Churn Prediction

Churn is a one of the biggest problem in the SME.In recent years, post-liberalization of the energy market in Europe, ElectricCo has had a growing problem with increasing customer defections above industry average. They would like to identify the drivers of this problem and to devise and implement a strategy to counter it. The churn issue is most acute in the SME division and thus they want it to be the first priority. The head of the SME division has asked whether it is possible to predict the customers which are most likely to churn so that they can trial a range of pre-emptive actions.

The first stage is to establish the viability of such a model. For training your model you are provided with a dataset which includes features of SME customers in January 2016 as well as the information about whether or not they have churned by March 2016. In addition to that you have received the prices from 2015 for these customers. While it is not mandatory, but you are encouraged to test multiple algorithms to build predictive model.

Using the trained model you shall “score” customers in the verification data set (provided in the eponymous file) and put them in descending order of the propensity to churn. You should also classify these customers into two classes: those which you predict to churn are to be labelled "1" and the remaining customers should be labelled "0" in the result template.

Information contained in the data set

The below table describes all the data fields which are found in the data (across three files). You will notice that the contents of some fields are meaningless text strings. This is due to "hashing" of text fields for data privacy. While their commercial interpretation is lost as a result of the hashing, they may still have predictive power.

A whole host of rich investigations are possible. Your ideas on what some next steps could be, armed with such data is also of interest.

Data fields and their description

Field name Description Present id contact id
activity_new category of the company's activity 6551 campaign_disc_ele code of the electricity campaign the customer last subscribed to (none)
channel_sales code of the sales channel 11878 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_first_activ date of first contract of the client 3508 date_modif_prod date of last modification of the product
date_renewal date of the next contract renewal
forecast_base_bill_ele forecasted electricity bill baseline for next month 3508 forecast_base_bill_year forecasted electricity bill baseline for calendar year 3508 forecast_bill_12m forecasted electricity bill baseline for 12 months 3508 forecast_cons_12m forecasted electricity consumption for next 12 months
forecast_cons_year forecasted electricity consumption for next calendar year
forecast_discount_energy forecasted value of current discount
forecast_meter_rent_12m forecasted bill of meter rental for the next 12 months
forecast_price_energy_p1 forecasted energy price for 1st period
forecast_price_energy_p2 forecasted energy price for 2nd period
forecast_price_pow_p1 forecasted power price for 1st period

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
price_date reference date

Data Source

We are going to use the SME churn Data that we looked at zip folder and here to try and predict which loans will default.

Import Libraries

In [102]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objs as go
import plotly.offline as py
from sklearn.model_selection import train_test_split, KFold, StratifiedKFold
import warnings
import sklearn.exceptions
warnings.filterwarnings("ignore", category=sklearn.exceptions.UndefinedMetricWarning)
%matplotlib inline
```

In [2]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
import plotly.graph_objs as go
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
from sklearn.metrics import roc_auc_score,roc_curve,scorer,auc
from sklearn.metrics import f1_score
import statsmodels.api as sm
from sklearn.metrics import precision_score,recall_score, confusion_matrix
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.cross_validation import KFold
```

```
C:\Users\kanan\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: D
eprecationWarning:

This module was deprecated in version 0.18 in favor of the model_selection m
odule into which all the refactored classes and functions are moved. Also no
te that the interface of the new CV iterators are different from that of thi
s module. This module will be removed in 0.20.
```

Import DataSet

In [3]:

```
df = pd.read_csv('Hackthon_case_training_data.csv')
dt = pd.read_csv('Hackthon_case_training_output.csv')
sm = pd.read_csv('sample_ouput.csv')
```

Pre-process Data & Visualization

This section is was created in here.

In [4]:

```
df.head()
```

Out[4]:

	id	activity_new	campaign_disc_ele	
0	48ada52261e7cf58715202705a0451c9	esoiiifxdlbkcsluxmfuacbdckommixw	NaN	lmkel
1	24011ae4ebbe3035111d65fa7c15bc57	NaN	NaN	foo
2	d29c2c54acc38ff3c0614d0a653813dd	NaN	NaN	
3	764c75f661154dac3a6c254cd082ea7d	NaN	NaN	foo
4	bba03439a292a1e166f80264c16191cb	NaN	NaN	lmkel

5 rows × 32 columns

In [5]:

```
df.describe()
```

Out[5]:

	campaign_disc_ele	cons_12m	cons_gas_12m	cons_last_month	forecast_base_bill_e
count	0.0	1.609600e+04	1.609600e+04	1.609600e+04	3508.00000
mean	NaN	1.948044e+05	3.191164e+04	1.946154e+04	335.84385
std	NaN	6.795151e+05	1.775885e+05	8.235676e+04	649.40600
min	NaN	-1.252760e+05	-3.037000e+03	-9.138600e+04	-364.94000
25%	NaN	5.906250e+03	0.000000e+00	0.000000e+00	0.00000
50%	NaN	1.533250e+04	0.000000e+00	9.010000e+02	162.95500
75%	NaN	5.022150e+04	0.000000e+00	4.127000e+03	396.18500
max	NaN	1.609711e+07	4.188440e+06	4.538720e+06	12566.08000

8 rows × 22 columns

In [6]:

```
df.index
```

Out[6]:

```
RangeIndex(start=0, stop=16096, step=1)
```

In [7]:

```
df.corr()
```

Out[7]:

	campaign_disc_ele	cons_12m	cons_gas_12m	cons_last_month	fore
campaign_disc_ele	NaN	NaN	NaN	NaN	
cons_12m	NaN	1.000000	0.471233	0.919545	
cons_gas_12m	NaN	0.471233	1.000000	0.447209	
cons_last_month	NaN	0.919545	0.447209	1.000000	
forecast_base_bill_ele	NaN	0.132991	0.085733	0.136207	
forecast_base_bill_year	NaN	0.132991	0.085733	0.136207	
forecast_bill_12m	NaN	0.149023	0.083604	0.134066	
forecast_cons	NaN	0.133147	0.076854	0.136816	
forecast_cons_12m	NaN	0.165168	0.059525	0.129574	
forecast_cons_year	NaN	0.139526	0.057619	0.151476	
forecast_discount_energy	NaN	-0.043708	-0.014945	-0.037773	
forecast_meter_rent_12m	NaN	0.085996	0.040327	0.076066	
forecast_price_energy_p1	NaN	-0.033546	-0.022416	-0.024242	
forecast_price_energy_p2	NaN	0.146758	0.078456	0.123164	
forecast_price_pow_p1	NaN	-0.025418	-0.027193	-0.020057	
imp_cons	NaN	0.139353	0.060609	0.153861	
margin_gross_pow_ele	NaN	-0.065500	-0.016867	-0.054114	
margin_net_pow_ele	NaN	-0.045779	-0.008242	-0.037696	
nb_prod_act	NaN	0.308567	0.272005	0.350711	
net_margin	NaN	0.120491	0.058930	0.096424	
num_years_antig	NaN	0.008810	-0.008626	0.004860	
pow_max	NaN	0.102423	0.052365	0.089565	

22 rows × 22 columns

In [8]:

```
df.columns
```

Out[8]:

```
Index(['id', 'activity_new', 'campaign_disc_ele', 'channel_sales', 'cons_12
m',
       'cons_gas_12m', 'cons_last_month', 'date_activ', 'date_end',
       'date_first_activ', 'date_modif_prod', 'date_renewal',
       'forecast_base_bill_ele', 'forecast_base_bill_year',
       'forecast_bill_12m', 'forecast_cons', 'forecast_cons_12m',
       'forecast_cons_year', 'forecast_discount_energy',
       'forecast_meter_rent_12m', 'forecast_price_energy_p1',
       'forecast_price_energy_p2', 'forecast_price_pow_p1', 'has_gas',
       'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'nb_prod_ac
t',
       'net_margin', 'num_years_antig', 'origin_up', 'pow_max'],
      dtype='object')
```

In [9]:

```
print ("Rows     : " ,df.shape[0])
print ("Columns  : " ,df.shape[1])
print ("\nFeatures : \n" ,df.columns.tolist())
print ("\nMissing values :  ", df.isnull().sum().values.sum())
print ("\nMissing  :  ", df.isnull().sum().values)
print ("\nUnique values :  \n",df.nunique())
```

```
Rows     :  16096
Columns  :  32

Features :
 ['id', 'activity_new', 'campaign_disc_ele', 'channel_sales', 'cons_12m', 'c
ons_gas_12m', 'cons_last_month', 'date_activ', 'date_end', 'date_first_acti
v', 'date_modif_prod', 'date_renewal', 'forecast_base_bill_ele', 'forecast_b
ase_bill_year', 'forecast_bill_12m', 'forecast_cons', 'forecast_cons_12m',
'forecast_cons_year', 'forecast_discount_energy', 'forecast_meter_rent_12m',
'forecast_price_energy_p1', 'forecast_price_energy_p2', 'forecast_price_pow_
p1', 'has_gas', 'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'n
b_prod_act', 'net_margin', 'num_years_antig', 'origin_up', 'pow_max']

Missing values :   93633

Missing  :   [    0  9545 16096  4218     0     0     0     0     2 12588
157    40
 12588 12588 12588 12588     0     0   126     0   126   126   126     0
     0    13    13     0    15     0    87     3]

Unique values :
 id                          16096
activity_new                  419
campaign_disc_ele               0
channel_sales                   7
cons_12m                    12002
cons_gas_12m                 2290
cons_last_month              5308
date_activ                   1961
date_end                      371
date_first_activ             1133
date_modif_prod              2307
date_renewal                  398
forecast_base_bill_ele       2042
forecast_base_bill_year      2042
forecast_bill_12m            3429
forecast_cons                1955
forecast_cons_12m           15422
forecast_cons_year           4895
forecast_discount_energy       14
forecast_meter_rent_12m      3938
forecast_price_energy_p1      617
forecast_price_energy_p2      412
forecast_price_pow_p1          46
has_gas                         2
imp_cons                     8765
margin_gross_pow_ele         2947
margin_net_pow_ele           2974
nb_prod_act                    11
net_margin                  13189
num_years_antig                15
origin_up                       5
```

```
pow_max                        867
dtype: int64
```

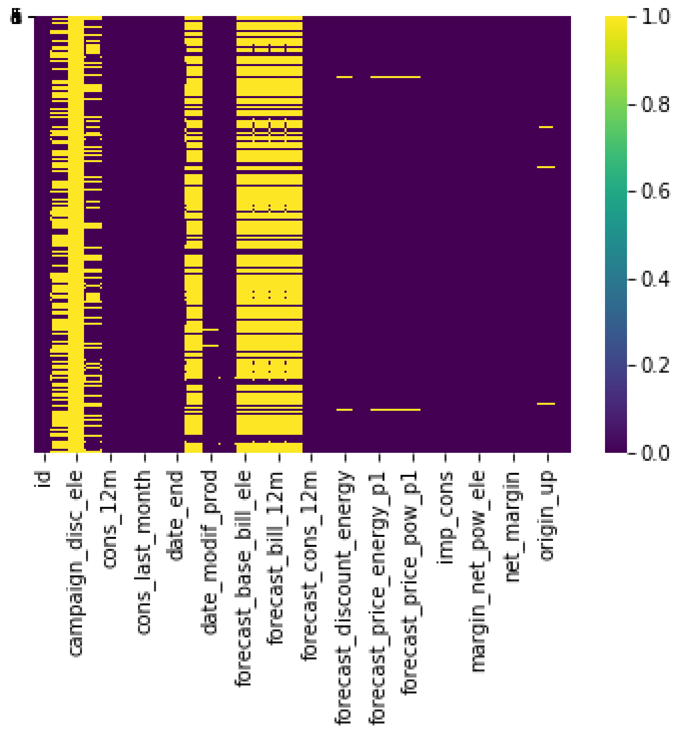
Heatmap for finding missing values

In [10]:

```
sns.heatmap(df.isnull(), cmap='viridis', yticklabels='False')
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x190f3d7e630>
```



In [11]:

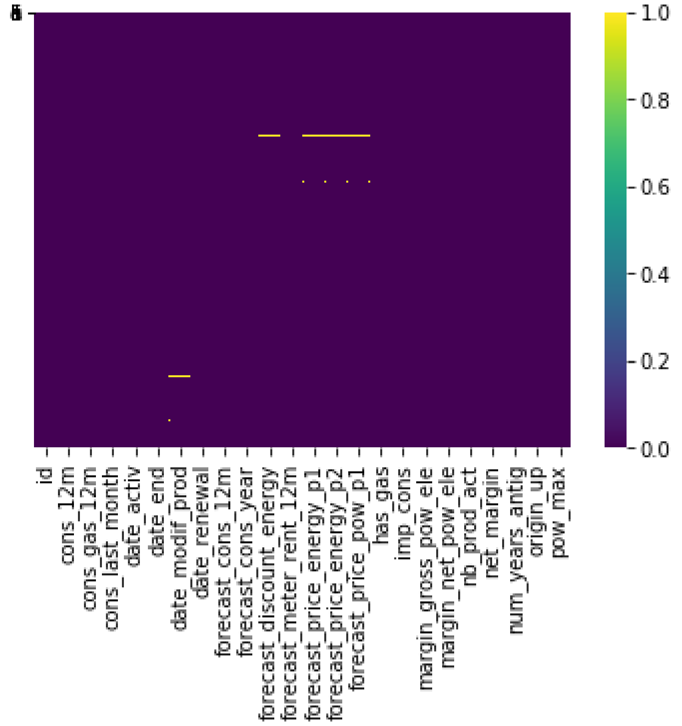
```
df = df.drop(['activity_new', 'campaign_disc_ele', 'forecast_base_bill_ele', 'forecast_base
```

In [12]:

```
sns.heatmap(df.isnull(), cmap='viridis', yticklabels='False')
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x190f40bde80>
```



In [13]:

```
print ("\nFeatures : \n" ,df.columns.tolist())
print ("\nMissing  :  ", df.isnull().sum().values)
print ("\nUnique values :  \n",df.nunique())
```

```
Features :
 ['id', 'cons_12m', 'cons_gas_12m', 'cons_last_month', 'date_activ', 'date_e
nd', 'date_modif_prod', 'date_renewal', 'forecast_cons_12m', 'forecast_cons_
year', 'forecast_discount_energy', 'forecast_meter_rent_12m', 'forecast_pric
e_energy_p1', 'forecast_price_energy_p2', 'forecast_price_pow_p1', 'has_ga
s', 'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'nb_prod_act',
'net_margin', 'num_years_antig', 'origin_up', 'pow_max']

Missing  :   [  0   0   0   0   0   2 157  40   0   0 126   0 126 126 126
0   0  13
  13   0  15   0  87   3]

Unique values :
 id                          16096
cons_12m                    12002
cons_gas_12m                 2290
cons_last_month              5308
date_activ                   1961
date_end                      371
date_modif_prod              2307
date_renewal                  398
forecast_cons_12m           15422
forecast_cons_year           4895
forecast_discount_energy       14
forecast_meter_rent_12m      3938
forecast_price_energy_p1      617
forecast_price_energy_p2      412
forecast_price_pow_p1          46
has_gas                         2
imp_cons                     8765
margin_gross_pow_ele         2947
margin_net_pow_ele           2974
nb_prod_act                    11
net_margin                  13189
num_years_antig                15
origin_up                       5
pow_max                       867
dtype: int64
```

In [14]:

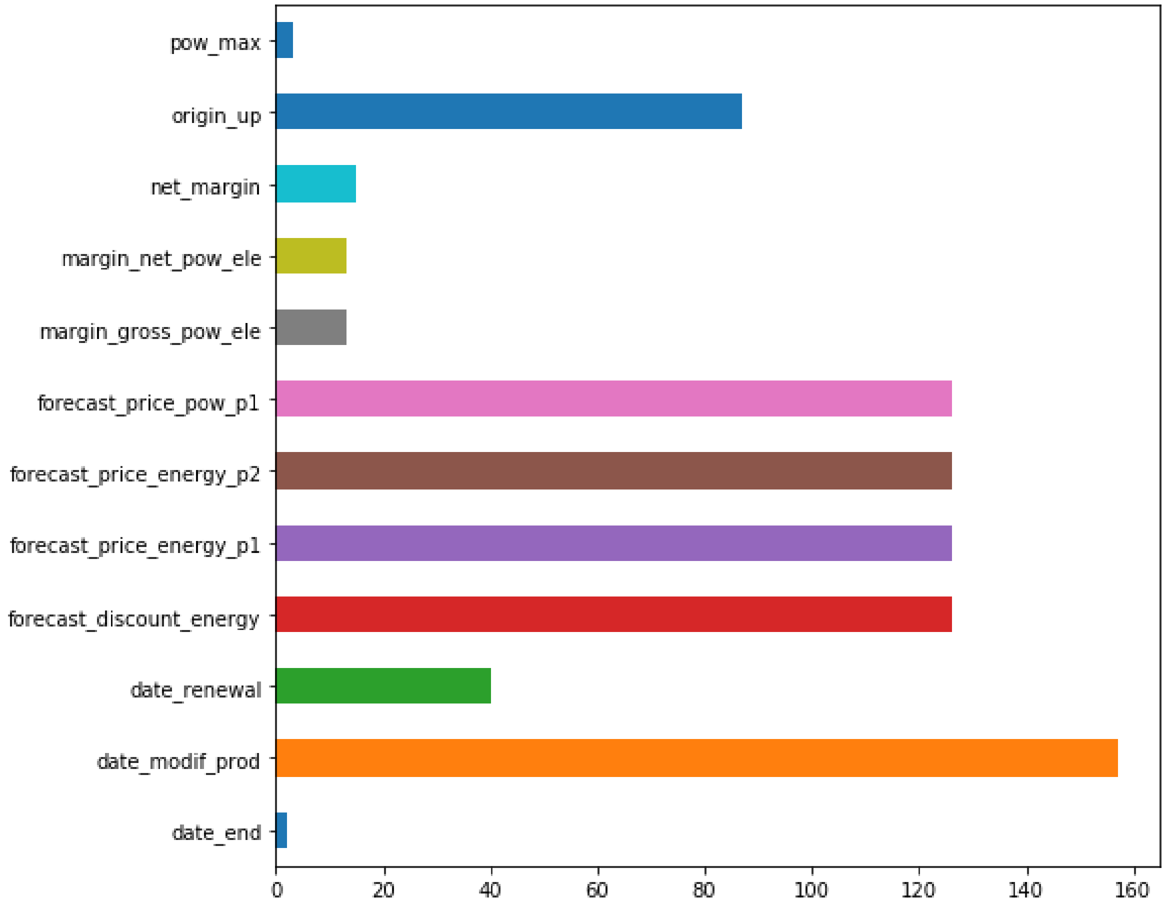
```
df.shape
```

Out[14]:

```
(16096, 24)
```

In [15]:

```
# Here I plot missing values:
data_null = df.isna().sum()
plt.figure(figsize=(8,8))
data_null[data_null!=0].plot(kind='barh');
```



In [16]:

```
df.head()
```

Out[16]:

	id	cons_12m	cons_gas_12m	cons_last_month	date_activ
0	48ada52261e7cf58715202705a0451c9	309275	0	10025	11/7/2012
1	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	6/15/2013
2	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	8/21/2009
3	764c75f661154dac3a6c254cd082ea7d	544	0	0	4/16/2010
4	bba03439a292a1e166f80264c16191cb	1584	0	0	3/30/2010

5 rows × 24 columns

In [17]:

```
df['date_activ'] = pd.to_datetime(df['date_activ'])
df['date_activ_year'] = df.date_activ.dt.year
df['date_activ_month'] = df.date_activ.dt.month
df['date_activ_day'] = df.date_activ.dt.day
df=df.drop(columns='date_activ',axis=1)
```

In [18]:

```
df.head()
```

Out[18]:

	id	cons_12m	cons_gas_12m	cons_last_month	date_end	c
0	48ada52261e7cf58715202705a0451c9	309275	0	10025	11/6/2016	
1	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	6/15/2016	
2	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	8/30/2016	
3	764c75f661154dac3a6c254cd082ea7d	544	0	0	4/16/2016	
4	bba03439a292a1e166f80264c16191cb	1584	0	0	3/30/2016	

5 rows × 26 columns

In [19]:

```
df['date_end'] = pd.to_datetime(df['date_end'])
df['date_end_year'] = df.date_end.dt.year
df['date_end_month'] = df.date_end.dt.month
df['date_end_day'] = df.date_end.dt.day
df=df.drop(columns='date_end',axis=1)
```

In [20]:

```
df['date_renewal'] = pd.to_datetime(df['date_renewal'])
df['date_renewal_year'] = df.date_renewal.dt.year
df['date_renewal_month'] = df.date_renewal.dt.month
df['date_renewal_day'] = df.date_renewal.dt.day
df=df.drop(columns='date_renewal',axis=1)
```

In [21]:

```
df['date_modif_prod'] = pd.to_datetime(df['date_modif_prod'])
df['date_modif_prod_year'] = df.date_modif_prod.dt.year
df['date_modif_prod_month'] = df.date_modif_prod.dt.month
df['date_modif_prod_day'] = df.date_modif_prod.dt.day
df=df.drop(columns='date_modif_prod',axis=1)
```

In [22]:

```
df.head()
```

Out[22]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	48ada52261e7cf58715202705a0451c9	309275	0	10025	2
1	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	
2	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	
3	764c75f661154dac3a6c254cd082ea7d	544	0	0	
4	bba03439a292a1e166f80264c16191cb	1584	0	0	

5 rows × 32 columns

In [23]:

```
mean = df['forecast_price_pow_p1'].mean()
mean1 = df['forecast_price_energy_p2'].mean()
mean2 = df['forecast_price_energy_p1'].mean()
mean3 = df['forecast_discount_energy'].mean()
df['forecast_price_pow_p1'] = df['forecast_price_pow_p1'].fillna(mean)
df['forecast_price_energy_p2'] = df['forecast_price_energy_p2'].fillna(mean1)
df['forecast_price_energy_p1'] = df['forecast_price_energy_p1'].fillna(mean2)
df['forecast_discount_energy'] = df['forecast_discount_energy'].fillna(mean3)
```

In [24]:

```
print ("\nFeatures : \n" ,df.columns.tolist())
print ("\nMissing  :  ", df.isnull().sum().values)
print ("\nUnique values :  \n",df.nunique())
```

```
Features : 
 ['id', 'cons_12m', 'cons_gas_12m', 'cons_last_month', 'forecast_cons_12m',
'forecast_cons_year', 'forecast_discount_energy', 'forecast_meter_rent_12m',
'forecast_price_energy_p1', 'forecast_price_energy_p2', 'forecast_price_pow_
p1', 'has_gas', 'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'n
b_prod_act', 'net_margin', 'num_years_antig', 'origin_up', 'pow_max', 'date_
activ_year', 'date_activ_month', 'date_activ_day', 'date_end_year', 'date_en
d_month', 'date_end_day', 'date_renewal_year', 'date_renewal_month', 'date_r
enewal_day', 'date_modif_prod_year', 'date_modif_prod_month', 'date_modif_pr
od_day']

Missing  :   [  0   0   0   0   0   0   0   0   0   0   0   0   0  13  13
0  15   0
  87   3   0   0   0   2   2   2  40  40  40 157 157 157]

Unique values :  
 id                          16096
cons_12m                    12002
cons_gas_12m                 2290
cons_last_month              5308
forecast_cons_12m           15422
forecast_cons_year           4895
forecast_discount_energy       15
forecast_meter_rent_12m      3938
forecast_price_energy_p1      618
forecast_price_energy_p2      413
forecast_price_pow_p1          47
has_gas                         2
imp_cons                     8765
margin_gross_pow_ele         2947
margin_net_pow_ele           2974
nb_prod_act                    11
net_margin                  13189
num_years_antig                15
origin_up                       5
pow_max                       867
date_activ_year                14
date_activ_month               12
date_activ_day                 31
date_end_year                   4
date_end_month                 12
date_end_day                   31
date_renewal_year               4
date_renewal_month             12
date_renewal_day               31
date_modif_prod_year           16
date_modif_prod_month          12
date_modif_prod_day            31
dtype: int64
```

In [25]:

```
m = int(df['date_modif_prod_year'].mean())
m1 = int(df['date_modif_prod_month'].mean())
m2 = int(df['date_modif_prod_day'].mean())
df['date_modif_prod_year'] = df['date_modif_prod_year'].fillna(m)
df['date_modif_prod_month'] = df['date_modif_prod_month'].fillna(m1)
df['date_modif_prod_day'] = df['date_modif_prod_day'].fillna(m2)
```

In [26]:

```
print ("\nMissing  :  ", df.isnull().sum().values)
```

```
Missing  :   [ 0  0  0  0  0  0  0  0  0  0  0  0  0 13 13  0 15  0 87  3  0
  0  0  2
  2  2 40 40 40  0  0  0]
```

In [27]:

```
l = int(df['date_renewal_year'].mean())
l1 = int(df['date_renewal_month'].mean())
l2 = int(df['date_renewal_day'].mean())
df['date_renewal_year'] = df['date_renewal_year'].fillna(l)
df['date_renewal_month'] = df['date_renewal_month'].fillna(l1)
df['date_renewal_day'] = df['date_renewal_day'].fillna(l2)
```

In [28]:

```
print ("\nMissing  :  ", df.isnull().sum().values)
```

```
Missing  :   [ 0  0  0  0  0  0  0  0  0  0  0  0  0 13 13  0 15  0 87  3  0
  0  0  2
  2  2  0  0  0  0  0  0]
```

In [29]:

```
l = int(df['date_renewal_year'].mean())
l1 = int(df['date_renewal_month'].mean())
l2 = int(df['date_renewal_day'].mean())
df['date_renewal_year'] = df['date_renewal_year'].fillna(l)
df['date_renewal_month'] = df['date_renewal_month'].fillna(l1)
df['date_renewal_day'] = df['date_renewal_day'].fillna(l2)
```

In [30]:

```
e = int(df['date_end_year'].mean())
e1 = int(df['date_end_month'].mean())
e2 = int(df['date_end_day'].mean())
df['date_end_year'] = df['date_end_year'].fillna(e)
df['date_end_month'] = df['date_end_month'].fillna(e1)
df['date_end_day'] = df['date_end_day'].fillna(e2)
```

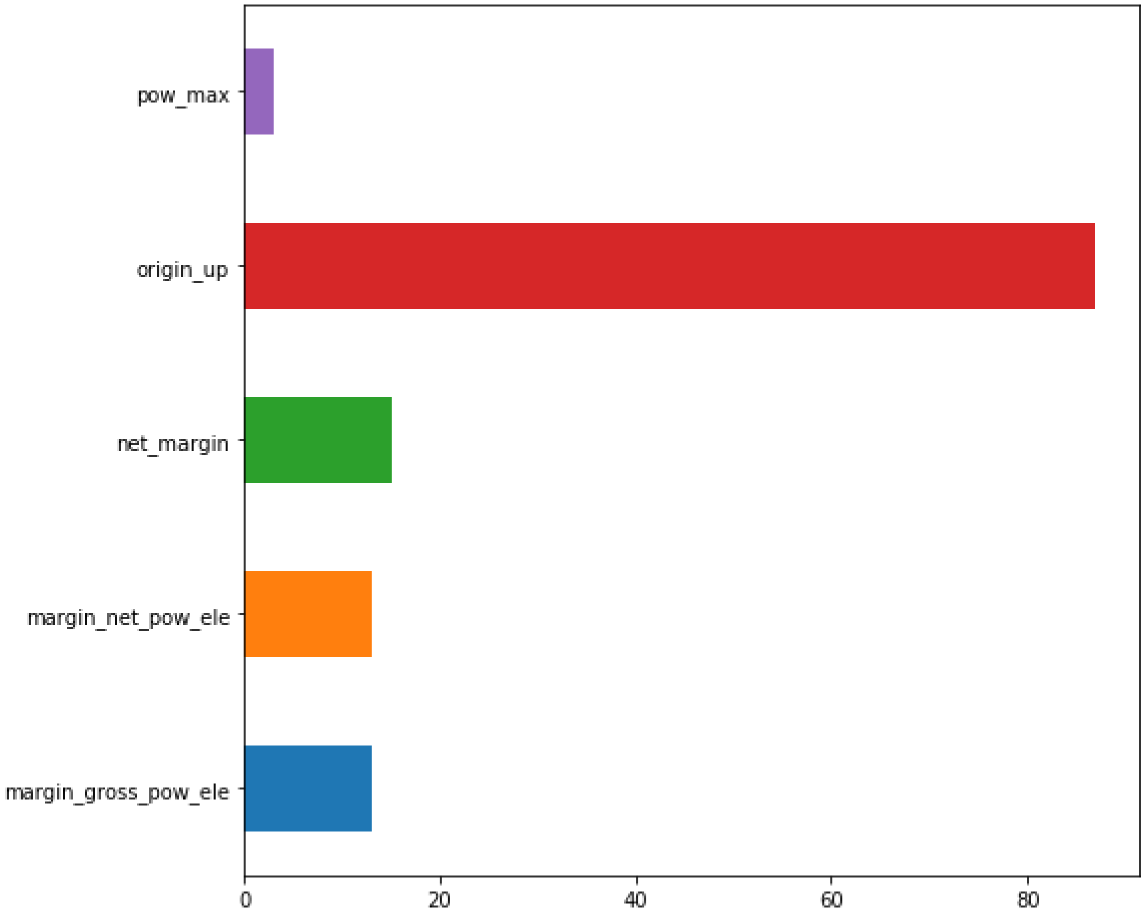
In [31]:

```
print ("\nMissing  :  ", df.isnull().sum().values)
```

```
Missing  :    [ 0  0  0  0  0  0  0  0  0  0  0  0  0 13 13  0 15  0 87  3  0
  0  0  0
  0  0  0  0  0  0  0  0]
```

In [32]:

```
# Here I plot missing values:
data_null = df.isna().sum()
plt.figure(figsize=(8,8))
data_null[data_null!=0].plot(kind='barh');
```

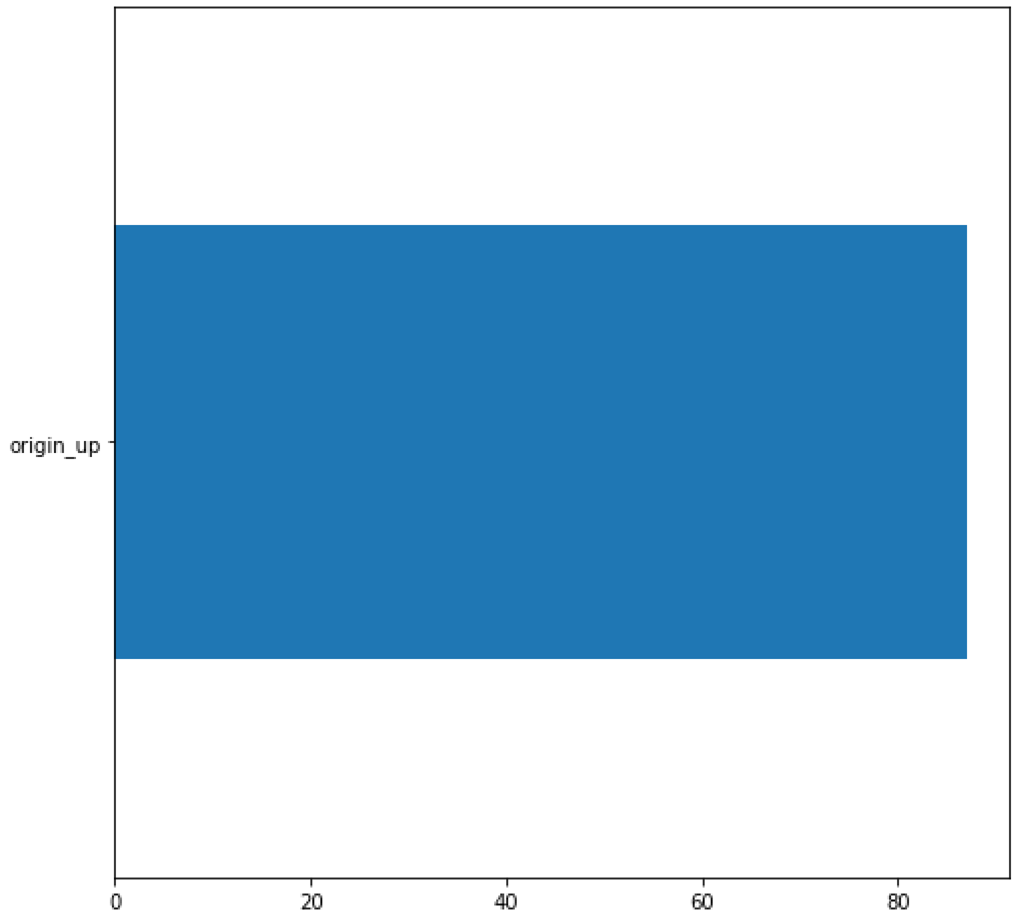


In [33]:

```
p = int(df['pow_max'].mean())
df['pow_max'] = df['pow_max'].fillna(p)
margin = int(df['net_margin'].mean())
df['net_margin'] = df['net_margin'].fillna(margin)
mn = int(df['margin_net_pow_ele'].mean())
df['margin_net_pow_ele'] = df['margin_net_pow_ele'].fillna(mn)
mg = int(df['margin_gross_pow_ele'].mean())
df['margin_gross_pow_ele'] = df['margin_gross_pow_ele'].fillna(mg)
```

In [34]:

```
# Here I plot missing values:
data_null = df.isna().sum()
plt.figure(figsize=(8,8))
data_null[data_null!=0].plot(kind='barh');
```



In [35]:

```
#replace values
df['has_gas'] = df['has_gas'].replace({"f":0,"t":1})
```

In [36]:

```
df.head()
```

Out[36]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	48ada52261e7cf58715202705a0451c9	309275	0	10025	2
1	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	
2	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	
3	764c75f661154dac3a6c254cd082ea7d	544	0	0	
4	bba03439a292a1e166f80264c16191cb	1584	0	0	

5 rows × 32 columns

One hot encoding

In [37]:

```
#df['origin_up'] = df['origin_up'].replace({"ewxeelcelemmiwuafmddpobolfuxioce":0,
#                                             "kamkkxfxxuwbdslkwifmmcsiusiuosws":1,
#                                             "ldkssxwpmemidmecebumciepifcamkci":2,
#                                             "lxidpiddsbxsbosboudacockeimpuepw":3,
#                                            "usapbepcfoloekilkwsdiboslwaxobdp":4})
df['origin_up'] = pd.get_dummies(df['origin_up'],drop_first=True)
```

In [38]:

```
df = df.drop(['origin_up'], axis=1)
```

In [39]:

```
#o = int(df['origin_up'].mean())
#df['origin_up'] = df['origin_up'].fillna(o)
```

In [40]:

```
print ("\nMissing  :  ", df.isnull().sum().values)
```

```
Missing  :   [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

In [41]:

```
df.head()
```

Out[41]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	48ada52261e7cf58715202705a0451c9	309275	0	10025	2
1	24011ae4ebbe3035111d65fa7c15bc57	0	54946	0	
2	d29c2c54acc38ff3c0614d0a653813dd	4660	0	0	
3	764c75f661154dac3a6c254cd082ea7d	544	0	0	
4	bba03439a292a1e166f80264c16191cb	1584	0	0	

5 rows × 31 columns

In [42]:

```
num_cols = df.nunique()[df.nunique()>=5].keys().tolist()
num_cols = num_cols[1:]
print("Total number of num_cols: "+ str(len(num_cols)) + "\n" + str(num_cols))
```

```
Total number of num_cols: 27
['cons_12m', 'cons_gas_12m', 'cons_last_month', 'forecast_cons_12m', 'foreca
st_cons_year', 'forecast_discount_energy', 'forecast_meter_rent_12m', 'forec
ast_price_energy_p1', 'forecast_price_energy_p2', 'forecast_price_pow_p1',
'imp_cons', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'nb_prod_act', 'ne
t_margin', 'num_years_antig', 'pow_max', 'date_activ_year', 'date_activ_mont
h', 'date_activ_day', 'date_end_month', 'date_end_day', 'date_renewal_mont
h', 'date_renewal_day', 'date_modif_prod_year', 'date_modif_prod_month', 'da
te_modif_prod_day']
```

Here we sort the trainin data and traing output then we take the label from training output and then combine with the traing data

In [43]:

```
#df = df.sort_values(['id'])
dt = dt.sort_values(['id'])
```

In [44]:

```
dt = dt.reset_index(drop=True)
```

In [45]:

```
d = pd.DataFrame(columns=['id', 'churn'])
d['id'] = pd.concat([dt['id'], sm['id']], ignore_index=True )
d['churn'] = pd.concat([dt['churn'], sm['churn']], ignore_index=True )
```

In [46]:

```
d.tail(10)
```

Out[46]:

	id	churn
16086	d10f449cc0f82d572309f2b1d955d9e5	NaN
16087	9d062df9b47c3befc1213c18fd2e4e4d	NaN
16088	087582129b59aaf28fcd19695e59d98f	NaN
16089	cdcfb46db2018af08ac79e9bc3f70c2b	NaN
16090	b564d9a1770b764cb35b3c98ea909aee	NaN
16091	f936975a849901448b282671cd2c3022	NaN
16092	c703d86615fc53e0fc78d2da8da9b5d1	NaN
16093	b9af50f0ec85c23b7c026e14dcc5bb2c	NaN
16094	32302714336600b283cb69b16e65a481	NaN
16095	27c730b7f5ff02371f916e2268f85682	NaN

In [47]:

```
sm.tail(10)
```

Out[47]:

	id	Probability	churn
586	d10f449cc0f82d572309f2b1d955d9e5	NaN	NaN
587	9d062df9b47c3befc1213c18fd2e4e4d	NaN	NaN
588	087582129b59aaf28fcd19695e59d98f	NaN	NaN
589	cdcfb46db2018af08ac79e9bc3f70c2b	NaN	NaN
590	b564d9a1770b764cb35b3c98ea909aee	NaN	NaN
591	f936975a849901448b282671cd2c3022	NaN	NaN
592	c703d86615fc53e0fc78d2da8da9b5d1	NaN	NaN
593	b9af50f0ec85c23b7c026e14dcc5bb2c	NaN	NaN
594	32302714336600b283cb69b16e65a481	NaN	NaN
595	27c730b7f5ff02371f916e2268f85682	NaN	NaN

In [48]:

```
print(d.shape)
print(d.isnull().sum().values)
d = d.sort_values('id')
d = d.reset_index(drop=True)
```

```
(16096, 2)
[  0 596]
```

In [49]:

```
d.head(10)
```

Out[49]:

	id	churn
0	0002203ffbb812588b632b9e628cc38d	0.0
1	0004351ebdd665e6ee664792efc4fd13	NaN
2	0010bcc39e42b3c2131ed2ce55246e3c	0.0
3	0010ee3855fdea87602a5b7aba8e42de	0.0
4	00114d74e963e47177db89bc70108537	0.0
5	00126c87cf78d7604278f0a9adeb689e	0.0
6	0013f326a839a2f6ad87a1859952d227	NaN
7	00184e957277eeef733a7b563fdabd06	0.0
8	001987ed9dbdab4efa274a9c7233e1f4	0.0
9	0019baf3ed1242cd99b3cb592030446f	1.0

In [50]:

```
df = df.sort_values(['id'])
```

In [51]:

```
df = df.reset_index(drop=True)
```

In [52]:

```
df.head(10)
```

Out[52]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	0002203ffbb812588b632b9e628cc38d	22034	0	3084	
1	0004351ebdd665e6ee664792efc4fd13	4060	0	0	
2	0010bcc39e42b3c2131ed2ce55246e3c	7440	0	1062	
3	0010ee3855fdea87602a5b7aba8e42de	4199490	728810	456462	1
4	00114d74e963e47177db89bc70108537	11272	0	0	
5	00126c87cf78d7604278f0a9adeb689e	104657	0	6760	1
6	0013f326a839a2f6ad87a1859952d227	267414	0	19394	
7	00184e957277eeef733a7b563fdabd06	16072	0	5501	
8	001987ed9dbdab4efa274a9c7233e1f4	72346	57630	7654	
9	0019baf3ed1242cd99b3cb592030446f	528	0	150	

10 rows × 31 columns

In [53]:

```
df['churn'] = d['churn']
```

In [54]:

```
df.head()
```

Out[54]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	0002203ffbb812588b632b9e628cc38d	22034	0	3084	
1	0004351ebdd665e6ee664792efc4fd13	4060	0	0	
2	0010bcc39e42b3c2131ed2ce55246e3c	7440	0	1062	
3	0010ee3855fdea87602a5b7aba8e42de	4199490	728810	456462	1
4	00114d74e963e47177db89bc70108537	11272	0	0	

5 rows × 32 columns

In [55]:

```
df.columns.tolist()
```

Out[55]:

```
['id',
 'cons_12m',
 'cons_gas_12m',
 'cons_last_month',
 'forecast_cons_12m',
 'forecast_cons_year',
 'forecast_discount_energy',
 'forecast_meter_rent_12m',
 'forecast_price_energy_p1',
 'forecast_price_energy_p2',
 'forecast_price_pow_p1',
 'has_gas',
 'imp_cons',
 'margin_gross_pow_ele',
 'margin_net_pow_ele',
 'nb_prod_act',
 'net_margin',
 'num_years_antig',
 'pow_max',
 'date_activ_year',
 'date_activ_month',
 'date_activ_day',
 'date_end_year',
 'date_end_month',
 'date_end_day',
 'date_renewal_year',
 'date_renewal_month',
 'date_renewal_day',
 'date_modif_prod_year',
 'date_modif_prod_month',
 'date_modif_prod_day',
 'churn']
```

In [56]:

```
df1 = df
df2 = df
```

In [57]:

```
df1.head()
```

Out[57]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	0002203ffbb812588b632b9e628cc38d	22034	0	3084	
1	0004351ebdd665e6ee664792efc4fd13	4060	0	0	
2	0010bcc39e42b3c2131ed2ce55246e3c	7440	0	1062	
3	0010ee3855fdea87602a5b7aba8e42de	4199490	728810	456462	1
4	00114d74e963e47177db89bc70108537	11272	0	0	

5 rows × 32 columns

In [58]:

```
df1 = df1.dropna(subset=['churn'])
```

In [59]:

```
df1.head()
```

Out[59]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_co
0	0002203ffbb812588b632b9e628cc38d	22034	0	3084	
2	0010bcc39e42b3c2131ed2ce55246e3c	7440	0	1062	
3	0010ee3855fdea87602a5b7aba8e42de	4199490	728810	456462	1
4	00114d74e963e47177db89bc70108537	11272	0	0	
5	00126c87cf78d7604278f0a9adeb689e	104657	0	6760	1

5 rows × 32 columns

In [60]:

```
count=0
c=0
for i in df1.churn:
    if(i==0):
        count+=1
    else:
        c+=1
print(count, c)
```

```
13957 1543
```

In [61]:

```
df1.shape
```

Out[61]:

```
(15500, 32)
```

Here, we take all row with Null value in churn column and It will taken for final prediction

In [62]:

```
df2 = df2[df2["churn"].isnull()]
```

In [63]:

```
df2.head()
```

Out[63]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_cc
1	0004351ebdd665e6ee664792efc4fd13	4060	0	0	
6	0013f326a839a2f6ad87a1859952d227	267414	0	19394	
16	002dc7935f7b6f855aaa3d1bd242ab9a	6542	0	951	
21	003fb333060c256bff67d8d550bff1fa	10026	19143	817	
68	00ccb1f5828d8ed38e8be755e092eb9a	642	0	141	

5 rows × 32 columns

In [64]:

```
df2 = df2.reset_index(drop=True)
```

In [65]:

```
df2.head()
```

Out[65]:

	id	cons_12m	cons_gas_12m	cons_last_month	forecast_coı
0	0004351ebdd665e6ee664792efc4fd13	4060	0	0	
1	0013f326a839a2f6ad87a1859952d227	267414	0	19394	
2	002dc7935f7b6f855aaa3d1bd242ab9a	6542	0	951	
3	003fb333060c256bff67d8d550bff1fa	10026	19143	817	
4	00ccb1f5828d8ed38e8be755e092eb9a	642	0	141	

5 rows × 32 columns

In [66]:

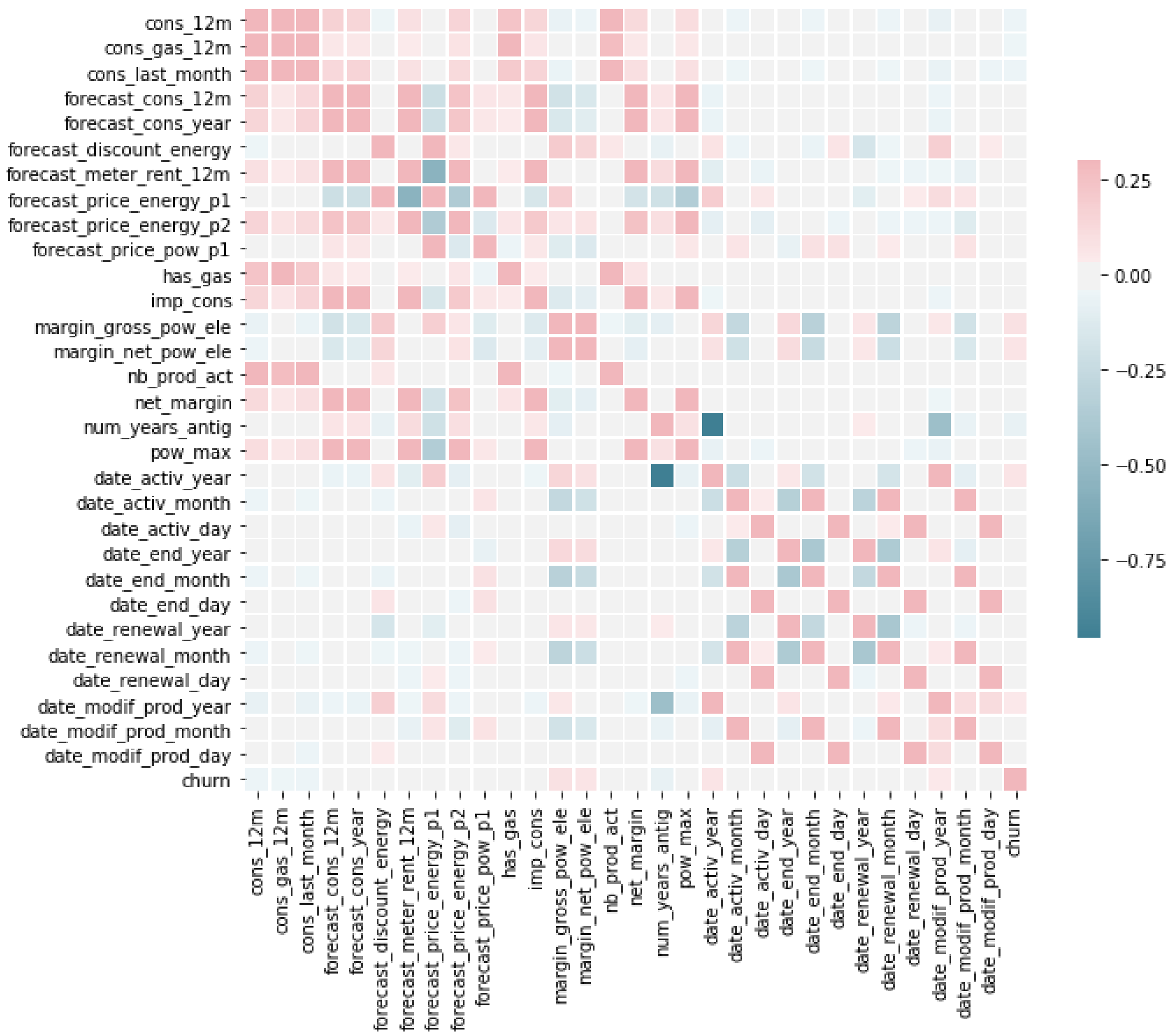
```
### correlation heatmap

plt.figure(figsize=(10,10))
corr = df1.corr()
mask = np.zeros_like(corr, dtype=np.bool)

cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[66]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x190f7ee7b00>
```



In [67]:

```
df1.corr()
```

Out[67]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	fore
cons_12m	1.000000	0.477361	0.917428	0.166022	
cons_gas_12m	0.477361	1.000000	0.449811	0.058296	
cons_last_month	0.917428	0.449811	1.000000	0.129460	
forecast_cons_12m	0.166022	0.058296	0.129460	1.000000	
forecast_cons_year	0.139565	0.056503	0.151420	0.745286	
forecast_discount_energy	-0.043176	-0.013331	-0.037131	0.012976	
forecast_meter_rent_12m	0.089812	0.040846	0.079341	0.390971	
forecast_price_energy_p1	-0.034438	-0.022285	-0.025083	-0.213989	
forecast_price_energy_p2	0.147845	0.076456	0.123167	0.240848	
forecast_price_pow_p1	-0.023727	-0.026969	-0.019231	0.060746	
has_gas	0.232466	0.373189	0.203973	0.058512	
imp_cons	0.139631	0.059637	0.154038	0.724287	
margin_gross_pow_ele	-0.065400	-0.015698	-0.053750	-0.189968	
margin_net_pow_ele	-0.045223	-0.007031	-0.037013	-0.145575	
nb_prod_act	0.315031	0.274279	0.355997	0.011149	
net_margin	0.120219	0.058210	0.096236	0.765657	
num_years_antig	0.008771	-0.008755	0.003850	0.064690	
pow_max	0.106156	0.051580	0.092597	0.584290	
date_activ_year	0.013938	0.015112	0.015715	-0.056429	
date_activ_month	-0.047792	-0.020508	-0.042188	-0.018435	
date_activ_day	-0.030793	-0.011392	-0.032126	-0.016374	
date_end_year	-0.009331	0.015534	-0.004682	-0.007626	
date_end_month	-0.050323	-0.010941	-0.043495	-0.028114	
date_end_day	-0.014747	-0.010424	-0.015356	-0.013385	
date_renewal_year	0.005213	0.016078	0.007705	-0.026403	
date_renewal_month	-0.047292	-0.011240	-0.041561	-0.014293	
date_renewal_day	-0.011604	-0.007240	-0.010851	-0.016822	
date_modif_prod_year	-0.071371	-0.029324	-0.064186	-0.052529	
date_modif_prod_month	-0.038565	-0.018128	-0.038740	-0.002197	
date_modif_prod_day	-0.038053	-0.028767	-0.044417	-0.002853	
churn	-0.051590	-0.040832	-0.046464	0.006797	

31 rows × 31 columns

Creating X and y variables

In [68]:

```
df_dum = df1.drop(['id'],axis=1)
```

In [69]:

```
### spliting into train and test set. fitting into linear regression model
X = df_dum.drop(['churn'], axis=1)
Y = df_dum['churn']
```

In [70]:

```
#X_train, X_test, Y_train, Y_test = train_test_split(X, y,test_size=0.2,random_state=5)
```

K-Fold CV

In [73]:

```
cv = KFold(n_splits=5, random_state=42, shuffle=True)
for train_index, test_index in cv.split(X):
    print("Train Index: ", train_index, "\n")
    print("Test Index: ", test_index)

    X_train, X_test, Y_train, Y_test = X.iloc[train_index], X.iloc[test_index], Y.iloc[trai
```

```
Train Index:  [    1     2     4 ... 15496 15497 15499]

Test Index:  [    0     3     8 ... 15485 15490 15498]
Train Index:  [    0     1     2 ... 15497 15498 15499]

Test Index:  [   10    17    23 ... 15469 15481 15494]
Train Index:  [    0     1     2 ... 15496 15497 15498]

Test Index:  [   12    20    26 ... 15493 15495 15499]
Train Index:  [    0     1     3 ... 15497 15498 15499]

Test Index:  [    2     6     7 ... 15489 15491 15496]
Train Index:  [    0     2     3 ... 15496 15498 15499]

Test Index:  [    1     4     5 ... 15480 15483 15497]
```

In [74]:

```
count=0
c=0
for i in Y_train:
    if(i==0):
        count+=1
    else:
        c+=1
print('No. of 0:',count,'\n','No. 0f 1:', c)
```

```
No. of 0: 11197
 No. 0f 1: 1203
```

In [75]:

```
#X_train = X
#Y_train = y
X_t = df2.drop(['id', 'churn'], axis=1)
```

Feature Scaling

In [76]:

```
sc = StandardScaler()

std_scale = sc.fit(X_train)
X_train = std_scale.transform(X_train)
X_test = std_scale.transform(X_test)
X_t = std_scale.transform(X_t)
```

In [77]:

```
#X_test.head()
```

LogisticRegression

In [94]:

```
### model fitting using logistic regression

lm = LogisticRegression(max_iter=10000)
fitted = lm.fit(X_train, Y_train)
pred = lm.predict(X_test)
scores = round(lm.score(X_test,Y_test)* 100, 2)
print("Logistic Regression score is.:" + str(lm.score(X_test,Y_test)))
print(classification_report(Y_test,pred))
```

```
Logistic Regression score is.:0.8903225806451613
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94      2760
        1.0       0.00      0.00      0.00       340

avg / total       0.79      0.89      0.84      3100
```

Support vector machine Classifier

In [95]:

```
### model fitting with SVC

svc = SVC(kernel = 'rbf', random_state = 0)
svc.fit(X_train, Y_train)
svc_pred = svc.predict(X_test)
svc_scores = round(svc.score(X_test,Y_test)* 100, 2)
print("SVC Regression scores is..:" + str(svc.score(X_test,Y_test)))
print(classification_report(Y_test,svc_pred))
```

```
SVC Regression scores is..:0.89
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94      2760
        1.0       0.00      0.00      0.00       340

avg / total       0.79      0.89      0.84      3100
```

Linear Support vector machine classifier

In [96]:

```
### model fitting using SVM svc

svm = LinearSVC(max_iter=10000)
svm_fitted = svm.fit(X_train, Y_train)
svm_pred = svm.predict(X_test)
svm_scores = round(svm.score(X_test,Y_test)* 100, 2)
print("SVM Regression scores is..:" + str(svm.score(X_test,Y_test)))
print(classification_report(Y_test,svm_pred))
```

```
SVM Regression scores is..:0.8903225806451613
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94      2760
        1.0       0.00      0.00      0.00       340

avg / total       0.79      0.89      0.84      3100
```

KNeighborsClassifier

In [81]:

```
knn = KNeighborsClassifier(n_neighbors =4)
knn.fit(X_train, Y_train)
Y_predknn = knn.predict(X_test)
acc_knn = round(knn.score(X_train, Y_train) * 100, 2)
print(" KNeighborsClassifier scores is..:" + str(acc_knn))
print(classification_report(Y_test,Y_predknn))
```

```
 KNeighborsClassifier scores is..:90.97
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94      2760
        1.0       0.55      0.04      0.07       340

avg / total       0.86      0.89      0.85      3100
```

Gaussian Naive Byes

In [82]:

```
gaussian = GaussianNB()
gaussian.fit(X_train, Y_train)
Y_predG = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(X_train, Y_train) * 100, 2)
print(" Gaussian Naive Bayes scores is..:" + str(acc_gaussian))
print(classification_report(Y_test,Y_predG))
```

```
 Gaussian Naive Bayes scores is..:56.25
             precision    recall  f1-score   support

        0.0       0.92      0.57      0.71      2760
        1.0       0.15      0.62      0.24       340

avg / total       0.84      0.58      0.66      3100
```

Perceptron

In [83]:

```
perceptron = Perceptron(max_iter=10000)
perceptron.fit(X_train, Y_train)
Y_predP = perceptron.predict(X_test)
acc_perceptron = round(perceptron.score(X_train, Y_train) * 100, 2)
print(" Perceptron scores is..:" + str(acc_perceptron))
print(classification_report(Y_test,Y_predP))
```

```
 Perceptron scores is..:83.81
             precision    recall  f1-score   support

        0.0       0.89      0.91      0.90      2760
        1.0       0.11      0.09      0.10       340

avg / total       0.80      0.82      0.81      3100
```

stochastic gradient descent

In [84]:

```
sgd = SGDClassifier(max_iter=10000)
sgd.fit(X_train, Y_train)
Y_predsgd = sgd.predict(X_test)
acc_sgd = round(sgd.score(X_train, Y_train) * 100, 2)
print(" Stochastic Gradient Descent scores is..:" + str(acc_sgd))
print(classification_report(Y_test,Y_predsgd))
```

```
 Stochastic Gradient Descent scores is..:90.3
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94      2760
        1.0       0.00      0.00      0.00       340

avg / total       0.79      0.89      0.84      3100
```

Decision tree

In [85]:

```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
Y_preddt = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(X_train, Y_train) * 100, 2)
print(" decision_tree scores is..:" + str(acc_decision_tree))
print(classification_report(Y_test,Y_preddt))
```

```
 decision_tree scores is..:100.0
             precision    recall  f1-score   support

        0.0       0.91      0.90      0.91      2760
        1.0       0.26      0.28      0.27       340

avg / total       0.84      0.84      0.84      3100
```

Random Forest

In [86]:

```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, Y_train)
Y_predrf = random_forest.predict(X_test)
random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
print(" random_forest scores is..:" + str(acc_random_forest))
print(classification_report(Y_test,Y_predrf))
```

```
 random_forest scores is..:99.99
             precision    recall  f1-score   support

        0.0       0.90      1.00      0.95      2760
        1.0       0.79      0.09      0.16       340

avg / total       0.89      0.90      0.86      3100
```

AdaBoostClassifier

In [87]:

```
from sklearn  import ensemble
adaboost =ensemble.AdaBoostClassifier()
adaboost.fit(X_train, Y_train)
Y_preda = adaboost.predict(X_test)
adaboost = round(adaboost.score(X_train, Y_train) * 100, 2)
print(" random_forest scores is..:" + str(adaboost))
print(classification_report(Y_test,Y_preda))
```

```
 random_forest scores is..:90.35
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94      2760
        1.0       0.33      0.01      0.01       340

avg / total       0.83      0.89      0.84      3100
```

DecisionTreeClassifier for Prediction

This machine learning alogorithm makes prediction of SAMPLE_OUTPUT

In [88]:

```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
Y_predd = decision_tree.predict(X_t)
churn_prob = decision_tree.predict_proba(X_t)
for i, enum in enumerate(Y_predd[:6]):
    print(i, enum)
```

```
0 0.0
1 1.0
2 0.0
3 0.0
4 0.0
5 0.0
```

Model Comparision

In [168]:

```
models = pd.DataFrame({
    'Model': ['SVM', 'KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes', 'Perceptron',
              'SGD', 'Linear SVC',
              'Decision Tree', 'Adaboost'],
    'Score': [svm_scores, acc_knn, scores,
              acc_random_forest, acc_gaussian, acc_perceptron,
              acc_sgd, svm_scores, acc_decision_tree, adaboost]})
m = models.sort_values(by='Score', ascending=False)
m.reset_index(drop=True)
```

Out[168]:

	Model	Score
0	Decision Tree	100.00
1	Random Forest	99.99
2	KNN	90.97
3	Adaboost	90.35
4	SGD	90.30
5	SVM	89.03
6	Logistic Regression	89.03
7	Linear SVC	89.03
8	Perceptron	83.81
9	Naive Bayes	56.25

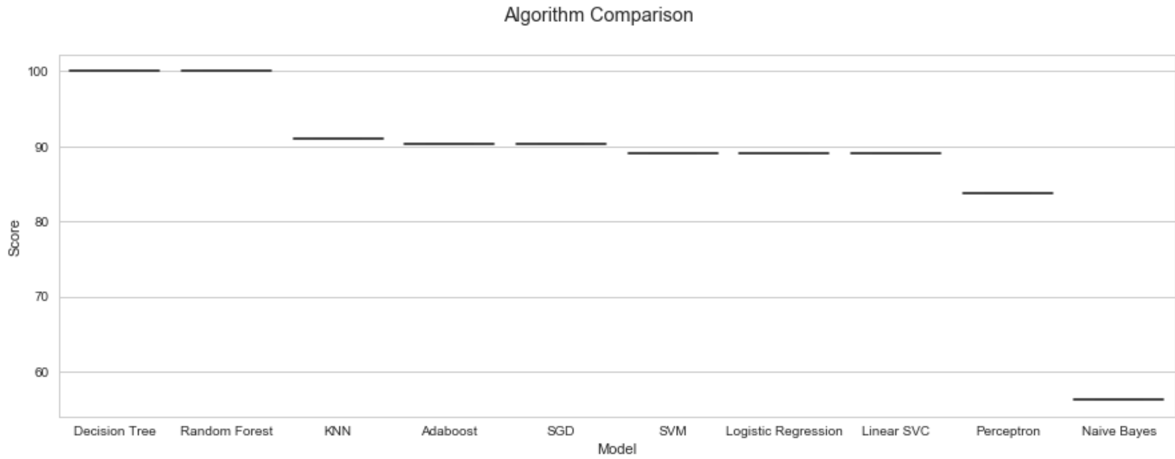
In [169]:

```
mod = []
soc = []
for i in m['Model']:
    mod.append(i)
for i in m['Score']:
    soc.append(i)
print(mod)
print(soc)
```

```
['Decision Tree', 'Random Forest', 'KNN', 'Adaboost', 'SGD', 'SVM', 'Logisti
c Regression', 'Linear SVC', 'Perceptron', 'Naive Bayes']
[100.0, 99.99, 90.97, 90.35, 90.3, 89.03, 89.03, 89.03, 83.81, 56.25]
```

In [178]:

```
# boxplot algorithm comparison
sns.set(style="whitegrid")
fig = plt.figure(figsize=(15,5))
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
sns.boxplot(x='Model',y='Score', data=m)
ax.set_xticklabels(mod)
plt.show()
```



Make dataframe & Submisson Result

In [89]:

```
prediction_df = pd.DataFrame(df2['id'], columns=['id', 'churn'])
prediction_df['churn'] = churn_prob[:,1]
prediction_df.to_csv('submission.csv', index=False)
```

In [90]:

```
prediction_df.head()
```

Out[90]:

	id	churn
0	0004351ebdd665e6ee664792efc4fd13	0.0
1	0013f326a839a2f6ad87a1859952d227	1.0
2	002dc7935f7b6f855aaa3d1bd242ab9a	0.0
3	003fb333060c256bff67d8d550bff1fa	0.0
4	00ccb1f5828d8ed38e8be755e092eb9a	0.0