An automated approach for sustainability evaluation based on Environmental, Social and Governance factors

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Abstract. This paper shortly describes a new approach for evaluation of Environmental, Social and Governance factors and combines them into an overall ESG rating. The proposed approach is based on automated calculations, implemented in a software system, called Sustainability Evaluator, that provides ESG ratings for small and medium-sized enterprises and organizations by using of known ESG ratings of other companies.

Keywords: Sustainability, Environment, Social, Governance, Multifactor, Validation, Neural Network.

1 Challenge and solution

The assessment of Environmental, Social and Governance (ESG) indicators plays an important role in investment analysis, affecting the reputation and trustworthiness of the financial market participants. Long-term sustainable development strategies require such analysis and for that reason ESG ratings are introduced. They are especially valuable when it comes to well-known companies and corporations. These ratings direct the attention toward socially responsible investments and facilitate the sustainable risk analysis.

In the past, several sustainability management standards, metrics and indices have been introduced, such as: Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), ISO 26000 Social Responsibility, Dow Jones Sustainability Indices (DJSI), Responsible Business Alliance (RBA), etc. The significance of such standards has increased over time and they have been adopted by corporations and investors [2][3].

ESG indicators measure the sustainable development of companies in different economy sectors and reflect whether corporate decisions and activities have taken into account multiple aspects concerning environmental protection, organizational effectiveness, social benefits, and so on. The ESG rating generates a long-term estimation of a company's trustworthiness. The companies without ESG rating might not be very attractive to the potential partners and investors, that normally prefer to take as informed as possible decisions.

The described methodology enables an automatic evaluation of ESG rating of states, organizations, companies, regions and municipalities, including small and less known companies. By analyzing a company's formal relations to other market participants, the methodology provides clear information on the target company and hence impacts investors' effectiveness, their decisions and strategies.

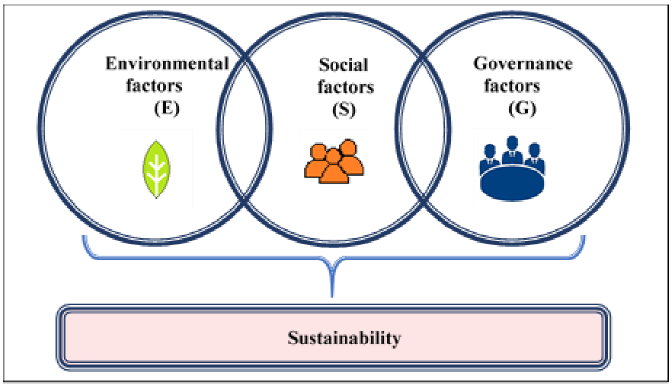

Fig. 1. Environmental, Social and Governance as indicators for sustainability.

2 Innovation

The current state of the art is that ESG ratings are evaluated for certain companies only, by using the common approach, that is based on expert created questionnaires. The questionnaires are composed of hard and soft facts that have to be identified first and then assessed for each of the three ESG factors (Environmental, Social and Governance), after which a numerical score is determined for each factor. Finally, the numerical scores are combined into a single score – the ESG rating. Factors that are taken into account, as well as their weights, often depend on the business sector. While hard facts represent directly measurable and indisputable data, soft facts are based on different opinions, which can be subjective. For that reason, this approach is considered subjective as well.

The challenges of the ESG rating estimation mainly concern the process of automation. Thus, both the ESG ratings become objective and the automation allows the ratings to be generated in short time periods. The automation is based on multifactor analysis, which consists of considering the historical company market data (e.g. share prices, products prices, etc.) and building a mathematical model by analyzing the dependency from such data of other companies. Since the historical data are based on decisions of multiple market participants, this method can be considered objective, thus truly reflecting the current state of a company. The mathematical model can be used by each market participant that is interested in evaluating a target company (e.g. a partner, a customer, etc.).

3 The Multifactor approach – methodology

Suppose we are given a finite number of discrete time series, called factors or variables, with equal length. They can represent arbitrary physical, social, financial or other processes or indicators. As such, their values correspond to measurements with certain frequency for all factors. One series is considered as a target factor and the others are explanatory factors. Explanatory factors represent independent variables, while the target factor is a dependent variable. The goal is to create a formula by which a series can be generated, using explanatory factors for a given historical period, which should be as close as possible to the given target series, using a chosen criterion [7, 8]. For simplification purposes, such a criterion can be the Euclidean distance between the given and generated target factor for all historical data points.

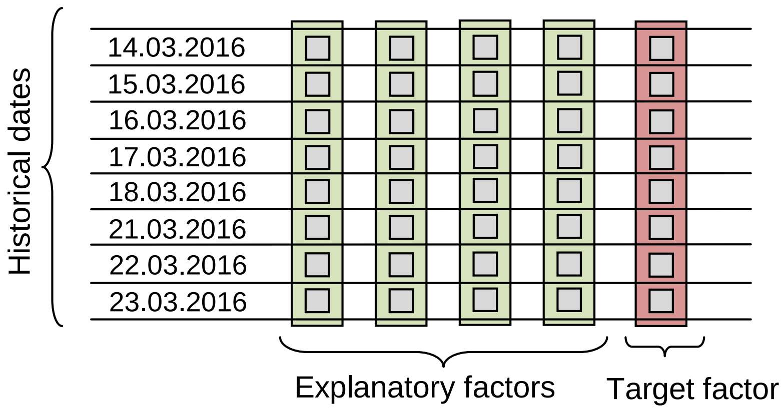

Fig. 2. Explanatory and target factor in multifactor modelling

Such a formula can be used for different purposes:

- Modelling of financial instruments. For example, an unknown composition of a stock index. Its model should be known in order to perform different calculations, such as simulations and Value at Risk (VaR) estimation.
- Sensitivity analysis, which evaluates the influence of changes of the explanatory factors on the target factor. This analysis can be quantitatively performed for one or more explanatory factors and the effect can be analyzed and practically interpreted.

According to our research, currently there is no software applications performing these operations in their clear form for the ESG rating evaluation. The formula can be in different forms, but in order to simplify the solution, the following polynomial form is used in our system:

$$y = \beta_1 f_1(f_1) + \beta_2 f_2(f_2) + \ldots + \beta_m f_m(f_m) + \beta_{m+1} \quad (1)$$

where f_1, f_2, …f_m represent arbitrary functions, called basis functions, β_1, β_2, … β_m represent numerical coefficients, called regression coefficients, and β_{m+1} is a free numerical term without an explanatory factor.

Formula Generation

The modelling stage starts with the selection of a target factor. In the practical multifactor modelling, all possible explanatory time series can participate in the formula. Since normally there are too many series that can be explanatory factors, a methodology for their selection must be chosen [9]. In our solution, a few alternative approaches are used, such as the selection of factors that most correlate to the target factor or minimally correlate to each other, etc.

When both target and explanatory factors are selected, the automatic modelling stage is performed by repeating the following steps:

1) Applying basis functions to explanatory factors;
2) Calculating the regression coefficients.

Performing the first step, in fact, produces new values for the explanatory factors, after which a new solution must be found by performing the next step. All this should be repeated as many times as needed in order to find the best combination of functions for the selected explanatory factors. In our software system, the first approach, does that randomly. The second implemented approach uses a more systematic procedure to find the best combination of functions. Considering that all functions can be applied to each of the selected factors, k^m combinations exist, where k is the number of basis functions and m is the number of explanatory factors. Usually, the explanatory factors are a few hundred and the basis functions are a few dozen. This means that, if the best combination must be found by brute force searching, there would be too many solutions to generate and calculate. That is why a heuristic approach is applied in our solution, using an evolutionary algorithm.

Finding the best combination of the basis functions

In practical solutions it is important for every experimental result to be reproducible. For that reason, our solution creates a main random generator that works with or without a seed value.

Initial set of candidate solutions

Provided that the functions are positioned in a fixed order, the main aim of the algorithm is to find a sequence of basis function indices that are as good as possible in respect to the Euclidean error between the generated and given target factor. For this purpose, a random integer sequence generator has been created that generates the initial population of integer sequences. Applying the functions to factors and calculating the regression coefficients produces a set of target factors, which are then compared to the real target. Thus, in terms of the evolutionary algorithm, an individual, that is a candidate solution, is represented as a sequence of integers with a length that are equals to the number of explanatory factors, while the goodness of fit is the distance between the generated and a given target factor. If a free term is being used, it is associated to a mock factor composed by values 1.0 for all historical dates.

Selection

Given a set of generated N individuals, the best L of them are selected. There are two alternative approaches: roulette wheel and truncation selection [10, 11]. The first is preferred in our solution as it allows each individual to continue the process regardless of the fact that its goodness of fit function produces poor result. Such individuals will just have a lesser chance to continue being part of the algorithm, even though it is not impossible.

Recombination and mutation

Recombination is performed by splitting the selected L individuals in one point and combining the split parts randomly. In our implementation, the splitting point is randomly generated at every step within the interval from 25% to 75% of the individual's length, rounded to the nearest integer.

Coefficients determination

The second step of the formula is calculating the regression coefficients, which is performed for every function combination to the explanatory factors. In our case, an ordinary least squares error is used, according to which coefficients are obtained in a matrix form, calculating the following matrix equation [9, 12, 13, 14]:

$$B = (A^T A)^{-1} A^T Y \qquad (2)$$

where B is the matrix of the regression coefficients, A is the matrix of factors with applied basis functions and Y is the target factor.

After the coefficients are calculated, they are being used for the computation of the generated target factor:

$$\hat{Y} = A \times B \qquad (3)$$

The distance between the generated and available target is:

$$d = \left\| Y - \hat{Y} \right\| \qquad (4)$$

This distance can be calculated with or without a decay factor [15].

Coefficients reduction

The formula terms with small coefficients can be removed, as they do not significantly influence the results. Removing small coefficients is optional in our solution and if it is performed the regression coefficients are calculated again.

Calibration

Using the generated formula for future calculations and modeling must be calibrated periodically and the formula must be reevaluated. This is needed, as with the progress of time, the accuracy of the formula decreases. The calibration process is shown in Fig. 3.

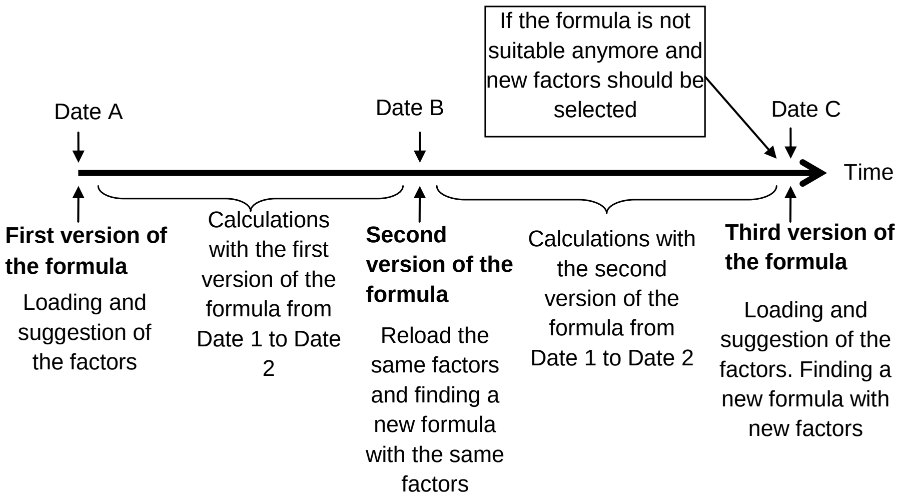

Fig. 3. Formula calibration

At first, target and explanatory factors are selected and loaded, creating the first version of the formula. This formula version is then applied to the calculations. After some time, when the generated target starts to deviate from the real values, the formula must be corrected. The selected explanatory factors, that have been used to build the first formula version, are applied again, but the formula is calibrated, new functions are selected and coefficients for the formula terms are produced. Thus, a second formula version is created, that is being used for the generation of the target until its values start again to deviate from the real target factor values. If this deviation is too significant, new explanatory factors should be selected. All factors are loaded again, a new factors selection is performed by one of the before mentioned automated approaches – clustering, min or max correlated – which can also be manually changed. The selected factors are used to generate the third formula version, where explanatory factors, basis functions and coefficients will be different in comparison to the previous formula versions. It can then be used for later calculations until a new calibration is needed.

Thus, there are two sorts of calibrations:

- Preserving currently selected explanatory factors and changing only the functions applied on them and on the regression coefficients, including the free term.
- Selecting new explanatory factors. In this case, new factors can be added, existing factors removed or both. The formula is being completely changed according to the basis functions and the regression coefficients.

In every formula calibration the settings can be changed, as the set of basis functions that can be used in the formula, with or without removing the terms with coefficients that are too small.

The experimental results show that the best results are obtained when the number of explanatory factors is close to, but not exceeding, the number of historical dates. It is not quite clear which basis functions should be supplied in the evolutionary algorithm for finding the best possible modeling formula. That is one of the issues that should be investigated further. Nevertheless, the system has already been introduced in real financial software solutions and has been used for the purposes stated in the introduction.

4 The Multifactor approach applied to the ESG rating calculation

Fig. 4. illustrates individual scorings of a sample company for each of the three main ESG factors – Environmental (39), Social (37) and Governance (54). The impact of each factor on the overall ESG rating, as well as on the balance between the three factors, can easily be derived from the figure.

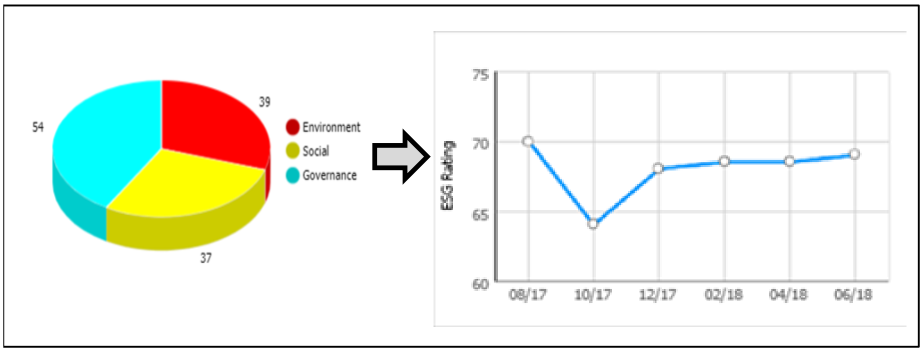

Fig. 4. Sustainability ESG categories and evolution of ESG rating

The ESG calculated ratings can be separated in two categories:

- Declarative rating – executed by the company itself. This rating is often considered subjective. It is not always clear how reliable it is, since companies tends to publish results that are in their own best interest.
- Requested rating – executed by rating providers on behalf of other companies. This rating can be considered as more reliable and it is in the focus of this research paper. Once developed, the methodology for an automatic rating evaluation can be used not only by rating providers, but also by any other company as well.

The presented approach represents an innovative, as well as objective and effective method for the evaluation of ESG ratings. Additionally, it saves human effort, which lessens the cost of a business organization and can advance its performance. One of its most important benefits, in contrast to current approaches, is the usage of objective market data (share prices, products prices, etc.), and not subjective company reported data. The data is comprised of time series of historical observations, which are used to construct a mathematical model that produces series that are as similar as possible to the target series. The target series contain public data observations of the company under evaluation (the target company) and explanatory series are comprised of data observations of indices with known ESG scores. The relation is expressed as a formula, which generates synthetic series that come closest to the target series, when applied historically. Some explanatory factors in the formula participate with positive weights, while others do so with negative weights. For example, if companies have environmental or social results that are similar in behavior to the ones in the target company, they participate with positive weights in the mathematical expression. Contrary to that, if the weights are negative, companies demonstrate negative values for the corresponding evaluated factors. The process of mathematical modelling is illustrated in Fig. 5.

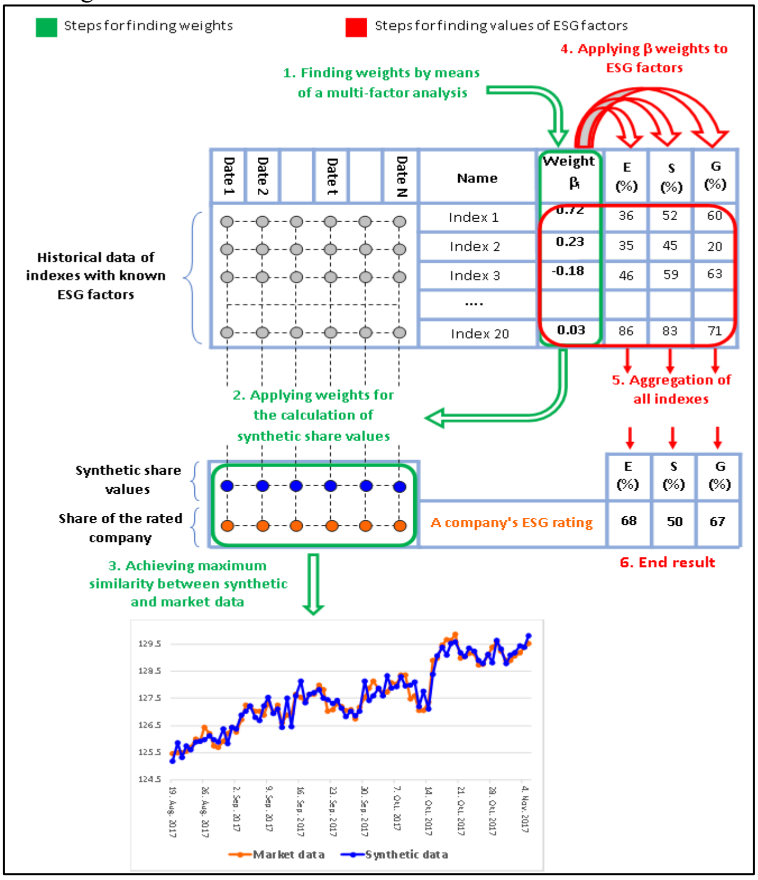

Fig. 5. Automated ESG rating calculation

First, weights β must be found in such a way that when applied to historical time series values, produce synthetic series that are as close as possible to the given target series of the target company. Once determined, these weights are applied to the known scores of factors E, S and G in order to produce estimations of unknown scores. Finally, the three values are represented in the same way as the results in Fig. 4 and are used to calculate the overall ESG rating.

An important step in the proposed automated approach is the selection of a proper subset of indices with known ESG ratings. This must be completed before determining their influence on the target company, whether positive or negative. This subset can be defined manually or it can be achieved by using an automatic suggestion approach, or both. Peer companies can either be within the same domain as the target company or from different domains. They determine the positively and negatively weighted explanatory factors for the target company:

- **Positively weighted explanatory factors** – Fig. 6. There is a positive correlation to the target company. For example, if the explanatory company has low CO_2 emissions, the target company too will have low CO_2 emissions.

- **Negatively weighted explanatory factors** – Fig. 7. There is a negative correlation to the target company. This means that a given factor of the explanatory company is in opposition to the same factor of the target company.
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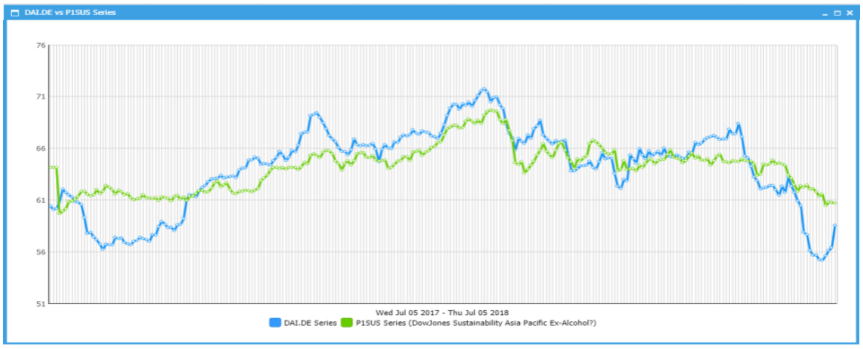

Fig. 6. Positive weight

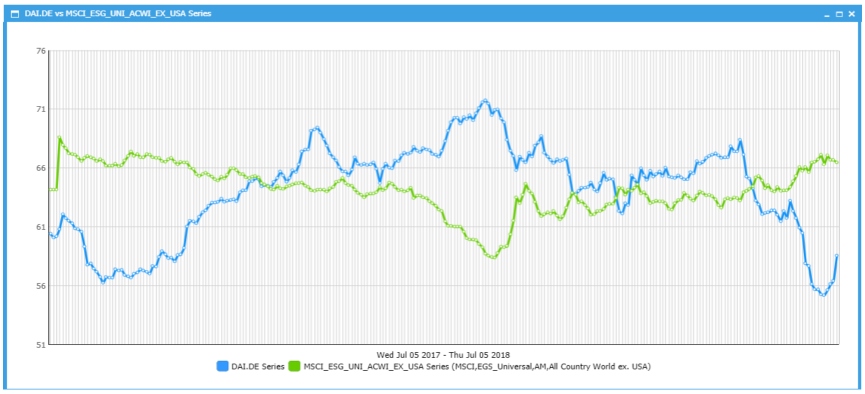

Fig. 7. Negative weight

Once built, the mathematical model can be used for future ESG rating estimations. A calibration is performed only when the accuracy of the model is below a given threshold. An automatic calibration can be scheduled in preliminary determined time frames.

The usage of the automated approach does not exclude the possibility of working with the current subjective questionnaire based approach, or combining them together. Both approaches can be used simultaneously, each of them participating with different percentages to calculate the final ESG rating score. The Sustainability Evaluator also allows the questionnaire-based approach to be validated, as shown in Fig. 8 and according to [1].

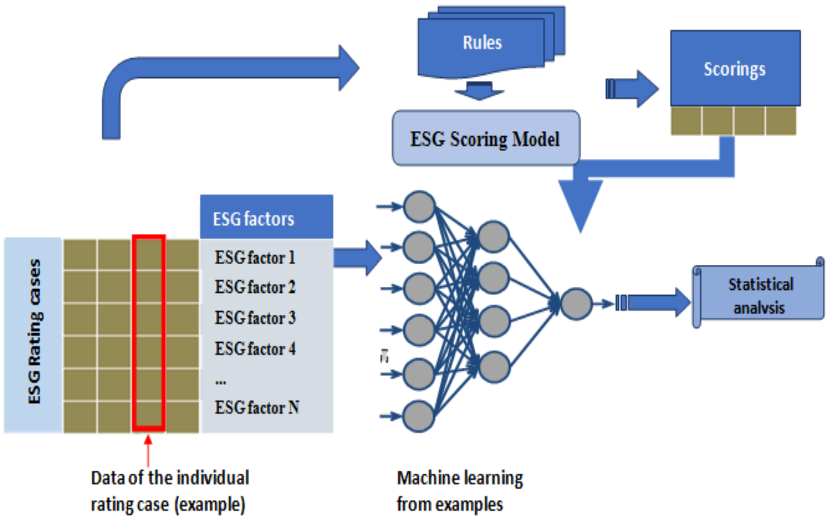

Fig. 8. Validation process of the subjective approach

The idea behind it is that the logic of the expert based questionnaire methodology is considered established and it is transferred to a neural network by training it with available examples. After that, the features of the system are evaluated by analyzing the neural network. Thus, the significance of indicators and certain internal concepts can be established.

Automated solutions that apply such artificial intelligence approaches have been widely used in the recent past due to improvements in hardware technologies and their increased effectiveness. Multi-factor modelling is already well-known in the financial sector and first experimental results have already demonstrated its usability when applied to the ESG rating evaluation in our solution. It automatically maps groups of data series into a target series, thereby creating a mathematically expressed relation between them and the target factor by a set of weights. The proposed automatic approach saves human effort and allows a more frequent ESG rating evaluation, compared to the traditional approach.

5 Conclusions and future work

Many companies use their own methodologies for ESG ratings evaluation, thereby providing analysis and additional information, such as compliance to standards and conventions, country ratings, etc. [4][5][6]. Some of the most active and most famous ESG rating providers worldwide are: Bloomberg (USA), MSCI (USA), Thomson Reuters (USA), Vigeo (France), EIRIS (UK), oekom (Germany), Inrate (Switzerland), Sustainalytics (Netherlands), Covalence (Switzerland), Corporate Governance Agency (Switzerland), Infras (Switzerland), SIRIS – Sustainable Investment Research Institute (Australia), CAER (Australia and New Zealand), Ecodes (Spain), Greeneye (Israel), IMUG (Germany) and KOCSR (South Korea), Trucost (UK), EthiFinance (France), Solaron (India), and others.

The Sustainability Evaluator can benefit a variety of market participants and has multiple advantages. First, investors will be better informed about available options they can choose in order to realize their investment strategies. ESG ratings help make informed decisions regarding a sustainable development of market participants. Second, the target company is also interested in improving its marketing policies by providing more information about non-financial ratings. Third, by paying attention to ESG ratings, companies are stimulated to improve their environmental, social and governmental activities, thus influencing and potentially improving the lives of their employees.

Even though ESG ratings do not represent financial information, they can be used by financial rating providers as additional data and can be applied to the assessment process of companies. ESG ratings are mainly used by financial institutions, credit rating agencies or in the insurance industry, but the Sustainability Evaluator can be integrated into any organization or industry that is engaged in production or providing services.

The majority of technical details concerning the Sustainability Evaluator have already been fully developed and were tested, while others are still in development. For example, the multi-factor methodology is used for other tasks as well, for instance, as a financial instrument for mapping and modelling the unknown content of indices. In time, it could also be used for multivariate prediction. The overall calculation of a single numeric ESG rating, generated from the scores of the three main factors, is also well-established. A demo software is available as a web application with various working functionalities. A validation methodology is being developed for financial credit ratings by a supervised trained neural network, which can be easily adapted to the Sustainability Evaluator.

Sustainability Evaluator enables any market participant to easily evaluate its own or other participants' ESG ratings. The solution can be integrated into other software systems; both web and desktop based and can work in different regimes.

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