DBChEx: Interactive Exploration of Data and Schema Change

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ABSTRACT

Data exploration is a visually-driven process that is often used as a first step to decide which aspects of a dataset are worth further investigation and analysis. It serves as an important tool to gain a first understanding of a dataset and to generate hypotheses. While there are many tools for exploring static datasets, dynamic datasets that change over time still lack effective exploration support.

To address this shortcoming, we present our innovative tool Database Change Explorer (DBChEx) that enables exploration of data and schema change through a set of exploration primitives. Users gain valuable insights into data generation processes and data or schema evolution over time by a mix of serendipity and guided investigation. The tool is a server-client application with a web front-end and an underlying database that stores the history of changes in the data and schema in a data model called the change-cube. Our demonstration of DBChEx shows how users can interactively explore data and schema change in two real-world datasets, IMDB and Wikipedia infoboxes.

1. INTRODUCTION

Data changes. This undeniable fact has led to the development of numerous methods and systems to manage and document changes to data. However, only recently the dropping prices of hard drive storage rendered it possible to now also keep all or at least a large portion of historical data for analysis of its changes. The nature of changes reveal rich insights that cannot be found in a static version of the dataset and can serve many purposes, such as summarization, compression, future prediction, provenance, or pattern discovery.

Imagine a data scientist *Alice* who has gathered a number of historical dumps of a dataset. She has only recently joined the organization, but she possesses domain knowledge and a rough understanding of the current state of the dataset. While analyzing the dataset, a set of questions arose that only the history of changes to the dataset can answer. For example: *Am I right to assume that attribute X is constant? How old are the entities in table Y? When were they last updated? Do the changes to entities of table Z correlate?* However, answering those questions using existing tools is a tedious task, especially if the historic dumps originate from different systems and use different legacy schemata.

Even if the dumps are all in the same relational format, the problem of how to access the previous versions still persists. A simple line-wise difference is easy to compute, but often lacks the necessary semantic meaning. Alice cannot simply load those multiple dumps in a DBMS, because this would cause naming conflicts and even if she can avoid that by, e.g., defining different namespaces in the same database, she would still store highly redundant data.

The queries to actually identify the change would also be non-trivial and probably inefficient, as one would have to join a large number of different relations. Due to the complexity and poor performance, Alice quickly loses interest and she is less creative than she could be: she writes ad-hoc queries, executes them, waits for their completion, reconsiders her assumptions, writes ad-hoc queries, ... If she did not face all of those issues, but had a suitable tool for exploration of changes, she would have quickly come up with new questions that she did not think of before. For example, the exploration might hint at seasonal behavior or periodicity that she did not consider and can now analyze with the appropriate tools.

Alice's issues are part of a larger research problem on how to recognize, explore, and evaluate change in data and schema. We have published a comprehensive vision paper on change exploration [2], which touches on many areas that aim, among others, to capture, explore, categorize, and predict changes in databases. We have also taken initial steps to make parts of this vision a reality. For example, we track objects in databases over time to understand their changes at a finer level. In addition, for an overview of the large number of changes, we developed a framework to map change histories to time series and cluster those time series [3]. We have also begun to take advantage of these insights, such as investigating on how historical changes can help with problems such as the automatic discovery of dependencies and

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constraints. However, these steps are just small parts that all fit under the big umbrella of our vision, which we are implementing as part of our project "JANUS"[1].

In this paper, we present an innovative tool that implements several aspects of this vision to support Alice in her exploration of change: the *Database Change Exploration (DBChEx)* tool. DBChEx allows Alice to interactively explore change data. The goal is to provide an easy, interactive way to obtain a high-level understanding of how a dataset changes over time. By physically implementing exploration primitives and operators from our vision, DBChEx allows users to:

- Interactively browse, filter, and group changes to rows, columns, values or entire tables
- View statistics and excerpts of the change data, such as its volatility and temporal distribution: a dualistic approach that synchronizes visual and statistical exploration that complement each other
- Mine changes, such as clustering changes according to their temporal behavior
- Feed exploration findings back into the process through a closed-loop approach
- Save the exploration history as bookmarks
- Export excerpts of the data for further inspection outside of the tool

In the next section we describe the general ideas behind change exploration with DBChEx. Then follows a more detailed description of the implementation of DBChEx including its architecture in Section 3. The demonstration in Section 4 shows how to use this implementation to discover interesting changes in two different datasets. Before we conclude in Section 6, we give a brief overview of related work in Section 5.

2. CHANGE EXPLORATION

As a data model to represent changes, DBChEx uses the notion of *change-cubes* [2], which are characterized as follows:

DEFINITION 1. *A* change c *is a quadruple of the form* $\langle \mathsf{timestamp}, \mathsf{id}, \mathsf{property}, \mathsf{value} \rangle$ *or in brief* $\langle \mathsf{t}, \mathsf{id}, \mathsf{p}, \mathsf{v} \rangle$. *We call a set of changes a* change-cube $C = \{c_1, \ldots, c_n\}$. *Among the changes, combinations of (t, id, p) are unique.*

A change $\langle \mathsf{t}, \mathsf{id}, \mathsf{p}, \mathsf{v} \rangle$ describes that at a certain point in time t (*When?*) the property p (*Where?*) of an entity with the stable identifier id (*What?*) was changed to the new value v (*How?*). The uniqueness constraint allows each entity/property combination to have only one value at a point in time. This value is valid until the chronologically next change with the same entity/property combination. Deletions of properties are modeled through setting its value to the NULL-value ($\perp$).

This format is flexible enough to handle changes in both data and schema, and general enough to integrate data from various different formats or domains. Thus, the DBChEx tool serves the exploration of changes from various sources of data, individually and jointly to reveal correlations between those changes. During the demonstration of DBChEx we show how Wikipedia infobox data and IMDB movie data changes over time.

[1]https://www.ianvs.org

Table 1: Exploration primitives on the change-cube.

Operator	Description
`sort`	sorts the changes within a change-cube
`slice`	filters the changes in a (set of) change-cube(s)
`split`	groups changes and splits the cube accordingly
`union`	unions multiple change-cubes into one
`rank`	sorts (a set of) change-cubes
`prune`	filters change-cubes by threshold
`top`	selects change-cubes by relative position

To enable the fine-grained exploration of change-cubes, we define a set of exploration primitives on top of our change-cube model. Table 1 gives an overview of the primitives defined on sets of change-cubes. For a more formal definition of those exploration primitives, we refer to our vision paper [2]. Because the defined operators are closed, we can compose them and we call such a composition of operators an *operator sequence*. An example of such an operator sequence is $\mathtt{split}_{\mathsf{p}} \circ \mathtt{rank}_{|\mathtt{distinct}\ \mathtt{v}|} \circ \mathtt{top}_5$, which results in a change-cube for each of the top five properties in the number of different values. In our tool it usually takes the user just a click to add, edit, or remove new operators from the current operator sequence.

Change exploration requires access not only to the current dataset, but also to its (at least partial) history. First, nearly all modern databases store some sort of log file or are able to back up snapshots. In addition, a surprising number of major public-domain datasets contain data that reflect their change over time as well, such as Wikipedia, IMDB, Musicbrainz, and DBLP. These projects release their data history at different levels of granularity. Although fine-granular changes are preferable, the change-cube format is also suitable for capturing changes from a series of snapshots, such as provided by IMDB. We hope that advances in research on change exploration will illustrate the great benefits of analyzing data histories; and that, in turn, will encourage more and more data owners to maintain those histories in the first place and also make them available.

Populating the change-cube is a problem that also requires good tooling support. However, it is not the focus of DBChEx, which assumes an already populated change-cube, even if it only is by a simple transformation. We already have change-cubes for the four sources mentioned above and are working on tooling to support more. These transformations from data sources to change-cubes can be relatively generic in the beginning, because the user may not know and understand the previous schemata.

The simplest, but not ideal, way to translate relational data into this model is to view each row of a table as an entity and treat the key as a stable identifier. All other columns become properties of this entity with the column name serving as a property identifier. A schema change can, however, cause much more change records than actually necessary. If columns and thus properties from one revision to the next no longer exist precisely the same way, they have to be deleted for each individual entity (set to $\perp$) and possibly others have to be added. This is the case even if the actual data values may not have changed at all.

Hence, we propose an iterative, closed-loop approach that improves the semantics of the change-cube over time. In this way, knowledge gained during exploration can be fed back into the transformation. For example, if users recog-

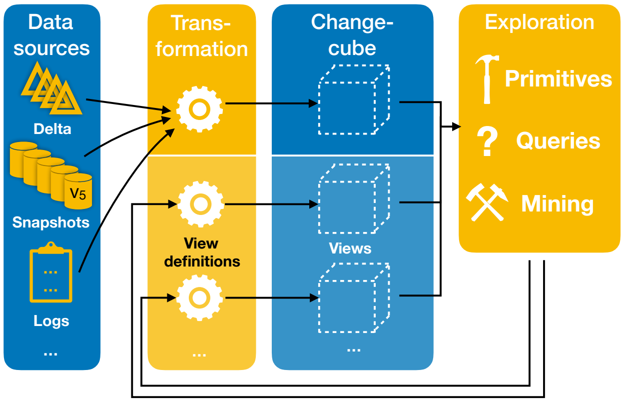


Figure 1: DBChEx workflow overview

nize that a property has been renamed, they can merge these two properties at the click of a button. Each of these transformations creates a view on the original change-cube. The view definitions can also be implemented with the help of operator sequences, in which the above operators are used to select the part of the cube to be transformed. The transformation on the selected quadruples is then achieved either via templates for frequent schema changes (such as renaming) or custom transformations defined in SQL or an external program. Figure 1 shows how we envision the general data change exploration workflow using DBChEx.

3. ARCHITECTURE

Figure 2 shows the general components of DBChEx. The user interacts with the system through a web client. This web client communicates with a node.js backend via http or WebSockets. The backend, in turn, uses a database via a SQL interface – in our current implementation MonetDB [8] – and a data clustering service that is currently implemented in Apache Spark [15].

3.1 Web client

The client is a browser application implemented in React[2]. Figure 3 gives an impression of the user interface. On the top, the tool displays the currently active operator sequence, in this case a single split by id. Below that operator sequence, the user can see and interact with its result: a set of change-cubes. This set can be sorted by multiple statistics, effectively turning that set into an ordered list. On the right side of the interface, two different tabs display previously visited operator sequences as well as bookmarks. The user-interface is designed to keep the user engaged and reduce the amount of required text input. Through clicking on elements that appear interesting, the user can modify the current operator sequence.

Operator sequences. The operator sequences are the primary navigation through the changes: they represent the current exploration path and show what the user currently focuses on (comparable to the navigation bar in a web browser). The user starts the exploration process by applying an operator on the initial full change-cube. The result of each operator sequence is one or multiple change-cubes.

[2]https://reactjs.org/

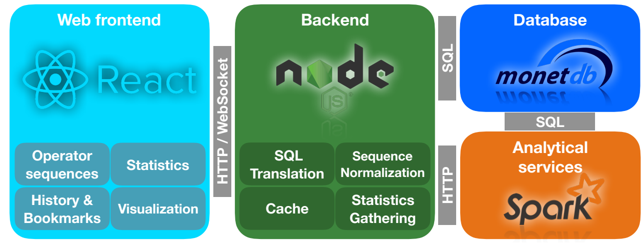


Figure 2: DBChEx architecture overview

The user can change the order of operators in the sequence of currently active operators as well as modify each of them.

While browsing through the space of possible sequences, the user might fear to lose track. Since this can cause counterproductive hesitation, we introduce two features that are inspired by web browsers: a history of previously executed operator sequences and the possibility to bookmark certain operator sequences that the user considers interesting enough to save for future investigation. The tool also offers the ability to explore datasets collaboratively: the URL in the browser reflects the current state of the exploration, so that the user can share the current view by simply copying that URL.

Statistics and analytical services. For each of the change-cubes, DBChEx computes multiple statistics and presents those to the user. For example, the tool shows the most frequent entities or properties in a change-cube, but also more complex statistics, such as a volatility measure for each of the cubes, i.e., a normalized measure for their degree of variation. These statistics and visualizations can serve as a recommendation and guidance to the user for further analysis. The user can click on any of the elements to apply a filter that removes unwanted entities or properties from the change-cubes.

At each point in the exploration it is possible to switch to visualizations that are in sync with the current exploration progress and guide further exploration steps. A helpful visualization for volatility is a heatmap that allows users to see at a glance which ID/Property combinations have particularly high or low values. An example of such a heatmap is shown in Figure 4. Cross-filtering is the idea that new operator sequences lead to new visualizations, but new operator sequences can also be generated through direct interaction with the visualization [14]. For example, clicking on one of the fields in the heat map activates a corresponding slice that focuses only on the changes that are responsible for the color of that field. At the moment, the visualizations in DBChEx are still rudimentary, but further visualizations are easy to add. Especially visualizations that rely on animations for the time domain similar to Gapminder[3] or map-based visualizations [11] could be very helpful.

While focusing on certain topics can already be helpful, sometimes it is difficult to spot interesting subgroups through critical inspection. In such cases, the tool can support the user by providing analytical services, such as outlier detection or clustering change-cubes based on certain features. For example, one clustering method maps each change-cube to a time series and uses time series clustering to group them based on their temporal behavior. The result of the clus-

[3]https://www.gapminder.org/

Figure 3: The DBChEx web user interface, here with one line/change-cube per settlement

Settlement	area_code	coordinates	image_caption	image_flag	image_map	name	population_as_of	postal_code	website	Sum
Berlin	19	7	103	18	18	383	19	20	251	838
Cape Town	56	2	100	89	50	55	78	57	63	550
Chicago	235	5	290	475	472	275	517	47	459	2775
Istanbul	100	3	294	6	4	162	163	101	107	940
London	116	1	554	51	439	620	397	384	390	2952
Potsdam	5	1	24	3	4	31	4	5	22	99
Rome	245	32	141	324	324	272	347	250	344	2279
Stockholm	20	1	46	10	12	32	99	58	56	334
Tokyo	135	15	166	156	156	754	149	135	503	2169
Sum	931	67	1718	1132	1479	2584	1773	1057	2195	12936

Figure 4: A heatmap for changes on selected Wikipedia settlement entities and selected infobox properties, color-coded relative to the absolute number of changes.

tering is an additional feature of the change-cubes that can serve as a filter or grouping criterion. Additionally, the clustering result can also be visualized by highlighting change-cubes in different colors.

Closed-loop approach. Because there are often several ways to transform the changes for a particular dataset to the change-cube, the user has to make modeling decisions. Depending on the user's knowledge, these are probably not perfect at first and in the course of exploration, the user will notice opportunities for improvement. Due to the closed-loop approach, our tool offers the possibility to implement these directly and to create a view on the change-cube with just a few clicks, which implements these insights. For example, the user can detect a renaming of a property, link these two properties, and profit from a longer history available for this new merged property. Users employ the already mentioned query operators to select the parts of the change-cube to be changed. The modification operators differ from the query operators in that they work at the change level and not at the cube level. The modification operators map previous changes to (a set of) new changes. A very simple modification operator is the `set` operator, which overwrites the values of a given dimension with a constant for all of the selected changes.

3.2 Server backend

Our web-based tool is currently backed by the columnar SQL server MonetDB [8]. A sequence of operators is mapped to a single SQL query and additional queries for the metrics that act as important metadata for the resulting cubes.

From operator sequences to SQL queries. The backend needs to translate the operator sequences to SQL queries to execute them on the database. In the database, all change records are stored in a table with four columns: `time`, `id`, `property`, `value`. For example, an operator sequence like $\texttt{split}_{\text{id}} \circ \texttt{rank}_{size} \circ \texttt{top}_{10} \circ \texttt{filter}_{\text{property}=a}$, which results in a change-cube for each of the ten most changed entities filtered to only changes that affect the property 'a', translates to the following query:

```
WITH t0(g0_0,pos) AS (SELECT ID AS g0,
    ROW_NUMBER() OVER(ORDER BY COUNT(*) DESC)
    FROM wiki GROUP BY g0)
SELECT id AS g0, COUNT(*) FROM changes, t0
WHERE t0.pos <= 10 AND id = t0.g0_0 AND prop =
    'a'
GROUP BY g0 ORDER BY COUNT(*) DESC LIMIT 20
    OFFSET 0;
```

The backend automatically transforms operator sequences to SQL queries by handling each operator in the sequence from left to right and incrementally building the query. Each operator adds and/or removes a combination of `WHERE`- or `GROUP BY`-clauses. For some operators it is necessary to create views (such as `t0` in the example above), which can then be used in the `WHERE`- or `GROUP BY`-clauses.

Cube modifications. The backend applies the cube modification operators that implement the closed-loop approach. Simple operators, such as the set operator, can even be executed directly in the database, although for more complex operators it is likely that the backend must implement them. In general, the modification operators remove and add some changes from the original change-cube. Based on the assumption that most modification operators touch only a small amount of the total changes, we construct two subqueries that return the removed and added changes. By simply linking the original change table by `EXCEPT` or `UNION` with the two subqueries, we obtain the modified cube.

This modified cube may contain changes that are either (i) inconsistent or (ii) redundant. Two changes are *inconsistent*, if they both set the value for the same property of the same entity at the same time and do not agree on that value. So they violate the uniqueness-constraint mentioned in Section 2. For now, we rely again on the database to detect those inconsistencies through grouping the changes by time, id, and property and counting the number of distinct values. If such inconsistencies are detected, we require the user to interactively resolve them by one of several options. Either the distinct values are concatenated, or one of the values is preferred, i.e., either the newly added changes have a higher priority or vice versa.

For redundant changes, no user input is required. Two changes are *redundant*, if they set the value of the same property of the same entity at two distinct points in time with no change of that entity/property-combination in between. If this is detected, the tool simply removes the second change from the change-cube. For detection, DBChEx uses a combination of SQL and backend code. The SQL query generates a list of possibly redundant change candidates and the backend code then checks whether they are really redundant.

Performance optimizations. We employ a number of optimizations to make this approach more efficient: first the operator sequences are normalized through a number of rules. For example, if an operator sequence contains multiple consecutive filter operators, the order of those filters does not matter and they can be arranged in a fixed order. This normalization is important for the prioritized cache that the tool uses to avoid reoccurring calculations. Through this normalization more operator sequences are known to deliver the same output and can therefore rely on the cache. In the example above, the result of the subquery that retrieves the ten most changed entities can easily be cached. For our test datasets this results in a satisfactory (subsecond) performance. Still, for larger datasets a more specialized solution with custom index structures could become necessary.

Analytical services. The analytical services receive a SQL query as input, which corresponds to the current operator sequence. By executing this query on the database, the analytical service can retrieve those change records, which form the basis of the analysis. Our analytical services are currently implemented in Scala and Spark, but of course other languages and frameworks can be used as well. Once the analysis is complete, the service writes the results back to the database and notifies the backend via an HTTP call. The latter can then inform the user, who can then proceed with inspecting the results. In addition to clustering, other potential analytical services could include outlier detection or an evaluation of individual changes in terms of quality or trustworthiness.

4. DEMONSTRATION

This section describes two interactive exploration scenarios using DBChEx on two different datasets: IMDB and Wikipedia infoboxes. For the Wikipedia dataset, the user is able to explore vandalism and edit wars. The dataset also contains a large number of genuine data changes and also schema changes that are to be discovered, such as distinct infobox templates that are merged or attributes that are renamed. For IMDB, the user can also observe schema-changes, but much less frequently. IMDB is an example that has attributes of highly different volatility. For instance, the number of votes on a movie (*numVotes*) have a high volatility in contrast to its *primaryTitle*. In the future we plan to make DBChEx an open-source tool and also provide our datasets in an accessible way.

4.1 Exploring Wikipedia infobox changes

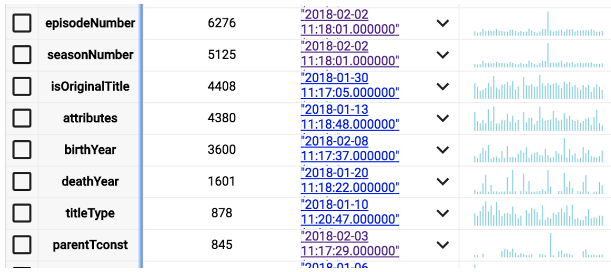
The DBChEx project homepage provides a short overview as well as two demonstration videos on the Wikipedia dataset of changes to settlement infoboxes[4]. In the first video, Alice focuses through clicking on the highly-volatile entity *Chicago* and thereby slicing. By inspecting the value domain, she detects that many changes contain the former mayor of Chicago *Richard M. Daley* in the value domain. As she had only expected one such change after his election in 2011, but instead there are 176 such changes. Through clicking on his name, she applies a filter to see only those changes and realizes that only the property *leader_name* of Chicago was changed to that value. She continues to inspect all changes to that property and finds – besides vandalism – a high disagreement among users on whether the *leader_name* should be updated after the mayoral election or after the inauguration.

Alice shares the URL of her findings to Bob, so he directly sees all the change-cubes Alice saw in her last step. He gets curious and wants to find out what other changes relate to Chicago. In the second video, Bob follows the traces of *Chicago* again, but unlike Alice he focuses on changes that contain *Chicago* in the value dimension. Here he finds a lot of changes on the same day that update the *subdivision_name3* of various locations in *Chicago*. At this point the following feature of DBChEx can help Bob: Once the user has found an interesting change, the tool provides a dataset-specific link back to the original source of the change. For Wikipedia, the tool provides context information (user, comment) and a link to the diff-page of the revision, while for other datasets the tool could for example show the relevant SQL `INSERT/UPDATE` statement. This feature greatly helps to understand the intentions of a certain change. In this case, some further investigation reveals that on that day two infobox templates (community area and settlements) were merged.

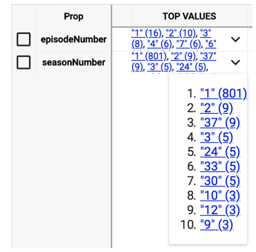
4.2 Exploring IMDB changes

Figure 5 gives a short overview of a small exploration scenario on IMDB, for which we have gathered 47 daily snapshots. Assume that Alice first performs a split by property, which results in one change-cube per property as shown in Figure 5a. For each of the change-cubes, the tool displays a number of statistics, for example the distribution of changes over time. A large spike of changes for the properties *episodeNumber* and *seasonNumber* on 2018-02-02 catches Alice's eye. For further inspection, she prunes all other change-cubes and keeps only those two change-cubes for both properties. Furthermore, by clicking on that timestamp, she

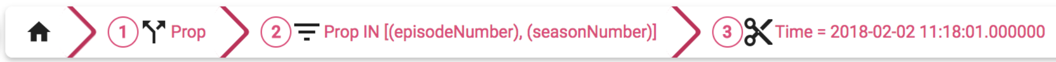
[4]https://hpi.de/naumann/projects/data-profiling-and-analytics/dbchex.html



(a) Split by property



(b) Top values



(c) Operator sequence

Figure 5: Individual steps of IMDB exploration

Table 2: Example transformation for an IMDB relation affected by a schema change

Time	Data	Changes (original)	Changes (transformed)
2018-02-05	`t001|"nm001,nm002"`	`2018-02-05,t001,principalCast,"nm001,nm002"`	`2018-02-05,t001|0,nconst,"nm001"` `2018-02-05,t001|1,nconst,"nm002"`
2018-02-06	`t001|"nm001,nm003"`	`2018-02-06,t001,principalCast,"nm001,nm003"`	`2018-02-05,t001|1,nconst,"nm003"`

2018-02-10	`t001|0|nm001|⊥|⊥|⊥`
	`t001|1|nm003|⊥|⊥|⊥`
		`2018-02-05,t001,principalCast,NULL`
		`2018-02-05,t001|0,nconst,"nm002"`
		`2018-02-05,t001|1,nconst,"nm003"`
			-

applies a filter that keeps only changes that happened on 2018-02-02, which results in the operator sequence shown in Figure 5c. Next she focuses on the value domain and finds that a large number of entities received an update that set their *seasonNumber* to 1. She looks up some of those entities and realizes that all of them are from the same series "*One Piece*". On that day more than 800 episodes of that series got merged into one season, which leads her to the conclusion that there must be a (semi-)automatic way that allows users to perform such bulk changes. Her assumption was substantiated when she inspected the other spike in Figure 5a for changes of the property *parentTconst*, which identifies the parent TV series. On 2018-02-03 this property was changed for 206 episodes from *tt0338640* to *tt0209736*.

Although the schema is quite static for this dataset, by inspecting the volatility of properties, Alice could also find a schema change that happened on 2018-02-10. For the relation *title.principals*, the schema changed from *tconst*, *principalCast* to *tconst, ordering*, *nconst*, *category*, *job*, *characters*. In this case, Alice can benefit from the closed-loop approach to have a longer history of data available across this schema change. *principalCast* was previously a comma-separated list of *nconst* references. By concatenating *tconst* and the position of individual *nconst* elements as ordering, new entity IDs are created that correspond to the new schema. These new entities have exactly one property *nconst*, while the other properties (*category, job, characters*) are all Null. This transformation may turn a change before 2018-02-10 into several changes affecting several entities, but some of the changes caused by the schema change may also disappear. How this transformation might look like for one particular movie is shown in Table 2.

5. RELATED WORK

Data exploration is a wide field of research [9]. However, most works either assume static data [10,12] or are domain-specific [13]. In contrast to related work, we treat the change itself as a first-class citizen. For instance, based on profiling results created by the Bellman tool [6], Dasu et al. have explored how data and schema changes in a database can be observed through a limited set of metadata [5]. That work has focussed on the case of only limited access to the database. In contrast, we assume full access to the database and its changes, and are thus able to focus on more fine-grained change exploration. Another related field is the visual analytics of data [7]. There are a large variety of visualizations for time-oriented data [1], some of which are also implemented by commercial tools, such as Tableau[5]. However, our tool offers more than just pure visualization. It allows primitive-based browsing and a closed-loop approach to enable the user to quickly select the relevant changes and to properly deal with schema changes. Query steering systems, such as DBNav [4], can help users in the ad-hoc navigation through the large space of possible explorations. Given meaningful transformations to time series, time series exploration techniques and tools [16] can also be used to visualize and interpret change behavior.

6. CONCLUSIONS

With *DBChEx* we present an interactive exploration tool that enables the user to explore changes of data and schema in an innovative way: it operates on the newly defined change-cubes through a set of exploration primitives. A unique feature is that our framework treats changes as first-class

[5]https://www.tableau.com/

citizens. From this point of view, the explored data is derived from changes, in contrast to changes derived from time-dependent data. That is, instead of exploring changing data, our tool supports the user in exploring data changes. We embrace the fact that these data changes also need some modelling through an iterative, closed-loop approach, which allows users to improve modeling decisions in the course of their exploration.

Our current approach scales as far as the database can answer the queries in reasonable time. However, for larger or streaming datasets there are possible improvements for future work: The tool could use a customized backend storage with appropriate index structures for the data model. Furthermore, the user might often be satisfied with an approximate, but fast result and request the exact result only when there is a real need for it. Similar to data warehouses, the more distant past often plays a less important role. A change-cube could therefore be compressed through lowering the resolution of the time or value dimension for older changes. This compression must ensure that statistics that combine data about compressed and non-compressed changes still support the correct conclusions.

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