Efficacy of Drug Policies

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As more and more states have started legalizing marijuana in the US, the traditional viewpoint of how governments punish drug use has come under question. Recently, countries like Portugal, Switzerland, and the Netherlands have developed extremely lenient policies regarding the sale and use of recreational drugs. Others, including Malaysia, China, and Iran, impose harsh penalties — including death — to any citizens caught with drugs. Rising rates of drug usage worldwide catalyze the need to understand the relationship between government regulations and a country's disease and death share attributed to drug use. In 2021, Oregon became the first US state to decriminalize possession of illegal drugs. As more US states start to consider more lenient drug policies, it is crucial to analyze the potential positive or negative effects associated with drug laws.

Deaths due to drug use in the United States have skyrocketed in recent years, coinciding with the inception of the War on Drugs initiated by the Nixon administration in the 1970s. Policies imposing strict punishments on possession of even minimal amounts of drugs are widespread across the country, yet the US has been number one worldwide in total deaths caused directly by drugs (accounting for population) since 2006. There have been individual success stories of countries drastically lowering their penalties on drug possession and use and in turn seeing a great decrease in their drug burden. In this analysis, we explore the possible effects that government penalties for illicit drugs, along with other demographics, have on the drug burden of a country. Our primary research question is whether more lenient drug policies lead to lesser drug burdens on countries.

1. Data Collection and Cleaning

By combining a series of datasets, we created one large set with numerous features from which we can construct a model. Our combined dataset contains the following variables:

Country (multiple sources, 170 included in aggregated dataset); **Region and Sub Region** (source: United Nations Office on Drug and Crimes); **Kilograms of Drugs Seized for 11 different Drug Groups and Total Seized** (source: United Nations Office on Drug and Crimes); **GDP per capita** (source: World Bank); **Population** (source: World Bank); **Year** (multiple sources, 1990-2016); **Year a Country Decriminalized Cannabis and All Drugs** (source: TalkingDrugs). We then researched and hand-coded each country's legal penalties regarding the possession of personal amounts of illegal drugs (referred to as 'Possession') and categorized them as either no punishment (coded as 'NONE'), a fine ('FINE'), less than 1 year in prison ('<1'), 1-5 years in prison ('1 to 5'), 5 or more years in prison ('5+'), and the death penalty ('DEATH'). For each of these penalties, we used the maximum penalty that is allowed by the country's penal code.

There are also two outcome variables in the dataset: **Direct Deaths from Drug Use Disorders/ Overdoses** (source: OurWorldinData, split by alcohol and illicit drugs); **Share of disease burden attributed to substance use disorders** (source: OurWorldinData, measured in Disability-Adjusted Life Years (**DALYs**) which considers both death rate and years lived without a disability/ health burden).

Due to merging multiple data sets, there are a few observations that contain missing values in one or more features. However, there are only 117 total observations out of 3477 in the training set that contain NA values (3.36%), so we decided to simply remove them and perform the analysis on the remaining entries.

There is an extreme value of Drug Seizures in the Africa region in the year 1996. To fix this, we replaced the value with the average of all the other values with the same features (Poppy plants in Egypt). We also checked online to see if there was a massive opioid drug bust in Egypt in 1996 but found no record of such an occurrence, so we can assume that this is most likely a data-entry error. This was the only significant outlier that we detected throughout the preliminary analyses.

We encoded the Possession laws, Region, and SubRegion features using one-hot encoding. We transformed GDP, population, total deaths, total seizures, and DALYs using a log transformation to obtain more normal distributions (as discussed later).

2. Data Exploration

After examining the relationships between the two outcome variables and the predictor variables in the dataset, we decided to use Share of disease burden attributed to substance use disorders (which we referred to as 'DALYs'). This is because Direct Deaths from Drug Use Disorders/ Overdoses is highly

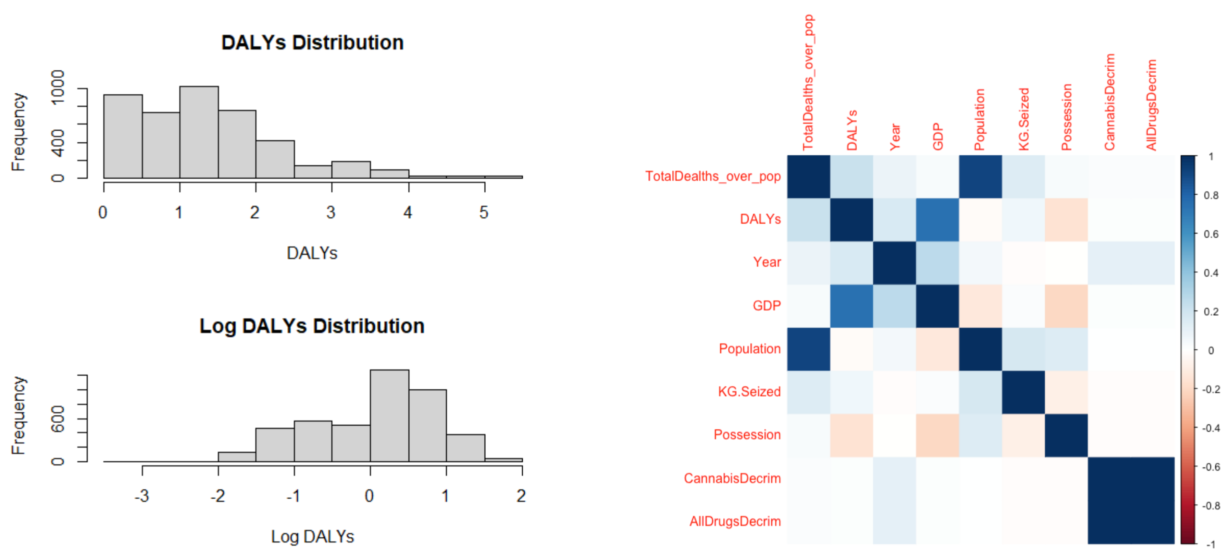

Figure 1: Log transformation of the DALYs response variable produces a more normal distribution (left) and correlation matrix of the variables included in the dataset (right).

correlated with population (as seen in Fig. 1), since logically the higher the population of a country, the higher the number of total deaths. Share of disease burden attributed to substance use disorders is a more normalized outcome variable to quantify the disease burden of a country. Because the distribution of DALYs was very skewed, we decided to regress our predictors on a log transformation of DALYs. Fig. 1 demonstrates how this transformation produces a significantly more normal distribution.

Using DALYs as the primary outcome variable, we then analyzed the basic relationships that each of our predictor variables had with drug burden (DALYs). GDP was the only numerical variable that had a correlation with DALYs above 0.02 (0.74), suggesting that population and total kg of drugs seized are likely not predictive of a country's drug burden.

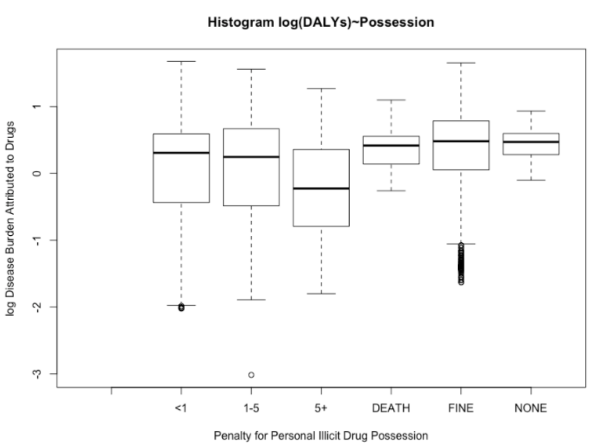

Figure 2: Box plots displaying the distributions of DALYs based on drug possession penalty.

When analyzing the relationship between drug burden and a country's penalty for the possession of a personal amount of drugs, we found that the drug burden for countries with penalties of 5+ years in prison tend to have lower drug burdens

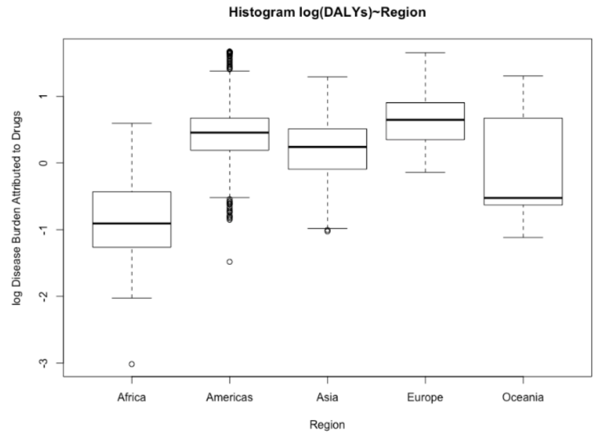

Figure 3: Box plots displaying the distributions of DALYs based on country reegion.

on average. It also appears that having no penalty listed for the possession of illicit drugs, does not necessarily change the average drug burden for a country. However, there were few observations with this categorization, so the true relationship between no penalty and drug burden is hard to deduce. It appears that a country's penalty for drug possession could be predictive of their drug burden. This relationship will be further explored in later models.

We also looked at the relationship between geographical region and drug burden. Based on the box plot in Fig. 3, there is a clear regional effect. Africa has the lowest disease burden attributed to drugs, while Europe has the highest. It is important to note that log(GDP) by region follows a similar trend to the boxplot for DALYs by region, and GDP is linearly associated with DALYs.

Before we performed our initial regressions, we decided to include Region as our only predictor variable for geographic location. Including 'Country' as a variable would require adding 170 additional variables through one-hot encoding, which surely would have caused our model to overfit. The variable

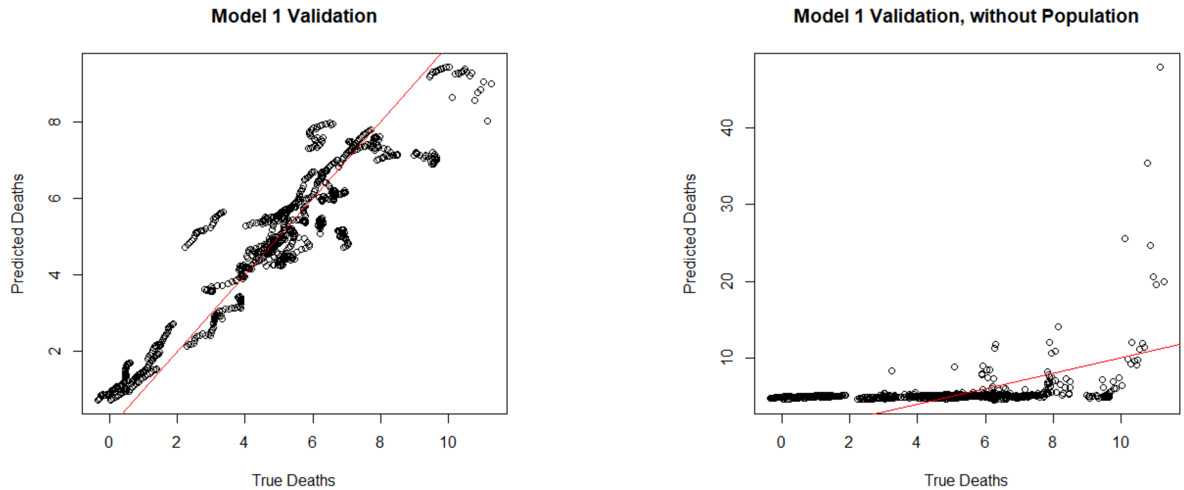

Figure 4: Validation accuracy of preliminary Model 1 and validation accuracy of preliminary Model 1 after removing Population.

'Sub Region' included 19 different sub regions, which also would require one-hot encoding and a large increase in the predictor variables to observations ratio. With these considerations in mind, we performed preliminary analyses considering DALYs, Year, GDP per capita, Population, Total kg of drugs seized, Region, and Possession Laws.

2. Preliminary Regressions

Model 1: log(Total Deaths) ~ log(Population) + log(GDP) + Drug Seizures

After reviewing the data and assessing which features might be important to include in our final model, we ran a preliminary linear regression with select features on log Total Deaths. While we planned to create a time-series model using the Year variable, we initially wanted to get a very basic overview of the linear effects of the features at our disposal.

We then used this model to make predictions on the validation set. As can be seen in Fig. 4, the model is somewhat accurate. However, when we remove Population as a factor, the model is no longer accurate, which means that most, if not all, of the predictive power of the first model is coming from Population This makes sense, because as the population of a country increases, the total number of deaths would likely increase as well. Due to this, as discussed earlier, we posit that Total Deaths is not a viable outcome variable to use to assess the predictor effects, and we will instead use Drug Burden (DALYs) as our outcome variable.

Model 2: log(DALYs) ~ log(GDP) + log(Population) + Drugs Seized

Next, we ran a preliminary linear regression of Year, log(GDP), log(Population), and each of the drugs seized values on log(DALYs). This appears to make better predictions, as shown in Fig. 6.

3. Lasso and Time-Series

We inferred from the preliminary analyses that not all the explanatory variables in the dataset were significant

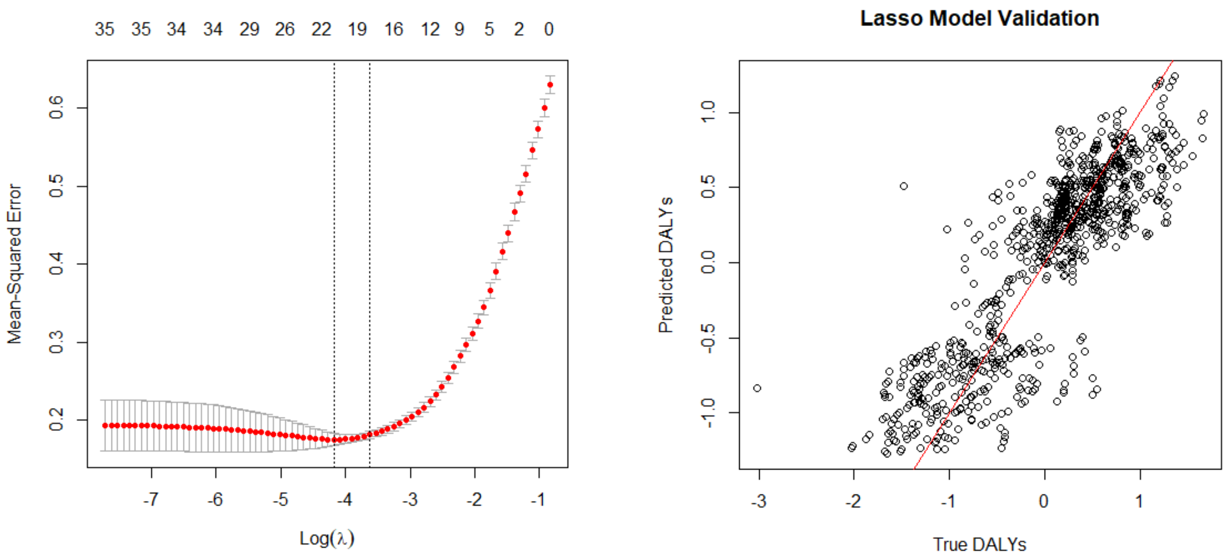

Figure 5: Mean-squared error of the lasso regression using 10-fold CV (left) and validation accuracy of the lasso model (right).

for the model. In order to statistically determine which variables we should incorporate into our final model, we decided to construct a regression model with a lasso regularizer. The lasso regularizer was chosen primarily due to its sparsity characteristics, and that it would allow us to eliminate unnecessary variables.

To select the best lambda for the lasso regularizer, we employed 10-fold cross validation on our training set. The optimal lambda value, according to this method, was 0.0153, and Fig. 5 shows the mean-squared error for each lambda value.

We then ran the lasso regression using the optimal lambda value. The model selected only the Year, Possession, and Region as significant predictors. All Seizures, Population, GDP, and Legalization dates had zero coefficients. The mean-squared error of this model on the validation set was 0.165, and Fig. 5 displays the prediction accuracy of the lasso model.

It can be seen in Fig. 5 that this model is fairly accurate, and far more so than the preliminary models. However, we believe that we can improve upon its performance using a time series autoregressive model.

A time series model should be a good choice for this data because this data is

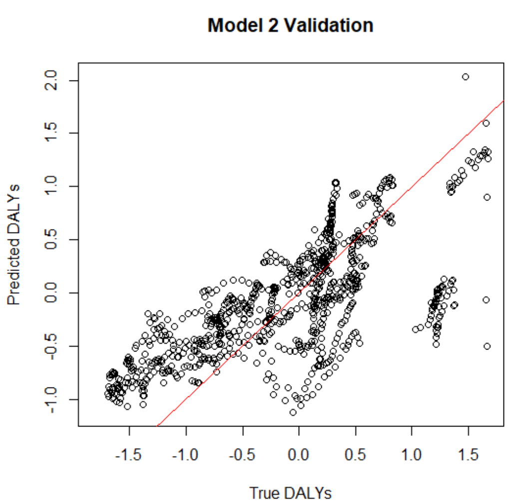

Figure 6: Validation accuracy of preliminary Model 2.

inherently time-constrained, as we are assessing drug burden by year.

Our hypothesis is that there may be some influence on year-to-year DALYs, so regressing the data on itself as well as the year prior (using an AR-1 model) may provide us with a better fit for the data.

To do this, we constructed a generalized linear model (GLM) framework with a Gaussian link function. We decided to use a GLM because we wanted to account for the inherent differences between each country. Constructing a single time-series model on all the data would assume constant explanatory variable influence on the DALYs response, but this is not the case. We partially address these differences using the Region and Possession variables, but because we do not have comprehensive breakdowns of all the geopolitical differences between each country, we thought it would be best to allow for this variability through the use of a GLM.

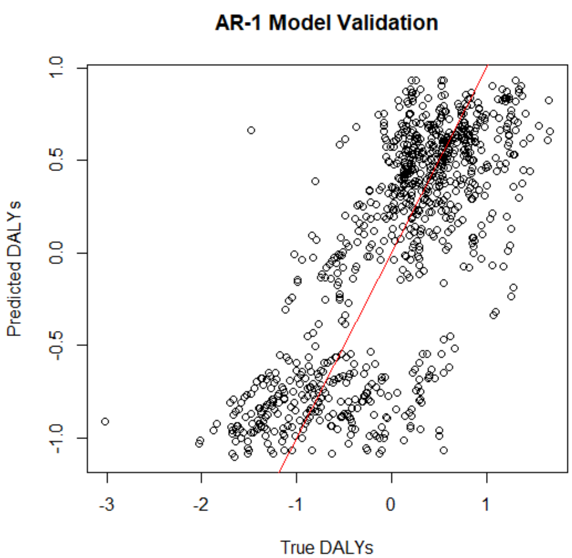

Figure 7: Validation accuracy of the AR-1 model.

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Coefficients:
                 Estimate  Std.err    Wald Pr(>|W|)    
(Intercept)     -33.30769  2.13721  242.88   <2e-16 ***
Year              0.01631  0.00107  233.95   <2e-16 ***
Possession<1     -0.16994  0.09152    3.45   0.0633 .  
Possession1-5    -0.12414  0.09138    1.85   0.1743    
Possession5+     -0.24798  0.09036    7.53   0.0061 ** 
PossessionDEATH   0.11098  0.09478    1.37   0.2416    
PossessionFINE   -0.15393  0.09367    2.70   0.1003    
PossessionNONE   -0.22928  0.09381    5.97   0.0145 *  
RegionAmericas    1.29160  0.02567 2531.33   <2e-16 ***
RegionAsia        0.94529  0.02791 1147.43   <2e-16 ***
RegionEurope      1.47038  0.02368 3854.25   <2e-16 ***
RegionOceania     0.69137  0.06241  122.73   <2e-16 ***
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Figure 8: Coefficients and statistical significance of each predictor variable in the AR-1 model.

We used the variables obtained from the lasso analysis (Year, Region, Possession) for this model as well. The mean-squared error for the time-series model was 0.256 and its prediction accuracy on the validation set is shown below in Fig. 7.

Surprisingly, this model performed worse than the less complex lasso model on the validation set. This could be due to several reasons. Firstly, increasing model complexity (as we did in this instance) could lead to overfitting on the training set and thus performing worse on the validation set. Secondly, it may be the case that this data is not correlated year-to-year and trying to impose that structure within the model was an incorrect assumption. This result appears to counter many of our initial hypotheses about the data. We thought that a year that experienced high drug burden might see a decrease in the following year due to increased attention to the issue. This may not be the case. Future analyses on this topic should further investigate the time series nature of disease burden due to drugs on a country.

4. AR-1 Time Series Discussion

The AR-1 time series results showed — as expected from the preliminary models —

year and all regions as significant predictors of log(DALYs). More notably, the only values for the Possession variable that are significant are ‘<1’, ‘NONE’, and ‘5+’. A negative coefficient for a Possession category should indicate that the penalty for illicit drug possession is associated with a decrease in drug burden. However, when analyzing the coefficients for ‘Possession <1’, ‘Possession 5+’, and ‘NONE’, they are all negative, with numerically similar values for the coefficients for ‘5+’ and ‘NONE’. This leads us to question the validity of the significant Possession categories.

Also notable was the coefficient value for countries that allow the death penalty as a punishment for the possession of a small amount of illicit drugs. The coefficient for the ‘Possession DEATH’ variable was the only Possession category that was positive, indicating that a possible punishment of death is associated with a higher drug burden for a country. Although the ‘Possession DEATH’ variable is not significant which means no conclusions should be drawn from this, it is an interesting take away given that greater threats of punishment are typically assumed to decrease the incentive to do drugs and in turn decrease drug burden.

4. Limitations

The primary limitation of this analysis is the lack of access to complete data. Many countries keep their data private, so while we were able to read many articles on the variable we were trying to incorporate, the raw data were very rarely available for non-government officials. Information specifically on the leniency of government policies on drug use was hard to gain access to. We hoped to include a numerical quantification for how harshly a country punishes drug possession/use such as the average prison sentence for the possession of personal amounts of drugs. This information was not available at the scale we needed, and we did not have the authorization to gain access to the smaller datasets. The “Possession”, “Cannabis”, and “AllDrugs” variables were utilized instead to qualify a government's position on drug crimes. Although we did find significance in certain levels of the “Possession” variable, a numerical variable would have provided more insights.

5. Fairness

Our model does not technically violate any criteria of fairness. This is largely because we are not predicting anything with the goal of enforcing a new policy. Rather, this project was more focused on further understanding the role that drug possession policies have on a country’s drug burden.

However, were we considering using our analysis to recommend a shift in national policy regarding penalties for drug possession, fairness would need to be assessed more strictly. Broad laws regarding drug possession may have unintended consequences due to fairness through unawareness; that is, by applying the same penalty (or lack thereof) to all instances of drug possession, we may reduce the accuracy of predicting drug burden. In terms of practical significance, there may be certain drugs for which it is essential to have harsher penalties to prevent a higher rate of drug burden, so recommending a lesser penalty would be a detriment.

At a minimum, the results of our model show that there is not overwhelming evidence to conclude that harsher penalties for drug possession help lower the negative effects that drugs have on a population's health. There are also additional considerations to account for when determining government policy, such as how increased harshness of penalties are historically applied disproportionately to minority groups. If any policy changes were to occur regarding drugs, especially in the United States, there would need to be additional research regarding how minorities would be implicitly affected.

6. Conclusion

The final AR-1 time series model, despite producing relatively good prediction accuracy on the validation set, is still not as accurate as we had envisioned when we began the project. Additionally, the basic lasso regression performed better than the AR-1 model based on mean-squared error on the validation set. While we were successfully able to build multiple models that performed relatively well, we were hoping that the time series model would be the most successful. Thus, there are multiple direction we can conceive for future research on this topic.

Firstly, access to a more comprehensive database would likely improve model accuracy and complexity. Secondly, research on how alternatives to prison such as rehabilitation clinics contribute to the change in a country's drug burden would be helpful to consider. Since this kind of alternative option is relatively new, tracking when and where it is implemented and the subsequent effects on the population would be beneficial. Thirdly, a more comprehensive dataset on drug penalties could allow an analysis based on specific drugs, not just "illicit drugs". Some metrics that would be particularly interesting is the proportion of arrests made for specific drug crimes and the proportion of prisoners in jail for specific drug crimes. Lastly, studies focused on developing a metric to quantify the overall "drug problem" of a country — including drug-related deaths, diseases, incarceration rates, and drug-related crimes — could use a model framework similar to the one we presented here.

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