

# Analyse des données européennes

FALL

2024-12-26

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## 1 Contexte général

Les données analysées dans ce projet concernent différents indicateurs socio-économiques et environnementaux pour un ensemble de pays européens. Ces indicateurs offrent une vision globale de divers aspects comme la démographie, l'économie, l'énergie, l'emploi et l'environnement. Les analyses visent à explorer les structures sous-jacentes et les relations entre ces variables, ainsi qu'à regrouper les pays selon des caractéristiques communes.

### *Description des variables*

Les données contiennent 16 variables descriptives, reflétant des dimensions clés :

Population au 1er janvier : Nombre absolu d'habitants.  
Population jeune (15-29 ans) : Pourcentage de jeunes dans la population totale.  
Premières demandes d'asile : Nombre absolu de demandes.  
Écart de rémunération entre les sexes : Pourcentage de différence de salaire horaire brut moyen entre hommes et femmes.  
Salaire minimum : Montant en euros par mois.  
Décrocheurs scolaires précoces : Pourcentage de la population âgée de 18 à 24 ans quittant prématurément l'école.  
Taux d'inflation : Variation en pourcentage par rapport à l'année précédente.  
Taux de chômage : Pourcentage de la population active âgée de 15 à 74 ans.  
Taux de chômage des jeunes : Pourcentage de la population active de moins de 25 ans.  
PIB par habitant : Produit intérieur brut en euros par habitant.  
Dette brute du gouvernement : Pourcentage de la dette brute par rapport au PIB.  
Émissions de gaz à effet de serre : Quantité moyenne en tonnes par habitant.  
Énergies renouvelables : Pourcentage dans la consommation finale brute d'énergie.  
Prix de l'électricité : Montant en euros par MWh, incluant les taxes.  
Dépendance aux importations d'énergie : Pourcentage de dépendance à l'énergie importée.  
Taux de risque de pauvreté ou d'exclusion sociale : Pourcentage de la population à risque de pauvreté ou d'exclusion sociale.

L'objectif de cette analyse est d'explorer et de réduire la dimensionnalité des données grâce à une analyse en composantes principales (ACP), puis de grouper les pays selon leurs caractéristiques à l'aide de méthodes de classification. L'ACP permet de visualiser les similitudes entre pays et d'identifier les variables les plus importantes. Les méthodes de classification, notamment la classification ascendante hiérarchique (CAH) et l'algorithme des centres mobiles (k-means), permettent d'interpréter les regroupements obtenus. Les résultats des classifications seront comparés afin de comprendre les proximités entre pays et leur cohérence.

Pour la préparation des données, une normalisation a été appliquée pour rendre les variables comparables. L'analyse inclut la création de matrices de dissimilarité, l'utilisation de la décomposition en valeurs propres pour l'ACP, et l'application des méthodes de classification sur les données normalisées. Les regroupements obtenus seront interprétés à travers l'étude des centres de gravité, des inerties et des plans factoriels. Enfin, une attention particulière sera portée à l'analyse des proximités des pays dans des zones spécifiques de l'espace factoriel, afin de mieux comprendre les similarités entre pays.

```
# Vérification et chargement des bibliothèques nécessaires
if (!require(ggplot2)) install.packages("ggplot2", dependencies = TRUE)
library(ggplot2)

# Chargement de TinyTeX si nécessaire (une seule fois)
if (!tinytex::is_tinytex()) {
  tinytex::install_tinytex()
}

euro_data <- read.csv("data/euro.csv", header = TRUE, sep = ";")

# Normalisation des données (Min-Max Scaling)
euro_data_normalized <- as.data.frame(lapply(euro_data[, -1], function(x) {
  (x - min(x, na.rm = TRUE)) / (max(x, na.rm = TRUE) - min(x, na.rm = TRUE))
})))

euro_data <- read.csv("data/euro.csv", header = TRUE, sep = ";")

# Normalisation des données (Min-Max Scaling)
euro_data_normalized <- as.data.frame(lapply(euro_data[, -1], function(x) {
  (x - min(x, na.rm = TRUE)) / (max(x, na.rm = TRUE) - min(x, na.rm = TRUE))
})))

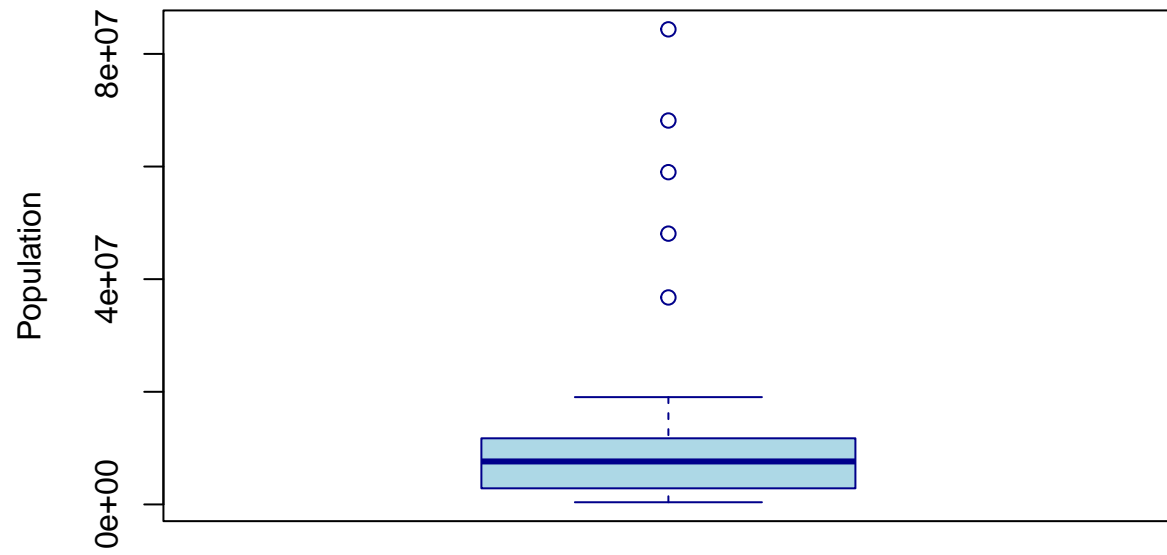
# Supprimer la première colonne si elle contient des noms (optionnel)
euro_data <- euro_data[, -1]

# Convertir les colonnes en numériques si nécessaire
euro_data <- data.frame(lapply(euro_data, function(x) as.numeric(as.character(x)))))

selected_columns <- colnames(euro_data)[1:2] # Diagrammes 1 à 2
for (col_name in selected_columns) {
  boxplot(euro_data[[col_name]],
    main = paste("Boîte à moustaches pour", col_name),
    ylab = col_name,
    col = "lightblue",
    border = "darkblue")

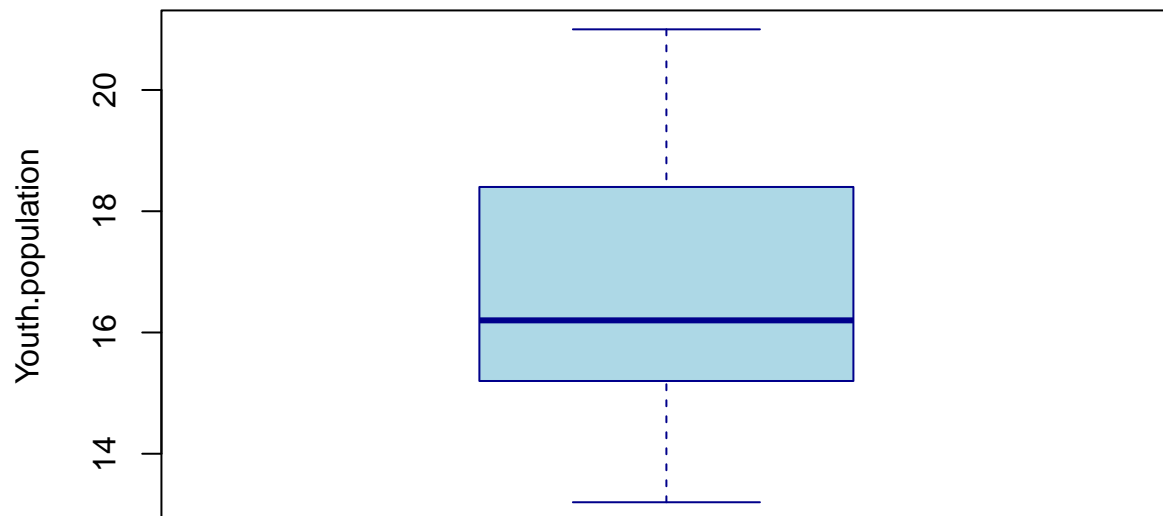
  # Interprétation
  cat(paste("\n**Interprétation pour", col_name, " :**\n"))
}
```

## Boîte à moustaches pour Population



```
##  
## **Interprétation pour Population :**
```

## Boîte à moustaches pour Youth.population

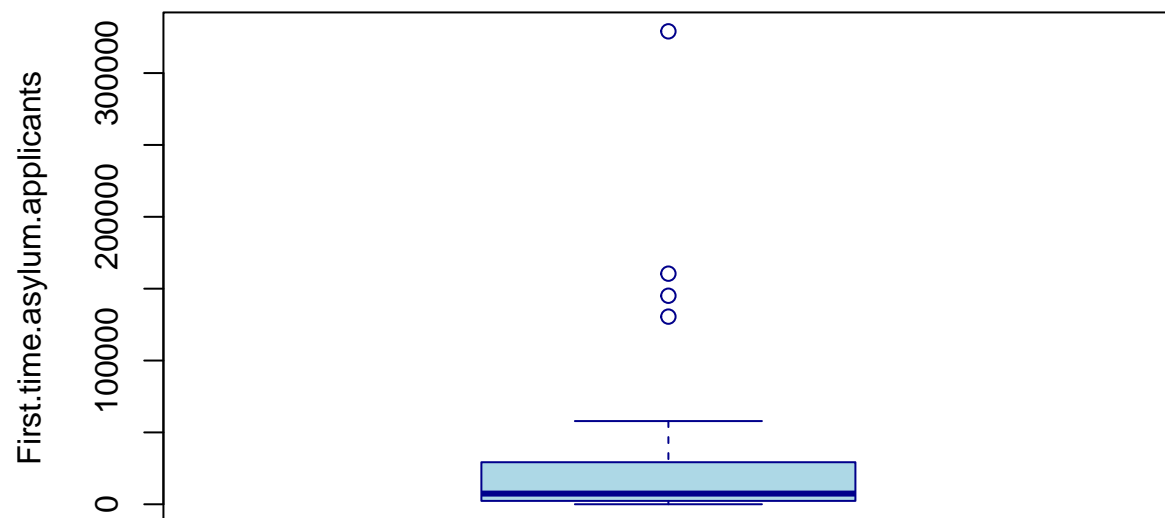


```
##
## **Interprétation pour Youth.population :**

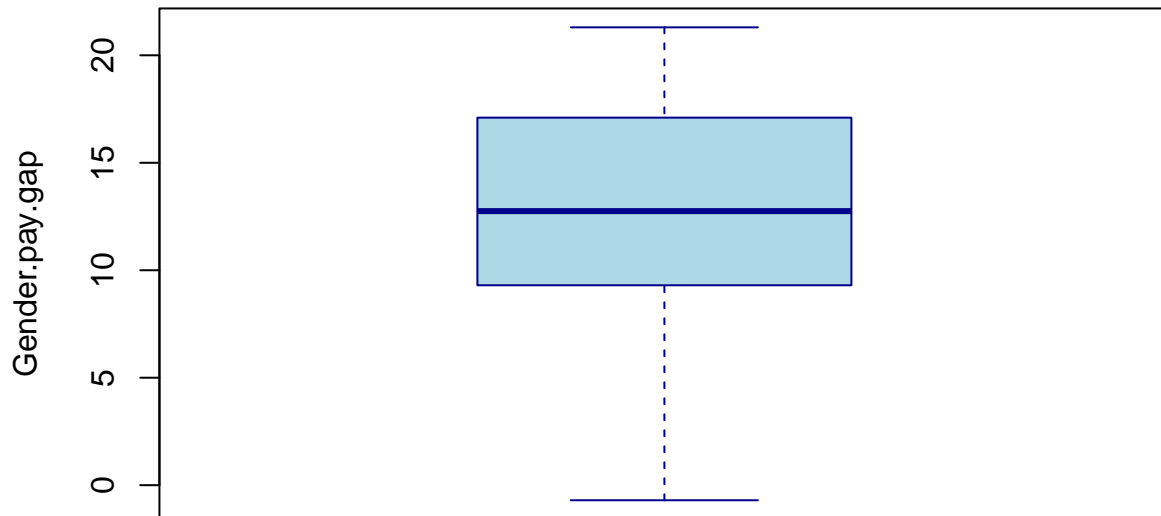
selected_columns <- colnames(euro_data)[3:4] # Diagrammes 1 à 2
for (col_name in selected_columns) {
  boxplot(euro_data[[col_name]],
    main = paste("Boîte à moustaches pour", col_name),
    ylab = col_name,
    col = "lightblue",
    border = "darkblue")

  # Interprétation
  # cat(paste("\n**Interprétation pour", col_name, " :**\n"))
}
```

### Boîte à moustaches pour First.time.asylum.applicants



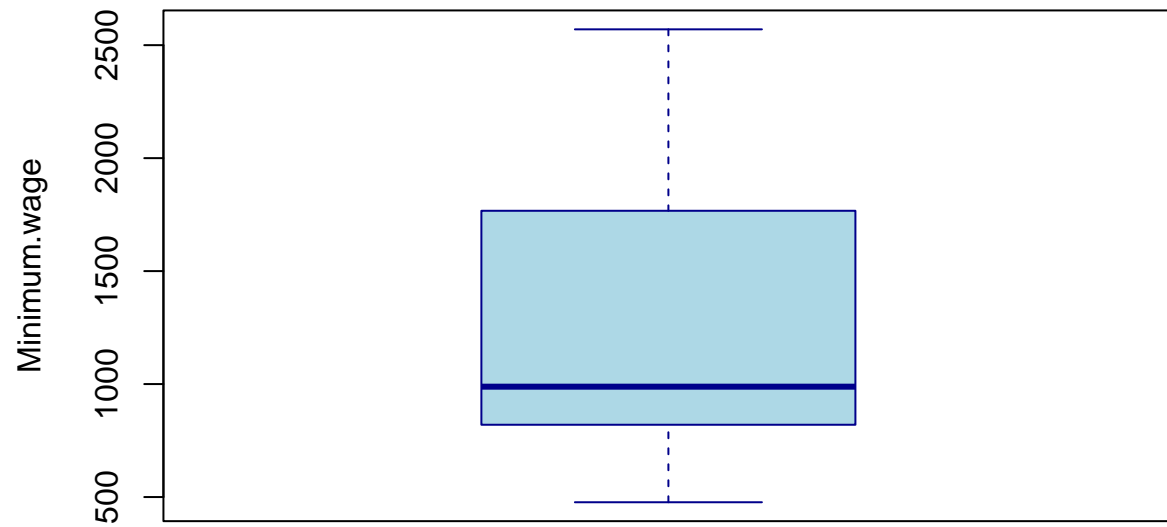
## Boîte à moustaches pour Gender.pay.gap



```
selected_columns <- colnames(euro_data)[5:6] # Diagrammes 1 à 2
for (col_name in selected_columns) {
  boxplot(euro_data[[col_name]],
    main = paste("Boîte à moustaches pour", col_name),
    ylab = col_name,
    col = "lightblue",
    border = "darkblue")

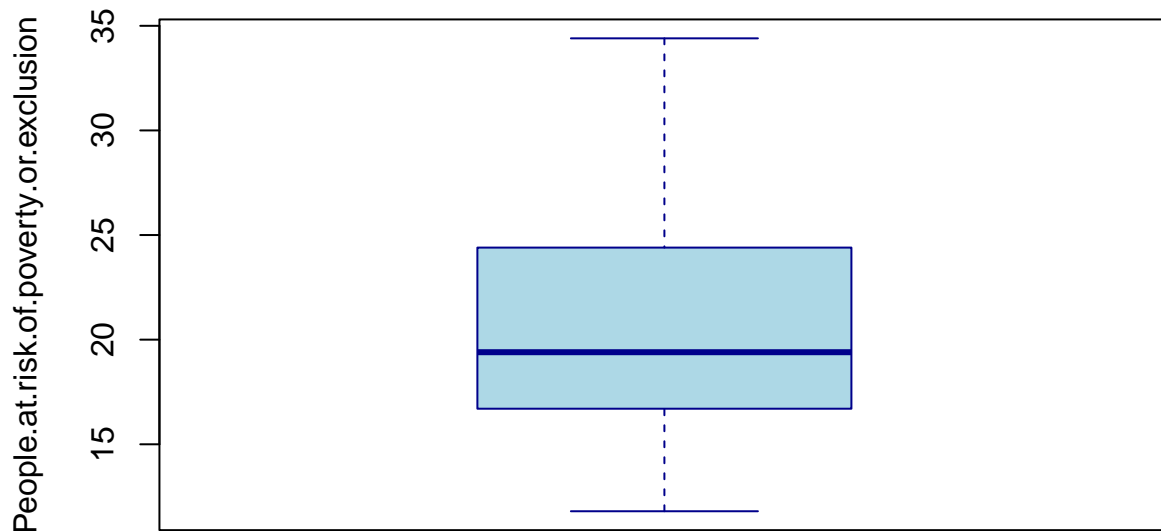
  # Interprétation
  cat(paste("\n**Interprétation pour", col_name, " :**\n"))
}
```

## Boîte à moustaches pour Minimum.wage



```
##  
## **Interprétation pour Minimum.wage : **
```

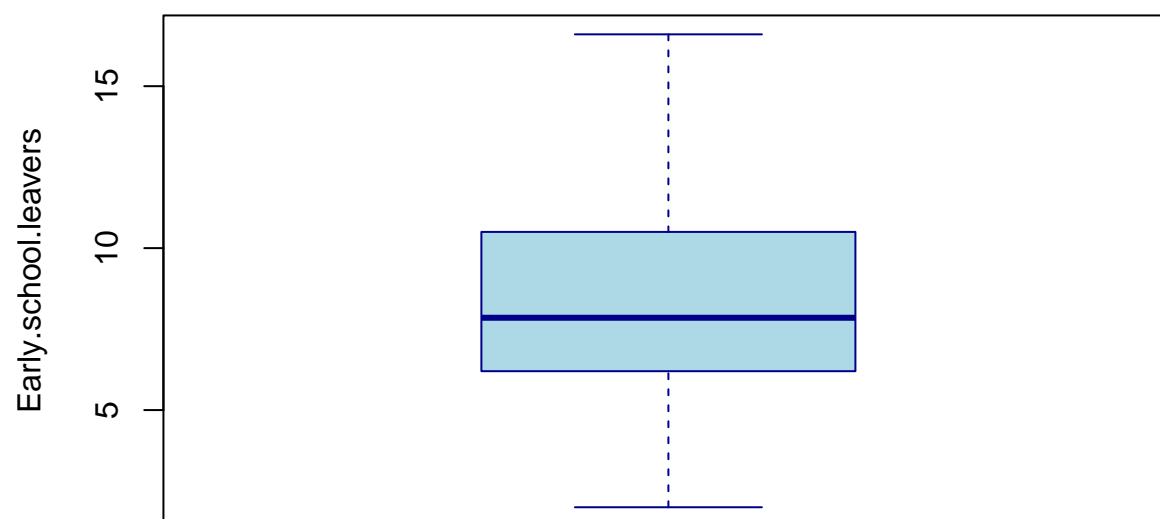
## Boîte à moustaches pour People.at.risk.of.poverty.or.exclusion



```
##  
## **Interprétation pour People.at.risk.of.poverty.or.exclusion :**  
  
selected_columns <- colnames(euro_data)[7:8] # Diagrammes 1 à 2  
for (col_name in selected_columns) {  
  boxplot(euro_data[[col_name]],  
    main = paste("Boîte à moustaches pour", col_name),  
    ylab = col_name,  
    col = "lightblue",  
    border = "darkblue")  
  
  # Interprétation  
  cat(paste("\n**Interprétation pour", col_name, " :**\n"))  
}
```

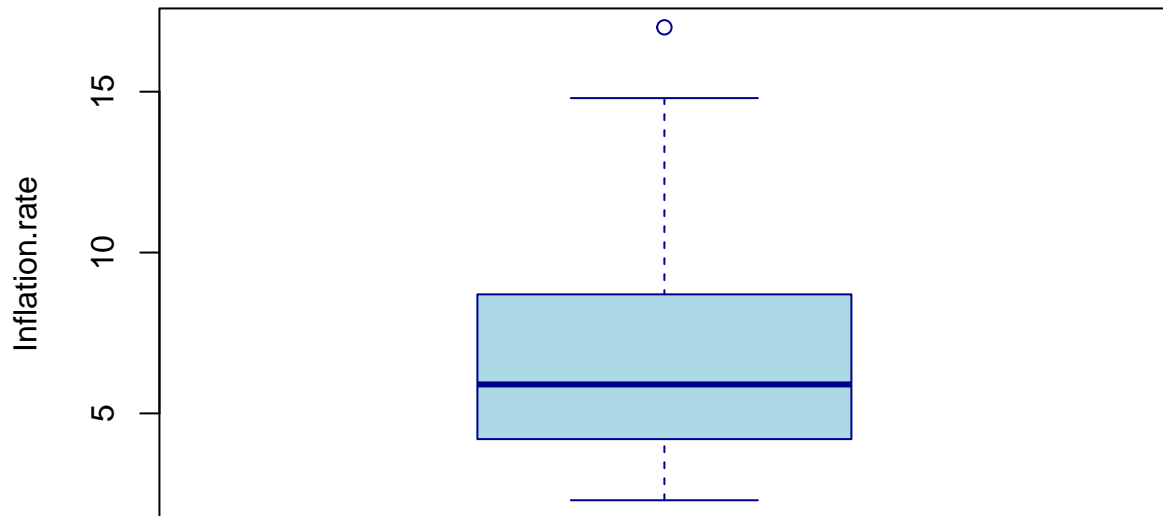


## Boîte à moustaches pour Early.school.leavers



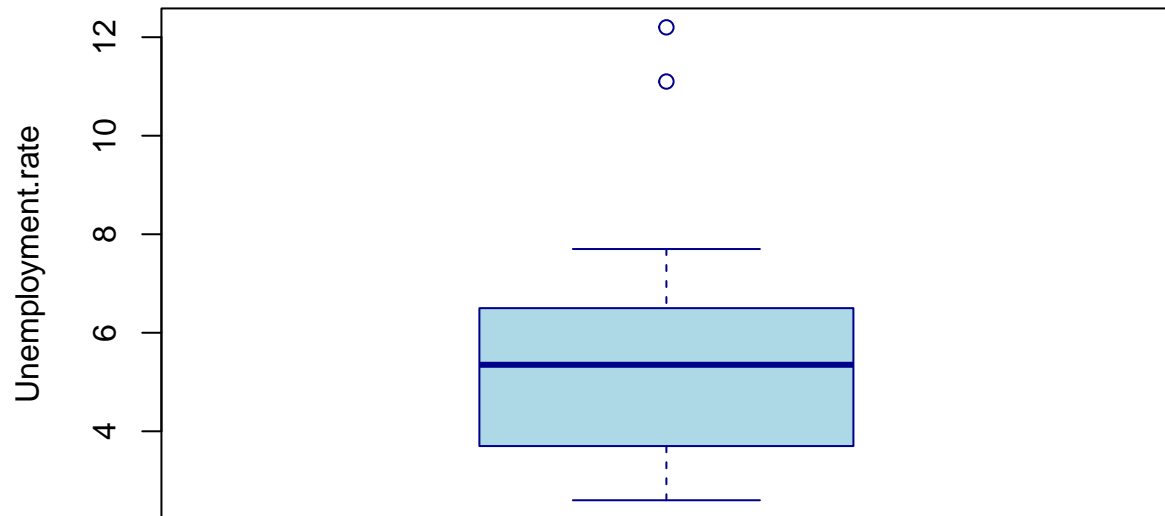
```
##  
## **Interprétation pour Early.school.leavers :**
```

## Boîte à moustaches pour Inflation.rate



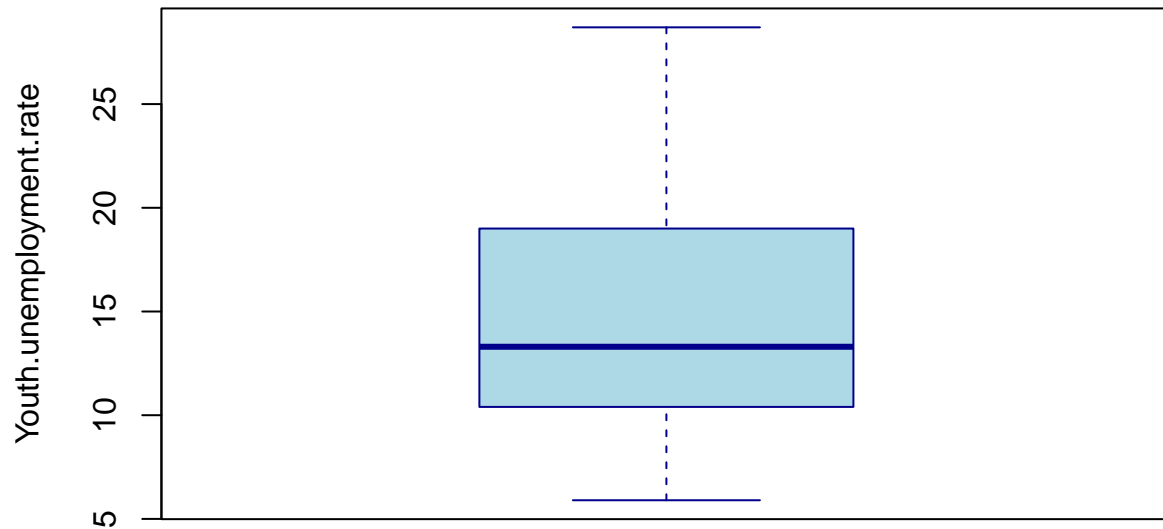
```
##  
## **Interprétation pour Inflation.rate :**  
  
selected_columns <- colnames(euro_data)[9:10] # Diagrammes 1 à 2  
for (col_name in selected_columns) {  
  boxplot(euro_data[[col_name]],  
    main = paste("Boîte à moustaches pour", col_name),  
    ylab = col_name,  
    col = "lightblue",  
    border = "darkblue")  
  
  # Interprétation  
  cat(paste("\n**Interprétation pour", col_name, " :**\n"))  
}
```

## Boîte à moustaches pour Unemployment.rate



```
##  
## **Interprétation pour Unemployment.rate :**
```

## Boîte à moustaches pour Youth.unemployment.rate



```
##
## **Interprétation pour Youth.unemployment.rate :**
```

```
# Centrer les données : soustraire la moyenne de chaque colonne
```

```
" Question 3 "
```

```
## [1] " Question 3 "
```

```
euro_data_centered <- scale(euro_data, center = TRUE, scale = FALSE)
```

```
# Calculer la matrice de variance-covariance
```

```
n <- nrow(euro_data) # Nombre d'observations
```

```
V <- (t(euro_data_centered) %*% euro_data_centered) / (n - 1)
```

```
# Afficher la matrice
```

```
print("Matrice de variance-covariance :")
```

```
## [1] "Matrice de variance-covariance :"
```

```
print(V)
```

```
## Population Youth.population
```

## Population	4.653257e+14	-6.839267e+06
## Youth.population	-6.839267e+06	3.260931e+00
## First.time.asylum.applicants	1.365717e+12	-1.592480e+04
## Gender.pay.gap	-6.195038e+06	-2.230724e+00
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	1.621818e+07	1.575862e+00
## Inflation.rate	-6.534739e+06	-2.646345e+00
## Unemployment.rate	8.017485e+06	-8.740690e-01
## Youth.unemployment.rate	1.445936e+07	-2.273414e+00
## GDP.per.capita	-2.857962e+10	2.394673e+04
## Government.gross.debt	2.994623e+08	-2.145276e+00
## Greenhouse.gas.emissions	-8.092486e+06	1.863724e+00
## Renewable.energy	-1.066077e+08	1.010286e+01
## Electricity.prices	7.486738e+08	-8.085862e-01
## Energy.imports.dependency	6.282654e+07	4.074517e+00
##	First.time.asylum.applicants	
## Population	1.365717e+12	
## Youth.population	-1.592480e+04	
## First.time.asylum.applicants	4.950971e+09	
## Gender.pay.gap	2.341646e+04	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	6.578850e+04	
## Inflation.rate	-5.499202e+04	
## Unemployment.rate	3.117897e+04	
## Youth.unemployment.rate	1.909011e+04	
## GDP.per.capita	3.054725e+07	
## Government.gross.debt	9.319273e+05	
## Greenhouse.gas.emissions	-1.295407e+04	
## Renewable.energy	-2.707843e+05	
## Electricity.prices	2.853515e+06	
## Energy.imports.dependency	3.598142e+05	
##	Gender.pay.gap	Minimum.wage
## Population	-6.195038e+06	NA
## Youth.population	-2.230724e+00	NA
## First.time.asylum.applicants	2.341646e+04	NA
## Gender.pay.gap	2.561895e+01	NA
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	-1.151034e+00	NA
## Inflation.rate	5.996276e+00	NA
## Unemployment.rate	-8.288276e-01	NA
## Youth.unemployment.rate	-9.091483e+00	NA
## GDP.per.capita	-2.329693e+04	NA
## Government.gross.debt	-3.046440e+01	NA
## Greenhouse.gas.emissions	-3.583356e+00	NA
## Renewable.energy	2.383613e+01	NA
## Electricity.prices	-5.713678e-01	NA
## Energy.imports.dependency	-3.493792e+01	NA
##	People.at.risk.of.poverty.or.exclusion	
## Population		NA
## Youth.population		NA
## First.time.asylum.applicants		NA

## Gender.pay.gap		NA
## Minimum.wage		NA
## People.at.risk.of.poverty.or.exclusion		NA
## Early.school.leavers		NA
## Inflation.rate		NA
## Unemployment.rate		NA
## Youth.unemployment.rate		NA
## GDP.per.capita		NA
## Government.gross.debt		NA
## Greenhouse.gas.emissions		NA
## Renewable.energy		NA
## Electricity.prices		NA
## Energy.imports.dependency		NA
##	Early.school.leavers	Inflation.rate
## Population	1.621818e+07	-6.534739e+06
## Youth.population	1.575862e+00	-2.646345e+00
## First.time.asylum.applicants	6.578850e+04	-5.499202e+04
## Gender.pay.gap	-1.151034e+00	5.996276e+00
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	1.255172e+01	7.158621e-01
## Inflation.rate	7.158621e-01	1.211614e+01
## Unemployment.rate	4.827586e-02	-2.516690e+00
## Youth.unemployment.rate	6.196552e-01	-3.752138e+00
## GDP.per.capita	-1.667793e+03	-4.017071e+04
## Government.gross.debt	6.283103e+00	-2.189462e+01
## Greenhouse.gas.emissions	1.055172e-01	-4.308966e-01
## Renewable.energy	1.908069e+01	-9.630897e+00
## Electricity.prices	-4.490414e+01	-9.986145e+01
## Energy.imports.dependency	-2.727517e+01	-2.880076e+01
##	Unemployment.rate	
## Population	8.017485e+06	
## Youth.population	-8.740690e-01	
## First.time.asylum.applicants	3.117897e+04	
## Gender.pay.gap	-8.288276e-01	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	4.827586e-02	
## Inflation.rate	-2.516690e+00	
## Unemployment.rate	5.049379e+00	
## Youth.unemployment.rate	1.156469e+01	
## GDP.per.capita	-8.682110e+03	
## Government.gross.debt	4.358007e+01	
## Greenhouse.gas.emissions	-1.953862e+00	
## Renewable.energy	-8.711034e-01	
## Electricity.prices	1.851538e+01	
## Energy.imports.dependency	7.197448e+00	
##	Youth.unemployment.rate	GDP.per.capita
## Population	1.445936e+07	-2.857962e+10
## Youth.population	-2.273414e+00	2.394673e+04
## First.time.asylum.applicants	1.909011e+04	3.054725e+07
## Gender.pay.gap	-9.091483e+00	-2.329693e+04
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA

## Early.school.leavers	6.196552e-01	-1.667793e+03
## Inflation.rate	-3.752138e+00	-4.017071e+04
## Unemployment.rate	1.156469e+01	-8.682110e+03
## Youth.unemployment.rate	3.455114e+01	-2.704445e+04
## GDP.per.capita	-2.704445e+04	3.983704e+08
## Government.gross.debt	1.032097e+02	-1.581849e+05
## Greenhouse.gas.emissions	-3.952966e+00	2.158401e+04
## Renewable.energy	-1.476659e+01	1.228200e+05
## Electricity.prices	-3.015093e+01	2.644578e+05
## Energy.imports.dependency	1.513148e+01	5.860834e+04
##	Government.gross.debt	
## Population	2.994623e+08	
## Youth.population	-2.145276e+00	
## First.time.asylum.applicants	9.319273e+05	
## Gender.pay.gap	-3.046440e+01	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	6.283103e+00	
## Inflation.rate	-2.189462e+01	
## Unemployment.rate	4.358007e+01	
## Youth.unemployment.rate	1.032097e+02	
## GDP.per.capita	-1.581849e+05	
## Government.gross.debt	1.240830e+03	
## Greenhouse.gas.emissions	-1.137271e+01	
## Renewable.energy	-1.327777e+02	
## Electricity.prices	6.659872e+02	
## Energy.imports.dependency	2.703910e+02	
##	Greenhouse.gas.emissions	
## Population	-8.092486e+06	
## Youth.population	1.863724e+00	
## First.time.asylum.applicants	-1.295407e+04	
## Gender.pay.gap	-3.583356e+00	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	1.055172e-01	
## Inflation.rate	-4.308966e-01	
## Unemployment.rate	-1.953862e+00	
## Youth.unemployment.rate	-3.952966e+00	
## GDP.per.capita	2.158401e+04	
## Government.gross.debt	-1.137271e+01	
## Greenhouse.gas.emissions	7.033057e+00	
## Renewable.energy	-2.733149e+00	
## Electricity.prices	1.906025e+01	
## Energy.imports.dependency	-3.686644e+00	
##	Renewable.energy	Electricity.prices
## Population	-1.066077e+08	7.486738e+08
## Youth.population	1.010286e+01	-8.085862e-01
## First.time.asylum.applicants	-2.707843e+05	2.853515e+06
## Gender.pay.gap	2.383613e+01	-5.713678e-01
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	1.908069e+01	-4.490414e+01
## Inflation.rate	-9.630897e+00	-9.986145e+01
## Unemployment.rate	-8.711034e-01	1.851538e+01

## Youth.unemployment.rate	-1.476659e+01	-3.015093e+01
## GDP.per.capita	1.228200e+05	2.644578e+05
## Government.gross.debt	-1.327777e+02	6.659872e+02
## Greenhouse.gas.emissions	-2.733149e+00	1.906025e+01
## Renewable.energy	3.593812e+02	-4.262927e+02
## Electricity.prices	-4.262927e+02	6.935113e+03
## Energy.imports.dependency	-2.903213e+02	7.416931e+02
##	Energy.imports.dependency	
## Population	6.282654e+07	
## Youth.population	4.074517e+00	
## First.time.asylum.applicants	3.598142e+05	
## Gender.pay.gap	-3.493792e+01	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	-2.727517e+01	
## Inflation.rate	-2.880076e+01	
## Unemployment.rate	7.197448e+00	
## Youth.unemployment.rate	1.513148e+01	
## GDP.per.capita	5.860834e+04	
## Government.gross.debt	2.703910e+02	
## Greenhouse.gas.emissions	-3.686644e+00	
## Renewable.energy	-2.903213e+02	
## Electricity.prices	7.416931e+02	
## Energy.imports.dependency	5.925486e+02	

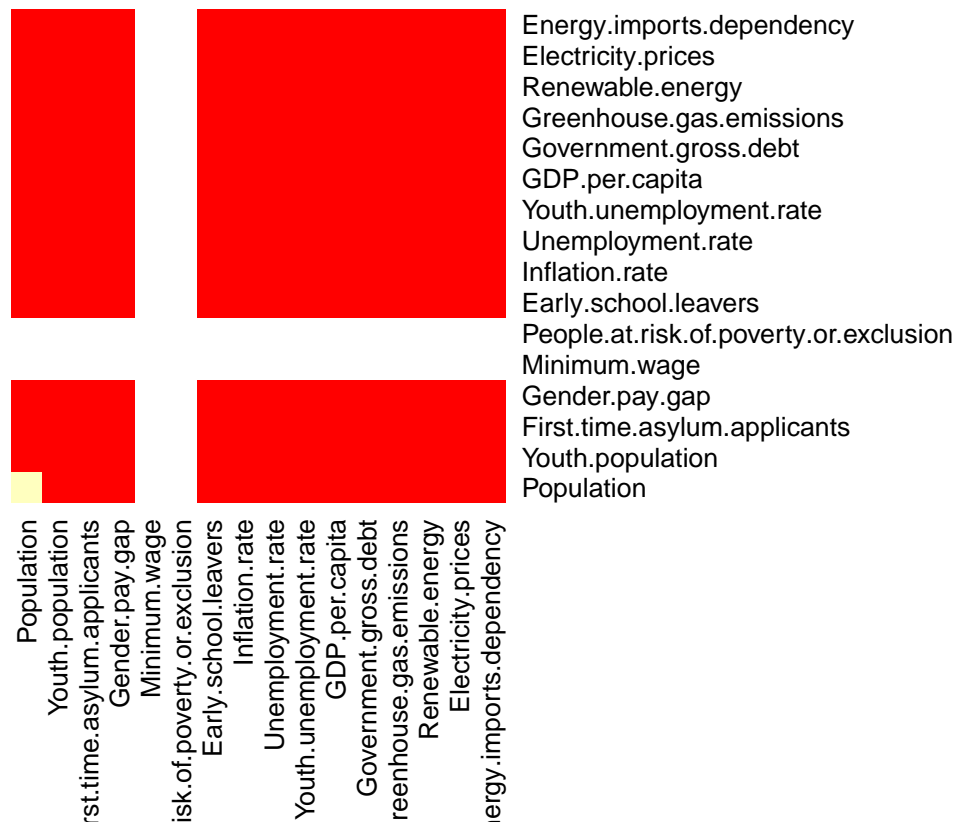
```

# Question 3 suite
V_rounded <- round(V, 2)
# Étape 3 : Créer la heatmap
heatmap(as.matrix(V_rounded),
        main = "Heatmap de la matrice de variance-covariance",
        Colv = NA, Rowv = NA, # Désactive le clustering
        scale = "none", # Pas de normalisation supplémentaire
        col = heat.colors(10), # Palette de couleurs
        margins = c(10, 10)) # Marges pour la lisibilité

```



## atmap de la matrice de variance-covariance



```
# Arrondir les valeurs de la matrice à 2 décimales
print("Matrice de variance-covariance (arrondie) :")
```

```
## [1] "Matrice de variance-covariance (arrondie) :"
```

```
round(V, 2)
```

```
##              Population Youth.population
## Population      4.653257e+14      -6839267.06
## Youth.population -6.839267e+06           3.26
## First.time.asylum.applicants  1.365717e+12      -15924.80
## Gender.pay.gap      -6.195038e+06       -2.23
## Minimum.wage                NA                NA
## People.at.risk.of.poverty.or.exclusion      NA                NA
## Early.school.leavers  1.621818e+07           1.58
## Inflation.rate      -6.534739e+06       -2.65
## Unemployment.rate    8.017485e+06       -0.87
## Youth.unemployment.rate  1.445936e+07       -2.27
## GDP.per.capita      -2.857962e+10       23946.73
## Government.gross.debt  2.994623e+08       -2.15
## Greenhouse.gas.emissions -8.092486e+06           1.86
## Renewable.energy     -1.066077e+08          10.10
## Electricity.prices    7.486738e+08       -0.81
## Energy.imports.dependency  6.282654e+07           4.07
## First.time.asylum.applicants
```

## Population	1.365717e+12
## Youth.population	-1.592480e+04
## First.time.asylum.applicants	4.950971e+09
## Gender.pay.gap	2.341646e+04
## Minimum.wage	NA
## People.at.risk.of.poverty.or.exclusion	NA
## Early.school.leavers	6.578850e+04
## Inflation.rate	-5.499202e+04
## Unemployment.rate	3.117897e+04
## Youth.unemployment.rate	1.909011e+04
## GDP.per.capita	3.054725e+07
## Government.gross.debt	9.319273e+05
## Greenhouse.gas.emissions	-1.295407e+04
## Renewable.energy	-2.707843e+05
## Electricity.prices	2.853515e+06
## Energy.imports.dependency	3.598142e+05
##	Gender.pay.gap Minimum.wage
## Population	-6195038.43 NA
## Youth.population	-2.23 NA
## First.time.asylum.applicants	23416.46 NA
## Gender.pay.gap	25.62 NA
## Minimum.wage	NA NA
## People.at.risk.of.poverty.or.exclusion	NA NA
## Early.school.leavers	-1.15 NA
## Inflation.rate	6.00 NA
## Unemployment.rate	-0.83 NA
## Youth.unemployment.rate	-9.09 NA
## GDP.per.capita	-23296.93 NA
## Government.gross.debt	-30.46 NA
## Greenhouse.gas.emissions	-3.58 NA
## Renewable.energy	23.84 NA
## Electricity.prices	-0.57 NA
## Energy.imports.dependency	-34.94 NA
##	People.at.risk.of.poverty.or.exclusion
## Population	NA
## Youth.population	NA
## First.time.asylum.applicants	NA
## Gender.pay.gap	NA
## Minimum.wage	NA
## People.at.risk.of.poverty.or.exclusion	NA
## Early.school.leavers	NA
## Inflation.rate	NA
## Unemployment.rate	NA
## Youth.unemployment.rate	NA
## GDP.per.capita	NA
## Government.gross.debt	NA
## Greenhouse.gas.emissions	NA
## Renewable.energy	NA
## Electricity.prices	NA
## Energy.imports.dependency	NA
##	Early.school.leavers Inflation.rate
## Population	16218178.45 -6534739.21
## Youth.population	1.58 -2.65
## First.time.asylum.applicants	65788.50 -54992.02

## Gender.pay.gap	-1.15	6.00
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	12.55	0.72
## Inflation.rate	0.72	12.12
## Unemployment.rate	0.05	-2.52
## Youth.unemployment.rate	0.62	-3.75
## GDP.per.capita	-1667.79	-40170.71
## Government.gross.debt	6.28	-21.89
## Greenhouse.gas.emissions	0.11	-0.43
## Renewable.energy	19.08	-9.63
## Electricity.prices	-44.90	-99.86
## Energy.imports.dependency	-27.28	-28.80
##	Unemployment.rate	
## Population	8017484.96	
## Youth.population	-0.87	
## First.time.asylum.applicants	31178.97	
## Gender.pay.gap	-0.83	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	0.05	
## Inflation.rate	-2.52	
## Unemployment.rate	5.05	
## Youth.unemployment.rate	11.56	
## GDP.per.capita	-8682.11	
## Government.gross.debt	43.58	
## Greenhouse.gas.emissions	-1.95	
## Renewable.energy	-0.87	
## Electricity.prices	18.52	
## Energy.imports.dependency	7.20	
##	Youth.unemployment.rate	GDP.per.capita
## Population	14459359.14	-2.857962e+10
## Youth.population	-2.27	2.394673e+04
## First.time.asylum.applicants	19090.11	3.054725e+07
## Gender.pay.gap	-9.09	-2.329693e+04
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	0.62	-1.667790e+03
## Inflation.rate	-3.75	-4.017071e+04
## Unemployment.rate	11.56	-8.682110e+03
## Youth.unemployment.rate	34.55	-2.704445e+04
## GDP.per.capita	-27044.45	3.983704e+08
## Government.gross.debt	103.21	-1.581849e+05
## Greenhouse.gas.emissions	-3.95	2.158401e+04
## Renewable.energy	-14.77	1.228200e+05
## Electricity.prices	-30.15	2.644578e+05
## Energy.imports.dependency	15.13	5.860834e+04
##	Government.gross.debt	
## Population	299462337.44	
## Youth.population	-2.15	
## First.time.asylum.applicants	931927.28	
## Gender.pay.gap	-30.46	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	

## Early.school.leavers	6.28	
## Inflation.rate	-21.89	
## Unemployment.rate	43.58	
## Youth.unemployment.rate	103.21	
## GDP.per.capita	-158184.92	
## Government.gross.debt	1240.83	
## Greenhouse.gas.emissions	-11.37	
## Renewable.energy	-132.78	
## Electricity.prices	665.99	
## Energy.imports.dependency	270.39	
##	Greenhouse.gas.emissions	
## Population	-8092485.69	
## Youth.population	1.86	
## First.time.asylum.applicants	-12954.07	
## Gender.pay.gap	-3.58	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	0.11	
## Inflation.rate	-0.43	
## Unemployment.rate	-1.95	
## Youth.unemployment.rate	-3.95	
## GDP.per.capita	21584.01	
## Government.gross.debt	-11.37	
## Greenhouse.gas.emissions	7.03	
## Renewable.energy	-2.73	
## Electricity.prices	19.06	
## Energy.imports.dependency	-3.69	
##	Renewable.energy	Electricity.prices
## Population	-106607660.88	748673833.24
## Youth.population	10.10	-0.81
## First.time.asylum.applicants	-270784.28	2853514.54
## Gender.pay.gap	23.84	-0.57
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	19.08	-44.90
## Inflation.rate	-9.63	-99.86
## Unemployment.rate	-0.87	18.52
## Youth.unemployment.rate	-14.77	-30.15
## GDP.per.capita	122820.02	264457.76
## Government.gross.debt	-132.78	665.99
## Greenhouse.gas.emissions	-2.73	19.06
## Renewable.energy	359.38	-426.29
## Electricity.prices	-426.29	6935.11
## Energy.imports.dependency	-290.32	741.69
##	Energy.imports.dependency	
## Population	62826536.59	
## Youth.population	4.07	
## First.time.asylum.applicants	359814.25	
## Gender.pay.gap	-34.94	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	-27.28	
## Inflation.rate	-28.80	
## Unemployment.rate	7.20	

```
## Youth.unemployment.rate 15.13
## GDP.per.capita 58608.34
## Government.gross.debt 270.39
## Greenhouse.gas.emissions -3.69
## Renewable.energy -290.32
## Electricity.prices 741.69
## Energy.imports.dependency 592.55
```

```
# Ajouter les noms de lignes et colonnes pour un tableau clair
rownames(V) <- colnames(V) <- colnames(euro_data)

# Afficher sous forme de tableau avec arrondi
print(round(V, 2))
```

```
## Population Youth.population
## Population 4.653257e+14 -6839267.06
## Youth.population -6.839267e+06 3.26
## First.time.asylum.applicants 1.365717e+12 -15924.80
## Gender.pay.gap -6.195038e+06 -2.23
## Minimum.wage NA NA
## People.at.risk.of.poverty.or.exclusion NA NA
## Early.school.leavers 1.621818e+07 1.58
## Inflation.rate -6.534739e+06 -2.65
## Unemployment.rate 8.017485e+06 -0.87
## Youth.unemployment.rate 1.445936e+07 -2.27
## GDP.per.capita -2.857962e+10 23946.73
## Government.gross.debt 2.994623e+08 -2.15
## Greenhouse.gas.emissions -8.092486e+06 1.86
## Renewable.energy -1.066077e+08 10.10
## Electricity.prices 7.486738e+08 -0.81
## Energy.imports.dependency 6.282654e+07 4.07
## First.time.asylum.applicants
## Population 1.365717e+12
## Youth.population -1.592480e+04
## First.time.asylum.applicants 4.950971e+09
## Gender.pay.gap 2.341646e+04
## Minimum.wage NA
## People.at.risk.of.poverty.or.exclusion NA
## Early.school.leavers 6.578850e+04
## Inflation.rate -5.499202e+04
## Unemployment.rate 3.117897e+04
## Youth.unemployment.rate 1.909011e+04
## GDP.per.capita 3.054725e+07
## Government.gross.debt 9.319273e+05
## Greenhouse.gas.emissions -1.295407e+04
## Renewable.energy -2.707843e+05
## Electricity.prices 2.853515e+06
## Energy.imports.dependency 3.598142e+05
## Gender.pay.gap Minimum.wage
## Population -6195038.43 NA
## Youth.population -2.23 NA
## First.time.asylum.applicants 23416.46 NA
## Gender.pay.gap 25.62 NA
## Minimum.wage NA NA
```

## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	-1.15	NA
## Inflation.rate	6.00	NA
## Unemployment.rate	-0.83	NA
## Youth.unemployment.rate	-9.09	NA
## GDP.per.capita	-23296.93	NA
## Government.gross.debt	-30.46	NA
## Greenhouse.gas.emissions	-3.58	NA
## Renewable.energy	23.84	NA
## Electricity.prices	-0.57	NA
## Energy.imports.dependency	-34.94	NA
##	People.at.risk.of.poverty.or.exclusion	
## Population		NA
## Youth.population		NA
## First.time.asylum.applicants		NA
## Gender.pay.gap		NA
## Minimum.wage		NA
## People.at.risk.of.poverty.or.exclusion		NA
## Early.school.leavers		NA
## Inflation.rate		NA
## Unemployment.rate		NA
## Youth.unemployment.rate		NA
## GDP.per.capita		NA
## Government.gross.debt		NA
## Greenhouse.gas.emissions		NA
## Renewable.energy		NA
## Electricity.prices		NA
## Energy.imports.dependency		NA
##	Early.school.leavers	Inflation.rate
## Population	16218178.45	-6534739.21
## Youth.population	1.58	-2.65
## First.time.asylum.applicants	65788.50	-54992.02
## Gender.pay.gap	-1.15	6.00
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	12.55	0.72
## Inflation.rate	0.72	12.12
## Unemployment.rate	0.05	-2.52
## Youth.unemployment.rate	0.62	-3.75
## GDP.per.capita	-1667.79	-40170.71
## Government.gross.debt	6.28	-21.89
## Greenhouse.gas.emissions	0.11	-0.43
## Renewable.energy	19.08	-9.63
## Electricity.prices	-44.90	-99.86
## Energy.imports.dependency	-27.28	-28.80
##	Unemployment.rate	
## Population	8017484.96	
## Youth.population	-0.87	
## First.time.asylum.applicants	31178.97	
## Gender.pay.gap	-0.83	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	0.05	
## Inflation.rate	-2.52	

## Unemployment.rate	5.05	
## Youth.unemployment.rate	11.56	
## GDP.per.capita	-8682.11	
## Government.gross.debt	43.58	
## Greenhouse.gas.emissions	-1.95	
## Renewable.energy	-0.87	
## Electricity.prices	18.52	
## Energy.imports.dependency	7.20	
##	Youth.unemployment.rate	GDP.per.capita
## Population	14459359.14	-2.857962e+10
## Youth.population	-2.27	2.394673e+04
## First.time.asylum.applicants	19090.11	3.054725e+07
## Gender.pay.gap	-9.09	-2.329693e+04
## Minimum.wage	NA	NA
## People.at.risk.of.poverty.or.exclusion	NA	NA
## Early.school.leavers	0.62	-1.667790e+03
## Inflation.rate	-3.75	-4.017071e+04
## Unemployment.rate	11.56	-8.682110e+03
## Youth.unemployment.rate	34.55	-2.704445e+04
## GDP.per.capita	-27044.45	3.983704e+08
## Government.gross.debt	103.21	-1.581849e+05
## Greenhouse.gas.emissions	-3.95	2.158401e+04
## Renewable.energy	-14.77	1.228200e+05
## Electricity.prices	-30.15	2.644578e+05
## Energy.imports.dependency	15.13	5.860834e+04
##	Government.gross.debt	
## Population	299462337.44	
## Youth.population	-2.15	
## First.time.asylum.applicants	931927.28	
## Gender.pay.gap	-30.46	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	6.28	
## Inflation.rate	-21.89	
## Unemployment.rate	43.58	
## Youth.unemployment.rate	103.21	
## GDP.per.capita	-158184.92	
## Government.gross.debt	1240.83	
## Greenhouse.gas.emissions	-11.37	
## Renewable.energy	-132.78	
## Electricity.prices	665.99	
## Energy.imports.dependency	270.39	
##	Greenhouse.gas.emissions	
## Population	-8092485.69	
## Youth.population	1.86	
## First.time.asylum.applicants	-12954.07	
## Gender.pay.gap	-3.58	
## Minimum.wage	NA	
## People.at.risk.of.poverty.or.exclusion	NA	
## Early.school.leavers	0.11	
## Inflation.rate	-0.43	
## Unemployment.rate	-1.95	
## Youth.unemployment.rate	-3.95	
## GDP.per.capita	21584.01	

```
## Government.gross.debt -11.37
## Greenhouse.gas.emissions 7.03
## Renewable.energy -2.73
## Electricity.prices 19.06
## Energy.imports.dependency -3.69
## Renewable.energy Electricity.prices
## Population -106607660.88 748673833.24
## Youth.population 10.10 -0.81
## First.time.asylum.applicants -270784.28 2853514.54
## Gender.pay.gap 23.84 -0.57
## Minimum.wage NA NA
## People.at.risk.of.poverty.or.exclusion NA NA
## Early.school.leavers 19.08 -44.90
## Inflation.rate -9.63 -99.86
## Unemployment.rate -0.87 18.52
## Youth.unemployment.rate -14.77 -30.15
## GDP.per.capita 122820.02 264457.76
## Government.gross.debt -132.78 665.99
## Greenhouse.gas.emissions -2.73 19.06
## Renewable.energy 359.38 -426.29
## Electricity.prices -426.29 6935.11
## Energy.imports.dependency -290.32 741.69
## Energy.imports.dependency
## Population 62826536.59
## Youth.population 4.07
## First.time.asylum.applicants 359814.25
## Gender.pay.gap -34.94
## Minimum.wage NA
## People.at.risk.of.poverty.or.exclusion NA
## Early.school.leavers -27.28
## Inflation.rate -28.80
## Unemployment.rate 7.20
## Youth.unemployment.rate 15.13
## GDP.per.capita 58608.34
## Government.gross.debt 270.39
## Greenhouse.gas.emissions -3.69
## Renewable.energy -290.32
## Electricity.prices 741.69
## Energy.imports.dependency 592.55
```

```
# Question 3 suite
```

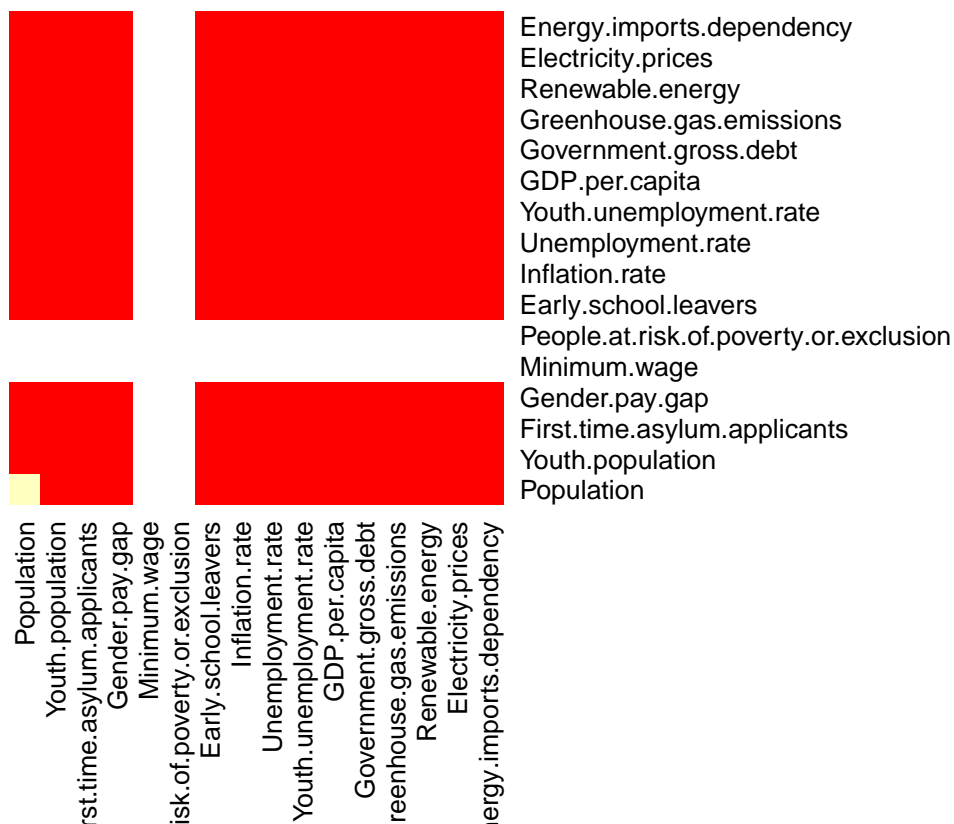
```
V_rounded <- round(V, 2)
```

```
# Étape 3 : Créer la heatmap
```

```
heatmap(as.matrix(V_rounded),
  main = "Heatmap de la matrice de variance-covariance",
  Colv = NA, Rowv = NA, # Désactive le clustering
  scale = "none", # Pas de normalisation supplémentaire
  col = heat.colors(10), # Palette de couleurs
  margins = c(10, 10)) # Marges pour la lisibilité
```



## atmap de la matrice de variance-covariance



```
# Question 4 améliorée
# Transformer la matrice de corrélation en format long
# Calculer la matrice de corrélation
correlation_matrix <- cor(euro_data, use = "complete.obs")

# Afficher un aperçu de la matrice
print("Matrice de corrélation (arrondie) :")
```

```
## [1] "Matrice de corrélation (arrondie) :"
```

```
round(correlation_matrix, 2)
```

```
##              Population Youth.population
## Population          1.00         -0.11
## Youth.population    -0.11          1.00
## First.time.asylum.applicants      0.90         -0.07
## Gender.pay.gap        -0.06         -0.25
## Minimum.wage          0.25          0.63
## People.at.risk.of.poverty.or.exclusion 0.13         -0.43
## Early.school.leavers      0.32          0.03
## Inflation.rate        -0.11         -0.52
## Unemployment.rate       0.14         -0.15
## Youth.unemployment.rate      0.08         -0.15
## GDP.per.capita         0.01          0.71
## Government.gross.debt      0.41         -0.06
```

## Greenhouse.gas.emissions	-0.13	0.30
## Renewable.energy	-0.22	-0.18
## Electricity.prices	0.40	0.23
## Energy.imports.dependency	0.04	0.49
##	First.time.asylum.applicants	
## Population		0.90
## Youth.population		-0.07
## First.time.asylum.applicants		1.00
## Gender.pay.gap		0.07
## Minimum.wage		0.34
## People.at.risk.of.poverty.or.exclusion		0.16
## Early.school.leavers		0.36
## Inflation.rate		-0.25
## Unemployment.rate		0.19
## Youth.unemployment.rate		0.03
## GDP.per.capita		0.10
## Government.gross.debt		0.38
## Greenhouse.gas.emissions		-0.06
## Renewable.energy		-0.16
## Electricity.prices		0.48
## Energy.imports.dependency		0.16
##	Gender.pay.gap Minimum.wage	
## Population	-0.06	0.25
## Youth.population	-0.25	0.63
## First.time.asylum.applicants	0.07	0.34
## Gender.pay.gap	1.00	-0.30
## Minimum.wage	-0.30	1.00
## People.at.risk.of.poverty.or.exclusion	-0.14	-0.35
## Early.school.leavers	-0.01	-0.10
## Inflation.rate	0.43	-0.63
## Unemployment.rate	-0.05	-0.09
## Youth.unemployment.rate	-0.29	-0.19
## GDP.per.capita	-0.37	0.90
## Government.gross.debt	-0.12	0.03
## Greenhouse.gas.emissions	-0.24	0.51
## Renewable.energy	0.43	-0.13
## Electricity.prices	-0.04	0.43
## Energy.imports.dependency	-0.40	0.37
##	People.at.risk.of.poverty.or.exclusion	
## Population		0.13
## Youth.population		-0.43
## First.time.asylum.applicants		0.16
## Gender.pay.gap		-0.14
## Minimum.wage		-0.35
## People.at.risk.of.poverty.or.exclusion		1.00
## Early.school.leavers		0.43
## Inflation.rate		-0.04
## Unemployment.rate		0.43
## Youth.unemployment.rate		0.45
## GDP.per.capita		-0.32
## Government.gross.debt		0.04
## Greenhouse.gas.emissions		-0.28
## Renewable.energy		0.09
## Electricity.prices		-0.18

## Energy.imports.dependency		-0.24
##	Early.school.leavers	Inflation.rate
## Population	0.32	-0.11
## Youth.population	0.03	-0.52
## First.time.asylum.applicants	0.36	-0.25
## Gender.pay.gap	-0.01	0.43
## Minimum.wage	-0.10	-0.63
## People.at.risk.of.poverty.or.exclusion	0.43	-0.04
## Early.school.leavers	1.00	0.01
## Inflation.rate	0.01	1.00
## Unemployment.rate	0.12	-0.38
## Youth.unemployment.rate	0.14	-0.25
## GDP.per.capita	-0.13	-0.58
## Government.gross.debt	-0.02	-0.29
## Greenhouse.gas.emissions	-0.28	-0.16
## Renewable.energy	0.13	-0.07
## Electricity.prices	0.02	-0.38
## Energy.imports.dependency	-0.15	-0.42
##	Unemployment.rate	
## Population	0.14	
## Youth.population	-0.15	
## First.time.asylum.applicants	0.19	
## Gender.pay.gap	-0.05	
## Minimum.wage	-0.09	
## People.at.risk.of.poverty.or.exclusion	0.43	
## Early.school.leavers	0.12	
## Inflation.rate	-0.38	
## Unemployment.rate	1.00	
## Youth.unemployment.rate	0.87	
## GDP.per.capita	-0.12	
## Government.gross.debt	0.62	
## Greenhouse.gas.emissions	-0.28	
## Renewable.energy	0.28	
## Electricity.prices	0.05	
## Energy.imports.dependency	0.09	
##	Youth.unemployment.rate	GDP.per.capita
## Population	0.08	0.01
## Youth.population	-0.15	0.71
## First.time.asylum.applicants	0.03	0.10
## Gender.pay.gap	-0.29	-0.37
## Minimum.wage	-0.19	0.90
## People.at.risk.of.poverty.or.exclusion	0.45	-0.32
## Early.school.leavers	0.14	-0.13
## Inflation.rate	-0.25	-0.58
## Unemployment.rate	0.87	-0.12
## Youth.unemployment.rate	1.00	-0.15
## GDP.per.capita	-0.15	1.00
## Government.gross.debt	0.57	-0.12
## Greenhouse.gas.emissions	-0.20	0.61
## Renewable.energy	0.06	-0.17
## Electricity.prices	-0.12	0.36
## Energy.imports.dependency	0.09	0.42
##	Government.gross.debt	
## Population	0.41	

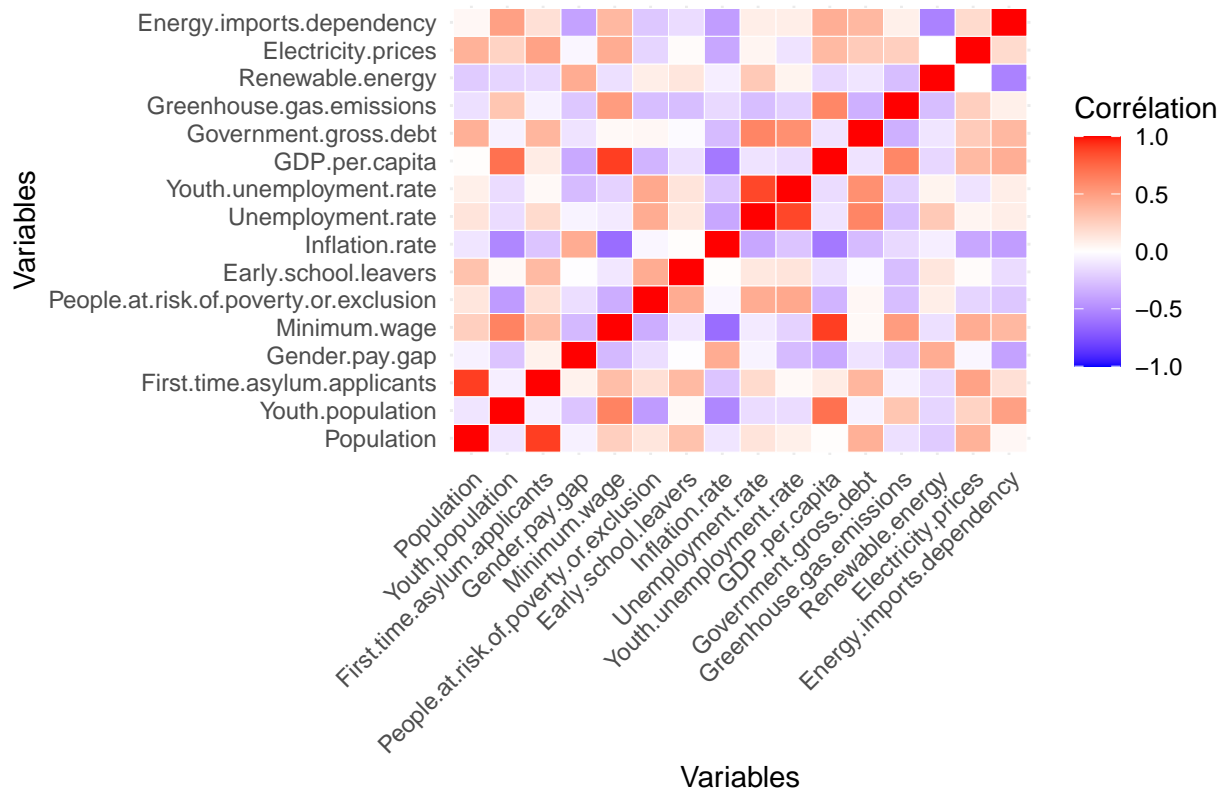
## Youth.population	-0.06
## First.time.asylum.applicants	0.38
## Gender.pay.gap	-0.12
## Minimum.wage	0.03
## People.at.risk.of.poverty.or.exclusion	0.04
## Early.school.leavers	-0.02
## Inflation.rate	-0.29
## Unemployment.rate	0.62
## Youth.unemployment.rate	0.57
## GDP.per.capita	-0.12
## Government.gross.debt	1.00
## Greenhouse.gas.emissions	-0.34
## Renewable.energy	-0.11
## Electricity.prices	0.27
## Energy.imports.dependency	0.37
##	Greenhouse.gas.emissions
## Population	-0.13
## Youth.population	0.30
## First.time.asylum.applicants	-0.06
## Gender.pay.gap	-0.24
## Minimum.wage	0.51
## People.at.risk.of.poverty.or.exclusion	-0.28
## Early.school.leavers	-0.28
## Inflation.rate	-0.16
## Unemployment.rate	-0.28
## Youth.unemployment.rate	-0.20
## GDP.per.capita	0.61
## Government.gross.debt	-0.34
## Greenhouse.gas.emissions	1.00
## Renewable.energy	-0.28
## Electricity.prices	0.25
## Energy.imports.dependency	0.08
##	Renewable.energy Electricity.prices
## Population	-0.22 0.40
## Youth.population	-0.18 0.23
## First.time.asylum.applicants	-0.16 0.48
## Gender.pay.gap	0.43 -0.04
## Minimum.wage	-0.13 0.43
## People.at.risk.of.poverty.or.exclusion	0.09 -0.18
## Early.school.leavers	0.13 0.02
## Inflation.rate	-0.07 -0.38
## Unemployment.rate	0.28 0.05
## Youth.unemployment.rate	0.06 -0.12
## GDP.per.capita	-0.17 0.36
## Government.gross.debt	-0.11 0.27
## Greenhouse.gas.emissions	-0.28 0.25
## Renewable.energy	1.00 0.00
## Electricity.prices	0.00 1.00
## Energy.imports.dependency	-0.54 0.19
##	Energy.imports.dependency
## Population	0.04
## Youth.population	0.49
## First.time.asylum.applicants	0.16
## Gender.pay.gap	-0.40

```
## Minimum.wage 0.37
## People.at.risk.of.poverty.or.exclusion -0.24
## Early.school.leavers -0.15
## Inflation.rate -0.42
## Unemployment.rate 0.09
## Youth.unemployment.rate 0.09
## GDP.per.capita 0.42
## Government.gross.debt 0.37
## Greenhouse.gas.emissions 0.08
## Renewable.energy -0.54
## Electricity.prices 0.19
## Energy.imports.dependency 1.00
```

```
# Transformer la matrice de corrélation en format long
correlation_long <- reshape2::melt(round(correlation_matrix, 2))
```

```
# Heatmap de la matrice de corrélation
ggplot(correlation_long, aes(Var1, Var2, fill = value)) +
  geom_tile(color = "white") +
  scale_fill_gradient2(low = "blue", high = "red", mid = "white",
    midpoint = 0, limit = c(-1, 1),
    name = "Corrélation") +
  theme_minimal() +
  labs(title = "Heatmap de la matrice de corrélation",
    x = "Variables",
    y = "Variables") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

### Heatmap de la matrice de corrélation



```
head(euro_data)
```

```
##      Population Youth.population First.time.asylum.applicants Gender.pay.gap
## 1      9104772           16.9                56135             18.4
## 2     11742796           17.8                29260              5.0
## 3      6447710           13.2                22390             13.0
## 4      3850894           15.9                 1635             12.5
## 5       920701           19.8                 11660            10.2
## 6     10827529           15.1                  1130             17.9
##      Minimum.wage People.at.risk.of.poverty.or.exclusion Early.school.leavers
## 1           1766                17.5                8.6
## 2           1994                18.7                6.2
## 3            477                32.2                9.3
## 4            840                19.9                2.0
## 5           1000                16.7               10.5
## 6            764                11.8                6.4
##      Inflation.rate Unemployment.rate Youth.unemployment.rate GDP.per.capita
## 1              7.7              5.1              10.4          37460
## 2              2.3              5.5              16.1          37300
## 3              8.6              4.3              12.1           7850
## 4              8.4              6.1              19.0         14750
## 5              3.9              6.1              16.9         27720
## 6             14.8              2.6               8.3         18480
##      Government.gross.debt Greenhouse.gas.emissions Renewable.energy
## 1              77.8              8.3              33.8
```

```
## 2          105.2          9.3          13.8
## 3          23.1          9.1          19.1
## 4          63.0          6.8          27.9
## 5          77.3          10.5         19.4
## 6          44.0          11.1         18.2
## Electricity.prices Energy.imports.dependency
## 1          288.5          74.5
## 2          377.2          74.0
## 3          119.4          37.1
## 4          154.3          60.3
## 5          351.9          92.0
## 6          303.9          41.8
```

*# Question 5*

*# Remplacer les NA par la moyenne*

```
euro_data_replace_na <- apply(euro_data, 2, function(x) ifelse(is.na(x), mean(x, na.rm = TRUE), x))
```

*# Calculer les composantes principales*

```
res <- prcomp(euro_data_replace_na, scale = TRUE, center = TRUE)
```

*# Vérification de l'orthogonalité et des normes*

```
orthogonality_check <- t(res$rotation) %*% res$rotation
```

```
cat("Produit scalaire des vecteurs propres (orthogonalité) :\n")
```

## Produit scalaire des vecteurs propres (orthogonalité) :

```
print(round(orthogonality_check, 2))
```

```
##      PC1 PC2 PC3 PC4 PC5 PC6 PC7 PC8 PC9 PC10 PC11 PC12 PC13 PC14 PC15 PC16
## PC1    1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## PC2    0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## PC3    0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0
## PC4    0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0
## PC5    0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0
## PC6    0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0
## PC7    0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0
## PC8    0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0
## PC9    0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0
## PC10   0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0
## PC11   0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0
## PC12   0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0
## PC13   0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0
## PC14   0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0
## PC15   0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0
## PC16   0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1
```

```
norms <- apply(res$rotation, 2, function(col) sqrt(sum(col^2)))
```

```
cat("Normes des vecteurs propres (1 attendu) :\n")
```

## Normes des vecteurs propres (1 attendu) :

```
print(round(norms, 2))
```

```
## PC1 PC2 PC3 PC4 PC5 PC6 PC7 PC8 PC9 PC10 PC11 PC12 PC13 PC14 PC15 PC16
## 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

```
# Afficher les premières coordonnées dans la nouvelle base
cat("Premières coordonnées des observations :\n")
```

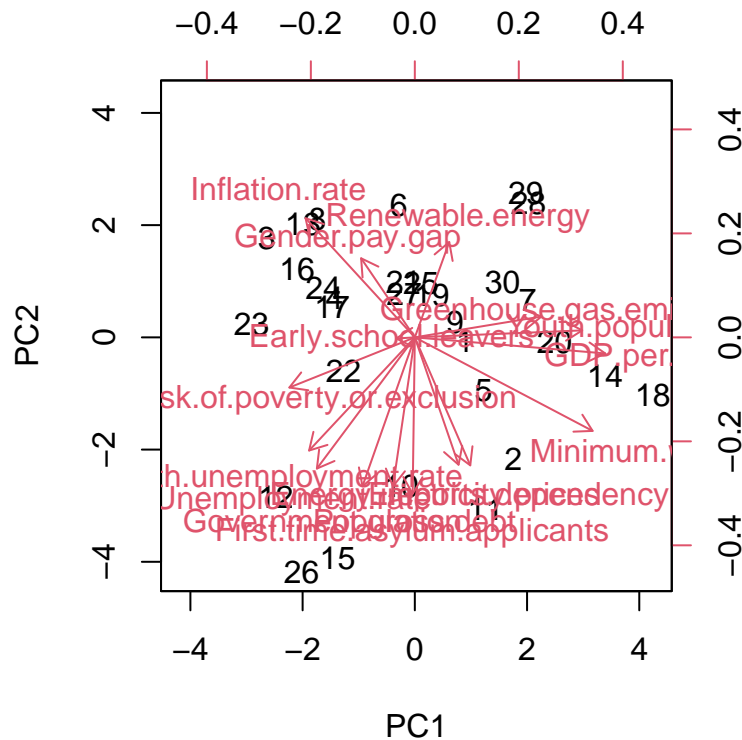
```
## Premières coordonnées des observations :
```

```
head(res$x)
```

```
##          PC1          PC2          PC3          PC4          PC5          PC6
## [1,] 0.8930784 -0.05981786 -0.97098080 -0.32722747 0.9238143 -0.4927803
## [2,] 1.7565034 -2.16393542 -0.07834658 1.31816585 -0.2325251 -0.1199267
## [3,] -2.6417622 1.77214093 -0.25429763 -0.23821400 -1.6690826 1.9269231
## [4,] -1.4323209 0.71295161 -0.13114739 1.72626176 0.5961859 -0.0925010
## [5,] 1.2302770 -0.94486199 0.27801253 1.08399558 -0.3331520 -1.0172092
## [6,] -0.2887514 2.35926409 -2.92285398 0.04385271 -0.1945308 -0.9634055
##          PC7          PC8          PC9          PC10          PC11          PC12
## [1,] 0.1009824 0.651241168 0.6247011 -0.2092549 0.2453571 0.5611628
## [2,] -0.3036975 0.514094776 -1.1343872 -0.1550909 -0.6500718 0.4742277
## [3,] -0.1860566 0.006445367 0.4886804 -1.1327358 -0.1528996 -0.3188954
## [4,] -0.1856331 -0.928931619 0.1125664 -0.3373321 -0.2422261 -0.2552262
## [5,] 0.4715290 1.995736250 -0.3374791 0.6185508 -0.1764931 -0.9572414
## [6,] -1.3480963 0.346571689 -0.3554556 0.7335514 0.3869734 -0.1430733
##          PC13          PC14          PC15          PC16
## [1,] 0.4778485 0.29771859 -0.17539637 -0.14631681
## [2,] 0.3592356 -0.10884273 -0.25695322 0.09789929
## [3,] 0.1384509 -0.30770441 0.12484341 0.06258464
## [4,] -0.5752980 0.25874542 -0.35628808 0.18537500
## [5,] -0.4161035 -0.02523226 0.02481071 0.02486392
## [6,] 0.1021369 -0.16528975 0.15868235 0.08522987
```

```
# Biplot pour visualiser les résultats
biplot(res, scale = 0)
```





```
# Question 6
# Étape 1 : Calculer les composantes principales (si non déjà fait)
euro_data_replace_na <- apply(euro_data, 2, function(x) ifelse(is.na(x), mean(x, na.rm = TRUE), x))
res <- prcomp(euro_data_replace_na, scale = TRUE, center = TRUE)

# Étape 2 : Récupérer les coordonnées dans la nouvelle base

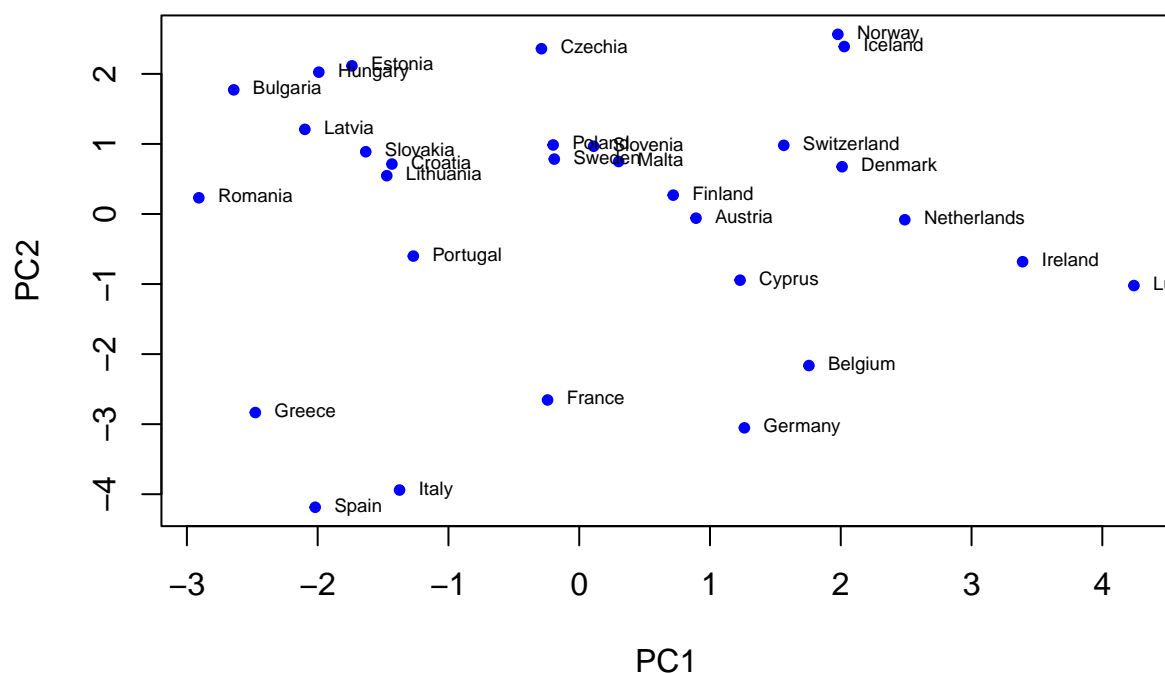
coord <- res$x

# Étape 3 : Ajouter les noms des pays comme noms de lignes
tmp <- read.csv("data/euro.csv", header = TRUE, sep = ";")
rownames(coord) <- tmp[, 1]

# Étape 4 : Créer le graphique du premier plan factoriel
plot(coord[, 1], coord[, 2],
      xlab = "PC1", ylab = "PC2",
      main = "Premier plan factoriel (PC1 vs PC2)",
      pch = 20, col = "blue")

# Étape 5 : Ajouter les noms des pays sur le graphique
text(coord[, 1], coord[, 2], labels = rownames(coord), pos = 4, cex = 0.6)
```

## Premier plan factoriel (PC1 vs PC2)



```
# Question 7
# Extraire les variances (valeurs propres)
variances <- res$sdev^2

# Calculer le pourcentage de variance expliquée
pourcentages <- variances / sum(variances) * 100

# Calculer la variance expliquée cumulée
cumul <- cumsum(pourcentages)

# Afficher les informations pour contrôle
cat("Valeurs propres :\n")
```

```
## Valeurs propres :
```

```
print(round(variances, 2))
```

```
## [1] 3.64 3.52 2.03 1.86 1.28 0.87 0.75 0.56 0.45 0.35 0.21 0.17 0.16 0.09 0.04
## [16] 0.03
```

```
cat("\nPourcentages de variances expliquées :\n")
```

```
##
```

```
## Pourcentages de variances expliquées :
```

```
print(round(pourcentages, 2))
```

```
## [1] 22.72 22.02 12.72 11.60 8.02 5.43 4.70 3.50 2.80 2.16 1.28 1.05
## [13] 0.99 0.56 0.26 0.19
```

```
cat("\nVariance expliquée cumulée :\n")
```

```
##
## Variance expliquée cumulée :
```

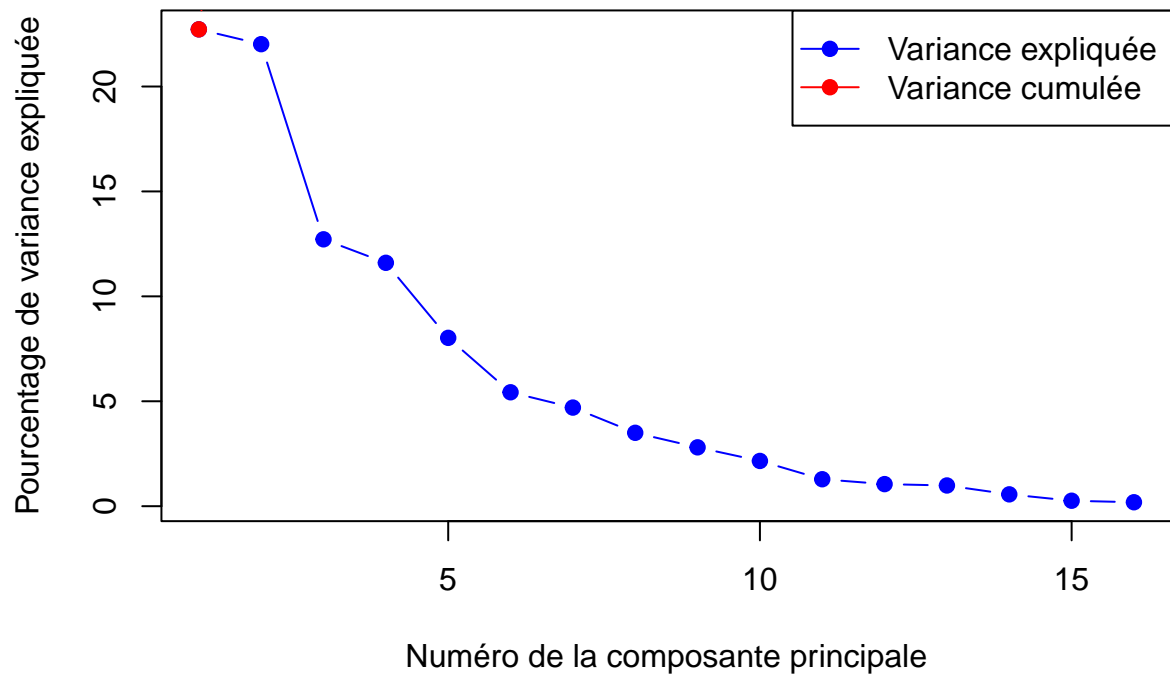
```
print(round(cumul, 2))
```

```
## [1] 22.72 44.74 57.46 69.06 77.08 82.51 87.21 90.70 93.51 95.66
## [11] 96.95 98.00 98.99 99.55 99.81 100.00
```

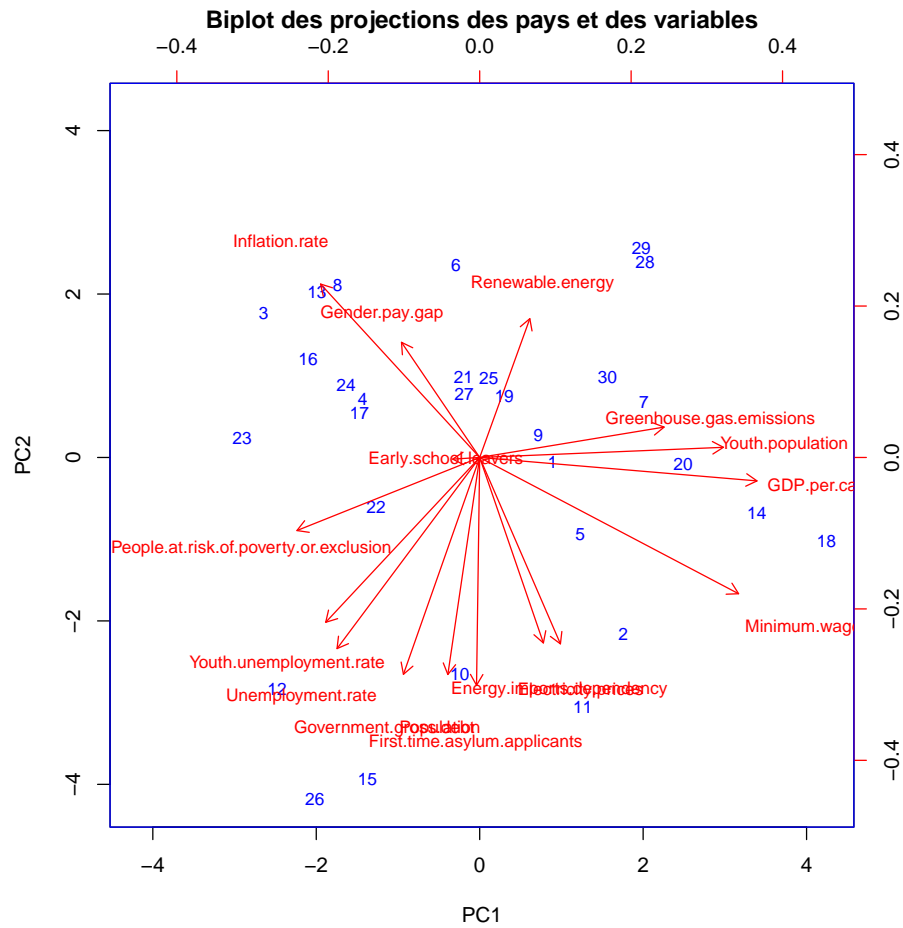
```
# Question 7
# Créer un graphique combiné
plot(pourcentages, type = "b", pch = 19, col = "blue",
     xlab = "Numéro de la composante principale",
     ylab = "Pourcentage de variance expliquée",
     main = "Ébouli des valeurs propres")
lines(cumul, type = "b", pch = 19, col = "red") # Ajouter la variance cumulée

# Ajouter une légende
legend("topright", legend = c("Variance expliquée", "Variance cumulée"),
     col = c("blue", "red"), pch = 19, lty = 1)
```

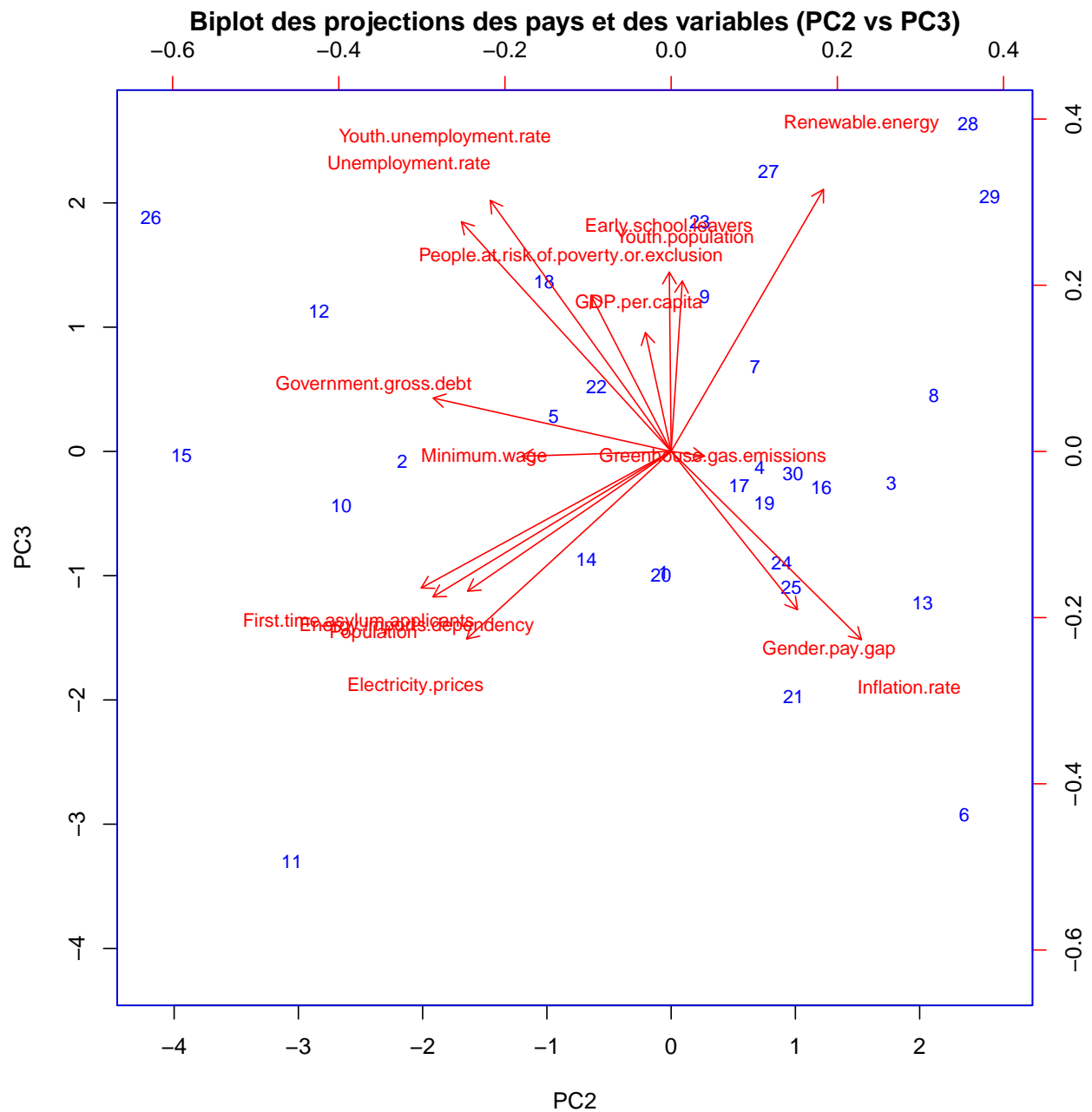
## Ébouli des valeurs propres



```
# Question 8
# Créer le biplot avec des couleurs et des tailles ajustées
biplot(res, scale = 0,
  main = "Biplot des projections des pays et des variables",
  cex = 0.8, # Taille des points et flèches
  col = c("blue", "red")) # Points des pays en bleu, flèches des variables en rouge
```

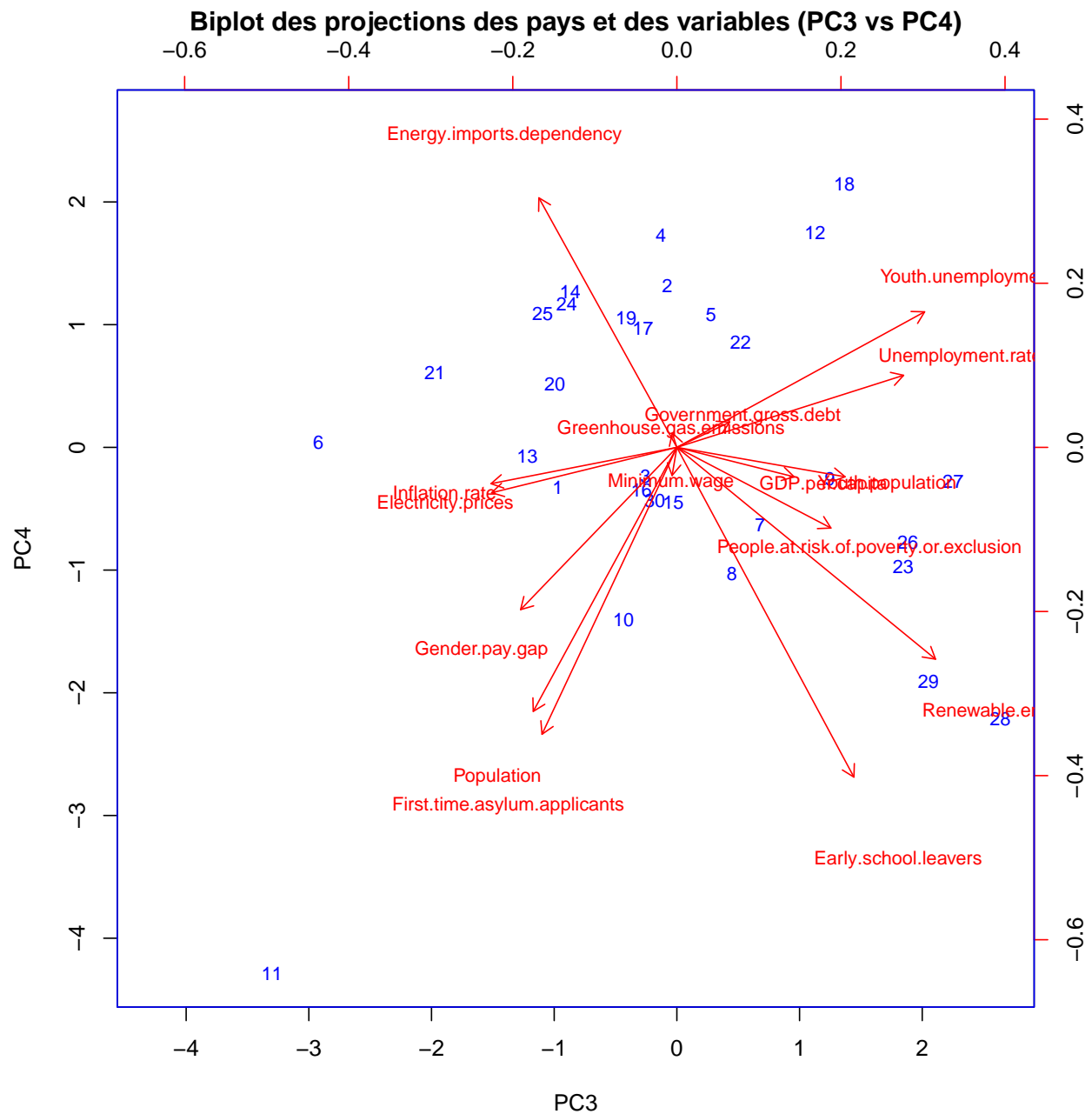


```
# Question 9 Observez d'autres plans factoriels, et commentez.
# Plan PC2 vs PC3
biplot(res, choices = c(2, 3), scale = 0,
       main = "Biplot des projections des pays et des variables (PC2 vs PC3)",
       cex = 0.8, # Taille des points et flèches
       col = c("blue", "red")) # Points des pays en bleu, flèches des variables en rouge
```



```
# Plan PC3 vs PC4
biplot(res, choices = c(3, 4), scale = 0,
  main = "Biplot des projections des pays et des variables (PC3 vs PC4)",
  cex = 0.8, # Taille des points et flèches
```

```
col = c("blue", "red")) # Points des pays en bleu, flèches des variables en rouge
```



```
# Question 10. Déterminez quelles sont les variables les mieux représentées par le premier plan factoriel
# Extraire les charges des vecteurs propres (coefficients de res$rotation)
loadings <- res$rotation
```

```
# Calculer le cos² pour le plan PC1-PC2
cos2_PC1_PC2 <- rowSums(loadings[, 1:2]^2) # Somme des carrés des charges sur PC1 et PC2
```

```
# Afficher les cos²
cat("Cos² des variables sur le plan PC1-PC2 :\n")
```

```
## Cos² des variables sur le plan PC1-PC2 :
```

```
print(round(cos2_PC1_PC2, 2))
```

```
##              Population              Youth.population
##              0.13              0.16
## First.time.asylum.applicants      Gender.pay.gap
##              0.14              0.05
## Minimum.wage People.at.risk.of.poverty.or.exclusion
##              0.23              0.11
## Early.school.leavers      Inflation.rate
##              0.00              0.15
## Unemployment.rate      Youth.unemployment.rate
##              0.16              0.14
## GDP.per.capita      Government.gross.debt
##              0.21              0.14
## Greenhouse.gas.emissions      Renewable.energy
##              0.10              0.06
## Electricity.prices      Energy.imports.dependency
##              0.11              0.10
```

```
# Identifier les variables les mieux représentées
best_variables <- names(sort(cos2_PC1_PC2, decreasing = TRUE))
cat("\nVariables les mieux représentées par PC1-PC2 (par ordre de qualité) :\n")
```

```
##
## Variables les mieux représentées par PC1-PC2 (par ordre de qualité) :
```

```
print(best_variables)
```

```
## [1] "Minimum.wage"
## [2] "GDP.per.capita"
## [3] "Youth.population"
## [4] "Unemployment.rate"
## [5] "Inflation.rate"
## [6] "Government.gross.debt"
## [7] "First.time.asylum.applicants"
## [8] "Youth.unemployment.rate"
## [9] "Population"
## [10] "Electricity.prices"
## [11] "People.at.risk.of.poverty.or.exclusion"
```



```
## [12] "Energy.imports.dependency"
## [13] "Greenhouse.gas.emissions"
## [14] "Renewable.energy"
## [15] "Gender.pay.gap"
## [16] "Early.school.leavers"
```

```
# Question 11
# Étape 1 : Extraire les scores des individus
scores <- res$x # Les coordonnées des individus dans le nouvel espace

# Étape 2 : Extraire les variances des composantes principales
variances <- res$sdev^2 # Valeurs propres

# Étape 3 : Calculer les contributions des individus sur chaque composante
# Contribution = (scores^2) / (variance de la composante)
contributions <- sweep(scores^2, 2, variances, "/")

# Étape 4 : Résumé des contributions
cat("Contributions des individus sur chaque composante principale :\n")
```

```
## Contributions des individus sur chaque composante principale :
```

```
print(round(contributions, 2)) # Contributions arrondies
```

```
##          PC1  PC2  PC3  PC4  PC5  PC6   PC7  PC8  PC9 PC10 PC11 PC12 PC13 PC14
## [1,] 0.22 0.00 0.46 0.06 0.66 0.28 0.01 0.76 0.87 0.13 0.29 1.87 1.45 0.98
## [2,] 0.85 1.33 0.00 0.94 0.04 0.02 0.12 0.47 2.87 0.07 2.06 1.34 0.82 0.13
## [3,] 1.92 0.89 0.03 0.03 2.17 4.27 0.05 0.00 0.53 3.72 0.11 0.60 0.12 1.05
## [4,] 0.56 0.14 0.01 1.61 0.28 0.01 0.05 1.54 0.03 0.33 0.29 0.39 2.10 0.74
## [5,] 0.42 0.25 0.04 0.63 0.09 1.19 0.30 7.12 0.25 1.11 0.15 5.45 1.10 0.01
## [6,] 0.02 1.58 4.20 0.00 0.03 1.07 2.42 0.21 0.28 1.56 0.73 0.12 0.07 0.30
## [7,] 1.11 0.13 0.23 0.21 0.66 0.22 0.26 0.70 0.28 1.96 1.71 0.03 0.01 0.72
## [8,] 0.83 1.27 0.10 0.57 0.04 0.93 4.24 1.01 1.45 0.49 1.85 0.45 0.01 0.90
## [9,] 0.14 0.02 0.76 0.04 1.05 0.38 0.33 0.04 0.32 0.00 1.20 0.02 5.32 0.07
## [10,] 0.02 2.00 0.09 1.06 0.29 0.54 0.00 3.02 0.24 0.01 3.33 1.48 2.41 0.43
## [11,] 0.44 2.65 5.35 9.89 0.06 0.43 0.01 0.01 0.33 0.12 0.06 0.95 0.03 0.47
## [12,] 1.69 2.28 0.62 1.65 1.23 0.62 1.67 0.51 1.02 4.76 0.18 0.16 0.71 0.71
## [13,] 1.09 1.16 0.73 0.00 0.60 3.79 1.43 0.07 2.56 0.79 1.29 3.53 0.00 0.01
## [14,] 3.16 0.13 0.37 0.87 0.08 1.16 0.85 0.67 0.04 0.17 0.27 4.07 1.54 0.23
## [15,] 0.52 4.41 0.00 0.11 0.45 0.15 0.01 0.06 3.52 0.00 3.39 0.12 0.01 0.63
## [16,] 1.21 0.41 0.04 0.07 0.78 1.52 0.09 1.56 0.83 0.00 0.01 1.46 0.00 1.69
## [17,] 0.60 0.08 0.04 0.51 0.00 1.08 0.10 0.15 0.00 0.02 0.23 0.01 0.02 7.92
## [18,] 4.95 0.30 0.92 2.48 3.90 1.30 0.75 1.28 2.35 0.30 1.92 0.15 0.35 0.13
## [19,] 0.02 0.16 0.08 0.60 0.35 0.03 11.17 0.11 0.11 0.57 0.29 0.45 0.11 0.18
## [20,] 1.70 0.00 0.49 0.14 0.00 0.00 0.81 0.23 1.43 0.36 3.32 0.01 0.01 0.02
## [21,] 0.01 0.28 1.91 0.20 0.99 0.10 1.09 2.97 2.49 0.00 0.31 1.05 1.60 0.06
## [22,] 0.44 0.10 0.13 0.39 0.49 0.26 0.25 0.03 0.50 0.19 0.13 0.10 0.64 0.76
## [23,] 2.33 0.02 1.67 0.51 5.34 1.24 1.12 0.07 0.85 1.12 0.21 2.12 0.00 0.42
## [24,] 0.73 0.22 0.40 0.74 0.26 0.57 0.01 0.03 1.18 1.74 0.27 0.52 0.01 0.47
## [25,] 0.00 0.27 0.59 0.64 0.00 0.11 0.01 1.65 2.51 0.76 0.07 0.25 7.63 0.03
## [26,] 1.12 4.97 1.74 0.32 0.01 0.01 0.01 0.04 1.04 1.37 0.12 2.03 0.94 0.65
## [27,] 0.01 0.17 2.49 0.04 2.13 0.21 0.01 3.00 0.49 3.21 0.01 0.00 0.66 1.73
## [28,] 1.13 1.62 3.41 2.64 1.77 4.17 0.50 0.66 0.34 3.40 0.01 0.01 0.81 2.98
```

```
## [29,] 1.08 1.87 2.07 1.96 0.30 0.23 0.00 1.02 0.00 0.15 1.78 0.03 0.00 4.37
## [30,] 0.67 0.27 0.02 0.10 4.97 3.10 1.32 0.01 0.30 0.60 3.43 0.23 0.53 0.24
##      PC15 PC16
## [1,] 0.74 0.71
## [2,] 1.59 0.32
## [3,] 0.37 0.13
## [4,] 3.05 1.14
## [5,] 0.01 0.02
## [6,] 0.61 0.24
## [7,] 1.16 0.32
## [8,] 0.25 0.18
## [9,] 0.22 2.69
## [10,] 1.72 0.18
## [11,] 3.44 0.80
## [12,] 0.01 1.17
## [13,] 0.10 0.09
## [14,] 0.30 1.16
## [15,] 0.24 0.81
## [16,] 0.68 0.07
## [17,] 1.73 0.26
## [18,] 0.18 0.25
## [19,] 0.16 0.49
## [20,] 0.10 1.09
## [21,] 0.81 3.21
## [22,] 1.95 4.43
## [23,] 1.82 0.17
## [24,] 2.12 0.14
## [25,] 0.12 4.48
## [26,] 3.52 0.52
## [27,] 1.56 1.31
## [28,] 0.06 0.02
## [29,] 0.36 0.89
## [30,] 0.02 1.67
```

```
# Étape 5 : Calcul des contributions totales par individu (somme sur toutes les composantes)
contributions_totales <- rowSums(contributions)
cat("\nContributions totales par individu :\n")
```

```
##
## Contributions totales par individu :
```

```
print(round(contributions_totales, 2))
```

```
## [1] 9.50 12.96 16.01 12.26 18.13 13.44 9.72 14.57 12.61 16.81 25.03 18.96
## [13] 17.24 15.08 14.42 10.42 12.74 21.50 14.88 9.73 17.08 10.81 18.99 9.42
## [25] 19.12 18.42 17.04 23.55 16.11 17.47
```

```
# Étape 6 : Identifier les individus avec des contributions faibles
seuil <- 1 / nrow(scores) # Seuil théorique de contribution moyenne
individus_faibles <- names(contributions_totales[contributions_totales < seuil])
cat("\nIndividus ayant une contribution faible (en dessous du seuil) :\n")
```

```
##
## Individus ayant une contribution faible (en dessous du seuil) :
```

```
print(individus_faibles)
```

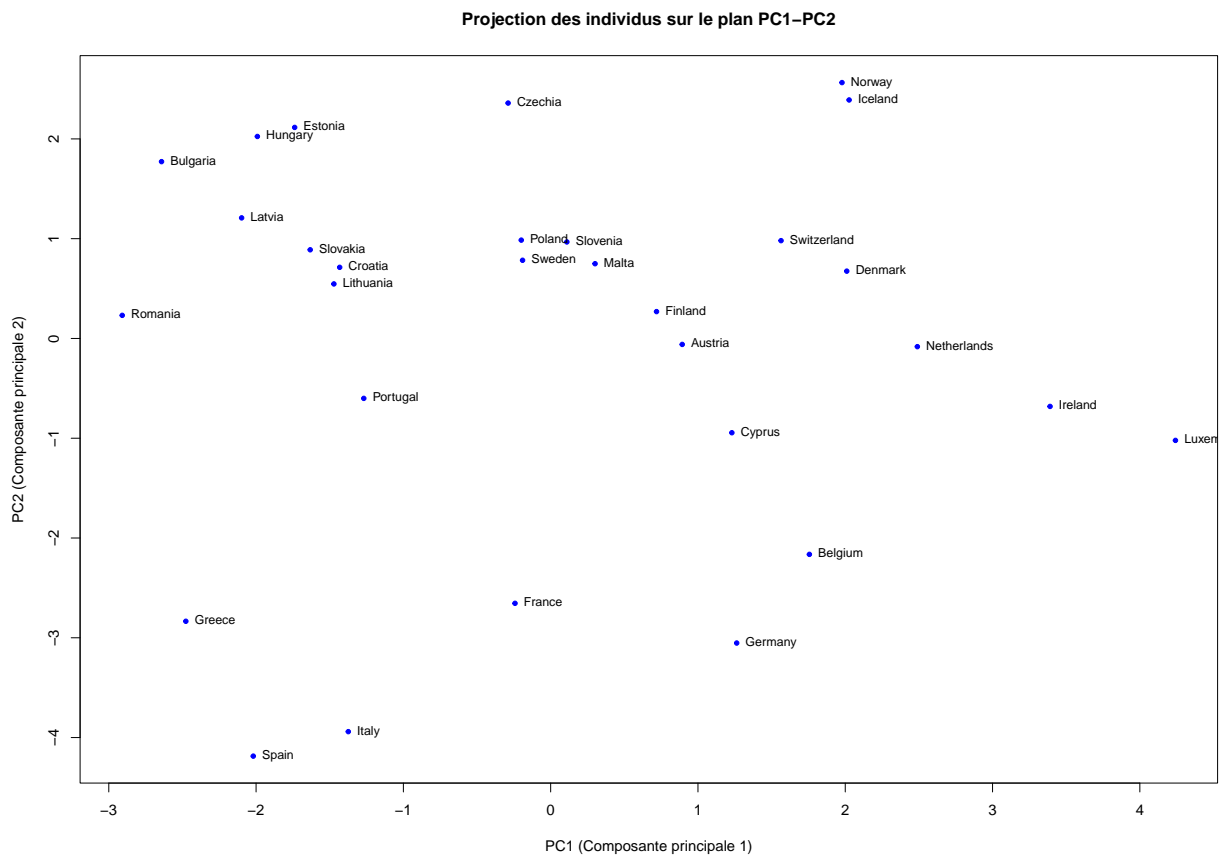
```
## NULL
```

```
# question 12
# Étape 1 : Extraire les scores
coord <- res$x # Scores des individus

# Étape 2 : Ajouter les noms des pays
tmp <- read.csv("data/euro.csv", header = TRUE, sep = ";") # Charger les noms
rownames(coord) <- tmp[, 1]

# Étape 3 : Créer le graphique
plot(coord[, 1], coord[, 2],
      xlab = "PC1 (Composante principale 1)",
      ylab = "PC2 (Composante principale 2)",
      main = "Projection des individus sur le plan PC1-PC2",
      pch = 20, col = "blue")

# Ajouter les noms des individus
text(coord[, 1], coord[, 2], labels = rownames(coord), pos = 4, cex = 0.8)
```



```
# TP2 *****
```

```
# Question 1
```

```
# Après avoir déterminé les deux matrices de dissimilarités en utilisant respectivement une métrique E  
# et une métrique réduite, effectuez une classification ascendante hiérarchique des données fondée pour  
# matrice sur le saut minimum.
```

```
# Matrice de dissimilarité Euclidienne (non normalisée)
```

```
dissimilarity_euclidean <- as.matrix(dist(euro_data, method = "euclidean"))
```

```
# Normaliser les données
```

```
euro_data_normalized <- scale(euro_data)
```

```
# Matrice de dissimilarité Euclidienne (normalisée)
```

```
dissimilarity_reduced <- as.matrix(dist(euro_data_normalized, method = "euclidean"))
```

```
# Afficher les matrices
```

```
cat("Matrice de dissimilarité Euclidienne (non normalisée) :\n")
```

```
## Matrice de dissimilarité Euclidienne (non normalisée) :
```

```
print(round(dissimilarity_euclidean, 2))
```

```
##           1           2           3           4           5           6           7
## 1          0.0  2638160.9  2657441.6  5254209.8  8184197.7  1723739.7  3172609.6
## 2  2638160.9          0.0  5295172.6  7891982.7  10822113.6  915893.4  5810224.2
## 3  2657441.6  5295172.6          0.0  2596908.1  5527055.2  4379883.5  517377.9
## 4  5254209.8  7891982.7  2596908.1          0.0  2930238.9  6976636.0  2082102.7
## 5  8184197.7  10822113.6  5527055.2  2930238.9          0.0  9906837.9  5012023.0
## 6  1723739.7  915893.4  4379883.5  6976636.0  9906837.9          0.0  4894993.5
## 7  3172609.6  5810224.2  517377.9  2082102.7  5012023.0  4894993.5          0.0
## 8  7739095.7  10376966.3  5081864.8  2485011.2  445423.9  9461646.0  4566922.4
## 9  3541179.2  6178875.8  884403.3  1713222.9  4643283.9  5263592.7  369016.5
## 10 59068272.1  56430300.0  61725394.4  64322245.8  67252408.7  57345630.8  62240489.5
## 11 75254567.8  72616667.8  77911743.7  80508619.6  83438748.0  73532049.3  78426873.1
## 12 1309339.5  1329246.9  3966447.0  6563330.6  9493397.5  417425.3  4481796.4
## 13  498677.6  2143374.4  3152120.1  5748850.2  8679061.1  1227792.4  3667289.2
## 14 3833770.1  6471512.3  1178083.5  1421690.0  4350916.7  5556402.2  661626.8
## 15 49892485.3  47254514.4  52549606.4  55146459.4  58076621.7  48169847.0  53064707.3
## 16 7222010.5  9859856.2  4564752.4  1967886.6  962468.6  8944522.6  4049836.8
## 17 6247781.6  8885592.0  3590504.5  993615.7  1936652.9  7970250.9  3075606.3
## 18 8444257.2  11082114.6  5787427.3  3190822.5  265931.4  10166927.0  5271935.1
## 19 8562908.8  11200787.2  5905729.2  3308864.2  378816.7  10285481.2  5390666.0
## 20 8706540.1  6068506.0  11363651.2  13960476.9  16890619.4  6983909.5  11878694.2
## 21 27649015.7  25010959.5  30306030.3  32902842.6  35833037.6  25926208.1  30821105.6
## 22 1412975.2  1226591.2  4068976.5  6665728.9  9595927.6  310914.0  4584084.3
## 23 9949920.8  7311827.9  12606844.4  15203656.9  18133855.5  8227027.8  13121964.2
## 24 3676462.9  6314104.5  1019192.6  1577899.5  4508119.1  5398737.4  505152.5
## 25 6987988.3  9625861.3  4330788.3  1733946.6  1196292.5  8710559.9  3815806.0
## 26 38980730.5  36342803.8  41637883.5  44234753.4  47164894.8  37258173.3  42153012.4
## 27 1464078.3  1261488.4  4207644.3  6889503.2  9915736.2  317260.5  4739409.5
## 28 9319046.8  12139076.8  6478490.5  3702359.4  569987.2  11160612.2  5927755.2
## 29 3734910.3  6459056.0  992533.1  1692844.2  4718327.5  5513902.8  458665.5
```

## 30	301607.7	3023539.1	2446003.6	5127617.3	8153693.3	2078822.6	2977400.6
##	8	9	10	11	12	13	14
## 1	7739095.7	3541179.23	59068272	75254568	1309339.5	498677.6	3833770.1
## 2	10376966.3	6178875.82	56430300	72616668	1329246.9	2143374.4	6471512.3
## 3	5081864.8	884403.26	61725394	77911744	3966447.0	3152120.1	1178083.5
## 4	2485011.2	1713222.94	64322246	80508620	6563330.6	5748850.2	1421690.0
## 5	445423.9	4643283.92	67252409	83438748	9493397.5	8679061.1	4350916.7
## 6	9461646.0	5263592.70	57345631	73532049	417425.3	1227792.4	5556402.2
## 7	4566922.4	369016.54	62240490	78426873	4481796.4	3667289.2	661626.8
## 8	0.0	4198142.43	66807245	82993600	9048259.5	8233861.0	3905930.1
## 9	4198142.4	0.00	62609165	78795544	4850339.3	4035840.0	294757.5
## 10	66807244.6	62609165.06	0	16186913	57759062.7	58573415.9	62901731.7
## 11	82993600.2	78795543.54	16186913	0	73945362.1	74759828.2	79088088.5
## 12	9048259.5	4850339.35	57759063	73945362	0.0	816305.6	5143049.7
## 13	8233861.0	4035839.96	58573416	74759828	816305.6	0.0	4328749.0
## 14	3905930.1	294757.49	62901732	79088088	5143049.7	4328749.0	0.0
## 15	57631457.5	53433380.51	9175789	25362422	48583274.2	49397631.5	53725951.5
## 16	517133.4	3681040.00	66290127	82476490	8531161.6	7716736.2	3388911.8
## 17	1491399.1	2706784.64	65315861	81502231	7556922.1	6742465.0	2414819.3
## 18	708356.7	4903380.29	67512337	83698686	9753540.9	8939201.5	4610612.9
## 19	823917.6	5021931.53	67631081	83817438	9872100.7	9057701.2	4729577.0
## 20	16445468.8	12247370.11	50361800	66548190	7397378.3	8211691.5	12539950.7
## 21	35387852.2	31189774.11	31419547	47606198	26339802.2	27153993.1	31482393.0
## 22	9150738.2	4952681.53	57656534	73842947	116587.4	916896.3	5245494.4
## 23	17688665.7	13490605.64	49118621	65305082	8640704.0	9454810.0	13783290.5
## 24	4062909.8	136788.50	62744354	78930740	4985522.6	4170952.5	167299.3
## 25	751126.5	3447031.16	66056150	82242504	8297165.5	7482779.5	3154818.4
## 26	46719740.1	42521678.83	20087624	36273877	37671519.1	38485952.9	42814244.4
## 27	9455987.4	5120180.96	59542299	76259541	124863.7	952600.0	5422417.0
## 28	1046036.9	5533605.49	72465604	89769540	10718665.1	9848070.9	5220936.5
## 29	4258721.0	85416.58	64739923	81457137	5087099.3	4245993.3	224880.3
## 30	7694009.0	3358237.98	61304387	78021579	1651970.6	812140.9	3660253.9
##	15	16	17	18	19	20	21
## 1	49892485	7222010.5	6247781.6	8444257.2	8562908.8	8706540	27649016
## 2	47254514	9859856.2	8885592.0	11082114.6	11200787.2	6068506	25010959
## 3	52549606	4564752.4	3590504.5	5787427.3	5905729.2	11363651	30306030
## 4	55146459	1967886.6	993615.7	3190822.5	3308864.2	13960477	32902843
## 5	58076622	962468.6	1936652.9	265931.4	378816.7	16890619	35833038
## 6	48169847	8944522.6	7970250.9	10166927.0	10285481.2	6983909	25926208
## 7	53064707	4049836.8	3075606.3	5271935.1	5390666.0	11878694	30821106
## 8	57631458	517133.4	1491399.1	708356.7	823917.6	16445469	35387852
## 9	53433381	3681040.0	2706784.6	4903380.3	5021931.5	12247370	31189774
## 10	9175789	66290127.4	65315860.8	67512336.5	67631081.0	50361800	31419547
## 11	25362422	82476490.1	81502231.0	83698685.7	83817438.5	66548190	47606198
## 12	48583274	8531161.6	7556922.1	9753540.9	9872100.7	7397378	26339802
## 13	49397632	7716736.2	6742465.0	8939201.5	9057701.2	8211692	27153993
## 14	53725952	3388911.8	2414819.3	4610612.9	4729577.0	12539951	31482393
## 15	0	57114340.6	56140074.3	58336558.1	58455294.8	41186016	22243808
## 16	57114341	0.0	974273.0	1224209.5	1341023.6	15928356	34870729
## 17	56140074	974273.0	0.0	2197538.9	2315257.5	14954089	33896458
## 18	58336558	1224209.5	2197538.9	0.0	131665.5	17150563	36092993
## 19	58455295	1341023.6	2315257.5	131665.5	0.0	17269291	36211688
## 20	41186016	15928356.0	14954089.2	17150563.2	17269290.8	0	18942493
## 21	22243808	34870728.6	33896457.8	36092992.5	36211687.6	18942493	0

##	22	48480750	8633615.5	7659343.8	9856017.3	9974572.6	7294799	26237116	
##	23	39942840	17171542.2	16197272.4	18393885.7	18512506.5	1244054	17699189	
##	24	53568569	3545785.7	2571513.5	4768452.2	4886751.3	12382589	31324945	
##	25	56880363	234200.3	740373.1	1457455.8	1574941.4	15694366	34636765	
##	26	10911881	46202627.6	45228366.0	47424850.3	47543579.1	30274323	11332659	
##	27	50065591	8921916.1	7915695.8	10184216.3	10306809.1	7528867	27092497	
##	28	62656277	1598777.4	2640185.5	295313.7	165765.1	18626576	38876876	
##	29	55263219	3724730.3	2718655.6	4986532.4	5109387.3	12726502	32290151	
##	30	51827680	7159963.7	6153770.5	8422071.9	8544791.2	9290960	28854655	
##		22	23	24	25	26	27	28	
##	1	1412975.22	9949921	3676462.90	6987988.3	38980731	1464078.30	9319046.8	
##	2	1226591.23	7311828	6314104.51	9625861.3	36342804	1261488.36	12139076.8	
##	3	4068976.47	12606844	1019192.57	4330788.3	41637884	4207644.26	6478490.5	
##	4	6665728.92	15203657	1577899.47	1733946.6	44234753	6889503.25	3702359.4	
##	5	9595927.61	18133856	4508119.13	1196292.5	47164895	9915736.15	569987.2	
##	6	310914.02	8227028	5398737.42	8710559.9	37258173	317260.51	11160612.2	
##	7	4584084.33	13121964	505152.48	3815806.0	42153012	4739409.52	5927755.2	
##	8	9150738.20	17688666	4062909.79	751126.5	46719740	9455987.39	1046036.9	
##	9	4952681.53	13490606	136788.50	3447031.2	42521679	5120180.96	5533605.5	
##	10	57656533.80	49118621	62744354.29	66056150.0	20087624	59542298.67	72465604.4	
##	11	73842947.40	65305082	78930739.77	82242504.0	36273877	76259541.21	89769540.2	
##	12	116587.45	8640704	4985522.60	8297165.5	37671519	124863.68	10718665.1	
##	13	916896.26	9454810	4170952.55	7482779.5	38485953	952599.98	9848070.9	
##	14	5245494.44	13783290	167299.32	3154818.4	42814244	5422416.95	5220936.5	
##	15	48480749.68	39942840	53568568.57	56880363.2	10911881	50065591.20	62656277.5	
##	16	8633615.51	17171542	3545785.73	234200.3	46202628	8921916.12	1598777.4	
##	17	7659343.84	16197272	2571513.54	740373.1	45228366	7915695.76	2640185.5	
##	18	9856017.34	18393886	4768452.21	1457455.8	47424850	10184216.28	295313.7	
##	19	9974572.55	18512507	4886751.32	1574941.4	47543579	10306809.06	165765.1	
##	20	7294799.49	1244054	12382588.81	15694365.8	30274323	7528867.06	18626576.4	
##	21	26237115.97	17699189	31324944.91	34636764.8	11332659	27092496.59	38876876.5	
##	22	0.00	8537935	5087830.52	8399650.6	37569072	27013.79	10828235.2	
##	23	8537935.36	0	13625760.74	16937580.4	29031207	8812907.74	19955666.8	
##	24	5087830.52	13625761	0.00	3311831.9	42656870	5259871.68	5389159.8	
##	25	8399650.60	16937580	3311831.85	0.0	45968645	8680248.27	1848726.3	
##	26	37569072.06	29031207	42656870.30	45968644.6	0	38796051.75	50991159.3	
##	27	27013.79	8812908	5259871.68	8680248.3	38796052	0.00	10833487.5	
##	28	10828235.15	19955667	5389159.79	1848726.3	50991159	10833487.50	0.0	
##	29	5192801.16	14010600	84618.29	3482978.5	43993668	5197695.75	5453536.8	
##	30	1757788.42	10575120	3498101.70	6918252.8	40558111	1762330.42	9009575.6	
##		29	30						
##	1	3734910.33	301607.7						
##	2	6459056.01	3023539.1						
##	3	992533.11	2446003.6						
##	4	1692844.17	5127617.3						
##	5	4718327.55	8153693.3						
##	6	5513902.84	2078822.6						
##	7	458665.48	2977400.6						
##	8	4258721.03	7694009.0						
##	9	85416.58	3358238.0						
##	10	64739922.94	61304386.8						
##	11	81457137.37	78021579.4						
##	12	5087099.33	1651970.6						
##	13	4245993.26	812140.9						

```
## 14 224880.27 3660253.9
## 15 55263218.86 51827680.0
## 16 3724730.34 7159963.7
## 17 2718655.56 6153770.5
## 18 4986532.40 8422071.9
## 19 5109387.27 8544791.2
## 20 12726501.58 9290960.2
## 21 32290151.02 28854655.5
## 22 5192801.16 1757788.4
## 23 14010599.65 10575119.5
## 24 84618.29 3498101.7
## 25 3482978.53 6918252.8
## 26 43993667.87 40558110.9
## 27 5197695.75 1762330.4
## 28 5453536.80 9009575.6
## 29 0.00 3435576.1
## 30 3435576.09 0.0
```

```
cat("\nMatrice de dissimilarité Euclidienne (normalisée) :\n")
```

```
##
## Matrice de dissimilarité Euclidienne (normalisée) :
```

```
print(round(dissimilarity_reduced, 2))
```

```
##      1      2      3      4      5      6      7      8      9     10     11     12     13     14     15
## 1  0.00  3.80  5.55  3.97  3.61  4.15  3.04  4.70  2.71  4.04  5.87  5.60  4.48  3.95  5.40
## 2  3.80  0.00  6.87  4.91  3.05  6.20  4.09  6.63  4.12  4.43  6.90  5.34  6.83  3.25  4.39
## 3  5.55  6.87  0.00  4.26  6.58  5.39  6.13  3.53  5.61  6.52  8.25  6.66  4.71  7.13  6.77
## 4  3.97  4.91  4.26  0.00  4.79  4.65  4.87  4.29  3.81  4.94  8.36  4.59  4.18  5.66  5.74
## 5  3.61  3.05  6.58  4.79  0.00  5.64  3.65  5.96  4.01  5.21  7.36  5.63  5.87  4.10  5.24
## 6  4.15  6.20  5.39  4.65  5.64  0.00  5.36  4.59  5.30  6.46  7.50  7.65  4.00  5.79  7.31
## 7  3.04  4.09  6.13  4.87  3.65  5.36  0.00  4.84  2.67  5.01  6.95  6.94  5.88  3.89  6.41
## 8  4.70  6.63  3.53  4.29  5.96  4.59  4.84  0.00  4.14  6.11  8.09  6.43  4.87  6.66  7.09
## 9  2.71  4.12  5.61  3.81  4.01  5.30  2.67  4.14  0.00  4.28  7.33  5.32  5.22  4.86  5.73
## 10 4.04  4.43  6.52  4.94  5.21  6.46  5.01  6.11  4.28  0.00  5.10  5.01  5.98  5.82  3.58
## 11 5.87  6.90  8.25  8.36  7.36  7.50  6.95  8.09  7.33  5.10  0.00  8.79  8.22  7.12  6.18
## 12 5.60  5.34  6.66  4.59  5.63  7.65  6.94  6.43  5.32  5.01  8.79  0.00  6.90  7.16  4.51
## 13 4.48  6.83  4.71  4.18  5.87  4.00  5.88  4.87  5.22  5.98  8.22  6.90  0.00  7.13  6.86
## 14 3.95  3.25  7.13  5.66  4.10  5.79  3.89  6.66  4.86  5.82  7.12  7.16  7.13  0.00  6.54
## 15 5.40  4.39  6.77  5.74  5.24  7.31  6.41  7.09  5.73  3.58  6.18  4.51  6.86  6.54  0.00
## 16 3.91  5.73  3.58  3.47  5.39  4.51  4.54  2.95  4.15  5.47  7.62  5.60  4.51  6.25  5.94
## 17 3.49  4.76  3.38  2.26  4.42  4.55  4.40  3.82  3.85  5.04  7.63  4.96  4.08  5.32  5.32
## 18 6.32  4.96  8.16  6.98  5.60  8.09  5.79  8.15  6.06  7.37  9.10  8.26  8.53  3.86  7.64
## 19 3.92  4.87  5.17  4.07  4.00  5.59  4.24  6.04  4.63  5.61  7.80  6.71  4.31  5.34  6.34
## 20 2.79  3.57  6.17  4.55  3.80  5.20  3.15  5.98  3.70  4.62  6.42  6.81  5.62  3.01  6.32
## 21 4.26  4.89  4.65  3.46  5.12  3.06  5.07  4.96  4.83  5.16  7.14  6.74  4.46  5.11  5.86
## 22 3.28  3.90  4.84  2.55  3.73  5.30  4.22  4.64  3.02  4.07  7.53  3.70  4.55  5.57  4.18
## 23 6.37  6.72  3.96  5.49  6.36  7.12  6.26  5.05  5.90  6.23  8.59  6.76  5.37  7.83  5.67
## 24 3.47  5.31  4.47  2.11  4.54  3.71  4.81  4.00  3.91  5.04  7.90  5.09  2.99  5.85  5.81
## 25 3.37  4.17  4.78  2.92  4.59  3.75  4.19  5.03  3.65  5.16  7.51  6.13  4.42  4.90  5.82
## 26 6.17  5.76  7.12  6.23  5.89  8.60  6.76  6.98  5.66  4.18  7.29  4.31  7.44  7.68  3.24
## 27 4.68  5.57  5.89  3.95  5.55  6.49  3.66  4.65  2.93  5.19  8.63  6.26  5.96  6.14  6.52
```

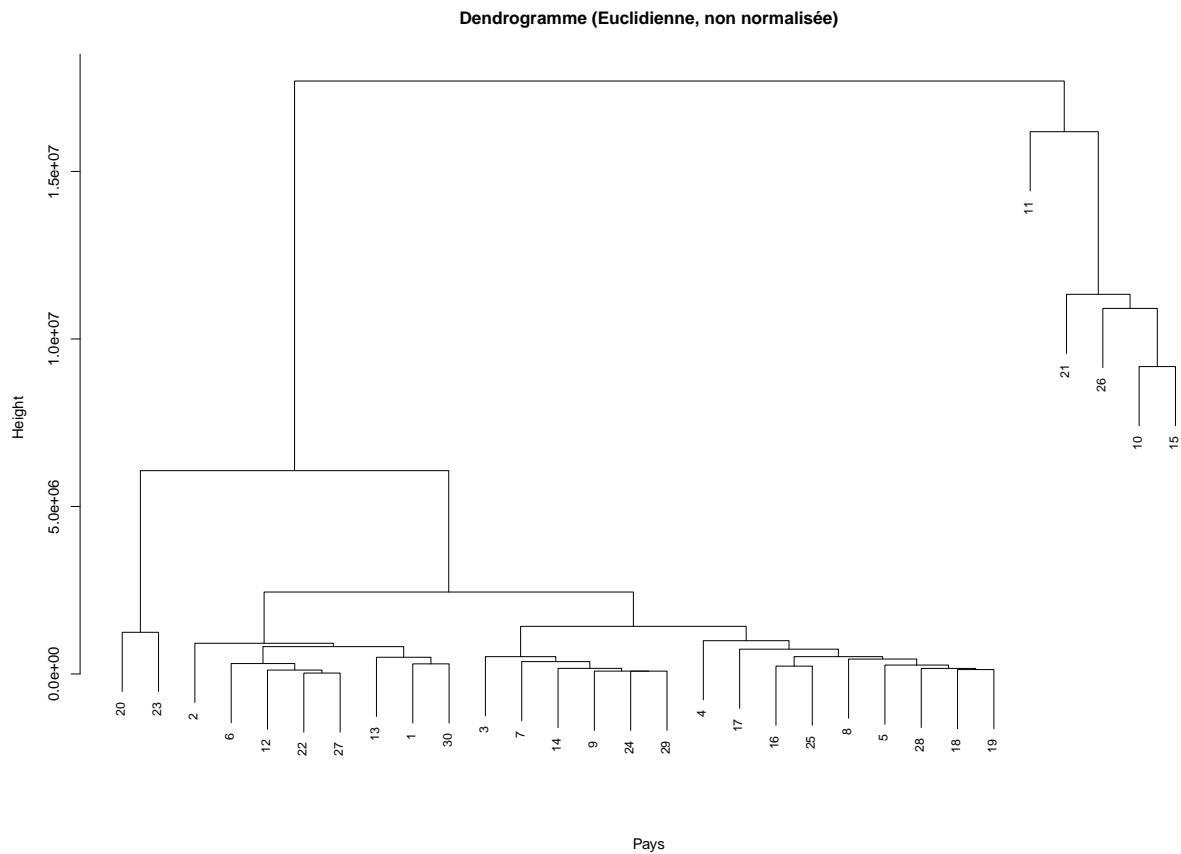
```
## 28 6.24 7.31 7.09 7.46 6.48 7.17 5.44 6.42 5.21 7.79 9.45 9.25 7.11 7.27 8.84
## 29 4.96 6.67 6.61 6.09 6.24 6.39 3.65 5.37 3.74 6.63 8.53 8.53 6.30 6.18 8.27
## 30 3.63 5.44 6.33 5.08 5.48 6.00 3.15 5.72 4.06 5.89 7.31 7.40 6.66 4.76 7.31
##      16      17      18      19      20      21      22      23      24      25      26      27      28      29      30
## 1   3.91 3.49 6.32 3.92 2.79 4.26 3.28 6.37 3.47 3.37 6.17 4.68 6.24 4.96 3.63
## 2   5.73 4.76 4.96 4.87 3.57 4.89 3.90 6.72 5.31 4.17 5.76 5.57 7.31 6.67 5.44
## 3   3.58 3.38 8.16 5.17 6.17 4.65 4.84 3.96 4.47 4.78 7.12 5.89 7.09 6.61 6.33
## 4   3.47 2.26 6.98 4.07 4.55 3.46 2.55 5.49 2.11 2.92 6.23 3.95 7.46 6.09 5.08
## 5   5.39 4.42 5.60 4.00 3.80 5.12 3.73 6.36 4.54 4.59 5.89 5.55 6.48 6.24 5.48
## 6   4.51 4.55 8.09 5.59 5.20 3.06 5.30 7.12 3.71 3.75 8.60 6.49 7.17 6.39 6.00
## 7   4.54 4.40 5.79 4.24 3.15 5.07 4.22 6.26 4.81 4.19 6.76 3.66 5.44 3.65 3.15
## 8   2.95 3.82 8.15 6.04 5.98 4.96 4.64 5.05 4.00 5.03 6.98 4.65 6.42 5.37 5.72
## 9   4.15 3.85 6.06 4.63 3.70 4.83 3.02 5.90 3.91 3.65 5.66 2.93 5.21 3.74 4.06
## 10  5.47 5.04 7.37 5.61 4.62 5.16 4.07 6.23 5.04 5.16 4.18 5.19 7.79 6.63 5.89
## 11  7.62 7.63 9.10 7.80 6.42 7.14 7.53 8.59 7.90 7.51 7.29 8.63 9.45 8.53 7.31
## 12  5.60 4.96 8.26 6.71 6.81 6.74 3.70 6.76 5.09 6.13 4.31 6.26 9.25 8.53 7.40
## 13  4.51 4.08 8.53 4.31 5.62 4.46 4.55 5.37 2.99 4.42 7.44 5.96 7.11 6.30 6.66
## 14  6.25 5.32 3.86 5.34 3.01 5.11 5.57 7.83 5.85 4.90 7.68 6.14 7.27 6.18 4.76
## 15  5.94 5.32 7.64 6.34 6.32 5.86 4.18 5.67 5.81 5.82 3.24 6.52 8.84 8.27 7.31
## 16  0.00 2.24 8.37 4.97 5.58 4.56 3.34 4.75 3.38 4.05 6.44 4.25 7.22 5.92 4.51
## 17  2.24 0.00 6.90 3.66 4.48 3.76 2.59 4.56 2.55 3.18 5.81 4.23 7.28 6.12 4.60
## 18  8.37 6.90 0.00 6.52 4.82 6.73 6.97 8.30 7.45 6.46 8.06 6.83 7.37 6.70 6.86
## 19  4.97 3.66 6.52 0.00 3.42 4.71 3.85 5.61 4.00 3.69 6.98 5.47 7.00 5.88 4.88
## 20  5.58 4.48 4.82 3.42 0.00 4.26 4.53 7.07 4.66 3.66 7.08 5.25 6.42 5.15 3.98
## 21  4.56 3.76 6.73 4.71 4.26 0.00 4.37 6.02 3.67 2.63 7.40 5.64 7.07 6.26 5.81
## 22  3.34 2.59 6.97 3.85 4.53 4.37 0.00 4.90 2.73 3.27 4.73 3.82 7.09 5.86 4.75
## 23  4.75 4.56 8.30 5.61 7.07 6.02 4.90 0.00 5.53 6.04 5.68 5.60 6.66 6.96 7.54
## 24  3.38 2.55 7.45 4.00 4.66 3.67 2.73 5.53 0.00 3.28 6.25 4.52 7.59 6.17 5.25
## 25  4.05 3.18 6.46 3.69 3.66 2.63 3.27 6.04 3.28 0.00 7.02 4.79 6.74 5.53 4.71
## 26  6.44 5.81 8.06 6.98 7.08 7.40 4.73 5.68 6.25 7.02 0.00 6.18 9.12 8.42 7.90
## 27  4.25 4.23 6.83 5.47 5.25 5.64 3.82 5.60 4.52 4.79 6.18 0.00 6.36 4.17 4.34
## 28  7.22 7.28 7.37 7.00 6.42 7.07 7.09 6.66 7.59 6.74 9.12 6.36 0.00 3.62 7.28
## 29  5.92 6.12 6.70 5.88 5.15 6.26 5.86 6.96 6.17 5.53 8.42 4.17 3.62 0.00 4.63
## 30  4.51 4.60 6.86 4.88 3.98 5.81 4.75 7.54 5.25 4.71 7.90 4.34 7.28 4.63 0.00
```

```
# Question 1 suite
# CAH avec la matrice non normalisée
cah_single_euclidean <- hclust(dist(euro_data, method = "euclidean"), method = "single")

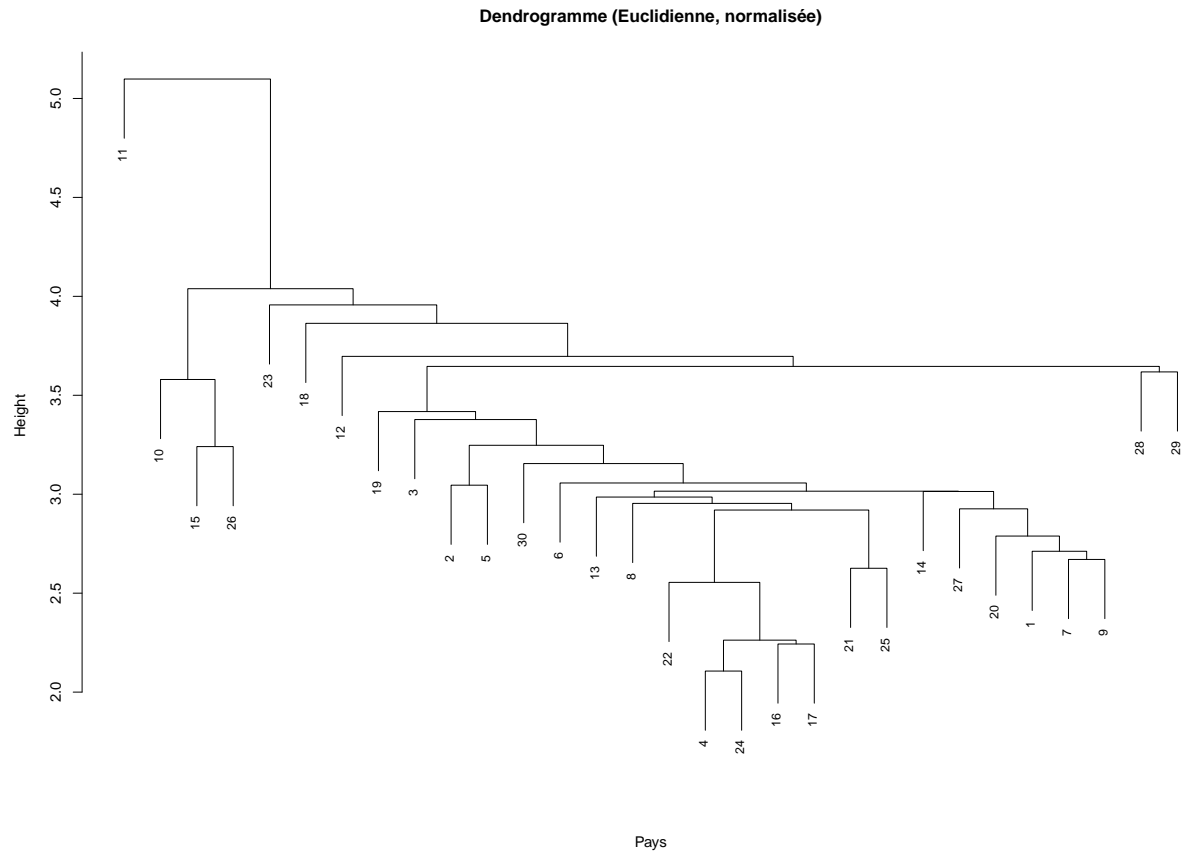
# CAH avec la matrice normalisée
cah_single_reduced <- hclust(dist(euro_data_normalized, method = "euclidean"), method = "single")

# Dendrogramme pour les données non normalisées
plot(cah_single_euclidean,
     main = "Dendrogramme (Euclidienne, non normalisée)",
     xlab = "Pays", sub = "", cex = 0.8)
```





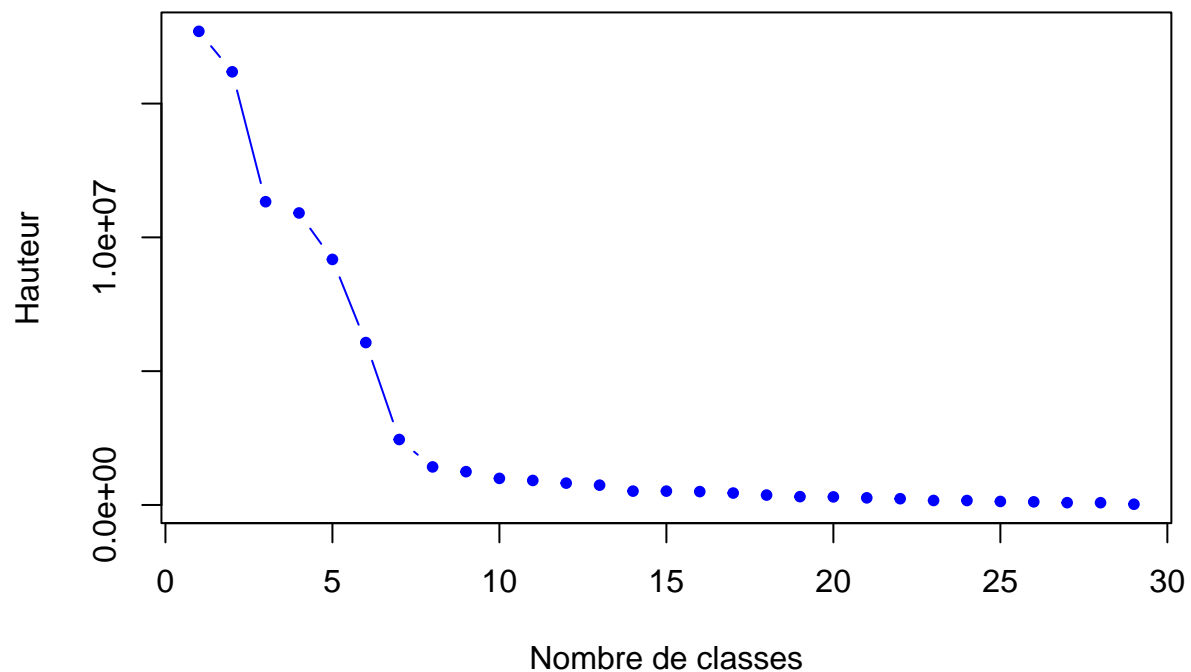
```
# Dendrogramme pour les données normalisées
plot(cah_single_reduced,
     main = "Dendrogramme (Euclidienne, normalisée)",
     xlab = "Pays", sub = "", cex = 0.8)
```



```
# Question 2
# Récupérer les hauteurs des fusions
heights_euclidean <- sort(cah_single_euclidean$height, decreasing = TRUE)
heights_reduced <- sort(cah_single_reduced$height, decreasing = TRUE)

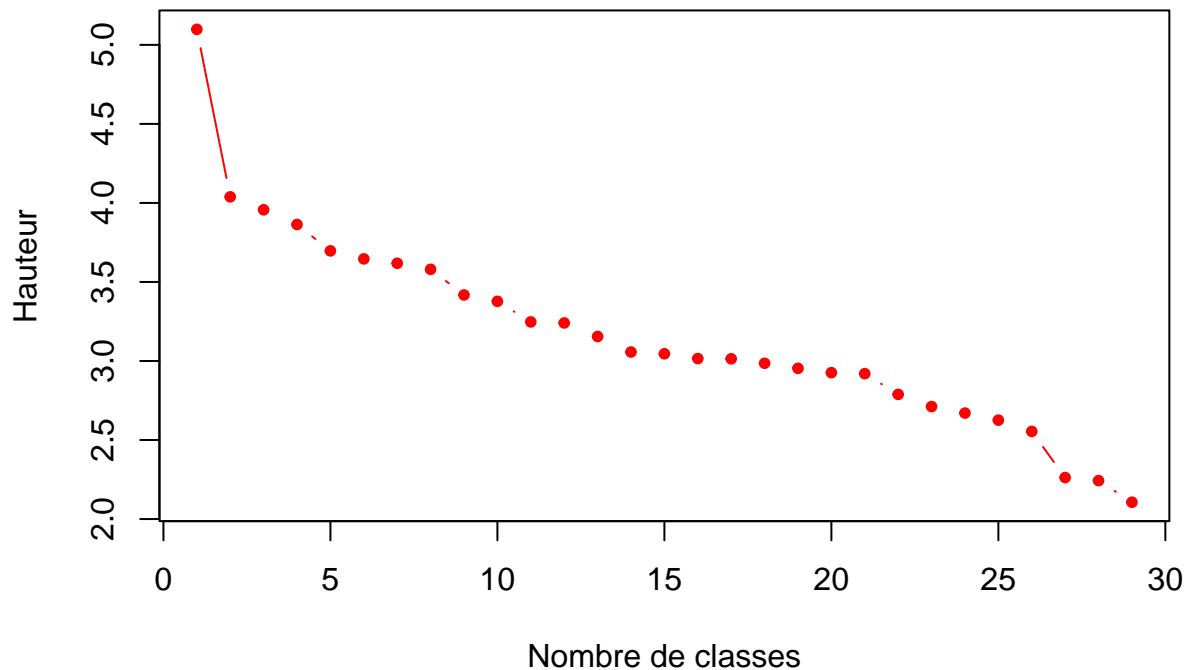
# Courbe des hauteurs pour la matrice non normalisée
plot(1:length(heights_euclidean), heights_euclidean,
     type = "b", col = "blue", pch = 20,
     xlab = "Nombre de classes",
     ylab = "Hauteur",
     main = "Hauteur en fonction du nombre de classes (Euclidienne, non normalisée)")
```

## Hauteur en fonction du nombre de classes (Euclidienne, non normalis)



```
# Courbe des hauteurs pour la matrice normalisée
plot(1:length(heights_reduced), heights_reduced,
     type = "b", col = "red", pch = 20,
     xlab = "Nombre de classes",
     ylab = "Hauteur",
     main = "Hauteur en fonction du nombre de classes (Euclidienne, normalisée)")
```

## Hauteur en fonction du nombre de classes (Euclidienne, normalisée)



```
# Question 3
# Fixer le nombre de classes (par exemple 4, basé sur la question 2)
k <- 4 # Ajuster selon la coupure choisie
classes <- cutree(cah_single_reduced, k = k)

# Ajouter les classes aux données
euro_data_with_classes <- data.frame(euro_data_normalized, Classe = classes)
# Fonction pour calculer le centre de gravité
calculate_center <- function(data, classes) {
  aggregate(. ~ Classe, data = data, FUN = mean)
}

# Centres de gravité
centers <- calculate_center(euro_data_with_classes, classes)
cat("Centres de gravité :\n")
```

```
## Centres de gravité :
```

```
print(centers)
```

```
##   Classe Population Youth.population First.time.asylum.applicants
## 1      1 -0.3638724          -0.09519565          -0.3345654
## 2      2  1.9919270          -0.31934053           1.5517476
## 3      3  3.1944601          -0.39317649           4.1619449
## 4      4  0.1671058          -0.50393043          -0.3739529
```

```
## Gender.pay.gap Minimum.wage People.at.risk.of.poverty.or.exclusion
## 1 0.08401396 -0.05205426 -0.1556766
## 2 -0.65922266 0.25663429 0.6338058
## 3 1.06621527 1.36679084 0.1302341
## 4 -1.54169854 -1.04355427 2.7061971
## Early.school.leavers Inflation.rate Unemployment.rate Youth.unemployment.rate
## 1 -0.3481198 0.1261332 -0.10087154 -0.09664735
## 2 0.5927446 -0.5401019 1.56054209 1.35022754
## 3 1.2137151 -0.2528137 -1.09475291 -1.53623117
## 4 2.2863006 0.8101529 0.01780086 1.16876059
## GDP.per.capita Government.gross.debt Greenhouse.gas.emissions
## 1 -0.1577956 -0.09869767 0.1213823
## 2 -0.1497554 1.54594803 -0.6561108
## 3 0.2074731 -0.01353189 0.3871305
## 4 -1.0971873 -0.43368304 -0.9326325
## Renewable.energy Electricity.prices Energy.imports.dependency
## 1 -0.2961284 -0.0170000 0.1781534
## 2 -0.5234557 0.5904368 0.4177909
## 3 -0.5076307 2.1122596 0.4232683
## 4 -0.3335557 -0.7456611 -1.0638536
```

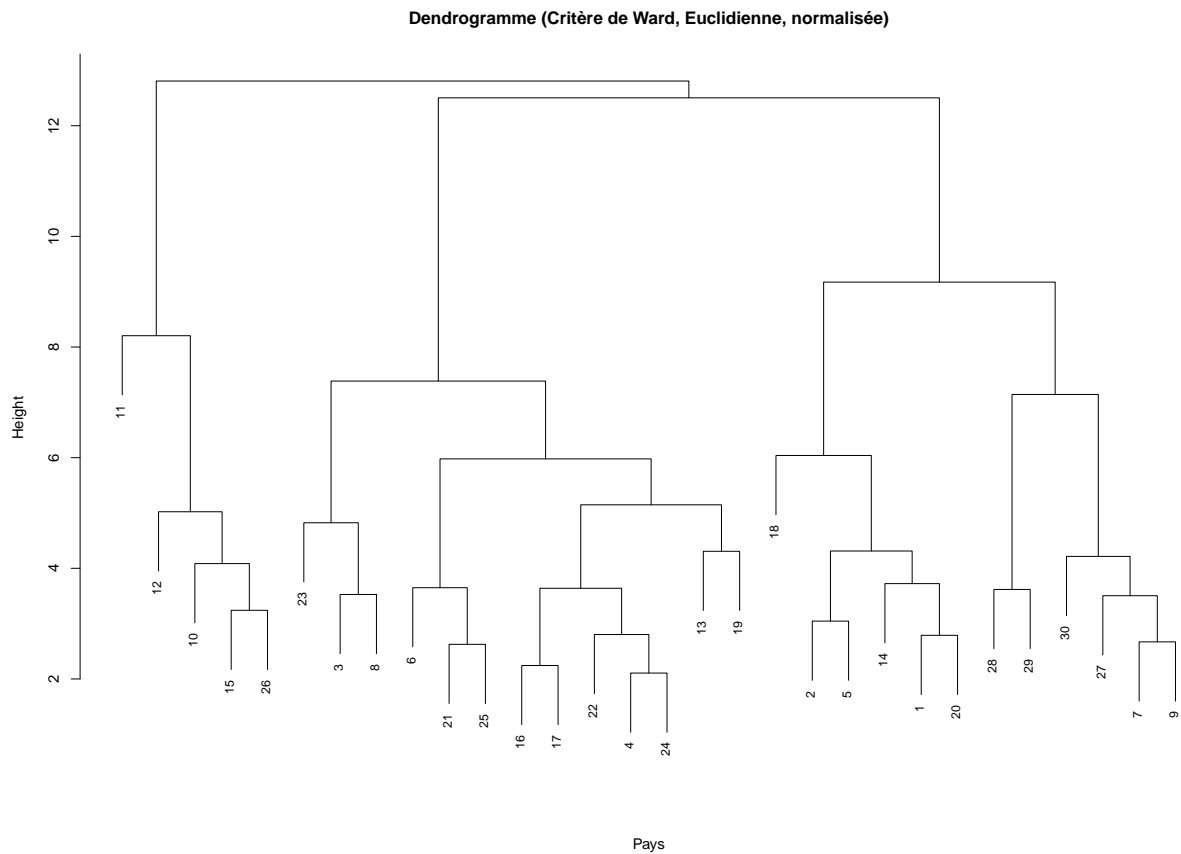
```
# Calculer l'inertie intra-classe
# Question 3 suite
calculate_inertia <- function(data, centers, classes) {
  inertia <- 0
  for (class in unique(classes)) {
    class_data <- data[classes == class, ]
    class_center <- centers[class, -ncol(centers)] # Exclure la colonne des classes
    inertia <- inertia + sum(rowSums((class_data - class_center)^2))
  }
  return(inertia)
}
```

```
# Inertie totale
inertia <- calculate_inertia(euro_data_normalized, centers, classes)
cat("\nInertie intra-classe totale : ", round(inertia, 2), "\n")
```

```
##
## Inertie intra-classe totale : 132.85
```

```
# Question 4
# Classification ascendante hiérarchique avec le critère de Ward
cah_ward <- hclust(dist(euro_data_normalized, method = "euclidean"), method = "ward.D2")

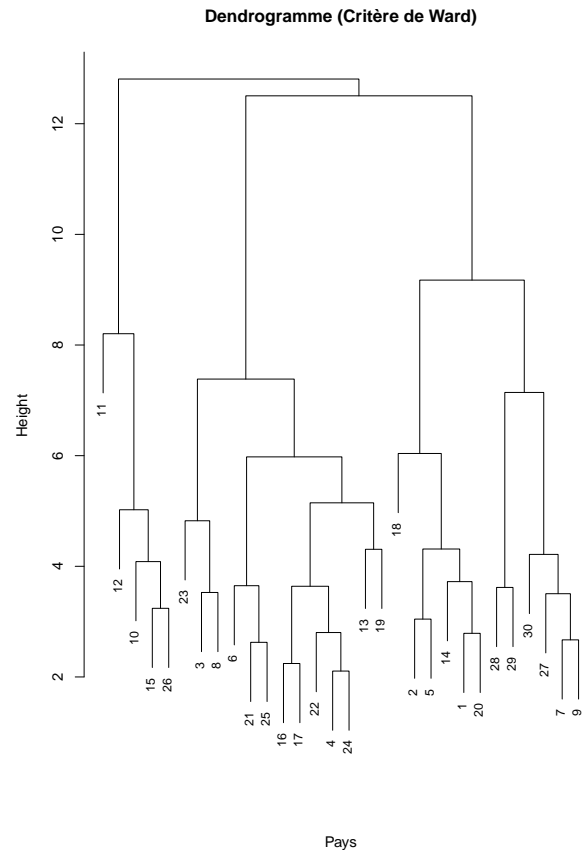
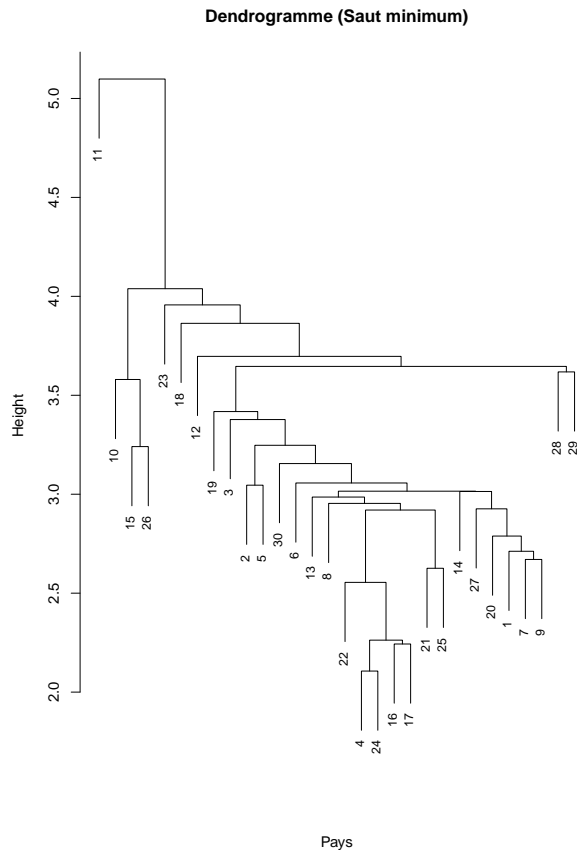
# Représenter le dendrogramme
plot(cah_ward,
     main = "Dendrogramme (Critère de Ward, Euclidienne, normalisée)",
     xlab = "Pays", sub = "", cex = 0.8)
```



```
par(mfrow = c(1, 2)) # Afficher les deux dendrogrammes côte à côte

# Dendrogramme avec le saut minimum
plot(cah_single_reduced,
     main = "Dendrogramme (Saut minimum)",
     xlab = "Pays", sub = "", cex = 0.8)

# Dendrogramme avec Ward
plot(cah_ward,
     main = "Dendrogramme (Critère de Ward)",
     xlab = "Pays", sub = "", cex = 0.8)
```



```
par(mfrow = c(1, 1)) # Réinitialiser l'affichage
```

```
# Question 4 Effectuez une autre classification en utilisant le critère de Ward. Commentez les différences
# Découpage en classes avec les deux méthodes
```

```
classes_single <- cutree(cah_single_reduced, k = 4)
classes_ward <- cutree(cah_ward, k = 4)
```

```
# Ajouter les classes aux données
```

```
euro_data_with_classes <- data.frame(euro_data_normalized, Classe_Single = classes_single, Classe_Ward = classes_ward)
```

```
# Afficher un aperçu
```

```
head(euro_data_with_classes)
```

```
## Population Youth.population First.time.asylum.applicants Gender.pay.gap
## 1 -0.2941425 0.1052162 0.28349361 1.20451373
## 2 -0.1718499 0.6036090 -0.09845354 -1.44291393
## 3 -0.4173177 -1.9437317 -0.19608989 0.13763990
## 4 -0.5377000 -0.4485535 -0.49105968 0.03885528
## 5 -0.6735369 1.7111484 -0.34858451 -0.41555394
## 6 -0.2142795 -0.8915692 -0.49823673 1.10572911
## Minimum.wage People.at.risk.of.poverty.or.exclusion Early.school.leavers
## 1 0.8677402 -0.5670191 0.02822593
## 2 1.2628220 -0.3346014 -0.64919646
## 3 -1.3658578 2.2800979 0.22580746
```

```
## 4 -0.7368461 -0.1021837 -1.83468565
## 5 -0.4595957 -0.7219642 0.56451866
## 6 -0.8685400 -1.6710032 -0.59274459
## Inflation.rate Unemployment.rate Youth.unemployment.rate GDP.per.capita
## 1 0.2355764 -0.20470989 -0.7706675 0.2660926
## 2 -1.3157803 -0.02670129 0.1990466 0.2580762
## 3 0.4941358 -0.56072710 -0.4814545 -1.2174325
## 4 0.4366782 0.24031161 0.6924098 -0.8717275
## 5 -0.8561190 0.24031161 0.3351468 -0.2219025
## 6 2.2753231 -1.31726367 -1.1279305 -0.6848465
## Government.gross.debt Greenhouse.gas.emissions Renewable.energy
## 1 0.38958609 0.01005534 0.1781191
## 2 1.16743348 0.38713049 -0.8768806
## 3 -1.16326982 0.31171546 -0.5973057
## 4 -0.03056505 -0.55555739 -0.1331058
## 5 0.37539180 0.83962068 -0.5814807
## 6 -0.56994828 1.06586577 -0.6447807
## Electricity.prices Energy.imports.dependency Classe_Single Classe_Ward
## 1 0.5788290 0.66564454 1 1
## 2 1.6439448 0.64510418 1 1
## 3 -1.4517357 -0.87077425 1 2
## 4 -1.0326540 0.08229837 1 2
## 5 1.3401407 1.38455708 1 1
## 6 0.7637533 -0.67769488 1 2
```

```
# Fixer le nombre de classes
# question 5
# Vérifier les NA ou NaN dans les données normalisées
cat("Y a-t-il des NA/NaN dans les données ?\n")
```

```
## Y a-t-il des NA/NaN dans les données ?
```

```
print(any(is.na(euro_data_normalized)))
```

```
## [1] TRUE
```

```
# Si des NA sont présents, afficher leur localisation
if (any(is.na(euro_data_normalized))) {
  cat("Position des NA/NaN :\n")
  print(which(is.na(euro_data_normalized), arr.ind = TRUE))
  euro_data_normalized <- apply(euro_data_normalized, 2, function(x) {
    ifelse(is.na(x), mean(x, na.rm = TRUE), x)
  })
  print(any(is.na(euro_data_normalized)))
}
```

```
## Position des NA/NaN :
```

```
##      row col
## [1,]  27   5
## [2,]  28   5
## [3,]  29   5
## [4,]  30   5
## [5,]  28   6
## [1] FALSE
```



```
euro_data_normalized <- apply(euro_data_normalized, 2, function(x) {
  ifelse(is.na(x), mean(x, na.rm = TRUE), x)
})
print(any(is.na(euro_data_normalized)))
```

```
## [1] FALSE
```

```
# Suite question 5
# Fixer le nombre de classes
k <- 4

# Appliquer k-means
set.seed(42) # Fixer la graine pour rendre les résultats reproductibles
kmeans_result <- kmeans(euro_data_normalized, centers = k, nstart = 10)

# Afficher les résultats
cat("Classes affectées par k-means :\n")
```

```
## Classes affectées par k-means :
```

```
print(kmeans_result$cluster)
```

```
## [1] 3 2 4 4 2 4 3 4 3 1 1 1 4 2 1 4 4 2 4 2 4 4 4 4 1 3 3 3 3
```

```
cat("\nCentres des classes :\n")
```

```
##
## Centres des classes :
```

```
print(round(kmeans_result$centers, 2))
```

```
## Population Youth.population First.time.asylum.applicants Gender.pay.gap
## 1      1.79      -0.44      1.83      -0.08
## 2      -0.38      1.10      -0.24      -0.98
## 3      -0.41      0.79      -0.30      0.41
## 4      -0.32      -0.68      -0.45      0.19
## Minimum.wage People.at.risk.of.poverty.or.exclusion Early.school.leavers
## 1      0.30      0.63      0.33
## 2      1.20      -0.44      -0.50
## 3      0.34      -0.50      0.42
## 4      -0.76      0.19      -0.16
## Inflation.rate Unemployment.rate Youth.unemployment.rate GDP.per.capita
## 1      -0.53      1.21      0.90      -0.18
## 2      -0.92      -0.28      -0.13      1.04
## 3      -0.44      -0.17      -0.40      0.88
## 4      0.79      -0.27      -0.08      -0.81
## Government.gross.debt Greenhouse.gas.emissions Renewable.energy
## 1      1.48      -0.34      -0.50
## 2      -0.12      1.16      -0.81
## 3      -0.34      -0.03      1.47
```

```
## 4          -0.34          -0.29          -0.29
## Electricity.prices Energy.imports.dependency
## 1          0.79          0.51
## 2          0.74          1.03
## 3         -0.26         -0.72
## 4         -0.45         -0.20
```

```
cat("\nInertie intra-classe totale :\n")
```

```
##
## Inertie intra-classe totale :
```

```
print(round(kmeans_result$tot.withinss, 2))
```

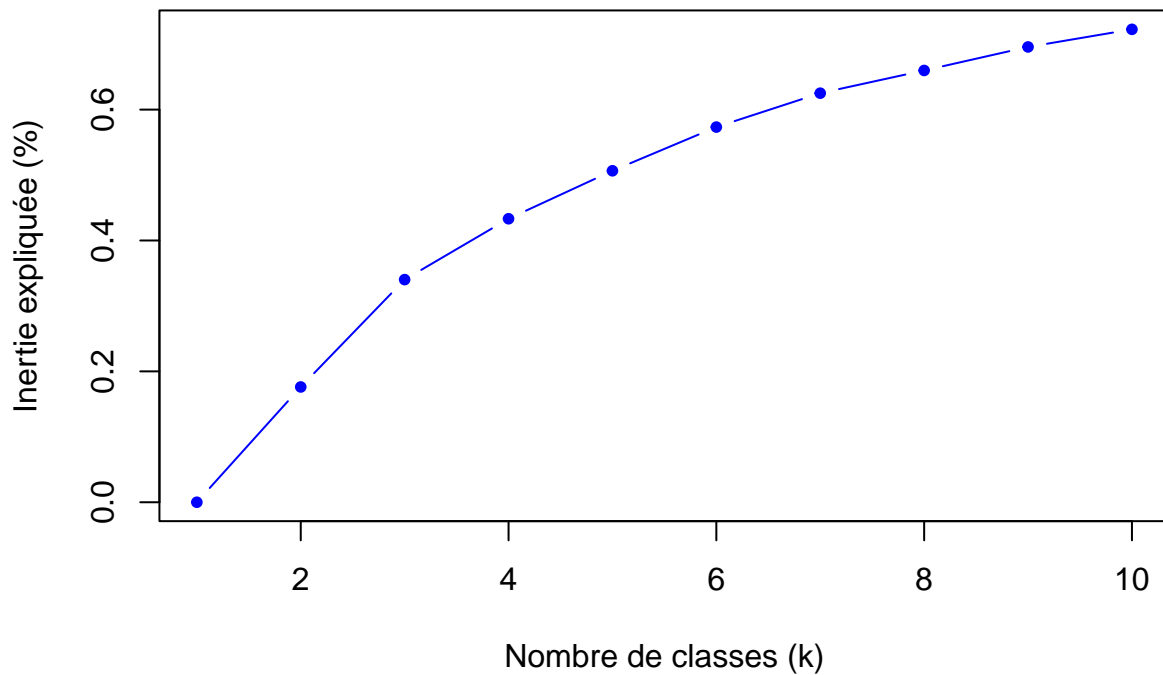
```
## [1] 260.15
```

```
# Initialiser les variables
max_k <- 10 # Tester jusqu'à 10 classes
inertie_totale <- sum(scale(euro_data_normalized, center = TRUE, scale = FALSE)^2)
inertie_intra <- numeric(max_k)
inertie_expliquee <- numeric(max_k)

# Calculer l'inertie intra-classe pour chaque k
for (k in 1:max_k) {
  set.seed(42) # Graine pour reproductibilité
  kmeans_result <- kmeans(euro_data_normalized, centers = k, nstart = 10)
  inertie_intra[k] <- kmeans_result$tot.withinss
  inertie_expliquee[k] <- 1 - (inertie_intra[k] / inertie_totale)
}

# Tracer la courbe
plot(1:max_k, inertie_expliquee, type = "b", pch = 20, col = "blue",
     xlab = "Nombre de classes (k)", ylab = "Inertie expliquée (%)",
     main = "Inertie expliquée en fonction du nombre de classes")
```

## Inertie expliquée en fonction du nombre de classes



```
# Question 7
# Étape 1 : Effectuer l'ACP
# Effectuer l'ACP sur les données normalisées
res_acp <- prcomp(euro_data_normalized, center = TRUE, scale. = TRUE)

# Résumé de l'ACP pour comprendre les variances expliquées
cat("Résumé de l'ACP :\n")
```

## Résumé de l'ACP :

```
print(summary(res_acp))
```

```
## Importance of components:
##              PC1    PC2    PC3    PC4    PC5    PC6    PC7
## Standard deviation  1.9068 1.8769 1.4265 1.3623 1.13291 0.93197 0.86710
## Proportion of Variance 0.2272 0.2202 0.1272 0.1160 0.08022 0.05428 0.04699
## Cumulative Proportion 0.2272 0.4474 0.5746 0.6906 0.77079 0.82507 0.87207
##              PC8    PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation  0.74801 0.66980 0.58743 0.45336 0.41016 0.39737 0.30054
## Proportion of Variance 0.03497 0.02804 0.02157 0.01285 0.01051 0.00987 0.00565
## Cumulative Proportion 0.90704 0.93508 0.95664 0.96949 0.98000 0.98987 0.99552
##              PC15    PC16
## Standard deviation  0.2040 0.17357
## Proportion of Variance 0.0026 0.00188
## Cumulative Proportion 0.9981 1.00000
```

```

# Étape 2 : Récupérer les résultats de classification
# Fixer le nombre de classes optimal
k <- 4 # Ajuster selon les résultats précédents

# Classes obtenues par CAH
classes_cah <- cutree(cah_single_reduced, k = k)

# Classes obtenues par k-means
classes_kmeans <- kmeans_result$cluster

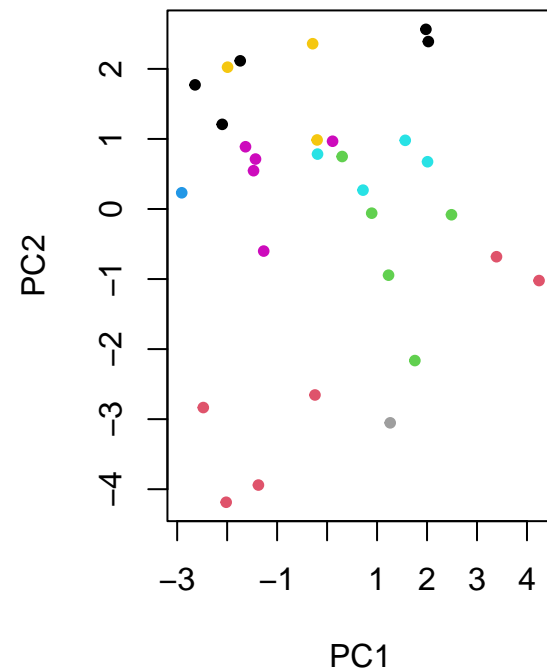
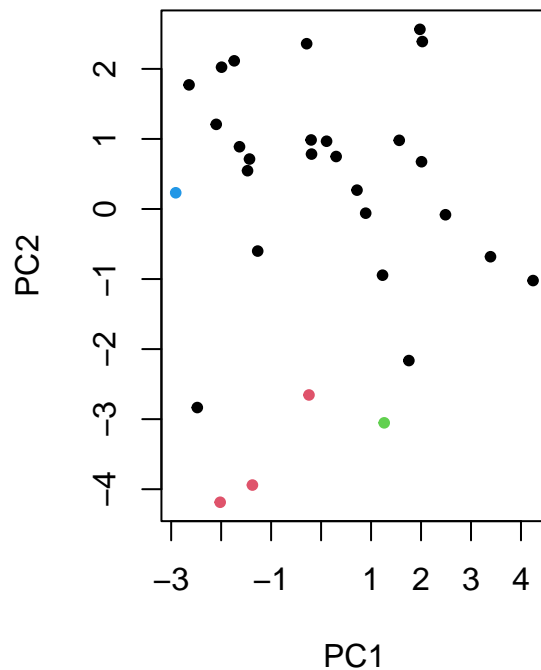
# Étape 3 : Représenter les classes dans le plan factoriel
par(mfrow = c(1, 2)) # Afficher les deux graphiques côte à côte

# Représentation des classes CAH
plot(res_acp$x[, 1], res_acp$x[, 2],
     col = classes_cah,
     pch = 20,
     xlab = "PC1", ylab = "PC2",
     main = "Plan factoriel avec classes CAH")

# Représentation des classes k-means
plot(res_acp$x[, 1], res_acp$x[, 2],
     col = classes_kmeans,
     pch = 20,
     xlab = "PC1", ylab = "PC2",
     main = "Plan factoriel avec classes k-means")

```

## Plan factoriel avec classes CAH Plan factoriel avec classes k-means



```
par(mfrow = c(1, 1)) # Réinitialiser l'affichage
```

```
# Étape 1 : Effectuer l'ACP
```

```
# Effectuer l'ACP sur les données normalisées
```

```
res_acp <- prcomp(euro_data_normalized, center = TRUE, scale. = TRUE)
```

```
# Résumé de l'ACP pour comprendre les variances expliquées
```

```
cat("Résumé de l'ACP :\n")
```

```
## Résumé de l'ACP :
```

```
print(summary(res_acp))
```

```
## Importance of components:
```

```
##          PC1    PC2    PC3    PC4    PC5    PC6    PC7
## Standard deviation  1.9068 1.8769 1.4265 1.3623 1.13291 0.93197 0.86710
## Proportion of Variance 0.2272 0.2202 0.1272 0.1160 0.08022 0.05428 0.04699
## Cumulative Proportion 0.2272 0.4474 0.5746 0.6906 0.77079 0.82507 0.87207
##          PC8    PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation  0.74801 0.66980 0.58743 0.45336 0.41016 0.39737 0.30054
## Proportion of Variance 0.03497 0.02804 0.02157 0.01285 0.01051 0.00987 0.00565
## Cumulative Proportion 0.90704 0.93508 0.95664 0.96949 0.98000 0.98987 0.99552
##          PC15    PC16
## Standard deviation  0.2040 0.17357
```

```
## Proportion of Variance 0.0026 0.00188
## Cumulative Proportion 0.9981 1.00000
```

```
# Étape 2 : Récupérer les classes des deux méthodes
# Fixer le nombre optimal de classes (par exemple, k = 4)
k <- 4
```

```
# Classes obtenues par CAH
classes_cah <- cutree(cah_single_reduced, k = k)
```

```
# Classes obtenues par k-means
classes_kmeans <- kmeans_result$cluster
```

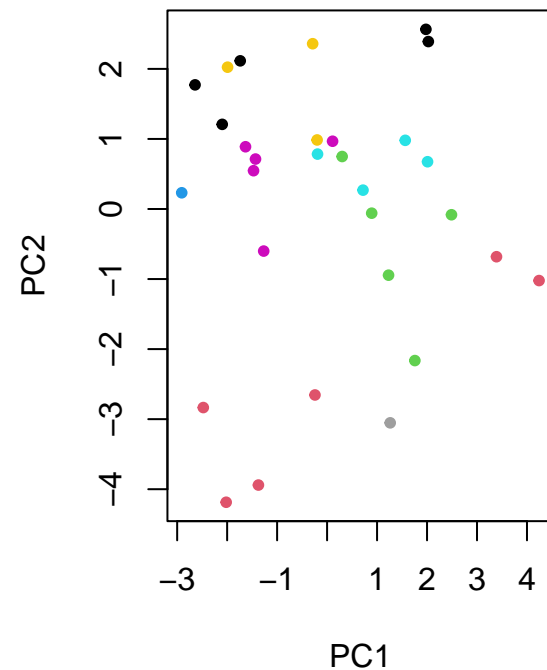
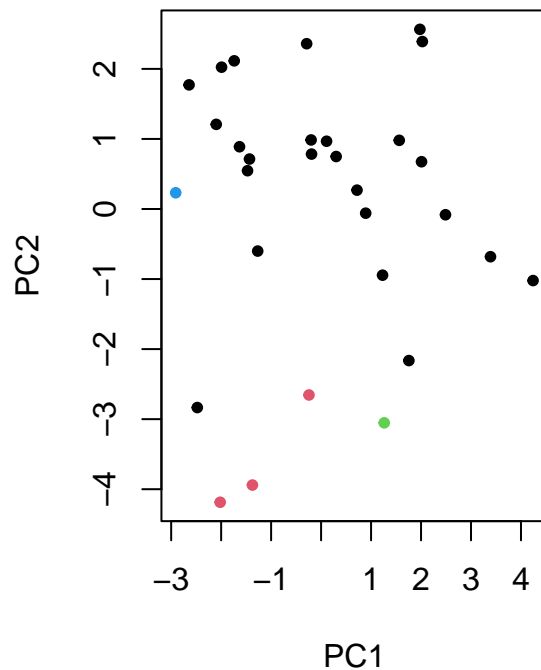
```
# Étape 3 : Ajouter les classes au tableau des coordonnées de l'ACP
coord_acp <- data.frame(res_acp$x[, 1:2], Classe_CAH = as.factor(classes_cah), Classe_Kmeans = as.factor(classes_kmeans))
```

```
# Étape 4 : Représenter les classes dans le plan factoriel
par(mfrow = c(1, 2)) # Afficher les deux graphiques côte à côte
```

```
# Représentation des classes CAH
plot(coord_acp$PC1, coord_acp$PC2,
      col = coord_acp$Classe_CAH,
      pch = 20,
      xlab = "PC1", ylab = "PC2",
      main = "Plan factoriel avec classes CAH")
```

```
# Représentation des classes k-means
plot(coord_acp$PC1, coord_acp$PC2,
      col = coord_acp$Classe_Kmeans,
      pch = 20,
      xlab = "PC1", ylab = "PC2",
      main = "Plan factoriel avec classes k-means")
```

## Plan factoriel avec classes CAH Plan factoriel avec classes k-means



```
par(mfrow = c(1, 1)) # Réinitialiser l'affichage
```

```
# Étape 1 : Définir une zone restreinte dans le plan factoriel
```

```
zone_restante <- coord_acp[coord_acp$PC1 > -1 & coord_acp$PC1 < 1 & coord_acp$PC2 > -1 & coord_acp$PC2 < 1]
```

```
# Afficher les pays dans la zone restreinte
```

```
cat("Pays dans la zone sélectionnée :\n")
```

```
## Pays dans la zone sélectionnée :
```

```
print(zone_restante)
```

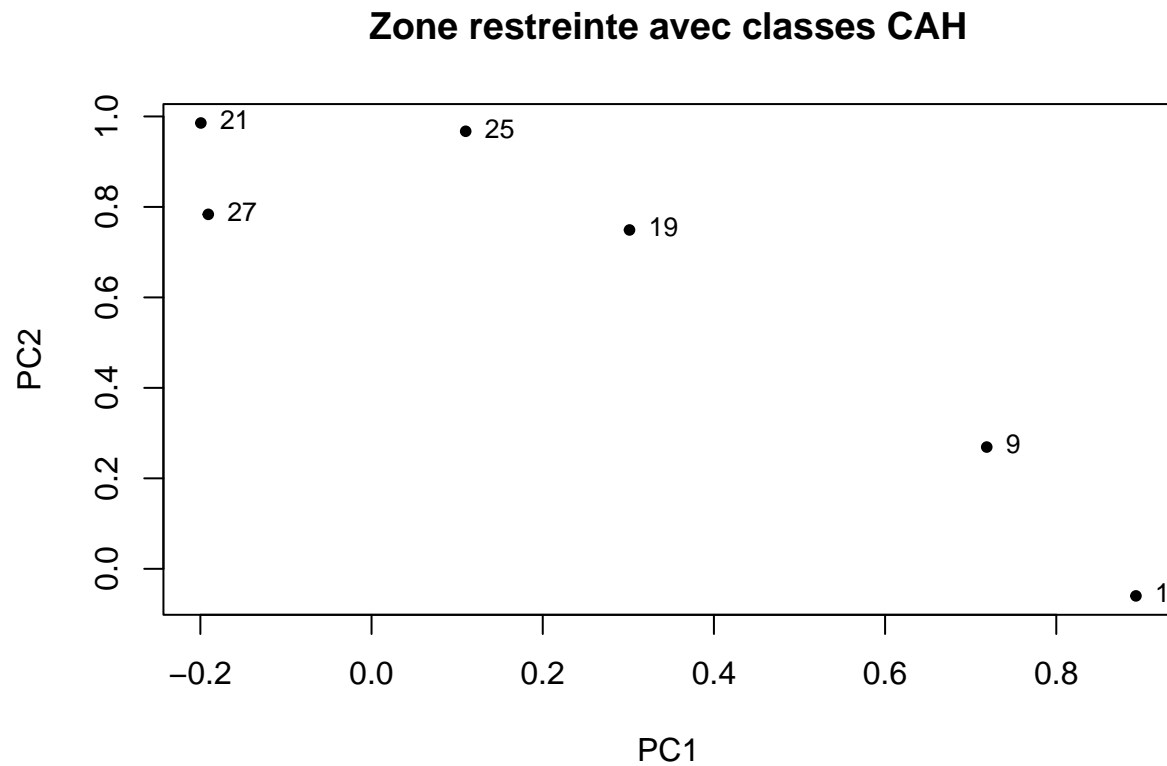
##	PC1	PC2	Classe_CAH	Classe_Kmeans
## 1	0.8930784	-0.05981786	1	3
## 9	0.7187603	0.26913474	1	5
## 19	0.3013992	0.74908977	1	3
## 21	-0.1994403	0.98555691	1	7
## 25	0.1100162	0.96722107	1	6
## 27	-0.1907443	0.78363267	1	5

```
# Étape 2 : Représenter graphiquement la zone
```

```
plot(zone_restante$PC1, zone_restante$PC2,
     col = zone_restante$Classe_CAH,
```

```
pch = 20,
xlab = "PC1", ylab = "PC2",
main = "Zone restreinte avec classes CAH")

# Ajouter les noms des pays
text(zone_restante$PC1, zone_restante$PC2, labels = rownames(zone_restante), pos = 4, cex = 0.8)
```



```
tinytex::is_tinytex()
```

```
## [1] TRUE
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.