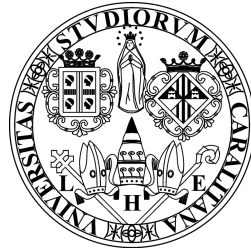
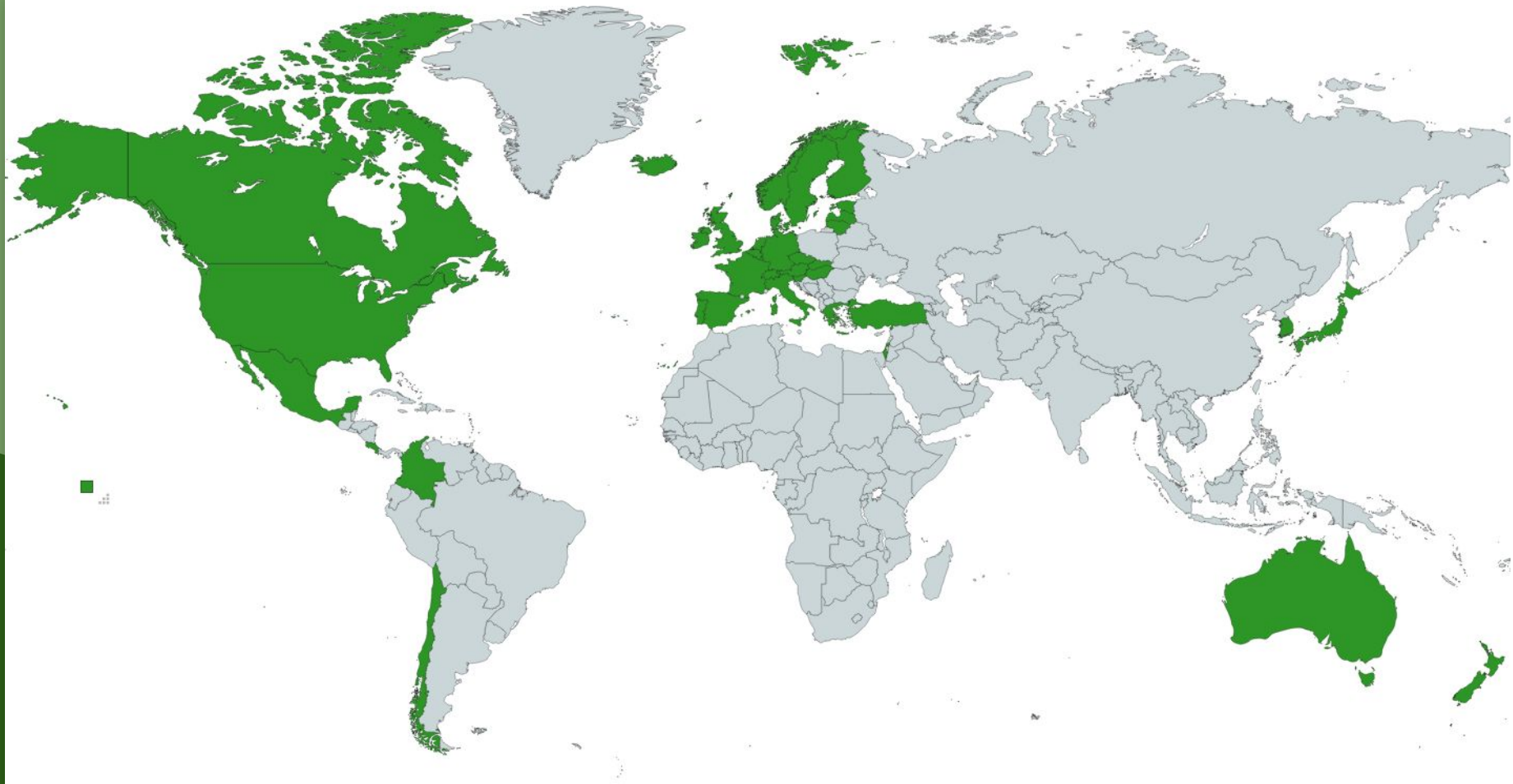


GREEN INVESTMENT CLASSIFICATOR



Giuseppe Grosso
Matteo Fercia



Which country should we
choose?



Social media



Economy



Energy



Pollution



Social Media

- Scraped tweets:

- ➡ Positive
- ➡ Negative
- ➡ Neutral



Energy

- Total production
- RE production
- % RE
- Avg consumption

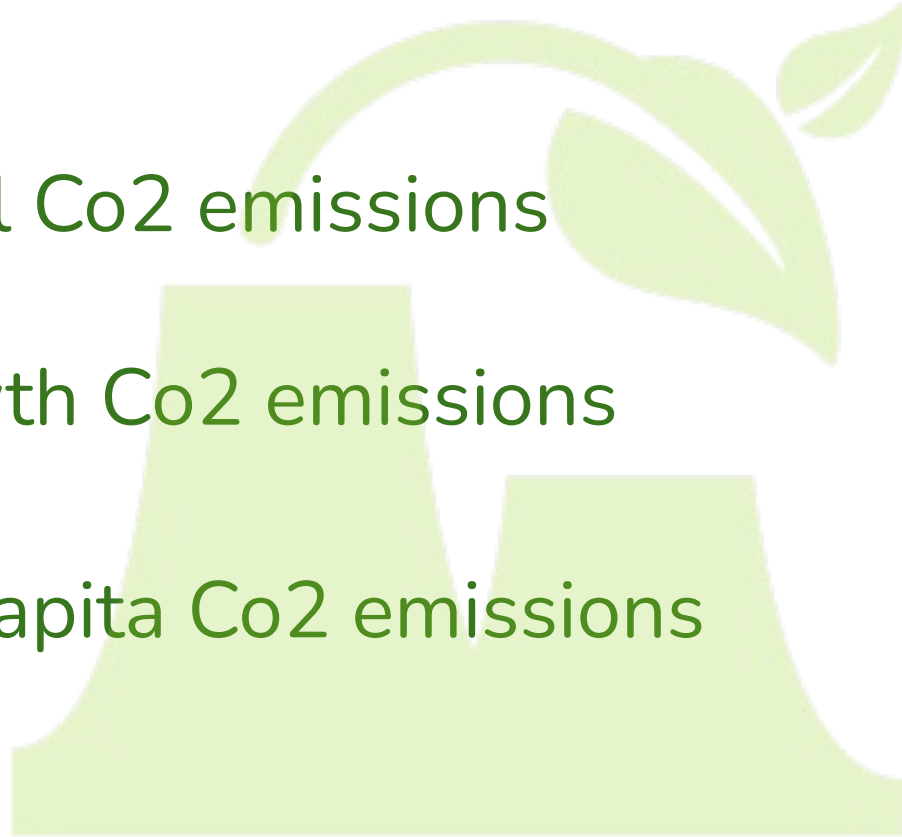
Economy

- Green Investment
- Official Development Assistance (Oda)
- Population



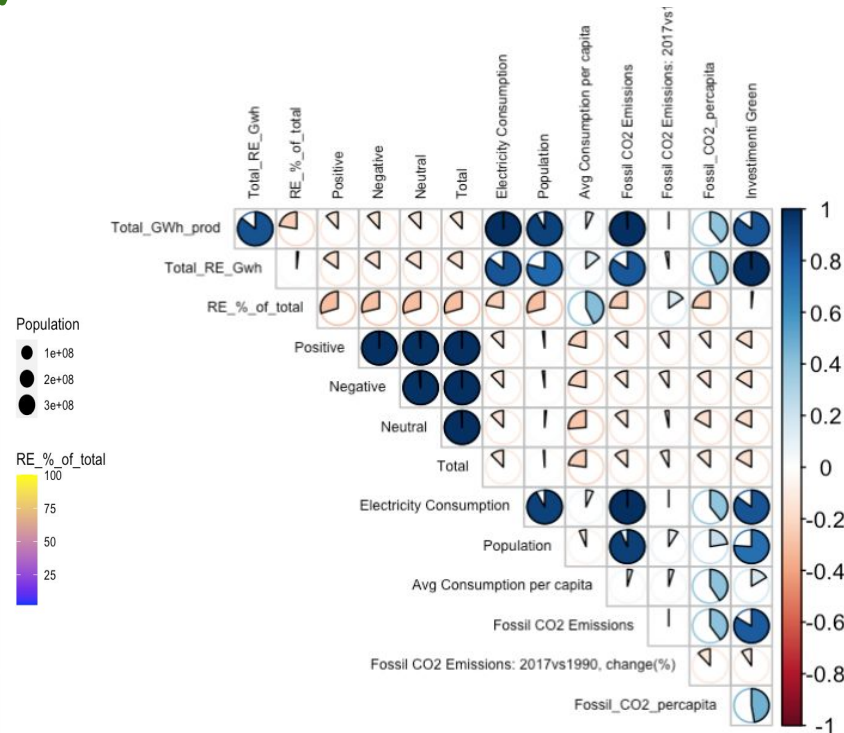
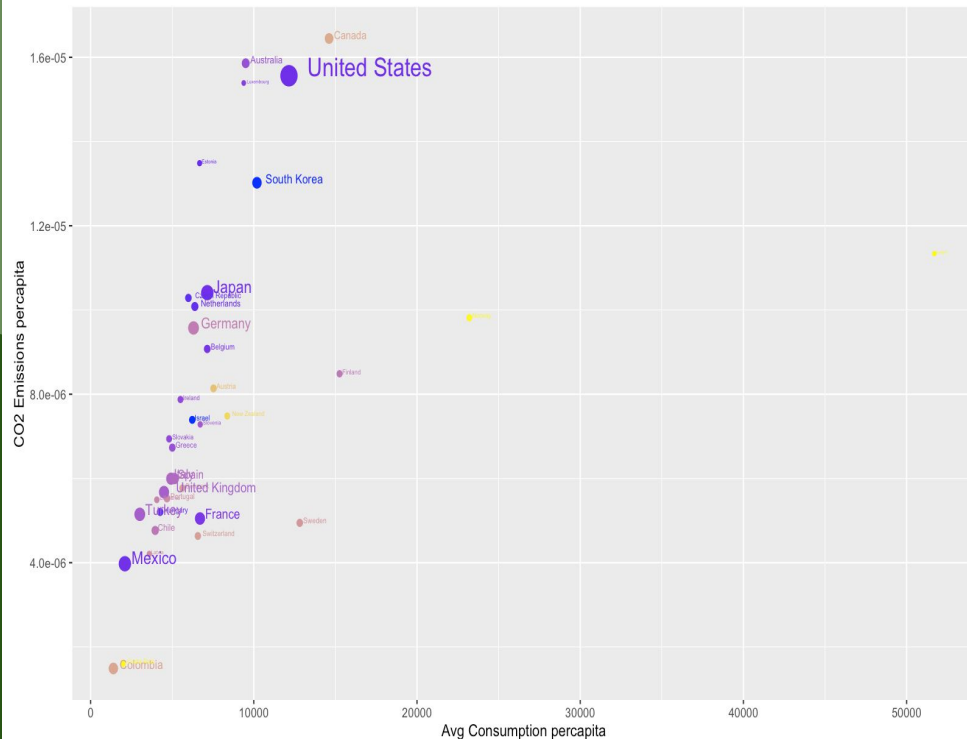
Pollution

- Fossil Co2 emissions
- Growth Co2 emissions
- Per capita Co2 emissions



Exploratory Data Analysis

Emissioni in base al consumo percapita



Classification

- Logistic Regression
- KNN
- Random forest
- SVM

Logistic Regression

Training set

```
Call:
glm(formula = `Risultato Investimento` ~ Population + `Investimenti Green` +
    Total_GWh_prod + Total_RE_Gwh, family = binomial, data = ds1,
    na.action = na.omit)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-5.641e-04	-2.000e-08	-2.000e-08	2.000e-08	5.469e-04

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.241e+00	1.246e+03	0.001	0.999
Population	-1.326e-05	9.427e-04	-0.014	0.989
`Investimenti Green`	-1.559e+02	1.266e+04	-0.012	0.990
Total_GWh_prod	-1.030e-02	6.877e-01	-0.015	0.988
Total_RE_Gwh	3.243e-02	2.137e+00	0.015	0.988

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 4.6626e+01 on 36 degrees of freedom
Residual deviance: 7.1783e-07 on 32 degrees of freedom
AIC: 10

Number of Fisher Scoring iterations: 25

Test set - CV

Generalized Linear Model

37 samples
16 predictors
2 classes: '0', '1'

No pre-processing

Resampling: Cross-Validated (10 fold)

Summary of sample sizes: 33, 34, 34, 33, 34, 33, ...

Resampling results:

Accuracy	Kappa
0.785	0.5785714

Precision, Recall and F1-score

```
precision_glm <- posPredValue(predictions_glm, y_glm, positive="Positive") # 1
recall_glm <- sensitivity(predictions_glm, y_glm, positive="Positive") # 1
```

```
F1_glm <- (2 * precision_glm * recall_glm) / (precision_glm + recall_glm) # 1
```

KNN

Training set / Test set

```
p.YTrain3 = knn(XTrain, XTrain, YTrain, k=12)
table(ds1$`Risultato Investimento`,p.YTrain3)
mean(p.YTrain3!=ds1$`Risultato Investimento`) ## ErrorRate = 0.3513514
mean(p.YTrain3==ds1$`Risultato Investimento`) ## Accuracy 0.6486486
```

```
p.YTrain3
  0  1
0 22  3
1 10  2
```

```
p.YTest3 = knn(XTrain, XTest, YTrain, k=12)
table(ds1[test,]$`Risultato Investimento`,p.YTest3)
mean(p.YTest3!=ds1[test,]$`Risultato Investimento`) #ErrorRate 0.1538462
mean(p.YTest3==ds1[test,]$`Risultato Investimento`) #Accuracy 0.8461538
```

```
p.YTest3
  0  1
0 10  0
1  2  1
```

Precision, Recall and F1-score

```
precision <- posPredValue(predictions, y, positive="Positive") # 0.4545455
recall <- sensitivity(predictions, y, positive="Positive") # 0.4166667
F1 <- (2 * precision * recall) / (precision + recall) # 0.4347826
```

Random Forest

Training set / Test set

```
rf2=randomForest(ds1_train$`Risultato Investimento`~.,  
                 data=ds1_train[,-c(4,9,11:16,19)],  
                 mtry=4,importance=TRUE,ntree=500, na.action = na.omit)
```

```
summary(rf2)
```

```
rf_preds2 = predict(rf2,newdata=ds1_test)
```

```
rf_preds2
```

```
table(rf_preds2, ds1_test$`Risultato Investimento`)
```

```
8/13 ## Accuracy = 0.6153846
```

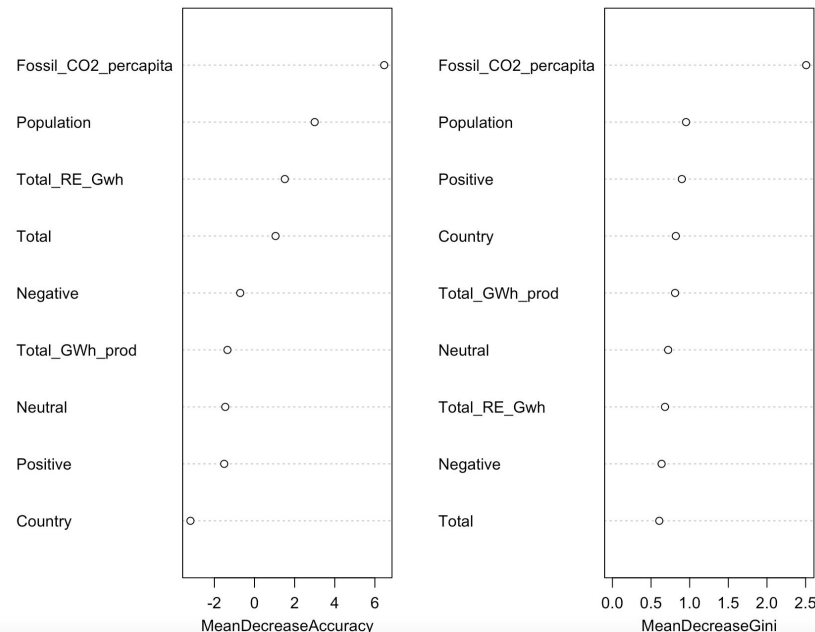
```
1-(8/13) ## ErrorRate = 0.3846154
```

```
rf_preds2 0 1  
          0 7 5  
          1 0 1
```

Precision, Recall and F1-score

```
precision_rf <- posPredValue(predictions_rf, y_rf, positive="1") # 1  
recall_rf <- sensitivity(predictions_rf, y_rf, positive="1") # 0.1666667  
F1_rf <- (2 * precision_rf * recall_rf) / (precision_rf + recall_rf) # 0.2857143
```

Variable Importance Plot



SVM

1st SVM

```
mean(pred_test1==ds_svm_test$`Risultato Investimento`) #accuracy 0.8461538
precision_svm <- posPredValue(predictions_svm, y_svm, positive="1") # 0.6666667
recall_svm <- sensitivity(predictions_svm, y_svm, positive="1") # 0.6666667
F1_svm <- (2 * precision_svm * recall_svm) / (precision_svm + recall_svm) #0.6666667
```

	pred	
truth	-1	1
	-1	9
	1	1

2nd SVM

```
pred_test2 <- predict(svm_model2, ds_svm_test)
table("truth"=ds_svm_test$`Risultato Investimento`, "pred"=pred_test2)
mean(pred_test2==ds_svm_test$`Risultato Investimento`) #[1] 0.8181818
mean(pred_test2!=ds_svm_test$`Risultato Investimento`) #[1] 0.1818182 tasso errata classificazione test
```

Precision, Recall and F1-score

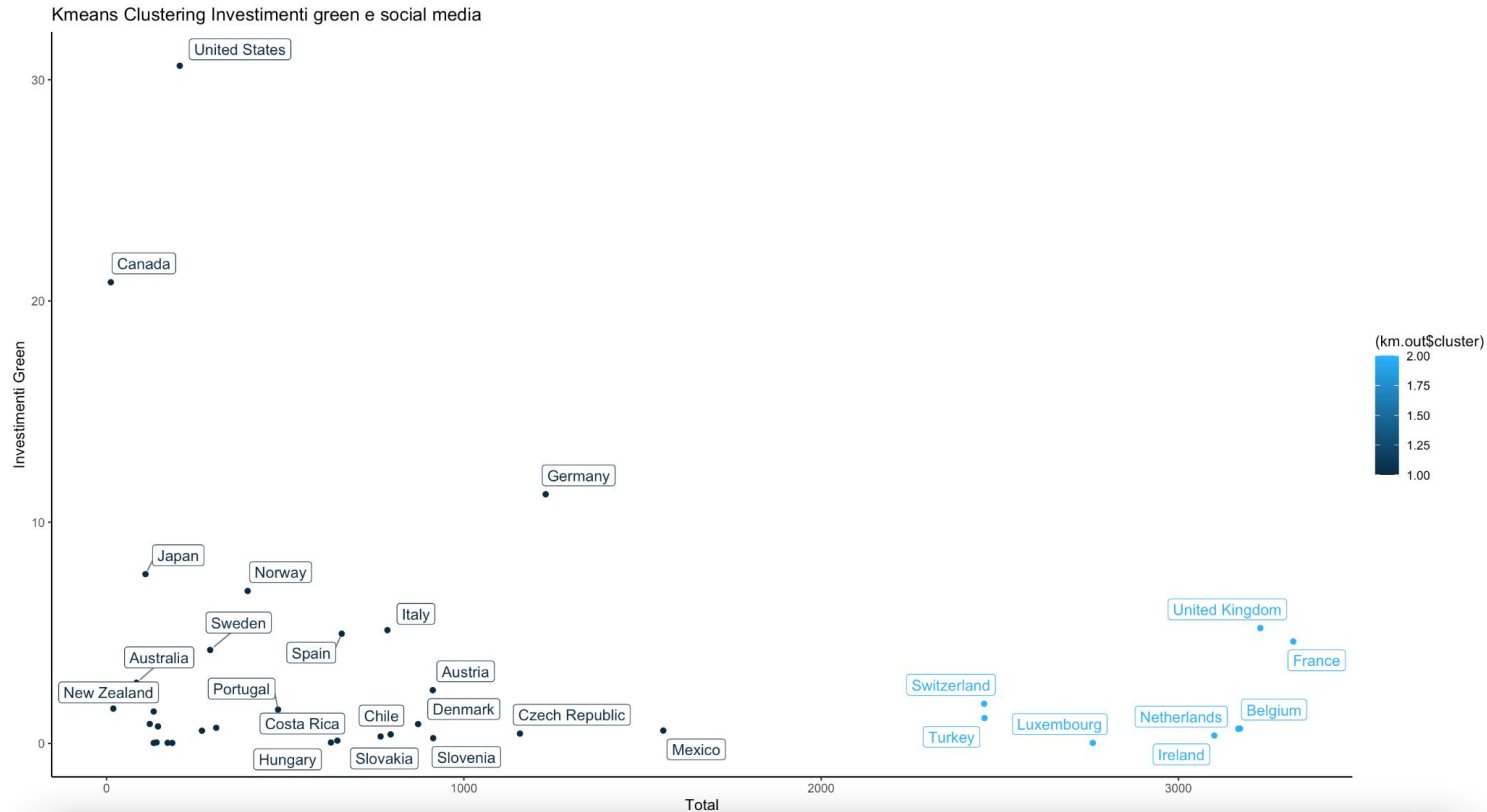
```
precision_svm <- posPredValue(predictions_svm, y_svm, positive="1") # 0.6666667
recall_svm <- sensitivity(predictions_svm, y_svm, positive="1") # 0.6666667

F1_svm <- (2 * precision_svm * recall_svm) / (precision_svm + recall_svm) # 0.6666667
```

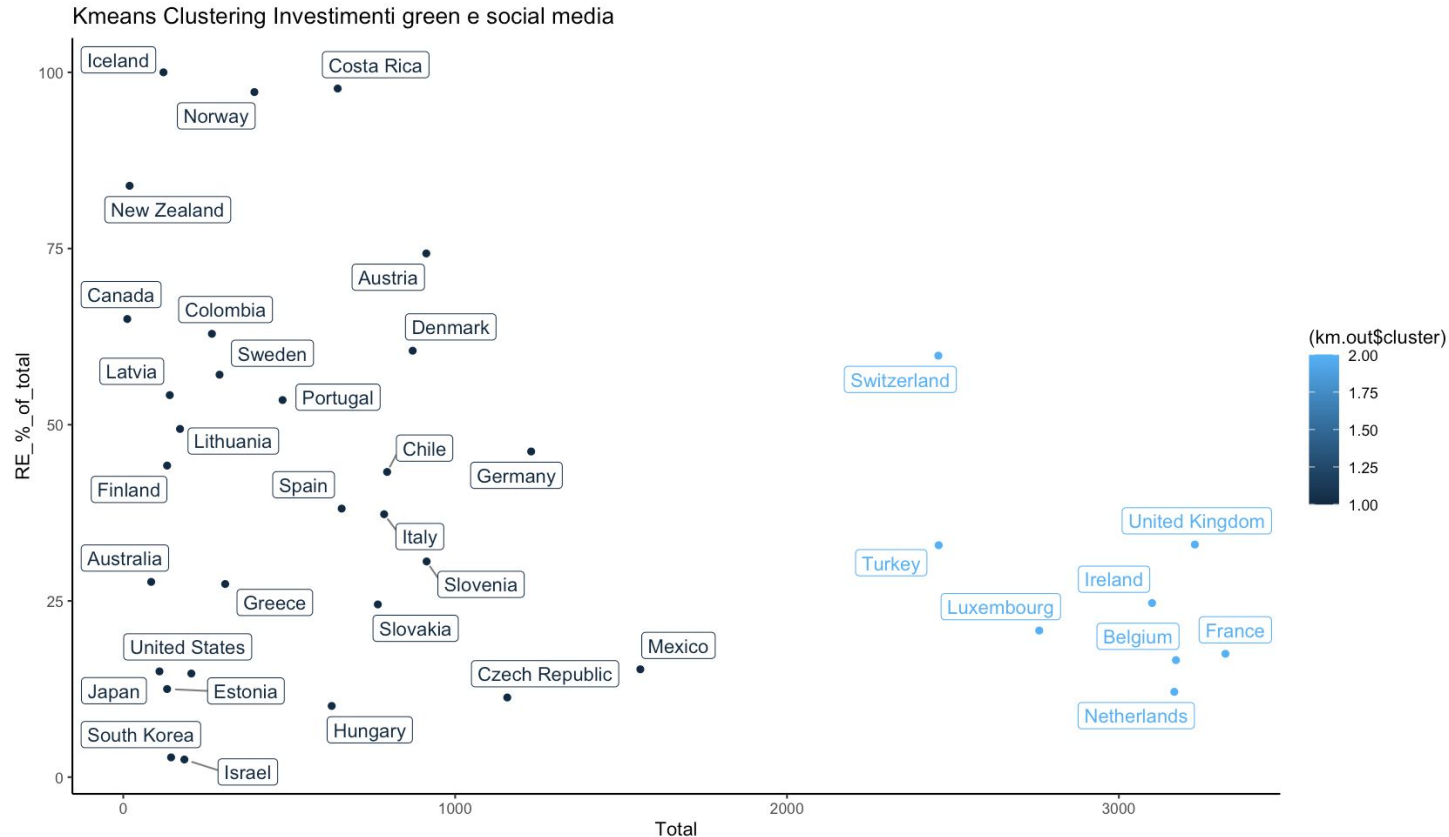
Cluster Analysis

- K-means Clustering
- Hierarchical Clustering
- Principal Component Analysis
- Clustering with PCA

K-Means Clustering - 1

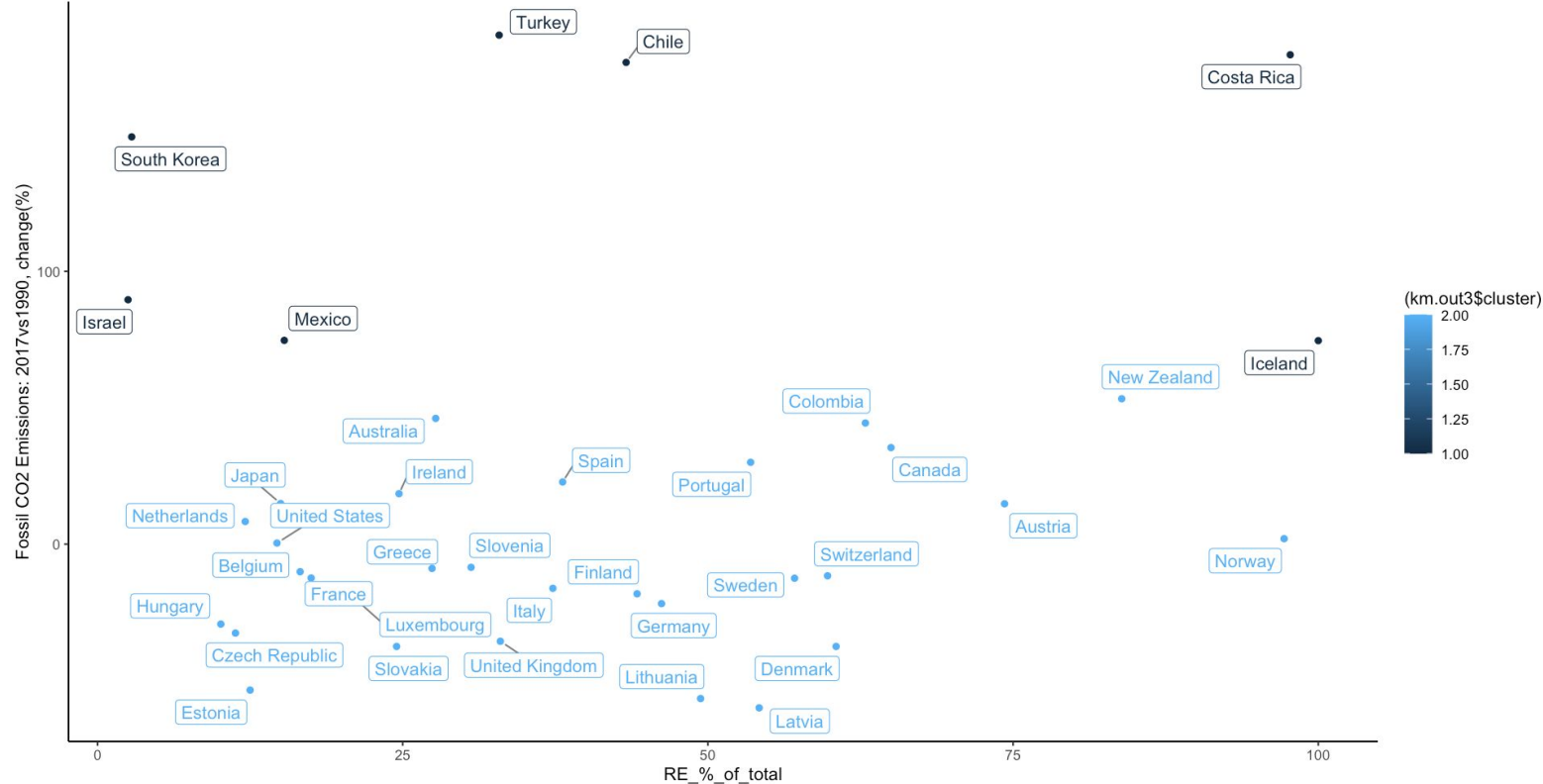


K-Means Clustering - 2



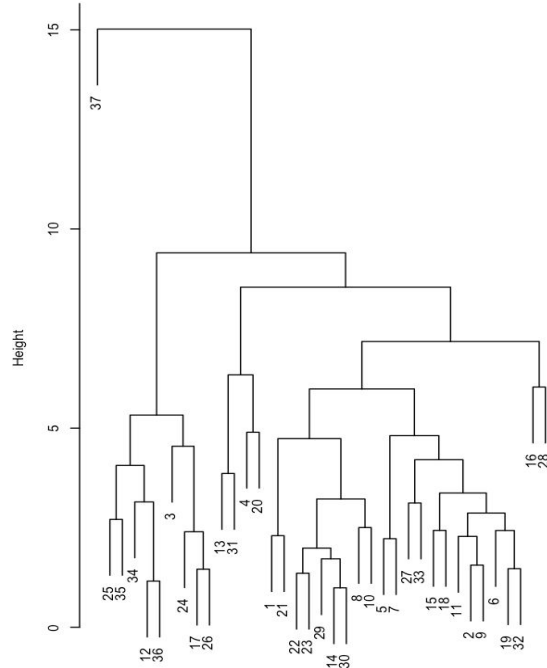
K-Means Clustering - 3

K-Means Clustering on Fossil CO2 Emissions: 2017vs1990, change(%) and RE_%_of_total with K=2



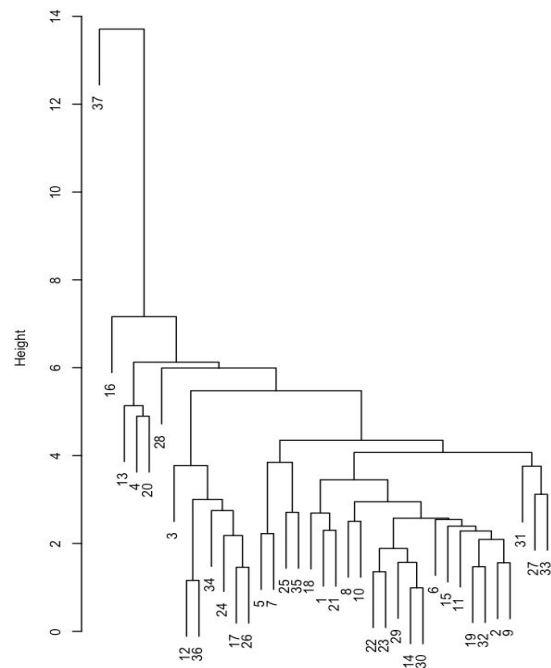
Hierarchical Clustering

Hierarchical Clustering with Scaled Features Complete



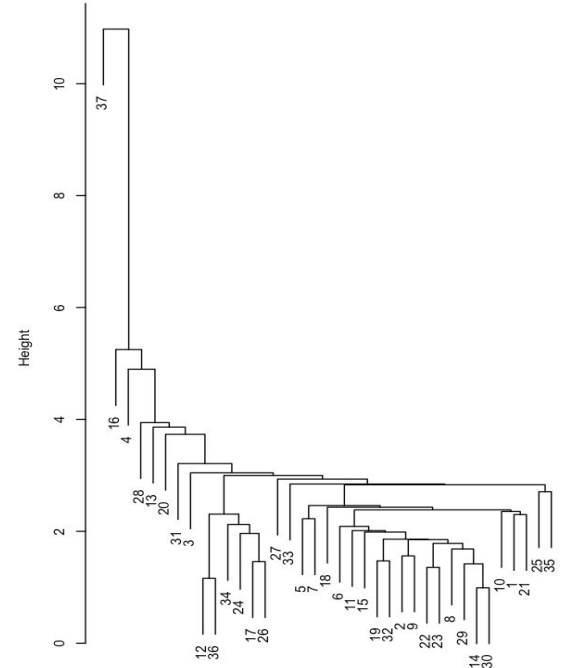
dist(xsc)
hclust("complete")

Hierarchical Clustering with Scaled Features Average Linkage



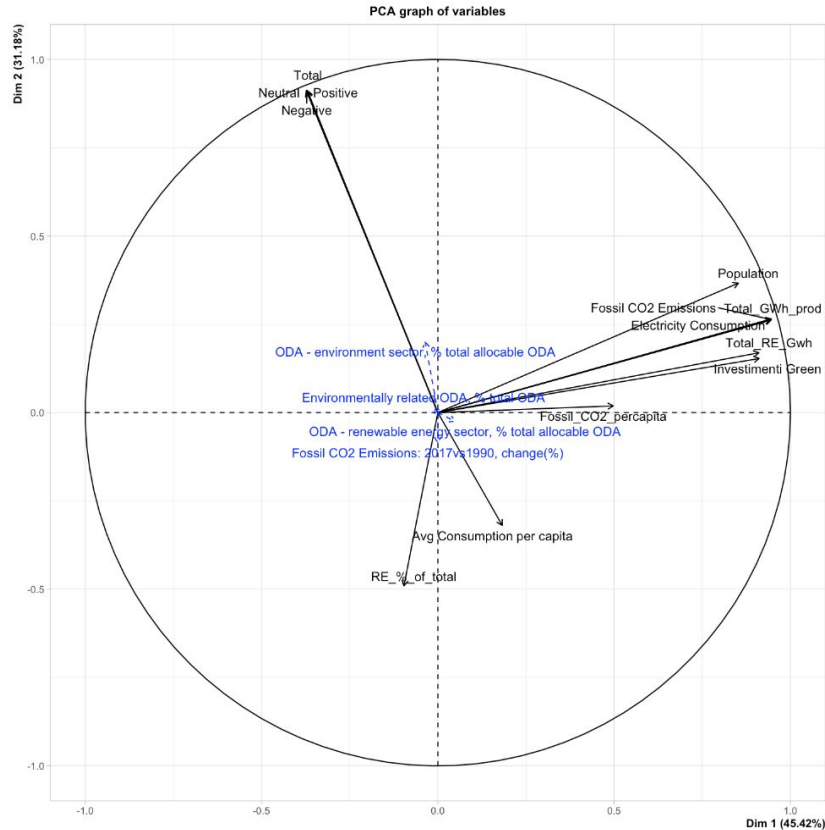
dist(xsc)
hclust("average")

Hierarchical Clustering with Scaled Features Single Linkage



dist(xsc)
hclust("single")

Principal Component Analysis - 1

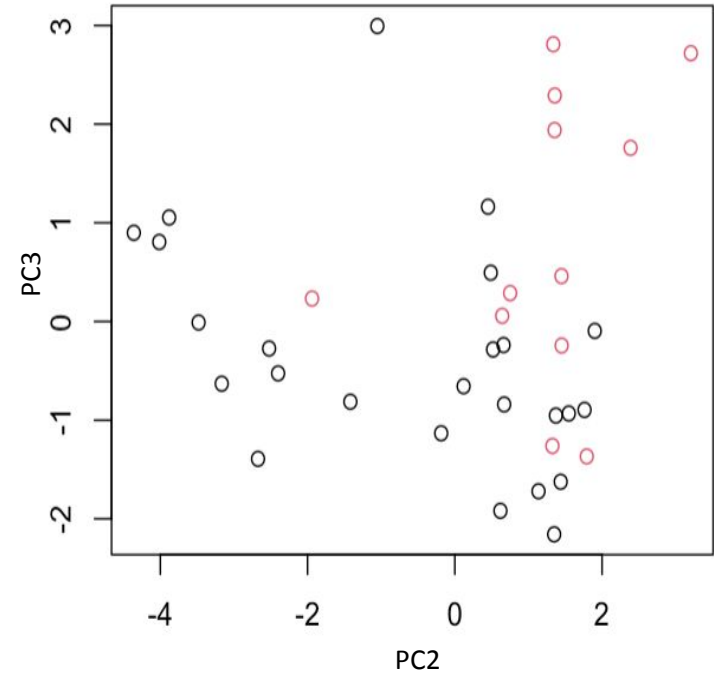
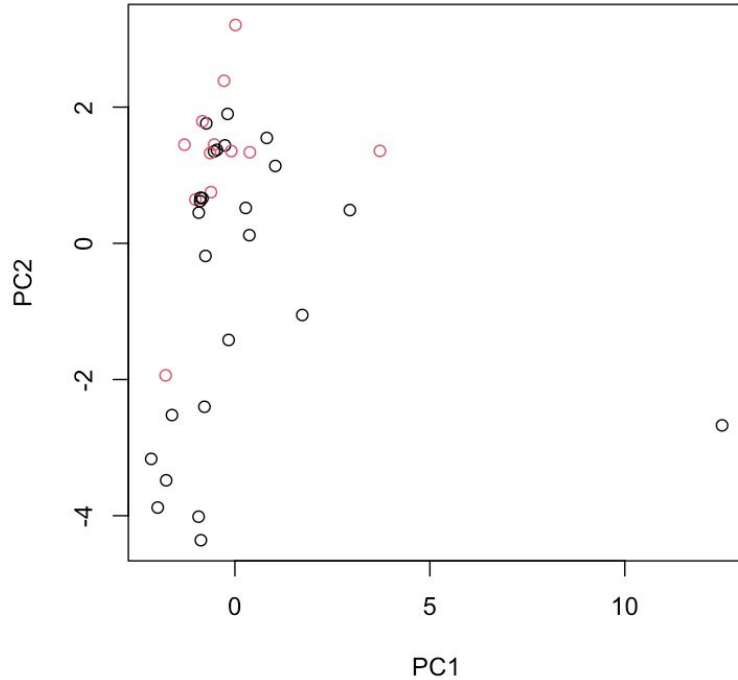


#Eigenvalues

#	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
#Variance	5.905	4.053	1.350	1.015	0.433
## of var.	45.424	31.180	10.386	7.810	
3.331					
#Cumulative % of var.	45.424	76.603	86.990	94.799	
98.130					

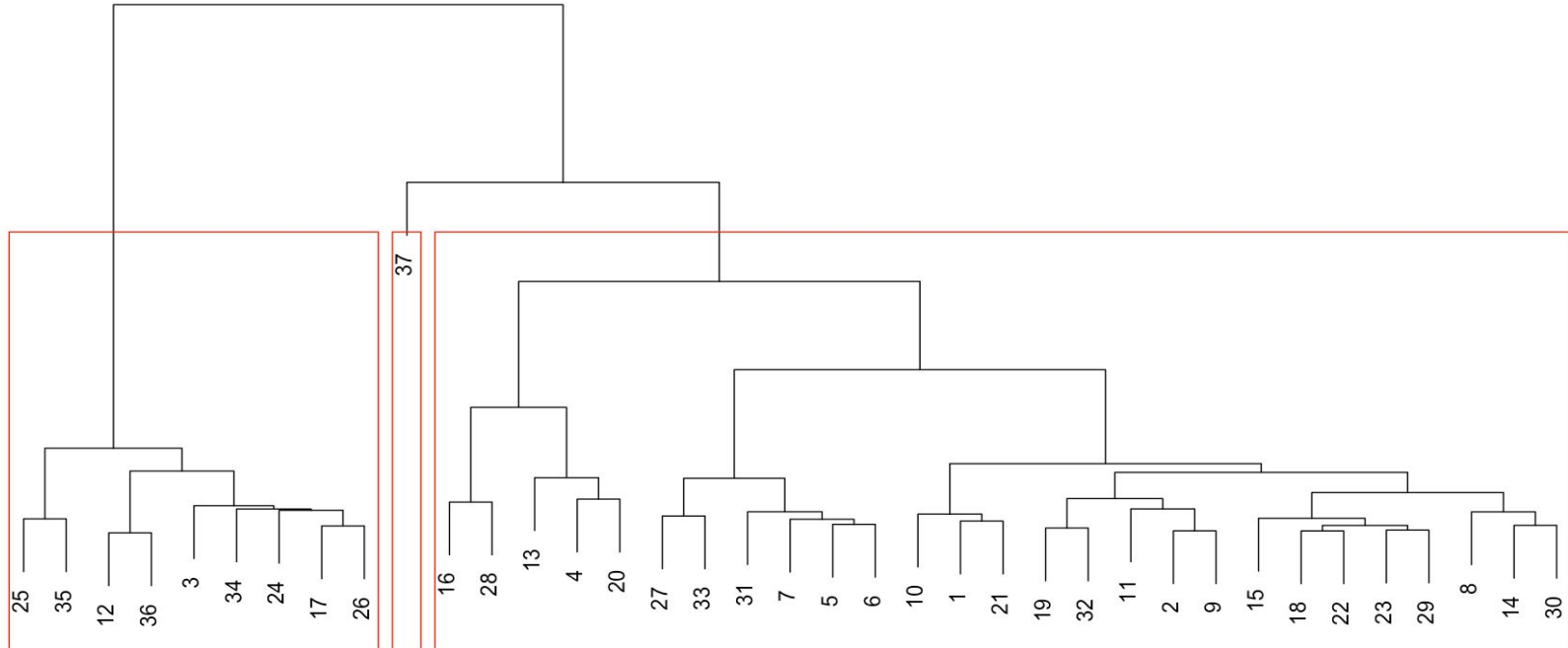
	Dim.5	Dim.6	Dim.7	Dim.8	Dim.9
#Variance	0.433	0.149	0.077	0.009	0.003
## of var.	3.331	1.145	0.593	0.070	0.026
#Cumulative % of var.	98.130	99.275	99.868	99.938	
99.963					

Principal Component Analysis - 2



Clustering with PCA

hClust Comp 1-4



A light green graphic in the background features a stylized leaf on the left and a power plug icon on the right, connected by a circular arrow, symbolizing a sustainable cycle.

Conclusions