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USING MACHINE LEARNING METHODS FOR PREDICTION OF DURABLE ECONOMIC DEVELOPMENT: ROMANIA CASE STUDY

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Abstract

Emerging economies tend to be impacted most by fluctuations in the global economy, due to their relatively low degree of economic stability. The actors from within these economies must consider various parameters of the economy and tackle many different aspects regarding inputs, methodologies and economic strategies. Thus, besides the obvious target of economic development, these economies must consider the alignment with the external factors, the social movements regarding workforce and social welfare, as well as the efficient usage of resources for production branches of the economy. The economy can be characterized by both quantitative and qualitative indicators, linked to Gross Domestic Product (GDP), but also to enterprise health status, thus related to the turnover, profitability and number of enterprises. The sustainability of a healthy economy is also shown by the concern related to the employment status, human development index (HDI) and the general consumption of the population at a national level. Last, but not least, the economy is durable related to resources issues, the impact of the economic branches on the environment (air, water, soil and biodiversity) being one of the major concerns in the context of a turbulent climate debate. In this paper, we will present the correlations between the economic development, the social climate and the economic environment impact in Romania. After using traditional statistic methods for presenting these correlations, we will create trend predictions using Machine Learning (ML) methods using the traditional ML methodology. The results will be then compared to the usual methods used for prediction in statistics.

Key words: *economic development, sustainability, machine learning, society*

INTRODUCTION

The health of a national economy relates to all the aspects that are involved in the production processes. This paper shows the correlations between economic indicators and entrepreneurial and social aspects, as well as the impact on the environment.

The whole market is an open space influenced by numerous and various parameters, each one of them adding their contribution to the general dynamic of the economy. Moreover, global movements can be started from actions of people, individuals or small enterprises.

Nowadays, market pleads for an integrated approach on the production of economic goods, which leads to a more efficient allocation of resources, happier customers, more engaged employees and better policies regarding the environment, leading to the increase of efficiency of the economic system.

European environment policy rests on the principles of precaution, prevention and rectifying pollution at source, and on the 'polluter pays' principle. Multiannual environmental action programs set the framework for future action in all areas of environment policy. They are embedded in horizontal strategies and considered in international environmental negotiations. Last but not least, implementation is crucial.

The European Union legislation has a strong point in relation to environmental issues. Thus, the main laws regarding Articles 11 and 191 to 193 of the Treaty on the Functioning of the European Union (TFEU) [12]. The sustainable economic development is based on the key concepts of sustainability [13] and compliance to the ecology [4], environmental laws and resource efficient use. Extended explanations regarding sustainability of the economic development [7] are shown in the works of [1] and [9].

This paper presents the general impact of the economic performance on the social factors and environmental components in Romania, the correlations between certain indicators of these and their dynamic during a decade (2007-2017). The general purpose of this presentation is to describe the economic and social environment and, based on this description, to use the ML techniques in order to predict the behaviour of the economic system in an integrated manner, using and processing the trained and tested historical data. In this matter, section 2 presents a literature review regarding the economic development and methods used in the literature for predictions. In section 3, we will present the methods that base the results obtained in the paper. Section 4 is the section regarding the Discussion area on the resulted data linked to the section 5 regarding the Results obtained for the ML-based methods.

MATERIALS AND METHODS

Presentation of main indicators

We will present some economic, social and environmental indicators for Romania in the period 1995-2019. These indicators consist in:

-***The Gross Domestic Product***, showing the increased value of the economy (Figure 1).

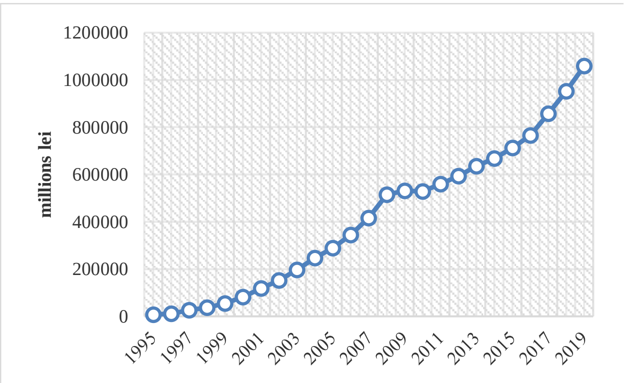
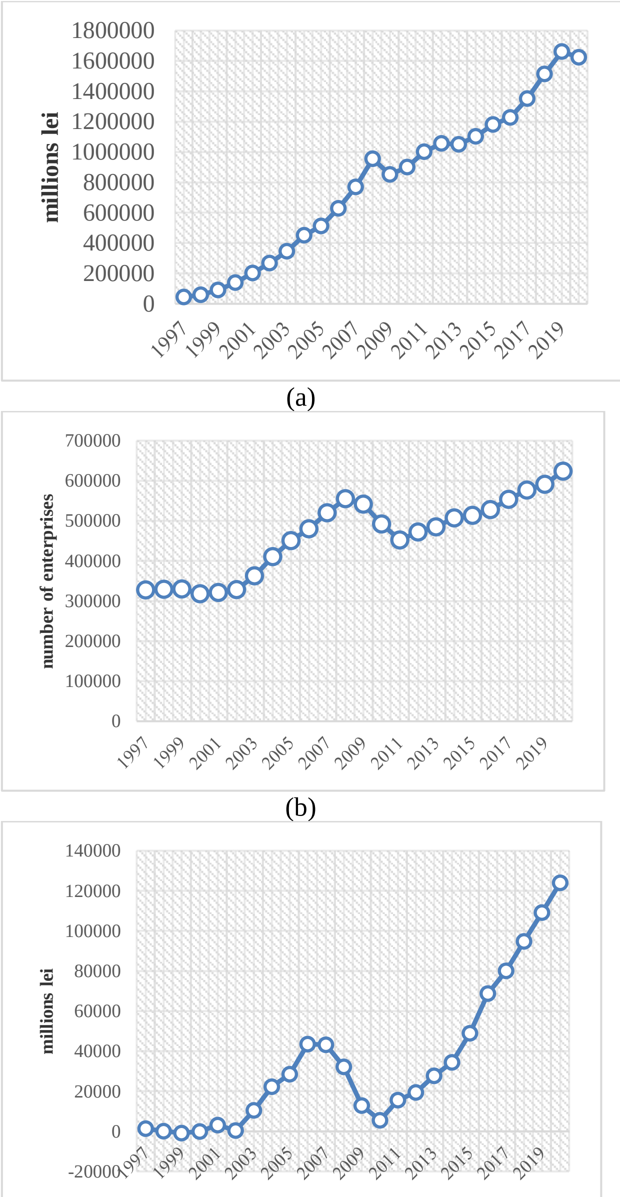


Fig. 1. GDP in Romania in the period 1995-2019.
Source: NIS, Tempo online [5].

- ***The economic indicators of the enterprises***: the turnover, showing the total value of the production within an enterprise for industrial and services branches, the profitability and the number of enterprises, showing the degree of atomicity within the economy (Figure 2, a, b, and c).



(c)

Fig. 2. (a) Total turnover in Romania for industry and services; (b) the number of enterprises; (c) the yearly result (profit/loss).
Source: NIS, Tempo online [5].

-***The social indicators of the economy***: the employment statistic, showing the number of people involved in the economy as employees, and the human development index (HDI), an index cumulating factors of human welfare (Figure 3, a and b).

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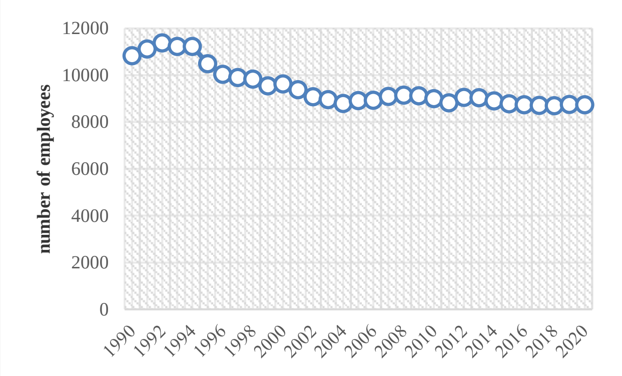
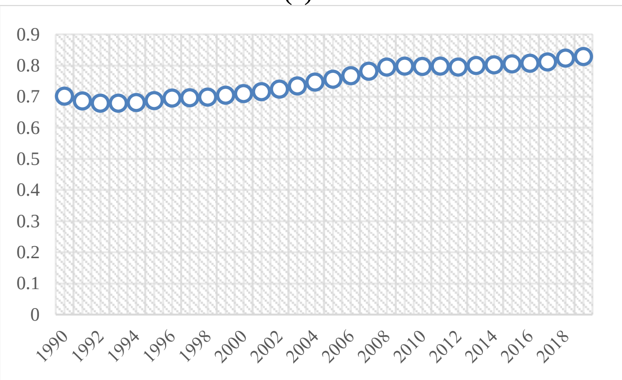


(a)



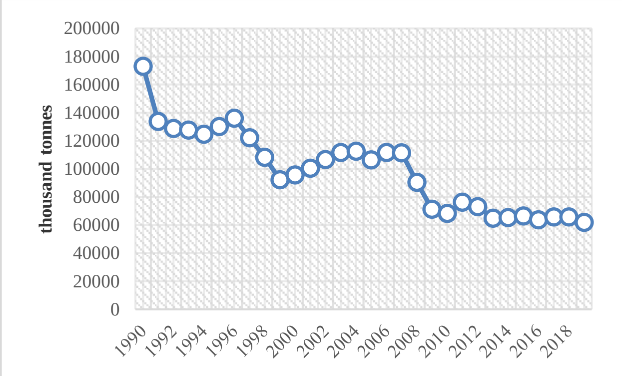
(b)

Fig. 3. (a) The employment statistic in Romania; (b) The Human Development Index
Sources: NIS, Tempo online and United Nations Development Programme, Human Development Reports [5, 14].

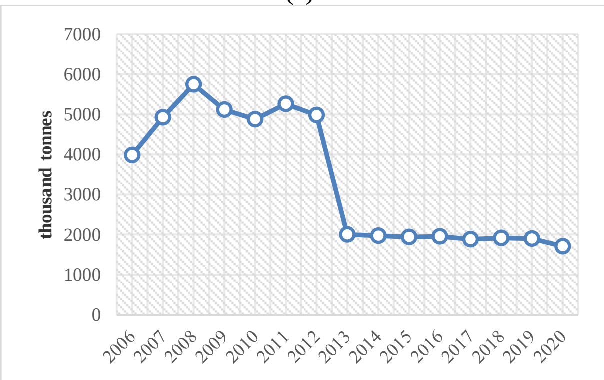
-***The environmental indicators***: the emissions of carbon dioxide, the wastewater quantity, and the costs regarding environmental impact for the four factors (water, air, soil and biodiversity) (Figure 4, a, b and c).

For some of the values, the lack of necessary data for training of the used instruments led to choosing more specific ones (e.g., the turnover for specific branches of the economy was taken into consideration), which shifted the objectives of the research to slightly different hypotheses.

For example, one of the most important one consisted in the need of the agricultural processing methods for obtaining raw materials for the other branches of the economy.



(a)



(b)

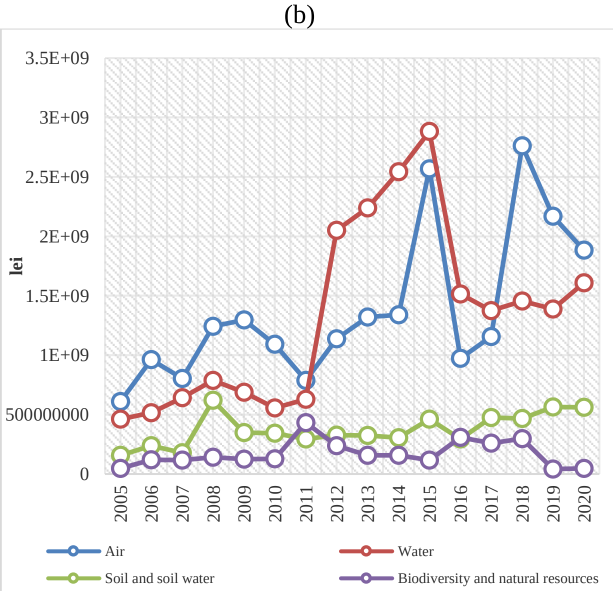


Fig. 4. (a) The CO_2 emissions in Romania; (b) The quantity of wastewater; (c) Costs related to environmental impact.
Source: NIS, Tempo online [5].

Using Linear Regression

We will use the linear regression model in order to show some correlations between the parameters listed in the previous subsection. The linear regression is a common-used approach in order to show the dependency of an independent x-value for a y-value that is considered to be influenced by the x-value.

Presentation of Machine Learning (ML) methods

Machine Learning is used in a variety of domains, such as economy [11], technology, networks and traffic [6], architecture [10], arts [2], education [8] and the list can be countless. For the dataset some Machine Learning methods were applied: firstly, they were trained, then used for prediction after checking them using some random test data. The methods chosen to be applied are:

-***Linear regression*** - Linear regression is an attractive model because the representation is so simple. The representation is a linear equation that combines a specific set of input values (x) the solution to which is the predicted output for that set of input values (y). As such, both the input values (x) and the output value are numeric. The linear equation assigns one scale factor to each input value or column, called a coefficient and represented by the capital Greek letter Beta (β). One additional coefficient is also added, giving the line an additional degree of freedom (e.g. moving up and down on a two-dimensional plot) and is often called the intercept or the bias coefficient.

-***K-means clustering*** - K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K. The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity.

-***KNN - K nearest neighbors*** is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970's as a non-parametric technique. A case is classified by a majority vote of its neighbors, with the case being assigned to the class most common amongst its K nearest neighbors measured by a distance function. If K = 1, then the case is simply assigned to the class of its nearest neighbor.

-***SVM - A Support Vector Machine (SVM)*** is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two-dimensional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.

We have made some correlations between economic parameters and those related to enterprise statistics, as well as the ones related to social and environmental aspects, using the classical linear regression method. The results are presented in Table 1 and they were obtained using PAST software [3].

It was considered that the economic dynamics can be resumed using the GDP indicator, the enterprises statistics by the total turnover, the profit and the number of enterprises, the social aspects by the number of employees and the Human Development Index and the environmental impact by CO_2 emissions, quantity of waste water and the costs related to environmental issues for four factors (air, water, soil and biodiversity).

RESULTS AND DISCUSSIONS

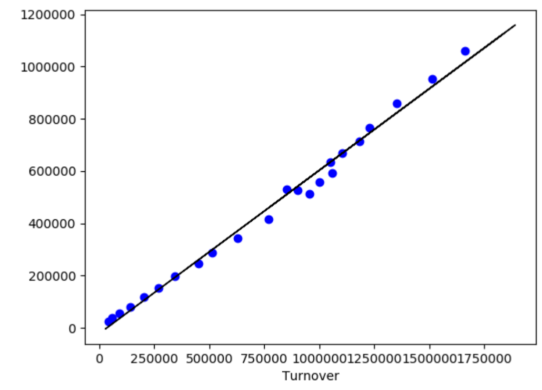
The linear regressions resulted above were obtained using classical statistical model. The model of linear regression can be extended using machine learning methods.

In this matter, we applied the machine learning methodology for the data series described above.

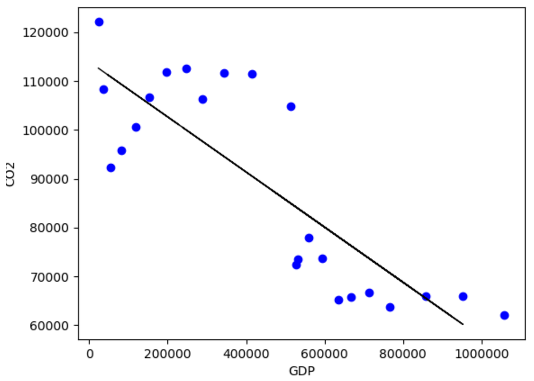
Regarding the training phase, the resulted plot for the Turnover-GDP correlation is shown in Fig. 5 (a and b).

While the number of statistical instruments for the analysis of the correlation of parameters have multiplied recently, the machine learning approach has the advantage of a better prediction based on historical data.

In Figure 5, the training phase is presented and shows the representation of the correlation between (a) the turnover and GDP and (b) GDP and CO_2 emissions. While the Turnover-GDP correlation is strong, given the low distance of the points to the mean, the second plot (b) shows a weaker connection between the parameters taken into consideration.



(a)



(b)

Fig. 5. Turnover-GDP correlation plot using machine learning method: (a) Turnover; (b) CO_2 emissions. Source: own determination.

In order to follow all the ML-based method phases, we used Python language and math-based libraries in order to train the data, test and predict.

```
''' Train with existent data '''
x_train =
f_data['Turnover'].values[:,numpy.newaxi
s]
y_train = f_data['GDP'].values

''' Apply regression '''
lm = LinearRegression()
lm.fit(x_train, y_train)

''' Generate 10 sample random data for
Turnover '''
x_test = numpy.random.randint(2000000,
size=(10, 1))
print(x_test)

''' Calculate prediction data for GDP
for the generated sample data '''
predictions = lm.predict(x_test)
print (predictions)

''' Plot data '''
plt.scatter(x_train, y_train, color='b')
plt.plot(x_test, predictions,
color='black', linewidth=1)
plt.xlabel('Turnover')
plt.ylabel('GDP')
plt.show()
```

For prediction, we have used randomly generated numbers for the turnover. The resulted values are shown in Table 1. Even if the data taken into consideration is random, the results show a close relationship between the historical data and the predicted data.

Table 1. The resulted data for GDP for random values of turnover based on ML prediction

GDP	Turnover
226,121.34	396,990
674,300.69	1,114,695
1,127,204.72	1,839,966
996,377.47	1,630,462
462,606.88	775,693
1,159,185.27	1,891,179
-4,399.98	27,838
272,926.61	471,943
1,116,937.31	1,823,524
463,009.04	776,337

Source: own determination.

We have applied the same algorithm for a GDP-CO_2 emissions correlation value. The values are shown in Table 2. The same remark can be given as for the previous data in Table 1.

```
''' Train with existent data '''
x_train = f_data['
GDP'].values[:,numpy.newaxis]
y_train = f_data['CO2'].values

''' Apply regression '''
lm = LinearRegression()
lm.fit(x_train, y_train)

''' Generate 20 sample random data for
GDP '''
x_test = numpy.random.randint(1000000,
size=(20, 1))
print(x_test)
```

```
''' Calculate prediction data for CO2
emissions for the generated sample data
'''
predictions = lm.predict(x_test)
print (predictions)

''' Plot data '''
plt.scatter(x_train, y_train, color='b')
plt.plot(x_test, predictions,
color='black', linewidth=1)
plt.xlabel('GDP')
plt.ylabel('CO2')
plt.show()
```

Table 2. The resulted data for CO_2 emissions for random values of GDP based on ML prediction

CO_2 emissions	GDP
70,595.55	768,482
68,001.32	814,456
70,157.05	776,253
69,179.09	793,584
92,573.99	378,988
100,552.14	237,602
66,968.01	832,768
81,935.41	567,521
87,661.24	466,050
72,045.64	742,784
70,059.54	777,981
66,517.21	840,757
60,189.58	952,893
87,079.69	476,356
61,792.87	924,480
111,326.20	46,668
102,125.25	209,724
101,053.79	228,712
101,992.92	212,069
112,637.48	23,430

Source: Own results.

We have also generated a cluster-based organization of some of the indicators taken into consideration, in order to show the level of each value of these indicators in correlation with others.

The chosen indicators were obviously measured using the same measure unit (million lei): GDP, turnover, profit and costs related to environmental impact. The results are shown in Fig. 6. The K-means clustering can be helpful in situations such as labelling unknown data, where certain values are given and the indicator of that value is unknown.

We have also made some correlations between economic parameters and those related to enterprise statistics, as well as the ones related to social and environmental aspects, using the classical linear regression method.

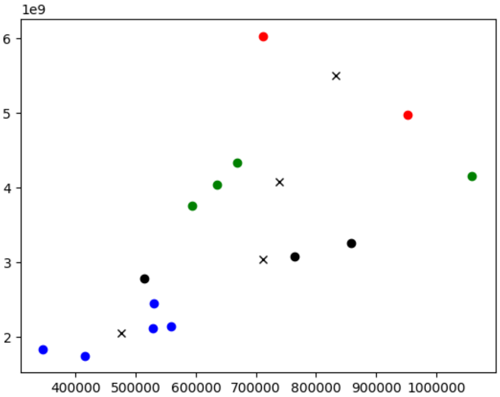


Fig. 6. K-means clustering for the presented values. Each colour represents the general cluster for each indicator
Source: own determination.

The results are presented in **Error! Reference source not found.** and they were obtained using PAST software (Hammer, Harper, & Ryan, 2001).

It was considered that the economic dynamics can be resumed using the GDP indicator, the enterprises statistics by the total turnover, the profit and the number of enterprises, the social aspects by the number of employees and the Human Development Index and the environmental impact by CO_2 emissions, quantity of waste water and the costs related to environmental issues for four factors (air, water, soil and biodiversity).

Firstly, the correlation plot (a) that highlights the behavior of the Turnover-GDP correlation shows that the two variables are strongly and positively correlated, which is shown by the high value of the correlation coefficient (0.9959). The correlation also has a high degree of trust, given by the value of R-squared coefficient (0.99181).

The positive correlation is somehow expectable, due to the same trend that both had during the period and the inclusion relation that can be established between them.

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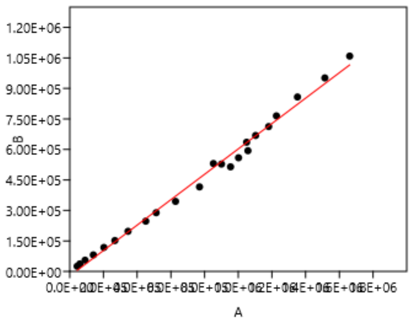
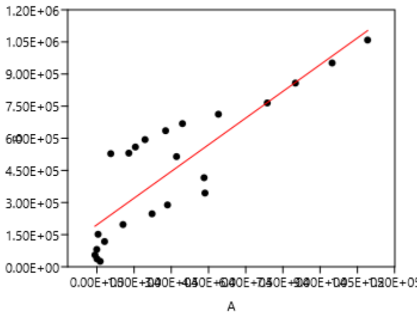
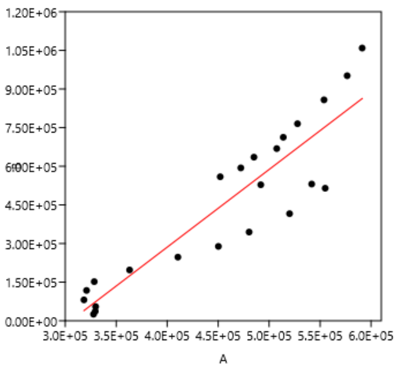
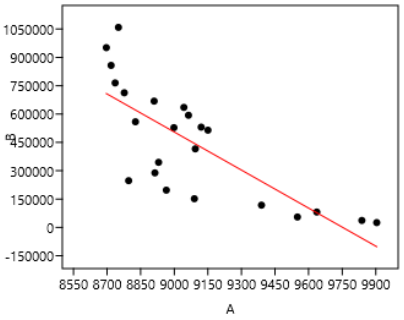
Table 3. Results of correlations between selected parameters

Correlation variables	**Plot**	**Correlation for linear regression**
(a) Turnover-GDP		Ordinary Least Squares Regression: A-B Slope a: 0.62446 Std. error a: 0.012381 t: 50.435 p (slope): 2.1169E-23 Intercept b: -21,784 Std. error b: 11,068 95% bootstrapped confidence intervals (N=1999): Slope a: (0.60352, 0.65435) Intercept b: (-36,170, -2,326.7) Correlation: r: 0.9959 r2: 0.99181 t: 50.435 p (uncorr.): 2.1169E-23 Permutation p: 0.0001
(b) Profit - GDP		Ordinary Least Squares Regression: A-B Slope a: 8.3059 Std. error a: 1.0939 t: 7.5927 p (slope): 1.8835E-07 Intercept b: 1.9627E05 Std. error b: 47,533 95% bootstrapped confidence intervals (N=1999): Slope a: (6.5981, 9.8886) Intercept b: (9,3441, 2.8033E05) Correlation: r: 0.85615 r2: 0.73299 t: 7.5927 p (uncorr.): 1.8835E-07 Permutation p: 0.0001
(c) Number of enterprises – GDP		Ordinary Least Squares Regression: A-B Slope a: 3.0177 Std. error a: 0.29198 t: 10.335 p (slope): 1.0841E-09 Intercept b: -9.2113E05 Std. error b: 1.3526E05 95% bootstrapped confidence intervals (N=1999): Slope a: (2.5335, 3.6138) Intercept b: (-1.1523E06, -7.1342E05) Correlation: r: 0.91417 r2: 0.8357 t: 10.335 p (uncorr.): 1.0841E-09 Permutation p: 0.0001

(d) Number of employees – GDP



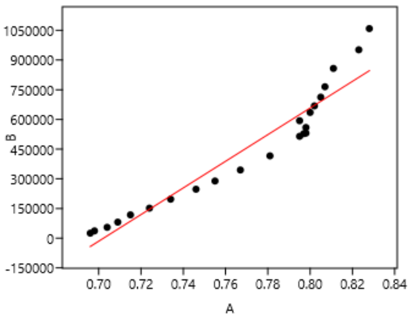
Ordinary Least Squares Regression: A-B

Slope a: -671.18
Std. error a: 121.36
t: 5.5305
p (slope): 1.7326E-05
Intercept b: 6.5455E06
Std. error b: 1.103E06

95% bootstrapped confidence intervals (N=1999):
Slope a: (-856.96, -406.73)
Intercept b: (4.1392E06, 8.2997E06)

Correlation:
r: -0.77001
r2: 0.59291
t: -5.5305
p (uncorr.): 1.7326E-05
Permutation p: 0.0001

(e) HDI – GDP



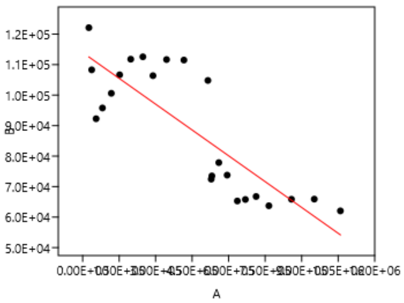
Ordinary Least Squares Regression: A-B

Slope a: 6.7295E06
Std. error a: 4.4069E05
t: 15.27
p (slope): 7.6194E-13
Intercept b: -4.7257E06 Std. error b: 3.3943E05

95% bootstrapped confidence intervals (N=1999):
Slope a: (5.7591E06, 7.6523E06)
Intercept b: (-5.4046E06, -3.9671E06)

Correlation:
r: 0.9578
r2: 0.91738
t: 15.27
p (uncorr.): 7.6194E-13
Permutation p: 0.0001

(f) GDP – CO_2 emissions



Ordinary Least Squares Regression: A-B

Slope a: -0.056428
Std. error a: 0.0081636
t: 6.9122
p (slope): 7.8866E-07
Intercept b: 1.1396E05
Std. error b: 4413.5

95% bootstrapped confidence intervals (N=1999):
Slope a: (-0.068003, -0.039971)
Intercept b: (1.0461E05, 1.2175E05)

Correlation:
r: -0.83347
r2: 0.69467
t: -6.9122
p (uncorr.): 7.8866E-07
Permutation p: 0.0001

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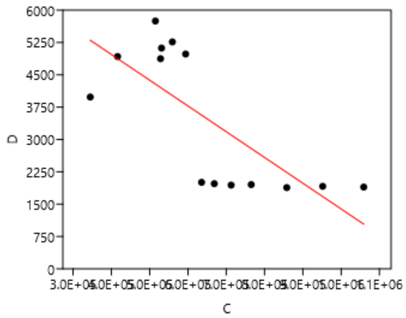
(g) GDP – Wastewater



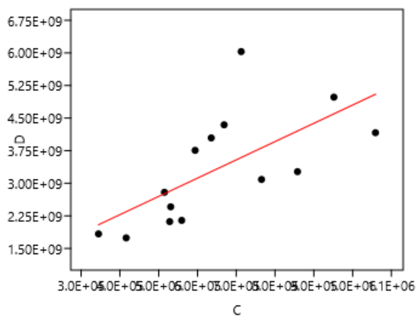
Ordinary Least Squares Regression: C-D

Slope a: -0.0059706
Std. error a: 0.001564
t: 3.8175
p (slope): 0.0024506
Intercept b: 7359.4
Std. error b: 1064.9

95% bootstrapped confidence intervals (N=1999):
Slope a: (-0.0078092, -0.0014593)
Intercept b: (4478.6, 8941.9)

Correlation:
r: -0.74055
r2: 0.54842
t: -3.8175
p (uncorr.): 0.0024506
Permutation p: 0.0018

(h) GDP – Environment costs



Ordinary Least Squares Regression: C-D

Slope a: 4204
Std. error a: 1371.8
t: 3.0645
p (slope): 0.0098166
Intercept b: 5.9587E08
Std. error b: 9.3405E08

95% bootstrapped confidence intervals (N=1999):
Slope a: (371.71, 6043.6)
Intercept b: (-7.8053E08, 2.6012E09)

Correlation:
r: 0.66259
r2: 0.43902
t: 3.0645
p (uncorr.): 0.0098166
Permutation p: 0.0104

Source: Own determination.

The p-value for the regression is lower than 0.05, meaning the correlation is extremely strong.
The Profit-GDP correlation analysis (b) shows a lower, but still strong degree of connection between the behaviour of the GDP and the profit trend. This means that the GDP values are influenced also by other parameters of the economy, namely production costs or any other external factors and, thus, the influence of the profit on the dynamics of GDP is slightly weaker than the previous one. While the p-value is higher than at the plot (a), it still classifies the correlation as valid and possible to be taken into consideration.
The Number of enterprises – GDP (c) correlation is studied regarding the influence of the number of enterprises on the GDP dynamic. The p-value of the correlation shows that the correlation is strong, and the measurement is valid. The high values of the correlation coefficient and the R-squared coefficient show that the number of enterprises influences positively the increase of GDP values. This fact may indicate that, in an emergent economy, the small and medium enterprises must be encouraged in order to create a more dynamic character to the economy. This behavior is a normal one, due to the effects of the small and medium enterprises on a national economy.
The plot (d) highlighting the connection between the number of employees and GDP shows that the correlation between the two parameters is a negative one. However, the value of R-squared coefficient is relatively low, meaning the relation is a weaker one than the previous. The p parameter has a small value, given the correlation is a strong one. The negative correlation coefficient shows

that a lower number of employees lead to an increase in GDP, which may lead to the conclusion that the dynamic of the number of employees influences the GDP values in an opposite way.

Regarding the Human Development Index – GDP correlation (e), the increase of the HD index influences positively the increase of GDP. This fact shows, in this manner, that the human welfare regarding the improvement of the economic, educational and social aspects of life leads to the increase of the value of GDP. The values of the correlation parameters make the results of the analysis more stable and trustable. This may stand as a good motivation for improving the social and economic policies and those related to human welfare, due to the good impact of the human welfare on the economic increase.

We will discuss now the impact of the economic increase on the environmental factors. Firstly, the impact of the GDP on the CO_2 emissions (f) in the studied period tends to be inversely proportional, the CO_2 emissions lowering as the GDP increases. This shows that an increase in costs related to CO_2 emissions policies and technologies reflected in the final value of products leads to a reduction in carbon dioxide emissions. The linear regression can still be improved, as shown by the R-squared coefficient and the values of the p parameter, which lead to the impression of a better approximation of the real correlation behavior. This also happens for the wastewater quantity (g), in this case an extra parameter that must be considered is the fact that not all the economic entities have water as production wastes. As expected, an increase in GDP reflects also in the costs related to environment protection (h).

Another point of research consisted in the dependance of GDP indicator by the Turnover, Profit, Number of enterprises and Number of employees indicators. In order to solve that point, a multiple linear regression was generated. The characteristics of the regressions were:

- the dependent variable: GDP
- the dataset volume (N): 23
- multiple R: 0.99758
- multiple R^2: 0.99516
- multiple R^2 adjusted: 0.99409

The ANOVA interpretation had the following characteristics:

- F: 925.91
- df1, df2: 4. 18
- p: 1.4419E-20

The values are shown in **Error! Reference source not found.**.

Table 4. The results of the multivariate linear regression

Variable	Slope	Error	Intercept	Error	r	p
CO_2 emissions	-0.067171	0.017104	1.2107E05	11,646	-0.74993	0.002009
Waste water quantity	-0.0059706	0.001564	7,359.4	1,064.9	-0.74055	0.0024506
Costs with the environmental impact	4,204	1,371.8	5.9587E08	9.3405E08	0.66259	0.0098166

Source: Own determination.

Overall, an implication that can be extracted from the regression is that the GDP has a mild effect on the environmental indicators.

Authors should discuss the results and how they can be interpreted in perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

CONCLUSIONS

Machine Learning can be successfully used as an analysis method for datasets regarding various economic developments and its sustainability. In this paper, we have shown that an increase in the investments regarding environmental protection can lead to better values regarding the value of the production. Also, the human welfare has the tendency to increase the GDP values, as a direct result of the mechanisms related to human behaviour and its influence on the economic production.

Also, one of the main conclusions is centered on the fact that, because turnover from industrial and services branches of the economy were taken into consideration, the further processing of the agricultural products must be made in order for an economic development to be obtained.

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