BCGX_churn

July 14, 2025

1 BCGX PowerCo Churn Analysis and Modeling

This project was completed as a part of BCG Data Science Job Simulation. Task for this project is to assist client PowerCo in churn analysis and modeling and analyze whether Price Senstivity is a major contributing factor for Customer Churn. Price Senstivity is defined as Change in Demand/Change in Price for this project. Throughout the project we followed BCGX guidance and completed steps as a Data Scientist would during the job at BCG.

Besides that, we have performed our own additional EDA and Churn Modeling, with our best model better than BCGX Model Answer by several times, five time better in F1 Score and 10 times better in recall performance as BCGX used a simple Random Forest while we used Gradient Boosting algorithm with hyper parameter tuning, Dense Neueral Network, and a BiDirectional LSTM-CNN models. Among them XGBoost model performed best and this corresponds to the industry norm where gradient boosting and other boosting algorithms worked better in structured tabular dataset, provided that we have limited data.

This project will be divided into following steps: 1. EDA and Feature Engineering 2. Model Training, Hyperparameter Tuning, and Evaluation 3. Conclusion

1.1 EDA and Feature Engineering

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1. Import packages
2. Load data
3. Feature engineering alongside indepth Analysis

1.2 1. Import packages

[1]:
```
#required packages

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.metrics import roc_curve, roc_auc_score, classification_report,␣
↪confusion_matrix, f1_score
from sklearn.model_selection import GridSearchCV
```

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
import tensorflow as tf
from tensorflow.keras.layers import Dense
from tensorflow.keras import Sequential
from tensorflow.keras.initializers import HeNormal
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.layers import Activation
from tensorflow.keras.layers import Masking, Bidirectional, LSTM, Conv1D,␣
↪GlobalMaxPooling1D, Dense, Dropout, Input
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping

import warnings
warnings.filterwarnings('ignore')
```

1.3 2. Load data

We have been given two datasets for this task. One contain Clients data and other contains Monthly Price data for clients over an year.Through out the EDA we will cover all the necessary columns for both datasets.

[ ]:
```
EDA and Feature Engineering
```

[2]:
```python
df = pd.read_csv('./clean_data_after_eda.csv')
df["date_activ"] = pd.to_datetime(df["date_activ"], format='%Y-%m-%d')
df["date_end"] = pd.to_datetime(df["date_end"], format='%Y-%m-%d')
df["date_modif_prod"] = pd.to_datetime(df["date_modif_prod"], format='%Y-%m-%d')
df["date_renewal"] = pd.to_datetime(df["date_renewal"], format='%Y-%m-%d')
```

[3]:
```python
df.head()
```

[3]:
```
                                 id                     channel_sales  \
0  24011ae4ebbe3035111d65fa7c15bc57  foosdfpfkusacimwkcsosbicdxkicaua
1  d29c2c54acc38ff3c0614d0a653813dd                           MISSING
2  764c75f661154dac3a6c254cd082ea7d  foosdfpfkusacimwkcsosbicdxkicaua
3  bba03439a292a1e166f80264c16191cb  lmkebamcaaclubfxadlmueccxoimlema
4  149d57cf92fc41cf94415803a877cb4b                           MISSING

   cons_12m  cons_gas_12m  cons_last_month date_activ   date_end  \
0         0         54946                0 2013-06-15 2016-06-15
1      4660             0                0 2009-08-21 2016-08-30
2       544             0                0 2010-04-16 2016-04-16
3      1584             0                0 2010-03-30 2016-03-30
```

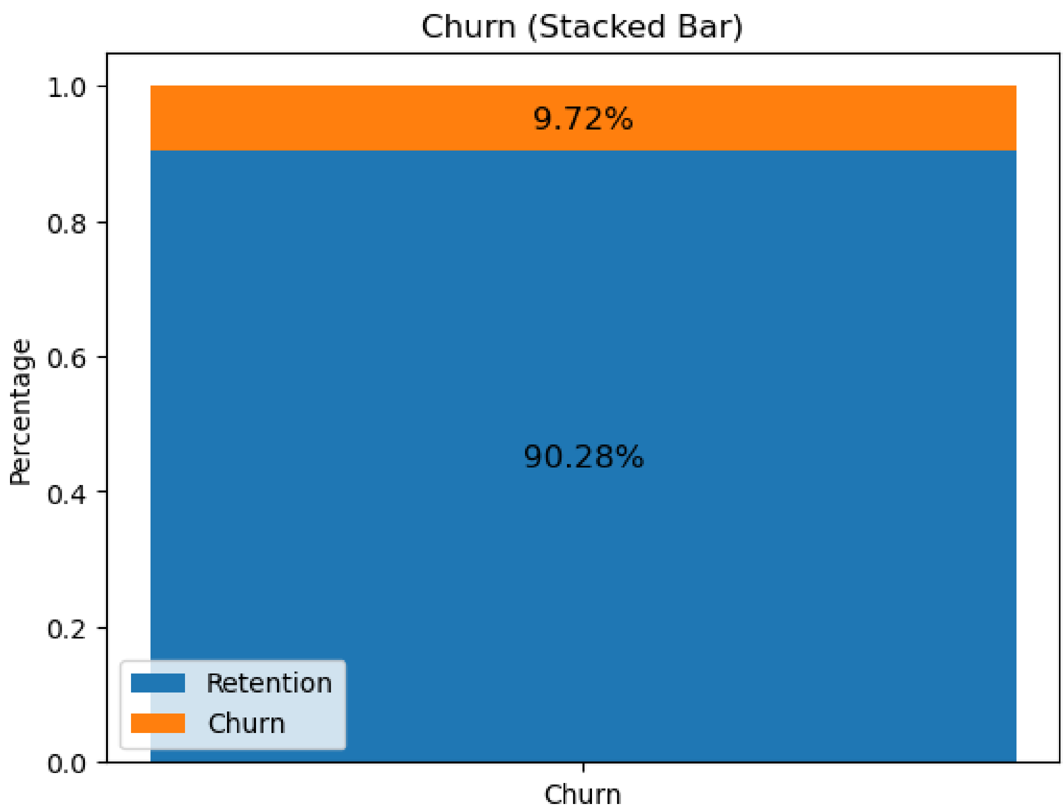
```
4      4425            0             526 2010-01-13 2016-03-07

  date_modif_prod date_renewal  forecast_cons_12m  …  \
0      2015-11-01   2015-06-23               0.00  …
1      2009-08-21   2015-08-31             189.95  …
2      2010-04-16   2015-04-17              47.96  …
3      2010-03-30   2015-03-31             240.04  …
4      2010-01-13   2015-03-09             445.75  …

   var_6m_price_off_peak_var  var_6m_price_peak_var  \
0                   0.000131           4.100838e-05
1                   0.000003           1.217891e-03
2                   0.000004           9.450150e-08
3                   0.000003           0.000000e+00
4                   0.000011           2.896760e-06

   var_6m_price_mid_peak_var  var_6m_price_off_peak_fix  \
0               9.084737e-04                   2.086294
1               0.000000e+00                   0.009482
2               0.000000e+00                   0.000000
3               0.000000e+00                   0.000000
4               4.860000e-10                   0.000000

   var_6m_price_peak_fix  var_6m_price_mid_peak_fix var_6m_price_off_peak  \
0              99.530517                  44.235794              2.086425
1               0.000000                   0.000000              0.009485
2               0.000000                   0.000000              0.000004
3               0.000000                   0.000000              0.000003
4               0.000000                   0.000000              0.000011

   var_6m_price_peak  var_6m_price_mid_peak  churn
0       9.953056e+01           4.423670e+01      1
1       1.217891e-03           0.000000e+00      0
2       9.450150e-08           0.000000e+00      0
3       0.000000e+00           0.000000e+00      0
4       2.896760e-06           4.860000e-10      0

[5 rows x 44 columns]
```

[4]:
```python
#We will start with overall churn rate
df_temp_churn = df['churn'].value_counts(normalize = True).reset_index()
df_temp_churn
```

[4]:
```
   churn  proportion
0      0    0.902848
1      1    0.097152
```

[5]:

```
#before going further we will see the churn percentages

plt.bar('Churn', df_temp_churn.iloc[0,1], label = 'Retention')
plt.bar('Churn', df_temp_churn.iloc[1,1], bottom = df_temp_churn.iloc[0,1]␣
↪,label = 'Churn')
plt.ylabel('Percentage')
plt.title('Churn (Stacked Bar)')
plt.text('Churn', df_temp_churn.iloc[0,1]/2, f"{df_temp_churn.iloc[0,1]:.2%}",␣
↪ha='center', va='center', color='black', fontsize=12)
plt.text('Churn', df_temp_churn.iloc[0,1] + df_temp_churn.iloc[1,1]/2,␣
↪f"{df_temp_churn.iloc[1,1]:.2%}", ha='center', va='center', color='black',␣
↪fontsize=12)
plt.legend()
plt.show()
```

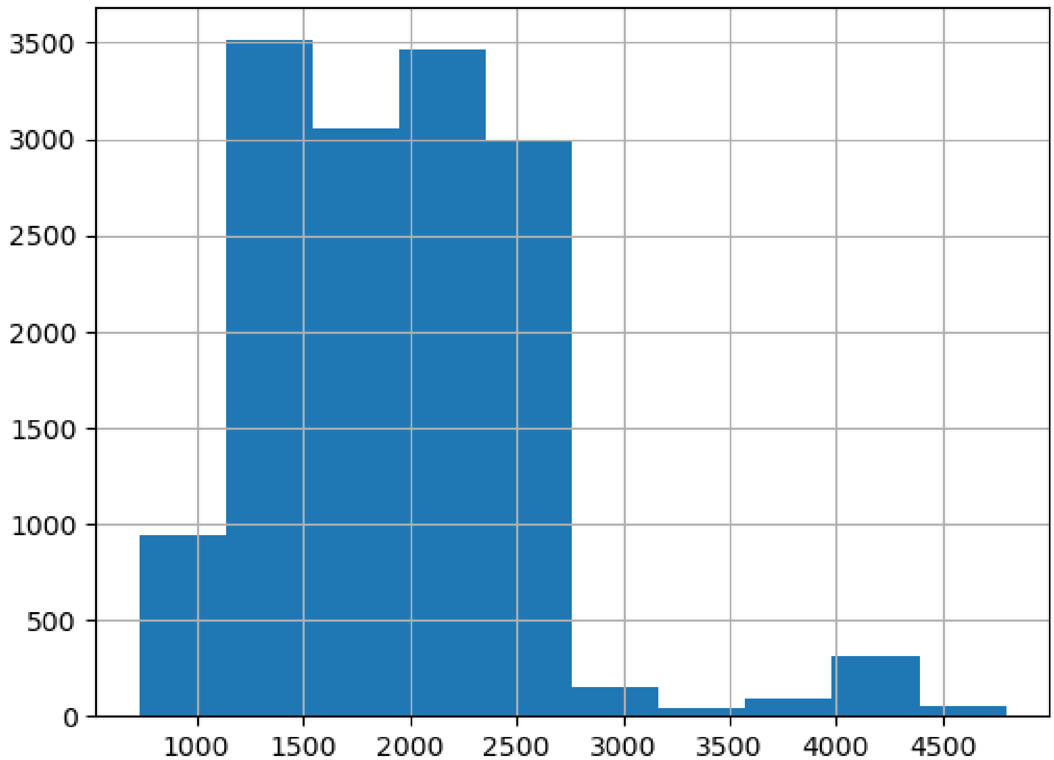


Overall, we have 9.72% churn rate which is more than what client expected. Our goal of this analysis is to study the dataset, observe the relationship between Churn and predictors, and make a predictive model for the client.

1.3.1 Date Analysis

[6]:
```
#Analyzing dates data
df['tenure'] = (df['date_end'] - df['date_activ']).dt.days #creating tenure␣
↪parameter
```

[7]:
```
df['tenure'].hist()
plt.show()
```



[8]:
```
def plot_distribution(dataframe, column, ax, bins_=50):
    """
    Plot variable distribution in a stacked histogram of churned or retained␣
↪company
    """
    # Create a temporal dataframe with the data to be plot
    temp = pd.DataFrame({"Retention": dataframe[dataframe["churn"]==0][column],
    "Churn":dataframe[dataframe["churn"]==1][column]})
    # Plot the histogram
    temp[["Retention","Churn"]].plot(kind='hist', bins=bins_, ax=ax,␣
↪stacked=True)
    # X-axis label
    ax.set_xlabel(column)
```

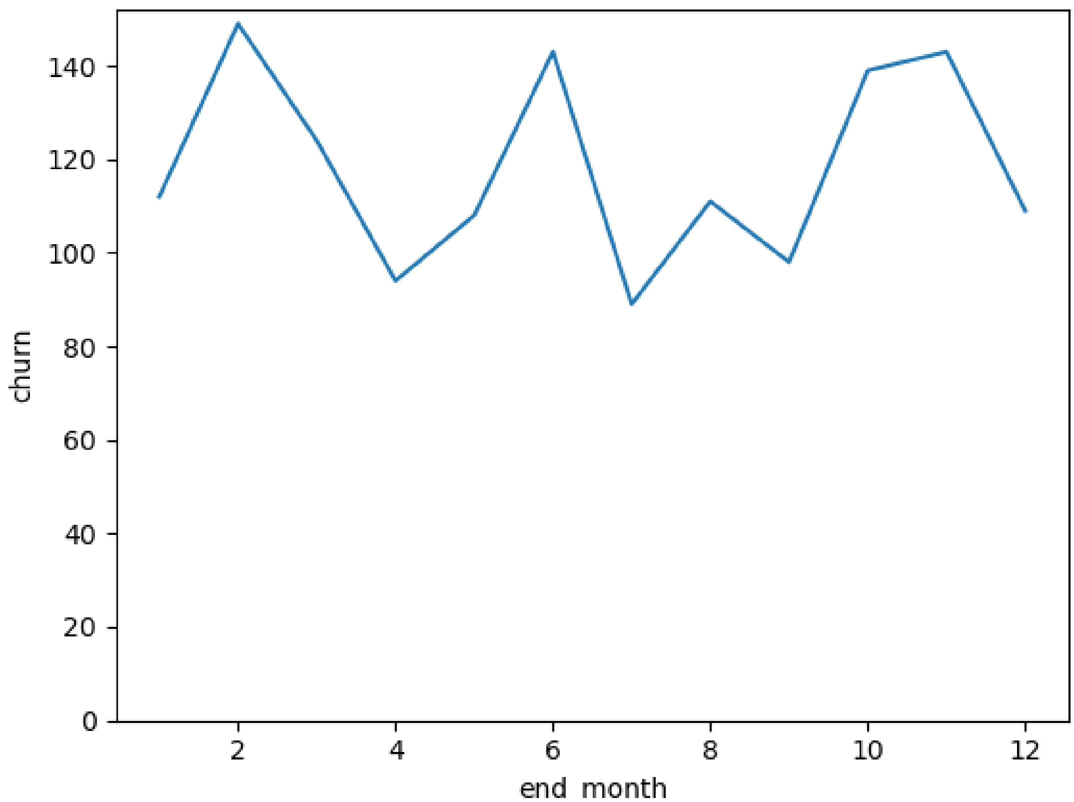
```python
    # Change the x-axis to plain style
    ax.ticklabel_format(style='plain', axis='x')
```

[9]:
```python
#Columns deemed not necessary for the task
df.drop(columns = ['date_modif_prod', 'date_renewal'], inplace = True)
```

[10]:
```python
#creating ending month column to see if some months have more churn than others
df['end_month'] = df['date_end'].dt.month
df.drop(columns = ['date_activ', 'date_end'], inplace = True)
```

[11]:
```python
print(df.groupby('end_month').sum()['churn'])
sns.lineplot(data = df.groupby('end_month').sum()['churn'].reset_index(), x =␣
 ↪'end_month', y = 'churn')
plt.ylim(bottom = 0)
plt.show()
```

```
end_month
1     112
2     149
3     124
4      94
5     108
6     143
7      89
8     111
9      98
10    139
11    143
12    109
Name: churn, dtype: int64
```



We are able to see three modes or peaks for churns happening across the years, February, June, and November. This signify that while churn happens across the year it peaks at the start of the year, in middle, and then in the end of the year with little variablity across them.

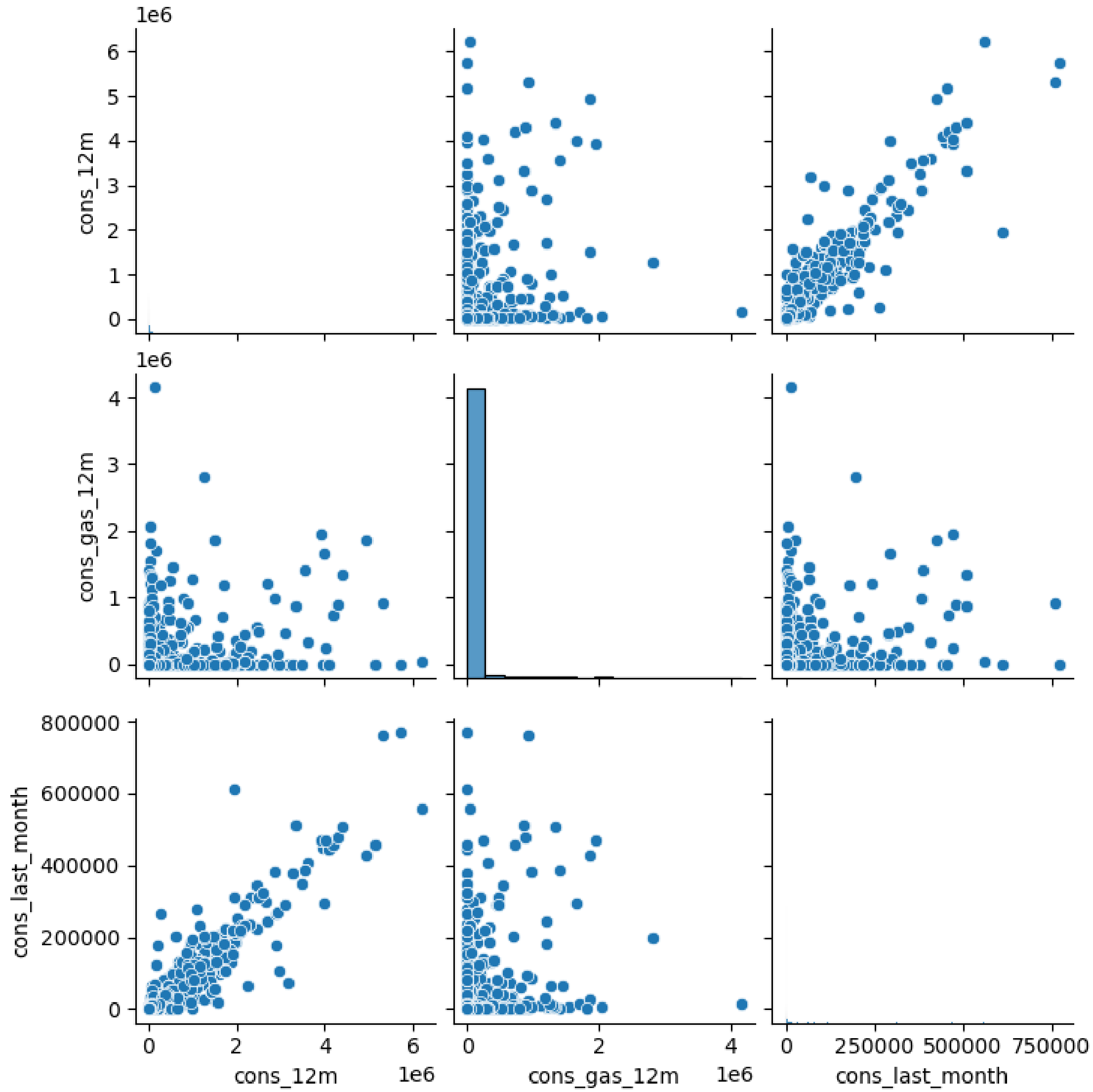
1.3.2 Consumption Variables

[12]:
```
df.filter(regex = '^cons_').corr()
```

[12]:

	cons_12m	cons_gas_12m	cons_last_month
cons_12m	1.000000	0.488474	0.968212
cons_gas_12m	0.488474	1.000000	0.507007
cons_last_month	0.968212	0.507007	1.000000

[13]:
```
sns.pairplot(df.filter(regex = '^cons_'))
plt.show()
```

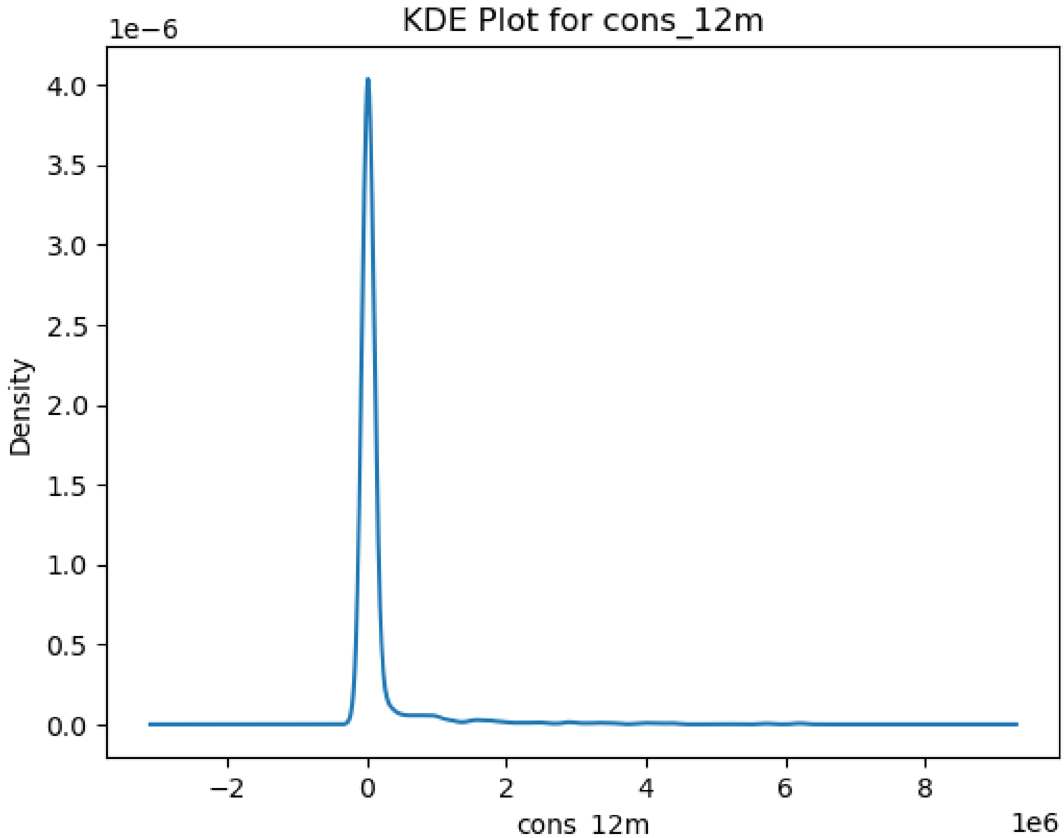


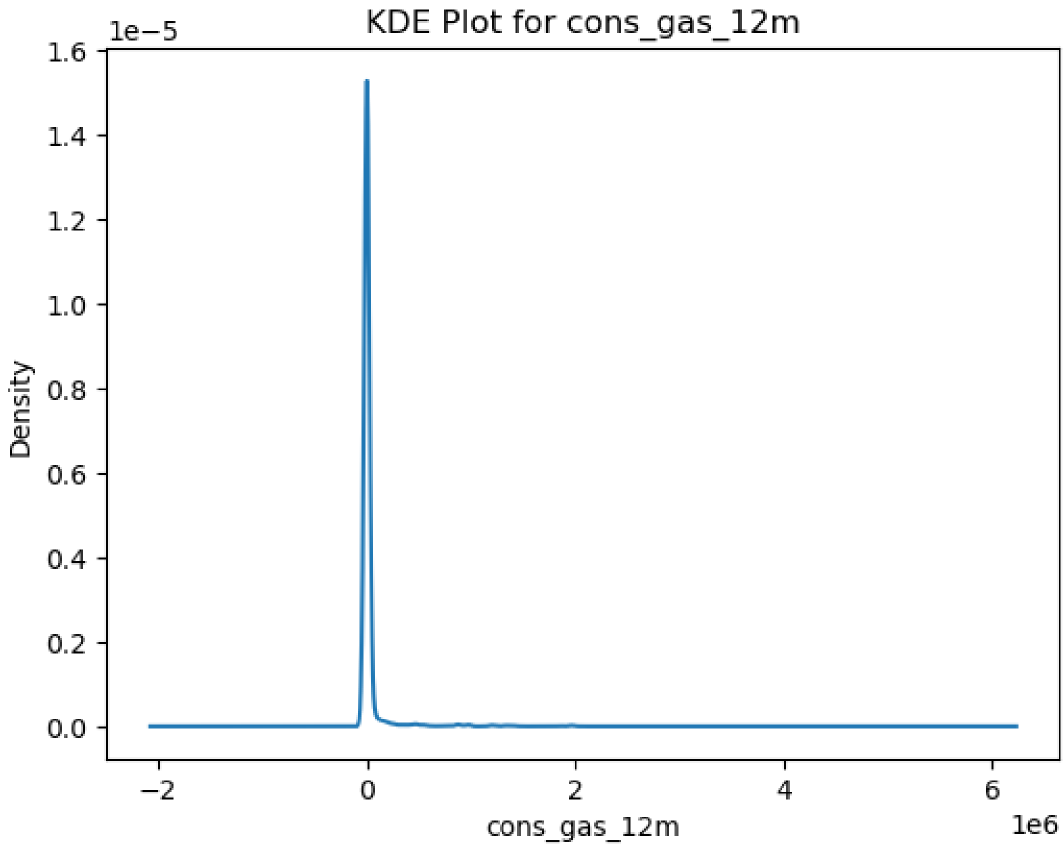
[14]:
```python
df.filter(regex = '^cons_').corr()
```

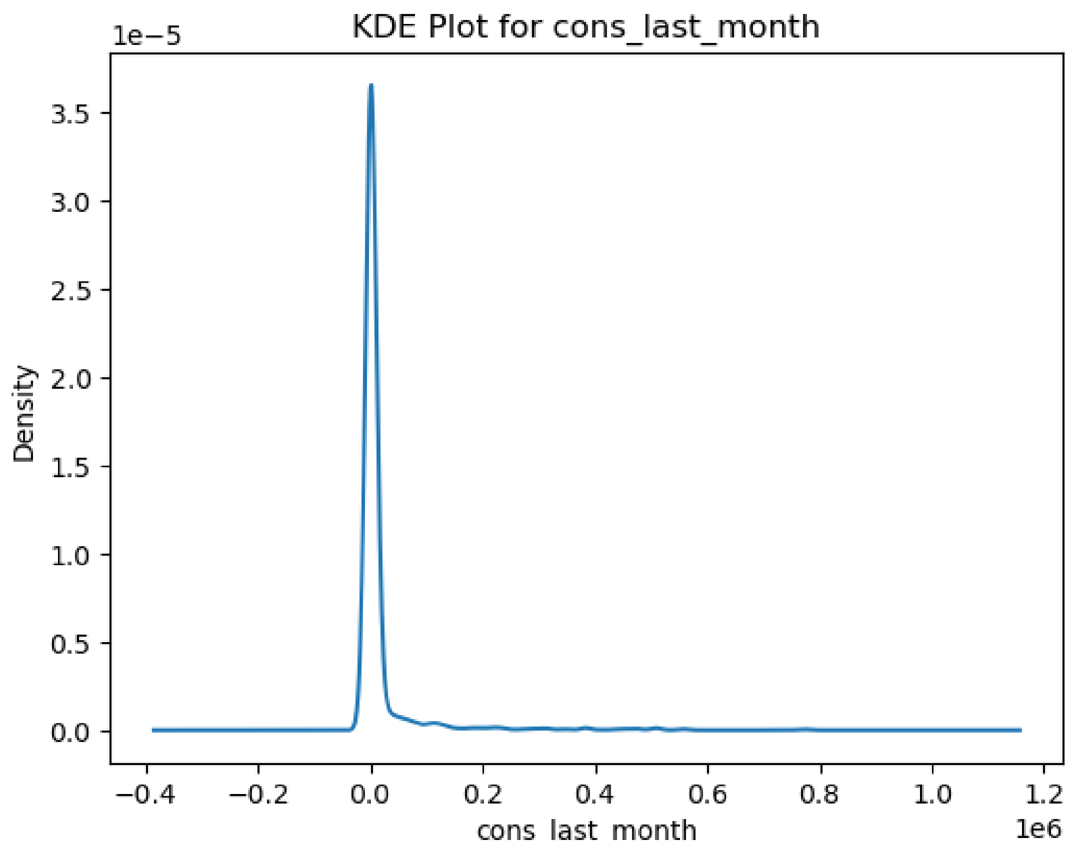
[14]:

	cons_12m	cons_gas_12m	cons_last_month
cons_12m	1.000000	0.488474	0.968212
cons_gas_12m	0.488474	1.000000	0.507007
cons_last_month	0.968212	0.507007	1.000000

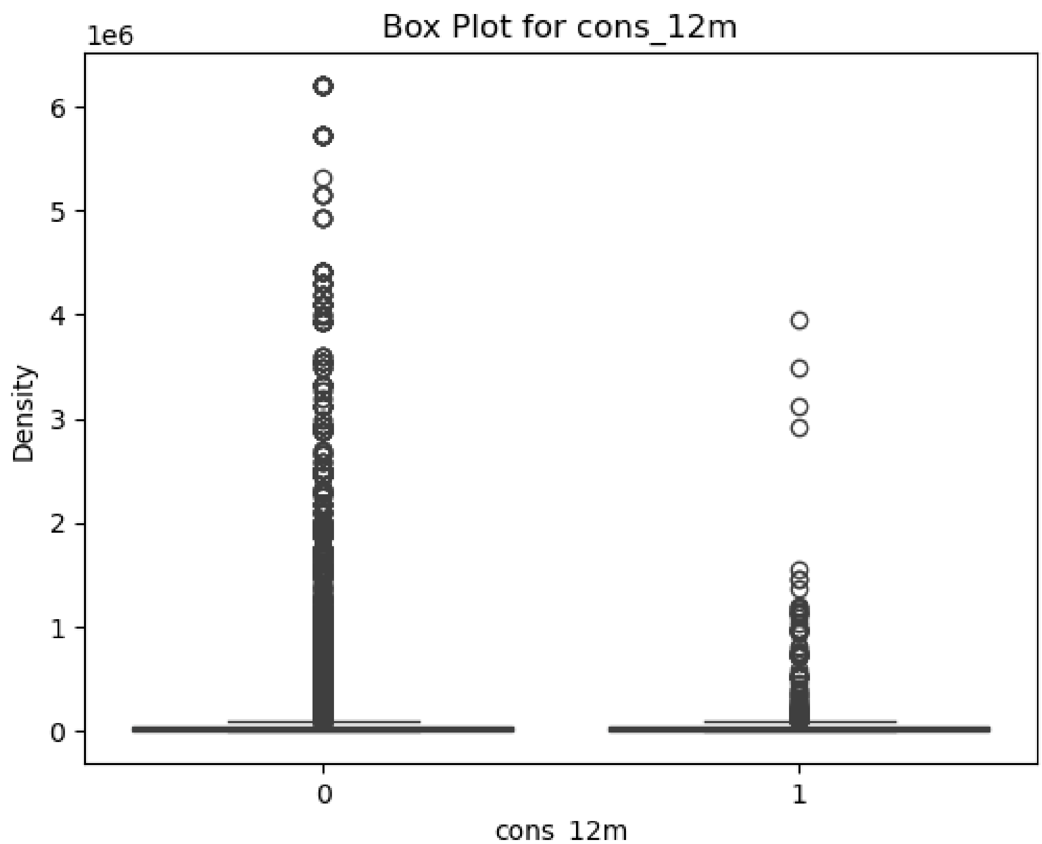
[15]:
```python
for col in df.filter(regex = '^cons_'):
    df[col].plot.kde()
    plt.title(f'KDE Plot for {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.show()
```


KDE Plot for cons_12m
1e−6
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Density
−2
0
2
4
6
8
cons_12m
1e6

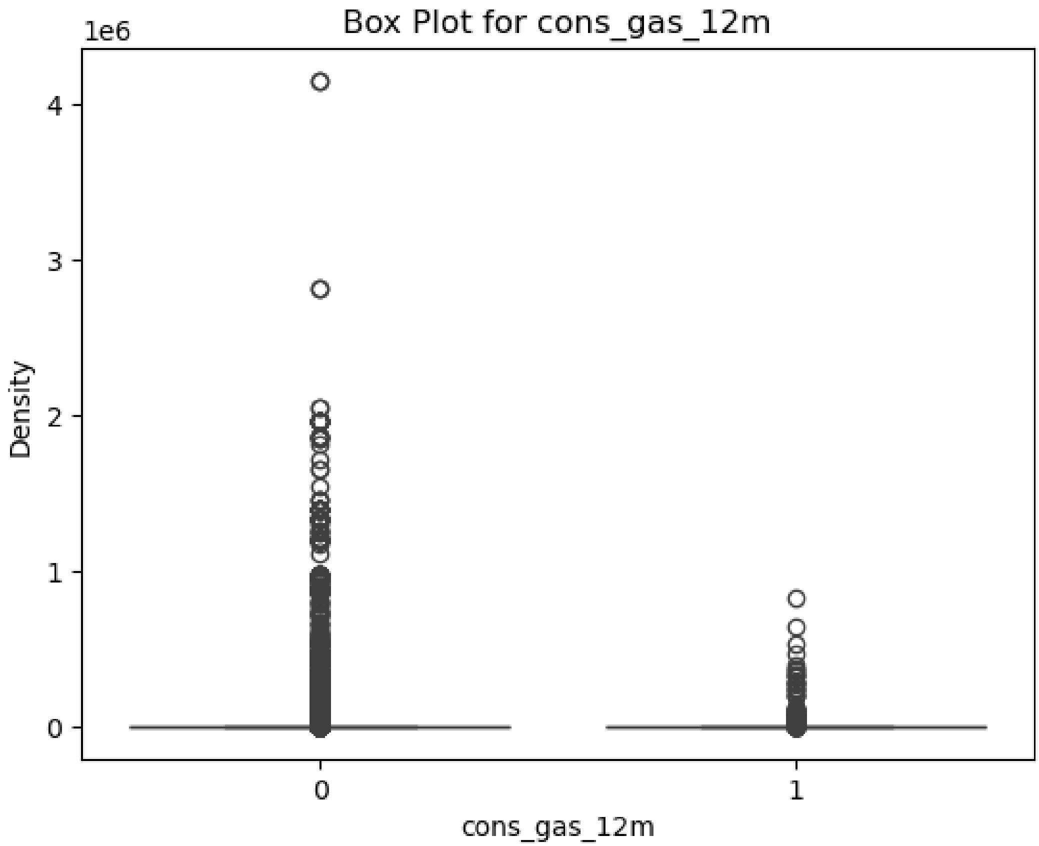

KDE Plot for cons_gas_12m
1e−5
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Density
−2
0
2
4
6
1e6
cons_gas_12m



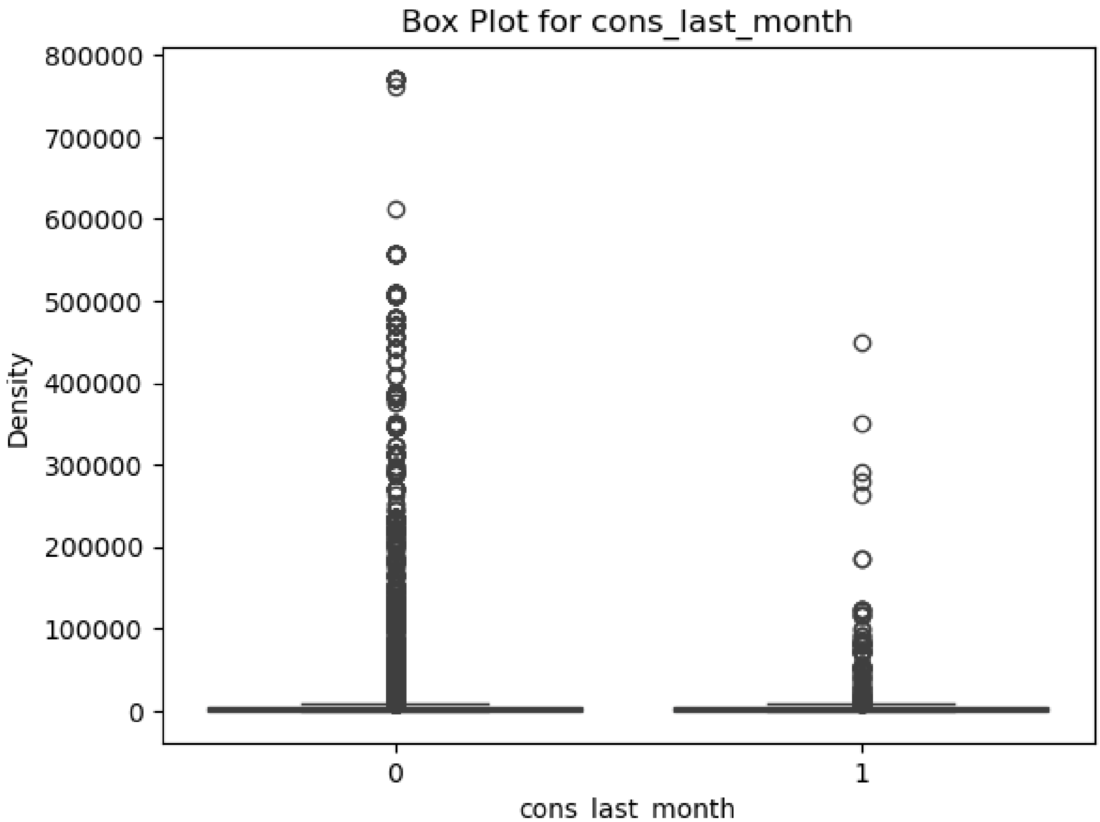
[16]:
```
for col in df.filter(regex = '^cons_'):
    plt.figure()
    sns.boxplot(x = df['churn'], y = df[col])
    plt.title(f'Box Plot for {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.show()
```



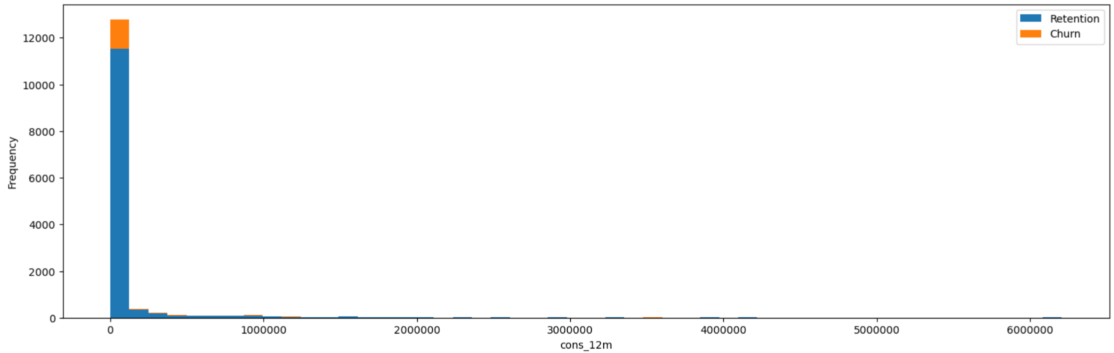
Box Plot for cons_12m
1e6
6
5
4
3
2
1
0
Density
0
1
cons_12m

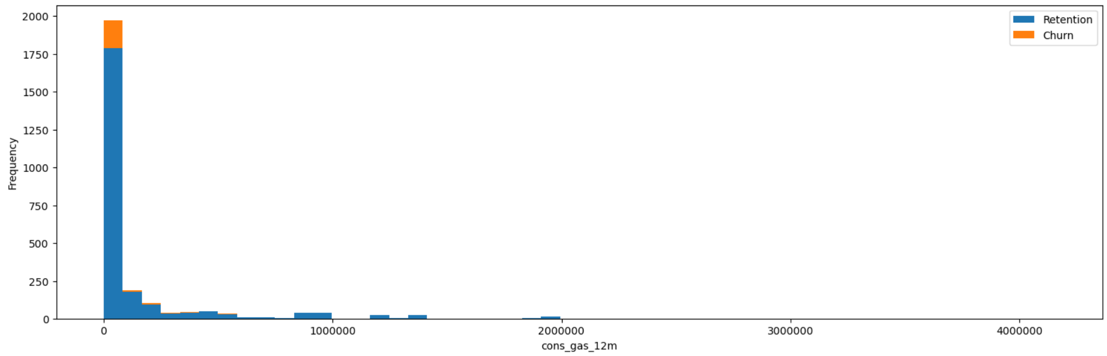


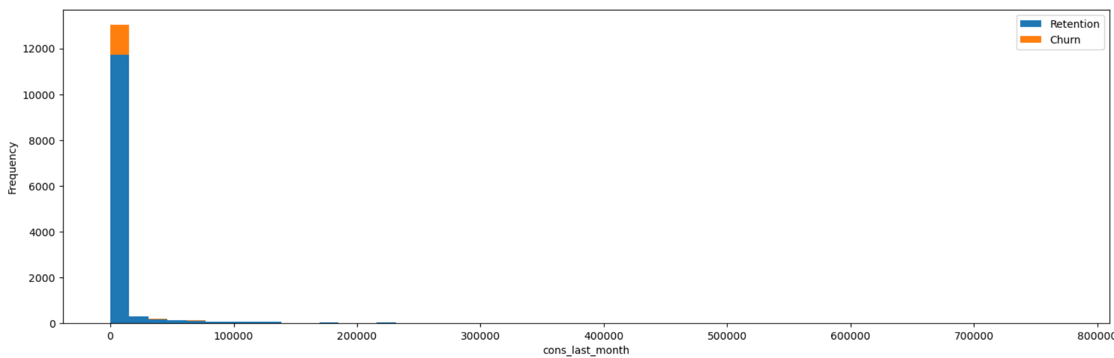
Box Plot for cons_gas_12m
1e6
4
3
2
1
0
Density
0
1
cons_gas_12m

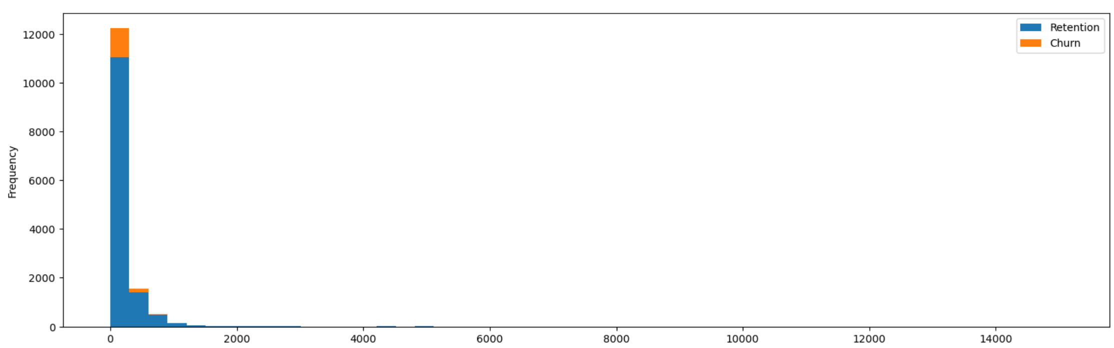


[17]:
```
fig, axs = plt.subplots(nrows=4, figsize=(18, 25))

plot_distribution(df, 'cons_12m', axs[0])
plot_distribution(df[df['has_gas'] == 't'], 'cons_gas_12m', axs[1])
plot_distribution(df, 'cons_last_month', axs[2])
plot_distribution(df, 'imp_cons', axs[3])
plt.show()
```









[18]:

```
df.filter(regex = '^cons_').describe()
```

[18]:

	cons_12m	cons_gas_12m	cons_last_month
count	1.460600e+04	1.460600e+04	14606.000000
mean	1.592203e+05	2.809238e+04	16090.269752
std	5.734653e+05	1.629731e+05	64364.196422
min	0.000000e+00	0.000000e+00	0.000000
25%	5.674750e+03	0.000000e+00	0.000000
50%	1.411550e+04	0.000000e+00	792.500000
75%	4.076375e+04	0.000000e+00	3383.000000
max	6.207104e+06	4.154590e+06	771203.000000

Consumption Variables are right skewed with most churns happening with customers with low consumption overall. Nevertheless, variables are highly skewed and there are a lot of outliers, and on top of that we are indeed in need for normalization for this dataset as range vary a lot across different categories.

1.3.3 Forecast

[19]:
```
df.filter(regex = 'forecast_').describe()
```

[19]:

	forecast_cons_12m	forecast_cons_year	forecast_discount_energy	\
count	14606.000000	14606.000000	14606.000000	
mean	1868.614880	1399.762906	0.966726	
std	2387.571531	3247.786255	5.108289	
min	0.000000	0.000000	0.000000	
25%	494.995000	0.000000	0.000000	
50%	1112.875000	314.000000	0.000000	
75%	2401.790000	1745.750000	0.000000	
max	82902.830000	175375.000000	30.000000	

	forecast_meter_rent_12m	forecast_price_energy_off_peak	\
count	14606.000000	14606.000000	
mean	63.086871	0.137283	
std	66.165783	0.024623	
min	0.000000	0.000000	
25%	16.180000	0.116340	
50%	18.795000	0.143166	
75%	131.030000	0.146348	
max	599.310000	0.273963	

	forecast_price_energy_peak	forecast_price_pow_off_peak
count	14606.000000	14606.000000
mean	0.050491	43.130056
std	0.049037	4.485988
min	0.000000	0.000000
25%	0.000000	40.606701
50%	0.084138	44.311378
75%	0.098837	44.311378

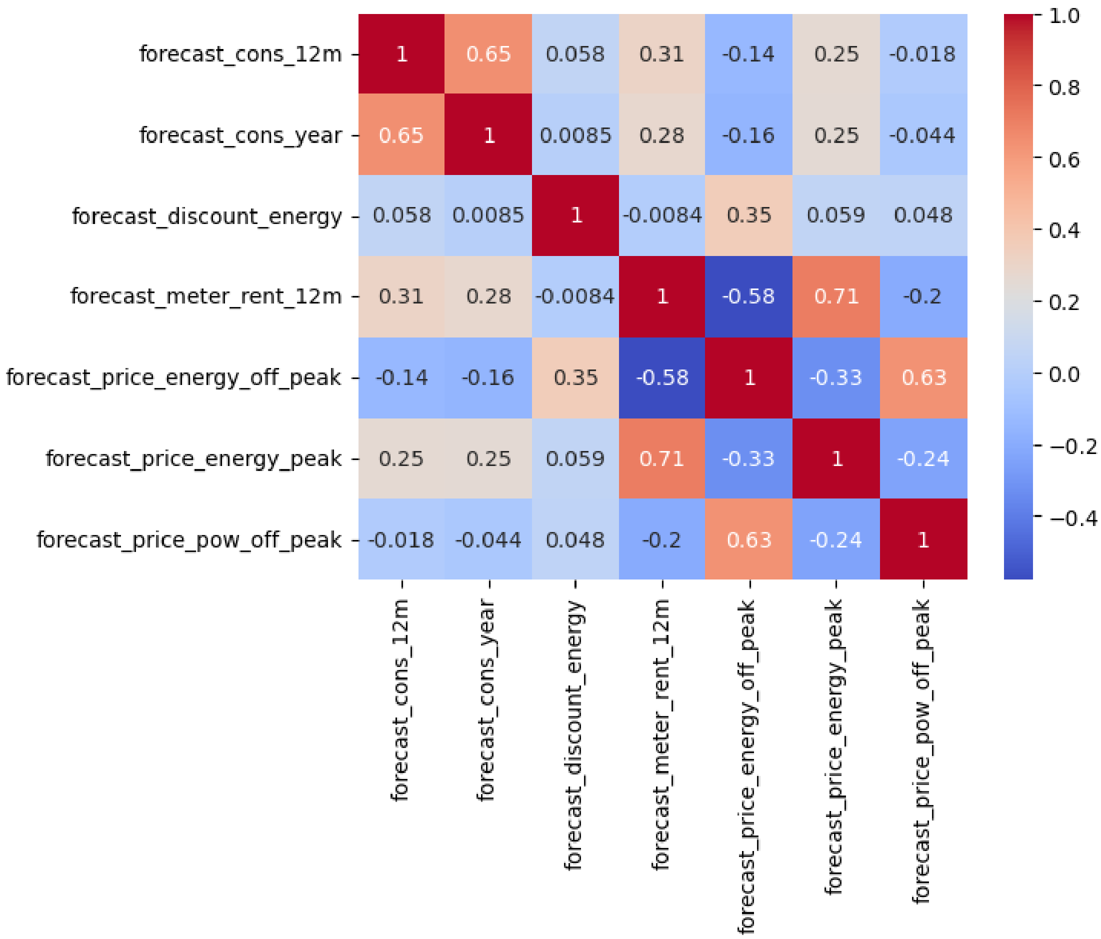
```
max                         0.195975                      59.266378
```

[20]:
```
df.filter(regex = 'forecast_').corr()
```

[20]:
```
                                forecast_cons_12m  forecast_cons_year  \
forecast_cons_12m                        1.000000            0.647727
forecast_cons_year                       0.647727            1.000000
forecast_discount_energy                 0.058435            0.008518
forecast_meter_rent_12m                  0.305627            0.276009
forecast_price_energy_off_peak          -0.135646           -0.158012
forecast_price_energy_peak               0.254056            0.251005
forecast_price_pow_off_peak             -0.018477           -0.044190

                                forecast_discount_energy  \
forecast_cons_12m                               0.058435
forecast_cons_year                              0.008518
forecast_discount_energy                        1.000000
forecast_meter_rent_12m                        -0.008388
forecast_price_energy_off_peak                  0.353735
forecast_price_energy_peak                      0.059318
forecast_price_pow_off_peak                     0.048024

                                forecast_meter_rent_12m  \
forecast_cons_12m                              0.305627
forecast_cons_year                             0.276009
forecast_discount_energy                      -0.008388
forecast_meter_rent_12m                        1.000000
forecast_price_energy_off_peak                -0.579353
forecast_price_energy_peak                     0.706376
forecast_price_pow_off_peak                   -0.203089

                                forecast_price_energy_off_peak  \
forecast_cons_12m                                    -0.135646
forecast_cons_year                                   -0.158012
forecast_discount_energy                              0.353735
forecast_meter_rent_12m                              -0.579353
forecast_price_energy_off_peak                        1.000000
forecast_price_energy_peak                           -0.330138
forecast_price_pow_off_peak                           0.630377

                                forecast_price_energy_peak  \
forecast_cons_12m                                  0.254056
forecast_cons_year                                 0.251005
forecast_discount_energy                           0.059318
forecast_meter_rent_12m                            0.706376
forecast_price_energy_off_peak                    -0.330138
forecast_price_energy_peak                         1.000000
```

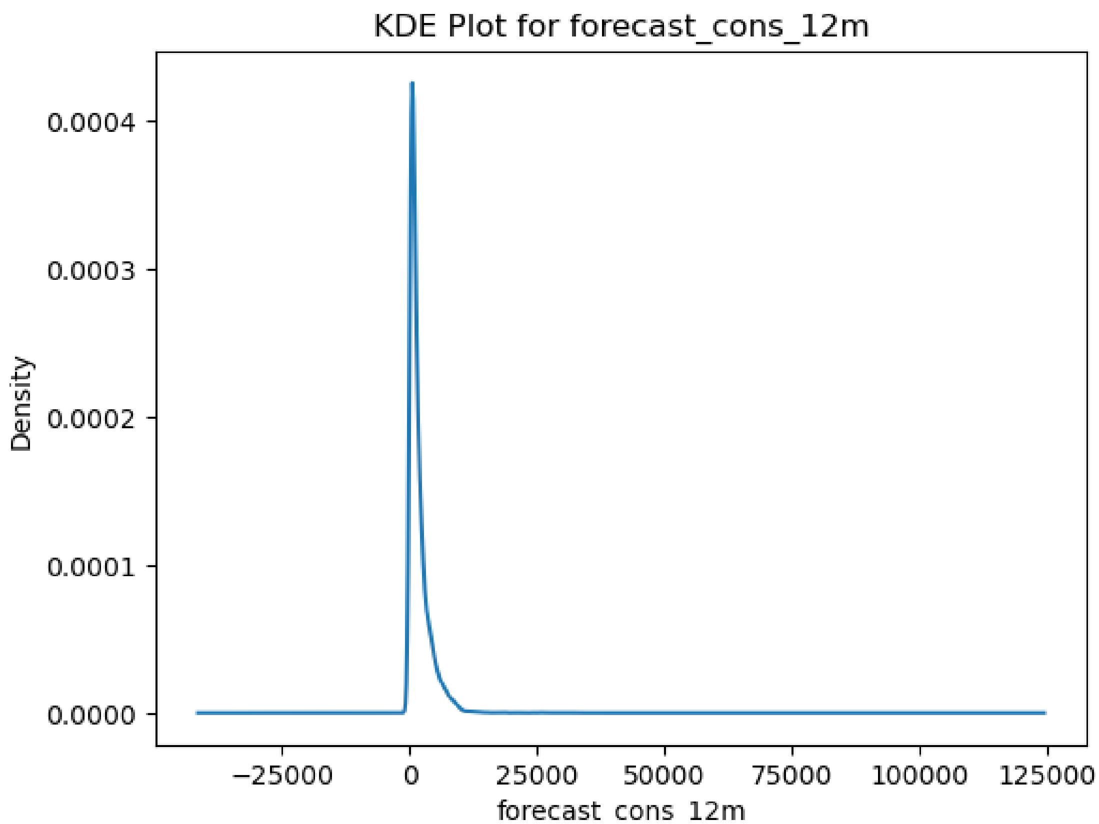
```
forecast_price_pow_off_peak                      -0.242017

                                 forecast_price_pow_off_peak
forecast_cons_12m                                  -0.018477
forecast_cons_year                                 -0.044190
forecast_discount_energy                            0.048024
forecast_meter_rent_12m                            -0.203089
forecast_price_energy_off_peak                      0.630377
forecast_price_energy_peak                         -0.242017
forecast_price_pow_off_peak                         1.000000
```

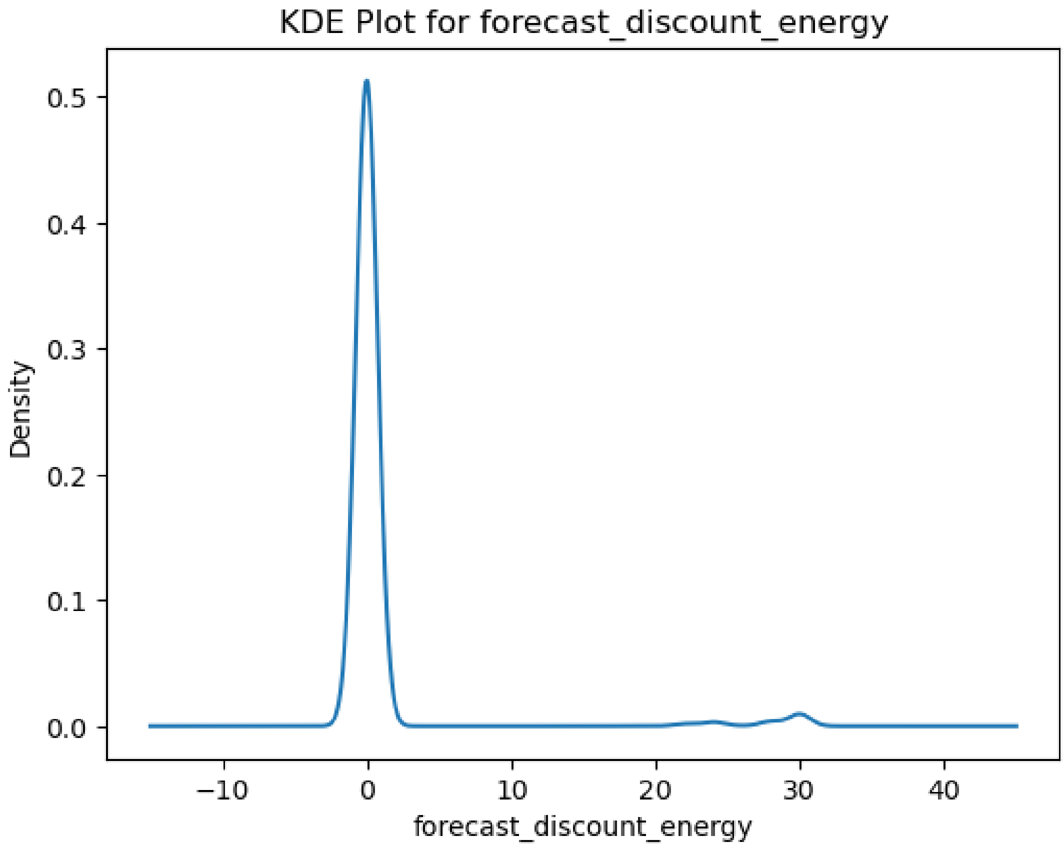
[21]:
```python
sns.heatmap(df.filter(regex = 'forecast_').corr(), cmap = 'coolwarm', annot =␣
↪True)
plt.show()
```

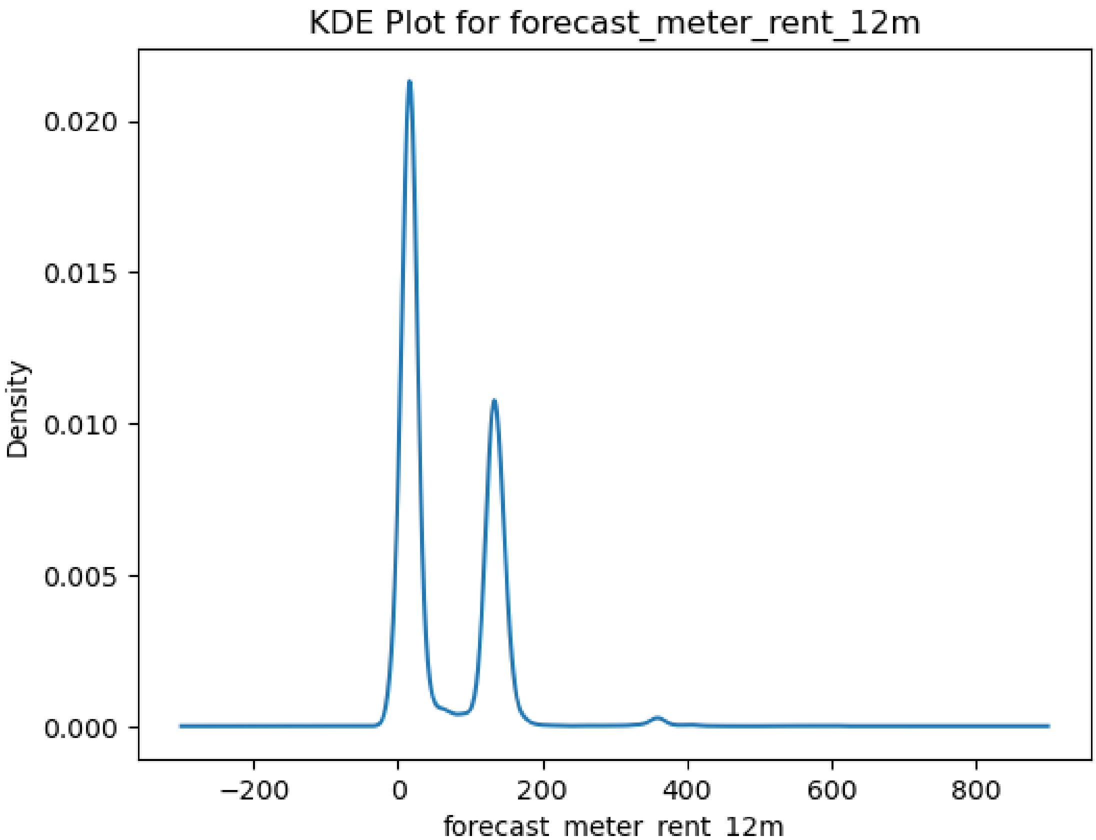


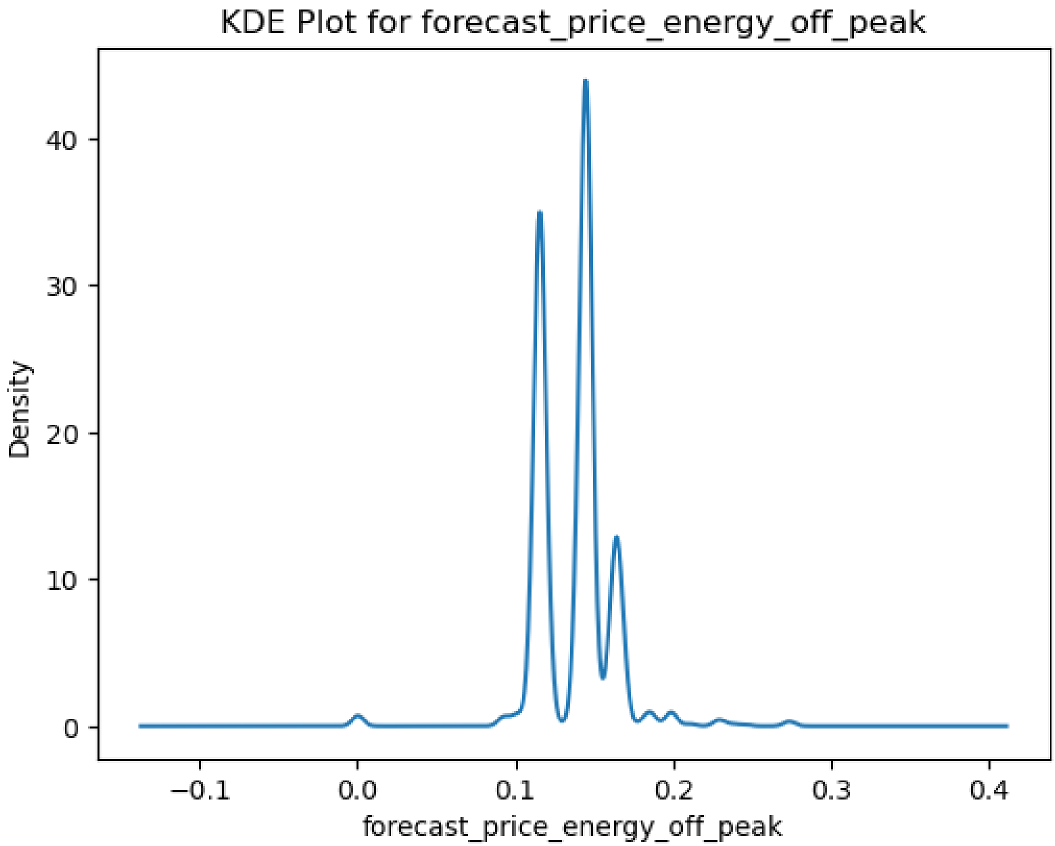
[22]:
```python
# Removing forecasted yearly consumption valuue as we will use 12 month forecast
df.drop(columns = 'forecast_cons_year', inplace = True)
```

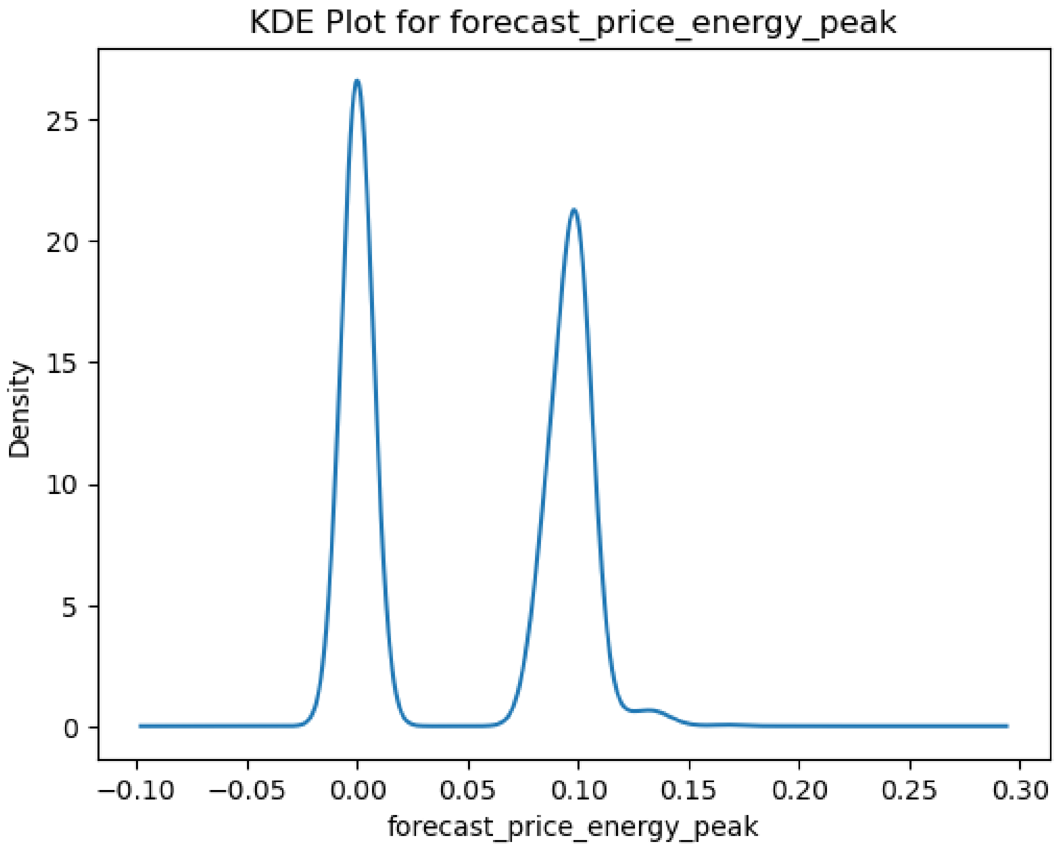
[23]:
```
for col in df.filter(regex = '^forecast_'):
    df[col].plot.kde()
    plt.title(f'KDE Plot for {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.show()
```



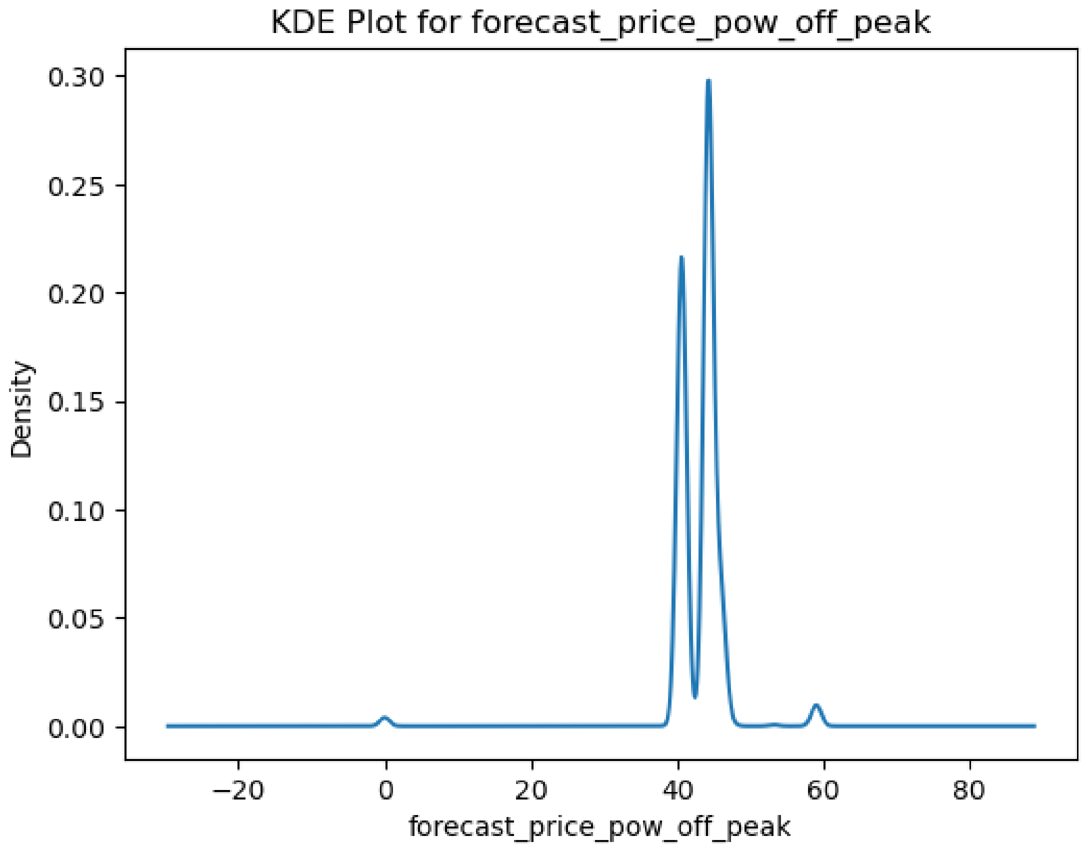

KDE Plot for forecast_discount_energy
Density
0.5
0.4
0.3
0.2
0.1
0.0
−10
0
10
20
30
40
forecast_discount_energy


KDE Plot for forecast_meter_rent_12m
0.020
0.015
0.010
0.005
0.000
Density
−200
0
200
400
600
800
forecast_meter_rent_12m

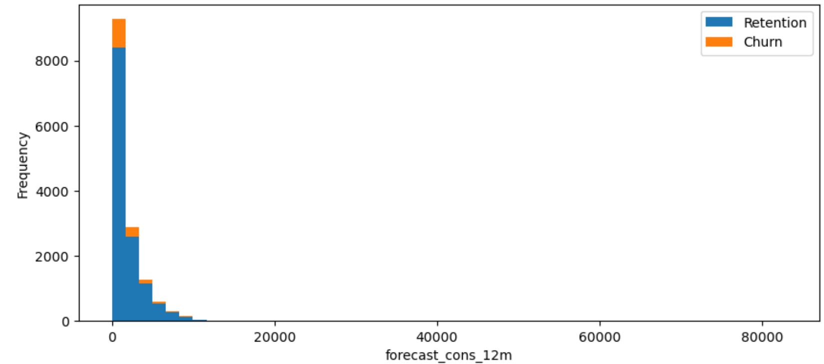

KDE Plot for forecast_price_energy_off_peak
Density
forecast_price_energy_off_peak
0
10
20
30
40
−0.1
0.0
0.1
0.2
0.3
0.4

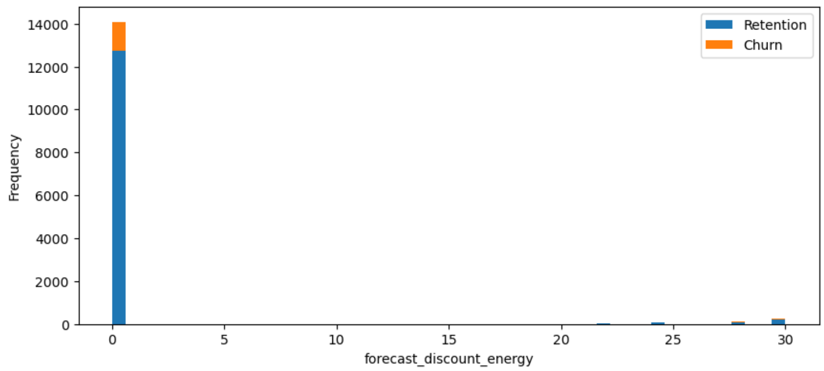


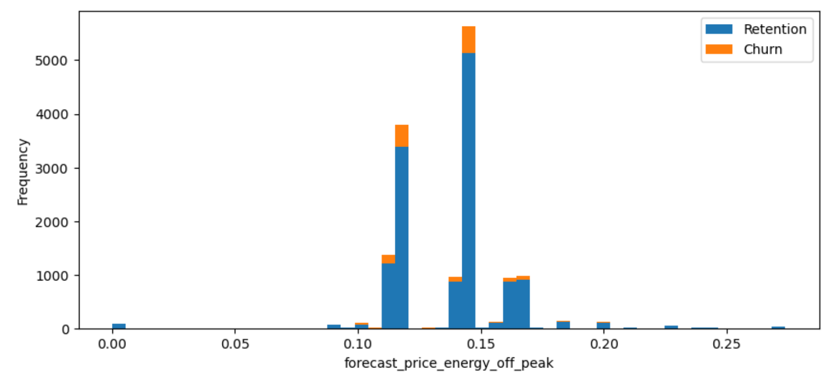
KDE Plot for forecast_price_energy_peak
Density
forecast_price_energy_peak
0
5
10
15
20
25
−0.10
−0.05
0.00
0.05
0.10
0.15
0.20
0.25
0.30

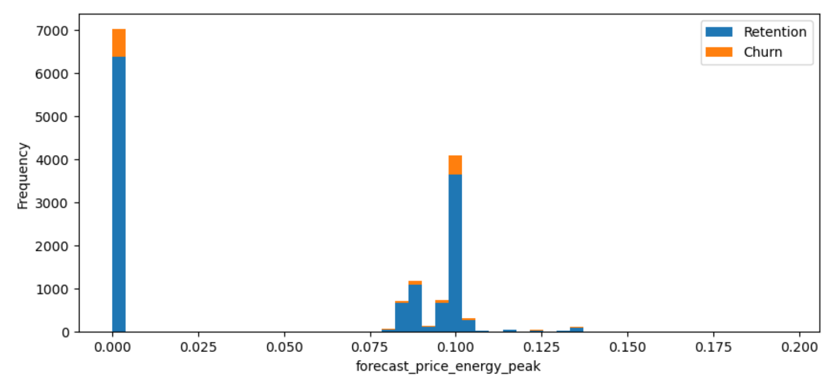


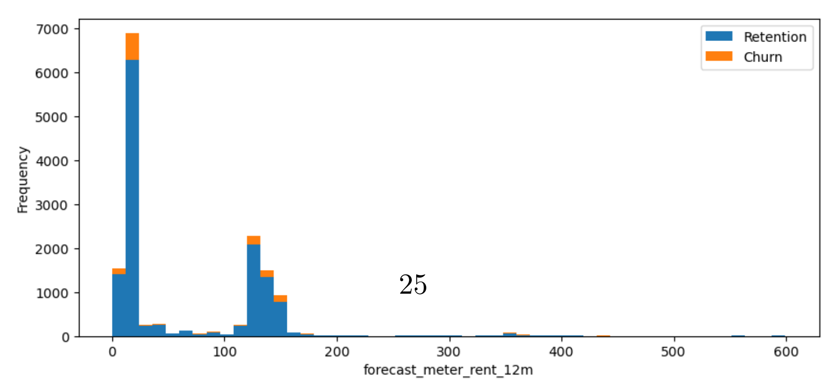
[24]:
```
fig, axs = plt.subplots(nrows=5, figsize=(10, 25))

plot_distribution(df, 'forecast_cons_12m', axs[0])
plot_distribution(df, 'forecast_discount_energy', axs[1])
plot_distribution(df, 'forecast_price_energy_off_peak', axs[2])
plot_distribution(df, 'forecast_price_energy_peak', axs[3])
plot_distribution(df, 'forecast_meter_rent_12m', axs[4])
plt.show()
```


Retention
Churn
Frequency
0
2000
4000
6000
8000
0
20000
40000
60000
80000
forecast_cons_12m


Retention
Churn
Frequency
0
2000
4000
6000
8000
10000
12000
14000
0
5
10
15
20
25
30
forecast_discount_energy


Retention
Churn
Frequency
0
1000
2000
3000
4000
5000
0.00
0.05
0.10
0.15
0.20
0.25
forecast_price_energy_off_peak


Retention
Churn
Frequency
0
1000
2000
3000
4000
5000
6000
7000
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
forecast_price_energy_peak


Retention
Churn
Frequency
0
1000
2000
3000
4000
5000
6000
7000
0
100
200
300
400
500
600
forecast_meter_rent_12m

[25]:
```
df.filter(regex = '^forecast_').describe()
```

[25]:

	forecast_cons_12m	forecast_discount_energy	forecast_meter_rent_12m
count	14606.000000	14606.000000	14606.000000
mean	1868.614880	0.966726	63.086871
std	2387.571531	5.108289	66.165783
min	0.000000	0.000000	0.000000
25%	494.995000	0.000000	16.180000
50%	1112.875000	0.000000	18.795000
75%	2401.790000	0.000000	131.030000
max	82902.830000	30.000000	599.310000

	forecast_price_energy_off_peak	forecast_price_energy_peak
count	14606.000000	14606.000000
mean	0.137283	0.050491
std	0.024623	0.049037
min	0.000000	0.000000
25%	0.116340	0.000000
50%	0.143166	0.084138
75%	0.146348	0.098837
max	0.273963	0.195975

	forecast_price_pow_off_peak
count	14606.000000
mean	43.130056
std	4.485988
min	0.000000
25%	40.606701
50%	44.311378
75%	44.311378
max	59.266378

Just like consumption data we have highly skewed variables for forecasting, which was expected. Our concern is why energy price for peak period is less than off peak periods. It should have been reversed, need confirmation if data was ported properly.

1.3.4 Others

Before analyzing other variables further it should be noted that variables covering variance of price over the period has been provided by BCGX without relevant mention in the datacard. We will cover them in brief besides other variables.

[ ]:
```

```

[26]:
```
df['has_gas'] = df['has_gas'].replace(['t','f'], [1,0])
```

```
/tmp/ipykernel_153168/2844197130.py:1: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['has_gas'] = df['has_gas'].replace(['t','f'], [1,0])
```

[27]:
```
#we have around 18% of observations with gas connection
print(df.loc[df['has_gas'] == 1,:].shape[0]/df.shape[0])
```

```
0.18150075311515815
```

[28]:
```
df.loc[df['has_gas'] == 1,:]['churn'].value_counts(normalize = True)
```

[28]:
```
churn
0    0.918144
1    0.081856
Name: proportion, dtype: float64
```

[29]:
```
df['churn'].value_counts(normalize = True)
```

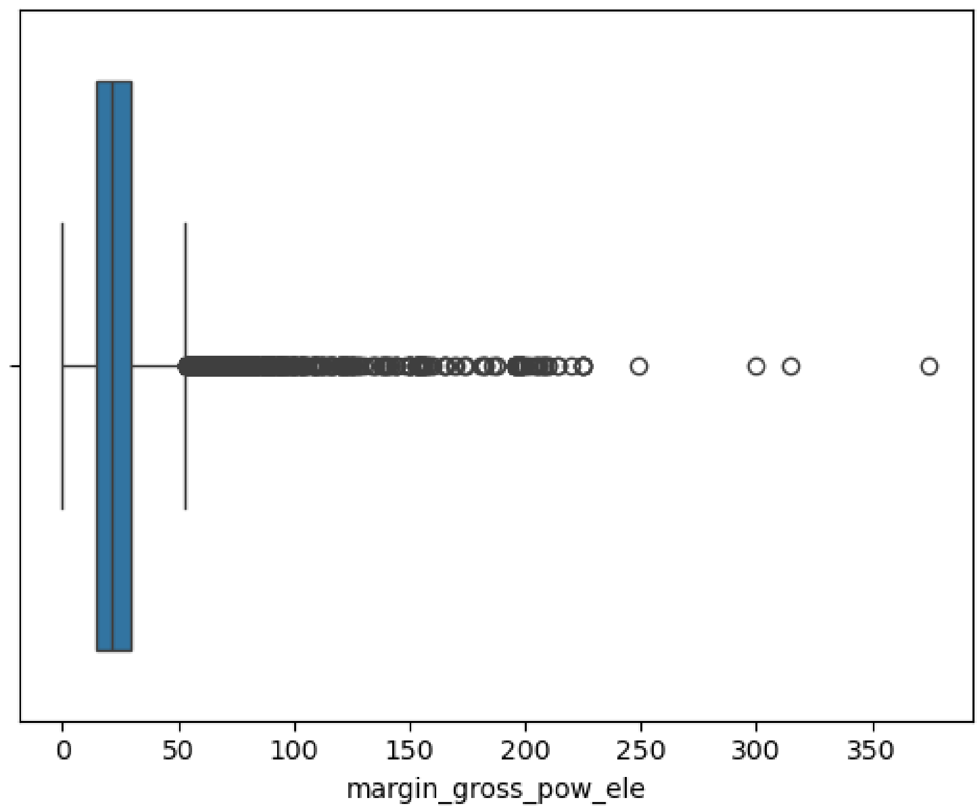
[29]:
```
churn
0    0.902848
1    0.097152
Name: proportion, dtype: float64
```

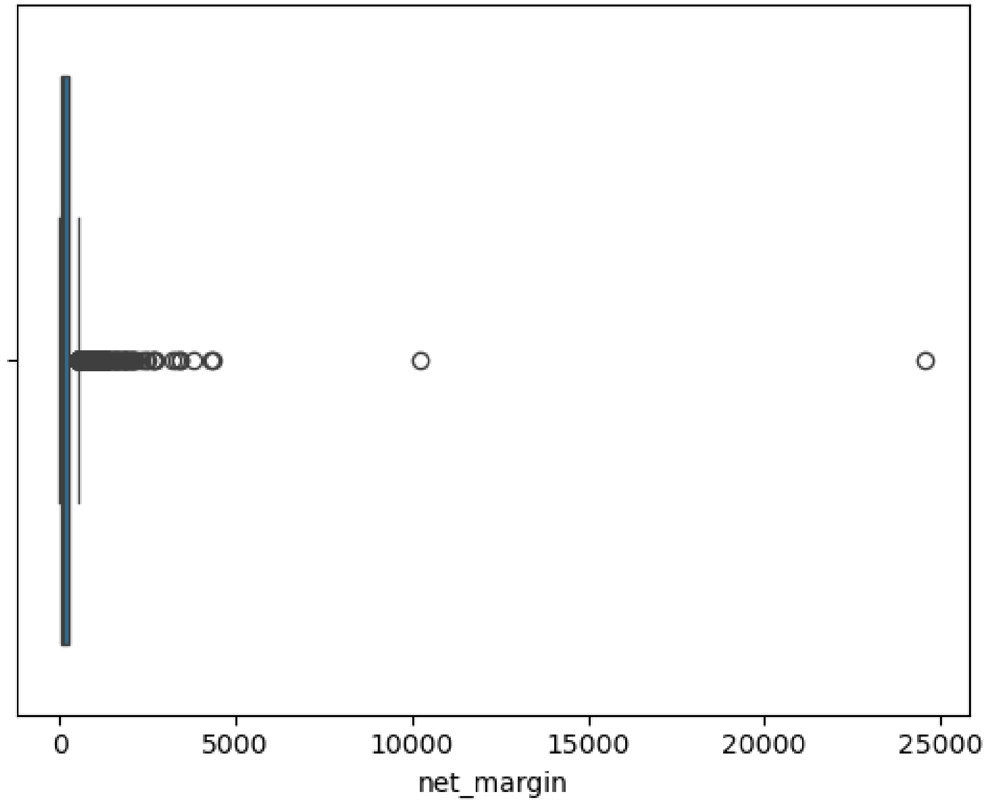
Churn rate for is quite lower for customers with gas connection.

[30]:
```
#As expected gross and net margin are highly correlated. We will remove net␣
↪margin for power subscription
print(df.filter(regex = 'margin').corr())
df.drop(columns = 'margin_net_pow_ele', inplace = True)
```

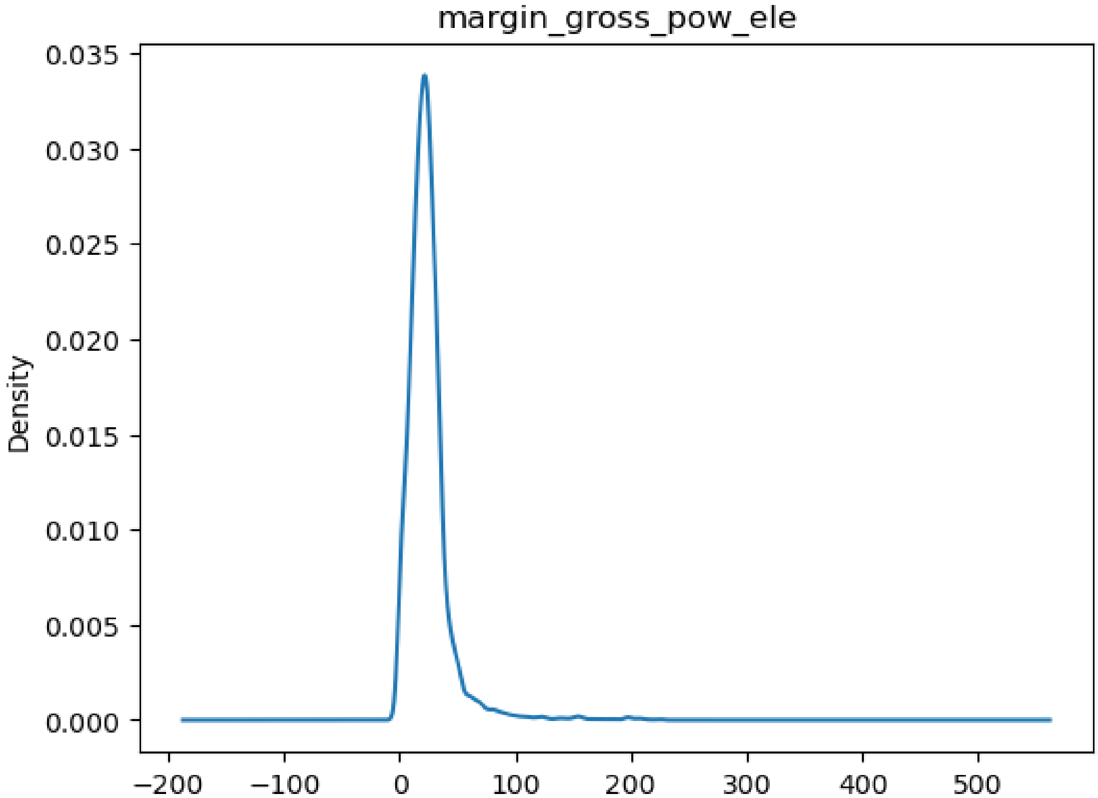
```
                    margin_gross_pow_ele  margin_net_pow_ele  net_margin
margin_gross_pow_ele            1.000000            0.999914    0.031814
margin_net_pow_ele              0.999914            1.000000    0.031639
net_margin                      0.031814            0.031639    1.000000
```

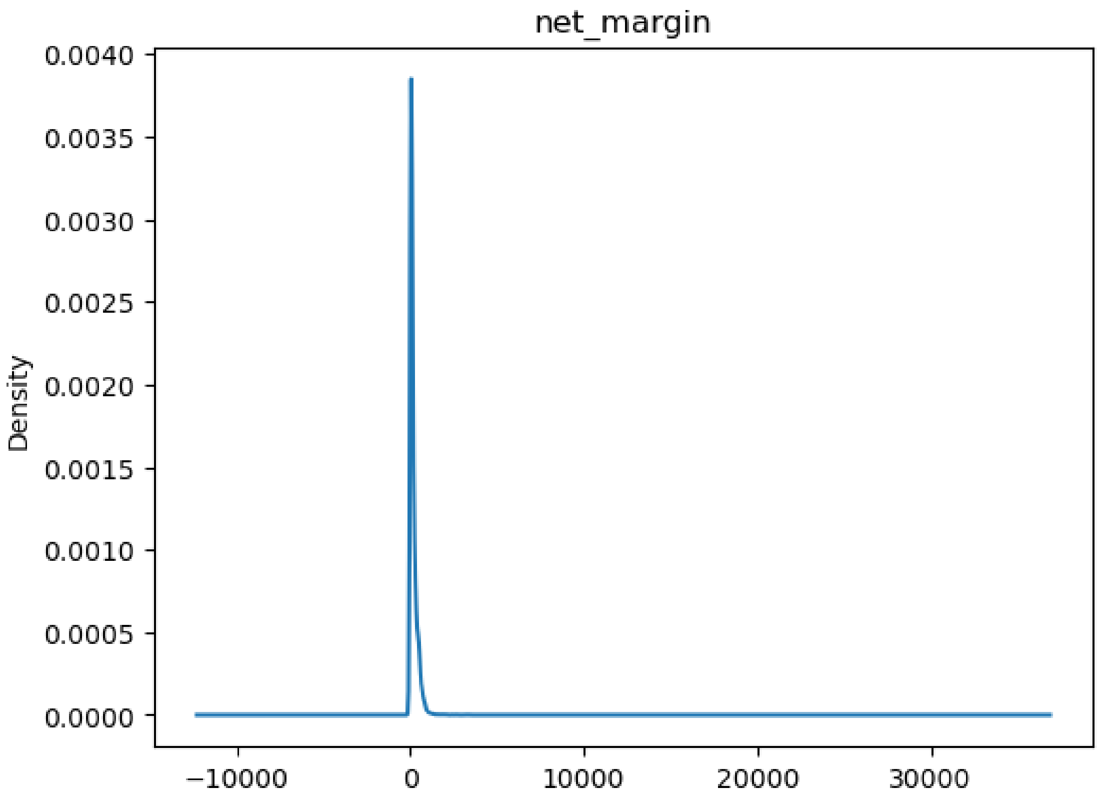
[31]:
```
for cols in df.filter(regex = 'margin'):
    sns.boxplot(x = df[cols])
    plt.show()
```


0
50
100
150
200
250
300
350
margin_gross_pow_ele



[32]:
```
for cols in df.filter(regex = 'margin'):
    df[cols].plot.kde()
    plt.title(f'{cols}')
    plt.show()
```


margin_gross_pow_ele
Density
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−200
−100
0
100
200
300
400
500

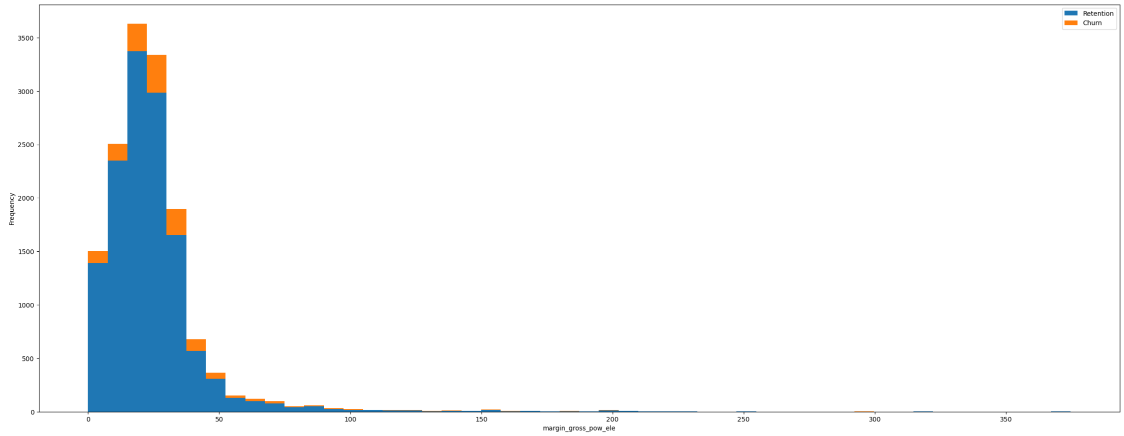


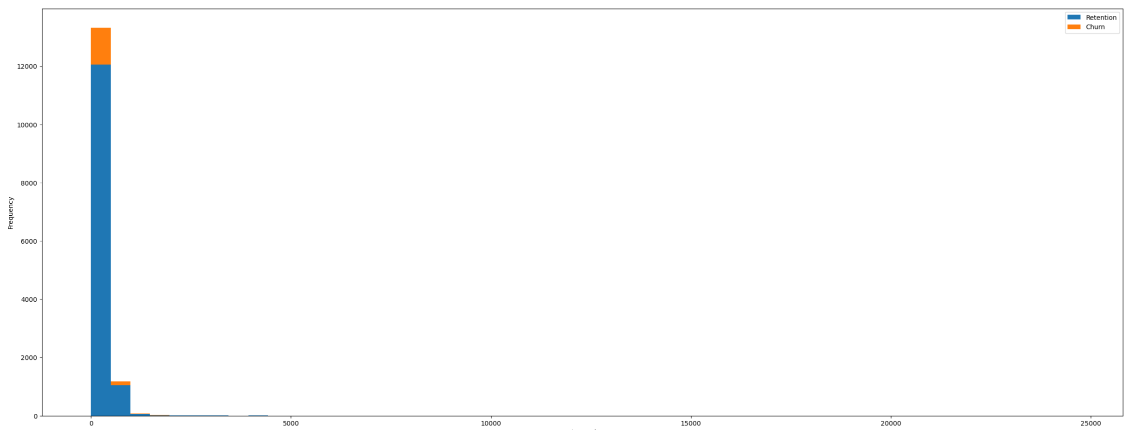
[33]:
```
df.filter(regex = 'margin').describe()
```

[33]:

	margin_gross_pow_ele	net_margin
count	14606.000000	14606.000000
mean	24.565121	189.264522
std	20.231172	311.798130
min	0.000000	0.000000
25%	14.280000	50.712500
50%	21.640000	112.530000
75%	29.880000	243.097500
max	374.640000	24570.650000

[34]:
```
fig, axs = plt.subplots(nrows=2, figsize=(30, 25))

plot_distribution(df, 'margin_gross_pow_ele', axs[0])
plot_distribution(df, 'net_margin', axs[1])
plt.show()
```





Logically, net margin should be lower than gross margin but here net margin is higher. It maybe due to the fact that we have gross margin only for power subscription.

[35]:
```
df.groupby('origin_up').sum()['churn'].sort_values(ascending = False)/df.
 ↪loc[df['churn'] == 1].shape[0]
```

[35]:
```
origin_up
lxidpiddsbxsbosboudacockeimpuepw    0.629316
ldkssxwpmemidmecebumciepifcamkci    0.186047
kamkkxfxxuwbdslkwifmmcsiusiuosws    0.181818
MISSING                             0.002819
ewxeelcelemmiwuafmddpobolfuxioce    0.000000
usapbepcfoloekilkwsdiboslwaxobdp    0.000000
Name: churn, dtype: float64
```

[36]:
```
df.loc[df['churn'] == 0].groupby('origin_up').count()['id'].
 ↪sort_values(ascending = False)/df.loc[df['churn'] == 0].shape[0]
```

```
[36]: origin_up
lxidpiddsbxsbosboudacockeimpuepw    0.470463
kamkkxfxxuwbdslkwifmmcsiusiuosws    0.306059
ldkssxwpmemidmecebumciepifcamkci    0.218700
MISSING                             0.004550
usapbepcfoloekilkwsdiboslwaxobdp    0.000152
ewxeelcelemmiwuafmddpobolfuxioce    0.000076
Name: id, dtype: float64
```

This shows us that proportion of customers churning across the origin program varies. If it does not vary then propertion of churn vs not churn should have been same for the groups. But we can clearly observe that lxi Electricity Campaign has higher proportion of churn than other groups relatively.

```
[37]: df.groupby('channel_sales').sum()['churn'].sort_values(ascending = False)/df.
       ↪loc[df['churn'] == 1].shape[0]
```

```
[37]: channel_sales
foosdfpfkusacimwkcsosbicdxkicaua    0.577872
MISSING                             0.199436
usilxuppasemubllopkaafesmlibmsdf    0.097252
lmkebamcaaclubfxadlmueccxoimlema    0.072586
ewpakwlliwisiwduibdlfmalxowmwpci    0.052854
epumfxlbckeskwekxbiuasklxalciiuu    0.000000
fixdbufsefwooaasfcxdxadsiekoceaa    0.000000
sddiedcslfslkckwlfkdpoeeailfpeds    0.000000
Name: churn, dtype: float64
```

```
[38]: df.loc[df['churn'] == 0].groupby('channel_sales').count()['id'].
       ↪sort_values(ascending = False)/df.loc[df['churn'] == 0].shape[0]
```

```
[38]: channel_sales
foosdfpfkusacimwkcsosbicdxkicaua    0.449989
MISSING                             0.261015
lmkebamcaaclubfxadlmueccxoimlema    0.131948
usilxuppasemubllopkaafesmlibmsdf    0.093805
ewpakwlliwisiwduibdlfmalxowmwpci    0.062031
sddiedcslfslkckwlfkdpoeeailfpeds    0.000834
epumfxlbckeskwekxbiuasklxalciiuu    0.000227
fixdbufsefwooaasfcxdxadsiekoceaa    0.000152
Name: id, dtype: float64
```

```
[39]: print(df.groupby('channel_sales')['churn'].value_counts(normalize = True))
```

```
channel_sales                     churn
MISSING                           0        0.924027
                                  1        0.075973
epumfxlbckeskwekxbiuasklxalciiuu  0        1.000000
```

```
ewpakwlliwisiwduibdlfmalxowmwpci  0         0.916013
                                  1         0.083987
fixdbufsefwooaasfcxdxadsiekoceaa  0         1.000000
foosdfpfkusacimwkcsosbicdxkicaua  0         0.878590
                                  1         0.121410
lmkebamcaaclubfxadlmueccxoimlema  0         0.944113
                                  1         0.055887
sddiedcslfslkckwlfkdpoeeailfpeds  0         1.000000
usilxuppasemubllopkaafesmlibmsdf  0         0.899636
                                  1         0.100364
Name: proportion, dtype: float64
```

[40]:

```
#Analyzing the breakup more in depth
print(df.groupby('origin_up')['churn'].value_counts(normalize = True))
print(df.groupby(['channel_sales','origin_up']).agg({'churn':'mean'}))
```

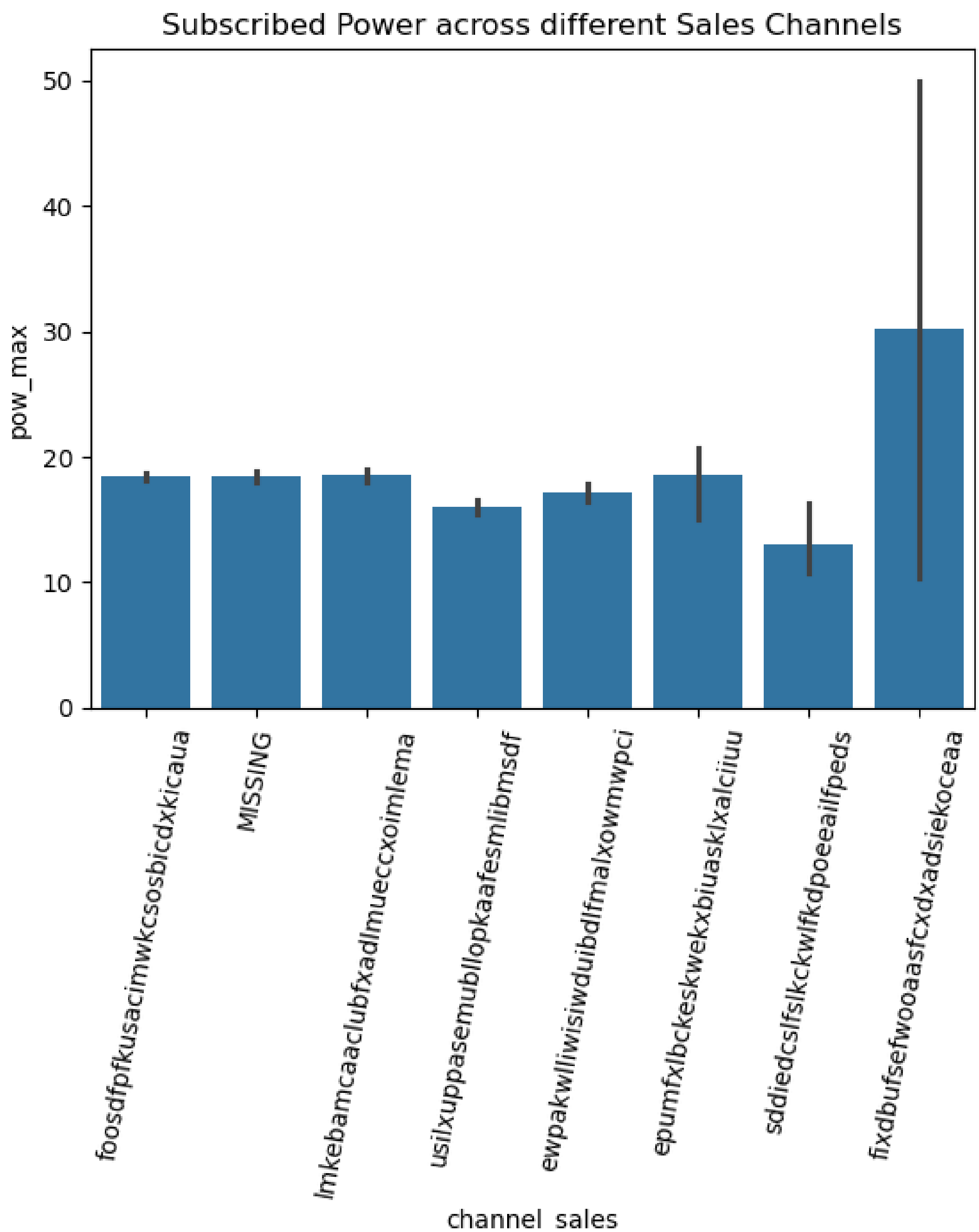
```
origin_up                         churn
MISSING                           0         0.937500
                                  1         0.062500
ewxeelcelemmiwuafmddpobolfuxioce  0         1.000000
kamkkxfxxuwbdslkwifmmcsiusiuosws  0         0.939916
                                  1         0.060084
ldkssxwpmemidmecebumciepifcamkci  0         0.916137
                                  1         0.083863
lxidpiddsbxsbosboudacockeimpuepw  0         0.874172
                                  1         0.125828
usapbepcfoloekilkwsdiboslwaxobdp  0         1.000000
Name: proportion, dtype: float64
                                                                      churn
channel_sales                    origin_up
MISSING                          MISSING                           0.000000
                                 ewxeelcelemmiwuafmddpobolfuxioce  0.000000
                                 kamkkxfxxuwbdslkwifmmcsiusiuosws  0.065330
                                 ldkssxwpmemidmecebumciepifcamkci  0.085601
                                 lxidpiddsbxsbosboudacockeimpuepw  0.080793
                                 usapbepcfoloekilkwsdiboslwaxobdp  0.000000
epumfxlbckeskwekxbiuasklxalciiuu ldkssxwpmemidmecebumciepifcamkci  0.000000
                                 lxidpiddsbxsbosboudacockeimpuepw  0.000000
ewpakwlliwisiwduibdlfmalxowmwpci MISSING                           0.000000
                                 kamkkxfxxuwbdslkwifmmcsiusiuosws  0.063452
                                 ldkssxwpmemidmecebumciepifcamkci  0.121107
                                 lxidpiddsbxsbosboudacockeimpuepw  0.073529
                                 usapbepcfoloekilkwsdiboslwaxobdp  0.000000
fixdbufsefwooaasfcxdxadsiekoceaa kamkkxfxxuwbdslkwifmmcsiusiuosws  0.000000
                                 ldkssxwpmemidmecebumciepifcamkci  0.000000
foosdfpfkusacimwkcsosbicdxkicaua MISSING                           0.093750
                                 kamkkxfxxuwbdslkwifmmcsiusiuosws  0.067033
                                 ldkssxwpmemidmecebumciepifcamkci  0.084877
```

```
                                 lxidpiddsbxsbosboudacockeimpuepw  0.135747
lmkebamcaaclubfxadlmueccxoimlema MISSING                           0.142857
                                 kamkkxfxxuwbdslkwifmmcsiusiuosws  0.036638
                                 ldkssxwpmemidmecebumciepifcamkci  0.054965
                                 lxidpiddsbxsbosboudacockeimpuepw  0.107558
sddiedcslfslkckwlfkdpoeeailfpeds kamkkxfxxuwbdslkwifmmcsiusiuosws  0.000000
                                 ldkssxwpmemidmecebumciepifcamkci  0.000000
                                 lxidpiddsbxsbosboudacockeimpuepw  0.000000
usilxuppasemubllopkaafesmlibmsdf MISSING                           0.000000
                                 kamkkxfxxuwbdslkwifmmcsiusiuosws  0.071984
                                 ldkssxwpmemidmecebumciepifcamkci  0.108527
                                 lxidpiddsbxsbosboudacockeimpuepw  0.119835
```

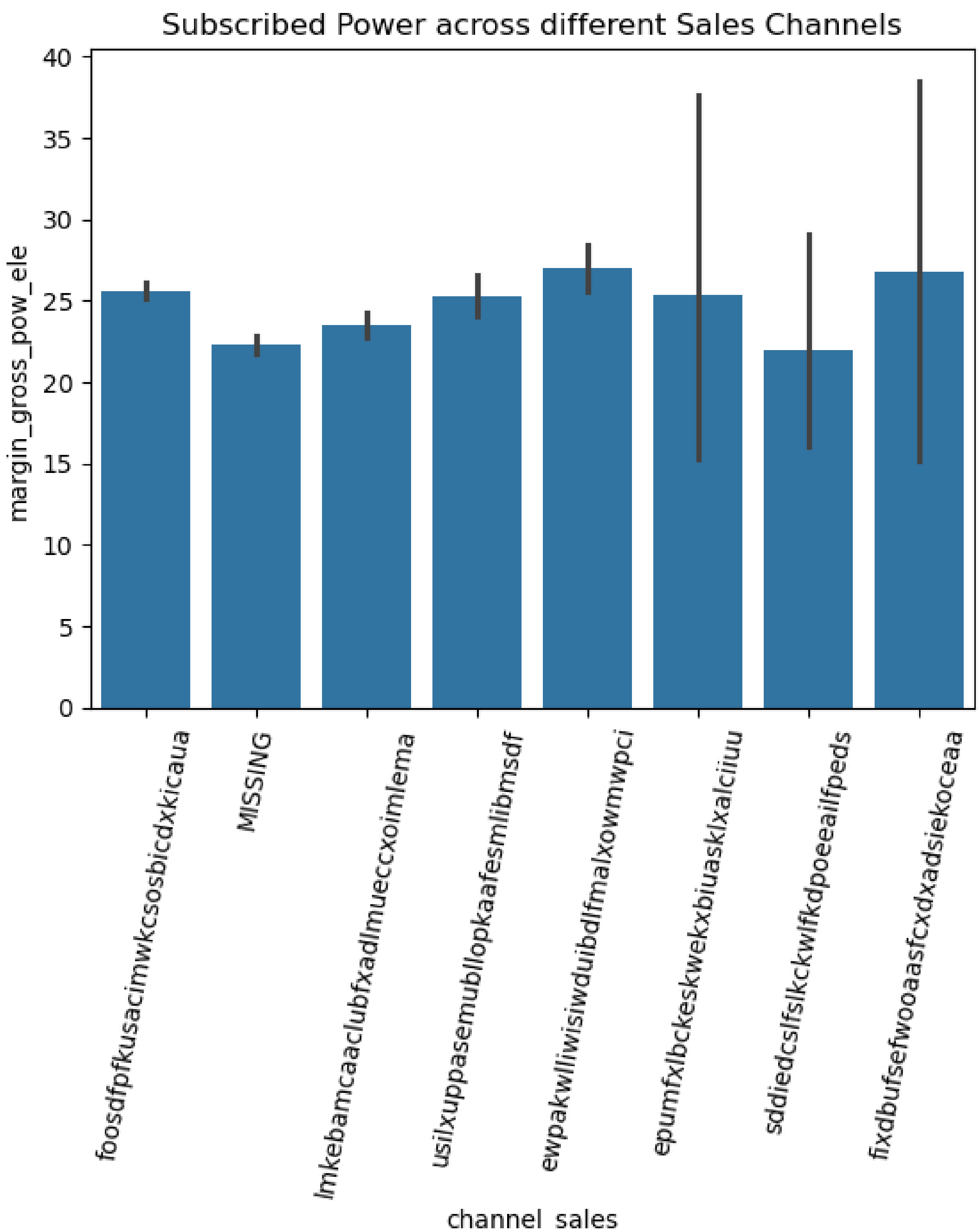
For the sales channels and campaigns, proportion of customers is similar to the churn customers proportion but for some groups churn rate is quite higher. For electricity campaigns we can observe that lxidpi has 12.6% churn rate which is quite higher than 9.72% churn rate generally. And for sales channel its 12.12% for foosdf channel. Overall, some sales channel and campaigns witnessed more than average customer churn rate.

And combining both of them in subgroups we can see that there are many subgroups with more than 12% churn rate with highest being at 14.3% churn rate which is 47% higher than average churn rate. All this is a metter of concerns and imply that churn rate varies a lot across different sales channel and promotion campaigns.

[41]:
```
sns.barplot(data = df, x = 'channel_sales', y = 'pow_max')
plt.xticks(rotation = 80)
plt.title('Subscribed Power across different Sales Channels')
plt.show()
```



[42]:
```python
sns.barplot(data = df, x = 'channel_sales', y = 'margin_gross_pow_ele')
plt.xticks(rotation = 80)
plt.title('Subscribed Power across different Sales Channels')
plt.show()
```



[43]:
```
#Analyzing antiquity of the clients
df['num_years_antig'].describe()
```

[43]:
```
count    14606.000000
mean         4.997809
std          1.611749
```

```
min           1.000000
25%           4.000000
50%           5.000000
75%           6.000000
max          13.000000
Name: num_years_antig, dtype: float64
```

[44]:
```
df.groupby('channel_sales').count()['num_years_antig']
```

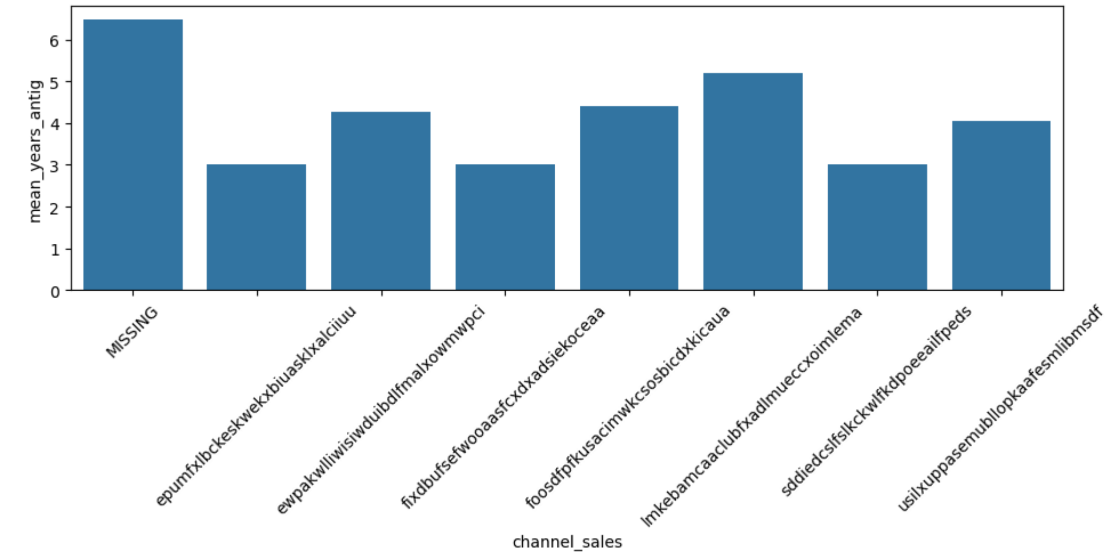
[44]:
```
channel_sales
MISSING                             3725
epumfxlbckeskwekxbiuasklxalciiuu       3
ewpakwlliwisiwduibdlfmalxowmwpci     893
fixdbufsefwooaasfcxdxadsiekoceaa       2
foosdfpfkusacimwkcsosbicdxkicaua    6754
lmkebamcaaclubfxadlmueccxoimlema    1843
sddiedcslfslkckwlfkdpoeeailfpeds      11
usilxuppasemubllopkaafesmlibmsdf    1375
Name: num_years_antig, dtype: int64
```

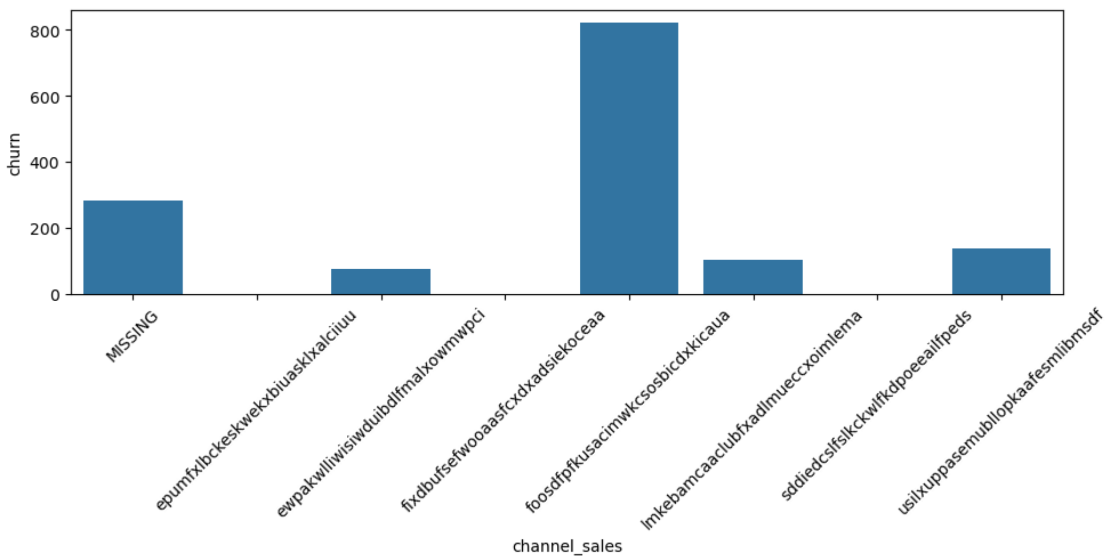
[45]:
```
temp_df = pd.merge(df.groupby('channel_sales').sum()['churn'].reset_index(),df.
↪groupby('channel_sales')[['num_years_antig']].mean().reset_index(), on =␣
↪'channel_sales', how = 'inner')

temp_df.columns = ['channel_sales', 'churn', 'mean_years_antig']
temp_df
```

[45]:

	channel_sales	churn	mean_years_antig
0	MISSING	283	6.492617
1	epumfxlbckeskwekxbiuasklxalciiuu	0	3.000000
2	ewpakwlliwisiwduibdlfmalxowmwpci	75	4.272116
3	fixdbufsefwooaasfcxdxadsiekoceaa	0	3.000000
4	foosdfpfkusacimwkcsosbicdxkicaua	820	4.414125
5	lmkebamcaaclubfxadlmueccxoimlema	103	5.196419
6	sddiedcslfslkckwlfkdpoeeailfpeds	0	3.000000
7	usilxuppasemubllopkaafesmlibmsdf	138	4.043636

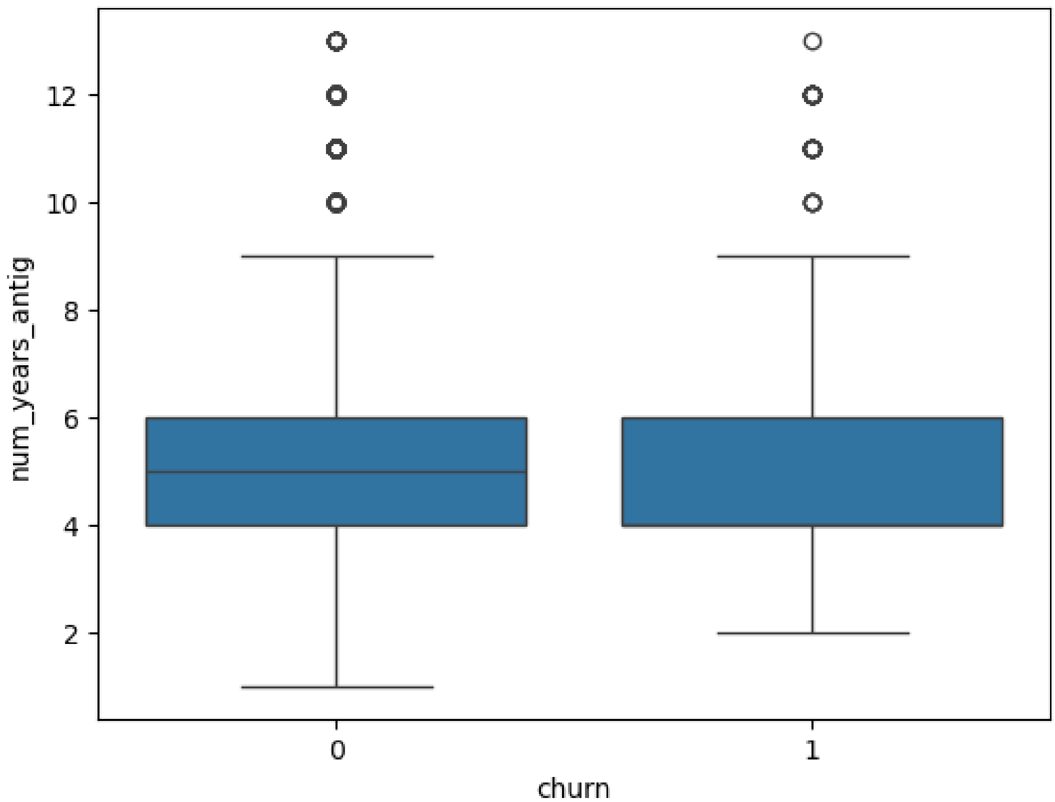
[46]:
```
fig, ax = plt.subplots(nrows = 2, figsize = (10,10))

sns.barplot(temp_df, x = 'channel_sales', y = 'mean_years_antig', ax = ax[0])
sns.barplot(temp_df, x = 'channel_sales', y = 'churn', ax = ax[1])
for ax in ax:
    ax.tick_params(axis='x', labelrotation=45)
plt.tight_layout()
plt.show()
```





[47]:

```
sns.boxplot(df, x = 'churn', y = 'num_years_antig')
plt.show()
```



Overall, customers churned has mean of atinquity is around 4 years. While distribution of churn and retention for customers is quite similar when we look across different sales channel it presents a different story.

We can observe churns happening in sales channels having antiquity more than the mean of 4 years. While the churn rate appears normal for all groups, 'foosdfpfkusacimwkcsosbicdxkicaua' sales group has a higher amount of churns than others. Yes, it has more customers too but even then it should have been 500-600 churns instead of 820 churns. This implies that this sales group witnessed higher than normal churn rate for PowerCo.

[48]:
```
df.filter(regex = 'var_').corr()
```

[48]:
```
                              var_year_price_off_peak_var  \
var_year_price_off_peak_var                      1.000000
var_year_price_peak_var                          0.268477
var_year_price_mid_peak_var                      0.245311
var_year_price_off_peak_fix                      0.515049
var_year_price_peak_fix                          0.227269
var_year_price_mid_peak_fix                      0.229893
var_year_price_off_peak                          0.515064
var_year_price_peak                              0.227272
var_year_price_mid_peak                          0.229894
```

```
var_6m_price_off_peak_var                          0.619343
var_6m_price_peak_var                              0.265968
var_6m_price_mid_peak_var                          0.269555
var_6m_price_off_peak_fix                          0.441878
var_6m_price_peak_fix                              0.264435
var_6m_price_mid_peak_fix                          0.264312
var_6m_price_off_peak                              0.441880
var_6m_price_peak                                  0.264437
var_6m_price_mid_peak                              0.264313

                             var_year_price_peak_var  \
var_year_price_off_peak_var                 0.268477
var_year_price_peak_var                     1.000000
var_year_price_mid_peak_var                 0.515645
var_year_price_off_peak_fix                 0.298254
var_year_price_peak_fix                     0.451123
var_year_price_mid_peak_fix                 0.475760
var_year_price_off_peak                     0.298256
var_year_price_peak                         0.451135
var_year_price_mid_peak                     0.475761
var_6m_price_off_peak_var                   0.295638
var_6m_price_peak_var                       0.647083
var_6m_price_mid_peak_var                   0.312539
var_6m_price_off_peak_fix                   0.278371
var_6m_price_peak_fix                       0.279135
var_6m_price_mid_peak_fix                   0.283905
var_6m_price_off_peak                       0.278372
var_6m_price_peak                           0.279144
var_6m_price_mid_peak                       0.283906

                             var_year_price_mid_peak_var  \
var_year_price_off_peak_var                     0.245311
var_year_price_peak_var                         0.515645
var_year_price_mid_peak_var                     1.000000
var_year_price_off_peak_fix                     0.296689
var_year_price_peak_fix                         0.948578
var_year_price_mid_peak_fix                     0.961481
var_year_price_off_peak                         0.296691
var_year_price_peak                             0.948579
var_year_price_mid_peak                         0.961483
var_6m_price_off_peak_var                       0.301787
var_6m_price_peak_var                           0.292145
var_6m_price_mid_peak_var                       0.666421
var_6m_price_off_peak_fix                       0.276626
var_6m_price_peak_fix                           0.637463
var_6m_price_mid_peak_fix                       0.638773
var_6m_price_off_peak                           0.276627
```

```
var_6m_price_peak                                      0.637464
var_6m_price_mid_peak                                  0.638774

                             var_year_price_off_peak_fix  \
var_year_price_off_peak_var                            0.515049
var_year_price_peak_var                                0.298254
var_year_price_mid_peak_var                            0.296689
var_year_price_off_peak_fix                            1.000000
var_year_price_peak_fix                                0.340722
var_year_price_mid_peak_fix                            0.310471
var_year_price_off_peak                                1.000000
var_year_price_peak                                    0.340724
var_year_price_mid_peak                                0.310471
var_6m_price_off_peak_var                              0.755875
var_6m_price_peak_var                                  0.425467
var_6m_price_mid_peak_var                              0.420256
var_6m_price_off_peak_fix                              0.919000
var_6m_price_peak_fix                                  0.460190
var_6m_price_mid_peak_fix                              0.426243
var_6m_price_off_peak                                  0.919000
var_6m_price_peak                                      0.460194
var_6m_price_mid_peak                                  0.426243

                             var_year_price_peak_fix  \
var_year_price_off_peak_var                        0.227269
var_year_price_peak_var                            0.451123
var_year_price_mid_peak_var                        0.948578
var_year_price_off_peak_fix                        0.340722
var_year_price_peak_fix                            1.000000
var_year_price_mid_peak_fix                        0.954353
var_year_price_off_peak                            0.340723
var_year_price_peak                                1.000000
var_year_price_mid_peak                            0.954354
var_6m_price_off_peak_var                          0.309477
var_6m_price_peak_var                              0.273434
var_6m_price_mid_peak_var                          0.649140
var_6m_price_off_peak_fix                          0.310610
var_6m_price_peak_fix                              0.662291
var_6m_price_mid_peak_fix                          0.637355
var_6m_price_off_peak                              0.310611
var_6m_price_peak                                  0.662291
var_6m_price_mid_peak                              0.637355

                             var_year_price_mid_peak_fix  \
var_year_price_off_peak_var                            0.229893
var_year_price_peak_var                                0.475760
var_year_price_mid_peak_var                            0.961481
```

var_year_price_off_peak_fix	0.310471
var_year_price_peak_fix	0.954353
var_year_price_mid_peak_fix	1.000000
var_year_price_off_peak	0.310472
var_year_price_peak	0.954354
var_year_price_mid_peak	1.000000
var_6m_price_off_peak_var	0.310865
var_6m_price_peak_var	0.283188
var_6m_price_mid_peak_var	0.664660
var_6m_price_off_peak_fix	0.290756
var_6m_price_peak_fix	0.650680
var_6m_price_mid_peak_fix	0.670265
var_6m_price_off_peak	0.290757
var_6m_price_peak	0.650680
var_6m_price_mid_peak	0.670265

	var_year_price_off_peak	var_year_price_peak \
var_year_price_off_peak_var	0.515064	0.227272
var_year_price_peak_var	0.298256	0.451135
var_year_price_mid_peak_var	0.296691	0.948579
var_year_price_off_peak_fix	1.000000	0.340724
var_year_price_peak_fix	0.340723	1.000000
var_year_price_mid_peak_fix	0.310472	0.954354
var_year_price_off_peak	1.000000	0.340725
var_year_price_peak	0.340725	1.000000
var_year_price_mid_peak	0.310472	0.954355
var_6m_price_off_peak_var	0.755879	0.309480
var_6m_price_peak_var	0.425468	0.273442
var_6m_price_mid_peak_var	0.420257	0.649141
var_6m_price_off_peak_fix	0.918999	0.310612
var_6m_price_peak_fix	0.460191	0.662291
var_6m_price_mid_peak_fix	0.426243	0.637355
var_6m_price_off_peak	0.918999	0.310613
var_6m_price_peak	0.460195	0.662291
var_6m_price_mid_peak	0.426244	0.637355

	var_year_price_mid_peak \
var_year_price_off_peak_var	0.229894
var_year_price_peak_var	0.475761
var_year_price_mid_peak_var	0.961483
var_year_price_off_peak_fix	0.310471
var_year_price_peak_fix	0.954354
var_year_price_mid_peak_fix	1.000000
var_year_price_off_peak	0.310472
var_year_price_peak	0.954355
var_year_price_mid_peak	1.000000
var_6m_price_off_peak_var	0.310865

var_6m_price_peak_var	0.283188
var_6m_price_mid_peak_var	0.664661
var_6m_price_off_peak_fix	0.290756
var_6m_price_peak_fix	0.650680
var_6m_price_mid_peak_fix	0.670265
var_6m_price_off_peak	0.290757
var_6m_price_peak	0.650681
var_6m_price_mid_peak	0.670265

	var_6m_price_off_peak_var	var_6m_price_peak_var \
var_year_price_off_peak_var	0.619343	0.265968
var_year_price_peak_var	0.295638	0.647083
var_year_price_mid_peak_var	0.301787	0.292145
var_year_price_off_peak_fix	0.755875	0.425467
var_year_price_peak_fix	0.309477	0.273434
var_year_price_mid_peak_fix	0.310865	0.283188
var_year_price_off_peak	0.755879	0.425468
var_year_price_peak	0.309480	0.273442
var_year_price_mid_peak	0.310865	0.283188
var_6m_price_off_peak_var	1.000000	0.468700
var_6m_price_peak_var	0.468700	1.000000
var_6m_price_mid_peak_var	0.475458	0.418850
var_6m_price_off_peak_fix	0.813497	0.459064
var_6m_price_peak_fix	0.480090	0.398631
var_6m_price_mid_peak_fix	0.473619	0.403081
var_6m_price_off_peak	0.813501	0.459065
var_6m_price_peak	0.480094	0.398645
var_6m_price_mid_peak	0.473620	0.403081

	var_6m_price_mid_peak_var \
var_year_price_off_peak_var	0.269555
var_year_price_peak_var	0.312539
var_year_price_mid_peak_var	0.666421
var_year_price_off_peak_fix	0.420256
var_year_price_peak_fix	0.649140
var_year_price_mid_peak_fix	0.664660
var_year_price_off_peak	0.420257
var_year_price_peak	0.649141
var_year_price_mid_peak	0.664661
var_6m_price_off_peak_var	0.475458
var_6m_price_peak_var	0.418850
var_6m_price_mid_peak_var	1.000000
var_6m_price_off_peak_fix	0.450765
var_6m_price_peak_fix	0.970093
var_6m_price_mid_peak_fix	0.976743
var_6m_price_off_peak	0.450766
var_6m_price_peak	0.970093

var_6m_price_mid_peak	0.976744

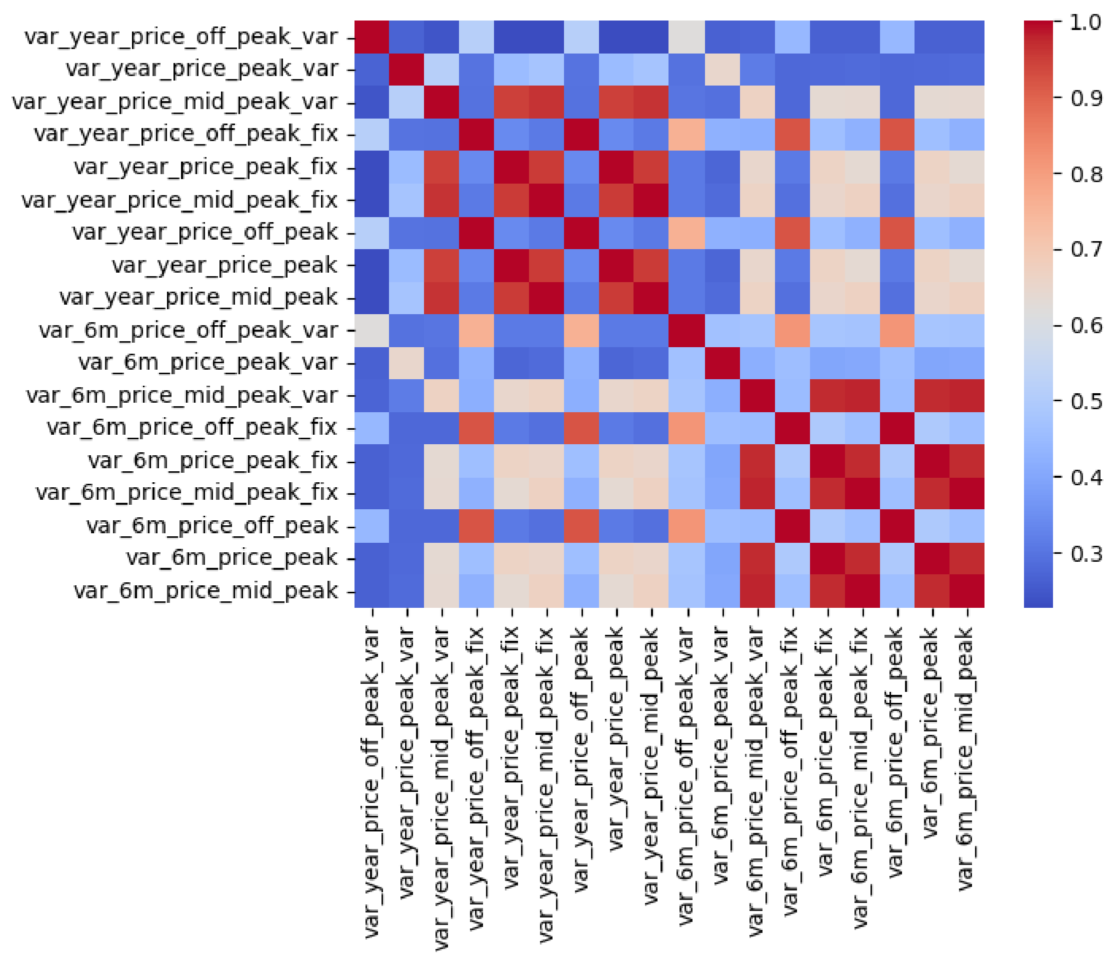
	var_6m_price_off_peak_fix	var_6m_price_peak_fix \
var_year_price_off_peak_var	0.441878	0.264435
var_year_price_peak_var	0.278371	0.279135
var_year_price_mid_peak_var	0.276626	0.637463
var_year_price_off_peak_fix	0.919000	0.460190
var_year_price_peak_fix	0.310610	0.662291
var_year_price_mid_peak_fix	0.290756	0.650680
var_year_price_off_peak	0.918999	0.460191
var_year_price_peak	0.310612	0.662291
var_year_price_mid_peak	0.290756	0.650680
var_6m_price_off_peak_var	0.813497	0.480090
var_6m_price_peak_var	0.459064	0.398631
var_6m_price_mid_peak_var	0.450765	0.970093
var_6m_price_off_peak_fix	1.000000	0.495431
var_6m_price_peak_fix	0.495431	1.000000
var_6m_price_mid_peak_fix	0.460428	0.970213
var_6m_price_off_peak	1.000000	0.495432
var_6m_price_peak	0.495436	1.000000
var_6m_price_mid_peak	0.460428	0.970214

	var_6m_price_mid_peak_fix	var_6m_price_off_peak \
var_year_price_off_peak_var	0.264312	0.441880
var_year_price_peak_var	0.283905	0.278372
var_year_price_mid_peak_var	0.638773	0.276627
var_year_price_off_peak_fix	0.426243	0.919000
var_year_price_peak_fix	0.637355	0.310611
var_year_price_mid_peak_fix	0.670265	0.290757
var_year_price_off_peak	0.426243	0.918999
var_year_price_peak	0.637355	0.310613
var_year_price_mid_peak	0.670265	0.290757
var_6m_price_off_peak_var	0.473619	0.813501
var_6m_price_peak_var	0.403081	0.459065
var_6m_price_mid_peak_var	0.976743	0.450766
var_6m_price_off_peak_fix	0.460428	1.000000
var_6m_price_peak_fix	0.970213	0.495432
var_6m_price_mid_peak_fix	1.000000	0.460429
var_6m_price_off_peak	0.460429	1.000000
var_6m_price_peak	0.970214	0.495436
var_6m_price_mid_peak	1.000000	0.460429

	var_6m_price_peak	var_6m_price_mid_peak
var_year_price_off_peak_var	0.264437	0.264313
var_year_price_peak_var	0.279144	0.283906
var_year_price_mid_peak_var	0.637464	0.638774
var_year_price_off_peak_fix	0.460194	0.426243

var_year_price_peak_fix	0.662291	0.637355
var_year_price_mid_peak_fix	0.650680	0.670265
var_year_price_off_peak	0.460195	0.426244
var_year_price_peak	0.662291	0.637355
var_year_price_mid_peak	0.650681	0.670265
var_6m_price_off_peak_var	0.480094	0.473620
var_6m_price_peak_var	0.398645	0.403081
var_6m_price_mid_peak_var	0.970093	0.976744
var_6m_price_off_peak_fix	0.495436	0.460428
var_6m_price_peak_fix	1.000000	0.970214
var_6m_price_mid_peak_fix	0.970214	1.000000
var_6m_price_off_peak	0.495436	0.460429
var_6m_price_peak	1.000000	0.970214
var_6m_price_mid_peak	0.970214	1.000000

[49]:
```
sns.heatmap(df.filter(regex = 'var').corr(), cmap = 'coolwarm')
plt.show()
```

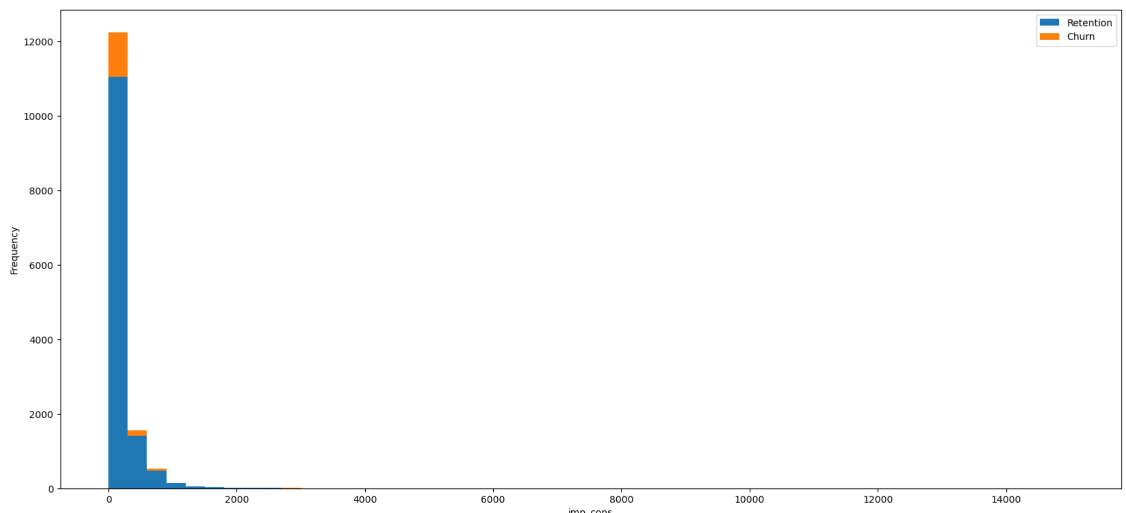


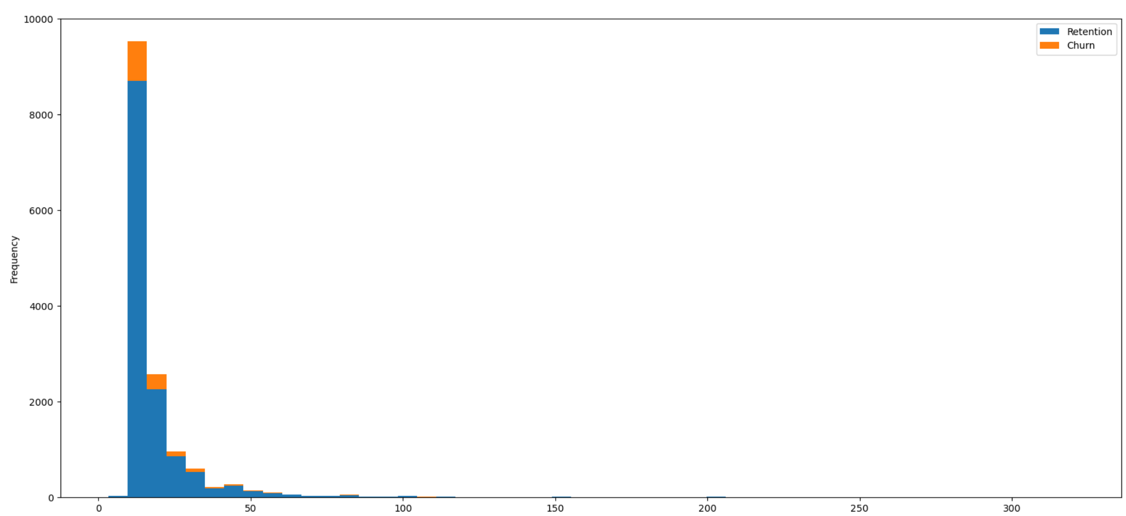
These are the columns added by BCGX team, we can observe high correlations across many of the columns. While we can remove some of them, for prediction we will use decision trees and neurel networks so this will not impact a lot.

[50]:
```
df.groupby('churn').sum()[['imp_cons']]
```

[50]:
```
          imp_cons
churn
0       2017138.69
1        214466.71
```

[51]:
```
fig, axs = plt.subplots(nrows=2, figsize=(20, 20))

plot_distribution(df, 'imp_cons', axs[0])
plot_distribution(df, 'pow_max', axs[1])
plt.show()
```





[52]:
```
df.groupby('origin_up').sum()['churn']
```

[52]:
```
origin_up
MISSING                                4
ewxeelcelemmiwuafmddpobolfuxioce       0
kamkkxfxxuwbdslkwifmmcsiusiuosws     258
ldkssxwpmemidmecebumciepifcamkci     264
lxidpiddsbxsbosboudacockeimpuepw     893
usapbepcfoloekilkwsdiboslwaxobdp       0
Name: churn, dtype: int64
```

1.3.5 Price Dataset EDA

[53]:
```
#Loading price data
df_price = pd.read_csv('price_data.csv')
df_price['price_date'] = pd.to_datetime(df_price['price_date'])
df_price['price_month'] = df_price['price_date'].dt.month #Converting date␣
↪column and extracting month
df_price.head()
```

[53]:
```
                                 id price_date  price_off_peak_var  \
0  038af19179925da21a25619c5a24b745 2015-01-01            0.151367
1  038af19179925da21a25619c5a24b745 2015-02-01            0.151367
2  038af19179925da21a25619c5a24b745 2015-03-01            0.151367
3  038af19179925da21a25619c5a24b745 2015-04-01            0.149626
4  038af19179925da21a25619c5a24b745 2015-05-01            0.149626

   price_peak_var  price_mid_peak_var  price_off_peak_fix  price_peak_fix  \
0             0.0                 0.0           44.266931             0.0
1             0.0                 0.0           44.266931             0.0
2             0.0                 0.0           44.266931             0.0
3             0.0                 0.0           44.266931             0.0
4             0.0                 0.0           44.266931             0.0

   price_mid_peak_fix  price_month
0                 0.0            1
1                 0.0            2
2                 0.0            3
3                 0.0            4
4                 0.0            5
```

[54]:
```
#extracting meaningful insights from date
```

```
df_price['is_weekend'] = df_price['price_date'].dt.dayofweek >= 5 #Weekend␣
↪price is generally more than weekdays
df_price['is_month_start'] = df_price['price_date'].dt.is_month_start #Month␣
↪start price
df_price['is_month_end'] = df_price['price_date'].dt.is_month_end #Month end␣
↪price
df_price['quarter'] = df_price['price_date'].dt.quarter #Quaterly price
```

[55]:
```
df_price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193002 entries, 0 to 193001
Data columns (total 13 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   id                  193002 non-null  object
 1   price_date          193002 non-null  datetime64[ns]
 2   price_off_peak_var  193002 non-null  float64
 3   price_peak_var      193002 non-null  float64
 4   price_mid_peak_var  193002 non-null  float64
 5   price_off_peak_fix  193002 non-null  float64
 6   price_peak_fix      193002 non-null  float64
 7   price_mid_peak_fix  193002 non-null  float64
 8   price_month         193002 non-null  int32
 9   is_weekend          193002 non-null  bool
 10  is_month_start      193002 non-null  bool
 11  is_month_end        193002 non-null  bool
 12  quarter             193002 non-null  int32
dtypes: bool(3), datetime64[ns](1), float64(6), int32(2), object(1)
memory usage: 13.8+ MB
```

[56]:
```
#More feature engineering on price variables. We are covering price␣
↪differences, average prices, and weekend prices

df_price['var_peak_offpeak_spread'] = df_price['price_peak_var'] -␣
↪df_price['price_off_peak_var']
df_price['fix_peak_offpeak_spread'] = df_price['price_peak_fix'] -␣
↪df_price['price_off_peak_fix']
df_price['avg_var_price'] = df_price[['price_off_peak_var', 'price_peak_var',␣
↪'price_mid_peak_var']].mean(axis=1)
df_price['avg_fix_price'] = df_price[['price_off_peak_fix', 'price_peak_fix',␣
↪'price_mid_peak_fix']].mean(axis=1)
df_price['peak_var_x_is_weekend'] = df_price['price_peak_var'] *␣
↪df_price['is_weekend'].astype(int)
```

[57]:
```
df_price.corr(numeric_only = True)
```

[57]:

```
                       price_off_peak_var  price_peak_var  \
price_off_peak_var               1.000000       -0.328580
price_peak_var                  -0.328580        1.000000
price_mid_peak_var              -0.594872        0.821353
price_off_peak_fix               0.417097       -0.098627
price_peak_fix                  -0.630018        0.796097
price_mid_peak_fix              -0.572229        0.807759
price_month                     -0.083796       -0.012409
is_weekend                      -0.016939       -0.003991
is_month_start                        NaN             NaN
is_month_end                          NaN             NaN
quarter                         -0.081647       -0.011674
var_peak_offpeak_spread         -0.660111        0.926359
fix_peak_offpeak_spread         -0.742420        0.771820
avg_var_price                   -0.174635        0.963302
avg_fix_price                   -0.502655        0.780654
peak_var_x_is_weekend           -0.155150        0.427270

                       price_mid_peak_var  price_off_peak_fix  \
price_off_peak_var              -0.594872            0.417097
price_peak_var                   0.821353           -0.098627
price_mid_peak_var               1.000000           -0.137848
price_off_peak_fix              -0.137848            1.000000
price_peak_fix                   0.973960           -0.000428
price_mid_peak_fix               0.979717           -0.252661
price_month                      0.003895            0.013119
is_weekend                       0.001135           -0.001878
is_month_start                        NaN                 NaN
is_month_end                          NaN                 NaN
quarter                          0.004327            0.012386
var_peak_offpeak_spread          0.890470           -0.244772
fix_peak_offpeak_spread          0.950930           -0.388586
avg_var_price                    0.840718            0.006916
avg_fix_price                    0.947287            0.168202
peak_var_x_is_weekend            0.355659           -0.044383

                       price_peak_fix  price_mid_peak_fix  price_month  \
price_off_peak_var          -0.630018           -0.572229    -0.083796
price_peak_var               0.796097            0.807759    -0.012409
price_mid_peak_var           0.973960            0.979717     0.003895
price_off_peak_fix          -0.000428           -0.252661     0.013119
price_peak_fix               1.000000            0.927308    -0.000862
price_mid_peak_fix           0.927308            1.000000    -0.001079
price_month                 -0.000862           -0.001079     1.000000
is_weekend                   0.001788            0.002100    -0.102431
is_month_start                    NaN                 NaN          NaN
is_month_end                      NaN                 NaN          NaN
```

quarter	-0.000344	-0.000579	0.971625
var_peak_offpeak_spread	0.884398	0.870628	0.023547
fix_peak_offpeak_spread	0.921579	0.952514	-0.005887
avg_var_price	0.799150	0.829294	-0.034696
avg_fix_price	0.980064	0.895341	0.002519
peak_var_x_is_weekend	0.345639	0.350978	-0.074579

	is_weekend	is_month_start	is_month_end	quarter \
price_off_peak_var	-0.016939	NaN	NaN	-0.081647
price_peak_var	-0.003991	NaN	NaN	-0.011674
price_mid_peak_var	0.001135	NaN	NaN	0.004327
price_off_peak_fix	-0.001878	NaN	NaN	0.012386
price_peak_fix	0.001788	NaN	NaN	-0.000344
price_mid_peak_fix	0.002100	NaN	NaN	-0.000579
price_month	-0.102431	NaN	NaN	0.971625
is_weekend	1.000000	NaN	NaN	-0.158085
is_month_start	NaN	NaN	NaN	NaN
is_month_end	NaN	NaN	NaN	NaN
quarter	-0.158085	NaN	NaN	1.000000
var_peak_offpeak_spread	0.003581	NaN	NaN	0.023275
fix_peak_offpeak_spread	0.002377	NaN	NaN	-0.005125
avg_var_price	-0.007841	NaN	NaN	-0.033266
avg_fix_price	0.001424	NaN	NaN	0.002840
peak_var_x_is_weekend	0.665309	NaN	NaN	-0.112290

	var_peak_offpeak_spread	fix_peak_offpeak_spread \
price_off_peak_var	-0.660111	-0.742420
price_peak_var	0.926359	0.771820
price_mid_peak_var	0.890470	0.950930
price_off_peak_fix	-0.244772	-0.388586
price_peak_fix	0.884398	0.921579
price_mid_peak_fix	0.870628	0.952514
price_month	0.023547	-0.005887
is_weekend	0.003581	0.002377
is_month_start	NaN	NaN
is_month_end	NaN	NaN
quarter	0.023275	-0.005125
var_peak_offpeak_spread	1.000000	0.909914
fix_peak_offpeak_spread	0.909914	1.000000
avg_var_price	0.835781	0.733662
avg_fix_price	0.821326	0.837749
peak_var_x_is_weekend	0.401691	0.335706

	avg_var_price	avg_fix_price	peak_var_x_is_weekend
price_off_peak_var	-0.174635	-0.502655	-0.155150
price_peak_var	0.963302	0.780654	0.427270
price_mid_peak_var	0.840718	0.947287	0.355659

```
price_off_peak_fix            0.006916      0.168202             -0.044383
price_peak_fix                0.799150      0.980064              0.345639
price_mid_peak_fix            0.829294      0.895341              0.350978
price_month                  -0.034696      0.002519             -0.074579
is_weekend                   -0.007841      0.001424              0.665309
is_month_start                     NaN           NaN                   NaN
is_month_end                       NaN           NaN                   NaN
quarter                      -0.033266      0.002840             -0.112290
var_peak_offpeak_spread       0.835781      0.821326              0.401691
fix_peak_offpeak_spread       0.733662      0.837749              0.335706
avg_var_price                 1.000000      0.818669              0.408921
avg_fix_price                 0.818669      1.000000              0.338626
peak_var_x_is_weekend         0.408921      0.338626              1.000000
```

As expected correlation is high for various columns. While multicollinearity is a negative aspect for a dataset decision trees, especially boosting techniques can counter it alongside Neurel Network approaches.

[58]:
```python
df_price['price_month']
```

[58]:
```
0          1
1          2
2          3
3          4
4          5
          ..
192997     8
192998     9
192999    10
193000    11
193001    12
Name: price_month, Length: 193002, dtype: int32
```

[59]:
```python
df_price[['price_peak_var', 'price_month']].groupby('price_month').
 ↪agg({'price_peak_var':'mean'})
```

[59]:
```
             price_peak_var
price_month
1                  0.054950
2                  0.055053
3                  0.055118
4                  0.056035
5                  0.055359
6                  0.055255
7                  0.055369
8                  0.053605
9                  0.053532
```

```
10                    0.053713
11                    0.053620
12                    0.053957
```

[60]:
```
df_price[['price_peak_fix', 'price_month']].groupby('price_month').
 ↪agg({'price_peak_fix':'mean'})
```

[60]:

price_month	price_peak_fix
1	10.692921
2	10.673719
3	10.644489
4	10.647277
5	10.602453
6	10.415769
7	10.642236
8	10.661678
9	10.602979
10	10.605431
11	10.641489
12	10.644109

Average peak price for Energy and Power is quite similar across the different months for an year. Overall prices are not varying much across the year.

[61]:
```
#Checking null values
print(df_price.isnull().sum())
```

```
id                          0
price_date                  0
price_off_peak_var          0
price_peak_var              0
price_mid_peak_var          0
price_off_peak_fix          0
price_peak_fix              0
price_mid_peak_fix          0
price_month                 0
is_weekend                  0
is_month_start              0
is_month_end                0
quarter                     0
var_peak_offpeak_spread     0
fix_peak_offpeak_spread     0
avg_var_price               0
avg_fix_price               0
peak_var_x_is_weekend       0
dtype: int64
```

[62]:
```python
print(df_price.describe())
```

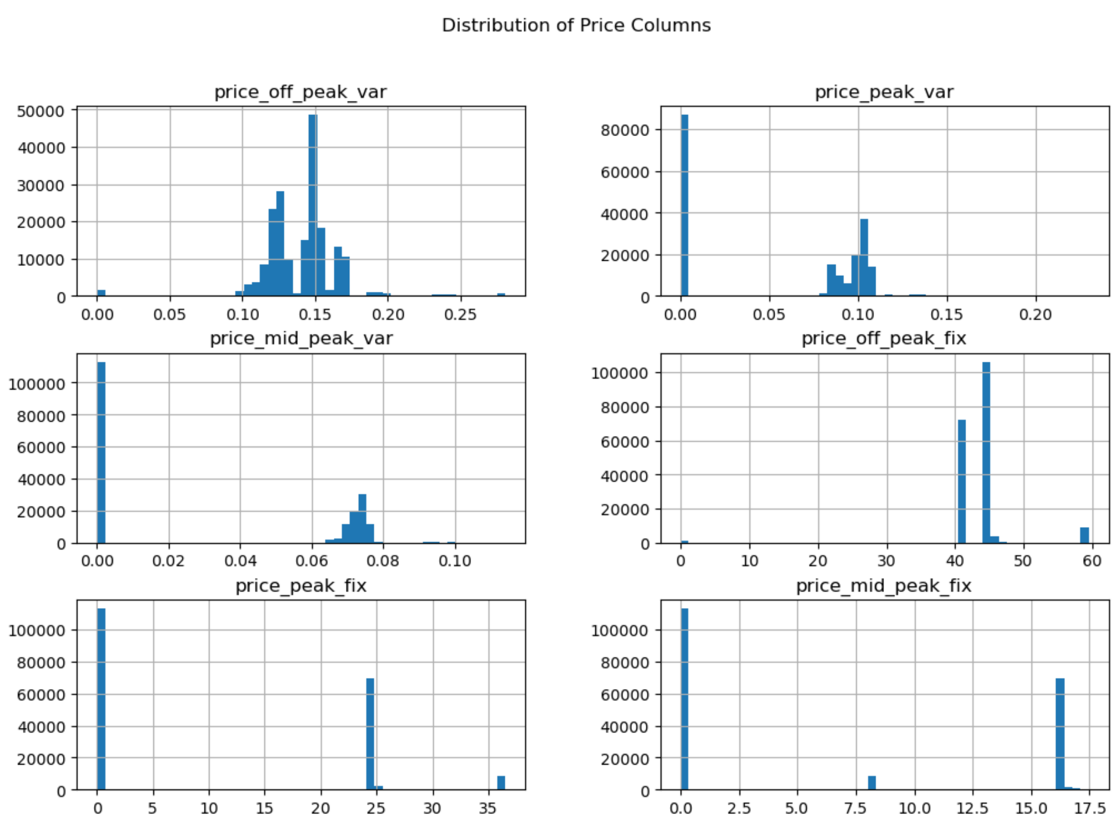
```
                          price_date  price_off_peak_var  price_peak_var  \
count                         193002       193002.000000   193002.000000
mean   2015-06-16 12:50:49.933161216            0.141027        0.054630
min              2015-01-01 00:00:00            0.000000        0.000000
25%              2015-04-01 00:00:00            0.125976        0.000000
50%              2015-07-01 00:00:00            0.146033        0.085483
75%              2015-10-01 00:00:00            0.151635        0.101673
max              2015-12-01 00:00:00            0.280700        0.229788
std                              NaN            0.025032        0.049924

       price_mid_peak_var  price_off_peak_fix  price_peak_fix  \
count       193002.000000       193002.000000   193002.000000
mean             0.030496           43.334477       10.622875
min              0.000000            0.000000        0.000000
25%              0.000000           40.728885        0.000000
50%              0.000000           44.266930        0.000000
75%              0.072558           44.444710       24.339581
max              0.114102           59.444710       36.490692
std              0.036298            5.410297       12.841895

       price_mid_peak_fix    price_month        quarter  \
count       193002.000000  193002.000000  193002.000000
mean             6.409984       6.501161       2.500368
min              0.000000       1.000000       1.000000
25%              0.000000       4.000000       2.000000
50%              0.000000       7.000000       3.000000
75%             16.226389      10.000000       4.000000
max             17.458221      12.000000       4.000000
std              7.773592       3.451935       1.117995

       var_peak_offpeak_spread  fix_peak_offpeak_spread  avg_var_price  \
count            193002.000000            193002.000000  193002.000000
mean                 -0.086397               -32.711602       0.075384
min                  -0.280700               -59.444710       0.000000
25%                  -0.148477               -44.266931       0.049852
50%                  -0.082931               -44.266930       0.084289
75%                  -0.022136               -16.291555       0.098433
max                   0.096908                 0.000000       0.163193
std                   0.062772                13.937180       0.024746

       avg_fix_price  peak_var_x_is_weekend
count  193002.000000          193002.000000
mean       20.122446               0.018117
min         0.000000               0.000000
25%        14.755644               0.000000
```

```
50%        14.814903              0.000000
75%        27.043980              0.000000
max        34.677296              0.229788
std         6.818637              0.038509
```

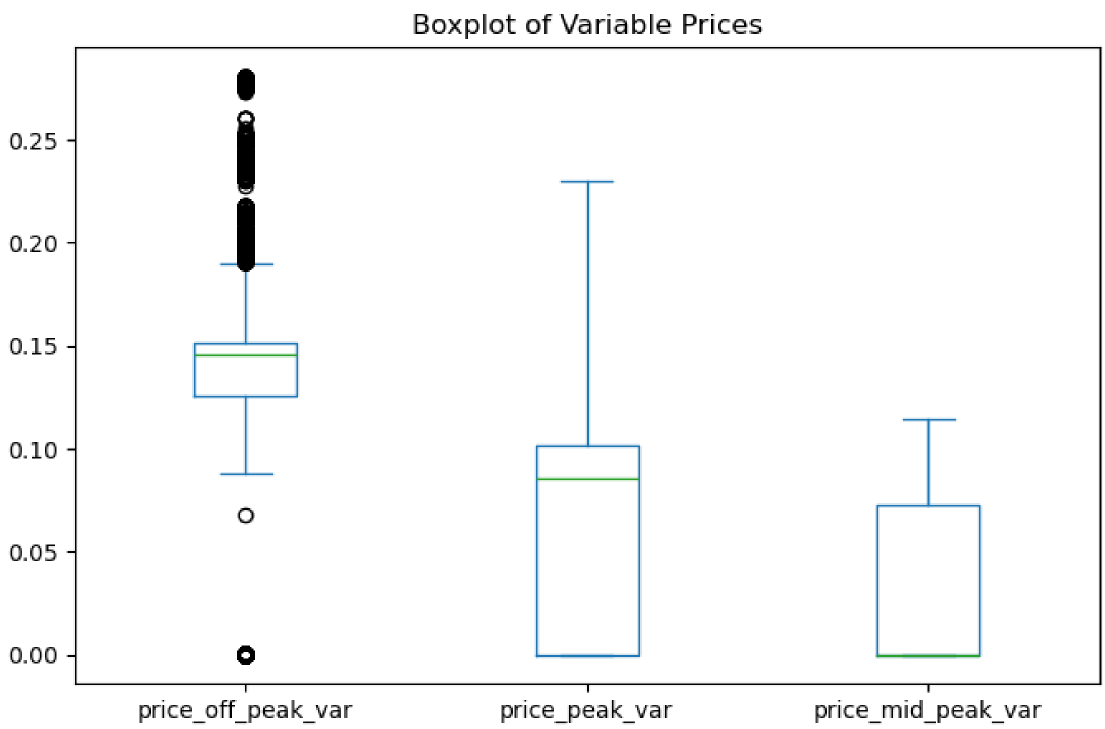
[63]:
```python
print(df_price[['is_weekend', 'is_month_start', 'is_month_end']].sum())
print(df_price['quarter'].value_counts())
```

```
is_weekend         64337
is_month_start    193002
is_month_end           0
dtype: int64
quarter
4    48266
3    48266
2    48244
1    48226
Name: count, dtype: int64
```

[64]:
```python
df_price[['price_off_peak_var', 'price_peak_var', 'price_mid_peak_var',
       'price_off_peak_fix', 'price_peak_fix', 'price_mid_peak_fix']].
 ↪hist(bins=50, figsize=(12,8))
plt.suptitle('Distribution of Price Columns')
plt.show()
```

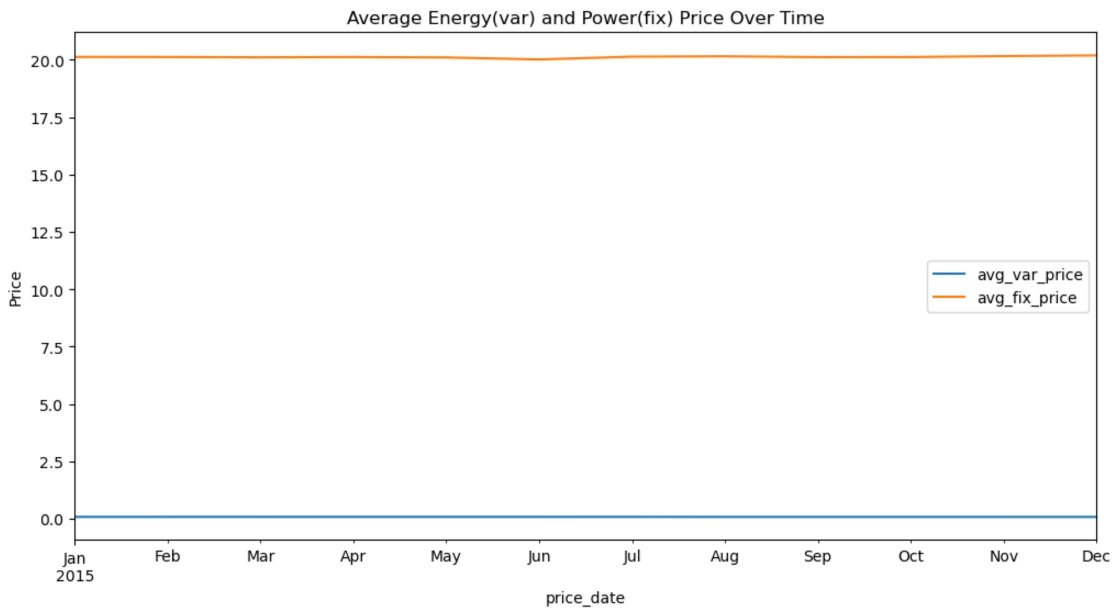


[65]:
```
df_price[['price_off_peak_var', 'price_peak_var', 'price_mid_peak_var']].
    ↪plot(kind='box', figsize=(8,5))
plt.title('Boxplot of Variable Prices')
plt.show()
```



There are a lot of outliers in off peak vs other categories. And again we are seeing peak pricing less than off peak when in reality it happens in inverse, most probably BCGX team adjusted the variables for the sake of anonymity of their client. Regardless of name of variables we can use the data for our predictive tasks.

[66]:
```
daily_avg = df_price.groupby('price_date')[['avg_var_price', 'avg_fix_price']].
    ↪mean()
daily_avg.plot(figsize=(12,6), title='Average Energy(var) and Power(fix) Price␣
    ↪Over Time')
plt.ylabel('Price')
plt.show()
```

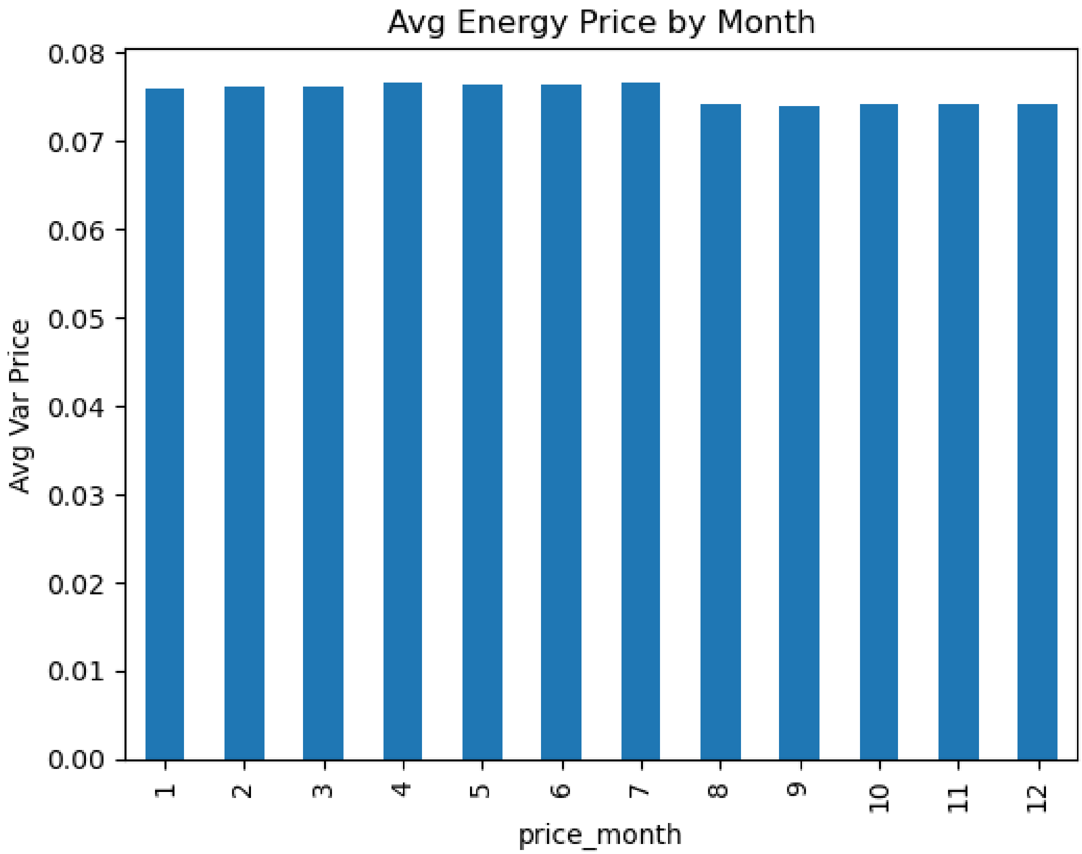


[67]:
```
#Average price for energy and power does not change much across the year
daily_avg.head()
```

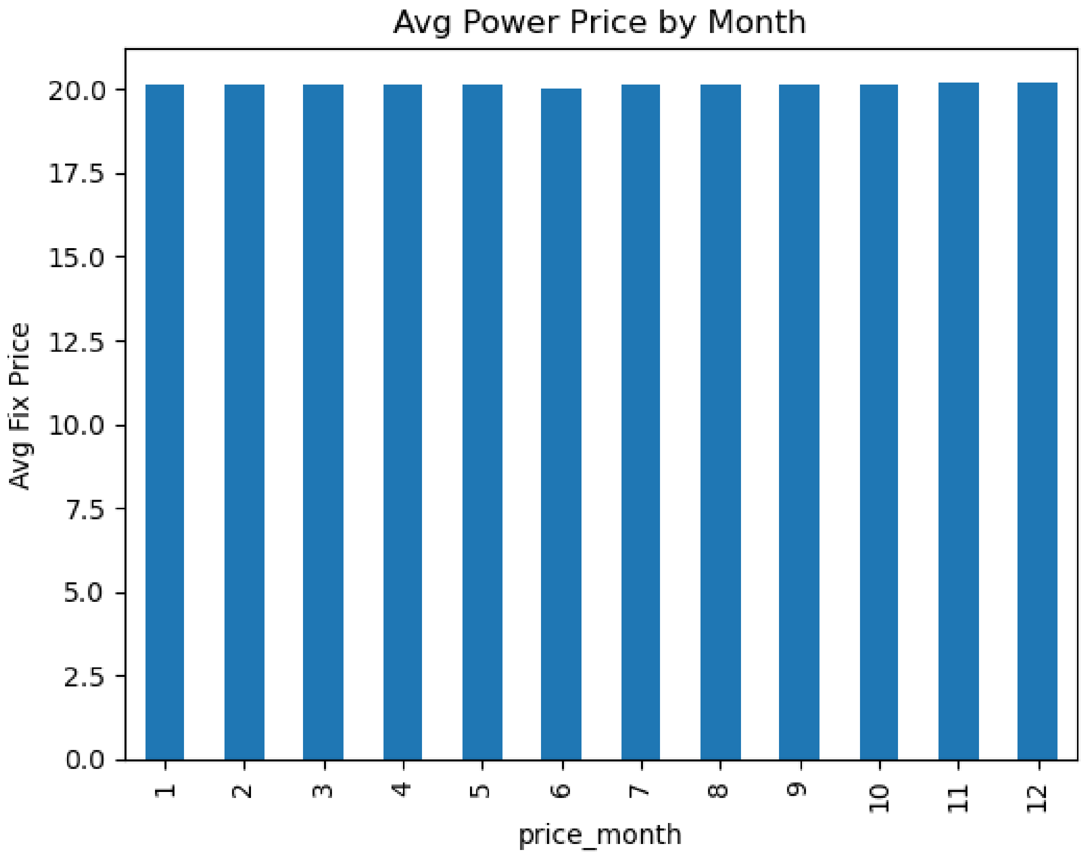
[67]:

	avg_var_price	avg_fix_price
price_date		
2015-01-01	0.075950	20.125141
2015-02-01	0.076063	20.120299
2015-03-01	0.076206	20.109548
2015-04-01	0.076595	20.119624
2015-05-01	0.076429	20.102882

[68]:
```
df_price.groupby('price_month')['avg_var_price'].mean().plot(kind='bar',␣
 ↪title='Avg Energy Price by Month')
plt.ylabel('Avg Var Price')
plt.show()
```

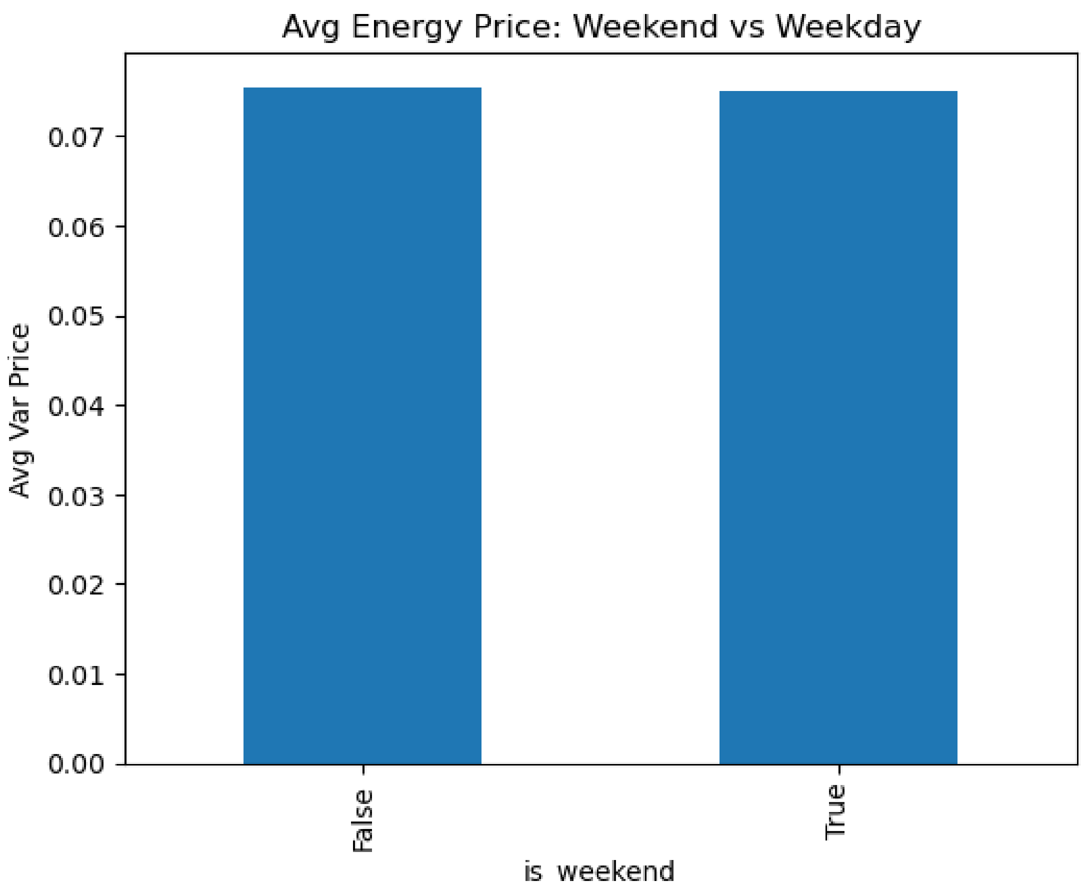


[69]:
```
df_price.groupby('price_month')['avg_fix_price'].mean().plot(kind='bar',␣
 ↪title='Avg Power Price by Month')
plt.ylabel('Avg Fix Price')
plt.show()
```

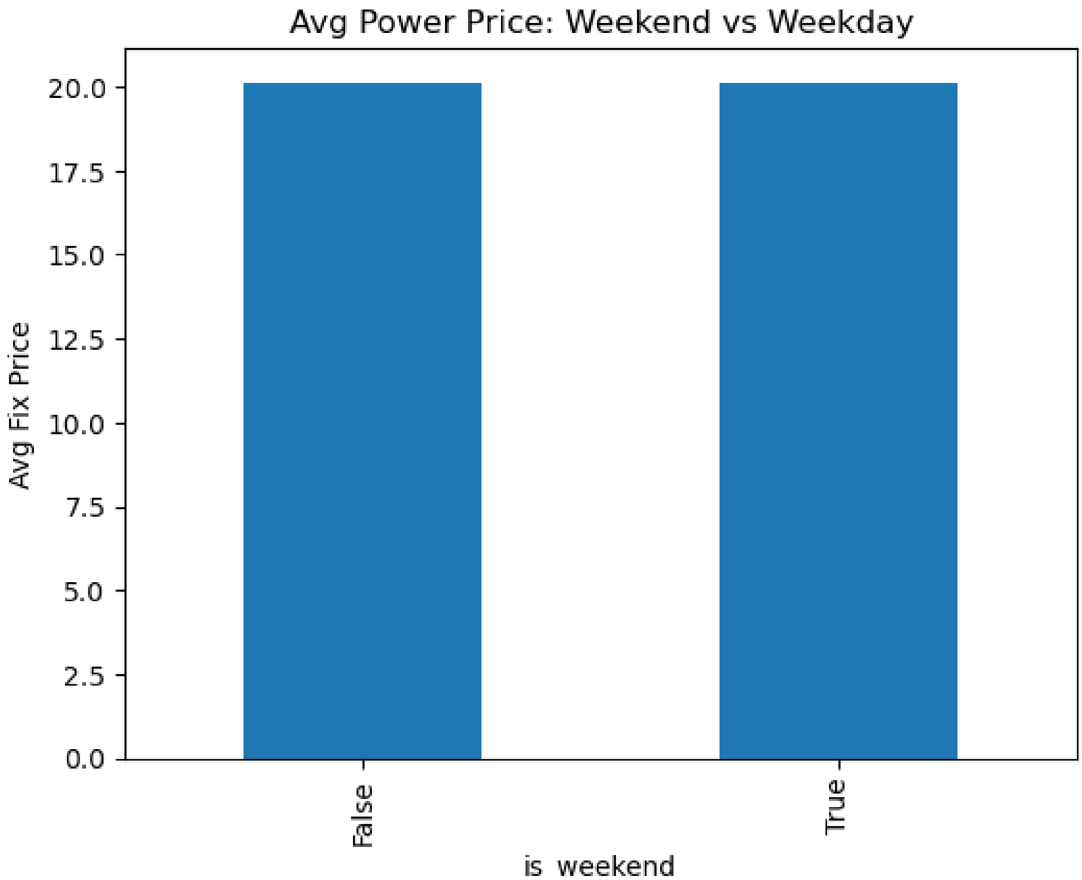


Average price for both energy and power connections are not varying much, client PowerCo has very stable pricing for the period.

[70]:
```
df_price.groupby('is_weekend')['avg_var_price'].mean().plot(kind='bar',␣
    ↪title='Avg Energy Price: Weekend vs Weekday')
plt.ylabel('Avg Var Price')
plt.show()
```



[71]:
```
df_price.groupby('is_weekend')['avg_fix_price'].mean().plot(kind='bar',␣
↪title='Avg Power Price: Weekend vs Weekday')
plt.ylabel('Avg Fix Price')
plt.show()
```



[72]:
```
print(df_price.groupby('is_weekend')['avg_var_price'].mean())
```

```
is_weekend
False    0.075522
True     0.075110
Name: avg_var_price, dtype: float64
```

[73]:
```
print(df_price.groupby('is_weekend')['avg_fix_price'].mean())
```

```
is_weekend
False    20.115581
True     20.136173
Name: avg_fix_price, dtype: float64
```

Overall for the weekends price is not varying much in both energy and power connections.

1.4 Model Training, Hyperparameter Tuning, and Evaluation

In this step we will cover model training, hyperparameter tuning, and evaluation for three types of models: XGBoost Ensemble Method based on Decision Trees, Dense Neural Network based on Dense Layers, and BiDirectional LSTM-CNN model which combines LSTM and CNN layers for Churn Prediction.

While XGBoost works fine with or without Scaled Paramteres we will scale the dataset for training as other two models need data scaling. For hyperparameter tuning we will focus on Gradient Boosting and BiLSTM - CNN. For the DNN Model hyperparameter we already tested some combinations in advance and used both regularization with early stopping.

We will evaluate the models on the basis of ROC-AUC Score, F1 Score, Recall, and Accuracy with less focus on Accuracy as ROC-AUC and Recall scores are better predictor for this task.

1.4.1 Data Preperation

In this step we will prepare data for modeling.

[74]:
```
#Merging price and client data with left join on price
df_price.drop(columns = 'price_date', inplace = True)
df_merge = df_price.merge(df, on = 'id', how = 'left')
df_merge.head()
```

[74]:
```
                                 id  price_off_peak_var  price_peak_var  \
0  038af19179925da21a25619c5a24b745            0.151367             0.0
1  038af19179925da21a25619c5a24b745            0.151367             0.0
2  038af19179925da21a25619c5a24b745            0.151367             0.0
3  038af19179925da21a25619c5a24b745            0.149626             0.0
4  038af19179925da21a25619c5a24b745            0.149626             0.0

   price_mid_peak_var  price_off_peak_fix  price_peak_fix  price_mid_peak_fix  \
0                 0.0           44.266931             0.0                 0.0
1                 0.0           44.266931             0.0                 0.0
2                 0.0           44.266931             0.0                 0.0
3                 0.0           44.266931             0.0                 0.0
4                 0.0           44.266931             0.0                 0.0

   price_month  is_weekend  is_month_start  …  var_6m_price_mid_peak_var  \
0            1       False            True  …                        0.0
1            2        True            True  …                        0.0
2            3        True            True  …                        0.0
3            4       False            True  …                        0.0
4            5       False            True  …                        0.0

   var_6m_price_off_peak_fix  var_6m_price_peak_fix  \
0                        0.0                    0.0
1                        0.0                    0.0
2                        0.0                    0.0
```

```
3                       0.0                    0.0
4                       0.0                    0.0

   var_6m_price_mid_peak_fix  var_6m_price_off_peak  var_6m_price_peak  \
0                        0.0               0.000003                0.0
1                        0.0               0.000003                0.0
2                        0.0               0.000003                0.0
3                        0.0               0.000003                0.0
4                        0.0               0.000003                0.0

   var_6m_price_mid_peak  churn  tenure  end_month
0                    0.0    0.0  1096.0        6.0
1                    0.0    0.0  1096.0        6.0
2                    0.0    0.0  1096.0        6.0
3                    0.0    0.0  1096.0        6.0
4                    0.0    0.0  1096.0        6.0

[5 rows x 56 columns]
```

BCGX standard answer did left merge on the client dataset but for this task left merge on price data is an industry norm because it helps us to capture more day to day data representations in the model and predictions.

[75]:
```
df_merge.info
```

[75]:
```
<bound method DataFrame.info of                                        id
price_off_peak_var  price_peak_var  \
0       038af19179925da21a25619c5a24b745            0.151367        0.000000
1       038af19179925da21a25619c5a24b745            0.151367        0.000000
2       038af19179925da21a25619c5a24b745            0.151367        0.000000
3       038af19179925da21a25619c5a24b745            0.149626        0.000000
4       038af19179925da21a25619c5a24b745            0.149626        0.000000
…                                    …                  …               …
192997  16f51cdc2baa19af0b940ee1b3dd17d5            0.119916        0.102232
192998  16f51cdc2baa19af0b940ee1b3dd17d5            0.119916        0.102232
192999  16f51cdc2baa19af0b940ee1b3dd17d5            0.119916        0.102232
193000  16f51cdc2baa19af0b940ee1b3dd17d5            0.119916        0.102232
193001  16f51cdc2baa19af0b940ee1b3dd17d5            0.119916        0.102232

        price_mid_peak_var  price_off_peak_fix  price_peak_fix  \
0                 0.000000           44.266931         0.00000
1                 0.000000           44.266931         0.00000
2                 0.000000           44.266931         0.00000
3                 0.000000           44.266931         0.00000
4                 0.000000           44.266931         0.00000
…                      …                  …              …
192997            0.076257           40.728885        24.43733
```

```
192998           0.076257           40.728885        24.43733
192999           0.076257           40.728885        24.43733
193000           0.076257           40.728885        24.43733
193001           0.076257           40.728885        24.43733

        price_mid_peak_fix  price_month  is_weekend  is_month_start  …  \
0                 0.000000            1       False            True  …
1                 0.000000            2        True            True  …
2                 0.000000            3        True            True  …
3                 0.000000            4       False            True  …
4                 0.000000            5       False            True  …
…                      …            …          …              …  …
192997           16.291555            8        True            True  …
192998           16.291555            9       False            True  …
192999           16.291555           10       False            True  …
193000           16.291555           11        True            True  …
193001           16.291555           12       False            True  …

        var_6m_price_mid_peak_var  var_6m_price_off_peak_fix  \
0                    0.000000e+00                        0.0
1                    0.000000e+00                        0.0
2                    0.000000e+00                        0.0
3                    0.000000e+00                        0.0
4                    0.000000e+00                        0.0
…                             …                        …
192997               4.860000e-10                        0.0
192998               4.860000e-10                        0.0
192999               4.860000e-10                        0.0
193000               4.860000e-10                        0.0
193001               4.860000e-10                        0.0

        var_6m_price_peak_fix  var_6m_price_mid_peak_fix  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         0.0                        0.0
4                         0.0                        0.0
…                         …                        …
192997                    0.0                        0.0
192998                    0.0                        0.0
192999                    0.0                        0.0
193000                    0.0                        0.0
193001                    0.0                        0.0

        var_6m_price_off_peak  var_6m_price_peak  var_6m_price_mid_peak churn  \
0                    0.000003           0.000000           0.000000e+00   0.0
1                    0.000003           0.000000           0.000000e+00   0.0
```

```
2                     0.000003           0.000000           0.000000e+00   0.0
3                     0.000003           0.000000           0.000000e+00   0.0
4                     0.000003           0.000000           0.000000e+00   0.0
…                        …                …                    …    …
192997                0.000011           0.000003           4.860000e-10   0.0
192998                0.000011           0.000003           4.860000e-10   0.0
192999                0.000011           0.000003           4.860000e-10   0.0
193000                0.000011           0.000003           4.860000e-10   0.0
193001                0.000011           0.000003           4.860000e-10   0.0

        tenure  end_month
0       1096.0        6.0
1       1096.0        6.0
2       1096.0        6.0
3       1096.0        6.0
4       1096.0        6.0
…         …         …
192997  1461.0        6.0
192998  1461.0        6.0
192999  1461.0        6.0
193000  1461.0        6.0
193001  1461.0        6.0

[193002 rows x 56 columns]>
```

[76]:

```python
#Checking na values
df_merge.isna().sum()
```

[76]:

```
id                              0
price_off_peak_var              0
price_peak_var                  0
price_mid_peak_var              0
price_off_peak_fix              0
price_peak_fix                  0
price_mid_peak_fix              0
price_month                     0
is_weekend                      0
is_month_start                  0
is_month_end                    0
quarter                         0
var_peak_offpeak_spread         0
fix_peak_offpeak_spread         0
avg_var_price                   0
avg_fix_price                   0
peak_var_x_is_weekend           0
channel_sales               17853
cons_12m                    17853
```

```
cons_gas_12m                      17853
cons_last_month                   17853
forecast_cons_12m                 17853
forecast_discount_energy          17853
forecast_meter_rent_12m           17853
forecast_price_energy_off_peak    17853
forecast_price_energy_peak        17853
forecast_price_pow_off_peak       17853
has_gas                           17853
imp_cons                          17853
margin_gross_pow_ele              17853
nb_prod_act                       17853
net_margin                        17853
num_years_antig                   17853
origin_up                         17853
pow_max                           17853
var_year_price_off_peak_var       17853
var_year_price_peak_var           17853
var_year_price_mid_peak_var       17853
var_year_price_off_peak_fix       17853
var_year_price_peak_fix           17853
var_year_price_mid_peak_fix       17853
var_year_price_off_peak           17853
var_year_price_peak               17853
var_year_price_mid_peak           17853
var_6m_price_off_peak_var         17853
var_6m_price_peak_var             17853
var_6m_price_mid_peak_var         17853
var_6m_price_off_peak_fix         17853
var_6m_price_peak_fix             17853
var_6m_price_mid_peak_fix         17853
var_6m_price_off_peak             17853
var_6m_price_peak                 17853
var_6m_price_mid_peak             17853
churn                             17853
tenure                            17853
end_month                         17853
dtype: int64
```

[77]:
```
missing_ids = set(df_price['id']) - set(df['id'])
print(f"Number of unmatched client ids: {len(missing_ids)}")
```

```
Number of unmatched client ids: 1490
```

[78]:
```
#Since Price dataset has more client ids than client df iteself we will only␣
↪cover data for client ids fallinf under sales channels
df_merge = df_merge[df_merge['channel_sales'].notnull()]
```

[79]:
```
df_merge.isna().sum()
```

[79]:
```
id                                0
price_off_peak_var                0
price_peak_var                    0
price_mid_peak_var                0
price_off_peak_fix                0
price_peak_fix                    0
price_mid_peak_fix                0
price_month                       0
is_weekend                        0
is_month_start                    0
is_month_end                      0
quarter                           0
var_peak_offpeak_spread           0
fix_peak_offpeak_spread           0
avg_var_price                     0
avg_fix_price                     0
peak_var_x_is_weekend             0
channel_sales                     0
cons_12m                          0
cons_gas_12m                      0
cons_last_month                   0
forecast_cons_12m                 0
forecast_discount_energy          0
forecast_meter_rent_12m           0
forecast_price_energy_off_peak    0
forecast_price_energy_peak        0
forecast_price_pow_off_peak       0
has_gas                           0
imp_cons                          0
margin_gross_pow_ele              0
nb_prod_act                       0
net_margin                        0
num_years_antig                   0
origin_up                         0
pow_max                           0
var_year_price_off_peak_var       0
var_year_price_peak_var           0
var_year_price_mid_peak_var       0
var_year_price_off_peak_fix       0
var_year_price_peak_fix           0
var_year_price_mid_peak_fix       0
var_year_price_off_peak           0
var_year_price_peak               0
var_year_price_mid_peak           0
var_6m_price_off_peak_var         0
```

```
var_6m_price_peak_var           0
var_6m_price_mid_peak_var       0
var_6m_price_off_peak_fix       0
var_6m_price_peak_fix           0
var_6m_price_mid_peak_fix       0
var_6m_price_off_peak           0
var_6m_price_peak               0
var_6m_price_mid_peak           0
churn                           0
tenure                          0
end_month                       0
dtype: int64
```

[80]:
```
df_merge.select_dtypes(include = ['object', 'category']).head()
```

[80]:
```
                                 id                     channel_sales  \
0  038af19179925da21a25619c5a24b745  foosdfpfkusacimwkcsosbicdxkicaua
1  038af19179925da21a25619c5a24b745  foosdfpfkusacimwkcsosbicdxkicaua
2  038af19179925da21a25619c5a24b745  foosdfpfkusacimwkcsosbicdxkicaua
3  038af19179925da21a25619c5a24b745  foosdfpfkusacimwkcsosbicdxkicaua
4  038af19179925da21a25619c5a24b745  foosdfpfkusacimwkcsosbicdxkicaua

                          origin_up
0  ldkssxwpmemidmecebumciepifcamkci
1  ldkssxwpmemidmecebumciepifcamkci
2  ldkssxwpmemidmecebumciepifcamkci
3  ldkssxwpmemidmecebumciepifcamkci
4  ldkssxwpmemidmecebumciepifcamkci
```

Now we will remove id variables. For channel_sales and origin_up we will use one hot encoding.

[81]:
```
df_merge = pd.get_dummies(df_merge, columns=['channel_sales', 'origin_up'],␣
↪drop_first=True, dtype=int)
```

One important note, in case of imbalance data generally oversampling on minority class is done using SMOTE however Gradient Boosting techniques are better suited for such dataset and generally SMOTE is not considered useful overall.

[87]:
```
#In order to avoid possible data leakage we will split the dataset on the basis␣
↪of clients with 20% clients going into test instead of 20% rows randomly
unique_customers = df_merge['id'].unique()
train_customers, test_customers = train_test_split(unique_customers, test_size␣
↪= 0.2, random_state = 10)
train_df = df_merge[df_merge['id'].isin(train_customers)]
test_df = df_merge[df_merge['id'].isin(test_customers)]
```

[93]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 140127 entries, 12 to 193001
Data columns (total 65 columns):
 #   Column                            Non-Null Count   Dtype
---  ------                            --------------   -----
 0   price_off_peak_var                140127 non-null  float64
 1   price_peak_var                    140127 non-null  float64
 2   price_mid_peak_var                140127 non-null  float64
 3   price_off_peak_fix                140127 non-null  float64
 4   price_peak_fix                    140127 non-null  float64
 5   price_mid_peak_fix                140127 non-null  float64
 6   price_month                       140127 non-null  int32
 7   is_weekend                        140127 non-null  bool
 8   is_month_start                    140127 non-null  bool
 9   is_month_end                      140127 non-null  bool
 10  quarter                           140127 non-null  int32
 11  var_peak_offpeak_spread           140127 non-null  float64
 12  fix_peak_offpeak_spread           140127 non-null  float64
 13  avg_var_price                     140127 non-null  float64
 14  avg_fix_price                     140127 non-null  float64
 15  peak_var_x_is_weekend             140127 non-null  float64
 16  cons_12m                          140127 non-null  float64
 17  cons_gas_12m                      140127 non-null  float64
 18  cons_last_month                   140127 non-null  float64
 19  forecast_cons_12m                 140127 non-null  float64
 20  forecast_discount_energy          140127 non-null  float64
 21  forecast_meter_rent_12m           140127 non-null  float64
 22  forecast_price_energy_off_peak    140127 non-null  float64
 23  forecast_price_energy_peak        140127 non-null  float64
 24  forecast_price_pow_off_peak       140127 non-null  float64
 25  has_gas                           140127 non-null  float64
 26  imp_cons                          140127 non-null  float64
 27  margin_gross_pow_ele              140127 non-null  float64
 28  nb_prod_act                       140127 non-null  float64
 29  net_margin                        140127 non-null  float64
 30  num_years_antig                   140127 non-null  float64
 31  pow_max                           140127 non-null  float64
 32  var_year_price_off_peak_var       140127 non-null  float64
 33  var_year_price_peak_var           140127 non-null  float64
 34  var_year_price_mid_peak_var       140127 non-null  float64
 35  var_year_price_off_peak_fix       140127 non-null  float64
 36  var_year_price_peak_fix           140127 non-null  float64
 37  var_year_price_mid_peak_fix       140127 non-null  float64
 38  var_year_price_off_peak           140127 non-null  float64
 39  var_year_price_peak               140127 non-null  float64
 40  var_year_price_mid_peak           140127 non-null  float64
 41  var_6m_price_off_peak_var         140127 non-null  float64
 42  var_6m_price_peak_var             140127 non-null  float64
```

```
 43  var_6m_price_mid_peak_var                         140127 non-null  float64
 44  var_6m_price_off_peak_fix                         140127 non-null  float64
 45  var_6m_price_peak_fix                             140127 non-null  float64
 46  var_6m_price_mid_peak_fix                         140127 non-null  float64
 47  var_6m_price_off_peak                             140127 non-null  float64
 48  var_6m_price_peak                                 140127 non-null  float64
 49  var_6m_price_mid_peak                             140127 non-null  float64
 50  churn                                             140127 non-null  float64
 51  tenure                                            140127 non-null  float64
 52  end_month                                         140127 non-null  float64
 53  channel_sales_epumfxlbckeskwekxbiuasklxalciiuu    140127 non-null  int64
 54  channel_sales_ewpakwlliwisiwduibdlfmalxowmwpci    140127 non-null  int64
 55  channel_sales_fixdbufsefwooaasfcxdxadsiekoceaa    140127 non-null  int64
 56  channel_sales_foosdfpfkusacimwkcsosbicdxkicaua    140127 non-null  int64
 57  channel_sales_lmkebamcaaclubfxadlmueccxoimlema    140127 non-null  int64
 58  channel_sales_sddiedcslfslkckwlfkdpoeeailfpeds    140127 non-null  int64
 59  channel_sales_usilxuppasemubllopkaafesmlibmsdf    140127 non-null  int64
 60  origin_up_ewxeelcelemmiwuafmddpobolfuxioce        140127 non-null  int64
 61  origin_up_kamkkxfxxuwbdslkwifmmcsiusiuosws        140127 non-null  int64
 62  origin_up_ldkssxwpmemidmecebumciepifcamkci        140127 non-null  int64
 63  origin_up_lxidpiddsbxsbosboudacockeimpuepw        140127 non-null  int64
 64  origin_up_usapbepcfoloekilkwsdiboslwaxobdp        140127 non-null  int64
dtypes: bool(3), float64(48), int32(2), int64(12)
memory usage: 66.7 MB
```

[339]:
```python
X_train = train_df.drop(columns = 'churn')
Y_train = train_df['churn']
X_test = test_df.drop(columns = 'churn')
Y_test = test_df['churn']
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(140127, 64)
(140127,)
(35022, 64)
(35022,)
```

[340]:
```python
scaler = StandardScaler() #normalizing skewed variables and other numerical␣
 ↪variables
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

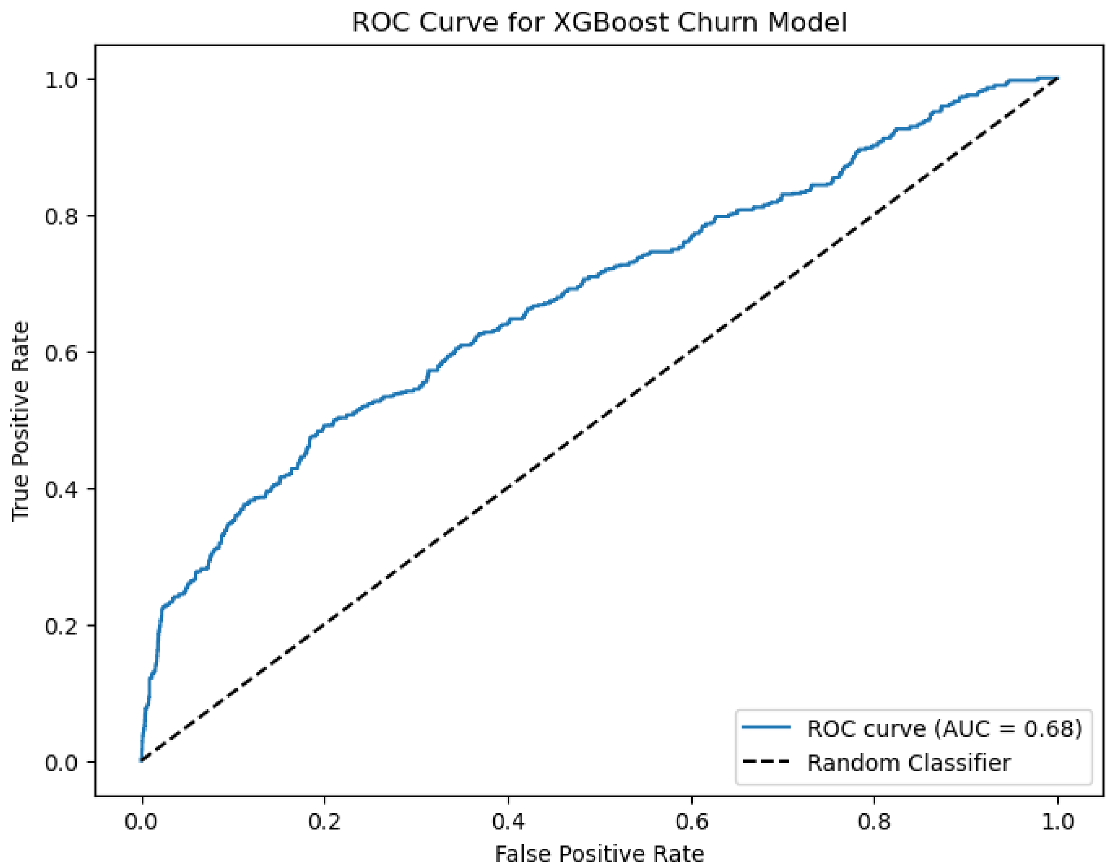
[155]:
```python
model_xg = XGBClassifier(n_estimators = 100,
                         learning_rate = 0.1,
                         max_depth = 8,
```

```
                              random_state = 10,
                              subsample = 0.8,
                              colsample_bytree = 0.8,
                              scale_pos_weight = 9)
```

[162]:
```
model_xg.fit(X_train_scaled, Y_train)
```

[162]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.1, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=8,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=100,
              n_jobs=None, num_parallel_tree=None, …)
```

[163]:
```
y_pred = model_xg.predict(X_test_scaled)
y_pred_proba = model_xg.predict_proba(X_test_scaled)[:, 1]

fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
roc_auc = roc_auc_score(Y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost Churn Model')
plt.legend(loc='lower right')
plt.show()

print(f"ROC AUC Score: {roc_auc:.2f}")
```



ROC AUC Score: 0.68

[164]:

```
# Classification report
print(classification_report(Y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(Y_test, y_pred)
print("Confusion Matrix:\n", cm)
print(f'F1 Score: {f1_score(Y_test, y_pred)}')
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.94      0.93     31649
         1.0       0.32      0.28      0.30      3373

    accuracy                           0.87     35022
   macro avg       0.62      0.61      0.61     35022
weighted avg       0.87      0.87      0.87     35022

Confusion Matrix:
```

```
[[29682  1967]
 [ 2438   935]]
F1 Score: 0.29800796812749003
```

Performing hyperparameter tuning for XGboost model.

[171]:
```python
param_grid = {"n_estimators": [100, 200, 300], #number of helper models
              "learning_rate": [0.1, 0.05, 0.01], #contribution rate for helper␣
 ↪models
              "max_depth": [3, 5, 8], #max depth of tree
              "subsample": [0.7, 0.8, 1.0], #percentage of training data␣
 ↪available
              "colsample_bytree": [0.7, 0.8, 1.0], #percentage of features␣
 ↪available
              "scale_pos_weight": [9] #used for unbalanced dataset
}

grid_search_xg = GridSearchCV(
              estimator = XGBClassifier(eval_metric = 'logloss'),
              param_grid = param_grid,
              scoring = 'roc_auc',
              cv = 5,
              verbose = 1,
              n_jobs = -1
)

grid_search_xg.fit(X_train_scaled, Y_train)
```

```
Fitting 5 folds for each of 243 candidates, totalling 1215 fits
```

[171]:
```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, device=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False,
                                     eval_metric='logloss', feature_types=None,
                                     feature_weights=None, gamma=None,
                                     grow_policy=None, importance_type=None,
                                     interaction_constraint…
                                     max_leaves=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     multi_strategy=None, n_estimators=None,
                                     n_jobs=None, num_parallel_tree=None, …),
             n_jobs=-1,
             param_grid={'colsample_bytree': [0.7, 0.8, 1.0],
                         'learning_rate': [0.1, 0.05, 0.01],
```

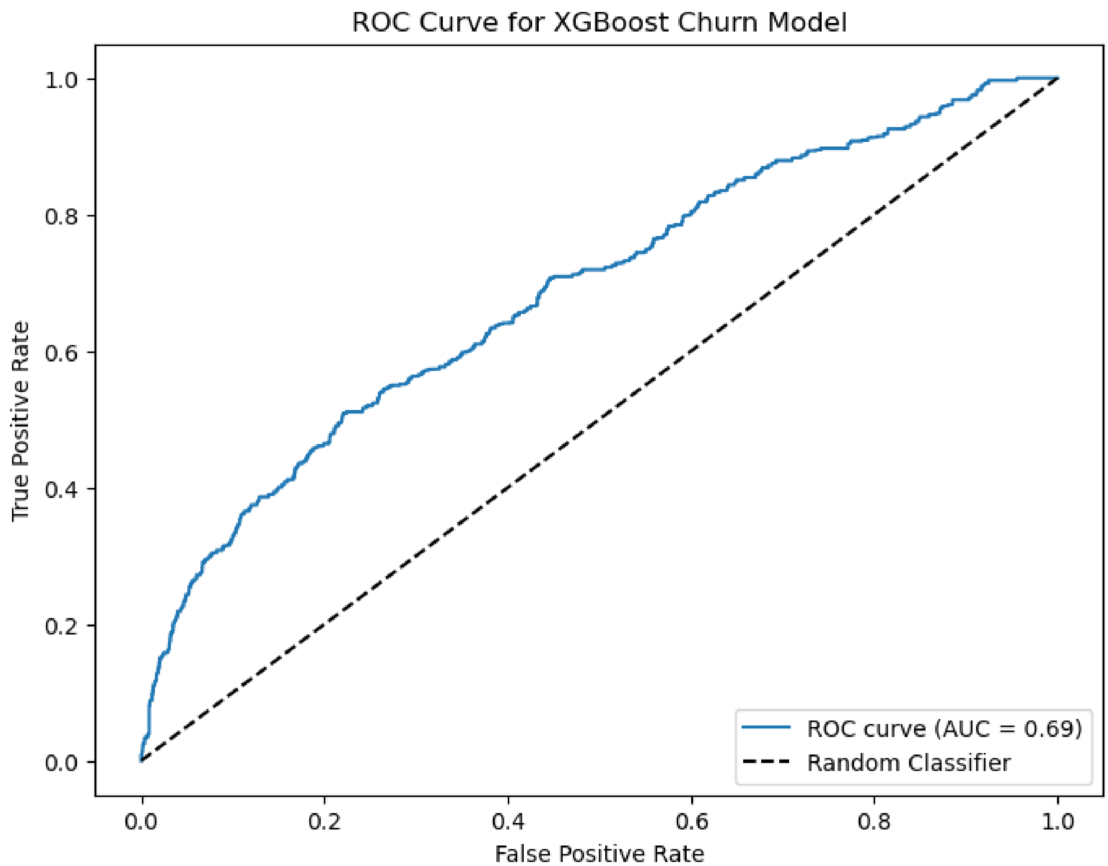
```
                         'max_depth': [3, 5, 8],
                         'n_estimators': [100, 200, 300],
                         'scale_pos_weight': [9],
                         'subsample': [0.7, 0.8, 1.0]},
             scoring='roc_auc', verbose=1)
```

[176]:
```
print(grid_search_xg.best_params_)
print(grid_search_xg.best_score_)
```

```
{'colsample_bytree': 0.7, 'learning_rate': 0.01, 'max_depth': 5, 'n_estimators':
300, 'scale_pos_weight': 9, 'subsample': 0.7}
0.6906782885031666
```

[173]:
```
best_model_xg = grid_search_xg.best_estimator_
```

[177]:
```
y_pred_proba = best_model_xg.predict_proba(X_test_scaled)[:,1]
fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
roc_auc = roc_auc_score(Y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost Churn Model')
plt.legend(loc='lower right')
plt.show()

print(f"ROC AUC Score: {roc_auc:.2f}")
```




```
ROC AUC Score: 0.69
```

[ ]:

```

```

[178]:

```python
# Predict class labels (default threshold 0.5)
y_pred = best_model_xg.predict(X_test_scaled)

# Classification report
print(classification_report(Y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(Y_test, y_pred)
print("Confusion Matrix:\n", cm)
print(f'F1 Score: {f1_score(Y_test, y_pred)}')
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.76      0.84     31649
         1.0       0.19      0.51      0.27      3373
```

```
    accuracy                           0.74     35022
   macro avg       0.56      0.64      0.56     35022
weighted avg       0.86      0.74      0.79     35022

Confusion Matrix:
 [[24195  7454]
 [ 1649  1724]]
F1 Score: 0.2747191458847901
```

State of the art industry Churn prediction models have f1 score of 0.5 and more with roc-auc score above 0.8. While our F1 score may look low, Churn prediction is a highly complex task in real world complex datasets and most companies start with models with such an F1 score and improve it further. In our case, our model is already far better than what BCGX proposed for this task. Their model was based on decision trees and had f1 score of 0.09 and recall of 0.05.

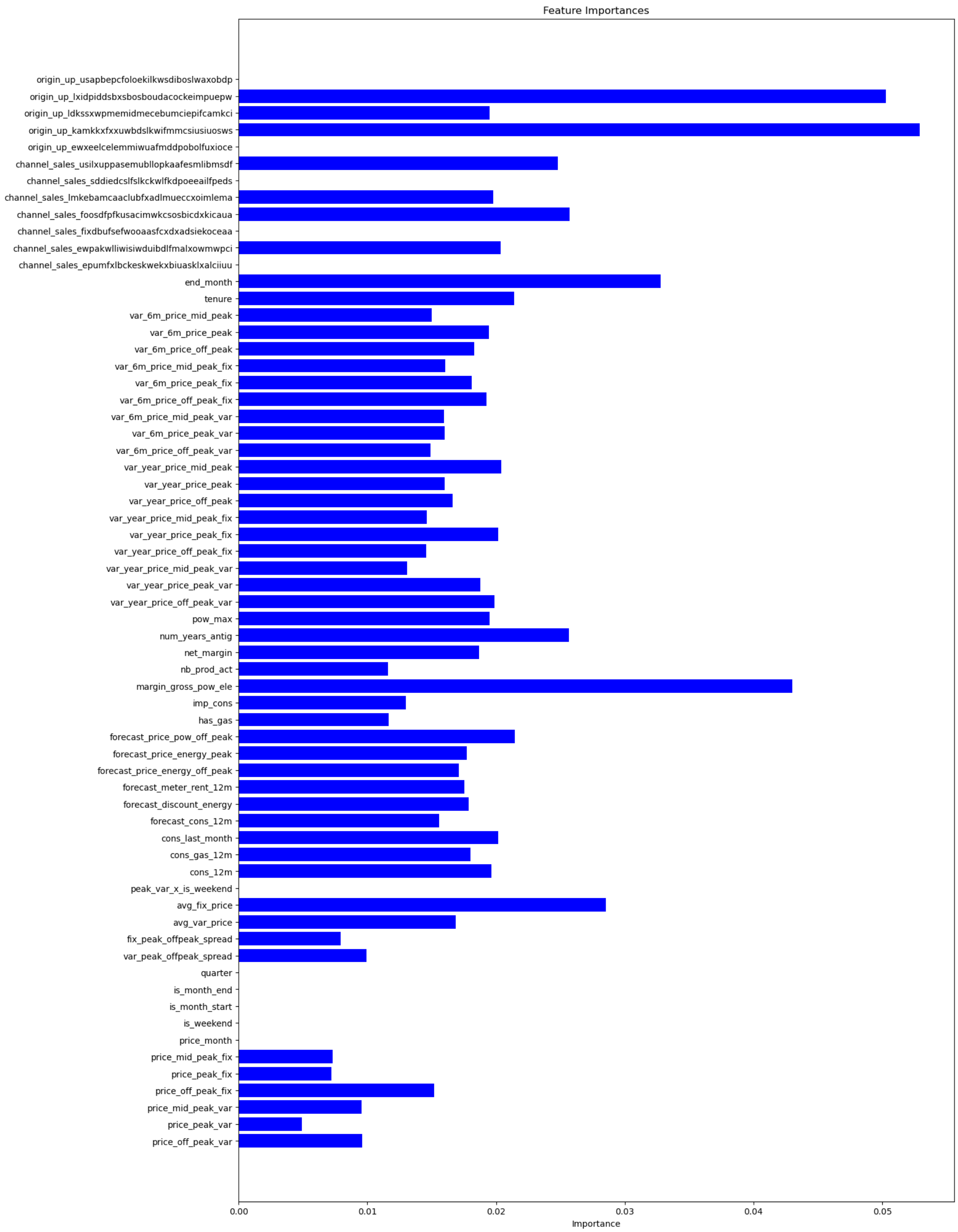
In contrast to that model our model is leagues ahead with 0.27 F1 and 0.51 recall. Our hyper-parameter tuning actually improved in recall as we focused on roc-auc score. If we focused on F1 Score, we would have gotten 0.28 F1 score and 0.33 recall. Generally, both F1 score and ROC-AUC score should be improved further by feature engineering and adding more data but we can't do them in our current project as we are limited to dataset obtained from BCGX.

[185]:
```python
feature_importance = pd.DataFrame({"features": X_train.columns, 'importance':
 ↪best_model_xg.feature_importances_})
feature_importance.sort_values('importance', ascending = False).head()
```

[185]:

	features	importance
60	origin_up_kamkkxfxxuwbdslkwifmmcsiusiuosws	0.052923
62	origin_up_lxidpiddsbxsbosboudacockeimpuepw	0.050283
27	margin_gross_pow_ele	0.043019
51	end_month	0.032805
14	avg_fix_price	0.028505

[187]:
```python
plt.figure(figsize=(15, 25))
plt.title('Feature Importances')
plt.barh(range(len(feature_importance)), feature_importance['importance'],
 ↪color='b', align='center')
plt.yticks(range(len(feature_importance)), feature_importance['features'])
plt.xlabel('Importance')
plt.show()
```



Based on the feature importance we can observe that Origin_up grouping is a major factor followed by gross margin, end month, and average price.

So, is price a good indicator for the churn prediction for PowerCO? On the basis of the above analysis, for our model top contributing factor is origin_up group and gross margin. Average price, one of the price indicator, has relative importance of 2.8% so its a relatively moderate contributor, not a top contributing factor. However, we need better feature engineer and more data to be sure.

A lot of predictors have near 0 feature importance so we would remove them for our final Xgboost model. However, while the model needs more feature engineering and data, after our analysis we can confirm that this dataset itself is limited and not usable for more feature engineering.

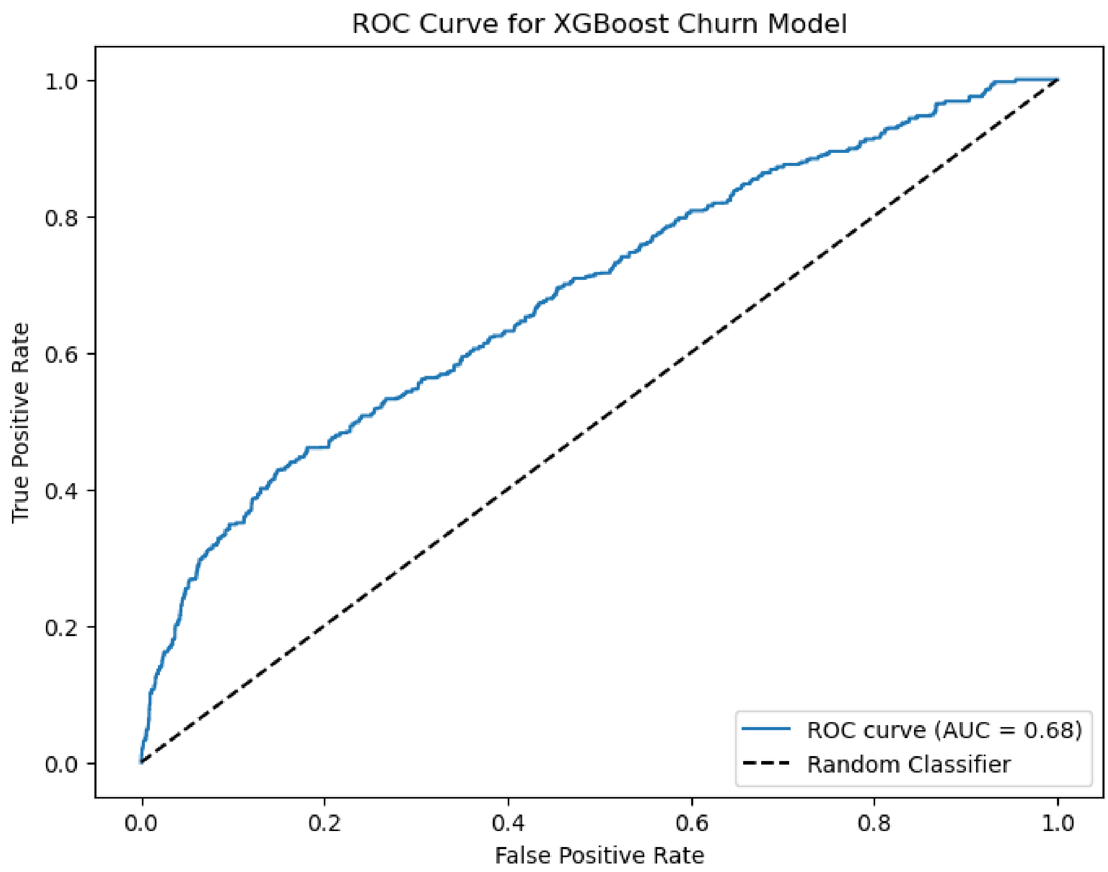
[213]:
```
X_train_xgb = X_train.drop(columns = list(feature_importance.
 ↪loc[feature_importance['importance'] == 0,].iloc[:,0]))
X_test_xgb = X_test.drop(columns = list(feature_importance.
 ↪loc[feature_importance['importance'] == 0,].iloc[:,0]))

#We will not scale the parameters this time as XG Boost is invariant to it␣
 ↪overall, we scaled to fit both XGboost and neurel network
```

[218]:
```
model_xgb = XGBClassifier(eval_metric = 'logloss',
                          colsample_bytree = 0.7,
                          learning_rate = 0.01,
                          max_depth = 5,
                          n_estimators = 300,
                          scale_pos_weight = 9,
                          subsample = 0.7)
model_xgb.fit(X_train_xgb, Y_train)
```

[218]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.7, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.01, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=300, n_jobs=None,
              num_parallel_tree=None, …)
```

[219]:
```
y_pred = model_xgb.predict(X_test_xgb)
y_pred_proba = model_xgb.predict_proba(X_test_xgb)[:, 1]

fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
roc_auc = roc_auc_score(Y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost Churn Model')
plt.legend(loc='lower right')
plt.show()

print(f"ROC AUC Score: {roc_auc:.2f}")
```




```
ROC AUC Score: 0.68
```

[220]:
```
# Predict class labels (default threshold 0.5)
y_pred = model_xgb.predict(X_test_xgb)

# Classification report
print(classification_report(Y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(Y_test, y_pred)
print("Confusion Matrix:\n", cm)
print(f'F1 Score: {f1_score(Y_test, y_pred)}')
```

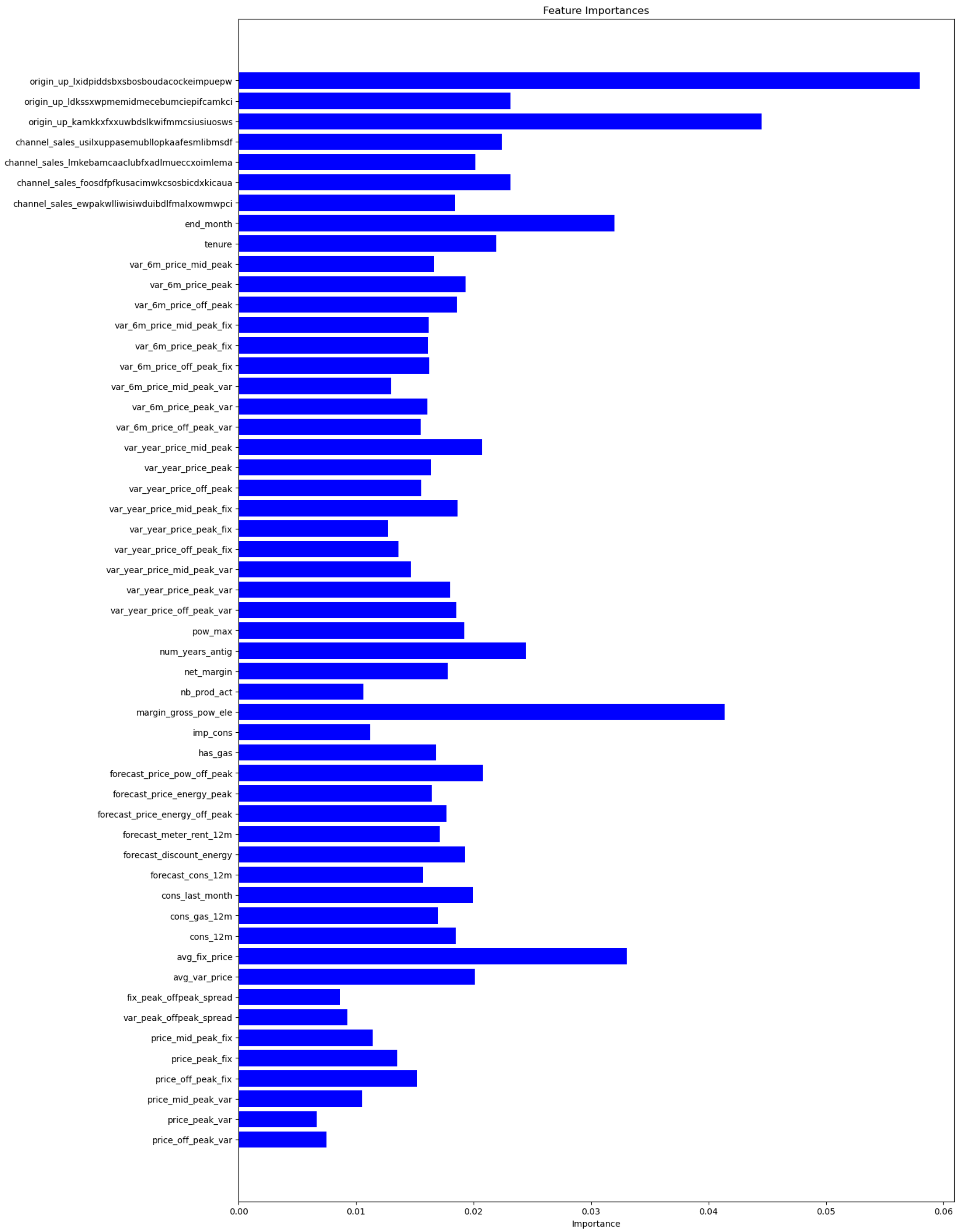
```
              precision    recall  f1-score   support

         0.0       0.93      0.76      0.84     31649
         1.0       0.18      0.50      0.27      3373

    accuracy                           0.74     35022
   macro avg       0.56      0.63      0.55     35022
weighted avg       0.86      0.74      0.79     35022

Confusion Matrix:
 [[24182  7467]
 [ 1692  1681]]
F1 Score: 0.26850890503953356
```

[222]:
```python
feature_importance = pd.DataFrame({"features": X_train_xgb.columns,␣
↪'importance': model_xgb.feature_importances_})
feature_importance.sort_values('importance', ascending = False).head()
```

[222]:

	features	importance
52	origin_up_lxidpiddsbxsbosboudacockeimpuepw	0.058003
50	origin_up_kamkkxfxxuwbdslkwifmmcsiusiuosws	0.044520
21	margin_gross_pow_ele	0.041389
9	avg_fix_price	0.033047
45	end_month	0.032014

[223]:
```python
plt.figure(figsize=(15, 25))
plt.title('Feature Importances')
plt.barh(range(len(feature_importance)), feature_importance['importance'],␣
↪color='b', align='center')
plt.yticks(range(len(feature_importance)), feature_importance['features'])
plt.xlabel('Importance')
plt.show()
```



Final XGBoost model has slightly lower performance but its not that different overall as its overall ROC drops by 1% to 68%. We can use either models as both of them are better than BCGX model answer where we had 52% ROC-AUC Score.

For feature importance we can observed that by removing redundant variables importance for most important variabled did improve. Overall, PowerCo was concerned with Churn Analysis and if price is a major churn variable. In BCGX model answer price predictors had around 2% importance but in ours we have price variable in top 5 most important feature.

Still, we can't say definitely that price impact churn in an impactful way like origin_up classification and gross margin, but still its an moderately impactful predictor for churn which does warrant further analysis.

1.4.2 Neurel Networks

In this step we will fit two tensorflow powered deep learning models. One will be based on Dense Layers based on relu actication while other will be based on BiDirectional LSTM-CNN Model.

For DNN model we will use relu activations throughout the model with proper batch normalization and weights initializer to avoid possible gradient exploding/shrinkage. And for BiLSTM-CNN model we will be using padding and masking for the time series data.

[228]:
```
#Checking GPU availability

print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))

hello = tf.constant("Hello TensorFlow!")
print(hello.numpy())
```

```
Num GPUs Available:  1
b'Hello TensorFlow!'
```

[232]:
```
X_train.shape[1]
```

[232]: 64

[248]:
```
#DNN Based model

model_dnn = Sequential([
    Dense(32, input_dim = X_train.shape[1], kernel_initializer = HeNormal()),
    BatchNormalization(),
    Activation('relu'),
    Dense(64, kernel_initializer = HeNormal()),
    BatchNormalization(),
    Activation('relu'),
    Dense(128, kernel_initializer = HeNormal()),
    BatchNormalization(),
    Activation('relu'),
    Dense(64, kernel_initializer = HeNormal()),
    BatchNormalization(),
    Activation('relu'),
    Dense(32, kernel_initializer = HeNormal()),
    BatchNormalization(),
    Activation('relu'),
```

```
    Dense(16, kernel_initializer = HeNormal()),
    BatchNormalization(),
    Activation('relu'),
    Dense(1, activation = 'linear')
])
```

[249]:
```
model_dnn.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_15 (Dense)	(None, 32)	2,080
batch_normalization_12 (BatchNormalization)	(None, 32)	128
activation_12 (Activation)	(None, 32)	0
dense_16 (Dense)	(None, 64)	2,112
batch_normalization_13 (BatchNormalization)	(None, 64)	256
activation_13 (Activation)	(None, 64)	0
dense_17 (Dense)	(None, 128)	8,320
batch_normalization_14 (BatchNormalization)	(None, 128)	512
activation_14 (Activation)	(None, 128)	0
dense_18 (Dense)	(None, 64)	8,256
batch_normalization_15 (BatchNormalization)	(None, 64)	256
activation_15 (Activation)	(None, 64)	0
dense_19 (Dense)	(None, 32)	2,080
batch_normalization_16 (BatchNormalization)	(None, 32)	128
activation_16 (Activation)	(None, 32)	0

```
 dense_20 (Dense)                 (None, 16)                        528

 batch_normalization_17           (None, 16)                         64
 (BatchNormalization)

 activation_17 (Activation)       (None, 16)                          0

 dense_21 (Dense)                 (None, 1)                          17
```

Total params: 24,737 (96.63 KB)

Trainable params: 24,065 (94.00 KB)

Non-trainable params: 672 (2.62 KB)

[247]:
```
early_stopping = EarlyStopping(monitor = 'val_AUC', patience = 10,␣
 ↪restore_best_weights=True)
```

[250]:
```
model_dnn.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001),
                  loss = tf.keras.losses.BinaryCrossentropy(from_logits = True),
                  metrics = ['accuracy', 'AUC'])
model_dnn.fit(X_train_scaled, Y_train, epochs = 100, batch_size = 32,␣
 ↪validation_split = 0.2, callbacks = [early_stopping])
```

```
Epoch 1/100
3504/3504                 23s 6ms/step -
AUC: 0.5030 - accuracy: 0.8685 - loss: 0.4226 - val_AUC: 0.5008 - val_accuracy:
0.9114 - val_loss: 0.2919
Epoch 2/100
3504/3504                 17s 5ms/step -
AUC: 0.5277 - accuracy: 0.9022 - loss: 0.2915 - val_AUC: 0.5298 - val_accuracy:
0.9094 - val_loss: 0.2960
Epoch 3/100
3504/3504                 17s 5ms/step -
AUC: 0.5614 - accuracy: 0.9070 - loss: 0.2739 - val_AUC: 0.5341 - val_accuracy:
0.9092 - val_loss: 0.2963
Epoch 4/100
3504/3504                 16s 5ms/step -
AUC: 0.5848 - accuracy: 0.9120 - loss: 0.2571 - val_AUC: 0.5480 - val_accuracy:
0.9114 - val_loss: 0.3088
Epoch 5/100
3504/3504                 17s 5ms/step -
AUC: 0.6026 - accuracy: 0.9128 - loss: 0.2520 - val_AUC: 0.5701 - val_accuracy:
```

```
0.9137 - val_loss: 0.3099
Epoch 6/100
3504/3504              16s 5ms/step -
AUC: 0.6247 - accuracy: 0.9183 - loss: 0.2343 - val_AUC: 0.5574 - val_accuracy:
0.9111 - val_loss: 0.3295
Epoch 7/100
3504/3504              16s 5ms/step -
AUC: 0.6366 - accuracy: 0.9203 - loss: 0.2264 - val_AUC: 0.5489 - val_accuracy:
0.9062 - val_loss: 0.3263
Epoch 8/100
3504/3504              16s 5ms/step -
AUC: 0.6508 - accuracy: 0.9225 - loss: 0.2197 - val_AUC: 0.5708 - val_accuracy:
0.9128 - val_loss: 0.3156
Epoch 9/100
3504/3504              16s 5ms/step -
AUC: 0.6600 - accuracy: 0.9244 - loss: 0.2155 - val_AUC: 0.5588 - val_accuracy:
0.9138 - val_loss: 0.3434
Epoch 10/100
3504/3504              16s 5ms/step -
AUC: 0.6644 - accuracy: 0.9246 - loss: 0.2111 - val_AUC: 0.5746 - val_accuracy:
0.9120 - val_loss: 0.3391
Epoch 11/100
3504/3504              18s 5ms/step -
AUC: 0.6746 - accuracy: 0.9279 - loss: 0.2043 - val_AUC: 0.5753 - val_accuracy:
0.9137 - val_loss: 0.3377
Epoch 12/100
3504/3504              17s 5ms/step -
AUC: 0.6804 - accuracy: 0.9279 - loss: 0.2022 - val_AUC: 0.5797 - val_accuracy:
0.9170 - val_loss: 0.3515
Epoch 13/100
3504/3504              17s 5ms/step -
AUC: 0.6859 - accuracy: 0.9276 - loss: 0.2000 - val_AUC: 0.5686 - val_accuracy:
0.9094 - val_loss: 0.3631
Epoch 14/100
3504/3504              18s 5ms/step -
AUC: 0.6944 - accuracy: 0.9307 - loss: 0.1913 - val_AUC: 0.5771 - val_accuracy:
0.9031 - val_loss: 0.3715
Epoch 15/100
3504/3504              17s 5ms/step -
AUC: 0.7000 - accuracy: 0.9307 - loss: 0.1898 - val_AUC: 0.5722 - val_accuracy:
0.9102 - val_loss: 0.3787
Epoch 16/100
3504/3504              17s 5ms/step -
AUC: 0.6993 - accuracy: 0.9305 - loss: 0.1916 - val_AUC: 0.5836 - val_accuracy:
0.9115 - val_loss: 0.3704
Epoch 17/100
3504/3504              17s 5ms/step -
AUC: 0.7095 - accuracy: 0.9325 - loss: 0.1820 - val_AUC: 0.5735 - val_accuracy:
```

```
0.9081 - val_loss: 0.3750
Epoch 18/100
3504/3504          17s 5ms/step -
AUC: 0.7135 - accuracy: 0.9326 - loss: 0.1812 - val_AUC: 0.5781 - val_accuracy:
0.9093 - val_loss: 0.3796
Epoch 19/100
3504/3504          17s 5ms/step -
AUC: 0.7154 - accuracy: 0.9326 - loss: 0.1815 - val_AUC: 0.5689 - val_accuracy:
0.9110 - val_loss: 0.4018
Epoch 20/100
3504/3504          18s 5ms/step -
AUC: 0.7248 - accuracy: 0.9348 - loss: 0.1753 - val_AUC: 0.5722 - val_accuracy:
0.9069 - val_loss: 0.3962
Epoch 21/100
3504/3504          17s 5ms/step -
AUC: 0.7266 - accuracy: 0.9356 - loss: 0.1741 - val_AUC: 0.5645 - val_accuracy:
0.9075 - val_loss: 0.4293
Epoch 22/100
3504/3504          17s 5ms/step -
AUC: 0.7317 - accuracy: 0.9354 - loss: 0.1721 - val_AUC: 0.5714 - val_accuracy:
0.9105 - val_loss: 0.3909
Epoch 23/100
3504/3504          17s 5ms/step -
AUC: 0.7321 - accuracy: 0.9361 - loss: 0.1712 - val_AUC: 0.5771 - val_accuracy:
0.9096 - val_loss: 0.4071
Epoch 24/100
3504/3504          17s 5ms/step -
AUC: 0.7361 - accuracy: 0.9368 - loss: 0.1697 - val_AUC: 0.5543 - val_accuracy:
0.9029 - val_loss: 0.4323
Epoch 25/100
3504/3504          17s 5ms/step -
AUC: 0.7387 - accuracy: 0.9376 - loss: 0.1673 - val_AUC: 0.5680 - val_accuracy:
0.9028 - val_loss: 0.4226
Epoch 26/100
3504/3504          17s 5ms/step -
AUC: 0.7472 - accuracy: 0.9395 - loss: 0.1616 - val_AUC: 0.5650 - val_accuracy:
0.9104 - val_loss: 0.4144
```

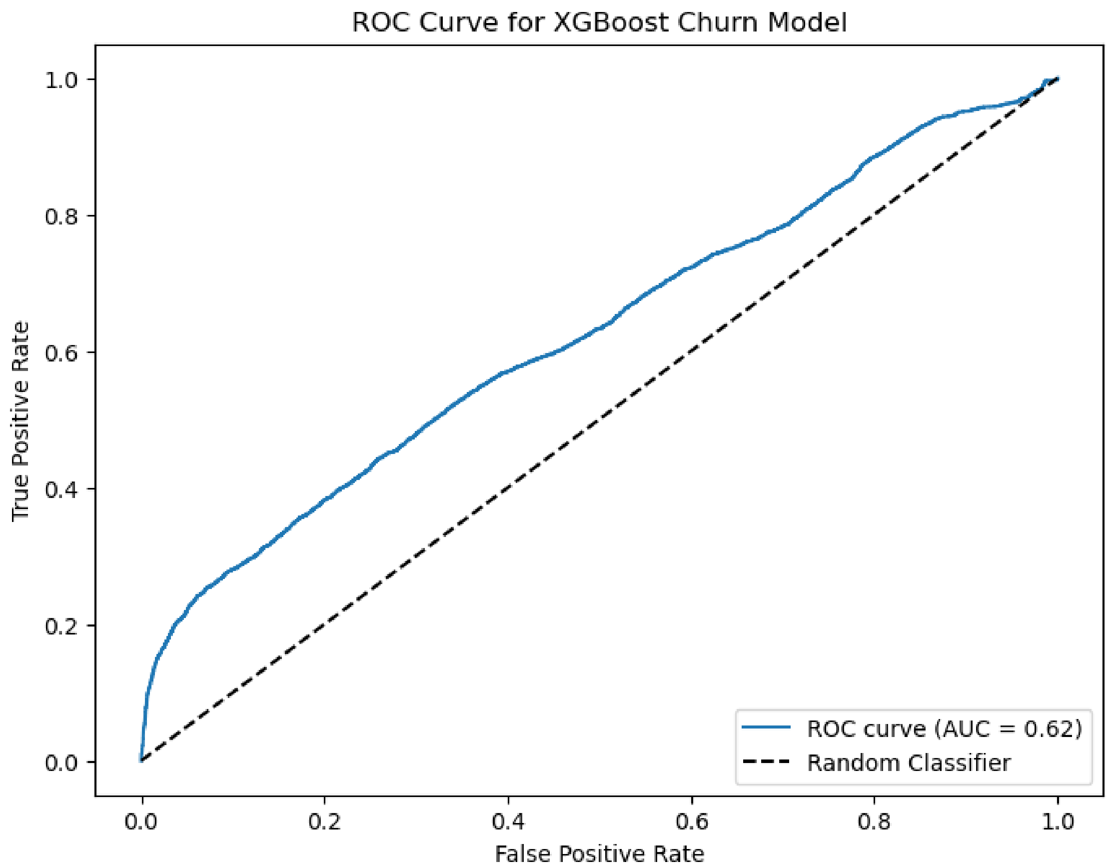
[250]: <keras.src.callbacks.history.History at 0x7695c04c7dd0>

[ ]:
```
y_pred = model_dnn.predict(X_test_xgb)
y_pred_proba = model_xgb.predict_proba(X_test_xgb)[:, 1]

fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
roc_auc = roc_auc_score(Y_test, y_pred_proba)

# Plot ROC curve
```

```python
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost Churn Model')
plt.legend(loc='lower right')
plt.show()

print(f"ROC AUC Score: {roc_auc:.2f}")
```

[341]:
```python
y_pred = tf.nn.sigmoid(model_dnn.predict(X_test_scaled)) > 0.5
y_pred_proba = tf.nn.sigmoid(model_dnn.predict(X_test_scaled))

fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
roc_auc = roc_auc_score(Y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost Churn Model')
plt.legend(loc='lower right')
plt.show()

print(f"ROC AUC Score: {roc_auc:.2f}")
```

```
1095/1095                2s 2ms/step
1095/1095                2s 1ms/step
```




```
ROC AUC Score: 0.62
```

[264]:

```python
# Classification report
print(classification_report(Y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(Y_test, y_pred)
print("Confusion Matrix:\n", cm)
print(f'F1 Score: {f1_score(Y_test, y_pred)}')
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.97      0.94     31649
         1.0       0.38      0.19      0.25      3373

    accuracy                           0.89     35022
   macro avg       0.65      0.58      0.60     35022
weighted avg       0.87      0.89      0.88     35022

Confusion Matrix:
```

```
 [[30632  1017]
 [ 2742   631]]
F1 Score: 0.2513443537143995
```

Our DNN model didn't work better than gradient boosting. Even when focus was done on AUC score on training we got a model with very less recall overall compared to XGBoosting algorithm.

Now we will fit a BiLSTM-CNN model based on the research paper: Customer churn prediction using composite deep learning technique Link: https://www.nature.com/articles/s41598-023-44396-w#:~:text=A%20composite%20deep%20learning%20model,dataset%20for%20predicting%20customer%20attritio

For this model we need timestamps as its based on LSTM layers and since we have 12 month data for each clients we can use this model effectively. Only concern here is the lack of proper 12 month data for churned clients as we can not source more data from BCGX, to fill this gap we will use Zero Padding for churned clients missing some monthly data and proper masking during the model training.

[300]:
```python
# Ensure data is sorted by client and month
df_merge_dm = df_merge.sort_values(['id', 'price_month'])

# List of all clients
clients = df_merge_dm['id'].unique()
num_clients = len(clients)
num_months = 12
num_features = 63

# List of feature columns (replace with your actual feature names)
feature_cols = [col for col in df_merge_dm.columns if col not in ['id',␣
↪'price_month', 'churn']]

# Initialize arrays
X = np.zeros((num_clients, num_months, num_features))
y = np.zeros(num_clients)

for i, client in enumerate(clients):
    client_data = df_merge_dm[df_merge_dm['id'] == client].
↪sort_values('price_month')
    # Get feature values
    features = client_data[feature_cols].values
    # Zero pad if less than 12 months
    if features.shape[0] < num_months:
        padded = np.zeros((num_months, num_features))
        padded[-features.shape[0]:, :] = features  # pad at the start, keep␣
↪recent months at the end
    else:
        padded = features[-num_months:, :]  # take last 12 months if more
    X[i] = padded
    y[i] = client_data['churn'].iloc[-1]
```

[298]:
```
#BiLSTM-CNN Model. It is based on the research paper mentioned before

inputs = Input(shape=(num_months, num_features))
x = Masking(mask_value=0.0)(inputs)
x = Bidirectional(LSTM(64, return_sequences = True))(x)
x = Conv1D(filters = 32, kernel_size = 3, activation = 'relu', padding =␣
↪'same')(x)
x = GlobalMaxPooling1D()(x)
x = Dense(64, activation = 'relu')(x)
x = Dropout(0.3)(x)
outputs = Dense(1, activation = 'sigmoid')(x)

model = Model(inputs, outputs)
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
↪['accuracy', 'AUC'])
model.summary()
```

[298]: (175149, 66)

[308]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size = 0.2,␣
↪random_state = 10)
```

[316]:
```
num_clients, num_months, num_features = X_train.shape

# Reshape to 2D for scaling
X_2d = X_train.reshape(-1, num_features)  # shape: (num_clients * num_months,␣
↪num_features)

# Fit scaler on training data only!
scaler = StandardScaler()
X_2d_scaled = scaler.fit_transform(X_2d)

# Reshape back to 3D
X_train_scaled = X_2d_scaled.reshape(num_clients, num_months, num_features)
```

[329]:
```
timesteps = 12
n_features = 63

inputs = tf.keras.Input(shape=(timesteps, n_features))

inputs = Input(shape=(num_months, num_features))
x = Masking(mask_value=0.0)(inputs) #masking for padded data
x = Bidirectional(LSTM(64, return_sequences=True))(x) #Bi-directional LSTM ␣
↪layer
x = Conv1D(filters=32, kernel_size=3, activation='relu', padding='same')(x)␣
↪#Convolutional Layer
x = GlobalMaxPooling1D()(x)
```

```python
x = Dense(64, activation='relu')(x)
x = Dropout(0.3)(x)
outputs = Dense(1, activation='sigmoid')(x)

model = models.Model(inputs, outputs)
model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001),
    loss = 'binary_crossentropy',
    metrics=['accuracy', tf.keras.metrics.AUC(name='auc'), tf.keras.metrics.
 ↪Precision(), tf.keras.metrics.Recall()]
)
model.summary()
```

```
Model: "functional_7"


 Layer (type)          Output Shape          Param #   Connected to

 input_layer_12        (None, 12, 63)              0   -
 (InputLayer)

 not_equal_2           (None, 12, 63)              0   input_layer_12[0…
 (NotEqual)

 masking_2 (Masking)   (None, 12, 63)              0   input_layer_12[0…

 any_2 (Any)           (None, 12)                  0   not_equal_2[0][0]

 bidirectional_5       (None, 12, 128)        65,536   masking_2[0][0],
 (Bidirectional)                                       any_2[0][0]

 conv1d_5 (Conv1D)     (None, 12, 32)         12,320   bidirectional_5[…

 global_max_pooling…   (None, 32)                  0   conv1d_5[0][0]
 (GlobalMaxPooling1…

 dense_32 (Dense)      (None, 64)              2,112   global_max_pooli…

 dropout_5 (Dropout)   (None, 64)                  0   dense_32[0][0]

 dense_33 (Dense)      (None, 1)                  65   dropout_5[0][0]


 Total params: 80,033 (312.63 KB)

 Trainable params: 80,033 (312.63 KB)
```

Non-trainable params: 0 (0.00 B)

[330]:
```
history = model.fit(X_train_scaled, Y_train, epochs = 50,
                    batch_size = 32, validation_split = 0.2,
                    callbacks = [EarlyStopping(monitor = 'val_AUC', patience =␣
 ↪10, restore_best_weights = True, mode = 'max')])
```

```
Epoch 1/50
293/293              10s 30ms/step -
accuracy: 0.8871 - auc: 0.5489 - loss: 0.3576 - precision_5: 0.0792 - recall_5:
0.0198 - val_accuracy: 0.9050 - val_auc: 0.6017 - val_loss: 0.3111 -
val_precision_5: 0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 2/50
293/293              8s 26ms/step -
accuracy: 0.9043 - auc: 0.6372 - loss: 0.3060 - precision_5: 0.0000e+00 -
recall_5: 0.0000e+00 - val_accuracy: 0.9050 - val_auc: 0.6376 - val_loss: 0.3082
- val_precision_5: 0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 3/50
293/293              8s 26ms/step -
accuracy: 0.9076 - auc: 0.6641 - loss: 0.2959 - precision_5: 0.0000e+00 -
recall_5: 0.0000e+00 - val_accuracy: 0.9050 - val_auc: 0.6300 - val_loss: 0.3084
- val_precision_5: 0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 4/50
293/293              8s 27ms/step -
accuracy: 0.9074 - auc: 0.7159 - loss: 0.2814 - precision_5: 0.6334 - recall_5:
0.0051 - val_accuracy: 0.9029 - val_auc: 0.6440 - val_loss: 0.3053 -
val_precision_5: 0.2222 - val_recall_5: 0.0090
Epoch 5/50
293/293              8s 27ms/step -
accuracy: 0.9046 - auc: 0.7129 - loss: 0.2895 - precision_5: 0.5843 - recall_5:
0.0476 - val_accuracy: 0.9046 - val_auc: 0.6297 - val_loss: 0.3113 -
val_precision_5: 0.4545 - val_recall_5: 0.0225
Epoch 6/50
293/293              8s 27ms/step -
accuracy: 0.9073 - auc: 0.7175 - loss: 0.2846 - precision_5: 0.6549 - recall_5:
0.0877 - val_accuracy: 0.9042 - val_auc: 0.6307 - val_loss: 0.3186 -
val_precision_5: 0.4688 - val_recall_5: 0.0676
Epoch 7/50
293/293              7s 25ms/step -
accuracy: 0.9106 - auc: 0.7367 - loss: 0.2751 - precision_5: 0.7484 - recall_5:
0.1178 - val_accuracy: 0.9059 - val_auc: 0.6182 - val_loss: 0.3173 -
val_precision_5: 0.5333 - val_recall_5: 0.0721
Epoch 8/50
293/293              8s 27ms/step -
accuracy: 0.9132 - auc: 0.7715 - loss: 0.2635 - precision_5: 0.7843 - recall_5:
```

```
0.1779 - val_accuracy: 0.9054 - val_auc: 0.6553 - val_loss: 0.3077 -
val_precision_5: 0.5152 - val_recall_5: 0.0766
Epoch 9/50
293/293            8s 26ms/step -
accuracy: 0.9156 - auc: 0.7750 - loss: 0.2559 - precision_5: 0.7717 - recall_5:
0.1370 - val_accuracy: 0.9024 - val_auc: 0.6663 - val_loss: 0.3165 -
val_precision_5: 0.4516 - val_recall_5: 0.1261
Epoch 10/50
293/293            8s 27ms/step -
accuracy: 0.9160 - auc: 0.7871 - loss: 0.2559 - precision_5: 0.7525 - recall_5:
0.2025 - val_accuracy: 0.9042 - val_auc: 0.6471 - val_loss: 0.3129 -
val_precision_5: 0.4706 - val_recall_5: 0.0721
Epoch 11/50
293/293            8s 27ms/step -
accuracy: 0.9233 - auc: 0.7854 - loss: 0.2411 - precision_5: 0.8325 - recall_5:
0.1990 - val_accuracy: 0.8930 - val_auc: 0.6318 - val_loss: 0.3352 -
val_precision_5: 0.3108 - val_recall_5: 0.1036
Epoch 12/50
293/293            8s 28ms/step -
accuracy: 0.9190 - auc: 0.7971 - loss: 0.2461 - precision_5: 0.8162 - recall_5:
0.2034 - val_accuracy: 0.8990 - val_auc: 0.6532 - val_loss: 0.3202 -
val_precision_5: 0.3793 - val_recall_5: 0.0991
Epoch 13/50
293/293            8s 27ms/step -
accuracy: 0.9164 - auc: 0.8110 - loss: 0.2467 - precision_5: 0.8274 - recall_5:
0.1970 - val_accuracy: 0.8999 - val_auc: 0.6173 - val_loss: 0.3404 -
val_precision_5: 0.4091 - val_recall_5: 0.1216
Epoch 14/50
293/293            8s 27ms/step -
accuracy: 0.9217 - auc: 0.8096 - loss: 0.2387 - precision_5: 0.8085 - recall_5:
0.2482 - val_accuracy: 0.8969 - val_auc: 0.6337 - val_loss: 0.3464 -
val_precision_5: 0.3662 - val_recall_5: 0.1171
Epoch 15/50
293/293            8s 28ms/step -
accuracy: 0.9226 - auc: 0.8157 - loss: 0.2353 - precision_5: 0.7771 - recall_5:
0.2612 - val_accuracy: 0.8964 - val_auc: 0.6266 - val_loss: 0.3502 -
val_precision_5: 0.3718 - val_recall_5: 0.1306
Epoch 16/50
293/293            8s 27ms/step -
accuracy: 0.9210 - auc: 0.8437 - loss: 0.2281 - precision_5: 0.8037 - recall_5:
0.2550 - val_accuracy: 0.8990 - val_auc: 0.6098 - val_loss: 0.3654 -
val_precision_5: 0.3906 - val_recall_5: 0.1126
Epoch 17/50
293/293            8s 28ms/step -
accuracy: 0.9278 - auc: 0.8379 - loss: 0.2197 - precision_5: 0.8639 - recall_5:
0.2781 - val_accuracy: 0.8982 - val_auc: 0.6492 - val_loss: 0.3523 -
val_precision_5: 0.3974 - val_recall_5: 0.1396
Epoch 18/50
```

```
293/293            8s 28ms/step -
accuracy: 0.9269 - auc: 0.8543 - loss: 0.2167 - precision_5: 0.8728 - recall_5:
0.3078 - val_accuracy: 0.8956 - val_auc: 0.6393 - val_loss: 0.3674 -
val_precision_5: 0.3690 - val_recall_5: 0.1396
Epoch 19/50
293/293            8s 27ms/step -
accuracy: 0.9268 - auc: 0.8642 - loss: 0.2161 - precision_5: 0.7765 - recall_5:
0.2923 - val_accuracy: 0.8969 - val_auc: 0.6374 - val_loss: 0.3727 -
val_precision_5: 0.3797 - val_recall_5: 0.1351
Epoch 20/50
293/293            8s 27ms/step -
accuracy: 0.9307 - auc: 0.8611 - loss: 0.2077 - precision_5: 0.8544 - recall_5:
0.3221 - val_accuracy: 0.8935 - val_auc: 0.6497 - val_loss: 0.3901 -
val_precision_5: 0.3333 - val_recall_5: 0.1216
Epoch 21/50
293/293            8s 27ms/step -
accuracy: 0.9237 - auc: 0.8709 - loss: 0.2136 - precision_5: 0.8240 - recall_5:
0.2953 - val_accuracy: 0.8887 - val_auc: 0.6475 - val_loss: 0.3956 -
val_precision_5: 0.2683 - val_recall_5: 0.0991
Epoch 22/50
293/293            8s 27ms/step -
accuracy: 0.9284 - auc: 0.8670 - loss: 0.2087 - precision_5: 0.8691 - recall_5:
0.3124 - val_accuracy: 0.8956 - val_auc: 0.6408 - val_loss: 0.4048 -
val_precision_5: 0.3472 - val_recall_5: 0.1126
Epoch 23/50
293/293            8s 28ms/step -
accuracy: 0.9339 - auc: 0.8855 - loss: 0.1957 - precision_5: 0.9045 - recall_5:
0.3508 - val_accuracy: 0.8935 - val_auc: 0.6526 - val_loss: 0.4077 -
val_precision_5: 0.3548 - val_recall_5: 0.1486
Epoch 24/50
293/293            8s 27ms/step -
accuracy: 0.9329 - auc: 0.8883 - loss: 0.1954 - precision_5: 0.8794 - recall_5:
0.3564 - val_accuracy: 0.8990 - val_auc: 0.6386 - val_loss: 0.4112 -
val_precision_5: 0.4079 - val_recall_5: 0.1396
Epoch 25/50
293/293            8s 27ms/step -
accuracy: 0.9316 - auc: 0.8942 - loss: 0.1963 - precision_5: 0.8959 - recall_5:
0.3726 - val_accuracy: 0.8943 - val_auc: 0.6529 - val_loss: 0.4689 -
val_precision_5: 0.3656 - val_recall_5: 0.1532
Epoch 26/50
293/293            8s 27ms/step -
accuracy: 0.9344 - auc: 0.8956 - loss: 0.1918 - precision_5: 0.8574 - recall_5:
0.3741 - val_accuracy: 0.8960 - val_auc: 0.6421 - val_loss: 0.4192 -
val_precision_5: 0.3735 - val_recall_5: 0.1396
Epoch 27/50
293/293            8s 27ms/step -
accuracy: 0.9344 - auc: 0.8929 - loss: 0.1864 - precision_5: 0.8711 - recall_5:
0.3643 - val_accuracy: 0.8866 - val_auc: 0.6482 - val_loss: 0.4417 -
```

```
val_precision_5: 0.3193 - val_recall_5: 0.1712
Epoch 28/50
293/293            8s 27ms/step -
accuracy: 0.9390 - auc: 0.9118 - loss: 0.1737 - precision_5: 0.8609 - recall_5:
0.4000 - val_accuracy: 0.8879 - val_auc: 0.6633 - val_loss: 0.4549 -
val_precision_5: 0.3246 - val_recall_5: 0.1667
Epoch 29/50
293/293            8s 27ms/step -
accuracy: 0.9335 - auc: 0.9017 - loss: 0.1868 - precision_5: 0.8444 - recall_5:
0.3910 - val_accuracy: 0.8870 - val_auc: 0.6402 - val_loss: 0.4376 -
val_precision_5: 0.2941 - val_recall_5: 0.1351
Epoch 30/50
293/293            8s 28ms/step -
accuracy: 0.9349 - auc: 0.9076 - loss: 0.1835 - precision_5: 0.8390 - recall_5:
0.4348 - val_accuracy: 0.8947 - val_auc: 0.6454 - val_loss: 0.4431 -
val_precision_5: 0.3776 - val_recall_5: 0.1667
Epoch 31/50
293/293            8s 28ms/step -
accuracy: 0.9398 - auc: 0.9146 - loss: 0.1711 - precision_5: 0.8789 - recall_5:
0.4168 - val_accuracy: 0.8956 - val_auc: 0.6253 - val_loss: 0.4744 -
val_precision_5: 0.3830 - val_recall_5: 0.1622
Epoch 32/50
293/293            8s 27ms/step -
accuracy: 0.9444 - auc: 0.9191 - loss: 0.1634 - precision_5: 0.8868 - recall_5:
0.4435 - val_accuracy: 0.8964 - val_auc: 0.6307 - val_loss: 0.4957 -
val_precision_5: 0.3936 - val_recall_5: 0.1667
Epoch 33/50
293/293            8s 27ms/step -
accuracy: 0.9397 - auc: 0.9178 - loss: 0.1690 - precision_5: 0.8659 - recall_5:
0.4221 - val_accuracy: 0.8900 - val_auc: 0.6382 - val_loss: 0.5027 -
val_precision_5: 0.3451 - val_recall_5: 0.1757
Epoch 34/50
293/293            8s 28ms/step -
accuracy: 0.9405 - auc: 0.9257 - loss: 0.1677 - precision_5: 0.8754 - recall_5:
0.4732 - val_accuracy: 0.8840 - val_auc: 0.6366 - val_loss: 0.5038 -
val_precision_5: 0.3287 - val_recall_5: 0.2117
Epoch 35/50
293/293            8s 27ms/step -
accuracy: 0.9418 - auc: 0.9207 - loss: 0.1669 - precision_5: 0.8682 - recall_5:
0.4875 - val_accuracy: 0.8952 - val_auc: 0.6200 - val_loss: 0.5509 -
val_precision_5: 0.3789 - val_recall_5: 0.1622
Epoch 36/50
293/293            8s 27ms/step -
accuracy: 0.9415 - auc: 0.9112 - loss: 0.1693 - precision_5: 0.8428 - recall_5:
0.4626 - val_accuracy: 0.8875 - val_auc: 0.6469 - val_loss: 0.5060 -
val_precision_5: 0.3481 - val_recall_5: 0.2117
Epoch 37/50
293/293            8s 27ms/step -
```

```
accuracy: 0.9443 - auc: 0.9203 - loss: 0.1588 - precision_5: 0.8744 - recall_5:
0.4524 - val_accuracy: 0.8973 - val_auc: 0.6386 - val_loss: 0.4936 -
val_precision_5: 0.4135 - val_recall_5: 0.1937
Epoch 38/50
293/293            8s 28ms/step -
accuracy: 0.9454 - auc: 0.9268 - loss: 0.1581 - precision_5: 0.8818 - recall_5:
0.4686 - val_accuracy: 0.8956 - val_auc: 0.6482 - val_loss: 0.4939 -
val_precision_5: 0.4018 - val_recall_5: 0.2027
Epoch 39/50
293/293            8s 28ms/step -
accuracy: 0.9485 - auc: 0.9378 - loss: 0.1476 - precision_5: 0.8863 - recall_5:
0.5135 - val_accuracy: 0.8887 - val_auc: 0.6444 - val_loss: 0.5439 -
val_precision_5: 0.3443 - val_recall_5: 0.1892
Epoch 40/50
293/293            8s 27ms/step -
accuracy: 0.9438 - auc: 0.9380 - loss: 0.1523 - precision_5: 0.8730 - recall_5:
0.4880 - val_accuracy: 0.8930 - val_auc: 0.6540 - val_loss: 0.4868 -
val_precision_5: 0.3704 - val_recall_5: 0.1802
Epoch 41/50
293/293            8s 27ms/step -
accuracy: 0.9464 - auc: 0.9331 - loss: 0.1549 - precision_5: 0.9044 - recall_5:
0.4901 - val_accuracy: 0.8956 - val_auc: 0.6459 - val_loss: 0.4923 -
val_precision_5: 0.3854 - val_recall_5: 0.1667
Epoch 42/50
293/293            8s 28ms/step -
accuracy: 0.9530 - auc: 0.9474 - loss: 0.1372 - precision_5: 0.9023 - recall_5:
0.5646 - val_accuracy: 0.8905 - val_auc: 0.6279 - val_loss: 0.5508 -
val_precision_5: 0.3482 - val_recall_5: 0.1757
Epoch 43/50
293/293            8s 27ms/step -
accuracy: 0.9438 - auc: 0.9455 - loss: 0.1483 - precision_5: 0.8872 - recall_5:
0.4983 - val_accuracy: 0.8879 - val_auc: 0.6289 - val_loss: 0.5745 -
val_precision_5: 0.3182 - val_recall_5: 0.1577
Epoch 44/50
293/293            8s 27ms/step -
accuracy: 0.9518 - auc: 0.9428 - loss: 0.1411 - precision_5: 0.9323 - recall_5:
0.5328 - val_accuracy: 0.8892 - val_auc: 0.6224 - val_loss: 0.5875 -
val_precision_5: 0.3333 - val_recall_5: 0.1667
Epoch 45/50
293/293            8s 28ms/step -
accuracy: 0.9462 - auc: 0.9412 - loss: 0.1489 - precision_5: 0.8961 - recall_5:
0.5054 - val_accuracy: 0.8939 - val_auc: 0.6340 - val_loss: 0.5849 -
val_precision_5: 0.3587 - val_recall_5: 0.1486
Epoch 46/50
293/293            8s 28ms/step -
accuracy: 0.9533 - auc: 0.9454 - loss: 0.1358 - precision_5: 0.9262 - recall_5:
0.5561 - val_accuracy: 0.8883 - val_auc: 0.6283 - val_loss: 0.5643 -
val_precision_5: 0.3415 - val_recall_5: 0.1892
```

```
Epoch 47/50
293/293            8s 28ms/step -
accuracy: 0.9532 - auc: 0.9465 - loss: 0.1347 - precision_5: 0.8708 - recall_5:
0.5730 - val_accuracy: 0.8870 - val_auc: 0.6269 - val_loss: 0.5829 -
val_precision_5: 0.3279 - val_recall_5: 0.1802
Epoch 48/50
293/293            8s 28ms/step -
accuracy: 0.9516 - auc: 0.9491 - loss: 0.1386 - precision_5: 0.9053 - recall_5:
0.5477 - val_accuracy: 0.8806 - val_auc: 0.6411 - val_loss: 0.6040 -
val_precision_5: 0.3161 - val_recall_5: 0.2207
Epoch 49/50
293/293            8s 27ms/step -
accuracy: 0.9483 - auc: 0.9511 - loss: 0.1427 - precision_5: 0.8736 - recall_5:
0.5566 - val_accuracy: 0.8947 - val_auc: 0.6112 - val_loss: 0.6340 -
val_precision_5: 0.3846 - val_recall_5: 0.1802
Epoch 50/50
293/293            8s 27ms/step -
accuracy: 0.9472 - auc: 0.9459 - loss: 0.1450 - precision_5: 0.8952 - recall_5:
0.5290 - val_accuracy: 0.8922 - val_auc: 0.6244 - val_loss: 0.5922 -
val_precision_5: 0.3636 - val_recall_5: 0.1802
```

[331]:
```
num_clients, num_months, num_features = X_test.shape

# Reshape to 2D for scaling
X_2d = X_test.reshape(-1, num_features)  # shape: (num_clients * num_months,
 ↪num_features)

# Fit scaler on training data only!
X_2d_scaled = scaler.transform(X_2d)

# Reshape back to 3D
X_test_scaled = X_2d_scaled.reshape(num_clients, num_months, num_features)
```

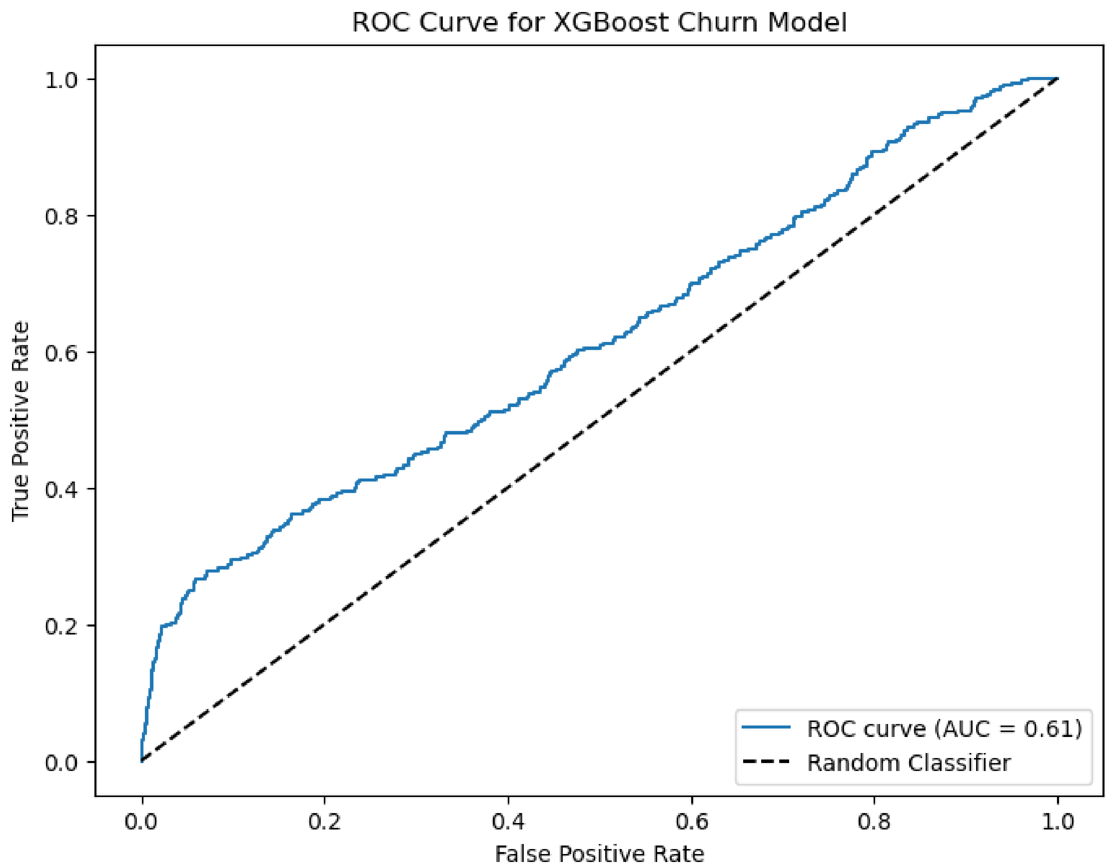
[335]:
```
Y_test.mean()
```

[335]:
```
np.float64(0.10130047912388775)
```

[337]:
```
y_pred = (model.predict(X_test_scaled) > 0.5).astype(int)
y_pred_proba = model.predict(X_test_scaled)

fpr, tpr, thresholds = roc_curve(Y_test, y_pred_proba)
roc_auc = roc_auc_score(Y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost Churn Model')
plt.legend(loc='lower right')
plt.show()

print(f"ROC AUC Score: {roc_auc:.2f}")
```

```
92/92                  1s 7ms/step
92/92                  1s 7ms/step
```




```
ROC AUC Score: 0.61
```

[338]:
```python
# Classification report
print(classification_report(Y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(Y_test, y_pred)
print("Confusion Matrix:\n", cm)
print(f'F1 Score: {f1_score(Y_test, y_pred)}')
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.97      0.94      2626
         1.0       0.45      0.20      0.28       296

    accuracy                           0.89      2922
   macro avg       0.68      0.59      0.61      2922
weighted avg       0.87      0.89      0.88      2922

Confusion Matrix:
 [[2554   72]
 [ 237   59]]
F1 Score: 0.27634660421545665
```

1.5 Conclusion

BiDirectional LSTM-CNN Model worked better than DNN we covered before. Summary for metrics for three models:

Model Performance Comparison

Model	F1 Score	Recall	ROC-AUC	Accuracy
BiLSTM-CNN	0.28	0.20	0.61	0.89
DNN	0.25	0.19	0.62	0.89
XGBoost	0.27	0.50	0.69	0.74

BiLSTM-CNN has highest F1 score among the three models we tested, however it has low AUC score and recall compared to Gradient Boost model. Generally, Gradient Boosting is considered industry standard for churn analysis and through this result we can observe that it is indeed better in getting higher recall which is essential for churn prediction.

This project was started with the client hypothesis that Price is a major factor leading to churn. Since XGBoost Model is best model here we used feature importance for that model and found that sale promotion id or group is most important factor leading to churn, solidiying our findings during EDA that proportion of churn for some subgroups of clients were higher than usual. Price was a reasonable factor, but not a major one as even margin is better indicator.

We got best model F1 score at 0.27 and recall of 0.50 with ROC-AUC score at 0.69. While accuracy is not important its 0.74 for XGBoost model, its not high but since we focused on improving ROC scores on all models it was acceptable trade. All of our models worked a lot better than BCGX model answer where we had F1 Score of 0.09, recall of 0.05, and ROC score of 0.52.

We can get better model performance but for that we need more data and better feature engineering which is not possible with the dataset in hand. Also, while both DNN Model and BiLSTM-CNN model underperformed compared to Gradient Boost model because they do not work good with such tabular data in general, it is to be noted that in scenario where we have a large amount of data both of these models could work better. And we can even use a mix of Gradient Boosting and BiLSTM-CNN models by using ensemble methods on BiLSTM-CNN model.