ViDeTTe Interactive Notebooks

Konstantinos Zarifis
University of California, San Diego
zarifis@cs.ucsd.edu

ABSTRACT

Interactive notebooks allow the use of popular languages, such as python, for composing data analytics projects. The interface they provide, enables data scientists to import data, analyze them and compose the results into easily readable report-like web pages, that can contain re-runnable code, visualizations and textual description of the entire process, all in one place. Scientists can then share such pages with other users in order to present their findings, collaborate and further explore the underlying data.

However, as we show in this work, interactive notebooks lack in interactivity and ease of use, both for the data scientist that composes the notebook and, even more so, for the reader of the resulting notebook. Specifically, while the user interface allows readers to rerun or extend the code included in a notebook, it does not allow them to directly interact with the generated visualizations in order to trigger additional computation and further explore the underlying data. This means that only code-literate readers can further interact with and extend such notebooks, while the rest can only passively read the provided report. This comes in stark contrast to OLAP data cube interfaces, which utilize the user interaction to trigger additional data exploratory capabilities. Adding OLAP-like reactive functionality in notebooks further increases the required technical expertise as event-driven logic has to be added by the data analyst.

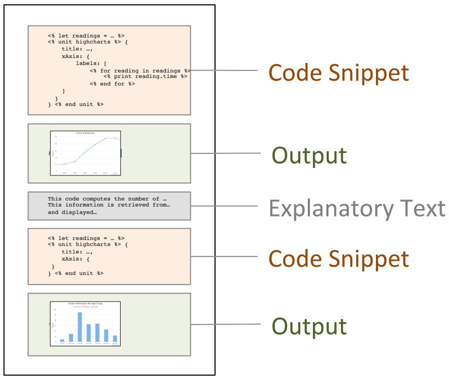
To address these issues, we propose ViDeTTe, an engine that enhances notebooks with capabilities that benefit both data scientists and non-technical notebook readers. ViDeTTe introduces a declarative language that simplifies data retrieval and data visualization for analysts. The generated visualizations are capable of collecting the reader's input and reacting to it. As the user interacts with the visualizations, ViDeTTe identifies subsequent parts of the notebook that depend on the user's input and causes their reevaluation. By doing this, ViDeTTe offers enhanced data exploratory capabilities to readers, without requiring any coding skills, while at the same time lowering the technical expertise needed for the development of reactive notebooks.

KEYWORDS

Jupyter Notebooks, Reactive Visualizations, Data Exploration

ACM Reference Format:
Konstantinos Zarifis. 2018. ViDeTTe Interactive Notebooks. In *Proceedings of Workshop on Human-In-the-Loop Data Analytics (HILDA'18).* ACM, New York, NY, USA, 7 pages. https://doi.org/10.475/123_4

HILDA'18, June 2018, Houston, TX, USA
© 2018 Copyright held by the owner/author(s).
ACM ISBN 123-4567-24-567/08/06.
https://doi.org/10.475/123_4



```
<% let readings = … %>
<% unit highcharts %> {
    title: …,
    xAxis: {
        labels: [
            <% for reading in readings %>
                <% print reading.time %>
            <% end for %>
    ]
  }
} <% end unit %>
```

```
This code computes the number of …
This information is retrieved from…
and displayed…
```

```
<% let readings = … %>
<% unit highcharts %> {
    title: …,
    xAxis: {
 }
} <% end unit %>
```

Figure 1: Notebook interface

1 INTRODUCTION

Jupyter notebooks [14] allow the use of popular, highly expressive, imperative languages, such as Python, for describing tasks such as data retrieval, processing and visualization, all in one platform. Due to the popularity of the languages they support, there is a massive collection of third-party utility libraries that can be used to facilitate such tasks. Furthermore, the web environment of interactive notebooks enables collaboration between data analysts, since it allows them to develop and run code that processes data and generates visualizations directly on the browser. Lastly, after completing an analysis, data analysts can compose their findings into an interactive report-like page, that contains re-runnable code, visualizations and textual description of the analysis, which can also be shared with non-technical users. Figure 1, shows the interface of Jupyter notebooks. It comprises a sequence of blocks that are created “on-demand" by the data analyst, each block can contain explanatory text or re-runnable coding snippets that once evaluated output the result (which could be a visualization or plain text) into the subsequent block.

Jupyter notebooks, however, have limitations that impact the exploratory capabilities that can be performed by the potentially non-technical, readers of the published notebooks. Particularly, while notebooks can contain visualizations that showcase important aspects of a data analysis, the readers cannot interact with them in the same way they could if these visualizations were part of a typical OLAP dashboard application. Specifically, even if the analyst that composes the notebook uses third-party web-based visualization libraries [1, 2, 4, 13] that support user interaction, the default side-effect of this interaction is to only cause local changes to the visualization the reader interacts with and, therefore, do not trigger additional data retrieval, computation or mutations to other visualizations that are included in the notebook (which could be generated by subsequent coding blocks). Adding more

Page Views					
id	vid	url	time	date	revenue

Visitors					
vid	name	lastname	username	age	gender

Table 1: Schema description of database tables.

elaborate side-effects that can perform such tasks requires complex event-driven logic that is typically used by web developers (in MVC applications) which entails a more advanced skill-set that data analysts might lack. For this reason, only code-literate readers, capable of extending the notebook with more coding snippets, are able to further explore the underlying data (or examine additional hypotheses about that data), while the rest are limited to passively reading the generated notebook.

We are investigating two methods, that can be used for the creation of reactive notebooks. Both these methods describe side-effects implicitly using a view-over-data approach, without requiring additional event-driven logic. The first method, presented in this paper, is using FORWARD [10, 11] and its DSL, with two differences: (a) Unlike FORWARD where the presentation layout is determined by markup [9], ViDeTTe assumes that the FORWARD DSL script is a sequence of pairs consisting of computation (essentially, computing a view) and a visual unit that visualizes the view, (b) the second difference is the extension of FORWARD towards interfacing with Python code - in particular, with Python functions. The second approach is based on using existing Jupyter (Python) coding blocks, (which describe the initial visualizations) and inferring how the outcome of each statement would be affected given a mutation. In this paper we will describe the first approach as the DSL makes static analysis and change propagation, needed for efficiency, far easier.

Contributions. In order to resolve these issues, we extend Jupyter interactive notebooks with the ViDeTTe notebook engine. The main contributions of this extension are: (a) visual constructs, capable of collecting the reader's input as they interact with the produced visualizations, (b) A declarative template language that can be used to declaratively describe computation, data transformations and user input collection, (c) A propagation algorithm, capable of inferring dependencies and propagating changes between visual constructs and described computations, thus introducing a truly reactive behavior to notebooks. These reactive capabilities, enable non-technical readers to further explore the underlying data without requiring complex event-driven logic from the data analysts that composed the notebooks.

2 RUNNING EXAMPLE

In order to illustrate the issues with existing notebooks and describe the extensions in ViDeTTe we will use the following example of a potential analysis:

Example 2.1. *Consider a data analyst, working for a news portal. The analyst wishes to convince the lead editor of the portal that by publishing more articles and advertisements that pertain to particular audiences during specific time-windows of the day, they can maximize the portal's revenue. In order to achieve this, the analyst intends to obtain and plot the number of readers that visit the website during the day; then for various time-windows she would like to obtain information about the readers' demographics (for instance, the visitors' age groups) and plot the result. Lastly, she would like to compute the portal's actual and predicted revenue (using a linear regression model) and plot the the results, side-by-side, thus illustrating whether there is room for improving revenue.*

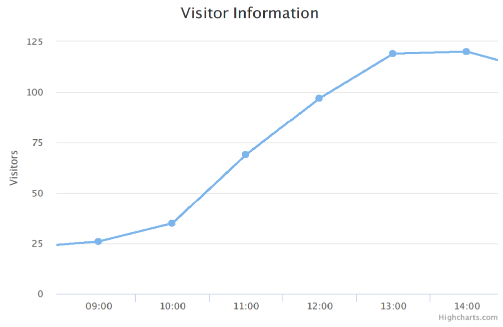


Figure 2: Line chart showing visitors per hour

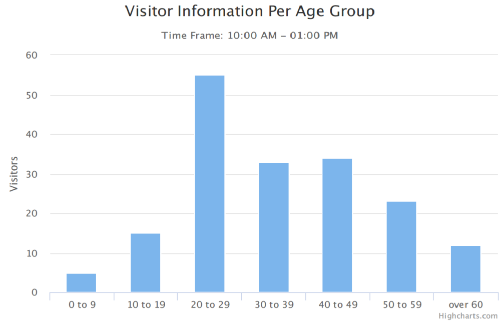


Figure 3: Bar chart showing age groups of visitors

Note that in this example, we can identify two types of users, the code-literate data scientist and a non-technical editor of the portal.

3 DATA ANALYSIS USING JUPYTER

We will now describe how a data scientist would perform this analysis with a traditional interactive notebook and illustrate how the limited interactive capabilities affect the level of data exploration that can be performed. We assume that the news portal maintains data about its reader-base in a Postgres database. Table 1 shows a potential schema, that could be used for storing visitor information. The database contains two tables, namely "Page Views" and "Visitors"; table "Visitors" contains information about each reader, such as the reader id, name, lastname, username, age and gender. The table "Page Views" maintains a tuple for each visit, and it consists of a visit id, the visitor id (foreign key referencing the visitor), the url of the visited page, the hour and date in which the user visited the website and the revenue collected during this visit. The reader information could have been retrieved, with their permission, from various social media services (such as Facebook, Google etc).

Data analysis steps. In order to construct this notebook, the data analyst must (a) retrieve website access information from the database, by joining the two tables on the visitor id (b) generate a plot that shows the number of users that visit the website during the day, (c) issue a query that counts the number of visitors per age group for a meaningful set of hours (time frame), (d) create a bar chart

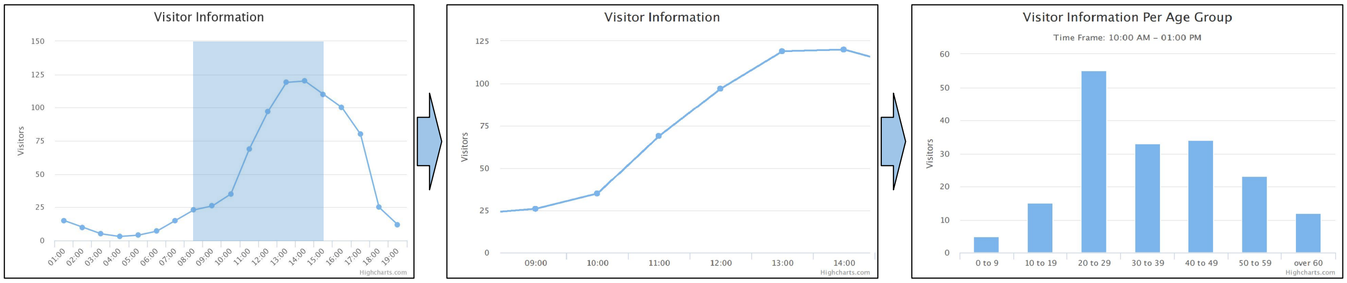


Figure 4: Demonstration of reactive charts. The reader's selection automatically updates both charts.

that shows the number of visitors per age group, (e) use an already trained predictive model in order to predict the expected revenue for the selected time window and (f) plot a bar chart, showing the actual and the predicted revenue generated in selected time window. Note that in order to perform these steps, the data analyst must employ a plethora of third-party Python libraries (database drivers, machine learning and visualization libraries etc.,) used for data access, data processing and visualization. Each of those libraries expects or returns data in a predefined schema, therefore, the analyst must manually perform schema transformations for each library they want to use. Most importantly, note that selecting a meaningful time frame (step c), is of utmost significance, because it will affect all the remaining steps of this analysis, and ultimately the insight, the portal editor will gain, about potential ways to increase the revenue

Limited interactivity impacts exploratory capabilities. Unfortunately, there is no straightforward way for selecting a meaningful time frame. The analyst will have to go through a process of trial and error, by issuing an arbitrary number of such queries and plotting the results, until she finds a set that produces valuable insight. Furthermore, even if the analyst goes through this process for the data corresponding to a particular day, the time frame selection they made, might not produce any valuable insight for the dataset corresponding to a different day. Most importantly the non-technical readers cannot use the notebook to test similar hypotheses, they are limited to passively reading the ones that were hardcoded by the analyst. This aspect of introducing the human in the loop is improved dramatically with ViDeTTe notebooks.

4 REACTIVE NOTEBOOKS

Ideal reactive behavior and functionality. Co-dependent reactive charts are tremendously useful in this scenario. If the analyst was able to introduce a chart that allows the reader to select a particular range of hours, by directly interacting with it, and use that input to retrieve and plot only the user demographics for this particular range, she could enable the readers (or in this case interactors) to further explore the underlying data without requiring any code literacy from them. Figure 4 graphically depicts this process (note that the charts that appear side-by-side in Figure 4 actually appear after the respective coding blocks that generated them in the notebook). The first figure shows the reader of the notebook, selecting a particular time frame; this causes the line chart to zoom in, thus showing only the selected time frame. After the reader performs the selection on the first chart, the subsequent bar chart is also updated thus only showing the age groups of the users that visited the portal during the selected hours. This feature adds useful exploratory capabilities to the notebook, which is of great value to readers. It enables them to further analyze the underlying dataset used by the notebook by simply interacting with the provided visualizations. (For a live demonstration that illustrates how this analysis can be performed using ViDeTTe, visit the page: https://czarifis.github.io/vidette-prototype/)

This kind of reactive behavior cannot be easily expressed in traditional interactive notebooks. It is important to note that implementing a reactive behavior that can collect user input and use it to access additional data or mutate existing visualizations is extremely arduous currently in interactive notebooks. It is identical to the process developers go through when implementing full blown web applications. It requires more time and effort as well as technical expertise (with third-party web components or input widgets) that data analysts, might lack. More specifically, describing reactive behavior entails the implementation of actions (functions) that have to be invoked when particular mouse events take place on the pixels of the browser that correspond to the visualization. These actions describe the side-effects that will by applied when such events occur. The developer must install observers that listen for such events and then provide the imperative application logic that asynchronously accesses back-end databases to retrieve new data based on the user's selection, process them appropriately and cause mutations to the visualizations that depend on them.

5 VIDETTE NOTEBOOKS

ViDeTTe notebooks support reactive behavior using a different approach. Instead of forcing analysts to provide logic that explicitly describes the side-effects (which typically include data access, processing and visualization steps) for each event that can take place, it allows them to implicitly describe them as a view-over-data. The advantage of this approach is that, when mutations occur at the underlying data (for instance, as a result of user interaction), the ViDeTTe engine can automatically infer which parts of the notebook code are affected and automatically cause their reevaluation.

In order to achieve this, ViDeTTe provides constructs, called **visual units**, that not only streamline the creation of visualizations given data, but most importantly they streamline the collection of user input from said visualizations. As readers interact with visualizations, the respective visual units cause mutations to the underlying data. Given such mutations ViDeTTe identifies the coding statements that depend on the mutated data and causes their

```
<% let readings = sql(
   SELECT count(time) as visits, time
   FROM (SELECT * FROM page_views pv
               join visitors v
         on pv.v_id = v.vid) AS joined_table
   GROUP BY time ORDER BY time ASC %>;)
```

(a) Data retrieval

```
1  <% unit highcharts %> {
2    title: 'Visitor information' , type: 'line',
3    xAxis : {
4      labels : ['08:00','09:00'...], min : '08:00', max : '22:00'
5    }
6    series: [{ data: [ {y:15}, {y:10}...] }]
7  } <% end unit %>
```

(b) Unit with evaluated unit state

```
readings = [ {visits: 15, time: '08:00'},...]
```

(c) Query Result

```
<% unit highcharts %> {
  title: 'Visitor information',
  type: 'line',
  xAxis : {
    labels : [
      <% for reading in readings %>
        <% print reading.time %>
      <% end for %>],
    min : <% bind min_time %>,
    max : <% bind max_time %>
  }
  series: [{
    data: [ <% for reading in readings %>
        {
          y  : <% print reading.count %>
        }  <% end for %> ]
  }] } <% end unit %>
```

(d) Template generating unit state of first chart

Figure 5: Declarative data retrieval, evaluated unit state and Template describing unit state for running example

reevaluation, thus automatically updating the state of (including the dependent computations and visualizations that appear on) the notebook. ViDeTTe also provides a domain specific **declarative template language**, which can be used for the invocation of system-provided functions that describe data access (namely, **source wrappers**) and invocation of reusable analyst-provided Python functions (that can describe an unbounded number of computations). This language can also describe schema conversions between visual units and source wrappers. When this template language is used, ViDeTTe can automatically identify the dependent expressions that could appear in subsequent coding blocks and causes their reevaluation.

Source wrappers. Source wrappers allow the use of source specific languages for querying database systems (for instance SQL can be used to query MySQL and PostgreSQL databases, N1QL for Couchbase etc.,). When using a ViDeTTe notebook, data analysts can directly issue queries from the notebook interface. This query is directed to the appropriate source wrapper, that evaluates it, propagates it to the respective database system and assigns the result to a Python variable. This variable can later be used in subsequent parts of the notebook (as will be described later in this section). Figure 5a contains the first query of the analysis that retrieves the dataset required to plot the chart shown in Figure 2. Specifically, the query joins the two tables: *visitors* and *page_views* on the id of the visitor, then groups the result on the *time* attribute and runs a *count* aggregate to count the visitors per unit of time. Lastly, it sorts the resulting dataset by time in ascending order and assigns the result the *readings* variable. Once the respective active function evaluates the query, it obtains and automatically parses the result into a Python array of dictionaries (used to maintain the tuples), as shown in Figure 5c. Note, that the analyst no longer needs to manually parse the results into python variables in order to use them in subsequent computations, this step is handled automatically by the respective source wrapper.

Visual Units. Visual units are constructs capable of generating fully reactive visualizations, that take advantage of the advanced interactive capabilities of modern browsers. In the eyes of an analyst a visual unit is simply a black box that takes as input a value that describes the state of the visualization. This value is called *unit instance*. The visual unit internally uses the unit instance to invoke the appropriate renderer calls that will generate the expected visualization, thus absolving the data analyst from having to perform these tasks manually. A particular instantiation of the unit can be described as **<% unit** U **%>** v **<% end unit %>**, where U the type of the visual unit and v the Python value corresponding to the unit instance. Figure 5b shows the unit instance of type `highcharts`, that once added to a coding block generates the visualization shown in Figure 2. The unit instance describes all the information that will be displayed in the visualization (such as the type and title of the chart, the labels on the x axis and so on). Each visual unit, comes with a unit instance schema that describes the format of the unit instance. As the reader interacts with visualizations, they can trigger mutations in the unit instance. For example, if the reader selects a particular area of the chart generated by the unit instance shown in Figure 5b, the min and max attributes (in lines 6-7) will be updated accordingly.

Templates. Despite the fact that both source wrappers and visual units use Python variables, data scientists often need to perform additional computation or schema transformations. In order to facilitate this process, without requiring the use of imperative logic, ViDeTTe provides a declarative template language that operates on Python variables. The template language supports a set of *template directives*, all of which operate on Python variables and simplify the task of creating nested data. Due to lack of space we do not include a formal definition of the grammar, instead we simply describe each of them in detail and provide a concrete example that illustrates their use.

Defining variables. A template may define variables that are added to the notebook's environment so that they can be used in subsequent statements. The **<% let** x **=** E **%>** directive defines variable x and assigns to it the result of the expression E. E can denote four types of expressions: (a) path navigation on nested Python variables, (b) invocation of a Python functions, (c) another subexpression containing directives that report data (defined in the next subsection) which generate nested values or (d) the invocation of a source wrapper. For instance, the template shown in Figure 5a employs a **let** directive to create a variable `readings` containing the visitor information that will be displayed in the chart (retrieved from a relational DBMS through an sql source wrapper).

```
<% let visits = sql(
   SELECT * FROM page_views pv join visitors v
   on pv.v_id = v.vid where time BETWEEN
   <% print min_time %> and <% print max_time %>;
<% let age_groups = sql(
   SELECT agegroup, count(*) AS total
   FROM (SELECT CASE
    WHEN age BETWEEN 0 AND 9 THEN '0 to 9'
    WHEN age BETWEEN 10 and 19 THEN '10 to 19'
     ...
    FROM  visits )
   GROUP BY agegroup
   ORDER BY agegroup ASC %>;)
```

(a) Data retrieval

```
age_groups = [
   {age_group: '0 to 9', total: 12},
   {age_group: '10 to 19', total: 67},  ...]
```

(b) Query Result

```
def predict_revenue(input):
  y_pred = LinearRegression.predict(input)
  return sum(y_pred)

def sum_revenue(input_list):
  return sum(item['revenue'] for item in input_list)
```

(c) Python functions predicting and summing actual revenue

```
<% unit highcharts %>
{
  title: 'Visitor information',
  type: 'bar',
  xAxis : {
    labels : [
      <% for v in age_groups %>
        <% print v.age_group %>
      <% end for %>]
  }
  series: [{
    data: [ <% for v in age_groups %>
        {
          y  : <% print v.total %>
        }
      <% end for %> ]
  }]
}
<% end unit %>
```

(d) Template generating unit state of second chart

```
1  <% unit highcharts %>
2  {title: 'Predicted and Actual revenue',
3    ...
4    data: [
5      {y : <% print predict_revenue(visits) %> }
6      {y : <% print sum_revenue(visits) %> }
7    ]...}
```

(e) Actual and Predictive revenue visualization

Figure 6: Declaration of "reactive" parameterized view, data visualization specifications and Python function declaration and invocation

Reporting data. Value assignments and iterations over collections are specified by using the **print** and **for** directives. The **<%print** *E***%>** directive evaluates the expression *E* and returns the result, while the **<%for** *x* **in** *E***%>** *B* **<%end for%>** directive specifies that variable *x* iterates over the result of *E* and, in each iteration, it instanciates the body *B* of the **for** loop. Specifically, in Figure 5d, in lines 6-8 and 13-17 a **for** directive is used to iterate over the readings retrieved from the database and for each reading, it generates a new value, with the use of the **print** directive. Particularly, in line 7 the template generates a string (the time label), which is added to the labels array (which contains the labels that will appear on the x axis of the chart). In lines 14-16 it generates a Python dictionary of the form {y: ...} and adds it to the data array. The data array in highcharts contains the points that will appear in the chart.

Invoking Python Functions. A template can also describe the invocation of Python functions, thus allowing any arbitrary computation. For instance, the snippet shown in Figure 6e (which generates the bar-chart illustrating the predicted and actual revenue) in lines 5 and 6 invokes two functions: the *predict_revenue*() and *sum_revenue*() by using the **print** directive while providing as input an array of dictionaries that is initialized in Figure 6a; function *predict_revenue*() (shown in 6c), inputs the array into a trained linear regression model and returns the revenue prediction, while function *sum_revenue*() (in the same Figure), simply computes the actual revenue.

Collecting data. The template's **bind** directive allows the analyst to specify user input collection. Specifically, the **<% bind x %>** directive describes a two-way binding between the part of the unit instance appearing on the left side of the directive and the variable *x*. Once the reader interacts with the generated visualization and causes mutations to the underlying unit instance, these mutations will be propagated to the respective bound variables. For instance, in Figure 5d in lines 9-10 we create a two-way binding between the min and max boundaries of the chart and the min and max values of the time labels that have been received from the database (namely min_time and max_time). As the reader interacts with the generated chart she can select a particular time frame by dragging and dropping the mouse over a region. This action updates the min and max attributes of the unit instance which in turn updates the values *min_time* and *max_time*.

ALGORITHM 1: Change Propagation Algorithm

```
function change-propagation(Notebook N, Environment env, Set of Input Diffs D)
    for each statement s in each coding snippet of N do
        if s is <% let x = E %> then
            if There is $\Delta(t) \in D$ with t that targets any subexpression of E then
                Reevaluate E and assign result r to x;
                Update env with new value of x;
                Construct $\Delta(x)$ and add it to D;
        else if s is <%unit U%> B <%end unit%> then
            if There is $\Delta(t) \in D$ with t that that targets any subexpression of B then
                Reevaluate B and invoke unit U with result r ;
```

Internal Data Model & Propagation Algorithm. Once a set of variables is mutated by a visual unit as a result of reader interaction, ViDeTTe is responsible for reflecting these changes to all other parts of the notebook that depend on those variables. For instance, in Figure 6a we show a parameterized query that collects all users that visited the website in the time-frame specified by *min_time* and *max_time*, categorizes them into age groups and lastly counts the users that correspond to each age group. The result of this query is assigned to the variable *age_groups* (Figure 6b shows the contents of this variable). The variable *age_groups* is then used in the template shown in Figure 6d (lines 7-9 and 12-16) to produce the bar chart appearing in Figure 3. In this scenario, if the reader's interaction with the chart shown in Figure 2, caused the mutation of variables *min_time* and *max_time* (note that the values *min_time* and *max_time* where collected by the visual unit shown in Figure 5d, lines 9 and 10), then ViDeTTe must trigger a chain reaction that causes the reevaluation of both the query and the following visualization in order to reflect the changes. We will now describe this process.

Representing mutations through Diffs. Once a variable is mutated, the respective visual unit or source wrapper produces a diff that describes this mutation. A *diff* is the internal data model that is shared between source wrappers, visual units and the change propagation algorithm, this data model is hidden from data analysts and notebook readers. A diff that targets a nested value is of the form $\Delta(\hat{p})$, where $\hat{p}$ is the path to the value that is being modified.

Change Propagation Algorithm.

Once a diff is generated for each mutated variable ViDeTTe invokes the change propagation algorithm, shown in 1. The algorithm takes as input a set of diffs, and only invokes the reevaluation of statements that depend on the targeted variables. Specifically, it iterates over each statement of each coding block that appears in the notebook (as shown in line 2) and performs the following checks:

- If the statement defines a new variable x (line 3), then the algorithm visits every sub-expression of the **let** directive and checks if it is targeted by any diff in D (line 4). If there is, the change propagation algorithm causes the reevaluation of the **let** statement (line 5), updates the notebook environment with the new value of x (line 6) and lastly constructs a new diff that describes the mutation to the variable x (line 7). Note that the Expression shown in Figure 6b is an SQL statement that contains subexpressions (parameters), so given a diff of type: $\Delta(min\hat{\_}time)$ (which could be created as the reader interacts with the chart), the propagation engine identifies that there is a subexpression targetted by that diff thus causing the reevaluation of the source wrapper, resulting in additional data.
- If the statement constructs a visualization using a visual unit of type U with body B (line 8), then the algorithm visits every sub-expression in body B and checks if it is targeted by any diff in D (line 9). If there is, the change propagation algorithm causes the reevaluation of the entire body B, thus generating the unit instance r and then reinvokes the unit U with new unit instance (line 10).

6 RELATED WORK

Prior work related to ViDeTTe notebooks can be classified into the following categories:

Grammar-based visualizations. The concept of using a formal grammar to specify visualizations can be traced back to Wilkinson's "The Grammar of Graphics" [25]. Since then multiple tools, such as Polaris [22] (later commercialized as Tableau), ggplot2 [24], Vega [19, 23] and others [5, 7, 12] have adopted this approach, thus enabling the description of visualizations (as well as the user interaction with such visualizations [20, 26]) in a terse and declarative manner. While the expressiveness of the employed grammars varies, their main focus is to effectively describe the specifics of the visualizations that will appear (for instance the dimensions of the chart, the colors, etc.), and not to describe data access or data processing and/or conversions. For that reason, such tools (due to their limited expressivity) do not provide constructs capable of retrieving data from diverse sources or performing arbitrary data transformations. Instead, the user has to provide imperative logic that performs these tasks manually and ultimately convert the dataset she wants to visualize into the format that is expected by the respective tool in order to generate the visualization.

Reactive Libraries. Some of the aforementioned tools (for instance ggplot2 [24], Vega [1, 2, 19, 23] and ggvis [12]), do allow readers to interact with visualizations, however, they don't allow, data analysts to declaratively specify the wide range of side effects that ViDeTTe allows. Specifically, while these tools can create visualizations (and widgets) that depend on one another, they cannot declaratively describe more elaborate side-effects that include retrieving additional data, or issuing arbitrary computations (for instance, linear regression as was shown in this paper). They take as input the entire dataset that can be included in the produced visualizations throughout their life-cycle and they provide a declarative language with limited data processing (essentially describing a subset of the operations that can be expressed in SQL) and no data access capabilities. Additionally, these tools operate in isolation with respect to the rest of the notebook, which means that they cannot be used to generate co-dependent visualizations that appear across multiple notebook coding blocks. For those reasons they offer more limited data exploratory capabilities compared to ViDeTTe.

Data exploration. Tools that use the human factor as an integral part of data exploration have gained in popularity in the past years. Such tools provide a simple to use way that describes both computation and visualizations, thus providing the required toolkit to effectively explore data and steer computation. Some of these tools enable this process by providing a declarative language capable of performing such tasks (such as Zenvisage [21] and Devise [18]), while others (such as Vizdom [6], DataHub [16] and more[3, 8, 15, 17, 27]) rely on the user interaction with a front-end, in order to compose the appropriate queries. As a result, the former tools assume a type of user with deep understanding in databases and query languages, while the latter offer a more user-friendly way of performing an analysis but at the same time allow a predetermined set of possible analyses. ViDeTTe notebooks bridge the gap between these two types of users; to a data analyst it provides constructs that allow rapid creation of notebooks for an arbitrary number of analyses, while to a non-technical user it provides the capability to interact with the produced visualization in order to further explore the underlying data.

7 CONCLUSION

We presented ViDeTTe an interactive notebook engine, that enhances interactive notebooks with capabilities that pertain to both data scientist that create notebooks and non-technical notebook readers. Specifically, ViDeTTe streamlines arduous tasks that usually have to be performed by data analysts, that compose such notebooks, while at the same time offering enhanced data exploratory capabilities to the readers of the published notebooks

REFERENCES

[1] Altair: Declarative visualization in python.

[2] ipyvega: Ipython/jupyter notebook module for vega and vega-lite.

[3] A. Bhardwaj, A. Deshpande, A. J. Elmore, D. Karger, S. Madden, A. Parameswaran, H. Subramanyam, E. Wu, and R. Zhang. Collaborative data analytics with datahub. *Proceedings of the VLDB Endowment*, 8(12):1916–1919, 2015.

[4] Bokeh Development Team. *Bokeh: Python library for interactive visualization*, 2014.

[5] M. Bostock and J. Heer. Protovis: A graphical toolkit for visualization. *IEEE transactions on visualization and computer graphics*, 15(6):1121–1128, 2009.

[6] A. Crotty, A. Galakatos, E. Zgraggen, C. Binnig, and T. Kraska. Vizdom: interactive analytics through pen and touch. *Proceedings of the VLDB Endowment*, 8(12):2024–2027, 2015.

[7] D3: Data-driven documents. https://d3js.org/.

[8] M. Derthick, J. Kolojejchick, and S. F. Roth. An interactive visual query environment for exploring data. In *Proceedings of the 10th annual ACM symposium on User interface software and technology*, pages 189–198. ACM, 1997.

[9] Forward. forward.ucsd.edu/visualizations.html.

[10] Y. Fu, K. Kowalczykowski, K. W. Ong, Y. Papakonstantinou, and K. K. Zhao. Ajax-based report pages as incrementally rendered views. In *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*, pages 567–578. ACM, 2010.

[11] Y. Fu, K. W. Ong, Y. Papakonstantinou, and M. Petropoulos. The sql-based all-declarative forward web application development framework. In *CIDR*, pages 69–78, 2011.

[12] ggvis: Interactive grammar of graphics for r. http://ggvis.rstudio.com/.

[13] P. T. Inc. Collaborative data science, 2015.

[14] Jupyter. http://jupyter.org/.

[15] N. Kamat, E. Wu, and A. Nandi. Trendquery: A system for interactive exploration of trends. In *Proceedings of the Workshop on Human-In-the-Loop Data Analytics*, HILDA '16, pages 12:1–12:4, New York, NY, USA, 2016. ACM.

[16] S. Krishnan, J. Wang, E. Wu, M. J. Franklin, and K. Goldberg. Activeclean: Interactive data cleaning for statistical modeling. *Proc. VLDB Endow.*, 9(12):948–959, Aug. 2016.

[17] E. Liarou and S. Idreos. dbtouch in action database kernels for touch-based data exploration. In *IEEE 30th International Conference on Data Engineering, Chicago, ICDE 2014, IL, USA, March 31 - April 4, 2014*, pages 1262–1265, 2014.

[18] M. Livny, R. Ramakrishnan, K. Beyer, G. Chen, D. Donjerkovic, S. Lawande, J. Myllymaki, and K. Wenger. Devise: integrated querying and visual exploration of large datasets. In *ACM SIGMOD Record*, volume 26, pages 301–312. ACM, 1997.

[19] A. Satyanarayan, D. Moritz, K. Wongsuphasawat, and J. Heer. Vega-lite: A grammar of interactive graphics. *IEEE Trans. Visualization & Comp. Graphics (Proc. InfoVis)*, 2017, 2015.

[20] A. Satyanarayan, R. Russell, J. Hoffswell, and J. Heer. Reactive vega: A streaming dataflow architecture for declarative interactive visualization. *IEEE transactions on visualization and computer graphics*, 22(1):659–668, 2016.

[21] T. Siddiqui, A. Kim, J. Lee, K. Karahalios, and A. G. Parameswaran. zenvisage: Effortless visual data exploration. *CoRR*, abs/1604.03583, 2016.

[22] C. Stolte, D. Tang, and P. Hanrahan. Polaris: A system for query, analysis, and visualization of multidimensional relational databases. *IEEE Transactions on Visualization and Computer Graphics*, 8(1):52–65, 2002.

[23] Vega, a visualization grammar. http://trifacta.github.io/.

[24] H. Wickham. *ggplot2: elegant graphics for data analysis*. Springer Science & Business Media, 2009.

[25] L. Wilkinson. *The Grammar of Graphics (Statistics and Computing)*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2005.

[26] Y. Wu, J. M. Hellerstein, and E. Wu. A devil-ish approach to inconsistency in interactive visualizations. In *Proceedings of the Workshop on Human-In-the-Loop Data Analytics*, HILDA '16, pages 15:1–15:6, New York, NY, USA, 2016. ACM.

[27] K. Zoumpatianos, S. Idreos, and T. Palpanas. Rinse: interactive data series exploration with ads+. *Proceedings of the VLDB Endowment*, 8(12):1912–1915, 2015.