**Analysis**

The following section illustrates the different steps undertaken to obtain a prediction model for pro-environmental action. In particular, the first step consists of Exploratory Data Analysis, to investigate climate change attitudes. Then, the best fitting models tested to predict the final price are presented.

**Exploratory Data Analysis: Macro-level**

Climate change attitudes do not vary only between countries but also between citizens in the same country (Xie et al., 2019). As you can see in figure 1, the percentage of those who believe that climate change is the single most serious problem varies significantly according to country. For example, Bulgaria and Croatia obtain a smaller percentage, that is 11% of citizens who think climate change is the single most serious problem. On the contrary, about 1 out 2 of Sweden’s citizens indicated climate change.



Figure 1: Single Most Serious Problem per Country

Another interesting example is the difference in the climate change risk perception. As you can see in figure 2, about half of the citizens of Malta and Luxemburg declared that they are extremely worried about the phenomenon studied.



Figure 2: Climate Change Risk Perception per Country



Figure 3: Pro-environemntal Behaviour per Country

Attitudes among countries could so vary since they are influenced by different contextual factors (Echavarren et al., 2019; Krajhanzl, 2010). According to Echavarren and colleagues (2019), opinion, perception, and behavior could change due to different natural hazards and political contexts. For example water deficit or temperature growth regarding natural hazards and the “level of environmentalism in the political arena of a given country” (Echavarren et al., 2019, p. 815) for political variables. These macro-variables should be significant mediators in explaining risk perception or pro-environmental behavior. Some indexes are considered with the sole purpose of remembering that they could affect and moderate the phenomenon studied. Then, they are not inserted in the final models since only the multilevel method could be adopted. Besides, the aim of the research is not to evidence national or cultural differences, but on the contrary, it is to find patterns at individual levels, regardless of the place of origin. However, these differences at the macro levels are presented.

For the natural hazards the 2020 Environmental Performance Index (EPI) is used (the 2019 EPI is not available to use the same data of year of the survey) (Yale Center for Environmental Law & Policy, 2020). EPI quantifies numerically environmental health and ecosystem vitality around the world. Some indicators that composed the index are air pollution, drinking water quality, species protection. These phenomena could positively affect climate change concerns and opinions (Echavarren et al., 2019). Citizens should perceive biodiversity loss or temperature increases, leading to greater apprehension. Figure 3 shows the score across European Union (EU). The best score is obtained from Denmark, while the worst from Bulgaria.

Figure 4: The 2020 EPI

For the political context, the 2019 Climate Change Policy Performance is selected, which is a measurement of national and international climate policies (Burck, 2018) developed by organization Germanwatch. It is one of the indicators that belong to the Climate Change Performance Index (CCPI). The indicator constitutes the measurements taken by governments to reduce the current level of GHG emissions per capita or the use of renewable energy. Briefly, it is defined as a measure of countries’ progress and their capacity for climate protection (Burck, 2018). In the Climate Change Policy, the record goes to Portugal and Bulgaria gets the lowest score in all European Union, as figure 4 shows.

According to scholars (Echavarren et al., 2019; van der Linden, 2015) socio-cultural context influces individual attitudes towards climate change concerns. Therefore, the notable diferencess in attitudes across coutries should be also due to these indicators. In fact, “sociological research suggests that contextual factors and processes can be powerful forces shaping how individuals and communities engage with the issue” (Lee et al., 2015, p. 1014). There are different ecological tax reforms or cultural habits that affect and shape individual climate change attitudes and behavior.

Figure 5:The 2019 Climate Change Policy

In this way, It is important to remember that these macro-factors should affect also individual preferences.

**Analysis: Data Exploratory**

**3.1 Correlation Class Analysis**



Figure 6: CCA

The first step is to perform CCA, a method for partitioning the dataset into classes to apprehend unobserved heterogeneity (Rossoni et al., 2021). For our dataset, the CCA algorithm produces five groups. Figure 5 illustrates the individual modules or classes created as a network. Each node corresponds to one item, while the edges show the statistically significant correlation between variables (Rossoni et al., 2021). The more line is thicker, the more significant is the correlation. [[1]](#footnote-1) In group 1 the correlations between all pairs of variables are set to 1. Group 2 obtains a high positive correlation (0.8) mainly between qb4\_3 and qb4\_5. Group 3 has a slight correlation among all variables, except for qb4\_5. In group 4 we find a strong positive correlation among qb7, qb8, and qb9 and separately between qb4\_3 and qb4\_5. Lastly, group 5 has a strong correlation between the following pair of variables: qb4\_5 and qb7; qb4\_5 and qb8; qb4\_5 and qb9. In this case, qb4\_3 is completely isolated.

Figure 7: CCA and Country

In the second place, it is interesting to analyse how CCA’s groups are distributed according to country, as shown in figure 6. The aim is to understand whether there are some shared meanings among citizens of the same country. We analyse the percentage of individuals belonging to the CCA’s groups for each country. Group 2, 4, and 5 are composed of a similar proportion of citizens from each country. Instead, if we look at the composition for each country, we find that over 30% of citizens from Cyprus, Ireland, Malta, Portugal, Slovakia, Spain, and United Kingdom belong to group 1. Additionally, over 30% of citizens from Austria, Bulgaria, Czech Republic, Estonia, Finland, France, Germany, Greece Italy, Latvia, Luxemburg, and Sweden belong to group 3. In both cases, we can not find some specific patterns, such as belonging to the same part of Europe. It is interesting to find similar shared meanings schemas among subjects in nations extremely different and opposite such as Italy and Estonia.

**3.2 Partitioning Around Medoids Clustering**

PAM clustering is an unsupervised method that looks for patterns without any knowledge of the classification purpose. The aim is to partition citizens into classes (clusters) according to similar *green-identity*. Clustering groups the similar observations within each group, while the observations in different groups are different from other clusters. Grouping the attitudes of citizens in clusters means dividing them according to similar opinions about the governance of climate change. We remember that also in this case the questions about climate change (qb4\_3, qb4\_5, qb7, qb8, qb9) are fitted in that algorithm.

PAM requires, as a parameter, the number of clusters. “One of the most commonly applied methods for assessing cluster validity is silhouette width which encompasses two clustering criteria: separation (i.e., the average distance to the closest other clusters) and compactness (i.e., average within‐cluster distance)” (Lengyel & Botta‐Dukát, 2019, pag. 13232). Silhouette width indicates how well each cluster divides observations, as shown in figure 7. The best choice is 2.

Figure 8: Clustering silhouette

Observations are then divided into two clusters with PAM. The summary results of PAM clustering are shown in Figure 8. The distribution is balanced: 11171 individuals belong to cluster 1, and 10807 belong to cluster 2. Although overall the level of agreement or importance of these questions is elevated (the mode of qb4\_3, qb4\_5 is 2, while the mode of qb7, qb8, qb9 is 1), we can see that 2 clusters resemble two different types of green-identity, which we call “moderate green identity”, “extreme green-identity”.

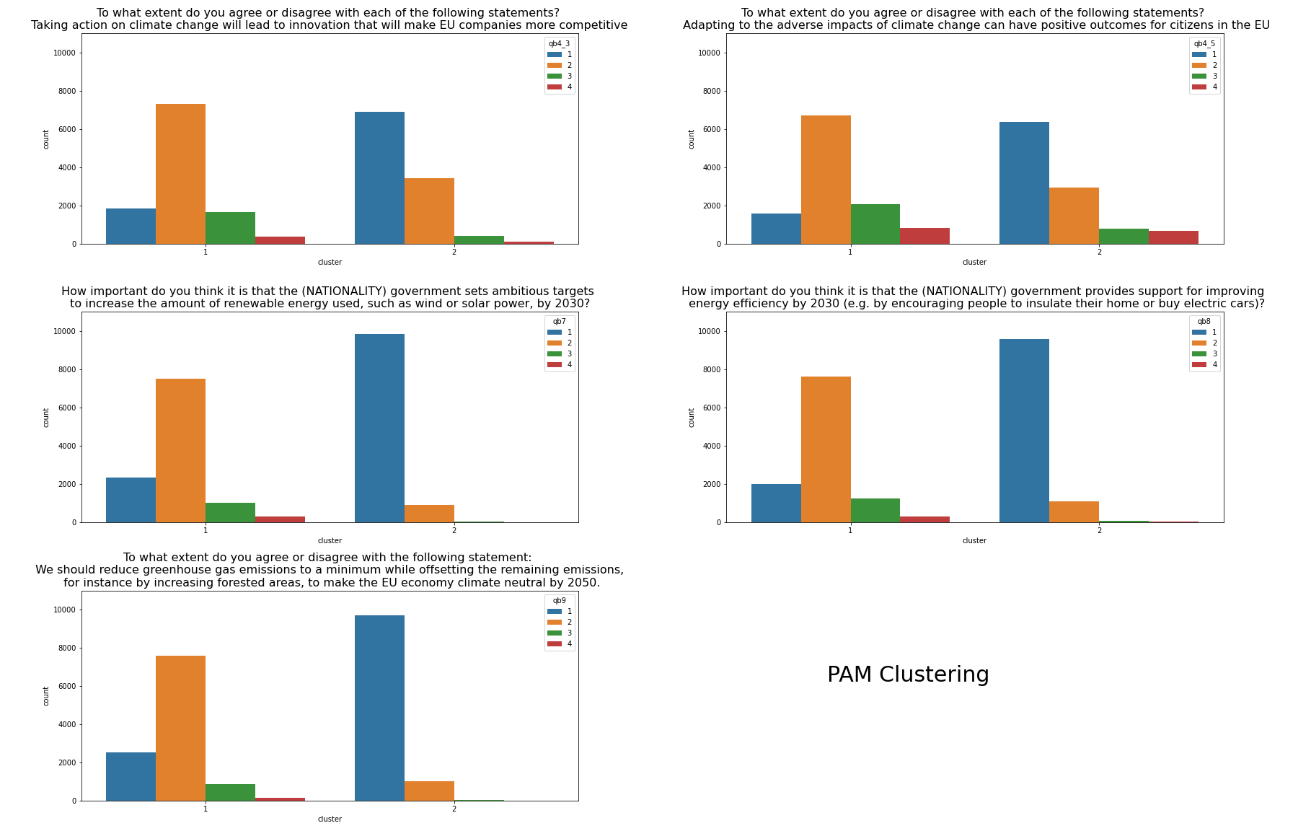


Figure 9: Summary of PAM Clustering

**Cluster 1: Moderate green identity**

* More than 75% answered questions (qb3\_4,qb4\_5, qb7, qb8, qb9 ) with moderate answers (option 2 or 3);
* There is no difference among genders;
* 70% of citizens belong to centre, centre-left or centre-right;
* 57% stopped studying at the latest at 19, 35% stopped studying after 20, 6% are still studying;
* More than 65% of the citizens of Czech Republic, Estonia, Finland, Latvia, Poland belong to this cluster;
* the average age is 51 years old;
* the average climate change risk perception is 7.2;
* 56% take place a pro-environmental behaviour.

**Cluster 2: Extreme green-identity**

* More than 60% answered qb3\_4 and qb4\_5 questions with the maximum answer (1), and about 90% answered qb7, qb8, qb9 questions with the maximum answer (1).
* There is no relevant difference among genders;
* 66% of citizens belong to centre, centre-left or centre-right
* 49% stopped studying at the latest at 19, 41% stopped studying after 20, 7% are still studying;
* More than 65% of the citizens of Cyprus, Denmark, Spain, United Kingdom belong to this cluster;
* The average age is 50 years old:
* The average climate change risk perception is8.6;
* 75% take place a pro-environmental behaviour.

To sum up, cluster 1 is composed of citizens that are more moderate in the answers to climate change items than the citizens of the opposite cluster. Additionally, cluster 2 is composed of slightly younger, more educated, more worried, and more active citizens.

**Prediction**

Sa mentioned in the literature review, the main predicotor of pro-environmental behaviour is climate change risk perception. However, other factors can shape the outcomes. The main focus is now on predictiong behaviour of citizens in a dummy outcomes.

**Evaluating Classification Models**

Before proceeding with the analysis, it is important to fist explain the ways the errors will be measured, since one of the main factors according to which we will choose the best model is the minimization of the error. We considere two measumerements of error:

* **Accuracy**: is the proportion of correct predictions to the total number of prediction (true positives and true negatives) given by the classifier (Battiti & Brunato, 2014). Accuracy is the most used metric that generally describes the goodness of a model. The formula is:

The range is 0-1, where 0 is the worst score and 1 the best score, all the inputs are predicted in a right way.

* **Macro F1-score average**: combine precision and recall, where the precision is the number of true positives divided by the total number of element labelled as positivea, and the recall is the number of true positives divided by the total number of elements that actually belong to the positive class (Shmueli, 2019). Macro F1-score is computed harmonic mean, as shown in the formula:

The range of the score is 0-1, where 0 is the worst score and 1 is the best score. It is used especially when for the class imbalance problem due to it is more sensitive to data distribution, as in this case.

In order to select the best model for each classifier, we decide to compite a first compromise: the balance between accuracy and f1-score macro average. The aim is to classify and predict as well both classes. On one side, this compromise can sometimes lead to losing a few percentage points of accuracy but, on the other side, it improve accuracy within the classes.

In closing, we explain how to understand what variables have a fondalment role in our models. We compute feature importance by the different algorithms in scikit-learn. Logistic regression finds a set of coefficients to use in the weighted sum in order to make a prediction. These coefficients can be used directly as a crude type of feature importance score. Instead, tree based models can measure feature importance in two way: Gini importance or Mean Decrease Accuraracy. Gini importance count the times a features is used to split a node. Mean Decrease Accuracy measures how much accuracy the model losses by excluding each variable. However, scikit-learn implemented Gini importance, also in our analysis it is adopted.

**Prediction**

In this part, the research study aims to identify and discover the most significant variables and offer a good prediction of pro-environental behaviour. As presented in the Methology (Chapter 2), different classifiers are trained and implemented to predict behaviour. The analysis stars with Logistic Regression, and continues with tree-based methods: Decision Tree, Random Forest, and Gradient Boosting. These algorithms are implementend in scikit-learn. For each classifier best tuning parameters, called hyperparameters, are fitted. The technique adopted for knowing the optimal hypermapameter is called random search (RandomizedSearchCV() in scikit-learn) (Benner, 2020).[[2]](#footnote-2) We adopt, in turn, for random search 3 fold cross validation, a resampling procedure to evaluate model performance. in practice, each possible random combination will train and evaluate for three different folds.

We remember that the independent variables, at individual level, of this part are:

* Climate change risk perception (qb2)
* CCA’s class (cca)
* Cluster’s class (cluster)
* Political orientation (d1)
* Maritial status (d7)
* Stopped full-time education (d8)
* Gender (d10)
* Age (d11)
* Residence (d25)
* Class identity (d63)
* Country

Table : Metrics comparison

|  |  |  |
| --- | --- | --- |
| **Models** | **Accuracy** | **Macro-f1 score** |
| **Logistic Regression** | 0.67 | 0.65 |
| **Decision Tree** | 0.64 | 0.62 |
| **Random Forest** | 0.70 | 0.67 |
| **Gradient Boosting** | 0.70 | 0.66 |

**Logistic regression**

The fist method explored is Logistic regression. This algorithm supposes that all the assumptions (~~independence of errors~~, linearity in the logit for continuous independent variables, the absence of multicollinearity, the absence of multicollinearity, lack of outliers) are satisfied. However, there are some violetions of different assumptions.

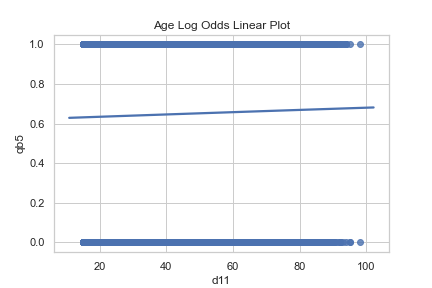
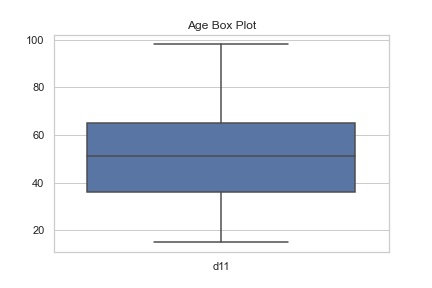
First, we check the assumption of linearity in the logit for continuous independent variables, also in this case only for the continuous variables. In this case, only age is continuous, and itdoes not verify this assumptions, as figure 10 displays (there should be an “s” curve line). Second, we can not check the absence of multicollinearity (independent variables), due to it is not possible to compute correlation with one vairble alone. Lastly, lack of outliers, always for continuos variables. Figure 11 shows that there are not outliers in the age variable.

Figure 10: Lack of outliers for Age

Figure 11: Linearity in the Logit for Age

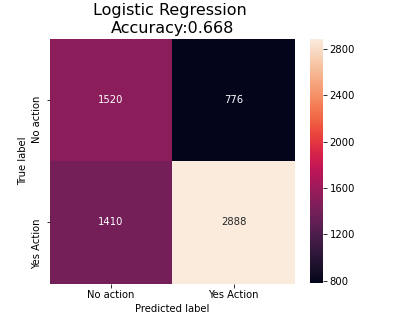
The fitted model, with the best tuning parameters, has 0.67 of accuracy and 0.66 of macro f1-score. As shown by figure 12,

Figure : Logistic Rigression- Confusion Matrix

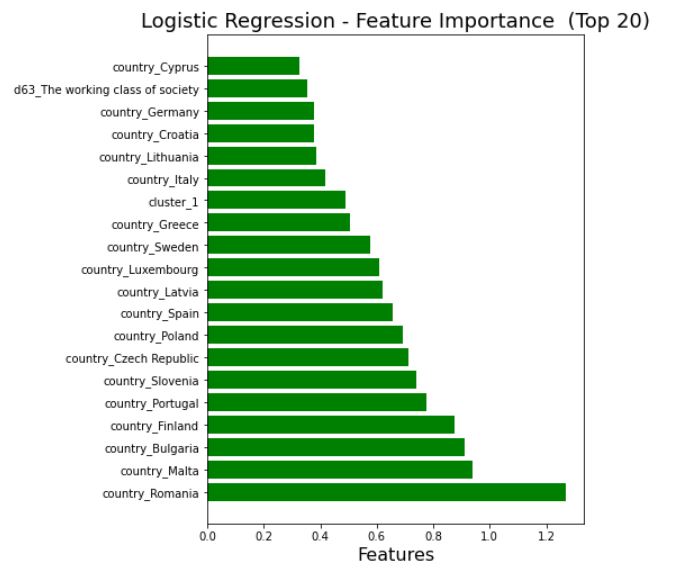


Figure : Logistic Regression- Feature Importance

**Decision Tree**

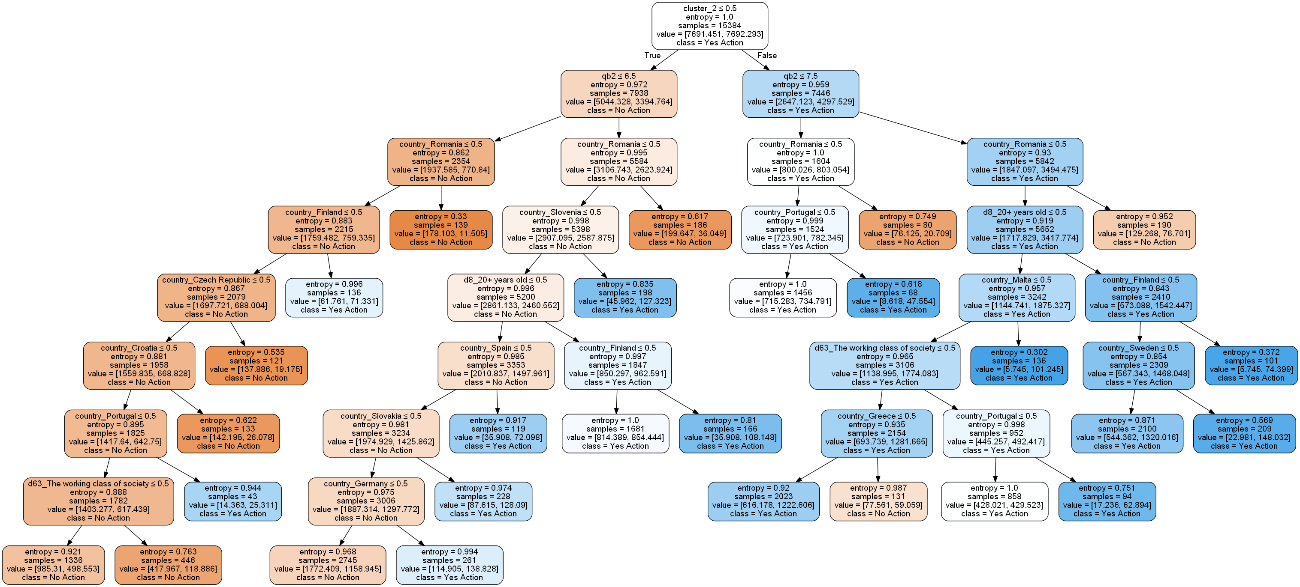


Figure : Decision Tree

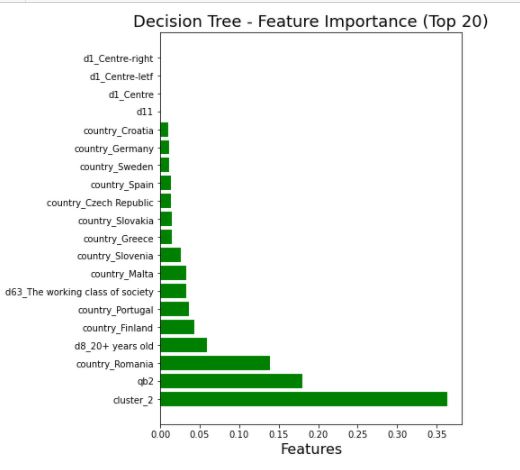


Figure : Decision Tree - Feature Importance

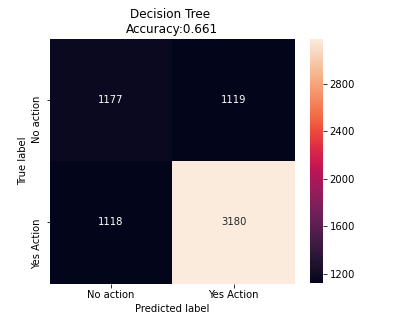
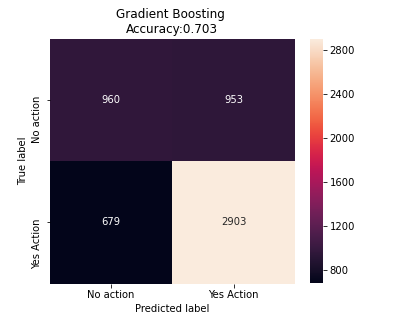
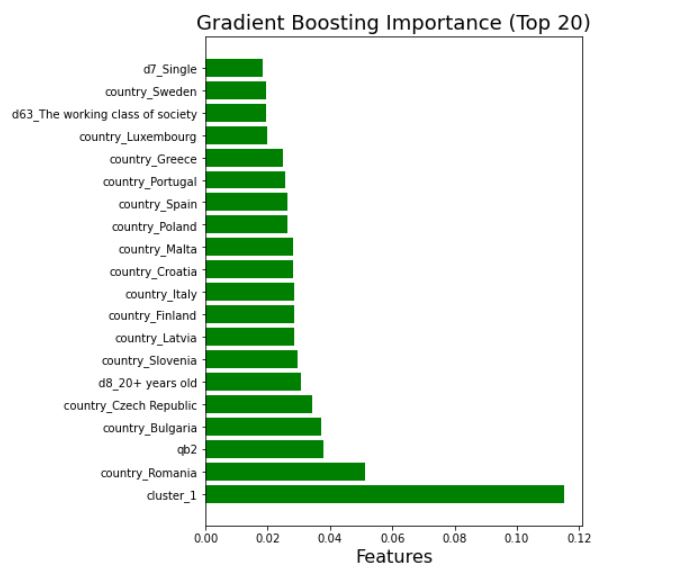
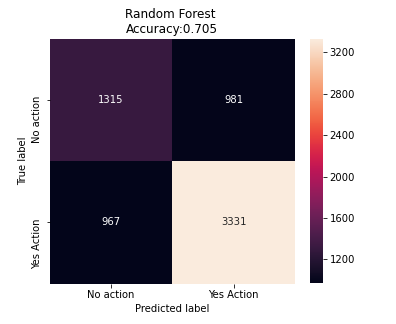


Figure 16: Decision Tree- Confusion Matrix

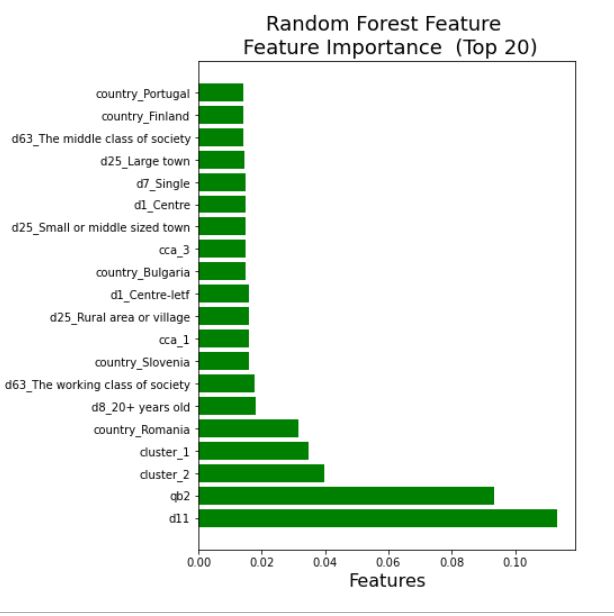
**Random Forest**

**Gradient Boosting**



Random Forest algorithm has yielded the best performance when compared to other classifiers, as shows the table. Ramndom Forest gets a better result both in accuracy and in marco f1-score average. 

Confusion matrix, figure, displays the quality of the output of the classifer. It shows the counts from predicted and actual values. In this case the conut are done with the test set, showing if the predictions math the reality and therefore are accurately classify or not (Battiti & Brunato, 2014). We can see that 1315 observations, for no action class, and 3331 for yes action class, are correctly classify. Instead, there are for each class about 900 cases of misclassification.



As shown in figure, analysing the feature importances of the model, we see that age and climate risk perception are the most impotant variable to classify and predict pro-environmental behaviour. The interpretation of feature importance is not simply and immediate. We expect that most young people take place pro-environmental action. However, this relantionship is not so clear. If we analyse the percentage of those who take place action within the age group, we find that on average 60% do something. This percentage drops for for classes over 80. Instead, climate change risk perception is more interesting to analyse. as referted in literature review (chapter 1), the more an individual worries, the more he tends to take place environmental action. This hypothesis is confirmed. in fact, if we analyse the perceptage of those who take place action within the level of perceived risk, we find that fot the classes with a low level there are more than 50% of individuals that declare to not take place action. The more the risk increases, the more the percentage of take place action increase in turn, as figure shows. Another importance features are the created clusters, which correspond to the different green-identity. Cluster 2 is composed by 70% of individuals who take place action, while cluster 1 by 55%. Therefore if an individual belongs to cluster 2 it is more probably that he/she do something for environment. Being of Romania is an discriminant to predict behaviour, since 66% of them declare do no do anything, as we have already explained. Lastly, an higher level of educated and the workeven if very ing class are other two important variables, even if much less that age and risk perception. 72% of those has an high level of education, or better has stopped to study after 20 years, has take place pro-environemtal action. The average of other classes of this variable sis 60%. The opposite case happens with working class where 40% of them does not anything, instead of other social class where the proportion is lower.

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**APPENDIX D. Correlation matrix for each CCA’s group.**

Group 1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | 1 | 1 | 1 | 1 |
| **qb4\_5** | 1 | 1 | 1 | 1 | 1 |
| **qb7** | 1 | 1 | 1 | 1 | 1 |
| **qb8** | 1 | 1 | 1 | 1 | 1 |
| **qb9** | 1 | 1 | 1 | 1 | 1 |

Group2

|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| --- | --- | --- | --- | --- | --- |
| **qb4\_3** | 1 | 0.8209258 | 0.34825902 | 0.1660830 | 0.22869773 |
| **qb4\_5** | 0.8209258 | 1 | 0.48758501 | 0.3021902 | 0.13889897 |
| **qb7** | 0.34825902 | 0.48758501 | 1 | 0.3923910 | -0.01232148 |
| **qb8** | 0.1660830 | 0.3021902 | 0.3923910 | 1 | -0.14657797 |
| **qb9** | 0.22869773 | 0.13889897 | -0.01232148 | -0.14657797 | 1 |

Group 3

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | 0.07469395 | 0.4400537 | 0.5437509 | 0.5195602 |
| **qb4\_5** | 0.07469395 | 1 | -0.1859863 | -0.1112473 | -0.1150310 |
| **qb7** | 0.44005368 | -0.18598635 | 1 | 0.4965637 | 0.4023176 |
| **qb8** | 0.54375089 | -0.11124727 | 0.4965637 | 1 | 0.5111735 |
| **qb9** | 0.51956019 | -0.11503102 | 0.4023176 | 0.5111735 | 1 |

Group 4

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | 0.9001736 | -0.2393692 | -0.2281035 | -0.2411191 |
| **qb4\_5** | 0.9001736 | 1 | -0.1607610 | -0.1477551 | -0.1715444 |
| **qb7** | -0.2393692 | -0.1607610 | 1 | 0.8869407 | 0.8548438 |
| **qb8** | -0.2281035 | -0.1477551 | 0.8869407 | 1 | 0.8476377 |
| **qb9** | -0.2411191 | -0.1715444 | 0.8548438 | 0.8476377 | 1 |

Group 5

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **qb4\_3** | **qb4\_5** | **qb7** | **qb8** | **qb9** |
| **qb4\_3** | 1 | -0.1514635 | -0.05905457 | -0.03462609 | -0.1298436 |
| **qb4\_5** | -0.15146353 | 1 | 0.75879238 | 0.73159084 | 0.8669082 |
| **qb7** | -0.05905457 | 0.7587924 | 1 | 0.54913637 | 0.6663558 |
| **qb8** | -0.03462609 | 0.7315908 | 0.54913637 | 1 | 0.6540521 |
| **qb9** | -0.12984356 | 0.8669082 | 0.66635581 | 0.65405206 | 1 |

APPENDIX E. Grid of parameters and Hyperparameters for complete model

***Logistic Regression***

{'solver': ['newton-cg', 'lbfgs', 'liblinear'],

'penalty': ['l2'],

'C': [100, 10, 1.0, 0.1, 0.01]}

LogisticRegression(C=0.1, class\_weight={0: 1.43631197, 1: 0.76700502}, 'solver': 'lbfgs', 'penalty': 'l2')

***Decision Tree***

{'criterion': ['gini', 'entropy'],

'max\_depth': range(1, 10),

'min\_samples\_split': range(0, 10),

'min\_samples\_leaf': range(1, 5)}

DecisionTreeClassifier(ccp\_alpha=0.000993163342228487,class\_weight={0: 1.43631197, 1: 0.76700502},criterion='entropy', max\_depth=8, min\_samples\_split=4,random\_state=123)

***Random Forest***

{'n\_estimators': [100, 300, 500, 800, 1200],

'max\_depth': [5, 8, 15, 25, 30],

'min\_samples\_split': [2, 5, 10, 15, 100],

'min\_samples\_leaf': [1, 2, 5, 10]}

RandomForestClassifier(bootstrap=False,class\_weight={0: 1.43631197, 1: 0.76700502}, max\_depth=30, max\_features='log2', max\_leaf\_nodes=49,min\_samples\_leaf=10, min\_samples\_split=10, n\_estimators=136)

***Gradient Boosting***

{'max\_depth': [3, 4, 5],

'learning\_rate': [0.1, 0.25, 0.5, 0.75, 1],

'n\_estimators': [50, 100, 150],

'gamma': [0.5, 1, 1.5, 2],

'min\_child\_weight': [1, 5, 10]}

XGBClassifier(class\_weight={0: 1.43631197, 1: 0.76700502}, gamma=0.5, max\_depth=4, min\_child\_weight=10, scale\_pos\_weight=0.75)

***Appendix F. Feature importance***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | Logistic Regression | Decision Tree | Random Forest | Gradient Boosting |
| cca\_1 | -0.2098577 | 0.0000000 | 0.0121672 | 0.0178557 |
| cca\_2 | 0.7383233 | 0.0000000 | 0.0031295 | 0.0062576 |
| cca\_3 | 0.0904803 | 0.0000000 | 0.0019191 | 0.0074507 |
| cca\_4 | -0.6934119 | 0.0000000 | 0.0023961 | 0.0085750 |
| cca\_5 | -0.3174920 | 0.0000000 | 0.0011631 | 0.0052379 |
| cluster\_1 | -0.3792837 | 0.0000000 | 0.1372381 | 0.1151946 |
| cluster\_2 | -0.2077151 | 0.3633486 | 0.1511412 | 0.0000000 |
| country\_Austria | 0.3768583 | 0.0000000 | 0.0067855 | 0.0158629 |
| country\_Belgium | -0.0847710 | 0.0000000 | 0.0009979 | 0.0120570 |
| country\_Bulgaria | -0.1109127 | 0.0000000 | 0.0247924 | 0.0372260 |
| country\_Croatia | 0.2331745 | 0.0103320 | 0.0088332 | 0.0281615 |
| country\_Cyprus | 0.0121429 | 0.0000000 | 0.0006509 | 0.0100005 |
| country\_Czech Republic | -0.0637693 | 0.0133283 | 0.0113103 | 0.0344699 |
| country\_Denmark | -0.3851777 | 0.0000000 | 0.0021834 | 0.0135749 |
| country\_Estonia | -0.4173172 | 0.0000000 | 0.0027299 | 0.0144012 |
| country\_Finland | 0.0338481 | 0.0437428 | 0.0270728 | 0.0283870 |
| country\_France | -0.1335332 | 0.0000000 | 0.0011726 | 0.0058990 |
| country\_Germany | -0.2604537 | 0.0110157 | 0.0092000 | 0.0181609 |
| country\_Greece | -0.9094870 | 0.0144454 | 0.0081387 | 0.0250329 |
| country\_Hungary | -0.3531485 | 0.0000000 | 0.0008173 | 0.0104115 |
| country\_Ireland | 0.1051436 | 0.0000000 | 0.0006669 | 0.0000000 |
| country\_Italy | -0.3275857 | 0.0000000 | 0.0098754 | 0.0283794 |
| country\_Latvia | -0.0780072 | 0.0000000 | 0.0157862 | 0.0285022 |
| country\_Lithuania | -0.7122050 | 0.0000000 | 0.0025980 | 0.0136724 |
| country\_Luxembourg | 0.3262814 | 0.0000000 | 0.0034684 | 0.0199415 |
| country\_Malta | 0.0016549 | 0.0325839 | 0.0316161 | 0.0280143 |
| country\_Netherlands | -0.0875741 | 0.0000000 | 0.0004468 | 0.0074088 |
| country\_Poland | -0.1299920 | 0.0000000 | 0.0188374 | 0.0265242 |
| country\_Portugal | -0.1195211 | 0.0358802 | 0.0228842 | 0.0256186 |
| country\_Romania | 0.1725878 | 0.1383761 | 0.0937798 | 0.0511590 |
| country\_Slovakia | 0.0646708 | 0.0142991 | 0.0051520 | 0.0121337 |
| country\_Slovenia | 0.0068130 | 0.0259060 | 0.0311926 | 0.0294748 |
| country\_Spain | -0.3055267 | 0.0131954 | 0.0199810 | 0.0264268 |
| country\_Sweden | -0.0549632 | 0.0111407 | 0.0187118 | 0.0193531 |
| country\_United Kingdom | -0.5040618 | 0.0000000 | 0.0035331 | 0.0164386 |
| d10\_Man | 0.0172800 | 0.0000000 | 0.0050192 | 0.0110375 |
| d10\_Woman | -0.0982383 | 0.0000000 | 0.0050647 | 0.0000000 |
| d11 | -0.1246435 | 0.0000000 | 0.0211843 | 0.0064029 |
| d1\_Centre | -0.0526564 | 0.0000000 | 0.0014180 | 0.0042561 |
| d1\_Centre-letf | -0.4886775 | 0.0000000 | 0.0058354 | 0.0106647 |
| d1\_Centre-right | 0.1899725 | 0.0000000 | 0.0020255 | 0.0085711 |
| d1\_Left | -0.2014557 | 0.0000000 | 0.0009525 | 0.0119130 |
| d1\_Not positionable | -0.0804944 | 0.0000000 | 0.0010363 | 0.0039606 |
| d1\_Right | 0.6574931 | 0.0000000 | 0.0016818 | 0.0054657 |
| d25\_Large town | -0.0903551 | 0.0000000 | 0.0009833 | 0.0065829 |
| d25\_Rural area or village | 0.0098651 | 0.0000000 | 0.0020722 | 0.0059912 |
| d25\_Small or middle sized town | 0.6082544 | 0.0000000 | 0.0011765 | 0.0084332 |
| d25\_dk | -0.0143819 | 0.0000000 | 0.0000000 | 0.0000000 |
| d63\_Refusal/Other | -0.2562657 | 0.0000000 | 0.0003495 | 0.0000000 |
| d63\_The higher class of society | -0.0568692 | 0.0000000 | 0.0000000 | 0.0000000 |
| d63\_The lower middle class of society | 0.5747200 | 0.0000000 | 0.0018210 | 0.0056497 |
| d63\_The middle class of society | -0.0931861 | 0.0000000 | 0.0029964 | 0.0063564 |
| d63\_The upper middle class of society | 0.7756973 | 0.0000000 | 0.0051292 | 0.0172957 |
| d63\_The working class of society | 0.8753633 | 0.0332011 | 0.0239096 | 0.0195175 |
| d7\_Partner | -0.1278101 | 0.0000000 | 0.0016760 | 0.0037242 |
| d7\_Partner and children | 0.1947280 | 0.0000000 | 0.0020636 | 0.0080501 |
| d7\_Refusal/Other | 0.1201380 | 0.0000000 | 0.0000000 | 0.0000000 |
| d7\_Single | -0.0446343 | 0.0000000 | 0.0037273 | 0.0183271 |
| d7\_Single with children | -0.1192031 | 0.0000000 | 0.0006165 | 0.0000000 |
| d8\_16-19 years old | 0.0722196 | 0.0000000 | 0.0145833 | 0.0065195 |
| d8\_20+ years old | -1.2688340 | 0.0596302 | 0.0456083 | 0.0306460 |
| d8\_Refusal/dk | -0.6200362 | 0.0000000 | 0.0015210 | 0.0076972 |
| d8\_Still studying | -0.2029141 | 0.0000000 | 0.0008196 | 0.0000000 |
| d8\_Up to 15 years old | 0.9372033 | 0.0000000 | 0.0018649 | 0.0076280 |
| qb2 | 0.3139469 | 0.1795745 | 0.1524956 | 0.0380454 |

1. See appendix D for the correlation of each class separately. [↑](#footnote-ref-1)
2. See appendix for the grids of parameters and the hyperparamenters for each algorithm [↑](#footnote-ref-2)