BENN: Bias Estimation Using Deep Neural Network

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Abstract

The need to detect bias in machine learning (ML) models has led to the development of multiple bias detection methods, yet utilizing them is challenging since each method: i) explores a different ethical aspect of bias, which may result in contradictory output among the different methods, ii) provides an output of a different range/scale and therefore, can’t be compared with other methods, and iii) requires different input, and therefore a human expert needs to be involved to adjust each method according to the examined model. In this paper, we present BENN— a novel bias estimation method that uses a pretrained unsupervised deep neural network. Given a ML model and data samples, BENN provides a bias estimation for every feature based on the model’s predictions. We evaluated BENN using three benchmark datasets and one proprietary churn prediction model used by a European Telco and compared it with an ensemble of 21 existing bias estimation methods. Evaluation results highlight the significant advantages of BENN over the ensemble, as it is generic (i.e., can be applied to any ML model) and there is no need for a domain expert, yet it provides bias estimations that are aligned with those of the ensemble.

1 Introduction

Many new and existing solutions and services use machine learning (ML) algorithms for various tasks. Induced ML models are prone to learning real-world behavior and patterns, including unethical discrimination and though inherit bias. Unethical discrimination may have legal implications (Malgieri 2020); for example, the European General Data Protection Regulation (GDPR) states that the result of personal data processing should be fair; consequently, the output of the induced ML model should not present any unethical bias. Yet, underlying bias exists in various domains, such as facial recognition (Buolamwini and Gebru 2018), object detection (Wilson, Hoffman, and Morgenstern 2019), commercial advertisements (Ali et al. 2019), healthcare (Obermeyer et al. 2019), recidivism prediction (Chouldechova 2017), and credit scoring (Li et al. 2019).

In order to detect this underlying bias, various methods have been proposed for bias detection and estimation (Hardt, Price, and Srebro 2016; Feldman et al. 2015; Berk et al. 2018; Verma and Rubin 2018; Narayanan 2018; Chouldechova 2017). However, these approaches are not applicable to real life settings for the following reasons: i) Most methods produce binary output (bias exists or not); therefore, comparing the level of bias detected in different models and features is not feasible. ii) While there are many bias detection and estimation methods, each explores a different ethical aspect of bias, which may result in contradictory output among the different methods, i.e., one method might determine that the examined ML model is fair, and another might detect underlying bias. Therefore, in order to ensure that bias is not present in an induced ML model, the best practice is to apply an ensemble of all methods. iii) Applying an ensemble of all methods is a challenging task, since the methods need to be scaled to produce consistent bias estimations (using the same scale and range). iv) Different methods may require different data parameters as input. This necessitates a domain expert to determine which methods can be applied to the examined ML model, task, data, and use case, i.e., manual and resource consuming analysis. For example, a method which uses the ground truth labels of samples cannot be used to evaluate an unsupervised ML model.

In this paper, we present BENN, a novel method for bias estimation that uses an unsupervised deep neural network (DNN). Given an ML model and data samples, BENN performs a comprehensive bias analysis and produces a single bias estimation for each feature examined. BENN is composed of two main components. The first component is a bias vector generator, which is an unsupervised DNN with a custom loss function. Its input is a feature vector (i.e., a sample), and its output is a bias vector, which indicates the degree of bias for each feature according to the input sample. The second component is the post-processor, which, given a set of bias vectors (generated by the bias vector generator), processes the vectors and provides a final bias estimation for each feature.

Note that all bias detection and estimation methods are based on the “fairness through unawareness” principle (Verma and Rubin 2018), which means that changes in feature with ethical significance should not change the ML model’s outcome.

Existing methods examine only one ethical aspect of this principle, whereas BENN evaluates all ethical aspects by ex-
amining how each feature affects the ML outcomes.

We empirically evaluated BENN on three bias benchmark datasets: the ProPublica COMPAS (Angwin et al. 2016), Adult Census Income (Blake and Merz 1998), and Statlog (German Credit Data) (Kamiran and Calders 2009) datasets. In addition, we evaluated BENN on a proprietary churn prediction model used by a European Telco, and used synthetic dataset that includes a biased feature and a fair one, allowing us to examine BENN in extreme scenarios. The results of our evaluation indicate that BENN’s bias estimations are capable of revealing model bias, while demonstrating similar behavior to existing methods. The results also highlight the significant advantages of BENN over existing methods; these advantages include the fact that BENN is generic and its application does not require a domain expert. Furthermore, BENN demonstrated similar behavior to existing methods after applying a re-weighting mitigation method on the models and datasets to reduce the unwanted bias.

The main contributions of this paper are as follows:

- To the best of our knowledge, BENN is the first bias estimation method which utilizes an unsupervised deep neural network. Since DNNs are able to learn significant patterns within the data during training, BENN performs a more in depth bias examination than existing methods.
- In contrast to all other methods which focus on just one ethical aspect, BENN performs a comprehensive bias estimation based on all of the ethical aspects currently addressed in the literature.
- BENN is a generic method which can be applied to any ML model, task, data, and use case evaluation; therefore, there is no need for domain experts or ensembles.
- While all bias estimation methods are assessing bias in one feature at a time (targeted), BENN estimates the bias for all of the features simultaneously (non-targeted). This enables the discovery of indirect bias in the induced ML model, i.e., discovering bias based on features that are correlated with the examined feature (Mehrabi et al. 2019).

2 Background

Machine learning fairness has been addressed from various social and ethical perspectives (Mehrabi et al. 2019). The most common one is group fairness (Dwork et al. 2012; Verma and Rubin 2018; Mehrabi et al. 2019), which is the absence of unethical discrimination towards any of the data distribution groups. For example, group fairness is present in the gender feature when men and women are treated the same by the ML model, i.e., discrimination towards one of them is not present. When an ML model demonstrates discrimination, it might be biased towards at least one of the data subgroups, i.e., men or women.

Several civil rights acts, such as the Fair Housing Act (FHA) and the Equal Credit Opportunity Act (ECOA) defined several protected features, such as gender, race, skin color, national origin, religion, and marital status (Mehrabi et al. 2019). Discrimination based on the values of such protected features, as they are termed, is considered ethically unacceptable (Mehrabi et al. 2019).

Bias detection techniques aim to reveal underlying bias presented toward the protected feature, while bias mitigation techniques aim at reducing ML model bias (Mehrabi et al. 2019); there are three main types of techniques: pre-processing (adjusting training data distribution), in-processing (adjusting the ML model during training), and post-processing (adjusting the ML model’s output) techniques (Friedler et al. 2019).

In our experiments, we used a pre-processing technique called re-weighting mitigation (Calders, Kamiran, and Pechenizkiy 2009), which tries to achieve fairness in the training data by replicating data samples that contribute to the training set fairness. This mitigation technique is based on optimizing the demographic parity fairness measure (Dwork et al. 2012).

3 Related Work

The main principle guiding bias detection methods is the “fairness through unawareness” principle, which can be partially represented by a statistical rule. Existing detection methods produce binary output by determining whether a certain statistical rule is met, and if so, the ML model will be considered fair (Verma and Rubin 2018).

Some existing methods, such as disparate impact (Feldman et al. 2015) and demographic parity (Dwork et al. 2012), require only the ML model predictions (i.e., minimal input). Other methods require ground truth labels (e.g., equalized odds (Hardt, Price, and Srebro 2016), balance error rate (Feldman et al. 2015), LR+ measure (Feldman et al. 2015), and equal positive prediction value (Berk et al. 2018)); others are based on a data property called the risk score. An example of the latter can be seen in the bank loan granting task. The loan duration can reflect the potential risk for the bank, and therefore it can be considered a risk score. Examples for such methods are calibration (Chouldechova 2017), prediction parity (Chouldechova 2017), and error rate balance with score (ERBS) (Chouldechova 2017).

As noted, each detection method explores a different ethical aspect. For example, sensitivity (Feldman et al. 2015) states that when the true positive rates (TPRs) of each protected feature value are equal, the ML model is considered fair. While the sensitivity method aims to achieve equal TPRs, the equal accuracy (Berk et al. 2018) method aims at achieving equal accuracy for each protected feature value. Both methods require the ML model predictions and ground truth as input, yet each one examines a different aspect of the ML model’s fairness. For that reason, the two methods may result in inconsistent output, i.e., the sensitivity method might determine that the examined ML model is fair and equal accuracy might not.

In addition, in order to determine which methods can be applied to the examined ML model, a domain expert is required. For example, any detection method that requires ground truth labels, such as treatment equality (Verma and
and equal false positive rate (Berk et al. 2018), cannot be applied on unsupervised ML models.

In contrast to methods aimed at the detection of bias, there are methods that produce bias estimations (Zliobaite 2017), i.e., provide a number instead of a binary value. Examples of such methods are the normalized difference (Zliobaite 2015), mutual information (Fukuchi, Kamishima, and Sakuma 2015), and balance residuals (Calders et al. 2015) methods. BENN’s output is an estimation, and therefore it is a bias estimation method.

Existing bias estimation methods produce estimations with different ranges and scales. For example, the normalized difference (Zliobaite 2015) method produces estimations that range between $[-1, 1]$, and mutual information (Fukuchi, Kamishima, and Sakuma 2015) produces estimations that range between $[0, 1]$ where zero indicates complete fairness.

As noted, the best practice for a comprehensive evaluation is to apply an ensemble of all methods, however since each method produces different output, a domain expert is required. For example, in order to adjust the equal accuracy (Berk et al. 2018) method to produce a scaled bias estimation, the accuracy of each protected feature value is measured; then the accuracy variance is calculated and must be scaled using a normalization techniques such as min-max normalization.

In addition, existing methods aim at evaluating the ML model for bias based on a specific feature, which we define as targeted evaluation. To allow existing methods to evaluate the bias of an ML model based on all available features, a targeted evaluation needs to be performed in a brute-force manner. This type of evaluation can be defined as a non-targeted evaluation. In contrast to existing methods, BENN supports both targeted and non-targeted bias evaluations in one execution.

4 BENN: Bias Estimation Using DNN

In this section, we introduce BENN’s components and structure (illustrated in Figure 1). First, we describe the bias vector generator, which is an unsupervised DNN with a custom loss function. By using our custom loss function, the bias vector generator is forced to induce a hidden representation of the input data, which indicates the ML model’s underlying bias for each feature. Second, we describe the post-processor, which, given a set of bias vectors, processes them into a bias estimation for each feature. As input, BENN receives a test set and black-box access to query the ML model examined; then BENN performs the evaluation and produces bias estimations for all of the features. Note that in order to perform accurate bias analysis, the test set should consist of at least one sample for all possible values for each feature examined and be sampled from the same distribution as the training set used to induce the examined ML model.

The notation used is as follows: Let $X \sim D^n(FP, FU)$ be test data samples with $n$ dimensions derived from a distribution $D$, while $FP$ and $FU$ be sets of protected and unprotected features accordingly. Let $f_p \in FP$ be a protected feature with values in $\{0, 1\}$ (as is customary in the field). Let $M$ be the ML model to be examined. For a data sample $x \in X$, let $M(x)$ be the $M$ outcome for $x$.

4.1 Bias Vector Generator

During the bias vector generator training, a custom loss function is used. The custom loss function has three components which, when combined, enables the production of vectors that represent the ML model’s underlying bias.

The first component of the loss function, referred to as the prediction change component, is defined according to the fairness through unawareness (Verma and Rubin 2018) principle (i.e., the protected features should not contribute to the model’s decision). This component explores the changes that need to be made to a given sample in order to alter the given sample prediction produced by the ML model. This component is formalized in Equation 1:

$$\max_{B(x)} (|M(x) - M(B(x) + x)|)$$ (1)

where $M(x)$ is the model $M$’s prediction for sample $x$, and $M(B(x) + x)$ is the model outcome for sample $x$ and the corresponding bias vector $B(x)$ element-wise sum. The prediction change component aims at maximizing the difference between the original outcome of the ML model and the outcome after adding the bias vector. According to the fairness through unawareness principle, in a fair ML model the protected features should have a value of zero in the corresponding bias vector entries, since they should not affect the ML model’s outcome.

However, enforcing only the prediction change component, in an attempt to maximize the change in the ML model’s outcome, may result in bias vectors with all non-zero entries. In order to prevent this scenario, we introduce a second loss function component, referred to as the feature selection component, which maximizes the number of entries with a zero value, i.e., minimizing the number of entries with a non-zero value. This component is formalized in Equation 2:

$$\min_{B(x)} \left( \sum_{i=1}^{n} (1 - \delta_{B(x)}) \right)$$ (2)

where $B(x)^i$ is the bias vector $B(x)$ value in the $i$ feature, $n$ is the number of features, and $\delta_{B(x)}$ is a Kronecker delta which is one if $B(x)_i = 0$ and zero if $B(x)_i \neq 0$. Accordingly, only the features that contribute the most to the model decision will have non-zero values in their corresponding entries (minimal change in a minimal number of features).

However, given two different samples, the generator may produce two different vectors. Therefore, forcing the two previous components may cause the bias vectors produced to be significantly different. Yet, when bias analysis is performed, the analysis should reflect all of the model decisions combined, i.e., the analysis should be performed at the feature level and not at the sample level. The third component, referred to as the similarity component, addresses this issue, as it enforces a minimal difference between the bias vectors, i.e., for bias vectors $B(x)$, $B(x')$, and a difference function $df$, the $df(B(x), B(x'))$ is minimized by the loss function. This component is formalized in Equation 3:

$$\min_{B_1, B_2} (df(B_1, B_2))$$ (3)
where $B_i, B_j$ are the bias vectors produced for samples $x^i, x^j$ correspondingly. Accordingly, the generator is encouraged to produce similar bias vectors, which reflect the model's behavior across all model outcomes.

The complete loss function is formalized in Equation 4:

$$L_{BENN} = -\lambda_1 \sum_{i=1}^{m} (M(B(x^i) + x^i) - M(x^i))^2$$

$$+ \lambda_2 \sum_{i=1}^{m} \left( \sum_{j=1}^{n} (1 - \delta_{B(x^j)}) \right)^2$$

$$+ \lambda_3 \sum_{i=1}^{m} \sum_{j=1}^{m} (B(x^i) - B(x^j))^2$$

(4)

where $x, x^i, x^j$ are samples, $\lambda_1, \lambda_2, \lambda_3$ are empirically chosen coefficients, $\delta_{B(x^j)}$ is a Kronecker delta which is one if $B(x^j) = 0$ and zero if $B(x^j) \neq 0$, $m$ is the number of vectors produced, and $B(x)$ is the bias vector generated according to $x$.

The generator's overall goal is to minimize the loss value, which produced according to the three components described above. The goal of the prediction change component is to maximize the change in the model’s prediction; therefore the value of this component is subtracted from the total loss value, i.e., greater model prediction change results in a smaller loss value. The goal of the feature selection component is to minimize the number of non-zero values in the bias vector; therefore the value of this component is added to the total loss value, i.e., a smaller number of non-zero values in the bias vector results in a smaller loss value. The goal of the similarity component is to minimize the difference between the bias vectors in the same training batch. For that reason, this component is added to the total loss value, i.e., a smaller difference between the bias vectors results in a smaller loss value.

The structure and hyperparameters of the bias vector generator are empirically chosen, as presented in Section 5.

### 4.2 Post-Processor

The main goal of the post-processor is to combine the bias vectors produced into a single vector representing the bias estimation for each feature. The post-processor performs a mathematical aggregation by calculating the absolute average of each entry across all the bias vectors. This aggregation is formalized in Equation 5:

$$post(b_i) = \frac{1}{m} \sum_{j=1}^{m} |b_i^{(j)}|$$

(5)

where $b_i$ is the bias vector entry in the $i$ place, and $m$ is the number of produced vectors. Note that in a targeted evaluation scenario, the values for the predefined protected features are extracted from the corresponding entries of the post-processor’s final output.

### 5 Evaluation

#### 5.1 Datasets

The following datasets were used to evaluate BENN:

- **ProPublica COMPAS** [Angwin et al., 2016] is a benchmark dataset that contains racial bias. The dataset was collected from the COMPAS system’s historical records, which were used to assess the likelihood of a defendant to be a repeat offender. After filtering samples with missing values and nonmeaningful features, the dataset contains 7,215 samples and 10 features.

- **Adult Census Income** [Blake and Merz, 1998] is a benchmark dataset that contains racial and gender-based bias. The dataset corresponds to an income level prediction task. After filtering samples with missing values and nonmeaningful features, the dataset contains 23,562 samples and 12 features.

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3 [github.com/propublica/compas-analysis/blob/master/compas-scores-two-years.csv](https://github.com/propublica/compas-analysis/blob/master/compas-scores-two-years.csv)

4 [archive.ics.uci.edu/ml/datasets/adult](https://archive.ics.uci.edu/ml/datasets/adult)
Statlog (German Credit Data) (Kamiran and Calders 2009; Dua and Graff 2017) is a benchmark dataset that contains gender-bias. The dataset corresponds to the task of determining whether the customer should qualify for a loan. After filtering samples with missing values and non-meaningful features, the dataset contains 1,000 samples and 20 features.

Telco Churn Additional experiments were performed on a European Telco’s churn prediction ML model and dataset. This ML model is a DNN-based model, which predicts customer churn, i.e., whether a customer will end his/her Telco subscription. The Telco’s churn dataset contains real customers information, therefore is not public. The data contains 95,704 samples and 28 features, and the protected feature is gender.

Synthetic Data In order to provide a sanity-check, we generated a synthetic dataset. The dataset contains three binary features, two of which are protected: one is a fair feature (has no bias) and one is extremely biased (has maximal bias). The dataset consists of 305 samples, which are composed from every possible combination of the feature values.

5.2 Ensemble Baseline

We compared BENN’s results to the results obtained by all 21 existing bias detection and estimation methods: equalized odds (Hardt, Price, and Srebro 2016), disparate impact (Feldman et al. 2015), demographic parity (Dwork et al. 2012), sensitivity (Feldman et al. 2015), specificity (Feldman et al. 2015), balance error rate (Feldman et al. 2015), LR+ measure (Feldman et al. 2015), equal positive prediction value (Berk et al. 2018), equal negative prediction value (Berk et al. 2018), equal accuracy (Berk et al. 2018), equal opportunity (Hardt, Price, and Srebro 2016), treatment equality (Verma and Rubin 2018), equal false positive rate (Berk et al. 2018), equal false negative rate (Berk et al. 2018), error rate balance (Narayan 2018), normalized difference (Zliobaite 2015), mutual information (Fukuchi, Kamishima, and Sakuma 2015), balance residuals (Calders et al. 2013), calibration (Chouldechova 2017), prediction parity (Chouldechova 2017), and error rate balance with score (ERBS) (Chouldechova 2017).

Due to the different outputs of the 21 existing methods, we adjusted them to produce bias estimations with the same range and scale. The adjustments were performed according to each method’s output type: binary bias detection or non-scaled bias estimation. In order to adjust the binary bias detection methods, we subtracted the two expressions that form the method’s statistical rule and scaled the difference between the two expressions so it is between [0, 1] (if needed). In the case of non-binary features (multiple values), we computed the method’s statistical rule for each feature value and used the results’ variance and scaled it (if needed). In order to adjust non-scaled bias estimation methods, we scaled their outputs to be between [0, 1], with zero indicating complete fairness.

In order to create one estimation to which we can compare BENN’s estimation, we constructed an ensemble baseline based on the 21 adjusted methods (as described above). Each method evaluates a different ethical aspect, which may result in inconsistent estimations, therefore the ensemble baseline’s estimation is set at the most severe estimation among the 21 different methods, i.e., the highest bias estimation produced for each feature.

Due to space limitations, we only present the ensemble baseline’s final results.

5.3 Evaluation Guidelines

In order for BENN’s estimations to be aligned with the ensemble’s estimations, the following guidelines must be hold:

First, BENN must not overlook bias that was detected by one of the 21 existing methods. Therefore, for a specific feature and ML model, BENN’s bias estimation should not be lower than the ensemble’s estimation. This is formalized in Expression 6

\[
BENN_{f_i} \geq Ensemble_{f_i}
\]  

where \(f_i\) is a specific examined feature.

Second, BENN must maintain the same ranking (order of feature estimations) as the ranking provided by the ensemble; i.e., by ranking the features in descending order based on their estimations, BENN and the ensemble should result in an identical ranking. This is formalized in Expression 7

\[
\text{rank}(BENN_{f_i}) = \text{rank}(Ensemble_{f_i})
\]

where \(f_i\) is a specific feature, and \(\text{rank}\) is the bias estimation rank.

Third, the differences between BENN’s estimations and the ensemble’s estimations must be similar (close to zero variance) for all data features. This formalized by Expression 8

\[
BENN_{f_i} - Ensemble_{f_i} \approx 0
\]

where \(f_i, f_j\) are examined features. This ensures that the differences between BENN and the ensemble are consistent (not random) across all data features.

5.4 Experimental Settings

All experiments were performed on the CentOS Linux 7 (Core) operating system using 24G of memory and a NVIDIA GeForce RTX 2080 Ti graphics card. BENN and all of the code used in the experiments was written using Python 3.7.4, scikit-learn 0.22, NumPy 1.17.4, and a TensorFlow GPU 2.0.0.

The structural properties of the bias vector generator (layers parameter, optimization function, etc.) were empirically chosen and are comprised as follows: The bias vector generator is comprised of eight dense layers with 40 units and the rectified linear unit (ReLU) as the activation function. The output layer has the same number of units as the number of data features and hyperbolic tangent (tanh) function as the activation function. The weight and bias initialization for every layer was randomly selected. In order to determine
the lambda parameters’ values we performed experiments using each possible value in the range \([0, 1]\) at steps of 0.01 for each lambda. As a result, the lambda values were empirically set to be equal to one. BENN was trained using mini-batch gradient descent optimization with a batch size of 128 and 300 epochs throughout all of the experiments. For each dataset, we induced a decision tree classifier using the scikit-learn library with the decision tree constructor default parameters. In order to train and evaluate the classifiers, we used five-fold cross-validation for each corresponding dataset, splitting the dataset into a training set and test set accordingly. The test sets were used to perform the bias evaluations. Each experiment was performed on one pair of dataset and its corresponding ML model, which refer to as experimental use case.

As noted, in order to perform a proper bias evaluation, the test set should consist of at least one sample for each feature value examined. For that reason, we set the seeds for different datasets differently: the seed for ProPublica COMPAS was 31, the Adult Census Income seed was 22, and the seed of the Statlog (German Credit Data) dataset was two. Note, in the churn use case, we used an European Telco proprietary ML model, and therefore, we did not induce an additional model.

For our experiments we defined two experimental settings: the original setting, which uses the original dataset without any changes, and the mitigation setting, which uses the dataset produced using the re-weighting mitigation technique [Calders, Kamiran, and Pechenizkiy 2009]. The mitigation technique parameters were set as follows: the weights of the replications with positive contribution were set at one, and the other replications weights were set at 0.1. In addition, the stopping criteria was defined as the probability variance threshold, which was defined as the variance of the probability for each protected feature group to obtain the positive outcome. When the probability variance of the training set reached the probability variance threshold, the sample replication process stopped. The variance threshold was set differently for each use case due to the difference in the initial variance: 0.0045 for the ProPublica COMPAS and Adult Census Income datasets, 0.0003 for the Statlog (German Credit Data) dataset, and 0.00003 for the churn data.

### 5.5 Experimental Results

Table 1 presents the experimental results for the original setting (non-mitigation setting) based on the synthetic data (fair and biased features), and the COMPAS (race, gender, and age), Adult (race and gender), Statlog (gender), and Churn prediction (gender) use cases. For each use case, the table presents: the ensemble baseline and BENN bias estimations, the use case rankings, the difference between the estimations, and the difference variance for each protected feature. The benchmark use case (COMPAS, Adult, Statlog) results were in the original setting validated by five-fold cross-validation, obtaining a standard deviation below 0.02 for every feature in every use case.

In Table 1, it can be seen that overall, BENN’s estimations upheld all of the guidelines with respect to the ensemble baseline. With the synthetic data, both BENN and the ensemble baseline produced a bias estimation of \(\sim 0\) for the fair feature and a bias estimation of \(\sim 1\) for the biased feature. Thus, BENN was effective in the extreme scenarios of completely fair and completely biased features correctly estimating the bias. With the COMPAS use case, the ensemble’s estimations ranged between \([\sim 0.29, \sim 0.45]\), and BENN’s estimations ranged between \([\sim 0.51, \sim 0.66]\). All of the guidelines were upheld: BENN’s estimations were higher than the ensemble’s estimations for every feature; the estimation rankings were identical for the ensemble and BENN; and the difference variance was 0.001. With the Adult use case, the ensemble’s estimations ranged between \([\sim 0.53, \sim 0.63]\), and BENN’s estimations ranged between \([\sim 0.6, \sim 0.69]\). All of the guidelines were upheld: BENN’s estimations were higher then the ensemble’s estimations for every feature; the estimation rankings were identical for the ensemble baseline and BENN; and the variance was 0.0002. In the Statlog use case, the ensemble’s estimation for the gender feature was 0.2215, and BENN’s estimation was 0.5293; therefore, the first guideline was upheld, i.e., BENN’s estimation was higher then the ensemble’s estimation; there was only one protected feature, so the second and third guidelines were degenerated. In the Churn prediction use case, the ensemble’s estimation for the gender feature was 0.29, and BENN’s estimation was 0.5306; therefore, the first guideline was upheld, i.e., BENN’s estimation was higher than the ensemble’s estimation; there was only one protected feature, so the second and third guidelines were degenerated.

Figure 2 presents the experimental results for the mitigation setting based on the COMPAS (race, gender, and age features), Adult (race and gender features), Statlog (gender feature), and Churn prediction (gender feature) use cases after re-weighting mitigation was performed. For each experiment, the charts present the change observed in BENN’s es-
Figure 2: Mitigation experiment output. Each plotted point is an observed change of a protected feature. The x-axis is the change observed for the ensemble after the mitigation. The y-axis is the observed change for BENN after the mitigation.

7 Conclusions and Future Work

In this research, we presented BENN – a novel method for bias estimation that uses an unsupervised DNN. Existing methods for bias detection and estimation are limited for various reasons: i) inconsistent and insufficient outputs made any comparison not visible, ii) each method explores a different ethical aspect of bias iii) each method receives different inputs. As a result, in order to perform a comprehensive bias evaluation, a domain expert must form an ensemble of the existing methods (as we formed). BENN is a generic method which i) produces scaled and comprehensive bias estimations, and ii) can be applied to any ML model without using a domain expert. Experimental results on three benchmark datasets and one proprietary churn prediction model used by a European Telco indicate that BENN’s estimations: i) capable of revealing ML models bias, and ii) demonstrate...
similar behavior to existing methods, as represented by an ensemble results baseline in various settings. Furthermore, experimental results on synthetic data indicate that BENN is capable of correctly estimating bias in extreme scenarios. Given this, BENN can be considered a complete bias estimation technique.

Potential future work may include adapting BENN for the performance of bias evaluation in unstructured data scenarios, i.e., when the protected feature may not be explicitly presented in the data (such as image datasets). For example, the feature gender is not explicitly noted in face recognition image datasets, as each image is not tagged according to the gender of its subject. In theory, utilizing object detection and classification solutions to extract the wanted feature from the data can be applied and extract the implicit feature. In addition, making changes to the input representation can enable the extraction of a more dense representation of the input (as in the use of convolutions). Combining both object detection and classification solutions and changing the input representation may result in an ML model and data that can be evaluated using BENN.

Future work may also include evaluating BENN in additional experimental settings (i.e., using different datasets, additional ML algorithms, various tasks, etc.); utilizing the bias vector generator structure and outputs to perform bias mitigation; and finally, developing an explainability mechanism to support BENN structure and bias estimations.

References

Ali, M.; Sapiezynski, P.; Bogen, M.; Korolova, A.; Mislove, A.; and Rieke, A. 2019. Discrimination through Optimization: How Facebook’s Ad Delivery Can Lead to Biased Outcomes. Proceedings of the ACM on Human-Computer Interaction 3(CSCW): 1–30.

Angwin, J.; Larson, J.; Mattu, S.; and Kirchner, L. 2016. Machine bias. ProPublica. See https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

Berk, R.; Heidari, H.; Jabbari, S.; Kearns, M.; and Roth, A. 2018. Fairness in criminal justice risk assessments: The state of the art. Sociological Methods & Research 0049124118782533.

Blake, C.; and Merz, C. 1998. Adult data set. UCI Repository of Machine Learning Databases.

Buolamwini, J.; and Gebru, T. 2018. Gender shades: Intersectional accuracy disparities in commercial gender classification. In Conference on fairness, accountability and transparency, 77–91.

Calders, T.; Kamiran, F.; and Pechenizkiy, M. 2009. Building classifiers with independency constraints. In 2009 IEEE International Conference on Data Mining Workshops, 13–18. IEEE.

Calders, T.; Karim, A.; Kamiran, F.; Ali, W.; and Zhang, X. 2013. Controlling attribute effect in linear regression. In 2013 IEEE 13th international conference on data mining, 71–80. IEEE.

Chouldechova, A. 2017. Fair prediction with disparate impact: A study of bias in recidivism prediction instruments. Big data 5(2): 153–163.

Dua, D.; and Graff, C. 2017. UCI Machine Learning Repository. URL http://archive.ics.uci.edu/ml.

Dwork, C.; Hardt, M.; Pitassi, T.; Reingold, O.; and Zemel, R. 2012. Fairness through awareness. In Proceedings of the 3rd innovations in theoretical computer science conference, 214–226.

Friedler, S. A.; Scheidegger, C.; Venkatasubramanian, S. 2015. Certifying and removing disparate impact. In proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining, 259–268.

Kamiran, F.; and Calders, T. 2009. Classifying without discrimination. In Proceedings of the 2009 2nd International Conference on Computer, Control and Communication, 1–6. IEEE.

Malgieri, G. 2020. The concept of fairness in the GDPR: a linguistic and contextual interpretation. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 154–166.

Mehrabi, N.; Morstatter, F.; Saxena, N.; Lerman, K.; and Galstyan, A. 2019. A survey on bias and fairness in machine learning. arXiv preprint arXiv:1908.09635.

Myers, C. M.; Freed, E.; Pardo, L. F. L.; Furqan, A.; Risi, S.; and Zhu, J. 2020. Revealing Neural Network Bias to Non-Experts Through Interactive Counterfactual Examples. arXiv preprint arXiv:2001.02271.

Narayanan, A. 2018. Translation tutorial: 21 fairness definitions and their politics. In Proc. Conf. Fairness Accountability Transp., New York, USA.

Obermeyer, Z.; Powers, B.; Vogeli, C.; and Mullainathan, S. 2019. Dissecting racial bias in an algorithm used to manage the health of populations. Science 366(6464): 447–453.

Verma, S.; and Rubin, J. 2018. Fairness definitions explained. In 2018 IEEE/ACM International Workshop on Software Fairness (FairWare), 1–7. IEEE.
Wilson, B.; Hoffman, J.; and Morgenstern, J. 2019. Predictive inequity in object detection. *arXiv preprint arXiv:1902.11097*.

Zliobaite, I. 2015. On the relation between accuracy and fairness in binary classification. *arXiv preprint arXiv:1505.05723*.

Zliobaite, I. 2017. Measuring discrimination in algorithmic decision making. *Data Mining and Knowledge Discovery* 31(4): 1060–1089.

### A Comparison with Existing Methods

Table 2 provides an overview of the existing bias detection and estimation methods with respect to various properties.

The first property is the ability to provide two different evaluation solutions: i) evaluate the machine learning (ML) model for bias based on a specific feature, which we define as *targeted* evaluation, and ii) evaluate the ML model for bias based on all available features, which we define as *non-targeted* evaluation. As seen in Table 2 none of the existing methods support non-targeted bias evaluation, i.e., in order to obtain a non-targeted evaluation, a targeted evaluation needs to be performed in a brute-force manner. In contrast, BENN offers both targeted and non-targeted bias evaluation solutions in one execution.

The second property is the ability to evaluate the ML model with limited access to information, i.e., just the ML model predictions. Table 2 shows that the majority of the methods require additional information, such as the ground truth labels, the data’s predefined risk score, etc. In contrast, BENN requires only the model predictions.

The third property is the method’s technical novelty. As seen in the table, all of the existing methods are based on statistical rules whereas BENN is based on an unsupervised deep neural network (DNN). As such, BENN provides a novel DNN-based bias evaluation that produces more well-founded bias estimations.

The fourth property is the method’s ability to perform bias evaluation for both supervised and unsupervised ML models. In Table 2 it can be seen that most of the methods are only suited for supervised learning due to their dependence on ground truth labels. In contrast, BENN supports both supervised and unsupervised learning as it considers only the model predictions.

The fifth property is the method’s ability to produce scaled bias estimations. Most of the methods require adaptation in order to produce bias estimations, as they are aimed solely at performing bias detection. While there are methods that can estimate bias, they produce bias estimations with different ranges and scales, making it difficult to compare their outputs. In contrast, BENN is capable of producing a scaled bias estimation for each of the examined features/models.

The sixth property is the method’s accessibility. Prior knowledge in the following fields is required in order to evaluate bias using the existing methods: ML, bias detection, bias estimation, data complexity, and domain constraints. Therefore, existing methods are not suitable for non-experts. To the best of our knowledge, the first and only attempt at making the bias evaluation process more accessible to the non-expert community was made by Myers et al. who introduced a visualization tool which aimed at discovering bias, referred to as CEB (Myers et al. 2020). However, CEB is just meant for visualization purposes and is only suitable for neural network (NN) based ML models (Myers et al. 2020). CEB visualizes the NN activation’s behavior and requires additional processing in order to perform manual bias evaluation (behavior analysis, etc). In contrast, BENN is both more accessible and better suited to the non-expert community.
Another property is the method’s ability to provide a complete ethical evaluation. As noted, all bias detection and estimation methods are based on the “fairness through unawareness” principle (Verma and Rubin 2018), which means that changes in features with ethical significance should not change the ML model’s outcome. Each existing method examines only one ethical aspect of this principle, and none of them examine the entire principle, i.e., none of them perform a complete ethical evaluation. In contrast, we empirically show that BENN performs a complete bias evaluation, as it examines the ML model for all ethical aspects derived from the “fairness through unawareness” principle (Verma and Rubin 2018).

Table 2 highlights the disadvantages and limitations of the existing methods for bias evaluation, pointing to the need for a generic, complete, and accessible bias evaluation technique like BENN.

### B The Ensemble Baseline

In this section, we describe how the ensemble baseline was created. As noted, the ensemble baseline is constructed using the 21 existing bias detection and estimation methods. Due to the different outputs of these methods, we adjusted them to produce bias estimations with the same range and scale. The adjustments were performed according to each method’s output type: binary bias detection or non-scaled bias estimation.

Existing detection methods produce binary output by determining whether a certain statistical rule is met, and if so, the ML model is considered fair (Verma and Rubin 2018).
In order to adjust the binary bias detection methods, we subtracted the two expressions that form the method’s statistical rule and scaled the difference between the two expressions so it is between \([0, 1]\) (if needed). In the case of non-binary features (multiple values), we computed the method’s statistical rule for each feature value and used the results’ variance and scaled it (if needed). In order to adjust non-scaled bias estimation methods, we scaled their outputs to be between \([0, 1]\), with zero indicating complete fairness.

In order to create one estimation to which we can compare BENN’s estimation, we constructed an ensemble baseline based on the 21 adjusted methods (as described above). Each method evaluates a different ethical aspect, therefore the ensemble baseline’s estimation is set at the most restrictive estimation produced by the 21 different methods, i.e., the highest bias estimation produced for each feature.

In this section, we discuss the 21 existing methods and explain how we adjusted them for a scaled bias estimation. The notation used is as follows: Let \(X \sim D^n(FP, FU)\) be test data samples with \(n\) dimensions, derived from distribution \(D\), and \(FP\) and \(FU\) be sets of protected and unprotected features accordingly. Let \(f_p \in FP\) be a protected feature with values in \([0, 1]\) (as is customary in the field). Let \(M\) be the ML model to be examined. For a data sample \(x \in X\), let \(M(x)\) be the model \(M\) outcome for \(x\) and \(y_t\) be \(x\) ground truth. Let \(C\) be a group of possible classes and \(c_i \in C\) be a possible class. Let \(S(x)\) be sample \(x\)’s risk score.

### B.1 Equalized Odds

The equalized odds method, presented in Equation \([9]\), produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
P(M(x) = 1|f_p = 0, y_t = c_i) = P(M(x) = 1|f_p = 1, y_t = c_i)\]

\(9\)

In order to produce a scaled bias estimation, we performed the calculations in Equation \([10]\) for the protected feature values:

\[
\forall c_i \in C, \forall v_p \in f_p \quad \text{Estimation} = \max\text{ (variance} (p(M(x) = 1|f_p = v_p, y_t = c_i))\]

\(10\)

### B.2 Disparate Impact

The disparate impact method, presented in Equation \([11]\) produces a non-scaled bias estimation output, therefore we processed it accordingly (as described at the beginning of this section).

\[
DI = \frac{P(M(x) = 1|f_p = 1)}{P(M(x) = 1|f_p = 0)}
\]

\(11\)

In order to produce a scaled bias estimation, we performed the calculations in Equation \([12]\) for the protected feature values:

\[
\text{Estimation} = \begin{cases} 0 & \min(DI) > 0.8 \min(DI) \\ 1 - \frac{\min(DI)}{0.8} & \min(DI) \leq 0.8 \end{cases}
\]

\(12\)

### B.3 Demographic parity

The demographic parity method, presented in Equation \([13]\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
P(M(x) = 1|f_p = 1) = P(M(x) = 1|f_p = 0)
\]

\(13\)

In order to produce a scaled bias estimation, we performed the calculations in Equation \([14]\) for the protected feature values:

\[
\text{Estimation} = \max(|P(M(x) = 1|f_p = 1) - P(M(x) = 1|f_p = 0)|)
\]

\(14\)

### B.4 Sensitivity

The sensitivity method, presented in Equation \([15]\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{TP_{f_p=1}}{TP_{f_p=1} + FN_{f_p=1}} = \frac{TP_{f_p=0}}{TP_{f_p=0} + FN_{f_p=0}}
\]

\(15\)

In order to produce a scaled bias estimation, we performed the calculations in Equation \([16]\) for the protected feature values:

\[
\text{Estimation} = \max\left(\frac{TP_{f_p=1}}{TP_{f_p=1} + FN_{f_p=1}} - \frac{TP_{f_p=0}}{TP_{f_p=0} + FN_{f_p=0}}\right)
\]

\(16\)

### B.5 Specificity

The specificity method, presented in Equation \([17]\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{TN_{f_p=1}}{TN_{f_p=1} + FP_{f_p=1}} = \frac{TN_{f_p=0}}{TN_{f_p=0} + FP_{f_p=0}}
\]

\(17\)

In order to produce a scaled bias estimation, we performed the calculations in Equation \([18]\) for the protected feature values:

\[
\text{Estimation} = \max\left(\frac{TN_{f_p=1}}{TN_{f_p=1} + FP_{f_p=1}} - \frac{TN_{f_p=0}}{TN_{f_p=0} + FP_{f_p=0}}\right)
\]

\(18\)

### B.6 Balance Error Rate

The balance error rate method, presented in Equation \([19]\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{FP_{f_p=1} + FN_{f_p=1}}{2} = \frac{FP_{f_p=0} + FN_{f_p=0}}{2}
\]

\(19\)

In order to produce a scaled bias estimation, we performed the calculations in Equation \([20]\) for the protected feature values:

\[
\text{Estimation} = \max\left(\frac{FP_{f_p=1} + FN_{f_p=1}}{2} - \frac{FP_{f_p=0} + FN_{f_p=0}}{2}\right)
\]

\(20\)
B.7 LR+ Measure
The LR+ measure method, presented in Equation \((21)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{TP_{f_p=1}}{TP_{f_p=1} + FP_{f_p=1}} = \frac{TP_{f_p=0}}{TP_{f_p=0} + FP_{f_p=0}} \tag{21}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((22)\) for the protected feature values:

\[
Estimation = \max \left( \frac{TP_{f_p=1}}{TP_{f_p=1} + FP_{f_p=1}} - \frac{TP_{f_p=0}}{TP_{f_p=0} + FP_{f_p=0}} \right) \frac{\text{data size}}{2} \tag{22}
\]

B.8 Equal Positive Prediction Value
The equal positive prediction value method, presented in Equation \((23)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{TP_{f_p=1}}{TP_{f_p=1} + FP_{f_p=1}} = \frac{TP_{f_p=0}}{TP_{f_p=0} + FP_{f_p=0}} \tag{23}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((24)\) for the protected feature values:

\[
Estimation = \max \left( \frac{TP_{f_p=1}}{TP_{f_p=1} + FP_{f_p=1}} - \frac{TP_{f_p=0}}{TP_{f_p=0} + FP_{f_p=0}} \right) \tag{24}
\]

B.9 Equal Negative Prediction Value
The equal negative prediction Value method, presented in Equation \((25)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{TN_{f_p=1}}{TN_{f_p=1} + FN_{f_p=1}} = \frac{TN_{f_p=0}}{TN_{f_p=0} + FN_{f_p=0}} \tag{25}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((26)\) for the protected feature values:

\[
Estimation = \max \left( \frac{TN_{f_p=1}}{TN_{f_p=1} + FN_{f_p=1}} - \frac{TN_{f_p=0}}{TN_{f_p=0} + FN_{f_p=0}} \right) \tag{26}
\]

B.10 Equal Accuracy
The equal accuracy method, presented in Equation \((27)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{TP_{f_p=1}}{TP_{f_p=1} + FP_{f_p=1}} = \frac{TN_{f_p=1} + TP_{f_p=1}}{TN_{f_p=0} + TP_{f_p=0}} \tag{27}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((28)\) for the protected feature values:

\[
Estimation = \max \left( \frac{TN_{f_p=1} + TP_{f_p=1}}{\text{data size}} - \frac{TN_{f_p=0} + TP_{f_p=0}}{\text{data size}} \right) \tag{28}
\]

B.11 Equal Opportunity
The equal opportunity method, presented in Equation \((29)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
P(M(x) = 1|f_p = 0, y_t = 1) = P(M(x) = 1|f_p = 1, y_t = 1) \tag{29}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((30)\) for the protected feature values:

\[
Estimation = 1 - \text{variance} \left( p \left( M(x) = 1|f_p = v_p, y_t = c_i \right) \right) \tag{30}
\]

B.12 Treatment Equality
The treatment equality method, presented in Equation \((31)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{FN_{f_p=1}}{FP_{f_p=1}} = \frac{FN_{f_p=0}}{FP_{f_p=0}} \tag{31}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((32)\) for the protected feature values:

\[
Estimation = \max \left( \frac{FN_{f_p=1}}{FP_{f_p=1}} - \frac{FN_{f_p=0}}{FP_{f_p=0}} \right) \frac{\text{data size}}{\text{data size}} \tag{32}
\]

B.13 Equal False Positive Rate
The equal false positive rate method, presented in Equation \((33)\) produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{FP_{f_p=1}}{TP_{f_p=1} + TN_{f_p=1}} = \frac{FP_{f_p=0}}{TP_{f_p=0} + TN_{f_p=0}} \tag{33}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation \((34)\) for the protected feature values:

\[
Estimation = \max \left( \frac{FP_{f_p=1}}{TP_{f_p=1} + TN_{f_p=1}} - \frac{FP_{f_p=0}}{TP_{f_p=0} + TN_{f_p=0}} \right) \tag{34}
\]
B.14 Equal False Negative Rate
The equal false negative rate method, presented in Equation 35, produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{FN_{f_p=1}}{FN_{f_p=1} + TP_{f_p=1}} = \frac{FN_{f_p=0}}{FN_{f_p=0} + TP_{f_p=0}}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation 36 for the protected feature values:

\[
\text{Estimation} = \max \left( \frac{FN_{f_p=1}}{FN_{f_p=1} + TP_{f_p=1}} - \frac{FN_{f_p=0}}{FN_{f_p=0} + TP_{f_p=0}} \right)
\]

B.15 Error Rate Balance
The error rate balance method, presented in Equation 37, produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
\frac{FN_{f_p=1}}{FN_{f_p=1} + TP_{f_p=1}} = \frac{FN_{f_p=0}}{FN_{f_p=0} + TP_{f_p=0}} \\
\text{and} \\
\frac{FP_{f_p=1}}{FP_{f_p=1} + TN_{f_p=1}} = \frac{FP_{f_p=0}}{FP_{f_p=0} + TN_{f_p=0}}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation 38 for the protected feature values:

\[
\text{Estimation} = 1 - \min (\text{Equal FNR Estimation}, \text{Equal FPR Estimation})
\]

B.16 Normalized Difference
The normalized difference method, presented in Equation 39, produces a non-scaled bias estimation output, therefore we processed it accordingly (as described at the beginning of this section).

\[
ND = \frac{P(M(x) = 1|f_p = 1) - P(M(x) = 1|f_p = 0)}{\max \left( \frac{P(M(x) = 1)}{p(f_p=0)} \cdot \frac{P(M(x) = 0)}{p(f_p=1)} \right)}
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation 40 for the protected feature values:

\[
\text{Estimation} = \max (|ND|)
\]

B.17 Mutual Information
The mutual information method, presented in Equation 41, produces a non-scaled bias estimation output, therefore we processed it accordingly (as described at the beginning of this section).

\[
MI = \frac{I(M(x), f_p)}{\sqrt{H(M(x))H(f_p)}}
\]

\[
I(M(x), f_p) = \sum_{M(x), f_p} P(M(x), f_p) \log \left( \frac{P(M(x), f_p)}{P(M(x))P(f_p)} \right)
\]

\[
H(a) = - \sum_a P(a) \log(p(a))
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation 42 for the protected feature values:

\[
\text{Estimation} = \max (|MI|)
\]

B.18 Balance Residuals
The balance residuals method, presented in Equation 43, produces a non-scaled bias estimation output, therefore we processed it accordingly (as described at the beginning of this section).

\[
BR = \frac{\sum_{f_p=1} |y_t - M(x)|}{|f_p = 1|} - \frac{\sum_{f_p=0} |y_t - M(x)|}{|f_p = 0|
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation 44 for the protected feature values:

\[
\text{Estimation} = \max (|BR|)
\]

B.19 Calibration
The calibration method, presented in Equation 45, produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
P(M(x) = 1|s(x), f_p = 1) = P(M(x) = 1|s(x), f_p = 0)
\]

In order to produce a scaled bias estimation, we performed the calculations in Equation 46 for the protected feature values:

\[
\text{Estimation} = \min (\text{variance} (P(M(x) = 1|s(x), f_p = v_p)))
\]

B.20 Prediction Parity
The prediction parity method, presented in Equation 47, produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
P(M(x) = 1|s(x) > t, f_p = 1) = P(M(x) = 1|s(x) > t, f_p = 0)
\]

where \( t \) is a given risk score threshold. In order to produce a scaled bias estimation, we performed the calculations in Equation 48 for the protected feature values:

\[
\text{Estimation} = 1 - \text{variance} (P(M(x) = 1|s(x) > t, f_p = v_p))
\]
B.21 Error Rate Balance with Score

The error rate balance with score method, presented in Equation 49, produces a binary bias detection output, therefore we processed it accordingly (as described at the beginning of this section).

\[
P(s(x) > t | M(x) = 0, f_p = 1) = \]
\[
P(s(x) > t | M(x) = 0, f_p = 0) \]
\[
and \]
\[
P(s(x) \leq t | M(x) = 1, f_p = 1) = \]
\[
P(s(x) \leq t | M(x) = 1, f_p = 0) \]

where \( t \) is a given risk score threshold. In order to produce a scaled bias estimation, we performed the calculations in Equation 50 for the protected feature values:

\[
Estimation = 1 - \min (\text{variance}(P(s(x) > t | M(x) = 0, f_p = v_p)), \text{variance}(P(s(x) \leq t | M(x) = 1, f_p = v_p)))
\]

C Ethical Aspects of the Compared Methods

In Table 3, we present the ethical aspects of the existing bias detection and estimation methods.

As noted, all bias detection and estimation methods are based on the “fairness through unawareness” principle (Verma and Rubin 2018), which means that changes in features with ethical significance should not change the ML model’s outcome. Each existing method examines only one ethical aspect derived from this principle, i.e., none of them perform a complete ethical evaluation.

In Table 3, we present the ethical aspect that is derived from the “fairness through unawareness” principle for each method. Each method examines a selected statistical property according to the ML model’s output, such as the ML model’s true positive rate (TPR), true negative rate (TNR), outcome’s entropy, etc.

As seen in Table 3, none of the existing methods evaluate the “fairness through unawareness” principle in its entirety. In contrast, BENN performs a complete bias evaluation, as it examines the ML model for all ethical aspects derived from the “fairness through unawareness” principle.

D Experimental Use Cases

In our experiments, we evaluated BENN on five different use cases:

**ProPublica COMPAS** (Angwin et al. 2016) is a benchmark dataset that contains racial bias. The COMPAS system is used in the US by Florida’s Department of Justice (judges and parole officers) to assess the likelihood of a defendant to be a repeat offender. The dataset was collected from the COMPAS system’s historical records of offenders from Broward County, Florida and contains the defendant’s demographic characteristics, criminal history, and COMPAS recidivism risk scores (ranging between [1, 10]), where one represents a low risk to commit another crime and 10 represents a high risk of doing so. ProPublica discovered that COMPAS tends to output low recidivism scores for Caucasian defendants, which results in discriminatory behavior toward any minority group in the dataset (such as African Americans or Asians). The discrimination can also be observed by examining the prediction errors of COMPAS, as the rate of offenders that were labeled as high risk but did not commit another crime is 23.5% for Caucasian defendants and 44.9% for African American defendants (Angwin et al. 2016). In addition, the rate of offenders that were labeled as low risk yet did commit another crime is 47.7% for Caucasian defendants and 28.0% for African American defendants (Angwin et al. 2016). After filtering samples with missing values and nonmeaningful features, the dataset contains 7,215 samples and 10 features.

**Adult Census Income** (Blake and Merz 1998) is a benchmark dataset that contains racial and gender-based bias. The Adult Census Income database contains census records that were collected between 1994 and 1995 by means of population surveys that were managed by the US Census Bureau. The dataset corresponds to an income level prediction task, i.e., income above 50K or below. After filtering samples with missing values and nonmeaningful features, the dataset contains 23,562 samples and 12 features.

**Statlog (German Credit Data)** (Kamiran and Calders 2009) is a benchmark dataset that contains gender-based bias. The dataset contains customers’ data, such as demographic information, account information, out-of-bank possessions, and loan request information. The dataset corresponds to the task of determining whether the customer should be considered for a loan. After filtering samples with missing values and nonmeaningful features, the dataset contains 1,000 samples and 20 features.

**Telco Churn** Additional experiments were performed on a European Telco’s churn prediction ML model and dataset. This ML model is a DNN-based model that predicts customer churn, i.e., whether a customer will terminate his/her Telco subscription. The model was trained and used internally, i.e., the model is not accessible through the Internet. The Telco’s churn dataset contains real customers’ accounts and demographic information. The data contains 95,704 samples and 28 features, and the protected feature is gender. Bias presented in the churn prediction task might result in the company offering different incentives to different customers, depending on the customer’s protected feature value. For example, bias towards female customers (assuming they will not churn) could potentially result in offering better incentives to male customers. In addition, bias in the churn prediction model may harm public relations and cause a reduction in revenue.

**Synthetic Data** In order to provide a sanity check, we generated a synthetic dataset. The dataset contains three binary
| Bias evaluation method                                                      | Ethical aspect examined                                                                                       |
|--------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| Equalized odds (Hardt, Price, and Srebro 2016)                            | Given a specific ground truth label, examines whether the protected feature value affects the ML model’s probability of producing a positive ML model’s outcome. |
| Disparate impact (Feldman et al. 2015)                                   | Examines whether the protected feature value affects the ML model’s probability of producing a positive ML model’s outcome. |
| Demographic parity (Dwork et al. 2012)                                   | Examines whether the protected feature value affects the ML model’s probability of producing a positive ML model’s outcome. |
| Sensitivity (Feldman et al. 2015)                                        | Examines whether the protected feature value affects the true positive rate (TPR) of the ML model’s outcomes. |
| Specificity (Feldman et al. 2015)                                       | Examines whether the protected feature value affects the true negative rate (TNR) of the ML model’s outcomes. |
| Balance error rate (Feldman et al. 2015)                                | Examines whether the protected feature value affects the error level of the ML model’s outcomes.             |
| LR+ measure (Feldman et al. 2015)                                        | Checks whether the protected feature value affects the TPR opposite ratio of the ML model’s outcomes.        |
| Equal positive prediction value (Berk et al. 2018)                       | Examines whether the protected feature value affects the precision of the ML model’s outcomes.                |
| Equal negative prediction value (Berk et al. 2018)                       | Examines whether the protected feature value affects the ratio between the number of true positive (TP) and negative outcomes. |
| Equal accuracy (Berk et al. 2018)                                        | Examines whether the protected feature value affects the accuracy of the ML model’s outcomes.                 |
| Equal opportunity (Hardt, Price, and Srebro 2016)                       | Given a positive ground truth label, examines whether the protected feature value affects the ML model’s probability of outputting a positive ML model’s outcome. |
| Treatment equality (Verma and Rubin 2018)                               | Examines whether the protected feature value affects the ratio between the number of false negative (FN) and false positive (FP) ML model outcomes. |
| Equal false positive rate (Berk et al. 2018)                            | Examines whether the protected feature value affects the false positive rate (FPR) of the ML model’s outcomes. |
| Equal false negative rate (Berk et al. 2018)                            | Examines whether the protected feature value affects the false negative rate (FNR) of the ML model’s outcomes. |
| Error rate balance (Narayanan 2018)                                     | Examines whether the protected feature value affects the FNR and FPR of the ML model’s outcomes.             |
| Normalized difference (Zliobaite 2015)                                  | Examines whether any of the protected feature values has an advantage in terms of obtaining a positive outcome from the ML model. |
| Mutual information (Fukuchi, Kamishima, and Sakuma 2015)                 | Examines whether the protected feature contributes to the entropy of the ML model’s outcomes, i.e., the effect of the protected feature on the ML model’s outcome. |
| Balance residuals (Calders et al. 2013)                                 | Examines whether the protected feature value affects the error rate of the ML model’s outcomes.             |
| Calibration (Chouldechova 2017)                                          | Given a specific risk score value, examines whether the protected feature value affects the ML model’s probability of outputting a positive ML model’s outcome. |
| Prediction parity (Chouldechova 2017)                                   | Given a risk score value higher than a specific risk score threshold, examines whether the protected feature value affects the ML model’s probability of outputting a positive ML model’s outcome. |
| Error rate balance with score (ERBS) (Chouldechova 2017)                | Given a negative/positive ML model outcome, examines whether the risk score value is higher/lower than a specific risk score threshold. |

Table 3: Existing bias detection and estimation methods and their ethical aspects

features, two of which are protected: one is a fair feature (has no bias) and one is extremely biased (has maximal bias), and a random feature. The dataset consists of 305 samples, which are composed from every possible combination of the feature values. In order to construct the protected bias feature, we set each record value in the biased feature to be correlated with the true label, i.e., if the record label was one, then the bias feature value is set at one as well. In order to construct the protected fair feature, we duplicate each possible record and set the fair feature at one for the first record and zero for the second.