

```
In [1]: import numpy as np
import pandas as pd
```

```
In [2]: df=pd.read_csv('df_autonomus.csv')
df
col1=list(df.self_driving)
col1
binary=[]
```

```
In [3]: for i in col1:
        if i=="Yes":
            binary.append(1)
        else:
            binary.append(0)
binary
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```
In [4]: df['new']=binary  
df.head(10)  
df.columns
```

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Out[4]: Index(['self_driving', 'safety_concern', 'carshare_level', 'rideshare_level',  
              'pevowner', 'income', 'householdvehicles', 'housing', 'parkingtype',  
              'new'],  
            dtype='object')
```

```
In [5]: resp=df['new']  
import statsmodels.formula.api as smf  
model = smf.logit(formula = 'new ~ safety_concern +carshare_level+ rideshare_level-  
model.summary()
```

```
Optimization terminated successfully.  
Current function value: 0.615207  
Iterations 6
```

Out[5]:

Logit Regression Results

Dep. Variable:	new	No. Observations:	3614
Model:	Logit	Df Residuals:	3598
Method:	MLE	Df Model:	15
Date:	Sun, 20 Nov 2022	Pseudo R-squ.:	0.1009
Time:	19:49:00	Log-Likelihood:	-2223.4
converged:	True	LL-Null:	-2472.8
Covariance Type:	nonrobust	LLR p-value:	9.765e-97

	coef	std err	z	P> z	[0.025	0.975]
Intercept	-0.6738	0.201	-3.352	0.001	-1.068	-0.280
safety_concern[T.Disagree]	0.9348	0.130	7.169	0.000	0.679	1.190
safety_concern[T.Neutral]	-0.7997	0.183	-4.367	0.000	-1.159	-0.441
carshare_level[T.Interested in participating]	-1.1363	0.141	-8.064	0.000	-1.413	-0.860
carshare_level[T.Not participating]	-0.6290	0.086	-7.286	0.000	-0.798	-0.460
rideshare_level[T.Interested in participating]	-0.2853	0.108	-2.641	0.008	-0.497	-0.074
rideshare_level[T.Not participating]	-0.3080	0.090	-3.415	0.001	-0.485	-0.131
pevowner[T.Yes]	-0.7011	0.146	-4.794	0.000	-0.988	-0.414
income[T.Low income]	0.3845	0.121	3.185	0.001	0.148	0.621
income[T.Middle income]	0.3431	0.101	3.382	0.001	0.144	0.542
householdvehicles[T.Three plus]	0.2899	0.108	2.674	0.007	0.077	0.502
householdvehicles[T.Two vehicle]	0.0926	0.086	1.076	0.282	-0.076	0.261
housing[T.Mobile based home]	-0.0124	0.277	-0.045	0.964	-0.556	0.531
housing[T.Others]	0.2625	0.580	0.453	0.651	-0.874	1.400
housing[T.Single family]	-0.1062	0.116	-0.913	0.361	-0.334	0.122
parkingtype[T.Shared parking]	-0.0326	0.114	-0.287	0.774	-0.255	0.190

INTERPRETATION Since p value ≤ 0.05 for

safety_concern,carshare_level,rideshare_level,pevowner,income and householdvehicles(Three plus) so these independent variables are significant

new model(discarding non significant values)

```
In [7]: # For the following columns the influence on the 'new' column or self driving
# will be zero or minimum since the values from 0.025 to 0.975 are changing
# from negative to positive.

#householdvehicles[T.Two vehicle]
#housing[T.Mobile based home]
#housing[T.Others]
```

```
#housing[T.Single family]
#parkingtype[T.Shared parking]
```

```
In [6]: model1 = smf.logit(formula = 'new ~ safety_concern + carshare_level + rideshare_level'
model1.summary()
```

Optimization terminated successfully.
Current function value: 0.615388
Iterations 6

Out[6]: Logit Regression Results

Dep. Variable:	new	No. Observations:	3614
Model:	Logit	Df Residuals:	3602
Method:	MLE	Df Model:	11
Date:	Sun, 20 Nov 2022	Pseudo R-squ.:	0.1006
Time:	19:49:03	Log-Likelihood:	-2224.0
converged:	True	LL-Null:	-2472.8
Covariance Type:	nonrobust	LLR p-value:	1.058e-99

	coef	std err	z	P> z	[0.025	0.975]
Intercept	-0.7517	0.173	-4.356	0.000	-1.090	-0.413
safety_concern[T.Disagree]	0.9306	0.130	7.150	0.000	0.675	1.186
safety_concern[T.Neutral]	-0.8031	0.183	-4.390	0.000	-1.162	-0.445
carshare_level[T.Interested in participating]	-1.1349	0.141	-8.061	0.000	-1.411	-0.859
carshare_level[T.Not participating]	-0.6282	0.086	-7.285	0.000	-0.797	-0.459
rideshare_level[T.Interested in participating]	-0.2828	0.108	-2.619	0.009	-0.494	-0.071
rideshare_level[T.Not participating]	-0.3056	0.090	-3.400	0.001	-0.482	-0.129
pevowner[T.Yes]	-0.7029	0.146	-4.808	0.000	-0.989	-0.416
income[T.Low income]	0.3967	0.120	3.320	0.001	0.162	0.631
income[T.Middle income]	0.3480	0.101	3.439	0.001	0.150	0.546
householdvehicles[T.Three plus]	0.2634	0.105	2.511	0.012	0.058	0.469
householdvehicles[T.Two vehicle]	0.0730	0.084	0.872	0.383	-0.091	0.237

In this output, all independent variables are statistically significant and the signs are logical, so this model can be used for further diagnosis.

```
In [7]: #calculating odds ratio
import numpy as np
conf = model1.conf_int()
conf['OR'] = model1.params
conf.columns = ['2.5%', '97.5%', 'OR']
print(np.exp(conf))
```

	2.5%	97.5%	OR
Intercept	0.336222	0.661340	0.471548
safety_concern[T.Disagree]	1.964963	3.272932	2.535979
safety_concern[T.Neutral]	0.312969	0.641128	0.447943
carshare_level[T.Interested in participating]	0.243954	0.423611	0.321468
carshare_level[T.Not participating]	0.450588	0.631803	0.533556
rideshare_level[T.Interested in participating]	0.609923	0.931284	0.753666
rideshare_level[T.Not participating]	0.617666	0.878570	0.736657
pevowner[T.Yes]	0.371810	0.659434	0.495161
income[T.Low income]	1.176418	1.879326	1.486901
income[T.Middle income]	1.161440	1.727050	1.416286
householdvehicles[T.Three plus]	1.059466	1.598391	1.301323
householdvehicles[T.Two vehicle]	0.912944	1.267628	1.075766

```
In [8]: #Predicting probabilities
from sklearn.metrics import confusion_matrix
predicted_values1 = model1.predict()
threshold=0.5
predicted_class1=np.zeros(predicted_values1.shape)
predicted_class1[predicted_values1>threshold]=1
cm1 = confusion_matrix(df['new'],predicted_class1)
print('Confusion Matrix : \n', cm1)
```

```
Confusion Matrix :
[[1514  534]
 [ 691  875]]
```

```
In [5]: # From confusion matrix we can say that 1514 are correctly predicted
# as not self_driving(True Negative) and 875 correctly predicted
# as self_driving (True Positive).

# 534 were predicted as self driving but all these were observed
#as non-self driving.(False Positive)

# 691 instances were predicted as non-self driving
#but were self-driving(False Negative)
```

```
In [6]: #From confusion matrix we can say that 1514 are correctly
#predicted as not self_driving and 875 correctly predicted
#self_driving

#The precision and recall values of the model are routinely
#assessed in a classification model.

#Precision tells us what percentage of predicted positive cases
#are correctly predicted.
#Recall tells us what percentage of actual positive cases are correctly predicted.
```

```
In [9]: from sklearn.metrics import classification_report
print(classification_report(df['new'],predicted_class1))
```

	precision	recall	f1-score	support
0	0.69	0.74	0.71	2048
1	0.62	0.56	0.59	1566
accuracy			0.66	3614
macro avg	0.65	0.65	0.65	3614
weighted avg	0.66	0.66	0.66	3614

```
In [4]: # Accuracy=66%
# Precision is 62% and Recall is 56% for self driving affinity
```

```
In [3]: #The precision and recall values of the model  
#are routinely assessed in a classification model.  
  
#Precision tells us what percentage of predicted positive cases  
#are correctly predicted.  
#Recall tells us what percentage of actual positive cases are correctly predicted.
```

```
In [10]: import numpy as np  
import pandas as pd
```

```
In [11]: df=pd.read_csv('df_autonomus.csv')  
df  
col1=list(df.self_driving)  
col1  
  
MNLogit=[]
```

```
In [12]: for i in col1:  
    if i=='Yes':  
        MNLogit.append(1)  
    elif i== 'Neutral':  
        MNLogit.append(2)  
    else:  
        MNLogit.append(3)  
MNLogit
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```

```
In [13]: df['MNLogit_new']=MNLogit  
df.head(10)  
df.columns
```

```
Out[13]: Index(['self_driving', 'safety_concern', 'carshare_level', 'rideshare_level',  
               'pevowner', 'income', 'householdvehicles', 'housing', 'parkingtype',  
               'MNLogit_new'],  
              dtype='object')
```

```
In [15]: from statsmodels.discrete.discrete_model import MNLogit  
formula = 'MNLogit_new ~ safety_concern + carshare_level + rideshare_level + pevowner +  
model_MNL = MNLogit.from_formula(formula=formula , data = df ).fit()  
print(model_MNL.summary())
```

Optimization terminated successfully.
Current function value: 0.958242
Iterations 6

MNLogit Regression Results

```

=====
Dep. Variable:          MNLogit_new    No. Observations:          3614
Model:                  MNLogit        Df Residuals:              3582
Method:                  MLE           Df Model:                  30
Date:                   Sun, 20 Nov 2022 Pseudo R-squ.:             0.09351
Time:                   19:51:21       Log-Likelihood:            -3463.1
converged:              True          LL-Null:                  -3820.3
Covariance Type:        nonrobust      LLR p-value:              4.721e-131
=====

```

```

=====
MNLogit_new=2      coef      std err      z
P>|z|      [0.025      0.975]
-----
Intercept      -1.4423      0.294      -4.903
0.000      -2.019      -0.866
safety_concern[T.Disagree]      0.2115      0.218      0.972
0.331      -0.215      0.638
safety_concern[T.Neutral]      2.1754      0.255      8.533
0.000      1.676      2.675
carshare_level[T.Interested in participating]      0.7351      0.184      3.999
0.000      0.375      1.095
carshare_level[T.Not participating]      0.5655      0.111      5.072
0.000      0.347      0.784
rideshare_level[T.Interested in participating]      0.0518      0.138      0.374
0.708      -0.219      0.323
rideshare_level[T.Not participating]      -0.0454      0.116      -0.390
0.697      -0.274      0.183
pevowner[T.Yes]      0.2319      0.200      1.161
0.246      -0.159      0.623
income[T.Low income]      -0.1716      0.156      -1.101
0.271      -0.477      0.134
income[T.Middle income]      -0.1523      0.133      -1.147
0.251      -0.412      0.108
householdvehicles[T.Three plus]      -0.2729      0.141      -1.941
0.052      -0.549      0.003
householdvehicles[T.Two vehicle]      -0.0653      0.109      -0.599
0.549      -0.279      0.148
housing[T.Mobile based home]      -0.0654      0.384      -0.170
0.865      -0.818      0.688
housing[T.Others]      0.4040      0.617      0.655
0.512      -0.804      1.612
housing[T.Single family]      0.2379      0.150      1.591
0.112      -0.055      0.531
parkingtype[T.Shared parking]      0.2292      0.143      1.605
0.109      -0.051      0.509

```

```

-----
MNLogit_new=3      coef      std err      z
P>|z|      [0.025      0.975]
-----
Intercept      0.5373      0.219      2.457
0.014      0.109      0.966
safety_concern[T.Disagree]      -1.3226      0.137      -9.688
0.000      -1.590      -1.055
safety_concern[T.Neutral]      0.1995      0.194      1.029
0.304      -0.181      0.580
carshare_level[T.Interested in participating]      1.3260      0.150      8.813
0.000      1.031      1.621

```

carshare_level[T.Not participating]	0.6690	0.097	6.886
0.000 0.479 0.859			
rideshare_level[T.Interested in participating]	0.4749	0.123	3.857
0.000 0.234 0.716			
rideshare_level[T.Not participating]	0.5506	0.104	5.316
0.000 0.348 0.754			
pevowner[T.Yes]	0.8897	0.154	5.775
0.000 0.588 1.192			
income[T.Low income]	-0.5079	0.135	-3.775
0.000 -0.772 -0.244			
income[T.Middle income]	-0.4464	0.111	-4.015
0.000 -0.664 -0.228			
householdvehicles[T.Three plus]	-0.2947	0.122	-2.406
0.016 -0.535 -0.055			
householdvehicles[T.Two vehicle]	-0.1050	0.097	-1.079
0.280 -0.296 0.086			
housing[T.Mobile based home]	0.0355	0.312	0.114
0.909 -0.576 0.647			
housing[T.Others]	-1.6333	1.109	-1.473
0.141 -3.807 0.541			
housing[T.Single family]	0.0160	0.131	0.123
0.902 -0.240 0.272			
parkingtype[T.Shared parking]	-0.1056	0.129	-0.819
0.413 -0.358 0.147			

=====

=====

```
In [ ]: # for both MNL =2 and MNL=3 tables some variables are not signigant
# hence i would later be fitting a regression model between those parameters that
# matter

# The values ranging from negative to positive in 0.025 and 0.975
# have no or minimum effect on our response variable

# only safety_concern[T.Neutral] and carshare_level are significant when
# compared to MNL_new = 1 for those who are taking neutral stand(MNL_new=2) in adop
# autonomous vehicles(P<0.05)

# Income[T.Low income] has odds ratio of e^-0.1716 = 0.8423 for MNL_new = 2
# and Income[T.Low income] has odds ratio of e^-0.5079 = 0.6017
# For both the values the lower income will reduce the odds for adoption
# of autonomous vehicles because the odds ratio values are less than 1.

#householdvehicles[T.Two vehicle],housing[T.Mobile based home],housing[T.Others]
#housing[T.Single family],parkingtype[T.Shared parking] are not significant
# with respect to People saying 'Yes' or MNL_new =1
```

```
In [ ]:
```

```
In [16]: model_MNL.params
np.exp(model_MNL.params)
```

Out[16]:

	0	1
Intercept	0.236390	1.711381
safety_concern[T.Disagree]	1.235509	0.266433
safety_concern[T.Neutral]	8.805343	1.220761
carshare_level[T.Interested in participating]	2.085759	3.766129
carshare_level[T.Not participating]	1.760378	1.952310
rideshare_level[T.Interested in participating]	1.053182	1.607932
rideshare_level[T.Not participating]	0.955638	1.734321
pevowner[T.Yes]	1.260941	2.434345
income[T.Low income]	0.842348	0.601763
income[T.Middle income]	0.858758	0.639910
householdvehicles[T.Three plus]	0.761154	0.744734
householdvehicles[T.Two vehicle]	0.936783	0.900284
housing[T.Mobile based home]	0.936711	1.036154
housing[T.Others]	1.497748	0.195292
housing[T.Single family]	1.268627	1.016157
parkingtype[T.Shared parking]	1.257552	0.899802

```
In [17]: #Marginal Effects
print(model_MNL.get_margeff().summary())
```


MNLogit Marginal Effects

Dep. Variable: MNLogit_new
Method: dydx
At: overall

	MNLogit_new=1		dy/dx	std err	z
P> z	[0.025	0.975]			

safety_concern[T.Disagree]			0.1533	0.029	5.204
0.000	0.096	0.211			
safety_concern[T.Neutral]			-0.2100	0.040	-5.243
0.000	-0.288	-0.131			
carshare_level[T.Interested in participating]			-0.2339	0.029	-7.944
0.000	-0.292	-0.176			
carshare_level[T.Not participating]			-0.1345	0.018	-7.488
0.000	-0.170	-0.099			
rideshare_level[T.Interested in participating]			-0.0659	0.023	-2.855
0.004	-0.111	-0.021			
rideshare_level[T.Not participating]			-0.0674	0.019	-3.512
0.000	-0.105	-0.030			
pevowner[T.Yes]			-0.1348	0.032	-4.261
0.000	-0.197	-0.073			
income[T.Low income]			0.0803	0.026	3.114
0.002	0.030	0.131			
income[T.Middle income]			0.0707	0.022	3.260
0.001	0.028	0.113			
householdvehicles[T.Three plus]			0.0613	0.023	2.647
0.008	0.016	0.107			
householdvehicles[T.Two vehicle]			0.0191	0.018	1.038
0.299	-0.017	0.055			
housing[T.Mobile based home]			0.0009	0.060	0.016
0.987	-0.116	0.118			
housing[T.Others]			0.1772	0.162	1.092
0.275	-0.141	0.495			
housing[T.Single family]			-0.0222	0.025	-0.892
0.372	-0.071	0.027			
parkingtype[T.Shared parking]			-0.0057	0.024	-0.236
0.814	-0.053	0.042			

	MNLogit_new=2		dy/dx	std err	z
P> z	[0.025	0.975]			

safety_concern[T.Disagree]			0.1279	0.031	4.148
0.000	0.067	0.188			
safety_concern[T.Neutral]			0.3258	0.034	9.692
0.000	0.260	0.392			
carshare_level[T.Interested in participating]			0.0199	0.025	0.807
0.419	-0.028	0.068			
carshare_level[T.Not participating]			0.0405	0.016	2.563
0.010	0.010	0.071			
rideshare_level[T.Interested in participating]			-0.0260	0.020	-1.308
0.191	-0.065	0.013			
rideshare_level[T.Not participating]			-0.0466	0.017	-2.783
0.005	-0.079	-0.014			
pevowner[T.Yes]			-0.0275	0.027	-1.015
0.310	-0.081	0.026			
income[T.Low income]			0.0096	0.022	0.436
0.663	-0.034	0.053			
income[T.Middle income]			0.0082	0.019	0.441

0.659	-0.028	0.045			
householdvehicles[T.Three plus]			-0.0215	0.020	-1.064
0.287	-0.061	0.018			
householdvehicles[T.Two vehicle]			-0.0027	0.016	-0.173
0.863	-0.033	0.028			
housing[T.Mobile based home]			-0.0128	0.057	-0.226
0.821	-0.124	0.098			
housing[T.Others]			0.1803	0.112	1.612
0.107	-0.039	0.399			
housing[T.Single family]			0.0361	0.021	1.690
0.091	-0.006	0.078			
parkingtype[T.Shared parking]			0.0434	0.020	2.142
0.032	0.004	0.083			

			MNLogit_new=3	dy/dx	std err	z
P> z	[0.025	0.975]				
safety_concern[T.Disagree]			-0.2812	0.024	-11.760	
0.000	-0.328	-0.234				
safety_concern[T.Neutral]			-0.1158	0.032	-3.616	
0.000	-0.179	-0.053				
carshare_level[T.Interested in participating]			0.2140	0.025	8.491	
0.000	0.165	0.263				
carshare_level[T.Not participating]			0.0940	0.018	5.343	
0.000	0.060	0.129				
rideshare_level[T.Interested in participating]			0.0918	0.023	4.057	
0.000	0.047	0.136				
rideshare_level[T.Not participating]			0.1140	0.019	5.993	
0.000	0.077	0.151				
pevowner[T.Yes]			0.1623	0.026	6.183	
0.000	0.111	0.214				
income[T.Low income]			-0.0899	0.024	-3.690	
0.000	-0.138	-0.042				
income[T.Middle income]			-0.0789	0.020	-3.959	
0.000	-0.118	-0.040				
householdvehicles[T.Three plus]			-0.0397	0.023	-1.752	
0.080	-0.084	0.005				
householdvehicles[T.Two vehicle]			-0.0164	0.018	-0.923	
0.356	-0.051	0.018				
housing[T.Mobile based home]			0.0118	0.059	0.199	
0.842	-0.105	0.128				
housing[T.Others]			-0.3575	0.218	-1.637	
0.102	-0.785	0.070				
housing[T.Single family]			-0.0138	0.024	-0.577	
0.564	-0.061	0.033				
parkingtype[T.Shared parking]			-0.0377	0.024	-1.600	
0.110	-0.084	0.008				

```
In [18]: MLE = model_MNL.llf
print("Maximum Likelihood Estimate = ", MLE)

Maximum Likelihood Estimate = -3463.088240295422
```

```
In [19]: p = 3
AIC_1 = - 2 * MLE + 2 * p
print("Akaike Information Criteria = ", AIC_1)

Akaike Information Criteria = 6932.176480590844
```

```
In [20]: #c) Bayesian Information Criteria (AIC)
BIC = model_MNL.bic
```

```
print("BIC", BIC)
```

BIC 7188.338735667714

```
In [21]: # prediction of probability
yprob = model_MNL.predict()
print(yprob)
```

```
def compute_yhat(prob):
```

```
    yhat = np.argmax(prob, axis=1)
```

```
    return yhat
```

```
ypred = compute_yhat(yprob)
```

```
ypred
```

```
[[0.47794928 0.2105058  0.31154493]
 [0.35980573 0.1877623  0.45243197]
 [0.27438853 0.46455712 0.26105434]
 ...
 [0.5383785  0.22953344 0.23208806]
 [0.66522622 0.20260384 0.13216994]
 [0.68352863 0.16554228 0.1509291  ]]
```

```
Out[21]: array([0, 2, 1, ..., 0, 0, 0], dtype=int64)
```

```
In [22]: from sklearn.metrics import accuracy_score
Accuracy = accuracy_score(ypred, df.MNLogit_new)
Accuracy
```

```
Out[22]: 0.06751521859435529
```

```
In [23]: #some parameters are not significant and hence i am neglecting those
#parameters and fitting a regression for those parameters that matter
```

```
In [24]: from statsmodels.discrete.discrete_model import MNLogit
formula = 'MNLogit_new ~ safety_concern + carshare_level + rideshare_level + pevowner +
model_MNL = MNLogit.from_formula(formula=formula, data = df).fit()
print(model_MNL.summary())
```

Optimization terminated successfully.
Current function value: 0.960692
Iterations 6

MNLogit Regression Results

```

=====
Dep. Variable:          MNLogit_new    No. Observations:          3614
Model:                  MNLogit        Df Residuals:              3594
Method:                  MLE           Df Model:                  18
Date:                   Sun, 20 Nov 2022 Pseudo R-squ.:             0.09119
Time:                   19:51:54       Log-Likelihood:            -3471.9
converged:              True          LL-Null:                  -3820.3
Covariance Type:        nonrobust      LLR p-value:               2.761e-136
=====

```

```

=====
MNLogit_new=2      coef      std err      z
P>|z|      [0.025      0.975]
-----
Intercept      -1.3287      0.245      -5.430
0.000      -1.808      -0.849
safety_concern[T.Disagree]      0.2158      0.217      0.994
0.320      -0.209      0.641
safety_concern[T.Neutral]      2.1918      0.254      8.621
0.000      1.694      2.690
carshare_level[T.Interested in participating]      0.7536      0.183      4.113
0.000      0.394      1.113
carshare_level[T.Not participating]      0.5720      0.111      5.137
0.000      0.354      0.790
rideshare_level[T.Interested in participating]      0.0429      0.138      0.311
0.756      -0.228      0.314
rideshare_level[T.Not participating]      -0.0443      0.116      -0.382
0.702      -0.271      0.183
pevowner[T.Yes]      0.1897      0.198      0.958
0.338      -0.198      0.578
income[T.Low income]      -0.1129      0.149      -0.757
0.449      -0.405      0.180
income[T.Middle income]      -0.1231      0.131      -0.940
0.347      -0.380      0.134
-----

```

```

-----
MNLogit_new=3      coef      std err      z
P>|z|      [0.025      0.975]
-----
Intercept      0.3628      0.166      2.186
0.029      0.038      0.688
safety_concern[T.Disagree]      -1.2942      0.136      -9.548
0.000      -1.560      -1.029
safety_concern[T.Neutral]      0.2354      0.193      1.219
0.223      -0.143      0.614
carshare_level[T.Interested in participating]      1.3380      0.150      8.916
0.000      1.044      1.632
carshare_level[T.Not participating]      0.6718      0.097      6.935
0.000      0.482      0.862
rideshare_level[T.Interested in participating]      0.4641      0.123      3.779
0.000      0.223      0.705
rideshare_level[T.Not participating]      0.5528      0.103      5.363
0.000      0.351      0.755
pevowner[T.Yes]      0.8569      0.153      5.618
0.000      0.558      1.156
income[T.Low income]      -0.4571      0.128      -3.562
0.000      -0.709      -0.206
income[T.Middle income]      -0.4146      0.109      -3.788
0.000      -0.629      -0.200
-----

```

=====

```
In [25]: # coeff for income[T.Low income] = -0.1129 for MNL_new=2 or 'Neutral'
# odds ratio is  $e^{-0.1129} = 0.89$ 
# Compared to MNL=1 Low income are less likely to show interest to
# use autonomous vehicles by  $1-0.89 = 0.11$ 

# coef for income[T.Low income] is -0.4571 for MNL_new =3 or 'No'
# odds ratio is  $e^{-0.4571} = 0.6333$ 
# odds ratio decreases by  $1-0.6333 = 0.366$  compared to MNL=1

# This means that lower income group members who say 'No'
# show less affinity towards self autonomous by 36.6%

# coeff for Income[T.Middle income] = -0.1231
# odds ratio is  $e^{-0.1231} = 0.8841$  or 88.41%
# odds will decrease by  $1-0.8841 = 0.1159$  or by 11.59%
```

```
In [ ]:
```

```
In [ ]: # coeff for income[T.Low income] = -0.1129
# odds ratio is  $e^{-0.1129} = 0.89$ 

# Compared to MNL=1 Low income are less likely to use autonomous
# vehicles by  $1-0.89 = 0.11$ 

# choice of selection of self driving autonomous vehicle(for neutral people) is 0.8
# or MNL_new = 1

# coef for income[T.Low income] is -0.4571 for MNL_new =3 or 'No'
# odds ratio is  $e^{-0.4571} = 0.6333$ 
# odds ratio decreases by  $1-0.6333 = 0.366$  compared to MNL=1
# This means that lower income group members who say 'No' show less affinity toward

# coeff for Income[T.Middle income] = -0.1231
# odds ratio is  $e^{-0.1231} = 0.8841$  or 88.41%
# odds will decrease by  $1-0.8841 = 0.1159$  or by 11.59%

# In general it seems like richer people are more likely to use
# self driving autonomous vehicles.

# The variables except safety_concern[T.Neutral] are all significant when
# compared with People who say 'Yes' in MNLogit_new =1 for people
# who are saying 'NO' in MNLogit_new = 2

# Among the people who are neutral with choice of autonomous vehicle the people who
# say that they are neutral with safety of auto vehicles and those
# who are interested in participating carshare_Level
# and not participating are significant. This is in comparison to MNL_new=1 or 'Yes'

#For Carshare_Level[T.Interested in participating],for MNL_new=2 or 'Neutral'
# the odds ratio is  $e^{0.7536} = 2.1246$  meaning that the people who are neutral with
# the adoption of self driving vehicles are 2.12 times more likely to adopt
# self driving autonomous vehicles.

#For Carshare_Level[T.Not participating] the odds ratio is
#  $e^{0.5720} = 1.7649$  hence the people who are not participating in
```

*# car share and have chosen neutral are 1.7649 times favarouble to use
#self driving autonomous vehicles.*