# DataExposer: Exposing Disconnect between Data and Systems

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## ABSTRACT

As data is a central component of many modern systems, the cause of a system malfunction may reside in the data, and, specifically, particular properties of the data. For example, a health-monitoring system that is designed under the assumption that weight is reported in imperial units (lbs) will malfunction when encountering weight reported in metric units (kilograms). Similar to software debugging, which aims to find bugs in the mechanism (source code or runtime conditions), our goal is to debug the data to identify potential sources of *disconnect* between the assumptions about the data and the systems that operate on that data. Specifically, we seek which *properties* of the data cause a data-driven system to malfunction. We propose DataExposer, a framework to identify data properties, called *profiles*, that are the root causes of performance degradation or failure of a system that operates on the data. Such identification is necessary to repair the system and resolve the disconnect between data and system. Our technique is based on *causal reasoning* through *interventions*: when a system malfunctions for a dataset, DataExposer alters the data profiles and observes changes in the system's behavior due to the alteration. Unlike statistical observational analysis that reports mere correlations, DataExposer reports causally verified root causes—in terms of data profiles—of the system malfunction. We empirically evaluate DataExposer on three real-world and several synthetic data-driven systems that fail on datasets due to a diverse set of reasons. In all cases, DataExposer identifies the root causes precisely while requiring orders of magnitude fewer interventions than prior techniques.

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## 1 INTRODUCTION

Traditional software debugging aims to identify errors and bugs in the mechanism—such as source code, configuration files, and runtime conditions—that may cause a system to malfunction [24, 35, 49]. However, in modern systems, data has become a central component that itself can cause a system to fail. Data-driven systems comprise complex pipelines that rely on data to solve a target task. Prior work addressed the problem of debugging machine-learning models [12] and finding root causes of failures in computational pipelines [51], where certain values of the pipeline parameters—such as a specific model and/or a specific dataset—cause the pipeline failure. However, just knowing that a pipeline fails for a certain dataset is not enough; naturally, we ask: what *properties* of a dataset caused the failure?

Two common reasons for malfunctions in data-driven systems are: (1) incorrect data, and (2) *disconnect* between the assumptions about the data and the design of the system that operates on the data. Such disconnects may happen when the system is not robust, i.e., it makes strict assumptions about metadata (e.g., data format, domains, ranges, and distributions), and when new data drifts from the data over which the system was tested on before deployment [58] (e.g., when a system expects a data stream to have a weekly frequency, but the data provider suddenly switches to daily data).

Therefore, in light of a failure, one should investigate potential issues in the data. Some specific examples of commonly observed system malfunctions caused by data include: (1) decline of a machine-learned model's accuracy (due to out-of-distribution data), (2) unfairness in model predictions (due to imbalanced training data), (3) excessive processing time (due to a system's failure to scale to large data), and (4) system crash (due to invalid input combination in the data tuples beyond what the system was designed to handle). These examples indicate a common problem: *disconnect* or *mismatch* between the data and the system design. Once the mismatch is identified, then possible fixes could be either to repair the data to suit the system design, or to adjust the system design (e.g., modify source code) to accommodate data with different properties.

A naïve approach to deal with potential issues in the data is to identify outliers: report tuples as potentially problematic based on how atypical they are with respect to the rest of the tuples in the dataset. However, without verifying whether the outliers actually cause unexpected outcomes, we can never be certain about the actual root causes. As pointed out in prior work [7]: *"With respect to a computation, whether an error is an outlier in the program's input distribution is not necessarily relevant. Rather, potential errors can be spotted by their effect on a program's output distribution."* To motivate our work, we start with an example taken from a real-world incident, where Amazon's delivery service was found to be racist [43].

Example 1 (Biased Classifier). *An e-commerce company wants to build an automated system that suggests who should get discounts. To this end, they collect information from the customers' purchases over one year and build a dataset over the attributes* `name`, `gender`, `age`, `race`, `zip_code`, `phone`, `products_purchased`, *etc. Anita, a*


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*data scientist, is then asked to develop a machine learning (ML) pipeline over this dataset to predict whether a customer will spend over a certain amount, and, subsequently, should be offered discounts. Within this pipeline, Anita decides to use a logistic regression classifier for prediction and implements it using an off-the-shelf ML library. To avoid discrimination over any group and to ensure that the classifier trained on this dataset is fair, Anita decides to drop the sensitive attributes—*`race` *and* `gender`*—during the pre-processing step of the ML pipeline, before feeding it to the classifier. However, despite this effort, the trained classifier turns out to be highly biased against African American people and women. After a close investigation, Anita discovers that: (1) In the training data,* `race` *is highly correlated with* `zip_code`*, and (2) The training dataset is imbalanced: a larger fraction of the people who purchase expensive products are male. Now she wonders: if these two properties did not hold in the dataset, would the learned classifier be fair? Have either (or both) of these properties caused the observed unfairness?*

Unfortunately, existing tools (e.g., CheckCell [7]) that blame individual cells (values) for unexpected outcomes cannot help here, as no single cell in the training data is responsible for the observed discrimination, rather, global statistical properties (e.g., correlation) that involve multiple attributes over the entire data are the actual culprits. Furthermore, Anita only identified two potential or *correlated* data issues that may or may not be the actual cause of the unfairness. To distinguish mere correlation from true causation and to verify if there is indeed a *causal* connection between the data properties and the observed unfairness, we need to dig deeper.

Example 1 is one among many incidents in real-world applications where issues in the data caused systems to malfunction [9, 33]. A recent study of 112 high-severity incidents in Microsoft Azure services showed that 21% of the bugs were due to inconsistent assumptions about data format by different software components or versions [50]. The study further found that 83% of the data-format bugs were due to inconsistencies between data producers and data consumers, while 17% were due to mismatch between interpretations of the same data by different data consumers. Similar incidents happened due to misspelling and incorrect date-time format [60], and issues pertaining to data fusion where schema assumptions break for a new data source [19, 71]. We provide another illustrative example where a system times out when the distribution of the data, over which the system operates, exhibits significant skew.

Example 2 (Process Timeout). *A toll collection software EZGo checks if vehicles passing through a gate have electronic toll pass installed. If it fails to detect a toll pass, it uses an external software OCR to extract the registration number from the vehicle's license plate. EZGo operates in a batch mode and processes every* 1000 *vehicles together by reserving AWS for one hour, assuming that one hour is sufficient for processing each batch. However, for some batches, EZGo fails. After a close investigation, it turns out that the external software OCR uses an algorithm that is extremely slow for images of black license plates captured in low illumination. As a result, when a batch contains a large number of such cases (significantly skewed distribution), EZGo fails.*

The aforementioned examples bring forth two key challenges. First, we need to correctly identify potential causes of unexpected outcomes and generate *hypotheses* that are expressive enough to capture the candidate root causes. For example, "outliers cause unexpected outcomes" is just one of the many possible hypotheses, which offers very limited expressivity. Second, we need to *verify* the hypotheses to confirm or refute them, which enables us to pinpoint the actual root causes, eliminating false positives.

*Data profile as root cause.* Towards solving the first challenge, our observation is that data-driven systems often function properly for certain datasets, but malfunction for others. Such malfunction is often rooted in certain *properties* of the data, which we call *data profiles*, that distinguish passing and failing datasets. Examples include size of a dataset, domains and ranges of attribute values, correlations between attribute pairs, conditional independence [73], functional dependencies and their variants [14, 23, 40, 45, 54], and other more complex data profiles [18, 48, 55, 69].

*Oracle-guided root cause identification.* Our second observation is that if we have access to an *oracle* that can indicate whether the system functions desirably or not, we can verify our hypotheses. Access to an oracle allows us to precisely isolate the correct root causes of the undesirable malfunction from a set of candidate causes. Here, an oracle is a mechanism that can characterize whether the system functions properly over the input data. The definition of proper functioning is application-specific; for example, achieving a certain accuracy may indicate proper functioning for an ML pipeline. Such oracles are often available in many practical settings, and have been considered in prior work [24, 51].

**Solution sketch.** In this paper, we propose DataExposer, a framework that identifies and exposes data profiles that cause a data-driven system to malfunction. Our framework involves two main components: (1) an intervention-based mechanism that alters the profiles of a dataset, and (2) a mechanism that speeds up analysis by carefully selecting appropriate interventions. Given a scenario where a system malfunctions (fails) over a dataset but functions properly (passes) over another, DataExposer focuses on the *discriminative* profiles, i.e., data profiles that significantly differ between the two datasets. DataExposer's intervention mechanism modifies the "failing" dataset to alter one of the discriminative profiles; it then observes whether this intervention causes the system to perform desirably, or the malfunction persists. DataExposer speeds up this analysis by favoring interventions on profiles that are deemed more likely causes of the malfunction. To estimate this likelihood, we leverage three properties of a profile: (1) *coverage*: the more tuples an intervention affects, the more likely it is to fix the system behavior, (2) *discriminating power*: the bigger the difference between the failing and the passing datasets over a profile, the more likely that the profile is a cause of the malfunction, and (3) *attribute association*: if a profile involves an attribute that is also involved with a large number of other discriminative profiles, then that profile has high likelihood to be a root cause. This is because altering such a profile is likely to passively repair other discriminative profiles as a side-effect (through the associated attribute). We also provide a group-testing-based technique that allows *group intervention*, which helps expedite the root-cause analysis further.

**Scope.** In this work, we assume knowledge of the classes of (domain-specific) data profiles that encompass the potential root causes. E.g., in Example 1, we assume the knowledge that correlation between attribute pairs and disparity between the conditional probability

distributions (the probability of belonging to a certain gender, given price of items bought) are potential causes of malfunction. This assumption is realistic because: (1) For a number of tasks there exists a well-known set of relevant profiles: e.g., class imbalance and correlation between sensitive and non-sensitive attributes are common causes of unfairness in classification [8]; and violation of conformance constraints [25], missing values, and out-of-distribution tuples are well-known causes of ML model's performance degradation. (2) Domain experts are typically aware of the likely class of data profiles for the specific task at hand and can easily provide this additional knowledge as a *conservative* approximation, i.e., they can include extra profiles just to err on the side of caution. Notably, this assumption is also extremely common in software debugging techniques [24, 49, 75], which rely on the assumption that the "predicates" (traps to extract certain runtime conditions) are expressive enough to encode the root causes, and software testing [52], validation [47], and verification [37] approaches, which rely on the assumption that the test cases, specifications, and invariants reasonably cover the codebase and correctness constraints.

To support a data profile, DataExposer further needs the corresponding mechanisms for discovery and intervention. In this work, we assume knowledge of the profile discovery and intervention techniques, as they are orthogonal to our work. Nevertheless, we discuss some common classes of data profiles supported in DataExposer and the corresponding discovery and intervention techniques. For data profile discovery, we rely on prior work on pattern discovery [56], statistical-constraint discovery [73], data-distribution learning [36], knowledge-graph-based concept identification [30], etc. While our evaluation covers specific classes of data profiles (for which there exist efficient discovery techniques), our approach is generic and works for any class of data profiles, as long as the corresponding discovery and intervention techniques are available.

**Limitations of prior work.** To find potential issues in data, Dagger [59, 60] provides data debugging primitives for human-in-the-loop interactions with data-driven computational pipelines. Other explanation-centric efforts [5, 17, 22, 71] report salient properties of historical data based only on observations. In contrast with observational techniques, the presence of an oracle allows for interventional techniques [51] that can query the oracle with additional, system-generated test cases to identify root causes of system malfunction more accurately. One such approach is CheckCell [7], which presents a ranked list of cells of data rows that unusually affect output of a given target function. CheckCell uses a fine-grained approach: it removes one cell of the data at a time, and observes changes in the output distribution. While it is suitable for small datasets, where it is reasonable to expect a human-in-the-loop paradigm to fix cells one by one, it is not suitable for large datasets, where no individual cell is significantly responsible, rather, a holistic property of the entire dataset (profile) causes the problem.

Interpretable machine learning is related to our problem, where the goal is to explain behavior of machine-learned models. However, prior work on interpretable machine learning [61, 62] typically provide *local* (tuple-level) explanations, as opposed to *global* (dataset-level) explanations. While some approaches provide feature importance as a global explanation for model behavior [15], they do not model feature interactions as possible explanations.

Software testing and debugging techniques [3, 4, 16, 28, 32, 34, 38, 44, 49, 75] are either application-specific, require user-defined test suites, or rely only on observational data. The key contrast between software debugging and our setting is that the former focuses on white-box programs: interventions, runtime conditions, program invariants, control-flow graphs, etc., all revolve around program source code and execution traces. Unlike programs, where lines have logical and semantic connections, tuples in data do not have similar associations. Data profiles significantly differ in their semantics, and discovery and intervention techniques from program profiles, and, thus, techniques for program profiling do not trivially apply here. We treat data as a first-class citizen in computational pipelines, while considering the program as a black box.

**Contributions.** In this paper, we make the following contributions:

- We formalize the novel problem of identifying root causes (and fixes) of the disconnect between data and data-driven systems in terms of data profiles (and interventions). (Sec 2)
- We design a set of data profiles that are common root causes of data-driven system malfunctions, and discuss their discovery and intervention techniques based on available technology. (Sec 3)
- We design and develop a novel interventional approach to pinpoint causally verified root causes. The approach leverages a few properties of the data profiles to efficiently explore the space of candidate root causes with a small number of interventions. Additionally, we develop an efficient group-testing-based algorithm that further reduces the number of required interventions. (Sec 4)
- We evaluate DataExposer on three real-world applications, where data profiles are responsible for causing system malfunction, and demonstrate that DataExposer successfully explains the root causes with a very small number of interventions (< 5). Furthermore, DataExposer requires 10–1000× fewer interventions when compared against two state-of-the-art techniques for root-cause analysis: BugDoc [51] and Anchors [62]. Through an experiment over synthetic pipelines, we further show that the number of required interventions by DataExposer increases sub-linearly with the number of discriminative profiles, thanks to our group-testing-based approach. (Sec 5)

## 2 PRELIMINARIES & PROBLEM DEFINITION

In this section, we first formalize the notions of system malfunction and data profile, its violation, and transformation function used for intervention. We then proceed to define explanation (cause and corresponding fix) of system malfunction and formulate the problem of data-profile-centric explanation of system malfunction.

**Basic notations.** We use $\mathcal{R}(A_1, A_2, \ldots, A_m)$ to denote a relation schema over $m$ attributes, where $A_i$ denotes the $i^{th}$ attribute. We use $\texttt{Dom}_i$ to denote the domain of attribute $A_i$. Then the set $\mathbf{Dom}^m = \texttt{Dom}_1 \times \cdots \times \texttt{Dom}_m$ specifies the domain of all possible tuples. A dataset $D \subseteq \mathbf{Dom}^m$ is a specific instance of the schema $\mathcal{R}$. We use $t \in \mathbf{Dom}^m$ to denote a tuple in the schema $\mathcal{R}$. We use $t.A_i \in \texttt{Dom}_i$ to denote the value of the attribute $A_i$ of the tuple $t$ and use $D.A_j$ to denote the multiset of values all tuples in $D$ take for attribute $A_j$.

### 2.1 Quantifying System Malfunction

To measure how much the system malfunctions over a dataset, we use the *malfunction score*.

Definition 3 (Malfunction score). *Let $D \subseteq \mathbf{Dom}^m$ be a dataset, and $S$ be a system operating on $D$. The malfunction score $m_S(D) \in [0, 1]$ is a real value that quantifies how much $S$* malfunctions *when operating on $D$.*

The malfunction score $m_S(D) = 0$ indicates that $S$ functions properly over $D$ and a higher value indicates a higher degree of malfunction, with 1 indicating extreme malfunction. A threshold parameter $\tau$ defines the acceptable degree of malfunction and translates the continuous notion of malfunction to a Boolean value. If $m_S(D) \leq \tau$, then $D$ is considered to pass with respect to $S$; otherwise, there exists a mismatch between $D$ and $S$, whose cause (and fix) we aim to expose.

Example 4. *For a binary classifier, its misclassification rate (additive inverse of accuracy) over a dataset can be used as a malfunction score. Given a dataset $D$, if a classifier $S$ makes correct predictions for tuples in $D' \subseteq D$ , and incorrect predictions for the remaining tuples, then $S$ achieves accuracy $\frac{|D'|}{|D|}$, and, thus, $m_S(D) = 1 - \frac{|D'|}{|D|}$.*

Example 5. *In fair classification, we can use disparate impact [39], which is defined by the ratio between the number of tuples with favorable outcomes within the unprivileged and the privileged groups, to measure malfunction.*

## 2.2 Profile-Violation-Transformation (PVT)

Once we detect existence of a mismatch, the next step is to investigate its cause. We characterize the issues in a dataset that are responsible for the mismatch between the dataset and the system using *data profiles*. Structure or schema of data profiles is given by profile *templates*, which contains holes for parameters. Parameterizing a profile template gives us a *concretization* of the corresponding profile ($P$). Given a dataset $D$, we use existing data-profiling techniques to find out parameter values to obtain concretized data profiles, such that $D$ satisfies the concretized profiles. To evaluate how much a dataset $D$ satisfies or violates a data profile, we need a corresponding violation function ($V$). Violation functions provide *semantics* of the data profiles. Finally, to alter a dataset $D$, with respect to a data profile and the corresponding violation function, we need a transformation function ($T$). Transformation functions provide the intervention mechanism to alter data profiles of a dataset and suggest fix to remove the cause of malfunction. DataExposer requires the following three components over the schema ⟨**P**rofile, **V**iolation function, **T**ransformation function⟩, PVT in short:

(1) $P$: a (concretized) profile along with its parameters, which follows the schema ⟨profile type, parameters⟩.
(2) $V(D, P)$: a violation function that computes how much the dataset $D$ violates the profile $P$ and returns a violation score.
(3) $T(D, P, V)$: a transformation function that transforms the dataset $D$ to another dataset $D'$ such that $D'$ no longer violates the profile $P$ with respect to the violation function $V$. (When clear from the context, we omit the parameters $P$ and $V$ when using the notation for transformation functions.)

For a PVT triplet $X$, we define $X_P$ as its profile, $X_V$ as the violation function and $X_T$ as the transformation function. We provide examples and additional discussions on data profiles, violation functions, and transformation functions in Section 3.

*2.2.1 Data Profile.* Intuitively, data profiles encode dataset characteristics. They can refer to a single attribute (e.g., mean of an attribute) or multiple attributes (e.g., correlation between a pair of attributes, functional dependencies, etc.).

Definition 6 (Data Profile). *Given a dataset $D$, a data profile $P$ denotes properties or constraints that tuples in $D$ (collectively) satisfy.*

*2.2.2 Profile Violation Function.* To quantify the degree of violation a dataset incurs with respect to a data profile, we use a *profile violation function* that returns a numerical violation score.

Definition 7 (Profile violation function). *Given a dataset $D$ and a data profile $P$, a* profile violation function $V(D, P) \mapsto [0, 1]$ *returns a real value that quantifies how much $D$ violates $P$.*

$V(D, P) = 0$ implies that $D$ fully complies with $P$ (does not violate it at all). In contrast, $V(D, P) > 0$ implies that $D$ violates $P$. The higher the value of $V(D, P)$, the higher the profile violation.

*2.2.3 Transformation Function.* In our work, we assume knowledge of a passing dataset for which the system functions properly, and a failing dataset for which the system malfunctions. Our goal is to identify which profiles of the failing dataset caused the malfunction. We seek answer to the question: how to "fix" the issues within the failing dataset such that the system no longer malfunctions on it (mismatch is resolved)? To this end, we apply *interventional causal reasoning*: we intervene on the failing dataset by altering its attributes such that the profile of the altered dataset matches the corresponding correct profile of the passing dataset. To perform intervention, we need *transformation functions* with the property that it should push the failing dataset "closer" to the passing dataset in terms of the profile that we are interested to alter. More formally, after the transformation, the profile violation score should decrease.

Definition 8 (Transformation function). *Given a dataset $D$, a data profile $P$, and a violation function $V$, a transformation function $T(D, P, V) \mapsto 2^{\mathbf{Dom}^m}$ alters $D$ to produce $D'$ such that $V(D', P) = 0$.*

A dataset can be transformed by applying a series of transformation functions, for which we use the composition operator ($\circ$).

Definition 9 (Composition of transformations). *Given a dataset $D$, and two PVT triplets $X$ and $Y$, $(X_T \circ Y_T)(D) = X_T(Y_T(D))$. Further, if $D'' = (X_T \circ Y_T)(D)$, then $X_V(D'', X_P) = Y_V(D'', Y_P) = 0$.*

## 2.3 Problem Definition

We expose a set of PVT triplets for explaining the system malfunction. The explanation contains both the *cause* and the corresponding *fix*: profile within a PVT triplet indicates the cause of system malfunction with respect to the corresponding transformation function, which suggests the fix.

Definition 10 (Explanation of system malfunction). *Given*
*(1) a system $S$ with a mechanism to compute $m_S(D)$ $\forall D \subseteq \mathbf{Dom}^m$,*
*(2) an allowable malfunction threshold $\tau$,*
*(3) a passing dataset $D_{pass}$ for which $m_S(D_{pass}) \leq \tau$,*
*(4) a failing dataset $D_{fail}$ for which $m_S(D_{fail}) > \tau$, and*
*(5) a set of candidate PVT triplets $\mathcal{X}$ such that $\forall X \in \mathcal{X}$ $X_V(D_{pass}, X_P) = 0 \wedge X_V(D_{fail}, X_P) > 0$,*
*the explanation of the malfunction of $S$ for $D_{fail}$, but not for $D_{pass}$, is a set of PVT triplets $\mathcal{X}^* \subseteq \mathcal{X}$ such that $m_S((\circ_{X \in \mathcal{X}^*} X_T)(D_{fail})) \leq \tau$.*

| | | Profile | Data type | Discovery over $D$ | Interpretation | Violation by $D$ | Transformation function |
|---|---|---|---|---|---|---|---|
| strict | 1 | $\langle$Domain, $A_j$, $\mathbb{S}\rangle$ | Categorical | $\mathbb{S} = \bigcup_{t \in D} \{t.A_j\}$ | Values are drawn from a specific domain. | $\frac{\sum_{t \in D} [\![t.A_j \notin \mathbb{S}]\!]}{\lvert D \rvert}$ | Map values outside $\mathbb{S}$ to values in $\mathbb{S}$ using domain knowledge. |
| | 2 | $\langle$Domain, $A_j$, $\mathbb{S}\rangle$ | Numerical | $\mathbb{S} = [\mathtt{lb}, \mathtt{ub}]$, where $\mathtt{lb} = \min_{t \in D} t.A_j$, $\mathtt{ub} = \max_{t \in D} t.A_j$ | Values lie within a bound. | $\frac{\sum_{t \in D} [\![t.A_j \notin \mathbb{S}]\!]}{\lvert D \rvert}$ | (1) Use monotonic linear transformation and transform all values. (2) Use winsorization techniques to replace the violating values only. |
| | 3 | $\langle$Domain, $A_j$, $\mathbb{S}\rangle$ | Text | $\mathbb{S} = [t \in \mathtt{Dom}_j \mid t \models \mathbb{P}]$, where $\mathbb{P}$ is a regex over $D.A_j$ learned via pattern discovery [56] | Values satisfy a regular expression or length of values lie within a bound. | $\frac{\sum_{t \in D} [\![t.A_j \notin \mathbb{S}]\!]}{\lvert D \rvert}$ | Minimally alter data to satisfy regular expression. For example, insert (remove) characters to increase (reduce) text length. |
| thresholded by data coverage | 4 | $\langle$Outlier, $A_j$, $O$, $\theta\rangle$ | All | $\theta = \frac{\sum_{t \in D} [\![O(D.A_j, t.A_j)]\!]}{\lvert D \rvert}$, where $O$ is learned from $D.A_j$'s distribution [36] | Fraction of outliers within an attribute does not exceed a threshold. | $\max\left(0, \frac{\sum_{t \in D} [\![O(D.A_j, t.A_j)]\!] - \theta \cdot \lvert D \rvert}{\lvert D \rvert \cdot (1-\theta)}\right)$ | (1) Replace outliers with the expected value (mean, median, mode) of the attribute. (2) Map all values above (below) the maximum (minimum) limit with highest (lowest) valid value. |
| | 5 | $\langle$Missing, $A_j$, $\theta\rangle$ | All | $\theta = \frac{\sum_{t \in D} [\![t.A_j = \mathtt{NULL}]\!]}{\lvert D \rvert}$ | Fraction of missing values within an attribute does not exceed a threshold. | $\max\left(0, \frac{\sum_{t \in D} [\![t.A_j = \mathtt{NULL}]\!] - \theta \cdot \lvert D \rvert}{\lvert D \rvert \cdot (1-\theta)}\right)$ | Use missing value imputation techniques. |
| | 6 | $\langle$Selectivity, $\mathbb{P}$, $\theta\rangle$ | All | $\theta = \frac{\lvert \sigma_{\mathbb{P}}(D) \rvert}{\lvert D \rvert}$ | Fraction of tuples satisfying a given constraint (selection predicate) does not exceed a threshold. | $\max\left(0, \frac{\lvert \sigma_{\mathbb{P}}(D) \rvert - \theta \cdot \lvert D \rvert}{\lvert D \rvert \cdot (1-\theta)}\right)$ | Undersample tuples that satisfy the predicate $\mathbb{P}$. |
| thresholded by parameter | 7 | $\langle$Indep, $A_j$, $A_k$, $\alpha\rangle$ | Categorical | $\alpha$ denotes Chi-squared statistic between $D.A_j$ and $D.A_k$ | $\chi^2$ statistic between a pair of attributes is below a threshold with a p-value $\leq 0.05$. | $1 - e^{-\max(0, \chi^2(D.A_j, D.A_k) - \alpha)}$ | Modify attribute values to remove/reduce dependence. |
| | 8 | $\langle$Indep, $A_j$, $A_k$, $\alpha\rangle$ | Numerical | $\alpha$ denotes Pearson correlation coefficient between $D.A_j$ and $D.A_k$ | PCC between a pair attributes is below a threshold with a p-value $\leq 0.05$. | $\max\left(0, \frac{\lvert \mathtt{PCC}(D.A_j, D.A_k) \rvert - \lvert \alpha \rvert}{1 - \lvert \alpha \rvert}\right)$ | Add noise to remove/reduce dependence between attributes. |
| | 9 | $\langle$Indep, $A_j$, $A_k$, $\alpha\rangle$ | Categorical, numerical | Learn causal graph and causal coefficients ($\alpha$) using TETRAD [66] | A causal relationship between a pair of attributes is unlikely (with causal coefficient less than $\alpha$). | $\max\left(0, \frac{\lvert \mathtt{coeff}(A_j, A_k) \rvert - \alpha}{1 - \alpha}\right)$ | Change data distribution to modify the causal relationship. |

**Figure 1: A list of PVT triplets that we consider in this paper, their syntax, and semantics.**

Informally, $\mathcal{X}^*$ explains the cause: why $S$ malfunctions for $D_{fail}$, but not for $D_{pass}$. More specifically, *failing to satisfy* the profiles of the PVT triplets in $\mathcal{X}^*$ are the causes of malfunction. Furthermore, the transformation functions of the PVT triplets in $\mathcal{X}^*$ suggest the fix: how can we repair $D_{fail}$ to eliminate system malfunction. However, there could be many possible such $\mathcal{X}^*$ and we seek a *minimal* set $\mathcal{X}^*$ such that transformation for every $X \in \mathcal{X}^*$ is necessary to bring down the malfunction score below the threshold $\tau$.

Definition 11 (Minimal explanation of system malfunction). *Given a system $S$ that malfunctions for $D_{fail}$ and an allowable malfunction threshold $\tau$, an explanation $\mathcal{X}^*$ of $S$'s malfunction for $D_{fail}$ is minimal if $\forall \mathcal{X}' \subset \mathcal{X}^*$ $m_S((\circ_{X \in \mathcal{X}'} X_T)(D_{fail})) > \tau$.*

Note that there could be multiple such minimal explanations and we seek any one of them, as any minimal explanation exposes the causes of mismatch and suggests minimal fixes.

Problem 12 (Discovering explanation of mismatch between data and system). *Given a system $S$ that malfunctions for $D_{fail}$ but functions properly for $D_{pass}$, the problem of discovering the explanation of mismatch between $D_{fail}$ and $S$ is to find a minimal explanation that captures (1) the cause why $S$ malfunctions for $D_{fail}$ but not for $D_{pass}$ and (2) how to repair $D_{fail}$ to remove the malfunction.*

# 3 DATA PROFILES, VIOLATION FUNCTIONS, & TRANSFORMATION FUNCTIONS

We now provide an overview of the data profiles we consider, how we discover them, how we compute the violation scores for a dataset w.r.t. a data profile, and how we apply transformation functions to alter profiles of a dataset. While a multitude of data-profiling primitives exist in the literature, we consider a carefully chosen subset of them that are particularly suitable for modeling issues in data that commonly cause malfunction or failure of a system. We focus on profiles that, by design, can better "discriminate" a pair of datasets as opposed to "generative" profiles (e.g., data distribution) that can profile the data better, but nonetheless are less useful for the task of discriminating between two datasets. However, the DataExposer framework is generic, and other profiles can be plugged into it.

As discussed in Section 2, a PVT triplet encapsulates a profile, and corresponding violation and transformation functions. Figure 1 provides a list of profiles along with the data types they support, how to learn their parameters from a given dataset, how to interpret them intuitively, and the corresponding violation and transformation functions. In this work, we assume that a profile can be associated with multiple transformation functions (e.g., rows 2 and 4), but each transformation function can be associated with at most one

profile. This assumption helps us to blame a unique profile as cause of the system malfunction when at least one of the transformation functions associated with that profile is verified to be a fix.

PVT triplets can be classified in different ways. Based on the strictness of the violation function, they can be classified as follows:

- *Strict*: *All* tuples are expected to satisfy the profile (rows 1–3).
- *Thresholded by data coverage:* Certain fraction ($\theta$) of data tuples are allowed to violate the profile (rows 4–6).
- *Thresholded by a parameter:* Some degree of violation is allowed with respect to a specific parameter ($\alpha$) (rows 7–9).

Further, PVT triplets can be classified in two categories based on the nature of the transformation functions:

- *Local* transformation functions can transform a tuple in isolation without the knowledge of how other tuples are being transformed (e.g., rows 1–3). Some local transformation functions only transform the violating tuples (e.g., row 2, transformation (2)), while others transform all values (e.g., row 2, transformation (1)). For instance, in case of unit mismatch (kilograms vs. lbs), it is desirable to transform all values and not just the violating ones.
- *Global* transformation functions are holistic, as they need the knowledge of how other tuples are being transformed while transforming a tuple (e.g., rows 6 and 9).

Example 13. ***Domain*** *requires two parameters: (1) an attribute $A_j \in \mathcal{R}(D)$, and (2) a set $\mathbb{S}$ specifying its domain. A dataset $D$ satisfies $\langle$Domain, $A_j, \mathbb{S}\rangle$ if $\forall t \in D \;\; t.A_j \in \mathbb{S}$. The profile $\langle$Domain, $A_j, \mathbb{S}\rangle$ is minimal w.r.t. $D$ if $\nexists \mathbb{S}' \subset \mathbb{S}$ s.t. $D$ satisfies the profile $\langle$Domain, $A_j, \mathbb{S}'\rangle$. The technique for discovering a domain $\mathbb{S}$ varies depending on the data type of the attribute. Rows 1–3 of Figure 1 show three different domain-discovery techniques for different data types.*

*$People_{fail}$ (Figure 2) satisfies $\langle$Domain, `gender`, $\{F, M\}\rangle$, as all tuples draw values from $\{F, M\}$ for the attribute* `gender`. *Our case studies of* `Sentiment Prediction` *and* `Cardiovascular Disease Prediction` *show the application of the profile* Domain *(Section 5).*

Example 14. ***Outlier*** *requires three parameters: (1) an attribute $A_j \in \mathcal{R}(D)$, (2) an outlier detection function $O(A, a) \mapsto \{$`True`, `False`$\}$ that returns* `True` *if $a$ is an outlier w.r.t. the values within $A$, and* `False` *otherwise, and (3) a threshold $\theta \in [0, 1]$. A dataset $D$ satisfies $\langle$Outlier, $A_j, O, \theta\rangle$ if the fraction of outliers within the attribute $A_j$—according to $O$—does not exceed $\theta$. Otherwise, we compute how much the fraction of outliers exceeds the allowable fraction of outliers ($\theta$) and then normalize it by dividing by $(1 - \theta)$. The profile $\langle$Outlier, $A_j, O, \theta\rangle$ is minimal if $\nexists \theta' < \theta$ s.t. $D$ satisfies $\langle$Outlier, $A_j, O, \theta'\rangle$.*

*An outlier detection function $O_{1.5}$ identifies values that are more than* 1.5 *standard deviation away from the mean as outliers. In $People_{fail}$,* `age` *has a mean* 34.5 *and a standard deviation* 11.78. *According to $O_{1.5}$, only $t_3$—which is* 0.1 *fraction of the tuples—is an outlier in terms of* `age` *as $t_3$'s age* $60 > (34.5 + 1.5 \times 11.78) = 52.17$. *Therefore, $People_{fail}$ satisfies $\langle$Outlier, `age`, $O_{1.5}, 0.1\rangle$.*

Example 15. ***Indep*** *requires three parameters: two attributes $A_j, A_k \in \mathcal{R}(D)$, and a real value $\alpha$. A dataset $D$ satisfies the profile $\langle$Indep, $A_j, A_k, \alpha\rangle$ if the dependency between $D.A_j$ and $D.A_k$ does not exceed $\alpha$. Different techniques exist to quantify the dependency and rows 6–9 of Figure 1 show three different ways to model dependency, where the first two are correlational and the last one is causal.*

| id | name | gender | age | race | zip code | phone | high expenditure |
|---|---|---|---|---|---|---|---|
| $t_1$ | Shanice Johnson | F | 45 | A | 01004 | 2088556597 | no |
| $t_2$ | DeShawn Bad | M | 40 | A | 01004 | 2085374523 | no |
| $t_3$ | Malik Ayer | M | 60 | A | 01005 | 2766465009 | no |
| $t_4$ | Dustin Jenner | M | 22 | W | 01009 | 7874891021 | yes |
| $t_5$ | Julietta Brown | F | 41 | W | 01009 | | yes |
| $t_6$ | Molly Beasley | F | 32 | W | | 7872899033 | no |
| $t_7$ | Jake Bloom | M | 25 | W | 01101 | 4047747803 | yes |
| $t_8$ | Luke Stonewald | M | 35 | W | 01101 | 4042127741 | yes |
| $t_9$ | Scott Nossenson | M | 25 | W | 01101 | | yes |
| $t_{10}$ | Gabe Erwin | M | 20 | W | | 4048421581 | yes |

**Figure 2: A sample dataset $People_{fail}$ with 10 entities. A logistic regression classifier trained over this dataset discriminates against African Americans (`race` = 'A') and women (`gender` = 'F') (Example 1).**

| id | name | gender | age | race | zip code | phone | high expenditure |
|---|---|---|---|---|---|---|---|
| $t_1$ | Darin Brust | M | 25 | W | 01004 | 2088556597 | no |
| $t_2$ | Rosalie Bad | F | 22 | W | 01005 | | no |
| $t_3$ | Kristine Hilyard | F | 50 | W | 01004 | 2766465009 | yes |
| $t_4$ | Chloe Ayer | F | 22 | A | | 7874891021 | yes |
| $t_5$ | Julietta Mchugh | F | 51 | W | 01009 | 9042899033 | yes |
| $t_6$ | Doria Ely | F | 32 | A | 01101 | | yes |
| $t_7$ | Kristan Whidden | F | 25 | W | 01101 | 4047747803 | no |
| $t_8$ | Rene Strelow | M | 35 | W | 01101 | 6162127741 | yes |
| $t_9$ | Arial Brent | M | 45 | W | 01102 | 4089065769 | yes |

**Figure 3: A sample dataset $People_{pass}$ with 9 entities. A logistic regression classifier trained over this dataset does not discriminate against any specific race or gender, and, thus, is fair (Example 1).**

$\langle$Indep, `race`, `high_expenditure`, 0.67$\rangle$ *is satisfied by $People_{fail}$ using the PVT triplet of row 7, as $\chi^2$-statistic between* `race` *and* `high_expenditure` *over $People_{fail}$ is* 0.67. *We show the application of the profile* Indep *in our case study involving the task of* `Income Prediction` *in Section 5.*

While the profiles in Figure 1 are defined over the entire data, analogous to conditional functional dependency [23], an extension to consider is *conditional* profiles, where only a subset of the data is required to satisfy the profiles.

## 4 INTERVENTION ALGORITHMS

We now describe our intervention algorithms to explain the mismatch between a dataset and a system malfunctioning on that dataset. Our algorithms consider a failing and a passing dataset as input and report a *collection* of PVT triplets (or simply PVTs) as the explanation (cause and fix) of the observed mismatch. To this end, we first identify a set of *discriminative* PVTs—whose profiles take different values in the failing and passing datasets—as potential explanation units, and then intervene on the failing dataset to alter the profiles and observe change in system malfunction. We develop two approaches that differ in terms of the number of PVTs considered simultaneously during an intervention. DataExposer$_{\text{GRD}}$ is a greedy approach that considers only one PVT at a time. However, in worst case, the number of interventions required by DataExposer$_{\text{GRD}}$ is linear in number of discriminative PVTs. Therefore, we propose a second algorithm DataExposer$_{\text{GT}}$, built on the group-testing paradigm, that considers multiple PVTs to reduce the number of interventions, where the number of required interventions is *logarithmically* dependent on the number of discriminative PVTs. We start with an example scenario to demonstrate how DataExposer$_{\text{GRD}}$ works and then proceed to describe our algorithms.

## 4.1 Example Scenario

Consider the task of predicting the attribute `high_expenditure` to determine if a customer should get a discount (Example 1). The system calculates bias of the trained classifier against the unprivileged groups (measured using disparate impact [39]) as its malfunction score. We seek the causes of mismatch between this prediction pipeline and $People_{fail}$ (Figure 2), for which the pipeline fails with a malfunction score of 0.75. We assume the knowledge of $People_{pass}$ (Figure 3), for which the malfunction score is 0.15. The goal is to identify a minimal set of PVTs whose transformation functions bring down the malfunction score of $People_{fail}$ below 0.20.

(Step 1) The first goal is to identify the profiles whose parameters differ between $People_{fail}$ and $People_{pass}$. To do so, DataExposer$_{GRD}$ identifies the exhaustive set of PVTs over $People_{pass}$ and $People_{fail}$ and discards the identical ones (PVTs with identical profile-parameter values). We call the PVTs of the passing dataset whose profile-parameter values differ over the failing dataset *discriminative* PVTs. Figure 5 lists a few profiles of the discriminative PVTs w.r.t. $People_{pass}$ and $People_{fail}$.

(Step 2) Next, DataExposer$_{GRD}$ ranks the set of discriminative PVTs based on their likelihood of offering an explanation of the system malfunction. Our intuition here is that if an attribute $A$ is related to the malfunction, then many PVTs containing $A$ in their profiles would differ between $People_{fail}$ and $People_{pass}$. Additionally, altering $A$ with respect to one PVT is likely to automatically "fix" other PVTs associated with $A$.[1] Based on this intuition, DataExposer$_{GRD}$ constructs a *bipartite graph*, called PVT-attribute graph, with discriminative PVTs on one side and data attributes on the other side (Figure 4). In this graph, a PVT $X$ is connected to an attribute $A$ if $X_P$ is defined over $A$. In the bipartite graph, the degree of an attribute $A$ captures the number of discriminative PVTs associated with $A$. During intervention, DataExposer$_{GRD}$ prioritizes PVTs associated with a high-degree attribute. For instance, since `high_expenditure` has the highest degree in Figure 4, PVTs associated with `high_expenditure` are considered for intervention before others.

(Step 3) DataExposer$_{GRD}$ further ranks the subset of the discriminative PVTs that are connected to the highest-degree attributes in the PVT-attribute graph based on their *benefit score*. Benefit score of a PVT $X$ encodes the likelihood of reducing system malfunction when the failing dataset is altered using $X_T$. The benefit score of $X$ is estimated from (1) the violation score that the failing dataset incurs w.r.t. $X_V$, and (2) the number of tuples in the failing dataset that are altered by $X_T$. For example, to break the dependence between `high_expenduture` and `race`, the transformation corresponding to Indep modifies five tuples in $People_{fail}$ by perturbing (adding noise to) `high_expenditure`. In contrast, the transformation for Missing needs to change only one value ($t_6$ or $t_{10}$). Since more tuples are affected by the former, it has higher likelihood of reducing the malfunction score. The intuition behind this is that if a transformation alters more tuples in the failing dataset, the more likely it is to reduce the malfunction score. This holds particularly in applications where the system optimizes aggregated statistics such as accuracy, recall, F-score, etc.

[1] Altering values of $A$ w.r.t. a PVT may also increase violation w.r.t. some other PVTs. However, for ease of exposition, we omit such issues in this example and provide a detailed discussion on such issues in our technical report [29].

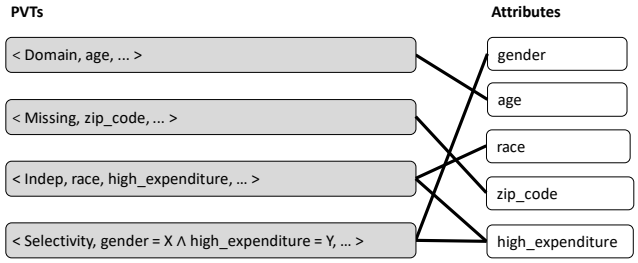



**Figure 4: PVT-attribute graph. The attribute `high_expenditure` is associated with two discriminative PVTs. For ease of exposition, we only show profile within a PVT to denote the entire PVT.**

| $People_{pass}$ | $People_{fail}$ |
|---|---|
| ⟨Domain, age, [22, 51]⟩ | ⟨Domain, age, [20, 60]⟩ |
| ⟨Missing, zip_code, 0.11⟩ | ⟨Missing, zip_code, 0.2⟩ |
| ⟨Indep, race, high_expenditure, 0.04⟩ | ⟨Indep, race, high_expenditure, 0.67⟩ |
| ⟨Selectivity, gender = F ∧high_expenditure = yes, 0.44⟩ | ⟨Selectivity, gender = F ∧high_expenditure = yes, 0.1⟩ |

**Figure 5: A list of PVTs that discriminate $People_{pass}$ (Figure 3) and $People_{fail}$ (Figure 2) based on the scenario of Example 1 . We omit the violation and transformation functions for ease of exposition.**

(Step 4) DataExposer$_{GRD}$ starts intervening on $People_{fail}$ using the transformation of the PVT corresponding to the profile ⟨Indep, `race`, `high_expenditure`, 0.04⟩ as its transformation offers the most likely fix. Then, it evaluates the malfunction of the system over the altered version of $People_{fail}$. Breaking the dependence between `high_expenditure` and `race` helps reduce bias in the trained classifier, and, thus, we observe a malfunction score of 0.35 w.r.t. the altered dataset. This exposes the first explanation of malfunction.

(Step 5) DataExposer$_{GRD}$ then removes the processed PVT (Indep) from the PVT-attribute graph, updates the graph according to the altered dataset, and re-iterates steps 2–4. Now the PVT corresponding to the profile Selectivity is considered for intervention as it has the highest benefit score. To do so, DataExposer$_{GRD}$ oversamples tuples corresponding to female customers with `high_expenditure` = *yes*. This time, DataExposer$_{GRD}$ intervenes on the transformed dataset obtained from the previous step. After this transformation, bias of the learned classifier further reduces and the malfunction score falls below the required threshold. Therefore, with these two interventions, DataExposer$_{GRD}$ is able to expose two issues that caused undesirable behavior of the prediction model trained on $People_{fail}$.

(Step 6) DataExposer$_{GRD}$ identifies an initial explanation over two PVTs: Indep and Selectivity. However, to verify whether it is a minimal, DataExposer$_{GRD}$ tries to drop from it one PVT at a time to obtain a proper subset of the initial explanation that is also an explanation. This procedure guarantees that the explanation only consists of PVTs that are *necessary*, and, thus, is minimal. In this case, both Indep and Selectivity are necessary, and, thus, are part of the minimal explanation. DataExposer$_{GRD}$ finally reports the following as a minimal explanation of the malfunction, where

failure to satisfy the profiles is the cause and the transformations indicate fix (violation and transformation functions are omitted).

{⟨Indep, race, high_expenditure, 0.04⟩,
⟨Selectivity, gender = F ∧ high_expenditure = yes, 0.44⟩}

## 4.2 Assumptions and Observations

We now proceed to describe our intervention algorithms more formally. We first state our assumptions and then proceed to present our observations that lead to the development of our algorithms.

*Assumptions.* DataExposer makes the following assumptions:

(A1) The ground-truth explanation of malfunction is captured by at least one of the discriminative PVTs. This assumption is prevalent in software-debugging literature where program predicates are assumed to be expressive enough to capture the root causes [24, 49].

(A2) If the fix corresponds to a composition of transformations, then the malfunction score achieved after applying the composition of transformations is less than the malfunction score achieved after applying any of the constituents, and all these scores are less than the malfunction score of the original dataset. For example, consider two discriminative PVTs $X$ and $Y$ and a failing dataset $D_{fail}$. Our assumption is that if $\{X, Y\}$ corresponds to a minimal explanation, then $m_S((Y_T \circ X_T)(D_{fail})) < m_S(X_T(D_{fail})) < m_S(D_{fail})$ and $m_S((Y_T \circ X_T)(D_{fail})) < m_S(Y_T(D_{fail})) < m_S(D_{fail})$. Intuitively, this assumption states that $X$ and $Y$ have consistent (independent) effect on reducing the malfunction score, regardless of whether they are intervened together or individually. If this assumption does not hold, DataExposer can still work with additional knowledge about multiple failing and passing datasets [29].

*Observations.* We make the following observations:

(O1) If the ground-truth explanation of malfunction corresponds to an attribute, then multiple PVTs that involve the same attribute are likely to differ across the passing and failing datasets. This observation motivates us to prioritize interventions based on PVTs that are associated with high-degree attributes in the PVT-attribute graph. Additionally, intervening on the data based on one such PVT is likely to result in an automatic "fix" of other PVTs connecting via the high-degree attribute. For example, adding noise to high_expenditure in Example 1 breaks its dependence with not only race but also with other attributes.

(O2) The PVT for which the failing dataset incurs higher violation score is more likely to be a potential explanation of malfunction.

(O3) A transformation function that affects a large number of data tuples is likely to result in a higher reduction in the malfunction score, after the transformation is applied.

**PVT-attribute graph.** DataExposer leverages observation O1 by constructing a bipartite graph ($G_{PA}$), *called PVT-attribute graph,* with all attributes $A \in \mathcal{R}(D)$ as nodes on one side and all discriminative PVTs $X \in \mathcal{X}$ on the other side. An attribute $A$ is connected to a PVT $X$ if and only if $X_P$ has $A$ as one of its parameters. E.g., Figure 4 shows the PVT-attribute graph w.r.t. $People_{fail}$ and $People_{pass}$ (Example 1). In this graph, the PVT corresponding to ⟨Indep, race, high_expenditure⟩ is connected to two attributes, race and high_expenditure. Intuitively, this graph captures the dependence relationship between PVTs and attributes, where an intervention with respect to a PVT $X$ modifies an attribute $A$ connected to it. If this intervention reduces the malfunction score then it could possibly fix other PVTs that are connected to $A$.

**Algorithm 1:** DataExposer$_{GRD}$ (greedy)

**Input:** Failing dataset $D_{fail}$, passing dataset $D_{pass}$, malfunction score threshold $\tau$
**Output:** A minimal explanation set of PVTs $\mathcal{X}^*$

```
1  X_f ← Discover-PVT(D_fail)
2  X_p ← Discover-PVT(D_pass)
3  X_∩ ← X_f ∩ X_p                                   /* Common PVTs */
4  X ← X_p \ X_∩                                     /* Discriminative PVTs */
5  G_PA(V_G, E_G) ← Construct-PVT-Attr-Graph(X, D_fail)
6  B ← Calculate-Benefit-Score(X, G_PA, D_fail)
7  X* ← ∅  /* Initialize minimal explanation set to be empty */
8  D ← D_fail     /* Initialize dataset to the failing dataset */
9  while m_S(D) > τ do
10     X_hda = {X∈X | (X,A)∈E_G ∧ A = arg max_{A∈R(D)} deg_G(A)}
           /* PVTs adjacent to high-degree attributes in G_PA */
11     X = arg max_{X∈X_hda} B(X)          /* Highest-benefit PVT */
12     Δ ← m_S(D) − m_S(X_T(D))            /* Malfunction reduction */
13     G_PA ← G_PA.Remove(X)               /* Update G_PA */
14     if Δ > 0 then                       /* Reduces malfunction */
15         D ← X_T(D)                      /* Apply transformation */
16         G_PA.Update(D)                  /* Update the PVT-attribute graph */
17         B.Update(D)                     /* Update benefit scores */
18         X* ← X* ∪ {X}                   /* Add P to explanation set */
19         X ← X \ {X}                     /* Remove P from the candidates */
20 X* = Make-Minimal(X*)                   /* Obtain minimality of X* */
21 return X*                               /* X* is a minimal explanation */
```

**Benefit score calculation.** DataExposer uses the aforementioned observations to compute a benefit score for each PVT to model their likelihood of reducing system malfunction if the corresponding transformation is used to modify the failing dataset $D_{fail}$. Intuitively, it assigns a high score to a PVT with a high violation score (O2) and if the corresponding transformation function modifies a large number of tuples in the dataset (O3). Formally, the benefit score of a PVT $X$ is defined as the product of violation score of $D_{fail}$ w.r.t. $X_V$ and the "coverage" of $X_T$. The coverage of $X_T$ is defined as the fraction of tuples that it modifies. Note that the benefit calculation procedure acts as a proxy of the likelihood of a PVT to offer an explanation, without actually applying any intervention.

## 4.3 Greedy Approach

Algorithm 1 presents the pseudocode of our greedy technique DataExposer$_{GRD}$, which takes a passing dataset $D_{pass}$ and a failing dataset $D_{fail}$ as input and returns the set of PVTs that corresponds to a minimal explanation of system malfunction.

**Lines 1-2** Identify two sets of PVTs $\mathcal{X}_f$ and $\mathcal{X}_p$ satisfied by $D_{fail}$ and $D_{pass}$, respectively.

**Lines 3-4** Discard the PVTs $\mathcal{X}_f \cap \mathcal{X}_p$ from $\mathcal{X}_p$ and consider the remaining discriminative ones $\mathcal{X} \equiv \mathcal{X}_p \setminus \mathcal{X}_f$ as candidates for potential explanation of system malfunction.

**Line 5** Compute the PVT-attribute graph $G_{PA}$, where the candidate PVTs $\mathcal{X}$ correspond to nodes on one side and the data attributes correspond to nodes on the other side.
**Line 6** Calculate the benefit score of each discriminative PVT $X \in \mathcal{X}$ w.r.t. $D_{fail}$. This procedure relies on the violation score using the violation function of the PVT and the coverage of the corresponding transformation function over $D_{fail}$.
**Line 7-8** Initialize the solution set $\mathcal{X}^*$ to $\emptyset$ and the dataset to perform intervention on $D$ to the failing dataset $\mathcal{D}_{fail}$. In subsequent steps, $\mathcal{X}^*$ will converge to a minimal explanation set and $D$ will be transformed to a dataset for which the system passes.
**Line 9** Iterate over the candidate PVTs $\mathcal{X}$ until the dataset $D$ (which is being transformed iteratively) incurs an acceptable violation score (less than the allowable threshold $\tau$).
**Line 10** Identify the subset of PVTs $\mathcal{X}_{\mathsf{hda}} \subseteq \mathcal{X}$ such that all $X \in \mathcal{X}_{\mathsf{hda}}$ are adjacent to at least one of the highest degree attributes in the current PVT-attribute graph (Observation O1).
**Line 11** Choose the PVT $X \in \mathcal{X}_{\mathsf{hda}}$ that has the maximum benefit.
**Line 12** Calculate the reduction in malfunction score if the dataset $D$ is transformed according to the transformation $X_T$.
**Line 13** Remove $X$ from $G_{PA}$ as it has been explored.
**Lines 14-19** If the malfunction score reduces over $X_T(D)$, then $X$ is added to the solution set $\mathcal{X}^*$, and $D$ is updated to $X_T(D)$, which is then used to update the PVT-attribute graph and benefit of each PVT. The update procedure recalculates the benefit scores of all PVTs that are connected to the attributes adjacent to $X$ in $G_{PA}$.
**Line 20** Post-process the set $\mathcal{X}^*$ to identify a minimal subset that ensure that malfunction score remains less than the threshold $\tau$. This procedure iteratively removes one PVT at a time (say $X$) from $\mathcal{X}^*$ and recalculates the malfunction score over the failing dataset $D_{fail}$ transformed according to the transformation functions of the PVTs in the set $\mathcal{X}' = \mathcal{X}^* \setminus \{X\}$. If the transformed dataset incurs a violation score less than $\tau$ then $\mathcal{X}^*$ is replaced with $\mathcal{X}'$.

## 4.4 Group-testing-based Approach

We now present our second algorithm DataExposer$_{\text{GT}}$, which performs group interventions to identify the minimal explanation that exposes the mismatch between a dataset and a system. The group intervention methodology is applicable under the following assumption along with assumptions $A_1$ and $A_2$ (Section 4.2).

(A3) The malfunction score incurred after applying a composition of transformations is less than the malfunction score incurred by the the original dataset if and only if at least one of the constituent transformations reduces the malfunction score. For two PVTs $X$ and $Y$, $m_S((X_T \circ Y_T)(D_{fail})) < m_S(D_{fail})$, iff $m_S(X_T(D_{fail})) < m_S(D_{fail})$ or $m_S(Y_T(D_{fail})) < m_S(D_{fail})$. Note that this assumption is crucial to consider group interventions and is prevalent in the group-testing literature [20].

DataExposer$_{\text{GT}}$ follows the classical adaptive group testing (GT) paradigm [20] for interventions. To this end, it iteratively partitions the set of discriminative PVTs into two "almost" equal subsets (when the number of discriminative PVTs is odd, then the size of the two partitions will differ by one). During each iteration, all PVTs in a partition are considered for intervention *together* (group intervention) to evaluate the change in malfunction score. If a partition does not help reduce the malfunction score, all PVTs within that partition are discarded. While traditional GT techniques [20] would use a random partitioning of the PVTs, DataExposer$_{\text{GT}}$ can leverage the dependencies among PVTs (inferred from the PVT-attribute graph) to achieve more effective partitioning. Intuitively, it is beneficial to assign all PVTs whose transformations operate on the same attribute to the same partition, which is likely to enable aggressive pruning of spurious PVTs that do not reduce malfunction.

**Algorithm 2:** DataExposer$_{\text{GT}}$ (group-testing-based)

**Input:** Failing dataset $D_{fail}$, passing dataset $D_{pass}$, malfunction score threshold $\tau$
**Output:** A minimal explanation set of PVTs $\mathcal{X}^*$

$\mathcal{X}_f \leftarrow$ Discover-PVT($D_{fail}$)
$\mathcal{X}_p \leftarrow$ Discover-PVT($D_{pass}$)
$\mathcal{X}_\cap \leftarrow \mathcal{X}_f \cap \mathcal{X}_p$ /* Common PVTs */
$\mathcal{X} \leftarrow \mathcal{X}_p \setminus \mathcal{X}_\cap$ /* Discriminative PVTs */
$G_{PA}(V_G, E_G) \leftarrow$ Construct-PVT-attr-Graph($\mathcal{X}, D_{fail}$)
$D, \mathcal{X}^* \leftarrow$ Group-Test($\mathcal{X}, D_{fail}, G^2_{PA}, \tau$) /* Obtain an exp. */
$\mathcal{X}^* =$ Make-Minimal($\mathcal{X}^*$) /* Obtain minimality of $\mathcal{X}^*$ */
**return** $\mathcal{X}^*$ /* $\mathcal{X}^*$ is a minimal cause */

DataExposer$_{\text{GRD}}$ captures the dependencies among PVTs by constructing a PVT-dependency graph $G_{PD}$. Two PVTs $U$ and $V$ are connected by an edge in $G_{PD}$ if they are connected via some attribute in $G_{PA}$. $G_{PD}$ is equivalent to $G^2_{PA}$ (transitive closure of $G_{PA}$), restricted to PVT nodes (excluding the attribute nodes). This ensures that PVTs that are associated via some attribute in $G_{PA}$ are connected in $G_{PD}$. DataExposer$_{\text{GRD}}$ partitions $G_{PD}$ such that the number of connections (edges) between PVTs that fall in different partitions are minimized. More formally, we aim to construct two "almost" equal-sized partitions of $\mathcal{X}$ such that the number of edges between PVTs from different partitions are minimized, which maps to the problem of finding the *minimum bisection* of a graph [31]. The minimum bisection problem is NP-hard [31] and approximate algorithms exist [26, 27]. In this work, we use the *local search algorithm* [26] (details are in our technical report [29]).

We proceed to demonstrate the benefit of using DataExposer$_{\text{GT}}$ as opposed to traditional GT with the following example.

Example 16. *Consider a set of* 8 *PVTs* $\mathcal{X} = \{X_1, \ldots, X_8\}$ *where the ground-truth (minimal) explanation is either* $\{X_1, X_6\}$ *or* $\{X_4, X_8\}$ *(disjunction). An example of steps for a traditional adaptive GT approach is shown in Figure 6(c). In this case, it requires a total of* 14 *interventions. Note that adaptive GT is a randomized algorithm and this example demonstrates one such execution. However, we observed similar results for other instances. In contrast to adaptive GT,* DataExposer$_{GT}$ *constructs a min-bisection of the graph during each iteration: it does not partition* $\{X_2, X_3\}$ *and* $\{X_5, X_7\}$ *as none of these PVTs help reduce the malfunction. Therefore, it requires only* 10 *interventions.*

Algorithm 2 presents the DataExposer$_{\text{GT}}$ algorithm. It starts with a set of discriminative PVTs $\mathcal{X}$ and the PVT-attribute graph $G_{PA}$. All candidate PVTs are then considered by Group-Test subroutine to identify the explanation $\mathcal{X}^*$.

**Group-Test.** Algorithm 3 presents the procedure that takes the set of discriminative PVTs $\mathcal{X}$, a failing dataset $D$, PVT-dependency graph $G_{PD}$, and the malfunction score threshold $\tau$ as input. It returns a transformed (fixed) dataset and an explanation.

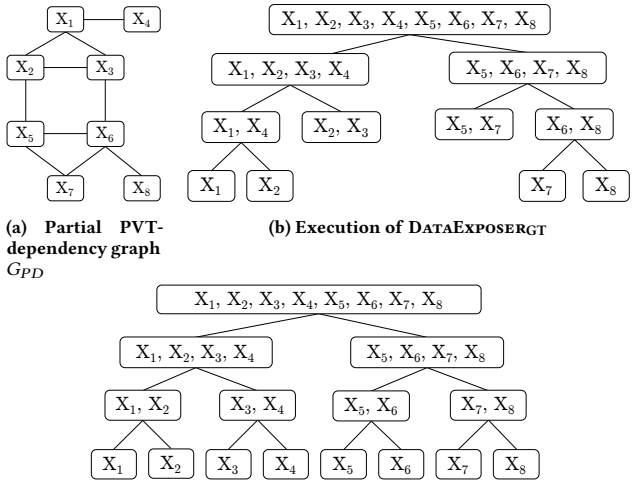
**Algorithm 3:** GROUP-TEST

**Input:** Candidate PVT $\mathcal{X}$, dataset $D$, PVT-dependency graph $G_{PD}$, malfunction score threshold $\tau$
**Output:** A transformed dataset $D'$ and an explanation set of PVTs $\mathcal{X}^*$

1 $\mathcal{X}^* \leftarrow \emptyset$ /* Initialize explanation set to be empty */
2 **if** $|\mathcal{X}| = 1$ **then** /* Only a single PVT is candidate */
3 **return** $T_{\mathcal{X}}(D), \mathcal{X}$
4 $\mathcal{X}^1, \mathcal{X}^2 \leftarrow$ GET-MIN-BISECTION$(G_{PD}, \mathcal{X})$ /* Partition $\mathcal{X}$ */
5 $\mathcal{M} \leftarrow m_S(D)$ /* Initial malfunction score */
6 $\Delta_1 \leftarrow \mathcal{M} - m_S(\mathcal{X}^1_T(D))$ /* Malfunction reduction by $\mathcal{X}^1_T$ */
7 **if** $\mathcal{M} - \Delta_1 > \tau$ **then** /* $\mathcal{X}^1$ alone is insufficient */
8 $\Delta_2 \leftarrow \mathcal{M} - m_S(\mathcal{X}^2_T(D))$ /* Malfunction reduction by $\mathcal{X}^2_T$ */
9 **if** $(\mathcal{M} - \Delta_1 \leq \tau)$ *OR* $(\Delta_1 > 0$ *AND* $\mathcal{M} - \Delta_2 > \tau)$ **then**
/* $\mathcal{X}_1$ is sufficient OR $\mathcal{X}_1$ helps AND $\mathcal{X}_2$ is insufficient */
10 $D, \mathcal{X}' \leftarrow$ GROUP-TEST$(\mathcal{X}_1, D, G_{PD})$
11 $\mathcal{X}^* = \mathcal{X}^* \cup \mathcal{X}'$ /* Augment explanation set */
12 **if** $\mathcal{M} - \Delta_1 \leq \tau$ **then** /* Malfunction is acceptable */
13 **return** $D, \mathcal{X}^*$ /* No need to check $\mathcal{X}_2$ */
14 **if** $\Delta_2 > 0$ **then** /* $T_{\mathcal{X}_2}$ reduces malfunction */
15 $D, \mathcal{X}' \leftarrow$ GROUP-TEST$(\mathcal{X}_2, D, G_{PD})$
16 $\mathcal{X}^* = \mathcal{X}^* \cup \mathcal{X}'$ /* Augment explanation set */
17 **return** $D, \mathcal{X}^*$

**Lines 1** Initialize the solution set $\mathcal{X}^*$ to $\emptyset$.
**Lines 2-3** Return the candidate PVT set $\mathcal{X}$ if its cardinality is 1.
**Lines 4** Partition $\mathcal{X}$ into $\mathcal{X}_1$ and $\mathcal{X}_2$ using min-bisection of the PVT-dependency graph $G_{PD}$.
**Lines 5** Calculate the malfunction score of the input dataset.
**Lines 6** Calculate the reduction in malfunction score $\Delta_1$ if $D$ is intervened w.r.t. all PVTs $\mathcal{X}_1$.
**Lines 7-8** If the malfunction exceeds $\tau$ even after intervening on $D$ w.r.t. all PVTs in $\mathcal{X}_1$ then try out $\mathcal{X}_2$: calculate the reduction in malfunction score $\Delta_2$ if $D$ is intervened w.r.t. all PVTs in $\mathcal{X}_2$.
**Lines 9-13** Recursively call GROUP-TEST on the partition $\mathcal{X}_1$ if one of the following conditions hold: (1) Intervening on $D$ w.r.t. all PVTs in $\mathcal{X}_1$ reduces the malfunction to be lower than $\tau$: the explanation over $\mathcal{X}_1$ is returned as the final explanation. (2) Intervening on $D$ w.r.t. all PVTs in $\mathcal{X}_1$ reduces the malfunction, but still remains above $\tau$, but intervening on $D$ w.r.t. all PVTs in $\mathcal{X}_2$ brings the malfunction below $\tau$: the explanation returned by the recursive call on $\mathcal{X}_1$ is added to the set $\mathcal{X}^*$ and $\mathcal{X}_2$ is processed next.
**Lines 14-16** Recursively call GROUP-TEST on $\mathcal{X}_2$ if intervening on all PVTs in $\mathcal{X}_2$ reduces malfunction. The set of PVTs returned by this recursive call of the algorithm are added to the solution set $\mathcal{X}^*$.

**Discussion on DATAEXPOSER$_{GRD}$ vs. DATAEXPOSER$_{GT}$.** DATAEXPOSER$_{GRD}$ intervenes by considering a single discriminative PVT at a time. Hence, in the worst case, it requires $O(|\mathcal{X}|)$ interventions where $\mathcal{X}$ denotes the set of discriminative PVTs. Note that DATAEXPOSER$_{GRD}$ requires much fewer interventions in practice and would require $O(|\mathcal{X}|)$ only when any of the mentioned observations (O1–O3) do not hold. In contrast, DATAEXPOSER$_{GT}$ performs group intervention by recursively partitioning the set of discriminative PVTs.




**(a) Partial PVT-dependency graph $G_{PD}$**
**(b) Execution of DATAEXPOSER$_{GT}$**
**(c) Execution of traditional group testing algorithm**

**Figure 6: Comparison between DATAEXPOSER$_{GT}$ and adaptive group testing on a toy example.**

Thus, the maximum number of interventions required by DATAEXPOSER$_{GT}$ is $O(t \log |\mathcal{X}|)$ where $t$ denotes the number of PVTs that help reduce system malfunction if the corresponding profile is altered. Note that, in expectation, DATAEXPOSER$_{GT}$ requires fewer interventions than DATAEXPOSER$_{GRD}$ whenever $t = o(|\mathcal{X}|/\log|\mathcal{X}|)$. DATAEXPOSER$_{GT}$ is particularly helpful when multiple PVTs *disjunctively* explain the malfunction. When a single PVT explains the malfunction, DATAEXPOSER$_{GT}$ and traditional group testing algorithm [20] both will require the same number of interventions, in expectation. However, group-testing techniques require an additional assumption assumption A3 (Section 4.4). We discuss the empirical impact of this assumption in Section 5.1 (Cardiovascular disease prediction). Overall, we conclude that DATAEXPOSER$_{GT}$ is beneficial for applications whenever $t = O(|\mathcal{X}|/\log|\mathcal{X}|)$ and observations O1-O3 hold (more details are in our technical report [29]).

## 5 EXPERIMENTAL EVALUATION

Our evaluation of the effectiveness of DATAEXPOSER addresses the following questions: (Q1) Is DATAEXPOSER able to identify the mismatch between the failing dataset and the system? (Q2) How does DATAEXPOSER's effectiveness compare to other techniques that can be adapted to uncover potential causes of malfunction? (Q3) Is DATAEXPOSER scalable with respect to the number of PVTs?

**Baselines.** Since there is no prior work on modifying a dataset according to a PVT, we adapted state-of-the-art debugging and explanation techniques to incorporate profile transformations and explain the cause of system failure. We consider three baselines: (1) `BugDoc` [51] is a recent debugging technique that explores different parameter configurations of the system to understand its behavior. We adapt `BugDoc` to consider each PVT as a parameter of the system and interventions as the modified configurations of the pipeline. (2) `Anchor` [62] is a local explanation technique for classifiers that explains individual predictions based on a surrogate model. We train `Anchor` with PVTs as features, and the prediction variable is Pass/Fail where Pass denotes the case where input dataset has malfunction below $\tau$ and Fail otherwise. In this technique, each

| | Number of Interventions | | | | | Execution Time | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Datasets | DataExposer$_{GRD}$ | DataExposer$_{GT}$ | BugDoc | Anchor | GrpTest | DataExposer$_{GRD}$ | DataExposer$_{GT}$ | BugDoc | Anchor | GrpTest |
| Sentiment | 2 | 3 | 10 | 303 | 3 | 25.1s | 23.4s | 64.6s | 4594.9s | 21.2s |
| Income | 1 | 8 | 20 | 800 | 10 | 11.8s | 12.5s | 20.0s | 195.5s | 10.4s |
| Cardiovascular | 1 | - | 100 | 5900 | - | 7.6s | - | 62.1s | 8602.9s | - |

**Figure 7: Comparison of number of interventions and running time of DataExposer with other baselines.**

intervention creates a new datapoint to train the surrogate model. (3) GrpTest [20] is an adaptive group testing approach that performs group interventions to expose the mismatch between the input dataset and the system. This algorithm is similar to DataExposer$_{GT}$ with a difference that the recursive partitioning of PVTs is performed randomly and not using the dependency graph.

## 5.1 Real-world Case Studies

We use well known ML techniques [1, 2, 57] to design black-box systems focusing on three different applications; we evaluate system malfunction in these three case studies using real-world datasets. (Figure 7 presents a summary of the results.)

**Sentiment Prediction.** The system in this study uses flair [2], a pre-trained classifier to predict sentiment, and computes misclassification rate as the malfunction score. It assumes a target attribute in the input data, indicating the ground truth sentiment: target= 1 denotes positive and target= $-1$ denotes negative sentiment. We test the system over IMDb dataset [41] (50$K$ tuples) and a twitter dataset [68] (around 1.6M tuples). The malfunction score of the system on the IMDb dataset is only 0.09 while on the twitter dataset it is 1. We considered IMDb as the passing dataset and twitter as the failing dataset and ran DataExposer to explain the mismatch between the twitter dataset and the system. DataExposer$_{GRD}$ identified a total of 3 discriminative PVTs between the two datasets. For example, the length of text in the twitter dataset is less than 280 characters but in the IMDb dataset it is between 32 and 13K characters. The ground truth cause of the malfunction is that the target attribute in the twitter dataset uses "4" to denote positive and "0" to denote negative sentiment [68]. The mismatch with the prediction algorithm's expectation of target values in $\{+1, -1\}$ leads to low accuracy and high malfunction score. DataExposer$_{GRD}$ performs two interventions and identifies that the malfunction score reduces to 0.36 by mapping $0 \rightarrow -1$ and $4 \rightarrow 1$. The corresponding PVT triplets are returned as the cause of system failure.

DataExposer$_{GT}$ and GrpTest perform 3 group interventions to derive the root cause of system malfunction. BugDoc and Anchor require 10 and 303 interventions, respectively. Anchor calculates system malfunction on datasets transformed according to various local perturbations of the PVTs in the failing dataset. It repeats some of the interventions to establish confidence, which contributes to its high complexity.

**Income Prediction.** The system in this study trains a Random Forest classifier [57] to predict the income of individuals while ensuring fairness towards marginalized groups. The pipeline returns the normalized disparate impact [39] of the trained classifier w.r.t. the protected attribute (sex), as the malfunction score. Our input data includes census records [21] containing demographic attributes of individuals along with information about income, education, etc. We create two datasets through a random selection of records, and manually add noise to one of them to break the dependence between target and sex. The system has malfunction score of 0.195 for the passing dataset and 0.58 for the failing dataset due to the dependence between target and sex. DataExposer$_{GRD}$ identifies a total of 43 discriminative PVTs and constructs a PVT-attribute graph. In this graph, the target attribute has degree 15 while all other attributes have degree 2. The PVTs that include target are then intervened in non-increasing order of benefit. The transformation on the target attribute breaks the dependence between target and all other attributes, thereby reducing the malfunction score to 0.32. Therefore, DataExposer$_{GRD}$ requires one intervention to explain the cause of the malfunction. Our group testing algorithm DataExposer$_{GT}$ and GrpTest require 8 and 10 interventions, respectively. Note that group testing is not very useful because the datasets contain few discriminative PVTs.

BugDoc and Anchor do not identify discriminative PVTs explicitly and consider all PVTs (136 for this dataset) as candidates for intervention. BugDoc identifies the ground truth cause of malfunction in 50% of the runs when allowed to run fewer than 10 interventions. It identifies the mismatch with intervention budget of 20 but the returned solution of PVTs is not minimal. For instance, BugDoc returns two PVTs: $\{\langle$Indep, target, education$\rangle$ and $\langle$Indep, target, sex$\rangle\}$ as the explanation of malfunction. Anchor performs 800 local interventions to explain the malfunction.

**Cardiovascular Disease Prediction.** This system trains an AdaBoost classifier [1] on patients' medical records [13] containing age, height (in centimeters) and weight along with other attributes. It predicts if the patient has a disease and does not optimize for false positives. Therefore, the system calculates recall over the patients having cardiovascular disease, and the goal is to achieve more than 0.70 recall. The pipeline returns the additive inverse of recall as the malfunction score. We tested the pipeline with two datasets generated through a random selection of records: (1) the passing dataset satisfies the format assumptions of the pipeline; (2) for the failing dataset we manually converted height to inches. DataExposer$_{GRD}$ identifies 86 discriminative PVTs with height, weight and age having the highest degree of 15 in the PVT-attribute graph. Among the PVTs involving these attributes, the Domain of height has the maximum benefit. DataExposer$_{GRD}$ alters the failing dataset by applying a linear transformation and it reduces the malfunction from 0.71 to 0.30. This explanation matches the ground truth difference in the passing and the failing dataset. Among baselines, BugDoc and Anchor performed 100 and 5900 interventions, respectively. Group testing techniques are not applicable because assumption A3 (Section 4.4) does not hold. We observe that the malfunction score with a composition of transformation functions is higher than the one in the original dataset if the composition involves Indep PVT. This behavior is observed because adding noise to intervene with respect to Indep PVT worsens the classifier performance. If we remove PVTs that violate this assumption, then DataExposer$_{GT}$ and GrpTest require 6 and 9 interventions, respectively.

**Efficiency.** Figure 7 compares the running time of presented techniques on real-world pipelines. DataExposer$_{GRD}$, DataExposer$_{GT}$ and GrpTest are highly efficient and require less than 30 seconds to explain the ground-truth cause of malfunction.

**Key takeaways.** Among all real-world pipelines, DataExposer$_{GRD}$ requires the fewest interventions to explain the cause of system malfunction. Group testing techniques, DataExposer$_{GT}$ and GrpTest, perform better than BugDoc and Anchor whenever the required assumptions hold. Anchor requires the most interventions due to performing many local transformations to explain the cause of failure. BugDoc optimizes interventions by leveraging combinatorial design algorithms; it requires more interventions than DataExposer but fewer than Anchor.

## 5.2 Synthetic Pipelines

We further evaluate the effectiveness of DataExposer$_{GRD}$ and DataExposer$_{GT}$ for a diverse set of synthetic scenarios.

**DataExposer$_{GRD}$ vs. DataExposer$_{GT}$.** In this experiment, we consider a pipeline where the ground-truth explanation of malfunction violates the observations discussed in Section 4.2. Specifically, the ground-truth explanation requires modifying one particular value in the dataset and its likelihood (as estimated by DataExposer$_{GRD}$) is ranked 54 among the discriminative PVTs. Therefore, it requires $\approx$ 50 interventions to explain the cause of malfunction. On the other hand, DataExposer$_{GT}$ performs group interventions and requires 9 interventions. This experiment demonstrates that DataExposer$_{GT}$ requires fewer interventions than DataExposer$_{GRD}$ when the failing dataset and corresponding PVTs do not satisfy the mentioned observations. We present additional experiments with varying complexity of ground-truth mismatch in our technical report [29].

**Scalability.** Figure 8 compares the running time of our techniques with varying number of dataset attributes and PVTs. We observe that the running time of our techniques grows logarithmically with increase in number of attributes and PVTs.

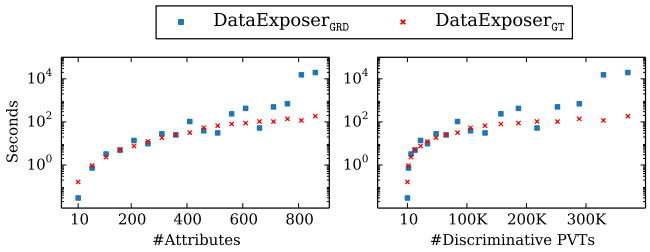



**Figure 8: Execution time of DataExposer$_{GRD}$ vs. DataExposer$_{GT}$ with varying number of data attributes (left) and discriminative PVTs (right) over synthetic pipelines.**

# 6 RELATED WORK

**Interventional debugging.** AID [24] uses an interventional approach to blame runtime conditions of a program for causing failure; but it is limited to software bugs and does not intervene on datasets. BugDoc [51] finds parameter settings in a black-box pipeline as root causes of pipeline failure; but it only reports whether a dataset is a root cause and does not explain why a dataset causes the failure. CADET [42] uses causal inference to derive root causes of non-functional faults for hardware platforms focused on performance issues. Capuchin [65] casts fairness in machine learning as a database repair problem and adds or removes rows in the training data to simulate a *fair world*; but it does not aim to find cause of unfairness.

**Data explanation.** Explanations for query results have been abundantly studied [5, 17, 22, 71]. Some works find causes of errors in data generation processes [71], while others discover relationships among attributes [5, 22], and across datasets [17]. ExceLint [6] exploits the spatial structure of spreadsheets to look for erroneous formulas. Unlikely interventional efforts, these approaches operate on observational data, and do not generate additional test cases.

**Model explanation.** Machine learning interpreters [61, 62] perturb testing data to learn a surrogate for models. Their goal is not to find mismatch between data and models. Debugging methods for ML pipelines are similar to data explanation [11, 12], where training data may cause model's underperformance. [70] and [46] discuss principled ways to find reasons of malfunctions. Wu et al. [72] allow users to *complain* about outputs of SQL queries, and presents data points whose removal resolves the complaints. [67] validates when models fail on certain datasets and assumes knowledge of the mechanism that corrupts the data. We aim to find discriminative profiles among datasets without such knowledge.

**Causal inference debugging.** Data-driven approaches have been taken for causal-inference-based fault localization [3, 4, 16, 34], software testing [28, 32, 38, 44, 74], and statistical debugging [49, 75]. However, they use a white-box strategy or are application-specific. Causal relational learning [64] infers causal relationships in relational data, but it does not seek mismatches between the data and the systems. Our work shares similarity with BugEx [63], which generates test cases to isolate root causes. However, it assumes complete knowledge of the program, and data-flow paths.

**Data debugging.** Porting concepts of debugging from software to data has gained attention in data management community [10, 53]. Dagger [59, 60] provides data debugging primitives for white-box interactions with data-driven pipelines. CheckCell [7] ranks data cells that unusually affect output of a given target. However, it is not meant for large datasets where single cells are unlikely to causes malfunction. Moreover, CheckCell cannot expose combination of root causes. DataExposer is general-purpose, application-agnostic, and interventional, providing causally verified issues mismatch between the data and the systems.

# 7 SUMMARY AND FUTURE DIRECTIONS

We introduced the problem of identifying causes and fixes of mismatch between data and systems that operate on data. To this end, we presented DataExposer, a framework that reports violation of data profiles as causally verified root causes of system malfunction and reports fixes in the form of transformation functions. We demonstrated the effectiveness and efficacy of DataExposer in explaining the reason of mismatch in several real-world and synthetic data-driven pipelines, significantly outperforming the state of the art. In future, we want to extend DataExposer to support more complex classes of data profiles. Additionally, we plan to investigate ways that can facilitate automatic repair of both data and the system guided by the identified data issues.

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