EDA No. 7 AAA Project Martin George mgeorgevienna@gmail.com

```
In [1]: %matplotlib inline
    import matplotlib.pyplot as plt
    import numpy as np
    import pandas as pd
    df = pd.read_csv('member_sample.csv', index_col = 0)
In []:
```

Application of using GAIN LIFT on a model on AAA data

```
In [2]: df.head()
        df.info()
        df.columns
        <class 'pandas.core.frame.DataFrame'>
        Int64Index: 21344 entries, 0 to 99998
        Columns: 112 entries, Individual Key to Was Towed To AAR Referral
        dtypes: float64(35), object(77)
        memory usage: 18.4+ MB
Out[2]: Index(['Individual Key', 'Household Key', 'Member Flag', 'City',
               'State - Grouped', 'ZIP5', 'ZIP9', 'FSV CMSI Flag',
               'FSV Credit Card Flag', 'FSV Deposit Program Flag',
               'SC Vehicle Manufacturer Name', 'SC Vehicle Model Name',
               'SVC Facility Name', 'SVC Facility Type', 'Total Cost',
               'Tow Destination Latitude', 'Tow Destination Longitude',
               'Tow Destination Name', 'Was Duplicated', 'Was Towed To AAR Referral'],
               dtype='object', length=112)
```

In [3]: df.head()

Out[3]:

	Individual Key	Household Key	Member Flag	City	State - Grouped	ZIP5	ZIP9	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	 SC Vehicle Manufacturer Name	SC Vehicle Model Name	SVC Facility Name	F
0	10000003.0	10462590.0	Υ	NEW HAVEN	СТ	6511.0	65111349.0	N	N	N	 NaN	NaN	NaN	
1	52211550.0	4500791.0	Υ	WEST WARWICK	RI	2893.0	28933850.0	N	Y	N	 ТОУОТА	CAMRY	ASTRO WRECKER SERVICE	indepe
2	52211550.0	4500791.0	Υ	WEST WARWICK	RI	2893.0	28933850.0	N	Υ	N	 ТОУОТА	CAMRY	Astro Wrecker Service	indepe
3	52211550.0	4500791.0	Υ	WEST WARWICK	RI	2893.0	28933850.0	N	Υ	N	 TOYOTA	CAMRY	ASTRO WRECKER SERVICE	indep€
4	52211550.0	4500791.0	Υ	WEST WARWICK	RI	2893.0	28933850.0	N	Y	N	 ТОУОТА	CAMRY	ASTRO WRECKER SERVICE	indepe
5 rd	ows × 112 co	olumns												

In [4]: df.groupby('FSV CMSI Flag').mean()

Out[4]:

	Individual Key	Household Key	ZIP5	ZIP9	Length Of Residence	Do Not Direct Mail Solicit	Email Available	ERS ENT Count Year 1	ERS ENT Count Year 2	ERS ENT Count Year 3	 Member Match Flag	Me Numbe Associa
FSV CMSI Flag												
N	3.403291e+07	1.600860e+07	2947.671848	2.948020e+07	11.552839	0.054041	0.52604	0.517824	0.921864	0.952447	 1.0	1.091986
Υ	2.398762e+07	1.515128e+07	2885.457413	2.885794e+07	11.088766	0.027340	0.75184	0.531746	1.193878	1.090703	 1.0	1.071187

2 rows × 35 columns

Consider a classification problem.

```
In [5]: def yn(x):
    return x.replace('N',0).replace('Y',1)

In [6]: products_c= [i for i in df.columns if i.startswith('FSV')]

In [7]: products = df[[i for i in df.columns if i.startswith('FSV')]]
```

In [8]: products

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
0	N	N	N	N	N	N
1	N	Υ	N	N	N	N
2	N	Υ	N	N	N	N
3	N	Υ	N	N	N	N
4	N	Υ	N	N	N	N
5	N	Υ	N	N	N	N
6	N	Υ	N	N	N	N
7	N	Υ	N	N	N	N
8	N	Υ	N	N	N	N
9	N	Υ	N	N	N	N
10	N	N	N	N	N	N
11	N	N	N	N	N	N
12	N	N	N	N	N	N
13	N	N	N	N	N	N
14	N	N	N	N	N	N
15	N	N	N	N	N	N
16	N	N	N	N	N	N
17	N	N	N	N	N	N
18	N	N	N	N	N	N
19	N	N	N	N	N	N
20	N	N	N	N	N	N
21	N	N	N	N	N	N
22	N	N	N	N	N	N
23	N	N	N	N	N	N
24	N	N	N	N	N	N
25	N	N	N	N	N	N
26	N	N	N	N	N	N
27	N	N	N	N	N	N
28	N	N	N	N	N	N

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
29	N	N	N	N	N	N
99968	N	N	N	N	N	N
99969	N	N	N	N	N	N
99970	N	N	N	N	N	N
99971	N	N	N	N	N	N
99972	N	N	N	N	N	N
99973	N	N	N	N	N	N
99974	N	N	N	N	N	N
99975	N	N	N	N	N	N
99976	N	N	N	N	N	N
99977	N	N	N	N	N	N
99979	N	N	N	N	N	N
99980	N	N	N	N	N	N
99981	N	N	N	N	N	N
99982	N	N	N	N	Υ	N
99983	Υ	N	N	N	N	N
99984	Υ	N	N	N	N	N
99985	Υ	N	N	N	N	N
99986	Υ	N	N	N	N	N
99987	Υ	N	N	N	N	N
99988	N	Υ	N	N	N	N
99989	Υ	N	N	N	N	N
99990	N	N	N	N	N	N
99991	N	N	N	N	N	N
99992	N	N	N	N	N	N
99993	N	N	N	N	N	N
99994	N	N	N	N	N	N
99995	N	N	N	N	N	N
99996	N	N	N	N	N	N

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
99997	N	N	N	N	N	N
99998	N	N	N	N	N	N

21344 rows × 6 columns

In []: #products['FSV CMSI Flag'].apply(yn)

In [10]: products

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
0	N	N	N	N	N	N
1	N	Υ	N	N	N	N
2	N	Υ	N	N	N	N
3	N	Υ	N	N	N	N
4	N	Υ	N	N	N	N
5	N	Υ	N	N	N	N
6	N	Υ	N	N	N	N
7	N	Υ	N	N	N	N
8	N	Υ	N	N	N	N
9	N	Υ	N	N	N	N
10	N	N	N	N	N	N
11	N	N	N	N	N	N
12	N	N	N	N	N	N
13	N	N	N	N	N	N
14	N	N	N	N	N	N
15	N	N	N	N	N	N
16	N	N	N	N	N	N
17	N	N	N	N	N	N
18	N	N	N	N	N	N
19	N	N	N	N	N	N
20	N	N	N	N	N	N
21	N	N	N	N	N	N
22	N	N	N	N	N	N
23	N	N	N	N	N	N
24	N	N	N	N	N	N
25	N	N	N	N	N	N
26	N	N	N	N	N	N
27	N	N	N	N	N	N
28	N	N	N	N	N	N

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
29	N	N	N	N	N	N
99968	N	N	N	N	N	N
99969	N	N	N	N	N	N
99970	N	N	N	N	N	N
99971	N	N	N	N	N	N
99972	N	N	N	N	N	N
99973	N	N	N	N	N	N
99974	N	N	N	N	N	N
99975	N	N	N	N	N	N
99976	N	N	N	N	N	N
99977	N	N	N	N	N	N
99979	N	N	N	N	N	N
99980	N	N	N	N	N	N
99981	N	N	N	N	N	N
99982	N	N	N	N	Υ	N
99983	Υ	N	N	N	N	N
99984	Υ	N	N	N	N	N
99985	Υ	N	N	N	N	N
99986	Υ	N	N	N	N	N
99987	Υ	N	N	N	N	N
99988	N	Υ	N	N	N	N
99989	Υ	N	N	N	N	N
99990	N	N	N	N	N	N
99991	N	N	N	N	N	N
99992	N	N	N	N	N	N
99993	N	N	N	N	N	N
99994	N	N	N	N	N	N
99995	N	N	N	N	N	N
99996	N	N	N	N	N	N

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
99997	N	N	N	N	N	N
99998	N	N	N	N	N	N

21344 rows × 6 columns

In [24]: products = products.apply(yn)

In [25]: products

Out[25]:

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
0	0	0	0	0	0	0
1	0	1	0	0	0	0
2	0	1	0	0	0	0
3	0	1	0	0	0	0
4	0	1	0	0	0	0
5	0	1	0	0	0	0
6	0	1	0	0	0	0
7	0	1	0	0	0	0
8	0	1	0	0	0	0
9	0	1	0	0	0	0
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	0	0	0
16	0	0	0	0	0	0
17	0	0	0	0	0	0
18	0	0	0	0	0	0
19	0	0	0	0	0	0
20	0	0	0	0	0	0
21	0	0	0	0	0	0
22	0	0	0	0	0	0
23	0	0	0	0	0	0
24	0	0	0	0	0	0
25	0	0	0	0	0	0
26	0	0	0	0	0	0
27	0	0	0	0	0	0
28	0	0	0	0	0	0

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
29	0	0	0	0	0	0
99968	0	0	0	0	0	0
99969	0	0	0	0	0	0
99970	0	0	0	0	0	0
99971	0	0	0	0	0	0
99972	0	0	0	0	0	0
99973	0	0	0	0	0	0
99974	0	0	0	0	0	0
99975	0	0	0	0	0	0
99976	0	0	0	0	0	0
99977	0	0	0	0	0	0
99979	0	0	0	0	0	0
99980	0	0	0	0	0	0
99981	0	0	0	0	0	0
99982	0	0	0	0	1	0
99983	1	0	0	0	0	0
99984	1	0	0	0	0	0
99985	1	0	0	0	0	0
99986	1	0	0	0	0	0
99987	1	0	0	0	0	0
99988	0	1	0	0	0	0
99989	1	0	0	0	0	0
99990	0	0	0	0	0	0
99991	0	0	0	0	0	0
99992	0	0	0	0	0	0
99993	0	0	0	0	0	0
99994	0	0	0	0	0	0
99995	0	0	0	0	0	0
99996	0	0	0	0	0	0

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag
99997	0	0	0	0	0	0
99998	0	0	0	0	0	0

21344 rows × 6 columns

In [26]: model_df = pd.concat([products , df[['Household Key','Total Cost']]], axis=1)

In [27]: | model_df

]:	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag	Household Key	Total Cost
0	0	0	0	0	0	0	10462590.0	NaN
1	0	1	0	0	0	0	4500791.0	32.50
2	0	1	0	0	0	0	4500791.0	30.00
3	0	1	0	0	0	0	4500791.0	32.50
4	0	1	0	0	0	0	4500791.0	30.00
5	0	1	0	0	0	0	4500791.0	53.00
6	0	1	0	0	0	0	4500791.0	30.00
7	0	1	0	0	0	0	4500791.0	32.00
8	0	1	0	0	0	0	4500791.0	32.00
9	0	1	0	0	0	0	4500791.0	32.50
10	0	0	0	0	0	0	4317516.0	NaN
11	0	0	0	0	0	0	11622991.0	58.85
12	0	0	0	0	0	0	11622991.0	53.00
13	0	0	0	0	0	0	11622991.0	53.00
14	0	0	0	0	0	0	11622991.0	NaN
15	0	0	0	0	0	0	11622991.0	NaN
16	0	0	0	0	0	0	11622991.0	53.00
17	0	0	0	0	0	0	11622991.0	53.00
18	0	0	0	0	0	0	11622991.0	53.00
19	0	0	0	0	0	0	11622991.0	29.00
20	0	0	0	0	0	0	579810.0	28.00
21	0	0	0	0	0	0	7187017.0	53.00
22	0	0	0	0	0	0	7187017.0	53.00
23	0	0	0	0	0	0	7187017.0	53.00
24	0	0	0	0	0	0	7187017.0	53.00
25	0	0	0	0	0	0	7187017.0	53.00
26	0	0	0	0	0	0	7187017.0	58.85
27	0	0	0	0	0	0	7728088.0	53.00
28	0	0	0	0	0	0	7728088.0	53.00

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag	Household Key	Total Cost
29	0	0	0	0	0	0	7728088.0	53.00
99968	0	0	0	0	0	0	1588987.0	NaN
99969	0	0	0	0	0	0	16604128.0	47.00
99970	0	0	0	0	0	0	16604128.0	58.85
99971	0	0	0	0	0	0	16604128.0	58.85
99972	0	0	0	0	0	0	16604128.0	53.00
99973	0	0	0	0	0	0	16604128.0	53.00
99974	0	0	0	0	0	0	16604128.0	58.85
99975	0	0	0	0	0	0	16604128.0	NaN
99976	0	0	0	0	0	0	45466286.0	NaN
99977	0	0	0	0	0	0	45466286.0	34.00
99979	0	0	0	0	0	0	15397653.0	NaN
99980	0	0	0	0	0	0	15397653.0	NaN
99981	0	0	0	0	0	0	15397653.0	NaN
99982	0	0	0	0	1	0	15397653.0	NaN
99983	1	0	0	0	0	0	13735475.0	29.00
99984	1	0	0	0	0	0	13735475.0	44.00
99985	1	0	0	0	0	0	13735475.0	29.00
99986	1	0	0	0	0	0	13735475.0	47.00
99987	1	0	0	0	0	0	13735475.0	44.00
99988	0	1	0	0	0	0	13735475.0	82.00
99989	1	0	0	0	0	0	5462399.0	29.43
99990	0	0	0	0	0	0	5462399.0	NaN
99991	0	0	0	0	0	0	5462399.0	NaN
99992	0	0	0	0	0	0	5462399.0	NaN
99993	0	0	0	0	0	0	20330346.0	53.00
99994	0	0	0	0	0	0	20330346.0	36.00
99995	0	0	0	0	0	0	20330346.0	53.00

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag	Household Key	Total Cost
99996	0	0	0	0	0	0	8325571.0	58.85
99997	0	0	0	0	0	0	8325571.0	58.85
99998	0	0	0	0	0	0	8325571.0	NaN

21344 rows × 8 columns

```
In [28]: from sklearn.linear_model import LogisticRegression
    from sklearn.ensemble import GradientBoostingClassifier

In [29]: lgr = LogisticRegression()
    gbr = GradientBoostingClassifier()

In [30]: #modet_df_g = modet_df.groupby(['Household Key'])['FSV CMSI FLag'].sum()

In [31]: #modet_df_g

In [32]: modet_df_g = modet_df.groupby(['Household Key']).sum()

In [33]: modet_df_g = modet_df.groupby(['Household Key']).sum()

In [34]: mg = modet_df_g.dropna()

In [35]: mg.shape

Out[35]: (5241, 7)
```

In [36]: model_df_g

Household Key 875.0 969.0 3338.0 8718.0 11524.0 13422.0 19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 0 0 0 1 0 0	1 0 0 0 0 0 0 0 0		0 0 0 0 0 0 0 0			1063.20 226.10 0.00 0.00 294.25 118.85 0.00 537.25 0.00 0.00 34.00 0.00
969.0 3338.0 8718.0 11524.0 13422.0 19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 0 0 1 0 0 0			0 0 0 0 0 0 0 0		0 0 0 0 0 0 0	226.10 0.00 0.00 294.25 118.85 0.00 537.25 0.00 0.00 34.00
3338.0 8718.0 11524.0 13422.0 19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 0 0 1 0 0 0		0 0 0 0 0 0 0	0 0 0 0 0 0 0	0 0 0 0 0 0 0	0 0 0 0 0 0 0	0.00 0.00 294.25 118.85 0.00 537.25 0.00 0.00 34.00
8718.0 11524.0 13422.0 19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 1 0 0 0	0 0 0 0 0 0 0	0 0 0 0 0 0 0	0 0 0 0 0 0 0	0 0 0 0 0 0	0 0 0 0 0 0	0.00 294.25 118.85 0.00 537.25 0.00 0.00 34.00
11524.0 13422.0 19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 1 0 0 0	0 0 0 0 0 0	0 0 0 0 0 0	0 0 0 0 0 0	0 0 0 0 0 0	0 0 0 0 0 0	294.25 118.85 0.00 537.25 0.00 0.00 34.00
13422.0 19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 1 0 0 0	0 0 0 0 0 0	0 0 0 0 0	0 0 0 0 0	0 0 0 0 0	0 0 0 0 0	118.85 0.00 537.25 0.00 0.00 34.00
19747.0 20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 1 0 0 0 0	0 0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0.00 537.25 0.00 0.00 34.00
20469.0 20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	1 0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	537.25 0.00 0.00 34.00
20850.0 25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 0	0 0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0.00 0.00 34.00
25365.0 30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 0 1	0 0 0	0	0	0	0	0.00 34.00
30007.0 37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 0 1	0	0	0	0	0	34.00
37468.0 38093.0 41756.0 43381.0 49578.0 55047.0	0 1	0					
38093.0 41756.0 43381.0 49578.0 55047.0	1		0	0	0	0	0.00
41756.0 43381.0 49578.0 55047.0		0					
43381.0 49578.0 55047.0	•	3	0	0	1	0	555.85
49578.0 55047.0	6	0	0	0	0	0	518.35
55047.0	0	0	0	0	0	0	102.00
	0	0	0	0	0	0	30.00
55295.0	0	0	0	2	2	0	60.00
	0	0	0	0	0	0	0.00
73421.0	0	0	0	0	1	0	0.00
93896.0	0	1	0	0	0	0	130.00
94927.0	0	0	0	0	0	0	0.00
103545.0	0	9	0	0	0	0	390.35
106487.0	0	0	0	0	0	0	178.70
115289.0	0	0	0	0	0	0	0.00
115306.0	0	0	0	0	0	0	0.00
115346.0	0	0	0	0	0	0	0.00
115351.0		2	0	0	0	0	38.00

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag	Total Cost
Household Key							
115430.0	0	0	0	0	0	0	53.00
116806.0	15	1	0	0	0	0	2189.60
117430.0	0	0	0	0	0	0	165.00
99800577.0	0	0	0	0	0	0	454.85
99817387.0	0	0	0	0	0	0	270.85
99817390.0	0	0	0	0	0	0	0.00
99839301.0	0	0	0	0	0	0	0.00
99843098.0	0	0	0	0	0	0	117.70
99851820.0	0	0	0	0	0	0	147.50
99873114.0	0	0	0	0	0	0	318.85
99881116.0	0	0	0	0	0	0	106.00
99953012.0	0	0	0	0	0	0	58.85
99987696.0	2	0	0	0	0	0	53.00
99991498.0	0	0	0	0	0	0	0.00
99992624.0	0	0	0	0	0	0	276.00
99992663.0	0	0	0	0	0	0	122.00
99993288.0	0	0	0	0	0	0	229.55
99996562.0	0	0	0	0	0	0	265.00
100004477.0	0	0	0	0	0	0	0.00
100016608.0	0	0	0	0	0	0	323.39
100020029.0	0	0	0	0	0	0	53.00
100022741.0	0	0	0	0	0	0	0.00
100023243.0	0	0	0	0	0	0	0.00
100035899.0	1	0	0	0	0	0	0.00
100053546.0	0	0	0	0	0	0	53.00
100064720.0	0	2	0	0	0	0	54.00
100065197.0	0	0	0	0	0	0	297.35

	FSV CMSI Flag	FSV Credit Card Flag	FSV Deposit Program Flag	FSV Home Equity Flag	FSV ID Theft Flag	FSV Mortgage Flag	Total Cost
Household Key							
100067809.0	0	0	0	0	0	0	212.00
100069201.0	0	0	0	0	0	0	106.00
100070004.0	0	0	0	0	0	0	60.00
100071861.0	0	0	0	0	0	0	447.40
100071870.0	0	0	0	0	0	0	211.00
100079136.0	14	0	0	0	0	0	771.75

5241 rows × 7 columns

Apply classification model (Logistics and GredeintBoost) on 'FSV CMSI Flag' and ' ÞSV Credit Card Flag' and compare the gain lift in each model.

```
In [37]: X = model_df_g[['Total Cost']]
In [38]: y = model_df_g[['FSV CMSI Flag']]
In [39]: y = np.where(y>0,1,0)
In [41]: from sklearn.model_selection import train_test_split
In [42]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
In [43]: lgr.fit(X train, y train)
         predicted probas = lgr.predict proba(X test)
```

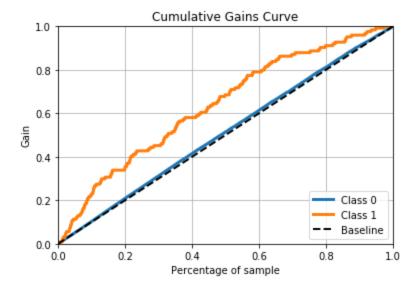
C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.py:73: DataConversionWarn ing: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n samples,), for exa mple using ravel().

return f(**kwargs)

In [44]: # The magic happens here import matplotlib.pyplot as plt import scikitplot as skplt skplt.metrics.plot_cumulative_gain(y_test, predicted_probas) plt.show()

C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib\cbook__init__.py:424: MatplotlibDeprec ationWarning:

Passing one of 'on', 'true', 'off', 'false' as a boolean is deprecated; use an actual boolean (True/False) instead. warn_deprecated("2.2", "Passing one of 'on', 'true', 'off', 'false' as a "



In [45]: gbr.fit(X_train, y_train)
 predicted_probas = gbr.predict_proba(X_test)

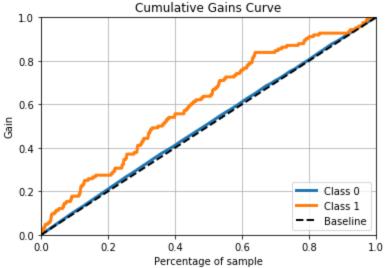
C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.py:73: DataConversionWarn ing: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

return f(**kwargs)

```
In [46]: skplt.metrics.plot_cumulative_gain(y_test, predicted_probas)
    plt.show()
```

C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib\cbook__init__.py:424: MatplotlibDeprec ationWarning:

Passing one of 'on', 'true', 'off', 'false' as a boolean is deprecated; use an actual boolean (True/False) instead. warn_deprecated("2.2", "Passing one of 'on', 'true', 'off', 'false' as a "



```
In [47]: lgr.score(X,y)
Out[47]: 0.9297843922915474

In [48]: gbr.score(X,y)
Out[48]: 0.9328372448006106

In [49]: y = model_df_g[['FSV Credit Card Flag']]

In [50]: y = np.where(y>0,1,0)

In [51]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
```

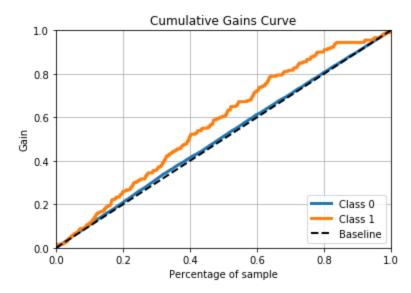
```
In [52]: lgr.fit(X_train, y_train)
    predicted_probas = lgr.predict_proba(X_test)
```

C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.py:73: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for exa
mple using ravel().
 return f(**kwargs)

```
In [53]: skplt.metrics.plot_cumulative_gain(y_test, predicted_probas)
    plt.show()
```

C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib\cbook__init__.py:424: MatplotlibDeprec ationWarning:

Passing one of 'on', 'true', 'off', 'false' as a boolean is deprecated; use an actual boolean (True/False) instead. warn_deprecated("2.2", "Passing one of 'on', 'true', 'off', 'false' as a "



In [54]: |lgr.score(X,y)

Out[54]: 0.8895248998282771

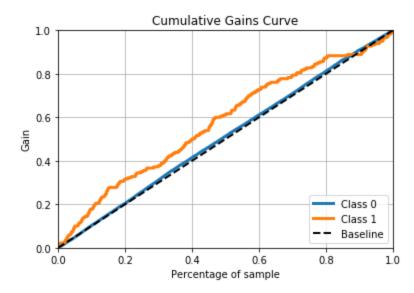
```
In [55]: gbr.fit(X_train, y_train)
    predicted_probas = gbr.predict_proba(X_test)
```

C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\validation.py:73: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for exa
mple using ravel().
 return f(**kwargs)

```
In [56]: skplt.metrics.plot_cumulative_gain(y_test, predicted_probas)
    plt.show()
```

C:\Users\george\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib\cbook__init__.py:424: MatplotlibDeprec ationWarning:

Passing one of 'on', 'true', 'off', 'false' as a boolean is deprecated; use an actual boolean (True/False) instead. warn_deprecated("2.2", "Passing one of 'on', 'true', 'off', 'false' as a "



In [57]: gbr.score(X,y)

Out[57]: 0.8912421293646251

```
In [63]: model_df_g['FSV Credit Card Flag'].value_counts()
Out[63]: 0
                4663
          1
                 341
          2
                   84
                   65
                   29
          6
                  15
          5
                  12
          7
                    8
          9
          11
          10
          13
          12
          15
          14
                    1
          17
          Name: FSV Credit Card Flag, dtype: int64
In [65]: | model_data = np.where(model_df_g>0,1,0)
In [68]: | model_data
Out[68]: array([[0, 1, 0, ..., 0, 0, 1],
                 [0, 0, 0, \ldots, 0, 0, 1],
                 [0, 0, 0, \ldots, 0, 0, 0],
                 [0, 0, 0, \ldots, 0, 0, 1],
                 [0, 0, 0, \ldots, 0, 0, 1],
                 [1, 0, 0, \ldots, 0, 0, 1]])
```

Drawing ROC curve

One of the most commonly used metrics nowadays is AUC-ROC (Area Under Curve - Receiver Operating Characteristics) curve. ROC curves are pretty easy to understand and evaluate once there is a good understanding of confusion matrix and different kinds of errors.

```
In [87]: from sklearn.metrics import roc curve
          from sklearn.metrics import roc auc score
In [88]: def plot_roc_curve(fpr, tpr):
              plt.plot(fpr, tpr, color='orange', label='ROC')
              plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--')
              plt.xlabel('False Positive Rate')
              plt.ylabel('True Positive Rate')
              plt.title('Receiver Operating Characteristic (ROC) Curve')
              plt.legend()
              plt.show()
In [96]: probs = lgr.predict proba(X test)
 In [97]: probs
Out[97]: array([[0.89739947, 0.10260053],
                 [0.86989481, 0.13010519],
                 [0.89321462, 0.10678538],
                 [0.89739947, 0.10260053],
                 [0.89479453, 0.10520547],
                 [0.89739947, 0.10260053]])
In [98]: probs = probs[:, 1]
 In [99]: | auc = roc_auc_score(y_test, probs)
          print('AUC: %.2f' % auc)
          AUC: 0.58
In [100]: fpr, tpr, thresholds = roc_curve(y_test, probs)
```

```
In [101]:
           plot_roc_curve(fpr, tpr)
                      Receiver Operating Characteristic (ROC) Curve
               1.0
                        ROC
               0.8
            True Positive Rate
               0.6
               0.4
               0.2
               0.0
                             0.2
                   0.0
                                      0.4
                                               0.6
                                                        0.8
                                                                 1.0
                                    False Positive Rate
  In [ ]:
  In [ ]:
  In [ ]:
  In [ ]:
  In [ ]:
 In [ ]:
           probs = gbr.predict_proba(X_test)
 In [89]:
 In [90]: probs
 Out[90]: array([[0.93032273, 0.06967727],
                    [0.81500049, 0.18499951],
                    [0.85242294, 0.14757706],
```

[0.93032273, 0.06967727], [0.81036009, 0.18963991], [0.93032273, 0.06967727]])

```
In [91]:
          probs = probs[:, 1]
In [92]:
          probs
Out[92]: array([0.06967727, 0.18499951, 0.14757706, ..., 0.06967727, 0.18963991,
                  0.06967727])
          auc = roc_auc_score(y_test, probs)
In [93]:
          print('AUC: %.2f' % auc)
          AUC: 0.58
          fpr, tpr, thresholds = roc curve(y test, probs)
In [95]:
          plot_roc_curve(fpr, tpr)
                    Receiver Operating Characteristic (ROC) Curve
             1.0
                      ROC
             0.8
           True Positive Rate
             0.4
             0.2
```

We can see that ROC AUC score of both classifiers are same. But the ROC curve of Gradient Boosting Regression has advantage as there is a clear improvement of ROC before 20% in True positive cases.

0.0

0.2

0.4

False Positive Rate

0.6

0.8

1.0

AUC-ROC curve is one of				
machine learning algorith	ms particularly in th	ie cases where we	have imbalar	nced datasets.

In []:	
In []:	