Trusted Analytics Documentation

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Part I

Technical Summary

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CHAPTER

ONE

OVERVIEW

Trusted Analytics is a platform that simplifies applying *graph analytics* and *machine learning* to big data for superior knowledge discovery and predictive modeling across a wide variety of use cases and solutions. Trusted Analytics provides an analytics pipeline (ATK) spanning feature engineering, graph construction, graph analytics, and machine learning using an extensible, modular framework. By unifying graph and entity-based machine learning, machine learning developers can incorporate an entity's nearby relationships to yield superior predictive models that better represent the contextual information in the data. All functionality operates at full scale, yet are accessed using a higher level Python data science programming abstraction to significantly ease the complexity of cluster computing and parallel processing. The platform is fully extensible through a plugin architecture that allows incorporating the full range of analytics and machine learning for any solution need in a unified workflow that frees the researchers from the overhead of understanding, integrating, and inefficiently iterating across a diversity of formats and interfaces.

CHAPTER

TWO

PYTHON AND DATA FRAME USER INTERFACE SUMMARY

ATK utilizes Python data science abstractions to make programming fully scalable big data analytic workflows using Spark/Hadoop clusters as familiar and accessible as using popular desktop machine learning solutions such as Pandas and SciKit Learn. The scalable data frame representation is more familiar and intuitive to data researchers compared to low level HDFS file and Spark RDD formats. ATK provides an extensive library to manipulate the data frames for feature engineering and exploration, such as joins and aggregations. User-defined transformations and filters can be written in Python and applied to terabytes (and more) of data using distributed processing. Machine learning algorithms are also invoked as higher-level data science API (Application Programming Interface) abstractions, making model development (such as creating parallel recommender systems or training classifier and clustering models) accessible to a broad population of researchers possessing mainstream data science programming skills. For more information, see the section on process flow and the Python website[1].

[1] http://www.python.org

CHAPTER

THREE

GRAPH PIPELINE SUMMARY

In addition to enabling use of entity-based data representations and algorithms, the toolkit provides a full graph pipeline to enable application of graph methods to big data. Graph representations are broadly useful, for example to link disparate data using arbitrary edge types, and then analyze the connections for powerful predictive signals that can otherwise be missed with entity-based methods. Working with graph representations can often be more intuitive and computationally efficient for data sets where the connections between data observations are more numerous and more important than the data points alone. ATK offers a representation of graph data as fully-scalable property graph objects with vertices, edges, and associated properties. The pipeline brings together into one workflow all the capabilities to create and analyze graph objects, including engineering features, linking data, performing rich traversal queries, and applying graph-based algorithms. Because data scientists often need to iterate analysis using both graph and frame representations (for example, applying a clustering algorithm to a vertex list with features developed using graph analytics), ATK provides the seamless ability to move between both data representations.

CHAPTER

FOUR

GRAPH ANALYTICS SUMMARY

Fully-scalable graph analytic algorithms are provided for uncovering central influences and communities in the data set. This ability is useful for exploring the data, as well as for incorporating as machine learning features that incorporate the context of an entity in the graph, thus creating better, more predictive, machine learning results.

CHAPTER

FIVE

MACHINE LEARNING SUMMARY

The toolkit provides algorithms for supervised, unsupervised, and semi-supervised machine learning using both entity and graphical machine learning tools. Graph machine learning algorithms such as label propagation and loopy belief propagation, exploit the connections in the graph structure and provide powerful new methods of labeling or classifying graph data. Examples of other machine learning capabilities provided include recommender systems using alternating least squares and conjugate gradient descent, topic modeling using Latent Dirchelet Allocation, clustering using K-means, and classification using logistic regression. See the section on machine learning and the API for further information.

CHAPTER

SIX

PLUGINS SUMMARY

In addition to the extensive set of capabilities provided, the platform is fully extensible using a plugin architecture. This allows developers to incorporate graph analytical tools into the existing range of machine learning abilities, expanding the capabilities of Trusted Analytics for new problem solutions. Plugins are developed using a thin Scala wrapper, and the ATK framework automatically generates a Python presentation for those added functions. Plug-ins can be used for a range of purposes, such as developing custom algorithms for specialized data types, building custom transformations for commonly used functions to get higher performance than a UDF (Python User-defined Function), or integrating other tools to further unify the workflow. See the Plugin Authoring Guide for more information.

Part II

User Manual

CHAPTER

SEVEN

GETTING STARTED

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7.1 Open-Source

Trusted Analytics uses standards and open-source routines from Apache Hadoop[1] such as HDFS (Hadoop Distributed File System), *MapReduce*, YARN, as well as Apache Giraph[2] for graph-based machine learning and graph analytics. The Titan graph database can be queried using the Gremlin[3] graph query language from TinkerPop.

7.2 Features

- Import routines read and convert data from several different formats
- Data cleaning tools prepare the data by removing erroneous values, transforming values to a normalized state and constructing new features through manipulating existing values
- Analysis and machine learning algorithms give deeper insight into the data

7.3 Script Examples

Trusted Analytics ships with example Python scripts and data sets that exercise the various features of the platform. The default location for the example scripts is atkuser's home directory '/home/atkuser'.

The examples are located in '/home/trustedanalytics/examples':

```
-rwxr-xr-- 1 atkuser atkuser  904 Jul 30 04:20 als.py
-rwxr-xr-- 1 atkuser atkuser  921 Jul 30 04:20 cgd.py
-rwxr-xr-- 1 atkuser atkuser 1078 Jul 30 04:20 lbp.py
-rwxr-xr-- 1 atkuser atkuser  707 Aug  7 18:21 lda.py
-rwxr-xr-- 1 atkuser atkuser  930 Jul 30 04:20 lp.py
```

[1] http://hadoop.apache.org/
[2] http://giraph.apache.org/
[3] https://github.com/tinkerpop/gremlin/wiki

```
-rwxr-xr-- 1 atkuser atkuser  859 Jul 30 04:20 movie_graph_5mb.py
-rwxr-xr-- 1 atkuser atkuser  861 Jul 30 04:20 movie_graph_small.py
-rwxr-xr-- 1 atkuser atkuser  563 Jul 30 04:20 pr.py
```

The datasets are located in '/home/trustedanalytics/examples/datasets' and 'hdfs://user/trustedanalytics/datasets/':

```
-rw-r--r--  ...  /user/trustedanalytics/datasets/README
-rw-r--r--  ...  /user/trustedanalytics/datasets/apl.csv
-rw-r--r--  ...  /user/trustedanalytics/datasets/lbp_edge.csv
-rw-r--r--  ...  /user/trustedanalytics/datasets/lp_edge.csv
-rw-r--r--  ...  /user/trustedanalytics/datasets/movie_sample_data_5mb.csv
-rw-r--r--  ...  /user/trustedanalytics/datasets/movie_sample_data_small.csv
-rw-r--r--  ...  /user/trustedanalytics/datasets/recommendation_raw_input.csv
-rw-r--r--  ...  /user/trustedanalytics/datasets/test_lda.csv
```

The datasets in '/home/trustedanalytics/examples/datasets' are for reference. The actual data that is being used by the Python examples and the Trusted Analytics server is in the HDFS system.

To get access to the scripts, login as atkuser and go to the example scripts directory:

```
$ sudo su atkuser
$ cd /home/trustedanalytics/examples
```

To run any of the Python example scripts type:

```
$ python <SCRIPT_NAME>
```

where "<SCRIPT_NAME>" is any of the scripts.

CHAPTER

EIGHT

PROCESS FLOW EXAMPLES

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8.1 Python Path Setup

It is recommended that the location of the 'trustedanalytics' directory be added to the PYTHONPATH environmental variable prior to starting Python. This can be done from a shell script, like this:

```
PYTHONPATH=$PYTHONPATH:/usr/lib/
export PYTHONPATH
python
```

This way, from inside Python, it is easy to load and connect to the REST server:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

8.2 Raw Data

Data is made up of variables of heterogeneous types (for example: strings, integers, and floats) that can be organized as a collection of rows and columns, similar to a table or spreadsheet. Each row corresponds to the data associated with one observation, and each column corresponds to a variable being observed. See the Python API *Data Types* for a current list of data types supported.

Connect to the server:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

Note: Sometimes it is helpful to see the details of the python stack trace upon error. Setting the *show_details* to `True` causes the full python stack trace to be printed, rather than a friendlier digest.

```
>>> ta.errors.show_details = True
```

To see the data types supported:

```
>>> print ta.valid_data_types
```

You should see a list of variable types similar to this:

```
float32, float64, int32, int64, unicode
(and aliases: float->float64, int->int32, long->int64, str->unicode)
```

Note: Although Trusted Analytics utilizes the NumPy package, NumPy values of positive infinity (np.inf), negative infinity (-np.inf) or nan (np.nan) are treated as None. Results of any user-defined functions which deal with such values are automatically converted to None, so any further usage of those data points should treat the values as None.

8.2.1 Ingesting the Raw Data

See the API section *Data Sources* for the various methods of ingesting data.

Importing a CSV file.

These are some rows from a CSV file:

```
"string",123,"again",25.125
"next",5,"or not",1.0
"fail",1,"again?",11.11
```

CSV files contain rows of information separated by new-line characters. Within each row, the data fields are separated from each other by some standard character. In the above example, the separating character is a comma (,).

To import data, you must tell the system how the input file is formatted. This is done by defining a *schema*. Schemas are constructed as a list of tuples, each of which contains pairs of *ASCII*-character names and data types (see *Valid Data Types*), ordered according to the order of columns in the input file.

Given a file *datasets/small_songs.csv* whose contents look like this:

```
1,"Easy on My Mind"
2,"No Rest For The Wicked"
3,"Does Your Chewing Gum"
4,"Gypsies, Tramps, and Thieves"
5,"Symphony No. 5"
```

Create a variable to hold the file name (for easier reuse):

```
>>> my_data_file = "datasets/small_songs.csv"
```

Create the schema *my_schema* with two columns: *id* (int32), and *title* (str):

```
>>> my_schema = [('id', ta.int32), ('title', str)]
```

The schema and file name are used in the CsvFile() command to describe the file format:

```
>>> my_csv_description = ta.CsvFile(my_data_file, my_schema)
```

The data fields are separated by a character delimiter. The default delimiter to separate column data is a comma. It can be changed with the parameter *delimiter*:

```
>>> my_csv_description = ta.CsvFile(my_data_file, my_schema, delimiter = ",")
```

This can be helpful if the delimiter is something other than a comma, for example, `\t` for tab-delimited records.

Occasionally, there are header lines in the data file. For example, these lines may describe the source or format of the data. If there are lines at the beginning of the file, they should be skipped by the import mechanism. The number of lines to skip is specified by the *skip_header_lines* parameter:

```
>>> csv_description = ta.CsvFile(my_data_file, my_schema, skip_header_lines = 5)
```

Now we use the schema and the file name to create CsvFile classes, which define the data layouts:

```
>>> my_csv = ta.CsvFile(my_data_file, my_schema)
>>> csv1 = ta.CsvFile(file_name="data1.csv", schema=schema_ab)
>>> csv2 = ta.CsvFile(file_name="more_data.txt", schema=schema_ab)

>>> raw_csv_data_file = "datasets/my_data.csv"
>>> column_schema_list = [("x", ta.float64), ("y", ta.float64), ("z", str)]
>>> csv4 = ta.CsvFile(file_name=raw_csv_data_file,
... schema=column_schema_list, delimiter='|', skip_header_lines=2)
```

8.3 Frames

A *Frame (capital F)* is a class of objects capable of accessing and controlling a *frame (lower case f)* containing "big data". The frame is visualized as a two-dimensional table structure of rows and columns. Trusted Analytics can handle frames with large volumes of data, because it is designed to work with data spread over multiple machines.

8.3.1 Create a Frame

There are several ways to create frames:

1. as "empty", with no schema or data
2. with a schema and data
3. by copying (all or a part of) another frame
4. as a return value from a Frame-based method; this is part of the ETL data flow.

See the Python API *Frames section* for more information.

Examples:

Create an empty frame:

```
>>> my_frame = ta.Frame()
```

The Frame *my_frame* is now a Python object which references an empty frame that has been created on the server.

For an example, to create a frame defined by the schema *my_csv* (see *Importing a CSV file.*), import the data, give the frame the name *myframe*, and create a Frame object, *my_frame*, to access it:

```
>>> my_frame = ta.Frame(source=my_csv, name='myframe')
```

To copy the frame *myframe*, create a Frame *my_frame2* to access it, and give it a new name, because the name must always be unique:

```
>>> my_frame2 = my_frame.copy(name = "copy_of_myframe")
```

To create a new frame with only columns *x* and *z* from the original frame *myframe*, and save the Frame object as *my_frame3*:

```
>>> my_frame3 = my_frame.copy(['x', 'z'], name = "copy2_of_myframe")
```

To create a frame copy of the original columns *x* and *z*, but only those rows where *z* is TRUE:

```
>>> my_frame4 = my_frame.copy(['x', 'z'], where = (lambda row: "TRUE" in row.z),
... name = "copy_of_myframe_true")
```

Frames (capital 'F') are not the same thing as frames (lower case 'f'). Frames (lower case 'f') contain data, viewed similarly to a table, while Frames are descriptive pointers to the data. Commands such as `f4 = my_frame` will only give you a copy of the Frame proxy pointing to the same data.

Let's create a Frame and check it out:

```
>>> small_songs = ta.Frame(my_csv, name = "small_songs")
>>> small_songs.inspect()
>>> small_songs.get_error_frame().inspect()
```

Append:

The *append* method adds rows and columns of data to a frame. Columns and rows are added to the database structure, and data is imported as appropriate. If columns are the same in both name and data type, the appended data will go into the existing column.

As an example, let's start with a frame containing two columns *a* and *b*. The frame can be accessed by Frame *my_frame1*. We can look at the data and structure of the database by using the *inspect* method:

```
>>> my_frame1.inspect()

  a:str   b:ta.int64
/--------------------/
  apple           182
  bear             71
  car            2048
```

Given another frame, accessed by Frame *my_frame2* with one column *c*:

```
>>> my_frame2.inspect()

  c:str
/-------/
  dog
  cat
```

With *append*:

```
>>> my_frame1.append(my_frame2)
```

The result is that the first frame would have the data from both frames. It would still be accessed by Frame *my_frame1*:

```
>>> my_frame1.inspect()

  a:str     b:ta.int64     c:str
/--------------------------------/
  apple        182          None
  bear          71          None
  car         2048          None
  None        None          dog
  None        None          cat
```

Try this example with data files *objects1.csv* and *objects2.csv*:

```
>>> objects1 = ta.Frame(ta.CsvFile("datasets/objects1.csv",
... schema=[('Object', str), ('Count', ta.int64)],
... skip_header_lines=1), 'objects1')
>>> objects2 = ta.Frame(ta.CsvFile("datasets/objects2.csv",
... schema=[('Thing', str)], skip_header_lines=1), 'objects2')

>>> objects1.inspect()
>>> objects2.inspect()

>>> objects1.append(objects2)
>>> objects1.inspect()
```

See also the *join* method in the API section.

8.3.2 Inspect the Data

Trusted Analytics provides several methods that allow you to inspect your data, including *inspect* and *take*. The Frame class also contains frame information like *row_count*.

Examples

To see the number of rows:

```
>>> objects1.row_count
```

To see the number of columns:

```
>>> len(objects1.schema)
```

To see all the Frame data:

```
>>> objects1
```

To see two rows of data:

```
>>> objects1.inspect(2)
```

Gives you something like this:

```
  a:ta.float64  b:ta.int64
/--------------------------/
    12.3000            500
   195.1230         183954
```

Using the take() method, makes a list of lists of frame data. Each list has the data from a row in the frame accessed by the Frame, in this case, 3 rows beginning from row 2.

```
>>> subset_of_objects1 = objects1.take(3, offset=2)
>>> print subset_of_objects1
```

Gives you something like this:

```
[[12.3, 500], [195.123, 183954], [12.3, 500]]
```

Note: The row sequence of the data is NOT guaranteed to match the sequence of the input file. When the data is spread out over multiple clusters, the original sequence of rows from the raw data is lost. Also, the sequence order of the columns is changed (from original data) by some commands.

Some more examples to try:

```
>>> animals = ta.Frame(ta.CsvFile("datasets/animals.csv",
... schema=[('User', ta.int32), ('animals', str), ('int1', ta.int64),
... ('int2', ta.int64), ('Float1', ta.float64), ('Float2',
... ta.float64)], skip_header_lines=1), 'animals')
>>> animals.inspect()
>>> freq = animals.top_k('animals', animals.row_count)
>>> freq.inspect(freq.row_count)

>>> from pprint import *
>>> summary = {}
>>> for col in ['int1', 'int2', 'Float1', 'Float2']:
...     summary[col] = animals.column_summary_statistics(col)
...     pprint(summary[col])
```

8.3.3 Clean the Data

The process of "data cleaning" encompasses the identification and removal or repair of incomplete, incorrect, or malformed information in a data set. The Trusted Analytics Python API provides much of the functionality necessary for these tasks. It is important to keep in mind that it was designed for data scalability. Thus, using external Python packages for these tasks, while possible, may not provide the same level of efficiency.

Warning: Unless stated otherwise, cleaning functions use the Frame proxy to operate directly on the data, so they change the data in the frame, rather than return a new frame with the changed data. It is recommended that you copy the data to a new frame on a regular basis and work on the new frame. This way, you have a fallback if something does not work as expected:

```
>>> next_frame = current_frame.copy()
```

In general, the following functions select rows of data based upon the data in the row. For details about row selection based upon its data see Python User Functions.

Example of data cleaning:

```
>>> def clean_animals(row):
...     if 'basset hound' in row.animals:
...         return 'dog'
...     elif 'guinea pig' in row.animals:
...         return 'cavy'
...     else:
...         return row.animals

>>> animals.add_columns(clean_animals, ('animals_cleaned', str))
>>> animals.drop_columns('animals')
>>> animals.rename_columns({'animals_cleaned' : 'animals'})
```

Drop Rows:

The *drop_rows* method takes a predicate function and removes all rows for which the predicate evaluates to `True`.

Examples:

Drop any rows in the animals frame where the value in column *int2* is negative:

```
>>> animals.drop_rows(lambda row: row['int2'] < 0)
```

To drop any rows where *a* is empty:

```
>>> my_frame.drop_rows(lambda row: row['a'] is None)
```

To drop any rows where any column is empty:

```
>>> my_frame.drop_rows(lambda row: any([cell is None for cell in row]))
```

Filter Rows:

The *filter* method is like *drop_rows*, except it removes all rows for which the predicate evaluates to False.

Examples:

To delete those rows where field *b* is outside the range of 0 to 10:

```
>>> my_frame.filter(lambda row: 0 >= row['b'] >= 10)
```

Drop Duplicates:

The *drop_duplicates* method performs a row uniqueness comparison across the whole table.

Examples:

To drop any rows where the data in *a* and column *b* are duplicates of some previously evaluated row:

```
>>> my_frame.drop_duplicates(['a', 'b'])
```

To drop all duplicate rows where the columns *User* and *animals* are duplicate:

```
>>> animals.drop_duplicates(['User', 'animals'])
>>> animals.inspect(animals.row_count)
```

Drop Columns:

Columns can be dropped either with a string matching the column name or a list of strings:

```
>>> my_frame.drop_columns('b')
>>> my_frame.drop_columns(['a', 'c'])
```

Rename Columns:

Columns can be renamed by giving the existing column name and the new name, in the form of a dictionary. Unicode characters should not be used for column names.

Rename *a* to "id":

```
>>> my_frame.rename_columns({'a': 'id'})
```

Rename column *b* to "author" and *c* to "publisher":

```
>>> my_frame.rename_columns({'b': 'author', 'c': 'publisher'})
```

8.3.4 Transform the Data

Often, you will need to create new data based upon the existing data. For example, you need the first name combined with the last name, or you need the number of times John spent more than five dollars, or you need the average age of students attending a college.

Add Columns:

Columns can be added to the frame using values from other columns as their value.

Add a column *int1_times_int2* as an ta.float64 and fill it with the contents of column *int1* and column *int2* multiplied together:

```
>>> animals.add_columns(lambda row: row.int1*row.int2, ('int1xint2',
... ta.float64))
```

Add a new column *all_ones* and fill the entire column with the value 1:

```
>>> animals.add_columns(lambda row: 1, ('all_ones', ta.int64))
```

Add a new column *float1_plus_float2* and fill the entire column with the value of column *float1* plus column *float2*, then save a summary of the frame statistics:

```
>>> animals.add_columns(lambda row: row.Float1 + row.Float2,
... ('Float1PlusFloat2', ta.float64))
>>> summary['Float1PlusFloat2'] =
... animals.column_summary_statistics('Float1PlusFloat2')
```

Add a new column *pwl*, type ta.float64, and fill the value according to this table:

value in column *float1_plus_float2*	value for column *pwl*
None	None
Less than 50	*float1_plus_float2* times 0.0046 plus 0.4168
At least 50 and less than 81	*float1_plus_float2* times 0.0071 plus 0.3429
At least 81	*float1_plus_float2* times 0.0032 plus 0.4025
None of the above	None

An example of Piecewise Linear Transformation:

```
>>> def piecewise_linear_transformation(row):
...     x = row.float1_plus_float2
...     if x is None:
...         return None
...     elif x < 50:
...         m, c =0.0046, 0.4168
...     elif 50 <= x < 81:
...         m, c =0.0071, 0.3429
...     elif 81 <= x:
...         m, c =0.0032, 0.4025
...     else:
...         return None
...     return m * x + c

>>> animals.add_columns(piecewise_linear_transformation, ('pwl', ta.float64))
```

Create multiple columns at once by making a function return a list of values for the new frame columns:

```
>>> animals.add_columns(lambda row: [abs(row.int1), abs(row.int2)],
... [('abs_int1', ta.int64), ('abs_int2', ta.int64)])
```

8.3.5 Examining the Data

To get standard descriptive statistics information about my_frame, use the frame function *column_summary_statistics*:

```
>>> my_frame.column_summary_statistics()
```

Group by (and aggregate):

Rows can be grouped together based on matching column values, after which an aggregation function can be applied on each group, producing a new frame.

Example process of using aggregation based on columns:

1. given our frame of animals

2. create a new frame and a Frame *grouped_animals* to access it
3. group by unique values in column *animals*
4. average the grouped values in column *int1* and save it in a column *int1_avg*
5. add up the grouped values in column *int1* and save it in a column *int1_sum*
6. get the standard deviation of the grouped values in column *int1* and save it in a column *int1_stdev*
7. average the grouped values in column *int2* and save it in a column *int2_avg*
8. add up the grouped values in column *int2* and save it in a column *int2_sum*

```
>>> grouped_animals = animals.group_by('animals', {'int1': [ta.agg.avg,
... ta.agg.sum, ta.agg.stdev], 'int2': [ta.agg.avg, ta.agg.sum]})
>>> grouped_animals.inspect()
```

Note: The only columns in the new frame will be the grouping column and the generated columns. In this case, regardless of the original frame size, you will get six columns.

Example process of using aggregation based on both column and row together:

1. Using our data accessed by *animals*, create a new frame and a Frame *grouped_animals2* to access it
2. Group by unique values in columns *animals* and *int1*
3. Using the data in the *float1* column, calculate each group's average, standard deviation, variance, minimum, and maximum
4. Count the number of rows in each group and put that value in column *int2_count*
5. Count the number of distinct values in column *int2* for each group and put that number in column *int2_count_distinct*

```
>>> grouped_animals2 = animals.group_by(['animals', 'int1'], {'Float1':
... [ta.agg.avg, ta.agg.stdev, ta.agg.var, ta.agg.min, ta.agg.max],
... 'int2': [ta.agg.count, ta.agg.count_distinct]})
```

Example process of using aggregation based on row:

1. Using our data accessed by *animals*, create a new frame and a Frame *grouped_animals2* to access it
2. Group by unique values in columns *animals* and *int1*
3. Count the number of rows in each group and put that value in column *count*

```
>>> grouped_animals2 = animals.group_by(['animals', 'int1'],
... ta.agg.count)
```

Note: `agg.count` is the only full row aggregation function supported at this time.

Aggregation currently supports using the following functions:

- avg
- count
- count_distinct
- max
- min
- stdev
- sum
- var (see glossary *Bias vs Variance*)

Join:

Create a **new** frame from a *join* operation with another frame.

Given two frames *my_frame* (columns *a*, *b*, *c*) and *your_frame* (columns *b*, *c*, *d*). For the sake of readability, in these examples we will refer to the frames and the Frames by the same name, unless needed for clarity:

```
>>> my_frame.inspect()

  a:str       b:str       c:str
/-----------------------------------/
  alligator   bear        cat
  auto        bus         car
  apple       berry       cantaloupe
  mirror      frog        ball

>>> your_frame.inspect()

  b:str       c:ta.int64     d:str
/----------------------------------/
  bus               871        dog
  berry            5218        frog
  blue                0        log
```

Column *b* in both frames is a unique identifier used to relate the two frames. Following this instruction will join *your_frame* to *my_frame*, creating a new frame with a new Frame to access it, with all of the data from *my_frame* and only that data from *your_frame* which has a value in *b* that matches a value in *my_frame b*:

```
>>> our_frame = my_frame.join(your_frame, 'b', how='left')
```

The result is *our_frame*:

```
>>> our_frame.inspect()

  a:str       b:str       c_L:str      c_R:ta.int64   d:str
/----------------------------------------------------------/
  alligator   bear        cat          None           None
  auto        bus         car           871           dog
  apple       berry       cantaloupe   5281           frog
  mirror      frog        ball         None           None
```

Doing an "inner" join this time will include only data from *my_frame* and *your_frame* which have matching values in *b*:

```
>>> inner_frame = my_frame.join(your_frame, 'b')
```

or

```
>>> inner_frame = my_frame.join(your_frame, 'b', how='inner')
```

Result is *inner_frame*:

```
>>> inner_frame.inspect()

  a:str       b:str       c_L:str      c_R:ta.int64   d:str
/----------------------------------------------------------/
  auto        bus         car              871        dog
  apple       berry       cantaloupe      5218        frog
```

Doing an "outer" join this time will include only data from *my_frame* and *your_frame* which do not have matching values in *b*:

```
>>> outer_frame = my_frame.join(your_frame, 'b', how='outer')
```

Result is *outer_frame*:

```
>>> outer_frame.inspect()

  a:str       b:str       c_L:str      c_R:ta.int64   d:str
/-----------------------------------------------------------/
  alligator   bear        cat            None         None
  mirror      frog        ball           None         None
  None        blue        None              0         log
```

If column *b* in *my_frame* and column *d* in *your_frame* are the common column: Doing it again but including all data from *your_frame* and only that data in *my_frame* which has a value in *b* that matches a value in *your_frame d*:

```
>>> right_frame = my_frame.join(your_frame, left_on='b', right_on='d',
... how='right')
```

Result is *right_frame*:

```
>>> right_frame.inspect()

  a:str      b_L:str      c:str      b_R:str    c:ta.int64   d:str
/---------------------------------------------------------------------/
  None       None         None       bus          871        dog
  mirror     frog         ball       berry       5218        frog
  None       None         None       blue           0        log
```

Flatten Column:

The function *flatten_column* creates a **new** frame by splitting a particular column and returns a Frame object. The column is searched for rows where there is more than one value, separated by commas. The row is duplicated and that column is spread across the existing and new rows.

Given a frame accessed by Frame *my_frame* and the frame has two columns *a* and *b*. The "original_data":

```
1-"solo,mono,single"
2-"duo,double"
```

Bring the data in where it can by worked on:

```
>>> my_csv = ta.CsvFile("original_data.csv", schema=[('a', ta.int64),
... ('b', str)], delimiter='-')
>>> my_frame = ta.Frame(source=my_csv)
```

Check the data:

```
>>> my_frame.inspect()

  a:ta.int64   b:string
/---------------------------------/
      1        solo, mono, single
      2        duo, double
```

Spread out those sub-strings in column *b*:

```
>>> your_frame = my_frame.flatten_column('b')
```

Now check again and the result is:

```
>>> your_frame.inspect()

  a:ta.int64   b:str
/-----------------------/
    1          solo
    1          mono
    1          single
    2          duo
    2          double
```

8.4 Seamless Graph

For the examples below, we will use a Frame *my_frame*, which accesses an arbitrary frame of data consisting of the `following`:

Employee	Manager	Title	Years
Bob	Steve	Associate	1
Jane	Steve	Sn Associate	3
Anup	Steve	Associate	3
Sue	Steve	Market Analyst	1
Mohit	Steve	Associate	2
Steve	David	Marketing Manager	5
Larry	David	Product Manager	3
David	Rob	VP of Sales	7

8.4.1 Build the Graph

Make an empty graph and give it a name:

```
>>> my_graph = ta.graph()
>>> my_graph.name = "personnel"
```

Define the vertex types:

```
>>> my_graph.define_vertex_type("employee")
>>> my_graph.define_vertex_type("manager")
>>> my_graph.define_vertex_type("title")
>>> my_graph.define_vertex_type("years")
```

Define the edge type:

```
>>> my_graph.define_edge_type('worksunder', 'Employee', 'Employee', directed=True)
```

Add the data:

```
>>> my_graph.vertices['Employee'].add_vertices(employees_frame,
... 'Employee', ['Title'])
>>> my_graph.edges['worksunder'].add_edges(employees_frame, 'Employee',
... 'Manager', ['Years'], create_missing_vertices = True)
```

Warning: Improperly built graphs can give inconsistent results. For example, given EdgeFrames with this data:

```
Movieid, movieTitle, Rating, userId
1, Titanic, 3, 1
1, My Own Private Idaho, 3, 2
```

If the vertices are built out of this data, the vertex with Movieid of 1 would sometimes have the Titanic data and sometimes would have the Idaho data, based upon which order the records are delivered to the function.

8.4.2 Other Graph Options

Inspect the graph:

```
>>> my_graph.vertex_count
>>> my_graph.edge_count
>>> my_graph.vertices['Employee'].inspect(20)
>>> my_graph.edges['worksunder'].inspect(20)
```

For further information, see the API section on *Graphs*. Export the graph to a TitanGraph:

```
>>> my_titan_graph = my_graph.export_to_titan("titan_graph")
```

Make a VertexFrame:

```
>>> my_vertex_frame = my_graph.vertices("employee")
```

Make an EdgeFrame:

```
>>> my_edge_frame = my_graph.edges("worksunder")
```

8.5 Titan Graph

For the examples below, we will use a Frame *my_frame*, which accesses an arbitrary frame of data consisting of the `following`:

Employee	Manager	Title	Years
Bob	Steve	Associate	1
Jane	Steve	Sn Associate	3
Anup	Steve	Associate	3
Sue	Steve	Market Analyst	1
Mohit	Steve	Associate	2
Steve	David	Marketing Manager	5
Larry	David	Product Manager	3
David	Rob	VP of Sales	7

8.5.1 Graph Creation

A Titan graph is created by exporting it from a seamless graph. For further information, as well as Titan graph attributes and methods, see the API section on *Titan Graph*.

Python User Functions

Table of Contents

A *UDF* is a Python function written by the user on the client-side which can execute in a distributed fashion on the cluster. The function is serialized and copies are distributed throughout the cluster as part of command execution. Various API command methods accept a UDF as a parameter. A UDF runs under the constraints of the particular command.

Frame Row UDF

A Frame Row UDF is a UDF which operates on a single row of a frame. The function has one parameter, a *row* object. Here is an example of a Row UDF that returns True for a row where the column named "score" has a value greater than zero:

```
>>> def my_custom_row_func(row):
...     return row['score'] > 0
```

This function would be useful in a Frame filter command, which filters a data frame keeping only those rows which meet certain criteria, – in this case, only rows with scores greater than zero:

```
>>> my_csv = CsvFile("tresults.txt", [('test', str), ('score', int32)])
>>> my_frame = Frame(my_csv)
>>> my_frame.filter(my_custom_row_func)
```

The filter command iterates over every row in the frame and evaluates the user-defined function on each one and keeps only those rows which evaluate to True.

Row Object Parameter The Row object is a read-only dictionary-like structure which contains the cell values for a particular row. The values are accessible using the column name, with typical Python square bracket lookup, as shown in the example above. The value of cell in column 'score' is accessed like this:

```
>>> row['score']
```

The cell values may also be accessed using *dot-member* notation. Here is an equivalent row function:

```
>>> def my_custom_row_func2(row):
...     return row.score > 0
```

The *dot-member* notation is provided for convenience (it follows the pandas DataFrame technique) and only works for columns whose names are legal Python variable names (it does not start with a number and is composed of alphanumeric characters and the underscore character). Columns whose names do not meet this criteria must be referenced using square brackets with strings.

New values must be added to a frame using the Frame's add_columns method.

The *row* object supports a few dictionary-like methods:

- *keys()* – returns a list of column names
- *values()* – returns a list of column values
- *items()* – returns a list of (key, value) tuples

- *types()* – returns a list of column types

These methods all produce lists in the same order, in other words, it is safe to correlate their indices.

Also, iterating on the row object is the equivalent of iterating on items(). For example:

```
>>> def row_sum(row):
...     """
...     sums the values in the row, except for column "name"
...     """
...     try:
...         s = 0
...         for k, v in row:
...             if k != 'name':
...                 sum += v
...         return s
...     except:
...         return -1

>>> frame.add_columns(row_sum, ('sum', int32))
```

Note: This example is for illustration only. There are other, perhaps more Pythonic, ways of doing this, like using a list comprehension.

UDF Guidelines

Here are some guidelines to follow when writing a UDF:

1. Error handling: Include error handling. If the function execution raises an exception, it will cause the entire command to fail and possibly leave the frame or graph in an incomplete state. The best practice is to put all UDF functionality in a `try: except:` block, where the `except:` clause returns a default value or performs a benign side effect. See the `row_sum` function example above, where we used a `try: except:` block and produced a -1 for rows which caused errors.
2. Dependencies: All dependencies used in the UDF must be available in **the same Python code file** as the UDF or available in the server's installed Python libraries. The serialization technique to get the code distributed throughout the cluster will only serialize dependencies in the same Python module (in other words, file) right now.
3. Simplicity: Stay within the intended simple context of the given command, like a row operation. Do not try to call other API methods or perform fancy system operations (which will fail due to permissions).
4. Performance: Be mindful of performance. These functions execute on every row of data, in other words, several times.
5. Printing: Printing (to stdout, stderr, . . .) within the UDF will not show up in the client REPL. Such messages will usually end up in the server logs. In general, avoid printing.
6. Lambda: Lambda syntax is valid, but discouraged:

   ```
   >>> frame.filter(lambda row: row.score > 0)
   ```

   This is legal and attractively shorter to write. However, lambdas do not provide error handling, nor do they have a "name" that would be useful in exception stack traces. They cannot be tested in isolation nor have embedded documentation. Lambdas are not very shareable.
7. Closures: Closures are read-only. Any closed over variables are copied during serialization, so it is not possible to obtain side-effects.

8. Multiple executions: Do not make any assumptions about how many times the function may get executed.

9. Parameterizing a UDF: Parameterizing a UDF is possible using Python techniques of closures and nesting function definitions. For example, the Row UDF only takes a single row object parameter. It could be useful to have a row function that takes a few other parameters. Let's augment the row_sum function above to take a list of columns to ignore:

```
>>> def get_row_sum_func(ignore_list):
...     """
...     returns a row function which sums the values in the row,
...     except for ignored columns
...     """
...     def row_sum2(row):
...         try:
...             s = 0
...             for k, v in row:
...                 if k not in ignore_list:
...                     s += v
...             return s
...         except:
...             return -1
...         return row_sum2

>>> frame.add_columns(get_row_sum_func(['name', 'address']), ('sum', int32))
```

The `row_sum2` function closes over the *ignore_list* argument making it available to the row function that executes on each row.

CHAPTER

NINE

MACHINE LEARNING

Machine learning is the study of constructing algorithms that can learn from data.

When someone uses a search engine to perform a query, they are returned a ranked list of websites, ordered according to predicted relevance. Ranking these sites is typically done using page content, as well as the relevance of other sites that link to a particular page. Machine learning is used to automate this process, allowing search engine companies to scale this process up to billions of potential web pages.

Online retailers often use a machine learning algorithm called collaborative filtering to suggest products users might be interested in purchasing. These suggestions are produced dynamically and without the use of a specific input query, so retailers use a customer's purchase and browsing history, along with those of customers with whom shared interests can be identified. Implementations of collaborative filtering enable these recommendations to be done automatically, without directly involving analysts.

There are many other problems that are amenable to *machine learning* solutions. Translation of text for example is a difficult issue. A corpus of pre-translated text can be used to teach an algorithm a mapping from one language to another.

9.1 Algorithms

9.1.1 Machine Learning Algorithms

Table of Contents

Collaborative Filtering

See the models section of the API for details.

Graphical Models

Graphical models find more insights from structured noisy data. See graph API for details of the *Label Propagation* (LP) and *Loopy Belief Propagation* (LBP).

Topic Modeling

For Topic Modeling, see the LDA Model section of the API and http://en.wikipedia.org/wiki/Topic_model

9.2 Supervision

Trusted Analytics incorporates supervised, unsupervised, and semi-supervised machine learning algorithms. Supervised algorithms are used to learn the relationship between features in a dataset and some labeling schema, such as is in classification. For example, binary logistic regression builds a model for relating a linear combination of input features (e.g., high and low temperatures for a collection of days) to a known binary label (e.g., whether or not someone went for a trail run on that day). Once the relationship between temperature and running activity is learned, then the model can be used to make predictions about new running activity, given the days temperatures. Unsupervised machine learning algorithms are used to find patterns or groupings in data for which class labels are unknown. For example, given a data set of observations about flowers (e.g., petal length, petal width, sepal length, and sepal width), an unsupervised clustering algorithm could be used to cluster observations according to similarity. Then, a researcher could look for reasonable patterns in the groupings, such as "similar species appear to cluster together." Semi-supervised learning is the natural combination of these two classes of algorithms, in which unlabeled data are supplemented with smaller amounts of labeled data, with the goal of increasing the accuracy of learning. For more information on these approaches, the respective Wikipedia entries to these approaches provide an easy-to-read overview of their strengths and limitations.

9.3 Other Resources

There is plenty of literature on *machine learning* for those who want to gain a more thorough understanding of it. We recommend: Introduction to Machine Learning[1] and Wikipedia: Machine Learning[2]. You might find this link helpful as well: Everything You Wanted to Know About Machine Learning, But Were Too Afraid To Ask (Part Two)[3].

[1] http://alex.smola.org/drafts/thebook.pdf

[2] http://en.wikipedia.org/wiki/Machine_learning

[3] http://blog.bigml.com/2013/02/21/everything-you-wanted-to-know-about-machine-learning-but-were-too-afraid-to-ask-part-two/

CHAPTER

TEN

SCORING ENGINE

This section covers the scoring engine installation, configuration and start-up.

10.1 Installation

The scoring engine repositories are automatically installed as part of the ATK repositories.

10.2 Scoring Models Implementation

The scoring engine is independent of the streaming scoring model implementation. To obtain information concerning the model implementation, the scoring engine expects three files in a tar file:

1. The model implementation jar file.
2. A file *modelname.txt* that contains the name of the class that implements the scoring in the jar file.
3. The file that has the model bytes used by the scoring.

Note: If Trusted Analytics is used to build models, the *publish* method on the model will create the tar file needed by the scoring engine.

10.3 Configuration of the Engine

The scoring engine provides a configuration template file *application.conf.tpl* which is used to create a working configuration file *application.conf*. Copy the configuration template file to the working file name in the same folder:

```
$ cd /etc/trustedanalytics/scoring
$ sudo cp application.conf.tpl application.conf
```

Open the file with a text editor:

```
$ sudo vim application.conf
```

Modify the scoring engine section to indicate where the scoring tar file is located:

```
trustedanalytics.scoring-engine {
  archive-tar = "hdfs://scoring-server.company.com:8020/user/atkuser/kmeans.tar"
}
```

10.4 Starting the Scoring Engine Service

Once the application.conf file has been modified, the scoring engine can be started:

```
$ sudo service scoring-engine start
```

Launch the rest server for the engine:

```
GET /v1/models/[name]?data=[urlencoded record 1]
```

See the *REST API* for more information.

10.5 Scoring Client

An example python script to connect to the scoring engine:

```
>>> import requests
>>> import json
>>> headers = {'Content-type': 'application/json',
...            'Accept': 'application/json,text/plain'}
>>> r = requests.post('http://localhost:9100/v1/models/testjson?data=2', headers=headers)
```

CHAPTER

ELEVEN

BEST KNOWN METHODS (USER)

Table of Contents

11.1 Python

11.1.1 Server Connection

Ping the server:

```
>>> import trustedanalytics as ta
>>> ta.server.ping()
Successful ping to Trusted Analytics ATK at http://localhost:9099/info
>>> ta.connect()
```

View and edit the server connection:

```
>>> print ta.server
host:    localhost
port:    9099
scheme:  http
version: v1

>>> ta.server.host
'localhost'

>>> ta.server.host = '10.54.99.99'
>>> ta.server.port = None
>>> print ta.server
host:    10.54.99.99
port:    None
scheme:  http
version: v1
```

Reset configuration back to defaults:

```
>>> ta.server.reset()
>>> print ta.server
host:     localhost
port:     9099
scheme:   http
version: v1
```

11.1.2 Errors

By default, the toolkit does not print the full stack trace when exceptions occur. To see the full Python stack trace of the last (i.e. most recent) exception:

```
>>> ta.errors.last
```

To enable always printing the full Python stack trace, set the *show_details* property:

```
>>> import trustedanalytics as ta

# show full stack traces
>>> ta.errors.show_details = True

>>> ta.connect()

# ... the rest of your script ...
```

If you enable this setting at the top of your script you get better error messages. The longer error messages are really helpful in bug reports, emails about issues, etc.

11.1.3 Tab Completion

Allows you to use the tab key to complete your typing for you.

If you are running with a standard Python REPL (not iPython, bPython, or the like) you will have to set up the tab completion manually:

Create a .pythonrc file in your home directory with the following contents:

```
>>> import rlcompleter, readline
>>> readline.parse_and_bind('tab:complete')
```

Or you can just run the two lines in your REPL session.

This will let you do the tab completion, but will also remember your history over multiple sessions:

```
# Add auto-completion and a stored history file of commands to your Python
# interactive interpreter. Requires Python 2.0+, readline.

>>> import atexit
>>> import os
>>> import readline
>>> import rlcompleter
>>> import sys

# Autocomplete is bound to the Esc key by default, so change it to tab.
>>> readline.parse_and_bind("tab: complete")

>>> historyPath = os.path.expanduser("~/.pyhistory")
```

```
>>> def save_history(historyPath=historyPath):
...     import readline
...     readline.write_history_file(historyPath)

>>> if os.path.exists(historyPath):
...     readline.read_history_file(historyPath)

>>> atexit.register(save_history)

# anything not deleted (sys and os) will remain in the interpreter session
>>> del atexit, readline, rlcompleter, save_history, historyPath
```

Note: If the .pythonrc does not take effect, add PYTHONSTARTUP in your .bashrc file:

```
export PYTHONSTARTUP=~/.pythonrc
```

Part III

Extending Trusted Analytics

CHAPTER

TWELVE

PLUGIN AUTHORING GUIDE

Table of Contents

12.1 Introduction

Trusted Analytics provides an extensibility framework that allows new commands and algorithms to be added to the system at runtime, without requiring Trusted Analytics source code, nor recompiling the application.

Plug-ins should be easy to write, and should not require the author to have a deep understanding of the REST server, the execution engine, or any of its supporting libraries. In particular, plug-in authors should not have to understand issues like how to manage multiple threads of execution, user authentication, or marshaling of data to and from JSON.

Plug-ins should also be isolated from the application as a whole, as well as from other plug-ins. Each plug-in should be allowed to use whatever libraries it needs, without concern for conflicts with the libraries that Trusted Analytics uses for its own needs.

12.2 Types of Plugins

12.2.1 Commands and Queries

The most common kinds of plugins are primarily divided into two categories, commands and queries. Commands are actions that are typically initiated by user, that have some impact on the system, such as loading a data frame, or removing columns from one.

Queries are also initiated by users, but their purpose is to return data to a client, with no side effects.

The interfaces that command and query plug-ins implement are very similar, but it is important to use the correct interface so the system can preserve the expected performance and semantics.

The outputs of commands and queries, and the processing of them, are monitored by the Trusted Analytics processing engine.

12.3 When to Write a Plugin

Many of the operations and algorithms that are desirable to express can be written in Python using the Python client. However, some kinds of operations are inconvenient to express in that format, or require better performance than Python can provide.

Anytime there is a new function such as an analytical or *machine learning* algorithm that would be desirable to publish for use via the Python client or REST server, it is worth considering writing a CommandPlugin.

12.4 Plugin Support Services

12.4.1 Plugin Life Cycle

Plugins are loaded at application start up, and a start() method is called to perform any necessary one-time setup operations. When the application ends, a stop() method is called to do clean up operations. Calling stop(), or allowing stop() to complete, is not guaranteed, depending on how the server is terminated.

Each invocation resulting from a user action or other source will provide an execution context object that encapsulates the arguments passed by the user as well as other relevant metadata.

12.4.2 Logging and Error Handling

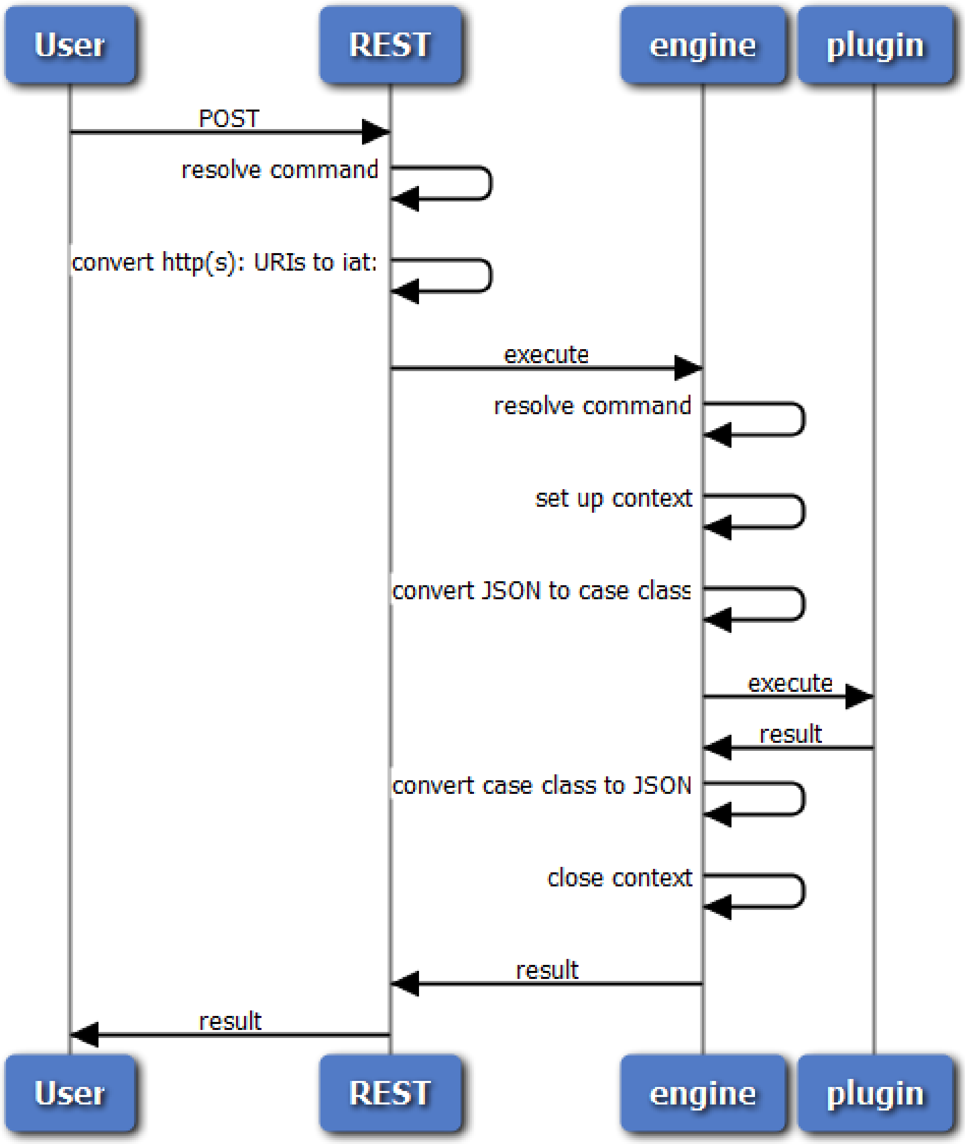
Errors that occur while running a plug-in will be trapped and reported in the same way that internal errors within Trusted Analytics are normally trapped and reported.

12.4.3 Defaulting Arguments

Authors should represent arguments that are not required using Option values. The system will supply default values for these optional values from the configuration system when the user's invocation does not provide them.

Configuration for commands and queries should be included in the Typesafe Config configuration file associated with the application (defaults can be provided by a reference.conf in the plugin's deployment jar). Configuration details are discussed in the "Configuration" section below. Plugins have access to the configuration, but only the section of it that contains settings that are relevant. For example, the Loopy Belief Propagation plugin gets its configuration from 'trustedanalytics.atk.giraph-plugins.command.graph.ml.loopy_belief_propagation.config'. Values that appear in this section are available to the plugin, and are passed to it during execution. The plugin does not have convenient access to other configuration parameters of the system, and plugin authors are strongly urged to take all configuration information from the Config instance they are passed rather than inspecting environment variables and so on.

12.4.4 Execution Flow



12.4.5 Accessing Spark or Other Components

For the time being, plugin authors may implement specific interfaces that declare their need for a particular service, for example, SparkSupport for direct access to a SparkContext.

See also `/dev_bkm`.

12.5 Creating a CommandPlugin

12.5.1 Naming

Naming the command correctly is crucial for the usability of the system. The Python client creates Python functions to match the commands in the engine, and it places them and names them in accordance with the name specified for the plugin.

Name components are separated by slashes. For instance, the command that drops columns from a dataframe is called dataframe/drop_column. The Python client sees that name, knows that dataframe commands are associated with the *Frame (capital F)* class, and therefore generates a function named drop_column on the Frame. When the user calls that function, its arguments will be converted to JSON, sent to the REST server, and then on to the engine for processing. The results from the engine flow back through the REST server, and are converted back to Python objects.

If the name of the command contains more than one slash, the Python client will create intermediate objects that allow functions to be grouped logically together. For example, if the command is named dataframe/ml/my_new_algorithm (of course, real algorithms will have better names!), then the method created in the Python client could be accessed on a frame *f* using `f.ml.my_new_algorithm()`. Commands can be nested as deeply as needed, any number of intermediary objects will be created automatically so the object model of the frame or graph matches the command tree structure defined by the command names in the system.

12.5.2 REST Input and Output

Each command or query plug-in should define two case classes: one for arguments, and one for return value. The plug-in framework will ensure that the user's Python (or JSON) commands are converted into an instance of the argument class, and the output from the plug-in will also be converted back to Python (or JSON) for storage in the command execution record for later return to the client.

12.5.3 Frame and Graph References

Usually, the commands associated with a frame or graph need to accept the frame or graph on which they should operate as a parameter. Use the class org.trustedanalytics.atk.domain.frame.FrameReference to represent frames, and org.trustedanalytics.atk.domain.graph.GraphReference to represent graphs.

12.5.4 Self Arguments

Use a FrameReference as the type, and place this parameter first in the case class definition if it is desired that this parameter is filled by the Frame instance whose method is being invoked by the user. Similarly, if the method is on a graph, using a GraphReference in the first position will do the trick for *TitanGraph* instances.

12.5.5 Single Value Results

The result returned by command plugins can be as complex as needed. It can also be very simple — for example, a single floating point value. Since the result type of the plugin must be a case class, the convention is to return a case class with one field, which must be named "value". When the client receives such a result, it should extract and return the single value.

12.6 Creating an Archive

Plugins are deployed in Archives – jar files that contain the plugin class, its argument and result classes, and any supporting classes it needs, along with a class that implements the Archive trait. The Archive trait provides the system with a directory of available services that the archive provides. On application start up, the application will query all the jar files it knows about (see below) to see what plugins they provide.

12.7 Deployment

Plug-Ins should be installed in the system using jar files. Jars that are found in the server's lib directory will be available to be loaded based on configuration. The plug-ins that will be installed must be listed in the application.conf file. Each command or query advertises the location at which it would prefer to be installed in the URL structure, and if no further directives appear in configuration, they will be installed according to their request. However, using the configuration file, it is also possible to remap a plug-in to a different location or an additional location in the URL structure.

In the future, plugin discovery may be further automated, and it may also be possible to add a plugin without restarting the server.

12.8 Configuration

Server-side configuration should be stored in the reference.conf file for the plugin archive. This is a Typesafe Config file (see https://github.com/typesafehub/config).

12.9 Archive Declaration

Each archive should have a reference.conf file stored as a resource in its jar file. For example, in a typical Maven-based project, this file might reside in the src/main/resources folder. The Typesafe Config library automatically finds resources named "reference.conf", so this is how the configuration file will be discovered.

The first section of the reference.conf should be the declaration of how the archive should be activated. This configuration should look like the following:

```
trustedanalytics.atk.component.archives {
    <archive-name> {
        class = "<archive-class>"
        parent = "<parent-archive>"
        config-path = "<path>"
    }
}
```

The <archive-name> is required. It should be replaced with the actual name of the archive (without the .jar suffix). For example, for graphon.jar, just use the word graphon by itself.

`<archive-class>` is optional. If provided, it must be the name of a class that can be found in the jar file or in its parent classloader. This class must implement the Archive trait, which makes it the archive manager. The archive manager is the service that the system uses to discover plugins in the archive. If omitted, this defaults to DefaultArchive, which uses the Config system for plugin registration and publishing.

`<parent>` is also optional. If provided, this archive is treated as dependent on whatever archive is specified here. For example, SparkCommand plugins should use "engine" for this entry, so that they have access to the same version of Spark the engine is using, as well as the SparkInvocation class.

`<config-path>` is also optional. It specifies the config path where the configuration for plugins for this archive can be found. If omitted, configuration is assumed to be included in the archive declaration block. It can be convenient to provide a vale for the config path because it leads to less nested config files.

Here is a sample config file for an archive that provides a single plugin. Note that it relies on the engine archive, and re-maps its configuration to "trustedanalytics.graphon" rather than including the configuration in the trustedanalytics.atk.component.archives.graphon section.

Also note the $-substitutions that allow configuration options from other sections to be pulled in so they're available to the plugin.

```
trustedanalytics.atk.component.archives {
    graphon {
        parent = "engine-core"
        config-path = "trustedanalytics.graphon"
    }
}

trustedanalytics.graphon {
    command {
        available = ["graphs.sampling.vertex_sample"]
        graphs {
            sampling {
                vertex_sample {
                    class = "com.trustedanalytics.spark.graphon.sampling.VertexSample"
                    config {
                        default-timeout = ${trustedanalytics.atk.engine.default-timeout}
                        titan = ${trustedanalytics.atk.engine.titan}
                    }
                }
            }
        }
    }
}

#included so that conf file can be read during unit tests,
#these will not be used when the application is actually running
trustedanalytics.atk.engine {
    default-timeout = 30s
    titan {}
}
```

12.10 Enabling the Archive

The command executor uses the config key "trustedanalytics.atk.engine.plugin.command.archives" to determine which archives it should check for command plugins. This setting is built into the reference.conf that is embedded in the engine archive (at the time of writing). For your installation, you can control this list using the application.conf file.

Once this setting has been updated, restart the server to activate the changes.

Part IV

Deploy and Run ATK App on DP2

CHAPTER THIRTEEN

INSTALLING REQUIRED PACKAGES

13.1 Install "golang" from the package manager

On RedHat/CentOS, ensure "EPEL" repo is enabled. For more information, see Yum Repo.

From the command line interface (terminal), install the "go" language and the required libraries.

```
$ sudo yum install golang
```

To read more about "go" see https://golang.org/ . To test the "go" installation, run the command `go`. The response should be similar to:

```
<show what it looks like>
```

Install the CloudFoundry CLI (Command Line Interface) package:

```
$ wget --content-disposition https://cli.run.pivotal.io/stable?release=redhat64
```

This downloads the pre-packaged RPM to your local machine. Install this package:

```
$ sudo yum install cf-cli_amd64.rpm
```

Note: See https://github.com/cloudfoundry/cli/releases for installation on a system not running RedHat/CentOS.

Test the package installation:

```
$ cf
< put response here>
```

Setting up CF for ATK deployment (Ireland instance): First run cf api https://api.run.gotapaas.eu to set your API endpoint. You should see a message like this: [hadoop@master[1] ~]$ cf api https://api.run.gotapaas.eu –skip-ssl-validation Setting api endpoint to https://api.run.gotapaas.eu... OK

API endpoint: https://api.run.gotapaas.eu (API version: 2.25.0) Not logged in. Use 'cf login' to log in. now try login by running the command "cf login -u admin -p c1oudc0w -o seedorg -s seedspace": Your output should look something like this:

```
[hadoop@master ~]$ cf login -u admin -p c1oudc0w -o seedorg -s seedspace
API endpoint: https://api.run.gotapaas.eu
Authenticating...
OK
Targeted org seedorg
Targeted space seedspace
API endpoint: https://api.run.gotapaas.eu (API version: 2.25.0)
```

[1] hadoop@master

```
User: admin
Org: seedorg
Space: seedspace
```

Verify that you are still connected by running "cf target" And your output looks like this:

```
[hadoop@master ~]$ cf target
API endpoint: https://api.run.gotapaas.eu (API version: 2.25.0)
User: admin
Org: seedorg
Space: seedspace
TBD
```

Prepare ATK tarball:

For QA:

ATK tarballs are built as part of the TeamCity build and are uploaded to S3. In order to download the file, simply run the command:

```
wget https://s3.amazonaws.com/gao-internal-archive/<Your_Branch_Name>/trustedanalytics.tar.gz
```

for example if you are on "master" branch you run:

```
wget https://s3.amazonaws.com/gao-internal-archive/master/trustedanalytics.tar.gz
```

For Dev:

You can build ATK tarball from scratch yourself. In order to do so, do the following:

1. CD to directory where your have the "atk" code checked out.
2. Build the atk code using Maven tool. Details for this change frequently, so please look at other Wiki pages like this one: Maven build
3. CD to "package" directory and from there run this script: "config/trustedanalytics-rest-server-tar/package.sh". This creates a tar file like "atk.tar.gz" in the current directory.
4. Deploy ATK to DP2 (Ireland instance): Create a directory anywhere on your system, for example at "~/vcap/app" and unpack your "trustedanalytics.tar.gz" inside that directory.
5. CD to "~/vcap/app" and create a file "manifest.yml" with this content: (For now please ensure you are using below memory and disk_quota values and do not change them)

```
applications:
- name: <YOUR_ATK_APP_NAME_HERE> for example "atk-ebi"
  command: bin/rest-server.sh
  memory: 1G
  disk_quota: 2G
  timeout: 180
  instances: 1
services:
- bryn-cdh
- <YOUR_POSTGRESQL_SERVICE_NAME_HERE> for example "pg-atk-ebi"
- bryn-zk
```

6. Create an instance of postgresql by running the command:

```
$ cf create-service postgresql93 free pg-atk-ebi
```

and you should see an output like this:

```
Creating service instance pg-atk-ebi in org seedorg / space seedspace as admin...
OK
```

7. Change conf/application.conf, making sure "fs.root" is set to:

```
fs.root = ${FS_ROOT}"/"${APP_NAME}
```

8. Change to the "~/vcap/app" folder (or wherever you have "trustedanalytics.tar.gz" unpacked).
9. Now run the command `cf push`. This takes a few minutes to run and you should see the following output:

```
[hadoop@master app]$ cf push
Using manifest file /home/hadoop/vcap/app/manifest.yaml
Creating app atk-ebi in org seedorg / space seedspace as admin...
OK
Using route atk-ebi.apps.gotapaas.eu
Binding atk-ebi.apps.gotapaas.eu to atk-ebi...
OK
Uploading atk-ebi...
Uploading app files from: /home/hadoop/vcap/app
Uploading 48.3K, 9 files
Done uploading
OK
Binding service bryn-cdh to app atk-ebi in org seedorg / space seedspace as admin...
OK
Binding service pg-atk-ebi to app atk-ebi in org seedorg / space seedspace as admin...
OK
Binding service bryn-zk to app atk-ebi in org seedorg / space seedspace as admin...
OK
Starting app atk-ebi in org seedorg / space seedspace as admin...
0 of 1 instances running, 1 starting
1 of 1 instances running
App started

OK
App atk-ebi was started using this command `bin/rest-server.sh`
Showing health and status for app atk-ebi in org seedorg / space seedspace as admin...
OK
requested state: started
instances: 1/1
usage: 1G x 1 instances
urls: atk-ebi.apps.gotapaas.eu
last uploaded: Wed May 20 22:22:54 UTC 2015
stack: cflinuxfs2
state since cpu memory disk details
#0 running 2015-05-20 03:25:13 PM 0.0% 622.9M of 1G 432.9M of 2G
```

If you like to see the complete configuration for your app, run the command "cf env atk-ebi".

10. Retrieve data from VCAP_APPLICATION uris.
11. Create a client credentials file. For more information, see https://github.com/trustedanalytics/atk/wiki/python-client
12. To tail your app logs:

```
cf logs atk-ebi
```

13. Open a Python2.7 or IPython session and do the following:

```
In [1]: import trustedanalytics as atk
In [2]: atk.connect("<PATH_TO_YOUR_CREDENTIALS_FILE")
Connected to intelanalytics server.
In [3]: atk.server.host
Out[3]: 'atk-ebi.apps.gotapaas.eu'
In [4]: exit
```

14. Ready to run some examples:

```
TBD
```

Part V

Python API

CHAPTER

FOURTEEN

CONNECT TO THE SERVER

Table of Contents

The Python client must 'connect' to an Trusted Analytics server before it can be used. Here is the 'connect' process described by the method's documentation:

`trustedanalytics.`**`connect`**`(`*self*, *credentials_file=None*`)`

Connect to the trustedanalytics server.

This method calls the server, downloads its API information and dynamically generates and adds the appropriate Python code to the Python package for this python session. Calling this method is required before invoking any server activity.

After the client has connected to the server, the server config cannot be changed. User must restart Python in order to change connection info.

Subsequent calls to this method invoke no action.

There is no "connection" object or notion of being continuously "connected". The call to connect is just a one-time process to download the API and prepare the client. If the server goes down and comes back up, this client will not recognize any difference from a connection point of view, and will still be operating with the API information originally downloaded.

Parameters credentials_file: str (optional)

file name of a credentials file. If supplied, it will override the settings authentication settings in the client's server configuration. The credentials file is normally obtained through the env.

14.1 Basic connecting

To use the default settings provided by the environment and/or configuration:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

To connect to a specific server:

```
>>> import trustedanalytics as ta
>>> ta.server.uri = 'myhost-name:port'
>>> ta.connect()
```

14.2 Connections requiring OAuth

To connect to a DP2 instance of Trusted Analytics, the python client must have an OAuth access token (see [oauth tokens](http://self-issued.info/docs/draft-ietf-oauth-v2-bearer.html)). The user must have a credentials file which holds an OAuth access token and a refresh token.

The user can create a credentials file using Trusted Analytics client running in an interactive python session. Call *create_credentials_file('filename_of_your_choice')* and interactively provide answers to its prompt.

```
$ python2.7

>>> import trustedanalytics as ta
>>> ta.create_connect_file('~/.ta/demo.creds')
OAuth server URI: uaa.my-dp2-domain.com
user name: dscientist9
Password: **********

Credentials created at '/home/dscientist9/.ta/demo.creds'
```

The credentials file can be specified when calling `connect` or set as an environmental variable $TA_CREDS.

```
>>> ta.connect('~/.ta/demo.creds')
Connected.  This client instance connected to
server http://my-ta-instance.my-dp2-apps-domain.com/v1
as user dscientist9 at 2015-06-19 10:27:21.583704.
```

The credentials file path must be relative to how python was launched. Full paths are recommended. Multiple credentials files can be created. They should be protected with appropriate OS privileges.

14.3 Using Environmental Variables

The URI of the Trusted Analytics server can be specified by the environmental variable `$TA_URI`. The python client will initialize its config setting to this value. It may still be overridden as shown above in the session or script.

```
$ export TA_URI=ta-server.demo-gotapaas.com
```

The credentials file can be specified by $TA_CREDS.

```
$ export TA_CREDS=~/.ta/demo.creds
```

With these two variables set, the simple connect sequence works.

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

14.4 Troubleshooting

14.4.1 Client's Server Settings

To see the client's configuration to find the server, look at `ta.server`:

```
>>> ta.server
{
    "headers": {
        "Accept": "application/json,text/plain",
        "Authorization": "eyJhbGciOiJSUzI1NiJ9.eyJqdGkiOiIyOTllYmMxZC0zNDgyLTRhOWEtODM2Z
        C03ZDM1ZmIzZWZiNmYiLCJzdWIiOiJiZTYzMWQ1OS1iYWM4LTRiOWQtOTFhNy05NzMyMTBhMWRhMTkiL
        CJzY29wZSI6WyJjbG91ZF9jb250cm9sbGVyX3NlcnZpY2VfcGVybWlzc2lvbnMucmVhZCIsImNsb3VkX
        2NvbnRyb2xsZXIud3JpdGUiLCJvcGVuaWQiLCJjbG91ZF9jb250cm9sbGVyLnJlYWQiXSwiY2xpZW50X
        2lkIjoiYXRrLWNsaWVudCIsImNpZCI6ImF0ay1jbGllbnQiLCJhenAiOiJhdGstY2xpZW50IiwiZ3Jhb
        nRfdHlwZSI6InBhc3N3b3JkIiwidXNlcl9pZCI6ImJlNjMxZDU5LWJhYzgtNGI5ZC05MWE3LTk3MzIxM
        GExZGExOSIsInVzZXJfbmFtZSI6ImFuamFsaS5zb29kQGludGVsLmNvbSIsImVtYWlsIjoiYW5qYWxpL
        nNvb2RAaW50ZWwuY29tIiwiaWF0IjoxNDM0NzUyODU4LCJleHAiOjE0MzQ3OTYwNTgsImlzcyI6Imh0d
        HBzOi8vdWFhLmRlbW8tZ290YXBhYXMuY29tL29hdXRoL3Rva2VuIiwiYXVkIjpbImF0ay1jbGllbnQiL
        CJjbG91ZF9jb250cm9sbGVyX3NlcnZpY2VfcGVybWlzc2lvbnMiLCJjbG91ZF9jb250cm9sbGVyIiwib
        3BlbmlkIl19.PAwF2OtC0Wd97-gmZ4OXQ36xpyaeCCUC2ErGgCk619m7s6uCGcqydrWveTtgehEjIkZx
        Z5jfaFI53_bU0cHLseKlxMi1llggk6xC0rWnaUePF47pw-u6eGm2z-rPIqP9i4_2TdTxDKCe9_qziNTQ
        zKOlrn2_yN6KSgtytGEKxkE",
        "Content-type": "application/json"
    },
    "scheme": "http",
    "oauth_uri": "uaa.my-dp2-domain.comdemo-gotapaas.com",
    "user": "dscientist9"
}
```

The settings may be individually modified with the `ta.server` object, before calling connect.

CHAPTER FIFTEEN

DATA TYPES

All data manipulated and stored using frames and graphs must fit into one of the supported Python data types.

```
>>> ta.valid_data_types

float32, float64, ignore, int32, int64, unicode, vector(n), datetime
(and aliases: float->float64, int->int32, list->vector, long->int64, str->unicode)
```

datetime	[ALPHA] (This is a function or feature which has been developed, but has not been completely tested. Use this function with caution. This function may be changed or eliminated in future releases.) object for date and time; equivalent to python's datetime.datetime class. Converts to and from strings using the ISO 8601 format. Inside the server, the object is represented by the nscala/joda DateTime object. When interfacing with various data sources and sinks that use different data types for datetime, the datetime value will be converted to a string by default.
float32	32-bit floating point number; equivalent to numpy.float32
float64	64-bit floating point number; equivalent to numpy.float64
ignore	type available to describe a field in a data source that the parser should ignore
int32	32-bit integer; equivalent to numpy.int32
int64	32-bit integer; equivalent to numpy.int64
unicode	Python's unicode representation for strings.
vector(n)	[ALPHA] Ordered list of n float64 numbers (array of fixed-length n); uses numpy.ndarray

Note: Numpy values of positive infinity (np.inf), negative infinity (-np.inf) or nan (np.nan) are treated as Python's None when sent to the server. Results of any user-defined functions which deal with such values are automatically converted to None. Any further usage of those data points should treat the values as None.

API Maturity Tags

> Functions in the API may be at different levels of software maturity. Where a function is not mature, the documentation will note it with one of the following tags. The absence of a tag means the function is standardized and fully tested.
>
> [ALPHA]
>
> [BETA] (This is a function or feature which has been developed and preliminarily tested, but has not been completely tested. Use this function with caution. This function may be changed in future releases.)
>
> [DEPRECATED] (This is a function or feature which is no longer supported. It is recommended that an alternate solution be found. This function may be removed in future releases.)

CHAPTER

SIXTEEN

DATA SOURCES

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16.1 CsvFile

class `trustedanalytics.`**`CsvFile`**(*file_name*, *schema*, *delimiter=',', skip_header_lines=0*)
Define a CSV file.

Attributes

`field_names`	Schema field names from the CsvFile class.
`field_types`	Schema field types from the CsvFile class.

`__init__`(*file_name*, *schema*, *delimiter=',', skip_header_lines=0*)
Define a CSV file.

Parameters **file_name** : str

The name of the file containing data in a CSV format. The file must be in the Hadoop file system. Relative paths are interpreted as being relative to the path set in the application configuration file. See Configure File System Root. Absolute paths (beginning with `hdfs://...`, for example) are also supported.

schema : list of tuples of the form (string, type)

A description of the fields of data in the form of a list of tuples, which describe each field. Each tuple is in the form (name, type), where the name is a string, and type is a supported data type, Upon import of the data, the name becomes the name of a column, so the names must be unique and follow column naming rules. For a list of valid data types, see *Data Types*. The type `ignore` may also be used if the field should be ignored on loads.

delimiter : str (optional)

A string which indicates the separation of the data fields. This is usually a single character and could be a non-visible character such as a tab. This string must be enclosed by quotes in the command declaration, for example `","`.

skip_header_lines : int (optional)

An integer for the numbers of lines to skip before parsing records.

Returns class

A class which holds both the name and schema of a CSV file.

Notes

Unicode characters should not be used in the column name, because some functions do not support them and will not operate properly.

Examples

Given a raw data file named 'raw_data.csv', located at 'hdfs://localhost.localdomain/user/trusted/data/'. It consists of three columns, *a*, *b*, and *c*. The columns have the data types *int32*, *int32*, and *str* respectively. The fields of data are separated by commas. There is no header to the file.

Import the Trusted Analytics:

```
>>> import trustedanalytics as ta
```

Define the data:

```
>>> csv_schema = [("a", ta.int32), ("b", ta.int32), ("c", str)]
```

Create a CsvFile object with this schema:

```
>>> csv_define = ta.CsvFile("data/raw_data.csv", csv_schema)
```

The default delimiter, a comma, was used to separate fields in the file, so it was not specified. If the columns of data were separated by a character other than comma, the appropriate delimiter would be specified. For example if the data columns were separated by the colon character, the instruction would be:

```
>>> ta.CsvFile("data/raw_data.csv", csv_schema, delimiter = ':')
```

If the data had some lines of header at the beginning of the file, the lines should be skipped:

```
>>> csv_data = ta.CsvFile("data/raw_data.csv", csv_schema, skip_header_lines=2)
```

For other examples see *Importing a CSV File*.

field_names

Schema field names from the CsvFile class.

Returns list

A list of field name strings.

Examples

Given a raw data file 'raw_data.csv' with columns *col1* (*int32*) and *col2* (*float32*):

```
>>> csv_class = ta.CsvFile("raw_data.csv",
... schema=[("col1", ta.int32), ("col2", ta.float32)])
>>> print(csv_class.field_names())
```

Results:

```
["col1", "col2"]
```

field_types
Schema field types from the CsvFile class.

Returns list

A list of field types.

Examples

Given a raw data file 'raw_data.csv' with columns *col1* (*int32*) and *col2* (*float32*):

Results:

```
[ta.int32, ta.float32]
```

16.2 HiveQuery

class trustedanalytics.**HiveQuery**(*query*)
Define the sql query to retrieve the data from a Hive table.

Methods

__init__(*query*)
Define the sql query to retrieve the data from a Hive table.

Only a subset of Hive data types are supported.

```
Data Type    Support
___________  ____________________________________

boolean      cast to int

bigint       native support
int          native support
tinyint      cast to int
smallint     cast to int

decimal      cast to double, may lose precision
double       native support
float        native support
```

```
date        cast to string
string      native support
timestamp   cast to string
varchar     cast to string

arrays      not supported
binary      not supported
char        not supported
maps        not supported
structs     not supported
union       not supported
```

Parameters **query** : str

The sql query to retrieve the data

Returns **class** : HiveQuery object

An object which holds Hive sql query.

Examples

Given a Hive table *person* having *name* and *age* among other columns. A simple query could be to get the query for the name and age .. code:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

Define the data:

```
>>> hive_query = ta.HiveQuery("select name, age from person")
```

Create a frame using the object:

```
>>> my_frame = ta.Frame(hive_query)
```

16.3 HBase

class `trustedanalytics.`**`HBaseTable`**(*table_name*, *schema*, *start_row=None*, *end_row=None*)

Define the object to retrieve the data from an hBase table.

Methods

`__init__`(*table_name*, *schema*, *start_row=None*, *end_row=None*)

Define the object to retrieve the data from an hBase table.

Parameters **my_table** : str

The table name

schema : List of (column family, column name, data type for the cell value)

Returns **class** : HBaseTable object

An object which holds hBase data.

Examples

```
>>> import trustedanalytics as ta
>>> ta.connect()
>>> h = tp.HBaseTable ("my_table", [("pants", "aisle", unicode), ("pants", "row", int),( "sh
>>> f = tp.Frame(h)
>>> f.inspect()
```

16.4 Jdbc

class `trustedanalytics.`**`JdbcTable`**(*table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)

Define the object to retrieve the data from an jdbc table.

Methods

`__init__`(*table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)

Define the object to retrieve the data from an jdbc table.

Parameters **table_name** : str

the table name

connector_type : str

the connector type

url : str

Jdbc connection string (as url)

driver_name : str

An optional driver name

query : initial query (for data filtering / processing)

Returns **class** : JdbcTable object

An object which holds jdbc data.

Examples

```
>>> import trustedanalytics as ta
>>> ta.connect()
>>> jdbcTable = tp.JdbcTable ("test",
                              "jdbc:sqlserver://localhost/SQLExpress;databasename=somedataba
                              "com.microsoft.sqlserver.jdbc.SQLServerDriver",
                              "select * FROM SomeTable")
>>> frame = tp.Frame(jdbcTable)
>>> frame.inspect()
```

16.5 JsonFile

class `trustedanalytics.JsonFile`(*file_name*)

Define a file as having data in JSON format.

`__init__`(*file_name*)

Define a file as having data in JSON format. When JSON files are loaded into the system all top level JSON objects are recorded into the frame as seperate elements.

Parameters **file_name** : str

Name of data input file. File must be in the Hadoop file system. Relative paths are interpreted relative to the `trustedanalytics.atk.engine.fs.root` configuration. Absolute paths (beginning with `hdfs://...`, for example) are also supported. See Configure File System Root.

Returns class

An object which holds both the name and tag of a JSON file.

Examples

Given a raw data file named 'raw_data.json' located at 'hdfs://localhost.localdomain/user/trusted/data/'. It consists of a 3 top level json objects with a single value each called obj. Each object contains the attributes color, size, and shape.

The example JSON file:

```
{ "obj": {
    "color": "blue",
    "size": 3,
    "shape": "square" }
}
{ "obj": {
    "color": "green",
    "size": 7,
    "shape": "triangle" }
}
{ "obj": {
    "color": "orange",
    "size": 10,
    "shape": "square" }
}
```

Import the Trusted Analytics:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

Define the data:

```
>>> json_file = ta.JsonFile("data/raw_data.json")
```

Create a frame using this JsonFile:

```
>>> my_frame = ta.Frame(json_file)
```

The frame looks like:

```
  data_lines
/------------------------/
  '{ "obj": {
      "color": "blue",
      "size": 3,
      "shape": "square" }
  }'
  '{ "obj": {
      "color": "green",
      "size": 7,
      "shape": "triangle" }
  }'
  '{ "obj": {
      "color": "orange",
      "size": 10,
      "shape": "square" }
  }'
```

Parse values out of the XML column using the add_columns method:

```
>>> def parse_my_json(row):
...     import json
...     my_json = json.loads(row[0])
...     obj = my_json['obj']
...     return (obj['color'], obj['size'], obj['shape'])

>>> my_frame.add_columns(parse_my_json, [("color", str), ("size", str),
... ("shape", str)])
```

Original XML column is no longer necessary:

```
>>> my_frame.drop_columns(['data_lines'])
```

Result:

```
>>> my_frame.inspect()

  color:str   size:str    shape:str
/-----------------------------------/
  blue        3           square
  green       7           triangle
  orange      10          square
```

16.6 LineFile

class `trustedanalytics.`**`LineFile`**(*file_name*)
Define a line-separated file.

`__init__`(*file_name*)
Define a line-separated file.

Parameters **file_name** : str

Name of data input file. File must be in the Hadoop file system. Relative paths are interpreted relative to the `trustedanalytics.atk.engine.fs.root` configuration. Absolute paths (beginning with `hdfs://...`, for example) are also supported. See Configure File System Root.

Returns class

A class which holds the name of a Line File.

Examples

Given a raw data file 'rawline_data.txt' located at 'hdfs://localhost.localdomain/user/trusted/data/'. It consists of multiple lines separated by new line character.

Import the Trusted Analytics:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

Define the data:

```
>>> linefile_class = ta.LineFile("data/rawline_data.txt")
```

16.7 Pandas

class trustedanalytics.**Pandas**(*pandas_frame*, *schema*, *row_index=True*)

Defines a pandas data source

Attributes

field_names	Schema field names.
field_types	Schema field types

__init__(*pandas_frame*, *schema*, *row_index=True*)

Defines a pandas data source

Parameters **pandas_frame** : a pandas dataframe object

schema : list of tuples of the form (string, type)

schema description of the fields for a given line. It is a list of tuples which describe each field, (field name, field type), where the field name is a string, and file is a supported type, (See data_types from the atktypes module). Unicode characters should not be used in the column name.

row_index : boolean (optional)

indicates if the row_index is present in the pandas dataframe and needs to be ignored when looking at the data values. Default value is True.

Returns class

An object which holds both the pandas dataframe and schema associated with it.

Examples

For this example, we are going to use a raw data file named "pandas_df.csv". It consists of three columns named: *a*, *b*, *c*. The columns have the data types: *int32*, *int32*, *str*. The fields of data are separated by commas. '0th' row in the file indicates the header.

First bring in the stuff:

```
import trustedanalytics as ta
import pandas
```

At this point create a schema that defines the data:

```
schema = [("a", ta.int32),
              ("b", ta.int32),
              ("c", str)]
```

your_pandas = pandas.read_csv("pandas_df.csv")

Now build a PandasFrame object with this schema:

```
my_pandas = ta.PandasFrame(your_pandas, schema, False)
```

field_names

Schema field names.

List of field names from the schema stored in the trustedanalytics pandas dataframe object

Returns list of string

Field names

Examples

For this example, we are going to use a pandas dataframe object *your_pandas* . It will have two columns *col1* and *col2* with types of *int32* and *float32* respectively:

```
my_pandas = ta.PandasFrame(your_pandas, schema=[("col1", ta.int32), ("col2", ta.float32)])
print(my_pandas.field_names())
```

The output would be:

```
["col1", "col2"]
```

field_types

Schema field types

List of field types from the schema stored in the trustedanalytics pandas dataframe object.

Returns list of types

Field types

Examples

For this example, we are going to use a pandas dataframe object *your_pandas* . It will have two columns *col1* and *col2* with types of *int32* and *float32* respectively:

```
my_pandas = ta.PandasFrame(your_pandas, schema=[("col1", ta.int32), ("col2", ta.float32)])
print(my_csv.field_types())
```

The output would be:

```
[numpy.int32, numpy.float32]
```

16.8 XmlFile

class `trustedanalytics.XmlFile`(*file_name*, *tag_name*)
Define an file as having data in XML format.

`__init__`(*file_name*, *tag_name*)
Define an file as having data in XML format.

When XML files are loaded into the system, individual records are separated into the highest level elements found with the specified tag name and placed into a column called data_lines.

Parameters file_name : str

Name of data input file. File must be in the Hadoop file system. Relative paths are interpreted relative to the `trustedanalytics.atk.engine.fs.root` configuration. Absolute paths (beginning with `hdfs://...`, for example) are also supported. See Configure File System Root.

tag_name : str

Tag name used to determine the split of elements into separate records.

Returns class

An object which holds both the name and tag of a XML file.

Examples

Given a raw data file named 'raw_data.xml' located at 'hdfs://localhost.localdomain/user/trusted/data/'. It consists of a root element called *shapes* with subelements with the tag names *square* and *triangle*. Each of these subelements has two potential subelements called *name* and *size*. One of the elements has an attribute called *color*. Additionally, the subelement *triangle* is not needed so we can skip it during the import.

The example XML file:

```
<?xml version="1.0" encoding="UTF-8"?>
<shapes>
    <square>
        <name>left</name>
        <size>3</size>
    </square>
    <triangle>
        <size>3</size>
    </triangle>
    <square color="blue">
        <name>right</name>
        <size>5</size>
    </square>
</shapes>
```

Import the Trusted Analytics:

```
>>> import trustedanalytics as ta
>>> ta.connect()
```

Define the data:

```
>>> xml_file = ta.XmlFile("data/raw_data.xml", "square")
```

Create a frame using this XmlFile:

```
>>> my_frame = ta.Frame(xml_file)
```

The frame looks like:

```
  data_lines
/------------------------/
  '<square>
        <name>left</name>
        <size>3</size>
   </square>'
  '<square color="blue">
        <name>right</name>
        <size>5</size>
   </square>'
```

Parse values out of the XML column using the add_columns method:

```
>>> def parse_my_xml(row):
...     import xml.etree.ElementTree as ET
...     ele = ET.fromstring(row[0])
...     return (ele.get("color"), ele.find("name").text, ele.find("size").text)

>>> my_frame.add_columns(parse_my_xml, [("color", str), ("name", str), ("size", str)])
```

Original XML column is no longer necessary:

```
>>> my_frame.drop_columns(['data_lines'])
```

Result:

```
>>> my_frame.inspect()

  color:str   name:str    size:str
/----------------------------------/
  None        left        3
  blue        right       5
```

CHAPTER

SEVENTEEN

FRAMES

Classes

17.1 *Frames* EdgeFrame

17.1.1 *EdgeFrame* __init__

__init__(*self*, *graph=None*, *label=None*, *src_vertex_label=None*, *dest_vertex_label=None*, *directed=None*)

Examples

Parameters **graph** : ? (default=None)

graph these edges belong to

label : ? (default=None)

edge label

src_vertex_label : ? (default=None)

label of the source vertex type

dest_vertex_label : ? (default=None)

label of the destination vertex type

directed : ? (default=None)

directed or undirected

Returns : VertexFrame object

An object with access to the frame.

Given a data file */movie.csv*, create a frame to match this data and move the data to the frame. Create an empty graph and define some vertex and edge types.

```
>>> my_csv = ta.CsvFile("/movie.csv", schema= [('user_id', int32),
...                                     ('user_name', str),
...                                     ('movie_id', int32),
...                                     ('movie_title', str),
...                                     ('rating', str)])
```

```
>>> my_frame = ta.Frame(my_csv)
>>> my_graph = ta.Graph()
>>> my_graph.define_vertex_type('users')
>>> my_graph.define_vertex_type('movies')
>>> my_graph.define_edge_type('ratings','users','movies',directed=True)
```

Add data to the graph from the frame:

```
>>> my_graph.vertices['users'].add_vertices(my_frame, 'user_id',
... ['user_name'])
>>> my_graph.vertices['movies'].add_vertices(my_frame, 'movie_id', ['movie_title'])
```

Create an edge frame from the graph, and add edge data from the frame.

```
>>> my_edge_frame = graph.edges['ratings']
>>> my_edge_frame.add_edges(my_frame, 'user_id', 'movie_id', ['rating']
```

Retrieve a previously defined graph and retrieve an EdgeFrame from it:

```
>>> my_old_graph = ta.get_graph("your_graph")
>>> my_new_edge_frame = my_old_graph.edges["your_label"]
```

Calling methods on an EdgeFrame:

```
>>> my_new_edge_frame.inspect(20)
```

Copy an EdgeFrame to a frame using the copy method:

```
>>> my_new_frame = my_new_edge_frame.copy()
```

17.1.2 *EdgeFrame* add_columns

---

add_columns (*self*, *func*, *schema*, *columns_accessed=None*)

Add columns to current frame.

Parameters **func** : UDF

User-Defined Function (UDF) which takkes the values in the row and produces a value, or collection of values, for the new cell(s).

schema : tuple | list of tuples

The schema for the results of the UDF, indicating the new column(s) to add. Each tuple provides the column name and data type, and is of the form (str, type).

columns_accessed : list (default=None)

List of columns which the UDF will access. This adds significant performance benefit if we know which column(s) will be needed to execute the UDF, especially when the frame has significantly more columns than those being used to evaluate the UDF.

Assigns data to column based on evaluating a function for each row.

Notes

1. The row UDF ('func') must return a value in the same format as specified by the schema. See Python User Functions.

2.Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

Examples

Given a Frame *my_frame* identifying a data frame with two int32 columns *column1* and *column2*. Add a third column *column3* as an int32 and fill it with the contents of *column1* and *column2* multiplied together:

```
>>> my_frame.add_columns(lambda row: row.column1*row.column2,
... ('column3', int32))
```

The frame now has three columns, *column1*, *column2* and *column3*. The type of *column3* is an int32, and the value is the product of *column1* and *column2*.

Add a string column *column4* that is empty:

```
>>> my_frame.add_columns(lambda row: '', ('column4', str))
```

The Frame object *my_frame* now has four columns *column1*, *column2*, *column3*, and *column4*. The first three columns are int32 and the fourth column is str. Column *column4* has an empty string (‘’) in every row.

Multiple columns can be added at the same time. Add a column *a_times_b* and fill it with the contents of column *a* multiplied by the contents of column *b*. At the same time, add a column *a_plus_b* and fill it with the contents of column *a* plus the contents of column *b*:

```
>>> my_frame.add_columns(lambda row: [row.a * row.b, row.a +
... row.b], [("a_times_b", float32), ("a_plus_b", float32))
```

Two new columns are created, “a_times_b” and “a_plus_b”, with the appropriate contents.

Given a frame of data and Frame *my_frame* points to it. In addition we have defined a UDF *func*. Run *func* on each row of the frame and put the result in a new int column *calculated_a*:

```
>>> my_frame.add_columns( func, ("calculated_a", int))
```

Now the frame has a column *calculated_a* which has been filled with the results of the UDF *func*.

A UDF must return a value in the same format as the column is defined. In most cases this is automatically the case, but sometimes it is less obvious. Given a UDF *function_b* which returns a value in a list, store the result in a new column *calculated_b*:

```
>>> my_frame.add_columns(function_b, ("calculated_b", float32))
```

This would result in an error because function_b is returning a value as a single element list like [2.4], but our column is defined as a tuple. The column must be defined as a list:

```
>>> my_frame.add_columns(function_b, [("calculated_b", float32)])
```

To run an optimized version of add_columns, columns_accessed parameter can be populated with the column names which are being accessed in UDF. This speeds up the execution by working on only the limited feature set than the entire row.

Let’s say a frame has 4 columns named *a*,*b*,*c* and *d* and we want to add a new column with value from column *a* multiplied by value in column *b* and call it *a_times_b*. In the example below, columns_accessed is a list with column names *a* and *b*.

```
>>> my_frame.add_columns(lambda row: row.a * row.b, ("a_times_b", float32), columns_accessed=["a
```

add_columns would fail if columns_accessed parameter is not populated with the correct list of accessed columns. If not specified, columns_accessed defaults to None which implies that all columns might be accessed by the UDF.

More information on a row UDF can be found at Python User Functions

17.1.3 *EdgeFrame* add_edges

---

add_edges (*self*, *source_frame*, *column_name_for_source_vertex_id*, *column_name_for_dest_vertex_id*, *column_names=None*, *create_missing_vertices=False*)

Add edges to a graph.

Parameters **source_frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame that will be the source of the edge data.

column_name_for_source_vertex_id : unicode

column name for a unique id for each source vertex (this is not the system defined _vid).

column_name_for_dest_vertex_id : unicode

column name for a unique id for each destination vertex (this is not the system defined _vid).

column_names : list (default=None)

Column names to be used as properties for each vertex, None means use all columns, empty list means use none.

create_missing_vertices : bool (default=False)

True to create missing vertices for edge (slightly slower), False to drop edges pointing to missing vertices. Defaults to False.

Returns : _Unit

Includes appending to a list of existing edges.

17.1.4 *EdgeFrame* assign_sample

---

assign_sample (*self*, *sample_percentages*, *sample_labels=None*, *output_column=None*, *random_seed=None*)

Randomly group rows into user-defined classes.

Parameters **sample_percentages** : list

Entries are non-negative and sum to 1. (See the note below.) If the *i*'th entry of the list is *p*, then then each row receives label *i* with independent probability *p*.

sample_labels : list (default=None)

Names to be used for the split classes. Defaults "TR", "TE", "VA" when the length of *sample_percentages* is 3, and defaults to Sample_0, Sample_1, ... otherwise.

output_column : unicode (default=None)

Name of the new column which holds the labels generated by the function.

random_seed : int32 (default=None)

Random seed used to generate the labels. Defaults to 0.

Returns : _Unit

Randomly assign classes to rows given a vector of percentages. The table receives an additional column that contains a random label. The random label is generated by a probability distribution function. The distribution function is specified by the sample_percentages, a list of floating point values, which add up to 1. The labels are non-negative integers drawn from the range $[0, len(S) - 1]$ where S is the sample_percentages. Optionally, the user can specify a list of strings to be used as the labels. If the number of labels is 3, the labels will default to “TR”, “TE” and “VA”.

Notes

The sample percentages provided by the user are preserved to at least eight decimal places, but beyond this there may be small changes due to floating point imprecision.

In particular:

1. The engine validates that the sum of probabilities sums to 1.0 within eight decimal places and returns an error if the sum falls outside of this range.
2. The probability of the final class is clamped so that each row receives a valid label with probability one.

17.1.5 *EdgeFrame* bin_column

---

bin_column (*self*, *column_name*, *cutoffs*, *include_lowest=None*, *strict_binning=None*, *bin_column_name=None*)

Classify data into user-defined groups.

Parameters **column_name** : unicode

Name of the column to bin.

cutoffs : list

Array of values containing bin cutoff points. Array can be list or tuple. Array values must be progressively increasing. All bin boundaries must be included, so, with N bins, you need N+1 values.

include_lowest : bool (default=None)

Specify how the boundary conditions are handled. True indicates that the lower bound of the bin is inclusive. False indicates that the upper bound is inclusive. Default is True.

strict_binning : bool (default=None)

Specify how values outside of the cutoffs array should be binned. If set to True, each value less than cutoffs[0] or greater than cutoffs[-1] will be assigned a bin value of -1. If set to False, values less than cutoffs[0] will be included in the first bin while values greater than cutoffs[-1] will be included in the final bin.

bin_column_name : unicode (default=None)

The name for the new binned column. Default is `<column_name>_binned`.

Returns : _Unit

Summarize rows of data based on the value in a single column by sorting them into bins, or groups, based on a list of bin cutoff points.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. Bins IDs are 0-index: the lowest bin number is 0.
3. The first and last cutoffs are always included in the bins. When include_lowest is `True`, the last bin includes both cutoffs. When include_lowest is `False`, the first bin (bin 0) includes both cutoffs.

17.1.6 *EdgeFrame* bin_column_equal_depth

---

bin_column_equal_depth(*self*, *column_name*, *num_bins=None*, *bin_column_name=None*)

Classify column into groups with the same frequency.

Parameters **column_name** : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is <column_name>_binned.

Returns : dict

A list containing the edges of each bin.

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal depth binning attempts to label rows such that each bin contains the same number of elements. For n bins of a column C of length m, the bin number is determined by:

$$\lceil n * \frac{f(C)}{m} \rceil$$

where f is a tie-adjusted ranking function over values of C. If there are multiples of the same value in C, then their tie-adjusted rank is the average of their ordered rank values.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has a quantity of :math"X elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.1.7 *EdgeFrame* bin_column_equal_width

bin_column_equal_width (*self*, *column_name*, *num_bins=None*, *bin_column_name=None*)
Classify column into same-width groups.

Parameters **column_name** : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is <column_name>_binned.

Returns : dict

A list of the edges of each bin.

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal width binning places column values into groups such that the values in each group fall within the same interval and the interval width for each group is equal.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.1.8 *EdgeFrame* categorical_summary

categorical_summary (*self*, *column_inputs=None*)
[ALPHA] Compute a summary of the data in a column(s) for categorical or numerical data types.

Parameters **column_inputs** : str | tuple(str, dict) (default=None)

Comma-separated column names to summarize or tuple containing column name and dictionary of optional parameters. Optional parameters (see below for details): top_k (default = 10), threshold (default = 0.0)

Returns : dict

Summary for specified column(s) consisting of levels with their frequency and percentage

The returned value is a Map containing categorical summary for each specified column.

For each column, levels which satisfy the top k and/or threshold cutoffs are displayed along with their frequency and percentage occurrence with respect to the total rows in the dataset.

Missing data is reported when a column value is empty ("") or null.

All remaining data is grouped together in the Other category and its frequency and percentage are reported as well.

User must specify the column name and can optionally specify top_k and/or threshold.

Optional parameters:

top_k Displays levels which are in the top k most frequently occurring values for that column.

threshold Displays levels which are above the threshold percentage with respect to the total row count.

top_k and threshold Performs level pruning first based on top k and then filters out levels which satisfy the threshold criterion.

defaults Displays all levels which are in Top 10.

Examples

```
>>> frame.categorical_summary('source','target')
>>> frame.categorical_summary(('source', {'top_k' : 2}))
>>> frame.categorical_summary(('source', {'threshold' : 0.5}))
>>> frame.categorical_summary(('source', {'top_k' : 2}), ('target',
... {'threshold' : 0.5}))
```

Sample output (for last example above):

```
>>> {u'categorical_summary': [{u'column': u'source', u'levels': [
... {u'percentage': 0.32142857142857145, u'frequency': 9, u'level': u'thing'},
... {u'percentage': 0.32142857142857145, u'frequency': 9, u'level': u'abstraction'},
... {u'percentage': 0.25, u'frequency': 7, u'level': u'physical_entity'},
... {u'percentage': 0.10714285714285714, u'frequency': 3, u'level': u'entity'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Missing'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Other'}]},
... {u'column': u'target', u'levels': [
... {u'percentage': 0.07142857142857142, u'frequency': 2, u'level': u'thing'},
... {u'percentage': 0.07142857142857142, u'frequency': 2,
...  u'level': u'physical_entity'},
... {u'percentage': 0.07142857142857142, u'frequency': 2, u'level': u'entity'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'variable'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'unit'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'substance'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'subject'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'set'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'reservoir'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'relation'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Missing'},
... {u'percentage': 0.5357142857142857, u'frequency': 15, u'level': u'Other'}]}]}
```

17.1.9 *EdgeFrame* classification_metrics

classification_metrics (*self*, *label_column*, *pred_column*, *pos_label=None*, *beta=None*)

Model statistics of accuracy, precision, and others.

Parameters label_column : unicode

The name of the column containing the correct label for each instance.

pred_column : unicode

The name of the column containing the predicted label for each instance.

pos_label : None (default=None)

beta : float64 (default=None)

This is the beta value to use for F_β measure (default F1 measure is computed); must be greater than zero. Defaults is 1.

Returns : dict

object <object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

Calculate the accuracy, precision, confusion_matrix, recall and F_β measure for a classification model.

- The **f_measure** result is the F_β measure for a classification model. The F_β measure of a binary classification model is the harmonic mean of precision and recall. If we let:
  - beta $\equiv \beta$,
  - T_P denotes the number of true positives,
  - F_P denotes the number of false positives, and
  - F_N denotes the number of false negatives

  then:

$$F_\beta = (1 + \beta^2) * \frac{\frac{T_P}{T_P + F_P} * \frac{T_P}{T_P + F_N}}{\beta^2 * \frac{T_P}{T_P + F_P} + \frac{T_P}{T_P + F_N}}$$

  The F_β measure for a multi-class classification model is computed as the weighted average of the F_β measure for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **recall** result of a binary classification model is the proportion of positive instances that are correctly identified. If we let T_P denote the number of true positives and F_N denote the number of false negatives, then the model recall is given by $\frac{T_P}{T_P + F_N}$.

  For multi-class classification models, the recall measure is computed as the weighted average of the recall for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **precision** of a binary classification model is the proportion of predicted positive instances that are correctly identified. If we let T_P denote the number of true positives and F_P denote the number of false positives, then the model precision is given by: $\frac{T_P}{T_P + F_P}$.

  For multi-class classification models, the precision measure is computed as the weighted average of the precision for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **accuracy** of a classification model is the proportion of predictions that are correctly identified. If we let T_P denote the number of true positives, T_N denote the number of true negatives, and K denote the total number of classified instances, then the model accuracy is given by: $\frac{T_P + T_N}{K}$.

  This measure applies to binary and multi-class classifiers.

- The **confusion_matrix** result is a confusion matrix for a binary classifier model, formatted for human readability.

Notes

The **confusion_matrix** is not yet implemented for multi-class classifiers.

17.1.10 *EdgeFrame* column_median

---

column_median (*self*, *data_column*, *weights_column=None*)

Calculate the (weighted) median of a column.

Parameters **data_column** : unicode

The column whose median is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the median calculation. Must contain numerical data. Default is all items have a weight of 1.

Returns : dict

varies The median of the values. If a weight column is provided and no weights are finite numbers greater than 0, None is returned. The type of the median returned is the same as the contents of the data column, so a column of Longs will result in a Long median and a column of Floats will result in a Float median.

The median is the least value X in the range of the distribution so that the cumulative weight of values strictly below X is strictly less than half of the total weight and the cumulative weight of values up to and including X is greater than or equal to one-half of the total weight.

All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If a weight column is provided and no weights are finite numbers greater than 0, None is returned.

17.1.11 *EdgeFrame* column_mode

---

column_mode (*self*, *data_column*, *weights_column=None*, *max_modes_returned=None*)

Evaluate the weights assigned to rows.

Parameters **data_column** : unicode

Name of the column supplying the data.

weights_column : unicode (default=None)

Name of the column supplying the weights. Default is all items have weight of 1.

max_modes_returned : int32 (default=None)

Maximum number of modes returned. Default is 1.

Returns : dict

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mode [A mode is a data element of maximum net weight.] A set of modes is returned. The empty set is returned when the sum of the weights is 0. If the number of modes is less than or equal to the parameter max_modes_returned, then all modes of the data are returned. If the number of modes is greater than the max_modes_returned parameter, only the first max_modes_returned many modes (per a canonical ordering) are returned.

weight_of_mode [Weight of a mode.] If there are no data elements of finite weight greater than 0, the weight of the mode is 0. If no weights column is given, this is the number of appearances of each mode.

total_weight [Sum of all weights in the weight column.] This is the row count if no weights are given. If no weights column is given, this is the number of rows in the table with non-zero weight.

mode_count [The number of distinct modes in the data.] In the case that the data is very multimodal, this number may exceed max_modes_returned.

Calculate the modes of a column. A mode is a data element of maximum weight. All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight greater than 0, no mode is returned.

Because data distributions often have mutliple modes, it is possible for a set of modes to be returned. By default, only one is returned, but by setting the optional parameter max_modes_returned, a larger number of modes can be returned.

17.1.12 *EdgeFrame* column_names

`column_names`

Column identifications in the current frame.

Parameters

Returns : list

list of names of all the frame's columns

Given a Frame object, *my_frame* accessing a frame. To get the column names:

```
>>> my_columns = my_frame.column_names
>>> print my_columns
```

Now, given there are three columns *col1*, *col2*, and *col3*, the result is:

```
["col1", "col2", "col3"]
```

17.1.13 *EdgeFrame* column_summary_statistics

`column_summary_statistics`(*self*, *data_column*, *weights_column=None*, *use_population_variance=None*)

Calculate multiple statistics for a column.

Parameters **data_column** : unicode

The column to be statistically summarized. Must contain numerical data; all NaNs and infinite values are excluded from the calculation.

weights_column : unicode (default=None)

Name of column holding weights of column values.

use_population_variance : bool (default=None)

If true, the variance is calculated as the population variance. If false, the variance calculated as the sample variance. Because this option affects the variance, it affects the standard deviation and the confidence intervals as well. Default is false.

Returns : dict

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mean [[double | None]] Arithmetic mean of the data.

geometric_mean [[double | None]] Geometric mean of the data. None when there is a data element <= 0, 1.0 when there are no data elements.

variance [[double | None]] None when there are <= 1 many data elements. Sample variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight minus 1. None when the sum of the weights is <= 1. Population variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight.

standard_deviation [[double | None]] The square root of the variance. None when sample variance is being used and the sum of weights is <= 1.

total_weight [long] The count of all data elements that are finite numbers. (In other words, after excluding NaNs and infinite values.)

minimum [[double | None]] Minimum value in the data. None when there are no data elements.

maximum [[double | None]] Maximum value in the data. None when there are no data elements.

mean_confidence_lower [[double | None]] Lower limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

mean_confidence_upper [[double | None]] Upper limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

bad_row_count [[double | None]] The number of rows containing a NaN or infinite value in either the data or weights column.

good_row_count [[double | None]] The number of rows not containing a NaN or infinite value in either the data or weights column.

positive_weight_count [[double | None]] The number of valid data elements with weight > 0. This is the number of entries used in the statistical calculation.

non_positive_weight_count [[double | None]] The number valid data elements with finite weight <= 0.

Notes

Sample Variance Sample Variance is computed by the following formula:

$$\left(\frac{1}{W-1}\right) * sum_i\ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Population Variance Population Variance is computed by the following formula:

$$\left(\frac{1}{W}\right) * sum_i\ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Standard Deviation The square root of the variance.

Logging Invalid Data A row is bad when it contains a NaN or infinite value in either its data or weights column. In this case, it contributes to bad_row_count; otherwise it contributes to good row count.

A good row can be skipped because the value in its weight column is less than or equal to 0. In this case, it contributes to non_positive_weight_count, otherwise (when the weight is greater than 0) it contributes to valid_data_weight_pair_count.

Equations `bad_row_count + good_row_count = # rows in the frame`

`positive_weight_count + non_positive_weight_count = good_row_count`

In particular, when no weights column is provided and all weights are 1.0, `non_positive_weight_count = 0` and `positive_weight_count = good_row_count`

17.1.14 *EdgeFrame* compute_misplaced_score

---

compute_misplaced_score (*self*, *gravity*)

Parameters **gravity** : float64

Similarity measure for computing tension between 2 connected items

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

17.1.15 *EdgeFrame* copy

---

copy (*self*, *columns=None*, *where=None*, *name=None*)

Create new frame from current frame.

Parameters **columns** : str | list of str | dict (default=None)

If not None, the copy will only include the columns specified. If dict, the string pairs represent a column renaming, {source_column_name: destination_column_name}

where : function (default=None)

If not None, only those rows for which the UDF evaluates to True will be copied.

name : str (default=None)

Name of the copied frame

Returns : Frame

A new Frame of the copied data.

Copy frame or certain frame columns entirely or filtered. Useful for frame query.

Examples

Build a Frame from a csv file with 5 million rows of data; call the frame "cust":

```
>>> my_frame = ta.Frame(source="my_data.csv")
>>> my_frame.name("cust")
```

Given the frame has columns *id*, *name*, *hair*, and *shoe*. Copy it to a new frame:

```
>>> your_frame = my_frame.copy()
```

Now we have two frames of data, each with 5 million rows. Checking the names:

```
>>> print my_frame.name()
>>> print your_frame.name()
```

Gives the results:

```
"cust"
"frame_75401b7435d7132f5470ba35..."
```

Now, let's copy *some* of the columns from the original frame:

```
>>> our_frame = my_frame.copy(['id', 'hair'])
```

Our new frame now has two columns, *id* and *hair*, and has 5 million rows. Let's try that again, but this time change the name of the *hair* column to *color*:

```
>>> last_frame = my_frame.copy(('id': 'id', 'hair': 'color'))
```

17.1.16 *EdgeFrame* correlation

---

correlation(*self*, *data_column_names*)

Calculate correlation for two columns of current frame.

Parameters **data_column_names** : list

The names of 2 columns from which to compute the correlation.

Returns : dict

Pearson correlation coefficient of the two columns.

This method applies only to columns containing numerical data.

17.1.17 *EdgeFrame* correlation_matrix

correlation_matrix (*self*, *data_column_names*, *matrix_name=None*)
Calculate correlation matrix for two or more columns.

Parameters **data_column_names** : list

The names of the columns from which to compute the matrix.

matrix_name : unicode (default=None)

The name for the returned matrix Frame.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A Frame with the matrix of the correlation values for the columns.

This method applies only to columns containing numerical data.

17.1.18 *EdgeFrame* count

count (*self*, *where*)
Counts the number of rows which meet given criteria.

Parameters **where** : function

UDF which evaluates a row to a boolean

Returns : int

number of rows for which the where UDF evaluated to True.

17.1.19 *EdgeFrame* covariance

covariance (*self*, *data_column_names*)
Calculate covariance for exactly two columns.

Parameters **data_column_names** : list

The names of two columns from which to compute the covariance.

Returns : dict

Covariance of the two columns.

This method applies only to columns containing numerical data.

17.1.20 *EdgeFrame* covariance_matrix

---

covariance_matrix (*self*, *data_column_names*, *matrix_name=None*)
Calculate covariance matrix for two or more columns.

Parameters **data_column_names** : list

The names of the column from which to compute the matrix. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

matrix_name : unicode (default=None)

The name of the new matrix.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A matrix with the covariance values for the columns.

This function applies only to columns containing numerical data.

17.1.21 *EdgeFrame* cumulative_percent

---

cumulative_percent (*self*, *sample_col*)
[BETA] Add column to frame with cumulative percent sum.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative percent sum.

Returns : _Unit

A cumulative percent sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the current percentage of the total sum accounted for at the current value.

Notes

This method applies only to columns containing numerical data. Although this method will execute for columns containing negative values, the interpretation of the result will change (for example, negative percentages).

17.1.22 *EdgeFrame* cumulative_sum

---

cumulative_sum (*self*, *sample_col*)
[BETA] Add column to frame with cumulative percent sum.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative sum.

Returns : _Unit

A cumulative sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the cumulative sum for each value.

Notes

This method applies only to columns containing numerical data.

17.1.23 *EdgeFrame* dot_product

dot_product (*self*, *left_column_names*, *right_column_names*, *dot_product_column_name*, *default_left_values=None*, *default_right_values=None*)

[ALPHA] Calculate dot product for each row in current frame.

Parameters left_column_names : list

Names of columns used to create the left vector (A) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

right_column_names : list

Names of columns used to create right vector (B) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

dot_product_column_name : unicode

Name of column used to store the dot product.

default_left_values : list (default=None)

Default values used to substitute null values in left vector. Default is None.

default_right_values : list (default=None)

Default values used to substitute null values in right vector. Default is None.

Returns : _Unit

Calculate the dot product for each row in a frame using values from two equal-length sequences of columns.

Dot product is computed by the following formula:

The dot product of two vectors $A = [a_1, a_2, ..., a_n]$ and $B = [b_1, b_2, ..., b_n]$ is $a_1 * b_1 + a_2 * b_2 + ... + a_n * b_n$. The dot product for each row is stored in a new column in the existing frame.

Notes

If default_left_values or default_right_values are not specified, any null values will be replaced by zeros.

17.1.24 *EdgeFrame* download

download (*self*, *n=100*, *offset=0*, *columns=None*)

Download a frame from the server into client workspace.

Parameters n : int (default=100)

The number of rows to download to the client

offset : int (default=0)

The number of rows to skip before copying

columns : list (default=None)

Column filter, the names of columns to be included (default is all columns)

Returns : pandas.DataFrame

A new pandas dataframe object containing the downloaded frame data

Copies an trustedanalytics Frame into a Pandas DataFrame.

Examples

Frame *my_frame* accesses a frame with millions of rows of data. Get a sample of 500 rows:

```
>>> pandas_frame = my_frame.download( 500 )
```

We now have a new frame accessed by a pandas DataFrame *pandas_frame* with a copy of the first 500 rows of the original frame.

If we use the method with an offset like:

```
>>> pandas_frame = my_frame.take( 500, 100 )
```

We end up with a new frame accessed by the pandas DataFrame *pandas_frame* again, but this time it has a copy of rows 101 to 600 of the original frame.

17.1.25 *EdgeFrame* drop_columns

---

drop_columns (*self*, *columns*)

Remove columns from the frame.

Parameters **columns** : list

Column name OR list of column names to be removed from the frame.

Returns : _Unit

The data from the columns is lost.

Notes

It is not possible to delete all columns from a frame. At least one column needs to remain. If it is necessary to delete all columns, then delete the frame.

17.1.26 *EdgeFrame* drop_duplicates

---

drop_duplicates (*self*, *unique_columns=None*)

Modify the current frame, removing duplicate rows.

Parameters **unique_columns** : None (default=None)

Returns : _Unit

Remove data rows which are the same as other rows. The entire row can be checked for duplication, or the search for duplicates can be limited to one or more columns. This modifies the current frame.

17.1.27 *EdgeFrame* drop_rows

---

drop_rows (*self*, *predicate*)
Erase any row in the current frame which qualifies.

Parameters **predicate** : function

UDF which evaluates a row to a boolean; rows that answer True are dropped from the Frame

Examples

For this example, my_frame is a Frame object accessing a frame with lots of data for the attributes of `lions`, `tigers`, and `ligers`. Get rid of the `lions` and `tigers`:

```
>>> my_frame.drop_rows(lambda row: row.animal_type == "lion" or
...     row.animal_type == "tiger")
```

Now the frame only has information about `ligers`.

More information on a UDF can be found at Python User Functions.

17.1.28 *EdgeFrame* ecdf

---

ecdf (*self*, *column*, *result_frame_name=None*)
Builds new frame with columns for data and distribution.

Parameters **column** : unicode

The name of the input column containing sample.

result_frame_name : unicode (default=None)

A name for the resulting frame which is created by this operation.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new Frame containing each distinct value in the sample and its corresponding ECDF value.

Generates the *empirical cumulative distribution* for the input column.

17.1.29 *EdgeFrame* entropy

---

entropy (*self*, *data_column*, *weights_column=None*)
Calculate the Shannon entropy of a column.

Parameters **data_column** : unicode

The column whose entropy is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the entropy calculation. Must contain numerical data. Default is using uniform weights of 1 for all items.

Returns : dict

Entropy.

The data column is weighted via the weights column. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements with a finite weight greater than 0, the entropy is zero.

17.1.30 *EdgeFrame* export_to_csv

---

export_to_csv (*self*, *folder_name*, *separator=None*, *count=None*, *offset=None*)

Write current frame to HDFS in csv format.

Parameters **folder_name** : unicode

The HDFS folder path where the files will be created.

separator : None (default=None)

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Returns : _Unit

Export the frame to a file in csv format as a Hadoop file.

17.1.31 *EdgeFrame* export_to_hbase

---

export_to_hbase (*self*, *table_name*, *key_column_name=None*, *family_name=None*)

Write current frame to HBase table.

Parameters **table_name** : unicode

The name of the HBase table that will contain the exported frame

key_column_name : unicode (default=None)

The name of the column to be used as row key in hbase table

family_name : unicode (default=None)

The family name of the HBase table that will contain the exported frame

Returns : _Unit

Table must exist in HBase. Export of Vectors is not currently supported.

17.1.32 *EdgeFrame* export_to_hive

---

export_to_hive (*self*, *table_name*)
Write current frame to Hive table.

Parameters **table_name** : unicode

The name of the Hive table that will contain the exported frame

Returns : _Unit

Table must not exist in Hive. Export of Vectors is not currently supported.

17.1.33 *EdgeFrame* export_to_jdbc

---

export_to_jdbc (*self*, *table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)
Write current frame to Jdbc table.

Parameters **table_name** : unicode

jdbc table name

connector_type : unicode (default=None)

(optional) jdbc connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Returns : _Unit

Table will be created or appended to. Export of Vectors is not currently supported.

17.1.34 *EdgeFrame* export_to_json

---

export_to_json (*self*, *folder_name*, *count=None*, *offset=None*)
Write current frame to HDFS in JSON format.

Parameters **folder_name** : unicode

The HDFS folder path where the files will be created.

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Returns : _Unit

Export the frame to a file in JSON format as a Hadoop file.

17.1.35 *EdgeFrame* filter

---

filter (*self*, *predicate*)

Select all rows which satisfy a predicate.

Parameters **predicate** : function

UDF which evaluates a row to a boolean; rows that answer False are dropped from the Frame

Modifies the current frame to save defined rows and delete everything else.

Examples

For this example, *my_frame* is a Frame object with lots of data for the attributes of `lizards`, `frogs`, and `snakes`. Get rid of everything, except information about `lizards` and `frogs`:

```
>>> def my_filter(row):
... return row['animal_type'] == 'lizard' or
... row['animal_type'] == "frog"

>>> my_frame.filter(my_filter)
```

The frame now only has data about `lizards` and `frogs`.

More information on a UDF can be found at Python User Functions.

17.1.36 *EdgeFrame* flatten_column

---

flatten_column (*self*, *column*, *delimiter=None*)

Spread data to multiple rows based on cell data.

Parameters **column** : unicode

The column to be flattened.

delimiter : unicode (default=None)

The delimiter string. Default is comma (,).

Returns : _Unit

Splits cells in the specified column into multiple rows according to a string delimiter. New rows are a full copy of the original row, but the specified column only contains one value. The original row is deleted.

17.1.37 *EdgeFrame* get_error_frame

---

get_error_frame (*self*)

Get a frame with error recordings.

Parameters

When a frame is created, another frame is transparently created to capture parse errors.

Returns **Frame** : error frame object

A new object accessing a frame that contains the parse errors of the currently active Frame or None if no error frame exists.

17.1.38 *EdgeFrame* group_by

---

group_by (*self*, *group_by_columns*, *aggregation_arguments=None*)

[BETA] Create summarized frame.

Parameters **group_by_columns** : list

Column name or list of column names

aggregation_arguments : dict (default=None)

Aggregation function based on entire row, and/or dictionaries (one or more) of { column name str : aggregation function(s) }.

Returns : Frame

A new frame with the results of the group_by

Creates a new frame and returns a Frame object to access it. Takes a column or group of columns, finds the unique combination of values, and creates unique rows with these column values. The other columns are combined according to the aggregation argument(s).

Notes

- Column order is not guaranteed when columns are added
- The column names created by aggregation functions in the new frame are the original column name appended with the '_' character and the aggregation function. For example, if the original field is *a* and the function is *avg*, the resultant column is named *a_avg*.
- An aggregation argument of *count* results in a column named *count*.
- The aggregation function *agg.count* is the only full row aggregation function supported at this time.
- Aggregation currently supports using the following functions:
  - avg
  - count
  - count_distinct
  - max
  - min

–stdev

–sum

–var (see glossary *Bias vs Variance*)

Examples

For setup, we will use a Frame *my_frame* accessing a frame with a column *a*:

```
>>> my_frame.inspect()

  a:str
/-------/
  cat
  apple
  bat
  cat
  bat
  cat
```

Create a new frame, combining similar values of column *a*, and count how many of each value is in the original frame:

```
>>> new_frame = my_frame.group_by('a', agg.count)
>>> new_frame.inspect()

  a:str       count:int
/-----------------------/
  cat             3
  apple           1
  bat             2
```

In this example, 'my_frame' is accessing a frame with three columns, *a*, *b*, and *c*:

```
>>> my_frame.inspect()

  a:int   b:str   c:float
/-------------------------/
  1       alpha     3.0
  1       bravo     5.0
  1       alpha     5.0
  2       bravo     8.0
  2       bravo    12.0
```

Create a new frame from this data, grouping the rows by unique combinations of column *a* and *b*. Average the value in *c* for each group:

```
>>> new_frame = my_frame.group_by(['a', 'b'], {'c' : agg.avg})
>>> new_frame.inspect()

  a:int   b:str   c_avg:float
/-----------------------------/
  1       alpha     4.0
  1       bravo     5.0
  2       bravo    10.0
```

For this example, we use *my_frame* with columns *a*, *c*, *d*, and *e*:

```
>>> my_frame.inspect()

  a:str   c:int   d:float e:int
/-------------------------------/
  ape     1       4.0     9
  ape     1       8.0     8
  big     1       5.0     7
  big     1       6.0     6
  big     1       8.0     5
```

Create a new frame from this data, grouping the rows by unique combinations of column *a* and *c*. Count each group; for column *d* calculate the average, sum and minimum value. For column *e*, save the maximum value:

```
>>> new_frame = my_frame.group_by(['a', 'c'], agg.count,
... {'d': [agg.avg, agg.sum, agg.min], 'e': agg.max})

  a    c    count  d_avg  d_sum  d_min  e_max
  str  int  int    float  float  float  int
/---------------------------------------------/
  ape  1    2      6.0    12.0   4.0    9
  big  1    3      6.333  19.0   5.0    7
```

For further examples, see *Group by (and aggregate):*.

17.1.39 *EdgeFrame* histogram

---

histogram(*self*, *column_name*, *num_bins=None*, *weight_column_name=None*, *bin_type='equalwidth'*)
[BETA] Compute the histogram for a column in a frame.

Parameters **column_name** : unicode

Name of column to be evaluated.

num_bins : int32 (default=None)

Number of bins in histogram. Default is Square-root choice will be used (in other words math.floor(math.sqrt(frame.row_count)).

weight_column_name : unicode (default=None)

Name of column containing weights. Default is all observations are weighted equally.

bin_type : unicode (default=equalwidth)

The type of binning algorithm to use: ["equalwidth"|"equaldepth"] Defaults is "equalwidth".

Returns : dict

histogram A Histogram object containing the result set. The data returned is composed of multiple components:

cutoffs [array of float] A list containing the edges of each bin.

hist [array of float] A list containing count of the weighted observations found in each bin.

density [array of float] A list containing a decimal containing the percentage of observations found in the total set per bin.

Compute the histogram of the data in a column. The returned value is a Histogram object containing 3 lists one each for: the cutoff points of the bins, size of each bin, and density of each bin.

Notes

The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. With equal depth binning, for example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.1.40 *EdgeFrame* inspect

---

inspect (*self*, *n=10*, *offset=0*, *columns=None*, *wrap=None*, *truncate=None*, *round=None*, *width=80*, *margin=None*)

Prints the frame data in readable format.

Parameters **n** : int (default=10)

The number of rows to print.

offset : int (default=0)

The number of rows to skip before printing.

columns : int (default=None)

Filter columns to be included. By default, all columns are included

wrap : int or 'stripes' (default=None)

If set to 'stripes' then inspect prints rows in stripes; if set to an integer N, rows will be printed in clumps of N columns, where the columns are wrapped

truncate : int (default=None)

If set to integer N, all strings will be truncated to length N, including a tagged ellipses

round : int (default=None)

If set to integer N, all floating point numbers will be rounded and truncated to N digits

width : int (default=80)

If set to integer N, the print out will try to honor a max line width of N

margin : int (default=None)

('stripes' mode only) If set to integer N, the margin for printing names in a stripe will be limited to N characters

Examples

Given a frame of data and a Frame to access it. To look at the first 4 rows of data:

```
>>> print my_frame.inspect(4)

column defs ->  animal:str  name:str    age:int     weight:float
              /---------------------------------------------------/
frame data ->   human       George        8            542.5
                human       Ursula        6            495.0
```

```
                    ape          Ape           41            400.0
                    elephant     Shep           5           8630.0
```

For other examples, see *Inspect the Data*.

17.1.41 *EdgeFrame* join

join (*self*, *right*, *left_on*, *right_on=None*, *how='inner'*, *name=None*)
[BETA] Join operation on one or two frames, creating a new frame.

Parameters right : Frame

Another frame to join with

left_on : str

Name of the column in the left frame used to match up the two frames.

right_on : str (default=None)

Name of the column in the right frame used to match up the two frames. Default is the same as the left frame.

how : str (default=inner)

How to qualify the data to be joined together. Must be one of the following: 'left', 'right', 'inner', 'outer'. Default is 'inner'

name : str (default=None)

Name of the result grouped frame

Returns : Frame

A new frame with the results of the join

Create a new frame from a SQL JOIN operation with another frame. The frame on the 'left' is the currently active frame. The frame on the 'right' is another frame. This method takes a column in the left frame and matches its values with a column in the right frame. Using the default 'how' option ['inner'] will only allow data in the resultant frame if both the left and right frames have the same value in the matching column. Using the 'left' 'how' option will allow any data in the resultant frame if it exists in the left frame, but will allow any data from the right frame if it has a value in its column which matches the value in the left frame column. Using the 'right' option works similarly, except it keeps all the data from the right frame and only the data from the left frame when it matches. The 'outer' option provides a frame with data from both frames where the left and right frames did not have the same value in the matching column.

Notes

When a column is named the same in both frames, it will result in two columns in the new frame. The column from the *left* frame (originally the current frame) will be copied and the column name will have the string "_L" added to it. The same thing will happen with the column from the *right* frame, except its name has the string "_R" appended. The order of columns after this method is called is not guaranteed.

It is recommended that you rename the columns to meaningful terms prior to using the `join` method. Keep in mind that unicode in column names will likely cause the drop_frames() method (and others) to fail!

Examples

For this example, we will use a Frame *my_frame* accessing a frame with columns *a*, *b*, *c*, and a Frame *your_frame* accessing a frame with columns *a*, *d*, *e*. Join the two frames keeping only those rows having the same value in column *a*:

```
>>> print my_frame.inspect()

  a:unicode   b:unicode   c:unicode
/---------------------------------------/
  alligator   bear        cat
  apple       berry       cantaloupe
  auto        bus         car
  mirror      frog        ball

>>> print your_frame.inspect()

  b:unicode   c:int   d:unicode
/--------------------------------------/
  berry        5218   frog
  blue            0   log
  bus           871   dog

>>> joined_frame = my_frame.join(your_frame, 'b', how='inner')
```

Now, joined_frame is a Frame accessing a frame with the columns *a*, *b*, *c_L*, *ci_R*, and *d*. The data in the new frame will be from the rows where column 'a' was the same in both frames.

```
>>> print joined_frame.inspect()

  a:unicode   b:unicode     c_L:unicode   c_R:int64   d:unicode
/-------------------------------------------------------------------/
  apple       berry         cantaloupe         5218   frog
  auto        bus           car                 871   dog
```

More examples can be found in the *user manual*.

17.1.42 *EdgeFrame* loadhbase

loadhbase (*self*, *table_name*, *schema*, *start_tag=None*, *end_tag=None*)

Append data from an hBase table into an existing (possibly empty) FrameRDD

Parameters **table_name** : unicode

hbase table name

schema : list

hbase schema as a list of tuples (columnFamily, columnName, dataType for cell value)

start_tag : unicode (default=None)

optional start tag for filtering

end_tag : unicode (default=None)

optional end tag for filtering

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial FrameRDD with the hbase data appended

Append data from an hBase table into an existing (possibly empty) FrameRDD

17.1.43 *EdgeFrame* loadhive

`loadhive` (*self*, *query*)

Append data from a hive table into an existing (possibly empty) frame

Parameters **query** : unicode

Initial query to run at load time

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial frame with the hive data appended

Append data from a hive table into an existing (possibly empty) frame

17.1.44 *EdgeFrame* loadjdbc

`loadjdbc` (*self*, *table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)

Append data from a Jdbc table into an existing (possibly empty) frame

Parameters **table_name** : unicode

table name

connector_type : unicode (default=None)

(optional) connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial frame with the Jdbc data appended

Append data from a Jdbc table into an existing (possibly empty) frame

17.1.45 *EdgeFrame* name

---

name

Set or get the name of the frame object.

Parameters

Change or retrieve frame object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_frame.name

"csv_data"

>>> my_frame.name = "cleaned_data"
>>> my_frame.name

"cleaned_data"
```

17.1.46 *EdgeFrame* quantiles

---

quantiles (*self*, *column_name*, *quantiles*)

New frame with Quantiles and their values.

Parameters **column_name** : unicode

The column to calculate quantiles.

quantiles : list

What is being requested.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame with two columns (float64): requested Quantiles and their respective values.

Calculate quantiles on the given column.

17.1.47 *EdgeFrame* rename_columns

---

rename_columns (*self*, *names*)

Rename columns for edge frame.

Parameters **names** : None

Returns : _Unit

17.1.48 *EdgeFrame* row_count

row_count

Number of rows in the current frame.

Parameters

Returns : int

The number of rows in the frame

Get the number of rows:

```
>>> my_frame.row_count
```

The result given is:

```
81734
```

17.1.49 *EdgeFrame* schema

schema

Current frame column names and types.

Parameters

Returns : list

list of tuples of the form (<column name>, <data type>)

The schema of the current frame is a list of column names and associated data types. It is retrieved as a list of tuples. Each tuple has the name and data type of one of the frame's columns.

Examples

Given that we have an existing data frame *my_data*, create a Frame, then show the frame schema:

```
>>> BF = ta.get_frame('my_data')
>>> print BF.schema
```

The result is:

```
[("col1", str), ("col2", numpy.int32)]
```

17.1.50 *EdgeFrame* sort

sort (*self*, *columns*, *ascending=True*)

[BETA] Sort the data in a frame.

Parameters **columns** : str | list of str | list of tuples

Either a column name, a list of column names, or a list of tuples where each tuple is a name and an ascending bool value.

ascending : bool (default=True)

True for ascending, False for descending.

Sort a frame by column values either ascending or descending.

Examples

Sort a single column:

```
>>> frame.sort('column_name')
```

Sort a single column ascending:

```
>>> frame.sort('column_name', True)
```

Sort a single column descending:

```
>>> frame.sort('column_name', False)
```

Sort multiple columns:

```
>>> frame.sort(['col1', 'col2'])
```

Sort multiple columns ascending:

```
>>> frame.sort(['col1', 'col2'], True)
```

Sort multiple columns descending:

```
>>> frame.sort(['col1', 'col2'], False)
```

Sort multiple columns: 'col1' ascending and 'col2' descending:

```
>>> frame.sort([ ('col1', True), ('col2', False) ])
```

17.1.51 *EdgeFrame* sorted_k

---

sorted_k (*self*, *k*, *column_names_and_ascending*, *reduce_tree_depth=None*)

[ALPHA] Get a sorted subset of the data.

Parameters **k** : int32

Number of sorted records to return.

column_names_and_ascending : list

Column names to sort by, and true to sort column by ascending order, or false for descending order.

reduce_tree_depth : int32 (default=None)

Advanced tuning parameter which determines the depth of the reduce-tree for the sorted_k plugin. This plugin uses Spark's treeReduce() for scalability. The default depth is 2.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame with the first k sorted rows from the original frame.

Take the first k (sorted) rows for the currently active Frame. Rows are sorted by column values in either ascending or descending order.

Returning the first k (sorted) rows is more efficient than sorting the entire frame when k is much smaller than the number of rows in the frame.

Notes

The number of sorted rows (k) should be much smaller than the number of rows in the original frame.

In particular:

1. The number of sorted rows (k) returned should fit in Spark driver memory.

   The maximum size of serialized results that can fit in the Spark driver is set by the Spark configuration parameter *spark.driver.maxResultSize*.

2. If you encounter a Kryo buffer overflow exception, increase the Spark

   configuration parameter *spark.kryoserializer.buffer.max.mb*.

3. Use Frame.sort() instead if the number of sorted rows (k) is

   very large (i.e., cannot fit in Spark driver memory).

17.1.52 *EdgeFrame* status

status

Current frame life cycle status.

Parameters

Returns : str

Status of the frame

One of three statuses: Active, Deleted, Deleted_Final Active: Frame is available for use Deleted: Frame has been scheduled for deletion can be unscheduled by modifying Deleted_Final: Frame's backend files have been removed from disk.

Examples

Given that we have an existing data frame *my_data*, create a Frame, then show the frame schema:

```
>>> BF = ta.get_frame('my_data')
>>> print BF.status
```

The result is:

```
u'Active'
```

17.1.53 *EdgeFrame* take

take (*self*, *n*, *offset=0*, *columns=None*)

Get data subset.

Parameters n : int

The number of rows to copy to the client from the frame.

offset : int (default=0)

The number of rows to skip before starting to copy

columns : str | iterable of str (default=None)

If not None, only the given columns' data will be provided. By default, all columns are included

Returns : list

A list of lists, where each contained list is the data for one row.

Take a subset of the currently active Frame.

Notes

The data is considered 'unstructured', therefore taking a certain number of rows, the rows obtained may be different every time the command is executed, even if the parameters do not change.

Examples

Frame *my_frame* accesses a frame with millions of rows of data. Get a sample of 5000 rows:

```
>>> my_data_list = my_frame.take( 5000 )
```

We now have a list of data from the original frame.

```
>>> print my_data_list

[[ 1, "text", 3.1415962 ]
 [ 2, "bob", 25.0 ]
 [ 3, "weave", .001 ]
 ...]
```

If we use the method with an offset like:

```
>>> my_data_list = my_frame.take( 5000, 1000 )
```

We end up with a new list, but this time it has a copy of the data from rows 1001 to 5000 of the original frame.

17.1.54 *EdgeFrame* tally

tally (*self*, *sample_col*, *count_val*)

[BETA] Count number of times a value is seen.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative count.

count_val : unicode

The column value to be used for the counts.

Returns : _Unit

A cumulative count is computed by sequentially stepping through the rows, observing the column values and keeping track of the the number of times the specified *count_value* has been seen.

17.1.55 *EdgeFrame* tally_percent

tally_percent (*self*, *sample_col*, *count_val*)

[BETA] Compute a cumulative percent count.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative sum.

count_val : unicode

The column value to be used for the counts.

Returns : _Unit

A cumulative percent count is computed by sequentially stepping through the rows, observing the column values and keeping track of the percentage of the total number of times the specified *count_value* has been seen up to the current value.

17.1.56 *EdgeFrame* top_k

top_k (*self*, *column_name*, *k*, *weights_column=None*)

Most or least frequent column values.

Parameters **column_name** : unicode

The column whose top (or bottom) K distinct values are to be calculated.

k : int32

Number of entries to return (If k is negative, return bottom k).

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the topK calculation. Must contain numerical data. Default is 1 for all items.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

An object with access to the frame of data.

Calculate the top (or bottom) K distinct values by count of a column. The column can be weighted. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight > 0, then topK is empty.

17.1.57 *EdgeFrame* unflatten_column

unflatten_column (*self*, *composite_key_column_names*, *delimiter=None*)

Compacts data from multiple rows based on cell data.

Parameters **composite_key_column_names** : list

name of the user column to be used as keys for unflattening.

delimiter : unicode (default=None)

separator for the data in the result columns. Default is comma (,).

Returns : _Unit

Groups together cells in all columns (less the composite key) using "," as string delimiter. The original rows are deleted. The grouping takes place based on a composite key passed as arguments.

class **EdgeFrame**

A list of Edges owned by a Graph.

An EdgeFrame is similar to a Frame but with a few important differences:

- EdgeFrames are not instantiated directly by the user, instead they are created by defining an edge type in a graph
- Each row of an EdgeFrame represents an edge in a graph
- EdgeFrames have many of the same methods as Frames but not all
- EdgeFrames have extra methods not found on Frames (e.g. add_edges())
- EdgeFrames have a dependency on one or two VertexFrames (adding an edge to an EdgeFrame requires either vertices to be present or for the user to specify create_missing_vertices=True)
- EdgeFrames have special system columns (_eid, _label, _src_vid, _dest_vid) that are maintained automatically by the system and cannot be modified by the user
- "Columns" on an EdgeFrame can also be thought of as "properties" on Edges

Attributes

column_names	Column identifications in the current frame.
name	Set or get the name of the frame object.
row_count	Number of rows in the current frame.
schema	Current frame column names and types.
status	Current frame life cycle status.

Methods

__init__(self[, graph, label, src_vertex_label, ...])	Examples
add_columns(self, func, schema[, columns_accessed])	Add columns to current frame.
add_edges(self, source_frame, column_name_for_source_vertex_id, ...[, ...])	Add edges to a graph.
assign_sample(self, sample_percentages[, sample_labels, ...])	Randomly group rows into user-defined classes.
bin_column(self, column_name, cutoffs[, include_lowest, strict_binning, ...])	Classify data into user-defined groups.

Table 17.1 – continued from previous page

bin_column_equal_depth(self, column_name[, num_bins, ...])	Classify column into groups with the same frequency.
bin_column_equal_width(self, column_name[, num_bins, ...])	Classify column into same-width groups.
categorical_summary(self, *column_inputs)	[ALPHA] Compute a summary of the data in a colun
classification_metrics(self, label_column, pred_column[, ...])	Model statistics of accuracy, precision, and others.
column_median(self, data_column[, weights_column])	Calculate the (weighted) median of a column.
column_mode(self, data_column[, weights_column, max_modes_returned])	Evaluate the weights assigned to rows.
column_summary_statistics(self, data_column[, ...])	Calculate multiple statistics for a column.
compute_misplaced_score(self, gravity)	
copy(self[, columns, where, name])	Create new frame from current frame.
correlation(self, data_column_names)	Calculate correlation for two columns of current fram
correlation_matrix(self, data_column_names[, matrix_name])	Calculate correlation matrix for two or more columns.
count(self, where)	Counts the number of rows which meet given criteria.
covariance(self, data_column_names)	Calculate covariance for exactly two columns.
covariance_matrix(self, data_column_names[, matrix_name])	Calculate covariance matrix for two or more columns.
cumulative_percent(self, sample_col)	[BETA] Add column to frame with cumulative percen
cumulative_sum(self, sample_col)	[BETA] Add column to frame with cumulative percen
dot_product(self, left_column_names, right_column_names, ...[, ...])	[ALPHA] Calculate dot product for each row in curre
download(self[, n, offset, columns])	Download a frame from the server into client workspa
drop_columns(self, columns)	Remove columns from the frame.
drop_duplicates(self[, unique_columns])	Modify the current frame, removing duplicate rows.
drop_rows(self, predicate)	Erase any row in the current frame which qualifies.
ecdf(self, column[, result_frame_name])	Builds new frame with columns for data and distributi
entropy(self, data_column[, weights_column])	Calculate the Shannon entropy of a column.
export_to_csv(self, folder_name[, separator, count, offset])	Write current frame to HDFS in csv format.
export_to_hbase(self, table_name[, key_column_name, family_name])	Write current frame to HBase table.
export_to_hive(self, table_name)	Write current frame to Hive table.
export_to_jdbc(self, table_name[, connector_type, url, driver_name, ...])	Write current frame to Jdbc table.
export_to_json(self, folder_name[, count, offset])	Write current frame to HDFS in JSON format.
filter(self, predicate)	Select all rows which satisfy a predicate.
flatten_column(self, column[, delimiter])	Spread data to multiple rows based on cell data.
get_error_frame(self)	Get a frame with error recordings.
group_by(self, group_by_columns, *aggregation_arguments)	[BETA] Create summarized frame.
histogram(self, column_name[, num_bins, weight_column_name, bin_type])	[BETA] Compute the histogram for a column in a fra
inspect(self[, n, offset, columns, wrap, truncate, round, width, margin])	Prints the frame data in readable format.
join(self, right, left_on[, right_on, how, name])	[BETA] Join operation on one or two frames, creatin
loadhbase(self, table_name, schema[, start_tag, end_tag])	Append data from an hBase table into an existing (pos
loadhive(self, query)	Append data from a hive table into an existing (possib
loadjdbc(self, table_name[, connector_type, url, driver_name, query])	Append data from a Jdbc table into an existing (possib
quantiles(self, column_name, quantiles)	New frame with Quantiles and their values.
rename_columns(self, names)	Rename columns for edge frame.
sort(self, columns[, ascending])	[BETA] Sort the data in a frame.
sorted_k(self, k, column_names_and_ascending[, reduce_tree_depth])	[ALPHA] Get a sorted subset of the data.
take(self, n[, offset, columns])	Get data subset.
tally(self, sample_col, count_val)	[BETA] Count number of times a value is seen.
tally_percent(self, sample_col, count_val)	[BETA] Compute a cumulative percent count.
top_k(self, column_name, k[, weights_column])	Most or least frequent column values.
unflatten_column(self, composite_key_column_names[, delimiter])	Compacts data from multiple rows based on cell data.

__init__(*self*, *graph=None*, *label=None*, *src_vertex_label=None*, *dest_vertex_label=None*, *directed=None*)

Examples

Parameters **graph** : ? (default=None)

graph these edges belong to

label : ? (default=None)

edge label

src_vertex_label : ? (default=None)

label of the source vertex type

dest_vertex_label : ? (default=None)

label of the destination vertex type

directed : ? (default=None)

directed or undirected

Returns : VertexFrame object

An object with access to the frame.

Given a data file */movie.csv*, create a frame to match this data and move the data to the frame. Create an empty graph and define some vertex and edge types.

```
>>> my_csv = ta.CsvFile("/movie.csv", schema= [('user_id', int32),
...                                           ('user_name', str),
...                                           ('movie_id', int32),
...                                           ('movie_title', str),
...                                           ('rating', str)])

>>> my_frame = ta.Frame(my_csv)
>>> my_graph = ta.Graph()
>>> my_graph.define_vertex_type('users')
>>> my_graph.define_vertex_type('movies')
>>> my_graph.define_edge_type('ratings','users','movies',directed=True)
```

Add data to the graph from the frame:

```
>>> my_graph.vertices['users'].add_vertices(my_frame, 'user_id',
... ['user_name'])
>>> my_graph.vertices['movies'].add_vertices(my_frame, 'movie_id', ['movie_title'])
```

Create an edge frame from the graph, and add edge data from the frame.

```
>>> my_edge_frame = graph.edges['ratings']
>>> my_edge_frame.add_edges(my_frame, 'user_id', 'movie_id', ['rating']
```

Retrieve a previously defined graph and retrieve an EdgeFrame from it:

```
>>> my_old_graph = ta.get_graph("your_graph")
>>> my_new_edge_frame = my_old_graph.edges["your_label"]
```

Calling methods on an EdgeFrame:

```
>>> my_new_edge_frame.inspect(20)
```

Copy an EdgeFrame to a frame using the copy method:

```
>>> my_new_frame = my_new_edge_frame.copy()
```

17.2 *Frames* VertexFrame

17.2.1 *VertexFrame* __init__

__init__(*self*, *source=None*, *graph=None*, *label=None*)
Examples

Parameters **source** : (default=None)

graph : (default=None)

label : (default=None)

Given a data file, create a frame, move the data to graph and then define a new VertexFrame and add data to it:

Retrieve a previously defined graph and retrieve a VertexFrame from it:

```
>>> my_graph = ta.get_graph("your_graph")
>>> my_vertex_frame = my_graph.vertices["your_label"]
```

Calling methods on a VertexFrame:

```
>>> my_vertex_frame.vertices["your_label"].inspect(20)
```

Convert a VertexFrame to a frame:

```
>>> new_Frame = my_vertex_frame.vertices["label"].copy()
```

17.2.2 *VertexFrame* add_columns

add_columns(*self*, *func*, *schema*, *columns_accessed=None*)
Add columns to current frame.

Parameters **func** : UDF

User-Defined Function (UDF) which takkes the values in the row and produces a value, or collection of values, for the new cell(s).

schema : tuple | list of tuples

The schema for the results of the UDF, indicating the new column(s) to add. Each tuple provides the column name and data type, and is of the form (str, type).

columns_accessed : list (default=None)

List of columns which the UDF will access. This adds significant performance benefit if we know which column(s) will be needed to execute the UDF, especially when the frame has significantly more columns than those being used to evaluate the UDF.

Assigns data to column based on evaluating a function for each row.

Notes

1. The row UDF ('func') must return a value in the same format as specified by the schema. See Python User Functions.

2. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

Examples

Given a Frame *my_frame* identifying a data frame with two int32 columns *column1* and *column2*. Add a third column *column3* as an int32 and fill it with the contents of *column1* and *column2* multiplied together:

```
>>> my_frame.add_columns(lambda row: row.column1*row.column2,
... ('column3', int32))
```

The frame now has three columns, *column1*, *column2* and *column3*. The type of *column3* is an int32, and the value is the product of *column1* and *column2*.

Add a string column *column4* that is empty:

```
>>> my_frame.add_columns(lambda row: '', ('column4', str))
```

The Frame object *my_frame* now has four columns *column1*, *column2*, *column3*, and *column4*. The first three columns are int32 and the fourth column is str. Column *column4* has an empty string ('') in every row.

Multiple columns can be added at the same time. Add a column *a_times_b* and fill it with the contents of column *a* multiplied by the contents of column *b*. At the same time, add a column *a_plus_b* and fill it with the contents of column *a* plus the contents of column *b*:

```
>>> my_frame.add_columns(lambda row: [row.a * row.b, row.a +
... row.b], [("a_times_b", float32), ("a_plus_b", float32))
```

Two new columns are created, "a_times_b" and "a_plus_b", with the appropriate contents.

Given a frame of data and Frame *my_frame* points to it. In addition we have defined a UDF *func*. Run *func* on each row of the frame and put the result in a new int column *calculated_a*:

```
>>> my_frame.add_columns( func, ("calculated_a", int))
```

Now the frame has a column *calculated_a* which has been filled with the results of the UDF *func*.

A UDF must return a value in the same format as the column is defined. In most cases this is automatically the case, but sometimes it is less obvious. Given a UDF *function_b* which returns a value in a list, store the result in a new column *calculated_b*:

```
>>> my_frame.add_columns(function_b, ("calculated_b", float32))
```

This would result in an error because function_b is returning a value as a single element list like [2.4], but our column is defined as a tuple. The column must be defined as a list:

```
>>> my_frame.add_columns(function_b, [("calculated_b", float32)])
```

To run an optimized version of add_columns, columns_accessed parameter can be populated with the column names which are being accessed in UDF. This speeds up the execution by working on only the limited feature set than the entire row.

Let's say a frame has 4 columns named *a*,*b*,*c* and *d* and we want to add a new column with value from column *a* multiplied by value in column *b* and call it *a_times_b*. In the example below, columns_accessed is a list with column names *a* and *b*.

```
>>> my_frame.add_columns(lambda row: row.a * row.b, ("a_times_b", float32), columns_accessed=["a
```

add_columns would fail if columns_accessed parameter is not populated with the correct list of accessed columns. If not specified, columns_accessed defaults to None which implies that all columns might be accessed by the UDF.

More information on a row UDF can be found at Python User Functions

17.2.3 *VertexFrame* add_vertices

---

add_vertices (*self*, *source_frame*, *id_column_name*, *column_names=None*)

Add vertices to a graph.

Parameters **source_frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame that will be the source of the vertex data.

id_column_name : unicode

Column name for a unique id for each vertex.

column_names : list (default=None)

Column names that will be turned into properties for each vertex.

Returns : _Unit

Includes appending to a list of existing vertices.

17.2.4 *VertexFrame* assign_sample

---

assign_sample (*self*, *sample_percentages*, *sample_labels=None*, *output_column=None*, *random_seed=None*)

Randomly group rows into user-defined classes.

Parameters **sample_percentages** : list

Entries are non-negative and sum to 1. (See the note below.) If the *i*'th entry of the list is *p*, then then each row receives label *i* with independent probability *p*.

sample_labels : list (default=None)

Names to be used for the split classes. Defaults "TR", "TE", "VA" when the length of *sample_percentages* is 3, and defaults to Sample_0, Sample_1, ... otherwise.

output_column : unicode (default=None)

Name of the new column which holds the labels generated by the function.

random_seed : int32 (default=None)

Random seed used to generate the labels. Defaults to 0.

Returns : _Unit

Randomly assign classes to rows given a vector of percentages. The table receives an additional column that contains a random label. The random label is generated by a probability distribution function. The distribution function is specified by the sample_percentages, a list of floating point values, which add up to 1. The labels are non-negative integers drawn from the range $[0, len(S) - 1]$ where S is the sample_percentages. Optionally, the user can specify a list of strings to be used as the labels. If the number of labels is 3, the labels will default to "TR", "TE" and "VA".

Notes

The sample percentages provided by the user are preserved to at least eight decimal places, but beyond this there may be small changes due to floating point imprecision.

In particular:

1. The engine validates that the sum of probabilities sums to 1.0 within eight decimal places and returns an error if the sum falls outside of this range.
2. The probability of the final class is clamped so that each row receives a valid label with probability one.

17.2.5 *VertexFrame* bin_column

`bin_column`(*self*, *column_name*, *cutoffs*, *include_lowest=None*, *strict_binning=None*, *bin_column_name=None*)

Classify data into user-defined groups.

Parameters **column_name** : unicode

Name of the column to bin.

cutoffs : list

Array of values containing bin cutoff points. Array can be list or tuple. Array values must be progressively increasing. All bin boundaries must be included, so, with N bins, you need N+1 values.

include_lowest : bool (default=None)

Specify how the boundary conditions are handled. True indicates that the lower bound of the bin is inclusive. False indicates that the upper bound is inclusive. Default is True.

strict_binning : bool (default=None)

Specify how values outside of the cutoffs array should be binned. If set to True, each value less than cutoffs[0] or greater than cutoffs[-1] will be assigned a bin value of -1. If set to False, values less than cutoffs[0] will be included in the first bin while values greater than cutoffs[-1] will be included in the final bin.

bin_column_name : unicode (default=None)

The name for the new binned column. Default is <column_name>_binned.

Returns : _Unit

Summarize rows of data based on the value in a single column by sorting them into bins, or groups, based on a list of bin cutoff points.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. Bins IDs are 0-index: the lowest bin number is 0.

3.The first and last cutoffs are always included in the bins. When include_lowest is `True`, the last bin includes both cutoffs. When include_lowest is `False`, the first bin (bin 0) includes both cutoffs.

17.2.6 *VertexFrame* bin_column_equal_depth

bin_column_equal_depth (*self*, *column_name*, *num_bins=None*, *bin_column_name=None*)
Classify column into groups with the same frequency.

Parameters **column_name** : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is <column_name>_binned.

Returns : dict

A list containing the edges of each bin.

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal depth binning attempts to label rows such that each bin contains the same number of elements. For n bins of a column C of length m, the bin number is determined by:

$$\lceil n * \frac{f(C)}{m} \rceil$$

where f is a tie-adjusted ranking function over values of C. If there are multiples of the same value in C, then their tie-adjusted rank is the average of their ordered rank values.

Notes

1.Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

2.The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has a quantity of :math"*X* elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.2.7 *VertexFrame* bin_column_equal_width

bin_column_equal_width (*self*, *column_name*, *num_bins=None*, *bin_column_name=None*)
Classify column into same-width groups.

Parameters **column_name** : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is <column_name>_binned.

Returns : dict

A list of the edges of each bin.

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal width binning places column values into groups such that the values in each group fall within the same interval and the interval width for each group is equal.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

2. The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.2.8 *VertexFrame* categorical_summary

`categorical_summary` (*self*, *column_inputs=None*)

[ALPHA] Compute a summary of the data in a column(s) for categorical or numerical data types.

Parameters **column_inputs** : str | tuple(str, dict) (default=None)

Comma-separated column names to summarize or tuple containing column name and dictionary of optional parameters. Optional parameters (see below for details): top_k (default = 10), threshold (default = 0.0)

Returns : dict

Summary for specified column(s) consisting of levels with their frequency and percentage

The returned value is a Map containing categorical summary for each specified column.

For each column, levels which satisfy the top k and/or threshold cutoffs are displayed along with their frequency and percentage occurrence with respect to the total rows in the dataset.

Missing data is reported when a column value is empty (“”) or null.

All remaining data is grouped together in the Other category and its frequency and percentage are reported as well.

User must specify the column name and can optionally specify top_k and/or threshold.

Optional parameters:

top_k Displays levels which are in the top k most frequently occurring values for that column.

threshold Displays levels which are above the threshold percentage with respect to the total row count.

top_k and threshold Performs level pruning first based on top k and then filters out levels which satisfy the threshold criterion.

defaults Displays all levels which are in Top 10.

Examples

```
>>> frame.categorical_summary('source','target')
>>> frame.categorical_summary(('source', {'top_k' : 2}))
>>> frame.categorical_summary(('source', {'threshold' : 0.5}))
>>> frame.categorical_summary(('source', {'top_k' : 2}), ('target',
... {'threshold' : 0.5}))
```

Sample output (for last example above):

```
>>> {u'categorical_summary': [{u'column': u'source', u'levels': [
... {u'percentage': 0.32142857142857145, u'frequency': 9, u'level': u'thing'},
... {u'percentage': 0.32142857142857145, u'frequency': 9, u'level': u'abstraction'},
... {u'percentage': 0.25, u'frequency': 7, u'level': u'physical_entity'},
... {u'percentage': 0.10714285714285714, u'frequency': 3, u'level': u'entity'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Missing'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Other'}]},
... {u'column': u'target', u'levels': [
... {u'percentage': 0.07142857142857142, u'frequency': 2, u'level': u'thing'},
... {u'percentage': 0.07142857142857142, u'frequency': 2,
...  u'level': u'physical_entity'},
... {u'percentage': 0.07142857142857142, u'frequency': 2, u'level': u'entity'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'variable'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'unit'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'substance'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'subject'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'set'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'reservoir'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'relation'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Missing'},
... {u'percentage': 0.5357142857142857, u'frequency': 15, u'level': u'Other'}]}]}
```

17.2.9 *VertexFrame* classification_metrics

classification_metrics (*self*, *label_column*, *pred_column*, *pos_label=None*, *beta=None*)

Model statistics of accuracy, precision, and others.

Parameters label_column : unicode

The name of the column containing the correct label for each instance.

pred_column : unicode

The name of the column containing the predicted label for each instance.

pos_label : None (default=None)

beta : float64 (default=None)

This is the beta value to use for F_β measure (default F1 measure is computed); must be greater than zero. Defaults is 1.

Returns : dict

object <object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

Calculate the accuracy, precision, confusion_matrix, recall and F_β measure for a classification model.

- The **f_measure** result is the F_β measure for a classification model. The F_β measure of a binary classification model is the harmonic mean of precision and recall. If we let:

  - beta $\equiv \beta$,
  - T_P denotes the number of true positives,
  - F_P denotes the number of false positives, and
  - F_N denotes the number of false negatives

  then:

$$F_\beta = (1+\beta^2) * \frac{\frac{T_P}{T_P+F_P} * \frac{T_P}{T_P+F_N}}{\beta^2 * \frac{T_P}{T_P+F_P} + \frac{T_P}{T_P+F_N}}$$

  The F_β measure for a multi-class classification model is computed as the weighted average of the F_β measure for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **recall** result of a binary classification model is the proportion of positive instances that are correctly identified. If we let T_P denote the number of true positives and F_N denote the number of false negatives, then the model recall is given by $\frac{T_P}{T_P + F_N}$.

  For multi-class classification models, the recall measure is computed as the weighted average of the recall for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **precision** of a binary classification model is the proportion of predicted positive instances that are correctly identified. If we let T_P denote the number of true positives and F_P denote the number of false positives, then the model precision is given by: $\frac{T_P}{T_P + F_P}$.

  For multi-class classification models, the precision measure is computed as the weighted average of the precision for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **accuracy** of a classification model is the proportion of predictions that are correctly identified. If we let T_P denote the number of true positives, T_N denote the number of true negatives, and K denote the total number of classified instances, then the model accuracy is given by: $\frac{T_P + T_N}{K}$.

  This measure applies to binary and multi-class classifiers.

- The **confusion_matrix** result is a confusion matrix for a binary classifier model, formatted for human readability.

Notes

The **confusion_matrix** is not yet implemented for multi-class classifiers.

17.2.10 *VertexFrame* column_median

column_median (*self*, *data_column*, *weights_column=None*)
Calculate the (weighted) median of a column.

Parameters data_column : unicode

The column whose median is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the median calculation. Must contain numerical data. Default is all items have a weight of 1.

Returns : dict

varies The median of the values. If a weight column is provided and no weights are finite numbers greater than 0, None is returned. The type of the median returned is the same as the contents of the data column, so a column of Longs will result in a Long median and a column of Floats will result in a Float median.

The median is the least value X in the range of the distribution so that the cumulative weight of values strictly below X is strictly less than half of the total weight and the cumulative weight of values up to and including X is greater than or equal to one-half of the total weight.

All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If a weight column is provided and no weights are finite numbers greater than 0, None is returned.

17.2.11 *VertexFrame* column_mode

column_mode (*self*, *data_column*, *weights_column=None*, *max_modes_returned=None*)
Evaluate the weights assigned to rows.

Parameters data_column : unicode

Name of the column supplying the data.

weights_column : unicode (default=None)

Name of the column supplying the weights. Default is all items have weight of 1.

max_modes_returned : int32 (default=None)

Maximum number of modes returned. Default is 1.

Returns : dict

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mode [A mode is a data element of maximum net weight.] A set of modes is returned. The empty set is returned when the sum of the weights is 0. If the number of modes is less than or equal to the parameter max_modes_returned, then all modes of the data are returned. If the number of modes is greater than the max_modes_returned parameter, only the first max_modes_returned many modes (per a canonical ordering) are returned.

weight_of_mode [Weight of a mode.] If there are no data elements of finite weight greater than 0, the weight of the mode is 0. If no weights column is given, this is the number of appearances of each mode.

total_weight [Sum of all weights in the weight column.] This is the row count if no weights are given. If no weights column is given, this is the number of rows in the table with non-zero weight.

mode_count [The number of distinct modes in the data.] In the case that the data is very multimodal, this number may exceed max_modes_returned.

Calculate the modes of a column. A mode is a data element of maximum weight. All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight greater than 0, no mode is returned.

Because data distributions often have mutliple modes, it is possible for a set of modes to be returned. By default, only one is returned, but by setting the optional parameter max_modes_returned, a larger number of modes can be returned.

17.2.12 *VertexFrame* column_names

column_names

Column identifications in the current frame.

Parameters

Returns : list

list of names of all the frame's columns

Given a Frame object, *my_frame* accessing a frame. To get the column names:

```
>>> my_columns = my_frame.column_names
>>> print my_columns
```

Now, given there are three columns *col1*, *col2*, and *col3*, the result is:

```
["col1", "col2", "col3"]
```

17.2.13 *VertexFrame* column_summary_statistics

column_summary_statistics(*self*, *data_column*, *weights_column=None*, *use_population_variance=None*)

Calculate multiple statistics for a column.

Parameters **data_column** : unicode

The column to be statistically summarized. Must contain numerical data; all NaNs and infinite values are excluded from the calculation.

weights_column : unicode (default=None)

Name of column holding weights of column values.

use_population_variance : bool (default=None)

If true, the variance is calculated as the population variance. If false, the variance calculated as the sample variance. Because this option affects the variance, it affects the standard deviation and the confidence intervals as well. Default is false.

Returns : dict

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mean [[double | None]] Arithmetic mean of the data.

geometric_mean [[double | None]] Geometric mean of the data. None when there is a data element <= 0, 1.0 when there are no data elements.

variance [[double | None]] None when there are <= 1 many data elements. Sample variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight minus 1. None when the sum of the weights is <= 1. Population variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight.

standard_deviation [[double | None]] The square root of the variance. None when sample variance is being used and the sum of weights is <= 1.

total_weight [long] The count of all data elements that are finite numbers. (In other words, after excluding NaNs and infinite values.)

minimum [[double | None]] Minimum value in the data. None when there are no data elements.

maximum [[double | None]] Maximum value in the data. None when there are no data elements.

mean_confidence_lower [[double | None]] Lower limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

mean_confidence_upper [[double | None]] Upper limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

bad_row_count [[double | None]] The number of rows containing a NaN or infinite value in either the data or weights column.

good_row_count [[double | None]] The number of rows not containing a NaN or infinite value in either the data or weights column.

positive_weight_count [[double | None]] The number of valid data elements with weight > 0. This is the number of entries used in the statistical calculation.

non_positive_weight_count [[double | None]] The number valid data elements with finite weight <= 0.

Notes

Sample Variance Sample Variance is computed by the following formula:

$$\left(\frac{1}{W-1}\right) * sum_i \ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Population Variance Population Variance is computed by the following formula:

$$\left(\frac{1}{W}\right) * sum_i \ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Standard Deviation The square root of the variance.

Logging Invalid Data A row is bad when it contains a NaN or infinite value in either its data or weights column. In this case, it contributes to bad_row_count; otherwise it contributes to good row count.

A good row can be skipped because the value in its weight column is less than or equal to 0. In this case, it contributes to non_positive_weight_count, otherwise (when the weight is greater than 0) it contributes to valid_data_weight_pair_count.

Equations `bad_row_count + good_row_count = # rows in the frame`

`positive_weight_count + non_positive_weight_count = good_row_count`

In particular, when no weights column is provided and all weights are 1.0, `non_positive_weight_count = 0` and `positive_weight_count = good_row_count`

17.2.14 *VertexFrame* compute_misplaced_score

---

compute_misplaced_score (*self*, *gravity*)

Parameters **gravity** : float64

Similarity measure for computing tension between 2 connected items

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

17.2.15 *VertexFrame* copy

---

copy (*self*, *columns=None*, *where=None*, *name=None*)

Create new frame from current frame.

Parameters **columns** : str | list of str | dict (default=None)

If not None, the copy will only include the columns specified. If dict, the string pairs represent a column renaming, {source_column_name: destination_column_name}

where : function (default=None)

If not None, only those rows for which the UDF evaluates to True will be copied.

name : str (default=None)

Name of the copied frame

Returns : Frame

A new Frame of the copied data.

Copy frame or certain frame columns entirely or filtered. Useful for frame query.

Examples

Build a Frame from a csv file with 5 million rows of data; call the frame "cust":

```
>>> my_frame = ta.Frame(source="my_data.csv")
>>> my_frame.name("cust")
```

Given the frame has columns *id*, *name*, *hair*, and *shoe*. Copy it to a new frame:

```
>>> your_frame = my_frame.copy()
```

Now we have two frames of data, each with 5 million rows. Checking the names:

```
>>> print my_frame.name()
>>> print your_frame.name()
```

Gives the results:

```
"cust"
"frame_75401b7435d7132f5470ba35..."
```

Now, let's copy *some* of the columns from the original frame:

```
>>> our_frame = my_frame.copy(['id', 'hair'])
```

Our new frame now has two columns, *id* and *hair*, and has 5 million rows. Let's try that again, but this time change the name of the *hair* column to *color*:

```
>>> last_frame = my_frame.copy(('id': 'id', 'hair': 'color'))
```

17.2.16 *VertexFrame* correlation

---

correlation (*self*, *data_column_names*)

Calculate correlation for two columns of current frame.

Parameters data_column_names : list

The names of 2 columns from which to compute the correlation.

Returns : dict

Pearson correlation coefficient of the two columns.

This method applies only to columns containing numerical data.

17.2.17 *VertexFrame* correlation_matrix

---

correlation_matrix (*self*, *data_column_names*, *matrix_name=None*)

Calculate correlation matrix for two or more columns.

Parameters data_column_names : list

The names of the columns from which to compute the matrix.

matrix_name : unicode (default=None)

The name for the returned matrix Frame.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A Frame with the matrix of the correlation values for the columns.

This method applies only to columns containing numerical data.

17.2.18 *VertexFrame* count

---

count (*self*, *where*)

Counts the number of rows which meet given criteria.

Parameters **where** : function

UDF which evaluates a row to a boolean

Returns : int

number of rows for which the where UDF evaluated to True.

17.2.19 *VertexFrame* covariance

---

covariance (*self*, *data_column_names*)

Calculate covariance for exactly two columns.

Parameters **data_column_names** : list

The names of two columns from which to compute the covariance.

Returns : dict

Covariance of the two columns.

This method applies only to columns containing numerical data.

17.2.20 *VertexFrame* covariance_matrix

---

covariance_matrix (*self*, *data_column_names*, *matrix_name=None*)

Calculate covariance matrix for two or more columns.

Parameters **data_column_names** : list

The names of the column from which to compute the matrix. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

matrix_name : unicode (default=None)

The name of the new matrix.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A matrix with the covariance values for the columns.

This function applies only to columns containing numerical data.

17.2.21 *VertexFrame* cumulative_percent

cumulative_percent(*self*, *sample_col*)

[BETA] Add column to frame with cumulative percent sum.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative percent sum.

Returns : _Unit

A cumulative percent sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the current percentage of the total sum accounted for at the current value.

Notes

This method applies only to columns containing numerical data. Although this method will execute for columns containing negative values, the interpretation of the result will change (for example, negative percentages).

17.2.22 *VertexFrame* cumulative_sum

cumulative_sum(*self*, *sample_col*)

[BETA] Add column to frame with cumulative percent sum.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative sum.

Returns : _Unit

A cumulative sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the cumulative sum for each value.

Notes

This method applies only to columns containing numerical data.

17.2.23 *VertexFrame* dot_product

dot_product(*self*, *left_column_names*, *right_column_names*, *dot_product_column_name*, *default_left_values=None*, *default_right_values=None*)

[ALPHA] Calculate dot product for each row in current frame.

Parameters **left_column_names** : list

Names of columns used to create the left vector (A) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

right_column_names : list

Names of columns used to create right vector (B) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

dot_product_column_name : unicode

Name of column used to store the dot product.

default_left_values : list (default=None)

Default values used to substitute null values in left vector. Default is None.

default_right_values : list (default=None)

Default values used to substitute null values in right vector. Default is None.

Returns : _Unit

Calculate the dot product for each row in a frame using values from two equal-length sequences of columns.

Dot product is computed by the following formula:

The dot product of two vectors $A = [a_1, a_2, ..., a_n]$ and $B = [b_1, b_2, ..., b_n]$ is $a_1 * b_1 + a_2 * b_2 + ... + a_n * b_n$. The dot product for each row is stored in a new column in the existing frame.

Notes

If default_left_values or default_right_values are not specified, any null values will be replaced by zeros.

17.2.24 *VertexFrame* download

download(*self*, *n=100*, *offset=0*, *columns=None*)

Download a frame from the server into client workspace.

Parameters **n** : int (default=100)

The number of rows to download to the client

offset : int (default=0)

The number of rows to skip before copying

columns : list (default=None)

Column filter, the names of columns to be included (default is all columns)

Returns : pandas.DataFrame

A new pandas dataframe object containing the downloaded frame data

Copies an trustedanalytics Frame into a Pandas DataFrame.

Examples

Frame *my_frame* accesses a frame with millions of rows of data. Get a sample of 500 rows:

```
>>> pandas_frame = my_frame.download( 500 )
```

We now have a new frame accessed by a pandas DataFrame *pandas_frame* with a copy of the first 500 rows of the original frame.

If we use the method with an offset like:

```
>>> pandas_frame = my_frame.take( 500, 100 )
```

We end up with a new frame accessed by the pandas DataFrame *pandas_frame* again, but this time it has a copy of rows 101 to 600 of the original frame.

17.2.25 *VertexFrame* drop_columns

---

drop_columns (*self*, *columns*)

Remove columns from the frame.

Parameters **columns** : list

Column name OR list of column names to be removed from the frame.

Returns : _Unit

The data from the columns is lost.

Notes

It is not possible to delete all columns from a frame. At least one column needs to remain. If it is necessary to delete all columns, then delete the frame.

17.2.26 *VertexFrame* drop_duplicates

---

drop_duplicates (*self*, *unique_columns=None*)

Remove duplicate vertex rows.

Parameters **unique_columns** : None (default=None)

Returns : _Unit

Remove duplicate vertex rows, keeping only one vertex row per uniqueness criteria match. Edges that were connected to removed vertices are also automatically dropped.

17.2.27 *VertexFrame* drop_rows

---

drop_rows (*self*, *predicate*)

Erase any row in the current frame which qualifies.

Parameters **predicate** : function

UDF which evaluates a row to a boolean; rows that answer True are dropped from the Frame

Examples

For this example, my_frame is a Frame object accessing a frame with lots of data for the attributes of `lions`, `tigers`, and `ligers`. Get rid of the `lions` and `tigers`:

```
>>> my_frame.drop_rows(lambda row: row.animal_type == "lion" or
...     row.animal_type == "tiger")
```

Now the frame only has information about `ligers`.

More information on a UDF can be found at Python User Functions.

17.2.28 *VertexFrame* drop_vertices

drop_vertices (*self*, *predicate*)

Delete rows that qualify.

Parameters predicate : function

UDF which evaluates a row (vertex) to a boolean; vertices that answer True are dropped from the Frame

Parameters predicate : UDF

UDF or *lambda* which takes a row argument and evaluates to a boolean value.

Examples

Given VertexFrame object *my_vertex_frame* accessing a graph with lots of data for the attributes of `lions`, `tigers`, and `ligers`. Get rid of the `lions` and `tigers`:

```
>>> my_vertex_frame.drop_vertices(lambda row:
...     row.animal_type == "lion" or
...     row.animal_type == "tiger")
```

Now the frame only has information about `ligers`.

More information on UDF can be found at Python User Functions

17.2.29 *VertexFrame* ecdf

ecdf (*self*, *column*, *result_frame_name=None*)

Builds new frame with columns for data and distribution.

Parameters column : unicode

The name of the input column containing sample.

result_frame_name : unicode (default=None)

A name for the resulting frame which is created by this operation.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new Frame containing each distinct value in the sample and its corresponding ECDF value.

Generates the *empirical cumulative distribution* for the input column.

17.2.30 *VertexFrame* entropy

entropy (*self*, *data_column*, *weights_column=None*)
Calculate the Shannon entropy of a column.

Parameters **data_column** : unicode

The column whose entropy is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the entropy calculation. Must contain numerical data. Default is using uniform weights of 1 for all items.

Returns : dict

Entropy.

The data column is weighted via the weights column. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements with a finite weight greater than 0, the entropy is zero.

17.2.31 *VertexFrame* export_to_csv

export_to_csv (*self*, *folder_name*, *separator=None*, *count=None*, *offset=None*)
Write current frame to HDFS in csv format.

Parameters **folder_name** : unicode

The HDFS folder path where the files will be created.

separator : None (default=None)

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Returns : _Unit

Export the frame to a file in csv format as a Hadoop file.

17.2.32 *VertexFrame* export_to_hbase

export_to_hbase (*self*, *table_name*, *key_column_name=None*, *family_name=None*)
Write current frame to HBase table.

Parameters **table_name** : unicode

The name of the HBase table that will contain the exported frame

key_column_name : unicode (default=None)

The name of the column to be used as row key in hbase table

family_name : unicode (default=None)

The family name of the HBase table that will contain the exported frame

Returns : _Unit

Table must exist in HBase. Export of Vectors is not currently supported.

17.2.33 *VertexFrame* export_to_hive

---

export_to_hive (*self*, *table_name*)

Write current frame to Hive table.

Parameters **table_name** : unicode

The name of the Hive table that will contain the exported frame

Returns : _Unit

Table must not exist in Hive. Export of Vectors is not currently supported.

17.2.34 *VertexFrame* export_to_jdbc

---

export_to_jdbc (*self*, *table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)

Write current frame to Jdbc table.

Parameters **table_name** : unicode

jdbc table name

connector_type : unicode (default=None)

(optional) jdbc connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Returns : _Unit

Table will be created or appended to. Export of Vectors is not currently supported.

17.2.35 *VertexFrame* export_to_json

---

export_to_json (*self*, *folder_name*, *count=None*, *offset=None*)

Write current frame to HDFS in JSON format.

Parameters **folder_name** : unicode

The HDFS folder path where the files will be created.

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Returns : _Unit

Export the frame to a file in JSON format as a Hadoop file.

17.2.36 *VertexFrame* filter

---

filter (*self*, *predicate*)

<Missing Doc>

Parameters **predicate** : function

UDF which evaluates a row to a boolean; vertices that answer False are dropped from the Frame

17.2.37 *VertexFrame* flatten_column

---

flatten_column (*self*, *column*, *delimiter=None*)

Spread data to multiple rows based on cell data.

Parameters **column** : unicode

The column to be flattened.

delimiter : unicode (default=None)

The delimiter string. Default is comma (,).

Returns : _Unit

Splits cells in the specified column into multiple rows according to a string delimiter. New rows are a full copy of the original row, but the specified column only contains one value. The original row is deleted.

17.2.38 *VertexFrame* get_error_frame

get_error_frame(*self*)

Get a frame with error recordings.

Parameters

When a frame is created, another frame is transparently created to capture parse errors.

Returns Frame : error frame object

A new object accessing a frame that contains the parse errors of the currently active Frame or None if no error frame exists.

17.2.39 *VertexFrame* group_by

group_by(*self*, *group_by_columns*, *aggregation_arguments=None*)

[BETA] Create summarized frame.

Parameters group_by_columns : list

Column name or list of column names

aggregation_arguments : dict (default=None)

Aggregation function based on entire row, and/or dictionaries (one or more) of { column name str : aggregation function(s) }.

Returns : Frame

A new frame with the results of the group_by

Creates a new frame and returns a Frame object to access it. Takes a column or group of columns, finds the unique combination of values, and creates unique rows with these column values. The other columns are combined according to the aggregation argument(s).

Notes

- Column order is not guaranteed when columns are added
- The column names created by aggregation functions in the new frame are the original column name appended with the '_' character and the aggregation function. For example, if the original field is *a* and the function is *avg*, the resultant column is named *a_avg*.
- An aggregation argument of *count* results in a column named *count*.
- The aggregation function *agg.count* is the only full row aggregation function supported at this time.
- Aggregation currently supports using the following functions:
  - avg
  - count
  - count_distinct
  - max
  - min

–stdev

–sum

–var (see glossary *Bias vs Variance*)

Examples

For setup, we will use a Frame *my_frame* accessing a frame with a column *a*:

```
>>> my_frame.inspect()

  a:str
/-------/
  cat
  apple
  bat
  cat
  bat
  cat
```

Create a new frame, combining similar values of column *a*, and count how many of each value is in the original frame:

```
>>> new_frame = my_frame.group_by('a', agg.count)
>>> new_frame.inspect()

  a:str       count:int
/-----------------------/
  cat             3
  apple           1
  bat             2
```

In this example, 'my_frame' is accessing a frame with three columns, *a*, *b*, and *c*:

```
>>> my_frame.inspect()

  a:int   b:str   c:float
/-------------------------/
  1       alpha     3.0
  1       bravo     5.0
  1       alpha     5.0
  2       bravo     8.0
  2       bravo    12.0
```

Create a new frame from this data, grouping the rows by unique combinations of column *a* and *b*. Average the value in *c* for each group:

```
>>> new_frame = my_frame.group_by(['a', 'b'], {'c' : agg.avg})
>>> new_frame.inspect()

  a:int   b:str   c_avg:float
/-----------------------------/
  1       alpha     4.0
  1       bravo     5.0
  2       bravo    10.0
```

For this example, we use *my_frame* with columns *a*, *c*, *d*, and *e*:

```
>>> my_frame.inspect()

  a:str   c:int   d:float e:int
/-------------------------------/
  ape     1       4.0     9
  ape     1       8.0     8
  big     1       5.0     7
  big     1       6.0     6
  big     1       8.0     5
```

Create a new frame from this data, grouping the rows by unique combinations of column *a* and *c*. Count each group; for column *d* calculate the average, sum and minimum value. For column *e*, save the maximum value:

```
>>> new_frame = my_frame.group_by(['a', 'c'], agg.count,
... {'d': [agg.avg, agg.sum, agg.min], 'e': agg.max})

  a    c    count  d_avg  d_sum  d_min  e_max
  str  int  int    float  float  float  int
/---------------------------------------------/
  ape  1    2      6.0    12.0   4.0    9
  big  1    3      6.333  19.0   5.0    7
```

For further examples, see *Group by (and aggregate):*.

17.2.40 *VertexFrame* histogram

histogram (*self*, *column_name*, *num_bins=None*, *weight_column_name=None*, *bin_type='equalwidth'*)

[BETA] Compute the histogram for a column in a frame.

Parameters **column_name** : unicode

Name of column to be evaluated.

num_bins : int32 (default=None)

Number of bins in histogram. Default is Square-root choice will be used (in other words math.floor(math.sqrt(frame.row_count)).

weight_column_name : unicode (default=None)

Name of column containing weights. Default is all observations are weighted equally.

bin_type : unicode (default=equalwidth)

The type of binning algorithm to use: ["equalwidth"|"equaldepth"] Defaults is "equalwidth".

Returns : dict

histogram A Histogram object containing the result set. The data returned is composed of multiple components:

cutoffs [array of float] A list containing the edges of each bin.

hist [array of float] A list containing count of the weighted observations found in each bin.

density [array of float] A list containing a decimal containing the percentage of observations found in the total set per bin.

Compute the histogram of the data in a column. The returned value is a Histogram object containing 3 lists one each for: the cutoff points of the bins, size of each bin, and density of each bin.

Notes

The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. With equal depth binning, for example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.2.41 *VertexFrame* inspect

inspect(*self*, *n=10*, *offset=0*, *columns=None*, *wrap=None*, *truncate=None*, *round=None*, *width=80*, *margin=None*)

Prints the frame data in readable format.

Parameters **n** : int (default=10)

The number of rows to print.

offset : int (default=0)

The number of rows to skip before printing.

columns : int (default=None)

Filter columns to be included. By default, all columns are included

wrap : int or 'stripes' (default=None)

If set to 'stripes' then inspect prints rows in stripes; if set to an integer N, rows will be printed in clumps of N columns, where the columns are wrapped

truncate : int (default=None)

If set to integer N, all strings will be truncated to length N, including a tagged ellipses

round : int (default=None)

If set to integer N, all floating point numbers will be rounded and truncated to N digits

width : int (default=80)

If set to integer N, the print out will try to honor a max line width of N

margin : int (default=None)

('stripes' mode only) If set to integer N, the margin for printing names in a stripe will be limited to N characters

Examples

Given a frame of data and a Frame to access it. To look at the first 4 rows of data:

```
>>> print my_frame.inspect(4)

column defs ->  animal:str  name:str    age:int     weight:float
              /--------------------------------------------------/
frame data ->   human       George        8            542.5
                human       Ursula        6            495.0
```

```
                    ape            Ape            41             400.0
                    elephant       Shep            5            8630.0
```

For other examples, see *Inspect the Data*.

17.2.42 *VertexFrame* join

join (*self*, *right*, *left_on*, *right_on=None*, *how='inner'*, *name=None*)

[BETA] Join operation on one or two frames, creating a new frame.

Parameters **right** : Frame

Another frame to join with

left_on : str

Name of the column in the left frame used to match up the two frames.

right_on : str (default=None)

Name of the column in the right frame used to match up the two frames. Default is the same as the left frame.

how : str (default=inner)

How to qualify the data to be joined together. Must be one of the following: 'left', 'right', 'inner', 'outer'. Default is 'inner'

name : str (default=None)

Name of the result grouped frame

Returns : Frame

A new frame with the results of the join

Create a new frame from a SQL JOIN operation with another frame. The frame on the 'left' is the currently active frame. The frame on the 'right' is another frame. This method takes a column in the left frame and matches its values with a column in the right frame. Using the default 'how' option ['inner'] will only allow data in the resultant frame if both the left and right frames have the same value in the matching column. Using the 'left' 'how' option will allow any data in the resultant frame if it exists in the left frame, but will allow any data from the right frame if it has a value in its column which matches the value in the left frame column. Using the 'right' option works similarly, except it keeps all the data from the right frame and only the data from the left frame when it matches. The 'outer' option provides a frame with data from both frames where the left and right frames did not have the same value in the matching column.

Notes

When a column is named the same in both frames, it will result in two columns in the new frame. The column from the *left* frame (originally the current frame) will be copied and the column name will have the string "_L" added to it. The same thing will happen with the column from the *right* frame, except its name has the string "_R" appended. The order of columns after this method is called is not guaranteed.

It is recommended that you rename the columns to meaningful terms prior to using the `join` method. Keep in mind that unicode in column names will likely cause the drop_frames() method (and others) to fail!

Examples

For this example, we will use a Frame *my_frame* accessing a frame with columns *a*, *b*, *c*, and a Frame *your_frame* accessing a frame with columns *a*, *d*, *e*. Join the two frames keeping only those rows having the same value in column *a*:

```
>>> print my_frame.inspect()

  a:unicode   b:unicode   c:unicode
/-------------------------------------/
  alligator   bear        cat
  apple       berry       cantaloupe
  auto        bus         car
  mirror      frog        ball

>>> print your_frame.inspect()

  b:unicode   c:int   d:unicode
/-------------------------------------/
  berry        5218   frog
  blue            0   log
  bus           871   dog

>>> joined_frame = my_frame.join(your_frame, 'b', how='inner')
```

Now, joined_frame is a Frame accessing a frame with the columns *a*, *b*, *c_L*, *ci_R*, and *d*. The data in the new frame will be from the rows where column 'a' was the same in both frames.

```
>>> print joined_frame.inspect()

  a:unicode   b:unicode     c_L:unicode   c_R:int64   d:unicode
/-------------------------------------------------------------------/
  apple       berry         cantaloupe         5218   frog
  auto        bus           car                 871   dog
```

More examples can be found in the *user manual*.

17.2.43 *VertexFrame* loadhbase

loadhbase (*self*, *table_name*, *schema*, *start_tag=None*, *end_tag=None*)

Append data from an hBase table into an existing (possibly empty) FrameRDD

Parameters **table_name** : unicode

hbase table name

schema : list

hbase schema as a list of tuples (columnFamily, columnName, dataType for cell value)

start_tag : unicode (default=None)

optional start tag for filtering

end_tag : unicode (default=None)

optional end tag for filtering

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial FrameRDD with the hbase data appended

Append data from an hBase table into an existing (possibly empty) FrameRDD

17.2.44 *VertexFrame* loadhive

loadhive (*self*, *query*)

Append data from a hive table into an existing (possibly empty) frame

Parameters **query** : unicode

Initial query to run at load time

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial frame with the hive data appended

Append data from a hive table into an existing (possibly empty) frame

17.2.45 *VertexFrame* loadjdbc

loadjdbc (*self*, *table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)

Append data from a Jdbc table into an existing (possibly empty) frame

Parameters **table_name** : unicode

table name

connector_type : unicode (default=None)

(optional) connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial frame with the Jdbc data appended

Append data from a Jdbc table into an existing (possibly empty) frame

17.2.46 *VertexFrame* name

name

Set or get the name of the frame object.

Parameters

Change or retrieve frame object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_frame.name

"csv_data"

>>> my_frame.name = "cleaned_data"
>>> my_frame.name

"cleaned_data"
```

17.2.47 *VertexFrame* quantiles

quantiles(*self*, *column_name*, *quantiles*)

New frame with Quantiles and their values.

Parameters **column_name** : unicode

The column to calculate quantiles.

quantiles : list

What is being requested.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame with two columns (float64): requested Quantiles and their respective values.

Calculate quantiles on the given column.

17.2.48 *VertexFrame* rename_columns

rename_columns(*self*, *names*)

Rename columns for vertex frame.

Parameters **names** : None

Returns : _Unit

17.2.49 *VertexFrame* row_count

row_count

Number of rows in the current frame.

Parameters

Returns : int

The number of rows in the frame

Get the number of rows:

```
>>> my_frame.row_count
```

The result given is:

```
81734
```

17.2.50 *VertexFrame* schema

schema

Current frame column names and types.

Parameters

Returns : list

list of tuples of the form (<column name>, <data type>)

The schema of the current frame is a list of column names and associated data types. It is retrieved as a list of tuples. Each tuple has the name and data type of one of the frame's columns.

Examples

Given that we have an existing data frame *my_data*, create a Frame, then show the frame schema:

```
>>> BF = ta.get_frame('my_data')
>>> print BF.schema
```

The result is:

```
[("col1", str), ("col2", numpy.int32)]
```

17.2.51 *VertexFrame* sort

sort (*self*, *columns*, *ascending=True*)

[BETA] Sort the data in a frame.

Parameters **columns** : str | list of str | list of tuples

Either a column name, a list of column names, or a list of tuples where each tuple is a name and an ascending bool value.

ascending : bool (default=True)

True for ascending, False for descending.

Sort a frame by column values either ascending or descending.

Examples

Sort a single column:

```
>>> frame.sort('column_name')
```

Sort a single column ascending:

```
>>> frame.sort('column_name', True)
```

Sort a single column descending:

```
>>> frame.sort('column_name', False)
```

Sort multiple columns:

```
>>> frame.sort(['col1', 'col2'])
```

Sort multiple columns ascending:

```
>>> frame.sort(['col1', 'col2'], True)
```

Sort multiple columns descending:

```
>>> frame.sort(['col1', 'col2'], False)
```

Sort multiple columns: 'col1' ascending and 'col2' descending:

```
>>> frame.sort([ ('col1', True), ('col2', False) ])
```

17.2.52 *VertexFrame* sorted_k

sorted_k (*self*, *k*, *column_names_and_ascending*, *reduce_tree_depth=None*)

[ALPHA] Get a sorted subset of the data.

Parameters **k** : int32

Number of sorted records to return.

column_names_and_ascending : list

Column names to sort by, and true to sort column by ascending order, or false for descending order.

reduce_tree_depth : int32 (default=None)

Advanced tuning parameter which determines the depth of the reduce-tree for the sorted_k plugin. This plugin uses Spark's treeReduce() for scalability. The default depth is 2.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame with the first k sorted rows from the original frame.

Take the first k (sorted) rows for the currently active Frame. Rows are sorted by column values in either ascending or descending order.

Returning the first k (sorted) rows is more efficient than sorting the entire frame when k is much smaller than the number of rows in the frame.

Notes

The number of sorted rows (k) should be much smaller than the number of rows in the original frame.

In particular:

1. The number of sorted rows (k) returned should fit in Spark driver memory.

   The maximum size of serialized results that can fit in the Spark driver is set by the Spark configuration parameter *spark.driver.maxResultSize*.

2. If you encounter a Kryo buffer overflow exception, increase the Spark

   configuration parameter *spark.kryoserializer.buffer.max.mb*.

3. Use Frame.sort() instead if the number of sorted rows (k) is

   very large (i.e., cannot fit in Spark driver memory).

17.2.53 *VertexFrame* status

---

status

Current frame life cycle status.

Parameters

Returns : str

Status of the frame

One of three statuses: Active, Deleted, Deleted_Final Active: Frame is available for use Deleted: Frame has been scheduled for deletion can be unscheduled by modifying Deleted_Final: Frame's backend files have been removed from disk.

Examples

Given that we have an existing data frame *my_data*, create a Frame, then show the frame schema:

```
>>> BF = ta.get_frame('my_data')
>>> print BF.status
```

The result is:

```
u'Active'
```

17.2.54 *VertexFrame* take

take (*self*, *n*, *offset=0*, *columns=None*)
Get data subset.

Parameters **n** : int

The number of rows to copy to the client from the frame.

offset : int (default=0)

The number of rows to skip before starting to copy

columns : str | iterable of str (default=None)

If not None, only the given columns' data will be provided. By default, all columns are included

Returns : list

A list of lists, where each contained list is the data for one row.

Take a subset of the currently active Frame.

Notes

The data is considered 'unstructured', therefore taking a certain number of rows, the rows obtained may be different every time the command is executed, even if the parameters do not change.

Examples

Frame *my_frame* accesses a frame with millions of rows of data. Get a sample of 5000 rows:

```
>>> my_data_list = my_frame.take( 5000 )
```

We now have a list of data from the original frame.

```
>>> print my_data_list

[[ 1, "text", 3.1415962 ]
 [ 2, "bob", 25.0 ]
 [ 3, "weave", .001 ]
 ...]
```

If we use the method with an offset like:

```
>>> my_data_list = my_frame.take( 5000, 1000 )
```

We end up with a new list, but this time it has a copy of the data from rows 1001 to 5000 of the original frame.

17.2.55 *VertexFrame* tally

tally (*self*, *sample_col*, *count_val*)
[BETA] Count number of times a value is seen.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative count.

count_val : unicode

The column value to be used for the counts.

Returns : _Unit

A cumulative count is computed by sequentially stepping through the rows, observing the column values and keeping track of the the number of times the specified *count_value* has been seen.

17.2.56 *VertexFrame* tally_percent

tally_percent (*self*, *sample_col*, *count_val*)

[BETA] Compute a cumulative percent count.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative sum.

count_val : unicode

The column value to be used for the counts.

Returns : _Unit

A cumulative percent count is computed by sequentially stepping through the rows, observing the column values and keeping track of the percentage of the total number of times the specified *count_value* has been seen up to the current value.

17.2.57 *VertexFrame* top_k

top_k (*self*, *column_name*, *k*, *weights_column=None*)

Most or least frequent column values.

Parameters **column_name** : unicode

The column whose top (or bottom) K distinct values are to be calculated.

k : int32

Number of entries to return (If k is negative, return bottom k).

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the topK calculation. Must contain numerical data. Default is 1 for all items.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

An object with access to the frame of data.

Calculate the top (or bottom) K distinct values by count of a column. The column can be weighted. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight > 0, then topK is empty.

17.2.58 *VertexFrame* unflatten_column

unflatten_column (*self*, *composite_key_column_names*, *delimiter=None*)

Compacts data from multiple rows based on cell data.

Parameters **composite_key_column_names** : list

name of the user column to be used as keys for unflattening.

delimiter : unicode (default=None)

separator for the data in the result columns. Default is comma (,).

Returns : _Unit

Groups together cells in all columns (less the composite key) using "," as string delimiter. The original rows are deleted. The grouping takes place based on a composite key passed as arguments.

class **VertexFrame**

A list of Vertices owned by a Graph..

A VertexFrame is similar to a Frame but with a few important differences:

- VertexFrames are not instantiated directly by the user, instead they are created by defining a vertex type in a graph
- Each row of a VertexFrame represents a vertex in a graph
- VertexFrames have many of the same methods as Frames but not all (for example, flatten_column())
- VertexFrames have extra methods not found on Frames (for example, add_vertices())
- Removing a vertex (or row) from a VertexFrame also removes edges connected to that vertex from the graph
- VertexFrames have special system columns (_vid, _label) that are maintained automatically by the system and cannot be modified by the user
- VertexFrames have a special user defined id column whose value uniquely identifies the vertex
- "Columns" on a VertexFrame can also be thought of as "properties" on vertices

Attributes

column_names	Column identifications in the current frame.
name	Set or get the name of the frame object.
row_count	Number of rows in the current frame.
schema	Current frame column names and types.
status	Current frame life cycle status.

Methods

__init__(self[, source, graph, label, _info])	Examples
add_columns(self, func, schema[, columns_accessed])	Add columns to current frame.
add_vertices(self, source_frame, id_column_name[, column_names])	Add vertices to a graph.
assign_sample(self, sample_percentages[, sample_labels, ...])	Randomly group rows into user-defined classes.

Table 17.2 – continued from previous page

bin_column(self, column_name, cutoffs[, include_lowest, strict_binning, ...])	Classify data into user-defined groups.
bin_column_equal_depth(self, column_name[, num_bins, ...])	Classify column into groups with the same frequency.
bin_column_equal_width(self, column_name[, num_bins, ...])	Classify column into same-width groups.
categorical_summary(self, *column_inputs)	[ALPHA] Compute a summary of the data in a colun
classification_metrics(self, label_column, pred_column[, ...])	Model statistics of accuracy, precision, and others.
column_median(self, data_column[, weights_column])	Calculate the (weighted) median of a column.
column_mode(self, data_column[, weights_column, max_modes_returned])	Evaluate the weights assigned to rows.
column_summary_statistics(self, data_column[, ...])	Calculate multiple statistics for a column.
compute_misplaced_score(self, gravity)	
copy(self[, columns, where, name])	Create new frame from current frame.
correlation(self, data_column_names)	Calculate correlation for two columns of current fram
correlation_matrix(self, data_column_names[, matrix_name])	Calculate correlation matrix for two or more columns.
count(self, where)	Counts the number of rows which meet given criteria.
covariance(self, data_column_names)	Calculate covariance for exactly two columns.
covariance_matrix(self, data_column_names[, matrix_name])	Calculate covariance matrix for two or more columns.
cumulative_percent(self, sample_col)	[BETA] Add column to frame with cumulative percer
cumulative_sum(self, sample_col)	[BETA] Add column to frame with cumulative percer
dot_product(self, left_column_names, right_column_names, ...[, ...])	[ALPHA] Calculate dot product for each row in curr
download(self[, n, offset, columns])	Download a frame from the server into client workspa
drop_columns(self, columns)	Remove columns from the frame.
drop_duplicates(self[, unique_columns])	Remove duplicate vertex rows.
drop_rows(self, predicate)	Erase any row in the current frame which qualifies.
drop_vertices(self, predicate)	Delete rows that qualify.
ecdf(self, column[, result_frame_name])	Builds new frame with columns for data and distributi
entropy(self, data_column[, weights_column])	Calculate the Shannon entropy of a column.
export_to_csv(self, folder_name[, separator, count, offset])	Write current frame to HDFS in csv format.
export_to_hbase(self, table_name[, key_column_name, family_name])	Write current frame to HBase table.
export_to_hive(self, table_name)	Write current frame to Hive table.
export_to_jdbc(self, table_name[, connector_type, url, driver_name, ...])	Write current frame to Jdbc table.
export_to_json(self, folder_name[, count, offset])	Write current frame to HDFS in JSON format.
filter(self, predicate)	<Missing Doc>
flatten_column(self, column[, delimiter])	Spread data to multiple rows based on cell data.
get_error_frame(self)	Get a frame with error recordings.
group_by(self, group_by_columns, *aggregation_arguments)	[BETA] Create summarized frame.
histogram(self, column_name[, num_bins, weight_column_name, bin_type])	[BETA] Compute the histogram for a column in a fra
inspect(self[, n, offset, columns, wrap, truncate, round, width, margin])	Prints the frame data in readable format.
join(self, right, left_on[, right_on, how, name])	[BETA] Join operation on one or two frames, creatin
loadhbase(self, table_name, schema[, start_tag, end_tag])	Append data from an hBase table into an existing (pos
loadhive(self, query)	Append data from a hive table into an existing (possib
loadjdbc(self, table_name[, connector_type, url, driver_name, query])	Append data from a Jdbc table into an existing (possib
quantiles(self, column_name, quantiles)	New frame with Quantiles and their values.
rename_columns(self, names)	Rename columns for vertex frame.
sort(self, columns[, ascending])	[BETA] Sort the data in a frame.
sorted_k(self, k, column_names_and_ascending[, reduce_tree_depth])	[ALPHA] Get a sorted subset of the data.
take(self, n[, offset, columns])	Get data subset.
tally(self, sample_col, count_val)	[BETA] Count number of times a value is seen.
tally_percent(self, sample_col, count_val)	[BETA] Compute a cumulative percent count.
top_k(self, column_name, k[, weights_column])	Most or least frequent column values.
unflatten_column(self, composite_key_column_names[, delimiter])	Compacts data from multiple rows based on cell data.

__init__(*self*, *source=None*, *graph=None*, *label=None*)

Examples

Parameters **source** : (default=None)

graph : (default=None)

label : (default=None)

Given a data file, create a frame, move the data to graph and then define a new VertexFrame and add data to it:

Retrieve a previously defined graph and retrieve a VertexFrame from it:

```
>>> my_graph = ta.get_graph("your_graph")
>>> my_vertex_frame = my_graph.vertices["your_label"]
```

Calling methods on a VertexFrame:

```
>>> my_vertex_frame.vertices["your_label"].inspect(20)
```

Convert a VertexFrame to a frame:

```
>>> new_Frame = my_vertex_frame.vertices["label"].copy()
```

17.3 *Frames* Frame

17.3.1 *Frame* __init__

__init__(*self*, *source=None*, *name=None*)

Create a Frame/frame.

Parameters **source** : CsvFile | Frame (default=None)

A source of initial data.

name : str (default=None)

The name of the newly created frame. Default is None.

Notes

A frame with no name is subject to garbage collection.

If a string in the CSV file starts and ends with a double-quote (") character, the character is stripped off of the data before it is put into the field. Anything, including delimiters, between the double-quote characters is considered part of the str. If the first character after the delimiter is anything other than a double-quote character, the string will be composed of all the characters between the delimiters, including double-quotes. If the first field type is str, leading spaces on each row are considered part of the str. If the last field type is str, trailing spaces on each row are considered part of the str.

Examples

Create a new frame based upon the data described in the CsvFile object *my_csv_schema*. Name the frame "myframe". Create a Frame *my_frame* to access the data:

```
>>> my_frame = ta.Frame(my_csv_schema, "myframe")
```

A Frame object has been created and *my_frame* is its proxy. It brought in the data described by *my_csv_schema*. It is named *myframe*.

Create an empty frame; name it "yourframe":

```
>>> your_frame = ta.Frame(name='yourframe')
```

A frame has been created and Frame *your_frame* is its proxy. It has no data yet, but it does have the name *yourframe*.

17.3.2 *Frame* add_columns

---

add_columns (*self*, *func*, *schema*, *columns_accessed=None*)

Add columns to current frame.

Parameters **func** : UDF

User-Defined Function (UDF) which takkes the values in the row and produces a value, or collection of values, for the new cell(s).

schema : tuple | list of tuples

The schema for the results of the UDF, indicating the new column(s) to add. Each tuple provides the column name and data type, and is of the form (str, type).

columns_accessed : list (default=None)

List of columns which the UDF will access. This adds significant performance benefit if we know which column(s) will be needed to execute the UDF, especially when the frame has significantly more columns than those being used to evaluate the UDF.

Assigns data to column based on evaluating a function for each row.

Notes

1. The row UDF ('func') must return a value in the same format as specified by the schema. See Python User Functions.
2. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

Examples

Given a Frame *my_frame* identifying a data frame with two int32 columns *column1* and *column2*. Add a third column *column3* as an int32 and fill it with the contents of *column1* and *column2* multiplied together:

```
>>> my_frame.add_columns(lambda row: row.column1*row.column2,
... ('column3', int32))
```

The frame now has three columns, *column1*, *column2* and *column3*. The type of *column3* is an int32, and the value is the product of *column1* and *column2*.

Add a string column *column4* that is empty:

```
>>> my_frame.add_columns(lambda row: '', ('column4', str))
```

The Frame object *my_frame* now has four columns *column1*, *column2*, *column3*, and *column4*. The first three columns are int32 and the fourth column is str. Column *column4* has an empty string (‘’) in every row.

Multiple columns can be added at the same time. Add a column *a_times_b* and fill it with the contents of column *a* multiplied by the contents of column *b*. At the same time, add a column *a_plus_b* and fill it with the contents of column *a* plus the contents of column *b*:

```
>>> my_frame.add_columns(lambda row: [row.a * row.b, row.a +
... row.b], [("a_times_b", float32), ("a_plus_b", float32))
```

Two new columns are created, “a_times_b” and “a_plus_b”, with the appropriate contents.

Given a frame of data and Frame *my_frame* points to it. In addition we have defined a UDF *func*. Run *func* on each row of the frame and put the result in a new int column *calculated_a*:

```
>>> my_frame.add_columns( func, ("calculated_a", int))
```

Now the frame has a column *calculated_a* which has been filled with the results of the UDF *func*.

A UDF must return a value in the same format as the column is defined. In most cases this is automatically the case, but sometimes it is less obvious. Given a UDF *function_b* which returns a value in a list, store the result in a new column *calculated_b*:

```
>>> my_frame.add_columns(function_b, ("calculated_b", float32))
```

This would result in an error because function_b is returning a value as a single element list like [2.4], but our column is defined as a tuple. The column must be defined as a list:

```
>>> my_frame.add_columns(function_b, [("calculated_b", float32)])
```

To run an optimized version of add_columns, columns_accessed parameter can be populated with the column names which are being accessed in UDF. This speeds up the execution by working on only the limited feature set than the entire row.

Let’s say a frame has 4 columns named *a*,*b*,*c* and *d* and we want to add a new column with value from column *a* multiplied by value in column *b* and call it *a_times_b*. In the example below, columns_accessed is a list with column names *a* and *b*.

```
>>> my_frame.add_columns(lambda row: row.a * row.b, ("a_times_b", float32), columns_accessed=["a
```

add_columns would fail if columns_accessed parameter is not populated with the correct list of accessed columns. If not specified, columns_accessed defaults to None which implies that all columns might be accessed by the UDF.

More information on a row UDF can be found at Python User Functions

17.3.3 *Frame* append

---

append(*self*, *data*)

Adds more data to the current frame.

Parameters data : Data source

Data source, see Data Sources

Examples

Given a frame with a single column, *col_1*:

```
      >>> my_frame.inspect(4)
        col_1:str
      /-----------/
        dog
        cat
        bear
        donkey

and a frame with two columns, *col_1* and *col_2*:

..code::

      >>> your_frame.inspect(4)
        col_1:str  col_qty:int32
      /--------------------------/
        bear          15
        cat            2
        snake          8
        horse          5
```

Column *col_1* means the same thing in both frames. The Frame *my_frame* points to the first frame and *your_frame* points to the second. To add the contents of *your_frame* to *my_frame*:

```
>>> my_frame.append(your_frame)
>>> my_frame.inspect(8)
  col_1:str  col_2:int32
/------------------------/
  dog           None
  bear            15
  bear          None
  horse            5
  cat           None
  cat              2
  donkey        None
  snake            5
```

Now the first frame has two columns, *col_1* and *col_2*. Column *col_1* has the data from *col_1* in both original frames. Column *col_2* has None (undefined) in all of the rows in the original first frame, and has the value of the second frame column, *col_2*, in the rows matching the new data in *col_1*.

Breaking it down differently, the original rows referred to by *my_frame* have a new column, *col_2*, and this new column is filled with non-defined data. The frame referred to by *your_frame*, is then added to the bottom.

17.3.4 *Frame* assign_sample

---

assign_sample(*self*, *sample_percentages*, *sample_labels=None*, *output_column=None*, *random_seed=None*)

Randomly group rows into user-defined classes.

Parameters sample_percentages : list

Entries are non-negative and sum to 1. (See the note below.) If the i'th entry of the list is p, then then each row receives label i with independent probability p.

sample_labels : list (default=None)

Names to be used for the split classes. Defaults "TR", "TE", "VA" when the length of *sample_percentages* is 3, and defaults to Sample_0, Sample_1, ... otherwise.

output_column : unicode (default=None)

Name of the new column which holds the labels generated by the function.

random_seed : int32 (default=None)

Random seed used to generate the labels. Defaults to 0.

Returns : _Unit

Randomly assign classes to rows given a vector of percentages. The table receives an additional column that contains a random label. The random label is generated by a probability distribution function. The distribution function is specified by the sample_percentages, a list of floating point values, which add up to 1. The labels are non-negative integers drawn from the range $[0, len(S) - 1]$ where S is the sample_percentages. Optionally, the user can specify a list of strings to be used as the labels. If the number of labels is 3, the labels will default to "TR", "TE" and "VA".

Notes

The sample percentages provided by the user are preserved to at least eight decimal places, but beyond this there may be small changes due to floating point imprecision.

In particular:

1. The engine validates that the sum of probabilities sums to 1.0 within eight decimal places and returns an error if the sum falls outside of this range.
2. The probability of the final class is clamped so that each row receives a valid label with probability one.

17.3.5 *Frame* bin_column

bin_column (*self*, *column_name*, *cutoffs*, *include_lowest=None*, *strict_binning=None*, *bin_column_name=None*)

Classify data into user-defined groups.

Parameters **column_name** : unicode

Name of the column to bin.

cutoffs : list

Array of values containing bin cutoff points. Array can be list or tuple. Array values must be progressively increasing. All bin boundaries must be included, so, with N bins, you need N+1 values.

include_lowest : bool (default=None)

Specify how the boundary conditions are handled. True indicates that the lower bound of the bin is inclusive. False indicates that the upper bound is inclusive. Default is True.

strict_binning : bool (default=None)

Specify how values outside of the cutoffs array should be binned. If set to True, each value less than cutoffs[0] or greater than cutoffs[-1] will be assigned a bin value of -1. If set to False, values less than cutoffs[0] will be included in the first bin while values greater than cutoffs[-1] will be included in the final bin.

bin_column_name : unicode (default=None)

The name for the new binned column. Default is <column_name>_binned.

Returns : _Unit

Summarize rows of data based on the value in a single column by sorting them into bins, or groups, based on a list of bin cutoff points.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. Bins IDs are 0-index: the lowest bin number is 0.
3. The first and last cutoffs are always included in the bins. When include_lowest is `True`, the last bin includes both cutoffs. When include_lowest is `False`, the first bin (bin 0) includes both cutoffs.

17.3.6 *Frame* bin_column_equal_depth

bin_column_equal_depth (*self*, *column_name*, *num_bins=None*, *bin_column_name=None*)

Classify column into groups with the same frequency.

Parameters **column_name** : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor\sqrt{m}\rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is <column_name>_binned.

Returns : dict

A list containing the edges of each bin.

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal depth binning attempts to label rows such that each bin contains the same number of elements. For n bins of a column C of length m, the bin number is determined by:

$$\lceil n * \frac{f(C)}{m} \rceil$$

where f is a tie-adjusted ranking function over values of C. If there are multiples of the same value in C, then their tie-adjusted rank is the average of their ordered rank values.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

2.The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has a quantity of :math"X elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.3.7 *Frame* bin_column_equal_width

`bin_column_equal_width` (*self*, *column_name*, *num_bins=None*, *bin_column_name=None*)

Classify column into same-width groups.

Parameters **column_name** : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is `<column_name>_binned`.

Returns : dict

A list of the edges of each bin.

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal width binning places column values into groups such that the values in each group fall within the same interval and the interval width for each group is equal.

Notes

1.Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

2.The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.3.8 *Frame* categorical_summary

`categorical_summary` (*self*, *column_inputs=None*)

[ALPHA] Compute a summary of the data in a column(s) for categorical or numerical data types.

Parameters **column_inputs** : str | tuple(str, dict) (default=None)

Comma-separated column names to summarize or tuple containing column name and dictionary of optional parameters. Optional parameters (see below for details): top_k (default = 10), threshold (default = 0.0)

Returns : dict

Summary for specified column(s) consisting of levels with their frequency and percentage

The returned value is a Map containing categorical summary for each specified column.

For each column, levels which satisfy the top k and/or threshold cutoffs are displayed along with their frequency and percentage occurrence with respect to the total rows in the dataset.

Missing data is reported when a column value is empty (“”) or null.

All remaining data is grouped together in the Other category and its frequency and percentage are reported as well.

User must specify the column name and can optionally specify top_k and/or threshold.

Optional parameters:

top_k Displays levels which are in the top k most frequently occurring values for that column.

threshold Displays levels which are above the threshold percentage with respect to the total row count.

top_k and threshold Performs level pruning first based on top k and then filters out levels which satisfy the threshold criterion.

defaults Displays all levels which are in Top 10.

Examples

```
>>> frame.categorical_summary('source','target')
>>> frame.categorical_summary(('source', {'top_k' : 2}))
>>> frame.categorical_summary(('source', {'threshold' : 0.5}))
>>> frame.categorical_summary(('source', {'top_k' : 2}), ('target',
... {'threshold' : 0.5}))
```

Sample output (for last example above):

```
>>> {u'categorical_summary': [{u'column': u'source', u'levels': [
... {u'percentage': 0.32142857142857145, u'frequency': 9, u'level': u'thing'},
... {u'percentage': 0.32142857142857145, u'frequency': 9, u'level': u'abstraction'},
... {u'percentage': 0.25, u'frequency': 7, u'level': u'physical_entity'},
... {u'percentage': 0.10714285714285714, u'frequency': 3, u'level': u'entity'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Missing'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Other'}]},
... {u'column': u'target', u'levels': [
... {u'percentage': 0.07142857142857142, u'frequency': 2, u'level': u'thing'},
... {u'percentage': 0.07142857142857142, u'frequency': 2,
...  u'level': u'physical_entity'},
... {u'percentage': 0.07142857142857142, u'frequency': 2, u'level': u'entity'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'variable'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'unit'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'substance'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'subject'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'set'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'reservoir'},
... {u'percentage': 0.03571428571428571, u'frequency': 1, u'level': u'relation'},
... {u'percentage': 0.0, u'frequency': 0, u'level': u'Missing'},
... {u'percentage': 0.5357142857142857, u'frequency': 15, u'level': u'Other'}]}]}
```

17.3.9 *Frame* classification_metrics

classification_metrics (*self*, *label_column*, *pred_column*, *pos_label=None*, *beta=None*)
Model statistics of accuracy, precision, and others.

Parameters **label_column** : unicode

The name of the column containing the correct label for each instance.

pred_column : unicode

The name of the column containing the predicted label for each instance.

pos_label : None (default=None)

beta : float64 (default=None)

This is the beta value to use for F_β measure (default F1 measure is computed); must be greater than zero. Defaults is 1.

Returns : dict

object <object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

Calculate the accuracy, precision, confusion_matrix, recall and F_β measure for a classification model.

- The **f_measure** result is the F_β measure for a classification model. The F_β measure of a binary classification model is the harmonic mean of precision and recall. If we let:

  - beta $\equiv \beta$,
  - T_P denotes the number of true positives,
  - F_P denotes the number of false positives, and
  - F_N denotes the number of false negatives

  then:

$$F_\beta = (1 + \beta^2) * \frac{\frac{T_P}{T_P+F_P} * \frac{T_P}{T_P+F_N}}{\beta^2 * \frac{T_P}{T_P+F_P} + \frac{T_P}{T_P+F_N}}$$

  The F_β measure for a multi-class classification model is computed as the weighted average of the F_β measure for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **recall** result of a binary classification model is the proportion of positive instances that are correctly identified. If we let T_P denote the number of true positives and F_N denote the number of false negatives, then the model recall is given by $\frac{T_P}{T_P + F_N}$.

  For multi-class classification models, the recall measure is computed as the weighted average of the recall for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **precision** of a binary classification model is the proportion of predicted positive instances that are correctly identified. If we let T_P denote the number of true positives and F_P denote the number of false positives, then the model precision is given by: $\frac{T_P}{T_P + F_P}$.

  For multi-class classification models, the precision measure is computed as the weighted average of the precision for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **accuracy** of a classification model is the proportion of predictions that are correctly identified. If we let T_P denote the number of true positives, T_N denote the number of true negatives, and K denote the total number of classified instances, then the model accuracy is given by: $\frac{T_P + T_N}{K}$.

  This measure applies to binary and multi-class classifiers.

- The **confusion_matrix** result is a confusion matrix for a binary classifier model, formatted for human readability.

Notes

The **confusion_matrix** is not yet implemented for multi-class classifiers.

17.3.10 *Frame* column_median

---

column_median (*self*, *data_column*, *weights_column=None*)

Calculate the (weighted) median of a column.

Parameters **data_column** : unicode

The column whose median is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the median calculation. Must contain numerical data. Default is all items have a weight of 1.

Returns : dict

varies The median of the values. If a weight column is provided and no weights are finite numbers greater than 0, None is returned. The type of the median returned is the same as the contents of the data column, so a column of Longs will result in a Long median and a column of Floats will result in a Float median.

The median is the least value X in the range of the distribution so that the cumulative weight of values strictly below X is strictly less than half of the total weight and the cumulative weight of values up to and including X is greater than or equal to one-half of the total weight.

All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If a weight column is provided and no weights are finite numbers greater than 0, None is returned.

17.3.11 *Frame* column_mode

---

column_mode (*self*, *data_column*, *weights_column=None*, *max_modes_returned=None*)

Evaluate the weights assigned to rows.

Parameters **data_column** : unicode

Name of the column supplying the data.

weights_column : unicode (default=None)

Name of the column supplying the weights. Default is all items have weight of 1.

max_modes_returned : int32 (default=None)

Maximum number of modes returned. Default is 1.

Returns : dict

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mode [A mode is a data element of maximum net weight.] A set of modes is returned. The empty set is returned when the sum of the weights is 0. If the number of modes is less than or equal to the parameter max_modes_returned, then all modes of the data are returned. If the number of modes is greater than the max_modes_returned parameter, only the first max_modes_returned many modes (per a canonical ordering) are returned.

weight_of_mode [Weight of a mode.] If there are no data elements of finite weight greater than 0, the weight of the mode is 0. If no weights column is given, this is the number of appearances of each mode.

total_weight [Sum of all weights in the weight column.] This is the row count if no weights are given. If no weights column is given, this is the number of rows in the table with non-zero weight.

mode_count [The number of distinct modes in the data.] In the case that the data is very multimodal, this number may exceed max_modes_returned.

Calculate the modes of a column. A mode is a data element of maximum weight. All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight greater than 0, no mode is returned.

Because data distributions often have mutliple modes, it is possible for a set of modes to be returned. By default, only one is returned, but by setting the optional parameter max_modes_returned, a larger number of modes can be returned.

17.3.12 *Frame* column_names

---

column_names

Column identifications in the current frame.

Parameters

Returns : list

list of names of all the frame's columns

Given a Frame object, *my_frame* accessing a frame. To get the column names:

```
>>> my_columns = my_frame.column_names
>>> print my_columns
```

Now, given there are three columns *col1*, *col2*, and *col3*, the result is:

```
["col1", "col2", "col3"]
```

17.3.13 *Frame* column_summary_statistics

column_summary_statistics(*self*, *data_column*, *weights_column=None*, *use_population_variance=None*)

Calculate multiple statistics for a column.

Parameters **data_column** : unicode

The column to be statistically summarized. Must contain numerical data; all NaNs and infinite values are excluded from the calculation.

weights_column : unicode (default=None)

Name of column holding weights of column values.

use_population_variance : bool (default=None)

If true, the variance is calculated as the population variance. If false, the variance calculated as the sample variance. Because this option affects the variance, it affects the standard deviation and the confidence intervals as well. Default is false.

Returns : dict

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mean [[double | None]] Arithmetic mean of the data.

geometric_mean [[double | None]] Geometric mean of the data. None when there is a data element <= 0, 1.0 when there are no data elements.

variance [[double | None]] None when there are <= 1 many data elements. Sample variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight minus 1. None when the sum of the weights is <= 1. Population variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight.

standard_deviation [[double | None]] The square root of the variance. None when sample variance is being used and the sum of weights is <= 1.

total_weight [long] The count of all data elements that are finite numbers. (In other words, after excluding NaNs and infinite values.)

minimum [[double | None]] Minimum value in the data. None when there are no data elements.

maximum [[double | None]] Maximum value in the data. None when there are no data elements.

mean_confidence_lower [[double | None]] Lower limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

mean_confidence_upper [[double | None]] Upper limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

bad_row_count [[double | None]] The number of rows containing a NaN or infinite value in either the data or weights column.

good_row_count [[double | None]] The number of rows not containing a NaN or infinite value in either the data or weights column.

positive_weight_count [[double | None]] The number of valid data elements with weight > 0. This is the number of entries used in the statistical calculation.

non_positive_weight_count [[double | None]] The number valid data elements with finite weight <= 0.

Notes

Sample Variance Sample Variance is computed by the following formula:

$$\left(\frac{1}{W-1}\right) * sum_i \ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Population Variance Population Variance is computed by the following formula:

$$\left(\frac{1}{W}\right) * sum_i \ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Standard Deviation The square root of the variance.

Logging Invalid Data A row is bad when it contains a NaN or infinite value in either its data or weights column. In this case, it contributes to bad_row_count; otherwise it contributes to good row count.

A good row can be skipped because the value in its weight column is less than or equal to 0. In this case, it contributes to non_positive_weight_count, otherwise (when the weight is greater than 0) it contributes to valid_data_weight_pair_count.

Equations `bad_row_count + good_row_count = # rows in the frame`

`positive_weight_count + non_positive_weight_count = good_row_count`

In particular, when no weights column is provided and all weights are 1.0, `non_positive_weight_count = 0` and `positive_weight_count = good_row_count`

17.3.14 *Frame* compute_misplaced_score

compute_misplaced_score (*self*, *gravity*)

Parameters **gravity** : float64

Similarity measure for computing tension between 2 connected items

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

17.3.15 *Frame* copy

copy (*self*, *columns=None*, *where=None*, *name=None*)

Create new frame from current frame.

Parameters **columns** : str | list of str | dict (default=None)

If not None, the copy will only include the columns specified. If dict, the string pairs represent a column renaming, {source_column_name: destination_column_name}

where : function (default=None)

If not None, only those rows for which the UDF evaluates to True will be copied.

name : str (default=None)

Name of the copied frame

Returns : Frame

A new Frame of the copied data.

Copy frame or certain frame columns entirely or filtered. Useful for frame query.

Examples

Build a Frame from a csv file with 5 million rows of data; call the frame "cust":

```
>>> my_frame = ta.Frame(source="my_data.csv")
>>> my_frame.name("cust")
```

Given the frame has columns *id*, *name*, *hair*, and *shoe*. Copy it to a new frame:

```
>>> your_frame = my_frame.copy()
```

Now we have two frames of data, each with 5 million rows. Checking the names:

```
>>> print my_frame.name()
>>> print your_frame.name()
```

Gives the results:

```
"cust"
"frame_75401b7435d7132f5470ba35..."
```

Now, let's copy *some* of the columns from the original frame:

```
>>> our_frame = my_frame.copy(['id', 'hair'])
```

Our new frame now has two columns, *id* and *hair*, and has 5 million rows. Let's try that again, but this time change the name of the *hair* column to *color*:

```
>>> last_frame = my_frame.copy(('id': 'id', 'hair': 'color'))
```

17.3.16 *Frame* correlation

correlation(*self*, *data_column_names*)

Calculate correlation for two columns of current frame.

Parameters **data_column_names** : list

The names of 2 columns from which to compute the correlation.

Returns : dict

Pearson correlation coefficient of the two columns.

This method applies only to columns containing numerical data.

17.3.17 *Frame* correlation_matrix

---

correlation_matrix (*self*, *data_column_names*, *matrix_name=None*)
Calculate correlation matrix for two or more columns.

Parameters **data_column_names** : list

The names of the columns from which to compute the matrix.

matrix_name : unicode (default=None)

The name for the returned matrix Frame.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A Frame with the matrix of the correlation values for the columns.

This method applies only to columns containing numerical data.

17.3.18 *Frame* count

---

count (*self*, *where*)
Counts the number of rows which meet given criteria.

Parameters **where** : function

UDF which evaluates a row to a boolean

Returns : int

number of rows for which the where UDF evaluated to True.

17.3.19 *Frame* covariance

---

covariance (*self*, *data_column_names*)
Calculate covariance for exactly two columns.

Parameters **data_column_names** : list

The names of two columns from which to compute the covariance.

Returns : dict

Covariance of the two columns.

This method applies only to columns containing numerical data.

17.3.20 *Frame* covariance_matrix

covariance_matrix (*self*, *data_column_names*, *matrix_name=None*)
Calculate covariance matrix for two or more columns.

Parameters **data_column_names** : list

The names of the column from which to compute the matrix. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

matrix_name : unicode (default=None)

The name of the new matrix.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A matrix with the covariance values for the columns.

This function applies only to columns containing numerical data.

17.3.21 *Frame* cumulative_percent

cumulative_percent (*self*, *sample_col*)
[BETA] Add column to frame with cumulative percent sum.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative percent sum.

Returns : _Unit

A cumulative percent sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the current percentage of the total sum accounted for at the current value.

Notes

This method applies only to columns containing numerical data. Although this method will execute for columns containing negative values, the interpretation of the result will change (for example, negative percentages).

17.3.22 *Frame* cumulative_sum

cumulative_sum (*self*, *sample_col*)
[BETA] Add column to frame with cumulative percent sum.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative sum.

Returns : _Unit

A cumulative sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the cumulative sum for each value.

Notes

This method applies only to columns containing numerical data.

17.3.23 *Frame* dot_product

dot_product (*self*, *left_column_names*, *right_column_names*, *dot_product_column_name*, *default_left_values=None*, *default_right_values=None*)

[ALPHA] Calculate dot product for each row in current frame.

Parameters **left_column_names** : list

Names of columns used to create the left vector (A) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

right_column_names : list

Names of columns used to create right vector (B) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

dot_product_column_name : unicode

Name of column used to store the dot product.

default_left_values : list (default=None)

Default values used to substitute null values in left vector. Default is None.

default_right_values : list (default=None)

Default values used to substitute null values in right vector. Default is None.

Returns : _Unit

Calculate the dot product for each row in a frame using values from two equal-length sequences of columns.

Dot product is computed by the following formula:

The dot product of two vectors $A = [a_1, a_2, ..., a_n]$ and $B = [b_1, b_2, ..., b_n]$ is $a_1 * b_1 + a_2 * b_2 + ... + a_n * b_n$. The dot product for each row is stored in a new column in the existing frame.

Notes

If default_left_values or default_right_values are not specified, any null values will be replaced by zeros.

17.3.24 *Frame* download

download (*self*, *n=100*, *offset=0*, *columns=None*)

Download a frame from the server into client workspace.

Parameters **n** : int (default=100)

The number of rows to download to the client

offset : int (default=0)

The number of rows to skip before copying

columns : list (default=None)

Column filter, the names of columns to be included (default is all columns)

Returns : pandas.DataFrame

A new pandas dataframe object containing the downloaded frame data

Copies an trustedanalytics Frame into a Pandas DataFrame.

Examples

Frame *my_frame* accesses a frame with millions of rows of data. Get a sample of 500 rows:

```
>>> pandas_frame = my_frame.download( 500 )
```

We now have a new frame accessed by a pandas DataFrame *pandas_frame* with a copy of the first 500 rows of the original frame.

If we use the method with an offset like:

```
>>> pandas_frame = my_frame.take( 500, 100 )
```

We end up with a new frame accessed by the pandas DataFrame *pandas_frame* again, but this time it has a copy of rows 101 to 600 of the original frame.

17.3.25 *Frame* drop_columns

---

drop_columns (*self*, *columns*)

Remove columns from the frame.

Parameters **columns** : list

Column name OR list of column names to be removed from the frame.

Returns : _Unit

The data from the columns is lost.

Notes

It is not possible to delete all columns from a frame. At least one column needs to remain. If it is necessary to delete all columns, then delete the frame.

17.3.26 *Frame* drop_duplicates

---

drop_duplicates (*self*, *unique_columns=None*)

Modify the current frame, removing duplicate rows.

Parameters **unique_columns** : None (default=None)

Returns : _Unit

Remove data rows which are the same as other rows. The entire row can be checked for duplication, or the search for duplicates can be limited to one or more columns. This modifies the current frame.

17.3.27 *Frame* drop_rows

drop_rows (*self*, *predicate*)
Erase any row in the current frame which qualifies.

Parameters **predicate** : function

UDF which evaluates a row to a boolean; rows that answer True are dropped from the Frame

Examples

For this example, my_frame is a Frame object accessing a frame with lots of data for the attributes of `lions`, `tigers`, and `ligers`. Get rid of the `lions` and `tigers`:

```
>>> my_frame.drop_rows(lambda row: row.animal_type == "lion" or
...     row.animal_type == "tiger")
```

Now the frame only has information about `ligers`.

More information on a UDF can be found at Python User Functions.

17.3.28 *Frame* ecdf

ecdf (*self*, *column*, *result_frame_name=None*)
Builds new frame with columns for data and distribution.

Parameters **column** : unicode

The name of the input column containing sample.

result_frame_name : unicode (default=None)

A name for the resulting frame which is created by this operation.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new Frame containing each distinct value in the sample and its corresponding ECDF value.

Generates the *empirical cumulative distribution* for the input column.

17.3.29 *Frame* entropy

entropy (*self*, *data_column*, *weights_column=None*)
Calculate the Shannon entropy of a column.

Parameters **data_column** : unicode

The column whose entropy is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the entropy calculation. Must contain numerical data. Default is using uniform weights of 1 for all items.

Returns : dict

Entropy.

The data column is weighted via the weights column. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements with a finite weight greater than 0, the entropy is zero.

17.3.30 *Frame* export_to_csv

---

export_to_csv (*self*, *folder_name*, *separator=None*, *count=None*, *offset=None*)

Write current frame to HDFS in csv format.

Parameters **folder_name** : unicode

The HDFS folder path where the files will be created.

separator : None (default=None)

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Returns : _Unit

Export the frame to a file in csv format as a Hadoop file.

17.3.31 *Frame* export_to_hbase

---

export_to_hbase (*self*, *table_name*, *key_column_name=None*, *family_name=None*)

Write current frame to HBase table.

Parameters **table_name** : unicode

The name of the HBase table that will contain the exported frame

key_column_name : unicode (default=None)

The name of the column to be used as row key in hbase table

family_name : unicode (default=None)

The family name of the HBase table that will contain the exported frame

Returns : _Unit

Table must exist in HBase. Export of Vectors is not currently supported.

17.3.32 *Frame* export_to_hive

export_to_hive (*self*, *table_name*)
Write current frame to Hive table.

Parameters **table_name** : unicode

The name of the Hive table that will contain the exported frame

Returns : _Unit

Table must not exist in Hive. Export of Vectors is not currently supported.

17.3.33 *Frame* export_to_jdbc

export_to_jdbc (*self*, *table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)
Write current frame to Jdbc table.

Parameters **table_name** : unicode

jdbc table name

connector_type : unicode (default=None)

(optional) jdbc connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Returns : _Unit

Table will be created or appended to. Export of Vectors is not currently supported.

17.3.34 *Frame* export_to_json

export_to_json (*self*, *folder_name*, *count=None*, *offset=None*)
Write current frame to HDFS in JSON format.

Parameters **folder_name** : unicode

The HDFS folder path where the files will be created.

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Returns : _Unit

Export the frame to a file in JSON format as a Hadoop file.

17.3.35 *Frame* filter

filter (*self*, *predicate*)
Select all rows which satisfy a predicate.

Parameters **predicate** : function

UDF which evaluates a row to a boolean; rows that answer False are dropped from the Frame

Modifies the current frame to save defined rows and delete everything else.

Examples

For this example, *my_frame* is a Frame object with lots of data for the attributes of `lizards`, `frogs`, and `snakes`. Get rid of everything, except information about `lizards` and `frogs`:

```
>>> def my_filter(row):
... return row['animal_type'] == 'lizard' or
... row['animal_type'] == "frog"

>>> my_frame.filter(my_filter)
```

The frame now only has data about `lizards` and `frogs`.

More information on a UDF can be found at Python User Functions.

17.3.36 *Frame* flatten_column

flatten_column (*self*, *column*, *delimiter=None*)
Spread data to multiple rows based on cell data.

Parameters **column** : unicode

The column to be flattened.

delimiter : unicode (default=None)

The delimiter string. Default is comma (,).

Returns : _Unit

Splits cells in the specified column into multiple rows according to a string delimiter. New rows are a full copy of the original row, but the specified column only contains one value. The original row is deleted.

17.3.37 *Frame* get_error_frame

get_error_frame (*self*)
Get a frame with error recordings.

Parameters

When a frame is created, another frame is transparently created to capture parse errors.

Returns **Frame** : error frame object

A new object accessing a frame that contains the parse errors of the currently active Frame or None if no error frame exists.

17.3.38 *Frame* group_by

group_by (*self*, *group_by_columns*, *aggregation_arguments=None*)
[BETA] Create summarized frame.

Parameters **group_by_columns** : list

Column name or list of column names

aggregation_arguments : dict (default=None)

Aggregation function based on entire row, and/or dictionaries (one or more) of { column name str : aggregation function(s) }.

Returns : Frame

A new frame with the results of the group_by

Creates a new frame and returns a Frame object to access it. Takes a column or group of columns, finds the unique combination of values, and creates unique rows with these column values. The other columns are combined according to the aggregation argument(s).

Notes

- Column order is not guaranteed when columns are added
- The column names created by aggregation functions in the new frame are the original column name appended with the '_' character and the aggregation function. For example, if the original field is *a* and the function is *avg*, the resultant column is named *a_avg*.
- An aggregation argument of *count* results in a column named *count*.
- The aggregation function *agg.count* is the only full row aggregation function supported at this time.
- Aggregation currently supports using the following functions:
  - avg
  - count
  - count_distinct
  - max
  - min

–stdev

–sum

–var (see glossary *Bias vs Variance*)

Examples

For setup, we will use a Frame *my_frame* accessing a frame with a column *a*:

```
>>> my_frame.inspect()

  a:str
/-------/
  cat
  apple
  bat
  cat
  bat
  cat
```

Create a new frame, combining similar values of column *a*, and count how many of each value is in the original frame:

```
>>> new_frame = my_frame.group_by('a', agg.count)
>>> new_frame.inspect()

  a:str       count:int
/-----------------------/
  cat             3
  apple           1
  bat             2
```

In this example, 'my_frame' is accessing a frame with three columns, *a*, *b*, and *c*:

```
>>> my_frame.inspect()

  a:int   b:str   c:float
/-------------------------/
  1       alpha     3.0
  1       bravo     5.0
  1       alpha     5.0
  2       bravo     8.0
  2       bravo    12.0
```

Create a new frame from this data, grouping the rows by unique combinations of column *a* and *b*. Average the value in *c* for each group:

```
>>> new_frame = my_frame.group_by(['a', 'b'], {'c' : agg.avg})
>>> new_frame.inspect()

  a:int   b:str   c_avg:float
/-----------------------------/
  1       alpha     4.0
  1       bravo     5.0
  2       bravo    10.0
```

For this example, we use *my_frame* with columns *a*, *c*, *d*, and *e*:

```
>>> my_frame.inspect()

  a:str   c:int   d:float e:int
/-------------------------------/
  ape     1       4.0     9
  ape     1       8.0     8
  big     1       5.0     7
  big     1       6.0     6
  big     1       8.0     5
```

Create a new frame from this data, grouping the rows by unique combinations of column *a* and *c*. Count each group; for column *d* calculate the average, sum and minimum value. For column *e*, save the maximum value:

```
>>> new_frame = my_frame.group_by(['a', 'c'], agg.count,
... {'d': [agg.avg, agg.sum, agg.min], 'e': agg.max})

  a    c    count  d_avg  d_sum  d_min  e_max
  str  int  int    float  float  float  int
/---------------------------------------------/
  ape  1    2      6.0    12.0   4.0    9
  big  1    3      6.333  19.0   5.0    7
```

For further examples, see *Group by (and aggregate):*.

17.3.39 *Frame* histogram

---

histogram(*self*, *column_name*, *num_bins=None*, *weight_column_name=None*, *bin_type='equalwidth'*)
[BETA] Compute the histogram for a column in a frame.

Parameters **column_name** : unicode

Name of column to be evaluated.

num_bins : int32 (default=None)

Number of bins in histogram. Default is Square-root choice will be used (in other words math.floor(math.sqrt(frame.row_count)).

weight_column_name : unicode (default=None)

Name of column containing weights. Default is all observations are weighted equally.

bin_type : unicode (default=equalwidth)

The type of binning algorithm to use: [”equalwidth”|”equaldepth”] Defaults is “equalwidth”.

Returns : dict

histogram A Histogram object containing the result set. The data returned is composed of multiple components:

cutoffs [array of float] A list containing the edges of each bin.

hist [array of float] A list containing count of the weighted observations found in each bin.

density [array of float] A list containing a decimal containing the percentage of observations found in the total set per bin.

Compute the histogram of the data in a column. The returned value is a Histogram object containing 3 lists one each for: the cutoff points of the bins, size of each bin, and density of each bin.

Notes

The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. With equal depth binning, for example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

17.3.40 *Frame* inspect

---

inspect (*self*, *n=10*, *offset=0*, *columns=None*, *wrap=None*, *truncate=None*, *round=None*, *width=80*, *margin=None*)

Prints the frame data in readable format.

Parameters n : int (default=10)

The number of rows to print.

offset : int (default=0)

The number of rows to skip before printing.

columns : int (default=None)

Filter columns to be included. By default, all columns are included

wrap : int or 'stripes' (default=None)

If set to 'stripes' then inspect prints rows in stripes; if set to an integer N, rows will be printed in clumps of N columns, where the columns are wrapped

truncate : int (default=None)

If set to integer N, all strings will be truncated to length N, including a tagged ellipses

round : int (default=None)

If set to integer N, all floating point numbers will be rounded and truncated to N digits

width : int (default=80)

If set to integer N, the print out will try to honor a max line width of N

margin : int (default=None)

('stripes' mode only) If set to integer N, the margin for printing names in a stripe will be limited to N characters

Examples

Given a frame of data and a Frame to access it. To look at the first 4 rows of data:

```
>>> print my_frame.inspect(4)

column defs ->   animal:str  name:str    age:int     weight:float
               /--------------------------------------------------/
frame data ->    human       George        8             542.5
                 human       Ursula        6             495.0
```

```
                    ape          Ape          41           400.0
                    elephant     Shep          5          8630.0
```

For other examples, see *Inspect the Data*.

17.3.41 *Frame* join

join (*self*, *right*, *left_on*, *right_on=None*, *how='inner'*, *name=None*)
[BETA] Join operation on one or two frames, creating a new frame.

Parameters **right** : Frame

Another frame to join with

left_on : str

Name of the column in the left frame used to match up the two frames.

right_on : str (default=None)

Name of the column in the right frame used to match up the two frames. Default is the same as the left frame.

how : str (default=inner)

How to qualify the data to be joined together. Must be one of the following: 'left', 'right', 'inner', 'outer'. Default is 'inner'

name : str (default=None)

Name of the result grouped frame

Returns : Frame

A new frame with the results of the join

Create a new frame from a SQL JOIN operation with another frame. The frame on the 'left' is the currently active frame. The frame on the 'right' is another frame. This method takes a column in the left frame and matches its values with a column in the right frame. Using the default 'how' option ['inner'] will only allow data in the resultant frame if both the left and right frames have the same value in the matching column. Using the 'left' 'how' option will allow any data in the resultant frame if it exists in the left frame, but will allow any data from the right frame if it has a value in its column which matches the value in the left frame column. Using the 'right' option works similarly, except it keeps all the data from the right frame and only the data from the left frame when it matches. The 'outer' option provides a frame with data from both frames where the left and right frames did not have the same value in the matching column.

Notes

When a column is named the same in both frames, it will result in two columns in the new frame. The column from the *left* frame (originally the current frame) will be copied and the column name will have the string "_L" added to it. The same thing will happen with the column from the *right* frame, except its name has the string "_R" appended. The order of columns after this method is called is not guaranteed.

It is recommended that you rename the columns to meaningful terms prior to using the `join` method. Keep in mind that unicode in column names will likely cause the drop_frames() method (and others) to fail!

Examples

For this example, we will use a Frame *my_frame* accessing a frame with columns *a*, *b*, *c*, and a Frame *your_frame* accessing a frame with columns *a*, *d*, *e*. Join the two frames keeping only those rows having the same value in column *a*:

```
>>> print my_frame.inspect()

  a:unicode   b:unicode   c:unicode
/-------------------------------------/
  alligator   bear        cat
  apple       berry       cantaloupe
  auto        bus         car
  mirror      frog        ball

>>> print your_frame.inspect()

  b:unicode   c:int   d:unicode
/------------------------------------/
  berry        5218   frog
  blue            0   log
  bus           871   dog

>>> joined_frame = my_frame.join(your_frame, 'b', how='inner')
```

Now, joined_frame is a Frame accessing a frame with the columns *a*, *b*, *c_L*, *ci_R*, and *d*. The data in the new frame will be from the rows where column 'a' was the same in both frames.

```
>>> print joined_frame.inspect()

  a:unicode   b:unicode     c_L:unicode   c_R:int64   d:unicode
/-------------------------------------------------------------------/
  apple       berry         cantaloupe         5218   frog
  auto        bus           car                 871   dog
```

More examples can be found in the *user manual*.

17.3.42 *Frame* label_propagation

label_propagation(*self*, *src_col_name*, *dest_col_name*, *weight_col_name*, *src_label_col_name*, *result_col_name=None*, *max_iterations=None*, *convergence_threshold=None*, *alpha=None*)

Label Propagation on Gaussian Random Fields.

Parameters **src_col_name** : unicode

The column name for the source vertex id.

dest_col_name : unicode

The column name for the destination vertex id.

weight_col_name : unicode

The column name for the edge weight.

src_label_col_name : unicode

The column name for the label properties for the source vertex.

result_col_name : unicode (default=None)

The column name for the results (holding the post labels for the vertices).

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid value range is all positive int. Default is 10.

convergence_threshold : float32 (default=None)

The amount of change in cost function that will be tolerated at convergence. If the change is less than this threshold, the algorithm exits earlier before it reaches the maximum number of supersteps. The valid value range is all float and zero. Default is 0.00000001f.

alpha : float32 (default=None)

The tradeoff parameter that controls how much influence an external classifier's prediction contributes to the final prediction. This is for the case where an external classifier is available that can produce initial probabilistic classification on unlabeled examples, and the option allows incorporating external classifier's prediction into the LP training process. The valid value range is [0.0,1.0]. Default is 0.

Returns : dict

A 2-column frame:

vertex: int A vertex id.

result [Vector (long)] label vector for the results (for the node id in column 1)

Label Propagation on Gaussian Random Fields.

This algorithm is presented in X. Zhu and Z. Ghahramani. Learning from labeled and unlabeled data with label propagation. Technical Report CMU-CALD-02-107, CMU, 2002[1].

Label Propagation (LP)

LP (Label Proopagation) is a message passing technique for inputing or *smoothing* labels in partially-labelled datasets. Labels are propagated from *labeled* data to *unlabeled* data along a graph encoding similarity relationships among data points. The labels of known data can be probabilistic, in other words, a known point can be represented with fuzzy labels such as 90% label 0 and 10% label 1. The inverse distance between data points is represented by edge weights, with closer points having a higher weight (stronger influence on posterior estimates) than points farther away. LP has been used for many problems, particularly those involving a similarity measure between data points. Our implementation is based on Zhu and Ghahramani's 2002 paper, Learning from labeled and unlabeled data.[2].

The Label Propagation Algorithm

In LP, all nodes start with a prior distribution of states and the initial messages vertices pass to their neighbors are simply their prior beliefs. If certain observations have states that are known deterministically, they can be given a prior probability of 100% for their true state and 0% for all others. Unknown observations should be given uninformative priors.

Each node, i, receives messages from its k neighbors and updates its beliefs by taking a weighted average of its current beliefs and a weighted average of the messages received from its neighbors.

[1] http://www.cs.cmu.edu/ zhuxj/pub/CMU-CALD-02-107.pdf
[2] http://www.cs.cmu.edu/ zhuxj/pub/CMU-CALD-02-107.pdf

The updated beliefs for node i are:

$$updated\ beliefs_i = \lambda * (prior\ belief_i) + (1 - \lambda)\ * \sum_k w_{i,k} * previous\ belief_k$$

where $w_{i,k}$ is the normalized weight between nodes i and k, normalized such that the sum of all weights to neighbors is 1.

λ is a leaning parameter. If λ is greater than zero, updated probabilities will be anchored in the direction of prior beliefs.

The final distribution of state probabilities will also tend to be biased in the direction of the distribution of initial beliefs. For the first iteration of updates, nodes' previous beliefs are equal to the priors, and, in each future iteration, previous beliefs are equal to their beliefs as of the last iteration. All beliefs for every node will be updated in this fashion, including known observations, unless `anchor_threshold` is set. The `anchor_threshold` parameter specifies a probability threshold above which beliefs should no longer be updated. Hence, with an `anchor_threshold` of 0.99, observations with states known with 100% certainty will not be updated by this algorithm.

This process of updating and message passing continues until the convergence criteria is met, or the maximum number of *supersteps* is reached. A node is said to converge if the total change in its cost function is below the convergence threshold. The cost function for a node is given by:

$$cost = \sum_k w_{i,k} * \Big[\big(1 - \lambda\big) * \big[previous\ \ belief_i^2 - w_{i,k} * previous\ belief_i *$$
$$previous\ belief_k\big] + 0.5 * \lambda * \big(previous\ belief_i\ \ - prior_i\big)^2\Big]$$

Convergence is a local phenomenon; not all nodes will converge at the same time. It is also possible that some (most) nodes will converge and others will not converge. The algorithm requires all nodes to converge before declaring global convergence. If this condition is not met, the algorithm will continue up to the maximum number of *supersteps*.

17.3.43 *Frame* loadhbase

---

loadhbase (*self*, *table_name*, *schema*, *start_tag=None*, *end_tag=None*)

Append data from an hBase table into an existing (possibly empty) FrameRDD

Parameters **table_name** : unicode

hbase table name

schema : list

hbase schema as a list of tuples (columnFamily, columnName, dataType for cell value)

start_tag : unicode (default=None)

optional start tag for filtering

end_tag : unicode (default=None)

optional end tag for filtering

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial FrameRDD with the hbase data appended

Append data from an hBase table into an existing (possibly empty) FrameRDD

17.3.44 *Frame* loadhive

loadhive (*self*, *query*)
Append data from a hive table into an existing (possibly empty) frame

Parameters **query** : unicode

Initial query to run at load time

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial frame with the hive data appended

Append data from a hive table into an existing (possibly empty) frame

17.3.45 *Frame* loadjdbc

loadjdbc (*self*, *table_name*, *connector_type=None*, *url=None*, *driver_name=None*, *query=None*)
Append data from a Jdbc table into an existing (possibly empty) frame

Parameters **table_name** : unicode

table name

connector_type : unicode (default=None)

(optional) connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

the initial frame with the Jdbc data appended

Append data from a Jdbc table into an existing (possibly empty) frame

17.3.46 *Frame* loopy_belief_propagation

loopy_belief_propagation (*self*, *src_col_name*, *dest_col_name*, *weight_col_name*, *src_label_col_name*, *result_col_name=None*, *ignore_vertex_type=None*, *max_iterations=None*, *convergence_threshold=None*, *anchor_threshold=None*, *smoothing=None*, *max_product=None*, *power=None*)
Message passing to infer state probabilities.

Parameters **src_col_name** : unicode

The column name for the source vertex id.

dest_col_name : unicode

The column name for the destination vertex id.

weight_col_name : unicode

The column name for the edge weight.

src_label_col_name : unicode

The column name for the label properties for the source vertex.

result_col_name : unicode (default=None)

The column name for the results (holding the post labels for the vertices).

ignore_vertex_type : bool (default=None)

If True, all vertex will be treated as training data. Default is False.

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid value range is all positive int. The default value is 10.

convergence_threshold : float32 (default=None)

The amount of change in cost function that will be tolerated at convergence. If the change is less than this threshold, the algorithm exits earlier before it reaches the maximum number of supersteps. The valid value range is all float and zero. The default value is 0.00000001f.

anchor_threshold : float64 (default=None)

The parameter that determines if a node's posterior will be updated or not. If a node's maximum prior value is greater than this threshold, the node will be treated as anchor node, whose posterior will inherit from prior without update. This is for the case where we have confident prior estimation for some nodes and don't want the algorithm to update these nodes. The valid value range is in [0, 1]. Default is 1.0.

smoothing : float32 (default=None)

The Ising smoothing parameter. This parameter adjusts the relative strength of closeness encoded edge weights, similar to the width of Gussian distribution. Larger value implies smoother decay and the edge weight beomes less important. Default is 2.0.

max_product : bool (default=None)

Should LBP (Loopy Belief Propagation) use max_product or not. Default is False.

power : float32 (default=None)

Power coefficient for power edge potential. Default is 0.

Returns : dict

a 2-column frame:

vertex: int A vertex id.

result [Vector (long)] label vector for the results (for the node id in column 1).

Loopy belief propagation on *Markov Random Fields* (MRF). *Belief Propagation* (BP) was originally designed for acyclic graphical models, then it was found that the BP (Belief Propagation) algorithm can be used in general graphs. The algorithm is then sometimes called "Loopy" Belief Propagation (LBP), because graphs typically contain cycles, or loops.

Loopy Belief Propagation (LBP)

Loopy Belief Propagation (LBP) is a message passing algorithm for inferring state probabilities, given a graph and a set of noisy initial estimates. The LBP implementation assumes that the joint distribution of the data is given by a Boltzmann distribution.

For more information about LBP, see: "K. Murphy, Y. Weiss, and M. Jordan, Loopy-belief Propagation for Approximate Inference: An Empirical Study, UAI 1999."

LBP has a wide range of applications in structured prediction, such as low-level vision and influence spread in social networks, where we have prior noisy predictions for a large set of random variables and a graph encoding relationships between those variables.

The algorithm performs approximate inference on an *undirected graph* of hidden variables, where each variable is represented as a node, and each edge encodes relations to its neighbors. Initially, a prior noisy estimate of state probabilities is given to each node, then the algorithm infers the posterior distribution of each node by propagating and collecting messages to and from its neighbors and updating the beliefs.

In graphs containing loops, convergence is not guaranteed, though LBP has demonstrated empirical success in many areas and in practice often converges close to the true joint probability distribution.

Discrete Loopy Belief Propagation

LBP is typically considered a *semi-supervised machine learning* algorithm as

1. there is typically no ground truth observation of states
2. the algorithm is primarily concerned with estimating a joint probability function rather than with *classification* or point prediction.

The standard (discrete) LBP algorithm requires a set of probability thresholds to be considered a classifier. Nonetheless, the discrete LBP algorithm allows Test/Train/Validate splits of the data and the algorithm will treat "Train" observations differently from "Test" and "Validate" observations. Vertices labelled with "Test" or "Validate" will be treated as though they have uninformative (uniform) priors and are allowed to receive messages, but not send messages. This simulates a "scoring scenario" in which a new observation is added to a graph containing fully trained LBP posteriors, the new vertex is scored based on received messages, but the full LBP algorithm is not repeated in full. This behavior can be turned off by setting the `ignore_vertex_type` parameter to True. When `ignore_vertex_type=True`, all nodes will be considered "Train" regardless of their sample type designation. The Gaussian (continuous) version of LBP does not allow Train/Test/Validate splits.

The standard LBP algorithm included with the toolkit assumes an ordinal and cardinal set of discrete states. For notational convenience, we'll denote the value of state s_i as i, and the prior probability of state s_i as $prior_i$.

Each node sends out initial messages of the form:

$$\ln\left(\sum_{s_j}\exp\left(-\frac{|i-j|^p}{n-1} * w * s + \ln(prior_i)\right)\right)$$

Where

- w is the weight between the messages destination and origin vertices
- s is the *smoothing* parameter
- p is the power parameter

- n is the number of states

The larger the weight between two nodes, or the higher the smoothing parameter, the more neighboring vertices are assumed to "agree" on states. We represent messages as sums of log probabilities rather than products of non-logged probabilities which makes it easier to subtract messages in the future steps of the algorithm. Also note that the states are cardinal in the sense that the "pull" of state i on state j depends on the distance between i and j. The *power* parameter intensifies the rate at which the pull of distant states drops off.

In order for the algorithm to work properly, all edges of the graph must be bidirectional. In other words, messages need to be able to flow in both directions across every edge. Bidirectional edges can be enforced during graph building, but the LBP function provides an option to do an initial check for bidirectionality using the `bidirectional_check=True` option. If not all the edges of the graph are bidirectional, the algorithm will return an error.

Look at a case where a node has two states, 0 and 1. The 0 state has a prior probability of 0.9 and the 1 state has a prior probability of 0.2. The states have uniform weights of 1, power of 1 and a smoothing parameter of 2. The nodes initial message would be $\left[\ln\left(0.2\ + 0.8e^{-2}\right), \ln\left(0.8 + 0.2e^{-2}\right)\right]$, which gets sent to each of that node's neighbors. Note that messages will typically not be proper probability distributions, hence each message is normalized so that the probability of all states sum to 1 before being sent out. For simplicity of discussion, we will consider all messages as normalized messages.

After nodes have sent out their initial messages, they then update their beliefs based on messages that they have received from their neighbors, denoted by the set k.

Updated Posterior Beliefs:

$$\ln(newbelief) = \propto \exp\left[\ln(prior) + \sum_k message_k\right]$$

Note that the messages in the above equation are still in log form. Nodes then send out new messages which take the same form as their initial messages, with updated beliefs in place of priors and subtracting out the information previously received from the new message's recipient. The recipient's prior message is subtracted out to prevent feedback loops of nodes "learning" from themselves.

$$\ln\left(\sum_{s_j} \exp\left(-\frac{|i-j|^p}{n-1}\ * w * s + \ln(newbelief_i) -\ previous\ message\ from\ recipient\right)\right)$$

In updating beliefs, new beliefs tend to be most influenced by the largest message. Setting the `max_product` option to "True" ignores all incoming messages other than the strongest signal. Doing this results in approximate solutions, but requires significantly less memory and run-time than the more exact computation. Users should consider this option when processing power is a constraint and approximate solutions to LBP will be sufficient.

This process of updating and message passing continues until the convergence criteria is met or the maximum number of *supersteps* is reached without converging. A node is said to converge if the total change in its distribution (the sum of absolute value changes in state probabilities) is less than the `convergence_threshold` parameter. Convergence is a local phenomenon; not all nodes will converge at the same time. It is also possible for some (most) nodes to converge and others to never converge. The algorithm requires all nodes to converge before declaring that the algorithm has converged overall. If this condition is not met, the algorithm will continue up to the maximum number of *supersteps*.

See: http://en.wikipedia.org/wiki/Belief_propagation.

17.3.47 *Frame* name

name

Set or get the name of the frame object.

Parameters

Change or retrieve frame object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_frame.name

"csv_data"

>>> my_frame.name = "cleaned_data"
>>> my_frame.name

"cleaned_data"
```

17.3.48 *Frame* quantiles

---

quantiles(*self*, *column_name*, *quantiles*)

New frame with Quantiles and their values.

Parameters **column_name** : unicode

The column to calculate quantiles.

quantiles : list

What is being requested.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame with two columns (float64): requested Quantiles and their respective values.

Calculate quantiles on the given column.

17.3.49 *Frame* rename_columns

---

rename_columns(*self*, *names*)

Rename columns

Parameters **names** : None

Returns : _Unit

17.3.50 *Frame* row_count

row_count
Number of rows in the current frame.

Parameters

Returns : int

The number of rows in the frame

Get the number of rows:

```
>>> my_frame.row_count
```

The result given is:

```
81734
```

17.3.51 *Frame* schema

schema
Current frame column names and types.

Parameters

Returns : list

list of tuples of the form (<column name>, <data type>)

The schema of the current frame is a list of column names and associated data types. It is retrieved as a list of tuples. Each tuple has the name and data type of one of the frame's columns.

Examples

Given that we have an existing data frame *my_data*, create a Frame, then show the frame schema:

```
>>> BF = ta.get_frame('my_data')
>>> print BF.schema
```

The result is:

```
[("col1", str), ("col2", numpy.int32)]
```

17.3.52 *Frame* sort

sort (*self*, *columns*, *ascending=True*)
[BETA] Sort the data in a frame.

Parameters **columns** : str | list of str | list of tuples

Either a column name, a list of column names, or a list of tuples where each tuple is a name and an ascending bool value.

ascending : bool (default=True)

True for ascending, False for descending.

Sort a frame by column values either ascending or descending.

Examples

Sort a single column:

```
>>> frame.sort('column_name')
```

Sort a single column ascending:

```
>>> frame.sort('column_name', True)
```

Sort a single column descending:

```
>>> frame.sort('column_name', False)
```

Sort multiple columns:

```
>>> frame.sort(['col1', 'col2'])
```

Sort multiple columns ascending:

```
>>> frame.sort(['col1', 'col2'], True)
```

Sort multiple columns descending:

```
>>> frame.sort(['col1', 'col2'], False)
```

Sort multiple columns: 'col1' ascending and 'col2' descending:

```
>>> frame.sort([ ('col1', True), ('col2', False) ])
```

17.3.53 *Frame* sorted_k

---

sorted_k (*self*, *k*, *column_names_and_ascending*, *reduce_tree_depth=None*)

[ALPHA] Get a sorted subset of the data.

Parameters **k** : int32

Number of sorted records to return.

column_names_and_ascending : list

Column names to sort by, and true to sort column by ascending order, or false for descending order.

reduce_tree_depth : int32 (default=None)

Advanced tuning parameter which determines the depth of the reduce-tree for the sorted_k plugin. This plugin uses Spark's treeReduce() for scalability. The default depth is 2.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame with the first k sorted rows from the original frame.

Take the first k (sorted) rows for the currently active Frame. Rows are sorted by column values in either ascending or descending order.

Returning the first k (sorted) rows is more efficient than sorting the entire frame when k is much smaller than the number of rows in the frame.

Notes

The number of sorted rows (k) should be much smaller than the number of rows in the original frame.

In particular:

1.The number of sorted rows (k) returned should fit in Spark driver memory.

The maximum size of serialized results that can fit in the Spark driver is set by the Spark configuration parameter *spark.driver.maxResultSize*.

2.If you encounter a Kryo buffer overflow exception, increase the Spark

configuration parameter *spark.kryoserializer.buffer.max.mb*.

3.Use Frame.sort() instead if the number of sorted rows (k) is

very large (i.e., cannot fit in Spark driver memory).

17.3.54 *Frame* status

status

Current frame life cycle status.

Parameters

Returns : str

Status of the frame

One of three statuses: Active, Deleted, Deleted_Final Active: Frame is available for use Deleted: Frame has been scheduled for deletion can be unscheduled by modifying Deleted_Final: Frame's backend files have been removed from disk.

Examples

Given that we have an existing data frame *my_data*, create a Frame, then show the frame schema:

```
>>> BF = ta.get_frame('my_data')
>>> print BF.status
```

The result is:

```
u'Active'
```

17.3.55 *Frame* take

take (*self*, *n*, *offset=0*, *columns=None*)
Get data subset.

Parameters n : int

The number of rows to copy to the client from the frame.

offset : int (default=0)

The number of rows to skip before starting to copy

columns : str | iterable of str (default=None)

If not None, only the given columns' data will be provided. By default, all columns are included

Returns : list

A list of lists, where each contained list is the data for one row.

Take a subset of the currently active Frame.

Notes

The data is considered 'unstructured', therefore taking a certain number of rows, the rows obtained may be different every time the command is executed, even if the parameters do not change.

Examples

Frame *my_frame* accesses a frame with millions of rows of data. Get a sample of 5000 rows:

```
>>> my_data_list = my_frame.take( 5000 )
```

We now have a list of data from the original frame.

```
>>> print my_data_list

[[ 1, "text", 3.1415962 ]
 [ 2, "bob", 25.0 ]
 [ 3, "weave", .001 ]
 ...]
```

If we use the method with an offset like:

```
>>> my_data_list = my_frame.take( 5000, 1000 )
```

We end up with a new list, but this time it has a copy of the data from rows 1001 to 5000 of the original frame.

17.3.56 *Frame* tally

tally (*self*, *sample_col*, *count_val*)
[BETA] Count number of times a value is seen.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative count.

count_val : unicode

The column value to be used for the counts.

Returns : _Unit

A cumulative count is computed by sequentially stepping through the rows, observing the column values and keeping track of the the number of times the specified *count_value* has been seen.

17.3.57 *Frame* tally_percent

---

tally_percent (*self*, *sample_col*, *count_val*)

[BETA] Compute a cumulative percent count.

Parameters **sample_col** : unicode

The name of the column from which to compute the cumulative sum.

count_val : unicode

The column value to be used for the counts.

Returns : _Unit

A cumulative percent count is computed by sequentially stepping through the rows, observing the column values and keeping track of the percentage of the total number of times the specified *count_value* has been seen up to the current value.

17.3.58 *Frame* top_k

---

top_k (*self*, *column_name*, *k*, *weights_column=None*)

Most or least frequent column values.

Parameters **column_name** : unicode

The column whose top (or bottom) K distinct values are to be calculated.

k : int32

Number of entries to return (If k is negative, return bottom k).

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the topK calculation. Must contain numerical data. Default is 1 for all items.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

An object with access to the frame of data.

Calculate the top (or bottom) K distinct values by count of a column. The column can be weighted. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight > 0, then topK is empty.

17.3.59 *Frame* unflatten_column

unflatten_column(*self*, *composite_key_column_names*, *delimiter=None*)
Compacts data from multiple rows based on cell data.

Parameters **composite_key_column_names** : list

name of the user column to be used as keys for unflattening.

delimiter : unicode (default=None)

separator for the data in the result columns. Default is comma (,).

Returns : _Unit

Groups together cells in all columns (less the composite key) using "," as string delimiter. The original rows are deleted. The grouping takes place based on a composite key passed as arguments.

class **Frame**
Large table of data.

Class with information about a large row and columnar data store in a frame, Has information needed to modify data and table structure.

Attributes

column_names	Column identifications in the current frame.
name	Set or get the name of the frame object.
row_count	Number of rows in the current frame.
schema	Current frame column names and types.
status	Current frame life cycle status.

Methods

__init__(self[, source, name, _info])	Create a Frame/frame.
add_columns(self, func, schema[, columns_accessed])	Add columns to current frame.
append(self, data)	Adds more data to the current frame.
assign_sample(self, sample_percentages[, sample_labels, ...])	Randomly group rows into user-defined classes.
bin_column(self, column_name, cutoffs[, include_lowest, strict_binning, ...])	Classify data into user-defined groups.
bin_column_equal_depth(self, column_name[, num_bins, ...])	Classify column into groups with the same frequency.
bin_column_equal_width(self, column_name[, num_bins, ...])	Classify column into same-width groups.
categorical_summary(self, *column_inputs)	[ALPHA] Compute a summary of the data in a colun
classification_metrics(self, label_column, pred_column[, ...])	Model statistics of accuracy, precision, and others.
column_median(self, data_column[, weights_column])	Calculate the (weighted) median of a column.
column_mode(self, data_column[, weights_column, max_modes_returned])	Evaluate the weights assigned to rows.
column_summary_statistics(self, data_column[, ...])	Calculate multiple statistics for a column.
compute_misplaced_score(self, gravity)	
copy(self[, columns, where, name])	Create new frame from current frame.
correlation(self, data_column_names)	Calculate correlation for two columns of current fram
correlation_matrix(self, data_column_names[, matrix_name])	Calculate correlation matrix for two or more columns.
count(self, where)	Counts the number of rows which meet given criteria.

Table 17.3 – continued from previous page

covariance(self, data_column_names)	Calculate covariance for exactly two columns.
covariance_matrix(self, data_column_names[, matrix_name])	Calculate covariance matrix for two or more columns.
cumulative_percent(self, sample_col)	[BETA] Add column to frame with cumulative percer
cumulative_sum(self, sample_col)	[BETA] Add column to frame with cumulative percer
dot_product(self, left_column_names, right_column_names, ...[, ...])	[ALPHA] Calculate dot product for each row in curre
download(self[, n, offset, columns])	Download a frame from the server into client workspa
drop_columns(self, columns)	Remove columns from the frame.
drop_duplicates(self[, unique_columns])	Modify the current frame, removing duplicate rows.
drop_rows(self, predicate)	Erase any row in the current frame which qualifies.
ecdf(self, column[, result_frame_name])	Builds new frame with columns for data and distributi
entropy(self, data_column[, weights_column])	Calculate the Shannon entropy of a column.
export_to_csv(self, folder_name[, separator, count, offset])	Write current frame to HDFS in csv format.
export_to_hbase(self, table_name[, key_column_name, family_name])	Write current frame to HBase table.
export_to_hive(self, table_name)	Write current frame to Hive table.
export_to_jdbc(self, table_name[, connector_type, url, driver_name, ...])	Write current frame to Jdbc table.
export_to_json(self, folder_name[, count, offset])	Write current frame to HDFS in JSON format.
filter(self, predicate)	Select all rows which satisfy a predicate.
flatten_column(self, column[, delimiter])	Spread data to multiple rows based on cell data.
get_error_frame(self)	Get a frame with error recordings.
group_by(self, group_by_columns, *aggregation_arguments)	[BETA] Create summarized frame.
histogram(self, column_name[, num_bins, weight_column_name, bin_type])	[BETA] Compute the histogram for a column in a fra
inspect(self[, n, offset, columns, wrap, truncate, round, width, margin])	Prints the frame data in readable format.
join(self, right, left_on[, right_on, how, name])	[BETA] Join operation on one or two frames, creating
label_propagation(self, src_col_name, dest_col_name, ...[, ...])	Label Propagation on Gaussian Random Fields.
loadhbase(self, table_name, schema[, start_tag, end_tag])	Append data from an hBase table into an existing (pos
loadhive(self, query)	Append data from a hive table into an existing (possib
loadjdbc(self, table_name[, connector_type, url, driver_name, query])	Append data from a Jdbc table into an existing (possib
loopy_belief_propagation(self, src_col_name, ...[, ...])	Message passing to infer state probabilities.
quantiles(self, column_name, quantiles)	New frame with Quantiles and their values.
rename_columns(self, names)	Rename columns
sort(self, columns[, ascending])	[BETA] Sort the data in a frame.
sorted_k(self, k, column_names_and_ascending[, reduce_tree_depth])	[ALPHA] Get a sorted subset of the data.
take(self, n[, offset, columns])	Get data subset.
tally(self, sample_col, count_val)	[BETA] Count number of times a value is seen.
tally_percent(self, sample_col, count_val)	[BETA] Compute a cumulative percent count.
top_k(self, column_name, k[, weights_column])	Most or least frequent column values.
unflatten_column(self, composite_key_column_names[, delimiter])	Compacts data from multiple rows based on cell data.

__init__(*self*, *source=None*, *name=None*)

Create a Frame/frame.

Parameters **source** : CsvFile | Frame (default=None)

A source of initial data.

name : str (default=None)

The name of the newly created frame. Default is None.

Notes

A frame with no name is subject to garbage collection.

If a string in the CSV file starts and ends with a double-quote (") character, the character is stripped off of the data before it is put into the field. Anything, including delimiters, between the double-quote characters is considered part of the str. If the first character after the delimiter is anything other than a double-quote character, the string will be composed of all the characters between the delimiters, including double-quotes. If the first field type is str, leading spaces on each row are considered part of the str. If the last field type is str, trailing spaces on each row are considered part of the str.

Examples

Create a new frame based upon the data described in the CsvFile object *my_csv_schema*. Name the frame "myframe". Create a Frame *my_frame* to access the data:

```
>>> my_frame = ta.Frame(my_csv_schema, "myframe")
```

A Frame object has been created and *my_frame* is its proxy. It brought in the data described by *my_csv_schema*. It is named *myframe*.

Create an empty frame; name it "yourframe":

```
>>> your_frame = ta.Frame(name='yourframe')
```

A frame has been created and Frame *your_frame* is its proxy. It has no data yet, but it does have the name *yourframe*.

17.4 *trustedanalytics* drop_frames

---

drop_frames (*items*)
Deletes the frame on the server.

Parameters **items** : [str | frame object | list [str | frame objects]]

Either the name of the frame object to delete or the frame object itself

17.5 *trustedanalytics* get_frame

---

get_frame (*identifier*)
Get handle to a frame object.

Parameters **identifier** : str | int

Name of the frame to get

Returns : Frame

frame object

17.6 *trustedanalytics* get_frame_names

---

get_frame_names()

Retrieve names for all the frame objects on the server.

Returns : list

List of names

Global Methods

drop_frames

get_frame

get_frame_names

CHAPTER

EIGHTEEN

GRAPHS

Classes

18.1 *Graphs* Graph

18.1.1 *Graph* __init__

__init__(*self*, *name=None*)

<Missing Doc>

Parameters **name** : str (default=None)

Name for the new graph. Default is None.

18.1.2 *Graph* fget

__private_ml

Access to object's ml functionality (See `GraphMl`)

Parameters

Returns : GraphMl

GraphMl object

18.1.3 *Graph* annotate_degrees

annotate_degrees(*self*, *output_property_name*, *degree_option=None*, *input_edge_labels=None*)

Make new graph with degrees.

Parameters **output_property_name** : unicode

The name of the new property. The degree is stored in this property.

degree_option : unicode (default=None)

Indicator for the definition of degree to be used for the calculation. Permitted values:

- "out" (default value) : Degree is calculated as the out-degree.
- "in" : Degree is calculated as the in-degree.
- "undirected" : Degree is calculated as the undirected degree. (Assumes that the edges are all undirected.)

Any prefix of the strings "out", "in", "undirected" will select the corresponding option.

input_edge_labels : list (default=None)

If this list is provided, only edges whose labels are included in the given set will be considered in the degree calculation. In the default situation (when no list is provided), all edges will be used in the degree calculation, regardless of label.

Returns : dict

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a column storing the annotated degree for the vertex in a user specified property. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

Creates a new graph which is the same as the input graph, with the addition that every vertex of the graph has its *degree* stored in a user-specified property.

Degree Calculation

A fundamental quantity in graph analyses is the degree of a vertex: The degree of a vertex is the number of edges adjacent to it.

For a directed edge relation, a vertex has both an out-degree (the number of edges leaving the vertex) and an in-degree (the number of edges entering the vertex).

The toolkit provides this routine for calculating the degrees of vertices. This calculation could be performed with a Gremlin query on smaller datasets because Gremlin queries cannot be executed on a distributed scale. The Trusted Analytics routine `annotate_degrees` can be executed at distributed scale.

In the presence of edge weights, vertices can have weighted degrees: The weighted degree of a vertex is the sum of weights of edges adjacent to it. Analogously, the weighted in-degree of a vertex is the sum of the weights of the edges entering it, and the weighted out-degree is the sum of the weights of the edges leaving the vertex.

The toolkit provides *annotate_weighted_degrees* for the distributed calculation of weighted vertex degrees.

18.1.4 *Graph* annotate_weighted_degrees

annotate_weighted_degrees (*self*, *output_property_name*, *degree_option=None*, *input_edge_labels=None*, *edge_weight_property=None*, *edge_weight_default=None*)

Calculates the weighted degree of each vertex with respect to an (optional) set of labels.

Parameters **output_property_name** : unicode

property name of where to store output

degree_option : unicode (default=None)

choose from 'out', 'in', 'undirected'

input_edge_labels : list (default=None) labels of edge types that should be included

edge_weight_property : unicode (default=None)

property name of edge weight, if not provided all edges are weighted equally

edge_weight_default : float64 (default=None)

default edge weight

Returns : dict

Pulls graph from underlying store, calculates weighted degrees and writes them into the property specified, and then writes the output graph to the underlying store.

Degree Calculation

A fundamental quantity in graph analyses is the degree of a vertex: The degree of a vertex is the number of edges adjacent to it.

For a directed edge relation, a vertex has both an out-degree (the number of edges leaving the vertex) and an in-degree (the number of edges entering the vertex).

The toolkit provides a routine *annotate_degrees* for calculating the degrees of vertices. This calculation could be performed with a Gremlin query on smaller datasets because Gremlin queries cannot be executed on a distributed scale. The Trusted Analytics routine `annotate_degrees` can be executed at distributed scale.

In the presence of edge weights, vertices can have weighted degrees: The weighted degree of a vertex is the sum of weights of edges adjacent to it. Analogously, the weighted in-degree of a vertex is the sum of the weights of the edges entering it, and the weighted out-degree is the sum of the weights of the edges leaving the vertex.

The toolkit provides this routine for the distributed calculation of weighted vertex degrees.

18.1.5 *Graph* clustering_coefficient

`clustering_coefficient` (*self*, *output_property_name=None*, *input_edge_labels=None*)

Coefficient of graph with respect to labels.

Parameters **output_property_name** : unicode (default=None)

The name of the new property to which each vertex's local clustering coefficient will be written. If this option is not specified, no output frame will be produced and only the global clustering coefficient will be returned.

input_edge_labels : list (default=None)

If this list is provided, only edges whose labels are included in the given set will be considered in the clustering coefficient calculation. In the default situation (when no list is provided), all edges will be used in the calculation, regardless of label. It is required that all edges that enter into the clustering coefficient analysis be undirected.

Returns : dict

Dictionary of the global clustering coefficient of the graph or, if local clustering coefficients are requested, a reference to the frame with local clustering coefficients stored at properties at each vertex.

Calculates the clustering coefficient of the graph with repect to an (optional) set of labels.

Pulls graph from underlying store, calculates degrees and writes them into the property specified, and then writes the output graph to the underlying store.

> **Warning:** THIS FUNCTION IS FOR UNDIRECTED GRAPHS. If it is called on a directed graph, its output is NOT guaranteed to calculate the local directed clustering coefficients.

Clustering Coefficients

The clustering coefficient of a graph provides a measure of how tightly clustered an undirected graph is. Informally, if the edge relation denotes "friendship", the clustering coefficient of the graph is the probability that two people are friends given that they share a common friend.

More formally:

$$cc(G) = \frac{\| \{ (u,v,w) \in V^3 :\ \{u,v\}, \{u,w\}, \{v,w\} \in \ E \} \|}{\| \{ (u,v,w) \in V^3 :\ \{u,v\}, \{u,w\} \in E \} \|}$$

Analogously, the clustering coefficient of a vertex provides a measure of how tightly clustered that vertex's neighborhood is. Informally, if the edge relation denotes "friendship", the clustering coefficient at a vertex v is the probability that two acquaintances of v are themselves friends.

More formally:

$$cc(v) = \frac{\| \{ (u,v,w) \in V^3 :\ \{u,v\}, \{u,w\}, \{v,w\} \in \ E \} \|}{\| \{ (u,v,w) \in V^3 :\ \{v,u\}, \{v,w\} \in E \} \|}$$

The toolkit provides the function clustering_coefficient which computes both local and global clustering coefficients for a given undirected graph.

For more details on the mathematics and applications of clustering coefficients, see http://en.wikipedia.org/wiki/Clustering_coefficient.

18.1.6 *Graph* copy

---

copy (*self*, *name=None*)

Make a copy of the current graph.

Parameters **name** : unicode (default=None)

The name for the copy of the graph. Default is None.

Returns : dict

A copy of the original graph.

18.1.7 *Graph* define_edge_type

---

define_edge_type (*self*, *label*, *src_vertex_label*, *dest_vertex_label*, *directed=False*)

Define an edge type.

Parameters **label** : unicode

Label of the edge type.

src_vertex_label : unicode

The src "type" of vertices this edge connects.

dest_vertex_label : unicode

The destination "type" of vertices this edge connects.

directed : bool (default=False)

True if edges are directed, false if they are undirected.

Returns : _Unit

18.1.8 *Graph* define_vertex_type

---

define_vertex_type (*self*, *label*)

Define a vertex type by label.

Parameters **label** : unicode

Label of the vertex type.

Returns : _Unit

18.1.9 *Graph* edge_count

---

edge_count

Get the total number of edges in the graph.

Parameters

Returns : int

Total number of edges in the graph

int32 The number of edges in the graph.

Examples

```
>>> my_graph.edge_count
```

The result given is:

```
1194
```

18.1.10 *Graph* edges

---

edges

Edge frame collection

Parameters

Examples

Inspect edges with the supplied label:

```
>>> my_graph.edges['label'].inspect()
```

18.1.11 *Graph* export_to_titan

---

export_to_titan (*self*, *new_graph_name=None*)

Convert current graph to TitanGraph.

Parameters **new_graph_name** : unicode (default=None)

The name of the new graph. Default is None.

Returns : dict

A new TitanGraph.

Convert this Graph into a TitanGraph object. This will be a new graph backed by Titan with all of the data found in this graph.

18.1.12 *Graph* graphx_connected_components

---

graphx_connected_components (*self*, *output_property*)

Implements the connected components computation on a graph by invoking graphx api.

Parameters **output_property** : unicode

The name of the column containing the connected component value.

Returns : dict

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a connected component column. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

Pulls graph from underlying store, sends it off to the ConnectedComponentGraphXDefault, and then writes the output graph back to the underlying store.

Connected Components (CC)

Connected components are disjoint subgraphs in which all vertices are connected to all other vertices in the same component via paths, but not connected via paths to vertices in any other component. The connected components algorithm uses message passing along a specified edge type to find all of the connected components of a graph and label each edge with the identity of the component to which it belongs. The algorithm is specific to an edge type, hence in graphs with several different types of edges, there may be multiple, overlapping sets of connected components.

The algorithm works by assigning each vertex a unique numerical index and passing messages between neighbors. Vertices pass their indices back and forth with their neighbors and update their own index as the minimum of their current index and all other indices received. This algorithm continues until there is no change in any of the vertex indices. At the end of the alorithm, the unique levels of the indices denote the distinct connected components. The complexity of the algorithm is proportional to the diameter of the graph.

18.1.13 *Graph* graphx_pagerank

---

graphx_pagerank(*self*, *output_property*, *input_edge_labels=None*, *max_iterations=None*, *reset_probability=None*, *convergence_tolerance=None*)

Determine which vertices are the most important.

Parameters **output_property** : unicode

Name of the property to which pagerank value will be stored on vertex and edge.

input_edge_labels : list (default=None)

List of edge labels to consider for pagerank computation. Default is all edges are considered.

max_iterations : int32 (default=None)

The maximum number of iterations that will be invoked. The valid range is all positive int. Invalid value will terminate with vertex page rank set to reset_probability. Default is 20.

reset_probability : float64 (default=None)

The probability that the random walk of a page is reset. Default is 0.15.

convergence_tolerance : float64 (default=None)

The amount of change in cost function that will be tolerated at convergence. If this parameter is specified, max_iterations is not considered as a stopping condition. If the change is less than this threshold, the algorithm exits earlier. The valid value range is all float and zero. Default is 0.001.

Returns : dict

dict((vertex_dictionary, (label, Frame)), (edge_dictionary,(label,Frame))).

Dictionary containing dictionaries of labeled vertices and labeled edges.

For the *vertex_dictionary* the vertex type is the key and the corresponding vertex's frame with a new column storing the page rank value for the vertex. Call vertex_dictionary['label'] to get the handle to frame whose vertex type is label.

For the *edge_dictionary* the edge type is the key and the corresponding edge's frame with a new column storing the page rank value for the edge. Call edge_dictionary['label'] to get the handle to frame whose edge type is label.

Pulls graph from underlying store, sends it off to the PageRankRunner, and then writes the output graph back to the underlying store.

This method (currently) only supports Titan for graph storage.

** Experimental Feature **

Basics and Background

PageRank is a method for determining which vertices in a directed graph are the most central or important. *PageRank* gives each vertex a score which can be interpreted as the probability that a person randomly walking along the edges of the graph will visit that vertex.

The calculation of *PageRank* is based on the supposition that if a vertex has many vertices pointing to it, then it is "important", and that a vertex grows in importance as more important vertices point to it. The calculation is based only on the network structure of the graph and makes no use of any side data, properties, user-provided scores or similar non-topological information.

PageRank was most famously used as the core of the Google search engine for many years, but as a general measure of *centrality* in a graph, it has other uses to other problems, such as *recommendation systems* and analyzing predator-prey food webs to predict extinctions.

Background references

- Basic description and principles: Wikipedia: PageRank[1]
- Applications to food web analysis: Stanford: Applications of PageRank[2]
- Applications to recommendation systems: PLoS: Computational Biology[3]

Mathematical Details of PageRank Implementation

The Trusted Analytics implementation of *PageRank* satisfies the following equation at each vertex v of the graph:

$$PR(v) = \frac{\rho}{n} + \rho \left(\sum_{u \in InSet(v)} \frac{PR(u)}{L(u)} \right)$$

Where:

v — a vertex
$L(v)$ — outbound degree of the vertex v
$PR(v)$ — *PageRank* score of the vertex v
$InSet(v)$ — set of vertices pointing to the vertex v
n — total number of vertices in the graph
ρ — user specified damping factor (also known as reset probability)

Termination is guaranteed by two mechanisms.

- The user can specify a convergence threshold so that the algorithm will terminate when, at every vertex, the difference between successive approximations to the *PageRank* score falls below the convergence threshold.
- The user can specify a maximum number of iterations after which the algorithm will terminate.

[1] http://en.wikipedia.org/wiki/PageRank
[2] http://web.stanford.edu/class/msande233/handouts/lecture8.pdf
[3] http://www.ploscompbiol.org/article/fetchObject.action?uri=info%3Adoi%2F10.1371%2Fjournal.pcbi.1000494&representation=PDF

18.1.14 *Graph* graphx_triangle_count

graphx_triangle_count (*self*, *output_property*, *input_edge_labels=None*)
Number of triangles among vertices of current graph.

Parameters **output_property** : unicode

The name of output property to be added to vertex/edge upon completion.

input_edge_labels : list (default=None)

The name of edge labels to be considered for triangle count. Default is all edges are considered.

Returns : dict

dict(label, Frame).

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a triangle_count column. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

** Experimental Feature **

Counts the number of triangles among vertices in an undirected graph. If an edge is marked bidirectional, the implementation opts for canonical orientation of edges hence counting it only once (similar to an undirected graph).

18.1.15 *GraphMl* belief_propagation

ml.**belief_propagation** (*self*, *prior_property*, *posterior_property*, *edge_weight_property=None*, *convergence_threshold=None*, *max_iterations=None*)
Classification on sparse data using Belief Propagation.

Parameters **prior_property** : unicode

Name of the vertex property which contains the prior belief for the vertex.

posterior_property : unicode

Name of the vertex property which will contain the posterior belief for each vertex.

edge_weight_property : unicode (default=None)

Name of the edge property that contains the edge weight for each edge.

convergence_threshold : float64 (default=None)

Belief propagation will terminate when the average change in posterior beliefs between supersteps is less than or equal to this threshold.

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid range is all positive int.

Returns : dict

Progress report for belief propagation in the format of a multiple-line string.

Belief propagation by the sum-product algorithm. This algorithm analyzes a graphical model with prior beliefs using sum product message passing. The priors are read from a property in the graph, the posteriors are written to another property in the graph. This is the GraphX-based implementation of belief propagation.

See *Loopy Belief Propagation* for a more in-depth discussion of BP and LBP.

18.1.16 *GraphMl* kclique_percolation

---

ml.**kclique_percolation**(*self*, *clique_size*, *community_property_label*)

[ALPHA] Find groups of vertices with similar attributes.

Parameters **clique_size** : int32

The sizes of the cliques used to form communities. Larger values of clique size result in fewer, smaller communities that are more connected. Must be at least 2.

community_property_label : unicode

Name of the community property of vertex that will be updated/created in the graph. This property will contain for each vertex the set of communities that contain that vertex.

Returns : dict

Dictionary of vertex label and frame, Execution time.

Community Detection Using the K-Clique Percolation Algorithm

Overview

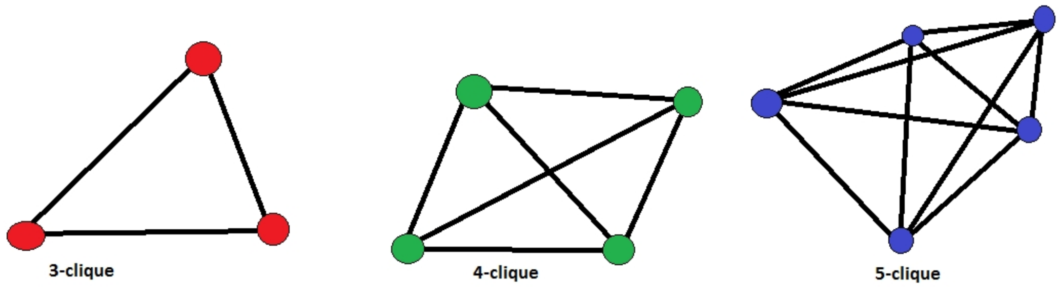
Modeling data as a graph captures relations, for example, friendship ties between social network users or chemical interactions between proteins. Analyzing the structure of the graph reveals collections (often termed 'communities') of vertices that are more likely to interact amongst each other. Examples could include a community of friends in a social network or a collection of highly interacting proteins in a cellular process.

Trusted Analytics provides community detection using the k-Clique percolation method first proposed by Palla et. al. *[R1]* that has been widely used in many contexts.

K-Clique Percolation

K-clique percolation is a method for detecting community structure in graphs. Here we provide mathematical background on how communities are defined in the context of the k-clique percolation algorithm.

A clique is a group of vertices in which every vertex is connected (via undirected edge) with every other vertex in the clique. This graphically looks like a triangle or a structure composed of triangles:

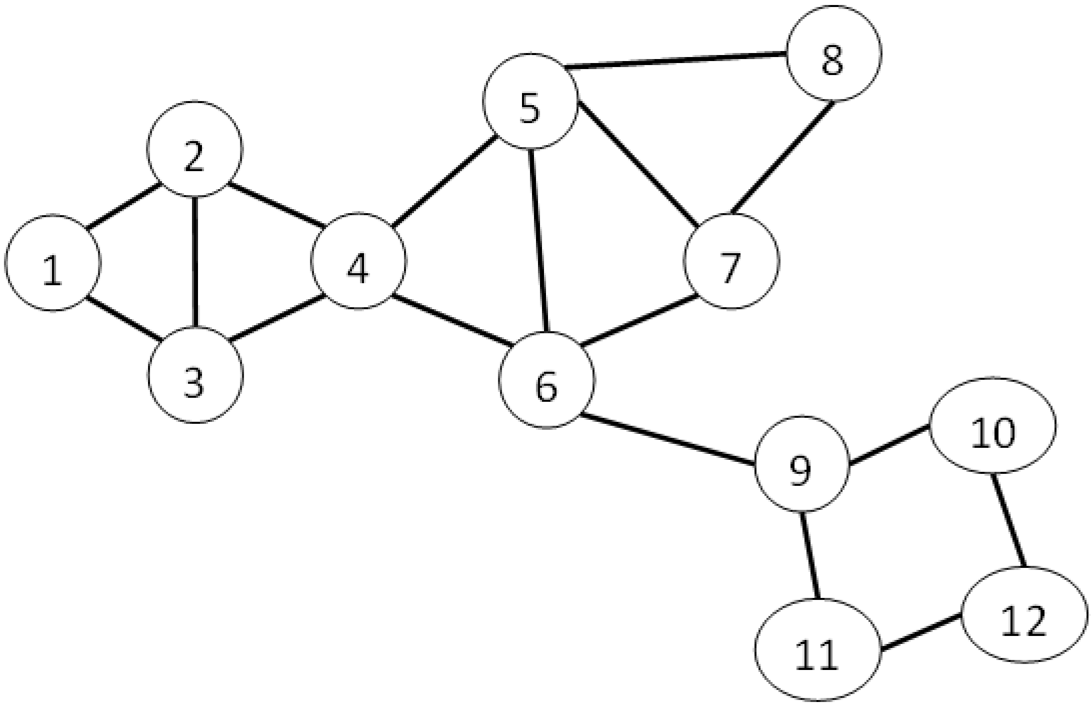


A clique is certainly a community in the sense that its vertices are all connected, but, it is too restrictive for most purposes, since it is natural some members of a community may not interact.

Mathematically, a k-clique has k vertices, each with $k-1$ common edges, each of which connects to another vertex in the k-clique. The k-clique percolation method forms communities by taking unions of k-cliques that have $k-1$ vertices in common.

K-Clique Example

In the graph below, the cliques are the sections defined by their triangular appearance and the 3-clique communities are $\{1, 2, 3, 4\}$ and $\{4, 5, 6, 7, 8\}$. The vertices 9, 10, 11, 12 are not in 3-cliques, therefore they do not belong to any community. Vertex 4 belongs to two distinct (but overlapping) communities.



Distributed Implementation of K-Clique Community Detection

The implementation of k-clique community detection in Trusted Analytics is a fully distributed implementation that follows the map-reduce algorithm proposed in Varamesh et. al. *[R2]* .

It has the following steps:

1. All k-cliques are *enumerated*.
2. k-cliques are used to build a "clique graph" by declaring each k-clique to be a vertex in a new graph and placing edges between k-cliques that share k-1 vertices in the base graph.
3. A *connected component* analysis is performed on the clique graph. Connected components of the clique graph correspond to k-clique communities in the base graph.
4. The connected components information for the clique graph is projected back down to the base graph, providing each vertex with the set of k-clique communities to which it belongs.

Notes

Spawns a number of Spark jobs that cannot be calculated before execution (it is bounded by the diameter of the clique graph derived from the input graph). For this reason, the initial loading, clique enumeration and clique-graph construction steps are tracked with a single progress bar (this is most of the time), and then successive iterations of analysis of the clique graph are tracked with many short-lived progress bars, and then finally the result is written out.

18.1.17 *Graph* name

---

name

Set or get the name of the graph object.

Parameters

Change or retrieve graph object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_graph.name

"csv_data"

>>> my_graph.name = "cleaned_data"
>>> my_graph.name

"cleaned_data"
```

18.1.18 *Graph* status

---

status

Current graph life cycle status.

Parameters

Returns : str

Status of the graph

One of three statuses: Active, Deleted, Deleted_Final Active: available for use Deleted: has been scheduled for deletion Deleted_Final: backend files have been removed from disk.

18.1.19 *Graph* vertex_count

---

vertex_count

Get the total number of vertices in the graph.

Parameters

Returns int32

The number of vertices in the graph.

Examples

```
>>> my_graph.vertex_count
```

The result given is:

```
1194
```

18.1.20 *Graph* vertices

vertices

Vertex frame collection

Parameters

Examples

Inspect vertices with the supplied label:

```
>>> my_graph.vertices['label'].inspect()
```

class Graph

Creates a seamless property graph.

A seamless graph is a collection of vertex and edge lists stored as frames. This allows frame-like operations against graph data. Many frame methods are available to work with vertices and edges. Vertex and edge properties are stored as columns.

A seamless graph is better suited for bulk *OLAP*-type operations whereas a Titan graph is better suited to *OLTP*.

Attributes

edge_count	Get the total number of edges in the graph.
edges	Edge frame collection
name	Set or get the name of the graph object.
status	Current graph life cycle status.
vertex_count	Get the total number of vertices in the graph.
vertices	Vertex frame collection

Methods

__init__(self[, name, _info])	<Missing Doc>
__init__(self, entity)	<Missing Doc>
annotate_degrees(self, output_property_name[, degree_option, ...])	Make new graph with degrees.
annotate_weighted_degrees(self, output_property_name[, ...])	Calculates the weighted degree of each vertex with respect to an (optional) set of labels.
clustering_coefficient(self[, output_property_name, ...])	Coefficient of graph with respect to labels.
copy(self[, name])	Make a copy of the current graph.
define_edge_type(self, label, src_vertex_label, dest_vertex_label)	Define an edge type.
define_vertex_type(self, label)	Define a vertex type by label.
export_to_titan(self[, new_graph_name])	Convert current graph to TitanGraph.
graphx_connected_components(self, output_property)	Implements the connected components computation on a graph by invoking graphx api.
graphx_pagerank(self, output_property[, input_edge_labels, ...])	Determine which vertices are the most important.
graphx_triangle_count(self, output_property[, input_edge_labels])	Number of triangles among vertices of current graph.
ml.belief_propagation(self, prior_property, posterior_property)	Classification on sparse data using Belief Propagation.
ml.kclique_percolation(self, clique_size, ...)	[ALPHA] Find groups of vertices with similar attributes.

__init__ (*self*, *name=None*)
<Missing Doc>

Parameters **name** : str (default=None)

Name for the new graph. Default is None.

18.2 *Graphs* TitanGraph

18.2.1 *TitanGraph* __init__

__init__ (*self*, *name=None*)
Initialize the graph.

Parameters **name** : (default=None)

18.2.2 *TitanGraph* fget

__private_ml
Access to object's ml functionality (See `TitanGraphMl`)

Parameters

Returns : TitanGraphMl

TitanGraphMl object

18.2.3 *TitanGraph* fget

`__private_query`
Access to object's query functionality (See `TitanGraphQuery`)

Parameters

Returns : TitanGraphQuery

TitanGraphQuery object

18.2.4 *TitanGraph* annotate_degrees

`annotate_degrees` (*self*, *output_property_name*, *degree_option=None*, *input_edge_labels=None*)
Make new graph with degrees.

Parameters **output_property_name** : unicode

The name of the new property. The degree is stored in this property.

degree_option : unicode (default=None)

Indicator for the definition of degree to be used for the calculation. Permitted values:

- "out" (default value) : Degree is calculated as the out-degree.
- "in" : Degree is calculated as the in-degree.
- "undirected" : Degree is calculated as the undirected degree. (Assumes that the edges are all undirected.)

Any prefix of the strings "out", "in", "undirected" will select the corresponding option.

input_edge_labels : list (default=None)

If this list is provided, only edges whose labels are included in the given set will be considered in the degree calculation. In the default situation (when no list is provided), all edges will be used in the degree calculation, regardless of label.

Returns : dict

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a column storing the annotated degree for the vertex in a user specified property. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

Creates a new graph which is the same as the input graph, with the addition that every vertex of the graph has its *degree* stored in a user-specified property.

Degree Calculation

A fundamental quantity in graph analyses is the degree of a vertex: The degree of a vertex is the number of edges adjacent to it.

For a directed edge relation, a vertex has both an out-degree (the number of edges leaving the vertex) and an in-degree (the number of edges entering the vertex).

The toolkit provides this routine for calculating the degrees of vertices. This calculation could be performed with a Gremlin query on smaller datasets because Gremlin queries cannot be executed on a distributed scale. The Trusted Analytics routine `annotate_degrees` can be executed at distributed scale.

In the presence of edge weights, vertices can have weighted degrees: The weighted degree of a vertex is the sum of weights of edges adjacent to it. Analogously, the weighted in-degree of a vertex is the sum of the weights of the edges entering it, and the weighted out-degree is the sum of the weights of the edges leaving the vertex.

The toolkit provides *annotate_weighted_degrees* for the distributed calculation of weighted vertex degrees.

18.2.5 *TitanGraph* annotate_weighted_degrees

---

annotate_weighted_degrees(*self*, *output_property_name*, *degree_option=None*, *input_edge_labels=None*, *edge_weight_property=None*, *edge_weight_default=None*)

Calculates the weighted degree of each vertex with respect to an (optional) set of labels.

Parameters **output_property_name** : unicode

property name of where to store output

degree_option : unicode (default=None)

choose from 'out', 'in', 'undirected'

input_edge_labels : list (default=None)

labels of edge types that should be included

edge_weight_property : unicode (default=None)

property name of edge weight, if not provided all edges are weighted equally

edge_weight_default : float64 (default=None)

default edge weight

Returns : dict

Pulls graph from underlying store, calculates weighted degrees and writes them into the property specified, and then writes the output graph to the underlying store.

Degree Calculation

A fundamental quantity in graph analyses is the degree of a vertex: The degree of a vertex is the number of edges adjacent to it.

For a directed edge relation, a vertex has both an out-degree (the number of edges leaving the vertex) and an in-degree (the number of edges entering the vertex).

The toolkit provides a routine *annotate_degrees* for calculating the degrees of vertices. This calculation could be performed with a Gremlin query on smaller datasets because Gremlin queries cannot be executed on a distributed scale. The Trusted Analytics routine `annotate_degrees` can be executed at distributed scale.

In the presence of edge weights, vertices can have weighted degrees: The weighted degree of a vertex is the sum of weights of edges adjacent to it. Analogously, the weighted in-degree of a vertex is the sum of the weights of the edges entering it, and the weighted out-degree is the sum of the weights of the edges leaving the vertex.

The toolkit provides this routine for the distributed calculation of weighted vertex degrees.

18.2.6 *TitanGraph* clustering_coefficient

clustering_coefficient (*self*, *output_property_name=None*, *input_edge_labels=None*)
Coefficient of graph with respect to labels.

Parameters **output_property_name** : unicode (default=None)

The name of the new property to which each vertex's local clustering coefficient will be written. If this option is not specified, no output frame will be produced and only the global clustering coefficient will be returned.

input_edge_labels : list (default=None)

If this list is provided, only edges whose labels are included in the given set will be considered in the clustering coefficient calculation. In the default situation (when no list is provided), all edges will be used in the calculation, regardless of label. It is required that all edges that enter into the clustering coefficient analysis be undirected.

Returns : dict

Dictionary of the global clustering coefficient of the graph or, if local clustering coefficients are requested, a reference to the frame with local clustering coefficients stored at properties at each vertex.

Calculates the clustering coefficient of the graph with repect to an (optional) set of labels.

Pulls graph from underlying store, calculates degrees and writes them into the property specified, and then writes the output graph to the underlying store.

> **Warning:** THIS FUNCTION IS FOR UNDIRECTED GRAPHS. If it is called on a directed graph, its output is NOT guaranteed to calculate the local directed clustering coefficients.

Clustering Coefficients

The clustering coefficient of a graph provides a measure of how tightly clustered an undirected graph is. Informally, if the edge relation denotes "friendship", the clustering coefficient of the graph is the probability that two people are friends given that they share a common friend.

More formally:

$$cc(G) = \frac{\| \{ (u,v,w) \in V^3 :\ \{u,v\}, \{u,w\}, \{v,w\} \in \ E \} \|}{\| \{ (u,v,w) \in V^3 :\ \{u,v\}, \{u,w\} \in E \} \|}$$

Analogously, the clustering coefficient of a vertex provides a measure of how tightly clustered that vertex's neighborhood is. Informally, if the edge relation denotes "friendship", the clustering coefficient at a vertex v is the probability that two acquaintances of v are themselves friends.

More formally:

$$cc(v) = \frac{\| \{ (u,v,w) \in V^3 :\ \{u,v\}, \{u,w\}, \{v,w\} \in \ E \} \|}{\| \{ (u,v,w) \in V^3 :\ \{v,u\}, \{v,w\} \in E \} \|}$$

The toolkit provides the function clustering_coefficient which computes both local and global clustering coefficients for a given undirected graph.

For more details on the mathematics and applications of clustering coefficients, see http://en.wikipedia.org/wiki/Clustering_coefficient.

18.2.7 *TitanGraph* copy

---

copy (*self*, *name=None*)
Make a copy of the current graph.

Parameters **name** : unicode (default=None)

The name for the copy of the graph. Default is None.

Returns : dict

A copy of the original graph.

18.2.8 *TitanGraph* export_to_graph

---

export_to_graph (*self*)
Export from ta.TitanGraph to ta.Graph.

Parameters

Returns : dict

18.2.9 *TitanGraph* graph_clustering

---

graph_clustering (*self*, *edge_distance*)
Performs graph clustering over an initial titan graph.

Parameters **edge_distance** : unicode

Column name for the edge distance.

Returns : _Unit

Performs graph clustering over an initial titan graph using a distributed edge collapse algorithm.

18.2.10 *TitanGraph* graphx_connected_components

---

graphx_connected_components (*self*, *output_property*)
Implements the connected components computation on a graph by invoking graphx api.

Parameters **output_property** : unicode

The name of the column containing the connected component value.

Returns : dict

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a connected component column. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

Pulls graph from underlying store, sends it off to the ConnectedComponentGraphXDefault, and then writes the output graph back to the underlying store.

Connected Components (CC)

Connected components are disjoint subgraphs in which all vertices are connected to all other vertices in the same component via paths, but not connected via paths to vertices in any other component. The connected components algorithm uses message passing along a specified edge type to find all of the connected components of a graph and label each edge with the identity of the component to which it belongs. The algorithm is specific to an edge type, hence in graphs with several different types of edges, there may be multiple, overlapping sets of connected components.

The algorithm works by assigning each vertex a unique numerical index and passing messages between neighbors. Vertices pass their indices back and forth with their neighbors and update their own index as the minimum of their current index and all other indices received. This algorithm continues until there is no change in any of the vertex indices. At the end of the alorithm, the unique levels of the indices denote the distinct connected components. The complexity of the algorithm is proportional to the diameter of the graph.

18.2.11 *TitanGraph* graphx_pagerank

`graphx_pagerank`(*self*, *output_property*, *input_edge_labels=None*, *max_iterations=None*, *reset_probability=None*, *convergence_tolerance=None*)

Determine which vertices are the most important.

Parameters **output_property** : unicode

Name of the property to which pagerank value will be stored on vertex and edge.

input_edge_labels : list (default=None)

List of edge labels to consider for pagerank computation. Default is all edges are considered.

max_iterations : int32 (default=None)

The maximum number of iterations that will be invoked. The valid range is all positive int. Invalid value will terminate with vertex page rank set to reset_probability. Default is 20.

reset_probability : float64 (default=None)

The probability that the random walk of a page is reset. Default is 0.15.

convergence_tolerance : float64 (default=None)

The amount of change in cost function that will be tolerated at convergence. If this parameter is specified, max_iterations is not considered as a stopping condition. If the change is less than this threshold, the algorithm exits earlier. The valid value range is all float and zero. Default is 0.001.

Returns : dict

dict((vertex_dictionary, (label, Frame)), (edge_dictionary,(label,Frame))).

Dictionary containing dictionaries of labeled vertices and labeled edges.

For the *vertex_dictionary* the vertex type is the key and the corresponding vertex's frame with a new column storing the page rank value for the vertex. Call vertex_dictionary['label'] to get the handle to frame whose vertex type is label.

For the *edge_dictionary* the edge type is the key and the corresponding edge's frame with a new column storing the page rank value for the edge. Call edge_dictionary['label'] to get the handle to frame whose edge type is label.

Pulls graph from underlying store, sends it off to the PageRankRunner, and then writes the output graph back to the underlying store.

This method (currently) only supports Titan for graph storage.

** Experimental Feature **

Basics and Background

PageRank is a method for determining which vertices in a directed graph are the most central or important. *PageRank* gives each vertex a score which can be interpreted as the probability that a person randomly walking along the edges of the graph will visit that vertex.

The calculation of *PageRank* is based on the supposition that if a vertex has many vertices pointing to it, then it is "important", and that a vertex grows in importance as more important vertices point to it. The calculation is based only on the network structure of the graph and makes no use of any side data, properties, user-provided scores or similar non-topological information.

PageRank was most famously used as the core of the Google search engine for many years, but as a general measure of *centrality* in a graph, it has other uses to other problems, such as *recommendation systems* and analyzing predator-prey food webs to predict extinctions.

Background references

- Basic description and principles: Wikipedia: PageRank[4]
- Applications to food web analysis: Stanford: Applications of PageRank[5]
- Applications to recommendation systems: PLoS: Computational Biology[6]

Mathematical Details of PageRank Implementation

The Trusted Analytics implementation of *PageRank* satisfies the following equation at each vertex v of the graph:

$$PR(v) = \frac{\rho}{n} + \rho\left(\sum_{u \in InSet(v)} \frac{PR(u)}{L(u)}\right)$$

Where:

v — a vertex
$L(v)$ — outbound degree of the vertex v
$PR(v)$ — *PageRank* score of the vertex v
$InSet(v)$ — set of vertices pointing to the vertex v
n — total number of vertices in the graph

[4] http://en.wikipedia.org/wiki/PageRank
[5] http://web.stanford.edu/class/msande233/handouts/lecture8.pdf
[6] http://www.ploscompbiol.org/article/fetchObject.action?uri=info%3Adoi%2F10.1371%2Fjournal.pcbi.1000494&representation=PDF

ρ — user specified damping factor (also known as reset probability)

Termination is guaranteed by two mechanisms.

- The user can specify a convergence threshold so that the algorithm will terminate when, at every vertex, the difference between successive approximations to the *PageRank* score falls below the convergence threshold.
- The user can specify a maximum number of iterations after which the algorithm will terminate.

18.2.12 *TitanGraph* graphx_triangle_count

---

graphx_triangle_count (*self*, *output_property*, *input_edge_labels=None*)

Number of triangles among vertices of current graph.

Parameters **output_property** : unicode

The name of output property to be added to vertex/edge upon completion.

input_edge_labels : list (default=None)

The name of edge labels to be considered for triangle count. Default is all edges are considered.

Returns : dict

dict(label, Frame).

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a triangle_count column. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

** Experimental Feature **

Counts the number of triangles among vertices in an undirected graph. If an edge is marked bidirectional, the implementation opts for canonical orientation of edges hence counting it only once (similar to an undirected graph).

18.2.13 *TitanGraphMl* belief_propagation

---

ml.**belief_propagation** (*self*, *prior_property*, *posterior_property*, *edge_weight_property=None*, *convergence_threshold=None*, *max_iterations=None*)

Classification on sparse data using Belief Propagation.

Parameters **prior_property** : unicode

Name of the vertex property which contains the prior belief for the vertex.

posterior_property : unicode

Name of the vertex property which will contain the posterior belief for each vertex.

edge_weight_property : unicode (default=None)

Name of the edge property that contains the edge weight for each edge.

convergence_threshold : float64 (default=None)

Belief propagation will terminate when the average change in posterior beliefs between supersteps is less than or equal to this threshold.

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid range is all positive int.

Returns : dict

Progress report for belief propagation in the format of a multiple-line string.

Belief propagation by the sum-product algorithm. This algorithm analyzes a graphical model with prior beliefs using sum product message passing. The priors are read from a property in the graph, the posteriors are written to another property in the graph. This is the GraphX-based implementation of belief propagation.

See *Loopy Belief Propagation* for a more in-depth discussion of BP and LBP.

18.2.14 *TitanGraph* name

name

Set or get the name of the graph object.

Parameters

Change or retrieve graph object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_graph.name

"csv_data"

>>> my_graph.name = "cleaned_data"
>>> my_graph.name

"cleaned_data"
```

18.2.15 *TitanGraphQuery* gremlin

query.**gremlin**(*self*, *gremlin*)

Executes a Gremlin query.

Parameters gremlin : unicode

The Gremlin script to execute.

Examples of Gremlin queries:

g.V[0..9] - Returns the first 10 vertices in graph g.V.userId - Returns the userId property from vertices g.V('name','hercules').out('father').out('father').name - Returns the name of Hercules' grandfather

Returns : dict

List of query results serialized to JSON and runtime of Gremlin query in seconds. The list of results is in GraphSON format(for vertices or edges) or JSON (for other results like counts). GraphSON is a JSON-based format for property graphs which uses reserved keys that begin with underscores to encode vertex and edge metadata.

Examples of valid GraphSON:

```
{ \"name\": \"lop\", \"lang\": \"java\",\"_id\": \"3\", \"_type\": \"vertex\" }
{ \"weight\": 1, \"_id\": \"8\", \"_type\": \"edge\", \"_outV\": \"1\", \"_inV\": \"4
```

See
https://github.com/tinkerpop/blueprints/wiki/GraphSON-Reader-and-Writer-Library

Executes a Gremlin query on an existing graph.

Notes

The query does not support pagination so the results of query should be limited using the Gremlin range filter [i..j], for example, g.V[0..9] to return the first 10 vertices.

18.2.16 *TitanGraph* status

`status`
Current graph life cycle status.

Parameters

Returns : str

Status of the graph

One of three statuses: Active, Deleted, Deleted_Final Active: available for use Deleted: has been scheduled for deletion Deleted_Final: backend files have been removed from disk.

18.2.17 *TitanGraph* vertex_sample

`vertex_sample` (*self*, *size*, *sample_type*, *seed=None*)
Make subgraph from vertex sampling.

Parameters **size** : int32

The number of vertices to sample from the graph.

sample_type : unicode

The type of vertex sample among: [’uniform’, ‘degree’, ‘degreedist’].

seed : int64 (default=None)

Random seed value.

Returns : dict

A new Graph object representing the vertex induced subgraph.

Create a vertex induced subgraph obtained by vertex sampling. Three types of vertex sampling are provided: 'uniform', 'degree', and 'degreedist'. A 'uniform' vertex sample is obtained by sampling vertices uniformly at random. For 'degree' vertex sampling, each vertex is weighted by its out-degree. For 'degreedist' vertex sampling, each vertex is weighted by the total number of vertices that have the same out-degree as it. That is, the weight applied to each vertex for 'degreedist' vertex sampling is given by the out-degree histogram bin size.

class TitanGraph

Proxy to a graph in Titan, supports Gremlin query

Attributes

name	Set or get the name of the graph object.
status	Current graph life cycle status.

Methods

__*init*__(self[, name, _info])	Initialize the graph.
__init__(self, entity)	<Missing Doc>
__init__(self, entity)	<Missing Doc>
annotate_degrees(self, output_property_name[, degree_option, ...])	Make new graph with degrees.
annotate_weighted_degrees(self, output_property_name[, ...])	Calculates the weighted degree of each vertex with respect to an (optional) set of labels.
clustering_coefficient(self[, output_property_name, ...])	Coefficient of graph with respect to labels.
copy(self[, name])	Make a copy of the current graph.
export_to_graph(self)	Export from ta.TitanGraph to ta.Graph.
graph_clustering(self, edge_distance)	Performs graph clustering over an initial titan graph.
graphx_connected_components(self, output_property)	Implements the connected components computation on a graph by invoking graphx api.
graphx_pagerank(self, output_property[, input_edge_labels, ...])	Determine which vertices are the most important.
graphx_triangle_count(self, output_property[, input_edge_labels])	Number of triangles among vertices of current graph.
ml.belief_propagation(self, prior_property, posterior_property)	Classification on sparse data using Belief Propagation.
query.gremlin(self, gremlin)	Executes a Gremlin query.
vertex_sample(self, size, sample_type[, seed])	Make subgraph from vertex sampling.

__init__(*self, name=None*)

Initialize the graph.

Parameters **name** : (default=None)

18.3 *trustedanalytics* get_graph

---

get_graph(*identifier*)

Get handle to a graph object.

Parameters **identifier** : str | int

Name of the graph to get

Returns : Graph

graph object

18.4 *trustedanalytics* drop_graphs

---

drop_graphs(*items*)

Deletes the graph on the server.

Parameters **items** : [str | graph object | list [str | graph objects]]

Either the name of the graph object to delete or the graph object itself

18.5 *trustedanalytics* get_graph_names

---

get_graph_names()

Retrieve names for all the graph objects on the server.

Returns : list

List of names

Global Methods

get_graph

drop_graphs

get_graph_names

CHAPTER

NINETEEN

MODELS

Classes

19.1 *Models* LibsvmModel

19.1.1 *LibsvmModel* new

__init__(*self*, *name=None*)

[ALPHA] model:libsvm/new

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.1.2 *LibsvmModel* name

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.1.3 *LibsvmModel* predict

---

predict (*self*, *frame*, *observation_columns=None*)

[ALPHA] New frame with new predicted label column.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. Default is the columns the LibsvmModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A new frame containing the original frame's columns and a column *predicted_label* containing the score calculated for each observation.

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

19.1.4 *LibsvmModel* publish

---

publish (*self*)

[BETA] Creates a tar file that will used as input to the scoring engine

Parameters

Returns : dict

Returns the HDFS path to the tar file

19.1.5 *LibsvmModel* score

---

score (*self*, *vector*)

[ALPHA] Calculate the prediction label for a single observation.

Parameters **vector** : None

Returns : dict

Predicted label.

19.1.6 *LibsvmModel* test

---

test (*self*, *frame*, *label_column*, *observation_columns=None*)

[ALPHA] Predict test frame labels and return metrics.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted.

label_column : unicode

Column containing the actual label for each observation.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted and tested. Default is to test over the columns the LibsvmModel was trained on.

Returns : dict

Object Object with binary classification metrics. The data returned is composed of multiple components:

<object>.accuracy [double] The degree of correctness of the test frame labels.

<object>.confusion_matrix [table] A specific table layout that allows visualization of the performance of the test.

<object>.f_measure [double] A measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score.

<object>.precision [double] The degree to which the correctness of the label is expressed.

<object>.recall [double] The fraction of relevant instances that are retrieved.

Predict the labels for a test frame and run classification metrics on predicted and target labels.

19.1.7 *LibsvmModel* train

`train` (*self*, *frame*, *label_column*, *observation_columns*, *svm_type=2*, *kernel_type=2*, *weight_label=None*, *weight=None*, *epsilon=0.001*, *degree=3*, *gamma=None*, *coef=0.0*, *nu=0.5*, *cache_size=100.0*, *shrinking=1*, *probability=0*, *nr_weight=1*, *c=1.0*, *p=0.1*)

[ALPHA] Train Lib Svm model based on another frame.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

svm_type : int32 (default=2)

Set type of SVM. Default is one-class SVM.

0 – C-SVC 1 – nu-SVC 2 – one-class SVM 3 – epsilon-SVR 4 – nu-SVR

kernel_type : int32 (default=2)

Specifies the kernel type to be used in the algorithm. Default is RBF.

0 – linear: u'*v 1 – polynomial: (gamma*u'*v + coef0)^degree 2 – radial basis function: exp(-gamma*|u-v|^2) 3 – sigmoid: tanh(gamma*u'*v + coef0)

weight_label : list (default=None)

Default is (Array[Int](0))

weight : list (default=None)

Default is (Array[Double](0.0))

epsilon : float64 (default=0.001)

Set tolerance of termination criterion

degree : int32 (default=3)

Degree of the polynomial kernel function ('poly'). Ignored by all other kernels.

gamma : float64 (default=None)

Kernel coefficient for 'rbf', 'poly' and 'sigmoid'. Default is 1/n_features.

coef : float64 (default=0.0)

Independent term in kernel function. It is only significant in 'poly' and 'sigmoid'.

nu : float64 (default=0.5)

Set the parameter nu of nu-SVC, one-class SVM, and nu-SVR.

cache_size : float64 (default=100.0)

Specify the size of the kernel cache (in MB).

shrinking : int32 (default=1)

Whether to use the shrinking heuristic. Default is 1 (true).

probability : int32 (default=0)

Whether to enable probability estimates. Default is 0 (false).

nr_weight : int32 (default=1)

NR Weight

c : float64 (default=1.0)

Penalty parameter c of the error term.

p : float64 (default=0.1)

Set the epsilon in loss function of epsilon-SVR.

Returns : _Unit

Creating a lib Svm Model using the observation column and label column of the train frame.

class `LibsvmModel`

model:libsvm/new

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	[ALPHA] model:libsvm/new
predict(self, frame[, observation_columns])	[ALPHA] New frame with new predicted label column.
publish(self)	[BETA] Creates a tar file that will used as input to the scoring engine
score(self, vector)	[ALPHA] Calculate the prediction label for a single observation.
test(self, frame, label_column[, observation_columns])	[ALPHA] Predict test frame labels and return metrics.
train(self, frame, label_column, observation_columns[, svm_type, ...])	[ALPHA] Train Lib Svm model based on another frame.

`__init__`(*self*, *name=None*)
[ALPHA] model:libsvm/new

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.2 *Models* RandomForestClassifierModel

19.2.1 *RandomForestClassifierModel* new

`__init__`(*self*, *name=None*)
Create a 'new' instance of random forest classifier model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.2.2 *RandomForestClassifierModel* name

`name`
Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.2.3 *RandomForestClassifierModel* predict

---

predict (*self*, *frame*, *observation_columns=None*)
[ALPHA] Predict the labels for the data points.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the RandomForestModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame A new frame consisting of the existing columns of the frame and a new column with predicted label for each observation.

19.2.4 *RandomForestClassifierModel* publish

---

publish (*self*)
[BETA] Creates a tar file that will be used as input to the scoring engine

Parameters

Returns : dict

Returns the HDFS path to the tar file

Creates a tar file with the trained Random Forest Classifier Model The tar file is used as input to the scoring engine to predict the class of an observation.

19.2.5 *RandomForestClassifierModel* test

---

test (*self*, *frame*, *label_column*, *observation_columns=None*)
[ALPHA] Predict test frame labels and return metrics.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

The frame whose labels are to be predicted

label_column : unicode

Column containing the true labels of the observations

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the RandomForest was trained on.

Returns : dict

object

An object with classification metrics. The data returned is composed of multiple components:

<object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

Predict the labels for a test frame and run classification metrics on predicted and target labels.

19.2.6 *RandomForestClassifierModel* train

---

train (*self*, *frame*, *label_column*, *observation_columns*, *num_classes=2*, *num_trees=1*, *impurity='gini'*, *max_depth=4*, *max_bins=100*, *seed=-1262125077*, *categorical_features_info=None*, *feature_subset_category=None*)

[ALPHA] Build Random Forests Classifier model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

num_classes : int32 (default=2)

Number of classes for classification

num_trees : int32 (default=1)

Number of tress in the random forest

impurity : unicode (default=gini)

Criterion used for information gain calculation. Supported values “gini” or “entropy”

max_depth : int32 (default=4)

Maximum depth of the tree

max_bins : int32 (default=100)

Maximum number of bins used for splitting features

seed : int32 (default=-1262125077)

Random seed for bootstrapping and choosing feature subsets

categorical_features_info : None (default=None)

feature_subset_category : unicode (default=None)

Number of features to consider for splits at each node. Supported values "auto","all","sqrt","log2","onethird"

Returns : dict

Creating a Random Forests Classifier Model using the observation columns and label column.

class **RandomForestClassifierModel**

Create a 'new' instance of random forest classifier model.

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	Create a 'new' instance of random forest classifier model.
predict(self, frame[, observation_columns])	[ALPHA] Predict the labels for the data points.
publish(self)	[BETA] Creates a tar file that will be used as input to the scoring engine
test(self, frame, label_column[, observation_columns])	[ALPHA] Predict test frame labels and return metrics.
train(self, frame, label_column, observation_columns[, num_classes, ...])	[ALPHA] Build Random Forests Classifier model.

__init__(*self*, *name=None*)

Create a 'new' instance of random forest classifier model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.3 *Models* PrincipalComponentsModel

19.3.1 *PrincipalComponentsModel* new

__init__(*self*, *name=None*)

Create a 'new' instance of principal component model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.3.2 *PrincipalComponentsModel* name

name
Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.3.3 *PrincipalComponentsModel* predict

predict (*self*, *frame*, *mean_centered=True*, *t_squared_index=False*, *observation_columns=None*, *c=None*, *name=None*)
[ALPHA] Predict using principal components model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame whose principal components are to be computed.

mean_centered : bool (default=True)

Option to mean center the columns. Default is true

t_squared_index : bool (default=False)

Indicator for whether the t-square index is to be computed. Default is false.

observation_columns : list (default=None)

List of observation column name(s) to be used for prediction. Default is the list of column name(s) used to train the model.

c : int32 (default=None)

The number of principal components to be predicted. Default is the count used to train the model.

name : unicode (default=None)

The name of the output frame generated by predict.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame with existing columns and 'c' additional columns containing the projections of V on the the frame and an additional column storing the t-square-index value if requested

Predicting on a dataframe's columns using a PrincipalComponents Model.

19.3.4 *PrincipalComponentsModel* publish

`publish` (*self*)

[BETA] Creates a tar file that will be used as input to the scoring engine

Parameters

Returns : dict

Returns the HDFS path to the tar file

Creates a tar file with the trained Principal Components Model. The tar file is used as input to the scoring engine to compute the principal components and t-squared index of the observation.

19.3.5 *PrincipalComponentsModel* train

`train` (*self*, *frame*, *observation_columns*, *mean_centered=True*, *k=None*)

Build principal components model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

observation_columns : list

List of column(s) containing the observations.

mean_centered : bool (default=True)

Option to mean center the columns

k : int32 (default=None)

Principal component count. Default is the number of observation columns

Returns : dict

Creating a PrincipalComponents Model using the observation columns.

class **`PrincipalComponentsModel`**

Create a 'new' instance of principal component model.

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	Create a 'new' instance of principal component model.
predict(self, frame[, mean_centered, t_squared_index, observation_columns, ...])	[ALPHA] Predict using principal components model.
publish(self)	[BETA] Creates a tar file that will be used as input to the scoring engine
train(self, frame, observation_columns[, mean_centered, k])	Build principal components model.

__init__(*self*, *name=None*)

Create a 'new' instance of principal component model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.4 *Models* CollaborativeFilteringModel

19.4.1 *CollaborativeFilteringModel* new

__init__(*self*, *name=None*)

Collaborative filtering recommend model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Collaborative Filtering

Collaborative filtering is a technique that is widely used in recommendation systems to suggest items (for example, products, movies, articles) to potential users based on historical records of items that users have purchased, rated, or viewed. The Trusted Analytics provides implementations of collaborative filtering with either Alternating Least Squares (ALS) or Conjugate Gradient Descent (CGD) optimization methods.

Both methods optimize the cost function found in Y. Koren, Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model[1] in ACM KDD 2008. For more information on optimizing using ALS see, Y. Zhou, D. Wilkinson, R. Schreiber and R. Pan, Large-Scale Parallel Collaborative Filtering for the Netflix Prize[2] , 2008.

[1] http://public.research.att.com/ volinsky/netflix/kdd08koren.pdf

[2] http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.173.2797

CGD provides a faster, more approximate optimization of the cost function and should be used when memory is a constraint.

A typical representation of the preference matrix P in Giraph is a bi-partite graph, where nodes at the left side represent a list of users and nodes at the right side represent a set of items (for example, movies), and edges encode the rating a user provided to an item. To support training, validation and test, a common practice in machine learning, each edge is also annotated by "TR", "VA" or "TE".

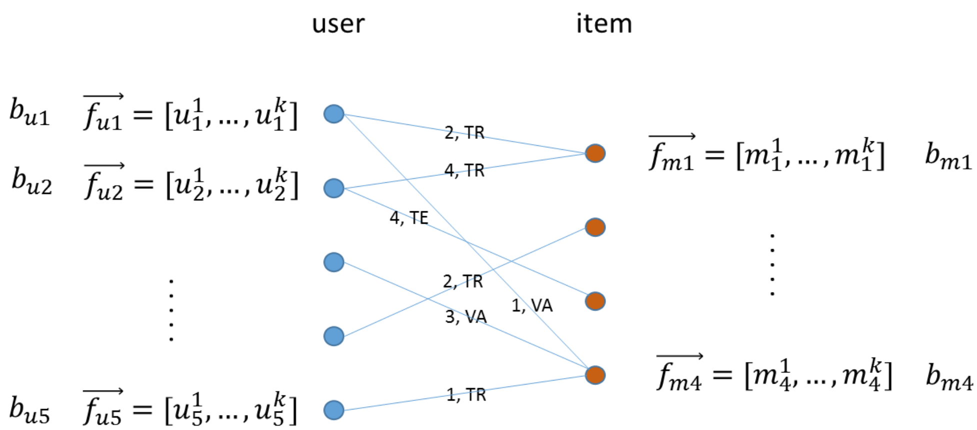


Fig. 19.1: A typical representation of the preference matrix P

Each node in the graph will be associated with a vector $\overrightarrow{f_x}$ of length k, where k is the feature dimension specified by the user, and a bias term b_x. The predictions for item m_j, from user u_i care given by dot product of the feature vector and the user vector, plus the item and user bias terms: /home/work/atk/engine-plugins/giraph-plugins/src/main/scala/org/trustedanalytics/atk/giraph/plugins/model/cf/CollaborativeFilteringNewPlugin.scala

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \ + b_{mj}$$

The parameters of the above equation are chosen to minimize the regularized mean squared error between known and predicted ratings:

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2 \right)$$

How this optimization is accomplished depends on whether the use uses the ALS or CGD functions respectively. It is recommended that the ALS method be used to solve collaborative filtering problems. The CGD method uses less memory than ALS, but it returns an approximate solution to the objective function and should only be used in cases when memory required for ALS is prohibitively high.

Using ALS Optimization to Solve the Collaborative Filtering Problem

ALS optimizes the vector $\overrightarrow{f}_*$ and the bias b_* alternatively between user profiles using least squares on users and items. On the first iteration, the first feature of each item is set to its average rating, while the others are set to small random numbers. The algorithm then treats the m 's as constant and optimizes $u_i^1, ..., u_i^k$ for each user, i. For an individual user, this is a simple ordinary least squares optimization over the items that user has ranked. Next, the algorithm takes the u 's as constant and optimizes the $m_j^1, ..., m_j^k$ for each item, j. This is again an ordinary least squares optimization predicting the user rating of person that has ranked item j.

At each step, the bias is computed for either items of users and the objective function, shown below, is evaluated. The bias term for an item or user, computed for use in the next iteration is given by:

$$b = \frac{\sum error}{(1 + \lambda) * n}$$

The optimization is said to converge if the change in the objective function is less than the convergence_threshold parameter or the algorithm hits the maximum number of *supersteps*.

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2 \right)$$

Note that the equations above omit user and item subscripts for generality. The l_2 regularization term, lambda, tries to avoid overfitting by penalizing the magnitudes of the parameters, and λ is a tradeoff parameter that balances the two terms and is usually determined by cross validation (CV).

After the parameters $\overrightarrow{f}_*$ and b_* are determined, given an item m_j the rating from user u_i can be predicted by the simple linear model:

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \ + b_{mj}$$

Matrix Factorization based on Conjugate Gradient Descent (CGD)

This is the Conjugate Gradient Descent (CGD) with Bias for collaborative filtering algorithm. Our implementation is based on the paper:

Y. Koren. Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model. In ACM KDD 2008. (Equation 5) http://public.research.att.com/~volinsky/netflix/kdd08koren.pdf

This algorithm for collaborative filtering is used in *recommendation systems* to suggest items (products, movies, articles, and so on) to potential users based on historical records of items that all users have purchased, rated, or viewed. The records are usually organized as a preference matrix P, which is a sparse matrix holding the preferences (such as, ratings) given by users to items. Similar to ALS, CGD falls in the category of matrix factorization/latent factor model that infers user profiles and item profiles in low-dimension space, such that the original matrix P can be approximated by a linear model.

This factorization method uses the conjugate gradient method for its optimization subroutine. For more on conjugate gradient descent in general, see: http://en.wikipedia.org/wiki/Conjugate_gradient_method.

The Mathematics of Matrix Factorization via CGD

Matrix factorization by conjugate gradient descent produces ratings by using the (limited) space of observed rankings to infer a user-factors vector p_u for each user u, and an item-factors vector q_i for each item i, and then producing a ranking by user u of item i by the dot-product $b_{ui} + p_u^T q_i$ where b_{ui} is a baseline ranking calculated as $b_{ui} = \mu + b_u + b_i$.

The optimum model is chosen to minimum the following sum, which penalizes square distance of the prediction from observed rankings and complexity of the model (through the regularization term):

$$\sum_{(u,i) \in \mathcal{K}} (r_{ui} - \mu - b_u - b_i - \ p_u^T q_i)^2 + \lambda_3 (||p_u||^2 + ||q_i||^2 + \ b_u^2 + b_i^2)$$

Where:

r_{ui} — Observed ranking of item i by user u
$\mathcal{K}$ — Set of pairs (u, i) for each observed ranking of item i by user u
μ — The average rating over all ratings of all items by all users.
b_u — How much user u's average rating differs from μ.
b_i — How much item i's average rating differs from μ
p_u — User-factors vector.
q_i — Item-factors vector.
λ_3 — A regularization parameter specified by the user.

This optimization problem is solved by the conjugate gradient descent method. Indeed, this difference in how the optimization problem is solved is the primary difference between matrix factorization by CGD and matrix factorization by ALS.

Comparison between CGD and ALS

Both CGD and ALS provide recommendation systems based on matrix factorization; the difference is that CGD employs the conjugate gradient descent instead of least squares for its optimization phase. In particular, they share the same bipartite graph representation and the same cost function.

- ALS finds a better solution faster - when it can run on the cluster it is given.
- CGD has slighter memory requirements and can run on datasets that can overwhelm the ALS-based solution.

When feasible, ALS is a preferred solver over CGD, while CGD is recommended only when the application requires so much memory that it might be beyond the capacity of the system. CGD has a smaller memory requirement, but has a slower rate of convergence and can provide a rougher estimate of the solution than the more computationally intensive ALS.

The reason for this is that ALS solves the optimization problem by a least squares that requires inverting a matrix. Therefore, it requires more memory and computational effort. But ALS, a 2nd-order optimization method, enjoys higher convergence rate and is potentially more accurate in parameter estimation.

On the otherhand, CGD is a 1.5th-order optimization method that approximates the Hessian of the cost function from the previous gradient information through N consecutive CGD updates. This is very important in cases where the solution has thousands or even millions of components.

Usage

The matrix factorization by CGD procedure takes a property graph, encoding a biparite user-item ranking network, selects a subset of the edges to be considered (via a selection of edge labels), takes initial ratings from specified edge property values, and then writes each user-factors vector to its user vertex in a specified vertex property name and each item-factors vector to its item vertex in the specified vertex property name.

19.4.2 *CollaborativeFilteringModel* name

---

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.4.3 *CollaborativeFilteringModel* recommend

recommend(*self*, *name*, *top_k*)
[BETA] Collaborative filtering (als/cgd) model

Parameters **name** : unicode

An entity name from the first column of the input frame

top_k : int32

positive integer representing the top recommendations for the name

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

see collaborative filtering train for more information

see collaborative filtering train for more information

19.4.4 *CollaborativeFilteringModel* train

train(*self*, *frame*, *user_col_name*, *item_col_name*, *rating_col_name*, *evaluation_function=None*, *num_factors=None*, *max_iterations=None*, *convergence_threshold=None*, *regularization=None*, *bias_on=None*, *min_value=None*, *max_value=None*, *learning_curve_interval=None*, *cgd_iterations=None*)
Collaborative filtering (als/cgd) model

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

user_col_name : unicode

Name of the user column from input data

item_col_name : unicode

Name of the item column from input data

rating_col_name : unicode

Name of the rating column from input data

evaluation_function : unicode (default=None)

als/cgd

num_factors : int32 (default=None)

Size of the desired factors (default is 3)

max_iterations : int32 (default=None)

Max number of iterations for Giraph

convergence_threshold : float64 (default=None)

float value between 0 .. 1

regularization : float32 (default=None)

float value between 0 .. 1

bias_on : bool (default=None)

bias on/off switch

min_value : float32 (default=None)

minimum edge weight value

max_value : float32 (default=None)

minimum edge weight value

learning_curve_interval : int32 (default=None)

iteration interval to output learning curve

cgd_iterations : int32 (default=None)

custom argument for cgd learning curve output interval (default: every iteration)

Returns : dict

Execution result summary for Giraph

class **`CollaborativeFilteringModel`**

Collaborative filtering recommend model.

Collaborative Filtering

Collaborative filtering is a technique that is widely used in recommendation systems to suggest items (for example, products, movies, articles) to potential users based on historical records of items that users have purchased, rated, or viewed. The Trusted Analytics provides implementations of collaborative filtering with either Alternating Least Squares (ALS) or Conjugate Gradient Descent (CGD) optimization methods.

Both methods optimize the cost function found in Y. Koren, Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model[3] in ACM KDD 2008. For more information on optimizing using ALS see, Y. Zhou, D. Wilkinson, R. Schreiber and R. Pan, Large-Scale Parallel Collaborative Filtering for the Netflix Prize[4] , 2008.

CGD provides a faster, more approximate optimization of the cost function and should be used when memory is a constraint.

A typical representation of the preference matrix P in Giraph is a bi-partite graph, where nodes at the left side represent a list of users and nodes at the right side represent a set of items (for example, movies), and edges encode the rating a user provided to an item. To support training, validation and test, a common practice in machine learning, each edge is also annotated by "TR", "VA" or "TE".

Each node in the graph will be associated with a vector $\overrightarrow{f_x}$ of length k, where k is the feature dimension specified by the user, and a bias term b_x. The predictions for item m_j, from user u_i care given by dot product of the feature vector and the user vector, plus the item and user bias terms: /home/work/atk/engine-plugins/giraph-plugins/src/main/scala/org/trustedanalytics/atk/giraph/plugins/model/cf/CollaborativeFilteringNewPlugin.scala

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \ + b_{mj}$$

The parameters of the above equation are chosen to minimize the regularized mean squared error between known and predicted ratings:

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2\right)$$

How this optimization is accomplished depends on whether the use uses the ALS or CGD functions respectively. It is recommended that the ALS method be used to solve collaborative filtering problems. The

[3] http://public.research.att.com/ volinsky/netflix/kdd08koren.pdf

[4] http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.173.2797

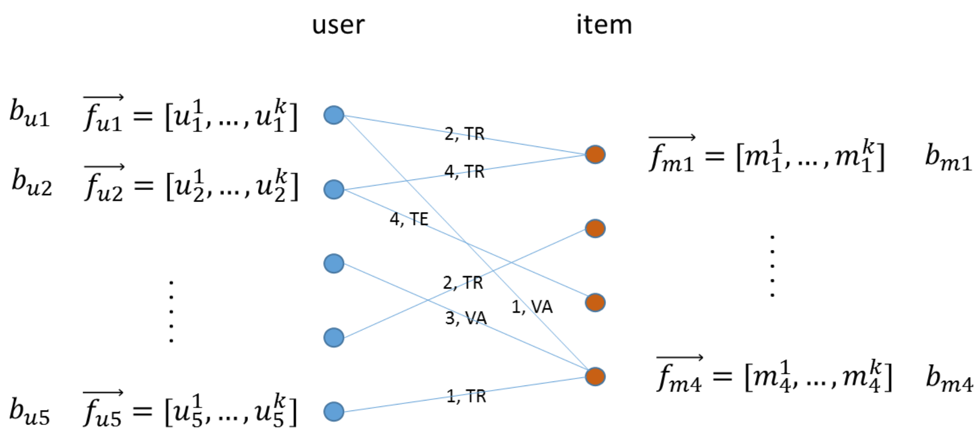


Fig. 19.2: A typical representation of the preference matrix P

CGD method uses less memory than ALS, but it returns an approximate solution to the objective function and should only be used in cases when memory required for ALS is prohibitively high.

Using ALS Optimization to Solve the Collaborative Filtering Problem

ALS optimizes the vector $\overrightarrow{f}_*$ and the bias b_* alternatively between user profiles using least squares on users and items. On the first iteration, the first feature of each item is set to its average rating, while the others are set to small random numbers. The algorithm then treats the m 's as constant and optimizes $u_i^1, ..., u_i^k$ for each user, i. For an individual user, this is a simple ordinary least squares optimization over the items that user has ranked. Next, the algorithm takes the u 's as constant and optimizes the $m_j^1, ..., m_j^k$ for each item, j. This is again an ordinary least squares optimization predicting the user rating of person that has ranked item j.

At each step, the bias is computed for either items of users and the objective function, shown below, is evaluated. The bias term for an item or user, computed for use in the next iteration is given by:

$$b = \frac{\sum error}{(1+\lambda) * n}$$

The optimization is said to converge if the change in the objective function is less than the convergence_threshold parameter or the algorithm hits the maximum number of *supersteps*.

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2\right)$$

Note that the equations above omit user and item subscripts for generality. The l_2 regularization term, lambda, tries to avoid overfitting by penalizing the magnitudes of the parameters, and λ is a tradeoff parameter that balances the two terms and is usually determined by cross validation (CV).

After the parameters $\overrightarrow{f}_*$ and b_* are determined, given an item m_j the rating from user u_i can be predicted by the simple linear model:

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This algorithm for collaborative filtering is used in *recommendation systems* to suggest items (products, movies, articles, and so on) to potential users based on historical records of items that all users have purchased, rated, or viewed. The records are usually organized as a preference matrix P, which is a sparse matrix holding the preferences (such as, ratings) given by users to items. Similar to ALS, CGD falls in the category of matrix factorization/latent factor model that infers user profiles and item profiles in low-dimension space, such that the original matrix P can be approximated by a linear model.

This factorization method uses the conjugate gradient method for its optimization subroutine. For more on conjugate gradient descent in general, see: http://en.wikipedia.org/wiki/Conjugate_gradient_method.

The Mathematics of Matrix Factorization via CGD

Matrix factorization by conjugate gradient descent produces ratings by using the (limited) space of observed rankings to infer a user-factors vector p_u for each user u, and an item-factors vector q_i for each item i, and then producing a ranking by user u of item i by the dot-product $b_{ui} + p_u^T q_i$ where b_{ui} is a baseline ranking calculated as $b_{ui} = \mu + b_u + b_i$.

The optimum model is chosen to minimum the following sum, which penalizes square distance of the prediction from observed rankings and complexity of the model (through the regularization term):

$$\sum_{(u,i)\in\mathcal{K}} (r_{ui} - \mu - b_u - b_i - \ p_u^T q_i)^2 + \lambda_3(||p_u||^2 + ||q_i||^2 + \ b_u^2 + b_i^2)$$

Where:

r_{ui} — Observed ranking of item i by user u
$\mathcal{K}$ — Set of pairs (u, i) for each observed ranking of item i by user u
μ — The average rating over all ratings of all items by all users.
b_u — How much user u's average rating differs from μ.
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This optimization problem is solved by the conjugate gradient descent method. Indeed, this difference in how the optimization problem is solved is the primary difference between matrix factorization by CGD and matrix factorization by ALS.

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Both CGD and ALS provide recommendation systems based on matrix factorization; the difference is that CGD employs the conjugate gradient descent instead of least squares for its optimization phase. In particular, they share the same bipartite graph representation and the same cost function.

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When feasible, ALS is a preferred solver over CGD, while CGD is recommended only when the application requires so much memory that it might be beyond the capacity of the system. CGD has a smaller memory requirement, but has a slower rate of convergence and can provide a rougher estimate of the solution than the more computationally intensive ALS.

The reason for this is that ALS solves the optimization problem by a least squares that requires inverting a matrix. Therefore, it requires more memory and computational effort. But ALS, a 2nd-order optimization method, enjoys higher convergence rate and is potentially more accurate in parameter estimation.

On the otherhand, CGD is a 1.5th-order optimization method that approximates the Hessian of the cost function from the previous gradient information through N consecutive CGD updates. This is very important in cases where the solution has thousands or even millions of components.

Usage

The matrix factorization by CGD procedure takes a property graph, encoding a biparite user-item ranking network, selects a subset of the edges to be considered (via a selection of edge labels), takes initial ratings from specified edge property values, and then writes each user-factors vector to its user vertex in a specified vertex property name and each item-factors vector to its item vertex in the specified vertex property name.

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	Collaborative filtering recommend model.
recommend(self, name, top_k)	[BETA] Collaborative filtering (als/cgd) model
train(self, frame, user_col_name, item_col_name, rating_col_name[, ...])	Collaborative filtering (als/cgd) model

__init__ (*self*, *name=None*)

Collaborative filtering recommend model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Collaborative Filtering

Collaborative filtering is a technique that is widely used in recommendation systems to suggest items (for example, products, movies, articles) to potential users based on historical records of items that users have purchased, rated, or viewed. The Trusted Analytics provides implementations of collaborative filtering with either Alternating Least Squares (ALS) or Conjugate Gradient Descent (CGD) optimization methods.

Both methods optimize the cost function found in Y. Koren, Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model[5] in ACM KDD 2008. For more information on optimizing using ALS see, Y. Zhou, D. Wilkinson, R. Schreiber and R. Pan, Large-Scale Parallel Collaborative Filtering for the Netflix Prize[6] , 2008.

CGD provides a faster, more approximate optimization of the cost function and should be used when memory is a constraint.

A typical representation of the preference matrix P in Giraph is a bi-partite graph, where nodes at the left side represent a list of users and nodes at the right side represent a set of items (for example, movies), and edges encode the rating a user provided to an item. To support training, validation and test, a common practice in machine learning, each edge is also annotated by “TR”, “VA” or “TE”.

[5] http://public.research.att.com/ volinsky/netflix/kdd08koren.pdf

[6] http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.173.2797

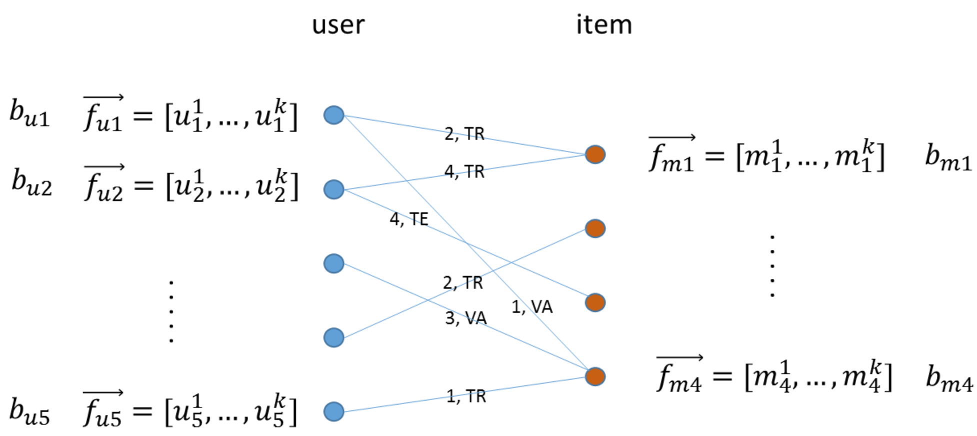

Fig. 19.3: A typical representation of the preference matrix P

Each node in the graph will be associated with a vector $\overrightarrow{f_x}$ of length k, where k is the feature dimension specified by the user, and a bias term b_x. The predictions for item m_j, from user u_i care given by dot product of the feature vector and the user vector, plus the item and user bias terms: /home/work/atk/engine-plugins/giraph-plugins/src/main/scala/org/trustedanalytics/atk/giraph/plugins/model/cf/CollaborativeFilteringNewPlugin.scala

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \; + b_{mj}$$

The parameters of the above equation are chosen to minimize the regularized mean squared error between known and predicted ratings:

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2 \right)$$

How this optimization is accomplished depends on whether the use uses the ALS or CGD functions respectively. It is recommended that the ALS method be used to solve collaborative filtering problems. The CGD method uses less memory than ALS, but it returns an approximate solution to the objective function and should only be used in cases when memory required for ALS is prohibitively high.

Using ALS Optimization to Solve the Collaborative Filtering Problem

ALS optimizes the vector $\overrightarrow{f}_*$ and the bias b_* alternatively between user profiles using least squares on users and items. On the first iteration, the first feature of each item is set to its average rating, while the others are set to small random numbers. The algorithm then treats the m 's as constant and optimizes $u_i^1, ..., u_i^k$ for each user, i. For an individual user, this is a simple ordinary least squares optimization over the items that user has ranked. Next, the algorithm takes the u 's as constant and optimizes the $m_j^1, ..., m_j^k$ for each item, j. This is again an ordinary least squares optimization predicting the user rating of person that has ranked item j.

At each step, the bias is computed for either items of users and the objective function, shown below, is evaluated. The bias term for an item or user, computed for use in the next iteration is given by:

$$b = \frac{\sum error}{(1 + \lambda) * n}$$

The optimization is said to converge if the change in the objective function is less than the convergence_threshold parameter or the algorithm hits the maximum number of *supersteps*.

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2 \right)$$

Note that the equations above omit user and item subscripts for generality. The l_2 regularization term, lambda, tries to avoid overfitting by penalizing the magnitudes of the parameters, and λ is a tradeoff parameter that balances the two terms and is usually determined by cross validation (CV).

After the parameters $\overrightarrow{f}_*$ and b_* are determined, given an item m_j the rating from user u_i can be predicted by the simple linear model:

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \ + b_{mj}$$

Matrix Factorization based on Conjugate Gradient Descent (CGD)

This is the Conjugate Gradient Descent (CGD) with Bias for collaborative filtering algorithm. Our implementation is based on the paper:

Y. Koren. Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model. In ACM KDD 2008. (Equation 5) http://public.research.att.com/~volinsky/netflix/kdd08koren.pdf

This algorithm for collaborative filtering is used in *recommendation systems* to suggest items (products, movies, articles, and so on) to potential users based on historical records of items that all users have purchased, rated, or viewed. The records are usually organized as a preference matrix P, which is a sparse matrix holding the preferences (such as, ratings) given by users to items. Similar to ALS, CGD falls in the category of matrix factorization/latent factor model that infers user profiles and item profiles in low-dimension space, such that the original matrix P can be approximated by a linear model.

This factorization method uses the conjugate gradient method for its optimization subroutine. For more on conjugate gradient descent in general, see: http://en.wikipedia.org/wiki/Conjugate_gradient_method.

The Mathematics of Matrix Factorization via CGD

Matrix factorization by conjugate gradient descent produces ratings by using the (limited) space of observed rankings to infer a user-factors vector p_u for each user u, and an item-factors vector q_i for each item i, and then producing a ranking by user u of item i by the dot-product $b_{ui} + p_u^T q_i$ where b_{ui} is a baseline ranking calculated as $b_{ui} = \mu + b_u + b_i$.

The optimum model is chosen to minimum the following sum, which penalizes square distance of the prediction from observed rankings and complexity of the model (through the regularization term):

$$\sum_{(u,i)\in\mathcal{K}} (r_{ui} - \mu - b_u - b_i - \ p_u^T q_i)^2 + \lambda_3(||p_u||^2 + ||q_i||^2 + \ b_u^2 + b_i^2)$$

Where:

r_{ui} — Observed ranking of item i by user u
$\mathcal{K}$ — Set of pairs (u, i) for each observed ranking of item i by user u
μ — The average rating over all ratings of all items by all users.
b_u — How much user u's average rating differs from μ.
b_i — How much item i's average rating differs from μ
p_u — User-factors vector.
q_i — Item-factors vector.
λ_3 — A regularization parameter specified by the user.

This optimization problem is solved by the conjugate gradient descent method. Indeed, this difference in how the optimization problem is solved is the primary difference between matrix factorization by CGD and matrix factorization by ALS.

Comparison between CGD and ALS

Both CGD and ALS provide recommendation systems based on matrix factorization; the difference is that CGD employs the conjugate gradient descent instead of least squares for its optimization phase. In particular, they share the same bipartite graph representation and the same cost function.

- ALS finds a better solution faster - when it can run on the cluster it is given.
- CGD has slighter memory requirements and can run on datasets that can overwhelm the ALS-based solution.

When feasible, ALS is a preferred solver over CGD, while CGD is recommended only when the application requires so much memory that it might be beyond the capacity of the system. CGD has a smaller memory requirement, but has a slower rate of convergence and can provide a rougher estimate of the solution than the more computationally intensive ALS.

The reason for this is that ALS solves the optimization problem by a least squares that requires inverting a matrix. Therefore, it requires more memory and computational effort. But ALS, a 2nd-order optimization method, enjoys higher convergence rate and is potentially more accurate in parameter estimation.

On the otherhand, CGD is a 1.5th-order optimization method that approximates the Hessian of the cost function from the previous gradient information through N consecutive CGD updates. This is very important in cases where the solution has thousands or even millions of components.

Usage

The matrix factorization by CGD procedure takes a property graph, encoding a biparite user-item ranking network, selects a subset of the edges to be considered (via a selection of edge labels), takes initial ratings from specified edge property values, and then writes each user-factors vector to its user vertex in a specified vertex property name and each item-factors vector to its item vertex in the specified vertex property name.

19.5 *Models* KMeansModel

19.5.1 *KMeansModel* new

`__init__`(*self*, *name=None*)

create a new model

Parameters **name** : unicode (default=None)

name for the model

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.5.2 *KMeansModel* name

`name`

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.5.3 *KMeansModel* predict

---

predict (*self*, *frame*, *observation_columns=None*)

[BETA] Predict the cluster assignments for the data points.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose clusters are to be predicted. By default, we predict the clusters over columns the KMeansModel was trained on. The columns are scaled using the same values used when training the model.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame A new frame consisting of the existing columns of the frame and new columns. The data returned is composed of multiple components:

'k' columns [double] Containing squared distance of each point to every cluster center.

predicted_cluster [int] Integer containing the cluster assignment.

19.5.4 *KMeansModel* publish

---

publish (*self*)

[BETA] Creates a tar file that will used as input to the scoring engine

Parameters

Returns : dict

Returns the HDFS path to the tar file

19.5.5 *KMeansModel* train

train (*self*, *frame*, *observation_columns*, *column_scalings*, *k=None*, *max_iterations=None*, *epsilon=None*, *initialization_mode=None*)

[BETA] Creates KMeans Model from train frame.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

observation_columns : list

Columns containing the observations.

column_scalings : list

Column scalings for each of the observation columns. The scaling value is multiplied by the corresponding value in the observation column.

k : int32 (default=None)

Desired number of clusters. Default is 2.

max_iterations : int32 (default=None)

Number of iterations for which the algorithm should run. Default is 20.

epsilon : float64 (default=None)

Distance threshold within which we consider k-means to have converged. Default is 1e-4.

initialization_mode : unicode (default=None)

The initialization technique for the algorithm. It could be either "random" or "k-means||". Default is "k-means||".

Returns : dict

dict Results. The data returned is composed of multiple components:

cluster_size [dict] Cluster size

ClusterId [int] Number of elements in the cluster 'ClusterId'.

within_set_sum_of_squared_error [double] The set of sum of squared error for the model.

Upon training the 'k' cluster centers are computed.

class **KMeansModel**

create a new model

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	create a new model
predict(self, frame[, observation_columns])	[BETA] Predict the cluster assignments for the data points.
publish(self)	[BETA] Creates a tar file that will used as input to the scoring engine
train(self, frame, observation_columns, column_scalings[, k, max_iterations, ...])	[BETA] Creates KMeans Model from train frame.

__init__(*self*, *name=None*)

create a new model

Parameters **name** : unicode (default=None)

name for the model

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.6 *Models* SvmModel

19.6.1 *SvmModel* new

__init__(*self*, *name=None*)

[ALPHA] create a new model

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.6.2 *SvmModel* name

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.6.3 *SvmModel* predict

predict (*self*, *frame*, *observation_columns=None*)
[ALPHA] Make new frame with additional column for predicted label.

Parameters frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the LogisticRegressionModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame containing the original frame's columns and a column with the predicted label

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

19.6.4 *SvmModel* test

test (*self*, *frame*, *label_column*, *observation_columns=None*)
[ALPHA] Predict test frame labels and return metrics.

Parameters frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

frame whose labels are to be predicted.

label_column : unicode

Column containing the actual label for each observation.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted and tested. Default is to test over the columns the SvmModel was trained on.

Returns : dict

object

An object with binary classification metrics. The data returned is composed of multiple components:

<object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

Predict the labels for a test frame and run classification metrics on predicted and target labels.

19.6.5 *SvmModel* train

---

train (*self*, *frame*, *label_column*, *observation_columns*, *intercept=None*, *num_iterations=None*, *step_size=None*, *reg_type=None*, *reg_param=None*, *mini_batch_fraction=None*)

[ALPHA] Train SVM model based on another frame.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

intercept : bool (default=None)

The algorithm adds an intercept. Default is true.

num_iterations : int32 (default=None)

Number of iterations. Default is 100.

step_size : int32 (default=None)

Step size for optimizer. Default is 1.0.

reg_type : unicode (default=None)

Regularization L1 or L2. Default is L2.

reg_param : float64 (default=None)

Regularization parameter. Default is 0.01.

mini_batch_fraction : float64 (default=None)

Mini batch fraction parameter. Default is 1.0.

Returns : _Unit

Creating a SVM Model using the observation column and label column of the train frame.

class **SvmModel**

create a new model

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	[ALPHA] create a new model
predict(self, frame[, observation_columns])	[ALPHA] Make new frame with additional column for predicted label.
test(self, frame, label_column[, observation_columns])	[ALPHA] Predict test frame labels and return metrics.
train(self, frame, label_column, observation_columns[, intercept, ...])	[ALPHA] Train SVM model based on another frame.

__init__(*self*, *name=None*)

[ALPHA] create a new model

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.7 *Models* LdaModel

19.7.1 *LdaModel* new

__init__(*self*, *name=None*)

Creates Latent Dirichlet Allocation model

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Topic Modeling with Latent Dirichlet Allocation

Topic modeling algorithms are a class of statistical approaches to partitioning items in a data set into subgroups. As the name implies, these algorithms are often used on corpora of textual data, where they are used to group documents in the collection into semantically-meaningful groupings. For an overall introduction to topic modeling, the reader might refer to the work of David Blei and Michael Jordan, who are credited with creating and popularizing topic modeling in the machine learning community. In particular, Blei's 2011 paper provides a nice introduction, and is freely-available online [7] .

LDA (Latent Dirichlet Allocation) is a commonly-used algorithm for topic modeling, but, more broadly, is considered a dimensionality reduction technique. It contrasts with other approaches (for example, latent semantic indexing), in that it creates what's referred to as a generative probabilistic model — a statistical model that allows the algorithm to generalize its approach to topic assignment to other, never-before-seen data points. For the purposes of exposition, we'll limit the scope of our discussion of LDA to the world of natural language processing, as it has an intuitive use there (though LDA can be used on other types of data). In general, LDA represents documents as random mixtures over topics in the corpus. This makes sense because any work of writing is rarely about a single subject. Take the case of a news article on the President of the

[7] http://www.cs.princeton.edu/~blei/papers/Blei2011.pdf

United States of America's approach to healthcare as an example. It would be reasonable to assign topics like President, USA, health insurance, politics, or healthcare to such a work, though it is likely to primarily discuss the President and healthcare.

LDA assumes that input corpora contain documents pertaining to a given number of topics, each of which are associated with a variety of words, and that each document is the result of a mixture of probabilistic samplings: first over the distribution of possible topics for the corpora, and second over the list of possible words in the selected topic. This generative assumption confers one of the main advantages LDA holds over other topic modeling approaches, such as probabilistic and regular LSI (Latent Semantic Indexing). As a generative model, LDA is able to generalize the model it uses to separate documents into topics to documents outside the corpora. For example, this means that using LDA to group online news articles into categories like Sports, Entertainment, and Politics, it would be possible to use the fitted model to help categorize newly-published news stories. Such an application is beyond the scope of approaches like LSI. What's more, when fitting an LSI model, the number of parameters that have to be estimated scale linearly with the number of documents in the corpus, whereas the number of parameters to estimate for an LDA model scales with the number of topics — a much lower number, making it much better-suited to working with large data sets.

The Typical Latent Dirichlet Allocation Workflow

Although every user is likely to have his or her own habits and preferred approach to topic modeling a document corpus, there is a general workflow that is a good starting point when working with new data. The general steps to the topic modeling with LDA include:

1. Data preparation and ingest
2. Assignment to training or testing partition
3. Graph construction
4. Training LDA
5. Evaluation
6. Interpretation of results

Data preparation and ingest

Most topic modeling workflows involve several data pre-processing and cleaning steps. Depending on the characteristics of the data being analyzed, there are different best-practices to use here, so it's important to be familiar with the standard procedures for analytics in the domain from which the text originated. For example, in the biomedical text analytics community, it is common practice for text analytics workflows to involve pre-processing for identifying negation statements (Chapman et al., 2001 [8]). The reason for this is many analysts in that domain are examining text for diagnostic statements — thus, failing to identify a negated statement in which a disease is mentioned could lead to undesirable false-positives, but this phenomenon may not arise in every domain. In general, both stemming and stop word filtering are recommended steps for topic modeling pre-processing. Stemming refers to a set of methods used to normalize different tenses and variations of the same word (for example, stemmer, stemming, stemmed, and stem). Stemming algorithms will normalize all variations of a word to one common form (for example, stem). There are many approaches to stemming, but the Porter Stemming (Porter, 2006 [9]) is one of the most commonly-used.

Removing common, uninformative words, or stop word filtering, is another commonly-used step in data pre-processing for topic modeling. Stop words include words like *the*, *and*, or *a*, but the full list of uninformative words can be quite long and depend on the domain producing the text in question. Example stop word lists online [10] can be a great place to start, but being aware of the best-practices in the applicalbe field is necessary to expand upon these.

[8] http://www.sciencedirect.com/science/article/pii/S1532046401910299

[9] http://tartarus.org/~martin/PorterStemmer/index.html

[10] http://www.textfixer.com/resources/common-english-words.txt

There may be other pre-processing steps needed, depending on the type of text being worked with. Punctuation removal is frequently recommended, for example. To determine what's best for the text being analyzed, it helps to understand a bit about what how LDA analyzes the input text. To learn the topic model, LDA will typically look at the frequency of individual words across documents, which are determined based on space-separation. Thus, each word will be interpreted independent of where it occurs in a document, and without regard for the words that were written around it. In the text analytics field, this is often referred to as a *bag of words* approach to tokenization, the process of separating input text into composite features to be analyzed by some algorithm. When choosing pre-processing steps, it helps to keep this in mind. Don't worry too much about removing words or modifying their format — you're not manipulating your data! These steps simply make it easier for the topic modeling algorithm to find the latent topics that comprise your corpus.

Assignment to training or testing partition

The random assignment to training and testing partitions is an important step in most every machine learning workflow. It is common practice to withhold a random selection of one's data set for the purpose of evaluating the accuracy of the model that was learned from the training data. The results of this evaluation allow the user to confidently speak about the generalizability of the trained model. When speaking in these terms, be cautious that you only discuss generalizability to the broader population from which your data was originally obtained. If a topic model is trained on neuroscience-related publications, for example, evaluating the model on other neuroscience-related publications is valid. It would not be valid to discuss the model's ability to work on documents from other domains.

There are various schools of thought for how to assign a data set to training and testing collections, but all agree that the process should be random. Where analysts disagree is in the ratio of data to be assigned to each. In most situations, the bulk of data will be assigned to the training collection, because the more data that can be used to train the algorithm, the better the resultant model will typically be. It's also important that the testing collection have sufficient data to be able to reflect the characteristics of the larger population from which it was drawn (this becomes an important issue when working with data sets with rare topics, for example). As a starting point, many people will use a 90%/10% training/test collection split, and modify this ratio based on the characteristics of the documents being analyzed.

Graph construction

Trusted Analytics uses a bipartite graph, to learn an LDA topic model. This graph contains vertices in two columns. The left-hand column contains unique ids, each corresponding to a document in the training collection, while the right-hand column contains unique ids corresponding to each word in the entire training set, following any pre-processing steps that were used. Connections between these columns, or edges, denote the number of times a particular word appears in a document, with the weight on the edge in question denoting the number of times the word was found there. After graph construction, many analysts choose to normalize the weights using one of a variety of normalization schemes. One approach is to normalize the weights to sum to 1, while another is to use an approach called term frequency-inverse document frequency (tfidf), where the resultant weights are meant to reflect how important a word is to a document in the corpus. Whether to use normalization — or what technique to use — is an open question, and will likely depend on the characteristics of the text being analyzed. Typical text analytics experiments will try a variety of approaches on a small subset of the data to determine what works best.

See *Figure 1*.

Training the Model

In using LDA, we are trying to model a document collection in terms of topics $\beta_{1:K}$, where each β_K describes a distribution over the set of words in the training corpus. Every document d, then, is a vector of proportions θ_d, where $\theta_{d,k}$ is the proportion of the d^{th} document for topic k. The topic assignment for document d is z_d, and $z_{d,n}$ is the topic assignment for the n^{th} word in document d. The words observed in document d are :math"*w_{d}*, and $w_{d,n}$ is the n^{th} word in document d. The generative process for LDA, then, is the joint

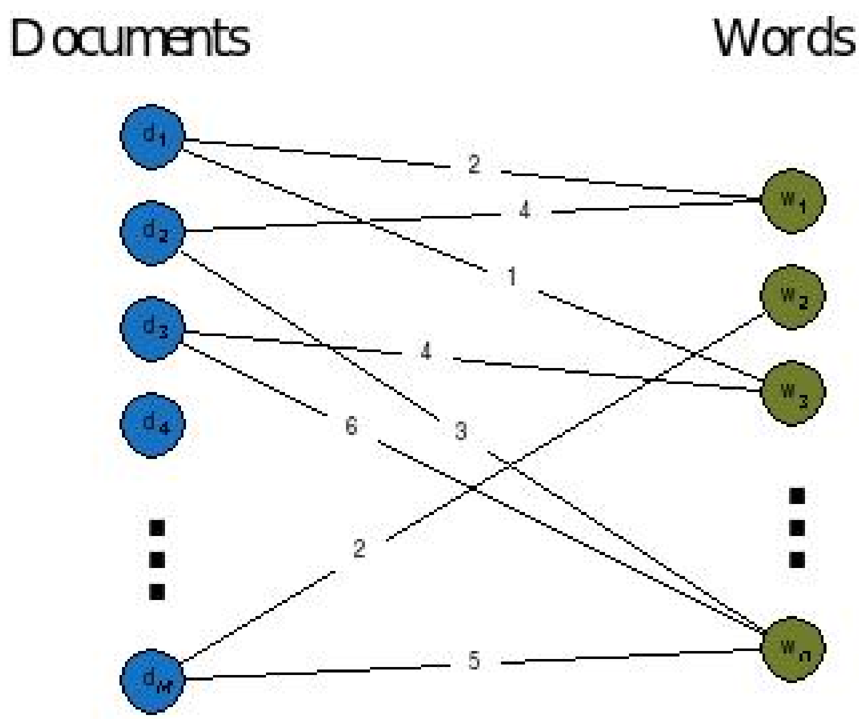

Fig. 19.4: Figure 1 - Example layout of a bipartite graph for LDA.
The left-hand column contains one vertex for each document in the input corpus, while the right-hand column contains vertices for each unique word found in them. Edges connecting left- and right-hand columns denote the number of times the word was found in the document the edge connects. The weights of the edges used in this example were not normalized.

distribution of hidden and observed values

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{i=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p\left(z_{d,n}|\theta_d\right) p\left(w_{d,n}|\beta_{1:K}, z_{d,n}\right) \right)$$

This distribution depicts several dependencies: topic assignment $z_{d,n}$ depends on the topic proportions θ_d, and the observed word $w_{d,n}$ depends on topic assignment $z_{d,n}$ and all the topics $\beta_{1:K}$, for example. Although there are no analytical solutions to learning the LDA model, there are a variety of approximate solutions that are used, most of which are based on Gibbs Sampling (for example, Porteous et al., 2008 [11]). The Trusted Analytics uses an implementation related to this. We refer the interested reader to the primary source on this approach to learn more (Teh et al., 2006 [12]).

Evaluation

As with every machine learning algorithm, evaluating the accuracy of the model that has been obtained is an important step before interpreting the results. With many types of algorithms, the best practices in this step are straightforward — in supervised classification, for example, we know the true labels of the data being classified, so evaluating performance can be as simple as computing the number of errors, calculating receiver operating characteristic, or F1 measure. With topic modeling, the situation is not so straightforward. This makes sense, if we consider with LDA we're using an algorithm to blindly identify logical subgroupings in our data, and we don't *a priori* know the best grouping that can be found. Evaluation, then, should proceed with this in mind, and an examination of homogeneity of the words comprising the documents in each grouping is often done. This issue is discussed further in Blei's 2011 introduction to topic modeling [13] . It is of course possible to evaluate a topic model from a statistical perspective using our hold-out testing document collection — and this is a recommended best practice — however, such an evaluation does not assess the topic model in terms of how they are typically used.

Interpretation of results

After running LDA on a document corpus, users will typically examine the top n most frequent words that can be found in each grouping. With this information, one is often able to use their own domain expertise to think of logical names for each topic (this situation is analogous to the step in principal components analysis, wherein statisticians will think of logical names for each principal component based on the mixture of dimensions each spans). Each document, then, can be assigned to a topic, based on the mixture of topics it has been assigned. Recall that LDA will assign each document a set of probabilities corresponding to each possible topic. Researchers will often set some threshold value to make a categorical judgment regarding topic membership, using this information.

footnotes

19.7.2 *LdaModel* name

---

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

[11] http://www.ics.uci.edu/~newman/pubs/fastlda.pdf
[12] http://machinelearning.wustl.edu/mlpapers/paper_files/NIPS2006_511.pdf
[13] http://www.cs.princeton.edu/~blei/papers/Blei2011.pdf

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.7.3 *LdaModel* predict

predict (*self*, *document*)
[BETA] Predict conditional probabilities of topics given document.

Parameters **document** : list

Document whose topics are to be predicted.

Returns : dict

dict Dictionary containing predicted topics. The data returned is composed of multiple components:

topics_given_doc [list of doubles] List of conditional probabilities of topics given document.

new_words_count [int] Count of new words in test document not present in training set.

new_words_percentage: double Percentage of new words in test document.

Predicts conditional probabilities of topics given document using trained Latent Dirichlet Allocation model. The input document is represented as a list of strings

19.7.4 *LdaModel* publish

publish (*self*)
[BETA] Creates a tar file that will used as input to the scoring engine

Parameters

Returns : dict

Returns the HDFS path to the tar file

Creates a tar file with the trained Latent Dirichlet Allocation model. The tar file is used as input to the scoring engine to predict the conditional topic probabilities for a document.

19.7.5 *LdaModel* train

train(*self*, *frame*, *document_column_name*, *word_column_name*, *word_count_column_name*, *max_iterations=None*, *alpha=None*, *beta=None*, *convergence_threshold=None*, *evaluate_cost=None*, *num_topics=None*)

[BETA] Creates Latent Dirichlet Allocation model

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Input frame data.

document_column_name : unicode

Column Name for documents. Column should contain a str value.

word_column_name : unicode

Column name for words. Column should contain a str value.

word_count_column_name : unicode

Column name for word count. Column should contain an int32 or int64 value.

max_iterations : int32 (default=None)

The maximum number of iterations that the algorithm will execute. The valid value range is all positive int. Default is 20.

alpha : float32 (default=None)

The hyper-parameter for document-specific distribution over topics. Mainly used as a smoothing parameter in *Bayesian inference*. Larger value implies that documents are assumed to cover all topics more uniformly; smaller value implies that documents are more concentrated on a small subset of topics. Valid value range is all positive float.

Default is 0.1.

beta : float32 (default=None)

The hyper-parameter for word-specific distribution over topics. Mainly used as a smoothing parameter in *Bayesian inference*. Larger value implies that topics contain all words more uniformly and smaller value implies that topics are more concentrated on a small subset of words. Valid value range is all positive float. Default is 0.1.

convergence_threshold : float32 (default=None)

The amount of change in LDA model parameters that will be tolerated at convergence. If the change is less than this threshold, the algorithm exits before it reaches the maximum number of supersteps. Valid value range is all positive float and 0.0. Default is 0.001.

evaluate_cost : bool (default=None)

"True" means turn on cost evaluation and "False" means turn off cost evaluation. It's relatively expensive for LDA to evaluate cost function. For time-critical applications, this option allows user to turn off cost function evaluation. Default is "False".

num_topics : int32 (default=None)

The number of topics to identify in the LDA model. Using fewer topics will speed up the computation, but the extracted topics might be more abstract or less specific; using more topics will result in more computation but lead to more specific topics. Valid value range is all positive int. Default is 10.

Returns : dict

dict The data returned is composed of multiple components:

topics_given_doc [Frame] Frame with conditional probabilities of topic given document.

word_given_topics [Frame] Frame with conditional probabilities of word given topic.

topics_given_word [Frame] Frame with conditional probabilities of topic given word.

report [str] The configuration and learning curve report for Latent Dirichlet Allocation as a multiple line str.

See the discussion about Latent Dirichlet Allocation at Wikipedia.[14]

class LdaModel

Creates Latent Dirichlet Allocation model

Topic Modeling with Latent Dirichlet Allocation

Topic modeling algorithms are a class of statistical approaches to partitioning items in a data set into subgroups. As the name implies, these algorithms are often used on corpora of textual data, where they are used to group documents in the collection into semantically-meaningful groupings. For an overall introduction to topic modeling, the reader might refer to the work of David Blei and Michael Jordan, who are credited with creating and popularizing topic modeling in the machine learning community. In particular, Blei's 2011 paper provides a nice introduction, and is freely-available online **[#LDA1]_** .

LDA is a commonly-used algorithm for topic modeling, but, more broadly, is considered a dimensionality reduction technique. It contrasts with other approaches (for example, latent semantic indexing), in that it creates what's referred to as a generative probabilistic model — a statistical model that allows the algorithm to generalize its approach to topic assignment to other, never-before-seen data points. For the purposes of exposition, we'll limit the scope of our discussion of LDA to the world of natural language processing, as it has an intuitive use there (though LDA can be used on other types of data). In general, LDA represents documents as random mixtures over topics in the corpus. This makes sense because any work of writing is rarely about a single subject. Take the case of a news article on the President of the United States of America's approach to healthcare as an example. It would be reasonable to assign topics like President, USA, health insurance, politics, or healthcare to such a work, though it is likely to primarily discuss the President and healthcare.

LDA assumes that input corpora contain documents pertaining to a given number of topics, each of which are associated with a variety of words, and that each document is the result of a mixture of probabilistic samplings: first over the distribution of possible topics for the corpora, and second over the list of possible words in the selected topic. This generative assumption confers one of the main advantages LDA holds over other topic modeling approaches, such as probabilistic and regular LSI. As a generative model, LDA is able to generalize the model it uses to separate documents into topics to documents outside the corpora. For example, this means that using LDA to group online news articles into categories like Sports, Entertainment, and Politics, it would be possible to use the fitted model to help categorize newly-published news stories. Such an application is beyond the scope of approaches like LSI. What's more, when fitting an LSI model, the number of parameters that have to be estimated scale linearly with the number of documents in the corpus, whereas the number of parameters to estimate for an LDA model scales with the number of topics — a much lower number, making it much better-suited to working with large data sets.

The Typical Latent Dirichlet Allocation Workflow

Although every user is likely to have his or her own habits and preferred approach to topic modeling a document corpus, there is a general workflow that is a good starting point when working with new data. The

[14] http://en.wikipedia.org/wiki/Latent_Dirichlet_allocation

general steps to the topic modeling with LDA include:

1. Data preparation and ingest
2. Assignment to training or testing partition
3. Graph construction
4. Training LDA
5. Evaluation
6. Interpretation of results

Data preparation and ingest

Most topic modeling workflows involve several data pre-processing and cleaning steps. Depending on the characteristics of the data being analyzed, there are different best-practices to use here, so it's important to be familiar with the standard procedures for analytics in the domain from which the text originated. For example, in the biomedical text analytics community, it is common practice for text analytics workflows to involve pre-processing for identifying negation statements (Chapman et al., 2001 **[#LDA2]_**). The reason for this is many analysts in that domain are examining text for diagnostic statements — thus, failing to identify a negated statement in which a disease is mentioned could lead to undesirable false-positives, but this phenomenon may not arise in every domain. In general, both stemming and stop word filtering are recommended steps for topic modeling pre-processing. Stemming refers to a set of methods used to normalize different tenses and variations of the same word (for example, stemmer, stemming, stemmed, and stem). Stemming algorithms will normalize all variations of a word to one common form (for example, stem). There are many approaches to stemming, but the Porter Stemming (Porter, 2006 **[#LDA3]_**) is one of the most commonly-used.

Removing common, uninformative words, or stop word filtering, is another commonly-used step in data pre-processing for topic modeling. Stop words include words like *the*, *and*, or *a*, but the full list of uninformative words can be quite long and depend on the domain producing the text in question. Example stop word lists online **[#LDA4]_** can be a great place to start, but being aware of the best-practices in the applicalbe field is necessary to expand upon these.

There may be other pre-processing steps needed, depending on the type of text being worked with. Punctuation removal is frequently recommended, for example. To determine what's best for the text being analyzed, it helps to understand a bit about what how LDA analyzes the input text. To learn the topic model, LDA will typically look at the frequency of individual words across documents, which are determined based on space-separation. Thus, each word will be interpreted independent of where it occurs in a document, and without regard for the words that were written around it. In the text analytics field, this is often referred to as a *bag of words* approach to tokenization, the process of separating input text into composite features to be analyzed by some algorithm. When choosing pre-processing steps, it helps to keep this in mind. Don't worry too much about removing words or modifying their format — you're not manipulating your data! These steps simply make it easier for the topic modeling algorithm to find the latent topics that comprise your corpus.

Assignment to training or testing partition

The random assignment to training and testing partitions is an important step in most every machine learning workflow. It is common practice to withhold a random selection of one's data set for the purpose of evaluating the accuracy of the model that was learned from the training data. The results of this evaluation allow the user to confidently speak about the generalizability of the trained model. When speaking in these terms, be cautious that you only discuss generalizability to the broader population from which your data was originally obtained. If a topic model is trained on neuroscience-related publications, for example, evaluating the model on other neuroscience-related publications is valid. It would not be valid to discuss the model's ability to work on documents from other domains.

There are various schools of thought for how to assign a data set to training and testing collections, but all agree that the process should be random. Where analysts disagree is in the ratio of data to be assigned to each. In most situations, the bulk of data will be assigned to the training collection, because the more data that can be used to train the algorithm, the better the resultant model will typically be. It's also important that the testing collection have sufficient data to be able to reflect the characteristics of the larger population from which it was drawn (this becomes an important issue when working with data sets with rare topics, for example). As a starting point, many people will use a 90%/10% training/test collection split, and modify this ratio based on the characteristics of the documents being analyzed.

Graph construction

Trusted Analytics uses a bipartite graph, to learn an LDA topic model. This graph contains vertices in two columns. The left-hand column contains unique ids, each corresponding to a document in the training collection, while the right-hand column contains unique ids corresponding to each word in the entire training set, following any pre-processing steps that were used. Connections between these columns, or edges, denote the number of times a particular word appears in a document, with the weight on the edge in question denoting the number of times the word was found there. After graph construction, many analysts choose to normalize the weights using one of a variety of normalization schemes. One approach is to normalize the weights to sum to 1, while another is to use an approach called term frequency-inverse document frequency (tfidf), where the resultant weights are meant to reflect how important a word is to a document in the corpus. Whether to use normalization — or what technique to use — is an open question, and will likely depend on the characteristics of the text being analyzed. Typical text analytics experiments will try a variety of approaches on a small subset of the data to determine what works best.

See *Figure 1*.

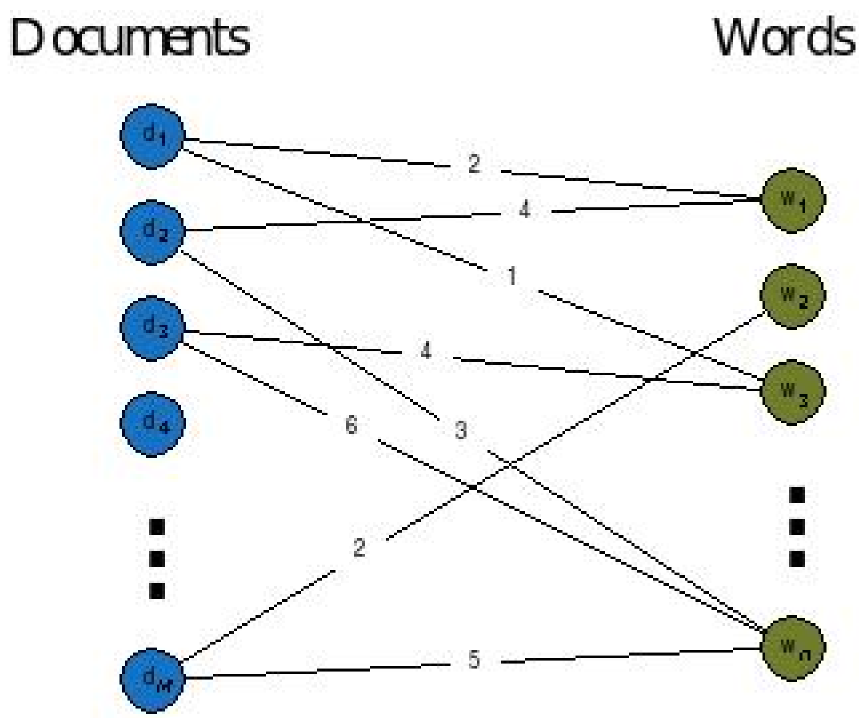

Fig. 19.5: Figure 1 - Example layout of a bipartite graph for LDA.
The left-hand column contains one vertex for each document in the input corpus, while the right-hand column contains vertices for each unique word found in them. Edges connecting left- and right-hand columns denote the number of times the word was found in the document the edge connects. The weights of the edges used in this example were not normalized.

Training the Model

In using LDA, we are trying to model a document collection in terms of topics $\beta_{1:K}$, where each β_K describes a distribution over the set of words in the training corpus. Every document d, then, is a vector of proportions θ_d, where $\theta_{d,k}$ is the proportion of the d^{th} document for topic k. The topic assignment for document d is z_d, and $z_{d,n}$ is the topic assignment for the n^{th} word in document d. The words observed in document d are :math"*w_{d}*, and $w_{d,n}$ is the n^{th} word in document d. The generative process for LDA, then, is the joint distribution of hidden and observed values

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{i=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p\left(z_{d,n}|\theta_d\right) p\left(w_{d,n}|\beta_{1:K}, z_{d,n}\ \right) \right)$$

This distribution depicts several dependencies: topic assignment $z_{d,n}$ depends on the topic proportions θ_d, and the observed word $w_{d,n}$ depends on topic assignment $z_{d,n}$ and all the topics $\beta_{1:K}$, for example. Although there are no analytical solutions to learning the LDA model, there are a variety of approximate solutions that are used, most of which are based on Gibbs Sampling (for example, Porteous et al., 2008 **[#LDA5]_**). The Trusted Analytics uses an implementation related to this. We refer the interested reader to the primary source on this approach to learn more (Teh et al., 2006 **[#LDA6]_**).

Evaluation

As with every machine learning algorithm, evaluating the accuracy of the model that has been obtained is an important step before interpreting the results. With many types of algorithms, the best practices in this step are straightforward — in supervised classification, for example, we know the true labels of the data being classified, so evaluating performance can be as simple as computing the number of errors, calculating receiver operating characteristic, or F1 measure. With topic modeling, the situation is not so straightforward. This makes sense, if we consider with LDA we're using an algorithm to blindly identify logical subgroupings in our data, and we don't *a priori* know the best grouping that can be found. Evaluation, then, should proceed with this in mind, and an examination of homogeneity of the words comprising the documents in each grouping is often done. This issue is discussed further in Blei's 2011 introduction to topic modeling **[#LDA7]_** . It is of course possible to evaluate a topic model from a statistical perspective using our hold-out testing document collection — and this is a recommended best practice — however, such an evaluation does not assess the topic model in terms of how they are typically used.

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After running LDA on a document corpus, users will typically examine the top n most frequent words that can be found in each grouping. With this information, one is often able to use their own domain expertise to think of logical names for each topic (this situation is analogous to the step in principal components analysis, wherein statisticians will think of logical names for each principal component based on the mixture of dimensions each spans). Each document, then, can be assigned to a topic, based on the mixture of topics it has been assigned. Recall that LDA will assign each document a set of probabilities corresponding to each possible topic. Researchers will often set some threshold value to make a categorical judgment regarding topic membership, using this information.

footnotes

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	Creates Latent Dirichlet Allocation model
predict(self, document)	[BETA] Predict conditional probabilities of topics given document.
publish(self)	[BETA] Creates a tar file that will used as input to the scoring engine
train(self, frame, document_column_name, word_column_name, word_count_column_name)	[BETA] Creates Latent Dirichlet Allocation model

__init__(*self*, *name=None*)

Creates Latent Dirichlet Allocation model

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User supplied name.

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See *Figure 1*.

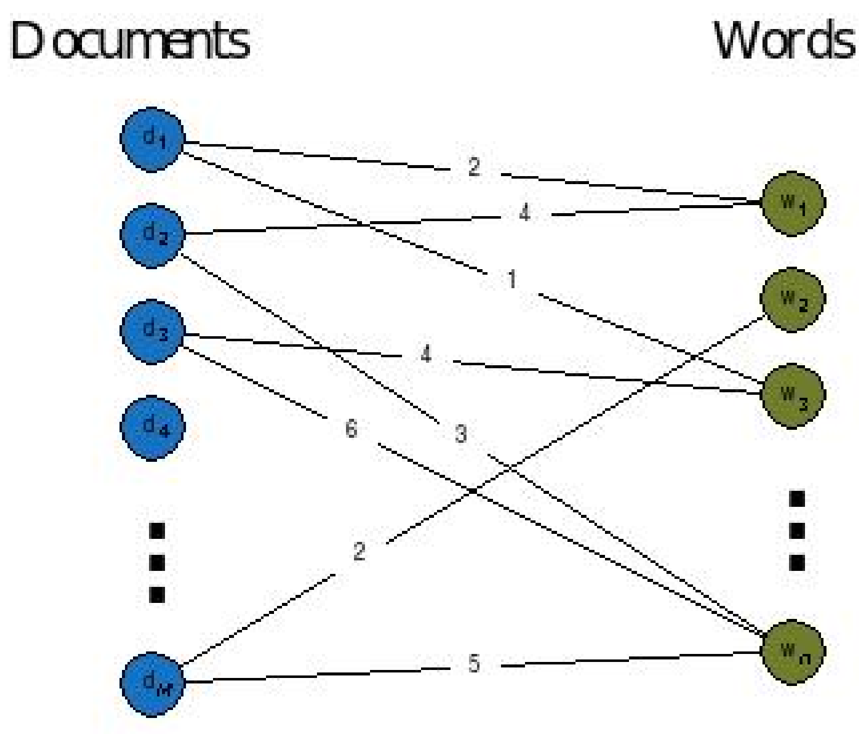

Fig. 19.6: Figure 1 - Example layout of a bipartite graph for LDA.
The left-hand column contains one vertex for each document in the input corpus, while the right-hand column contains vertices for each unique word found in them. Edges connecting left- and right-hand columns denote the number of times the word was found in the document the edge connects. The weights of the edges used in this example were not normalized.

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Interpretation of results

After running LDA on a document corpus, users will typically examine the top n most frequent words that can be found in each grouping. With this information, one is often able to use their own domain expertise to think of logical names for each topic (this situation is analogous to the step in principal components analysis, wherein statisticians will think of logical names for each principal component based on the mixture of dimensions each spans). Each document, then, can be assigned to a topic, based on the mixture of topics it has been assigned. Recall that LDA will assign each document a set of probabilities corresponding to each possible topic. Researchers will often set some threshold value to make a categorical judgment regarding topic membership, using this information.

footnotes

19.8 *Models* LogisticRegressionModel

19.8.1 *LogisticRegressionModel* new

`__init__`(*self*, *name=None*)

Create a 'new' instance of logistic regression model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.8.2 *LogisticRegressionModel* name

---

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.8.3 *LogisticRegressionModel* predict

---

predict (*self*, *frame*, *observation_columns=None*)

[ALPHA] Make a new frame with a column for label prediction.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the LogisticRegressionModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame containing the original frame's columns and a column with the predicted label.

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

19.8.4 *LogisticRegressionModel* test

test (*self*, *frame*, *label_column*, *observation_columns=None*)
[ALPHA] Predict test frame labels and show metrics.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

frame whose labels are to be predicted.

label_column : unicode

Column containing the actual label for each observation.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted and tested. Default is to test over the columns the SvmModel was trained on.

Returns : dict

object An object with binary classification metrics. The data returned is composed of multiple components:

<object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

Predict the labels for a test frame and run classification metrics on predicted and target labels.

19.8.5 *LogisticRegressionModel* train

train (*self*, *frame*, *label_column*, *observation_columns*, *frequency_column=None*, *num_classes=2*, *optimizer='LBFGS'*, *compute_covariance=True*, *intercept=True*, *feature_scaling=False*, *threshold=0.5*, *reg_type='L2'*, *reg_param=0.0*, *num_iterations=100*, *convergence_tolerance=0.0001*, *num_corrections=10*, *mini_batch_fraction=1.0*, *step_size=1*)
[ALPHA] Build logistic regression model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

frequency_column : unicode (default=None)

Optional column containing the frequency of observations.

num_classes : int32 (default=2)

Number of classes

optimizer : unicode (default=LBFGS)

Set type of optimizer. LBFGS - Limited-memory BFGS. LBFGS supports multinomial logistic regression. SGD - Stochastic Gradient Descent. SGD only supports binary logistic regression.

compute_covariance : bool (default=True)

If true, compute covariance matrix for the model.

intercept : bool (default=True)

If true, add intercept column to training data.

feature_scaling : bool (default=False)

If true, perform feature scaling before training model.

threshold : float64 (default=0.5)

Threshold for separating positive predictions from negative predictions.

reg_type : unicode (default=L2)

Set type of regularization L1 - L1 regularization with sum of absolute values of coefficients L2 - L2 regularization with sum of squares of coefficients

reg_param : float64 (default=0.0)

Regularization parameter

num_iterations : int32 (default=100)

Maximum number of iterations

convergence_tolerance : float64 (default=0.0001)

Convergence tolerance of iterations for L-BFGS. Smaller value will lead to higher accuracy with the cost of more iterations.

num_corrections : int32 (default=10)

Number of corrections used in LBFGS update. Default 10. Values of numCorrections less than 3 are not recommended; large values of numCorrections will result in excessive computing time.

mini_batch_fraction : float64 (default=1.0)

Fraction of data to be used for each SGD iteration

step_size : int32 (default=1)

Initial step size for SGD. In subsequent steps, the step size decreases by stepSize/sqrt(t)

Returns : dict

object An object with a summary of the trained model. The data returned is composed of multiple components:

numFeatures [Int] Number of features in the training data

numClasses [Int] Number of classes in the training data

summaryTable: table A summary table composed of:

covarianceMatrix: Frame (optional) Covariance matrix of the trained model. The covariance matrix is the inverse of the Hessian matrix for the trained model. The Hessian matrix is the second-order partial derivatives of the model's log-likelihood function

“”

Creating a LogisticRegression Model using the observation column and label column of the train frame.

class **`LogisticRegressionModel`**

Create a ‘new’ instance of logistic regression model.

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	Create a ‘new’ instance of logistic regression model.
predict(self, frame[, observation_columns])	[ALPHA] Make a new frame with a column for label prediction.
test(self, frame, label_column[, observation_columns])	[ALPHA] Predict test frame labels and show metrics.
train(self, frame, label_column, observation_columns[, frequency_column, ...])	[ALPHA] Build logistic regression model.

`__init__`(*self*, *name=None*)

Create a ‘new’ instance of logistic regression model.

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.9 *Models* NaiveBayesModel

19.9.1 *NaiveBayesModel* new

`__init__`(*self*, *name=None*)

create a new model

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.9.2 *NaiveBayesModel* name

name
Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.9.3 *NaiveBayesModel* predict

predict (*self*, *frame*, *observation_columns=None*)
[ALPHA] Predict

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the NaiveBayesModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

19.9.4 *NaiveBayesModel* train

train (*self*, *frame*, *label_column*, *observation_columns*, *lambda_parameter=None*)
[ALPHA] Build a naive bayes model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

lambda_parameter : float64 (default=None)

Additive smoothing parameter Default is 1.0.

Returns : _Unit

Train a NaiveBayesModel using the observation column, label column of the train frame and an optional lambda value.

class **NaiveBayesModel**
create a new model

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	create a new model
predict(self, frame[, observation_columns])	[ALPHA] Predict
train(self, frame, label_column, observation_columns[, lambda_parameter])	[ALPHA] Build a naive bayes model.

__init__ (*self*, *name=None*)
create a new model

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.10 *Models* LinearRegressionModel

19.10.1 *LinearRegressionModel* new

__init__ (*self*, *name=None*)

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.10.2 *LinearRegressionModel* name

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.10.3 *LinearRegressionModel* predict

predict (*self*, *frame*, *observation_columns=None*)

[ALPHA] Make new frame with column for label prediction.

Parameters frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the LogisticRegressionModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame containing the original frame's columns and a column with the predicted label.

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

19.10.4 *LinearRegressionModel* train

train (*self*, *frame*, *label_column*, *observation_columns*, *intercept=None*, *num_iterations=None*, *step_size=None*, *reg_type=None*, *reg_param=None*, *mini_batch_fraction=None*)

[ALPHA] Build linear regression model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

intercept : bool (default=None)

The algorithm adds an intercept. Default is true.

num_iterations : int32 (default=None)

Number of iterations. Default is 100.

step_size : int32 (default=None)

Step size for optimizer. Default is 1.0.

reg_type : unicode (default=None)

Regularization L1 or L2. Default is L2.

reg_param : float64 (default=None)

Regularization parameter. Default is 0.01.

mini_batch_fraction : float64 (default=None)

Mini batch fraction parameter. Default is 1.0.

Returns : _Unit

Creating a LinearRegression Model using the observation column and label column of the train frame.

class **LinearRegressionModel**

Entity LinearRegressionModel

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	
predict(self, frame[, observation_columns])	[ALPHA] Make new frame with column for label prediction.
train(self, frame, label_column, observation_columns[, intercept, ...])	[ALPHA] Build linear regression model.

__init__(*self*, *name=None*)

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.11 *Models* RandomForestRegressorModel

19.11.1 *RandomForestRegressorModel* new

__init__ (*self*, *name=None*)

<Missing Doc>

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.11.2 *RandomForestRegressorModel* name

name

Set or get the name of the model object.

Parameters

Change or retrieve model object identification. Identification names must start with a letter and are limited to alphanumeric characters and the _ character.

Examples

```
>>> my_model.name

"csv_data"

>>> my_model.name = "cleaned_data"
>>> my_model.name

"cleaned_data"
```

19.11.3 *RandomForestRegressorModel* predict

predict (*self*, *frame*, *observation_columns=None*)

[ALPHA] Predict the values for the data points.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the RandomForestModel was trained on.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame A new frame consisting of the existing columns of the frame and a new column with predicted value for each observation.

19.11.4 *RandomForestRegressorModel* publish

---

publish (*self*)

[BETA] Creates a tar file that will be used as input to the scoring engine

Parameters

Returns : dict

Returns the HDFS path to the tar file

Creates a tar file with the trained Random Forest Regressor Model The tar file is used as input to the scoring engine to predict the value of an observation.

19.11.5 *RandomForestRegressorModel* train

---

train (*self*, *frame*, *label_column*, *observation_columns*, *num_trees=1*, *impurity='variance'*, *max_depth=4*, *max_bins=100*, *seed=-544689744*, *categorical_features_info=None*, *feature_subset_category=None*)

[ALPHA] Build Random Forests Regressor model.

Parameters **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on

label_column : unicode

Column name containing the label for each observation

observation_columns : list

Column(s) containing the observations

num_trees : int32 (default=1)

Number of tress in the random forest

impurity : unicode (default=variance)

Criterion used for information gain calculation. Supported values "variance"

max_depth : int32 (default=4)

Maxium depth of the tree

max_bins : int32 (default=100)

Maximum number of bins used for splitting features

seed : int32 (default=-544689744)

Random seed for bootstrapping and choosing feature subsets

categorical_features_info : None (default=None)

feature_subset_category : unicode (default=None)

Number of features to consider for splits at each node. Supported values “auto”, “all”, “sqrt”,”log2”, “onethird”

Returns : dict

Creating a Random Forests Regressor Model using the observation columns and label column.

class **`RandomForestRegressorModel`**

<Missing Doc>

Attributes

name	Set or get the name of the model object.

Methods

__init__(self[, name, _info])	<Missing Doc>
predict(self, frame[, observation_columns])	[ALPHA] Predict the values for the data points.
publish(self)	[BETA] Creates a tar file that will be used as input to the scoring engine
train(self, frame, label_column, observation_columns[, num_trees, impurity, ...])	[ALPHA] Build Random Forests Regressor model.

`__init__`(*self*, *name=None*)

<Missing Doc>

Parameters **name** : unicode (default=None)

User supplied name.

Returns : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

19.12 *trustedanalytics* get_model

`get_model`(*identifier*)

Get handle to a model object.

Parameters **identifier** : str | int

Name of the model to get

Returns : Model

model object

19.13 *trustedanalytics* drop_models

---

drop_models(*items*)

Deletes the model on the server.

Parameters items : [str | model object | list [str | model objects]]

Either the name of the model object to delete or the model object itself

19.14 *trustedanalytics* get_model_names

---

get_model_names()

Retrieve names for all the model objects on the server.

Returns : list

List of names

Global Methods

get_model

drop_models

get_model_names

Part VI

REST API

CHAPTER

TWENTY

REST API COMMANDS

20.1 *Commands* Issue Command

Issue a command for execution.

20.1.1 POST /v1/commands

Request

Route

```
POST /v1/commands
```

Body

Name	Description
name	full name of the command
arguments	JSON object specifying the command arguments

Here's an example showing how to issue the "assign_sample" command on frame 16:

```
{
  "name": "frame/assign_sample",
  "arguments": {
    "sample_labels": [
      "train",
      "test",
      "validate"
    ],
    "frame": 16,
    "random_seed": null,
    "sample_percentages": [
      0.5,
      0.3,
      0.2
    ],
    "output_column": null
  }
}
```

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command. It is the same. Note that POSTing to 'commands' creates the command and issues it for execution and immediately returns. To determine the command progress and status, use Get Command.

20.2 *Commands* Get Command

Gets information about a specific command.

20.2.1 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/25
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

Returns information about the command

Name	Description
id	command instance id (engine-assigned)
name	command name
correlation_id	correlation id
links	links to the command
arguments	the arguments that were passed to the command
progress	command execution progress `progress`: percentage complete `tasks_info`: info about each task in the command including number of retries
complete	boolean indicating if the command has finished
result	the return data from command completion. (field will not appear until 'complete' is true)

Example response body for command 18, 'assign_sample' on frame 16 which is in the middle of execution:


```
{
  "id": 18,
  "name": "frame/assign_sample",
  "correlation_id": "",
  "arguments": {
    "sample_labels": ["train", "test", "validate"],
    "frame": 16,
    "random_seed": null,
    "sample_percentages": [0.5, 0.3, 0.2],
    "output_column": null
  },
  "progress": [{
     "progress": 33.33000183105469,
     "tasks_info": {
       "retries": 0
     }
  }],
  "complete": false,
  "links": [{
    "rel": "self",
    "uri": "http://localhost:9099/v1/commands/18",
    "method": "GET"
  }]
}
```


Example response body for command 17, a 'load' on frame 16 which has completed:


```
{
  "id": 17,
  "name": "frame:/load",
  "correlation_id": "3d074058-54bd-4170-a8a7-2219e6e3a894",
  "arguments": {
    "source": {
      "source_type": "file",
      "parser": {
        "name": "builtin/line/separator",
        "arguments": {
          "separator": ",",
          "skip_rows": 0,
          "schema": {
            "columns": [["c", "int32"], ["number", "unicode"]]
          }
        }
      },
      "data": null,
      "uri": "/join_left.csv"
    },
    "destination": 16
  },
  "progress": [{
    "progress": 100.0,
    "tasks_info": {
      "retries": 0
    }
```

```
    }],
    "complete": true,
    "result": {
      "id": 16,
      "name": "super_frame",
      "schema": {
        "columns": [{
          "name": "c",
          "data_type": "int32",
          "index": 0
        }, {
          "name": "number",
          "data_type": "string",
          "index": 1
        }]
      },
      "status": 1,
      "created_on": "2015-05-15T14:58:23.369-07:00",
      "modified_on": "2015-05-15T14:58:35.272-07:00",
      "storage_format": "file/parquet",
      "storage_location": "hdfs://paulsimon.hf.trustedanalytics.com/user/atkuser/trustedanalytics/fra
      "row_count": 3,
      "modified_by": 1,
      "materialized_on": "2015-05-15T14:58:32.611-07:00",
      "materialization_complete": "2015-05-15T14:58:35.258-07:00",
      "last_read_date": "2015-05-15T14:58:23.369-07:00",
      "uri": "frames/16",
      "entity_type": "frame:"
    },
    "links": [{
      "rel": "self",
      "uri": "http://localhost:9099/v1/commands/17",
      "method": "GET"
    }]
}
```

Headers

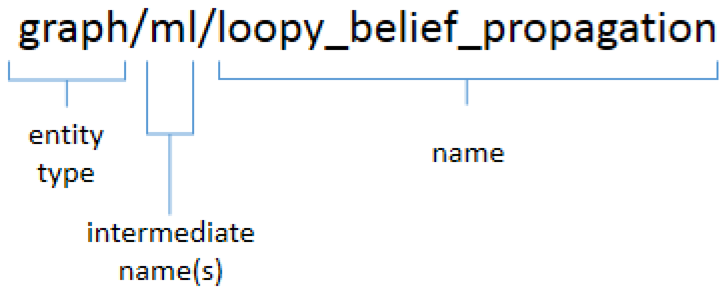
```
Content-Length: 405
Content-Type: application/json; charset=UTF-8
Date: Thu, 14 May 2015 23:42:27 GMT
```

Note

[Some notes could go here recommending polling strategies, and more info about the progress field]

20.3 *Commands* About Command Names

Command names are structured hierarchically according to entities and any intermediate scoping names. The full name of a command is delimited with the `/` character.



All commands are associated with an entity type, like a frame or a graph. The command name begins with the **entity type**. The `:` character indicates subtyping, where no `:` means all related entities inherit the command. Example entity types:

```
frame               # corresponds to all *Frame entity types
frame:              # indicates the standard Frame entity type
frame:vertex        # indicates the VertexFrame entity type
model:kmeans        # indicates the KmeansModel entity type
```

This means the command `frame/bin_columns` is available on any type of Frame object, where `frame:vertex/add_vertices` is only available on `VertexFrame` entities. The first argument to any command is the id of an entity instance. This entity instance must correspond to the supported entity type(s) indicated in the command's full name.

After the entity type, but before the name, there may be one or more intermediate names that provide additional scope.

Finally comes the name which identifies the operation.

20.4 *Commands* _admin:/_explicit_garbage_collection

<Missing Doc>

20.4.1 POST /v1/commands/

20.4.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name _admin:/_explicit_garbage_collection

arguments **age_to_delete_data** : unicode (default=None)

Minimum age of entity for data deletion. Defaults to server config.

age_to_delete_meta_data : unicode (default=None)

Minimum age of entity for meta data deletion. Defaults to server config.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.4.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.5 *Commands* frame:/filter

Select all rows which satisfy a predicate.

20.5.1 POST /v1/commands/

20.5.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

Note - An argument for this command requires a Python User-Defined Function (UDF). This function must be especially prepared (wrapped/serialized) in order for it to run in the engine. **If this argument is needed for your call (i.e. it may be optional), then this particular command usage is NOT practically available as a REST API.** Today, the trustedanalytics Python client does the special function preparation and calls this API.

name frame:/filter

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

udf : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Modifies the current frame to save defined rows and delete everything else.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.5.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.6 *Commands* frame:/join

[BETA] Join two data frames (similar to SQL JOIN).

20.6.1 POST /v1/commands/

20.6.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:/join

arguments **left_frame** : None

<Missing Description>

right_frame : None

<Missing Description>

how : unicode

Methods of join (inner, left, right or outer).

name : unicode (default=None)

Name of new frame to be created.

skewed_join_type : unicode (default=None)

The type of skewed join: 'skewedhash' or 'skewedbroadcast'

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.6.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

20.7 *Commands* frame:/label_propagation

Label Propagation on Gaussian Random Fields.

20.7.1 POST /v1/commands/

20.7.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:/label_propagation

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

src_col_name : unicode

The column name for the source vertex id.

dest_col_name : unicode

The column name for the destination vertex id.

weight_col_name : unicode

The column name for the edge weight.

src_label_col_name : unicode

The column name for the label properties for the source vertex.

result_col_name : unicode (default=None)

The column name for the results (holding the post labels for the vertices).

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid value range is all positive int. Default is 10.

convergence_threshold : float32 (default=None)

The amount of change in cost function that will be tolerated at convergence. If the change is less than this threshold, the algorithm exits earlier before it reaches the maximum number of supersteps. The valid value range is all float and zero. Default is 0.00000001f.

alpha : float32 (default=None)

The tradeoff parameter that controls how much influence an external classifier's prediction contributes to the final prediction. This is for the case where an external classifier is available that can produce initial probabilistic classification on unlabeled examples, and the option allows incorporating external classifier's prediction into the LP training process. The valid value range is [0.0,1.0]. Default is 0.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Label Propagation on Gaussian Random Fields.

This algorithm is presented in X. Zhu and Z. Ghahramani. Learning from labeled and unlabeled data with label propagation. Technical Report CMU-CALD-02-107, CMU, 2002[1].

Label Propagation (LP)

LP is a message passing technique for inputing or *smoothing* labels in partially-labelled datasets. Labels are propagated from *labeled* data to *unlabeled* data along a graph encoding similarity relationships among data points. The labels of known data can be probabilistic, in other words, a known point can be represented with fuzzy labels such as 90% label 0 and 10% label 1. The inverse distance between data points is represented by edge weights, with closer points having a higher weight (stronger influence on posterior estimates) than points farther away. LP has been used for many problems, particularly those involving a similarity measure between data points. Our implementation is based on Zhu and Ghahramani's 2002 paper, Learning from labeled and unlabeled data.[2].

[1] http://www.cs.cmu.edu/ zhuxj/pub/CMU-CALD-02-107.pdf
[2] http://www.cs.cmu.edu/ zhuxj/pub/CMU-CALD-02-107.pdf

The Label Propagation Algorithm

In LP, all nodes start with a prior distribution of states and the initial messages vertices pass to their neighbors are simply their prior beliefs. If certain observations have states that are known deterministically, they can be given a prior probability of 100% for their true state and 0% for all others. Unknown observations should be given uninformative priors.

Each node, i, receives messages from its k neighbors and updates its beliefs by taking a weighted average of its current beliefs and a weighted average of the messages received from its neighbors.

The updated beliefs for node i are:

$$updated\ beliefs_i = \lambda * (prior\ belief_i) + (1 - \lambda)\ * \sum_k w_{i,k} * previous\ belief_k$$

where $w_{i,k}$ is the normalized weight between nodes i and k, normalized such that the sum of all weights to neighbors is 1.

λ is a leaning parameter. If λ is greater than zero, updated probabilities will be anchored in the direction of prior beliefs.

The final distribution of state probabilities will also tend to be biased in the direction of the distribution of initial beliefs. For the first iteration of updates, nodes' previous beliefs are equal to the priors, and, in each future iteration, previous beliefs are equal to their beliefs as of the last iteration. All beliefs for every node will be updated in this fashion, including known observations, unless `anchor_threshold` is set. The `anchor_threshold` parameter specifies a probability threshold above which beliefs should no longer be updated. Hence, with an `anchor_threshold` of 0.99, observations with states known with 100% certainty will not be updated by this algorithm.

This process of updating and message passing continues until the convergence criteria is met, or the maximum number of *supersteps* is reached. A node is said to converge if the total change in its cost function is below the convergence threshold. The cost function for a node is given by:

$$\begin{aligned} cost = \sum_k w_{i,k} * \Big[(1 - \lambda) * \big[previous\ \ belief_i^2 - w_{i,k} * previous\ belief_i * \\ previous\ belief_k \big] + 0.5 * \lambda * \big(previous\ belief_i\ - prior_i \big)^2 \Big] \end{aligned}$$

Convergence is a local phenomenon; not all nodes will converge at the same time. It is also possible that some (most) nodes will converge and others will not converge. The algorithm requires all nodes to converge before declaring global convergence. If this condition is not met, the algorithm will continue up to the maximum number of *supersteps*.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.7.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

A 2-column frame:

vertex: int A vertex id.

result [Vector (long)] label vector for the results (for the node id in column 1)

20.8 *Commands* frame:/load

Append data from a csv/xml into an existing (possibly empty) frame

20.8.1 POST /v1/commands/

20.8.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:/load

arguments **destination** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

source : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Append data from a csv/xml into an existing (possibly empty) frame

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.8.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.9 *Commands* frame:/loopy_belief_propagation

Message passing to infer state probabilities.

20.9.1 POST /v1/commands/

20.9.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:/loopy_belief_propagation

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

src_col_name : unicode

The column name for the source vertex id.

dest_col_name : unicode

The column name for the destination vertex id.

weight_col_name : unicode

The column name for the edge weight.

src_label_col_name : unicode

The column name for the label properties for the source vertex.

result_col_name : unicode (default=None)

The column name for the results (holding the post labels for the vertices).

ignore_vertex_type : bool (default=None)

If True, all vertex will be treated as training data. Default is False.

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid value range is all positive int. The default value is 10.

convergence_threshold : float32 (default=None)

The amount of change in cost function that will be tolerated at convergence. If the change is less than this threshold, the algorithm exits earlier before it reaches the maximum number of supersteps. The valid value range is all float and zero. The default value is 0.00000001f.

anchor_threshold : float64 (default=None)

The parameter that determines if a node's posterior will be updated or not. If a node's maximum prior value is greater than this threshold, the node will be treated as anchor node, whose posterior will inherit from prior without update. This is for the case where we have confident prior estimation for some nodes and don't want the algorithm to update these nodes. The valid value range is in [0, 1]. Default is 1.0.

smoothing : float32 (default=None)

The Ising smoothing parameter. This parameter adjusts the relative strength of closeness encoded edge weights, similar to the width of Gussian distribution. Larger value implies smoother decay and the edge weight beomes less important. Default is 2.0.

max_product : bool (default=None)

Should LBP use max_product or not. Default is False.

power : float32 (default=None)

Power coefficient for power edge potential. Default is 0.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Loopy belief propagation on *Markov Random Fields* (MRF). *Belief Propagation* (BP) was originally designed for acyclic graphical models, then it was found that the BP algorithm can be used in general graphs. The algorithm is then sometimes called "Loopy" Belief Propagation (LBP), because graphs typically contain cycles, or loops.

Loopy Belief Propagation (LBP)

Loopy Belief Propagation (LBP) is a message passing algorithm for inferring state probabilities, given a graph and a set of noisy initial estimates. The LBP implementation assumes that the joint distribution of the data is given by a Boltzmann distribution.

For more information about LBP, see: "K. Murphy, Y. Weiss, and M. Jordan, Loopy-belief Propagation for Approximate Inference: An Empirical Study, UAI 1999."

LBP has a wide range of applications in structured prediction, such as low-level vision and influence spread in social networks, where we have prior noisy predictions for a large set of random variables and a graph encoding relationships between those variables.

The algorithm performs approximate inference on an *undirected graph* of hidden variables, where each variable is represented as a node, and each edge encodes relations to its neighbors. Initially, a prior noisy estimate of state probabilities is given to each node, then the algorithm infers the posterior distribution of each node by propagating and collecting messages to and from its neighbors and updating the beliefs.

In graphs containing loops, convergence is not guaranteed, though LBP has demonstrated empirical success in many areas and in practice often converges close to the true joint probability distribution.

Discrete Loopy Belief Propagation

LBP is typically considered a *semi-supervised machine learning* algorithm as

1. there is typically no ground truth observation of states
2. the algorithm is primarily concerned with estimating a joint probability function rather than with *classification* or point prediction.

The standard (discrete) LBP algorithm requires a set of probability thresholds to be considered a classifier. Nonetheless, the discrete LBP algorithm allows Test/Train/Validate splits of the data and the algorithm will treat "Train" observations differently from "Test" and "Validate" observations. Vertices labelled with "Test" or "Validate" will be treated as though they have uninformative (uniform) priors and are allowed to receive messages, but not send messages. This simulates a "scoring scenario" in which a new observation is added to a graph containing fully trained LBP posteriors, the new vertex is scored based on received messages, but the full LBP algorithm is not repeated in full. This behavior can be turned off by setting the `ignore_vertex_type` parameter to True. When `ignore_vertex_type=True`, all nodes will be considered "Train" regardless of their sample type designation. The Gaussian (continuous) version of LBP does not allow Train/Test/Validate splits.

The standard LBP algorithm included with the toolkit assumes an ordinal and cardinal set of discrete states. For notational convenience, we'll denote the value of state s_i as i, and the prior probability of state s_i as $prior_i$.

Each node sends out initial messages of the form:

$$\ln\left(\sum_{s_j}\exp\left(-\frac{|i-j|^p}{n-1}\ *w*s+\ln(prior_i)\right)\right)$$

Where

- w is the weight between the messages destination and origin vertices
- s is the *smoothing* parameter
- p is the power parameter
- n is the number of states

The larger the weight between two nodes, or the higher the smoothing parameter, the more neighboring vertices are assumed to "agree" on states. We represent messages as sums of log probabilities rather than products of non-logged probabilities which makes it easier to subtract messages in the future steps of the algorithm. Also note that the states are cardinal in the sense that the "pull" of state i on state j depends on the distance between i and j. The *power* parameter intensifies the rate at which the pull of distant states drops off.

In order for the algorithm to work properly, all edges of the graph must be bidirectional. In other words, messages need to be able to flow in both directions across every edge. Bidirectional edges can be enforced during graph building, but the LBP function provides an option to do an initial check for bidirectionality using the `bidirectional_check=True` option. If not all the edges of the graph are bidirectional, the algorithm will return an error.

Look at a case where a node has two states, 0 and 1. The 0 state has a prior probability of 0.9 and the 1 state has a prior probability of 0.2. The states have uniform weights of 1, power of 1 and a smoothing parameter of 2. The nodes initial message would be $\left[\ln\left(0.2\ +0.8e^{-2}\right),\ln\left(0.8+0.2e^{-2}\right)\right]$, which gets sent to each of that node's neighbors. Note that messages will typically not be proper probability distributions, hence each message is normalized so that the probability of all states sum to 1 before being sent out. For simplicity of discussion, we will consider all messages as normalized messages.

After nodes have sent out their initial messages, they then update their beliefs based on messages that they have received from their neighbors, denoted by the set k.

Updated Posterior Beliefs:

$$\ln(newbelief) = \propto \exp\left[\ln(prior) + \sum_k message_k\right]$$

Note that the messages in the above equation are still in log form. Nodes then send out new messages which take the same form as their initial messages, with updated beliefs in place of priors and subtracting out the information previously received from the new message's recipient. The recipient's prior message is subtracted out to prevent feedback loops of nodes "learning" from themselves.

$$\ln\left(\sum_{s_j} \exp\left(-\frac{|i-j|^p}{n-1} * w * s + \ln(newbelief_i) - \; previous\ message\ from\ recipient\right)\right)$$

In updating beliefs, new beliefs tend to be most influenced by the largest message. Setting the `max_product` option to "True" ignores all incoming messages other than the strongest signal. Doing this results in approximate solutions, but requires significantly less memory and run-time than the more exact computation. Users should consider this option when processing power is a constraint and approximate solutions to LBP will be sufficient.

This process of updating and message passing continues until the convergence criteria is met or the maximum number of *supersteps* is reached without converging. A node is said to converge if the total change in its distribution (the sum of absolute value changes in state probabilities) is less than the `convergence_threshold` parameter. Convergence is a local phenomenon; not all nodes will converge at the same time. It is also possible for some (most) nodes to converge and others to never converge. The algorithm requires all nodes to converge before declaring that the algorithm has converged overall. If this condition is not met, the algorithm will continue up to the maximum number of *supersteps*.

See: http://en.wikipedia.org/wiki/Belief_propagation.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.9.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

a 2-column frame:

vertex: int A vertex id.

result [Vector (long)] label vector for the results (for the node id in column 1).

20.10 *Commands* frame:/rename_columns

Rename columns

20.10.1 POST /v1/commands/

20.10.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:/rename_columns

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

names : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.10.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.11 *Commands* frame:edge/add_edges

Add edges to a graph.

20.11.1 POST /v1/commands/

20.11.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:edge/add_edges

arguments **edge_frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

source_frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame that will be the source of the edge data.

column_name_for_source_vertex_id : unicode

column name for a unique id for each source vertex (this is not the system defined _vid).

column_name_for_dest_vertex_id : unicode

column name for a unique id for each destination vertex (this is not the system defined _vid).

column_names : list (default=None)

Column names to be used as properties for each vertex, None means use all columns, empty list means use none.

create_missing_vertices : bool (default=False)

True to create missing vertices for edge (slightly slower), False to drop edges pointing to missing vertices. Defaults to False.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Includes appending to a list of existing edges.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.11.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.12 *Commands* frame:edge/rename_columns

Rename columns for edge frame.

20.12.1 POST /v1/commands/

20.12.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:edge/rename_columns

arguments **frame** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

names : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.12.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.13 *Commands* frame:vertex/add_vertices

Add vertices to a graph.

20.13.1 POST /v1/commands/

20.13.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:vertex/add_vertices

arguments **vertex_frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

source_frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame that will be the source of the vertex data.

id_column_name : unicode

Column name for a unique id for each vertex.

column_names : list (default=None)

Column names that will be turned into properties for each vertex.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Includes appending to a list of existing vertices.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.13.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.14 *Commands* frame:vertex/drop_duplicates

Remove duplicate vertex rows.

20.14.1 POST /v1/commands/

20.14.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:vertex/drop_duplicates

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

unique_columns : None (default=None)

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Remove duplicate vertex rows, keeping only one vertex row per uniqueness criteria match. Edges that were connected to removed vertices are also automatically dropped.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.14.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.15 *Commands* frame:vertex/filter

20.15.1 POST /v1/commands/

20.15.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

Note - An argument for this command requires a Python User-Defined Function (UDF). This function must be especially prepared (wrapped/serialized) in order for it to run in the engine. **If this argument is needed for your call (i.e. it may be optional), then this particular command usage is NOT practically available as a REST API.** Today, the trustedanalytics Python client does the special function preparation and calls this API.

name frame:vertex/filter

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

udf : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.15.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.16 *Commands* frame:vertex/rename_columns

Rename columns for vertex frame.

20.16.1 POST /v1/commands/

20.16.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame:vertex/rename_columns

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

names : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.16.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.17 *Commands* frame/_coalesce

Calls underlying Spark RDD method.

20.17.1 POST /v1/commands/

20.17.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/_coalesce

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

number_partitions : int32

number of Spark RDD partitions

shuffle : bool (default=False)

shuffle data between partitions

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.17.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.18 *Commands* frame/_partition_count

Calls underlying Spark RDD method.

20.18.1 POST /v1/commands/

20.18.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/_partition_count

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.18.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

dict

20.19 *Commands* frame/_repartition

Calls underlying Spark RDD method.

20.19.1 POST /v1/commands/

20.19.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/_repartition

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

number_partitions : int32

number of RDD partitions

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.19.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.20 *Commands* frame/_size_on_disk

Calculate the size on disk in bytes of a frame.

20.20.1 POST /v1/commands/

20.20.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/_size_on_disk

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.20.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.21 *Commands* frame/add_columns

Add columns to current frame.

20.21.1 POST /v1/commands/

20.21.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

> **Note** - An argument for this command requires a Python User-Defined Function (UDF). This function must be especially prepared (wrapped/serialized) in order for it to run in the engine. **If this argument is needed for your call (i.e. it may be optional), then this particular command usage is NOT practically available as a REST API.** Today, the trustedanalytics Python client does the special function preparation and calls this API.
>
> **name** frame/add_columns
>
> **arguments** **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
>
> Frame to which new columns need to be added
>
> **column_names** : list
>
> List of names for the new columns
>
> **column_types** : list
>
> List of data types for the new columns
>
> **udf** : None
>
> <Missing Description>
>
> **columns_accessed** : list
>
> List of columns which the UDF will access. This adds significant performance benefit if we know which column(s) will be needed to execute the UDF, especially when the frame has significantly more columns than those being used to evaluate the UDF.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Assigns data to column based on evaluating a function for each row.

Notes

1. The row UDF ('func') must return a value in the same format as specified by the schema. See Python User Functions.
2. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.21.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.22 *Commands* frame/assign_sample

Randomly group rows into user-defined classes.

20.22.1 POST /v1/commands/

20.22.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/assign_sample

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

sample_percentages : list

Entries are non-negative and sum to 1. (See the note below.) If the i'th entry of the list is p, then then each row receives label i with independent probability p.

sample_labels : list (default=None)

Names to be used for the split classes. Defaults "TR", "TE", "VA" when the length of *sample_percentages* is 3, and defaults to Sample_0, Sample_1, ... otherwise.

output_column : unicode (default=None)

Name of the new column which holds the labels generated by the function.

random_seed : int32 (default=None)

Random seed used to generate the labels. Defaults to 0.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Randomly assign classes to rows given a vector of percentages. The table receives an additional column that contains a random label. The random label is generated by a probability distribution function. The distribution function is specified by the sample_percentages, a list of floating point values, which add up to 1. The labels are non-negative integers drawn from the range $[0, len(S) - 1]$ where S is the sample_percentages. Optionally, the user can specify a list of strings to be used as the labels. If the number of labels is 3, the labels will default to "TR", "TE" and "VA".

Notes

The sample percentages provided by the user are preserved to at least eight decimal places, but beyond this there may be small changes due to floating point imprecision.

In particular:

1. The engine validates that the sum of probabilities sums to 1.0 within eight decimal places and returns an error if the sum falls outside of this range.
2. The probability of the final class is clamped so that each row receives a valid label with probability one.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.22.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.23 *Commands* frame/bin_column

Classify data into user-defined groups.

20.23.1 POST /v1/commands/

20.23.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/bin_column

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column_name : unicode

Name of the column to bin.

cutoffs : list

Array of values containing bin cutoff points. Array can be list or tuple. Array values must be progressively increasing. All bin boundaries must be included, so, with N bins, you need N+1 values.

include_lowest : bool (default=None)

Specify how the boundary conditions are handled. True indicates that the lower bound of the bin is inclusive. False indicates that the upper bound is inclusive. Default is True.

strict_binning : bool (default=None)

Specify how values outside of the cutoffs array should be binned. If set to True, each value less than cutoffs[0] or greater than cutoffs[-1] will be assigned a bin value of -1. If set to False, values less than cutoffs[0] will be included in the first bin while values greater than cutoffs[-1] will be included in the final bin.

bin_column_name : unicode (default=None)

The name for the new binned column. Default is `<column_name>_binned`.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Summarize rows of data based on the value in a single column by sorting them into bins, or groups, based on a list of bin cutoff points.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. Bins IDs are 0-index: the lowest bin number is 0.
3. The first and last cutoffs are always included in the bins. When include_lowest is `True`, the last bin includes both cutoffs. When include_lowest is `False`, the first bin (bin 0) includes both cutoffs.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.23.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.24 *Commands* frame/bin_column_equal_depth

Classify column into groups with the same frequency.

20.24.1 POST /v1/commands/

20.24.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/bin_column_equal_depth

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Identifier for the input dataframe.

column_name : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is `<column_name>_binned`.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal depth binning attempts to label rows such that each bin contains the same number of elements. For n bins of a column C of length m, the bin number is determined by:

$$\lceil n * \frac{f(C)}{m} \rceil$$

where f is a tie-adjusted ranking function over values of C. If there are multiples of the same value in C, then their tie-adjusted rank is the average of their ordered rank values.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has a quantity of :math"*X* elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.24.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

A list containing the edges of each bin.

20.25 *Commands* frame/bin_column_equal_width

Classify column into same-width groups.

20.25.1 POST /v1/commands/

20.25.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/bin_column_equal_width

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Identifier for the input dataframe.

column_name : unicode

The column whose values are to be binned.

num_bins : int32 (default=None)

The maximum number of bins. Default is the Square-root choice $\lfloor \sqrt{m} \rfloor$, where m is the number of rows.

bin_column_name : unicode (default=None)

The name for the new column holding the grouping labels. Default is `<column_name>_binned`.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Group rows of data based on the value in a single column and add a label to identify grouping.

Equal width binning places column values into groups such that the values in each group fall within the same interval and the interval width for each group is equal.

Notes

1. Unicode in column names is not supported and will likely cause the drop_frames() method (and others) to fail!
2. The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. For example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.25.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

A list of the edges of each bin.

20.26 *Commands* frame/categorical_summary

Build summary of the data.

20.26.1 POST /v1/commands/

20.26.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/categorical_summary

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column_input : list

List of Categorical Column Input consisting of column, topk and/or threshold

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Optional parameters:

> **top_k** ***: int*** Displays levels which are in the top k most frequently occurring values for that column. Default is 10.
>
> **threshold** ***: float*** Displays levels which are above the threshold percentage with respect to the total row count. Default is 0.0.

Compute a summary of the data in a column(s) for categorical or numerical data types. The returned value is a Map containing categorical summary for each specified column.

For each column, levels which satisfy the top k and/or threshold cutoffs are displayed along with their frequency and percentage occurrence with respect to the total rows in the dataset.

Performs level pruning first based on top k and then filters out levels which satisfy the threshold criterion.

Missing data is reported when a column value is empty (“”) or null.

All remaining data is grouped together in the Other category and its frequency and percentage are reported as well.

User must specify the column name and can optionally specify top_k and/or threshold.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.26.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Summary for specified column(s) consisting of levels with their frequency and percentage.

20.27 *Commands* frame/classification_metrics

Model statistics of accuracy, precision, and others.

20.27.1 POST /v1/commands/

20.27.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/classification_metrics

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

label_column : unicode

The name of the column containing the correct label for each instance.

pred_column : unicode

The name of the column containing the predicted label for each instance.

pos_label : None (default=None)

<Missing Description>

beta : float64 (default=None)

This is the beta value to use for F_β measure (default F1 measure is computed); must be greater than zero. Defaults is 1.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Calculate the accuracy, precision, confusion_matrix, recall and F_β measure for a classification model.

- The **f_measure** result is the F_β measure for a classification model. The F_β measure of a binary classification model is the harmonic mean of precision and recall. If we let:
  - beta $\equiv \beta$,
  - T_P denotes the number of true positives,
  - F_P denotes the number of false positives, and
  - F_N denotes the number of false negatives

  then:

  $$F_\beta = (1 + \beta^2) * \frac{\frac{T_P}{T_P + F_P} * \frac{T_P}{T_P + F_N}}{\beta^2 * \frac{T_P}{T_P + F_P} + \frac{T_P}{T_P + F_N}}$$

  The F_β measure for a multi-class classification model is computed as the weighted average of the F_β measure for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **recall** result of a binary classification model is the proportion of positive instances that are correctly identified. If we let T_P denote the number of true positives and F_N denote the number of false negatives, then the model recall is given by $\frac{T_P}{T_P + F_N}$.

  For multi-class classification models, the recall measure is computed as the weighted average of the recall for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **precision** of a binary classification model is the proportion of predicted positive instances that are correctly identified. If we let T_P denote the number of true positives and F_P denote the number of false positives, then the model precision is given by: $\frac{T_P}{T_P + F_P}$.

  For multi-class classification models, the precision measure is computed as the weighted average of the precision for each label, where the weight is the number of instances of each label. The determination of binary vs. multi-class is automatically inferred from the data.

- The **accuracy** of a classification model is the proportion of predictions that are correctly identified. If we let T_P denote the number of true positives, T_N denote the number of true negatives, and K denote the total number of classified instances, then the model accuracy is given by: $\frac{T_P + T_N}{K}$.

  This measure applies to binary and multi-class classifiers.

- The **confusion_matrix** result is a confusion matrix for a binary classifier model, formatted for human readability.

Notes

The **confusion_matrix** is not yet implemented for multi-class classifiers.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.27.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

> object <object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

20.28 *Commands* frame/column_median

Calculate the (weighted) median of a column.

20.28.1 POST /v1/commands/

20.28.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/column_median

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column : unicode

The column whose median is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the median calculation. Must contain numerical data. Default is all items have a weight of 1.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

The median is the least value X in the range of the distribution so that the cumulative weight of values strictly below X is strictly less than half of the total weight and the cumulative weight of values up to and including X is greater than or equal to one-half of the total weight.

All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If a weight column is provided and no weights are finite numbers greater than 0, None is returned.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.28.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

varies The median of the values. If a weight column is provided and no weights are finite numbers greater than 0, None is returned. The type of the median returned is the same as the contents of the data column, so a column of Longs will result in a Long median and a column of Floats will result in a Float median.

20.29 *Commands* frame/column_mode

Evaluate the weights assigned to rows.

20.29.1 POST /v1/commands/

20.29.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/column_mode

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column : unicode

Name of the column supplying the data.

weights_column : unicode (default=None)

Name of the column supplying the weights. Default is all items have weight of 1.

max_modes_returned : int32 (default=None)

Maximum number of modes returned. Default is 1.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Calculate the modes of a column. A mode is a data element of maximum weight. All data elements of weight less than or equal to 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight greater than 0, no mode is returned.

Because data distributions often have mutliple modes, it is possible for a set of modes to be returned. By default, only one is returned, but by setting the optional parameter max_modes_returned, a larger number of modes can be returned.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.29.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mode [A mode is a data element of maximum net weight.] A set of modes is returned. The empty set is returned when the sum of the weights is 0. If the number of modes is less than or equal to the parameter max_modes_returned, then all modes of the data are returned. If the number of modes is greater than the max_modes_returned parameter, only the first max_modes_returned many modes (per a canonical ordering) are returned.

weight_of_mode [Weight of a mode.] If there are no data elements of finite weight greater than 0, the weight of the mode is 0. If no weights column is given, this is the number of appearances of each mode.

total_weight [Sum of all weights in the weight column.] This is the row count if no weights are given. If no weights column is given, this is the number of rows in the table with non-zero weight.

mode_count [The number of distinct modes in the data.] In the case that the data is very multimodal, this number may exceed max_modes_returned.

20.30 *Commands* frame/column_summary_statistics

Calculate multiple statistics for a column.

20.30.1 POST /v1/commands/

20.30.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/column_summary_statistics

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column : unicode

The column to be statistically summarized. Must contain numerical data; all NaNs and infinite values are excluded from the calculation.

weights_column : unicode (default=None)

Name of column holding weights of column values.

use_population_variance : bool (default=None)

If true, the variance is calculated as the population variance. If false, the variance calculated as the sample variance. Because this option affects the variance, it affects the standard deviation and the confidence intervals as well. Default is false.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Notes

Sample Variance Sample Variance is computed by the following formula:

$$\left(\frac{1}{W-1}\right) * sum_i \ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Population Variance Population Variance is computed by the following formula:

$$\left(\frac{1}{W}\right) * sum_i \ (x_i - M)^2$$

where W is sum of weights over valid elements of positive weight, and M is the weighted mean.

Standard Deviation The square root of the variance.

Logging Invalid Data A row is bad when it contains a NaN or infinite value in either its data or weights column. In this case, it contributes to bad_row_count; otherwise it contributes to good row count.

A good row can be skipped because the value in its weight column is less than or equal to 0. In this case, it contributes to non_positive_weight_count, otherwise (when the weight is greater than 0) it contributes to valid_data_weight_pair_count.

Equations `bad_row_count + good_row_count = # rows in the frame`

`positive_weight_count + non_positive_weight_count = good_row_count`

In particular, when no weights column is provided and all weights are 1.0, `non_positive_weight_count = 0` and `positive_weight_count = good_row_count`

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.30.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

dict Dictionary containing summary statistics. The data returned is composed of multiple components:

mean [[double | None]] Arithmetic mean of the data.

geometric_mean [[double | None]] Geometric mean of the data. None when there is a data element <= 0, 1.0 when there are no data elements.

variance [[double | None]] None when there are <= 1 many data elements. Sample variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight minus 1. None when the sum of the weights is <= 1. Population variance is the weighted sum of the squared distance of each data element from the weighted mean, divided by the total weight.

standard_deviation [[double | None]] The square root of the variance. None when sample variance is being used and the sum of weights is <= 1.

total_weight [long] The count of all data elements that are finite numbers. (In other words, after excluding NaNs and infinite values.)

minimum [[double | None]] Minimum value in the data. None when there are no data elements.

maximum [[double | None]] Maximum value in the data. None when there are no data elements.

mean_confidence_lower [[double | None]] Lower limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

mean_confidence_upper [[double | None]] Upper limit of the 95% confidence interval about the mean. Assumes a Gaussian distribution. None when there are no elements of positive weight.

bad_row_count [[double | None]] The number of rows containing a NaN or infinite value in either the data or weights column.

good_row_count [[double | None]] The number of rows not containing a NaN or infinite value in either the data or weights column.

positive_weight_count [[double | None]] The number of valid data elements with weight > 0. This is the number of entries used in the statistical calculation.

non_positive_weight_count [[double | None]] The number valid data elements with finite weight <= 0.

20.31 *Commands* frame/compute_misplaced_score

20.31.1 POST /v1/commands/

20.31.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/compute_misplaced_score

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

gravity : float64

Similarity measure for computing tension between 2 connected items

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.31.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

20.32 *Commands* frame/copy

New frame with copied columns.

20.32.1 POST /v1/commands/

20.32.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

Note - An argument for this command requires a Python User-Defined Function (UDF). This function must be especially prepared (wrapped/serialized) in order for it to run in the engine. **If this argument is needed for your call (i.e. it may be optional), then this particular command usage is NOT practically available as a REST API.** Today, the trustedanalytics Python client does the special function preparation and calls this API.

name frame/copy

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

columns : None (default=None)

<Missing Description>

where : None (default=None)

<Missing Description>

name : unicode (default=None)

name of the frame copy

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Copies specified columns into a new Frame object, optionally renaming them and/or filtering them.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.32.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

New Frame object.

20.33 *Commands* frame/correlation

Calculate correlation for two columns of current frame.

20.33.1 POST /v1/commands/

20.33.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/correlation

arguments **frame** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column_names : list

The names of 2 columns from which to compute the correlation.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Notes

This method applies only to columns containing numerical data.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.33.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Pearson correlation coefficient of the two columns.

20.34 *Commands* frame/correlation_matrix

Calculate correlation matrix for two or more columns.

20.34.1 POST /v1/commands/

20.34.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/correlation_matrix

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column_names : list

The names of the columns from which to compute the matrix.

matrix_name : unicode (default=None)

The name for the returned matrix Frame.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Notes

This method applies only to columns containing numerical data.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.34.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

A Frame with the matrix of the correlation values for the columns.

20.35 *Commands* frame/count_where

Counts qualified rows.

20.35.1 POST /v1/commands/

20.35.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

Note - An argument for this command requires a Python User-Defined Function (UDF). This function must be especially prepared (wrapped/serialized) in order for it to run in the engine. **If this argument is needed for your call (i.e. it may be optional), then this particular command usage is NOT practically available as a REST API.** Today, the trustedanalytics Python client does the special function preparation and calls this API.

name frame/count_where

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

udf : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Counts rows which meet criteria specified by a UDF predicate.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.35.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Number of rows matching qualifications.

20.36 *Commands* frame/covariance

Calculate covariance for exactly two columns.

20.36.1 POST /v1/commands/

20.36.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/covariance

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column_names : list

The names of two columns from which to compute the covariance.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Notes

This method applies only to columns containing numerical data.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.36.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Covariance of the two columns.

20.37 *Commands* frame/covariance_matrix

Calculate covariance matrix for two or more columns.

20.37.1 POST /v1/commands/

20.37.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/covariance_matrix

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column_names : list

The names of the column from which to compute the matrix. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

matrix_name : unicode (default=None)

The name of the new matrix.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Notes

This function applies only to columns containing numerical data.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.37.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>`

A matrix with the covariance values for the columns.

20.38 *Commands* frame/cumulative_percent

[BETA] Add column to frame with cumulative percent sum.

20.38.1 POST /v1/commands/

20.38.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/cumulative_percent

arguments **frame** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

sample_col : unicode

The name of the column from which to compute the cumulative percent sum.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

A cumulative percent sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the current percentage of the total sum accounted for at the current value.

Notes

This method applies only to columns containing numerical data. Although this method will execute for columns containing negative values, the interpretation of the result will change (for example, negative percentages).

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.38.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.39 *Commands* frame/cumulative_sum

[BETA] Add column to frame with cumulative percent sum.

20.39.1 POST /v1/commands/

20.39.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/cumulative_sum

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Identifier for the input dataframe

sample_col : unicode

The name of the column from which to compute the cumulative sum.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

A cumulative sum is computed by sequentially stepping through the rows, observing the column values and keeping track of the cumulative sum for each value.

Notes

This method applies only to columns containing numerical data.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.39.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.40 *Commands* frame/dot_product

[ALPHA] Calculate dot product for each row in current frame.

20.40.1 POST /v1/commands/

20.40.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/dot_product

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

left_column_names : list

Names of columns used to create the left vector (A) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

right_column_names : list

Names of columns used to create right vector (B) for each row. Names should refer to a single column of type vector, or two or more columns of numeric scalars.

dot_product_column_name : unicode

Name of column used to store the dot product.

default_left_values : list (default=None)

Default values used to substitute null values in left vector. Default is None.

default_right_values : list (default=None)

Default values used to substitute null values in right vector. Default is None.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Calculate the dot product for each row in a frame using values from two equal-length sequences of columns.

Dot product is computed by the following formula:

The dot product of two vectors $A = [a_1, a_2, ..., a_n]$ and $B = [b_1, b_2, ..., b_n]$ is $a_1 * b_1 + a_2 * b_2 + ... + a_n * b_n$. The dot product for each row is stored in a new column in the existing frame.

Notes

If default_left_values or default_right_values are not specified, any null values will be replaced by zeros.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.40.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.41 *Commands* frame/drop_columns

Remove columns from the frame.

20.41.1 POST /v1/commands/

20.41.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/drop_columns

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

columns : list

Column name OR list of column names to be removed from the frame.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

The data from the columns is lost.

Notes

It is not possible to delete all columns from a frame. At least one column needs to remain. If it is necessary to delete all columns, then delete the frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.41.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.42 *Commands* frame/drop_duplicates

Modify the current frame, removing duplicate rows.

20.42.1 POST /v1/commands/

20.42.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/drop_duplicates

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

unique_columns : None (default=None)

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Remove data rows which are the same as other rows. The entire row can be checked for duplication, or the search for duplicates can be limited to one or more columns. This modifies the current frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.42.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.43 *Commands* frame/ecdf

Builds new frame with columns for data and distribution.

20.43.1 POST /v1/commands/

20.43.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/ecdf

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column : unicode

The name of the input column containing sample.

result_frame_name : unicode (default=None)

A name for the resulting frame which is created by this operation.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Generates the *empirical cumulative distribution* for the input column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.43.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

A new Frame containing each distinct value in the sample and its corresponding ECDF value.

20.44 *Commands* frame/entropy

Calculate the Shannon entropy of a column.

20.44.1 POST /v1/commands/

20.44.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/entropy

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

data_column : unicode

The column whose entropy is to be calculated.

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the entropy calculation. Must contain numerical data. Default is using uniform weights of 1 for all items.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

The data column is weighted via the weights column. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements with a finite weight greater than 0, the entropy is zero.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.44.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Entropy.

20.45 *Commands* frame/export_to_csv

Write current frame to HDFS in csv format.

20.45.1 POST /v1/commands/

20.45.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/export_to_csv

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

folder_name : unicode

The HDFS folder path where the files will be created.

separator : None (default=None)

<Missing Description>

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Export the frame to a file in csv format as a Hadoop file.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.45.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.46 *Commands* frame/export_to_hbase

Write current frame to HBase table.

20.46.1 POST /v1/commands/

20.46.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/export_to_hbase

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame being exported to HBase

table_name : unicode

The name of the HBase table that will contain the exported frame

key_column_name : unicode (default=None)

The name of the column to be used as row key in hbase table

family_name : unicode (default=None)

The family name of the HBase table that will contain the exported frame

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Table must exist in HBase. Export of Vectors is not currently supported.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.46.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.47 *Commands* frame/export_to_hive

Write current frame to Hive table.

20.47.1 POST /v1/commands/

20.47.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/export_to_hive

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

table_name : unicode

The name of the Hive table that will contain the exported frame

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Table must not exist in Hive. Export of Vectors is not currently supported.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.47.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.48 *Commands* frame/export_to_jdbc

Write current frame to Jdbc table.

20.48.1 POST /v1/commands/

20.48.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/export_to_jdbc

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame to be exported to jdbc

table_name : unicode

jdbc table name

connector_type : unicode (default=None)

(optional) jdbc connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Table will be created or appended to. Export of Vectors is not currently supported.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.48.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.49 *Commands* frame/export_to_json

Write current frame to HDFS in JSON format.

20.49.1 POST /v1/commands/

20.49.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/export_to_json

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

folder_name : unicode

The HDFS folder path where the files will be created.

count : int32 (default=None)

The number of records you want. Default, or a non-positive value, is the whole frame.

offset : int32 (default=None)

The number of rows to skip before exporting to the file. Default is zero (0).

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Export the frame to a file in JSON format as a Hadoop file.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.49.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.50 *Commands* frame/flatten_column

Spread data to multiple rows based on cell data.

20.50.1 POST /v1/commands/

20.50.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/flatten_column

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column : unicode

The column to be flattened.

delimiter : unicode (default=None)

The delimiter string. Default is comma (,).

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Splits cells in the specified column into multiple rows according to a string delimiter. New rows are a full copy of the original row, but the specified column only contains one value. The original row is deleted.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.50.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.51 *Commands* frame/group_by

[BETA] Summarized Frame with Aggregations.

20.51.1 POST /v1/commands/

20.51.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/group_by

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

group_by_columns : list

list of columns to group on

aggregations : list

the aggregations to perform

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Create a Summarized Frame with Aggregations (Avg, Count, Max, Min, Mean, Sum, Stdev, ...).

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.51.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>`

Summarized Frame.

20.52 *Commands* frame/histogram

[BETA] Compute the histogram for a column in a frame.

20.52.1 POST /v1/commands/

20.52.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/histogram

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column_name : unicode

Name of column to be evaluated.

num_bins : int32 (default=None)

Number of bins in histogram. Default is Square-root choice will be used (in other words math.floor(math.sqrt(frame.row_count)).

weight_column_name : unicode (default=None)

Name of column containing weights. Default is all observations are weighted equally.

bin_type : unicode (default=equalwidth)

The type of binning algorithm to use: [”equalwidth”|”equaldepth”] Defaults is “equalwidth”.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Compute the histogram of the data in a column. The returned value is a Histogram object containing 3 lists one each for: the cutoff points of the bins, size of each bin, and density of each bin.

Notes

The num_bins parameter is considered to be the maximum permissible number of bins because the data may dictate fewer bins. With equal depth binning, for example, if the column to be binned has 10 elements with only 2 distinct values and the *num_bins* parameter is greater than 2, then the number of actual number of bins will only be 2. This is due to a restriction that elements with an identical value must belong to the same bin.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.52.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

> **histogram** A Histogram object containing the result set. The data returned is composed of multiple components:
>
> **cutoffs** [array of float] A list containing the edges of each bin.
>
> **hist** [array of float] A list containing count of the weighted observations found in each bin.
>
> **density** [array of float] A list containing a decimal containing the percentage of observations found in the total set per bin.

20.53 *Commands* frame/loadhbase

Append data from an hBase table into an existing (possibly empty) FrameRDD

20.53.1 POST /v1/commands/

20.53.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/loadhbase

arguments **destination** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

table_name : unicode

hbase table name

schema : list

hbase schema as a list of tuples (columnFamily, columnName, dataType for cell value)

start_tag : unicode (default=None)

optional start tag for filtering

end_tag : unicode (default=None)

optional end tag for filtering

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Append data from an hBase table into an existing (possibly empty) FrameRDD

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.53.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

the initial FrameRDD with the hbase data appended

20.54 *Commands* frame/loadhive

Append data from a hive table into an existing (possibly empty) frame

20.54.1 POST /v1/commands/

20.54.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/loadhive

arguments **destination** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

DataFrame to load data into.Should be either a uri or id.

query : unicode

Initial query to run at load time

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Append data from a hive table into an existing (possibly empty) frame

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.54.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

the initial frame with the hive data appended

20.55 *Commands* frame/loadjdbc

Append data from a Jdbc table into an existing (possibly empty) frame

20.55.1 POST /v1/commands/

20.55.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/loadjdbc

arguments **destination** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

DataFrame to load data into.Should be either a uri or id.

table_name : unicode

table name

connector_type : unicode (default=None)

(optional) connector type

url : unicode (default=None)

(optional) connection url (includes server name, database name, user acct and password

driver_name : unicode (default=None)

(optional) driver name

query : unicode (default=None)

(optional) query for filtering. Not supported yet.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Append data from a Jdbc table into an existing (possibly empty) frame

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.55.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

the initial frame with the Jdbc data appended

20.56 *Commands* frame/quantiles

New frame with Quantiles and their values.

20.56.1 POST /v1/commands/

20.56.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/quantiles

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column_name : unicode

The column to calculate quantiles.

quantiles : list

What is being requested.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Calculate quantiles on the given column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.56.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

A new frame with two columns (float64): requested Quantiles and their respective values.

20.57 *Commands* frame/rename

Change the name of the current frame.

20.57.1 POST /v1/commands/

20.57.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/rename

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

new_name : unicode

The new name of the frame.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Set the name of this frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.57.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.58 *Commands* frame/sort

[BETA] Sort by one or more columns.

20.58.1 POST /v1/commands/

20.58.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/sort

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column_names_and_ascending : list

Column names to sort by, true for ascending, false for descending.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.58.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.59 *Commands* frame/sorted_k

[ALPHA] Get a sorted subset of the data.

20.59.1 POST /v1/commands/

20.59.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/sorted_k

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

k : int32

Number of sorted records to return.

column_names_and_ascending : list

Column names to sort by, and true to sort column by ascending order, or false for descending order.

reduce_tree_depth : int32 (default=None)

Advanced tuning parameter which determines the depth of the reduce-tree for the sorted_k plugin. This plugin uses Spark's treeReduce() for scalability. The default depth is 2.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Take the first k (sorted) rows for the currently active Frame. Rows are sorted by column values in either ascending or descending order.

Returning the first k (sorted) rows is more efficient than sorting the entire frame when k is much smaller than the number of rows in the frame.

Notes

The number of sorted rows (k) should be much smaller than the number of rows in the original frame.

In particular:

1. The number of sorted rows (k) returned should fit in Spark driver memory.

   The maximum size of serialized results that can fit in the Spark driver is set by the Spark configuration parameter *spark.driver.maxResultSize*.

2. If you encounter a Kryo buffer overflow exception, increase the Spark

   configuration parameter *spark.kryoserializer.buffer.max.mb*.

3. Use Frame.sort() instead if the number of sorted rows (k) is

   very large (i.e., cannot fit in Spark driver memory).

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.59.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>`

A new frame with the first k sorted rows from the original frame.

20.60 *Commands* frame/tally

[BETA] Count number of times a value is seen.

20.60.1 POST /v1/commands/

20.60.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/tally

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

sample_col : unicode

The name of the column from which to compute the cumulative count.

count_val : unicode

The column value to be used for the counts.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

A cumulative count is computed by sequentially stepping through the rows, observing the column values and keeping track of the the number of times the specified *count_value* has been seen.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.60.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.61 *Commands* frame/tally_percent

[BETA] Compute a cumulative percent count.

20.61.1 POST /v1/commands/

20.61.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/tally_percent

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

sample_col : unicode

The name of the column from which to compute the cumulative sum.

count_val : unicode

The column value to be used for the counts.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

A cumulative percent count is computed by sequentially stepping through the rows, observing the column values and keeping track of the percentage of the total number of times the specified *count_value* has been seen up to the current value.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.61.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.62 *Commands* frame/top_k

Most or least frequent column values.

20.62.1 POST /v1/commands/

20.62.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/top_k

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

column_name : unicode

The column whose top (or bottom) K distinct values are to be calculated.

k : int32

Number of entries to return (If k is negative, return bottom k).

weights_column : unicode (default=None)

The column that provides weights (frequencies) for the topK calculation. Must contain numerical data. Default is 1 for all items.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Calculate the top (or bottom) K distinct values by count of a column. The column can be weighted. All data elements of weight <= 0 are excluded from the calculation, as are all data elements whose weight is NaN or infinite. If there are no data elements of finite weight > 0, then topK is empty.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.62.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

An object with access to the frame of data.

20.63 *Commands* frame/unflatten_column

Compacts data from multiple rows based on cell data.

20.63.1 POST /v1/commands/

20.63.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name frame/unflatten_column

arguments **frame** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

composite_key_column_names : list

name of the user column to be used as keys for unflattening.

delimiter : unicode (default=None)

separator for the data in the result columns. Default is comma (,).

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Groups together cells in all columns (less the composite key) using "," as string delimiter. The original rows are deleted. The grouping takes place based on a composite key passed as arguments.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.63.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.64 *Commands* graph:/_info

Get debug info about a graph.

20.64.1 POST /v1/commands/

20.64.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/_info

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.64.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.65 *Commands* graph:/define_edge_type

Define an edge type.

20.65.1 POST /v1/commands/

20.65.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/define_edge_type

arguments **graph_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

label : unicode

Label of the edge type.

src_vertex_label : unicode

The src "type" of vertices this edge connects.

dest_vertex_label : unicode

The destination "type" of vertices this edge connects.

directed : bool (default=False)

True if edges are directed, false if they are undirected.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.65.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

_Unit

20.66 *Commands* graph:/define_vertex_type

Define a vertex type by label.

20.66.1 POST /v1/commands/

20.66.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/define_vertex_type

arguments **graph_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

label : unicode

Label of the vertex type.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.66.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.67 *Commands* graph:/edge_count

Get the total number of edges in the graph.

20.67.1 POST /v1/commands/

20.67.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/edge_count

arguments **graph** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.67.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.68 *Commands* graph:/export_to_titan

Convert current graph to TitanGraph.

20.68.1 POST /v1/commands/

20.68.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/export_to_titan

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

new_graph_name : unicode (default=None)

The name of the new graph. Default is None.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Convert this Graph into a TitanGraph object. This will be a new graph backed by Titan with all of the data found in this graph.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.68.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

A new TitanGraph.

20.69 *Commands* graph:/ml/kclique_percolation

[ALPHA] Find groups of vertices with similar attributes.

20.69.1 POST /v1/commands/

20.69.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/ml/kclique_percolation

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

clique_size : int32

The sizes of the cliques used to form communities. Larger values of clique size result in fewer, smaller communities that are more connected. Must be at least 2.

community_property_label : unicode

Name of the community property of vertex that will be updated/created in the graph. This property will contain for each vertex the set of communities that contain that vertex.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Community Detection Using the K-Clique Percolation Algorithm

Overview

Modeling data as a graph captures relations, for example, friendship ties between social network users or chemical interactions between proteins. Analyzing the structure of the graph reveals collections (often termed 'communities') of vertices that are more likely to interact amongst each other. Examples could include a community of friends in a social network or a collection of highly interacting proteins in a cellular process.

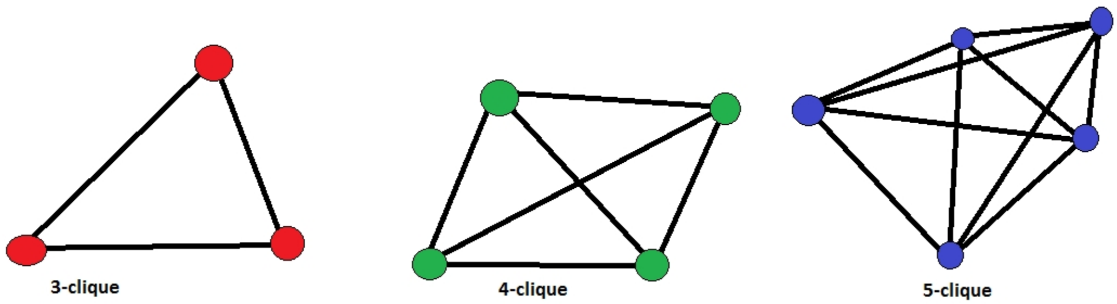
Trusted Analytics provides community detection using the k-Clique percolation method first proposed by Palla et. al. [3] that has been widely used in many contexts.

K-Clique Percolation

[3] G. Palla, I. Derenyi, I. Farkas, and T. Vicsek. Uncovering the overlapping community structure of complex networks in nature and society. Nature, 435:814, 2005 (See http://hal.elte.hu/cfinder/wiki/papers/communitylettm.pdf)

K-clique percolation is a method for detecting community structure in graphs. Here we provide mathematical background on how communities are defined in the context of the k-clique percolation algorithm.

A clique is a group of vertices in which every vertex is connected (via undirected edge) with every other vertex in the clique. This graphically looks like a triangle or a structure composed of triangles:

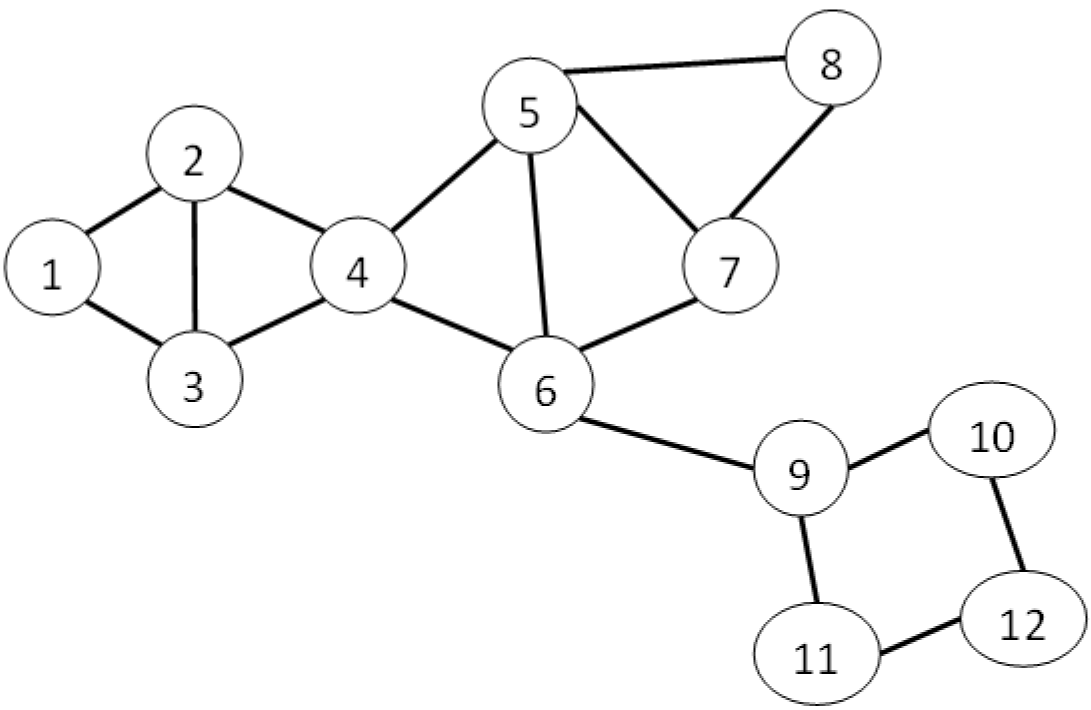


A clique is certainly a community in the sense that its vertices are all connected, but, it is too restrictive for most purposes, since it is natural some members of a community may not interact.

Mathematically, a k-clique has k vertices, each with $k - 1$ common edges, each of which connects to another vertex in the k-clique. The k-clique percolation method forms communities by taking unions of k-cliques that have $k - 1$ vertices in common.

K-Clique Example

In the graph below, the cliques are the sections defined by their triangular appearance and the 3-clique communities are $\{1, 2, 3, 4\}$ and $\{4, 5, 6, 7, 8\}$. The vertices 9, 10, 11, 12 are not in 3-cliques, therefore they do not belong to any community. Vertex 4 belongs to two distinct (but overlapping) communities.



Distributed Implementation of K-Clique Community Detection

The implementation of k-clique community detection in Trusted Analytics is a fully distributed implementation that follows the map-reduce algorithm proposed in Varamesh et. al. [4] .

[4] Varamesh, A.; Akbari, M.K.; Fereiduni, M.; Sharifian, S.; Bagheri, A., "Distributed Clique Percolation based community detection on social

It has the following steps:

1. All k-cliques are *enumerated*.
2. k-cliques are used to build a "clique graph" by declaring each k-clique to be a vertex in a new graph and placing edges between k-cliques that share k-1 vertices in the base graph.
3. A *connected component* analysis is performed on the clique graph. Connected components of the clique graph correspond to k-clique communities in the base graph.
4. The connected components information for the clique graph is projected back down to the base graph, providing each vertex with the set of k-clique communities to which it belongs.

Notes

Spawns a number of Spark jobs that cannot be calculated before execution (it is bounded by the diameter of the clique graph derived from the input graph). For this reason, the initial loading, clique enumeration and clique-graph construction steps are tracked with a single progress bar (this is most of the time), and then successive iterations of analysis of the clique graph are tracked with many short-lived progress bars, and then finally the result is written out.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.69.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

networks using MapReduce," Information and Knowledge Technology (IKT), 2013 5th Conference on, vol., no., pp.478,483, 28-30 May 2013

Response

Status

```
200 OK
```

Body

`dict`

Dictionary of vertex label and frame, Execution time.

20.70 *Commands* graph:/vertex_count

Get the total number of vertices in the graph.

20.70.1 POST /v1/commands/

20.70.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:/vertex_count

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.70.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.71 *Commands* graph:titan/export_to_graph

Export from ta.TitanGraph to ta.Graph.

20.71.1 POST /v1/commands/

20.71.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:titan/export_to_graph

arguments **graph** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.71.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.72 *Commands* graph:titan/graph_clustering

Performs graph clustering over an initial titan graph.

20.72.1 POST /v1/commands/

20.72.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:titan/graph_clustering

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

edge_distance : unicode

Column name for the edge distance.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Performs graph clustering over an initial titan graph using a distributed edge collapse algorithm.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.72.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.73 *Commands* graph:titan/query/gremlin

Executes a Gremlin query.

20.73.1 POST /v1/commands/

20.73.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:titan/query/gremlin

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

gremlin : unicode

The Gremlin script to execute.

Examples of Gremlin queries:

g.V[0..9] - Returns the first 10 vertices in graph g.V.userId - Returns the userId property from vertices g.V('name','hercules').out('father').out('father').name - Returns the name of Hercules' grandfather

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Executes a Gremlin query on an existing graph.

Notes

The query does not support pagination so the results of query should be limited using the Gremlin range filter [i..j], for example, g.V[0..9] to return the first 10 vertices.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.73.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

List of query results serialized to JSON and runtime of Gremlin query in seconds. The list of results is in GraphSON format(for vertices or edges) or JSON (for other results like counts). GraphSON is a JSON-based format for property graphs which uses reserved keys that begin with underscores to encode vertex and edge metadata.

Examples of valid GraphSON:

```
    { \"name\": \"lop\", \"lang\": \"java\",\"_id\": \"3\", \"_type\": \"vertex\" }
    { \"weight\": 1, \"_id\": \"8\", \"_type\": \"edge\", \"_outV\": \"1\", \"_inV\": \"4\", \"_labe
```

See https://github.com/tinkerpop/blueprints/wiki/GraphSON-Reader-and-Writer-Library

20.74 *Commands* graph:titan/vertex_sample

Make subgraph from vertex sampling.

20.74.1 POST /v1/commands/

20.74.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph:titan/vertex_sample

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

size : int32

The number of vertices to sample from the graph.

sample_type : unicode

The type of vertex sample among: ['uniform', 'degree', 'degreedist'].

seed : int64 (default=None)

Random seed value.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Create a vertex induced subgraph obtained by vertex sampling. Three types of vertex sampling are provided: 'uniform', 'degree', and 'degreedist'. A 'uniform' vertex sample is obtained by sampling vertices uniformly at random. For 'degree' vertex sampling, each vertex is weighted by its out-degree. For 'degreedist' vertex sampling, each vertex is weighted by the total number of vertices that have the same out-degree as it. That is, the weight applied to each vertex for 'degreedist' vertex sampling is given by the out-degree histogram bin size.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.74.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

A new Graph object representing the vertex induced subgraph.

20.75 *Commands* graph/annotate_degrees

Make new graph with degrees.

20.75.1 POST /v1/commands/

20.75.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/annotate_degrees

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

output_property_name : unicode

The name of the new property. The degree is stored in this property.

degree_option : unicode (default=None)

Indicator for the definition of degree to be used for the calculation. Permitted values:

- "out" (default value) : Degree is calculated as the out-degree.
- "in" : Degree is calculated as the in-degree.
- "undirected" : Degree is calculated as the undirected degree. (Assumes that the edges are all undirected.)

Any prefix of the strings "out", "in", "undirected" will select the corresponding option.

input_edge_labels : list (default=None)

If this list is provided, only edges whose labels are included in the given set will be considered in the degree calculation. In the default situation (when no list is provided), all edges will be used in the degree calculation, regardless of label.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creates a new graph which is the same as the input graph, with the addition that every vertex of the graph has its *degree* stored in a user-specified property.

Degree Calculation

A fundamental quantity in graph analyses is the degree of a vertex: The degree of a vertex is the number of edges adjacent to it.

For a directed edge relation, a vertex has both an out-degree (the number of edges leaving the vertex) and an in-degree (the number of edges entering the vertex).

The toolkit provides this routine for calculating the degrees of vertices. This calculation could be performed with a Gremlin query on smaller datasets because Gremlin queries cannot be executed on a distributed scale. The Trusted Analytics routine `annotate_degrees` can be executed at distributed scale.

In the presence of edge weights, vertices can have weighted degrees: The weighted degree of a vertex is the sum of weights of edges adjacent to it. Analogously, the weighted in-degree of a vertex is the sum of the weights of the edges entering it, and the weighted out-degree is the sum of the weights of the edges leaving the vertex.

The toolkit provides *annotate_weighted_degrees* for the distributed calculation of weighted vertex degrees.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.75.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a column storing the annotated degree for the vertex in a user specified property. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

20.76 *Commands* graph/annotate_weighted_degrees

Calculates the weighted degree of each vertex with respect to an (optional) set of labels.

20.76.1 POST /v1/commands/

20.76.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/annotate_weighted_degrees

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

output_property_name : unicode

property name of where to store output

degree_option : unicode (default=None)

choose from 'out', 'in', 'undirected'

input_edge_labels : list (default=None)

labels of edge types that should be included

edge_weight_property : unicode (default=None)

property name of edge weight, if not provided all edges are weighted equally

edge_weight_default : float64 (default=None)

default edge weight

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Pulls graph from underlying store, calculates weighted degrees and writes them into the property specified, and then writes the output graph to the underlying store.

Degree Calculation

A fundamental quantity in graph analyses is the degree of a vertex: The degree of a vertex is the number of edges adjacent to it.

For a directed edge relation, a vertex has both an out-degree (the number of edges leaving the vertex) and an in-degree (the number of edges entering the vertex).

The toolkit provides a routine *annotate_degrees* for calculating the degrees of vertices. This calculation could be performed with a Gremlin query on smaller datasets because Gremlin queries cannot be executed on a distributed scale. The Trusted Analytics routine `annotate_degrees` can be executed at distributed scale.

In the presence of edge weights, vertices can have weighted degrees: The weighted degree of a vertex is the sum of weights of edges adjacent to it. Analogously, the weighted in-degree of a vertex is the sum of the weights of the edges entering it, and the weighted out-degree is the sum of the weights of the edges leaving the vertex.

The toolkit provides this routine for the distributed calculation of weighted vertex degrees.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.76.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.77 *Commands* graph/clustering_coefficient

Coefficient of graph with respect to labels.

20.77.1 POST /v1/commands/

20.77.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/clustering_coefficient

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

output_property_name : unicode (default=None)

The name of the new property to which each vertex's local clustering coefficient will be written. If this option is not specified, no output frame will be produced and only the global clustering coefficient will be returned.

input_edge_labels : list (default=None)

If this list is provided, only edges whose labels are included in the given set will be considered in the clustering coefficient calculation. In the default situation (when no list is provided), all edges will be used in the calculation, regardless of label. It is required that all edges that enter into the clustering coefficient analysis be undirected.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Calculates the clustering coefficient of the graph with repect to an (optional) set of labels.

Pulls graph from underlying store, calculates degrees and writes them into the property specified, and then writes the output graph to the underlying store.

Warning: THIS FUNCTION IS FOR UNDIRECTED GRAPHS. If it is called on a directed graph, its output is NOT guaranteed to calculate the local directed clustering coefficients.

Clustering Coefficients

The clustering coefficient of a graph provides a measure of how tightly clustered an undirected graph is. Informally, if the edge relation denotes "friendship", the clustering coefficient of the graph is the probability that two people are friends given that they share a common friend.

More formally:

$$cc(G) = \frac{\| \{ (u,v,w) \in V^3 : \ \{u,v\}, \{u,w\}, \{v,w\} \in \ E \} \|}{\| \{ (u,v,w) \in V^3 : \ \{u,v\}, \{u,w\} \in E \} \|}$$

Analogously, the clustering coefficient of a vertex provides a measure of how tightly clustered that vertex's neighborhood is. Informally, if the edge relation denotes "friendship", the clustering coefficient at a vertex v is the probability that two acquaintances of v are themselves friends.

More formally:

$$cc(v) = \frac{\| \{ (u,v,w) \in V^3 : \ \{u,v\}, \{u,w\}, \{v,w\} \in \ E \} \|}{\| \{ (u,v,w) \in V^3 : \ \{v,u\}, \{v,w\} \in E \} \|}$$

The toolkit provides the function clustering_coefficient which computes both local and global clustering coefficients for a given undirected graph.

For more details on the mathematics and applications of clustering coefficients, see http://en.wikipedia.org/wiki/Clustering_coefficient.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.77.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Dictionary of the global clustering coefficient of the graph or, if local clustering coefficients are requested, a reference to the frame with local clustering coefficients stored at properties at each vertex.

20.78 *Commands* graph/copy

Make a copy of the current graph.

20.78.1 POST /v1/commands/

20.78.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

Note - An argument for this command requires a Python User-Defined Function (UDF). This function must be especially prepared (wrapped/serialized) in order for it to run in the engine. **If this argument is needed for your call (i.e. it may be optional), then this particular command usage is NOT practically available as a REST API.** Today, the trustedanalytics Python client does the special function preparation and calls this API.

name graph/copy

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

name : unicode (default=None)

The name for the copy of the graph. Default is None.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.78.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

A copy of the original graph.

20.79 *Commands* graph/graphx_connected_components

Implements the connected components computation on a graph by invoking graphx api.

20.79.1 POST /v1/commands/

20.79.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/graphx_connected_components

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

output_property : unicode

The name of the column containing the connected component value.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Pulls graph from underlying store, sends it off to the ConnectedComponentGraphXDefault, and then writes the output graph back to the underlying store.

Connected Components (CC)

Connected components are disjoint subgraphs in which all vertices are connected to all other vertices in the same component via paths, but not connected via paths to vertices in any other component. The connected components algorithm uses message passing along a specified edge type to find all of the connected components of a graph and label each edge with the identity of the component to which it belongs. The algorithm is specific to an edge type, hence in graphs with several different types of edges, there may be multiple, overlapping sets of connected components.

The algorithm works by assigning each vertex a unique numerical index and passing messages between neighbors. Vertices pass their indices back and forth with their neighbors and update their own index as the minimum of their current index and all other indices received. This algorithm continues until there is no change in any of the vertex indices. At the end of the alorithm, the unique levels of the indices denote the distinct connected components. The complexity of the algorithm is proportional to the diameter of the graph.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.79.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a connected component column. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

20.80 *Commands* graph/graphx_pagerank

Determine which vertices are the most important.

20.80.1 POST /v1/commands/

20.80.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/graphx_pagerank

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

output_property : unicode

Name of the property to which pagerank value will be stored on vertex and edge.

input_edge_labels : list (default=None)

List of edge labels to consider for pagerank computation. Default is all edges are considered.

max_iterations : int32 (default=None)

The maximum number of iterations that will be invoked. The valid range is all positive int. Invalid value will terminate with vertex page rank set to reset_probability. Default is 20.

reset_probability : float64 (default=None)

The probability that the random walk of a page is reset. Default is 0.15.

convergence_tolerance : float64 (default=None)

The amount of change in cost function that will be tolerated at convergence. If this parameter is specified, max_iterations is not considered as a stopping condition. If the change is less than this threshold, the algorithm exits earlier. The valid value range is all float and zero. Default is 0.001.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Pulls graph from underlying store, sends it off to the PageRankRunner, and then writes the output graph back to the underlying store.

This method (currently) only supports Titan for graph storage.

** Experimental Feature **

Basics and Background

PageRank is a method for determining which vertices in a directed graph are the most central or important. *PageRank* gives each vertex a score which can be interpreted as the probability that a person randomly walking along the edges of the graph will visit that vertex.

The calculation of *PageRank* is based on the supposition that if a vertex has many vertices pointing to it, then it is "important", and that a vertex grows in importance as more important vertices point to it. The calculation is based only on the network structure of the graph and makes no use of any side data, properties, user-provided scores or similar non-topological information.

PageRank was most famously used as the core of the Google search engine for many years, but as a general measure of *centrality* in a graph, it has other uses to other problems, such as *recommendation systems* and analyzing predator-prey food webs to predict extinctions.

Background references

- Basic description and principles: Wikipedia: PageRank[5]
- Applications to food web analysis: Stanford: Applications of PageRank[6]
- Applications to recommendation systems: PLoS: Computational Biology[7]

Mathematical Details of PageRank Implementation

The Trusted Analytics implementation of *PageRank* satisfies the following equation at each vertex v of the graph:

$$PR(v) = \frac{\rho}{n} + \rho \left(\sum_{u \in InSet(v)} \frac{PR(u)}{L(u)} \right)$$

Where:

v — a vertex
$L(v)$ — outbound degree of the vertex v
$PR(v)$ — *PageRank* score of the vertex v
$InSet(v)$ — set of vertices pointing to the vertex v
n — total number of vertices in the graph
ρ — user specified damping factor (also known as reset probability)

[5] http://en.wikipedia.org/wiki/PageRank
[6] http://web.stanford.edu/class/msande233/handouts/lecture8.pdf
[7] http://www.ploscompbiol.org/article/fetchObject.action?uri=info%3Adoi%2F10.1371%2Fjournal.pcbi.1000494&representation=PDF

Termination is guaranteed by two mechanisms.

- The user can specify a convergence threshold so that the algorithm will terminate when, at every vertex, the difference between successive approximations to the *PageRank* score falls below the convergence threshold.
- The user can specify a maximum number of iterations after which the algorithm will terminate.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.80.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

dict((vertex_dictionary, (label, Frame)), (edge_dictionary,(label,Frame))).

Dictionary containing dictionaries of labeled vertices and labeled edges.

For the *vertex_dictionary* the vertex type is the key and the corresponding vertex's frame with a new column storing the page rank value for the vertex. Call vertex_dictionary['label'] to get the handle to frame whose vertex type is label.

For the *edge_dictionary* the edge type is the key and the corresponding edge's frame with a new column storing the page rank value for the edge. Call edge_dictionary['label'] to get the handle to frame whose edge type is label.

20.81 *Commands* graph/graphx_triangle_count

Number of triangles among vertices of current graph.

20.81.1 POST /v1/commands/

20.81.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/graphx_triangle_count

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

output_property : unicode

The name of output property to be added to vertex/edge upon completion.

input_edge_labels : list (default=None)

The name of edge labels to be considered for triangle count. Default is all edges are considered.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

** Experimental Feature **

Counts the number of triangles among vertices in an undirected graph. If an edge is marked bidirectional, the implementation opts for canonical orientation of edges hence counting it only once (similar to an undirected graph).

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.81.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

dict(label, Frame).

Dictionary containing the vertex type as the key and the corresponding vertex's frame with a triangle_count column. Call dictionary_name['label'] to get the handle to frame whose vertex type is label.

20.82 *Commands* graph/ml/belief_propagation

Classification on sparse data using Belief Propagation.

20.82.1 POST /v1/commands/

20.82.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/ml/belief_propagation

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

prior_property : unicode

Name of the vertex property which contains the prior belief for the vertex.

posterior_property : unicode

Name of the vertex property which will contain the posterior belief for each vertex.

edge_weight_property : unicode (default=None)

Name of the edge property that contains the edge weight for each edge.

convergence_threshold : float64 (default=None)

Belief propagation will terminate when the average change in posterior beliefs between supersteps is less than or equal to this threshold.

max_iterations : int32 (default=None)

The maximum number of supersteps that the algorithm will execute. The valid range is all positive int.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Belief propagation by the sum-product algorithm. This algorithm analyzes a graphical model with prior beliefs using sum product message passing. The priors are read from a property in the graph, the posteriors are written to another property in the graph. This is the GraphX-based implementation of belief propagation.

See *Loopy Belief Propagation* for a more in-depth discussion of BP and LBP.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.82.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Progress report for belief propagation in the format of a multiple-line string.

20.83 *Commands* graph/rename

Rename a graph in the database.

20.83.1 POST /v1/commands/

20.83.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name graph/rename

arguments **graph** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b30d0>>

<Missing Description>

new_name : unicode

the new name for the graph

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.83.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.84 *Commands* model:collaborative_filtering/new

Collaborative filtering recommend model.

20.84.1 POST /v1/commands/

20.84.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:collaborative_filtering/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Collaborative Filtering

Collaborative filtering is a technique that is widely used in recommendation systems to suggest items (for example, products, movies, articles) to potential users based on historical records of items that users have purchased, rated, or viewed. The Trusted Analytics provides implementations of collaborative filtering with either Alternating Least Squares (ALS) or Conjugate Gradient Descent (CGD) optimization methods.

Both methods optimize the cost function found in Y. Koren, Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model[8] in ACM KDD 2008. For more information on optimizing using ALS see, Y. Zhou, D. Wilkinson, R. Schreiber and R. Pan, Large-Scale Parallel Collaborative Filtering for the Netflix Prize[9] , 2008.

CGD provides a faster, more approximate optimization of the cost function and should be used when memory is a constraint.

A typical representation of the preference matrix P in Giraph is a bi-partite graph, where nodes at the left side represent a list of users and nodes at the right side represent a set of items (for example, movies), and edges encode the rating a user provided to an item. To support training, validation and test, a common practice in machine learning, each edge is also annotated by "TR", "VA" or "TE".

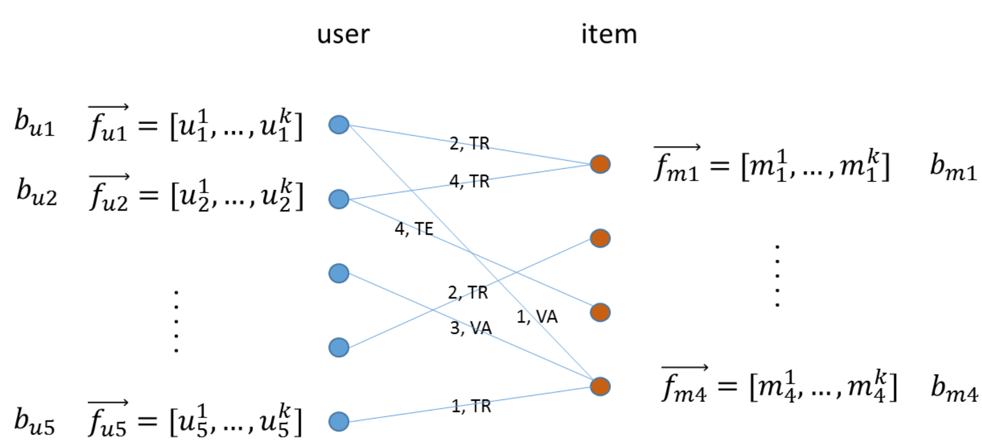


Fig. 20.1: A typical representation of the preference matrix P

Each node in the graph will be associated with a vector $\overrightarrow{f_x}$ of length k, where k is the feature dimension specified by the user, and a bias term b_x. The predictions for item m_j, from user u_i care given by dot product of the feature vector and the user vector, plus the item and user bias terms: /home/work/atk/engine-plugins/giraph-plugins/src/main/scala/org/trustedanalytics/atk/giraph/plugins/model/cf/CollaborativeFilteringNewPlugin.scala

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \ + b_{mj}$$

[8] http://public.research.att.com/ volinsky/netflix/kdd08koren.pdf

[9] http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.173.2797

The parameters of the above equation are chosen to minimize the regularized mean squared error between known and predicted ratings:

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2 \right)$$

How this optimization is accomplished depends on whether the use uses the ALS or CGD functions respectively. It is recommended that the ALS method be used to solve collaborative filtering problems. The CGD method uses less memory than ALS, but it returns an approximate solution to the objective function and should only be used in cases when memory required for ALS is prohibitively high.

Using ALS Optimization to Solve the Collaborative Filtering Problem

ALS optimizes the vector $\overrightarrow{f}_*$ and the bias b_* alternatively between user profiles using least squares on users and items. On the first iteration, the first feature of each item is set to its average rating, while the others are set to small random numbers. The algorithm then treats the m 's as constant and optimizes $u_i^1, ..., u_i^k$ for each user, i. For an individual user, this is a simple ordinary least squares optimization over the items that user has ranked. Next, the algorithm takes the u 's as constant and optimizes the $m_j^1, ..., m_j^k$ for each item, j. This is again an ordinary least squares optimization predicting the user rating of person that has ranked item j.

At each step, the bias is computed for either items of users and the objective function, shown below, is evaluated. The bias term for an item or user, computed for use in the next iteration is given by:

$$b = \frac{\sum error}{(1 + \lambda) * n}$$

The optimization is said to converge if the change in the objective function is less than the convergence_threshold parameter or the algorithm hits the maximum number of *supersteps*.

$$cost = \frac{\sum error^2}{n} + \lambda * \left(bias^2 + \sum f_k^2 \right)$$

Note that the equations above omit user and item subscripts for generality. The l_2 regularization term, lambda, tries to avoid overfitting by penalizing the magnitudes of the parameters, and λ is a tradeoff parameter that balances the two terms and is usually determined by cross validation (CV).

After the parameters $\overrightarrow{f}_*$ and b_* are determined, given an item m_j the rating from user u_i can be predicted by the simple linear model:

$$r_{ij} = \overrightarrow{f_{ui}} \cdot \overrightarrow{f_{mj}} + b_{ui} \ + b_{mj}$$

Matrix Factorization based on Conjugate Gradient Descent (CGD)

This is the Conjugate Gradient Descent (CGD) with Bias for collaborative filtering algorithm. Our implementation is based on the paper:

Y. Koren. Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model. In ACM KDD 2008. (Equation 5) http://public.research.att.com/~volinsky/netflix/kdd08koren.pdf

This algorithm for collaborative filtering is used in *recommendation systems* to suggest items (products, movies, articles, and so on) to potential users based on historical records of items that all users have purchased, rated, or viewed. The records are usually organized as a preference matrix P, which is a sparse matrix holding the preferences (such as, ratings) given by users to items. Similar to ALS, CGD falls in the category of matrix factorization/latent factor model that infers user profiles and item profiles in low-dimension space, such that the original matrix P can be approximated by a linear model.

This factorization method uses the conjugate gradient method for its optimization subroutine. For more on conjugate gradient descent in general, see: http://en.wikipedia.org/wiki/Conjugate_gradient_method.

The Mathematics of Matrix Factorization via CGD

Matrix factorization by conjugate gradient descent produces ratings by using the (limited) space of observed rankings to infer a user-factors vector p_u for each user u, and an item-factors vector q_i for each item i, and then producing a ranking by user u of item i by the dot-product $b_{ui} + p_u^T q_i$ where b_{ui} is a baseline ranking calculated as $b_{ui} = \mu + b_u + b_i$.

The optimum model is chosen to minimum the following sum, which penalizes square distance of the prediction from observed rankings and complexity of the model (through the regularization term):

$$\sum_{(u,i)\in\mathcal{K}} (r_{ui} - \mu - b_u - b_i - \ p_u^T q_i)^2 + \lambda_3(||p_u||^2 + ||q_i||^2 + \ b_u^2 + b_i^2)$$

Where:

r_{ui} — Observed ranking of item i by user u
$\mathcal{K}$ — Set of pairs (u, i) for each observed ranking of item i by user u
μ — The average rating over all ratings of all items by all users.
b_u — How much user u's average rating differs from μ.
b_i — How much item i's average rating differs from μ
p_u — User-factors vector.
q_i — Item-factors vector.
λ_3 — A regularization parameter specified by the user.

This optimization problem is solved by the conjugate gradient descent method. Indeed, this difference in how the optimization problem is solved is the primary difference between matrix factorization by CGD and matrix factorization by ALS.

Comparison between CGD and ALS

Both CGD and ALS provide recommendation systems based on matrix factorization; the difference is that CGD employs the conjugate gradient descent instead of least squares for its optimization phase. In particular, they share the same bipartite graph representation and the same cost function.

- ALS finds a better solution faster - when it can run on the cluster it is given.
- CGD has slighter memory requirements and can run on datasets that can overwhelm the ALS-based solution.

When feasible, ALS is a preferred solver over CGD, while CGD is recommended only when the application requires so much memory that it might be beyond the capacity of the system. CGD has a smaller memory requirement, but has a slower rate of convergence and can provide a rougher estimate of the solution than the more computationally intensive ALS.

The reason for this is that ALS solves the optimization problem by a least squares that requires inverting a matrix. Therefore, it requires more memory and computational effort. But ALS, a 2nd-order optimization method, enjoys higher convergence rate and is potentially more accurate in parameter estimation.

On the otherhand, CGD is a 1.5th-order optimization method that approximates the Hessian of the cost function from the previous gradient information through N consecutive CGD updates. This is very important in cases where the solution has thousands or even millions of components.

Usage

The matrix factorization by CGD procedure takes a property graph, encoding a biparite user-item ranking network, selects a subset of the edges to be considered (via a selection of edge labels), takes initial ratings from specified edge property values, and then writes each user-factors vector to its user vertex in a specified vertex property name and each item-factors vector to its item vertex in the specified vertex property name.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.84.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.85 *Commands* model:collaborative_filtering/recommend

[BETA] Collaborative filtering (als/cgd) model

20.85.1 POST /v1/commands/

20.85.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:collaborative_filtering/recommend

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode

An entity name from the first column of the input frame

top_k : int32

positive integer representing the top recommendations for the name

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

see collaborative filtering train for more information

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.85.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

see collaborative filtering train for more information

20.86 *Commands* model:collaborative_filtering/train

Collaborative filtering (als/cgd) model

20.86.1 POST /v1/commands/

20.86.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:collaborative_filtering/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

<Missing Description>

user_col_name : unicode

Name of the user column from input data

item_col_name : unicode

Name of the item column from input data

rating_col_name : unicode

Name of the rating column from input data

evaluation_function : unicode (default=None)

als/cgd

num_factors : int32 (default=None)

Size of the desired factors (default is 3)

max_iterations : int32 (default=None)

Max number of iterations for Giraph

convergence_threshold : float64 (default=None)

float value between 0 .. 1

regularization : float32 (default=None)

float value between 0 .. 1

bias_on : bool (default=None)

bias on/off switch

min_value : float32 (default=None)

minimum edge weight value

max_value : float32 (default=None)

minimum edge weight value

learning_curve_interval : int32 (default=None)

iteration interval to output learning curve

cgd_iterations : int32 (default=None)

custom argument for cgd learning curve output interval (default: every iteration)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.86.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Execution result summary for Giraph

20.87 *Commands* model:k_means/new

create a new model

20.87.1 POST /v1/commands/

20.87.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:k_means/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

name for the model

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.87.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.88 *Commands* model:k_means/predict

[BETA] Predict the cluster assignments for the data points.

20.88.1 POST /v1/commands/

20.88.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:k_means/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose clusters are to be predicted. By default, we predict the clusters over columns the KMeansModel was trained on. The columns are scaled using the same values used when training the model.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.88.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

Frame A new frame consisting of the existing columns of the frame and new columns. The data returned is composed of multiple components:

'k' columns [double] Containing squared distance of each point to every cluster center.

predicted_cluster [int] Integer containing the cluster assignment.

20.89 *Commands* model:k_means/publish

[BETA] Creates a tar file that will used as input to the scoring engine

20.89.1 POST /v1/commands/

20.89.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:k_means/publish

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Returns the HDFS path to the tar file

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.89.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.90 *Commands* model:k_means/train

[BETA] Creates KMeans Model from train frame.

20.90.1 POST /v1/commands/

20.90.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:k_means/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

observation_columns : list

Columns containing the observations.

column_scalings : list

Column scalings for each of the observation columns. The scaling value is multiplied by the corresponding value in the observation column.

k : int32 (default=None)

Desired number of clusters. Default is 2.

max_iterations : int32 (default=None)

Number of iterations for which the algorithm should run. Default is 20.

epsilon : float64 (default=None)

Distance threshold within which we consider k-means to have converged. Default is 1e-4.

initialization_mode : unicode (default=None)

The initialization technique for the algorithm. It could be either “random” or “k-means||”. Default is “k-means||”.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Upon training the ‘k’ cluster centers are computed.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.90.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

dict Results. The data returned is composed of multiple components:

cluster_size [dict] Cluster size

ClusterId [int] Number of elements in the cluster 'ClusterId'.

within_set_sum_of_squared_error [double] The set of sum of squared error for the model.

20.91 *Commands* model:lda/new

Creates Latent Dirichlet Allocation model

20.91.1 POST /v1/commands/

20.91.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:lda/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Topic Modeling with Latent Dirichlet Allocation

Topic modeling algorithms are a class of statistical approaches to partitioning items in a data set into subgroups. As the name implies, these algorithms are often used on corpora of textual data, where they are used to group documents in the collection into semantically-meaningful groupings. For an overall introduction to topic modeling, the reader might refer to the work of David Blei and Michael Jordan, who are credited with creating and popularizing topic modeling in the machine learning community. In particular, Blei's 2011 paper provides a nice introduction, and is freely-available online [10] .

LDA is a commonly-used algorithm for topic modeling, but, more broadly, is considered a dimensionality reduction technique. It contrasts with other approaches (for example, latent semantic indexing), in that it creates what's referred to as a generative probabilistic model — a statistical model that allows the algorithm to generalize its approach to topic assignment to other, never-before-seen data points. For the purposes of exposition, we'll limit the scope of our discussion of LDA to the world of natural language processing, as it has an intuitive use there (though LDA can be used on other types of data). In general, LDA represents documents as random mixtures over topics in the corpus. This makes sense because any work of writing is rarely about a single subject. Take the case of a news article on the President of the United States of America's approach to healthcare as an example. It would be reasonable to assign topics like President, USA, health insurance, politics, or healthcare to such a work, though it is likely to primarily discuss the President and healthcare.

[10] http://www.cs.princeton.edu/~blei/papers/Blei2011.pdf

LDA assumes that input corpora contain documents pertaining to a given number of topics, each of which are associated with a variety of words, and that each document is the result of a mixture of probabilistic samplings: first over the distribution of possible topics for the corpora, and second over the list of possible words in the selected topic. This generative assumption confers one of the main advantages LDA holds over other topic modeling approaches, such as probabilistic and regular LSI. As a generative model, LDA is able to generalize the model it uses to separate documents into topics to documents outside the corpora. For example, this means that using LDA to group online news articles into categories like Sports, Entertainment, and Politics, it would be possible to use the fitted model to help categorize newly-published news stories. Such an application is beyond the scope of approaches like LSI. What's more, when fitting an LSI model, the number of parameters that have to be estimated scale linearly with the number of documents in the corpus, whereas the number of parameters to estimate for an LDA model scales with the number of topics — a much lower number, making it much better-suited to working with large data sets.

The Typical Latent Dirichlet Allocation Workflow

Although every user is likely to have his or her own habits and preferred approach to topic modeling a document corpus, there is a general workflow that is a good starting point when working with new data. The general steps to the topic modeling with LDA include:

1. Data preparation and ingest
2. Assignment to training or testing partition
3. Graph construction
4. Training LDA
5. Evaluation
6. Interpretation of results

Data preparation and ingest

Most topic modeling workflows involve several data pre-processing and cleaning steps. Depending on the characteristics of the data being analyzed, there are different best-practices to use here, so it's important to be familiar with the standard procedures for analytics in the domain from which the text originated. For example, in the biomedical text analytics community, it is common practice for text analytics workflows to involve pre-processing for identifying negation statements (Chapman et al., 2001 [11]). The reason for this is many analysts in that domain are examining text for diagnostic statements — thus, failing to identify a negated statement in which a disease is mentioned could lead to undesirable false-positives, but this phenomenon may not arise in every domain. In general, both stemming and stop word filtering are recommended steps for topic modeling pre-processing. Stemming refers to a set of methods used to normalize different tenses and variations of the same word (for example, stemmer, stemming, stemmed, and stem). Stemming algorithms will normalize all variations of a word to one common form (for example, stem). There are many approaches to stemming, but the Porter Stemming (Porter, 2006 [12]) is one of the most commonly-used.

Removing common, uninformative words, or stop word filtering, is another commonly-used step in data pre-processing for topic modeling. Stop words include words like *the*, *and*, or *a*, but the full list of uninformative words can be quite long and depend on the domain producing the text in question. Example stop word lists online [13] can be a great place to start, but being aware of the best-practices in the applicalbe field is necessary to expand upon these.

There may be other pre-processing steps needed, depending on the type of text being worked with. Punctuation removal is frequently recommended, for example. To determine what's best for the text being analyzed, it helps to understand a bit about what how LDA analyzes the input text. To learn the topic model, LDA will typically look at the frequency of individual words across documents, which are determined based on space-separation. Thus, each word will be interpreted independent of where it occurs in a document, and without regard for the words that were written around it. In the text analytics field, this is often referred to as a *bag of words* approach to tokenization, the

[11] http://www.sciencedirect.com/science/article/pii/S1532046401910299
[12] http://tartarus.org/~martin/PorterStemmer/index.html
[13] http://www.textfixer.com/resources/common-english-words.txt

process of separating input text into composite features to be analyzed by some algorithm. When choosing pre-processing steps, it helps to keep this in mind. Don't worry too much about removing words or modifying their format — you're not manipulating your data! These steps simply make it easier for the topic modeling algorithm to find the latent topics that comprise your corpus.

Assignment to training or testing partition

The random assignment to training and testing partitions is an important step in most every machine learning workflow. It is common practice to withhold a random selection of one's data set for the purpose of evaluating the accuracy of the model that was learned from the training data. The results of this evaluation allow the user to confidently speak about the generalizability of the trained model. When speaking in these terms, be cautious that you only discuss generalizability to the broader population from which your data was originally obtained. If a topic model is trained on neuroscience-related publications, for example, evaluating the model on other neuroscience-related publications is valid. It would not be valid to discuss the model's ability to work on documents from other domains.

There are various schools of thought for how to assign a data set to training and testing collections, but all agree that the process should be random. Where analysts disagree is in the ratio of data to be assigned to each. In most situations, the bulk of data will be assigned to the training collection, because the more data that can be used to train the algorithm, the better the resultant model will typically be. It's also important that the testing collection have sufficient data to be able to reflect the characteristics of the larger population from which it was drawn (this becomes an important issue when working with data sets with rare topics, for example). As a starting point, many people will use a 90%/10% training/test collection split, and modify this ratio based on the characteristics of the documents being analyzed.

Graph construction

Trusted Analytics uses a bipartite graph, to learn an LDA topic model. This graph contains vertices in two columns. The left-hand column contains unique ids, each corresponding to a document in the training collection, while the right-hand column contains unique ids corresponding to each word in the entire training set, following any pre-processing steps that were used. Connections between these columns, or edges, denote the number of times a particular word appears in a document, with the weight on the edge in question denoting the number of times the word was found there. After graph construction, many analysts choose to normalize the weights using one of a variety of normalization schemes. One approach is to normalize the weights to sum to 1, while another is to use an approach called term frequency-inverse document frequency (tfidf), where the resultant weights are meant to reflect how important a word is to a document in the corpus. Whether to use normalization — or what technique to use — is an open question, and will likely depend on the characteristics of the text being analyzed. Typical text analytics experiments will try a variety of approaches on a small subset of the data to determine what works best.

See *Figure 1*.

Training the Model

In using LDA, we are trying to model a document collection in terms of topics $\beta_{1:K}$, where each β_K describes a distribution over the set of words in the training corpus. Every document d, then, is a vector of proportions θ_d, where $\theta_{d,k}$ is the proportion of the d^{th} document for topic k. The topic assignment for document d is z_d, and $z_{d,n}$ is the topic assignment for the n^{th} word in document d. The words observed in document d are :math"*w_{d}*, and $w_{d,n}$ is the n^{th} word in document d. The generative process for LDA, then, is the joint distribution of hidden and observed values

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{i=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p\left(z_{d,n}|\theta_d\right) p\left(w_{d,n}|\beta_{1:K}, z_{d,n}\right) \right)$$

This distribution depicts several dependencies: topic assignment $z_{d,n}$ depends on the topic proportions θ_d, and the observed word $w_{d,n}$ depends on topic assignment $z_{d,n}$ and all the topics $\beta_{1:K}$, for example. Although there are no analytical solutions to learning the LDA model, there are a variety of approximate solutions that are used, most of which are based on Gibbs Sampling (for example, Porteous et al., 2008 [14]). The Trusted Analytics uses an

[14] http://www.ics.uci.edu/~newman/pubs/fastlda.pdf

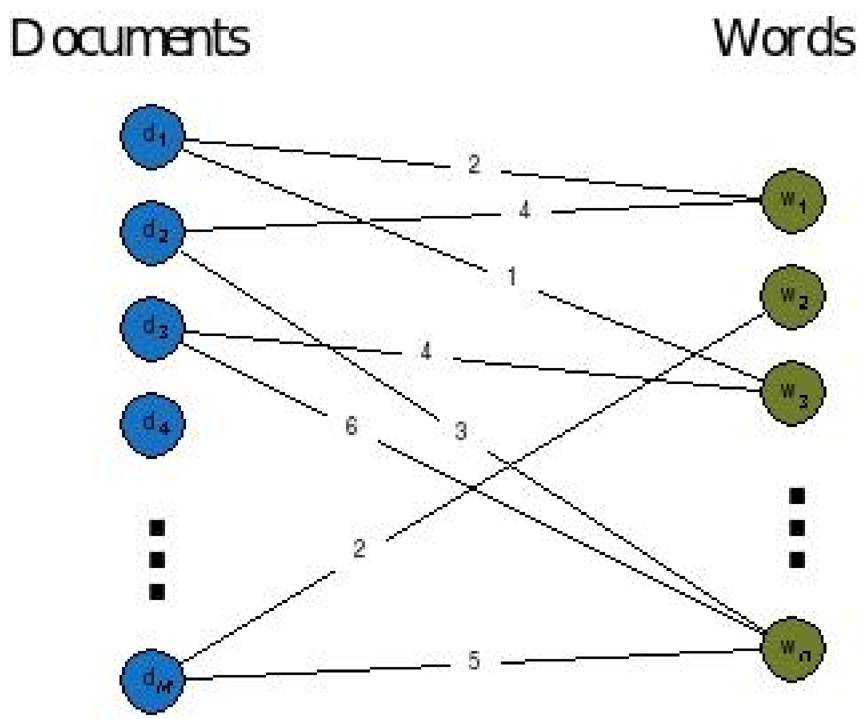


Fig. 20.2: Figure 1 - Example layout of a bipartite graph for LDA.
The left-hand column contains one vertex for each document in the input corpus, while the right-hand column contains vertices for each unique word found in them. Edges connecting left- and right-hand columns denote the number of times the word was found in the document the edge connects. The weights of the edges used in this example were not normalized.

implementation related to this. We refer the interested reader to the primary source on this approach to learn more (Teh et al., 2006 [15]).

Evaluation

As with every machine learning algorithm, evaluating the accuracy of the model that has been obtained is an important step before interpreting the results. With many types of algorithms, the best practices in this step are straightforward — in supervised classification, for example, we know the true labels of the data being classified, so evaluating performance can be as simple as computing the number of errors, calculating receiver operating characteristic, or F1 measure. With topic modeling, the situation is not so straightforward. This makes sense, if we consider with LDA we're using an algorithm to blindly identify logical subgroupings in our data, and we don't *a priori* know the best grouping that can be found. Evaluation, then, should proceed with this in mind, and an examination of homogeneity of the words comprising the documents in each grouping is often done. This issue is discussed further in Blei's 2011 introduction to topic modeling [16] . It is of course possible to evaluate a topic model from a statistical perspective using our hold-out testing document collection — and this is a recommended best practice — however, such an evaluation does not assess the topic model in terms of how they are typically used.

Interpretation of results

After running LDA on a document corpus, users will typically examine the top n most frequent words that can be found in each grouping. With this information, one is often able to use their own domain expertise to think of logical names for each topic (this situation is analogous to the step in principal components analysis, wherein statisticians will think of logical names for each principal component based on the mixture of dimensions each spans). Each document, then, can be assigned to a topic, based on the mixture of topics it has been assigned. Recall that LDA will assign each document a set of probabilities corresponding to each possible topic. Researchers will often set some threshold value to make a categorical judgment regarding topic membership, using this information.

footnotes

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.91.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

[15] http://machinelearning.wustl.edu/mlpapers/paper_files/NIPS2006_511.pdf
[16] http://www.cs.princeton.edu/~blei/papers/Blei2011.pdf

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.92 *Commands* model:lda/predict

[BETA] Predict conditional probabilities of topics given document.

20.92.1 POST /v1/commands/

20.92.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:lda/predict

arguments **model** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Reference to the model for which topics are to be determined.

document : list

Document whose topics are to be predicted.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predicts conditional probabilities of topics given document using trained Latent Dirichlet Allocation model. The input document is represented as a list of strings

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.92.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

dict Dictionary containing predicted topics. The data returned is composed of multiple components:

topics_given_doc [list of doubles] List of conditional probabilities of topics given document.

new_words_count [int] Count of new words in test document not present in training set.

new_words_percentage: double Percentage of new words in test document.

20.93 *Commands* model:lda/publish

[BETA] Creates a tar file that will used as input to the scoring engine

20.93.1 POST /v1/commands/

20.93.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:lda/publish

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creates a tar file with the trained Latent Dirichlet Allocation model. The tar file is used as input to the scoring engine to predict the conditional topic probabilities for a document.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.93.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Returns the HDFS path to the tar file

20.94 *Commands* model:lda/train

[BETA] Creates Latent Dirichlet Allocation model

20.94.1 POST /v1/commands/

20.94.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:lda/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Input frame data.

document_column_name : unicode

Column Name for documents. Column should contain a str value.

word_column_name : unicode

Column name for words. Column should contain a str value.

word_count_column_name : unicode

Column name for word count. Column should contain an int32 or int64 value.

max_iterations : int32 (default=None)

The maximum number of iterations that the algorithm will execute. The valid value range is all positive int. Default is 20.

alpha : float32 (default=None)

The hyper-parameter for document-specific distribution over topics. Mainly used as a smoothing parameter in *Bayesian inference*. Larger value implies that documents are assumed to cover all topics more uniformly; smaller value implies that documents are more concentrated on a small subset of topics. Valid value range is all positive float.

Default is 0.1.

beta : float32 (default=None)

The hyper-parameter for word-specific distribution over topics. Mainly used as a smoothing parameter in *Bayesian inference*. Larger value implies that topics contain all words more uniformly and smaller value implies that topics are more concentrated on a small subset of words. Valid value range is all positive float. Default is 0.1.

convergence_threshold : float32 (default=None)

The amount of change in LDA model parameters that will be tolerated at convergence. If the change is less than this threshold, the algorithm exits before it reaches the maximum number of supersteps. Valid value range is all positive float and 0.0. Default is 0.001.

evaluate_cost : bool (default=None)

"True" means turn on cost evaluation and "False" means turn off cost evaluation. It's relatively expensive for LDA to evaluate cost function. For time-critical applications, this option allows user to turn off cost function evaluation. Default is "False".

num_topics : int32 (default=None)

The number of topics to identify in the LDA model. Using fewer topics will speed up the computation, but the extracted topics might be more abstract or less specific; using more topics will result in more computation but lead to more specific topics. Valid value range is all positive int. Default is 10.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

See the discussion about Latent Dirichlet Allocation at Wikipedia.[17]

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.94.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

[17] http://en.wikipedia.org/wiki/Latent_Dirichlet_allocation

dict The data returned is composed of multiple components:

topics_given_doc [Frame] Frame with conditional probabilities of topic given document.

word_given_topics [Frame] Frame with conditional probabilities of word given topic.

topics_given_word [Frame] Frame with conditional probabilities of topic given word.

report [str] The configuration and learning curve report for Latent Dirichlet Allocation as a multiple line str.

20.95 *Commands* model:libsvm/new

[ALPHA] model:libsvm/new

20.95.1 POST /v1/commands/

20.95.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:libsvm/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.95.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>`

20.96 *Commands* model:libsvm/predict

[ALPHA] New frame with new predicted label column.

20.96.1 POST /v1/commands/

20.96.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:libsvm/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. Default is the columns the LibsvmModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.96.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

A new frame containing the original frame's columns and a column *predicted_label* containing the score calculated for each observation.

20.97 *Commands* model:libsvm/publish

[BETA] Creates a tar file that will used as input to the scoring engine

20.97.1 POST /v1/commands/

20.97.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:libsvm/publish

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Returns the HDFS path to the tar file

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.97.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.98 *Commands* model:libsvm/score

[ALPHA] Calculate the prediction label for a single observation.

20.98.1 POST /v1/commands/

20.98.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:libsvm/score

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

vector : None

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.98.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Predicted label.

20.99 *Commands* model:libsvm/test

[ALPHA] Predict test frame labels and return metrics.

20.99.1 POST /v1/commands/

20.99.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:libsvm/test

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted.

label_column : unicode

Column containing the actual label for each observation.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted and tested. Default is to test over the columns the LibsvmModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and run classification metrics on predicted and target labels.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.99.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Object Object with binary classification metrics. The data returned is composed of multiple components:

<object>.accuracy [double] The degree of correctness of the test frame labels.

<object>.confusion_matrix [table] A specific table layout that allows visualization of the performance of the test.

<object>.f_measure [double] A measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score.

<object>.precision [double] The degree to which the correctness of the label is expressed.

<object>.recall [double] The fraction of relevant instances that are retrieved.

20.100 *Commands* model:libsvm/train

[ALPHA] Train Lib Svm model based on another frame.

20.100.1 POST /v1/commands/

20.100.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:libsvm/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

svm_type : int32 (default=2)

Set type of SVM. Default is one-class SVM.

0 – C-SVC 1 – nu-SVC 2 – one-class SVM 3 – epsilon-SVR 4 – nu-SVR

kernel_type : int32 (default=2)

Specifies the kernel type to be used in the algorithm. Default is RBF.

0 – linear: u'*v 1 – polynomial: (gamma*u'*v + coef0)^degree 2 – radial basis function: exp(-gamma*|u-v|^2) 3 – sigmoid: tanh(gamma*u'*v + coef0)

weight_label : list (default=None)

Default is (Array[Int](0))

weight : list (default=None)

Default is (Array[Double](0.0))

epsilon : float64 (default=0.001)

Set tolerance of termination criterion

degree : int32 (default=3)

Degree of the polynomial kernel function ('poly'). Ignored by all other kernels.

gamma : float64 (default=None)

Kernel coefficient for 'rbf', 'poly' and 'sigmoid'. Default is 1/n_features.

coef : float64 (default=0.0)

Independent term in kernel function. It is only significant in 'poly' and 'sigmoid'.

nu : float64 (default=0.5)

Set the parameter nu of nu-SVC, one-class SVM, and nu-SVR.

cache_size : float64 (default=100.0)

Specify the size of the kernel cache (in MB).

shrinking : int32 (default=1)

Whether to use the shrinking heuristic. Default is 1 (true).

probability : int32 (default=0)

Whether to enable probability estimates. Default is 0 (false).

nr_weight : int32 (default=1)

NR Weight

c : float64 (default=1.0)

Penalty parameter c of the error term.

p : float64 (default=0.1)

Set the epsilon in loss function of epsilon-SVR.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a lib Svm Model using the observation column and label column of the train frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.100.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.101 *Commands* model:linear_regression/new

20.101.1 POST /v1/commands/

20.101.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:linear_regression/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.101.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.102 *Commands* model:linear_regression/predict

[ALPHA] Make new frame with column for label prediction.

20.102.1 POST /v1/commands/

20.102.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:linear_regression/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the LogisticRegressionModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.102.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

Frame containing the original frame's columns and a column with the predicted label.

20.103 *Commands* model:linear_regression/train

[ALPHA] Build linear regression model.

20.103.1 POST /v1/commands/

20.103.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:linear_regression/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

intercept : bool (default=None)

The algorithm adds an intercept. Default is true.

num_iterations : int32 (default=None)

Number of iterations. Default is 100.

step_size : int32 (default=None)

Step size for optimizer. Default is 1.0.

reg_type : unicode (default=None)

Regularization L1 or L2. Default is L2.

reg_param : float64 (default=None)

Regularization parameter. Default is 0.01.

mini_batch_fraction : float64 (default=None)

Mini batch fraction parameter. Default is 1.0.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a LinearRegression Model using the observation column and label column of the train frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.103.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.104 *Commands* model:logistic_regression/new

Create a 'new' instance of logistic regression model.

20.104.1 POST /v1/commands/

20.104.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:logistic_regression/new

arguments dummy_model_ref : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.104.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.105 *Commands* model:logistic_regression/predict

[ALPHA] Make a new frame with a column for label prediction.

20.105.1 POST /v1/commands/

20.105.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:logistic_regression/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the LogisticRegressionModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.105.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>`

Frame containing the original frame's columns and a column with the predicted label.

20.106 *Commands* model:logistic_regression/test

[ALPHA] Predict test frame labels and show metrics.

20.106.1 POST /v1/commands/

20.106.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:logistic_regression/test

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

frame whose labels are to be predicted.

label_column : unicode

Column containing the actual label for each observation.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted and tested. Default is to test over the columns the SvmModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and run classification metrics on predicted and target labels.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.106.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

object An object with binary classification metrics. The data returned is composed of multiple components:

<object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

20.107 *Commands* model:logistic_regression/train

[ALPHA] Build logistic regression model.

20.107.1 POST /v1/commands/

20.107.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:logistic_regression/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

frequency_column : unicode (default=None)

Optional column containing the frequency of observations.

num_classes : int32 (default=2)

Number of classes

optimizer : unicode (default=LBFGS)

Set type of optimizer. LBFGS - Limited-memory BFGS. LBFGS supports multinomial logistic regression. SGD - Stochastic Gradient Descent. SGD only supports binary logistic regression.

compute_covariance : bool (default=True)

If true, compute covariance matrix for the model.

intercept : bool (default=True)

If true, add intercept column to training data.

feature_scaling : bool (default=False)

If true, perform feature scaling before training model.

threshold : float64 (default=0.5)

Threshold for separating positive predictions from negative predictions.

reg_type : unicode (default=L2)

Set type of regularization L1 - L1 regularization with sum of absolute values of coefficients L2 - L2 regularization with sum of squares of coefficients

reg_param : float64 (default=0.0)

Regularization parameter

num_iterations : int32 (default=100)

Maximum number of iterations

convergence_tolerance : float64 (default=0.0001)

Convergence tolerance of iterations for L-BFGS. Smaller value will lead to higher accuracy with the cost of more iterations.

num_corrections : int32 (default=10)

Number of corrections used in LBFGS update. Default 10. Values of numCorrections less than 3 are not recommended; large values of numCorrections will result in excessive computing time.

mini_batch_fraction : float64 (default=1.0)

Fraction of data to be used for each SGD iteration

step_size : int32 (default=1)

Initial step size for SGD. In subsequent steps, the step size decreases by stepSize/sqrt(t)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a LogisticRegression Model using the observation column and label column of the train frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.107.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

object An object with a summary of the trained model. The data returned is composed of multiple components:

numFeatures [Int] Number of features in the training data

numClasses [Int] Number of classes in the training data

summaryTable: table A summary table composed of:

covarianceMatrix: Frame (optional) Covariance matrix of the trained model. The covariance matrix is the inverse of the Hessian matrix for the trained model. The Hessian matrix is the second-order partial derivatives of the model's log-likelihood function

“”

20.108 *Commands* model:naive_bayes/new

create a new model

20.108.1 POST /v1/commands/

20.108.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:naive_bayes/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.108.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.109 *Commands* model:naive_bayes/predict

[ALPHA] Predict

20.109.1 POST /v1/commands/

20.109.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:naive_bayes/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the NaiveBayesModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.109.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

20.110 *Commands* model:naive_bayes/train

[ALPHA] Build a naive bayes model.

20.110.1 POST /v1/commands/

20.110.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:naive_bayes/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

lambda_parameter : float64 (default=None)

Additive smoothing parameter Default is 1.0.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Train a NaiveBayesModel using the observation column, label column of the train frame and an optional lambda value.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.110.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.111 *Commands* model:principal_components/new

Create a 'new' instance of principal component model.

20.111.1 POST /v1/commands/

20.111.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:principal_components/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.111.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.112 *Commands* model:principal_components/predict

[ALPHA] Predict using principal components model.

20.112.1 POST /v1/commands/

20.112.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:principal_components/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle to the model to be used.

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

Frame whose principal components are to be computed.

mean_centered : bool (default=True)

Option to mean center the columns. Default is true

t_squared_index : bool (default=False)

Indicator for whether the t-square index is to be computed. Default is false.

observation_columns : list (default=None)

List of observation column name(s) to be used for prediction. Default is the list of column name(s) used to train the model.

c : int32 (default=None)

The number of principal components to be predicted. Default is the count used to train the model.

name : unicode (default=None)

The name of the output frame generated by predict.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predicting on a dataframe's columns using a PrincipalComponents Model.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.112.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

A frame with existing columns and ‘c’ additional columns containing the projections of V on the the frame and an additional column storing the t-square-index value if requested

20.113 *Commands* model:principal_components/publish

[BETA] Creates a tar file that will be used as input to the scoring engine

20.113.1 POST /v1/commands/

20.113.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:principal_components/publish

arguments **model** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creates a tar file with the trained Principal Components Model. The tar file is used as input to the scoring engine to compute the principal components and t-squared index of the observation.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.113.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Returns the HDFS path to the tar file

20.114 *Commands* model:principal_components/train

Build principal components model.

20.114.1 POST /v1/commands/

20.114.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:principal_components/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle to the model to be used.

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

observation_columns : list

List of column(s) containing the observations.

mean_centered : bool (default=True)

Option to mean center the columns

k : int32 (default=None)

Principal component count. Default is the number of observation columns

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a PrincipalComponents Model using the observation columns.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.114.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.115 *Commands* model:random_forest_classifier/new

Create a 'new' instance of random forest classifier model.

20.115.1 POST /v1/commands/

20.115.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_classifier/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.115.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

20.116 *Commands* model:random_forest_classifier/predict

[ALPHA] Predict the labels for the data points.

20.116.1 POST /v1/commands/

20.116.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_classifier/predict

arguments **model** : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle of the model to be used

frame : <bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the RandomForestModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.116.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

Frame A new frame consisting of the existing columns of the frame and a new column with predicted label for each observation.

20.117 *Commands* model:random_forest_classifier/publish

[BETA] Creates a tar file that will be used as input to the scoring engine

20.117.1 POST /v1/commands/

20.117.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_classifier/publish

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creates a tar file with the trained Random Forest Classifier Model The tar file is used as input to the scoring engine to predict the class of an observation.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.117.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Returns the HDFS path to the tar file

20.118 *Commands* model:random_forest_classifier/test

[ALPHA] Predict test frame labels and return metrics.

20.118.1 POST /v1/commands/

20.118.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_classifier/test

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle of the model to be used

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

The frame whose labels are to be predicted

label_column : unicode

Column containing the true labels of the observations

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the RandomForest was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and run classification metrics on predicted and target labels.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.118.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

object

An object with classification metrics. The data returned is composed of multiple components:

<object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

20.119 *Commands* model:random_forest_classifier/train

[ALPHA] Build Random Forests Classifier model.

20.119.1 POST /v1/commands/

20.119.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_classifier/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle to the model to be used.

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

num_classes : int32 (default=2)

Number of classes for classification

num_trees : int32 (default=1)

Number of tress in the random forest

impurity : unicode (default=gini)

Criterion used for information gain calculation. Supported values “gini” or “entropy”

max_depth : int32 (default=4)

Maximum depth of the tree

max_bins : int32 (default=100)

Maximum number of bins used for splitting features

seed : int32 (default=-1262125077)

Random seed for bootstrapping and choosing feature subsets

categorical_features_info : None (default=None)

<Missing Description>

feature_subset_category : unicode (default=None)

Number of features to consider for splits at each node. Supported values “auto”,”all”,”sqrt”,”log2”,”onethird”

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a Random Forests Classifier Model using the observation columns and label column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.119.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.120 *Commands* model:random_forest_regressor/new

<Missing Doc>

20.120.1 POST /v1/commands/

20.120.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_regressor/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.120.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>`

20.121 *Commands* model:random_forest_regressor/predict

[ALPHA] Predict the values for the data points.

20.121.1 POST /v1/commands/

20.121.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_regressor/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle of the model to be used

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the RandomForestModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.121.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

Frame A new frame consisting of the existing columns of the frame and a new column with predicted value for each observation.

20.122 *Commands* model:random_forest_regressor/publish

[BETA] Creates a tar file that will be used as input to the scoring engine

20.122.1 POST /v1/commands/

20.122.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_regressor/publish

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creates a tar file with the trained Random Forest Regressor Model The tar file is used as input to the scoring engine to predict the value of an observation.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.122.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

Returns the HDFS path to the tar file

20.123 *Commands* model:random_forest_regressor/train

[ALPHA] Build Random Forests Regressor model.

20.123.1 POST /v1/commands/

20.123.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:random_forest_regressor/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

Handle to the model to be used.

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on

label_column : unicode

Column name containing the label for each observation

observation_columns : list

Column(s) containing the observations

num_trees : int32 (default=1)

Number of tress in the random forest

impurity : unicode (default=variance)

Criterion used for information gain calculation. Supported values "variance"

max_depth : int32 (default=4)

Maxium depth of the tree

max_bins : int32 (default=100)

Maximum number of bins used for splitting features

seed : int32 (default=-544689744)

Random seed for bootstrapping and choosing feature subsets

categorical_features_info : None (default=None)

<Missing Description>

feature_subset_category : unicode (default=None)

Number of features to consider for splits at each node. Supported values "auto", "all", "sqrt","log2", "onethird"

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a Random Forests Regressor Model using the observation columns and label column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.123.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

20.124 *Commands* model:svm/new

[ALPHA] create a new model

20.124.1 POST /v1/commands/

20.124.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:svm/new

arguments **dummy_model_ref** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

name : unicode (default=None)

User supplied name.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.124.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`<bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>`

20.125 *Commands* model:svm/predict

[ALPHA] Make new frame with additional column for predicted label.

20.125.1 POST /v1/commands/

20.125.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:svm/predict

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame whose labels are to be predicted. By default, predict is run on the same columns over which the model is trained.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted. By default, we predict the labels over columns the LogisticRegressionModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and create a new frame revision with existing columns and a new predicted label's column.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.125.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>
```

A frame containing the original frame's columns and a column with the predicted label

20.126 *Commands* model:svm/test

[ALPHA] Predict test frame labels and return metrics.

20.126.1 POST /v1/commands/

20.126.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:svm/test

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

frame whose labels are to be predicted.

label_column : unicode

Column containing the actual label for each observation.

observation_columns : list (default=None)

Column(s) containing the observations whose labels are to be predicted and tested. Default is to test over the columns the SvmModel was trained on.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Predict the labels for a test frame and run classification metrics on predicted and target labels.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.126.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`dict`

object

An object with binary classification metrics. The data returned is composed of multiple components:

<object>.accuracy : double <object>.confusion_matrix : table <object>.f_measure : double <object>.precision : double <object>.recall : double

20.127 *Commands* model:svm/train

[ALPHA] Train SVM model based on another frame.

20.127.1 POST /v1/commands/

20.127.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model:svm/train

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

frame : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3090>>

A frame to train the model on.

label_column : unicode

Column name containing the label for each observation.

observation_columns : list

Column(s) containing the observations.

intercept : bool (default=None)

The algorithm adds an intercept. Default is true.

num_iterations : int32 (default=None)

Number of iterations. Default is 100.

step_size : int32 (default=None)

Step size for optimizer. Default is 1.0.

reg_type : unicode (default=None)

Regularization L1 or L2. Default is L2.

reg_param : float64 (default=None)

Regularization parameter. Default is 0.01.

mini_batch_fraction : float64 (default=None)

Mini batch fraction parameter. Default is 1.0.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Creating a SVM Model using the observation column and label column of the train frame.

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.127.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

`_Unit`

20.128 *Commands* model/rename

rename a model

20.128.1 POST /v1/commands/

20.128.2 GET /v1/commands/:id

Request

Route

```
POST /v1/commands/
```

Body

name model/rename

arguments **model** : <bound method AtkEntityType.__name__ of <trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>

<Missing Description>

new_name : unicode

The name to which the model will be renamed.

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Description

Response

Status

```
200 OK
```

Body

Returns information about the command. See the Response Body for Get Command here below. It is the same.

20.128.3 GET /v1/commands/:id

Request

Route

```
GET /v1/commands/18
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

```
<bound method AtkEntityType.__name__ of
<trustedanalytics.rest.jsonschema.AtkEntityType object at 0x7f3d406b3110>>
```

20.129 Command List

Command Name (explained here)	Description
frame/add_columns	Add columns to current frame.
frame/assign_sample	Randomly group rows into user-defined classes.
frame/bin_column	Classify data into user-defined groups.
frame/bin_column_equal_depth	Classify column into groups with the same frequency.
frame/bin_column_equal_width	Classify column into same-width groups.
frame/categorical_summary	Build summary of the data.
frame/classification_metrics	Model statistics of accuracy, precision, and others.
frame/column_median	Calculate the (weighted) median of a column.
frame/column_mode	Evaluate the weights assigned to rows.
frame/column_summary_statistics	Calculate multiple statistics for a column.
frame/compute_misplaced_score	
frame/copy	New frame with copied columns.
frame/correlation	Calculate correlation for two columns of current frame.
frame/correlation_matrix	Calculate correlation matrix for two or more columns.
frame/count_where	Counts qualified rows.
frame/covariance	Calculate covariance for exactly two columns.

Continued on next page

Table 20.1 – continued from previous page

Command Name (explained here)	Description
frame/covariance_matrix	Calculate covariance matrix for two or more columns.
frame/cumulative_percent	[BETA] Add column to frame with cumulative percent sum.
frame/cumulative_sum	[BETA] Add column to frame with cumulative percent sum.
frame/dot_product	[ALPHA] Calculate dot product for each row in current frame.
frame/drop_columns	Remove columns from the frame.
frame/drop_duplicates	Modify the current frame, removing duplicate rows.
frame/ecdf	Builds new frame with columns for data and distribution.
frame/entropy	Calculate the Shannon entropy of a column.
frame/export_to_csv	Write current frame to HDFS in csv format.
frame/export_to_hbase	Write current frame to HBase table.
frame/export_to_hive	Write current frame to Hive table.
frame/export_to_jdbc	Write current frame to Jdbc table.
frame/export_to_json	Write current frame to HDFS in JSON format.
frame/flatten_column	Spread data to multiple rows based on cell data.
frame/group_by	[BETA] Summarized Frame with Aggregations.
frame/histogram	[BETA] Compute the histogram for a column in a frame.
frame/loadhbase	Append data from an hBase table into an existing (possibly empty) FrameRDD
frame/loadhive	Append data from a hive table into an existing (possibly empty) frame
frame/loadjdbc	Append data from a Jdbc table into an existing (possibly empty) frame
frame/quantiles	New frame with Quantiles and their values.
frame/rename	Change the name of the current frame.
frame/sort	[BETA] Sort by one or more columns.
frame/sorted_k	[ALPHA] Get a sorted subset of the data.
frame/tally	[BETA] Count number of times a value is seen.
frame/tally_percent	[BETA] Compute a cumulative percent count.
frame/top_k	Most or least frequent column values.
frame/unflatten_column	Compacts data from multiple rows based on cell data.
frame:/filter	Select all rows which satisfy a predicate.
frame:/join	[BETA] Join two data frames (similar to SQL JOIN).
frame:/label_propagation	Label Propagation on Gaussian Random Fields.
frame:/load	Append data from a csv/xml into an existing (possibly empty) frame
frame:/loopy_belief_propagation	Message passing to infer state probabilities.
frame:/rename_columns	Rename columns
frame:edge/add_edges	Add edges to a graph.
frame:edge/rename_columns	Rename columns for edge frame.
frame:vertex/add_vertices	Add vertices to a graph.
frame:vertex/drop_duplicates	Remove duplicate vertex rows.
frame:vertex/filter	
frame:vertex/rename_columns	Rename columns for vertex frame.
graph/annotate_degrees	Make new graph with degrees.
graph/annotate_weighted_degrees	Calculates the weighted degree of each vertex with respect to an (optional) set of labels.
graph/clustering_coefficient	Coefficient of graph with respect to labels.
graph/copy	Make a copy of the current graph.
graph/graphx_connected_components	Implements the connected components computation on a graph by invoking graphx api.
graph/graphx_pagerank	Determine which vertices are the most important.
graph/graphx_triangle_count	Number of triangles among vertices of current graph.
graph/ml/belief_propagation	Classification on sparse data using Belief Propagation.
graph/rename	Rename a graph in the database.
graph:/define_edge_type	Define an edge type.

Continued on next page

Table 20.1 – continued from previous page

Command Name (explained here)	Description
graph:/define_vertex_type	Define a vertex type by label.
graph:/edge_count	Get the total number of edges in the graph.
graph:/export_to_titan	Convert current graph to TitanGraph.
graph:/ml/kclique_percolation	[ALPHA] Find groups of vertices with similar attributes.
graph:/vertex_count	Get the total number of vertices in the graph.
graph:titan/export_to_graph	Export from ta.TitanGraph to ta.Graph.
graph:titan/graph_clustering	Performs graph clustering over an initial titan graph.
graph:titan/query/gremlin	Executes a Gremlin query.
graph:titan/vertex_sample	Make subgraph from vertex sampling.
model/rename	rename a model
model:collaborative_filtering/new	Collaborative filtering recommend model.
model:collaborative_filtering/recommend	[BETA] Collaborative filtering (als/cgd) model
model:collaborative_filtering/train	Collaborative filtering (als/cgd) model
model:k_means/new	create a new model
model:k_means/predict	[BETA] Predict the cluster assignments for the data points.
model:k_means/publish	[BETA] Creates a tar file that will used as input to the scoring engine
model:k_means/train	[BETA] Creates KMeans Model from train frame.
model:lda/new	Creates Latent Dirichlet Allocation model
model:lda/predict	[BETA] Predict conditional probabilities of topics given document.
model:lda/publish	[BETA] Creates a tar file that will used as input to the scoring engine
model:lda/train	[BETA] Creates Latent Dirichlet Allocation model
model:libsvm/new	[ALPHA] model:libsvm/new
model:libsvm/predict	[ALPHA] New frame with new predicted label column.
model:libsvm/publish	[BETA] Creates a tar file that will used as input to the scoring engine
model:libsvm/score	[ALPHA] Calculate the prediction label for a single observation.
model:libsvm/test	[ALPHA] Predict test frame labels and return metrics.
model:libsvm/train	[ALPHA] Train Lib Svm model based on another frame.
model:linear_regression/new	
model:linear_regression/predict	[ALPHA] Make new frame with column for label prediction.
model:linear_regression/train	[ALPHA] Build linear regression model.
model:logistic_regression/new	Create a 'new' instance of logistic regression model.
model:logistic_regression/predict	[ALPHA] Make a new frame with a column for label prediction.
model:logistic_regression/test	[ALPHA] Predict test frame labels and show metrics.
model:logistic_regression/train	[ALPHA] Build logistic regression model.
model:naive_bayes/new	create a new model
model:naive_bayes/predict	[ALPHA] Predict
model:naive_bayes/train	[ALPHA] Build a naive bayes model.
model:principal_components/new	Create a 'new' instance of principal component model.
model:principal_components/predict	[ALPHA] Predict using principal components model.
model:principal_components/publish	[BETA] Creates a tar file that will be used as input to the scoring engine
model:principal_components/train	Build principal components model.
model:random_forest_classifier/new	Create a 'new' instance of random forest classifier model.
model:random_forest_classifier/predict	[ALPHA] Predict the labels for the data points.
model:random_forest_classifier/publish	[BETA] Creates a tar file that will be used as input to the scoring engine
model:random_forest_classifier/test	[ALPHA] Predict test frame labels and return metrics.
model:random_forest_classifier/train	[ALPHA] Build Random Forests Classifier model.
model:random_forest_regressor/new	<Missing Doc>
model:random_forest_regressor/predict	[ALPHA] Predict the values for the data points.
model:random_forest_regressor/publish	[BETA] Creates a tar file that will be used as input to the scoring engine

Continued on next page

Table 20.1 – continued from previous page

Command Name (explained here)	Description
model:random_forest_regressor/train	[ALPHA] Build Random Forests Regressor model.
model:svm/new	[ALPHA] create a new model
model:svm/predict	[ALPHA] Make new frame with additional column for predicted label.
model:svm/test	[ALPHA] Predict test frame labels and return metrics.
model:svm/train	[ALPHA] Train SVM model based on another frame.

CHAPTER

TWENTYONE

REST API ENTITIES

21.1 *Entities* Create Entity

Creates a new entity, like a frame, graph, or model.

21.1.1 POST /v1/:entities/

Request

Route

```
POST /v1/frames/
POST /v1/graphs/
POST /v1/models/
```

Body

Name	Description	Default	Valid Values	Example Values
name	name for the entity	null	alphanumeric UTF-8 strings	'weather_frame1'

```
{
    "name": "weather_frame1"
}
```

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

Returns a summary of the entity.

Name	Description
uri	entity id (engine-assigned)
name	entity name (user-assigned)
links	links to the entity
entity_type	e.g. “frame:”, “frame:vertex”, “graph:”
status	status: Active, Deleted, Deleted_Final

Extra fields specific to frames:

Name	Description
schema	frame schema info columns: [(name, type)]
row_count	number of rows in the frame


```
{
  "name": "weather_frame1",
  "uri": "frames/8",
  "schema": {
      "columns": []
  },
  "row_count": 0,
  "links": [
      {
          "rel": "self",
          "uri": "http://localhost:9099/v1/frames/8",
          "method": "GET"
      }
  ],
  "entity_type": "frame:",
  "status": "Active"
}
```


Headers

```
Content-Length: 279
Content-Type: application/json; charset=UTF-8
Date: Thu, 14 May 2015 23:42:27 GMT
Server: spray-can/1.3.1
build_id: TheReneNumber
```

21.2 *Entities* Drop Entity

Deletes an entity

21.2.1 DELETE /v1/:entities/:id

Request

Route

```
DELETE /v1/frames/25
DELETE /v1/graphs/6
DELETE /v1/models/4
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

(None)

21.3 *Entities* Get Entity

Gets information about specific entity, like a frame, graph, or model. There are two options: get by id or get by name.

21.3.1 GET /v1/:entities/:id

21.3.2 GET /v1/:entities?name=

Request

Route

```
GET /v1/frames/3
GET /v1/graphs/1
GET /v1/models/4
GET /v1/frames?name=weather_frame1
GET /v1/graphs?name=networkB
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

Returns information about the entity

Name	Description
uri	entity id (engine-assigned)
name	entity name (user-assigned)
links	links to the entity
entity_type	e.g. “frame:”, “frame:vertex”, “graph:”
status	status: Active, Deleted, Deleted_Final

Extra fields specific to frames:

Name	Description
schema	frame schema info columns: [(name, type)]
row_count	number of rows in the frame


```
{
 "uri": "frames/7",
 "name": "super_frame",
 "entity_type": "frame:",
 "status": "Active"
 "links": [{
   "rel": "self",
   "uri": "http://localhost:9099/v1/frames/7",
   "method": "GET"
 }],
 "schema": {
   "columns": [{
     "name": "c",
     "data_type": "int32",
     "index": 0
   }, {
     "name": "twice",
     "data_type": "int32",
     "index": 1
   }, {
     "name": "sample_bin",
     "data_type": "string",
     "index": 2
   }, {
     "name": "c_binned",
     "data_type": "int32",
```

```
      "index": 3
    }]
  },
  "row_count": 8675309,
}
```


Headers

```
Content-Length: 279
Content-Type: application/json; charset=UTF-8
Date: Thu, 14 May 2015 23:42:27 GMT
Server: spray-can/1.3.1
build_id: TheReneNumber
```

21.4 *Entities* Get Named Entities

Gets list of short entries for all named entities in the entity collection.

21.4.1 GET /v1/:entities

Request

Route

```
GET /v1/frames
GET /v1/graphs
GET /v1/models
```

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
```

Response

Status

```
200 OK
```

Body

Returns a list of entity entries for the given collection, where an entry is defined as...

Name	Description
id	entity id (engine-assigned)
name	entity name (user-assigned)
url	url to the entity
entity_type	**e.g. "frame:", "frame:vertex", "graph:",** "model:kmeans"

```
Example for GET /v1/frames:
[
  {
      "id": 7,
      "name": "super_frame",
      "url": "http://localhost:9099/v1/frames/7",
      "entity_type": "frame:"
  },
  {
      "id": 8,
      "name": "weather_frame1",
      "url": "http://localhost:9099/v1/frames/8",
      "entity_type": "frame:"
  }
]
```

Headers:

```
Content-Length: 279
Content-Type: application/json; charset=UTF-8
Date: Thu, 14 May 2015 23:42:27 GMT
```

21.5 *Entities* Get Frame Data

Gets data from a frame by rows.

21.5.1 GET /v1/frames/:id/data?offset=:offset&count=:count

Request

Route

```
GET /v1/frames/7/data?offset=0&count=10
```

Parameters

offset: index of the starting row

count: number of rows to retrieve

Body

(None)

Headers

```
Authorization: test_api_key_1
Content-type: application/json
Accept: application/json,text/plain
```

Response

Status

```
200 OK
```

Body

Returns rows of data

Name	Description
name	name of the operation "getRows"
complete	boolean indicating completion of data fetch
result	data: list of rows of data
	schema: row structure (column names and data types)

```
{
  "name": "getRows",
  "complete": true,
  "result": {
    "data": [[1, 2, "validate", 0], [2, 4, "validate", 0], [3, 6, "validate", 1], [2, 4, "validate",
    "schema": {
      "columns": [{
        "name": "c",
        "data_type": "int32",
        "index": 0
      }, {
        "name": "twice",
        "data_type": "int32",
        "index": 1
      }, {
        "name": "sample_bin",
        "data_type": "string",
        "index": 2
      }, {
        "name": "c_binned",
        "data_type": "int32",
        "index": 3
      }]
    }
  },
}
```

Headers

```
Content-Length: 753
Content-Type: application/json; charset=UTF-8
Date: Thu, 14 May 2015 23:42:27 GMT
```

Notes

The data is considered 'unstructured', therefore taking a certain number of rows, the rows obtained may be different every time the command is executed, even if the parameters do not change.

[Need a note in here about performance and recommended usage]

CHAPTER

TWENTYTWO

REST API INFO

Basic server information supplying API versions.

22.1 GET /info

22.1.1 Request

Route

```
GET /info
```

Body

(None)

Headers

(None)

22.1.2 Response

Status

```
200 OK
```

Body

Returns server information and API versions.

```
 {
  "name": "Trusted Analytics",
  "identifier": "ia",
  "versions": [
      "v1"
  ]
}
```

Headers

```
Content-Length: 75
Content-Type: application/json; charset=UTF-8
Date: Thu, 14 May 2015 23:42:27 GMT
```

Part VII

References

CHAPTER

TWENTYTHREE

GLOSSARY

Adjacency List A representation of a graph as a list. Each line of the list consists of a unique vertex identification, and a list of all of that vertex's neighboring vertices.

Example:

```
  Node   Connection List
/------------------------/
   A         B, D
   B         A, C, D
   C         B
   D         A, B
```

Aggregation Function A mathematical function which is usually computed over a single column. Supported functions:

- avg : The average (mean) value in the column
- count : The count of the rows
- count_distinct : The count of unique rows
- max : The largest (most positive) value in the column
- min : The least (most negative) value in the column
- stdev : The standard deviation of the values in the column, see Wikipedia: Standard Deviation[1]
- sum : The result of adding all the values in the column together
- var : The variance of the values in the column, see Wikipedia: Variance[2] and *Bias vs Variance*

Alpha See *API Maturity Tags*.

Alternating Least Squares A method used in some approaches to multidimensional scaling, where a goodness-of-fit measure for some data is minimized in a series of steps, each involving the application of the *least squares* method of parameter estimation.

See the API section on the *Collaborative Filter Model* for an in-depth discussion of this method.

API Maturity Tags Functions in the API may be at different levels of software maturity. Where a function is not mature, the documentation will note it with one of the following tags. The absence of a tag means the function is standardized and fully tested.

[ALPHA] Indicates a function or feature which has been developed, but has not been completely tested. Use this function with caution. This function may be changed or eliminated in future releases.

[1] http://en.wikipedia.org/wiki/Standard_deviation
[2] https://en.wikipedia.org/wiki/Variance

[BETA] Indicates a function or feature which has been developed and preliminarily tested, but has not been completely tested. Use this function with caution. This function may be changed in future releases.

[DEPRECATED] Indicates a function or feature which is no longer supported. It is recommended that an alternate solution be found. This function may be removed in future releases.

ASCII Abbreviated from American Standard Code for Information Interchange, ASCII is a character-encoding scheme. Originally based on the English alphabet, it encodes 128 specified characters into 7-bit binary integers.

Average Path Length In network topology, the average number of steps along the shortest paths for all possible pairs of vertices.

Bayesian Inference A probabilistic graphical model representing the conditional dependencies amongst a set of random variables with a directed acyclic graph.

Contrast with *Markov Random Fields*

For more information, see Wikipedia: Bayesian Network[3].

Belief Propagation See *Loopy Belief Propagation*.

Beta See *API Maturity Tags*.

Bias vs Variance In this context, "bias" means accuracy, while "variance" means accounting for outlier data points.

Bias-variance tradeoff In supervised classifier training, the problem of minimizing two sources of prediction error: erroneous assumptions in the learning algorithm, and sensitivity to small details in the training data (in other words, over-fitting) when generalizing to a testing data set.

Central Tendency A typical value for a probability distribution. It may also be called a center or location of the distribution. Colloquially, measures of central tendency are often called averages.

Centrality From Wikipedia: Centrality[4]:

> In graph theory and network analysis, centrality of a vertex measures its relative importance within a graph. Applications include how influential a person is within a social network, how important a room is within a building (space syntax), and how well-used a road is within an urban network. There are four main measures of centrality: degree, betweenness, closeness, and eigenvector. Centrality concepts were first developed in social network analysis, and many of the terms used to measure centrality reflect their sociological origin. [5]

Centrality (Katz) See *Katz Centrality*.

Centrality (PageRank) See *Centrality*.

Character-Separated Values A file containing tabular data (numbers and text) in plain-text form. The file can consist of any number of records, separated by a unique character. New line characters are ususally used for this purpose. Each record consists of one or more fields, separated by some unique character. Commas are usually used for this purpose. Tab characters are also quite common.

Classification The process of predicting category membership for a set of observations based on a model learned from the known categorical groupings of another set of observations.

Clustering See *Collaborative Clustering*.

Collaborative Clustering The unsupervised grouping of observations based on one or more character traits.

Collaborative Filtering The process of filtering for information or patterns using techniques involving collaboration among multiple agents, viewpoints, data sources, etc. [6]

[3] http://en.wikipedia.org/wiki/Bayesian_network

[4] http://en.wikipedia.org/wiki/Centrality

[5] Newman, M.E.J. 2010. Networks: An Introduction. Oxford, UK: Oxford University Press.

[6] Terveen, Loren; Hill, Will (2001). Beyond Recommender Systems: Helping People Help Each Other pp. 6. Addison-Wesley.

Comma-Separated Variables See *Character-Separated Values*.

Community Structure Detection For complex networks, the process of identifying vertices that can be easily grouped into densely-connected sub-groupings.

Confusion Matrices Plural form of *Confusion Matrix*

Confusion Matrix In machine learning, a table describing the performance of a supervised classification algorithm, in which each column corresponds to instances of a predicted class, while each row represents the instances of the true class. Also known as contingency table, error matrix, or misclassification matrix.

Conjugate Gradient Descent Trusted Analytics implements this algorithm. Specifically, it uses CGD with bias for collaborative filtering.

For more information: Factorization Meets the Neighborhood (pdf)[7] (see equation 5).

Connected Component In graph theory, a sub-graph in which any two vertices are interconnected but share no connections with other vertices in the sub-graph.

Convergence Where a calculation (often an iterative calculation) reaches a certain value.

For more information see: Wikipedia: Convergence (mathematics)[8].

CSV See *Character-Separated Values*

Degree The degree of a vertex is the number of edges incident to the vertex. Loops are counted twice. The maximum and minimum degree of a graph are the maximum and minimum degree of its vertices.

For more information see: Wikipedia: Degree (graph theory)[9].

Deprecated See *API Maturity Tags*.

Directed Acyclic Graph (DAG) In mathematics and computer science, a graph formed by a collection of vertices and directed edges, each edge connecting one vertex to another, such that there is no way to start at some vertex v and follow a sequence of edges that eventually loops back to v again.

Contrast with *Undirected Graph*.

See Wikipedia: Directed Acyclic Graph[10].

ECDF See *Empirical Cumulative Distribution*

Edge A connection — either directed or not — between two vertices in a graph.

Empirical Cumulative Distribution $\hat{F}_n(t)$ is a step function with jumps i/n at observation values, where i is the number of tied observations at that value. Missing values are ignored.

For observations $x = (x_1, x_2, ...x_n)$, $\hat{F}_n(t)$ is the fraction of observations less than or equal to t.

$$\hat{F}_n(t) = \frac{x_i \leq t}{n} = \frac{1}{n} \sum_{i=1}^{n} Indicator\{x_i \leq t\}.$$

where $Indicator\{A\}$ is the indicator of event A. For a fixed t, the indicator $Indicator\{x_i \leq t\}$ is a Bernoulli random variable with parameter $p = F(t)$, hence $n\hat{F}_n(t)$ is a binomial random variable with mean $nF(t)$ and variance $nF(t)(1 - F(t))$. This implies that $\hat{F}_n(t)$ is an unbiased estimator for $F(t)$.

Enumerate Verb — To specify each member of a sequence individually in incrementing order.

Equal Depth Binning Equal depth binning places column values into groups such that each group contains the same number of elements.

[7] http://public.research.att.com/ volinsky/netflix/kdd08koren.pdf
[8] http://en.wikipedia.org/wiki/Convergence_(mathematics)
[9] https://en.wikipedia.org/wiki/Degree_(graph_theory)
[10] https://en.wikipedia.org/wiki/Directed_acyclic_graph

Equal Width Binning Equal width binning places column values into groups such that the values in each group fall within the same interval and the interval width for each group is equal.

Extract, Transform, and Load From Wikipedia: Extract, Transform, and Load[11]:

> In computing, ETL (extract, transform, and load) refers to a process in database usage and especially in data warehousing that:
>
> - Extracts data from outside sources
> - Transforms it to fit operational needs, which can include quality levels
> - Loads it into the end target (database, more specifically, operational data store, data mart, or data warehouse)
>
> ETL systems are commonly used to integrate data from multiple applications, typically developed and supported by different vendors or hosted on separate computer hardware. The disparate systems containing the original data are frequently managed and operated by different employees. For example a cost accounting system may combine data from payroll, sales and purchasing.

F-Measure In machine learning, a metric that quantifies a classifier's accuracy. Traditionally defined as the harmonic mean of precision and recall. Also known as F1 score.

F-Score See *F-Measure*.

F1 Score See *F-Measure*.

float32 A real number with 32 bits of precision.

float64 A real number with 64 bits of precision.

Frame (capital F) A class object with the functionality to manipulate the data in a *frame (lower case f)*.

frame (lower case f) A table database with rows and columns containing data.

GaBP See *Gaussian Belief Propagation*.

Gaussian Belief Propagation A special case of belief propagation when the underlying distributions are *Gaussian* (Weiss & Freeman [12]).

Gaussian Distribution, Normal Distribution A group of values, where the probability of any specific value:

- will fall between two real limits,
- is evenly centered around the mean,
- approaches zero on either side of the mean.

A Gaussian distribution is defined as:

$$f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-i\frac{(x-i\mu)^2}{2i\sigma^2}}$$

- μ is the mean of the distribution.
- σ is the standard deviation.

Gaussian Random Fields A random group of vertices displaying a *Gaussian distribution* of one or more sets of properties.

Global Clustering Coefficient The global clustering coefficient is based on triplets of vertices. A triplet consists of three vertices that are connected by either two (open triplet) or three (closed triplet) undirected edges. A

[11] http://en.wikipedia.org/wiki/Extract,_transform,_load

[12] Weiss, Yair; Freeman, William T. (October 2001). "Correctness of Belief Propagation in Gaussian Graphical Models of Arbitrary Topology". Neural Computation 13 (10): 2173|EM|2200. doi:10.1162/089976601750541769. PMID 11570995.

triangle consists of three closed triplets, one centered on each of the vertices. The global clustering coefficient is the number of closed triplets (or 3 x triangles) over the total number of triplets (both open and closed).

For more information see: Wikipedia: Global Clustering Coefficient[13].

See also *Local Clustering Coefficient*.

Graph A representation of a set of vertices, where some pairs of objects are connected by edges. The links that connect some pairs of vertices are called edges. Typically, a graph is depicted in diagrammatic form as a set of dots for the vertices, joined by lines or curves for the edges. Graphs are one of the objects of study in discrete mathematics.

For more information see: Wikipedia: Graph (mathematics)[14].

Graph Analytics The broad category of methods used to examine the statistical and structural properties of a graph, including:

1. Traversals – Algorithmic walk throughs of the graph to determine optimal paths and relationship between vertices.
2. Statistics – Important attributes of the graph such as degrees of separation, number of triangular counts, centralities (highly influential nodes), and so on.

Some are user-guided interactions, where the user navigates through the data connections, others are algorithmic, where a result is calculated by the software.

Graph learning is a class of graph analytics applying machine learning and data mining algorithms to graph data. This means that calculations are iterated across the nodes of the graph to uncover patterns and relationships. Thus, finding similarities based on relationships, or recursively optimizing some parameter across nodes.

For more information, see the article Graph Analytics[15] by Pak Chung Wong.

Graph Database Directions As a shorthand, graph database terminology uses relative directions, assumed to be from whatever vertex you are currently using. These directions are:

- **left**: The calling frame's index
- **right**: The input frame's index
- **inner**: An intersection of indexes

So a direction like this: "The suffix to use from the left frame's overlapping columns" means to use the suffix from the calling frame's index.

Graph Element A graph element is an object that can have any number of key-value pairs, that is, properties, associated with it. Each element can have zero properties as well.

Gremlin A graph query language. Gremlin works with the Titan Graph Database, though it is made by a different company. For more information see: Gremlin Wiki[16].

HBase Apache HBase is the Hadoop database, a distributed, scalable, big data store.

int32 An integer is a member of the set of positive whole numbers {1, 2, 3, . . . }, negative whole numbers {-1, -2, -3, . . . }, and zero {0}. Since a computer is limited, the computer representation of it can have 32 bits of precision.

int64 An integer is a member of the set of positive whole numbers {1, 2, 3, . . . }, negative whole numbers {-1, -2, -3, . . . }, and zero {0}. Since a computer is limited, the computer representation of it can have 64 bits of precision.

[13] https://en.wikipedia.org/wiki/Clustering_coefficient#Global_clustering_coefficient
[14] http://en.wikipedia.org/wiki/Graph_(mathematics)
[15] http://vacommunity.org/article26
[16] https://github.com/tinkerpop/gremlin/wiki

Ising Smoothing Parameter The smoothing parameter in the Ising model. For more information see: Wikipedia: Ising Model[17].

You can use any positive float number, so 3, 2.5, 1, or 0.7 are all valid values. A larger smoothing value implies stronger relationships between adjacent random variables in the graph.

JSON Data in the JavaScript Object Notation format. An open standard format that uses human-readable text to transmit data objects consisting of attributevalue pairs. For more information see **'http:/json.org'__**.

K-S (Kolmogorov-Smirnov) Test From Wikipedia: Kolmogorov|EM|Smirnov Test[18]:

> In statistics, the K-S test is a nonparametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution (one-sample K-S test), or to compare two samples (two-sample K-S test). The K-S statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, or between the empirical distribution functions of two samples.

Katz Centrality From Wikipedia: Katz Centrality[19]:

> In Social Network Analysis (SNA) there are various measures of *centrality* which determine the relative importance of an actor (or node) within the network. Katz centrality was introduced by Leo Katz in 1953 and is used to measure the degree of influence of an actor in a social network. [20] Unlike typical centrality measures which consider only the shortest path (the geodesic) between a pair of actors, Katz centrality measures influence by taking into account the total number of walks between a pair of actors. [21]

Label Propagation A multi-pass process for grouping vertices.

See *Label Propagation (LP)*.

For additional reference: Learning from Labeled and Unlabeled Data with Label Propagation[22].

Labeled Data vs Unlabeled Data From Wikipedia: Machine Learning / Algorithm Types[23]:

> Supervised learning algorithms are trained on labeled examples, in other words, input where the desired output is known. While Unsupervised learning algorithms operate on unlabeled examples, in other words, input where the desired output is unknown.

Many machine-learning researchers have found that unlabeled data, when used in conjunction with a small amount of labeled data, can produce considerable improvement in learning accuracy.

For more information see: Wikipedia: Semi-Supervised Learning[24].

Lambda Adapted from: Stanford: Machine Learning[25]:

> This is the tradeoff parameter, used in *Label Propagation* on *Gaussian Random Fields*. The regularization parameter is a control on fitting parameters. It is used in machine learning algorithms to prevent overfitting. As the magnitude of the fitting parameter increases, there will be an increasing penalty on the cost function. This penalty is dependent on the squares of the parameters as well as the magnitude of lambda.

17 http://en.wikipedia.org/wiki/Ising_model
18 http://en.wikipedia.org/wiki/K-S_Test
19 http://en.wikipedia.org/wiki/Katz_centrality
20 Katz, L. (1953). A New Status Index Derived from Sociometric Index. Psychometrika, 39-43.
21 Hanneman, R. A., & Riddle, M. (2005). Introduction to Social Network Methods (http://faculty.ucr.edu/ hanneman/nettext/).
22 http://lvk.cs.msu.su/ bruzz/articles/classification/zhu02learning.pdf
23 http://en.wikipedia.org/wiki/Machine_learning#Algorithm_types
24 http://en.wikipedia.org/wiki/Semi-supervised_learning
25 http://openclassroom.stanford.edu/MainFolder/DocumentPage.php?course=MachineLearning&doc=exercises/ex5/ex5.html

Lambda Function An anonymous function or function literal in code. Lambda functions are used when a method requires a function as an input parameter and the function is coded directly in the method call.

Further examples and explanations can be found at this page: Python User Functions.

Related term: *Python User-defined Function*.

> **Warning:** This term is often used where a *Python user-defined function* is more accurate. A key distinction is that the lambda function is not referable by a name.

Latent Dirichlet Allocation From Wikipedia: Latent Dirichlet Allocation[26]:

> [A] generative model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. For example, if observations are words collected into documents, it posits that each document is a mixture of a small number of topics and that each word's creation is attributable to one of the document's topics. LDA is an example of a topic model and was first presented as a graphical model for topic discovery by David Blei, Andrew Ng, and Michael Jordan in 2003.

Least Squares A mathematical procedure for finding the best-fitting curve to a given set of points by minimizing the sum of the squares of the offsets ("the residuals") of the points from the curve. The sum of the squares of the offsets is used instead of the offset absolute values because this allows the residuals to be treated as a continuous differentiable quantity. However, because squares of the offsets are used, outlying points can have a disproportionate effect on the fit, a property which may or may not be desirable depending on the problem at hand.

LineFile A data format where the records are line-delimited.

Local Clustering Coefficient The local clustering coefficient of a vertex in a graph quantifies how close its neighbors are to being a clique (complete graph).

For more information see: Wikipedia: Local Clustering Coefficient[27].

See also *Global Clustering Coefficient*.

Loopy Belief Propagation Belief Propagation is an algorithm that makes inferences on graph models, like a *Bayesian inference* or *Markov Random Fields*. It is called Loopy when the algorithm runs iteratively until convergence.

For more information see: Wikipedia: Belief Propagation[28].

Machine Learning Machine learning is a branch of artificial intelligence. It is about constructing and studying software that can "learn" from data. The more iterations the software computes, the better it gets at making that calculation. For more information, see Wikipedia[29].

MapReduce MapReduce is a programming model for processing large data sets with a parallel, distributed algorithm on a cluster. It is composed of a map() procedure that performs filtering and sorting (such as sorting students by first name into queues, one queue for each name) and a reduce() procedure that performs a summary operation (such as counting the number of students in each queue, yielding name frequencies). The "MapReduce System" (also called "infrastructure" or "framework") orchestrates by marshaling the distributed servers, running the various tasks in parallel, managing all communications and data transfers between the various parts of the system, and providing for redundancy and fault tolerance.

For more information see: Wikipedia: MapReduce[30].

[26] http://en.wikipedia.org/wiki/Latent_Dirichlet_allocation
[27] https://en.wikipedia.org/wiki/Clustering_coefficient#Local_clustering_coefficient
[28] http://en.wikipedia.org/wiki/Loopy_belief_propagation
[29] https://en.wikipedia.org/wiki/Machine_learning
[30] http://en.wikipedia.org/wiki/Map_reduce

Markov Random Fields Markov Random fields, or Markov Network, are an undirected graph model that may be cyclic. This contrasts with *Bayesian inference*, which is directed and acyclic.

For more information see: Wikipedia: Markov Random Field[31].

OLAP Online analytical processing. An approach to answering MDA (Multi-Dimensional Analytical) queries swiftly. The term OLAP (OnLine Analytical Processing) was created as a slight modification of the traditional database term OLAP.

For more information see: Wikipedia: Online analytical processing[32].

OLTP Online transaction processing. A class of information systems that facilitate and manage transaction-oriented applications. OLAP involves gathering input information, processing the information and updating existing information to reflect the gathered and processed information.

For more information see: Wikipedia: Online transaction processing[33].

PageRank An algorithm to measure the importance of vertices.

PageRank works by counting the number and quality of edges to a vertex to determine a rough estimate of how important the vertex is. The underlying assumption is that more important vertices are likely to have more edges from other vertices.

For more information see: Wikipedia: PageRank[34].

PageRank Centrality See *Centrality*.

Precision/Recall From Wikipedia: Precision and Recall[35]:

> In pattern recognition and information retrieval with binary classification, precision (also called positive predictive value) is the fraction of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance.

Property Map A property map is a key-value map. Both edges and vertices have property maps.

For more information see: Tinkerpop: Property Graph Model[36].

Python User-defined Function A Python User-defined Function (UDF) is a Python function written by the user on the client-side which can execute in a distributed fashion on the cluster. For further explanation, see Python User Functions

Further examples and explanations can be found at Python User Functions.

Related: *Lambda Function*.

Quantile One value of a set that partitions a collection of data. Each partition (also known as a quantile) contains all the collection elements from the given value, up to (but not including) the lowest value of the next quantile.

RDF See *Resource Description Framework*

Receiver Operating Characteristic From Wikipedia: Receiver Operating Characteristic[37]:

> In signal detection theory, a receiver operating characteristic (ROC), or simply ROC curve, is a graphical plot which illustrates the performance of a binary classifier system as its discrimination threshold is varied. It is created by plotting the fraction of true positives out of the total actual positives (TPR = true positive rate) vs. the fraction of false positives out of the total actual negatives

[31] http://en.wikipedia.org/wiki/Markov_random_field
[32] https://en.wikipedia.org/wiki/Online_analytical_processing
[33] https://en.wikipedia.org/wiki/Online_transaction_processing
[34] http://en.wikipedia.org/wiki/PageRank
[35] http://en.wikipedia.org/wiki/Precision_and_recall
[36] https://github.com/tinkerpop/blueprints/wiki/Property-Graph-Model
[37] https://en.wikipedia.org/wiki/Receiver_operating_characteristic

(FPR = false positive rate), at various threshold settings. TPR is also known as sensitivity or recall in machine learning. The FPR is also known as the fall-out and can be calculated as one minus the more well known specificity. The ROC curve is then the sensitivity as a function of fall-out. In general, if both of the probability distributions for detection and false alarm are known, the ROC curve can be generated by plotting the Cumulative Distribution Function (area under the probability distribution from -inf to +inf) of the detection probability in the y-axis versus the Cumulative Distribution Function of the false alarm probability in x-axis.

Recommendation Systems From Wikipedia: Recommender System[38]:

> Recommender systems or recommendation systems (sometimes replacing "system" with a synonym such as platform or engine) are a subclass of information filtering system that seek to predict the 'rating' or 'preference' that user would give to an item [39] [40] .

Resource Description Framework A specific format for storing graphs. Vertices also referred to as resources, have property/value pairs describing the resource. A vertex is any object which can be pointed to by a URI. Properties are attributes of the vertex, and values are either specific values for the attribute, or the URI for another vertex. For example, information in a particular vertex, might include the property "Author". The value for the Author property could be either a string giving the name of the author, or a link to another resource describing the author. Sets of properties are defined within RDF Vocabularies (or schemas). A vertex may include properties defined in different schemas. The properties within a resource description are associated with a certain schema definition using the XML namespace mechanism.

ROC See *Receiver Operating Characteristic*

Row Functions Refer to *Lambda Function* and *Python User-defined Function*

Schema A computer structure that defines the structure of something else.

Semi-Supervised Learning In Semi-Supervised learning algorithms, most the input data are not labeled and a small amount are labeled. The expectation is that the software "learns" to calculate faster than in either supervised or unsupervised algorithms.

For more information see: *Supervised Learning*, and *Unsupervised Learning*.

Simple Random Sampling In statistics, a simple random sample (SRS) is a subset of individuals (a sample) chosen from a larger set (a population). Each individual is chosen randomly and entirely by chance, such that each individual has the same probability of being chosen at any stage during the sampling process, and each subset of *k* individuals has the same probability of being chosen for the sample as any other subset of *k* individuals [41]. This process and technique is known as simple random sampling. A simple random sample is an unbiased surveying technique.

For more information see: Wikipedia: Simple Random Sample[42].

Smoothing Smoothing means to reduce the "noise" in a data set. "In smoothing, the data points of a signal are modified so individual points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased leading to a smoother signal."

For more information see:

> Wikipedia: Smoothing[43]
> Wikipedia: Relaxation (iterative method)[44]

[38] http://en.wikipedia.org/wiki/Recommendation_system
[39] Francesco Ricci and Lior Rokach and Bracha Shapira (2011). Recommender Systems Handbook, pp. 1-35. Springer.
[40] Lev Grossman (2010). How Computers Know What We Want |EM| Before We Do (http://content.time.com/time/magazine/article/0,9171,1992403,00.html). Time.
[41] Yates, Daniel S.; David S. Moore, Daren S. Starnes (2008). The Practice of Statistics, 3rd Ed. Freeman. ISBN 978-0-7167-7309-2.
[42] https://en.wikipedia.org/wiki/Simple_random_sampling
[43] http://en.wikipedia.org/wiki/Smoothing
[44] http://en.wikipedia.org/wiki/Relaxation_(iterative_method

Stratified Sampling In statistics, stratified sampling is a method of sampling from a population. In statistical surveys, when subpopulations within an overall population vary, it is advantageous to sample each subpopulation (stratum) independently. Stratification is the process of dividing members of the population into homogeneous subgroups before sampling. The strata should be mutually exclusive: every element in the population must be assigned to only one stratum. The strata should also be collectively exhaustive: no population element can be excluded. Then simple random sampling or systematic sampling is applied within each stratum. This often improves the representativeness of the sample by reducing sampling error. It can produce a weighted mean that has less variability than the arithmetic mean of a simple random sample of the population.

For more information see: Wikipedia: Stratified Sampling[45].

Superstep, Supersteps A single iteration of an algorithm.

Supervised Learning Supervised learning refers to algorithms where the input data are all labeled, and the outcome of the calculation is known. These algorithms train the software to make a certain calculation.

For more information see: *Unsupervised Learning*, and *Semi-Supervised Learning*.

Tab-Separated Variables See *Character-Separated Values*.

TitanGraph A class object with the functionality to manipulate the data in a *graph*.

Topic Modeling Topic models provide a simple way to analyze large volumes of unlabeled text. A "topic" consists of a cluster of words that frequently occur together. Using contextual clues, topic models can connect words with similar meanings and distinguish between uses of words with multiple meanings.

Transaction Processing From Wikipedia: Transaction Processing[46]:

> In computer science, transaction processing is information processing that is divided into individual, indivisible operations, called transactions. Each transaction must succeed or fail as a complete unit; it cannot be only partially complete.

Transactional Functionality See *Transaction Processing*.

UDF See *Python User-defined Function*.

Undirected Graph An undirected graph is one in which the edges have no orientation (direction). The edge (a, b) is identical to the edge (b, a), in other words, they are not ordered pairs, but sets {u, v} (or 2-multisets) of vertices. The maximum number of edges in an undirected graph without a self-loop is $\frac{n(n-1)}{2}$

Contrast with *Directed Acyclic Graph (DAG)*.

For more information see: Wikipedia: Undirected Graph[47].

Unicode A data type consisting of a string of characters designed to represent all characters in the world, a universal character set.

Unsupervised Learning Unsupervised learning refers to algorithms where the input data are not labeled, and the outcome of the calculation is unknown. In this case, the software needs to "learn" how to make the calculation.

For more information see: *Supervised Learning*, and *Semi-Supervised Learning*.

Vertex A vertex is an object in a graph. Each vertex has an ID and a property map. In Giraph, a long integer is used as ID for each vertex. The property map may contain 0 or more properties. Each vertex is connected to others by edges.

For more information see: *Edge*, and Tinkerpop: Property Graph Model[48].

[45] https://en.wikipedia.org/wiki/Stratified_sampling
[46] http://en.wikipedia.org/wiki/Transaction_processing
[47] http://en.wikipedia.org/wiki/Undirected_graph#Undirected_graph
[48] https://github.com/tinkerpop/blueprints/wiki/Property-Graph-Model

Vertex Degree From Wikipedia: Vertex Degree[49]:

> In graph theory, the degree (or valency) of a vertex of a graph is the number of edges incident to the vertex, with loops counted twice [50]. The degree of a vertex v is denoted $\deg(v)$. The maximum degree of a graph G, denoted by $\Delta(G)$, and the minimum degree of a graph, denoted by $\delta(G)$, are the maximum and minimum degree of its vertices.

Vertex Degree Distribution From Wikipedia: Degree Distribution[51]:

> In the study of graphs and networks, the degree of a node in a network is the number of connections it has to other nodes and the degree distribution is the probability distribution of these degrees over the whole network.

Vertices Plural form of *Vertex*.

[49] http://en.wikipedia.org/wiki/Vertex_degree
[50] Diestel, Reinhard (2005). Graph Theory (3rd ed.). Berlin, New York: Springer-Verlag. ISBN 978-3-540-26183-4.
[51] http://en.wikipedia.org/wiki/Degree_distribution

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LEGAL STATEMENT

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APPENDICES

26.1 Appendix A — Sample Application Configuration File

```
# BEGIN REQUIRED SETTINGS

trustedanalytics.atk {
#bind address - change to 0.0.0.0 to listen on all interfaces
//api.host = "127.0.0.1"

#bind port
//api.port = 9099

# The host name for the Postgresql database in which the metadata will be stored
metastore.connection-postgresql.host = "localhost"
metastore.connection-postgresql.port = "5432"
metastore.connection-postgresql.database = "ta_metastore"
metastore.connection-postgresql.username = "atkuser"
metastore.connection-postgresql.password = "MyPassword"
metastore.connection-postgresql.url =
    "jdbc:postgresql://"${trustedanalytics.atk.metastore.connection-postgresql.host}":
    "${trustedanalytics.atk.metastore.connection-postgresql.port}"/
    "${trustedanalytics.atk.metastore.connection-postgresql.database}

# This allows for the use of postgres for a metastore.
# Service restarts will not affect the data stored in postgres.
metastore.connection = ${trustedanalytics.atk.metastore.connection-postgresql}

# This allows the use of an in memory data store.
# Restarting the REST server will create a fresh database and any
# data in the h2 DB will be lost
//metastore.connection = ${trustedanalytics.atk.metastore.connection-h2}

engine {

    # The hdfs URL where the trustedanalytics folder will be created
    # and which will be used as the starting point for any relative URLs
    fs.root = "hdfs://master.silvern.gao.cluster:8020/user/atkuser"

    # The (comma separated, no spaces) Zookeeper hosts that
    # Comma separated list of host names with zookeeper role assigned
    titan.load.storage.hostname = "node01, node02, node01"

    # Titan storage backend.
    # Available options are hbase and cassandra.
```

```
    # The default is hbase.
    //titan.load.storage.backend = "hbase"

    # Titan storage port, defaults to 2181 for HBase ZooKeeper.
    # Use 9160 for Cassandra.
    titan.load.storage.port = "2181"

    # The URL for connecting to the Spark master server
    #spark.master = "spark://master.silvern.gao.cluster:7077"
    yarn-client = "spark://master.silvern.gao.cluster:7077"


    spark.conf.properties {
        # Memory should be same or lower than what is listed as available
        # in Cloudera Manager.
        # Values should generally be in gigabytes, e.g. "64g".
        spark.executor.memory = "103079215104"
    }
}

}
# END REQUIRED SETTINGS

# The settings below are all optional.
# Some may need to be configured depending on the
# specifics of your cluster and workload.

trustedanalytics.atk {
  engine {
    auto-partitioner {
      # auto-partitioning spark based on the file size
      file-size-to-partition-size = [{ upper-bound="1MB", partitions = 15 },
                                      { upper-bound="1GB", partitions = 45 },
                                      { upper-bound="5GB", partitions = 100 },
                                      { upper-bound="10GB", partitions = 200 },
                                      { upper-bound="15GB", partitions = 375 },
                                      { upper-bound="25GB", partitions = 500 },
                                      { upper-bound="50GB", partitions = 750 },
                                      { upper-bound="100GB", partitions = 1000 },
                                      { upper-bound="200GB", partitions = 1500 },
                                      { upper-bound="300GB", partitions = 2000 },
                                      { upper-bound="400GB", partitions = 2500 },
                                      { upper-bound="600GB", partitions = 3750 }]
  # max-partitions is used if value is above the max upper-bound
          max-partitions = 10000
      }
    }

    # Configuration for the Trusted Analytics ATK REST API server
    api {
      # this is reported by the API server in the /info results -
      # it can be used to identify a particular server or cluster.
      //identifier = "ta"

      #The default page size for result pagination
      //default-count = 20

      #Timeout for waiting for results from the engine
```

```
    //default-timeout = 30s

    #HTTP request timeout for the REST server
    //request-timeout = 29s
  }

    #Configuration for the processing engine
    engine {
        //default-timeout = 30s
       //page-size = 1000

  spark {

    # When master is empty the system defaults to spark://`hostname`:7070
    # where hostname is calculated from the current system.
    # For local mode (useful only for development testing) set master = "local[4]"
    # in cluster mode, set master and home like the example
    # master = "spark://MASTER_HOSTNAME:7077"
    # home = "/opt/cloudera/parcels/CDH/lib/spark"

    # When home is empty the system will check expected locations on the
    # local system and use the first one it finds.
    # If spark is running in yarn-cluster mode (spark.master = "yarn-cluster"),
    # spark.home needs to be set to the spark directory on CDH cluster
    # ("/usr/lib/spark","/opt/cloudera/parcels/CDH/lib/spark/", etc)
    //home = ""

    conf {
      properties {
        # These key/value pairs will be parsed dynamically and provided
        # to SparkConf().
        # See Spark docs for possible values
        # http://spark.apache.org/docs/0.9.0/configuration.html.
        # All values should be convertible to Strings.

        #Examples of other useful properties to edit for performance tuning:

        # Increased Akka frame size from default of 10MB to 100MB to
        # allow tasks to send large results to Spark driver
        # (e.g., using collect() on large datasets).
        //spark.akka.frameSize=100

        #spark.akka.retry.wait=30000
        #spark.akka.timeout=200
        #spark.akka.timeout=30000

        //spark.shuffle.consolidateFiles=true

        # Enabling RDD compression to save space (might increase CPU cycles)
        # Snappy compression is more efficient
        //spark.rdd.compress=true
        //spark.io.compression.codec=org.apache.spark.io.SnappyCompressionCodec

        #spark.storage.blockManagerHeartBeatMs=300000
        #spark.storage.blockManagerSlaveTimeoutMs=300000

        #spark.worker.timeout=600
        #spark.worker.timeout=30000
```

```
        spark.eventLog.enabled=true
        spark.eventLog.dir=
        "hdfs://master.silvern.gao.cluster:8020/user/spark/applicationHistory"
      }

    }
  }

  giraph {
    #Overrides of normal Hadoop settings that are used when running Giraph jobs
    giraph.maxWorkers = 30
    //giraph.minWorkers = 1
    //giraph.SplitMasterWorker = true
    mapreduce.map.memory.mb = 4096
    mapreduce.map.java.opts = "-Xmx3072m"
    //giraph.zkIsExternal = false
  }


  titan {
    load {
      # documentation for these settings is available on Titan website
      # http://s3.thinkaurelius.com/docs/titan/current/titan-config-ref.html
      storage {

        # Whether to enable batch loading into the storage backend.
        # Set to true for bulk loads.
        //batch-loading = true

        # Size of the batch in which mutations are persisted.
        //buffer-size = 2048

        lock {
          # Number of milliseconds the system waits for a lock application
          # to be acknowledged by the storage backend.
          //wait-time = 400

          # Number of times the system attempts to acquire a lock before
          # giving up and throwing an exception.
          //retries = 15
        }

        hbase {
          # Pre-split settngs for large datasets
          //region-count = 12
          //compression-algorithm = "SNAPPY"
        }

        cassandra {
          # Cassandra configuration options
        }
      }

      ids {
        # Globally reserve graph element IDs in chunks of this size.
        # Setting this too low will make commits
        # frequently block on slow reservation requests.
        # Setting it too high will result in IDs wasted when a graph
```

```
    # instance shuts down with reserved but mostly-unused blocks.
    //block-size = 300000

    # Number of partition block to allocate for placement of vertices.
    //num-partitions = 10

    # The number of milliseconds that the Titan id pool manager will
    # wait before giving up on allocating a new block of ids.
    //renew-timeout = 150000

    # When true, vertices and edges are assigned IDs immediately upon
    # creation.
    # When false, IDs are assigned only when the transaction commits.
    # Must be disabled for graph partitioning to work.
    //flush = true

    authority {
      # This setting helps separate Titan instances sharing a single
      # graph storage backend avoid contention when reserving ID
      # blocks, increasing overall throughput.
      # The options available are:
      # NONE = Default in Titan
      # LOCAL_MANUAL = Expert feature: user manually assigns each
      # Titan instance a unique conflict avoidance tag in its local
      # graph configuration.
      # GLOBAL_MANUAL = User assigns a tag to each Titan instance.
      # The tags should be globally unique for optimal performance,
      # but duplicates will not compromise correctness
      # GLOBAL_AUTO = Titan randomly selects a tag from the space of
      # all possible tags when performing allocations.
      //conflict-avoidance-mode = "GLOBAL_AUTO"

      # The number of milliseconds the system waits for an ID block
      # reservation to be acknowledged by the storage backend.
      //wait-time = 300

      # Number of times the system attempts ID block reservations
      # with random conflict avoidance tags
      # before giving up and throwing an exception
      //randomized-conflict-avoidance-retries = 10
    }
  }

  auto-partitioner {
    hbase {
      # Number of regions per regionserver to set when creating
      # Titan/HBase table.
      regions-per-server = 2

      # Number of input splits for Titan reader is based on number of
      # available cores and minimum split size as follows: Number of
      # splits = Minimum(input-splits-per-spark-core * spark-cores,
      # graph size in HBase/minimum-input-splits-size-mb).
      input-splits-per-spark-core = 20
    }

    enable = true
  }
```

```
      }

      query {
        storage {
          # query does use the batch load settings in titan.load
          backend = ${trustedanalytics.atk.engine.titan.load.storage.backend}
          hostname =  ${trustedanalytics.atk.engine.titan.load.storage.hostname}
          port =  ${trustedanalytics.atk.engine.titan.load.storage.port}
        }
        cache {
          # Adjust cache size parameters if you experience OutOfMemory
          # errors during Titan queries.
          # Either increase heap allocation for TrustedAnalytics Engine, or
          # reduce db-cache-size.
          # Reducing db-cache will result in cache misses and increased
          # reads from disk.
          //db-cache = true
          //db-cache-clean-wait = 20
          //db-cache-time = 180000
          #Allocates 30% of available heap to Titan (default is 50%)
          //db-cache-size = 0.3
        }
      }
    }
  }
}
```

CHAPTER

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ERRATA

- Frame column name can accept unicode characters, but it should be avoided because some functions such as delete_column will fail.
- Renaming a graph to a name containing one or more of the special characters @#$%^&* will cause the application to hang for a long time and then raise an error.
- Attempting to create a frame with a parenthesis in the name will raise the error:

```
trustedanalytics.rest.command.CommandServerError: Job aborted due to
stage failure: Task 7.0:5 failed 4 times, most recent failure:
Exception failure in TID 426 on host node03.zonda.cluster:
java.lang.IllegalArgumentException: No enum constant parquet
.schema.OriginalType.
```

- Creating a table with an invalid source data file name causes the server to return an error message and abort, but also creates the empty (named) frame.
- When importing CSV data files to frames, small datasets may affect the number of lines skipped.

[R1] G. Palla, I. Derenyi, I. Farkas, and T. Vicsek. Uncovering the overlapping community structure of complex networks in nature and society. Nature, 435:814, 2005 (See http://hal.elte.hu/cfinder/wiki/papers/communitylettm.pdf)

[R2] Varamesh, A.; Akbari, M.K.; Fereiduni, M.; Sharifian, S.; Bagheri, A., "Distributed Clique Percolation based community detection on social networks using MapReduce," Information and Knowledge Technology (IKT), 2013 5th Conference on, vol., no., pp.478,483, 28-30 May 2013

Symbols

A

B

C

D

E

F

G

H

I

J

K

L

M

N

O

P

Q

R

S

T

U

V

X