

# What factors influence the apparition of pathologies?

**BRFSS 2020** 





# Data cleaning and preparation of the dataset on Python

### **Before cleaning**

- **401 957** rows
- **279** columns

	_STATE	FMONTH	IDATE	IMONTH	IDAY	IYEAR	DISPCODE	SEQNO
0	1.0	1.0	1042020	1	4	2020	1100.0	2020000001
1	1.0	1.0	2072020	2	7	2020	1200.0	2020000002
2	1.0	1.0	1232020	1	23	2020	1100.0	2020000003
3	1.0	1.0	1092020	1	9	2020	1100.0	2020000004
4	1.0	1.0	1042020	1	4	2020	1100.0	2020000005

### **After cleaning**

- **245 992** rows (38% of the initial dataset)
- 44 columns, including 11 variables to explain

ID	age	sex	marital_status	race	education_level	employment	household_income
1	55- 64 years	Female	Divorced	White	College graduate	Out of work less than 1 year	< \\$10,000
2	65- 79 years	Male	Separated	White	High school graduate	Unable to work	\\$25,000 - \\$35,000
3	65- 79 years	Female	Married	White	High school graduate	Retired	\\$35,000 - \\$50,000



### **Dashboard**

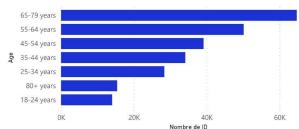




### An unbalanced population on some points

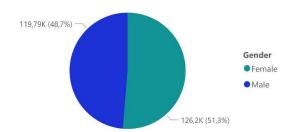
### **PROFILE OF RESPONDENTS**

#### Age distribution of respondents

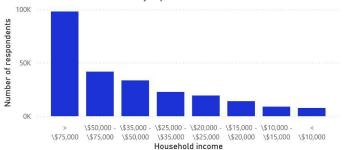


1,19
Mean of disease count

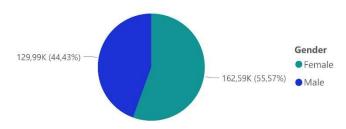
#### Gender distribution of respondents



#### Household income distribution by repondents



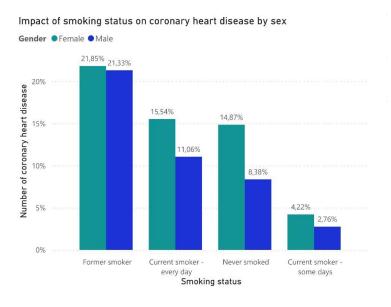
### Repartition of individuals with diseases by gender



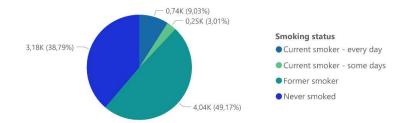


# Smoking status: formers smoker are the most affected by disease

### **HEART DISEASE OVERVIEW**

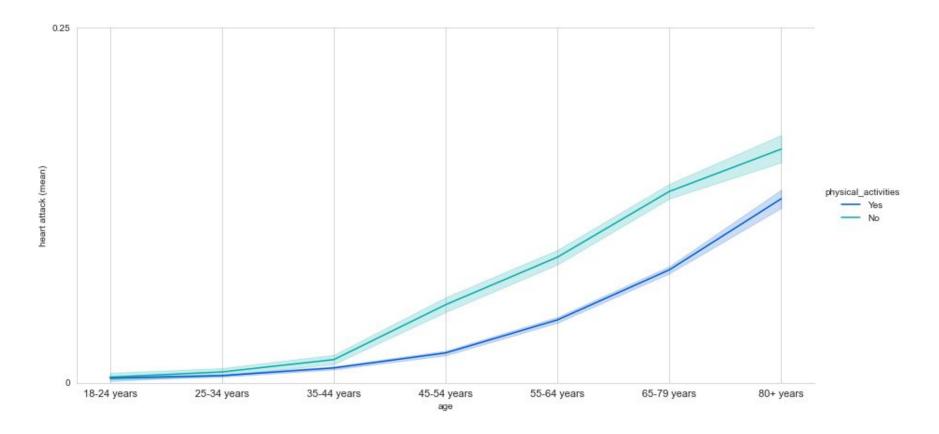


#### Smoking profiles among individuals with heart attacks (+65)





# Impact of physical activities on heart attacks across the life

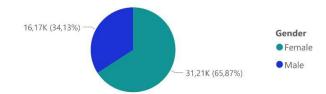




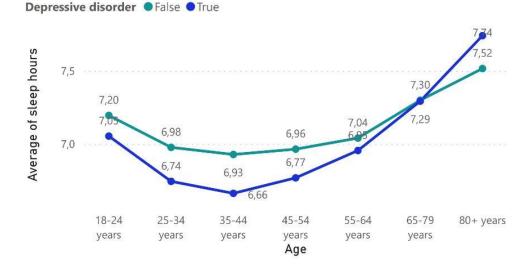
### Depressive disorder impacted by demographic factors

### **DEPRESSIVE DISORDER OVERVIEW**

#### Gender distribution among individuals with depressive disorder



### Average sleep hours by depressive disorder and age



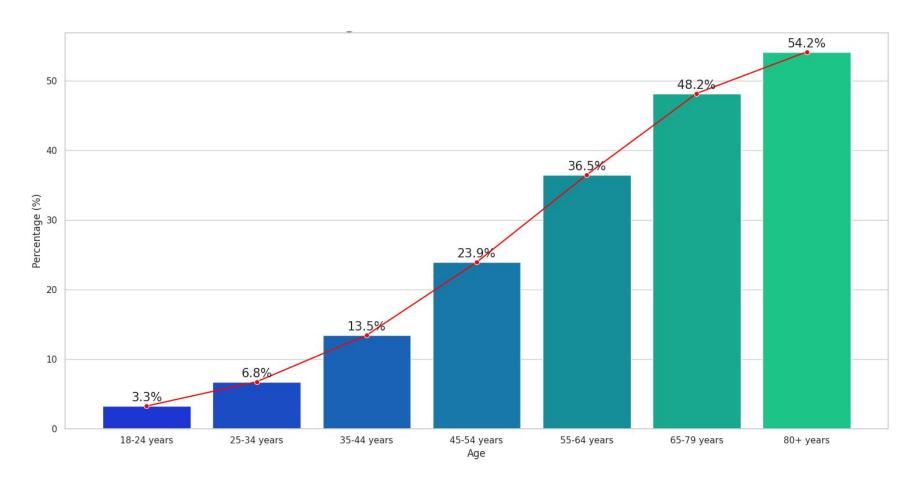


To go further...



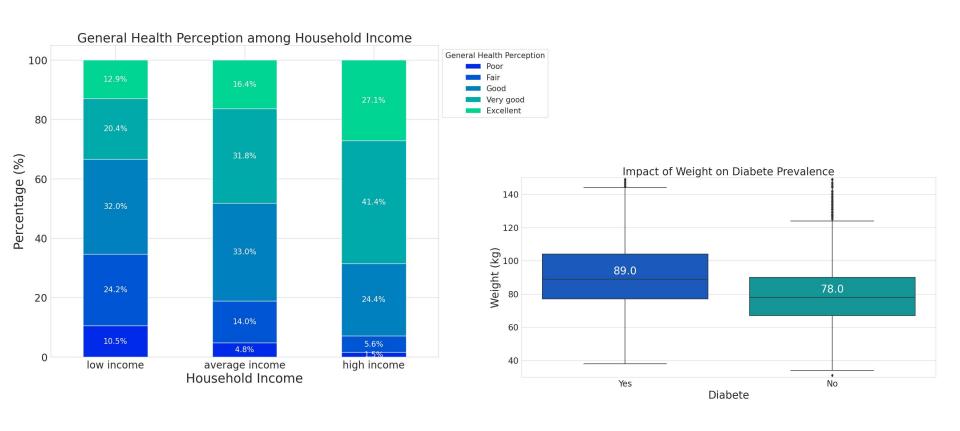


### Evolution of arthritis across the life



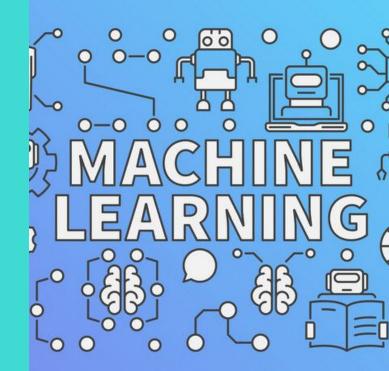


### Others factors: household income and weight



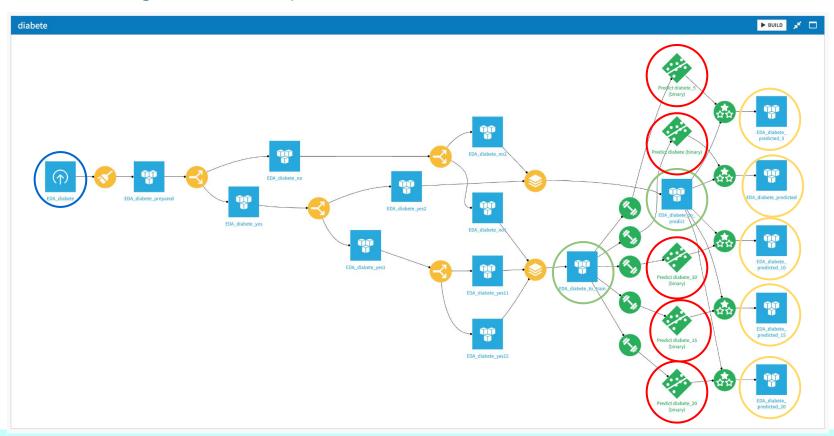


# **Machine learning**





# Machine learning Predicting the Development of Diabetes





We are choosing the F1 score as our metric, a higher F1 score indicates a more effective model, useful for our objective : minimizing the rate of false negatives

Disease	Model	F1 Score	Feature Handling	Number of Records (k)	Predict Score (%)
chronic obstructive pulmonary disease	LightGBM	80	TOP 15	18	76,2
kidney disease	Gradient Boosted Trees	76	TOP 15	8,8	64
diabète	LightGBM	78	TOP 20	31,6	87,8
depressive_disorder	LightGBM	77	TOP 15	47,2	72,5
skin cancer	<b>Gradient Boosted Trees</b>	75	TOP 20	22,8	57,9
asthma	Random forest	67	TOP 5	32,4	73,3
heart attack	<b>Gradient Boosted Trees</b>	80	TOP 10	12,6	79,4
stroke	<b>Gradient Boosted Trees</b>	77	TOP 5	8,7	64,1
arthritis	Logistic Regression	76	TOP 15	74	67,6
all type cancer	<b>Gradient Boosted Trees</b>	74	TOP 15	22	55
coronary heart disease	Logistic Regression	82	TOP 10	13,6	78,7



## Conclusion

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- Correlations between lifestyle habits and diseases :
  - Smoking with cardiovascular and pulmonary pathologies.
  - Women are more prone to depression than men.
  - Arthritis is deeply linked to age.
  - Weight plays a role in the onset of diabetes.



# Any questions?

