BCG Gamma

Technical Challenge

PowerCo_v5

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Agenda

1. Scenario
2. Approach
3. Findings
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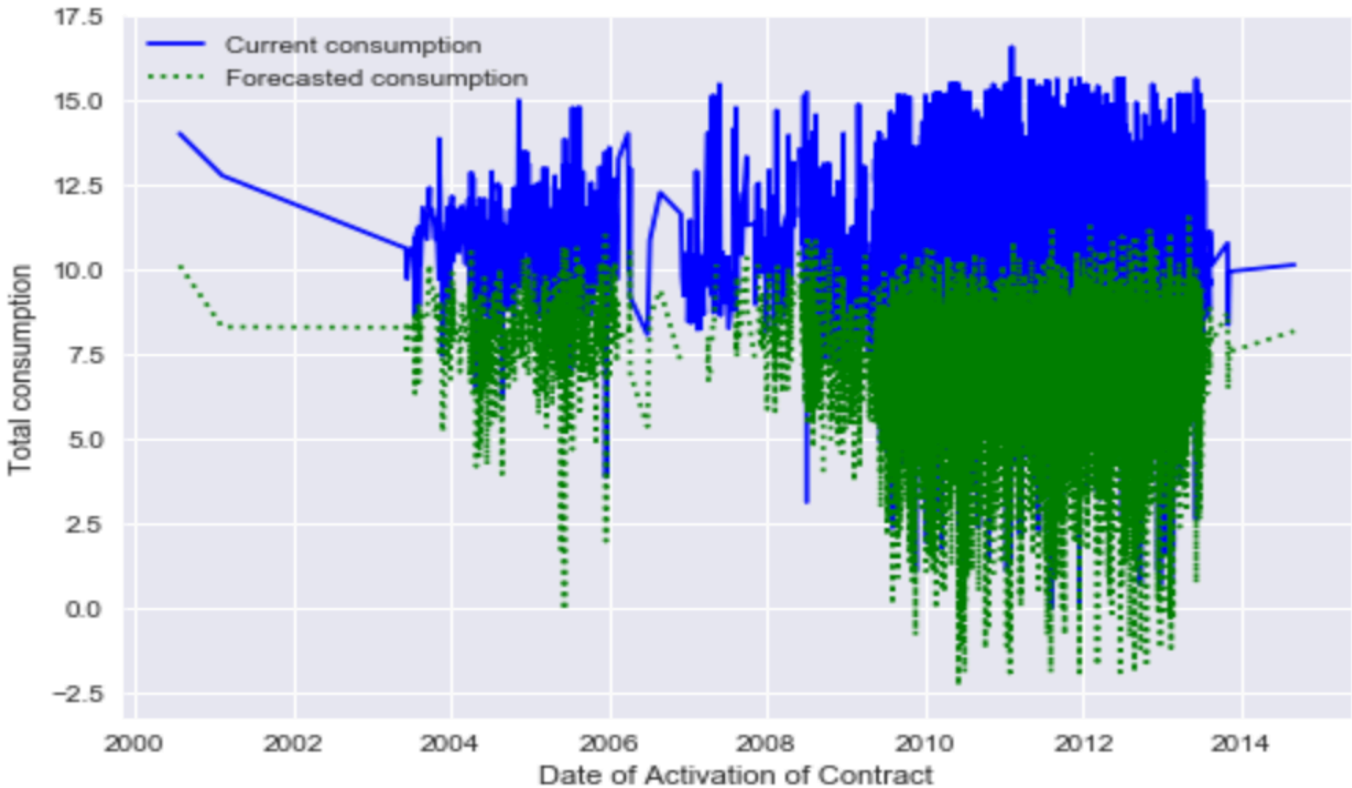
Scenario - Forecast shows power subscription to decrease in the future

With actual consumption following a similar trend to forecasted consumption, a recognized churn issue in the future means lower actual future consumption



Can we identify customers more likely to churn? Is there pre-emptive action we can take to prevent defection to competitors?

Approach – Develop an algorithmic model that can predict customers most likely to churn

Model	Decision Tree	Logistic Regression	Bagging Classifier	Random Forest	Adaptive Boosting
Reason	Easy to implement; sets a good benchmark	Gives a smooth fit when working with continuous data	Averages out variances and biases of estimators, which is important due to high variance in data	Corrects over fitting by implementing many decision trees	Accounts for anomalies and outliers in the dataset by weighing classifiers based on performance
Time efficiency	1.34 s	4.60 s	1.38 s	5.91 s	9.93 s
Accuracy on training data (RoC)	0.63	0.59	0.93	0.96	1.00

Voting Classifier

Combines all 3 to give the majority classification

Margins and date of activation are the top 3 important factors in our model

```
Feature importance:

                                        Feature  Importance
16                          margin_net_pow_ele    0.195327
15                        margin_gross_pow_ele    0.129410
3                                   date_activ    0.088858
35        origin_up_lxidpiddsbxsbosboudacockeimpuepw    0.072867
2                              cons_last_month    0.068439
6                                 date_renewal    0.065548
10                       forecast_meter_rent_12m    0.064408
24    channel_sales_foosdfpfkusacimwkcsosbicdxkicaua    0.039183
18                                  net_margin    0.036204
0                                     cons_12m    0.034778
```

- High price elasticity can be assumed due to high importance to net margin and gross margin
- Later activated contracts more likely to result in customers churning. This may be due to changes in market landscape, such as increase in competition due to liberalization of European energy market
- Poor performance of lxidpiddsbxsbosboudacockeimpuepw campaign. We could look into issues related to transparency of campaign details, and levels of customer engagement
- Lower consumptions for previous month more likely to result in customers defecting. This implies that customers are gradually decreasing consumption before defecting

We can see that one of the sales channels is performing poorly

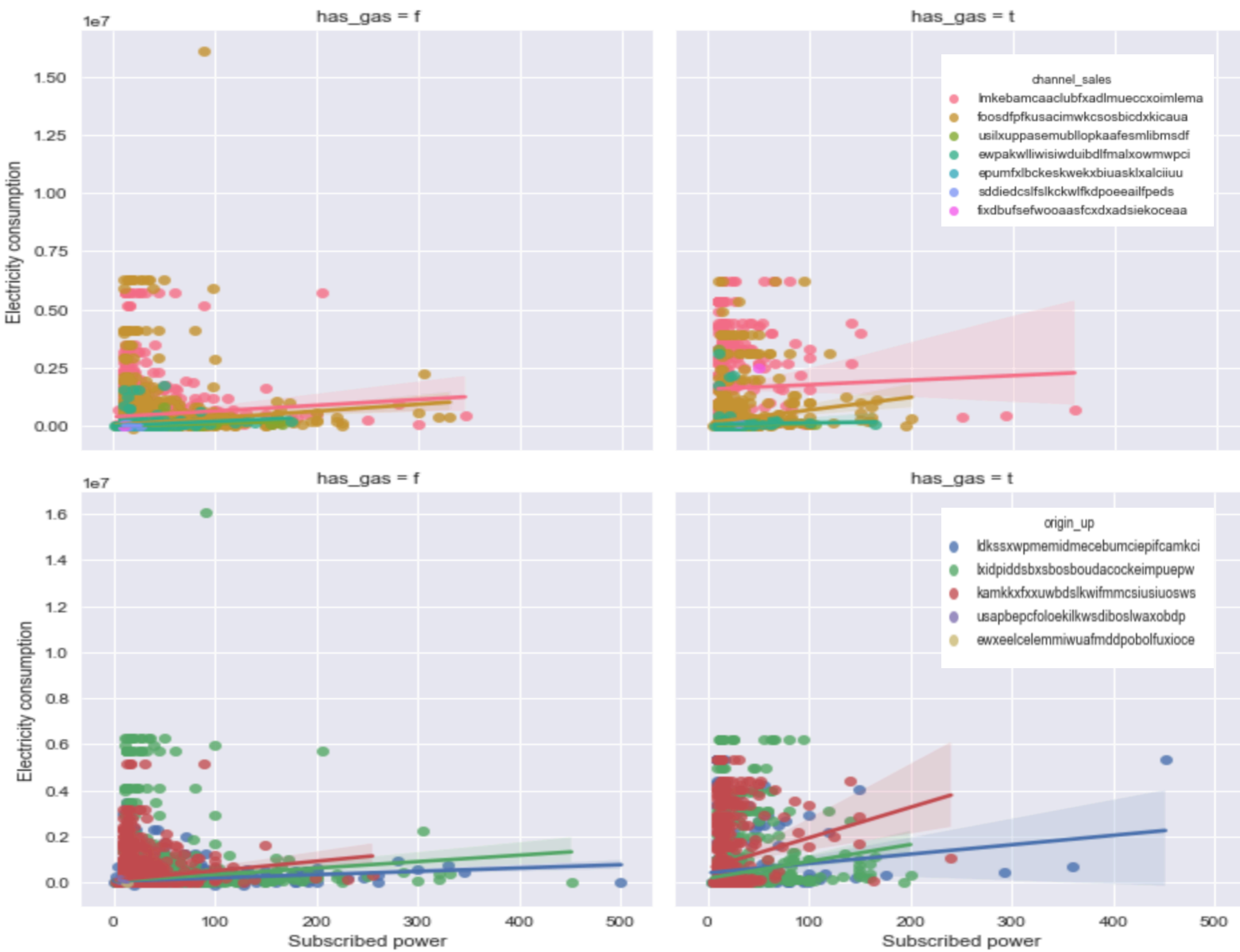
Sales channel	Customers (%)	Probability of churn given channel
foodsfpfkusacimwkcsosbicdxkicaua	**60.34%**	**0.9**
lmkebamcaaclubfxadlmueccxoimlema	17.79%	0
usilxuppasemubllopkaafesmlibmsdf	13.21%	0
ewpakwlliwisiwduibdlfmalxowmwpci	8.49%	0.1
fixdbufsefwooaasfcxdxadsiekoceaa	0.07%	0
epumfxlbckeskwekxbiuasklxalciiuu	0.07%	0
sddiedcslfslkckwlfkdpoeeailfpeds	0.03%	0

9 out of 10 customers that are churning are consuming through this channel!

Important because high probability assigned to churning customer consuming through this channel

Also important because this channel is the significantly most widely used channel!

Why higher power subscription incentives will not necessarily translate into higher consumption?



These graphs show the correlations broken down by sales channels and electricity campaigns

The correlation between overall subscribed power and electricity consumption:

Pearson correlation = 0.102
Kendall correlation = 0.282

Weak positive correlation, not strong enough to spend efforts in increasing subscribed power in order to drive consumption

20% discount keeps customers from defecting and results in a positive profit to PowerCo!

```
12 month consumption for churned customers:

40      342593
256      54072
1471    154251
1628     86232
1973     53819
2206     48667
2673     86232
3449     54072
3490    154251
3964    154251
```

```
Forecasted 12 month consumption for churned customers:

40      1169.39
256      326.69
1471    1333.69
1628     302.46
1973     251.04
2206     273.93
2673     317.18
3449     292.13
3490    1160.26
3964       0.00
```

```
Percentage difference:

40      -99.658665
256     -99.395824
1471    -99.135377
1628    -99.649249
1973    -99.533548
2206    -99.437134
2673    -99.632178
3449    -99.459739
3490    -99.247810
3964   -100.000000
```

```
Profit loss from churning customers:
$ 105100.70968491897

Profit recovered from churning customers with 20% discount:
$ 84080.56774793519
```

The model suggests that the 20% discount definitely makes sense for the forecasted time period!

However, what are its implications for the future?

What other analysis can be done to give PowerCo a concrete justified suggestion?

Realistically, PowerCo will not be able to go back to the original price after offering the 20% discount to the churned customers. Moreover, through word-of-mouth the customers that are not churning would threaten to defect if their prices were not discounted. Hence, we would have to recalculate the profits if the 20% discount was offered to all customers.

I would also look at the average time between date of activation and renewal of contracts for both churned and non-churned customers. Through this, we can infer a timeline of customer engagement, which can be used alongside proven campaigns.

We can assess which time periods the churning customers seem to be consuming their electricity in and apply a price discount for those periods only. Unlike a 20% discount on all prices, this method allows PowerCo to retain the churners and offer a 20% discount on that time period to other customers as well.

Although my classifiers worked well, I would use more classifiers, such as Naïve Bayes to look at the correlation between training features in an attempt to get a better accuracy on the training data. I can potentially develop a neural network to provide more efficient and accurate results.

Appendix

Assumptions

We cannot make inferences from columns that have a lot of empty cells/ missing values but we can generalize results from columns that do have a low proportion of empty cells

For columns, we do not know whether an empty cell implies missing value or nothing worth mentioning. Hence, we will fill them with "unknown" in the case of categorical data such as sales channel, and the mean value in the case of numerical data such as net margin.

We have no prior knowledge of which feature (factor) is more likely to affect the probability of a customer churning

We will assume that the training data is a good representation of the testing data, and therefore split our training data into random groups of training and testing data to test the accuracy of our model on at least the training data.

For the pricing data, we will assume that empty cells are the same as 0, and that a 0 means that there was no consumption in that time period. Further, we will assume that time time periods are three, 8 hour periods with period 1 representing the period of maximum consumption for each customer and not any one particular period. We will also assume that the prices are in cents and are monthly prices, with the prices for power being variable prices, and prices for energy being fixed prices.

We will then average the average monthly variable price to get the average annual variable price and sum the sum of monthly fixed prices to get the total fixed price.

Revenue = Annual var price * Consumption for 12 months + Total fixed price