Exercise - Logistic Regression

DATA 3300

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Q1

Using the (full) voters.csv dataset, conduct a logistic regression analysis in Python. Assume the data set has already been checked for collinear independent variables, and found none.

Be sure to:

- Load in required libraries and import dataset
- Dummy code all categorical variables, leaving out a reference group
- Dummy code DV variable
- Create an object for your IVs ('x') and an object for your DV ('y')
- Exclude unwanted variables from analysis

```
import warnings
warnings.filterwarnings("ignore")
```

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
```

```
# read in and display the dataset
df = pd.read_csv('/content/voters.csv')
df
```

	ResponseID	Age	IncomeCat	MStatus	Religion	Homeowner	Defense	Healthcare
0	1	61	2	married	Agnostic	y	3	3
1	2	26	1	married	Christian	n	2	5
2	3	28	2	divorced	Jewish	n	2	3
3	4	23	1	married	Christian	n	3	1
4	5	25	2	married	Christian	y	5	3
...	...	...	...	...	...	...	...	...
293	294	40	1	married	Other	n	3	5
294	295	42	2	divorced	Other	n	4	1
295	296	47	5	married	Agnostic	y	1	2
296	297	47	1	divorced	Christian	n	4	3
297	298	59	4	divorced	Christian	y	3	3

298 rows × 11 columns

Next steps: View recommended plots

```
df['Religion'].value_counts()
```

```
Christian    137
Agnostic      78
Other         39
Jewish        24
Muslim        20
Name: Religion, dtype: int64
```

```
x = df.drop(['ResponseID', 'VIntent'], axis=1)         # replace with code to remov
x = pd.get_dummies(data = x, drop_first = True)   # dummy codes categorical IVs
#replace with code to preview this x object
x.head()
```

	Age	IncomeCat	Defense	Healthcare	Privacy	Education	MStatus_married	MStat
0	61	2	3	3	4	2	1	
1	26	1	2	5	3	4	1	
2	28	2	2	3	1	5	0	
3	23	1	3	1	3	2	1	
4	25	2	5	3	3	2	1	

Next steps: View recommended plots

```
y = df['VIntent'] # replace with code to create y object
y = pd.get_dummies(data = y, drop_first = True) # replace with code to fill in get_(
y
```

	Kodos
0	0
1	0
2	1
3	1
4	1
...	...
293	1
294	1
295	1
296	1
297	0

298 rows × 1 columns

Next steps: View recommended plots

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.2, random_sta

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(238, 14)
(60, 14)
(238, 1)
(60, 1)
```

```
x_train_Sm = sm.add_constant(x_train) # adds a constant (y-intercept) to x_train
log_reg = sm.Logit(y_train, x_train_Sm).fit() # fits a Logit model
# replace with code to print the summary
print(log_reg.summary())
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Kodos   No. Observations:                  238
Model:                          Logit   Df Residuals:                      223
Method:                           MLE   Df Model:                           14
Date:                Thu, 21 Mar 2024   Pseudo R-squ.:                     inf
Time:                        19:42:33   Log-Likelihood:                   -inf
converged:                       True   LL-Null:                        0.0000
Covariance Type:            nonrobust   LLR p-value:                     1.000
===============================================================================
                         coef    std err          z      P>|z|      [0.025
-------------------------------------------------------------------------------
const                  4.0556      1.223      3.315      0.001       1.658
Age                   -0.0424      0.020     -2.173      0.030      -0.081
IncomeCat             -0.7240      0.197     -3.668      0.000      -1.111
Defense                0.0927      0.148      0.626      0.531      -0.197
Healthcare            -0.5651      0.144     -3.936      0.000      -0.846
Privacy                0.3373      0.169      1.993      0.046       0.006
Education              0.6304      0.154      4.102      0.000       0.329
MStatus_married       -1.0150      0.467     -2.172      0.030      -1.931
MStatus_single         1.0760      0.581      1.853      0.064      -0.062
MStatus_widowed       -2.0984      0.705     -2.975      0.003      -3.481
Religion_Christian    -1.6109      0.495     -3.256      0.001      -2.581
Religion_Jewish       -0.4194      0.777     -0.540      0.589      -1.942
Religion_Muslim       -1.4602      0.814     -1.793      0.073      -3.056
Religion_Other        -1.2986      0.621     -2.092      0.036      -2.515
Homeowner_y           -1.1433      0.484     -2.364      0.018      -2.091
===============================================================================
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:595: HessianIr
  warnings.warn('Inverting hessian failed, no bse or cov_params '
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  warnings.warn('Inverting hessian failed, no bse or cov_params '
```

1A

Are there any *non-significant* variables at the α = 0.1 level? State how you know this (list the metric, its value, and its interpretation).

Note that if one class of a categorical variable is significant, the entire variable is significant.

Defense has a p value of 0.531, higher than our a = 0.1 value, making it not statisically significant.

1B

If all of the IVs had a value of 0, for which candidate would the model predict a voter would intend to vote? How do we know this?

If all the IVs were set to 0, that voter would be more likely (greater than 50%) to vote for Kodos than Kang. We know this because the intercept value has a log-odds above 0.

1C

The reference group for Marital Status is divorced. Are married individuals significantly different in their likelihood of voting for Kodos as compared to divorced individuals? How do you know this, and are they more or less likely on average to vote for Kodos?

There is a statistically significant difference in the likelihood of married and divorced individuals to vote for Kodos ($p < 0.1$). Married individuals are significantly less likely to vote for Kodos compared to Divorced individuals, indicated by the negative log-odds of the coefficient (about -1.0).

1D

Rerun the model dropping out any non-significant variables, then produce the summary table.

```
x_train_Sm = x_train_Sm.drop(['Defense'], axis=1) # add in var name to be dropped
log_reg = sm.Logit(y_train, x_train_Sm).fit()
print(log_reg.summary())
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Kodos   No. Observations:                  238
Model:                          Logit   Df Residuals:                      224
Method:                           MLE   Df Model:                           13
Date:                Thu, 21 Mar 2024   Pseudo R-squ.:                     inf
Time:                        19:42:33   Log-Likelihood:                   -inf
converged:                       True   LL-Null:                        0.0000
Covariance Type:            nonrobust   LLR p-value:                     1.000
===============================================================================
                  coef    std err          z      P>|z|      [0.025
-------------------------------------------------------------------------------
const           4.3016      1.166      3.689      0.000       2.016
Age            -0.0410      0.019     -2.120      0.034      -0.079
IncomeCat      -0.7262      0.197     -3.687      0.000      -1.112
Healthcare     -0.5527      0.142     -3.892      0.000      -0.831
Privacy         0.3253      0.168      1.935      0.053      -0.004
```

```
Education              0.6280      0.153      4.093      0.000       0.327
MStatus_married       -1.0036      0.467     -2.151      0.032      -1.918
MStatus_single         1.0926      0.578      1.891      0.059      -0.040
MStatus_widowed       -2.0613      0.701     -2.943      0.003      -3.434
Religion_Christian    -1.6095      0.495     -3.251      0.001      -2.580
Religion_Jewish       -0.4361      0.778     -0.560      0.575      -1.962
Religion_Muslim       -1.4138      0.809     -1.748      0.081      -2.999
Religion_Other        -1.2881      0.617     -2.088      0.037      -2.497
Homeowner_y           -1.1718      0.480     -2.439      0.015      -2.114
====================================================================================
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:595: HessianIr
  warnings.warn('Inverting hessian failed, no bse or cov_params '
/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:595: HessianIr
  warnings.warn('Inverting hessian failed, no bse or cov_params '
```

1E

Using the coefficients, write out the full model in equation form.

$$Logit_{VIntent_Kodos} = 4.3016 - Age * 0.0410 - IncomeCat * 0.7262 - Healthcare * 0.5527$$
$$* 0.6280 - MStatus_married * 1.0036 + MStatus_single * 1.0926 - MStatus_widowed *$$
$$- Religion_Jewish * 0.4361 - Religion_Muslim * 1.4138 - Religion_Other * 1.2881 - Ho$$

Q2

Consider a voter who is Jewish, single, owns a home, 40 years old, falls into Income Category 4, and is lukewarm on the importance of defense, healthcare, privacy, and education (i.e., has a value of "3" for each of these).

2A

What would be the *log-odds* of this voter voting for Kodos? (Show the equation you used for this calculation; perform this calculation using your formula)

```
Logit_Kodos = 4.3016 - (40*0.0410) - (4*0.7262) - (3*0.5527) + (3*0.3253) + (3*0.62
print("Logit(Kodos) =", Logit_Kodos)
```

```
Logit(Kodos) = 0.44329999999999998
```

2B

What would be the *odds* of this voter voting for Kodos? (Show your formula; use 2.718 as the value of e.)

```
odds = 2.718 ** 0.443
print("odds(Kodos) =", odds)
```

```
odds(Kodos) = 1.5573008025528459
```

```
np.exp(0.443)# using np.exp
```

```
1.5573723343417794
```

2C

What would be the *probability* of this voter voting for Kodos? (Show your formula).

```
p = odds/(1 + odds)
print("P(Kodos) = ", p)
```

```
P(Kodos) =  0.6089627004372179
```

The probability of this individual voting for Kodos is about 61%, meaning they are more likely to vote for Kodos than for Kang

Q3

Now that we've interpretted our model, let's see how it performs on the test set to get an idea of how accurate our model would be in predicting the voter intent of new voters.

```
x_test = x_test.drop(['Defense'], axis=1) # which variable(s) need(s) to be dropped
# replace with code to add a constant to x_test
x_test_Sm = sm.add_constant(x_test)
```

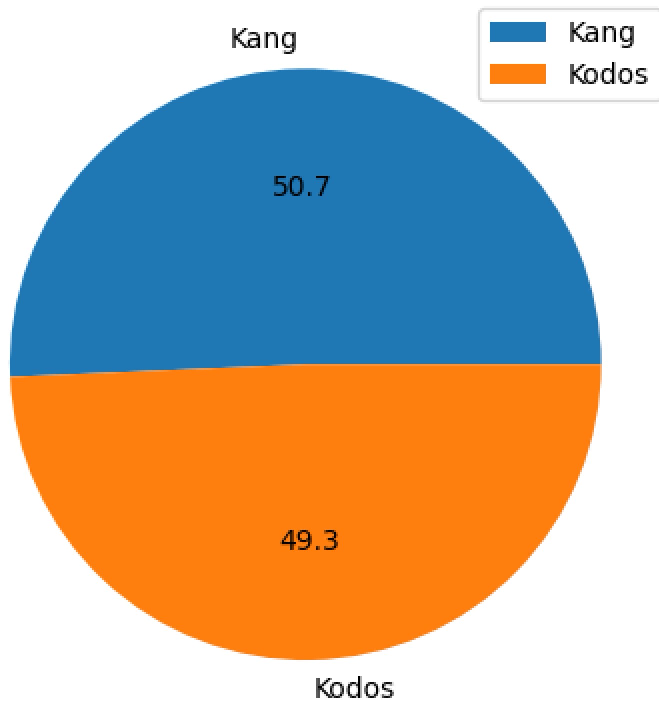
```
model = LogisticRegression() # brings in LogisticRegression predictive model from sl
model.fit(x_train_Sm, y_train) # fits the model to the training data

predictions = model.predict(x_test_Sm) # make predictions onto x_test_Sm
predictions
```

```
print(classification_report(y_test, predictions)) # replace with code to add in para
```

Q4

Develop a data visualization illustrating which candidate received the majority of votes from voters in this dataset. Provide a caption for your figure.

```
# create a voter_counts object to display in a pie chart
voter_counts = df['VIntent'].value_counts()
plt.pie(voter_counts.values, labels = voter_counts.index.values, autopct = '%1.1f')
plt.legend()
plt.show()
```



Breakdown of Voter Intent - Indicating Kang as the likely winner