Using R in Production

Lessons from The Observatory of Economic Complexity

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Data

Sources

All of the product data shown on the OEC site is classified using either

- *SITC* (Standard International Trade Classification)
- *HS* (Harmonized System).

For historical SITC classification data (1962 - 2000), the OEC is using data from [Feenstra et al., 2005]. For more recent data (2001 - 2016), the OEC is using data provided by UN COMTRADE.

Availability

Classification	Availability
HS rev 1992	1992 – 2016
HS rev 1996	1996 – 2016
HS rev 2002	2002 – 2016
HS rev 2007	2007 – 2016
HS rev 2012	2012 – 2016
SITC rev 2	2000 – 2016

Tidy Data

- I followed Tidy Data principles to obtain an output that in our opinion can be useful for others.
- Tidy Data principles are closely tied to those of relational databases and Codd's relational algebra.
- I did not innovate at this point and I only limited to follow the principles exposed in [Wickham, 2014b] and [Wickham and Grolemund, 2016] above all matters related to performing code and coding style.

Tidy Data

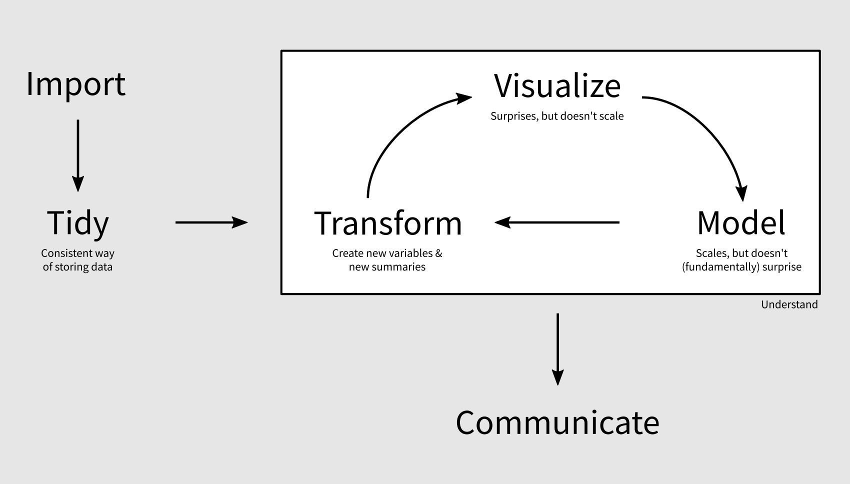


Figure 1: Data pipeline

Filling some gaps in our data

- For each NA or 0 import/export value I tried to fill the gap.
- If country A reported NA or 0 exports (imports) of product B to (from) country C, then I searched what country C reported of imports (exports) of product B from (to) country A.

Filling some gaps in our data

I provide column `marker` indicating those replacements under this labels:

marker	meaning
1	imports with replacements
2	exports with replacements
3	imports and exports with replacements
NA	no replacements needed

Filling some gaps in our data

Figure 2: Example of gap in data

Countries not included in rankings and indicators

- The curated data includes all the countries available from UN Comtrade data.
- RCA based calculations such as ECI, PCI, Proximity consider 128 countries that account for
  - 99% of world trade
  - 97% of the world's total GDP
  - and 95% of the world's population according to [Hidalgo et al., 2014].

Countries not included in rankings and indicators

I considered simultaneously:

- Countries with population greater or equal to 1.2 million
- Countries whose traded value is greater or equal than 1 billion

Countries not included in rankings and indicators

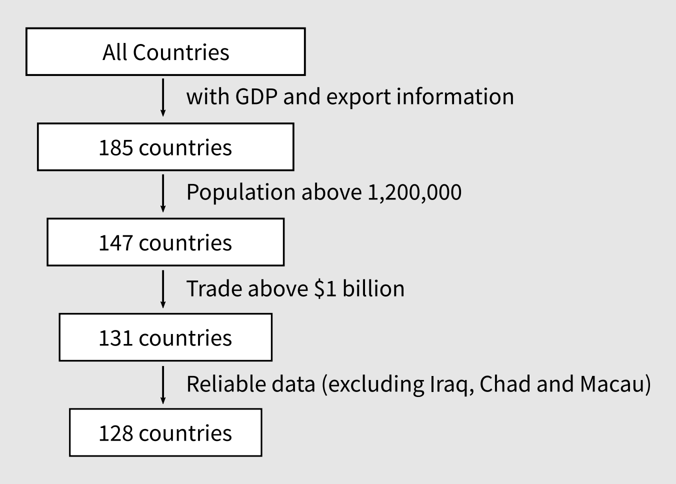


Figure 3: Country filtering

Hardware & Software

Hardware

- Intel© Xeon 2.27GHz processor (eight cores)
- 32 GB (four DDR3 cards of eight gigabytes each)

Software

- Ubuntu Server 16.04
- R 3.4.3
- RStudio Server Pro 1.1
- I built R from binaries and linked to Intel MKL 2017 so I benefit from multi-threaded BLAS/LAPACK libraries

Packages

- packrat
- pacman
- data.table
- dplyr
- tidyr
- doParallel
- Matrix
- RcppArmadillo
- feather
- RPostgreSQL

Limitations

- The project is divided in three big tasks:
  - download raw data
  - clean data following Tidy Data principles
  - write data to PostgreSQL DB

Limitations

- Functions such as download (i.e run `wget` on eight cores) do not suppose a problem
- Functions that involve matrix computation (i.e compute economic complexity rankings) were run on four cores because I detected a *large* overhead due to data communication with cores when using more cores.

Efficiency

Slowness has several explanations

- Running many processes
- Hardware bottlenecks (i.e faster RAM versus more RAM, same for HDD)
- Numerical libraries
- Coding

Efficiency

Numerical libraries can make a difference

Efficiency

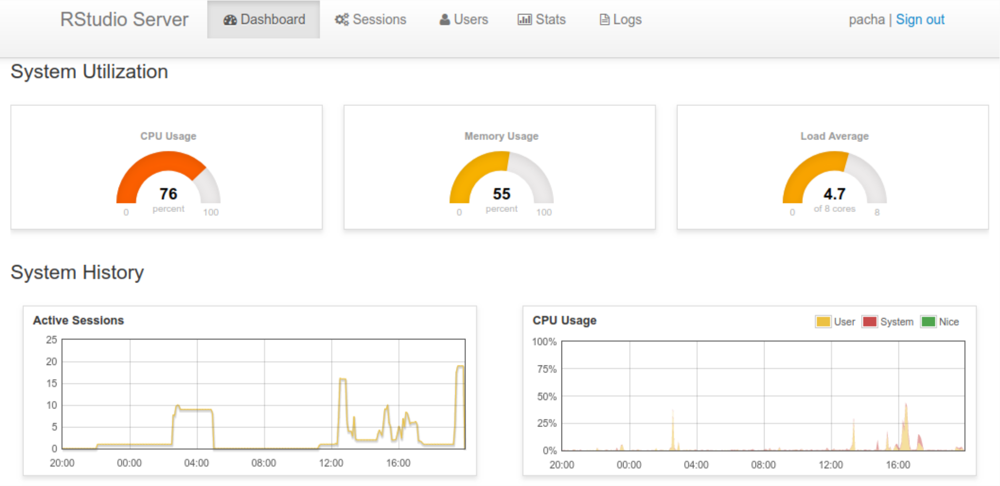


Figure 4: RStudio admin panel while running scripts to clean data and compute economic complexity rankings

Efficiency

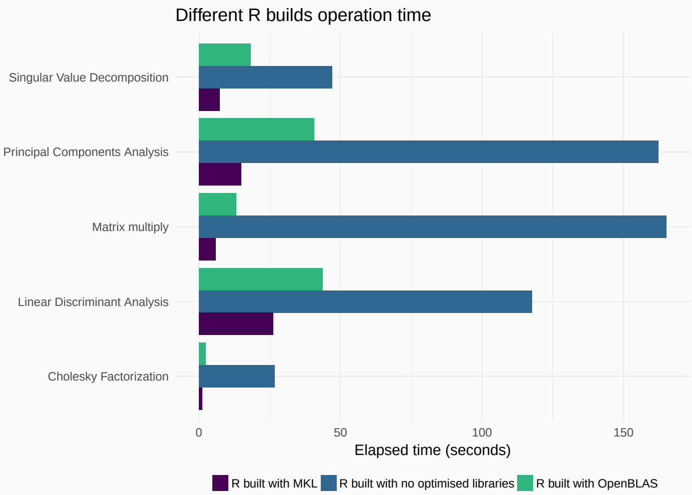


Figure 5: Performance exhibited running unmodified Microsoft benchmark script (edited R builds location)

Efficiency

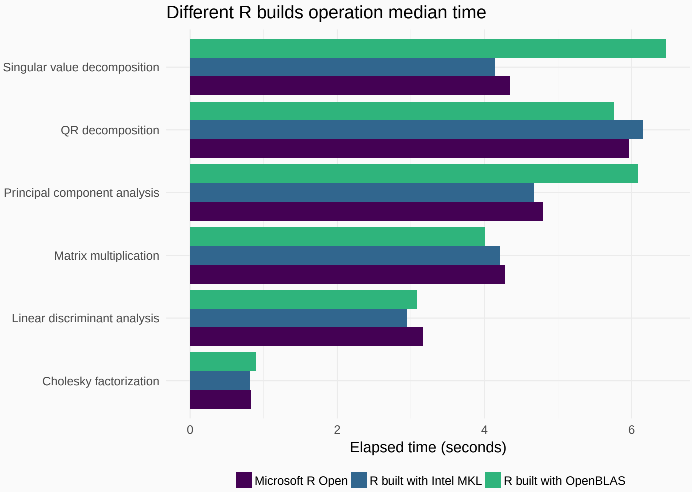


Figure 6: Performance exhibited running modified ATT script (modified to run fresh 100 times and then store the median result)

Coding

Syntax

- I used Tidyverse Style Guide
- As cornerstone references for performant code I followed [Wickham, 2014a] and [Peng et al., 2017]
- Readability is *really* important (specially after one ytd and you don't remember what you were doing)
- Over this project I moved from doing most of tasks with `data.table` to `tidyverse` because of *readability*

Performant code

- Some matrix operations are written in Rcpp to take advantage of C++ speed
- To take full advantage of hardware and numerical libraries I are using sparse matrices as it is explained in [Ni et al., 2018]
- As a general reccomendation using sparse matrices is a *good* practise with respect to both speed and memory usage

Reproducibility

- The full project is organized in different GitHub repositories
- Uploading to GitHub is not enought
- For full reproducibility I thought about
    - Using packrat to have an isolated repository of packages
    - Making packages bundle available
    - Considering literate programming to write scripts
    - Documenting everything

Reproducibility

- I have reproducility flaws
  - UN COMTRADE access
  - Parallelization is OS-specific
- Potential solutions
  - Collaborate with UN COMTRADE
  - Move to a parallelization type different than `FORK`

Economic Complexity

What is Economic Complexity?

- We owe to Adam Smith the idea that the division (specialization) of labor is the secret of the wealth of nations.
- The division of labor into markets and organizations is what allows the knowledge held by few to reach many, making us collectively wiser.

What is Economic Complexity?

- The complexity of an economy is related to the multiplicity of useful knowledge embedded in it.
- Because individuals are limited in what they know, the only way societies can expand their knowledge base is by facilitating the interaction of individuals in increasingly complex networks in order to make products.
- We can measure economic complexity by the mix of these products that countries are able to make.

What is Economic Complexity?

- Some products, like medical imaging devices or jet engines, embed large amounts of knowledge and are the results of very large networks of people and organizations.
- These products cannot be made in simpler economies that are missing parts of this network's capability set.
- Economic complexity, therefore, is expressed in the composition of a country's productive output and reflects the structures that emerge to hold and combine knowledge.

What is Economic Complexity?

In particular [Mariani et al., 2015] and [Kemp-Benedict, 2014] provide useful technical details.

Revealed Comparative Advantage (RCA)

Let $x_{c,p}$ represent the exports of country c in product p, we can express the Revealed Comparative Advantage that country c has in product p as:

$$RCA_{c,p} = \frac{x_{c,p}}{\sum_c x_{c,p}} / \frac{\sum_p x_{c,p}}{\sum_c \sum_p x_{c,p}} \tag{1}$$

Revealed Comparative Advantage (RCA)

RCA is the basic indicator to measure economic complexity

Revealed Comparative Advantage (RCA)

Exercise

- Open RStudio and load `fantasy_world_long.rdata` to your workspace
- Use `dplyr` to compute RCA
- Remember RCA definition

$$RCA_{c,p} = \frac{x_{c,p}}{\sum_c x_{c,p}} / \frac{\sum_p x_{c,p}}{\sum_c \sum_p x_{c,p}}$$

Revealed Comparative Advantage (RCA)

Exploring the dataset

```r
library(dplyr)
load("fantasy_world_long.rdata")
fantasy_world_long %>% print(n = 3)
```

```
## # A tibble: 108 x 3
##   country        product export_val
##   <chr>          <chr>        <int>
## 1 patolandia     alpha            0
## 2 mordor         alpha            0
## 3 neverneverland alpha            0
## # ... with 105 more rows
```

Revealed Comparative Advantage (RCA)

```r
rca_long <- fantasy_world_long %>%
  rename(c = country,
         p = product,
         xcp = export_val) %>%
  group_by(c) %>%
  mutate(sum_c_xcp = sum(xcp)) %>%
  group_by(p) %>%
  mutate(sum_p_xcp = sum(xcp)) %>%
  ungroup() %>%
  mutate(sum_c_p_xcp = sum(xcp)) %>%
  mutate(rca = (xcp / sum_c_xcp) /
           (sum_p_xcp / sum_c_p_xcp))
```

Revealed Comparative Advantage (RCA)

```
## # A tibble: 108 x 3
##   c              p       rca
##   <chr>          <chr> <dbl>
## 1 patolandia     alpha   0.
## 2 mordor         alpha   0.
## 3 neverneverland alpha   0.
## 4 thematrix      alpha  12.1
## 5 lilliput       alpha   0.
## # ... with 103 more rows
```

Revealed Comparative Advantage (RCA)

Exercise

- Now create a matrix M with entries

$$m_{c,p} = \begin{cases} 1 & \text{if } RCA_{c,p} \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

- Try to create it as if the dataset was actually large

Revealed Comparative Advantage (RCA)

```r
rca_matrix <- rca_long %>%
      select(c, p, rca) %>%
      mutate(rca = ifelse(rca > 1, 1, 0)) %>%
      spread(p, rca)
```

Smooth Revealed Comparative Advantage (SRCA)

- In the OEC real data we use a modified RCA to reduce trade fluctuations
- We smooth changes in export volumes induced by the price fluctuation of commodities by using a modification of (1) in which $x_{c,p}$ is averaged over the previous three years by using weights:

$$SRCA_{c,p}^{(t)} = \frac{\hat{x}_{c,p}^{(t)}}{\sum_c \hat{x}_{c,p}^{(t)}} \Big/ \frac{\sum_p \hat{x}_{c,p}^{(t)}}{\sum_c \sum_p \hat{x}_{c,p}^{(t)}}$$

Where

$$\hat{x}_{c,p}^{(t)} = \frac{2x_{c,p}^{(t)} + x_{c,p}^{(t-1)} + x_{c,p}^{(t-2)}}{4}$$

Diversity and Ubiquity

- With M defined as in the previous sections, we can measure Diversity and Ubiquity simply by summing over the rows or columns of that matrix.
- Diversity:

$$k_c^{(0)} = \sum_p m_{c,p}$$

- Ubiquity:

$$k_p^{(0)} = \sum_c m_{c,p}$$

Diversity and Ubiquity

Exercise

- Compute diversity and ubiquity
- Store the result in two matrices D and U

Diversity and Ubiquity

```r
diversity <- rca_long %>% select(c) %>% distinct()
ubiquity <- tibble(p = colnames(rca_matrix)) %>%
  filter(row_number() > 1)

rca_matrix <- rca_matrix %>%
  select(-c) %>%
  as.matrix()
```

Diversity and Ubiquity

```r
# convert to sparse class
library(Matrix)
rca_matrix <- Matrix(rca_matrix, sparse = T)

diversity <- diversity %>%
  mutate(val = rowSums(rca_matrix)) %>%
  filter(val > 0)

ubiquity <- ubiquity %>%
  mutate(val = colSums(rca_matrix)) %>%
  filter(val > 0)
```

Diversity and Ubiquity

```r
rownames(rca_matrix) <- diversity$c

D <- as.matrix(diversity$val, ncol = 1)
U <- as.matrix(ubiquity$val, ncol = 1)
```

Reflections Method

- The information that diversity and ubiquity carry can be used each one to correct the other.
- For countries, this is to calculate the average ubiquity of the products that it exports.
- For products, this is to calculate the average diversity of the countries that make them.

Reflections Method

The last slide can be expressed by the recursion:

$$k_c^{(n)} = \frac{1}{k_c^{(0)}} \sum_p m_{c,p} k_p^{(n-1)} \tag{3}$$

$$k_p^{(n)} = \frac{1}{k_p^{(0)}} \sum_c m_{c,p} k_c^{(n-1)} \tag{4}$$

We then insert (4) into (3) to obtain:

$$k_c^{(n)} = \sum_c \left[\frac{1}{k_c^{(0)}} \sum_p m_{c,p} \frac{1}{k_p^{(0)}} m_{c,p} \right] k_c^{(n-2)} \tag{5}$$

Reflections Method

Exercise

- Remove null rows and columns from `rca_matrix` using the names in D and U
- Store the result as `Mcp` and remove `rca_matrix`
- Save D and U using `numeric` class as `kc0` and `kp0` respectively

Reflections Method

```r
# remove null rows and cols
Mcp <- rca_matrix[
  which(rownames(rca_matrix) %in% unlist(diversity$c)) ,
  which(colnames(rca_matrix) %in% unlist(ubiquity$p))]
rm(rca_matrix)

# diversity and ubiquity following the Atlas notation
kc0 <- as.numeric(D)
kp0 <- as.numeric(U)
```

Exercise

- Using `kc0` and `kp0` create two matrices `kc` and `kp` with 20 columns each
- Compute kc j^{th} column from of kp $j-1^{th}$ column
- Compute kp j^{th} column from kc $j-1^{th}$ column

Remember

$$k_c^{(n)} = \frac{1}{k_c^{(0)}} \sum_p m_{c,p} k_p^{(n-1)} \qquad k_p^{(n)} = \frac{1}{k_p^{(0)}} \sum_c m_{c,p} k_c^{(n-1)}$$

Reflections Method

```r
kcinv <- 1 / kc0
kpinv <- 1 / kp0

# create empty matrices
kc <- Matrix(0, nrow = length(kc0), ncol = 20, sparse = T)
kp <- Matrix(0, nrow = length(kp0), ncol = 20, sparse = T)

# fill the first column with kc0 and kp0 to start iterating
kc[ ,1] <- kc0
kp[ ,1] <- kp0
```

Reflections Method

```r
# compute cols 2 to 20 by iterating from col 1
for (c in 2:ncol(kc)) {
  kc[ ,c] <- kcinv * (Mcp %*% kp[ ,(c - 1)])
  kp[ ,c] <- kpinv * (t(Mcp) %*% kc[ ,(c - 1)])
}
```

Reflections Method

- The interpretation of the scores changes when considering odd or even iteration order n
- High-order iterations are difficult to interpret, and the process asymptotically converges to a trivial fixed point
- To compute rankings I used `kc` 19^{th} column and `kp` 20^{th} column

Economic Complexity Index (ECI)

From the Reflections Method,the Economic Complexity Index (ECI) is defined as:

$$ECI_c = \frac{v_c - \mu_v}{\sigma_v} \tag{6}$$

Where

- $\vec{v}$ is defined as `v <- kc[ ,19]`.
- $\mu_v = \sum_c v_c / C$ (mean of $\vec{v}$)
- $\sigma_v = \sqrt{\sum_c (v_c - \mu_v)^2 / (C - 1)}$ (standard deviation of $\vec{v}$)

Product Complexity Index (PCI)

Similar to the Economic Complexity Index (ECI), the Product Complexity Index (PCI) is defined as:

$$PCI_p = \frac{w_p - \mu_w}{\sigma_w} \tag{7}$$

Where

- $\vec{w}$ is defined as `w <- kp[ ,20]`
- $\mu_w = \sum_p w_p / P$ (mean of $\vec{w}$)
- $\sigma_w = \sqrt{\sum_p (w_p - \mu_w)^2 / (P - 1)}$ (standard deviation of $\vec{w}$)

Economic and Product Complexity Index

Exercise

- Compute ECI and PCI
- Arrange the results in decreasing order
- Show the results and conclude

Economic and Product Complexity Index

```r
eci_reflections <- as_tibble(
      (kc[ ,19] - mean(kc[ ,19])) / sd(kc[ ,19])
    ) %>%
      mutate(country = diversity$c) %>%
      select(country, value) %>%
      arrange(desc(value))
```

Economic and Product Complexity Index

Table 3: ECI for Fantasy World (top 5)

country	value
narnia	0.903
patolandia	0.823
pandora	0.604
neverneverland	0.417
xanadu	0.326

Economic and Product Complexity Index

```r
pci_reflections <- as_tibble(
      (kp[, 20] - mean(kp[ ,20])) / sd(kp[ ,20])
    ) %>%
      mutate(product = ubiquity$p) %>%
      select(product, value) %>%
      arrange(desc(value))
```

Economic and Product Complexity Index

Table 4: PCI for Fantasy World (top 5)

product	value
theta	0.782
epsilon	0.606
eta	0.538
mu	0.530
alpha	0.513

Proximity

- To make products you need chunks of embedded knowledge which we call capabilities.
- The capabilities needed to produce one good may or may not be useful in the production of other goods.
- Capabilities are not observed directly,
- Proximity is a measure that infers the similarity between the capabilities required by a pair of goods by looking at the probability that they are coexported.

Proximity

Example

- In the year 2008, 17 countries exported wine, 24 exported grapes and 11 exported both, all with $RCA > 1$.
- Then, the product proximity between wines and grapes is 11/24=0.46.
- Note that I divide by 24 instead of 17 to minimize false positives

Proximity

For a pair of goods p and p' Product Proximity $\Phi \in \mathbb{R}^{P \times P}$ is defined as:

$$\Phi = (M^t M) \odot U$$

Where $\odot$ denotes element-wise multiplication and

$$u_{p,p'} = 1/\max(k_p^{(0)}, k_{p'}^{(0)})$$

In other terms, each entry of Φ corresponds to:

$$\phi_{p,p'} = \frac{\sum_c m_{c,p} m_{c,p'}}{\max(k_p^{(0)}, k_{p'}^{(0)})}$$

Proximity

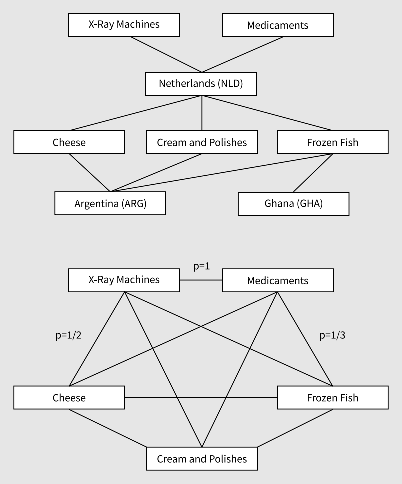


Figure 7: An illustrative example for the product proximity measure

Proximity

Country Proximity $\Lambda \in \mathbb{R}^{C \times C}$ is similarly defined:

$$\Lambda = (MM^t) \odot D$$

Where

$$d_{c,c'} = 1/\max(k_c^{(0)}, k_{c'}^{(0)})$$

In other terms, each entry of Λ corresponds to:

$$\lambda_{c,c'} = \frac{\sum_p m_{c,p} m_{c,p'}}{\max(k_c^{(0)}, k_{c'}^{(0)})}$$

Exercise

- Write an Rcpp function titled proximity_products_denominator
- Use that function to make the next code work:

```
Phi_pp <- (t(Mcp) %*% Mcp) /
  proximity_products_denominator(Mcp, U, cores = n_cores)
Phi_pp_l <- Phi_pp
Phi_pp_l[upper.tri(Phi_pp_l, diag = T)] <- NA

Phi_pp_long <- as_tibble(as.matrix(Phi_pp_l)) %>%
  mutate(id = rownames(Phi_pp)) %>%
  gather(id2, value, -id) %>%
  filter(!is.na(value))
```

Proximity

```cpp
#include <omp.h>
#include <RcppArmadillo.h>

// [[Rcpp::depends(RcppArmadillo)]]
// [[Rcpp::plugins(openmp)]]

using namespace Rcpp;

// [[Rcpp::export]]
arma::mat proximity_products_denominator(
    arma::sp_mat Mcp, arma::mat U, int cores = 1) {
  // Constants
  int N = (int) Mcp.n_cols;
```

Proximity

```
// Output
  arma::mat Phi_down(N,N);

  // Filling with ones
  Phi_down.ones();

  // Number of cores
  omp_set_num_threads(cores);
```

Proximity

```cpp
#pragma omp parallel for shared(Mcp, U, N, Phi_down) default(none)
  for (int i=0; i<N; i++)
    for (int j=0; j<=i; j++) {
      // Fill the lower part
      Phi_down.at(i,j) = std::max(U(i,0), U(j,0));
      // Fill the upper part
      Phi_down.at(j,i) = Phi_down.at(i,j);
    }

    return Phi_down;
}
```

Proximity

```r
Rcpp::sourceCpp("proximity_products_denominator.cpp")
n_cores <- 4

Phi_pp <- (t(Mcp) %*% Mcp) /
  proximity_products_denominator(Mcp, U, cores = n_cores)
Phi_pp_l <- Phi_pp
Phi_pp_l[upper.tri(Phi_pp_l, diag = T)] <- NA

Phi_pp_long <- as_tibble(as.matrix(Phi_pp_l)) %>%
  mutate(id = rownames(Phi_pp)) %>%
  gather(id2, value, -id) %>%
  filter(!is.na(value))
```

Proximity

Table 5: Exploring proximity results

id	id2	value
beta	alpha	0.00
delta	alpha	1.00
epsilon	alpha	0.25
eta	alpha	0.00
gamma	alpha	0.00

Exercise

- Write an Rcpp function titled `proximity_countries_denominator`
- Use that function to make the next code work:

```r
Phi_cc <- (Mcp %*% t(Mcp)) /
  proximity_countries_denominator(Mcp, D, cores = n_cores)
Phi_cc_l <- Phi_cc
Phi_cc_l[upper.tri(Phi_cc_l, diag = T)] <- NA

Phi_cc_long <- as_tibble(as.matrix(Phi_cc_l)) %>%
  mutate(id = rownames(Phi_cc)) %>%
  gather(id2, value, -id) %>%
  filter(!is.na(value))
```

Proximity

```cpp
#include <omp.h>
#include <RcppArmadillo.h>

// [[Rcpp::depends(RcppArmadillo)]]
// [[Rcpp::plugins(openmp)]]

using namespace Rcpp;

// [[Rcpp::export]]
arma::mat proximity_countries_denominator(
    arma::sp_mat Mcp, arma::mat D, int cores = 1) {
  // Constants
  int M = (int) Mcp.n_rows;
```

Proximity

```
// Output
  arma::mat Phi_down(M,M);

  // Filling with ones
  Phi_down.ones();

  // Number of cores
  omp_set_num_threads(cores);
```

Proximity

```
#pragma omp parallel for shared(Mcp, D, M, Phi_down) default(none)
  for (int i=0; i<M; i++)
    for (int j=0; j<=i; j++) {
      // Fill the lower part
      Phi_down.at(i,j) = std::max(D(i,0), D(j,0));
      // Fill the upper part
      Phi_down.at(j,i) = Phi_down.at(i,j);
    }

    return Phi_down;
}
```

Proximity

```r
Rcpp::sourceCpp("proximity_countries_denominator.cpp")
n_cores <- 4

Phi_cc <- (Mcp %*% t(Mcp)) /
  proximity_countries_denominator(Mcp, D, cores = n_cores)
Phi_cc_l <- Phi_cc
Phi_cc_l[upper.tri(Phi_cc_l, diag = T)] <- NA

Phi_cc_long <- as_tibble(as.matrix(Phi_cc_l)) %>%
  mutate(id = rownames(Phi_cc)) %>%
  gather(id2, value, -id) %>%
  filter(!is.na(value))
```

Proximity

Table 6: Exploring proximity results

id	id2	value
mordor	patolandia	0.0
neverneverland	patolandia	0.4
thematrix	patolandia	0.0
lilliput	patolandia	0.0
narnia	patolandia	0.5

Product Space

Product Space

- To visualize the product space we use some simple design criteria.
- First, we want the visualization of the product space to be a connected network.
- The second criteria is that we want the network visualization to be relatively sparse.
- Trying to visualize too many links can create unnecessary visual complexity where the most relevant connections will be occluded.

Product Space

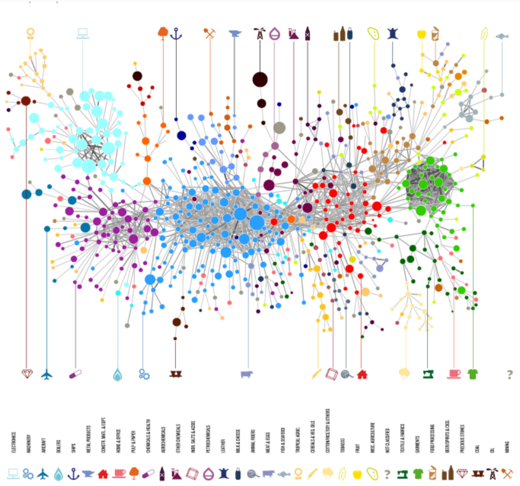


Figure 8: The product space

Exercise

- Create a tibble that includes all pairs with a product proximity higher or equal than 0.4
- Use `ggraph` package to sketch Fantasy World's Product Space
- Ignore any disconnected products for now

Product Space

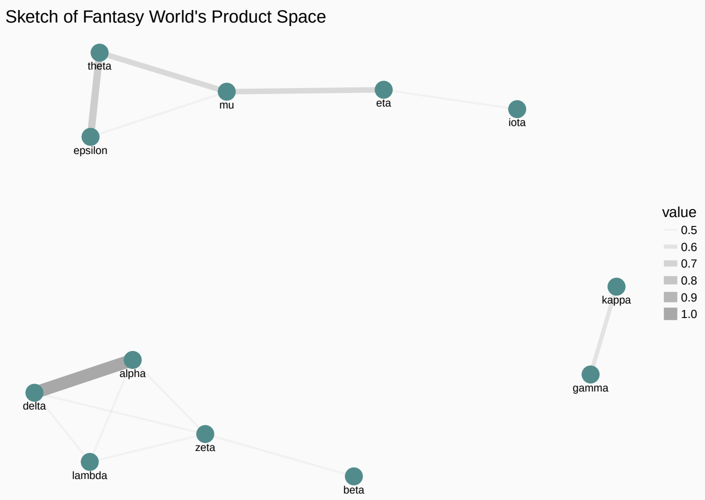
```
if (!require("pacman")) install.packages("pacman")
p_load(igraph, ggraph)
```

Product Space

```r
set.seed(1717)

Phi_pp_long %>%
  filter(value >= 0.4) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = value,  edge_width = value),
                 edge_colour = "#a8a8a8") +
  geom_node_point(color = "darkslategray4", size = 8) +
  geom_node_text(aes(label = name), vjust = 2.2) +
  ggtitle("Sketch of Fantasy World's Product Space") +
  theme_void(base_size = 15)
```

Product Space



Exercise

- Obtain a Maximum Spanning Tree by using ape package
- Append missing pairs of products with a proximity higher than 0.3 to your MST
- Sketch the connected Product Space

Product Space

```r
p_load(ape)

Phi_pp_2 <- (t(Mcp) %*% Mcp) /
  proximity_products_denominator(Mcp, U, cores = n_cores)
Phi_pp_3 <- -1 * Phi_pp_2

mst_pp <- ape::mst(Phi_pp_3)
mst_pp[upper.tri(mst_pp, diag = T)] <- NA
class(mst_pp) <- "matrix"
```

Product Space

```r
mst_pp_long <- as_tibble(mst_pp) %>%
  mutate(id = rownames(mst_pp)) %>%
  gather(id2, value, -id) %>%
  filter(!is.na(value),
         value > 0)
```

Product Space

```r
Phi_pp_2[upper.tri(Phi_pp_2, diag = T)] <- NA

additions_pp_long <- as_tibble(as.matrix(Phi_pp_2)) %>%
  mutate(id = rownames(mst_pp)) %>%
  gather(id2, value, -id) %>%
  filter(!is.na(value),
         value >= 0.3) %>%
  anti_join(mst_pp_long, by = c("id", "id2"))

graph_long <- mst_pp_long %>%
  bind_rows(additions_pp_long)
```

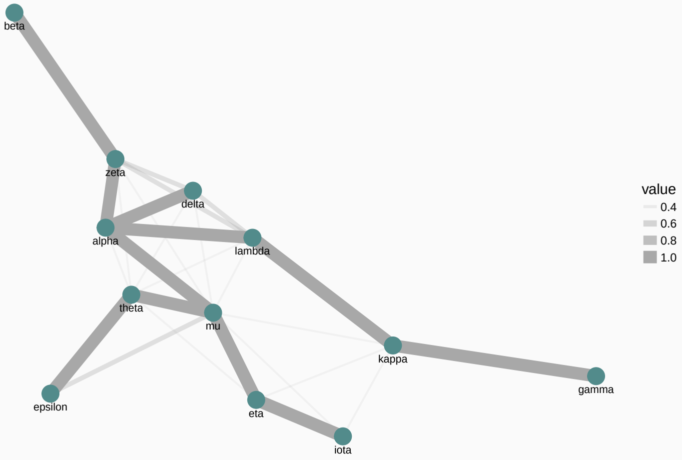
Product Space

```r
set.seed(1717)

graph_long %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = value, edge_width = value),
                 edge_colour = "#a8a8a8") +
  geom_node_point(color = "darkslategray4", size = 8) +
  geom_node_text(aes(label = name), vjust = 2.2) +
  ggtitle("Sketch of Fantasy World's Country Space") +
  theme_void(base_size = 15)
```

Product Space

Sketch of Fantasy World's Country Space



Country Space

Exercise

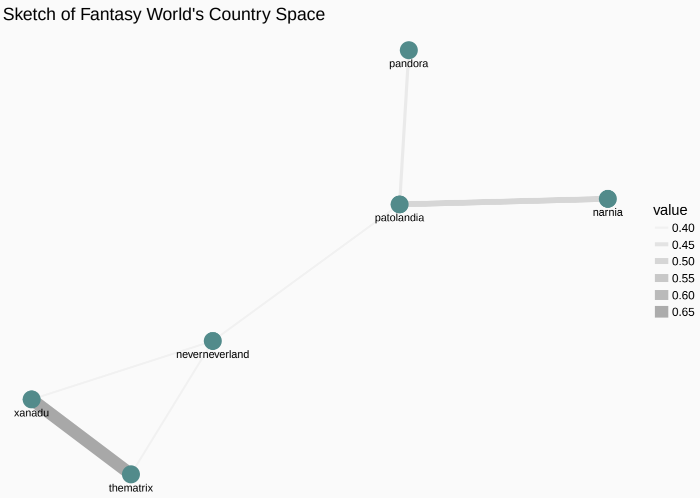
- Create a tibble that includes all pairs with a country proximity higher or equal than 0.4
- Use `ggraph` package to sketch Fantasy World's Country Space
- Ignore any disconnected countries for now

Country Space

```r
set.seed(1717)

Phi_cc_long %>%
  filter(value >= 0.4) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = value, edge_width = value),
                 edge_colour = "#a8a8a8") +
  geom_node_point(color = "darkslategray4", size = 8) +
  geom_node_text(aes(label = name), vjust = 2.2) +
  ggtitle("Sketch of Fantasy World's Product Space") +
  theme_void()
```

Country Space



Questions?

Contact

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