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Marketing Analytics Group Assignment 1 | April 10, 2024

Cell2Cell Write-Up

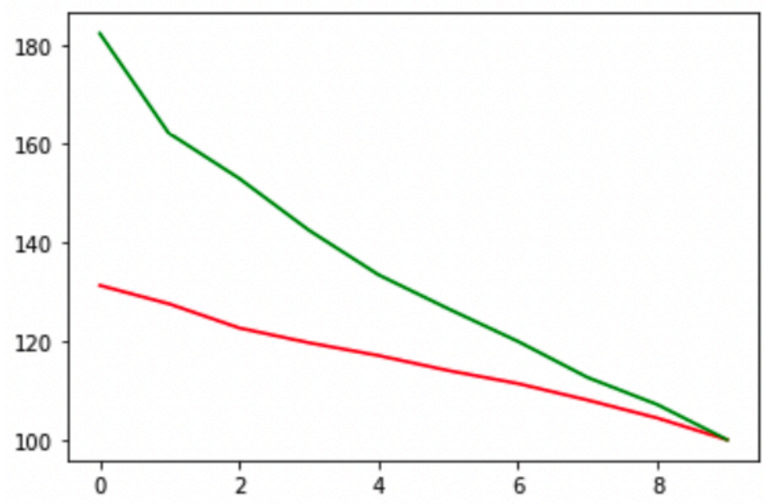
1. Briefly describe your predictive churn model. How did you select variables to be included in the model?

We initially developed our churn model with the dependent variable “churndep” and all of the independent variables provided. We ran regressions with regularization and tested multiple alpha values to capture the characteristics of customers who churn. We then measured the performance of the different models by plotting the lift with the various alpha values. Because we were looking for a lift of at least 170, we chose to use alpha = 30 because it exceeded 170 and because it seemed to strike the right balance such that it was not overfitting and not generalized. The logistic regression (alpha = 30) dropped 19 variables and among the variables included, 28 of them were statistically significant (p-value < 0.05). When we reviewed the variables that were statistically significant, we also felt that based on domain knowledge, the included variables made sense given the question we are trying to answer with this analysis.

We applied .predict to the logistic regression with regularization model (alpha = 30) to predict churn for calibration data, and graded it, revealing a mean of 0.498 . We likewise applied .predict on the validation data, graded it, and revealed a mean of 0.478 . Plotting the lift (using 170 as the given benchmark) and gains, we found a lift slightly above 180 . Lastly, we inverted and rescaled our odds ratio.

2. Demonstrate the predictive performance of the model. Is the performance adequate?

We evaluated the predictive performance of the model by examining the lift. First, we ran the model on the calibration data and the validation data and computed the respective predicted churn rates. Then we created a lift chart for both the calibration data and the validation data. The model generated an approximate lift of 130 for the calibration data and an approximate lift of 180 for the validation data, which means that, on average, the model’s predictions are about 180% better at identifying churn compared to random guessing. Since the lift value is higher than the requirement (a lift of at least 170), we were confident to draw the conclusion that the performance of our predictive model was adequate.



3. What are the key factors that predict customer churn? Do these factors make sense? What is their relative importance?

We found many variables that were statistically significant in predicting customer churn. After normalizing our odds ratios and inverting, we applied a threshold of a greater than 10% change (i.e., normalized odds ratio greater than 1.10) to narrow to eight key variables.

	Odds ratios	***Norm w Invert from Notebook***	***P-values***
eqpdays	*1.001408779932910*	*1.4353400869870000*	*0.000*
uniqsubs	*1.1800048239981400*	*1.2430780952880500*	*0.000*
months	*0.980846826669976*	*1.2045787840487100*	*0.000*
mou	*0.9997182341445520*	*1.159374057761870*	*0.000*
changem	*0.9995074555608680*	*1.1364608869945500*	*0.000*
retcall	*1.8937279587126400*	*1.134016700056510*	*0.001*
actvsubs	*0.8461966700532010*	*1.1211601473886200*	*0.000*
creditaa	*0.7304758388208030*	*1.106691624448040*	*0.000*

- **Equipment days**: increasing the number of days of using current equipment by one standard deviation increases the odds of churn by 43.5%. This makes intuitive sense, where we expect the length of time a customer has had their current equipment to be a predictor of their likelihood to churn. For example, as customers hold equipment which is starting to reach the end of its lifespan, or as newer models with better performance are released, they may choose to churn.
- **Unique subscription**: increasing the number of unique subscriptions by one standard deviation increases the odds of churn by 24%. The more people who are on an account, the more likely they are to churn: e.g., each person on a family plan is likely to have different needs from a service, or competitors may have stronger family plan discounts or bundling offers.
- **Months in service**: decreasing the number of months in service by one standard deviation, increases the odds of churn by 20.5%. As expected, a relatively newer customer may be more likely to churn than one who has been with the service for a longer period.
- **Mean monthly minutes of use:** decreasing mean monthly minutes of use by one standard deviation increases the odds of churn by 16%. This makes sense because if a customer is not using their service, they may be less interested in paying for it and would churn.
- **% change in minutes of use:** decreasing the percentage change in minutes of use by one std deviation, increases the odds of churn increase by 13.6%. Similar to months in service, a customer who has a lower number of minutes of use is more likely to churn as this might reflect that they are using the service relatively less than other customers.
- **Retention Call:** When a customer has made a call to the retention team, it increases odds of churn by 89%. Note: while this variable indicates the highest odds of churn by far, we have not chosen this for our incentive plan because we are proposing a proactive churn management strategy as opposed to the traditional reactive churn management strategy, which incentives deal-shopping between carriers.
- **Active subscriptions**: decreasing the number of active subscriptions by one std deviation, increases the odds of churn increase by 12%. For example, if there are 4

customers on a plan (4 unique subscribers), 2 are active users, and that drops to 1 active user, then this signals a likelihood that all of these customers are likely to churn.

- **Creditaa:** When someone doesn't have a credit aa rating, it decreases the odds of churn rate by 27%. In other words, customers with a lower credit rating are less likely to churn. This can be due to the difficulty in being able to qualify for a competitor's plan, and lead them to stay with their existing plan. While this variable had the 2nd highest magnitude of predicting churn, we decided not to offer an incentive given that the number of customers who have a high credit rating is relatively low.

4. What offers should be made to which customers to encourage them to remain with Cell2Cell? Assume that your objective is to generate net positive cash flow, i.e., generate additional customer revenues after subtracting out the cost of the incentive.

We decided to focus on the key predictive variable **Months in Service**. Because a customer who has been with the service for a shorter period of time is more likely to churn than one who has been with the service longer (per the normalized and inverted odds ratios), we want to incentivize customers to sign longer-term contracts to increase the number of months they stay with Cell2Cell. Per the data provided, based on the current revenue from a customer who stays with the service for 18 months, their average payment per month is $58.28. Thus the net present value of expected profit for the lifetime of a customer who stays with us for 18 months is $815.72 (note: assumptions for the LTV calculations are provided in the Appendix). In order to offer a discount for a 24-month contract, we would need to generate at least $43.71 in revenue each month for 24 months. This value represents 75% of the original expected revenue for an 18-month period, and thus the break-even rate for revenue is currently 25%. So any offer below that threshold would generate a profit.

We decided to offer a 10% discount for the 24-month contract. We assumed that we would run targeted emails to both brand new customers and existing customers that are likely to churn. We assume that these costs will be minimal, at about $2 a customer (one-time payment at month 1). Even with the incentive costs (opportunity cost of offering the 10% discount) of $5.83 per customer per month, our expected profit is $985.54 for the 24-month lifetime of an average customer. This represents a 21% increase in expected profit through our incentive program.

We anticipate that this incentive is likely to have positive effects on other key predictive variables, including an increase in equipment days and minutes of use (given that customers are staying with our service longer), a reduction in retention calls (given that customers are locked into their contracts), as well as increase in active and unique subscriptions given that our 24-month contract would be priced more competitively.

5. Assuming these actions were implemented, how would you determine whether they had worked?

To determine whether these actions were successful, we would run a difference in differences study. This would be conducted through randomly dividing customers into two groups to avoid any selection bias. The treatment group would be comprised of those customers who are offered and accept the 10% discount for a 24-month contract. This group would include brand new customers and customers at month 12 who sign up for the new contract. The control group would consist of those customers who are not offered the discount and who continue on a month-to-month or any other existing plan without the incentive. This latter group churns after 18 months, on average.

To analyze whether the plan worked we would look at two differences:

- First difference in average LTV at month 18 (the average number of months customers use the service before churning) and average LTV at month 24 in each group.
    - **Treatment Group Change (LTV) = Treatment Group LTV(24 months)-Treatment Group LTV(18 months)**
    - **Control Group Change (LTV) = Control Group LTV(24 months) -Control Group LTV(18 months)**
- The second difference to observe the effect of the incentive plan (assuming other factor are held constant in both groups)
    - **Difference-in-Differences (DiD)=Treatment Group Change in LTV−Control Group Change in LTV**

A positive DiD in the LTVs will indicate that our plan is working because it indicates increase in profits and ultimately LTV as a result of the incentive plan reducing churn rates. We chose to use the Difference in Difference approach because in a business environment where difference factors could affect LTV, this approach isolates the effect of the incentive plan from other external influences.

LTV w/o incentive plan

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Revenues		58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	0.00	0.00	0.00	0.00	0.00	0.00
Product/Service Costs		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Marketing costs		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
customer profit		$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$58.28	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
probability of being active	100	98%	96%	94%	92%	90%	89%	87%	85%	83%	82%	80%	78%	77%	75%	74%	72%	71%	70%	68%	67%	65%	64%	63%	62%
Expected profit		$57.11	$55.97	$54.85	$53.76	$52.68	$51.63	$50.59	$49.58	$48.59	$47.62	$46.67	$45.73	$44.82	$43.92	$43.04	$42.18	$41.34	$40.51	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
Present Value of Expected Profit		$57.11	$55.51	$53.95	$52.43	$50.96	$49.53	$48.14	$46.78	$45.47	$44.19	$42.95	$41.74	$40.57	$39.43	$38.32	$37.25	$36.20	$35.18	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00

$1,049.04 Current revenue from a customer who stays with the service for 18 months and pays the average rate of $58.28/month

$43.71 In order to offer a discount for a 24-month contract, we would need to generate at least the following revenue each month for 24 months.

75.00% Break-even revenue divided by original revenue

25.00% The new revenue amount is 75% of the original, meaning we could offer up to a 25% discount and break even

Let's say that we do a 10% discount for the 24-month contract

Let's assume that we run targeted emails to both brand new customers and existing customers (excluding those who have already signed a 24-month contract) so they can sign to a new contract at least 6 months before they are likely to churn. We assume that these costs will be minimal, at about $2 a customer.

$815.72 Present value of expected profit for the lifetime of a customer who stays with us for 18 months, given a 10% discount rate on a yearly basis.

LTV with incentive plan

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
Revenues		58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	58.28	
Product/Service Costs		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Marketing costs		2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Incentive costs		$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	$5.83	
customer profit		$50.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	$52.45	
probability of being active	100	98%	96%	94%	92%	90%	89%	87%	85%	83%	82%	80%	78%	77%	75%	74%	72%	71%	70%	68%	67%	65%	64%	63%	62%	
Expected profit		$49.44	$50.37	$49.37	$48.38	$47.41	$46.46	$45.53	$44.62	$43.73	$42.86	$42.00	$41.16	$40.34	$39.53	$38.74	$37.96	$37.21	$36.46	$35.73	$35.02	$34.32	$33.63	$32.96	$32.30	
Present Value of Expected Profit	0	$49.44	$49.96	$48.55	$47.19	$45.86	$44.58	$43.32	$42.11	$40.92	$39.77	$38.66	$37.57	$36.51	$35.49	$34.49	$33.52	$32.58	$31.66	$5.84	$5.21	$4.64	$4.13	$3.68	$3.28	
																									LTV	#VALUE!

$985.54 Present value of the expected profit for the lifetime of a customer who stays with us for 24 months

$169.82 Expected profit increase per customer under the 24-month contract

0.2081825453 Profit increase in %

Cell2Cell Assignment

April 9, 2024

[1]:
```
import shared.mba263 as mba263
import pandas
import matplotlib.pyplot as plt
```

[2]:
```
import numpy
```

[3]:
```
data = pandas.read_csv('cell2cell.csv')
```

[4]:
```
data
```

[4]:
```
       customer  calibrat  churn  churndep     revenue      mou   recchrge  \
0       1000002         0      0       NaN   57.492500   482.75  37.424999
1       1000006         0      0       NaN   82.275002  1312.25  75.000000
2       1000010         0      0       NaN   31.662500    25.50  29.990000
3       1000011         0      0       NaN   62.127499    97.50  65.985001
4       1000014         0      0       NaN   25.225000     2.50  25.000000
…             …       …     …         …           …        …          …
71042   1099987         1      1       1.0  117.490000   384.00  29.990000
71043   1099988         1      1       1.0         NaN      NaN        NaN
71044   1099990         1      1       1.0         NaN      NaN        NaN
71045   1099992         1      1       1.0         NaN      NaN        NaN
71046   1099995         1      1       1.0         NaN      NaN        NaN

       directas  overage  roam  …  retaccpt  newcelly  newcelln  refer  \
0        0.2475    22.75   0.0  …         0         0         1      0
1        1.2375     0.00   0.0  …         0         1         0      0
2        0.2475     0.00   0.0  …         0         0         1      0
3        2.4750     0.00   0.0  …         0         1         0      0
4        0.0000     0.00   0.0  …         0         1         0      0
…             …        …     …  …         …         …         …
71042    0.0000   250.00   0.0  …         0         0         0      0
71043       NaN      NaN   NaN  …         0         0         0      0
71044       NaN      NaN   NaN  …         0         0         0      0
71045       NaN      NaN   NaN  …         0         1         0      0
71046       NaN      NaN   NaN  …         0         0         0      0

       incmiss  income  mcycle  setprcm      setprc  retcall
```

```
0          0    5    0    0  149.989990     0
1          0    6    0    0    9.989998     0
2          0    9    0    0   29.989990     0
3          0    6    0    0   29.989990     0
4          0    7    0    0   29.989990     0
…     …   …    …    …    …       …
71042      0    2    0    0   29.989990     0
71043      0    6    0    1    0.000000     0
71044      0    6    0    0   59.989990     0
71045      0    8    0    1    0.000000     0
71046      0    7    0    0   79.989990     0

[71047 rows x 70 columns]
```

[5]:
```python
mba263.tabulate(data['calibrat'])
```

[5]:
```
   Name  Count  Frequency
0     0  31047   0.436992
1     1  40000   0.563008
```

[6]:
```python
mba263.tabulate(data['churn'])
```

[6]:
```
   Name  Count  Frequency
0     0  50438   0.709924
1     1  20609   0.290076
```

[7]:
```python
mba263.tabulate(data['churndep'])
```

[7]:
```
       Name  Count  Frequency
31047   0.0  20000   0.281504
31048   1.0  20000   0.281504
0       NaN      1   0.000014
1       NaN      1   0.000014
2       NaN      1   0.000014
…      …    …          …
31042   NaN      1   0.000014
31043   NaN      1   0.000014
31044   NaN      1   0.000014
31045   NaN      1   0.000014
31046   NaN      1   0.000014

[31049 rows x 3 columns]
```

[8]:
```python
data_calibration=data[data['calibrat']==1]
```

[9]:
```python
data_validation=data[data['calibrat']==0]
```

[10]:
```
data_calibration['churn'].mean()
```

[10]: 0.5

[11]:
```
data_validation['churn'].mean()
```

[11]: 0.019615421779882115

[12]:
```
column_names = data.columns.tolist()
```

[13]:
```
column_names
```

[13]:
```
['customer',
 'calibrat',
 'churn',
 'churndep',
 'revenue',
 'mou',
 'recchrge',
 'directas',
 'overage',
 'roam',
 'changem',
 'changer',
 'dropvce',
 'blckvce',
 'unansvce',
 'custcare',
 'threeway',
 'mourec',
 'outcalls',
 'incalls',
 'peakvce',
 'opeakvce',
 'dropblk',
 'callfwdv',
 'callwait',
 'months',
 'uniqsubs',
 'actvsubs',
 'phones',
 'models',
 'eqpdays',
 'age1',
 'age2',
 'children',
 'credita',
```

```
 'creditaa',
 'prizmrur',
 'prizmub',
 'prizmtwn',
 'refurb',
 'webcap',
 'truck',
 'rv',
 'occprof',
 'occcler',
 'occcrft',
 'occstud',
 'occhmkr',
 'occret',
 'occself',
 'ownrent',
 'marryun',
 'marryyes',
 'mailord',
 'mailres',
 'mailflag',
 'travel',
 'pcown',
 'creditcd',
 'retcalls',
 'retaccpt',
 'newcelly',
 'newcelln',
 'refer',
 'incmiss',
 'income',
 'mcycle',
 'setprcm',
 'setprc',
 'retcall']
```

[14]:
```
varlist = [
 'revenue',
 'mou',
 'recchrge',
 'directas',
 'overage',
 'roam',
 'changem',
 'changer',
 'dropvce',
 'blckvce',
```

```
'unansvce',
'custcare',
'threeway',
'mourec',
'outcalls',
'incalls',
'peakvce',
'opeakvce',
'dropblk',
'callfwdv',
'callwait',
'months',
'uniqsubs',
'actvsubs',
'phones',
'models',
'eqpdays',
'age1',
'age2',
'children',
'credita',
'creditaa',
'prizmrur',
'prizmub',
'prizmtwn',
'refurb',
'webcap',
'truck',
'rv',
'occprof',
'occcler',
'occcrft',
'occstud',
'occhmkr',
'occret',
'occself',
'ownrent',
'marryun',
'marryyes',
'mailord',
'mailres',
'mailflag',
'travel',
'pcown',
'creditcd',
'retcalls',
'retaccpt',
```

```
 'newcelly',
 'newcelln',
 'refer',
 'incmiss',
 'income',
 'mcycle',
 'setprcm',
 'setprc',
 'retcall']
```

[15]:
```
#Logit with regularization (alpha = 0)
```

[16]:
```
res_logit0=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=0)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6715330588481454
            Iterations: 201
            Function evaluations: 256
            Gradient evaluations: 201
```

[17]:
```
res_logit0.summary()
```

[17]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38874
Method:                           MLE   Df Model:                           66
Date:                Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03117
Time:                        01:57:38   Log-Likelihood:                -26150.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                 6.012e-308
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1499      0.095      1.573      0.116      -0.037       0.337
revenue        0.0020      0.001      2.460      0.014       0.000       0.004
mou           -0.0003   4.96e-05     -5.657      0.000      -0.000      -0.000
recchrge      -0.0031      0.001     -3.514      0.000      -0.005      -0.001
directas      -0.0012      0.006     -0.201      0.840      -0.013       0.010
overage        0.0008      0.000      2.711      0.007       0.000       0.001
roam           0.0071      0.002      3.436      0.001       0.003       0.011
changem       -0.0005   5.35e-05     -9.194      0.000      -0.001      -0.000
changer        0.0023      0.000      6.247      0.000       0.002       0.003
dropvce        0.0113      0.007      1.563      0.118      -0.003       0.026
```

blckvce	0.0064	0.007	0.894	0.371	−0.008	0.020
unansvce	0.0009	0.000	2.058	0.040	4.38e-05	0.002
custcare	−0.0060	0.003	−2.331	0.020	−0.011	−0.001
threeway	−0.0303	0.011	−2.691	0.007	−0.052	−0.008
mourec	0.0001	0.000	1.018	0.309	−0.000	0.000
outcalls	0.0011	0.001	1.894	0.058	-3.87e-05	0.002
incalls	−0.0031	0.001	−2.937	0.003	−0.005	−0.001
peakvce	−0.0007	0.000	−3.058	0.002	−0.001	−0.000
opeakvce	−0.0002	0.000	−0.783	0.434	−0.001	0.000
dropblk	−0.0031	0.007	−0.442	0.658	−0.017	0.011
callfwdv	−0.0026	0.023	−0.114	0.909	−0.048	0.043
callwait	0.0021	0.003	0.664	0.507	−0.004	0.008
months	−0.0213	0.002	−10.652	0.000	−0.025	−0.017
uniqsubs	0.1844	0.020	9.226	0.000	0.145	0.224
actvsubs	−0.2057	0.028	−7.372	0.000	−0.260	−0.151
phones	0.0487	0.018	2.680	0.007	0.013	0.084
models	0.0137	0.028	0.493	0.622	−0.041	0.068
eqpdays	0.0014	7.47e-05	19.309	0.000	0.001	0.002
age1	−0.0033	0.001	−3.786	0.000	−0.005	−0.002
age2	−0.0012	0.001	−1.719	0.086	−0.003	0.000
children	0.0944	0.028	3.355	0.001	0.039	0.150
credita	−0.1780	0.036	−5.015	0.000	−0.248	−0.108
creditaa	−0.3627	0.035	−10.488	0.000	−0.430	−0.295
prizmrur	0.0665	0.050	1.342	0.179	−0.031	0.164
prizmub	−0.0396	0.024	−1.623	0.104	−0.087	0.008
prizmtwn	0.0462	0.031	1.470	0.141	−0.015	0.108
refurb	0.2340	0.032	7.322	0.000	0.171	0.297
webcap	−0.1562	0.038	−4.158	0.000	−0.230	−0.083
truck	0.0268	0.036	0.744	0.457	−0.044	0.097
rv	0.0121	0.048	0.252	0.801	−0.082	0.106
occprof	−0.0198	0.033	−0.610	0.542	−0.084	0.044
occcler	0.0394	0.075	0.526	0.599	−0.107	0.186
occcrft	−0.0198	0.063	−0.315	0.753	−0.143	0.103
occstud	0.1198	0.122	0.983	0.326	−0.119	0.359
occhmkr	0.2562	0.190	1.348	0.178	−0.116	0.629
occret	−0.0399	0.091	−0.441	0.659	−0.217	0.138
occself	−0.0710	0.081	−0.881	0.379	−0.229	0.087
ownrent	0.0025	0.043	0.060	0.952	−0.081	0.086
marryun	0.1088	0.034	3.198	0.001	0.042	0.176
marryyes	0.0558	0.032	1.716	0.086	−0.008	0.119
mailord	0.0009	0.086	0.011	0.991	−0.167	0.169
mailres	−0.1299	0.086	−1.509	0.131	−0.299	0.039
mailflag	−0.0483	0.084	−0.572	0.567	−0.214	0.117
travel	−0.0006	0.047	−0.012	0.991	−0.093	0.092
pcown	0.0343	0.031	1.108	0.268	−0.026	0.095
creditcd	0.0419	0.044	0.959	0.337	−0.044	0.128
retcalls	0.0120	0.184	0.066	0.948	−0.348	0.372

```
retaccpt      -0.1277      0.108     -1.186      0.236      -0.339       0.083
newcelly      -0.0705      0.027     -2.585      0.010      -0.124      -0.017
newcelln      -0.0050      0.032     -0.160      0.873      -0.067       0.057
refer         -0.0500      0.042     -1.188      0.235      -0.133       0.033
incmiss       -0.0915      0.060     -1.524      0.128      -0.209       0.026
income        -0.0132      0.006     -2.194      0.028      -0.025      -0.001
mcycle         0.1222      0.089      1.373      0.170      -0.052       0.297
setprcm       -0.0964      0.041     -2.379      0.017      -0.176      -0.017
setprc         0.0006      0.000      2.193      0.028     6.6e-05       0.001
retcall        0.7936      0.195      4.078      0.000       0.412       1.175
==============================================================================
"""
```

[18]:
```
mba263.odds_ratios(res_logit0)
```

[18]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001965	0.000800	2.457656	0.014	1.000414	1.003517
mou	0.999719	0.000050	5.657852	0.000	0.999623	0.999815
recchrge	0.996882	0.000886	3.519019	0.000	0.995163	0.998601
directas	0.998804	0.005932	0.201561	0.840	0.987297	1.010312
overage	1.000761	0.000281	2.710142	0.007	1.000216	1.001305
…	…	…	…	…	…	…
income	0.986846	0.005955	2.208819	0.027	0.975293	0.998399
mcycle	1.129973	0.100550	1.292612	0.196	0.934905	1.325040
setprcm	0.908111	0.036791	2.497601	0.013	0.836737	0.979485
setprc	1.000620	0.000283	2.192644	0.028	1.000071	1.001169
retcall	2.211280	0.430283	2.815076	0.005	1.376531	3.046030

[66 rows x 6 columns]

[19]:
```
#Logit with regularization (alpha = 5)
```

[20]:
```
res_logit5=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=5)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6720343123918141
            Iterations: 242
            Function evaluations: 298
            Gradient evaluations: 242
```

[21]:
```
res_logit5.summary()
```

[21]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
```

Dep. Variable:	churndep	No. Observations:	38941
Model:	Mba263Logit	Df Residuals:	38881
Method:	MLE	Df Model:	59
Date:	Sun, 07 Apr 2024	Pseudo R-squ.:	0.03110
Time:	02:00:27	Log-Likelihood:	-26152.
converged:	True	LL-Null:	-26992.
Covariance Type:	nonrobust	LLR p-value:	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0979	0.091	1.078	0.281	-0.080	0.276
revenue	0.0020	0.001	2.455	0.014	0.000	0.004
mou	-0.0003	4.96e-05	-5.661	0.000	-0.000	-0.000
recchrge	-0.0031	0.001	-3.479	0.001	-0.005	-0.001
directas	-0.0013	0.006	-0.212	0.832	-0.013	0.010
overage	0.0008	0.000	2.727	0.006	0.000	0.001
roam	0.0071	0.002	3.436	0.001	0.003	0.011
changem	-0.0005	5.35e-05	-9.206	0.000	-0.001	-0.000
changer	0.0023	0.000	6.248	0.000	0.002	0.003
dropvce	0.0106	0.007	1.465	0.143	-0.004	0.025
blckvce	0.0057	0.007	0.800	0.424	-0.008	0.020
unansvce	0.0009	0.000	2.084	0.037	5.54e-05	0.002
custcare	-0.0060	0.003	-2.343	0.019	-0.011	-0.001
threeway	-0.0296	0.011	-2.630	0.009	-0.052	-0.008
mourec	0.0001	0.000	1.006	0.314	-0.000	0.000
outcalls	0.0011	0.001	1.876	0.061	-4.94e-05	0.002
incalls	-0.0031	0.001	-2.943	0.003	-0.005	-0.001
peakvce	-0.0007	0.000	-3.069	0.002	-0.001	-0.000
opeakvce	-0.0002	0.000	-0.757	0.449	-0.001	0.000
dropblk	-0.0024	0.007	-0.337	0.736	-0.016	0.011
callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0019	0.003	0.613	0.540	-0.004	0.008
months	-0.0209	0.002	-10.551	0.000	-0.025	-0.017
uniqsubs	0.1816	0.020	9.108	0.000	0.143	0.221
actvsubs	-0.1985	0.028	-7.123	0.000	-0.253	-0.144
phones	0.0491	0.018	2.707	0.007	0.014	0.085
models	0.0138	0.028	0.497	0.619	-0.041	0.068
eqpdays	0.0014	7.46e-05	19.301	0.000	0.001	0.002
age1	-0.0032	0.001	-3.689	0.000	-0.005	-0.002
age2	-0.0012	0.001	-1.719	0.086	-0.002	0.000
children	0.0935	0.028	3.334	0.001	0.039	0.149
credita	-0.1669	0.035	-4.703	0.000	-0.236	-0.097
creditaa	-0.3528	0.035	-10.214	0.000	-0.421	-0.285
prizmrur	0.0578	0.049	1.169	0.243	-0.039	0.155
prizmub	-0.0388	0.024	-1.594	0.111	-0.087	0.009
prizmtwn	0.0423	0.031	1.345	0.179	-0.019	0.104
refurb	0.2319	0.032	7.263	0.000	0.169	0.295

```
webcap         -0.1428      0.038     -3.807      0.000      -0.216      -0.069
truck           0.0303      0.036      0.842      0.400      -0.040       0.101
rv              0.0036      0.048      0.074      0.941      -0.090       0.098
occprof        -0.0143      0.032     -0.452      0.651      -0.076       0.048
occcler         0.0170      0.075      0.227      0.820      -0.129       0.163
occcrft              0        nan        nan        nan         nan         nan
occstud         0.0477      0.122      0.392      0.695      -0.191       0.286
occhmkr         0.0872      0.188      0.463      0.643      -0.282       0.456
occret         -0.0007      0.090     -0.008      0.994      -0.177       0.176
occself        -0.0384      0.080     -0.481      0.630      -0.195       0.118
ownrent              0        nan        nan        nan         nan         nan
marryun         0.0988      0.034      2.907      0.004       0.032       0.165
marryyes        0.0462      0.032      1.426      0.154      -0.017       0.110
mailord              0        nan        nan        nan         nan         nan
mailres        -0.1245      0.028     -4.421      0.000      -0.180      -0.069
mailflag       -0.0130      0.084     -0.154      0.878      -0.178       0.152
travel               0        nan        nan        nan         nan         nan
pcown           0.0285      0.031      0.928      0.353      -0.032       0.089
creditcd        0.0437      0.041      1.070      0.285      -0.036       0.124
retcalls             0        nan        nan        nan         nan         nan
retaccpt       -0.0498      0.099     -0.501      0.616      -0.245       0.145
newcelly       -0.0663      0.027     -2.499      0.012      -0.118      -0.014
newcelln             0        nan        nan        nan         nan         nan
refer          -0.0409      0.042     -0.972      0.331      -0.123       0.042
incmiss        -0.0652      0.058     -1.116      0.264      -0.180       0.049
income         -0.0115      0.006     -1.915      0.056      -0.023       0.000
mcycle          0.0836      0.089      0.941      0.347      -0.091       0.258
setprcm        -0.0824      0.040     -2.035      0.042      -0.162      -0.003
setprc          0.0007      0.000      2.433      0.015       0.000       0.001
retcall         0.7485      0.079      9.464      0.000       0.593       0.903
==============================================================================
"""
```

[22]:
```python
mba263.odds_ratios(res_logit5)
```

[22]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001961	0.000799	2.452823	0.014	1.000410	1.003512
mou	0.999719	0.000050	5.661516	0.000	0.999623	0.999815
recchrge	0.996914	0.000886	3.484635	0.000	0.995196	0.998632
directas	0.998743	0.005927	0.212122	0.832	0.987244	1.010242
overage	1.000765	0.000281	2.725891	0.006	1.000220	1.001309
…	…	…	… …	…	…	
income	0.988614	0.005913	1.925675	0.054	0.977144	1.000085
mcycle	1.087233	0.096607	0.902965	0.367	0.899815	1.274651
setprcm	0.920918	0.037273	2.121687	0.034	0.848609	0.993228
setprc	1.000687	0.000283	2.431816	0.015	1.000139	1.001236
retcall	2.113791	0.167182	6.662136	0.000	1.789457	2.438124

```
[66 rows x 6 columns]
```

[23]:
```
#Logit with regularization (alpha = 10)
```

[24]:
```
res_logit10=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=10)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6724454477315632
            Iterations: 174
            Function evaluations: 229
            Gradient evaluations: 174
```

[25]:
```
res_logit10.summary()
```

[25]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Mba263Logit Regression Results
==============================================================================
Dep. Variable:                churndep   No. Observations:                38941
Model:                     Mba263Logit   Df Residuals:                    38888
Method:                            MLE   Df Model:                           52
Date:                 Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03096
Time:                         02:02:48   Log-Likelihood:                -26156.
converged:                        True   LL-Null:                       -26992.
Covariance Type:             nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0425      0.091      0.469      0.639      -0.135       0.220
revenue        0.0020      0.001      2.455      0.014       0.000       0.004
mou           -0.0003   4.96e-05     -5.663      0.000      -0.000      -0.000
recchrge      -0.0031      0.001     -3.437      0.001      -0.005      -0.001
directas      -0.0013      0.006     -0.223      0.823      -0.013       0.010
overage        0.0008      0.000      2.740      0.006       0.000       0.001
roam           0.0071      0.002      3.432      0.001       0.003       0.011
changem       -0.0005   5.34e-05     -9.216      0.000      -0.001      -0.000
changer        0.0023      0.000      6.249      0.000       0.002       0.003
dropvce        0.0098      0.007      1.363      0.173      -0.004       0.024
blckvce        0.0050      0.007      0.704      0.481      -0.009       0.019
unansvce       0.0009      0.000      2.110      0.035    6.73e-05       0.002
custcare      -0.0060      0.003     -2.344      0.019      -0.011      -0.001
threeway      -0.0290      0.011     -2.580      0.010      -0.051      -0.007
mourec         0.0001      0.000      0.991      0.322      -0.000       0.000
outcalls       0.0011      0.001      1.846      0.065    -6.7e-05       0.002
incalls       -0.0031      0.001     -2.949      0.003      -0.005      -0.001
```

peakvce	-0.0007	0.000	-3.083	0.002	-0.001	-0.000
opeakvce	-0.0002	0.000	-0.729	0.466	-0.001	0.000
dropblk	-0.0016	0.007	-0.232	0.816	-0.015	0.012
callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0018	0.003	0.562	0.574	-0.004	0.008
months	-0.0205	0.002	-10.340	0.000	-0.024	-0.017
uniqsubs	0.1788	0.020	8.977	0.000	0.140	0.218
actvsubs	-0.1910	0.028	-6.862	0.000	-0.246	-0.136
phones	0.0496	0.018	2.735	0.006	0.014	0.085
models	0.0141	0.028	0.508	0.612	-0.040	0.069
eqpdays	0.0014	7.45e-05	19.292	0.000	0.001	0.002
age1	-0.0030	0.001	-3.550	0.000	-0.005	-0.001
age2	-0.0011	0.001	-1.679	0.093	-0.002	0.000
children	0.0918	0.028	3.283	0.001	0.037	0.147
credita	-0.1561	0.035	-4.405	0.000	-0.226	-0.087
creditaa	-0.3432	0.035	-9.945	0.000	-0.411	-0.276
prizmrur	0.0496	0.049	1.003	0.316	-0.047	0.146
prizmub	-0.0379	0.024	-1.557	0.119	-0.086	0.010
prizmtwn	0.0388	0.031	1.237	0.216	-0.023	0.100
refurb	0.2300	0.032	7.213	0.000	0.168	0.293
webcap	-0.1292	0.037	-3.447	0.001	-0.203	-0.056
truck	0.0318	0.029	1.094	0.274	-0.025	0.089
rv	0	nan	nan	nan	nan	nan
occprof	-0.0103	0.031	-0.334	0.738	-0.071	0.050
occcler	0	nan	nan	nan	nan	nan
occcrft	0	nan	nan	nan	nan	nan
occstud	0	nan	nan	nan	nan	nan
occhmkr	0	nan	nan	nan	nan	nan
occret	0	nan	nan	nan	nan	nan
occself	-0.0078	0.079	-0.098	0.922	-0.163	0.148
ownrent	0	nan	nan	nan	nan	nan
marryun	0.0890	0.034	2.625	0.009	0.023	0.155
marryyes	0.0376	0.032	1.163	0.245	-0.026	0.101
mailord	0	nan	nan	nan	nan	nan
mailres	-0.1194	0.028	-4.262	0.000	-0.174	-0.064
mailflag	0	nan	nan	nan	nan	nan
travel	0	nan	nan	nan	nan	nan
pcown	0.0227	0.031	0.744	0.457	-0.037	0.082
creditcd	0.0460	0.041	1.127	0.260	-0.034	0.126
retcalls	0	nan	nan	nan	nan	nan
retaccpt	0	nan	nan	nan	nan	nan
newcelly	-0.0630	0.027	-2.375	0.018	-0.115	-0.011
newcelln	0	nan	nan	nan	nan	nan
refer	-0.0312	0.042	-0.743	0.458	-0.113	0.051
incmiss	-0.0396	0.058	-0.680	0.497	-0.154	0.075
income	-0.0098	0.006	-1.652	0.099	-0.021	0.002
mcycle	0.0468	0.089	0.527	0.598	-0.127	0.221

```
setprcm       -0.0682      0.040     -1.687      0.092     -0.147       0.011
setprc         0.0008      0.000      2.676      0.007      0.000       0.001
retcall        0.7065      0.057     12.297      0.000      0.594       0.819
==============================================================================
"""
```

[26]:
```python
mba263.odds_ratios(res_logit10)
```

[26]:
```
          Odds ratios   std err         z  P>|z|    [0.025    0.975]
revenue      1.001960  0.000799  2.452361  0.014  1.000410  1.003511
mou          0.999719  0.000050  5.663710  0.000  0.999623  0.999815
recchrge     0.996953  0.000885  3.442211  0.001  0.995235  0.998670
directas     0.998678  0.005923  0.223260  0.823  0.987187  1.010168
overage      1.000768  0.000280  2.738893  0.006  1.000224  1.001312
…                 …         …         …    …         …         …
income       0.990240  0.005879  1.660163  0.097  0.978834  1.001645
mcycle       1.047887  0.093040  0.514687  0.607  0.867388  1.228385
setprcm      0.934043  0.037769  1.746325  0.081  0.860770  1.007315
setprc       1.000756  0.000283  2.675133  0.007  1.000208  1.001304
retcall      2.026815  0.116438  8.818543  0.000  1.800925  2.252705

[66 rows x 6 columns]
```

[27]:
```python
#Logit with regularization (alpha = 15)
```

[28]:
```python
res_logit15=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=15)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6728115378239092
            Iterations: 170
            Function evaluations: 225
            Gradient evaluations: 170
```

[29]:
```python
res_logit15.summary()
```

[29]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38890
Method:                           MLE   Df Model:                           50
Date:                Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03085
Time:                        02:05:04   Log-Likelihood:                -26159.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                     0.000
```

	coef	std err	z	P>|z|	[0.025	0.975]
const	0	nan	nan	nan	nan	nan
revenue	0.0020	0.001	2.459	0.014	0.000	0.004
mou	-0.0003	4.96e-05	-5.671	0.000	-0.000	-0.000
recchrge	-0.0030	0.001	-3.443	0.001	-0.005	-0.001
directas	-0.0013	0.006	-0.224	0.823	-0.013	0.010
overage	0.0008	0.000	2.745	0.006	0.000	0.001
roam	0.0071	0.002	3.429	0.001	0.003	0.011
changem	-0.0005	5.34e-05	-9.220	0.000	-0.001	-0.000
changer	0.0023	0.000	6.247	0.000	0.002	0.003
dropvce	0.0090	0.007	1.255	0.210	-0.005	0.023
blckvce	0.0043	0.007	0.603	0.546	-0.010	0.018
unansvce	0.0010	0.000	2.137	0.033	7.91e-05	0.002
custcare	-0.0060	0.003	-2.348	0.019	-0.011	-0.001
threeway	-0.0285	0.011	-2.536	0.011	-0.051	-0.006
mourec	0.0001	0.000	0.980	0.327	-0.000	0.000
outcalls	0.0011	0.001	1.810	0.070	-8.85e-05	0.002
incalls	-0.0031	0.001	-2.954	0.003	-0.005	-0.001
peakvce	-0.0007	0.000	-3.087	0.002	-0.001	-0.000
opeakvce	-0.0002	0.000	-0.719	0.472	-0.001	0.000
dropblk	-0.0009	0.007	-0.125	0.901	-0.015	0.013
callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0017	0.003	0.529	0.597	-0.004	0.008
months	-0.0201	0.002	-10.306	0.000	-0.024	-0.016
uniqsubs	0.1756	0.020	8.834	0.000	0.137	0.215
actvsubs	-0.1837	0.028	-6.664	0.000	-0.238	-0.130
phones	0.0501	0.018	2.763	0.006	0.015	0.086
models	0.0139	0.027	0.507	0.612	-0.040	0.067
eqpdays	0.0014	7.36e-05	19.467	0.000	0.001	0.002
age1	-0.0029	0.001	-3.521	0.000	-0.005	-0.001
age2	-0.0011	0.001	-1.618	0.106	-0.002	0.000
children	0.0893	0.028	3.195	0.001	0.035	0.144
credita	-0.1463	0.035	-4.173	0.000	-0.215	-0.078
creditaa	-0.3341	0.034	-9.794	0.000	-0.401	-0.267
prizmrur	0.0405	0.049	0.823	0.411	-0.056	0.137
prizmub	-0.0373	0.024	-1.535	0.125	-0.085	0.010
prizmtwn	0.0350	0.031	1.118	0.264	-0.026	0.096
refurb	0.2280	0.032	7.208	0.000	0.166	0.290
webcap	-0.1187	0.034	-3.526	0.000	-0.185	-0.053
truck	0.0318	0.029	1.094	0.274	-0.025	0.089
rv	0	nan	nan	nan	nan	nan
occprof	-0.0050	0.031	-0.165	0.869	-0.065	0.055
occcler	0	nan	nan	nan	nan	nan
occcrft	0	nan	nan	nan	nan	nan
occstud	0	nan	nan	nan	nan	nan

```
occhmkr             0        nan        nan        nan        nan        nan
occret              0        nan        nan        nan        nan        nan
occself             0        nan        nan        nan        nan        nan
ownrent             0        nan        nan        nan        nan        nan
marryun        0.0791      0.034      2.358      0.018      0.013      0.145
marryyes       0.0296      0.032      0.915      0.360     -0.034      0.093
mailord             0        nan        nan        nan        nan        nan
mailres       -0.1147      0.028     -4.105      0.000     -0.169     -0.060
mailflag            0        nan        nan        nan        nan        nan
travel              0        nan        nan        nan        nan        nan
pcown          0.0166      0.030      0.548      0.584     -0.043      0.076
creditcd       0.0457      0.039      1.179      0.239     -0.030      0.122
retcalls            0        nan        nan        nan        nan        nan
retaccpt            0        nan        nan        nan        nan        nan
newcelly      -0.0599      0.026     -2.260      0.024     -0.112     -0.008
newcelln            0        nan        nan        nan        nan        nan
refer         -0.0224      0.042     -0.533      0.594     -0.105      0.060
incmiss       -0.0168      0.053     -0.318      0.751     -0.120      0.087
income        -0.0082      0.006     -1.418      0.156     -0.019      0.003
mcycle         0.0103      0.089      0.116      0.908     -0.164      0.184
setprcm       -0.0570      0.036     -1.567      0.117     -0.128      0.014
setprc         0.0008      0.000      2.973      0.003      0.000      0.001
retcall        0.6918      0.057     12.076      0.000      0.579      0.804
==============================================================================
"""
```

[30]:
```
mba263.odds_ratios(res_logit15)
```

[30]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001962	0.000799	2.456501	0.014	1.000413	1.003511
mou	0.999719	0.000050	5.671861	0.000	0.999623	0.999815
recchrge	0.996972	0.000878	3.447782	0.001	0.995268	0.998676
directas	0.998677	0.005914	0.223790	0.823	0.987204	1.010149
overage	1.000769	0.000280	2.743697	0.006	1.000225	1.001313
…	…	…	… …	…	…	
income	0.991861	0.005717	1.423651	0.155	0.980769	1.002952
mcycle	1.010352	0.089674	0.115439	0.908	0.836384	1.184320
setprcm	0.944552	0.034376	1.612997	0.107	0.877863	1.011241
setprc	1.000810	0.000272	2.971936	0.003	1.000281	1.001338
retcall	1.997251	0.114413	8.716277	0.000	1.775291	2.219211

[66 rows x 6 columns]

[31]:
```
#Logit with regularization (alpha = 20)
```

[32]:
```
res_logit20=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=20)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6731532815013931
            Iterations: 149
            Function evaluations: 204
            Gradient evaluations: 149
```

[33]:
```
res_logit20.summary()
```

[33]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38892
Method:                           MLE   Df Model:                           48
Date:                Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03075
Time:                        02:07:11   Log-Likelihood:                -26161.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const               0        nan        nan        nan        nan         nan
revenue        0.0020      0.001      2.451      0.014      0.000       0.004
mou           -0.0003   4.95e-05     -5.683      0.000     -0.000      -0.000
recchrge      -0.0031      0.001     -3.483      0.000     -0.005      -0.001
directas      -0.0012      0.006     -0.205      0.838     -0.013       0.010
overage        0.0008      0.000      2.745      0.006      0.000       0.001
roam           0.0071      0.002      3.430      0.001      0.003       0.011
changem       -0.0005   5.34e-05     -9.224      0.000     -0.001      -0.000
changer        0.0023      0.000      6.245      0.000      0.002       0.003
dropvce        0.0082      0.007      1.142      0.253     -0.006       0.022
blckvce        0.0035      0.007      0.497      0.619     -0.010       0.018
unansvce       0.0010      0.000      2.149      0.032   8.44e-05       0.002
custcare      -0.0060      0.003     -2.367      0.018     -0.011      -0.001
threeway      -0.0279      0.011     -2.488      0.013     -0.050      -0.006
mourec         0.0001      0.000      0.981      0.327     -0.000       0.000
outcalls       0.0010      0.001      1.781      0.075     -0.000       0.002
incalls       -0.0031      0.001     -2.938      0.003     -0.005      -0.001
peakvce       -0.0007      0.000     -3.052      0.002     -0.001      -0.000
opeakvce      -0.0002      0.000     -0.748      0.454     -0.001       0.000
dropblk       -0.0001      0.007     -0.017      0.987     -0.014       0.014
callfwdv            0        nan        nan        nan        nan         nan
callwait       0.0017      0.003      0.528      0.597     -0.004       0.008
months        -0.0198      0.002    -10.197      0.000     -0.024      -0.016
uniqsubs       0.1721      0.020      8.672      0.000      0.133       0.211
actvsubs      -0.1783      0.028     -6.474      0.000     -0.232      -0.124
```

```
phones        0.0506      0.018      2.792      0.005       0.015       0.086
models        0.0112      0.027      0.410      0.682      -0.042       0.065
eqpdays       0.0014   7.36e-05     19.351      0.000       0.001       0.002
age1         -0.0029      0.001     -3.486      0.000      -0.005      -0.001
age2         -0.0010      0.001     -1.509      0.131      -0.002       0.000
children      0.0868      0.028      3.113      0.002       0.032       0.141
credita      -0.1390      0.035     -3.968      0.000      -0.208      -0.070
creditaa     -0.3275      0.034     -9.608      0.000      -0.394      -0.261
prizmrur      0.0297      0.049      0.602      0.547      -0.067       0.126
prizmub      -0.0371      0.024     -1.526      0.127      -0.085       0.011
prizmtwn      0.0301      0.031      0.962      0.336      -0.031       0.091
refurb        0.2243      0.032      7.092      0.000       0.162       0.286
webcap       -0.1160      0.034     -3.446      0.001      -0.182      -0.050
truck         0.0301      0.029      1.048      0.295      -0.026       0.086
rv                 0        nan        nan        nan         nan         nan
occprof            0        nan        nan        nan         nan         nan
occcler            0        nan        nan        nan         nan         nan
occcrft            0        nan        nan        nan         nan         nan
occstud            0        nan        nan        nan         nan         nan
occhmkr            0        nan        nan        nan         nan         nan
occret             0        nan        nan        nan         nan         nan
occself            0        nan        nan        nan         nan         nan
ownrent            0        nan        nan        nan         nan         nan
marryun       0.0664      0.033      1.985      0.047       0.001       0.132
marryyes      0.0206      0.032      0.637      0.524      -0.043       0.084
mailord            0        nan        nan        nan         nan         nan
mailres      -0.1096      0.028     -3.954      0.000      -0.164      -0.055
mailflag           0        nan        nan        nan         nan         nan
travel             0        nan        nan        nan         nan         nan
pcown         0.0109      0.030      0.367      0.713      -0.047       0.069
creditcd      0.0392      0.039      1.012      0.311      -0.037       0.115
retcalls           0        nan        nan        nan         nan         nan
retaccpt           0        nan        nan        nan         nan         nan
newcelly     -0.0570      0.026     -2.153      0.031      -0.109      -0.005
newcelln           0        nan        nan        nan         nan         nan
refer        -0.0136      0.042     -0.324      0.746      -0.096       0.069
incmiss      -0.0047      0.053     -0.090      0.928      -0.108       0.099
income       -0.0071      0.006     -1.241      0.215      -0.018       0.004
mcycle             0        nan        nan        nan         nan         nan
setprcm      -0.0542      0.036     -1.491      0.136      -0.126       0.017
setprc        0.0008      0.000      3.041      0.002       0.000       0.001
retcall       0.6761      0.057     11.831      0.000       0.564       0.788
==============================================================================
"""
```

[34]:
```
mba263.odds_ratios(res_logit20)
```

[34]:
```
          Odds ratios   std err         z  P>|z|    [0.025    0.975]
revenue      1.001955  0.000798  2.448785  0.014  1.000406  1.003503
mou          0.999718  0.000050  5.684086  0.000  0.999622  0.999815
recchrge     0.996938  0.000878  3.487856  0.000  0.995235  0.998641
directas     0.998790  0.005912  0.204724  0.838  0.987321  1.010258
overage      1.000769  0.000280  2.744119  0.006  1.000225  1.001313
…                 …         …       …     …        …         …
income       0.992891  0.005707  1.245706  0.213  0.981820  1.003962
mcycle       1.000000       NaN       NaN    NaN       NaN       NaN
setprcm      0.947221  0.034458  1.531692  0.126  0.880374  1.014069
setprc       1.000828  0.000272  3.039568  0.002  1.000299  1.001356
retcall      1.966244  0.112368  8.598953  0.000  1.748250  2.184237

[66 rows x 6 columns]
```

[35]:
```
#Logit with regularization (alpha = 25)
```

[36]:
```
res_logit25=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=25)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.673477385865285
            Iterations: 130
            Function evaluations: 185
            Gradient evaluations: 130
```

[37]:
```
res_logit25.summary()
```

[37]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38894
Method:                           MLE   Df Model:                           46
Date:                Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03065
Time:                        02:09:06   Log-Likelihood:                -26164.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const               0        nan        nan        nan         nan         nan
revenue        0.0019      0.001      2.446      0.014       0.000       0.004
mou           -0.0003   4.95e-05     -5.690      0.000      -0.000      -0.000
recchrge      -0.0031      0.001     -3.521      0.000      -0.005      -0.001
directas      -0.0011      0.006     -0.185      0.853      -0.013       0.010
```

overage	0.0008	0.000	2.747	0.006	0.000	0.001
roam	0.0071	0.002	3.437	0.001	0.003	0.011
changem	-0.0005	5.34e-05	-9.229	0.000	-0.001	-0.000
changer	0.0023	0.000	6.244	0.000	0.002	0.003
dropvce	0.0081	0.002	4.974	0.000	0.005	0.011
blckvce	0.0034	0.001	3.119	0.002	0.001	0.006
unansvce	0.0010	0.000	2.157	0.031	8.78e-05	0.002
custcare	-0.0060	0.003	-2.383	0.017	-0.011	-0.001
threeway	-0.0274	0.011	-2.442	0.015	-0.049	-0.005
mourec	0.0001	0.000	0.976	0.329	-0.000	0.000
outcalls	0.0010	0.001	1.760	0.078	-0.000	0.002
incalls	-0.0031	0.001	-2.931	0.003	-0.005	-0.001
peakvce	-0.0007	0.000	-3.030	0.002	-0.001	-0.000
opeakvce	-0.0002	0.000	-0.775	0.438	-0.001	0.000
dropblk	0	nan	nan	nan	nan	nan
callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0016	0.003	0.525	0.599	-0.004	0.008
months	-0.0196	0.002	-10.110	0.000	-0.023	-0.016
uniqsubs	0.1688	0.020	8.520	0.000	0.130	0.208
actvsubs	-0.1727	0.027	-6.288	0.000	-0.227	-0.119
phones	0.0511	0.018	2.820	0.005	0.016	0.087
models	0.0089	0.027	0.329	0.742	-0.044	0.062
eqpdays	0.0014	7.32e-05	19.327	0.000	0.001	0.002
age1	-0.0029	0.001	-3.580	0.000	-0.004	-0.001
age2	-0.0009	0.001	-1.404	0.160	-0.002	0.000
children	0.0843	0.028	3.026	0.002	0.030	0.139
credita	-0.1316	0.035	-3.758	0.000	-0.200	-0.063
creditaa	-0.3207	0.034	-9.416	0.000	-0.387	-0.254
prizmrur	0.0179	0.049	0.364	0.716	-0.079	0.114
prizmub	-0.0366	0.024	-1.513	0.130	-0.084	0.011
prizmtwn	0.0253	0.031	0.811	0.418	-0.036	0.087
refurb	0.2207	0.032	6.993	0.000	0.159	0.283
webcap	-0.1125	0.033	-3.440	0.001	-0.177	-0.048
truck	0.0279	0.029	0.975	0.330	-0.028	0.084
rv	0	nan	nan	nan	nan	nan
occprof	0	nan	nan	nan	nan	nan
occcler	0	nan	nan	nan	nan	nan
occcrft	0	nan	nan	nan	nan	nan
occstud	0	nan	nan	nan	nan	nan
occhmkr	0	nan	nan	nan	nan	nan
occret	0	nan	nan	nan	nan	nan
occself	0	nan	nan	nan	nan	nan
ownrent	0	nan	nan	nan	nan	nan
marryun	0.0561	0.030	1.889	0.059	-0.002	0.114
marryyes	0.0134	0.031	0.427	0.669	-0.048	0.075
mailord	0	nan	nan	nan	nan	nan
mailres	-0.1039	0.028	-3.753	0.000	-0.158	-0.050

```
mailflag           0       nan       nan       nan       nan       nan
travel             0       nan       nan       nan       nan       nan
pcown         0.0063     0.030     0.213     0.831    -0.052     0.064
creditcd      0.0313     0.036     0.871     0.384    -0.039     0.102
retcalls           0       nan       nan       nan       nan       nan
retaccpt           0       nan       nan       nan       nan       nan
newcelly     -0.0543     0.026    -2.051     0.040    -0.106    -0.002
newcelln           0       nan       nan       nan       nan       nan
refer        -0.0051     0.042    -0.121     0.903    -0.087     0.077
incmiss            0       nan       nan       nan       nan       nan
income       -0.0064     0.005    -1.249     0.212    -0.017     0.004
mcycle             0       nan       nan       nan       nan       nan
setprcm      -0.0500     0.035    -1.413     0.158    -0.119     0.019
setprc        0.0009     0.000     3.160     0.002     0.000     0.001
retcall       0.6608     0.057    11.590     0.000     0.549     0.772
==============================================================================
"""
```

[38]:
```
mba263.odds_ratios(res_logit25)
```

[38]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001950	0.000798	2.443369	0.015	1.000402	1.003497
mou	0.999718	0.000050	5.691172	0.000	0.999622	0.999814
recchrge	0.996912	0.000876	3.526893	0.000	0.995213	0.998610
directas	0.998905	0.005909	0.185331	0.853	0.987441	1.010369
overage	1.000769	0.000280	2.745519	0.006	1.000226	1.001313
…	…	…	…	…	…	…
income	0.993589	0.005116	1.253286	0.210	0.983665	1.003513
mcycle	1.000000	NaN	NaN	NaN	NaN	NaN
setprcm	0.951237	0.033658	1.448764	0.147	0.885940	1.016534
setprc	1.000852	0.000270	3.158412	0.002	1.000329	1.001375
retcall	1.936255	0.110386	8.481625	0.000	1.722105	2.150404

[66 rows x 6 columns]

[15]:
```
#Logit with regularization (alpha = 30) (28 stat significant, 18 not, 20 nan)
```

[16]:
```
res_logit30=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=30)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6737856740633501
            Iterations: 127
            Function evaluations: 183
            Gradient evaluations: 127
```

[17]:
```
res_logit30.summary()
```

[17]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38894
Method:                           MLE   Df Model:                           46
Date:                Tue, 09 Apr 2024   Pseudo R-squ.:                 0.03053
Time:                        18:14:00   Log-Likelihood:                -26168.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const               0        nan        nan        nan        nan        nan
revenue        0.0019      0.001      2.441      0.015      0.000      0.004
mou           -0.0003   4.95e-05     -5.698      0.000     -0.000     -0.000
recchrge      -0.0031      0.001     -3.545      0.000     -0.005     -0.001
directas      -0.0010      0.006     -0.167      0.868     -0.013      0.011
overage        0.0008      0.000      2.748      0.006      0.000      0.001
roam           0.0071      0.002      3.439      0.001      0.003      0.011
changem       -0.0005   5.34e-05     -9.234      0.000     -0.001     -0.000
changer        0.0023      0.000      6.243      0.000      0.002      0.003
dropvce        0.0081      0.002      4.961      0.000      0.005      0.011
blckvce        0.0035      0.001      3.135      0.002      0.001      0.006
unansvce       0.0010      0.000      2.161      0.031   8.98e-05      0.002
custcare      -0.0060      0.003     -2.391      0.017     -0.011     -0.001
threeway      -0.0268      0.011     -2.395      0.017     -0.049     -0.005
mourec         0.0001      0.000      0.967      0.334     -0.000      0.000
outcalls       0.0010      0.001      1.742      0.082     -0.000      0.002
incalls       -0.0031      0.001     -2.923      0.003     -0.005     -0.001
peakvce       -0.0007      0.000     -3.011      0.003     -0.001     -0.000
opeakvce      -0.0002      0.000     -0.797      0.425     -0.001      0.000
dropblk             0        nan        nan        nan        nan        nan
callfwdv            0        nan        nan        nan        nan        nan
callwait       0.0016      0.003      0.520      0.603     -0.004      0.008
months        -0.0193      0.002     -9.986      0.000     -0.023     -0.016
uniqsubs       0.1655      0.020      8.365      0.000      0.127      0.204
actvsubs      -0.1670      0.027     -6.085      0.000     -0.221     -0.113
phones         0.0515      0.018      2.847      0.004      0.016      0.087
models         0.0069      0.027      0.253      0.800     -0.046      0.060
eqpdays        0.0014   7.32e-05     19.236      0.000      0.001      0.002
age1          -0.0029      0.001     -3.595      0.000     -0.004     -0.001
age2          -0.0009      0.001     -1.294      0.196     -0.002      0.000
children       0.0817      0.028      2.935      0.003      0.027      0.136
credita       -0.1244      0.035     -3.554      0.000     -0.193     -0.056
creditaa      -0.3141      0.034     -9.226      0.000     -0.381     -0.247
```

```
prizmrur      0.0067      0.049      0.137      0.891      -0.090       0.103
prizmub      -0.0358      0.024     -1.482      0.138      -0.083       0.012
prizmtwn      0.0210      0.031      0.674      0.500      -0.040       0.082
refurb        0.2173      0.032      6.887      0.000       0.155       0.279
webcap       -0.1079      0.033     -3.303      0.001      -0.172      -0.044
truck         0.0254      0.029      0.885      0.376      -0.031       0.081
rv                 0        nan        nan        nan         nan         nan
occprof            0        nan        nan        nan         nan         nan
occcler            0        nan        nan        nan         nan         nan
occcrft            0        nan        nan        nan         nan         nan
occstud            0        nan        nan        nan         nan         nan
occhmkr            0        nan        nan        nan         nan         nan
occret             0        nan        nan        nan         nan         nan
occself            0        nan        nan        nan         nan         nan
ownrent            0        nan        nan        nan         nan         nan
marryun       0.0471      0.030      1.585      0.113      -0.011       0.105
marryyes      0.0067      0.031      0.213      0.831      -0.055       0.068
mailord            0        nan        nan        nan         nan         nan
mailres      -0.0980      0.028     -3.541      0.000      -0.152      -0.044
mailflag           0        nan        nan        nan         nan         nan
travel             0        nan        nan        nan         nan         nan
pcown         0.0018      0.030      0.062      0.950      -0.056       0.060
creditcd      0.0216      0.036      0.602      0.547      -0.049       0.092
retcalls      0.0064      0.170      0.038      0.970      -0.326       0.339
retaccpt           0        nan        nan        nan         nan         nan
newcelly     -0.0511      0.026     -1.933      0.053      -0.103       0.001
newcelln           0        nan        nan        nan         nan         nan
refer              0        nan        nan        nan         nan         nan
incmiss            0        nan        nan        nan         nan         nan
income       -0.0059      0.005     -1.150      0.250      -0.016       0.004
mcycle             0        nan        nan        nan         nan         nan
setprcm      -0.0453      0.035     -1.280      0.201      -0.115       0.024
setprc        0.0009      0.000      3.261      0.001       0.000       0.001
retcall       0.6385      0.193      3.305      0.001       0.260       1.017
==============================================================================
"""
```

[18]:
```python
mba263.odds_ratios(res_logit30)
```

[18]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001944	0.000797	2.438198	0.015	1.000397	1.003492
mou	0.999718	0.000049	5.698443	0.000	0.999622	0.999814
recchrge	0.996892	0.000875	3.550479	0.000	0.995194	0.998590
directas	0.999015	0.005907	0.166788	0.868	0.987556	1.010474
overage	1.000769	0.000280	2.747227	0.006	1.000226	1.001313
…	…	…	… …	…	…	
income	0.994096	0.005117	1.153835	0.249	0.984170	1.004023

```
mcycle       1.000000        NaN        NaN    NaN        NaN        NaN
setprcm      0.955745   0.033798   1.309391  0.190   0.890177   1.021313
setprc       1.000879   0.000270   3.259847  0.001   1.000356   1.001402
retcall      1.893728   0.365932   2.442336  0.015   1.183821   2.603635

[66 rows x 6 columns]
```

[43]:
```
#Logit with regularization (alpha = 35) (28 stat significant, 15 not, 23 nan)
```

[44]:
```
res_logit35=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=35)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.674079229818459
            Iterations: 138
            Function evaluations: 193
            Gradient evaluations: 138
```

[45]:
```
res_logit35.summary()
```

[45]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38897
Method:                           MLE   Df Model:                           43
Date:                Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03040
Time:                        02:12:56   Log-Likelihood:                -26171.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const               0        nan        nan        nan        nan        nan
revenue        0.0019      0.001      2.434      0.015      0.000      0.003
mou           -0.0003   4.94e-05     -5.695      0.000     -0.000     -0.000
recchrge      -0.0031      0.001     -3.570      0.000     -0.005     -0.001
directas      -0.0009      0.006     -0.150      0.881     -0.012      0.011
overage        0.0008      0.000      2.750      0.006      0.000      0.001
roam           0.0071      0.002      3.441      0.001      0.003      0.011
changem       -0.0005   5.33e-05     -9.240      0.000     -0.001     -0.000
changer        0.0023      0.000      6.241      0.000      0.002      0.003
dropvce        0.0081      0.002      4.948      0.000      0.005      0.011
blckvce        0.0035      0.001      3.152      0.002      0.001      0.006
unansvce       0.0010      0.000      2.165      0.030   9.13e-05      0.002
custcare      -0.0061      0.003     -2.397      0.017     -0.011     -0.001
```

threeway	-0.0263	0.011	-2.349	0.019	-0.048	-0.004
mourec	0.0001	0.000	0.958	0.338	-0.000	0.000
outcalls	0.0010	0.001	1.726	0.084	-0.000	0.002
incalls	-0.0031	0.001	-2.911	0.004	-0.005	-0.001
peakvce	-0.0007	0.000	-2.994	0.003	-0.001	-0.000
opeakvce	-0.0002	0.000	-0.818	0.414	-0.001	0.000
dropblk	0	nan	nan	nan	nan	nan
callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0016	0.003	0.514	0.607	-0.005	0.008
months	-0.0191	0.002	-9.865	0.000	-0.023	-0.015
uniqsubs	0.1622	0.020	8.208	0.000	0.123	0.201
actvsubs	-0.1614	0.027	-5.892	0.000	-0.215	-0.108
phones	0.0519	0.018	2.868	0.004	0.016	0.087
models	0.0050	0.027	0.183	0.854	-0.048	0.058
eqpdays	0.0014	7.31e-05	19.154	0.000	0.001	0.002
age1	-0.0029	0.001	-3.621	0.000	-0.004	-0.001
age2	-0.0008	0.001	-1.262	0.207	-0.002	0.000
children	0.0788	0.027	2.901	0.004	0.026	0.132
credita	-0.1173	0.035	-3.354	0.001	-0.186	-0.049
creditaa	-0.3073	0.034	-9.036	0.000	-0.374	-0.241
prizmrur	0	nan	nan	nan	nan	nan
prizmub	-0.0347	0.024	-1.467	0.142	-0.081	0.012
prizmtwn	0.0171	0.031	0.558	0.577	-0.043	0.077
refurb	0.2140	0.032	6.790	0.000	0.152	0.276
webcap	-0.1033	0.033	-3.172	0.002	-0.167	-0.039
truck	0.0226	0.028	0.795	0.427	-0.033	0.078
rv	0	nan	nan	nan	nan	nan
occprof	0	nan	nan	nan	nan	nan
occcler	0	nan	nan	nan	nan	nan
occcrft	0	nan	nan	nan	nan	nan
occstud	0	nan	nan	nan	nan	nan
occhmkr	0	nan	nan	nan	nan	nan
occret	0	nan	nan	nan	nan	nan
occself	0	nan	nan	nan	nan	nan
ownrent	0	nan	nan	nan	nan	nan
marryun	0.0381	0.028	1.385	0.166	-0.016	0.092
marryyes	0	nan	nan	nan	nan	nan
mailord	0	nan	nan	nan	nan	nan
mailres	-0.0926	0.027	-3.404	0.001	-0.146	-0.039
mailflag	0	nan	nan	nan	nan	nan
travel	0	nan	nan	nan	nan	nan
pcown	0	nan	nan	nan	nan	nan
creditcd	0.0121	0.036	0.338	0.735	-0.058	0.082
retcalls	0.0197	0.170	0.116	0.908	-0.313	0.353
retaccpt	0	nan	nan	nan	nan	nan
newcelly	-0.0481	0.026	-1.820	0.069	-0.100	0.004
newcelln	0	nan	nan	nan	nan	nan

```
refer                 0          nan          nan          nan          nan          nan
incmiss               0          nan          nan          nan          nan          nan
income          -0.0054        0.005       -1.064        0.288       -0.015        0.005
mcycle                0          nan          nan          nan          nan          nan
setprcm         -0.0406        0.035       -1.153        0.249       -0.110        0.028
setprc           0.0009        0.000        3.367        0.001        0.000        0.001
retcall          0.6089        0.193        3.152        0.002        0.230        0.988
==============================================================================
"""
```

[46]:
```python
mba263.odds_ratios(res_logit35)
```

[46]:
```
          Odds ratios   std err         z  P>|z|    [0.025    0.975]
revenue      1.001938  0.000797  2.431374  0.015  1.000392  1.003485
mou          0.999718  0.000049  5.696068  0.000  0.999623  0.999814
recchrge     0.996873  0.000875  3.575124  0.000  0.995177  0.998570
directas     0.999113  0.005904  0.150288  0.881  0.987658  1.010567
overage      1.000770  0.000280  2.748889  0.006  1.000226  1.001313
…                 …         …       …      …       …         …
income       0.994596  0.005067  1.066444  0.286  0.984766  1.004426
mcycle       1.000000       NaN       NaN    NaN       NaN       NaN
setprcm      0.960210  0.033801  1.177185  0.239  0.894636  1.025784
setprc       1.000906  0.000269  3.365375  0.001  1.000384  1.001429
retcall      1.838490  0.355146  2.360976  0.018  1.149508  2.527473

[66 rows x 6 columns]
```

[47]:
```python
#Logit with regularization (alpha = 40) (27 stat significant, 16 non)
```

[48]:
```python
res_logit40=mba263.
↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=40)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6743604477685254
            Iterations: 126
            Function evaluations: 181
            Gradient evaluations: 126
```

[49]:
```python
res_logit40.summary()
```

[49]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38897
Method:                           MLE   Df Model:                           43
```

Date:	Sun, 07 Apr 2024	Pseudo R-squ.:	0.03027
Time:	02:14:49	Log-Likelihood:	-26174.
converged:	True	LL-Null:	-26992.
Covariance Type:	nonrobust	LLR p-value:	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
const	0	nan	nan	nan	nan	nan
revenue	0.0019	0.001	2.429	0.015	0.000	0.003
mou	-0.0003	4.94e-05	-5.691	0.000	-0.000	-0.000
recchrge	-0.0032	0.001	-3.600	0.000	-0.005	-0.001
directas	-0.0008	0.006	-0.135	0.893	-0.012	0.011
overage	0.0008	0.000	2.749	0.006	0.000	0.001
roam	0.0070	0.002	3.433	0.001	0.003	0.011
changem	-0.0005	5.33e-05	-9.243	0.000	-0.001	-0.000
changer	0.0023	0.000	6.239	0.000	0.002	0.003
dropvce	0.0080	0.002	4.934	0.000	0.005	0.011
blckvce	0.0035	0.001	3.154	0.002	0.001	0.006
unansvce	0.0010	0.000	2.160	0.031	8.93e-05	0.002
custcare	-0.0061	0.003	-2.406	0.016	-0.011	-0.001
threeway	-0.0257	0.011	-2.299	0.022	-0.048	-0.004
mourec	0.0001	0.000	0.951	0.341	-0.000	0.000
outcalls	0.0010	0.001	1.714	0.087	-0.000	0.002
incalls	-0.0030	0.001	-2.899	0.004	-0.005	-0.001
peakvce	-0.0006	0.000	-2.977	0.003	-0.001	-0.000
opeakvce	-0.0002	0.000	-0.825	0.409	-0.001	0.000
dropblk	0	nan	nan	nan	nan	nan
callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0016	0.003	0.504	0.614	-0.005	0.008
months	-0.0188	0.002	-9.746	0.000	-0.023	-0.015
uniqsubs	0.1589	0.020	8.048	0.000	0.120	0.198
actvsubs	-0.1561	0.027	-5.704	0.000	-0.210	-0.102
phones	0.0523	0.018	2.893	0.004	0.017	0.088
models	0.0028	0.027	0.105	0.917	-0.050	0.056
eqpdays	0.0014	7.31e-05	19.054	0.000	0.001	0.002
age1	-0.0029	0.001	-3.642	0.000	-0.005	-0.001
age2	-0.0008	0.001	-1.237	0.216	-0.002	0.000
children	0.0744	0.027	2.741	0.006	0.021	0.128
credita	-0.1100	0.035	-3.147	0.002	-0.179	-0.041
creditaa	-0.3006	0.034	-8.842	0.000	-0.367	-0.234
prizmrur	0	nan	nan	nan	nan	nan
prizmub	-0.0331	0.024	-1.400	0.161	-0.079	0.013
prizmtwn	0.0135	0.031	0.440	0.660	-0.047	0.074
refurb	0.2106	0.032	6.684	0.000	0.149	0.272
webcap	-0.0994	0.033	-3.055	0.002	-0.163	-0.036
truck	0.0190	0.028	0.670	0.503	-0.037	0.075
rv	0	nan	nan	nan	nan	nan

```
occprof              0      nan      nan      nan       nan       nan
occcler              0      nan      nan      nan       nan       nan
occcrft              0      nan      nan      nan       nan       nan
occstud              0      nan      nan      nan       nan       nan
occhmkr              0      nan      nan      nan       nan       nan
occret               0      nan      nan      nan       nan       nan
occself              0      nan      nan      nan       nan       nan
ownrent              0      nan      nan      nan       nan       nan
marryun         0.0316    0.028    1.150    0.250    -0.022     0.086
marryyes             0      nan      nan      nan       nan       nan
mailord              0      nan      nan      nan       nan       nan
mailres        -0.0880    0.027   -3.236    0.001    -0.141    -0.035
mailflag             0      nan      nan      nan       nan       nan
travel               0      nan      nan      nan       nan       nan
pcown                0      nan      nan      nan       nan       nan
creditcd        0.0035    0.036    0.099    0.921    -0.066     0.073
retcalls        0.0335    0.170    0.197    0.844    -0.299     0.366
retaccpt             0      nan      nan      nan       nan       nan
newcelly       -0.0449    0.026   -1.700    0.089    -0.097     0.007
newcelln             0      nan      nan      nan       nan       nan
refer                0      nan      nan      nan       nan       nan
incmiss              0      nan      nan      nan       nan       nan
income         -0.0051    0.005   -0.995    0.320    -0.015     0.005
mcycle               0      nan      nan      nan       nan       nan
setprcm        -0.0367    0.035   -1.044    0.296    -0.106     0.032
setprc          0.0009    0.000    3.459    0.001     0.000     0.001
retcall         0.5790    0.193    2.998    0.003     0.200     0.957
==============================================================================
"""
```

[50]:
```python
mba263.odds_ratios(res_logit40)
```

[50]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001934	0.000797	2.426528	0.015	1.000388	1.003480
mou	0.999719	0.000049	5.692275	0.000	0.999623	0.999815
recchrge	0.996848	0.000874	3.605381	0.000	0.995152	0.998544
directas	0.999203	0.005903	0.134973	0.893	0.987752	1.010654
overage	1.000769	0.000280	2.747575	0.006	1.000226	1.001312
…	…	…	… …	…	…	
income	0.994944	0.005067	0.997727	0.318	0.985114	1.004775
mcycle	1.000000	NaN	NaN	NaN	NaN	NaN
setprcm	0.963921	0.033919	1.063686	0.287	0.898118	1.029724
setprc	1.000931	0.000269	3.457339	0.001	1.000408	1.001453
retcall	1.784175	0.344587	2.275697	0.023	1.115677	2.452673

[66 rows x 6 columns]

[51]:
```
#Logit with regularization (alpha = 50)
```

[52]:
```
res_logit50=mba263.
 ↪logit_reg(data_calibration['churndep'],data_calibration[varlist],alpha=50)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.6748906392518981
            Iterations: 122
            Function evaluations: 177
            Gradient evaluations: 122
```

[53]:
```
res_logit50.summary()
```

[53]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                        Mba263Logit Regression Results
==============================================================================
Dep. Variable:               churndep   No. Observations:                38941
Model:                    Mba263Logit   Df Residuals:                    38899
Method:                           MLE   Df Model:                           41
Date:                Sun, 07 Apr 2024   Pseudo R-squ.:                 0.03001
Time:                        02:16:43   Log-Likelihood:                -26182.
converged:                       True   LL-Null:                       -26992.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const               0        nan        nan        nan         nan         nan
revenue        0.0019      0.001      2.416      0.016       0.000       0.003
mou           -0.0003   4.94e-05     -5.687      0.000      -0.000      -0.000
recchrge      -0.0032      0.001     -3.666      0.000      -0.005      -0.001
directas      -0.0006      0.006     -0.095      0.924      -0.012       0.011
overage        0.0008      0.000      2.749      0.006       0.000       0.001
roam           0.0070      0.002      3.424      0.001       0.003       0.011
changem       -0.0005   5.33e-05     -9.253      0.000      -0.001      -0.000
changer        0.0023      0.000      6.237      0.000       0.002       0.003
dropvce        0.0080      0.002      4.904      0.000       0.005       0.011
blckvce        0.0035      0.001      3.159      0.002       0.001       0.006
unansvce       0.0010      0.000      2.149      0.032    8.43e-05       0.002
custcare      -0.0061      0.003     -2.423      0.015      -0.011      -0.001
threeway      -0.0246      0.011     -2.200      0.028      -0.046      -0.003
mourec         0.0001      0.000      0.939      0.348      -0.000       0.000
outcalls       0.0010      0.001      1.696      0.090      -0.000       0.002
incalls       -0.0030      0.001     -2.881      0.004      -0.005      -0.001
peakvce       -0.0006      0.000     -2.942      0.003      -0.001      -0.000
opeakvce      -0.0002      0.000     -0.851      0.395      -0.001       0.000
dropblk             0        nan        nan        nan         nan         nan
```

callfwdv	0	nan	nan	nan	nan	nan
callwait	0.0015	0.003	0.496	0.620	-0.005	0.008
months	-0.0184	0.002	-10.013	0.000	-0.022	-0.015
uniqsubs	0.1521	0.020	7.730	0.000	0.114	0.191
actvsubs	-0.1458	0.027	-5.339	0.000	-0.199	-0.092
phones	0.0524	0.012	4.205	0.000	0.028	0.077
models	0	nan	nan	nan	nan	nan
eqpdays	0.0014	7.16e-05	19.226	0.000	0.001	0.002
age1	-0.0030	0.001	-3.957	0.000	-0.005	-0.002
age2	-0.0008	0.001	-1.189	0.235	-0.002	0.000
children	0.0654	0.027	2.412	0.016	0.012	0.119
credita	-0.0959	0.035	-2.747	0.006	-0.164	-0.027
creditaa	-0.2873	0.034	-8.471	0.000	-0.354	-0.221
prizmrur	0	nan	nan	nan	nan	nan
prizmub	-0.0298	0.024	-1.264	0.206	-0.076	0.016
prizmtwn	0.0067	0.031	0.218	0.827	-0.053	0.067
refurb	0.2031	0.031	6.519	0.000	0.142	0.264
webcap	-0.0931	0.032	-2.914	0.004	-0.156	-0.030
truck	0.0118	0.028	0.416	0.677	-0.044	0.068
rv	0	nan	nan	nan	nan	nan
occprof	0	nan	nan	nan	nan	nan
occcler	0	nan	nan	nan	nan	nan
occcrft	0	nan	nan	nan	nan	nan
occstud	0	nan	nan	nan	nan	nan
occhmkr	0	nan	nan	nan	nan	nan
occret	0	nan	nan	nan	nan	nan
occself	0	nan	nan	nan	nan	nan
ownrent	0	nan	nan	nan	nan	nan
marryun	0.0206	0.027	0.765	0.444	-0.032	0.074
marryyes	0	nan	nan	nan	nan	nan
mailord	0	nan	nan	nan	nan	nan
mailres	-0.0796	0.027	-2.935	0.003	-0.133	-0.026
mailflag	0	nan	nan	nan	nan	nan
travel	0	nan	nan	nan	nan	nan
pcown	0	nan	nan	nan	nan	nan
creditcd	0	nan	nan	nan	nan	nan
retcalls	0.0612	0.170	0.360	0.719	-0.272	0.394
retaccpt	0	nan	nan	nan	nan	nan
newcelly	-0.0385	0.026	-1.459	0.145	-0.090	0.013
newcelln	0	nan	nan	nan	nan	nan
refer	0	nan	nan	nan	nan	nan
incmiss	0	nan	nan	nan	nan	nan
income	-0.0052	0.005	-1.119	0.263	-0.014	0.004
mcycle	0	nan	nan	nan	nan	nan
setprcm	-0.0298	0.035	-0.851	0.395	-0.099	0.039
setprc	0.0010	0.000	3.631	0.000	0.000	0.002
retcall	0.5188	0.193	2.687	0.007	0.140	0.897

```
===============================================================================
"""
```

[54]:
```
mba263.odds_ratios(res_logit50)
```

[54]:
```
            Odds ratios   std err          z  P>|z|    [0.025    0.975]
revenue        1.001922  0.000796   2.413205  0.016  1.000377  1.003467
mou            0.999719  0.000049   5.688234  0.000  0.999623  0.999815
recchrge       0.996795  0.000873   3.671738  0.000  0.995101  0.998488
directas       0.999439  0.005897   0.095077  0.924  0.987999  1.010880
overage        1.000769  0.000280   2.747945  0.006  1.000226  1.001312
…                   …         …        …     …        …         …
income         0.994840  0.004601   1.121417  0.262  0.985915  1.003766
mcycle         1.000000       NaN        NaN    NaN       NaN       NaN
setprcm        0.970591  0.034060   0.863446  0.388  0.904516  1.036667
setprc         1.000975  0.000269   3.629643  0.000  1.000454  1.001496
retcall        1.680048  0.324354   2.096620  0.036  1.050800  2.309295

[66 rows x 6 columns]
```

[19]:
```
data_calibration['predchurn']=res_logit30.predict(data_calibration[varlist])
data_calibration['predchurn'].head(10)
```

[19]:
```
31047    0.786116
31048    0.338607
31049    0.265287
31050    0.507691
31051    0.433779
31052    0.322732
31053    0.309051
31054    0.369053
31055    0.212615
31056    0.443585
Name: predchurn, dtype: float64
```

[20]:
```
data_calibration['predchurn'].mean()
```

[20]: 0.497925788094733

[57]:
```
data_calibration['predchurn5']=res_logit5.predict(data_calibration[varlist])
```

[58]:
```
data_calibration['predchurn5'].mean()
```

[58]: 0.4980126590356273

[59]:
```
data_calibration['predchurn10']=res_logit10.predict(data_calibration[varlist])
```

[60]:
```
data_calibration['predchurn10'].mean()
```

[60]: 0.49788295255711507

[61]:
```
data_calibration['predchurn15']=res_logit15.predict(data_calibration[varlist])
```

[62]:
```
data_calibration['predchurn15'].mean()
```

[62]: 0.49780525074382476

[63]:
```
data_calibration['predchurn20']=res_logit20.predict(data_calibration[varlist])
```

[64]:
```
data_calibration['predchurn20'].mean()
```

[64]: 0.4978609752114147

[65]:
```
data_calibration['predchurn25']=res_logit25.predict(data_calibration[varlist])
```

[66]:
```
data_calibration['predchurn25'].mean()
```

[66]: 0.49790052055204853

[67]:
```
data_calibration['predchurn30']=res_logit30.predict(data_calibration[varlist])
```

[68]:
```
data_calibration['predchurn30'].mean()
```

[68]: 0.497925788094733

[69]:
```
data_calibration['predchurn35']=res_logit35.predict(data_calibration[varlist])
```

[70]:
```
data_calibration['predchurn35'].mean()
```

[70]: 0.4979529718573638

[71]:
```
data_calibration['predchurn40']=res_logit40.predict(data_calibration[varlist])
```

[72]:
```
data_calibration['predchurn40'].mean()
```

[72]: 0.4979920787978932

[73]:
```
data_calibration['predchurn50']=res_logit50.predict(data_calibration[varlist])
```

[74]:
```
data_calibration['predchurn50'].mean()
```

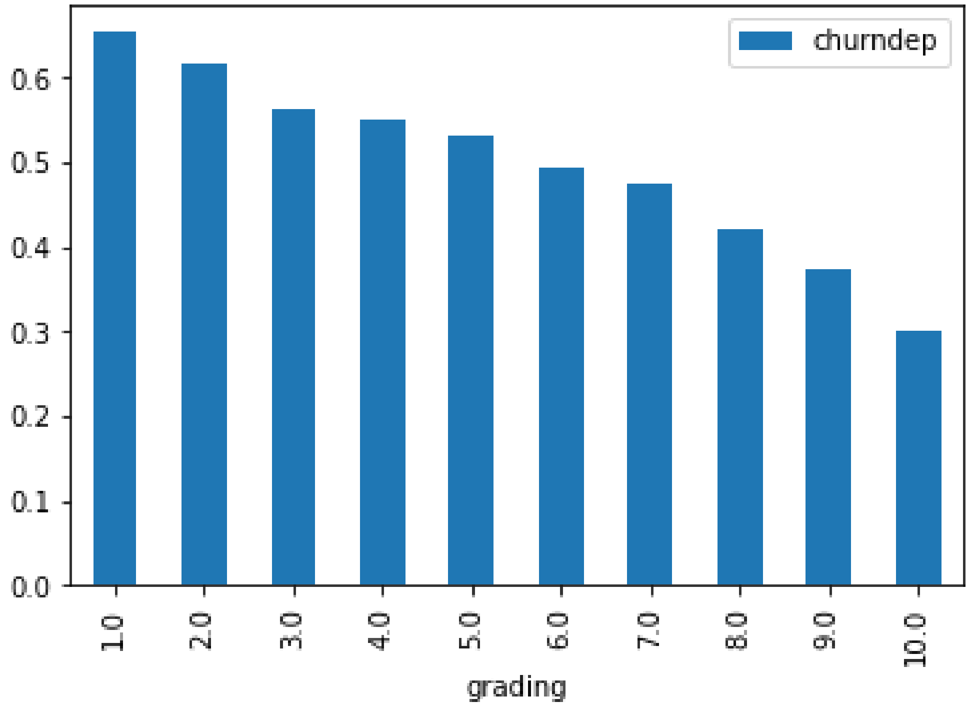
[74]: 0.4980905595881214

[21]:
```
#grading
```

[22]:
```
data_calibration['grading']=10-mba263.ntile(data_calibration['predchurn'],10)
```

[23]:
```
data_calibration[ ['grading','churndep'] ].groupby('grading').mean().
 ↪plot(kind='bar')
```

[23]: <AxesSubplot:xlabel='grading'>



[24]:
```
data_validation['predchurn']=res_logit30.predict(data_validation[varlist])
```

[25]:
```
data_validation['predchurn'].head(10)
```

[25]:
```
0    0.268225
1    0.275962
2    0.353664
3    0.313440
4    0.367491
5    0.465665
6    0.449327
7    0.336729
8    0.258999
9    0.289266
Name: predchurn, dtype: float64
```

[26]:
```
data_validation['predchurn'].mean()
```

[26]: 0.47817732814947045

[27]:
```
data_validation['churn'].mean()
```

[27]: 0.019615421779882115

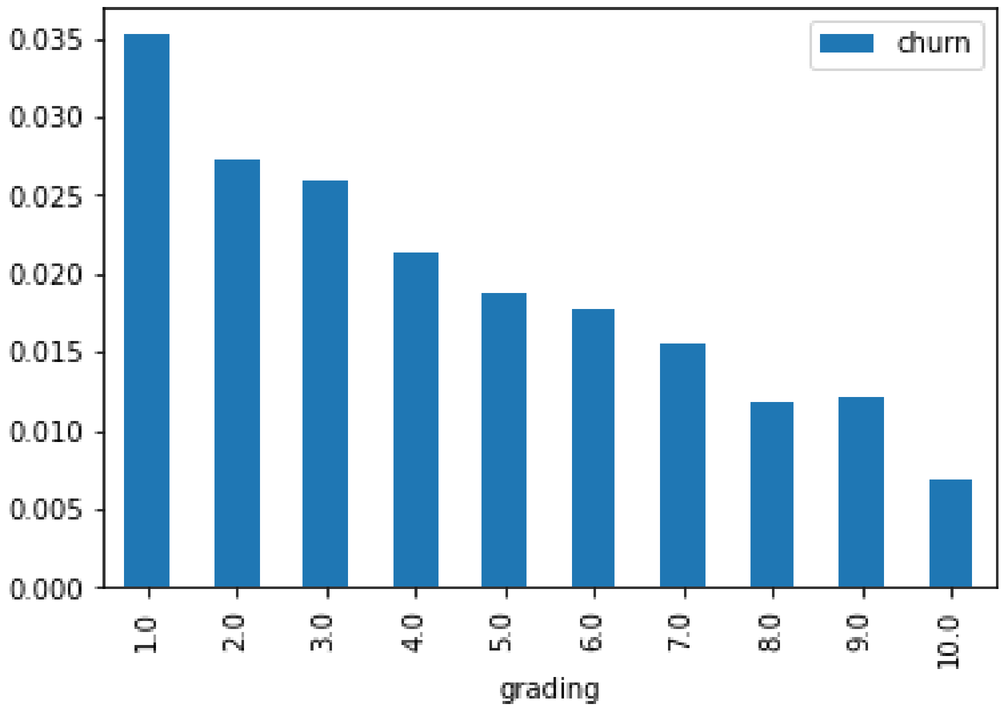
[28]:
```
data_validation['grading']=10-mba263.ntile(data_validation['predchurn'],10)
```

[29]:
```
data_validation['grading'].head(10)
```

[29]:
```
0    10.0
1    10.0
2    10.0
3    10.0
4     9.0
5     6.0
6     7.0
7    10.0
8    10.0
9    10.0
Name: grading, dtype: float64
```

[30]:
```
data_validation[ ['churn','grading'] ].groupby('grading').mean().
 ↪plot(kind='bar')
```

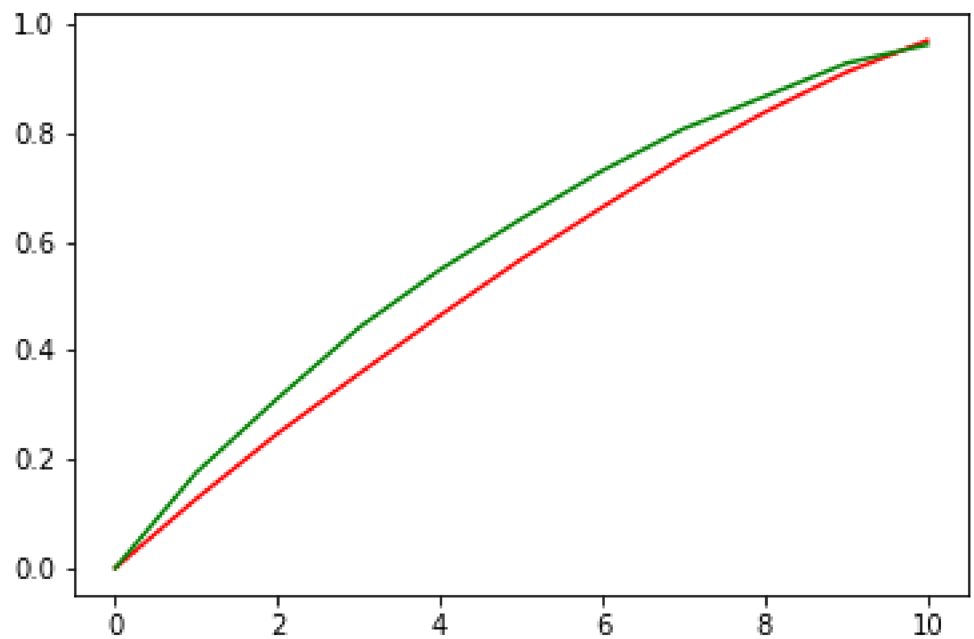
[30]: <AxesSubplot:xlabel='grading'>



[31]:
```
gain_calibration= mba263.
  ↪gain(data_calibration['churndep'],data_calibration['predchurn'],10)
gain_validation= mba263.
  ↪gain(data_validation['churn'],data_validation['predchurn'],10)
```

[32]:
```
plt.plot(gain_calibration,'r')
plt.plot(gain_validation,'g')
```

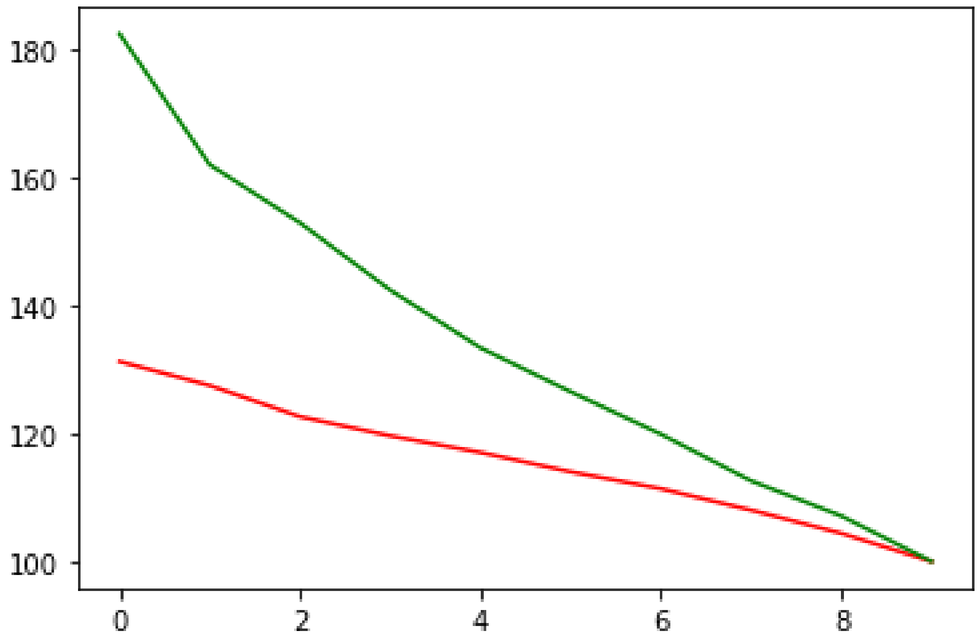
[32]: [<matplotlib.lines.Line2D at 0x7f340b26bf10>]



[33]:
```
lift_calibration= mba263.
  ↪lift(data_calibration['churndep'],data_calibration['predchurn'],10)
lift_validation= mba263.
  ↪lift(data_validation['churn'],data_validation['predchurn'],10)
```

[34]:
```
plt.plot(lift_calibration,'r')
plt.plot(lift_validation,'g')
```

[34]: [<matplotlib.lines.Line2D at 0x7f33fbd87ee0>]



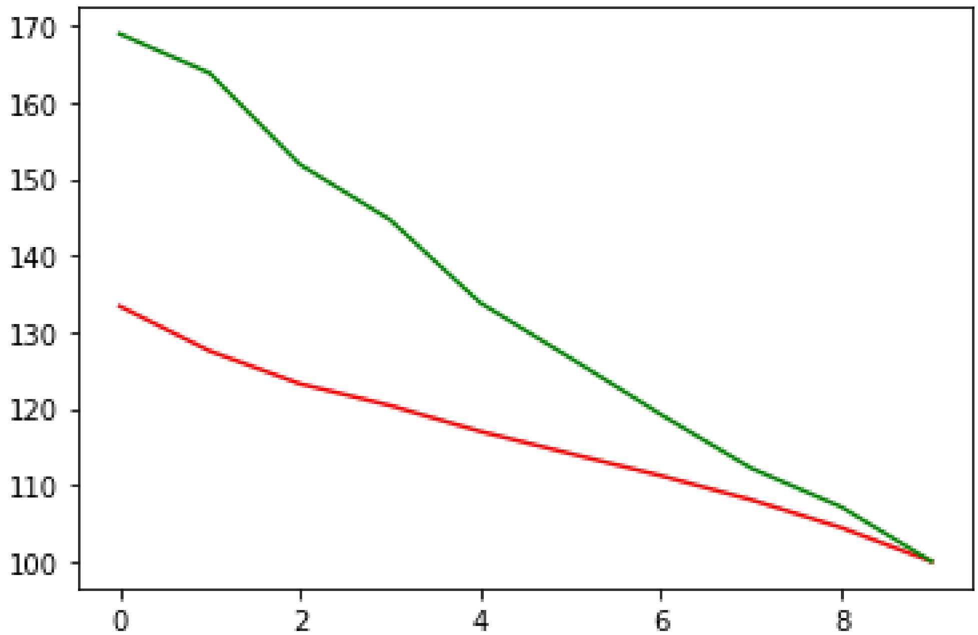
[89]:
```
#lift for different alpha (alpha=5)
```

[90]:
```
data_validation['predchurn5']=res_logit5.predict(data_validation[varlist])
```

[91]:
```
lift_calibration5= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn5'],10)
lift_validation5= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn5'],10)
```

[92]:
```
plt.plot(lift_calibration5,'r')
plt.plot(lift_validation5,'g')
```

[92]: [<matplotlib.lines.Line2D at 0x7f4f6e6e2d60>]



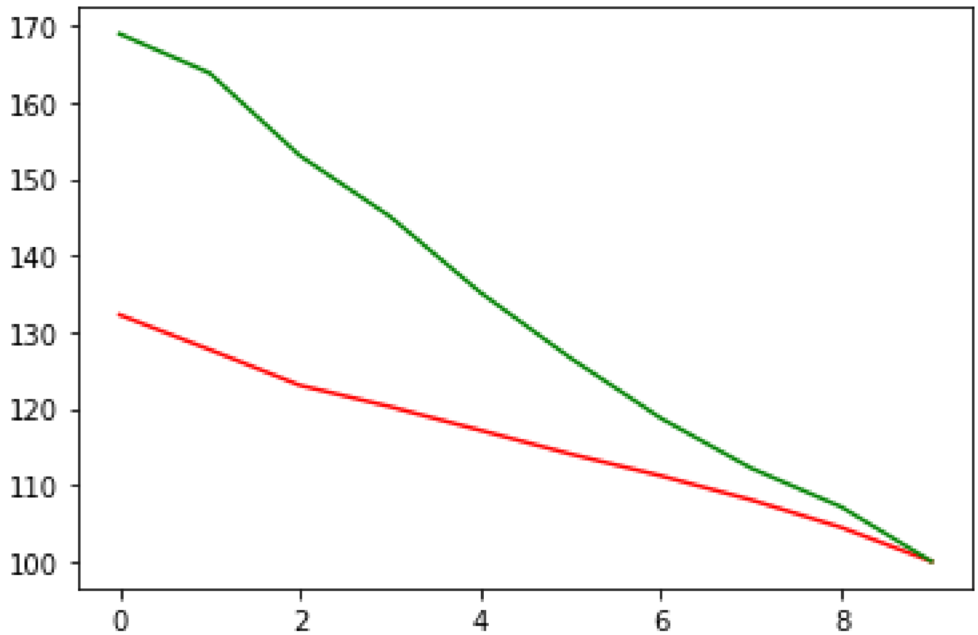
[93]:
```
#lift for different alpha (alpha=10)
```

[94]:
```
data_validation['predchurn10']=res_logit10.predict(data_validation[varlist])
```

[95]:
```
lift_calibration10= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn10'],10)
lift_validation10= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn10'],10)
```

[96]:
```
plt.plot(lift_calibration10,'r')
plt.plot(lift_validation10,'g')
```

[96]:
```
[<matplotlib.lines.Line2D at 0x7f4f742e2280>]
```



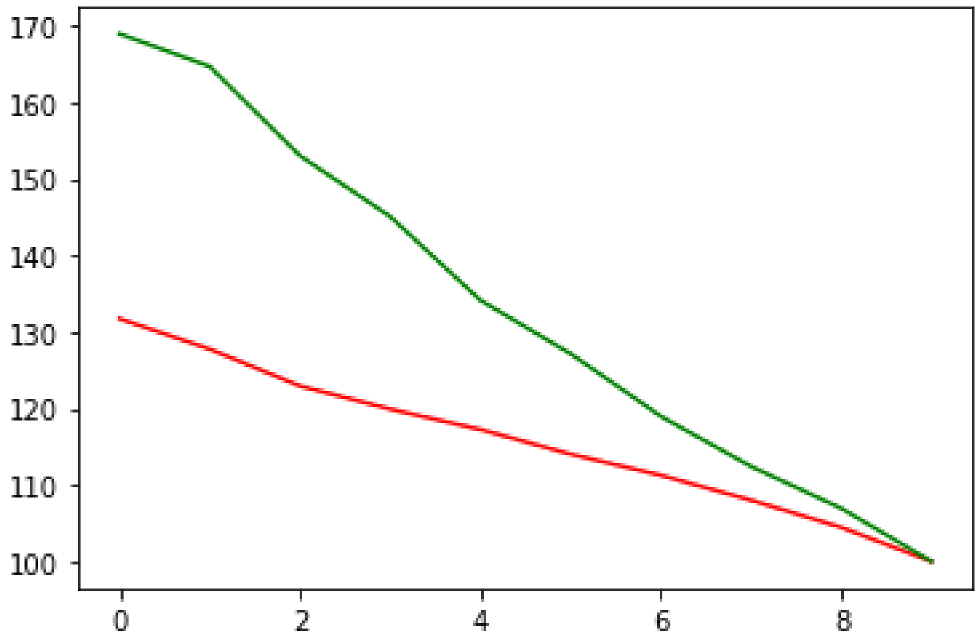
[97]:
```
#lift for different alpha (alpha=15)
```

[98]:
```
data_validation['predchurn15']=res_logit15.predict(data_validation[varlist])
```

[99]:
```
lift_calibration15= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn15'],10)
lift_validation15= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn15'],10)
```

[100]:
```
plt.plot(lift_calibration15,'r')
plt.plot(lift_validation15,'g')
```

[100]: [<matplotlib.lines.Line2D at 0x7f4f68366880>]



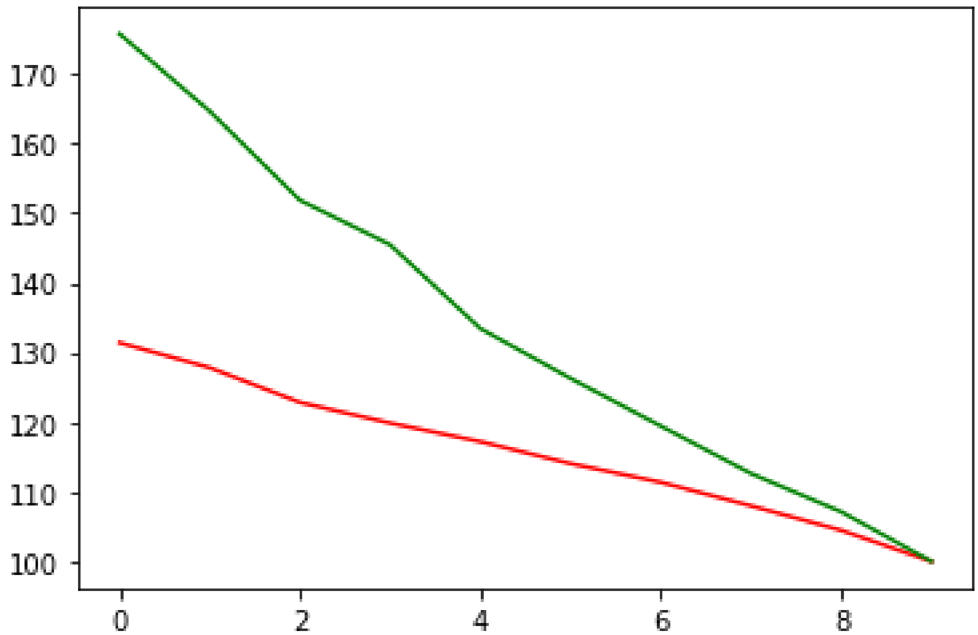
[101]:
```
#lift for different alpha (alpha=20)
```

[102]:
```
data_validation['predchurn20']=res_logit20.predict(data_validation[varlist])
```

[103]:
```
lift_calibration20= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn20'],10)
lift_validation20= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn20'],10)
```

[104]:
```
plt.plot(lift_calibration20,'r')
plt.plot(lift_validation20,'g')
```

[104]:
```
[<matplotlib.lines.Line2D at 0x7f4f698bfd90>]
```



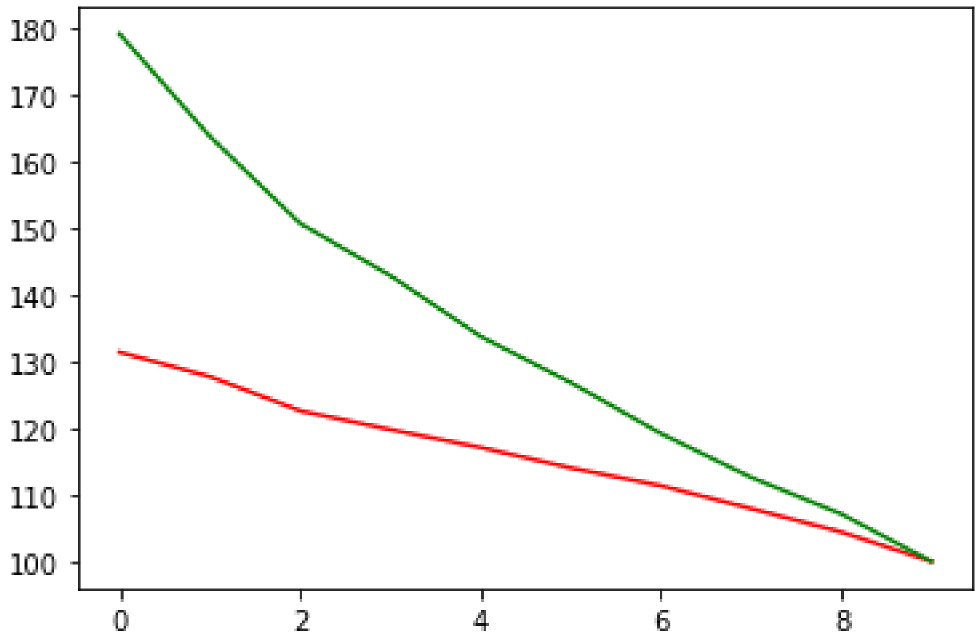
[105]:
```
#lift for different alpha (alpha=25)
```

[106]:
```
data_validation['predchurn25']=res_logit25.predict(data_validation[varlist])
```

[107]:
```
lift_calibration25= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn25'],10)
lift_validation25= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn25'],10)
```

[108]:
```
plt.plot(lift_calibration25,'r')
plt.plot(lift_validation25,'g')
```

[108]: [<matplotlib.lines.Line2D at 0x7f4f77b59400>]



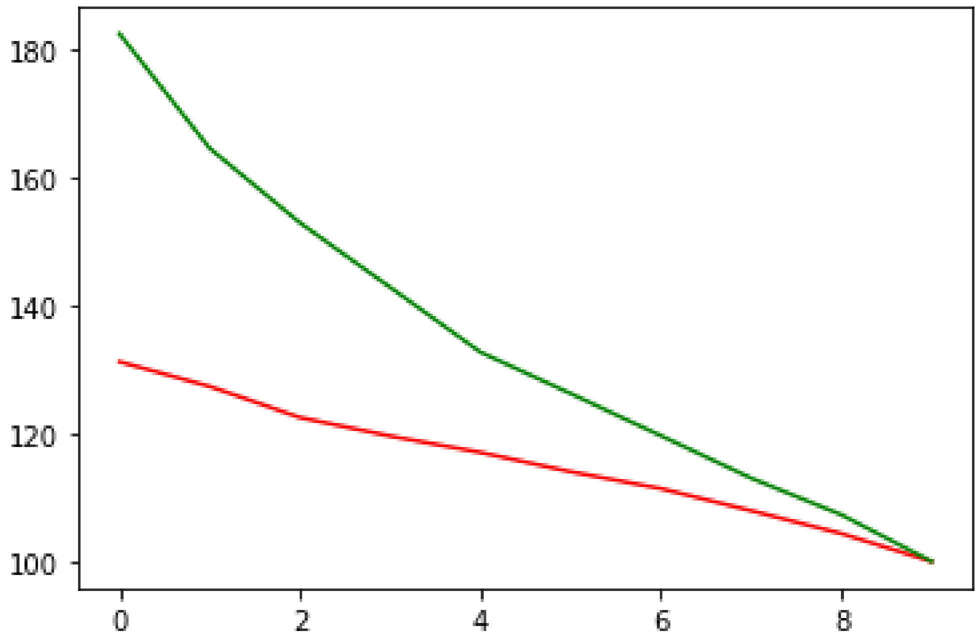
[109]:
```
#lift for different alpha (alpha=35)
```

[110]:
```
data_validation['predchurn35']=res_logit35.predict(data_validation[varlist])
```

[111]:
```
lift_calibration35= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn35'],10)
lift_validation35= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn35'],10)
```

[112]:
```
plt.plot(lift_calibration35,'r')
plt.plot(lift_validation35,'g')
```

[112]:
```
[<matplotlib.lines.Line2D at 0x7f4f77b39fa0>]
```



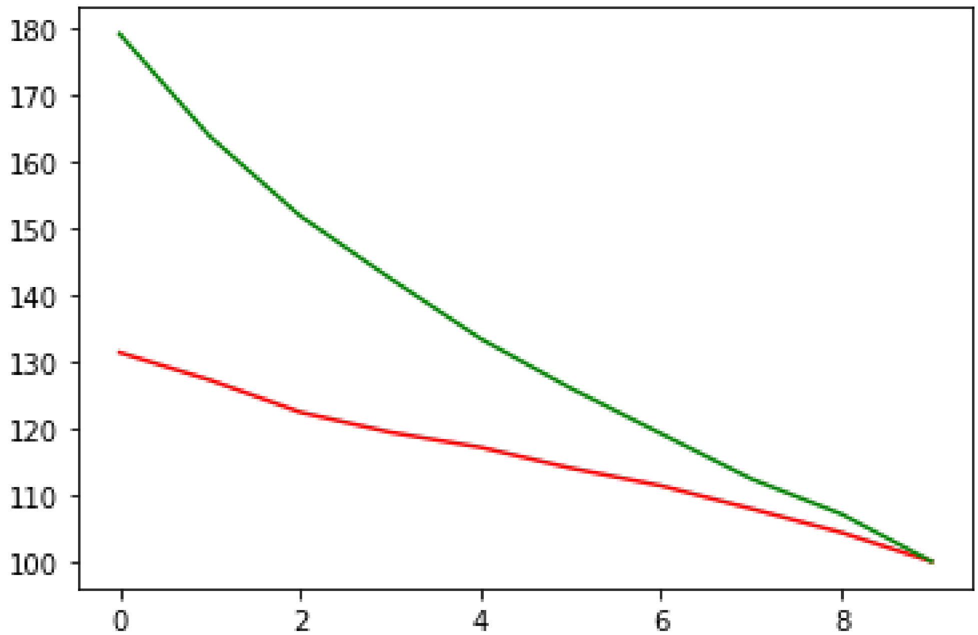
[113]:
```
#lift for different alpha (alpha=40)
```

[114]:
```
data_validation['predchurn40']=res_logit40.predict(data_validation[varlist])
```

[115]:
```
lift_calibration40= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn40'],10)
lift_validation40= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn40'],10)
```

[116]:
```
plt.plot(lift_calibration40,'r')
plt.plot(lift_validation40,'g')
```

[116]: [<matplotlib.lines.Line2D at 0x7f4f778a7490>]



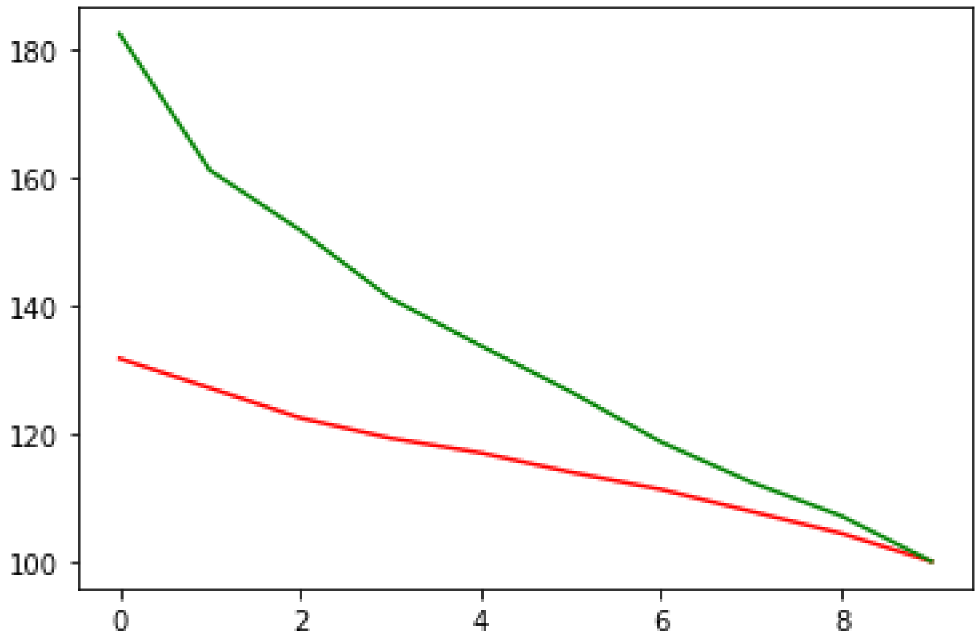
[117]:
```
#lift for different alpha (alpha=50)
```

[118]:
```
data_validation['predchurn50']=res_logit50.predict(data_validation[varlist])
```

[119]:
```
lift_calibration50= mba263.
 ↪lift(data_calibration['churndep'],data_calibration['predchurn50'],10)
lift_validation50= mba263.
 ↪lift(data_validation['churn'],data_validation['predchurn50'],10)
```

[120]:
```
plt.plot(lift_calibration50,'r')
plt.plot(lift_validation50,'g')
```

[120]:
```
[<matplotlib.lines.Line2D at 0x7f4f776d50a0>]
```



[41]:
```
#Determine and rank the economic importance of the predictor variables
```

[42]:
```
mba263.odds_ratios(res_logit30)
```

[42]:

	Odds ratios	std err	z	P>|z|	[0.025	0.975]
revenue	1.001944	0.000797	2.438198	0.015	1.000397	1.003492
mou	0.999718	0.000049	5.698443	0.000	0.999622	0.999814
recchrge	0.996892	0.000875	3.550479	0.000	0.995194	0.998590
directas	0.999015	0.005907	0.166788	0.868	0.987556	1.010474
overage	1.000769	0.000280	2.747227	0.006	1.000226	1.001313
…	…	…	… …	…	…	
income	0.994096	0.005117	1.153835	0.249	0.984170	1.004023
mcycle	1.000000	NaN	NaN	NaN	NaN	NaN
setprcm	0.955745	0.033798	1.309391	0.190	0.890177	1.021313
setprc	1.000879	0.000270	3.259847	0.001	1.000356	1.001402
retcall	1.893728	0.365932	2.442336	0.015	1.183821	2.603635

[66 rows x 6 columns]

[43]:
```
x_std=data_validation[varlist].std()
x_std
```

[43]:
```
revenue       44.372524
mou          536.601264
recchrge      24.149383
directas       2.348869
```

```
overage       93.803961
                  …
income         3.127723
mcycle         0.112496
setprcm        0.497041
setprc        57.561782
retcall        0.158540
Length: 66, dtype: float64
```

[44]:
```python
x_std.head(66)
```

[44]:
```
revenue       44.372524
mou          536.601264
recchrge      24.149383
directas       2.348869
overage       93.803961
                  …
income         3.127723
mcycle         0.112496
setprcm        0.497041
setprc        57.561782
retcall        0.158540
Length: 66, dtype: float64
```

[45]:
```python
odds_ratios=mba263.odds_ratios(res_logit30)['Odds ratios']
odds_ratios
```

[45]:
```
revenue     1.001944
mou         0.999718
recchrge    0.996892
directas    0.999015
overage     1.000769
              …
income      0.994096
mcycle      1.000000
setprcm     0.955745
setprc      1.000879
retcall     1.893728
Name: Odds ratios, Length: 66, dtype: float64
```

[46]:
```python
normalized_odds_ratios=numpy.power(odds_ratios,x_std)
normalized_odds_ratios
```

[46]:
```
revenue     1.090020
mou         0.859661
recchrge    0.927593
directas    0.997688
```

```
overage     1.074815
              …
income      0.981650
mcycle      1.000000
setprcm     0.977753
setprc      1.051869
retcall     1.106537
Length: 66, dtype: float64
```

[47]:
```
normalized_odds_ratios[normalized_odds_ratios<1]=1/
 ↪normalized_odds_ratios[normalized_odds_ratios<1]
```

[48]:
```
normalized_odds_ratios.sort_values(ascending=False)
```

[48]:
```
eqpdays     1.422264
months      1.213187
mou         1.163249
uniqsubs    1.148901
changem     1.130822
              …
ownrent     1.000000
occself     1.000000
occret      1.000000
occhmkr     1.000000
mailflag    1.000000
Length: 66, dtype: float64
```

[49]:
```
normalized_odds_ratios.sort_values(ascending=False).head(66)
```

[49]:
```
eqpdays     1.422264
months      1.213187
mou         1.163249
uniqsubs    1.148901
changem     1.130822
              …
ownrent     1.000000
occself     1.000000
occret      1.000000
occhmkr     1.000000
mailflag    1.000000
Length: 66, dtype: float64
```

[60]:
```
normalized_odds_ratios.sort_values(ascending=False).head(10)
```

[60]:
```
eqpdays     1.422264
months      1.213187
mou         1.163249
```

```
uniqsubs    1.148901
changem     1.130822
creditaa    1.115781
actvsubs    1.110315
retcall     1.106537
revenue     1.090020
changer     1.089781
dtype: float64
```

[141]:
```
normalized_odds_ratios.sort_values(ascending=False).
  ↪to_csv('cell2cell_normalized.csv')
```

[143]:
```
normalized_odds_ratios.to_csv('cell2cell_normalized_original_order.csv')
```

#predictor variables that we deem important based on normalized odds ratios: eqpdays 1.422264 months 1.213187 mou 1.163249 uniqsubs 1.148901 changem 1.130822 creditaa 1.115781 actvsubs 1.110315

[136]:
```
odds_ratios_df = mba263.odds_ratios(res_logit30)
```

[138]:
```
odds_ratios_df.to_csv('cell2cell_odds_ratios.csv')
```

[50]:
```
#calculating odds ratio using std calculated using data_calibration
```

[51]:
```
x_std_calibration=data_calibration[varlist].std()
x_std_calibration
```

[51]:
```
revenue      44.142432
mou         524.759890
recchrge     23.714145
directas      2.072555
overage      98.272111
               …
income        3.144329
mcycle        0.117285
setprcm       0.494208
setprc       56.620460
retcall       0.196956
Length: 66, dtype: float64
```

[52]:
```
x_std_calibration.head(66)
```

[52]:
```
revenue      44.142432
mou         524.759890
recchrge     23.714145
directas      2.072555
overage      98.272111
```

```
               …
income         3.144329
mcycle         0.117285
setprcm        0.494208
setprc        56.620460
retcall        0.196956
Length: 66, dtype: float64
```

[53]:
```
odds_ratios=mba263.odds_ratios(res_logit30)['Odds ratios']
odds_ratios
```

[53]:
```
revenue     1.001944
mou         0.999718
recchrge    0.996892
directas    0.999015
overage     1.000769
              …
income      0.994096
mcycle      1.000000
setprcm     0.955745
setprc      1.000879
retcall     1.893728
Name: Odds ratios, Length: 66, dtype: float64
```

[54]:
```
normalized_odds_ratios2=numpy.power(odds_ratios,x_std_calibration)
normalized_odds_ratios2
```

[54]:
```
revenue     1.089533
mou         0.862534
recchrge    0.928851
directas    0.997959
overage     1.078515
              …
income      0.981554
mcycle      1.000000
setprcm     0.977879
setprc      1.050999
retcall     1.134017
Length: 66, dtype: float64
```

[55]:
```
normalized_odds_ratios2[normalized_odds_ratios2<1]=1/
 ↪normalized_odds_ratios2[normalized_odds_ratios2<1]
```

[56]:
```
normalized_odds_ratios2.sort_values(ascending=False)
```

[56]:
```
eqpdays     1.435340
uniqsubs    1.243078
```

```
months      1.204579
mou         1.159374
changem     1.136461
              …
occstud     1.000000
occcrft     1.000000
occcler     1.000000
occprof     1.000000
rv          1.000000
Length: 66, dtype: float64
```

[57]:
```
normalized_odds_ratios2.sort_values(ascending=False).head(10)
```

[57]:
```
eqpdays     1.435340
uniqsubs    1.243078
months      1.204579
mou         1.159374
changem     1.136461
retcall     1.134017
actvsubs    1.121160
creditaa    1.106692
changer     1.095552
revenue     1.089533
dtype: float64
```

[58]:
```
normalized_odds_ratios2.sort_values(ascending=False).
 ↪to_csv('cell2cell_normalized2.csv')
```

[59]:
```
normalized_odds_ratios2.to_csv('cell2cell_normalized_original_order2.csv')
```

[62]:
```
x_std_calibration.to_csv('cell2cell_x_std_calibration.csv')
```

[64]:
```
odds_ratios.to_csv('cell2cell_odds_ratios_updated.csv')
```

[ ]:
```

```