vertica-ml-python0.1 Documentation

Flexible as Python, Fast as Vertica

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Executive Summary

This documentation explains the `vertica-ml-python` library by detailing all the functions and providing significant examples to each one. It allows the user to use his `Vertica` Database with `Python` without loading the data in his personal machine first. All the functions execute requests directly in the database in order to gain in efficiency. It combines `Vertica` aggregations and `Python` flexibility to create an object similar to `pandas.Dataframe` with the power of a columnar oriented analytic database: `Vertica`.

`vertica-ml-python` allows users to use the RVD (Resilient Vertica Dataset). This object keeps in memory all the users modifications in order to use optimized SQL queries to compute all the necessary aggregations. Thanks to this object, the table is intact and will never be modified. The purpose is to explore, preprocess and clean the object without changing the initial table.

What contains vertica-ml-python?

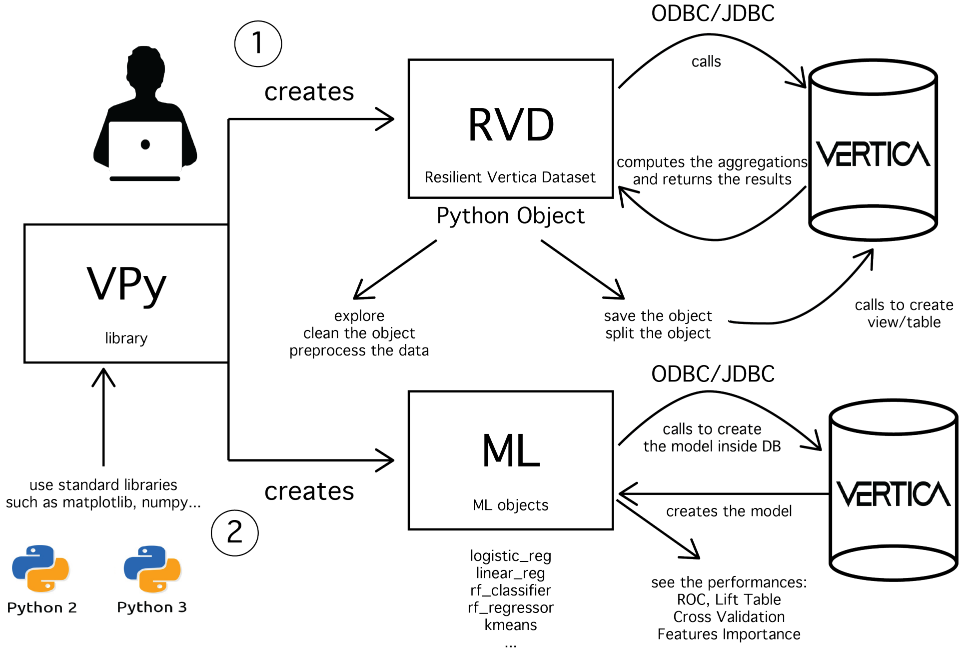
This library contains many functions for:

- Data Exploration, Preprocessing and Cleaning: `vertica_ml_python.rvd`
- Machine Learning (Regression, Classification, Clustering): `vertica_ml_python.vml`

`vertica-ml-python` helps to explore, preprocess and clean the data without changing the initial table. It uses scalable Machine Learning Algorithms such as Logistic Regression, Random Forest and SVM. It allows also to use cross validation of the different models and to compare them.

`vertica-ml-python` uses only the standard `Python` libraries. To connect to the database, it can use both JDBC and ODBC connection. When the structure is well understood, it is very easy to create the object that the user really wants.

Significant examples using very well-known datasets are available and will help the user to master the different objects. The next figure sums up how the `vertica-ml-python` library works.



Contents

VERTICA ML PYTHON

> *"Science knows no country, because knowledge belongs to humanity, and is the torch which illuminates the world."*
>
> **Louis Pasteur**

1 Prerequires

1.1 Python Version

`vertica-ml-python` works with Python2 and Python3 and it will try to be adapted for both if it is possible.

1.2 Standard Libraries

`vertica-ml-python` library is only using the standard `Python` libraries such as `pyodbc`, `matplotlib`, `time`, `shutil` (only for Python3) and `numpy`. If one is missing, you can use the following command in your terminal to install it:

```
root@ubuntu:~$ pip install pyodbc
```

Other libraries can be used as `anytree` for tree visualization or `sqlparse` for SQL indentation but they are optional.

1.3 Installation

`vertica-ml-python` doesn't really need installation.
To import easily the `vertica-ml-python` library from anywhere in your computer just copy paste the entire `vertica_ml_python` folder in the `site-package` folder of the Python framework. In the MAC environment, you can find it in:
`/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages`

Another way is to call the library from where it is located.

You can then import each library element using a simple syntax.

```
# to import the RVD
from vertica_ml_python import RVD
# to import the logistic regression
from vertica_ml_python import logistic_reg
```

Everything is well detailed in the following documentation.

1.4 Connection to the Database

This step is useless if `pyodbc` is already installed and you have a DSN in your machine. With this configuration, you do not need to manually create a cursor. It is possible to create a RVD using directly the DSN.

1.4.1 ODBC

To connect to the database, the user can use an ODBC connection to the `Vertica` database. `pyodbc` provides a cursor that will point to the database. It will be used by the `vertica-ml-python` to create all its objects.

```
import pyodbc

# Connection using all the DSN information
driver="/Library/Vertica/ODBC/lib/libverticaodbc.dylib"
server="10.211.55.14"
database="testdb"
port="5433"
uid="dbadmin"
pwd="XxX"
dsn=("DRIVER={};SERVER={};DATABASE={};PORT={};UID={};PWD={};").format(
        driver,server,database,port,uid,pwd)
cur=pyodbc.connect(dsn).cursor()

# Connection using directly the DSN
dsn=("DSN=VerticaDSN")
cur=pyodbc.connect(dsn).cursor()
```

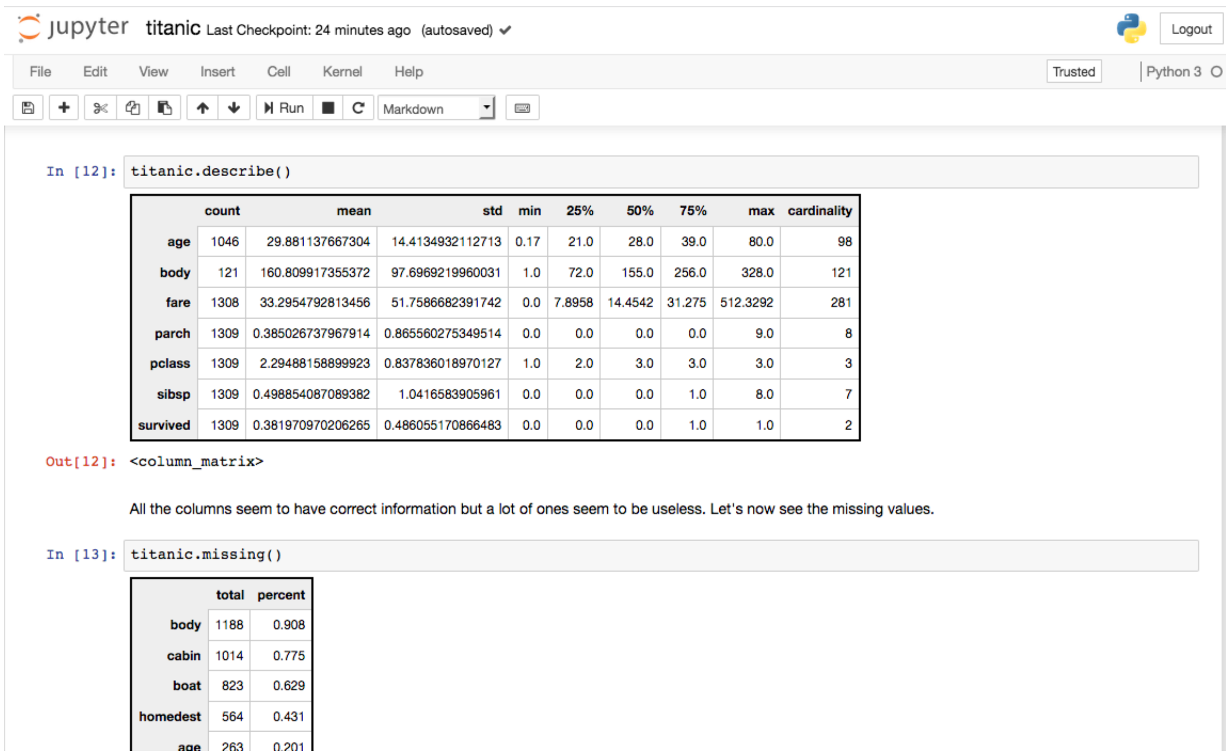
1.4.2 JDBC

The user can also use a JDBC connection to the `Vertica` database. For example, `jaydebeapi` provides the cursor used by `vertica-ml-python`.

```
import jaydebeapi

uid="dbadmin"
pwd="XxX"
driver="/Library/Vertica/JDBC/vertica-jdbc-9.0.1-0.jar" #Path to JDBC Driver
url='jdbc:vertica://10.211.55.14:5433/'
name='com.vertica.jdbc.Driver'
cur=jaydebeapi.connect(name,[url,uid,pwd],driver).cursor()
```

2 Jupyter

Jupyter offers a really beautiful interface to use vertica-ml-python. If you want to see how to do fast and easy analytics and ML, feel free to install and use Jupyter.



	count	mean	std	min	25%	50%	75%	max	cardinality
age	1046	29.881137667304	14.4134932112713	0.17	21.0	28.0	39.0	80.0	98
body	121	160.809917355372	97.6969219960031	1.0	72.0	155.0	256.0	328.0	121
fare	1308	33.2954792813456	51.7586682391742	0.0	7.8958	14.4542	31.275	512.3292	281
parch	1309	0.385026737967914	0.865560275349514	0.0	0.0	0.0	0.0	9.0	8
pclass	1309	2.29488158899923	0.837836018970127	1.0	2.0	3.0	3.0	3.0	3
sibsp	1309	0.498854087089382	1.0416583905961	0.0	0.0	0.0	1.0	8.0	7
survived	1309	0.381970970206265	0.486055170866483	0.0	0.0	0.0	1.0	1.0	2

Out[12]: <column_matrix>

All the columns seem to have correct information but a lot of ones seem to be useless. Let's now see the missing values.

In [13]: titanic.missing()

	total	percent
body	1188	0.908
cabin	1014	0.775
boat	823	0.629
homedest	564	0.431
age	263	0.201

Besides a lot of notebooks will be available in order to understand the library.

3 Comparison between vertica-ml-python and pandas+scikit

All the results of this section are obtained using a single node machine (to have a real comparaison) with 128Gb of memory. As pandas is highly distributed, the comparison using this machine is really fare and significant.

3.1 Limitations

3.1.1 vertica-ml-python

vertica-ml-python has no limitation as it uses Vertica to compute all the aggregation it needs. If we want to increase the speed, we can increase the number of nodes or their memory.

3.1.2 pandas+scikit

pandas has real limitation. It loads data in memory and we can not increase it indefinitely.

3.2 Time to load the data

3.2.1 vertica-ml-python

If the data is inside a Vertica database, no operation is needed. In the other case, we need to transfer the data to Vertica. It is highly recommended to already have the data inside Vertica even if the time to create the table is still largely lower than the time to create the pandas.Dataframe.

3.2.2 pandas+scikit

The data must be loaded in memory. It can take a lot of time depending on where the data is. To give a first idea, you can see the following result.

```
# Connector Creation
import pandas
import time
conn=pyodbc.connect(dsn)

# Using 35M of rows (the whole dataset)
start_time=time.time()
expedia_df=pandas.read_sql("select * from expedia_train",conn)
print(time.time()-start_time)

# Output
1135.22843092306093

# Using 10M of rows
start_time=time.time()
expedia_df=pandas.read_sql("select * from expedia_train limit 10000000",conn)
print(time.time()-start_time)

# Output
281.51524472236633

# Using 1M of rows
start_time=time.time()
expedia_df=pandas.read_sql("select * from expedia_train limit 1000000",conn)
print(time.time()-start_time)

# Output
42.53745484352112
```

3.3 Object Size

3.3.1 vertica-ml-python

The size of a RVD will never exceed some bytes.

```
import sys
```

```
print(sys.getsizeof(expedia_rvd))

# Output
56
```

3.3.2 pandas+scikit

The size of a pandas.Dataframe can become really big.

```
print(sys.getsizeof(expedia_df))

# Output
10846031144
```

More than a GB of memory is used... We can imagine the impact in our personal machine. If the user wants to use pandas on very huge dataset, he needs a machine with a lot of memories. Knowing that it is hard to have today a personal machine exceeding 32GB of RAM, the limitation is obvious to small datasets (less than 10GB) and we can not call it big data (we can consider the big data border as 1TB).

3.4 Time to execute some queries

3.4.1 vertica-ml-python

Let's see what it gives for vertica-ml-python.

```
# Using 35M of rows (the whole dataset)
#
# describe
#
start_time=time.time()
expedia_rvd.describe()
print(time.time()-start_time)

# Output
94.45896601676941


#
# categorical hist
#
start_time=time.time()
expedia_rvd["is_mobile"].hist()
print(time.time()-start_time)

# Output
0.480072021484375

# Using 10M of rows
#
```

```
# describe
#
start_time=time.time()
expedia_rvd.describe()
print(time.time()-start_time)

# Output
28.198142528533936

#
# categorical hist
#
start_time=time.time()
expedia_rvd["is_mobile"].hist()
print(time.time()-start_time)

# Output
0.4742517471313477

# Using 1M of rows
#
# describe
#
start_time=time.time()
expedia_rvd.describe()
print(time.time()-start_time)

# Output
2.8560750484466553

#
# categorical hist
#
start_time=time.time()
expedia_rvd["is_mobile"].hist()
print(time.time()-start_time)

# Output
0.3278229236602783
```

3.4.2 pandas+scikit

And now for pandas.

```
# Using 35M of rows (the whole dataset)
#
# describe
```

```
#
start_time=time.time()
expedia_df.describe()
print(time.time()-start_time)

# Output
75.72856092453003

#
# categorical hist
#
start_time=time.time()
expedia_df["is_mobile"].hist()
print(time.time()-start_time)

# Output
3.210484266281128

# Using 10M of rows
#
# describe
#
start_time=time.time()
expedia_df.describe()
print(time.time()-start_time)

# Output
20.789332389831543

#
# categorical hist
#
start_time=time.time()
expedia_df["is_mobile"].hist()
print(time.time()-start_time)

# Output
0.36867237091064453

# Using 1M of rows
#
# describe
#
start_time=time.time()
expedia_df.describe()
print(time.time()-start_time)

```

```
# Output
1.2540433406829834

#
# categorical hist
#
start_time=time.time()
expedia_df["is_mobile"].hist()
print(time.time()-start_time)

# Output
0.08945250511169434
```

3.5 Conclusion

At the end, we have more or less the same execution time with a little advantage to scikit-learn for some functions but do not forget that when the data is inside memory some computation can be faster if the system is highly parallelized. Besides, the loading time can increase considerably if the dataset is bigger (in this example, vertica-ml-python is using an ODBC connection which can add some additional time depending on the case). At the end, vertica-ml-python is more robust and offers more possibilities (without speaking about data exploration where vertica-ml-python is only using standard libraries and offers much more possibilities). Besides some functions to prepare the data will take a lot of time using pandas whereas it will take no time for vertica-ml-python as only the grammar of the transformation is kept in memory. If the projections are correctly made and if we use many nodes, we can use really huge dataset very fast using vertica-ml-python and the power of Vertica.

4 vertica_ml_python.rvd

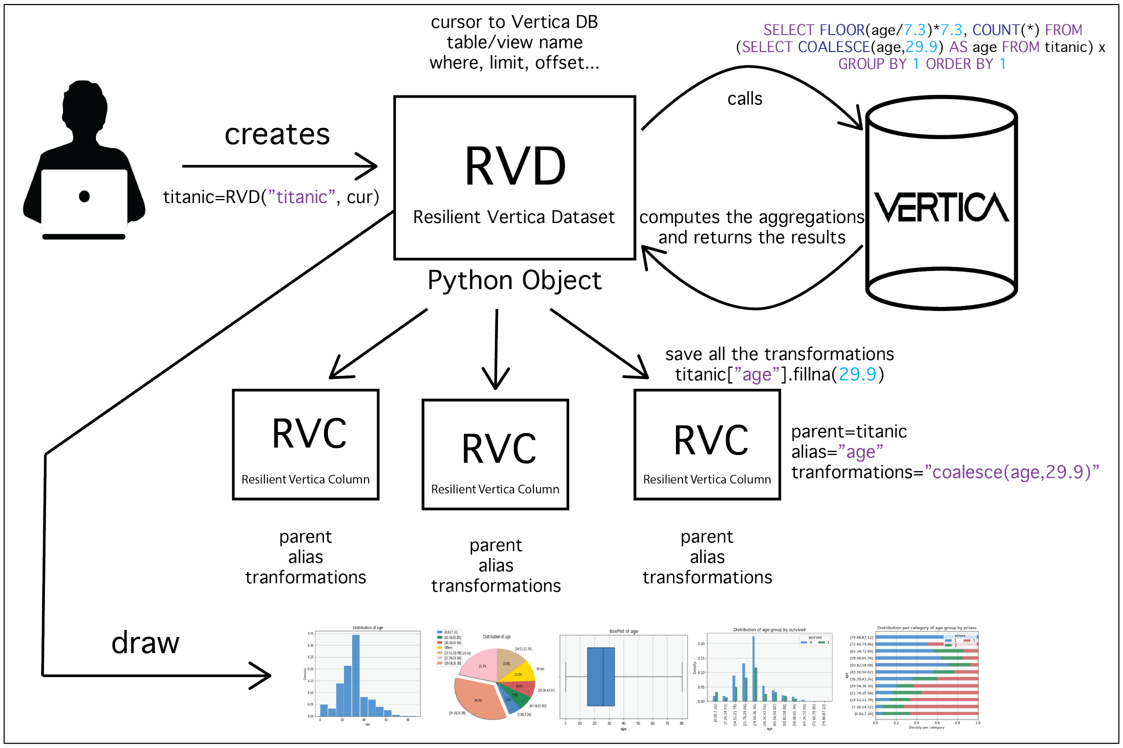
4.1 Warning

⚠ **Before creating a RVD be sure that the names of your table/view columns do not contain illegal characters such as space ' ', dot '.', comma ',',... Be sure to have the required libraries installed and check your Vertica version. You can have information about what you can do using the $RVD.version()$ method.**

4.2 Resilient Vertica Dataset (RVD)

The RVD is a `Python` object which will keep in mind all the user modifications in order to use an optimized SQL query. It will send the query to the database which will use its aggregations to compute fast results. It is created using a view or a table stored in the user database and a database cursor. It will create for each column of the table a RVC (Resilient Vertica Column) which will store for each column its name, its imputations and allows to do easy modifications and explorations.

RVC and RVD coexist and one can not live without the other. RVC will use the RVD information and reciprocally. It is imperative to understand both structures to know how to use the entire object.



When the user imputes or filters the data, the RVD gets in memory all the transformations to select for each query the needed data in the input relation. Let's try to understand thanks to an example.

```
# We create the RVD
titanic=RVD('titanic',cur)

# We filter some values
titanic.filter("fare<100")

85 elements were filtered

# We impute the column age
titanic["age"].fillna(method="mean")

258 elements were filled

# We drop some missing values
titanic["fare"].dropna()

Nothing was dropped

# We encode the column embarked
titanic["embarked"].label_encode()

embarked        encoding
Q                      0
```

```
C                     1
S                     2
The label encoding was successfully done.

# We print all the queries used during the next executions
titanic.sql_on_off(reindent=True)

# We summarize our RVD
titanic.describe()
```

We can see as follows, the query which was generated by our RVD.

```
select summarize_numcol(age, body, embarked, fare, parch, pclass, sibsp,
    survived) over ()
from
  (select *
   from
     (select coalesce(age,29.3879399585921) as age,
             boat as boat,
             body as body,
             cabin as cabin,
             decode(embarked,NULL,0,'Q',1,'C',2,'S',3,4) as embarked,
             fare as fare,
             homedest as homedest,
             name as name,
             parch as parch,
             pclass as pclass,
             sex as sex,
             sibsp as sibsp,
             survived as survived,
             ticket as ticket
      from
        (select age as age,
                boat as boat,
                body as body,
                cabin as cabin,
                embarked as embarked,
                fare as fare,
                homedest as homedest,
                name as name,
                parch as parch,
                pclass as pclass,
                sex as sex,
                sibsp as sibsp,
                survived as survived,
                ticket as ticket
         from titanic) t1
      where fare<100
```

```
        offset 0) t2
    where fare is not null) new_table
```

The RVD will try to keep in mind where the transformations occurred in order to use the appropriate query. In that case, when the user has done a lot of transformations, it is highly recommended to save the RVD in order to gain in efficiency (using the save method). We can also see all the modifications using the `history` method.

```
titanic.history()

#Output
The RVD was modified many times:
 * {Tue Feb  6 15:44:51 2018} [Filter]: 85 elements were filtered using the
   filter 'fare<100'
 * {Tue Feb  6 15:44:51 2018} [Fillna]: 258 missing values of the RVC 'age'
   were filled using the imputation 'coalesce({},29.3879399585921)'.
 * {Tue Feb  6 15:44:52 2018} [Label Encode]: The RVC 'embarked' was imputed
   with the 'label encoding'.
  None => 0
  Q => 1
  C => 2
  S => 3
  others => 4
```

4.2.1 why RVD?

It is normal to ask the question. When we look at the definition of resilience, we can see that "Resilience is the ability to provide and maintain an acceptable level of service in the face of faults and challenges to normal operation" (Wikipedia). As the RVD keeps in mind all the user actions, it can easily be recreated from scratch. Besides, if the connection to the database failed, it is easy to set a new database cursor using the `set_cursor` method or if the connection was made using a DSN the `dsn_restart` method. The RVD will never load data inside, all the aggregations are computed thanks to Vertica. Having this information, we know that the object will never crash because of the data. It is then resilient according to the definition.

As all the data are inside Vertica, we can call it Vertica Dataset. We can even call the object RVVD (Resilient Virtual Vertica Dataset) as none of the modifications are made in the table. The RVD will just send SQL queries to get the information it needs.

4.2.2 initialization

To instantiate a new RVD, the user can use a database cursor and the name of a relation (table or view).

```
from vertica_ml_python import RVD

myRVD=RVD(input_relation,cursor)
```

The simplest way is to use directly a DSN (without setting a cursor).

```
myRVD=RVD(input_relation,dsn="VerticaDSN")
```

Using this method, the RVD keeps in mind the DSN name and in case of connection failure the user can restart a connection using the dsn_restart method.

Example

```
titanic=RVD("titanic",cursor)
print(titanic)

#Output
        age      boat     body     cabin     embarked        fare    \\
0       None        1     None     None             S    26.00000    \\
1       None       10     None     E101             Q    12.35000    \\
2       None       10     None     None             S    16.10000    \\
3       None       11     None     None             S    33.00000    \\
4       None       13     None     None             Q     7.72080    \\
5       None       13     None     None             Q     7.73330    \\
6       None       13     None     None             Q     7.75000    \\
7       None       13     None     None             Q     7.78750    \\
8       None       13     None     None             Q     7.82920    \\
9       None       13     None     None             Q     7.87920    \\
10      None       13     None     None             S     8.11250    \\
11      None       13     None     None             S    56.49580    \\
12      None       14     None     None             C    30.69580    \\
13      None       14     None     None             Q     7.75000    \\
14      None       14     None     None             S    13.00000    \\
15      None       15     None     None             C     7.22920    \\
16      None       15     None     None             Q     7.75000    \\
17      None       15     None     None             S     7.05000    \\
18      None    15 16     None     None             Q     7.75000    \\
19      None       16     None     None             Q     7.73330    \\
20      None       16     None     None             Q     7.73750    \\
21      None       16     None     None             Q     7.75000    \\
22      None       16     None     None             Q     7.75000    \\
23      None       16     None     None             Q     7.87920    \\
24      None       16     None     None             Q    15.50000    \\
25      None       16     None     None             Q    15.50000    \\
26      None       16     None     None             Q    15.50000    \\
27      None       16     None     None             Q    23.25000    \\
28      None       16     None     None             Q    23.25000    \\
29      None       16     None     None             Q    23.25000    \\
...     ...       ...      ...      ...           ...         ...    \\
--More--
Name: titanic, Number of rows: 1309, Number of columns: 14
```

In all the examples used, we consider that we created the four following RVDs:

```
titanic=RVD("titanic",cursor)
iris=RVD("iris",cursor)
```

```
expedia=RVD("expedia",cursor)
```

4.2.3 attributes

When the RVD is created, it will creates as many RVC as there are columns in the input relation (`columns` attribute). It will keep in minds the cursor, the input relation and the dsn if this connection method is used. It will also create 8 other attributes in order to keep in mind the user modifications.

- `limit`: the maximum number of elements took into account.
- `offset`: the number of skipped elements in the relation.
- `query_on`: print all the queries executed by the RVD in the terminal.
- `reindent`: indent all the queries printed by the RVD using sqlparse (available in github)
- `time_on`: print all the queries elapsed time in the terminal.
- `legend_loc`: the legend location.
- `rvd_history`: keep in mind all the user actions.
- `colors`: the colors used to draw the different charts.

For example, when the user wants to create a new column in the RVD. The RVD will create a new RVC and will add it in the list of RVC (`columns` attribute). If it wants to delete a column, the RVD will simply delete it from the list of RVC. The table initial is then never changed !

4.2.4 methods

4.2.4.1 add_feature

```
RVD.add_feature(alias, imputation)
```

Add a new feature to the RVD (a new RVC will be created).

Parameters

- **alias:** *<str>*
  Name of the new feature.
- **imputation:** *<str>*
  Relation used to compute the new feature.

Example

```
titanic.add_feature(alias="family_size",imputation="parch+sibsp+1")

#Output
The new RVC 'family_size' was added to the RVD.
```

4.2.4.2 bar

```
RVD.bar(columns, method="density", of=None, max_cardinality=[6,6], h=[None,
    None], color=None, limit_distinct_elements=200)
```

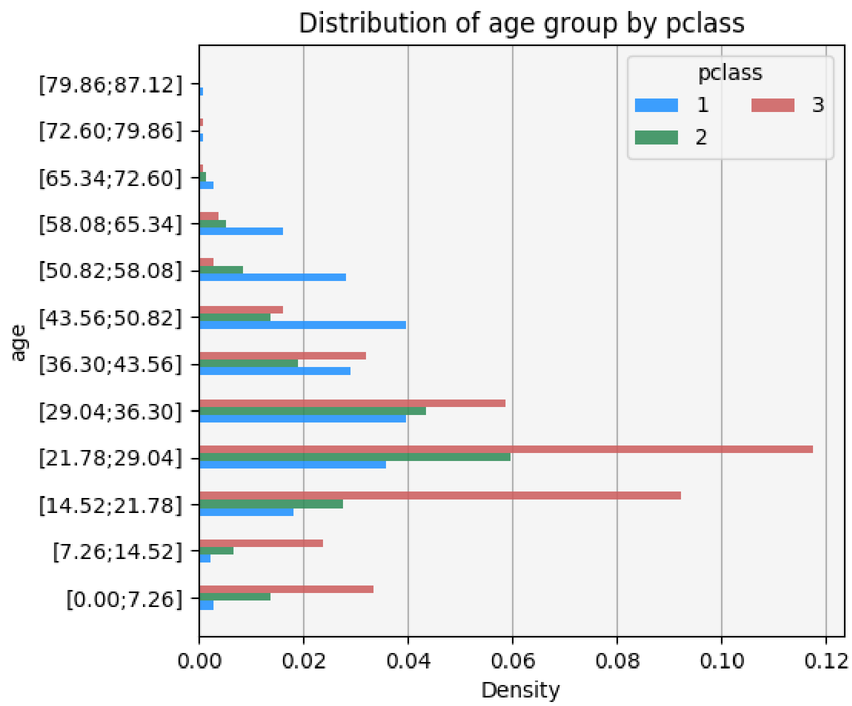
Draw the corresponding 2 variables bar chart.

Parameters

- **columns:** *<list of str>*
  The two columns used to draw the bar chart (first will be on the x-axis and the second in the y-axis)
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<list of positive int>*, optional
  The maximum cardinality of each column. Under this number the column is automatically considered as categorical.
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **color:** *<list of str>*, optional
  The color list for each category
- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.

Example

```
titanic.bar(columns=["age","pclass"])
```



4.2.4.3 corr

```
RVD.corr(columns=[], cmap="PRGn", show=True)
```

Compute the correlation matrix of the corresponding RVD columns, excluding NA/null values.

Parameters

- **columns:** *<list of str>*, optional
  List of the columns the user wants to consider.
- **cmap:** *<str>*, optional
  Color Maps.
- **show:** *<bool>*, optional
  Display the result using matplotlib.

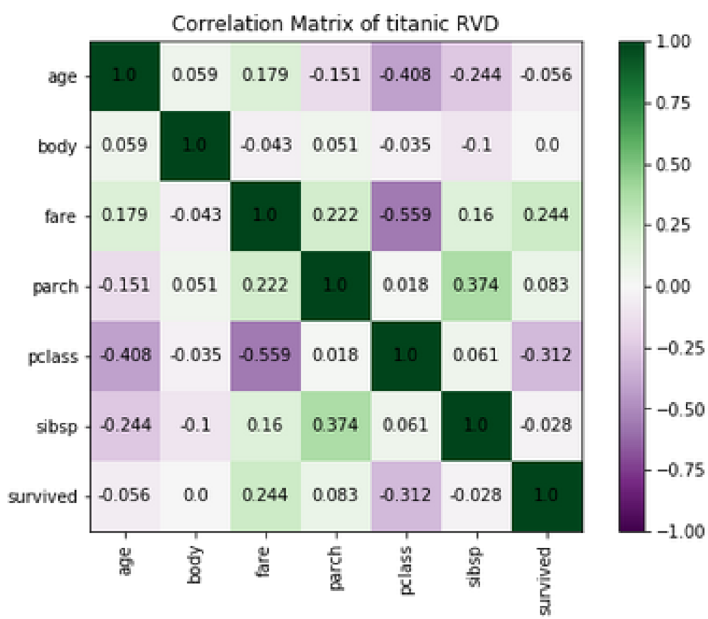
Returns

An object named column_matrix containing the matrix (the information will be stored in the data_columns attribute).

Example

```
titanic.corr()

#Output
```

```
                 age      body      fare     parch    pclass   \\
age                1     0.059     0.179    -0.151    -0.408   \\
body           0.059         1    -0.043     0.051    -0.035   \\
fare           0.179    -0.043         1     0.222    -0.559   \\
parch         -0.151     0.051     0.222         1     0.018   \\
pclass        -0.408    -0.035    -0.559     0.018         1   \\
sibsp         -0.244      -0.1      0.16     0.374     0.061   \\
survived      -0.056         0     0.244     0.083    -0.312   \\
               sibsp   survived
age           -0.244     -0.056
body            -0.1          0
fare            0.16      0.244
parch          0.374      0.083
pclass         0.061     -0.312
sibsp              1     -0.028
survived      -0.028          1
```



4.2.4.4 corr_log

```
RVD.corr_log(columns=[], cmap="PRGn", epsilon=1e-8, show=True)
```

Compute the log correlation matrix of the corresponding RVD columns, excluding NA/null values.

Parameters

- **columns:** *<list of str>*, optional
  List of the columns the user wants to consider.

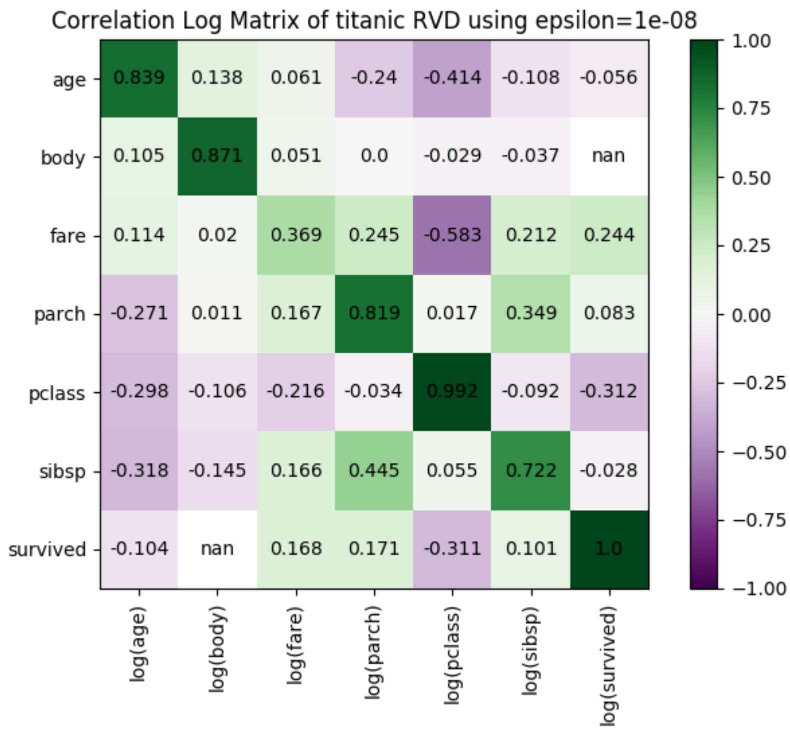
- **cmap:** *<str>*, optional
  Color Maps.
- **epsilon:** *<float>*, optional
  Add epsilon to the log computation in order to avoid forbidden values.
- **show:** *<bool>*, optional
  Display the result using matplotlib.

Returns

An object named column_matrix containing the matrix (the information will be stored in the data_columns attribute).

Example

```
titanic.corr()

#Output
                    log(age)    log(body)    log(fare)    log(parch)    log(pclass)   \\
age                    0.839        0.138        0.061         -0.24        -0.414   \\
body                   0.105        0.871        0.051           0.0        -0.029   \\
fare                   0.114         0.02        0.369         0.245        -0.583   \\
parch                 -0.271        0.011        0.167         0.819         0.017   \\
pclass                -0.298       -0.106       -0.216        -0.034         0.992   \\
sibsp                 -0.318       -0.145        0.166         0.445         0.055   \\
survived              -0.104         None        0.168         0.171        -0.311   \\
                    log(sibsp)    log(survived)
age                     -0.108           -0.056
body                    -0.037             None
fare                     0.212            0.244
parch                    0.349            0.083
pclass                  -0.092           -0.312
sibsp                    0.722           -0.028
survived                 0.101              1.0
```



4.2.4.5 count

```
RVD.count()
```

Returns

Returns the RVD count.

Example

```
titanic.count()

#Output
1309
```

4.2.4.6 current_table

```
RVD.current_table()
```

Returns

Returns the RVD current virtual table.

Example

```
titanic.current_table()

#Output
"(select * from (select coalesce(age,avg(age) over (partition by pclass,gender
    )) as age, decode(embarked,'Q',0,'C',1,'S',2,3) as embarked, fare as fare,
     parch as parch, pclass as pclass, sibsp as sibsp, survived as survived,
    decode(gender,'female',0,'male',1,2) as gender from (select age as age,
    embarked as embarked, fare as fare, parch as parch, pclass as pclass,
    sibsp as sibsp, survived as survived, sex as gender from titanic) t1
    offset 0) t2 where embarked is not null and fare is not null) new_table"
```

4.2.4.7 describe

```
RVD.describe(mode="auto", columns=None, include_cardinality=True)
```

Summarize the dataset with mathematical information.

Parameters

- **mode:** *<str>*, optional
  auto | all | categorical | date
  auto (default): This mode is used to have only numerical information. Other types are ignored.
  all: This mode is used to print each column information one by one.
  categorical: This mode is used to only print the categorical variables information (text or $cardinality \leq 6$)
  date: This mode is used to only print the date variables information
- **columns:** *<list of str>*, optional
  The columns used to compute the mathematical information.
- **include_cardinality:** *<bool>*, optional
  Include the cardinality of each element in the computation (only used when mode is "auto")

Returns

Only when mode is "auto": An object named column_matrix containing all the summarized information (they will be stored in the data_columns attribute).

Note

The mathematical information are different depending on the data type and if they are categorical. For more flexibility, the user can use the RVC `describe` method which is specific to each column of the dataset.

Example

```
#auto
titanic.describe()

#Output
```

```
                count                mean                 std    min   \\
age              1046    29.881137667304    14.4134932112713   0.17   \\
body              121   160.809917355372    97.6969219960031    1.0   \\
fare             1308   33.2954792813456    51.7586682391741    0.0   \\
parch            1309  0.385026737967914   0.865560275349515    0.0   \\
pclass           1309   2.29488158899923   0.837836018970128    1.0   \\
sibsp            1309  0.498854087089381     1.0416583905961    0.0   \\
survived         1309  0.381970970206264   0.486055170866483    0.0   \\
                  25%        50%        75%        max    cardinality
age              21.0       28.0       39.0       80.0             98
body             72.0      155.0      256.0      328.0            121
fare           7.8958    14.4542     31.275   512.3292            281
parch             0.0        0.0        0.0        9.0              8
pclass            2.0        3.0        3.0        3.0              3
sibsp             0.0        0.0        1.0        8.0              7
survived          0.0        0.0        1.0        1.0              2

#all
titanic.describe(mode="all")

#Output
count                       1046
mean             29.881137667304
std             14.4134932112713
min                         0.17
25%                         21.0
50%                         28.0
75%                         39.0
max                         80.0
cardinality                   98
Name: age,dtype: numeric(6,3)
------------------------------
823              None
252            Others
39                 13
38                  C
37                 15
33                 14
31                  4
cardinality        27
Name: boat,dtype: varchar(30)
------------------------------
count                        121
mean            160.809917355372
std             97.6969219960031
min                          1.0
25%                         72.0
```

```
50%                         155.0
75%                         256.0
max                         328.0
cardinality                   121
Name: body,dtype: int
----------------------
--More--
```

4.2.4.8 drop_columns

```
RVD.drop_columns(columns=[])
```

Drop all the selected RVC from the RVD.

Parameters

- **columns:** *<list of str>*
  Name of the different columns.

Example

```
titanic.drop_columns(columns=["body","cabin","boat","homedest","ticket"])

#Output
RVC 'body' deleted from the RVD.
RVC 'cabin' deleted from the RVD.
RVC 'boat' deleted from the RVD.
RVC 'homedest' deleted from the RVD.
RVC 'ticket' deleted from the RVD.
```

4.2.4.9 dsn_restart

```
RVD.dsn_restart()
```

Set a new RVD cursor using the corresponding DSN.

Example

```
# If the connection to the Vertica DB failed and you used a DSN to create the
    RVD
titanic.dsn_restart()
```

4.2.4.10 dtypes

```
RVD.dtypes()
```

Print all the RVC of the RVD and their corresponding types.

Example

```
titanic.dtypes()

#Output
                               type
age                   numeric(6,3)
boat                   varchar(30)
body                           int
cabin                  varchar(30)
embarked               varchar(20)
fare                 numeric(10,5)
homedest              varchar(100)
name                  varchar(164)
parch                          int
pclass                         int
sex                    varchar(20)
sibsp                          int
survived                       int
ticket                 varchar(36)
Name: titanic,Number of rows: 1309,Number of columns: 14
```

4.2.4.11 filter

```
RVD.filter(conditions)
```

Filter the values of the RVD (adding a where clause) following the conditions.

Parameters

- **conditions:** *<list of str>*
  The filtering conditions.

Example

```
titanic.filter(["age>3","fare<100"])

#Output
304 elements were filtered
```

```
78 elements were filtered
```

4.2.4.12 fully_stacked_bar

```
RVD.fully_stacked_bar(columns, max_cardinality=[6,6], h=[None,None], color=
    None, limit_distinct_elements=200)
```

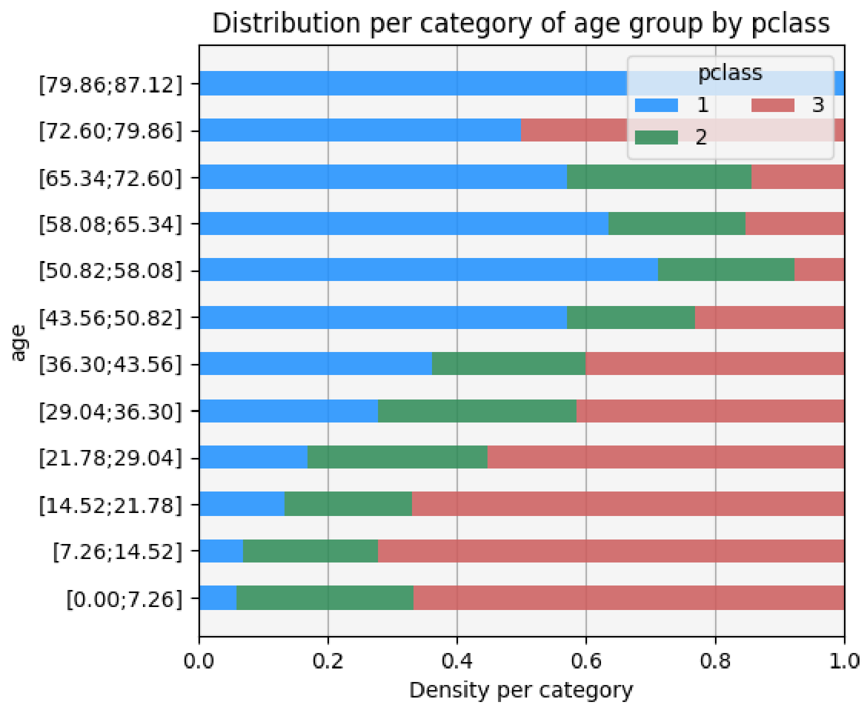
Draw the corresponding 2 variables fully stacked bar chart.

Parameters

- **columns:** *<list of str>*
  The two columns used to draw the bar chart (first will be on the x-axis and the second in the y-axis)
- **max_cardinality:** *<list of positive int>*, optional
  The maximum cardinality of each column. Under this number the column is automatically considered as categorical.
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically.
- **color:** *<list of str>*, optional
  The color list for each category
- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.

Example

```
titanic.fully_stacked_bar(columns=["age","pclass"])
```



4.2.4.13 group_by

```
RVD.group_by(columns, aggregations, order_by=None, limit=1000)
```

Group the aggregations by the corresponding columns.

Parameters

- **columns:** *<list of str>*
  List of the columns to use for the group by.
- **aggregations:** *<list of str>*
  List of all the aggregations to compute.
- **order_by:** *<list of str>*, optional
  List of all the columns to order with.
- **limit:** *<positive int>*, optional
  The maximum number of elements to take into account.

Returns

An object named column_matrix containing all the grouped information (they will be stored in the data_columns attribute).

Example

```
titanic.group_by(['pclass','age'], ["count(*)","sum(survived)","sum(fare)"],
    limit=20)

#Output
      pclass        age     count     sum_survived        sum_fare
0          1       None        39               19      2072.26650
1          1      0.920         1                1       151.55000
2          1      2.000         1                0       151.55000
3          1      4.000         1                1        81.85830
4          1      6.000         1                1       134.50000
5          1     11.000         1                1       120.00000
6          1     13.000         1                1       262.37500
7          1     14.000         1                1       120.00000
8          1     15.000         1                1       211.33750
9          1     16.000         3                3       183.87920
10         1     17.000         4                3       323.88330
11         1     18.000         6                5       791.55000
12         1     19.000         5                3       463.46250
13         1     21.000         5                4       505.55000
14         1     22.000         7                6       579.66250
15         1     23.000         6                5       698.55830
16         1     24.000         9                6      1003.25000
17         1     25.000         5                3       379.51260
18         1     26.000         3                3       245.62920
19         1     27.000         7                5       808.12920
...      ...        ...       ...              ...             ...
count=212 rows, elapsed_time=0.012332916259765625
```

4.2.4.14 head

```
RVD.head(n=5)
```

Print in the terminal the first RVD rows.

Parameters

- **n:** *<positive int>*
  The number of rows to print.

Example

```
titanic.head()

#Output
      age    boat    body    cabin    embarked        fare   \\
```

```
0    None       1    None     None           S    26.00000   \\
1    None      10    None     E101           Q    12.35000   \\
2    None      10    None     None           S    16.10000   \\
3    None      11    None     None           S    33.00000   \\
4    None      13    None     None           Q     7.72080   \\
...   ...     ...     ...      ...         ...         ...   \\
                 homedest                                      name   \\
0            New York, NY                    Salomon, Mr. Abraham L   \\
1          Harrisburg, PA                       Keane, Miss. Nora A   \\
2                    None  Thorneycroft, Mrs. Percival (Florence...   \\
3    London / Chicago, IL                Leitch, Miss. Jessie Wills   \\
4                    None           Riordan, Miss. Johanna Hannah     \\
...                   ...                                       ...   \\
--More--
Name: titanic, Number of rows: 1309, Number of columns: 14
```

4.2.4.15 help

```
RVD.help()
```

Return information about the RVD.

Example

```
titanic.help()

#Output

############################
#   _______      _______   #
#  |  __ \ \    / /  __ \  #
#  | |__) \ \  / /| |  | | #
#  |  _  / \ \/ / | |  | | #
#  | | \ \  \  /  | |__| | #
#  |_|  \_\  \/   |_____/  #
#                          #
#############################
#                           #
# Resilient Vertica Dataset #
#                           #
#############################

The RVD is a Python object which will keep in mind all the user modifications in order to use an optimized SQL query.
--More--
```

4.2.4.16 hexbin

```
RVD.hexbin(columns, method="count", of=None, cmap='Blues', gridsize=10, color=
    None)
```

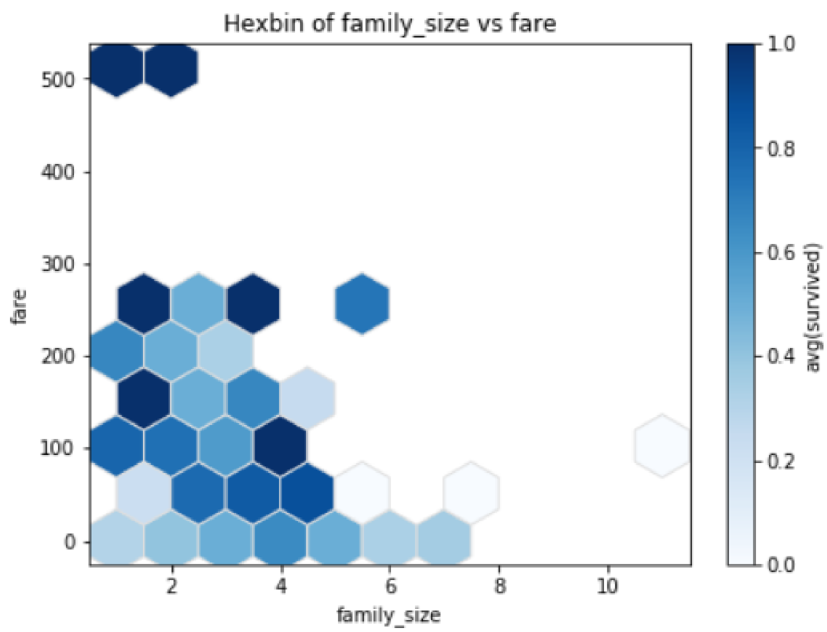
Draw the corresponding hexbin plot.

Parameters

- **columns:** *<list of str>*
  The two columns used to draw the hexbin (first will be on the x-axis and the second in the y-axis)
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count (default): count is used as aggregation
  density: density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **cmap:** *<str>*, optional
  Color Maps.
- **gridsize:** *<positive int>*, optional
  Grid Size.
- **color:** *<str>*, optional
  Hexbin outline color.

Example

```
titanic.hexbin(columns=["family_size","fare"],method="avg",of="survived")
```



4.2.4.17 hist

```
RVD.hist(columns, method="density", of=None, max_cardinality=[6,6], h=[None,
    None], color=None, limit_distinct_elements=200)
```

Draw the corresponding 2 variables histogram.

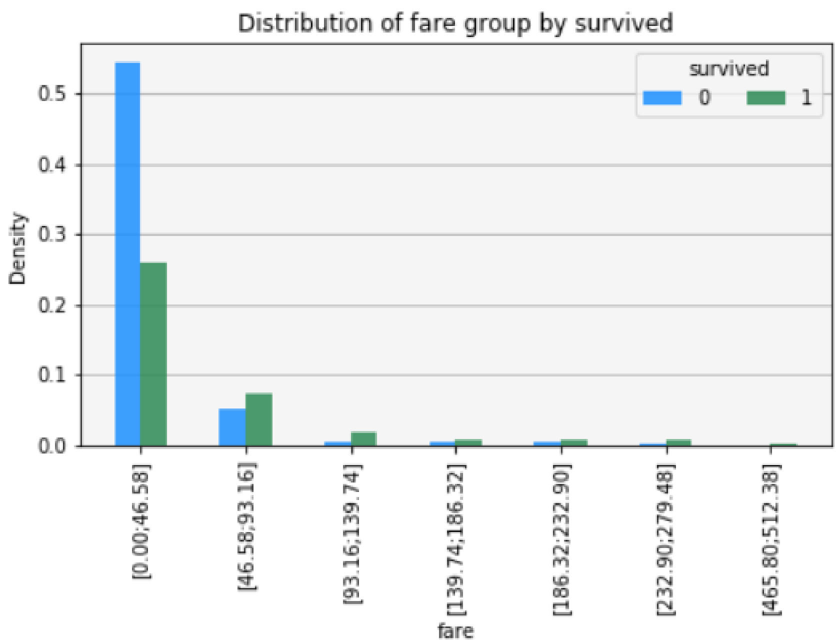
Parameters

- **columns:** *<list of str>*
  The two columns used to draw the hist (first will be on the x-axis and the second in the y-axis)
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<list of positive int>*, optional
  The maximum cardinality of each column. Under this number the column is automatically considered as categorical.
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **color:** *<list of str>*, optional
  The color list for each category

- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.

Example

```
titanic.hist(columns=["fare","survived"])
```



4.2.4.18 history

```
RVD.history()
```

Resume all the modifications made on the RVD.

Example

```
# Modifications
titanic["body"].drop_column()
titanic["cabin"].drop_column()
titanic["boat"].drop_column()
titanic["homedest"].drop_column()
titanic["sex"].rename('gender')
titanic["ticket"].drop_column()
titanic["gender"].label_encode()
titanic["embarked"].dropna()
titanic["embarked"].label_encode()
titanic["name"].drop_column()
```

```
titanic["fare"].dropna()
titanic["age"].fillna(method="avg",by=["pclass","gender"])

# History
titanic.history()

#Output
The RVD was modified many times:
 * {Tue Jan 30 18:10:48 2018} [Drop Column]: Column 'body' was deleted from
    the RVD.
 * {Tue Jan 30 18:10:48 2018} [Drop Column]: Column 'cabin' was deleted from
    the RVD.
 * {Tue Jan 30 18:10:48 2018} [Drop Column]: Column 'boat' was deleted from
    the RVD.
 * {Tue Jan 30 18:10:48 2018} [Drop Column]: Column 'homedest' was deleted
    from the RVD.
 * {Tue Jan 30 18:10:48 2018} [Drop Column]: Column 'sex' was deleted from the
     RVD.
 * {Tue Jan 30 18:10:48 2018} [Rename]: The RVC 'sex' was renamed 'gender'.
 * {Tue Jan 30 18:10:49 2018} [Drop Column]: Column 'ticket' was deleted from
    the RVD.
 * {Tue Jan 30 18:10:49 2018} [label Encode]: The RVC 'gender' was imputed
    with the 'label encoding'.
   female => 0
   male => 1
   others => 2
 * {Tue Jan 30 18:10:49 2018} [Dropna]: The 2 missing elements of column '
    embarked' were dropped from the RVD.
 * {Tue Jan 30 18:10:49 2018} [label Encode]: The RVC 'embarked' was imputed
    with the 'label encoding'.
   Q => 0
   C => 1
   S => 2
   others => 3
 * {Tue Jan 30 18:10:49 2018} [Drop Column]: Column 'name' was deleted from
    the RVD.
 * {Tue Jan 30 18:10:49 2018} [Dropna]: The only missing element of column '
    fare' was dropped from the RVD.
 * {Tue Jan 30 18:10:49 2018} [Fillna]: 263 missing values of the RVC 'age'
    were filled using the imputation 'coalesce({},avg({}) over (partition by
    pclass,gender))'.
```

4.2.4.19 missing

```
RVD.missing()
```

Print the array of all the RVD missing values.

Returns

An object named column_matrix containing all the missing information (they will be stored in the data_columns attribute).

Example

```
titanic.missing()

#Output
              total    percent
body           1188      0.908
cabin          1014      0.775
boat            823      0.629
homedest        564      0.431
age             263      0.201
embarked          2      0.002
fare              1      0.001
name              0        0.0
ticket            0        0.0
pclass            0        0.0
sibsp             0        0.0
survived          0        0.0
parch             0        0.0
sex               0        0.0
```

4.2.4.20 multiple_hist

```
RVD.multiple_hist(columns, method="density", of=None, h=None, color=None)
```

Draw the corresponding numerical variables histograms in the same figure.

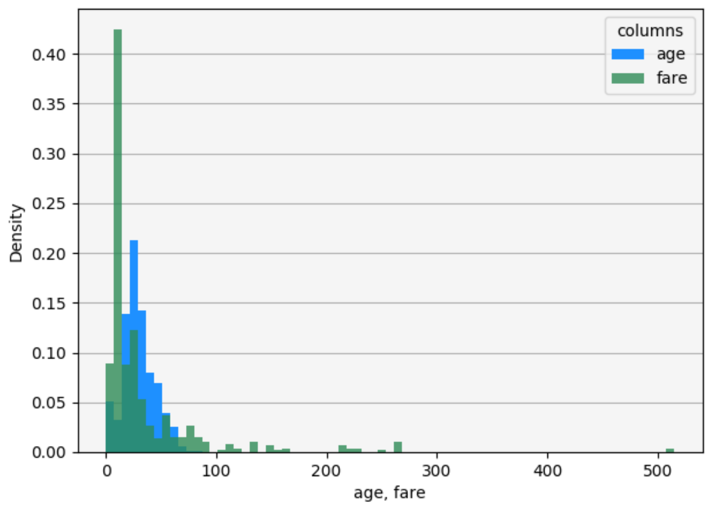
Parameters

- **columns:** *<list of str>*
  The columns used to draw the histograms (they must be numerical)
  The maximum number of columns is 5.
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed

- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **color:** *<list of str>*, optional
  The color list for each column.
- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.

Example

```
titanic.multiple_hist(columns=["age","fare"])
```



4.2.4.21 normalize

```
RVD.normalize(method="zscore", with_int=False)
```

Normalize the numerical columns of the RVD using the corresponding method.

Parameters

- **method:** *<str>*, optional
  The method to be used: {zscore | robust_zscore | minmax}
- **with_int:** *<bool>*, optional
  Include integer columns for the global normalization.

Example

```
titanic.normalize()

#Output
The RVC 'age' was successfully normalized.
The RVC 'fare' was successfully normalized.
```

4.2.4.22 pivot_table

```
RVD.pivot_table(columns, method="count", of=None, max_cardinality=[20,20], h=[
    None, None], cmap='Blues', limit_distinct_elements=1000)
```

Draw the corresponding pivot table.

Parameters

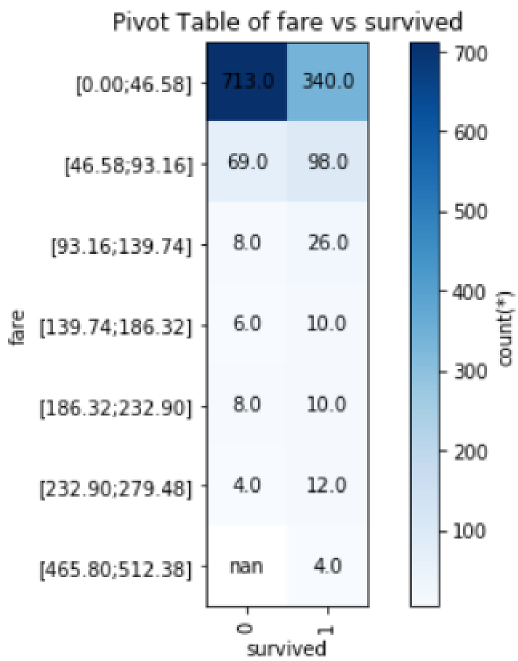
- **columns:** *<list of str>*
  The two columns used to build the pivot table.
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count (default): count is used as aggregation
  density: density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed.
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<list of positive int>*, optional
  The maximum cardinality of each column. Under this number the column is automatically considered as categorical.
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **cmap:** *<str>*, optional
  Color Maps
- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.
- **show:** *<bool>*, optional
  Draw the pivot table using matplotlib.
- **show:** *<bool>*, optional
  Draw the pivot table using matplotlib.

Returns

An object named column_matrix containing the pivot table (the information will be stored in the data_columns attribute).

Example

```
titanic.pivot_table(columns=["fare","survived"])

#Output
fare/survived          0      1
[0.00;46.58]         713    340
[46.58;93.16]         69     98
[93.16;139.74]         8     26
[139.74;186.32]        6     10
[186.32;232.90]        8     10
[232.90;279.48]        4     12
[465.80;512.38]               4
```



4.2.4.23 save

```
RVD.save(name, columns=None, mode="view", affect=True)
```

Save the RVD by creating a new relation in the database.

- **name:** *<str>*
  Name of the new relation.
- **columns:** *<list of str>*, optional
  The columns used to build the relation. If it is not a list, all the columns will be considered in the creation.
- **mode:** *<str>*, optional
  view (default) | table | temporary table

- **affect:** *<bool>*, optional
  Affect the new RVD created thanks to the new input relation. In this case, it will be impossible to undo imputation or filtering.

Note

By saving, the efficiency will be maximal as the requests to the database will contain smaller queries. The input relation of the RVD will become this new relation.

Example

```
titanic.save(name="titanic_temp")

#Output
The RVD was successfully saved.
```

4.2.4.24 scatter

```
RVD.scatter(columns, h=None,max_cardinality=3, cat_priority=None, with_others=
    True, color=None, marker=["^","o","+","*","h","x","D","1"]*10,
    max_nb_points=1000)
```

Draw the scatter plot of the considered columns. It is recommended to use the method 'scatter2D' or 'scatter3D' for respectively 2D and 3D scatter Plot (they have exactly the same parameters). This function will try to find the most adapted plot between 2D and 3D

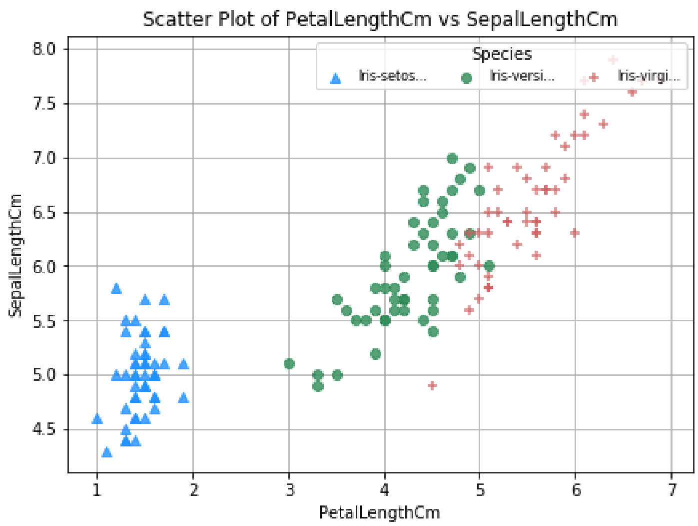
Parameters

- **columns:** *<list of str>*
  The two, three or four columns used to draw the scatter plot
- **h:** *<positive float>*, optional
  The interval size of the categorical column (third or fourth position in "columns" depending on the case)
- **max_cardinality:** *<positive int>*, optional
  The maximum cardinality of the categorical column (third or fourth position in "columns" depending on the case), all the other categories are merged to create the "others" category.
- **cat_priority:** *<list of str>*, optional
  The list of the categories took into account during the computation.
- **with_others:** *<bool>*, optional
  Include the "others" category.
- **color:** *<list of str>*, optional
  The color list for each category.
- **marker:** *<list of str>*, optional
  The list of categories markers.

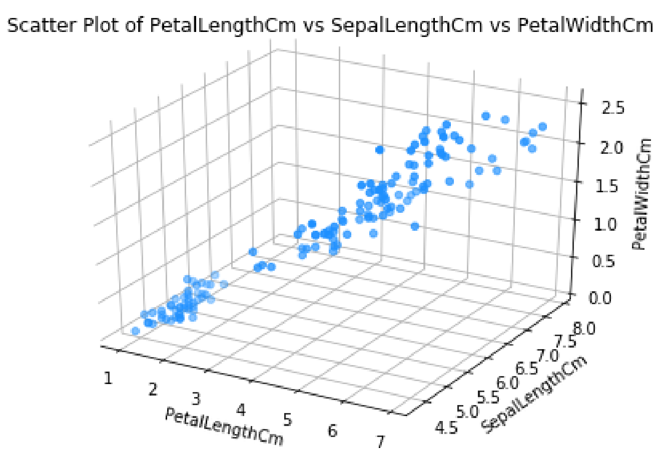
- **max_nb_points:** <*positive int*>, optional
  The maximum number of points in the scatter plot. The points are taken randomly from the table.

Examples

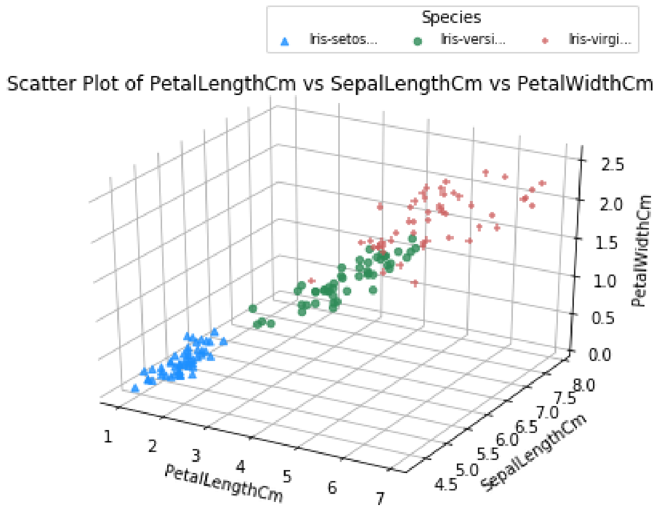
```
iris.scatter(columns=["PetalLengthCm","SepalLengthCm","Species"])
```



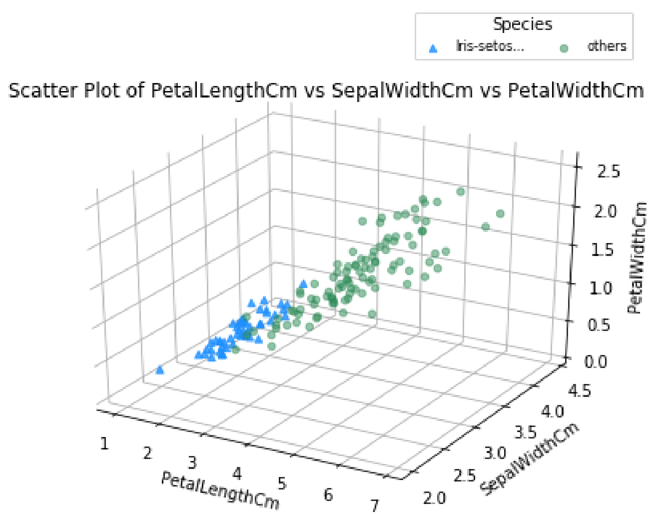

```
iris.scatter(columns=["PetalLengthCm","SepalLengthCm","PetalWidthCm"], mode="3
    D")
```




```
iris.scatter(columns=["PetalLengthCm","SepalLengthCm","PetalWidthCm","Species"
    ])
```




```
iris.scatter(columns=["PetalLengthCm","SepalWidthCm","PetalWidthCm","Species"
    ], cat_priority=["Iris-setosa"])
```



4.2.4.25 scatter_matrix

```
RVD.scatter_matrix(columns=None, color=None)
```

Draw the scatter matrix of the corresponding columns.

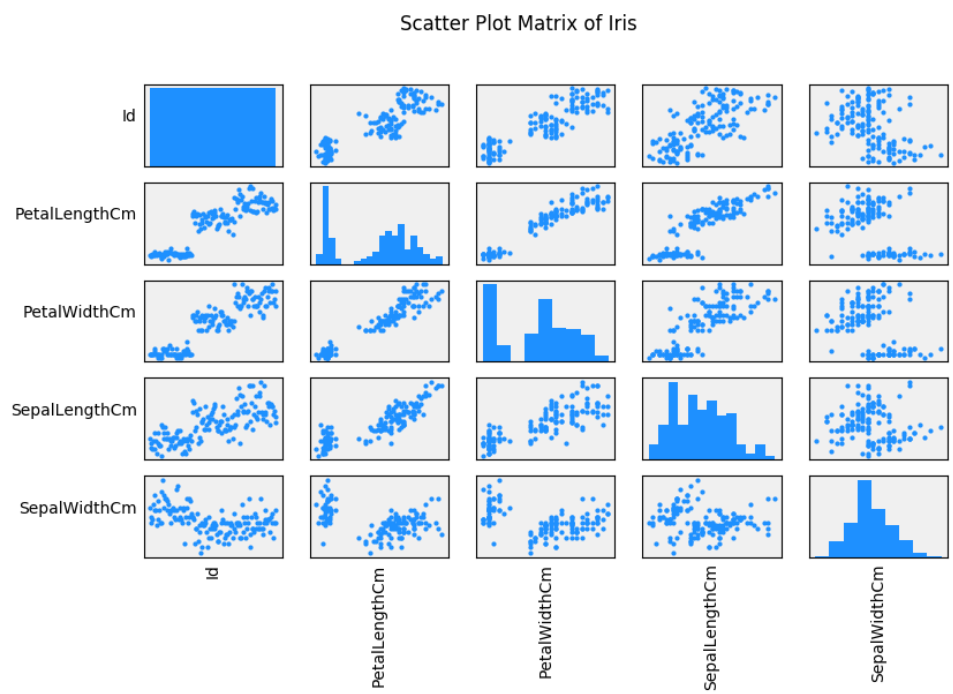
Parameters

- **columns:** *<list of str>*
  The columns used to draw the scatter matrix.

- **color:** *<str>*, optional
  The color of the scatter matrix.

Example

```
iris.scatter_matrix()
```



4.2.4.26 select

```
RVD.select(columns, order_by=None, asc=True, limit=100)
```

Group the aggregations by the corresponding columns.

Parameters

- **columns:** *<list of str>*
  List of the columns to select.
- **order_by:** *<list of str>*, optional
  List of all the columns to order with.
- **asc:** *<bool>*, optional
  To order asc.
- **limit:** *<positive int>*, optional
  The maximum number of elements to take into account.

Returns

An object named column_matrix containing all the selected information (they will be stored in the data_columns attribute).

Example

```
titanic.select(['pclass','age'], limit=20)

#Output
      pclass     age
0          1     None
1          2     None
2          3     None
3          2     None
4          3     None
5          3     None
6          3     None
7          3     None
8          3     None
9          3     None
10         3     None
11         3     None
12         1     None
13         3     None
14         2     None
15         3     None
16         3     None
17         3     None
18         3     None
19         3     None
...       ...     ...
count=1309 rows, elapsed_time=0.006971836090087891
```

4.2.4.27 set_colors

```
RVD.set_colors(colors)
```

Replace the current colors used to plot the different charts for the new ones.

- **colors:** *<list of str>*
  The list of colors.

4.2.4.28 set_cursor

```
RVD.set_cursor(cursor)
```

Replace the current cursor for a new one.

- **cursor:** *<object>*
  The database cursor.

4.2.4.29 set_dsn

```
RVD.set_dsn(dsn)
```

Replace the current dsn for a new one.

- **dsn:** *<object>*
  Vertica DSN.

Example

```
titanic.set_dsn("VerticaDSN")
```

4.2.4.30 set_figure_size

```
RVD.set_figure_size(figsize=(7,5))
```

Change the figure size for all the RVD chart.

- **figsize:** *<tuple>*, optional
  Size of the figures.

Example

```
titanic.set_figure_size(figsize=(10,8))
```

4.2.4.31 set_legend_loc

```
RVD.set_legend_loc(bbox_to_anchor=None, ncol=None, loc=None)
```

Change the legend position for all the RVD chart.

- **bbox_to_anchor:** *<tuple>*, optional
  Position of the legend following "loc".
- **ncol:** *<positive int>*, optional
  Number of columns of the legend.
- **loc:** *<str>*, optional
  Location of the legend.

Example

```
titanic.set_legend_loc(bbox_to_anchor=(0.5,1), ncol=2, loc="upper right")
```

4.2.4.32 set_limit

```
RVD.set_limit(limit=None)
```

Change the RVD limit.

- **limit:** *<positive int>*, optional
  New RVD limit value.

Example

```
titanic.set_limit(limit=100)
```

4.2.4.33 set_offset

```
RVD.set_offset(offset=0)
```

Change the RVD offset.

- **offset:** *<positive int>*, optional
  New RVD offset value.

Example

```
titanic.set_offset(offset=100)
```

4.2.4.34 sql_on_off

```
RVD.sql_on_off(reindent=False)
```

Print all the sql queries used by the RVD in the terminal. If it is already enable, it will turn it off.

Parameters

- **reindent:** *<bool>*, optional
  Use sqlparse available in github to indent all the queries.

Example

```
titanic.sql_on_off(reindent=True)
titanic.describe()

#Output
-------------------------------------------------------------------------------

select summarize_numcol(age,body,fare,parch,pclass,sibsp,survived) over ()
from
  (select age as age,
          boat as boat,
          body as body,
          cabin as cabin,
          embarked as embarked,
          fare as fare,
          homedest as homedest,
          name as name,
          parch as parch,
          pclass as pclass,
          sex as sex,
          sibsp as sibsp,
          survived as survived,
          ticket as ticket
   from titanic) x
-------------------------------------------------------------------------------

-------------------------------------------------------------------------------

select count(distinct age),
       count(distinct body),
       count(distinct fare),
       count(distinct parch),
       count(distinct pclass),
       count(distinct sibsp),
       count(distinct survived)
```

```
from
  (select age as age,
          boat as boat,
          body as body,
          cabin as cabin,
          embarked as embarked,
          fare as fare,
          homedest as homedest,
          name as name,
          parch as parch,
          pclass as pclass,
          sex as sex,
          sibsp as sibsp,
          survived as survived,
          ticket as ticket
   from titanic) x
-------------------------------------------------------------------------------


--More--
```

4.2.4.35 stacked_bar

```
RVD.stacked_bar(columns, method="density", of=None, max_cardinality=[6,6], h=[
    None, None], color=None, limit_distinct_elements=200)
```

Draw the corresponding 2 variables stacked bar chart.

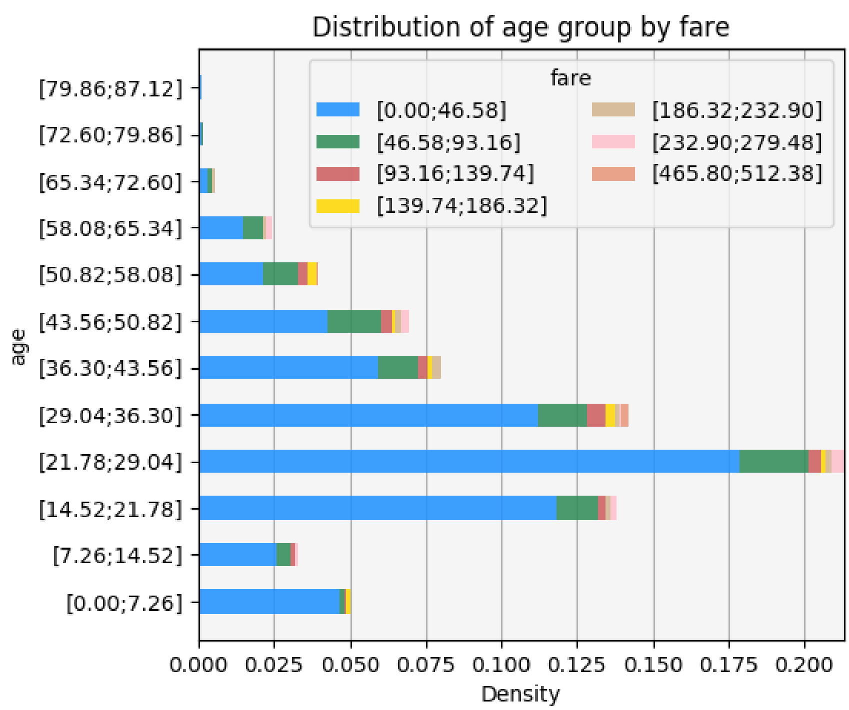
Parameters

- **columns:** *<list of str>*
  The two columns used to draw the stacked bar (first will be on the x-axis and the second in the y-axis)
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<list of positive int>*, optional
  The maximum cardinality of each column. Under this number the column is automatically considered as categorical.
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.

- **color:** *<list of str>*, optional
  The color list for each category
- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.

Example

```
titanic.stacked_bar(columns=["age","fare"])
```



4.2.4.36 stacked_hist

```
RVD.stacked_hist(columns, method="density", of=None, max_cardinality=[6,6], h
    =[None,None], color=None, limit_distinct_elements=200)
```

Draw the corresponding 2 variables stacked histogram.

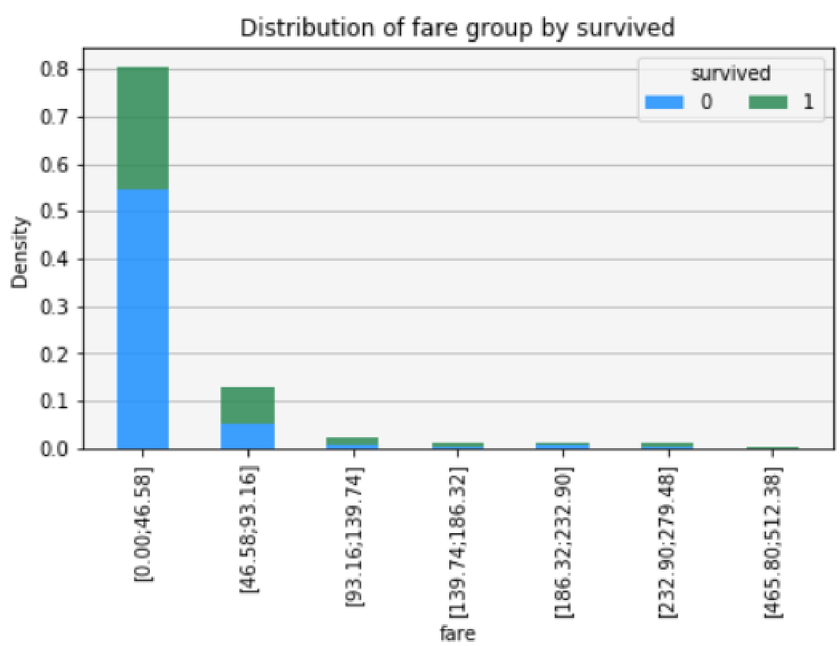
Parameters

- **columns:** *<list of str>*
  The two columns used to draw the stacked hist (first will be on the x-axis and the second in the y-axis)
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed

- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<list of positive int>*, optional
  The maximum cardinality of each column. Under this number the column is automatically considered as categorical.
- **h:** *<list of positive float>*, optional
  The interval size of each column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **color:** *<list of str>*, optional
  The color list for each category
- **limit_distinct_elements:** *<positive int>*, optional
  The maximum number of distinct elements. The other categories will be ignored.

Example

```
titanic.stacked_hist(columns=["fare","survived"])
```



4.2.4.37 time_on_off

```
RVD.time_on_off()
```

Print all the queries elapsed time used by the RVD in the terminal. If it is already enable, it will turn it off.

Example

```
titanic.time_on_off()
titanic.describe()

#Output
Elapsed Time: 0.013292789459228516
------------------------------------------------------------------------------------
Elapsed Time: 0.04647397994995117
------------------------------------------------------------------------------------
```

4.2.4.38 train_test_split

```
RVD.train_test_split(split=None, test_name=None, train_name=None, columns="*",
    test_size=0.33, mode="view")
```

Separate the data into two relations using a specific column.

Parameters

- **split:** *<str>*, optional
  Name of the column used to split the data. If it doesn't exist a table with one random float column will be created and used to split the data.
- **test_name:** *<str>*, optional
  Name of the test set.
- **train_name:** *<str>*, optional
  Name of the training set.
- **columns:** *<list of str>*, optional
  List of the columns to be used.
- **test_size:** *<float in [0,1]>*, optional
  Size of the test set.
- **mode:** *<str>*, optional
  view | table | temporary table
  The mode is used to create the new relations.

⚠ **Warning**

If no name is given to test or train, the function will always generate default names (test_(input_relation)_0(test_size) and train_(input_relation)_0(test_size)). If these relations already exist, it will drop them. Besides, if the column "split" does not exist, a new table having only one column of random numbers (between 0 and 1) and the same number of rows than the RVD will be created. If the table already exists (default name = random_vpython_table_(input_relation)), it will use it for computation without creating a new one. This table will be used to separate the data (using a natural join on the row number). Do not delete this column if you are using the view mode !

Example

```
titanic.train_test_split()

#Output
The random table random_vpython_table_titanic was successfully created
The views test_titanic033 and train_titanic067 were successfully created.

(       age    boat    body    cabin    embarked        fare   \\
 0     None       1    None     None           S    26.00000   \\
 1     None      10    None     E101           Q    12.35000   \\
 2     None      11    None     None           S    33.00000   \\
 3     None      13    None     None           Q     7.72080   \\
 4     None      13    None     None           Q     7.73330   \\
 5     None      13    None     None           Q     7.75000   \\
 6     None      13    None     None           Q     7.78750   \\
 7     None      13    None     None           Q     7.82920   \\
 8     None      13    None     None           Q     7.87920   \\
 9     None      13    None     None           S     8.11250   \\
 10    None      13    None     None           S    56.49580   \\
 11    None      14    None     None           C    30.69580   \\
 12    None      15    None     None           S     7.05000   \\
 13    None      16    None     None           Q     7.73330   \\
 14    None      16    None     None           Q     7.75000   \\
 15    None      16    None     None           Q     7.75000   \\
 16    None      16    None     None           Q     7.87920   \\
 17    None      16    None     None           Q    15.50000   \\
 18    None      16    None     None           Q    15.50000   \\
 19    None      16    None     None           Q    15.50000   \\
 20    None      16    None     None           Q    23.25000   \\
 21    None      16    None     None           Q    23.25000   \\
 22    None      16    None     None           Q    23.25000   \\
 23    None      16    None     None           S    16.10000   \\
 24    None       3    None     C106           S    30.50000   \\
 25    None       4    None     None           C   110.88330   \\
 26    None       5    None     None           C    27.72080   \\
 27    None       5    None     None           S   133.65000   \\
 28    None     5 7    None     C126           S    52.00000   \\
 29    None       6    None      B78           C   146.52080   \\
 ...    ...     ...     ...      ...         ...         ...   \\
 --More--
```

4.2.4.39 undo_all_filters

```
RVD.undo_all_filters()
```

Undo all the filters.

4.2.4.40 undo_filter

```
RVD.undo_filter()
```

Undo the last filter.

4.2.4.41 version

```
RVD.version()
```

Return the Vertica DB version and information about the RVD adaptation for this version.

Example

```
titanic.version()

#Output

######################################################
#                         _   _                      #
#                        | | | |                     #
#      __   ___ __  _   _| |_| |__   ___  _ __       #
#      \ \ / / '_ \| | | | __| '_ \ / _ \| '_ \      #
#       \ V /| |_) | |_| | |_| | | | (_) | | | |     #
#        \_/ | .__/ \__, |\__|_| |_|\___/|_| |_|     #
#            | |     __/ |                           #
#            |_|    |___/                            #
#                                                    #
######################################################
#
# Author: Badr Ouali, Datascientist at Vertica
#
# You are currently using Vertica Analytic Database v9.0.1-0
#
# You have a perfectly adapted version for using RVD and Vertica ML
#
# For more information about the RVD you can use the help() method
(9, 0)
```

4.3 Resilient Vertica Column (RVC)

4.3.1 attributes

When the RVD is created, it will creates as many RVC as there are columns in the input relation. The RVC has only 3 attributes.

- `parent`: the RVC parent (must be a RVD).
- `alias`: the alias of the column.
- `transformations`: list of all the transformations since the beginning with their types and categories.

4.3.2 methods

4.3.2.1 abs

```
RVC.abs()
```

Apply the abs function to the RVC.

4.3.2.2 acos

```
RVC.acos()
```

Apply the acos function to the RVC.

4.3.2.3 add

```
RVC.add(x)
```

Add a number to the RVC.

Parameters

- **x:** *<positive float or int>*
  Value to add.

4.3.2.4 asin

```
RVC.asin()
```

Apply the asin function to the RVC.

4.3.2.5 atan

```
RVC.atan()
```

Apply the atan function to the RVC.

4.3.2.6 bar

```
RVC.bar(method="density", of=None, max_cardinality=6, bins=None, h=None, color
    =None)
```

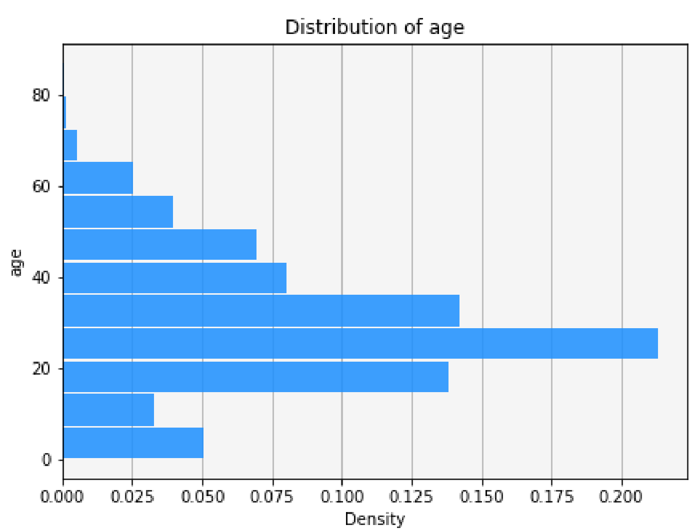
Draw the RVC bar.

Parameters

- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<positive int>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.
- **bins:** *<positive int>*, optional
  The number of the histogram bins.
- **h:** *<positive float>*, optional
  The interval size of the column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **color:** *<list of str>*, optional
  The histogram color.

Example

```
titanic["age"].bar()
```



4.3.2.7 boxplot

```
RVC.boxplot(by=None, h=None, max_cardinality=8, cat_priority=None)
```

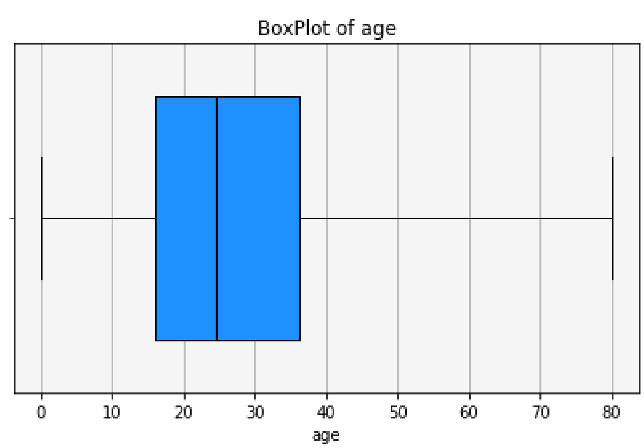
Draw the RVC boxplot.

Parameters

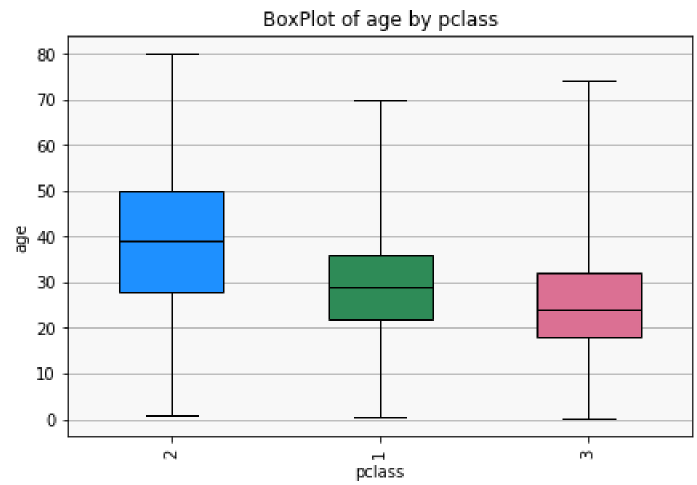
- **by:** *<str>*, optional
  The group by column. It is uses to separate the column per categories.
- **max_cardinality:** *<positive int>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.
- **h:** *<positive float>*, optional
  The interval size of the column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically.
- **cat_priority:** *<list of str>*, optional
  The principal categories to show.

Example

```
titanic["age"].boxplot()
```




```
titanic["age"].boxplot(by="pclass")
```



4.3.2.8 cardinality

```
RVC.cardinality()
```

Returns

Returns the RVC cardinality.

Example

```
titanic["pclass"].cardinality()

#Output
3
```

4.3.2.9 category

```
RVC.category()
```

Returns

Returns the RVC current category.

Example

```
titanic["pclass"].category()

#Output
int
```

4.3.2.10 convert_to_num

```
RVC.convert_to_num()
```

Try to convert a categorical RVC to a numerical one.

4.3.2.11 count

```
RVC.count()
```

Returns

Returns the RVC count (number of non-missing values).

Example

```
titanic["age"].count()

#Output
1046
```

4.3.2.12 cos

```
RVC.cos()
```

Apply the cos function to the RVC.

4.3.2.13 cosh

```
RVC.cosh()
```

Apply the cosh function to the RVC.

4.3.2.14 cot

```
RVC.cot()
```

Apply the cot function to the RVC.

4.3.2.15 date_part

```
RVC.date_part(field="month")
```

Extract the date part from the RVC.

Parameters

- **field:** *<str>*
  The field must be in {century | day | decade | doq | dow | doy | epoch | hour | isodow | isoweek | isoyear | microseconds | millenium | milliseconds | minute | month | quarter | second | timezone | timezone_hour | timezone_minute | week | year}

Example

```
expedia["date_time"].date_part(field="month")
expedia["date_time"]

#Output
0       1.0
1       1.0
2       1.0
3       1.0
4       1.0
5       1.0
--More--
...     ...
Name: date_time, dtype: int
```

4.3.2.16 decode

```
RVC.decode(categories, values, others=None)
```

Apply the decode function to the RVC.

Parameters

- **categories:** *<list of str>*
  The different categories to compare.
- **values:** *<list of str/int/float>*
  The new categories values.
- **others:** *<str>*, optional
  The value in the other case.

Example

```
titanic["name"].regexp_substr(' ([A-Za-z]+)\.')
titanic["name"].decode([" Mr."," Miss."," Mrs."," Ms."," Mlle."," Lady."," Mme
    ."," Sir."," Rev."," Dr."," Col."," Major."," Capt."], ["Mr","Miss","Mrs",
    "Miss","Miss","Mrs","Mrs","Mr","Rev","Dr","Army","Army","Army"], "Rare")
titanic["name"].describe(max_cardinality=8)

#Output
758    Mr
264  Miss
199   Mrs
65   Rare
8     Rev
8      Dr
7    Army
Name: name,dtype: varchar(6)
```

4.3.2.17 degrees

```
RVC.degrees()
```

Apply the degrees function to the RVC.

4.3.2.18 density

```
RVC.density(a=None, kernel="gaussian", smooth=200, color=None)
```

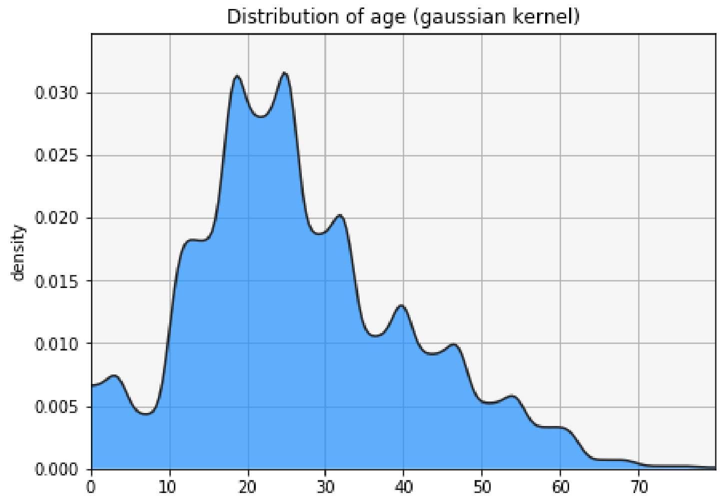
Draw the RVC density plot.

Parameters

- **a:** *<float>*, optional
  The kernel window. If it is not informed, an optimal one is computed.
- **kernel:** *<str>*, optional
  gaussian (default) | logistic | sigmoid | silverman
  The Kernel used for the plot.
- **smooth:** *<positive int>*, optional
  The number of points used for the smoothing.
- **color:** *<str>*, optional
  The density plot color.

Example

```
titanic["age"].density()
```



4.3.2.19 describe

```
RVC.describe(mode="auto", max_cardinality=6)
```

Summarize the RVC with mathematical information.

Parameters

- **mode:** *<str>*, optional
  auto | categorical | numerical
  auto (default): This mode is used to detect the correct category.
  numerical: This mode is used to print numerical information if it is possible.
  categorical: This mode is used to only print the categorical variables information (text or $cardinality \leq max\_cardinality$).
  date: This mode is used to only print the date variables information
- **max_cardinality:** *<bool>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.

Returns

An object named column_matrix containing all the summarized information (they will be stored in the data_column attribute).

Note

The mathematical information are different depending on the data type and if they are categorical.

Example

```
titanic["age"].describe()

#Output
count                    1046
mean          29.881137667304
std          14.4134932112713
min                      0.17
25%                      21.0
50%                      28.0
75%                      39.0
max                      80.0
cardinality                98
Name: age,dtype: numeric(6,3)

titanic["pclass"].describe()

#Output
709   3
323   1
277   2
Name: pclass,dtype: int
```

4.3.2.20 distinct

```
RVC.distinct()
```

Returns

Returns the RVC list of distinct elements.

Example

```
titanic["pclass"].distinct()

#Output
[1, 2, 3]
```

4.3.2.21 div

```
RVC.div(x)
```

Div the RVC by a number.

Parameters

- **x:** *<float or int>*
  Value to div with.

4.3.2.22 donut

```
RVC.donut(method="density", of=None, max_cardinality=6, h=None, colors=['
    dodgerblue','seagreen','indianred','gold','tan','pink','darksalmon','
    lightskyblue','lightgreen','palevioletred','coral']*10)
```

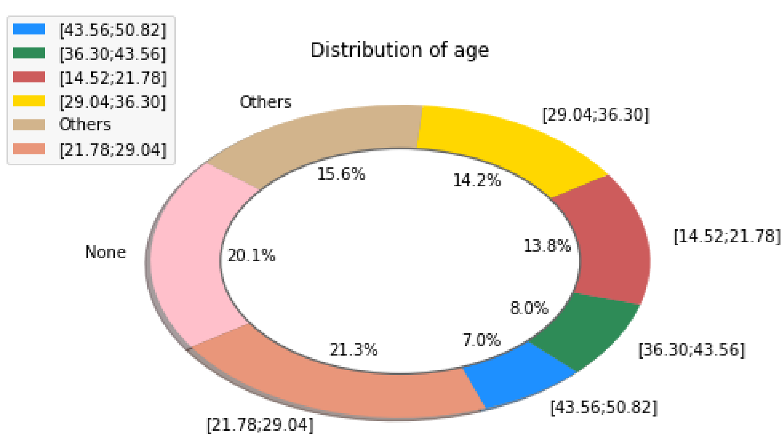
Draw the RVC donut chart.

Parameters

- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed
- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<positive int>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.
- **h:** *<positive float>*, optional
  The interval size of the column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **colors:** *<list of str>*, optional
  The donut chart colors.

Example

```
titanic["age"].donut()
```



4.3.2.23 drop_column

```
RVC.drop_column()
```

Drop the RVC from the RVD.

Example

```
titanic["pclass"].drop_column()

#Output
RVC 'pclass' deleted from the RVD.

titanic["pclass"]

#Output
Error: 'RVD' object has no attribute 'pclass'
```

4.3.2.24 dropna

```
RVC.dropna()
```

Drop the RVC missing values.

Example

```
titanic["pclass"].dropna()

#Output
263 elements were dropped
```

4.3.2.25 dtype

```
RVC.dtype()
```

Print the RVC data type.

Example

```
titanic["pclass"].dtype()

#Output
col    numeric(6,3)
dtype: object
```

4.3.2.26 duplicate

```
RVC.duplicate(name=None)
```

Duplicate the RVC.

Parameters

- **name:** *<str>*, optional
  Duplicate RVC name.

Example

```
titanic["age"].duplicate()

#Output
Duplication age4779 added to the RVD.
'age4779'
```

4.3.2.27 enum

```
RVC.enum(h=None)
```

Try to convert the RVC to enum.

Parameters

- **h:** *<positive float>*, optional
  The interval size of the column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically.

Example

```
titanic["fare"].enum()
print(titanic["fare"])

#Output
0        [0.00;46.58]
1        [0.00;46.58]
2        [0.00;46.58]
3        [0.00;46.58]
4        [0.00;46.58]
5        [0.00;46.58]
--More--
...                 ...
Name: fare, dtype: varchar
```

4.3.2.28 exp

```
RVC.exp()
```

Apply the exp function to the RVC.

4.3.2.29 fillna

```
RVC.fillna(val=None, method=None, by=[], compute_before=True)
```

Impute the RVC following the corresponding method.

Parameters

- **val:** *<str>*, optional
  The value used for the imputation.
- **method:** *<str>*, optional
  mean | median | lead | lag
  The method used for the imputation.
- **by:** *<list of str>*, optional
  List of the group by columns.
- **compute_before:** *<bool>*, optional
  Compute all the needed statistical information before the imputation.

Example

```
titanic["age"].fillna(method="avg",by=["pclass","sex"])

#Output
263 elements were filled
```

4.3.2.30 final_transformation

```
RVC.final_transformation()
```

Return the RVC final transformation (if every transformation is applied).

Example

```
titanic["embarked"].label_encode()
titanic["embarked"].final_transformation()

#Output
decode(embarked,'Q',0,'C',1,'S',2,NULL)
```

4.3.2.31 floor

```
RVC.floor()
```

Apply the floor function to the RVC.

4.3.2.32 head

```
RVC.head(n=5)
```

Print in the terminal the first RVC rows.

Parameters

- **n:** *<positive int>*
  The number of rows to print

Example

```
titanic["age"].head()

#Output
0       None
1       None
2       None
3       None
4       None
...     ...
Name: age, dtype: numeric(6,3)
```

4.3.2.33 hist

```
RVC.hist(method="density", of=None, max_cardinality=6, bins=None, h=None,
    color=None)
```

Draw the RVC histogram.

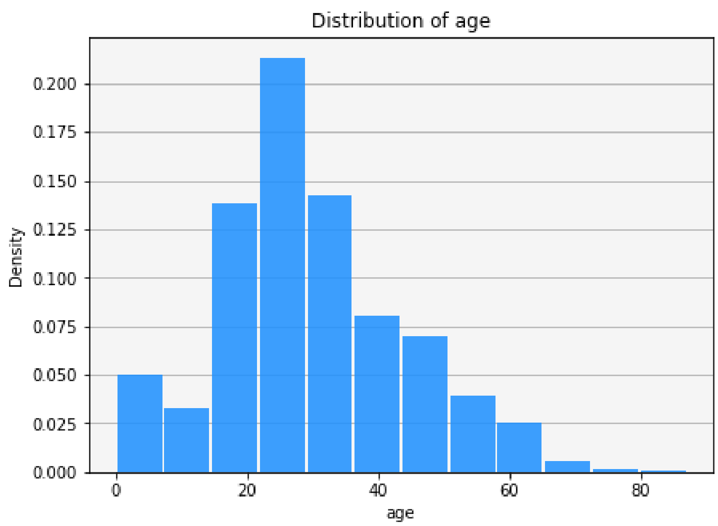
Parameters

- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed

- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}
- **max_cardinality:** *<positive int>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.
- **bins:** *<positive int>*, optional
  The number of the histogram bins.
- **h:** *<positive float>*, optional
  The interval size of the column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **color:** *<list of str>*, optional
  The histogram color.

Example

```
titanic["age"].hist()
```



4.3.2.34 label_encode

```
RVC.label_encode(cat_priority=None, values=None, others=None, order_by="count"
    , force_encoding=False, show=True)
```

Use the label encoding to encode the RVC.

Parameters

- **cat_priority:** *<list of str>*
  The different categories to encode.

- **values:** *<list of float/int>*
  The new categories values.
- **others:** *<str>*, optional
  The value in the other case.
- **order_by:** *<str>*, optional
  Order the encoding by count.
- **force_encoding:** *<bool>*, optional
  Allow the encoding even for numerical variables.
- **show:** *<bool>*, optional
  Print all the label encoding in the terminal.

Example

```
titanic["embarked"].label_encode()

#Output
embarked      encoding
Q                    0
C                    1
S                    2
The label encoding was successfully done.
```

4.3.2.35 log

```
RVC.log()
```

Apply the log function to the RVC.

4.3.2.36 max

```
RVC.max()
```

Returns

Returns the RVC maximum.

Example

```
titanic["age"].max()

#Output
80.0
```

4.3.2.37 mean

```
RVC.mean()
```

Returns

Returns the RVC average.

Example

```
titanic["age"].mean()

#Output
29.881137667304
```

4.3.2.38 mean_encode

```
RVC.mean_encode(response_column)
```

Apply a mean encoding using a specific response column.

Parameters

- **response_column:** *<str>*
  the response column (must be a RVC in the main RVD)

Example

```
titanic["embarked"].mean_encode("survived")

The mean encoding was successfully done.

titanic["embarked"].describe()
#Output
                       value
0.332603938730853        914
0.555555555555556        270
0.357723577235772        123
1                          2
Name: embarked,dtype: int
```

4.3.2.39 median

```
RVC.median()
```

Returns

Returns the RVC median.

Example

```
titanic["age"].median()

#Output
28.0
```

4.3.2.40 min

```
RVC.min()
```

Returns

Returns the RVC minimum.

Example

```
titanic["age"].min()

#Output
0.17
```

4.3.2.41 mod

```
RVC.mod(n)
```

Use the mod function on the RVC.

Parameters

- **n:** *<int>*
  Value of the mod.

4.3.2.42 mult

```
RVC.mult(x)
```

Mult the RVC by a number.

Parameters

- **x:** *<float or int>*
  Value to mult with.

4.3.2.43 normalize

```
RVC.normalize(method="zscore", compute_before=True)
```

Normalize the RVC.

Parameters

- **compute_before:** *<bool>*, optional
  Compute all the needed statistical information before the normalization.
- **method:** *<str>*, optional
  zscore (default) | robust_zscore | minmax
  The method used for the normalization.

Example

```
titanic["fare"].normalize()
print(titanic["fare"])

#Output
The RVC 'fare' was successfully normalized.
0        -0.14095183530676586
1          -0.4046757769067325
2        -0.33222414459904936
3       -0.005708788332423966
4           -0.494113935914393
5          -0.4938724304733674
--More--
...                         ...
Name: fare, dtype: numeric(10,5)
```

4.3.2.44 one_hot_encoder

```
RVC.one_hot_encoder()
```

Apply a one hot encoder to encode the RVC.

Example

```
titanic["pclass"].one_hot_encoder()

#Output
3 new features: pclass_1, pclass_2, pclass_3

print(titanic["pclass_1"])
```

```

#Output
0       1
1       0
2       0
3       0
4       0
5       0
6       0
7       0
8       0
9       0
10      0
11      0
12      1
13      0
14      0
--More--
```

4.3.2.45 outliers

```
RVC.outliers(max_number=10, threshold=3)
```

Detect the RVC outliers using the corresponding threshold.

Parameters

- **max_number:** *<positive int>*, optional
  The maximum of detected outliers.
- **threshold:** *<float>*, optional
  The outliers threshold

Example

```
titanic["fare"].outliers()

#Output
           fare      normalized_fare
0      512.3292     9.25513999906382
1      512.3292     9.25513999906382
2      512.3292     9.25513999906382
3      512.3292     9.25513999906382
4         263.0     4.43799132653881
5         263.0     4.43799132653881
6         263.0     4.43799132653881
```

```
7         263.0     4.43799132653881
8         263.0     4.43799132653881
9         263.0     4.43799132653881
...         ...                    ...
Total of 10 outliers detected.
```

4.3.2.46 percentile_cont

```
RVC.percentile_cont(x)
```

Returns

The corresponding percentile cont.

Parameters

- **x:** *<float in [0,1]>*
  Percentile Cont.

Example

```
titanic["age"].percentile_cont(0.25)

#Output
21.0
```

4.3.2.47 pie

```
RVC.pie(method="density", of=None, max_cardinality=6, h=None, colors=['
    dodgerblue','seagreen','indianred','gold','tan','pink','darksalmon','
    lightskyblue','lightgreen','palevioletred','coral']*10)
```

Draw the RVC pie chart.

Parameters

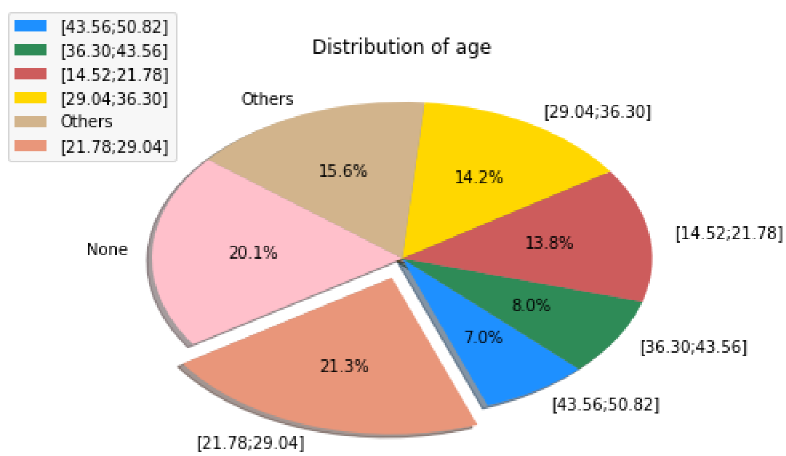
- **method:** *<str>*, optional
  count | density | avg | min | max | sum
  count: count is used as aggregation
  density (default): density is used as aggregation
  avg | min | max | sum: these aggregations are used only if "of" is informed

- **of:** *<str>*, optional
  The column used to compute the aggregation. This variable is used only if "method" in {avg | min |max | sum}

- **max_cardinality:** *<positive int>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.
- **h:** *<positive float>*, optional
  The interval size of the column. It is used if the column is numerical. In the other case, if h is not informed. The best "h" will be computed automatically. If the column is a date, h represents the interval size in seconds.
- **colors:** *<list of str>*, optional
  The pie chart colors.

Example

```
titanic["age"].pie()
```



4.3.2.48 pow

```
RVC.pow(n)
```

Use the pow function on the RVC.

Parameters

- **n:** *<float>*
  Value of the pow.

4.3.2.49 radians

```
RVC.radians()
```

Apply the radians function to the RVC.

4.3.2.50 regexp_substr

```
RVC.regexp_substr(expression)
```

Extract regular expression from each RVC raw.

Parameters

- **expression:** *<str>*
  The Regular Expression.

Example

```
titanic["name"].regexp_substr(' ([A-Za-z]+)\.')
titanic["name"].describe()

#Output
757              Mr.
260            Miss.
197             Mrs.
61           Master.
14            Others
8                Dr.
8               Rev.
cardinality        18
Name: name,dtype: varchar(164)
```

4.3.2.51 rename

```
RVC.rename(new_name)
```

Rename the RVC.

Parameters

- **new_name:** *<str>*
  New RVC name.

Example

```
titanic["sex"].rename(new_name="gender")
```

4.3.2.52 round

```
RVC.round(n)
```

Rounds the RVC.

Parameters

- **n:** *<int>*
  Value for the round.

4.3.2.53 sign

```
RVC.sign()
```

Apply the sign function to the RVC.

4.3.2.54 sin

```
RVC.sin()
```

Apply the sin function to the RVC.

4.3.2.55 sinh

```
RVC.sinh()
```

Apply the sinh function to the RVC.

4.3.2.56 sqrt

```
RVC.sqrt()
```

Apply the sqrt function to the RVC.

4.3.2.57 std

```
RVC.std()
```

Returns

Returns the RVC standard deviation.

Example

```
titanic["age"].std()

#Output
14.4134932112713
```

4.3.2.58 sub

```
RVC.sub(x)
```

Sub a number to the RVC.

Parameters

- **x:** *<positive float or int>*
  Value to sub.

4.3.2.59 tan

```
RVC.tan()
```

Apply the tan function to the RVC.

4.3.2.60 tanh

```
RVC.tanh()
```

Apply the tanh function to the RVC.

4.3.2.61 undo_impute

```
RVC.undo_impute()
```

Undo the last imputation.

4.3.2.62 value_counts

```
RVC.value_counts(max_cardinality=6)
```

Summarize the RVC categories using the count aggregation.

Parameters

- **max_cardinality:** *<bool>*, optional
  The maximum cardinality of the column. Under this number the column is automatically considered as categorical.

Returns

An object named column_matrix containing all the summarized information (they will be stored in the data_column attribute).

Example

```
titanic["pclass"].value_counts()

#Output
709  3
323  1
277  2
Name: pclass,dtype: int
```

4.4 Functions

4.4.1 drop_table

```
drop_table(input_relation, cursor)
```

Drop the corresponding input relation.

Parameters

- **input_relation:** *<str>*
  Name of the input relation (table or temporary table).
- **cursor:** *<object>*
  Database cursor.

Warning

Be sure before dropping a table, this action is irreversible !

Example

```
drop_table("titanic",cur)

#Output
The table titanic was successfully dropped.
```

4.4.2 drop_view

```
drop_view(view_name, cursor)
```

Drop the corresponding view.

Parameters

- **view_name:** *<str>*
  Name of the view.
- **cursor:** *<object>*
  Database cursor.

Warning

Be sure before dropping a view, this action is irreversible !

Example

```
drop_view("titanic_temp",cur)

#Output
The view titanic_temp was successfully dropped.
```

4.4.3 read_csv

```
read_csv(path, cursor, local=True, input_relation=None, delimiter=',', columns
    =None, types=None, null='',enclosed_by='"',escape='\\',skip=1, temporary=
    False, skip_all=False, split=False, split_name='vpython_split')
```

Read a CSV file and create an input relation automatically or manually.

Parameters

- **path:** *<str>*
  Path to the file in the Vertica server.
- **cursor:** *<object>*
  Database cursor.
- **local:** *<bool>*
  To use a local path instead of the node path.
- **input_relation:** *<str>*, optional
  Name of the new input relation.
- **delimiter:** *<str>*, optional
  Delimiter used to parse the file.

- **columns:** *<list of str>*, optional
  List of the different columns ("types" and "columns" must have the same size).
- **types:** *<list of str>*, optional
  List of the different types ("types" and "columns" must have the same size).
- **null:** *<str>*, optional
  How the null elements are encoded.
- **enclosed_by:** *<str>*, optional
  How the text elements are enclosed.
- **escape:** *<str>*, optional
  How the escape is encoded.
- **skip:** *<positive int>*, optional
  Number of elements to skip.
- **temporary:** *<bool>*, optional
  Create a temporary table instead of a table.
- **skip_all:** *<bool>*, optional
  To skip the types changements.
- **split:** *<bool>*, optional
  Add a split column to the table (random numbers between 0 and 1).
- **split_name:** *<str>*, optional
  Name of the split column.

Returns

The RVD of the new table.

Example

```
titanic=read_csv('titanic.csv',cur)

#Output
The parser guess the following columns and types:
age: Numeric(6,3)
boat: Integer
body: Integer
cabin: Varchar(30)
embarked: Varchar(20)
fare: Numeric(10,5)
home.dest: Varchar(100)
name: Varchar(164)
parch: Integer
pclass: Integer
sex: Varchar(20)
sibsp: Integer
survived: Integer
ticket: Varchar(36)
```

```
Illegal characters in the columns names will be erased.
Is any type wrong?
If one of the types is not correct, it will be considered as Varchar(100).
0 - There is one type that I want to modify.
1 - I wish to continue.
2 - I wish to see the columns and their types again.
#Input=1
/!\ Warning: Type of boat was changed to Varchar(100)
The table titanic has been successfully created.
```

4.4.4 run_query

```
run_query(query, cursor, limit=1000)
```

Return a query result (only for a select statement).

Parameters

- **query:** *<str>*
  The sql query.
- **cursor:** *<object>*
  The database cursor.
- **limit:** *<positive int>*, optional
  The maximum number of element to return.

Returns

An object named column_matrix containing the query result (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import run_query

run_query("select survived, pclass, sex, count(*) from titanic group by sex,
    pclass, survived;", cur)

#Output

      survived    pclass      sex    count
0            0         1     male      118
1            1         1     male       61
2            1         2   female       94
3            0         2   female       12
4            1         2     male       25
5            0         2     male      146
```

```
6            0         3    female      110
7            1         3    female      106
8            0         3      male      418
9            1         3      male       75
10           1         1    female      139
11           0         1    female        5
count=12 rows, elapsed_time=0.0224916934967041
```

5 vertica_ml_python.vml

VML (Vertica Machine Learning) is a package containing a set of functions for Machine Learning. Each Machine Learning algorithm is an object easy to explore. The user can see the performance of each algorithm. He will be able to see which algorithm is the best for the case and he will have all he needs to try to build a better one. He can also add the prediction to the RVD in order to use all the RVD methods.

5.1 Functions

5.1.1 accuracy

```
accuracy(model, threshold=0.5, input_class=1)
```

Compute the accuracy of a model using the corresponding threshold for the input class.

Parameters

- **model:** *<object>*
  The model used to compute the accuracy.
- **threshold:** *<float in [0,1]>*, optional
  The model threshold.
- **input_class:** *<str>*, optional
  The input class used to compute the accuracy.

Returns

The model accuracy.

Example

```
from vertica_ml_python import accuracy

accuracy(logit)

#Output
0.8051044083526679
```

5.1.2 auc

```
accuracy(model, input_class=1)
```

Compute the auc of a model for the input class.

Parameters

- **model:** *<object>*
  The model used to compute the auc.
- **input_class:** *<str>*, optional
  The input class used to compute the auc.

Returns

The model auc.

Example

```
from vertica_ml_python import auc

auc(logit)

#Output
0.8317227859778604
```

5.1.3 champion_challenger_binomial

```
champion_challenger_binomial(input_relation, response_column,
    predictor_columns, cursor, fold_count=3, max_iterations=100,
    logit_optimizer='Newton', logit_regularization='None', logit_alpha=0.5,
    rf_ntree=20, rf_mtry=None, rf_max_depth=5, rf_sampling_size=0.632)
```

Champion Challenger for Binomial Model: Compare all the binomial models to find the best one.

Parameters

- **input_relation:** *<str>*
  The table or view to consider.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.

- **fold_count:** *<positive int>*, optional
  The number of fold to compute.
- **rf_ntree:** *<positive int>*, optional
  Number of trees for the RF.
- **rf_mtry:** *<positive int>*, optional
  A positive integer number that indicates the number of features to be considered at the split of a tree node for the RF.
- **rf_sampling_size:** *<float in [0,1]>*, optional
  A number that indicates what portion of the input data set will randomly be picked for training each tree for the RF.
- **rf_max_depth:** *<int in [1,100]>*, optional
  A positive integer number that specifies the maximum depth for growing each tree for the RF.
- **max_iterations:** *<positive int>*, optional
  Determines the maximum number of iterations each algorithm performs before achieving the specified accuracy result.
- **logit_regularization:** *<str>*, optional
  L1 | L2 | ENet | None (default)
  Determines the method of regularization for the Logit.
- **logit_alpha:** *<positive float in [0,1]>*, optional
  ENet mixture parameter that defines how much L1 versus L2 regularization to provide for the Logit. This argument will send a warning if it is used without ENet regularization.
- **logit_optimizer:** *<str>*, optional
  BFGS | CGD | Newton (default)
  The optimizer method used to train the model for the Logit. If no optimizer is set and regularization is set to L1, the default optimizer switches to CGD.

Returns

An object named column_matrix containing the champion challenger result (the information will be stored in the data_columns attribute).

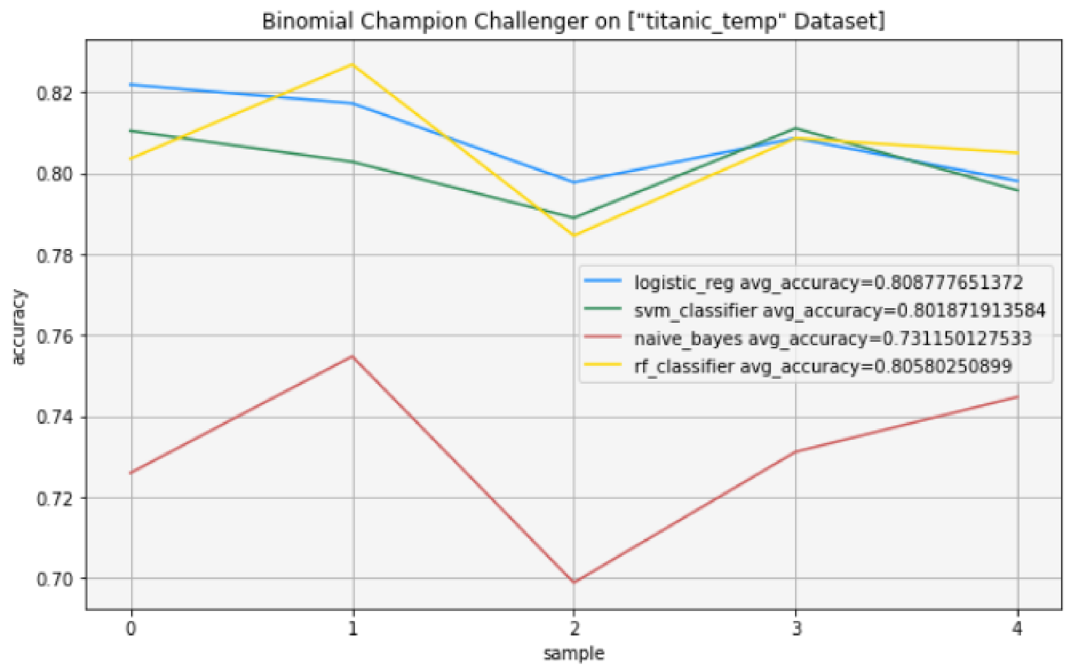
⚠ **Warning**

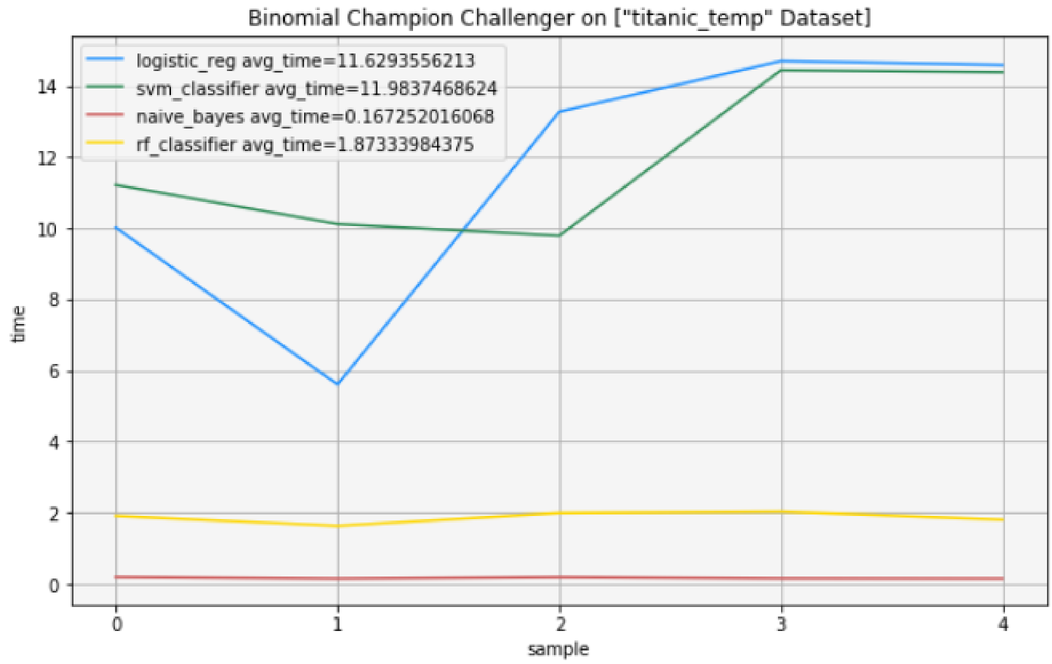
This function can take a lot of time as a lot of models are computed.

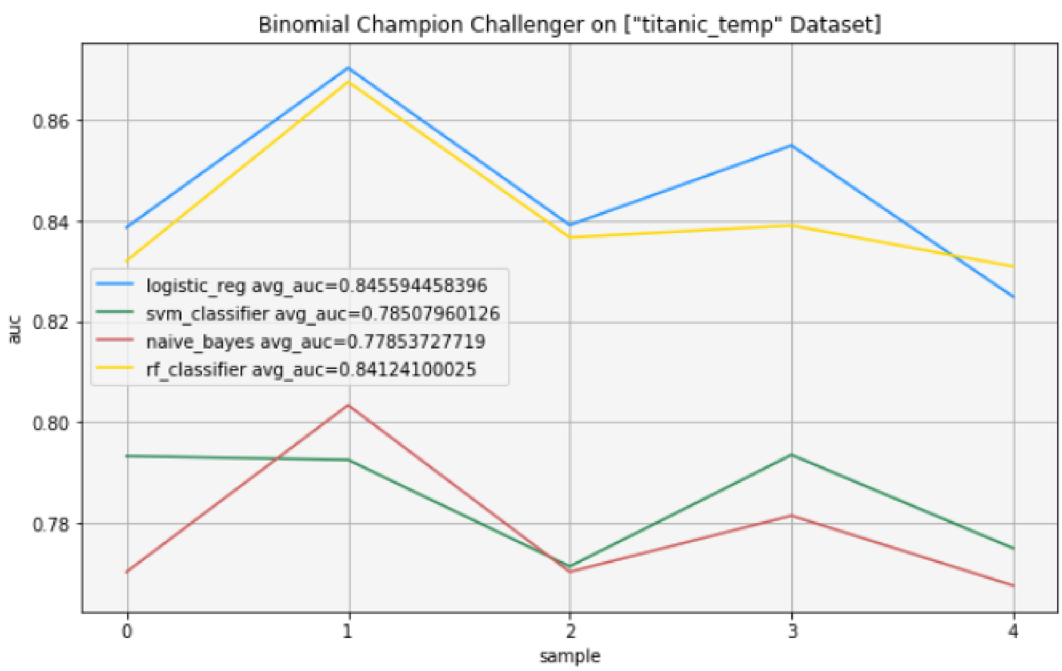
Example

```
from vertica_ml_python import champion_challenger_binomial

champion_challenger_binomial('titanic_temp', 'survived',['is_Army', 'is_Dr', 'is_Rev', 'is_Mrs', 'is_Miss', 'is_Mr', 'embarked_C', 'embarked_Q', 'embarked_S', 'fare', 'age', 'pclass', 'gender', 'family_size', 'parch', 'sibsp'], cur, logit_optimizer="BFGS", fold_count=5)

#Output
                              avg_time             avg_auc       avg_accuracy
    std_accuracy
```

```
logistic_reg         11.6293556213     0.845594458396     0.808777651372
    0.00978741350056
svm_classifier       11.9837468624      0.78507960126     0.801871913584
    0.00852471877201
naive_bayes         0.167252016068      0.77853727719     0.731150127533
    0.0190351874381
rf_classifier        1.87333984375      0.84124100025      0.80580250899
    0.0134801561568
```







5.1.4 confusion_matrix

```
confusion_matrix(model, threshold=0.5, input_class=1)
```

Compute the confusion matrix of a model using the corresponding threshold for the input class.

Parameters

- **model:** *<object>*
  The model used to compute the confusion matrix.
- **threshold:** *<float in [0,1]>*, optional
  The model threshold.
- **input_class:** *<str>*, optional
  The input class used to compute the confusion matrix.

Returns

An object named column_matrix containing the confusion matrix (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import confusion_matrix

confusion_matrix(logit)

#Output
Confusion Matrix
           0       1
0        459      72
1        109     217
```

5.1.5 drop_model

```
drop_model(model_name, cursor)
```

Drop the corresponding model.

Parameters

- **model_name:** *<str>*, optional
  Model Name.
- **cursor:** *<object>*, optional
  The database cursor.

⚠ Warning

Be sure before dropping a model, this action is irreversible !

Example

```
from vertica_ml_python import drop_model

drop_model("iris_kmeans",cur)

#Output
The model iris_kmeans was successfully dropped.
```

5.1.6 elbow

```
elbow(input_relation, input_columns, cursor, max_num_cluster=15,
    max_iterations=10, epsilon=1e-4, init_method="kmeanspp")
```

Compute the Elbow curve in order to determine the optimal number of clusters.

Parameters

- **input_relation:** *<str>*
  The input relation.
- **input_columns:** *<list of str>*
  The columns used to perform the kmeans.
- **cursor:** *<object>*
  The database cursor.
- **max_num_cluster:** *<positive int>*, optional
  The maximum number of cluster, the user wants to have.
- **max_iterations:** *<positive int>*, optional
  The maximum number of iterations the algorithm performs.
- **epsilon:** *<positive float>*, optional
  Determines whether the algorithm has converged. If, after an iteration, no component of any cluster center changes more than the value of epsilon, the algorithm has converged.
- **init_method:** *<str>*, optional
  random | kmeanspp (default)
  The method used to find the initial cluster centers.

Returns

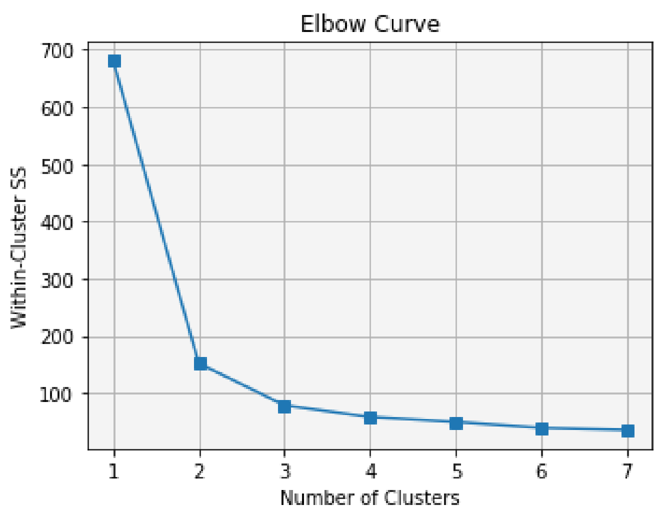
An object named column_matrix containing the all within cluster SS per number of clusters (the information will be stored in the data_columns attribute).

⚠ Warning

max_num_cluster models are computed. It can take a lot of time depending on the case.

Example

```
from vertica_ml_python import elbow

elbow(input_relation="Iris", input_columns=["PetalLengthCm","SepalLengthCm","
    PetalWidthCm","SepalWidthCm"], cursor=cur, max_num_cluster=8)

#Output
num_clusters       all_within_cluster_SS
1                              680.8244
2                             152.36871
3                             78.945066
4                             58.458695
5                             49.748082
6                             39.498349
7                             35.826633
```



5.1.7 error_rate

```
error_rate(model, threshold=0.5, input_class=1)
```

Compute the error rate of a model using the corresponding threshold for the input class.

Parameters

- **model:** *<object>*
  The model used to compute the error rate.
- **threshold:** *<float in [0,1]>*, optional
  The model threshold.
- **input_class:** *<str>*, optional
  The input class used to compute the error rate.

Returns

An object named column_matrix containing the error rate (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import error_rate

error_rate(logit)

#Output
Error Rate
                   error_rate
0           0.135593220338983
1           0.334355828220859
total        0.21120186697783
```

5.1.8 features_importance

```
features_importance(model, show=True, with_intercept=False)
```

Compute the features importance of a model.

Parameters

- **model:** *<object>*
  The model used to compute the features importance.
- **show:** *<bool>*, optional
  Display the result using matplotlib.
- **with_intercept:** *<bool>*, optional
  Include the intercept coefficient in the computation if there is one.

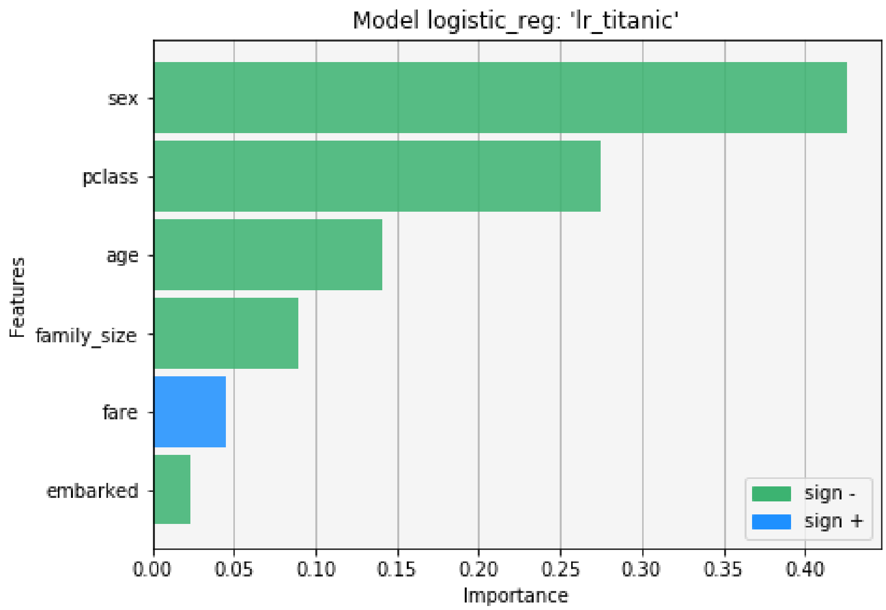
Returns

An object named column_matrix containing the features importance (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import features_importance

features_importance(logit)

#Output
                              Importance
embarked            0.0236733870066072 6
```

```
fare               0.04501061381123661
family_size        0.08998333220194923
age                0.14109667320278477
pclass              0.2746966760328248
sex                 0.4255393660505437
```



5.1.9 lift_table

```
lift_table(model, num_bins=200, color=["dodgerblue","#444444"], show=True,
    input_class=1)
```

Draw the lift table of a model.

Parameters

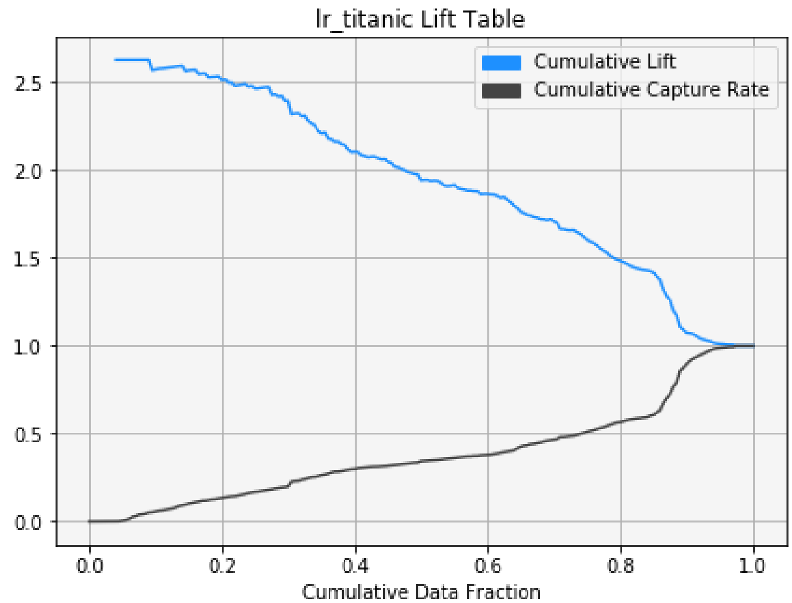
- **model:** *<object>*
  The model used to compute the lift table.
- **num_bins:** *<positive int>*, optional
  The number of bins used to draw the lift table.
- **color:** *<list of str>*, optional
  The color of the lift table and random line.
- **show:** *<bool>*, optional
  Display the result using matplotlib.
- **input_class:** *<str>*, optional
  The input class used to draw the lift table.

Returns

An object named column_matrix containing the lift table information (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import lift_table

lift_table(logit)

#Output
       decision_boundary    positive_prediction_ratio                 lift
0                    0.0                          0.0                  nan
1                  0.005                          0.0                  nan
2                   0.01                          0.0                  nan
3                  0.015                          0.0                  nan
4                   0.02                          0.0                  nan
5                  0.025                          0.0                  nan
6                   0.03                          0.0                  nan
7                  0.035                          0.0                  nan
8                   0.04         0.001166861143523920    2.62883435582822
9                  0.045         0.001166861143523920    2.62883435582822
10                  0.05         0.004667444574095680    2.62883435582822
11                 0.055         0.008168028004667440    2.62883435582822
12                  0.06           0.015169194865811    2.62883435582822
13                 0.065          0.0256709451575263    2.62883435582822
14                  0.07          0.0303383897316219    2.62883435582822
15                 0.075          0.0385064177362894    2.62883435582822
16                  0.08          0.0408401400233372    2.62883435582822
17                 0.085           0.044340723453909    2.62883435582822
18                  0.09          0.0513418903150525    2.62883435582822
19                 0.095          0.0525087514585764    2.57041581458759
20                   0.1          0.0571761960326721    2.57518467509703
--More--
```



5.1.10 load_model

```
load_model(model_name, cursor, input_relation=None)
```

Load the ML model.

Parameters

- **model_name:** *<str>*
  The model name.
- **cursor:** *<object>*
  The database cursor.
- **input_relation:** *<str>*, optional
  The input relation used by the model.

Returns

The corresponding ML model.

Example

```
from vertica_ml_python import load_model

rf_test=load_model("rf_titanic", cur, input_relation="test_titanic033")
```

5.1.11 logloss

```
logloss(model)
```

Compute the logloss of a multinomial model.

Parameters

- **model:** *<object>*
  The model used to compute the logloss.

Returns

The model logloss (classification only).

Example

```
from vertica_ml_python import logloss

logloss(logit)

#Output
0.201103505898445
```

5.1.12 metric_rf_curve_ntree

```
metric_rf_curve_ntree(input_relation, test_relation, response_column,
    predictor_columns, cursor, mode='logloss', ntree_begin=1, ntree_end=20,
    mtry=None, sampling_size=0.632, max_depth=5, max_breadth=32, min_leaf_size
    =5, min_info_gain=0.0, nbins=32, test_only=True)
```

Compute the corresponding metric RF curve in order to determine the optimal number of trees.

Parameters

- **input_relation:** *<str>*
  The table or view that contains the training samples.
- **test_relation:** *<str>*
  The table or view where the function will compute the corresponding metric.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.

- **mode:** *<str>*, optional
  logloss | accuracy | error_rate | auc
  The metric to be computed.
- **ntree_begin:** *<positive int>*, optional
  Number of trees to begin with.
- **ntree_end:** *<positive int>*, optional
  Number of trees to end with.
- **mtry:** *<positive int>*, optional
  A positive integer number that indicates the number of features to be considered at the split of a tree node.
- **sampling_size:** *<float in [0,1]>*, optional
  A number that indicates what portion of the input data set will randomly be picked for training each tree.
- **max_depth:** *<int in [1,100]>*, optional
  A positive integer number that specifies the maximum depth for growing each tree.
- **max_breadth:** *<int in [1,1e9]>*, optional
  A positive integer number that specifies the maximum number of leaf nodes a tree in the forest can have.
- **min_leaf_size:** *<int in [1,1e6]>*, optional
  A positive integer number that specifies the minimum samples each branch must have after splitting a node. A split that causes fewer remaining samples will be discarded.
- **min_info_gain:** *<float in [0,1]>*, optional
  A non-negative number. Any split with information gain less than this threshold will be discarded.
- **nbins:** *<int in [2,1000]>*, optional
  A positive integer number that indicates the number of bins to use for continuous features.
- **test_only:** *<bool>*, optional
  Plot the two curves (train and test).

Returns

A list of two objects [mode_test, mode_train] named column_matrix containing the corresponding metric per number of trees (the information will be stored in the data_columns attribute).

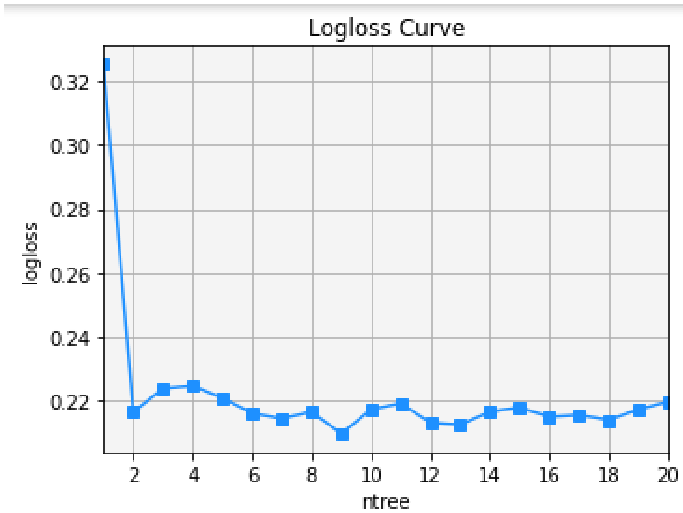
⚠ **Warning**

ntree_end-ntree_begin+1 models are computed. It can take a lot of time depending on the case.

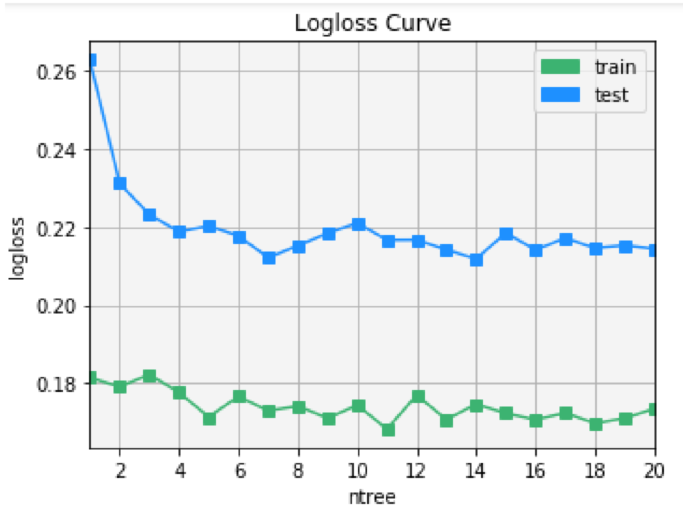
Example

```
from vertica_ml_python import metric_rf_curve_ntree

metric_rf_curve_ntree(input_relation='train_titanic067', test_relation='test_titanic033' response_column='survived', predictor_columns=["age","sex","family_size","embarked","pclass","name"], cursor=cur)

#Output
(ntree                logloss_test
 1            0.32532798483408 35
 2           0.21629507754633498
```

```
 3            0.2237076208677535
 4           0.22451867403603498
 5            0.2207204740572145
--More--
```




```
from vertica_ml_python import metric_rf_curve_ntree

metric_rf_curve_ntree(input_relation='train_titanic067', test_relation='
    test_titanic033' response_column='survived', predictor_columns=["age","sex
    ","family_size","embarked","pclass","name"], cursor=cur, test_only=False)

#Output
(ntree             logloss_test
 1            0.2629559858572835
 2           0.23122991569256252
 3            0.2231809471918855
 4             0.218823242607503
 5            0.2202786826615065
--More--
```



5.1.13 metric_rf_curve_depth

```
metric_rf_curve_depth(input_relation, test_relation, response_column,
    predictor_columns, cursor, mode='logloss',
            ntree=20, mtry=None, sampling_size=0.632, max_depth_begin=1,
    max_depth_end=12,
            max_breadth=32, min_leaf_size=5, min_info_gain=0.0, nbins=32,
    test_only=True)
```

Compute the corresponding metric RF curve in order to determine the optimal max depth.

Parameters

- **input_relation:** *<str>*
  The table or view that contains the training samples.
- **test_relation:** *<str>*
  The table or view where the function will compute the corresponding metric.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **mode:** *<str>*, optional
  logloss | accuracy | error_rate | auc
  The metric to be computed.
- **ntree:** *<positive int>*, optional
  Number of trees.
- **mtry:** *<positive int>*, optional
  A positive integer number that indicates the number of features to be considered at the split of a tree node.

- **sampling_size:** *<float in [0,1]>*, optional
  A number that indicates what portion of the input data set will randomly be picked for training each tree.
- **max_depth_begin:** *<int in [1,100]>*, optional
  A positive integer number that specifies the maximum depth for growing each tree to begin with.
- **max_depth_end:** *<int in [1,100]>*, optional
  A positive integer number that specifies the maximum depth for growing each tree to end with.
- **max_breadth:** *<int in [1,1e9]>*, optional
  A positive integer number that specifies the maximum number of leaf nodes a tree in the forest can have.
- **min_leaf_size:** *<int in [1,1e6]>*, optional
  A positive integer number that specifies the minimum samples each branch must have after splitting a node. A split that causes fewer remaining samples will be discarded.
- **min_info_gain:** *<float in [0,1]>*, optional
  A non-negative number. Any split with information gain less than this threshold will be discarded.
- **nbins:** *<int in [2,1000]>*, optional
  A positive integer number that indicates the number of bins to use for continuous features.
- **test_only:** *<bool>*, optional
  Plot the two curves (train and test).

Returns

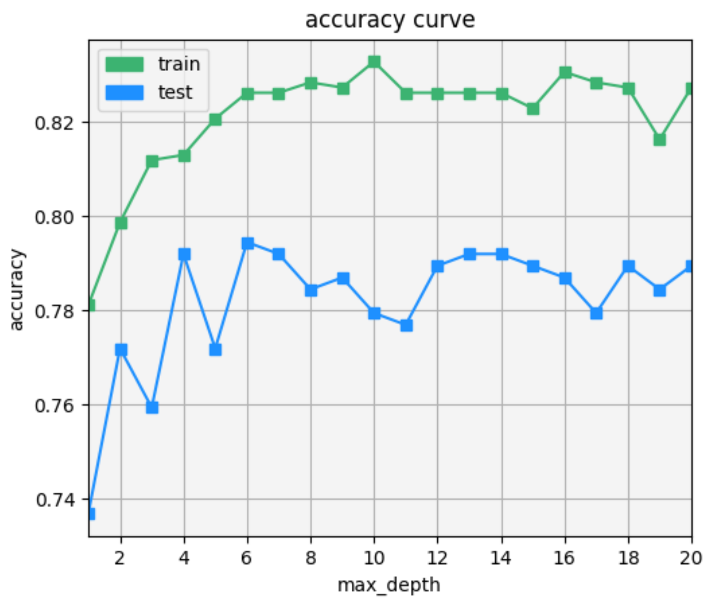
A list of two objects [mode_test, mode_train] named column_matrix containing the metric per depth (the information will be stored in the data_columns attribute).

⚠ Warning

max_depth_end-max_depth_begin+1 models are computed. It can take a lot of time depending on the case.

Example

```python
from vertica_ml_python import metric_rf_curve_depth

metric_rf_curve_depth(input_relation='train_titanic067', test_relation='test_titanic033' response_column='survived', predictor_columns=["age","sex","family_size","embarked","pclass","name"], cursor=cur, test_only=False, mode='accuracy')

#Output
(max_depth        accuracy_test
1               0.736842105263
2               0.771929824561
3               0.759398496241
4               0.791979949875
5               0.771929824561
--More--
```



5.1.14 mse

```
mse(model)
```

Compute the mse of a regression model.

Parameters

- **model:** *<object>*
  The model used to compute the mse.

Returns

The model mse.

Example

```
from vertica_ml_python import mse

mse(my_reg)

#Output
0.00230293988121166
```

5.1.15 reg_metrics

```
reg_metrics(model)
```

Compute the rsquared and mse of a regression model.

Parameters

- **model:** *<object>*
  The model used to compute the rsquared and mse.

Returns

An object named column_matrix containing the mse and rsquared of the model (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import reg_metrics

reg_metrics(my_reg)

#Output
                              value
mse            0.00230293988121166
rsquared         0.266308495008143
```

5.1.16 rsquared

```
rsquared(model)
```

Compute the rsquared of a regression model.

Parameters

- **model:** *<object>*
  The model used to compute the rsquared.

Returns

The model rsquared.

Example

```
from vertica_ml_python import rsquared

rsquared(my_reg)

#Output
0.266308495008143
```

5.1.17 roc

```
roc(model, num_bins=200, color=["dodgerblue","#444444"], show=True,
    input_class=1)
```

Draw the roc curve of a model.

Parameters

- **model:** *<object>*
  The model used to compute the roc.
- **num_bins:** *<positive int>*, optional
  The number of bins used to draw the roc.
- **color:** *<list of str>*, optional
  The color of the roc and random line.
- **show:** *<bool>*, optional
  Display the result using matplotlib.
- **input_class:** *<str>*, optional
  The input class used to draw the roc.

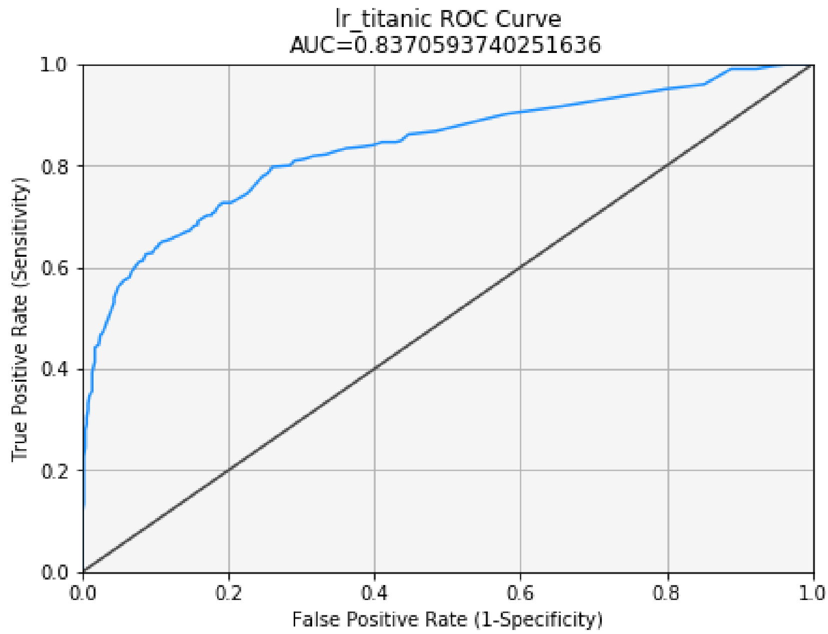
Returns

A list of two objects named column_matrix containing the roc information (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import roc

roc(logit)

#Output
(                                  value
 auc                   0.8370593740251636
 best_threshold                     0.57 ,
        threshold         false_positive          true_positive
 0            0.0                    1.0                    1.0
 1           0.01                    1.0                    1.0
 2           0.02                    1.0                    1.0
 3           0.03      0.990583804143126                    1.0
 4           0.04      0.988700564971751                    1.0
 5           0.05      0.981167608286252                    1.0
 6           0.06      0.969868173258004                    1.0
 7           0.07      0.947269303201507      0.996932515337423
 8           0.08      0.922787193973635       0.99079754601227
 9           0.09      0.888888888888889       0.99079754601227
 10           0.1      0.851224105461394      0.960122699386503
```

```
 11          0.11       0.7984934086629      0.950920245398773
 12          0.12       0.657250470809793    0.917177914110429
--More--
```



5.1.18 summarize_model

```
summarize_model(model_name, cursor)
```

Summarize the corresponding model.

Parameters

- **model_name:** *<str>*
  Name of the model to summarize.
- **cursor:** *<object>*
  The database cursor.

Returns

The summarized information.

Example

```
from vertica_ml_python import summarize_model

print(summarize_model("lr_titanic",cur))
```

```
#Output
coeff names: {Intercept, age, sex, family_size, embarked, fare, pclass}
coefficients: {4.494253459, -0.03180813173, -2.55322967, -0.1658014114, -0.1024176438, 0.002514827327, -0.9404607164}
std_err:      {0.5927, 0.008183, 0.1911, 0.0671, 0.1353, 0.002364, 0.1438}
z_value:      {7.583, -3.887, -13.36, -2.471, -0.7568, 1.064, -6.541}
p_value:      {3.376e-14, 0.0001014, < 1e-20, 0.01347, 0.4492, 0.2875, 6.116e-11}
Regularization method: none, lambda: 1
Number of iterations: 4, Number of skipped samples: 0, Number of processed samples: 857
Call:
logistic_reg('public.lr_titanic', 'train_titanic067', '"survived"', 'age,sex,family_size,embarked,fare,pclass'
USING PARAMETERS optimizer='newton', epsilon=1e-06, max_iterations=100, regularization='none', lambda=1, alpha=0.5)
```

5.1.19 tree

```
tree(model, n=0)
```

Print the tree in the terminal using the `anytree` API.

Parameters

- **model:** *<str>*
  The model used to compute the tree (must be a random forest).
- **n:** *<positive int>*
  The tree ID.

⚠ **Warning**

Be sure to have `anytree` installed in your computer and to have a folder named `anytree` where you execute the command (to draw a png of the tree, the name will be (model_name)_(input_relation)(n).png).

```
root@ubuntu:~$ pip install anytree
```

Returns

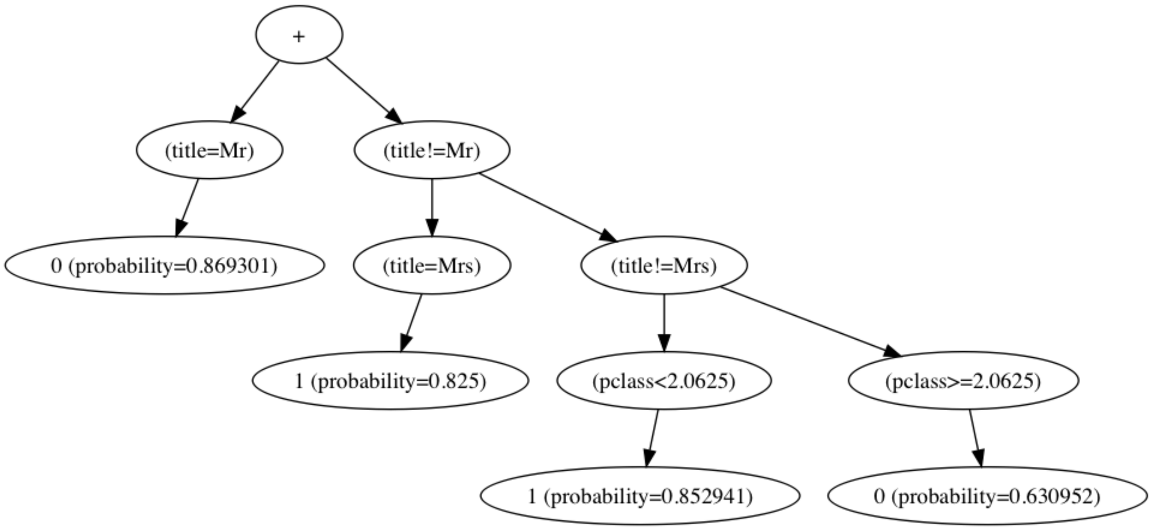
An objects named column_matrix containing the tree information (the information will be stored in the data_columns attribute).

Example

```
from vertica_ml_python import tree
from vertica_ml_python import rf_classifier

```

```
rf=rf_classifier(model_name="rf_titanic", input_relation="train_titanic067",
    response_column="survived", predictor_columns=["age","gender","pclass","
    title"], cursor=cur, max_depth=3)
print(rf.tree(n=0))

#Output
--------------------------------------------------------------------------------------

Tree Id: 0
Number of Nodes: 7
Tree Depth: 3
Tree Breadth: 3
--------------------------------------------------------------------------------------

+
+++ (title=Mr)
+    +++ 0 (probability=0.869301)
+++ (title!=Mr)
     +++ (title=Mrs)
     +    +++ 1 (probability=0.825)
     +++ (title!=Mrs)
          +++ (pclass<2.0625)
          +    +++ 1 (probability=0.852941)
          +++ (pclass>=2.0625)
               +++ 0 (probability=0.630952)
Tree0
NodeID      Node Depth    isLeaf    isSplitCategorical    split on   \\
1                    0         0                     1       title   \\
2                    1         1                     -           -   \\
3                    1         0                     1       title   \\
6                    2         1                     -           -   \\
7                    2         0                     0      pclass   \\
14                   3         1                     -           -   \\
15                   3         1                     -           -   \\
NodeID      threshold    leftChildID    rightChildID    prediction   \\
1                  Mr              2               3             -   \\
2                   -              -               -             0   \\
3                 Mrs              6               7             -   \\
6                   -              -               -             1   \\
7              2.0625             14              15             -   \\
14                  -              -               -             1   \\
15                  -              -               -             0   \\
NodeID      probability
1                     -
2              0.869301
3                     -
6                 0.825
```

```
7                     -
14              0.852941
15              0.630952
```



5.2 Machine Learning Models

Each machine learning model is represented by an object. This object has many methods and can sometimes call one of the ML functions described before. If it is the case, please refer directly to the function to know the parameters significations.

5.2.1 Cross Validation (cross_validate)

5.2.1.1 initialization

```
cross_validate(algorithm, input_relation, response_column, predictor_columns,
    cursor, model_name=None, fold_count=5, hyperparams=None, prediction_cutoff
    =0.5)
```

Performs cross validation on a learning algorithm using an input relation, and performs grid search for hyper parameters. The output is an average performance indicator of the selected algorithm.

Parameters

- **algorithm:** *<str>*
  svm_classifier | naive_bayes | logistic_reg
  The name of the training function of the algorithm.
- **input_relation:** *<str>*
  The table or view that contains the data used for training and testing.
- **response_column:** *<str>*
  The name of the column in the input_relation that contains the response.

- **predictor_columns:** *<list of str>*
  A list of the columns in the input_relation that are passed to the algorithm as predictors.
- **cursor:** *<object>*
  The database cursor.
- **model_name:** *<str>*, optional
  The name that is used to retrieve the result of the cross validation process.
- **fold_count:** *<int>*, optional
  The number of folds to split the data into.
- **hyperparams:** *<str>*, optional
  A JSON string that describes the combination of parameters for use in grid search of hyper parameters.
- **prediction_cutoff:** *<float in [0,1]>*, optional
  The cutoff threshold that is passed to the prediction stage of logistic regression.

Example

```
from vml import cross_validate

cross_validate(algorithm="logistic_reg", input_relation="train_titanic067", response_column="survived", predictor_columns=["age","sex","family_size","embarked","fare","pclass"], cursor=cur)

#Output
model_type='cross_validation'
model_name='_vpython_cv_2638'
Counters:
           counter_name    counter_value
0     accepted_row_count             881
1     rejected_row_count               0
2          feature_count               6
Fold Info:
     fold_id    row_count
0          0          160
1          1          164
2          2          179
3          3          208
4          4          170
Details:
     fold_id    iteration_count              accuracy            error_rate
0          0                  5               0.81875               0.18125
1          1                  5     0.786585365853659     0.213414634146341
2          2                  5     0.776536312849162     0.223463687150838
3          3                  5     0.798076923076923     0.201923076923077
4          4                  5     0.817647058823529     0.182352941176471
Averages:
              accuracy           error_rate
0    0.799519132120655    0.200480867879345
```

```
The model _vpython_cv_2638 was successfully dropped.
```

5.2.1.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **model_type:** Model type (="cross_validation").

5.2.1.3 methods

Cross Validation has only one method:

```
cross_validate.get_model_attribute(attr_name="run_details")
```

Returns

A list of two objects named column_matrix containing the roc information (the information will be stored in the data_columns attribute).

Parameters

- **attr_name:** *<str>*
  run_details (default) | run_average | fold_info | counters | call_string
  Attribute name.

5.2.2 Kmeans (kmeans)

5.2.2.1 initialization

```
kmeans(model_name, input_relation, input_columns, num_clusters, cursor,
    max_iterations=10, epsilon=1e-4, init_method="kmeanspp", initial_centers=
    None)
```

Executes the k-means algorithm on an input table or view.

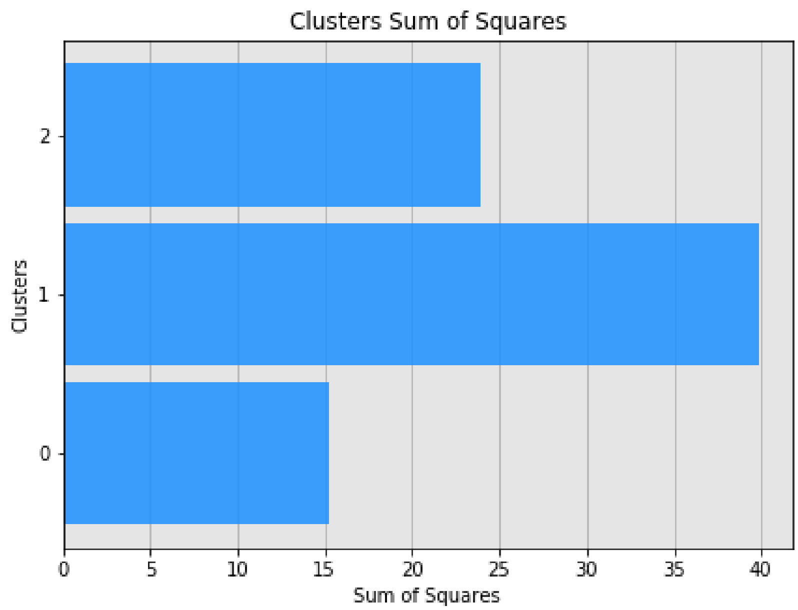
Parameters

- **model_name:** *<str>*
  Model name.
- **input_relation:** *<str>*
  The input relation.
- **input_columns:** *<list of str>*
  The columns used to perform the kmeans.
- **cursor:** *<object>*
  The database cursor.

- **max_iterations:** *<positive int>*, optional
  The maximum number of iterations the algorithm performs.
- **epsilon:** *<positive float>*, optional
  Determines whether the algorithm has converged. If, after an iteration, no component of any cluster center changes more than the value of epsilon, the algorithm has converged.
- **init_method:** *<str>*, optional
  random | kmeanspp (default)
  The method used to find the initial cluster centers.
- **initial_centers:** *<list of points>*, optional
  The list of the initial cluster centers to use.

Example

```
from vml import kmeans

iris_kmeans=kmeans(model_name="iris_kmeans", input_relation="Iris", input_columns=["PetalLengthCm","SepalLengthCm","PetalWidthCm","SepalWidthCm"], num_clusters=3, cursor=cur, initial_centers=[(1,2,3,4),(2,3,4,5),(3,4,5,6)])

print(iris_kmeans)
iris_kmeans.cluster_SS()

#Output
model_type='kmeans'
model_name='iris_kmeans'
input_relation='Iris'
input_columns='PetalLengthCm,SepalLengthCm,PetalWidthCm,SepalWidthCm'
Clusters:
        PetalLengthCm      SepalLengthCm       PetalWidthCm   \\
0               1.464              5.006              0.244   \\
1    4.39354838709677   5.90161290322581   1.43387096774194   \\
2     5.7421052631579               6.85   2.07105263157895   \\
         SepalWidthCm
0               3.418
1    2.74838709677419
2    3.07368421052632

     Cluster SS
0       15.2404
1      39.820968
2      23.879474
```



5.2.2.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **input_columns:** Input Columns.
- **num_clusters:** Number of Clusters.
- **model_type:** Model type (="kmeans").
- **model_category:** Model category (="clustering").

5.2.2.3 methods

```
kmeans.add_to_rvd(rvd, name="kmeans_cluster"+str(np.random.randint(10000)))
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name

kmeans.converged()
# Returns if the kmeans converged

kmeans.features_importance(show=True)
# Returns the model features importance

kmeans.between_cluster_SS()
# Returns the kmeans between cluster SS

```

```
kmeans.cluster_SS(show=True, display=True)
# Returns the kmeans cluster SS
# show = print the result in the terminal
# display = display the result using matplotlib

kmeans.total_SS()
# Returns the kmeans total SS

kmeans.within_cluster_SS()
# Returns the kmeans within cluster SS
```

5.2.3 Linear Regression (linear_reg)

5.2.3.1 initialization

```
linear_reg(model_name, input_relation, response_column, predictor_columns,
    cursor, optimizer='Newton', epsilon=1e-6, max_iterations=100,
    regularization="None", l=0.0, alpha=0.5)
```

Executes linear regression on an input table or view.

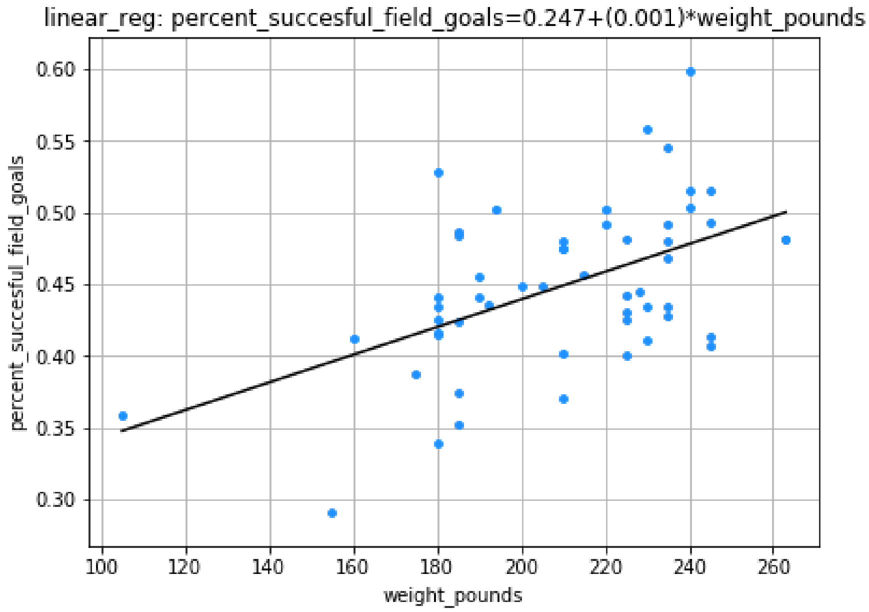
Parameters

- **model_name:** *<str>*
  Model name.
- **input_relation:** *<str>*
  The input relation.
- **response_column:** *<str>*
  The name of the column in the input_relation that represents the dependent variable, or outcome.
- **predictor_columns:** *<list of str>*
  A list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **optimizer:** *<str>*, optional
  BFGS | CGD | Newton (default)
  The optimizer method used to train the model. If no optimizer is set and regularization is set to L1, the default optimizer switches to CGD.
- **epsilon:** *<positive float>*, optional
  Determines whether the algorithm has reached the specified accuracy result.
- **max_iterations:** *<positive int>*, optional
  Determines the maximum number of iterations the algorithm performs before achieving the specified accuracy result.
- **regularization:** *<str>*, optional
  L1 | L2 | ENet | None (default)
  Determines the method of regularization.

- **l:** *<positive float>*, optional
  The regularization parameter value. The value must be zero or positive.
- **alpha:** *<positive float in [0,1]>*, optional
  ENet mixture parameter that defines how much L1 versus L2 regularization to provide. This argument will send a warning if it is used without ENet regularization.

Example

```
from vertica_ml_python import linear_reg

basketball=linear_reg(model_name="linear_reg_basketball", input_relation="
    basketball",  response_column="percent_succesful_field_goals",
    predictor_columns=["weight_pounds"], cursor=cur)
print(basketball)
basketball.plot()

#Output
model_type='linear_reg'
model_name='linear_reg_basketball'
input_relation='basketball'
response_column='percent_succesful_field_goals'
predictor_columns='weight_pounds'
regularization: none
lambda: 0.0
rejected_row_count: 0
accepted_row_count: 54
Parameters:
                             coefficient                std_error
    t_value    \\
Intercept              0.246705484199406       0.047062130975949
    5.24212310584671    \\
weight_pounds       0.000964261478009015     0.000221951360156074
    4.34447203806707    \\
                                 p_value
Intercept           2.93605818609063e-06
weight_pounds       6.49503578237179e-05
```



5.2.3.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.
- **model_type:** Model type (="linear_reg").
- **model_category:** Model category (="regression").

5.2.3.3 methods

```
linear_reg.add_to_rvd(rvd, name="linear_reg_pred"+str(np.random.randint(10000)
    ))
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name

linear_reg.details()
# Returns the model details.

linear_reg.features_importance(show=True)
# Returns the model features importance.

linear_reg.metrics()
```

```
# Returns the model metrics.

linear_reg.mse()
# Returns the model mse.

linear_reg.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = regularization | lambda | rejected_row_count |
    accepted_row_count | *
# show = Print the parameter in the Terminal

linear_reg.plot(color=None, projection=None, max_nb_points=1000)
# Plot the linear regression using matplotlib
# color = [points_color, plan_color]
# projection = project the plan in a smaller space
# max_nb_points = maximum number of points in the graph

linear_reg.rsquared()
# Returns the model rsquared.
```

5.2.4 Logistic Regression (logistic_reg)

5.2.4.1 initialization

```
logistic_reg(model_name, input_relation, response_column, predictor_columns,
    cursor, optimizer='Newton', epsilon=1e-6, max_iterations=100,
    regularization='None', l=1, alpha=0.5)
```

Executes logistic regression on an input table or view.

Parameters

- **model_name:** *<str>*
  Model name.
- **input_relation:** *<str>*
  The input relation.
- **response_column:** *<str>*
  The name of the column in the input_relation that represents the dependent variable, or outcome.
- **predictor_columns:** *<list of str>*
  A list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **optimizer:** *<str>*, optional
  BFGS | CGD | Newton (default)
  The optimizer method used to train the model. If no optimizer is set and regularization is set to L1, the default optimizer switches to CGD.

- **epsilon:** *<positive float>*, optional
  Determines whether the algorithm has reached the specified accuracy result.
- **max_iterations:** *<positive int>*, optional
  Determines the maximum number of iterations the algorithm performs before achieving the specified accuracy result.
- **regularization:** *<str>*, optional
  L1 | L2 | ENet | None (default)
  Determines the method of regularization.
- **l:** *<positive float>*, optional
  The regularization parameter value. The value must be zero or positive.
- **alpha:** *<positive float in [0,1]>*, optional
  ENet mixture parameter that defines how much L1 versus L2 regularization to provide. This argument will send a warning if it is used without ENet regularization.

Example

```
from vertica_ml_python import logistic_reg

logit=logistic_reg(model_name="lr_titanic", input_relation="train_titanic067",
     response_column="survived", predictor_columns=["age","sex","family_size",
    "embarked","fare","pclass"], cursor=cur)
print(logit)

#Output
model_type='logistic_reg'
model_name='lr_titanic'
input_relation='train_titanic067'
response_column='survived'
predictor_columns='age,sex,family_size,embarked,fare,pclass'
regularization: none
lambda: 1.0
rejected_row_count: 0
accepted_row_count: 881
Parameters:
                          coefficient              std_error
    t_value   \\
Intercept           5.26886364572958       0.620218968589887
    8.49516688873403   \\
age              -0.0414010724097224     0.00796877387136067
    -5.19541313106092   \\
sex                 -2.40595338730162       0.188879068874741
    -12.7380625160598   \\
family_size        -0.181861830912543      0.0672217913391124
    -2.70539994977385   \\
embarked           -0.260251676377847       0.135648823577091
    -1.91856935810389   \\
```

```
fare                0.00249310752912507     0.00272746881552252
    0.914073706337666    \\
pclass               -1.08507579965827       0.151212578985253
    -7.17583025790531    \\
                               p_value
Intercept           1.97648714752969e-17
age                 2.04265703445367e-07
sex                 3.63305310975195e-37
family_size          0.00682221957084204
embarked              0.0550388566073697
fare                    0.36067811758821
pclass              7.18696796176092e-13
```

5.2.4.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.
- **model_type:** Model type (="logistic_reg").
- **model_category:** Model category (="binomial").

5.2.4.3 methods

```
logistic_reg.accuracy(threshold=0.5)
# Returns the model accuracy

logistic_reg.add_to_rvd(rvd, name="logistic_reg_pred"+str(np.random.randint
    (10000)), prediction_type='response', cutoff=0.5)
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name
# prediction_type = response (default) | probability
# cutoff = logistic regression cut-off

logistic_reg.auc()
# Returns the model auc

logistic_reg.confusion_matrix(threshold=0.5)
# Returns the model confusion matrix

logistic_reg.details()
```

```
# Returns the model details.

logistic_reg.error_rate(threshold=0.5)
# Returns the model error rate.

logistic_reg.features_importance(show=True)
# Returns the model features importance.

logistic_reg.lift_table(num_bins=100, color=["dodgerblue","#444444"], show=
    True, input_class=1)
# Draw model lift table.

logistic_reg.logloss()
# Returns the model logloss.

logistic_reg.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = regularization | lambda | rejected_row_count |
    accepted_row_count | *
# show = Print the parameter in the Terminal

logistic_reg.plot(marker=["o","^"], color=None, projection=None, max_nb_points
    =None)
# Plot the logistic regression regression using matplotlib
# marker = [0_marker, 1_marker]
# color = [0_color, 1_color, logit_color]
# projection = project the plan in a smaller space
# max_nb_points = maximum number of points in the graph

logistic_reg.roc(num_bins=100, color=["dodgerblue","#444444"], show=True)
# Draw model roc.
```

5.2.5 Naive Bayes (naive_bayes)

5.2.5.1 initialization

```
naive_bayes(model_name, input_relation, response_column, predictor_columns,
    cursor, alpha=1.0)
```

Executes the Naive Bayes algorithm on an input table or view.

Parameters

- **model_name:** *<str>*
  Model name.

- **input_relation:** *<str>*
  The input relation.
- **response_column:** *<str>*
  The name of the column in the input_relation that represents the dependent variable, or outcome.
- **predictor_columns:** *<list of str>*
  A list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **alpha:** *<float>*, optional
  The parameter used to control Laplace smoothing. Specifies use of Laplace smoothing if the event model is categorical, multinomial, or Bernoulli.

Example

```
from vertica_ml_python import naive_bayes

nb=naive_bayes(model_name="nb_titanic",input_relation="train_titanic067",
    response_column="survived",
                        predictor_columns=["age","sex","family_size","embarked","
    pclass"],cursor=cur)
print(nb)

#Output
model_type='naive_bayes'
model_name='nb_titanic'
input_relation='train_titanic067'
response_column='survived'
predictor_columns='age,sex,family_size,embarked,pclass'
alpha: 1.0
rejected_row_count: 0
accepted_row_count: 881
Probabilities:
class                   value
0           0.625425652667423
1           0.374574347332577
```

5.2.5.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.

- **model_type:** Model type (="naive_bayes").
- **model_category:** Model category (="binomial"/"multinomial").

5.2.5.3 methods

```
naive_bayes.accuracy(threshold=0.5, input_class=None)
# Returns the model accuracy

naive_bayes.add_to_rvd(rvd, name="naive_bayes_pred"+str(np.random.randint
    (10000)), prediction_type='response', input_class=None)
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name
# prediction_type = response (default) | probability
# input_class = The class used when prediction_type="probability"

naive_bayes.auc(input_class=None)
# Returns the model auc

naive_bayes.confusion_matrix(threshold=0.5, input_class=None)
# Returns the model confusion matrix

naive_bayes.details()
# Returns the model details.

naive_bayes.error_rate(threshold=0.5, input_class=None)
# Returns the model error rate.

naive_bayes.lift_table(num_bins=100, color=["dodgerblue","#444444"], show=True
    , input_class=None)
# Draw the model lift table.

naive_bayes.logloss()
# Returns the model logloss.

naive_bayes.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = alpha | rejected_row_count | accepted_row_count | *
# show = Print the parameter in the Terminal

naive_bayes.roc(num_bins=100, color=["dodgerblue","#444444"], show=True,
    input_class=None)
# Draw the model roc.
```

5.2.6 Random Forest Classifier (rf_classifier)

5.2.6.1 initialization

```
rf_classifier(model_name, input_relation, response_column, predictor_columns,
    cursor, ntree=20, mtry=None, sampling_size=0.632, max_depth=5, max_breadth
    =32, min_leaf_size=1, min_info_gain=0.0, nbins=32)
```

Trains a random forest model for classification on an input table or view.

Parameters

- **model_name:** *<str>*
  The model name.
- **input_relation:** *<str>*
  The table or view that contains the training samples.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **ntree:** *<positive int>*, optional
  Number of trees.
- **mtry:** *<positive int>*, optional
  A positive integer number that indicates the number of features to be considered at the split of a tree node.
- **sampling_size:** *<float in [0,1]>*, optional
  A number that indicates what portion of the input data set will randomly be picked for training each tree.
- **max_depth:** *<int in [1,100]>*, optional
  A positive integer number that specifies the maximum depth for growing each tree.
- **max_breadth:** *<int in [1,1e9]>*, optional
  A positive integer number that specifies the maximum number of leaf nodes a tree in the forest can have.
- **min_leaf_size:** *<int in [1,1e6]>*, optional
  A positive integer number that specifies the minimum samples each branch must have after splitting a node. A split that causes fewer remaining samples will be discarded.
- **min_info_gain:** *<float in [0,1]>*, optional
  A non-negative number. Any split with information gain less than this threshold will be discarded.
- **nbins:** *<int in [2,1000]>*, optional
  A positive integer number that indicates the number of bins to use for continuous features.

Example

```
from vertica_ml_python import rf_classifier

rf=rf_classifier(model_name="rf_titanic", input_relation="train_titanic067",
    response_column="survived", predictor_columns=["age","sex","family_size","
    embarked","pclass","name"], cursor=cur)

#Output
model_type='rf_classifier'
model_name='rf_titanic'
input_relation='train_titanic067'
response_column='survived'
predictor_columns='age,sex,family_size,embarked,pclass,name'
tree_count: 20
rejected_row_count: 2
accepted_row_count: 897
column                        type
age                          float
sex                 char or varchar
family_size                    int
embarked            char or varchar
pclass                         int
name                char or varchar
```

5.2.6.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.
- **model_type:** Model type (="rf_classifier").
- **model_category:** Model category (="binomial"/"multinomial").

5.2.6.3 methods

```
rf_classifier.accuracy(threshold=0.5, input_class=None)
# Returns the model accuracy

rf_classifier.add_to_rvd(rvd, name="rf_classifier_pred"+str(np.random.randint
    (10000)), prediction_type='response', input_class=None)
# Add the prediction to the RVD
# rvd = the corresponding RVD
```

```
# name = RVC name
# prediction_type = response (default) | probability
# input_class = The class used when prediction_type="probability"

rf_classifier.auc(input_class=None)
# Returns the model auc

rf_classifier.confusion_matrix(threshold=0.5, input_class=None)
# Returns the model confusion matrix

rf_classifier.details()
# Returns the model details.

rf_classifier.error_rate(threshold=0.5, input_class=None)
# Returns the model error rate.

rf_classifier.features_importance(show=True)
# /!\ Coming Soon: Returns the model features importance.

rf_classifier.lift_table(num_bins=100, color=["dodgerblue","#444444"], show=
    True, input_class=None)
# Draw the model lift table.

rf_classifier.logloss()
# Returns the model logloss.

rf_classifier.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = tree_count | rejected_row_count | accepted_row_count | *
# show = Print the parameter in the Terminal

rf_classifier.roc(num_bins=100, color=["dodgerblue","#444444"], show=True,
    input_class=None)
# Draw the model roc.

rf_classifier.tree(n=0)
# Print the Tree with the corresponding ID.
```

5.2.7 Random Forest Regressor (rf_regressor)

5.2.7.1 initialization

```
rf_regressor(model_name, input_relation, response_column, predictor_columns,
    cursor, ntree=20, mtry=None, sampling_size=0.632, max_depth=5, max_breadth
    =32, min_leaf_size=1, min_info_gain=0.0, nbins=32)
```

Trains a random forest model for regression on an input table or view.

Parameters

- **model_name:** *<str>*
  The model name.
- **input_relation:** *<str>*
  The table or view that contains the training samples.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **ntree:** *<positive int>*, optional
  Number of trees.
- **mtry:** *<positive int>*, optional
  A positive integer number that indicates the number of features to be considered at the split of a tree node.
- **sampling_size:** *<float in [0,1]>*, optional
  A number that indicates what portion of the input data set will randomly be picked for training each tree.
- **max_depth:** *<int in [1,100]>*, optional
  A positive integer number that specifies the maximum depth for growing each tree.
- **max_breadth:** *<int in [1,1e9]>*, optional
  A positive integer number that specifies the maximum number of leaf nodes a tree in the forest can have.
- **min_leaf_size:** *<int in [1,1e6]>*, optional
  A positive integer number that specifies the minimum samples each branch must have after splitting a node. A split that causes fewer remaining samples will be discarded.
- **min_info_gain:** *<float in [0,1]>*, optional
  A non-negative number. Any split with information gain less than this threshold will be discarded.
- **nbins:** *<int in [2,1000]>*, optional
  A positive integer number that indicates the number of bins to use for continuous features.

Example

```
from vertica_ml_python import rf_regressor

rf_basketball=rf_regressor(model_name="rf_basketball", input_relation="
    basketball_temp", response_column="percent_succesful_field_goals",
    predictor_columns=["weight_pounds"], cursor=cur)
print(rf_basketball)

#Output
model_type='rf_regressor'
```

```
model_name='rf_basketball'
input_relation='basketball_temp'
response_column='percent_succesful_field_goals'
predictor_columns='weight_pounds'
tree_count: 20
rejected_row_count: 0
accepted_row_count: 54
column               type
weight_pounds       float
```

5.2.7.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.
- **model_type:** Model type (="rf_regressor").
- **model_category:** Model category (="regression").

5.2.7.3 methods

```
rf_regressor.add_to_rvd(rvd, name="rf_regressor_pred"+str(np.random.randint
    (10000)))
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name

rf_regressor.details()
# Returns the model details.

rf_regressor.features_importance(show=True)
# /!\ Coming Soon: Returns the model features importance.

rf_regressor.metrics()
# Returns the model metrics.

rf_regressor.mse()
# Returns the model mse.

rf_regressor.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = tree_count | rejected_row_count | accepted_row_count | *
```

```
# show = Print the parameter in the Terminal

rf_regressor.rsquared()
# Returns the model rsquared.

rf_regressor.tree(n=0)
# Print the Tree with the corresponding ID.
```

5.2.8 SVM Classifier (svm_classifier)

5.2.8.1 initialization

```
svm_classifier(model_name, input_relation, response_column, predictor_columns,
    cursor, C=1.0, epsilon=1e-3, max_iterations=100)
```

Trains the SVM model on an input table or view.

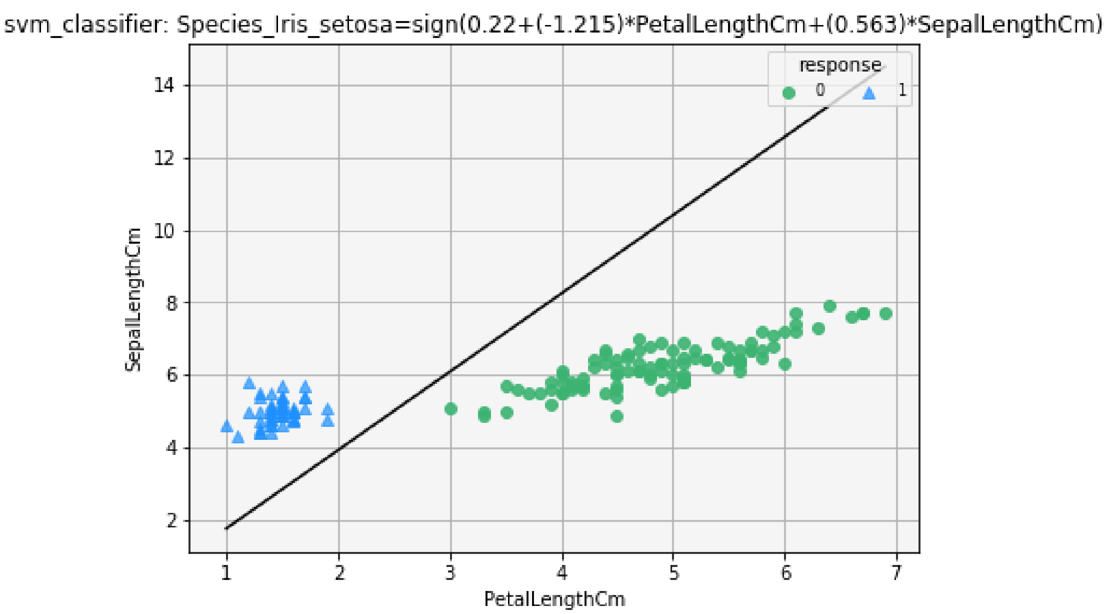
Parameters

- **model_name:** *<str>*
  The model name.
- **input_relation:** *<str>*
  The table or view that contains the training samples.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **C:** *<positive float>*, optional
  Sets the weight for misclassification cost. The algorithm minimizes the regularization cost and the misclassification cost.
- **epsilon:** *<positive float>*, optional
  Used to control accuracy.
- **max_iterations:** *<positive int>*, optional
  Determines the maximum number of iterations that the algorithm performs before achieving the specified accuracy result.

Example

```
from vertica_ml_python import svm_classifier

svm_iris=svm_classifier(model_name="svm_iris", input_relation="iris_temp",
    response_column="Species_Iris_setosa", predictor_columns=["PetalLengthCm",
    "SepalLengthCm",], cursor=cur)
```

```
print(svm_iris)
svm_iris.plot()

#Output
model_type='svm_classifier'
model_name='svm_iris'
input_relation='iris_temp'
response_column='Species_Iris_setosa'
predictor_columns='PetalLengthCm,SepalLengthCm'
iteration_count: 6
rejected_row_count: 0
accepted_row_count: 150
Parameters:
                          coefficient
Intercept             0.22005691793408
petallengthcm        -1.21492250709494
sepallengthcm        0.563205058441283
```



5.2.8.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.

- **model_type:** Model type (="svm_classifier").
- **model_category:** Model category (="binomial").

5.2.8.3 methods

```
svm_classifier.accuracy(threshold=0.5)
# Returns the model accuracy

svm_classifier.add_to_rvd(rvd, name="svm_classifier_pred"+str(np.random.
    randint(10000)))
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name

svm_classifier.auc()
# Returns the model auc

svm_classifier.confusion_matrix()
# Returns the model confusion matrix

svm_classifier.details()
# Returns the model details.

svm_classifier.error_rate()
# Returns the model error rate.

svm_classifier.features_importance(show=True, with_intercept=False)
# Returns the model features importance.

svm_classifier.lift_table(num_bins=100, color=["dodgerblue","#444444"], show=
    True)
# Draw model lift table.

svm_classifier.logloss()
# Returns the model logloss.

svm_classifier.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = iteration_count | rejected_row_count | accepted_row_count |
     *
# show = Print the parameter in the Terminal

svm_classifier.plot(marker=["o","^"], color=None, projection=None,
    max_nb_points=None)
# Plot the logistic regression regression using matplotlib
# marker = [0_marker, 1_marker]
```

```
# color = [0_color, 1_color, logit_color]
# projection = project the plan in a smaller space
# max_nb_points = maximum number of points in the graph

svm_classifier.roc(color=["dodgerblue","#444444"], show=True)
# Draw model roc.
```

5.2.9 SVM Regressor (svm_regressor)

5.2.9.1 initialization

```
svm_regressor(model_name, input_relation, response_column, predictor_columns,
    cursor, C=1.0, epsilon=1e-3, max_iterations=100)
```

Trains the SVM model on an input table or view.

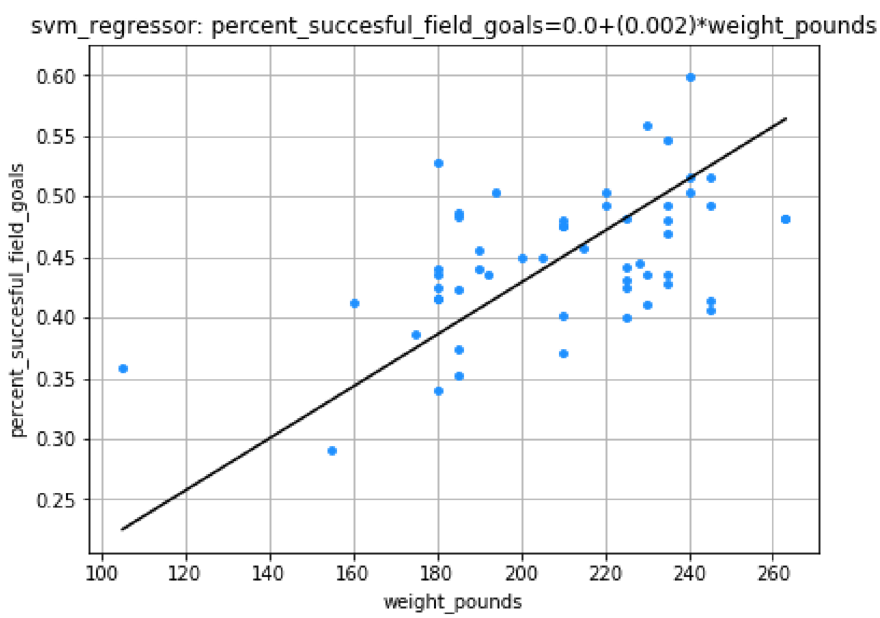
Parameters

- **model_name:** *<str>*
  The model name.
- **input_relation:** *<str>*
  The table or view that contains the training samples.
- **response_column:** *<list of str>*
  The name of the column in input_relation that represents the dependent variable.
- **predictor_columns:** *<list of str>*
  The list of the columns in the input_relation that represent the independent variables for the model.
- **cursor:** *<object>*
  The database cursor.
- **C:** *<positive float>*, optional
  Sets the weight for misclassification cost. The algorithm minimizes the regularization cost and the misclassification cost.
- **epsilon:** *<positive float>*, optional
  Used to control accuracy.
- **max_iterations:** *<positive int>*, optional
  Determines the maximum number of iterations that the algorithm performs before achieving the specified accuracy result.

Example

```
from vertica_ml_python import svm_regressor

svm_basketball=svm_regressor(model_name="svm_reg_basketball",input_relation="
    basketball", response_column="percent_succesful_field_goals",
    predictor_columns=["weight_pounds"], cursor=cur)
```

```
print(svm_basketball)
svm_basketball.plot()

#Output
model_type='svm_regressor'
model_name='svm_reg_basketball'
input_relation='basketball'
response_column='percent_succesful_field_goals'
predictor_columns='weight_pounds'
iteration_count: 39
rejected_row_count: 0
accepted_row_count: 54
Parameters:
                               coefficient
Intercept            1.06783202914075e-05
weight_pounds         0.00214424218188763
```



5.2.9.2 attributes

- **cursor:** Database cursor.
- **model_name:** Model name.
- **input_relation:** Input Relation.
- **response_column:** Response Column.
- **predictor_columns:** Predictor Columns.
- **model_type:** Model type (="svm_regressor").
- **model_category:** Model category (="regression").

5.2.9.3 methods

```
svm_regressor.add_to_rvd(rvd, name="svm_regressor_pred"+str(np.random.randint
    (10000)))
# Add the prediction to the RVD
# rvd = the corresponding RVD
# name = RVC name

svm_regressor.details()
# Returns the model details.

svm_regressor.features_importance(show=True)
# Returns the model features importance.

svm_regressor.metrics()
# Returns the model metrics.

svm_regressor.mse()
# Returns the model mse.

svm_regressor.parameter_value(parameter_name="*", show=True)
# Returns the parameter value
# parameter_name = iteration_count | rejected_row_count | accepted_row_count |
    *
# show = Print the parameter in the Terminal

svm_regressor.plot(color=None, projection=None, max_nb_points=1000)
# Plot the svm regression using matplotlib
# color = [points_color, plan_color]
# projection = project the plan in a smaller space
# max_nb_points = maximum number of points in the graph

svm_regressor.rsquared()
# Returns the model rsquared.
```