VTRUST : CONTROLLABLE VALUE FUNCTION BASED SUBSET SELECTION FOR DATA-CENTRIC TRUSTWORTHY AI

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ABSTRACT

Trustworthy AI is crucial to the widespread adoption of AI in high-stakes applications with *explainability, fairness and robustness* being some of the key trustworthiness metrics. *Data-Centric AI* (DCAI) aims to construct high quality datasets for efficient training of trustworthy models. In this work, we propose a controllable framework for data-centric trustworthy AI (DCTAI)- VTruST, that allows users to control the trade-offs between the different trustworthiness metrics of the constructed training datasets. A key challenge in implementing an efficient DCTAI framework is to design an online value-function-based training data subset selection algorithm. We pose the training data valuation and subset selection problem as an online sparse approximation formulation, where the features for each training datapoint is obtained in an online manner through an iterative training algorithm. We propose a novel online-version of the OMP algorithm for solving this problem. We also derive conditions on the data matrix, that guarantee the exact recovery of the sparse solution. We demonstrate the generality and effectiveness of our approach by designing data-driven value functions for the above trustworthiness metrics. Experimental results show that VTruST outperforms the state-of-the-art baselines for fair learning as well as robust training, on standard fair and robust datasets. We also demonstrate that VTruST can provide effective tradeoffs between different trustworthiness metrics through pareto optimal fronts. Finally, we show that the data valuation generated by VTruST can provide effective data-centric explanations for different trustworthiness metrics.

1 INTRODUCTION

The field of artificial intelligence (AI) has seen rapid advancements leading to its involvement in our daily lives. This usefulness comes with heightened responsibility especially in high-stake applications such as predicting the risk of criminal recidivism (Angwin et al., 2016), autonomous driving (Kohli & Chadha, 2020; Chen et al., 2021), disaster management (Linardos et al., 2022) and many more. In order for users to trust the decision of the AI algorithms, it is essential for them to be fair, reliable and robust under different circumstances. There is a substantial body of research in the area of model-centric AI where the need for making the models robust (Wang et al., 2022; Hataya & Nakayama, 2022) or fair (Roh et al., 2020; Romano et al., 2020) or unbiased (Gat et al., 2020; Majumdar et al., 2021) or explainable (Pillai & Pirsiavash, 2021; Sarkar et al., 2022) has been explored while keeping the data fixed. However, the core input to the models, *the data*, has undergone reasonably less exploration. With the upcoming progress in the field of *Data-Centric AI* [1] (Hajij et al., 2021; Motamedi et al., 2021), currently the focus has shifted to creating quality datasets to avoid data cascades in real world setting [2]. The DCAI approach comes with several advantages - identifying data points that explain certain model characteristics (Seedat et al., 2022b; Ethayarajh et al., 2022), selecting useful datapoints for efficient training (Das et al., 2021a; Pooladzandi et al., 2022), discarding noisy samples deviating training trajectory (Pruthi et al., 2020; Das et al., 2021b),

[1] `https://datacentricai.org/`

[2] `https://ai.googleblog.com/2021/06/data-cascades-in-machine-learning.html`

scoring datapoints based on a value function reflecting their contribution to the task (Yoon et al., 2020; Lin et al., 2022) and many more.

In this work, we design a data-centric approach to achieving trustworthy AI through a controllable data valuation framework with the composition of several value functions aimed at key trustworthy AI metrics - fairness, robustness, and explainability. Additionally, we allow the users to control the balance between the trustworthiness metrics. We pose the problem of training data valuation and selection as an online sparse approximation problem, which we execute using a novel online version of OMP (Cai & Wang, 2011). Unlike in OMP where the decision of including the optimal variables happens iteratively *looking at the entire data each time*, our proposed method, VTruST, works in an online setup where the data arrives incrementally and the decision of inclusion/exclusion happens on the fly by *only iterating over the already included variables*. We add a *DataReplace* component which enforces conditions based on the projections leading to the replacement of already selected non-optimal features. To the best of our knowledge, this is one of the first works to provide a single unified framework for balancing between the multiple value functions, followed by data valuation and extraction of subsets. These subsets when trained from scratch, lead to fairer, more robust, or more accurate models depending on the usage of value functions.

To summarize, our main contributions in the paper are: (1) We design a data-centric controllable selection framework that helps us obtain a subset of training datapoints specifically suited for trustworthiness metrics. (2) We formulate the value functions for the metrics of fairness, robustness, and accuracy. We also design a sampling algorithm for constructing augmented datasets for robustness. (3) We provide theoretical derivations of the conditions used in VTruST and show that they are sufficient for the exact recovery of the sparse solution. (4) We demonstrate that VTruST with subsets of even 20% of the original dataset, is able to outperform all state-of-the-art baselines by $\sim 10-20\%$ in both the tasks of fairness and robustness and can also provide data-centric explanations behind its performance.

2 VTruST: Value-driven Trustworthy AI through Selection of Training Data

We propose a controllable value function-based framework for developing trustworthy models using a data-centric paradigm. Our system has two main components: (1) A general value function-based framework that allows users to specify a combination of trustworthiness metrics, and (2) a novel online subset selection algorithm for constructing high-quality training dataset based on the specified value function. Section 2.1 describes the framework under which different value functions can be specified for different trustworthiness metrics. Section 2.2 defines different value functions for data-centric trustworthy AI. Section 2.3 describes the sparse approximation-based online subset selection algorithm that efficiently selects subset which can optimally approximate the value function.

2.1 A Controllable Value Function-based Framework for DCTAI

Let $\mathcal{D} = \{d_i = (u_i, w_i) | i = 1, 2, .., N\}$ be the training dataset for a supervised learning task with input $u_i \in \mathcal{U}$ and labels $w_i \in \mathcal{W}$. Similarly, let $\mathcal{D}' = \{d'_j = (u'_j, w'_j) | j = 1, 2, .., M\}$ be the validation dataset which is used for assigning values/scores to a training datapoint $d_i \in \mathcal{D}$ based on a value function. The total value function, $\mathcal{V}^T(d'_j) = \sum_{t=1}^{T} \sum_{i=1}^{N} v_i^t(d'_j)\ \forall d'_j \in \mathcal{D}'$, defines a measure of the utility of the training dataset, defined for each datapoint validation dataset $\mathcal{D}'$. We also overload the notation to define the value function vector $\mathcal{V}^T(\mathcal{D}') = \sum_{t=1}^{T} \sum_{i=1}^{N} v_i^t(\mathcal{D}')$. The total value function is defined as an additive function over $v_i^t(\mathcal{D}')$, the value contributed by the training datapoints d_i on the t^{th} epoch, $t = 1, ..., T$. A commonly used value function in the data valuation literature (Pruthi et al., 2020), which is defined as the decrease in loss incurred due to an SGD update using the datapoint d_i: $v_i^t(d'_j) = l(\theta_t^{i-1}, d'_j) - l(\theta_t^i, d'_j)$, where θ_t^{i-1} and θ_t^i are the model parameters before and after the SGD update involving the training datapoint d_i in the t^{th} epoch. We call this the value function for accuracy, since each term measures the contribution of the training datapoint d_i towards improving the validation loss which is a proxy for the validation accuracy: $\mathcal{V}_a(d'_j) = \sum_{t=1}^{T} \sum_{i=1}^{N} v_i^t(d'_j) = \sum_{t=1}^{T} \sum_{i=1}^{N} (l(\theta_t^{i-1}, d'_j) - l(\theta_t^i, d'_j))$. Other value functions for fairness and robustness are defined in the next section.

Given any value function $\mathcal{V}$, our aim is to find a subset of training datapoints $S \in \mathcal{D}$ that lead to an accurate approximation of the total value function in each epoch, as a weighted summation of contributions from the selected set of points S. Let $y_t(d'_j) = \mathcal{V}^t(d'_j) = \sum_{k=1}^{t} \sum_{i=1}^{N} v_i^k(d'_j)$ be the cumulative value function till the t^{th} epoch. We are interested in the following sparse approximation: $y_t(d'_j) \approx \sum_{d_i \in S \subseteq \mathcal{D}} \alpha_i [\sum_{k=1}^{t} v_i^k(d'_j)]$, where α_i are the weights for each training datapoint d_i. Using a second order Taylor series expansion of the loss function $l(\theta_t^i, d'_j)$ around $l(\theta_t^{i-1}, d'_j)$, and plugging in the SGD update formula $\theta_t^i - \theta_t^{i-1} = \eta_t \nabla l(\theta_t^{i-1}, d_i)$, we obtain the following approximation for each term in the value function $l(\theta_t^i, \mathcal{D}') - l(\theta_t^{i-1}, \mathcal{D}') \approx \eta_t \nabla l(\theta_t^{i-1}, d_i)^T \nabla l(\theta_t^{i-1}, \mathcal{D}') + \mathcal{O}(||\theta_t^i - \theta_t^{i-1}||_2^2)$. We truncate the Taylor expansion till the second-order terms, and absorb the learning rates η_t in the learned coefficients α_i, in order to arrive at the following sparse approximation problem:

$$y_t(d'_j) \approx \sum_{d_i \in S} \alpha_i \sum_{k=1}^{t} \left[X_i^k(d'_j)\right] \; \forall d'_j \in \mathcal{D}', \; t = 1, ..., T \tag{1}$$

where $X_i^k(d'_j) = \nabla l(\theta_k^{i-1}, d_i)^T \nabla l(\theta_k^{i-1}, d'_j) + \frac{(\nabla l(\theta_k^{i-1}, d_i)^T \nabla l(\theta_k^{i-1}, d'_j))^2}{2}$ are the features for the i^{th} training point calculated in epoch t. We use the vectors $\vec{y_t} = [y_t(d'_j) | j \in \mathcal{D}']$ and $\vec{X}_i^t = [X_i^t(d'_j) | j \in \mathcal{D}']$ to denote the predictor and predicted variables over the entire validation set.

The main challenge in solving the above sparse approximation problem is that we need to store the cumulative features: $\sum_{k=1}^{t} X_i^k(d'_j)$, for all training and validation point-pairs (i, j) and for all epochs $t = 1, ..., T$. This becomes computationally prohibitive for many practical scenarios. Instead, we solve the following *online sparse approximation* (OSA) problem for each epoch t:

$$y_t(d'_j) \approx \sum_{(p,q) \in S_t} \beta_p^q \left[X_p^q(d'_j)\right] \; \forall d'_j \in \mathcal{D}', \; t = 1, ..., T \tag{2}$$

Here, S_t is the set of selected training datapoints at the end of the t^{th} epoch. Note that the set S_t can contain features from any of the epochs $q = 1, ..., t$. We constrain the size of the selected training datapoints to be less than a user-specified parameter k. To summarize, we pose the online sparse approximation problem as: $\min_{S_1, S_2, .., S_T, \vec{\beta}} \sum_{t=1}^{T} || \sum_{(p,q) \in S_t} (\beta_p^q \vec{X}_p^q) - \vec{y_t} ||_2^2 \quad s.t. |S_t| \leq k \; \forall t = 1, ..., T$, where $\vec{\beta}$ is the set of all learned coefficients β_p^q for all $(p, q) \in S_t$. Note that at any point in time t, we only need to store the $\vec{\beta}$ and S_t for only the current time instance. In section 2.3, we describe an online algorithm for solving the above problem. We also highlight that the value function $\mathcal{V}(d'_j)$ only needs to satisfy an additive property over the training datapoints and epochs in order for the above formulation to be valid. Hence, this framework is applicable to a composite value function $\mathcal{V}(d'_j) = \sum_f \lambda_f \mathcal{V}_f(d'_j)$, where each value function $\mathcal{V}_f(.)$ satisfies the additive property. This leads us to a general *controllable* framework for incorporating many trustworthiness value functions, controlled using the user-specified weights λ_f.

2.2 Value Functions for Trustworthy Data-centric AI

In this section, we define additive value functions aimed at the trustworthiness metrics - *robustness* and *fairness*.

Robustness Value Function: It was observed in (Rebuffi et al., 2021; Addepalli et al., 2022) that data augmentation improves robust accuracy and reduces robust overfitting. We use this idea of augmenting datapoints and define the *robust value function* ($\mathcal{V}_{rvf}(\mathcal{D}', \mathcal{D}'_a)$) as a composite value function over accuracy ($\mathcal{V}_a(\mathcal{D}')$) and robustness($\mathcal{V}_r(\mathcal{D}'_a)$). We define the accuracy value function $\mathcal{V}_a(\mathcal{D}') = \sum_{t=1}^{T} \sum_{d_i \in \{\mathcal{D} \cup \mathcal{D}_a\}} l(\theta_t^i, \mathcal{D}') - l(\theta_t^{i-1}, \mathcal{D}')$ using both validation dataset $\mathcal{D}'$ as described above. The robustness value function is defined as $\mathcal{V}_r(\mathcal{D}'_a) = \sum_{t=1}^{T} \sum_{d_i \in \{\mathcal{D} \cup \mathcal{D}_a\}} l(\theta_t^i, \mathcal{D}'_a) - l(\theta_t^{i-1}, \mathcal{D}'_a)$, where $\mathcal{D}_a$ and $\mathcal{D}'_a$ are the augmented data (formed by adding brightness, impulse noise, etc.) from $\mathcal{D}$ and $\mathcal{D}'$ respectively. Hence, the overall value function used for robustness experiments is $\mathcal{V}_{rvf}(\mathcal{D}', \mathcal{D}'_a) = \lambda \mathcal{V}_a(\mathcal{D}') + (1 - \lambda) \mathcal{V}_r(\mathcal{D}'_a)$ where λ is a user-defined parameter controlling the tradeoffs between accuracy and robustness. We note that above value function can also be arrived at by simply defining the combined loss function: $l_c(\theta_t^i, \mathcal{D}', \mathcal{D}'_a) = \lambda l(\theta_t^i, \mathcal{D}') + (1 - \lambda) l(\theta_t^i, \mathcal{D}'_a)$, and then defining the value function as usual: $\mathcal{V}_{rvf}(\mathcal{D}', \mathcal{D}'_a) = \sum_{t=1}^{T} \sum_{d_i \in \{\mathcal{D} \cup \mathcal{D}_a\}} l_c(\theta_t^i, \mathcal{D}', \mathcal{D}'_a) - l_c(\theta_t^{i-1}, \mathcal{D}', \mathcal{D}'_a)$. Hence, the above framework works directly in this setting. Note that, the obtained training subset is a mixture of both unaugmented and augmented data.

Fairness Value Function: Existing literature in fairness (Roh et al., 2020; Romano et al., 2020) uses equalized odds disparity and demographic parity disparity for achieving fair models. We use the *equalized odds disparity*-based (EOD) objective function defined in (Roh et al., 2020) as our compositional value function for fairness. Let $x \in \mathcal{X}$ be the input domain, $\{y_0, y_1\} \in \mathcal{Y}$ be the true binary labels, and $\{z_0, z_1\} \in \mathcal{Z}$ be the sensitive binary attributes. As before, we define the *fair value function* $\mathcal{V}_{fvf}(\mathcal{D}')$ as the compositional value function over accuracy ($\mathcal{V}_a(\mathcal{D}')$) and fairness ($\mathcal{V}_f(\mathcal{D}')$) i.e $\mathcal{V}_{fvf}(\mathcal{D}') = \lambda \mathcal{V}_a(\mathcal{D}') + (1 - \lambda)\mathcal{V}_f(\mathcal{D}')$. Analogous to other value functions, we define fairness value function as the change in EOD: $\mathcal{V}_f(\mathcal{D}') = \sum_{t=1}^{T} \sum_{d_i \in \mathcal{D}} ed(\theta_t^i, \mathcal{D}') - ed(\theta_t^{i-1}, \mathcal{D}')$. Here the EOD is defined as the maximum difference in accuracy between the sensitive groups ($z \in \mathcal{Z}$) pre-conditioned on the true label ($y \in \mathcal{Y}$): $ed(\theta, \mathcal{D}') = max(\|l(\theta, \mathcal{D}'_{y_0, z_0}) - l(\theta, \mathcal{D}'_{y_0, z_1})\|, \|l(\theta, \mathcal{D}'_{y_1, z_0}) - l(\theta, \mathcal{D}'_{y_1, z_1})\|)$ (Roh et al., 2021b). We note that contrary to the accuracy and robustness value functions, where there is one value for every validation datapoint, there is a single disparity measure for the entire validation dataset for fairness. As previously, we can redefine $\mathcal{V}_{fvf}(\mathcal{D}') = \sum_{t=1}^{T} \sum_{d_i \in \mathcal{D}} ld_c(\theta_t^i, \mathcal{D}') - ld_c(\theta_t^{i-1}, \mathcal{D}')$ where $ld_c(\theta, \mathcal{D}')$ is a combined loss function involving accuracy and disparity metric: $ld_c(\theta, \mathcal{D}') = \lambda.l(\theta, \mathcal{D}') + (1 - \lambda).ed(\theta, \mathcal{D}')$.

2.3 AN ONLINE-OMP ALGORITHM FOR ONLINE SPARSE APPROXIMATION

In this section, we describe a novel online-OMP based algorithm for the *online sparse approximation problem*(OSA): $\min_{S_1, S_2, .., S_T, \vec{\beta}} \sum_{t=1}^{T} || \sum_{(p,q) \in S_t} (\beta_p^q \vec{X}_p^q) - \vec{y_t}||_2^2 \quad s.t. |S_t| \leq k \ \forall t = 1, ..., T$. The key difference between OSA and standard sparse approximation setting is that in OSA, new columns $\vec{X}_p^q$ are added and the target value $\vec{y_t}$ is updated at each epoch t. Algorithm 1 describes the novel online OMP-based algorithm for OSA. Line 9 adds new columns $\vec{X}_i^t$ till the cardinality of S_t reaches k. Once the buffer is saturated, the *DataReplace* module in Algorithm 2 is invoked in line 7 to potentially replace an existing selected column with the current new column. The criteria for replacement is to select the columns in the S_t that contribute to a better approximation of the current value function $\vec{y_t}$. Hence a new column $\vec{X}_i^t$ gets selected if the current approximation error reduces after the replacement.We compute the projection of the current column, $\vec{X}_i^t$ and that of the selected columns $\vec{X}_q^p \ \forall p, q \in S_t$ on the existing residual vector $\vec{\rho}_t$, measured by π and π' respectively. We also denote by γ, the contribution of column $p, q \in S_t$ (β_q^p). The column (p, q) in S_t whose additive impact ($\pi' + \gamma$) is smaller than that of incoming colmun (i, t), but larger than the current feature for replacement ($\vec{X}_q^p$), gets substituted with the incoming point in line 14 having conditioned on the projection and the beta quotient in line 8 of Algorithm 2.

Note that the proposed algorithm is different from OMP Cai & Wang (2011) since OMP scans the entire list of columns for improvement on approximation error till k columns are selected. Hence it cannot be used in the online sparse approximation setting. A related work by Jain et al. (2011) proposes OMPR (OMP with replacement) which replaces columns using hard thresholding on the projections of columns on residuals. However, it is not applied in an online setting and the entire data is expected to be available during the approximation. Bayesian OMP Herzet & Dremeau (2014) unrealistically assumes knowledge of the distribution of columns. To the best of our knowledge, the current work is the first to attempt the problem of online sparse approximation. The per-epoch time complexity of OMP is $\mathcal{O}(kMN)$ and that of OMPR (Jain et al., 2011) $\mathcal{O}(\tau kMN)$ where τ is the total number of iterations for the convergence of their algorithm. The proposed method, *VTruST* has a total time complexity of $\mathcal{O}(kM(N - k))$.

Conditions for Optimality of the Selected Subset: The proposed algorithm solves the online sparse approximation problem, where the optimal selected subset depends on the order in which the columns are added to the problem. We derive the conditions for an ordering $\Pi(\vec{X})$ of columns of the global matrix $\vec{X}$ to produce an optimal set of columns $\vec{X}_{(T)}$, as the selected set using the VTruST algorithm. For simplicity, we follow the notation in Cai & Wang (2011). Let $\vec{X}$ be the set of all columns $\{\vec{X}_1, .., \vec{X}_N\}$ and $\vec{X}_{(T)}$ be an optimal set of columns approximating the value function $\vec{y}$. Also, let $\vec{X}_{(O)}$ denote the set of columns not included in the optimal set $\vec{X}_{(T)}$. We index the columns corresponding to selected datapoints by $\vec{X}_{(s_m)}$ where $m \in \{1, 2, .., N\}$. Using $\vec{X}_{(T)}$, we can obtain the set of optimal selected columns as $\vec{X}_{(c_m)} : \vec{X}_{(s_m)} \cap \vec{X}_{(T)}$; and the non-optimal ones as $\vec{X}_{(o_m)} : \vec{X}_{(s_m)} \setminus \vec{X}_{(c_m)}$. The algorithm aims to reduce the residual $\vec{\rho}_m$ which as we know is $\vec{\rho}_m = \vec{y} - \vec{\beta}_{(s_m)}\vec{X}_{(s_m)}$. Using the above, we can also rewrite as: $\vec{\rho}_m = \vec{y} - \vec{\beta}_{(c_m)}\vec{X}_{(c_m)} - \vec{\beta}_{(o_m)}\vec{X}_{(o_m)}$. We define the theorem which states the conditions for selection of an optimal set of elements.

Theorem 2.1 (Conditions in terms of Algorithm) $\forall m \in \{k+1, \dots N\}\ \exists \vec{X}_{(T)} \in \mathcal{X}\ s.t.\ \forall x \in \vec{X}_{(T)}$, $\forall z \in \vec{X}_{(o_m)}$ *if* $|\vec{\rho}_m^T x| > |\vec{\rho}_m^T z|$ *and* $\beta_z < 0$, *then* x *will be included in* $\vec{X}_{(s_{m+1})}$ *by replacing* z *that satisfies the condition* $max_z |\vec{\rho}_m^T z| + \beta_z$

The proof is provided in the Appendix.

Algorithm 1 : **VTruST**

```
Input:
  i. $k$ : Total number of datapoints to be selected
  ii. $\vec{y}$ : Targeted value function
  iii. $\vec{X}_i$ : Features of all training points $d_i \in \mathcal{D}$
  iv. $S$ : Set of selected datapoint indices
  v. $\vec{\beta} \in \mathbb{R}^{|S|}$: Weight of selected datapoints
Initialize:
  $S \longleftarrow \phi$ //Indices of selected datapoints
for each epoch $t \in \{1, 2, \dots, T\}$ do
    for each datapoint $d_i \in \mathcal{D}$ do
        Input: $\vec{y}_t, X_i^t \quad \forall i \in \{1, 2, .., N\}, ||X_i^t||_2 = 1$
        Process:
        if $|S_{t-1}| = k$ then
            $S_t \longleftarrow$ DataReplace($\vec{y}_t, \vec{\xi}_{t-1}, S_{t-1}, \vec{\beta}_{t-1}, \vec{X}_i^t$)
        else
            $S_t \longleftarrow S_{t-1} \cup \{i\}$
        end if
        Update $\vec{\beta}_t = \text{argmin}_\beta \|\vec{y}_t - \sum_{p,q \in S_t}(\beta_q^p \vec{X}_q^p)||_2$
        Update $\vec{\xi}_t = \sum_{p,q \in S_t} \beta_q^p \vec{X}_q^p$
    end for
end for
Output:Final set of selected datapoint indices $S_T$, learned coefficients
  $\{\beta_q^p | p, q \in S_T\}$
```

Algorithm 2 : **DataReplace**($\vec{y}_t, \vec{\xi}_t, S_t, \vec{\beta}_t, \vec{X}_i^t$)

```
$\vec{\rho}_t = \vec{y}_t - \vec{\xi}_t$
$\pi_{max} = -\infty$
$(a, b) = \phi$
$\pi \longleftarrow \text{abs}(\vec{X}_i^t . \vec{\rho}_t)$
for each index $p, q \in S_t$ do
    $\pi' \longleftarrow \text{abs}(\vec{X}_q^p . \vec{\rho}_t)$
    $\gamma \longleftarrow \beta_q^p$
    if $\pi > \pi'$ & $\gamma \leq 0$ & $(\pi' + \gamma) > \pi_{max}$ then
        $\pi_{max} \longleftarrow \pi' + \gamma$
        $a, b \longleftarrow p, q$
    end if
end for
if $(a, b) \neq \phi$ then
    $S \longleftarrow S \setminus \{a, b\} \cup \{t, i\}$
end if
return $S$
```

3 Experimental Evaluation

In this section, we describe the datasets, models, and evaluation metrics used for the standard performance and trustworthiness metrics - Robustness and Fairness. We analyze the performance of *VTruST* using data-centric explanations of the subsets. All our experiments have been executed on a single Tesla V100 GPU.

3.1 Error rate, Fairness and Robustness on Tabular Data

We evaluate VTruST against baselines (wholedata standard training (ST), random, SSFR (Roh et al., 2021a), FairMixup Mroueh et al. (2021) and FairDummies (Romano et al., 2020)) on four classification datasets: COMPAS (Angwin et al., 2016) , Adult Census (Kohavi et al., 1996), MEPS-20 (mep) and a synthetic dataset proposed by (Roh et al., 2021a). We use a 2-layer neural network for all the datasets. For evaluation, we use the error-rate (ER) and fairness measures of equalised odds (Hardt et al., 2016) and demographic parity (Feldman et al., 2015) following (Roh et al., 2021a).

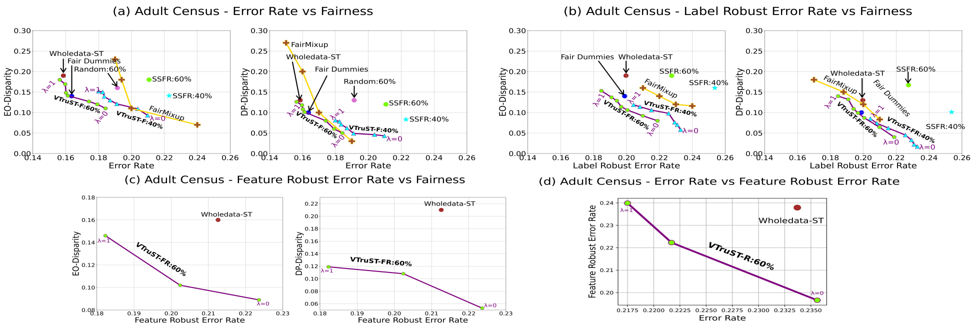
Fairness and Error Rate comparison (VTruST-F) with baselines: We compare the performance metrics of VTruST-F with the baselines in Table 1. The better the model is, the lower its ER as well as its disparity/fairness measures. We can observe in Table 1 that VTruST-F with 60% selected subset outperforms all the other methods in terms of fairness measures by a margin of 0.01-0.10, and performs close to Wholedata-ST that yields the lowest ER. This denotes that it is able to condemn the error-fairness tradeoff to a certain extent, emerging out to be the best performing method. We report these results with standard deviation across 3 runs.

Table 1: **Comparison of VTruST-F with baselines over 60% subset for fairness evaluation.**

Methods	Synthetic			COMPAS			AdultCensus			MEPS20		
	ER ±std	EO Disp ±std	DP Disp ±std	ER ±std	EO Disp ±std	DP Disp ±std	ER ±std	EO Disp ±std	DP Disp ±std	ER ±std	EO Disp ±std	DP Disp ±std
Wholedata-ST	0.27 ±0.001	0.28 ±0.03	0.28 ±0.02	0.34 ±0.001	0.31 ±0.05	0.24 ±0.03	0.16 ±0.002	0.19 ±0.06	0.13 ±0.06	0.09 ± 0.001	0.09 ± 0.007	0.08 ± 0.0008
Random	0.29 ±0.001	0.24 ±0.02	0.26 ±0.02	0.35 ±0.002	0.20 ±0.10	0.23 ±0.09	0.19 ±0.002	0.16 ±0.05	0.13 ±0.05	0.12 ±0.017	0.06 ±0.02	0.08 ±0.005
SSFR	0.29 ±0.002	0.25 ±0.02	0.29 ±0.01	0.35 ±0.002	0.26 ±0.03	0.17 ±0.02	0.21 ±0.001	0.18 ±0.03	0.12 ±0.01	0.14 ±0.003	0.10 ±0.011	0.06 ±0.005
Fair-Dummies	0.29 ±0.002	0.22 ±0.02	0.22 ±0.01	0.35 ±0.002	0.24 ±0.02	0.17 ±0.01	0.16 ±0.002	0.14 ±0.01	0.10 ±0.01	0.12 ±0.001	0.13 ±0.005	0.08 ±0.003
Fair-Mixup	0.29 ±0.02	0.18 ±0.03	0.20 ±0.05	0.35 ±0.03	0.15 ±0.03	0.13 ±0.04	0.24 ±0.04	0.11 ±0.05	0.1 ±0.02	0.89 ±0.02	0.02 ±0.04	0.05 ±0.03
VTruST-F	0.28 ±0.001	**0.17 ±0.01**	**0.19 ±0.01**	0.34 ±0.002	**0.15 ±0.01**	**0.13 ±0.01**	0.18 ±0.001	**0.11 ±0.03**	**0.05 ±0.01**	0.09 ±0.003	**0.01 ±0.001**	**0.05 ±0.0008**

Tradeoffs between Error rate, Fairness and Robustness (VTrust-F , VTruST-FR, VTrust-R): We observe the tradeoffs between error rate vs fairness (VTruST-F: Figure 1a), fairness vs robustness (VTruST-FR: Figure 1b and 1c), and error rate vs robustness (VTruST-R: Figure 1d) through pareto frontal curve. Figure 1 shows the pareto frontier for the different combinations. We perform the experiments of robustness on tabular data in 2 ways: (a) label flipping following Roh et al. (2021a) and (b) feature augmentation using SMOTE (Chawla et al., 2002). Error rate is measured on the clean test sets while robust error rates are measured on the flipped and augmented test sets.

For VTruST-F and VTruST-FR, we vary the weightage $\lambda \in \{0, 0.1, 0.3, 0.5, 0.7, 0.9, 1\}$ and for VTruST-R, we vary it between $0 - 1$ in steps of 0.5. The factor $\lambda = 0$ puts the entire weightage on the disparity measure in the case of VTruST-F and VTruST-FR, and on robust error rate for VTruST-R. Figure 1 shows that VTruST-F, VTrust-FR, and VTruST-R follow the desired pattern across all the setups. We can observe that Wholedata-ST has a lower error rate but high disparity/robust error values. The other baselines continue to have a higher error rate and disparity compared to VTruST. *Note that we report the remaining results on other datasets in the Appendix.*


(a) Adult Census - Error Rate vs Fairness

(b) Adult Census - Label Robust Error Rate vs Fairness

(c) Adult Census - Feature Robust Error Rate vs Fairness

(d) Adult Census - Error Rate vs Feature Robust Error Rate

Figure 1: **Controlling tradeoffs in trustworthiness metrics in clean and augmented data setup for tabular domain.**

3.2 Accuracy and Robustness on Image Data

We evaluate VTruST on three image datasets: CIFAR10 (Krizhevsky et al., 2009) , MNIST (Deng, 2012) and Tinyimagenet (Le & Yang, 2015). We use ResNet-18 model (He et al., 2016) for all datasets. For evaluation, we use the standard accuracy (SA) computed on the clean test sets and the robust accuracy (RA) computed on their respective corrupted test sets, CIFAR-10-C, Tiny ImageNet-C (Hendrycks & Dietterich, 2019) and MNIST-C (Mu & Gilmer, 2019).

Despite the fact that augmentation leads to robustness (Rebuffi et al., 2021), it also leads to a large dataset with redundancy. Hence we use our framework to select a high-quality data for further evaluation. We adopt the data-centric approach in creating an augmented set followed by subset selection using VTruST. Next, we define the setup of the baselines.

(i) *Clean-ST*: Trained on unaugmented training set. (ii) *Uniform Augmentation (UAug)*: Trained on datasets added with augmentations chosen uniformly at random. (iii) *Sampled Augmentation (SAug)*: Trained on datasets added with augmentations sampled using Algorithm **??**. (Wang et al., 2021) (iv) *SSR* (Roh et al., 2021a): Trained on subset obtained using the objective function only for robustness. (v) *AugMax* (Wang et al., 2021).

Table 3: **Comparison of VTruST-R over varying subset sizes for robustness evaluation. The numbers in brackets indicate the difference with the second best among baselines.**

Methods	MNIST			CIFAR10				TinyImagenet			
	#Data points	**SA**	**RA**	**#Data points**	**SA**	**RA**	**Train Time (min/ep)**	**#Data points**	**SA**	**RA**	**Train Time (min/ep)**
Clean-ST	60K	99.35	87.00	50K	95.64	83.95	3.03	100K	63.98	23.36	10.02
AugMax	240K	97.62	88.79	200K	94.74	86.44	13.78	400K	54.82	40.98	61.2
SAug	260K	**99.36** (1.74)	**97.31** (8.52)	200K	**94.9** (0.16)	**90.13** (3.69)	12.1	300K	**62.04** (7.22)	**42.04** (1.06)	28.7
After subset selection from SAug											
SSR:20%	52K	98.79	86.51	40K	92.17	79.29	2.45	60K	20.26	16.05	10.35
VTruST-R:20%	52K	98.76	**92.46** (3.67)	40K	92.25	85.54	2.45	60K	49.0	34.14	10.35
SSR:40%	104K	98.98	94.96	80K	93.3	85.73	4.9	120K	32.82	24.42	13.5
VTruST-R:40%	104K	**99.04** (0.06)	**96.29** (1.33)	80K	**94.74**	**88.23** (1.79)	4.9	120K	**57.3** (2.48)	39.69	13.5
SSR:60%	156K	99.07	96.53	120K	93.77	88.0	7.4	180K	41.94	30.07	22.32
VTruST-R:60%	156K	**99.12** (0.05)	**97.09** (0.56)	120K	**94.77** (0.03)	**89.21** (1.21)	7.4	180K	**60.88** (6.03)	**41.50** (0.52)	22.32

Table 4: **Performance comparison with data valuation methods on CIFAR10**

Methods	GraNd	GradMatch	TracIn	Data Shapley	DVRL	VTrust-R
SA	85.1	71.1	62.76	61.13	82.1	**87.0**

Why Sampled Augmentation? We train models for individual augmentations (viz. brightness, impulse noise etc.) and test on all the corrupted test sets. A sample heatmap in Figure 2 for CIFAR10 depicts the difference in performance across augmentations. Based on this heatmap, we develop an algorithm *Sampled Augmentation (SAug)* that samples images based on how far the current model is from the self-trained augmentation model's performance (diagonal elements) which turns out to be best for any augmentation. We define Sampling Number (*SN*) for augmentation j as a normalised difference between the average RA for aug j (RA_j) and the self-trained accuracy. We compare SAug vs UAug in Table 2(with dataset size in brackets) where it can be seen that SAug outperforms UAug by a significant margin thus turning out to be our augmented data for further experiments.

Robustness and Accuracy comparison (VTruST-R) with baselines: We compare VTruST-R with the baselines in Table 3 where it can be clearly seen that model using clean datasets (*Clean-ST*) performs abysmally in terms of RA, thus indicating the need of augmentations. In some cases, VTruST-R outperforms AugMax in terms of RA even at fractions $<$ 60% (MNIST 20% , CIFAR10 40%), thus indicating that data-centric approaches help in creating quality training datasets. Additionally, we also experiment with some existing data valuation methods (GraNd (Paul et al., 2021), GradMatch (Killamsetty et al., 2021) , TracIn (Pruthi et al., 2020), Data Shapley (Ghorbani & Zou, 2019), DVRL (Yoon et al., 2020)) on CIFAR10 where we train on 20% subset of the *original unaugmented data* and report the Standard Accuracy (SA) in Table 4. We intentionally refrain from reporting the Robust Accuracy (RA) since it is expected to underperform due to the absence of augmented data as seen from Clean-ST's performance in Table 3. In this case too, VTruST is observed to outperform the considered methods by a reasonable margin.

Figure 2: **Performance of self-trained augmentation models on augmented test sets.**

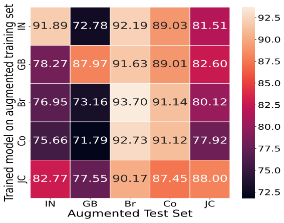
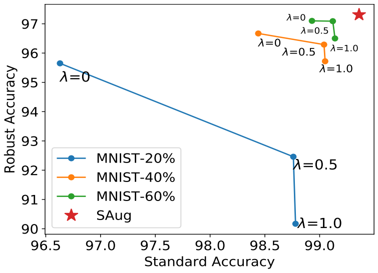


Table 2: **Comparison of Uniform Augmentation with Sampled Augmentation.**

Methods	Standard Accuracy	Robust Accuracy
UAug(260K) MNIST	99.34	97.12
SAug(260K) MNIST	**99.37** **(0.04)**	**97.31** **(0.19)**
UAug(200K) CIFAR10	94.84	89.06
SAug(200K) CIFAR10	**94.9** **(0.06)**	**90.13** **(1.07)**
UAug(300K) TinyImageNet	60.92	26.87
SAug(300K) TinyImageNet	**62.04** **(1.12)**	**42.04** **(15.87)**

Figure 3: **Performance across fractions of subset for varying weights (λ).**



Tradeoff between Accuracy and Robustness: We vary the weightage (λ) on $\mathcal{V}_{rvf}$ and observe in Figure 3 that both the accuracies vary as per λ, with 20% subset showing considerably larger change. Note that unlike the tradeoff in error-rate/accuracy vs fairness, a large tradeoff is not observed between SA and RA (as also observed by (Yang et al., 2020)) across all the fractions. It is likely to be an artifact of the datasets used.

3.3 Data-centric analysis: Post hoc explanation

We pose the following question: *From a data-centric point of view, what characteristics do the selected instances on a per data point level, hold that leads to the fair or robust subset and eventually a fair or robust model?* In this section, we intend to explore some properties/characteristics of the selected samples along with some anecdotal examples.

Explanation for fairness:

Exploring the area of counterfactual fairness, we arrive at the question: *Given we change only the sensitive attribute of the selected instances, how does the decision of the model change?* The lesser it changes, fairer the algorithm is. We use the metric *Counterfactual Token Fairness Gap (CF-Gap)*(Garg et al., 2019) and *Prediction Sensitivity*(Maughan & Near, 2020) for our evaluation.

Given a selected instance x, we generate a counterfactual instance x' by altering its sensitive attribute. From (Garg et al., 2019), we define CF-Gap(x) as $\|f(x_i) - f(x'_i)|$ where $f(x)$ corresponds to the model confidence on the target label. Alongside, prediction sensitivity quantifies the extent to which $f(x)$ depends on the sensitive attribute z and is defined as $\frac{\partial f(x)}{\partial z}$. We plot the distribution of both these metrics in Figure 4. It can be observed that VTruST-F acquires the least values across both the measures and datasets, justifying its retainment of fair subsets leading to fair models.

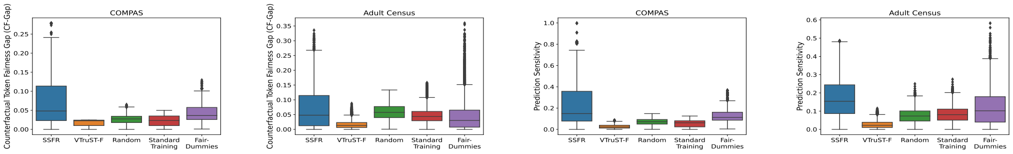


Figure 4: **Box plot representation of CF-gap and prediction sensitivity on the selected subsets from VTruST-F and other baselines.**

We show 10 anecdotal samples from Adult Census dataset in Table 5 on the basis of high *CF-Gap* and we can observe that SSFR has a large number of redundant samples with similar attribute values like that of *(Private, Married-civ-spouse, Husband, White, Male, United States)*, while VTruST-F which anyway has relatively lower CF-gap contains a diverse set of samples. Similar pattern is observed in terms of *Prediction Sensitivity* which we show in the Appendix.

Table 5: **Sample instances with High Counterfactual Token Fairness Gap**

VTruST-F								SSFR							
Feat	**Age**	**WCl**	**MS**	**Rel**	**Race**	**Sex**	**NC**	***Feat***	**Age**	**WCl**	**MS**	**Rel**	**Race**	**Sex**	**NC**
D_1	25	Priv	SEP	ORel	B	F	JM	D_1	55	Priv	MCS	Husb	W	M	US
D_2	41	FedG	NM	NIF	W	M	US	D_2	41	Priv	MCS	Husb	W	M	US
D_3	43	StG	NM	NIF	W	M	US	D_3	29	Priv	MCS	Husb	W	M	US
D_4	29	Priv	NM	OC	API	F	TW	D_4	55	Priv	MCS	Husb	W	M	US
D_5	60	Priv	MCS	Husb	W	M	US	D_5	42	LoG	MCS	Husb	W	M	US
D_6	35	Priv	Div	UnM	W	F	US	D_6	30	Priv	MCS	Husb	W	M	US
D_7	51	SEnI	MCS	Wife	W	F	US	D_7	25	Priv	NM	NIF	W	M	US
D_8	23	Priv	NM	OC	W	M	US	D_8	23	Priv	NM	OC	W	M	US
D_9	39	Priv	Div	NIF	AIE	F	Col	D_9	35	Priv	MCS	Husb	W	M	DE
D_{10}	34	Priv	NM	UnM	W	F	DE	D_{10}	18	Priv	NM	OC	W	M	US

Explanation for robustness:

Delving into the literature ((Swayamdipta et al., 2020) (Huang et al., 2018)), we pick two measures - *uncertainty* and *distinctiveness*. Having a set of hard-to-learn and distinguishable samples in the subsets makes the model more generalizable and robust. We quantify uncertainty of an instance x in the form of predictive entropy $(-f(x)logf(x))$ and distinctiveness as $\mathbb{E}_{e\in X(s)}dist(fv(x), fv(e))$ where $dist(,)$ is the euclidean distance and $fv(.)$ is the feature from the model's penultimate layer.

We visualize the datapoints in the two dimensions - Uncertainty and Distinctiveness in Figure 5 where we choose a random set of 5000 points from CIFAR and TinyImagenet datasets, followed by marking them as *selected* and *not selected* by VTruST-R and SSR respectively. We can observe that points with relatively high uncertainty and high distinctiveness(HD-HU) values mostly belong to the *selected set of VTruST-R*, while the *unselected points from SSR* mostly cover the HD-HU region.

We also show some anecdotal samples in Figure 6 having High Distinctiveness-High Uncertainty(HD-HU). It can be seen from the anecdotal samples as well as the histogram visualisation, that for VTruST-R, diverse samples with difficult augmentations like Impulse noise, Glass Blur are more observed in HD-HU category, while similar(mostly white-background) and unaugmented or No-Noise(NN) samples or easier augmentation based samples like that of brightness are more observed in SSR anecdotal samples, thus justifying the robust selection using VTruST-R.

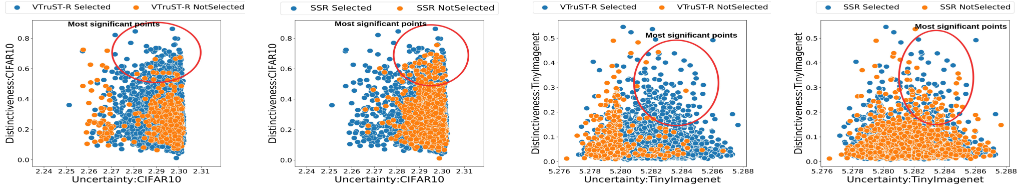


Figure 5: **Data Map for randomly taken 5000 samples from CIFAR10 and TinyImagenet augmented training dataset**

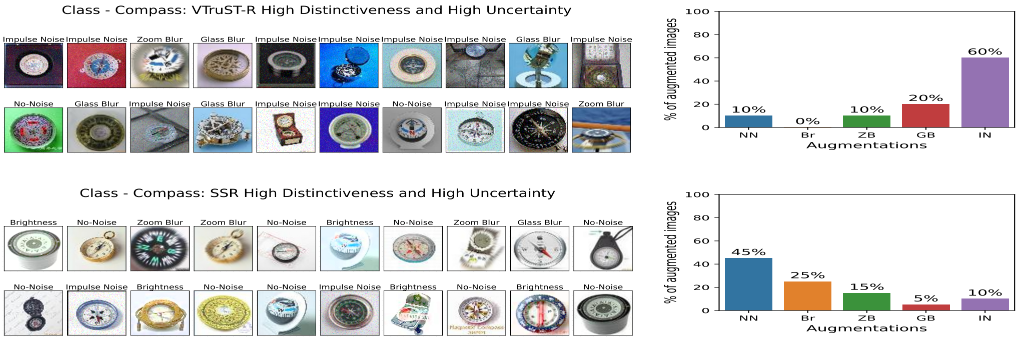


Figure 6: **Anecdotal samples from VTruST-R & SSR with High Distinctiveness and Uncertainty from TinyImagenet for class Compass.**

4 Related Work and Discussion

Besides the usual building of trustworthy models, (Liang et al., 2022) highlights the need for proper data sculpting in order to make the AI systems more trustworthy.The primary task in the robustness and fairness literature is to design robust (Wang et al., 2021), (Chen et al., 2022) and fair (Zemel et al., 2013),(Roh et al., 2020),(Romano et al., 2020),(Sattigeri et al., 2022),(Chuang & Mroueh, 2021) models. To begin with, they use pre-trained models and optimize them further to achieve the desired trustworthy goals. On the contrary, we aim to obtain a subset targeted at a pre-defined trustworthy objective followed by training them from scratch. Broadly, there are two approaches in DCAI for obtaining quality data : (a) data quality measures (Swayamdipta et al., 2020; Ethayarajh et al., 2022; Seedat et al., 2022a;b) and data valuation techniques (Yoon et al., 2020; Ghorbani & Zou, 2019; Pruthi et al., 2020; Das et al., 2021b; Wang & Jia, 2022; Paul et al., 2021). Our work is closely related to the latter among which, most of the works provide a generic method of valuation. The works of (Ghorbani & Zou, 2019; Wang & Jia, 2022) uses value functions that turn out to be expensive due to the usage of MCMC-based approaches. To the best of our knowledge, ours is one of the first works in DCAI that develops a controllable framework to balance the different trustworthiness metrics (fairness and robustness) leading to desired subsets in an online training paradigm. We validate the efficacy of VTruST empirically and also show that this data-centric oriented approach aids in providing data-centric explanations behind its performance.

Exploring suitable value functions for other aspects of trustworthy AI like privacy in the context of subset selection is an open problem. For example, one can use privacy loss as a part of a compositional value function as $\mathcal{V}_p = max(|l(\theta, \mathcal{D}') - l(\theta, \mathcal{D}'_a|)$. The privacy loss shall ensure to retain such datapoints from the training set ($\mathcal{D} \cup \mathcal{D}_a$) that shall keep it at a minimum thus reducing the risk of membership inference attacks thereby maintaining privacy. Hence, one can definitely explore our framework by constructing suitable value functions for the remaining aspects of trustworthy AI.

Reproducibility Statement

We run all our experiments on publicly available datasets and thus all our results can be seamlessly reproduced. We also attach our code (with README) in the Supplementary to aid reproducibility. Details on model architectures and datasets are provided in the main paper. The remaining details for obtaining reproducible results can be found in the Appendix and the attached code repository.

References

Medical expenditure panel survey. URL https://meps.ahrq.gov/data_stats/data_use.jsp.

Sravanti Addepalli, Samyak Jain, et al. Efficient and effective augmentation strategy for adversarial training. *Advances in Neural Information Processing Systems*, 35:1488–1501, 2022.

Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner. Machine bias. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing, 2016.

T. Tony Cai and Lie Wang. Orthogonal matching pursuit for sparse signal recovery with noise. *IEEE Transactions on Information Theory*, 57(7):4680–4688, 2011. doi: 10.1109/TIT.2011.2146090.

Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002.

Long Chen, Shaobo Lin, Xiankai Lu, Dongpu Cao, Hangbin Wu, Chi Guo, Chun Liu, and Fei-Yue Wang. Deep neural network based vehicle and pedestrian detection for autonomous driving: A survey. *IEEE Transactions on Intelligent Transportation Systems*, 22(6):3234–3246, 2021.

Tianlong Chen, Peihao Wang, Zhiwen Fan, and Zhangyang Wang. Aug-nerf: Training stronger neural radiance fields with triple-level physically-grounded augmentations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 15191–15202, June 2022.

Ching-Yao Chuang and Youssef Mroueh. Fair mixup: Fairness via interpolation. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=DNl5s5BXeBn.

Soumi Das, Harikrishna Patibandla, Suparna Bhattacharya, Kshounis Bera, Niloy Ganguly, and Sourangshu Bhattacharya. Tmcoss: Thresholded multi-criteria online subset selection for data-efficient autonomous driving. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 6341–6350, 2021a.

Soumi Das, Arshdeep Singh, Saptarshi Chatterjee, Suparna Bhattacharya, and Sourangshu Bhattacharya. Finding high-value training data subset through differentiable convex programming. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 666–681. Springer, 2021b.

Li Deng. The mnist database of handwritten digit images for machine learning research. *IEEE Signal Processing Magazine*, 29(6):141–142, 2012.

Kawin Ethayarajh, Yejin Choi, and Swabha Swayamdipta. Understanding dataset difficulty with $\mathcal{V}$ - usable information. In *International Conference on Machine Learning*, pp. 5988–6008. PMLR, 2022.

Michael Feldman, Sorelle A Friedler, John Moeller, Carlos Scheidegger, and Suresh Venkatasubramanian. Certifying and removing disparate impact. In *proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining*, pp. 259–268, 2015.

Sahaj Garg, Vincent Perot, Nicole Limtiaco, Ankur Taly, Ed H Chi, and Alex Beutel. Counterfactual fairness in text classification through robustness. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 219–226, 2019.

Itai Gat, Idan Schwartz, Alexander Schwing, and Tamir Hazan. Removing bias in multi-modal classifiers: Regularization by maximizing functional entropies. *Advances in Neural Information Processing Systems*, 33:3197–3208, 2020.

Amirata Ghorbani and James Zou. Data shapley: Equitable valuation of data for machine learning. In *International Conference on Machine Learning*, pp. 2242–2251. PMLR, 2019.

Mustafa Hajij, Ghada Zamzmi, Karthikeyan Natesan Ramamurthy, and Aldo Guzman Saenz. Data-centric ai requires rethinking data notion. *arXiv preprint arXiv:2110.02491*, 2021.

Moritz Hardt, Eric Price, and Nati Srebro. Equality of opportunity in supervised learning. *Advances in neural information processing systems*, 29, 2016.

Ryuichiro Hataya and Hideki Nakayama. Djmix: Unsupervised task-agnostic image augmentation for improving robustness of convolutional neural networks. In *2022 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8, 2022. doi: 10.1109/IJCNN55064.2022.9892068.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016.

Dan Hendrycks and Thomas Dietterich. Benchmarking neural network robustness to common corruptions and perturbations. *Proceedings of the International Conference on Learning Representations*, 2019.

Cédric Herzet and Angélique Dremeau. Bayesian pursuit algorithms. *CoRR*, abs/1401.7538, 2014. URL `http://arxiv.org/abs/1401.7538`.

Sheng-Jun Huang, Jia-Wei Zhao, and Zhao-Yang Liu. Cost-effective training of deep cnns with active model adaptation. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 1580–1588, 2018.

Prateek Jain, Ambuj Tewari, and Inderjit Dhillon. Orthogonal matching pursuit with replacement. *Advances in neural information processing systems*, 24, 2011.

Krishnateja Killamsetty, Durga Sivasubramanian, Baharan Mirzasoleiman, Ganesh Ramakrishnan, Abir De, and Rishabh Iyer. Grad-match: A gradient matching based data subset selection for efficient learning. *arXiv preprint arXiv:2103.00123*, 2021.

Ron Kohavi et al. Scaling up the accuracy of naive-bayes classifiers: A decision-tree hybrid. In *Kdd*, volume 96, pp. 202–207, 1996.

Puneet Kohli and Anjali Chadha. Enabling pedestrian safety using computer vision techniques: A case study of the 2018 uber inc. self-driving car crash. In *Advances in Information and Communication: Proceedings of the 2019 Future of Information and Communication Conference (FICC), Volume 1*, pp. 261–279. Springer, 2020.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Ya Le and Xuan Yang. Tiny imagenet visual recognition challenge. *CS 231N*, 7(7):3, 2015.

Weixin Liang, Girmaw Abebe Tadesse, Daniel Ho, L Fei-Fei, Matei Zaharia, Ce Zhang, and James Zou. Advances, challenges and opportunities in creating data for trustworthy ai. *Nature Machine Intelligence*, 4(8):669–677, 2022.

Jinkun Lin, Anqi Zhang, Mathias Lécuyer, Jinyang Li, Aurojit Panda, and Siddhartha Sen. Measuring the effect of training data on deep learning predictions via randomized experiments. In *International Conference on Machine Learning*, pp. 13468–13504. PMLR, 2022.

Vasileios Linardos, Maria Drakaki, Panagiotis Tzionas, and Yannis L Karnavas. Machine learning in disaster management: Recent developments in methods and applications. *Machine Learning and Knowledge Extraction*, 4(2):446–473, 2022.

Puspita Majumdar, Richa Singh, and Mayank Vatsa. Attention aware debiasing for unbiased model prediction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 4133–4141, 2021.

Krystal Maughan and Joseph P Near. Towards a measure of individual fairness for deep learning. *arXiv preprint arXiv:2009.13650*, 2020.

Mohammad Motamedi, Nikolay Sakharnykh, and Tim Kaldewey. A data-centric approach for training deep neural networks with less data. *arXiv preprint arXiv:2110.03613*, 2021.

Youssef Mroueh et al. Fair mixup: Fairness via interpolation. In *International Conference on Learning Representations*, 2021.

Norman Mu and Justin Gilmer. MNIST-C: A robustness benchmark for computer vision. *CoRR*, abs/1906.02337, 2019.

Mansheej Paul, Surya Ganguli, and Gintare Karolina Dziugaite. Deep learning on a data diet: Finding important examples early in training. *Advances in Neural Information Processing Systems*, 34:20596–20607, 2021.

Vipin Pillai and Hamed Pirsiavash. Explainable models with consistent interpretations. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pp. 2431–2439, 2021.

Omead Pooladzandi, David Davini, and Baharan Mirzasoleiman. Adaptive second order coresets for data-efficient machine learning. In *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*. PMLR, 2022.

Garima Pruthi, Frederick Liu, Satyen Kale, and Mukund Sundararajan. Estimating training data influence by tracing gradient descent. In *Advances in Neural Information Processing Systems*, 2020.

Sylvestre-Alvise Rebuffi, Sven Gowal, Dan Andrei Calian, Florian Stimberg, Olivia Wiles, and Timothy A Mann. Data augmentation can improve robustness. *Advances in Neural Information Processing Systems*, 34:29935–29948, 2021.

Yuji Roh, Kangwook Lee, Steven Euijong Whang, and Changho Suh. Fairbatch: Batch selection for model fairness. *arXiv preprint arXiv:2012.01696*, 2020.

Yuji Roh, Kangwook Lee, Steven Whang, and Changho Suh. Sample selection for fair and robust training. *Advances in Neural Information Processing Systems*, 34:815–827, 2021a.

Yuji Roh, Kangwook Lee, Steven Euijong Whang, and Changho Suh. Fairbatch: Batch selection for model fairness. In *ICLR*, 2021b. URL `https://openreview.net/forum?id=YNnpaAKeCfx`.

Yaniv Romano, Stephen Bates, and Emmanuel Candes. Achieving equalized odds by resampling sensitive attributes. *Advances in Neural Information Processing Systems*, 33:361–371, 2020.

Anirban Sarkar, Deepak Vijaykeerthy, Anindya Sarkar, and Vineeth N Balasubramanian. A framework for learning ante-hoc explainable models via concepts. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10286–10295, 2022.

Prasanna Sattigeri, Soumya Ghosh, Inkit Padhi, Pierre Dognin, and Kush R Varshney. Fair infinitesimal jackknife: Mitigating the influence of biased training data points without refitting. *arXiv preprint arXiv:2212.06803*, 2022.

Nabeel Seedat, Jonathan Crabbé, Ioana Bica, and Mihaela van der Schaar. Data-iq: Characterizing subgroups with heterogeneous outcomes in tabular data. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 23660–23674. Curran Associates, Inc., 2022a. URL `https://proceedings.neurips.cc/paper_files/paper/2022/file/95b6e2ff961580e03c0a662a63a71812-Paper-Conference.pdf`.

Nabeel Seedat, Jonathan Crabbe, and Mihaela van der Schaar. Data-suite: Data-centric identification of in-distribution incongruous examples. *arXiv preprint arXiv:2202.08836*, 2022b.

Swabha Swayamdipta, Roy Schwartz, Nicholas Lourie, Yizhong Wang, Hannaneh Hajishirzi, Noah A. Smith, and Yejin Choi. Dataset cartography: Mapping and diagnosing datasets with training dynamics. In *Proceedings of EMNLP*, 2020. URL `https://arxiv.org/abs/2009.10795`.

Haotao Wang, Chaowei Xiao, Jean Kossaifi, Zhiding Yu, Anima Anandkumar, and Zhangyang Wang. Augmax: Adversarial composition of random augmentations for robust training. *Advances in neural information processing systems*, 34:237–250, 2021.

Haotao Wang, Aston Zhang, Shuai Zheng, Xingjian Shi, Mu Li, and Zhangyang Wang. Removing batch normalization boosts adversarial training. In *International Conference on Machine Learning*, pp. 23433–23445. PMLR, 2022.

Tianhao Wang and Ruoxi Jia. Data banzhaf: A data valuation framework with maximal robustness to learning stochasticity. *arXiv preprint arXiv:2205.15466*, 2022.

Yao-Yuan Yang, Cyrus Rashtchian, Hongyang Zhang, Russ R Salakhutdinov, and Kamalika Chaudhuri. A closer look at accuracy vs. robustness. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems*, volume 33, pp. 8588–8601. Curran Associates, Inc., 2020. URL `https://proceedings.neurips.cc/paper/2020/file/61d77652c97ef636343742fc3dcf3ba9-Paper.pdf`.

Jinsung Yoon, Sercan Arik, and Tomas Pfister. Data valuation using reinforcement learning. In *International Conference on Machine Learning*, pp. 10842–10851. PMLR, 2020.

Rich Zemel, Yu Wu, Kevin Swersky, Toni Pitassi, and Cynthia Dwork. Learning fair representations. In Sanjoy Dasgupta and David McAllester (eds.), *Proceedings of the 30th International Conference on Machine Learning*, volume 28 of *Proceedings of Machine Learning Research*, pp. 325–333, Atlanta, Georgia, USA, 17–19 Jun 2013. PMLR.