Prosto Documentation

Release latest

Prosto Data

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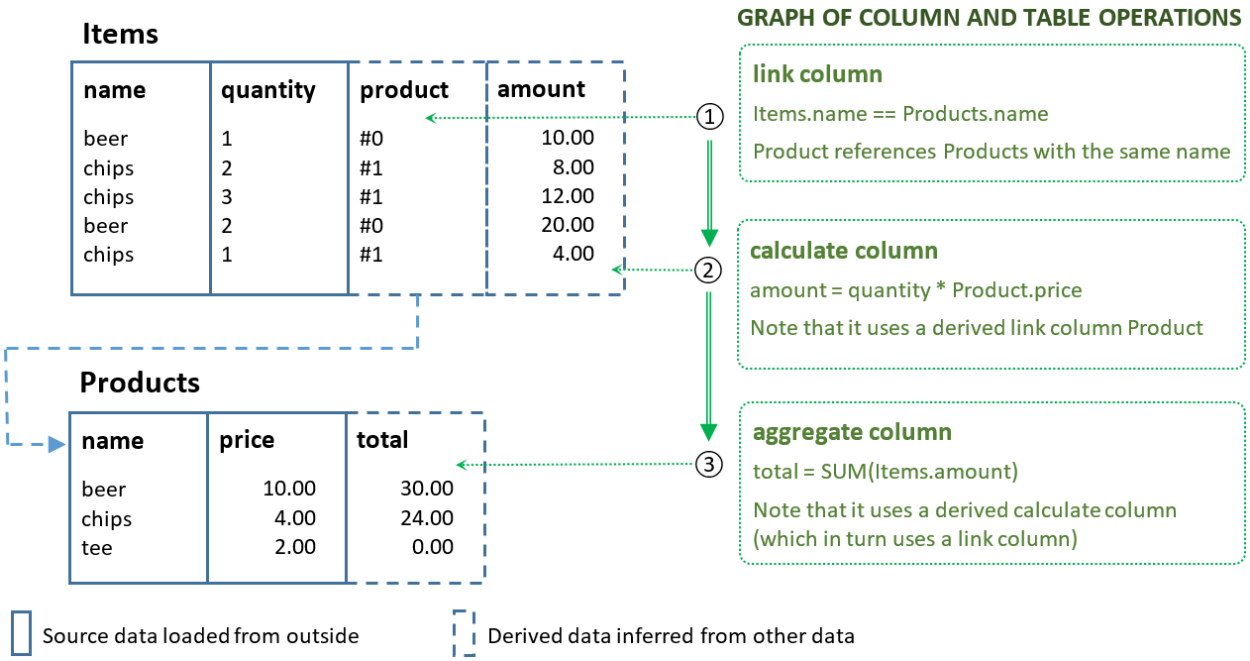
Contents

Prosto is a Python data processing toolkit to programmatically author and execute complex data processing workflows. Conceptually, it is an alternative to purely *set-oriented* approaches to data processing like map-reduce, relational algebra, SQL or data-frame-based tools like *pandas*.

Prosto radically changes the way data is processed by relying on a novel data processing paradigm: concept-oriented model of data [1]. It treats columns (modelled via mathematical functions) as first-class elements of the data processing pipeline having the same rights as tables. If a traditional data processing graph consists of only set operations than the *Prosto* workflow consists of two types of operations:

- *Table operations* produce (populate) new tables from existing tables. A table is an implementation of a mathematical *set* which is a collection of tuples.
- *Column operations* produce (evaluate) new columns from existing columns. A column is an implementation of a mathematical *function* which maps tuples from one set to another set.

An example of such a *Prosto* workflow consisting of 3 column operations is shown below. The main difference from traditional approaches is that this *Prosto* workflow will not modify any table - it changes only columns. Formally, if traditional approaches apply set operations by generating new sets from already inferred sets, then *Prosto* derives new *functions* from existing functions. In many cases, using functions (column operations) is much simpler and more natural.



Prosto operations are demonstrated in notebooks which can be found in the "notebooks" folder in the main repo. Do your own experiments by tweaking them and playing around with the code: https://github.com/asavinov/prosto/tree/master/notebooks

CHAPTER 1

Contents

1.1 Quick start

1.1.1 Importing Prosto

`Prosto` is a toolkit and it is intended to be used from another (Python) application. Before its data processing functions can be used, the module has to be imported:

```
import prosto as pr
```

1.1.2 Defining a workflow

A workflow contains *definitions* of data elements (tables and columns) as well as *operations* for data generation. Before data processing operations can be defined, a `Prosto` workflow has to be created:

```
prosto = pr.Prosto("My Prosto Workflow")
```

More info: Workflow and operations

1.1.3 Defining a table

Each table has some structure which is defined by its *attributes*. Table data is defined by the tuples it consists of and each tuple is a combination of some attribute values.

There exist many different ways to populate a table with tuples (attribute values). One of the simplest one is a table `populate` operation. It relies on a *user-defined function* which is supposed to "know" how to populate this table by returning a `pandas` data frame with the data.

Below we define a table with three attributes which will be populated by the specified user-defined function:

```
sales_data = {
    "product_name": ["beer", "chips", "chips", "beer", "chips"],
    "quantity": [1, 2, 3, 2, 1],
    "price": [10.0, 5.0, 6.0, 15.0, 4.0]
}

sales = prosto.populate(
    # Table definition consists of a name and list of attributes
    table_name="Sales", attributes=["product_name", "quantity", "price"],

    # Table operation is an UDF, list of input tables and model (parameters for UDF)
    func=lambda **m: pd.DataFrame(sales_data), tables=[], model={}
)
```

The user-defined function in this example returns a `pandas` data frame with in-memory sales data. In a more realistic case, the data could be loaded from a CSV file or database. This data frame has to contain all attributes declared for this table.

Other table operations like `project`, `product` and `filter` allow for processing table data from already existing input tables which in turn could be populated using other operations.

More info: Table operations

1.1.4 Defining a column

A column is formally interpreted as a mathematical function which maps tuples (defined by table attributes) of this table to tuples in another table.

There exist many different ways to compute a mapping form one table to another table. One of the simplest column operations is a `calculate` column which *computes* output values of the mapping using the values of the specified input columns of the same table:

```
calc_column = prosto.calculate(
    # Column definition consists of a name and table it belongs to
    name="amount", table=sales.id,

    # Column operation is UDF, list of input columns and model (parameters for UDF)
    func=lambda x: x["quantity"] * x["price"], columns=["quantity", "price"],␣
↪model=None
)
```

This new column will store the amount computed for each record as a product of quantity and price. Note that the input columns could be also derived columns computed from some other data in this or other tables.

Other column operations like `link`, `aggregate` or `roll` allow for producing link columns referencing records in other tables and aggregate data.

More info: Column operations

1.1.5 Executing a workflow

When a workflow is defined it is not executed - it stores only operation definitions. In order to really process data, the workflow has to be executed:

```
prosto.run()
```

Prosto translates a workflow into a graph of operations (topology) taking into account their dependencies and then executes each operation: table operations will populate tables and column operations will evaluate columns.

Now we can explore the result by reading data form the table along with the calculate column:

```
df = table.get_df()
print(df)
```

```
   product_name quantity price amount
0  beer         1        10.0  10.0
1  chips        2        5.0   10.0
2  chips        3        6.0   18.0
3  beer         2        15.0  30.0
4  chips        1        4.0   4.0
```

Although it looks like a normal table, the last column was derived from the data in other columns. If we change input data, then we can again run this workflow and the derived column will contain updated results.

The full power of Prosto comes from the ability to process data in multiple tables by definining derived links (instead of joins) and then aggregating data based on these links (without groupby). Note that both linking and aggregation do not require and will not produce new tables: only columns are defined and evaluated. For example, we might use column paths like my_derived_link::my_column in operations in order to access data in other tables.

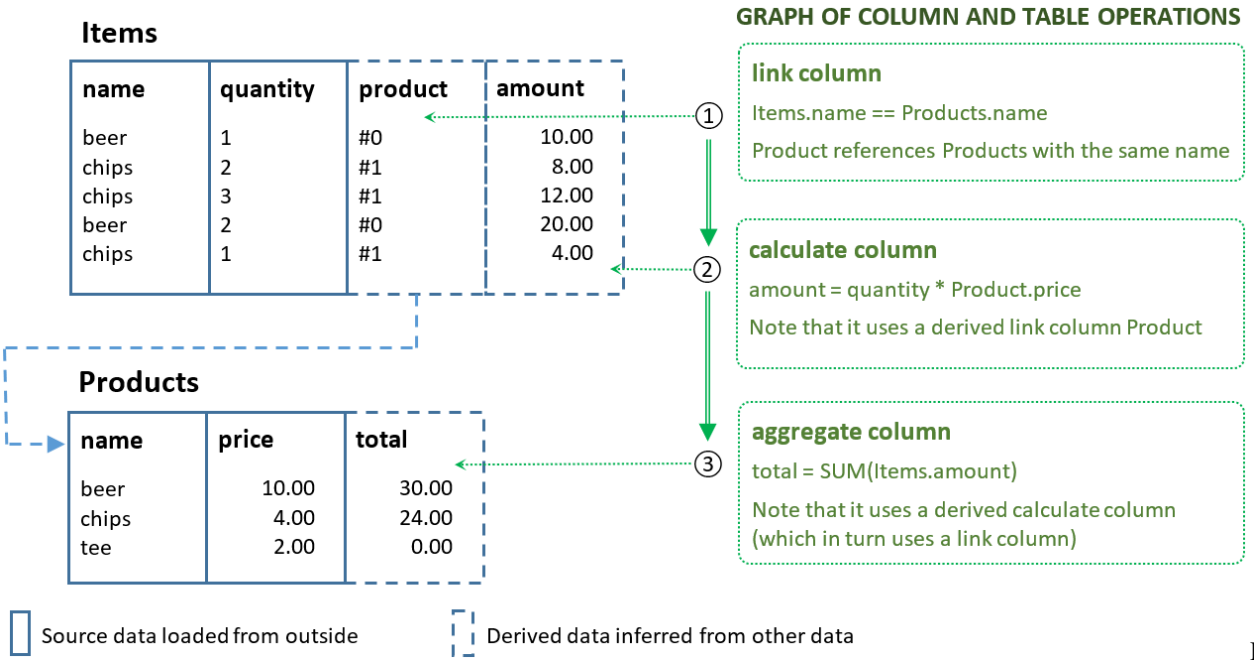
1.2 Motivation: Why Prosto?

1.2.1 Why functions and column-orientation?

In traditional approaches to data processing we frequently need to produce a new table even though we need to define a new attribute. For example, in SQL, a new relation has to be produced even if we want to define a new calculated attribute. We also need to produce a new relation (using join) if we want to process data from another table. Data aggregation by means of groupy operation produces a new relation too although the goal is to compute a new attribute.

Thus processing data using *only* set operations is in many quite important cases counter-intuitive. In particular, this is why map-reduce, join-groupby (including SQL) and similar approaches require high expertise and are error-prone. The main unique novel feature of Prosto is that it adds mathematical *functions* (implemented as columns) to its model by significantly simplifying data processing and analysis. Now, if we want to define a new attribute then we can do it directly without defining new unnecessary table, collection or relation.

Below we describe three use cases where applying set operations is an unnecessary and counter-intuitive step. The example data model shown in this diagram is used for demonstration purposes. (Note however that it does not exactly corresponds to the use cases.)



Data processing workflow

Calculating data

One of the simplest operations in data processing is computing a new attribute using already existing attributes. For example, if we have a table `Items` containing orders characterized by `quantity` and `price` then we could compute a new attribute `amount` as their arithmetic product:

```
SELECT *, quantity * price AS amount FROM Items
```

This wide spread data processing pattern may seem very natural and almost trivial but it actually has one significant conceptual flaw:

> the task was to compute a new *attribute* while the query produces a new *table*

Although the result table does contain the required attribute, the question is why not to do exactly what has been requested? Why is it necessary to produce a new table if we actually want to compute only an attribute?

The same problem exists in map-reduce. If our goal is to compute a new field then we apply the map operation which will emit completely new collection of objects having this new field. Here again the same problem: our intention was not to create a new collection with new objects – we wanted to add a new computed property to already existing objects. However, the data processing framework forces us to describe this task in terms of operations with collections. We simply do not have any choice because such data models provide only sets and set operations, and the only way to add a new attribute is to produce a new set with this attribute.

An alternative approach consists in using *column operations* for data transformations so that we can do exactly what is requested: adding (calculated) attributes to existing tables.

Linking data

Another wide spread task consists in computing links or references between different tables: given an element of one table, how can I access attributes in a related table? For example, assume that `price` is not an attribute of the `Items` table as in the above example but rather it is an attribute of a `Products` table. Here we have two tables, `Items` and `Products`, each having `name` attribute which relates their records. If now we want to compute the amount for

each item then the price needs to be retrieved from the related `Products` table. The standard solution is to copy the necessary attributes into a *new table* by using the relational (left) join operation for matching the records:

```
SELECT item.*, product.price FROM Items item
JOIN Products product ON item.name = product.name
```

This new result table can be now used for computing the amount precisely as we described earlier because it has the necessary attributes copied from the two source tables. Let us again compare this solution with the problem formulation. Do we really need a new table? No. Our goal was to have a possibility to access attributes from the second `Products` table (while computing a new attribute in the first table). Hence this again can be viewed as a workaround rather than a solution:

> a new set is not needed for the solution and it is produced just because there is no possibility not to produce it

A principled solution to this problem would be a data model which uses *column operations* for data processing so that a link can be defined as a new column in an existing table.

Aggregating data

Assume that for each product, we want to compute the total number of items ordered. This task can be solved using group-by operation:

```
SELECT name, COUNT(name) AS totalQuantity
FROM Items GROUP BY name
```

Here again we see the same problem:

> a new unnecessary *table* is produced although the goal is to produce a new (aggregated) attribute in an existing table

Indeed, what we really want is to add a new attribute to the `Products` table which would be equivalent to all other attributes (like product `price` used in the previous example). This `totalQuantity` could be then used to compute some other properties of products. Of course, this also can be done using set operations in SQL but then we will have to again use join to combine the group-by result with the original `Products` table followed by producing yet another table with new calculated attributes. It is apparently not how it should work in a good data model because the task formulation does not mention and does not actually require any new tables - only attributes. Thus we see that the use of set operations in this and above cases is a problem-solution mismatch.

A solution to this problem again would be a column oriented data model where aggregated columns could be defined without adding new tables.

1.2.2 Benefits of Prosto

Easily processing data in multiple tables

New derived columns are added directly to tables without creating multiple intermediate tables.

We can easily implement calculate columns using `apply` method of `pandas`. However, we cannot use this technique in the case of multiple tables. `Prosto` is intended for and makes it easy to process data stored in many tables by relying on `link` columns which are also evaluated from the data.

Getting rid of join and group-by

Column definitions such as link columns and aggregate columns are used instead of join and groupby set operations.

Data in multiple tables can be processed using the relational join operation. However, it is tedious, error prone and requires high expertise especially in the case of many tables. `Prosto` does not use joins. Instead, it relies on `link` columns which also have definitions and are evaluated during workflow execution.

Data aggregation is typically performed using some kind of group-by operation. `Prosto` does not use this relational operation by providing column operations for that purpose which are simpler and more natural especially in describing complex analytical workflows.

Flexibility and modularization via user-defined functions

UDFs describe what needs to be done with the data only in this operation using arbitrary Python code. If UDF for an operation changes then it is not necessary to update other operations.

`Prosto` is very flexible in defining how data will be processed because it relies on user-defined functions which are its minimal units of data processing. They provide the logic of processing at the level of individual values while the logic of looping through the sets is implemented by the system according to the type of operation applied. User-defined functions can be as simple as format conversion and as complex as as a machine learning algorithm.

Parameterization of operations by a model object

A model can be as simple as one value and as complex as a trained deep neural network. This feature leads to a novel view of how data analysis should be organized by combining feature engineering and machine learning so that both model training and model use (predictions or transformations) are part of one data processing workflow. Currently models are supported only as static parameters but in future there will be a possibility to train model within the same workflow

Future directions

- In future, `Prosto` will implement such features as *incremental evaluation* for processing only what has changed, *model training* for training models as part of the workflow, data/model persistence and other data processing and analysis operations.
- *Data Dictionary* (DD) for declaring schema, tables and columns, and *Feature Store* (FS) for defining operations over these data objects

1.2.3 References

[1]: A.Savinov. On the importance of functions in data modeling, Eprint: arXiv:2012.15570 [cs.DB], 2019. https://www.researchgate.net/publication/348079767_On_the_importance_of_functions_in_data_modeling

[2]: A.Savinov. Concept-oriented model: Modeling and processing data using functions, Eprint: arXiv:1606.02237 [cs.DB], 2019. https://www.researchgate.net/publication/337336089_Concept-oriented_model_Modeling_and_processing_data_using_functions

[3]: A.Savinov. From Group-By to Accumulation: Data Aggregation Revisited, Proc. IoTBDS 2017, 370-379. https://www.researchgate.net/publication/316551218_From_Group-by_to_Accumulation_Data_Aggregation_Revisited

[4]: A.Savinov. Concept-oriented model: the Functional View, Eprint: arXiv:1606.02237 [cs.DB], 2016. https://www.researchgate.net/publication/303840097_Concept-Oriented_Model_the_Functional_View

[5]: A.Savinov. Joins vs. Links or Relational Join Considered Harmful, Proc. IoTBD 2016, 362-368. https://www.researchgate.net/publication/301764816_Joins_vs_Links_or_Relational_Join_Considered_Harmful

1.3 Concepts behind Prosto

1.3.1 Matrixes vs. sets

It is important to understand the following crucial difference between matrixes and sets expressed in terms of multidimensional spaces:

> A cell of a matrix is a point in the multidimensional space defined by the matrix axes - the space has as many dimensions as the matrix has axes. Values are defined for all points of the space. A tuple of a set is a point in the space defined by the table columns - the space has as many dimensions as the table has column. Values are defined only for a subset of all points of the space.

It is summarized in the table:

| Property | Matrix | Set | | — | — | — | | Dimension | Axis | Attribute | | Point coordinates | Cell axes values | Tuple attribute values | | Dimensionality | Number of axes | Number of attributes | | Represents | Distribution | Predicate | | Point | Value of distribution | True of false |

The both structures can represent some distribution over a multidimensional space but do it in different ways. Obviously, these differences make it extremely difficult to combine these two semantics in one framework.

`Prosto` is an implementation of the set-oriented approach where a table represents a set and its rows represent tuples. Note however that `Prosto` supports an extended version of the set-oriented approach which includes also functions as first-class elements of the model.

1.3.2 Sets vs. functions

Tuples are a formal representation of data values. A tuple has structure declared by its *attributes*.

A *set* is a formal representation of a collection of tuples representing data values. Tuples (data values) can be only added to or removed from a set. In `Prosto`, sets are implemented via table objects.

A *function* is a mapping from an input set to an output set. Given an input value, the output value can be read from the function or set for the function. In `Prosto`, functions are implemented via column objects.

1.3.3 Attributes vs. columns

Attributes define the structure of tuples and they are not evaluated. Attribute values are set by the table population procedure.

Columns implement functions (mappings between sets) and their values are computed by the column evaluation procedure.

1.3.4 `Pandas` vs. `Prosto`

`Pandas` is a very powerful toolkit which relies on the notion of matrix for data representation. In other words, matrix is the main unit of data representation in `pandas`. Yet, `pandas` supports not only matrix operations (in this case, having `numpy` would be enough) but also set operations, relational operations, map-reduce, multidimensional and OLAP as well as some other conceptions. In this sense, `pandas` is a quite eclectic toolkit.

In contrast, `Prosto` is based on a solid theoretical basis: the concept-oriented model of data. For simplicity, it can be viewed as a purely set-oriented model (not the relational model) along with a function-oriented model. Yet, `Prosto` relies on `pandas` in its implementation just because `pandas` provides a powerful set of highly optimized operations with data.

1.4 Workflow and operations

1.4.1 Structure of workflow

TBD

1.4.2 List of operations

`Prosto` provides two types of operations which can be used in a workflow:

- A *table population operation* adds new records to the table given records from one or more input tables
- A *column evaluation operation* generates values of the column given values of one or more input columns

`Prosto` currently supports the following operations:

- Column operations
  - `compute`: A complete new column is computed from the input columns of the same table. It is analogous to the table `populate` operation
  - `calculate`: New column values are computed from other values in the same table and row
  - `link`: New column values uniquely represent rows from another table
  - `merge`: New columns values are copied from a linked column in another table
  - `roll`: New column values are computed from the subset of rows in the same table
  - `aggregate`: New column values are computed from a subset of row in another table
  - `discretize`: New column values are a finite number of groups like numeric intervals
- Table operations
  - `populate`: A complete table with all its rows is populated and returned by the specified UDF similar to the column `compute` operaiton
  - `product`: A new table consists of all combinations of rows in the inputs tables
  - `filter`: A new table is a subset of rows from another table selected using the specified UDF
  - `project`: A new table consists of all unique combinations of the specified columns of the input table

Examples of these operations can be found in unit tests or Jupyter notebooks in the `notebooks` project folder.

1.4.3 Operation parameters

An operation in Prosto provides a general logic of data processing and it does not do anything by itself. An operation needs additional parameters which specify what exactly has to be done with the data. Below we describe parameters which are common to almost all operation types.

- Data elements and operations. It is important to understand that data elements and operations are different types of objects and they are managed separately in `Prosto`. We can create, update and delete them separately. Yet, for simplicity, Prosto provides functions which create an operation along with the corresponding new data element. For example, we call the `calculate` function then it will define one column and one operation. A new data element and a new operation are described by different parameters of the function.

- Data element definition. First two parameters of an operation define a data element. If it is a column operation like `link` then it defines a new column using its `name` and (existing) `table`. If it is a table operation like `project` then it is its `table_name` and a list of `attributes`. The rest of the operation parameters define an operation.
- Function. Most operations have a `func` argument which provides a user-defined function (UDF). This function "knows" what to do with the data. There are two types of functions: (i) functions which are called in an internal loop and take/return data values, (ii) functions which are called only once and take/return collections of values (columns or tables). For each operation it is specified which kind of UDF it uses.
- Data. Here we can specify what data has to be processed by the operation (and the corresponding UDF). For many column operations, it is a list of `columns` of the input table. It is assumed that only these columns have to be processed. For many table operations, it is a list of `tables`.
- Model. This argument of an operation is intended for providing additional parameter for data processing. The model object is passed to UDF which has to know how to use it. It can be as simple as one value and as complex as a trained data mining model. It can be a tuple, dictionary or an arbitrary Python object. A tuple will be unpacked in a list of positional arguments of UDF. A dictionary will be unpacked into a list of keyword arguments. An object will be passed as one positional argument.

1.5 Table operations

1.5.1 Populate table

A new table will be populated with data returned by the specified user-defined function. This operation is analogous to `compute` column operation with the difference that a complete table is returned rather than a complete column.

1.5.2 Product of tables (instead of join)

This table is intended to produce all combinations of rows in other tables. Its main difference from the relational model is that the result table stores links to the rows of the source tables rather than copies of its rows. The result table has as many attributes as it has source tables in its definition. (In contrast, the number of attributes in a relational product is equal to the sum of attributes in all source tables.)

Uses:

- Creating a cube table from dimension tables for multi-dimensional analysis. It is typically followed by aggregating data in the fact table.

1.5.3 Filter table (instead of select-where)

It is one of the most frequently used operations. The main difference form conventional implementations is that the result never includes the source table columns. Instead, the result (filtered) table references the selected source rows using an automatically created link column. If it is necessary to use the source table data (and it is almost always the case) then they are accessible via the created link column.

1.5.4 Project table (instead of select-distinct)

This operation has these important uses:

- Creating a table with group elements for aggregation because (in contrast to other approaches) it must exist
- Creating a dimension table for multi-dimensional analysis in the case it does not exist

Check out the `project.ipynb` notebook for a working example of the `project` operaiton.

1.5.5 Range table

Not implemented yet.

This operation populates a table with one attribute which contains values from a range described in the model. A range specification typically has such parameters as `start`, `end`, `step` size (or frequency), `origin` and others depending on the range type.

Links:

- https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.date_range.html
- https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#generating-ranges-of-timestamps

1.6 Column operations

1.6.1 Compute column

A `compute` column is intended for computing a new column based the values in other columns in the same row. It is defined via a Python user-defined function which gets several input columns and returns one output column which is then added to the table.

1.6.2 Calculate column (instead of map operation)

Probably the simplest and most frequent operation in `Prosto` is computing a new column of the table which is done by defining a `calculate` column. The main computational part of the definition is a (Python) function which returns a single value computed from one or more input values in its arguments.

This function will be evaluated for each row of the table and its outputs will be stored as a new column.

It is similar to how `apply` works in `pandas` (and actually it relies on it in its implementation) but it is different from how `map` operation works because a calculated column does not add any new table while `map` computes a new collection (which makes computations less efficient).

The `Prosto` approach is somewhat similar to spreadsheets with the difference that new columns depend on only one coordinate - other columns - while cells in spreadsheets depend on two coordinates - row and column addresses. The both however are equally simple and natural.

Check out the `calculate.ipynb` notebook for a working example of the `calculate` operaiton.

1.6.3 Link column (instead of join)

We can define and evaluate new columns only in individual tables but we cannot define a new column which depends on the data in another table. Link columns solve this problem. A link column stores values which uniquely represent rows of a target (linked) table. In this sense, it is a normal column with some values which are computed using some definition. The difference is how these values are computed and their semantics. They do not have a domain-specific semantics but rather they are understood only by the system. More specifically, each value of a link column is a reference to a row in the linked table or None in the case it does not reference anything.

The main part of the definition is a criterion for finding a target row which matching this row. The most wide spread criterion is based on equality of some values in two rows and the definition includes lists of the columns which have to be equal in order for this row to reference the target row.

Link columns have several major uses:

- Data in other (linked) tables can be accessed when doing something in this table, say, when defining its calculate columns
- Data can be grouped using linked rows interpreted as groups, that is, all rows of this table referencing the same row of the target table are interpreted as one group
- Link columns are used when defining aggregate columns

There could be other criteria for matching rows and defining link columns which will be implemented in future versions.

Check out the `link.ipynb` notebook for a working example of the `link` operaiton.

1.6.4 Merge column (instead of join)

Once we have defined link columns and interlinked our (initially isolated) set of tables, the question is how we can use these links? There are two major conceptual alternatives:

- move the whole linked columns to the source tables as one dedicated operation performed before the data in this column is used
- do not move the whole column but rather use this link to access individual data values in the linked column from within each operation which needs this data.

The second approach requires less memory because the (linked) data is used where it resides but it is less efficient because each value is accessed via the link. The first approach require more memory because we duplicate the linked column by moving it to the table where it will be used. However, access to this data will be as fast as to all other columns within this source table.

Currently, the first approach is implemented via the dedicated `merge` column operation. This operation specified a sequence of link columns from the source table to a target column in another table. Its result is a new column in this source table which contains the same data as in the target column and it can be used precisely as any other column in this table. The merged (copied) column can be then used in other operations like calculate columns or aggregate columns.

It is important that it is not necessary to use this operation explicitly. In other words, if we want to use a linked column in some operation, then we could merge it first but it is an explict and optional way. A simpler approach is to specify a *column path* as our column name in the operation. A column path is a sequence of simple column names separated by some symbol, '::' (two colons) by default. The translator will find such column paths and automatically insert the necessary merge operation.

1.6.5 Rolling aggregation (instead of over-partition)

This column will aggregate data located in "neighbor" rows of this same table. These rows to be aggregated are selected using criteria in the `window` object. For example, we can specify how many previous rows to select.

Currently, its logic is equivalent to that of the rolling aggregation in `pandas` with the difference that the result column is immediately added to the table and this operation is part of the whole workflow.

The `roll` operation can distinguish different groups of rows and process them separately as if they were stored in different tables. We refer to this mode as rolling aggregation with grouping. If the `link` parameter is not empty then its value specifies a column or attribute used for grouping.

Check out the `roll.ipynb` notebook for a working example of rolling aggregation.

1.6.6 Aggregate column (instead of groupby)

This column aggregates data in groups of rows selected from another table. The selection is performed by specifying an existing link column which links the fact table with this (group) table. The new column is added to this (group) table.

Currently, its logic is equivalent to that of the groupby in `pandas` with the difference that the result column is added to the existing table and the two tables must be linked beforehand.

Check out the `aggregate.ipynb` notebook for a working example of aggregation.

1.6.7 Discretize column

Let us assume that we have a numeric column but we want to partition it into a finite number of intervals and then use these intervals intead of numeric values. The `discretize` coumn produces a new column with a finite number of values where each such value represents a group the input value belongs to.

How the groups are identified and how the input space is partitioned is defined in the model. In the simplest case, there is one numeric column and the model defines intervals with equal length. These intervals are identified by their border value (left or right). The output columm will contain border values for the intervals input values belong to. For example, if we have temperature values in the input column like 21.1, 23.3, 22.2 etc. but we want to use discrete values like 21, 23, 22, then we need to define a `discretize` column. In this case, it is similar to rounding (which can be implemented using a `calculate` column) but the logic of discretization can be more complicated.

Links:

- https://numpy.org/doc/stable/reference/generated/numpy.digitize.html

1.7 Install and test

1.7.1 Install from source code

Check out the source code and execute this command in the project directory (where `setup.py` is located):

```
$ pip install .
```

Or alternatively:

```
$ python setup.py install
```

1.7.2 Install from PYPI

This command will install the latest release of `Prosto` from PYPI:

```
$ pip install prosto
```

1.7.3 How to test

Run tests from the project root:

```
$ python -m pytest
```

or

```
$ python setup.py test
```

CHAPTER 2

Indices and tables

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- modindex
- search