[WELFARE AND INEQUALITY ANALYSIS]

Hye-Jin Cho-Drugeon

<u>Choh9323@gmail.com</u>

This presentation file is only for RNCP certification. It contains the preliminary data work.

It is not intended to be distributed elsewhere. Thank you.

ROADMAP

- 1. Introduction
- 2. Data and data sources
- 3. Data collection
- 4. Data cleaning and Exploratory data analysis
- 5. Data base type selection
- 6. Entities. ERD
- 7. DATA Visualization

INTRO

Business Use Case

Goal: This project studies intergenerational transfers such as tax and social security in the field of welfare and inequality for Euro-currency using countries with the OECD distribution data.

It intends to explain the behavior of working age generation of 18-65 and old generation of above 65.

Domain: Economics and Statistics

Plan

- 1. Planning of my project in Jira
- 2. Code in Python for Data collection and cleaning
- 3. ER Diagram
- 4. Data source and Meta Data
- 5. Database Script
- 6. Report (10 pages)
- 7. Slides

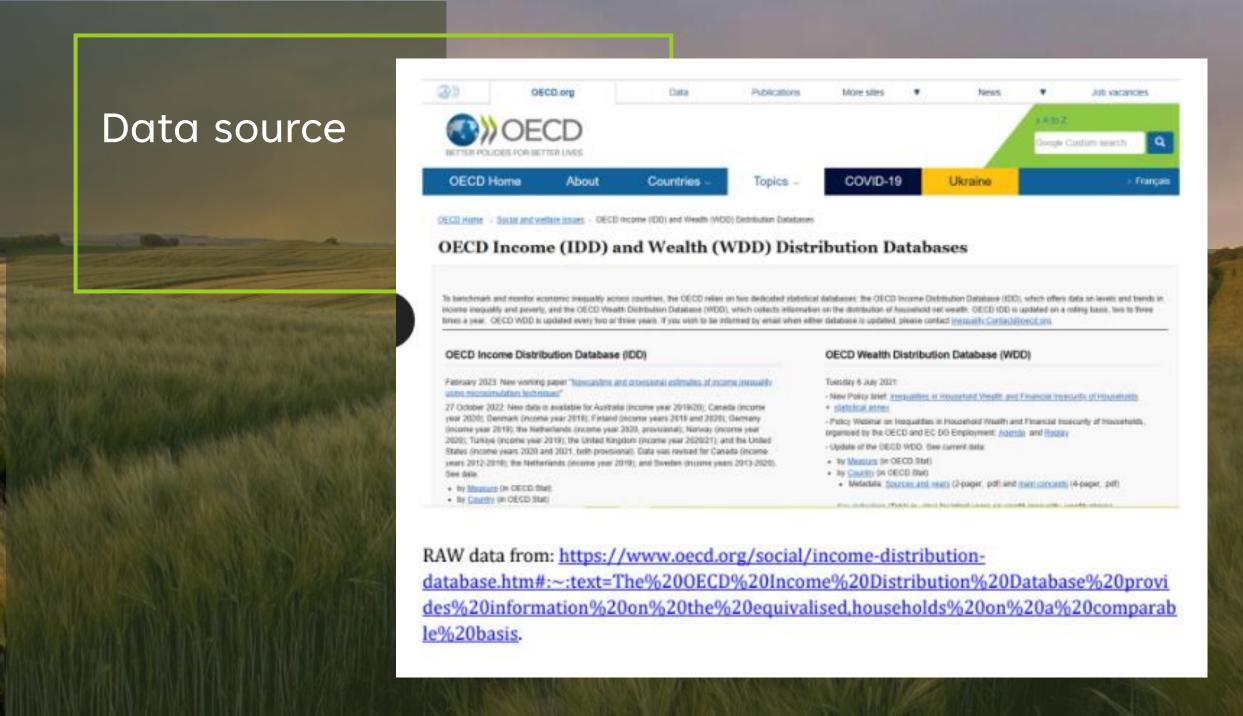


SOLUTION

Output

In Github DAFT_0410/module5 at main · chatlapin/DAFT_0410 · GitHub

#SQL, API, Python Toymodel (France), Python ML #starter Iira OECD.sql Datadescription.pdf OECD.API31.ipynb #ER, Data Cleaning, EDA Project Toymodel.ipynb Erdiagram_OECD.drawio.pdf ProjectBig.ipynb OECD Data Cleaning and EDA.ipynb OECDRawData.ipynb #Euro-using country stationary test results #Data, cleaned (by variables) UnitRootTestOECD meandi.ipynb Clean_data_pivotedCl.csv UnitRootTestOECDCl.ipynb Clean_data_pivotedCPI.csv UnitRootTestOECDCPI.ipynb UnitRootTestOECDP90P10.ipynb Clean_data_pivotedMDI.csv Clean_data_pivotedP90.csv UnitRootTestOECDTE.ipynb UnitRootTestOECDtaxsecu.ipynb Clean_data_pivotedTE.csv Clean_data_pivotedTaxsecu.csv UnitRootTestOECD transfer.ipynb Clean_data_pivotedtransfer.csv #Rawdata (by world, France, Euro-using country Clean_data_pivotedCPI.csv group, each variable) France.csv #Data, pivoted (by variables) data_pivotedCl.csv Monde (1).csv data_pivotedCPI.csv Welfare(1).csv Welfare.csv data_pivotedMDI.csv # Data Visualisation data_pivotedP90.csv data_pivotedTE.csv Welfare_DataVisualisation.xlsx data_pivotedTaxsecu.csv data_pivotedtransfer.csv data_pivotedCPl.csv



df.sample(4)

	LOCATION	Country	MEASURE	Measure	AGE	Age group	DEFINITION	Definition	METHODO	Methodology	***	Year
9190	ESP	Spain	PVTAAS	Age group 51-65: Poverty rate after taxes and _	тот	Total population	CURRENT	Current definition	METH2012	New income definition since 2012	-	2011
18845	NOR	Norway	GINIG	(gross income, before taxes)	OLD	Retirement age population: above 65	CURRENT	Current definition	METH2012	New income definition since 2012		2020
15389	POL	Poland	TRROTCTOTAL	Current transfers received from non- profit ins	WA	Working age population: 18-65	CURRENT	Current definition	METH2012	New income definition since 2012	-	2017

SAMPLING

MACHINE LEARNING: SUPERVISED LEARNING

TOY MODEL: FRANCE 2012_2019 DESCRIPTIVE STATISTICS

	totalearning	capitalincome	transferrec	transferpaid	priceindex2015	meandi	saving
count	8.000000	8.000000	8.000000	8.00000	8.000000	8.000000	8.00000
mean	21618.750000	2343.750000	5708.750000	-5001.25000	100.843026	26693.750000	2343.06875
std	1254.232121	189.581306	49.117207	313.16073	1.909861	903.199669	186.82237
min	20240.000000	2070.000000	5640.000000	-5470.00000	98.605000	25850.000000	2156.60000
25%	20760.000000	2272,500000	5667.500000	-5115.00000	99.835420	26142.500000	2192.83250
50%	21250.000000	2345.000000	5715.000000	-4930.00000	100.090835	26280.000000	2284.43000
75%	22265.000000	2402.500000	5742.500000	-4822.50000	101.685025	27020.000000	2463.00500
max	23790.000000	2710.000000	5780.000000	-4590.00000	104.232500	28390.000000	2617.00000

WELFARE

MACHINE LEARNING: SUPERVISED LEARNING TOY MODEL: FRANCE 2012_2019

```
model.coef_
array([32.25850999, 86.42024677])
model.intercept_
0.007303861711072557
```

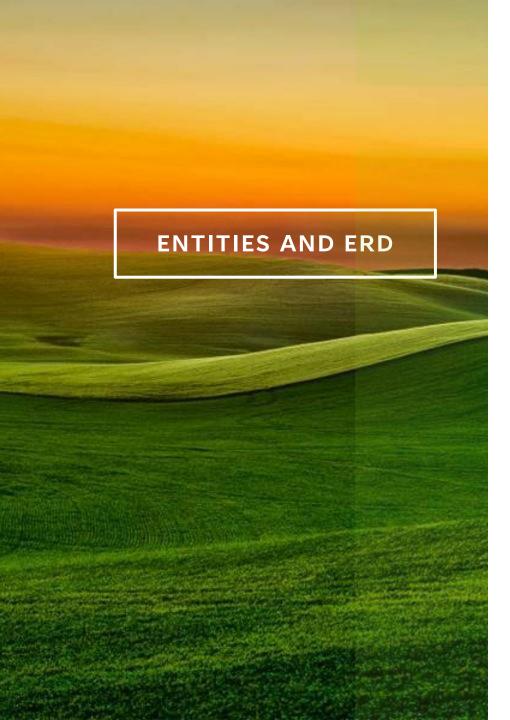
5. Predict labels for unknown data

```
# new instances where we do not know the answer
Xfit, _ = make_regression(n_samples=3, n_features=2, noise=0.1, random_state=1)
# make a prediction
yfit = model.predict(Xfit)
# show the inputs and predicted outputs
for i in range(len(Xnew)):
    print("X=%s, Predicted=%s" % (Xfit[i], yfit[i]))

X=[-1.07296862 -0.52817175], Predicted=-80.2497983168563
X=[-0.61175641  1.62434536], Predicted=120.649280643451
X=[-2.3015387  0.86540763], Predicted=0.5518357031231957

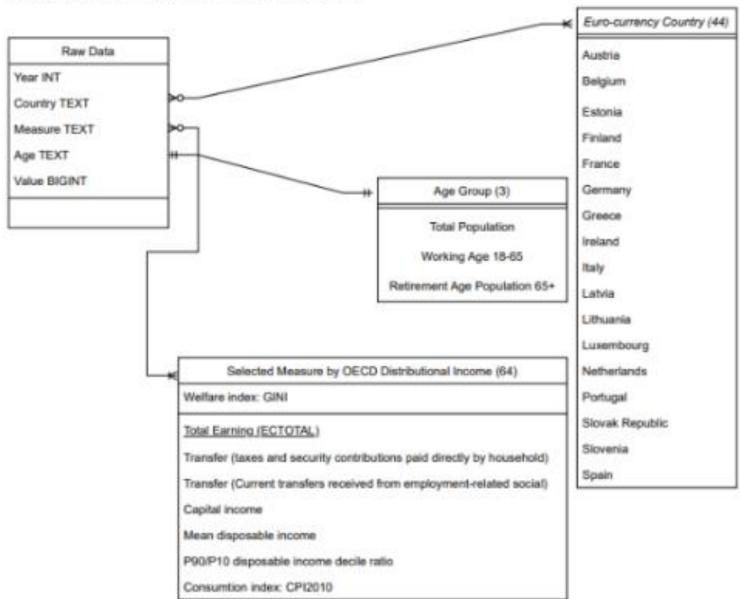
yfit = model.predict(Xfit)
```

WELFARE



Raw Data. Shape (77182, 21) (#Number) : Unique at Raw Data)

https://chatlapin.atlassian.net/jira/software/projects/CHAT/boards/1







For analyzing entity relation, SQL is useful to check which kind of joints are possibly applied. For cross-country data, it is not easy to make left-join or outer join, the reason is the number of row and variables are reduced due to duplicated elements. When we did pivot in Python, it's the delicate method from the same reason.

Though, when we use SQL, the entity relation of data is automatically captured. In addition, by using functions such as group by, order by, sum, avg, min, max, it was useful to check the data structure as below.

SQL OR NO SQL

```
Afunction I: Group by
Ashno the table with selected form-using countries with measures.
                                                                  # function 3: UNION
SELECT *
                                                                 SELECT *
FROM OECD, monde (1)
                                                                  FROM DECD, monde (I)
GROUP BY Country;
                                                                  WHERE Ages 'DUD'
                                                                  UNION
Atotal generations
                                                                  SELECT *
SELECT *
                                                                  FROM OECO, monde (1)"
FROM OECD, monde (1)
                                                                  MHERE Age- "MA" |
WHERE Age- TOT 3
                                                                  #(1) measure: GINI
Maverage values for total generations (young and old)
                                                                 SELECT *
                                                                  FROM OCCO, monde (1)
SHIELT avg('values')
                                                                  MHERE Age-'OLD'
from (select *
                                                                  and Measure- "GIRL" &
FROM OECD, monde (1)
group by Age- 707
                                                                  #GROUP FUNCTIONS: MAX(4), MIN(5), AV6(6), SUM(7), COUNT(7)
limit 5) summarys
                                                             · SELECT MAX('values') as max,
                                                                  min( 'values') as min,
# function 2: Order by
                                                                  AVG("values") as average,
Aworking-aging generations
                                                                  SUM( 'values') as total,
SELECT *
                                                                  COURT('values') as MUN_columns
FROM OECD, monde (1)
                                                                  FROM DECD. monde (1)
INTERE Age: "IIA."
                                                                  WHERE Age OLD
ORDER BY Country;
                                                                  and Neasure- "DINI" p.
```

DATA TYPE SELECTION

World data from a toy model of France

Summary: Stationary Test by Dickey-Fuller test: Except for Capital Income, variables are stationary.

data31['saving	data31['meandi	data31['priceindex201 5']	data31['transferpai d']
ADF Statistic: -2.09	ADF Statistic: 1.32	ADF Statistic: -0.44 Critial Values:	ADF Statistic: - 0.72
1%, -6.05	Critial Values: 1%, -6.05	1%, -6.05 Critial Values: 5%, -3.93	Critial Values: 1%, -4.94 Critial Values:
Values: 5%, -3.93	Critial Values: 5%, -3.93	Critial Values: 10%, -2.99	5%, -3.48 Critial Values: 10%, -2.84
	Critial Values: 10%, -2.99	p-value: 0.90 Stationary	p-value: 0.84 Stationary
p-value: 0.25 Stationary	p-value: 1.00 Stationary		

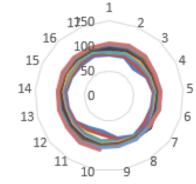
DATA TYPE SELECTION

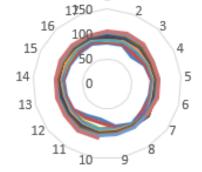
data31['transferrec']	data31['capitalincome']	data31['totalearning']
ADF Statistic: -0.93	ADF Statistic: -8.90	ADF Statistic: 1.85
Critial Values:	Critial Values:	Critial Values:
1%, -4.94	1%, -6.05	1%, -5.35
Critial Values:	Critial Values:	Critial Values:
5%, -3.48	5%, -3.93	5%, -3.65
Critial Values:	Critial Values:	Critial Values:
10%, -2.84	10%, -2.99	10%, -2.90
p-value: 0.78	p-value: 0.00	p-value: 1.00
Stationary	Stationary	Stationary
	p-value: 0.00	
	Non-Stationary	

DATA VISUALISATION -INTERGENERATIONAL TRANSFER

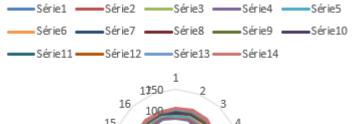
CPI2015 TOTAL

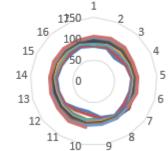






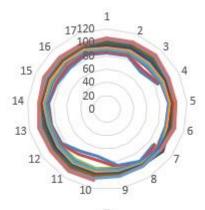
CPI2015 Working Age



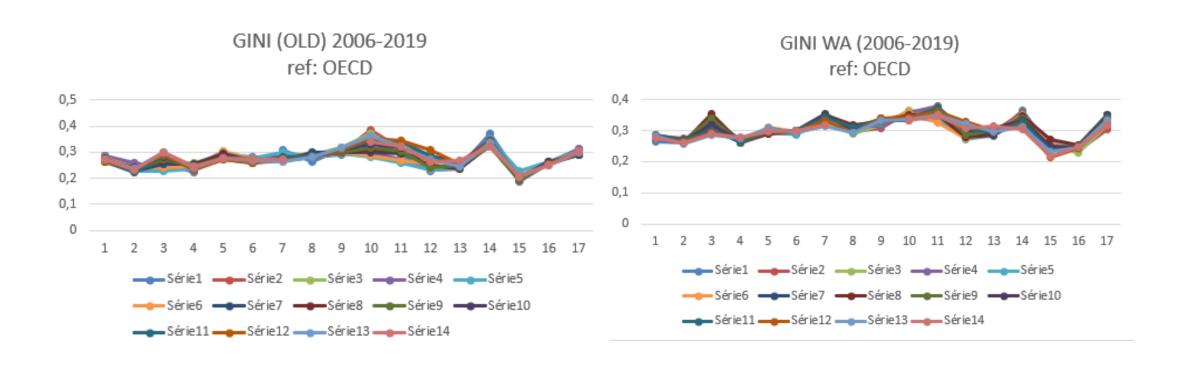


CPI2015 OLD

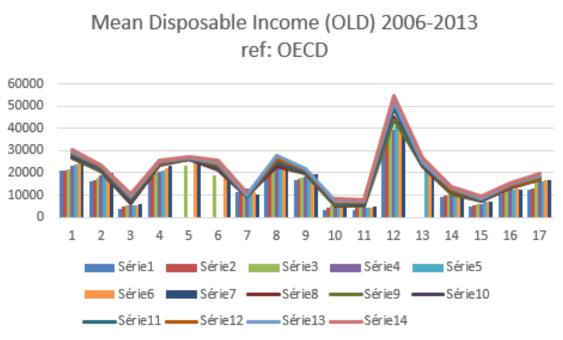


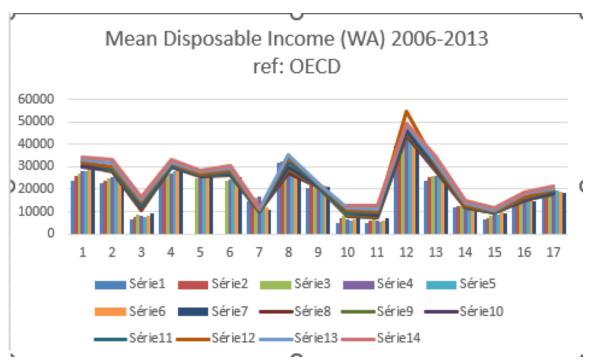


DATA VISUALISATION INEQUALITY AND GINI INDEX

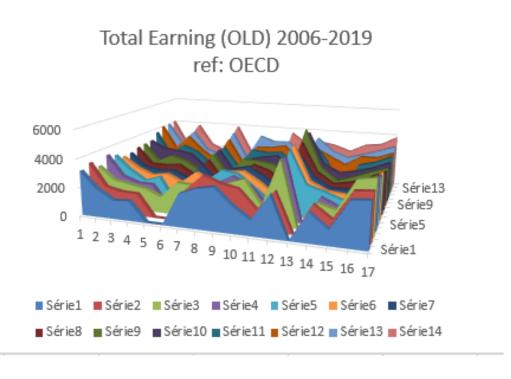


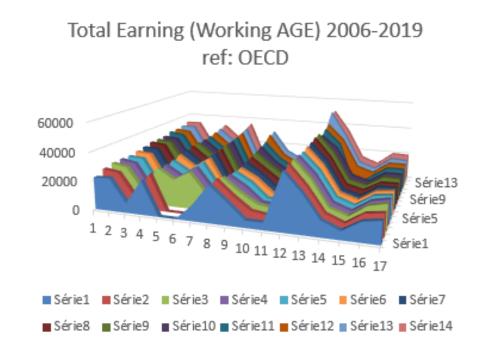
DATA VISUALISATION - MEAN DISPOSABLE INCOME: ESTIMATED AS THE GREATER AMOUNT AMONG VARIABLES. TARGET VARIABLE



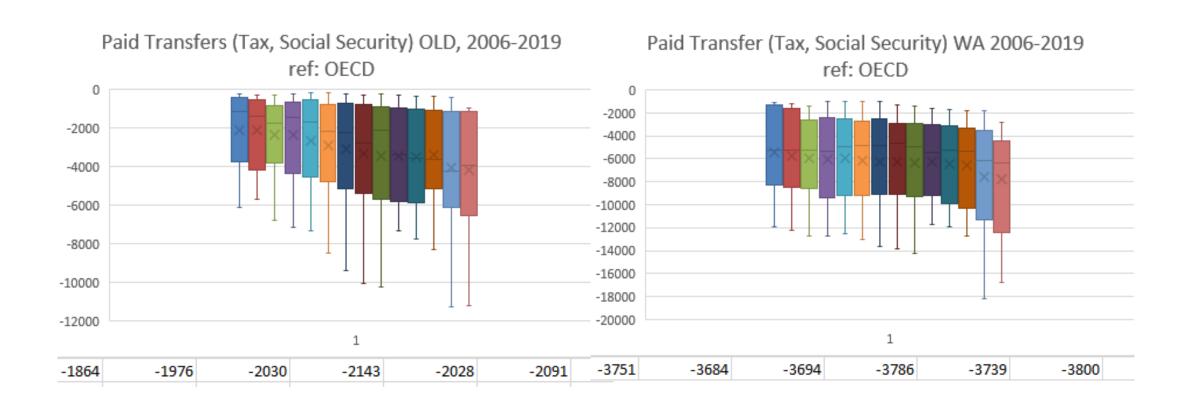


DATA VISUALISATION TOTAL YEARLY EARNING PER PERSON

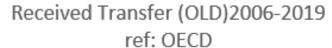


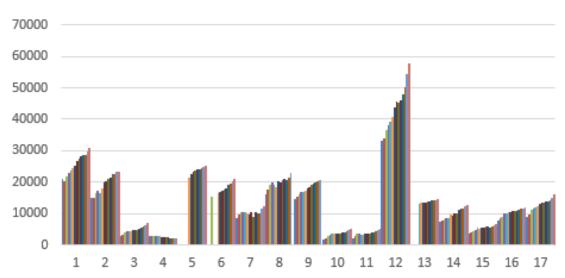


DATA VISUALISATION PAID TRANSFER (TAX, INSURANCE)

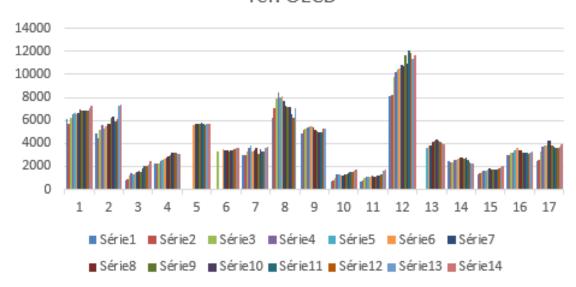


DATA VISUALISATION RECEIVED TRANSFER (TAX, INSURANCE)

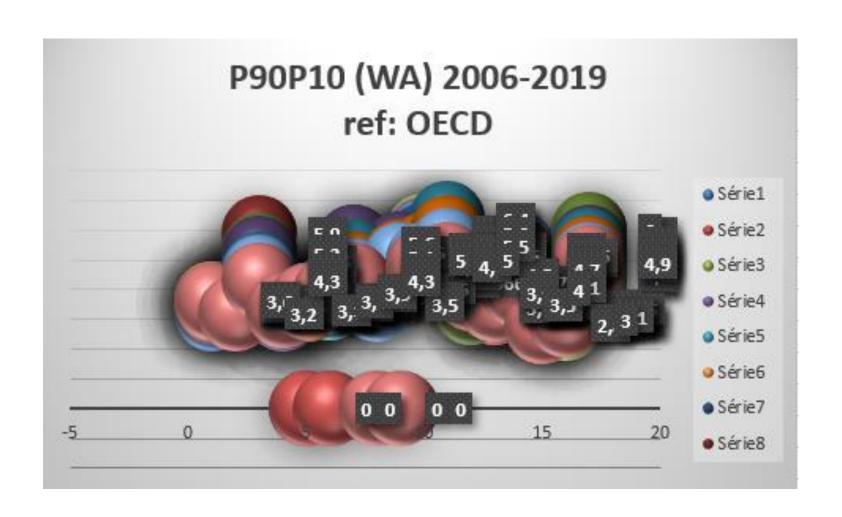




Received Transfer (WA) 2006-2019 ref: OECD



DATA VISUALISATION INEQUALITY FOR THE WORKING AGE GROUP



Thank you.