Explaining Dataset Changes for Semantic Data Versioning with Explain-Da-V (Technical Report)

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ABSTRACT

In multi-user environments in which data science and analysis is collaborative, multiple versions of the same datasets are generated. While managing and storing data versions has received some attention in the research literature, the semantic nature of such changes has remained under-explored. In this work, we introduce Explain-Da-V, a framework aiming to explain changes between two given dataset versions. Explain-Da-V generates *explanations* that use *data transformations* to explain changes. We further introduce a set of measures that evaluate the validity, generalizability, and explainability of these explanations. We empirically show, using an adapted existing benchmark and a newly created benchmark, that Explain-Da-V generates better explanations than existing data transformation synthesis methods.

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The source code, data, and/or other artifacts have been made available at https://github.com/shraga89/ExplainDaV.

1 INTRODUCTION

Data is one of the most important ingredients in any decision making process. The amount and size of data is growing and datasets are being reused for multiple analyses. Data may be stored in different systems (e.g., data lakes [73]), vary in their formats, and may or may not contain metadata. Data projects often involve multiple users that work on datasets conjointly or independently, creating different data versions. Accordingly, *data versioning* becomes an important ingredient in data management [21]. Nevertheless, even if versions are well managed [22], the documentation may be superficial, e.g., embedded in filenames, which can be very inadequate. In addition, the collaboration itself may not be structured or properly managed and each user may perform different, often *undocumented* processing steps on data [53, 58–60, 100]. For example, some users may clean the data by removing rows or columns if they have duplicated or missing information. Other users extract features, transforming the current data to create new columns.

Current tools have limited data versioning support [58]. Generally speaking, data, as opposed to code, may be less documented [59, 100] and data changes, even if documented, are rarely accompanied by useful descriptions, making it difficult to understand them [53]. Within a close collaboration group, a notebook containing transformation code may be shared, but between organizations this is rarely done. Consider, for example, the many versions of important datasets shared on open data portals [40, 41, 54] where transformations are generally not shared. The lack of sufficient version documentation results in reduced reproducibility and trust among users using the data [60, 100]. While managing and storing data versions has received attention in literature [21, 22, 55, 83, 99], the semantic nature of such changes has remained under-explored. We motivate our work using the following example.

a0	a1	a2	a3	a4
m1	The Godfather (A)	175	9.2	Drama
m2	Hamilton (PG-13)	160	8.6	Drama
m3	The Avengers (UA)	143	8.0	Action
m4	Inception (UA)	NaN	8.8	Action
m5	Moana (U)	107	7.6	Animation

(a) Dataset version created by UserA

a0	a1	a2	a3	a4	a5	a6	a7	a8
m1	The Godfather (A)	175	9.2	Drama	A	2.91	4	17
m2	Hamilton (PG-13)	160	8.6	Drama	PG-13	2.67	3	16
m3	The Avengers (UA)	143	8.0	Action	UA	2.38	3	17
m5	Moana (U)	107	7.6	Animation	U	1.78	2	9

(b) Dataset version created by UserB

Figure 1: Example dataset versions about movies created by two users. Attribute names are provided in Example 1.

Example 1. *Figure 1 presents two dataset versions about movies. We discard the column names from the figure to illustrate a realistic (data lake) scenario. For readability,* a0 *is a tuple id,* a1 *represents the movie title,* a2 *measures the movie runtime in minutes,* a3 *assigns a rating to the movie, and* a4 *provides the genre of the movie. For convenience of presentation, lets assume that the table on the bottom (Figure 1b) was created by UserB as a derivation of the table on the top (Figure 1a) that was created by UserA. Even properly naming the tables, e.g., Table 1a as* data1_v1.csv *and Table 1b as* data1_v2.csv*, or knowing that Table 1b is derived from Table 1a [21], does not help UserA to get a* semantic *understanding of what UserB changed in the table or, more importantly, what data processing steps UserB has performed.*

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Example 1 illustrates the need for a semantic understanding of a new dataset version. Aiming to fill this gap, this work provides the setup and new solution to *explain* the semantic changes between two dataset versions. Specifically, our goal is to *automatically* explain (in a simple user friendly way) the steps leading from one version of dataset to the other. For example, *how was column* a6 *in Figure 1b created?* or *why was the fourth row in Figure 1a deleted?* Note that the changer's intent, which is subjective, cannot be truly reverse engineered. Our objective is to provide the other user an accurate explanation, e.g., a set of functions, that describes the changes. Following this goal, we return to our motivating example.

Example 1 (cont.). *Figure 2 illustrates an annotated version of Figure 1b, that explains the changes. In other words, Figure 2 reverse engineers the changes made by UserB in a way that a user can understand. Specifically, UserB cleaned the rows that contain* NaN *values (in this case* m4*) and extracted numerical features. The certification of the movie, given in parenthesis in* a1*, was extracted to create* a5 *and the column* a6 *converts the units of* a2*, the runtime of the movie, from minutes to hours. Since the range of movie ratings (*a3*) is limited, UserB also discretized the values to create four rating classes in column* a7*. Aiming to examine the effect of title length (an effect found for paper citations [42]) within the domain of movies, UserB added column* a8 *that provides the length of titles from* a1*.*

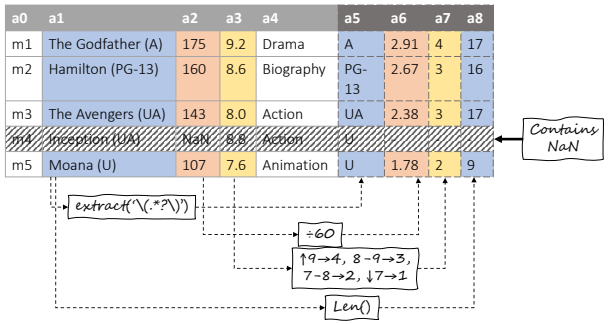


Figure 2: An interpretation of the changes between the dataset versions given in Figure 1. The columns are colored based on their origin (e.g., a5 is blue because it originates from the blue a1) and annotated column transformations are given at the bottom. The annotated row transformation is given on the right, in this case removing a row, which is also illustrated by diagonal stripes over the row.

As illustrated in Example 1, there are a variety of possible transformations (e.g., multiplying/dividing the values of a numeric column, e.g., a3, by a constant), potentially creating an infinite possible number of changes to a dataset. These changes can be vertical (changing columns) or horizontal (changing rows), they can add information (adding columns/rows) or remove information (removing columns/rows) and they can involve different data types, e.g., textual to numeric (a1 to a8) or numeric to categorical (a3 to a7). In addition, a user may also change a cell in the table, e.g., replacing the NaN value in row m4 by 146.25 (the mean value of the other values in the column), or perform a full-table operation, e.g., transposing the table. Transformation discovery methods are used for multiple data management tasks including fuzzy joins [103], data wrangling [25], entity consolidation [43] and more [18, 50, 52, 56] mainly focusing on textual (text-to-text) transformations and consider the transformed values (rather than the transformation itself). Our method mainly focuses on data versioning, for which, the transformations themselves, as a means of explaining changes among different dataset versions, is the main interest. Our resolved transformations also cover transformations that involve, among others, numeric transformations. The term "explanation" became quite common recently and may be associated with multiple meanings. For example, both El Gebaly et al. [45] and Kim et al. [61] use data summaries as explanations. Explain3D [95], which shares a similar context to ours, explains dataset disagreements with syntactic provenance-based and value-based modification mappings. In this work the main component of an explanation is a transformation that explains change. This paper makes the following contributions.

(1) **Semantic Data Versioning Definition:** we define and solve a novel problem of semantic data versioning by explaining the changes between two dataset versions.

(2) **Vertical and Horizontal Data Transformation Resolution Across Different Data Types:** we present a solution to the problem of semantic data versioning that examines both vertical (adding/removing columns) and horizontal (adding/removing rows) transformations that involve multiple data types.

(3) **Semantic Data Versioning Metrics:** we provide a set of evaluation measures to examine the quality of explanations in terms of validity, generalizablity, and explainability.

(4) **Semantic Data Versioning Benchmark:** we introduce a new data versioning benchmark composed of 5 version-sets including 342 different dataset versions representing a total of 1702 changes.[1]

(5) **Empirical Evaluation:** our experiments show that Explain-Da-V performs better than multiple baselines on both our new version benchmark and on an existing data science pipeline benchmark [1]. We analyze the impact of different components of our solution on performance.

In this paper, we assume two tables are given where one is known to have been derived from the other (i.e., is a version it) and we know a match between the attributes and tuples the two tables share. This work focuses on "internal" additions, deletions, or modifications (modeled as deletions followed by additions). External additions, e.g., finding joinable tables [102] and joining them with a table to create a new version, are reserved for future work.

2 RELATED WORK

We are, to the best of our knowledge, the first to address the semantic aspect of data versioning. Yet, related research exists ranging from synthesizing data transformations to exploring data change.

2.1 Data Versioning

Data versioning research mainly focus on developing version managers to decrease the need for storing many versions of large datasets [73]. For example, DataHub provides a git-like interface to manage, store, recreate, and retrieve versions using a directed version graph [21]. Follow-up research further studied the trade-off between recreation and storage in a principled way analyzing six different settings [22]. Recently, Schüle et al. presented TardisDB [83],

[1] We will make code and benchmark publicly available upon acceptance. Main parts of the code and a benchmark sample are available [15].

an SQL extension to support version management. TardisDB uses named branches over tables, to monitor table versions and track their modification history. In contrast, we focus on the semantic aspects of data versioning, zooming in on explaining the semantic differences between dataset versions. Schema versioning has also been studied [80]. Although schemata may change over time [89], which provides semantic hints to data change, we assume metadata is not always complete and may be ambiguous [73]. Hence, we focus only on the versioning of the data itself.

2.2 Data Change, Difference, and Integration

We assume that some match between the attributes and tuples of the versions is given. This assumption is rooted in many years of data integration research, exploring attribute matching (schema matching) [79, 85], tuple matching (entity resolution) [46, 66], and others [20, 69]. Earlier works looked into change and copy detection in structured data [33, 34], which was later extended also to semi-structured documents such as XML [37, 74, 96].

Acknowledging data change, Bleifuß et al. [23] envision systems that can interactively explore such change. They present a model of what changed, where, when and how, using what they call a change-cube to monitor the history of changes over time using methodologies such as time-series clustering [26]. DBChEx [24] is a tool to explore data and schema change using a set of exploration primitives. While similar in nature, this line of work focuses mainly on how to *explore* change aiming to answer questions such as "How many changes have there been in recent minutes?" and "How old are the entities in table Y? When were they last updated?" [23, 24]. Our work focuses on local changes between versions and *how* the changes were performed (which transformations were applied?), e.g., how did UserB create the table in Figure 1b from Figure 1a.

Another related research area is explaining query answers [68, 82]. Given a query and a database, they explain query answers using the tuples in the given database, e.g., using provenance [35]. We, in contrast, explain dataset changes using data transformations. While changes can be thought of as a set of queries, explanations for queries that involve non-trivial transformations (e.g., adding `a5` in Example 1) cannot be explained only using the tuples.

2.3 Data Transformation By Example

The final related line of research we cover aims to automatically transform data. Largely, given input and output tables (datasets) or their subsets (examples), the goal of such approaches is to find a transformation (program) such that if it is applied over the input we get the output. It is worth noting that earlier work has referred to this problem as query reverse engineering [75, 93], which is roughly the same idea, i.e., finding a query that generates the output using the input. This line of work can be divided into two main groups.

The first group is rooted in a paradigm called programming-by-example (PBE) [25, 48, 50, 56, 57, 87, 88, 103], where the goal is to synthesize a program that manipulates a given input to get a given output. To do so, methods design different search spaces (operators to be applied over the input) and apply different search algorithms. For example, Foofah [56] creates a search space using operators such as drop (delete a column) and split (separate a column by some delimiter) and search the space using A* heuristic search. Clx [57] also introduces string patterns such as regular expressions to the search space and tokenizations. Data Diff [90] applies a search approach to "patch" transformations, summarizing distribution changes, including one numeric patch (operator) supporting linear transformations with pre-defined (randomly selected) parameters. Muller et al. describes differences between relational databases with what they call "update distance" [71] using a similar searching approach. Finally, Bogatu et al. introduced functional dependencies to navigate the search space [25], which we also use in our work.

The second group focuses on creating transformation repositories from external sources such as Web Forms, Knowledge Bases [18, 76], GitHub and Stackoverflow [51, 52]. Transform Data by Example (TDE) [51], instead of searching through a space of predefined possible operations, creates a search engine where transformation functions are crawled from GitHub and Stackoverflow. Instead of applying heuristic search such as A*, TDE ranks candidate functions to find relevant functions. TDE was later extended to allow transformation search based on patterns [52]. DataXFormer [18] and Proteus [76] create a repository of tables from which desired output values can be extracted.

A similar line of research revolves around resolving data preparation and analysis transformations [19, 97, 98]. AutoPandas [19] focuses on Pandas library [14] and aims to synthesize a program using pandas functions. Auto-pipeline [98] extends the "by-example" paradigm to "by-target", meaning that the output the user provides is not necessarily aligned with the input and can require table-reshaping operations (e.g., group by). Auto-pipeline comes in two variations, namely, search (which is equivalent, yet extended to what is described above) and deep reinforcement learning. The former can be a candidate baseline for our approach. The latter requires training data which we assume does not exist in our setting.

In contrast to PBE and query reverse engineering, we do not focus on matching input to output. Rather than looking only at success rates (is the transformation valid), our search is guided by the principle of creating valid, generalizable, and explainable transformations. In our approach, these transformations can be multi-dimensional (adding/removing attributes/tuples) and address multiple data-types (e.g., numeric, categorial, and text transformations). While our string-based transformation resolution is based on an extended Foofah, we also support numeric transformations using explainable machine-learning algorithms to *fit the appropriate transformation* rather than searching a very large space of possible transformations. We go beyond Foofah to support text-to-numeric transformations (e.g., measuring the length of a string) and text cleaning operations (e.g., stopword removal and lemmatization).

3 SEMANTIC DATA VERSIONING

A dataset is denoted by a table T, composed of a set of attributes $T_A = \{A_1, \ldots, A_n\}$ and tuples $T_r = \{r_1, \ldots, r_m\}$. Each tuple is defined as $r_i = \langle r_{i0}, r_{i1}, \ldots, r_{in} \rangle$, such that r_{i0} is the tuple identifier and r_{ij} ($j \neq 0$) is a value assigned to the attribute A_j in the tuple r_i. Often we may have two datasets and know one was derived from the other but the actual transformation code or documentation has been lost [53, 58–60, 100]. In what follows, we address the problem of explaining the changes between two dataset versions.

Given two dataset versions, T and T', we assume the latter, wlog, is a *derived table*, i.e., a user changed the table T and as a result obtained the table T' with $T'_A = \{A'_1, \ldots, A'_n\}$ and tuples $T'_r = \{r'_1, \ldots, r'_m\}$. We assume that an alignment between T_A and T'_A (attribute-match, denoted Σ_A) is given and that tuples in T and T' with the same identifier (r_{0i} and r'_{0i}) are assumed to represent the same real world entity. An attribute $A_i \in T$ (or $A'_j \in T'$) is considered unmatched if it does not appear in Σ_A. A record $r_i \in T$ (or $r'_j \in T'$) is considered unmatched if there is no record in T' (respectively, T) with the same identifier.

Given an attribute-match Σ_A, we define the changes between the two dataset versions to be explained using a three symbols notation. The first refers to whether the dataset is the left-hand one (L) or the right-hand (revised) one (R), the second to whether it is the matched (∇) or unmatched (unmatched is also called delta (Δ)), and the third refers to attributes (A) or tuples (r). Specifically, $L\Delta_A$(left-hand delta attributes) and $L\nabla_A$(left-hand matched attributes) are the set of unmatched (delta) and matched (consistent) attributes in T, respectively. Similarly, $R\Delta_A$ and $R\nabla_A$ are the unmatched and matched attributes in T'. Using these sets, we create *projected* tuples. Let r_j be a tuple of table T, the projected tuple is given by $\pi_{L\nabla_A}[r_j]$, projecting out non-matching attributes. Given such projected tuples, we can define similar sets for tuples, namely $L\Delta_r$(left-hand delta tuples), $R\Delta_r$(right-hand delta tuples), $L\nabla_r$(left-hand consistent tuples) and $R\nabla_r$(right-hand consistent tuples). We summarize this notation in Table 1. Intuitively, we are interested in explaining the deltas between the datasets, i.e., $L\Delta_A$, $R\Delta_A$, $L\Delta_r$, and $R\Delta_r$.

Example 2. *Given the dataset versions in Figures 1a (T) and 1b (T'), the attribute-match is simply given by aligning the columns headers (e.g.,* `a2` $\leftrightarrow$ `a2`*). The tuple ids are given under* `a0` *(e.g.,* `m1` $\leftrightarrow$ `m1`*). The following are the change sets: $L\Delta_A = \emptyset$ (no removed columns), $R\Delta_A$ = {`a5`, `a6`, `a7`, `a8`} (four added attributes), $L\Delta_r$ = {`m4`} (one removed tuple), and $R\Delta_r = \emptyset$ (no added tuples).*

3.1 Change Explanations

We use the term *explanation* to refer to a user friendly way to interpret a change between two relations. Intuitively, an explanation is a transformation $\mathcal{P}$ from an origin $\mathcal{O}$ to a goal $\mathcal{G}$. Formally, an explanation $\mathcal{E}$ is defined with respect to a *goal* $\mathcal{G}$ with a name $\mathcal{G}_{name}$ and an associated relation $\mathcal{G}_{relation}$ it represents. As the goal, the origin is also associated with a name ($\mathcal{O}_{name}$) and a relation ($\mathcal{O}_{relation}$). A transformation $\mathcal{P}$ is an expression that transforms the origin relation $\mathcal{O}_{relation}$ into the goal relation $\mathcal{G}_{relation}$. The origin relation may also be empty. A formal definition is as follows

Definition 3 (Explanation ($\mathcal{E}$)). *Let $\mathcal{G}$ be a goal. An* explanation $\mathcal{E}_{\mathcal{G}} = (\mathcal{O}, \mathcal{P})$ *of $\mathcal{G}$ is composed of an origin $\mathcal{O}$ and a transformation $\mathcal{P}$, such that $\mathcal{G}_{relation} = \mathcal{P}(\mathcal{O}_{relation})$.*

3.2 Explaining Dataset Changes

We focus on two *orientations* of explanations, namely, *vertical* explanations and *horizontal* explanations. We further distinguish between *removal* and *addition* explanations. Modifications can be modeled as a removal followed by an addition. Explanation types differ in the type of relations that the origin and the goal represent.

Table 1: Notations used in the paper. The changes $L\Delta_A$, $L\nabla_A$, $L\Delta_r$, and $L\nabla_r$ are defined wrt the left-hand table T. The right-hand notation can be obtained by replacing T with T' below.

	Notation	Meaning
Basic	T	Left-hand dataset
	T'	Right-hand (revised) dataset
	T_A	The attribute set of dataset T
	T_r	The tuple set of dataset T
Changes	$L\Delta_A$	The set of unmatched attributes in T $\{A_i : A_i \in T_A \wedge \nexists A'_j \in T' : (A_i, A'_j) \in \Sigma_A\}$
	$L\nabla_A$	The set of matched attributes in T $T_A \setminus L\Delta_A$
	$L\Delta_r$	The set of unmatched tuples in T $\{\pi_{L\nabla_A}[r_j] : r_j \in T_r \wedge \nexists r'_i \in T : r_{0i} = r'_{0i}\}$
	$L\Delta_r$	The set of matched tuples in T $\{\pi_{L\nabla_A}[r_j] : r_j \in T_r\} \setminus L\Delta_r$

The goal ($\mathcal{G}_{relation}$) and origin ($\mathcal{O}_{relation}$) relations are defined with respect to versions T or T'. Specifically, the relations $\mathcal{O}_{relation}$ and $\mathcal{G}_{relation}$ can be a projection (subset of attributes) or selection (subset of tuples) over either T or T'. In vertical explanations (adding or removing attributes), the associated goal and origin names ($\mathcal{G}_{name}$ and $\mathcal{O}_{name}$) are the projected attributes. For horizontal explanations (adding or removing tuples), $\mathcal{G}_{name}$ and $\mathcal{O}_{name}$ correspond to the set of tuple ids in the subset. When clear from context, we refer to the goal and the origin by their names.

Example 4. *Recall the versions in Figures 1a (T) and 1b (T'). An example explanation for a goal $\mathcal{G} = (a6, \pi_{a6}[T'])$ is composed of an origin $\mathcal{O} = (a2, \pi_{a2}[T])$ and a transformation $\mathcal{P} = \pi_{a2}[T] \div 60$, which is tuple-based, i.e., divide each tuple in $\pi_{a2}[T]$ by 60. When clear from context, we denote this explanation as $\mathcal{E}_{a6} = (a2, a2 \div 60)$.*

Recalling the change sets, we aim to find vertical addition explanations for $L\Delta_A$, vertical removal explanations for $R\Delta_A$, horizontal addition explanations for $L\Delta_r$, and horizontal removal explanations for $R\Delta_r$. An explicit problem definition, that relies on the quality of explanations is provided in Section 7.2.

Example 5. *Recall the versions of Figure 1, annotated changes in Figure 2, and $L\Delta_A$, $R\Delta_A$, $L\Delta_r$, and $R\Delta_r$, defined in Example 2. A possible set of explanations to explain the changes is as follows*

$$\mathcal{E}_{\mathtt{a5}} = (a1, \mathtt{extract(a1, '(.*?)')})$$
$$\mathcal{E}_{\mathtt{a6}} = (a2, a2 \div 60)$$
$$\mathcal{E}_{\mathtt{a7}} = \left(a3, \begin{cases} 4, & \text{if } 9 \le a3 \\ 3, & \text{if } 8 \le a3 < 9 \\ 2, & \text{if } 7 \le a3 < 8 \\ 1, & \text{otherwise} \end{cases}\right)$$
$$\mathcal{E}_{\mathtt{a8}} = (a1, \mathtt{len(a1)})$$
$$\mathcal{E}_{\mathtt{m4}} = (\emptyset, \mathtt{has\_NaN})$$

Most of the explanations are self-explanatory (as they should be). Interesting cases are $\mathcal{E}_{a5}$, that extracts value in parenthesis. Another example is the horizontal explanation $\mathcal{E}_{m4}$, for which the origin is an empty set and the tuple was removed due to a `NaN` *(null equivalent)*

value. Although the goal is m4, the transformation we find is one that removes m4 and no other tuples.

Explain-Da-V is a data-driven[2] method composed of four parts corresponding to adding/removing attributes/tuples. We first describe our core explanation methods (Section 4), which are then utilized to explain vertical (Section 5) and horizontal changes (Section 6).

4 CORE SEMANTIC EXPLANATION METHODS

Our core explanation methods rely on fitting an appropriate explanation methodology to data types we find in the origin O and the goal $\mathcal{G}$. Rather than the traditional database attribute types (strings, integers, floats, etc.), given the nature of our analysis, we look into ML feature types [84]. We focus on three main types, namely, *Numeric*, *Categorical* and *Textual* (mixed types are considered textual), which characterizes the core changes Explain-Da-V covers.[3] Aiming to resolve a high variety of changes, we develop methods that are built on top of different types of origin sets using multiple approaches that exploit the type of change. Accordingly, Explain-Da-V can be applied over any pair of versions, regardless of how far apart the versions are (meaning how many transformations have been applied). If an explanation is not found for a specific change, it is declared idiopathic (unexplained).

Note that among the different changes, the vertical additions are the most common and complex and, thus, the presented methods mostly address such a scenario. Specifically, for the presentation of methods, we assume the goal as a single attribute (a right-hand attribute to be explained) with its data values. Also, given a goal, finding its origin is not straight forward. For the moment, assume the origin is the original left-hand table T. We discuss a method to "find" an origin, given a goal, in Section 4.6.

4.1 Numeric Change Explanations

Whenever we need to explain a numeric goal using an origin that contains numeric data, we position the problem as *regression* in which the origin relation tuples are treated as independent variables and the goal relation tuples as dependent variables. Aiming at explainable transformations, we build on top of linear regression [30]. To reduce model complexity and prevent over-fitting [91], we experiment with Lasso and Ridge regularization.

Example 6. *A numeric transformation is given in Figure 1b, where explaining* a6 *can be resolved by fitting a regressor* $\frac{1}{60} \cdot a2$.

Not all numeric transformations can be covered by a linear function. Accordingly, to allow richer, more flexible, numeric transformations, we *extend* the feature space (i.e., the origin) by generating additional features. Note that while these extensions are motivated by commonly used data science and engineering operations [63], they do not (and cannot) cover every possible transformation.

Polynomial Regression and Inter-relation Features: To explain polynomial transformations, we generate additional polynomial features [44] over O. Given a predefined degree d, the polynomial extension of O is given by $poly(O)$ whose attributes correspond to $\{A_i^2, \ldots, A_i^d, \forall A_i \in O_{name}\}$. The extended origin relation is created on a tuple level by applying the associated operation. For example, the attribute A_i^2 of the tuple r_j in the extended relation would get the value in attribute A_i squared, meaning $\pi_{A_i}[r_j]^2$. We also introduce feature inter-relation, that is, multiplication and division between different attribute values in O. Note that addition and subtraction are already supported when using linear regression. The inter-relation extension of O, $inter(O)$ corresponds to $\{A_i \cdot A_j, A_i \div A_j \ldots, \forall A_i, A_j \in O \wedge A_i \neq A_j\}$. Also here the transformations are done on the tuple level, e.g., the attribute $A_i \cdot A_j$ of the tuple r_j would get the value $\pi_{A_i}[r_j] \cdot \pi_{A_j}[r_j]$. The extensions can also be applied consecutively, e.g., $inter(poly(O))$ to create attributes such as $A_i \div A_j^2$ to resolve, for example, the BMI formula ($kg \div m^2$). For example, recall Figure 1 and let $O_{name} = \{a_2, a_3\}$, the extended features using $poly(inter(O))$ with $d = 2$ would be:

a3	a4	$a3^2$	$a4^2$	$a3 \cdot a4$	$\frac{a3}{a4}$	$\frac{a4}{a3}$	$a3^2 \cdot a4$	...
175	9.2	30625	84.64	1610	19.02	0.05	281750	...
160	8.6	25600	73.96	1376	18.6	0.05	220160	...
143	8.0	20449	64	1144	17.88	0.06	163592	...
NaN	8.8	NaN	77.44	NaN	NaN	NaN	NaN	...
107	7.6	11449	57.76	813.2	14.08	0.07	87012	...

Figure 3: Polynomial and Inter-relation extensions over a3 and a4 Figure 1a.

Mathematical Transformations: When generating new features over numeric data, it is also common to use mathematical operations [27]. Specifically, to support this type of explanation we generate a math extension of O, $math(O)$, with the attributes $\{log(A_i), sqrt(A_i), reciprocal(A_i), exp(A_i), \ldots, \forall A_i \in O\}$, where $sqrt(A_i) = \sqrt{A_i}$, $reciprocal(A_i) = A_i^{-1}$, and $exp(A_i) = e^{A_i}$. The transformations are tuple-based, e.g., the feature $log(A_i)$ of the tuple r_j in the extended relation would get the value $log(\pi_{A_i}[r_j])$. For illustration, recall our running example, the extended features using $math(\{a_2, a_3\})$ would be:

a3	a4	$log(a3)$	$sqrt(a3)$	$reciprocal(a3)$	...	$exp(a4)$
175	9.2	2.24	13.23	0.006	...	9897
160	8.6	2.20	12.65	0.006	...	5432
143	8.0	2.155	11.96	0.007	...	2981
NaN	8.8	NaN	NaN	NaN	...	6634
107	7.6	2.029	10.34	0.009	...	1998

Figure 4: Math extension over a3 and a4 Figure 1a.

Global Aggregations: We also generate aggregate features. This extended set is especially important when looking at one of the most common transformations in machine learning, that is, (value) normalization [101]. We introduce an extension of O, $agg(O)$, with the attributes $\{sum(A_i), mean(A_i), max(A_i), min(A_i) \ldots, \forall A_i \in O\}$. Here, although assigned on a tuple level, the extended values are computed over all the values in the attribute. For example, the feature $sum(A_i)$ of the tuple r_j would get the value $\sum_{r_{ik} \in \pi_{A_i(T)}} r_{ik}$. Then, if a user applies a sum normalization over A_i, the feature-set $agg(inter(O))$ that includes the feature $A_i \div sum(A_i)$ would be able

[2] Data-driven reflects that we only use data values (we do not use meta-data).
[3] Explain-Da-V can be easily extended to support additional types such as dates.

to resolve and explain this added attribute. Similarly, in the case of min-max normalization [101] the additional features of $min(A_i)$ and $max(A_i)$ can be used to generate accurate explanations. Another example is the common collaborative filtering transformation of subtracting the mean value ($A_i - mean(A_i)$) [67]. Recalling our running example and let $O = \{a_2, a_3\}$, the extended features using $agg(O)$ would be:

a3	a4	$sum(a3)$	$mean(a3)$	$std(a3)$	$min(a3)$	...	$max(a4)$
175	9.2	585	146.25	25.33	107	...	9.2
160	8.6	585	146.25	25.33	107	...	9.2
143	8.0	585	146.25	25.33	107	...	9.2
NaN	8.8	585	146.25	25.33	107	...	9.2
107	7.6	585	146.25	25.33	107	...	9.2

Figure 5: Aggregation extension over a3 and a4 Figure 1a.

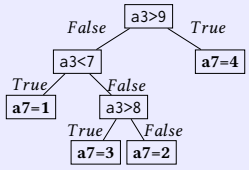
An extended feature-set is used to fit a regressor that assigns coefficients for extended feature-set. A perfect regressor would be able to deal one all-inclusive feature-set (i.e., $poly(inter(\dots(O) \cup inter(poly(\dots(O), \dots)$; yet, since it is not realistic to expect that (from an explainable regressor), we apply each set independently (power-set of the extensions) and generate multiple "possible" explanations. Section 7.4 addresses the issue of choosing among them.

Note that the transformation is "learned" (fitted) only based on the two dataset versions T and T' and **no additional training data** is required. Section 5.1 discusses the main application of numeric change explanations and illustrates it using multiple examples.

4.2 Categorical Change Explanations

Aiming to explain a categorical goal using an origin relation that contains numeric, we position the problem as *classification*, in which the tuples of the origin relation are treated as explanatory variables and the goal relation tuples are used as the output class labels. The output class can be binary (e.g., is movie longer than two hours) or multi-class (e.g., a7, Example 1). Aiming at explainability, we focus on decision trees [30]. Note that decision trees cover only explanations that can be represented as disjunction of conjunctions [70]. Each path from the root to a leaf corresponds to a conjunction and the tree is the disjunction of these conjunctions.

Example 7. *Figure 1b provides an example a categorical transformation, namely,* a7*, which can be resolved with the help of the following decision tree.*



4.3 Textual Change Explanations

When the origin and/or goal are textual, we follow the PBE approach (see Section 2.3), using a search-based solution. Specifically, we adopt an existing framework called Foofah [56]. The PBE solution is composed of designing a space of possible operators and a search algorithm. The search algorithm (A*, following Foofah) navigates the space of operators using a heuristic function (based on dissimilarity of tables) that estimates the cost of any proposed partial solution. The space is pruned to boost search speed [56].

4.3.1 Textual-to-Textual. Addressing data versioning, we extend the traditional PBE operators to include operators the cover frequent text-processing steps [94], including text lowering, lemmatization, removal of special charterers (e.g., punctuations and numeric values) and tokens (e.g., stop-words and html tags). All implemented additional operators for foofah are given in our repository [6].

Unlike Foofah, we also consider textual-to-numeric and textual-to-categorical. Note that although in recent years transformer-based models have become a standard way to extract (latent) features from text, traditional feature engineering over text, that is, extracting manual numeric and categorical features from textual values, is still an important ingredient in NLP [36, 39, 62] and in other research disciplines such as HCI [31] and information management [49].

4.3.2 Textual-to-Numeric. The search space defined for resolving this kind of transformation includes a meta-operation that counts the occurrences of some pattern *pat* in a value ($\texttt{count}_{pat}(r_{ij})$), where r_{ij} is a value in the table, see Section 3). Using this operation we can define operations such as $\texttt{number\_of\_words} = \texttt{count}_{\text{`␣'}}(r_{ij})$ and $\texttt{number\_of\_questions} = \texttt{count}_{\text{`?'}}(r_{ij})$. We also cover counting a pre-defined set of stop-words and punctuation marks.

4.3.3 Textual-to-Categorical. We define a similar meta-operation for a pattern existence ($\texttt{contains}_{pat}(r_{ij})$), which is used to generate operations such as $\texttt{contains\_percent} = \texttt{contains}_{\text{`\%'}}(r_{ij})$.

Example 8. *Figure 1b provides an example of textual-to-textual transformation, namely,* a5*, which can be resolved with the help of the foofah environment in its original implementation. Specifically, if we consider* a1 *as an origin, foofah would consider* $\pi_{a1}[T]$ *as input examples and* $\pi_{a5}[T']$ *as corresponding output examples (goal in our terms) and synthesize a tuple-based data transformation program* (1) t = split(t, 0, '('), (2) t = split(t, 1, ')'), (3) t = drop(t, 0), (4) t = drop(t, 2) *the tuple value* `Moana (U)`*, for example, would be transformed as follows* `[Moana , U)]` →`[Moana , U, ]` → `[U, ]` → `U`.

Resolving a8 *requires* `Explain-Da-V`*'s extensions that includes textual-to-numeric transformations (*`len()`*).*

Note that Foofah aims to synthesize transformations using a given set of example tuples, and is often able to do so using just a few examples. Our goal, in contrast, is to generate an explanation that correctly explains a full table transformation (a dataset version). Hence, our tremendous expansion of the search space beyond text-to-text transformations plays a critical role. Moreover, Section 4.6 introduces a technique that prunes the search space in this context.

4.4 Categorical-encoding Change Explanations

Whenever dealing with mixed types, textual and categorical values may be encoded. A common encoding approach, which we use here, is one-hot-encoding [81]. Let $A_i \in O$ be a textual/categorical attribute in the origin. One-hot-encoding of this attribute generates an additional attribute for each unique value (or category) in A_i and assigns a value of 1 to each tuple that corresponds to this value (category). This addition, not only allows the resolution of this common encoding scheme, but also a richer representation that can be used to resolve other types of encoding (e.g., ordinal encoding) and additional transformations. Such encodings are also commonly used in data preparation for machine learning [28]. Recalling Example 1,

if a user aims to predict the rating of a movie, extracting features such as `Is_Drama` or `Is_Action` can be beneficial for learning.

4.5 Reshaping Change Explanations

Generally group-by is a table-reshaping operation [98], i.e., a natural attribute-match and tuple-match do not exist. However, when it comes to feature engineering, group-by can also be used to generate aggregated features based on some other attribute. The latter is addressed in a manner that is similar to numeric change explanations. An extended origin, similar to Section 4.1, would be created for each numeric attribute $A_j \in T_A$ with respect to each textual/categorical attribute $A_i \in O$ independently or conjointly (grouping by multiple attributes). We use an SQL syntax for clarity. A helper query (Figure 6) can be used to generate the extended group-by features of the numeric attribute $A_j \in T_A$ with respect to a textual/-categorical attribute $A_i \in O$.

```
SELECT A_i, mean(A_j), max(A_j)...
FROM T
GROUP BY A_i
```

Figure 6: Group by Query

If more than one numeric attribute exists, it will be added to the GROUP BY and SELECT clauses. Using this helper query, by joining it with the origin, we obtain the additional possible attributes. Consider, for example, the attribute `a4` of Figure 1a. The additional aggregation features would be generated over the numeric attributes `a2` and `a3` and joined into the table, as illustrated in Fig. 7. Among these, we can find the mean `a2` (runtime) and `a3` (rating) per `a4` (genre), supporting such explanations.

a3	a4	a5	*sum(a3) by a5*	*mean(a3) by a5*	...	*min(a4) by a5*	*max(a4) by a5*
175	9.2	Drama	167.5	335	...	8.6	9.2
160	8.6	Drama	167.5	335	...	8.6	9.2
143	8.0	Action	143	143	...	8	8.8
NaN	8.8	Action	143	143	...	8	8.8
107	7.6	Animation	107	107	...	7.6	7.6

Figure 7: Groupby feature extension over `a3` and `a4` Figure 1a.

We also consider the reshaping scenario introduced in previous work, e.g., [98]. Reshaping is often considered as a possible operation that can be applied over a table throughout the search (see Section 2.3). We introduce an alternative data-driven approach. Specifically, reshaping is associated only with attribute-match when there is no tuple-match. We explicitly reshape the table using the query of Figure 6 and fit a regressor over it. Currently, `Explain-Da-V` does not support other reshaping transformations such as transpose and pivot, which we intend to explore in future work.

4.6 Finding the Origin

In our discussion so far, we have assumed that the origin for the transformations $\mathcal{P}$ is the original relation T. However, we can make our search more efficient if we can determine that for a specific goal, the origin is only a portion of T. Accordingly, we aim to *"find the origin"*. Different from some related literature where the input-output scope is clear (see Section 2.3), in data versioning we do not know what was used to derive a specifical goal. Hence, our approach first searches for an origin for the transformation.

A naïve solution to use all available data values. For example, in the context of adding attributes, using all attributes of T as an origin, i.e., $O = (T_A, T)$. The problem with this method is twofold. First, unrelated attributes may serve as noise when aiming to find a proper transformation for the goal. For example, referring back to Example 1, aiming to resolve `a5` using all attributes (`a1`-`a4`) presents a much larger search space than aiming to resolve it using `a2`. A second issue has to do with the data types. Using a numeric change explanation (Section 4.1) may be more beneficial than a textual change explanation (Section 4.3). For example, using `a2` as an origin to explain `a5` instead of using `a1` to `a4`.

When examining the creation of a new attribute from existing attributes, we observe a side effect of creating a *functional dependency* between the origin and the new attribute (goal). For example, if two movies have the same runtime in minutes (`a2`), they will have the same runtime in hours (`a5`), which, by definition constructs a functional dependency between `a2` and `a5`. Accordingly, we use a functional dependency discovery algorithm [77] to find the origin.[4] We find dependencies in which our goal is the dependent set and the discovered determinant is used as the origin. Note that there can be more than one attribute set that determines the goal and accordingly multiple origins may be generated.

We analyze all determining attribute sets by considering each one of them as a candidate origin. Accordingly, multiple explanations may be generated for a goal. Section 7.4 describes how we choose among them. Specifically, we rank the determinants by size and cardinality and, if desired, an early stop condition can be introduced based on the size or quality of the discovered transformation.

Example 9. *Recall Figure 1 and consider attribute* `a7` *as a goal. Since the example tables are small, any combination of attributes in {*`a1`, `a2`, `a3`, `a4`*} can be considered as an origin. If no high quality explanations are found for singleton attributes, the algorithm can consider combinations of attributes. In a larger real example, only a few attributes or combinations of them may be an origin.*

5 EXPLAINING VERTICAL CHANGES

With our arsenal of explanation methods, we now consider how to use them to explain changes. We begin with attribute additions, after which, we describe our approach to handling attribute removal.

5.1 Addition Explanations for $R\Delta_A$

Adding an attribute is a very common operation in data science, mainly revolving around data preparation and feature engineering for machine learning (ML) [101]. Added attributes are usually a result of applying some transformation over the existing data. We first find the origin (Section 4.6) an then utilize the core explanation methods (Section 4) to find transformations that, when applied to the origin relation, generate the desired goal relation. Figure 8 provides a sketch of the approach (left and middle parts) and highlights its main novelties (right part) in the context of adding attributes.

`Explain-Da-V` attribute addition explanation algorithm is provided in Algorithm 1. `Explain-Da-V` works iteratively, aiming to resolve each added attribute (i.e., the goal $\mathcal{G} = (A_i, \pi_{A_i}[T'])$) at a time (Lines 4-25). After a set of possible origins O_{A_i} is found (Line 5),

[4] In our experiments we use a discovery algorithm called FDEP [47].

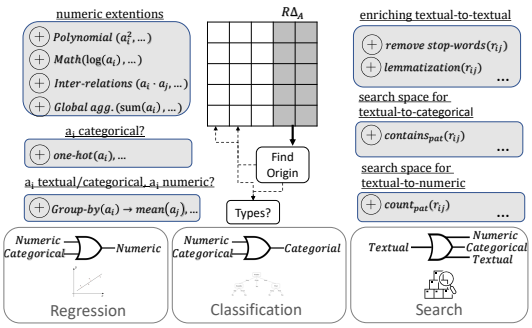


Figure 8: Explaining attribute additions

Algorithm 1: Explaining Attribute Additions

1 **Input**: A set of attributes to-be-explained $R\Delta_A$
2 **Output**: A set of explanations for each attribute $\mathcal{E}_{R\Delta_A}$
3 $\mathcal{E}_{R\Delta_A} := \emptyset$
4 **for** $A_i \in R\Delta_A$ **do**
5 $\quad \mathcal{E}_{A_i} := \emptyset$; O_{A_i} := *find origin* (Section 4.6)
6 $\quad$ **for** $O \in O_{A_i}$ **do**
7 $\quad\quad$ **if** A_i *is numeric* **then**
8 $\quad\quad\quad$ **if** O *is numeric* **then**
9 $\quad\quad\quad\quad \mathcal{E}^O_{A_i} \leftarrow$ Numeric Explanations (Section 4.1)
10 $\quad\quad\quad$ **else**
11 $\quad\quad\quad\quad \mathcal{E}^O_{text} \leftarrow$ Textual Explanations (Section 4.3)
12 $\quad\quad\quad\quad \mathcal{E}^O_{encode} \leftarrow$ Encoding Explanations (Section 4.4)
13 $\quad\quad\quad\quad \mathcal{E}^O_{reshape} \leftarrow$ Reshaping Explanations (Section 4.5)
14 $\quad\quad\quad\quad \mathcal{E}^O_{A_i} \leftarrow \mathcal{E}^O_{encode} \cup \mathcal{E}^O_{reshape}$
15 $\quad\quad$ **else if** A_i *is categorical* **then**
16 $\quad\quad\quad$ **if** O *is numeric* **then**
17 $\quad\quad\quad\quad \mathcal{E}^O_{A_i} \leftarrow$ Categorical Explanations (Section 4.2)
18 $\quad\quad\quad$ **else**
19 $\quad\quad\quad\quad \mathcal{E}^O_{text} \leftarrow$ Textual Explanations (Section 4.3)
20 $\quad\quad\quad\quad \mathcal{E}^O_{encode} \leftarrow$ Encoding Explanations (Section 4.4)
21 $\quad\quad\quad\quad \mathcal{E}^O_{reshape} \leftarrow$ Reshaping Explanations (Section 4.5)
22 $\quad\quad\quad\quad \mathcal{E}^O_{A_i} \leftarrow \mathcal{E}^O_{encode} \cup \mathcal{E}^O_{reshape}$
23 $\quad\quad$ **else if** A_i *is textual* **then**
24 $\quad\quad\quad \mathcal{E}^O_{A_i} \leftarrow$ Textual Explanations (Section 4.3)
25 $\quad \mathcal{E}_{R\Delta_A} \leftarrow \mathcal{E}_{R\Delta_A} \cup \mathcal{E}_{A_i}$
26 **Return**:$\mathcal{E}_{R\Delta_A}$

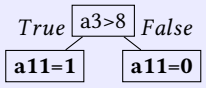
we utilize the core explanation methods to generate a set of explanations $\mathcal{E}^O_{A_i}$ for each origin (Lines 6-24). For example, if a numeric origin is found for a numeric goal (Line 9), Explain-Da-V uses the numeric explanation method (Section 4.1). Note that multiple explanations are generated for each target, for which we introduce a search strategy in Section 7.4. We illustrate it over Figure 9, which provides an additional version of the table in Figure 1a.

a0	a1	a2	a3	a4	a9	a10	a11	a12	a13	a14
m1	The Godfather (A)	175	9.2	Drama	0.28	3.15	1	godfather a	8.9	1
m2	Hamilton (PG-13)	160	8.6	Drama	0.28	3.23	1	hamilton pg	8.9	1
m3	The Avengers (UA)	143	8.0	Action	0.24	3.36	0	avengers ua	8.0	2
m5	Moana (U)	107	7.6	Animation	0.23	4.26	0	moana u	7.6	3

Figure 9: Dataset version created by UseRC over Figure 1a.

Example 10. *Among the new added attributes* a9 *and* a10 *are numeric (Lines 8). The attribute* a9 *is a (sum) normalization of the values in* a3 *(normalized rating).* Explain-Da-V *would first find its origins (Line 5). As in the case of* a6 *(see Example 9), also* a9 *can be determined by multiple attribute sets. Among the possible origins, consider* O =a3. *Since both* a3 *and* a9 *are numeric,* Explain-Da-V *uses numeric change explanations (Line 9). Zooming in on the method (Section 4.1), a baseline explanation will be generated by fitting a regressor over* O. *Then, different extensions will be applied over the origin, each will be associated with an explanation by fitting a regressor. Among the generated extensions we will find* $agg(inter(O))$, *that contains the feature* a3÷sum(a3) *over which a transformation* a9=a3÷sum(a3) *will be fitted to generate an explanation* $\mathcal{E}_{a9} = (a3, a3 \div sum(a3))$ *that will be added to* $\mathcal{E}^O_{a9}$. *Similarly,* a10 *is determined by multiple attribute sets. Among them, consider* O ={a2, a3}, *over which the following explanation will be generated* $\mathcal{E}_{a10} = (\{a2, a3\}, 60 \cdot a3 \div a2)$ *(rating per hour) and added to* $\mathcal{E}^O_{a10}$.

Example 10 (cont.). *Next we look at* a11, *which is categorical, and for example, consider the origin* O =a3. *Accordingly,* Explain-Da-V *uses categorical change explanations (Line 17) and might fit the following decision tree to explain* a11. *Note that* a11 *might been created by applying* a3>8.5 *which differs from* Explain-Da-V*'s data-driven explanation. Our goal however is to provide an accurate explanation which both are. Interestingly, if we consider* a2 *as an origin we can derive a similar decision tree rooted at* a2 > 150. *These issues refer to the* generalizability *of explanations which will be discussed in Section 7.*



The added attribute a12 *is textual and focuses on text cleaning. Consider an origin* O =a1, Explain-Da-V *will execute Line 24 and specifically Section 4.3.1 which describes text-to-text transformations. The resolved transformation includes removing punctuation marks (e.g., '(') and numeric values ('13') and lowering the text. Note that such a transformation requires our extensions to Foofah and would not be accurately resolved using the original implementation of Foofah [56]. A textual-to-categorical (Section 4.3.3) example would be to use 'contains_multiple_words?', in this case the tuples* m1 *and* m3 *would get the value 1 and* m2 *and* m5 *the value 0.*

Next, consider a13, *which is numeric and among possible origins, consider* O ={a3, a4}, *which is mixed.* Explain-Da-V *would turn to encoding (Line* **??***) and reshaping (Line* **??***). Consider the latter and note that new generated features are illustrated in Figure 7.* Explain-Da-V *will generate an explanation using the transformation* $1 \cdot (mean(a3)$ *by* $a4)$ *with represents a group by* a4 *and computing the mean of* a3 *(mean rating by genre).*

Finally, attribute a14 *is categorical and consider,* a4 *as an origin. In addition to applying trying to find textual explanations (Line 19),* Explain-Da-V *would also turn to encoding (Line 20) and reshaping (Line 21) explanations. Consider the former and note that* a14 *is an ordinal encoding of attribute* a4 *(Drama→1, Action→2, Animation→3). The three encoded attributes, namely* is_Drama, is_Action? *and* is_Animation? *are used to resolve* a14. *Note*

that in a real-world scenario, an attribute like `a14` *would not necessarily be recognized as a categorical (e.g., high cardinality or misclassification as a numeric value). In this case* `Explain-Da-V` *would turn to Line 12 resulting in the transformation* `1·is_Drama? + 2·is_Action? + 3·is_Animation?`.

5.2 Removal Explanations for $L\Delta_A$

Removing attributes is less common and usually include superficial transformations. We treat each attribute in $L\Delta_A$ separately as a goal. We cover two main types of explanations for removal reflecting data cleaning (removing duplicated and noisy attributes).

First, we examine a *table-independent* attribute removal, which in our terms reflects an empty origin ($O = \emptyset$). Specifically, we use a threshold to decide whether a attribute was removed because it has too many (above a threshold) missing (NaN) values.[5] In this case an explanation for a removed attribute $A_i \in L\Delta_A$ will be in the form of $\mathcal{E}_{A_i} = (\emptyset, \text{'contains missing information'})$. Formally, the 'contains missing information' can be defined as $A_i = \begin{cases} \emptyset, & \text{if ratio of NaN values} > \alpha \\ A_i, & \text{otherwise} \end{cases}$, where $\alpha \in [0, 1]$ is some threshold.

As a second case, we look into duplicated information. A trivial explanation can be provided for an identical attribute in T'. Given a goal A_i, the origin is some attribute $A'_j \in T'$ such that $A'_j \notin T$ and $\pi_{A_i}[T] = \pi_{A'_j}[T']$ (full overlap of values). A natural extension of finding duplications is looking into similarities between attributes. We look into two types of similarities, measuring the overlap between attributes and if there is a one-to-one dependency between them. Overlap is measured and, if it meets some threshold, an explanation is generated using the overlapping attribute A'_j as the origin and an 'overlaps with A'_j' transformation, which is defined similar to above. We also check if some attribute in T' determines (using a similar methodology as described in Section 4.6) $A_i \in L\Delta_A$. Obviously many other measures of similarity exist, which we intend to explore in future work. Finally, note that sometimes attribute removal can be idiopathic, i.e., the user simply removed an attribute because they are not interested in some parts of the data.

6 EXPLAINING HORIZONTAL CHANGES

We begin with the common data cleaning operation of tuple removal, after which we discuss adding tuples.

6.1 Removal Explanations for $L\Delta_r$

Tuple removal is a very common operation in data preparation, which mainly revolves around cleaning data. Our examination begins iteratively by looking into each removed tuple in $L\Delta_r$ independently. This may, for example, result in the horizontal explanation $\mathcal{E}_{m4}$ from Example 5. Finally, we explore if a *predicate* was applied to remove them all remaining (unexplained) tuples conjointly.

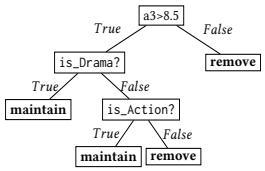
As in Section 5.2, we aim to find tuples that were removed collectively in a table-independent manner due to missing values (NaNs), see the `m4` explanation in Example 5. For table-dependent explanations, we find duplicated tuples, which is a common result of data cleaning using entity resolution [46, 66]. We focus only on identical tuple removal. Note that this strict requirement can be relaxed and any entity resolution technique, e.g., using declarative rules [29], can be used to find duplicated-tuple removal explanations. Specifically, if a duplicated tuple $r'_j \in T'$ is found for a goal tuple $r_i \in L\Delta_r$, we create a horizontal explanation of the form $\mathcal{E}_{r_i} = (\emptyset, \text{duplicated of } r'_j)$. This transformation can be expressed as follows $r_i = \begin{cases} \emptyset, & \exists r'_j \in T' s.t. r_i = r'_j \\ r_i, & \text{otherwise} \end{cases}$

Finally, outlier detectors (Z-method and IQR-method [32, 92]) also serve as explanations for removed tuples.

Not all tuples can be explained independently, thus, for all unexplained tuples, $L\Delta_{r\,unexplained}$, we aim to find a joint explanation in the form of a predicate. Given a set of unexplained tuples, we use a categorical explanation method (Section 4.2) to find a joint explanation. Similar to Section 5.1, in case the origin has mixed types, a decision tree is applied also over encoded (using categorical-encoding change explanation, Section 4.4) attributes in the table.

a0	a1	a2	a3	a4
m1	The Godfather (A)	175	9.2	Drama
m2	Hamilton (DC+A)	160	8.5	Biography
m3	The Avengers (UA)	143	8.0	Action
m4	Inception (UA)	NaN	8.8	Action
m5	Moana (U)	107	7.6	Animation

(a) Dataset version created by UserD over Figure 1a.



(b) Tree

Figure 10: UserD version of Figure 1a and its explanation.

Example 11. *In the example of Figure 1b we present a simple example of tuple removal due to NaN value. Figure 10a provides an example of applying a predicate over the table. To resolve this predicate,* `Explain-Da-V` *will first add the one-hot-encoded features corresponding to* `a4` *(*`is_Drama?`*,* `is_Action?` *and* `is_Animation?`*), then, using a decision tree, it will try to resolve the predicate. The decision tree in Figure 10b will be generated.*

6.2 Addition Explanations for $R\Delta_r$

The non-idiopathic addition of tuples may be a result of oversampling (bootstrapping). To detect such a transformation, we use a similar methodology as in Section 6.1. Given an added tuple $r'_i \in R\Delta_r$, we aim to find a duplicated (equal or similar) tuple $r_j \in T$ to create an explanation noting that the tuple has been bootstrapped.

7 EVALUATING EXPLANATIONS

We aim to generate user friendly explanations that capture the semantics of changes. Specifically, the explanation (transformation) can reproduce the change and generalize it beyond a specific setup. Aiming to assess such semantics, we now describe how we evaluate explanations. Sometimes multiple explanations can be generated with respect to a change. Recall Example 10 in which we present two possible valid explanations for `a11`. The first decision tree explanation is rooted at $a3 > 8$ and the second is rooted at $a2 > 150$. Also a decision tree rooted at $a3 > 7.5$ is a possible (invalid) explanation. In what follows, an important question that needs to be asked is *how to compare (and choose among) possible explanations?*

[5] The threshold can be treated as an hyper-parameter or a user-provided input.

Related work on data transformation (see Section 2.3) employ success rates that measure whether the output was generated successfully by applying the transformation over the input. Yang et al. also introduce a ranking measure (MRR) over possible transformations (pipelines in their terms), which still views the transformation as a whole [98]. We claim that solely using such a measure does not capture the true nature of the transformation, especially when evaluating an attribute-to-attribute (Section 5.1) transformations. To provide a more fine-grained evaluation, we evaluate both the *validity* and *generalizablity* computed over the transformed values to assess the coverage of the transformation. As we are interested in providing explainable solutions, we also use two *explainability* dimensions, *conciseness* and *concentration*.

7.1 Explanation Validity and Generalizablity

Attribute (vertical) addition explanations are richer than removal or tuple transformations, so their evaluation is addressed accordingly.
Vertical Additions: We separate this evaluation into validity (*does the generated transformation recreate the goal using the origin?*) and generalizability (*will the generated transformation be able to recreate a similar goal using a similar origin?*). Recall Definition 3 and the notation of origin (O), goal ($\mathcal{G}$), and transformation ($\mathcal{P}$). For simplicity, we denote the output of a transformation applied to an origin relation as $\hat{\mathcal{G}} = \mathcal{P}(O_{relation})$. Validity is computed in a tuple-based manner over value-pairs $(\hat{r}_{ij}, r_{ij})$ such that $\hat{r}_{ij} \in \hat{\mathcal{G}}$ is a transformed value corresponding to a goal value $r_{ij} \in \mathcal{G}_{relation}$, i.e., $\hat{r}_{i0} = r_{i0}$ (r_{i0} is the tuple id so this means the tuples are matching, see Section 3). Explanation validity is measured as follows:

$$Val(\mathcal{E}_{\mathcal{G}}) = \frac{1}{|\mathcal{G}_{relation}|} \sum_{\substack{\hat{r}_{ij} \in \hat{\mathcal{G}}, r_{ij} \in \mathcal{G}_{relation}: \\ s.t. \hat{r}_{i0} = r_{i0}}} \mathbb{I}(\hat{r}_{ij} = r_{ij}) \quad (1)$$

where $\mathbb{I}(\hat{r}_{ij} = r_{ij})$ is an indicator returning the value 1 if the transformed value equals to the corresponding goal value and 0 otherwise. The validity can be viewed as a tuple-based success rate, i.e., the proportion of the tuples that were successfully transformed.

Example 12. *Recall the vertical explanation $\mathcal{E}_{a9} = (a3, a3 \div sum(a3))$ which was created for the attribute* a9 *in Figure 9 (see Example 6). Also consider an alternative vertical explanation $\mathcal{E}'_{a9} = (a3, a3 \div 33.4)$. Both explanations would have a validity score of* 1 *as applying the corresponding transformation recreates* a9 *perfectly.*

As illustrated in the example, validity only looks at the given dataset versions T and T', which may result in overfitting (e.g., selecting $a3 \div 33.4$ over $a3 \div sum(a3)$). Aiming to measure such scenarios, we now introduce generalizability, measuring the extent to which a generated solution can explain an equivalent set of versions. Specifically, generalizability can be measured if a pair of versions $\tilde{T}$ and $\tilde{T}'$ exist such that $\tilde{T}'$ was generated as a version of $\tilde{T}$ using the same transformations that were used to generate the version T' from T. Let $\tilde{O}$ be the origin over $\tilde{T}$ and $\tilde{\mathcal{G}}$ the goal over $\tilde{T}'$. The generalizability of an explanation $Gen(\mathcal{E}_{\mathcal{G}})$ is measured by applying $\mathcal{P}$ over $\tilde{O}$ to generate $\hat{\tilde{\mathcal{G}}}$ and is computed as in Eq. 1 over $\hat{\tilde{\mathcal{G}}}$ and $\tilde{\mathcal{G}}$. When designing our newbenchmark (Section 8.1.1), we generate an annotated *hold-out* set, which is not available for Explain-Da-V and used it to compute generalizability. We illustrate the importance of generalizability using the following example.

a0	a1	a2	a3	a4
m6	Pulp Fiction (A)	154	8.9	Drama
m7	Saw (UA)	103	7.6	Horror
m8	Snatch (UA)	104	NaN	Crime
m9	King Kong (Passed)	100	7.9	Adventure

a0	a1	a2	a3	a4	a9	a10	a11	a12	a13	a14
m6	Pulp Fiction (A)	154	8.9	Drama	0.36	3.47	1	pulp fiction a	8.9	1
m7	Saw (UA)	103	7.6	Horror	0.31	4.43	0	saw ua	7.6	4
m9	King Kong (Passed)	100	7.9	Adventure	0.32	4.74	0	king kong passed	7.9	5

Figure 11: Example versions for generalizability

Example 13. *Fig. 11 provides two dataset versions. The top table is similar to Fig. 1a and the bottom table corresponds to Fig. 9 such that the same transformations over Fig. 1a generates Fig. 9. Recall the explanations $\mathcal{E}_{a9} = (a3, a3 \div sum(a3))$ and $\mathcal{E}'_{a9} = (a3, a3 \div 33.4)$. While these two are valid, using Fig. 11, we observe that $\mathcal{E}_{a9}$ is also generalizable while $\mathcal{E}'_{a9}$ is not. Specifically, if we apply $\mathcal{E}_{a9}$ over* a3 *in Fig. 11 we obtain the values of* a9 *in the bottom table. However, if we apply $\mathcal{E}'_{a9}$, we obtain the values* 0.27, 0.23, *and* 0.24 *for the records* m6, m7, *and* m9, *respectively, resulting in a* 0 *generalizability.*

Other Explanations: For tuple removal, we apply a reconstruction methodology to evaluate validation and generalizability globally. We gather all generated explanations and apply them over T and try to regenerate T'. Then, we check the overlap between the removed tuples and the tuples that are not included in T'. For example, if a a3>8 predicate was used to explain the removed tuples, the same predicate would be applied over T and compared to T'. This overlap, i.e., the proportion of tuples that were correctly removed using the explanations of Explain-Da-V, is used as the overall validity of tuple removal. The generalizability is measured similar to above using an additional dataset version pair $\tilde{T}$ and $\tilde{T}'$.

We also compute validity and generalizability for other explanations. Validation and generalizability of a removed attribute or added tuple are computed independently, i.e., a score of 1 is given if an attribute was removed correctly or a tuple was added correctly.

7.2 Problem Definition

We now formally state the problem of explaining data versions. Recall the change sets defined over the T and T' (see Section 3.2).

Definition 14. *Given T', a version of T where the goals are $L\Delta_A$(left-hand delta attributes), $R\Delta_A$(right-hand delta attributes), $L\Delta_r$(left-hand delta tuples), and $R\Delta_r$(right-hand delta tuples). From a search space of possible explanations, the version explanation problem is to find, for each goal, a set of explanations with the highest validity.*

Hence, a solution to the version explanation problem is a set of explanations that composed come closest to producing T' from T. Note that with validity alone we may have ties (as in our examples where multiple explanations have validity 1). Among multiple solutions to the problem, we also aim to choose "explanable" explanations, that is, explanations that a user can better understand.

7.3 Explanation Explainability

As motivated above, we care about the explainability of the generated solution. We, again, mainly focus on the attribute addition

transformations. Since we use different models to generate explanations (regressors, decision trees, and programs), we seek a common ground to measure explainability. Inspired by Narayanan et al. [72] and Lakkaraju et al. [64], who focus on decision sets, we introduce two explainability dimensions, namely *conciseness*, and *concentration*, that can be measured across different explanations types.

Explainability Conciseness: Studies show that the fewer the components in a model and the shorter it is, the easier it is for a user to understand it [38, 78]. In what follows, we measure the conciseness of the transformation as the number of components (N_c) it holds. For regression models we use the *number of coefficients*, for decision trees we use the *number of nodes*, and for programs we use the *number of implementation lines*.

Example 15. *Consider an $exp(A_i)$ transformation. Obviously a desired explanation would use the $math(\cdot)$ extension (Section 4.1) to generate a valid and generalizable explanation $(A_i, exp(A_i))$ that obtains an explainability conciseness of 1 (a sole coefficient).*

An alternative explanation would use a Taylor Series over the $poly(\cdot)$ extension to generate a valid and generalizable explanation $(A_i, 1 + A_i + \frac{A_i^2}{2} + \frac{A_i^3}{6} + \dots)$ with an explainability conciseness of $\frac{1}{d+1}$, where d is the polynomial degree. Note that this case also highlights the trade-off between validity (or generalizability) and explainability. The bigger the selected degree, the higher the validity (and generalizability) and the lower the explainability.

Explainability Concentration: While a more concise explanation is favorable, it should also contain as few components as possible [65] (i.e., it should be as concentrated as possible). Specifically, since humans have a limited working memory, a solution that is grouped into fewer chunks of information is favorable [72]. For example, a linear regression function is easier to understand than a polynomial regression with reciprocal and logarithmic transformations, even if the former is longer. For regressors, we count *the extensions that were used* (e.g., polynomials and math operations). For decision trees, we count *the number of internal nodes* that represent conditions and for programs we use *the number of intermediate transformations*. Let N_g be the number of chunks, the explainability concentration is then given as $1 \div N_g$ such that a more concentrated transformation gets a higher score.

Example 16. *The concentration of $(A_i, exp(A_i))$ and $(A_i, 1 + A_i + \frac{A_i^2}{2} + \dots)$ is 0.5 (1 extension, 1 degree) and $\frac{1}{d}$, respectively.*

To highlight the difference between conciseness and concentration consider, for example, $\mathcal{E}_1 = A_1 + A_2 + 5$ and $\mathcal{E}_2 = log(A_1) + A_2^2 \cdot A_1$. While $\mathcal{E}_1$ is less concise ($\frac{1}{3}$ vs $\frac{1}{2}$ of $\mathcal{E}_2$), it is more concentrated (1) than $\mathcal{E}_2$ ($\frac{1}{3}$) which involves two additional extensions.

The *total explanability* is a linear combination of conciseness and concentration that can be defined by a user or a system.[6]

7.4 On Choosing an Explanation

`Explain-Da-V` works iteratively, aiming to find valid explanations for each detected change following Section 5 and Section 6. As mentioned above, for each goal, multiple explanations can be generated, for example, if there are multiple origins (Section 4.6) or we have more than one methodology to explain a transformation (e.g., different extensions in Section 4.1). `Explain-Da-V` chooses the most *explainable valid* explanation for each goal.

Each independent explanation is derived in a way that optimizes some notion of error within the respective context that is not always the same as our definition of validity. A regressor (Section 4.1) minimizes the mean squared errors, a PBE solution (Section 4.3) directly optimizes accuracy via search and a decision tree (greedily) optimizes the split functions of nodes. Given a set of explanations, we choose one as follows. (1) Find the highest validity in the set. (2) If multiple explanations share this value, return the most explainable based on total explainability (see Section 7.3).

Note that generalizability can not be used for explanation selection unless we have access to a $\tilde{T}$ and $\tilde{T}'$ (see Section 7.1).

Potentially, there can be a large number of transformations. Dealing with this size, the explanations in a set are generated in a sorted order by the size and cardinally of their origin (see Section 4.6). Similarly, among regression models the explanations are sorted by the amount of extensions that were applied (i.e., first, a model without extensions is considered). Accordingly, we introduce an *early stop condition* such that if an explanation meets a predefined threshold of validity and explainability, it is returned and the search is stopped.[7] Empirically, almost 70% of cases are terminated early.

8 EMPIRICAL EVALUATION

We now compare our performance to baselines (Section 8.2) and analyze the components using an ablation study (Section 8.3).

8.1 Experimental Setup

We now detail our benchmarks, implementation, and baselines.

8.1.1 Benchmarks. We design a new benchmark for the novel task of semantic data versioning, termed Semantic Data Versioning Benchmark (SDVB), composed of five *version-sets*. We also adopt a publicly available dataset designed by Yang et al. [98] for a similar task of synthesizing data pipelines.

Semantic Data Versioning Benchmark (SDVB): SDVB contains a total of 342 dataset versions (136 version pairs) over five different topics, ranging in length (number of tuples) and width (number of attributes).[8] Each topic represents a *version-set* that was derived from a well-known seed dataset detailed in Table 2, which includes smaller datasets (e.g., IRIS) along side bigger datasets (e.g., WINE).

Version Generation: Given a seed dataset, we revise it to generate a version of it by first selecting a subset of change dimensions (e.g., $R\Delta_A$and $L\Delta_r$). Then, based on the dimension, we perform a set of transformations (some sampled and some manually created). We provide a benchmark sample and its generation notebook in our repository [15].[9] We assure that each of the five version-sets cover all change dimensions. Prior to version generating, each dataset is split into T and $\tilde{T}$ (80%-20%), where the latter is a hold-out to compute generalizability. Following Section 7.1, the same changes applied to T to generate T' are applied to $\tilde{T}$ to generate $\tilde{T}'$.[10]

[6] In our experiments we use a uniform combination.

[7] In our experiments the threshold was set to .95.

[8] Not all versions use all original attributes.

[9] The full SDVB and its generation code will become available upon acceptance.

[10] The numbers reported in Table 2 include the hold-outs.

Table 2: Semantic Data Versioning Benchmark Details.

Topic (Name)	# of Original Tuples	# of Original Attributes	# of Versions	# of Version-pairs
Movies and TV shows [8] (IMDB)	1,000	6	72	29
NBA Players [10] (NBA)	11,700	9	68	27
Wines Reviews [12] (WINE)	129,971	6	72	29
Iris Flowers [9] (IRIS)	150	5	58	22
Titanic Passengers [11] (TITANIC)	891	6	72	29

Finally, note that a version may be created using more than one change and, in practice, the aforementioned number of versions is actually **composed of 1,702 changes**. For example, to create the 72 WINE dataset versions, a total of 681 changes were applied over the original dataset and its versions.

Auto-Pipeline Benchmark [1]: This benchmark contains real data pipelines extracted from Github notebooks. As we focus on dataset versions, we filter out pipelines that include more than one table (e.g., those that use a join). Following Yang et al. [98], we consider the "test" table as T and the "target" table as T'. For a fair comparison, we run `Explain-Da-V` and all baselines on all the data and do not consider generalizability for this benchmark.

8.1.2 Implementation. `Explain-Da-V` was implemented in python, following Sections 5 and 6. Main parts of the code are provided in our repository [15]. Linear regression with Lasso [13] and Rigde [16],[11] regularization and decision trees [3] were implemented with Scikit-learn. We extended Foofah's python publicly available implementation [7]. We use the Featuretools [5] framework to generate aggregated and group by features (see Section 5.1).

8.1.3 Baselines. **Foofah** [56] is used as a PBE baseline (see Section 2.3). **Foofah+** denotes Foofah with our novel extensions (e.g., textual-to-numeric, see Section 4.3). As Auto-pipeline's implementation is not publicly available, we reproduced its search methodology[12] using Foofah's framework by implementing the operators provided by Yang et al. (**Auto-pipeline***) [98]. Search has an exponential worst case time complexity, so we apply a 60 second timeout for all methods following the default in Foofah [56].[13]

We also ran AutoPandas [19] using their available implementation [2]. AutoPandas creates a search space based on pandas [14] operations and prunes the space of programs using deep learning. Similar to the reported performance in Auto-pipeline [98], AutoPandas performance was inferior and thus not reported. We also experimented with SQUARES [75], a recent query reverse engineering framework, and, similarly, do not report its inferior results. Since SQUARES was designed to synthesize traditional SQL queries it can sometimes resolve selection predicates; yet, it fails to cope with other changes such as attributes added using transformations.

Finally, a naïve implementation of the baselines would use all of T and T' as input-output examples. However, to allow a fair comparison, we "find the origin" (see Section 4.6) for each of the baselines and vertical explanations are solved iteratively (each attribute at a time). For horizontal addition explanations the tuples of T are used as input and the tuples of T' as output (similarly for horizontal removal with T' as input and T as output).

[11] We first tried applying Lasso and if failed we applied Rigde.

[12] Reinforcement learning requires training data, which we assume unavailable.

[13] We note that Auto-pipeline default timeout limit is an hour

8.1.4 Evaluation Measures. The explanations provided by our baselines are of a single type (programs, not regressors or decision trees), thus, in Section 8.2, we compare the Validity (Val.) and Generalizability (Gen.) of `Explain-Da-V` to the baselines. Since `Explain-Da-V` can return explanations that do not have a validity/generalizability score of 1.0, we also report the proportion of such explanations out of all output explanations. We further report the average number of explanations (# $\mathcal{E}$) from which the method selects the most explainable valid (see Section 7.4). We also compare and report runtimes. Section 8.3 also uses explainability (conciseness and concentration).

8.2 `Explain-Da-V` Compared to Baselines

The comparison between `Explain-Da-V` and the baselines (Section 8.1.3) over the benchmarks (Section 8.1.1) is reported in Table 6.

`Explain-Da-V` performs much better than the baselines mainly due to its ability to cope with varying data types (numeric and categorical in addition to textual). The adapted Auto-pipeline benchmark is an exception where `Explain-Da-V` only performs slightly better than Auto-pipeline*. Also, even if we zoom-in only on textual transformations (provided in a technical report [86]), `Explain-Da-V` still out-performs all baselines. Even when we evaluate only the 100% valid/generalizable explanations returned by `Explain-Da-V` (denoted in parenthesis in Table 6), we observe a significant improvement. Across baselines, we observe that extending Foofah (Foofah+) provides an average validity and generalizability boost of 9.5%, showing the benefit of the extended search space. All methods select among multiple explanations (# $\mathcal{E}$, see Section 8.1.4) based on multiple origins (see Section 8.1.3). `Explain-Da-V` considers almost twice as many explanations since it generates expanded origins for numeric explanations (see Section 4.1).

Comparing among version-sets, we observe that in the IRIS dataset, `Explain-Da-V` obtained the best performance (.927 Val. and .831 Gen.) and the highest improvement. For the IMDB version-set, `Explain-Da-V` obtained the worst performance (.732 Val. and .602 Gen.) and lowest improvement (among the newly suggested benchmark version-sets). IRIS is mostly composed of numeric attributes (4 out of 5) which are solved using our numeric change explanations (Section 4.1) and are not dealt with by the baselines. Note that accordingly, `Explain-Da-V` considers almost three times as many explanations. Yet, the numeric extensions introduced in Section 4.1 and the fact that we find the origin helps to home in on a valid solution quite quickly (see runtime below). The IMDB version-set, on the other hand, contains more textual attributes (5 out of 6) and involves changes that `Explain-Da-V` fails to solve. For example, one of the IMDB version-sets involves a transformation that adds an attribute containing the count of the number of genres from a `Genre` attribute. In the `Genre` attribute, the genres are separated by a comma (e.g., `Drama, Romance`). A correct transformation would, for example, count the number of commas and add 1. While finding a transformation that counts the number of commas is a practical task for `Explain-Da-V` (which includes textual transformations and aggregations), such a composition is not currently possible. Instead, the explanation `Explain-Da-V` chose (most valid, see Section 7.4) uses an `IMDB Rating` attribute to determine the number of genres using a decision tree with a validity of 0.65.[14]

[14] The explanation is available in the repository [4].

Table 3: Performance in terms of Validity (Val), Generalizability (Gen) and average number of explanations the method chooses from (# $\mathcal{E}$). For `Explain-Da-V`, we also report (in parenthesis) the proportion of explanations with Val/Gen score of 1.

Dataset→	IMDB			NBA			WINE			IRIS			TITANIC			Auto-pipeline		
↓Method	Val	Gen	# $\mathcal{E}$	Val	Gen	# $\mathcal{E}$	Val	Gen	# $\mathcal{E}$	Val	Gen	# $\mathcal{E}$	Val	Gen	# $\mathcal{E}$	Val	Gen	# $\mathcal{E}$
Foofah	.42	.42	3.7	.28	.28	4.2	.29	.29	3.9	.23	.23	3.1	.29	.29	4.1	.55	-	3.3
Foofah+	.44	.44	3.7	.29	.29	4.2	.34	.34	3.9	.25	.25	3.1	.37	.37	4.1	.55	-	3.3
Auto-pipeline*	.44	.44	3.7	.30	.30	4.2	.33	.33	3.9	.26	.26	3.1	.37	.37	4.1	.78	-	3.3
`Explain-Da-V`	**.73** (.64)	**.60** (.56)	6.4	**.90** (.89)	**.79** (.69)	7.3	**.87** (.76)	**.81** (.59)	6.8	**.93** (.88)	**.83** (.76)	8.9	**.88** (.79)	**.77** (.68)	7.2	**.82** (.78)	-	5.7
+ over baseline	+65%	+36%		+202%	+167%		+156%	+138%		+254%	+217%		+140%	+109%		+5%	-	

Table 4: Foofah, Foofah+, Auto-pipeline*, and `Explain-Da-V` performance in terms of Validity (Val.) and Generalizability (Gen.) for Numeric goals

Dataset→	IMDB		NBA		WINE		IRIS		TITANIC	
↓Method	Val.	Gen.	Val.	Gen.	Val.	Gen.	Val.	Gen.	Val.	Gen.
Foofah	.20	.20	.11	.11	.14	.14	.18	.18	.12	.12
Foofah+	.20	.20	.15	.15	.16	.16	.21	.21	.24	.24
Auto-pipeline*	.22	.22	.16	.16	.18	.18	.22	.22	.26	.26
`Explain-Da-V`	**.97** (+340%)	**.85**(+286%)	**.72** (+350%)	**.66** (+313%)	**.87** (+383%)	**.75** (+316%)	**.99** (+350%)	**.85** (+286%)	**.92** (+253%)	**.84** (+223%)

Table 5: Foofah, Foofah+, Auto-pipeline*, and `Explain-Da-V` performance in terms of Validity (Val.) and Generalizability (Gen.) for Categorical goals

Dataset→	IMDB		NBA		WINE		IRIS		TITANIC	
↓Method	Val.	Gen.	Val.	Gen.	Val.	Gen.	Val.	Gen.	Val.	Gen.
Foofah	.15	.15	.09	.09	.16	.16	.23	.23	.22	.22
Foofah+	.25	.25	.12	.12	.18	.18	.25	.25	.22	.22
Auto-pipeline*	.27	.27	.12	.12	.17	.17	.26	.26	.22	.22
`Explain-Da-V`	**.86** (+218%)	**.86**(+218%)	**.99** (+725%)	**.87** (+625%)	**.89** (+423%)	**.78** (+358%)	**.98** (+277%)	**.91** (+250%)	**.88** (+300%)	**.83** (+277%)

Table 6: Foofah, Foofah+, Auto-pipeline*, and `Explain-Da-V` performance in terms of Validity (Val.) and Generalizability (Gen.) for Textual goals

Dataset→	IMDB		NBA		WINE		IRIS		TITANIC	
↓Method	Val.	Gen.	Val.	Gen.	Val.	Gen.	Val.	Gen.	Val.	Gen.
Foofah	.50	.50	.48	.48	.44	.44	.33	.33	.47	.47
Foofah+	.52	.52	.50	.50	.53	.53	.42	.42	.48	.48
Auto-pipeline*	.52	.52	.56	.56	.53	.53	.38	.38	.50	.50
`Explain-Da-V`	**.62** (+19%)	**.57**(+10%)	**.88** (+57%)	**.67** (+20%)	**.58** (+9%)	**.56** (+6%)	**.82** (+115%)	**.72** (+89%)	**.79** (+58%)	**.69** (+38%)

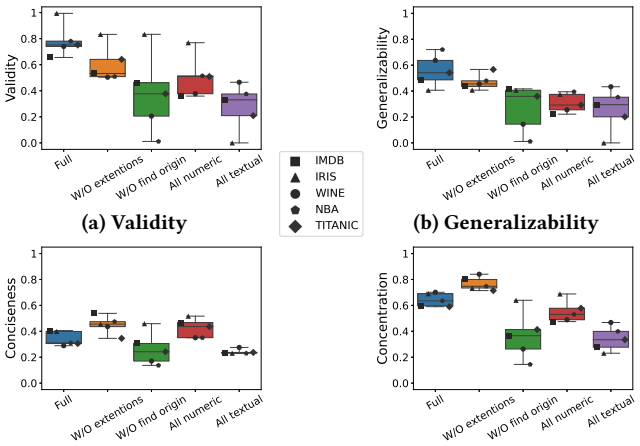
Finally, we note that the performance varies with respect to the different change dimensions. Interestingly, if we only look at vertical removals (Section 5.2), all three baselines have a validity and generalizability score of 1. The reason for that is their ability to discover projections (in their terms applying a `drop` operation over an attribute). Although it successfully finds these transformations, it lacks the ability to explain the semantics of the attribute removal. `Explain-Da-V`, although not perfectly valid and generalizable (.95), is more expressive in term of explaining the removal. For example, explaining that an attribute was removed because it contains duplicated information (see Section 5.2). When looking at tuple removal, `Explain-Da-V` performs much better than the baselines. Since Auto-pipeline does "not consider row-level filtering" [98], we recall the comparison against SQUARES (see Section 8.1.3). Despite its focus on learning a selection predicate, SQUARES is able to resolve cases where a predicate was applied with 0.6 validity (`Explain-Da-V` obtains 0.73 over these changes). This is because SQUARES was not able to resolve removing tuples containing NaN values and duplicate tuples (two cases in the benchmark).

Runtime: In these experiments, excluding timeouts (see Section 8.1.3), finding an explanation using foofah took an average of 4.9 seconds, foofah+ 12.4 seconds, Auto-pipeline* 8.1 seconds, and `Explain-Da-V` 2.4 seconds. A reason for that difference is that fitting a regressor (linear time complexity) and learning a decision tree (quadratic complexity) are more efficient than search (exponential).

8.3 `Explain-Da-V` Ablation Study

Figure 12 provides an ablation study of `Explain-Da-V`. We focus on vertical addition explanations and analyze `Explain-Da-V` performance without finding the origin (W/O find origin), i.e., using T as a whole to explain a given goal and without the extensions for numeric-to-numeric transformations (W/O extensions). We also analyze the resolved data types by applying `Explain-Da-V` assuming all types are numeric (All numeric) or all textual (All textual).

As illustrated in Figures 12a and 12b, the full `Explain-Da-V` provides the most valid and generalizable performance. Adding extensions and finding the origin provide an average performance boost of 30% and 107%, respectively, in terms of validity, while addressing all attribute types as numeric and textual decreases



(a) Validity (b) Generalizability

(c) Conciseness (d) Concentration

Figure 12: Ablation Study over SDVB datasets.

the validity by 35% and 64%, respectively. The NBA version-set demonstrates an interesting case. Since it contains diverse attributes of varying types, without finding origin, `Explain-Da-V` obtains very low validity and generalizability. Similarly, as mentioned above, since the IRIS version-set mainly consists of numeric attributes, treating all attributes as textual results in very low performance.

Examining the explainability (Figures 12c-12d), we observe that while less valid and generalizable, explanations without extensions are more concise and concentrated. If an origin is not found, the explanations are usually less concise and much less concentrated. Finally, numeric explanations are more explainable than textual explanations especially in terms of conciseness. **Limitations via Interesting Cases:** Consider the NBA version-set. One vertical addition in this dataset creates a binary attribute representing an indicator for a "double double" performance.[15] A valid and generalizable transformation generated by `Explain-Da-V` returns 1 if $A_{ast} > 10$ (more than 10 assists) simply because for each tuple $r_i \in T$ such that $\pi_{A_{ast}}[r_i] > 10$ it also happens that $\pi_{A_{pts}}[r_i] > 10$ (more than 10 points). While correct in the specific scenario, it does not capture the semantics of a double double.

Another interesting case considers a square-root transformation over movie rating (A_{rating}) in the IMDB version-set. `Explain-Da-V` generated two valid and generalizable explanations one using the transformation $sqrt(A_{rating})$ (using the *math* extensions) and one using a polynomial transformation $1.074 + 0.262 \cdot A_{rating} - 0.005 \cdot A^2_{rating}$. Obviously, these two transformations are different; however, if we zoom in on the range $x \in [6, 10]$ (typical ratings in IMDB), we observe that the transformations behave almost identically. For example, a rating of 9 would be transformed to 3 and 3.02, respectively. An illustration is given in our repository [17].

9 CONCLUSION

This work laid the groundwork for explaining semantic changes in data versioning. `Explain-Da-V`, uses different types of techniques to resolve and explain changes between a pair of dataset versions. We introduced measures to evaluate explanations and show that `Explain-Da-V` performs better than multiple baselines over an existing adapted benchmark and a newly introduced data versioning benchmark. In future work, we intend to extend `Explain-Da-V` to address additional data types, e.g., dates, and address changes that are triggered by external data such as performing joins and unions.

[15] In basketball, a double-double is when a player accumulates ten or more in two of statistical categories https://en.wikipedia.org/wiki/Double-double.

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