Exploiting Outlier Explanation to Unveil Key-aspects of High Green Comparative Advantage Nations

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Abstract

Climate change is observable in the drastic modification of world ecosystems and weather patterns. The potential effects of this phenomenon make the research of successful strategies to delimit the problem an absolute priority. Objectives 7, 12 and 13 of the United Nations' Agenda 2030 [1] are only some examples of the importance of this problem on a worldwide scale. The development and diffusion of low-carbon technologies are among the key points in politics against climate change due to the massive impact human activities have on carbon emissions.

Deep Learning techniques, currently widely used in many aspects of everyday life, can also help in this field. This work, in particular, aims to demonstrate the effectiveness of M^{2}OE, a transformation-based outlier explanation technique, in extracting actionable explanations in the green economy context. Specifically, we analyze the Low Carbon Technologies Comparative Advantage, an index measuring the relative economic advantage in developing low carbon technologies, by looking at the nations exhibiting a high comparative advantage to qualitatively evaluate the insights the method provides to the user.

To this aim, we have gathered data concerning 7 indicators related to the comparative advantage of low-carbon technologies in the 2019-2021 time period. This data extraction work has resulted in the Green Comparative Advantage (GreenCA) tabular data set, in which the information retrieved for the reference time horizon is organized and summarized. By a set of experiments exploiting this data collection together with the M^{2}OE method, we catch a glimpse to gain interesting insights about which politics are successful in promoting a change in favour of green energies.

Keywords

Outlier Explanation, Green Economy, Low Carbon Technologies Comparative Advantage

1. Introduction

The worrying frequency of extraordinary natural events is making evident the climate change problem, which is dramatically marking the planet's equilibrium and our ecosystems and is affecting human life [2]. Timely actions and a change in lifestyle and environmental politics are required to mitigate the effect of a problem primarily caused by human activities. Thanks to its power to push technology and economics forward to more sustainable models, politics has a main role in attenuating the climate change issue [3]. Fortunately, the undeniable evidence of the above-introduced problem has inducted world countries to commit their efforts to discuss effective strategies to promote policy, technologies and behaviours tailored to reduce the CO_2 emissions, that are causing this phenomenon. The annual United Nations Climate Change Conference and the Agenda 2030 7, 12 and 13 goals focused respectively on affordable green energy, responsible consumption and production and climate changes [1], testify a spread in the interest of world politics in discussing environmental subjects and in the green economy, thus, considering both the economical and the sustainability aspects.

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As a consequence of socioeconomic, geography and morphology differences, each county's government implements different policies to deal with the exigence of a more sustainable lifestyle and economy. Unfortunately, not all the strategies adopted are equally effective in reaching the goal of promoting the reduction of CO_2 emissions. In this regard, always looking at the green economy matter, decision-makers could be facilitated by having techniques providing insights about the aspect characterizing the policies of countries attaining sustainability goals, since it potentially provides them with the instruments to make more informed explanations.

In this paper, we aim to witness the effectiveness of M^2OE [4, 5], a transformation-based Outlier Explanation technique, in gaining actionable explanations in the green economy context. In particular, we qualitatively analyze the actionability of explanations related to the Low Carbon Technologies Comparative Advantage (hereafter referred to as Green Comparative Advantage), an index measuring the relative advantage of a country in producing low-carbon technologies. We have chosen this index for its potential to promote investments in technologies reducing the environmental impact and thus to test the effectiveness of the M^2OE explanations in a relevant real-world scenario.

To this aim, we have collected and arranged the data shared by the International Monetary Fund containing information relating to environmental taxes, investment in environmental protection, fossil fuel subsidies, energy (both renewable and non-renewable), forests and trade in low-carbon technologies products. Our efforts resulted in the **Green Comparative Advantage (GreenCA)** dataset providing in a tabular shape, a rich and, hopefully, complete overview of the policies applied and peculiarities of a set of countries. More specifically we have collected information for 54 countries, more details are going to be provided in section 2. The number of samples skewed toward countries with a low green comparative advantage makes it suitable to be analyzed in an outlier explanation setting by considering the less numerous class of countries with high comparative advantage as outliers.

Given reference data considered as "normal" and one or more outlying samples, the goal of the previously referred Outlier Explanation task is figuring out the aspects characterizing point outlierness and, thus what makes the analyzed sample or groups behave differently from the rest of the data. Two are the most diffused ways to approach this problem. The first of them shapes the considered problem as the search of the set of features characterizing the outlying samples or associating a score to each feature by, for example, using separability as a quality criterion [6], finding invertible projections that make the outlying sample better recognisable and then obtaining the features contributing to this mapping [7], or by leveraging features selection methods equipping them with properly-designed sampling methods to deal with extremely unbalanced data [8]. Other approaches perform the selection through outlierness metrics based on the relative frequency of value combinations, applied to single outliers in datasets having categorical [9] or continuous features [10], or groups of anomalies [11]. Alternatively, find exceptional values by estimating the distribution of the value frequencies [12]. In the second instead, the features are ranked and, for each of them a score is provided, by using scoring criteria ranging from the distance between the studied sample and its k-nearest neighbours [13], measures extracted through kernel density estimation [14] or other criteria studied to be dimensional unbiased, thus not dependent from the number of features of the sample [15].

Beyond this information, the here-considered M^2OE technique [4, 5] is tailored to extract richer insights by considering transformation-based explanations [16], whose goal is to find a group of features to change and for each of them a value describing how to change the value of that feature. It follows that it potentially gives actionable explanations guiding decision-makers to change the observed status making appropriate changes to the features available, which are particularly useful in real-world contexts like that considered in this paper.

The rest of the paper is structured as follows. Section 2 presents the GreenCA dataset by describing the data collection, the building process and the information included, Section 3 presents the M^2OE Outlier Explanation method, Section 4 qualitatively evaluates the actionability of the collected explanations and, finally, Section 5 draw the conclusion of this work.

2. The Green Comparative Advantage dataset

As already stated in this paper's introduction, designing effective strategies to promote green and sustainable technologies is crucial to follow the right path to have a less impacting society and lifestyle and to try to remedy the negative effects observed as a consequence of global pollution. To gain insights into the most effective way to make the development and adoption of low-carbon technologies advantageously from an economic perspective, thus, hopefully, to incentive this category of technologies, we want to study which are the differences characterizing countries having a high comparative advantage from green technologies in comparison with the others.

To look out at the insights given by M^{2}OE on what characterizes counties exhibiting a high comparative advantage with the purpose of checking their usefulness, data for 6 mitigation indicator groups has been collected from the International Monetary Fund Climate Dashboard, which includes information about national policies to contain and reduce carbon emissions, shaped as time series. Deeper into details, the indicator groups considered are the following:

- **Environmental Taxes (ET)** [17]: Charges levied by measuring, through a physical unity or some proxy criterion, something that is proven to harm the environment.
- **Environmental Protection Expenditures (EP)** [18]: Money amount invested in environmental protection activities like, for example, waste management, pollution abatement and biodiversity and landscape protection.
- **Forest and Carbon (FC)** [19]: Data about Forest Extends and Carbon stored by forests providing a high-level summary of the forest state in each country.
- **Fossil Fuel Subsidies (FF)** [20]: Estimated values of explicit and implicit government subsidies.
- **Renewable Energy (RE)** [21]: Information about electricity generation and electricity installed capacity, where energy is classified as renewable or non-renewable.
- **Trade in Low-carbon Technology Products (TT)** [22]: Data about trade in low carbon technology product.

The original data sources for each indicator group consist of sets of time series, each of them taking care of reporting the features for one nation and one kind of measure. In the following, we describe the process performed to extract analyzed data. Table 1 reports an overview of the features included in the here presented data collection.

2.1. Data collection methodology

The GreenCA dataset presented in this work comes as the upshot of a data collection and summarization process. Indeed, the International Monetary Fund Climate Dashboard provides users with varied, and, sometimes, redundant data, to make them usable for different kinds of analytics. The objective is to rationalize data through reshaping and filtering operations to obtain a two-class tabular dataset.

Data is divided using the Green Comparative Advantage as a discriminant feature. This value represents the economic advantage over the other nations in exporting low-carbon technologies, which consists of all the technological products tailored to reduce the impact of human activities on the environment. Surveyed nations are distinguished between those exhibiting a high Green Comparative Advantage, thus that have a value greater than 1 for this index, to which we assign the target label 1, and those instead having a value lower than 1, to which the label 0 is assigned.

To avoid scale problems, when more than one unit is available for the considered indicator and when applicable, we consider only information from records measuring the analyzed indicator as a percentage.

We selected the more recent three-year period satisfying data availability, so, in the presented dataset, we chose the 2019-2021 years as the target period for our analysis. However, the described data processing procedure can be applied to updated data by considering a different time horizon to obtain an up-to-date version of this dataset. To summarize the information relating to the considered period

ID	Description	Unit	Indicator Group
ET_0	Environmental Taxes	Percent of GDP	Enviromental Taxes
ET_1	Taxes on Energy	Percent of GDP	
ET_2	Taxes on Pollution	Percent of GDP	
ET_3	Taxes on Resources	Percent of GDP	
ET_4	Taxes on Transport	Percent of GDP	
EP_0	Expenditure on biodiversity & landscape protection	Percent of GDP	Environmental Protection Expenditures
EP_1	Expenditure on environment protection	Percent of GDP	
EP_2	Expenditure on environmental protection n.e.c.	Percent of GDP	
EP_3	Expenditure on environmental protection R&D	Percent of GDP	
EP_4	Expenditure on pollution abatement	Percent of GDP	
EP_5	Expenditure on waste management	Percent of GDP	
EP_6	Expenditure on waste of water management	Percent of GDP	
FC_0	Carbon stocks in forests	Million tonnes	Forest and Carbon
FC_1	Forest area	1000 HA	
FC_2	Index of carbon stocks in forests	Index	
FC_3	Index of forest extent	Index	
FC_4	Land area	1000 HA	
FC_5	Share of forest area	Percent	
FF_0	Implicit Fossil Fuel Subsidies	Percent of GDP	Fossil Fuel Subsidies
FF_1	Explicit Fossil Fuel Subsidies	Percent of GDP	
FF_2	Total Fossil Fuel Subsidies	Percent of GDP	
RE_0_0	Renewable Electricity Generation	Gigawatt-hours (GWh)	Renewable Energy
RE_0_1	Non-Renewable Electricity Generation	Gigawatt-hours (GWh)	
RE_1_0	Renewable Electricity Installed Capacity	Megawatt (MW)	
RE_1_1	Non-Renewable Electricity Installed Capacity	Megawatt (MW)	
TT_0	Trade balance in low carbon technology products	Percent	Trade in Low-carbon Technology Products
TT_1	Total trade in low carbon technology products	Percent	

Table 1
GreenCA dataset features overview

we apply, for each indicator, the mean operation to the values for the considered years. To prevent working with null data, we drop from the 104 registered nations those with at least one unspecified value. The above-described data extraction procedure resulted in a dataset containing information from 54 countries, among which 16 have a high comparative advantage and the remaining a low comparative advantage. Table 1 lists the set of features available, where a description, the unity of the measurement and the connected thematic area are reported for each feature.

Since there are only a few outstanding countries in which low-carbon technologies are economically advantageous, the dataset presented in this work can be looked at as an outlier detection dataset, in which the minority class can be seen as anomalous. The GreenCA dataset presented in this section can be found at the following link https://www.kaggle.com/datasets/simonanistico/greenca.

3. M^{2}OE

Masking **M**odels for **O**utlier **E**xplanation, shortly **M^{2}OE**, tackles the Outlier Explanation problem by providing the user with transformation-based explanations, describing the outlier peculiarities by suggesting alterations that, applied to the analyzed outlier, makes it behaving similar to normal samples. More in detail, given an object $o \in DS$, the explanation consists of a set e of feature-value pairs $\{(f_{i_1}, v_{i_1}), \dots, (f_{i_k}, v_{i_k})\}$ codifying a *transformation* $t_e(o)$ of o resulting in a new object o' such that $o'[f_j] = o[f_j] + v_j$ for $j \in \{i_1, \dots, i_k\}$ and $o'[f_j] = o[f_j]$ otherwise. The just-described transformation potentially represents an actionable explanation providing users with insights on how to change the features of the outlier to make it act as a normal sample.

The pipeline proposed to find the previously introduced explanation form is depicted by Figure 1. As

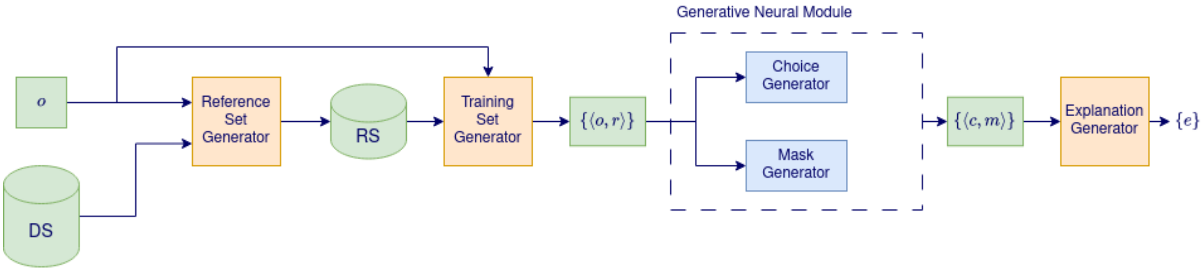

Figure 1: M²OE pipeline

reported in the figure, to compute an explanation, M²OE takes the outlier o and a dataset DS of normal samples as input. The pipeline input is first given to the *Reference Set Generator*, devoted to finding a reference set RS for o, which is a subset of DS consisting of k samples selected according to some criterion to act as a prototype of the normality concept to which o should conform to. The reference set RS is then given, together with the outlier o to the *Training Set Generator* module that is in charge of building the training set TS leveraged to the subsequent module consisting of a set $\{\langle o, r\rangle : r \in RS\}$ of k tuples containing the outlier o and one of the reference set samples. The so-obtained training set TS is then used by the *Generative Neural Module*, representing the core of the pipeline and composed of two neural networks: the *Choice Generator* charged of finding the set of features to modify, codified by the *choice* binary vector c having one component for each feature and values equal to 1 only for the features involved in the transformation, and the *Mask Generator* module answering for figuring out how to change each of the features pointed out by the Choice generation network. The Mask Generator codifies the alteration to apply as a real values vector that, coherently to the Choice Generator, has one component for each feature and shows not-null components only for indexes corresponding to features to change. Finally, after the training phase of the neural module is completed, the k choice and mask couples, given as output by the Generative Neural module are provided to the Explanation Generator module devoted to combining the collected information to build a set of minimal disjoint explanations for the outlier o.

To compute this set of explanations, we collect the set C consisting of all the choices associated with objects of the reference set RS and find the frequent itemsets F_C (in our context each feature represent an item). Then, for each of the frequent itemsets found (representing a frequent choice) f in F_C we apply a clustering algorithm to the reference set samples whose corresponding choice contains f, in particular, in this work, we have leveraged DBSCAN [23]. After this clustering step, we take for each cluster its medoid as a representative point used to find a mask related to that set of samples, which, together with f, is one of the explanations provided to the user.

3.1. Explanation computation

Both the previously referred Choice Generator and Mask Applier networks consist of feed-forward dense neural networks having $l_g \geq 3$ layers having a number $n_{g1} \cdot d$ ($n_{g1} \geq 3$) of neurons. The layers of the latter of the two modules have linear activation functions, while, for the first neural network, the hidden layers are equipped with a ReLU activation function and the output layer with a sigmoid. This results in returning the d-dimensional real-valued choice vector $\tilde{c}$, having values $\tilde{c}_i \in [0, 1]$ which are eventually converted into a binary format $c_i \in \{0, 1\}$ through a thresholding operation.

To carry out the training, M²OE has to compute a statistic vector s on RS, whose i-th feature ($1 \leq i \leq d$) is the mean feature-wise squared differences between normal points:

$$s_i = \frac{2}{k(k-1)} \sum_{r,r' \in RS} (r_i - r'_i)^2.$$

Given this vector, the outlier o and the reference sample r, the loss function leading the neural networks training is the following:

$$\mathscr{L}(o,r) = \alpha_1 \cdot \frac{\sum_{i=1}^{d} s_i \cdot \tilde{c}_i}{\left[\sum_{i=1}^{d}(o_i - r_i)^2 \cdot \tilde{c}_i\right] + \epsilon} + \alpha_2 \cdot \sum_{i=1}^{d} \left[(\tilde{o}_i' - r_i)^2 \cdot \tilde{c}_i\right] + \alpha_3 \cdot ||\tilde{c}||^2 \tag{1}$$

in which α_1, α_2 and α_3 are values used to weigh the contributions of the three terms appearing in the loss function, ϵ is a small constant to avoid division by zero and $\tilde{o}'$ is the sample resulting from the transformation application. The three-fold objective of this loss is to find the subspaces in which the outlier deviates most from the normal samples (first term) while making the transformed outlier $\tilde{o}'$ as similar as possible to the normal samples (second term) and keeping the number of features included in the explanation low (last term).

4. Case of study

In our previous works [4, 5], the performances of M^{2}OE have been thoroughly discussed. In particular, it has been shown that, despite not being specifically tailored to search for subspace-based explanations, the quality of the set of features included in the transformation is in almost all cases better than those of the competitors involved in our experiments, namely ATOM and COIN, or at least comparable. Furthermore, we have shown that the transformations provided as an explanation, a novelty in the outlier explanation field, can get the outlier closer to behaving as a normal sample. In this section, our efforts are focused on observing the explanations provided by M^{2}OE to check the insights they offer and their actionability. To carry out this experiment we have used the dataset described in Section 2, which is presented for the first time in this work. In our Outlier Explanation setting, countries showing a high Green Comparative Advantage are the outlier samples whose behaviour is under study. So, to summarize, we consider 16 countries exhibiting a high relative advantage in exporting low-carbon technologies in which an economic boost potentially pushes forward the development of these low-impacting technologies.

For this analysis, the M^{2}OE method is set up as follows. Due to the small number of samples available, we consider as a reference dataset all the samples not belonging to the studied group, so 38 countries. The neural modules being part of the Generative Neural Module are trained for 30 epochs, with loss weights equal to 1.0, 1.2 and 0.3 respectively, and a learning rate equal to 0.001.

The results of the explanation for the considered countries are depicted in Figure 2, where, for each of them, the characterizing features are listed by showing the alteration suggested to make the comparative advantage of that nation low. To improve the delivery of the explanations, we present the transformation values as percentages of the original values of the features. In the following, we summarize the findings extracted by M^{2}OE, however, the explanations reported in the figure supply detailed explanations showing also how to change pointed-out features expressed as a percentage of the original feature value.

- According to the explanations provided by M^{2}OE, Austria's comparative advantage is due to its taxes on transport (Figure 2a), indeed decreasing them by about 30% causes a loss of this behoof. Taxes bear a high level for this index also for the Republic of Croatia (Figure 2b), Hungary (Figure 2g) and Slovak Republic (Figure 2n). Indeed, according to the results of the methodology considered in this work, a decrease in Taxes on Energy and Environmental taxes for the first, and taxes on pollution for the last two would make them have a low value for the considered index.
- Another group of countries stand out in terms of comparative advantage due to investments related to the environment. More in detail, the Czech Republic (Figure 2c) is characterized by expenditure on biodiversity and landscape protection, Estonia (Figure 2e) on environmental protection R&D, Italy (Figure 2i) on waste management and environmental protection R&D, North Macedonia (Figure 2k) on environmental protection for unclassified aspects and, finally, United Kingdom (Figure 2p) on waste management.
- Another frequent pattern is that in which the policies are supposed to combine expenditures and targeted taxes. According to the information we have retrieved, it happens in Denmark (Figure

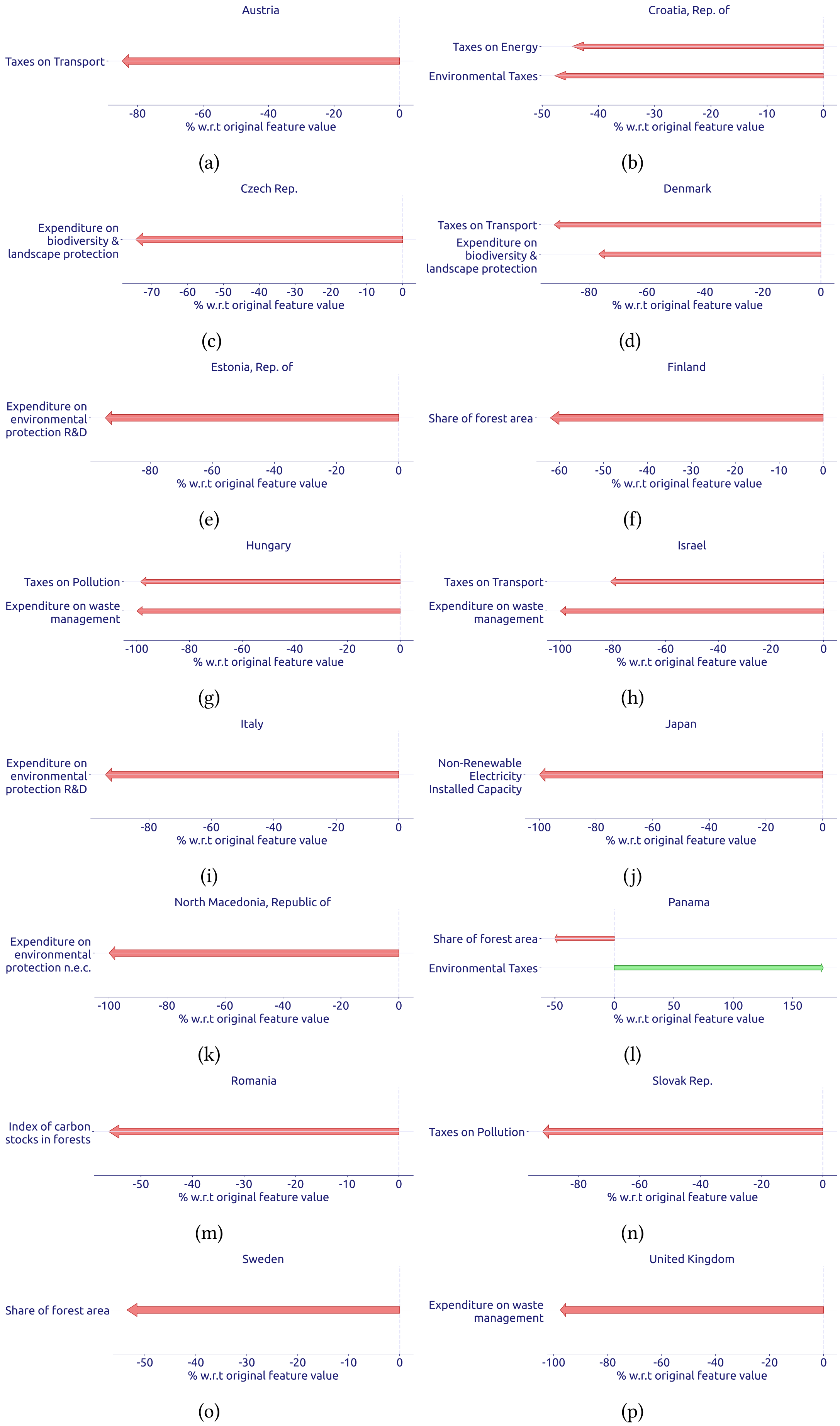

Figure 2: M²OE's explanations for the 16 countries having a green comparative advantage.

2d) whose policy is characterized by a mix of taxes on transport and investment in biodiversity and landscape protection and in Israel (Figure 2h) where investments on waste management are combined with taxes on transport.

- In other cases, the pivotal feature for comparative advantage relates to geographical aspects like the share of forest area for Finland and Sweden (Figures 2f and 2o respectively) and the index of carbon stocks in forests for Romania (Figure 2m). In both cases, a reduction is supposed to cause a low comparative advantage.
- Finally, the remaining two nations, namely Japan (Figure 2j) and Panama (Figure 2l), exhibit an explanation differing from the previously described patterns. As for the first of them, M^{2}OE says that to reduce its comparative advantage a decrease in non-renewable electricity generation is needed, while, as for the second, the proposed method's suggestion is to reduce the forest area a little and increase environmental taxes heavily.

Since the object of our analysis is also to assess the ability of M^{2}OE to effectively unveil the key aspects of countries of high comparative advantage, it is useful to recall that explanations need to be read in such a way: the features included in the explanation are the important aspects and features positively impact the considered index if the transformation suggests lowering their value and negatively otherwise.

The previously performed analysis testifies that the suggestions from M^{2}OE's explanations can be translated into actions that decision-makers can perform.

To further confirm the quality of the observed results, we have measured the outlierness score of the analyzed samples in the space given by the features included in the explanation. More in detail, we have computed the mean value of the outlierness score on the original outliers and the samples resulting from the transformation. Moreover, we have measured the fraction of correctly patched samples, that is to say, the portion of outliers for which the returned transformation has lowered their anomaly score of at least 5%. The outlierness score involved in our analysis is the iForest score [24], based on the Isolation Forest anomaly detection method, whose underlying idea is that the anomalies are few and isolated from the normal samples. This score has been chosen for its dimension unbiasedness, which makes comparable even explanations with different numbers of features. The outliers in the set of features provided by the explanations show a mean outlierness of 0.65, which is consistently higher than that shown by the full feature space equal to 0.42. Instead, the samples resulting from the transformation exhibit an outlierness score of 0.45, which is substantially lower than that of the outliers, indeed, the 96% of the samples has been correctly transformed. This further confirms our conviction on the actionability of the explanations provided by M^{2}OE in the considered context, also witnessed by the previous qualitative evaluation.

5. Conclusion

In this paper, we have analyzed M^{2}OE, a transformation-based outlier explanation method, in the green economy context to study its effectiveness in extracting actionable explanations.

To analyze this context, we have designed a tabular dataset, named the Green Comparative Advantage (GreenCA) dataset, representing one of the contributions of this paper. This data collection summarizes and reshapes information accessed from the International Monetary Fund about many indicators relative to the Green Comparative Advantage, which is an index measuring the relative benefit of exporting low-carbon technologies.

Inspecting the explanations provided for 16 nations exhibiting a high comparative advantage, we have seen how the transformations provided by M^{2}OE as explanations can be considered actionable since they provide useful suggestions showing how to make that countries have a low comparative advantage by acting on the policies or natural aspects like the share of forests. This information is useful in a complementary analysis to unveil the aspects characterizing countries having a high comparative advantage. The quality of the observed explanations has also been validated through a numerical analysis. In future work, we plan to deepen our analysis by considering social, economic and environmental diversity to observe how they influence the Green Comparative Advantage.

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References

[1] D. o. E. United Nations, S. A. S. Development, Transforming our world: the 2030 agenda for sustainable development, 2015. URL: https://sdgs.un.org/2030agenda.

[2] K. Abbass, M. Z. Qasim, H. Song, M. Murshed, H. Mahmood, I. Younis, A review of the global climate change impacts, adaptation, and sustainable mitigation measures, Environmental Science and Pollution Research 29 (2022) 42539–42559.

[3] F. C. Moore, K. Lacasse, K. J. Mach, Y. A. Shin, L. J. Gross, B. Beckage, Determinants of emissions pathways in the coupled climate–social system, Nature 603 (2022) 103–111.

[4] F. Angiulli, F. Fassetti, S. Nisticó, L. Palopoli, Counterfactuals explanations for outliers via subspaces density contrastive loss, in: International Conference on Discovery Science, Springer, 2023, pp. 159–173.

[5] F. Angiulli, F. Fassetti, S. Nisticò, L. Palopoli, Explaining outliers and anomalous groups via subspace density contrastive loss, Machine Learning (2024) 1–25.

[6] B. Micenková, R. T. Ng, X.-H. Dang, I. Assent, Explaining outliers by subspace separability, in: 2013 IEEE 13th international conference on data mining, IEEE, 2013, pp. 518–527.

[7] X. H. Dang, I. Assent, R. T. Ng, A. Zimek, E. Schubert, Discriminative features for identifying and interpreting outliers, in: 2014 IEEE 30th international conference on data engineering, IEEE, 2014, pp. 88–99.

[8] T. Mokoena, T. Celik, V. Marivate, Why is this an anomaly? explaining anomalies using sequential explanations, Pattern Recognition 121 (2022) 108227.

[9] F. Angiulli, F. Fassetti, L. Palopoli, Detecting outlying properties of exceptional objects, Acm transactions on database systems (tods) 34 (2009) 1–62.

[10] F. Angiulli, F. Fassetti, G. Manco, L. Palopoli, Outlying property detection with numerical attributes, Data mining and knowledge discovery 31 (2017) 134–163.

[11] F. Angiulli, F. Fassetti, L. Palopoli, Discovering characterizations of the behavior of anomalous subpopulations, IEEE Transactions on knowledge and data engineering 25 (2012) 1280–1292.

[12] F. Angiulli, F. Fassetti, L. Palopoli, C. Serrao, A density estimation approach for detecting and explaining exceptional values in categorical data, Applied Intelligence 52 (2022) 17534–17556.

[13] J. Zhang, M. Lou, T. W. Ling, H. Wang, Hos-miner: A system for detecting outlying subspaces of high-dimensional data, in: Proceedings of the 30th International Conference on Very Large Data Bases (VLDB'04), Morgan Kaufmann Publishers Inc., 2004, pp. 1265–1268.

[14] L. Duan, G. Tang, J. Pei, J. Bailey, A. Campbell, C. Tang, Mining outlying aspects on numeric data, Data Mining and Knowledge Discovery 29 (2015) 1116–1151.

[15] N. X. Vinh, J. Chan, S. Romano, J. Bailey, C. Leckie, K. Ramamohanarao, J. Pei, Discovering outlying aspects in large datasets, Data mining and knowledge discovery 30 (2016) 1520–1555.

[16] F. Angiulli, F. Fassetti, S. Nisticò, L. Palopoli, Outlier explanation through masking models, in: European Conference on Advances in Databases and Information Systems, Springer, 2022, pp. 392–406.

[17] International Monetary Fund, Climate change indicators dashboard. environmental taxes, https://climatedata.imf.org/pages/access-data, 2022. Accessed on 2024-09-07.

[18] International Monetary Fund, Climate change indicators dashboard. environmental protection expenditures, https://climatedata.imf.org/pages/access-data, 2022. Accessed on 2024-09-07.

[19] International Monetary Fund, Climate change indicators dashboard. forest and carbon, https://climatedata.imf.org/pages/access-data, 2022. Accessed on 2024-09-07.
[20] International Monetary Fund, Climate change indicators dashboard. fossil fuel subsidies, https://climatedata.imf.org/pages/access-data, 2022. Accessed on 2024-09-07.
[21] International Monetary Fund, Climate change indicators dashboard. renewable energy, https://climatedata.imf.org/pages/access-data, 2022. Accessed on 2024-09-07.
[22] International Monetary Fund, Climate change indicators dashboard. trade in low-carbon technology products, https://climatedata.imf.org/pages/access-data, 2022. Accessed on 2024-09-07.
[23] M. Ester, H.-P. Kriegel, J. Sander, X. Xu, et al., A density-based algorithm for discovering clusters in large spatial databases with noise., in: kdd, volume 96, 1996, pp. 226–231.
[24] F. T. Liu, K. M. Ting, Z.-H. Zhou, Isolation forest, in: 2008 eighth ieee international conference on data mining, IEEE, 2008, pp. 413–422.