


Module 4
Lesson 1 - Categorical Explanatory Variables with More
Than Two Categories

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binary (2 categories)

quantitative

*categorical with 3+
categories??*



dummy coding

parameterization

*Response = # of nicotine
dependence symptoms*

*Effect coding
Effect parameterization*

*Compare one
group to the
average of the
other groups*

The background of the slide is a blurred image of several cigarettes. Some cigarettes are lying horizontally, while one is angled upwards in the upper right. The focus is soft, with the cigarettes in the foreground being slightly more defined than those in the background.

Reference group coding
Reference group
parameterization

Compare each
group to a
reference group

*Response = # of nicotine
dependence symptoms*

*Compare each
group to a
reference group*

```

290 sub4 = sub1[['NDSymptoms', 'numbercigsmoked', 'DYSLIFE',
291 'MAJORDEPLIFE', 'AGE', 'SEX']].dropna()
292
293 # dysphoria & depression
294 reg4 = smf.ols('NDSymptoms ~ DYSLIFE + MAJORDEPLIFE', data=sub1).fit()
295 print (reg4.summary())
296
297 # dysphoria & depression + other covariates
298 sub1['age_c']=(sub1['AGE'] - sub1['AGE'].mean())
299 print (sub1['age_c'].mean())
300
301 reg5 = smf.ols('NDSymptoms ~ DYSLIFE + MAJORDEPLIFE + numbercigsmoked_c + age_c + SEX', data=sub1).fit()
302 print (reg5.summary())
303
304
305 |
306 # adding 4 category ethnicity/race. Default reference group is the first (Hispanic)
307 reg6 = smf.ols('NDSymptoms ~ DYSLIFE + MAJORDEPLIFE + numbercigsmoked_c + age_c + SEX + C(ETHRACE)',
308               data=sub1).fit()
309 print (reg6.summary())
310

```

python default parameterization: Reference (Treatment) group coding


```
...: print(regb.summary())
```

OLS Regression Results

```
=====
Dep. Variable:      NDSymptoms      R-squared:      0.139
Model:              OLS              Adj. R-squared: 0.134
Method:             Least Squares    F-statistic:    26.30
Date:               Sat, 14 Nov 2015  Prob (F-statistic): 5.76e-38
Time:               10:08:36          Log-Likelihood: -2588.9
No. Observations:   1313             AIC:             5196.
Df Residuals:       1304             BIC:             5242.
Df Model:           8
Covariance Type:    nonrobust
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	2.2970	0.184	12.454	0.000	1.935 2.659
C(ETHRACE)[T.1]	-0.1116	0.134	-0.830	0.407	-0.375 0.152
C(ETHRACE)[T.2]	-0.0851	0.178	-0.478	0.633	-0.435 0.264
C(ETHRACE)[T.3]	0.3260	0.231	1.412	0.158	-0.127 0.779
DYSLIFE	0.2756	0.209	1.322	0.186	-0.133 0.685
MAJORDEPLIFE	1.2881	0.116	11.078	0.000	1.060 1.516
numercigsmoked_c	0.0371	0.006	6.355	0.000	0.026 0.049
age_c	-0.0406	0.022	-1.837	0.066	-0.084 0.003
SEX	-0.0279	0.099	-0.281	0.779	-0.223 0.167

```
=====
Omnibus:            69.969      Durbin-Watson:      2.071
Prob(Omnibus):      0.000      Jarque-Bera (JB):    47.818
Skew:               0.353      Prob(JB):            4.13e-11
Kurtosis:           2.387      Cond. No.             50.4
=====
```

1 = non-Hispanic White
2 = non-Hispanic Black
3 = non-Hispanic Other


```

290 sub4 = sub1[['NDSymptoms', 'numbercigs smoked', 'DYSLIFE',
291 'HAJORDEPLIFE', 'AGE', 'SEX']].dropna()
292
293 # dysphoria & depression
294 reg4 = smf.ols('NDSymptoms ~ DYSLIFE + HAJORDEPLIFE', data=sub1).fit()
295 print (reg4.summary())
296
297 # dysphoria & depression + other covariates
298 sub1['age_c']=(sub1['AGE'] - sub1['AGE'].mean())
299 print (sub1['age_c'].mean())
300
301 reg5 = smf.ols('NDSymptoms ~ DYSLIFE + HAJORDEPLIFE + numbercigs smoked_c + age_c + SEX', data=sub1).fit()
302 print (reg5.summary())
303
304
305
306 # adding 4 category ethnicity/race. Reference group coding is called "Treatment" coding in python
307 # and the default reference category is the group with a value = 0 (Hispanic)
308 reg6 = smf.ols('NDSymptoms ~ DYSLIFE + HAJORDEPLIFE + numbercigs smoked_c + age_c + SEX + C(ETHRACE)',
309               data=sub1).fit()
310 print (reg6.summary())
311
312 # can override the default and specify a different reference group
313 # non-Hispanic white as reference group
314 reg7 = smf.ols('NDSymptoms ~ DYSLIFE + HAJORDEPLIFE + numbercigs smoked_c + age_c + SEX + C(ETHRACE, Treatment(reference=1))',
315               data=sub1).fit()
316 print (reg7.summary())
317
318
319
320
321
322 |

```

called "Treatment" coding in python

$\beta = \theta$ (Hispanic)

smoked_c + age_c + SEX + C(ETHRACE)',

up

smoked_c + age_c + SEX + C(ETHRACE, Treatment(reference=1))',

OLS Regression Results

```

=====
Dep. Variable:      NDSymptoms      R-squared:      0.139
Model:              OLS              Adj. R-squared: 0.134
Method:             Least Squares    F-statistic:    26.30
Date:               Sat, 14 Nov 2015  Prob (F-statistic): 5.76e-38
Time:               10:36:41          Log-Likelihood: -2588.9
No. Observations:   1313             AIC:            5196.
Df Residuals:       1304             BIC:            5242.
Df Model:           8
Covariance Type:    nonrobust
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	2.1855	0.163	13.385	0.000	1.865 2.506
C(ETHRACE, Treatment(reference=1))[T.0]	0.1116	0.134	0.830	0.407	-0.152 0.375
C(ETHRACE, Treatment(reference=1))[T.2]	0.0265	0.150	0.177	0.860	-0.267 0.320
C(ETHRACE, Treatment(reference=1))[T.3]	0.4376	0.209	2.091	0.037	0.027 0.848
DYSLIFE	0.2756	0.209	1.322	0.186	-0.133 0.685
MAJORDEPLIFE	1.2881	0.116	11.078	0.000	1.060 1.516
numbercigsmoked_c	0.0371	0.006	6.355	0.000	0.026 0.049
age_c	-0.0406	0.022	-1.837	0.066	-0.084 0.003
SEX	-0.0279	0.099	-0.281	0.779	-0.223 0.167

```

=====
Omnibus:           69.969      Durbin-Watson:      2.071
Prob(Omnibus):     0.000      Jarque-Bera (JB):    47.818
Skew:              0.353      Prob(JB):            4.13e-11
Kurtosis:          2.387      Cond. No.             40.0
=====

```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Module 3
Lesson 6 - A Few Things to Keep in Mind

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**Bad data
will produce
meaningless
results**

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Module 4
Lesson 3 - Logistic Regression for a Binary Response Variable

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MULTIPLE REGRESSION for Quantitative Variables


```
6 """
7
8 import numpy
9 import pandas
10 import statsmodels.api as sm
11 import statsmodels.formula.api as smf
12
13 data = pandas.read_csv('nesarc_pds.csv', low_memory=False)
14
15 #setting variables you will be working with to numeric
16
17 data['IDNUM'] = pandas.to_numeric(data['IDNUM'], errors='coerce')
18 data['TAB12MDX'] = pandas.to_numeric(data['TAB12MDX'], errors='coerce')
19 data['SOCPODLIFE'] = pandas.to_numeric(data['SOCPODLIFE'], errors='coerce')
20 data['MAJORDEPLIFE'] = pandas.to_numeric(data['MAJORDEPLIFE'], errors='coerce')
21
22 # subset data
23 sub1=data[(data['AGE']<=25) & (data['CHECK321']==1) & (data['S3AQ3B1']==1)]
24
25
26 # create binary nicotine dependence variable
27 def NICOTINEDEP (x):
28     if x['TAB12MDX']==1:
29         return 1
30     else:
31         return 0
32 sub1['NICOTINEDEP'] = sub1.apply (lambda x: NICOTINEDEP (x), axis=1)
33 print (pandas.crosstab(sub1['TAB12MDX'], sub1['NICOTINEDEP']))
34
```



```
28     if x['TAB12MDX']==1:
29         return 1
30     else:
31         return 0
32 sub1['NICOTINEDEP'] = sub1.apply (lambda x: NICOTINEDEP (x), axis=1)
33 print (pandas.crosstab(sub1['TAB12MDX'], sub1['NICOTINEDEP']))
34
35
36 # logistic regression social phobia
37 lreg1 = smf.logit(formula = 'NICOTINEDEP ~ SOCPDLIFE', data = sub1).fit()
38 print (lreg1.summary())
39
40
41
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55
56
```

```
In [28]: lreg1 = smf.logit(formula = 'NICOTINEDEP ~ SOCPDLIFE', data = sub1).fit()
```

```
...: print(lreg1.summary())
```

Optimization terminated successfully.

Current function value: 0.664381

Iterations 5

Logit Regression Results

```
=====
Dep. Variable:          NICOTINEDEP    No. Observations:          1320
Model:                  Logit          Df Residuals:              1318
Method:                 MLE            Df Model:                  1
Date:                   Sat, 07 Nov 2015 Pseudo R-squ.:             0.009574
Time:                   12:35:30        Log-Likelihood:            -876.98
converged:              True            LL-Null:                  -885.46
                                   LLR p-value:              3.829e-05
=====
```

```
=====
              coef      std err          z      P>|z|      [95.0% Conf. Int.]
-----
Intercept    0.3776     0.057      6.569     0.000     0.265     0.490
SOCPDLIFE    1.2318     0.335      3.674     0.000     0.575     1.889
=====
```

```
In [29]:
```

```
In [28]: lreg1 = smf.logit(formula = 'NICOTINEDEP ~ SOCPDLIFE', data = sub1).fit()
```

```
...: print(lreg1.summary())
```

Optimization terminated successfully.

Current function value: 0.664381

Iterations 5

Logit Regression Results

```
=====
Dep. Variable:          NICOTINEDEP    No. Observations:          1320
Model:                  Logit          Df Residuals:              1318
Method:                 MLE            Df Model:                  1
Date:                   Sat, 07 Nov 2015 Pseudo R-squ.:             0.009574
Time:                   12:35:30        Log-Likelihood:           -876.98
converged:              True            LL-Null:                  -885.46
                                   LLR p-value:              3.829e-05
=====
```

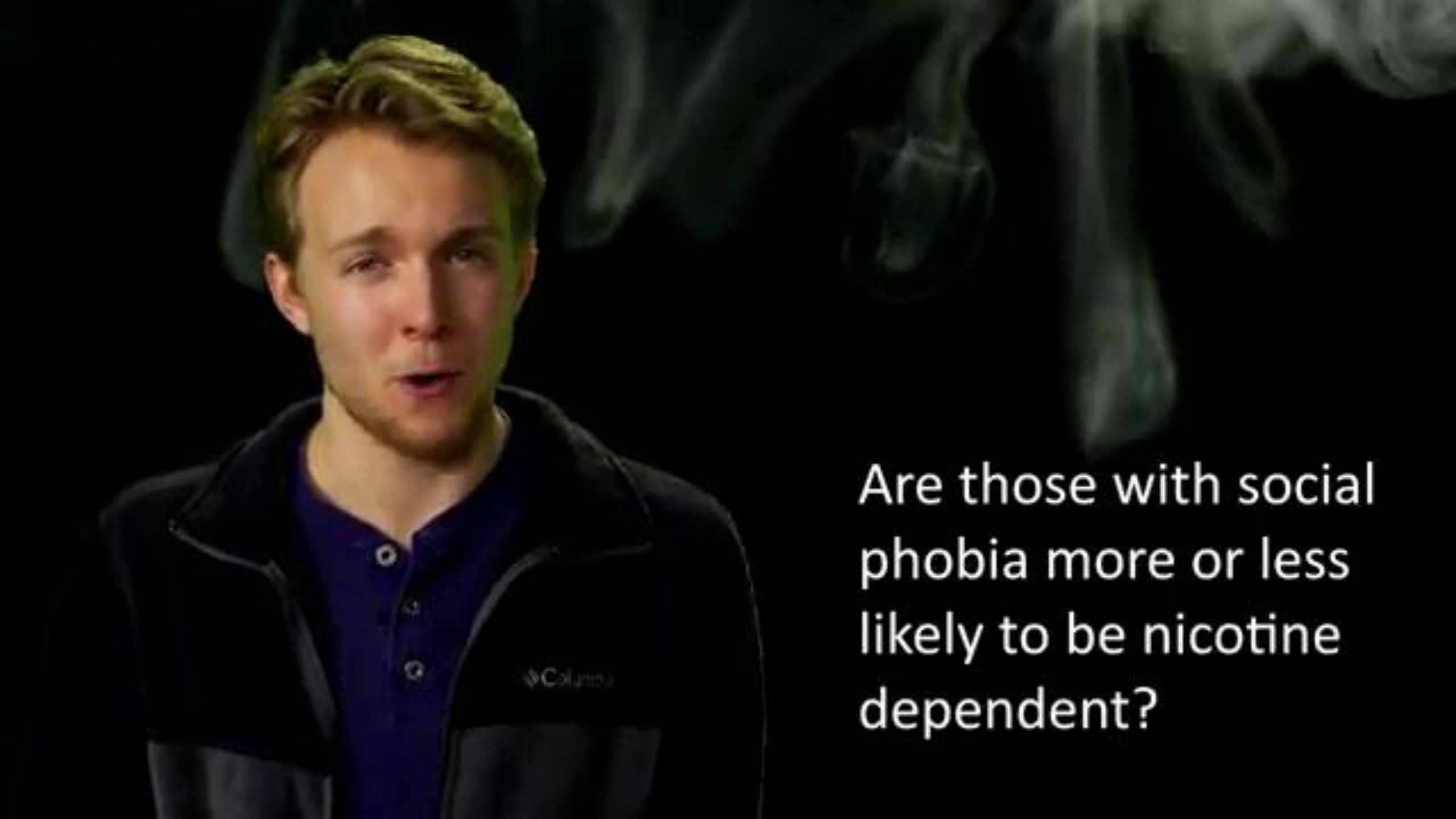
	coef	std err	z	P> z	[95.0% Conf. Int.]
Intercept	0.3776	0.057	6.569	0.000	0.265 0.490
SOCPDLIFE	1.2318	0.335	3.674	0.000	0.575 1.889

```
=====
```

```
In [29]:
```

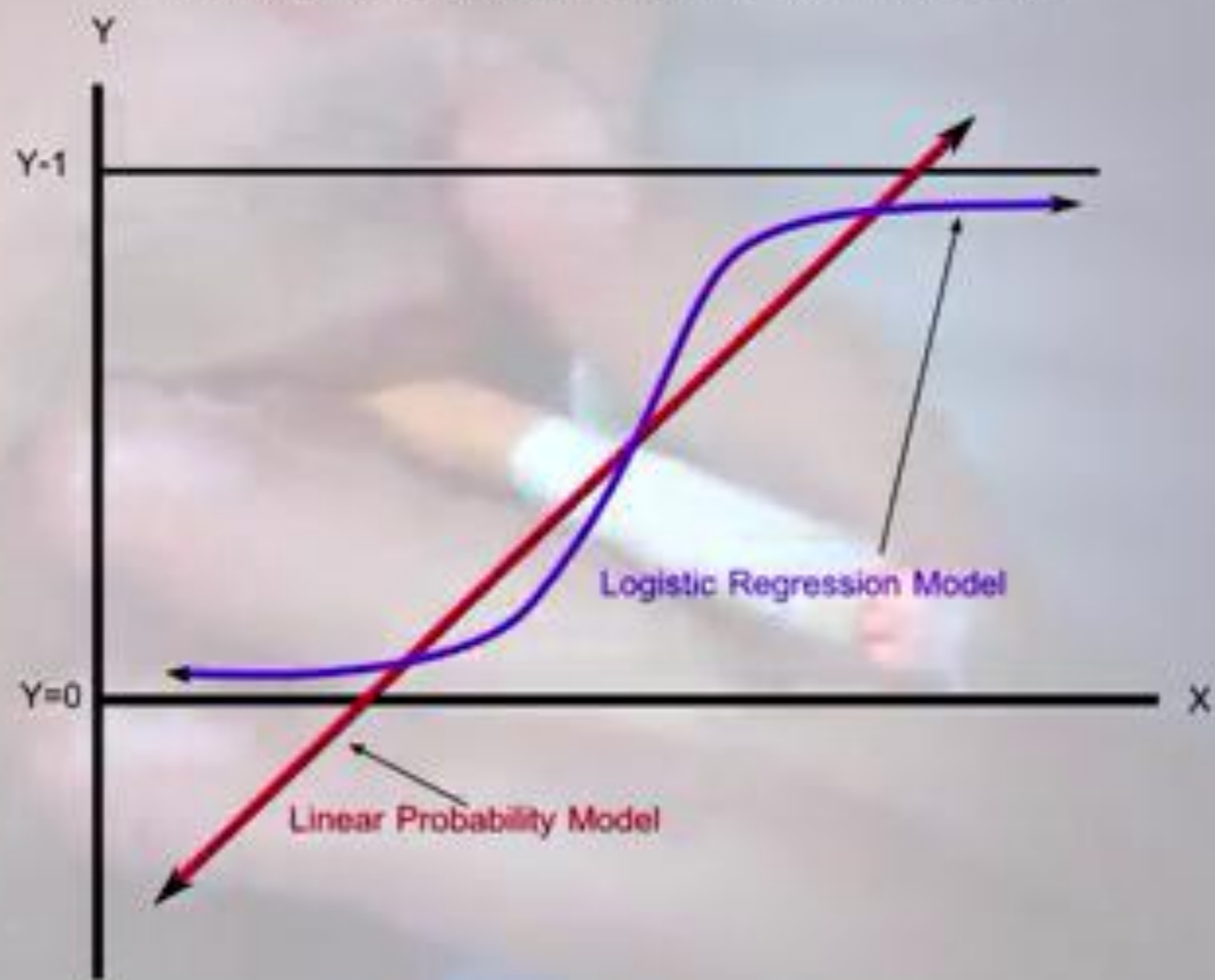
$\text{NICOTINEDEP} = 0.38 + 1.23 * \text{SOCPLDIFE}$





Are those with social
phobia more or less
likely to be nicotine
dependent?

Comparing the LP and Logit Models



Odds Ratio

$$0 \rightarrow \infty$$

OR = 1 model statistically non-significant

OR > 1 as explanatory variable increases, response variable more likely.

OR < 1 as explanatory variable increases, response variable is less likely.

```
Method: MLE Df Model: 1
Date: Sat, 07 Nov 2015 Pseudo R-squ.: 0.009574
Time: 12:35:30 Log-Likelihood: -876.98
converged: True LL-Null: -885.46
LLR p-value: 3.829e-05
```

```
=====
```

	coef	std err	z	P> z	[95.0% Conf. Int.]	
Intercept	0.3776	0.057	6.569	0.000	0.265	0.490
SOCPO LIFE	1.2318	0.335	3.674	0.000	0.575	1.889

```
=====
```

```
In [29]: print ("Odds Ratios")
...: print (numpy.exp(lreg1.params))
...:
...:
```

```
Odds Ratios
Intercept 1.46
SOCPO LIFE 3.43
dtype: float64
```

```
In [30]:
```



```

Model:          Logit      Df Residuals:      1318
Method:          MLE       Df Model:          1
Date:            Sat, 07 Nov 2015    Pseudo R-squ.:      0.009574
Time:            12:30:19    Log-Likelihood:      -876.98
converged:       True        LL-Null:          -885.46
                                LLR p-value:      3.829e-05

```

```

=====
              coef      std err          z      P>|z|      [95.0% Conf. Int.]
-----
Intercept      0.3776      0.057       6.569      0.000      0.265      0.490
SOCPDLIFE      1.2318      0.335       3.674      0.000      0.575      1.889
=====

```

Odds Ratios

```

Intercept      1.46
SOCPDLIFE      3.43

```

dtype: float64

```

In [26]: params = lreg1.params
...: conf = lreg1.conf_int()
...: conf['OR'] = params
...: conf.columns = ['Lower CI', 'Upper CI', 'OR']
...: print(numpy.exp(conf))
...:

```

```

              Lower CI  Upper CI  OR
Intercept      1.30      1.63  1.46
SOCPDLIFE      1.78      6.61  3.43

```

In [27]:



Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
SOCPLIFE	3.427	<u>1.777</u>	<u>6.611</u>


```
80 # odd ratios with 95% confidence intervals
```

```
81 params = lreg1.params
```

```
82 conf = lreg1.conf_int()
```

```
83 conf['OR'] = params
```

```
84 conf.columns = ['Lower CI', 'Upper CI', 'OR']
```

```
85 print (numpy.exp(conf))
```

```
86
```

```
86 #social phobia and depression
```

```
87 lreg2 = smf.logit(formula = 'NICOTINEDEP ~ SOCPDLIFE + MAJORDEPLIFE', data = sub1).fit()
```

```
88 print (lreg2.summary())
```

```
89
```

```
90 # odd ratios with 95% confidence intervals
```

```
91 print ("Odds Ratios")
```

```
92 params = lreg2.params
```

```
93 conf = lreg2.conf_int()
```

```
94 conf['OR'] = params
```

```
95 conf.columns = ['Lower CI', 'Upper CI', 'OR']
```

```
96 print (numpy.exp(conf))
```

```
97
```

```
98
```

```
99
```

```
100
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```

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```

Logit Regression Results

```

=====
Dep. Variable:          NICOTINEDEP    No. Observations:          1320
Model:                  Logit          Df Residuals:              1317
Method:                 MLE           Df Model:                  2
Date:                  Sun, 08 Nov 2015 Pseudo R-squ.:             0.05758
Time:                  14:43:10        Log-Likelihood:            -834.47
converged:              True           LL-Null:                  -885.46
                                   LLR p-value:              7.177e-23
=====

```

```

=====
              coef      std err          z      P>|z|      [95.0% Conf. Int.]
-----
Intercept      0.0939      0.065      1.444      0.149      -0.034      0.221
SOCPDLIFE      0.8393      0.347      2.416      0.016      0.158      1.520
MAJORDEPLIFE    1.3072      0.152      8.588      0.000      1.009      1.606
=====

```

Odds Ratios

	Lower CI	Upper CI	OR
Intercept	0.967033	1.247795	1.098480
SOCPDLIFE	1.171534	4.573507	2.314740
MAJORDEPLIFE	2.742580	4.980617	3.695909

In [17]: |

Logit Regression Results

```

=====
Dep. Variable:          NICOTINEDEP    No. Observations:          1320
Model:                  Logit          Df Residuals:              1317
Method:                 MLE            Df Model:                  2
Date:                   Sun, 08 Nov 2015  Pseudo R-squ.:          0.05758
Time:                   14:43:10          Log-Likelihood:           -834.47
converged:              True             LL-Null:                 -885.46
                                   LLR p-value:              7.177e-23
=====

```

	coef	std err	z	P> z	[95.0% Conf. Int.]
Intercept	0.0939	0.065	1.444	0.149	-0.034 0.221
SOCPLIFE	0.8393	0.347	2.416	0.016	0.158 1.520
MAJORDEPLIFE	1.3072	0.152	8.588	0.000	1.009 1.606

Odds Ratios

	Lower CI	Upper CI	OR
Intercept	0.967033	1.247795	1.098480
SOCPLIFE	1.171534	4.573507	2.314740
MAJORDEPLIFE	2.742580	4.980617	3.695909

In [17]: |

```
11 params = lreg2.params
12 conf = lreg2.conf_int()
13 conf['OR'] = params
14 conf.columns = ['Lower CI', 'Upper CI', 'OR']
15 print (numpy.exp(conf))
16
17 # logistic regression panic
18 lreg3 = smf.logit(formula = 'NICOTINEDEP ~ PANIC', data = sub1).fit()
19 print (lreg3.summary())
20
21 # odds ratios
22 print ("Odds Ratios")
23 print (numpy.exp(lreg3.params))
24
25 # odd ratios with 95% confidence intervals
26 params = lreg3.params
27 conf = lreg3.conf_int()
28 conf['OR'] = params
29 conf.columns = ['Lower CI', 'Upper CI', 'OR']
30 print (numpy.exp(conf))
31
32
33
34
35
36
37
38
39
40
```

```
...:
Optimization terminated successfully.
Current function value: 0.662762
Iterations 5
```

Logit Regression Results

```
=====
Dep. Variable:          NICOTINEDEP    No. Observations:          1320
Model:                  Logit          Df Residuals:              1318
Method:                  NLE           Df Model:                  1
Date:                   Sun, 08 Nov 2015 Pseudo R-squ.:            0.01199
Time:                   14:26:47        Log-Likelihood:            -874.85
converged:              True           LL-Null:                  -885.46
                                   LLR p-value:                  4.079e-06
=====
```

```
=====
              coef      std err          z      P>|z|      [95.0% Conf. Int.]
-----
Intercept      0.3202      0.061      5.278      0.000      0.201      0.439
PANIC          0.7590      0.172      4.423      0.000      0.423      1.095
=====
```

Odds Ratios

```
Intercept      1.377399
PANIC          2.136134
```

```
dtype: float64
```

```

Lower CI  Upper CI      OR
Intercept 1.222987 1.551306 1.377399
PANIC     1.526024 2.990167 2.136134
```

```
In [13]:
```

Console 1/A
Current function value: 0.633241
Iterations: 5

```
lreg4 = smf.logit(formula = 'NICOTINEDEP ~ PANIC + MAJORDEPLIFE', data = sub1).fit()
```

```
Dep. Variable:          Nicot/DEP         No. Observations:          1320  
Model:                Logit      Df Residuals:          1317  
Method:                NLE      Df Model:              2  
Date:                Sun, 08 Nov 2015    Pseudo R-squ.:          0.05600  
Time:                14:30:41    Log-Likelihood:         -835.88  
converged:              True      LL-Null:             -885.46  
                        LLR p-value:        2.930e-22
```

```
=====
```

	coef	std err	z	P> z	[95.0% Conf. Int.]
Intercept	0.0826	0.066	1.243	0.214	-0.048 0.213
PANIC	0.3554	0.183	1.941	0.052	-0.003 0.714
MAJORDEPLIFE	1.2848	0.155	8.266	0.000	0.980 1.589

```
=====
```

Odds Ratios

```
Intercept      1.086115  
PANIC          1.426815  
MAJORDEPLIFE   3.613795
```

dtype: float64

	Lower CI	Upper CI	OR
Intercept	0.953426	1.237270	1.086115
PANIC	0.996509	2.042933	1.426815
MAJORDEPLIFE	2.664843	4.900671	3.613795

In [15]: |

Current function value: 0.633241

Iterations 5

Logit Regression Results

```

=====
Dep. Variable:          NICOTINEDEP    No. Observations:          1320
Model:                  Logit          Df Residuals:              1317
Method:                  NLE           Df Model:                  2
Date:                   Sun, 08 Nov 2015 Pseudo R-squ.:             0.05600
Time:                   14:30:41        Log-Likelihood:            -835.88
converged:               True           LL-Null:                  -885.46
                                   LLR p-value:                2.930e-22
=====

```

```

=====
              coef      std err          z      P>|z|      [95.0% Conf. Int.]
-----
Intercept      0.0826      0.066      1.243      0.214      -0.048      0.213
PANIC           0.3554      0.183      1.941      0.052      -0.003      0.714
MAJORDEPLIFE    1.2848      0.155      8.266      0.000      0.980      1.589
=====

```

Odds Ratios

```

Intercept      1.086115
PANIC           1.426815
MAJORDEPLIFE    3.613795

```

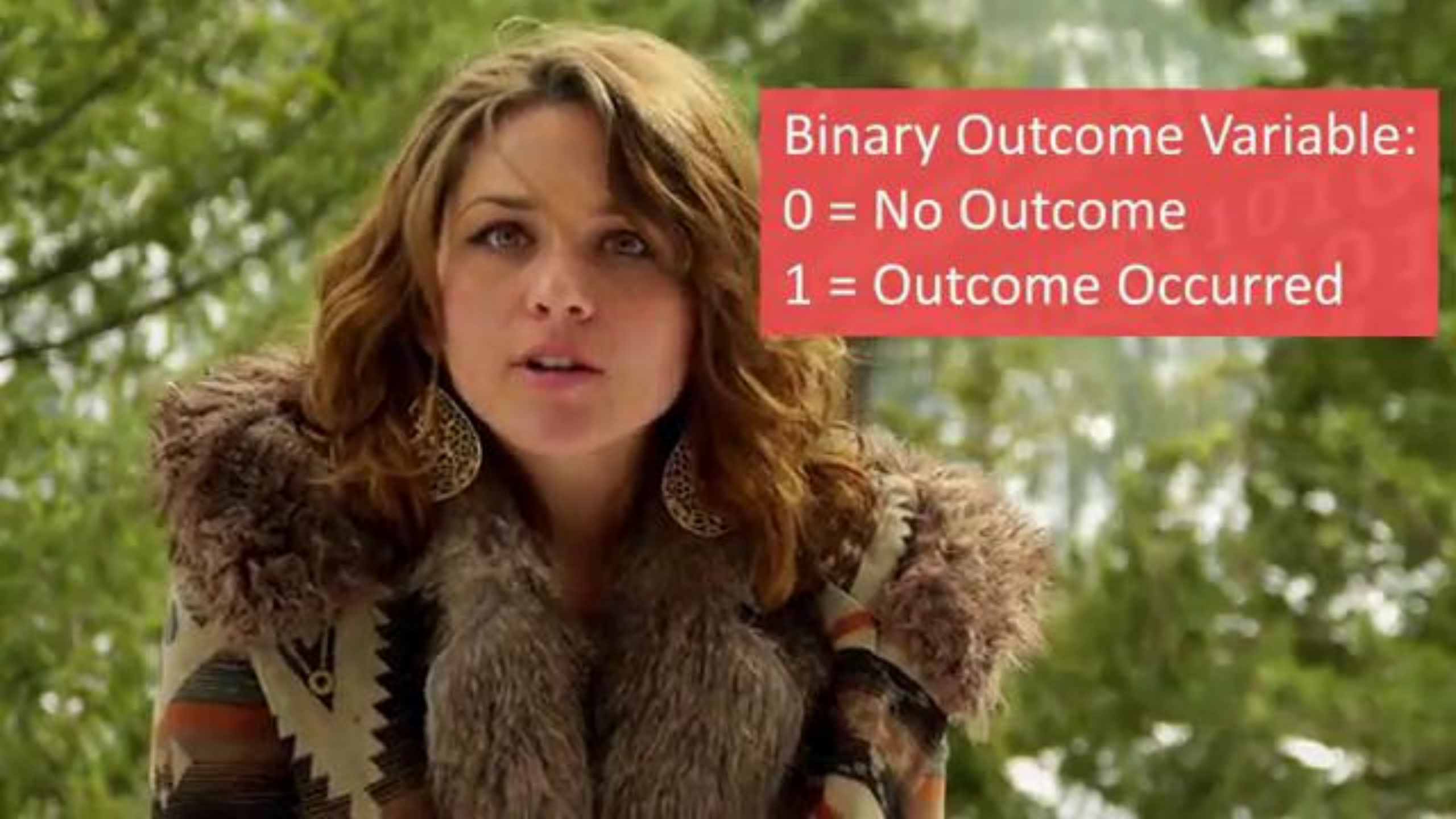
dtype: float64

```

      Lower CI  Upper CI      OR
Intercept  0.953426  1.237270  1.086115
PANIC      0.996509  2.042933  1.426815
MAJORDEPLIFE 2.664843  4.900671  3.613795

```

In [15]: |



Binary Outcome Variable:
0 = No Outcome
1 = Outcome Occurred