An expert system for semi-automated classification of product and industry descriptions

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The AfCIOT Project

AfCIOT Project background

- Joint project with UNECA, WTO, and OECD
- International Trade, Environmental and Employment Indicators
- International and multidisciplinary team
- Industry and product classification, gap estimation, policy simulation and visualization
- Key result: A shiny app for reporting, visualization and policy simulation
- Several important challenges for the multinational scope

World Trade Organization

OECD

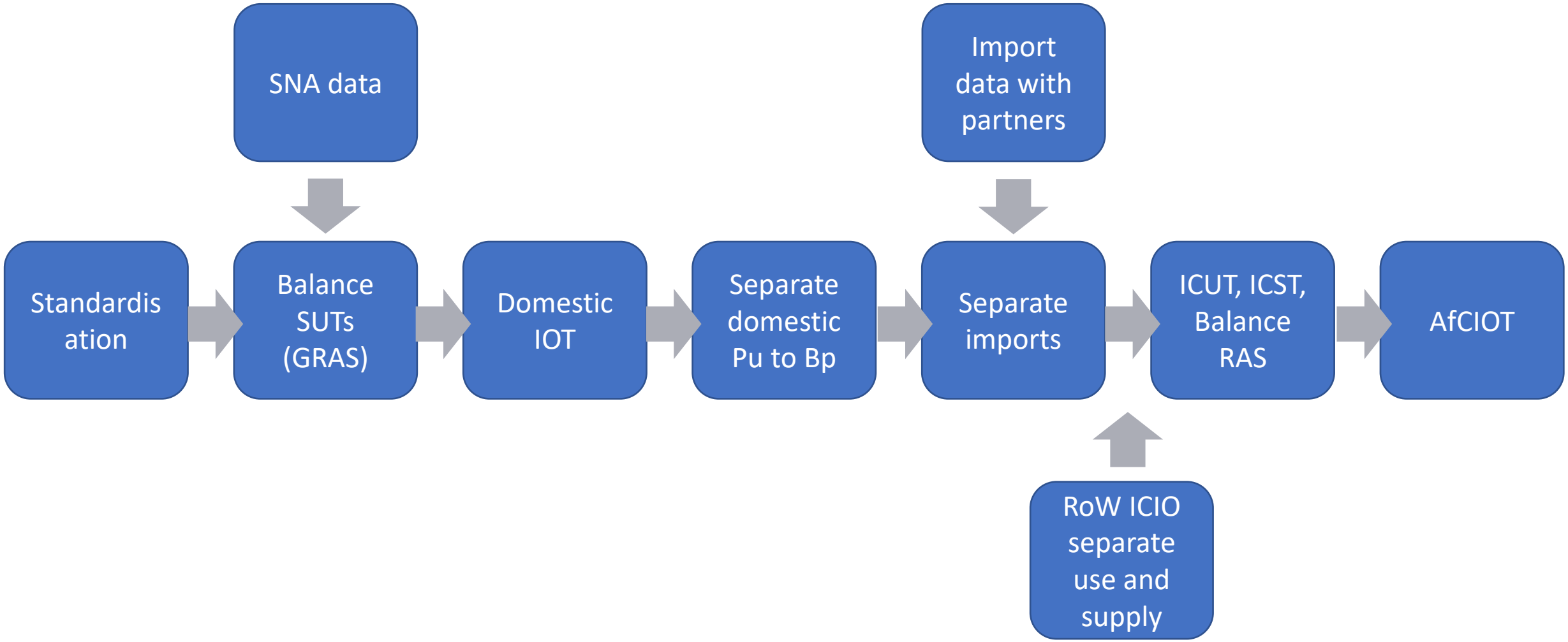
United Nations Economic Commission for Africa

African **C**ontinental **I**nput-**O**utput **T**able (AfCIOT)

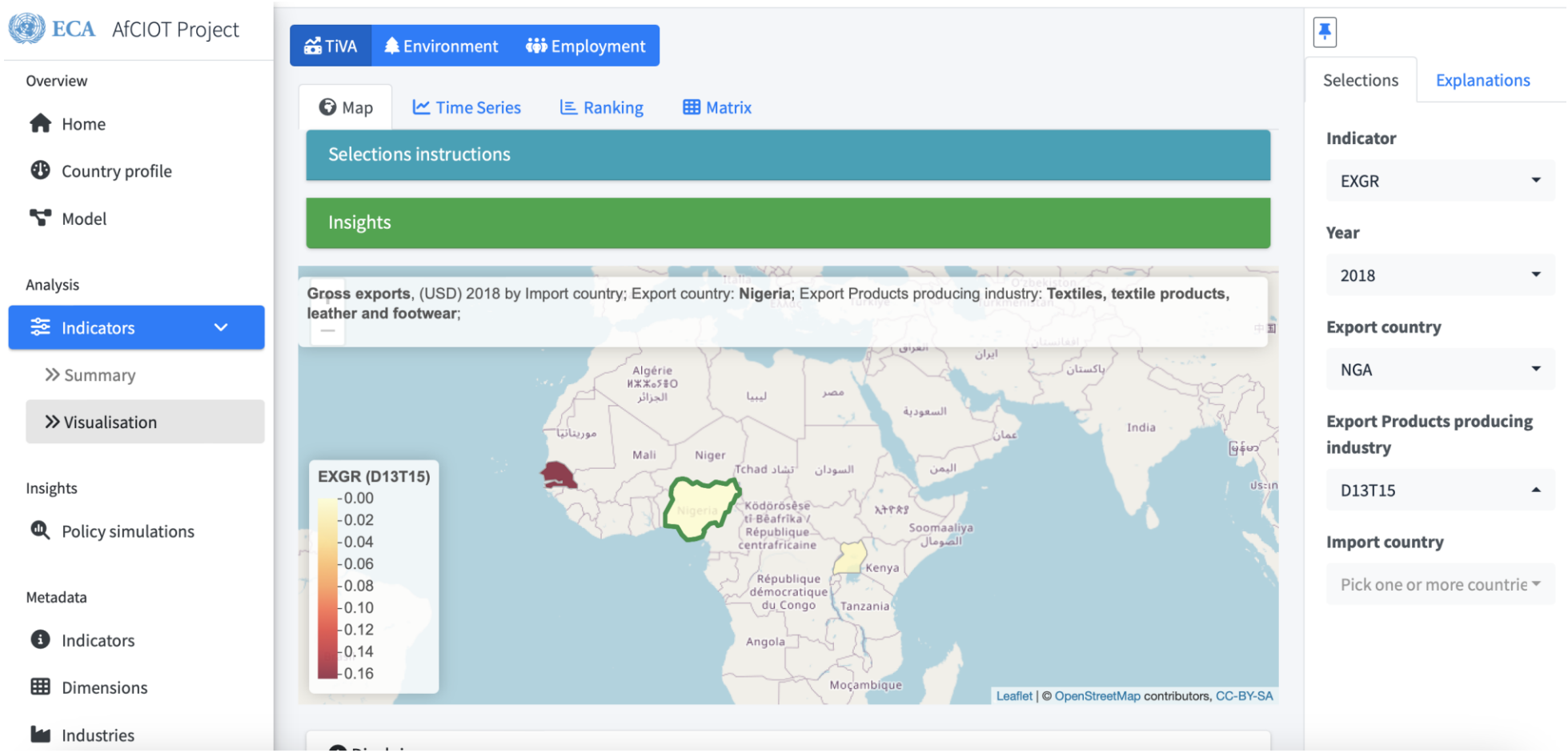
- From National Accounts to TiVA indicators
- Via Supply and Use Tables (SUT)
- Each country using different classifications
- Different languages
- Transformations needed to standardize into 45 economic activities of TiVA

Image from Gerd Altmann at Pixabay

AfCIOT Methodology



Visualization dashboard



The classification task

The problem

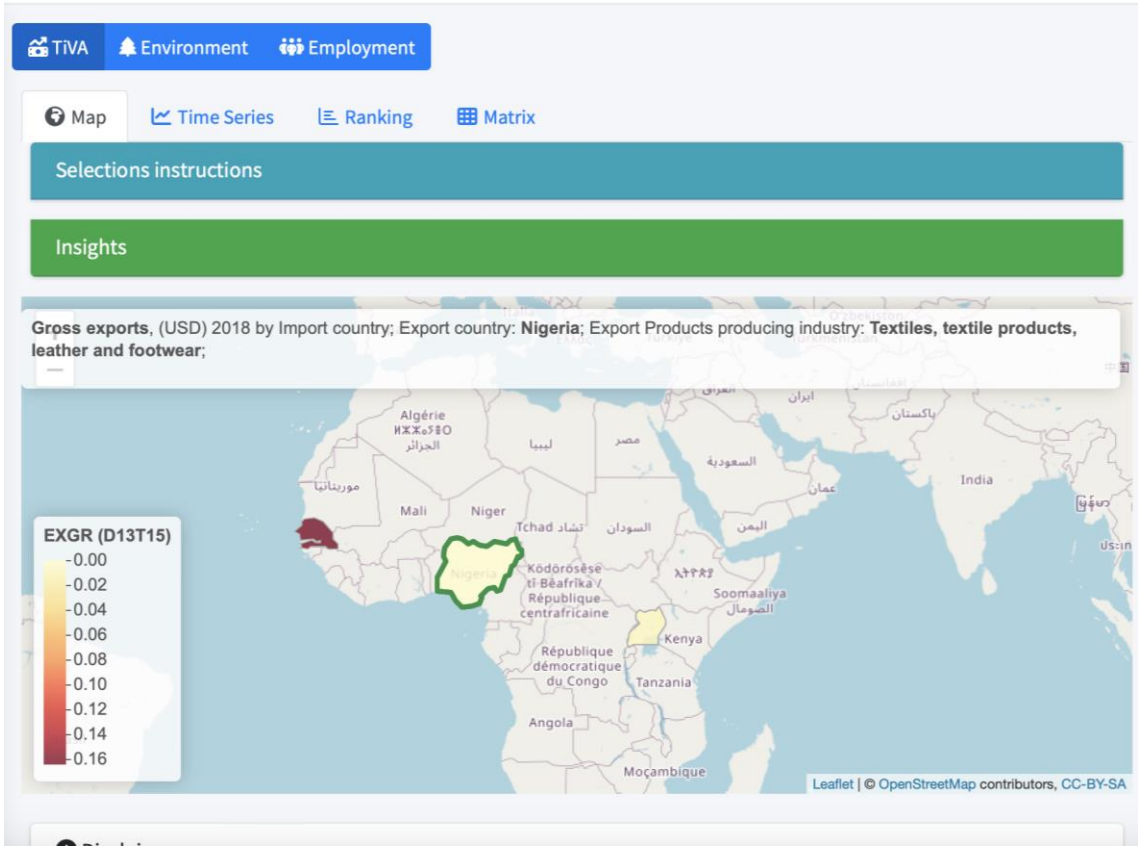
Match national products and industries descriptions with standard CPA 2.1 and ISIC 4 codes at two digits level

Image from OpenClipart-Vectors at Pixabay

Initial input vs. final result

A	B	C	D
code		1	2
		AGRICULTURE VIVRIERE	AGRICULTURE D'EXPORTATION
1	PRODUITS DE L'AGRICULT		
2	PRODUITS AGRICOLES DES		
3	PROD. SYLVICULTURE EXP		
4	PRODUITS DE L'ELEVAGE E		
5	PRODUITS DE LA PECHE		
6	PRODUITS D'EXTRACTION		
7	INDUSTRIES AGROALIMEN		
8	AUTRES INDUSTRIES MANU		
9	PRODUCTION D'ELECTRICI		
10	TRAVAUX DE CONSTRUCTI		
11	COMMERCE, SERVICES DE		
12	TRANSPORTS ET ACTIVITES		
13	SERVICES D'INTERMEDIATI		
14	AUTRES SERVICES MARCHA		
15	SERVICES D'ADMINISTRATI		
16	EDUCATION		
17	SANTE ET ACTION SOCIALE		
18	ACTIVITES A CARACTERE C		
19	ACTIVITES DES MENAGES E		
20	SIFIM		
21	CORRECTION TERRITORIAL		
999	PRODUITS EN ATTENTES		
P1			

Código dos produtos	Descrição dos produtos	Oferta total a preços de consumidor
01.01	Milho, trigo e outros cereais	75.634
01.02	Mandioca	17.392
01.03	Feijão	92.049
01.04	Batata rena	23.627
01.05	Outros legumes, raízes e tubérculos	167.594
01.06	Banana	17.412
01.07	Outros produtos agrícolas	29.451
01.08	Gado bovino, outros gados e animais vivos	6.077
01.09	Aves domésticas	16.266
01.10	Leite, ovos e outros produtos de origem animal	11.050
01.11	Carvão vegetal	26.623
01.12	Lenha e outros produtos da silvicultura	8.093
02.01	Peixe vivo, fresco e refrigerado	169.079
02.02	Outros produtos da pesca	17.941
03.01	Petróleo bruto e gás associado	4.568.457
03.02	Serviços petrolíferos	147.949
04.01	Diamantes	94.371
04.02	Minerais metálicos e outros minerais não metálicos	24.091
05.01	Carnes e cortes comestíveis de gados bovinos, de outr	61.198
05.02	Carnes e cortes comestíveis de aves, frescas, refrigerad	48.185
05.03	Conservas e preparados de carne	25.929
05.04	Preparados e conservas de peixes, outros produtos da	49.272
06.01	Óleos e gorduras animais e vegetais	40.156
07.01	Produtos lácteos	30.063
08.01	Farinha e fuba de milho	139.363
08.02	Farinha e fuba de mandioca	30.100
08.03	Farinha de trigo	34.561



Technological options

- Machine Learning
  - Worked well for 1 digit classification
  - Lack of labeled samples
  - No one-to-one matching
  - Needs large amount of data
- LLMs (chatGPT and friends)
  - Not enough mature (IMHO)
  - Ethical concerns
- Expert assignment
  - Subjective
  - Very slow

Image from Jan Alexander at Pixabay

Chosen method: stepwise algorithm

0. Standards consolidation with their relationships

1. Text mining data curation
2. Exact matches
3. Less (lemmatized) string distance
4. Number of word matches
5. Expert review and final code allocation

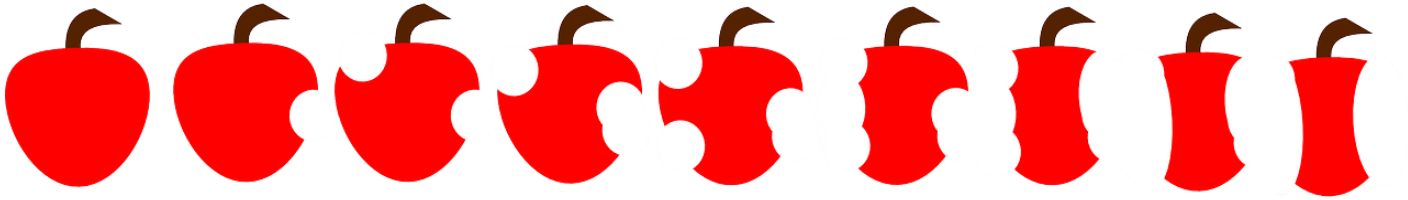


Image from OpenClipart-Vectors at Pixabay

AfCIOT data

Input classifications

- African countries
- Heterogenous levels of detail
- Different languages
- Initial set of countries, but further to come

country	language	# Categories
Guinea	fr	19
Kenya	en	154
Mali	fr	38
Mauritania	fr	26
Mauritius	en	59
Mozambique	pt	175
Rwanda	en	80

Standards data

Myriad of standards

- Target: CPA 2.1 & ISIC 4
- Target level: 2 digits
- Existing relationships
  - Other standards
  - Different versions
  - Different sources

Correspondence tables

CPC Correspondence Tables

FROM / TO	CPC prov	CPC Ver. 1.0	CPC Ver. 1.1	CPC Ver. 2	CPC Ver. 2.1
CPC prov	-	✓	✓	-	-
CPC Ver. 1.0	✓	-	✓	-	-
CPC Ver. 1.1	✓	✓	-	✓	-
CPC Ver. 2	-	-	✓	-	✓
CPC Ver. 2.1	-	-	-	✓ ✓	-
ISIC Rev. 3	✓ ✓	✓ ✓	-	-	-
ISIC Rev. 3.1	-	-	✓ ✓	-	-
ISIC Rev. 4	-	-	-	✓ ✓	✓ ✓
BEC Rev. 5	-	-	-	-	✓ ✓
SITC Rev. 4	-	-	-	✓	-

https://unstats.un.org/unsd/classifications/Econ#Correspondences

Relationships consolidation+lemmatization

code	name	language	standard	cpa21
A	agriculture, forestry and fishing	en	isic4	
01	crop and animal production, hunting and related service activities	en	isic4	
011	growing of non-perennial crops	en	isic4	
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.11
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.11
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.12
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.12
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.20
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.20
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	01.11.31

To classify a new name:

1. Look for exact matches
2. Lemmatize new name
3. Look for partial matches
4. Get target code

code	name	language	standard	tokens	lemmas
A	agriculture, forestry and fishing	en	isic4	agriculture fishing forestry	agriculture fishing forestry
01	crop and animal production, hunting and related service activities	en	isic4	activities animal crop hunting production related service	activity animal crop hunt production relate service
011	growing of non-perennial crops	en	isic4	crops growing nonperennial	crop grow nonperennial
0111	growing of cereals (except rice), leguminous crops and oil seeds	en	isic4	cereals crops growing leguminous oil rice seeds	cereal crop grow leguminous oil rice seed
0112	growing of rice	en	isic4	growing rice	grow rice
0113	growing of vegetables and melons, roots and tubers	en	isic4	growing melons roots tubers vegetables	grow melon root tuber vegetable
0114	growing of sugar cane	en	isic4	cane growing sugar	cane grow sugar
0115	growing of tobacco	en	isic4	growing tobacco	grow tobacco
0116	growing of fibre crops	en	isic4	crops fibre growing	crop fibre grow
0119	growing of other non-perennial crops	en	isic4	crops growing nonperennial	crop grow nonperennial

Implementation

R Statistical Software

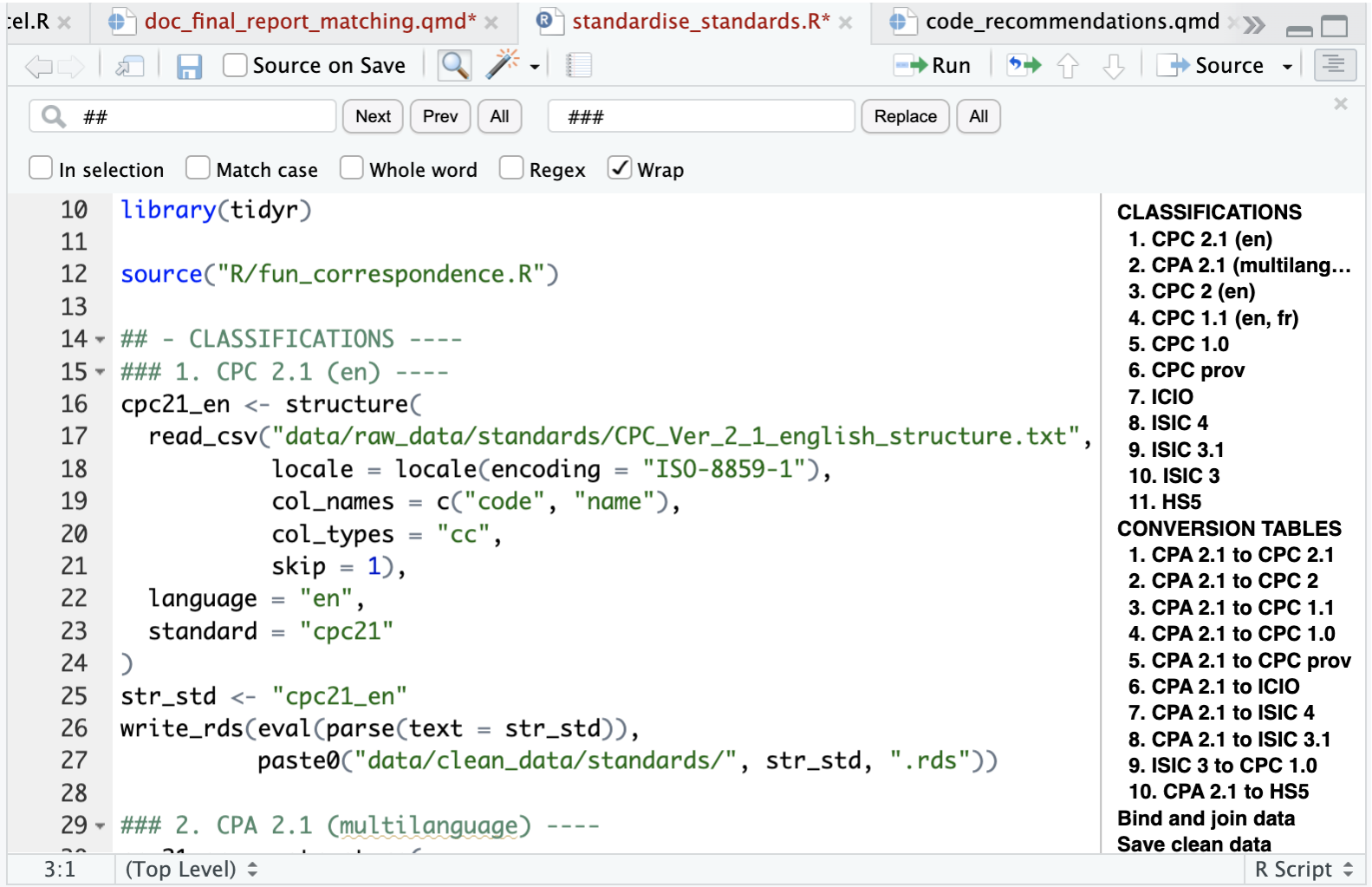
R

- Open source
- Statistical software and programming language
- ML, TM, and any modelling method

Shiny apps

- Framework for building reactive web applications with just R regular code

Scripts for building the standards data frames



Core function

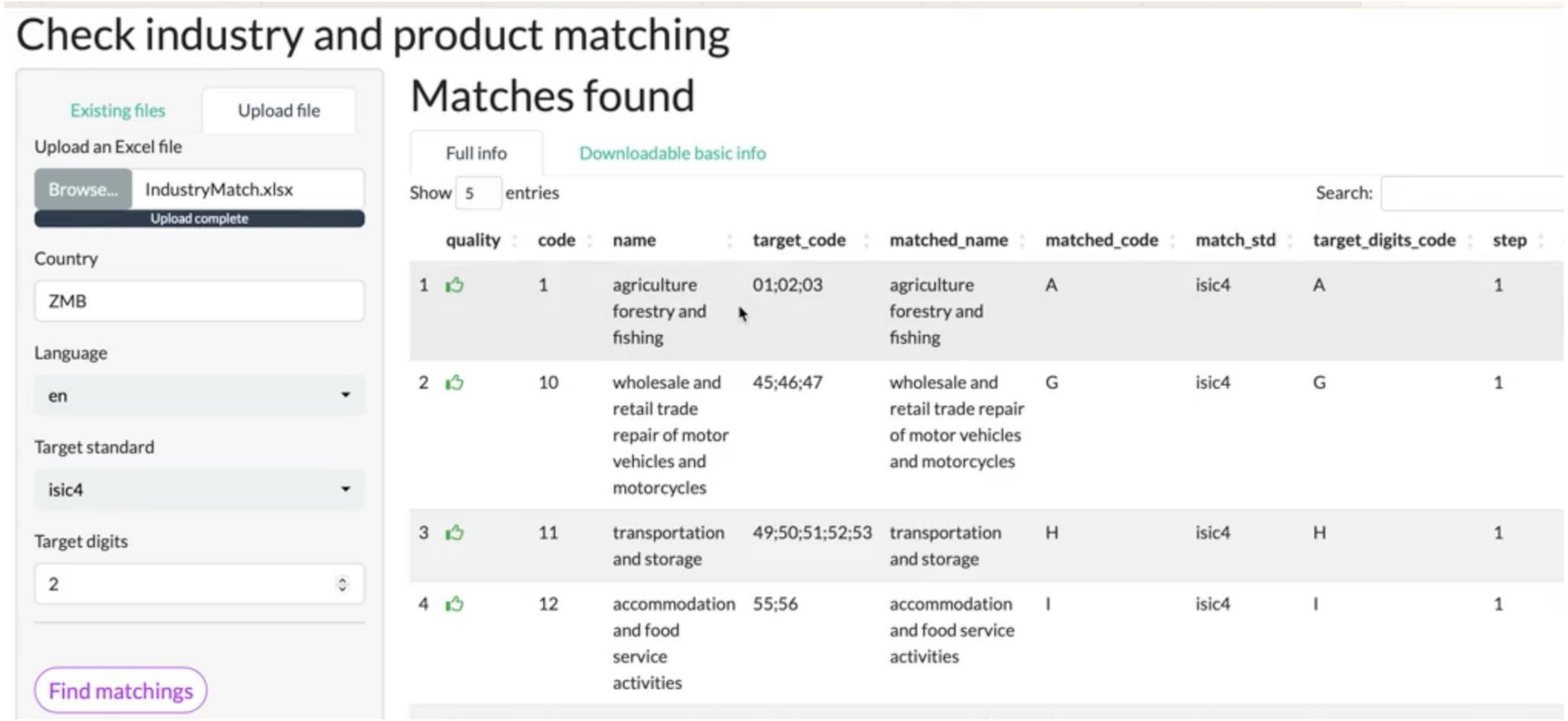
```
source("R/matching_algorithm.R")
pnew <- read_rds("data/clean_data/pnew.rds") |>
              filter(country == "Guinea") |> slice(1:3)

std_corresp <- read_rds("data/clean_data/cpa21_corresp.rds")
lstandards <- read_rds("data/model_data/lstandards.rds")

test <- match_names(dfnew = pnew,
            newcountry = "Guinea",
            target = "cpa21",
            std_corresp = std_corresp,
            lstandards = lstandards,
            model_path = "data/model_data",
            fpath = "R",
            save = FALSE)
```

`dfnew`: any arbitrary data frame with codes and names

Shiny app



https://lcano.com/share/tmp/screencast_classification_app_V1.mp4

Discussion

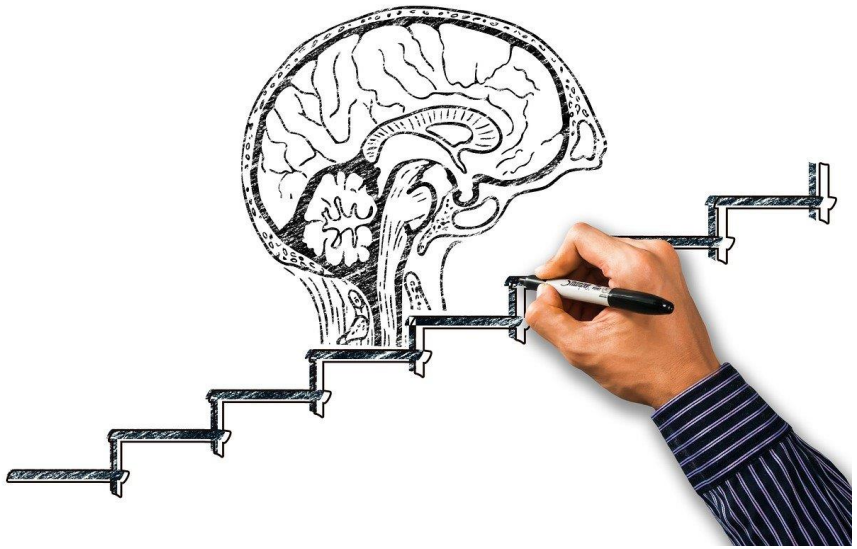
Conclusions

- Standardization of categories appears in the initial steps of the indicators building pipeline
- Wrong classifications may lead to wrong indicator values, hence in wrong information for decision making (garbage in-garbage out)
- Automatic classification and matching is a major challenge in economic statistics
- Hybrid models are useful in many situations and provide robustness

Image from Peggy und Marco Lachmann-Anke at Pixabay

Room for improvement

- Add more standards and their relationships
- Include models that learn from the experts' input
- Explore how to include LLMs for difficult matches
- Add rule-based controls to avoid clear missclassifications and manage one-to-many and many-to-many relationships
- Try further Data Science techniques, e.g., unsupervised classification or Bayesian models.



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Thanks!

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