BCG Inside Sherpa Feature Engineering

In [1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt
from matplotlib.ticker import PercentFormatter
```

In [2]:
```python
df = pd.read_csv('../Data/cleaned_data.csv')

df.drop(df.columns[0], inplace = True, axis = 1)

df.head(5)
```

Out[2]:

	id	activity_new	channel_sales	cons_12m	cons_gas_12m	cons_la
0	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	lmkebamcaaclubfxadlmueccxoimlema	309275.0	0.0	
1	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	lmkebamcaaclubfxadlmueccxoimlema	309275.0	0.0	
2	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	lmkebamcaaclubfxadlmueccxoimlema	309275.0	0.0	
3	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	lmkebamcaaclubfxadlmueccxoimlema	309275.0	0.0	
4	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	lmkebamcaaclubfxadlmueccxoimlema	309275.0	0.0	

5 rows × 38 columns

1. Simplify Information

Simplify Categorical Information

In [3]:
```python
# Convert date information to date data type
# We repeat this process because after loading the data back from csv, the format for the date columns reset

def convert_to_dates(df):
    col_to_convert = ['date_activ', 'date_modif_prod',
                      'price_date', 'date_end', 'date_renewal']

    for col in col_to_convert:
        df[col] = pd.to_datetime(df[col], format = '%Y-%m-%d')

convert_to_dates(df)
```

In [4]:
```python
def simplify_cols(df):
    col_to_simplyfiy = list(df.dtypes[df.dtypes == object].index)

    for col in col_to_simplyfiy:
        df[col] = [x[0:4] for x in df[col]]
simplify_cols(df)
```

Simplify Date Information

In [5]:
```python
def simplify_date(df):
    cols = df.dtypes[df.dtypes == 'datetime64[ns]'].index

    for col in cols:
        df[col] = df[col].dt.year
        df[col].rename('month'+col)

simplify_date(df)
```

2. Identify and Change Outlier

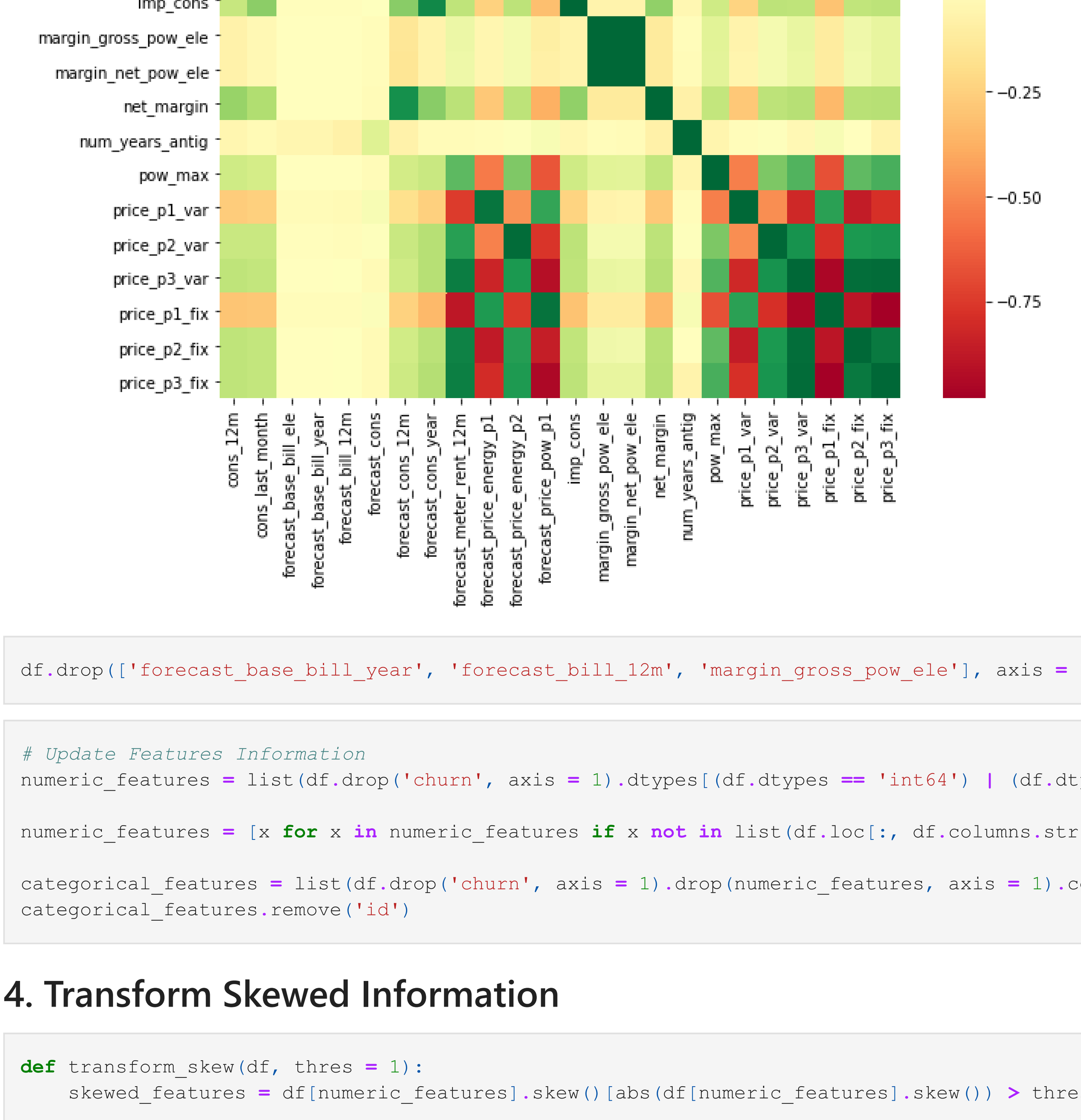
In [6]:
```python
numeric_features = list(df.drop('churn', axis = 1).dtypes[(df.dtypes == 'int64') | (df.dtypes == 'float64')]

numeric_features = [x for x in numeric_features if x not in list(df.loc[:, df.columns.str.contains("date")].

categorical_features = list(df.drop(numeric_features, axis = 1).columns)
categorical_features.remove('id')
```

In [7]:
```python
def deal_outlier(df):
    cols = df.drop('churn', axis = 1).dtypes[(df.dtypes == 'float64') | (df.dtypes == 'int64')].index

    for col in cols:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1

        outlier_indicator = (df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR))
        df.loc[outlier_indicator, col] = df.loc[~outlier_indicator, col].mean()

        if sum(outlier_indicator) != 0:
            print('Changed ' + str(sum(outlier_indicator)) + ' on ' + col)
deal_outlier(df)
```

```
Changed 30637 on cons_12m
Changed 35078 on cons_gas_12m
Changed 30086 on cons_last_month
Changed 6046 on date_activ
Changed 11920 on date_end
Changed 24 on date_modif_prod
Changed 16926 on date_renewal
Changed 42042 on forecast_base_bill_ele
Changed 42042 on forecast_base_bill_year
Changed 42042 on forecast_bill_12m
Changed 42042 on forecast_cons
Changed 16456 on forecast_cons_12m
Changed 19011 on forecast_cons_year
Changed 6944 on forecast_discount_energy
Changed 4590 on forecast_meter_rent_12m
Changed 5601 on forecast_price_energy_p1
Changed 10188 on forecast_price_pow_p1
Changed 18037 on imp_cons
Changed 8828 on margin_gross_pow_ele
Changed 8577 on margin_net_pow_ele
Changed 42391 on nb_prod_act
Changed 14245 on net_margin
Changed 5890 on num_years_antig
Changed 24072 on pow_max
Changed 5633 on price_p1_var
Changed 10452 on price_p1_fix
```

3. Removing Multicolinearity Data

In [8]:
```python
corr_matrix = df[numeric_features].drop(['cons_gas_12m', 'forecast_discount_energy',
                                          'nb_prod_act'], axis = 1).corr()


plt.figure(figsize=(10,10))
g = sns.heatmap(corr_matrix,annot=False,cmap="RdYlGn")
```



In [9]:
```python
df.drop(['forecast_base_bill_year', 'forecast_bill_12m', 'margin_gross_pow_ele'], axis = 1, inplace = True)
```

In [10]:
```python
# Update Features Information
numeric_features = list(df.drop('churn', axis = 1).dtypes[(df.dtypes == 'int64') | (df.dtypes == 'float64')]

numeric_features = [x for x in numeric_features if x not in list(df.loc[:, df.columns.str.contains("date")].

categorical_features = list(df.drop('churn', axis = 1).drop(numeric_features, axis = 1).columns)
categorical_features.remove('id')
```

4. Transform Skewed Information

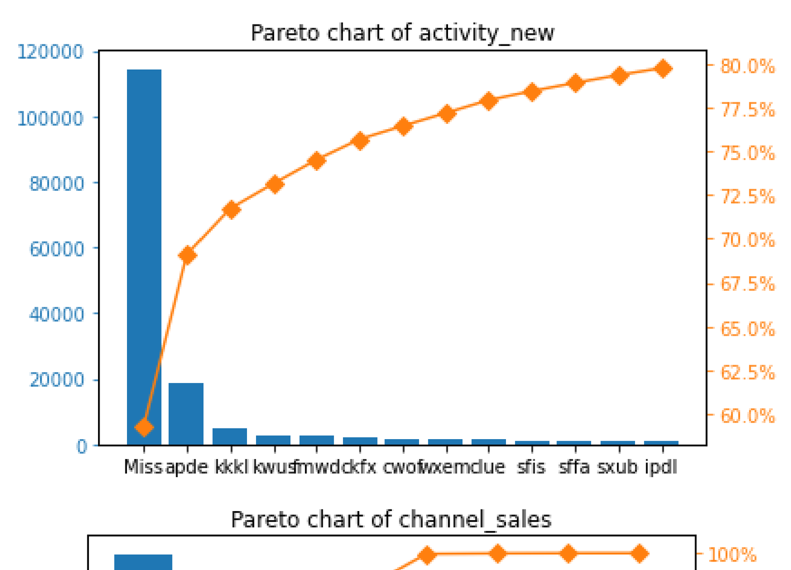
In [11]:
```python
def transform_skew(df, thres = 1):
    skewed_features = df[numeric_features].skew()[abs(df[numeric_features].skew()) > thres].index

    for feat in skewed_features:
        df[feat] = np.log10(df[feat] + 1)

    for changed in skewed_features:
        print('changed ' + changed)

transform_skew(df)
```

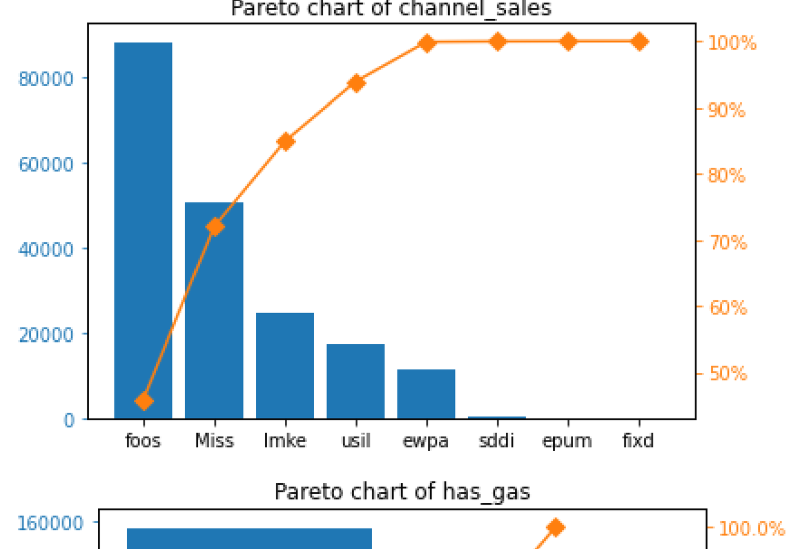
```
changed cons_12m
changed cons_last_month
changed forecast_cons_12m
changed forecast_cons_year
changed imp_cons
changed net_margin
changed pow_max
```

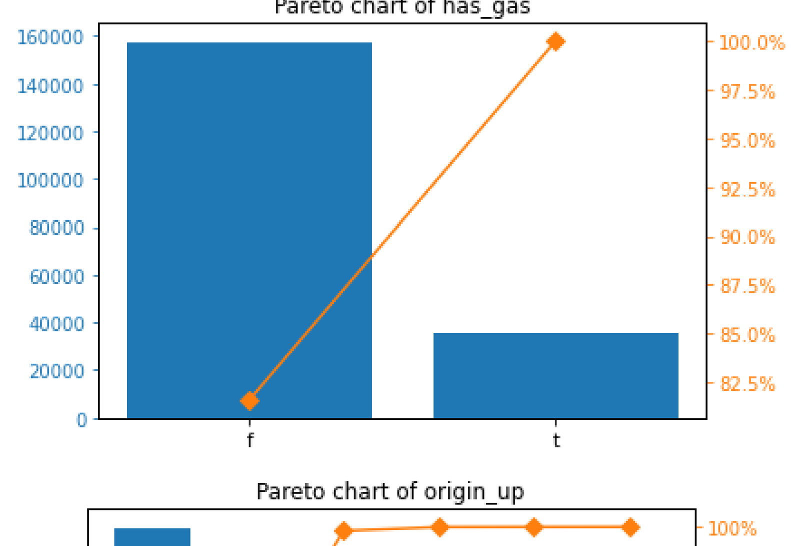
5. Encoding Categorical Variables

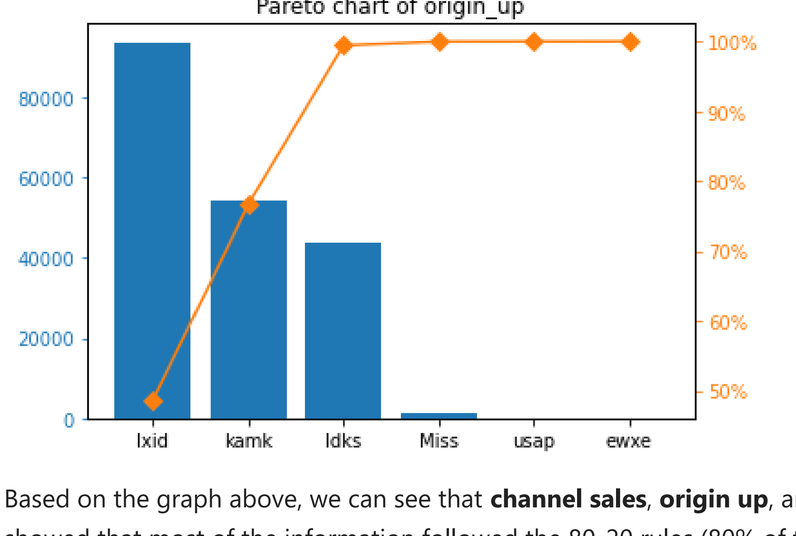
In [12]:
```python
def make_pareto(df, cols, cutoff = 100):

    for col in cols:
        temp_df = df[col].copy()
        temp_df = pd.DataFrame(temp_df.value_counts().sort_values(ascending = False))

        temp_df["cumpercentage"] = temp_df[col].cumsum()/temp_df[col].sum()*100

        if len(temp_df) > 10:
            temp_df = temp_df[temp_df['cumpercentage'] < cutoff]

        fig, ax = plt.subplots()

        ax.bar(temp_df.index, temp_df[col], color="C0")
        ax2 = ax.twinx()
        ax2.plot(temp_df.index, temp_df["cumpercentage"], color="C1", marker="D", ms=7)
        ax2.yaxis.set_major_formatter(PercentFormatter())

        ax.tick_params(axis="y", colors="C0")
        ax2.tick_params(axis="y", colors="C1")

        plt.title('Pareto chart of ' + col)

        plt.show()
```

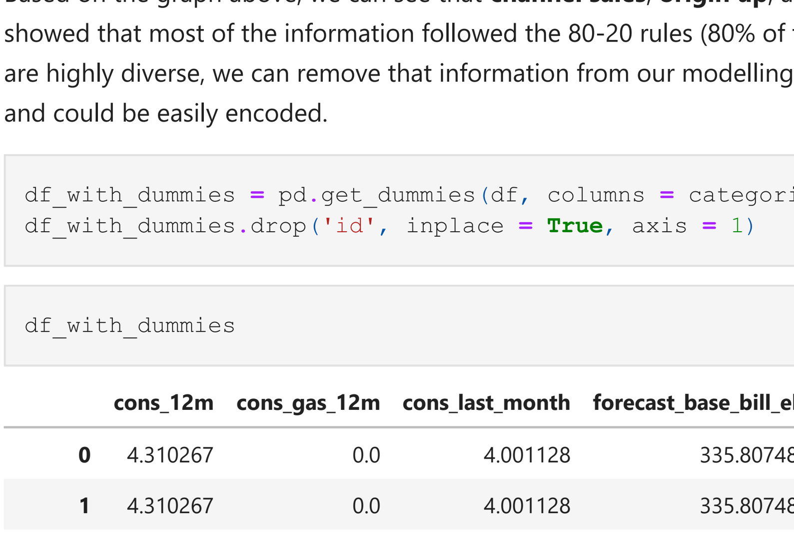
In [13]:
```python
cols_ = ['id', 'activity_new', 'channel_sales', 'has_gas', 'origin_up']

make_pareto(df, cols = cols_, cutoff = 80)
```











Based on the graph above, we can see that **channel sales**, **origin up**, and **activity new** could be kept for further analysis because it showed that most of the information followed the 80-20 rules (80% of the information is explained by the 20%). Also, since **Id** features are highly diverse, we can remove that information from our modelling process. **Has gas** feature can also be kept because it is a binary, and could be easily encoded.

In [14]:
```python
df_with_dummies = pd.get_dummies(df, columns = categorical_features)
df_with_dummies.drop('id', inplace = True, axis = 1)
```

In [19]:
```python
df_with_dummies
```

Out[19]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_base_bill_ele	forecast_cons	forecast_cons_12m	forecast_cons_year	forecast_disc
0	4.310267	0.0	4.001128	335.807483	206.800605	3.179547	2.932604	
1	4.310267	0.0	4.001128	335.807483	206.800605	3.179547	2.932604	
2	4.310267	0.0	4.001128	335.807483	206.800605	3.179547	2.932604	
3	4.310267	0.0	4.001128	335.807483	206.800605	3.179547	2.932604	
4	4.310267	0.0	4.001128	335.807483	206.800605	3.179547	2.932604	
...	...	...	...	...	...	...	...	
192997	3.941064	0.0	0.000000	335.807483	206.800605	2.882758	0.000000	
192998	3.941064	0.0	0.000000	335.807483	206.800605	2.882758	0.000000	
192999	3.941064	0.0	0.000000	335.807483	206.800605	2.882758	0.000000	
193000	3.941064	0.0	0.000000	335.807483	206.800605	2.882758	0.000000	
193001	3.941064	0.0	0.000000	335.807483	206.800605	2.882758	0.000000	

193002 rows × 487 columns

In [16]:
```python
df_with_dummies.to_csv('../Data/data_ready.csv')
```