#### Political Stability Presentation

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#### Introduction: Political Stability Across the Globe

Why does political stability vary across the globe? Are some nations innately built upon stability producing institutions while others are doomed, or can instability be triggered even within the most stable regimes? My research project will investigate the factors the produce political stability, or fail to, within the various countries across the globe.

#### The Data

- ▶ We will utilizes The World Bank's data set on political stability measured by the absence of violence and terrorism. The time-series data contains 213 countries and provides estimates on political stability from 1996 to 2019. The estimate of political stability ranges from -2.5 (weak stability) to 2.5 (strong stability).
- ► The data is combine with additional data from The World Bank the includes predictors: population, fuel exports, military expenditure, ease of conducting business, inflation rate, literacy rate, and access to electricity.

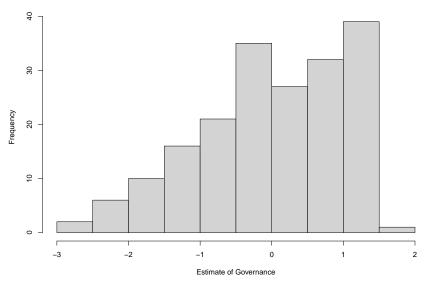
#### Reprocessing

The data required a great deal of cleaning and pre-processing. Functions such as pivot-longer and dplyr's join functions were used.

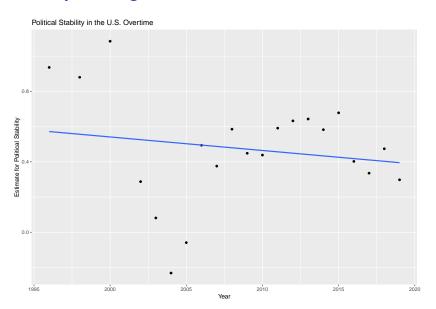
#### head(clean\_stability)

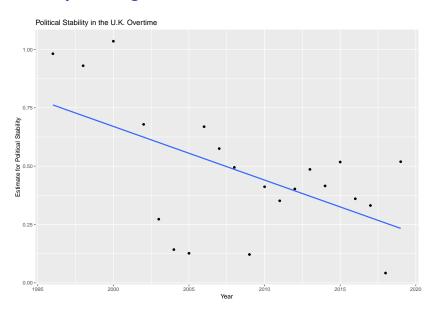
```
## # A tibble: 6 x 4
##
     country code
                    year estimate
##
     <chr> <chr> <dbl> <chr>
                    1996 1.1701573133468628
## 1 Andorra ADO
  2 Andorra ADO
                    1998 1.1836445331573486
  3 Andorra ADO
                    2000 1.1670020818710327
  4 Andorra ADO
                    2002 1.282038688659668
## 5 Andorra ADO
                    2003 1.4649856090545654
  6 Andorra ADO
                    2004 1.4014873504638672
```

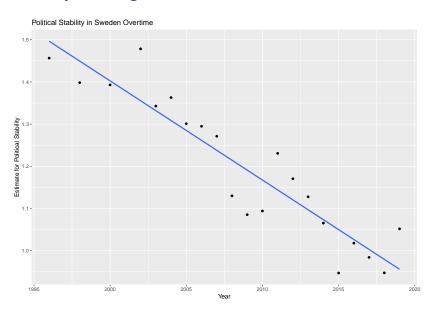
Distribution of Political Stability for 1996

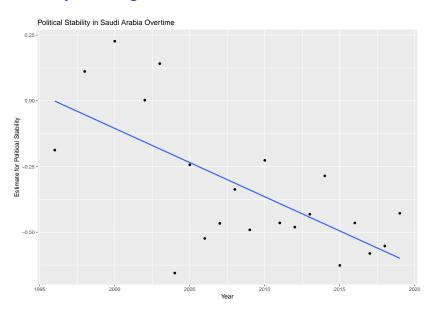


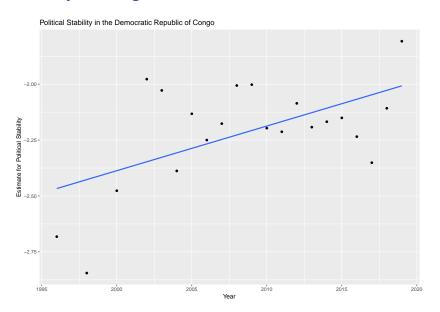
# Preliminary Investigation
Distribution of Political Stability for 2019

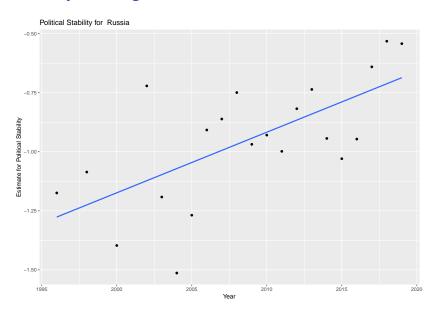


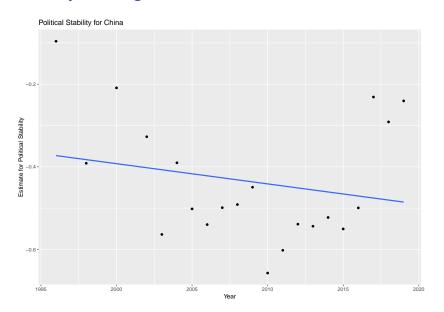












#### Adding More Data

```
## [1] "country"

## [4] "estimate"

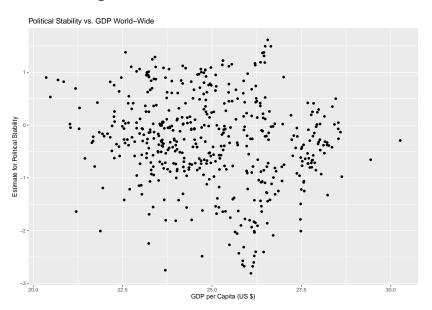
## [7] "fuel_ex"

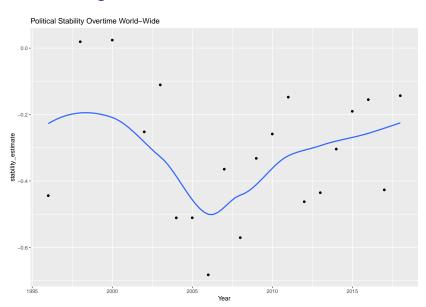
## [10] "lit_rate"
```

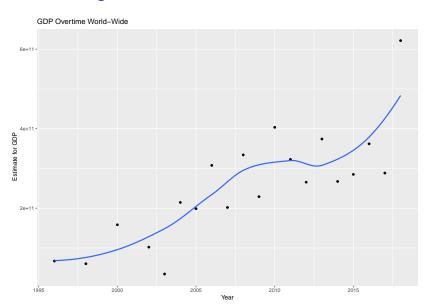
```
"code" "yea:
"gdp" "pop"
"military_expenditure" "inf:
"electric_access"
```

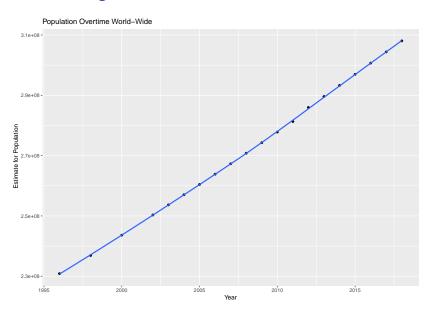
## Adding More Data

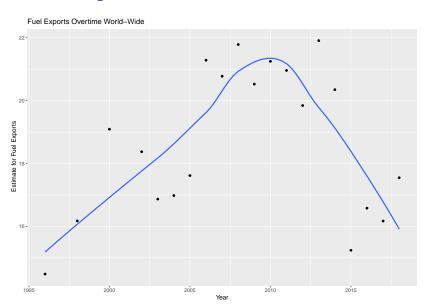
##	country	code	year	
##	Length: 495	Length: 495	Min. :1996 M:	
##	Class :character	Class :character	1st Qu.:2007 1s	
##	Mode :character	Mode :character	Median:2011 Me	
##			Mean :2011 Me	
##			3rd Qu.:2015 31	
##			Max. :2018 Ma	
##	gdp	population	fuel_ex	
##	Min. :6.975e+0	8 Min. :8.372e+04	Min. : 0.000	
##	1st Qu.:1.748e+1	0 1st Qu.:6.094e+06	1st Qu.: 1.374	
##	Median :6.091e+1	0 Median :1.527e+07	Median : 6.673	
##	Mean :3.096e+1	1 Mean :5.612e+07	Mean :21.303	
##	3rd Qu.:2.717e+1	1 3rd Qu.:4.729e+07	3rd Qu.:29.116	
##	Max. :1.389e+1	3 Max. :1.393e+09	Max. :99.986	
##	inflation	lit_rate elec	tric_access	
##	Min. :-4.863	Min. :12.85 Min.	: 3.696	
##	1st Qu.: 2.283	1st Qu.:77.20 1st	Qu.: 76.887	
##	Median : 4.199	Median: 92.06 Media	an : 98.035	

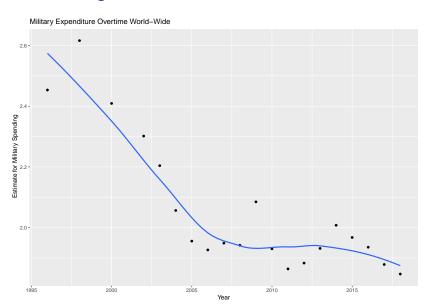


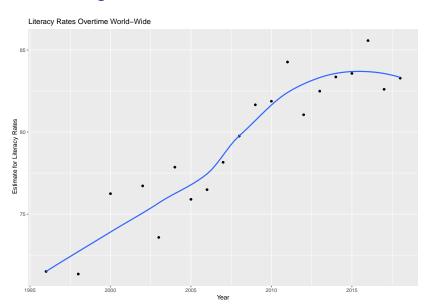












```
Variable Selection and Model Building
   ##
   ## Call:
   ## lm(formula = estimate ~ gdp + population + fuel_ex + mi
   ##
          inflation + lit_rate + electric_access, data = pred:
   ##
   ## Residuals:
           Min
                     10 Median
                                       30
   ##
                                               Max
   ## -1.98265 -0.48470 0.00826 0.51707 1.87188
   ##
   ## Coefficients:
   ##
                             Estimate Std. Error t value Pr(>
   ## (Intercept)
                           -1.078e+00 1.837e-01 -5.866 8.25e
   ## gdp
                                                           0.5
                           6.298e-14 5.949e-14 1.059
   ## population
                          -1.440e-09 3.228e-10 -4.460 1.026
```

-3.654e-03 1.363e-03 -2.680 0.0

## fuel\_ex

0.

## military\_expenditure -1.496e-02 2.320e-02 -0.645

## inflation -3.326e-02 6.065e-03 -5.484 6.70e

1.713e-02 3.022e-03 5.668 2.476

## lit\_rate

# Variable Selection and Model Building ##

##						
##	Model Ind	dex Pre	dictors			
##						
##	1	lit	_rate			
##	2	inf	lation lit_ra	ate		
##	3	pop	population inflation lit_rate			
##	4	pop	ulation fuel	_ex inflation	lit_rate	
##	5	pop	ulation fuel	_ex inflation	lit_rate ele	
##	6	gdp	population :	fuel_ex infla	tion lit_rate	
##	7	gdp	population :	fuel_ex milit	ary_expenditu	
##						
##						
##					Sul	
##						
##			Adj.	Pred		
##	Model	R-Square	R-Square	R-Square	C(p)	

Best Subsets Regress:

#### Optimal Linear Model ##

```
## Call:
## lm(formula = estimate ~ lit_rate, data = predictor_stab:
##
## Residuals:
      Min 1Q Median 3Q Max
##
## -2.14793 -0.54198 0.02002 0.57854 1.83231
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -1.507444 0.174928 -8.618 < 2e-16 ***
```

## lit\_rate 0.014295 0.002037 7.016 7.57e-12 \*\*\* ## ---

##

## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.05 '.' 0.3

## Residual standard error: 0.8223 on 493 degrees of freedom

## Multiple R-squared: 0.09079, Adjusted R-squared: 0

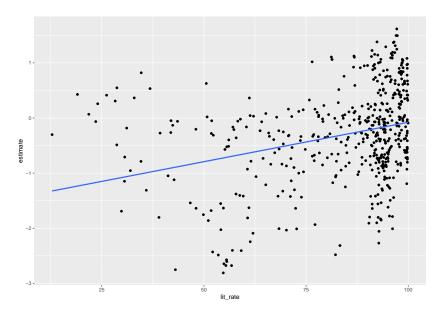
## F-statistic: 49.23 on 1 and 493 DF, p-value: 7.571e-12

#### Lack of Fit Test

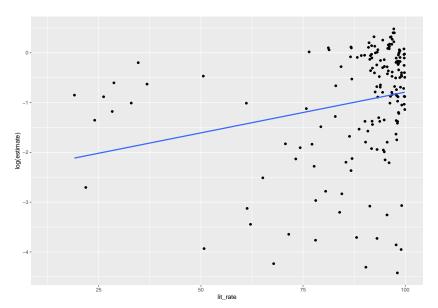
- Test assumption of linearity between political stability and literacy.
- ► With a small p-value we may have evidence against linearity. This need to be further investigated.

```
## Analysis of Variance Table
##
## Model 1: estimate ~ lit_rate
## Model 2: estimate ~ as.factor(lit_rate)
## Res.Df RSS Df Sum of Sq F Pr(>F)
## 1 493 333.35
## 2 2 0.01 491 333.34 148.11 0.006729 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.3
```

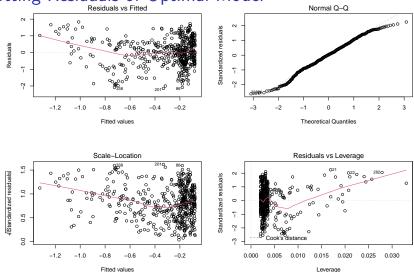
## Linearity investigation



## Linearity investigation



## Plotting Residuals of Optimal Model



# KNN

## Min. 1st Qu. Median Mean 3rd Qu. Max. ## 12.85 77.20 92.06 83.92 95.86 99.97

#### **KNN**

 $\# KNN + Our \ first \ round \ when \ K = 3 \ gives \ a \ classification accuracy rate of <math display="inline">30.06\%$ 

```
## knn.results
## Y.testing High
## High 117
## Low 246
## Standard 124
## Very High 1
## Very Low 1
## [1] 0.2392638
```

#### **KNN**

▶ A loops is then used to test our classification accuracy rate for all values of K from 1 to 20. We find that our optimal K with the highest classification accuracy rate is when K = 1 which gives a classification accuracy rate of 33.12%

```
## [1] 1
## [1] 0.2392638
```

"