LIFE QUALITY AND OVERPOPULATION

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Problem

The world population has been noticeably growing during the last decades, as a consequence, the equilibrium of the environment has been significantly disrupted affecting the quality of life.

- Understanding the behavior of people in different countries, could allow us:

➡ To know, for example, how flights or meat consumption could be impacting the quality of life in different countries.

➡ To look at how could we decrease the human impact on the environment.

Goal

➡ To look at how human behavior (e.g., meat consumption or travels/flights) increases or decreases their happiness.

Questions

➡ How features like the population, meat consumption, flights, life expectancy, happiness, and generosity can be interpreted in terms of the pollution (CO_2 emission) ?

➡ How are these quantities compared by country?

Cleaned data

CO2 emission in

Beef consumption in

	co2_1	co2_2	co2_3	co2_4	co2_5	Beef1	Beef2	Beef3	Beef4	Beef5	...	trust_1	trust_2	trust_3	trust_4
0	192.366	190.930	187.416	190.930	190.930	2528.688000	2417.000000	2608.530998	2608.316551	2584.341559	...	0.08484	0.07296	0.059740	0.054
1	401.555	411.032	415.097	411.032	411.032	674.528526	765.779532	737.115489	730.567972	729.569784	...	0.35637	0.32331	0.301184	0.302
2	72.835	75.857	80.324	75.857	75.857	204.000000	204.000000	204.100723	201.228504	200.364477	...	0.12569	0.12583	0.123718	0.144
3	495.214	478.443	484.588	478.443	478.443	7602.828979	7682.368664	7987.269937	8033.591780	8000.274932	...	0.17521	0.14166	0.111093	0.088
4	575.907	564.033	572.834	564.033	564.033	856.407049	900.375632	960.562971	961.037544	974.517333	...	0.32957	0.31329	0.287372	0.291

5 rows × 40 columns

Trust

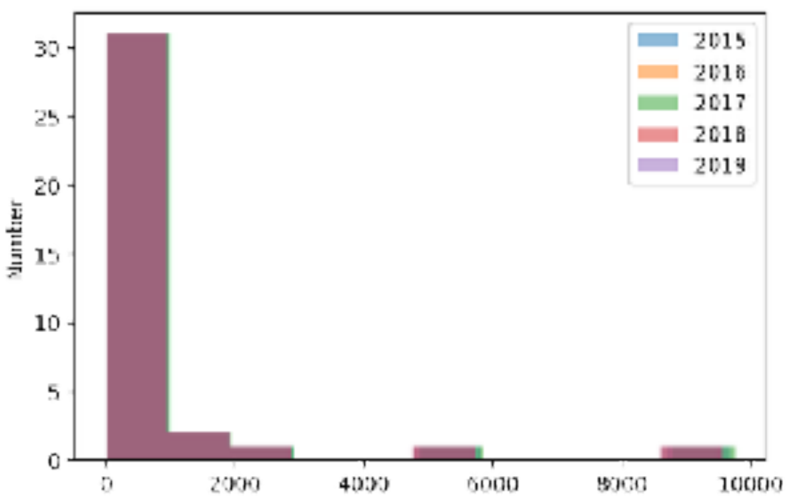
Health

trust_5	health_1	health_2	health_3	health_4	health_5
0.050	0.78723	0.69711	0.695137	0.744	0.881
0.290	0.93156	0.85120	0.843887	0.910	1.036
0.143	0.60164	0.52989	0.533241	0.579	0.723
0.086	0.69702	0.61415	0.616552	0.675	0.802
0.308	0.90563	0.82760	0.834558	0.896	1.039

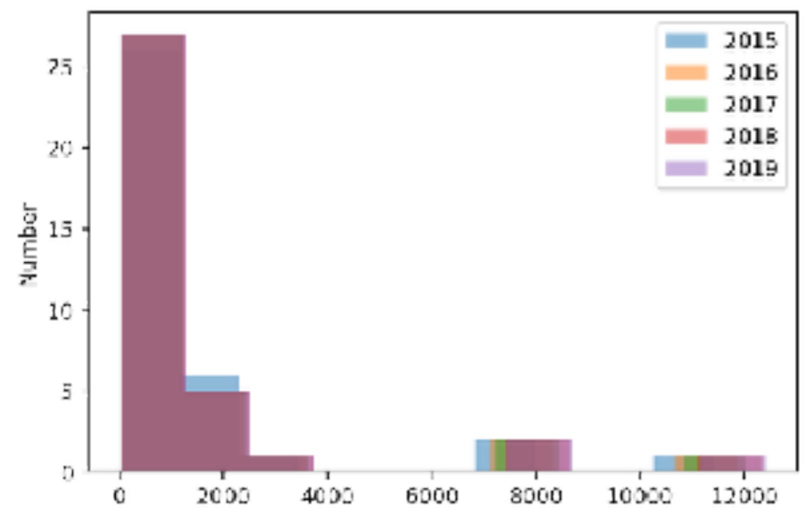
Each observation correspond to a country around the world.

Analysis

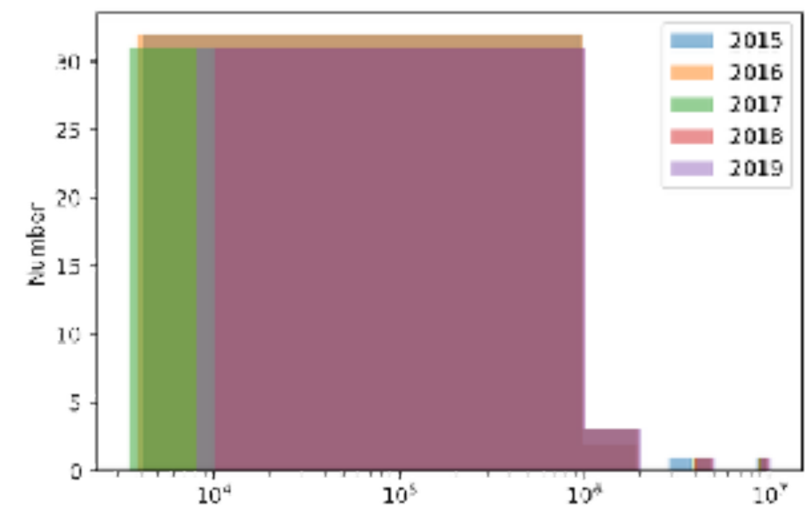
- On average, there is not significative differences during 2015, 2016, 2017, 2018 and 2019.



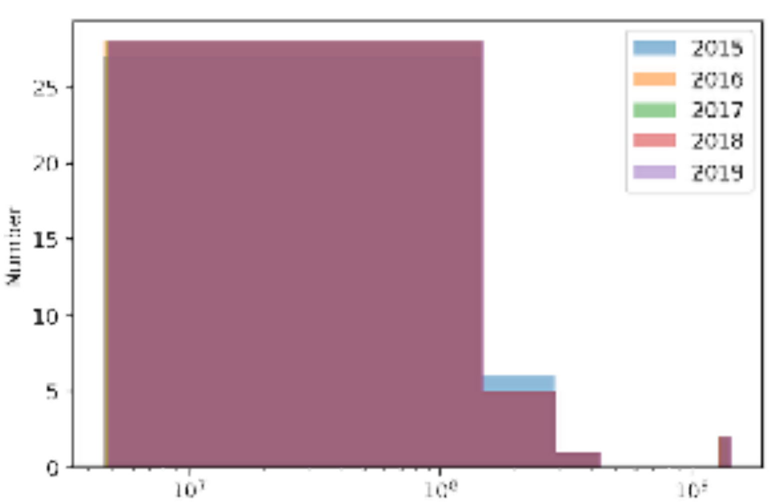
CO2



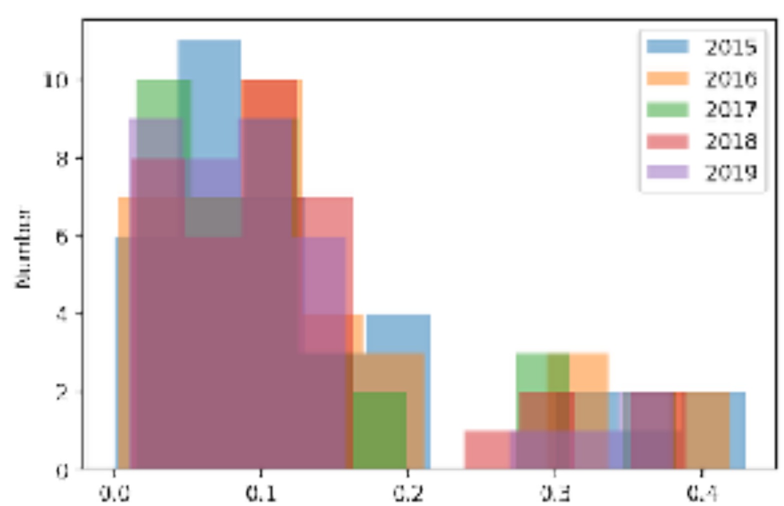
Beef [thousand tonnes]



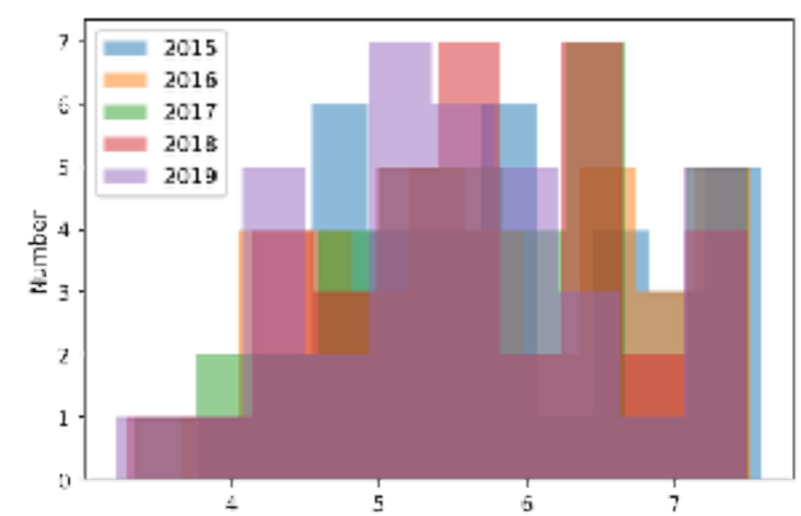
Number of flights



Population



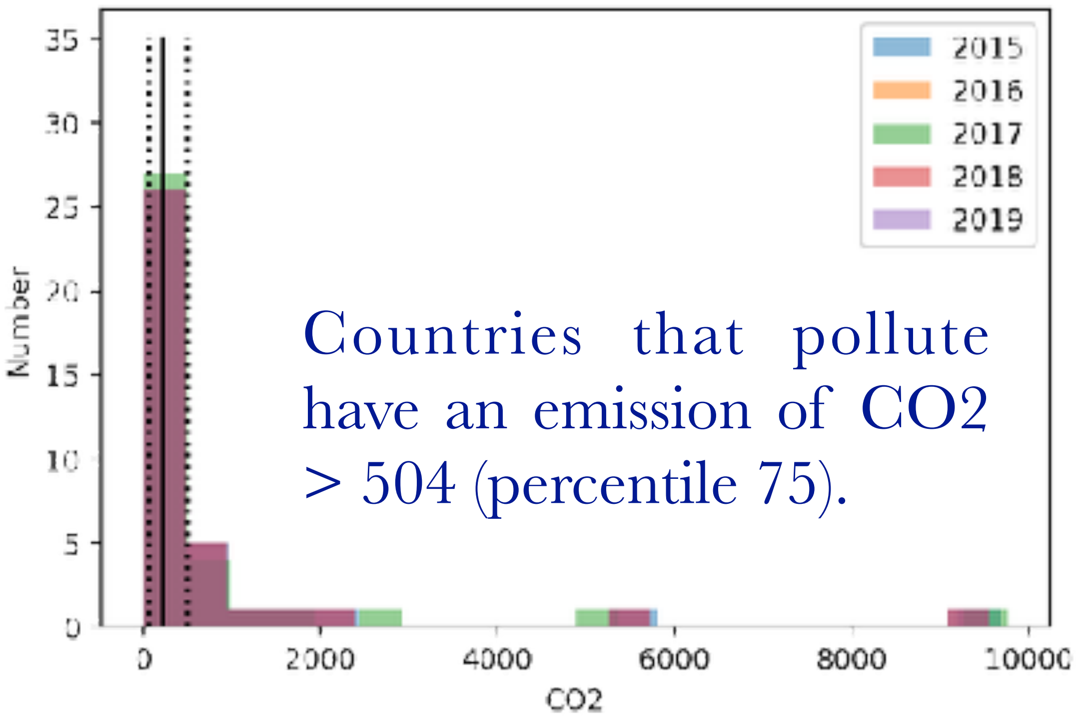
Trust



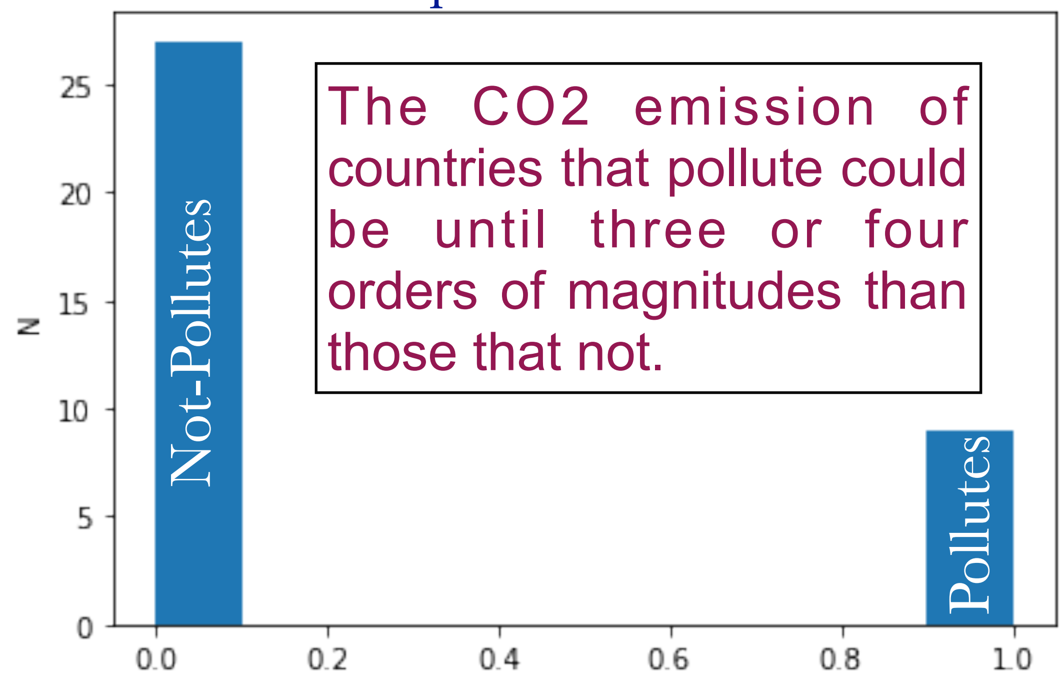
Happiness

Data for modeling

CO2 distribution in the world



Dependent variable



Features

Data for 2015

36 observations in total

	Beef5	Dep5	pop_5	hap_5	eco_5	trust_5	health_5
0	974.517333	1215983.0	3.741100e+07	7.278	1.365	0.308	1.039
1	8517.757172	4963752.0	1.433784e+09	5.191	1.029	0.100	0.893
2	741.288517	808265.0	2.706260e+08	5.192	0.931	0.028	0.660
3	1026.711652	1209803.0	1.366418e+09	4.015	0.755	0.085	0.588
4	392.323650	186006.0	8.291400e+07	4.548	1.100	0.125	0.785

Each observation correspond to a country around the world.

Countries: Argentina, Australia, Bangladesh, Brazil, Canada, Switzerland, Chile, China, Colombia, Algeria, Egypt, Ethiopia, Ghana, Indonesia, India, Iran, Israel, Japan, Kazakhstan, Mexico, Malaysia, Nigeria, New Zealand, Pakistan, Peru, Philippines, Paraguay, Russia, Saudi Arabia, Thailand, Turkey, Tanzania, Ukraine, Unite States, Vietnam, South Africa.

Modelling

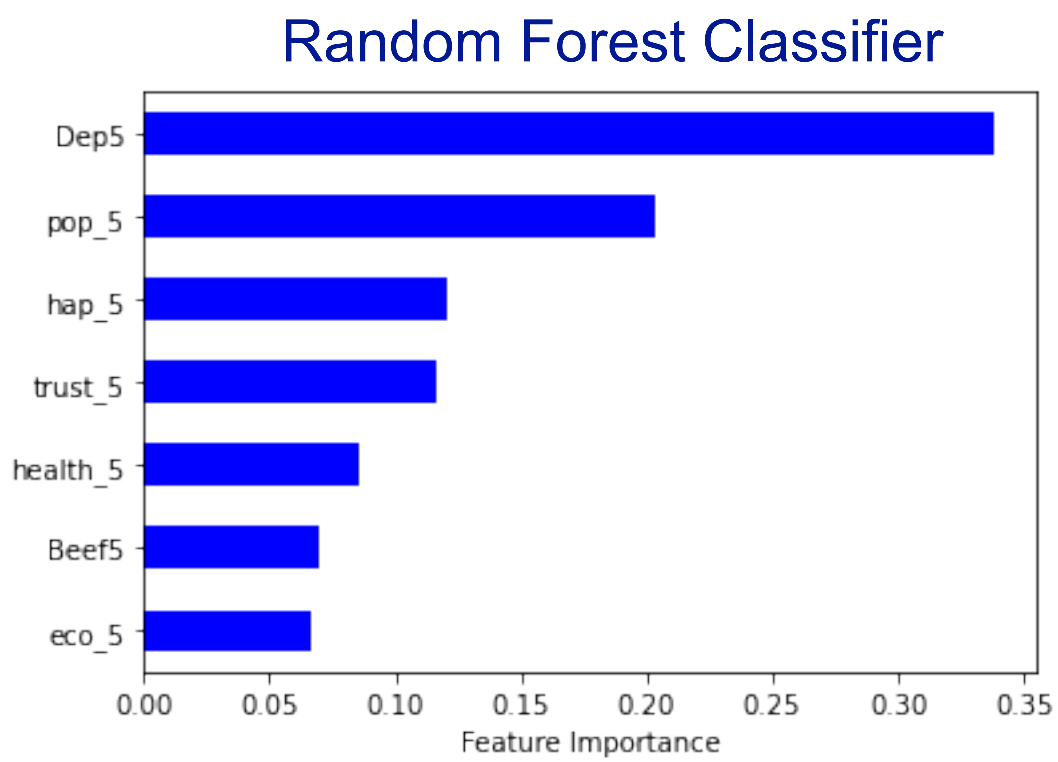
- Machine learning classification models

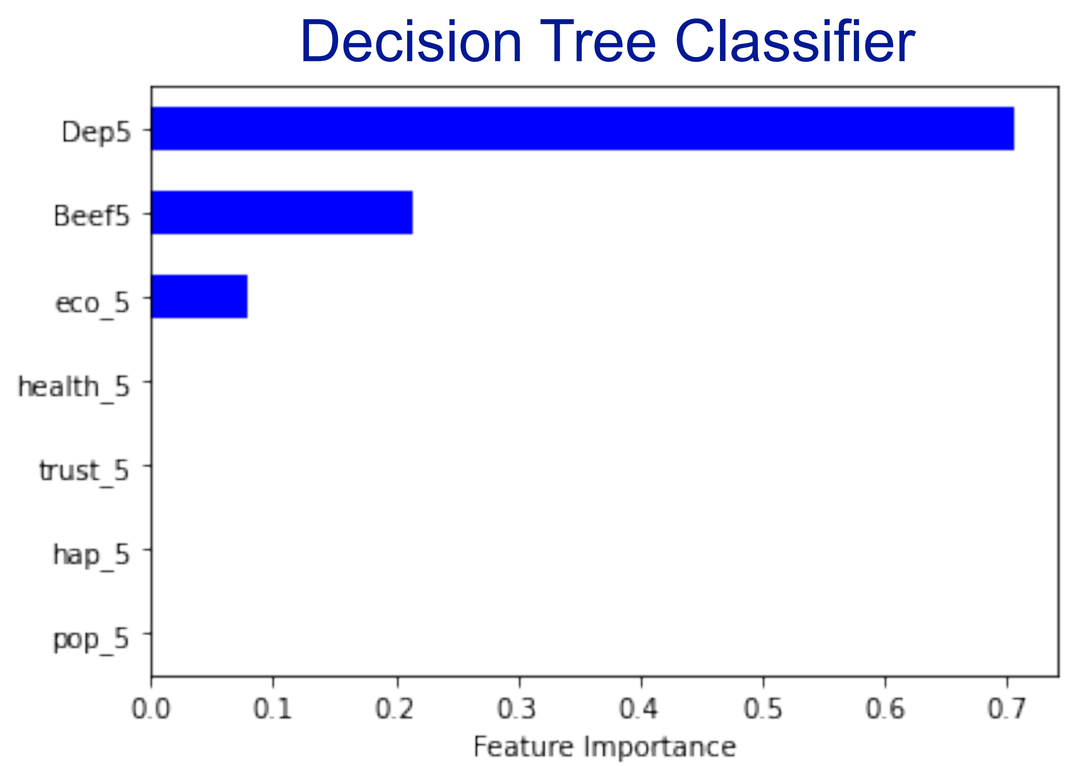
```
algos_Class = []
algos_Class.append(('Random Forest Classifier', rf))
algos_Class.append(('Decision Tree Classifier', dtree))
algos_Class.append(('GradientBoostingClassifier', gradientb))
```

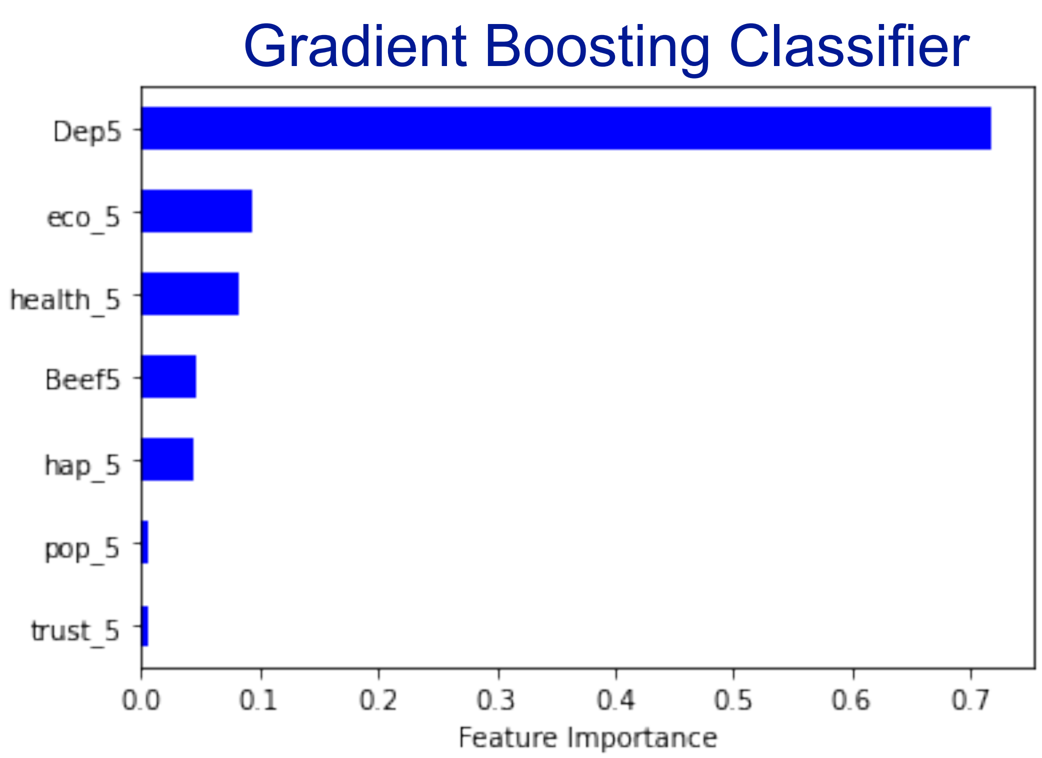
- Accuracy comparison

  - Random Forest Classifier: 86%
  - Decision Tree Classifier: 84%
  - Gradient Boosting Classifier: 89%

Feature importances







Accuracy

Random Forest Classifier

	precision	recall	f1-score	support
0	0.89	1.00	0.94	8
1	1.00	0.67	0.80	3
accuracy			0.91	11
macro avg	0.94	0.83	0.87	11
weighted avg	0.92	0.91	0.90	11

Decision Tree Classifier

	precision	recall	f1-score	support
0	1.00	0.75	0.86	8
1	0.60	1.00	0.75	3
accuracy			0.82	11
macro avg	0.80	0.88	0.80	11
weighted avg	0.89	0.82	0.83	11

Gradient Boosting Classifier

	precision	recall	f1-score	support
0	1.00	0.75	0.86	8
1	0.60	1.00	0.75	3
accuracy			0.82	11
macro avg	0.80	0.88	0.80	11
weighted avg	0.89	0.82	0.83	11

Confusion Matrix

Random Forest Classifier

Actual Predicted	Not Default	Default
Not Default	8	0
Default	1	2

Decision Tree Classifier

Actual Predicted	Not Default	Default
Not Default	5	2
Default	0	3

Gradient Boosting Classifier

Actual Predicted	Not Default	Default
Not Default	5	2
Default	0	3

Choosing the RF classifier we found:

- There is a group of countries that pollutes when the number of departures per year is > =746218 flights.

- There is another group that despite having a low number of departures (<=300951) also pollutes. Therefore, it is likely that in this case the pollution is being produced for another source.

- For example, the model predicts that countries with a beef consumption >= 608000 tonnes per year pollute.

- Curiously, the model predicts that countries that do not pollute tend to have a higher happiness index than those that pollute.

Conclusion and recommendation

- Pollution (CO_2 emission) affects the levels of happiness in the countries studied.

Therefore…

- It is recommended that countries look for their sources of CO_2 emission (as also other greenhouses gases), measure their emissions, and control the maximum levels that allow having a healthy environment.

- A healthy environment makes people happier and, therefore, could impact positively in their production.

Artificial intelligence is an excellent tool that can help us to understand how to do responsible consumption.

Thank you