Investigating Fairness Disparities in Peer Review: A Language Model Enhanced Approach

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ABSTRACT
Double-blind peer review mechanism has become the skeleton of academic research across multiple disciplines including computer science, yet several studies have questioned the quality of peer reviews and raised concerns on potential biases in the process. In this paper, we conduct a thorough and rigorous study on fairness disparities in peer review with the help of large language models (LMs). We collect, assemble, and maintain a comprehensive relational database for the International Conference on Learning Representations (ICLR) conference from 2017 to date by aggregating data from OpenReview, Google Scholar, arXiv, and CSRanking, and extracting high-level features using language models. We postulate and study fairness disparities on multiple protective attributes of interest, including author gender, geography, author, and institutional prestige. We observe that the level of disparity differs and textual features are essential in reducing biases in the predictive modeling. We distill several insights from our analysis on study the peer review process with the help of large LMs. Our database also provides avenues for studying new natural language processing (NLP) methods that facilitate the understanding of the peer review mechanism. We study a concrete example towards automatic machine review systems and provide baseline models for the review generation and scoring tasks such that the database can be used as a benchmark.

KEYWORDS
datasets, algorithmic fairness, natural language processing

1 INTRODUCTION
The current scientific development relies heavily on the peer review mechanism for authors to publish and share their research. With the sheer number of submissions, many venues have experienced an extremely large demands for reviewers, and many authors have complained they have received unfair or bogus reviews. Indeed, the famous NeurIPS experiments [4] assigned a different set of reviewers to the same submissions, and found the reviewer ratings are sometimes strikingly different. In parallel, algorithmic fairness has attracted attention of practitioners of various domains to analyze the intrinsic bias of either the dataset or the model trained on the dataset. It is thus natural to wonder, whether one could use lessons from fairness to analyze the peer review process? For example, in Figure 1, we note north America (NA) has the most accepted papers of all year, and in Figure 2, we note “reinforcement learning” and “graph neural networks” are much more popular, does this mean ICLR favors authors in the US and/or working on those popular topics? In order to study questions of this flavor, a comprehensive dataset, proper fairness formulations, and principled application of language modeling techniques are needed.

As the first step, we assemble a database consisting of submissions to the International Conference on Learning Representations (ICLR) that is most comprehensive and up-to-date. Our database

Figure 1: Geographical disparity: does ICLR favors north American authors more?

1 See https://cogcomp.github.io/iclr_database.

2 Both in 2014 [1] and 2021, see https://blog.neurips.cc/2021/12/08/the-neurips-2021-consistency-experiment/.
We investigate several commonly used fairness notions, including demographic disparity (DP), equalized odds difference (EO), and AUC difference (AUC). For a given sensitive attribute $A$, these measures are defined as

$$
\begin{align*}
\text{DP} &= \max_{a \neq a'} \frac{|P(\hat{y} = 1|A = a) - P(\hat{y} = 1|A = a')|}{P(\hat{y} = 1|A = a')}, \\
\text{EO} &= \max_{a \neq a', y} |P(\hat{y} = 1|A = a, y = 1) - P(\hat{y} = 1|A = a', y = 1)|, \\
\text{AUC} &= \max_{a \neq a', A} |\text{AUC}(\hat{y}, y|A = a) - \text{AUC}(\hat{y}, y|A = a')|.
\end{align*}
$$

where $\hat{y} \in \{0, 1\}$ is the binary label (e.g., either accept or reject), $A$ is the sensitive attribute, and $\text{AUC}(\hat{y}, y|A = a)$ computes the area under curve (AUC) of the receiver operating characteristic (ROC) curve of the subgroup $A = a$. This formulation allows us to assess disparities in both data itself (by setting $\hat{y}$ to be the true label) as well as in predictive models (by setting $\hat{y}$ as the predictors). Although our database allows investigations on various disparities, we zoom in the following three that we think might be the most crucial: (i) Geographical disparity: $A$ is the set of the (dominant) geography of the authors in a submission. (ii) Gender disparity: $A$ represents the gender of the authors of a submission (mode, or whether a certain gender is present). (iii) Prestige disparity: $A$ represents the prestige of the authors of a submission (citation count, institution ranking).

A popular criticism of peer review is that the reviewer rating is somewhat “random” as demonstrated by the NeurIPS experiments. To assess such randomness at different peer review stages quantitatively, we assess the goodness-of-fit when fitting predictive models such as logistic regression on the dataset. We found that in general, simple models can fit the decision stage well but even more complicated models fail to capture the essence of the reviewing stage. This suggests that the randomness sentiment many authors have echoed might be mainly from the reviewing stage.

This observation naturally motivate us to set foot in evaluating existing large language models (or their fine-tuned variants) on their ability to approximate human-reviewers. This is by definition a very challenging problem and we observe that more efforts need to be taken towards automatic machine reviewing systems.

### 2.2 Related Work

**Fairness disparities.** In modern data science, it is increasingly important for models to be non-discriminatory or fair with respect to some sensitive attributes (e.g., race or gender). Many fairness notions have been proposed to regularize models to mitigate the bias
of models, both from individual level [2, 5] and group level [7, 9]. Among them, demographic parity [7] and equalized odds [9] are arguably two of the most popular fairness notions. Demographic parity states that the proportion of each segment of a protected group (e.g., gender) should receive the positive outcome (e.g., making a loan) at equal rates. On the other hand, a classifier satisfies equalized odds if the subjects in the protected and unprotected groups have equal true positive rate and equal false positive rate. Although being of great academic and social interest, there are very few studies on fairness disparities and equalized odds in the peer review mechanism, especially when textual features are present.

Peer review mechanism. As an important social network, the peer review network has attracted more and more attentions in the community. For example, Kang et al. [12] proposed a high-quality dataset contains paper from ACL, NeurIPS (formerly NIPS), and ICLR. Plank and van Dalen [15] create a large-scale dataset that covers over 3,000 papers from machine learning conferences. Gao et al. [8] create a dataset that focuses on investigating the effect of rebuttals in NLP conferences. On top of these datasets, many recent research has been proposed to investigate the bias inside the review process [14, 17], argument mining [10], automatically review generation [24], improved review process [11, 16], and review explanation [23]. Nonetheless, none of the existing work has investigated the fairness violation or worked through the lens of large language models. We summarize key differences between the most relevant datasets and ours in Table 1. Notably, to the best of our knowledge, our dataset is the most comprehensive one, backed up by various off-the-shelf features extracted from large language models for downstream analysis.

3 DATABASE CONSTRUCTION

3.1 ICLR Data

We use the OpenReview\textsuperscript{3} Python API\textsuperscript{4} to crawl conference data from OpenReview, which include submissions, author profiles, reviews, rebuttals, and decisions in ICLR 2017-2022. We are able to obtain in total 10289 submissions, 21808 distinct authors, 36453 reviews, 68721 author responses, and 4436 public comments. The crawling process is done in Feb 2022 after ICLR2022 announced its decisions. We exclude desk-rejected or author-withdrawn submissions from the dataset. We tabulate per-year counts in Table 2. Note that from table we note the natural distributional differences across gender groups of authors. We next briefly describe the schema for each data entity while the full Entity-Relation (ER) diagram and the covariate table are given in the Appendix.

Submission. Each submission entity contains a paper number (unique within the same conference), a title, an abstract, a link to the pdf file, an one-sentence summary (11dr), a list of self-provided paper keywords, and a list of author identifiers referring to the authors in author table.

Author. Author entities contain the author names, their emails (only domain is visible), and optionally, self-reported gender, homepage, Google Scholar, DBLP, LinkedIn, Semantic Scholar, Wikipedia, and ORCID. In addition, authors can optionally report their current and past affiliations with corresponding positions.

Review. Although the specific review format changes each year, there is generally a textual review, a numerical rating (usually in the range of 1 to 10), and a numerical confidence score (usually in the range of 1 to 5). In certain years, there are more specific scores such as technical soundness, novelty, etc. In total, there are 35717 reviews corresponding to 10289 submission with an average number of reviews per submission being 3.47.

Table 2: Summary of the dataset. In 2017-2018, submissions to the main conference may be invited to workshop tracks. Note that we exclude desk-rejected/withdrawn papers.

| Institution | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|-------------|------|------|------|------|------|------|
| MIT         | 732  | 1303 | 1385 | 2380 | 2928 | 3120 |
| Stanford     | 1497 | 2699 | 3531 | 5687 | 7328 | 7864 |
| CMU         | 119   | 224  | 366  | 590  | 845  | 883  |
| UC Berkeley | 504   | 872  | 899  | 1295 | 1485 | 1502 |
| Princeton   | 301   | 448  | 628  | 936  | 1228 | 1411 |
| KAIST       | 75    | 115  | 173  | 277  | 303  | 360  |
| CMU         | 119   | 224  | 366  | 590  | 845  | 883  |
| UCL         | 504   | 872  | 899  | 1295 | 1485 | 1502 |
| UC Berkeley | 301   | 448  | 628  | 936  | 1228 | 1411 |

\textsuperscript{3}https://pypi.org/project/openreview-py/  
\textsuperscript{4}https://api.openreview.net/api/
Author responses, public comments, and decisions. Author response, public comment, and decision entities include a title, a comment, a forum field that refers to the submission it points to, and a "reply-to" field that points to its parent node in a discussion thread.

3.2 Academic Profile Data
To complement the author information, we obtain academic profiles using the scholarly API\(^6\) for Google Scholar\(^7\), which include the citation counts (as of Feb 2022), five-year citation counts, \(h\)-index, five-year \(h\)-index, \(i10\)-index, five-year \(i10\)-index, and per-year citation counts, \(h\)-index, and \(i10\)-index. Among all 21808 distinct authors, we are able to find 21031 associated Google Scholar profiles. There are 4180 authors report their scholar profile in their OpenReview profile. For other authors, we concatenate their name with their latest institution (if reported) to form the search string, and select the most relevant query result from Google Scholar, which results in 3566 matches. If no results are found, we remove the institution string, search again, and select the most relevant query result. We are able to find another 4180 matches.

3.3 Institution Ranking
We obtain institutional rankings from CSRankings\(^7\), a metric-based ranking of 582 computer science institutions based on per-year citations counts of publications in various venues that are divided into 4 areas (Artificial Intelligence, Systems, Theory, and Interdisciplinary Areas) and 26 sub-areas. We match the reported institution from author profiles with those in the CSRanking by thresholding the normalized Levenshtein distance at 0.8 between institution names (both are uncased). We find 852 matches out of 4745 unique institutions.

Nonetheless, since the ranking from CSRanking is the aggregated ranking weighting all sub-domain of computer science equally, it might not be the most representative; furthermore, the institutions available in the CSRanking only cover about \(1/6\) institutions authors reported in OpenReview. To this end, we also consider a data-driven ranking that ranks each institute at a particular year by the total number of accepted papers in all previous years, which we refer to as the "ICLR ranking." We show the top-50 institutions with highest ranks as of 200, grouped by their per-year acceptance counts in Figure 3.

3.4 arXiv Matching
A crucial component in the analysis of reviewing stage bias is whether a submission is put onto the arXiv before the review releasing date. This provides us with a proxy to assess whether there might be a possible mechanism for the reviewers to gain information on authors’ identities. We use the python wrapper for the arXiv API\(^8\) to obtain the five most relevant results based on the title of the submission for subsequent filtering. Similar to Kang et al.\(^9\), we compute Jacard similarity and normalized Levenshtein similarity between authors; in additional, we also use the Specter model\(^10\) developed by Cohan et al.\(^3\) to compute the cosine-similarity of the title-abstract embedding. We fine-tune the filtering threshold to be 0.5 for all similarity measures such that the number of the matched papers are approximately the same as in Tran et al.\(^9\).

4 LANGUAGE MODEL ENHANCEMENTS
In this section, we describe how we augment the dataset by extracting various high-level features, mostly with the help of large language models.

4.1 Submission Features
We process all submissions in pdf format in the dataset, with a total of 36GB to extract full texts.

Summary statistics. We use Grobid\(^11\) to extract bibliographical data and obtain sections/figures/tables with their corresponding headings. We are able to obtain the counts of figures, tables, and sections in this way.

Keywords. Authors can optionally provide a list of keywords alongside with their submission. There are 9537 submissions that provide a total of 36004 keywords and among them on average 3.84 keywords are provided per submission. On top of the raw keywords provided by authors, we also cluster keywords together by thresholding the Levenshtein distance \(13\). Note that processed keyword clusters may correspond to different but relevant research topics (e.g., convex optimization vs. non-convex optimization).

Textual complexity. An essential problem is to quantify the mathematical complexity of a paper. A "superficial" way of doing this is to assess how well the texts of the paper aligns with English grammar since equations and mathematical symbols usually violate it. We used a pre-trained RoBERTa model used for assessing text fluency called Parrot\(^11\) for this purpose. The fluency score ranges from 0 to 1, with a higher score represents less complicated texts. As a sanity check, we compute this fluency score on 100 randomly drawn papers from 16 different arXiv categories spanning pure mathematics, physics, and various domains of computer science. In Figure 4m and Figure 4n, we plot the histogram of complexity scores against 16 categories. We note that the bulk of the scores concentrate around 0.85 and the distributional difference is aligned with intuition (harder subjects such as algebraic geometry have a generally lower complexity score).

Specter embedding. The Specter embedding provides us a means of clustering submissions into different cluster through spectral clustering.\(^3\) We show the t-SNE\(^22\) plot in Figure 4o, where each color/marker corresponds to a different arXiv primary category; we also show altogether the primary category of a few random data points. We observe the clusters are interpretable: "language modelling" and "contrastive learning" are far away from each other while "deep learning" are prevalent in many clusters. On a practical note, this embedding can be used to assess the relevance among submissions.

\(^5\)https://pypi.org/project/scholarly
\(^6\)https://scholar.google.com
\(^7\)https://csrankings.org/
\(^8\)https://pypi.org/project/arxiv/
\(^9\)https://huggingface.co/allenai/specter
\(^10\)https://github.com/kermitt2/grobid
\(^11\)https://huggingface.co/prithvivasu/paraphraser_on_T5
Figure 4: Exploratory data analysis. Roughly speaking, the first row focuses on the submissions, the second row on reviews and authors, and the third row on high-level features extracted from LMs. (m)-(o) are done on a control dataset we randomly sampled from arXiv to illustrate those high-level features work as expected. We provide more details and discussions of the plots in Section 5.1.

4.2 Review Features

Tone and sentiment. Aside from integer-valued rating and confidence (and sometimes more aspects such as technical soundness), the tone or sentiment of the review may also affect the decision stage. We use the RoBERTa model trained on Twitter sentiment\(^{12}\) to extract a sentiment score ranges between 0 and 1 for each review (1 signifies most positive). Although this model was trained on Twitter, we found the sentiments it generates are highly correlated with the review rating, indicating a good representation, as shown in Figures 4g and 4h.

4.3 Author Features

Reported and perceived gender. Although each author may optionally report their gender information in their OpenReview profiles, this reported gender may not be the same as the perceived gender. We use the first name gender dictionary approach appeared in [20], which assigns a 'male' score ranging from 0 to 1 to each first name according to its frequency on Wikipedia.

Geographical information. We use the domain name from the email address of author profile to identify the geographical information of each author. Since the author affiliation might change over time, if the author provides its affiliation history, we use the email record at the year of the conference submission to identify the author’s geography, and thus the same author’s geography might change for different submissions.

5 INVESTIGATING FAIRNESS DISPARITIES

In this section, we investigate fairness disparities in the decision process. For the ease of exposition, we dichotomize the sensitive attributes as (i) whether a paper’s majority of authors are from North America; (ii) whether a paper’s leading author is Female; (iii) whether a paper’s most highly-cited authors falls in the top 1% authors. We will first perform exploratory data analysis to explore potential fairness disparities in the data. We then zoom in several sensitive attributes of interest and study their marginal effects on the submission acceptance. To imitate the decision process, we fit predictive models given various features to predict acceptance probability. If the model captures this process well, we may use it as a surrogate to study the existence of fairness disparities and trace their roots.

5.1 Exploratory Data Analysis

We first explore the dataset among various dimensions and provide intuitive insights into the dataset [21]. We select several features of interest and plot their relationships in Figure 4.
Geographical disparity. Gender disparity. Decision Author prestige disparity.

| Max. Author Citation (log 10) | # Submissions | # Submissions | # Submissions | Count |
|-----------------------------|---------------|---------------|---------------|-------|
| 10                          | 1000          | 1000          | 1000          |       |
| 400                         |               |               |               | 12    |
| 200                         |               |               |               | 5.20  |
| 600                         |               |               |               | 5.67  |
| 800                         |               |               |               | 5.80  |

We first study fairness disparities based on the Figure 4h, which aligns with our intuition. views of various lengths Figure 4f. The extracted review sentiment varies little across the five most common keywords. In Figure 4l, the results in Figures 5 and 6. We note that the empirical acceptance struct confidence bands based on sample variances. We summarize probability of a acceptance at each average rating level and con-

5.2 Marginal Disparity Analysis

We first study fairness disparities based on the marginals of various sensitive attributes while averaging out all other factors given reviewer ratings. In this setup, we estimate the (empirical) marginal probability of a acceptance at each average rating level and construct confidence bands based on sample variances. We summarize the results in Figures 5 and 6. We note that the empirical acceptance probabilities are visually similar across four sensitive attributes considered. Nonetheless, we note at certain level of average rating (mostly borderline ratings between 5 to 7), some sensitive attributes exhibit statistically significant difference (e.g., in Figure 5b around rating 6.25). In Figure 6, we zoom in to the borderline papers for the prestige disparity (measured by author institution ranking and citation count at the year of submission). We found that although the ranges of accepted/rejected papers overlap, their means can be strikingly different. Marginal analysis provides us with rough idea of when disparities may occur but falls short of providing explanations, which will be the focus of the next subsection.

5.3 Joint Disparity Analysis

Although the estimations of the marginal probability and their confidence bands are non-parametric thus not relying on any modelling assumptions, it is inconvenient to condition on multiple factors simultaneously. In this subsection, we aim at studying fairness violations in the decision stage using predictive models, which also brings the additional benefits of selecting the most important features for the prediction.

We use the submission data form 2017-2021 as the training set and data in 2022 as the test set to fit a logistic regression model using the combination of the following sets of features: (i) base: submission features (including textual features); (ii) +author: base features plus all author features; (iii) +rev base features plus review ratings and confidences; (iv) +revnlp base features plus all review

Figure 5: Acceptance probability conditioning on average review rating. (a) Histogram of average review ratings of accepted/rejected papers with borderline range marked. (b) Empirical acceptance probability across groups. The horizontal axis signifies average rating, the left vertical axis corresponds to the histogram of samples from two groups and the right vertical axis corresponds to the probability. We observe that at certain ratings, there appears to be a statistically significant difference between two groups.

Figure 6: Decision for papers of various prestige among borderline scores. Note that although samples overlap, their means can differ significantly at certain score levels.
features including sentiment and length. Specifically, for submission features, we also assign a cluster number \( k \in [20] \) to each submission by running spectral clustering using cosine similarity on the specter embeddings. We show the diagnosis curves in Figure 7 including the receiver operating characteristics (ROC) curve and the calibration curves of the models trained on different sets of features when evaluating on the test set. In Table 3, we tabulate several disparity measures on models trained using different sets of features and in Figure 8 we plot the distributional disparity across the sensitive attributes. In what follows we discuss in greater detail the results.

Decision stage is less noisy. The ROC curve together with its area under the curve (AUC) capture the discrimination power of classifier. Notice that after review features are added, the ROC curve is close to the (0, 1) diagonal and its AUC is around 0.95. In Figure 7b, we plot the calibration curve with true probabilities and predicted probabilities. A well-calibrated model should be centered around the main diagonal. We found that although the model is simple, after including review features, it can capture the most of the variations in the dataset and generalizes well. This implies that the biases and noises in the decision process are low given the review ratings.

Fairness violations differ. Together with DP, we also compute two other commonly used fairness metrics, equalized odds difference (EO) and AUC difference (AUC). We tabulate the violations on both \(+rev\) and \(+revnlp\) (marked by +R) in Table 3. We note that the violations are relatively mild (mostly less than 0.1). Together with Figure 7, we see that in the decision stage, a simple model can capture both the discriminatory power as well as fairness constraints. Nonetheless, the level of disparity varies across sensitive attributes: geographical disparity appears to be generally higher than gender disparity.

Large language models help explain disparities. In Figure 7, we note that the ROC behavior of both \(+rev\) and \(+revnlp\) models are similarly good but the latter generally has smaller fairness violations (columns marked with +R in Table 3). This implies that textual features produced by large LMs are helpful in assessing fairness disparities, and thus should be incorporated into other related analyses. The same observation can be drawn from Figure 8, where we plot the cumulative probability function of the predicted acceptance probability across different sensitive attribute groups. A fair classifier would not distinguish the two curves and the maximum disparity between the two curves is used to measure distributional disparity. We observe that the inclusion of textual features (+revnlp) often helps in reducing the disparity.

5.4 Summary

In this section we perform fairness analysis on models trained to mimic the decision process in peer-review. Although fairness disparities often exist as a result of the underlying data distribution being imbalanced, the inclusion of high-level textual features generated by LMs can often help to ameliorate such parities.

6 TOWARDS AUTOMATIC REVIEWING SYSTEMS

In this section, we discuss concrete examples how our database has the potential of motivating more challenging NLP tasks. Our focus lies in the review stage and we aim at defining tasks that facilitate the understanding of the review process, and more broadly, towards automatic machine reviewing systems. We train all models on NVIDIA RTX 2080 Ti GPUs with 10GB memory, except for the Longformer, which requires 45GB memory to exploit its maximum token limit. All fine-tuning are completed within 12 hours.

Review Generation. The first step of an automatic reviewing system is generating reviews from the submission. There has been a large literature on using LMs for summarization tasks ([18]); the difference here is that in the review generation task, the desirable output is the opinions rather than summaries of the paper. To this end, we fine-tune Longformer Encoder-Decoder (LED) models for conditional generation tasks on submission and review samples. Generated reviews are tabulated in Table 4, where (+) and (-) signify whether the model is trained on positive or negative samples. We found that most of the time, adding LM features helps reduce fairness disparities in the model.
We assemble a comprehensive data of peer-reviews and postulate

Table 4: Samples of generated reviews using LED. The LED model is fine-tuned on ICLR2017-2021 while the above samples are

Figure 8: Model disparity when including different sets of features. Here the disparity is measured by the maximum disparity of the cumulative probability function of predicted acceptance probabilities over sensitive groups. We observe that in general, the inclusion of high-level textual features to the model helps to reduce this type of fairness disparity.

Submission ID: Figg0OshG
LED Output (+)
Summary: This paper studies the continual learning problem in PLMs. The authors analyze the performance of different combinations of PLMs and CL methods on 3 benchmark datasets, including task-incremental learning and class-incremental learning. The paper is well-written and easy to follow. The authors claim that the paper provides a thorough analysis of the continual learning problem in PLMs. The paper does not provide a thorough analysis of the continual learning problem in PLMs. The paper does not provide a thorough analysis of the continual learning problem in PLMs.

LED Output (-)
Review Sample
This paper conducts a comparative study of the performance of different continual learning methods and CL methods. The authors conduct experiments on three continual learning settings, namely task-incremental learning, class-incremental learning, and class-incremental learning. The paper is well-written and easy to follow. The authors claim that the paper provides a thorough analysis of the continual learning problem in PLMs. The paper does not provide a thorough analysis of the continual learning problem in PLMs. The paper does not provide a thorough analysis of the continual learning problem in PLMs.

Table 4: Samples of generated reviews using LED. The LED model is fine-tuned on ICLR2017-2021 while the above samples are from ICLR2022. The symbols (+) and (-) signify whether the model is trained on positive or negative reviews. We note that the generated samples are on-topic (as compared with the real review sample), contains a summary of the paper, and also provides opinions, however, the model still struggles to generate more general and consistent argument, highlighting the difficulty of this task.

for the paper quality. We fine-tune RoBERTa and Longformer models on the 2017-2021 submissions and evaluate them on the 2022 submissions, which achieve 0.881 and 0.891 F1 scores respectively.

7 DISCUSSIONS AND CONCLUSIONS
We assemble a comprehensive data of peer-reviews and postulate the study of fairness violations using three commonly used fairness metrics. We observe that in the decision stage, such violations differ for sensitive attributes, and language model features help alleviate disparities in the decision stage models. Yet, we do not find compelling evidence that such differences are significant.

We also demonstrate the potential of our database to be used in benchmarking new and important NLP tasks, we provide baseline models for the example of automatic machine review tasks.

Limitations and Future Work: (i) Move beyond association analysis: the fairness analysis we considered are by nature association analysis and we are not able to draw any causal conclusion. (ii) Choice of statistical parity measures: there are various type of statistical parity measures, and we believe there may be more interesting conclusions could be drawn for other measures besides those we chose.
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A DATABASE DETAILS

The summary of all covariates of the database is given in Table 5; we also include the entity-relation (ER) diagram in Figure 9. All collected data are open data, which are granted access by the owner.
Table 5: Summary of the covariates (CSRanking data are omitted).
Figure 9: ER diagram of the database (CSRanking related entities are omitted).