DATAPRISM: Exposing Disconnect between Data and Systems

Sainyam Galhotra  
University of Chicago  
sainyam@uchicago.edu

Anna Fariha  
Microsoft  
annafariha@microsoft.com

Raoni Lourenço  
New York University  
raoni@nyu.edu

Juliana Freire  
New York University  
juliana.freire@nyu.edu

Alexandra Meliou  
University of Massachusetts Amherst  
ameli@cs.umass.edu

Divesh Srivastava  
AT&T Chief Data Office  
divesh@att.com

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 DATAPRISM, 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 data and resolve the disconnect between data and system. Our technique is based on causal reasoning through interventions: when a system malfunctions for a dataset, DATAPRISM alters the data profiles and observes changes in the system’s behavior due to the alteration. Unlike statistical observational analysis that reports mere correlations, DATAPRISM reports causally verified root causes—in terms of data profiles—of the system malfunction. We empirically evaluate DATAPRISM on four real-world and several synthetic data-driven systems that fail on certain datasets due to a diverse set of reasons. In all cases, DATAPRISM identifies the root causes precisely while requiring orders of magnitude fewer interventions than prior techniques.

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 [28, 36, 50]. 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 [16] and finding root causes of failures in computational pipelines [52], 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, and distributions), and when new data drifts away from the data over which the system was tested on before deployment [60] (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, possible fixes can be either to repair or reformat the data to comply with the system design, or to adjust the system design (i.e. 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 [11]: “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 inspired from a real-world incident, where Amazon’s delivery service was found to be racist [44].
Example 1 (Biased Classifier). An e-commerce company wants to build an automated system to offer customer discounts. To this end, they organize data of customers’ purchases over a year into a dataset with attributes: name, gender, age, race, zip_code, phone, products_purchased, etc. Anita, a data scientist, is 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. Anita decides to use an off-the-shelf ML algorithm that is trained over historical data. 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 Americans 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 customers 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 [11]) 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, merely 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 [13, 34]. 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 [51]. 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 [63], and issues pertaining to data fusion where schema assumptions about data format by different software components or services showed that 21% of the bugs were due to inconsistent assumptions about data format by different software components or versions [51].

Solution sketch. We propose DataPrism, a framework that identifies and exposes data profiles that cause an opaque data-driven system (i.e., a system whose internal mechanisms are unknown) 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 an opaque system malfunctions (fails) over a dataset but functions properly (passes) over another, DataPrism focuses on the discriminative profiles, i.e., data profiles that significantly differ between the two datasets. DataPrism’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 desirable, or the malfunction persists. DataPrism speeds up this analysis by favoring interventions on profiles that are 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 change 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). While an intervention may involve a large number of tuples, it is conceptually succinct (e.g., gender=male).
**Scope.** In this work, we only focus on the cases where system malfunction is due to some holistic profile(s) over the input dataset. Note that prior data-debugging approaches target different classes of data issues [10, 63] and assume access to the internal mechanisms of the system. In contrast, DataPrism is completely agnostic to the type of data-driven system and can support any system ranging from machine-learned prediction models (e.g., binary classifiers, regression models, deep neural networks, etc.) that learn from data to other general software that just operate on data. However, DataPrism over a diverse set of opaque systems that internally deploy different ML models such as logistic regression, neural network, AdaBoost, and random forest classifier. However, DataPrism can not be used to prevent malfunctions from happening in the first place as it requires the knowledge of contrasting scenarios where the system under consideration malfunctions (fails) over a dataset versus functions properly (passes) over another dataset.

DataPrism requires the 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 [12]; and violation of conformance constraints [29], 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 [28, 50, 79], 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 [53], validation [48], and verification [38] approaches, which rely on the assumption that the test cases, specifications, and invariants reasonably cover the codebase and correctness constraints.

**Data profiles.** While we use data profiles to explain the cause of malfunction, developing data profiling techniques [1] is orthogonal to our work. A number of data profiling primitives exist in the literature along with corresponding techniques to extract them from a dataset. DataPrism assumes access to a suite of data-profiling techniques and uses them to extract profiles from the data. DataPrism then examines these profiles to identify the causes of system malfunction. To support a new data profile, DataPrism needs the corresponding mechanisms for their discovery and intervention. We discuss some common classes of data profiles as representative ones, which are currently supported in the implementation of DataPrism, and the corresponding discovery and intervention techniques. For data-profile discovery, we rely on prior work on pattern discovery [58], statistical-constraint discovery [77], data-distribution learning [37], knowledge-graph-based concept identification [31], conformance-constraint discovery [29], etc. While our evaluation covers specific data profiles (for which efficient discovery techniques exist), DataPrism 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, Daggert [62, 63] provides data debugging primitives for human-in-the-loop interactions with data-driven computational pipelines. Other explanation-centric efforts [9, 21, 26, 75] report salient properties of historical data based only on observations. In contrast with observational techniques, the presence of an oracle allows for intervention techniques [52] 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 [11], 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. Kapurchin [69] is an interventional approach that, similar to us, alters the dataset to remove attribute correlations, a prime cause for prediction bias in ML algorithms. However, Kapurchin does not verify if there is indeed a causal connection between attribute correlation and prediction bias. In contrast, DataPrism offers a general solution to verify and isolate the true root cause of system malfunction for diverse set of systems.

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 [65, 66] 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 [19], they do not model feature interactions as possible explanations.

**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). (Section 2)
- We design a set of data profiles that are common root causes of system malfunctions, and discuss their discovery and intervention techniques based on available technology. (Section 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.
- We evaluate DataPrism on four real-world applications, where data profiles are responsible for causing system malfunction, and demonstrate that DataPrism successfully explains the root causes with very few interventions (fewer than 10). Furthermore, DataPrism requires 10–1000× fewer interventions compared to two state-of-the-art techniques for root-cause analysis: BugDoc [52] and Anchors [66]. Over synthetic pipelines, we further show that the number of required interventions by DataPrism increases sub-linearly with the number of discriminative profiles.
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 $R(A_1, A_2, \ldots, A_m)$ to denote a relation schema over $m$ attributes, where $A_i$ denotes the $i^{th}$ attribute. We use $\text{Dom}_i$ to denote the domain of attribute $A_i$. Then the set $\text{Dom}^m = \text{Dom}_1 \times \cdots \times \text{Dom}_m$ specifies the domain of all possible tuples. A dataset $D \subseteq \text{Dom}^m$ is a specific instance of the schema $R$. We use $t \in \text{Dom}^m$ to denote a tuple in the schema $R$. We use $t.A_i \in \text{Dom}_i$ 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 $A_j$. We use $A$ to denote an ordered list of all attributes.

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 $D \subseteq \text{Dom}^m$ 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 $\tau$ 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 w.r.t $S$; otherwise, a mismatch between $D$ and $S$ exists, 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 [40], 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 a mismatch, the next step is to investigate its cause. We use data profiles to model the possible causes of mismatch. The schema of a data profile is given as a template that can be parameterized with different values. Populating a profile template with a particular set of values produces an instantiation of the profile ($P$). Given a dataset $D$, we use existing data-profiling techniques to discover parameter values, such that $D$ satisfies the corresponding profile instances. To measure how much a dataset $D$ satisfies or violates a data profile, we need a violation function ($V$) that gives semantics to the data profiles. Finally, to repair a dataset $D$, with respect to a data profile and its corresponding violation function, we need a transformation function ($T$). Transformation functions provide an intervention mechanism to alter data and suggest repairs to remove the cause of malfunction. DATAPRISM requires the following three components over the schema (Profile, Violation function, Transformation function), PVT in short:

1. $P$: an instantiated profile, which follows the schema (profile type, parameters).
2. $V(D, P)$: a violation function that follows the schema (profile type, parameters).
3. $T(D, P, V)$: a transformation function that computes how much the dataset $D$ violates the profile $P$ and returns a violation score.

For a PVT triplet $X$, we use $X_P$, $X_V$, and $X_T$ to denote its profile, violation function, and transformation function, respectively. As an example, consider a profile $P$ in a PVT ($P, V, T$) over a dataset $D$: $D$ may correspond to the ideal domain of an attribute $A$ in $D$, specified by $\text{Dom}(A)$. $V(D, P)$ may correspond to the fraction of out-of-domain values in $D.A$, and $T(D, P, V)$ can be to remove all tuples $t \in D$ that contain out-of-domain values (i.e., $t.A \notin \text{Dom}(A)$). We provide detailed examples and additional discussion on data profiles, violation functions, and transformation functions in Section 3. We proceed to formalize these notions.

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 this 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 $P$, a selection predicate $\varnothing$ and a violation function $V$, a transformation function $T(D, P, V, \varnothing) \mapsto \text{Dom}^m$ alters tuples in $\sigma_\varnothing(D)$ to produce $D'$ such that $V(D', P) < V(D, P)$. 

We expose a set of PVT triplets for explaining the system malfunc-
tion (details are in our technical report [8]). If we seek any one of them, as any minimal explanation exposes the
cause, which suggests the fix.

Given a system $D$ that can be altered during transformation, and helps limit trans-
mformation within certain subset of the data. An empty $S$ indicates that any tuple can be transformed. 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 $X_T(D''', X_p) = Y_T(D''', Y_p) = 0$.

### 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 $m_S(D) \forall D \subseteq \text{Dom}^m$, (2) an allowable malfunction threshold $\tau$, (3) a passing dataset $D_{\text{pass}}$ for which $m_S(D_{\text{pass}}) \leq \tau$, (4) a failing dataset $D_{\text{fail}}$ for which $m_S(D_{\text{fail}}) > \tau$, and (5) a set of candidate PVT triplets $X$ such that $\forall X \in X$ $X_T(D_{\text{pass}}, X_p) = 0$ and $X_T(D_{\text{fail}}, X_p) > \tau$, the explanation of the malfunction of $S$ for $D_{\text{fail}}$ but not for $D_{\text{pass}}$, is a set of PVT triplets $X^* \subseteq X$ such that $m_S((x_{X} \in X - X_p)(D_{\text{fail}})) \leq \tau$.

Informally, $X^*$ explains the cause: why $S$ malfunctions for $D_{\text{fail}}$, but not for $D_{\text{pass}}$. More specifically, failing to satisfy the profiles of the PVT triplets in $X^*$ are the causes of malfunction. Furthermore, the transformation functions of the PVT triplets in $X^*$ suggest the fix: how can we repair $D_{\text{fail}}$ to eliminate system malfunction. However, there could be many possible such $X^*$ and we seek a minimal set $X^*$ such that a transformation for every $X \in X^*$ 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 $D_{\text{fail}}$ and an allowable malfunction threshold $\tau$, an explanation $X^*$ of $S$'s malfunction for $D_{\text{fail}}$ is minimal if $\forall X' \subset X^*$ $m_S((x_{X} \in X - X_p)(D_{\text{fail}})) > \tau$.

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.

**DataPrism** requires knowledge of a passing dataset to guide the search for the cause of mismatch between $D_{\text{fail}}$ and $S$. Assuming availability of such knowledge is realistic in many real-world scenarios and has been considered in prior work [28, 50]. For instance, in ML, the training set can be considered as a passing dataset.

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

Certain applications allow access to multiple passing datasets or multiple malfunction metrics. **DataPrism** extends to this setting as well (details are in our technical report [8]).

### 3 DATA PROFILES, VIOLATION FUNCTIONS, AND 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 (Figure 1). 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 **DataPrism** framework is generic, and other profiles can be plugged into it. In this work, we just pick these profiles to show the efficacy of **DataPrism** over a set of real-world use cases.

As discussed in Section 2, a PVT triplet encapsulates a profile, and corresponding violation and transformation functions. Figure 1 provides a list of profiles (not exhaustive) 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. The PVTs are specified according to the data types of the attributes (numerical, categorical, dates, etc.) to reduce the effort of defining PVTs individually for each attribute1. In this work, we assume that a profile can be associated with multiple transformation functions (e.g., row 3), 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 any of its transformation functions is verified to be a fix. When the assumption does not hold, **DataPrism** may blame multiple profiles, which are potentially related via a disjunctive relationship, as possible cause. In such cases, some of the reported profiles may be false positives, but the true cause will never be missed (no false negatives).

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 and 2).
- **Thresholded by data coverage**: Certain fraction ($\theta$) of data tuples are allowed to violate the profile (rows 3–6).
- **Thresholded by a parameter**: Some degree of violation is allowed with respect to a specific parameter ($\alpha$) (rows 7 and 8).

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., row 1). Some local transformation functions only transform the violating tuples (e.g., row 3, transformation (2)), while others transform all values (e.g., row 1).
- **Global** transformation functions are holistic, as they need the knowledge of how other tuples are being transformed while transforming a tuple (e.g., row 4).

Many transformation functions may exist, including some extreme ones such as removing all tuples from the dataset. Prior data-cleaning techniques can be used as transformations to obey

---

1Specifying different PVTs for each attribute and their combination (not just data types) requires significant user effort but **DataPrism** is flexible to consider such PVTs.
Values are drawn from a specific domain.

\[ \sum_{x \in X} \left( |A| \neq 2 \right) \]

Map values outside \( S \) to values in \( S \) using domain knowledge.

Remove tuples (or add duplicates) to satisfy the size requirements.

Example 13. **Domain** requires two parameters: (1) an attribute \( A \in \mathbb{R}(D) \), and (2) a set \( S \) specifying its domain. A dataset \( D \) satisfies \( \text{Domain}(A, S) \) if \( \forall X \in X \) the attribute \( A \) is in \( S \). The profile \( \text{Domain}(A, S) \) is minimal w.r.t. \( D \) if \( \mathbb{R}^S \subseteq \mathbb{S} \cdot \mathbb{S} \) and \( S \cdot \mathbb{D} \) satisfies the profile \( \text{Domain}(A, S') \).

Example 14. **Indep** requires three parameters: two attributes \( A, B \in \mathbb{R}(D) \), and a real value \( a \). A dataset \( D \) satisfies the profile \( \text{Indep}(A, B, a) \) if the dependency between \( D.A \) and \( D.B \) does not exceed \( a \). Different techniques exist to quantify the dependency. We show its application in our case study involving the task of Income Prediction in Section 5.

**CorrCons** (jointly with \( \alpha \), \( \theta \), \( \tau \)) is learning coefficients in [29] such that \( \chi^2 \) statistic between a pair of attributes is below a threshold with a p-value \( \leq 0.05 \).

We modify attribute values to remove/reduce dependence.

There is a linear arithmetic relationship among the numerical attributes, captured by low-variance (a) projections (\( \tau \)).

Perform linear transformation over the numerical attributes to satisfy the conformance constraint.

**4 INTERVENTION ALGORITHM**

We now describe our intervention algorithm to explain the mismatch between a dataset and a system malfunctioning on that dataset. Our algorithm considers a failure and a passing dataset as input and reports 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. Our greedy strategy, **DataPrism** iteratively involves one PVT at a time based on their estimated likelihood to reduce system malfunction. We start with an example scenario to demonstrate how **DataPrism** works and then proceed to describe the algorithm.

4.1 Example Scenario

Consider the task of predicting the attribute high_expense 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 [40]) as its malfunction score. We seek the causes of mismatch between this prediction pipeline and **Peopletfail** (Figure 2), for which the pipeline fails with a malfunction score of 0.75. We assume the knowledge of **Peopletpass** (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 **Peopletfail** below 0.20.
(Step 1) To identify the profiles whose parameters differ between \textit{People}_{\text{fail}} and \textit{People}_{\text{pass}}. \textsc{DataPrism} identifies the exhaustive set of PVTs over \textit{People}_{\text{pass}} and \textit{People}_{\text{fail}} and discards the identical ones (in terms of profile-parameter values). We call the PVTs of the passing dataset whose profile-parameter values differ from the failing one \textit{discriminative PVTs}. Figure 5 lists a few profiles of the discriminative PVTs wrt \textit{People}_{\text{pass}} and \textit{People}_{\text{fail}}.

(Step 2) Next, \textsc{DataPrism} ranks the set of discriminative PVTs based on their likelihood of offering an explanation of the 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 \textit{People}_{\text{fail}} and \textit{People}_{\text{pass}}. Additionally, altering \( A \) with respect to one PVT is likely to automatically “fix” other PVTs associated with \( A \)\textsuperscript{2}. Based on this intuition, \textsc{DataPrism} 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 \( X \) 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, \textsc{DataPrism} prioritizes PVTs associated with a high-degree attributes. For instance, since \textit{high}\textsubscript{spenditure} has the highest degree in Figure 4, PVTs associated with it are considered for intervention before others.

(Step 3) \textsc{DataPrism} 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 \( X \). The benefit score of \( X \) is estimated from (1) the violation score that the failing dataset incurs w.r.t. \( X \), and (2) the number of tuples in the failing dataset that are altered by \( X \). For example, to break the dependence between \textit{high}\textsubscript{expenditure} and \textit{race}, the transformation corresponding to \textit{Indep} modifies five tuples in \textit{People}_{\text{fail}} by perturbing (adding noise to) \textit{high}\textsubscript{expenditure}. In contrast, the transformation for \textit{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.

(Step 4) \textsc{DataPrism} starts intervening on \textit{People}_{\text{fail}} using the transformation of the PVT corresponding to the profile \( \text{Indep, race, high}\textsubscript{expenditure}, 0.04 \) as its transformation offers the most likely fix. Then, it evaluates the malfunction of the system over the altered version of \textit{People}_{\text{fail}}. Breaking the dependence between \textit{high}\textsubscript{expenditure} and \textit{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) \textsc{DataPrism} then removes the processed PVT (\textit{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 \textit{Selectivity} is considered for intervention as it has the highest benefit score. To do so, \textsc{DataPrism} oversamples tuples

\begin{itemize}
  \item DataPrism extends to the case when altering values of \textit{A} w.r.t a PVT increases violation w.r.t some other PVTs, however, may require sub-optimal number of interventions.
\end{itemize}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
\textbf{id} & \textbf{name} & \textbf{gender} & \textbf{race} & \textbf{zip code} & \textbf{phone} & \textbf{high expenditure} \\
\hline
1 & Shane Johnson & F & 45 & A & 01004 & 208855697 & no \\
2 & DeShawn Boud & M & 40 & A & 01004 & 2085374523 & no \\
3 & Malik Ayer & M & 60 & A & 01005 & 2766465890 & no \\
4 & Dustin Jenner & M & 22 & W & 01009 & 7847891021 & yes \\
5 & Julietta Brown & F & 41 & W & 01009 & 7872989033 & yes \\
6 & Molly Beasley & F & 32 & W & 01011 & 4047747875 & yes \\
7 & Jake Bloom & M & 25 & W & 01011 & 4047747875 & yes \\
8 & Luke Stonewald & M & 35 & W & 01101 & 4042127741 & yes \\
9 & Scott Nossenberg & M & 25 & W & 01101 & 4048421581 & yes \\
\hline
\end{tabular}
\caption{A sample dataset \textit{People}_{\text{fail}} with 10 entities. A logistic regression classifier trained over this dataset discriminates against African Americans (race = ‘A’) and women (gender = ‘F’) (Example 1).}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
\textbf{id} & \textbf{name} & \textbf{gender} & \textbf{race} & \textbf{zip code} & \textbf{phone} & \textbf{high expenditure} \\
\hline
1 & Darin Brust & M & 25 & W & 01004 & 208855697 & no \\
2 & Rosalie Bad & F & 22 & W & 01005 & yes \\
3 & Kristine Hilyard & F & 50 & W & 01004 & 2766465890 & yes \\
4 & Chloe Ayer & F & 22 & A & 7847891021 & yes \\
5 & Julietta McHugh & F & 51 & W & 01009 & 9042899033 & yes \\
6 & Dora Elly & F & 32 & A & 01101 & yes \\
7 & Kristian Whidden & F & 25 & W & 01101 & 4047747875 & no \\
8 & Rene Strelow & M & 35 & W & 01101 & 6162127741 & yes \\
9 & Ariel Bent & M & 45 & W & 01102 & 4089656769 & yes \\
\hline
\end{tabular}
\caption{A sample dataset \textit{People}_{\text{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).}
\end{table}

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.

\textbf{Assumptions.} \textsc{DataPrism} makes the following assumptions:

(1) 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 [28, 50].

(2) 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 corresponding to female customers with \textit{high}\textsubscript{expenditure} = yes. This time, \textsc{DataPrism} 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, \textsc{DataPrism} is able to expose two issues that caused undesirable behavior of the prediction model trained on \textit{People}_{\text{fail}}.

(Step 6) \textsc{DataPrism} identifies an initial explanation over two PVTs: \textit{Indep} and \textit{Selectivity}. However, to verify whether it is a minimal, \textsc{DataPrism} 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 \textit{Indep} and \textit{Selectivity} are necessary, and, thus, are part of the minimal explanation. \textsc{DataPrism} 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).

\{(\textit{Indep}, race, \textit{high}\textsubscript{expenditure}, 0.04),

(\textit{Selectivity}, gender = F \land \textit{high}\textsubscript{expenditure} = yes, 0.44)\}

\section{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.

\textbf{Assumptions.} \textsc{DataPrism} makes the following assumptions:

(1) 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 [28, 50].

(2) 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

\begin{itemize}
  \item [\textsc{DataPrism}]
\end{itemize}
the malfunction score of the original dataset. E.g., 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 \( m_S(\text{fail}|X, Y) < m_S(X) < m_S(Y) \). 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 in any order. This assumption generally holds when different causes of malfunction involve different attributes. Consider a failing dataset that contains formatting error in address and correlation between race and income. Here, the transformation to fix the formatting issues in address does not affect race or income. Therefore, applying transformations in any order would have similar effect on system malfunction. We empirically observed that this assumption generally holds for most real-world scenarios.

**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 change in the malfunction score, after the transformation is applied.

**PVT-attribute graph.** DataPrism leverages observation O1 by constructing a bipartite graph (\( GP_A \)), called PVT-attribute graph, with all attributes \( A \in R(D) \) as nodes on one side and all discriminative PVTs \( X \in X \) on the other side. An attribute \( A \) is connected to a PVT \( X \) if and only if \( XP \) 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 (Missing, 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 \( A \).

**Benefit score calculation.** DataPrism 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. \( X \), and the “coverage” of \( X \). The coverage of \( X \) 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 DataPrism, 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.

---

**Algorithm 1: DataPrism**

<table>
<thead>
<tr>
<th>Input: Failing dataset ( D_{fail} ), passing dataset ( D_{pass} ), malfunction score threshold ( r )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output: A minimal explanation set of PVTs ( X^* )</td>
</tr>
</tbody>
</table>

1. \( X_F \leftarrow \text{Discover-PVT}(D_{fail}) \)
2. \( X_P \leftarrow \text{Discover-PVT}(D_{pass}) \)
3. \( X_S \leftarrow X_F \cap X_P \) / Common PVTs /
4. \( X \leftarrow X_P \setminus X_S \) / Discriminative PVTs /
5. \( GP_A(V_G,E_G) \leftarrow \text{Construct-PVT-Attr-Graph}(X,D_{fail}) \)
6. \( B \leftarrow \text{Calculate-Benefit-Score}(X,GP_A,D_{fail}) \)
7. \( X^* \leftarrow \emptyset \) / Initialize minimal explanation set to be empty /
8. \( D \leftarrow D_{fail} \) / Initialize dataset to the failing dataset /
9. while \( m_S(D) > r \) do
10. \( X_{data} = \{X \in X | (X,A) \in E_G \land A = \arg \max \text{\textit{AttrScore}}(D) \} \text{deg}(A) \} \)
11. \( X = \arg \max X_{data} B(X) \) / PVTs adjacent to high-degree attributes in \( G_{P_A} \) /
12. \( \Delta \leftarrow m_S(D) - m_S(X(D)) \) / Malfunction reduction /
13. \( GP_A \leftarrow GP_A \text{Remove}(X) \) / Update \( G_{P_A} \) /
14. if \( \Delta > 0 \) then
15. \( D \leftarrow X(D) \) / Apply transformation /
16. \( GP_A \text{Update}(D) \) / Update the PVT-attribute graph /
17. \( B \text{Update}(D) \) / Update benefit scores /
18. \( X^* \leftarrow X^* \cup \{X\} \) / Add \( P \) to explanation set /
19. \( X \leftarrow X \setminus \{X\} \) / Remove \( P \) from the candidates /
20. \( X^* = \text{Make-Minimal}(X^*) \) / Obtain minimality of \( X^* \) /
21. return \( X^* \) / \( X^* \) is a minimal explanation
Our experiments aim to answer the following research questions:

- (RQ1) In practice, can DataPrism correctly identify the cause and corresponding fix of mismatch between a system and a dataset for which the system fails? (Section 5.1)
- (RQ2) How sensitive is DataPrism to the choices of system parameters and facets of the framework? (Sections 5.2 and 5.3)
- (RQ3) Is DataPrism scalable and robust to varying problem complexity? (Section 5.4)
- (RQ4) How efficient is DataPrism compared to other alternative techniques? (Sections 5.1 and 5.4)

Baseline. Since no prior work supports dataset-level interventions guided by PVTs, we adapted state-of-the-art interventional debugging and explanation techniques that aim to explain the cause of system failure. To adapt these approaches to our problem settings, we replaced their intervention mechanism with the transformation functions we use in DataPrism. We consider three baselines:

- BugDoc [52] is a recent debugging technique that explores different parameter configurations of the system. We adapt BugDoc to consider each PVT as a parameter of the system configuration and interventions as modified configurations.
- Anchor [66] is a local explanation technique for classifiers that explains individual predictions based on a surrogate model. We train Anchor with PVTs over a dataset as features for the task of predicting whether the system malfunctions over the dataset or not. Each intervention plan is considered as a data point and is used to train the surrogate model.
- GroupTest (GT) [24] is an adaptive group-testing approach that performs group interventions to expose the mismatch between the input dataset and the system. It recursively partitions the PVTs until a PVT that reduces system malfunction is identified. However, it requires additional assumptions, which we discuss in our case study involving cardiovascular-disease prediction (Section 5.1.3).

Settings. We consider open-source implementations of Anchor and BugDoc with the default parameter settings. Since BugDoc requires a budget on the number of interventions, we specify the smallest value that guarantees BugDoc to expose the ground-truth cause as budget. We implemented GroupTest and DataPrism in Python 3.6.

DataPrism automatically identifies attribute types (text, categorical, or numerical) of each data attribute to construct corresponding PVTs. If an attribute contains values of heterogeneous types, then DataPrism constructs different PVTs for each homogenous partition. E.g., for an attribute with 90% numerical and 10% text values, DataPrism generates two DOMAIN PVTs, one for text and one for numerical values. DataPrism generates all PVTs discussed in Section 3. Additionally, DataPrism generates conditional PVTs by considering the subset of tuples that share the same value for other categorical attribute(s). E.g., consider a dataset with two attributes: X ∈ {x1, ..., x10} and Y ∈ {y1, ..., y10}. DataPrism generates 14 conditional PVTs: 4 pivoting on X and 10 pivoting on Y. One such conditional PVT is DOMAIN of Y over the tuples where X = x2.

For synthetic pipelines (Section 5.4) we generate numerical attributes in a dataset within the range [1, 10]. We inject error in the data by randomly choosing noisy attributes and then modifying their data distribution. Unless otherwise specified, all datasets for the synthetic pipelines contain 10 attributes, the ground-truth cause of malfunction is characterized by the DOMAIN PVT, and the malfunction-score threshold is 0.

5.1 Real-world Case Studies

We design seven case studies focusing on real applications—consisting of a diverse set of ML models [4, 5, 59] and data-analysis tasks—as opaque systems over real-world datasets. Figure 6 presents a summary of our evaluation results.
The system incurs a malfunction score of 0.322. **DATA Prism** requires only 2 interventions to discover the cause of malfunction. This study demonstrates the effectiveness of intervening on PVTs in non-increasing order of benefit (observations O2 and O3).

**GroupTest** requires 10 interventions, which is in the order of \( \log n \) where \( n \) is the number of discriminative PVTs (132 in this case). **BugDoc** and **Anchor** do not identify discriminative PVTs explicitly and consider all PVTs (136 in this case) for intervention. **Anchor** performs 103 local interventions to find the correct cause, while **BugDoc** finds a valid cause with an intervention budget of 20.

5.1.1 **Sentiment Prediction.** The system in this study predicts sentiment of input text (reviews/tweets) and we consider misclassification rate as the malfunction score. Internally, it uses flair [5], a neural-network model. The system assumes that for the target attribute, ’1’ indicates positive sentiment and ’-1’ indicates negative sentiment. We test the system over two datasets: **IMDb** [42] (~ 50K tuples) and **Twitter** [71] (~ 1.6M tuples). The malfunction score of the system over **IMDb** is only 0.09 while it is 1.0 over **twitter**.

We considered **IMDb** as the passing dataset and **twitter** as the failing dataset and used **DATA Prism** to find the cause of mismatch between **twitter** and the system. **DATA Prism** identifies a total of 3 discriminative PVTs, including **Domain** of the target attribute that differs between the two datasets: \((-1, 1)\) for **IMDb** and \([0, 4]\) for **twitter**. **DATA Prism** performs two interventions and finds that a 64% reduction in malfunction score is achieved when the following transformation is applied on the target attribute in **twitter**: \(0 \rightarrow -1\) and \(4 \rightarrow 1\). Consequently, **DATA Prism** reports this as a cause of the malfunction. With a close investigation, we found that **twitter** uses ’4’ to denote positive and ’0’ to denote negative sentiment [71], which matches the reported explanation.

When compared with other baselines, **GroupTest** requires 3 group interventions to explain the cause while **BugDoc** and **Anchor** require 4 and 303 interventions, respectively. Note that **Anchor** calculates system malfunction on many datasets that are transformed according to various local perturbations guided by the PVTs.

5.1.2 **Income Prediction.** From the study in fair machine learning, it is known that correlation between data attributes can cause the learned model to discriminate against marginalized groups. In this case study, we demonstrate how **DATA Prism** can expose cause of ML discrimination. The system trains a Random Forest classifier [59] to predict the income of individuals. We use normalized disparate impact [40] (a metric to measure discrimination) of the trained classifier wrt the sensitive attribute (sex) as the malfunction score.

We create two datasets—from census records [25] that contain demographic attributes of individuals—through a random selection of tuples, and manually add noise to the latter to break the correlation between income (target attribute) and sex (sensitive attribute). The system incurs a malfunction score of 0.195 for the latter dataset and 0.58 for the former. The malfunction (unfairness) here is caused by the existence of correlation between income and sex.

**DATA Prism** identifies 132 discriminative PVTs and constructs a PVT-attribute graph, where income has a degree of 19 and all other attributes have smaller degrees. As a result, **DATA Prism** prioritizes exploring PVTs that involve income. The transformations corresponding to the PVT **INDEPENDENT** between income and other attributes break the dependence between income and all other attributes, thereby, reducing the malfunction score to 0.32. **DATA Prism** requires only 2 interventions to discover the cause of malfunction.

5.1.3 **Cardiovascular Disease Prediction.** This system trains an AdaBoost classifier [4] on patients’ medical records [17]—containing age, height (in centimeters), weight etc.—to predict patients with disease. 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 tuples: (1) the passing dataset satisfies the format assumptions of the pipeline; (2) for the failing dataset we inject noise by converting height to inches.

**DATA Prism** identifies 87 discriminative PVTs with height, weight, and age having the highest degree of 16 in the PVT-attribute graph. **DATA Prism** considers the **Domain** of height as the fifth intervention, where it alters the failing dataset by applying a linear transformation, which reduces the malfunction from 0.71 to 0.30. This explanation matches the ground-truth cause of malfunction.

Among baselines, **BugDoc** and **Anchor** performed 100 and 3500 interventions, respectively. **GroupTest** does not identify the ground-truth cause of system malfunction in this case, because, performing groups of transformations together increases system malfunction. Specifically, we observe that the malfunction score with a composition of transformation functions is higher than that of the original dataset if the composition involves the PVT **INDEPENDENT**. This behavior is observed because adding noise to intervene with respect to **INDEPENDENT** worsens the classifier performance. **GroupTest** is applicable only in cases where different groups of interventions do not worsen the malfunction score, i.e., if \(X\) and \(Y\) correspond to any two discriminative PVTs, then \(m_S(Y_r \circ X_T)(D_{fail}) < m_S(D_{fail})\) if \(m_S(Y_f(D_{fail})) < m_S(D_{fail})\) or \(m_S(X_f(D_{fail})) < m_S(D_{fail})\).

### Conditional PVTs

We considered a modified failing dataset where the heights of admitted (inactive = 1) individuals were recorded in inches but others were in centimeters. The malfunction score in the failing dataset is 0.55 and the goal is to reduce it to below 0.30. In this case, we augmented the PVTs discussed in Figure 1 with conditional PVTs. The number of conditional PVTs is about 12 times the number of the original PVTs. **DATA Prism** requires 12 interventions to identify that transforming the height of individuals with inactive = 1 reduces the system malfunction to 0.30. This explanation matches the ground-truth cause of the malfunction. During the search process, **DATA Prism** considers all PVTs that contain the height attribute before all others, as it has the highest degree in the PVT-attribute graph. However, transformations involving all tuples have a higher benefit and are considered before the conditional PVTs. Therefore, it explores multiple different conditional PVTs that involve height to identify that only the subset having inactive = 1 should be transformed.

<table>
<thead>
<tr>
<th>Case study</th>
<th>Number of Interventions</th>
<th>Execution Time (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Must</td>
<td>BugDoc</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sentiment</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Income</td>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td>Cardiovascular</td>
<td>5</td>
<td>100</td>
</tr>
<tr>
<td>Flights</td>
<td>9</td>
<td>78</td>
</tr>
<tr>
<td>Amazon</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>Open Data</td>
<td>8</td>
<td>14</td>
</tr>
<tr>
<td>Physicians</td>
<td>30</td>
<td>46</td>
</tr>
</tbody>
</table>

Figure 6: Comparison wrt number of interventions and execution time of **DATA Prism** (denoted by DP) with other baselines. ‘-’ denotes that the technique failed to identify the cause of malfunction because assumption A3 did not hold.
5.1.4 Flight Delay Prediction. This system considers a logistic regression based pipeline trained by Fariha et al. [29] to predict the delay in flight duration. The pipeline is trained on a dataset containing more than 5.4M tuples and tested on two different datasets corresponding to daytime flights and overnight flights, respectively [29]. The system returns mean absolute error (MAE) of the predicted delay for the test dataset. We observe that the unnormalized malfunction score is less than 20 for daytime flights (passing dataset) and 81 for overnight flights (failing dataset). As reported in [29], the ground-truth explanation of system malfunction is the violation of conformance constraints by certain overnight flights, where the arrival time (next day) is before the departure time (previous day). DATAPrism identifies 91 discriminative PVTs on these datasets and the ground-truth cause of malfunction is ranked 9 according to the benefit of discriminative PVTs and is identified as the cause of system malfunction in fewer than 10 interventions. In contrast, violation of conformance constraints was identified as a root cause by BugDoc and Anchor in 78 and 601 interventions, respectively. GroupTest does not operate on this dataset because intervening on multiple PVTs worsens system malfunction even if one of the involved PVTs is the ground-truth cause of malfunction.

5.1.5 Amazon Entity Linking. The system comprises of an NLP pipeline that parses the input text to identify different entities in the text and maps the entities to a knowledge graph. The pipeline returns two malfunction scores, where the first malfunction score = 1 if the average time taken to run entity linking per row is more than 200ms, and the second malfunction score = 1 if the pipeline fails due to time out (runs for more than 30 min). We test the system with a dataset containing short text like Amazon product titles (< 11 tuples) as passing dataset. A dataset containing reviews of products on Amazon (~ 100K tuples) is considered failing as the pipeline exceeded 30 minutes, and incurred a malfunction score of 1 wrt both criteria. The larger text length of reviews is the ground-truth cause of the first malfunction and large size of reviews dataset is the ground-truth cause of the second malfunction.

DATAPrism identified numerous discriminative PVTs, among which DATASize PVT is connected to all attributes in the PVT-attribute graph. The benefit calculation component ranks it as the most beneficial PVT and identifies it as a cause of malfunction in the first intervention. After performing this intervention, it ranks the length of review text as the most beneficial PVT and considers it for intervention. Therefore, DATAPrism identifies both ground-truth causes of time out in 2 interventions. GroupTest identifies the ground-truth cause in 4 interventions, while BugDoc and Anchor require 8 and 303 interventions, respectively.

5.1.6 Open data analysis and visualization. The system in this study clusters different locations in the input dataset according to their attributes and generates a visualization. The system extracts first three characters of telephone number as area code, which is used for clustering. The dataset from NYC Open Data repository contains telephone numbers in different formats, for example many tuples contain the area code in parentheses, e.g., (213) 352-0235. For such tuples, area code is incorrectly identified as ‘21‘ which is not a numeric and the distance estimation function of the clustering algorithm throws an exception, crashing the code. The system returns a malfunction score of 1 if it crashes or the clusters are inaccurate and 0 otherwise. We tested the pipeline by considering above mentioned dataset as failing, and a small cleaned dataset as passing with a malfunction threshold of 0.

DATAPrism identifies different domain for the telephone number attribute (captured by Domain PVT) as one of the discriminative PVTs. The subsequent components intervene on this PVT in fewer than 8 interventions. The corresponding transformation of removing parentheses from telephone numbers is identified as the ground truth transformation. GroupTest does not identify the ground truth explanation in this dataset because the simultaneous transformations lead to inaccurate clustering output. BugDoc found the ground-truth in 14 interventions. Anchor performed more than 100 interventions and returned an incorrect result as Anchor does not operate on non-numeric PVTs.

Conditional PVTs. To test the effectiveness of conditional PVTs in this application, we considered an alternate pipeline that identifies the area code from the postal code of the tuple. If the postal code is missing, it uses telephone number to identify the area code. The noisy dataset for this study is generated by randomly removing postal code of some tuples. In this dataset, the ground truth explanation is a conditional PVT that performs the transformation only on tuples where postal code is missing. Transforming all tuples is a valid intervention that reduces system malfunction, but is not the minimal cause. DATAPrism identifies that transforming all tuples is sufficient to reduce system malfunction in 8 interventions but requires 3 more interventions to identify the minimal cause, which transforms telephone numbers of tuples with missing postal code and not all tuples. Therefore, DATAPrism successfully identifies the ground truth cause of malfunction in 11 interventions.

5.1.7 Physicians: Data Integration. The system considered in this study ingests the dataset into SQL to integrate information from multiple databases. The system ensures data quality by testing functional dependencies involving Zip code, State and County name such that two tuples with same zip code should have same state and county name (denoted by Zip Code→ State, CountyName), and two tuples with same county name should have the same state. It outputs the fraction of tuples that do not satisfy these functional dependencies as the malfunction score. Physicians dataset has a number of data quality issues like ‘0’ is mistakenly written as ‘0’ in zip code, county names and state have spelling mistakes, e.g., ‘xl’ instead of ‘al’ (Alaska). This dataset is commonly used to benchmark data cleaning techniques [61]. We construct two datasets through a random selection of tuples, where one of them is considered failing and the other dataset is repaired using a popular data-cleaning technique (Holoclean [61]) to be used as a passing dataset.

The failing dataset returns a malfunction score of 0.12 and the passing dataset has 0 malfunction. We test DATAPrism with a malfunction threshold of 0. The minimal ground-truth cause of malfunction comprises of violation of two functional dependencies a) ZipCode→ CountyName b) CountyName→ State. DATAPrism identifies a total of 327 discriminative PVTs and returns the ground truth cause of malfunction in fewer than 30 interventions. We observe that intervening with respect to ZipCode→ CountyName functional dependency reduces malfunction from 0.12 to 0.02 and it is identified as one of the causes of malfunction within 11 interventions. DATAPrism requires the rest of the interventions to identify

[53x298]
In this section, we test the quality of two different variants of DataPrism. (i) \text{DataPrism}\_{N\to G}\ does\ not\ construct\ the\ PVT-attribute\ graph\ and\ directly\ considers\ all\ discriminative\ PVTs\ for\ benefit\ calculation\ and\ subsequent\ stages.\ (ii) \text{DataPrism}\_{N\to B}\ does\ not\ perform\ benefit\ calculation\ and\ ranks\ PVTs\ only\ based\ on\ their\ degree\ in\ PVT-attribute\ graph. Table\ 7\ presents\ the\ number\ of\ interventions\ required\ in\ each\ case\ as\ compared\ to\ DataPrism\ for\ all\ case\ studies.\ Overall,\ we\ observed\ that\ DataPrism\ requires\ the\ least\ number\ of\ interventions\ across\ all\ pipelines.\ In\ cases\ where\ the\ highest-degree\ attribute\ in\ the\ PVT-attribute\ graph\ correctly\ captures\ the\ ground\ truth\ cause\ of\ malfunction,\ ignoring\ benefit\ calculation\ does\ not\ worsen\ the\ number\ of\ required\ interventions\ drastically\ (income\ case\ study).\ However,\ in\ the\ income\ case\ study,\ ignoring\ the\ PVT-attribute\ graph\ prioritizes\ the\ PVTs\ that\ have\ high\ benefit\ but\ are\ focussed\ on\ low-degree\ attributes.\ Therefore,\ \text{DataPrism}\_{N\to G}\ requires\ 51\ interventions\ as\ compared\ to\ 2\ interventions\ by\ DataPrism.\ The\ varied\ advantages\ of\ PVT-attribute\ graph\ and\ benefit\ calculation\ across\ different\ scenarios\ justify\ the\ need\ to\ use\ a\ two-step\ procedure,\ as\ followed\ by\ DataPrism.\ The\ only\ case\ where\ ignoring\ the\ PVT-attribute\ graph\ improves\ overall\ number\ of\ interventions\ is\ open\ data\ pipeline,\ where\ observation\ O1\ does\ not\ hold\ (the\ \textsc{domain}\ of\ telephone\ numbers\ has\ a\ smaller\ degree\ than\ other\ numerical\ and\ categorical\ attributes).\ Efficiency.\ Figure\ 6\ presents\ the\ execution\ time\ of\ the\ techniques\ for\ the\ real-world\ applications.\ DataPrism\ and\ GroupTest\ are\ highly\ efficient\ and\ require\ less\ than\ 30\ seconds\ to\ find\ the\ ground-truth\ cause\ of\ malfunction.\ In\ contrast,\ Anchor\ is\ extremely\ inefficient,\ needing\ more\ than\ 143\ minutes\ for\ cardiovascular,\ while\ BugDoc\ explains\ the\ malfunction\ within\ 63\ seconds.\ Key\ takeaways.\ Among\ all\ real-world\ case\ studies,\ the\ greedy\ approach\ DataPrism\ requires\ the\ fewest\ interventions\ to\ explain\ the\ cause\ of\ malfunction.\ Anchor\ requires\ the\ highest\ number\ of\ interventions\ as\ it\ performs\ many\ local\ transformations\ (small\ changes\ to\ profiles\ of\ the\ failing\ dataset)\ to\ identify\ the\ cause\ of\ failure.\ For\ each\ candidate\ explanation,\ it\ samples\ instances\ with\ replacement\ (that\ will\ be\ translated\ into\ PVT\ interventions)\ to\ confirm\ or\ discard\ them.\ BugDoc\ optimizes\ interventions\ by\ leveraging\ combinatorial\ design: it\ requires\ more\ interventions\ than\ DataPrism\ as\ its\ interventions\ increase\ with\ the\ number\ of\ PVTs,\ but\ fewer\ than\ Anchor.\ GroupTest\ requires\ fewer\ interventions\ than\ BugDoc\ and\ Anchor\ whenever\ it\ is\ applicable.\ GroupTest\ makes\ an\ assumption\ that\ intervening\ groups\ of\ PVTs\ improve\ system\ malfunction\ if\ any\ of\ the\ PVT\ in\ the\ group\ reduces\ system\ malfunction\ when\ applied\ individually.\ Empirically,\ we\ observe\ that\ GroupTest\ is\ not\ applicable\ when\ different\ PVTs\ include\ \textsc{indep}\ PVT\ and\ the\ system\ measures\ quality\ of\ classifier\ prediction\ to\ return\ malfunction\ score.

5.3 Effect of Malfunction Threshold
In this experiment, we test the effect of varying the malfunction threshold on the number of required interventions. First, we tested the cardiovascular pipeline with malfunction threshold varied from 0 to the malfunction of the failing dataset (in intervals of 0.10). In this case, failing dataset has a malfunction of 0.71 and no combination of transformation can achieve less than 0.30 malfunction. Whenever the malfunction threshold is varied in the range [0.30, 0.70], DataPrism identifies the ground truth cause of malfunction correctly in fewer than 5 interventions. However, when the malfunction threshold is in the range [0, 0.30], our algorithm returns a PVT that transforms the height from inches to centimeters. This PVT reduces the system malfunction to 0.31 and it is the minimum achievable malfunction for this dataset. Therefore, DataPrism’s explanation guarantees a minimal set of PVTs having the minimum achievable malfunction if the input requirement is not feasible. We observe a similar trend in case of open data case study, where higher malfunction threshold requires fewer interventions as compared to lower values of malfunction threshold.

To further investigate the effect of malfunction threshold, we considered complex synthetic pipelines where a system fails due to a) wrong domain of input data and b) missing data. In this experiment, all value ranges of malfunction threshold are feasible. Figure 9 shows the effect of increasing malfunction threshold on the number of required interventions. Overall, the number of interventions is stable across a small change in the threshold and it shows a downward trend on average. This evaluation justifies that the effort spent by DataPrism reduces as the malfunction threshold increases.

5.4 Scalability and Robustness
In this experiment, we test the effect of different parameters on the quality of the identified explanation, number of required interventions, and running time of DataPrism. We investigate several configurations by varying the number of data attributes, number of discriminative PVTs, and type of ground truth cause of malfunction.

5.4.1 Effect of the Number of Attributes and PVTs. This experiment tests the effect of the number of dataset attributes and the number of discriminative PVTs on the efficacy of DataPrism, and contrast those with other state-of-the-art baselines for synthetically generated pipelines. We also investigate the influence of the number of PVTs involved in the root causes and their interactions on the number of interventions each method requires.

Figure 8(a) presents the effect of changing the number of attributes in the datasets on the number of required interventions. DataPrism requires fewer than 5 interventions on average. In contrast, BugDoc and Anchor require orders of magnitude more interventions. The number of interventions required by BugDoc grows linearly with the number of attributes. At the same time, Anchor perturbs all PVTs to solve a multi-armed bandit problem: the more PVTs affect the pipeline errors, the more interventions are required.
needed. GroupTest requires more interventions than DataPrism, and grows logarithmically with the number of data attributes.

Figure 8(b) depicts the effect of the number of discriminative PVTs on the number of required interventions. DataPrism shows superior performance, requiring fewer than 10 interventions even with more than 100 discriminative PVTs. Here, we observe trends similar to the one in Figure 8(a) for other baselines as the number of PVTs are positively correlated with the number of attributes.

5.4.2 Effect of the size of ground-truth cause. The pipelines presented in Figures 8(a) and 8(b) have a single PVT as the ground-truth cause of the malfunction. In Figure 8(c), we fix the number of attributes to 15 and the number of discriminative PVTs between the passing and the failing datasets to 136. We modify the ground-truth cause to be a conjunction over a set of PVTs of varying cardinalities. We find that the cardinality of the root-cause set (length of the conjunctive cause) does not impact the number of interventions as much as the number of attributes and the number of discriminative PVTs do. However, having more than one cause for malfunction (i.e., a disjunctive cause) requires many more interventions for Anchor and GroupTest, as shown in Figure 8(d). DataPrism still needs orders of magnitude fewer interventions than these other approaches, although the probability of failing to find any feasible transformation, which decreases malfunctions scores, increases with the number of possible root causes within the disjunction.

We performed this analysis on another set of synthetic pipelines, where a constant fraction of values are deleted from the noisy dataset and the system returns the fraction of missing values as the malfunction score. We observed similar patterns for all the experiments. However, the average number of interventions for all methods increases as the number of discriminative PVTs increases. Due to space constraints, the plot appears in our technical report [8].

Scalability. We compare running time of different approaches with increasing number of attributes and discriminative PVTs. The time required by DataPrism to explain the malfunction grows sub-linearly in the number of attributes and discriminative PVTs. We observe similar trend of the number of required interventions on varying these parameters. This experiment demonstrates that DataPrism requires fewer than $O(|X|)$ interventions in practice (where $X$ denotes the set of discriminative profiles).

5.4.3 Effect of the set of input PVTs. In this experiment, we consider the synthetic pipelines from the previous experiment (same as Figure 8 with 5 attributes) and vary the set of considered PVTs to explain the cause of malfunction. We generated a random sample of the set of PVT templates as input along with the ground truth cause, if it is not present in the sample. This variation of the number of PVTs drastically affect the number of required interventions for BugDoc and Anchor. On the other hand, DataPrism is more stable (fewer than 10 interventions across different settings) and requires fewer interventions than BugDoc and Anchor.

6 RELATED WORK

Interventional debugging. AID [28] 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 [52] finds parameter settings in an opaque-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. Prior techniques on data-cleaning [61, 64], fair ML [32, 54, 69, 73], and data profiling [2, 3] evaluate the quality of a dataset for a specific application and propose data transformations for data cleaning or bias removal. These techniques can be modeled using PVTs in DataPrism framework. We demonstrated the flexibility of DataPrism by considering two representative data cleaning techniques: (1) HoloClean [61] to transform a dataset with respect to functional dependencies, and (2) techniques described in [29] to transform a dataset with respect to conformance constraints. Identifying useful PVTs for a given application is orthogonal to our contribution.

Data explanation. Explanations for query results have been abundantly studied [9, 10, 21, 26, 75]. Some techniques find causes of errors in data generation processes [75], while others discover relationships among attributes [9, 26], and across datasets [21]. Unlike interventional efforts, which DataPrism focuses on, these approaches operate on observational data.

Model explanation. Machine learning interpreters [65, 66] perturb test data to learn a surrogate for models, but their goal is not to find mismatch between data and models. Debugging methods for ML pipelines are similar to data explanation [15, 16], where training data may cause model’s underperformance. [74] and [47] discuss principled ways to find reasons of malfunctions. Wu et al. [76] allow users to complain about outputs of SQL queries, and presents data points whose removal resolves the complaints. [70] validates when models fail on certain datasets and assumes knowledge of

Figure 8: Average number of interventions required by DataPrism and three other techniques for varying number of attributes, discriminative PVTs, size of single conjunctive root causes, and size of disjunctive root causes. Ground-truth cause of malfunction: DOMAIN PVT

Figure 9: #Interventions for varying malfunction threshold for two data issues: (Left) out-of-domain values, (right) missing values
We introduced the problem of identifying causes and fixes of misuse and presented [10] Daniel W. Barowy, Emery D. Berger, and Benjamin Zorn. 2018. ExceLint: Automating requirements from users to generate minimal and interpretable reports fixes in the form of transformation functions. We demonstrated the effectiveness and efficacy of DataPrism 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 plan to extend DataPrism to support multi-objective requirements from users to generate minimal and interpretable explanations, and support applications that may exhibit multiple types of malfunction.

REFERENCES
