A.append((a * (n - 14 + month) + b) *
                               seasonality_indices_without_trend[month] / 100)
             forecast_B.append(
                 (a * (n - 14 + month) + b) * seasonality_indices[month] / 100)

         print(len(forecast_A), '=', 6, ', yes? OK')
         print(forecast_A)
```

```
        print(len(forecast_B), '=', 6, ', yes? OK')
        forecast_B
```

```
6 = 6 , yes? OK
[94762296.83261052, 160082611.8526852, 179004434.94144273, 249502371.9259139, 325073757.382022
6 = 6 , yes? OK
```

Out[27]:
```
[170397755.88394773,
 177920372.69120908,
 187546728.75563416,
 241352977.00793555,
 306282532.5390955,
 352176681.18345225]
```

In [28]:
```
# comparison of actual turnover and forecast for the second half of 2017
comparison_table = {
    'Factual turnover': total_monthly_turnover[42:48],
    'Forecast (A)': forecast_A,
    'Forecast (B)': forecast_B
}

fact_and_forecast = ['Factual turnover', 'Forecast (A)', 'Forecast (B)']

fig, axes = plt.subplots(figsize=(18, 10))

custom_plot(
    axes,
    'comparison',
    fact_and_forecast,
    comparison_table,
    ylabel='Turnover, rub.',
    xdata=[_ for _ in range(7, 13)],
    title='Comparison of factual turnover and forecast for the second half of 2017')

plt.show()
```



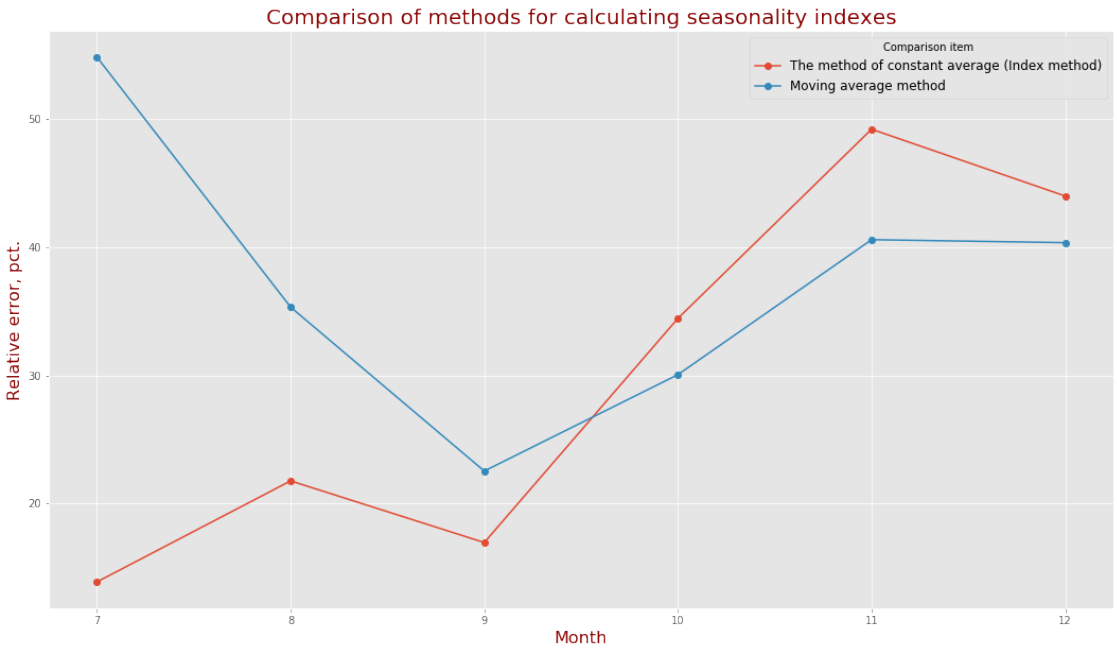
10.0.4 6.C. Calculate average relative error

In [29]:
```
# http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-6.html
# calculate error of forecast (column 12)
Y_p_A = []
Y_p_B = []

for month in range(6, 12):
    Y_p_A.append((a * (n - 14 + month) + b) *
                 seasonality_indices_without_trend[month] / 100)
    Y_p_B.append((a * (n - 14 + month) + b) * seasonality_indices[month] / 100)

Y_p_A = np.array(Y_p_A)
Y_p_B = np.array(Y_p_B)

print(len(Y_p_A), '=', 6, ', yes? OK')
print(Y_p_A)
print(len(Y_p_B), '=', 6, ', yes? OK')
print(Y_p_B)

upsilon_A = 100 * abs(total_monthly_turnover[42:48] -
                      Y_p_A) / total_monthly_turnover[42:48]
upsilon_B = 100 * abs(total_monthly_turnover[42:48] -
                      Y_p_B) / total_monthly_turnover[42:48]

print(len(upsilon_A), '=', 6, ', yes? OK')
```

```
        print(upsilon_A)
        print(len(upsilon_B), '=', 6, ', yes? OK')
        print(upsilon_B)

        average_upsilon_A = round(upsilon_A.sum() / 6, 2)
        average_upsilon_B = round(upsilon_B.sum() / 6, 2)

        print('Average relative error (A) =', average_upsilon_A)
        print('Average relative error (B) =', average_upsilon_B)
```

```
6 = 6 , yes? OK
[9.47622968e+07 1.60082612e+08 1.79004435e+08 2.49502372e+08
 3.25073757e+08 3.61311851e+08]
6 = 6 , yes? OK
[1.70397756e+08 1.77920373e+08 1.87546729e+08 2.41352977e+08
 3.06282533e+08 3.52176681e+08]
6 = 6 , yes? OK
[13.88037897 21.76951082 16.95556127 34.45737331 49.2309242  44.01351758]
6 = 6 , yes? OK
[54.8568434  35.33810135 22.53681275 30.06564659 40.60447624 40.37237525]
Average relative error (A) = 30.05
Average relative error (B) = 37.3
```

In [30]:
```
        # comparison of average relative error calculated by 3.A.c
        # and average relative error calculated by 3.B
        # for forecast for the second half of 2017
        comparison_table = {
            'The method of constant average (Index method)': upsilon_A,
            'Moving average method': upsilon_B
        }

        methods = [
            'The method of constant average (Index method)', 'Moving average method'
        ]

        fig, axes = plt.subplots(figsize=(18, 10))

        custom_plot(
            axes,
            'comparison',
            methods,
            comparison_table,
            ylabel='Relative error, pct.',
            xdata=[_ for _ in range(7, 13)],
            title='Comparison of methods for calculating seasonality indexes')

        plt.show()
```



http://www.ekonomika-st.ru/drugie/metodi/metodi-prognoz-1-2.html

Conclusion The accuracy of the forecast (The method of constant average (Index method)) is 30.05%. The accuracy of the forecast (Moving average method) is 37.3%. The accuracy of the forecast is satisfactory, since it is in the range of 20-50%.

Table 1 - Interpretation of the average relative error values

Average relative error (), %	Interpretation
<10	Forecast accuracy is high
10-20	Accuracy is good
20-50	Accuracy satisfactory
>50	Accuracy unsatisfactory