Дана таблица клиентов с различной информацией относительно предпочтений покупок, частоты и сумм (For_clustering.xlsx). Необходимо провести сегментацию клиентов для выделения различных групп.

In [1]:
```
import pandas as pd
import numpy as np
from scipy import stats
import seaborn as sns
sns.set()

from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

from scipy.spatial import distance as sci_distance
from sklearn import cluster as sk_cluster
```

Кластеризация K-means: Определение числа кластеров для алгоритма K-means Выполнение кластеризации Анализ результатов

In [2]:
```
# настройки отображения графиков
%matplotlib inline
plt.style.use('ggplot')
plt.rcParams['figure.figsize'] = (15, 5)
plt.rcParams['font.family'] = 'sans-serif'
```

In [3]:
```
df = pd.read_csv(
    '/opt/kate_repo/real_data_analysis/digital_line/for_clustering.csv')
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27508 entries, 0 to 27507
Data columns (total 45 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Id_client                 27508 non-null  int64  
 1   InWeek_amount             27508 non-null  float64
 2   InWeek_SKU                27508 non-null  int64  
 3   Checkinmonth_average      27508 non-null  int64  
 4   Checkamount_mean          27508 non-null  float64
 5   Count_transac             27508 non-null  int64  
 6   Total_amount              27508 non-null  int64  
 7   Total_SKU_qnt             27508 non-null  float64
 8   Count_departments         27508 non-null  int64  
 9   Count_shop                27508 non-null  int64  
 10  Count_city                27508 non-null  int64  
 11  Tenure                    27508 non-null  int64  
 12  SKU_meanbytransac         27508 non-null  float64
 13  Amount_last6mnth          27508 non-null  float64
 14  Check_qntlast6mnth        27508 non-null  int64  
 15  SKU_price_mean            27508 non-null  float64
 16  Gender                    27267 non-null  object 
 17  Age                       27356 non-null  float64
 18  Age_group                 27356 non-null  object 
 19  Interval_visit            27508 non-null  int64  
 20  Days_pastvisit            27508 non-null  int64  
 21  Cat_householdchem_qnt     27508 non-null  int64  
 22  Cat_householdchem_amount  27508 non-null  int64  
 23  Cat_householdchem_share   27508 non-null  float64
 24  Cat_careproducts_qnt      27508 non-null  int64  
 25  Cat_careproducts_amount   27508 non-null  int64  
 26  Cat_careproducts_share    27508 non-null  float64
 27  Cat_toiletries_qnt        27508 non-null  int64  
 28  Cat_toiletries_amount     27508 non-null  int64  
 29  Cat_toiletries_share      27508 non-null  float64
 30  Cat_healthwellnes_qnt     27508 non-null  int64  
 31  Cat_healthwellnes_amount  27508 non-null  int64  
 32  Cat_healthwellnes_share   27508 non-null  float64
 33  Cat_babyprod_qnt          27508 non-null  int64  
 34  Cat_babyprod_amount       27508 non-null  int64  
 35  Cat_babyprod_share        27508 non-null  float64
 36  Communication_3month      27508 non-null  int64  
 37  Response_communcation     27508 non-null  int64  
 38  SKU_LastMonthqnt          27508 non-null  int64  
 39  Checks_LastMonthqnt       27508 non-null  int64  
 40  Amount_LastMonth          27508 non-null  float64
 41  Discount                  27508 non-null  int64  
 42  Discount_LastMonth        27508 non-null  int64  
 43  _SEGMENT_                 27508 non-null  int64  
 44  EM_SEGMENT                27508 non-null  int64  
dtypes: float64(13), int64(30), object(2)
memory usage: 9.4+ MB
```

In [5]:
```
df.iloc[:,21:35].head()
```

Out[5]:

	Cat_householdchem_qnt	Cat_householdchem_amount	Cat_householdchem_share	Cat_careproducts_qnt	Cat_careproducts_amount	Cat
0	175	2748	0.22	278	3490	
1	199	4098	0.32	279	4027	
2	18	121	0.04	62	2013	
3	798	5177	0.26	500	5094	
4	59	639	0.26	73	808	

In [6]:
```
# Уникальные значения для идентификации категориальных признаков
unique_val = df.nunique()
unique_val
```

Out[6]:
```
Id_client                   27508
InWeek_amount               20343
InWeek_SKU                     50
Checkinmonth_average           10
Checkamount_mean            17546
Count_transac                 435
Total_amount                13869
Total_SKU_qnt                2256
Count_departments              32
Count_shop                     34
Count_city                      8
Tenure                         11
SKU_meanbytransac              29
Amount_last6mnth            24722
Check_qntlast6mnth             71
SKU_price_mean              27508
Gender                          2
Age                            85
Age_group                       6
Interval_visit                 31
Days_pastvisit                 33
Cat_householdchem_qnt         694
Cat_householdchem_amount     5604
Cat_householdchem_share        71
Cat_careproducts_qnt          815
Cat_careproducts_amount      7553
Cat_careproducts_share         89
Cat_toiletries_qnt           1338
Cat_toiletries_amount        6899
Cat_toiletries_share           96
Cat_healthwellnes_qnt         378
Cat_healthwellnes_amount     2696
Cat_healthwellnes_share        49
Cat_babyprod_qnt              219
Cat_babyprod_amount          2472
Cat_babyprod_share             49
Communication_3month            2
Response_communcation           2
SKU_LastMonthqnt              149
Checks_LastMonthqnt            70
Amount_LastMonth            25123
Discount                        2
Discount_LastMonth              2
_SEGMENT_                       3
EM_SEGMENT                      3
dtype: int64
```

In [7]:
```
# Список долей отсутствующих записей для каждого признака
for col in df.columns:
    pct_missing = np.mean(df[col].isnull())
    if pct_missing > 0:
        print('{} - {}%'.format(col, round(pct_missing * 100)))
```

```
Gender - 1%
Age - 1%
Age_group - 1%
```

In [8]:
```
# Удаление строк с отсутствующими значениями
filtered_df = df[df['Gender'].isnull()]
df = df.drop(filtered_df.index)
```

In [9]:
```
# описательная статистика данных
df.describe()
```

Out[9]:

	Id_client	InWeek_amount	InWeek_SKU	Checkinmonth_average	Checkamount_mean	Count_transac	Total_amount	Total_SK
count	27267.000000	27267.000000	27267.000000	27267.000000	27267.000000	27267.000000	27267.000000	27267.0
mean	210554.677412	314.727811	31.429677	2.558844	159.693143	82.136795	9585.637217	762.8
std	121847.905725	144.464145	11.376459	1.195365	111.530548	62.795554	4712.872902	451.2
min	5743.000000	34.470000	2.000000	2.000000	10.240000	4.000000	739.000000	33.0
25%	105584.500000	212.995000	23.000000	2.000000	85.935000	39.000000	5889.000000	431.0
50%	212782.000000	289.200000	31.000000	2.000000	128.850000	66.000000	8809.000000	673.0
75%	309896.500000	385.205000	41.000000	2.000000	199.415000	108.000000	12622.000000	1001.5
max	830188.000000	2180.010000	51.000000	20.000000	1326.120000	990.000000	22748.000000	5058.0

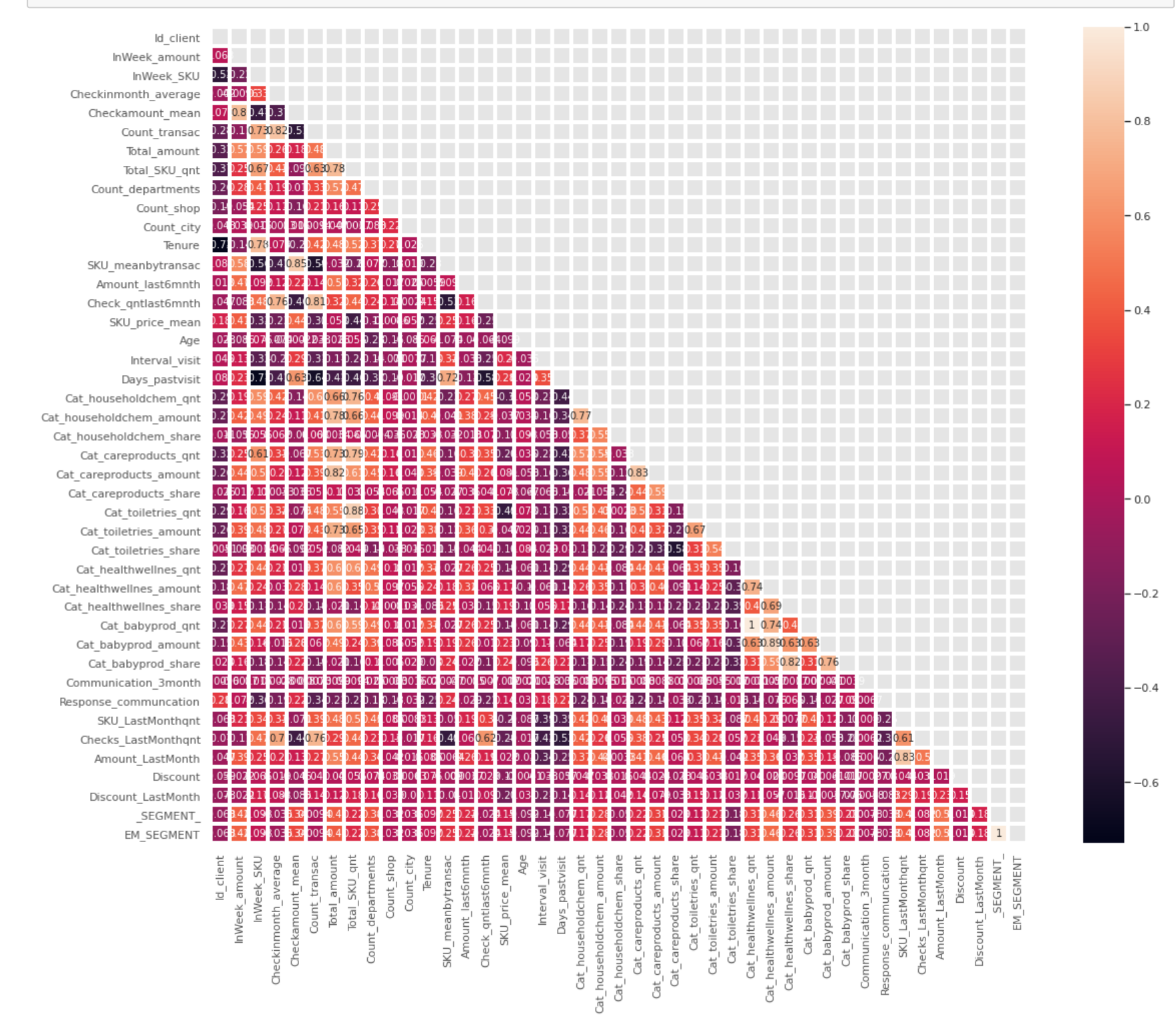
8 rows × 43 columns

In [10]:
```
# проверка на уникальность ID
from collections import Counter
[k for k, v in Counter(df['Id_client']).items() if v > 1]
```

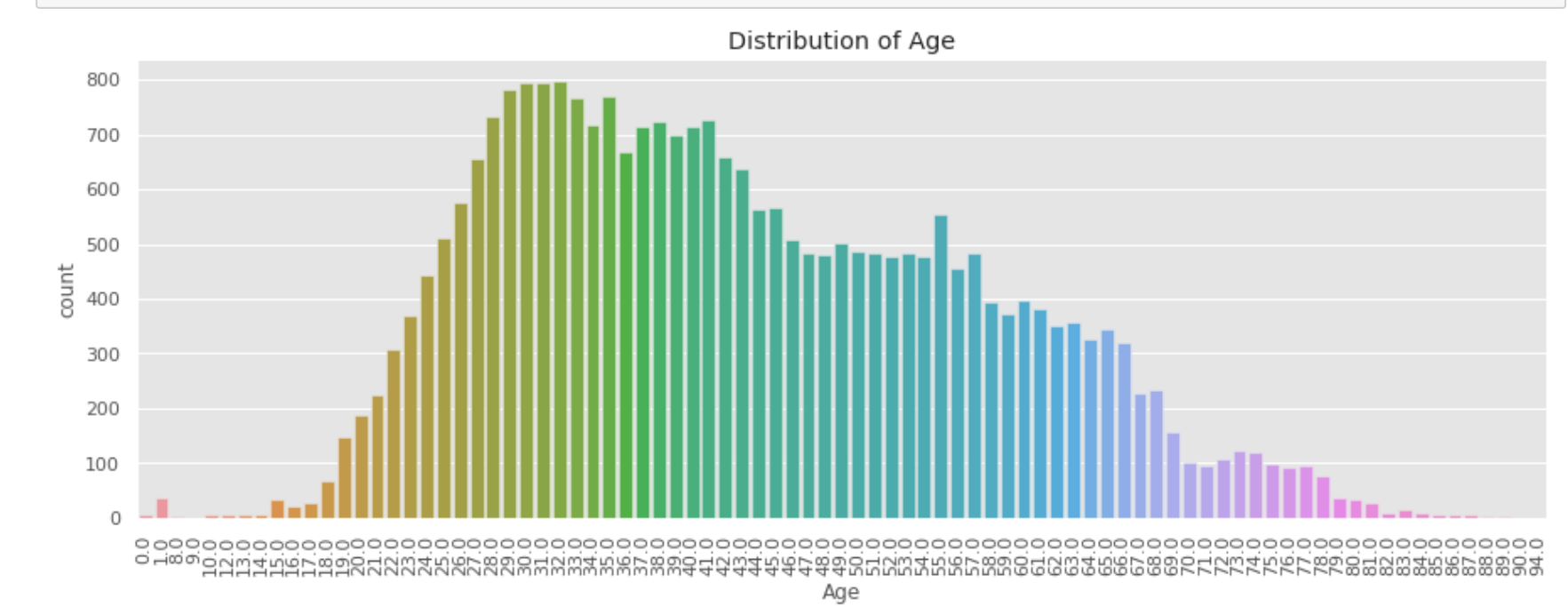
Out[10]: []

номера Id_client уникальны

In [11]:
```
# матрица корреляции для отбора параметров для алгоритма кластеризации
fig, ax = plt.subplots(figsize=(20, 15))
corr = df.corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style('dark'):
    ax = sns.heatmap(corr,
                     mask=mask,
                     square=True,
                     cbar=True,
                     annot=True,
                     linewidths=3)
```

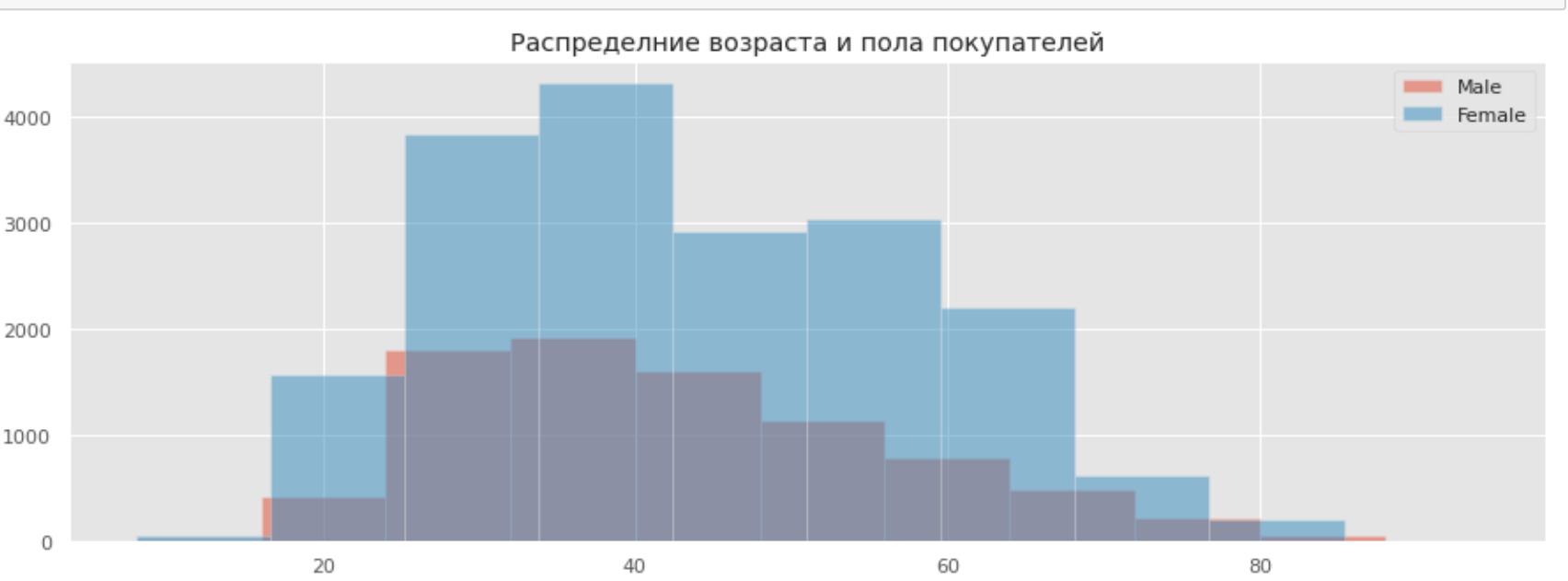


In [12]:
```
# оценка распределения данных о возрасте
sns.countplot(x='Age', data=df)
plt.title('Distribution of Age')
plt.xticks(rotation=90);
```



In [13]:
```
# Убрать потребителей с возрастом менее 8 лет как выбросы
unrelevant_info = df[df['Age'] < 8]
df = df.drop(unrelevant_info.index)
```

In [14]:
```
# Возраст и пол
plt.hist('Age', data=df[df['Gender'] == 'M'], alpha=0.5, label='Male')
plt.hist('Age', data=df[df['Gender'] == 'F'], alpha=0.5, label='Female')
plt.title('Распредление возраста и пола покупателей')
plt.xlabel('Age')
plt.legend();
```



In [15]:
```
# Расходы и пол
plt.hist('Total_amount', data=df[df['Gender'] == 'M'], alpha=0.5, label='Male')
plt.hist('Total_amount',
         data=df[df['Gender'] == 'F'],
         alpha=0.5,
         label='Female')
plt.title('Распределение суммы расходов по гендерному признаку')
plt.xlabel('Сумма расходов')
plt.legend()
```

Out[15]: <matplotlib.legend.Legend at 0x7fb1463599a0>

In [16]:
```
# Средняя сумма расходов по гендеру
male_df = df[df['Gender'] == 'M']
female_df = df[df['Gender'] == 'F']

print('Средний расход мужчин: %.3f' % male_df['Total_amount'].mean())
print('Средний расход женщин: %.3f' % female_df['Total_amount'].mean())
```

```
Средний расход мужчин: 9717.955
Средний расход женщин: 9526.777
```

In [17]:
```
# Возраст, пол и сумма расходов
sns.scatterplot('Age', 'Total_amount', hue='Gender', data=df)
plt.title('Карта отношений возраста, пола и расходов')
```

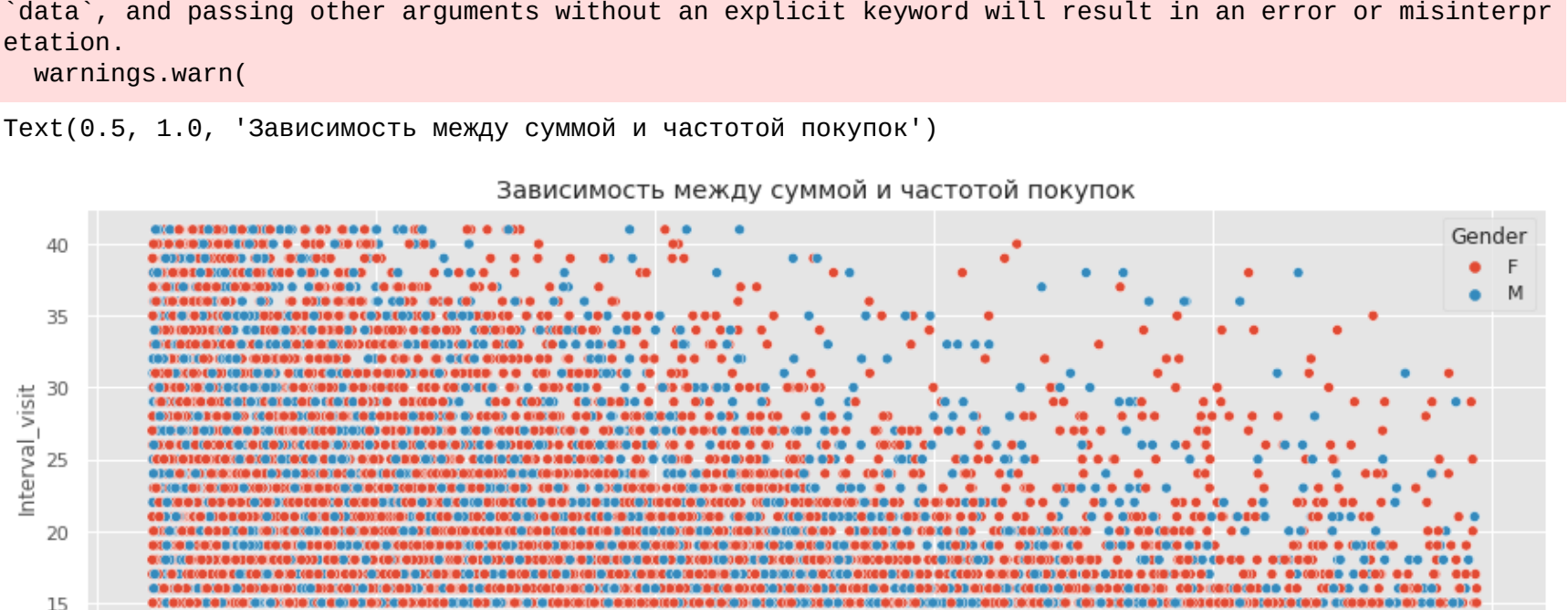
```
/home/kate/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[17]: Text(0.5, 1.0, 'Карта отношений возраста, пола и расходов')

In [18]:
```
# сумма и давность покупок
sns.scatterplot('Amount_LastMonth', 'Interval_visit', hue='Gender', data=df)
plt.title('Зависимость между суммой и частотой покупок')
```

```
/home/kate/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

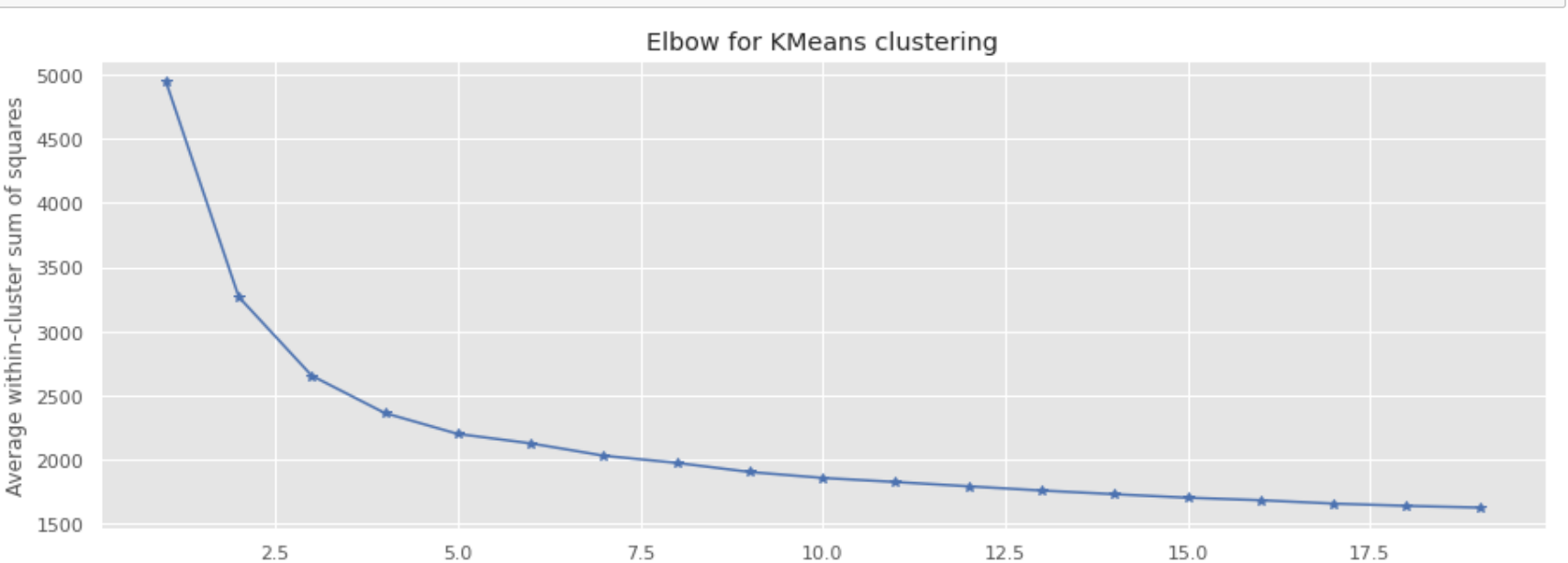
Out[18]: Text(0.5, 1.0, 'Зависимость между суммой и частотой покупок')



In [19]:
```
# Чтобы определить число кластеров для алгоритма, используется график значений сумм квадратов внутри групп
# по числу извлеченных кластеров. Необходимое число кластеров будет находиться на изгибе графика.

columns = [
"InWeek_amount", "Count_transac", "Total_amount", "Count_departments", "Count_shop",
"Count_city","Tenure", "Amount_last6mnth", "Check_qntlast6mnth", "SKU_price_mean", "Age", "Interval_visit",
"Cat_householdchem_amount", "Cat_careproducts_amount", "Cat_toiletries_amount", "Cat_healthwellnes_amount",
"Communication_3month", "Response_communcation", "Amount_LastMonth", "Discount", "_SEGMENT_","Cat_babyprod_amount"
]
cdata = df[columns]
K = range(1, 20)
KM = (sk_cluster.KMeans(n_clusters=k).fit(cdata) for k in K)
centroids = (k.cluster_centers_ for k in KM)

D_k = (sci_distance.cdist(cdata, cent, 'euclidean') for cent in centroids)
dist = (np.min(D, axis=1) for D in D_k)
avgWithinSS = [sum(d) / cdata.shape[0] for d in dist]
plt.plot(K, avgWithinSS, 'b*-')
plt.grid(True)
plt.xlabel('Number of clusters')
plt.ylabel('Average within-cluster sum of squares')
plt.title('Elbow for KMeans clustering')
plt.show()
```



In [20]:
```
# Данные о кластерах
n_clusters = 4

means_cluster = sk_cluster.KMeans(n_clusters=n_clusters, random_state=111)
est = means_cluster.fit(df[columns])
clusters = est.labels_
df['cluster'] = clusters

# Значения показателей в кластерах

for c in range(n_clusters):
    cluster_members = df[df['cluster'] == c][:]
    print('Cluster{}(n={}):'.format(c, len(cluster_members)))
    print('-' * 17)
```

```
Cluster0(n=9049):
-----------------
Cluster1(n=3505):
-----------------
Cluster2(n=8215):
-----------------
Cluster3(n=6453):
-----------------
```

In [21]:

```
# Средние значения расходов на группы товаров в кластерах
group_clients = df.groupby(['cluster']).mean()
group_clients[["Cat_healthwellnes_amount", "Cat_careproducts_amount", "Cat_toiletries_amount",
          "Cat_healthwellnes_amount","Cat_babyprod_amount"]]
```

Out[21]:

cluster	Cat_healthwellnes_amount	Cat_careproducts_amount	Cat_toiletries_amount	Cat_healthwellnes_amount	Cat_babyprod_amount
0	641.531661	2799.210189	2574.537960	641.531661	487.720522
1	1344.673039	6303.018260	5394.462767	1344.673039	1030.414551
2	363.869994	1409.638344	1453.635666	363.869994	286.931589
3	969.733147	4316.002170	3852.707733	969.733147	740.274601

В результате кластеризации клиенты разделены на 4 группы с отличным друг от друга поведением. Для лучшего понимания каждого кластера необходимо детальное изучение результатов.