Predictive Analysis of State Human Rights Records

Relating Data on the Preservation of Physical Integrity Rights, Repression, and Civil-Political Rights to States' Respect for Human Rights

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Introduction and Methods

The objective of this predictive analysis is to determine if certain explanatory variables can accurately classify a state's level of respect for human rights. The dataset, compiled by the CIRIGHTS Data Project, assesses states' human rights records using scores based on 72 internationally recognized human rights. Python was used for the analysis. Three explanatory variables were selected based on their correlation to the human rights score variable through scatter plot analysis: 'phys_int' measures physical integrity rights (PIR), 'civpol_sum' gauges civil and political rights (CPR), and 'repression_sum' quantifies state repression (SR) (barcharts in appendix; interpreted in next section). Higher scores means better PIR, CPR, and SR, respectively. The dummy variable was then created, classifying states as 0 (lower respect) or 1 (higher respect) based on a threshold of 52, the mean human rights scores from 0 to 100 (greater score means better human rights). Next, logistic regression was conducted using the logit() function from the StatsModels library. The function arguments included the dummy variable, and the 3 subsetted explanatory variables; once run, the results were converted to exponential form for easy interpretation. Next, the same regression was run using the logit(), this time using the Sklearn library to split the data into train and test sets to carry out the regression on the train data and test it on the test data; accuracy scores were then calculated. Finally, a predictive model was created through the Sklearn library using the 3 subsetted explanatory variables and the dummy variable. The data was split into train and test, and the same steps as above were followed, except this time with the LogisticRegression() from Sklearn, and a confusion matrix was obtained. After that, the accuracy of the model was assessed by running it on the test data, and finding the accuracy parameters such as the precision score and the macro average.

Findings and Analysis

Logistic Regression via StatsModels Only: Before running the logistic regression, three grouped bar charts were created to understand the relationship between the explanatory variables and the respect level. Figure 1 shows that the states with higher repression scores generally have higher respect for human rights, while states with lower repression scores generally have lower respect for human rights. Figure 2 shows that the states with higher PIR scores generally have higher respect for human rights, while states with lower PIR scores generally have lower respect for human rights. Figure 3 shows that the states with higher CPR scores generally have higher respect for human rights, while states with lower CPR scores generally have lower respect for human rights. The first simple logistic regression run using the StatsModels library yielded the results in Figure 4. The coefficients were then converted to their exponential form for better interpretation in Figure 5. These outcomes mean that when the PIR of a state improves by 1 unit, the odds that the state has higher respect for human rights is 0.607570 times as large as the odds that it has lower respect for human rights, given that the effects of SR and CPR are held constant. Also, when the SR of a state improves by one unit, the odds that the state has higher respect for human rights is 3.813823 times as large as the odds that it has lower respect for human rights, given that the effects of PIR and CPR are held constant. Finally, when the CPR of a state improves by 1 unit, the odds that the state has higher respect for human rights is 0.739653 times as large as the odds that it has lower respect for human rights, given that the effects of PIR and SR are held constant. Looking at the coefficient, when CPR, SR, and PIR are at their lowest, 0, the odds that the state has higher respect for human rights is 0.000076 times as large as the odds that it has lower respect for human rights.

Logistic Regression via StatsModels and Sklearn for Specific Features: The logistic regression run using the StatsModels and Sklearn libraries yielded the results shown in Figure 6. The coefficients were then converted to their exponential form for better interpretation in Figure 7. These outcomes mean that when the PIR of a state improves by 1 unit, the odds that the state has higher respect for human rights is 0.564799 times as large as the odds that it has lower respect for human rights, given that the effects of SR and CPR are held constant. Also, when the SR of a state improves by one unit, the odds that the state has higher respect for human rights is 3.953047 times as large as the odds that it has lower respect for human rights, given that the effects of PIR and CPR are held constant. Finally, when the CPR of a state improves by 1 unit, the odds that the state has higher respect for human rights is 0.704605 times as large as the odds that it has lower respect for human rights, given that the effects of PIR and SR are held constant. Looking at the coefficient, when CPR, SR, and PIR are at their lowest, 0, the odds that the state has higher respect for human rights is 0.000096 times as large as the odds that it has lower respect for human rights. These coefficients only slightly differ from those of the first model. The accuracy parameter of the model, which measures the ratio of correctly predicted instances to the sample size, providing an overall assessment of how well the model performs, was 0.89, and a confusion matrix (converted to heatmap) was generated fusing the test data to view the proportions of predicted true positives, true negatives, false positives, and false negatives in Figure 8.This heatmap shows that the model accurately predicted 216 states to have lower respect for human rights, while it falsely predicted that 29 states had higher respect when they actually had lower respect. It also predicted correctly that 196 states had higher respect for human rights, but falsely predicted that 20 states had lower respect when they actually had higher respect.

Predictive Modeling via Sklearn Only: The results of this model were the same as the previous section in regards to the confusion matrix quantities, since the same train and test method was used on the data. Therefore, the accuracy score was still 0.89 and the classification report is in Figure 9. The macro average provides an overall unweighted summary of the model's performance without considering class imbalances for precision, recall, and f1-scores, while the weighted average does the same but takes the class imbalances into account. The averages for these values are all 0.89, according to the chart.

Discussion

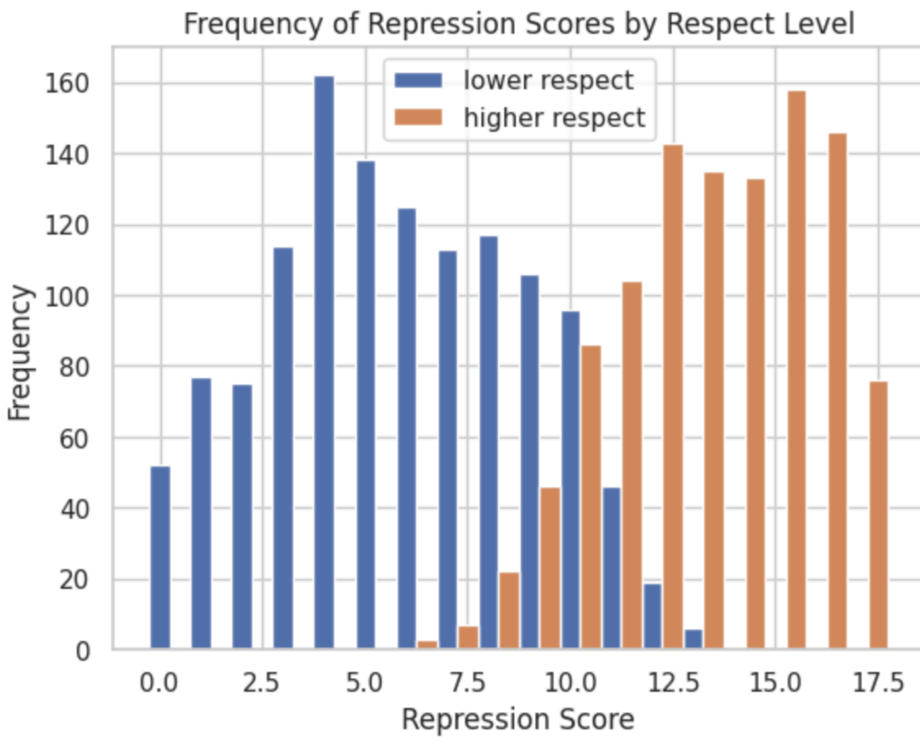
Utilizing repression, civil and political rights, and physical integrity rights as explanatory variables, the model is 89% correct in predicting the chances of whether a state has a higher or lower level of respect for human rights. This means that the model is mostly accurate at predicting the correct classification of a state, so the explanatory variables chosen were apt in this model. Furthermore, the precision scores, which measures the ability of the model to correctly identify positive instances by taking ratio of true positives over all the positive predictions, were 0.92 and 0.87 for lower respect and higher respect, which means that the precision is high as well. The recall scores, which measures the ability of the model to correctly predict all positive cases by taking the ratio of true positives to the sum of true positives and false negatives, were 0.9 and 0.89 for lower respect and higher respect, indicating a stronger ability to capture all the states with high levels of respect. The f1-score, which provides a balanced measure of precision and recall by taking the ratio of (precision x recall) to (precision + recall), was 0.90 and 0.89, for lower and high respect; these scores are in between the values for their respective precision and recall scores, showing that the f1-score is well balanced. The macro average and weighted average for precision, recall, and f1-scores were largely equivalent because there is less imbalance in the data; the sample size for the lower respect group is 245, while the high respect group is 216, which does not yield a significant difference in the averages when accounting for weightage. Though the model is quite accurate in prediction overall, to improve its accuracy, it may be beneficial to include more explanatory variables, such as one that measures workers' rights in the labor market for states to reduce the proportions of false positive and negative predictions.

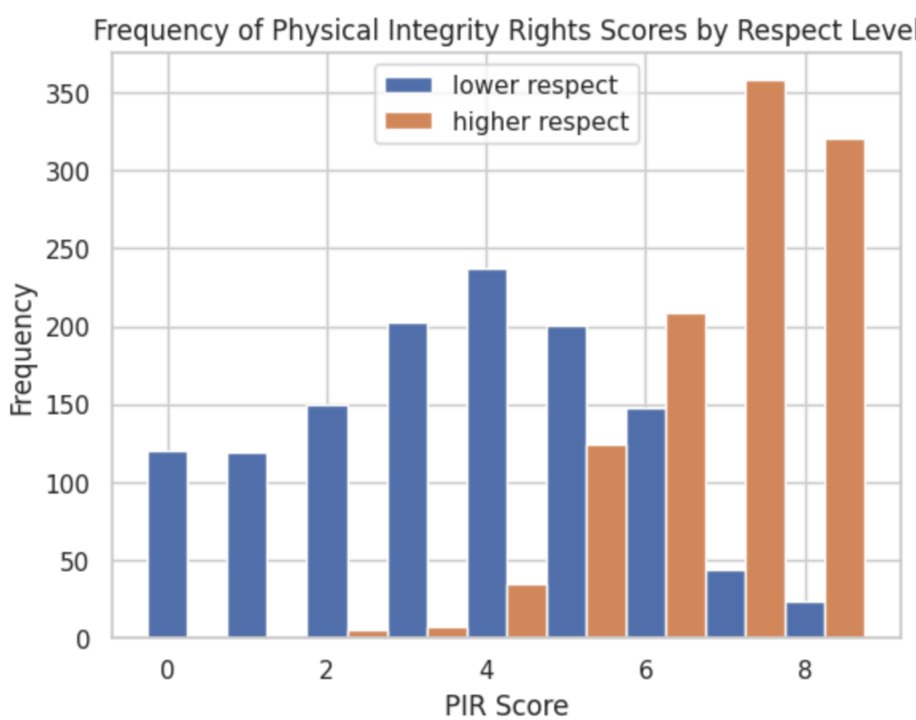
Conclusion

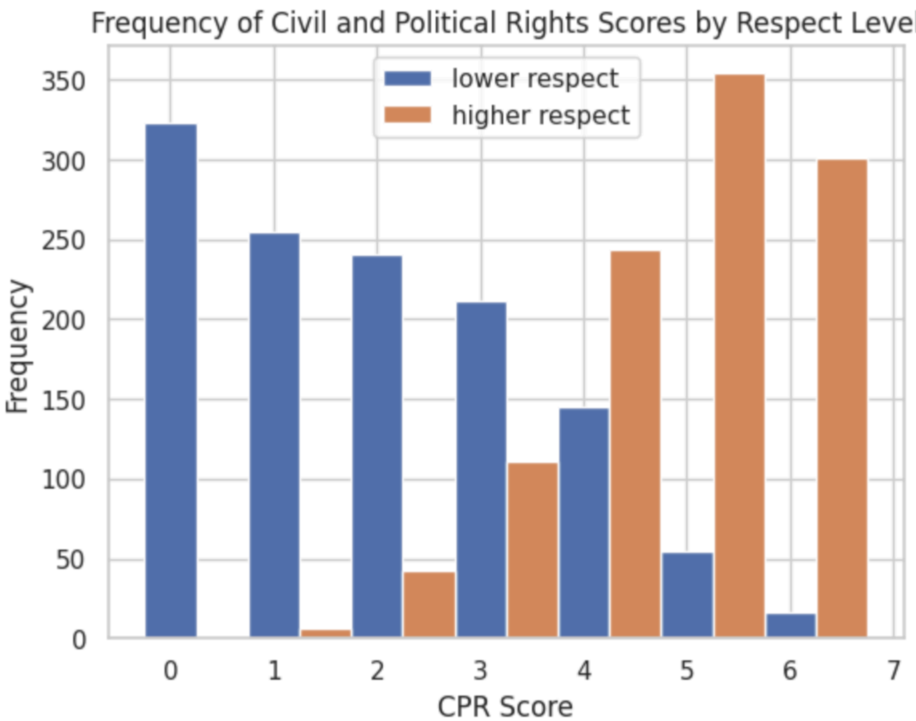
The predictive analysis was conducted in Python using the Cirights dataset to ascertain whether certain indicators can predict the respect a state has for human rights. First, a logistic regression was done via the StatsModel library, then the same was repeated, but the data was split into train and test sets via the Sklearn library; finally, a predictive model was built using only the Sklearn library to determine how accurate the prediction ability is of the model using metrics such as the confusion matrix. The results of the analysis showed that the repression scores had the most impact on the increase in probability of a state's respect being high, while physical integrity rights had the least impact on this increase in all models. The explanatory variables were mostly successful in predicting the level of respect a state has for human rights; with an accuracy score of 89%, this model overall has been largely accurate in prediction, however further explanatory variables can be added to the model to improve its accuracy, such as workers' rights scores.

Appendix

Figures 1, 2 and 3: bar charts showing frequency of explanatory variable by level of respect for human rights







Figures 4 and 5: Simple Logistic Regression Results

```
                           Logit Regression Results
==============================================================================
Dep. Variable:          respect_level   No. Observations:                 2305
Model:                          Logit   Df Residuals:                     2301
Method:                           MLE   Df Model:                            3
Date:                Fri, 03 Nov 2023   Pseudo R-squ.:                  0.6877
Time:                        00:30:29   Log-Likelihood:                -496.62
converged:                       True   LL-Null:                       -1590.1
Covariance Type:            nonrobust   LLR p-value:                     0.000
==================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept         -9.4877      0.483    -19.626      0.000     -10.435      -8.540
physint_sum       -0.4983      0.131     -3.791      0.000      -0.756      -0.241
repression_sum     1.3386      0.115     11.659      0.000       1.114       1.564
civpol_sum        -0.3016      0.121     -2.502      0.012      -0.538      -0.065
==================================================================================
```

Coefficient	**Magnitude**
Physical Integrity Rights	0.564799
Repression	3.953047
Civil and Political Rights	0.704605
Intercept	0.000096

Figures 6 and 7: Train and Test Method Logistic Regression Results

```
                           Logit Regression Results
==============================================================================
Dep. Variable:          respect_level   No. Observations:                 1844
Model:                          Logit   Df Residuals:                     1840
Method:                           MLE   Df Model:                            3
Date:                Thu, 02 Nov 2023   Pseudo R-squ.:                  0.6853
Time:                        19:11:30   Log-Likelihood:                -400.12
converged:                       True   LL-Null:                       -1271.4
Covariance Type:            nonrobust   LLR p-value:                     0.000
==================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept         -9.2484      0.526    -17.571      0.000     -10.280      -8.217
physint_sum       -0.5713      0.145     -3.947      0.000      -0.855      -0.288
repression_sum     1.3745      0.128     10.743      0.000       1.124       1.625
civpol_sum        -0.3501      0.134     -2.616      0.009      -0.612      -0.088
==================================================================================
```

Coefficient	**Magnitude**
Physical Integrity Rights	0.564799
Repression	3.953047
Civil and Political Rights	0.704605
Intercept	0.000096

Figure 8: Confusion Matrix/Heatmap

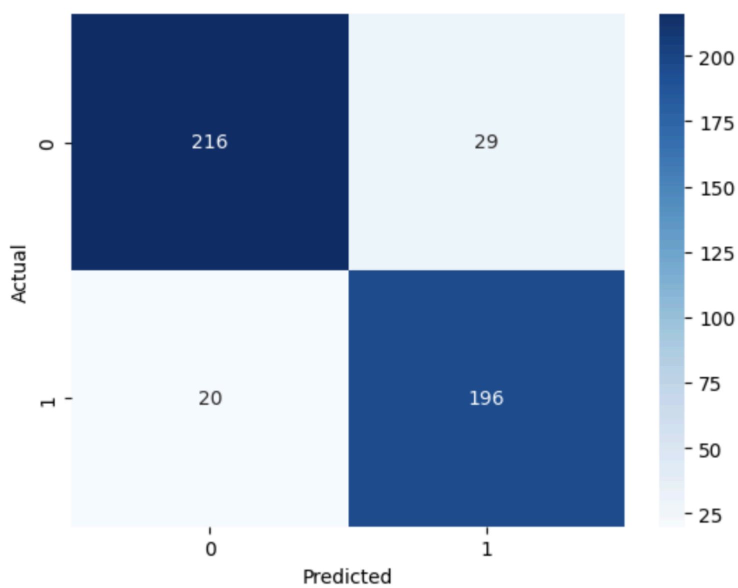


Figure 9: Classification Report:

	Precision	**Recall**	**f1-Score**	**Support**
0	0.92	0.88	0.90	245
1	0.87	0.91	0.89	216
Accuracy			0.89	461
Macro Avg	0.89	0.89	0.89	461
Weighted Avg	0.89	0.89	0.89	461