

Estimating Overreporting in the Creditor Reporting System on Climate Adaptation Finance Using Text Classification and Bayesian Correction

Janos Borst

Leipzig University, Germany

janos.borst@uni-leipzig.de

Thomas Wencker

German Institute for Development Evaluation

Thomas.Wencker@deval.org

Andreas Niekler

Leipzig University, Germany

andreas.niekler@uni-leipzig.de

Abstract

Development funds are essential to finance climate change adaptation and are thus an important part of international climate policy. However, the absence of a common reporting practice makes it difficult to assess the amount and distribution of such funds. This problem has attracted attention in international affairs research and is increasingly being investigated using methods of the broader field of computational social science. Lately, the mentioned research field has questioned the credibility of reported figures, indicating that adaptation financing is in fact lower than published figures suggest. Projects claiming a greater relevance to climate change adaptation than they target are referred to as "overreported". To estimate realistic rates of overreporting in large data sets over time, we propose an approach based on state-of-the-art text classification. To date, assessments of credibility have relied on small, manually evaluated samples. We use such a sample data set to train a classifier with an accuracy of $89.81\% \pm 0.83\%$ (tenfold cross-validation) and extrapolate to larger data sets to identify overreporting. Additionally, we propose a method that incorporates evidence of smaller, higher-quality data to correct predicted rates using Bayes' theorem. This enables a comparison of different annotation schemes to estimate the degree of overreporting in climate change adaptation. Our results support findings that indicate extensive overreporting of 32.03% with a credible interval of [19.81%; 48.34%].

1 Introduction

The climate crisis is one of the greatest challenges of our time. Climate change is accelerating toward a catastrophe that will almost certainly become a humanitarian crisis as well. According to a United Nations committee, the next decade counts: The latest IPCC reports make it clear that limiting global warming to a relatively safe level still is possible, but it requires global cooperation and billions in

financial support (Plumer, 2023; Mukherji et al., 2023). Failure of the global community to respond to the climate crisis will result in millions of people having to live with the consequences of extreme heat, food and water shortages, as well as the proliferation of pathogens, all of which add to the humanitarian crisis. Therefore, ensuring that populations are able to secure their livelihoods necessitates focus on both adaptation to the impacts and mitigation of the effects of climate change. Implementation of climate change adaptation measures is one of five targets set to reach the 13th Sustainable Development Goal (SDG): "Take urgent action to combat climate change and its impacts". There is international consensus on the need to respond to the global threat posed by climate change (Paris Accord, Article 2). Development funds are essential to finance climate change adaptation and are thus an important part of international climate policy. Specifically, Article 9.1 of the Paris Agreement states that "[d]eveloped country parties shall provide financial resources to assist developing country parties with respect to both mitigation and adaptation in continuation of their existing obligations under the Convention."¹ Prior to that, the 2009 Copenhagen Accord had already declared a goal of mobilizing USD 100 billion by 2020. Based on these agreements, the Conference of the Parties (COP) meets annually to assess implementation efforts and to ensure effective implementation of the conventions. One basis for this activity is the Creditor Reporting System (CRS), which is administered by the OECD Development Assistance Committee (DAC). It monitors financial flows for adaptation and climate change mitigation activities that flow from OECD DAC member countries to developing countries. As such, it is the central system for monitoring and evaluating the efforts of the international community to address climate change. To

¹https://unfccc.int/sites/default/files/english_paris_agreement.pdf

date, this dataset includes more than 1.5M aid activities. One of the challenges in ensuring valid reporting – or at least comparable figures – across reporting countries is that these agreements lack standardized indicators. These tasks and this area of activity of international politics can be classified as a field of research in international affairs, which is increasingly being researched using methods of the broader field of computational social science (Tavoni, 2023).

To this end, in 2009 the OECD DAC established the “Rio markers” for climate change adaptation (CCA) and mitigation (CCM). For each aid activity, donors self-report whether it contributes to CCA, i.e. reducing “the vulnerability of human or natural systems to the current and expected impacts of climate change, including climate variability, by maintaining or increasing resilience, through increased ability to adapt to, or absorb, climate change stresses, shocks and variability and/or by helping reduce exposure to them” (OECD DAC, 2022, 4). Activities are eligible for a marker if “a) the climate change adaptation objective is explicitly indicated in the activity documentation; and b) the activity contains specific measures targeting the definition above.” (OECD DAC, 2022, 4). The Rio marker r can take three values: 2, if CCA is the principal objective; 1, if CCA is a significant objective; and 0, if CCA is neither a principal nor a significant objective. However, there is increasing evidence that the level of adaptation financing is in fact lower than public figures suggest (Weikmans et al., 2017; Junghans and Harmeling, 2012). The authors refer to this phenomenon as *overreporting*, which primarily indicates a discrepancy between the qualitative descriptions of the financing purposes and the specified Rio markers. One possible reason is that there is no common practice for reporting climate finance (Weikmans and Roberts, 2019; Weikmans et al., 2020) and reporting agencies thus follow different reporting rules. This makes it difficult to assess the total amount of CCA or CCM finance, to compare commitments between donors, and to assess the geographical and sectoral distribution of funding (Weikmans and Roberts, 2019). Moreover, CCA finance estimates vary among reporting agencies (Yeo, 2019). Hence, aggregate figures of adaptation finance are increasingly considered unreliable given that they comprise thousands of individual aid activity descriptions from the CRS data. Consequently, assessments of credibility have

to date relied on analysis of small samples covering a limited period of time (Weikmans et al., 2017). Returning to the fact that the COP is utilizing these reports, among other things, as source of information the unreliable nature of these reports jeopardizes the well-being of the people who are affected by climate change. Regardless of whether this discrepancy is result of deliberate misreporting or due to the inconsistent nature of the reporting procedure, this system, with all its strengths and weaknesses, is part of global communication about the environment and environmental issues.

This study applies state-of-the-art machine learning methods for Natural Language Processing to estimate overreporting of CCA finance for all aid activities as reported in the OECD DAC CRS since the introduction of Rio markers. We model the information and knowledge contained in the reports using NLP methods to aid the requirement that the assessment of the reports is consistent, thorough and complete. This contributes to effective and targeted measures based on realistic assessments so that the necessary assistance can be provided to protect people’s livelihoods and social structures.

Our main challenge in applying machine learning methodology is the quality and quantity of available annotated data. We have access to two data sets re-evaluated by experts and published in previous work: The first is small, but following a thorough re-evaluation process, we regard it as high-quality. One concern is that the current de facto standard of fine-tuning language models tends to be unstable with very small data sets and is hard to evaluate properly. The second set is much larger, but because it was re-evaluated with access to less information, we regard it as lower quality; nevertheless, its size makes it adequate for training. We propose to combine these two data sets, using the larger for training and extrapolation, and the smaller, higher-quality set to correct first estimates. The contribution of this paper is two-fold: 1. We propose and evaluate a machine learning model to detect overreporting in the CRS data and discuss extrapolation. 2. We propose and attempt to use a Bayesian Framework for correction of extrapolated overreporting rates.

2 Related Work

In recent years, several studies have estimated the level of overreporting in CCA finance (Michaelowa and Michaelowa, 2011; Weikmans et al., 2017;

Junghans and Harmeling, 2012; Schramek and Harmeling, 2021). These studies are distinguished, first, by the rigor of their methodology to assess overreporting and, second, by the number of aid activities they analyze. Some studies classify multiple aid activities but employ, rather simplistically, keyword searches only on short descriptions of aid activity (Michaelowa and Michaelowa, 2011; Roberts et al., 2008; Junghans and Harmeling, 2012). Other studies examine only a few aid activities by scrutinizing extant project documentation against in-country expert assessments (Schramek and Harmeling, 2021). Weikmans et al. (2017) strike a balance by manually assessing a large number of short project descriptions.

We are among the first to apply state-of-the-art machine learning - which allows us to code all aid activities reported in the OECD DAC CRS database - to fully automate the process of detecting overreporting of CCA finance. Moreover, our method can be easily applied to future data releases of the OECD DAC CRS data as well as comparable text data.

Machine learning approaches to classify official development assistance are still rare. Pincet et al. (2019) used machine learning to classify SDGs. More recently, Toetzke et al. (2022) developed a machine-learning classifier to identify climate finance based on the title and descriptions of bilateral aid activities in the OECD DAC CRS dataset. ClimateFinanceBERT first classifies the relevance of aid activities to adaptation, mitigation, or the environment. Subsequently, relevant activities are further differentiated into ten categories. In contrast, our classifier directly predicts Rio Markers for climate change adaptation. Moreover, we address possible shortcomings due to the limited information contained in the OECD DAC CRS descriptions by integrating evidence from a high-quality re-evaluation.

Here, we rely on textual resources to automatically assign Rio markers to CRS Reports. Project reports typically contain both short and long descriptions of the project goals, ranging from one to a few sentences. Currently, neural networks produce virtually every state-of-the-art result in text classification, either by training task-specific architectures, e.g. (Kim, 2014) or adapting pre-trained language models to a given task (Devlin et al., 2019; Liu et al., 2019; Yang et al., 2019; Aly et al., 2019; Pal et al., 2020). Also, recent works have achieved both

higher overall performance (Devlin et al., 2019; Yang et al., 2019) and greater sample efficiency, achieving better results with less data (Halder et al., 2020). The typical problems of previous classical machine learning approaches in text classification, like out-of-vocabulary or ambiguity, are directly handled by the language model, which is especially important in this case, because not all of the texts we deal with are free of orthographic and syntactical anomalies. We experiment with these models in various combinations to find the best fit for the task at hand.

3 Automatic Classification of Climate Change Adaptation Markers

3.1 Data

The CRS tracks OECD DAC member countries' aid activities. This study works with the original CRS data and two re-evaluated data sets:

Creditor Reporting System (CRS): The publicly available CRS contains harmonized data on aid activities. We use CRS data from 2006 to 2019 containing 1,529,984 aid activities. It includes up to 91 fields of data for each aid activity. The most important information in our context is flagged by: donor, recipient, Rio marker, project title, and short and long description.

WK: Weikmans et al. (2017) sampled 4,757 aid activities from 2012 CRS data and manually re-evaluated the Rio markers based on the aid activity descriptions. The re-evaluation includes a new marker (99) to indicate insufficient information for determining the Rio marker. (Weikmans et al., 2017) argue that label 99 can be treated as 0 (not climate adaptation related) because the Rio marker methodology explicitly requires a CCA objective to be indicated in the aid activity documentation.

CARE: Schramek and Harmeling (2021) of the Cooperative for Assistance and Relief Everywhere (CARE) sampled 117 aid activities from the CRS. Each case was re-evaluated and assigned a new Rio marker by experts with access to detailed project-level information beyond the data contained in the CRS.

3.2 Approach

We consider CARE as a high-quality re-evaluation with very few samples. The WK data set has substantially more observations, but the re-evaluation had access only to CRS information. Since infor-

mation from the CRS can be very limited, especially in cases where CCA is not the primary goal, this likely leads to a higher proportion of projects being considered overreported. However, the WK data set is substantially larger than the CARE data set and can be used to train a classifier, which is why we use WK for the training and CARE to estimate a correction factor to extrapolate the CARE annotations implicitly.

Our approach is as follows: First, we train a high-quality classification model on the WK data set using information only from the CRS meta fields and the re-evaluated Rio markers. We mark a project as overreported if the classifier predicts a lower Rio marker than reported. Second, we calculate the classifier’s overreporting rate on the CARE data set. By comparing overreporting with the high-quality re-evaluation, we can estimate an error factor between the two annotation schemes in a Bayesian framework. Finally, we extrapolate to the complete CRS database and estimate overreporting rates for both annotation schemes.

3.3 Model Training and Model Selection

The WK data in the CRS provides us with text descriptions and the corresponding Rio markers (0, 1, 2 and 99), which we consider input and target of the classifier respectively. To find the best model, we test various language models with standard finetuning and in combination with a CNN architecture to find the best model. The CNN architecture follows (Kim, 2014) and comprises four 1D-convolutions with kernel sizes 3,4,5 and 6, with 100 filters each. The resulting vectors are max-pooled and projected by a linear layer onto the number of classes.

We conduct experiments with a RoBERTa (Liu et al., 2019) base model, a BERT (Devlin et al., 2019) base model and a distilled version of RoBERTa (Sanh et al., 2019) as published in the Hugging Face ‘transformers’ library (Wolf et al., 2020). We use the AdamW (Loshchilov and Hutter, 2019) optimizer with a learning rate of $5e-6$, a batch size of 32, 25 epochs, and check-pointing to restore the best model with regards to average macro F1 score. To ensure stability and quality, we test these hyper-parameters for all models with tenfold cross-validation to identify the best model. The results of the cross-validation experiments for all model combinations are shown in Table 1. We used one Tesla V100 32GB for these experiments, one tenfold cross-validation for one model combi-

nation (one row in Table 1) took around five hours to complete for BERT and RoBERTa, and around 2.5 h for the distilled RoBERTa. After ensuring an average performance, we randomly split the data 80/20 and train a model with the same parameters.²

As shown in Table 1, the combination of CNN and RoBERTa not only reaches the highest average scores in accuracy and macro F1, but also the lowest standard deviation in the tenfold cross-validation. This leads us to believe that this model will not only generalize well but also will less likely deviate from the performance, which is why we choose this model as our classifier. Table 2 shows detailed results for the final model per label. It shows that predicting the label 1 is most difficult. Label "99" can be predicted with an F1 value of around 83%. We follow the argumentation in Weikmans et al. (2017) and regard these predictions as Rio marker 0. The influence of these examples is negligible as, ultimately, 99 is predicted in only $< 0.04\%$ of the CRS in the end.

The Rio marker classification model is a proxy to identify overreported cases. We are interested in those cases where our classification algorithm differs from the reported Rio marker, specifically classifying lower than the reported value. We define overreporting o of activity x as

$$o(x) = \begin{cases} 1 & \text{if reported}(x) > \text{classifier}(x) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

This leads to three cases of overreporting: The classifier predicts 0 and the Rio marker reports 1 or 2, and the much harder case where Rio marker reports 2 and the classifier predicts 1.

3.4 CARE Data

We apply our classifier to the CARE data set and compare the findings to the manual CARE annotations. The set of examples in CARE data set are distinct from those in the WK data. We create an overreported flag for the CARE data by comparing the reported Rio marker to their re-evaluation markers using Equation (1). This marks 21.80% of the data as overreported. Our classifier predicts an overreporting rate of 54.14% on the same data, indicating a significant difference in the annotation schemes. WK annotations appear stricter, leading to higher rates of overreporting than the CARE re-evaluation.

²Code and final model will be made available upon publication to not jeopardize anonymity of the review.

		accuracy	macro P	R	F1
CNN	roBERTa-base	89.81 ± 0.83	84.83 ± 2.0	80.54 ± 2.03	82.31 ± 1.8
	BERT	88.89 ± 1.3	83.35 ± 2.13	79.64 ± 2.81	80.97 ± 2.28
	distilroberta	89.16 ± 1.3	83.47 ± 2.24	81.28 ± 2.96	82.12 ± 2.21
Transformer	RoBERTa-base	89.64 ± 1.61	84.1 ± 2.33	80.58 ± 3.74	82.0 ± 2.87
	BERT	89.27 ± 1.5	84.57 ± 3.39	79.59 ± 2.41	81.52 ± 2.36
	distilroberta	89.14 ± 1.19	83.93 ± 2.76	79.47 ± 1.98	81.35 ± 1.93

Table 1: Aggregated results of the tenfold cross-validation for all tested models. Best results for each metric are highlighted in bold.

	F1	P	R
0	94.17 ± 0.64	92.83 ± 1.13	95.57 ± 0.95
1	59.62 ± 7.28	64.68 ± 9.55	56.15 ± 8.38
2	86.74 ± 2.09	86.11 ± 4.2	87.52 ± 2.02
99	88.72 ± 3.09	95.69 ± 4.19	82.94 ± 5.04

Table 2: Detailed per-class results of the cross-validation for the chosen model (CNN + RoBERTa).

3.5 Extrapolation of CARE Annotation using the Bayesian Formula

Using the Bayesian formula, we estimate the difference in annotation scheme and extrapolate it. As discussed above, our training relies on the WK data set. The approach of training and classifying new data ultimately transfers their annotation scheme to other data sets. Given the high number of hand-coded aid activities, the WK data set is well suited for training purposes. However, comparing the resulting classification with CARE data, we find that this might overestimate overreporting. We estimate the probability that if the classifier would mark any sample as overreported according to the WK data annotations, CARE annotations would agree, and vice versa. Using the Bayesian formula, we update the estimation of our classification. In mathematical formulation we define two events: W (classifier marks sample as overreported) and C (CARE annotates sample as overreported). We further denote the data set from which we calculate the corresponding term as the parameter D . The Bayesian formula is then:

$$P(C; D=\text{CRS}) = \frac{P(C|W; D=\text{CARE})}{P(W|C; D=\text{CARE})} \cdot P(W; D=\text{CRS}) \quad (2)$$

We note that this Bayesian formulation makes implicit assumptions about the independence of annotation schemes and data samples. We argue that since the CRS data is the basis for all of these samples, that these simplifications are acceptable and lead to a simple model to show the potential and

benefits of this approach. We plan to investigate and apply more complex models to these dependencies in future work.

We calculate $P(W|C)$, i.e. the probability that our classifier would agree with CARE, and $P(C|W)$, i.e. the probability that CARE would agree with our classifier, from the CARE data set. Since the calculation is based on a small sample, we consider the uncertainty of the estimate using the beta distribution to approximate the factors and simulate the propagation of these uncertainties:

$$P(W|C) \propto \text{beta}(1 + n, 1 + m), \quad (3)$$

where n is the number of positive examples and m the number of negative examples in the data. We then report the credible interval of 95%. This leads to the correction factor

$$\frac{P(C|W)}{P(W|C)} = 42.57\% ([26.47\%; 64.39\%]) \quad . \quad (4)$$

We denote the credible interval of 95% in brackets behind the point estimate. Using the same procedure, we propagate the correction factor to adjust the overall overreporting rate using Equation (2).

3.6 Extrapolation and Exploration

We can now apply the classification algorithm to the CRS data. We restrict the CRS to projects that have a Rio marker higher than 0, otherwise, by definition, they cannot be overreported in Equation (1) and we consider only at the top five DAC donors: France, Germany, Japan, the United Kingdom and the United States. We use the fastText (Joulin et al., 2017) language detection to classify the language of the descriptions. While Germany, Japan, the United Kingdom and the United States report almost all their projects in English, France tends to report in French. The classifier was also trained on French descriptions from the WK set, however, we predict Rio markers for these projects using both the original French descriptions and also automated

translations into English using Google Translate (the influence of which is discussed below). After that, the data set contains 46,280 projects from 2010 to 2019 with short and long textual descriptions and a reported Rio marker of 1 or 2. This also complies with how data was sampled in the WK and the CARE data sets.

Figure 1 shows the results of the extrapolation. Table 5 in Appendix A shows the underlying values and the number of observations. Extrapolation is done, again, by concatenating the project title and long description into a text string and feeding it into the network. The network assigns a Rio marker prediction to every project. After that we use Equation (1) to mark all activities with a flag for overreporting. The classifier detects an overall overreporting rate of **75.35 %** in the CRS in terms of WK annotations and an estimated **32.03%** (**[19.81%; 48.34%]**) in terms of CARE annotation.

3.7 The Influence of Input Length

Systematic variation of text length by donor or year might bias our results. Longer descriptions usually contain more information and thus improve the validity of the classification. Elaborating on the difficulty of classifying short texts is beyond the scope of this paper and is its own established field of research, e.g. (Chen et al., 2019; Wang et al., 2017). This should specifically pertain to cases where CCA is a ‘significant’ but not a ‘principal’ objective (i.e., $r = 1$). Here, descriptions might not mention CCA because it is not the main motivation of the aid activity. Moreover, it seems likely that very short descriptions are mostly classified as $r = 0$ for lack of information.

We find evidence that classification quality correlates with description length. As we do not know the true Rio marker for aid activities, we use the rate of agreement between our classification and the assigned Rio marker as an indicator of classification quality. We assume that very low rates of agreement indicate poor performance of classification. As Figure 2 shows, the share of cases where classification results and Rio marker are identical increases with description length.

Description lengths systematically differ by donor and year (for both: $p < 0.00$, Kruskal-Wallis rank sum test), although the distribution of description lengths across donors and years shows that, overall, absolute differences are not large. Regard-

ing donors, Japan is an exception, with considerably shorter descriptions than the median of the other donors (78 vs. 315 characters, respectively). The time series shows an increasing trend where the median of description length increased from 231 to 345 characters between 2010 and 2019 (see also Appendix B, Figure 4). If classification quality depends on description lengths, and description lengths vary by donor and year, this could introduce confounding bias distorting the comparison of overreporting rates across years and donors. More specifically, an increase in description lengths could be interpreted erroneously as a decrease in overreporting. As an example, Japan’s high rates of overreporting (see Figure 3) could be partly explained by the brevity of aid descriptions in the CRS.

To account for possible distortion of our results, we rerun our analysis excluding short descriptions from our estimation of overreporting. We used the interquartile range (IQR) method to identify outliers (Ilyas and Chu, 2019, p. 12), i.e. we excluded descriptions with lengths below the threshold of $Q1 - 1.5 \times IQR$ (in our case, 62 characters; logarithmic: 4.1). This seems appropriate as indicated by an increase in agreement between Rio marker and classifier (see Figure 2).

We rerun the analysis that created Table 5, but excluded all projects with fewer than 62 characters. We also excluded from the CARE data set data points shorter than 62 characters, when calculating the correction factor. A comparison of the results is presented in Figure 1. The overall overreporting rate per year drops slightly, while the estimation based on CARE increases. This stems from the fact that the classifier agrees with the high-quality CARE re-evaluation more often for longer texts. The correction factor and uncertainty in this case slightly increases from 42.57% ([26.47%; 64.39%]) to 44.32% ([27.55%; 66.62%]). Overall this leads to slightly lower overreporting rate according to WK but a slightly higher estimate for CARE-corrected overreporting.

In summary, we do find evidence that systematic variation of text length by donor or year can bias results. However, robustness tests indicate that the bias does not change overall conclusions.

3.8 Extrapolation Per Donor Per Year

The values in Table 3 show overreporting as identified by the classifier based on the WK data set from

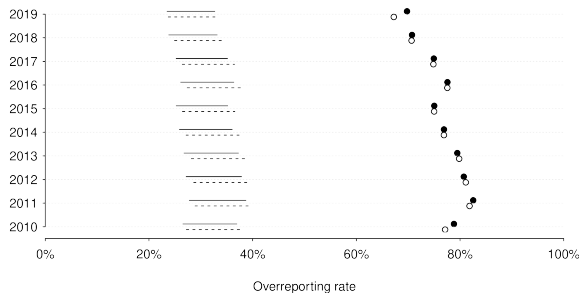


Figure 1: Estimated overreporting rate extrapolation of WK data by year (dots) and estimated correction based on CARE data (lines). Black dots and solid lines show estimates based on the full sample. Hollow circles and dashed lines show estimates based on samples excluding very short descriptions.

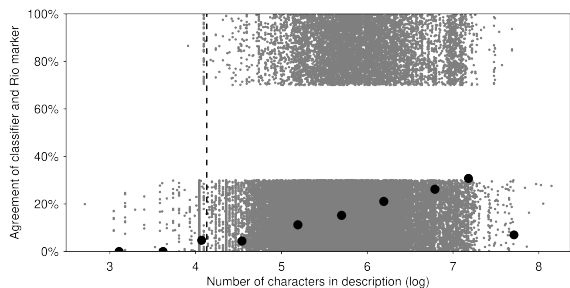


Figure 2: Agreement of classifier with Rio marker by lengths of activity description. Random noise is added to the point locations in the y-direction for better visibility. Circles show averages of binned data. The vertical dotted line indicates the cut-off for outliers based on the IQR method for outliers.

2010 to 2019. France had the lowest number of projects in CRS reported with at least Rio marker 1 in 2011 and 2012 with 84 and 114 projects respectively. The rates in Table 3 for 2012 coincide rather well with the findings in (Weikmans et al., 2017) for Germany (81%), Japan (92%) and the United Kingdom (82%). The United States was not part of the sample in (Weikmans et al., 2017).

The classifier detects significantly lower overreporting rates for France (76.32%) than in the original paper (92%) in 2012. We found that, of the 114 projects reported in 2012 by France, only 58 have unique descriptions, which produces very high uncertainty. Manual evaluation shows that there are cases of the same description occurring up to 11 times and is marked as not overreported. This alone can account for around a 10% difference in overreporting measure when classified differently. We therefore marked the fields where there are a fewer data points than 500 in orange in Table 3 to show

Year	France	Germany	Japan	U.K.	U.S.
2010	74.8%	74.66%	78.99%	73.11%	90.09%
2011	88.1%	84.16%	79.94%	71.95%	87.63%
2012	76.32%	77.52%	90.68%	74.47%	85.76%
2013	90.87%	74.57%	91.75%	69.9%	84.17%
2014	82.61%	75.3%	89.36%	56.46%	83.07%
2015	90.66%	74.78%	89.62%	58.52%	78.43%
2016	96.46%	74.41%	88.8%	55.26%	81.68%
2017	97.91%	72.92%	92.15%	49.76%	79.27%
2018	95.87%	72.04%	92.62%	41.12%	74.44%
2019	94.31%	69.23%	94.28%	45.61%	69.01%

Table 3: Overreporting rates - extrapolation of WK data split by donor country. Note that colored cells have fewer than 500 data points. Darker color corresponds to fewer data points.

where these effects could have larger impact.

Figure 3 also shows the classification results when translating the French descriptions to English (dotted line). There are significant differences in overreporting rates in the period 2013-2015, while the two lines are reasonably close between 2016 and 2019. The year 2014 in particular shows a difference of around 50%, from 33.7% in the translated case to 82.6% when using the original French descriptions. We argue that this happens for two reasons: First, the years with the biggest differences when translating descriptions coincide with the years when very few projects reported, thus the influence of a single misclassification is higher. Second, there is considerable noise in the data, which further increases variance in prediction when switching language.

In 2014, France reported 184 projects, but there are only 53 unique descriptions. The most frequent description was used 36 times, each of the occurrences having a unique ID in the CRS. Half of these 36 projects are reported with a Rio marker 1 and half with Rio marker 2. Every classifier predicting a Rio marker on the basis of these descriptions will therefore differ from the reported value at least half the time. This alone accounts for a difference in overreporting of 10% in that year. This argument also holds for the second and third most frequent project descriptions, which were used 19 and 18 times respectively. When considering only the unique descriptions, the predictions' detection of overreporting in English and French agree in 77% of cases, while only in 51% of cases overall. In general, the larger the number of projects, the smaller the influence of this phenomenon. However, of the projects that France reported, only around 40% of the descriptions are unique (see Table 4 for more

details).

Year	Over-reported	Over-reported (translated)	Count	Unique	Unique (relative)
2010	74.80%	81.71%	246	133	54.07%
2011	88.10%	82.14%	84	80	95.24%
2012	76.32%	64.04%	114	57	50.00%
2013	90.87%	66.54%	263	186	70.72%
2014	82.61%	33.70%	184	53	28.80%
2015	90.66%	66.54%	257	89	34.63%
2016	96.46%	95.29%	594	171	28.79%
2017	97.91%	94.91%	1100	477	43.36%
2018	95.87%	93.74%	847	372	43.92%
2019	94.31%	86.91%	1054	669	63.47%

Table 4: Overreporting for France following the WK data set by years. The second and third columns denote the estimated overreporting rate for French descriptions and English translations, respectively. The following columns show: number of projects, number of unique descriptions, and the ratio of these two.

4 Discussion

Our re-evaluation of aid activities reported as contributing to CCA indicates a lack of quality in the self-reporting of donors. A substantial share of reported adaptation aid activities does not explicitly mention CCA in project descriptions. This is problematic because valid indicators are required to assess whether the international community is meeting its climate policy obligations as described in, for example the Paris Accord. Our finding indicates an overestimation of adaptation aid. Even after downward adjustment of our estimates to account for insufficient information from short project descriptions, our best estimate suggests that about every third activity categorized by donors as adaptation aid is not adaptation related. However, we cannot say whether this is due to a lack of clear reporting standards (Weikmans et al., 2020), a lack of compliance with reporting standards, or even incentives to report more than is actually delivered (Michaelowa and Michaelowa, 2011). Moreover, our estimates are subject to considerable uncertainty because an unambiguous classification of aid activities based on the Rio Marker methodology requires extensive knowledge of individual aid activities.

Although the estimates are somewhat uncertain, our results confirm earlier findings of a substantial discrepancy between the figures reported by donors and re-evaluations by independent re-

searchers (Michaelowa and Michaelowa, 2011; Weikmans et al., 2017; Junghans and Harmeling, 2012; Schramek and Harmeling, 2021). This can be partly explained by the fact that our approach draws on earlier classifications as training data and is thus not completely independent. However, our study also goes well beyond existing research in temporal and geographical scope: We assess every adaptation aid activity reported by OECD DAC donors since the Rio marker on adaptation aid was introduced in 2010. If donors had changed their reporting practice, we would likely see this in our data, yet, overall, we find no indication that reporting practices have changed significantly since 2010. The share of overreporting remains at a high level between 2010 and 2019. Although the classifier indicates a slight decrease of overreporting, the fluctuations are within the range of uncertainty of our adjusted estimates. Nevertheless, the results are mainly driven by a significant decrease in overreporting by the United Kingdom. However, we are careful to infer from our data substantial differences in reporting standards between countries; Country-specific results should be examined more closely in future research. We have no reason to suspect that the classifier has particular problems with data reported by the UK based on the results of the cross-validation and given the fact that most project descriptions are in English.

5 Conclusion

In this paper we propose an automated way of detecting overreporting of climate adaptation finance based on CRS project descriptions. Our approach is based on state-of-the-art text classification using finetuning neural language models. We consider the quality of the annotations of our training data when estimating overall overreporting rates, and propose a Bayesian approach to estimate an extrapolation of high-quality annotations. Our approach indicates significant overreporting throughout the study period.

There are two key challenges with this approach: The quality and quantity of annotation scheme data, and the quality of the textual input. While, ultimately, the first challenge can be overcome by extending data with higher-quality annotations, the second proves trickier. Unfortunately, the CRS data does not have uniform quality built into its textual descriptions. We have discussed the influence of description length and language on the quality of our

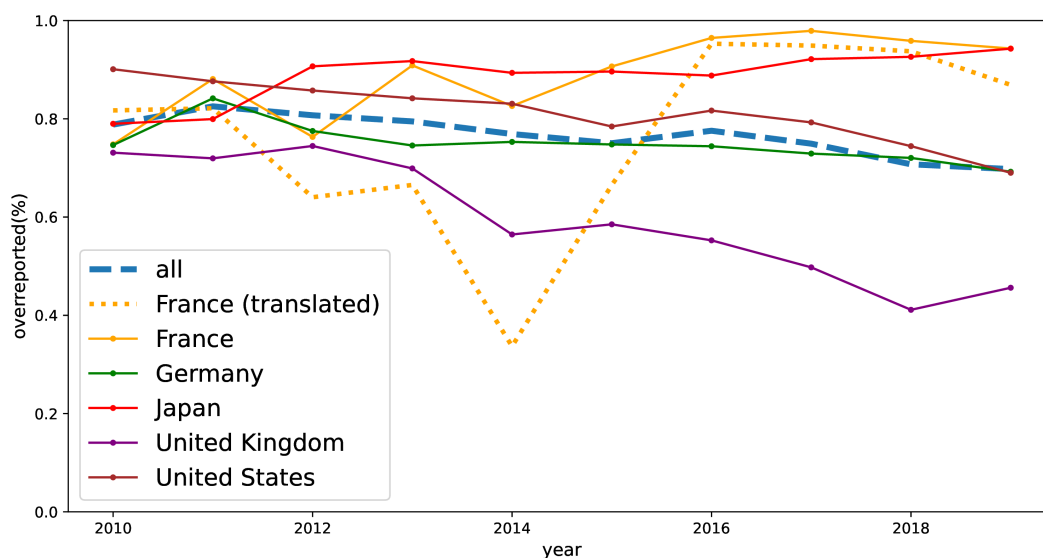


Figure 3: Rates of overreporting by donor country, 2010 to 2019

classifier, but while future work may incorporate techniques from short-text classification research, in many cases the information the CRS contains will likely not suffice to use techniques like augmentation or conceptualization. To improve on this, additional external data would be necessary, to which, at this point, we had no access. Especially deciding if the CCA aspects of a project comprises a "significant" or "principal" object should benefit from this. Another way to improve would be to pay more attention to multi lingual classification research and either incorporate techniques for multi lingual text classification or utilize a high-quality pipeline for translation.

References

- Rami Aly, Steffen Remus, and Chris Biemann. 2019. [Hierarchical Multi-label Classification of Text with Capsule Networks](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 323–330, Florence, Italy. Association of Computational Linguistics.
- Jindong Chen, Yizhou Hu, Jingping Liu, Yanghua Xiao, and Haiyun Jiang. 2019. [Deep short text classification with knowledge powered attention](#). *Computing Research Repository*, arxiv:1902.08050.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for*

Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics.

- Kishaloy Halder, Alan Akbik, Josip Krapac, and Roland Vollgraf. 2020. [Task-aware representation of sentences for generic text classification](#). In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 3202–3213, Barcelona, Spain (Online). International Committee on Computational Linguistics.
- Ihab F. Ilyas and Xu Chu. 2019. *Data cleaning*, 1st edition. Number 28 in ACM Books. Association for Computing Machinery.
- Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2017. [Bag of tricks for efficient text classification](#). In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Short Papers*, volume 2, pages 427–431, Valencia, Spain. Association for Computational Linguistics.
- Lisa Junghans and Sven Harmeling. 2012. [Different tales from different countries: A first assessment of the oecd 'adaptation marker'](#). *Germanwatch Briefing Paper*. (Accessed 2022-01-07).
- Yoon Kim. 2014. [Convolutional Neural Networks for Sentence Classification](#). In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1746–1751, Doha, Qatar. Association for Computational Linguistics.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, M. Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta:

- A robustly optimized bert pretraining approach. *Computing Research Repository*, arxiv:1907.11692.
- Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In *International Conference on Learning Representations (ICLR)*.
- Axel Michaelowa and Katharina Michaelowa. 2011. Coding error or statistical embellishment? the political economy of reporting climate aid. *World Development*, 39.
- Aditi Mukherji, Peter Thorne, William W L Cheung, Sarah L Connors, Matthias Garschagen, Oliver Geden, Bronwyn Hayward, Nicholas P Simpson, Edmond Totin, Kornelis Blok, Siri Eriksen, Erich Fischer, Gregory Garner, Céline Guivarch, Marjolijn Haasnoot, Tim Hermans, Debora Ley, Jared Lewis, Zebedee Nicholls, Leila Niamir, Sophie Szopa, Blair Trewin, Mark Howden, Carlos Méndez, Joy Pereira, Ramón Pichs, Steven K Rose, Yamina Saheb, Roberto Sánchez, Cunde Xiao, and Nouredine Yassaa. 2023. **SYNTHESIS REPORT OF THE IPCC SIXTH ASSESSMENT REPORT (AR6)**. SYNTHESIS REPORT (AR6), The Intergovernmental Panel on Climate Change (IPCC).
- OECD DAC. 2022. **OECD DAC Rio Markers for Climate: Handbook**. (Accessed 2022-01-07).
- Ankit Pal, Muru Selvakumar, and Malaikannan Sankarababu. 2020. **Magnet: Multi-label text classification using attention-based graph neural network**. *Proceedings of the 12th International Conference on Agents and Artificial Intelligence*.
- Arnaud Pincet, Shu Okabe, and Martin Pawelczyk. 2019. **Linking Aid to the Sustainable Development Goals – a machine learning approach**. OECD Development Co-operation Working Papers 52, OECD Publishing.
- Brad Plumer. 2023. **Climate change is speeding toward catastrophe. the next decade is crucial, u.n. panel says**. New york times (accessed 2023-03-23). Section: Climate.
- J. Timmons Roberts, Kara Starr, Thomas Jones, and Dinah Abdel-Fattah. 2008. **The Reality of Official Climate Aid**. (Accessed 2022-07-01).
- Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. In *The 5th Workshop on Energy Efficient Machine Learning and Cognitive Computing (NeurIPS)*.
- Camilla Schramek and Sven Harmeling. 2021. **Adaptation finance : Fact or fiction ?** (Accessed 2022-01-07).
- Massimo Tavoni. 2023. **Computational climate change: How data science and numerical models can help build good climate policies and practices**. In Eleonora Bertoni, Matteo Fontana, Lorenzo Gabrielli, Serena Signorelli, and Michele Vespe, editors, *Handbook of Computational Social Science for Policy*, pages 261–277. Springer International Publishing.
- Malte Toetzke, Anna Stünzi, and Florian Egli. 2022. **Consistent and replicable estimation of bilateral climate finance**. *Nature Climate Change*, 12(10):897–900. Number: 10 Publisher: Nature Publishing Group.
- Jin Wang, Zhongyuan Wang, Dawei Zhang, and Jun Yan. 2017. Combining knowledge with deep convolutional neural networks for short text classification. In *International Joint Conference on Artificial Intelligence (IJCAI)*.
- Romain Weikmans and J. Timmons Roberts. 2019. **The International Climate Finance Accounting Muddle: Is There Hope on the Horizon?** *Climate and Development*, 11(2):97–111.
- Romain Weikmans, J. Timmons Roberts, J. Baum, María Camila Bustos, and Alexis Durand. 2017. Assessing the credibility of how climate adaptation aid projects are categorised. *Development in Practice*, 27:458 – 471.
- Romain Weikmans, J. Timmons Roberts, and Stacy-Ann Robinson. 2020. **What counts as climate finance? Define urgently**. *Nature*, 588(7837).
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. **Transformers: State-of-the-art natural language processing**. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45. Association for Computational Linguistics.
- Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. 2019. **XLNet: Generalized Autoregressive Pretraining for Language Understanding**. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems (NeurIPS)*, pages 5754–5764.
- Sophie Yeo. 2019. **Climate Finance: The Money Trail**. *Nature*, 573:328–331.

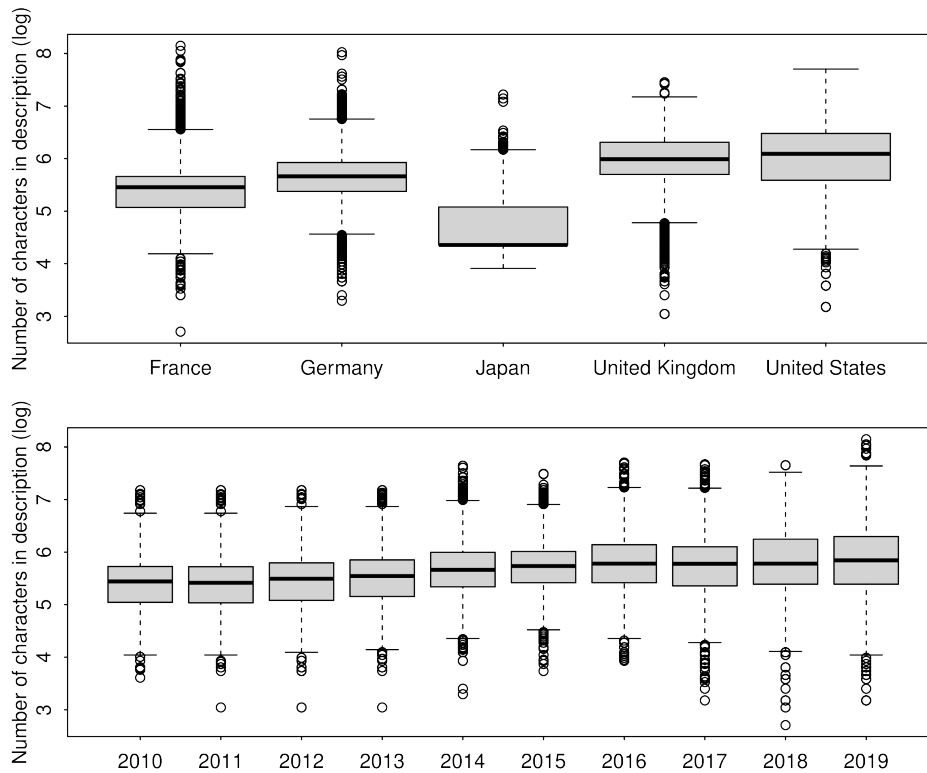


Figure 4: Activity description lengths (logarithmic) by donor (top figure) and by years (bottom figure).

year	Classifier	CARE Estimated	count
2010	77.06%	20.31 – 49.46%	1683%
2011	81.76%	21.55 – 52.48%	3076%
2012	81.0%	21.35 – 51.99%	2858%
2013	79.75%	21.02 – 51.18%	3698%
2014	76.79%	20.24 – 49.28%	3739%
2015	74.91%	19.75 – 48.08%	4308%
2016	77.49%	20.43 – 49.73%	5300%
2017	74.78%	19.71 – 48.0%	7284%
2018	70.5%	18.58 – 45.25%	6631%
2019	66.99%	17.66 – 43.0%	7111%

Table 5: Overreporting rates - extrapolation of WK data and the estimated correction of CARE data.

year	Classifier	CARE Estimated	count
2010	77.12%	27.22 – 37.61%	1683
2011	81.83%	28.88 – 39.9%	3076
2012	81.11%	28.62 – 39.55%	2858
2013	79.83%	28.17 – 38.93%	3698
2014	76.89%	27.14 – 37.5%	3739
2015	75.0%	26.47 – 36.57%	4308
2016	77.55%	27.37 – 37.82%	5300
2017	74.86%	26.42 – 36.51%	7284
2018	70.65%	24.93 – 34.46%	6631
2019	67.22%	23.72 – 32.78%	7111

Table 6: Overreporting rates - extrapolation of WK data and the estimated correction of CARE data after eliminating all inputs with fewer than 62 characters.

A Overreporting per Year

Tables 5 and 6 show detailed numerical results on estimating overreporting split by year. These two tables were summarized in Figure 3, comparing the resulting rates.

B Analysis of Text Length

Figure 4 illustrates increasing average descriptions lengths over the study period in a standard box plot, for the argument in section 3.7. Also, Japan tends to use fewer characters in descriptions compared to the other donors. This supplements Figure 2 and informs the decision to use the *IQR* range to quantify the lower limit for the number of characters. This also checks that cutting off at 62 characters (logarithmic: 4.1) does not introduce a bias for a particular year or donor.