Task 2 Exploratory Data Analysis & Data Cleaning This notebook is for Historical pricing data: variable and fixed pricing data etc **Data Dictionary** Summary **Import Libraries** import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import statsmodels.api as sm import datetime from datetime import datetime, timedelta import scipy.stats %matplotlib inline #sets the default autosave frequency in seconds **%autosave** 60 sns.set style('dark') sns.set(font scale=1.2) import warnings warnings.filterwarnings('ignore') #import feature engine.missing data imputers as mdi #from feature engine.outlier removers import Winsorizer #from feature engine import categorical encoders as ce pd.set option('display.max columns', None) #pd.set option('display.max rows',None) pd.set option('display.width', 1000) np.random.seed(0) np.set_printoptions(suppress=True) Autosaving every 60 seconds df = pd.read_csv("histdata.csv",parse_dates=['price_date'], dayfirst=True) df Out[3]: price_date price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix **0** 038af19179925da21a25619c5a24b745 2015-01-01 0.151367 0.000000 0.000000 44.266931 0.00000 0.000000 **1** 038af19179925da21a25619c5a24b745 2015-02-01 0.000000 0.00000 0.000000 0.151367 0.000000 44.266931 2 038af19179925da21a25619c5a24b745 2015-03-01 0.00000 0.000000 0.151367 0.000000 0.000000 44.266931 **3** 038af19179925da21a25619c5a24b745 2015-04-01 0.00000 0.000000 0.149626 0.000000 0.000000 44.266931 **4** 038af19179925da21a25619c5a24b745 2015-05-01 0.149626 0.000000 0.000000 44.266931 0.00000 0.000000 **192997** 16f51cdc2baa19af0b940ee1b3dd17d5 2015-08-01 0.076257 24.43733 0.119916 0.102232 40.728885 16.291555 **192998** 16f51cdc2baa19af0b940ee1b3dd17d5 2015-09-01 0.102232 0.119916 0.076257 40.728885 24.43733 16.291555 192999 16f51cdc2baa19af0b940ee1b3dd17d5 2015-10-01 0.102232 40.728885 24.43733 0.119916 0.076257 16.291555 16f51cdc2baa19af0b940ee1b3dd17d5 2015-11-01 193000 0.119916 0.102232 0.076257 40.728885 24.43733 16.291555 **193001** 16f51cdc2baa19af0b940ee1b3dd17d5 2015-12-01 0.102232 40.728885 0 119916 0.076257 24.43733 16.291555 193002 rows × 8 columns **Exploratory Data Analysis** In [4]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 193002 entries, 0 to 193001 Data columns (total 8 columns): Non-Null Count Dtype # Column --------0 id 193002 non-null object 1 price date 193002 non-null datetime64[ns] 2 price_p1_var 191643 non-null float64 3 price_p2_var 191643 non-null float64 price_p3_var 191643 non-null float64 price_p1_fix 191643 non-null float64 price_p2_fix 191643 non-null float64 price_p3_fix 191643 non-null float64 dtypes: datetime64[ns](1), float64(6), object(1) memory usage: 11.8+ MB df.describe() Out[5]: price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix **count** 191643.000000 191643.000000 191643.000000 191643.000000 191643.000000 191643.000000 mean 0.140991 0.054412 0.030712 43.325546 10.698201 6.455436 std 0.025117 0.050033 0.036335 5.437952 12.856046 7.782279 0.000000 0.000000 0.000000 -0.177779 -0.097752 -0.065172 25% 0.125976 0.000000 0.000000 40.728885 0.000000 0.000000**50**% 0.146033 0.085483 0.000000 44.266930 0.000000 0.000000**75**% 0.151635 0.101780 0.072558 44.444710 24.339581 16.226389 0.280700 0.229788 0.114102 59.444710 36.490692 17.458221 max df.columns In [6]: Out[6]: Index(['id', 'price_date', 'price_p1_var', 'price_p2_var', 'price_p3_var', 'price_p1_fix', 'price_p2_fix', 'price_p3_fix'], dtype='object') df["id"].value_counts() Out[7]: 86d4239a622874b4803a940ae83d1b42 e0006d2afdacab622d44e6cd410989d7 12 4c0f9d0109b4defb54291d5101030b5c 12 23fd68a696417a48402d576d45872d2d 12 5c89a926f4606bd126f2e1b8b33b9b6c 3e459d61dc831e29f8a9a9a59f95efd2 8 83cf18b07114e495ae8b7fb235e45ee2 8 bf89f2d8c1b133a134fd93603cb4c947 15b36e47cf04bf151e3f4438d12672e5 c5dcd5c506e565aaabffa29bc1ec0a37 Name: id, Length: 16096, dtype: int64 df["price_date"].value_counts() Out[8]: 2015-12-01 16094 2015-08-01 16094 2015-07-01 16090 2015-11-01 16087 2015-10-01 16085 2015-06-01 16085 2015-09-01 16082 16082 2015-02-01 2015-05-01 16080 2015-04-01 16079 2015-03-01 16074 2015-01-01 16070 Name: price_date, dtype: int64 df.groupby(["price date"]).mean() price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix price_date 2015-01-01 0.142561 0.054884 0.030399 43.224372 10.716260 6.469952 6.469121 2015-02-01 0.142757 0.054958 0.030462 43.226638 10.706995 2015-03-01 0.143091 0.054987 0.030527 43.241339 10.690361 6.457830 2015-04-01 0.143213 0.055551 0.030993 43.269548 10.822268 6.528723 2015-05-01 0.143512 0.055089 0.030665 43.304062 10.697581 6.448145 0.054739 2015-06-01 0.143692 0.030413 43.328810 10.593585 6.388537 2015-07-01 0.143669 0.055200 0.030809 43.337050 10.702093 6.457581 2015-08-01 0.137905 10.698239 0.053495 0.030822 43.362274 6.453573 0.137888 0.053355 2015-09-01 0.030776 43.346782 10.661984 6.427358 2015-10-01 0.137844 0.053499 0.030848 43.348056 10.677121 6.439320 2015-11-01 0.137880 0.053505 0.030848 43.419709 10.679994 6.444858 2015-12-01 0.137945 0.053696 0.030987 43.497869 10.732132 6.480254 df.groupby(["price_date"]).median() price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix price_date 0.148825 2015-01-01 0.0 0.084991 0.0 44.266931 0.0 0.085058 2015-02-01 0.148825 0.0 44.266931 0.0 0.0 2015-03-01 0.148825 0.085058 0.0 44.266931 0.0 0.0 2015-04-01 0.148825 0.085658 0.0 0.0 0.0 44.266930 2015-05-01 0.148825 0.085658 0.0 44.266930 0.0 0.0 2015-06-01 0.148825 0.085390 0.0 0.0 44.266930 0.0 2015-07-01 0.148825 0.085658 0.0 44.266930 0.0 0.0 2015-08-01 0.084905 0.0 0.0 0.0 0.144524 44.266930 0.144524 2015-09-01 0.085165 0.0 44.266930 0.0 0.0 2015-10-01 0.144292 0.085568 0.0 44.266930 0.0 0.0 2015-11-01 0.144292 0.086087 0.0 44.266930 0.0 0.0 2015-12-01 0.144524 0.086328 0.0 0.0 0.0 44.444710 df.groupby(["id"]).mean() price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix id 0002203ffbb812588b632b9e628cc38d 0.124338 0.103794 0.073160 40.701732 24.421038 16.280694 0004351ebdd665e6ee664792efc4fd13 0.146426 0.000000 0.000000 44.385450 0.000000 0.000000 0010bcc39e42b3c2131ed2ce55246e3c 0.181558 0.000000 0.000000 45.319710 0.000000 0.000000 0010ee3855fdea87602a5b7aba8e42de 0.118757 0.098292 0.069032 40.647427 24.388455 16.258971 00114d74e963e47177db89bc70108537 0.147926 0.000000 0.000000 44.266930 0.000000 0.000000 0.115125 0.080780 40.896427 24.637456 fffac626da707b1b5ab11e8431a4d0a2 0.147137 0.000000 0.000000 44.311375 0.000000 0.000000 fffc0cacd305dd51f316424bbb08d1bd 0.153879 0.129497 0.094842 41.160171 24.895768 16.763569 fffe4f5646aa39c7f97f95ae2679ce64 0.123858 0.103499 0.073735 40.606699 24.364017 16.242678 ffff7fa066f1fb305ae285bb03bf325a 0.125360 0.104895 0.075635 40.647427 24.388455 16.258971 16096 rows × 6 columns company = pd.DataFrame(df.groupby(["id"]).mean()) company price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix id 0002203ffbb812588b632b9e628cc38d 0.124338 0.103794 0.073160 40.701732 24.421038 16.280694 0004351ebdd665e6ee664792efc4fd13 0.146426 0.000000 0.000000 44.385450 0.000000 0.000000 0010bcc39e42b3c2131ed2ce55246e3c 0.181558 0.000000 0.000000 45.319710 0.000000 0.000000 0010ee3855fdea87602a5b7aba8e42de 0.118757 0.098292 0.069032 40.647427 24.388455 16.258971 00114d74e963e47177db89bc70108537 0.147926 0.000000 0.000000 44.266930 0.000000 0.000000 ffef185810e44254c3a4c6395e6b4d8a 0.138863 0.115125 0.080780 40.896427 24.637456 16.507972 0.147137 0.000000 fffac626da707b1b5ab11e8431a4d0a2 0.000000 44.311375 0.000000 0.000000 0.153879 0.129497 0.094842 fffc0cacd305dd51f316424bbb08d1bd 41.160171 24.895768 16.763569 fffe4f5646aa39c7f97f95ae2679ce64 0.123858 0.103499 0.073735 40.606699 24.364017 16.242678 24.388455 ffff7fa066f1fb305ae285bb03bf325a 0.125360 0.104895 0.075635 40.647427 16.258971 16096 rows × 6 columns output = pd.read_csv("output.csv", index_col="id") In [14]: output churn id 48ada52261e7cf58715202705a0451c9 24011ae4ebbe3035111d65fa7c15bc57 d29c2c54acc38ff3c0614d0a653813dd 764c75f661154dac3a6c254cd082ea7d bba03439a292a1e166f80264c16191cb 18463073fb097fc0ac5d3e040f356987 d0a6f71671571ed83b2645d23af6de00 10e6828ddd62cbcf687cb74928c4c2d2 1cf20fd6206d7678d5bcafd28c53b4db 563dde550fd624d7352f3de77c0cdfcd 16096 rows × 1 columns df3 = pd.merge(left=company, right=output, how="inner", left_index=True, right_index=True) df3 price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix churn id 0002203ffbb812588b632b9e628cc38d 0.124338 0.103794 0.073160 40.701732 24.421038 16.280694 0 0004351ebdd665e6ee664792efc4fd13 0.000000 0.146426 0.000000 44.385450 0.000000 0.000000 0.000000 0010bcc39e42b3c2131ed2ce55246e3c 0.181558 0.000000 0.000000 45.319710 0.000000 0 0.098292 0.069032 0010ee3855fdea87602a5b7aba8e42de 0.118757 40.647427 24.388455 16.258971 0.000000 44.266930 00114d74e963e47177db89bc70108537 0.147926 0.000000 0.000000 0.000000 0 0.080780 ffef185810e44254c3a4c6395e6b4d8a 0.138863 0.115125 40.896427 24.637456 16.507972 0 0.000000 0.000000 fffac626da707b1b5ab11e8431a4d0a2 0.147137 0.000000 0.000000 44.311375 fffc0cacd305dd51f316424bbb08d1bd 0.129497 0.153879 0.094842 41.160171 24.895768 16.763569 0 fffe4f5646aa39c7f97f95ae2679ce64 16.242678 0.123858 0.103499 0.073735 40.606699 24.364017 ffff7fa066f1fb305ae285bb03bf325a 0.125360 0.104895 0.075635 40.647427 24.388455 16.258971 0 16096 rows × 7 columns In [18]: df3["churn"].value counts() 14501 1595 Name: churn, dtype: int64 print("Percentage of churn customers: {:.2f}%".format(1595/14501*100)) Percentage of churn customers: 11.00% #df3.to_csv("customerchurn.csv",index=False) **Data Visualization Univariate Data Exploration** df.hist(bins=50, figsize=(20,10)) plt.suptitle('Feature Distribution', x=0.5, y=1.02, ha='center', fontsize='large') plt.tight_layout() plt.show() Feature Distribution price_p2_var price_p1_var 80000 40000 60000 40000 20000 20000 10000 0.00 0.05 0.15 0.20 0.25 0.00 0.05 0.10 0.15 0.20 price_p3_var price_p1_fix 100000 100000 80000 80000 60000 60000 40000 20000 0 0 0.02 0.08 0.10 0.00 0.06 30 price_p2_fix price_p3_fix 100000 100000 80000 80000 40000 40000 20000 20000 df.boxplot(figsize=(20,5)) plt.suptitle('BoxPlot', x=0.5, y=1.02, ha='center', fontsize='large') plt.tight_layout() plt.show() **BoxPlot** 40 20 10 price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix fig = plt.figure(figsize=(20,40)) plt.subplot(7,2,1)plt.title("Power price 1st period vs churn") sns.barplot(x=df3.churn, y=df3.price_p1_fix, data=df3) plt.subplot(7,2,2)plt.title("Power price 2nd period vs churn") sns.barplot(x=df3.churn, y=df3.price_p2_fix, data=df3) plt.subplot(7,2,3)plt.title("Power price 3rd period vs churn") sns.barplot(x=df3.churn, y=df3.price_p3_fix, data=df3) plt.subplot(7,2,4)plt.title("Energy price 1st period vs churn") sns.barplot(x=df3.churn, y=df3.price_p1_var, data=df3) plt.subplot(7,2,5)plt.title("Energy price 2nd period vs churn") sns.barplot(x=df3.churn, y=df3.price_p2_var, data=df3) plt.subplot(7,2,6)plt.title("Energy price 3rd period vs churn") sns.barplot(x=df3.churn, y=df3.price_p3_var, data=df3) plt.tight_layout() plt.show() Power price 1st period vs churn Power price 2nd period vs churn 12 40 30 price_p2_fix Power price 3rd period vs churn Energy price 1st period vs churn 0.14 0.12 xij_Ed_4 0.08 0.06 0.06 0.02 0.00 Energy price 2nd period vs churn Energy price 3rd period vs churn 0.06 0.035 0.05 0.030 0.025 0.04 ര്പ് 0.020 0.03 9 0.015 0.02 0.010 0.01 0.005 0.00 Note: Churn happens in second and third period **Time-Series Analysis** fig = plt.figure(figsize=(30,10)) In [24]: sns.lineplot(x=df.price_date, y=df.price_p1_fix, data=df, estimator="mean") plt.title("Price of power in Period 1", fontsize = 25) plt.show() Price of power in Period 1 43.50 43.45 43.40 price_p1_fix 43.35 43.30 43.25 price_date fig = plt.figure(figsize=(30,10)) sns.lineplot(x=df.price_date,y=df.price_p2_fix,data=df, estimator="mean") plt.title("Price of power in Period 2", fontsize = 25) plt.show() Price of power in Period 2 10.80 10.75 10.65 10.60 2015-09 price_date fig = plt.figure(figsize=(30,10)) sns.lineplot(x=df.price_date,y=df.price_p3_fix,data=df, estimator="mean") plt.title("Price of power in Period 3", fontsize = 25) Price of power in Period 3 6.48 6.44 6.42 6.40 2015-01 2015-05 2015-09 fig = plt.figure(figsize=(30,10)) sns.lineplot(x=df.price_date,y=df.price_pl_var,data=df, estimator="mean") plt.title("Price of energy in Period 1", fontsize = 25) plt.show() Price of energy in Period 1 0.143 ਲੋ_{। 0.141} 0.140 0.138 2015-01 2015-03 2015-05 2015-09 2015-11 price_date fig = plt.figure(figsize=(30,10)) sns.lineplot(x=df.price_date, y=df.price_p2_var, data=df, estimator="mean") plt.title("Price of energy in Period 2", fontsize = 25) plt.show() Price of energy in Period 2 0.0555 0.0550 0.0535 2015-01 2015-03 2015-05 2015-09 fig = plt.figure(figsize=(30,10)) sns.lineplot(x=df.price_date, y=df.price_p3_var, data=df, estimator="mean") plt.title("Price of energy in Period 3", fontsize = 25) Price of energy in Period 3 0.0309 0.0308 입 0.0307 0.0306 0.0305 0.0304 2015-01 2015-03 2015-05 2015-09 price_date **Pairplots** plt.figure(figsize=(20,20)) sns.pairplot(df.sample(500)) plt.suptitle('Pairplots of features', x=0.5, y=1.02, ha='center', fontsize='large') plt.show() <Figure size 1440x1440 with 0 Axes> Pairplots of features 0.25 0.20 p1 var 0.15 9 0.10 0.05 0.10 0.00 0.15 price_p2_var 0.00 0.00 0.00 0.10 0.08 0.06 p3 0.04 0.02 0.00 60 price_p1_fix 05 05 0 30 ĭ price_p2_f 0 0 0 15 price p3 fix 10 5 0 0.1 0.00 0.05 20 price_p2_var price_p3_fix price_p1_var price_p3_var price_p1_fix price_p2_fix Correlation df.corr() price_p1_var price_p2_var price_p3_var price_p1_fix price_p2_fix price_p3_fix price_p1_var 1.000000 -0.329950 -0.595257 0.416443 -0.630465 -0.572522 1.000000 -0.329950 0.828230 -0.099764 0.802757 0.814439 price_p2_var -0.595257 0.828230 1.000000 0.973831 0.979617 price_p3_var -0.137346 0.416443 -0.099764 0.000941 price_p1_fix -0.137346 1.000000 -0.251511 price_p2_fix -0.630465 0.802757 0.973831 0.000941 1.000000 0.926955 price_p3_fix -0.572522 0.814439 0.979617 -0.251511 0.926955 1.000000 plt.figure(figsize=(16,9)) sns.heatmap(df.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2) plt.show() 1.00 -0.33 -0.60 0.42 -0.63-0.57price p1 fix price p3 var price p2 var price p1 var - 0.8 -0.331.00 0.83 -0.100.80 0.81 - 0.6 - 0.4 -0.60 0.83 1.00 -0.140.97 0.98 - 0.2 -0.25-0.100.00 0.42 -0.141.00 - 0.0 -0.20.80 -0.630.97 0.00 1.00 0.93 price p2 fix - -0.4 -0.25-0.570.81 0.98 0.93 1.00 ξĭ price_p3_var price_p1_fix price_p3_fix price_p1_var price_p2_var price_p2_fix Note: price p2 and p3 are highly correlated to each other Loading [MathJax]/extensions/Safe.js