A NLP-Based Analysis of Alignment of Organizations' Climate-Related Risk Disclosures with Material Risks and Metrics

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Abstract

The Sustainability Accounting Standards Board (SASB) establishes standards to guide the disclosures of material sustainability and ESG (Environment, Social, Governance)-related information across industries. The availability of quality, comparable and decision-useful information is required to assess risks and opportunities later integrated into financial decision-making. Particularly, standardized, industry-specific climate risk metrics and topics can support these efforts. SASB's latest climate risk technical bulletin introduces three climate-related risks that are financially material - physical, transition and regulatory risks - and maps these across industries. The main objective of this work is to create a framework that can analyze climate related risk disclosures using an AI-based tool that automatically extracts and categorizes climate-related risks and related metrics from company disclosures based on SASB's latest climate risk guidance. This process will help with automating large-scale analysis and add much-needed transparency vis-a-vis the current state of climate-related disclosures, while also assessing how far along companies are currently disclosing information on climate risks relevant to their industry. As it stands, this much needed type of analysis is made mostly manually or using third-party metrics, often opaque and biased, as proxies. In this work, we will first create a climate risk dictionary that will be trained on a large amount of climate risk text. By combining climate risk keywords in this dictionary with recent advances in natural language processing (NLP), we will then be able to quantitatively and qualitatively compare climate risk information in different sectors and industries using a novel climate risk score that will be based on SASB standards.

1 Introduction

The importance of effective climate-related financial risk information and risk communication is crucial to both financial and non-financial actors. In its latest Global Risks Report, the World Economic Forum again identified climate-related risks among the highest likelihood and impact risks of the next ten years [1]. Several frameworks and standards were released to support the development of decision-relevant, climate-related risk disclosures, including Task Force on Climate-related Financial Disclosures (TCFD), Sustainability Accounting Standards Board (SASB), Carbon Disclosure Project (CDP) and Climate Disclosure Sustainability Board (CDSB) to name a few. While

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their overall aim is to improve the availability of quality, comparable and decision-useful information to be integrated into financial decision-making, the reality is that disclosures around material risks are not currently readily available in a standardized format, nor are they systematically reported given the voluntary nature of climate-related disclosures in most jurisdictions. In fact, a review of over 800 annual reports from TCFD-supporting companies showed evidence of cherry picking in the selection of corporate disclosures, which generally ignored material risk information, with little improvement in the quality of disclosures following TCFD implementation [2]. Thus, the availability and high level of transparency of climate-related reporting is necessary to assess climate-related exposures and risks, reduce information asymmetry and enable the efficient allocation of financial resources.

Assessing and managing exposures related to climate risks and opportunities requires industry-tailored disclosures as climate change is likely to materialize differently across industries. As such, SASB's 2021 Climate Risk Technical Bulletin [3] aims to address one of the most commonly cited challenges in implementing TCFD recommendations: the lack of standardized, industry-specific climate risk metrics [4]. While a standardized climate-related disclosure framework has yet to be developed, SASB is recognized as a leader in sustainability-related frameworks, and is positioning itself to play a key role in the future of standardization of climate-related disclosure. It is therefore critical to consider SASB carefully. Further, the expectation of an industry-specific climate-risk disclosure framework like SASB's ESG disclosure framework is highly relevant as it could be used as "a practical tool for companies to use when implementing the TCFD's principles-based recommendations"[1].

The framework proposed by SASB focuses on three categories of climate risks, namely the physical effects of climate change (physical), transition to a low-carbon, resilient economy (transition), and regulatory risks. It also highlights the climate risk categories most relevant and material to each of SASB's 77 SICS industries to create a map of the industries impacted by the various climate risk categories. Using an AI-powered tool, this proposed project will thus make use of the newest NLP technology to review all publicly available disclosures for selected companies, and assess the degree to which past and current disclosures are consistent with the climate risk category mapping presented in SASB's 2021 Technical Bulletin [3]. The main goal of this project is to bring additional clarity on the current state of climate risk reporting in order to improve and increase reporting of climate-related risk financial information.

Climate-related corporate disclosures are relied upon by numerous stakeholders, including investors and financial institutions, to regularly assess associated risks, opportunities and impacts linked to their investment, lending and/or insurance portfolios. They may also be used by financial supervisors and regulatory authorities for prudential purposes. The proposed project will be relevant to investors and financial participants alike as it will help develop a process for determining whether corporations are reporting and sharing climate-related information deemed relevant and material within their industry. This process may also inform corporations themselves on the climate risk categories that may merit further attention in corporate disclosures. Some industry benchmarking may be performed to provide a more holistic view of the state of material disclosures among industry peers, and to assess the gap between a particular corporation relative to its peers. Further regional segmentation over time may be pursued. Similarly, regulators and policymakers may also benefit from this work to assess the current state of industry-specific climate risk disclosures. Finally, the outcome of this project may also benefit frameworks like SASB in better understanding alignment with their industry standards.

More specifically, the use of AI and machine learning applied to climate risk can help with the automated analysis of a high volume of company disclosures. Furthermore, by specializing (open-source) NLP algorithms to ESG domains, we seek to enable the extraction of climate-relevant information (thus reducing the dependency on commercial data providers) which takes us one step closer towards increasing overall transparency. Recently, two types of methodologies have been used to extract climate risk information from company text data such as disclosures, news, and earning calls: 1) traditional, and 2) AI/statistical-based approaches. The traditional approach involves classifying text based on the existence of predefined related keywords [5]. It thus only considers the existence of keywords in a document. In the context of climate change, which is fast-evolving and complex, keyword-based models are not adequate, and require context and interpretation to detect topic patterns which can be implicit and sometimes ambiguous. On the other hand, a statistical-based approach has been used to create bigram to classify text as climate opportunity, physical risk, and regulatory risk [6]. Both approaches are not very good at extracting and measuring contextualized

[1]SASB Climate Risk Technical Bulletin [3]

information like the one present in disclosures. Recent advances in NLP techniques and AI, can be now leveraged and existing capabilities to extract climate-related risk information have been improved substantially [7]. For instance, a BERT model [2] classified pairs of sentences to physical and transition risks in addition to non-climate related data. On the other hand, one downside is that supervised classification models need a large amount of labeled data, particularly to cover the distribution of non-climate risk related data.

To address these limitations, we propose a combination of both keyword and context based approaches to increase the accuracy of the classification model and reduce data labelization tasks for non-climate risk data. In order to do this, we start by developing a climate risk dictionary (see Appendix A.1) which is trained on climate risk corpus to cover a high number of both unigrams and bigrams. This is the first contribution of our work. In previous works, only 58 climate related unigram keywords are used [8] and Sautner et. al [6] use only bigrams. In this work , we construct both unigram and bigram keywords which are specifically trained from climate risk text data, such as climate risk disclosures and guidance. To the best of our knowledge, this work will be the first AI-based tool applied onto SASB's Climate Technical Bulletin [3].

The dictionary and the language models are the building blocks of a classification task which is the central component of our contribution. We set up a classification task (see Appendix A.2) where the objective is to classify a given text according to four categories: physical risk, transition risk, regulatory risk and non-climate related. To train and validate the model the data set (see Appendix A.2) is extracted from disclosures found in annual reports as well as sustainability and climate reports, such as TCFD, corporate social responsibility, and ESG reports. We do this for the eleven sectors defined in the SASB financial impact channels. After the validation of models, in the final analysis, we apply the classification models to disclosures which cover all SASB's 77 SICS industries. The result of the models helps us to answer the questions if specific language is used in explanation of climate risk in each industry or sector in addition to if companies disclose material climate risk, topics, and metrics in their reports.

2 Expected Results

The main objective of this work is to create a framework to analyze climate related risk disclosures based on SASB's climate risk bulletin. In that regard, we expect to present:

- validation metrics (accuracy, precision, recall, F1 score) for the classification BERT model compared to other models in the following two areas:
  - Training and testing models in climate risk classifications for each one of the eleven sectors from SASB financial channel separately;
  - Training and testing one model for all sectors,
- specific climate risk dictionaries for each sector and industry to show how differently companies explain their climate risks. The dictionaries will include unigram and bigram words,
- a new climate risk score that reflects the presence of disclosures in reports aligned with SASB's climate risk categories. It is in terms of the existence of three climate risks which is hinged on Table 2 "SASB CLIMATE RISK MAP" in SASB climate risk technical bulletin 2021 [3]. We also count the number of sentences for each type of climate risk and take it to account in the climate risk score.
- an analysis of the change of the score over time by sector, industry and region will also be conducted. We visualize the evolution of SASB framework alignment using the climate risk score.
- a comparison of our results with a firm-specific climate risk exposure in the literature [9]. We check if there is a correlation between our climate risk score and the climate risk exposure.

[2]One of the state-of-the-art model in NLP is Bidirectional, Encoder, Representations from Transformers (BERT) developed by Google [8].

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A Appendix

A.1 Climate Risk Dictionary

The aforementioned dictionary is constructed by training customized climate risk word embeddings on climate related risk documents from the TCFD knowledge hub [3]. To do so, we also created an automated web scraping tool to download climate risk documents from multiple, publicly available online sources. We automate the extraction and text clean-up processes sourced from downloaded documents using python scripts. On that corpus, we train a word embedding model using GloVe [4] [10] on the climate risk related data, which is approximately 30 M tokens with 400 K unique words. The GloVe model has an advantage over the Word2Vec [11] model as it considers the frequency of words over the entire corpus. As a result, in the dictionary, we can consider the specific vocabulary and expressions which are used to disclose information related to climate risk. The trained GloVe model contains both unigrams and bigrams.

We then initialize a list of unigram and bigram keywords for each of the three categories of climate risk in the SASB's technical Bulletin [3], namely physical, transition and regulatory risks. Two sets of similar keywords are found based on cosine similarity of the keywords with 1) the trained climate risk GloVe and 2) a pretrained GloVe model [5]. As an example, for physical risk, the initial unigram keyword was '*drought*', which subsequently was associated with '*frequency intensity*', '*volatility weather*', '*extreme catastrophic*', '*storm*', '*wildfire*', '*heat waves*', '*intensity flood*', '*increased frequency*', '*inundated flood*' on our trained dictionary and '*famine*', '*devastating*', '*plagued*', '*severe*', '*shortage*' in the pretrained GloVe vocabulary. In our climate risk dictionary, we only keep

[3] https://www.tcfdhub.org/

[4] Global Vectors for Word Representation

[5] glove.6B - Wikipedia 2014 + Gigaword 5 (https://nlp.stanford.edu/projects/glove/)

the similar words from the pretrained model that exist in our trained GloVe model. This dictionary is the main building block for our classification model.

A.2 Classification: Dataset and Methodology

We set up a text classification task according to four categories: physical risk, transition risk, regulatory risk and non-climate related. We do this for eleven sectors as defined in the SASB financial impact channels. The following gives a description of the methodology used in this classification task.

For our training and validation data set, we pick subsets of disclosures of North American and European companies which disclose consistent with TCFD or SASB guidance. This choice is made on the reasonable hypothesis that companies that are a TCFD or a SASB supporter may be more advanced in terms of climate-related disclosures. Another criteria in our selection is to include companies that cover all 11 sectors in SASB financial impact channels [6] to ensure we cover the wide range of keywords specific to each sector [7] since these are the categories we are classifying.

Annual and sustainability reports of publicly-listed companies are readily available and can be downloaded from online sources. These reports are typically either in PDF or HTML format. As part of the project, we develop python scripts to extract and clean up text from these reports. To detect climate risk related text, our scripts first split the data into paragraphs. We assumed that each paragraph would generally cover a unique topic.

We define a relevance score for a term by relating the frequency of a word in one report to a ratio of length of the paragraph over the length of the entire report. We consider a weight for each keyword with the inverse document frequency in the entire gathered text from disclosures for the specific sector. Using the relevance score with a predefined threshold, we retrieve climate risk related paragraphs which represents a first filter in the construction of our data set. Indeed, filtering the text based on predefined words in the dictionary allows us to exclude the parts of reports that are not related to climate risk. To create the training data, we are not required to label a variety of non-climate related text, which is a challenging task to cover its vast distribution. In our experiment, the filtering excluded around 25% of paragraphs in some reports. Therefore, in our data set, although the non-climate related labeled data might have mutual words with climate risk labeled but since the context is not related to climate risk we label it as non-climate related. This helps the model to distinguish between the classes better.

To prepare the data for labeling, we concatenate the filtered text in a single report and then split it again into pairs of sentences as it is done in the previous work [7]. This makes the labelization easier and there is no need to cut some text as BERT is limited to only 512 tokens. The pairs of sentences are labeled by climate-risk analysts to three categories of climate risk in addition to non-climate related risk. In our labelization, we consider the sector and industry of the company which we get inspired by "SASB climate-related disclosure topics and metrics by Industry" [8].

We train a BERT model and finetune it on the dataset to be able to apply the model for detecting and classifying climate risks from disclosures for large volume companies. Then, in order to compare the performance of the model, we also train other models such as tfidf-vectorizer. In this work, it is important for us to know how the performance of models would be different if we train a specific model for a sector rather than a single model for all sectors. This helps us to answer the question, "do companies in different sectors or industries use different language to express their climate risk?". This is based on "SASB climate-related disclosure topics and metrics by Industry", SASB climate risk definition and categorization, and the materiality which are specific for each industry.

[6] Table 2 in SASB climate risk technical bulletin [3]

[7] based on Table 3 in SASB climate risk technical bulletin [3])

[8] Table 3 in SASB climate risk technical bulletin [3])