Evaluating Blocking Biases in Entity Matching

Mohmmad Hossein Moslemi
The University of Western Ontario
London, Ontario, Canada
mohammad.moslemi@uwo.ca

Harini Balamurugan
The University of Western Ontario
London, Ontario, Canada
hbalamur@uwo.ca

Mostafa Milani
The University of Western Ontario
London, Ontario, Canada
mostafa.milani@uwo.ca

Abstract—Entity Matching (EM) is crucial for identifying equivalent data entities across different sources, a task that becomes increasingly challenging with the growth and heterogeneity of data. Blocking techniques, which reduce the computational complexity of EM, play a vital role in making this process scalable. Despite advancements in blocking methods, the issue of fairness—where blocking may inadvertently favor certain demographic groups—has been largely overlooked. This study extends traditional blocking metrics to incorporate fairness, providing a framework for assessing bias in blocking techniques. Through experimental analysis, we evaluate the effectiveness and fairness of various blocking methods, offering insights into their potential biases. Our findings highlight the importance of considering fairness in EM, particularly in the blocking phase, to ensure equitable outcomes in data integration tasks.

I. INTRODUCTION

Entity Matching (EM) involves determining whether two or more data entities from the same or different sources refer to the same real-world object. Also known as entity linkage or record matching, EM is crucial for data integration and has extensive applications across various industries [1], [2], [3], [4], [5], [6], [7]. EM methods typically consist of a matching component that compares entities and labels them as either "match" or "non-match." A major challenge in EM is its computational complexity, often scaling quadratically as each entity must be compared to all others, making it an $O(n^2)$ problem. This complexity becomes prohibitive for large datasets with millions of records. To mitigate this, blocking methods are used as a preliminary step to reduce the number of comparisons [8], [9], [10]. As a result, EM systems typically operate in two phases: blocking to limit comparisons, followed by matching to produce the final labels.

Blocking reduces the number of entity comparisons by grouping similar entities into distinct or overlapping blocks, thus limiting comparisons within these smaller, more manageable groups. This approach is crucial for improving the scalability of EM by mitigating its quadratic complexity and reducing computational load. Over time, blocking methods have evolved from basic heuristic-based approaches to more sophisticated techniques. Traditional methods, such as Standard Blocking and Sorted Neighborhoods [11], [12], provided foundational strategies for grouping entities. More recent advances include methods that leverage machine learning and deep learning for enhanced efficiency, such as Canopy Clustering [13] and various modern frameworks that optimize attribute selection and candidate generation [8], [14], [15], [10].

In recent years, fairness in ML has gained significant attention [16], [17], [18] due to its critical impact on real-life applications. Fairness is particularly important in the context of EM because both EM and blocking systems can produce biased results, often exhibiting higher accuracy for one demographic group over another. Despite the significant implications of EM on real-life decisions, research on the fairness of EM remains limited, with only a few studies exploring this issue [19], [20], [21], [22]. Even fewer studies have addressed the fairness of blocking methods, leaving this area largely unexplored. To the best of our knowledge, only one study has investigated the fairness of blocking [23], which merely touched on the topic by defining a fairness metric for blocking based on the representation ratio, similar to RR, and proposing simple algorithms to address bias in blocking.

In this paper, we investigate fairness in blocking methods for EM. Traditional fairness metrics, such as Equalized Odds, Equal Opportunity, and Demographic Parity [17], [18], are typically used for classification tasks in machine learning models and do not apply to blocking methods. We extend existing blocking metrics, such as Reduction Ratio (RR), Pair Completeness (PC), and their harmonic mean, and define biases in blocking methods. Our study evaluates these extended metrics to assess bias across various blocking techniques. We conduct an experimental analysis to identify fairness issues, detect biases, and understand their impact on EM and end-to-end matching tasks. The aim is to uncover biases, understand their origins, and develop debiasing methods that ensure blocking methods are both accurate and fair.

The paper is structured as follows. Section II presents related work, including a summary of the state-of-the-art blocking methods. Section III provides a formal definition of EM and blocking and reviews the metrics used to evaluate blocking. In Section IV, we extend these blocking metrics to fairness measures, proposing them as a sufficient method for assessing bias in blocking. Section V presents our experimental results, highlighting the effectiveness of various blocking methods and the biases they may introduce. Section VI offers our conclusions. All the implementations are available at https://github.com/mhmoslemi2338/pre-EM-bias.

II. RELATED WORK

We briefly review the existing blocking methods for EM and then discuss fairness in EM and related areas such as clustering and ranking.

A. Blocking Methods

Over the years, a wide range of blocking techniques has been developed, from simple heuristic-based methods to advanced approaches involving deep neural networks (for surveys, see [24], [25], [11]). These blocking methods can be categorized in various ways, each providing a different perspective on how these techniques function and their applications. One way is by distinguishing between learning-based and non-learning-based algorithms. Rule-based methods, a type of non-learning-based approach, rely on expert knowledge or simple heuristics to define the blocking criteria. In contrast, learning-based methods require training data to learn how to block the data using machine learning techniques.

Another categorization is based on schema awareness. Schema-aware methods perform blocking by focusing on the most important attributes of the data, while schema-agnostic methods treat the entire entity as a single attribute, utilizing all available information. A third categorization concerns redundancy awareness, dividing methods into redundancy-free, redundancy-positive, and redundancy-neutral subcategories, which differ in how they handle the assignment of entities to blocks and the overlap between blocks [24]. Redundancy-free methods create disjoint blocks by assigning each entity to only one block, leading to higher similarity between two entities if they share a greater number of identical blocks. In contrast, redundancy-positive methods form overlapping blocks, with each entity placed in multiple blocks; here, the likelihood of a match between two entities is proportional to the total number of blocks they share. Redundancy-neutral methods also produce overlapping blocks, but in such a way that most entity pairs share nearly the same number of blocks, rendering redundancy insignificant in determining the similarity between entities. These various categorizations highlight the diversity of blocking techniques available, each suited to different scenarios depending on the data and the desired balance between computational efficiency and match accuracy.

Traditional blocking methods such as Standard Blocking [26] and Sorted Neighborhoods [27] have fundamentally shaped the field. Standard Blocking categorizes records according to a blocking key, such as a phone number or surname initials, to conduct intensive comparisons within these blocks. However, this method risks inefficiencies when block sizes are large. In contrast, Sorted Neighborhood enhances efficiency by sorting records according to a key and employing a sliding window for comparisons, though it may overlook matches when key values exceed the window's boundaries.

Advanced approaches like Canopy Clustering [13] have been introduced to address some of the limitations of traditional methods. This technique uses a less costly, coarse similarity measure to initially group records, which are then subjected to more precise and computationally demanding comparisons within each canopy. Although designed to minimize the total number of comparisons, this method may occasionally result in the erroneous grouping of distinct entities [14].

Blocking techniques, such as BSL (Blocking Scheme Learner) [8] and BGP (Blocking based on Genetic Programming) [14], have further enhanced the efficiency and accuracy of the traditional methods. These more advanced methods leverage machine learning to refine blocking schemes, focusing on attribute selection and comparison methods to generate candidate matches efficiently. CBLOCK offers an automated approach to canopy formation within a map-reduce framework, tailored specifically for large-scale de-duplication tasks involving diverse datasets, thus optimizing the trade-off between recall and computational efficiency [28]. Additionally, Token-Based Blocking effectively addresses challenges in heterogeneous datasets by comparing records based on shared tokens, providing a versatile solution for integrating diverse data sources.

Deep learning has recently revolutionized the blocking phase in EM, shifting from traditional heuristic methods to more adaptive and automated approaches. Frameworks like AutoBlock and DeepER exploit deep learning for representation learning and nearest neighbor search, demonstrating significant effectiveness across varied, large-scale datasets [15], [10]. DeepBlock, which merges syntactic and semantic similarities through deep learning, further enhances blocking quality by accurately grouping similar records, even in noisy or heterogeneous datasets [29].

Various metrics have been used to measure the quality of blocking. Still, three are most commonly used and considered the most comprehensive in assessing the effectiveness of blocking methods: RR, PQ, and PC [30], [31], [25]. RR measures the extent to which a blocking system reduces the total number of comparisons, PQ denotes the percentage of candidate pairs that are true matches after blocking, and PC indicates the percentage of true matches in the candidate set after blocking.

There is little agreement on the evaluation measures in the literature on blocking. Some studies only consider PC and RR as their primary metrics [15], [32], [10], [33], [34], [35], [8], [9], [36], while some only considered PC and PQ [29], [37]. Several studies also consider runtime as a main evaluation measure in blocking methods [38], [39], [40], [41]. There is also research that employs the harmonic mean of PC and RR [42], [43], [44], [45], [46] or the harmonic mean of PC and PQ [25]. We will formally define these metrics in Section III and discuss what measure provides a more meaningful way to evaluate the methods considered in Section V.

B. Fairness in Entity Matching

Fairness is a growing concern in EM systems, especially as these systems are widely employed in data-driven decision-making processes. A key concern is that EM processes can unintentionally perpetuate biases present in the data, leading to

unfair outcomes. A real-world example that underscores these fairness issues is the use of "no-fly" lists, where individuals, particularly people of color, have been wrongly matched with the list and flagged as security threats due to misidentification, resulting in denial of services [47]. Another notable example is Google's advertising algorithms, which have been found to match and display prestigious job advertisements more frequently to men than to women. This bias occurs because the algorithms tend to match male profiles more closely with the job requirements [48]. These discrepancies highlight how EM algorithms can perpetuate existing gender biases, resulting in unequal opportunities and outcomes. These examples illustrate the necessity for developing end-to-end matching algorithms (including blocking) that ensure fair and equitable treatment across all demographic groups.

Recent research has aimed to address fairness challenges in matching methods. The FairER algorithm, introduced by [19], incorporates fairness constraints directly into EM methods, emphasizing the importance of considering fairness from the outset of the data cleaning pipeline. Additionally, [20] proposed an AUC-based fairness metric to evaluate the performance of EM methods that return matching scores, assessing their effectiveness across different groups. Further, recent studies by [23] and [21] extensively explore biases in EM as a data preparation task to prevent disproportionate exclusion or misrepresentation of groups. However, these works primarily focus on EM and offer limited discussion on the fairness of blocking methods.

C. Fairness in Clustering

Blocking can be seen as clustering entities before matching. We, therefore, briefly review fairness concepts in clustering as a related task. Fairness in clustering is assessed using metrics that ensure equitable treatment across demographic groups. In clustering, fairness is evaluated by the balance within clusters, using metrics like demographic parity and balance ratio [49] to measure proportional representation. Techniques such as *Fairlet Decomposition* [50] utilize these metrics to create balanced groups across sensitive attributes before final clustering, ensuring fair representation. While having balanced clusters is a reasonable fairness requirement for clustering, it does not apply to blocking, where the goal is not equal representation within blocks but rather to create small blocks that include all equivalent record pairs.

III. BACKGROUND

We start from a relation schema $\mathcal{S}$ consisting of a set of attributes $A_1, ..., A_m$ with domains $\mathrm{DOM}(A_i), i \in [1, m]$. An entity (record) t with schema $\mathcal{S}$ is a member of $\mathrm{DOM}(A_1) \times ... \times \mathrm{DOM}(A_m)$, the set of all possible entities, which we denote by $\mathcal{D}$. We use $t[A_i]$ to refer to the value of attribute A_i in entity t. A relation $D \subseteq \mathcal{D}$ is a set of entities.

EM generally has two major phases: blocking and matching [1]. We start with matching and then explain blocking.

A. Entity Matching

Given two relations D_1, D_2, the problem of *entity matching (EM)* is to find a subset M of $D_1 \times D_2$ that consists of entity pairs referring to the same real-world entities. We refer to such entity pairs as *equivalent pairs*.

A entity matcher (matcher in short) for entities of schema $\mathcal{S}$ is a binary classifier $f : \mathcal{D} \times \mathcal{D} \mapsto \{0, 1\}$; that labels entity pairs 1, called they match, or 0, saying they don't match. Given relations D_1, D_2 with schema $\mathcal{S}$ and equivalent entity pairs $M \subseteq D_1 \times D_2$, the goal of f is to find the equivalent entities in M, i.e., label the entity pairs in M as a match and the non-equivalent entities as non-match, where the accuracy of f, e.g., accuracy rates and F1 score, are defined based on whether the equivalent entity pairs are correctly labeled.

B. Blocking

The set of entity pairs for relations D_1, D_2 in a matching setting, which we denote by $P = D_1 \times D_2$, grows quadratically in size w.r.t the size of D_1 and D_2. This makes it costly to run expensive matching methods for all possible pairs. The problem of blocking is to find a candidate set $C \subseteq P$, which is much smaller than P, while it still includes all equivalent pairs; $M \subseteq C$. A blocking method is expected to run much faster than a matching method for comparing all possible pairs. Blocking saves unnecessary checking of some of the non-equivalent pairs while searching for the equivalent pairs.

Definition III.1 (Blocking). *Given two datasets, D_1 and D_2 with the set of all possible pairs $P = D_1 \times D_2$, the goal of blocking is the fast computation of a candidate set C s.t. $|C| \ll |P|$ (there are much fewer candidates compared to total pairs) and $M \subseteq C$.*

Blocking Metrics: How effective a blocking method is measured using three main quality measures defined as follows:

$$\mathrm{RR} = 1 - \frac{|C|}{|P|} \qquad \mathrm{PC} = \frac{|C \cap M|}{|M|} \qquad \mathrm{PQ} = \frac{|C \cap M|}{|C|} \qquad (1)$$

Reduction ratio (RR) is the ratio of the reduction in the number of comparisons after blocking to the total number of possible comparisons. A higher RR value signifies a greater reduction in the number of candidate entity pairs. This measure does not consider the quality of the generated candidate entity pairs. *Pairs completeness* PC represents the ratio of equivalent pairs retained after blocking to the total number of equivalent pairs. This measure evaluates how effectively C preserves equivalences, corresponding to recall in information retrieval [51]. PC ranges from 0 to 1, where a value of 1 indicates that the blocker retains all true matches. *Pairs quality* (PQ) denotes the fraction of equivalent pairs produced by C relative to the total number of pairs. A higher PQ indicates that C is efficient, primarily generating true matches. In contrast, a lower PQ suggests that many non-matching pairs are included. PQ is equivalent to precision in information retrieval [11]. PQ ranges from 0 to 1, with higher values indicating that the blocker is more effective at eliminating non-matches.

Between these metrics, PQ is typically sensitive to small changes in RR. In large datasets with millions of pairs with a much smaller number of equivalent pairs, a small change in RR leads to a significant increase in the size of the candidate set that greatly impacts PQ, which leads to the high sensitivity of PQ. Therefore, in most studies, PC, RR, and their harmonic mean are used as the key metrics for evaluating blocking methods [24], [40], [33], [45]. The harmonic mean, which balances the trade-off between PC and RR, is defined as:

$$F_{\text{PC,RR}} = \frac{2 \times \text{PC} \times \text{RR}}{\text{PC} + \text{RR}} \qquad (2)$$

In addition to evaluating the effectiveness of blocking methods, their efficiency is equally important. Specifically, the runtime of a blocking method plays a crucial role in determining the optimal approach. A detailed numerical analysis of these measures and their relationships is provided in Section V. We explain these measures using an example.

Example III.2. *Figure 1 shows a relation D with ten entities. We consider matching entities in the same relation with entity pairs $P = D \times D$. The red dotted lines show the equivalent pairs; $M = \{(t_2, t_6), (t_6, t_7), (t_2, t_7), (t_4, t_5), (t_8, t_9), (t_8, t_{10}), (t_9, t_{10})\}$. The solid black lines show a blocking method that specifies three blocks that result in $3 + 6 + 3 = 12$ candidate pairs. The blocking result misses two equivalent pairs, (t_2, t_6) and (t_2, t_7), but reduces the number of pairs to check from 45 to 12, resulting in $RR = 1 - \frac{12}{45} \approx 0.73$, $PC = \frac{5}{7} \approx 0.71$, and $F_{RR,PC} \approx 0.72$.*

IV. Measuring Bias in Blocking

Blocking methods can suffer from disparities; the quality of blocking might differ for the minority group compared with the majority, leading either to missing equivalent minority pairs or being ineffective in reducing unnecessary matching of non-equivalent methods.

To define biases in blocking, we assume the relation schema $\mathcal{S}$ includes a sensitive (or protected) attribute A (e.g., gender or ethnicity) with domains $\text{DOM}(A) = a, b$, where a and b correspond to the minority (e.g., female) and majority groups (e.g., male), respectively. This means that an entity t with $t[A] = a$ belongs to the minority group, while $t[A] = b$ indicates it belongs to the majority group. In the context of matching, we use the protected attribute of entities in a record pair to determine whether the pair concerns minority or majority groups. We define a minority pair as any pair of entities $(t_1, t_2) \in D_1 \times D_2$ where at least one entity belongs to the minority group based on the specified sensitive attribute (e.g., ethnicity, gender). Conversely, a majority pair consists of both entities from the majority group. Intuitively, minority pairs are those that could result in an EM decision negatively affecting a minority entity. This can occur if the entity is incorrectly matched with another minority or majority entity or if the opportunity to match it correctly with another entity is missed.

In our definition of blocking disparities, we use P_g, C_g, and M_g with $g \in \{a, b\}$ to respectively refer to the set of
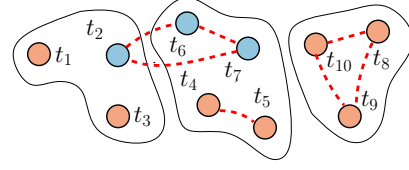

Fig. 1: Disparity in blocking: minority and majority entities are highlighted in blue and red resp. and the equivalent pairs are linked by dotted lines. Solid lines show the blocks.

pairs in group g, and the set of candidate pairs in group g, and the set of equivalent pairs in group g. Then we define the reduction ratio and pair completeness for the minority groups g as follows:

$$\text{RR}_g = 1 - \frac{|C_g|}{|P_g|} \qquad \text{PC}_g = \frac{|C_g \cap M|}{|M_g|} \qquad (3)$$

Intuitively, the reduction ratio per group g specifies the reduction in the number of comparisons for the entity pairs in group g. Similarly, pair completeness per group g metrics these metrics between the pairs in the group g only. We don't define and use PQ as we explained due to its sensitivity and redundancy with RR and PC. Using RR and PC per group, we define their harmonic mean per group g that is $F_{RR,PC}^g$.

We define disparities as the differences between the blocking quality metrics for the majority and minority groups. For example, $\Delta RR = RR_b - RR_a$ represents the reduction ratio disparity, $\Delta PC = PC_b - PC_a$ denotes the pair completeness disparity, and $\Delta F_{RR,PC} = F_{RR,PC}^b - F_{RR,PC}^a$ indicates the mean disparity.

We now use our running example to explain these quality metrics per group g.

Example IV.1. *Continuing with the example in Figure 1, three entities are from the minority group, and seven are from the majority groups, as highlighted by different colors. These give five majority pairs (with both entities from the majority group) and $3 \times 7 + 3 = 24$ minority pairs (with at least one entity from the minority group). The following are the blocking quality metrics per group: $RR_a = 1 - 7/24 \approx 0.71$ (there are seven minority pairs after blocking), $PC_a = 1/3 \approx 0.33$, $F_{RR,PC}^a \approx 0.45$ $RR_b = 1 - 5/21 = 0.76$, $PC_b = 4/4 = 1$, and $F_{RR,PC}^b \approx 0.86$. These metrics give reduction ratio and pair completeness disparities of $\Delta RR \approx 0.76 - 0.71 = 0.05$, $\Delta PC \approx 0.66$, and 0.45, respectively. In this example, all disparities are positive, indicating a lower blocking quality for the minority group a. This is evident in the missing equivalences for the minority pairs (2 missing pairs for the minority vs. none for the majority) and the smaller reduction gain for the minority group (reduction from 24 to 7 for the minority vs. 21 to 5 for the majority).*

Introducing these disparity metrics allows for the evaluation of the fairness of blocking techniques. The metric ΔRR measures the difference in reduction ratios between pairs associated with minority and majority groups. A lower

reduction ratio for a group can result in ineffective blocking for that group, leading to an increased number of non-equivalent pairs being passed to the matching process. This can cause the matching method to either fail to identify true matches or mistakenly match non-equivalent pairs. ΔPC measures the difference in pair completeness and reveals biases in blocking. It indicates that more equivalent pairs are incorrectly excluded for a group, reducing the effectiveness of the overall matching process. ΔF$_{RR,PC}$ captures both types of biases by combining ΔRR and ΔPC, thereby reflecting overall disparities in the blocking process. By quantifying these differences in blocking quality across demographic groups, we can identify potential biases and inequalities in the blocking procedure.

V. EVALUATION AND ANALYSIS

The purpose of our experiments is twofold: first, to understand the quality of the existing blocking methods for the benchmarks we employed in this paper where we use RR, PC, F$_{RR,PC}$, and time to compare (Sections V-B1 and V-B2); second, to analyze the same methods in terms of their possible biases using the introduced measures of disparity (Section V-B3 and V-B4).

A. Experimental Setup

We briefly explain the datasets and the blocking methods used in this paper before presenting the experimental results.

1) Datasets: We use datasets from prominent EM benchmarks: Amazon-Google (`AMZ-GOO`), Walmart-Amazon (`WAL-AMZ`), DBLP-Google Scholar (`DBLP-GOO`), DBLP-ACM (`DBLP-ACM`), Beer (`BEER`), Fodors-Zagat (`FOD-ZAG`), iTunes-Amazon (`ITU-AMZ`), and Febrl (`FEBRL`), as referenced in [1], [52]. The research community commonly adopts these datasets to evaluate EM system performance. Their full details are available in our GitHub repository.

Consistent with prior studies [20], [21], [22], we categorize entities into minority and majority groups across various datasets. For instance, in `DBLP-ACM`, including a female name in the "authors" attribute defines the minority. Entities in the `FEBRL` dataset are considered a minority if the "Given Name" attribute is female. In `FOD-ZAG`, entities with the "Type" attribute exactly equal to "Asian" are classified as minority. In `AMZ-GOO`, the presence of "Microsoft" in the "manufacturer" attribute defines a minority group. For `WAL-AMZ`, entities classified as "printers" under the "category" attribute are considered a minority group. In `DBLP-GOO`, entities are considered minority if the "venue" attribute includes "vldb j,". For `BEER`, entities with "Beer Name" containing the phrase "red" are classified as minority. Finally, in `ITU-AMZ`, the minority group includes those where the "Genre" attribute contains the word "Dance,".

Detailed statistical information about these datasets is provided in Table I. The numbers in the bracket refer to the corresponding parameter in the minority group, e.g., 2.6k (96) for $|D_1|$ in `WAL-AMZ` means there are 2.6k entities in D_1 while only 96 are a minority. The parameters for the majority group can be clearly inferred from the data in the table.

Dataset	#Attr.	$|D_1|$	$|D_2|$	$|P|$	$|M|$
WAL-AMZ	5	2.6k (96)	22.0k (172)	56.4m (2.5m)	962 (88)
BEER	4	4.3k (1.3k)	3.0k (932)	13.0m (6.8m)	68 (29)
AMZ-GOO	3	1.4k (83)	3.2k (4)	4.4m (272.9k)	1.2k (60)
FOD-ZAG	6	533 (72)	331 (3)	176.4k (25.2k)	111 (10)
ITU-AMZ	8	6.9k (1.9k)	55.9k (12.7k)	386.2m	132 (40)
DBLP-GOO	4	2.6k (191)	64.3k (389)	168.1m	5.3k (403)
DBLP-ACM	4	2.6k (251)	2.3k (225)	6.0m (1.1m)	2.2k (310)

TABLE I: Datasets and their characteristics.

2) Blocking Methods: The blocking methods used in our study are as follows:

i) *Standard Blocking (`StdBlck`)*: This hash-based method groups records using concatenated attribute values (blocking keys) to form redundancy-free blocks. However, it is sensitive to noise; any variation in the key may exclude matching records from the same block [26].

ii) *Q-Grams (`QGram`) and Extended Q-Grams Blocking (`XQGram`)*: Q-grams blocking splits blocking keys into subsequences of q characters, improving noise tolerance but potentially increasing block size and number. Extended Q-Grams further combines q-grams for more distinctive keys, reducing block size and enhancing efficiency [25], [53].

iii) *Suffix (`Suffix`) and Extended Suffix (`XSuffix`) Arrays Blocking*: Suffix Arrays Blocking converts blocking keys into suffixes of a minimum length to form blocks, filtering out common suffixes to prevent oversized blocks. Extended Suffix Arrays consider all substrings longer than the minimum length, boosting noise tolerance [25], [53].

iv) *AutoEncoder (`AUTO`) and Cross-Tuple Training (`CTT`) Blocking*: These deep learning methods group similar records into blocks using embeddings. `AUTO` generates embeddings via an autoencoder to handle diverse and noisy data, while `CTT` uses a Siamese Summarizer to create embeddings from synthetic data, enhancing distinction between matching and non-matching tuples [1].

v) *Semantic-Based Graph Blocking (`GRAPH`)*: The algorithm concatenates entity attributes into a single string, from which a transformer-based model extracts context-aware embeddings. These embeddings are reduced to a lower-dimensional space for efficiency. A k-nearest neighbor (KNN) algorithm then constructs a graph of database tuples, connecting nodes based on embedding proximity. Unsupervised clustering is applied to group similar entities, framing the blocking task as a graph clustering problem [46].

We selected these blocking methods as they represent the best-performing approaches in their respective categories. `StdBlck`, `QGram`, and `Suffix` (along with their extended versions) are widely recognized traditional methods and remain commonly used in practice due to their effectiveness and efficiency. With the growing trend of employing deep learning in blocking, we included `AUTO` and `CTT`, which have demonstrated superior performance in handling complex and noisy data. Additionally, we chose `GRAPH`, an innovative and

recent approach, to represent cutting-edge advancements in the blocking problem.

B. Experimental Results

Our experimental results include an analysis of blocking methods based on their performance—specifically, the quality of blocking and runtime—which aligns with our first experimental objective. Additionally, we conduct an extensive analysis of the existing biases in these methods to address our second objective.

1) Runtime and Scalability: A primary concern in blocking is ensuring that the methods are not only fast compared to matching methods but also scale effectively as the data size increases. Table II and Figure 2 present the runtime of various blocking methods across datasets of different sizes (measured by the number of entity pairs). These results reflect the average runtime over five runs per dataset, with a negligible standard deviation (less than 0.5 seconds) and thus not reported. Notably, all methods were completed within a reasonable timeframe (less than 1 hour), even for datasets with up to 500 million pairs. Some methods even finished in under a minute for the largest datasets.

While all methods are relatively fast, their scalability varies. This variance can be attributed to the underlying computational processes of each approach. Among the methods tested, `Suffix` and `XSuffix` exhibited the fastest performance and best scalability. These methods generate suffixes from blocking keys, a process known for its linear or near-linear time complexity. Their straightforward operations, like filtering out common suffixes to prevent oversized blocks, enable them to maintain speed even as dataset sizes increase, making them particularly suitable for large-scale applications.

In contrast, `AUTO` and `CTT`, though fast, do not match the performance of the suffix-based methods. These approaches use deep learning models to generate embeddings that group similar records into blocks. Although deep learning can be computationally intensive, `AUTO` and `CTT` are optimized for efficiency. `AUTO`, for instance, employs an autoencoder—a relatively simple neural network—to produce embeddings quickly. Similarly, `CTT` uses a Siamese network to generate embeddings that effectively distinguish between matching and non-matching records. Despite their efficiency, the additional complexity of these methods results in slightly lower performance and scalability compared to the suffix-based methods.

On the other hand, `QGram` and `XQGram`, which split blocking keys into multiple subsequences, perform faster on smaller datasets but do not scale as well as `AUTO` and `CTT`. The increase in block size and the number of comparisons required as the dataset grows significantly impacts their efficiency. Finally, `GRAPH` is the slowest among the tested methods. It involves generating embeddings using a transformer-based model and constructing a graph of database tuples—processes that are computationally intensive. This complexity, especially in the graph clustering stage, leads to longer runtimes and poorer scalability when handling larger datasets.

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	4.9s	1.4m	3.5m	8.5s	3.2s	0.5s	22.3m
QGram	5.1s	1.8m	3.6m	9.7s	4.0s	0.5s	42.0m
XQGram	5.1s	1.9m	2.7m	8.1s	4.2s	0.5s	51.8m
Suffix	**1.5s**	<u>7.9s</u>	18.9s	2.4s	1.8s	0.3s	9.6s
XSuffix	<u>2.0s</u>	**7.8s**	<u>24.7s</u>	4.0s	2.4s	<u>0.4s</u>	15.7s
AUTO	5.2s	18.9s	58.1s	7.0s	9.2s	0.7s	1.9m
CTT	5.3s	27.6s	1.5m	7.5s	10.2s	0.6s	2.6m
GRAPH	58.9s	8.2m	19.2m	2.1m	1.2m	8.2s	14.2m

TABLE II: Runtime of blocking methods

a) All datasets   b) WAL-AMZ
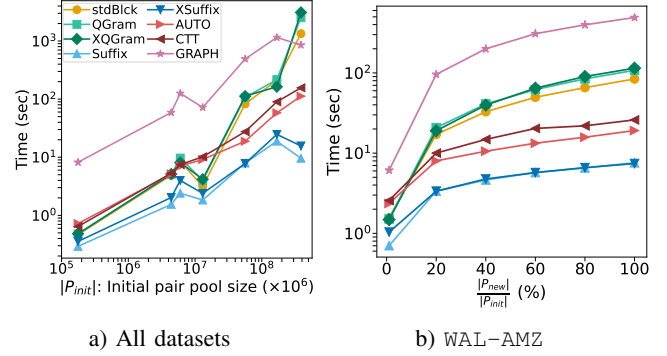
Fig. 2: Runtime of blocking methods

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	99.73	99.81	99.94	99.94	<u>99.91</u>	98.72	99.86
QGram	99.69	99.77	99.95	99.94	99.90		99.79
XQGram	99.70	99.75	99.95	99.94	99.90	98.88	99.77
Suffix	<u>99.85</u>	<u>99.96</u>	<u>99.98</u>	99.95	**99.95**	<u>99.31</u>	**99.99**
XSuffix	**99.86**	**99.97**	**99.99**	99.94	**99.95**	**99.33**	**99.99**
AUTO	98.45	99.77	99.92	97.82	98.33	84.89	<u>99.91</u>
CTT	98.45	99.77	99.92	97.82	98.33	84.89	<u>99.91</u>
GRAPH	97.74	97.59	98.14	**99.96**	98.91	97.26	98.37

TABLE III: RR values for different models across datasets, with best (bold), second-best (underlined), and worst (framed) highlighted

2) Quality of Blocking: Table III presents RR of various blocking methods across multiple datasets. Across most datasets, all methods achieve high RR values close to 1, indicating their general effectiveness in reducing candidate pairs. However, `Suffix` and `XSuffix` consistently outperform the other methods, with `XSuffix` achieving the highest RR in most cases. This superior performance can be attributed to the inherent efficiency of suffix-based methods in generating compact and discriminative blocks. By focusing on suffixes and filtering out common ones, these methods avoid generating overly large blocks, which is particularly beneficial when handling large datasets with significant redundancy.

Why RR is significantly lower in deep learning methods in `FOD-ZAG`, `CTT`, `AUTO`, and `GRAPH`. This is because of smaller datasets size in `FOD-ZAG` while these methods are based on DL and perform better with large datasets for effectively generating embeddings. `GRAPH` is not significantly lower than the other two methods. The `GRAPH` method, which involves generating embeddings using a

transformer-based model and applying graph clustering, shows the lowest RR values in multiple datasets, including **AMZ-GOO**, **WAL-AMZ**, and **ITU-AMZ**. This method's lower performance could be due to the computationally intensive nature of both embedding generation and graph clustering, which may not scale well for larger datasets. Additionally, the graph construction process might introduce noise or redundancy, leading to larger blocks that reduce the overall RR. The method performs better in **DBLP-ACM**, where it achieves the highest RR, indicating that it may be more suited to datasets where the relationships between records are complex but the dataset size is manageable.

On the other hand, **AUTO** and **CTT**, while generally effective, show noticeable underperformance in specific datasets such as **FOD-ZAG**. This lower RR could be linked to the complexity and diversity of the data in this particular dataset. **AUTO** and **CTT** rely on deep learning-based embeddings to group similar records into blocks. While these embeddings are powerful in capturing complex patterns, they may not be as effective when the dataset size is smaller or when there is less variation among records, as seen in **FOD-ZAG**. The deep learning models might struggle to generate sufficiently discriminative embeddings, leading to less effective blocking and a subsequent drop in RR.

Interestingly, the overall RR is lower in the FOD-ZAG dataset for all methods, which might be due to the smaller size of this dataset. In smaller datasets, the relative lack of variation and fewer distinct blocking keys can result in less effective blocking. As a result, even high-performing methods like Suffix and XSuffix show a slight decrease in RR. The specific underperformance of AUTO, CTT, and GRAPH in this dataset suggests that methods relying heavily on complex models or embeddings may not always be well-suited to smaller datasets with less diversity.

However, it is important to keep in mind the initial goal of using RR as a measure. We aim to use RR to ensure that the matcher can efficiently process the output of the blocker, so there is no pre-set lower limit for RR. The appropriate RR depends on the computational power of the matcher and the size of the initial dataset. For instance, a model with an RR of 99.99% for **ITU-AMZ** produces a similar number of pairs as output as it would if it had only an 80% RR for the **FOD-ZAG** dataset.

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	**98.29**	**99.06**	<u>98.73</u>	99.86	**95.59**	100.0	**97.73**
QGram	95.72	**99.06**	**98.75**	**99.95**	92.65	100.0	73.48
XQGram	94.17	<u>98.75</u>	97.59	**99.95**	91.18	**100.0**	71.97
Suffix	88.52	91.16	82.38	<u>99.91</u>	88.24	100.0	50.76
XSuffix	83.89	88.36	76.47	99.46	89.71	<u>97.32</u>	51.52
AUTO	88.52	96.36	95.23	99.86	85.29	**100.0**	90.15
CTT	<u>95.97</u>	97.51	95.96	99.86	<u>94.12</u>	100.0	<u>91.67</u>
GRAPH	93.92	83.89	79.13	98.78	88.24	73.21	54.55

TABLE IV: PC values for different models across datasets

Table IV illustrates PC. Unlike RR, where most meth-ods perform uniformly well, PC values reveal significant variations in performance. In datasets like **AMZ-GOO**, **Suffix**, **XSuffix**, and **AUTO** underperform compared to **StdBlck**, **QGram**, and **CTT**, which achieve higher PC values. For **Suffix** and **XSuffix**, in cases where the suffixes are not sufficiently distinctive, these methods may over-partition the data, causing some true matches to be split into different blocks, thereby reducing PC. **AUTO**

Similarly, in the ITU-AMZ dataset, QGram, XQGram, Suffix, and XSuffix show significantly lower PC values, indicating that they miss a substantial number of true matches. This could be due to the highly variable or sparse nature of the data in this dataset, where blocking keys may not align well across records. As a result, these methods struggle to capture all true matches. In contrast, StdBlck, AUTO, and CTT perform better in preserving most equivalences in ITU-AMZ. AUTO and CTT, which use embeddings to capture more complex similarities between records, manage to maintain higher PC even in challenging datasets.

The poor performance of GRAPH in several datasets, such as WAL-AMZ and FOD-ZAG, highlights the limitations of graph-based methods when the embedding space does not align well with the underlying data structure. In cases where the data lacks clear relational patterns or where the embeddings fail to capture these patterns accurately, GRAPH may struggle to retain true matches, leading to lower PC.

A general takeaway is that suffix-based methods like Suffix and XSuffix may perform well for datasets with structured and consistent blocking keys. However, deep learning-based methods like AUTO and CTT, which generate embeddings that can capture complex similarities, may be more effective for datasets with more complex or noisy data. For datasets where the relationships between records are intricate and graph-like, methods like GRAPH could be considered, although their performance may vary depending on how well the embeddings align with the data structure.

Mohammad-Hossein: In addition to the dataset structure and the architecture of the blocking method, the ratio $\frac{|M|}{|P|}$ is a factor that can affect the PC of different blocking methods. Intuitively, as this ratio decreases, the blocker faces a more challenging task of identifying the true matches among the non-matches. For example, this ratio is on the order of $O(10^{-7})$ for ITU-AMZ, whereas it is on the order of $O(10^{-3})$ for FOD-ZAG. As shown in Table III, different methods exhibit a significantly higher PC in FOD-ZAG compared to ITU-AMZ. This observation generally holds true across other datasets we examined. The reason this is not always the case is that this ratio is not the only parameter influencing the overall PC, as discussed earlier.

Mohammad-Hossein: Additionally, a low PC of a blocking method on a dataset does not necessarily indicate that the situation is significantly worse compared to another blocking method with a higher PC. For example, in the BEER dataset, the 10% difference between the best and worst PC means that AUTO missed 7 more true matches out of the 13 million initial pairs compared to StdBlck, which has the highest PC in the

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	9.58	0.90	5.34	_66.26_	0.54	4.96	0.02
QGram	8.29	0.75	6.22	59.22	0.51	5.40	0.01
XQGram	8.40	0.69	5.99	60.25	0.48	_5.66_	0.01
Suffix	_16.06_	_3.49_	**16.61**	**73.06**	0.88	9.23	**0.24**
XSuffix	**15.85**	**4.31**	_17.78_	60.34	**0.89**	9.23	_0.19_
AUTO	1.52	0.73	3.89	1.69	0.03	0.42	0.03
CTT	1.64	_0.73_	3.92	1.69	0.03	0.42	0.04
GRAPH	0.45	0.01	0.01	61.75	0.02	1.70	0.001

TABLE V: PQ values for different models across datasets

The data in Table V highlights the sensitivity of PQ to RR, demonstrating that even a small variation in RR can lead to a significant change in PQ. For instance, in the AMZ-GOO dataset, Suffix achieves a PQ of 16.06, while AUTO, with a slightly lower RR (99.85 for Suffix versus 98.45 for AUTO), sees a drastic drop in PQ to 1.52. This substantial decline can be attributed to the large number of candidate pairs in AMZ-GOO; when RR decreases, the number of candidate pairs increases, diluting the concentration of true matches and thereby reducing PQ. A similar trend is observed in the WAL-AMZ dataset when comparing Suffix and XQGram. Suffix, with its slightly higher RR, maintains a higher PQ (3.49) compared to XQGram (0.69). In the DBLP-ACM dataset, XSuffix achieves a PQ of 17.78, outperforming CTT (3.92), despite both methods having relatively high RR. These examples further illustrate how PQ is influenced by even small changes in RR, particularly in datasets with a large number of pairs.

Interestingly, the impact of RR on PQ is less pronounced in smaller datasets like BEER and ITU-AMZ. For these datasets, the absolute number of candidate pairs is lower, so variations in RR have a smaller effect on PQ. For example, in the ITU-AMZ dataset, the PQ values for most methods remain relatively low across the board, with only minor differences between them. This observation supports the idea that in smaller datasets, where the pool of candidate pairs is naturally limited, the effect of RR on PQ is diminished.

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	**99.00**	**99.44**	_99.33_	99.90	**97.70**	99.36	**98.78**
QGram	_97.66_	_99.42_	**99.34**	99.95	96.14	99.41	84.64
XQGram	96.86	99.25	98.75	**99.95**	95.34	_99.44_	83.62
Suffix	93.84	95.36	90.33	_99.93_	93.73	**99.65**	67.34
XSuffix	91.18	93.80	86.66	99.70	94.55	98.32	68.00
AUTO	93.22	98.04	97.52	98.83	91.35	91.83	94.78
CTT	97.20	98.63	97.90	98.83	96.18	91.83	_95.61_
GRAPH	95.78	90.22	87.61	99.37	93.27	83.54	70.18

TABLE VI: $F_{RR,PC}$ values for different models across datasets

As the final quality measure, we report the F1 measure ($F_{RR,PC}$) in Table VI. The results indicate that no single method consistently outperforms the others across all datasets, reflecting the variability observed in PC. However, some methods, such as StdBlck, consistently deliver strong performance across various datasets, showcasing stable and reliable results overall. StdBlck, in particular, achieves the highest or near-highest $F_{RR,PC}$ values in most cases, making it a robust choice for different dataset characteristics. Other methods, like QGram and Suffix, also demonstrate strong performance in specific datasets, but their effectiveness varies depending on the dataset's properties. For example, Suffix performs exceptionally well in datasets like FOD-ZAG, which achieves the highest $F_{RR,PC}$, but it struggles in ITU-AMZ, where its $F_{RR,PC}$ drops significantly. This variability underscores the importance of selecting a blocking method that aligns with the specific characteristics of the dataset being analyzed. In contrast, methods like AUTO and GRAPH tend to have more variable $F_{RR,PC}$ scores, reflecting their sensitivity to the dataset's complexity and the nature of the data. AUTO, for instance, performs well in some datasets but falls behind in others, particularly in DBLP-ACM and BEER. Similarly, GRAPH shows significant fluctuations in $F_{RR,PC}$, with particularly low scores in datasets like FOD-ZAG and ITU-AMZ, highlighting its potential limitations in handling certain types of data. Overall, while StdBlck emerges as a consistently strong performer across datasets, the choice of the optimal blocking method should still be guided by the specific requirements and characteristics of the dataset. The variability in $F_{RR,PC}$ values across methods emphasizes the need for careful consideration when selecting a blocking strategy, especially in scenarios where both high PC and RR are critical.

Mosatafa: Up to hear.

3) Bias Analysis of Blocking Methods: We now turn our analysis to studying biases in the blocking methods. We start with disparities in the reduction ratio, ΔRR. Table VII shows RR per minority and majority group together with their difference, which defines the disparity per dataset and per method. The disparities are insignificant (less than one percentage point) across all blocking methods and datasets. This can be attributed to the fact that RR was close to 1, its maximum value, as reported in Table III. However, some methods exhibit higher disparities, such as GRAPH in most datasets and AUTO in DBLP-ACM. These methods also have slightly lower overall RR, as reported in Table III. Mohammad-Hossein: Given that the RR is generally high (with the worst-case scenario being 84.89 in FOD-ZAG, a very small dataset), and the difference between minority and majority groups is minimal (a maximum difference of less than 2%), a higher RR for a particular group indicates that the model faced challenges in reducing the size of that group compared to the other. This bias typically favors the larger majority group. However, a lower RR for the minority group is not a significant concern because the minority group is relatively small, and even in the worst case, the minority group's RR remained above 80%, which is still acceptable.

An important observation from our experimental analysis is that these disparities can be negative; this contrasts with general disparities in fairness literature, such as demographic disparity, where disparities are typically assumed to be non-negative (i.e., minorities can only be discriminated against). In the context of blocking, some methods may actually perform better for minority groups due to the specific nature of the blocking task—a topic we further discuss in the experimental section.

Mohammad-Hossein: Consequently, the primary focus of bias mitigation algorithms should be on PC and $F_{RR,PC}$, with a lesser emphasis on RR. Additionally, given that RR is typically very high, $F_{RR,PC}$ will exhibit behavior similar to PC. This implies that reducing bias in PC will eventually lead to a reduction in bias in $F_{RR,PC}$, considering that RR remains high and its bias is low. Furthermore, a low PC for a group suggests that the blocker missed more true matches for that group, negatively impacting the overall quality of the EM pipeline. Therefore, it is advisable to employ a blocking method that achieves a higher overall PC and minimizes PC disparity among different subgroups.

Mohammad-Hossein: This approach contrasts with the bias mitigation algorithm proposed by [23], which aims to eliminate bias in RR. However, addressing RR bias alone will not resolve any significant issues and could potentially reduce PC. This reduction could occur if pairs from a subgroup are removed to increase that subgroup's RR, thus reducing RR disparity but simultaneously decreasing PC for that group.

4) Impact of Removing Sensitive Attributes: As a first step to mitigating biases, we conducted a simple experiment to test "fairness through unawareness" in the context of blocking methods. The idea is that an algorithm is considered fair if it does not use sensitive attributes like race or gender in its decision-making process. This approach is limited because the algorithm may still inadvertently act on correlated attributes, leading to biased outcomes. The purpose of this experiment is to test this hypothesis.

VI. CONCLUSION

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Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	0.08 (99.73, 99.66)	0.14 (99.82, 99.68)	-0.05 (99.94, 99.99)	**-0.01** (99.94, 99.95)	**-0.01** (99.90, 99.91)	0.01 (98.72, 98.71)	-0.13 (99.80, 99.93)
QGram	0.38 (99.72, 99.33)	0.25 (99.79, 99.54)	-0.03 (99.95, 99.98)	**-0.01** (99.93, 99.95)	**-0.01** (99.90, 99.91)	-0.20 (98.80, 99.00)	-0.15 (99.73, 99.88)
XQGram	0.41 (99.73, 99.32)	0.18 (99.76, 99.58)	-0.03 (99.95, 99.97)	**-0.01** (99.94, 99.95)	**-0.01** (99.90, 99.90)	-0.16 (98.86, 99.01)	-0.20 (99.68, 99.88)
Suffix	0.07 (99.86, 99.79)	-0.01 (99.95, 99.97)	**-0.00** (99.98, 99.98)	**-0.01** (99.95, 99.96)	-0.02 (99.94, 99.96)	-0.18 (99.28, 99.46)	**-0.00** (99.99, 99.99)
XSuffix	0.04 (99.86, 99.82)	0.00 (99.96, 99.97)	0.00 (99.99, 99.99)	**-0.01** (99.94, 99.95)	-0.02 (99.30, 99.48)	-0.18 (99.30, 99.48)	**-0.00** (99.99, 99.99)
AUTO	**-0.01** (98.45, 98.46)	-0.01 (99.77, 99.79)	0.01 (99.92, 99.91)	-0.48 (97.73, 98.21)	0.04 (98.36, 98.31)	0.90 (85.02, 84.12)	-0.04 (99.89, 99.93)
CTT	**-0.01** (98.45, 98.46)	0.01 (99.77, 99.77)	0.01 (99.92, 99.92)	-0.21 (97.78, 97.99)	-0.09 (98.29, 98.38)	**0.00** (84.89, 84.89)	-0.04 (99.89, 99.93)
GRAPH	0.30 (97.74, 97.45)	0.81 (97.62, 96.81)	1.39 (98.25, 96.85)	**-0.01** (99.95, 99.97)	-0.24 (98.79, 99.03)	0.98 (97.40, 96.42)	-1.09 (97.89, 98.98)

TABLE VII: For each cell, a (b,c) shows RR values within minority and majority groups (b,c) and the RR disparities (a)

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	0.91 (99.05, 98.14)	0.81 (99.51, 98.69)	0.37 (99.36, 98.99)	-0.08 (99.89, 99.97)	**-0.88** (97.32, 98.20)	**0.01** (99.36, 99.35)	3.83 (99.90, 96.07)
QGram	**-0.33** (97.65, 97.98)	0.87 (99.49, 98.62)	0.66 (99.39, 98.73)	**-0.03** (99.94, 99.97)	-3.65 (94.55, 98.20)	-0.10 (99.39, 99.49)	-6.13 (82.71, 88.84)
XQGram	3.53 (97.04, 93.51)	0.66 (99.31, 98.65)	0.58 (98.80, 98.22)	**-0.03** (99.94, 99.97)	-5.09 (93.11, 98.20)	-0.07 (99.42, 99.49)	**-0.58** (83.43, 84.02)
Suffix	9.77 (94.31, 84.54)	2.95 (95.62, 92.67)	0.16 (90.35, 90.18)	**-0.06** (99.92, 99.98)	-4.77 (91.64, 96.41)	-0.09 (99.64, 99.73)	0.96 (67.62, 66.67)
XSuffix	11.79 (91.73, 79.94)	**0.53** (93.85, 93.32)	1.07 (86.74, 85.67)	-0.32 (99.65, 99.97)	-3.28 (93.12, 96.41)	-1.59 (98.15, 99.74)	1.90 (68.57, 66.66)
AUTO	5.20 (93.48, 88.27)	2.50 (98.26, 95.76)	-0.30 (97.50, 97.80)	-0.32 (98.78, 99.10)	**-0.89** (90.97, 91.86)	0.58 (91.91, 91.33)	-3.81 (93.59, 97.40)
CTT	1.44 (97.27, 95.83)	2.49 (98.85, 96.36)	**0.24** (97.92, 97.68)	-0.18 (98.80, 98.99)	-2.25 (95.20, 97.46)	**0.02** (91.83, 91.81)	-0.67 (95.41, 96.07)
GRAPH	1.39 (95.86, 94.47)	11.13 (91.14, 80.01)	-3.70 (87.32, 91.02)	-0.53 (99.29, 99.82)	-1.49 (92.62, 94.11)	-3.82 (83.63, 87.44)	-3.76 (68.99, 72.74)

TABLE VIII: $F_{RR,PC}$ disparities and $F_{RR,PC}$ values within the minority and majority groups

Model	AMZ-GOO	WAL-AMZ	DBLP-GOO	DBLP-ACM	BEER	FOD-ZAG	ITU-AMZ
StdBlck	1.71 (98.37, 96.67)	1.47 (99.20, 97.73)	0.77 (98.79, 98.01)	-0.16 (99.84, 100.00)	-1.68 (94.87, 96.55)	**0.00** (100.00, 100.00)	7.50 (100.00, 92.50)
QGram	**-1.00** (95.66, 96.67)	1.47 (99.20, 97.73)	1.33 (98.85, 97.52)	**-0.05** (99.95, 100.00)	-6.81 (89.74, 96.55)	**0.00** (100.00, 100.00)	-9.35 (70.65, 80.00)
XQGram	6.16 (94.49, 88.33)	1.13 (98.86, 97.73)	1.15 (97.67, 96.53)	**-0.05** (99.95, 100.00)	-9.37 (87.18, 96.55)	**0.00** (100.00, 100.00)	**-0.76** (71.74, 72.50)
Suffix	16.01 (89.34, 73.33)	5.28 (91.65, 86.36)	**0.27** (82.40, 82.13)	-0.10 (99.90, 100.00)	-8.49 (84.62, 93.10)	**0.00** (100.00, 100.00)	1.09 (51.09, 50.00)
XSuffix	18.16 (84.82, 66.67)	**0.94** (88.44, 87.50)	1.66 (76.60, 74.94)	-0.63 (99.37, 100.00)	-5.92 (87.18, 93.10)	-2.97 (97.03, 100.00)	2.17 (52.17, 50.00)
AUTO	8.98 (88.98, 80.00)	4.75 (96.80, 92.05)	-0.60 (95.19, 95.78)	-0.16 (99.84, 100.00)	**-1.59** (84.62, 86.21)	**0.00** (100.00, 100.00)	-6.96 (88.04, 95.00)
CTT	2.78 (96.12, 93.33)	4.76 (97.94, 93.18)	0.46 (96.00, 95.53)	-0.16 (99.84, 100.00)	-4.24 (92.31, 96.55)	**0.00** (100.00, 100.00)	-1.20 (91.30, 92.50)
GRAPH	2.37 (94.04, 91.67)	17.29 (85.47, 68.18)	-7.28 (78.58, 85.86)	-1.04 (98.64, 99.68)	-2.48 (87.18, 89.66)	-6.73 (73.27, 80.00)	-4.24 (53.26, 57.50)

TABLE IX: PC disparities and PC values within the minority and majority groups

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