ESG Tracker: Unbiased and Explainable ESG Profile from Real-time Data

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Abstract

Environmental, social, and governance (ESG) criteria are a set of standards for a company's operations that investors who are conscious about sustainability use to screen potential investments. Many sustainable investors use ESG criteria ratings provided by ESG rating providers, which are mainly based on corporate disclosures. However, the source of data and the diversity of their assessment methodologies have posed several challenges that lead to biased and non-transparent results. We propose a system that provides an unbiased ESG profile for companies from real-time data collected from the dynamic Web (online News and Social media platforms) that is explainable.

Introduction

In order to make our world a better place, while at the same time ensuring financial returns, Sustainable Investing has received considerable attention recently. Environmental, Social, and Governance (ESG) criteria are a set of standards for a company's operations that investors use to screen potential investments. ESG rating providers support the company/investment selection process through scores or a range of ratings. Rating providers mainly rely on corporate disclosures, such as annual sustainability reports and company questionnaires put together by institutional investors.

However, only relying on these reports and available ratings is challenging due to: (1) sustainable assets increasing over time and reports being hundreds of pages long and requiring huge amounts of human resources to analyze them, (2) corporate reports being hardly ever completely transparent and frequently biased as companies may choose to leave certain things out of their annual reports. Furthermore, companies adjust their language, wording, and reporting in order to achieve maximum impact with algorithms that analyze corporate disclosures (Sean Cao 2020; Mokhberian et al. 2020), (3) reports are static and not reflecting on changes in the company in real-time, but only reflecting on an accumulation of changes over a fixed period, and (4) the differences in how rating providers calculate ESG scores can result in a biased result and assessing ratings are not transparent enough.

We propose the ESG tracker system, an approach to sustainable investing that takes real-time alternative third-party (not provided by corporate only) changes into account while also reducing the complexity of analyzing sustainability reports. More precisely, our solution uses real-time, current news and social media coverage to give investors unbiased insight into a company's ESG-related activities. It tracks the daily sentiment and volume of discussion about companies related to ESG criteria. Accordingly, it enables end-users to observe and evaluate how these discussions develop over time and then form an opinion as to the company's performance. In our system ESG criteria are defined using CFA criteria and categories [1].

Applications and Impact Our proposed system uses computational methods to analyze online reports, news articles, and social media posts inferring important ESG centric insights. This gives sustainable investors more efficiency and scalability, making the rating system more dynamic by also looking at real-time changes while at the same time reducing human error and the complexity of analyzing reports manually. Additionally, our proposed scores are transparent and explainable.

Technical Specifications and Requirements

Given the nature of this domain and its unique vocabulary, for our system, we train a set of BERT (Devlin et al. 2018) models (for different sources of information and types of documents, short tweets or full articles) by further pretraining Google's BERT language model on large unstructured text corpora (tweets and news articles) about ESG. The ESG domain has a unique vocabulary that our BERT models are able to understand. These models help to find matches between companies and ESG criteria. Furthermore, by adding additional model layers they can help us to perform sentiment analysis for each company with regard to ESG criteria.

Potential Biases: Nevertheless, it is important to note that besides the advantages of our proposed system, we should also consider some potential general and more specific biases of such a system. ACCF's research (Doyle 2018) shows that there are inherent biases that affect most of ESG ratings: (1) Size bias, companies with greater market capitalization

[1]https://www.cfainstitute.org/en/research/esg-investing

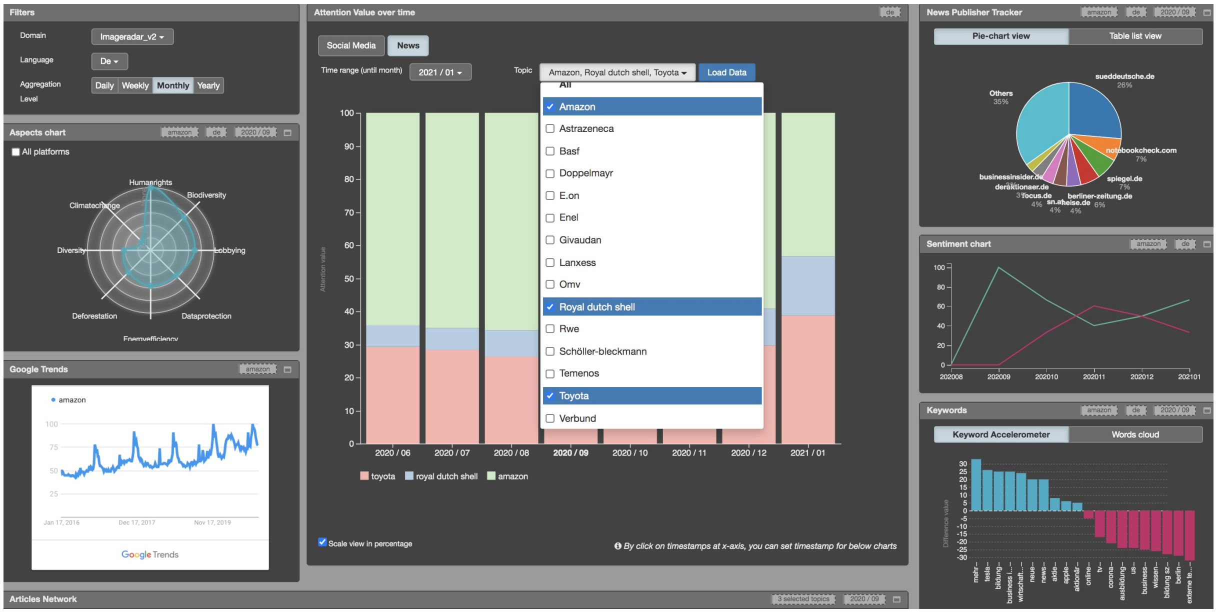

Figure 1: Starting dashboard. Stack bar chart shows attention value to each company related to ESG and spider chart shows related matches between ESG criteria and the selected company.

have higher ratings, (2) Geographic bias, companies in regions with mandatory reporting requirements score higher than their peers in geographies without mandatory reporting (3) Industry sector bias, companies in the same industry are unfairly evaluated by ratings resulting from differences in business models or risk exposure, and (4) Sampling bias (Noboa et al. 2018), from a technical point of view, many social media and News platforms (such as Google News) only provide a sample of the complete data, which results in a biased sampling. Therefore, it is important to consider how reliable it is to infer from an incomplete set of articles.

ESG Tracker Demo

Data Collection

To monitor ESG relevant data, we continuously collect data from different online sources in different languages (Demo is set for English and German). The back end of our system consists of an array of low-cost virtual machines and containers that either connect to application programming interfaces (APIs) or employ crawling mechanisms to retrieve data. The first version of the system starts searching for 1000 international companies (such as Amazon, Toyota, etc) from different sectors. The collection procedure differs for each data source: For **Twitter** we collect tweets with the help of the Twitter Streaming API. It allows us to retrieve data by providing a list of company names and for each company name, the system collects related tweets, mentions, and retweets. The system processes a significant number of tweets in order to have a representative set for company activities and overcome the sampling bias. For **News platforms** in order to retrieve online news media articles, we use a combination of Google News and Microsoft Bing. More precisely, we developed a crawler that searches for each company close to real-time for the latest published news links. After extracting the links from the news aggregators, the crawler processes articles directly from a news source. Our system is built to use news mostly from relevant news sources that are established, in order to reduce the incorporation of potential fake News.

Main Features

We can summarise the main features of the system as follow:

- **Scalability and Real-time:** The system crawls a large amount of data close to real-time from the Web, enables users to compare companies using different sources, and is not only limited to company-supplied information.
- **Unbiasd:** The main dashboard, shown in Figure 1, enables users to search for and select favorite companies. Then, the stack bar chart in the middle of the dashboard shows relative attention value to each company related to ESG criteria. Relative attention values are calculated related to the size and region of the company. Furthermore, a filter allows ratings of companies within the same peer-group regarding size, industry, and geographical location to be compared.
- **Transparency and Explainability:** The upper left part of Figure 1 shows the spider chart, which enables users to understand attention values in more detail at the level of each ESG point of reference. By clicking on each company name, users can see the related spider chart related to different categories for different sources (shown in Figure 2). By clicking on each node on the spider chart, the user can follow

Figure 2: ESG matching for each company and clickable node to the level of article source for better transparency of quantified results.

relevant articles at the level of the articles' source directly. Furthermore, the pie chart at the upper right side of the dashboard shows the percentage of each source of information. Finally, our system also provides an infobox for each item of information provided for calculating attention values and weighting related to company size, region, and sector.

- **Semantic and Trend Analysis:** The system also provides sentiment and emotion orientation of each company with regard to ESG criteria using our BERT models, shown by line chart (shown in the right upper part of Figure 1). Furthermore, the keyword accelerometer (shown in the lower right part of Figure 1) shows related topics and keywords to companies that are not pre-defined (Momeni et al. 2018).

Furthermore, in the future version of the system in order to reduce the sector-related bias, the system will suggest a sector-specific weighting of ESG criteria (higher scores in one domain due to higher relevancy or very low scores in another domain). This weighting will be fully transparent and, additionally, it will be possible to overrule it by the system user. Finally, in order to increase the transparency, we also develop a knowledge graph from extracted information for finding matches and making the system more explainable.

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