is-eda-bcg-intership-task-insights

March 6, 2024

1 kINDLY UPVOTE THE NOTEBOOK IF YOU FIND IT INSIGHTFUL

2 Importing Required libraries

client_data.csv

- id = client company identifier
- activity_new = category of the company's activity *channel_sales = code of the sales channel* cons_12m = electricity consumption of the past 12 months *cons_gas_12m = gas consumption of the past 12 months* cons_last_month = electricity consumption of the last month *date_activ = date of activation of the contract* date_end = registered date of the end of the contract *date_modif_prod = date of the last modification of the product* date_renewal = date of the next contract renewal *forecast_cons_12m = forecasted electricity consumption for next 12 months* forecast_cons_year = forecasted electricity consumption for the next calendar year *forecast_discount_energy = forecasted value of current discount* forecast_meter_rent_12m = forecasted bill of meter rental for the next 2 months *forecast_price_energy_off_peak = forecasted energy price for 1st period (off peak)* forecast_price_energy_peak = forecasted energy price for 2nd period (peak) *forecast_price_pow_off_peak = forecasted power price for 1st period (off peak)* has_gas = indicated if client is also a gas client *imp_cons = current paid consumption* margin_gross_pow_ele = gross margin on power subscription *margin_net_pow_ele = net margin on power subscription* nb_prod_act = number of active products and services *net_margin = total net margin* num_years_antig = antiquity of the client (in number of years) *origin_up = code of the electricity campaign the customer first subscribed to* pow_max = subscribed power *churn = has the client churned over the next 3 months

price_data.csv

- id = client company identifier
- price_date = reference date
- price_off_peak_var = price of energy for the 1st period (off peak)
- price_peak_var = price of energy for the 2nd period (peak)
- price_mid_peak_var = price of energy for the 3rd period (mid peak)
- price_off_peak_fix = price of power for the 1st period (off peak)
- price_peak_fix = price of power for the 2nd period (peak)
- price_mid_peak_fix = price of power for the 3rd period (mid peak)

Note: some fields are hashed text strings. This preserves the privacy of the original data but the

commercial meaning is retained and so they may have predictive power

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as mn
plt.rcParams['axes.facecolor']=(0.72, 0.807, 0.898)
pd.set_option('display.max_columns', 50)
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A
NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy
(detected version 1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

[2]:
```
client=pd.read_csv('/kaggle/input/bcgtask/client.csv')
```

[3]:
```
price=pd.read_csv("/kaggle/input/bcgtask/price.csv")
```

[4]:
```
df=pd.merge(client,price,on='id')
```

[5]:
```
df.head()
```

[5]:

	id	channel_sales	\
0	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	
1	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	
2	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	
3	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	
4	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	

	cons_12m	cons_gas_12m	cons_last_month	date_activ	date_end	\
0	0	54946	0	2013-06-15	2016-06-15	
1	0	54946	0	2013-06-15	2016-06-15	
2	0	54946	0	2013-06-15	2016-06-15	
3	0	54946	0	2013-06-15	2016-06-15	
4	0	54946	0	2013-06-15	2016-06-15	

	date_modif_prod	date_renewal	forecast_cons_12m	forecast_cons_year	\
0	2015-11-01	2015-06-23	0.0	0	
1	2015-11-01	2015-06-23	0.0	0	
2	2015-11-01	2015-06-23	0.0	0	
3	2015-11-01	2015-06-23	0.0	0	
4	2015-11-01	2015-06-23	0.0	0	

	forecast_discount_energy	forecast_meter_rent_12m	\
0	0.0	1.78	
1	0.0	1.78	
2	0.0	1.78	

```
3                      0.0                    1.78
4                      0.0                    1.78

   forecast_price_energy_off_peak  forecast_price_energy_peak  \
0                        0.114481                    0.098142
1                        0.114481                    0.098142
2                        0.114481                    0.098142
3                        0.114481                    0.098142
4                        0.114481                    0.098142

   forecast_price_pow_off_peak has_gas  imp_cons  margin_gross_pow_ele  \
0                    40.606701       t       0.0                 25.44
1                    40.606701       t       0.0                 25.44
2                    40.606701       t       0.0                 25.44
3                    40.606701       t       0.0                 25.44
4                    40.606701       t       0.0                 25.44

   margin_net_pow_ele  nb_prod_act  net_margin  num_years_antig  \
0               25.44            2      678.99                3
1               25.44            2      678.99                3
2               25.44            2      678.99                3
3               25.44            2      678.99                3
4               25.44            2      678.99                3

                         origin_up  pow_max  churn  price_date  \
0  lxidpiddsbxsbosboudacockeimpuepw   43.648      1  2015-01-01
1  lxidpiddsbxsbosboudacockeimpuepw   43.648      1  2015-02-01
2  lxidpiddsbxsbosboudacockeimpuepw   43.648      1  2015-03-01
3  lxidpiddsbxsbosboudacockeimpuepw   43.648      1  2015-04-01
4  lxidpiddsbxsbosboudacockeimpuepw   43.648      1  2015-05-01

   price_off_peak_var  price_peak_var  price_mid_peak_var  price_off_peak_fix  \
0            0.125976        0.103395            0.071536           40.565969
1            0.125976        0.103395            0.071536           40.565969
2            0.125976        0.103395            0.071536           40.565973
3            0.125976        0.103395            0.071536           40.565973
4            0.125976        0.103395            0.071536           40.565973

   price_peak_fix  price_mid_peak_fix
0       24.339581           16.226389
1       24.339581           16.226389
2       24.339578           16.226383
3       24.339578           16.226383
4       24.339578           16.226383
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 175149 entries, 0 to 175148
Data columns (total 33 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   id                              175149 non-null  object 
 1   channel_sales                   175149 non-null  object 
 2   cons_12m                        175149 non-null  int64  
 3   cons_gas_12m                    175149 non-null  int64  
 4   cons_last_month                 175149 non-null  int64  
 5   date_activ                      175149 non-null  object 
 6   date_end                        175149 non-null  object 
 7   date_modif_prod                 175149 non-null  object 
 8   date_renewal                    175149 non-null  object 
 9   forecast_cons_12m               175149 non-null  float64
 10  forecast_cons_year              175149 non-null  int64  
 11  forecast_discount_energy        175149 non-null  float64
 12  forecast_meter_rent_12m         175149 non-null  float64
 13  forecast_price_energy_off_peak  175149 non-null  float64
 14  forecast_price_energy_peak      175149 non-null  float64
 15  forecast_price_pow_off_peak     175149 non-null  float64
 16  has_gas                         175149 non-null  object 
 17  imp_cons                        175149 non-null  float64
 18  margin_gross_pow_ele            175149 non-null  float64
 19  margin_net_pow_ele              175149 non-null  float64
 20  nb_prod_act                     175149 non-null  int64  
 21  net_margin                      175149 non-null  float64
 22  num_years_antig                 175149 non-null  int64  
 23  origin_up                       175149 non-null  object 
 24  pow_max                         175149 non-null  float64
 25  churn                           175149 non-null  int64  
 26  price_date                      175149 non-null  object 
 27  price_off_peak_var              175149 non-null  float64
 28  price_peak_var                  175149 non-null  float64
 29  price_mid_peak_var              175149 non-null  float64
 30  price_off_peak_fix              175149 non-null  float64
 31  price_peak_fix                  175149 non-null  float64
 32  price_mid_peak_fix              175149 non-null  float64
dtypes: float64(17), int64(7), object(9)
memory usage: 45.4+ MB
```

[7]:
```
df.drop_duplicates(inplace=True)
```

[8]:
```
date=['date_activ','date_end','date_modif_prod','date_renewal','price_date']
for i in date:
  df[i]=pd.to_datetime(df[i])
```

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 175149 entries, 0 to 175148
Data columns (total 33 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   id                              175149 non-null  object
 1   channel_sales                   175149 non-null  object
 2   cons_12m                        175149 non-null  int64
 3   cons_gas_12m                    175149 non-null  int64
 4   cons_last_month                 175149 non-null  int64
 5   date_activ                      175149 non-null  datetime64[ns]
 6   date_end                        175149 non-null  datetime64[ns]
 7   date_modif_prod                 175149 non-null  datetime64[ns]
 8   date_renewal                    175149 non-null  datetime64[ns]
 9   forecast_cons_12m               175149 non-null  float64
 10  forecast_cons_year              175149 non-null  int64
 11  forecast_discount_energy        175149 non-null  float64
 12  forecast_meter_rent_12m         175149 non-null  float64
 13  forecast_price_energy_off_peak  175149 non-null  float64
 14  forecast_price_energy_peak      175149 non-null  float64
 15  forecast_price_pow_off_peak     175149 non-null  float64
 16  has_gas                         175149 non-null  object
 17  imp_cons                        175149 non-null  float64
 18  margin_gross_pow_ele            175149 non-null  float64
 19  margin_net_pow_ele              175149 non-null  float64
 20  nb_prod_act                     175149 non-null  int64
 21  net_margin                      175149 non-null  float64
 22  num_years_antig                 175149 non-null  int64
 23  origin_up                       175149 non-null  object
 24  pow_max                         175149 non-null  float64
 25  churn                           175149 non-null  int64
 26  price_date                      175149 non-null  datetime64[ns]
 27  price_off_peak_var              175149 non-null  float64
 28  price_peak_var                  175149 non-null  float64
 29  price_mid_peak_var              175149 non-null  float64
 30  price_off_peak_fix              175149 non-null  float64
 31  price_peak_fix                  175149 non-null  float64
 32  price_mid_peak_fix              175149 non-null  float64
dtypes: datetime64[ns](5), float64(17), int64(7), object(4)
memory usage: 45.4+ MB
```

[10]:
```
df.shape
```

[10]: (175149, 33)

[11]:
```
df.columns
```

[11]:
```
Index(['id', 'channel_sales', 'cons_12m', 'cons_gas_12m', 'cons_last_month',
       'date_activ', 'date_end', 'date_modif_prod', 'date_renewal',
       'forecast_cons_12m', 'forecast_cons_year', 'forecast_discount_energy',
       'forecast_meter_rent_12m', 'forecast_price_energy_off_peak',
       'forecast_price_energy_peak', 'forecast_price_pow_off_peak', 'has_gas',
       'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'nb_prod_act',
       'net_margin', 'num_years_antig', 'origin_up', 'pow_max', 'churn',
       'price_date', 'price_off_peak_var', 'price_peak_var',
       'price_mid_peak_var', 'price_off_peak_fix', 'price_peak_fix',
       'price_mid_peak_fix'],
      dtype='object')
```

[12]:
```
df['channel_sales'].unique()
```

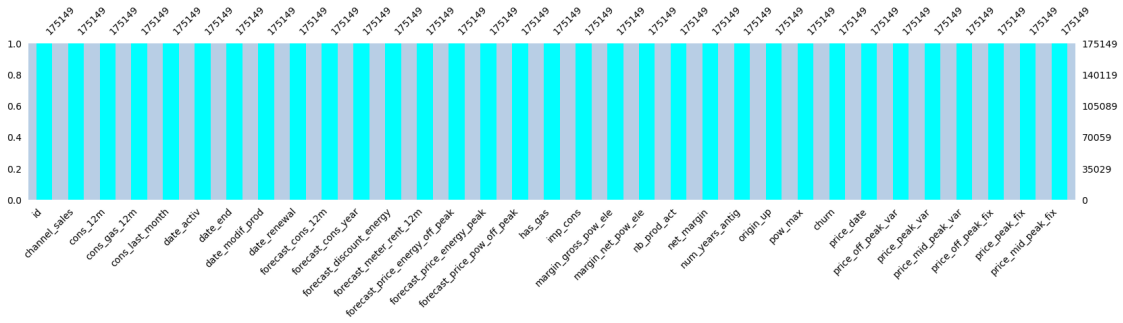
[12]:
```
array(['foosdfpfkusacimwkcsosbicdxkicaua', 'MISSING',
       'lmkebamcaaclubfxadlmueccxoimlema',
       'usilxuppasemubllopkaafesmlibmsdf',
       'ewpakwlliwisiwduibdlfmalxowmwpci',
       'epumfxlbckeskwekxbiuasklxalciiuu',
       'sddiedcslfslkckwlfkdpoeeailfpeds',
       'fixdbufsefwooaasfcxdxadsiekoceaa'], dtype=object)
```

[13]:
```
df.shape
```

[13]:
```
(175149, 33)
```

[14]:
```
mn.bar(df,figsize=(20,3),fontsize=10,color='cyan')
```

[14]:
```
<Axes: >
```



[15]:
```
#first half of int and float columns
df[['cons_12m',
 'cons_gas_12m',
```

```
 'cons_last_month',
 'forecast_cons_12m',
 'forecast_cons_year',
 'forecast_discount_energy',
 'forecast_meter_rent_12m',
 'forecast_price_energy_off_peak',
 'forecast_price_energy_peak',
 'forecast_price_pow_off_peak',
 'imp_cons',
 'margin_gross_pow_ele',
 'margin_net_pow_ele']].describe().round(3)
```

[15]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m
count	175149.000	175149.000	175149.000	175149.000
mean	159260.579	28080.718	16095.518	1868.344
std	573541.331	162940.034	64376.742	2387.560
min	0.000	0.000	0.000	0.000
25%	5674.000	0.000	0.000	494.980
50%	14115.000	0.000	792.000	1112.610
75%	40763.000	0.000	3383.000	2400.350
max	6207104.000	4154590.000	771203.000	82902.830

	forecast_cons_year	forecast_discount_energy	forecast_meter_rent_12m
count	175149.000	175149.000	175149.000
mean	1399.782	0.967	63.075
std	3248.331	5.109	66.144
min	0.000	0.000	0.000
25%	0.000	0.000	16.180
50%	314.000	0.000	18.790
75%	1745.000	0.000	131.030
max	175375.000	30.000	599.310

	forecast_price_energy_off_peak	forecast_price_energy_peak
count	175149.000	175149.000
mean	0.137	0.050
std	0.025	0.049
min	0.000	0.000
25%	0.116	0.000
50%	0.143	0.084
75%	0.146	0.099
max	0.274	0.196

	forecast_price_pow_off_peak	imp_cons	margin_gross_pow_ele
count	175149.000	175149.000	175149.000
mean	43.130	152.790	24.567
std	4.487	341.427	20.234
min	0.000	0.000	0.000

```
25%                      40.607       0.000              14.280
50%                      44.311      37.390              21.640
75%                      44.311     193.990              29.880
max                      59.266   15042.790             374.640

       margin_net_pow_ele
count          175149.000
mean               24.564
std                20.234
min                 0.000
25%                14.280
50%                21.640
75%                29.880
max               374.640
```

[16]:
```
#2nd half of int and float columns
df[['nb_prod_act',
 'net_margin',
 'num_years_antig',
 'pow_max',
 'churn',
 'price_off_peak_var',
 'price_peak_var',
 'price_mid_peak_var',
 'price_off_peak_fix',
 'price_peak_fix',
 'price_mid_peak_fix']].describe().round(3)
```

[16]:
```
       nb_prod_act  net_margin  num_years_antig     pow_max       churn  \
count   175149.000  175149.000       175149.000  175149.000  175149.000
mean         1.292     189.245            4.998      18.135       0.097
std          0.710     311.847            1.612      13.536       0.296
min          1.000       0.000            1.000       3.300       0.000
25%          1.000      50.710            4.000      12.500       0.000
50%          1.000     112.500            5.000      13.856       0.000
75%          1.000     243.000            6.000      19.180       0.000
max         32.000   24570.650           13.000     320.000       1.000

       price_off_peak_var  price_peak_var  price_mid_peak_var  \
count          175149.000      175149.000          175149.000
mean                0.142           0.052               0.028
std                 0.023           0.050               0.036
min                 0.000           0.000               0.000
25%                 0.127           0.000               0.000
50%                 0.147           0.084               0.000
75%                 0.152           0.102               0.073
max                 0.281           0.230               0.114
```

```
       price_off_peak_fix  price_peak_fix  price_mid_peak_fix
count           175149.000      175149.000          175149.000
mean                42.929           9.459               6.096
std                  4.621          12.133               7.822
min                  0.000           0.000               0.000
25%                 40.729           0.000               0.000
50%                 44.267           0.000               0.000
75%                 44.445          24.340              16.226
max                 59.445          36.491              17.458
```

[17]:
```
df.describe(include=['object'])
```

[17]:
```
                                    id                    channel_sales  \
count                           175149                           175149
unique                           14606                                8
top     24011ae4ebbe3035111d65fa7c15bc57  foosdfpfkusacimwkcsosbicdxkicaua
freq                                12                            80971

       has_gas                         origin_up
count   175149                            175149
unique       2                                 6
top          f  lxidpiddsbxsbosboudacockeimpuepw
freq    143364                             85086
```

[18]:
```
#kurtosis and skewness

  # Skewness > 0: Positively skewed (tail on the right)
  # Skewness < 0: Negatively skewed (tail on the left)
  #Skewness = 0: Symmetric distribution

  #Kurtosis > 3: Leptokurtic (more peaked than a normal distribution, with␣
 ↪heavier tails)
  #Kurtosis < 3: Platykurtic (less peaked than a normal distribution, with␣
 ↪lighter tails)
  #Kurtosis = 3: Mesokurtic (similar peakedness to a normal distribution)

skew=df.select_dtypes(include=['int','float']).skew().to_frame().reset_index()
skew.columns=['col_names','Skewness']
kurt=df.select_dtypes(include=['int','float']).kurtosis().to_frame().
 ↪reset_index()
kurt.columns=['col_names','kurtosis']
a=pd.merge(skew,kurt,on='col_names')
a.index.name='sno'
a
```

[18]:

sno	col_names	Skewness	kurtosis
0	cons_12m	5.996313	42.669832
1	cons_gas_12m	9.601588	126.427130
2	cons_last_month	6.389957	47.732548
3	forecast_cons_12m	7.159049	147.470752
4	forecast_cons_year	16.587522	653.463987
5	forecast_discount_energy	5.153648	24.836366
6	forecast_meter_rent_12m	1.503670	4.483410
7	forecast_price_energy_off_peak	-0.120054	8.363671
8	forecast_price_energy_peak	-0.014138	-1.890489
9	forecast_price_pow_off_peak	-4.999296	54.681957
10	imp_cons	13.198335	380.733638
11	margin_gross_pow_ele	4.472289	35.875438
12	margin_net_pow_ele	4.472982	35.884061
13	nb_prod_act	8.639788	259.013937
14	net_margin	36.571063	2642.018779
15	num_years_antig	1.445985	4.076234
16	pow_max	5.787392	59.196858
17	churn	2.721894	5.408768
18	price_off_peak_var	-0.708908	12.360176
19	price_peak_var	-0.023695	-1.895772
20	price_mid_peak_var	0.505937	-1.709054
21	price_off_peak_fix	-5.353341	55.392708
22	price_peak_fix	0.540461	-1.599137
23	price_mid_peak_fix	0.518144	-1.715927

From the above table inferences most of the features are right skewed and followed by heavy tailed distributions

3 EDA

[19]:
```
churn=df['churn'].value_counts().to_frame().reset_index()
churn.columns=['Status','Churn']
churn.at[0,'Status']='NO'    # replacing 0 with NO
churn['Status'][1]='Yes'     # replaceing 1 with Yes

#converting into churn status percentage for Churn column in the dataframe

churn['Churn']=churn['Churn'].apply(lambda x: (x/churn['Churn'].sum())*100)
churn
```

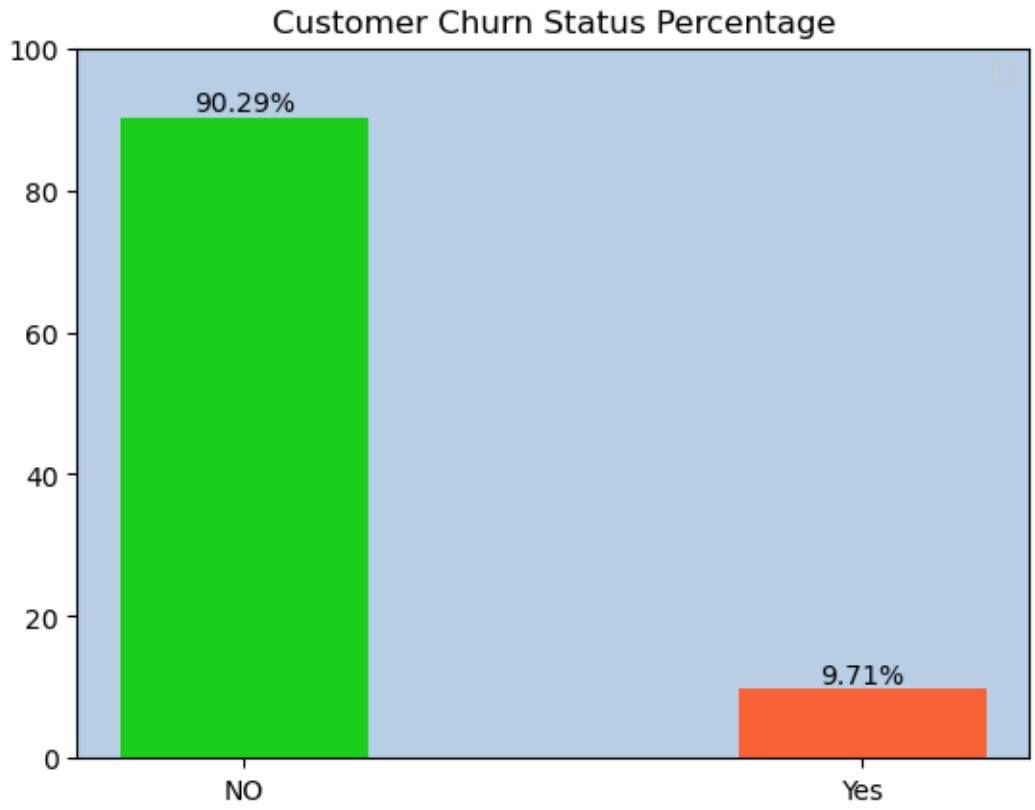
```
/tmp/ipykernel_32/478852479.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
churn['Status'][1]='Yes'    # replaceing 1 with Yes
```

[19]:

	Status	Churn
0	NO	90.292265
1	Yes	9.707735

[20]:
```
plt.bar(x='Status',height='Churn',data=churn,color=[(0.031, 0.803, 0.015),(1, 0.
↪337, 0.141)],alpha=0.9,width=0.4)
plt.rcParams['axes.facecolor'] = (0.72, 0.807, 0.898)
for index, value in enumerate(churn['Churn']):
    plt.text(index, value, f'{value:.2f}%', ha='center', va='bottom')␣
↪#va-vertical alignment for text label, ha- horizontal alignment for text␣
↪label

plt.ylim(0,100)
plt.title('Customer Churn Status Percentage')
plt.legend()
plt.show()
```



From the above bar graph we can easily infer that,

Total no of Customers not churned = 91.39%

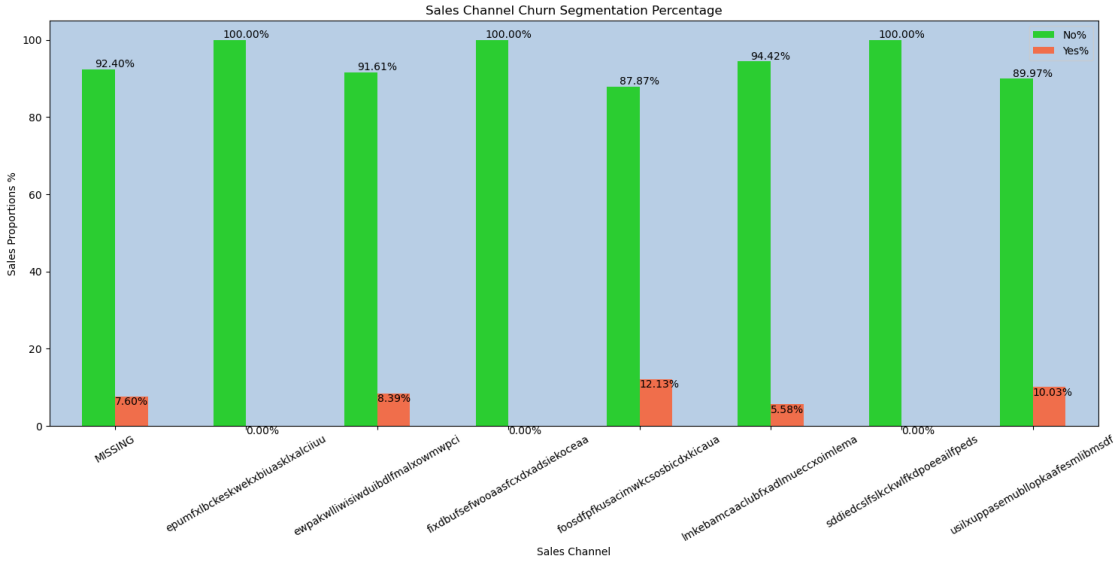
Total no of Customers actually Churned = 9.71%

[21]:
```
#Sales channel

sc=df[['id','channel_sales','churn']]
sc=sc.groupby(['channel_sales','churn'])['id'].count().unstack().fillna(0)
sc.columns=['No','Yes']
for i in sc.columns:
  sc[f'{i}%'] = sc[i] / (sc['No'] + sc['Yes']) * 100

sc
```

[21]:

channel_sales	No	Yes	No%	Yes%
MISSING	41290.0	3394.0	92.404440	7.595560
epumfxlbckeskwekxbiuasklxalciiuu	36.0	0.0	100.000000	0.000000
ewpakwlliwisiwduibdlfmalxowmwpci	9813.0	899.0	91.607543	8.392457
fixdbufsefwooaasfcxdxadsiekoceaa	24.0	0.0	100.000000	0.000000
foosdfpfkusacimwkcsosbicdxkicaua	71149.0	9822.0	87.869731	12.130269
lmkebamcaaclubfxadlmueccxoimlema	20871.0	1234.0	94.417553	5.582447
sddiedcslfslkckwlfkdpoeeailfpeds	131.0	0.0	100.000000	0.000000
usilxuppasemubllopkaafesmlibmsdf	14832.0	1654.0	89.967245	10.032755

[22]:
```
sc[['No%','Yes%']].plot(kind='bar',stacked=False,color=[(0.031, 0.803, 0.
↪015),(1, 0.337, 0.141)],alpha=0.8,figsize=(18,7),width=0.5)
plt.rcParams['axes.facecolor'] = (0.72, 0.807, 0.898)
for index,value in enumerate(sc['No%']):
  plt.text(index,value,f'{value:.2f}%',ha='center',va='bottom')#'top',␣
↪'bottom', 'center', 'baseline', 'center_baseline' va
for index,value in enumerate(sc['Yes%']):
  plt.text(index,value,f'{value:.2f}%',ha='left',va='top')#'center', 'right',␣
↪'left' ha
plt.title('Sales Channel Churn Segmentation Percentage')
plt.xlabel('Sales Channel')
plt.ylabel('Sales Proportions %')
plt.xticks(rotation=30)
plt.show()
```



In Sales channel "MISSING" values is presented and it contains data about 44,648 values.In later part this will be important for modelling purposes.

[23]:
```
#consumption

cons=df[['id','cons_12m', 'cons_gas_12m',␣
 ↪'cons_last_month','has_gas','imp_cons','churn']]
cons.head(4)
```

[23]:

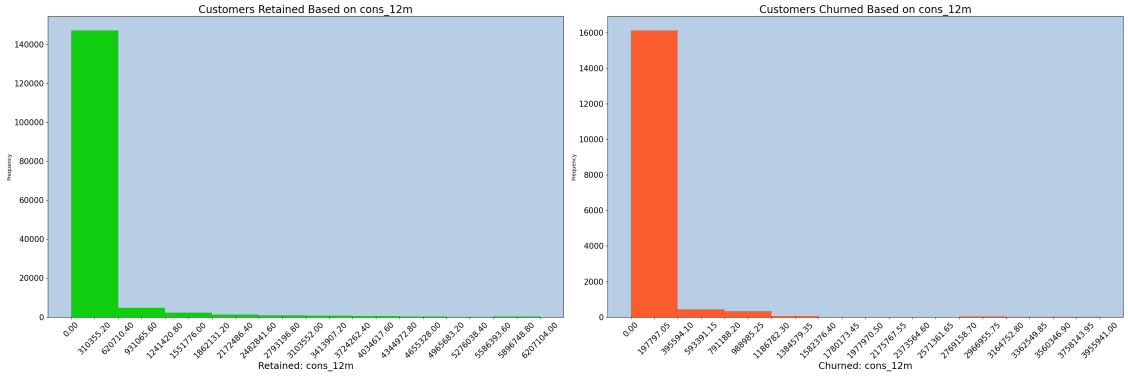
	id	cons_12m	cons_gas_12m	cons_last_month	\
0	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	
1	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	
2	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	
3	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	

	has_gas	imp_cons	churn
0	t	0.0	1
1	t	0.0	1
2	t	0.0	1
3	t	0.0	1

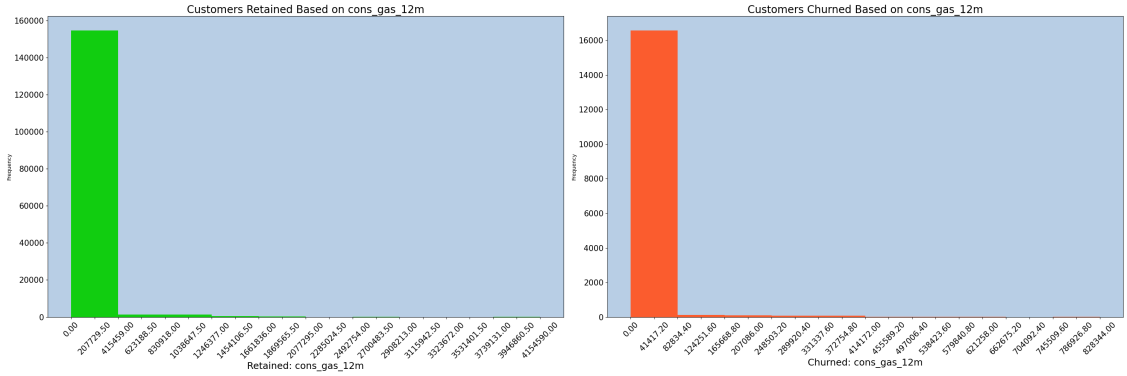
[24]:
```
def plotting(dataframe, col):

  condf=pd.DataFrame({'C_Retained': dataframe[dataframe['churn']==0][col],
                      'C_Churned': dataframe[dataframe['churn']==1][col]})

  fig,axs=plt.subplots(1,2,figsize=(30,10))

  c1,x1=np.histogram(dataframe[dataframe['churn']==0][col],20)
```

```
 c2,x2=np.histogram(dataframe[dataframe['churn']==1][col],20)

 condf['C_Retained'].plot(kind='hist',ax=axs[0],xticks=x1,alpha=0.95,color=(0.
↪031, 0.803, 0.015))
 axs[0].set_facecolor((0.72, 0.807, 0.898))
 axs[0].set_title(f"Customers Retained Based on {col}",fontsize=20)
 axs[0].set_xlabel(f"Retained: {col}",fontsize=18)
 axs[0].set_xticklabels([f"{t1:.2f}" for t1 in axs[0].
↪get_xticks()],rotation=45,fontsize=15)
 axs[0].tick_params(axis='y',labelsize=15)


 condf['C_Churned'].plot(kind='hist',ax=axs[1],xticks=x2,color=(1, 0.337, 0.
↪141),alpha=0.95)
 axs[1].set_title(f"Customers Churned Based on {col}",fontsize=20)
 axs[1].set_facecolor((0.72, 0.807, 0.898))
 axs[1].set_xlabel(f"Churned: {col}",fontsize=18)
 axs[1].set_xticklabels([f"{t2:.2f}" for t2 in axs[1].
↪get_xticks()],rotation=45,fontsize=15)
 axs[1].tick_params(axis='y',labelsize=15)



 plt.subplots_adjust(wspace=0.3)
 plt.tight_layout()
 plt.show()
```

[25]:
```
plotting(cons, 'cons_12m')
```

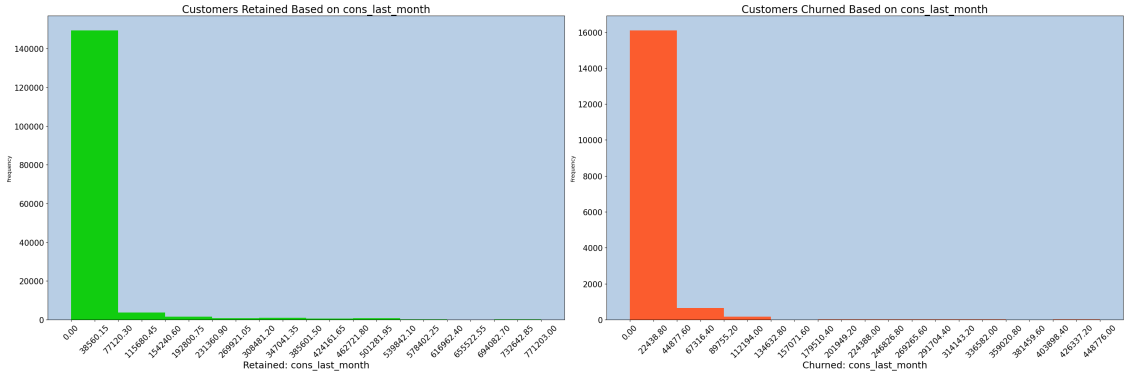


[26]:
```
plotting(cons, 'cons_gas_12m')
```

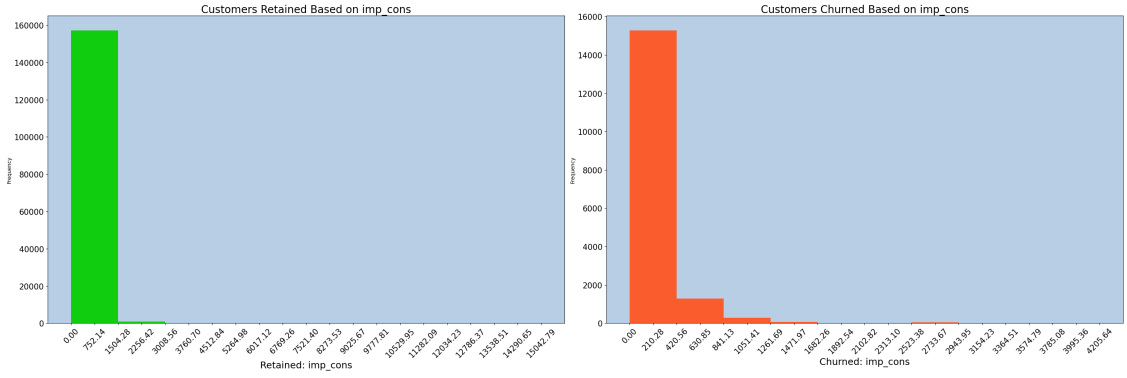


Consumption of Gas for past 12 months

[27]:
```
plotting(cons, 'cons_last_month')
```



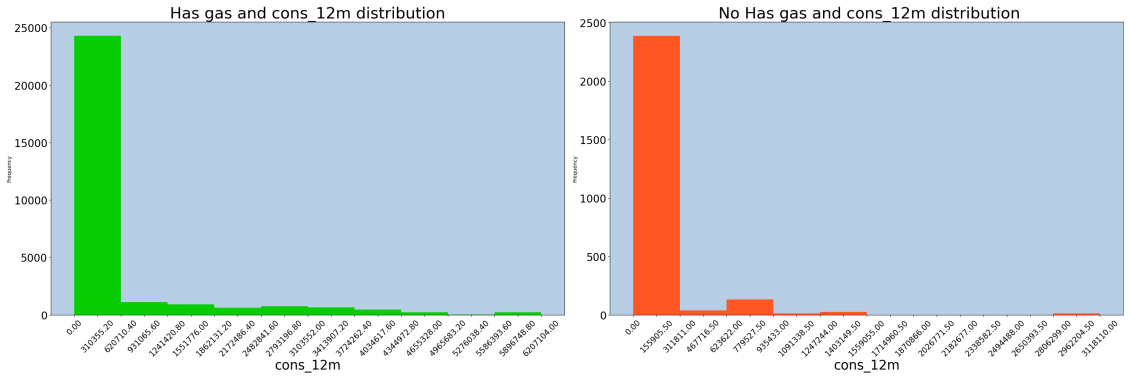
[28]:
```
plotting(cons, 'imp_cons')
```



From the above visuals features such as 'cons_12m', 'cons_gas_12m', 'cons_last_month','has_gas','imp_cons' having right skewed and heavly tailed distribution

pattern

[29]:
```
fig,axs=plt.subplots(1,2,figsize=(30,10))

count1,bin1=np.histogram(cons[(cons['has_gas']=='t')&␣
 ↪(cons['churn']==0)]['cons_12m'],20)
count2,bin2=np.histogram(cons[(cons['has_gas']=='t')&␣
 ↪(cons['churn']==1)]['cons_12m'],20)

cons[(cons['has_gas']=='t')& (cons['churn']==0)]['cons_12m'].
 ↪plot(kind='hist',ax=axs[0],xticks=bin1,color=(0.031, 0.803, 0.015))
axs[0].set_facecolor((0.72, 0.807, 0.898))
axs[0].set_title('Has gas and cons_12m distribution',fontsize=30)
axs[0].set_xlabel('cons_12m',fontsize=25)
axs[0].set_xticklabels([f"{tick:.2f}" for tick in axs[0].
 ↪get_xticks()],rotation=45,fontsize=15)
axs[0].tick_params(axis='y',labelsize=20)


cons[(cons['has_gas']=='t')& (cons['churn']==1)]['cons_12m'].
 ↪plot(kind='hist',ax=axs[1],xticks=bin2,color=(1, 0.337, 0.141),alpha=1)
axs[1].set_facecolor((0.72, 0.807, 0.898))
axs[1].set_title(' No Has gas and cons_12m distribution',fontsize=30)
axs[1].set_xlabel('cons_12m',fontsize=25)
axs[1].set_xticklabels([f"{tic:.2f}" for tic in axs[1].get_xticks()],␣
 ↪rotation=45,fontsize=15)
axs[1].tick_params(axis='y',labelsize=20)


plt.subplots_adjust(wspace=0.3)

plt.tight_layout()
plt.show()
```

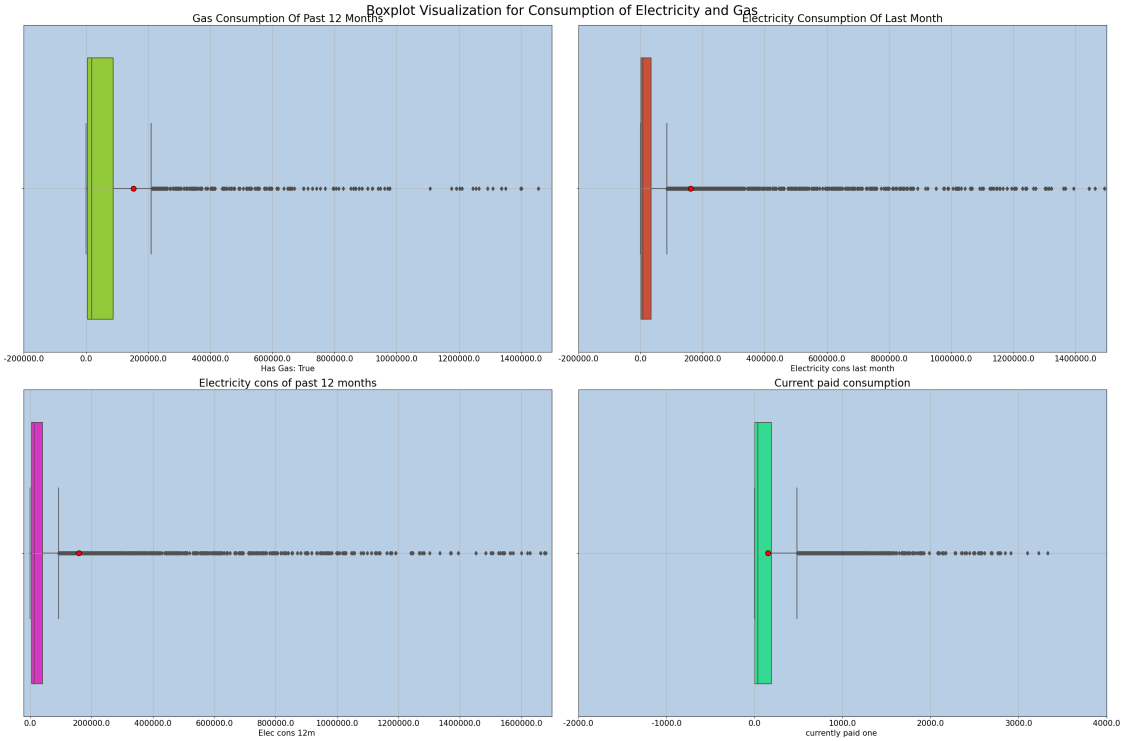


- The above histogram depicts that Customers who own Gas contract retained mostly closer to 25000 and lies more in bin range between 0 to 620710.
- But right side histogram belongs to the Customers who actually churned their Gas contract closer to 2500 and lies more in the bin range of 0 to 311811. And some few humps are founded on their tails.

[30]:
```
fig,axs=plt.subplots(2,2,figsize=(30,20))
plt.rcParams['axes.facecolor']=(0.72, 0.807, 0.898)
fig.suptitle('Boxplot Visualization for Consumption of Electricity and Gas',␣
 ↪fontsize=25)


#hasgas True consgas 12m
sns.boxplot(x=cons[cons['has_gas']=='t']['cons_gas_12m'],ax=axs[0,0],color=(0.
 ↪6, 0.886, 0.133),showmeans=True,meanprops={'marker':'o',
                                                                              ␣
 ↪                                          'markerfacecolor':'red',
                                                                              ␣
 ↪                                          'markeredgecolor':'black',
                                                                              ␣
 ↪                                          'markersize':'10'})
axs[0,0].set_xlim(-200000,1500000)
axs[0,0].set_xlabel('Has Gas: True',fontsize=15)
axs[0,0].set_title(f"Gas Consumption Of Past 12 Months",fontsize=20)
axs[0,0].set_xticklabels([f"{t00}"for t00 in axs[0,0].get_xticks()],fontsize=15)
axs[0,0].grid()


#Electricity cons of last months
sns.boxplot(x=cons['cons_last_month'],ax=axs[0,1],color=(0.886, 0.247, 0.
 ↪133),showmeans=True,meanprops={'marker':'o',
                                                                              ␣
 ↪                                            'markerfacecolor':'red',
                                                                              ␣
 ↪                                            'markeredgecolor':'black',
                                                                              ␣
 ↪                                            'markersize':'10'})
axs[0,1].set_xlim(-20000,150000)
axs[0,1].set_xlabel('Electricity cons last month',fontsize=15)
axs[0,1].set_title(f"Electricity Consumption Of Last Month",fontsize=20)
axs[0,1].set_xticklabels([f"{t01}"for t01 in axs[0,0].get_xticks()],fontsize=15)
axs[0,1].grid()


#Electricity cons of past 12 months
```

```
sns.boxplot(x=cons['cons_12m'],ax=axs[1,0],color=(0.960, 0.098, 0.
 ↪843),showmeans=True,meanprops={'marker':'o','markerfacecolor':'red',
                                                                    ⊔
 ↪                 'markeredgecolor':'black','markersize':'10'})
axs[1,0].set_xlabel('Elec cons 12m ',fontsize=15)
axs[1,0].set_xlim(-20000,1700000)
axs[1,0].set_title(f"Electricity cons of past 12 months",fontsize=20)
axs[1,0].set_xticklabels([f"{t10}" for t10 in axs[1,0].
 ↪get_xticks()],fontsize=15)
axs[1,0].grid()

#Current paid consumption
sns.boxplot(x=cons['imp_cons'],ax=axs[1,1],color=(0.098, 0.960, 0.
 ↪588),showmeans=True,meanprops={'marker':'o','markerfacecolor':'red',
                                                                    ⊔
 ↪                 'markeredgecolor':'black','markersize':'10'})
axs[1,1].set_xlabel('currently paid one ',fontsize=15)
axs[1,1].set_xlim(-2000,4000)
axs[1,1].set_title(f"Current paid consumption",fontsize=20)
axs[1,1].set_xticklabels([f"{t11}" for t11 in axs[1,1].
 ↪get_xticks()],fontsize=15)
axs[1,1].grid()


plt.subplots_adjust(wspace=0.5,hspace=0.5)
plt.tight_layout()
plt.show()
```

```
/tmp/ipykernel_32/3871391435.py:14: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axs[0,0].set_xticklabels([f"{t00}"for t00 in
axs[0,0].get_xticks()],fontsize=15)
/tmp/ipykernel_32/3871391435.py:26: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axs[0,1].set_xticklabels([f"{t01}"for t01 in
axs[0,0].get_xticks()],fontsize=15)
/tmp/ipykernel_32/3871391435.py:36: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axs[1,0].set_xticklabels([f"{t10}" for t10 in
axs[1,0].get_xticks()],fontsize=15)
/tmp/ipykernel_32/3871391435.py:45: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axs[1,1].set_xticklabels([f"{t11}" for t11 in
axs[1,1].get_xticks()],fontsize=15)
```



The Boxplot visuals for the feature contains more number of outliers in the data. It wil be dealed later part

[31]:
```
forecast=df[['churn','has_gas',
          'forecast_cons_12m', 'forecast_cons_year',␣
 ↪'forecast_discount_energy','forecast_meter_rent_12m',
          'forecast_price_energy_off_peak','forecast_price_energy_peak',␣
 ↪'forecast_price_pow_off_peak']]


forecast['churn']=forecast['churn'].map({1:'Churned',0:'Retained'})
forecast.head()
```

```
/tmp/ipykernel_32/1094931643.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  forecast['churn']=forecast['churn'].map({1:'Churned',0:'Retained'})
```

[31]:

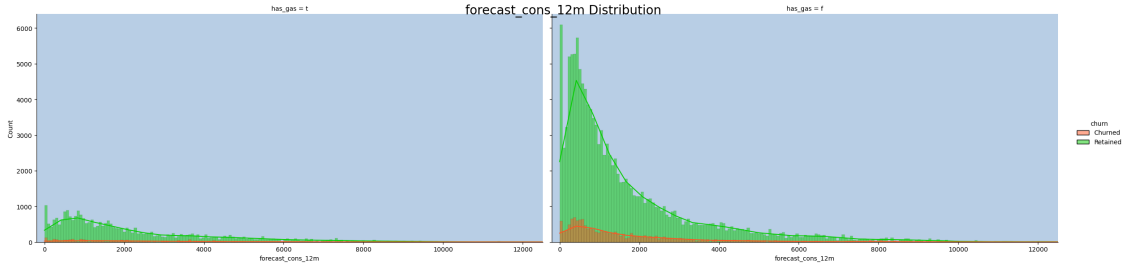
	churn	has_gas	forecast_cons_12m	forecast_cons_year	\
0	Churned	t	0.0	0	
1	Churned	t	0.0	0	

```
2  Churned       t                0.0                    0
3  Churned       t                0.0                    0
4  Churned       t                0.0                    0

   forecast_discount_energy  forecast_meter_rent_12m  \
0                       0.0                     1.78
1                       0.0                     1.78
2                       0.0                     1.78
3                       0.0                     1.78
4                       0.0                     1.78

   forecast_price_energy_off_peak  forecast_price_energy_peak  \
0                        0.114481                    0.098142
1                        0.114481                    0.098142
2                        0.114481                    0.098142
3                        0.114481                    0.098142
4                        0.114481                    0.098142

   forecast_price_pow_off_peak
0                    40.606701
1                    40.606701
2                    40.606701
3                    40.606701
4                    40.606701
```

[32]:
```
def displott(data, col,lim):
  plt.figure(figsize=(20,13))
  sns.displot(data, x=col, kde=True,hue='churn',col='has_gas',height=6,aspect=2,
              palette=[(1, 0.337, 0.141),(0.031, 0.803, 0.015)])
  plt.suptitle(f"{col} Distribution",fontsize=20)
  plt.xlim(lim)
  plt.show()
```

[33]:
```
displott(forecast,'forecast_cons_12m',(-200,12500))
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<Figure size 2000x1300 with 0 Axes>
```

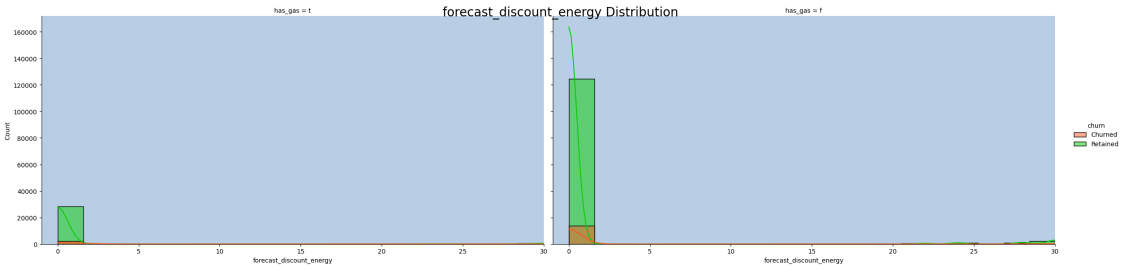


- The people who dont own the Gas contract Churned a lot when compared to the people who own the Gas contract

[34]:
```
displott(forecast,  'forecast_discount_energy',(-1,30))
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x1300 with 0 Axes>
```

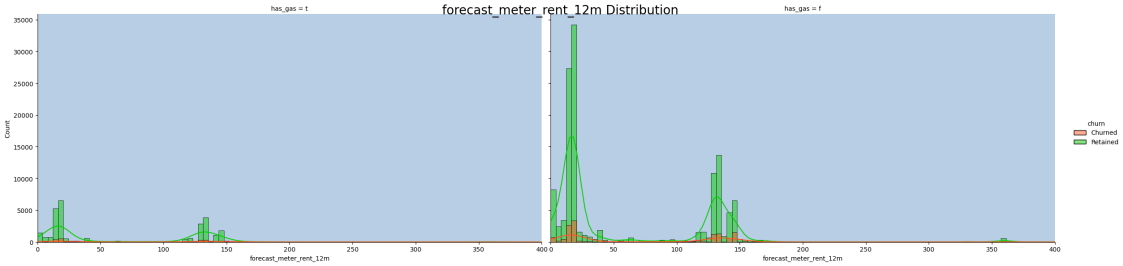


For the Forecasted value of current discount for the pople own Gas contract have the much less churn rate.

[35]:
```
displott(forecast, 'forecast_meter_rent_12m',(0,400))
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x1300 with 0 Axes>
```

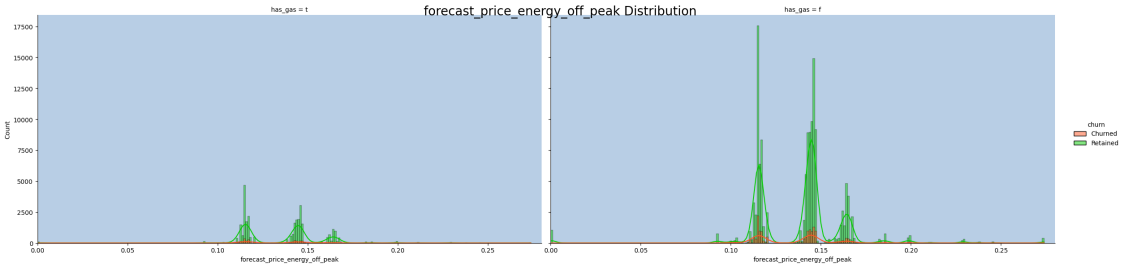


Forecasted bill of meter rental for the next 12 months with Gas contract likely to be less churned from the analysis of the visualization

[36]:
```
displott(forecast, 'forecast_price_energy_off_peak',(0,0.28))
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x1300 with 0 Axes>
```

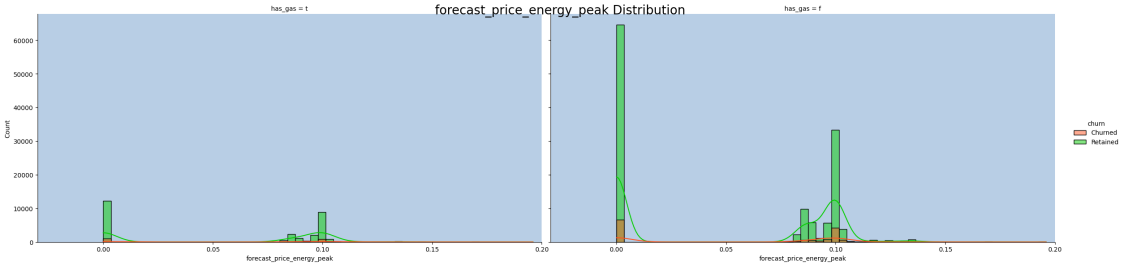


Forecasted energy price for 1st period of both type of Gas contract lies more in the range of 0.10 to 0.20 area and much lesser to intital point of the visual.

[37]:
```
displott(forecast, 'forecast_price_energy_peak',(-0.03,0.2))
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x1300 with 0 Axes>
```

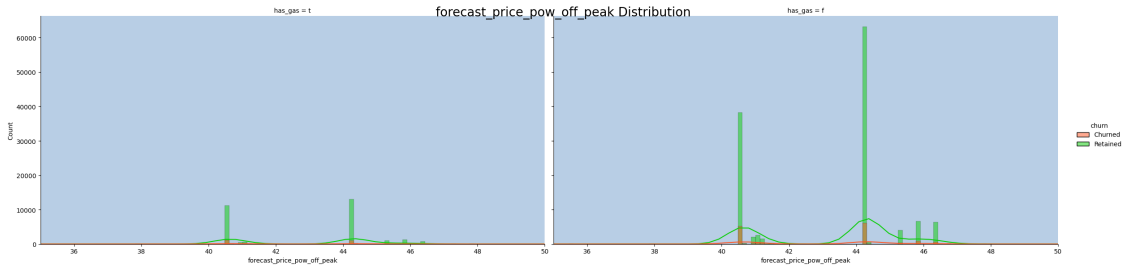


For Forecasted energy price for 2nd period (peak) with Gas contract and without contract peaked simulataneously on two areas around 0 and 0.08 to .11 and churning chances are more high with the people who does not own the Gas contract.

[38]:
```
displott(forecast, 'forecast_price_pow_off_peak',(35,50))
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

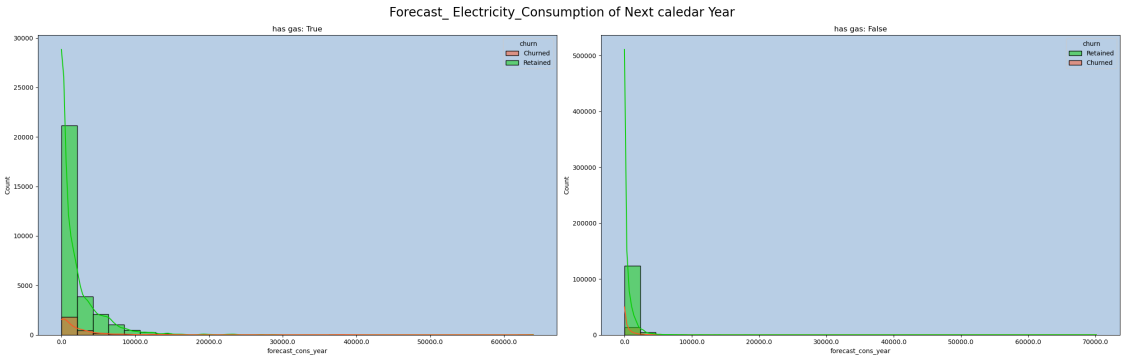
```
<Figure size 2000x1300 with 0 Axes>
```



For Forecasted power price for 1st period (off peak) values are much less in both the ends.There is some sudden peakdness occurs between 40 and 46 both type of contracts.

[39]:
```
fig,axs=plt.subplots(1,2,figsize=(25,8))
c1,b1=np.histogram(forecast[forecast['has_gas']=='t']['forecast_cons_year'],30)
c2,b2=np.histogram(forecast[forecast['has_gas']=='f']['forecast_cons_year'],30)
plt.suptitle('Forecast_ Electricity_Consumption of Next caledar␣
 ↪Year',fontsize=20)
sns.
 ↪histplot(data=forecast[forecast['has_gas']=='t'],x='forecast_cons_year',hue='churn',ax=axs[
 ↪0.337, 0.141),(0.031, 0.803, 0.015)])
axs[0].set_xticklabels([f"{f1}"for f1 in axs[0].get_xticks()],fontsize=10)
axs[0].set_title('has gas: True')

sns.
 ↪histplot(data=forecast[forecast['has_gas']=='f'],x='forecast_cons_year',hue='churn',ax=axs[
 ↪031, 0.803, 0.015),(1, 0.337, 0.141)])
axs[1].set_xticklabels([f"{f10}"for f10 in axs[0].get_xticks()],fontsize=10)
axs[1].set_title('has gas: False')
plt.subplots_adjust(wspace=0.3)
plt.tight_layout()
plt.show()
```

```
/tmp/ipykernel_32/1006807505.py:6: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axs[0].set_xticklabels([f"{f1}"for f1 in axs[0].get_xticks()],fontsize=10)
/tmp/ipykernel_32/1006807505.py:10: UserWarning: FixedFormatter should only be
used together with FixedLocator
  axs[1].set_xticklabels([f"{f10}"for f10 in axs[0].get_xticks()],fontsize=10)
```



For the Forecasted Electricity consumption of next calendar year people will consumes much between 0 to 200 and churning rate will be high with people's who owns the Gas contract compared to who does not own the contract

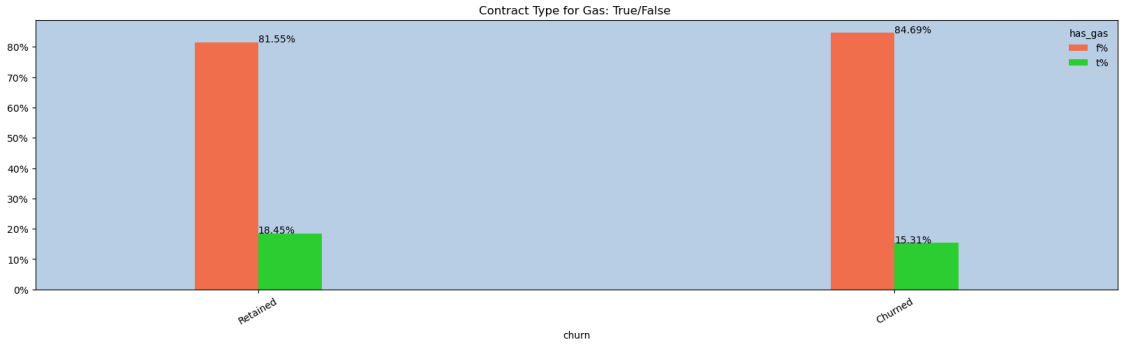
[40]:
```
#contract type
contract=df[['id','has_gas','churn']]
c=contract.groupby(['churn','has_gas'])['id'].count().unstack()
c.index=c.index.map({0:'Retained',1:'Churned'})
for i in ['f','t']:
  c[f"{i}%"]=c[i]/((c['f']+c['t']))*100
c.T
```

[40]:

churn	Retained	Churned
has_gas		
f	128965.000000	14399.000000
t	29181.000000	2604.000000
f%	81.548063	84.685056
t%	18.451937	15.314944

[41]:
```
c=c[['f%','t%']]
ax=c.plot(kind='bar',color=[(1, 0.337, 0.141),(0.031, 0.803, 0.015)],alpha=0.
  ↪8,figsize=(20,5),width=0.2)
for i in c.columns:
  for index,value in enumerate(c[i]):
    plt.text(index,value,f"{value:.2f}%")
plt.xticks(rotation=30)
plt.title('Contract Type for Gas: True/False ')
plt.gca().set_yticklabels([f"{int(y)}%" for y in plt.gca().get_yticks()])
plt.show()
```

```
/tmp/ipykernel_32/1915274806.py:8: UserWarning: FixedFormatter should only be
used together with FixedLocator
  plt.gca().set_yticklabels([f"{int(y)}%" for y in plt.gca().get_yticks()])
```



the comparison between the owning the Gas contract: * People who does not own the contract will be retained around 82% and who own the contract likely to be retained 18%

- People who does not own the contract will be churned around 85% and who own the contract likely to be churned 15%

[42]:
```
#margins

margins=df[['id','margin_gross_pow_ele', 'margin_net_pow_ele',
       'net_margin', 'churn']]
margins.churn=margins.churn.map({1:'Churned',0:'Retained'})
margins.head()
```

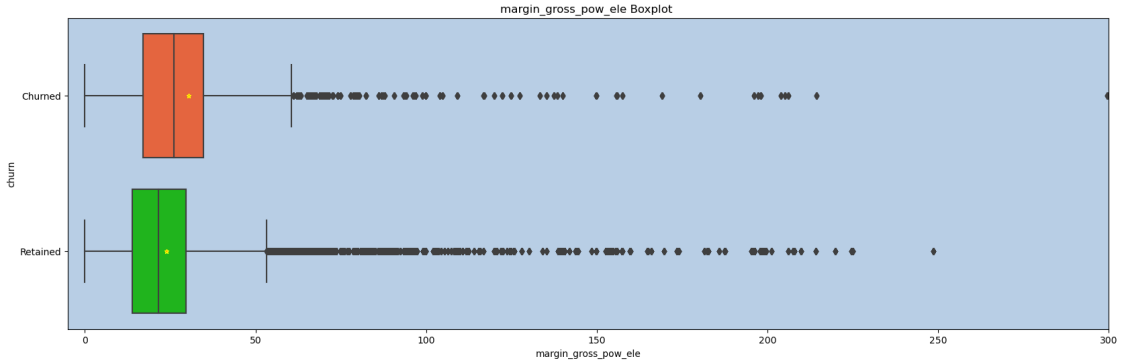
```
/tmp/ipykernel_32/3147618325.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  margins.churn=margins.churn.map({1:'Churned',0:'Retained'})
```

[42]:

	id	margin_gross_pow_ele	margin_net_pow_ele	net_margin	churn
0	24011ae4ebbe3035111d65fa7c15bc57	25.44	25.44	678.99	Churned
1	24011ae4ebbe3035111d65fa7c15bc57	25.44	25.44	678.99	Churned
2	24011ae4ebbe3035111d65fa7c15bc57	25.44	25.44	678.99	Churned
3	24011ae4ebbe3035111d65fa7c15bc57	25.44	25.44	678.99	Churned
4	24011ae4ebbe3035111d65fa7c15bc57	25.44	25.44	678.99	Churned

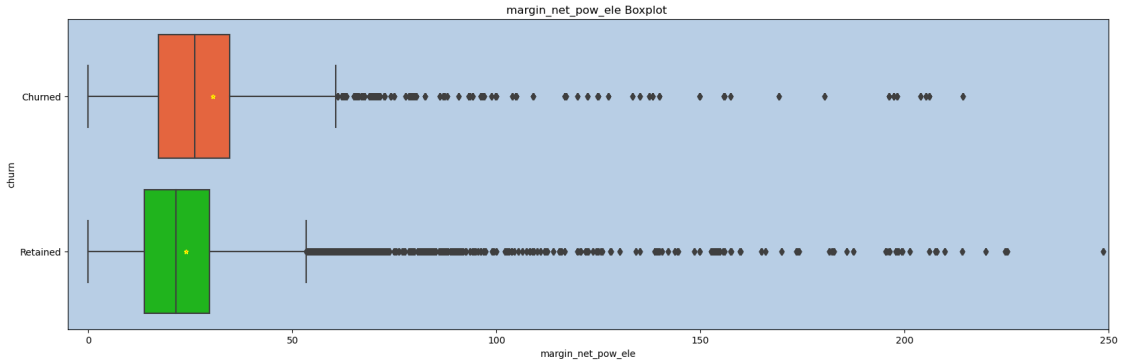
[43]:
```
def distribution(dataframe,col,lim):
  plt.figure(figsize=(20,6))
  sns.boxplot(data=dataframe,x=col,y=dataframe['churn'],
              showmeans=True,meanprops={'marker':'*','markerfacecolor':
 ↪'Red','markeredgecolor':'yellow','markersize':'5'},
              palette=[(1, 0.337, 0.141),(0.031, 0.803, 0.015)])
  plt.title(f"{col} Boxplot ")
  plt.xlim(lim)
  plt.show()
```

[44]:
```
distribution(margins,'margin_gross_pow_ele',(-5,300))
```



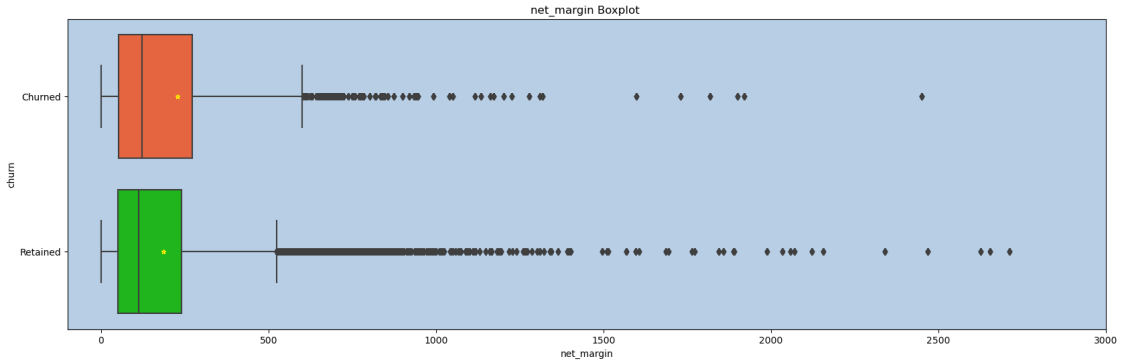
The Gross margin on power subcription for both churned and Retained customer boxplot contains outliers in the data.

[45]:
```
distribution(margins, 'margin_net_pow_ele',(-5,250))
```



Net margin on power subscription of the customers may like to churn a lot compared to retained ones and outliers are numerous in the data.

[46]:
```
distribution(margins, 'net_margin',(-100,3000))
```



Total Net Margin for the customer churn is also high when compared to people will be less likey to pursue it.

[47]:
```
#rest columns

rest=df[[ 'id', 'origin_up','nb_prod_act','num_years_antig','pow_max', 'churn']]
rest['churn']=rest['churn'].replace({1:'Churned',0:"Retained"})
rest.head()
```

```
/tmp/ipykernel_32/751089983.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  rest['churn']=rest['churn'].replace({1:'Churned',0:"Retained"})
```

[47]:

	id	origin_up	nb_prod_act	num_years_antig	pow_max	churn
0	24011ae4ebbe3035111d65fa7c15bc57	lxidpiddsbxsbosboudacockeimpuepw	2	3	43.648	Churned
1	24011ae4ebbe3035111d65fa7c15bc57	lxidpiddsbxsbosboudacockeimpuepw	2	3	43.648	Churned
2	24011ae4ebbe3035111d65fa7c15bc57	lxidpiddsbxsbosboudacockeimpuepw	2	3	43.648	Churned
3	24011ae4ebbe3035111d65fa7c15bc57	lxidpiddsbxsbosboudacockeimpuepw	2	3	43.648	Churned
4	24011ae4ebbe3035111d65fa7c15bc57	lxidpiddsbxsbosboudacockeimpuepw	2	3	43.648	Churned

[48]:
```
m={}
for i in ['Retained','Churned']:
  meanvalue=rest[rest['churn']==i]['pow_max'].mean()
```

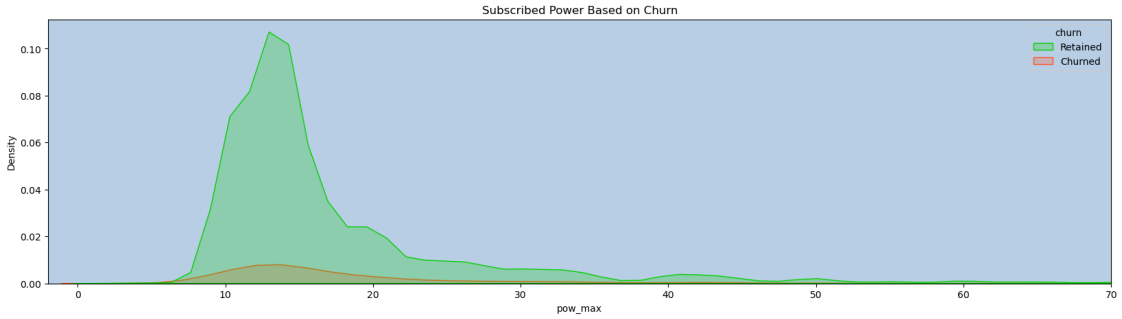
```
  stdevalue=rest[rest['churn']==i]['pow_max'].std()
  m[i]=meanvalue,stdevalue

m=pd.DataFrame(m).reset_index()

m['index']=m['index'].replace({0:'Mean',1:'Standard Deviation'})
m
```

[48]:

	index	Retained	Churned
0	Mean	17.999910	19.390412
1	Standard Deviation	13.154539	16.617392

[49]:
```
plt.figure(figsize=(20,5))
sns.kdeplot(data=rest,␣
 ↪x='pow_max',hue='churn',hue_order=['Retained','Churned'],fill=True,␣
 ↪palette=[(0.031, 0.803, 0.015),(1, 0.337, 0.141)])
plt.xlim(-2,70)
plt.title('Subscribed Power Based on Churn')
plt.show
```

[49]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



- Subscribed Power people Retained are higher rate and the distribution plays around the mean of 18 and varies around standard deviation around 13 and right skewed in nature ie, more number of people using the power around 8 to 23.
- For the Churned pople of subscribed power are having the curve nature of platykurtic nature and curve varies around the mean of 19 and standard deviation of 16

[50]:
```
def grps(dataframe,cols,slasher):
  d=dataframe.groupby([*cols])[slasher].count().unstack()
  if any(d.isna()):
    d.fillna(0,inplace=True)

    for i in ['Churned','Retained']:
      d[f"{i}%"]=d[i]/(d['Churned']+d['Retained'])*100
```

```
    else:
       for i in ['Churned','Retained']:
        d[f"{i}%"]=d[i]/(d['Churned']+d['Retained'])*100
    d1=d[['Churned%','Retained%']]
  return d1,d
```

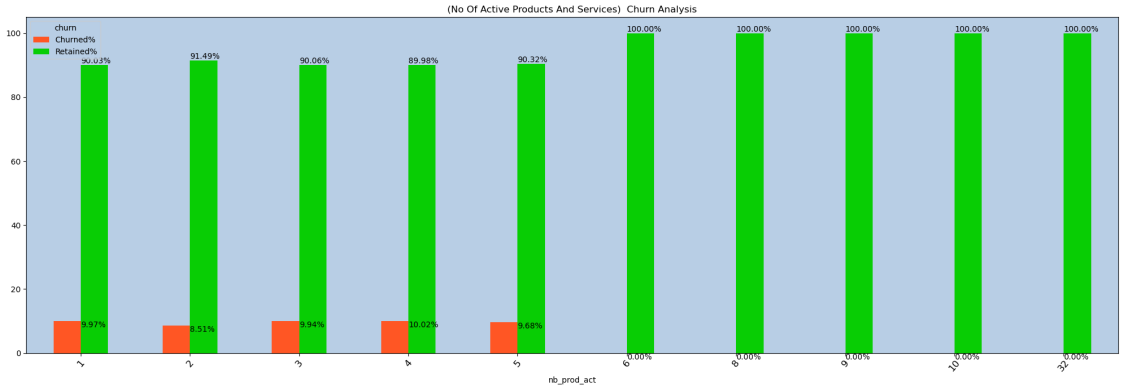
[51]:
```
#bar graph function (dataframe+col)
def bars(dataframe, o,t):
    dataframe[['Churned%', 'Retained%']].plot(kind='bar', stacked=False,␣
 ↪color=[(1, 0.337, 0.141), (0.031, 0.803, 0.015)], figsize=(20, 7))
    for index, val in enumerate(dataframe['Retained%']):
        plt.text(index, val, f"{val:.2f}%", ha='left', va='bottom')
    for index1, val1 in enumerate(dataframe['Churned%']):
        plt.text(index1, val1, f"{val1:.2f}%", ha='left', va='top')
    plt.xticks(rotation=50,fontsize=12)
    plt.title(f'({t:<})  Churn Analysis')
    plt.xlabel(f"{o}")
    plt.tight_layout()
    plt.show()
```

[52]:
```
nbprod,n_=grps(rest,['nb_prod_act','churn'],'id')
n_
```

[52]:

churn	Churned	Retained	Churned%	Retained%
nb_prod_act				
1	13669.0	123415.0	9.971258	90.028742
2	2494.0	26816.0	8.509041	91.490959
3	624.0	5651.0	9.944223	90.055777
4	180.0	1616.0	10.022272	89.977728
5	36.0	336.0	9.677419	90.322581
6	0.0	96.0	0.000000	100.000000
8	0.0	48.0	0.000000	100.000000
9	0.0	132.0	0.000000	100.000000
10	0.0	24.0	0.000000	100.000000
32	0.0	12.0	0.000000	100.000000

[53]:
```
bars(nbprod,'nb_prod_act','No Of Active Products And Services')
```



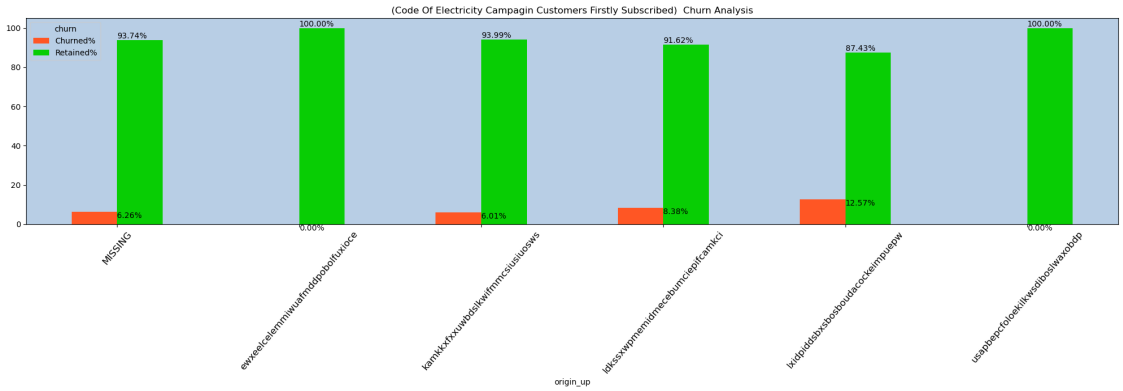
In Number of active products and services only the products 1,2,3,4 and 5 contains the people with churned behaviour and other products have 100% retention rate.

[54]:
```
origin,o_=grps(rest,['origin_up','churn'],'id')
o_
```

[54]:

churn	Churned	Retained	Churned%	Retained%
origin_up				
MISSING	48.0	719.0	6.258149	93.741851
ewxeelcelemmiwuafmddpobolfuxioce	0.0	12.0	0.000000	100.000000
kamkkxfxxuwbdslkwifmmcsiusiuosws	3093.0	48410.0	6.005475	93.994525
ldkssxwpmemidmecebumciepifcamkci	3163.0	34594.0	8.377255	91.622745
lxidpiddsbxsbosboudacockeimpuepw	10699.0	74387.0	12.574337	87.425663
usapbepcfoloekilkwsdiboslwaxobdp	0.0	24.0	0.000000	100.000000

[55]:
```
bars(origin,'origin_up','Code Of Electricity Campagin Customers Firstly␣
↪Subscribed')
```



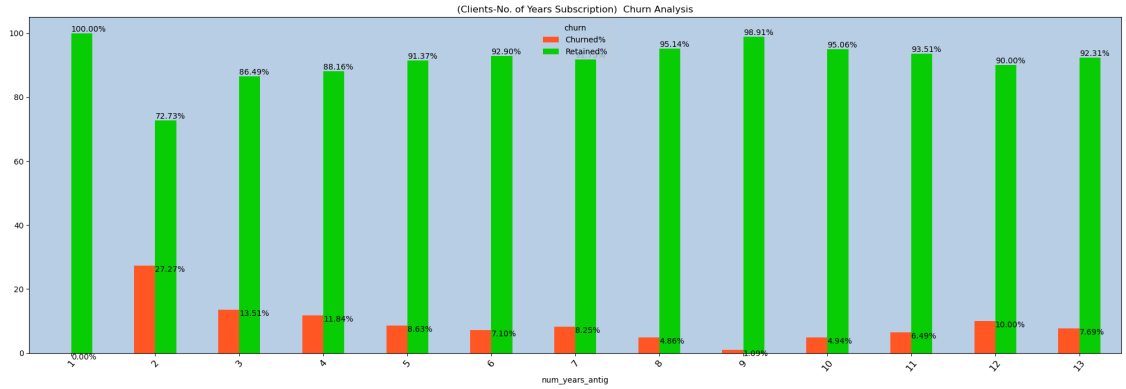
In code of the electricity campaign the customer first subscribed only two id's have the 100% retention rate and other have churned history. And Missing value is also here.

[56]:
```
natig,na_=grps(rest,['num_years_antig','churn'],'id')
na_
```

[56]:

churn	Churned	Retained	Churned%	Retained%
num_years_antig				
1	0.0	12.0	0.000000	100.000000
2	36.0	96.0	27.272727	72.727273
3	3941.0	25221.0	13.514162	86.485838
4	5651.0	42084.0	11.838274	88.161726
5	2399.0	25391.0	8.632602	91.367398
6	4064.0	53141.0	7.104274	92.895726
7	504.0	5604.0	8.251473	91.748527
8	60.0	1174.0	4.862237	95.137763
9	12.0	1092.0	1.086957	98.913043
10	48.0	924.0	4.938272	95.061728
11	144.0	2075.0	6.489410	93.510590
12	132.0	1188.0	10.000000	90.000000
13	12.0	144.0	7.692308	92.307692

[57]:
```
bars(natig,'num_years_antig','Clients-No. of Years Subscription')
```



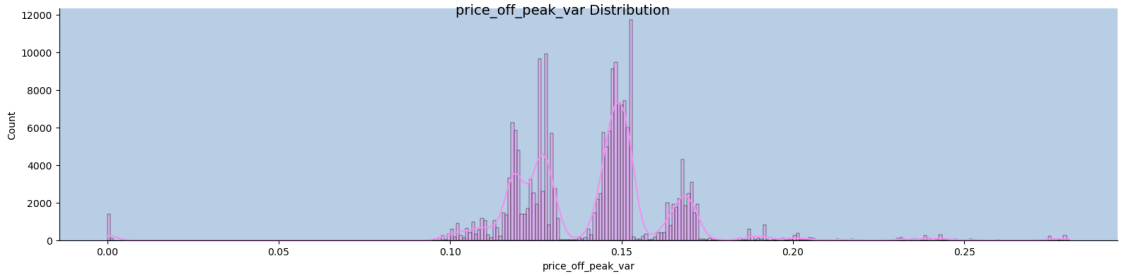
People with 1 year of subscription have 100% retention rate. similar for the people who with 9 years of subcription. Higher churning rate with the people with 2 years of subscription. Some attention needed here to address this issue.

[58]:
```
def displott(data, col):
  plt.figure(figsize=(20,5))
  sns.displot(data, x=col, kde=True,height=4,aspect=4,
              color=(0.956, 0.564, 0.949))
  plt.suptitle(f"{col} Distribution",fontsize=14)
  plt.show()
```

[59]:
```
for i in [ 'price_off_peak_var', 'price_peak_var',
       'price_mid_peak_var', 'price_off_peak_fix', 'price_peak_fix',
       'price_mid_peak_fix']:
       displott(price,i)
```

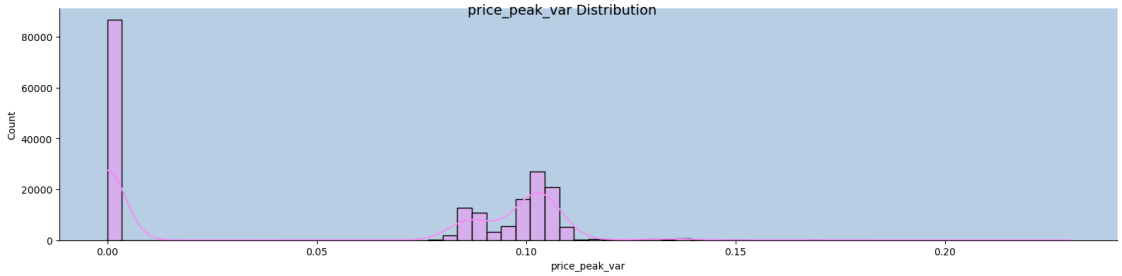
```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x500 with 0 Axes>
```



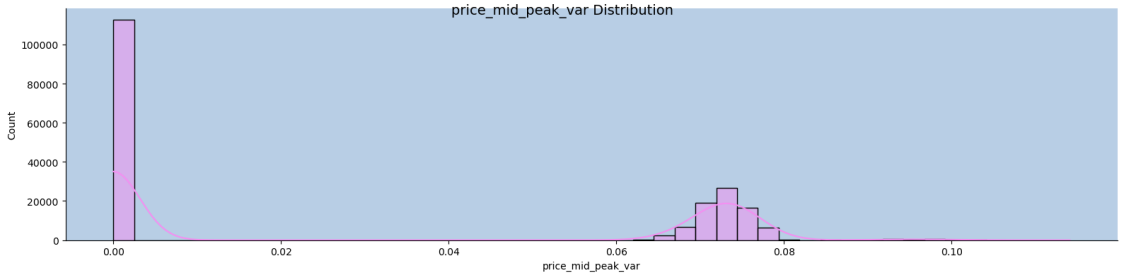

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x500 with 0 Axes>
```



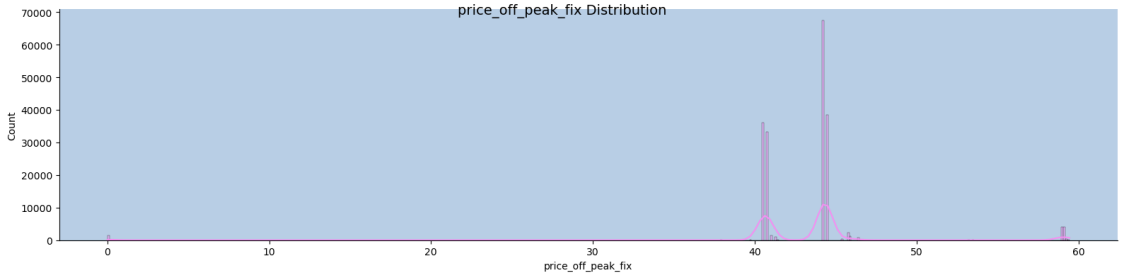

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x500 with 0 Axes>
```



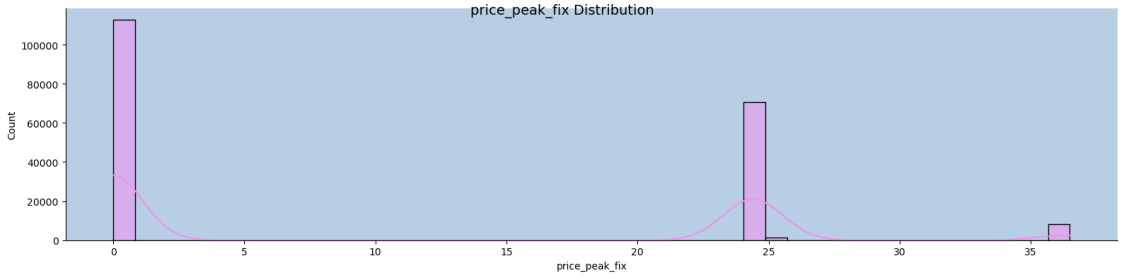

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x500 with 0 Axes>
```



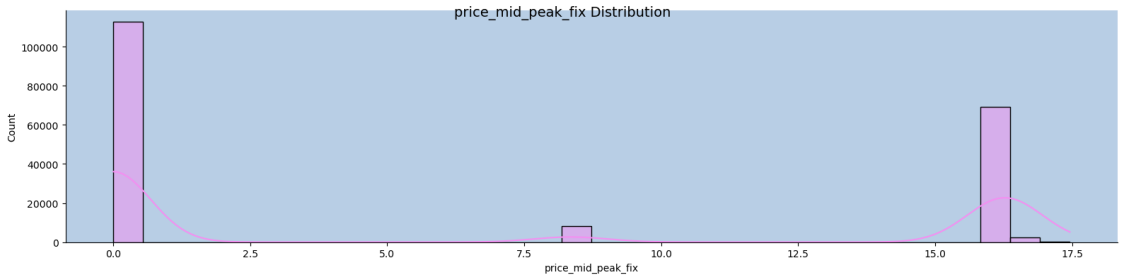

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x500 with 0 Axes>
```




```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

```
<Figure size 2000x500 with 0 Axes>
```



4 Price Sensitivity Analysis

PRICE SENSITIVITY or PRICE ELASTICITY:

- A simple measure in which calculates how much the change in price of goods and services affect the willigness to buy the particular product or brand.
- Price sensitivity,Ps= (% change in Quantity demand)/(% change in price of the brand or product)
- If Ps $>$ 1: Demand is elastic (price-sensitive).
- If Ps $=$ 1: Demand is unitary elastic.
- If 0 $<$ Ps $<$ 1: Demand is inelastic (less price-sensitive).
- If Ps $=$ 0: Demand is perfectly inelastic (not price-sensitive).

Here, correlation to measure the relationship between price variations and churn rate for each customer segment.

[60]:
```
print(f"Price Date Min: {price.price_date.min()} and Price Date Max: {price.
↪price_date.max()}")
```

```
Price Date Min: 2015-01-01 and Price Date Max: 2015-12-01
```

[61]:
```
year_var=price.groupby(['id','price_date']).mean().groupby('id').var().
↪reset_index()
year_var.head()
for i in ['price_off_peak_var', 'price_peak_var', 'price_mid_peak_var',
       'price_off_peak_fix', 'price_peak_fix', 'price_mid_peak_fix']:
       year_var=year_var.rename(columns={i:f"y_{i}"})
year_var
```

[61]:

	id	y_price_off_peak_var	\
0	0002203ffbb812588b632b9e628cc38d	0.000016	
1	0004351ebdd665e6ee664792efc4fd13	0.000005	
2	0010bcc39e42b3c2131ed2ce55246e3c	0.000676	
3	0010ee3855fdea87602a5b7aba8e42de	0.000025	

```
4      00114d74e963e47177db89bc70108537              0.000005
…                                   …                   …
16091  ffef185810e44254c3a4c6395e6b4d8a              0.000688
16092  fffac626da707b1b5ab11e8431a4d0a2              0.000004
16093  fffc0cacd305dd51f316424bbb08d1bd              0.000009
16094  fffe4f5646aa39c7f97f95ae2679ce64              0.000021
16095  ffff7fa066f1fb305ae285bb03bf325a              0.000023

       y_price_peak_var  y_price_mid_peak_var  y_price_off_peak_fix  \
0              0.000004          1.871602e-06          4.021438e-03
1              0.000000          0.000000e+00          7.661891e-03
2              0.000000          0.000000e+00          5.965909e-01
3              0.000007          1.627620e-07          7.238536e-03
4              0.000000          0.000000e+00          3.490909e-13
…                 …                   …                   …
16091          0.000422          1.563148e-04          3.062232e-02
16092          0.000000          0.000000e+00          6.464760e-03
16093          0.000006          1.857770e-05          7.211360e-03
16094          0.000006          2.220744e-07          5.428835e-03
16095          0.000006          4.345784e-07          7.238536e-03

       y_price_peak_fix  y_price_mid_peak_fix
0              0.001448              0.000643
1              0.000000              0.000000
2              0.000000              0.000000
3              0.002606              0.001158
4              0.000000              0.000000
…                 …                   …
16091          0.043691              0.051094
16092          0.000000              0.000000
16093          0.002638              0.001196
16094          0.001954              0.000869
16095          0.002606              0.001158

[16096 rows x 7 columns]
```

[62]:
```
year_var['yv_price _off_peak␣
 ↪p1']=year_var['y_price_off_peak_var']+year_var['y_price_off_peak_fix']
year_var['yv_price_peak␣
 ↪p2']=year_var['y_price_peak_var']+year_var['y_price_peak_fix']
year_var['yv_price_midpeak␣
 ↪p3']=year_var['y_price_mid_peak_var']+year_var['y_price_mid_peak_fix']


year_var
```

[62]:
```
                                    id  y_price_off_peak_var  \
0      0002203ffbb812588b632b9e628cc38d              0.000016
```

```
1       0004351ebdd665e6ee664792efc4fd13              0.000005
2       0010bcc39e42b3c2131ed2ce55246e3c              0.000676
3       0010ee3855fdea87602a5b7aba8e42de              0.000025
4       00114d74e963e47177db89bc70108537              0.000005
…                                    …                     …
16091   ffef185810e44254c3a4c6395e6b4d8a              0.000688
16092   fffac626da707b1b5ab11e8431a4d0a2              0.000004
16093   fffc0cacd305dd51f316424bbb08d1bd              0.000009
16094   fffe4f5646aa39c7f97f95ae2679ce64              0.000021
16095   ffff7fa066f1fb305ae285bb03bf325a              0.000023

        y_price_peak_var  y_price_mid_peak_var  y_price_off_peak_fix  \
0               0.000004          1.871602e-06          4.021438e-03
1               0.000000          0.000000e+00          7.661891e-03
2               0.000000          0.000000e+00          5.965909e-01
3               0.000007          1.627620e-07          7.238536e-03
4               0.000000          0.000000e+00          3.490909e-13
…                  …                    …                     …
16091           0.000422          1.563148e-04          3.062232e-02
16092           0.000000          0.000000e+00          6.464760e-03
16093           0.000006          1.857770e-05          7.211360e-03
16094           0.000006          2.220744e-07          5.428835e-03
16095           0.000006          4.345784e-07          7.238536e-03

        y_price_peak_fix  y_price_mid_peak_fix  yv_price _off_peak p1  \
0               0.001448              0.000643                0.004037
1               0.000000              0.000000                0.007667
2               0.000000              0.000000                0.597267
3               0.002606              0.001158                0.007264
4               0.000000              0.000000                0.000005
…                  …                     …                      …
16091           0.043691              0.051094                0.031311
16092           0.000000              0.000000                0.006469
16093           0.002638              0.001196                0.007221
16094           0.001954              0.000869                0.005450
16095           0.002606              0.001158                0.007262

        yv_price_peak p2  yv_price_midpeak p3
0               0.001452             0.000645
1               0.000000             0.000000
2               0.000000             0.000000
3               0.002613             0.001158
4               0.000000             0.000000
…                  …                    …
16091           0.044114             0.051251
16092           0.000000             0.000000
16093           0.002644             0.001215
```

```
16094          0.001960             0.000869
16095          0.002611             0.001159

[16096 rows x 10 columns]
```

[63]:
```
#6 months price sensitivity

_6mps=price[price['price_date']>'2015-06'].groupby(['id','price_date']).mean().
 ↪groupby('id').var().reset_index()
_6mps.head()
```

[63]:
```
                                 id  price_off_peak_var  price_peak_var  \
0  0002203ffbb812588b632b9e628cc38d            0.000016        0.000004
1  0004351ebdd665e6ee664792efc4fd13            0.000005        0.000000
2  0010bcc39e42b3c2131ed2ce55246e3c            0.000005        0.000000
3  0010ee3855fdea87602a5b7aba8e42de            0.000020        0.000005
4  00114d74e963e47177db89bc70108537            0.000005        0.000000

   price_mid_peak_var  price_off_peak_fix  price_peak_fix  price_mid_peak_fix
0        6.942857e-10            0.000000        0.000000            0.000000
1        0.000000e+00            0.000000        0.000000            0.000000
2        0.000000e+00            0.000000        0.000000            0.000000
3        8.554557e-08            0.003791        0.001365            0.000607
4        0.000000e+00            0.000000        0.000000            0.000000
```

[64]:
```
for i in ['price_off_peak_var', 'price_peak_var', 'price_mid_peak_var',
       'price_off_peak_fix', 'price_peak_fix', 'price_mid_peak_fix']:
       _6mps=_6mps.rename(columns={i:f"6_{i}"})
_6mps
```

[64]:
```
                                   id  6_price_off_peak_var  \
0      0002203ffbb812588b632b9e628cc38d              0.000016
1      0004351ebdd665e6ee664792efc4fd13              0.000005
2      0010bcc39e42b3c2131ed2ce55246e3c              0.000005
3      0010ee3855fdea87602a5b7aba8e42de              0.000020
4      00114d74e963e47177db89bc70108537              0.000005
…                                   …                     …
16091  ffef185810e44254c3a4c6395e6b4d8a              0.000384
16092  fffac626da707b1b5ab11e8431a4d0a2              0.000004
16093  fffc0cacd305dd51f316424bbb08d1bd              0.000016
16094  fffe4f5646aa39c7f97f95ae2679ce64              0.000019
16095  ffff7fa066f1fb305ae285bb03bf325a              0.000019

       6_price_peak_var  6_price_mid_peak_var  6_price_off_peak_fix  \
0              0.000004          6.942857e-10              0.000000
1              0.000000          0.000000e+00              0.000000
2              0.000000          0.000000e+00              0.000000
```

```
3              0.000005          8.554557e-08              0.003791
4              0.000000          0.000000e+00              0.000000
…                 …                    …                      …
16091          0.000236          8.959353e-05              0.016040
16092          0.000000          0.000000e+00              0.009030
16093          0.000004          6.942857e-10              0.000000
16094          0.000005          3.190963e-07              0.007583
16095          0.000005          2.279256e-07              0.003791

       6_price_peak_fix  6_price_mid_peak_fix
0              0.000000              0.000000
1              0.000000              0.000000
2              0.000000              0.000000
3              0.001365              0.000607
4              0.000000              0.000000
…                 …                     …
16091          0.022886              0.026764
16092          0.000000              0.000000
16093          0.000000              0.000000
16094          0.002730              0.001214
16095          0.001365              0.000607

[16096 rows x 7 columns]
```

[65]:
```
_6mps['6mps_price_off_peak p1']=␣
 ↪_6mps['6_price_off_peak_var']+_6mps['6_price_off_peak_fix']
_6mps['6mps_price_peak p2']= _6mps['6_price_peak_var']+_6mps['6_price_peak_fix']
_6mps['6mps_price_mid_peak␣
 ↪p3']=_6mps['6_price_mid_peak_fix']+_6mps['6_price_mid_peak_var']
_6mps
```

[65]:
```
                                    id  6_price_off_peak_var  \
0      0002203ffbb812588b632b9e628cc38d              0.000016
1      0004351ebdd665e6ee664792efc4fd13              0.000005
2      0010bcc39e42b3c2131ed2ce55246e3c              0.000005
3      0010ee3855fdea87602a5b7aba8e42de              0.000020
4      00114d74e963e47177db89bc70108537              0.000005
…                                   …                     …
16091  ffef185810e44254c3a4c6395e6b4d8a              0.000384
16092  fffac626da707b1b5ab11e8431a4d0a2              0.000004
16093  fffc0cacd305dd51f316424bbb08d1bd              0.000016
16094  fffe4f5646aa39c7f97f95ae2679ce64              0.000019
16095  ffff7fa066f1fb305ae285bb03bf325a              0.000019

       6_price_peak_var  6_price_mid_peak_var  6_price_off_peak_fix  \
0              0.000004          6.942857e-10              0.000000
1              0.000000          0.000000e+00              0.000000
```

```
2              0.000000          0.000000e+00              0.000000
3              0.000005          8.554557e-08              0.003791
4              0.000000          0.000000e+00              0.000000
…                 …                 …                      …
16091          0.000236          8.959353e-05              0.016040
16092          0.000000          0.000000e+00              0.009030
16093          0.000004          6.942857e-10              0.000000
16094          0.000005          3.190963e-07              0.007583
16095          0.000005          2.279256e-07              0.003791

       6_price_peak_fix  6_price_mid_peak_fix  6mps_price_off_peak p1  \
0              0.000000              0.000000                0.000016
1              0.000000              0.000000                0.000005
2              0.000000              0.000000                0.000005
3              0.001365              0.000607                0.003811
4              0.000000              0.000000                0.000005
…                 …                     …                      …
16091          0.022886              0.026764                0.016424
16092          0.000000              0.000000                0.009034
16093          0.000000              0.000000                0.000016
16094          0.002730              0.001214                0.007602
16095          0.001365              0.000607                0.003810

       6mps_price_peak p2  6mps_price_mid_peak p3
0                0.000004            6.942857e-10
1                0.000000            0.000000e+00
2                0.000000            0.000000e+00
3                0.001370            6.068555e-04
4                0.000000            0.000000e+00
…                   …                     …
16091            0.023122            2.685350e-02
16092            0.000000            0.000000e+00
16093            0.000004            6.942857e-10
16094            0.002735            1.213859e-03
16095            0.001370            6.069979e-04

[16096 rows x 10 columns]
```

[66]:
```
s=pd.merge(year_var,_6mps,on='id')
s.head()
```

[66]:
```
                                 id  y_price_off_peak_var  y_price_peak_var  \
0  0002203ffbb812588b632b9e628cc38d              0.000016          0.000004
1  0004351ebdd665e6ee664792efc4fd13              0.000005          0.000000
2  0010bcc39e42b3c2131ed2ce55246e3c              0.000676          0.000000
3  0010ee3855fdea87602a5b7aba8e42de              0.000025          0.000007
4  00114d74e963e47177db89bc70108537              0.000005          0.000000
```

```
   y_price_mid_peak_var  y_price_off_peak_fix  y_price_peak_fix  \
0          1.871602e-06          4.021438e-03          0.001448
1          0.000000e+00          7.661891e-03          0.000000
2          0.000000e+00          5.965909e-01          0.000000
3          1.627620e-07          7.238536e-03          0.002606
4          0.000000e+00          3.490909e-13          0.000000

   y_price_mid_peak_fix  yv_price _off_peak p1  yv_price_peak p2  \
0              0.000643               0.004037          0.001452
1              0.000000               0.007667          0.000000
2              0.000000               0.597267          0.000000
3              0.001158               0.007264          0.002613
4              0.000000               0.000005          0.000000

   yv_price_midpeak p3  6_price_off_peak_var  6_price_peak_var  \
0             0.000645              0.000016          0.000004
1             0.000000              0.000005          0.000000
2             0.000000              0.000005          0.000000
3             0.001158              0.000020          0.000005
4             0.000000              0.000005          0.000000

   6_price_mid_peak_var  6_price_off_peak_fix  6_price_peak_fix  \
0          6.942857e-10              0.000000          0.000000
1          0.000000e+00              0.000000          0.000000
2          0.000000e+00              0.000000          0.000000
3          8.554557e-08              0.003791          0.001365
4          0.000000e+00              0.000000          0.000000

   6_price_mid_peak_fix  6mps_price_off_peak p1  6mps_price_peak p2  \
0              0.000000                0.000016            0.000004
1              0.000000                0.000005            0.000000
2              0.000000                0.000005            0.000000
3              0.000607                0.003811            0.001370
4              0.000000                0.000005            0.000000

   6mps_price_mid_peak p3
0            6.942857e-10
1            0.000000e+00
2            0.000000e+00
3            6.068555e-04
4            0.000000e+00
```

[67]:
```
price_analysis=pd.merge(s,df[['id','churn']],on='id')
price_analysis.head(4)
```

[67]:

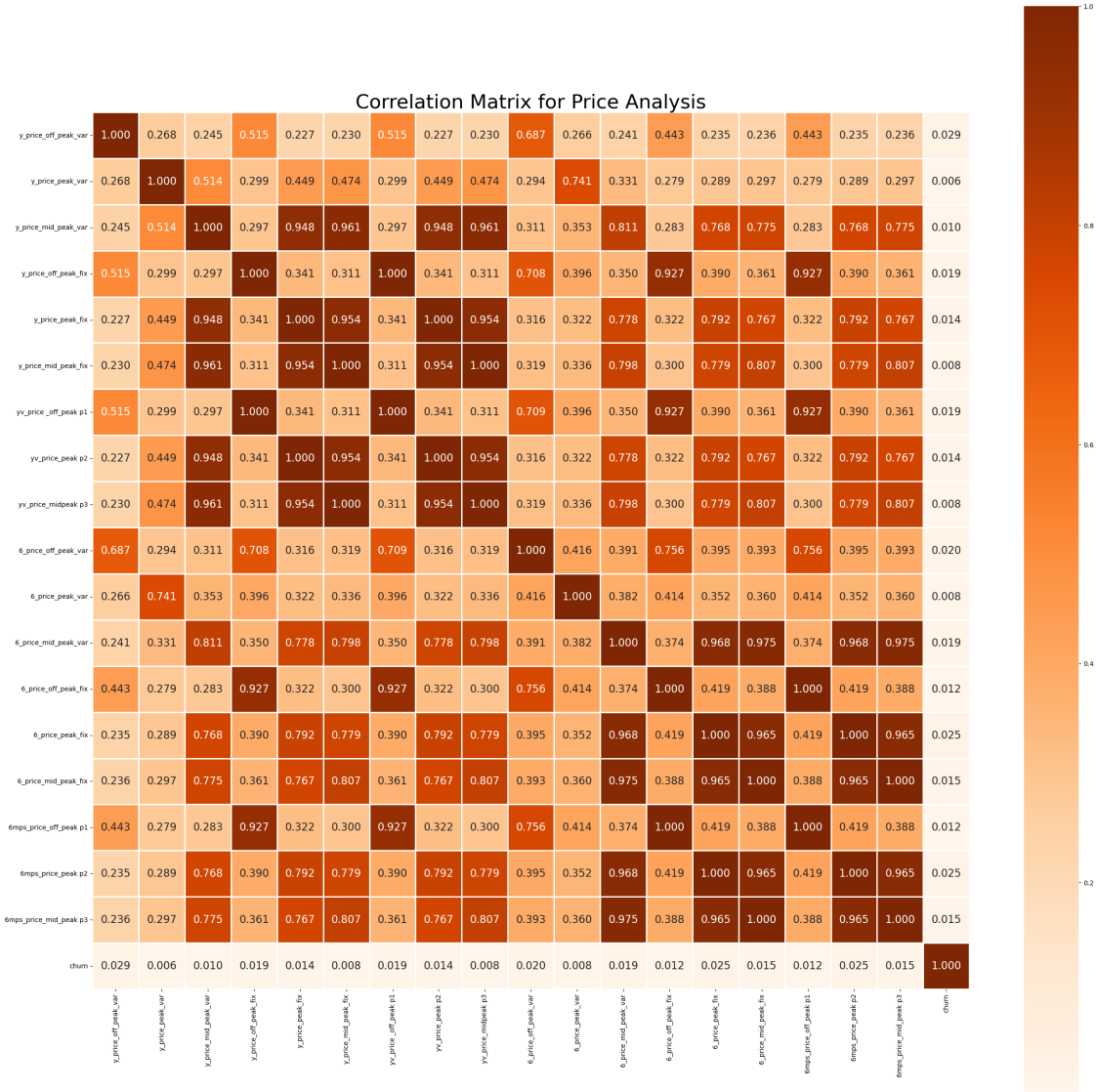
	id	y_price_off_peak_var	y_price_peak_var	y_price_mid_peak_var	y_price_off_peak_fix	y_price_peak_fix	y_price_mid_peak_fix	yv_price _off_peak p1	yv_price_peak p2	yv_price_midpeak p3	6_price_off_peak_var	6_price_peak_var	6_price_mid_peak_var	6_price_off_peak_fix	6_price_peak_fix	6_price_mid_peak_fix	6mps_price_off_peak p1	6mps_price_peak p2	6mps_price_mid_peak p3	churn
0	0002203ffbb812588b632b9e628cc38d	0.000016	0.000004	0.000002	0.004021	0.001448	0.000643	0.004037	0.001452	0.000645	0.000016	0.000004	6.942857e-10	0.0	0.0	0.0	0.000016	0.000004	6.942857e-10	0
1	0002203ffbb812588b632b9e628cc38d	0.000016	0.000004	0.000002	0.004021	0.001448	0.000643	0.004037	0.001452	0.000645	0.000016	0.000004	6.942857e-10	0.0	0.0	0.0	0.000016	0.000004	6.942857e-10	0
2	0002203ffbb812588b632b9e628cc38d	0.000016	0.000004	0.000002	0.004021	0.001448	0.000643	0.004037	0.001452	0.000645	0.000016	0.000004	6.942857e-10	0.0	0.0	0.0	0.000016	0.000004	6.942857e-10	0
3	0002203ffbb812588b632b9e628cc38d	0.000016	0.000004	0.000002	0.004021	0.001448	0.000643	0.004037	0.001452	0.000645	0.000016	0.000004	6.942857e-10	0.0	0.0	0.0	0.000016	0.000004	6.942857e-10	0

[68]:
```
c=price_analysis.corr(method='pearson')
```

```
/tmp/ipykernel_32/2946853885.py:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
```

```
to silence this warning.
  c=price_analysis.corr(method='pearson')
```

[69]:
```
plt.figure(figsize=(30,30))
sns.heatmap(c,annot=True,fmt='.
  ↪3f',square=True,cmap='Oranges',linewidths=2,annot_kws={"size": 16})
plt.title('Correlation Matrix for Price Analysis',fontsize=30)
plt.show()
```



For price sensitive analysis using correlation method churning is likely to be have weak relationship with the price sensitivity. And Higher inter correlation found between the price sensitivity features.

[70]:
```
task2=pd.merge(client.drop(columns='churn'),price_analysis,on='id')
task2.to_excel('task2.xlsx')
```

FINDINGS:

- Most of the features are right skewed and followed by heavly tailed distributions.
- Dataset contains more number of outliers
- People who dont own the Gas contract Churned a lot when compared to the people who own the Gas contract.
- Forecasted value of current discount for the pople own Gas contract have the much less churn rate.
- comparison between the owning the Gas contract: @ People who does not own the contract will be retained around 82% and who own the contract likely to be retained 18%

  @ People who does not own the contract will be churned around 85% and who own the contract likely to be churned 15%.
- Around 10% people are like to be churned and 90% will be retained.
- Number of active products and services only the products 1,2,3,4 and 5 contains the people with churned behaviour and other products have 100% retention rate.
- People with 1 year of subscription have 100% retention rate. similar for the people who with 9 years of subcription. Higher churning rate with the people with 2 years of subscription. Some attention needed here to address this issue.
- price sensitive analysis using correlation method churning is likely to be have weak relationship with the price sensitivity. And Higher inter correlation found between the price sensitivity features

5 kINDLY UPVOTE THE NOTEBOOK IF YOU FIND IT INSIGHTFUL