Through the Fairness Lens: Experimental Analysis and Evaluation of Entity Matching

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ABSTRACT

Entity matching (EM) is a challenging problem studied by different communities for over half a century. Algorithmic fairness has also become a timely topic to address machine bias and its societal impacts. Despite extensive research on these two topics, little attention has been paid to the fairness of entity matching.

Towards filling this gap, we perform an extensive experimental evaluation of a variety of EM techniques in this paper. Our findings underscore the need for unbiased training data and techniques, such as ensemble learning for EM. Besides, while various fairness definitions are valuable for different settings, due to EM's class imbalance nature, measures such as positive predictive value parity and true positive rate parity are, in general, more potent in revealing EM unfairnesses.

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1 INTRODUCTION

Entity matching (EM) seeks to match pairs of entity records from (the same or different) data sources that refer to the same real-world object. EM is very useful in many applications domains, including (a) healthcare, where matching of patient records from different healthcare facilities (e.g., emergency rooms, hospitals, etc.) can be used to determine if they refer to the same real-world person; (b) airline security, where airline passenger records are matched against terrorist watch list records to identify persons who should be prevented from boarding flights or undergoing additional screening; (c) e-commerce, where product records from different retailers' websites can be matched to identify popular products and fraudulent knockoffs; and so on.

EM is a challenging problem that has been extensively investigated for over half a century by different communities, e.g., statistics, databases (DB), natural language processing (NLP), and machine learning (ML), resulting in a variety of techniques proposed in the literature for addressing this problem. These challenges arise because entities in autonomous data sources can be represented in a variety of ways (e.g., highly structured records versus textual descriptions), using different conventions (e.g., the many ways in which person names and postal addresses are represented), data quality issues (e.g., misspellings, missing values), and so on. A consequence is that, despite significant advances in recent years (especially with recent neural techniques like Ditto [24]), EM techniques still result in both false positives (non-matching entity record pairs that are declared as matches) and false negatives (matching record pairs that are declared as non-matches).

These errors can have serious consequences in practice. For example, false positives in airline security can lead to significantly inconveniencing passengers whose names happen to be the same as or similar to those of known terrorists, while false negatives can result in known terrorists being permitted to board flights with undesirable consequences. When such errors (e.g., false positives) occur in a systematic way for some demographic groups/subgroups (e.g., many Asians may have the same name and date of birth; image matchers may have much worse accuracy for dark-skinned people) thereby disadvantaging them over others, concerns about the *fairness* of EM techniques arise. While the fairness of ML models has been the topic of much recent work in the literature [5, 13, 14, 14, 17, 23, 38, 39, 41], not much attention has been paid to the fairness of EM techniques.

In this paper, we seek to address this gap in the literature and perform an extensive experimental evaluation and analysis of a variety of EM techniques on a range of benchmark datasets through the *fairness lens*. We make the following technical contributions.

- Given the pairwise nature of EM, we propose the use of *single fairness* and *pairwise fairness* to evaluate entity matchers. We adopt 11 popular fairness measures from the literature for this task and analyze their suitability for EM.
- We select a suite of 13 EM techniques (including 1 declarative rule-based technique, 7 non-neural ML techniques, and 5 neural ML techniques) and 6 benchmark datasets that have been used in prior work on entity matching (including 2 structured datasets, 2 textual datasets and 2 dirty datasets) for fairness evaluation.
- We evaluated all the combinations of EM techniques, benchmark datasets, and fairness measures and analyzed the outcomes to obtain generalizable results. We classified the results into four classes of configurations based on whether an (EM technique, benchmark dataset, fairness measure) yielded (i) accurate or inaccurate matching results, and (ii) fair or unfair matching results. Interestingly, all four classes contained configurations involving ML-based classifiers.

Some of our findings in this study are as follows.

- Our results underscore that responsible EM requires unbiased training data that covers different possibilities from various (demographic) groups.
- While different fairness measures are valuable for different settings, due to the class-imbalance property of EM, measures such

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as *positive predictive value parity* and *true positive rate parity* are more capable of revealing EM unfairnesses.
- Significantly relying on proxy attributes such as name, salary, etc., can cause unfairness in non-neural models. On the other hand, relying on pre-trained language models and embeddings, or not fully considering the dataset structures can cause unfairness in neural matchers.
- Different matching techniques may perform differently for groups of a given dataset, emphasizing the importance of techniques such *ensemble learning* for responsible EM.

2 FAIRNESS EVALUATION FRAMEWORK

2.1 Background

Given two sets of entities $A \in S_A$ and $B \in S_B$ from data sources S_A and S_B, the EM problem is to identify all correspondences between entities in $A \times B$ that correspond to the same real-world object. A correspondence $c = (e_i, e_j, s)$ interrelates two entities e_i and e_j with a confidence value $s \in [0, 1]$ that indicates the similarity of e_i and e_j or the confidence of a matcher about e_i and e_j referring to the same object. [21]. To decide whether the entity pair of $c = (e_i, e_j, s)$ is a *match* or *non-match*, matchers often apply a threshold on s [4, 37]. We decouple the choice of a threshold from the outcome of the matching and consider the outcome of an EM task as pairs of matching and non-matching entities. Formally, we consider the following EM problem in this paper:

Definition 1 (Entity Matching Problem). *Consider two sets of entities $A \in S_A$ and $B \in S_B$ from data sources S_A and S_B. For every pair of entities $(e_i, e_j) \in A \times B$, let y_{ij} be the ground truth label indicating if e_i and e_j refer to the same object. Given all pairs $(e_i, e_j) \in A \times B$, the EM problem is to predict y_{ij} with a label h_{ij}. That is, h_{ij} refers to the decision of the matcher about the label of e_i and e_j (match or non-match).*

In a fairness-sensitive setting, entities are accompanied with sensitive attributes (e.g. `genre`, `language`, `race`, etc.). Let $\mathcal{A} = \{A_1, \ldots, A_n\}$ be the sensitive attributes, $dom(A_i)$ be the domain of A_i, and $\mathcal{G} = \{g_1, \ldots, g_m\}$ be the set of all groups of interest, i.e. $\mathcal{G} = \bigcup_{A_i \in \mathcal{A}} dom(A_i)$. The mapping $L(e_i)$ relates an entity to its associated groups $G_i \subseteq \mathcal{G}$. In other words, G_i is the group that e_i belongs to.

Given two sets of entities $A \in S_A$ and $B \in S_B$ from data sources S_A and S_B, and the set $[(e_i, e_j, G_i, G_j, h_{ij}, y_{ij})]_{\forall (e_i, e_j) \in A \times B}$, we would like to audit the fairness of a matcher with respect to groups and the combination of groups (subgroups).

2.2 Single and Pairwise Lens

2.2.1 Group Selection. The first step in auditing an entity matcher for fairness is identifying meaningful groups/subgroups in sensitive attributes. An input dataset to a matcher $\mathcal{M}$ includes entity ids, the value (group/subgroup) of each entity for sensitive attributes, the decisions of $\mathcal{M}$, as well as true labels for the entity pairs. Depending on the type, cardinality, and number of sensitive attributes, multiple fairness cases may happen. Table 1

The space of groups for a single attribute with binary or multiple values is the domain of the corresponding attribute. In multiple-attributes settings, we can define intersectional subgroups. The subgroups can be presented in a hierarchical data structure, where

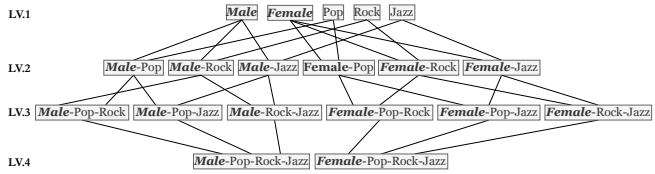

Figure 1: Intersectional subgroup hierarchy for single setwise and multiple attributes

the first level includes all groups (of all attributes), while the k-th level includes the set of non-overlapping groups created by combining groups from k different attributes. When one attribute is of the single setwise type, level k includes $k - 1$ groups from the setwise attribute with one group from a binary or multi-value attribute.

Example 1: Figure 1 shows the intersectional subgroup hierarchy of sensitive attributes `gender` and `genre` for a dataset that matches songs of different artists. Note that `gender` is a binary attribute and `genre` is a setwise attribute. The level-2 of this hierarchy includes all combinations of groups from `gender` and `genre` in level-1. Level-3 enumerates 2-combinations of the domain of `genre` with groups from `gender`. □

Note that a subgroup hierarchy represents the space of groups and does not mean a data set must or does contain all these groups. In addition to enabling fairness audit on a particular group selected by a user, we allow batch auditing subgroups of each level. That is, a matcher's fairness is evaluated for all subgroups of a particular level selected by a user.

2.2.2 Single and Pairwise Fairness Evaluation. Given the pairwise nature of EM tasks, there are two ways to audit entity matchers:

- *Single Fairness:* The performance of a matcher is evaluated for one subgroup s against either entity in a pair. Given a correspondence $c = (e_i, e_j, h, y)$ and a subgroup s of interest, c is legitimate, if either e_i or e_j belong to subgroups s.
- *Pairwise Fairness:* The performance of a matcher is evaluated for a pair of subgroups s, s' against both entities in a pair. Given a correspondence $c = (e_i, e_j, h, y)$ and a pair of sub-groups (s, s') of interest, c is legitimate, if e_i belongs to s and e_j belongs to s', or vice versa. From an encoding perspective, we concatenate the encodings of subgroups s and s' into a vector c and the encodings (explained in the supplimentary materials) of e_i and e_j into a vector e and validates vector e belongs to c with both directions of $\langle s, s' \rangle$ and $\langle s', s \rangle$.

We consider the EM task to be symmetric in single and pairwise fairness definitions. We remark that these definitions can be extended to ordered single and ordered pairwise fairness where the subgroups are defined on left or right entities. In this paper, we focus on non-directional single and pairwise fairness.

2.3 Correctness

The correctness of a matcher measures how well its matching predictions match the ground truth. Given a test dataset with correspondences of $t = (e_i, e_j, h, y)$, where h is a binary variable indicating the result of EM (*match* or *non-match*) for entities with

Table 1: Fairness types based on the number and cardinality of sensitive attributes.

Type	Description	Example
Single Attribute w/ Binary Values	Each entity belongs to one of two groups in the attribute domain.	attribute: `gender={male, female}` `group(e) = {female}`
Single attribute w/ multiple exclusive values	Each entity belongs to exactly one group in the attribute domain.	attribute: `gender={male, female, transgender, non-binary, other}` `group(e) = {non-binary}`
Single setwise attribute	Each entity belongs to a subset of values in the attribute domain.	attribute: `genre={Pop, Rock, Jazz}` `group(e) ={Pop, Rock}`
Multiple attributes	Groups could be either one or a combination of the three cases above.	attributes: `genre` and `gender` `group(e) = {male-Pop, male-Rock, male-Jazz}`

encodings e_i and e_j, and y is a binary variable indicating the ground-truth for matching, we profile predictions of h using the numbers of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), respectively. Unlike a classification task, in the confusion matrix of a matching task, the result is counted both for the group(s) of e_i and the group(s) of e_j.

Example 2: Consider a test dataset, shown in Table 2, for a matcher $\mathcal{M}$, where columns id_1 and id_2 contain entity encodings, column h is the output decision of $\mathcal{M}$, and column y is the ground-truth. Comparing columns h and y, we add and populate column *Result* for each entity pair. Consider the simple case of having two groups $\mathcal{G} = \{g_1, g_2\}$. Suppose we would like to evaluate single fairness for g_1 and g_2. We describe how the confusion matrices of these groups are created. Consider the first row in Table 2a, which happens to be an FP. Since e_1 and e_2 both belong to subgroup g_1, the value 2 will be added to the count of FPs in the confusion matrix of g_1. However, in the second row which happens to be a TN, e_3 belongs to g_2 while e_4 belongs to g_1. Thereby, we will add one to both TN values of the confusion matrix corresponding to subgroup g_1 and g_2. We repeat the same procedure for rows three and four. The completed confusion matrices are shown in Figures 2b and 2c. □

id_1	id_2	group(id_1)	group(id_2)	h	y	Result
e_1	e_2	g_1	g_1	'M'	'N'	FP
e_3	e_4	g_2	g_1	'N'	'N'	TN
e_1	e_4	g_1	g_1	'M'	'M'	TP
e_2	e_3	g_1	g_2	'N'	'M'	FN

(a)

Predicted \ Actual	y='M'	y='N'
h='M'	TP=2	FP=2
h='N'	FN=1	TN=1

(b)

Predicted \ Actual	y='M'	y='N'
h='M'	TP=0	FP=0
h='N'	FN=1	TN=1

(c)

Figure 2: (a) Matching Results (b) Confusion Matrix of g_1 (c) Confusion Matrix of g_2.

We measure correctness for single and pairwise fairness through well-studied metrics in literature, including precision, recall, and F-1 score.

2.4 Fairness Measures

At a high level, fairness definitions can be viewed from three perspectives: group, subgroup, and individual fairness [5]. The most granular notion of fairness is individual fairness that requires similar outcomes for similar individuals [13]. The more popular perspective of fairness, group/subgroup fairness, requires similar treatment for different groups/subgroups. A model/algorithm satisfies some fairness constraints if it has equal or similar performance (according to some fairness measure) on different subgroups. *The focus of this paper is on group/subgroup fairness.* Most of the group fairness measures belong to one of the four categories [2, 5]. (1) *Independence* requires independence of analysis outcome from demographic groups. (2) *Separation* requires independence of the outcome from demographic groups conditioned on the target variable. (3) *Sufficiency* requires independence of the target variable from demographic groups conditioned on the outcome. (4) *Causation* requires that in a counterfactual world, the decision would not change had the individual belonged to a different demographic group. Since we only assume access to a matcher's decisions and true labels, we will not consider Causal fairness in our audit.

In Table 2, we present a suite of fairness measures, based on notions of fairness in classification [5], repurposed for auditing an entity matcher $\mathcal{M}$ for a set $\mathcal{G}$ of (sub)groups. We note that some of the measures cannot be applied in pairwise fairness scenarios where conceptually, the equality of groups restricts matching results. In some scenarios, two entities with different groups can never be considered *match* in the ground-truth. For instance, in a matching task defined between *DBLP* and *ACM* publications, two entities with different venues (after standardization) and years are never a true *match*. More concretely, when pairwise fairness is evaluated on subgroups with non-overlapping groups, TPs and FNs are always zero; therefore, fairness measures that rely on TPs and FNs become inapplicable.

2.5 Insights for Selecting Fairness Measures in the Context of Entity Matching

Depending on the context of an EM task at hand, proper fairness measures should be employed. Besides, a major difference between EM and regular classification tasks is that the input to EM tasks is a pair of entities. In the following, we provide insights for selecting fairness measures for EM.

Table 2: Fairness measures. $h(e, e')$ is the output of a matcher $\mathcal{M}$ (*match* ('M') or *non-match* ('N')) and y is the ground-truth on entities e and e'.

Name	Description	Equation ($\forall g_i \in \mathcal{G}$)
Accuracy Parity (AP)	requires the independence of matchers's accuracy from groups	$Pr(h(e,e') = y \mid g_i) \simeq Pr(h(e,e') = y)$
Statistical Parity (SP)	requires the independence of the matcher from groups	$Pr(h(e,e') = \text{'M'} \mid g_i) \simeq Pr(h(e,e') = \text{'M'})$
[1]**True Positive Rate Parity (TPRP)**	aka *Equal Opportunity*; in the group of true matches requires the independence of match predictions from groups	$Pr(h(e,e') = \text{'M'} \mid g_i, y = \text{'M'}) \simeq Pr(h(e,e') = \text{'M'} \mid y = \text{'M'})$
False Positive Rate Parity (FPRP)	in the group of true non-matches, requires the independence of match predictions from groups	$Pr(h(e,e') = \text{'M'} \mid g_i, y = \text{'N'}) \simeq Pr(h(e,e') = \text{'M'} \mid y = \text{'N'})$
[1]**False Negative Rate Parity (FNRP)**	in the group of true matches, requires the independence of non-match predictions from groups	$Pr(h(e,e') = \text{'N'} \mid g_i, y = \text{'M'}) \simeq Pr(h(e,e') = \text{'N'} \mid y = \text{'M'})$
True Negative Rate Parity (TNRP)	in the group of true non-matches, requires the independence of non-match predictions from groups	$Pr(h(e,e') = \text{'N'} \mid g_i, y = \text{'N'}) \simeq Pr(h(e,e') = \text{'N'} \mid y = \text{'N'})$
[1]**Equalized Odds (EO)**	in both groups of true matches and true non-matches requires the independence of match predictions from groups	$Pr(h(e,e') = \text{'M'} \mid g_i, y = \text{'M'}) \simeq Pr(h(e,e') = \text{'M'} \mid y = \text{'M'})$ $Pr(h(e,e') = \text{'M'} \mid g_i, y = \text{'N'}) \simeq Pr(h(e,e') = \text{'M'} \mid y = \text{'N'})$
[1]**Positive Predictive Value Parity (PPVP)**	among the pairs predicted as match requires the independence true matches from groups	$Pr(y = \text{'M'} \mid h(e,e') = \text{'M'}, g_i) \simeq Pr(y = \text{'M'} \mid h(e,e') = \text{'M'})$
[1]**Negative Predictive Value Parity (NPVP)**	among the pairs predicted as non-match, requires the independence of true non-matches from groups	$Pr(y = \text{'N'} \mid h(e,e') = \text{'N'}, g_i) \simeq Pr(y = \text{'N'} \mid h(e,e') = \text{'N'})$
[1]**False Discovery Rate Parity (FDRP)**	among the pairs predicted as match, requires the independence of true non-matches from groups	$Pr(y = \text{'N'} \mid g_i, h(e,e') = \text{'M'}) \simeq Pr(y = \text{'N'} \mid h(e,e') = \text{'M'})$
[1]**False Omission Rate Parity (FORP)**	among the pairs predicted as non-match, requires the independence of true matches from groups	$Pr(y = \text{'M'} \mid g_i, h(e,e') = \text{'N'}) \simeq Pr(y = \text{'M'} \mid h(e,e') = \text{'N'})$

2.5.1 Apriori Insights. Which fairness measures to choose depends on the importance of TPs, FPs, FNs, and TNs in the problem context and how forgiving we can be towards each. Among the fairness measures, *statistical parity* does not consider the ground-truth labels, and requires the independence of the matching prediction from the groups. In simple words, it requires equal match ratios from different groups, independent of whether they really are a match or not. As a result, this measure (and other measures in the independence category) is not reasonable fairness for deduplication tasks using EM. However, it may be useful for EM in table joins to ensure equal representation of different groups in the results. *True* (resp. *false*) *positive rate parity* is useful when correctly predicting the matches is crucial, while false match predictions (resp. correct match predictions) are not costly. Similarly, *true* (resp. *false*) *negative rate parity* is useful when predicting the non-matches correctly is crucial, while false non-match predictions (resp. correct match predictions) are not costly. *Equalized odds*, also known as *positive rate parity*, is a good choice when correctly predicting matches and minimizing false match predictions are both highly important. *Positive* (resp. *negative*) *predictive value parity* is useful when guaranteeing equal chance of correct predictions when predicting the match (resp. non-match) is important. Finally, *false discovery* (resp. *omission*) *rate parity* is a good choice when guaranteeing an equal chance of making a mistake when predicting the match (resp. non-match) is important.

[1]This measure is only meaningful for *single* fairness and only extends to *pairwise* fairness cases where sensitive attributes are either setwise or left and right groups are identical.

2.5.2 Aposteriori Insights. Due to its pairwise matching nature, *class imbalance* is a distinguishing property of EM, compared to regular classification tasks. To better explain this, let us consider a toy example, where two data sources D and D' contain exactly the same set of n entities. Each pair of entities $e \in D$ and $e' \in D'$ is passed as an input to an entity matcher. In this setting, only n of the n^2 pairs are a match, and the others are non-match. In other words, the probability a random pair is a match is as low as $\frac{1}{n}$. Indeed, blocking techniques [29] can help in reducing the extreme class imbalance. However, even after blocking, class imbalance is expected for EM tasks. Besides, blocking is an engineering step that may or/may-not be applied, independent of the choice of EM technique, while our objective is to evaluate the fairness of EM techniques. Nevertheless, when the input to the EM task is imbalanced and most of the pairs are non-match, some measures are more capable of revealing the unfairness of matchers – as we shall explain in the following. First, note that even a matcher that marks all pairs as non-match has high accuracy in this setting. Subsequently, accuracy parity may not reveal the unfairnesses. Similarly, measures such as FPRP and TNRP may fail to reveal unfairnesses in detecting true matches. In these settings where true matches are considered as *rare events*, a matcher's goal is to successfully discover the matches. Therefore, as explained in § 2.5.1, the fairness measure for successfully discovering these events is **Positive Predictive Value Parity (PPVP)**. Another important measure in this context is **True Positive Predictive Rate Parity (TPRP)**, aka **Equal Opportunity**, which focuses on correct match predictions among the (rare) true matches. This also is consistent with our

comprehensive experiments on several data sets, where PPVP and TPRP were the two measures that could reveal the unfairnesses of the matchers. We will further explain this in § 4.

2.6 Measuring Unfairness

Consider a fairness notion and a subgroup $g_i \in \mathcal{G}$. In a perfect situation, the matcher should satisfy the parity (equality) between two probabilities in the following form:

$$\forall g_i \in \mathcal{G}, Pr(\alpha \mid \beta, g_i) = Pr(\alpha \mid \beta) \tag{1}$$

where α and β are specified by the fairness measure. For example, for Positive Predictive Parity, α is $y =$ 'M' and β is $h(e, e') =$ 'M'.

On the other hand, due to the trade-offs [19] between different fairness notions and the impossibilities theorems [9], it is often not possible to satisfy complete parity on all fairness measures. As a result, considering a threshold value (e.g., the 20% rule [14] suggests the threshold as 0.2), the objective is to make sure that *disparity* (as known as *unfairness*) is less than the threshold. Given a fairness notion and a subgroup $g_i \in \mathcal{G}$, the disparity can be computed using subtraction [6], as follows:

$$F^{(s)}_{\alpha,\beta}(g_i) = \max\Big(0\,,\ Pr(\alpha \mid \beta) - Pr(\alpha \mid \beta, g_i)\Big) \tag{2}$$

For example, for accuracy parity (α is $h(e, e') = y$ and β is null) the disparity can be computed as

$$F^{(s)}_{\text{AP}}(g_i) = \max\Big(0\,,\ Pr(h(e, e') = y) - Pr(h(e, e') = y \mid g_i)\Big)$$

Note that if the accuracy for the subgroup g_i is higher than the average accuracy of the model, it is not considered as unfairness. Also, note that Equation 2 considers the higher the probability, the better. Depending on fairness measures (and application), the direction may be as the lower the probability, the better. For example, for FNRP, a lower probability of the false negative is preferred. For such cases, one should consider $Pr(h(e, e') = y \mid g_i) - Pr(h(e, e') = y)$ when computing disparity. As a result, for false negative rate (α is $h(e, e') =$ 'N' and β is $y =$ 'M') the disparity can be computed as

$$\begin{aligned} F^{(s)}_{\text{FNRP}}(g_i) = \max\Big(0\,,\ & Pr(h(e, e') = 0 \mid y = \text{'}M\text{'}, g_i) \\ & - Pr(h(e, e') = 0 \mid y = \text{'}M\text{'})\Big) \end{aligned} \tag{3}$$

Alternatively, given a fairness notion and a subgroup $g_i \in \mathcal{G}$, the disparity can be computed using division [14, 14] , as following:

$$F^{(d)}_{\alpha,\beta}(g_i) = \max\Big(0\,,1 - \frac{Pr(\alpha \mid \beta, g_i)}{Pr(\alpha \mid \beta)}\Big) \tag{4}$$

Similar to Equation 2, Equation 4 also considers the higher the probabilities the better. For the cases (such as FNRP or FDRP) where the lower probabilities are better, one should swap the nominator and the denominator in the equation. Therefore, for false discovery rate (α is $y = 0$ and β is $h(x) = 1$) the disparity can be computed as

$$F^{(d)}_{\text{FDRP}}(g_i) = \max\Big(0\,,1 - \frac{Pr(y = \text{'}N\text{'} \mid h(e, e') = \text{'}M\text{'})}{Pr(y = \text{'}N\text{'} \mid h(e, e') = \text{'}M\text{'}, g_i)}\Big)$$

Our proposal in this paper is agnostic to the choice of operation for computing the disparities. Still, in our experiments, without any preference, we use subtraction to compute the disparities.

3 ENTITY MATCHING APPROACHES

The existing techniques for EM fall into one of the following three categories: 1) declarative rule-based, 2) ML-based, and 3) crowdsourcing-based approaches. The last class of techniques relies on crowd-worker knowledge for EM tasks. We do not include this group of techniques in our analysis. From each of the remaining categories, we select a few important matchers to be assessed for fairness. The specifications of the evaluated matchers are presented in Table 3.

3.1 Rule-based Matchers

Rule-based approaches perform EM based on the conjunction/disjunction of a few logical predicates, each specifying a matching condition. Each matching condition consists of a similarity measure (e.g., Hamming, cosine, Levenshtein, Affine, Jaccard, etc.) computed between entity pair columns, a comparison operator (e.g., <, =, >), and a threshold value specifying the similarity value. Rule-based matchers are scalable to large settings and provide results that are explainable. However, they highly depend on human experts with relevant domain knowledge to assist with rule declaration.

3.2 ML-based Matchers

A crucial part of rule-based matching that affects the overall correctness of the task is the selection and configuration of the rules used for comparison. This task is difficult and laborious even for domain experts. ML-based supervised EM approaches reduce the associated manual labor by benefiting from the training data at hand. They significantly reduce the rule discovery efforts by extracting fitting parameters (e.g., model weights) from the data. However, preparing the training data itself imposes an additional cost. Furthermore, such techniques are computationally expensive (demanding a blocking phase to reduce the search space) and are less explainable on account of using black-box classification methods. Depending on the employed classification technique, ML-based matchers belong to one of the *non-neural* or *neural* categories.

3.2.1 Non-neural Matchers. This category of matchers uses traditional ML algorithms such as decision tree, SVM, logistic regression, etc., to decide whether or not a pair of entities are a match. Since the number of meaningful insights that can be extracted from data and fed as features to the learning algorithm is limited to word-level similarity metrics and TF-IDF scores, non-neural matchers may not perform well for cases where datasets are less structured, and column values are more in a textual format consisting of long spans of text.

3.2.2 Neural Matchers. Deep learning techniques have recently shown promising results in NLP applications. Due to the growing demand for matching textual data instances, it only makes sense to adopt such techniques where the other approaches usually fall short. Deep learning methods transform text into numerical values using character/word embeddings often through pre-trained embedding models such as word2vec [26], GloVe [30], fastText [7]. Due to the sequential nature of text, to better capture the semantics of the data, sequence models such as RNN and its variants (e.g., LSTM, GRU, etc.), where prior sequences of inputs can affect the current input and output, are utilized [4]. Further improvement

mechanisms such as attention [34], pre-trained language models [11], domain knowledge injection, data augmentation, summarization, etc., deliver further insights into the models to make better matching decisions. The superiority of neural matchers for textual and dirty data sets has been pointed out in the existing research [27]. However, there are associated challenges, such as high computation costs and large training data requirements, making them not suitable for every EM scenario.

4 EVALUATION AND ANALYSIS

4.1 Evaluation Plan

To evaluate the matchers for fairness, we investigate the performance of matchers in terms of single and pairwise fairness for all valid subgroups in the data sets w.r.t. a variety of fairness definitions. To present a side-by-side comparison and visualization, we aggregate the results based on the dataset and the type of fairness (i.e., single and pairwise). Next, we look into some of the identified discriminated subgroups from different settings and investigate the reasoning behind the unfair behavior of matchers.

4.1.1 Experimental Settings. We conducted the experiments on a 3.5 GHz Intel Core i9 processor, 128 GB memory, running Ubuntu. The evaluation framework was implemented in Python. We accessed the source code of the entity matchers either through the authors' public GitHub or by directly contacting the authors.

4.1.2 Datasets. Data in the context of EM tasks usually fall into one of the following categories:

- *Structured:* In this category of datasets, attribute values are atomic, meaning that they can not be broken into multiple values. Furthermore, there are no missing values in the data.
- *Dirty:* This category of datasets is similar to structured datasets; however, they include far too many random missing values in their columns. Therefore an attribute value may appear for an entity while it does not exist for another one.
- *Textual:* Textual datasets are made of a single attribute per entity containing a textual description.

For the completeness of our experiments, we select two datasets from each category on which we evaluate the matchers. The datasets are chosen from WDC [31] and Magellan [27] repositories which are the standard benchmark corpora used in EM literature. Aside from the dataset type, we carefully handpicked the datasets w.r.t. domain, sensitive attribute type, and ground-truth class balance to cover a variety of possible settings. For the textual datasets Shoes and Cameras, we extract the manufacturer of the corresponding product from the description as the sensitive attribute. Table 4 shows the details of the selected datasets.

4.1.3 Entity Matchers. To cover the breadth of existing methods in our experiments, we picked 13 EM tools from each of the discussed approaches (1 rule-based, 7 non-neural, and 5 neural). The selection criteria included the public availability and error-free execution of the source codes. To ensure the satisfactory performance of the entity matchers, we took the following steps:

BooleanRuleMatcher. We used the automatic feature generation tool provided in the Magellan library to extract features based on the similarity of the columns in the input table w.r.t. multiple distance measures. Next, we handpick some of the generated features based on which we declare matching conditions. Depending on the attribute involved in the generated features, we either use the exact match of the attribute values (for attributes with short and atomic values, e.g., *year*) or similarity of greater than 0.5 (for attributes with longer values, e.g., *paper title*).

Non-neural Matchers. For all non-neural matchers except for Dedupe, we used the automatic feature generation tool in the Magellan library. Next, all of the generated features are fed to the models for training. Dedupe's active learning component requires manual labeling of difficult entity pairs, which is an uphill task. To bypass this step, we converted the training data into Dedupe's generated cache file format and utilized the entire training samples to keep the experiment consistent with the other matchers. Finally, Dedupe did not scale for Shoes and Cameras datasets.

Neural Matchers. We tuned the hyper-parameters of all the matchers according to their results on the validation set. For DeepMatcher, HierMatcher, and Mcan we trained the models for 10 epochs with a batch size of 16 and used *fastText* [7] pre-trained word embeddings. We used the *hybrid* model of DeepMatcher that reportedly performs superior compared to the other models. For HierMatcher, we used the attribute-aware attention mechanism. For Mcan, we utilized self-attention, pair-attention, global-attention, and gating mechanisms that reportedly would achieve the best results. For Gnem, we trained the GCN models for 10 epochs with a batch size of 2 and 768 nodes at each layer. For Ditto, we trained the models for 40 epochs with a batch size of 64 while using the DistilBERT language model and optimizations such as data augmentation, sequence summarization, and domain knowledge injection.

For all datasets except Cricket, we declare a pair of entities as a "match" if the similarity between the two is greater than 0.5. For the Cricket dataset, due to the high similarity of all pairs, we had to choose a higher similarity threshold of 0.9 because otherwise, all of the models would predict all pairs as "match", which would affect the models' correctness.

As for the fairness threshold, we follow EEOC's 80% rule [10], that only 20% disparity is tolerated.

4.2 Correctness

Neural matchers are more accurate than non-neural matchers on textual and dirty data. The correctness results of the textual datasets: Shoes and Camera, can be found in Table 5. Non-neural matchers extensively suffer in F-1 score, compared to neural matchers that have higher ranges of F-1 score. Modern neural matchers such as Ditto and DeepMatcher draw on external knowledge by incorporating language models, which helps a matcher to learn the relevance of entities despite the lack of structure and syntactic similarity in text entities. This result is consistent with what is reported by the state-of-art matchers.

Non-neural matchers are more accurate than neural matchers on structured data. Considering the structured datasets: iTunes-Amazon and Dblp-Acm, although all matchers, with the exception of BooleanRuleMatcher, perform quite well, the non-neural matchers have slightly higher F-1 scores overall.

The main job of a matcher is to find matching entities. A failure in doing so results in a low number of TPs, which reflects in not only a low F-1 score but also unfairness with respect to TPRP and

Table 3: List of EM approaches evaluated for fairness

Name	Type	Description
BooleanRuleMatcher [20]	Rule-based	Conjunction of rules defined using a similarity measure, a comparison operator, and a threshold value between the entity pair columns, part of Magellan framework
Dedupe [16]	Non-neural	Uses regularized logistic regression for agglomerative hierarchical clustering of entities
DTMatcher [20]	Non-neural	Uses decision tree classifier for matching, part of Magellan framework
SVMMatcher [20]	Non-neural	Uses SVM classifier for matching, part of Magellan framework
RFMatcher [20]	Non-neural	Uses random forest classifier for matching, part of Magellan framework
LogRegMatcher [20]	Non-neural	Uses logistic regression classifier for matching, part of Magellan framework
LinRegMatcher [20]	Non-neural	Uses linear regression classifier for matching, part of Magellan framework
NBMatcher [20]	Non-neural	Uses naive bayes classifier for matching, part of Magellan framework
DeepMatcher [27]	Neural	Provides a variety of deep learning approaches such as aggregation-based, RNN-based, attention-based and, hybrid (RNN+attention) to learn latent semantic features for a pair of entities
Ditto [24]	Neural	Deep learning approach utilizing pre-trained transformer-based language models and optimizing performance using domain knowledge injection, text summarization, and data augmentation techniques
GNEM [8]	Neural	One-to-set neural framework (in contrast to the remaining pairwise solutions) benefiting from graph neural networks
HierMatcher [15]	Neural	Deep learning approach based on RNN, attribute-aware attention mechanism and cross attribute token alignment, built on top of DeepMatcher framework
MCAN [40]	Neural	Deep learning approach based on RNN and multi-context attention mechanisms such as self-attention, pair-attention, global-attention, and gating mechanism, built on top of DeepMatcher framework

Table 4: overview of the datasets used in our analysis

Name	Repository	Domain	Type	Train	Test	% Pos.	# Attr.	Sens. Attr.	Sens. Attr. Type
iTunes-Amazon	Magellan	Music	Structured	321	109	24.7%	8	Genre	Single setwise attr.
Dblp-Acm	Magellan	Publications	Structured	7417	2473	17.9%	4	Venue	Single attr. w/ multiple exclusive values
Dblp-Scholar	Magellan	Publications	Dirty	225	100	19%	10	Entry type	Single attr. w/ multiple exclusive values
Cricket	Magellan	Sports	Dirty	2277	1013	96.5%	20	Batting style	Single attr. w/ binary values
Shoes	WDC	Products	Textual	24111	10717	10.3%	1	Company	Single attr. w/ multiple exclusive values
Cameras	WDC	Products	Textual	5476	2434	17.2%	1	Company	Single attr. w/ multiple exclusive values

PPVP measures for many groups across the board, as we observe in Fig. 13 and 15. Recall that these measures verify how well a matcher performs in identifying true positives. Similar observations can be made in both datasets regarding the unfairness of the BooleanRuleMatcher. One interesting observation in Gnem, which is the only neural matcher with a low F-1 score for the Dblp-Acm dataset, is that the high number of FNs of Gnem results in the pairwise unfairness for $g_i|g_i$ pairs (e.g., `SIGMOD|SIGMOD` and `ACM TODS|ACM TODS`). Gnem does not demonstrate NPVP unfairness on $g_i|g_j$ pairs, particularly in the Dblp-Acm dataset, because often two entities with $g_i|g_j$ are not a match (e.g. it is rare that a `ACM TODS` publication is matched with a publication `SIGMOD`).

The flip side of correctness and fairness also exists in EM. For example, the BooleanRuleMatcher and Gnem have low accuracy and F-1 score on Dblp-Acm, while no unfairness issue is reported for these matchers, in Fig. 5. This can be explained by the low accuracy of these matchers for all groups across the board which makes the disparity a low value. In Table 3, we present a selective overview of the unfairness and accuracy of matchers across all datasets. The general message is that similar to accuracy, unfairness is dataset and measure dependent. First, no matcher is unfair across all datasets. For example, Gnem is unfair for iTunes-Amazon and Dblp-Acm but is not unfair for the Cricket dataset. No matcher is unfair across all measures. For example, on Dblp-Scholar dataset, HierMatcher is only unfair with respect to PPVP and FPRP and not other measures. We will have a more detailed discussion on the behavior of macther w.r.t measures in § 4.3.

Matcher	iTunes-Amazon		Dblp-Acm		Dblp-Scholar		Cricket		Shoes		Camera	
	Acc	F-1	Acc	F-1	Acc	F-1	Acc	F-1	Acc	F-1	Acc	F-1
BooleanRuleMatcher	0.29	0.41	0.41	0.38	0.38	0.38	0.03	0.0	0.82	0.28	0.81	0.4
DeepMatcher	0.94	0.88	0.99	0.98	0.97	0.92	0.87	0.92	0.96	0.82	0.93	0.81
Ditto	0.91	0.84	0.99	0.98	0.95	0.87	0.96	0.98	0.95	0.78	0.91	0.76
Gnem	0.64	0.31	0.70	0.18	0.83	0.58	0.96	0.98	0.96	0.80	0.97	0.91
HierMatcher	0.93	0.87	0.95	0.88	0.96	0.9	0.81	0.89	0.96	0.81	0.94	0.83
Mcan	0.97	0.94	0.99	0.99	0.97	0.92	0.95	0.97	0.95	0.73	0.93	0.78
SvmMatcher	0.92	0.84	0.96	0.90	0.94	0.86	0.96	0.98	0.89	0.0	0.84	0.27
RfMatcher	0.94	0.89	0.99	0.97	0.98	0.94	0.96	0.98	0.88	0.29	0.82	0.38
NbMatcher	0.88	0.78	0.98	0.97	0.99	0.97	0.96	931	0.86	0.26	0.82	0.38
LogRegMatcher	0.91	0.83	0.99	0.97	0.99	0.97	0.96	0.98	0.89	0.04	0.84	0.31
LinRegMatcher	0.97	0.94	0.97	0.93	0.95	0.88	0.96	0.97	0.89	0.0	0.84	0.30
Dedupe	0.94	0.89	0.95	0.85	0.95	0.87	0.96	0.98	-	-	-	-
DtMatcher	0.94	0.89	0.99	0.97	0.98	0.94	0.93	0.96	0.85	0.30	0.84	0.31

Table 5: Overall performance of matchers across different datasets[2](Acc: Accuracy)

Accurate	Fair	Evidence
×	×	RfMatcher: Cameras: {TPRP,PPVP} BooleanRuleMatcher: iTunes-Amazon: {AP,SP,PPVP} Gnem: iTunes-Amazon: {AP,PPVP,...}
×	✓	LinRegMatcher: Shoes Gnem: Dblp-Acm BooleanRuleMatcher: Cricket
✓	×	HierMatcher: iTunes-Amazon: {AP,PPVP,...} SvmMatcher: Dblp-Acm: PPVP Mcan: Cameras: TPRP Ditto: Dblp-Scholar: {AP,TPRP,...} DeepMatcher: Camera: {PPVP,TPRP}
✓	✓	Mcan: Dblp-Acm Ditto: Cricket NbMatcher: Dblp-Scholar

Figure 3: Fairness and accuracy synergies

4.3 Fairness: Measure Types

Some fairness measures are not applicable to EM and some are more capable of revealing the unfairness of matcher. We have extensively discussed this point in § 2.5. Here, we bring some empirical evidence of such scenarios.

First, as we observe in the majority of experiments, PPVP and TPRP are the measures that discover unfairness the most across all datasets and matchers. Second, it is not the case that one measure fits all. When data has match/non-match negative imbalance, i.e., the number of matching pairs is much higher than non-matching pairs in the ground truth, NPVP and FPRP are the most appropriate measures. This is because while the majority of pairs are positive instances, the failure of a matcher in identifying non-matches makes it unfair to certain groups. Consider the Cricket dataset that contains a larger number of pairs of matching cricket batters than non-matching batters. As we observe in Fig. 11, NPVP allows us to detect the unfairness of a matcher such as LogRegMatcher to left-handed batters, due to the large number of FNs generated by this matcher. Third, SP could potentially identify false unfairness when the underlying data has label bias. Recall SP does not consider the ground-truth labels and requires the independence of the matching prediction from the groups. In other words, SP requires equal matches ratios from different groups, independent of whether they really are match or not. Then, when the ground truth has match/non-match imbalance for a group, that is the ratio of matched pairs to unmatched ones is low, the SP measure falsely identifies a matcher as unfair for that group. An example of this phenomenon can be observed in Fig. 7, for `French-Pop` group in the iTunes-Amazon dataset, where SP unfairness is indeed due to the fact that the ground truth only contains TNs.

Some measures can be explained by others. For example, let us consider the AP unfairness of Gnem on iTunes-Amazon for the group of country genres, including `Country`, `Cont. Country`, and `Honky Tonk`, reported in Fig. 7. This matcher has low accuracy for this group of genres because it identifies a small number of true matches (i.e., has a low number of TPs, thus, suffers from TPRP), instead, the matchers falsely identify many pairs as non-match (i.e., has a high number of FPs, thus, suffers from NPVP). Similarly, we

[2]For the evaluation of ML-based matchers, we used random train/test splits from the datasets published by Magellan [20]. To be consistent, all matchers are evaluated in a standard framework against the same datasets. We acknowledge that these results may not exactly match the accuracy results reported by matchers' papers.
[3]Across all plots, Equalized Odds (EO) is the union of FPRP and TPRP rows. That is a matcher that is appears either in row 3 or row 4 of any column is unfair from EO perspective.

Model	Marker
DeepMatcher	●
Ditto	●
Gnem	●
HierMatcher	●
Mcan	●
SvmMatcher	★
RfMatcher	★
NbMatcher	★
LogRegMatcher	★
LinRegMatcher	★
DtMatcher	★
Dedupe	★
BooleanRuleMatcher	★

Figure 4: plot markers for the entity matchers

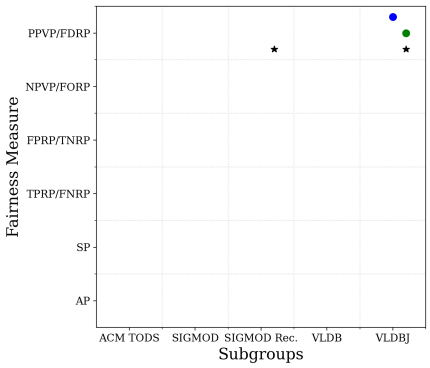

Figure 5: DBLP-ACM: Single Fairness[3]

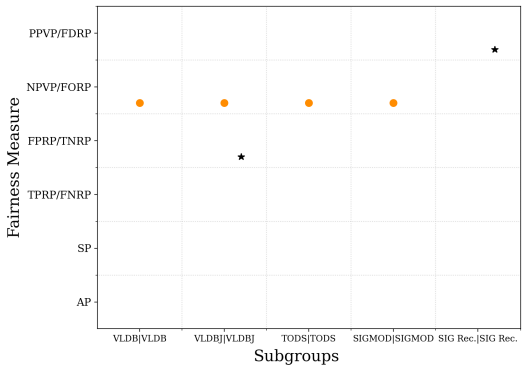

Figure 6: DBLP-ACM: Pairwise Fairness

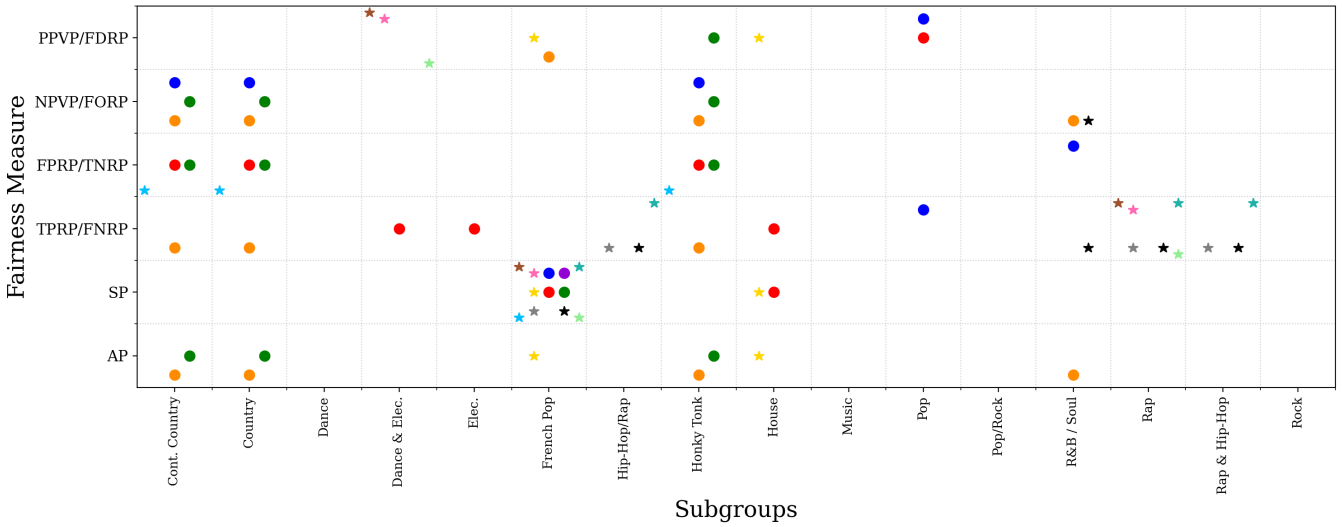

Figure 7: iTunes-Amazon: Single Fairness

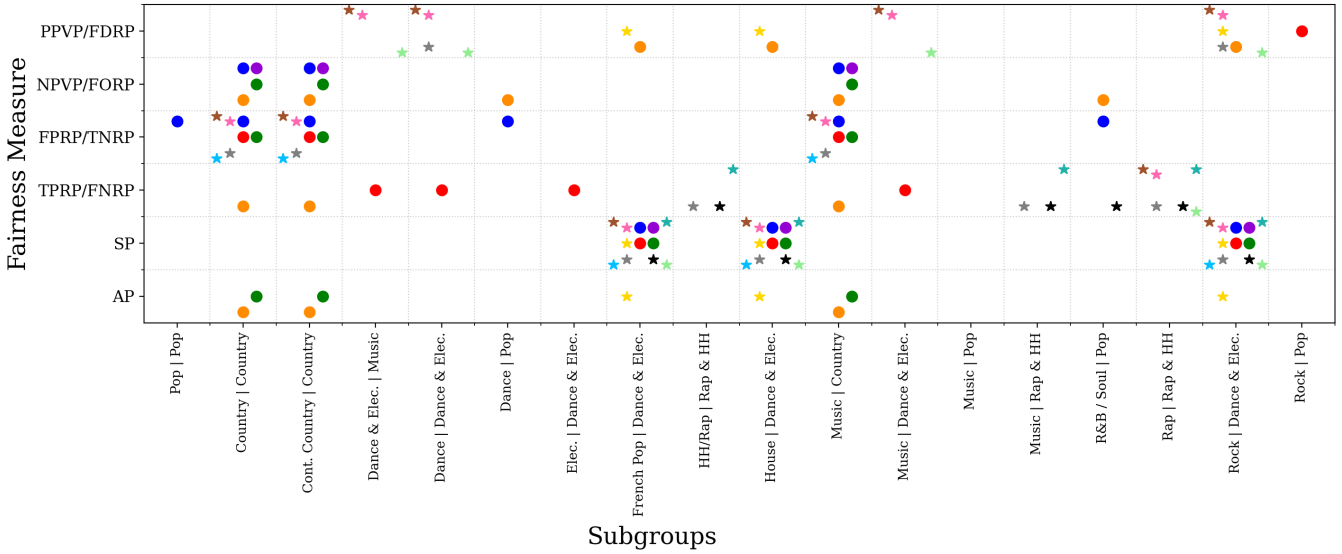

Figure 8: iTunes-Amazon: Pairwise Fairness. (HH: Hip-Hop, Elec.: Electronic, Cont.: Contemporary)

Model	Marker
DeepMatcher	
Ditto	
Gnem	
HierMatcher	
Mcan	
SvmMatcher	
RfMatcher	
NbMatcher	
LogRegMatcher	
LinRegMatcher	
DtMatcher	
Dedupe	
BooleanRuleMatcher	

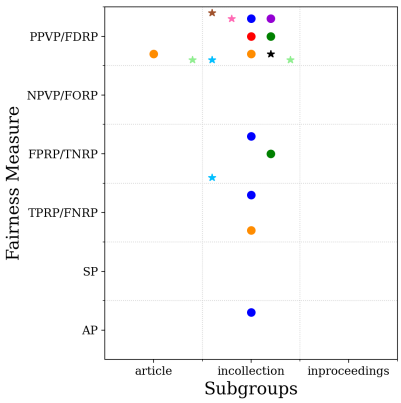

Figure 9: Dblp-Scholar: **Single**

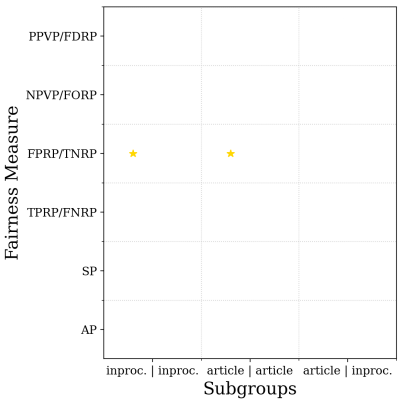

Figure 10: Dblp-Scholar: **Pairwise**

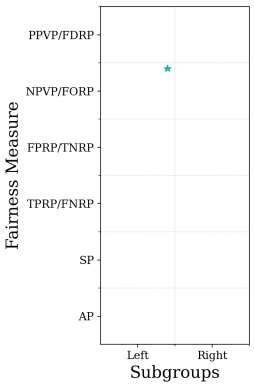

Figure 11: Cricket: **Single**

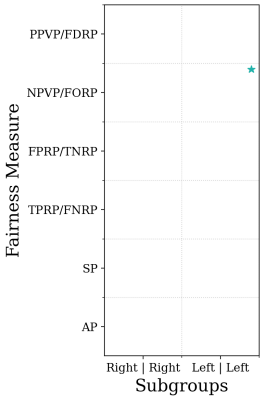

Figure 12: Cricket: **Pairwise**

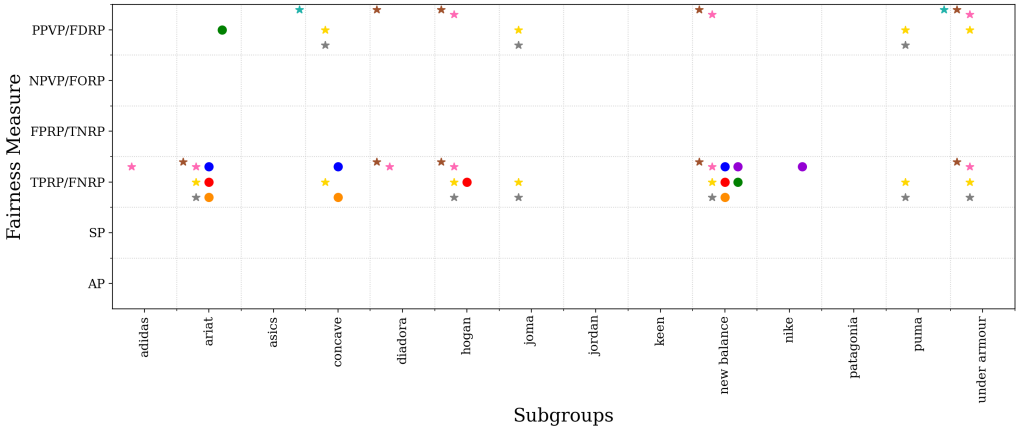

Figure 13: Shoes: **Single Fairness**

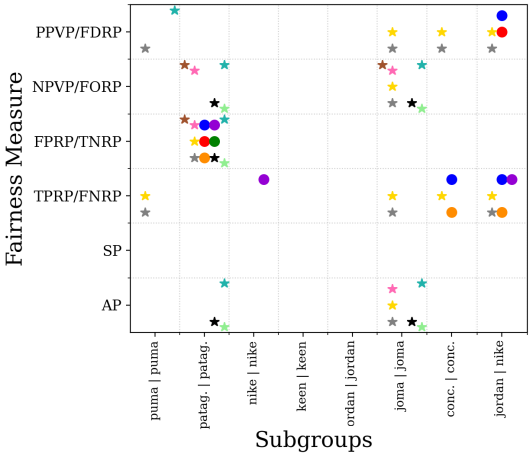

Figure 14: Shoes: **Pairwise Fairness**

observe that HierMatcher demonstrates AP unfairness on iTunes-Amazon for the group of country genres, because it incurs a large number of FPs, thus, suffers from FPRP unfairness.

Single unfairness can potentially propagate to pairwise fairness. In Fig. 11 and 12, we observe that the unfairness of LogRegMatcher for the single `Left Handed` group incurs its unfairness for the pairwise `Left Handed-Left Handed` groups, because in fact most likely only a left-handed batter can be matched with another left-handed batter.

4.4 Fairness: Matcher Types

4.4.1 Neural Matchers. Neural matchers demonstrate more unfairness on structured datasets than non-neural matchers, as shown in Fig. 7, 8, and 9. One reason is that matchers such as Ditto merge the content of different attributes as a single block and use token similarity as a signal for matching. However, for structured data, this technique may lose the important information specified by the structure. In particular, in the following example from Dblp-Acm dataset, the two entities have similar titles and are predicted as match despite the fact that they are (i) written by different authors (ii) published in different venues, and (iii) published in different years.

`(left entity)` **title:** `lineage tracing for general data warehouse transformations;` **author:** `jennifer widom , yingwei cui;` **venue:** `VLDBJ;` **year:** `2003`
`(right entity)` **title:** `data extraction and transformation for the data warehouse;` **author:** `case squire;` **venue:** `SIGMOD;` **year:** `1995`

One of the reasons Ditto was unfair for `VLDBJ` is that, similar to the

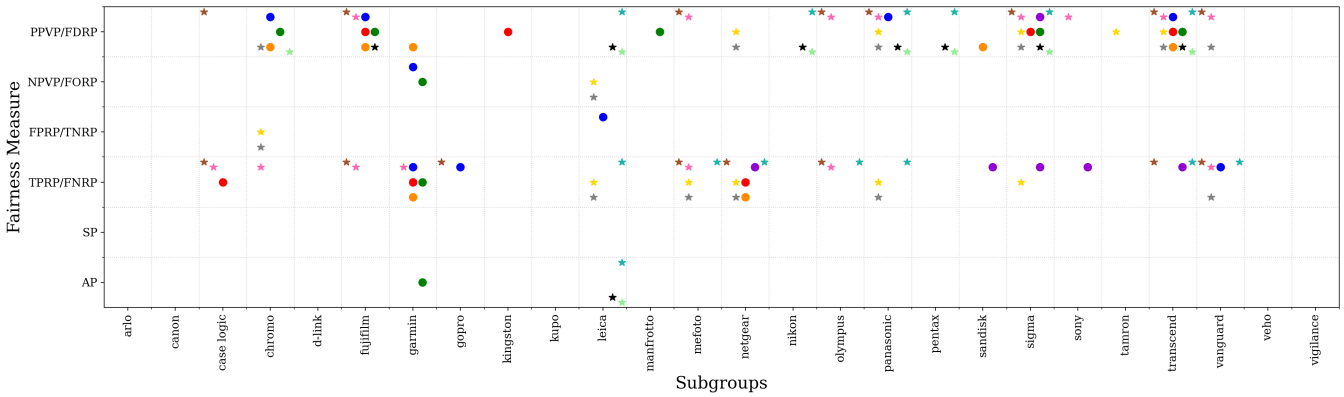

Figure 15: CAMERAS: Single Fairness

following example, it is common to publish extended versions of previously published papers in this venue. As a result, after merging different attributes as a block of text for each entity, similar titles and authors may cause enough similarity between the two phrases that the DITTO mistakenly predicts them as match.

(left entity) **title:** efficient schemes for managing multiversionxml documents; **author:** shu-yao chien , carlo zaniolo , vassilis j. tsotras; **venue:** VLDBJ; **year:** 2002
(right entity) **title:** efficient management of multiversion documents by object referencing; **author:** shu-yao chien , vassilis j. tsotras , carlo zaniolo; **venue:** VLDB; **year:** 2001

External bias could be injected into neural through the use of language models and word embeddings.

For example, HIERMATCHER uses language models and *word embeddings* to compare the attribute similarities of entities. As a result, it may mistakenly match articles with similar titles. Below is an FP example for HIERMATCHER. Both articles are published in the same year. But, they appear in different venues and are written by different authors. Still, language models find sufficient similarity between titles to persuade the matcher to label the entities as matcher. Perhaps this is because of the similarity of words like "efficient" and "effective" in the embedding space.

(left entity) **title:** efficient and cost-effective techniques for browsing and indexing large video databases; **author:** kien a. hua , jung-hwan oh; **venue:** SIGMOD; **year:** 2000
(right entity) **title:** effective timestamping in databases; **author:** kristian torp , christian s. jensen , richard thomas snodgrass; **venue:** VLDBJ; **year:** 2000

Another example we bring is from ITUNES-AMAZON dataset. The following pair entities is an FP by DITTO. First, both songs are by Kenny Chesney. But more importantly, using a pre-trained language model, `Likes Me` and `Loves Me` are considered (almost) identical. As a result the model mistakenly labeled the left and right songs as match. Interestingly, such cases happen to be more frequent in genres such `Country`, resulting in FPRP unfairness for those groups, as shown in Fig. 7.

(left entity) **song:** Tequila Loves Me; **artist:** K. Chesney
(right entity) **song:** Likes Me; **artist:** K. Chesney

Our fourth example is from the CAMERAS dataset. In this dataset, camera entities are matched based on their descriptions. A successful matcher on a dataset that includes descriptions in many languages requires extensive coverage of language models on various languages. For example, MCAN returns the following pair of entities as an FN, although the model and the brand match and *Prijzen* is the Dutch translation of word *Prices*. We suspect that this is due to the poor coverage of word embeddings on Dutch language.

(left entity) **title:** Sony Cyber-shot RX100@en RX100 Prices - CNET@en
(right entity) **tile:** Sony Cyber-shot RX100 Zwart - Prijzen @NL Tweakers@NL

One model does not fit all. In ITUNES-AMAZON dataset, an interesting observation is that neural matchers perform poorly for the class of country (because a neural matcher creates a curvy decision boundary for all groups and fails for easy groups) while non-neural matchers perform poorly for the class of rap (because non-neurals make simple decision boundaries which may not work for a difficult group such as the class of rap genres).

For setwise attributes, matchers demonstrate similar unfair behavior on groups with overlapping semantics. In practice, we observe that, in single setwise sensitive attributes, different sets of groups highly overlap. This is sometimes due to the existence of a semantic hierarchy of groups. For example, in the ITUNES-AMAZON dataset, `Honky Tonk` and `Cont. Country` are a subclass of `Country` in the semantic taxonomy of Wikipedia. As a result, we observe similar behavior of matchers across these groups. For instance, Fig. 7 shows extensive unfair behavior of neural matchers on country music groups: `Honky Tonk`, `Cont. Country`, and `Country`. Following the same trend, non-neural matchers perform poorly on groups `Hip-hop/Rap` and `Rap` and `Rap & Hip-Hop`, suggesting these matchers are unfair to rap and hip-hop singers. In Fig. 8, the same phenomena happens in the pairwise matching of `Dance & Electronic` with `Music` and `Dance`.

4.4.2 Non-neural Matchers. The non-neural matchers universally failed for the textual datasets (CAMERA and SHOES), with F-1 measures as low as zero in several cases. This underscores that these matchers are not fit for unstructured data. Still, in some settings these matchers were both inaccurate and unfair for different groups, as shown in Figures 13, 14, 15, and 16. Note that a matcher that is fair in these cases, simply means that it equally *failed* for all groups, not that it is a good choice. For example, LINREGMATCHER was fair for the SHOES dataset. However, looking at its overall performance, it turns out it did not correctly find *any* of the true matches for any of the groups, hence was equally bad for all groups.

On the other hand, non-neural matchers performed well for the structured datasets. Still, similar to the neural matchers, all of them showed unfairnesses in multiple cases. Further investigating these unfairnesses, we realized that minimizing the overall error, these models put high weights on attributes that often indicate a match. In other words, overall, those attributes are good *proxies* for the ground-truth labels. However, when it comes to certain groups, they may not be as good proxies, causing the model to underperform for those groups. For example, let us consider SvmMatcher for the Dblp-Acm dataset, which was unfair for SIGMOD Rec. and VLDBJ. First, we realized that both these groups have frequently published reports or editorial articles with the same title, but different years and authors. Being trained to perform for all groups, the SvmMatcher model assigned a high weight to the title, assuming that different articles should not have identical titles. Therefore, for examples like the one below it matched them despite the fact that those are written by different authors in different years. This caused a higher ratio of false match detection (FP) compared to the other groups resulting in PPVP unfairness.

(left entity) **title:** guest editorial; **author:** alon y. halevy; **venue:** VLDBJ; **year:** 2002
(right entity) **title:** guest editorial ; **author:** vijay atluri , anupam joshi , yelena yesha; **venue:** VLDBJ; **year:** 2003

Besides, looking at Figure 10 the unfairness due to the high FP for SIGMOD Rec. and VLDBJ, caused pairwise unfairness for these two groups as well. Note that this issue is not necessarily limited to the non-neural matchers. For example, [12] also reports that an RNN-based matcher heavily relied on the "time" attribute when matching songs in the iTunes-Amazon dataset.

Let us now generalize this issue to real-world scenarios. Matching individuals' records are popular for tasks such as Terrorist Watch List Screening [22]. *(First&last)-name* is usually an important indicator in such tasks as it is usually the case that two entities with the same names refer to the same person. As a result, similar to our Dblp-Acm experiment, a matcher trained on historical data may put a significantly high weight on the attribute name. On the other hand, while names are more unique in certain geographical regions, identical names for different individuals is common in regions such as East-Asian countries. As a result, it is expected that such matchers also violate PPVP for those groups.

Lack of proper coverage [3, 33] in the data to sufficiently include different combinations is the reason the models do not get well-trained for those. For example, in the Dblp-Acm case, the training data did not include enough non-match cases with identical or almost identical titles to reduce the correlation of the title with the ground-truth label.

5 LESSONS AND DISCUSSION

The lessons learned in this study include, but not limited to, the following.

(i) *Call for action to collect entity matching benchmarks on societal applications:* Perhaps the most challenging burden when auditing EM techniques from the fairness perspective is *lack of proper benchmark* datasets. Fairness is a societal issue and is meaningful when the EM task is on *individual records*. In real-world, EM is frequently used for tasks such as terrorist watch list screening [22], record linkage for data integration on medical data [1, 28], individual records deduplication [32], and many more. On the other hand, due to reasons such as privacy, such data are not publicly available. As a result, in this study, we were limited to using publicly available benchmarks to identify fairness-related insights that generalize to real-world scenarios. Although the EM community already has some benchmarks [20, 35], a thorough audit of existing and future EM techniques requires benchmark entity-matching data for societal applications.

(ii) *Unbiased and coverage-aware data:* Responsible training of EM techniques requires access to unbiased data with proper coverage on different groups and possible cases. In particular, equal ground-truth label (match, non-match) ratios for different groups are required or it is not possible to satisfy statistical parity while maintaining high model performance which is fair from other definitions' perspectives. Lack of proper coverage of different groups can bias the model performance in favor of some of the groups, making the model unfair.

(iii) *Proper fairness measures for entity-matching:* Different fairness definitions are valuable for different settings. Still, due to its pairwise matching nature, class-imbalance with most of the records being non-match is a distinguishing property of EM. In this setting, *positive predictive value parity* and *true positive rate parity* aka equal opportunity is more capable of revealing the matchers' unfairnesses. Finally, some of the unfairnesses of a matcher, such as AP, could be explained using other measures such as TPRP.

(iv) *Proper Matching techniques for different settings:* Different matching techniques performed differently for different dataset types. At a high-level, non-neural matchers, while performing well for structured data, fail for textual datasets. Lack of proper coverage in training data can bias these models to significantly rely on attributes (such as name, salary, etc.) that are highly correlated with the ground-truth label but may bias their performance for the minority groups. Neural matchers, on the other hand, generally perform well for different dataset types. Still, (a) using pre-trained language models and embeddings, (b) relying less on the structure of data caused these matchers to be unfair for different settings.

(v) *Ensemble Learning for Fair Entity Matching:* We observed that, in a fixed dataset, some groups needed matchers with more complex decision boundaries, while some other groups required matchers with more simple decision boundaries. As a result, adapting either of the neural/non-neural matchers would show unfairness for some of the groups. This observation underscores the need for techniques such as *ensemble learning* to consider a range of matchers with different properties to assure similar performances across different groups. Fortunately, the importance of ensemble-learning based approaches for EM [18, 36] and data problems in general [25] been recognized.

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A GROUP ENCODING

To unify all attribute-value types, we summarize sub-groups in an encoding and use this encoding to represent individual entities and entity pairs. Given a set of sensitive attributes $\mathcal{A} = \{A_1, \ldots, A_n\}$ and value domains $dom(A_i)$ for attributes A_i, $\mathcal{G} = \{g_1, \ldots, g_m\}$ denotes the set of all level-1 groups, i.e. $\mathcal{G} = \bigcup_{A_i \in \mathcal{A}} dom(A_i)$. We represent a subgroup s of level k (k-combination) consisting of groups $s = \{g_1, \ldots, g_k\}$, with a binary encoding $s = \langle a_1, \ldots, a_m \rangle$, where $m = |dom(A_1)| \times \ldots |dom(A_i)|$) and a_i is one if $g_i \in s$ and is zero otherwise. Note that for a k-combination subgroup, exactly k entries of s get the value one. We represent an entity e associated with groups $G \subseteq \mathcal{G}$ with a binary encoding $\langle b_1, \ldots, b_m \rangle$, where b_i is one if $g_i \in G$ and is zero otherwise. An entity e with groups G belongs to subgroup s if $s \subseteq G$. Given an entity encoding $e = \langle b_1, \ldots, b_m \rangle$ and a subgroup encoding $s = \langle a_1, \ldots, a_m \rangle$, we say e belongs to subgroup s if s AND e $==$ s, i.e. the entity belongs to every group that define the subgroup s. The encoding of an entity pair e_i, e_j is the concatenation of the encodings of e_i and e_j.

Example 3: Consider attributes `genre` and `gender` of Figure 1. Assuming a lexicographical order on all groups, the encoding of entity e with associated groups G={`Female`, `Pop`, `Rock`} is $\langle 1, 0, 0, 1, 1 \rangle$. The encoding of a level-2 subgroup s={`Female`, `Pop`} is $\langle 1, 0, 0, 1, 0 \rangle$. □

B ADDITIONAL EXPERIMENTS

B.1 CAMERAS dataset: Pairwise fairness

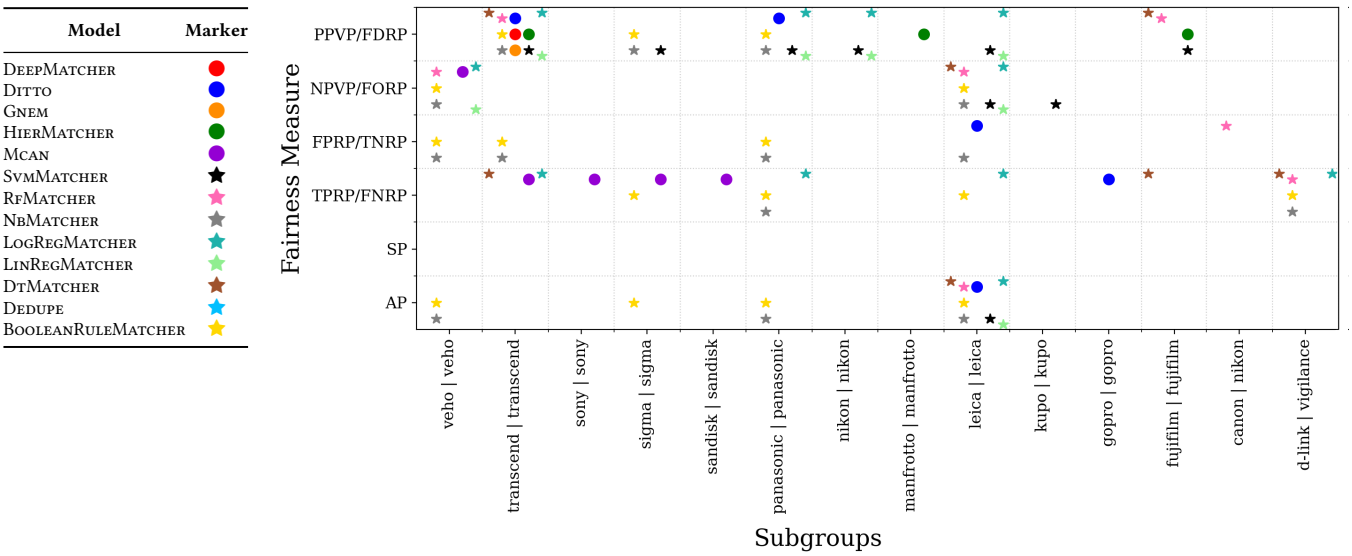

Figure 16: Cameras: Pairwise Fairness.