DATA SCIENCE BCG INSIDE SHERPA CASE

PowerCo is looking to solve one of its problem to see whether price sensitivity can be used to predict customers behaviour to churn or not.

Merging Data

In [1]:
```python
import pandas as pd
import numpy as np
from datetime import datetime,  timedelta
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
```

In [2]:
```python
dt1 = pd.read_csv('../Data/ml_case_training_data.csv')
print('Shape of the data: {0[0]} rows with {0[1]} columns.'.format(dt1.shape))
```

```
Shape of the data: 16096 rows with 32 columns.
```

In [3]:
```python
dt2 = pd.read_csv('../Data/ml_case_training_hist_data.csv')
print('Shape of the data: {0[0]} rows with {0[1]} columns.'.format(dt2.shape))
```

```
Shape of the data: 193002 rows with 8 columns.
```

In [4]:
```python
dt3 = pd.read_csv('../Data/ml_case_training_output.csv')
print('Shape of the data: {0[0]} rows with {0[1]} columns.'.format(dt3.shape))
```

```
Shape of the data: 16096 rows with 2 columns.
```

In [5]:
```python
df = pd.merge(dt1, dt2, on = 'id')
df = pd.merge(df, dt3, on = 'id')
print('Shape of the data: {0[0]} rows with {0[1]} columns.'.format(df.shape))
```

```
Shape of the data: 193002 rows with 40 columns.
```

Peeking and Cleaning the Data

In [6]:
```python
# Find features with missing values and understand the missing values ratio.
def check_na(df):
    nas =  pd.DataFrame([(x, df[x].isnull().sum()*100/len(df)) for x in df]).rename(columns= {0: 'Nas_Featur

    if nas['Missing Values Ratio'].sum() == 0:
        print('No Missing Values Found.')
    else:
        return nas[nas['Missing Values Ratio'] != 0]
```

In [7]:
```python
check_na(df)
```

Out[7]:

	Nas_Features	Missing Values Ratio
1	activity_new	59.290577
2	campaign_disc_ele	100.000000
3	channel_sales	26.214754
8	date_end	0.010881
9	date_first_activ	78.216806
10	date_modif_prod	0.971493
11	date_renewal	0.247148
12	forecast_base_bill_ele	78.216806
13	forecast_base_bill_year	78.216806
14	forecast_bill_12m	78.216806
15	forecast_cons	78.216806
18	forecast_discount_energy	0.780821
20	forecast_price_energy_p1	0.780821
21	forecast_price_energy_p2	0.780821
22	forecast_price_pow_p1	0.780821
25	margin_gross_pow_ele	0.080828
26	margin_net_pow_ele	0.080828
28	net_margin	0.093263
30	origin_up	0.539891
31	pow_max	0.018653
33	price_p1_var	0.704138
34	price_p2_var	0.704138
35	price_p3_var	0.704138
36	price_p1_fix	0.704138
37	price_p2_fix	0.704138
38	price_p3_fix	0.704138

Exploratory Data Analysis

Top 8 activity with customer churning at the end

In [8]:
```python
df.groupby('activity_new').agg(sum)['churn'].sort_values(ascending = False)[0:8]
```

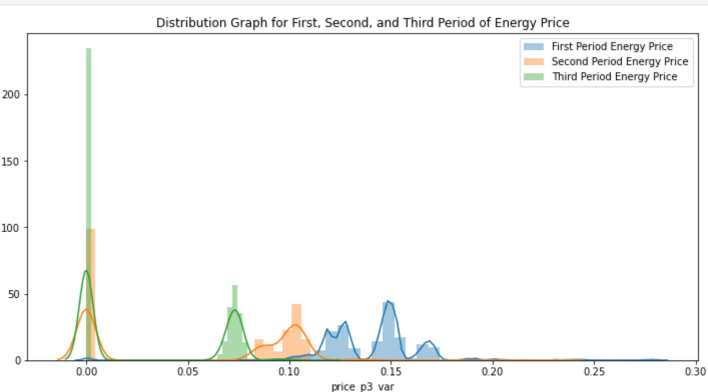
Out[8]:
```
activity_new
apdekpcbwosbxepsfxclislboipuxpop    1116
kkklcdamwfafdcfwofuscwfwadblfmce     455
fmwdwsxillemwbbwelxsampiuwwpcdcb     384
kwuslieomapmswolewpobpplkaooaaew     359
wxemiwkumpibllwklfbcooafckufkdlm     204
cluecxlameloamldmasudocsbmaoamdw     168
ckfxocssowaeipxueikxcmaxdmcduxsa     156
cwofmuicebbcmiaaxufmfimpowpacobu     144
Name: churn, dtype: int64
```

Top 8 channel sales with customer churning at the end

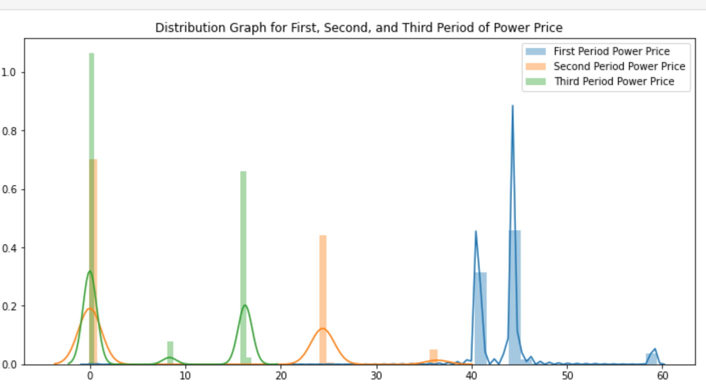
In [9]:
```python
df.groupby('channel_sales').agg(sum)['churn'].sort_values(ascending = False)[0:8]
```

Out[9]:
```
channel_sales
foosdfpfkusacimwkcsosbicdxkicaua    11041
usilxuppasemubllopkaafesmlibmsdf     1798
lmkebamcaaclubfxadlmueccxoimlema     1390
ewpakwlliwisiwduibdlfmalxowmwpci      983
sddiedcslfslkckwlfkdpoeeailfpeds        0
fixdbufsefwooaasfcxdxadsiekoceaa        0
epumfxlbckeskwekxbiuasklxalciiuu        0
Name: churn, dtype: int64
```

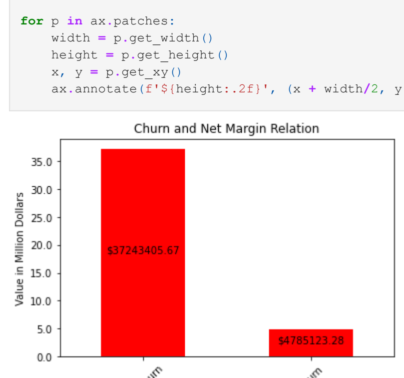
In [10]:
```python
plt.figure(figsize = (12, 6))
sns.distplot(df['price_p1_var'], label = 'First Period Energy Price')
sns.distplot(df['price_p2_var'], label = 'Second Period Energy Price')
sns.distplot(df['price_p3_var'], label = 'Third Period Energy Price')
plt.title('Distribution Graph for First, Second, and Third Period of Energy Price')
plt.legend();
```



In [11]:
```python
plt.figure(figsize = (12, 6))
sns.distplot(df['price_p1_fix'], label = 'First Period Power Price')
sns.distplot(df['price_p2_fix'], label = 'Second Period Power Price')
sns.distplot(df['price_p3_fix'], label = 'Third Period Power Price')
plt.title('Distribution Graph for First, Second, and Third Period of Power Price')
plt.legend();
```

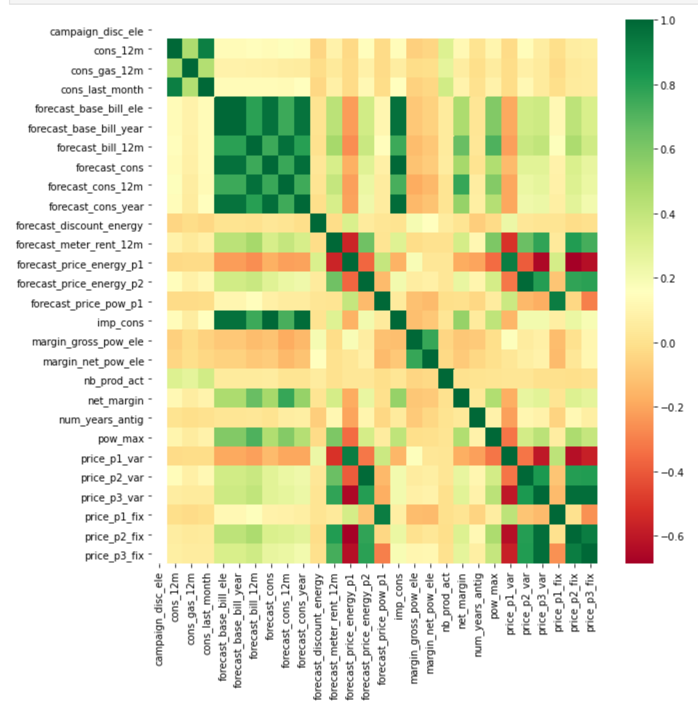


In [12]:
```python
ax = df.groupby('churn').agg('sum')['net_margin'].plot(kind = 'bar',
                                                       color = 'red', )

plt.title('Churn and Net Margin Relation')
plt.xticks([0, 1],['Not Churn', 'Churn'], rotation = 45)
plt.xlabel('')
plt.ylabel('Value in Million Dollars')

ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x)/10**6, ',')))

for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'${height:.2f}', (x + width/2, y + height*.5), ha='center')
```



Identifying values with high correlation.

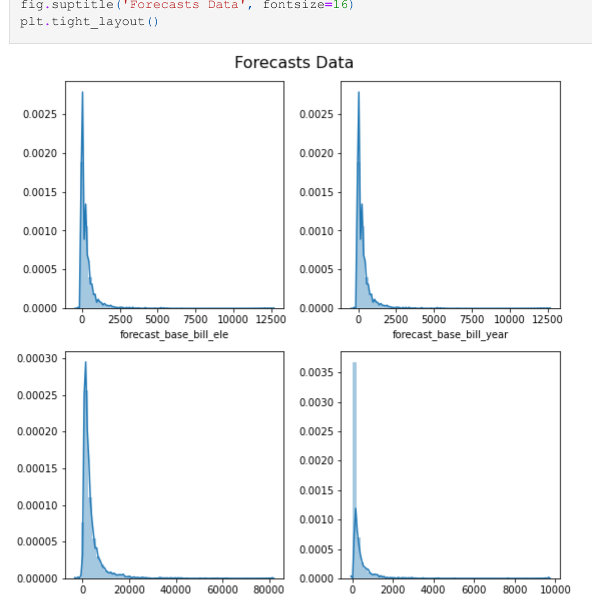
In [13]:
```python
numeric_features =  df.drop('churn', axis = 1).dtypes[df.dtypes != 'object'].index

cormat = df[numeric_features].corr()
plt.figure(figsize=(10,10))
g = sns.heatmap(cormat,annot=False,cmap="RdYlGn")
```



Simple Imputer to fill missing values with their average.

First we shall convert the skewed data into more of a normal distribution using log transformation.

In [14]:
```python
i = 1
fig, axs = plt.subplots(2, 2, figsize = (8, 8))
for x in ['forecast_base_bill_ele', 'forecast_base_bill_year',
          'forecast_bill_12m', 'forecast_cons']:
    plt.subplot(2, 2, i)
    sns.distplot(df[x])
    df[x] = df[x].fillna(df[x].mean(skipna=True))
    i=i+1;
fig.suptitle('Forecasts Data', fontsize=16)
plt.tight_layout()
```



In [15]:
```python
check_na(df)
```

Out[15]:

	Nas_Features	Missing Values Ratio
1	activity_new	59.290577
2	campaign_disc_ele	100.000000
3	channel_sales	26.214754
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25	margin_gross_pow_ele	0.080828
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30	origin_up	0.539891
31	pow_max	0.018653
33	price_p1_var	0.704138
34	price_p2_var	0.704138
35	price_p3_var	0.704138
36	price_p1_fix	0.704138
37	price_p2_fix	0.704138
38	price_p3_fix	0.704138

Some features are filled with a lot of missing values. Also we have some columns that we probably won't need for this problem. The next step is to deal with this problem.

In [16]:
```python
# Imputing Missing values on dates data

def impute_dates(df):
    columns_dates = ['date_modif_prod','date_end', 'date_renewal']

    for col in columns_dates:
        df.loc[df[col].isnull(), col] = df[col].value_counts().index[0]
impute_dates(df)
```

In [17]:
```python
# Convert date information to date data type

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 [19]:
```python
# Replace Negative Values with averages.

def replace_negatives(df):
    col_to_find = df.drop('churn', axis = 1).dtypes[(df.dtypes == 'int64') | (df.dtypes == 'float64')].index

    for x in list(col_to_find):
        df.loc[df[x] < 0 , x] = df.loc[df[x]>0, x].mean()

replace_negatives(df)
```

In [20]:
```python
# Fill in Missing Categorical information

def fill_na(df):
    col_to_impute = ['activity_new', 'channel_sales', 'id', 'origin_up']

    for col in col_to_impute:

        name_ = 'Missing_' + col
        df[col_to_impute]= df[col_to_impute].fillna(name_)

fill_na(df)
```

In [21]:
```python
# Fill in Missing Numeric Variable
def impute_numeric(df):
    col_to_find = df.drop('churn', axis = 1).dtypes[df.dtypes == 'float64'].index
    for x in list(col_to_find):
        median = df[x].median(skipna = True)
        df.loc[df[x].isnull(), x] = median
impute_numeric(df)
```

In [22]:
```python
list_to_drop = ['campaign_disc_ele', 'date_first_activ']

df.drop(list_to_drop, inplace = True, axis = 1 ,errors = 'raise')

df.dropna(axis = 0, inplace = True)
```

In [23]:
```python
check_na(df)
print('Shape of the data: {0[0]} rows with {0[1]} columns.'.format(df.shape))
```

```
No Missing Values Found.
Shape of the data: 193002 rows with 38 columns.
```

In [24]:
```python
df
```

Out[24]:

	id	activity_new	channel_sales	cons_12m	cons_gas_12m
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
...	...	...	...	...	...
192997	563dde550fd624d7352f3de77c0cdfcd	Missing_activity_new	Missing_activity_new	8730.0	0.0
192998	563dde550fd624d7352f3de77c0cdfcd	Missing_activity_new	Missing_activity_new	8730.0	0.0
192999	563dde550fd624d7352f3de77c0cdfcd	Missing_activity_new	Missing_activity_new	8730.0	0.0
193000	563dde550fd624d7352f3de77c0cdfcd	Missing_activity_new	Missing_activity_new	8730.0	0.0
193001	563dde550fd624d7352f3de77c0cdfcd	Missing_activity_new	Missing_activity_new	8730.0	0.0

193002 rows × 38 columns

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