In [1]:

```
%config Completer.use_jedi=False

import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Read data & check basic info

In [3]:

```
df = pd.read_csv('data/LTV.csv')
display(df.head().style.set_caption(f'IBM data for CLTV prediction of shape {df.shape}')
)
```

IBM data for CLTV prediction of shape (9134, 24)

	Customer	State	Customer Lifetime Value	Response	Coverage	Education	Effective To Date	EmploymentStatus	Gender	Income	Lo
0	BU79786	Washington	2763.519279	No	Basic	Bachelor	2/24/11	Employed	F	56274	Sub
1	QZ44356	Arizona	6979.535903	No	Extended	Bachelor	1/31/11	Unemployed	F	0	Sub
2	AI49188	Nevada	12887.431650	No	Premium	Bachelor	2/19/11	Employed	F	48767	Sub
3	WW63253	California	7645.861827	No	Basic	Bachelor	1/20/11	Unemployed	M	0	Sub
4	HB64268	Washington	2813.692575	No	Basic	Bachelor	2/3/11	Employed	M	43836	

In [4]:

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9134 entries, 0 to 9133
Data columns (total 24 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Customer                       9134 non-null   object
 1   State                          9134 non-null   object
 2   Customer Lifetime Value        9134 non-null   float64
 3   Response                       9134 non-null   object
 4   Coverage                       9134 non-null   object
 5   Education                      9134 non-null   object
 6   Effective To Date              9134 non-null   object
 7   EmploymentStatus               9134 non-null   object
 8   Gender                         9134 non-null   object
 9   Income                         9134 non-null   int64
 10  Location Code                  9134 non-null   object
 11  Marital Status                 9134 non-null   object
 12  Monthly Premium Auto           9134 non-null   int64
 13  Months Since Last Claim        9134 non-null   int64
 14  Months Since Policy Inception  9134 non-null   int64
```

```
 15  Number of Open Complaints       9134 non-null   int64
 16  Number of Policies              9134 non-null   int64
 17  Policy Type                     9134 non-null   object
 18  Policy                          9134 non-null   object
 19  Renew Offer Type                9134 non-null   object
 20  Sales Channel                   9134 non-null   object
 21  Total Claim Amount              9134 non-null   float64
 22  Vehicle Class                   9134 non-null   object
 23  Vehicle Size                    9134 non-null   object
dtypes: float64(2), int64(6), object(16)
memory usage: 1.7+ MB
None
```

In [5]:

```
print(df.nunique())
```

```
Customer                         9134
State                               5
Customer Lifetime Value          8041
Response                            2
Coverage                            3
Education                           5
Effective To Date                  59
EmploymentStatus                    5
Gender                              2
Income                           5694
Location Code                       3
Marital Status                      3
Monthly Premium Auto              202
Months Since Last Claim            36
Months Since Policy Inception     100
Number of Open Complaints           6
Number of Policies                  9
Policy Type                         3
Policy                              9
Renew Offer Type                    4
Sales Channel                       4
Total Claim Amount               5106
Vehicle Class                       6
Vehicle Size                        3
dtype: int64
```

In [6]:

```
display(df.describe())
```

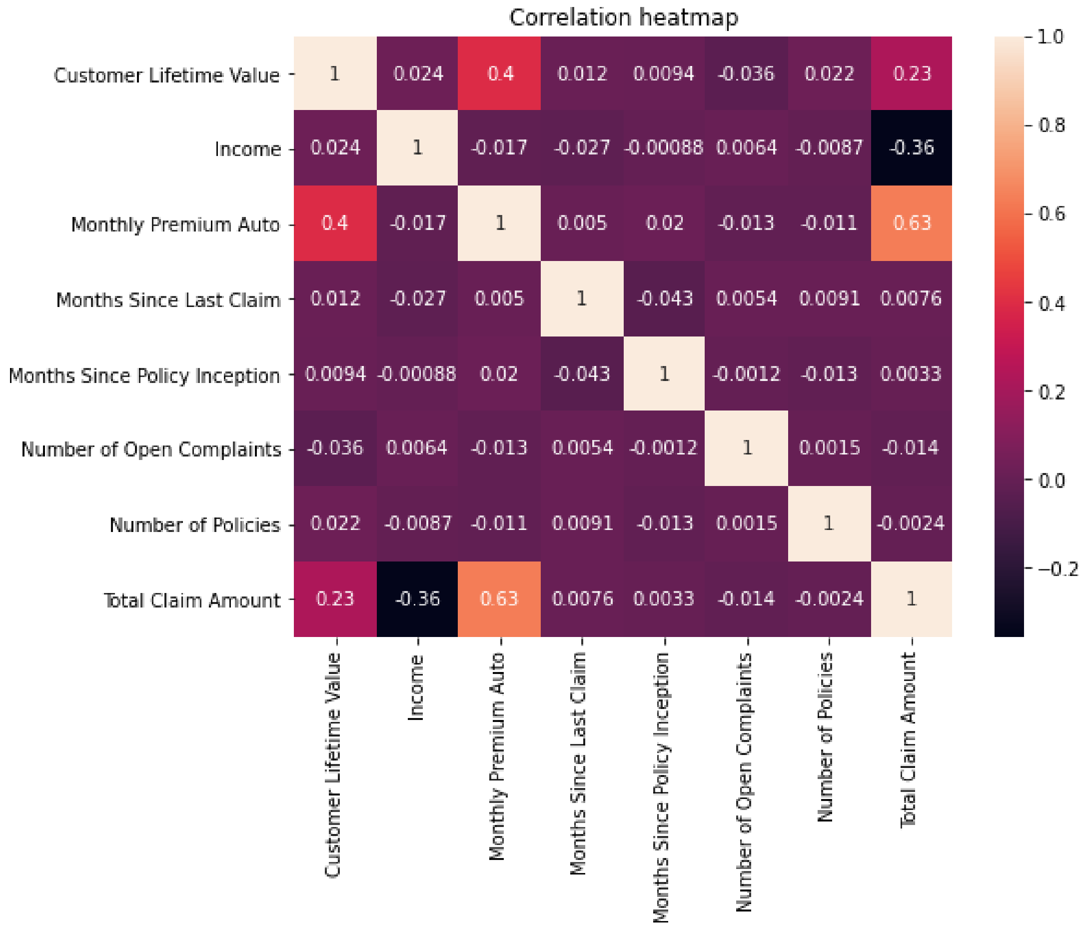
	Customer Lifetime Value	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policies	Total Claim Amount
count	9134.000000	9134.000000	9134.000000	9134.000000	9134.000000	9134.000000	9134.000000	9134.000000
mean	8004.940475	37657.380009	93.219291	15.097000	48.064594	0.384388	2.966170	434.088794
std	6870.967608	30379.904734	34.407967	10.073257	27.905991	0.910384	2.390182	290.500092
min	1898.007675	0.000000	61.000000	0.000000	0.000000	0.000000	1.000000	0.099007
25%	3994.251794	0.000000	68.000000	6.000000	24.000000	0.000000	1.000000	272.258244
50%	5780.182197	33889.500000	83.000000	14.000000	48.000000	0.000000	2.000000	383.945434
75%	8962.167041	62320.000000	109.000000	23.000000	71.000000	0.000000	4.000000	547.514839
max	83325.381190	99981.000000	298.000000	35.000000	99.000000	5.000000	9.000000	2893.239678

Check Correlation

In [7]:

```
plt.figure(figsize=[8, 6])
```

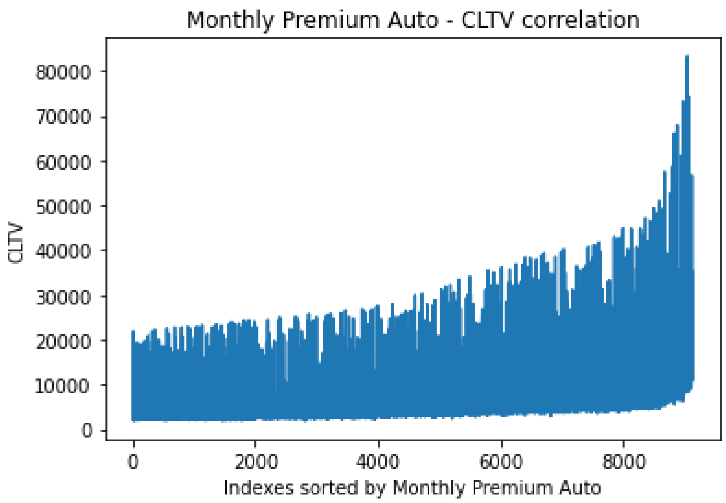
```
sns.heatmap(df.corr(), annot=True)
plt.title('Correlation heatmap')
plt.show()
```



Можно заметить высокую корреляцию между таргетом и `Monthly Premium Auto`. Отсортирует данные по этому признаку и построим график

In [8]:

```
df.sort_values(by=['Monthly Premium Auto'], ascending=True).reset_index()['Customer Life
time Value'].plot()
plt.title('Monthly Premium Auto - CLTV correlation')
plt.xlabel('Indexes sorted by Monthly Premium Auto')
plt.ylabel('CLTV')
plt.show()
```

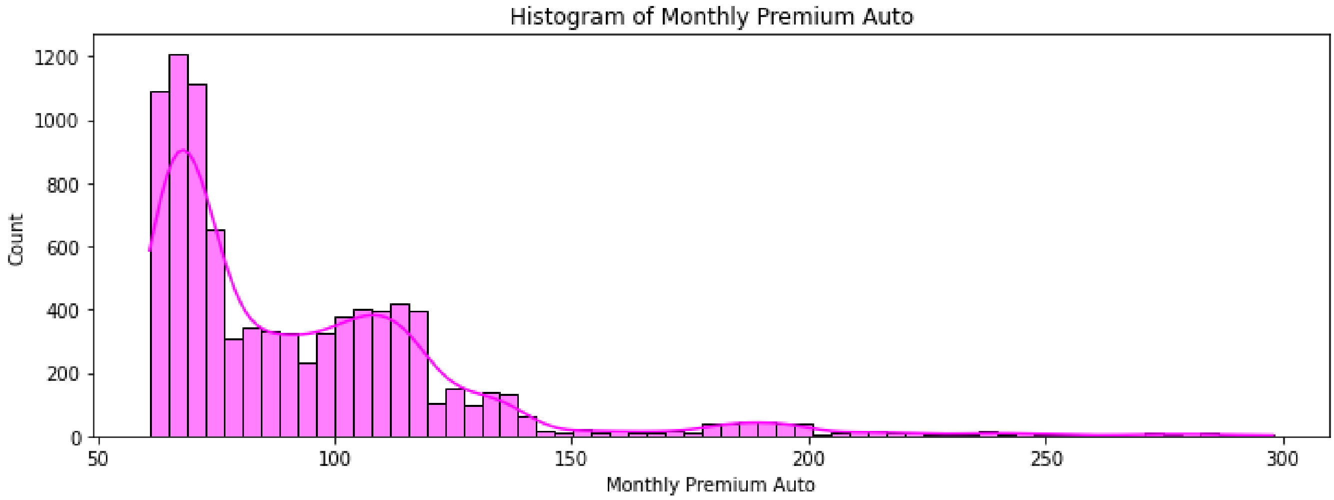


Действительно, в среднем таргет растёт с ростом `Monthly Premium Auto`

Look at Monthly Premium Auto

In [8]:

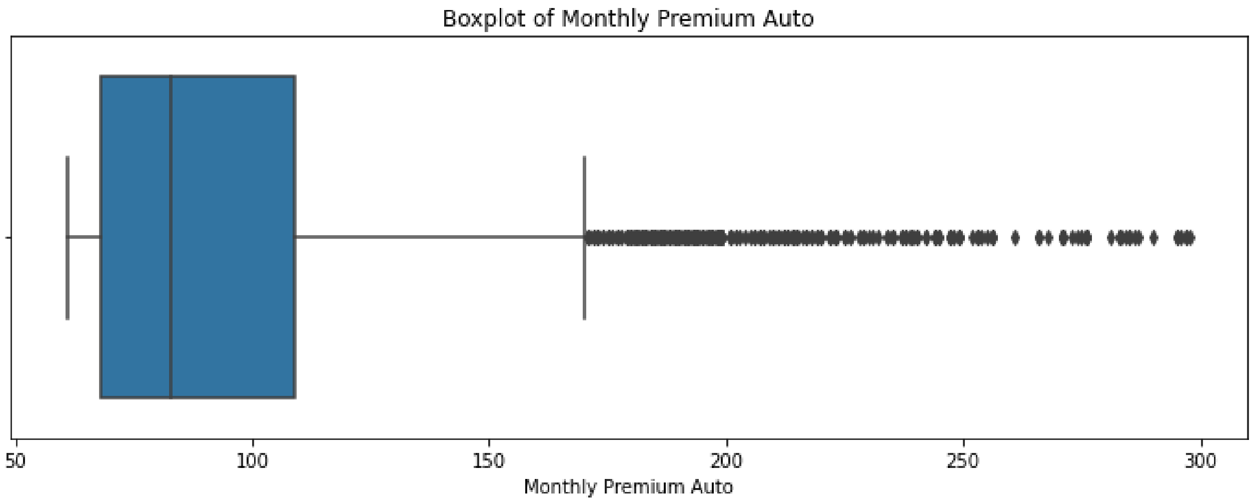
```
plt.figure(figsize=[12, 4])
sns.histplot(df['Monthly Premium Auto'], color='magenta', kde=True)
plt.title('Histogram of Monthly Premium Auto')
plt.show()
```



Значения `Monthly Premium Auto` находятся в районе ~**60-300,** среднее значение ~**90**

In [9]:

```
plt.figure(figsize=[12, 4])
sns.boxplot(x=df['Monthly Premium Auto'])
plt.title('Boxplot of Monthly Premium Auto')
plt.show()
```

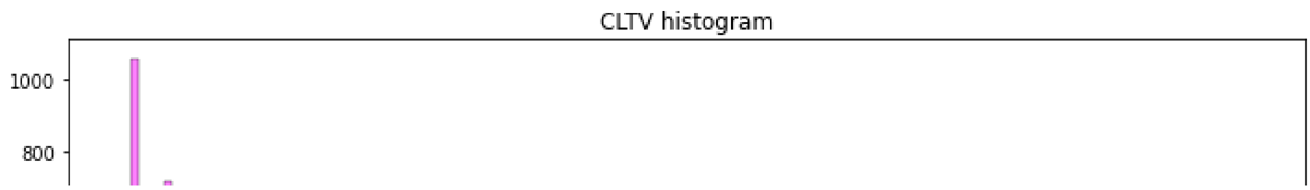


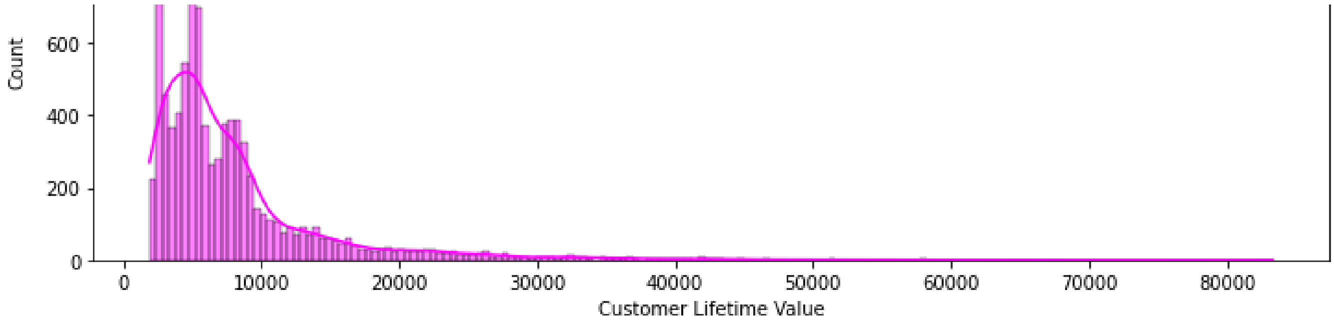
Достаточно много выбросов, но в основном они идут более менее непрерывно. Крайне отличающихся единичных выбросов нет

Look at LTV

In [10]:

```
plt.figure(figsize=[12, 4])
sns.histplot(df['Customer Lifetime Value'], color='magenta', kde=True)
plt.title('CLTV histogram')
plt.show()
```

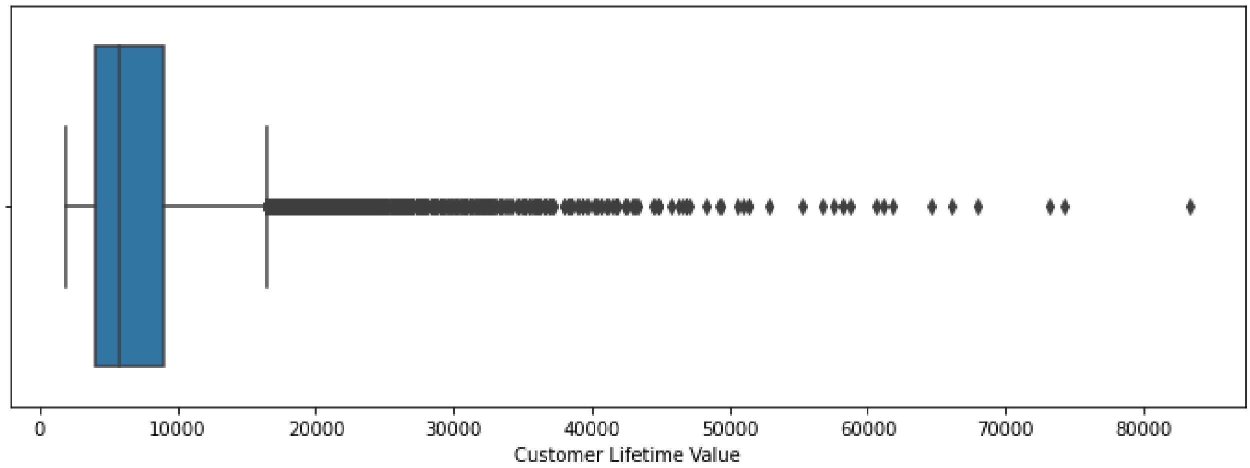




Среднее значение таргета находится в районе **8000,** при этом достаточно много значений находятся между **2000** и **5000**

In [11]:

```
plt.figure(figsize=[12, 4])
sns.boxplot(x=df['Customer Lifetime Value'])
plt.show()
```



По графику **boxplot** видно**,** что таргет имеет достаточно много выбросов**,** а также совсем экстремально большие значения в **70000-80000,** в то время как правая граница "усов" графика находится в районе **16000.** Для обучения моделей будем использовать логарифм таргета**.** Редкие большие значения удалим**,** чтобы модели не сбивались

Look at LTV for males and females separately

In [12]:

```
male_df = df.query('Gender == "M"')
female_df = df.query('Gender == "F"')
```

In [13]:

```
print('Male max LTV', male_df['Customer Lifetime Value'].max())
print('Male min LTV', male_df['Customer Lifetime Value'].min())
print('Male mean LTV', male_df['Customer Lifetime Value'].mean())
```

```
Male max LTV 83325.38119
Male min LTV 1898.007675
Male mean LTV 7909.55148797967
```

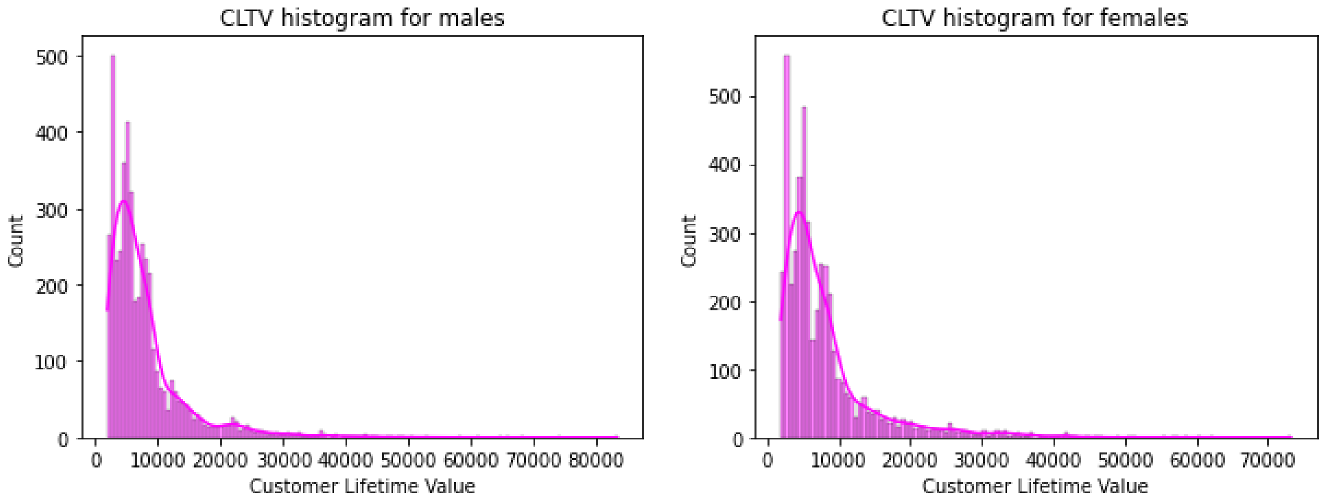
In [14]:

```
print('Female max LTV', female_df['Customer Lifetime Value'].max())
print('Female min LTV', female_df['Customer Lifetime Value'].min())
print('Female mean LTV', female_df['Customer Lifetime Value'].mean())
```

```
Female max LTV 73225.95652
Female min LTV 1898.683686
Female mean LTV 8096.60236975848
```

In [15]:

```
plt.figure(figsize=[12, 4])

plt.subplot(1, 2, 1)
sns.histplot(male_df['Customer Lifetime Value'], color='magenta', kde=True)
plt.title('CLTV histogram for males')

plt.subplot(1, 2, 2)
sns.histplot(female_df['Customer Lifetime Value'], color='magenta', kde=True)
plt.title('CLTV histogram for females')

plt.show()
```

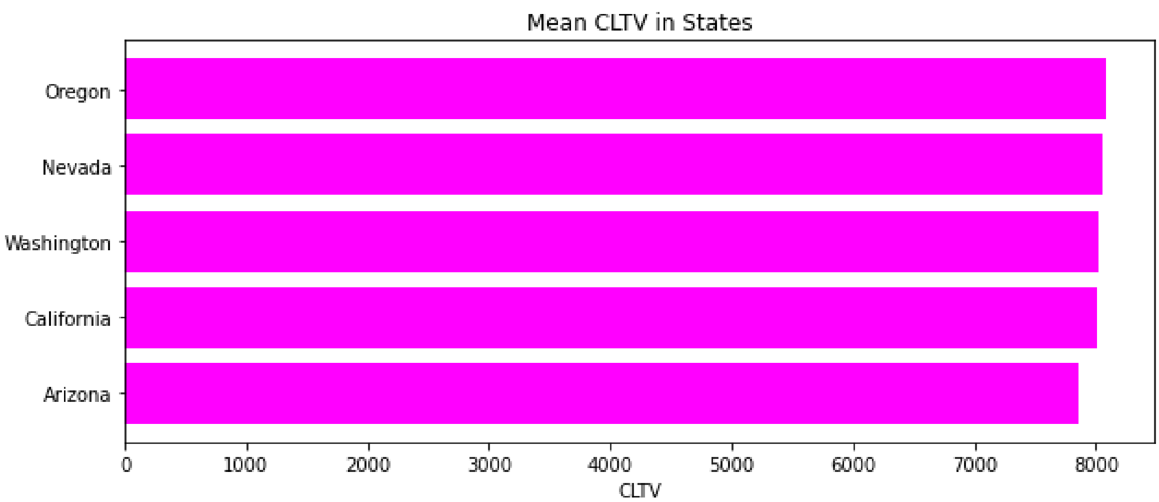


Максимальные значения **LTV** находятся среди мужчин**,** в то время как в среднем женщины тратят чуть больше**.** Но в целом значения не сильно отличаются от значений общего датасета

Look at mean CLTV difference between states

In [17]:

```
values = df.groupby('State').mean()['Customer Lifetime Value'].values
features = df.groupby('State').mean()['Customer Lifetime Value'].index
indices = np.argsort(values)

plt.figure(figsize=[10, 4])
plt.title('Mean CLTV in States')
plt.barh(range(len(indices)), values[indices], color='magenta', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('CLTV')
plt.show()
```

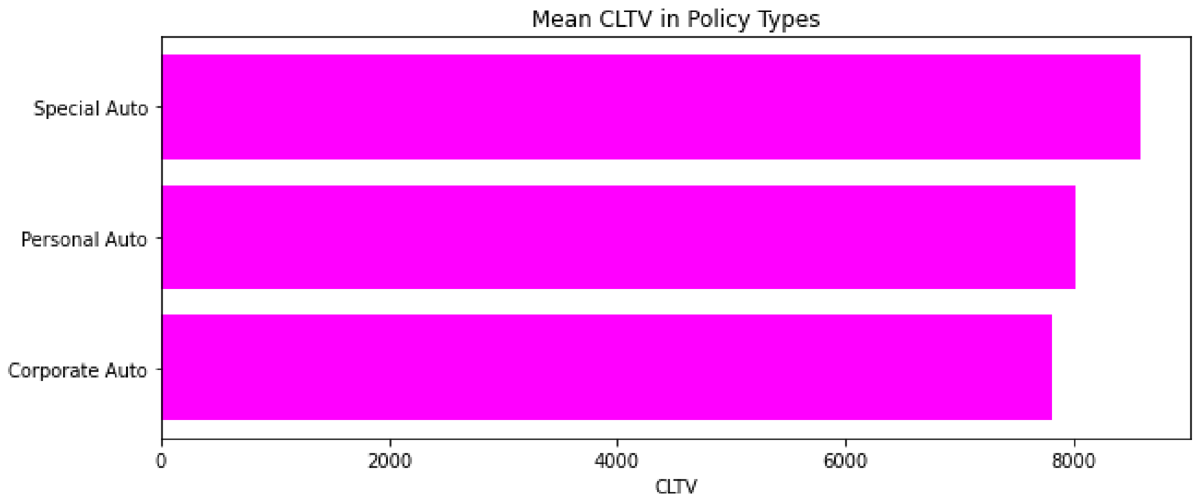


Существенной разницы по штатам не наблюдается

Look at mean CLTV difference between policy types

In [20]:

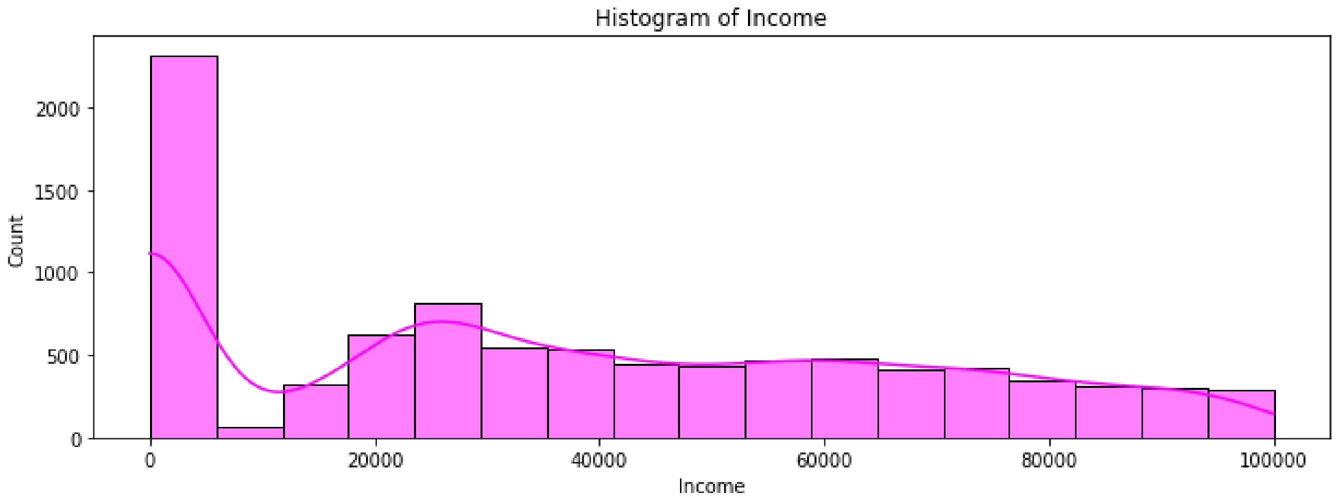
```
values = df.groupby('Policy Type').mean()['Customer Lifetime Value'].values
features = df.groupby('Policy Type').mean()['Customer Lifetime Value'].index
indices = np.argsort(values)

plt.figure(figsize=[10, 4])
plt.title('Mean CLTV in Policy Types')
plt.barh(range(len(indices)), values[indices], color='magenta', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('CLTV')
plt.show()
```



Look at Income

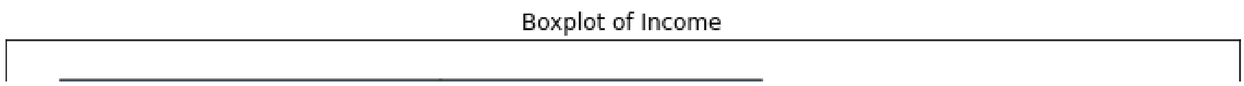
In [16]:

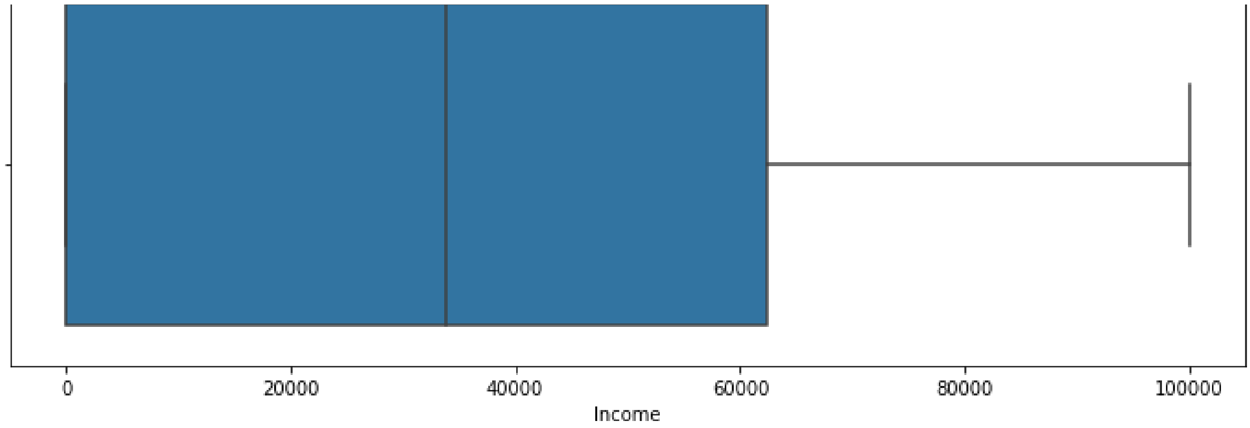
```
plt.figure(figsize=[12, 4])
sns.histplot(df['Income'], color='magenta', kde=True)
plt.title('Histogram of Income')
plt.show()
```



In [17]:

```
plt.figure(figsize=[12, 4])
sns.boxplot(x=df['Income'])
plt.title('Boxplot of Income')
plt.show()
```





Достаточно много людей не имеют дохода. Количество людей с разной суммой дохода не равной **0** распределено достаточно равномерно, явных выбросов нет

In [18]:

```
print(df.query('Income == 0')['EmploymentStatus'].unique())
```

```
['Unemployed']
```

Все, у кого доход равен **0**, не устроены на работу

Look at Effective To Date

In [19]:

```
df['Effective To Date']
```

Out[19]:

```
0       2/24/11
1       1/31/11
2       2/19/11
3       1/20/11
4        2/3/11
         ...
9129    2/10/11
9130    2/12/11
9131     2/6/11
9132     2/3/11
9133    2/14/11
Name: Effective To Date, Length: 9134, dtype: object
```

In [20]:

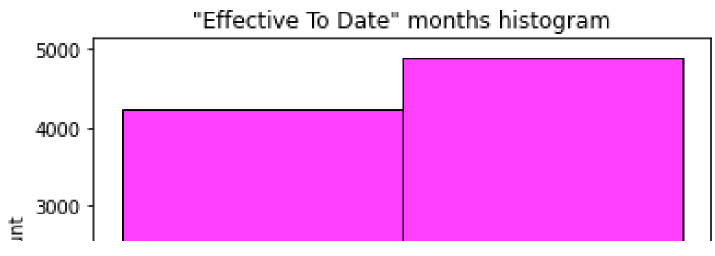
```
print(df['Effective To Date'].apply(lambda x: x.split('/')[2]).unique())
```

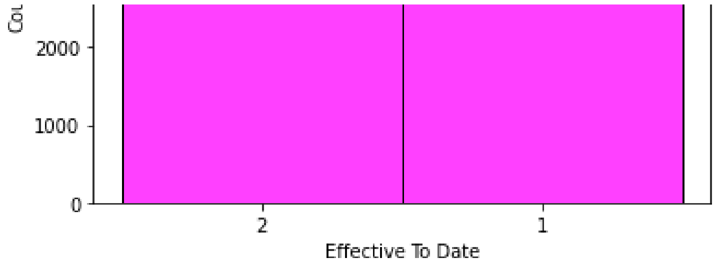
```
['11']
```

Все данные по сроку действия страховки датированы **11**-ым годом

In [21]:

```
sns.histplot(df['Effective To Date'].apply(lambda x: x.split('/')[0]), color='magenta')
plt.title('"Effective To Date" months histogram')
plt.show()
```

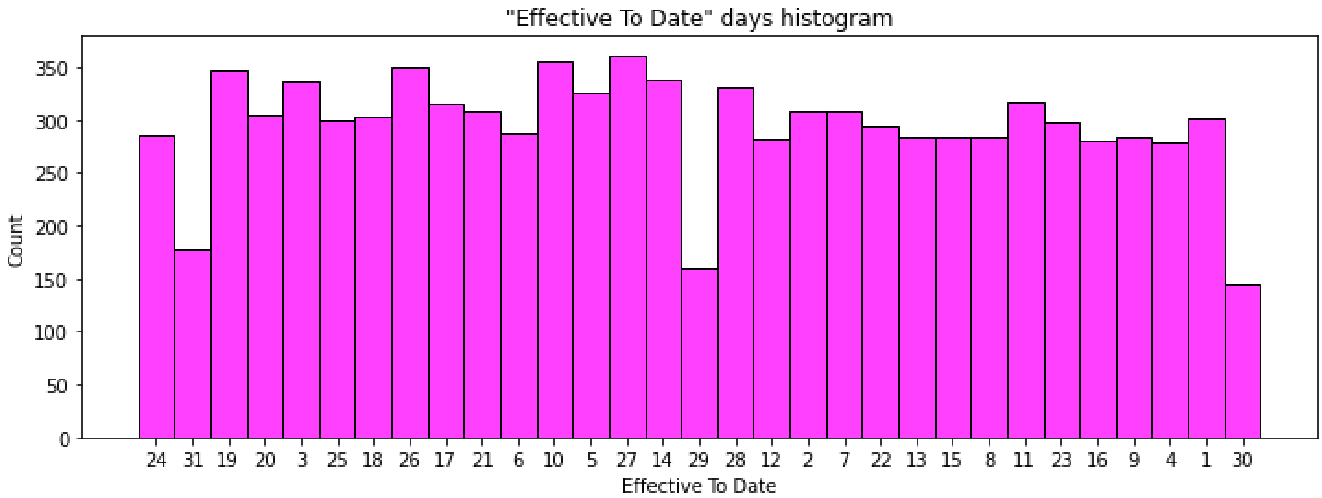




Данные по месяцам имеют всего **2** уникальных значения

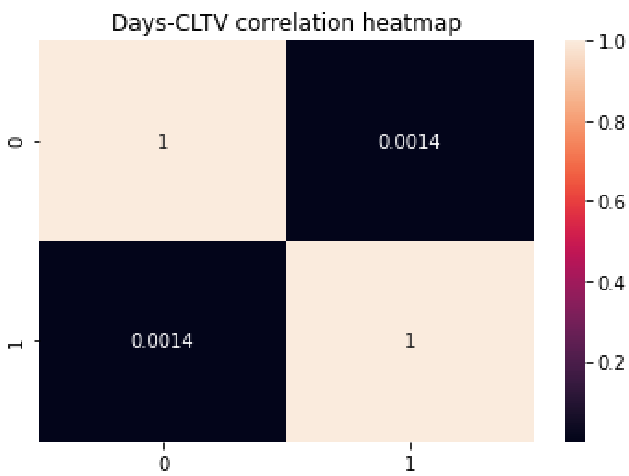
In [22]:

```
plt.figure(figsize=[12, 4])
sns.histplot(df['Effective To Date'].apply(lambda x: x.split('/')[1]), color='magenta')
plt.title('"Effective To Date" days histogram')
plt.show()
```



In [23]:

```
# Посмотрим на корреляцию дней и таргета
sns.heatmap(
    np.corrcoef(df['Effective To Date'].apply(lambda x: int(x.split('/')[1])), df['Custo
mer Lifetime Value']),
    annot=True
)
plt.title('Days-CLTV correlation heatmap')
plt.show()
```

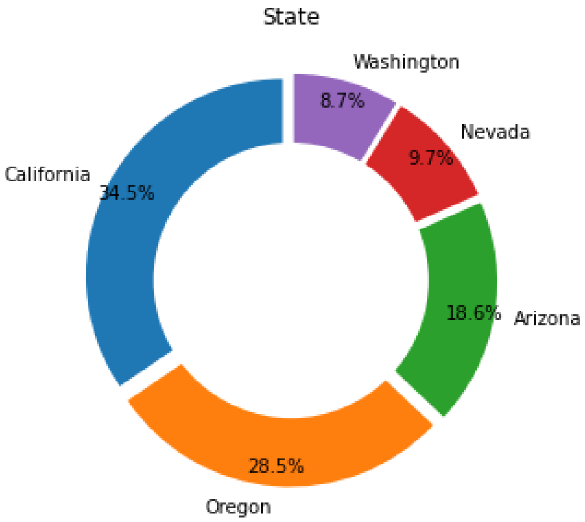


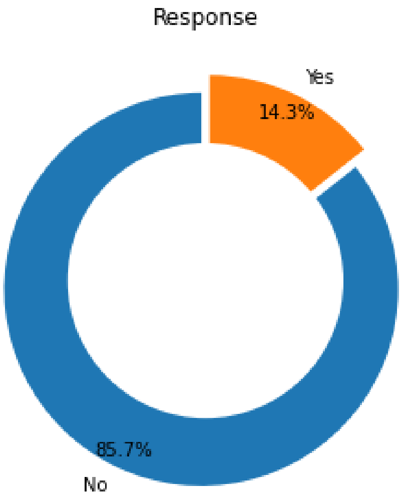
По дням имеются значения от **1** до **31,** но в целом достать какую-то полезную информацию из `Effective To Date` не видится возможным

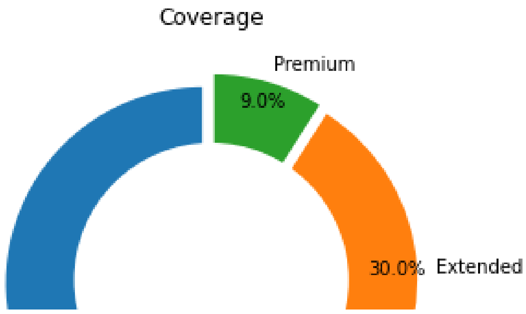
Pie Plots

In [24]:

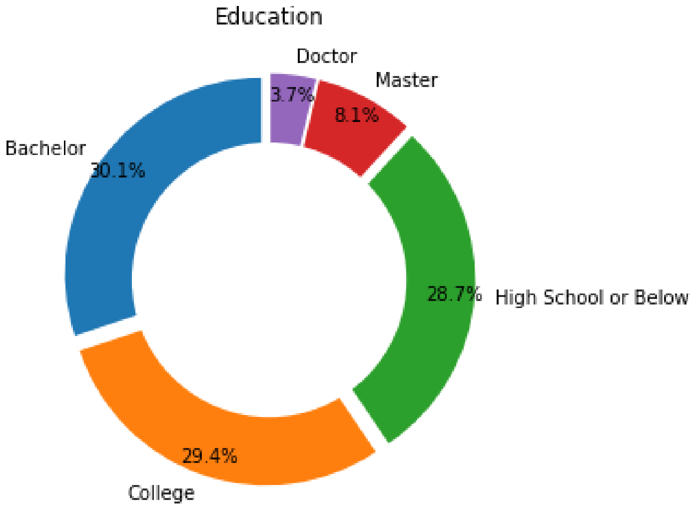
```
cols = df.columns

for col in cols:
    if df[col].nunique() < 10:

        labels = list(df[col].value_counts().index)
        sizes = list(df[col].value_counts())
        explode = (0.05, ) * len(labels)

        plt.pie(sizes,
                labels=labels,
                autopct='%1.1f%%',
                startangle=90,
                pctdistance=0.9,
                explode=explode,
                radius=1)
        centre_circle = plt.Circle((0,0) , 0.70, fc='white')
        fig = plt.gcf()
        fig.gca().add_artist(centre_circle)
        plt.tight_layout()
        plt.title(col)
        plt.show()
```

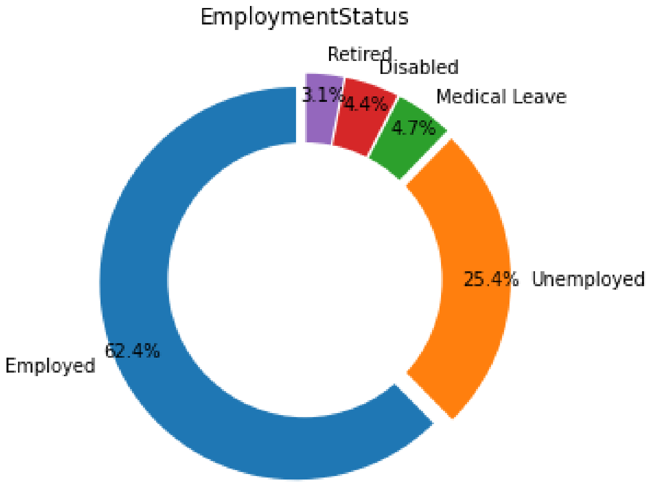


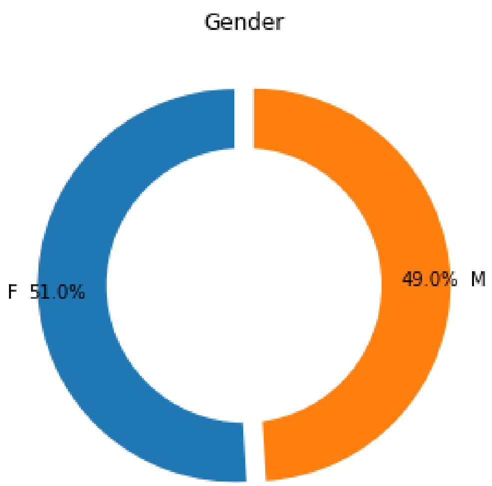


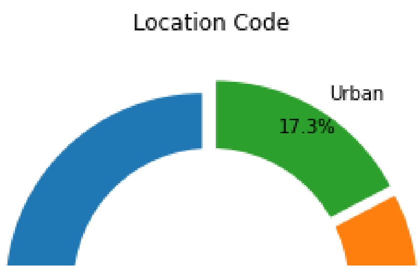



Basic
61.0%

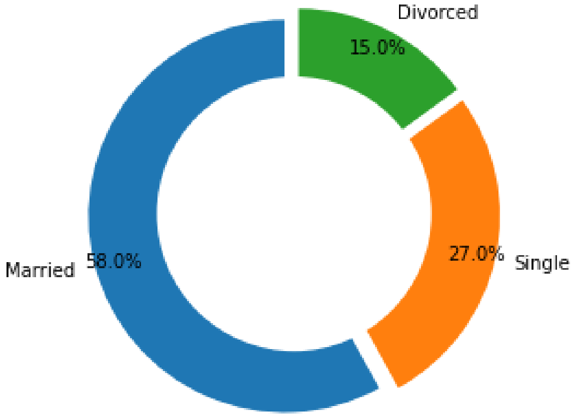

Education
Doctor
3.7%
Master
8.1%
Bachelor
30.1%
28.7%
High School or Below
29.4%
College


EmploymentStatus
Retired
3.1%
Disabled
4.4%
Medical Leave
4.7%
25.4%
Unemployed
Employed
62.4%

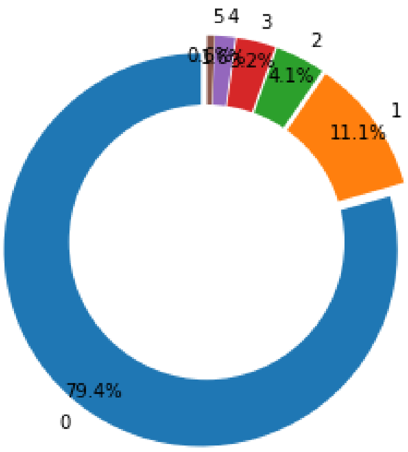

Gender
F
51.0%
49.0%
M


Location Code
Urban
17.3%

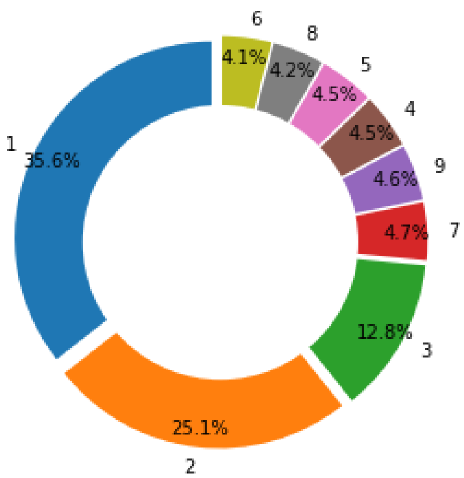
Marital Status



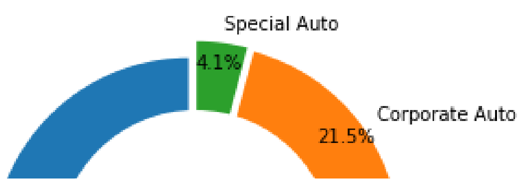
Number of Open Complaints

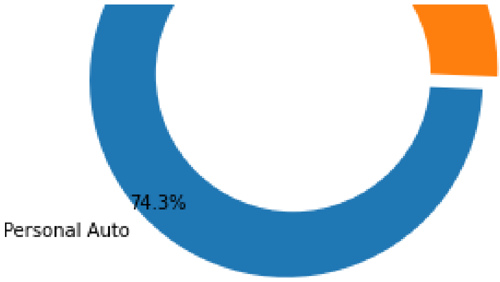


Number of Policies

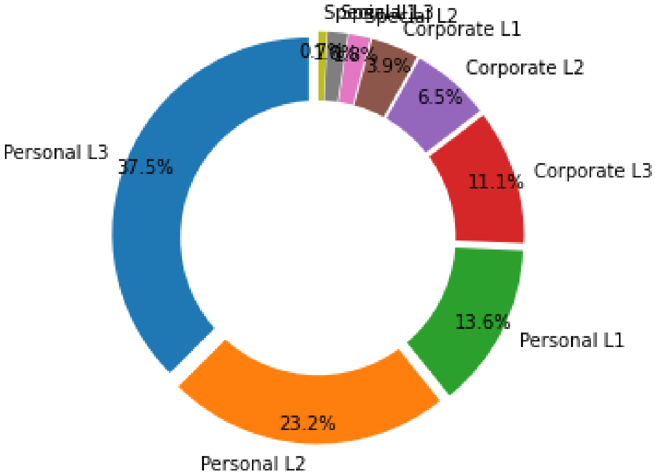


Policy Type

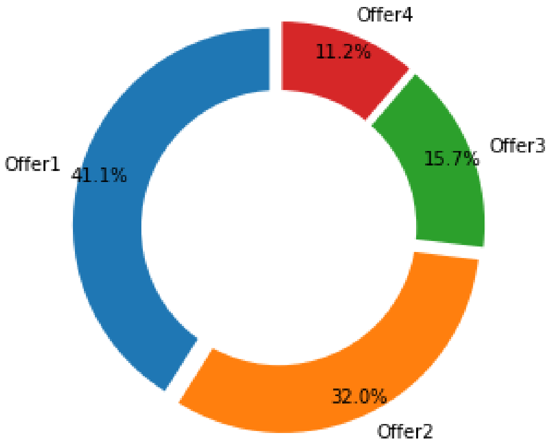




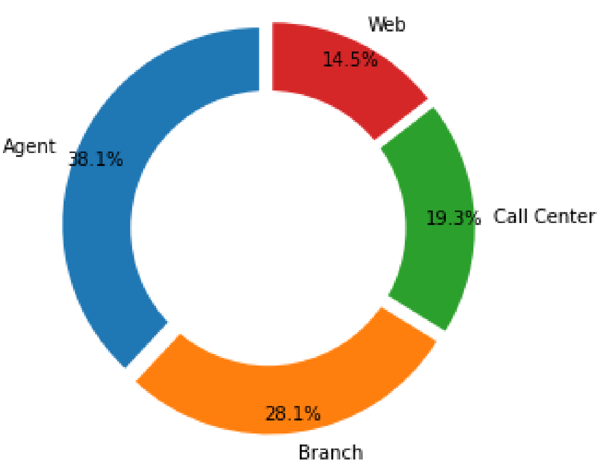
Policy



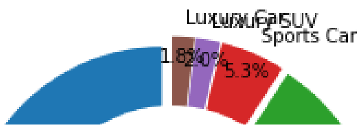
Renew Offer Type

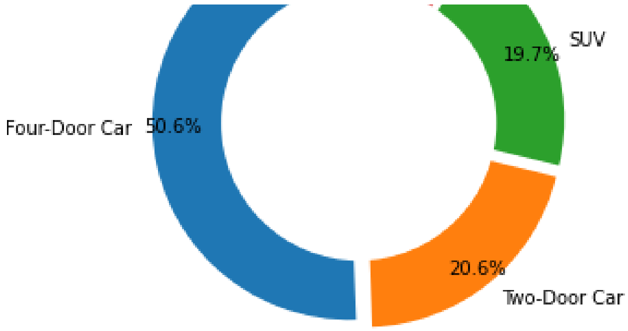


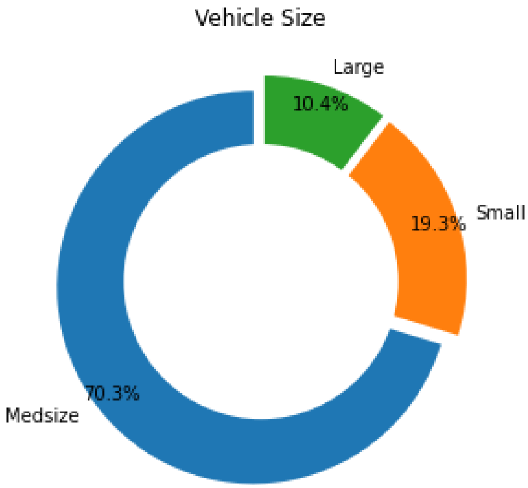
Sales Channel



Vehicle Class







По этим диаграммам мы можем наблюдать, как распределены группы внутри признаков в процентах

```
In [ ]:
```