A PREDICTIVE ANALYSIS FOR CUSTOMER RETENTION AND REVENUE OPTIMIZATION AT POWERCO

FINAL REPORT FOR THE BDM CAPSTONE PROJECT

SUBMITTED BY

KOHIL SHARMA

22F3001103

IITM Online BS Degree Program,

Indian Institute of Technology, Madras, Chennai

Tamil Nadu, India, 600036

CONTENTS

I. EXECUTIVE SUMMARY

PowerCo, a leading utility provider in New Zealand, faces two major challenges: customer churn among small and medium enterprises (SMEs) and revenue instability caused by seasonal energy demand. This project analyzed customer behavior, energy consumption trends, and pricing strategies to provide actionable solutions.

The analysis identified that churn is highest among new and low-margin customers, primarily driven by pricing sensitivity and gaps in early engagement. Seasonal peaks in electricity usage during summer (May–June) and gas consumption in winter (November) highlight opportunities for targeted campaigns. Predictive modeling revealed key churn predictors, including annual electricity consumption and net margin, offering clear direction for retention strategies.

To address these challenges, recommendations include dynamic pricing aligned with seasonal trends, tailored onboarding programs for new customers, and optimization of underperforming sales channels. These strategies can help PowerCo reduce churn, stabilize revenue streams, and strengthen customer loyalty, ensuring sustainable growth in a competitive market.

II. PROOF OF ORIGINALITY

The dataset for this project was sourced from Kaggle, a reputable platform for data science and machine learning datasets. This dataset provides comprehensive information on customer demographics, energy consumption patterns, pricing details, and churn indicators, making it suitable for analyzing customer retention and revenue optimization strategies. It's details are:

Title: PowerCo

Curator: Erol Masimov

Source URL: https://www.kaggle.com/datasets/erolmasimov/powerco

Description: The dataset includes variables such as customer identifiers, activity categories, sales channels, consumption metrics, contract dates, forecasted consumption, pricing details, and churn status.

Google Colab Analysis Notebook Link

III. META DATA

The dataset used in this analysis consists of two files: ***client_data.csv*** and ***price_data.csv***, sourced from Kaggle ([PowerCo Dataset]). These datasets provide insights into customer behavior, energy consumption, pricing trends, and churn. Below is a detailed description of the variables:

- **Client Data (client_data.csv)**

  This file contains information about customers, their consumption patterns, and profitability metrics. Key variables are:

Variable Name	Data Type	Description	Example Value
id	Categorical	Unique identifier for each client	"24011ae4ebbe3035 111d65fa7c15bc57"
channel_sales	Categorical	Code for the sales channel	"foosdfpfkusacimw kcsosbicdxkicaua"
cons_12m	Numeric	Electricity consumption in the past 12 months (kWh)	54946
cons_gas_12m	Numeric	Gas consumption in the past 12 months (kWh)	32000
date_activ	DateTime	Date of activation of the contract	"2013-06-15"
date_end	DateTime	Registered date of the end of the contract	"2016-06-15"
forecast_cons_12m	Numeric	Forecasted electricity consumption for the next 12 months	189.95
has_gas	Binary	Indicates if the client also has a gas subscription (t/f)	"t"

net_margin	Numeric	Total net margin	678.99
num_years_antig	Numeric	Antiquity of the client (years)	3
imp_cons	Numeric	Current paid consumption (kWh)	120.50
pow_max	Numeric	Subscribed power (kW)	43.648
churn	Binary	Binary flag indicating if the client churned (1 = Yes)	1

Table 1. Metadata of the client data file

- **Price Data (price_data.csv)**

  This file contains historical pricing information for different periods. Key variables are:

Variable Name	Data Type	Description	Example Value
id	Categorical	Unique identifier for each client	"24011ae4ebbe3035111d65fa7c15bc57"
price_date	DateTime	Reference date for the recorded price	"2015-01-01"
price_off_peak_var	Numeric	Price for off-peak electricity	0.151367
price_peak_var	Numeric	Price for peak electricity	0.149626
price_mid_peak_var	Numeric	Price for mid-peak electricity	0.145876
price_off_peak_fix	Numeric	Price for off-peak power	44.27
price_peak_fix	Numeric	Price for peak power	45.10
price_mid_peak_fix	Numeric	Price for mid-peak power	43.20

Table 2. Metadata of the pricing data file

IV. DESCRIPTIVE STATISTICS

Descriptive statistics provide a summary of key data features, such as averages, variability, and trends, helping to identify patterns, outliers, and insights for deeper analysis.
Complete analysis of this project can be found on Google Colab.

A. Analysis of Client Data

The client data consists of **14,606** records having **26** variables. Descriptive statistics for some key variables are as follows:

- ***cons_12m*** (Annual Electricity Consumption):
  - Mean: **159,220 kWh**; Median: **14,115 kWh**; Max: **6,207,104 kWh**.
  - High skewness, with a few customers consuming significantly more electricity than the majority.
  - Should be normalized for better analysis.
- ***cons_gas_12m*** (Annual Gas Consumption):
  - Mean: **28,092 kWh**; 75% of customers have no gas consumption (0 at 25th, 50th, and 75th percentiles).
  - Implies a majority of customers rely solely on electricity.
- ***forecast_cons_12m*** (Forecasted Electricity Consumption):
  - Mean: **1,869 kWh**; Median: **1,113 kWh**; Max: **82,903 kWh**.
  - High variability suggests diverse customer segments.
- ***margin_gross_pow_ele*** (Gross Power Margin):
  - Mean: **24.57**, with a relatively narrow range compared to other metrics.
  - Indicates profitability stability across most customers.
- ***net_margin*** (Net Profit Margin):
  - Mean: **$189.26**; Median: **$112.53**; Max: **$24,570**.
  - Wide range implies significant variation in customer profitability.
- ***num_years_antig*** (Client Tenure):
  - Mean: **4.99 years**; Median: **5 years**.
  - Most customers have been with the company for 4–6 years, indicating loyalty.
- ***pow_max*** (Maximum Subscribed Power):
  - Mean: **18.14 kW**; Median: **13.86 kW**; Max: **320 kW**.
  - Industrial customers likely represent the upper range.

- ***churn***:
    - Mean: **0.097** (≈**10%** churn rate).
    - Most customers are retained, but the 10% churned group needs targeted retention strategies.
- ***channel_sales*** (Sales channel):
    - **8** unique categories with the channel "*foosdfpfkusacimwkcsosbicdxkicaua*" appearing **6,754** times.
    - A single channel dominates the dataset, suggesting it could be the primary acquisition channel. Lesser-used channels could be explored for potential growth.
- ***origin_up*** (Origin of Subscription):
    - **6** unique categories with the channel "*lxidpiddsbxsbosboudacockeimpuepw*" appearing **7,097** times.
    - Over half of the subscriptions originate from one campaign, which might indicate effective marketing but also a potential over-reliance on one channel.

B. Analysis of Pricing Data

The pricing data contains **193,002** records for **16,096** clients spread across **8** variables. Descriptive statistics for all the variables are as follows:

- ***price_off_peak_var*** (Off-Peak Energy Price):
    - Mean: **$0.141**, Median: **$0.146**, Range: **$0.0–$0.280**.
    - Most values cluster around **$0.146** (as seen from the 50th percentile and a small standard deviation of **$0.025**).
    - Minimal variability, indicating consistent pricing for off-peak periods.
- ***price_peak_var*** (Peak Energy Price):
    - Mean: **$0.055**, Median: **$0.085**, with a larger spread (Std Dev: **$0.050**).
    - Some customers benefit from **$0.0** pricing during peak hours.
- ***price_mid_peak_var*** (Mid-Peak Energy Price):
    - Mean: **$0.030**, Median: **$0.0**.
    - Most customers are not charged for mid-peak energy pricing, as shown by the 25th and 50th percentiles at **$0.0**.

- ***price_off_peak_fix*** (Off-Peak Power Price):
    - Mean: **$43.33**, Median: **$44.27**, Range: **$0.0–$59.44**.
    - Pricing is highly consistent for most customers, with clustering near **$44.27**
- ***price_peak_fix*** (Peak Power Price):
    - Mean: **$10.62**, Median: **$0.0**, with a wide spread (Std Dev: **$12.84**).
    - Indicates many customers are not charged power fees during peak periods.
- ***price_mid_peak_fix*** (Mid-Peak Power Price):
    - Mean: **$6.41**, Median: **$0.0**, with a smaller maximum (**$17.45**).
    - Similarly, most customers are not charged fixed prices for mid-peak periods.

V. DETAILED EXPLANATION OF ANALYSIS METHOD

The analysis was conducted to address PowerCo's high customer churn rates and seasonal revenue fluctuations. Data preparation, exploratory analysis, feature engineering, and predictive modeling were carried out using Python.

A. Importing and Initial Data Inspection

Steps Taken: Imported necessary libraries like Pandas, NumPy, Seaborn, and Matplotlib for data manipulation and visualization. Warnings were suppressed to enhance readability of the code outputs.

Reason: These tools are industry standards for handling and exploring large datasets, offering powerful functions to identify trends, correlations, and anomalies.

B. Loading Data

- **Client Data**: Contains customer identifiers, contract details, consumption patterns, and churn status.
- **Price Data**: Provides details on energy pricing across peak and off-peak times.

Reason: Splitting data into client and pricing helps isolate trends related to customer behavior and revenue-generation strategies.

C. Exploratory Data Analysis (EDA)

Descriptive Statistics:

- Checked summary statistics to identify data ranges, means, and standard deviations.
- Focused on features like ***cons_12m*** (electricity consumption over 12 months), ***net_margin***, and ***churn***.
- Highlighted skewed distributions in ***cons_12m***, ***cons_gas_12m***, and pricing variables.
- Missing values and duplicates were checked and handled.

Reason: Identifying data distribution and gaps ensures that preprocessing and modeling can handle potential biases.

Visualizations:

- Histograms were used to analyze distributions of electricity and gas consumption.
- Box plots highlighted outliers in features like ***net_margin*** and ***pow_max***.
- Time series plots compared churn vs. non-churn energy pricing across months.
- Heatmaps were used for correlation analysis.

Reason: Visual tools offer intuitive insights into patterns and potential relationships that can be used to guide feature engineering.

D. Data Preparation

- Verified and confirmed no missing data across both datasets.
- Variables like ***cons_12m***, ***net_margin***, and ***pow_max*** had significant outliers, which were capped at the 99th percentile to reduce skewness without losing important variability.
- Logarithmic transformations were applied to highly skewed variables (***cons_12m, net_margin***) to stabilize variance.
- Converted to *datetime* and further transformed into numeric features (e.g., ***months_activ, months_to_end***) for predictive modeling.

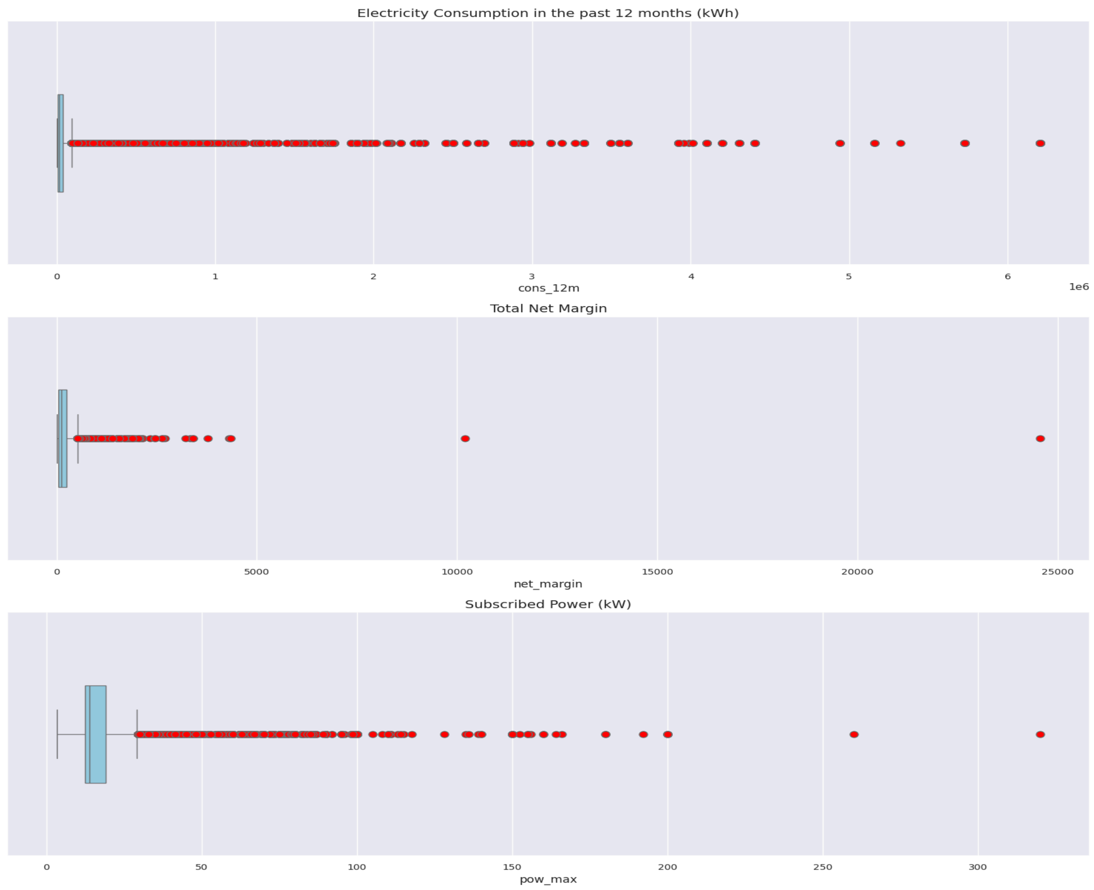

Fig 1. Box plots of cons_12m, net_margin and pow_max showing outliers

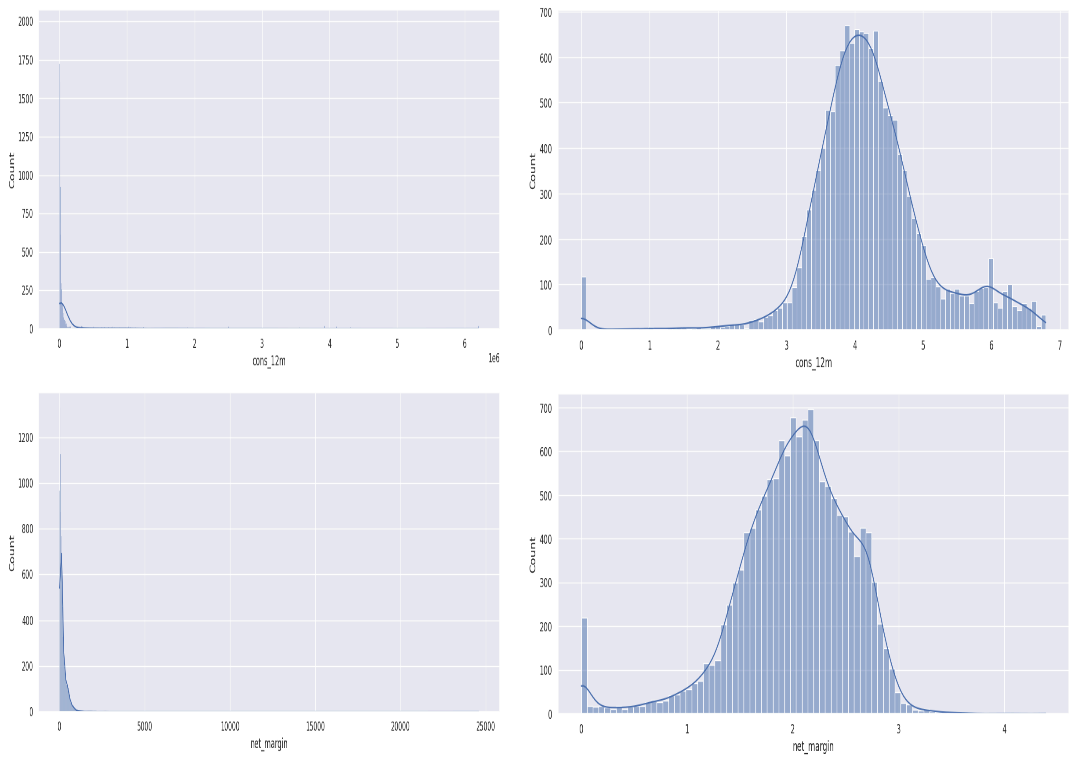

Fig 2. Before and after transformation of skewed variables cons_12m and net_margin

E. Feature Engineering

Steps Taken:

- **Price Differentials**:
  - Calculated differences in ***price_off_peak_var*** and ***price_peak_var*** between December and January to analyze seasonal trends.
  - Created average and maximum price change features for peak and off-peak periods.
- **Time Features**:
  - Extracted customer tenure (***date_activ*** to ***date_end***) to measure loyalty.
  - Added features for months to renewal and months since last modification.
- **Categorical Transformations**:
  - Converted ***channel_sales*** and ***origin_up*** into dummy variables while removing sparse categories.
  - Converted ***has_gas*** into a binary flag to represent multi-product customers.
- **Skewness Correction**:
  - Applied log transformations to variables like ***cons_12m***, ***forecast_cons_12m***, and ***net_margin***.

Reason:

- Capturing seasonality, loyalty, and customer engagement helps predict churn more effectively.
- Categorical and binary encoding ensures compatibility with machine learning algorithms.
- Skewness correction stabilizes data and reduces model overfitting.

Outlier Detection and Removal

Steps Taken:

- Used Z-score calculations to identify and replace outliers with the mean for highly skewed variables.
- Focused on variables like ***forecast_cons_12m***, ***margin_gross_pow_ele***, and ***net_margin***.

Reason:

- Outliers can heavily bias model predictions. Replacing them ensures data integrity while maintaining statistical properties.

F. Modeling

Model Used: Random Forest Classifier.

Why Random Forest?:

- Handles non-linear relationships between variables.
- Robust to multicollinearity and scales well with high-dimensional data.
- Does not require extensive feature scaling.

Steps Taken:

- Split data into training and test sets (80/20 split).
- Addressed class imbalance in churn prediction using appropriate evaluation metrics (Precision, Recall).

Evaluation Metrics:

- **Accuracy**: Measures overall performance.
- **Precision**: Reduces false positives.
- **Recall**: Ensures critical churn cases are not missed.

Reason: Churn prediction requires a balance between identifying churners and minimizing false alarms, making Precision and Recall more relevant than accuracy alone.

VI. RESULTS AND FINDINGS

Results and findings highlight key insights and trends uncovered during the analysis, providing a basis for informed decision-making and actionable recommendations.

- **Churn Distribution**

Retention Rate:

- **90.3% of companies are retained**, indicating strong overall customer loyalty and satisfaction.
- This reflects effective engagement and retention strategies for the majority of the customer base.

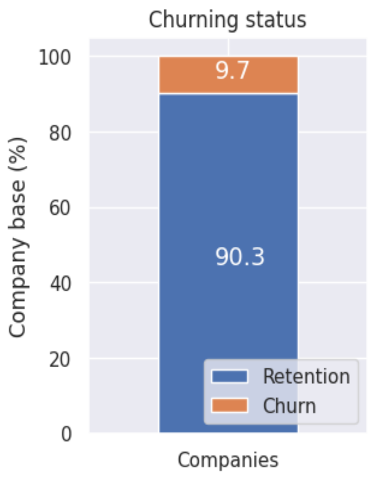

Fig 3. Churn proportion

Churn Rate:

- **9.7% of companies churned** over the observed period.
- While the churn rate appears low, this percentage could represent a significant revenue impact, especially if high-margin customers are included in this group.

- **Sales Distribution**

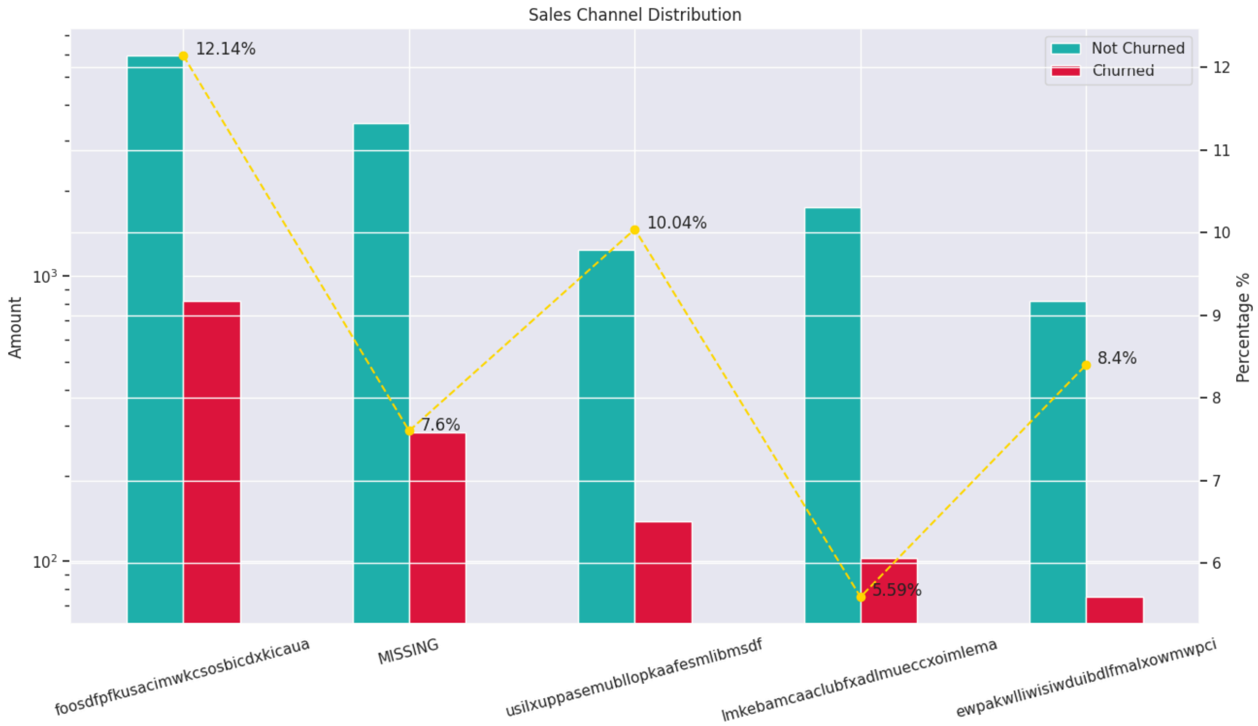

Fig 4. Sales channel distribution for each churn status

Highest Churn Rate:

- The sales channel ***"foosdfpfkusacimwkcsosbicdxkicaua"*** exhibits the **highest churn rate (12.14%)**.
- This channel likely has inefficiencies or issues leading to customer dissatisfaction.

Lowest Churn Rate:

- The ***"lmkebamcaaclubfxadlmueccxoimlema"*** channel has the **lowest churn rate (5.59%)**.
- Indicates effective customer acquisition or engagement strategies in this channel.

Moderate Churn Rates:

- Channels like ***"usilxuppasemubllopkaafesmlibmsdf"*** and ***"ewpakwlliwisiwduibdlfmalxownwpci"*** show churn rates of **10.04%** and **8.4%**, respectively.
- These channels may require some adjustments to improve retention rates.
- The ***"MISSING"*** category has a churn rate of **7.6%**, which may reflect either incomplete data or better-than-average retention.

- **Loyalty and Margin**

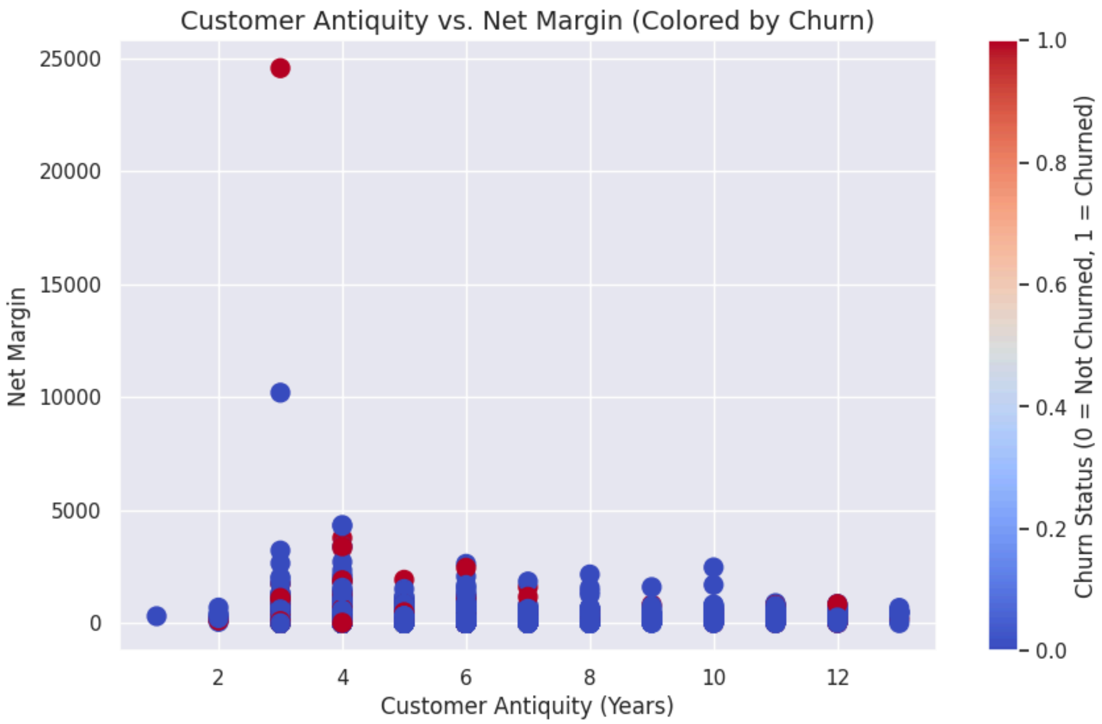

Fig 5. Customer Antiquity vs. Net Margin Plot

Churn and Antiquity (Tenure):

- Churn (represented by red dots) is concentrated among customers with **lower antiquity (1–4 years)**.
- Customers with **longer antiquity (5+ years)** are predominantly retained, with minimal churn observed.

Net Margin Distribution:

- **Low Net Margins (0–500)**: Most customers, both churned and retained, fall in this range, indicating low profitability for a majority of the customer base.
- **High Net Margins (>5,000)**: Few high-margin customers are present, and churn is rare among this group, except for an outlier.

Outliers:

- There is a significant churn outlier with **net margin exceeding 25,000**, indicating dissatisfaction or another critical issue among even high-value customers.

- **Energy Price Trends**

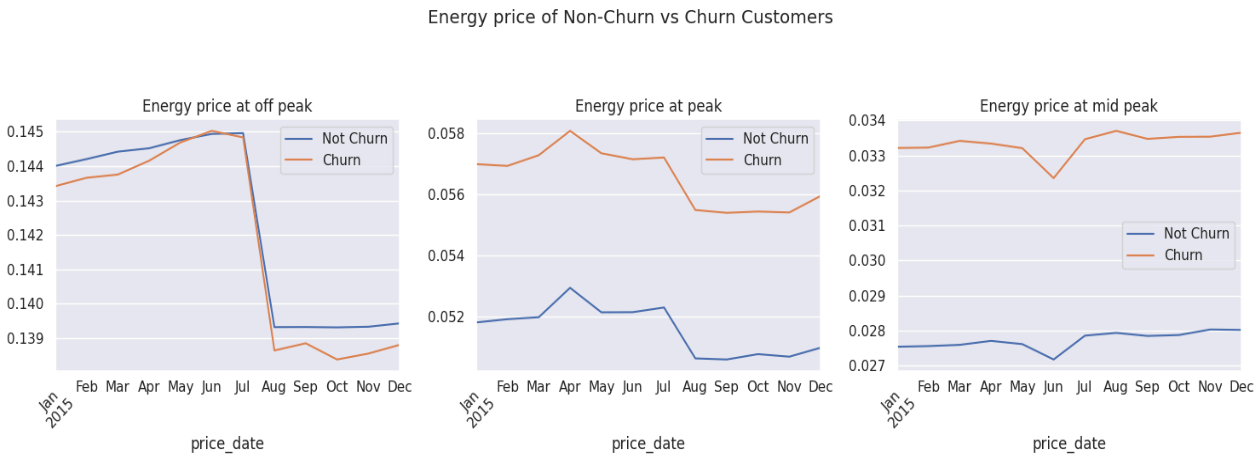

Fig 6. Energy Price of Non-churn vs. Churn customers

Energy Price at Off-Peak:

- Churned customers consistently faced slightly higher off-peak prices (e.g., **~$0.145** in May) compared to retained customers.

- A sharp price drop occurred in **August and September** for both churned and non-churned customers, but churned customers experienced a steeper decline, which could indicate dissatisfaction with prior price hikes.

Energy Price at Peak:

- Churned customers faced consistently higher peak energy prices than retained customers.
- While retained customers saw relatively stable peak prices (**~$0.052–$0.053**), churned customers experienced higher volatility (e.g., **~$0.058** in May, dropping to **~$0.056** in December).

Energy Price at Mid-Peak:

- Churned customers consistently paid higher mid-peak prices than retained customers throughout the year.
- Retained customers experienced more stable mid-peak prices (**~$0.027–$0.030**), while churned customers faced an increasing trend toward the end of the year (**~$0.034** in December).

- ## Monthly Utilities Consumption

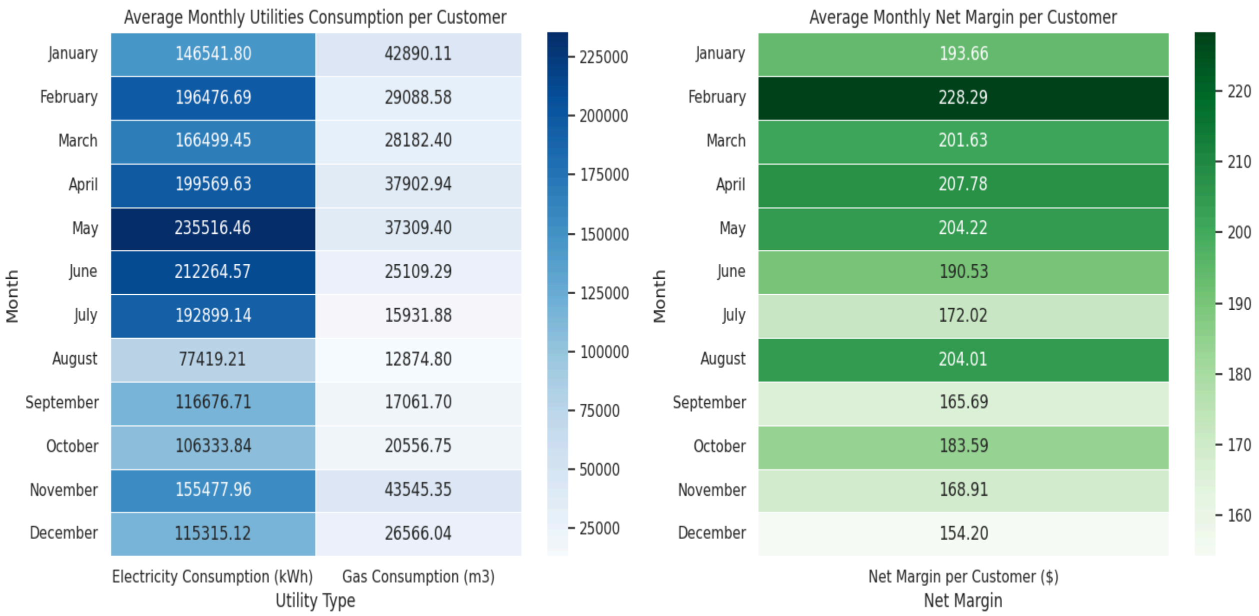

Fig 7. Monthly Utilities Consumption and Net Margin Heatmaps

Electricity Consumption (kWh)

- **Peak Consumption**:
    - May (**~235,516 kWh**) has the highest electricity consumption, likely driven by increased cooling needs in warmer months.
    - June (**~212,264 kWh**) follows closely, indicating consistent high demand during summer.
- **Lowest Consumption**:
    - August **(~77,419 kWh**) shows the lowest electricity usage, coinciding with milder weather or reduced demand.

Gas Consumption (m^3)

- **Peak Consumption**:
    - November (**~43,545 m^3**) reflects the highest gas consumption, aligning with heating demands during colder months.
    - December (**~26,566 m^3**) shows reduced but still significant gas consumption, likely due to ongoing winter needs.
- **Lowest Consumption**:
    - July (**~15,931 m^3**) and August (**~12,874 m^3**) represent the lowest gas usage, as expected during the warm summer period.

Net Margin per Customer ($)

- **Highest Margins**:
    - February (**~$228.29** per customer) achieves the highest net margin, possibly due to optimized pricing and stable energy usage in winter.
    - April (**$207.78**) and May (**$204.22**) also show strong margins, despite high electricity consumption, suggesting effective pricing strategies.
- **Lowest Margins**:
    - December (**~$154.20** per customer) has the lowest margins, likely due to increased costs during the holiday season or pricing inefficiencies.

- ## Model Training

The Random Forest model was trained with the following parameters:

n_estimators=500, max_depth=50, and ***criterion='entropy'***

Evaluation Metrics

The model's performance was assessed using:

- **Accuracy**: **90.31%**
- **Precision**: **89.47%**
- **Recall**: **5.7%**
- **F1-Score**: **11%**

```
------------------------------------------
Performance on Test Set
------------------------------------------
              precision    recall  f1-score   support

           0       0.90      1.00      0.95      2623
           1       0.89      0.06      0.11       298

    accuracy                           0.90      2921
   macro avg       0.90      0.53      0.53      2921
weighted avg       0.90      0.90      0.86      2921
```

Fig 8. Model Performance on Test Data

Confusion Matrix

True Positives (Churn correctly identified): **17**

False Positives (Non-churn misclassified as churn): **2**

True Negatives (Non-churn correctly identified): **2,621**

False Negatives (Churn misclassified as non-churn): **281**

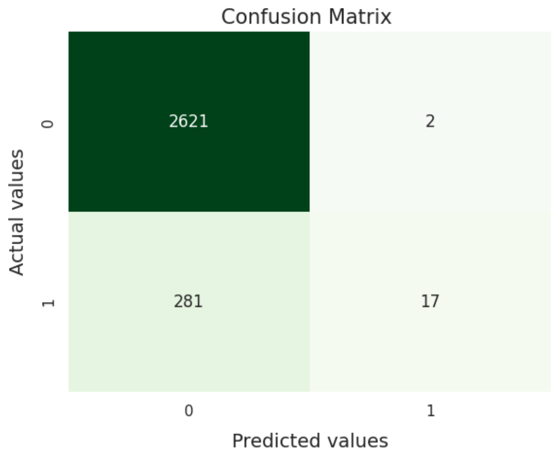

Fig. 9 Confusion Matrix

- **Feature Importance**

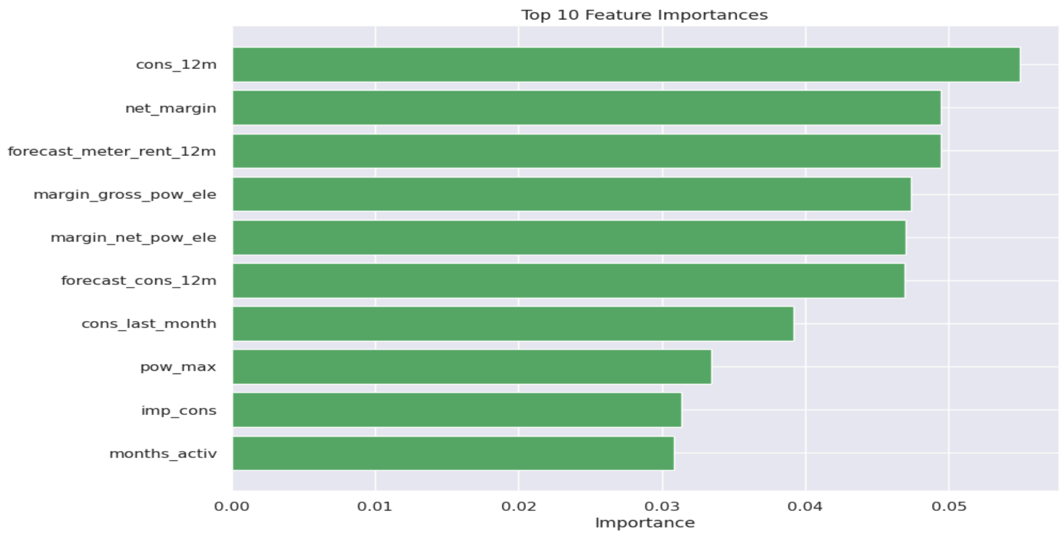

Fig 10. Top 10 Most Important Features

High Impact Features:

- ***cons_12m***: Annual electricity consumption is the strongest predictor of churn, highlighting long-term usage patterns as critical.
- ***net_margin***: Low net margins strongly correlate with churn, emphasizing the importance of profitability.

Forecasting and Margins:

- ***forecast_meter_rent_12m*** and ***forecast_cons_12m***: Predictive consumption and pricing play key roles, suggesting that customers' expectations of future costs affect churn.
- **Margins (*gross* and *net*)**: Both are critical in identifying at-risk customers, indicating profitability's role in retention.

Short-Term Behavior:

- ***cons_last_month***: Recent electricity usage offers valuable insights into churn tendencies, emphasizing immediate consumption trends.

Tenure and Contract Factors:

- ***months_activ***: Longer-tenure customers are less likely to churn, confirming loyalty improves with time.

- ## Key Findings

1. **Customer Churn:**
    - **Churn Rate: 9.7%** of customers churned, with high churn observed among newer customers (**1–4** years of tenure).
    - **Sales Channels:** Specific channels, like ***`"foosdfpfkusacimwkcsosbicdxkicaua"`***, exhibit the highest churn rate (**12.14%**), indicating service or engagement issues.
2. **Seasonal Trends:**
    - **Electricity Usage:** Peaks in **May** (~235,516 kWh) and **June** (~212,264 kWh),

driven by cooling needs, with a low in **August** (~77,419 kWh).

  - **Gas Usage:** Peaks in **November** (~43,545 m^3), aligning with heating demands, with a low in **July** (~15,931 m^3).

3. **Net Margin:**
   - **Highest Margin: February** (~$228.29) due to stable usage and pricing.
   - **Lowest Margin: December** (~$154.20), possibly due to holiday-related costs or inefficiencies.
4. **Energy Pricing and Churn:**
   - **Higher Prices for Churned Customers:** Churned customers faced consistently higher and more volatile energy prices, particularly during peak and mid-peak periods.
5. **Customer Loyalty and Profitability:**
   - Retained customers tend to have longer tenures (**5+** years) and higher net margins.
   - Churn is more prevalent among customers with lower net margins (~**$0–$500**).
6. **Predictive Model Performance:**
   - The Random Forest model achieved **90.31%** accuracy, but recall for churn cases was low (**5.7%**), suggesting potential improvements in identifying high-risk customers.

7. Key Predictors of Churn:

- Feature importance analysis revealed that **net margin**, **electricity consumption over 12 months**, and **time-related variables** (e.g., tenure, months to contract renewal) were the strongest churn predictors.
- Pricing sensitivity, while contributing to churn, was not a primary driver.

These findings offer valuable insights into how customers behave, how revenue changes with the seasons, and patterns of customer churn. By understanding these trends, businesses can develop focused strategies to improve customer retention and boost profitability.

VII. INTERPRETATION OF RESULTS AND RECOMMENDATIONS

- ### Customer Retention Insights

High Churn in Specific Segments:

- Short-tenure customers (1–4 years) are more likely to churn, indicating early dissatisfaction or misaligned expectations.
- Certain sales channels, like ***"foosdfpfkusacimwkcsosbicdxkicaua"***, show disproportionately high churn rates (12.14%), highlighting operational inefficiencies or engagement gaps.
- **Takeaway:** Early engagement, onboarding improvements, and targeted retention programs are critical for reducing churn in these segments.

High-Margin Customer Retention:

- High-margin customers are less likely to churn, except in outlier cases, but their departure results in significant revenue loss.
- **Takeaway**: Proactively monitor and offer exclusive benefits to high-margin customers to ensure loyalty and prevent churn.

- ## Pricing and Profitability

Pricing Sensitivity and Volatility:

- Churned customers consistently faced higher and more volatile pricing, particularly during peak and mid-peak periods.
- **Takeaway:** Stabilize pricing and offer tailored discounts to price-sensitive customers, particularly during critical periods of usage spikes.

Net Margin Trends:

- February recorded the highest average margin per customer ($228.29), while December had the lowest ($154.20), suggesting opportunities for cost optimization during the holiday season.
- **Takeaway:** Evaluate operational inefficiencies and pricing strategies during low-margin months to maintain profitability.

- ## Seasonal Consumption Patterns

Electricity Demand:

- Peaks in May and June (~235,516 kWh and ~212,264 kWh) reflect cooling needs, while August (~77,419 kWh) sees the lowest consumption.
- **Takeaway:** Capitalize on summer peaks with dynamic pricing strategies and promotional campaigns to drive engagement and retention.

- **Gas Consumption:**
  - Peaks in November (~43,545 m^3) and dips in summer (July, August), showing clear seasonal heating demands.
  - **Takeaway:** Bundle gas and electricity plans during complementary seasons to smooth revenue fluctuations and increase cross-utility sales.

- **Sales Channel Optimization**

Channel Performance Variability:

- Some sales channels demonstrate exemplary retention performance (e.g., ***"lmkebamcaaclubfxadlmueccxoimlema"*** with a churn rate of 5.59%), while others (e.g., ***"foosdfpfkusacimwkcsosbicdxkicaua"***) show inefficiencies.
- **Takeaway:** Investigate underperforming channels, replicate strategies from successful ones, and standardize engagement practices across all channels.

- **Predictive Modeling Benefits**

Top Predictors:

- Features like ***cons_12m*** (electricity consumption over 12 months) and ***net_margin*** emerged as the strongest indicators of churn.
- **Takeaway:** Use these predictors to refine customer segmentation, focusing retention efforts on high-risk, high-value customers.

Model Limitations:

- The random forest model achieved high accuracy (90.31%) but struggled with Recall (5.7%), underestimating churn cases.
- **Takeaway:** Explore alternative modeling approaches (e.g., XGBoost or

LightGBM) or enhance feature engineering to improve churn detection.

- **Revenue Stability**

  Misaligned Pricing and Demand:

  - Net margins do not peak during high-demand periods, indicating inefficiencies in pricing alignment with seasonal consumption.
  - **Takeaway:** Adjust pricing models to capitalize on peak consumption months (e.g., May, November) while maintaining competitive rates to retain customers.

  Cross-Utility Sales Opportunities:

  - Significant seasonal gaps between electricity and gas consumption create opportunities for cross-selling.
  - **Takeaway:** Promote bundled plans to encourage year-round engagement across utilities.

- **Operational Efficiency**

  Data-Driven Insights:

  - Feature importance analysis reveals actionable insights into customer behavior, highlighting opportunities for targeted interventions.
  - **Takeaway:** Invest in continuous data monitoring and refinement of predictive models to stay ahead of churn trends.

  Operational Adjustments:

  - Operational inefficiencies during December (low margins) suggest a need for process optimization.
  - **Takeaway:** Evaluate cost drivers during low-margin months to streamline operations and maintain profitability.
