

Spatial Economics – Assignment 1

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Exercise A

For our independent variables, we use per capita crime rate by town, average number of rooms per dwelling, Charles River dummy variable (= 1 if tract bounds river; 0 otherwise), nitrogen oxides concentration (parts per 10 million) and a constant.

Below we wrote a function which computes: OLS point estimates for the intercept, slope parameters, and the error variance. Suitable test statistics with corresponding p-values for the relevant coefficients. Intervals of the coefficients for a confidence level of 95%.

```
OLS <- function(X,Y){  
  
  # OLS estimates for coefficients  
  beta_hat <- solve(t(X) %*% X) %*% t(X) %*% Y  
  Y_hat <- X %*% beta_hat    # Fitted values  
  
  e <- Y - Y_hat            # residuals  
  n <- nrow(X)              # Number of observations  
  k <- ncol(X) - 1          # Number of covariates excluding intercept  
  
  s <- as.numeric(t(e)%*%e / (n-k))      # SSR adjusted for degrees of freedom  
  sigma <- s*solve(t(X) %*% X)          # VCV of Beta hat  
  
  se <- sqrt(diag(sigma))                # standard error  
  t_stat <- (beta_hat-0) / se             # Compute t-statistic  
  p <- pt(abs(t_stat), n-k, lower.tail=FALSE) # Compute p-value
```

```

# 95% Confidence interval
th <- qt(0.975, n-k)
conf <- cbind(beta_hat-th*se, beta_hat+th*se)

colnames(beta_hat) <- "estimate"
colnames(conf) <- c("2.5%", "97.5%")
colnames(t_stat) <- "t-statistic"
colnames(p) <- "p-value"

error_variance <- s

list(rbind(beta_hat, error_variance), cbind(t_stat, p), conf)
}

```

The output of the function is presented below:

OLS(X,Y)

```

## [[1]]
##              estimate
## Constant      -17.259625
## Crime          -0.184610
## Rooms          7.706840
## Charles_River  4.673807
## NO_pp10m       -14.960358
## error_variance 35.771378
##
## [[2]]
##              t-statistic      p-value
## Constant      -5.373025 5.935625e-08
## Crime         -5.358215 6.414580e-08
## Rooms         19.155659 4.233091e-62
## Charles_River  4.388052 6.974274e-06
## NO_pp10m      -5.674181 1.178869e-08
##
## [[3]]
##              2.5%      97.5%
## Constant     -23.5707812 -10.9484684
## Crime        -0.2523012 -0.1169189
## Rooms         6.9163879  8.4972927
## Charles_River 2.5811627  6.7664511
## NO_pp10m     -20.1404236 -9.7802928

```

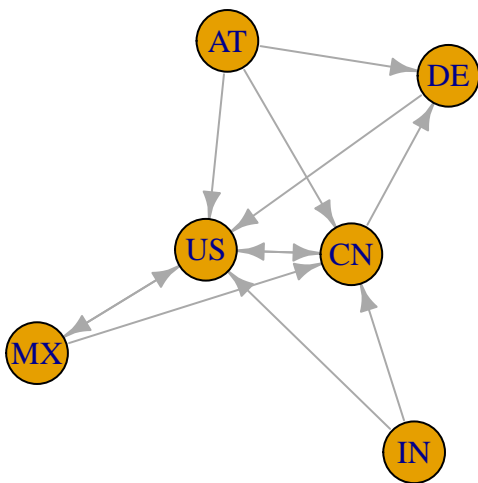
Exercise B

1. Draw a graph of the network; create the adjacency matrix in R.

We could consider 6 different countries and an indicator of a high trade between them. For illustration, we could consider a rule where there is directed edge from A to B, if B is one of the top 5 export destinations of A. We don't actually check for biggest trading partners empirically,

but let's assume that such procedure gives rise to following network (arrows are mostly made up to achieve 12 edges and nice interpretations):

Trade network



The corresponding adjacency matrix is:

##	US	MX	DE	AT	CN	IN
## US	0	1	0	0	1	0
## MX	1	0	0	0	1	0
## DE	1	0	0	0	0	0
## AT	1	0	1	0	1	0
## CN	1	0	1	0	0	0
## IN	1	0	0	0	1	0

- Who are the most and least central agents in the network? Name, explain, and try to quantify different notions of centrality.

A very basic concept of centrality could define an agent as most central, if it has the highest number of directed edges pointing towards itself (i.e. if it is important export country for most other countries). Using this criterion we can see from the graph that or from columns of adjacency matrix that US the most central agents in this network, because it is top 5 trading partner for all 5 other countries. The least central agents would be Austria and India, since they are not a top 5 export country for any country from this network.

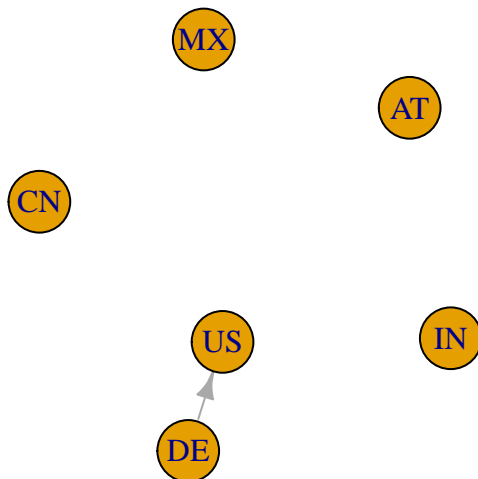
Another basic criterion of centrality could be the amount of outwards pointing arrows of an agent. Thus a country would be considered central if it exports to highest number of countries from this network. In this sense, Germany is least central with only 1 outward arrow, while Austria is most central with 3 outward arrows.

Eigenvector centrality: There is no sink, but not possible to get to Austria. ? Page Rank: weights (probs) need to be defined?

- How would centralities change if you considered a row-normalized network instead?

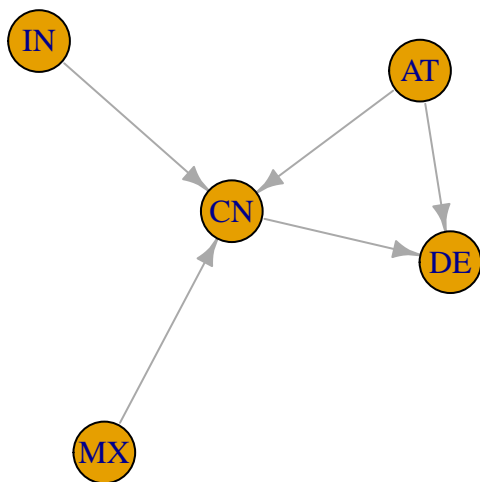
Germany which had only 1 connection, is the only row with sum of 1. Thus it's the only edge which survives row normalization. Thus here depending on criterion US or Germany would be most central agent. Other countries would be all least central.

Trade network row normalized



- How would the network change if you removed or added a specific agent? Lets consider the case of removing US:

Trade network excl. US



Based on Inflowing arrows, China becomes the most central agent and India, Austria and Mexico the least central agents. Based on Outflowing arrows, Austria is still the most central agent, while Germany is the least central agent.

3. Simulate some agent characteristic based on a standard Normal distribution; use this characteristic to simulate responses following a liner-in-means model with your network. Repeat this a couple of times, and compare estimates of a standard linear model ($y_i = x_{\beta} + \varepsilon_i$) with the true values that you used to simulate the data

We simulate the data based on the row normalized adjacency matrix for trade partner connections, that we created in the preceding exercise.

Let's say we are interested in estimating the impact of a countries fentanyl precursor production (x) on the log of a countries drug deaths (y). Then Wx denotes the average of neighboring countries fentanyl precursor production. We hypothesize that if a countries close trade partners fentanyl precursor production rate is high (as measured by Wx), then the fentanyl related drug deaths are high. Moreover, there are spillover effects with regards to the trading partners fentanyls related

deaths from connected countries (W_y).

We specify the following linear-in-means model to estimate the relationship.

$$y = W_y\lambda + W_x\delta + x\beta + \varepsilon$$

Where W_y denotes the average death rate from drugs of countries that are close neighbors.

To simulate the values for y , we need to solve for the reduced form.

$$y = (I - W\lambda)^{-1}(W_x\delta + x\beta + \varepsilon)$$

```
set.seed(123)
# number of agents
N = 6

# parameters definition
sigma2 = 1
lambda = 0.6
delta = 0.3
beta = 2 # true beta is 2
W = adj.rn

simulations <- 10000
times <- c(1:simulations)
result <- numeric(simulations)

for (i in times) {

  # simulation of vecotrs
  x = rnorm(N, 0, 1)
  e = rnorm(N, 0, sigma2)

  # caluclating means
  Wx <- W %*% x

  # calculating S
  S = diag(N) - lambda * W

  # generating y's
  y = solve(S, Wx * delta + x * beta + e)

  model <- lm(y ~ x)

  result[i] <- coef(model)["x"]
}

inconsistent_estimate <- mean(result)

my_data <- data.frame(
```

```

Name = c("Simulated coef", "Real coef"),
Estimate = c(inconsistent_estimate, beta)
)

knitr::kable(my_data, format = "markdown")

```

Name	Estimate
Simulated coef	1.718638
Real coef	2.000000

We set the true value for β to 2, λ to 0.6, and δ to 0.3. We then regress y on x , repeat this a 1000 times, and find that the mean of the estimand is 1.718638. Thus using the simple linear regression fails to recover the true value of β .

Exercise C

Download a suitable shapefile for NUTS2 regions (from here or using R directly) and some dataset of interest at the same level of aggregation (e.g. from here). Install and load the `sf` and `ggplot2` packages together with their dependencies.

1. Read in the shapefile, and find out what projection and CRS the file uses. Map the data to use another projection and/or CRS of your choosing:

```

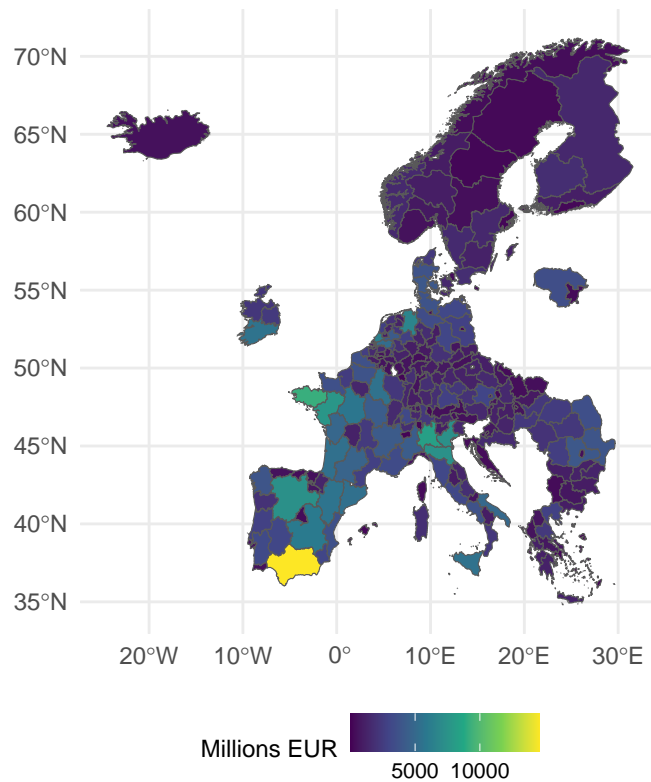
## Reading layer `NUTS_RG_03M_2021_4326_LEVL_2' from data source
##   `/Users/gustavpirich/Desktop/GITHUB/spatial_econ/assignment_1/data'
##   using driver `ESRI Shapefile'
## Simple feature collection with 334 features and 9 fields
## Geometry type: MULTIPOLYGON
## Dimension:      XY
## Bounding box:   xmin: -63.15176 ymin: -21.38696 xmax: 55.83509 ymax: 80.83426
## Geodetic CRS:   WGS 84
## [1] "WGS 84"
## [1] "EPSG:27700"

```

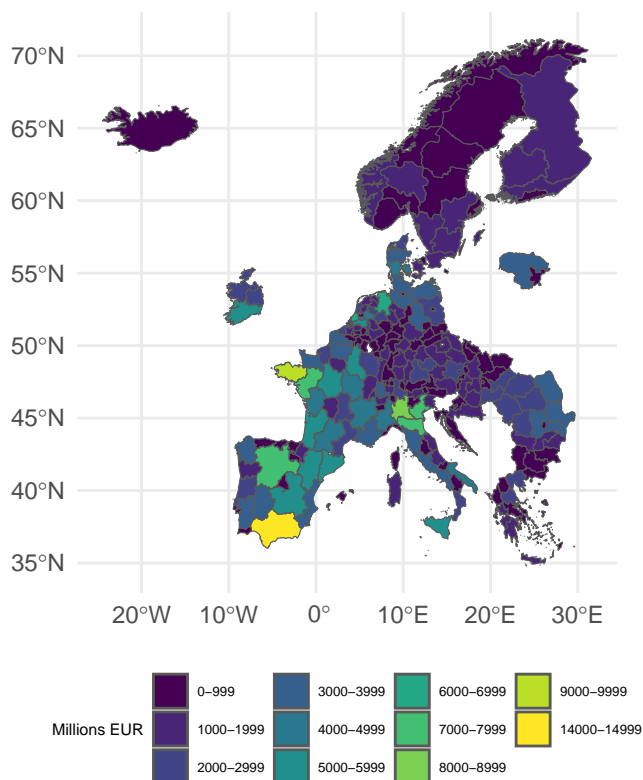
The projection used is the “World Geodetic System 1984” or for short “WGS 84” (EPSG 4326). We then map the data to the “North American Datum 1983” (NAD83) projection, which is extremely similar to the WGS 84.

2. Merge the shapefile and the chosen dataset Create tow meaningful visualizations of the chosen dataset using different scales (e.g. continuous versus discrete scaling of the data)

Agricultural Value Added by NUTS–2 Region in 2021



Binned Agricultural Value Added per NUTS–2 Region in



The discrete scaling shows the agricultural value added in million Euros at a NUTS-2 Level in 2021. While the first map visualizes the value added in continuous scaling. The second map portrays agricultural value added in a binned scaling. Note that animal production and fishing is also included, which accounts for the high agricultural value added in Western France.

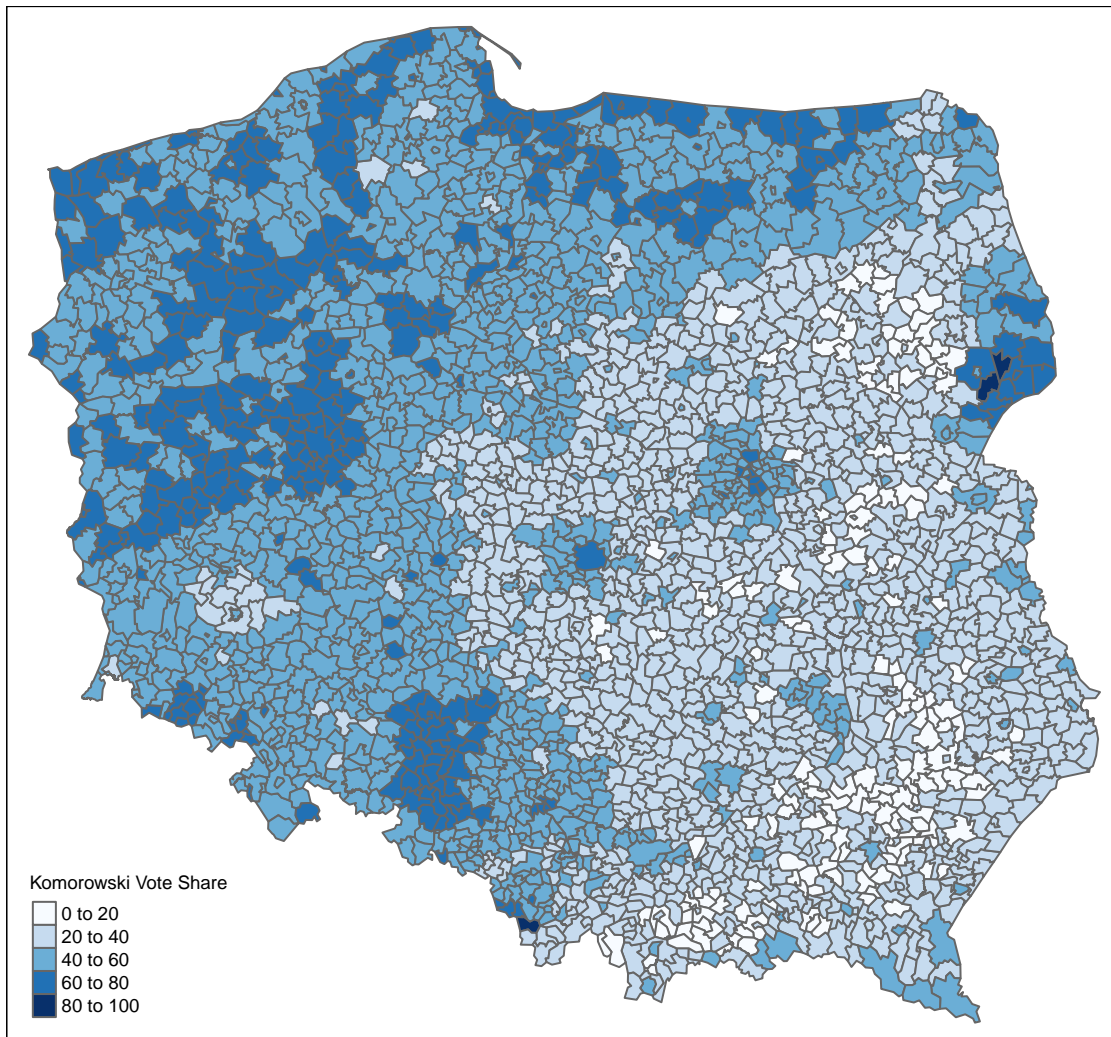
- Briefly explain what two conceptually different ways there are to store visualizations, and name two formats each. Which ones are more appropriate for which types of visualizations

and why? Use the one you think is more appropriate to store your visualizations.

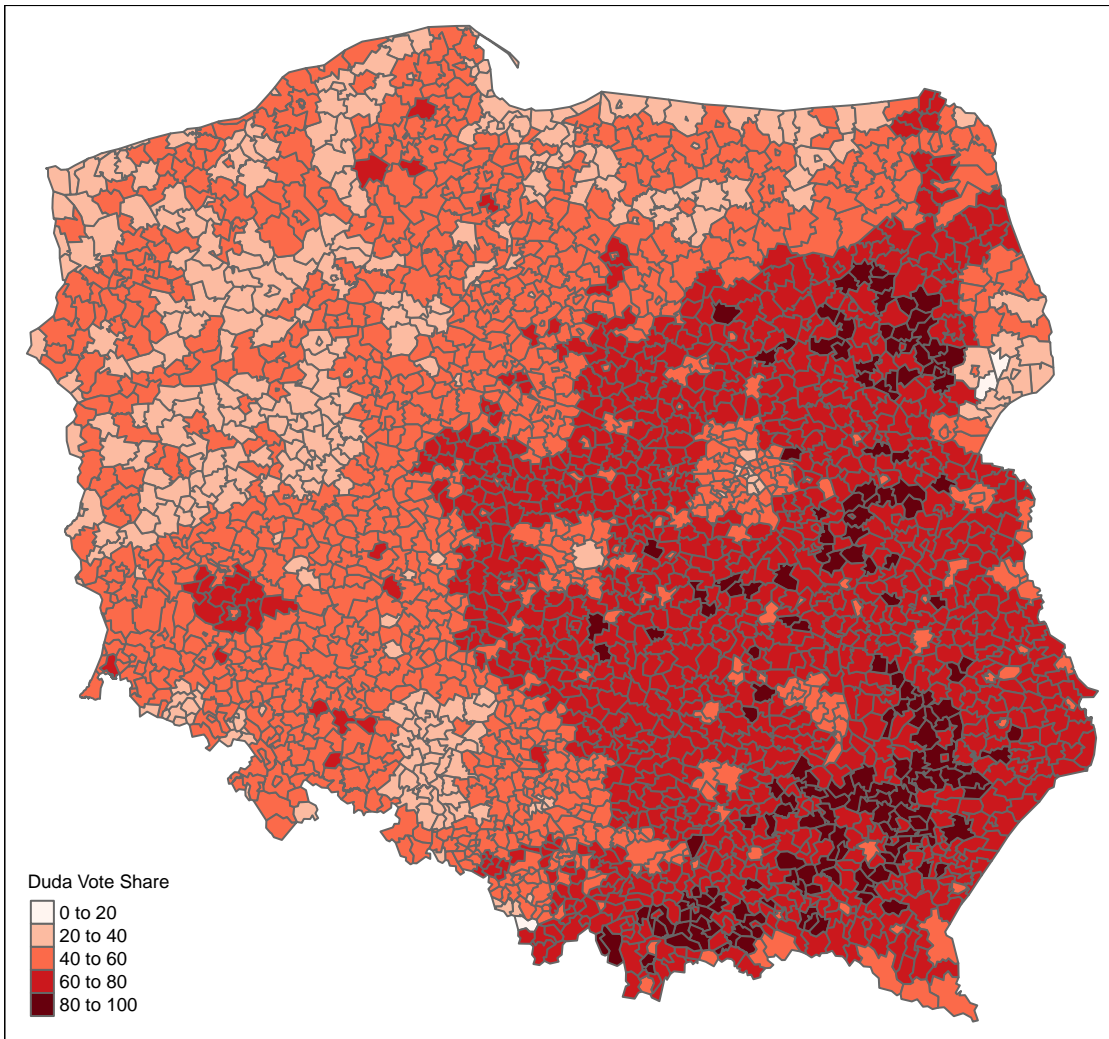
There are two types of spatial data, raster and vector data. Raster graphics can be stored as a png and jpeg. Vector graphics can be stored as a svg (Scalable Vector Graphics) or eps (Encapsulated PostScript) file. Vector graphics use mathematical equations like shapes, colours, and lines. An advantage of vector graphics is that they do not lose resolution when you zoom in on them.

Exercise D

Komorowski Second Round Votes in %



Duda Second Round Votes in %



#Preliminaries

```
install.packages("spDataLarge", repos = "https://geocompr.r-universe.dev")
```

```
##
```

```
## The downloaded binary packages are in
```

```
## /var/folders/qn/v8g2k85538166gyk25t5c2kw0000gn/T//Rtmp55am5Z/downloaded_packages
```

```
library(tmap)
```

```
library(spDataLarge)
```

```
data("pol_pres15")
```

```
summary(pol_pres15$I_Duda_share)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

```
## 0.06433 0.30362 0.38993 0.40091 0.48993 0.78566
```

```
summary(pol_pres15$I_Komorowski_share)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

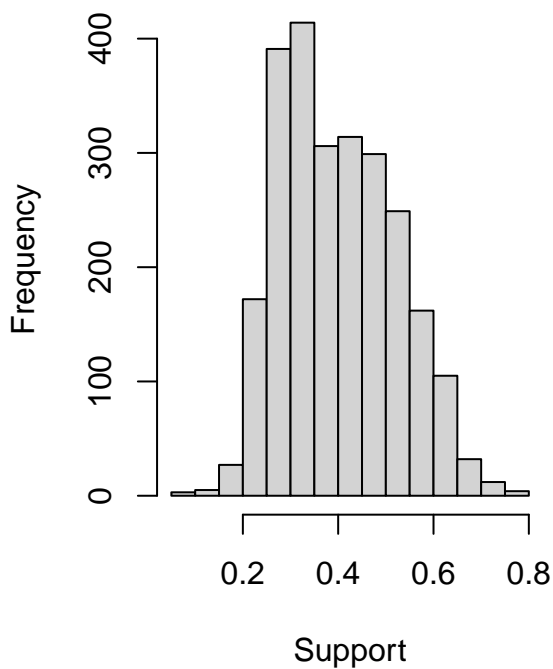
```
## 0.03747 0.20285 0.29594 0.29540 0.38709 0.66901
```

```
par(mfrow = c(1, 2))
```

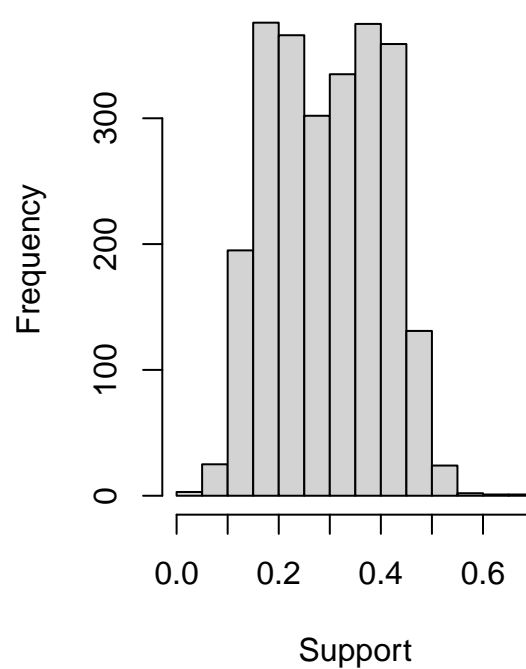
```
hist(pol_pres15$I_Duda_share, main = "Support for Komorowski", xlab = "Support")
```

```
hist(pol_pres15$I_Komorowski_share, main = "Support for Duda", xlab = "Support")
```

Support for Komorowski



Support for Duda



```
par(mfrow = c(1, 1))
```

##Possible Issues with voting envelopes

The next map is showing possible issues with voting envelopes. Specifically, we wanted to investigate if all envelopes sent were also received. If the number of envelopes received is equal to the number of the envelopes sent, the municipality is visualized green. If the municipality is visualized in grey, that means that there were no voting envelopes used for the election. If a municipality is red however, that indicates that the total number of envelopes sent is higher than the number of envelopes received (at a threshold off 99 percent). That indicates that there were probably issues with the delievery of the voting envelopes. We can observe red clusters especially in urban regions (Warsaw, Katowice and Krakow). An interesting side fact however is that one can clearly see that in urban areas, voting envelopes were used more often than in rural areas of Poland:

