IDENTIFYING RESEARCH SUPPORTING THE UNITED NATIONS SUSTAINABLE DEVELOPMENT GOALS

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ABSTRACT

The United Nations (UN) Sustainable Development Goals (SDGs) challenge the global community to build a world where no one is left behind. Recognizing that research plays a fundamental part in supporting these goals, attempts have been made to classify research publications according to their relevance in supporting each of the UN’s SDGs. In this paper, we outline the methodology that we followed when mapping research articles to SDGs and which is adopted by Times Higher Education in their Social Impact rankings. We also discuss various aspects in which the methodology can be improved and generalized to other types of content apart from research articles. The results presented in this paper are the outcome of the SDG Research Mapping Initiative that was established as a partnership between the University of Southern Denmark, the Aurora European Universities Alliance (represented by Vrije Universiteit Amsterdam), the University of Auckland, and Elsevier to bring together broad expertise and share best practices on identifying research contributions to UN’s Sustainable Development Goals.

Introduction

Numerous approaches to mapping research to the United Nations (UN) Sustainable Development Goals (SDGs) have been documented [1, 2, 3, 4, 5]. These approaches vary with regard to the framework used to define inclusion and exclusion criteria, the methodology employed to retrieve publications, and the publication database used. For example, the approach to defining inclusion and exclusion criteria may be set conservatively to limit publications to those documenting actions made to achieve the SDG targets, or conversely, may be set using a more liberal approach, thereby including any papers that increase knowledge on the overall topic. With regard to the methodology employed to retrieve publications, publication sets for a specific SDG can use a Boolean approach only or be complemented

[1] http://metadata.un.org/sdg/
by machine learning algorithms. The source of publications that the methodology is applied to can also introduce variability, given the availability of many data sources, ranging from open access, subscription-based, or a mixture of both.

To date, there is no broadly agreed-upon methodology for mapping research to the SDGs and existing methods produce quite different results [2]. A common approach to identifying research related to a topic is to use Boolean search expressions. The Boolean method involves the use of keywords, either alone or in combination, using conditional functions and applied to specified text sections (title, abstracts, keywords, etc.) of scientific publications, and results in the exclusive retrieval of articles within which the defined search expressions were found. The authors of [2] applied the Boolean method, taking an approach to limit their SDG publication sets to publications with a direct contribution to targets and/or indicators, with efforts made to reduce the impact of issues raised on the Boolean technique, resulting in a more restrictive publication set. Bordignon’s strategy [3] aimed at reducing the polysemy of terms by limiting keywords from Elsevier 2020 queries [1] to relevant subject areas using the All Science Journal Classification (ASJC). A text-mining tool (CorTexT) was then used to enrich those selected publications. The Aurora European Universities Alliance [6] developed and released their 169 target-level SDG queries [2] also using keyword combinations,Boolean and proximity operators. The University of Auckland [4] developed queries informed by the researchers within their network, this resulted in a localized version able to count in more papers that are specific to Australian and New Zealand research topics. In [4], the authors employ a two-step approach, involving building SDG-specific terms obtained from many sources (policy reports, publications, forums, etc), applying a selection process to the terms, and then using the terms to identify citation-based communities of publications. However, as described in [2], this process involves challenges related to the interpretation of the themes and concepts of the SDGs, decisions around which publications to designate as a “contribution” to the chosen interpretation of the SDG, and the translation of concepts into a search query that will accurately identify publications.

An alternative or complementary approach to query-based methods involves using machine learning to map research articles to SDGs: either in a supervised manner, i.e. performing classification, or unsupervised manner, i.e. performing clustering. Supervised methods typically resort to the same SDG queries to obtain a labeled dataset to train the model [8,9]. Clustering is typically done with paper text representations or citation graphs where the resulting clusters are later mapped to SDGs either directly or via intermediate clusters, e.g. “topics” [10,11]. Refer to [12] for an overview of some more methods of classifying documents into SDGs. However they all face the same challenges noted above, and machine learning further introduces the problem of interpretability of the model predictions or the clusters attained.

Since 2018, Elsevier has endeavored to map research to the SDGs, releasing in 2020 publicly available queries to facilitate transparency and reproducibility [1]. Herein, we describe the approach taken to improve former attempts to map research to the SDGs, taking feedback into account, resulting in the creation of a more comprehensive query set with sub-queries addressing targets and indicators and the application of a machine learning model to increase recall. This methodology (“Elsevier 2021 SDG mapping” [13]) captures on average twice as many articles as the 2020 version while keeping precision above 80%. Times Higher Education (THE) are using Elsevier SDG mapping as part of their Social Impact rankings [14]. “Elsevier 2022 SDG mapping” (to be released in late 2022) is the most up-to-date simplified version of the queries & ML model differing from the 2021 version in Covid-related enhancement to SDG 3 queries and queries designed for SDG 17 “Partnerships for the goals”.

To evaluate the approach, the output generated using the developed methodology was compared to the results generated by Digital Science [10], Aurora European Universities Alliance [15], and the University of Auckland [17].

1 Methodology

1.1 Developing SDG queries

The SDGs are goals to achieve rather than research topics, each SDG encompassing many targets. Using Boolean search expressions to build SDG-specific publication sets presents many challenges. We implemented a bottom-up approach to the construction of each SDG-relevant publication set, whereby several sub-queries were first constructed for each SDG target, and then aggregated at the SDG level.

1.1.1 Building a query for each target within an SDG

Criteria for delineating the publication sets relevant to each SDG were designed by a team consisting of a minimum of four analysts and were based on an extensive literature review done by the team to gain an understanding of the SDG. As a first step, the SDG was further subdivided into themes to facilitate the creation of specific criteria linked to specific

[2]https://github.com/Aurora-Network-Global/sdg-queries
SDG targets. The criteria defined for each theme aimed to specify topics of focus as well as any requirements for “action terms” in association with the topics. For example, for the topic of “poverty” the action term “alleviate”, or other action terms holding similar meaning, might be deemed a requirement. To ensure homogeneity in the approach, criteria developed by the team of analysts were submitted to a review committee consisting of both those on the SDG team and those external to the team. The review committee was responsible for reviewing the criteria, recommending changes, and final approval of the criteria. Table 1 presents the criteria for SDG1 overall (SDG1-Main) and subcategories related to SDG1. These criteria were defined for each SDG and theme related to the SDG.

Table 1: An example of SDG 1 subtopics and associated SDG targets.

| Subset code | Criteria                                                                 | Associated target                                      |
|-------------|--------------------------------------------------------------------------|--------------------------------------------------------|
| SDG1-Main   | Research focused on poverty and research as defined for any SDG1-subset below. “Action term” specified: the action term, “alleviate” was applied to make the topic term “poverty” more specific. | Target 1.1: eradicate extreme poverty Target 1.2: reduce poverty by half All Targets associated with SDG1-Subsets |
| SDG1-Theme1 | Research focused on social programs, including all articles discussing social security systems related to health, finance, and work. No “action terms” were required for inclusion of the topics above. | Target 1.3: Implement nationally appropriate social protection systems |
| SDG1-Theme2 | Research focused on microfinance, access to property, inheritance, natural resources, new technologies as they relate to facilitating access, equality and human rights. “Action term” specified: the action term, “access to” was applied. | Target 1.4: equal rights to economic resources and basic services |
| SDG1-Theme3 | Research focused on resilience, exposure and vulnerability to disasters (financial, climate-related, social..), particularly on understanding poor and vulnerable people and communities. No “action terms” were required for inclusion of the topics above. | Target 1.5: build the resilience of the poor |
| SDG1-Theme4 | Research focused on financial aid, policies, government support (such as food banks, support distribution strategies), strategies to eradicate poverty. No “action terms” were required for inclusion of the topics above. | Target 1A: Ensure significant mobilization of resources from a variety of sources Target 1B: Create sound policy frameworks |

Following the establishment of criteria defining the research areas of focus relevant for each SDG (overall and per SDG-Theme), these criteria were used to guide the development of queries to retrieve publication sets. Where possible, the analyst responsible for query development was selected due to subject matter expertise in the field. Otherwise, the process was informed by a literature review. An iterative approach was taken to assess the precision with which individual keywords and sets of keywords identified publications that met the criteria. Keywords from the Elsevier 2020 [1] and Aurora European Universities Alliance [6] queries were assessed first. Additional keywords were identified using term-frequency and inverse-document frequency (TF-IDF) analyses of text from titles, abstracts, and author keywords from publications meeting the criteria. Additional efforts were taken to identify publications that may have been excluded based on the developed query. Specifically, (1) the query results were analyzed to identify specialized journals that would be expected to include a high percentage of publications that fit the criteria, and (2) the citation network of the publications retrieved using the query was assessed to identify publications within the citation network of the results (i.e. publications citing or cited by the publications retrieved by the query) that were not retrieved by the query. Publications from these specialized journals or the citation network that were not being retrieved by the query were assessed to identify additional keywords to include in the query to increase recall. Relevant exclusions were built into the queries to increase precision and could result in the exclusion of specific terms using Boolean operators or the exclusion of fields of science deemed to be outside the scope of the criteria.

To facilitate the continuous evaluation of the query, publications were manually reviewed to assess their fit against the criteria. An evaluation of a minimum of 100 random publications by two independent analysts was done to support the calculation of precision metrics for each query and a minimum precision threshold of 90% was required for a query to be considered acceptable. The recall was assessed against independent publication sets developed by an analyst
consisting of publications from specialized journals identified to fit the criteria. As most specialized journals do not exclusively focus their content on a single SDG, a minimum recall of 60% was required for a query to be considered acceptable. In cases where no single journal was specific enough for all publications within that journal to fit the criteria set for an SDG or SDG-Theme, a publication set was constructed by manually selecting publications from a journal with high relevance to the SDG (or SDG-Theme), and recall was assessed against this set.

Below we refer to the mentioned recall evaluation dataset as to the *Science-Metrix recall dataset*.

1.2 Machine learning applied to SDG classification

On top of the mapping produced by the queries described above, additional articles are mapped to the SDGs by a machine learning model.

In a nutshell, the model is a logistic regression trained with TF-IDF representations of titles, keywords, abstracts, and two more optional text fields – main terms extracted from the full text, and subject areas of the journal that published the paper. Thus, the model learns similar keyphrases for each SDG and helps to improve the recall of the queries. To keep precision high, we keep only those papers that are classified by the model with 95% or higher predicted probability for some SDG.

In the “Elsevier 2021 SDG mapping” release [13] we specify the input data for the model, the targets that it’s trained with, the technical details of the model itself, and model performance. Also, to ease the interpretation of the model classification outcomes, we share the SDG-specific key phrases learned by the model, as well as sample articles classified by the model. Please refer to the mentioned documentation for more details on the machine learning component of our approach.

1.3 Combining the queries and the model

The end-to-end approach to map Scopus records to SDGs is two-staged:

- first, the keyword SDG queries are run (orange in Fig. 1)
- then, the ML model adds about 3.5% of papers (blue in Fig. 1) on top of what is classified by the keyword queries. We only keep the most confident model predictions by thresholding predicted scores at 0.95.

Figure 1: Distribution of the number of papers mapped by the queries (SM, orange) and by the model (ML, blue), by SDG (ignoring SDG 17).
Table 2: SDG classification methods (both keyword queries and ML models) used in the evaluation.

| Classification method          | Description                                                                 | Web location |
|--------------------------------|-----------------------------------------------------------------------------|--------------|
| Elsevier queries 2020         | “Identifying research supporting the United Nations Sustainable Development Goals” [1] | link         |
| Elsevier queries+ML 2021      | “Improving the Scopus and Aurora queries to identify research that supports the United Nations Sustainable Development Goals (SDGs) 2021” [13] | link         |
| Elsevier queries+ML 2022      | A simplified version of “Elsevier queries+ML 2021” with Covid-related addendum to SDG 3 to be shared in late 2022 |              |
| Aurora queries v5 (2020)      | “Mapping Research Output to the Sustainable Development Goals (SDGs)” [16]       | link         |
| Auckland queries v2           | To gain a better understanding of our research contribution, the University of Auckland SDG Keywords Dictionary Project seeks to build on the processes developed by the United Nations and THE in order to create an expanded list of keywords that can be used to identify SDG-relevant research | link         |
| Aurora ML v0.2 (2021)         | “AI for mapping multi-lingual academic papers to the United Nations’ Sustainable Development Goals (SDGs)” [15]       | link         |
| Bergen SDG queries            | The Bergen approach created queries for Web of Science to retrieve SDG-related publications for a limited number of SDGs. The queries have been translated for Scopus and a sample of the results has been taken as positive examples. These have been supplemented by other publications which did not appear in the queries as negative examples. Two datasets were created, one based on the Action Approach queries and one based on the Topic Approach queries – referred to as Bergen TAA and Bergen TBA respectively. [2] | link         |
| Digital Science               | "Contextualizing Sustainable Development Research” [10]                        | ---          |

2 Results

2.1 Comparison between the SDG queries

Below we describe the SDG queries and validation datasets that we used for the comparison in terms of precision, recall, and F1 scores.

2.1.1 Query models

Table 2 describes the different classification methods that we compared. These can be either keyword queries (“Elsevier queries 2020”, “Aurora queries v5”, “Auckland queries v2”, and ”Bergen SDG queries”) or machine learning models (“Aurora ML v0.2”) or both (“Elsevier queries+ML 2021”, “Elsevier queries+ML 2022”).

2.1.2 Validations sets; collection method, sizes, and quality

Table 3 provides details on the validation datasets used in the comparison. It also mentions the associated limitations and biases. It is important to mention that there’s no single best validation dataset to evaluate the output of SDG classification. In particular, for the 6 datasets that we used in the evaluation:

- the Science-Metrix recall dataset described in Sec. [1.1.1] (referred to as “sm_recall” in Table 3) served well for query development but it is noisy in the sense that not all papers from an SDG-specific journal are relevant to the same SDG. Hence we don’t aim at 100% recall w.r.t. to this dataset nor can this dataset serve as a source of ground truth SDG labels;
- The Aurora survey dataset (“au_survey” in Table 3) is fairly small and it has an intrinsic bias: the survey was limited to researchers from western European countries;
- the Aurora suggested papers dataset (“au_sugg” in Table 3) is fairly small and it has an intrinsic bias: researchers might have an intention to mention their own research;
| Valid. set | Description & method of collection | Web location | Size of the corpus | Remarks on quality |
|-----------|-----------------------------------|--------------|-------------------|-------------------|
| Science Metrix recall dataset | See Sec. 1.1.1 | Shared via ICSR Lab, see 3.3 | 465k | The dataset is noisy in the sense that not all papers from an SDG-specific journal are relevant to the same SDGs. Hence we don’t aim at 100% recall w.r.t. to this dataset |
| Aurora Survey | "Survey data of “Mapping Research output to the SDGs” by Aurora European Universities Alliance (AUR)" 244 senior researchers from different universities in Europe and US filled in a survey. They were only allowed to enter the survey if they were familiar with the SDG they had selected to evaluate. The first question was to provide a list of research papers they believe are relevant to that selected SDG. The second question was to handpick from a given set of 100 randomly drawn papers in the Aurora query result set, the papers they believe (based on reading the title, abstract, journal name, and authors) belong to the selected SDG. The suggested papers and the selected papers are included in the validation set. | | 6741 | Bias: the researchers located at western European universities. |
| Aurora suggested papers | The papers suggested by researchers, see "Survey data of “Mapping Research output to the SDGs”." | | 3964 | The dataset is noisy in the sense that researchers are not specialists in SDGs. They might also have an incentive to cite their own research |
| Elsevier multi-label | The dataset consists of 6000 papers annotated by 3 experts each. These papers come from 5 data sources to span as diverse as possible set of SDG-related papers | Shared via ICSR Lab, see 3.3 | 6000 | Annotators are not as versed in SDGs as Science-Metrix analysts |
| Chilean multi-label | The dataset is provided by Pontificia Universidad Católica (PUC) based in Chile and consists of about 1200 papers self-assessed by PUC researchers and labeled with 0, 1 or 2 SDGs. | | 1200 | Biases: self-assessment, only Chilean researchers |
| OSDG Community Dataset | A public dataset of thousands of text excerpts, which were validated by approximately 1,000 OSDG Community Platform (OSDG-CP) citizen scientists from over 110 countries, with respect to the Sustainable Development Goals. | | 32431 | Crowd-sourced dataset, the annotators are not versed in SDGs |
Table 4: F1 scores with micro/macro average (percents, %) for 8 classification methods and 6 validation datasets. Bolded is the best result in the column, asterisk for multiple “winners” depending on micro- or macro-averaging.

| Method \ dataset | sm_recall | au_survey | au_suggested | els_2021 | chile | osdg |
|-----------------|-----------|-----------|--------------|----------|-------|------|
| auckland_v2     | 63/40     | 53/41     | 51/35        | 71/60    | 69/39 | 55/47*|
| aurora_ml       | 57/35     | 58/45     | 40/31        | 66/54    | 56/37 | 53/46 |
| aurora_v5       | 48/35     | 73/54     | 36/33        | 63/53    | 48/34 | 55/43 |
| els_2020        | 76/43*    | 60/43     | 65/37*       | 74/55    | 80/37*| 57/46*|
| els_2021        | 73/48*    | 55/44     | 51/36        | 77/67    | 71/45*| 52/46 |
| els_2022        | 73/48*    | 55/44     | 51/37        | 78/67*   | 71/45*| 52/46 |

Table 5: F1 scores with micro/macro average (percents, %) for 6 classification methods and 6 validation datasets. Here the validation is performed only against a subset of SDGs: SDG 1 (No poverty), SDG 2 (Zero hunger), SDG 3 (Good health and well-being), SDG 7 (Affordable and clean energy), SDG 13 (Climate action), and SDG 14 (Life below water).

| Method \ dataset | sm_recall | au_survey | au_suggested | els_2021 | chile | osdg |
|-----------------|-----------|-----------|--------------|----------|-------|------|
| auckland_v2     | 91/66     | 83/63     | 81/57        | 92/84    | 92/65 | 82/82|
| aurora_ml       | 89/62     | 82/63     | 65/47        | 86/77    | 85/62 | 80/81|
| aurora_v5       | 73/61     | 89/66*    | 54/51        | 83/78    | 70/53 | 78/72|
| bergen_baa      | 69/39     | 42/24     | 17/23        | 26/34    | 19/15 | —    |
| bergen_bta      | 84/63     | 66/50     | 59/46        | 81/75    | 63/41 | —    |
| els_2020        | 93/69     | 88/68*    | 92/67        | 93/79    | 96/67 | 83/82|
| els_2021        | 94/73*    | 86/66     | 84/66        | 94/89*   | 91/65 | 79/80|
| els_2022        | 94/73*    | 86/66     | 84/66        | 94/89*   | 91/65 | 80/81|

- The Elsevier multi-label dataset (“els_2021” in Table 4) is labeled with a 3rd party, and the annotators are not specialists in SDGs;
- The Chilean multi-label dataset (“chile” in Table 4) is very small and has intrinsic biases: it's limited to Chilean research and also researchers performed self-assessment;
- Similarly, the OSDG Community Dataset (“osdg” in Table 4) is crowd-sourced, with annotators not being versed in SDGs.

2.1.3 Performance; query models measured against validation sets

Table 4 provides the evaluation results for 6 SDG classification methods outlined in Table 2 and 6 evaluation datasets described in Table 3. Each cell shows 2 values: micro-average F1-score and macro-average F1-score, in percent (%).

To compare with Bergen queries, Table 5 provides similar metrics only considering a subset of 6 SDGs, namely, SDG 1 (No poverty), SDG 2 (Zero hunger), SDG 3 (Good health and well-being), SDG 7 (Affordable and clean energy), SDG 13 (Climate action), and SDG 14 (Life below water).

The code reproducing the experiments presented in this subsection is found on GitHub:

[https://github.com/Yorko/sdg_mapping_queries_n_ml_benchmarks](https://github.com/Yorko/sdg_mapping_queries_n_ml_benchmarks)

Note that micro-averaging favors well-represented, frequent classes (like SDG 3 in our case) while high macro-averaged scores mean then the method works fairly well across all SDGs because bad results for a single SDG affect macro-averaged metrics much more than micro-averaged ones. By attending to both micro- and macro-averaged F1 scores we try to assess both aspects: how well the method is at classifying papers into frequent or rare classes.

We conclude that there is no single best approach performing well across all validation datasets, although Elsevier 2020 are among the best-performing for 4 datasets out of 6 both when 16 SDGs or 6 SDGs are considered (see Tables 4 and 5). This finding supports the general criticism that SDG classification faces: different mapping methods typically kick off with the same keywords but then result in poorly-overlapping mappings [2] [18]. Apart from these “qualitative” problems with SDG mappings we now establish the “quantitative” problem: when evaluated against several hand-labeled SDG datasets, different approaches fail to select a clear winner.
Table 6: Elsevier queries validated against the Science-Metrix recall dataset (see Sec. 1) and the Elsevier multi-label SDG dataset (See Table 3). P stands for precision, R – for recall, F1 – for F1-score. Micro- and macro-averaged values are reported.

| Method | Dataset | sm_recall | els_2021 |
|--------|---------|-----------|----------|
|        |         | R | P | R | F1 |
| els_2020 | 87/61 | 72/58 | 77/56 | 74/55 |
| els_2021 | 92/84 | 69/59 | 89/81 | 77/67 |
| els_2022 | 92/84 | 69/59 | 89/81 | 78/67 |

Some notes and observations:

- **Bergen BAA queries** generalize badly to all datasets which reinforces the points made in paper [2]: it’s not that the queries are “wrong”, it’s rather that action-based queries are much more restrictive than topic-based queries, hence low recall;
- We notice a clear “overfitting” phenomenon: **Elsevier queries+ML 2022** are best when validated against the Elsevier’s multi-labeled dataset while **Aurora queries v.5/Aurora ML model** achieve the highest F1 scores against the Aurora survey dataset. A probable explanation is that the datasets were crafted for a specific definition/operationalization of SDGs and these definitions are undoubtedly different from one project to another.
- Note that the sm_recall dataset was mostly used to assess recall of Elsevier 2021 queries at the time of their development hence it makes more sense to study recall w.r.t. this dataset, we are doing this in Sec. 2.2

2.2 Tracking the progress of Elsevier queries

Table 6 shows recall scores for different Elsevier queries as measured against the Science-Metrix recall dataset described in detail in Sec. 1) and the Elsevier multi-label SDG dataset described in Table 3). Note that due to the specifics of our SDG query creation methodology, it makes sense to report only recall for the first dataset, while looking at precision, recall, and F1-scores is interesting in case of the Elsevier multi-label SDG dataset.

We see that both Elsevier 2021 and 2022 queries perform about the same in terms of metrics, and both provide a considerable improvement over earlier 2020 version of the queries.

2.3 Direct comparison to the SDG mapping by Digital Science

Independently, Elsevier did a face-to-face comparison to the SDG mapping solution provided by Digital Science [10]. The protocol of the experiments is the same as described above. We only report these results separately as the comparisons were done with subsets of records or SDGs for two reasons:

- the Digital Science solution used the WebOfScience dataset rather than Scopus hence the overlap with the datasets mentioned above was not as high as to include the results in Table 4 (2-3k. records);
- The comparison to Digital Science includes the datasets provided by Bergen queries which are limited to SDGs 1, 2, 3, 7, 13, and 14.

Figure 2: micro-averaged F1 scores for Elsevier and Digital Science SDG mappings reported for 6 datasets.
From these comparisons, we conclude that Elsevier’s approach is on par with the one by Digital Science in terms of precision, and considerably outperforms Digital Science’s solution in terms of recall and hence in F1 scores. Fig. 2 shows micro-averaged F1 scores achieved by both Elsevier queries + ML 2021 and Digital Science’s methods w.r.t. to 6 datasets:

- 4 of them are the same as presented in Table 4,
- plus Bergen SDG datasets [19] that accompany paper [2].

Additionally, Fig. 3 shows F1 scores per SDG reported for two datasets: Aurora suggested papers and Elsevier multi-label SDG dataset.

3 Discussion

In previous sections, we described the methodology and evaluation results. Below, we outline possible improvements to the SDG mapping approach, including localization of the SDG queries, query generalization to non-English languages, and extending the approach to non-article content.

3.1 Localization

Research activities do not stand alone; they are an integral part of the geographical place they were initiated and the communities they serve. An attempt to measure SDG-related research activities can be improved by infusing the local context within which the research activities take place. A localization approach can further foster understanding of, for example, the degree to which the prevailing SDG mapping approaches capture SDG research in the geographical region that may or may not have been described by keywords and keyphrases with close semantic relatedness to the keyword-based queries, e.g. Elsevier 2020 queries.

The University of Auckland’s approach is one such localization attempt based on Elsevier’s earlier 2020 queries, a mixture of the UN official targets and indicators, and the suggested search terms by the Sustainable Development Solutions Network (SDSN). The n-gram model was applied to two samples of Scopus publication metadata, i.e., a global publication sample and a University of Auckland publication sample. The n-gram tokens were scored by a range of factors, including counts and measures of frequency, and were then ranked by those scores. Keywords with a high rank were then evaluated in more detail and manually reviewed and improved for SDG alignments. Table 7 shows the number of University of Auckland publications between 2009-2020 captured by the University’s queries compared with those captured by Elsevier 2020 queries.

For 13 out of the 16 SDGs documented in Table 7, the Auckland queries capture more SDG-related publications. In some cases, the number of publications captured by the Auckland queries double that captured by the Elsevier 2021 approach. A significant proportion of the additional publications are captured through localized keywords and search terms. For example, “Te Whāriki” – the New Zealand national curriculum document for early childhood education – was used as an SDG4 keyphrase under the Auckland approach. It retrieved 19 SDG4 papers published by the University of Auckland, of which only 6 papers were counted by the Elsevier 2021 approach. In some other cases, the Auckland
Table 7: Comparison of Auckland v2 queries and Elsevier 2020 queries.

| SDG | Auckland queries output | Elsevier 2021 output | Intersection |
|-----|-------------------------|----------------------|--------------|
| 1   | 522                     | 229                  | 125          |
| 2   | 1975                    | 420                  | 264          |
| 3   | 16894                   | 7966                 | 6894         |
| 4   | 2484                    | 1043                 | 745          |
| 5   | 611                     | 609                  | 360          |
| 6   | 684                     | 486                  | 362          |
| 7   | 1152                    | 1187                 | 799          |
| 8   | 428                     | 440                  | 154          |
| 9   | 1044                    | 1139                 | 519          |
| 10  | 1528                    | 977                  | 500          |
| 11  | 1886                    | 1462                 | 779          |
| 12  | 921                     | 438                  | 158          |
| 13  | 1032                    | 577                  | 466          |
| 14  | 1390                    | 744                  | 552          |
| 15  | 1641                    | 769                  | 473          |
| 16  | 891                     | 779                  | 409          |

queries also gave rise to additional keywords that are fit for the global settings. For example, “marine biodiversity” as an Auckland keyphrase retrieved 24 SDG14 papers published by the University of Auckland, of which 19 papers were counted by the Elsevier 2021 approach.

3.2 Multilingual queries

In CRISs systems and repositories there are many more publications that are not included in Scopus and are written in the local language of the country to serve a different audience. We found out we could not simply replace the keywords in the queries and have the search work the same in other languages, because of the syntax and morphology rules. That’s why Aurora chose to train mBERT models to classify SDGs. Due to the lack of non-English SDG labeled data, we used only English training data, specifically paper abstracts.

During the evaluation, the models for SDGs 1 to 5 and 11 were applied to classify 888 German paper titles. To have a qualitative benchmark, we performed a manual SDG classification only on titles as well. In doing the latter, we tended to take a strict approach and tried to stick very close to the respective SDG indicators (e.g., non-assignment of SDG4 to publications on teacher training in Germany, as the SDG indicators only refer to teacher training in the Global South).

The manual classification resulted in 43 SDG-related publications, whilst the ML models resulted in 58 publications SDG-related publications. The total overlap between these two methods was 8 publications. It was mainly for SDG3 – Good Health and Wellbeing (5/8) and can most likely be explained by great similarities in terminology between English and German for issues such as multiple sclerosis, psychotherapy, suicide, alcohol, and illegal drugs (in German: Multiple Sklerose, Psychotherapie, Suizid, Alkohol, illegale Drogen).

At the current phase of evaluation, the multilingual ability of the ML models for research output in German cannot be positively assessed. However, further analysis including the abstracts of publications for the classification of the ML models may offer improvements in classification quality.

3.3 Generalization to other types of content

In addition to SDG-related research outputs, higher education institutions have a strong interest in understanding SDG-related educational activities, as done in Aurora SDG Course Catalogue. These SDG labels have been added manually by the course coordinators, but such a process is labor-intensive, and not sustainable since this needs to be done year after year.

Similar to publication metadata (e.g. title, abstract, keywords), many course catalogs and curriculum management systems capture metadata in a similar way (e.g. title, course short description, course long description). Whether the
SDG research mapping techniques can be translated and applied to SDG course mapping represents an interesting topic to many.

A study was conducted by the University of Auckland to apply the Auckland queries to classify courses taught by the university. The mapping results identified 792 SDG courses out of 2441 courses in total offered to students in the academic year 2020. Compared with the frequency and distribution of keywords in research mapping, course mapping demonstrated a higher concentration of keywords used to convey the SDG topics. For example, the 24 University of Auckland courses related to SDG14 are fully captured by the top ten keywords in the Auckland queries by frequency (i.e. marine; fisheries; coastal management; pollut*; aquaculture; marine environment; fisheries management; eutrophical*; aquatic ecosystem; alga*).

**Conclusion**

In this paper, we outlined the methodology behind research mapping to United Nations (UN) Sustainable Development Goals (SDGs), how it compares to other existing methods and how well it performs with existing SDG validation datasets. We conclude that there is no single best approach performing well across all validation datasets, although Elsevier queries are slightly more stable. We observed that Elsevier’s queries have seen a measurable improvement from the original 2020 version to 2021/2022 versions. In a separate comparison to Digital Science’s solution, we found that Elsevier’s approach leads to a considerably higher recall across the validation datasets. Finally, we discussed possible improvements to the existing approach: localization of the queries, and generalization to other languages and data types.

**Data availability**

The data underlying the results presented in the study (including the processed version of publicly available datasets listed in Table 3) are available, for scholarly research and upon [application](https://icsrlab.elsevier.com/) from Elsevier BV on the ICSR Lab. ICSR Lab is intended for scholarly research only and is a cloud-based computational platform that enables researchers to analyze large structured datasets, including aggregated data from Scopus author profiles, PlumX Metrics, SciVal Topics, and Peer Review Workbench.

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