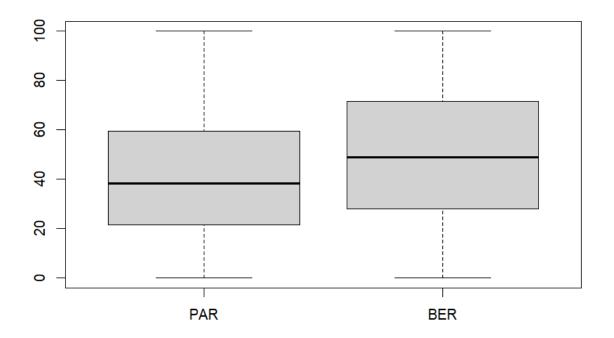
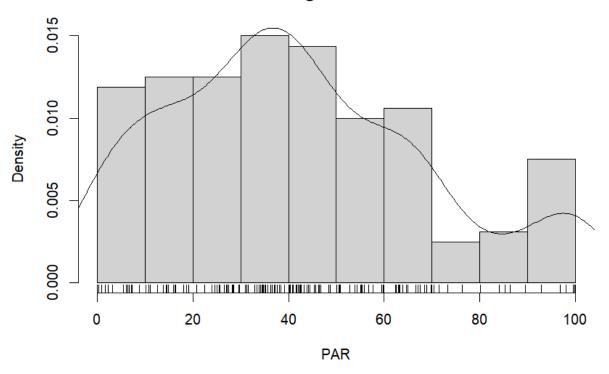
Ryan Lee Data Analytics October 14, 2025

Assignment 2

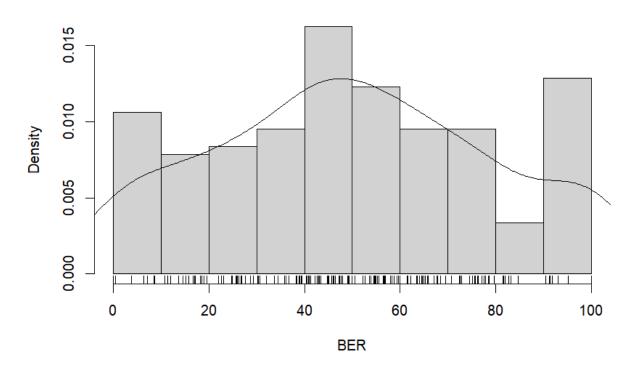
Variable Distribution

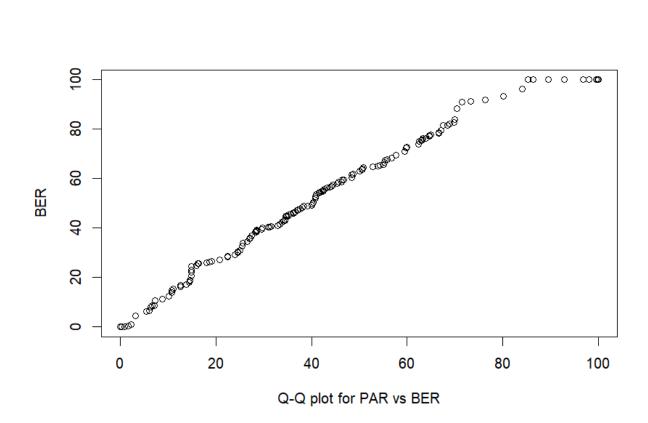


Histogram of PAR

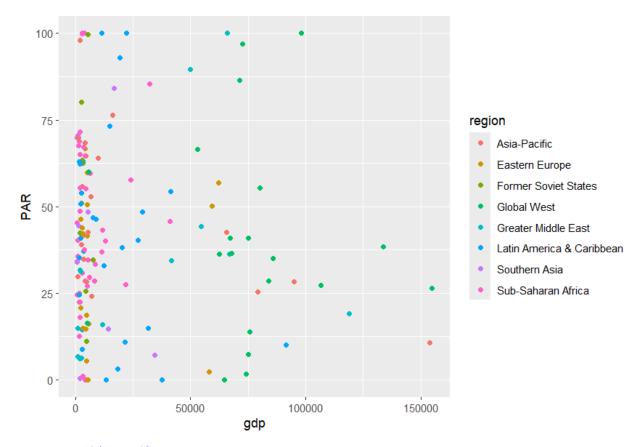


Histogram of BER





Linear Models



> summary(lin.mod0)

Call:

lm(formula = PAR ~ gdp, data = epi.data)

Residuals:

Min 1Q Median 3Q Max -42.643 -19.388 -2.628 17.284 62.563

Coefficients:

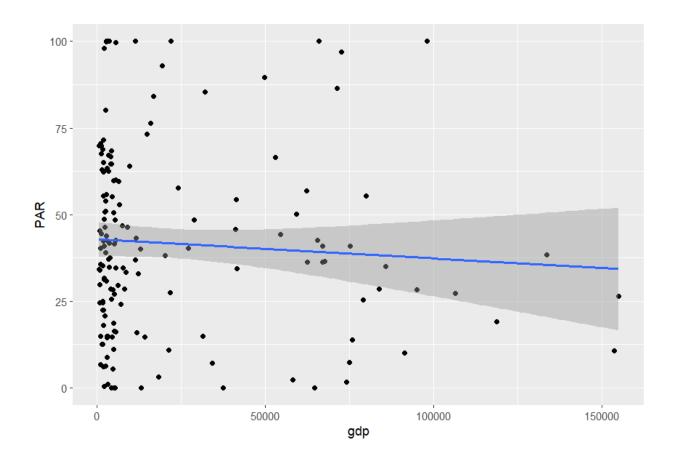
Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.288e+01 2.566e+00 16.711 <2e-16 ***
gdp -5.548e-05 6.535e-05 -0.849 0.397

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

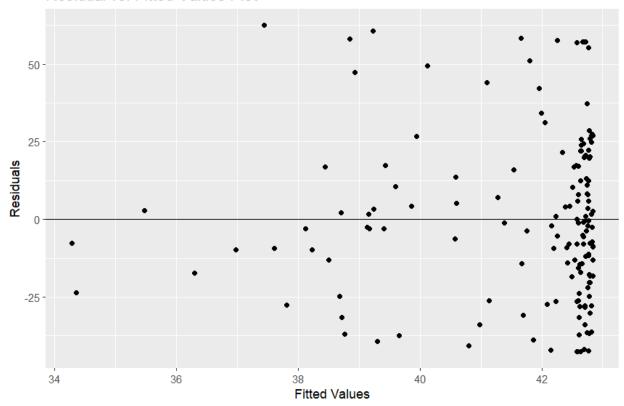
Residual standard error: 26.87 on 157 degrees of freedom (1 observation deleted due to missingness)

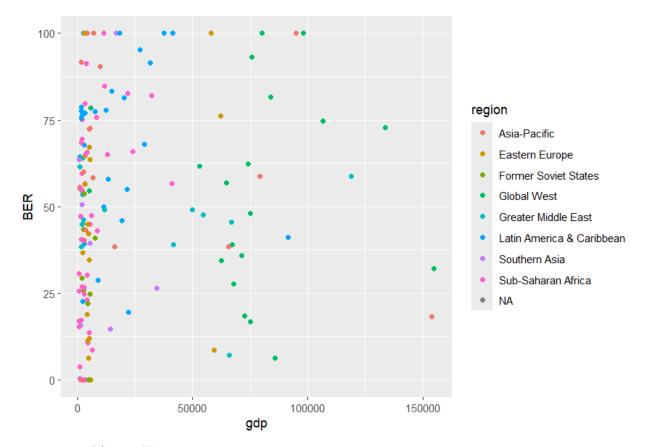
Multiple R-squared: 0.00457, Adjusted R-squared: -0.00177

F-statistic: 0.7208 on 1 and 157 DF, p-value: 0.3972



Residual vs. Fitted Values Plot





> summary(lin.mod1)

Call:

lm(formula = BER ~ gdp, data = epi.data)

Residuals:

Min 1Q Median 3Q Max -50.312 -23.344 0.421 22.155 49.892

Coefficients:

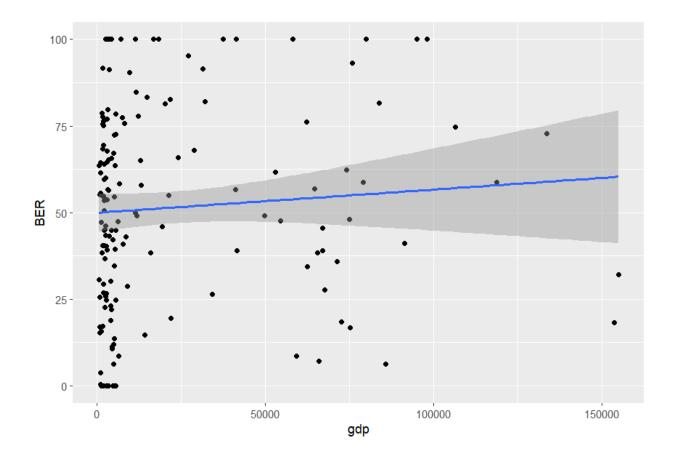
Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.994e+01 2.786e+00 17.927 <2e-16 ***
gdp 6.697e-05 7.094e-05 0.944 0.347

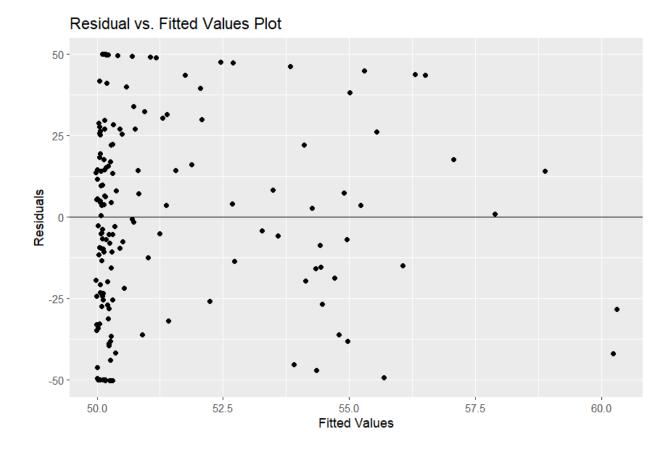
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Residual standard error: 29.17 on 157 degrees of freedom (20 observations deleted due to missingness)

Multiple R-squared: 0.005645, Adjusted R-squared: -0.0006882

F-statistic: 0.8913 on 1 and 157 DF, p-value: 0.3466





Observing both models here, it's very clear that these models aren't very good because visually seems like these models are most likely not linear. However, between the two models, the BER linear model is much better because it produces a lower p-value and high t-statistic.

kNN Classification

Display results

> cm1

Confusion Matrix and Statistics

_	_			
ν	2 + د	2r	Δn	ce

1	vererence		
Prediction	Asia-Pacific Global	West Latin	America & Caribbean
Southern Asia			
Asia-Pacific	2	0	1
0			
Global West	0	0	0
0			
Latin America & Caribbean	0	0	3
0			
Southern Asia	0	0	0
0			
Sub-Saharan Africa	0	0	0
0			

Reference

Prediction	Sub-Saharan	Africa
Asia-Pacific		0
Global West		0
Latin America & Caribbean		0
Southern Asia		0
Sub-Saharan Africa		0

Overall Statistics

Accuracy: 0.8333

95% CI : (0.3588, 0.9958)

No Information Rate : 0.6667 P-Value [Acc > NIR] : 0.3512

Kappa : 0.6667

Mcnemar's Test P-Value : NA

Statistics by Class:

Class: Asia-Pacific Class: Global West Class: Latin

America & Caribbean		
Sensitivity	1.0000	NA
0.7500		
Specificity	0.7500	1
1.0000		
Pos Pred Value	0.6667	NA
1.0000		
Neg Pred Value	1.0000	NA
0.6667		

Prevalence	0.3333	0
0.6667		
Detection Rate	0.3333	0
0.5000		
Detection Prevalence	0.5000	0
0.5000		
Balanced Accuracy	0.8750	NA
0.8750		

Class: Southern Asia Class: Sub-Saharan Africa Sensitivity NA Specificity 1 1 Pos Pred Value NA NA Neg Pred Value NA NA Prevalence 0 0 Detection Rate 0 0 Detection Prevalence 0 0 Balanced Accuracy NA NA

> cm2

Confusion Matrix and Statistics

Reference

Prediction	Asia-Pacific	Global West	Latin America	& Caribbean
Southern Asia				
Asia-Pacific	0	0		1
0				
Global West	0	0		0
0				
Latin America & Caribbean	2	0		3
0				
Southern Asia	0	0		0
0				
Sub-Saharan Africa	0	0		0
0				

Reference

Prediction	Sub-Saharan	Africa
Asia-Pacific		0
Global West		0
Latin America & Caribbean		0
Southern Asia		0
Sub-Saharan Africa		0

Overall Statistics

Accuracy : 0.5

95% CI: (0.1181, 0.8819)

No Information Rate : 0.6667 P-Value [Acc > NIR] : 0.8999

Kappa : -0.2857

Mcnemar's Test P-Value : NA

Statistics by Class:

	Class:	Asia-Pacific	Class:	Global	West	Class:	Latin
America & Caribbean							
Sensitivity		0.0000			NA		
0.7500							
Specificity		0.7500			1		
0.0000							
Pos Pred Value		0.0000			NA		
0.6000							
Neg Pred Value		0.6000			NA		
0.0000							
Prevalence		0.3333			0		
0.6667							
Detection Rate		0.0000			0		
0.5000		0 1668			0		
Detection Prevalence		0.1667			0		
0.8333		0 2750			3.77		
Balanced Accuracy 0.3750		0.3750			NA		
0.3730	Clagg	Southern Asia	. Clagg	Cub_C	aharan	7 fria	2
Sensitivity	Class.	NA		Sub-So	allaLall	AIIIC	
Specificity		INE	=				1
Pos Pred Value		NA NA	='			N.	_
Neg Pred Value		NZ NZ	=			N/	-
Prevalence		1/12	=				0
Detection Rate		(0
Detection Prevalence		(0
Balanced Accuracy		N.				N	A
_							

>

> cat("Model 1 Accuracy:", round(acc1, 7), "\n")

Model 1 Accuracy: 0.8333333

> cat("Model 2 Accuracy:", round(acc2, 7), " \n ")

Model 2 Accuracy: 0.5

Since Model 1's accuracy is greater than Model 2, Model 1 seems to be the better model. Model 1's features were ECO, BDH, and MKP new columns. Both kNN models experienced a train test split of 70% and 30% with 10-fold cross validation across varying k-values. After plotting their contingency matrices and picking out their accuracies, Model 1 displayed better results.