Understanding Socio-Economic Dynamics in France

Insights into population, establishments, salaries & gender inequalities

Presented by Stéphanie PRAGASSAM | IRONHACK | DATA ANALYTICS | APRIL 2024

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01

INTRODUCTION

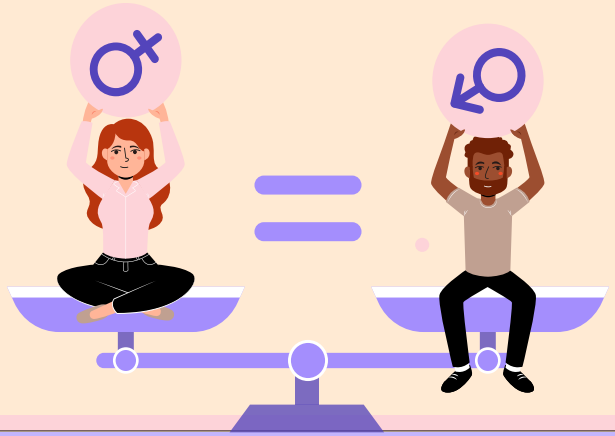
On November 6, 2023, at 11:25 a.m., women in France began working for free compared to men, highlighting the ongoing gender pay gap issue

In 2020, this disparity was evident on November 4, at 04:16 p.m

INTRODUCTION

- Analyzing socio-economic factors in France, including population demographics, establishment distributions, and job categories
- Leveraging datasets from the French National Institute of Statistics and Economic Studies (INSEE) from 2020
- Focusing on gender inequalities in the labor market, particularly in salary structures and representation in leadership roles
- Aim to uncover patterns and trends through advanced data analysis to inform policy-making and promote socio-economic progress

Goals
& Project Planning



To illuminate socio-economic dynamics in France and advocate for a more inclusive future...

Explore demographic trends and disparities in France

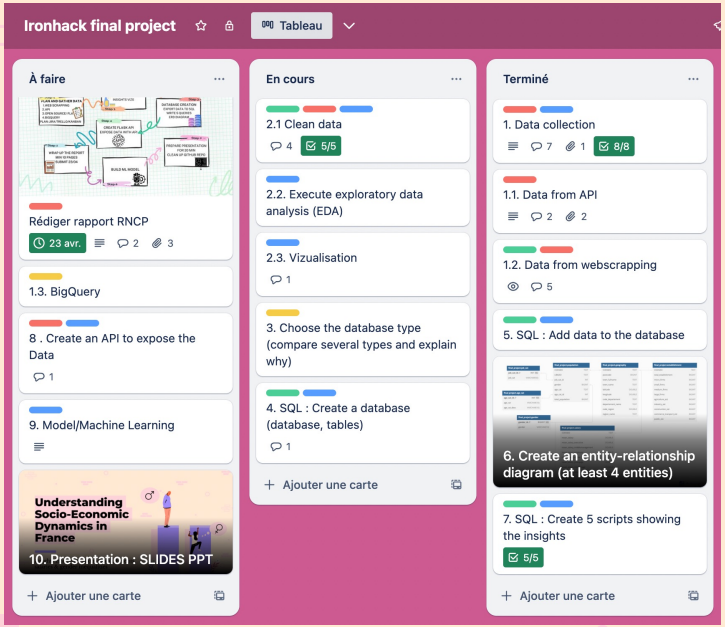
Investigate the representation of women in managerial positions

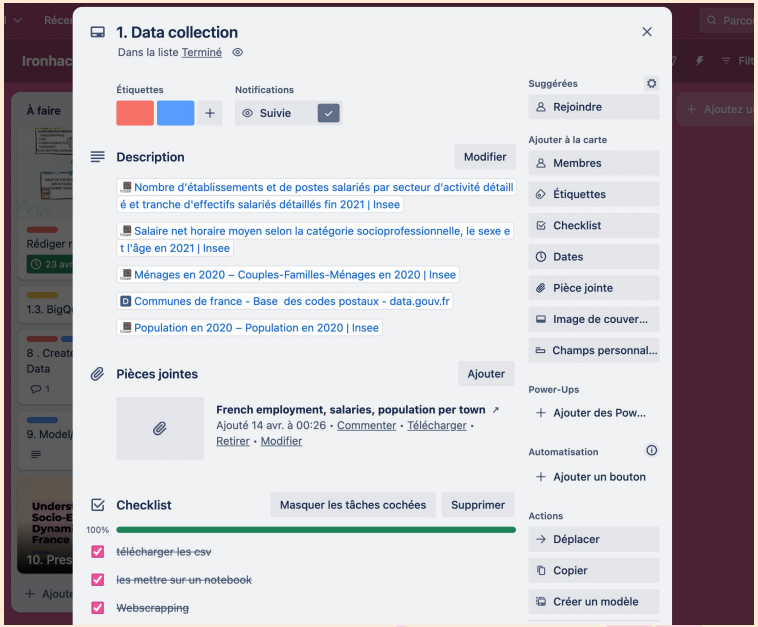
GOALS

Analyze salary distributions across different demographics and job categories

Identify correlations between population demographics and establishment data

TRELLO FOR PROJECT PLANNING





02

DATA GATHERING

Flat files | API | Web Scrap | BigQuery

DATA GATHERING

DATA SOURCES

01

FLAT FILES

INSEE datasets and
data.gouv.fr platform

02

API

United Nations Statistics
Division SDG API

03

WEBSCRAP

Wikipedia page on professions
and socio-professional categories

04

BIG QUERY

Cleaned CSV files uploaded
for query execution

DATA GATHERING

FLAT FILES

SOURCES — Reliable sources: National Institute of Statistics and Economic Studies (INSEE) & data.gouv.fr platform

DATA YEAR — 2020

RATIONALE — Ensures consistency, reliability, and completeness in analysis, facilitating meaningful comparisons across different variables and indicators.

DATA GATHERING : FLAT FILES

Number of Active Establishments

- Description: Provides insights into the distribution of establishments across five major sectors.
- Source: INSEE
- File: etablissement.csv | Rows: 34,980 | Columns: 61

Average Net Hourly Wage

- Description: Details average net hourly wage by socio-professional category, gender, and age.
- Source: INSEE
- File: salaire_par_commune.csv | Rows: 5,421 | Columns: 25

DATA GATHERING : FLAT FILES

Population Demographics

- Description: Presents demographic information on population over 15 years old by gender, age, and socio-professional category
- Source: INSEE
- File: population.csv | Rows: 1,738,965 | Columns: 7

French Municipalities - Base of Postal Codes

- Description: Includes names of regions, departments, and municipalities along with their respective INSEE codes
- Source: La Poste - data.gouv.fr
- File: communes-departement-region.csv | Rows: 5,421 | Columns: 15

DATA GATHERING : API

United Nations Statistics Division SDG API

Description

Accessible data related to the proportion of women in managerial roles from 2000 to 2022

Parameters

Target : 5.5 - Insights into women's leadership participation

Area code : 250 - France

File

- ‘api_data5.5_raw.csv’
- Rows: 140 | Columns: 25

DATA GATHERING : WEBSCRAPING

fr.wikipedia.org

Description

Table of correspondence between socio-professional categories (PCS) and groups
- Statistical classification of occupations established by the INSEE in 1982 -

Parameters

Target : 3rd table of the webpage
- Professions et catégories socioprofessionnelles en France

File

- ‘cat_job_webscrap_raw.csv’
- Rows: 42 | Columns: 4

03

DATA PREPARATION

Data Cleaning & Wrangling |
SQL : Database creation | ERD | Queries |

DATA CLEANING & WRANGLING

- Handling null values, duplicates
- Value formating
- Renaming, dropping & reorganizing columns
- Reduce the number of categories (age groups & firm sizes)
- Data homogenization & normalization

*Notebook available in the Github Repository

AFTER CLEANING

Cleaned datasets

population

- Shape : 826,266 x 6
- Before : 1,738,965 x 7

establishment

- Shape : 34,980 x 11
- Before : 34,980 x 61

geography

- Shape : 36,370 x 10
- Before : 5,421 x 15

salary

- Shape : 10,842 x 10
- Before : 5,421 x 25

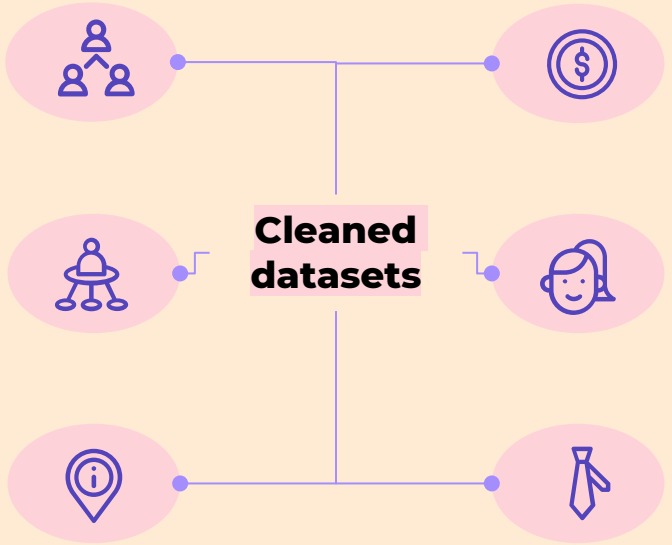
woman_managerial_position

- Shape : 19 x 4
- Before : 140 x 25

french_cat_job

Shape : 42 x 4

AFTER CLEANING



population*

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salary**

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- Before : 5,421 x 25

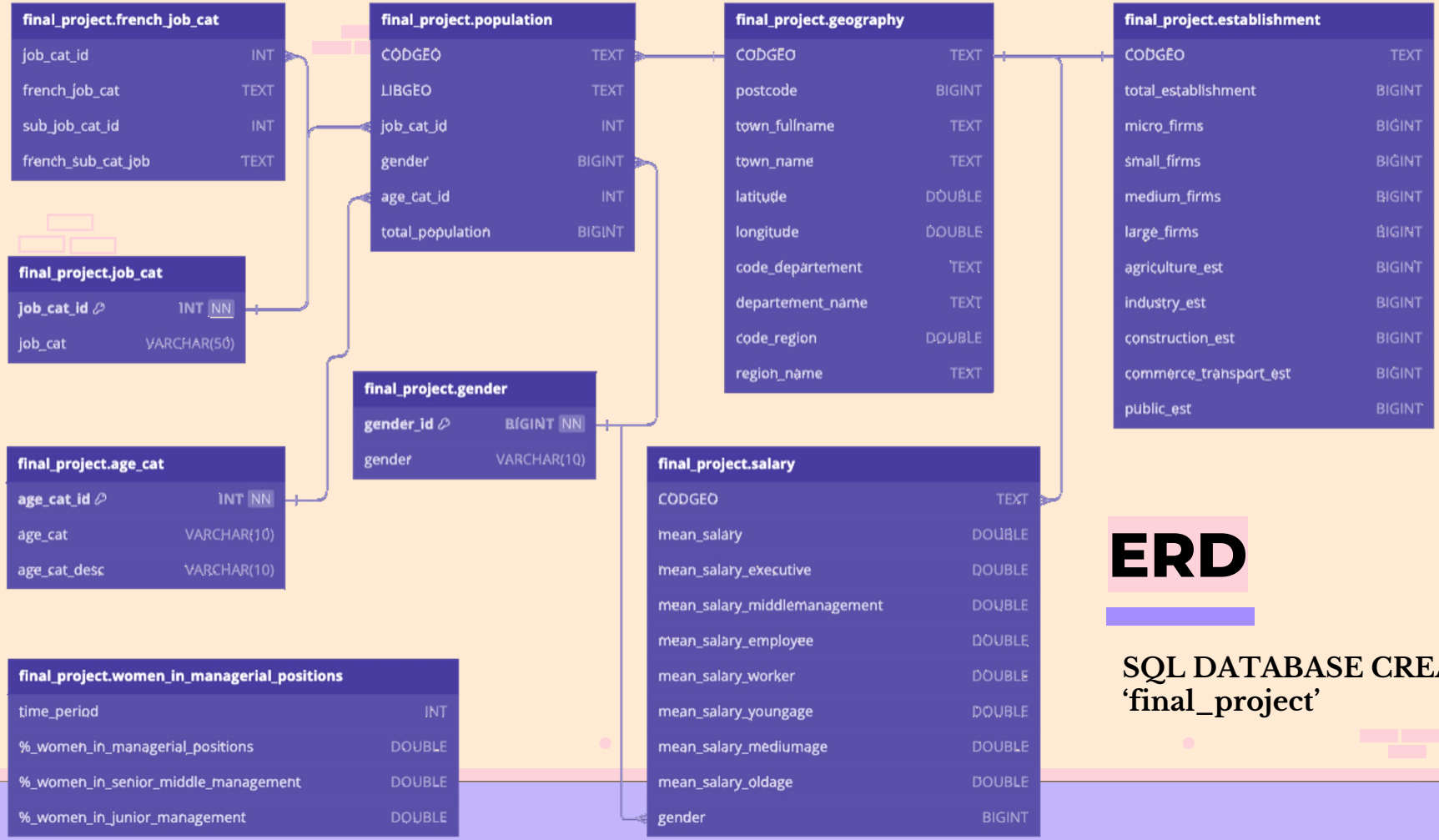
woman_managerial_position

- Shape : 19 x 4
- Before : 140 x 25

french_cat_job

Shape : 42 x 4

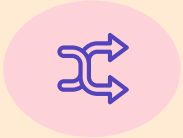
*population_all = population before age grouping
**salary_all = salary before normalization (male/female)



ERD

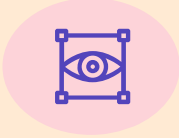
SQL DATABASE CREATION : ‘final_project’

SQL QUERIES* used for ...



Pearson Corr. for EDA

between total population & establishments



Views for API endpoints

with joint tables & new aggregated columns

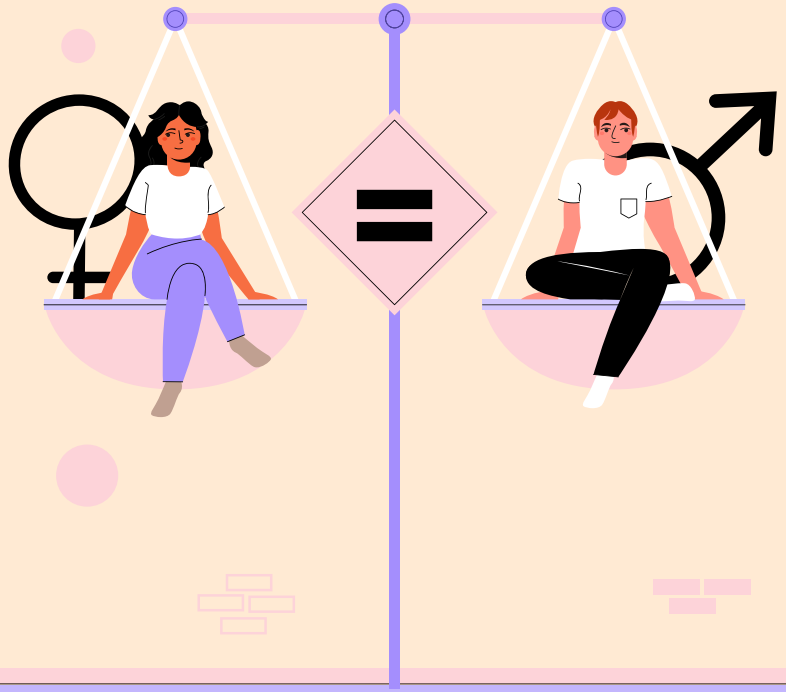
Paygap for Tableau

exported as .csv from MySQL & uploaded for visualization

TOP 10 for EDA

highest & lowest gender pay gap by department

*SQL script available in the Github Repository

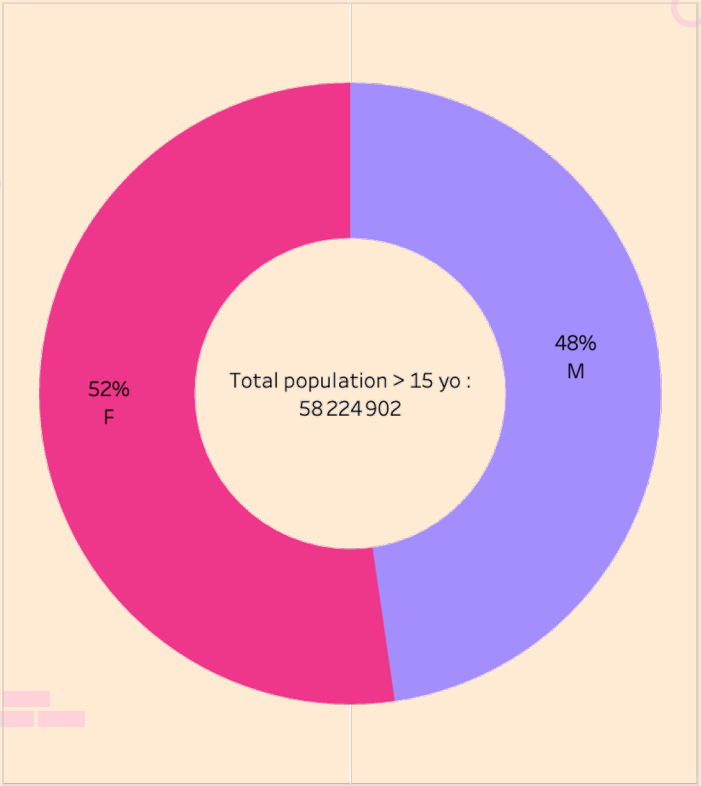


04

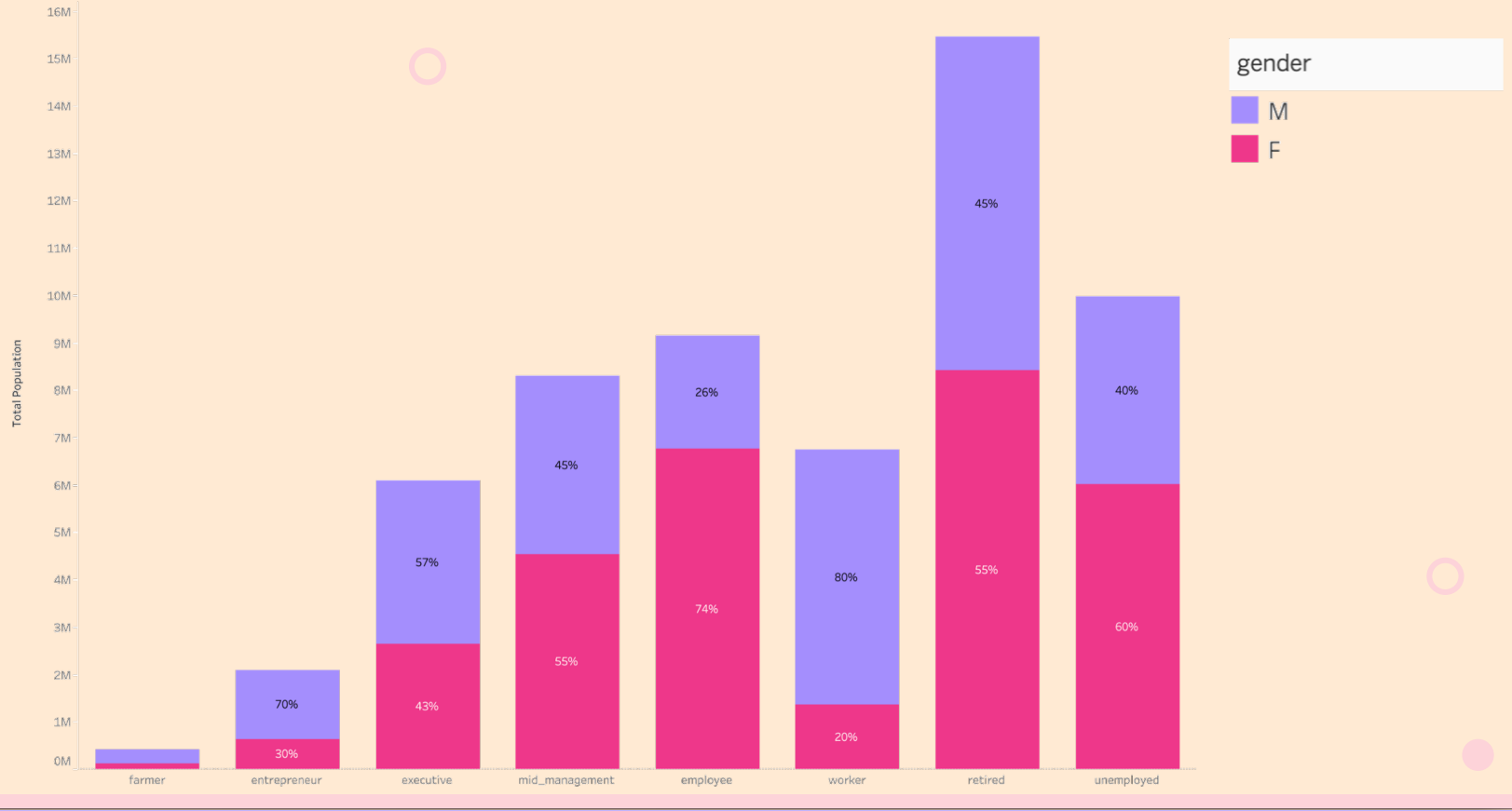
DATA EXPLORING

Exploratory Data Analysis
& Visualization

POPULATION INFOGRAPHICS BY GENDER



GENDER REPRESENTATION BY JOB CATEGORY



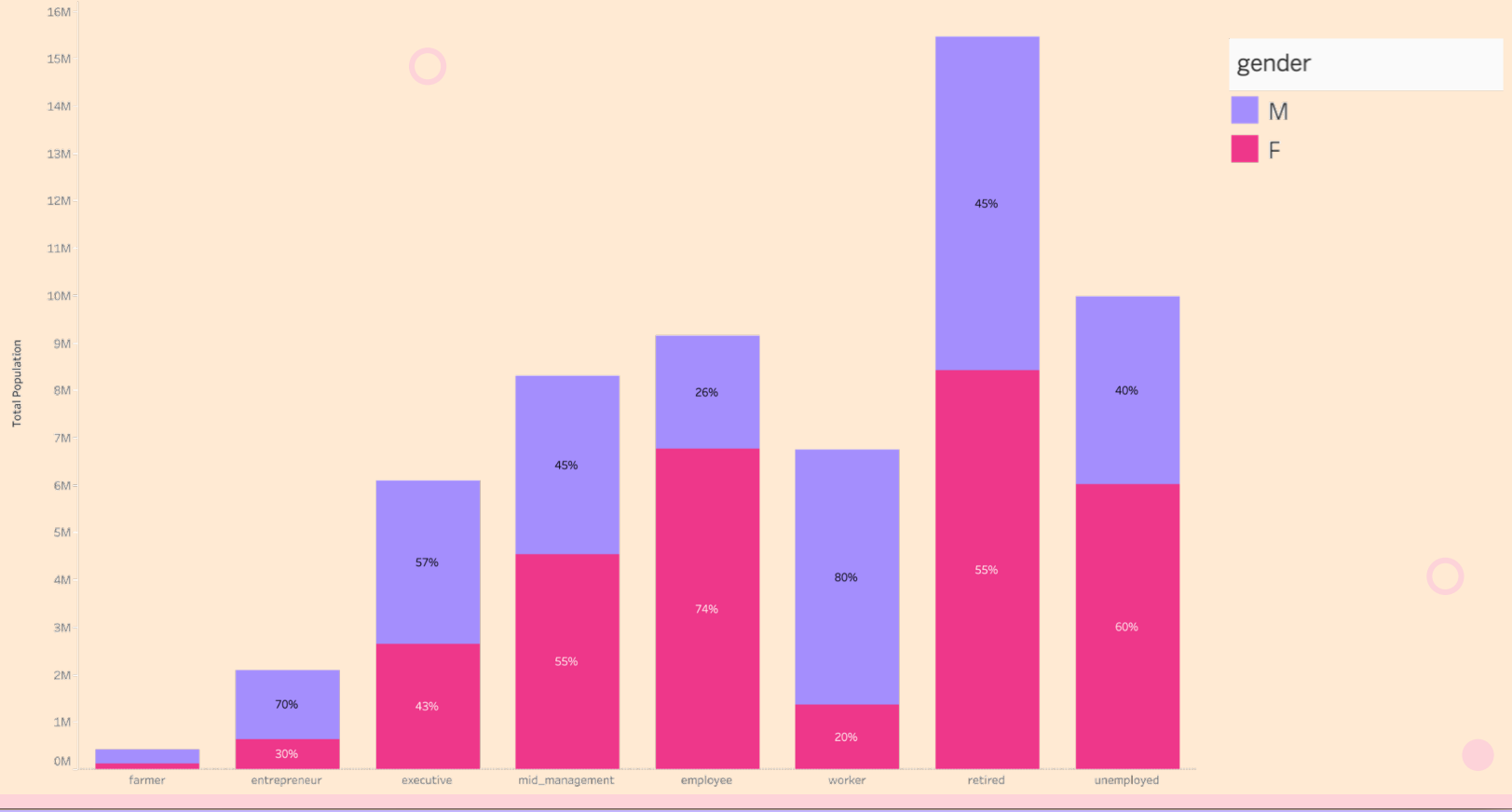
GENDER REPRESENTATION BY JOB CATEGORY

The joint calculation of these two measures provides information on whether **women are more represented in junior management** than in senior and middle management, thus pointing to an eventual **ceiling for women** to access higher-level management positions

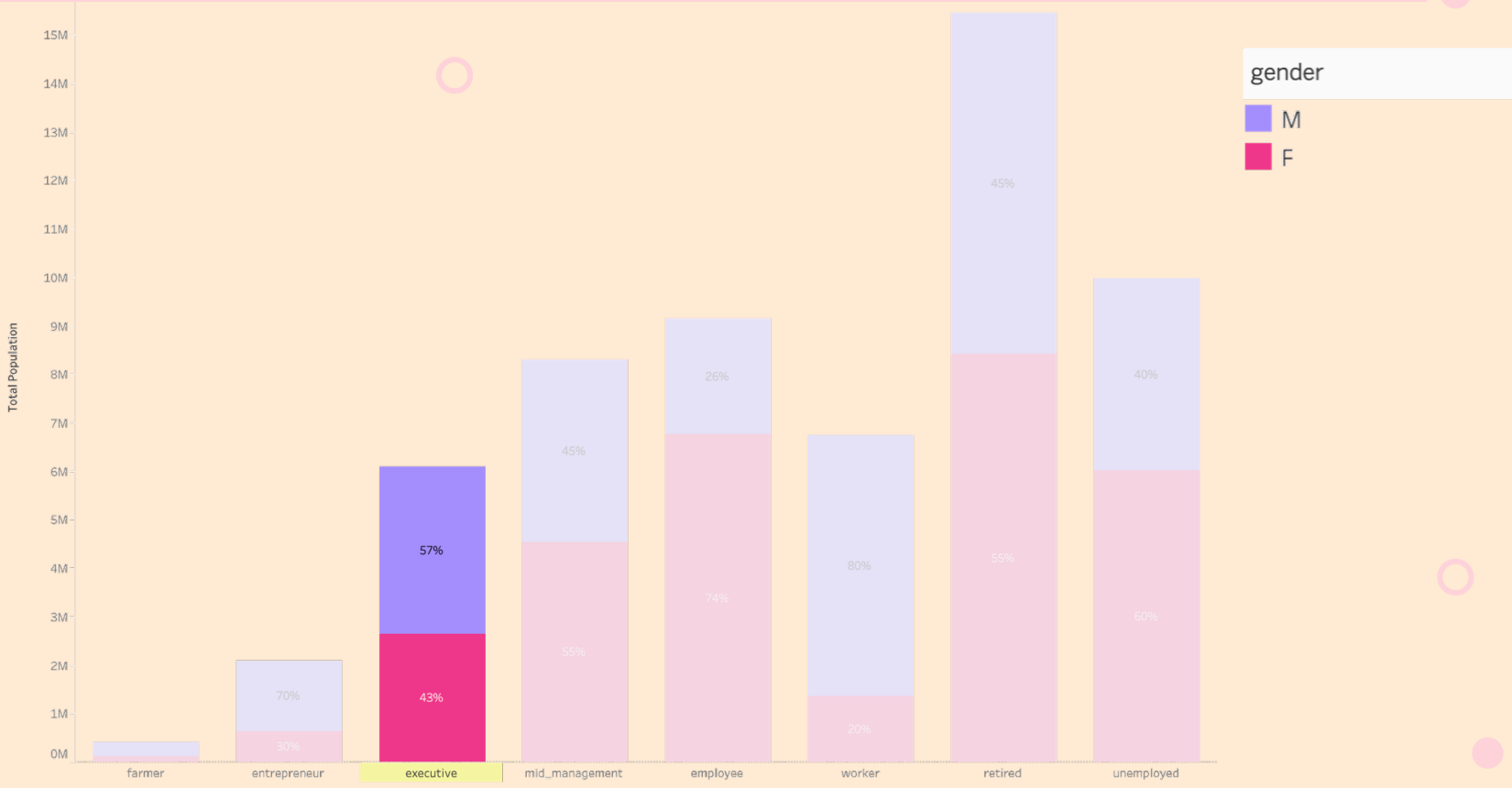
Proportion of woman in a managerial position

Year of Time Period	% Women In Managerial Positions	% Women In Senior Middle Management
2004	35,89	33,46
2005	37,60	36,37
2006	37,88	37,01
2007	37,83	36,46
2008	38,50	36,79
2009	38,09	37,37
2010	38,54	38,59
2011	39,34	39,13
2012	39,32	39,20
2013	36,00	35,58
2014	32,74	32,03
2015	31,66	30,93
2016	32,91	31,07
2017	33,44	32,64
2018	34,44	34,38
2019	34,67	34,30
2020	35,53	34,95
2021	37,79	36,77
2022	39,89	39,39

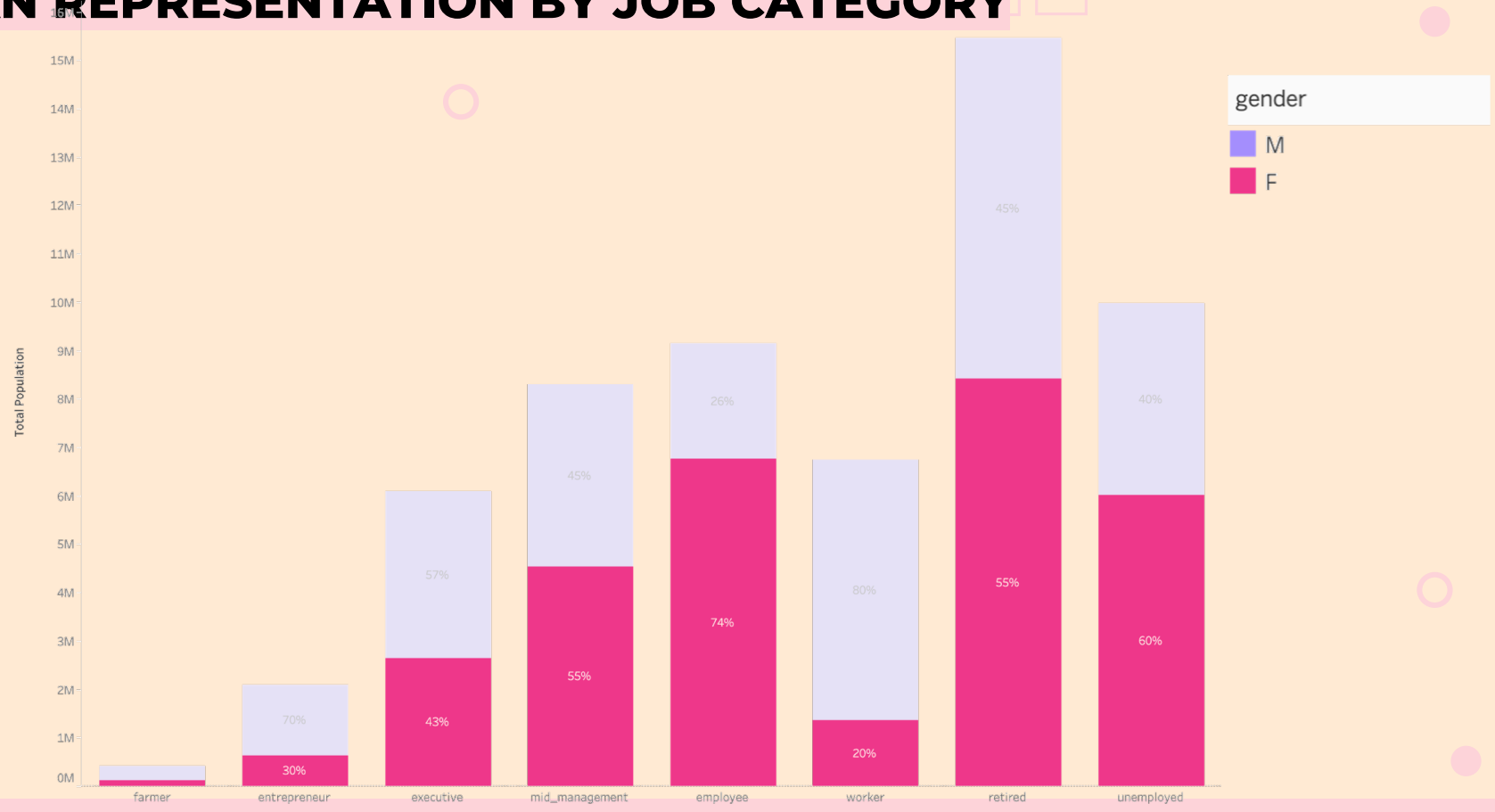
GENDER REPRESENTATION BY JOB CATEGORY



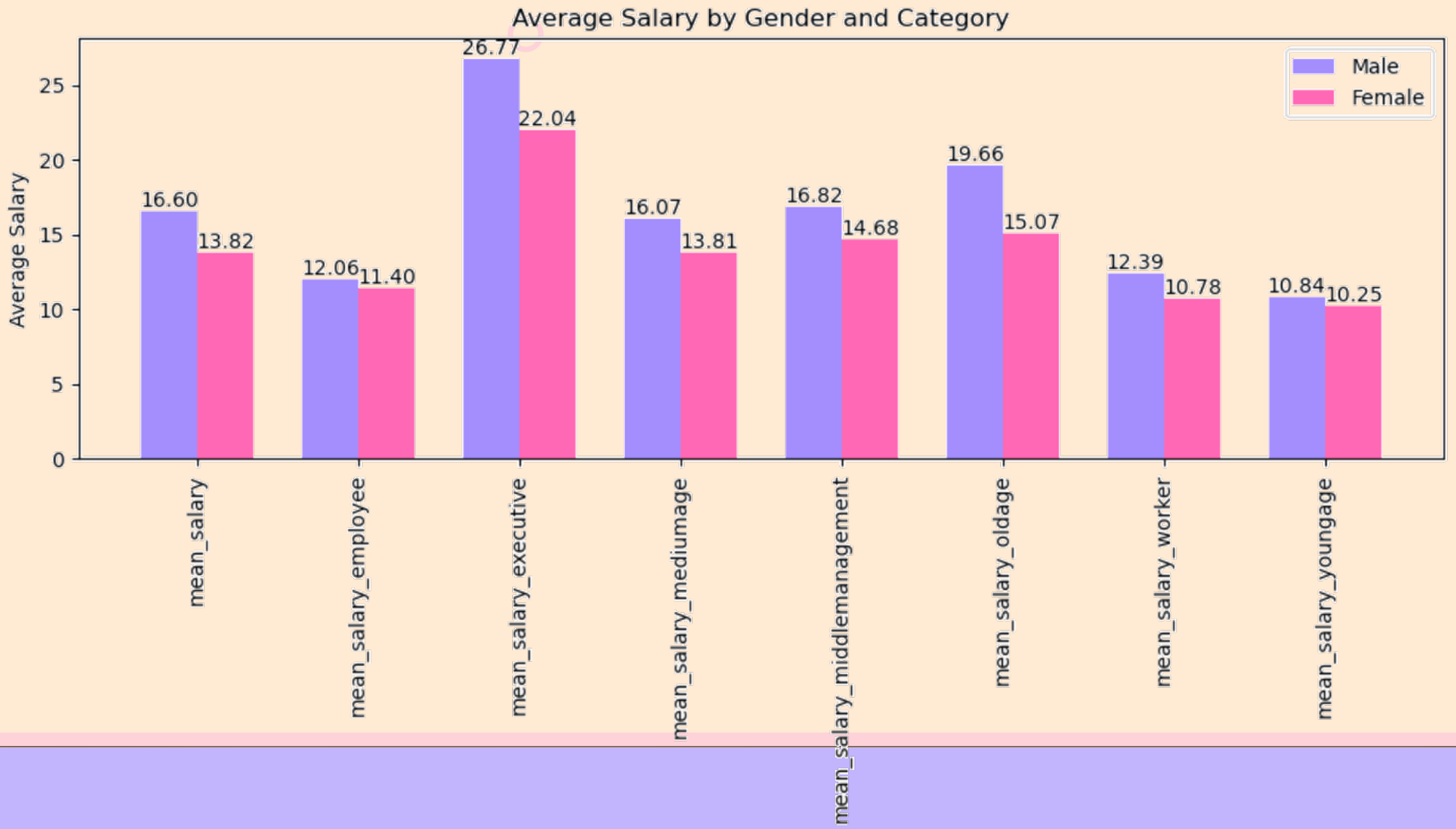
GENDER REPRESENTATION IN SENIOR MANAGERIAL POSITION



WOMAN REPRESENTATION BY JOB CATEGORY



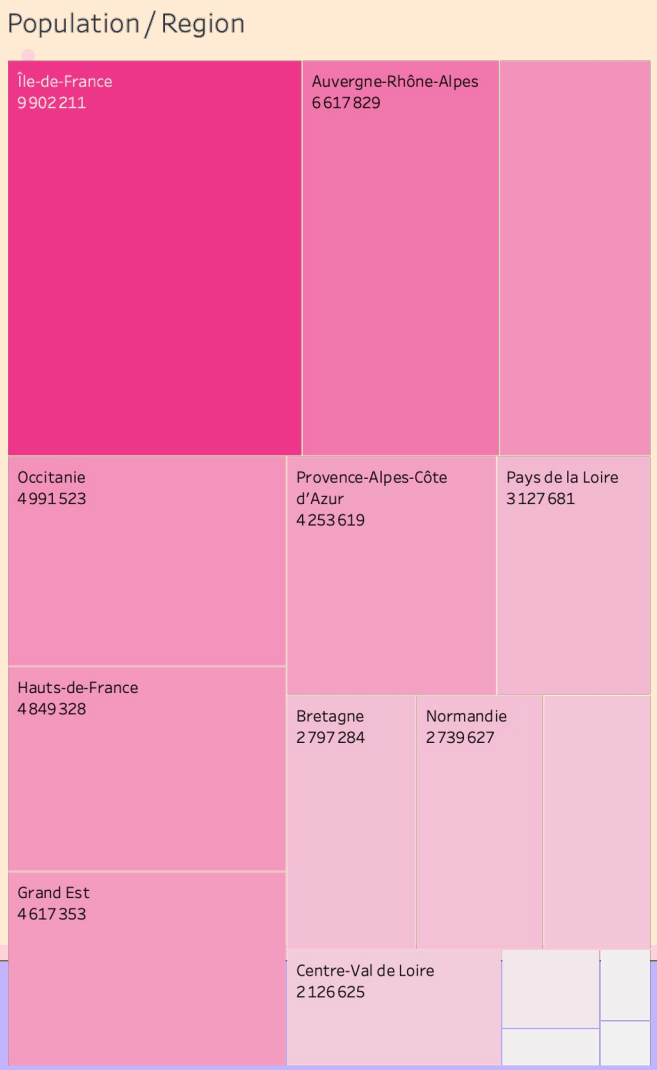
GENDER PAY GAP BY JOB CATEGORY

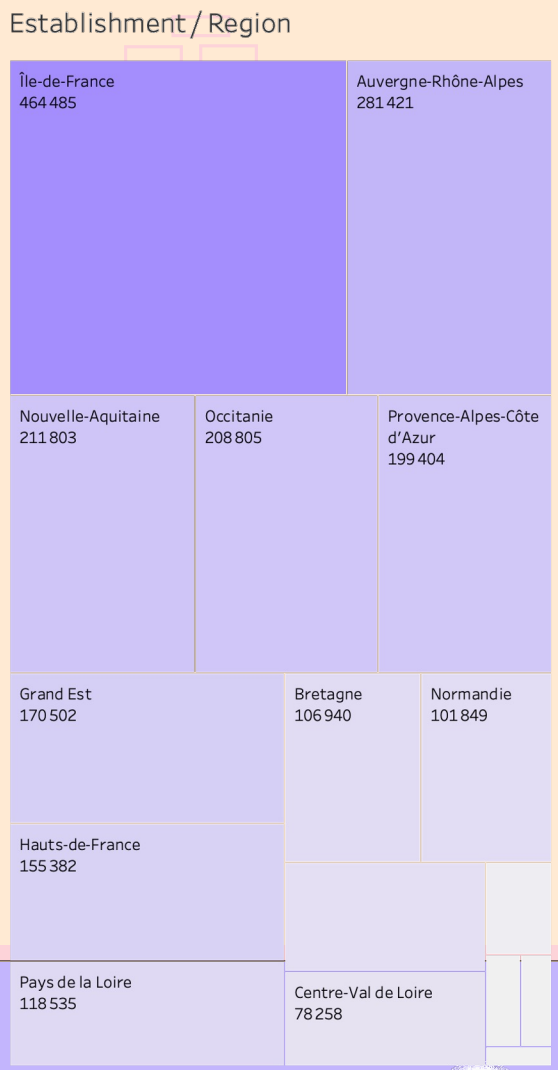


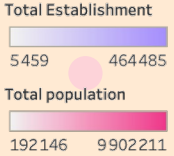
Population & establishment correlation

Pearson correlation =

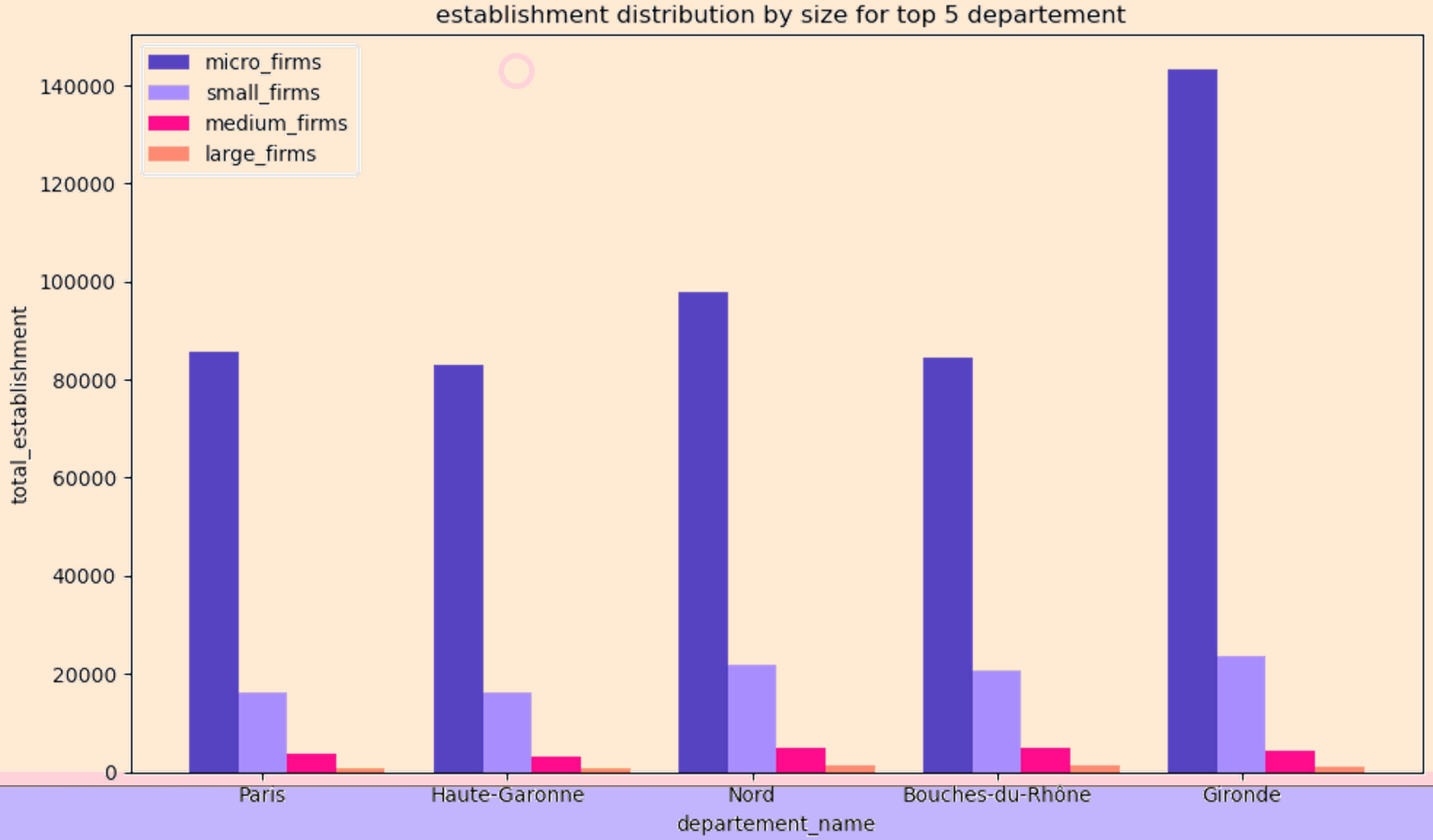
population_establishment_correlation
0.59





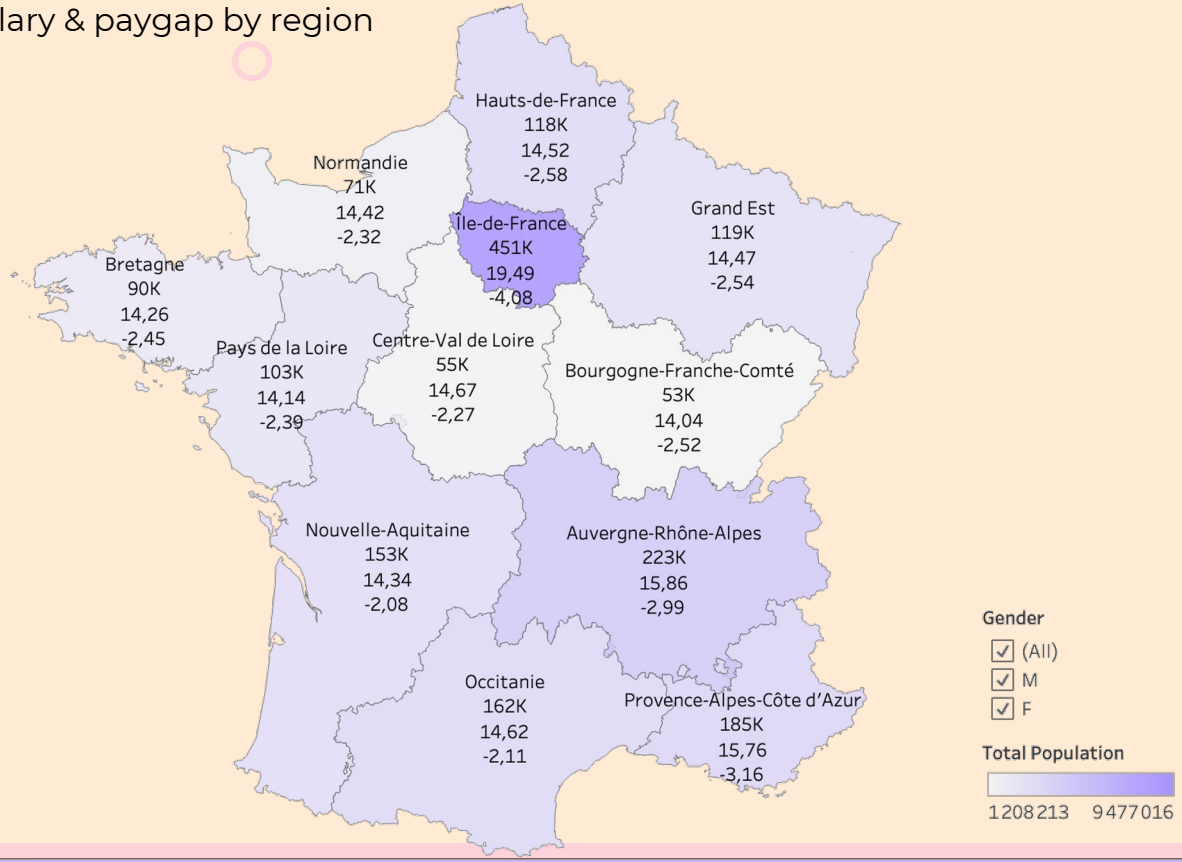


Population & establishment correlation



Regions most populated have a higher salary, but also a higher gender pay gap

Establishments, mean salary & paygap by region



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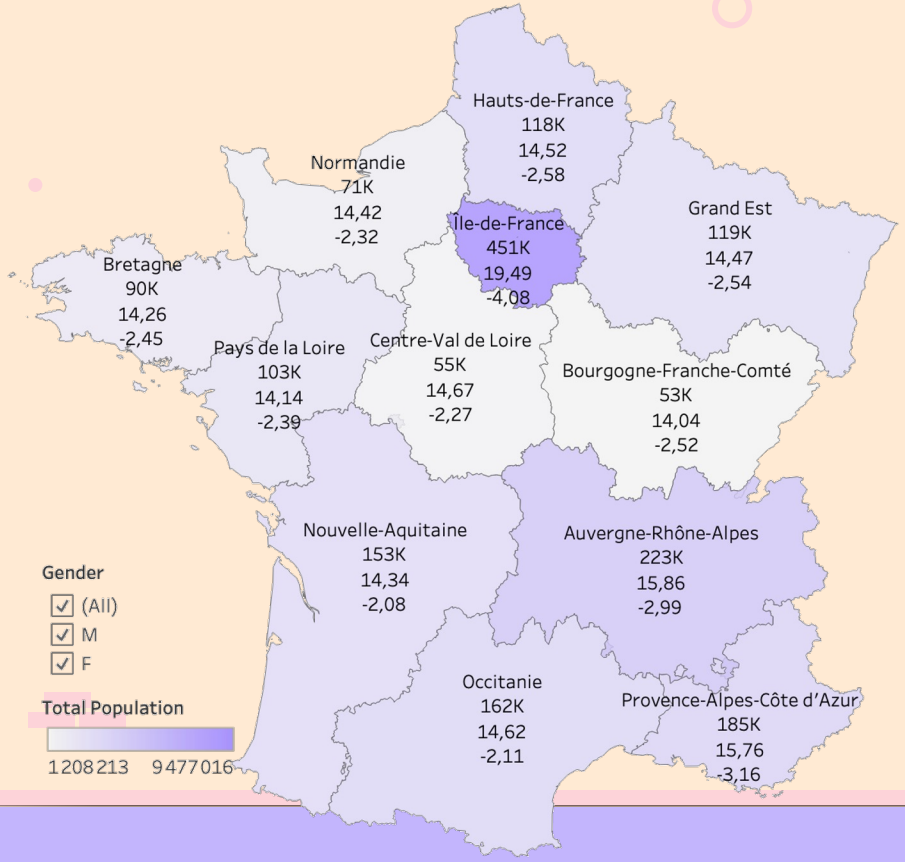
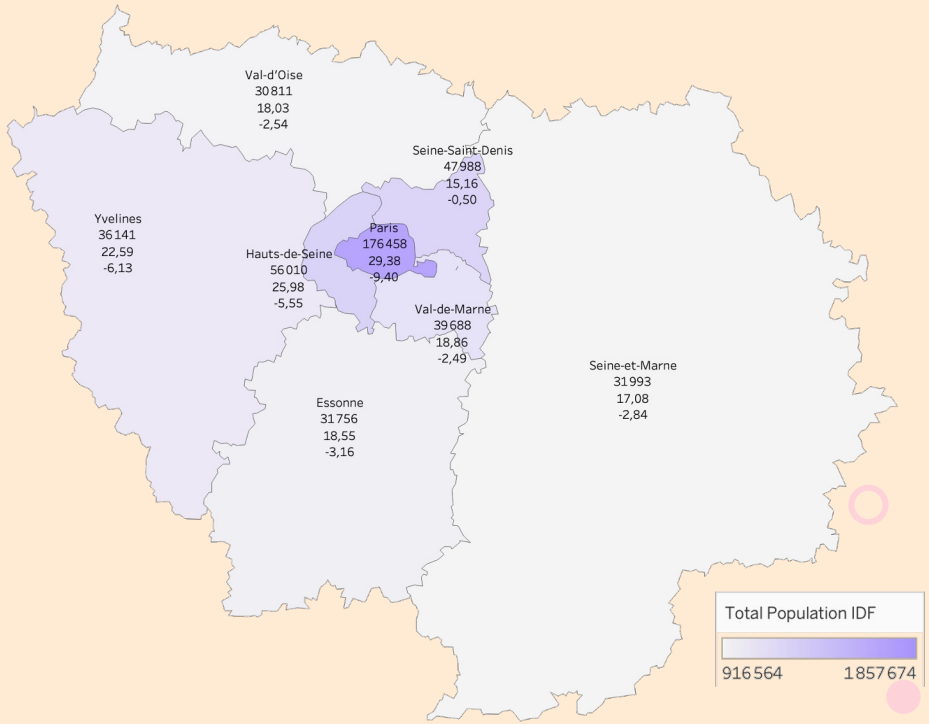


Establishments, mean salary & paygap in IDF



The pay gap is negative all over France

Top 10 – highest pay gap by department

code_departem...	departement_na...	avg_salary_male	avg_salary_female	avg_salary_all	gender_pay_gap
75	Paris	34.67	25.27	29.97	-9.4
78	Yvelines	25.65	19.52	22.59	-6.13
92	Hauts-de-Seine	28.78	23.22	26	-5.55
69	Rhône	20.43	16.16	18.3	-4.27
90	Territoire de Belfort	17.83	13.73	15.78	-4.11
31	Haute-Garonne	18.75	14.99	16.87	-3.76
13	Bouches-du-Rhône	18.53	14.76	16.64	-3.76
38	Isère	18.47	14.82	16.65	-3.65
73	Savoie	17.26	13.96	15.61	-3.3
68	Haut-Rhin	16.5	13.28	14.89	-3.22

Top 10 – lowest pay gap by department

code_departem...	departement_na...	avg_salary_male	avg_salary_female	avg_salary_all	gender_pay_gap
93	Seine-Saint-Denis	15.38	14.88	15.13	-0.5
23	Creuse	12.82	12.14	12.48	-0.68
48	Lozère	13.15	12.16	12.65	-0.99
974	La Réunion	13.89	12.77	13.33	-1.12
971	Guadeloupe	14.69	13.56	14.12	-1.12
973	Guyane	15.09	13.96	14.52	-1.13
79	Deux-Sèvres	14.64	13.19	13.91	-1.45
972	Martinique	15.09	13.64	14.36	-1.45
36	Indre	13.82	12.31	13.06	-1.51
24	Dordogne	13.98	12.4	13.19	-1.58

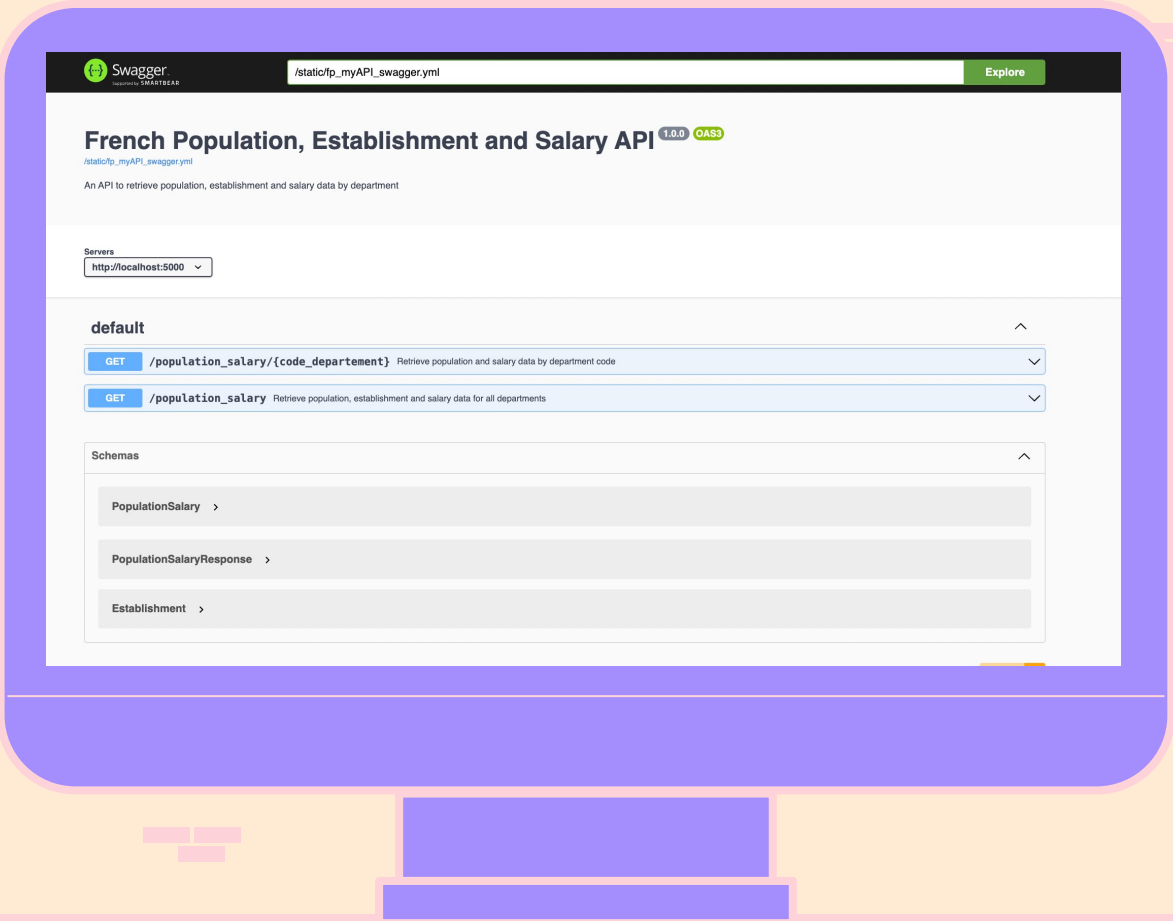
05

DATA DISPLAYING

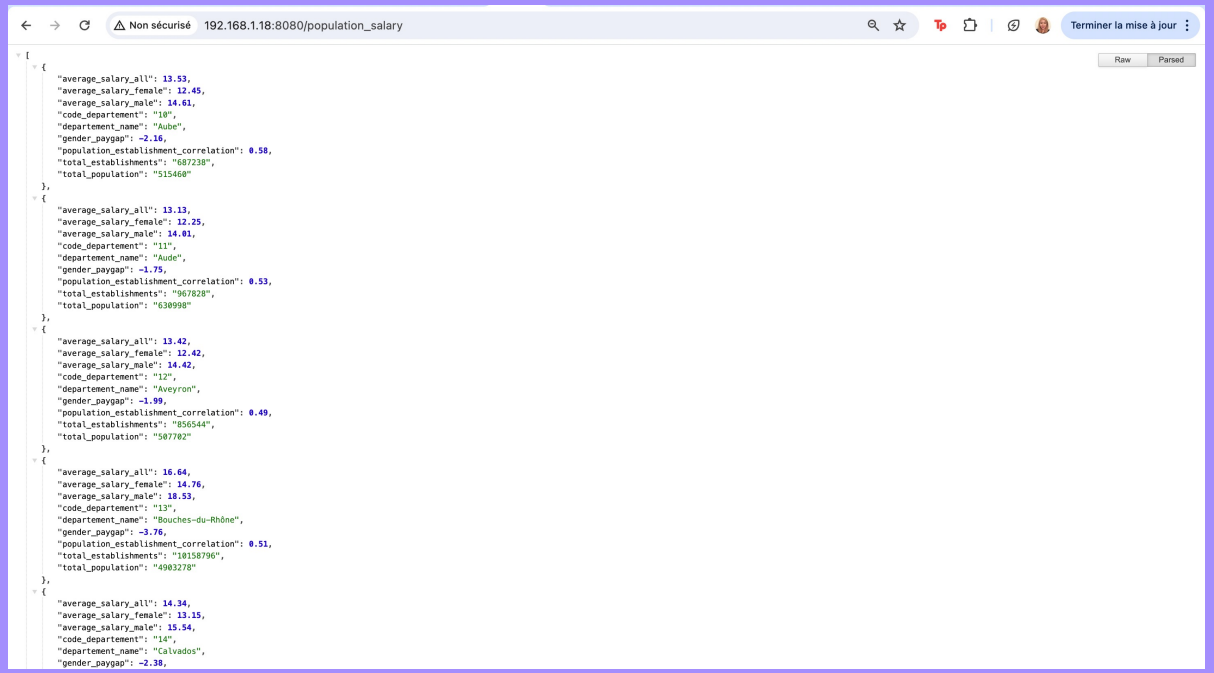
French Population, Establishments, and Salaries Insights API

SWAGGER

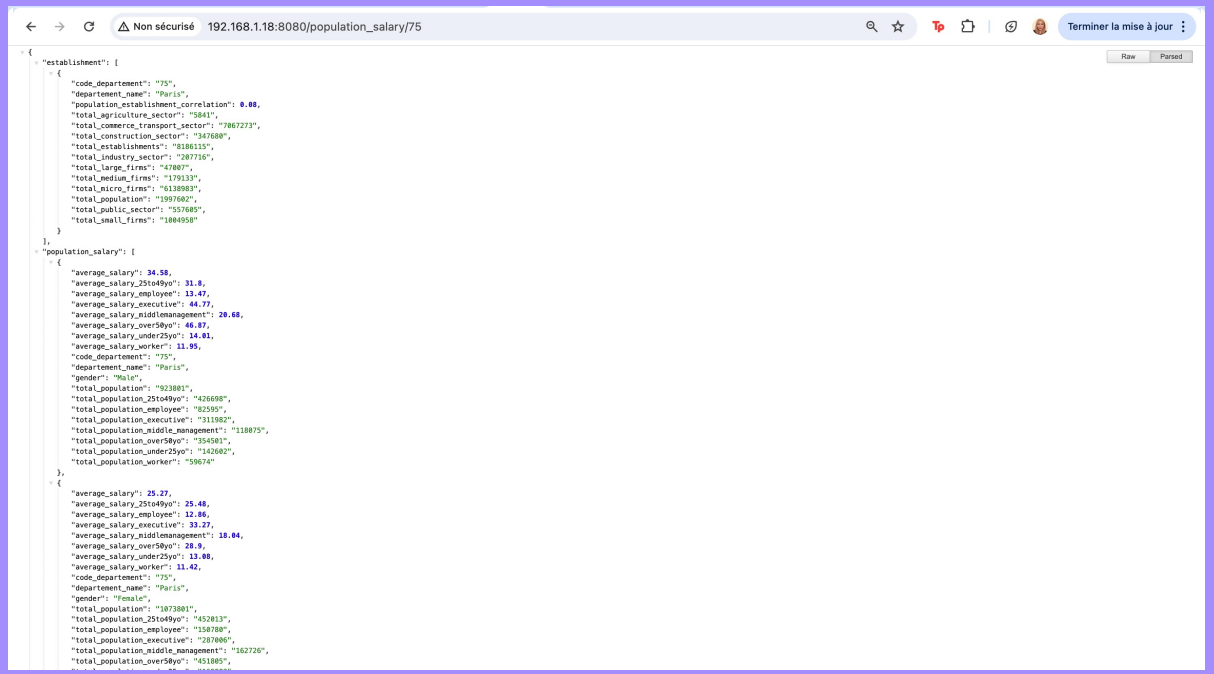
This Swagger documentation outlines the structure of the French Population, Establishments, and Salaries API



/population_salary



/population_salary/<code_department>



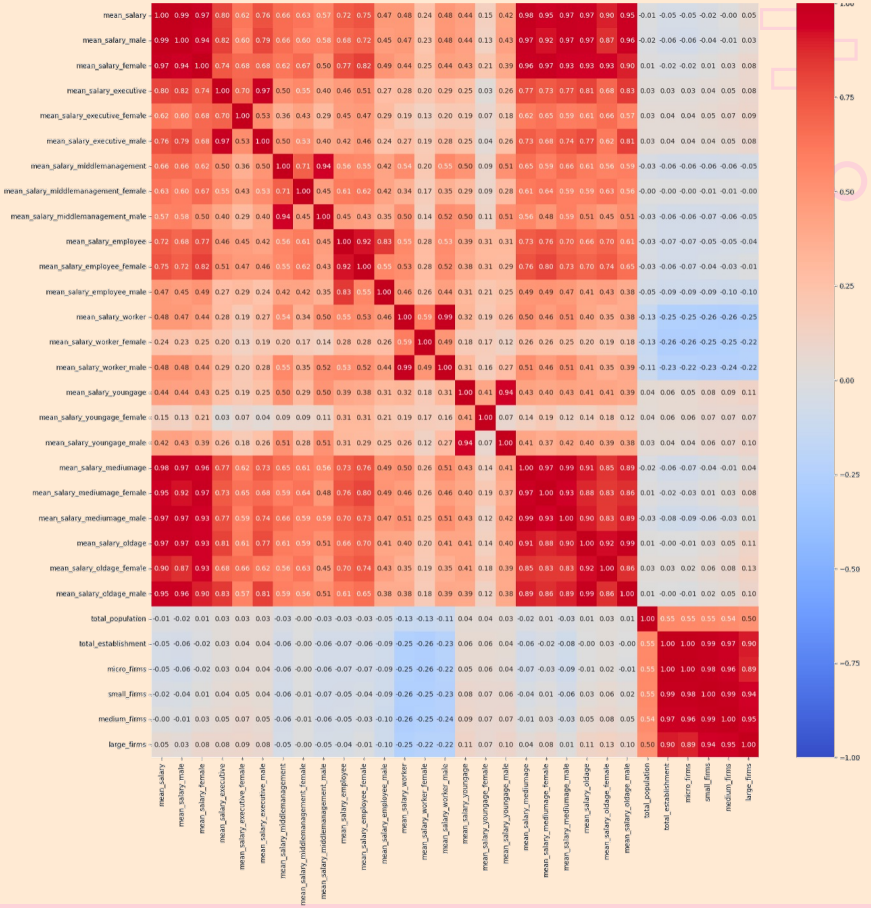
06

MACHINE LEARNING

Gender pay gap prediction within municipalities

Correlation Matrix

Heatmap visualization of feature correlations to note potential relationships between features



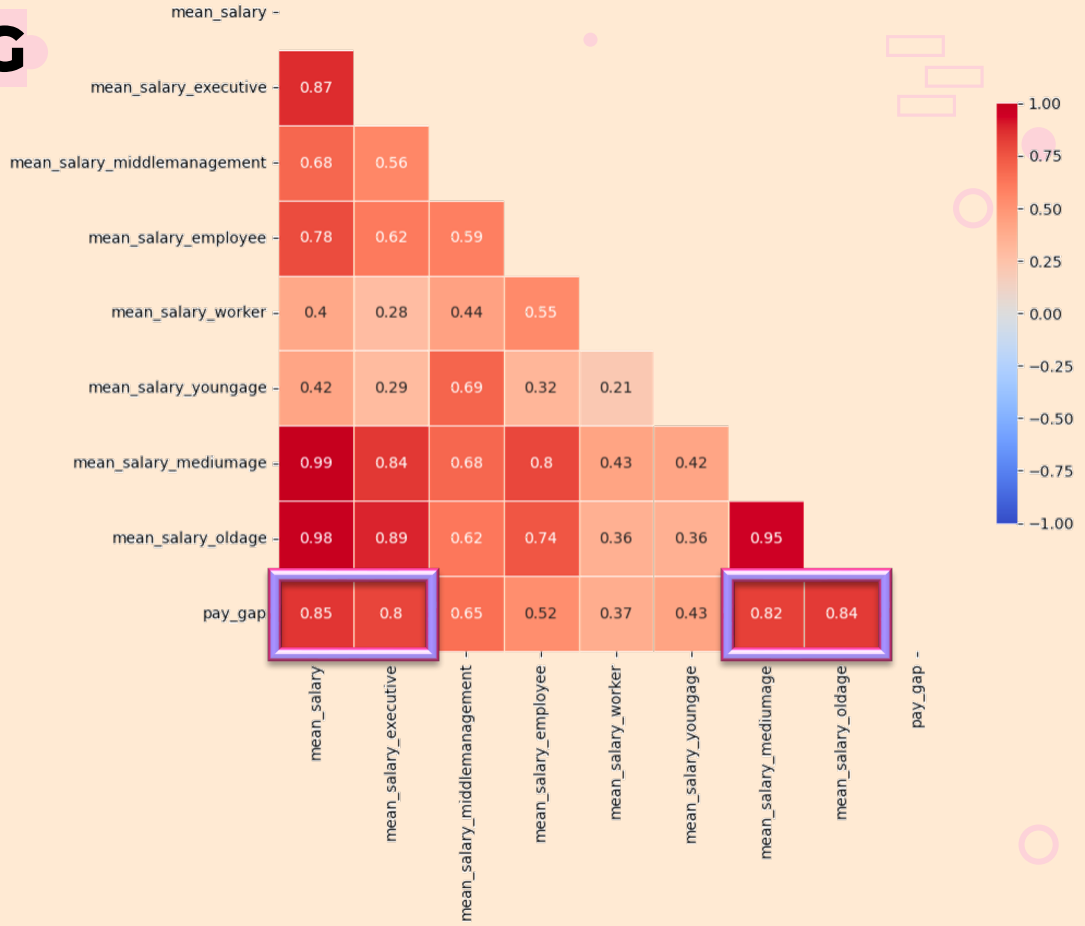
- Merged DataFrames **establishment, geography, salary_all** and **population** based on the CODGEO column
- Selected columns for creating the heatmap, including various mean salary categories, total population, and establishment sizes
- Calculated the correlation matrix between the selected variables

**salary_all = salary dataframe before normalization (male/female)

FEATURE ENGEENIRING

Features selection

Pay gap has a high correlation with the mean salary, the executive salary, and the middle and old age salaries.



MACHINE LEARNING OVERVIEW

Objective :	• Predict the **gender pay gap** within various communes
Target Variable :	• **Pay gap** defined as the **numerical** difference in mean salaries between genders
Regression Model Choice :	• Effective for predicting **numerical outcomes** with linear or combined linear relationships between input variables (features) and the output variable (target) • Our model will help analyze how different salary components, like mean salaries across various job categories and age groups, influence the gender pay gap
Model Selection :	• Random forest regressor • Bagging regressor with and without pasting • AdoBoost regressor

EVALUATION METRICS

AdaBoost Regressor

Hyperparameter Tuning

Random Search CV

MAE 0.507
RMSE 0.703
R2 score 0.778

Grid Search CV

MAE 0.511
RMSE 0.714
R2 score 0.771

Without HPT

MAE 0.509
RMSE 0.705
R2 score 0.777

EVALUATION METRICS

Without HPT

Random Forest

MAE 0.516
RMSE 0.711
R2 score 0.773

Bagging

MAE 0.530
RMSE 0.724
R2 score 0.765

Bagging w/ pasting

MAE 0.528
RMSE 0.725
R2 score 0.764

EVALUATION METRICS

AdaBoost Regressor

Hyperparameter Tuning

Random Search CV

MAE 0.507
RMSE 0.703
R2 score 0.778

Best parameters :

- n_estimators: **1200**
- max_leaf_nodes: **2166**
- max_depth: **90**

07

CHALLENGES | NEXT STEPS

THANKS!

DO YOU HAVE ANY QUESTIONS?

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